```
!pip install numpy==1.26.4
!pip install scikit-learn-extra
```

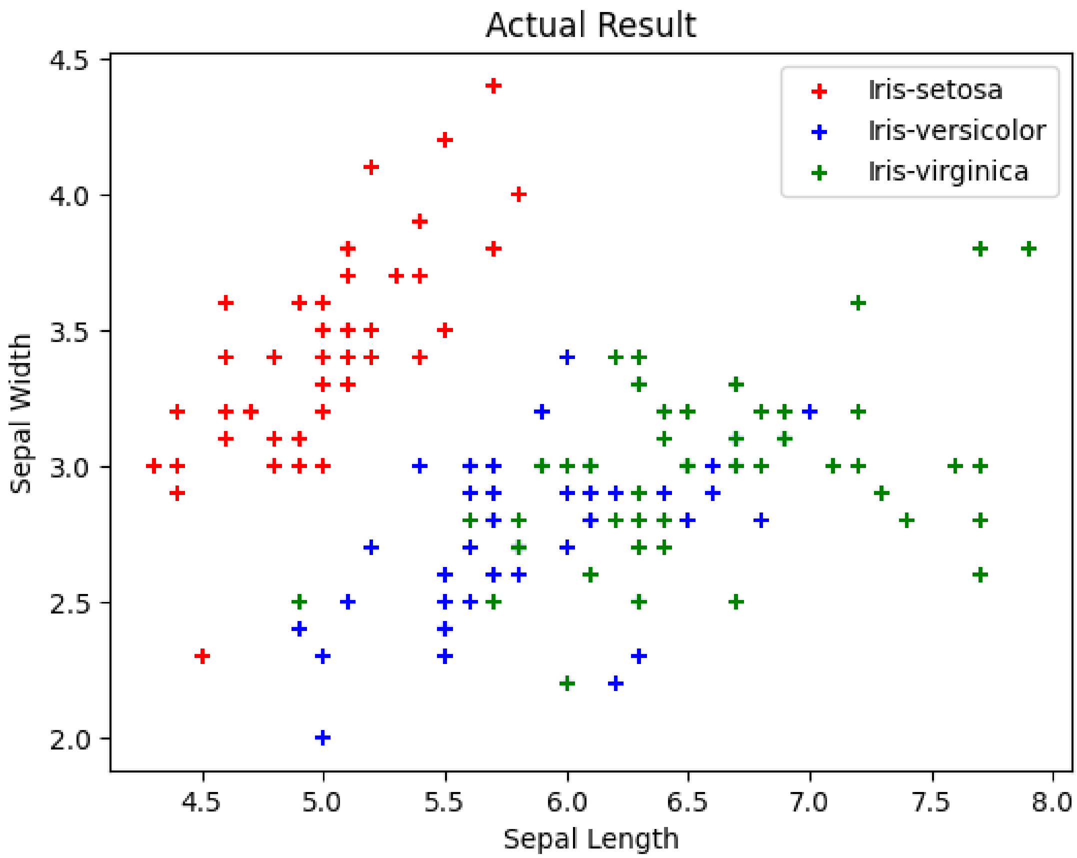
```
Requirement already satisfied: numpy==1.26.4 in
/usr/local/lib/python3.12/dist-packages (1.26.4)
Collecting scikit-learn-extra
  Using cached scikit-learn-extra-0.3.0.tar.gz (818 kB)
  Installing build dependencies ... ents to build wheel ... etadata
(pyproject.toml) ... ent already satisfied: numpy>=1.13.3 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn-extra)
(1.26.4)
Requirement already satisfied: scipy>=0.19.1 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn-extra)
(1.16.3)
Requirement already satisfied: scikit-learn>=0.23.0 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn-extra)
(1.6.1)
Requirement already satisfied: joblib>=1.2.0 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.23.0-
>scikit-learn-extra) (1.5.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.23.0-
>scikit-learn-extra) (3.6.0)
Building wheels for collected packages: scikit-learn-extra
  Building wheel for scikit-learn-extra (pyproject.toml) ...
e=scikit_learn_extra-0.3.0-cp312-cp312-linux_x86_64.whl size=2178125
sha256=ed6e0a19625be810860a21bd17d60c4984f826658dc9b09466e8c9765741a0f
1
  Stored in directory:
/root/.cache/pip/wheels/17/4d/c3/c6d5d563c1bf8146d059d63be3678abc2f280
1fba0aaf5f0b8
Successfully built scikit-learn-extra
Installing collected packages: scikit-learn-extra
Successfully installed scikit-learn-extra-0.3.0
```

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import silhouette_score,
calinski_harabasz_score,davies_bouldin_score
```

#Clustering in Iris Dataset

```
from sklearn.datasets import load_iris
import pandas as pd
import matplotlib.pyplot as plt

# Load iris dataset
iris = load_iris()
```

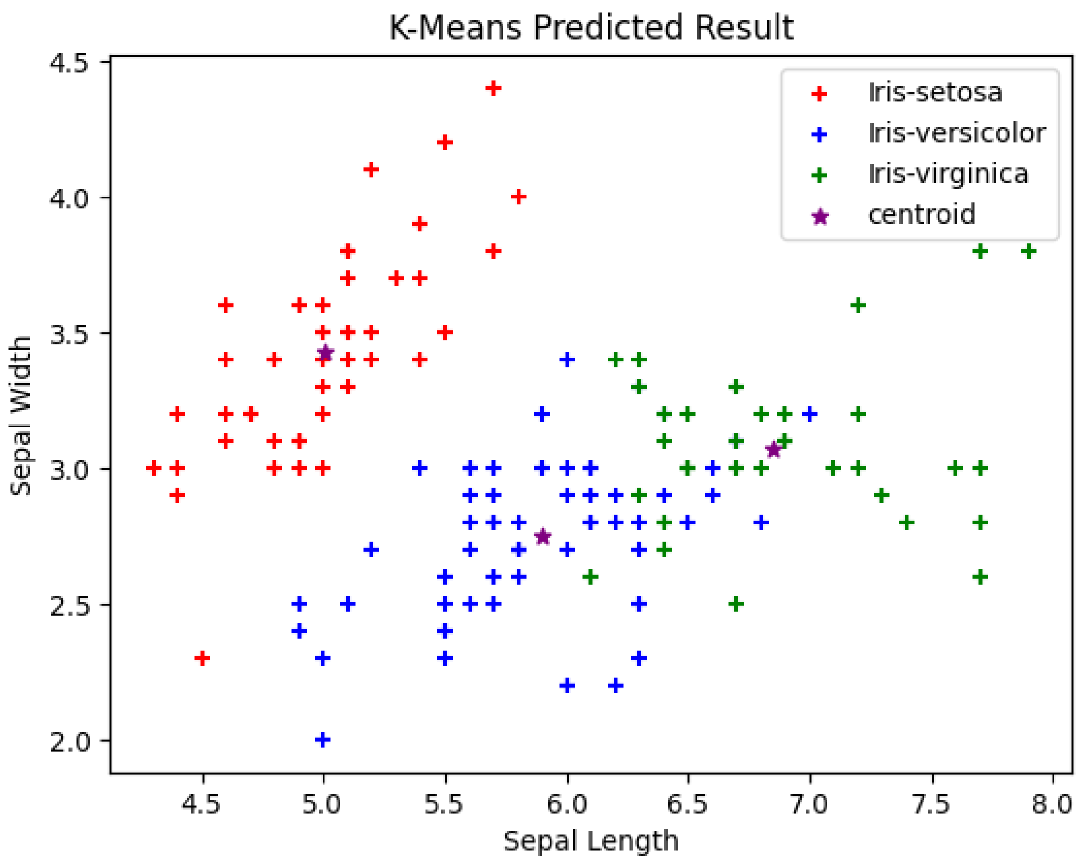
```python
df_iris = pd.DataFrame(iris.data, columns=iris.feature_names)
df_iris['species'] = [iris.target_names[i] for i in iris.target]

# Rename columns to match your plotting code
df_iris.columns = ['sepal_length', 'sepal_width', 'petal_length',
'petal_width', 'species']

# Prepare data
X = df_iris.drop('species', axis=1)
y = df_iris.species

# Actual Clustering Result
newDf0 = df_iris[df_iris.species == "setosa"]
newDf1 = df_iris[df_iris.species == "versicolor"]
newDf2 = df_iris[df_iris.species == "virginica"]

# Plot
plt.title("Actual Result")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(newDf0.sepal_length, newDf0.sepal_width, color="red",
marker="+", label="Iris-setosa")
plt.scatter(newDf1.sepal_length, newDf1.sepal_width, color="blue",
marker="+", label="Iris-versicolor")
plt.scatter(newDf2.sepal_length, newDf2.sepal_width, color="green",
marker="+", label="Iris-virginica")
plt.legend()

# □ This line displays the plot
plt.show()
```



#Partition Based: K-means Clustering in Iris Dataset

```
from sklearn.cluster import KMeans
km = KMeans(n_clusters=3, n_init=10)
y_predicted = km.fit_predict(X)
newDf = df_iris
newDf["cluster"] = y_predicted
newDf0 = newDf[newDf.cluster==0]
newDf1 = newDf[newDf.cluster==1]
newDf2 = newDf[newDf.cluster==2]
plt.title("K-Means Predicted Result")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(newDf0.sepal_length, newDf0.sepal_width, color="red",
marker="+", label="Iris-setosa")
plt.scatter(newDf1.sepal_length, newDf1.sepal_width, color="blue",
marker="+", label="Iris-versicolor")
plt.scatter(newDf2.sepal_length, newDf2.sepal_width, color="green",
marker="+", label="Iris-virginica")
plt.scatter(km.cluster_centers_[:,0], km.cluster_centers_[:,1],
color="purple", marker="*", label="centroid")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f37dbda0740>
```



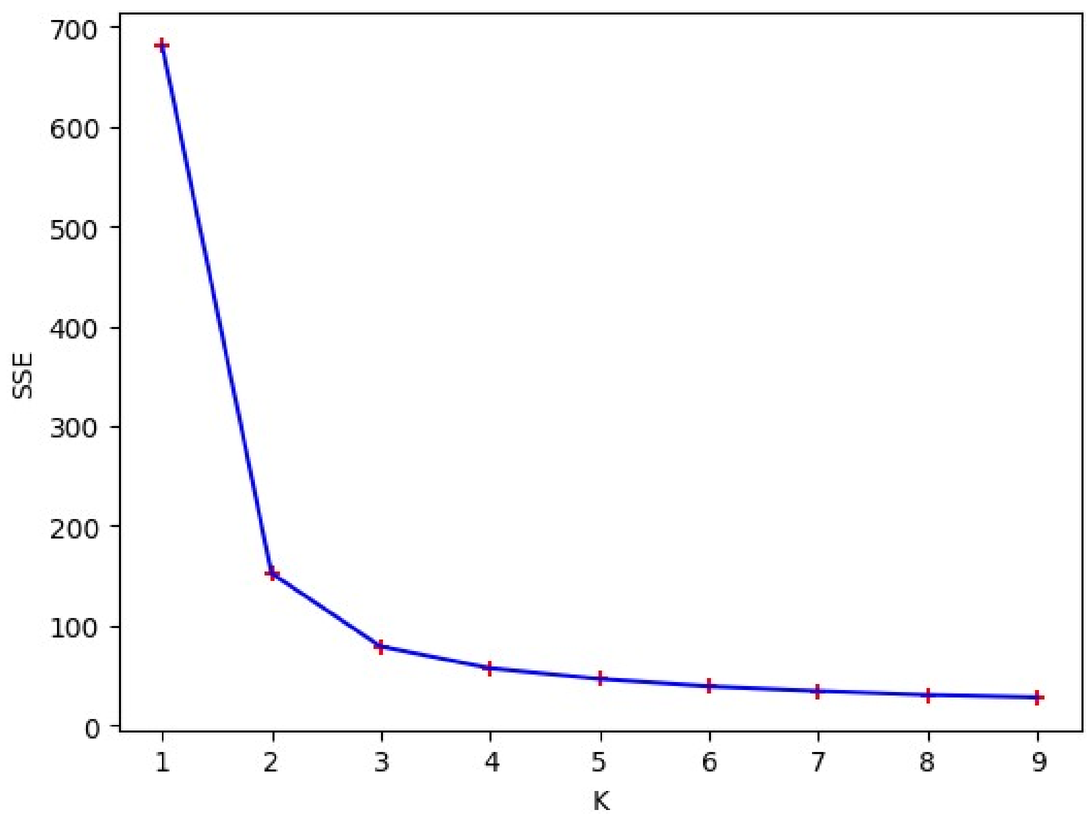

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score

# True labels
y_true = df_iris['species']

# Predicted cluster labels
y_pred = newDf['cluster']

# Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
```

```
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.8797
Adjusted Rand Index: 0.7302
Mutual Information: 0.8256
Adjusted Mutual Information: 0.7551
Normalized Mutual Information: 0.7582
```

```
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
```

```
[<matplotlib.lines.Line2D at 0x7f37d8de3b60>]
```



```
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion_scores}")
print(f"Separation Score: {separation}")
```

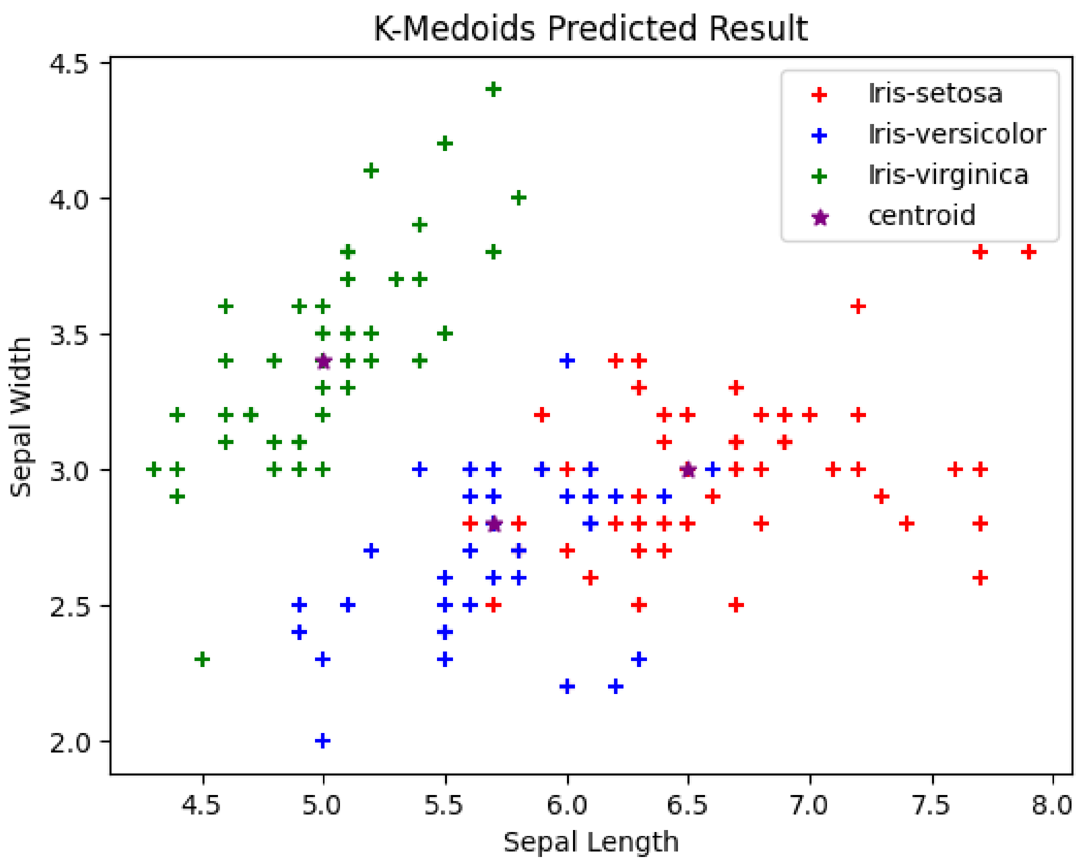
```
Silhouette Score:  0.34595488596099394
Calinski Harabasz Score:  413.4066203439807
Davies Bouldin Score:  0.9323507432928486

Cohesion Score: sepal_length    0.052216
sepal_width     0.055265
petal_length    0.049625
petal_width     0.028636
dtype: float64
Separation Score: 0.07008197767145138

/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is
deprecated, in a future version this will reduce over both axes and
return a scalar. To retain the old behavior, pass axis=0 (or do not
pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

#Partition Based: K-medoids Clustering in Iris Dataset

```
# Clustering using K-medoids algorithm
from sklearn_extra.cluster import KMedoids
km = KMedoids(n_clusters=3)
y_predicted = km.fit_predict(X)
newDf = df_iris
newDf["cluster"] = y_predicted
newDf0 = newDf[newDf.cluster==0]
newDf1 = newDf[newDf.cluster==1]
```

```
newDf2 = newDf[newDf.cluster==2]
plt.title("K-Medoids Predicted Result")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(newDf0.sepal_length, newDf0.sepal_width, color="red",
marker="+", label="Iris-setosa")
plt.scatter(newDf1.sepal_length, newDf1.sepal_width, color="blue",
marker="+", label="Iris-versicolor")
plt.scatter(newDf2.sepal_length, newDf2.sepal_width, color="green",
marker="+", label="Iris-virginica")
plt.scatter(km.cluster_centers_[:,0], km.cluster_centers_[:,1],
color="purple", marker="*", label="centroid")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f37dbbe8740>
```



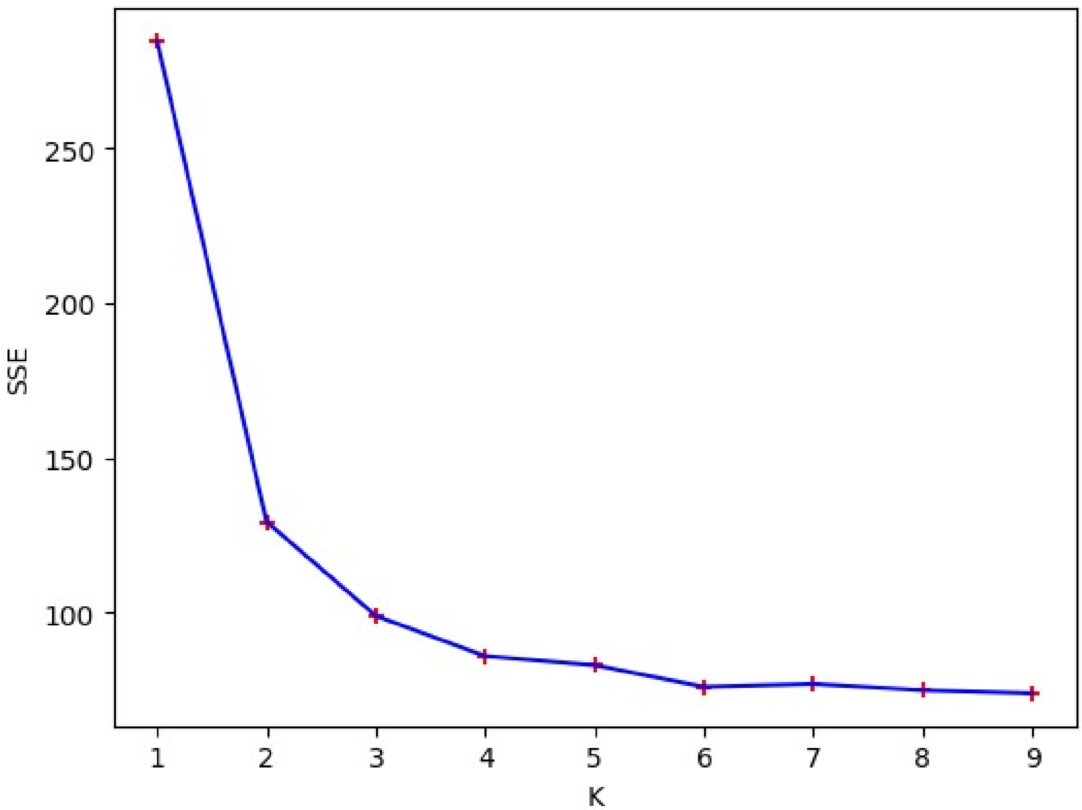

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score

# True labels
y_true = df_iris['species']
```

```python
# Predicted cluster labels
y_pred = newDf['cluster']

# Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.8923
Adjusted Rand Index: 0.7583
Mutual Information: 0.8555
Adjusted Mutual Information: 0.7830
Normalized Mutual Information: 0.7857
```

```python
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMedoids(n_clusters=k)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
```

```
[<matplotlib.lines.Line2D at 0x7f37d6478fe0>]
```




```
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

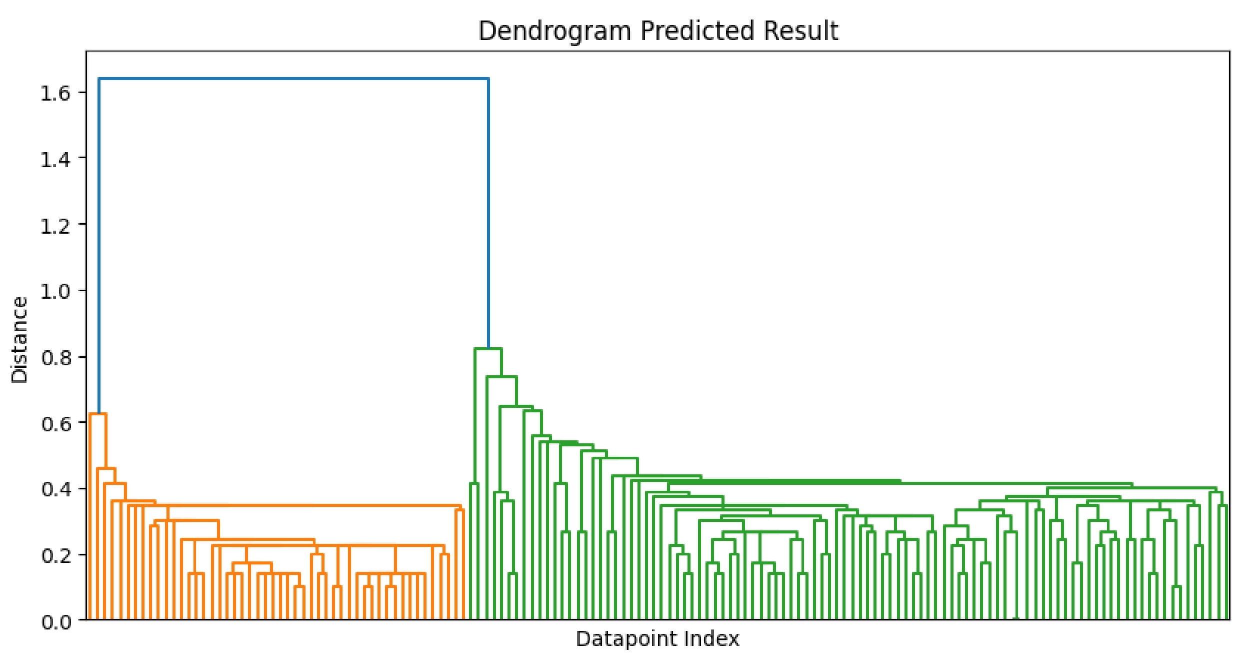
```
Silhouette Score:  0.37568265737828305
Calinski Harabasz Score:  237.92818231224678
Davies Bouldin Score:  1.1192653552269658
```

```
Cohesion Score: 0.08663333333333338
Separation Score: 0.06466666666666666
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is
deprecated, in a future version this will reduce over both axes and
return a scalar. To retain the old behavior, pass axis=0 (or do not
pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

#Hierarchical: Dendrogram Clustering in Iris Dataset

```
# Clustering using Dendrogram Clustering algorithm
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
Z = linkage(X, method='single')
# Create and plot the dendrogram
plt.figure(figsize=(10, 5))
dn = dendrogram(Z, no_labels=True)
plt.title('Dendrogram Predicted Result')
plt.xlabel('Datapoint Index')
plt.ylabel('Distance')
plt.show()
```




```
from scipy.cluster.hierarchy import fcluster
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score
```

```
# True labels (numeric)
y_true = df_iris['species']

# Cut the dendrogram to form 3 clusters
y_pred = fcluster(Z, t=3, criterion='maxclust')

# Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7766
Adjusted Rand Index: 0.5638
Mutual Information: 0.6459
Adjusted Mutual Information: 0.7126
Normalized Mutual Information: 0.7175
```

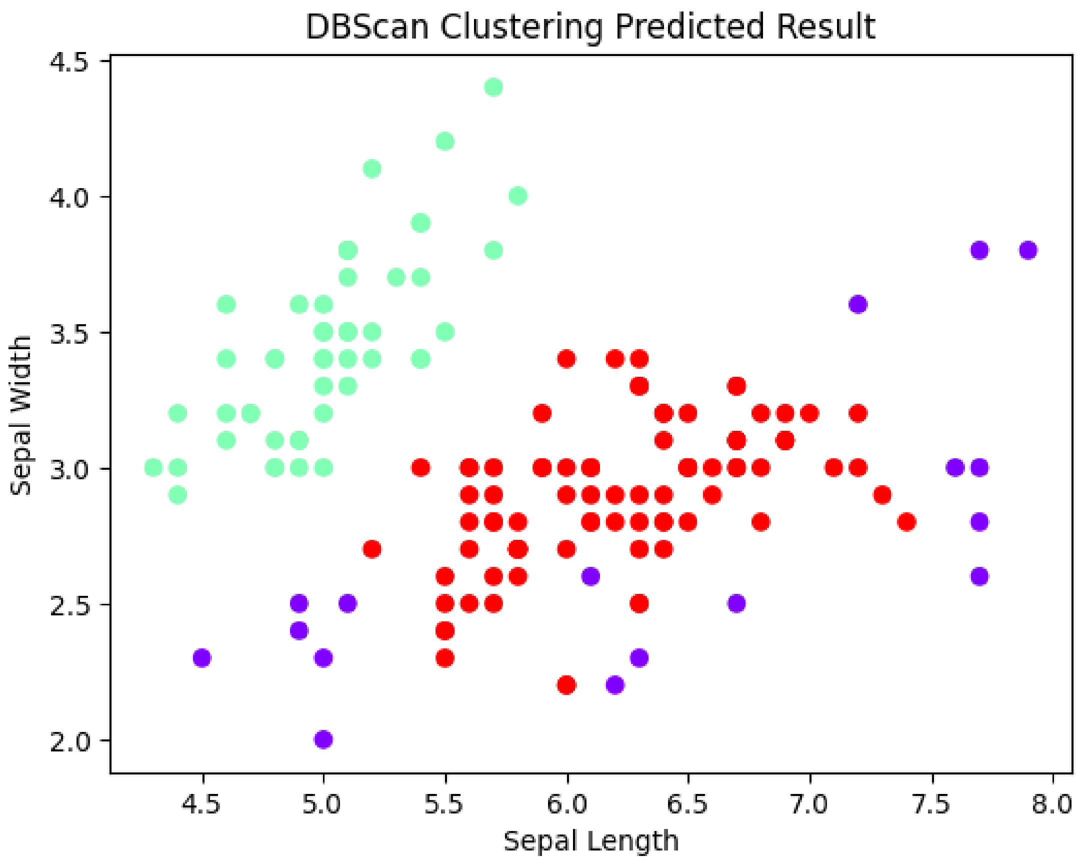
```
labels = fcluster(Z, 3, criterion='maxclust')
silhouette_result = silhouette_score(X, labels)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, labels)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, labels)
print("Davies Bouldin Score: ", davies_result)
```

```
Silhouette Score:  0.5121107753649307
Calinski Harabasz Score:  277.99467626461944
Davies Bouldin Score:  0.4471537628542408
```

#Density Based: DBSCAN Clustering in Iris Dataset

```
# Clustering using DBSCAN Clustering algorithm
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps=0.5, algorithm='auto', metric='euclidean')
y = dbscan.fit_predict(X)
plt.scatter(df_iris.sepal_length, df_iris.sepal_width,
c=dbscan.labels_, cmap='rainbow')
plt.xlabel('Sepal Length')
```

```
plt.ylabel('Sepal Width')
plt.title('DBScan Clustering Predicted Result')
plt.show()
```




```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score

# True labels
y_true = df_iris['species']

# Predicted cluster labels from DBSCAN
y_pred = dbscan.labels_

# If you want to ignore noise points (-1), you can filter them:
# mask = y_pred != -1
# y_true_filtered = y_true[mask]
# y_pred_filtered = y_pred[mask]

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)
```

```python
# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7719
Adjusted Rand Index: 0.5206
Mutual Information: 0.6152
Adjusted Mutual Information: 0.5990
Normalized Mutual Information: 0.6044
```

```python
y_pred
```

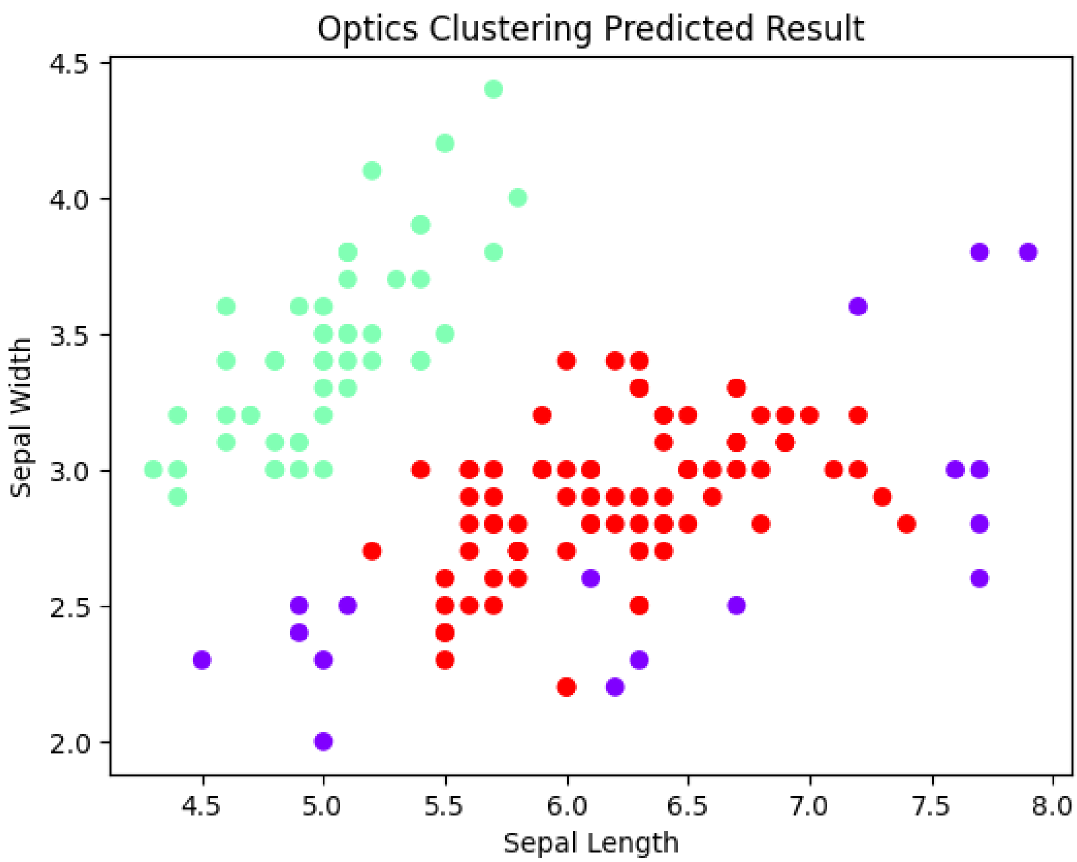
```
array([ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
0,
        0,  0,  0,  0,  0,  0,  0, -1,  0,  0,  0,  0,  0,  0,  0,  0,
1,
        1,  1,  1,  1,  1,  1, -1,  1,  1, -1,  1,  1,  1,  1,  1,  1,
1,
       -1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
1,
        1,  1, -1,  1,  1,  1,  1,  1, -1,  1,  1,  1,  1, -1,  1,  1,
1,
        1,  1,  1, -1, -1,  1, -1, -1,  1,  1,  1,  1,  1,  1,  1, -1,
-1,
        1,  1,  1, -1,  1,  1,  1,  1,  1,  1,  1,  1, -1,  1,  1, -1,
-1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1])
```

```python
# Evaluating Metrics
silhouette_result = silhouette_score(X, dbscan.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, dbscan.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, dbscan.labels_)
print("Davies Bouldin Score: ", davies_result)
```

```
Silhouette Score:  0.48603419703456857
Calinski Harabasz Score:  220.29751498443005
Davies Bouldin Score:  7.222448016359581
```

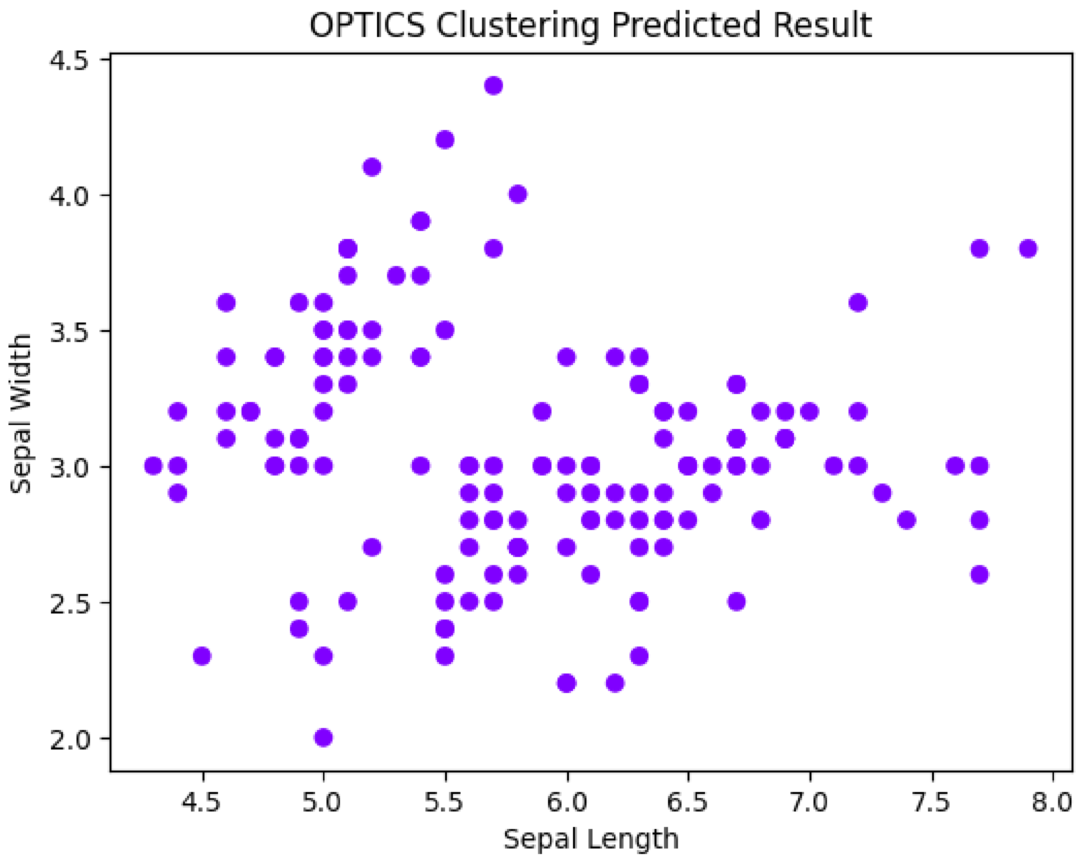
#Density Based: Optics Clustering in Iris Dataset

```python
# Clustering using Optics Clustering algorithm
from sklearn.cluster import OPTICS
optics_cluster = OPTICS(min_samples=5, xi=0.05,
cluster_method='dbscan')
optics_cluster.fit(X)
plt.scatter(df_iris.sepal_length, df_iris.sepal_width,
c=dbscan.labels_, cmap='rainbow')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('Optics Clustering Predicted Result')
plt.show()
```




```python
from sklearn.cluster import OPTICS
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score
import matplotlib.pyplot as plt

# Run OPTICS
optics_cluster = OPTICS(min_samples=5, xi=0.05,
cluster_method='dbscan')
y_pred = optics_cluster.fit_predict(X)  # predicted cluster labels
```

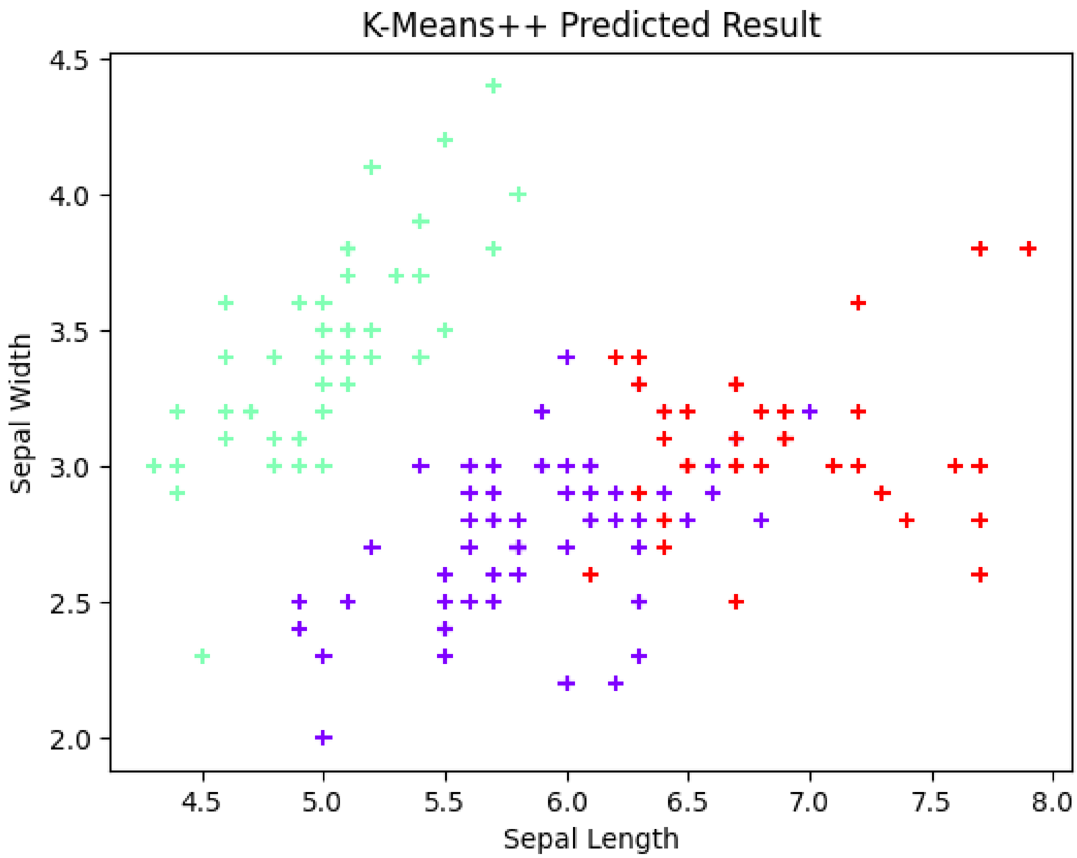
```python
# Plot clusters
plt.scatter(df_iris.sepal_length, df_iris.sepal_width, c=y_pred,
cmap='rainbow')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('OPTICS Clustering Predicted Result')
plt.show()

# True labels
y_true = df_iris['species']

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```




```
Rand Index: 0.3289
Adjusted Rand Index: 0.0000
Mutual Information: 0.0000
Adjusted Mutual Information: 0.0000
Normalized Mutual Information: 0.0000
```

#K-means++ Clustering in Iris Dataset

```
# Clustering using K-means++ algorithm
from sklearn.cluster import KMeans
km = KMeans(init='k-means++', n_clusters=3, n_init=10, max_iter=300,
random_state=42)
km = KMeans(n_clusters=3, n_init=10)
y_predicted = km.fit_predict(X)
plt.title("K-Means++ Predicted Result")
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.scatter(df_iris.sepal_length, df_iris.sepal_width, c=km.labels_,
cmap='rainbow', marker="+")
plt.show()
```



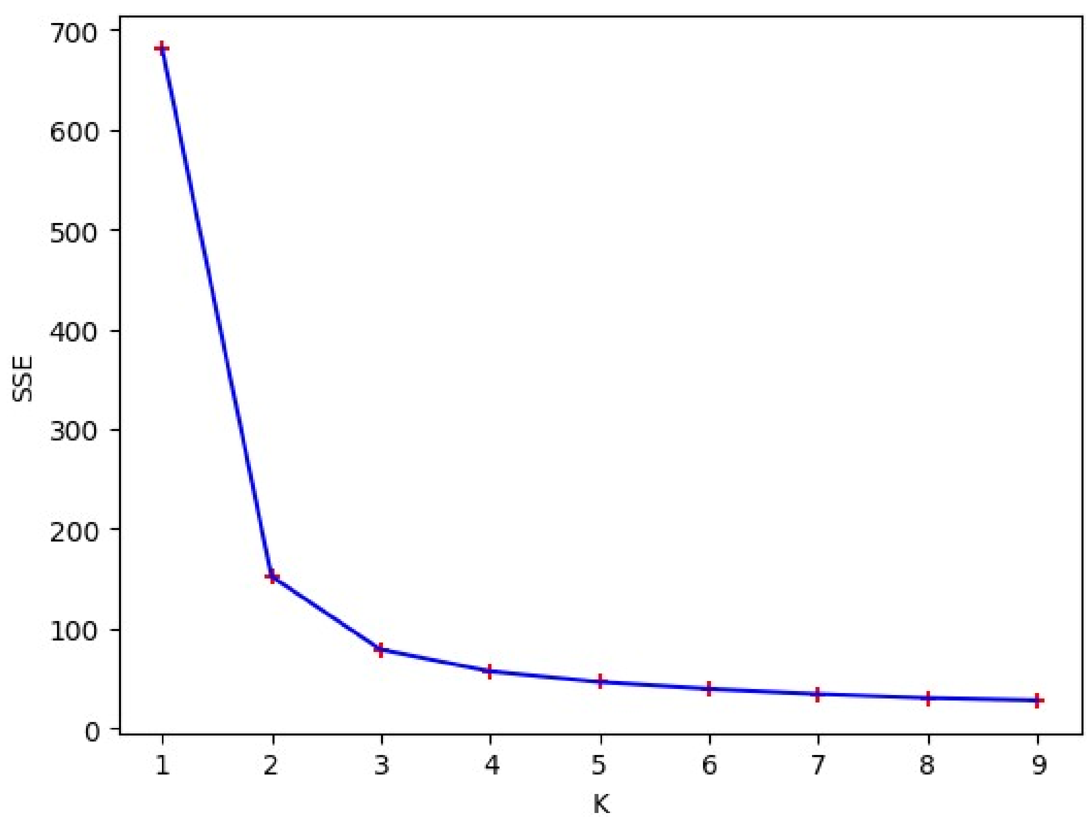

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score

# True labels
y_true = df_iris['species']

# Predicted cluster labels from K-Means++
y_pred = km.labels_  # or y_predicted

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
```

```
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.8797
Adjusted Rand Index: 0.7302
Mutual Information: 0.8256
Adjusted Mutual Information: 0.7551
Normalized Mutual Information: 0.7582
```

```
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

```
[<matplotlib.lines.Line2D at 0x7f37d64d2660>]
```



```
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

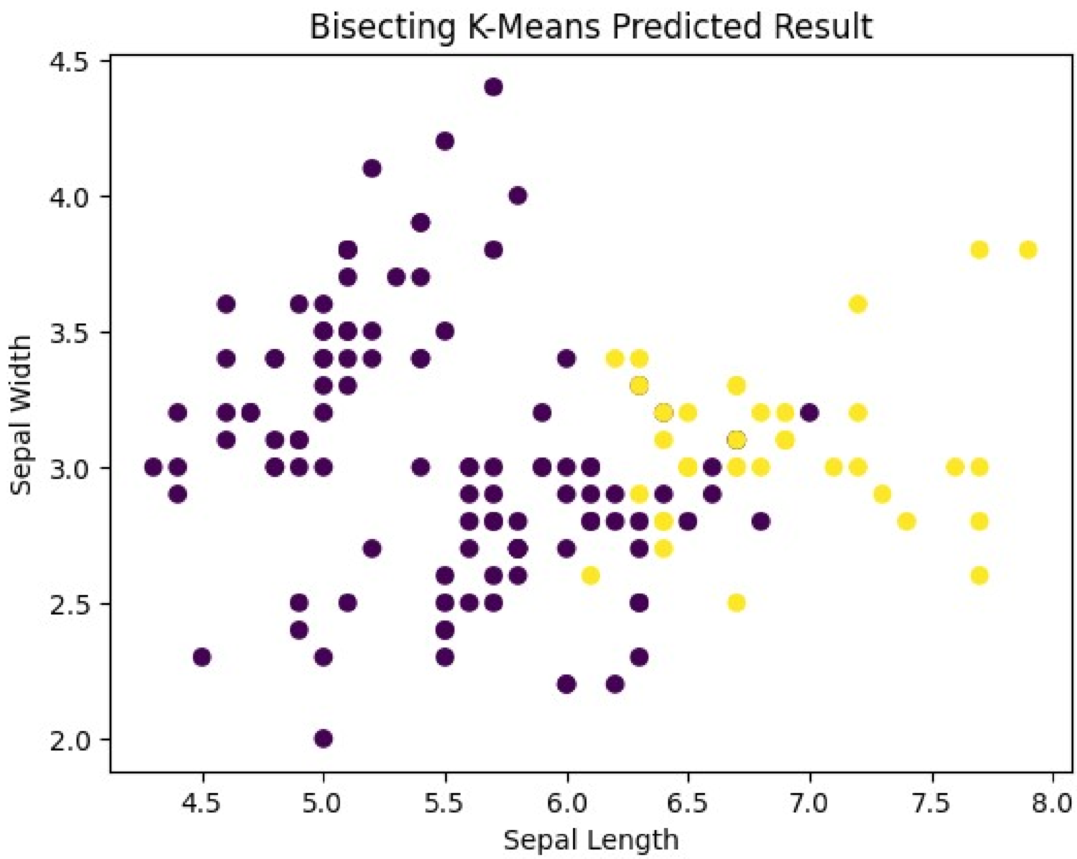
```
Silhouette Score:  0.3378546885898792
Calinski Harabasz Score:  411.52322749485984
Davies Bouldin Score:  0.9413635338364712

Cohesion Score: 0.04663950610221205
Separation Score: 0.06730188405797104
```

```
/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is
deprecated, in a future version this will reduce over both axes and
return a scalar. To retain the old behavior, pass axis=0 (or do not
pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

#Bisecting K-means Clustering in Iris Dataset

```
# Clustering using Bisecting K-means algorithm
from sklearn.cluster import KMeans
km = KMeans(n_clusters=1, n_init=10, random_state=0).fit(X)
K=3
for i in range(K-1):
 largest_cluster = np.argmax(np.bincount(km.labels_))
 largest_cluster_mask = (km.labels_ == largest_cluster)
 X_split = X[largest_cluster_mask]
 km.labels_[largest_cluster_mask] = KMeans(n_clusters=2, n_init=10,
random_state=0).fit(X_split).labels_
plt.title("Bisecting K-Means Predicted Result")
plt.xlabel("Sepal Length")
```

```
plt.ylabel("Sepal Width")
plt.scatter(df_iris.sepal_length, df_iris.sepal_width, c=km.labels_,
cmap='viridis')
plt.show()
```



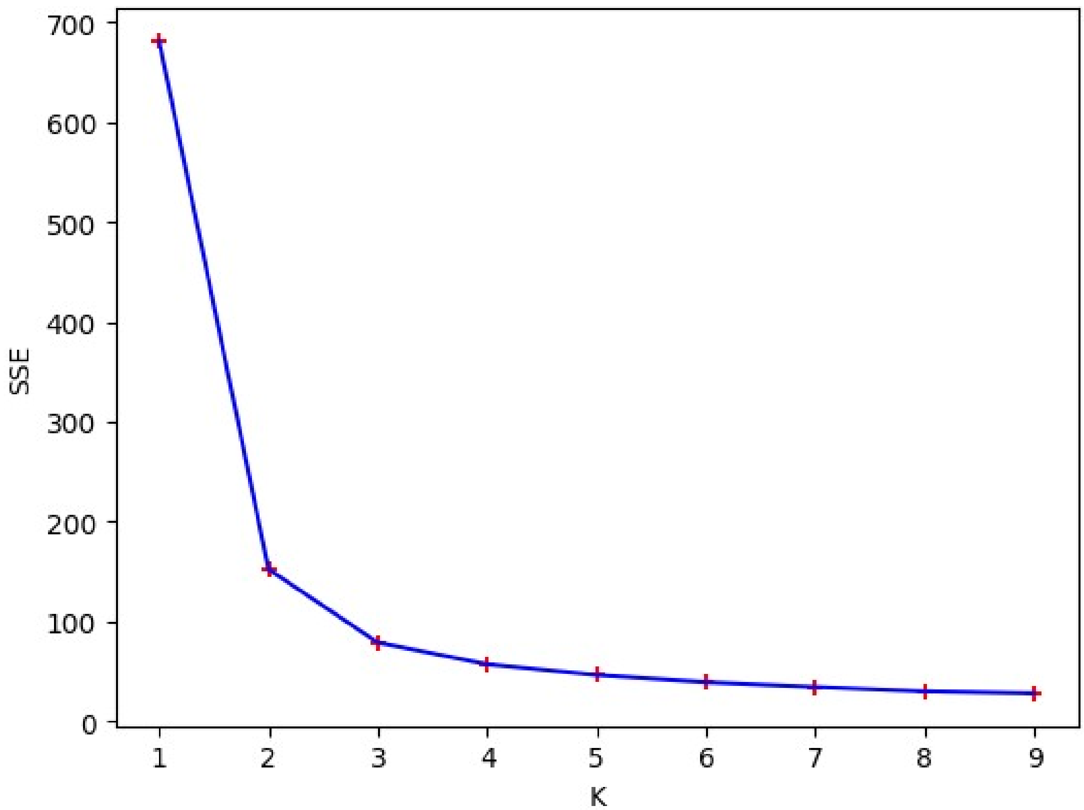

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score

# True labels
y_true = df_iris['species']

# Predicted cluster labels from Bisecting K-Means
y_pred = km.labels_

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)
```

```python
# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.6023
Adjusted Rand Index: 0.2646
Mutual Information: 0.3123
Adjusted Mutual Information: 0.3701
Normalized Mutual Information: 0.3753
```

```python
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

```
[<matplotlib.lines.Line2D at 0x7f37d61fbe00>]
```




```
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.32896717315538904
Calinski Harabasz Score:  411.03766427011516
Davies Bouldin Score:  0.9795798529492818
```

```
Cohesion Score: 0.046692336523125974
Separation Score: 0.06444795321637428

/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is
deprecated, in a future version this will reduce over both axes and
return a scalar. To retain the old behavior, pass axis=0 (or do not
pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

#WINE DATASET

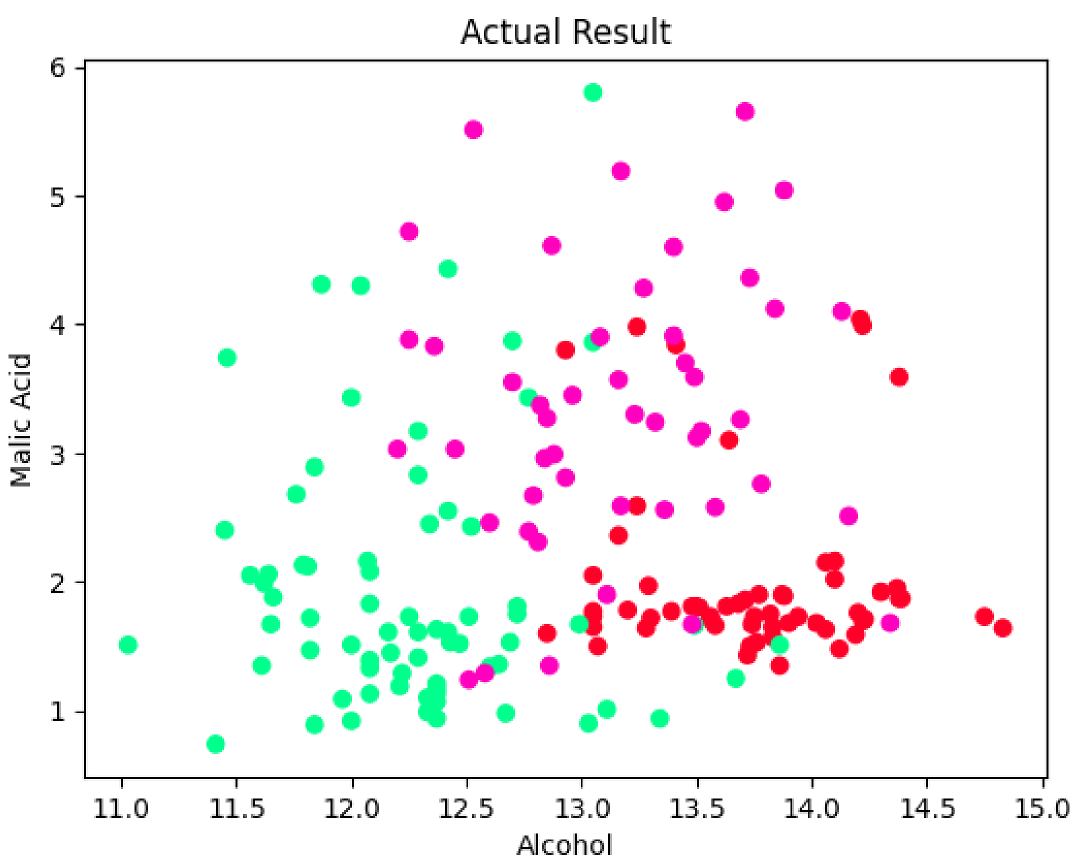
```
pip install ucimlrepo

Collecting ucimlrepo
  Downloading ucimlrepo-0.0.7-py3-none-any.whl.metadata (5.5 kB)
Requirement already satisfied: pandas>=1.0.0 in
/usr/local/lib/python3.12/dist-packages (from ucimlrepo) (2.2.2)
Requirement already satisfied: certifi>=2020.12.5 in
/usr/local/lib/python3.12/dist-packages (from ucimlrepo) (2025.10.5)
Requirement already satisfied: numpy>=1.26.0 in
/usr/local/lib/python3.12/dist-packages (from pandas>=1.0.0-
>ucimlrepo) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.12/dist-packages (from pandas>=1.0.0-
>ucimlrepo) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.12/dist-packages (from pandas>=1.0.0-
>ucimlrepo) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.12/dist-packages (from pandas>=1.0.0-
>ucimlrepo) (2025.2)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.12/dist-packages (from python-dateutil>=2.8.2-
>pandas>=1.0.0->ucimlrepo) (1.17.0)
Downloading ucimlrepo-0.0.7-py3-none-any.whl (8.0 kB)
Installing collected packages: ucimlrepo
Successfully installed ucimlrepo-0.0.7

from ucimlrepo import fetch_ucirepo

# fetch dataset
wine = fetch_ucirepo(id=109)

# data (as pandas dataframes)
X = wine.data.features
y = wine.data.targets

# metadata
```

```
print(wine.metadata)

# variable information
print(wine.variables)
df = X.copy()
df['class'] = y  # add target column
print(df.head())
```


```
{'uci_id': 109, 'name': 'Wine', 'repository_url':
'https://archive.ics.uci.edu/dataset/109/wine', 'data_url':
'https://archive.ics.uci.edu/static/public/109/data.csv', 'abstract':
'Using chemical analysis to determine the origin of wines', 'area':
'Physics and Chemistry', 'tasks': ['Classification'],
'characteristics': ['Tabular'], 'num_instances': 178, 'num_features':
13, 'feature_types': ['Integer', 'Real'], 'demographics': [],
'target_col': ['class'], 'index_col': None, 'has_missing_values':
'no', 'missing_values_symbol': None, 'year_of_dataset_creation': 1992,
'last_updated': 'Mon Aug 28 2023', 'dataset_doi': '10.24432/C5PC7J',
'creators': ['Stefan Aeberhard', 'M. Forina'], 'intro_paper': {'ID':
246, 'type': 'NATIVE', 'title': 'Comparative analysis of statistical
pattern recognition methods in high dimensional settings', 'authors':
'S. Aeberhard, D. Coomans, O. Vel', 'venue': 'Pattern Recognition',
'year': 1994, 'journal': None, 'DOI': '10.1016/0031-3203(94)90145-7',
'URL':
'https://www.semanticscholar.org/paper/83dc3e4030d7b9fbdbb4bde03ce12ab
70ca10528', 'sha': None, 'corpus': None, 'arxiv': None, 'mag': None,
'acl': None, 'pmid': None, 'pmcid': None}, 'additional_info':
{'summary': 'These data are the results of a chemical analysis of
wines grown in the same region in Italy but derived from three
different cultivars. The analysis determined the quantities of 13
constituents found in each of the three types of wines. \r\n\r\nI
think that the initial data set had around 30 variables, but for some
reason I only have the 13 dimensional version. I had a list of what
the 30 or so variables were, but a.)  I lost it, and b.), I would not
know which 13 variables are included in the set.\r\n\r\nThe attributes
are (dontated by Riccardo Leardi, riclea@anchem.unige.it )\r\n1)
Alcohol\r\n2) Malic acid\r\n3) Ash\r\n4) Alcalinity of ash  \r\n5)
Magnesium\r\n6) Total phenols\r\n7) Flavanoids\r\n8) Nonflavanoid
phenols\r\n9) Proanthocyanins\r\n10)Color intensity\r\n11)Hue\r\
n12)OD280/OD315 of diluted wines\r\n13)Proline \r\n\r\nIn a
classification context, this is a well posed problem with "well
behaved" class structures. A good data set for first testing of a new
classifier, but not very challenging.           ', 'purpose': 'test',
'funded_by': None, 'instances_represent': None,
'recommended_data_splits': None, 'sensitive_data': None,
'preprocessing_description': None, 'variable_info': 'All attributes
are continuous\r\n\t\r\nNo statistics available, but suggest to
standardise variables for certain uses (e.g. for us with classifiers
which are NOT scale invariant)\r\n\r\nNOTE: 1st attribute is class
```

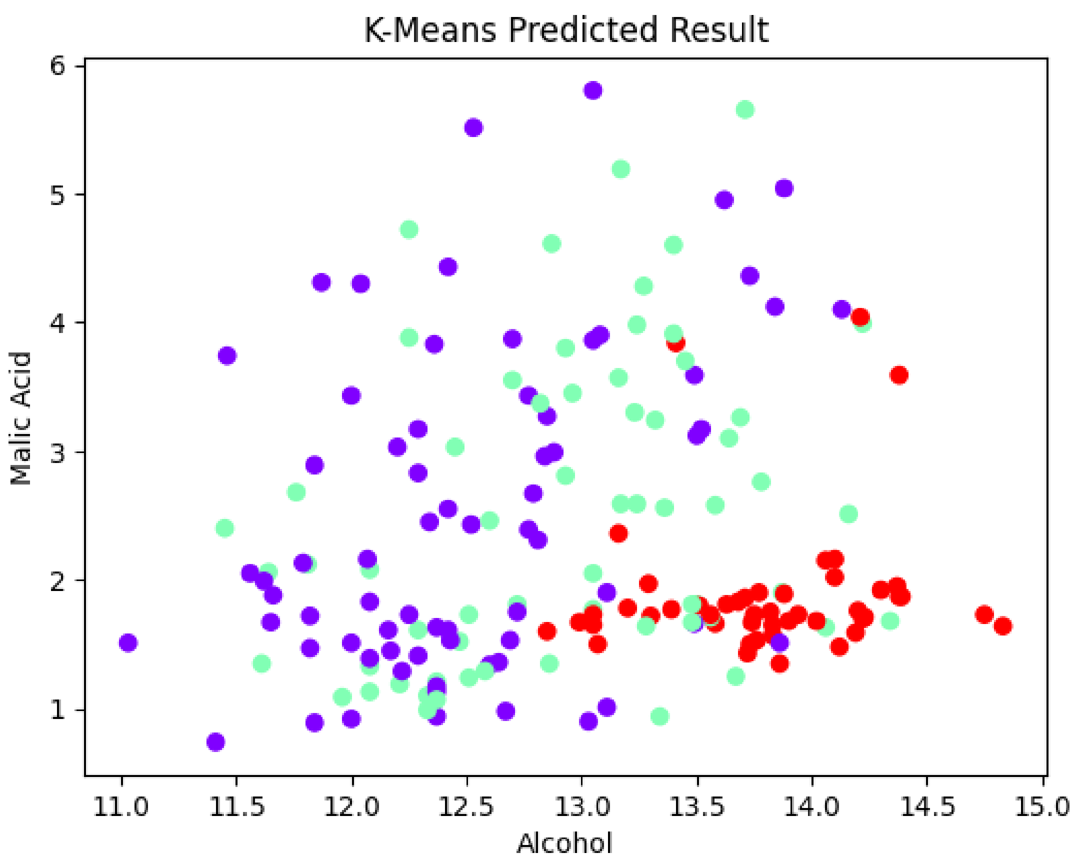
```
identifier (1-3)', 'citation': None}}
                             name     role         type demographic  \
0                           class   Target  Categorical        None   
1                         Alcohol  Feature   Continuous        None   
2                       Malicacid  Feature   Continuous        None   
3                             Ash  Feature   Continuous        None   
4               Alcalinity_of_ash  Feature   Continuous        None   
5                       Magnesium  Feature      Integer        None   
6                   Total_phenols  Feature   Continuous        None   
7                      Flavanoids  Feature   Continuous        None   
8            Nonflavanoid_phenols  Feature   Continuous        None   
9                 Proanthocyanins  Feature   Continuous        None   
10                Color_intensity  Feature   Continuous        None   
11                            Hue  Feature   Continuous        None   
12   0D280_0D315_of_diluted_wines  Feature   Continuous        None   
13                        Proline  Feature      Integer        None   

   description units missing_values  
0         None  None             no  
1         None  None             no  
2         None  None             no  
3         None  None             no  
4         None  None             no  
5         None  None             no  
6         None  None             no  
7         None  None             no  
8         None  None             no  
9         None  None             no  
10        None  None             no  
11        None  None             no  
12        None  None             no  
13        None  None             no  
   Alcohol  Malicacid   Ash  Alcalinity_of_ash  Magnesium
Total_phenols  \
0    14.23       1.71  2.43               15.6        127
2.80   
1    13.20       1.78  2.14               11.2        100
2.65   
2    13.16       2.36  2.67               18.6        101
2.80   
3    14.37       1.95  2.50               16.8        113
3.85   
4    13.24       2.59  2.87               21.0        118
2.80   

   Flavanoids  Nonflavanoid_phenols  Proanthocyanins  Color_intensity
Hue  \
0        3.06                  0.28             2.29             5.64
1.04   
```

```
1        2.76                     0.26             1.28             4.38
1.05
2        3.24                     0.30             2.81             5.68
1.03
3        3.49                     0.24             2.18             7.80
0.86
4        2.69                     0.39             1.82             4.32
1.04

   OD280_OD315_of_diluted_wines  Proline  class
0                          3.92     1065      1
1                          3.40     1050      1
2                          3.17     1185      1
3                          3.45     1480      1
4                          2.93      735      1

plt.title("Actual Result")
plt.xlabel('Alcohol')
plt.ylabel('Malic Acid')
plt.scatter(df.Alcohol, df.Malicacid, c=df["class"],
cmap='gist_rainbow')

<matplotlib.collections.PathCollection at 0x7f37d6088b60>
```



#Partition Based: K-means Clustering in Wine Dataset

```
# Clustering using K-means algorithm
from sklearn.cluster import KMeans
km = KMeans(init="random", n_clusters=3, n_init=10, max_iter=300,
random_state=42)
y_predicted = km.fit_predict(X)
plt.title("K-Means Predicted Result")
plt.xlabel("Alcohol")
plt.ylabel("Malic Acid")
plt.scatter(df.Alcohol, df.Malicacid, c=km.labels_, cmap='rainbow')
plt.show()
```



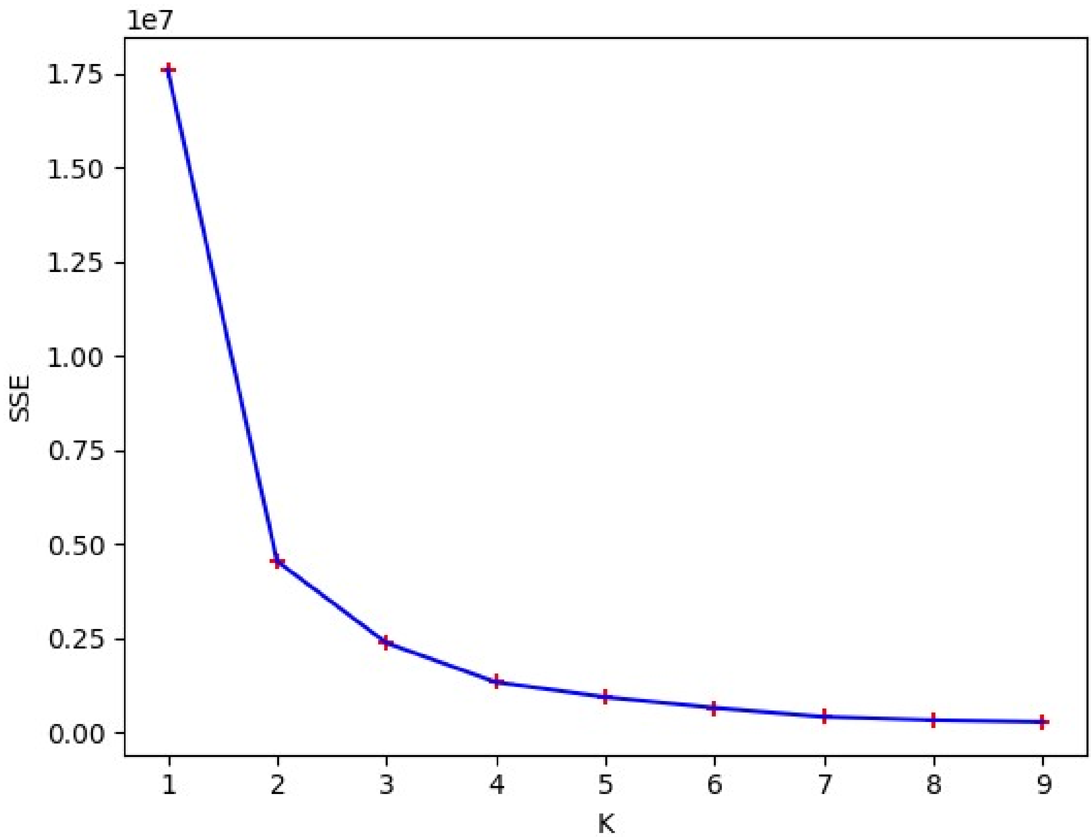

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score

# True labels (numeric for Wine dataset)
y_true = df['class']

# Predicted cluster labels from K-Means
y_pred = km.labels_  # or y_predicted
```

```python
# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7187
Adjusted Rand Index: 0.3711
Mutual Information: 0.4657
Adjusted Mutual Information: 0.4227
Normalized Mutual Information: 0.4288
```

```python
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

```
[<matplotlib.lines.Line2D at 0x7f37d62f9d90>]
```



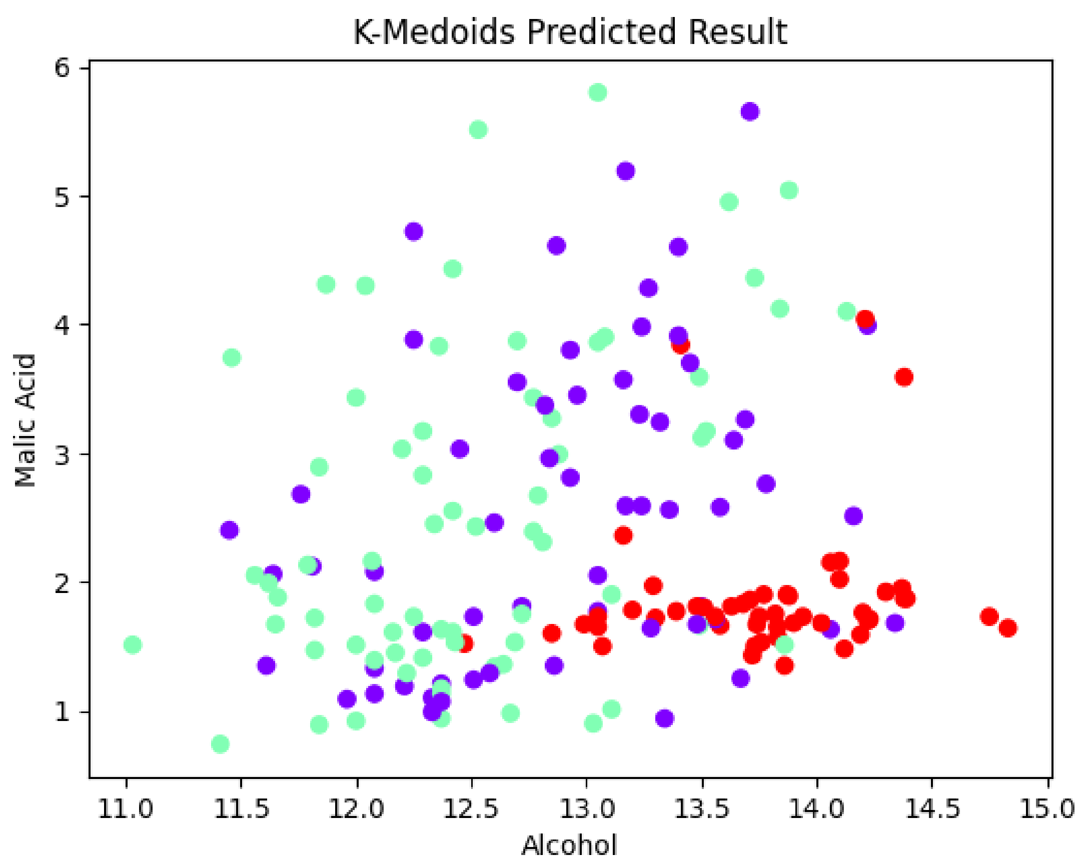

```
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.5239463119014728
Calinski Harabasz Score:  1340.0671272004263
```

```
Davies Bouldin Score:  0.5257452806465699

Cohesion Score: 117.98762726768221
Separation Score: 497.82895932885464

/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is
deprecated, in a future version this will reduce over both axes and
return a scalar. To retain the old behavior, pass axis=0 (or do not
pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

#Partition Based: K-medoids Clustering in Wine Dataset

```python
# Clustering using K-medoids algorithm
from sklearn_extra.cluster import KMedoids
km = KMedoids(n_clusters=3)
y_predicted = km.fit_predict(X)
plt.title("K-Medoids Predicted Result")
plt.xlabel("Alcohol")
plt.ylabel("Malic Acid")
plt.scatter(df.Alcohol, df.Malicacid, c=km.labels_, cmap='rainbow')
plt.show()
```

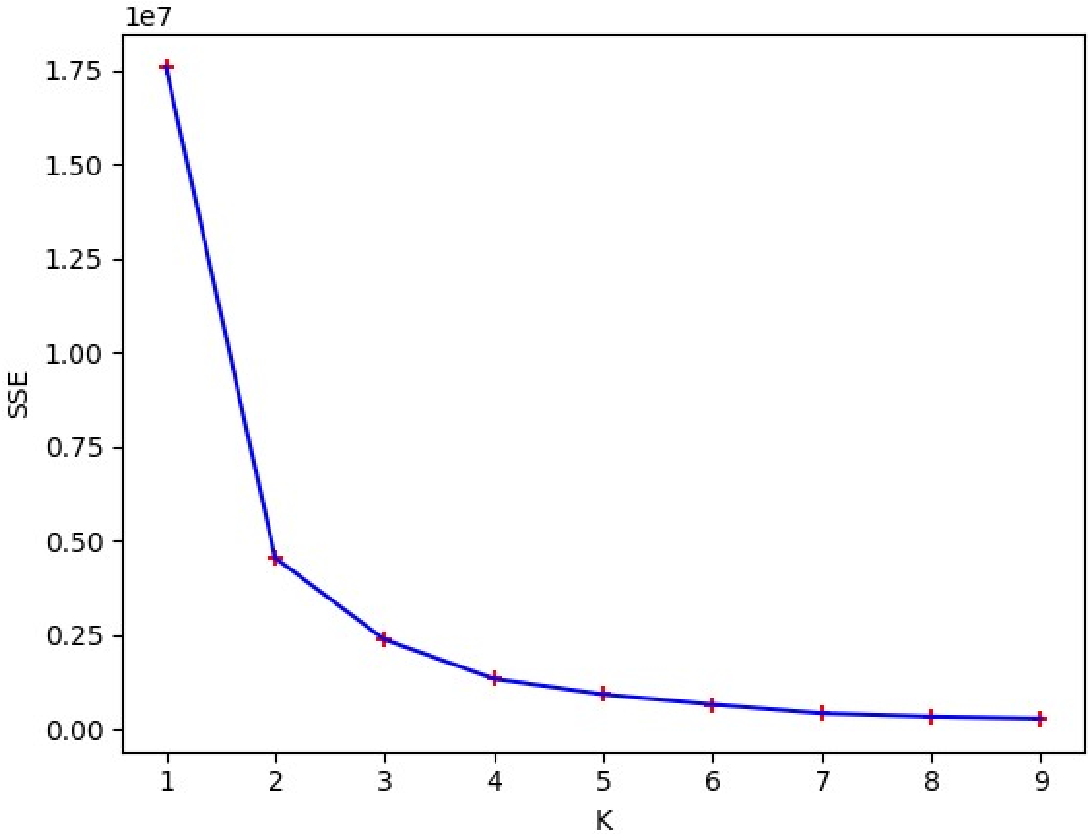


```python
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score

# True labels (numeric)
y_true = df['class']

# Predicted cluster labels from K-Medoids
y_pred = km.labels_  # or y_predicted

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7295
Adjusted Rand Index: 0.3941
Mutual Information: 0.4737
Adjusted Mutual Information: 0.4292
Normalized Mutual Information: 0.4352
```

```python
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

```
[<matplotlib.lines.Line2D at 0x7f37d6479700>]
```



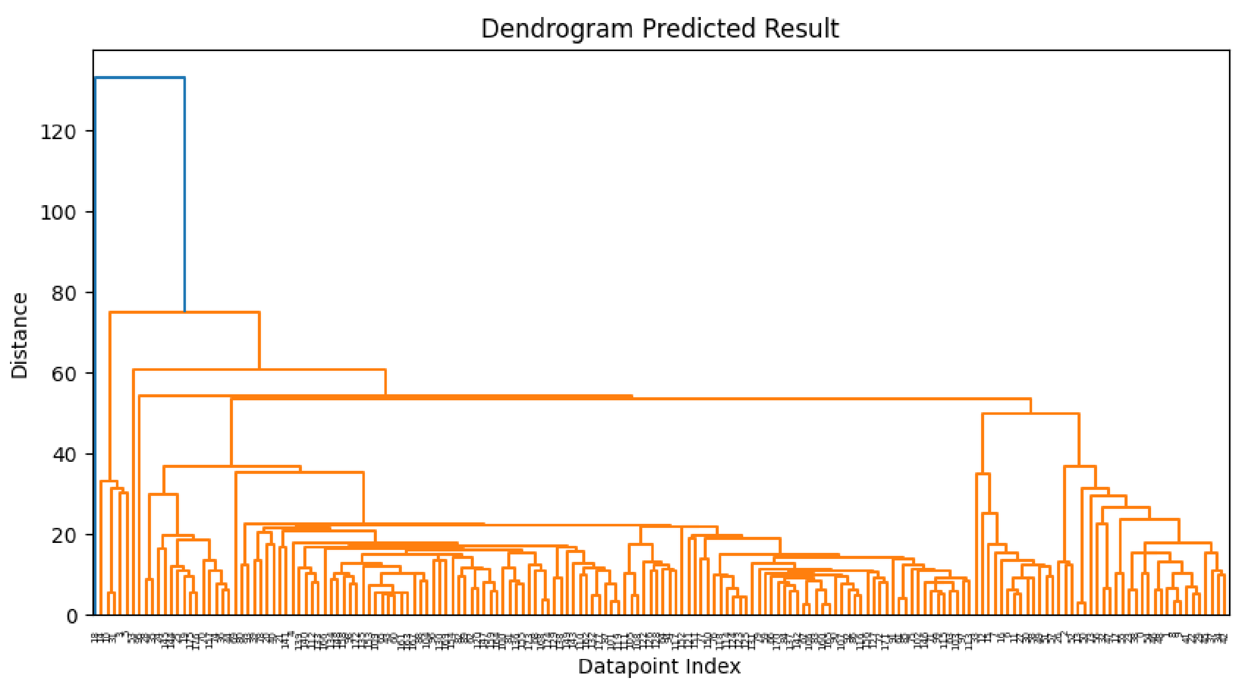

```python
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.527941546551372
Calinski Harabasz Score:  1354.516032526727
```

```
Davies Bouldin Score:  0.5307163453404704

Cohesion Score: 116.74835625456451
Separation Score: 578.7648547517636

/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is
deprecated, in a future version this will reduce over both axes and
return a scalar. To retain the old behavior, pass axis=0 (or do not
pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

#Hierarchical: Dendrogram Clustering in Wine Dataset

```python
# Clustering using Dendrogram Clustering algorithm
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
Z = linkage(X, method='single')
# Create and plot the dendrogram
plt.figure(figsize=(10, 5))
dn = dendrogram(Z)
plt.title('Dendrogram Predicted Result')
plt.xlabel('Datapoint Index')
plt.ylabel('Distance')
plt.show()
```



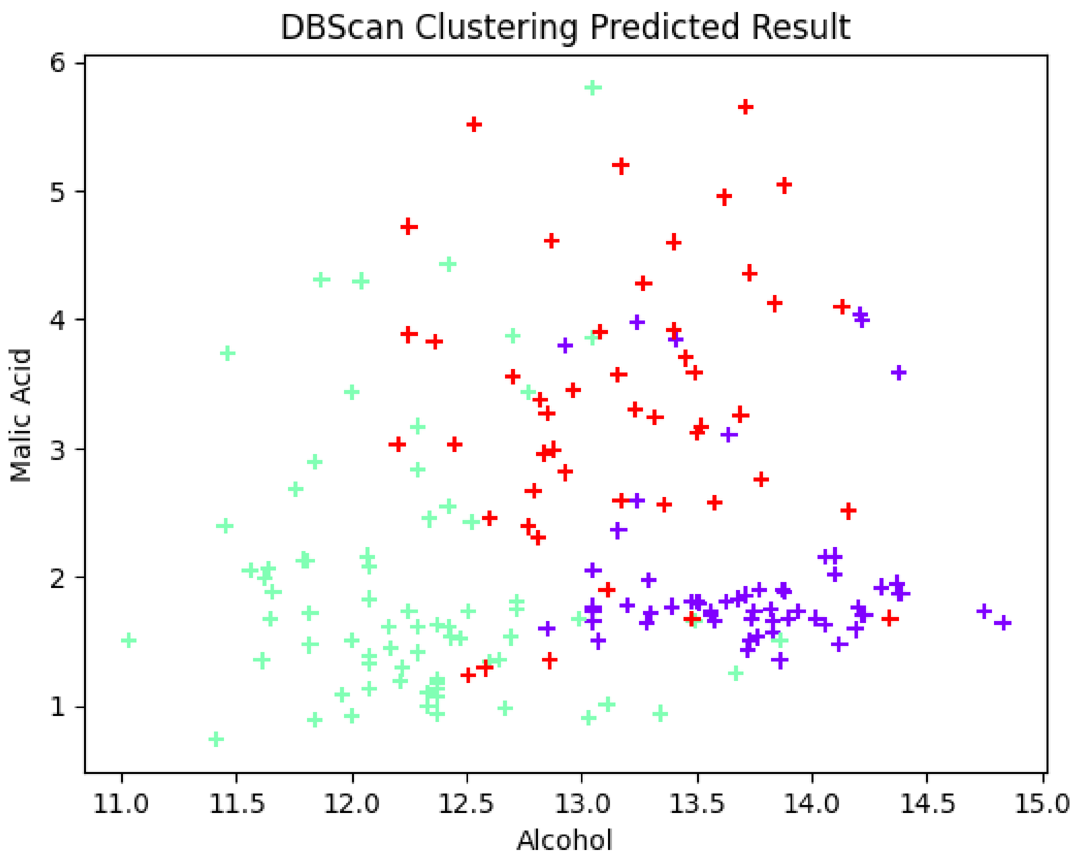

```python
from scipy.cluster.hierarchy import fcluster
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
```

```
adjusted_mutual_info_score, normalized_mutual_info_score

# Cut dendrogram to form 3 clusters
y_pred = fcluster(Z, t=3, criterion='maxclust')

# True labels (numeric)
y_true = df['class']

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")

Rand Index: 0.3628
Adjusted Rand Index: 0.0054
Mutual Information: 0.0384
Adjusted Mutual Information: 0.0416
Normalized Mutual Information: 0.0615

# Evaluating Metrics
labels = fcluster(Z, 3, criterion='maxclust')
from sklearn.metrics import silhouette_score
silhouette_result = silhouette_score(X, labels)
print("Silhouette Score: ", silhouette_result)
from sklearn.metrics import calinski_harabasz_score
calinski_result = calinski_harabasz_score(X, labels)
print("Calinski Harabasz Score: ", calinski_result)
from sklearn.metrics import davies_bouldin_score
davies_result = davies_bouldin_score(X, labels)
print("Davies Bouldin Score: ", davies_result)

Silhouette Score:  0.4879820335189063
Calinski Harabasz Score:  24.42036238154286
Davies Bouldin Score:  0.30814096183494405
```

#Density Based: DBSCAN Clustering in Wine Dataset

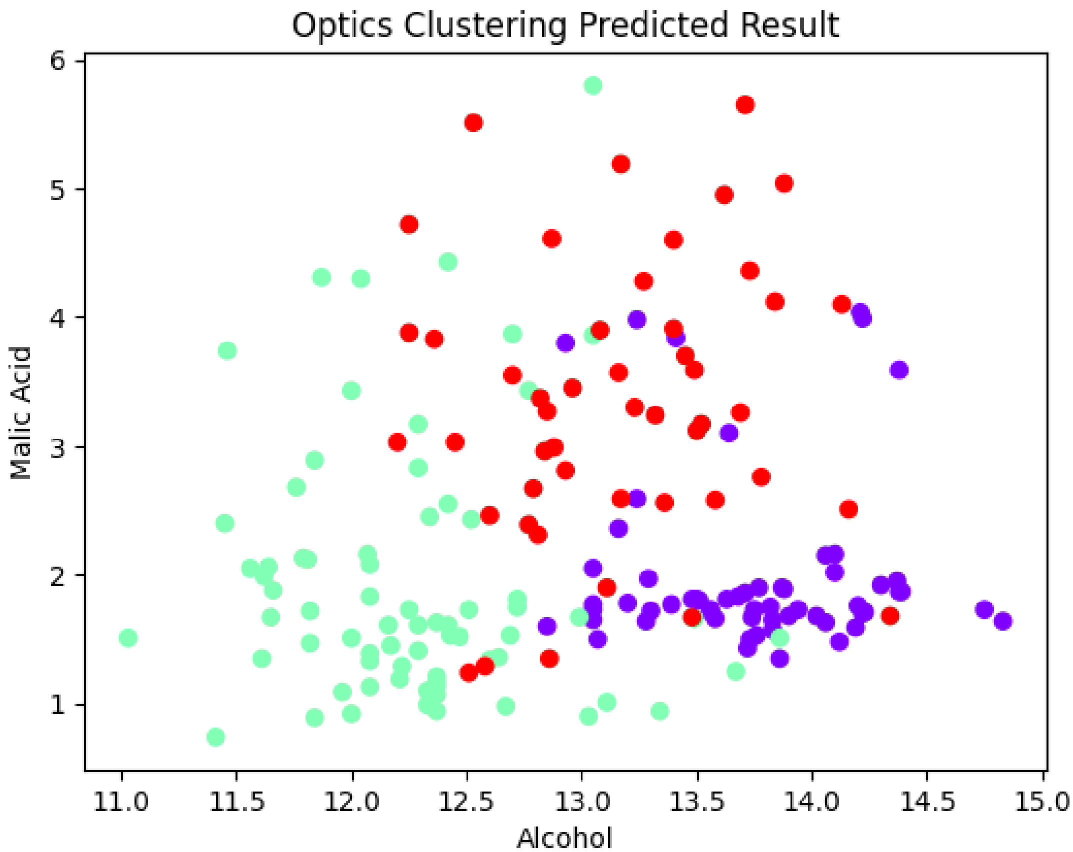
```
# Clustering using DBSCAN Clustering algorithm
from sklearn.cluster import DBSCAN
```

```
dbscan = DBSCAN(eps=0.5, algorithm='auto', metric='euclidean')
y = dbscan.fit_predict(X)
plt.title('DBScan Clustering Predicted Result')
plt.xlabel('Alcohol')
plt.ylabel('Malic Acid')
plt.scatter(df.Alcohol, df.Malicacid, c=df["class"], cmap='rainbow',
marker="+")
plt.show()
```



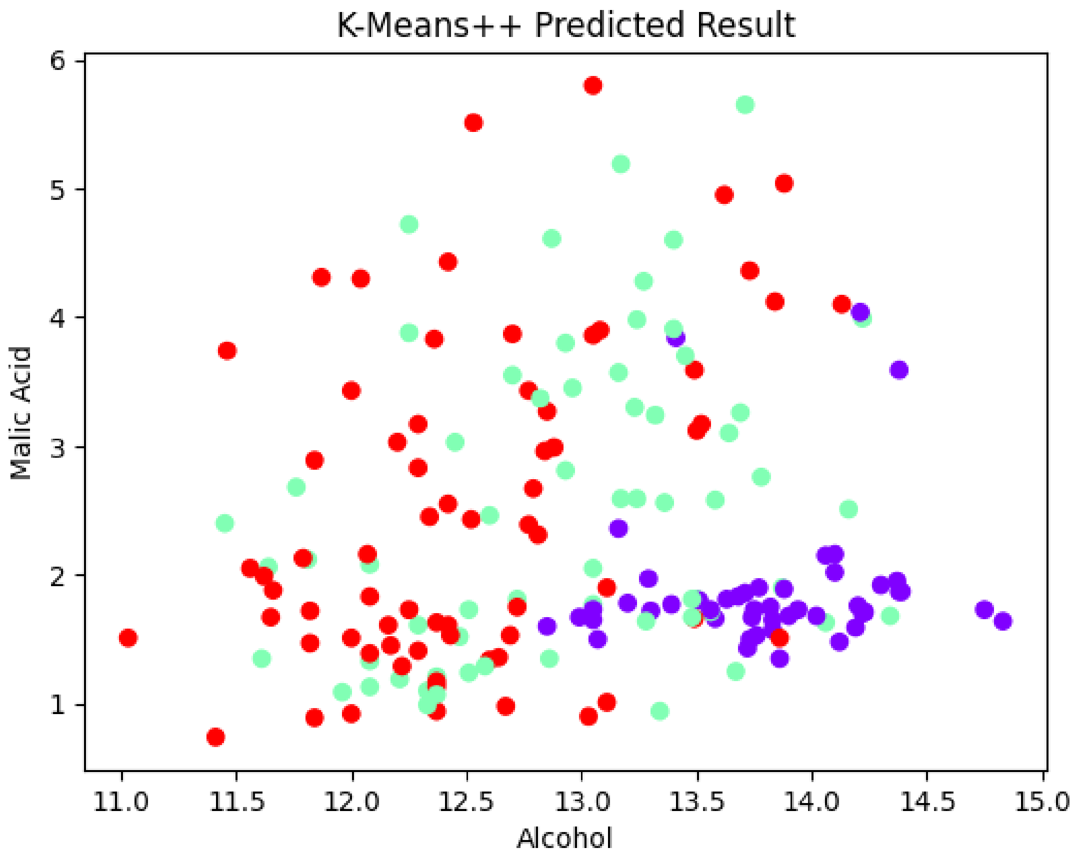
#Density Based: Optics Clustering in Wine Dataset

```
# Clustering using Optics Clustering algorithm
from sklearn.cluster import OPTICS
optics_cluster = OPTICS(min_samples=5, xi=0.05,
cluster_method='dbscan')
optics_cluster.fit(X)
plt.scatter(df.Alcohol, df.Malicacid, c=df["class"], cmap='rainbow')
plt.xlabel('Alcohol')
plt.ylabel('Malic Acid')
plt.title('Optics Clustering Predicted Result')
plt.show()
```



#K-means++ Clustering in Wine Dataset

```
# Clustering using K-means++ algorithm
from sklearn.cluster import KMeans
km = KMeans(init='k-means++', n_clusters=3, n_init=10, max_iter=300,
random_state=42)
km = KMeans(n_clusters=3, n_init=10)
y_predicted = km.fit_predict(X)
plt.title("K-Means++ Predicted Result")
plt.xlabel("Alcohol")
plt.ylabel("Malic Acid")
plt.scatter(df.Alcohol, df.Malicacid, c=km.labels_, cmap='rainbow')
plt.show()
```



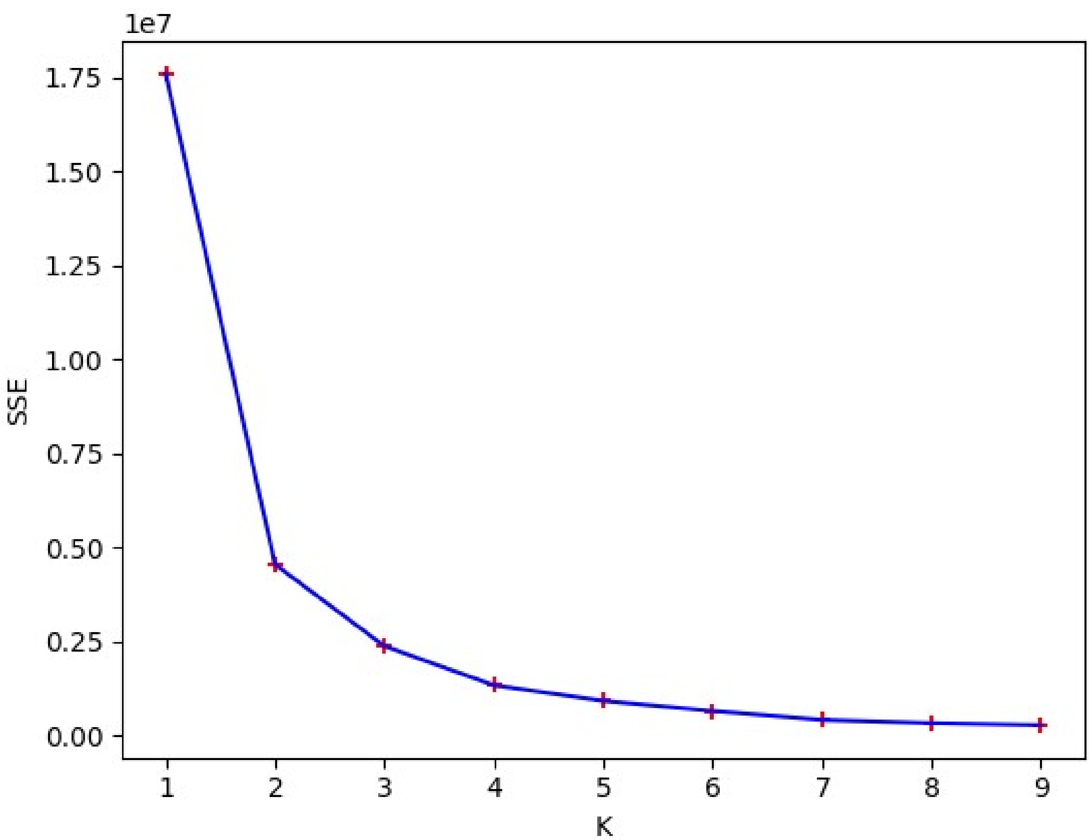

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score

# True labels
y_true = df['class']

# Predicted cluster labels from K-Means++
y_pred = km.labels_  # or y_predicted

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
```

```
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.7187
Adjusted Rand Index: 0.3711
Mutual Information: 0.4657
Adjusted Mutual Information: 0.4227
Normalized Mutual Information: 0.4288
```

```
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

```
[<matplotlib.lines.Line2D at 0x7f37d5de1700>]
```



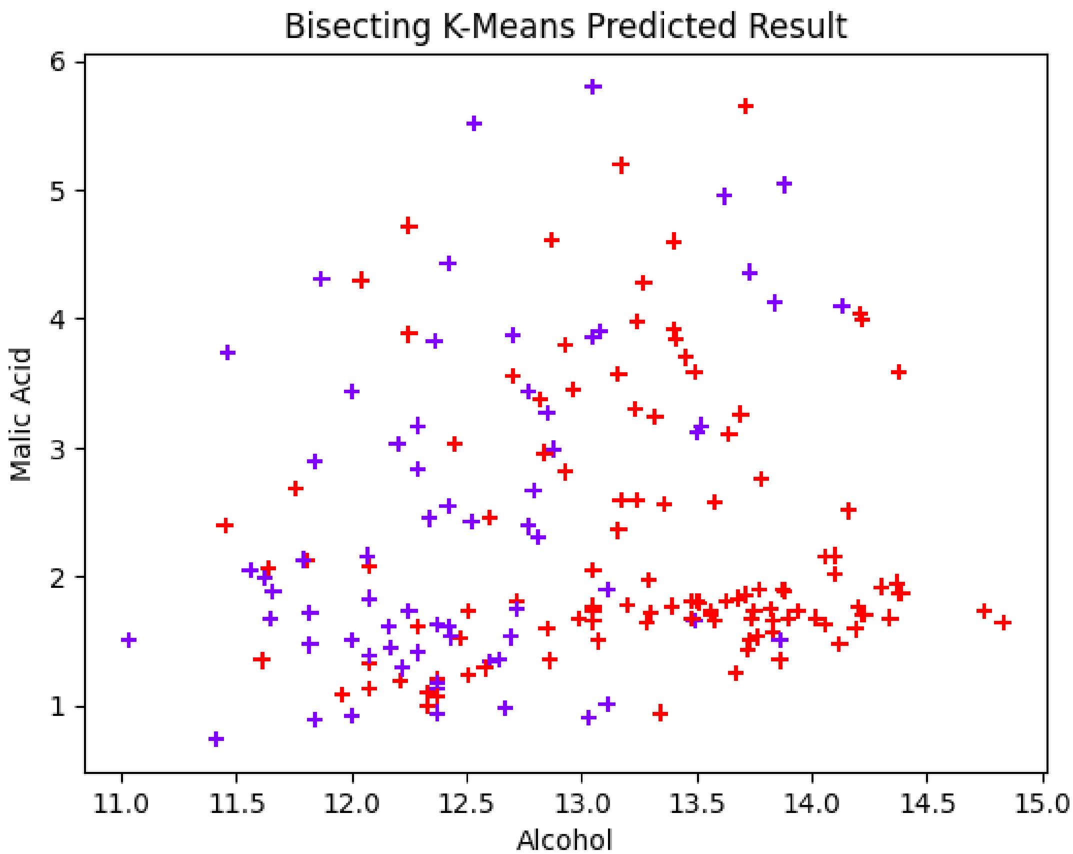
```
# Evaluating Metrics
from sklearn.metrics import silhouette_score
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
from sklearn.metrics import calinski_harabasz_score
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
from sklearn.metrics import davies_bouldin_score
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.527999057875864
Calinski Harabasz Score:  1349.5503166007632
Davies Bouldin Score:  0.5215893651849661

Cohesion Score: 117.17131504353662
Separation Score: 748.9315069233312

/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is
deprecated, in a future version this will reduce over both axes and
return a scalar. To retain the old behavior, pass axis=0 (or do not
pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

#Bisecting K-means Clustering in Wine Dataset

```
# Clustering using Bisecting K-means algorithm
from sklearn.cluster import KMeans
km = KMeans(n_clusters=1, n_init=10, random_state=0).fit(X)
K=3
for i in range(K-1):
 largest_cluster = np.argmax(np.bincount(km.labels_))
 largest_cluster_mask = (km.labels_ == largest_cluster)
 X_split = X[largest_cluster_mask]
 km.labels_[largest_cluster_mask] = KMeans(n_clusters=2, n_init=10,
```

```
random_state=0).fit(X_split).labels_
plt.title("Bisecting K-Means Predicted Result")
plt.xlabel("Alcohol")
plt.ylabel("Malic Acid")
plt.scatter(df.Alcohol, df.Malicacid, c=km.labels_, cmap='rainbow',
marker="+")
plt.show()
```



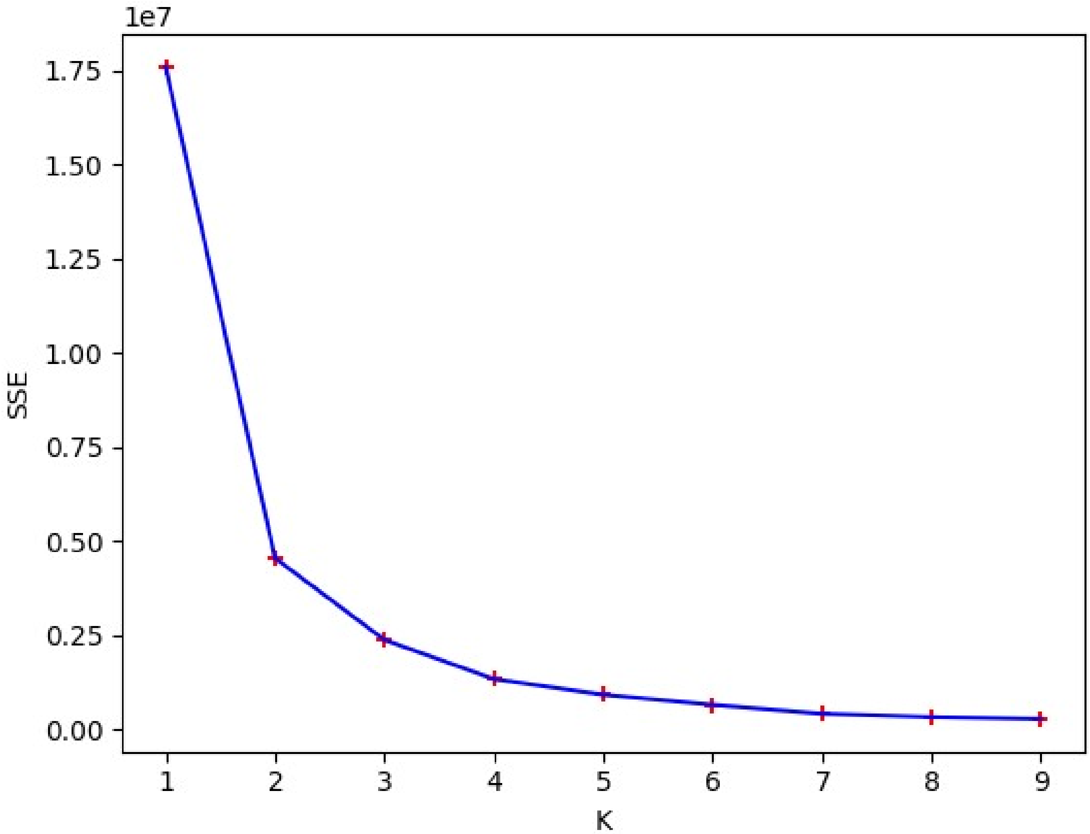

```
from sklearn.metrics import rand_score, adjusted_rand_score
from sklearn.metrics import mutual_info_score,
adjusted_mutual_info_score, normalized_mutual_info_score

# True labels
y_true = df['class']

# Predicted cluster labels from Bisecting K-Means
y_pred = km.labels_

# Compute Rand Index
ri = rand_score(y_true, y_pred)
ari = adjusted_rand_score(y_true, y_pred)

# Compute Mutual Information scores
```

```
mi = mutual_info_score(y_true, y_pred)
ami = adjusted_mutual_info_score(y_true, y_pred)
nmi = normalized_mutual_info_score(y_true, y_pred)

# Print results
print(f"Rand Index: {ri:.4f}")
print(f"Adjusted Rand Index: {ari:.4f}")
print(f"Mutual Information: {mi:.4f}")
print(f"Adjusted Mutual Information: {ami:.4f}")
print(f"Normalized Mutual Information: {nmi:.4f}")
```

```
Rand Index: 0.6034
Adjusted Rand Index: 0.2224
Mutual Information: 0.2372
Adjusted Mutual Information: 0.2670
Normalized Mutual Information: 0.2718
```

```
# Visualisation of SSE (Sum of Squared Errors) & Elbow Graph:
sse = []
k_range = range(1, 10)
for k in k_range:
 km = KMeans(n_clusters=k, n_init=10)
 km.fit_predict(X)
 sse.append(km.inertia_)
plt.xlabel("K")
plt.ylabel("SSE")
plt.scatter(k_range, sse, color="red", marker="+")
plt.plot(k_range, sse, color="blue")
# We can see here, our elbow is at K=3
```

```
[<matplotlib.lines.Line2D at 0x7f37d5de2660>]
```




```
# Evaluating Metrics
silhouette_result = silhouette_score(X, km.labels_)
print("Silhouette Score: ", silhouette_result)
calinski_result = calinski_harabasz_score(X, km.labels_)
print("Calinski Harabasz Score: ", calinski_result)
davies_result = davies_bouldin_score(X, km.labels_)
print("Davies Bouldin Score: ", davies_result)
# Evaluating Cohesion & Separation
labels = km.labels_
centroids = km.cluster_centers_
SSE = np.sum((X - centroids[labels])**2)
overall_centroid = np.mean(X, axis=0)
SSB = np.sum([np.sum((X[labels == i] - centroids[i])**2) for i in
range(3)])
N = X.shape[0]
cohesion_scores = SSE/N
cohesion = np.mean(cohesion_scores)
separation = SSB/N
print(f"\nCohesion Score: {cohesion}")
print(f"Separation Score: {separation}")
```

```
Silhouette Score:  0.527999057875864
Calinski Harabasz Score:  1349.5503166007634
```

```
Davies Bouldin Score:  0.5215893651849662

Cohesion Score: 117.17131504353662
Separation Score: 435.5555168610419

/usr/local/lib/python3.12/dist-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is
deprecated, in a future version this will reduce over both axes and
return a scalar. To retain the old behavior, pass axis=0 (or do not
pass axis)
  return reduction(axis=axis, out=out, **passkwargs)
```

Github Link - https://github.com/Deep131203/ML-Lab/tree/main/Assignment-4