Hierarchal Clustering

In [7]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

The Data

In [9]:
```
df = pd.read_csv('data/cluster_mpg.csv')
```

In [3]:
```
df = df.dropna()
```

In [4]:
```
df.head()
```

Out[4]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	origin
0	18.0	8	307.0	130.0	3504	12.0	70	usa
1	15.0	8	350.0	165.0	3693	11.5	70	usa
2	18.0	8	318.0	150.0	3436	11.0	70	usa
3	16.0	8	304.0	150.0	3433	12.0	70	usa
4	17.0	8	302.0	140.0	3449	10.5	70	usa

In [5]:
```
df.describe()
```

Out[5]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	mode
count	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000	392.0
mean	23.445918	5.471939	194.411990	104.469388	2977.584184	15.541327	75.9
std	7.805007	1.705783	104.644004	38.491160	849.402560	2.758864	3.6
min	9.000000	3.000000	68.000000	46.000000	1613.000000	8.000000	70.0
25%	17.000000	4.000000	105.000000	75.000000	2225.250000	13.775000	73.0
50%	22.750000	4.000000	151.000000	93.500000	2803.500000	15.500000	76.0
75%	29.000000	8.000000	275.750000	126.000000	3614.750000	17.025000	79.0
max	46.600000	8.000000	455.000000	230.000000	5140.000000	24.800000	82.0

In [6]:
```
df['origin'].value_counts()
```

Out[6]:
```
origin
usa       245
japan      79
europe     68
Name: count, dtype: int64
```

In [ ]:

In [7]:
```
df_w_dummies = pd.get_dummies(df.drop('name',axis=1))
```

In [8]:
```
df_w_dummies
```

Out[8]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	origin_
0	18.0	8	307.0	130.0	3504	12.0	70	
1	15.0	8	350.0	165.0	3693	11.5	70	
2	18.0	8	318.0	150.0	3436	11.0	70	
3	16.0	8	304.0	150.0	3433	12.0	70	
4	17.0	8	302.0	140.0	3449	10.5	70	
...	...	...	...	...	...	...	...	
387	27.0	4	140.0	86.0	2790	15.6	82	
388	44.0	4	97.0	52.0	2130	24.6	82	
389	32.0	4	135.0	84.0	2295	11.6	82	
390	28.0	4	120.0	79.0	2625	18.6	82	
391	31.0	4	119.0	82.0	2720	19.4	82	

392 rows × 10 columns

In [9]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [10]:
```
scaler = MinMaxScaler()
```

In [11]:
```
scaled_data = scaler.fit_transform(df_w_dummies)
```

In [12]:
```
scaled_data
```

Out[12]:
```
array([[0.2393617 , 1.        , 0.61757106, ..., 0.        , 0.        ,
        1.        ],
       [0.15957447, 1.        , 0.72868217, ..., 0.        , 0.        ,
        1.        ],
       [0.2393617 , 1.        , 0.64599483, ..., 0.        , 0.        ,
        1.        ],
       ...,
       [0.61170213, 0.2       , 0.17312661, ..., 0.        , 0.        ,
        1.        ],
       [0.50531915, 0.2       , 0.13436693, ..., 0.        , 0.        ,
        1.        ],
       [0.58510638, 0.2       , 0.13178295, ..., 0.        , 0.        ,
        1.        ]])
```

In [13]:
```
scaled_df = pd.DataFrame(scaled_data,columns=df_w_dummies.columns)
```

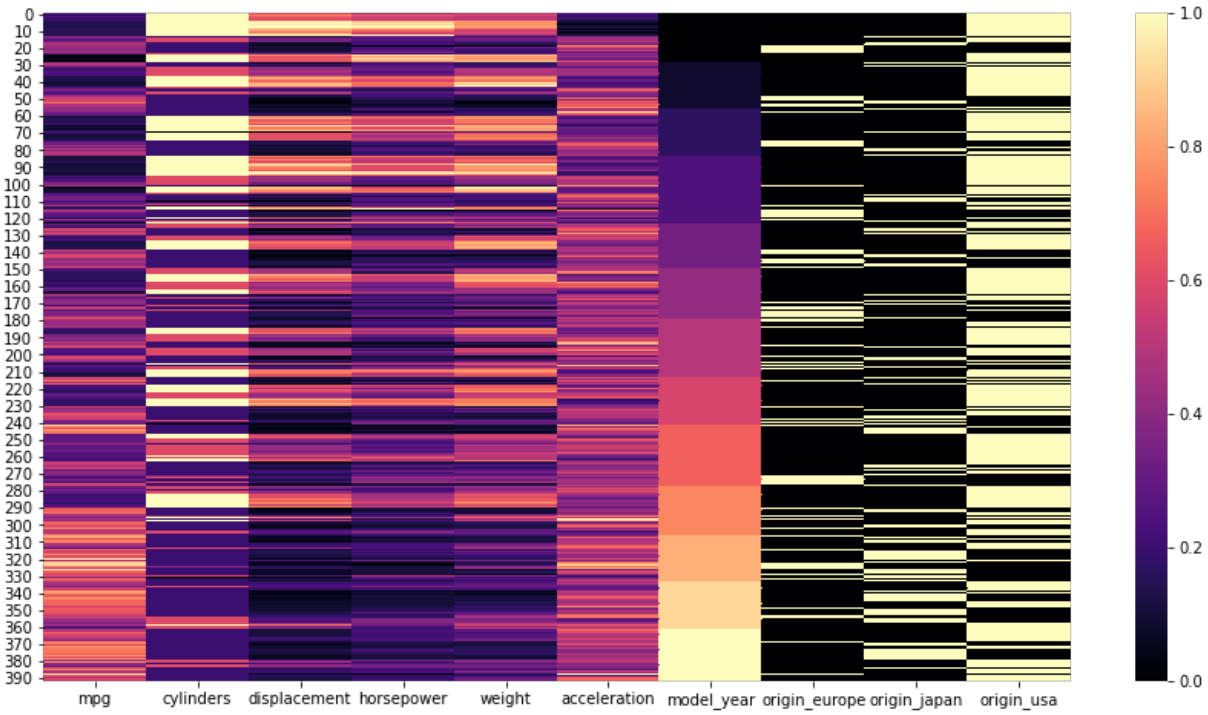
In [14]:
```
scaled_df
```

Out[14]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_year	o
0	0.239362	1.0	0.617571	0.456522	0.536150	0.238095	0.0	
1	0.159574	1.0	0.728682	0.646739	0.589736	0.208333	0.0	
2	0.239362	1.0	0.645995	0.565217	0.516870	0.178571	0.0	
3	0.186170	1.0	0.609819	0.565217	0.516019	0.238095	0.0	
4	0.212766	1.0	0.604651	0.510870	0.520556	0.148810	0.0	
...	...	...	...	...	...	...	...	
387	0.478723	0.2	0.186047	0.217391	0.333711	0.452381	1.0	
388	0.930851	0.2	0.074935	0.032609	0.146583	0.988095	1.0	
389	0.611702	0.2	0.173127	0.206522	0.193365	0.214286	1.0	
390	0.505319	0.2	0.134367	0.179348	0.286929	0.630952	1.0	
391	0.585106	0.2	0.131783	0.195652	0.313864	0.678571	1.0	

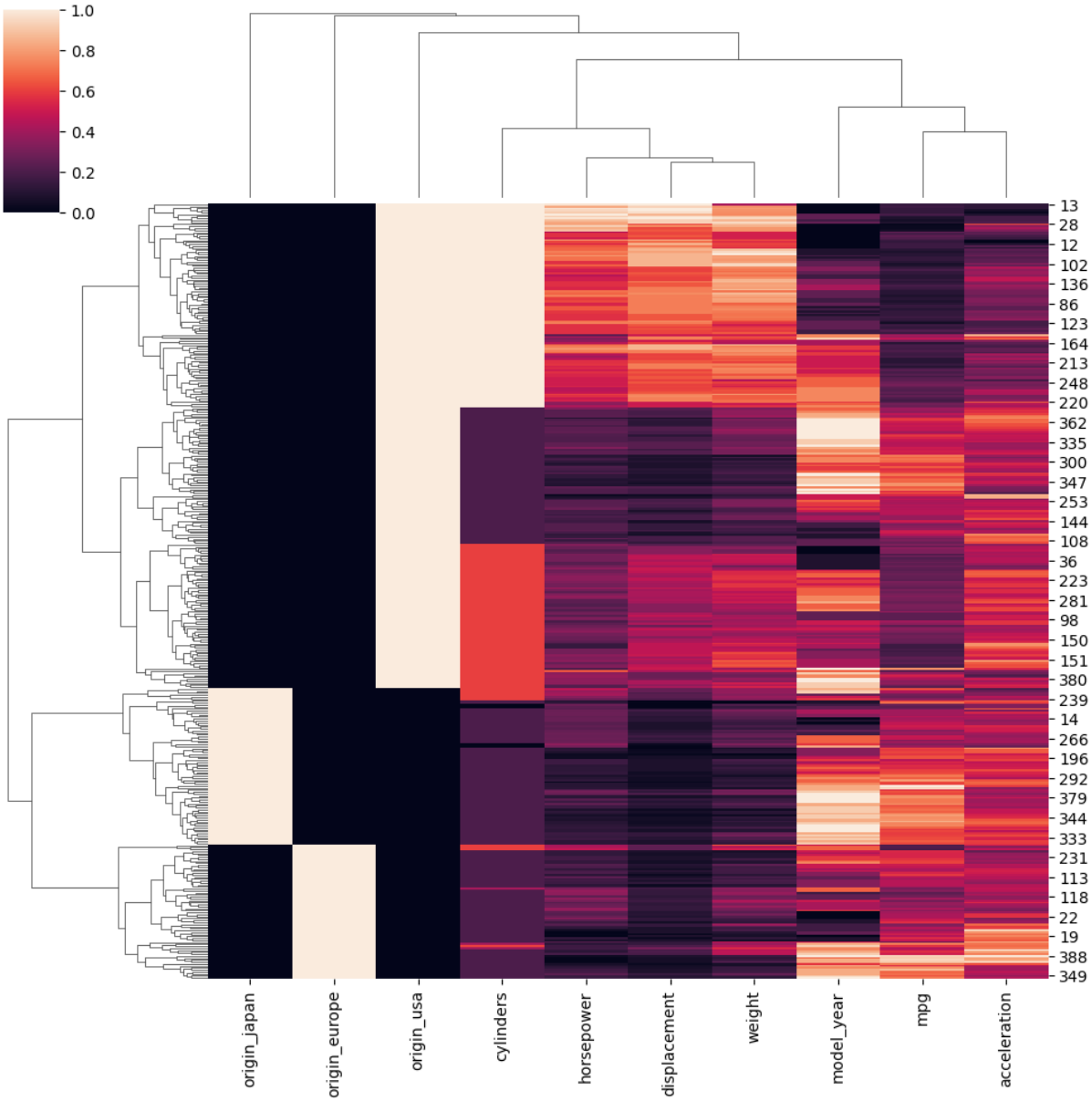
392 rows × 10 columns

In [15]:
```
plt.figure(figsize=(15,8))
sns.heatmap(scaled_df,cmap='magma');
```



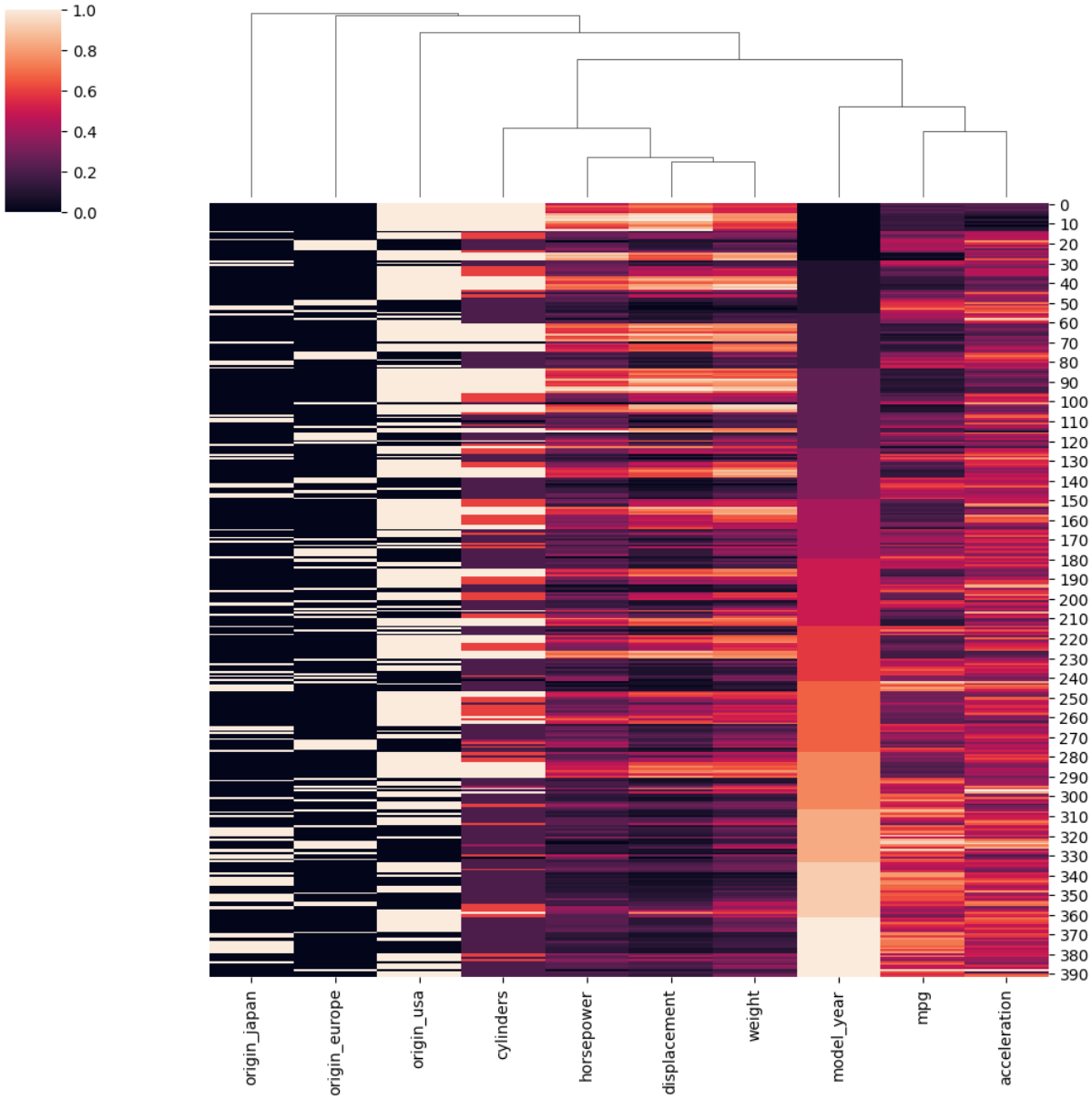
In [18]:
```
sns.clustermap(scaled_df)
```

Out[18]: <seaborn.matrix.ClusterGrid at 0x19e0546c3e0>



In [19]:
```
sns.clustermap(scaled_df,row_cluster=False)
```

Out[19]:
```
<seaborn.matrix.ClusterGrid at 0x19e0546c9d0>
```



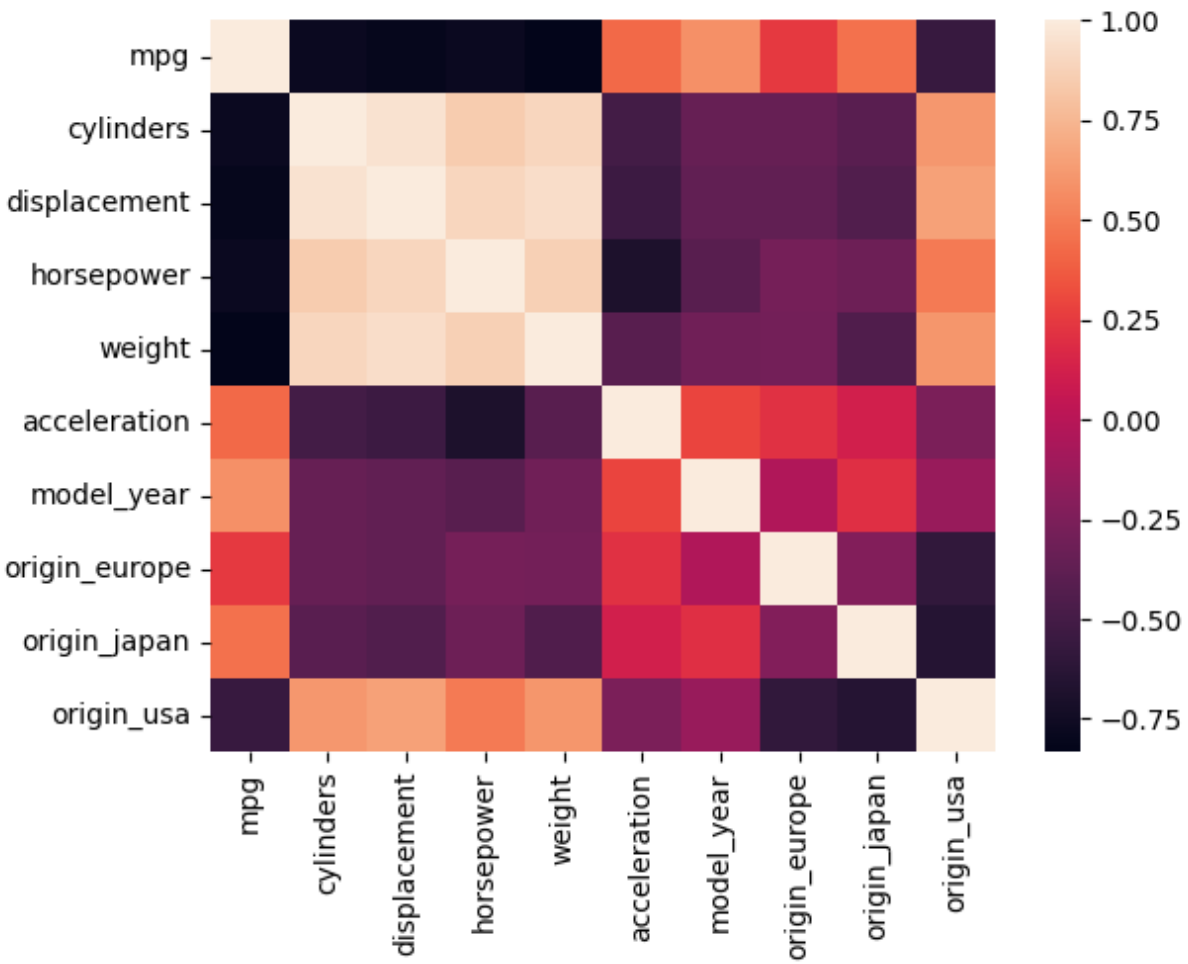
In [22]:
```
scaled_df.corr()
```

Out[22]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	mo
mpg	1.000000	-0.777618	-0.805127	-0.778427	-0.832244	0.423329	
cylinders	-0.777618	1.000000	0.950823	0.842983	0.897527	-0.504683	-
displacement	-0.805127	0.950823	1.000000	0.897257	0.932994	-0.543800	-
horsepower	-0.778427	0.842983	0.897257	1.000000	0.864538	-0.689196	-
weight	-0.832244	0.897527	0.932994	0.864538	1.000000	-0.416839	-
acceleration	0.423329	-0.504683	-0.543800	-0.689196	-0.416839	1.000000	
model_year	0.580541	-0.345647	-0.369855	-0.416361	-0.309120	0.290316	
origin_europe	0.244313	-0.352324	-0.371633	-0.284948	-0.293841	0.208298	-
origin_japan	0.451454	-0.404209	-0.440825	-0.321936	-0.447929	0.115020	
origin_usa	-0.565161	0.610494	0.655936	0.489625	0.600978	-0.258224	-

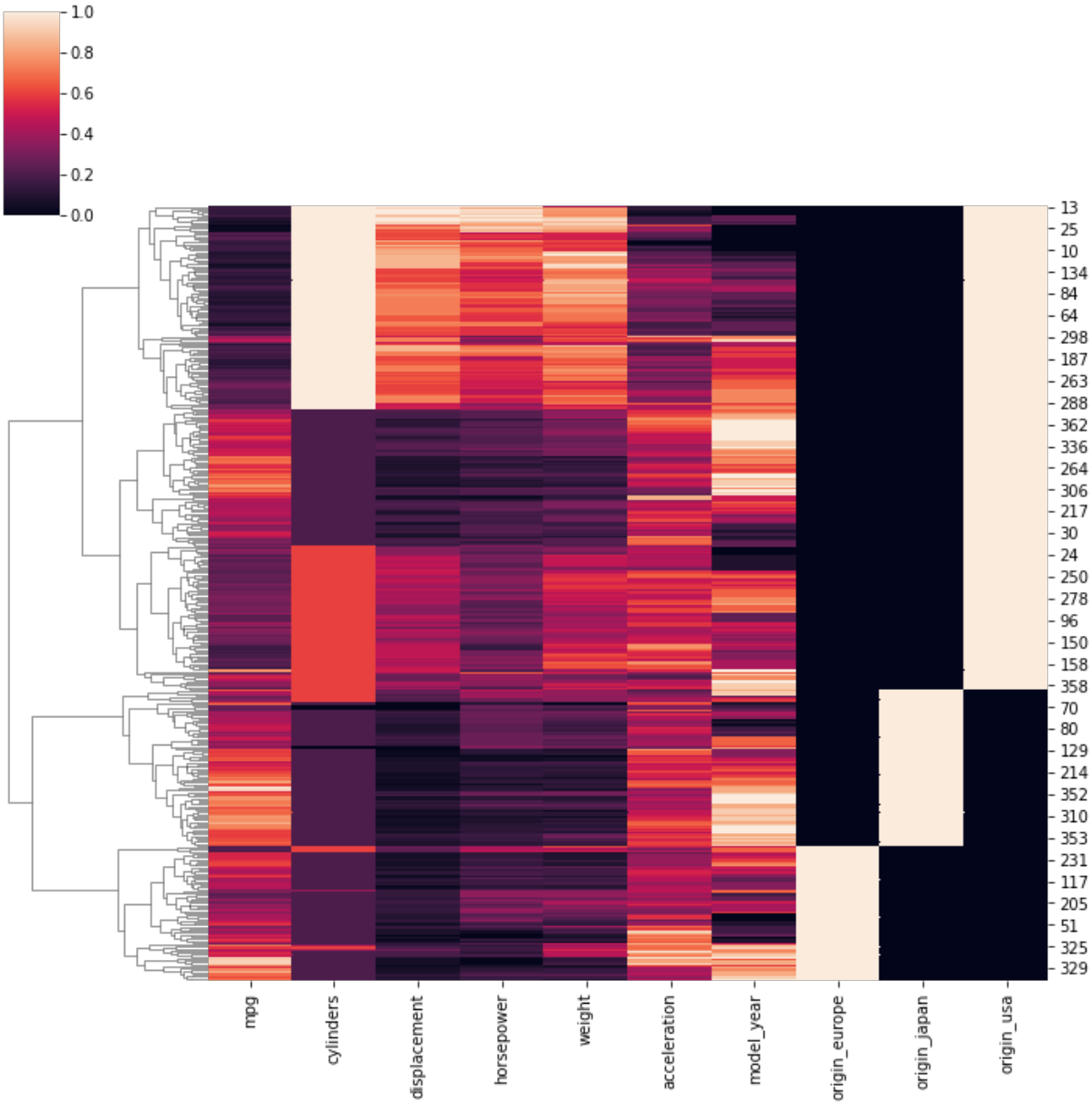
In [21]:
```
sns.heatmap(scaled_df.corr())
```

Out[21]: <Axes: >



In [17]:
```
sns.clustermap(scaled_df,col_cluster=False)
```

Out[17]: <seaborn.matrix.ClusterGrid at 0x1a8a45f21c0>



Using Scikit-Learn

In [23]:
```
from sklearn.cluster import AgglomerativeClustering
```

In [24]:
```
model = AgglomerativeClustering(n_clusters=4)
```

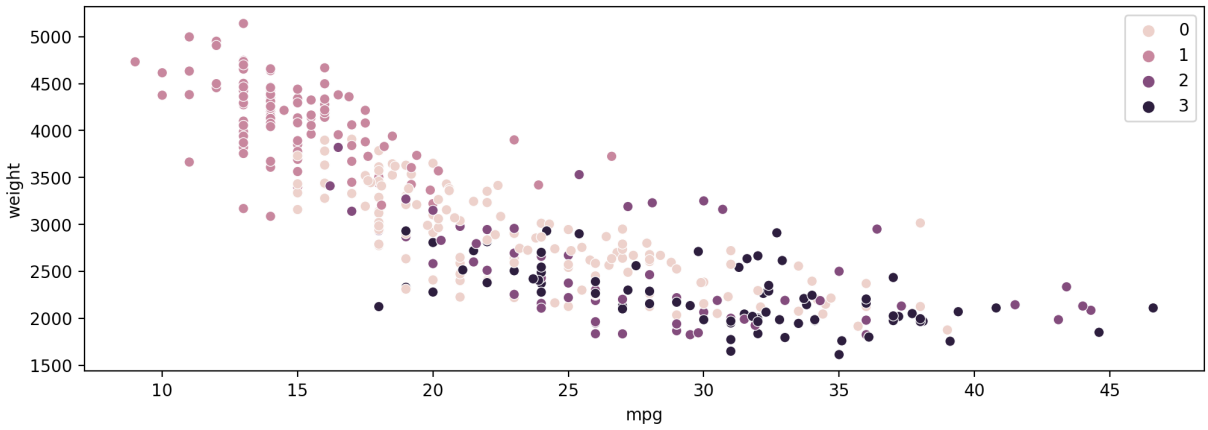
In [25]:
```
cluster_labels = model.fit_predict(scaled_df)
```

In [26]:
```
cluster_labels
```

Out[26]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 3, 0, 0, 0, 3, 2, 2, 2,
       2, 2, 0, 1, 1, 1, 1, 3, 0, 3, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1,
       0, 0, 0, 0, 0, 2, 2, 2, 3, 3, 2, 0, 3, 0, 2, 0, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 3, 1, 1, 1, 1, 2, 2, 2, 2, 0, 3, 3, 0, 3, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 2, 1, 1, 1, 1, 0, 3, 0, 3,
       3, 0, 0, 2, 1, 1, 2, 2, 2, 2, 1, 2, 3, 1, 0, 0, 0, 3, 0, 3, 0, 0,
       0, 0, 1, 1, 1, 1, 1, 2, 2, 2, 3, 3, 0, 2, 2, 3, 3, 2, 0, 0, 0, 0,
       1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 3, 0, 0, 0, 3, 2, 3, 0, 2, 0, 2,
       2, 2, 2, 3, 2, 2, 0, 0, 2, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 2, 3, 0,
       0, 0, 0, 2, 3, 3, 0, 2, 1, 2, 3, 2, 1, 1, 1, 1, 3, 0, 2, 0, 3, 1,
       1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 2, 0, 3, 0, 0, 0, 3, 2, 3, 2, 3,
       2, 0, 3, 3, 3, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1,
       0, 3, 3, 0, 3, 0, 0, 3, 2, 2, 2, 2, 2, 3, 0, 0, 0, 0, 0, 1, 1, 1,
       1, 1, 1, 1, 1, 2, 3, 0, 0, 2, 1, 2, 1, 0, 0, 3, 2, 0, 0, 0, 0, 2,
       3, 0, 3, 0, 0, 0, 0, 2, 3, 3, 3, 3, 3, 0, 3, 2, 2, 2, 2, 3, 3, 2,
       3, 3, 2, 3, 0, 0, 0, 0, 0, 3, 0, 3, 3, 3, 3, 3, 0, 0, 0, 2, 3, 3,
       3, 3, 2, 2, 3, 3, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 3, 3, 0, 0,
       3, 3, 3, 3, 3, 3, 0, 0, 0, 0, 3, 0, 0, 0, 2, 0, 0, 0])
```

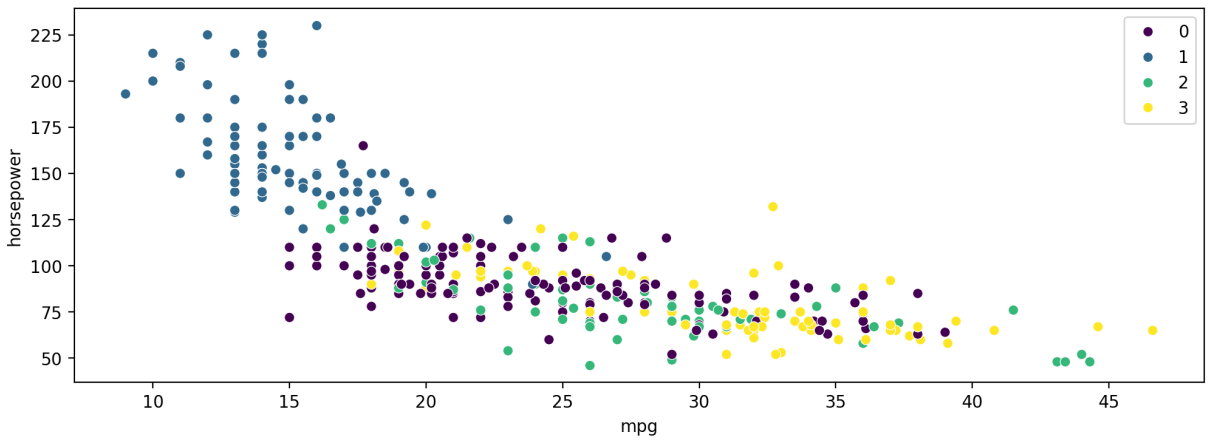
In [22]:
```
plt.figure(figsize=(12,4),dpi=200)
sns.scatterplot(data=df,x='mpg',y='weight',hue=cluster_labels)
```

Out[22]: <AxesSubplot:xlabel='mpg', ylabel='weight'>



In [28]:
```
plt.figure(figsize=(12,4),dpi=200)
sns.scatterplot(data=df,x='mpg',y='horsepower',hue=cluster_labels, palette='viridis
```

Out[28]: <Axes: xlabel='mpg', ylabel='horsepower'>



Exploring Number of Clusters with Dendrograms

Make sure to read the documentation online! https://docs.scipy.org/doc/scipy/reference/generated/scipy.cluster.hierarchy.dendrogram.html

Assuming every point starts as its own cluster

In [31]:
```
# max distance possible?
# sqrt(N_features)
len(scaled_df.columns)
```

Out[31]:
```
10
```

In [33]:
```
np.sqrt(10) # Max distance possible between two points (MIN/MAX scaling)
```

Out[33]:
```
np.float64(3.1622776601683795)
```

In [38]:
```
model = AgglomerativeClustering(n_clusters=None,distance_threshold=0)
```

In [39]:
```
cluster_labels = model.fit_predict(scaled_df)
```

In [40]:
```
cluster_labels
```

Out[40]:
```
array([247, 252, 360, 302, 326, 381, 384, 338, 300, 279, 217, 311, 377,
       281, 232, 334, 272, 375, 354, 333, 317, 345, 329, 289, 305, 383,
       290, 205, 355, 269, 202, 144, 245, 297, 386, 358, 199, 337, 330,
       339, 293, 352, 283, 196, 253, 168, 378, 331, 201, 268, 256, 361,
       250, 197, 246, 371, 324, 230, 203, 261, 380, 376, 308, 389, 332,
       306, 236, 391, 350, 274, 288, 313, 231, 298, 100, 295, 210, 248,
       187, 390, 373, 266, 307, 379, 212, 357, 191, 314, 208, 249, 343,
       294, 374, 322, 323, 362, 188, 296, 369, 286, 251, 229, 244, 285,
       349, 365, 259, 213, 276, 215, 222, 204, 359, 287, 166, 387, 291,
       220, 216, 260, 129, 367, 340, 346, 301, 342, 228, 388, 370, 218,
       255, 327, 347, 278, 271, 258, 282, 318, 273, 123, 172, 382, 363,
       356, 195, 280, 239, 364, 267, 351, 186, 257, 277, 299, 127, 366,
       234, 385, 192, 372, 292, 233, 270, 263, 133, 165, 161, 198,  97,
       315, 134, 207, 147, 175, 262, 348,  98, 214,  48, 353, 177, 325,
       128, 284, 275, 182, 184, 145, 344, 321, 200, 149, 240, 241, 235,
       226, 160, 341, 193, 320, 101, 224, 162, 243, 146,  99, 185, 119,
       219, 209, 265, 221, 335,  66, 121, 316, 319, 254, 264, 124, 336,
       304, 206, 106, 148, 368, 122, 164, 131, 142,  95, 173, 194, 152,
       138, 157, 110, 159, 107, 312, 328, 225, 150, 211, 140, 163, 242,
       116,  81,  93,  96,  72, 189, 303, 167,  73, 115, 143, 132, 181,
       141, 103, 170, 130,  49,  83, 309, 120,  82, 227, 310, 151, 117,
       104, 109,  57,  75,  79, 169,  71,  84, 153,  35,  47, 238, 180,
        74, 237, 176, 190, 139, 125, 135, 156, 108, 171, 136,  53,  23,
        67,  94, 113, 112,  41,  70, 174,  61, 102,  40,  64,  65,  60,
       118, 223, 137,  63,  86, 155, 178,  36,  31,  88,  87,  58,  54,
       114, 111, 158,  78,  92,  50,  26,  17,  85, 183,  80,  42,  69,
        32, 154,  51,  20,  76,  34, 179,  68,  39,  59,  33,  56, 126,
        19,  15,  37,  89,  62,  77,  29,  38, 105,  52,  28,  90,  46,
        55,  43,   9,  91,  18,  16,  25,   7,  45,  27,  44,   8,  30,
        22,  24,  21,  10,   4,  14,  13,  12,  11,   5,   6,   2,   3,
         1,   0])
```

In [41]:
```
from scipy.cluster.hierarchy import dendrogram
from scipy.cluster import hierarchy
```

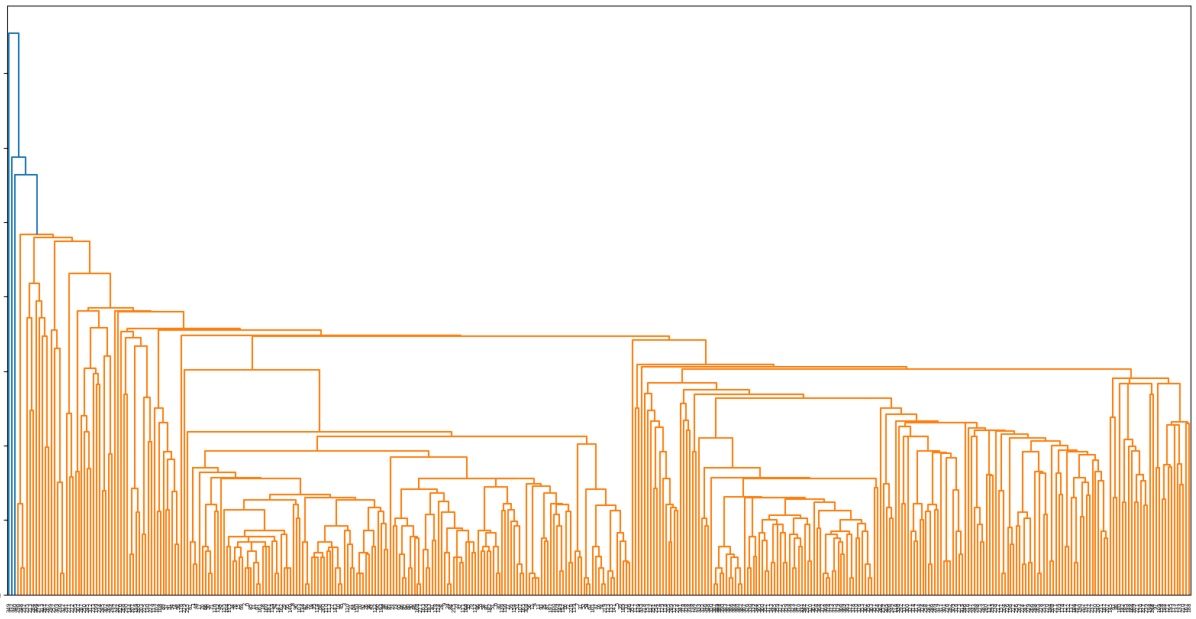
Linkage Model

In [42]:
```
linkage_matrix = hierarchy.linkage(model.children_)
```

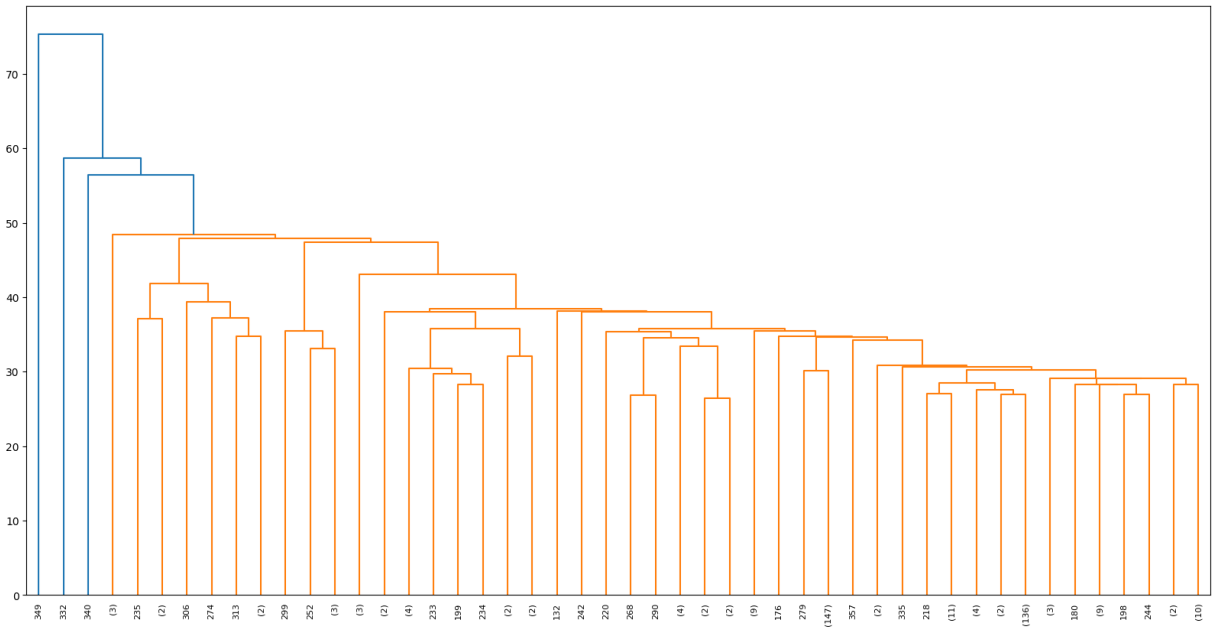
In [28]:
```
linkage_matrix
```

Out[28]:
```
array([[ 67.        , 161.        ,   1.41421356,   2.        ],
       [ 10.        ,  45.        ,   1.41421356,   2.        ],
       [ 47.        ,  99.        ,   1.41421356,   2.        ],
       ...,
       [340.        , 777.        ,  56.40035461, 389.        ],
       [332.        , 778.        ,  58.69412236, 390.        ],
       [349.        , 779.        ,  75.32595834, 391.        ]])
```

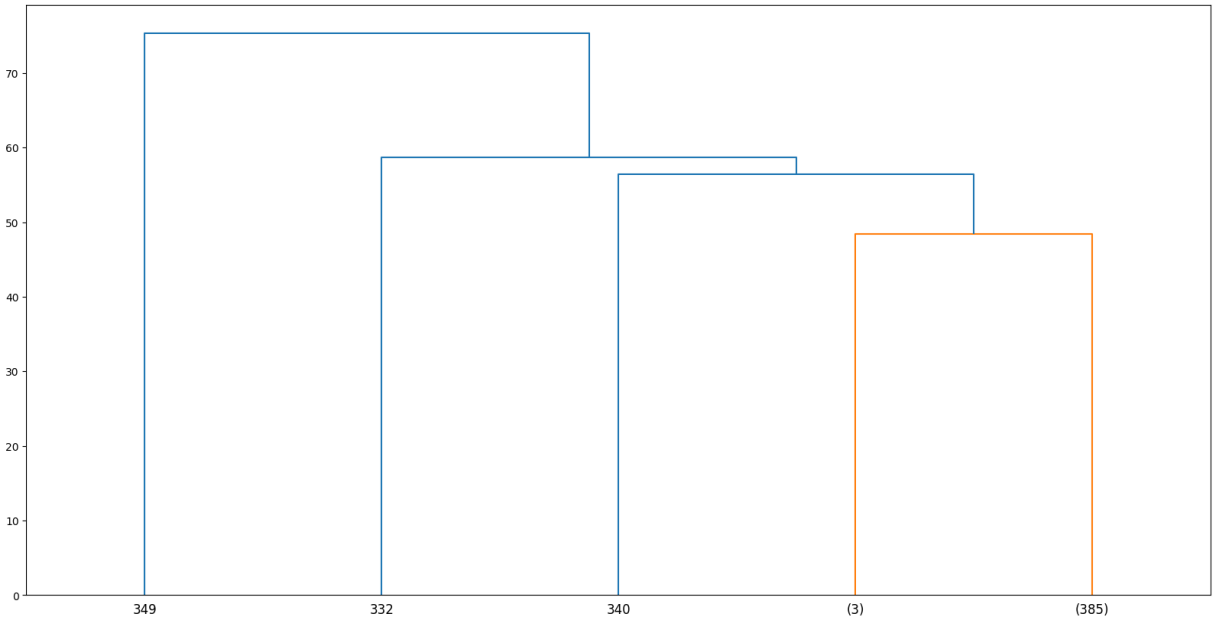
In [44]:
```
plt.figure(figsize=(20,10))
# Warning! This plot will take awhile!!
dn = hierarchy.dendrogram(linkage_matrix)
```



In [45]:
```
plt.figure(figsize=(20,10))
dn = hierarchy.dendrogram(linkage_matrix,truncate_mode='lastp',p=48)
```



In [46]:
```
plt.figure(figsize=(20,10))
dn = hierarchy.dendrogram(linkage_matrix,truncate_mode='level',p=3)
```



Choosing a Threshold Distance

What is the distance between two points?

In [31]:
```
scaled_df.describe()
```

Out[31]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model_
count	392.000000	392.000000	392.000000	392.000000	392.000000	392.000000	392.00
mean	0.384200	0.494388	0.326646	0.317768	0.386897	0.448888	0.49
std	0.207580	0.341157	0.270398	0.209191	0.240829	0.164218	0.30
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
25%	0.212766	0.200000	0.095607	0.157609	0.173589	0.343750	0.25
50%	0.365691	0.200000	0.214470	0.258152	0.337539	0.446429	0.50
75%	0.531915	1.000000	0.536822	0.434783	0.567550	0.537202	0.75
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00

In [32]:
```
scaled_df['mpg'].idxmax()
```

Out[32]: 320

In [33]:
```
scaled_df['mpg'].idxmin()
```

Out[33]: 28

In [34]:
```
# https://stackoverflow.com/questions/1401712/how-can-the-euclidean-distance-be-cal
a = scaled_df.iloc[320]
b = scaled_df.iloc[28]
dist = np.linalg.norm(a-b)
```

In [35]:
```
dist # point distance, not cluster distance!
```

Out[35]: 2.3852929970374714

Max possible distance?

Recall Euclidean distance: https://en.wikipedia.org/wiki/Euclidean_distance

In [36]:
```
np.sqrt(len(scaled_df.columns))
```

Out[36]: 3.1622776601683795

Creating a Model Based on Distance Threshold

- distance_threshold
  - The linkage distance threshold above which, clusters will not be merged.

In [252…
```
model = AgglomerativeClustering(n_clusters=None,distance_threshold=2)
```

In [253…
```
cluster_labels = model.fit_predict(scaled_data)
```

In [254…
```
cluster_labels
```

Out[254…
```
array([ 3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  1,  4,  4,
        4,  1,  0,  0,  0,  0,  0,  4,  3,  3,  3,  3,  1,  7,  1,  4,  4,
        4,  4,  4,  3,  3,  3,  3,  3,  3,  3,  4,  7,  4,  4,  7,  0,  0,
        0,  1,  1,  0,  7,  1,  7,  0,  7,  7,  3,  3,  3,  3,  3,  3,  3,
        3,  3,  1,  3,  3,  3,  3,  0,  0,  0,  0,  7,  1,  1,  7,  1,  3,
        3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  4,  4,  4,  4,  4,  0,
        3,  3,  3,  3,  4,  1,  7,  1,  1,  7,  4,  0,  3,  3,  0,  0,  0,
        0,  3,  0, 10,  3,  4,  4,  4,  1,  7,  1,  7,  4,  4,  4,  3,  3,
        3,  3,  3,  0,  0,  0,  1,  1,  7,  0,  0,  1,  1,  0,  4,  4,  4,
        4,  5,  3,  3,  3,  4,  4,  4,  4,  4,  5,  5,  1,  7,  4,  7,  1,
        0,  1,  4,  0,  4,  0,  0,  0,  0,  1,  0,  0,  7,  7,  0,  5,  5,
        5,  5,  4,  4,  4,  4,  7,  7,  0,  1,  9,  4,  9,  4,  0,  1,  1,
        7,  0,  5,  8, 10,  0,  5,  5,  5,  5,  1,  2,  8,  7,  1,  5,  5,
        5,  5,  9,  9,  9,  9,  5,  5,  5,  5,  0,  7,  1,  7,  2,  2,  1,
        0, 10,  0, 10,  8,  2,  1,  6,  1,  5,  5,  5,  9,  9,  9,  7,  9,
        9,  9,  9,  9,  9,  5,  9,  5,  5,  2, 10, 10,  2, 10,  2,  2, 10,
        0,  0,  0,  0,  8,  1,  9,  9,  2,  9,  9,  5,  5,  5,  5,  5,  5,
        5,  5,  8,  1,  2,  2,  8,  5,  8,  5,  2,  2,  1,  8,  2,  9,  9,
        2,  8,  6,  2,  6,  2,  2,  2,  9,  8,  6,  6,  6,  6,  6,  2,  6,
        8,  8,  8,  8,  6,  6,  8, 10, 10,  8,  6,  2,  2,  2,  9,  2,  6,
        2,  6,  6,  6,  6,  6,  2,  2,  2,  8,  6,  6,  6,  6,  8,  8, 10,
       10,  9,  5,  9,  9,  2,  2,  2,  2,  2,  2,  2,  8,  6,  6,  2,  2,
        6,  6,  6,  6,  6,  6,  9,  9,  2,  9,  6,  2,  2,  2,  8,  2,  2,
        2], dtype=int64)
```

In [255…
```
np.unique(cluster_labels)
```

Out[255…
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10], dtype=int64)
```

Linkage Matrix

Source: https://docs.scipy.org/doc/scipy/reference/generated/scipy.cluster.hierarchy.linkage.html#scipy.cluster.hierarchy.linkage

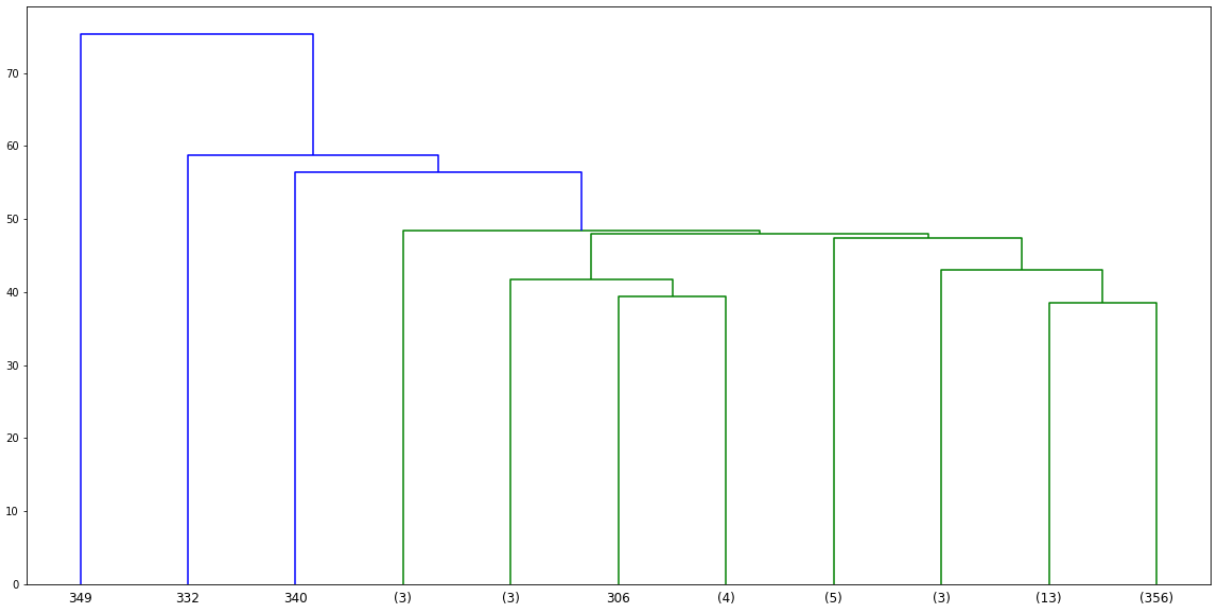
> A (n-1) by 4 matrix Z is returned. At the i-th iteration, clusters with indices Z[i, 0] and Z[i, 1] are combined to form cluster n + i. A cluster with an index less than n corresponds to one of the original observations. The distance between clusters Z[i, 0] and Z[i, 1] is given by Z[i, 2]. The fourth value Z[i, 3] represents the number of original observations in the newly formed cluster.

In [256…
```
linkage_matrix = hierarchy.linkage(model.children_)
```

In [257…
```
linkage_matrix
```

Out[257…
```
array([[ 67.        , 161.        ,   1.41421356,   2.        ],
       [ 10.        ,  45.        ,   1.41421356,   2.        ],
       [ 47.        ,  99.        ,   1.41421356,   2.        ],
       ...,
       [340.        , 777.        ,  56.40035461, 389.        ],
       [332.        , 778.        ,  58.69412236, 390.        ],
       [349.        , 779.        ,  75.32595834, 391.        ]])
```

In [258…
```
plt.figure(figsize=(20,10))
dn = hierarchy.dendrogram(linkage_matrix,truncate_mode='lastp',p=11)
```



In [ ]: