19075153_O'Leary_PartA1_KM

October 16, 2021

[1]:
```
import pandas
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import warnings
from pandas.plotting import scatter_matrix
import seaborn as sns
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import tree
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from numpy import set_printoptions
from sklearn.decomposition import PCA
from sklearn import preprocessing

warnings.filterwarnings('ignore')
```

1 Data load and pre-processing

[2]:
```
min_max_scaler = preprocessing.MinMaxScaler()

#################
# load data sales
#################
path_sales = "/mnt/c/Users/T828808/Study/AUT/COMP809/Ass2/
↪Sales_Transactions_Dataset_Weekly.csv"
rawdata_sales = pandas.read_csv(path_sales)
# categorise everything and create array
list_of_columns_sales = rawdata_sales.columns
rawdata_sales[list_of_columns_sales] = rawdata_sales[list_of_columns_sales].
↪apply(lambda col:pandas.Categorical(col).codes)
# Create array
array_sales = rawdata_sales.values
predictors_sales = array_sales[:, 0:107]
# Print some stats
```

```
print(rawdata_sales.shape)
print(rawdata_sales.head())

#################
# load data seoul
#################
path_seoul = "/mnt/c/Users/T828808/Study/AUT/COMP809/Ass2/SeoulBikeData.csv"
rawdata_seoul = pandas.read_csv(path_seoul)
# categorise everything and create array
list_of_columns_seoul = rawdata_seoul.columns
rawdata_seoul[list_of_columns_seoul] = rawdata_seoul[list_of_columns_seoul].
 ↪apply(lambda col:pandas.Categorical(col).codes)
# Create array
array_seoul = rawdata_seoul.values
predictors_seoul = array_seoul[:, 0:14]
# Print some stats
print(rawdata_seoul.shape)
print(rawdata_seoul.head())

#################
# load data water
#################
path_water = "/mnt/c/Users/T828808/Study/AUT/COMP809/Ass2/water-treatment.data"
rawdata_water = pandas.read_csv(path_water)
rawdata_water.columns =␣
 ↪['DATE','Q-E','ZN-E','PH-E','DBO-E','DQO-E','SS-E','SSV-E','SED-E','COND-E','PH-P','DBO-P',
# categorise everything and create array
list_of_columns_water = rawdata_water.columns
rawdata_water[list_of_columns_water] = rawdata_water[list_of_columns_water].
 ↪apply(lambda col:pandas.Categorical(col).codes)
# Create array
array_water = rawdata_water.values
predictors_water = array_water[:, 0:39]
# Print some stats
print(rawdata_water.shape)
print(rawdata_water.head())
```

```
(811, 107)
   Product_Code  W0  W1  W2  W3  W4  W5  W6  W7  W8  …  Normalized 42  \
0             0  11  12  10   8  13  12  14  21   6  …              3
1           111   7   6   3   2   7   1   6   3   3  …             17
2           222   7  11   8   9  10   8   7  13  12  …             24
3           331  12   8  13   5   9   6   9  13  13  …             37
4           442   8   5  13  11   6   7   9  14   9  …             24

   Normalized 43  Normalized 44  Normalized 45  Normalized 46  Normalized 47  \
0             20             26             35             46              0
```

1	38	47	7	6	35
2	83	16	15	32	40
3	45	4	9	20	30
4	51	25	56	16	15

	Normalized 48	Normalized 49	Normalized 50	Normalized 51
0	16	13	7	35
1	44	7	55	0
2	82	41	41	32
3	65	31	25	31
4	8	49	29	36

[5 rows x 107 columns]

(8760, 14)

	Date	Rented Bike Count	Hour	Temperature(C)	Humidity(%)	\
0	11	253	0	111	28	
1	11	203	1	108	29	
2	11	172	2	103	30	
3	11	106	3	101	31	
4	11	77	4	103	27	

	Wind speed (m/s)	Visibility (10m)	Dew point temperature(C)	\
0	22	1788	114	
1	8	1788	114	
2	10	1788	113	
3	9	1788	114	
4	23	1788	104	

	Solar Radiation (MJ/m2)	Rainfall(mm)	Snowfall (cm)	Seasons	Holiday	\
0	0	0	0	3	1	
1	0	0	0	3	1	
2	0	0	0	3	1	
3	0	0	0	3	1	
4	0	0	0	3	1	

	Functioning Day
0	1
1	1
2	1
3	1
4	1

(526, 39)

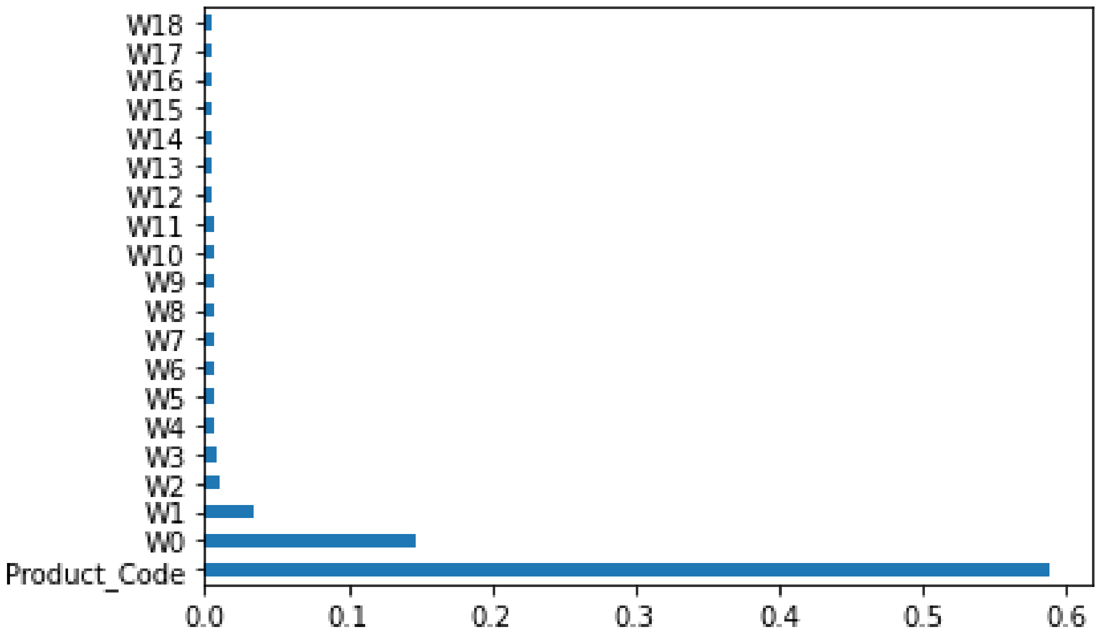
	DATE	Q-E	ZN-E	PH-E	DBO-E	DQO-E	SS-E	SSV-E	SED-E	COND-E	…	\
0	197	330	116	6	204	169	57	201	50	409	…	
1	427	99	143	5	204	231	42	208	28	303	…	
2	443	219	126	8	93	256	45	171	36	402	…	
3	461	282	66	9	126	211	37	164	33	381	…	
4	479	319	116	7	90	117	42	197	36	295	…	

```
   COND-S  RD-DBO-P  RD-SS-P  RD-SED-P  RD-DBO-S  RD-DQO-S  RD-DBO-G  \
0     372       314      165       104       184       233       155
1     334       314      143       111       184        37       155
2     322       100      196       108       131       165        95
3     349       314      183       111       184       153       114
4     301       314      157       118       125       216        94

   RD-DQO-G  RD-SS-G  RD-SED-G
0       134      126         0
1       101       92        26
2       158      101         0
3       121       82        37
4        78       61         0

[5 rows x 39 columns]
```

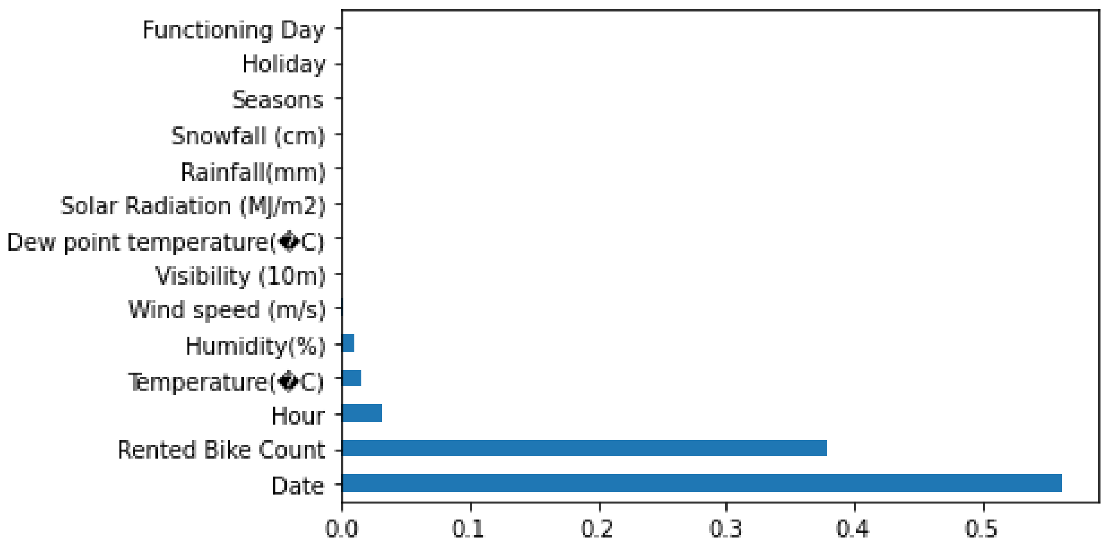
2 Feature importance

[3]:

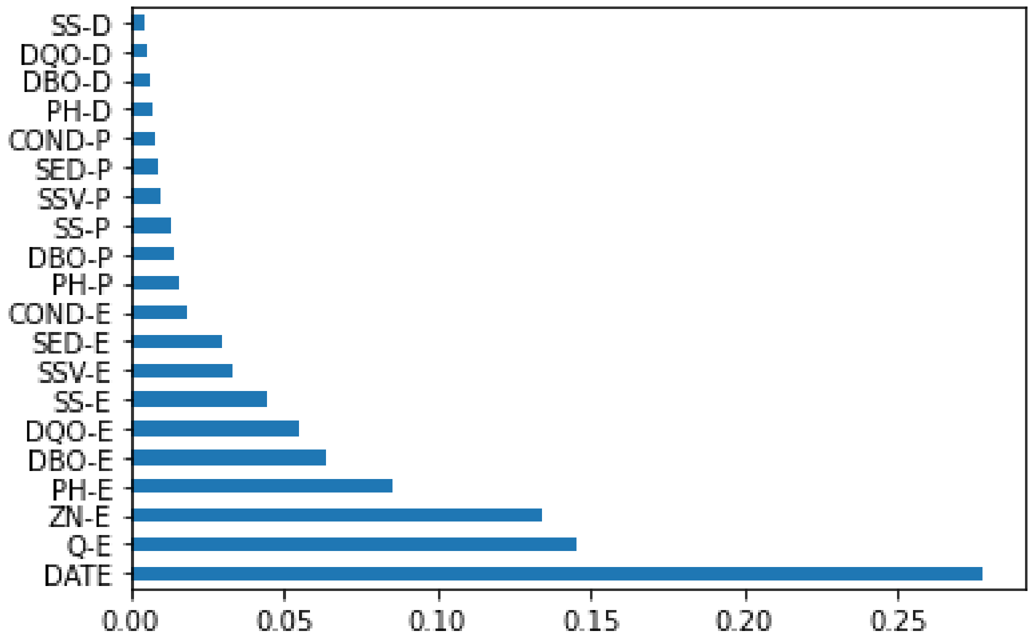
```
#################
# Sales
#################
# Run PCA
pca_sales = PCA()
pca_fit_sales = pca_sales.fit(predictors_sales)
# summarize components
feat_importances_sales = pandas.Series(pca_fit_sales.explained_variance_ratio_,␣
 ↪index=rawdata_sales.columns)
feat_importances_sales.nlargest(20).plot(kind='barh')
# Get only the first two components as they explain almost all of the variance
pca_sales = PCA(n_components=2)
pca_fit_sales = pca_sales.fit(predictors_sales)
pca_data_sales = rawdata_sales[['W0','W1','Product_Code']]
```



[4]:
```
#################
# Seoul
#################
# Run PCA
pca_seoul = PCA()
pca_fit_seoul = pca_seoul.fit(predictors_seoul)
# summarize components
feat_importances_seoul = pandas.Series(pca_fit_seoul.explained_variance_ratio_,␣
↪index=rawdata_seoul.columns)
feat_importances_seoul.nlargest(20).plot(kind='barh')
# Get only the first two components as they explain almost all of the variance
pca_seoul = PCA(n_components=2)
pca_fit_seoul = pca_seoul.fit(predictors_seoul)
pca_data_seoul = rawdata_seoul[['Hour','Rented Bike␣
↪Count','Date','Temperature( C)']]
```



[5]:
```
################
# Water
################
# Run PCA
pca_water = PCA()
pca_fit_water = pca_water.fit(predictors_water)
# summarize components
feat_importances_water = pandas.Series(pca_fit_water.explained_variance_ratio_,␣
↪index=rawdata_water.columns)
feat_importances_water.nlargest(20).plot(kind='barh')
# Get only the first two components as they explain almost all of the variance
pca_water = PCA(n_components=2)
pca_fit_water = pca_water.fit(predictors_water)
pca_data_water = rawdata_water[['DATE','Q-E','ZN-E','PH-E','DBO-E']]
```



3 Clustering

[6]:
```
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples, silhouette_score
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import numpy as np
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import DBSCAN
import time


def do_sse(X, cluster_labels, n_clusters, model):
    cluster_centers = [X[cluster_labels == i].mean(axis=0) for i in␣
↪range(n_clusters)]
    clusterwise_sse = [0, 0, 0, 0, 0, 0]
    for point, label in zip(X, cluster_labels):
        clusterwise_sse[label] += np.square(point - cluster_centers[label]).
↪sum()
    clusterwise_sse_avg = np.mean(clusterwise_sse)
    return clusterwise_sse_avg

def do_cluster_analysis(name):
```

```
    # To find out the optimal number of clusters we can search through range of␣
↪clusters.
    range_n_clusters = [2, 3, 4, 5, 6]
    for n_clusters in range_n_clusters:

        ␣
↪print('==================================================================================
        print('n_clusters = ', n_clusters)
        ␣
↪print('==================================================================================
        start_time = time.time()

        # Create a subplot with 1 row and 2 columns
        fig, (ax1, ax2) = plt.subplots(1, 2)
        fig.set_size_inches(18, 7)

        # The 1st subplot is the silhouette plot
        # The silhouette coefficient can range from -1, 1
        # but in this example code all lie within [-0.1, 1]

        ax1.set_xlim([-0.1, 1])

        # # The (n_clusters+1)*10 is for inserting blank space between
        # silhouette plots of individual clusters, to demarcate them
        # clearly.

        ax1.set_ylim([0, len(X) + (n_clusters + 1) * 10])

        #Apply k-means
        clusterer = KMeans(n_clusters, random_state=0)
        cluster_labels = clusterer.fit_predict(X)

        # The silhouette_score gives the average value for all the
        # samples.This gives a perspective into the density and
        # separation of the formed clusters

        silhouette_avg = silhouette_score(X, cluster_labels)
        #␣
↪//////////////////////////////////////////////////////////////////////////////////////
        # Print the values
        #␣
↪//////////////////////////////////////////////////////////////////////////////////////
        print("For n_clusters =", n_clusters, "The average silhouette_score is :
↪", silhouette_avg)
```

```
        print("For n_clusters =", n_clusters, "The average SSE is :", do_sse(X,␣
↪clusterer.labels_, n_clusters, clusterer))

        # Compute the silhouette scores for each sample
        sample_silhouette_values = silhouette_samples(X, cluster_labels)
        y_lower = 10

        for i in range(n_clusters):
            # Aggregate the silhouette scores for samples belonging to
            # cluster i, and sort them

            #␣
↪//////////////////////////////////////////////////////////////////////////////////////
            # Create the plot
            #␣
↪//////////////////////////////////////////////////////////////////////////////////////

            # Aggregate the silhouette scores for samples belonging to
            # cluster i, and sort them
            ith_cluster_silhouette_values =␣
↪sample_silhouette_values[cluster_labels == i]

            ith_cluster_silhouette_values.sort()
            size_cluster_i = ith_cluster_silhouette_values.shape[0]
            y_upper = y_lower + size_cluster_i
            color = cm.nipy_spectral(float(i) / n_clusters)

            ax1.fill_betweenx(np.arange(y_lower, y_upper),
                              0, ith_cluster_silhouette_values,
                              facecolor=color, edgecolor=color,
                              alpha=0.7)

            # Label the silhouette plots with their cluster numbers at the
            # middle

            ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

            # Compute the new y_lower for next plot

            y_lower = y_upper + 10  # 10 for the 0 samples
            ax1.set_title("The silhouette plot for the various clusters.")
            ax1.set_xlabel("The silhouette coefficient values")
            ax1.set_ylabel("Cluster label")

            # The vertical line for average silhouette score of all the
            # values
```

```
            ax1.axvline(x=silhouette_avg, color="red", linestyle="--")
            ax1.set_yticks([])  # Clear the yaxis labels / ticks
            ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])

            # 2nd Plot showing the actual clusters formed
            colors = cm.nipy_spectral(cluster_labels.astype(float) / n_clusters)
            ax2.scatter(X[:, 0],
                        X[:, 1],
                        marker='.',
                        s=30,
                        lw=0,
                        alpha=0.7,
                        c=colors,
                        edgecolor='k')

            # Labeling the clusters by centers
            centers = clusterer.cluster_centers_

            # Draw white circles at cluster centers
            ax2.scatter(centers[:, 0],
                        centers[:, 1],
                        marker='o',
                        c="white",
                        alpha=1,
                        s=200,
                        edgecolor='k')

            for i, c in enumerate(centers):
                ax2.scatter(c[0],
                            c[1],
                            marker='$%d$' % i,
                            alpha=1,
                            s=50,
                            edgecolor='k')

            ax2.set_title("The visualization of the clustered data.")
            ax2.set_xlabel("Feature space for the 1st feature")
            ax2.set_ylabel("Feature space for the 2nd feature")
            plt.suptitle(("Silhouette analysis for KMeans clustering on sample␣
↪data with n_clusters = %d" % n_clusters),
                         fontsize=14,
                         fontweight='bold')

        # Time to run
        print("--- %s seconds ---" % (time.time() - start_time))

#################
```

```python
# Sales
#################
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
print('sales')
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
X = pca_data_sales
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(X)
X = x_scaled
do_cluster_analysis('sales')

#################
# Water
#################
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
print('water')
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
X = pca_data_water
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(X)
X = x_scaled
do_cluster_analysis('water')

#################
# Seoul
#################
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
print('seoul')
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
print('||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||')
X = pca_data_seoul
min_max_scaler = preprocessing.MinMaxScaler()
x_scaled = min_max_scaler.fit_transform(X)
X = x_scaled
do_cluster_analysis('seoul')
```

```
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sales
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```

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||||
||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
||||
================================================================================
====
n_clusters =  2
================================================================================
====
For n_clusters = 2 The average silhouette_score is : 0.5529922804905653
For n_clusters = 2 The average SSE is : 14.437368116537462
--- 0.39674830436706543 seconds ---
================================================================================
====
n_clusters =  3
================================================================================
====
For n_clusters = 3 The average silhouette_score is : 0.488051563750343
For n_clusters = 3 The average SSE is : 8.004891084595682
--- 0.3482513427734375 seconds ---
================================================================================
====
n_clusters =  4
================================================================================
====
For n_clusters = 4 The average silhouette_score is : 0.4956690385768799
For n_clusters = 4 The average SSE is : 6.000403406587895
--- 0.36387038230895996 seconds ---
================================================================================
====
n_clusters =  5
================================================================================
====
For n_clusters = 5 The average silhouette_score is : 0.48706090844597216
For n_clusters = 5 The average SSE is : 4.577621604668537
--- 0.3974940776824951 seconds ---
================================================================================
====
n_clusters =  6
================================================================================
====
For n_clusters = 6 The average silhouette_score is : 0.4905602367765982
For n_clusters = 6 The average SSE is : 3.540858712458992
--- 0.4951903820037842 seconds ---
||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
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||||
water
```

```
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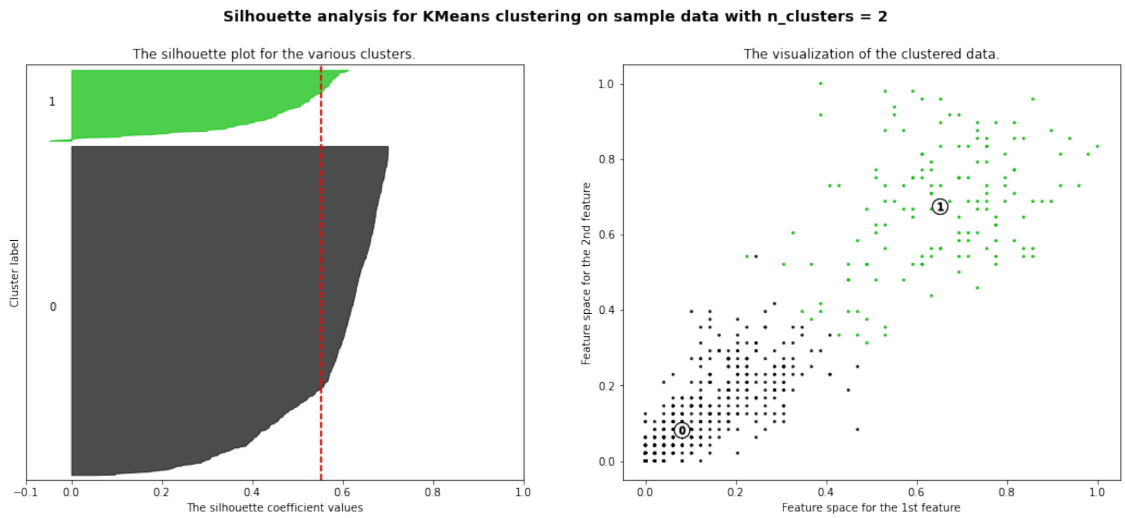
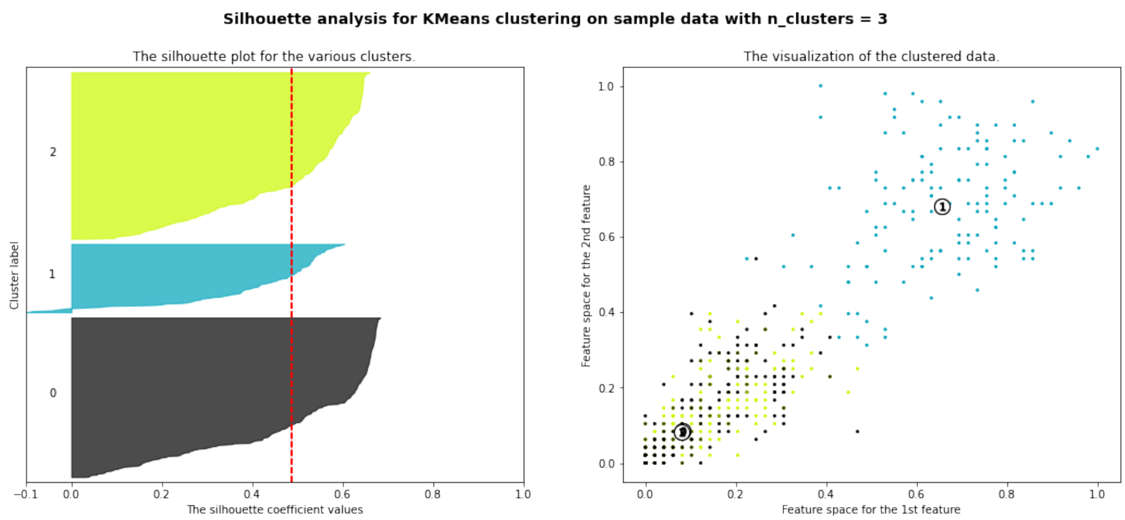
||||
||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
||||
================================================================================
====
n_clusters =  2
================================================================================
====
For n_clusters = 2 The average silhouette_score is : 0.19182821192769825
For n_clusters = 2 The average SSE is : 23.774174486620684
--- 0.2271566390991211 seconds ---
================================================================================
====
n_clusters =  3
================================================================================
====
For n_clusters = 3 The average silhouette_score is : 0.18095097792392195
For n_clusters = 3 The average SSE is : 20.271440855256856
--- 0.2882091999053955 seconds ---
================================================================================
====
n_clusters =  4
================================================================================
====
For n_clusters = 4 The average silhouette_score is : 0.1962198321867441
For n_clusters = 4 The average SSE is : 17.68019667536556
--- 0.3564331531524658 seconds ---
================================================================================
====
n_clusters =  5
================================================================================
====
For n_clusters = 5 The average silhouette_score is : 0.19376529853466307
For n_clusters = 5 The average SSE is : 15.661026408267285
--- 0.5259983539581299 seconds ---
================================================================================
====
n_clusters =  6
================================================================================
====
For n_clusters = 6 The average silhouette_score is : 0.1979742286699438
For n_clusters = 6 The average SSE is : 14.219162585579324
--- 0.42758846282958984 seconds ---
||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
||||
||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
||||
```

```
seoul
||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
||||
||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||||
||||
================================================================================
====
n_clusters =  2
================================================================================
====
For n_clusters = 2 The average silhouette_score is : 0.2736422972611256
For n_clusters = 2 The average SSE is : 297.7696053888172
--- 5.6746766567230225 seconds ---
================================================================================
====
n_clusters =  3
================================================================================
====
For n_clusters = 3 The average silhouette_score is : 0.260409768356324
For n_clusters = 3 The average SSE is : 237.01495785978295
--- 5.756635904312134 seconds ---
================================================================================
====
n_clusters =  4
================================================================================
====
For n_clusters = 4 The average silhouette_score is : 0.2749784228827367
For n_clusters = 4 The average SSE is : 191.5564379329348
--- 7.438884973526001 seconds ---
================================================================================
====
n_clusters =  5
================================================================================
====
For n_clusters = 5 The average silhouette_score is : 0.2715519364075326
For n_clusters = 5 The average SSE is : 163.49507869017359
--- 6.142277956008911 seconds ---
================================================================================
====
n_clusters =  6
================================================================================
====
For n_clusters = 6 The average silhouette_score is : 0.263011224680275
For n_clusters = 6 The average SSE is : 145.85463685892572
--- 6.458942413330078 seconds ---
```

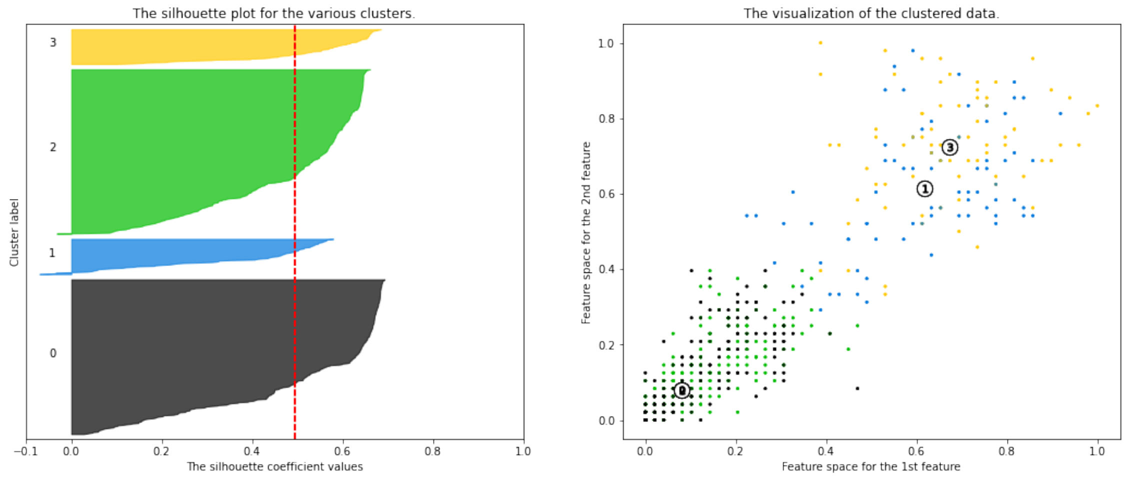


Silhouette analysis for KMeans clustering on sample data with n_clusters = 2
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature

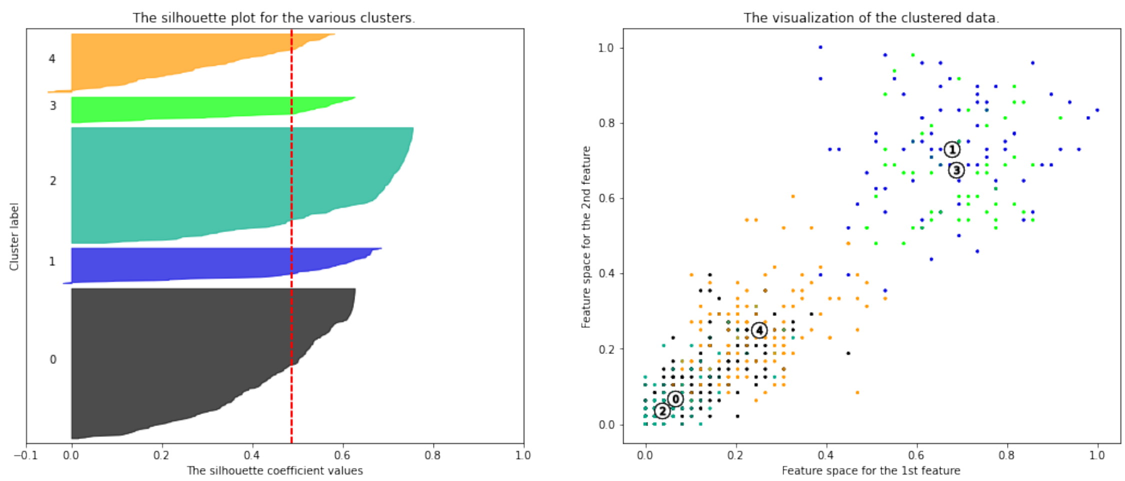


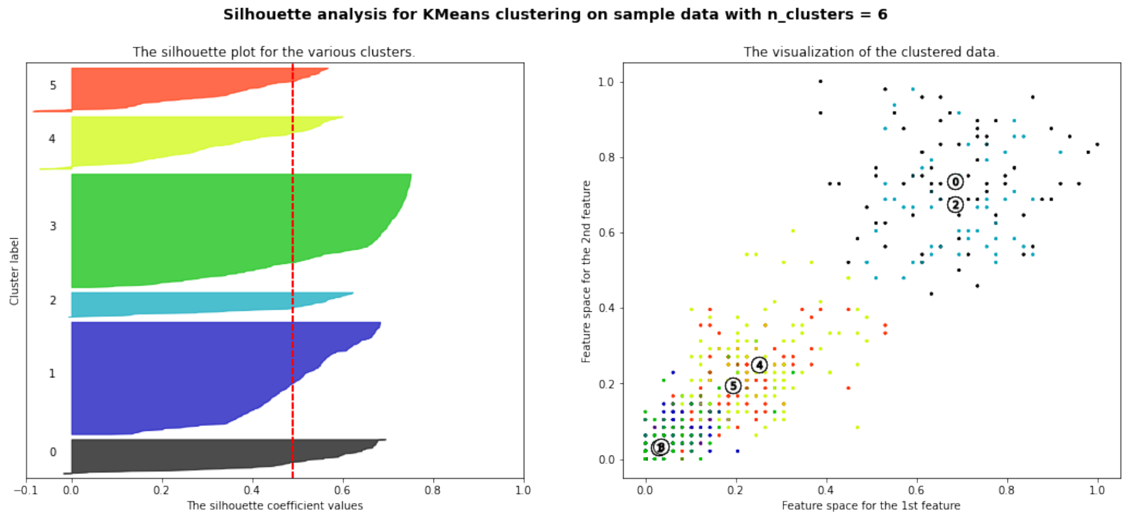
Silhouette analysis for KMeans clustering on sample data with n_clusters = 3
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature

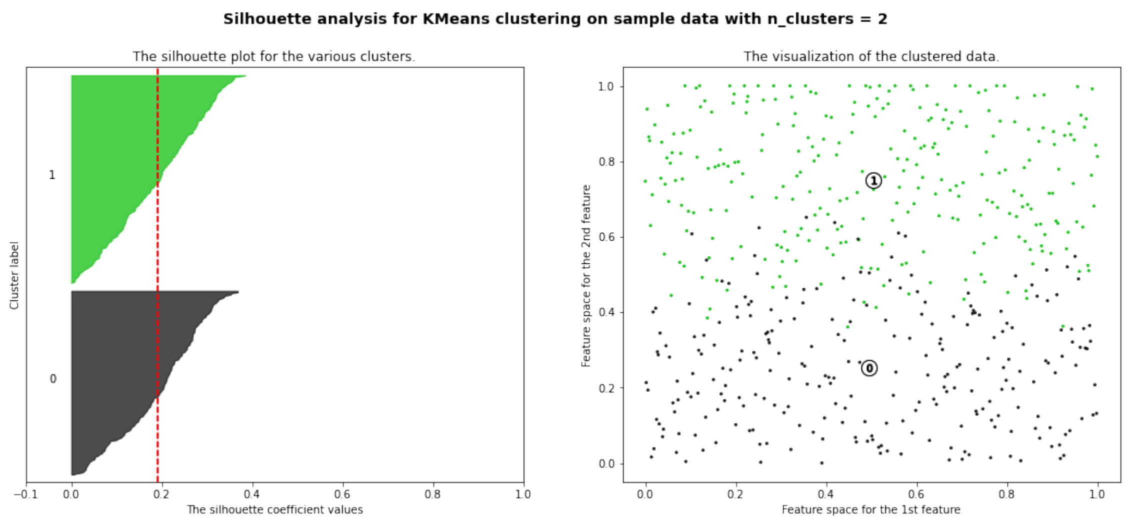
Silhouette analysis for KMeans clustering on sample data with n_clusters = 4



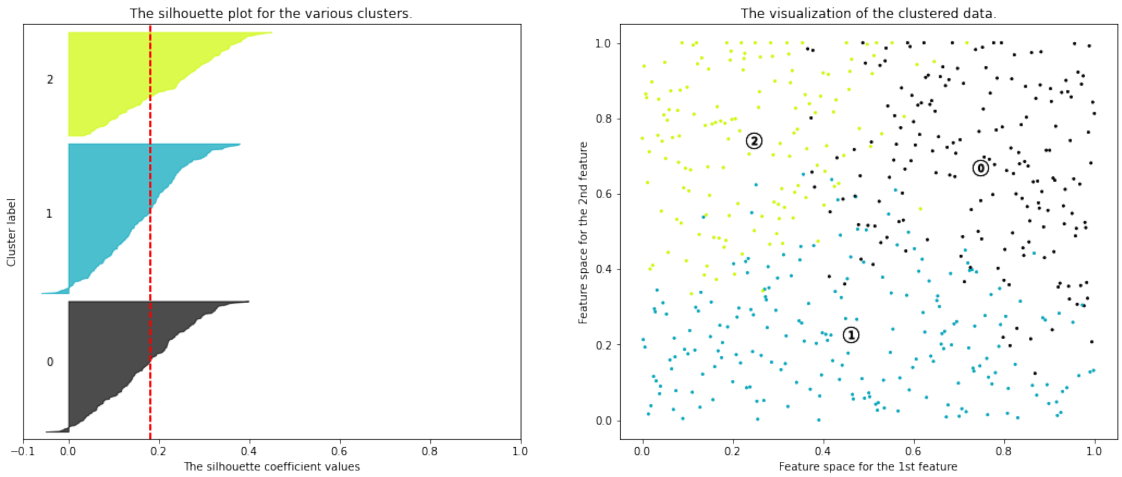
Silhouette analysis for KMeans clustering on sample data with n_clusters = 5



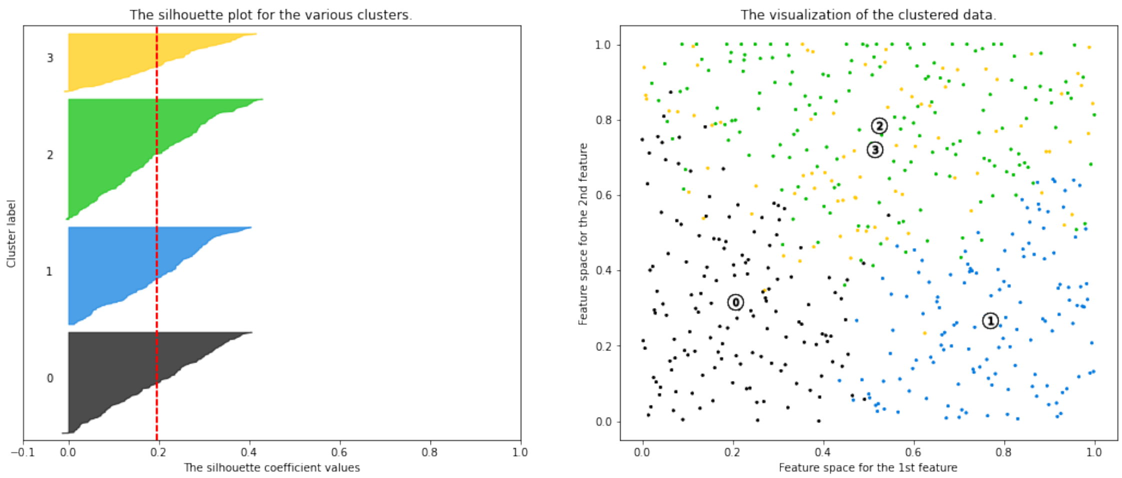

Silhouette analysis for KMeans clustering on sample data with n_clusters = 6
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature

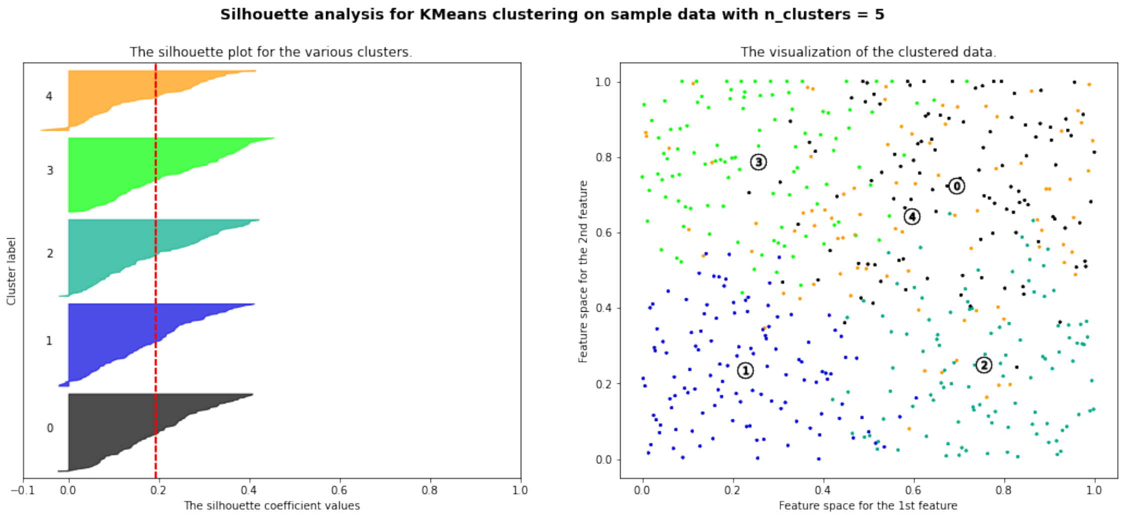

Silhouette analysis for KMeans clustering on sample data with n_clusters = 2
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature

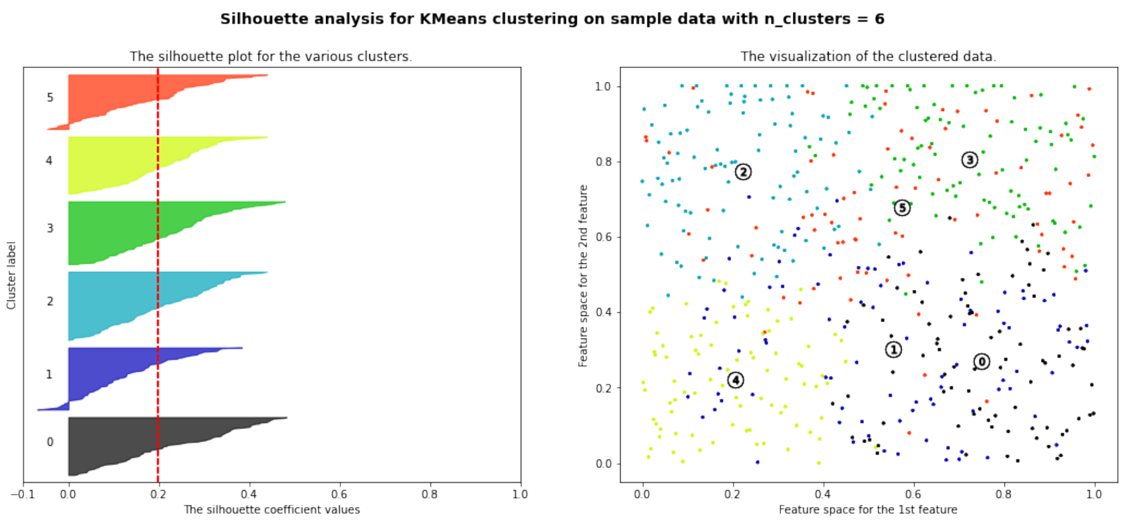
Silhouette analysis for KMeans clustering on sample data with n_clusters = 3

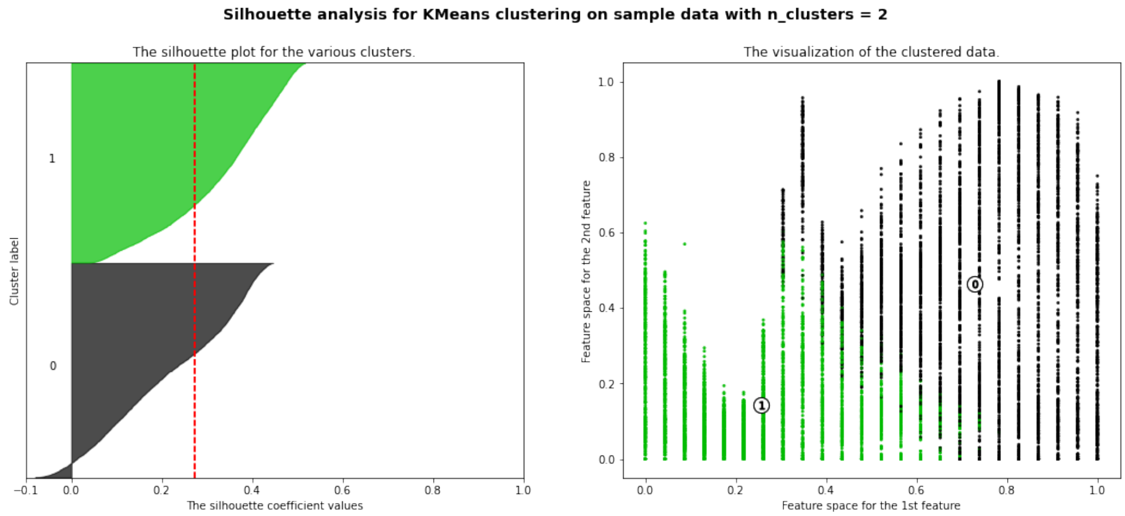


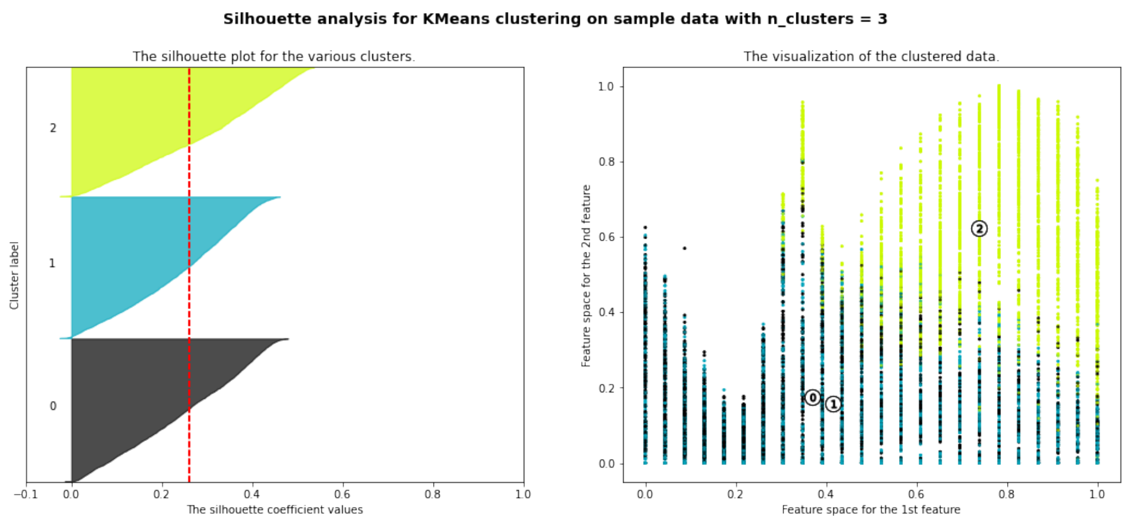
Silhouette analysis for KMeans clustering on sample data with n_clusters = 4



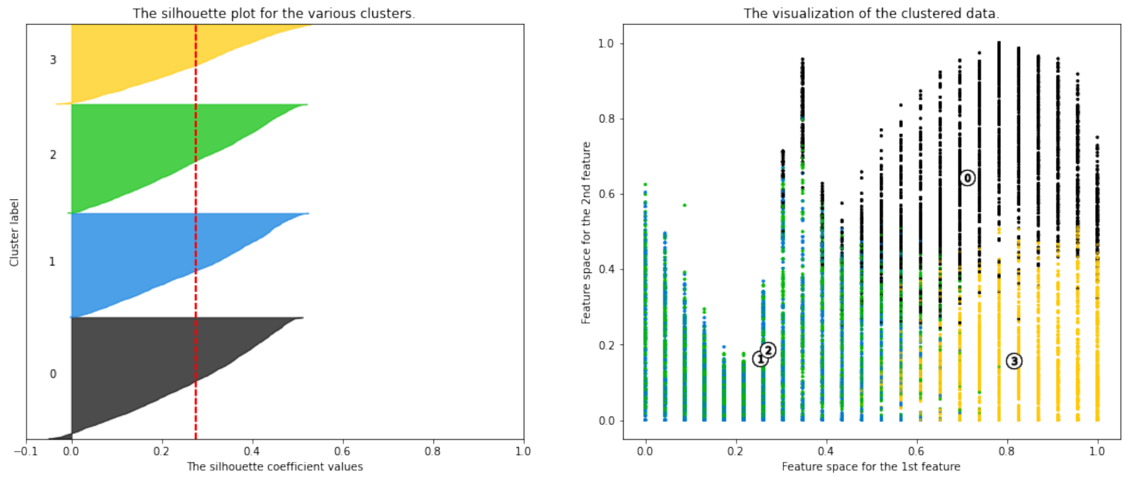

Silhouette analysis for KMeans clustering on sample data with n_clusters = 5
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature


Silhouette analysis for KMeans clustering on sample data with n_clusters = 6
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature

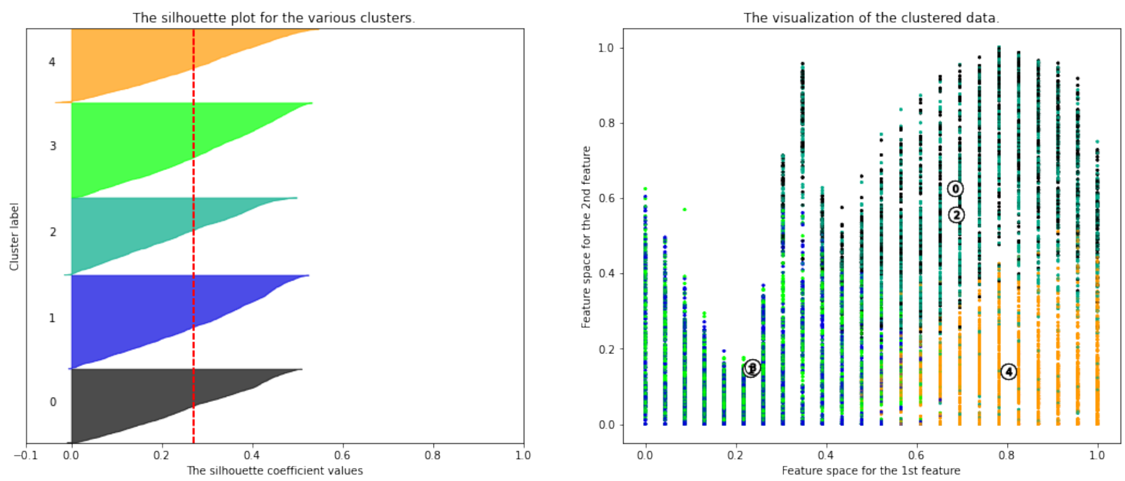

Silhouette analysis for KMeans clustering on sample data with n_clusters = 2
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature


Silhouette analysis for KMeans clustering on sample data with n_clusters = 3
The silhouette plot for the various clusters.
Cluster label
The silhouette coefficient values
The visualization of the clustered data.
Feature space for the 2nd feature
Feature space for the 1st feature

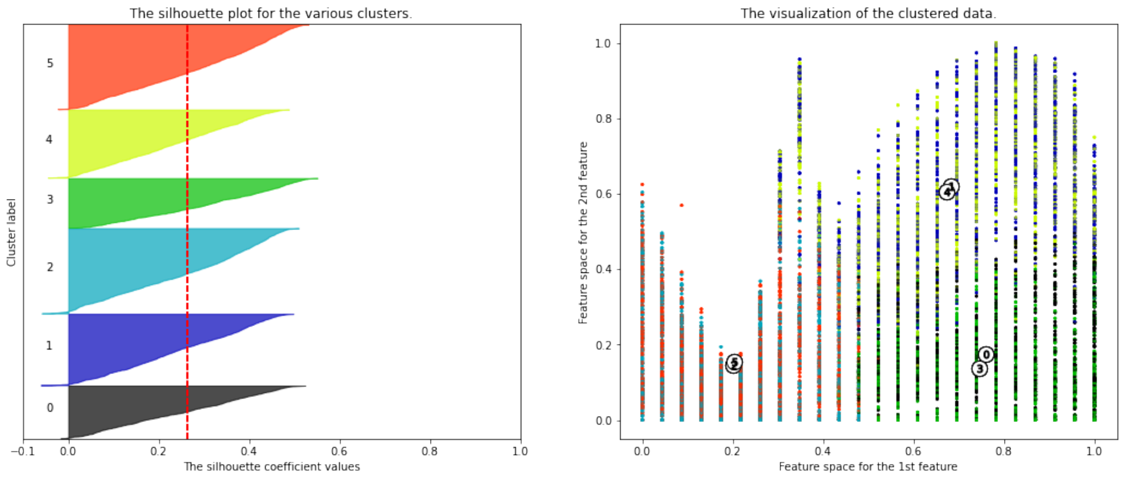
Silhouette analysis for KMeans clustering on sample data with n_clusters = 4



Silhouette analysis for KMeans clustering on sample data with n_clusters = 5



Silhouette analysis for KMeans clustering on sample data with n_clusters = 6



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