Project 4 Report

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CS458

P4-1. Hierarchical Clustering Dendrogram

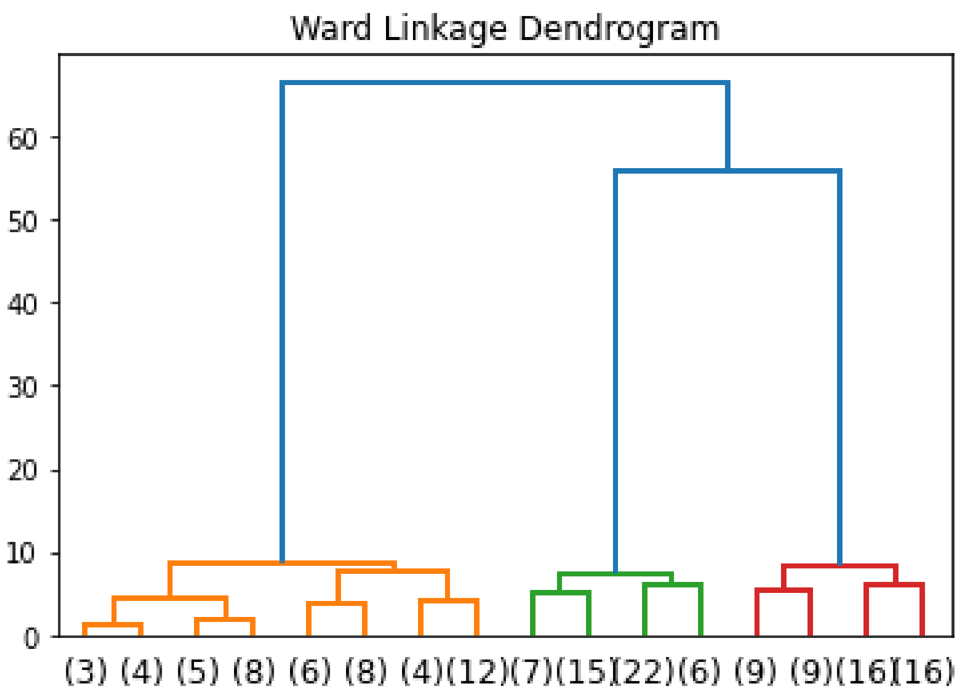
(a) Randomly generate the following data points:

```
import numpy as np
np.random.seed(0)
X1 = np.random.randn(50,2)+[2,2]
X2 = np.random.randn(50,2)+[6,10]
X3 = np.random.randn(50,2)+[10,2]
X = np.concatenate((X1,X2,X3))
```

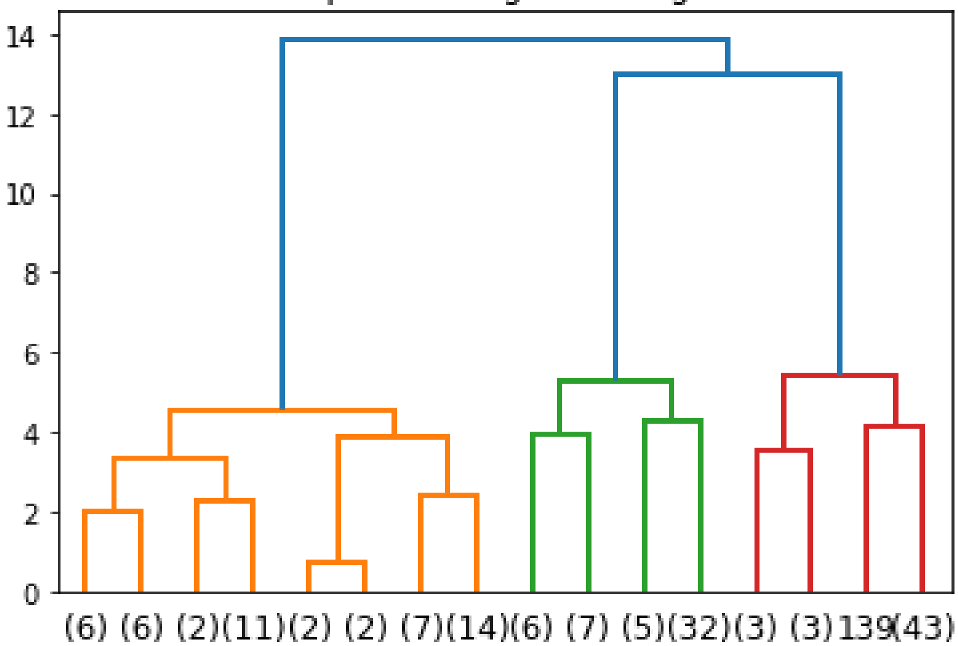
(b) Use sklearn.cluster.AgglomerativeClustering to cluster the points generated in (a). Plot your Dendrogram using different linkage{"ward", "complete", "average", "single"}.

```
from sklearn.cluster import AgglomerativeClustering
from matplotlib import pyplot as plt
from scipy.cluster.hierarchy import dendrogram
#Function to reduce repetition
def createDendrogram(link):
    model = AgglomerativeClustering(linkage = link,
distance_threshold=0, n_clusters=None)
    model.fit(X)
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count
        matrix = np.column_stack([model.children_, model.distances_,
counts]).astype(float)
        dendrogram(matrix, truncate_mode = "level", p=3)

#fig, ax = plt.subplots()


# Ward linkage
plt.title("Ward Linkage Dendrogram")
```

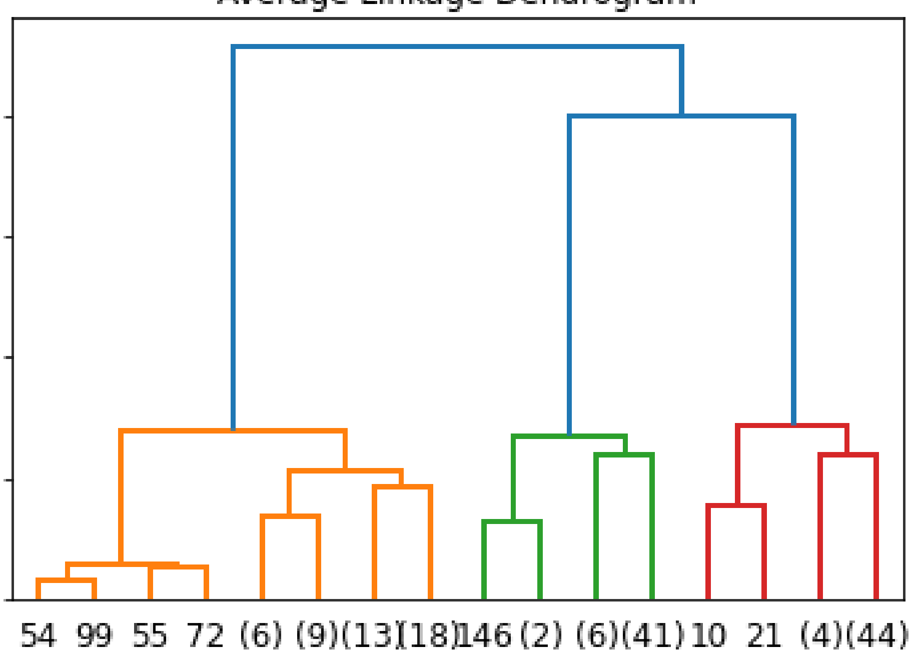
```python
createDendrogram("ward")
plt.show()

# Complete Linkage
plt.title("Complete Linkage Dendrogram")
createDendrogram("complete")
plt.show()

# Average Linkage
plt.title("Average Linkage Dendrogram")
createDendrogram("average")
plt.show()
# Single Linkage Dendrogram
plt.title("Single Linkage Dendrogram")
createDendrogram("single")
plt.show()
```

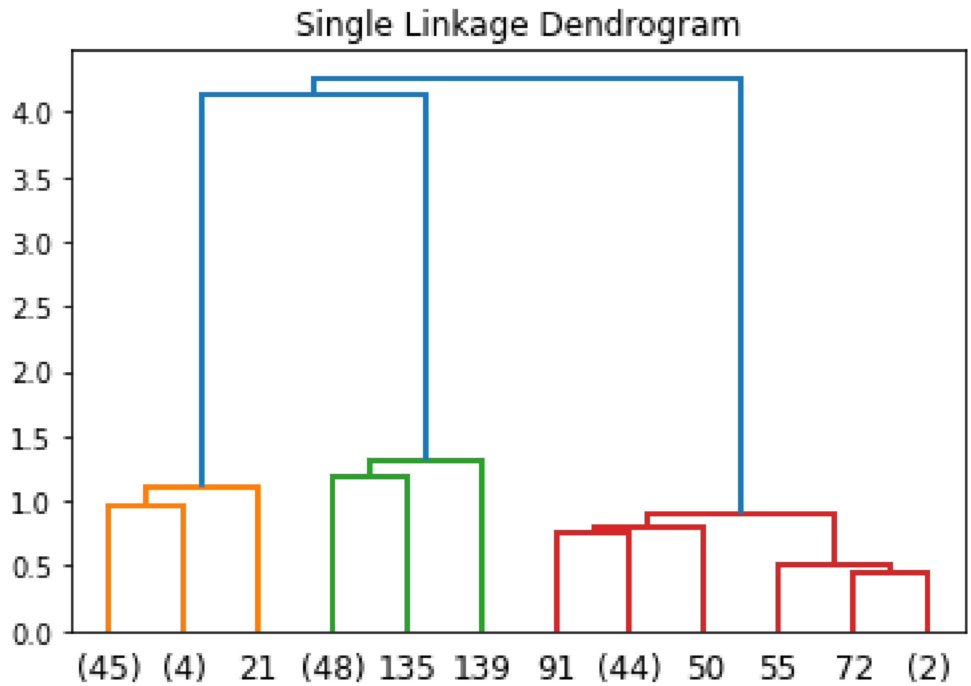


Complete Linkage Dendrogram



Average Linkage Dendrogram





P4-2. Clustering structured dataset

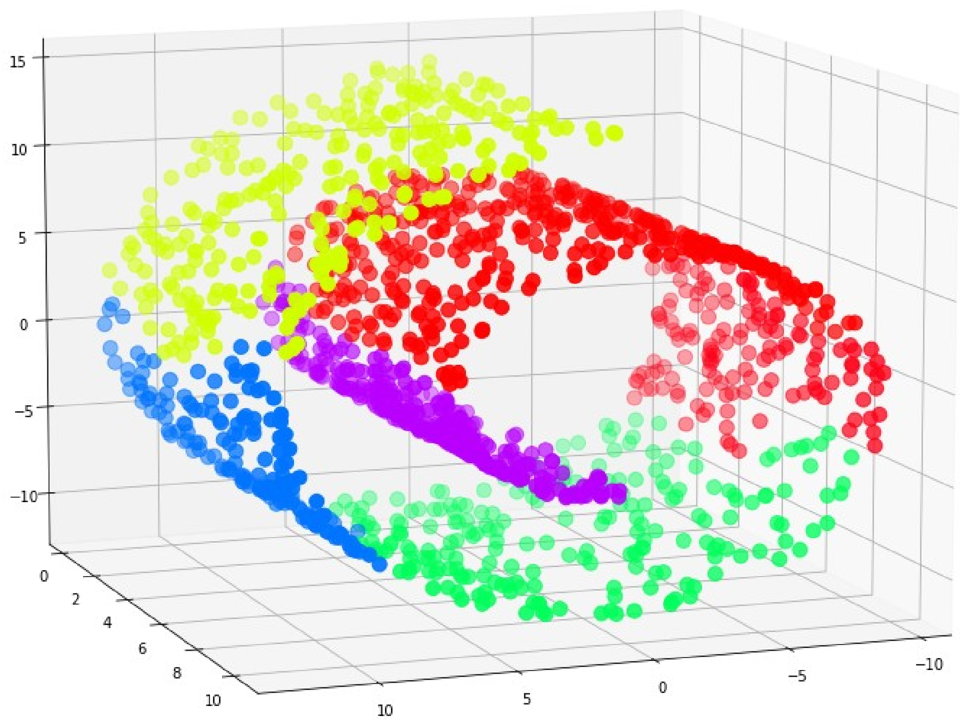
(a) Generate a swiss roll dataset:

```
from sklearn.datasets import make_swiss_roll
from sklearn.neighbors import kneighbors_graph
# Generate data (swiss roll dataset)
n_samples = 1500
noise = 0.05
X, _ = make_swiss_roll(n_samples, noise=noise)
# Make it thinner
X[:, 1] *= .5
```

(b) Use sklearn.cluster.AgglomerativeClustering to cluster the points generated in (a)

```
connectivity = kneighbors_graph(X, n_neighbors=10, include_self=False)
model = AgglomerativeClustering(n_clusters=6,
connectivity=connectivity, linkage='ward')
model.fit(X)

fig = plt.figure(figsize=(14,14))
ax = fig.add_subplot(111, projection='3d')

x = np.array(X[:,0])
y = np.array(X[:,1])
z = np.array(X[:,2])
cluster = np.array(model.labels_)
```

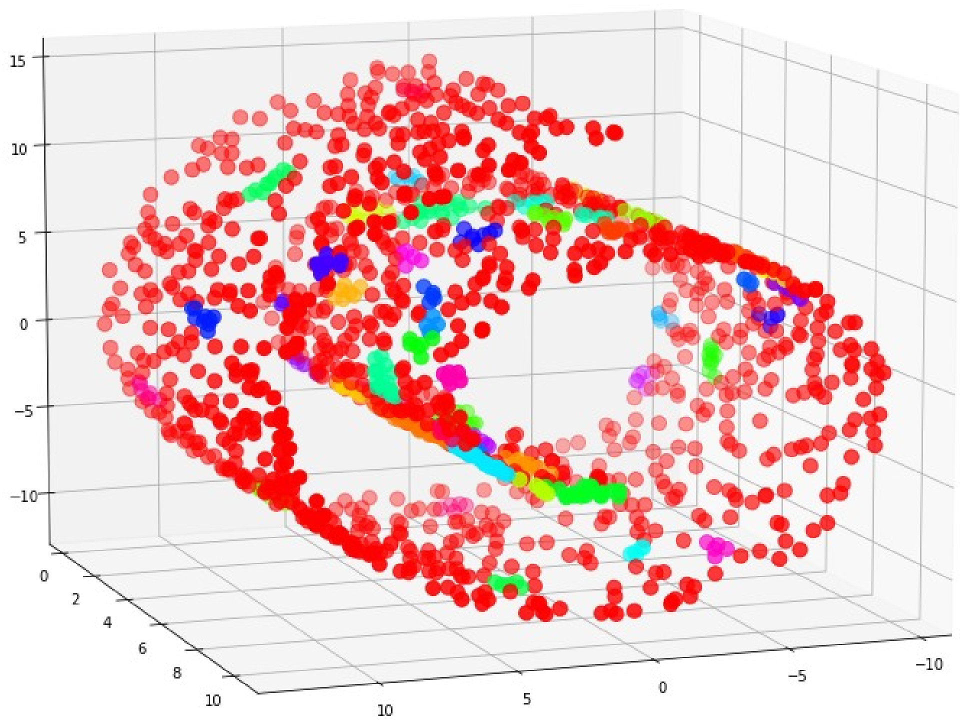
```
ax.view_init(elev=10., azim=70)
ax.scatter(x,y,z, c = cluster, s = 100, cmap = plt.cm.hsv)
plt.show()
```



(c) Use sklearn.cluster.DBSCAN to cluster the points generated in (a).

```
from sklearn.cluster import DBSCAN
model = DBSCAN(min_samples = 5, eps = .6)
model.fit(X)

fig = plt.figure(figsize=(14,14))
ax = fig.add_subplot(111, projection='3d')

cluster = np.array(model.labels_)

ax.view_init(elev=10., azim=70)
```

```
ax.scatter(x,y,z, c = cluster, s = 100, cmap = plt.cm.hsv)
plt.show()
```



Agglomerative clustering provides much cleaner results thatn DBSCAN when used with this data. I believe this could be because of the ability to select exact number of clusters. I have tried different parameters with DBSCAN and cannot yield any usefult results. I also believe that this is because of the relatively consistent density throughout the Swiss Roll data.

P4-3. Clustering the handwritten digits data

(a) Use the following methods to cluster the data:

```
from sklearn import datasets
from sklearn.cluster import KMeans
from sklearn.metrics import classification_report
```

```
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA

digits = datasets.load_digits()
data = scale(digits.data)

X_train, X_test, y_train, y_test = train_test_split(data,
digits.target,test_size=0.2, random_state=42)

n_samples, n_features = X_train.shape
n_digits = len(np.unique(y_train))
labels = y_train

clf = KMeans(init='k-means++', n_clusters=10, random_state=42)
clf.fit(X_train)

y_pred = clf.predict(X_test)


print ("Addjusted rand score:
{:.2}".format(metrics.adjusted_rand_score(y_test, y_pred)))
print ("Homogeneity score:{:.2}
".format(metrics.homogeneity_score(y_test, y_pred)))
print ("Completeness score: {:.2}
".format(metrics.completeness_score(y_test, y_pred)))
print ("Confusion matrix")
print (metrics.confusion_matrix(y_test, y_pred))

cr = classification_report(y_test, y_pred)
print(cr)

# pca = PCA(n_components=2).fit(X_train)
# reduced_X_train = pca.transform(X_train)

# kmeans = KMeans(init='k-means++', n_clusters=n_digits, n_init=10)
# kmeans.fit(reduced_X_train, y_train)

# x_min, x_max = reduced_X_train[:, 0].min() + 1, reduced_X_train[:,
0].max() - 1
# y_min, y_max = reduced_X_train[:, 1].min() + 1, reduced_X_train[:,
1].max() - 1
# xx, yy = np.meshgrid(np.arange(x_min, x_max, .01), np.arange(y_min,
y_max, .01))

# Z = kmeans.predict(np.c_[xx.ravel(), yy.ravel()])
```

```
# print ("Addjusted rand score:
{:.2}".format(metrics.adjusted_rand_score(y_test, Z)))
# print ("Homogeneity score:{:.2}
".format(metrics.homogeneity_score(y_test, Z)))
# print ("Completeness score: {:.2}
".format(metrics.completeness_score(y_test, Z)))
# print ("Confusion matrix")
# print (metrics.confusion_matrix(y_test, Z))
```

```
Addjusted rand score:0.54
Homogeneity score:0.66
Completeness score: 0.74
Confusion matrix
[[ 0  0  0  0 32  1  0  0  0  0]
 [ 0 16  0  0  0  7  0  0  5  0]
 [ 0  4  1  0  0  1  0  0 27  0]
 [ 0  2 30  1  0  0  0  0  1  0]
 [ 4  0  0  0  0 40  1  1  0  0]
 [ 0  0 14 32  0  0  1  0  0  0]
 [ 0  0  0  0  1  0 34  0  0  0]
 [30  0  0  1  0  0  0  3  0  0]
 [ 1 21  7  1  0  0  0  0  0  0]
 [ 2  1 33  1  0  3  0  0  0  0]]
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        33
           1       0.36      0.57      0.44        28
           2       0.01      0.03      0.02        33
           3       0.03      0.03      0.03        34
           4       0.00      0.00      0.00        46
           5       0.00      0.00      0.00        47
           6       0.94      0.97      0.96        35
           7       0.75      0.09      0.16        34
           8       0.00      0.00      0.00        30
           9       0.00      0.00      0.00        40

    accuracy                           0.15       360
   macro avg       0.21      0.17      0.16       360
weighted avg       0.19      0.15      0.15       360
```

```
from sklearn.cluster import DBSCAN

digits = datasets.load_digits()
data = scale(digits.data)

X_train, X_test, y_train, y_test = train_test_split(data,
digits.target,test_size=0.2, random_state=42)
```

```
clf = DBSCAN(eps = .4, min_samples=8, leaf_size = 25)

pred = clf.fit_predict(X_test)

cr = classification_report(y_test, pred)
print(cr)
```

```
precision    recall  f1-score   support

          -1       0.00      0.00      0.00       0.0
           0       0.00      0.00      0.00      33.0
           1       0.00      0.00      0.00      28.0
           2       0.00      0.00      0.00      33.0
           3       0.00      0.00      0.00      34.0
           4       0.00      0.00      0.00      46.0
           5       0.00      0.00      0.00      47.0
           6       0.00      0.00      0.00      35.0
           7       0.00      0.00      0.00      34.0
           8       0.00      0.00      0.00      30.0
           9       0.00      0.00      0.00      40.0

    accuracy                           0.00     360.0
   macro avg       0.00      0.00      0.00     360.0
weighted avg       0.00      0.00      0.00     360.0
```

Base on the methods, the KMeans clustering technically gives me better accuracy, but I have unfortunately been unable to get them to produce any meaningful results or accuracies. I have tried different parameters and dimension reductions and have still had very poor results.