ML0101EN-Clus-Hierarchical-Cars-py-v1

March 4, 2019

Hierarchical Clustering

Welcome to Lab of Hierarchical Clustering with Python using Scipy and Scikit-learn package.

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```

Hierarchical Clustering - Agglomerative

We will be looking at a clustering technique, which is Agglomerative Hierarchical Clustering. Remember that agglomerative is the bottom up approach. In this lab, we will be looking at Agglomerative clustering, which is more popular than Divisive clustering. We will also be using Complete Linkage as the Linkage Criteria. NOTE: You can also try using Average Linkage wherever Complete Linkage would be used to see the difference!

```
In [1]: import numpy as np
        import pandas as pd
        from scipy import ndimage
        from scipy.cluster import hierarchy
        from scipy.spatial import distance_matrix
        from matplotlib import pyplot as plt
        from sklearn import manifold, datasets
        from sklearn.cluster import AgglomerativeClustering
        from sklearn.datasets.samples_generator import make_blobs
        %matplotlib inline
```

Generating Random Data
We will be generating a set of data using the make_blobs class. Input these parameters into make_blobs:

```
<li> <b>n_samples</b>: The total number of points equally divided among clusters. </li>
<ul> <li> Choose a number from 10-1500 </li> </ul>
<li> <b>centers</b>: The number of centers to generate, or the fixed center locations. </li>
<ul> <li> Choose arrays of x,y coordinates for generating the centers. Have 1-10 centers (ex. ce
<li> <b>cluster_std</b>: The standard deviation of the clusters. The larger the number, the furt
<ul> <li> Choose a number between 0.5-1.5 </li> </ul>
```

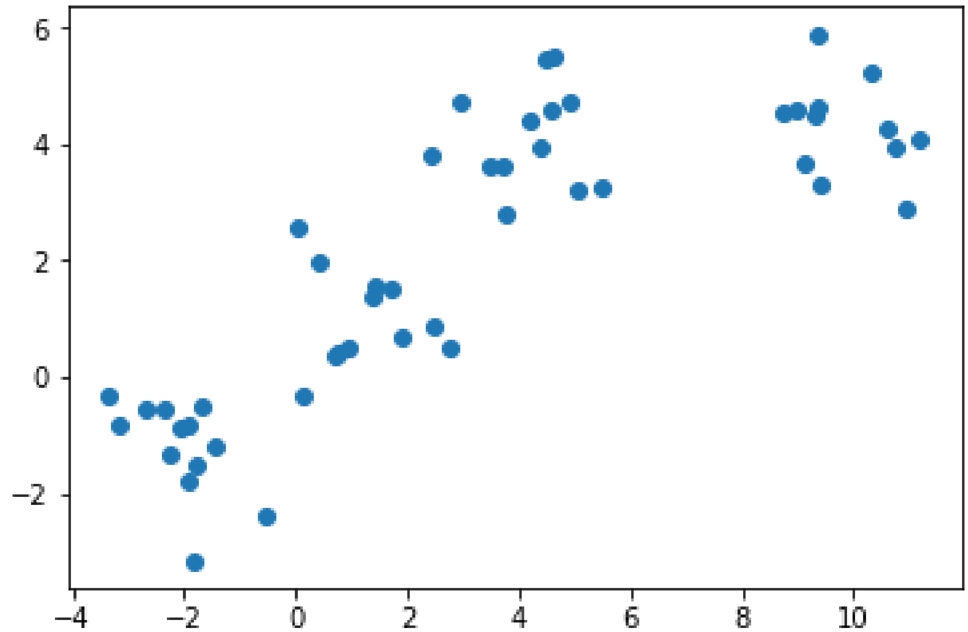
Save the result to X1 and y1.

```
In [2]: X1, y1 = make_blobs(n_samples=50, centers=[[4,4], [-2, -1], [1, 1], [10,4]], cluster_std
```

Plot the scatter plot of the randomly generated data

```
In [11]: plt.scatter(X1[:, 0], X1[:, 1], marker='o')

Out[11]: <matplotlib.collections.PathCollection at 0x7f3e7beb80b8>
```




```
In [ ]:
```

Agglomerative Clustering
We will start by clustering the random data points we just created.
The Agglomerative Clustering class will require two inputs:

```
<li> <b>n_clusters</b>: The number of clusters to form as well as the number of centroids to gen
<ul> <li> Value will be: 4 </li> </ul>
<li> <b>linkage</b>: Which linkage criterion to use. The linkage criterion determines which dist
<ul>
    <li> Value will be: 'complete' </li>
    <li> <b>Note</b>: It is recommended you try everything with 'average' as well </li>
</ul>
```

Save the result to a variable called agglom

In [12]:
```python
agglom = AgglomerativeClustering(n_clusters = 4, linkage = 'average')
```

Fit the model with X2 and y2 from the generated data above.

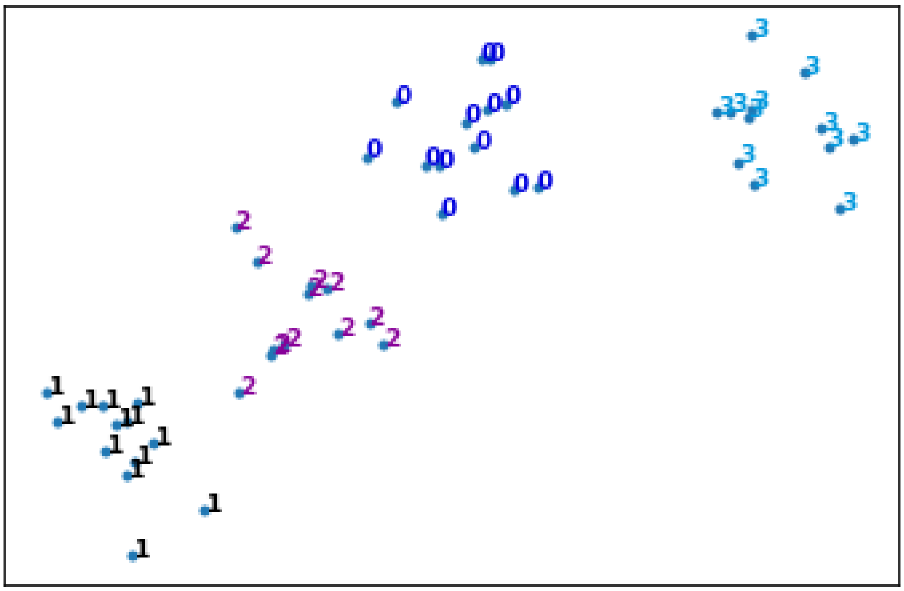
In [14]:
```python
agglom.fit(X1,y1)
```

Out[14]:
```
AgglomerativeClustering(affinity='euclidean', compute_full_tree='auto',
            connectivity=None, linkage='average', memory=None,
            n_clusters=4, pooling_func='deprecated')
```

Run the following code to show the clustering! Remember to read the code and comments to gain more understanding on how the plotting works.

In [15]:
```python
# Create a figure of size 6 inches by 4 inches.
plt.figure(figsize=(6,4))

# These two lines of code are used to scale the data points down,
# Or else the data points will be scattered very far apart.

# Create a minimum and maximum range of X1.
x_min, x_max = np.min(X1, axis=0), np.max(X1, axis=0)

# Get the average distance for X1.
X1 = (X1 - x_min) / (x_max - x_min)

# This loop displays all of the datapoints.
for i in range(X1.shape[0]):
    # Replace the data points with their respective cluster value
    # (ex. 0) and is color coded with a colormap (plt.cm.spectral)
    plt.text(X1[i, 0], X1[i, 1], str(y1[i]),
             color=plt.cm.nipy_spectral(agglom.labels_[i] / 10.),
             fontdict={'weight': 'bold', 'size': 9})

# Remove the x ticks, y ticks, x and y axis
plt.xticks([])
plt.yticks([])
#plt.axis('off')
```

```python
# Display the plot of the original data before clustering
plt.scatter(X1[:, 0], X1[:, 1], marker='.')
# Display the plot
plt.show()
```



Dendrogram Associated for the Agglomerative Hierarchical Clustering

Remember that a distance matrix contains the distance from each point to every other point of a dataset . Use the function distance_matrix, which requires two inputs. Use the Feature Matrix, X2 as both inputs and save the distance matrix to a variable called dist_matrix Remember that the distance values are symmetric, with a diagonal of 0's. This is one way of making sure your matrix is correct. (print out dist_matrix to make sure it's correct)

```python
In [22]: dist_matrix = distance_matrix(X1,X1)
         print(dist_matrix)
```

```
[[0.         0.00919071 0.43282507 ... 0.08600995 0.80273065 0.75382814]
 [0.00919071 0.         0.42363482 ... 0.09268719 0.81043636 0.76200064]
 [0.43282507 0.42363482 0.         ... 0.49641106 1.18716484 1.15413697]
 ...
 [0.08600995 0.09268719 0.49641106 ... 0.         0.71891602 0.67259715]
 [0.80273065 0.81043636 1.18716484 ... 0.71891602 0.         0.09289012]
 [0.75382814 0.76200064 1.15413697 ... 0.67259715 0.09289012 0.        ]]
```

Using the linkage class from hierarchy, pass in the parameters:

```
<li> The distance matrix </li>
<li> 'complete' for complete linkage </li>
```

Save the result to a variable called Z

```
In [26]: Z = hierarchy.linkage(dist_matrix, 'complete')
```

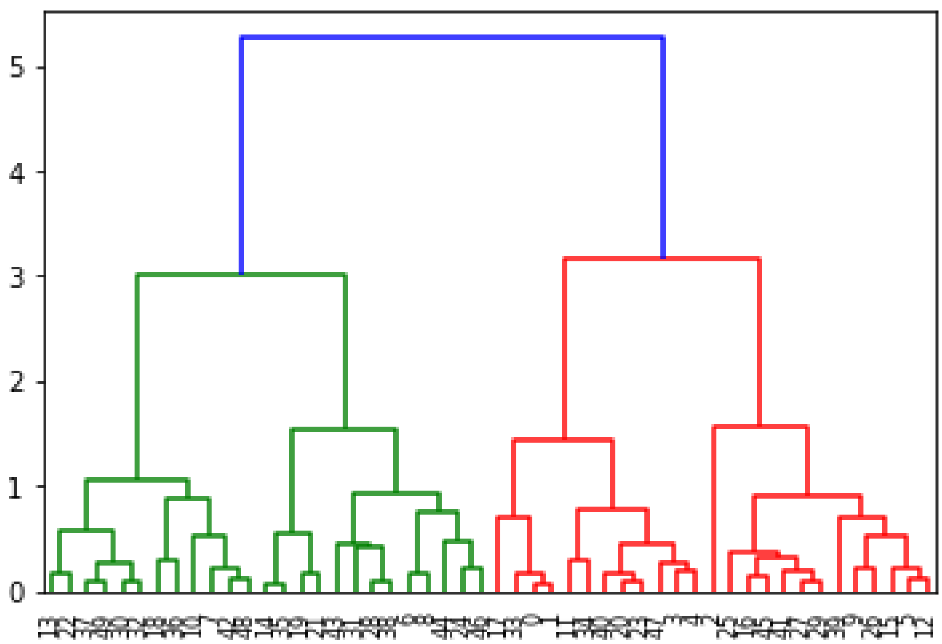
```
/home/jupyterlab/conda/lib/python3.6/site-packages/ipykernel_launcher.py:1: ClusterWarning: scip
  """Entry point for launching an IPython kernel.
```

A Hierarchical clustering is typically visualized as a dendrogram as shown in the following cell. Each merge is represented by a horizontal line. The y-coordinate of the horizontal line is the similarity of the two clusters that were merged, where cities are viewed as singleton clusters. By moving up from the bottom layer to the top node, a dendrogram allows us to reconstruct the history of merges that resulted in the depicted clustering.

Next, we will save the dendrogram to a variable called dendro. In doing this, the dendrogram will also be displayed. Using the dendrogram class from hierarchy, pass in the parameter:

Z

```
In [25]: dendro = hierarchy.dendrogram(Z)
```

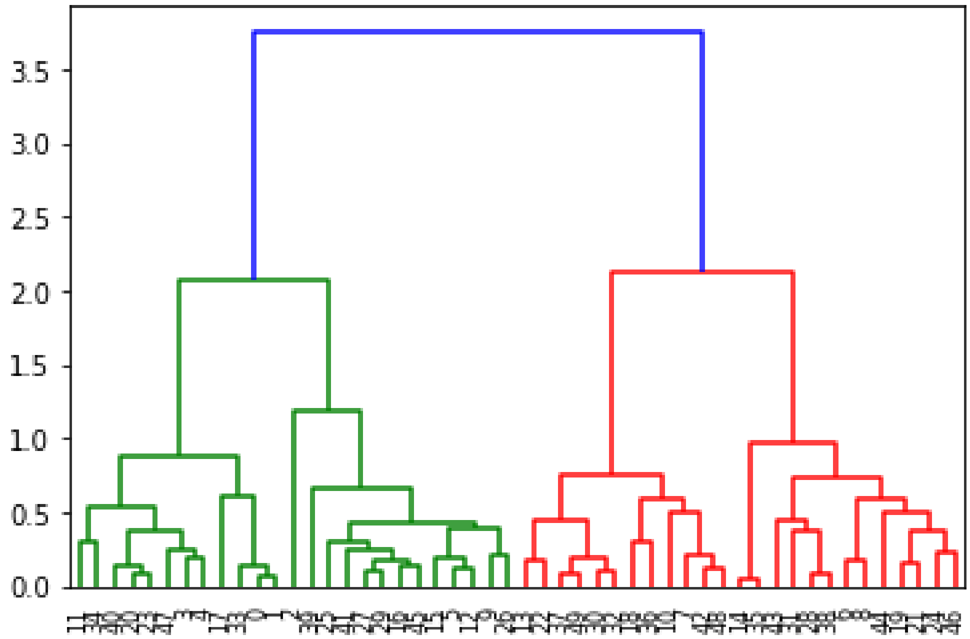


0.1 Practice

We used **complete** linkage for our case, change it to **average** linkage to see how the dendogram changes.

```
In [32]: # write your code here

         Z = hierarchy.linkage(dist_matrix, 'average')
         dendro = hierarchy.dendrogram(Z)
```

```
/home/jupyterlab/conda/lib/python3.6/site-packages/ipykernel_launcher.py:3: ClusterWarning: scip
  This is separate from the ipykernel package so we can avoid doing imports until
```



Double-click **here** for the solution.

Clustering on Vehicle dataset

Imagine that an automobile manufacturer has developed prototypes for a new vehicle. Before introducing the new model into its range, the manufacturer wants to determine which existing vehicles on the market are most like the prototypes--that is, how vehicles can be grouped, which group is the most similar with the model, and therefore which models they will be competing against.

Our objective here, is to use clustering methods, to find the most distinctive clusters of vehicles. It will summarize the existing vehicles and help manufacturers to make decision about the supply of new models.

0.1.1 Download data

To download the data, we will use `!wget` to download it from IBM Object Storage.

Did you know? When it comes to Machine Learning, you will likely be working with large datasets. As a business, where can you host your data? IBM is offering a unique opportunity for businesses, with 10 Tb of IBM Cloud Object Storage: Sign up now for free

```
In [33]: !wget -O cars_clus.csv https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-dat
```

```
--2019-03-04 01:41:50--  https://s3-api.us-geo.objectstorage.softlayer.net/cf-courses-data/Cogni
Resolving s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.net).
Connecting to s3-api.us-geo.objectstorage.softlayer.net (s3-api.us-geo.objectstorage.softlayer.n
```

```
HTTP request sent, awaiting response... 200 OK
Length: 17774 (17K) [text/csv]
Saving to: cars_clus.csv

cars_clus.csv       100%[===================>]  17.36K  --.-KB/s    in 0.02s

2019-03-04 01:41:50 (820 KB/s) - cars_clus.csv saved [17774/17774]
```

0.2 Read data

lets read dataset to see what features the manufacturer has collected about the existing models.

```
In [34]: filename = 'cars_clus.csv'

         #Read csv
         pdf = pd.read_csv(filename)
         print ("Shape of dataset: ", pdf.shape)

         pdf.head(5)
```

```
Shape of dataset:  (159, 16)
```

```
Out[34]:   manufact    model   sales  resale   type   price engine_s horsepow wheelbas  \
         0    Acura  Integra  16.919  16.360  0.000  21.500    1.800  140.000  101.200
         1    Acura       TL  39.384  19.875  0.000  28.400    3.200  225.000  108.100
         2    Acura       CL  14.114  18.225  0.000  $null$    3.200  225.000  106.900
         3    Acura       RL   8.588  29.725  0.000  42.000    3.500  210.000  114.600
         4     Audi       A4  20.397  22.255  0.000  23.990    1.800  150.000  102.600

            width   length curb_wgt fuel_cap     mpg lnsales  partition
         0  67.300  172.400    2.639   13.200  28.000   2.828        0.0
         1  70.300  192.900    3.517   17.200  25.000   3.673        0.0
         2  70.600  192.000    3.470   17.200  26.000   2.647        0.0
         3  71.400  196.600    3.850   18.000  22.000   2.150        0.0
         4  68.200  178.000    2.998   16.400  27.000   3.015        0.0
```

The feature sets include price in thousands (price), engine size (engine_s), horsepower (horsepow), wheelbase (wheelbas), width (width), length (length), curb weight (curb_wgt), fuel capacity (fuel_cap) and fuel efficiency (mpg).

Data Cleaning

lets simply clear the dataset by dropping the rows that have null value:

```
In [38]: print ("Shape of dataset before cleaning: ", pdf.size)
         pdf[[ 'sales', 'resale', 'type', 'price', 'engine_s',
                'horsepow', 'wheelbas', 'width', 'length', 'curb_wgt', 'fuel_cap',
                'mpg', 'lnsales']] = pdf[['sales', 'resale', 'type', 'price', 'engine_s',
```

```
                'horsepow', 'wheelbas', 'width', 'length', 'curb_wgt', 'fuel_cap',
                'mpg', 'lnsales']].apply(pd.to_numeric, errors='coerce')
        pdf = pdf.dropna()
        pdf = pdf.reset_index(drop=True)
        print ("Shape of dataset after cleaning: ", pdf.size)
        pdf.head(5)
        pdf.shape
```

```
Shape of dataset before cleaning:  1872
Shape of dataset after cleaning:  1872
```

```
Out[38]: (117, 16)
```

0.2.1 Feature selection

Lets select our feature set:

```
In [39]: featureset = pdf[['engine_s',  'horsepow', 'wheelbas', 'width', 'length', 'curb_wgt', '
```

0.2.2 Normalization

Now we can normalize the feature set. **MinMaxScaler** transforms features by scaling each feature to a given range. It is by default (0, 1). That is, this estimator scales and translates each feature individually such that it is between zero and one.

```
In [40]: from sklearn.preprocessing import MinMaxScaler
         x = featureset.values #returns a numpy array
         min_max_scaler = MinMaxScaler()
         feature_mtx = min_max_scaler.fit_transform(x)
         feature_mtx [0:5]
```

```
Out[40]: array([[0.11428571, 0.21518987, 0.18655098, 0.28143713, 0.30625832,
                 0.2310559 , 0.13364055, 0.43333333],
                [0.31428571, 0.43037975, 0.3362256 , 0.46107784, 0.5792277 ,
                 0.50372671, 0.31797235, 0.33333333],
                [0.35714286, 0.39240506, 0.47722343, 0.52694611, 0.62849534,
                 0.60714286, 0.35483871, 0.23333333],
                [0.11428571, 0.24050633, 0.21691974, 0.33532934, 0.38082557,
                 0.34254658, 0.28110599, 0.4       ],
                [0.25714286, 0.36708861, 0.34924078, 0.80838323, 0.56724368,
                 0.5173913 , 0.37788018, 0.23333333]])
```

Clustering using Scipy
In this part we use Scipy package to cluster the dataset:
First, we calculate the distance matrix.

```
In [41]: import scipy
         leng = feature_mtx.shape[0]
```

```
D = scipy.zeros([leng,leng])
for i in range(leng):
    for j in range(leng):
        D[i,j] = scipy.spatial.distance.euclidean(feature_mtx[i], feature_mtx[j])
```

In agglomerative clustering, at each iteration, the algorithm must update the distance matrix to reflect the distance of the newly formed cluster with the remaining clusters in the forest. The following methods are supported in Scipy for calculating the distance between the newly formed cluster and each: - single - complete - average - weighted - centroid

We use **complete** for our case, but feel free to change it to see how the results change.

```
In [46]: import pylab
         import scipy.cluster.hierarchy
         Z = hierarchy.linkage(D, 'complete')
         #dendro = hierarchy.dendrogram(Z)
```

```
/home/jupyterlab/conda/lib/python3.6/site-packages/ipykernel_launcher.py:3: ClusterWarning: scip
  This is separate from the ipykernel package so we can avoid doing imports until
```

Essentially, Hierarchical clustering does not require a pre-specified number of clusters. However, in some applications we want a partition of disjoint clusters just as in flat clustering. So you can use a cutting line:

```
In [57]: from scipy.cluster.hierarchy import fcluster
         max_d = 3
         clusters = fcluster(Z, max_d, criterion='distance')
         clusters
```

```
Out[57]: array([ 1,  5,  5,  6,  5,  4,  6,  5,  5,  5,  5,  5,  4,  4,  5,  1,  6,
                 5,  5,  5,  4,  2, 11,  6,  6,  5,  6,  5,  1,  6,  6, 10,  9,  8,
                 9,  3,  5,  1,  7,  6,  5,  3,  5,  3,  8,  7,  9,  2,  6,  6,  5,
                 4,  2,  1,  6,  5,  2,  7,  5,  5,  5,  4,  4,  3,  2,  6,  6,  5,
                 7,  4,  7,  6,  6,  5,  3,  5,  5,  6,  5,  4,  4,  1,  6,  5,  5,
                 5,  6,  4,  5,  4,  1,  6,  5,  6,  6,  5,  5,  5,  7,  7,  7,  2,
                 2,  1,  2,  6,  5,  1,  1,  1,  7,  8,  1,  1,  6,  1,  1],
               dtype=int32)
```

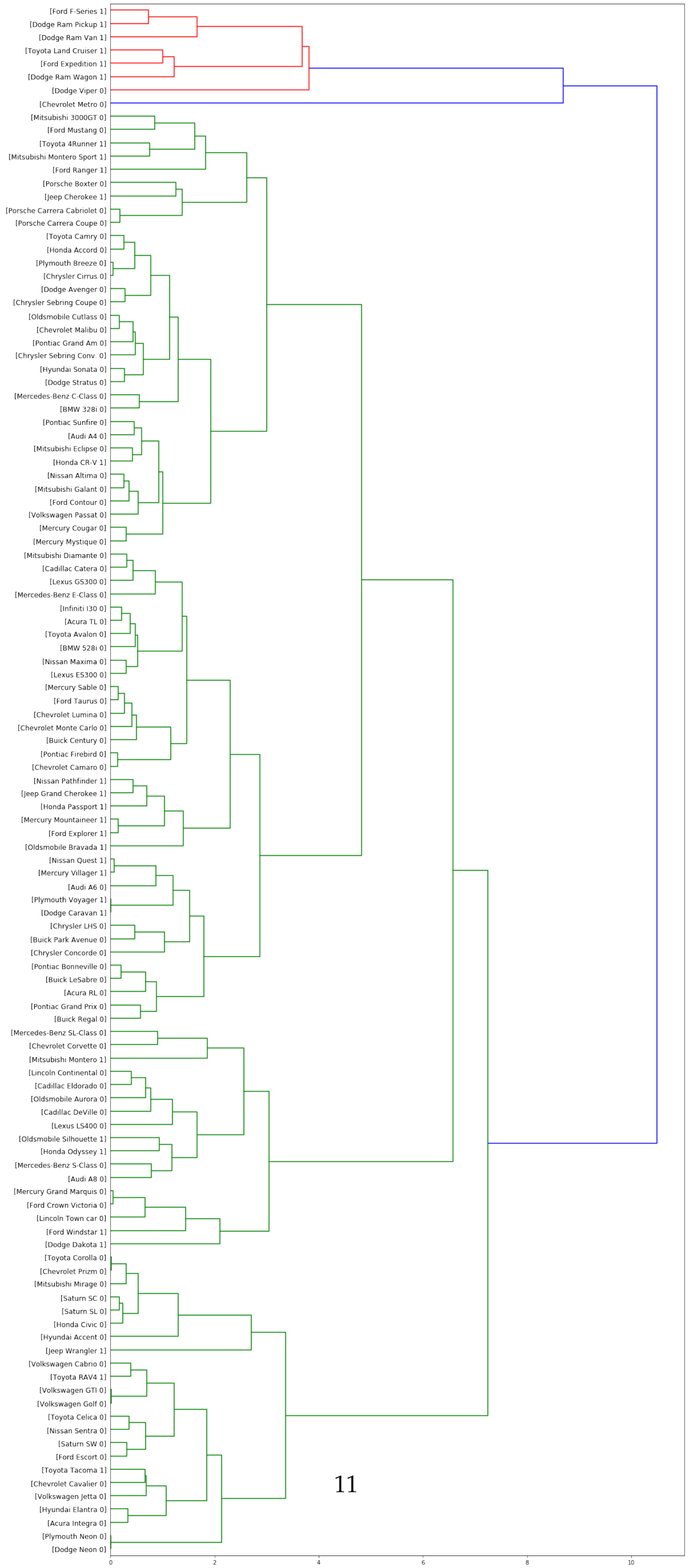
Also, you can determine the number of clusters directly:

```
In [56]: from scipy.cluster.hierarchy import fcluster
         k = 5
         clusters = fcluster(Z, k, criterion='maxclust')
         clusters
```

```
Out[56]: array([1, 3, 3, 3, 3, 2, 3, 3, 3, 3, 3, 3, 2, 2, 3, 1, 3, 3, 3, 3, 2, 1,
                5, 3, 3, 3, 3, 3, 1, 3, 3, 4, 4, 4, 4, 2, 3, 1, 3, 3, 3, 2, 3, 2,
                4, 3, 4, 1, 3, 3, 3, 2, 1, 1, 3, 3, 1, 3, 3, 3, 3, 2, 2, 2, 1, 3,
                3, 3, 3, 2, 3, 3, 3, 3, 2, 3, 3, 3, 3, 2, 2, 1, 3, 3, 3, 3, 3, 2,
                3, 2, 1, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 1, 1, 1, 1, 3, 3, 1, 1, 1,
                3, 4, 1, 1, 3, 1, 1], dtype=int32)
```

Now, plot the dendrogram:

```
In [58]: fig = pylab.figure(figsize=(18,50))
         def llf(id):
             return '[%s %s %s]' % (pdf['manufact'][id], pdf['model'][id], int(float(pdf['type']

         dendro = hierarchy.dendrogram(Z,  leaf_label_func=llf, leaf_rotation=0, leaf_font_size
```


[Ford F-Series 1]
[Dodge Ram Pickup 1]
[Dodge Ram Van 1]
[Toyota Land Cruiser 1]
[Ford Expedition 1]
[Dodge Ram Wagon 1]
[Dodge Viper 0]
[Chevrolet Metro 0]
[Mitsubishi 3000GT 0]
[Ford Mustang 0]
[Toyota 4Runner 1]
[Mitsubishi Montero Sport 1]
[Ford Ranger 1]
[Porsche Boxter 0]
[Jeep Cherokee 1]
[Porsche Carrera Cabriolet 0]
[Porsche Carrera Coupe 0]
[Toyota Camry 0]
[Honda Accord 0]
[Plymouth Breeze 0]
[Chrysler Cirrus 0]
[Dodge Avenger 0]
[Chrysler Sebring Coupe 0]
[Oldsmobile Cutlass 0]
[Chevrolet Malibu 0]
[Pontiac Grand Am 0]
[Chrysler Sebring Conv. 0]
[Hyundai Sonata 0]
[Dodge Stratus 0]
[Mercedes-Benz C-Class 0]
[BMW 328i 0]
[Pontiac Sunfire 0]
[Audi A4 0]
[Mitsubishi Eclipse 0]
[Honda CR-V 1]
[Nissan Altima 0]
[Mitsubishi Galant 0]
[Ford Contour 0]
[Volkswagen Passat 0]
[Mercury Cougar 0]
[Mercury Mystique 0]
[Mitsubishi Diamante 0]
[Cadillac Catera 0]
[Lexus GS300 0]
[Mercedes-Benz E-Class 0]
[Infiniti I30 0]
[Acura TL 0]
[Toyota Avalon 0]
[BMW 528i 0]
[Nissan Maxima 0]
[Lexus ES300 0]
[Mercury Sable 0]
[Ford Taurus 0]
[Chevrolet Lumina 0]
[Chevrolet Monte Carlo 0]
[Buick Century 0]
[Pontiac Firebird 0]
[Chevrolet Camaro 0]
[Nissan Pathfinder 1]
[Jeep Grand Cherokee 1]
[Honda Passport 1]
[Mercury Mountaineer 1]
[Ford Explorer 1]
[Oldsmobile Bravada 1]
[Nissan Quest 1]
[Mercury Villager 1]
[Audi A6 0]
[Plymouth Voyager 1]
[Dodge Caravan 1]
[Chrysler LHS 0]
[Buick Park Avenue 0]
[Chrysler Concorde 0]
[Pontiac Bonneville 0]
[Buick LeSabre 0]
[Acura RL 0]
[Pontiac Grand Prix 0]
[Buick Regal 0]
[Mercedes-Benz SL-Class 0]
[Chevrolet Corvette 0]
[Mitsubishi Montero 1]
[Lincoln Continental 0]
[Cadillac Eldorado 0]
[Oldsmobile Aurora 0]
[Cadillac DeVille 0]
[Lexus LS400 0]
[Oldsmobile Silhouette 1]
[Honda Odyssey 1]
[Mercedes-Benz S-Class 0]
[Audi A8 0]
[Mercury Grand Marquis 0]
[Ford Crown Victoria 0]
[Lincoln Town car 0]
[Ford Windstar 1]
[Dodge Dakota 1]
[Toyota Corolla 0]
[Chevrolet Prizm 0]
[Mitsubishi Mirage 0]
[Saturn SC 0]
[Saturn SL 0]
[Honda Civic 0]
[Hyundai Accent 0]
[Jeep Wrangler 1]
[Volkswagen Cabrio 0]
[Toyota RAV4 1]
[Volkswagen GTI 0]
[Volkswagen Golf 0]
[Toyota Celica 0]
[Nissan Sentra 0]
[Saturn SW 0]
[Ford Escort 0]
[Toyota Tacoma 1]
[Chevrolet Cavalier 0]
[Volkswagen Jetta 0]
[Hyundai Elantra 0]
[Acura Integra 0]
[Plymouth Neon 0]
[Dodge Neon 0]
0
2
4
6
8
10

Clustering using scikit-learn
Lets redo it again, but this time using scikit-learn package:

```
In [59]: dist_matrix = distance_matrix(feature_mtx,feature_mtx)
         print(dist_matrix)
```

```
[[0.         0.57777143 0.75455727 ... 0.28530295 0.24917241 0.18879995]
 [0.57777143 0.         0.22798938 ... 0.36087756 0.66346677 0.62201282]
 [0.75455727 0.22798938 0.         ... 0.51727787 0.81786095 0.77930119]
 ...
 [0.28530295 0.36087756 0.51727787 ... 0.         0.41797928 0.35720492]
 [0.24917241 0.66346677 0.81786095 ... 0.41797928 0.         0.15212198]
 [0.18879995 0.62201282 0.77930119 ... 0.35720492 0.15212198 0.        ]]
```

Now, we can use the 'AgglomerativeClustering' function from scikit-learn library to cluster the dataset. The AgglomerativeClustering performs a hierarchical clustering using a bottom up approach. The linkage criteria determines the metric used for the merge strategy:

- Ward 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 tackled with an agglomerative hierarchical approach.
- Maximum or complete linkage minimizes the maximum distance between observations of pairs of clusters.
- Average linkage minimizes the average of the distances between all observations of pairs of clusters.

```
In [60]: agglom = AgglomerativeClustering(n_clusters = 6, linkage = 'complete')
         agglom.fit(feature_mtx)
         agglom.labels_
```

```
Out[60]: array([1, 2, 2, 1, 2, 3, 1, 2, 2, 2, 2, 2, 3, 3, 2, 1, 1, 2, 2, 2, 5, 1,
                4, 1, 1, 2, 1, 2, 1, 1, 1, 5, 0, 0, 0, 3, 2, 1, 2, 1, 2, 3, 2, 3,
                0, 3, 0, 1, 1, 1, 2, 3, 1, 1, 1, 2, 1, 1, 2, 2, 2, 3, 3, 3, 1, 1,
                1, 2, 1, 2, 2, 1, 1, 2, 3, 2, 3, 1, 2, 3, 5, 1, 1, 2, 3, 2, 1, 3,
                2, 3, 1, 1, 2, 1, 1, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1,
                2, 0, 1, 1, 1, 1, 1])
```

And, we can add a new field to our dataframe to show the cluster of each row:

```
In [61]: pdf['cluster_'] = agglom.labels_
         pdf.head()
```

```
Out[61]:   manufact    model   sales  resale  type  price  engine_s  horsepow  \
         0    Acura  Integra  16.919  16.360   0.0  21.50       1.8     140.0
         1    Acura       TL  39.384  19.875   0.0  28.40       3.2     225.0
         2    Acura       RL   8.588  29.725   0.0  42.00       3.5     210.0
```

```
3     Audi       A4  20.397  22.255   0.0  23.99       1.8     150.0
4     Audi       A6  18.780  23.555   0.0  33.95       2.8     200.0

   wheelbas  width  length  curb_wgt  fuel_cap   mpg  lnsales  partition  \
0     101.2   67.3   172.4     2.639      13.2  28.0    2.828        0.0
1     108.1   70.3   192.9     3.517      17.2  25.0    3.673        0.0
2     114.6   71.4   196.6     3.850      18.0  22.0    2.150        0.0
3     102.6   68.2   178.0     2.998      16.4  27.0    3.015        0.0
4     108.7   76.1   192.0     3.561      18.5  22.0    2.933        0.0

   cluster_
0         1
1         2
2         2
3         1
4         2
```

In [62]:
```python
import matplotlib.cm as cm
n_clusters = max(agglom.labels_)+1
colors = cm.rainbow(np.linspace(0, 1, n_clusters))
cluster_labels = list(range(0, n_clusters))

# Create a figure of size 6 inches by 4 inches.
plt.figure(figsize=(16,14))

for color, label in zip(colors, cluster_labels):
    subset = pdf[pdf.cluster_ == label]
    for i in subset.index:
            plt.text(subset.horsepow[i], subset.mpg[i],str(subset['model'][i]), rotatio
    plt.scatter(subset.horsepow, subset.mpg, s= subset.price*10, c=color, label='cluste
#    plt.scatter(subset.horsepow, subset.mpg)
plt.legend()
plt.title('Clusters')
plt.xlabel('horsepow')
plt.ylabel('mpg')
```

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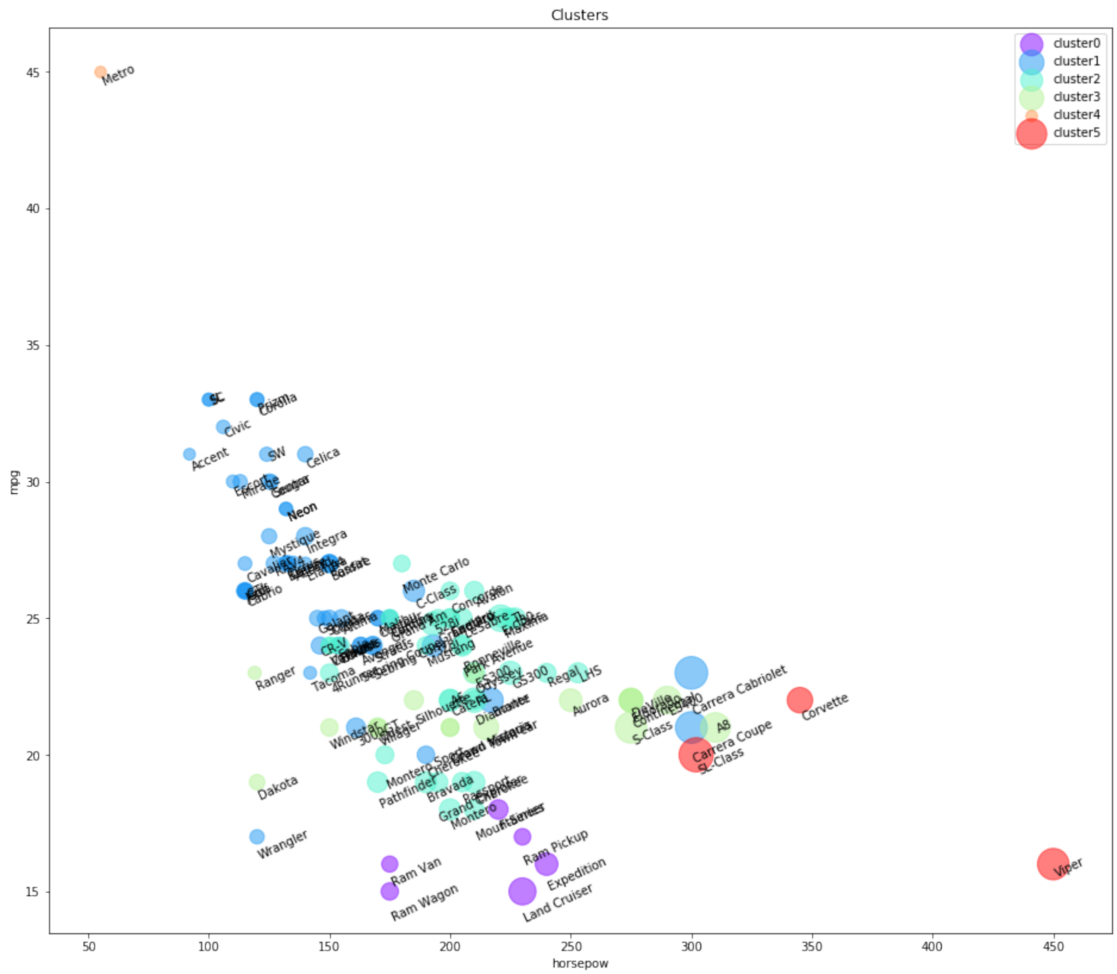
```

Out[62]: Text(0, 0.5, 'mpg')



As you can see, we are seeing the distribution of each cluster using the scatter plot, but it is not very clear where is the centroid of each cluster. Moreover, there are 2 types of vehicles in our dataset, "truck" (value of 1 in the type column) and "car" (value of 1 in the type column). So, we use them to distinguish the classes, and summarize the cluster. First we count the number of cases in each group:

```
In [63]: pdf.groupby(['cluster_','type'])['cluster_'].count()
```

```
Out[63]: cluster_  type
         0         1.0      6
         1         0.0     47
                   1.0      5
         2         0.0     27
                   1.0     11
         3         0.0     10
                   1.0      7
         4         0.0      1
         5         0.0      3
         Name: cluster_, dtype: int64
```

Now we can look at the characteristics of each cluster:

```
In [64]: agg_cars = pdf.groupby(['cluster_','type'])['horsepow','engine_s','mpg','price'].mean()
         agg_cars
```

Out[64]:

cluster_	type	horsepow	engine_s	mpg	price
0	1.0	211.666667	4.483333	16.166667	29.024667
1	0.0	146.531915	2.246809	27.021277	20.306128
	1.0	145.000000	2.580000	22.200000	17.009200
2	0.0	203.111111	3.303704	24.214815	27.750593
	1.0	182.090909	3.345455	20.181818	26.265364
3	0.0	256.500000	4.410000	21.500000	42.870400
	1.0	160.571429	3.071429	21.428571	21.527714
4	0.0	55.000000	1.000000	45.000000	9.235000
5	0.0	365.666667	6.233333	19.333333	66.010000

It is obvious that we have 3 main clusters with the majority of vehicles in those.

Cars: - Cluster 1: with almost high mpg, and low in horsepower. - Cluster 2: with good mpg and horsepower, but higher price than average. - Cluster 3: with low mpg, high horsepower, highest price.

Trucks: - Cluster 1: with almost highest mpg among trucks, and lowest in horsepower and price. - Cluster 2: with almost low mpg and medium horsepower, but higher price than average. - Cluster 3: with good mpg and horsepower, low price.

Please notice that we did not use **type** , and **price** of cars in the clustering process, but Hierarchical clustering could forge the clusters and discriminate them with quite high accuracy.

```
In [66]: plt.figure(figsize=(16,10))
         for color, label in zip(colors, cluster_labels):
             subset = agg_cars.loc[(label,),]
             for i in subset.index:
                 plt.text(subset.loc[i][0]+5, subset.loc[i][2], 'type='+str(int(i)) + ', price='
             plt.scatter(subset.horsepow, subset.mpg, s=subset.price*20, c=color, label='cluster
         plt.legend()
         plt.title('Clusters')
         plt.xlabel('horsepow')
         plt.ylabel('mpg')
```

```
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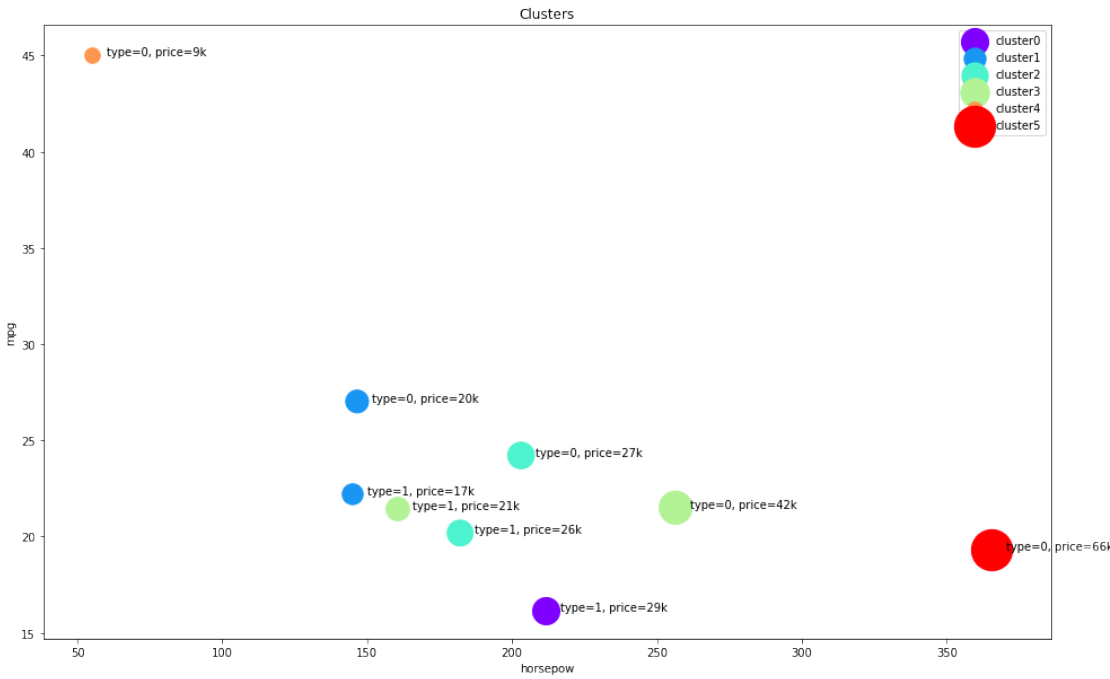
```

```
Out[66]: Text(0, 0.5, 'mpg')
```



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Thanks for completing this lesson!

Author: Saeed Aghabozorgi

Saeed Aghabozorgi, PhD is a Data Scientist in IBM with a track record of developing enterprise level applications that substantially increases clients' ability to turn data into actionable knowledge. He is a researcher in data mining field and expert in developing advanced analytic methods like machine learning and statistical modelling on large datasets.