```
In [1]: import pandas as pd
    from sklearn.datasets import load_iris

# Load the Iris dataset
    iris = load_iris()
    X = iris.data

# Create a DataFrame
    df = pd.DataFrame(X, columns=iris.feature_names)

# Show the first few rows of the DataFrame
    df.head()
```

Out[1]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

Clustering Algorithm Implementation

A) KMeans Clustering

Description: KMeans clustering partitions data into k clusters where each data point belongs to the cluster with the nearest mean.

The algorithm works as follows: Initialize k cluster centroids randomly. Assign each data point to the nearest centroid. Recalculate the centroids based on the current cluster memberships. Repeat steps 2 and 3 until convergence (i.e., centroids do not change significantly).

Suitability: KMeans clustering is suitable for the Iris dataset because it can effectively find distinct clusters in the dataset with a clear separation between them, assuming the dataset has a spherical distribution of clusters.

```
In [2]: import matplotlib.pyplot as plt
        from sklearn.cluster import KMeans
        # Range of k values to test
        k_values = range(1, 11) # Test for k from 1 to 10
        wcss = [] # List to store the WCSS values
        # Compute KMeans clustering for each k value and calculate WCSS
        for k in k_values:
            kmeans = KMeans(n_clusters=k, random_state=42)
            kmeans.fit(X)
            wcss.append(kmeans.inertia_) # Inertia is the WCSS
        # Plotting the Elbow Method
        plt.figure(figsize=(8, 6))
        plt.plot(k_values, wcss, marker='o', linestyle='--')
        plt.title('Elbow Method for Optimal k')
        plt.xlabel('Number of Clusters (k)')
        plt.ylabel('Within-Cluster Sum of Squares (WCSS)')
        plt.xticks(k_values)
        plt.grid(True)
        plt.show()
```

```
C:\Users\sheej\anaconda3\Lib\site-packages\sklearn\cluster\_kmeans.py:141
2: FutureWarning: The default value of `n init` will change from 10 to 'a
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  super()._check_params_vs_input(X, default_n_init=10)
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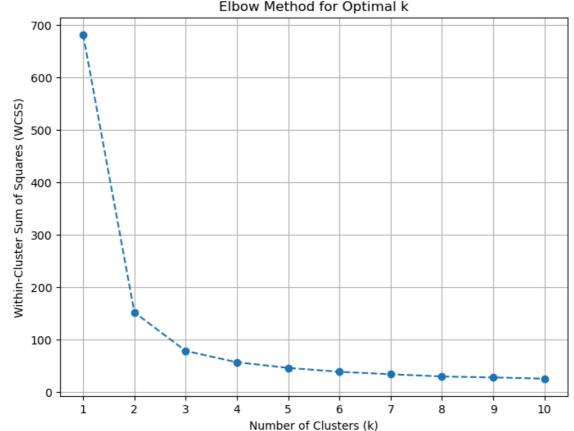
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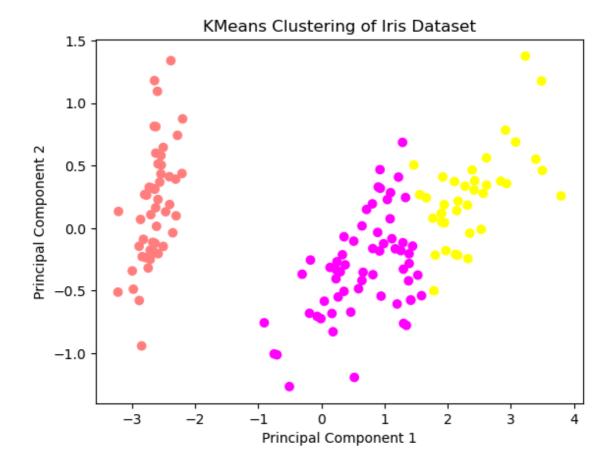
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In [10]:
         import numpy as np
         import matplotlib.pyplot as plt
         from sklearn.datasets import load_iris
         from sklearn.cluster import KMeans
         from sklearn.decomposition import PCA
         # From the plot, let's assume the optimal number of clusters is 3 (as in th
         optimal_k = 3
         # Step 2: Apply KMeans clustering with the optimal number of clusters
         kmeans = KMeans(n_clusters=optimal_k, random_state=42)
         kmeans_labels = kmeans.fit_predict(X)
         # Reduce dimensionality to 2D for visualization
         pca = PCA(n_components=2)
         X_pca = pca.fit_transform(X)
         # Plotting the KMeans clustering results
         plt.scatter(X_pca[:, 0], X_pca[:, 1], c=kmeans_labels, cmap='spring', market
         plt.title('KMeans Clustering of Iris Dataset')
         plt.xlabel('Principal Component 1')
         plt.ylabel('Principal Component 2')
         plt.show()
```

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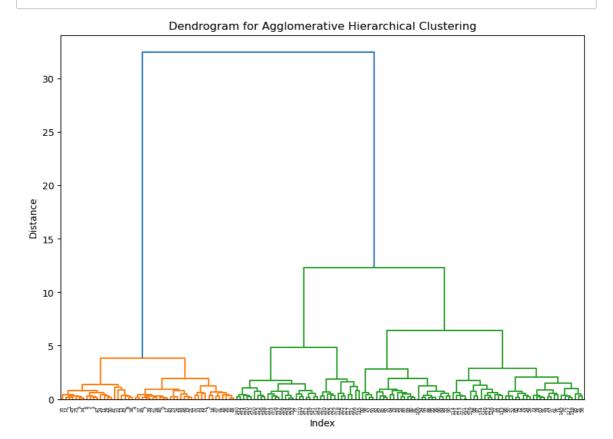
B) Hierarchical Clustering

Description: Hierarchical clustering creates a hierarchy of clusters either by:

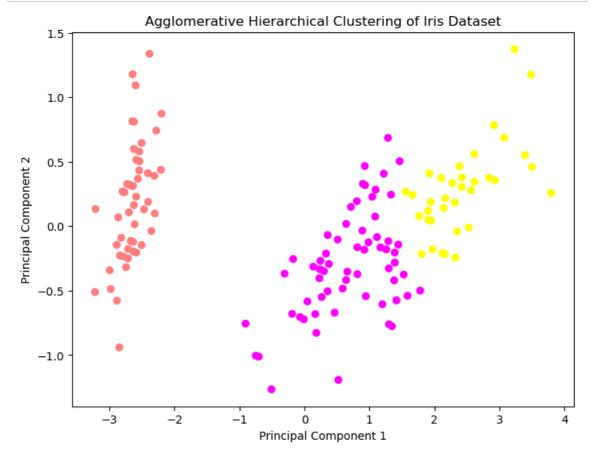
Agglomerative: Starting with each data point as a separate cluster and merging the closest pairs of clusters. Divisive: Starting with all data points in one cluster and recursively splitting them.

Suitability: Hierarchical clustering is suitable for the Iris dataset as it can reveal the nested structure of the data and does not require specifying the number of clusters upfront. It provides a dendrogram which can help in determining the number of clusters.

```
In [13]:
         import matplotlib.pyplot as plt
         import numpy as np
         import pandas as pd
         from sklearn.datasets import load_iris
         from sklearn.cluster import AgglomerativeClustering
         import scipy.cluster.hierarchy as sch
         from sklearn.decomposition import PCA
         # Load the Iris dataset
         iris = load iris()
         X = iris.data
         # Apply Agglomerative Hierarchical Clustering
         n_clusters = 3 # Number of clusters, similar to the number of species in t
         agglomerative = AgglomerativeClustering(n_clusters=n_clusters)
         agglomerative_labels = agglomerative.fit_predict(X)
         # Reduce dimensionality to 2D for visualization
         pca = PCA(n_components=2)
         X_pca = pca.fit_transform(X)
         # Plot the Dendrogram
         plt.figure(figsize=(10, 7))
         dendrogram = sch.dendrogram(sch.linkage(X, method='ward'))
         plt.title('Dendrogram for Agglomerative Hierarchical Clustering')
         plt.xlabel('Index')
         plt.ylabel('Distance')
         plt.show()
```



```
In [15]: # Plotting the Agglomerative Clustering results
    plt.figure(figsize=(8, 6))
    plt.scatter(X_pca[:, 0], X_pca[:, 1], c=agglomerative_labels, cmap='spring'
    plt.title('Agglomerative Hierarchical Clustering of Iris Dataset')
    plt.xlabel('Principal Component 1')
    plt.ylabel('Principal Component 2')
    plt.show()
```



```
In [ ]:
```