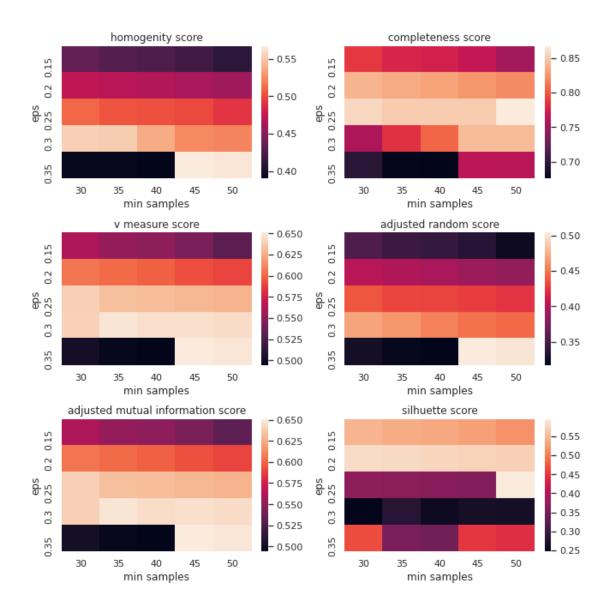
DBSCAN

June 14, 2021

```
[1]: import pandas as pd
      import numpy as np
      import seaborn as sns
      from matplotlib import pyplot as plt
      from sklearn.cluster import KMeans, DBSCAN
      from utils import get_data_train, get_columns
[10]: import numpy as np
      from sklearn.cluster import DBSCAN
      from sklearn import metrics
      from sklearn.datasets import make_blobs
      from sklearn.preprocessing import StandardScaler
      from tqdm import tqdm
 [2]: df = get_data_train()
      chosen_cols = get_columns(df, n_cols=25) + ['activity', 'subject']
 [4]: X = df[chosen_cols].drop(['activity', 'subject'], axis=1)
      y = df['activity']
[60]: epss = [0.15, 0.2, 0.25, 0.3, 0.35]
      min_samples = [30, 35, 40, 45, 50]
      n_epss = len( epss)
      n_min_samples = len( min_samples)
      homogenities = np.ndarray((n_epss, n_min_samples),)
      completenesses = np.ndarray((n_epss, n_min_samples),)
      v_measures = np.ndarray((n_epss, n_min_samples),)
      adjusted_rands = np.ndarray((n_epss, n_min_samples),)
      adjusted_mutual_infos = np.ndarray((n_epss, n_min_samples),)
      silhuettes = np.ndarray((n_epss, n_min_samples),)
[61]: for i in tqdm(range( n_epss)):
          for j in range( n_min_samples):
              db = DBSCAN(eps=epss[i], min_samples=min_samples[j]).fit(X)
              labels = db.labels_
```

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homogenities[i,j] = metrics.homogeneity_score(y, labels)
              completenesses[i,j] = metrics.completeness_score(y, labels)
              v_measures[i,j] = metrics.v_measure_score(y, labels)
              adjusted_rands[i,j] = metrics.adjusted_rand_score(y, labels)
              adjusted_mutual_infos[i,j] = metrics.adjusted_mutual_info_score(y,_
       →labels)
              silhuettes[i,j] = metrics.silhouette_score(X, labels)
     100%|
               | 5/5 [00:34<00:00, 6.84s/it]
[57]: import seaborn as sns; sns.set_theme()
      import pandas as pd
[62]: homogenities_df = pd.DataFrame(homogenities, columns=min_samples, index=epss)
      completenesses_df = pd.DataFrame( completenesses, columns=min_samples,__
      →index=epss )
      v_measures_df = pd.DataFrame( v_measures, columns=min_samples, index=epss )
      adjusted_rands_df = pd.DataFrame( adjusted_rands, columns=min_samples,_u
      →index=epss )
      adjusted_mutual_infos_df = pd.DataFrame( adjusted_mutual_infos,__

→columns=min_samples, index=epss )
      silhuettes df = pd.DataFrame( silhuettes, columns=min samples, index=epss )
[63]: fig, axs = plt.subplots(3, 2, figsize=(9,9), constrained layout=True)
      #fig.tight_layout()
      sns.heatmap( ax = axs[0,0], data = homogenities_df).set(title='homogenity_
      →score', ylabel="eps", xlabel = "min samples")
      sns.heatmap( ax = axs[0,1], data = completenesses_df).set(title='completeness_L
      →score', ylabel="eps", xlabel = "min samples")
      sns.heatmap( ax = axs[1,0], data = v_measures_df).set(title='v measure score',_
      →ylabel="eps", xlabel = "min samples")
      sns.heatmap( ax = axs[1,1], data = adjusted_rands_df).set(title='adjusted__
      →random score', ylabel="eps", xlabel = "min samples")
      sns.heatmap( ax = axs[2,0], data = adjusted_mutual_infos_df).
      ⇒set(title='adjusted mutual information score', ylabel="eps", xlabel = "min_
      →samples")
      sns.heatmap( ax = axs[2,1], data = silhuettes_df).set(title='silhuette score',_
      →ylabel="eps", xlabel = "min samples")
      plt.show()
```



Powyższe obrazy sugerują, ze parametry $\epsilon=0.25$ oraz min_samples= 50 dają dobre rezultaty.

```
[47]: import sklearn from matplotlib.ticker import MaxNLocator
```

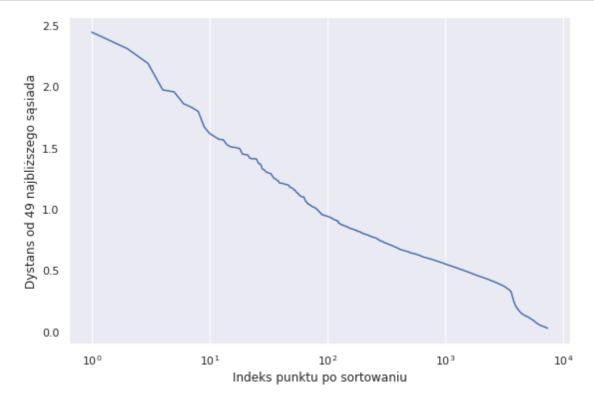
Dobieranie bardziej typowo:

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[76]: minPts = 2*25
nbrs = sklearn.neighbors.NearestNeighbors(n_neighbors=minPts).fit( X)
distances, indices = nbrs.kneighbors( X)
distanceDec = sorted(distances[:,minPts-1], reverse=True)
#fig = plt.figure(figsize=(9,6))
#ax1 = fig.add_subplot(111)
fig,axes=plt.subplots(1,1, figsize=(9,6))
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axes.xaxis.set_major_locator(MaxNLocator(10))
plt.xlabel('Indeks punktu po sortowaniu')
plt.ylabel('Dystans od 49 najbliższego sąsiada')
plt.plot(list(range(1, X.shape[0]+1)), distanceDec)

plt.xscale('log')
plt.grid(axis='y')

plt.show()
```



zdaje się, że wartość $\epsilon=0.25$ jest optymalna

```
[64]: db = DBSCAN(eps=0.25, min_samples=50).fit(X)
[68]: np.unique( db.labels_)
```

[68]: array([-1, 0, 1])