Tutorial 2 for Chapter 3

Case study 11: Mining business areas based on operator base station datasets by hierachical clustering

Reference: 数据挖掘原理与应用

For the course AMA546 Statistical Data Mining
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Contents

Objectives of the analysis

Operator base station can collect imfomation including ‘Base station ID', 'Average stay length during working hours on weekdays', 'Average stay length in early morning','Average stay length on weekends', 'Average daily footfall' near each base station.

There is a 431 × 5 table in **'Hierachy.csv'** shows this information.

We aim to cluster this dataset and divide these base stations into different business areas.

Description of the data

In [1]:
```
import pandas as pd
from sklearn.preprocessing import scale
import matplotlib
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
```

In [2]:
```
data = pd.read_csv(
    '/Users/.../Hierarchical/Hierachy.csv'
     encoding = 'utf8', engine='python'
)
```

In [3]:
```
data.head()
```

Out[3]:

	Base station ID	Average stay length during working hours on weekdays	Average stay length in early morning	Average stay length on weekends	Average daily footfall
0	36902	78	521	602	2863
1	36903	144	600	521	2245
2	36904	95	457	468	1283
3	36905	69	596	695	1054
4	36906	190	527	691	2051

In [4]:
```
# fcolums = ['Base station ID', 'Average stay length during working
#               'Average stay length in early morning','Average stay
# data.columns = fcolums
# data.head()
```

In [5]:
```
data.dtypes
```

Out[5]:
```
Base station ID                                          int64
Average stay length during working hours on weekdays     int64
Average stay length in early morning                     int64
Average stay length on weekends                          int64
Average daily footfall                                   int64
dtype: object
```

In [6]:
```
data.shape
```

Out[6]:
```
(431, 5)
```

Exploratory data analysis

In [7]:
```
data.describe()
```

Out[7]:

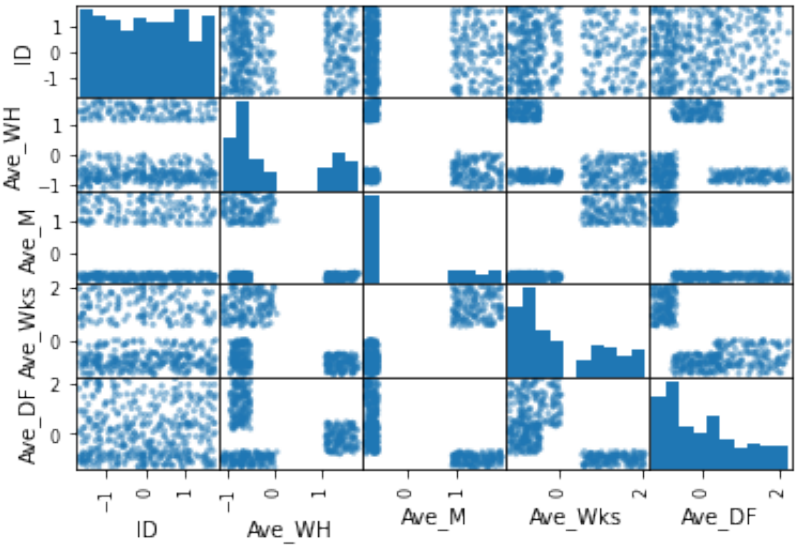
	Base station ID	Average stay length during working hours on weekdays	Average stay length in early morning	Average stay length on weekends	Average daily footfall
count	431.000000	431.000000	431.000000	431.000000	431.000000
mean	36977.515081	194.109049	218.241299	288.946636	5375.433875
std	1156.990679	140.076490	201.200426	199.834477	3423.142810
min	35038.000000	35.000000	50.000000	50.000000	811.000000
25%	35980.000000	84.500000	69.500000	126.500000	2353.000000
50%	36940.000000	117.000000	91.000000	194.000000	4750.000000
75%	37967.000000	362.500000	439.500000	473.500000	7726.500000
max	38999.000000	449.000000	600.000000	699.000000	12942.000000

We want to reduce dimensions by PCA, but we need to scale data before implementing PCA. Exploring the relationships among variables also needs scaling data.

In [8]:
```
from sklearn.preprocessing import scale
```

In [9]:
```
fcolums_short = ['ID', 'Ave_WH',
                 'Ave_M','Ave_Wks', 'Ave_DF']
scaleData = pd.DataFrame(
    scale(data), columns=fcolums_short
)
```

In [10]:
```
# Draw the scatter plot
axes = scatter_matrix(scaleData, diagonal='hist')
```



The scatter plot above indicates that four features do not have a linear relationship, so there is no need to remove collinear features.

Data preprocessing

In [11]:
```
from sklearn.decomposition import PCA
```

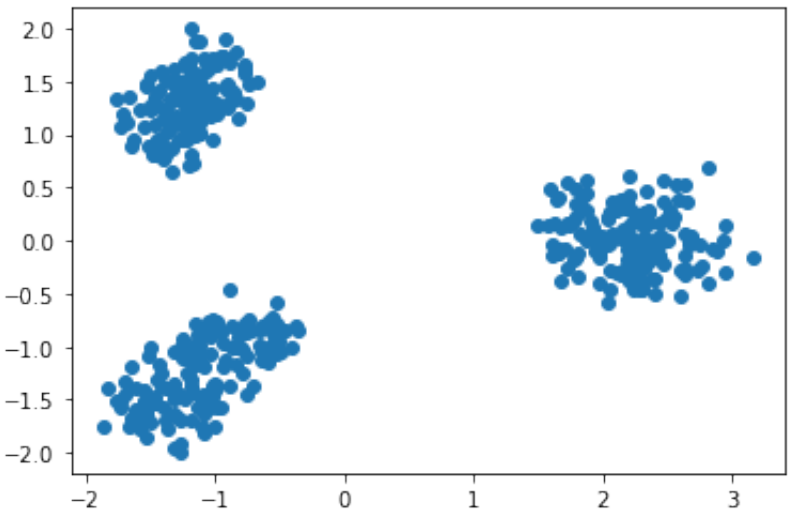
Use PCA to reduce the dimensionality of our dataset by transforming the original 4 features into 2 principal components.

In [12]:
```
pca2 = PCA(n_components= 2) # reduce to 2 features
data_pca2 = pd.DataFrame(
    pca2.fit_transform(scaleData)
)
```

Visualize the reduced dimensional features obtained from PCA by creating a scatter plot

In [13]:
```
plt.scatter(
    data_pca2[0],
    data_pca2[1]
)
```

Out[13]:
```
<matplotlib.collections.PathCollection at 0x7f9351933fd0>
```



We can clearly see that there are three clusters, so we need to tune the k to 3.

Hierachical clustering

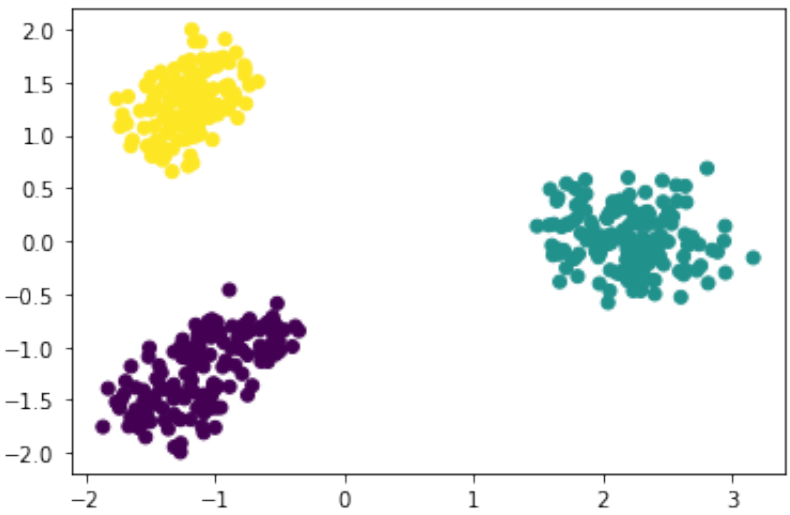
In sklearn module, we implement hirechical clustering by AgglomerativeClustering function.

In [14]:
```
from sklearn.cluster import AgglomerativeClustering
```

Set the value of k to 3 and assign a unique color to each cluster.

In [15]:
```
agglomerativeClustering = AgglomerativeClustering(n_clusters=3)
# We set 3 clusters
pTarget = agglomerativeClustering.fit_predict(scaleData) #fit
plt.figure()
plt.scatter(
    data_pca2[0],
    data_pca2[1],
    c=pTarget
)
```

Out[15]:
```
<matplotlib.collections.PathCollection at 0x7f9351785340>
```



From the scatter plot, it is evident that the data points belonging to each cluster are well-separated.

Next, we want to draw a hierarchical tree.

In [16]:
```
import scipy.cluster.hierarchy as hcluster
```

Recall the distance methods (slides p30-):

Assume $d(s,t)$ is the distance between two clusters s and t.

The algorithm begins with a forest of clusters that have yet to be used in the hierarchy being formed. When two clusters s and t from this forest are combined into a single cluster u, s and t are removed from the forest, and u is added to the forest. When only one cluster remains in the forest, the algorithm stops, and this cluster becomes the root.

Suppose cardinality $|u|$ is the number of original observations in cluster , i.e. $u[0], \ldots, u[|u|-1]$, so does $|v|$. s and t are combined to form cluster u, and let v be any remaining cluster in the forest that is not u.

- Single link (MIN)
  $d(u,v) = min(dist(u[i], v[j]))$
  for all points i in cluster u and j in cluster v.
- Complete link (MAX)
  $d(u,v) = max(dist(u[i], v[j]))$
  for all points i in cluster u and j in cluster v. (similar to MIN)
- Group average
  $d(u,v) = \sum_{ij} \frac{d(u(i),v(j))}{|u| \times |v|}$
  Where $|u|$ and $|v|$ are cardinalities
- Distance between centroids
  $dist(s,t) = ||c_s - c_t||_2$
  Where c_s and c_t are the centroids of clusters s and t, respevtively.

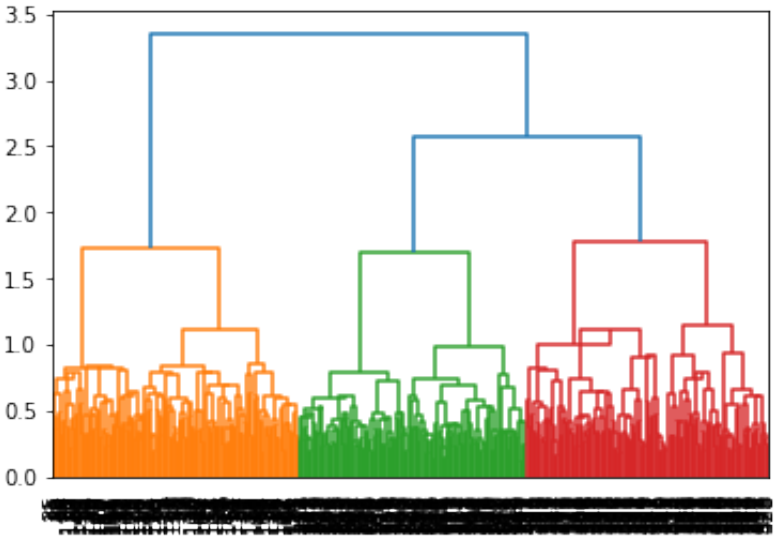
Now, construct the hierarchical tree by scipy.cluster.hierarchy.linkage function.
The output is a ndarray, which means the hierarchical clustering encoded as a linkage matrix.

In [17]:
```
# Construct the hierarchical Tree (dendrogram)
linkage = hcluster.linkage(
    scaleData,
    method='centroid' #method=’single’,’complete’,'average'
)
linkage
```

Out[17]:
```
array([[2.00000000e+02, 2.67000000e+02, 1.08605527e-01, 2.00000000
e+00],
       [2.26000000e+02, 2.78000000e+02, 1.24183728e-01, 2.00000000
e+00],
       [1.64000000e+02, 2.57000000e+02, 1.44113030e-01, 2.00000000
e+00],
       ...,
       [8.54000000e+02, 8.55000000e+02, 1.76940813e+00, 1.46000000
e+02],
       [8.56000000e+02, 8.58000000e+02, 2.56691634e+00, 2.83000000
e+02],
       [8.57000000e+02, 8.59000000e+02, 3.35563046e+00, 4.31000000
e+02]])
```

After obtaining the linkage matrix, we visualize the hierarchical tree.

In [18]:
```
#Draw the tree
plt.figure()
hcluster.dendrogram(
    linkage,
    leaf_font_size=10.
)
plt.show()
```



Then let's compute results by fcluster function. The output is a ndarry, An array of length n. $T[i]$ is the flat cluster number to which original observation i belongs.

This function can be used to flatten the dendrogram, obtaining as a result an assignation of the original data points to single clusters.

Notes: If we don't add 'plt.show()' at last, then it will output all the results. Including 'plt.show()' allows us to display only the tree plot.

In [19]:
```
# Compute the results

_pTarget = hcluster.fcluster(
    linkage, 3,
    criterion='maxclust'
)
_pTarget
```

Out[19]:
```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2,
2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
2, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3], dtype=int32)
```

We also can use parallel coordinates to explain main features after clustering.

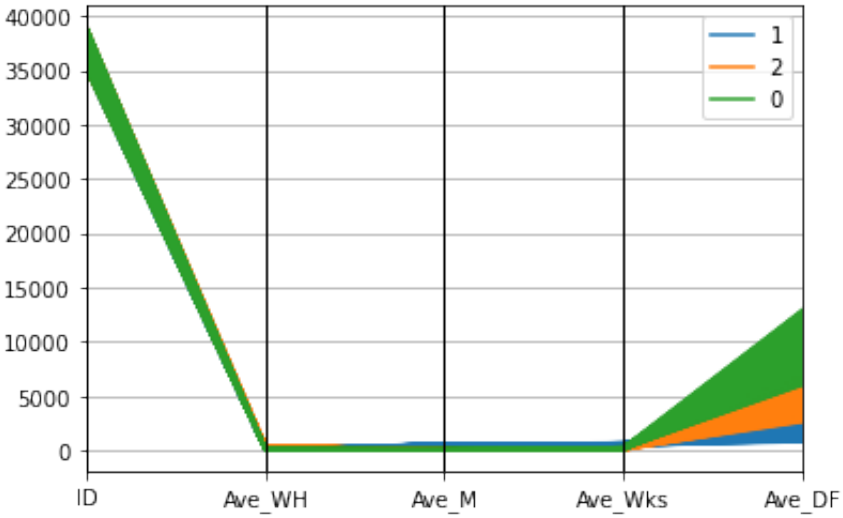
In [20]:
```
import seaborn as sns
from pandas.plotting import parallel_coordinates
```

In [21]:
```
data_short = data
data_short['type'] = pTarget
data.columns = fcolums_short + ['type']
data_short.head()
```

Out[21]:

	ID	Ave_WH	Ave_M	Ave_Wks	Ave_DF	type
0	36902	78	521	602	2863	1
1	36903	144	600	521	2245	1
2	36904	95	457	468	1283	1
3	36905	69	596	695	1054	1
4	36906	190	527	691	2051	1

In [22]:
```
plt.figure()    # blank
ax = pd.plotting.parallel_coordinates(
    data_short, 'type',
    color=sns.color_palette(),
)
```



The parallel coordinates plot illustrates that there are clear boundaries among different clusters. Thus, it's easy to explain the clustering results.

Summary report

Objectives

Our objective is to group the data in this dataset into clusters, with the aim of clustering the base stations into different business areas, where we applied the **Hierachical clustering** algorithm. In this study, we will utilize the PCA to reduce dimensions and then clustering by Hierachical clustering algorithm.

Organisation of the data

The data set contains a total of 430 samples and 5 attributes/variables/features: 'Base station ID', 'Average stay length during working hours on weekdays', 'Average stay length in early morning','Average stay length on weekends' and 'Average daily footfall'. For convenience, we adopted some abbreviates for title in latter analysis.

Exploratory data analysis：

In the course of the exploratory data analysis, we find that the four variables do not have a linear relationship, so there is no need to remove collinear features.

Model specification

The analysis objective suggested a clustering algorithm that assigns the base stations into different business areas. Here we consider the '**Hierachical clustering**': Firstly, adopt the existing package '*AgglomerativeClusteringpro*' , then draw a dendrogram for this clustering algorithm (See slides p31).In addition, we used PCA before implementing the hierachical clustering. Finally we also use scatter and parallel coordinates plot to check the performance of hierachical clustering algorithm for this dataset.