Day_13 Hierrachial Clustering

August 24, 2018

In this experiment, we discuss hierarchical clustering methods. Heirarchial clustering algorithms build nested clusters by repeatedly merging two clusters in the bottom up approach and successively splitting a cluster into two in the top-down approach. This hierarchy of clusters is represented as a dendrogram. Dendrogram is a tree diagram popularly used to illustrate the arrangement of the heirarchy of clusters produced by hierarchical clustering algorithms. MNIST is a classic dataset of handwritten images. It is a popular dataset used for benchmarking classification algorithms. Hierarchical clustering generally fall into two types: Agglomerative: This is a "bottom up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy. Divisive: This is a "top down" approach: all observations start in one cluster, and splits are performed recursively as one moves down the hierarchy.

Exercise 1 : Import the data set and visualise the clusters formed. Use from sklearn import datasets to import mnist data set and visualise the clusters formed

Exercise 2 : Use SpectralEmbedding to Embed in 2D and plot using agglomerative clustering

Exercise 3 : The linkage criteria determines the distance metric used for the merge strategy:

Use ward which minimizes the sum of squared differences within all clusters. It is a variance-minimizing approach and in this sense is similar to the k-means objective function but addressed with an agglomerative hierarchical approach. Also check with other linkage criteria.

Exercise 4 : Plot dendogram

Exercise 5 : If we define the clusters to be the set of points with distance between each other equal to 20, visualise how many number of clusters will be obtained?

```
In [42]: from keras.datasets import mnist

         (X_train, y_train), (X_test, y_test) = mnist.load_data()
```

```
In [43]: import pandas as pd
         from sklearn.decomposition import PCA
         import matplotlib.pyplot as plt
         import numpy as np
```

```
In [44]: X_train=X_train[0:6000]
```

```
In [45]: X=[]
         for i in range(len(X_train)):
             X.append(X_train[i].flatten())
         X=np.array(X)
```

```
In [46]: X.shape
```

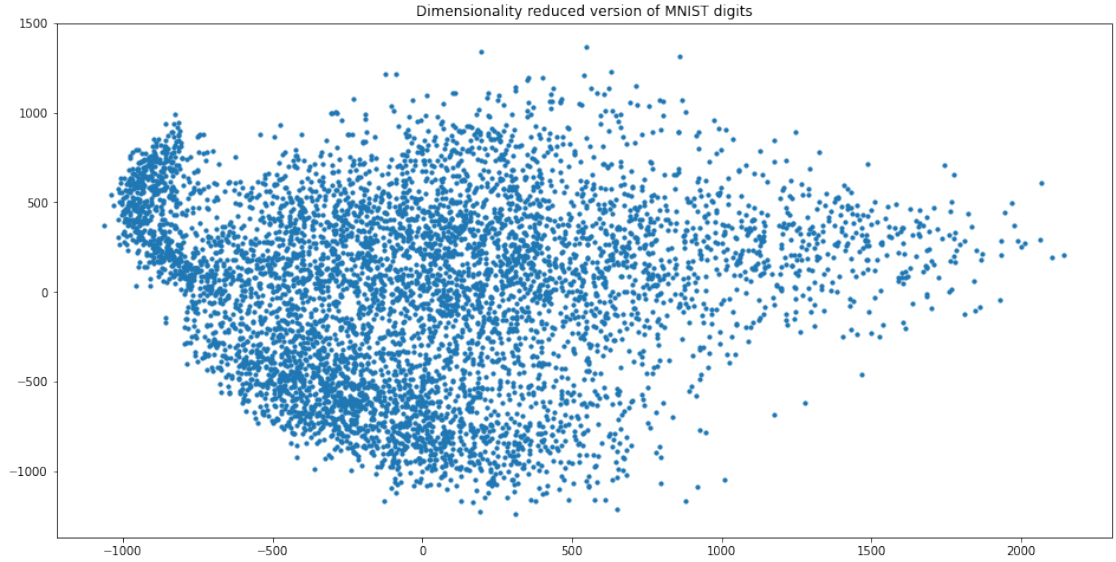
Out[46]: (6000, 784)

In [47]:
```
pca = PCA(n_components=2)
pca_result = pca.fit_transform(X)
```

In [48]:
```
df=pd.DataFrame(pca_result,columns=['ax1','ax2'])
```

In [49]:
```
plt.figure(figsize=(16,8))
plt.scatter(df['ax1'],df['ax2'],s=10)
plt.title('Dimensionality reduced version of MNIST digits')
```

Out[49]: Text(0.5,1,'Dimensionality reduced version of MNIST digits')

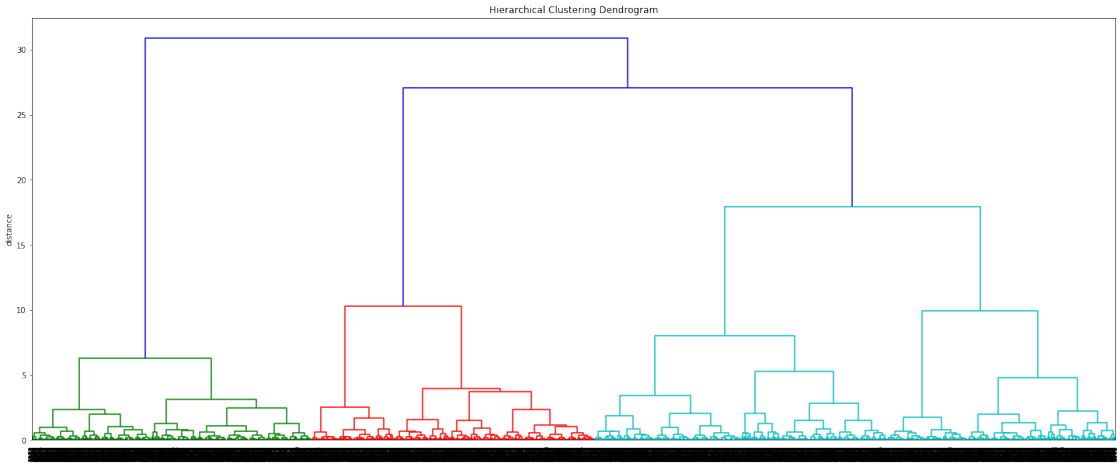


In [50]:
```
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
```

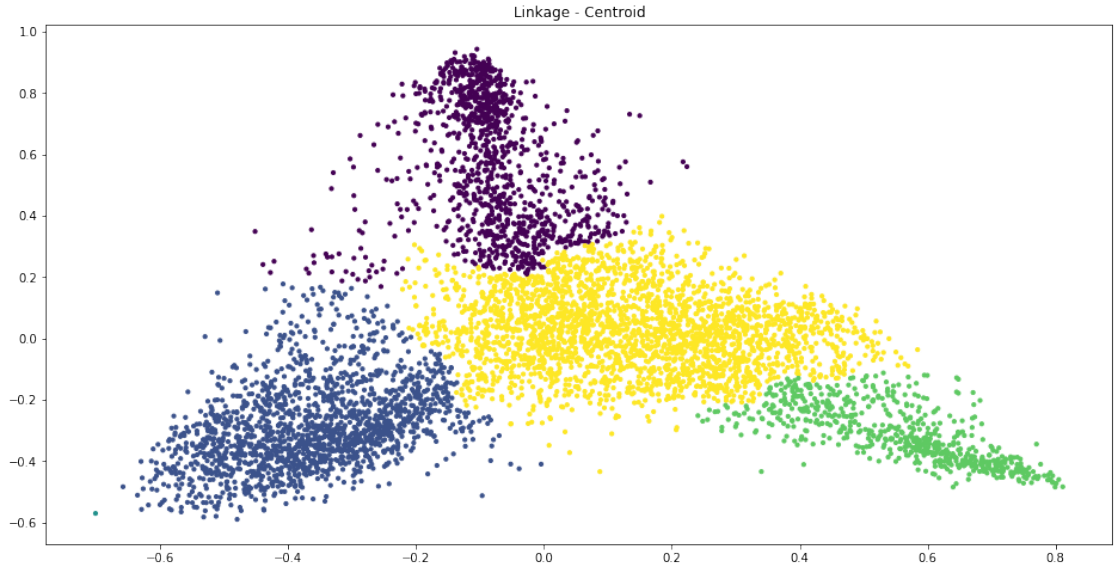
In [51]:
```
Z = linkage(df_red.values, 'ward')
```

In [62]:
```
Z2 = linkage(df_red.values, 'centroid')
```

In [52]:
```
plt.figure(figsize=(25, 10))
plt.title('Hierarchical Clustering Dendrogram')
plt.ylabel('distance')
dendrogram(
    Z,
    leaf_rotation=90.,  # rotates the x axis labels
    leaf_font_size=8.,  # font size for the x axis labels
)
plt.show()
```

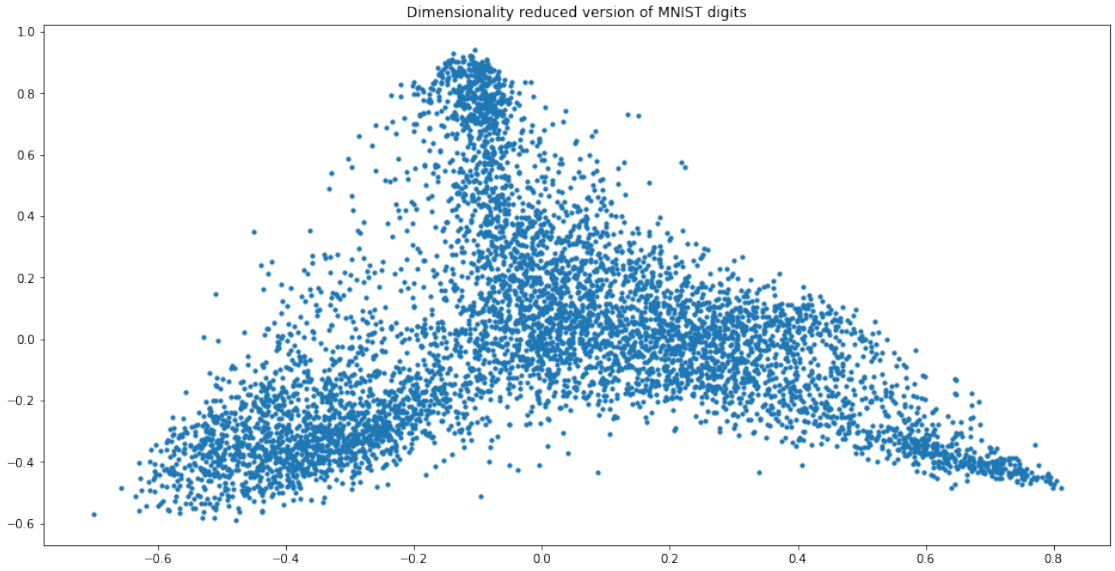



```
In [53]: assign=fcluster(Z,t=5,criterion='maxclust')
         assign

Out[53]: array([3, 2, 1, ..., 4, 3, 1], dtype=int32)

In [63]: assignZ2=fcluster(Z2,t=5,criterion='maxclust')
         assignZ2

Out[63]: array([5, 4, 2, ..., 5, 4, 2], dtype=int32)

In [67]: plt.figure(figsize=(16,8))
         plt.scatter(df_red['ax1'],df_red['ax2'],c=assignZ2,s=10)
         plt.title('Linkage - Centroid')

Out[67]: Text(0.5,1,'Linkage - Centroid')
```



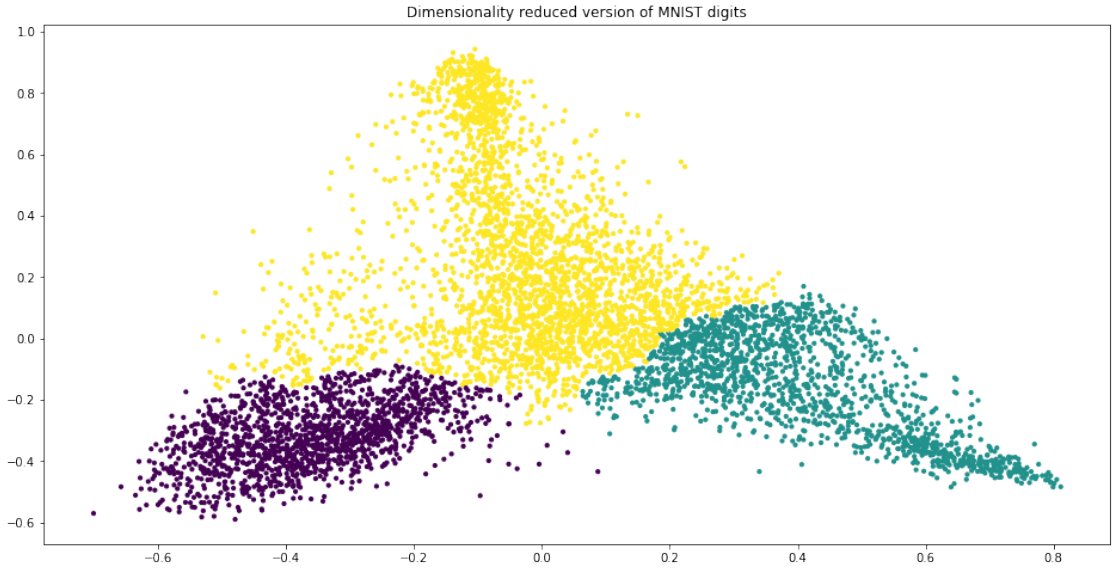
In [59]:
```
plt.figure(figsize=(16,8))
plt.scatter(df_red['ax1'],df_red['ax2'],s=10)
plt.title('Dimensionality reduced version of MNIST digits')
```

Out[59]: Text(0.5,1,'Dimensionality reduced version of MNIST digits')



In [61]:
```
plt.figure(figsize=(16,8))
plt.scatter(df_red['ax1'],df_red['ax2'],s=10,c=assign2)
plt.title('Dimensionality reduced version of MNIST digits')
```

Out[61]: Text(0.5,1,'Dimensionality reduced version of MNIST digits')



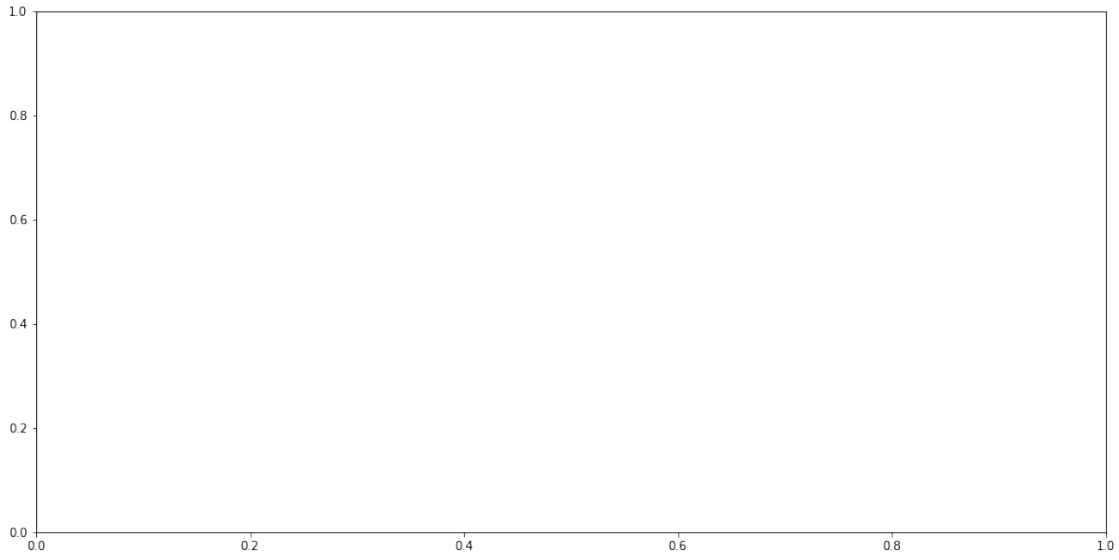
```
In [55]: assign2=fcluster(Z,t=20,criterion='distance')
         assign2

Out[55]: array([2, 2, 1, ..., 3, 2, 1], dtype=int32)

In [56]: assign2

Out[56]: array([2, 2, 1, ..., 3, 2, 1], dtype=int32)

In [57]: from sklearn import manifold
         X_red = manifold.SpectralEmbedding(n_components=2).fit_transform(X)
         X_red

Out[57]: array([[ 0.1977579 ,  0.01788963],
                [ 0.75832212, -0.44048398],
                [-0.18443844, -0.17119093],
                ...,
                [ 0.05532697,  0.15194331],
                [ 0.38600139, -0.14230132],
                [-0.41762613, -0.36585128]])

In [60]: df_red=pd.DataFrame(data=X_red,columns=['ax1','ax2'])
         plt.figure(figsize=(16,8))
         plt.scatter(df_red['ax1'],df_red['ax2'],s=10,c='assign2')
         plt.title('Dimensionality reduced version of MNIST digits')


         ---------------------------------------------------------------------------

         KeyError                                  Traceback (most recent call last)

         /opt/usr/anaconda3/lib/python3.6/site-packages/matplotlib/colors.py in to_rgba(c, alpha)
         131     try:
     --> 132         rgba = _colors_full_map.cache[c, alpha]
         133     except (KeyError, TypeError):  # Not in cache, or unhashable.


         KeyError: ('a', None)


     During handling of the above exception, another exception occurred:


         ValueError                                Traceback (most recent call last)

         /opt/usr/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py in scatter(self,
```

```
   3985                 # must be acceptable as PathCollection facecolors
-> 3986                 colors = mcolors.to_rgba_array(c)
   3987             except ValueError:


    /opt/usr/anaconda3/lib/python3.6/site-packages/matplotlib/colors.py in to_rgba_array(c,
    232     for i, cc in enumerate(c):
--> 233         result[i] = to_rgba(cc, alpha)
    234     return result


    /opt/usr/anaconda3/lib/python3.6/site-packages/matplotlib/colors.py in to_rgba(c, alpha)
    133     except (KeyError, TypeError):  # Not in cache, or unhashable.
--> 134         rgba = _to_rgba_no_colorcycle(c, alpha)
    135         try:


    /opt/usr/anaconda3/lib/python3.6/site-packages/matplotlib/colors.py in _to_rgba_no_color
    177             pass
--> 178         raise ValueError("Invalid RGBA argument: {!r}".format(orig_c))
    179     # tuple color.


    ValueError: Invalid RGBA argument: 'a'


During handling of the above exception, another exception occurred:


    AttributeError                            Traceback (most recent call last)

    <ipython-input-60-96a5f836d800> in <module>()
      1 df_red=pd.DataFrame(data=X_red,columns=['ax1','ax2'])
      2 plt.figure(figsize=(16,8))
----> 3 plt.scatter(df_red['ax1'],df_red['ax2'],s=10,c='assign2')
      4 plt.title('Dimensionality reduced version of MNIST digits')


    /opt/usr/anaconda3/lib/python3.6/site-packages/matplotlib/pyplot.py in scatter(x, y, s,
   3376                         vmin=vmin, vmax=vmax, alpha=alpha,
   3377                         linewidths=linewidths, verts=verts,
-> 3378                         edgecolors=edgecolors, data=data, **kwargs)
   3379     finally:
   3380         ax._hold = washold


    /opt/usr/anaconda3/lib/python3.6/site-packages/matplotlib/__init__.py in inner(ax, *args
   1715                     warnings.warn(msg % (label_namer, func.__name__),
```

```
   1716                                     RuntimeWarning, stacklevel=2)
-> 1717             return func(ax, *args, **kwargs)
   1718         pre_doc = inner.__doc__
   1719         if pre_doc is None:
```

```
/opt/usr/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py in scatter(self,
   3989                 msg = ("c of shape {0} not acceptable as a color sequence "
   3990                        "for x with size {1}, y with size {2}")
-> 3991                 raise ValueError(msg.format(c.shape, x.size, y.size))
   3992         else:
   3993             colors = None  # use cmap, norm after collection is created
```

```
AttributeError: 'str' object has no attribute 'shape'
```



0.1 SKlearn Implementation

In [ ]:
```
from sklearn import manifold, datasets
import numpy as np
from scipy import ndimage
from matplotlib import pyplot as plt

digits = datasets.load_digits(n_class=10)
X = digits.data
y = digits.target
n_samples, n_features = X.shape
np.random.seed(0)
```

```
In [ ]: def nudge_images(X, y):
            # Having a larger dataset shows more clearly the behavior of the
            # methods, but we multiply the size of the dataset only by 2, as the
            # cost of the hierarchical clustering methods are strongly
            # super-linear in n_samples
            shift = lambda x: ndimage.shift(x.reshape((8, 8)),.3 * np.random.normal(size=2),mode
            X = np.concatenate([X, np.apply_along_axis(shift, 1, X)])
            Y = np.concatenate([y, y], axis=0)
            return X, Y


        X, y = nudge_images(X, y)

In [ ]: def plot_clustering(X_red, X, labels, title=None):
            x_min, x_max = np.min(X_red, axis=0), np.max(X_red, axis=0)
            X_red = (X_red - x_min) / (x_max - x_min)

            plt.figure(figsize=(6, 4))
            for i in range(X_red.shape[0]):
                plt.text(X_red[i, 0], X_red[i, 1], str(y[i]),
                         color=plt.cm.nipy_spectral(labels[i] / 10.),
                         fontdict={'weight': 'bold', 'size': 9})

            plt.xticks([])
            plt.yticks([])
            if title is not None:
                plt.title(title, size=17)
            plt.axis('off')
            plt.tight_layout()

In [ ]: print("Computing embedding")
        X_red = manifold.SpectralEmbedding(n_components=2).fit_transform(X)
        print("Done.")

        from sklearn.cluster import AgglomerativeClustering

        for linkage in ('ward', 'average', 'complete'):
            clustering = AgglomerativeClustering(linkage=linkage, n_clusters=10)
            clustering.fit(X_red)
            print("%s " % (linkage))

            plot_clustering(X_red, X, clustering.labels_, "%s linkage" % linkage)


        plt.show()
```