Grouping Customers by Power Consumption

April 17, 2023

1 Grouping Customers by Power Consumption

Based on customer energy consumption data, we are going to group consumers by similarity in order to understand customer behavior and its relationship with energy consumption.

Dataset: https://archive.ics.uci.edu/ml/datasets/Individual+household+electric+power+consumption

[1]:
```python
# Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import pylab
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from scipy.spatial.distance import cdist, pdist
from sklearn.metrics import silhouette_score
import warnings
warnings.filterwarnings("ignore")
%matplotlib inline
```

[2]:
```python
# Loading data
dataset = pd.read_csv('data/household_power_consumption.txt', delimiter = ';',␣
↪low_memory = False)
```

[3]:
```python
dataset.head()
```

[3]:
```
         Date      Time Global_active_power Global_reactive_power  Voltage  \
0  16/12/2006  17:24:00               4.216                 0.418  234.840
1  16/12/2006  17:25:00               5.360                 0.436  233.630
2  16/12/2006  17:26:00               5.374                 0.498  233.290
3  16/12/2006  17:27:00               5.388                 0.502  233.740
4  16/12/2006  17:28:00               3.666                 0.528  235.680

  Global_intensity Sub_metering_1 Sub_metering_2  Sub_metering_3
0           18.400          0.000          1.000            17.0
1           23.000          0.000          1.000            16.0
2           23.000          0.000          2.000            17.0
```

```
3          23.000          0.000          1.000          17.0
4          15.800          0.000          1.000          17.0
```

[4]:
```python
dataset.shape
```

[4]:
```
(2075259, 9)
```

[5]:
```python
dataset.dtypes
```

[5]:
```
Date                     object
Time                     object
Global_active_power      object
Global_reactive_power    object
Voltage                  object
Global_intensity         object
Sub_metering_1           object
Sub_metering_2           object
Sub_metering_3          float64
dtype: object
```

[6]:
```python
# Checking for missing values
dataset.isnull().values.any()
```

[6]:
```
True
```

[7]:
```python
# Remove records with NA values and remove the first two columns (not needed)
dataset = dataset.iloc[0:, 2:9].dropna()
```

[8]:
```python
dataset.head()
```

[8]:
```
  Global_active_power Global_reactive_power  Voltage Global_intensity  \
0               4.216                 0.418  234.840           18.400
1               5.360                 0.436  233.630           23.000
2               5.374                 0.498  233.290           23.000
3               5.388                 0.502  233.740           23.000
4               3.666                 0.528  235.680           15.800

  Sub_metering_1 Sub_metering_2  Sub_metering_3
0          0.000          1.000            17.0
1          0.000          1.000            16.0
2          0.000          2.000            17.0
3          0.000          1.000            17.0
4          0.000          1.000            17.0
```

[9]:
```python
# Checking for missing values
dataset.isnull().values.any()
```

[9]:
```
False
```

[10]:
```
# Get attribute values
dataset_atrib = dataset.values
```

[11]:
```
dataset_atrib
```

[11]:
```
array([['4.216', '0.418', '234.840', …, '0.000', '1.000', 17.0],
       ['5.360', '0.436', '233.630', …, '0.000', '1.000', 16.0],
       ['5.374', '0.498', '233.290', …, '0.000', '2.000', 17.0],
       …,
       ['0.938', '0.000', '239.820', …, '0.000', '0.000', 0.0],
       ['0.934', '0.000', '239.700', …, '0.000', '0.000', 0.0],
       ['0.932', '0.000', '239.550', …, '0.000', '0.000', 0.0]],
      dtype=object)
```

[12]:
```
# Collects a sample of 1% of the data so as not to compromise the computer's␣
 ↪memory
sample1, sample2 = train_test_split(dataset_atrib, train_size = .01)
```

[13]:
```
sample1.shape
```

[13]:
```
(20492, 7)
```

[14]:
```
# Apply dimensionality reduction
pca = PCA(n_components = 2).fit_transform(sample1)
```

[15]:
```
# Determining a range of K
k_range = range(1,12)
```

[16]:
```
# Applying the K-Means model to each value of K (this cell can take a long time␣
 ↪to run)
k_means_var = [KMeans(n_clusters = k).fit(pca) for k in k_range]
```

[17]:
```
# Adjusting the cluster centroid for each model
centroids = [X.cluster_centers_ for X in k_means_var]
```

[18]:
```
# Calculating the Euclidean distance of each data point to the centroid
k_euclid = [cdist(pca, cent, 'euclidean') for cent in centroids]
dist = [np.min(ke, axis = 1) for ke in k_euclid]
```

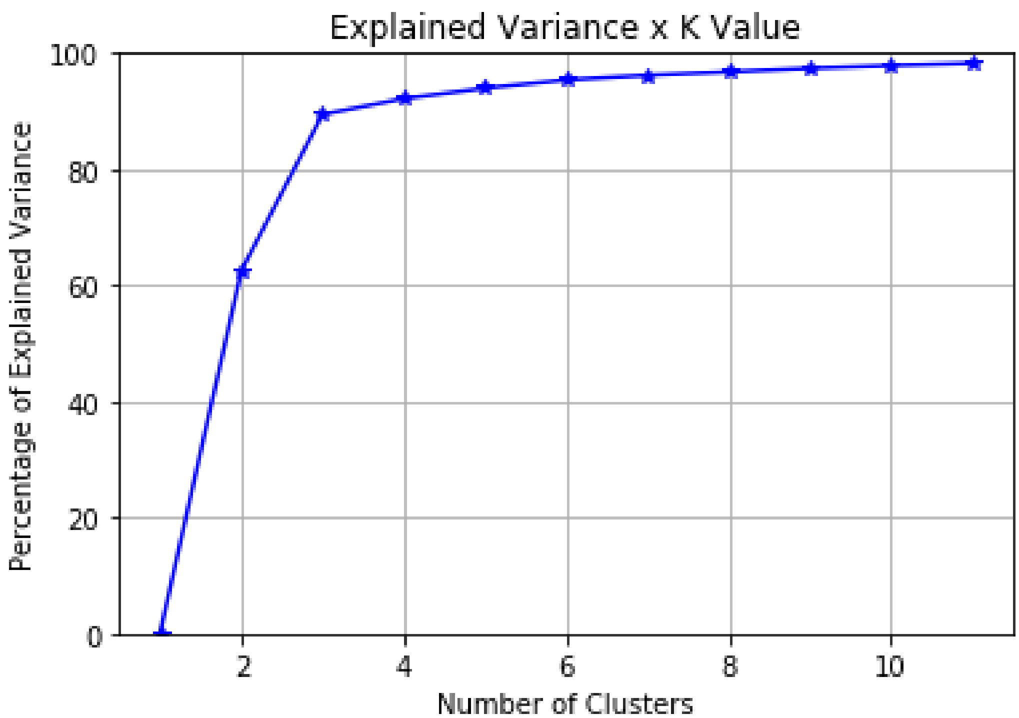
[19]:
```
# Sum of squares of distances within the cluster
squares_sum_intra_cluster = [sum(d**2) for d in dist]
```

[20]:
```
# Total sum of squares
total_sum = sum(pdist(pca)**2)/pca.shape[0]
```

[21]:
```
# Sum of squares between clusters
squares_sum_intra_cluster = total_sum - squares_sum_intra_cluster
```

[22]:
```
# Elbow Curve
fig = plt.figure()
ax = fig.add_subplot(111)
ax.plot(k_range, squares_sum_intra_cluster/total_sum * 100, 'b*-')
ax.set_ylim((0,100))
plt.grid(True)
plt.xlabel('Number of Clusters')
plt.ylabel('Percentage of Explained Variance')
plt.title('Explained Variance x K Value')
```

[22]:
```
Text(0.5, 1.0, 'Explained Variance x K Value')
```



[23]:
```
# Creating a model with K = 8
model_v1 = KMeans(n_clusters = 8)
model_v1.fit(pca)
```

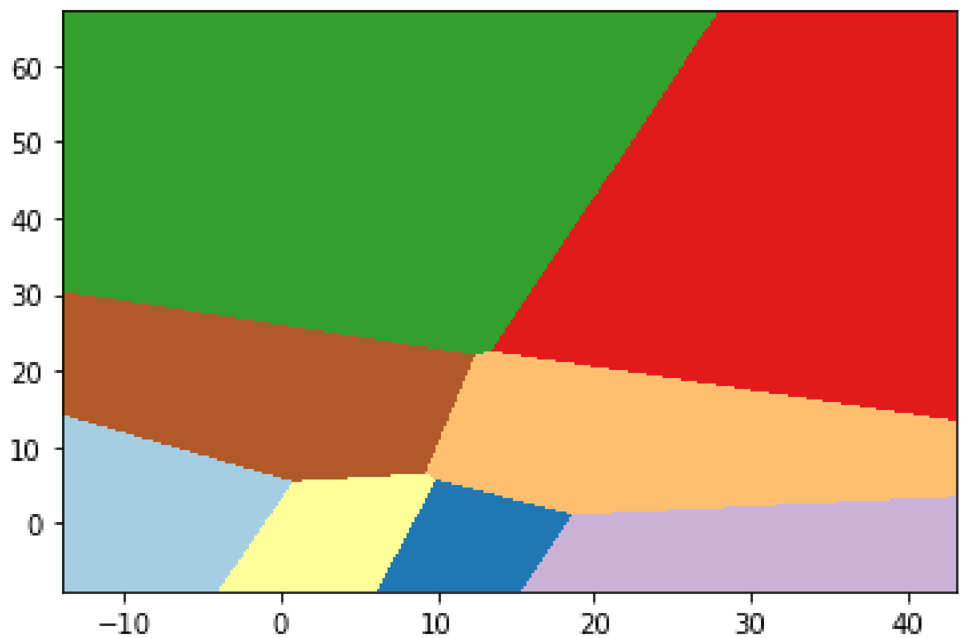
[23]:
```
KMeans()
```

[24]:
```
# Get the minimum and maximum values and organize the shape
x_min, x_max = pca[:, 0].min() - 5, pca[:, 0].max() - 1
y_min, y_max = pca[:, 1].min() + 1, pca[:, 1].max() + 5
xx, yy = np.meshgrid(np.arange(x_min, x_max, .02), np.arange(y_min, y_max, .02))
Z = model_v1.predict(np.c_[xx.ravel(), yy.ravel()])
```

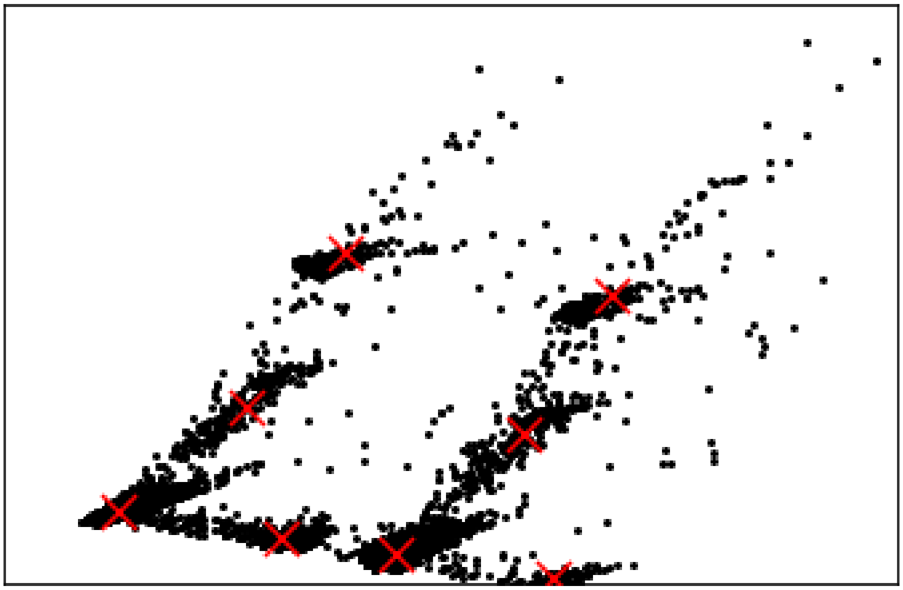
```
Z = Z.reshape(xx.shape)
```

[25]:
```
# Plot of cluster areas
plt.figure(1)
plt.clf()
plt.imshow(Z,
           interpolation = 'nearest',
           extent = (xx.min(), xx.max(), yy.min(), yy.max()),
           cmap = plt.cm.Paired,
           aspect = 'auto',
           origin = 'lower')
```

[25]: <matplotlib.image.AxesImage at 0x1abc3ad5048>



[26]:
```
# Plot of centroids
plt.plot(pca[:, 0], pca[:, 1], 'k.', markersize = 4)
centroids = model_v1.cluster_centers_
inert = model_v1.inertia_
plt.scatter(centroids[:, 0], centroids[:, 1], marker = 'x', s = 169, linewidths
 = 3, color = 'r', zorder = 8)
plt.xlim(x_min, x_max)
plt.ylim(y_min, y_max)
plt.xticks(())
plt.yticks(())
plt.show()
```



[27]:
```
# Silhouette Score
labels = model_v1.labels_
silhouette_score(pca, labels, metric = 'euclidean')
```

[27]: 0.8109285557286058

[28]:
```
# Creating a model with K = 10
model_v2 = KMeans(n_clusters = 10)
model_v2.fit(pca)
```

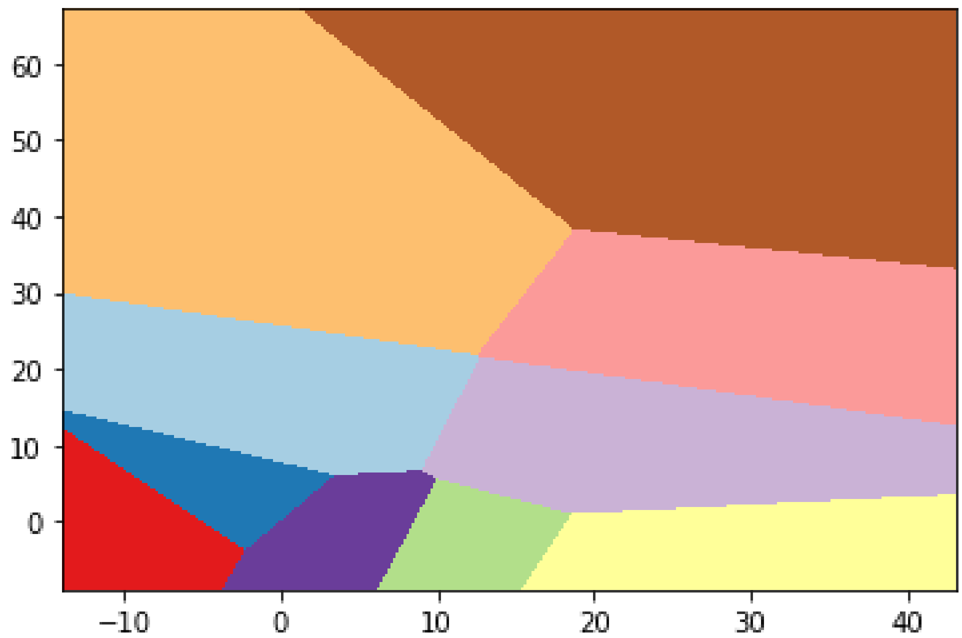
[28]: KMeans(n_clusters=10)

[29]:
```
# Get the minimum and maximum values and organize the shape
x_min, x_max = pca[:, 0].min() - 5, pca[:, 0].max() - 1
y_min, y_max = pca[:, 1].min() + 1, pca[:, 1].max() + 5
xx, yy = np.meshgrid(np.arange(x_min, x_max, .02), np.arange(y_min, y_max, .02))
Z = model_v2.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
```

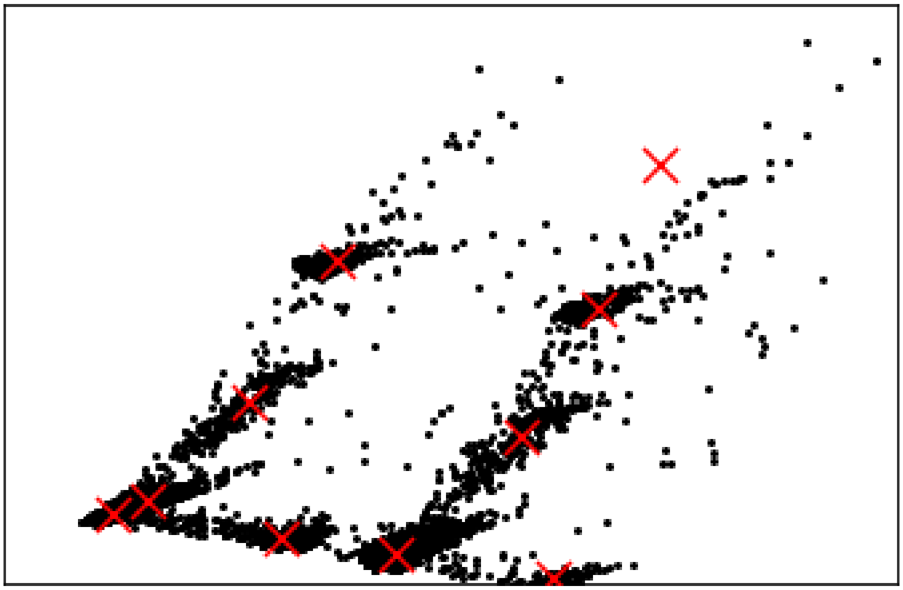
[30]:
```
# Plot of cluster areas
plt.figure(1)
plt.clf()
plt.imshow(Z,
           interpolation = 'nearest',
           extent = (xx.min(), xx.max(), yy.min(), yy.max()),
           cmap = plt.cm.Paired,
           aspect = 'auto',
```

```
            origin = 'lower')
```

[30]: <matplotlib.image.AxesImage at 0x1abd5df2fc8>



[31]:
```
# Plot of centroids
plt.plot(pca[:, 0], pca[:, 1], 'k.', markersize = 4)
centroids = model_v2.cluster_centers_
inert = model_v2.inertia_
plt.scatter(centroids[:, 0], centroids[:, 1], marker = 'x', s = 169, linewidths␣
↪= 3, color = 'r', zorder = 8)
plt.xlim(x_min, x_max)
plt.ylim(y_min, y_max)
plt.xticks(())
plt.yticks(())
plt.show()
```



[32]:
```
# Silhouette Score
labels = model_v2.labels_
silhouette_score(pca, labels, metric = 'euclidean')
```

[32]: 0.6622334485962933

Creating the Cluster Map with the clusters of Model V1 that presented the best Silhouette Score.

[33]:
```
# List of column names
names = ['Global_active_power', 'Global_reactive_power', 'Voltage',␣
 ↪'Global_intensity', 'Sub_metering_1', 'Sub_metering_2', 'Sub_metering_3']
```

[34]:
```
# Create the cluster map
cluster_map = pd.DataFrame(sample1, columns = names)
cluster_map['Global_active_power'] = pd.
 ↪to_numeric(cluster_map['Global_active_power'])
cluster_map['cluster'] = model_v1.labels_
```

[35]:
```
cluster_map
```

[35]:
```
        Global_active_power Global_reactive_power  Voltage Global_intensity  \
0                     0.348                 0.114  242.240            1.600
1                     1.470                 0.214  241.030            6.000
2                     0.254                 0.076  241.020            1.000
3                     2.436                 0.000  241.550           10.000
4                     0.438                 0.220  241.390            2.000
…                       …                     …       …                 …
```

```
20487                2.342                 0.062  242.840             9.600
20488                1.284                 0.112  239.970             5.200
20489                1.238                 0.082  237.170             5.200
20490                0.516                 0.076  240.730             2.400
20491                0.608                 0.000  245.750             2.600

      Sub_metering_1 Sub_metering_2 Sub_metering_3  cluster
0              0.000          0.000              0        0
1              0.000          2.000             18        1
2              0.000          0.000              1        0
3              0.000          0.000             19        1
4              0.000          1.000              0        0
…              …             …             …      …
20487          0.000          0.000              0        0
20488          0.000          0.000             17        1
20489          0.000          0.000             17        1
20490          0.000          0.000              0        0
20491          0.000          0.000              1        0

[20492 rows x 8 columns]
```

[36]:
```python
# Calculate average power consumption per cluster
cluster_map.groupby('cluster')['Global_active_power'].mean()
```

[36]:
```
cluster
0    0.505289
1    1.799310
2    3.536876
3    4.568310
4    3.804424
5    2.418526
6    1.090223
7    2.551672
Name: Global_active_power, dtype: float64
```

1.0.1 End