In [ ]:

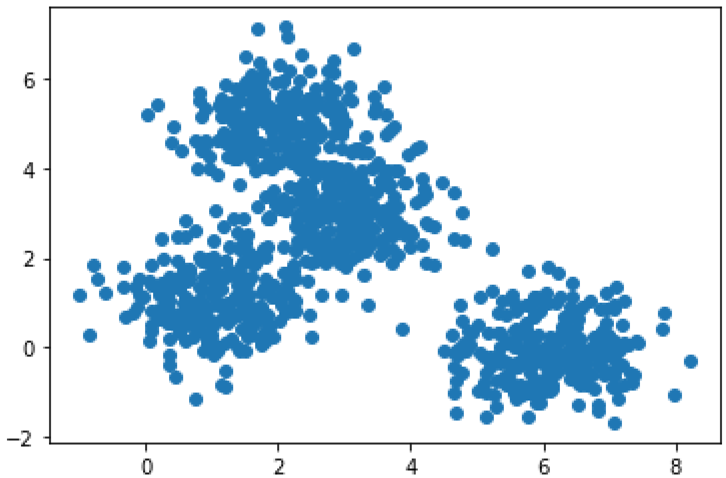
```python
#Clustering.

import pandas as pd
import numpy as np
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
```

In [ ]:

```python
x, y = make_blobs(n_samples = 1000, centers = [[1,1], [2, 5], [3,3], [6, 0]], cluster_std=0.7)
plt.scatter(x[:,0], x[:,1], marker = 'o')
```

Out[ ]:

```
<matplotlib.collections.PathCollection at 0x1aa0e6009a0>
```



In [ ]:

```python
#Linkage : {'ward', 'complete', 'average', 'single'}, default='ward' Which linkage criterion to use. The linkage criteric
#which distance to use between sets of observation. The algorithm will merge the pairs of cluster that minimize this crit
#'ward' minimizes the variance of the clusters being merged.
#'average' uses the average of the distances of each observation of the two sets.
#'complete' or 'maximum' linkage uses the maximum distances between all observations of the two sets.
#'single' uses the minimum of the distances between all observations of the two sets.
```

```
agglom = AgglomerativeClustering(n_clusters = 4, linkage = 'average')
agglom.fit(x, y)
```

Out[ ]:
```
AgglomerativeClustering(linkage='average', n_clusters=4)
```

In [ ]:
```
agglom
```

Out[ ]:
```
AgglomerativeClustering(linkage='average', n_clusters=4)
```

In [ ]:
```
x
```

Out[ ]:
```
array([[1.73190834, 0.89781415],
       [3.10123016, 2.00044963],
       [0.83335403, 0.9479239 ],
       ...,
       [0.16261693, 5.41553182],
       [2.87614288, 3.39429156],
       [2.75950008, 1.99533172]])
```

In [ ]:
```
#Simple method to scale the x values
xmin, xmax = np.min(x, axis = 0), np.max(x, axis = 0)
x1 = (x - xmin)/(xmax - xmin)
x1
```

Out[ ]:
```
array([[0.2965632 , 0.29190786],
       [0.44542686, 0.4165633 ],
       [0.19887829, 0.29757288],
       ...,
       [0.12596016, 0.8026461 ],
       [0.42095685, 0.5741403 ],
       [0.40827621, 0.41598471]])
```

In [ ]:
```
from sklearn.preprocessing import StandardScaler
```

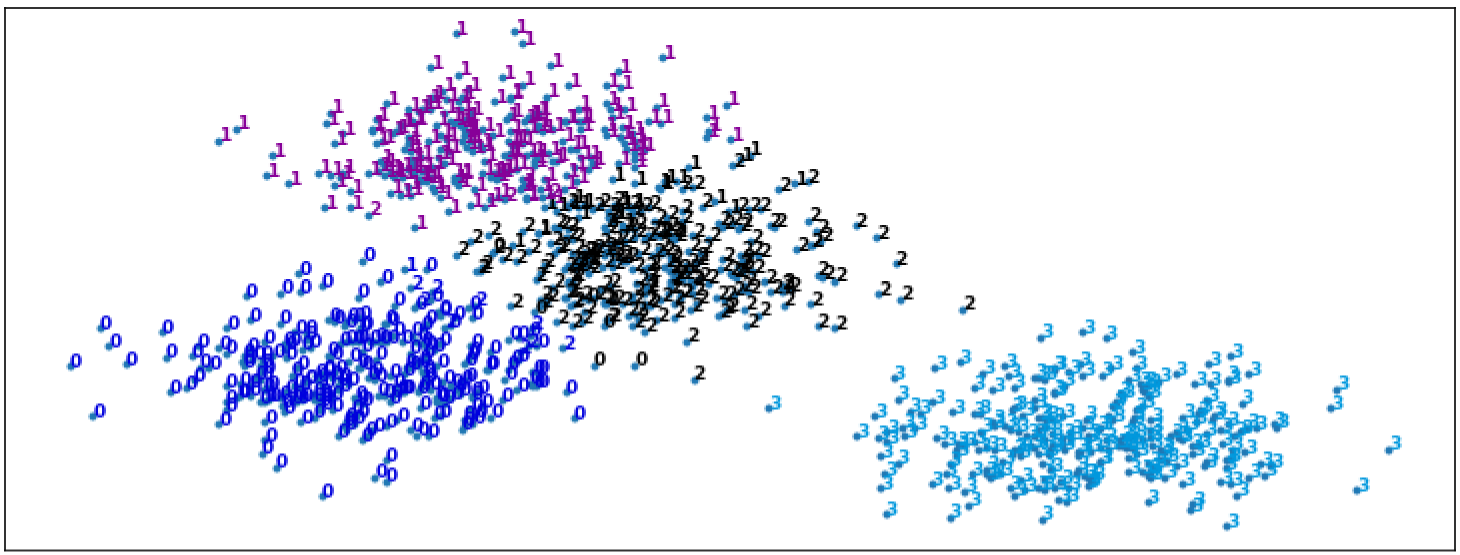
In [ ]:
```
x2 = np.nan_to_num(x)
x3 = StandardScaler().fit_transform(x2)
x3
```

Out[ ]:
```
array([[-0.65460096, -0.65160774],
       [ 0.02342302, -0.11397841],
```

```
       [-1.09952293, -0.62717494],
       ...,
       [-1.4316405 ,  1.55116693],
       [-0.08802965,  0.56563903],
       [-0.1457857 , -0.11647383]])
```

In [ ]:

```
#Plot the blobs
plt.figure(figsize = (13, 5))
xmin, xmax = np.min(x, axis = 0), np.max(x, axis = 0)
x = (x - xmin)/(xmax - xmin)

for i in range(x.shape[0]):
    plt.text(x[i, 0], x[i,1], str(y[i]), color = plt.cm.nipy_spectral(agglom.labels_[i] / 10.), fontdict={'weight': 'bold

plt.xticks([])
plt.yticks([])

plt.scatter(x[:,0], x[:,1], marker = '.')
plt.show()
```



In [ ]:

```
#Calculate a distance matrix, or a matrix of distances between points
dist_matrix = distance_matrix(x, x)
print(dist_matrix)
```

```
[[0.         0.19416325 0.09784904 ... 0.53847836 0.30842978 0.16695767]
```

```
 [0.19416325 0.         0.27376069 ... 0.50111764 0.15946564 0.03715515]
 [0.09784904 0.27376069 0.         ... 0.51030972 0.35469483 0.24055946]
 ...
 [0.53847836 0.50111764 0.51030972 ... 0.         0.37314601 0.47875816]
 [0.30842978 0.15946564 0.35469483 ... 0.37314601 0.         0.15866313]
 [0.16695767 0.03715515 0.24055946 ... 0.47875816 0.15866313 0.        ]]
```

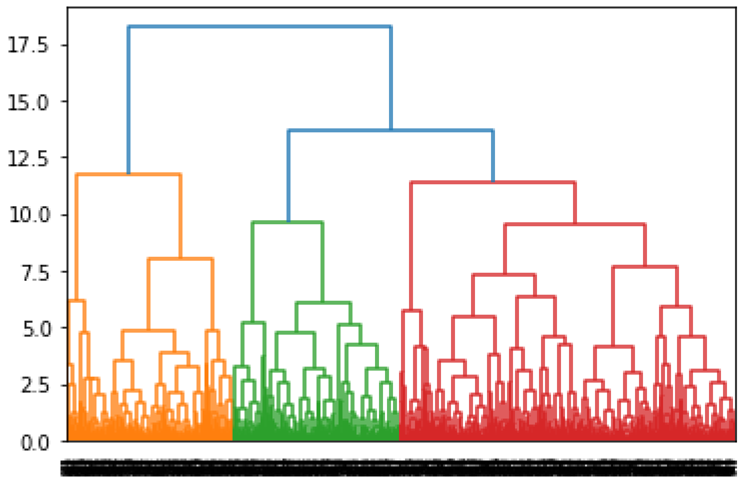
In [ ]:

```
#Create hierarchy based on distance matrix
z = hierarchy.linkage(dist_matrix, 'complete')
```

```
C:\Users\Gabri\AppData\Local\Temp/ipykernel_15428/2642424508.py:1: ClusterWarning: scipy.cluster: The symmetric non-negat
ive hollow observation matrix looks suspiciously like an uncondensed distance matrix
  z = hierarchy.linkage(dist_matrix, 'complete')
```

In [ ]:

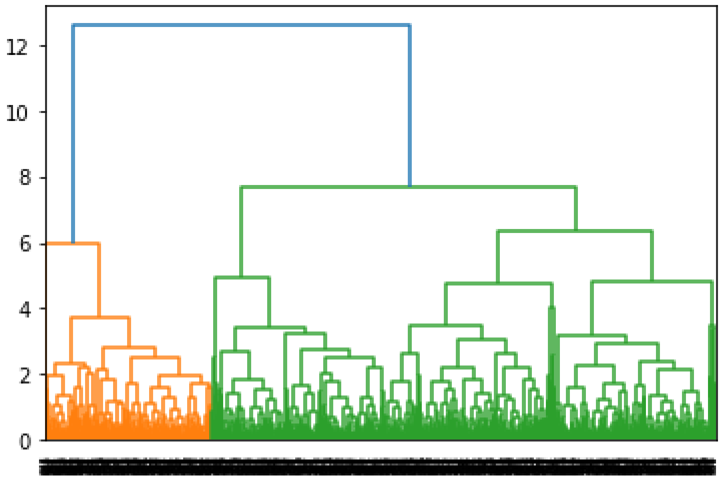
```
#Create dendrogram based on distance hierarchy
dendro = hierarchy.dendrogram(z)
```



In [ ]:

```
#Dendrogram again, this time using the 'average' method instead of the 'complete' method
z = hierarchy.linkage(dist_matrix, 'average')
dendro = hierarchy.dendrogram(z)
```

```
C:\Users\Gabri\AppData\Local\Temp/ipykernel_15428/3862025947.py:1: ClusterWarning: scipy.cluster: The symmetric non-negat
ive hollow observation matrix looks suspiciously like an uncondensed distance matrix
  z = hierarchy.linkage(dist_matrix, 'average')
```



In [ ]:
```
#Download a new dataset on cars
!wget -O cars_clus.csv https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-ML010
```

```
--2021-10-17 09:02:16--  https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBMDeveloperSkillsNetwork-ML0
101EN-SkillsNetwork/labs/Module%204/data/cars_clus.csv
Resolving cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud (cf-courses-data.s3.us.cloud-object-storage.appdomai
n.cloud)... 169.45.118.108
Connecting to cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud (cf-courses-data.s3.us.cloud-object-storage.appd
omain.cloud)|169.45.118.108|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 17774 (17K) [text/csv]
Saving to: 'cars_clus.csv'

     0K .......... .......                                     100% 1.01M=0.02s

2021-10-17 09:02:17 (1.01 MB/s) - 'cars_clus.csv' saved [17774/17774]
```

In [ ]:
```
cars = pd.read_csv('cars_clus.csv')
cars.head()
```

Out[ ]:

	manufact	model	sales	resale	type	price	engine_s	horsepow	wheelbas	width	length	curb_wgt	fuel_cap	mpg	lnsale
0	Acura	Integra	16.919	16.360	0.000	21.500	1.800	140.000	101.200	67.300	172.400	2.639	13.200	28.000	2.828
1	Acura	TL	39.384	19.875	0.000	28.400	3.200	225.000	108.100	70.300	192.900	3.517	17.200	25.000	3.673

	manufact	model	sales	resale	type	price	engine_s	horsepow	wheelbas	width	length	curb_wgt	fuel_cap	mpg	lnsale
2	Acura	CL	14.114	18.225	0.000	*null*	3.200	225.000	106.900	70.600	192.000	3.470	17.200	26.000	2.64
3	Acura	RL	8.588	29.725	0.000	42.000	3.500	210.000	114.600	71.400	196.600	3.850	18.000	22.000	2.15
4	Audi	A4	20.397	22.255	0.000	23.990	1.800	150.000	102.600	68.200	178.000	2.998	16.400	27.000	3.01

In [ ]:

```
cars.describe()
```

Out[ ]:

	partition
count	159.000000
mean	0.012579
std	0.111799
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

In [ ]:

```
cars.columns
```

Out[ ]:

```
Index(['manufact', 'model', 'sales', 'resale', 'type', 'price', 'engine_s',
       'horsepow', 'wheelbas', 'width', 'length', 'curb_wgt', 'fuel_cap',
       'mpg', 'lnsales', 'partition'],
      dtype='object')
```

In [ ]:

```
print(cars.size)
cars[['sales', 'resale', 'type', 'price', 'engine_s', 'horsepow', 'wheelbas', 'width', 'length', 'curb_wgt',
'fuel_cap','mpg', 'lnsales', 'partition']] = cars[['sales', 'resale', 'type', 'price', 'engine_s', 'horsepow',
'wheelbas', 'width', 'length', 'curb_wgt', 'fuel_cap','mpg', 'lnsales', 'partition']].apply(pd.to_numeric, errors = 'coer
cars = cars.dropna()
cars = cars.reset_index(drop=True)
```

```
print(cars.size)
cars.head()
```

2544
1872

Out[ ]:

	manufact	model	sales	resale	type	price	engine_s	horsepow	wheelbas	width	length	curb_wgt	fuel_cap	mpg	lnsales	pa
0	Acura	Integra	16.919	16.360	0.0	21.50	1.8	140.0	101.2	67.3	172.4	2.639	13.2	28.0	2.828	
1	Acura	TL	39.384	19.875	0.0	28.40	3.2	225.0	108.1	70.3	192.9	3.517	17.2	25.0	3.673	
2	Acura	RL	8.588	29.725	0.0	42.00	3.5	210.0	114.6	71.4	196.6	3.850	18.0	22.0	2.150	
3	Audi	A4	20.397	22.255	0.0	23.99	1.8	150.0	102.6	68.2	178.0	2.998	16.4	27.0	3.015	
4	Audi	A6	18.780	23.555	0.0	33.95	2.8	200.0	108.7	76.1	192.0	3.561	18.5	22.0	2.933	

In [ ]:

```
features = cars[['engine_s', 'horsepow', 'wheelbas', 'width', 'length', 'curb_wgt', 'fuel_cap','mpg']]
```

In [ ]:

```
from sklearn.preprocessing import MinMaxScaler
```

In [ ]:

```
#Another method to scale the x values
x = features.values
min_max_scaler = MinMaxScaler()
feature_mtx = min_max_scaler.fit_transform(x)
feature_mtx[0:5]
```

Out[ ]:

```
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]])
```

In [ ]:

```
#Create distance matrix using scipy. as before
```

```python
import scipy
leng = feature_mtx.shape[0]
D = np.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])

D
```

Out[ ]:

```
array([[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.        ]])
```

In [ ]:

```python
import pylab
z = hierarchy.linkage(D, 'complete')
```

```
C:\Users\Gabri\AppData\Local\Temp/ipykernel_15428/1282917177.py:2: ClusterWarning: scipy.cluster: The symmetric non-negat
ive hollow observation matrix looks suspiciously like an uncondensed distance matrix
  z = hierarchy.linkage(D, 'complete')
```

In [ ]:

```python
max_d = 3
clusters = hierarchy.fcluster(z, max_d, criterion = 'distance')
clusters
```

Out[ ]:

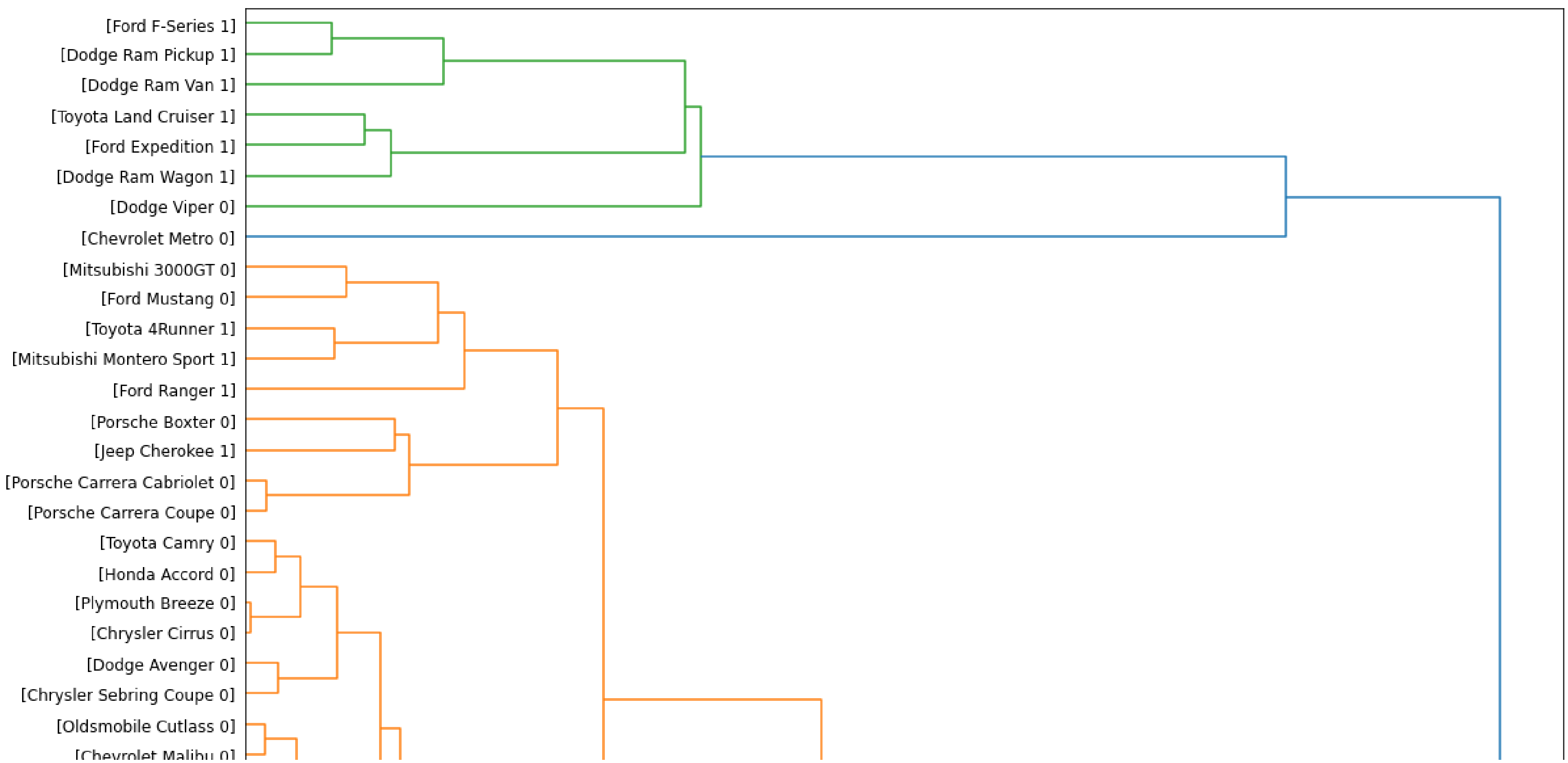
```
array([ 1,  5,  5,  6,  5,  4,  6,  5,  5,  5,  5,  5,  4,  4,  5,  1,  6,
        5,  5,  5,  4,  2, 11,  6,  6,  5,  6,  5,  1,  6,  6, 10,  9,  8,
        9,  3,  5,  1,  7,  6,  5,  3,  5,  3,  8,  7,  9,  2,  6,  6,  5,
        4,  2,  1,  6,  5,  2,  7,  5,  5,  5,  4,  4,  3,  2,  6,  6,  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)
```

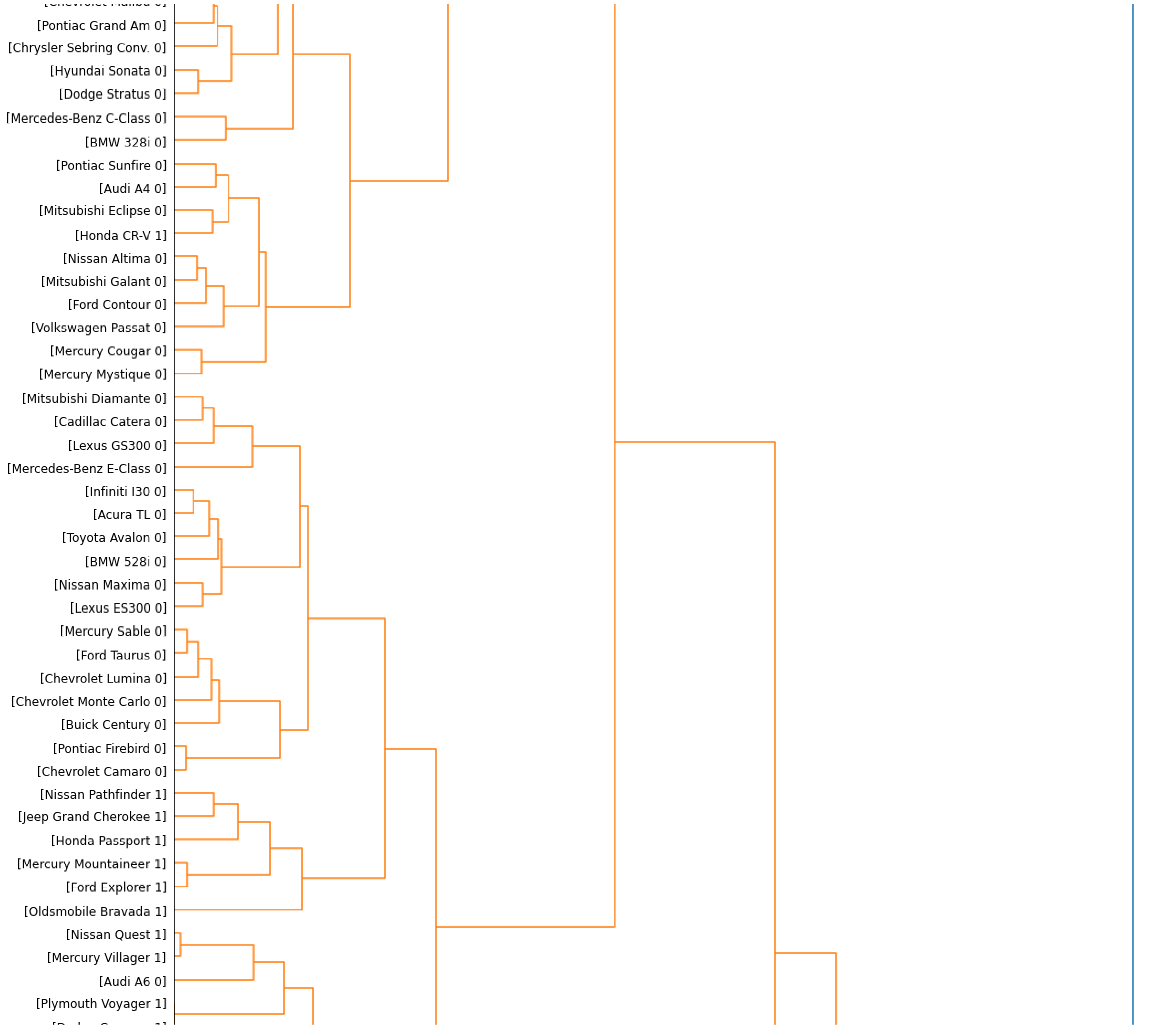
In [ ]:

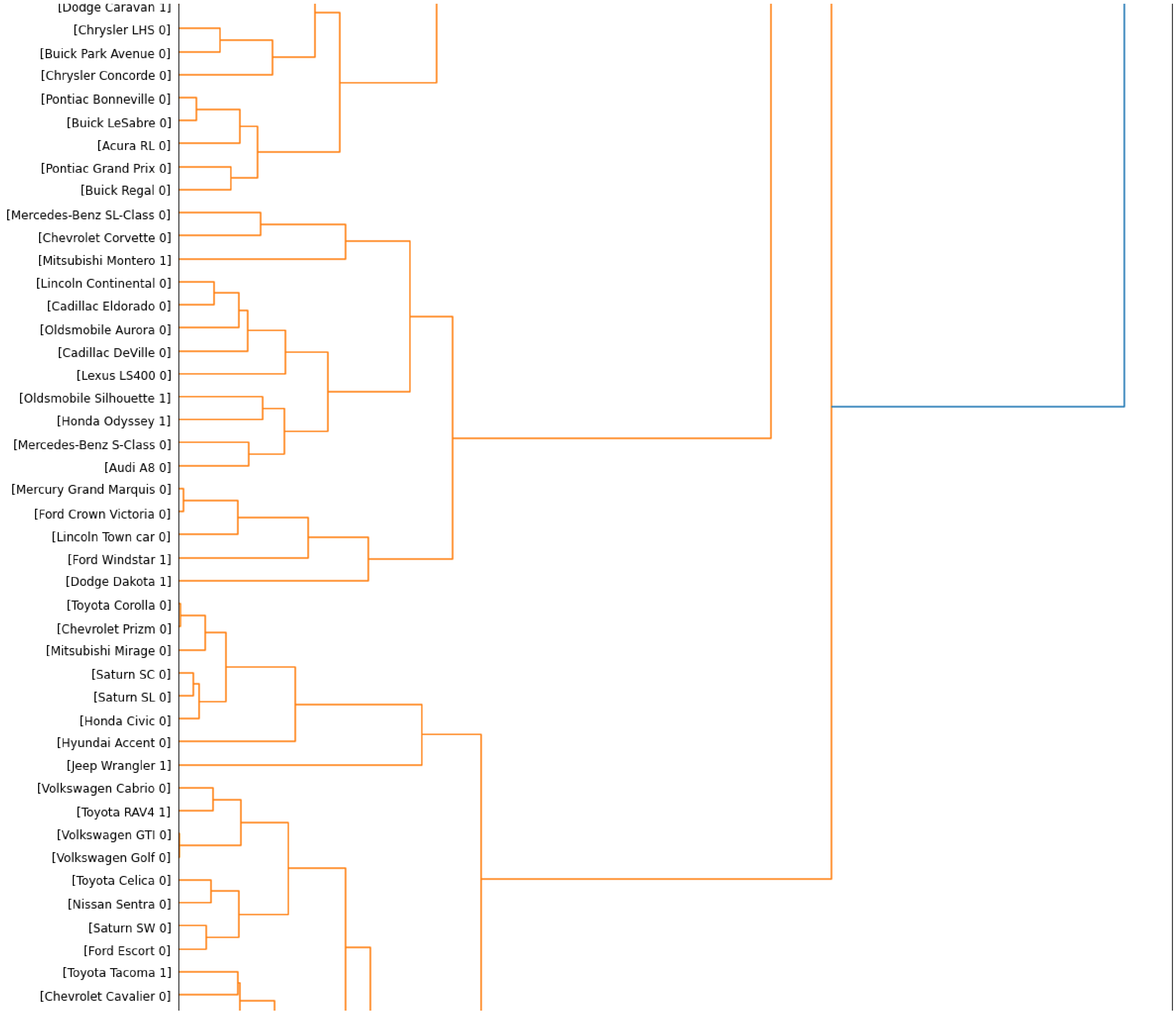
```
k = 5
clusters = hierarchy.fcluster(z, k, criterion = 'maxclust')
clusters
```

Out[ ]:
```
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)
```

In [ ]:
```
#Create dendrogram

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

dendro = hierarchy.dendrogram(z, leaf_label_func=llf, leaf_rotation=0, leaf_font_size=12, orientation= 'right')
```




[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]

In [ ]:

```
#Create distance matrix using sklearn

from sklearn.metrics.pairwise import euclidean_distances
dist_matrix = euclidean_distances(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.        ]]
```

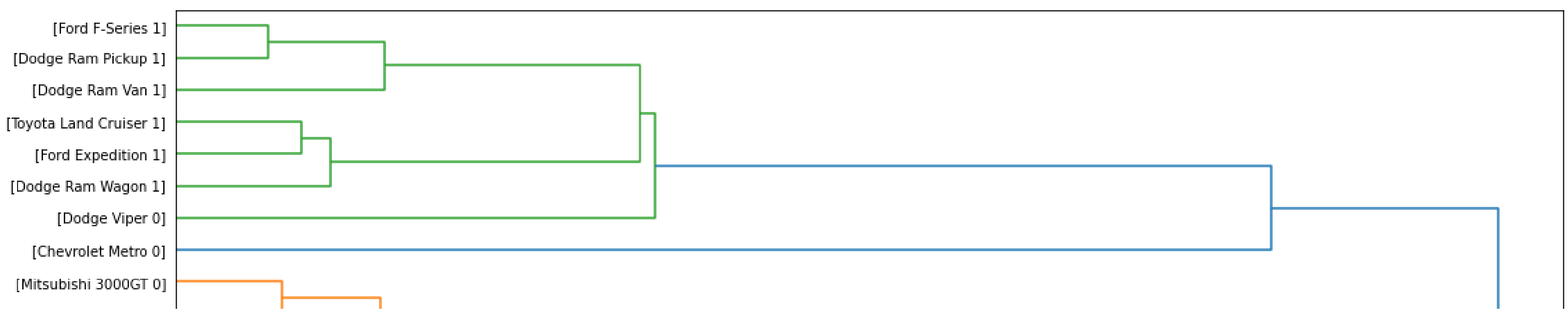
In [ ]:

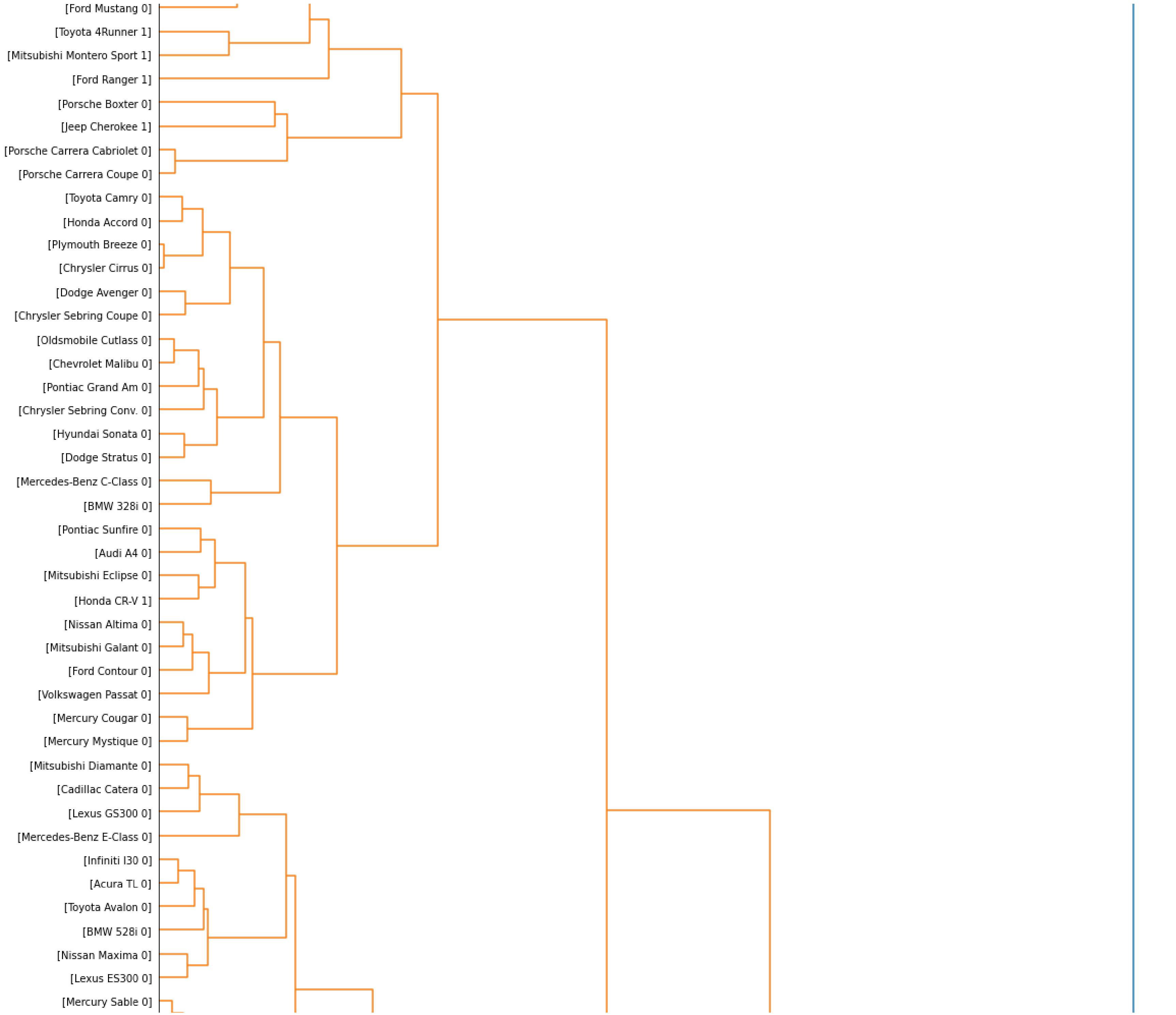
```
z_using_dist_matrix = hierarchy.linkage(dist_matrix, 'complete')
```

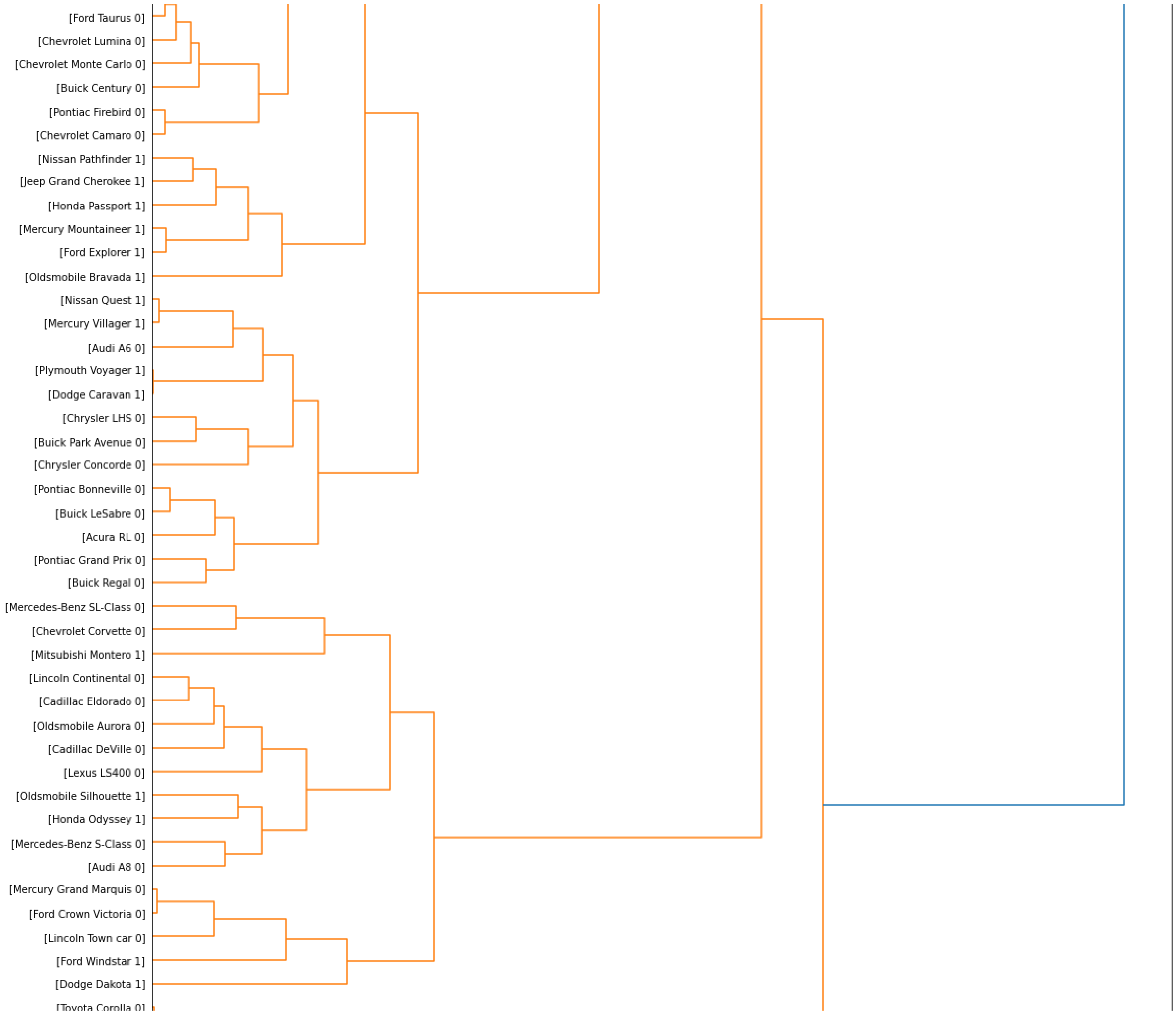
```
C:\Users\Gabri\AppData\Local\Temp/ipykernel_15428/3855052826.py:1: ClusterWarning: scipy.cluster: The symmetric non-negat
ive hollow observation matrix looks suspiciously like an uncondensed distance matrix
  z_using_dist_matrix = hierarchy.linkage(dist_matrix, 'complete')
```

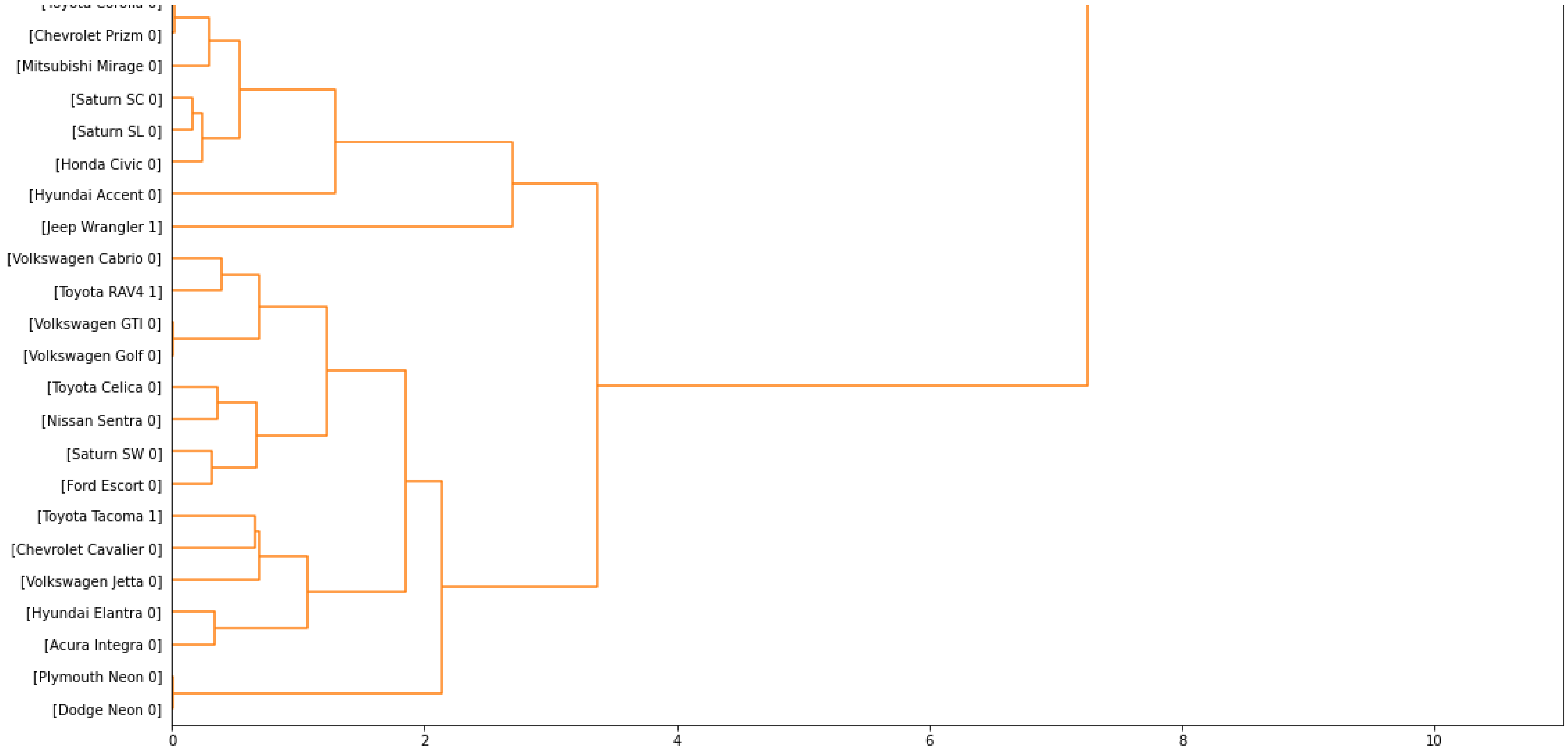
In [ ]:

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

dendro = hierarchy.dendrogram(z_using_dist_matrix, leaf_label_func= llf, leaf_rotation=0, leaf_font_size=10, orientation=
```




[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]



In [ ]:

```
agglom = AgglomerativeClustering(n_clusters = 6, linkage = 'complete')
agglom.fit(dist_matrix)

agglom.labels_
```

```
C:\Users\Gabri\AppData\Local\Programs\Python\Python39\lib\site-packages\sklearn\cluster\_agglomerative.py:493: ClusterWar
ning: scipy.cluster: The symmetric non-negative hollow observation matrix looks suspiciously like an uncondensed distance
matrix
  out = hierarchy.linkage(X, method=linkage, metric=affinity)
```

Out[ ]:

```
array([1, 2, 2, 3, 2, 4, 3, 2, 2, 2, 2, 2, 4, 4, 2, 1, 3, 2, 2, 2, 4, 1,
       5, 3, 3, 2, 3, 2, 1, 3, 3, 0, 0, 0, 0, 4, 2, 1, 3, 3, 2, 4, 2, 4,
       0, 3, 0, 1, 3, 3, 2, 4, 1, 1, 3, 2, 1, 3, 2, 2, 2, 4, 4, 4, 1, 3,
       3, 2, 3, 4, 3, 3, 3, 2, 4, 2, 2, 3, 2, 4, 4, 1, 3, 2, 2, 2, 3, 4,
       2, 4, 1, 3, 2, 3, 3, 2, 2, 2, 3, 3, 3, 1, 1, 1, 1, 3, 2, 1, 1, 1,
       3, 0, 1, 1, 3, 1, 1], dtype=int64)
```

In [ ]:

```
cars['cluster'] = agglom.labels_
cars.head()
```

Out[ ]:

	manufact	model	sales	resale	type	price	engine_s	horsepow	wheelbas	width	length	curb_wgt	fuel_cap	mpg	lnsales	pa
0	Acura	Integra	16.919	16.360	0.0	21.50	1.8	140.0	101.2	67.3	172.4	2.639	13.2	28.0	2.828	
1	Acura	TL	39.384	19.875	0.0	28.40	3.2	225.0	108.1	70.3	192.9	3.517	17.2	25.0	3.673	
2	Acura	RL	8.588	29.725	0.0	42.00	3.5	210.0	114.6	71.4	196.6	3.850	18.0	22.0	2.150	
3	Audi	A4	20.397	22.255	0.0	23.99	1.8	150.0	102.6	68.2	178.0	2.998	16.4	27.0	3.015	
4	Audi	A6	18.780	23.555	0.0	33.95	2.8	200.0	108.7	76.1	192.0	3.561	18.5	22.0	2.933	

In [ ]:

```python
cars.groupby('cluster').mean()
```

Out[ ]:

	sales	resale	type	price	engine_s	horsepow	wheelbas	width	length	curb_wgt	fuel_cap	
cluster												
0	135.930857	25.027857	0.857143	34.839000	4.985714	245.714286	120.200000	78.114286	203.371429	4.364571	26.500000	16.1
1	56.946000	10.669348	0.130435	14.234696	1.943478	119.956522	100.043478	67.691304	171.743478	2.569783	13.643478	28.6
2	54.601111	18.186111	0.277778	27.469778	3.322222	197.611111	109.375000	72.422222	193.494444	3.602528	18.497222	23.1
3	59.106576	17.784848	0.151515	23.953364	2.600000	166.212121	104.354545	69.493939	183.430303	3.051333	16.627273	24.6
4	42.167941	26.020000	0.294118	39.914765	4.158824	239.823529	114.147059	74.258824	201.229412	3.939824	21.170588	21.1
5	21.855000	5.160000	0.000000	9.235000	1.000000	55.000000	93.100000	62.600000	149.400000	1.895000	10.300000	45.0

In [ ]:

```python
cars.head()
```

Out[ ]:

	manufact	model	sales	resale	type	price	engine_s	horsepow	wheelbas	width	length	curb_wgt	fuel_cap	mpg	lnsales	pa
0	Acura	Integra	16.919	16.360	0.0	21.50	1.8	140.0	101.2	67.3	172.4	2.639	13.2	28.0	2.828	
1	Acura	TL	39.384	19.875	0.0	28.40	3.2	225.0	108.1	70.3	192.9	3.517	17.2	25.0	3.673	
2	Acura	RL	8.588	29.725	0.0	42.00	3.5	210.0	114.6	71.4	196.6	3.850	18.0	22.0	2.150	

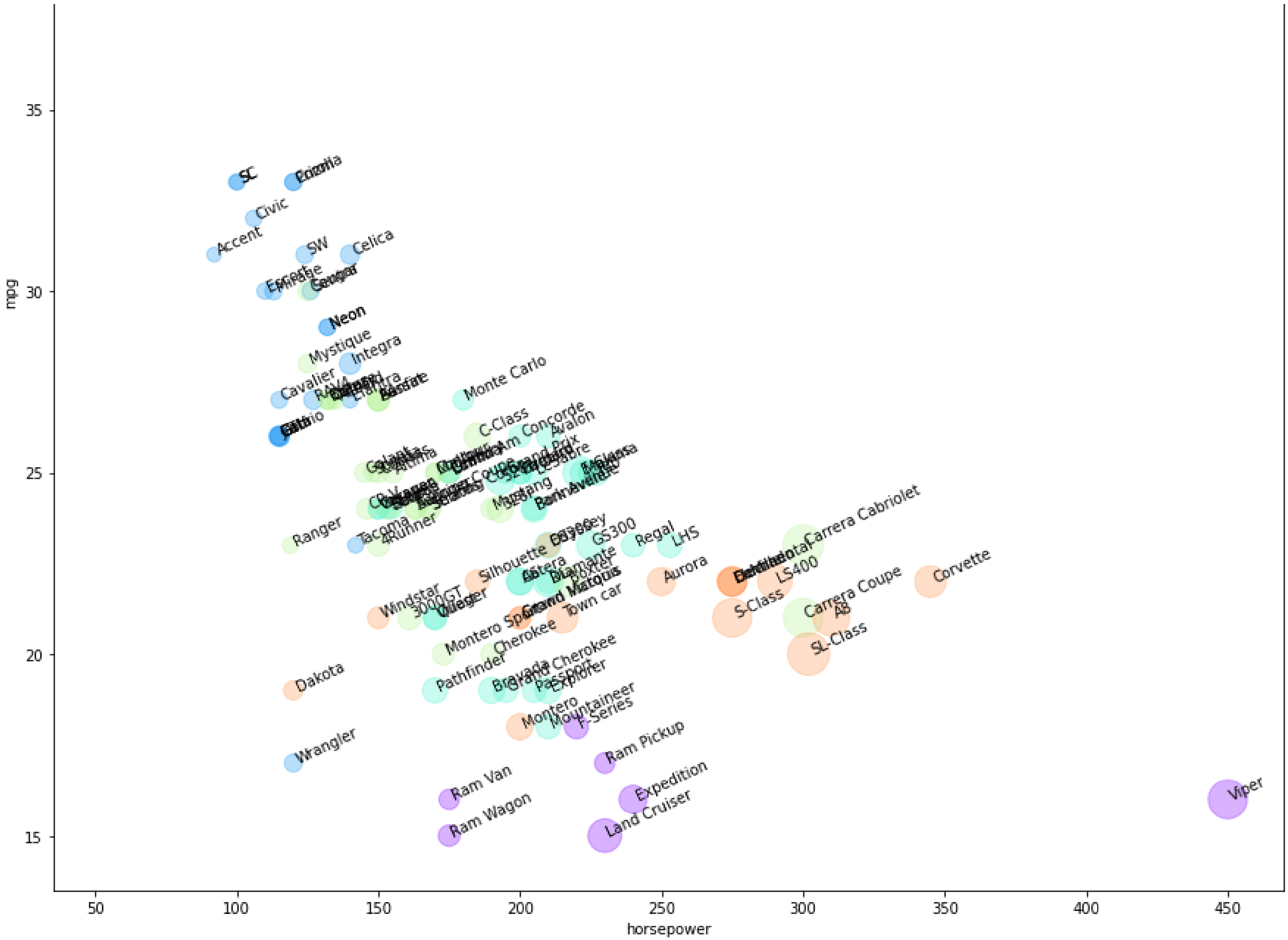
	manufact	model	sales	resale	type	price	engine_s	horsepow	wheelbas	width	length	curb_wgt	fuel_cap	mpg	lnsales	pa
3	Audi	A4	20.397	22.255	0.0	23.99	1.8	150.0	102.6	68.2	178.0	2.998	16.4	27.0	3.015	
4	Audi	A6	18.780	23.555	0.0	33.95	2.8	200.0	108.7	76.1	192.0	3.561	18.5	22.0	2.933	

In [ ]:

```
#Plot the clusters on a graph

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 new figure
plt.figure(figsize = (15, 15))

for color, label in zip(colors, cluster_labels):
    subset = cars[cars.cluster == label]
    for i in subset.index:
        plt.text(subset.horsepow[i], subset.mpg[i], str(subset['model'][i]), rotation = 25)
    plt.scatter(subset.horsepow, subset.mpg, s = subset.price*10, color = color, label = 'cluster'+str(label), alpha = 0.

plt.legend()
plt.title('Clusters')
plt.xlabel('horsepower')
plt.ylabel('mpg')
```

Out[ ]:

```
Text(0, 0.5, 'mpg')
```



In [ ]:

```
#Next, set up plotting of the cluster groups, not of the individual cars

cars.groupby(['cluster', 'type'])['cluster'].count()
```

Out[ ]:

```
cluster  type
0        0.0      1
         1.0      6
1        0.0     20
         1.0      3
2        0.0     26
         1.0     10
3        0.0     28
         1.0      5
4        0.0     12
         1.0      5
5        0.0      1
Name: cluster, dtype: int64
```

In [ ]:

```
agg_cars = cars.groupby(['cluster', 'type'])[['horsepow', 'engine_s', 'mpg', 'price']].mean()
agg_cars
```

Out[ ]:

cluster	type	horsepow	engine_s	mpg	price
0	0.0	450.000000	8.000000	16.000000	69.725000
	1.0	211.666667	4.483333	16.166667	29.024667
1	0.0	118.500000	1.890000	29.550000	14.226100
	1.0	129.666667	2.300000	22.333333	14.292000
2	0.0	203.615385	3.284615	24.223077	27.988692
	1.0	182.000000	3.420000	20.300000	26.120600
3	0.0	168.107143	2.557143	25.107143	24.693786
	1.0	155.600000	2.840000	22.000000	19.807000
4	0.0	267.666667	4.566667	21.416667	46.417417
	1.0	173.000000	3.180000	20.600000	24.308400
5	0.0	55.000000	1.000000	45.000000	9.235000

In [ ]:

```
subset = agg_cars.loc[(2,),]
for i in subset.index:
```

```
    print(i)
    print(subset['horsepow'])
```

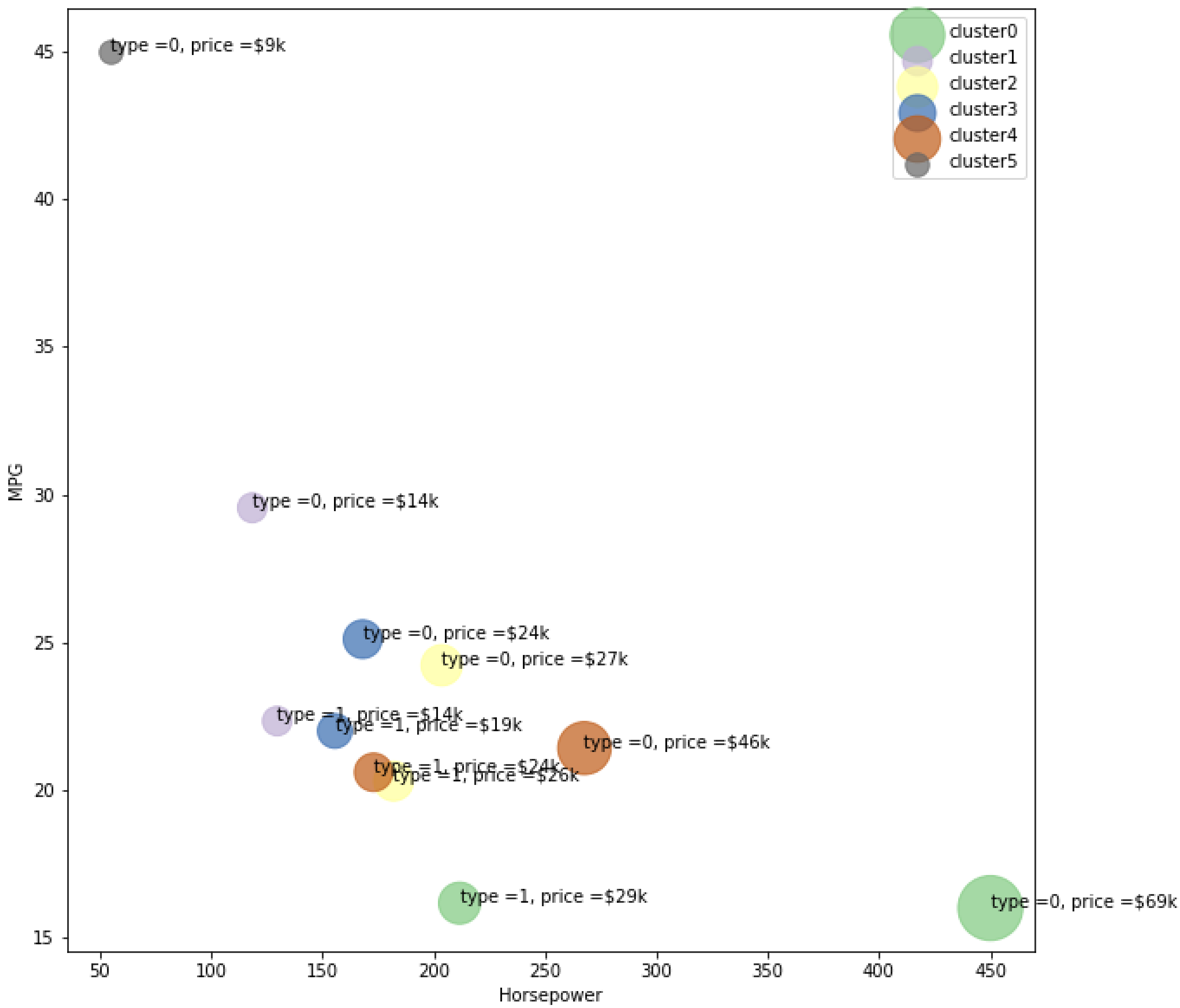
```
0.0
type
0.0    203.615385
1.0    182.000000
Name: horsepow, dtype: float64
1.0
type
0.0    203.615385
1.0    182.000000
Name: horsepow, dtype: float64
```

In [ ]:

```
#Now plot the cluster groups

plt.figure(figsize = (10, 10))

colors = cm.Accent(np.linspace(0, 1, n_clusters))


for color, label in zip(colors, cluster_labels):
    subset = agg_cars.loc[(label,),]
    for i in subset.index:
        plt.text(subset.loc[i][0], subset.loc[i][2], str('type ='+str(int(i)) + ', price =$'+str(int(subset.loc[i][3]))+'
    plt.scatter(subset['horsepow'], subset['mpg'], color = color, s = subset['price']*20, label = 'cluster'+str(label), a
    #Below line works the same as above line
    #plt.scatter(subset.horsepow, subset.mpg, color = color, s = subset.price*20, label = 'cluster'+str(label), alpha = 0

plt.legend()
plt.xlabel('Horsepower')
plt.ylabel('MPG')
```

Out[ ]:

```
Text(0, 0.5, 'MPG')
```



cluster0
cluster1
cluster2
cluster3
cluster4
cluster5
type =0, price =$9k
type =0, price =$14k
type =0, price =$24k
type =0, price =$27k
type =1, price =$14k
type =1, price =$19k
type =0, price =$46k
type =1, price =$24k
type =1, price =$26k
type =1, price =$29k
type =0, price =$69k
MPG
Horsepower

In [ ]: