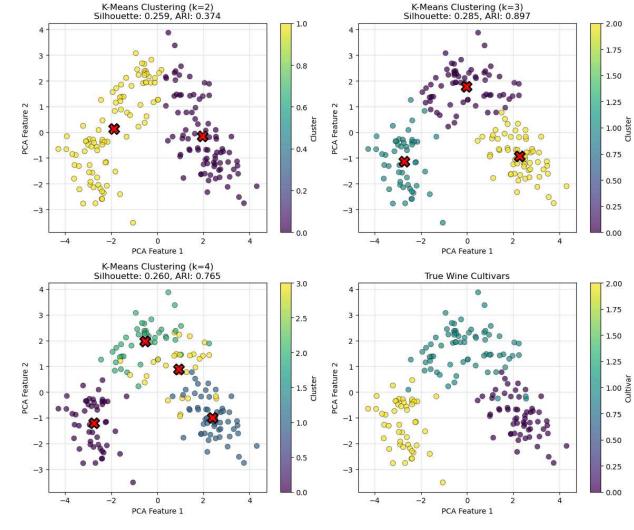
```
In [1]: import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
        from sklearn.datasets import load_wine
        from sklearn.preprocessing import StandardScaler
        from sklearn.cluster import KMeans
        from sklearn.decomposition import PCA
        from sklearn.metrics import silhouette score, adjusted rand score, confusion matrix
        import seaborn as sns
In [3]: wine = load_wine()
        X = wine.data
        y = wine.target
        feature_names = wine.feature_names
        wine_df = pd.DataFrame(X, columns=feature_names)
        wine df['target'] = y
In [4]: print(f"Dataset shape: {X.shape}")
        print(f"Number of classes: {len(np.unique(y))}")
        print(f"Class distribution: {pd.Series(y).value_counts().to_dict()}")
        Dataset shape: (178, 13)
        Number of classes: 3
        Class distribution: {1: 71, 0: 59, 2: 48}
In [5]: scaler = StandardScaler()
        X_scaled = scaler.fit_transform(X)
In [7]: k_values = [2, 3, 4]
        kmeans_models = {}
        silhouette_scores = {}
        for k in k_values:
            # Fit K-Means
            kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
            clusters = kmeans.fit_predict(X_scaled)
            # Store model and predictions
            kmeans models[k] = kmeans
            # 4. Evaluation - Calculate silhouette score
            silhouette_avg = silhouette_score(X_scaled, clusters)
            silhouette_scores[k] = silhouette_avg
            print(f"For k={k}, silhouette score: {silhouette_avg:.3f}")
            # Calculate and print ARI score (comparison with true labels)
            ari_score = adjusted_rand_score(y, clusters)
            print(f"For k={k}, Adjusted Rand Index: {ari_score:.3f}")
            # Create confusion matrix to compare clusters with true labels
            cm = confusion matrix(y, clusters)
            print(f"Confusion matrix for k={k}:")
            print(cm)
             print("\n")
        # Find the best k based on silhouette score
```

```
best k = max(silhouette scores, key=silhouette scores.get)
        print(f"Best k based on silhouette score: {best_k}")
        c:\Users\nhrid\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1436: UserWarni
        ng: KMeans is known to have a memory leak on Windows with MKL, when there are less ch
        unks than available threads. You can avoid it by setting the environment variable OMP
        NUM THREADS=1.
          warnings.warn(
        For k=2, silhouette score: 0.259
        For k=2, Adjusted Rand Index: 0.374
        Confusion matrix for k=2:
        [[59 0 0]
        [28 43 0]
         [ 0 48 0]]
        c:\Users\nhrid\anaconda3\Lib\site-packages\sklearn\cluster\ kmeans.py:1436: UserWarni
        ng: KMeans is known to have a memory leak on Windows with MKL, when there are less ch
        unks than available threads. You can avoid it by setting the environment variable OMP
        _NUM_THREADS=1.
        warnings.warn(
        For k=3, silhouette score: 0.285
        For k=3, Adjusted Rand Index: 0.897
        Confusion matrix for k=3:
        [[ 0 0 59]
        [65 3 3]
         [ 0 48 0]]
        c:\Users\nhrid\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:1436: UserWarni
        ng: KMeans is known to have a memory leak on Windows with MKL, when there are less ch
        unks than available threads. You can avoid it by setting the environment variable OMP
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        warnings.warn(
        For k=4, silhouette score: 0.260
        For k=4, Adjusted Rand Index: 0.765
        Confusion matrix for k=4:
        [[ 0 55 0 4]
         [ 1 0 45 25]
         [48 0 0 0]
         [0 0 0 0]]
        Best k based on silhouette score: 3
In [8]: # 5. Visualization using PCA
        # Reduce to 2 dimensions for visualization
        pca = PCA(n_components=2)
        X_pca = pca.fit_transform(X_scaled)
        # Plot the results for the best k
        plt.figure(figsize=(12, 10))
        # Plot for each k value
        for i, k in enumerate(k values):
            plt.subplot(2, 2, i+1)
            clusters = kmeans models[k].predict(X scaled)
            # Scatter plot of points
```

```
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=clusters, cmap='viridis',
                         alpha=0.7, s=50, edgecolor='k', linewidth=0.5)
    # Plot centroids
    centroids pca = pca.transform(kmeans models[k].cluster centers )
    plt.scatter(centroids_pca[:, 0], centroids_pca[:, 1], c='red', marker='X', s=200,
                edgecolor='k', linewidth=2)
    plt.title(f'K-Means Clustering (k={k})\nSilhouette: {silhouette_scores[k]:.3f}, '
              f'ARI: {adjusted_rand_score(y, clusters):.3f}')
    plt.xlabel('PCA Feature 1')
    plt.ylabel('PCA Feature 2')
    plt.colorbar(scatter, label='Cluster')
    plt.grid(alpha=0.3)
# Plot the true labels
plt.subplot(2, 2, 4)
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis',
                     alpha=0.7, s=50, edgecolor='k', linewidth=0.5)
plt.title('True Wine Cultivars')
plt.xlabel('PCA Feature 1')
plt.ylabel('PCA Feature 2')
plt.colorbar(scatter, label='Cultivar')
plt.grid(alpha=0.3)
plt.tight_layout()
plt.savefig('wine_clustering.png', dpi=300, bbox_inches='tight')
plt.show()
```



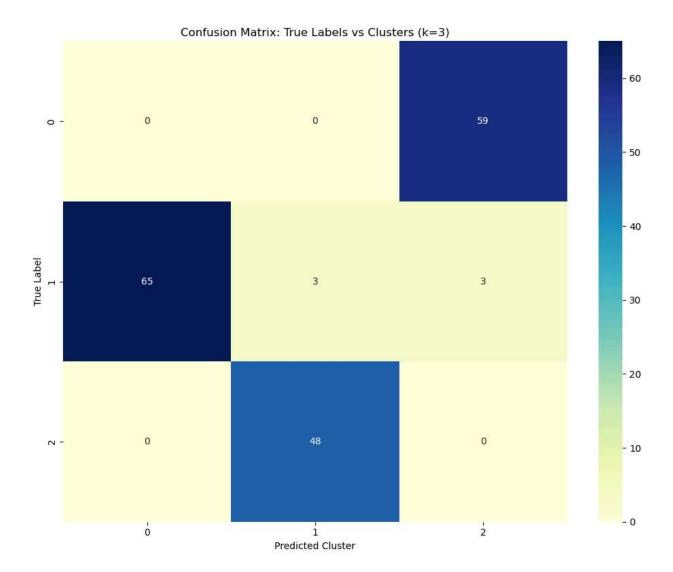
6. Detailed comparison with true labels for the best k value best_clusters = kmeans_models[best_k].predict(X_scaled) # Create a DataFrame to see the relationship between clusters and true labels comparison_df = pd.DataFrame({ 'True Label': y, f'Cluster (k={best_k})': best_clusters }) # Create a cross-tabulation to see the relationship cross_tab = pd.crosstab(comparison df['True Label'], comparison_df[f'Cluster (k={best_k})'], rownames=['True Label'], colnames=['Predicted Cluster']) print("\nCluster distribution vs. true labels:") print(cross tab) # Plot confusion matrix as a heatmap plt.figure(figsize=(10, 8)) sns.heatmap(cross_tab, annot=True, cmap="YlGnBu", fmt='d') plt.title(f'Confusion Matrix: True Labels vs Clusters (k={best_k})') plt.tight layout() plt.savefig('confusion_matrix.png', dpi=300, bbox_inches='tight') plt.show()

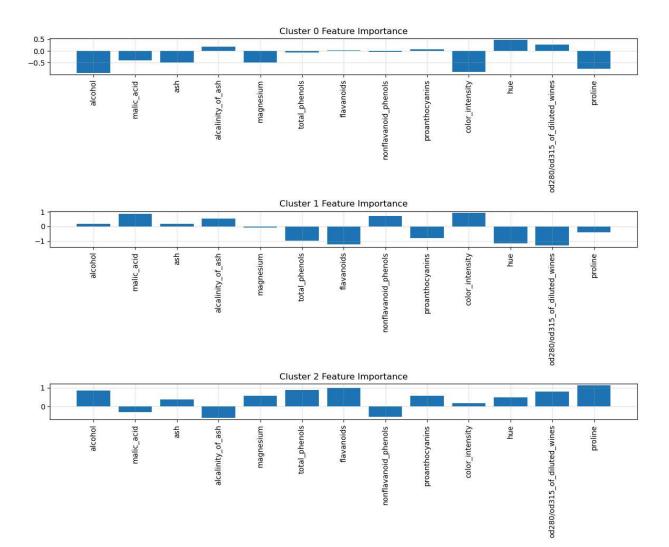
```
# Feature importance analysis for the best k
best_kmeans = kmeans_models[best_k]
centers = best_kmeans.cluster_centers_
# Plot feature importance per cluster
plt.figure(figsize=(12, 10))
for i in range(best_k):
    plt.subplot(best_k, 1, i+1)
    plt.bar(feature_names, centers[i])
    plt.title(f'Cluster {i} Feature Importance')
    plt.xticks(rotation=90)
    plt.grid(alpha=0.3)
plt.tight layout()
plt.savefig('feature_importance.png', dpi=300, bbox_inches='tight')
plt.show()
# Calculate the optimal number of clusters using the Elbow Method
inertia = []
k_range = range(1, 11)
for k in k_range:
    kmeans = KMeans(n clusters=k, random state=42, n init=10)
    kmeans.fit(X scaled)
    inertia.append(kmeans.inertia )
# Plot the Elbow Method
plt.figure(figsize=(10, 6))
plt.plot(k_range, inertia, 'o-', markersize=8)
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.grid(alpha=0.3)
plt.savefig('elbow_method.png', dpi=300, bbox_inches='tight')
plt.show()
Cluster distribution vs. true labels:
Predicted Cluster 0 1 2
True Label
                   0 0 59
```

65 3 3

0 48

1





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