```
from sklearn import datasets
import numpy as np
import pandas as pd
pd.set_option('display.max.columns', 55)
from matplotlib import pyplot as plt
import tracemalloc
import random
import scipy
```

Ćwiczenie zaliczeniowe

Celem ćwiczenia jest:

• przećwiczenie wiedzy o klasyfikatorach

Zadanie:

Część 1:

- pobierz bazę danych covertype (https://archive.ics.uci.edu/ml/datasets/Covertype))
 należy wykorzystać funkcję: https://scikit-learn.org/stable/modul/generated/sklearn.datasets.fetch_covtype.html
 /stable/modules/generated/sklearn.datasets.fetch_covtype.html
- zwizualizuj dane przy użyciu TSNE
- napisz własna implementację klasyfikatora kNN
- naucz klasyfikator kNN
- naucz KNeighborsClassifier ze scikit-learn
- przeanalizuj i porównaj wyniki klasyfikatorów (confusion matrix, accuracy)
- napisz własną implementację klasyfikatora kNM
- naucz klasyfikator kNM
- porównaj accuracy własnego kNM z obiema wersjami kNN
- porównaj zużycie pamięci obu typów klasyfikacji

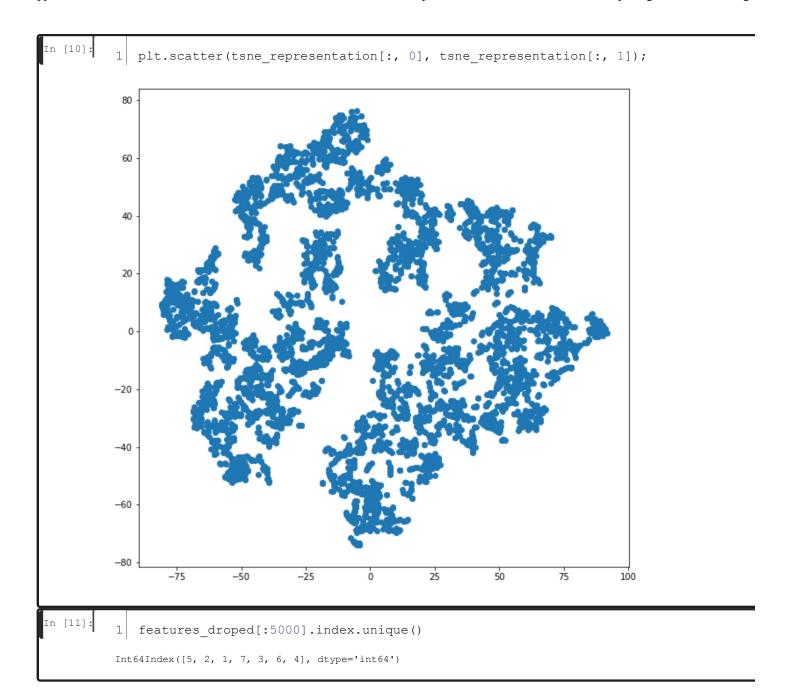
Część 2:

- wykorzystując bazę danych GTSRB zbuduj własną reprezentac znakach (własny wektor cech, minimum 5 cech)
- zwizualizuj dane przy użyciu TSNE
- w oparciu o stworzony zestaw cech porównaj klasyfikatory z cze

Część 1

```
In [2]:
             dataset = datasets.fetch covtype(return X y = True)
             features, target = datasets.fetch covtype(return X y = True)
In [3]:
          1
             features df = pd.DataFrame(data = features, index = target)
             features df
                0
                      1
                          2
                                3
                                     4
                                            5
                                                  6
                                                       7
                                                             8
                                                                    9
                                                                      10
                                                                                                17 18 19
                                                                          11 12 13
                                                                                     14 15
                                                                                            16
            2596.0 51.0
                        3.0
                             258.0 0.0
                                        510.0
                                               221.0
                                                    232.0 148.0 6279.0 1.0
                                                                          0.0 0.0 0.0
                                                                                     0.0 0.0 0.0
         5
            2590.0 56.0
                        2.0
                             212.0 -6.0
                                        390.0
                                               2
            2804.0 139.0 9.0
                             268.0 65.0
                                        2
            2785.0 155.0
                       18.0 242.0
                                  118.0
                                        3090.0
                                              238.0
                                                    238.0 122.0 6211.0
                                                                     1.0 0.0 0.0 0.0 0.0 0.0
                                                                                            0.0
                                                                                                0.0 0.0 0.0
            2595.0 45.0
                        2.0
                             153.0
                                  -1.0
                                        391.0
                                               220.0
                                                   234.0 150.0 6172.0 1.0 0.0 0.0 0.0 0.0 0.0
                                   ...
                                        ---
            2396.0 153.0 20.0 85.0
                                  17.0
                                        108.0
                                               240.0 237.0 118.0
                                                               837.0
                                                                          0.0 1.0 0.0 0.0 1.0
                                                                                            0.0
                                                                                                0.0 0.0 0.0
         3
                                                                      0.0
            2391.0 152.0 19.0 67.0
                                   12.0
                                        95.0
                                               240.0 237.0 119.0 845.0
                                                                      0.0
                                                                          0.0 1.0 0.0 0.0 1.0
                                                                                            0.0 0.0 0.0 0.0
            2386.0 159.0 17.0
                             60.0
                                   7.0
                                        90.0
                                               236.0 241.0 130.0 854.0
                                                                          0.0 1.0
                                                                                 0.0 0.0 1.0
                                                                                                 0.0 0.0 0.0
                                                                      0.0
                                                                                            0.0
            2384.0 170.0 15.0 60.0
                                   5.0
                                        90.0
                                               230.0 245.0 143.0 864.0
                                                                      0.0
                                                                          0.0 1.0 0.0 0.0 1.0 0.0
                                                                                                0.0 0.0 0.0
            2383.0 165.0 13.0 60.0
                                  4.0
                                        67.0
                                               231.0 244.0 141.0 875.0
                                                                      0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 0.0 0.0
        581012 rows x 54 columns
In [4]:
              from sklearn.manifold import TSNE
          2
             from sklearn.preprocessing import StandardScaler
In [5]:
             features droped = features df.drop([i for i in range(10, 54)], axis=1)
             A = features droped[:5000]
             B = features droped[5000:20000]
In [6]:
             features droped
                     1
                                3
                                            5
                                                  6
                                                       7
                                                             8
            2596.0 51.0
                        3.0
                             258.0 0.0
                                        510.0
                                               221.0
                                                    232.0 148.0 6279.0
            2590.0 56.0
                        2.0
                             212.0
                                  -6.0
                                        390.0
                                               220.0 235.0 151.0 6225.0
         2
            2804.0 139.0 9.0
                             268.0 65.0
                                        3180.0 234.0
                                                    238.0 135.0 6121.0
            2785.0 155.0
                       18.0 242.0 118.0
                                        3090.0 238.0 238.0 122.0 6211.0
         5
            2595.0 45.0
                        2.0
                             153.0
                                  -1.0
                                        391.0
                                               220.0
                                                    234.0 150.0 6172.0
                                   ...
                                        ...
            2396.0 153.0 20.0 85.0
                                  17.0
                                        108.0
                                               240.0 237.0 118.0
                                                               837.0
         3
            2391.0 152.0 19.0 67.0
                                   12.0
                                        95.0
                                               240.0 237.0 119.0 845.0
         3
            2386.0 159.0
                       17.0
                             60.0
                                  7.0
                                        90.0
                                               236.0
                                                   241.0 130.0 854.0
            2384.0 170.0 15.0 60.0
                                   5.0
                                        90.0
                                               230.0 245.0 143.0 864.0
            2383.0 165.0 13.0 60.0
                                  4.0
                                        67.0
                                               231.0 244.0 141.0 875.0
        581012 rows × 10 columns
```

```
In [7]:
              scaler = StandardScaler()
              A = scaler.fit transform(A)
In [8]:
          1 A
          array([[ 1.46471134e-02, -9.52803948e-01, -1.55323806e+00, ...,
                  6.54715715e-01, 3.40156162e-01, 3.59472542e+00],
                 [-7.64411643e-04, -9.07228152e-01, -1.65963151e+00, ...,
                  7.74007980e-01, 3.99353563e-01, 3.55395870e+00],
                 [ 5.48913315e-01, -1.50669936e-01, -9.14877323e-01, ...,
                  8.93300245e-01, 8.36340887e-02, 3.47544503e+00],
                 [ 1.67138606e+00, -9.43688789e-01, 3.61844142e-01, ...,
                 -1.01537600e+00, -8.43791867e-01, 1.72549597e+00],
                 [ 9.98416130e-01, -1.16245261e+00, 7.87417964e-01, ...,
                 -1.49254506e+00, -5.87269794e-01, 1.55789947e+00],
                 [ 1.11400257e+00, -1.87130573e-01, -9.14877323e-01, ...,
                   8.13772068e-01, 4.41691545e-02, -1.97334160e-01]])
In [9]:
           1
              %%time
              tsne = TSNE(random state=17)
           3
              tsne representation = tsne.fit transform(A)
              plt.rcParams['figure.figsize'] = (10, 10)
          Wall time: 43 s
```



```
In [12]:
            plt.scatter(tsne_representation[:, 0], tsne_representation[:, 1],
         2
                         c=features_droped[:5000].index.map({ 1: 'red', 2: 'orange', 3: 'yell
          80
          60
          40
          20
           0
         -20
         -40
         -60
         -80
                 -75
                          -50
                                  -25
                                                     25
                                                                      75
                                                              50
                                                                               100
          Część 1 - KNN
In [13]:
             from sklearn.metrics import confusion matrix
             from sklearn.metrics import accuracy score
            from sklearn.neighbors import KNeighborsClassifier
             from memory_profiler import memory_usage,profile
```

```
in [14]:
              features df
                 0
                       1
                            2
                                               5
                                                           7
                                  3
                                                     6
                                                                 8
                                                                        9
                                                                          10
                                                                              11 12 13 14 15 16
                                                                                                      17
             2596.0 51.0
                          3.0
                               258.0 0.0
                                           510.0
                                                  221.0
                                                       232.0 148.0 6279.0 1.0
                                                                              0.0 0.0 0.0 0.0 0.0 0.0
                                                                                                       0.0 0.0 0.0
             2590.0 56.0
                          2.0
                               212.0 -6.0
                                           390.0
                                                  3180.0 234.0 238.0 135.0 6121.0 1.0 0.0 0.0 0.0 0.0 0.0 0.0
             2804.0 139.0 9.0
                               268.0 65.0
                                                                                                      0.0 0.0 0.0
             2785.0 155.0
                         18.0 242.0
                                    118.0
                                           3090.0 238.0
                                                       238.0 122.0 6211.0
                                                                          1.0 0.0 0.0 0.0 0.0 0.0
                                                                                                  0.0
             2595.0 45.0
                               153.0 -1.0
                                           391.0
                                                  220.0 234.0 150.0 6172.0 1.0 0.0 0.0 0.0 0.0 0.0
                          2.0
                                                                                                  0.0
                                                                                                      0.0 0.0 0.0
             2396.0 153.0 20.0 85.0
                                     17.0
                                           108.0
                                                  240.0 237.0 118.0 837.0
                                                                          0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 0.0 0.0
          3
             2391.0 152.0 19.0 67.0
                                     12.0
                                           95.0
                                                  240.0 237.0 119.0
                                                                   845.0
                                                                          0.0
                                                                               0.0 1.0
                                                                                      0.0 0.0 1.0
                                                                                                  0.0
                                                                                                      0.0 0.0 0.0
             2386.0 159.0 17.0 60.0
                                           90.0
                                                  236.0 241.0 130.0 854.0
                                     7.0
                                                                          0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 0.0 0.0
             2384.0 170.0 15.0 60.0
                                           90.0
                                                  230.0 245.0 143.0 864.0
                                                                          0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 0.0 0.0
                                     5.0
                                                                          0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 0.0 0.0
             2383.0 165.0 13.0 60.0
                                     4.0
                                           67.0
                                                  231.0 244.0 141.0 875.0
         581012 \text{ rows} \times 54 \text{ columns}
In [15]:
               features droped = features df.drop([i for i in range(10, 54)], axis=1)
           2
              A = features droped[:500] #train
           3
              B = features droped[500:1000] #test
               from sklearn import preprocessing
              min max scaler = preprocessing.MinMaxScaler()
In [16]:
           1
              В
                 0
                       1
                            2
                                  3
                                              5
                                                    6
                                                          7
                                                                8
             2617.0 15.0
                          14.0 30.0
                                     0.0
                                          1652.0
                                                 207.0 211.0
                                                             139.0
                                                                  1383.0
             2998.0 340.0 7.0
                               108.0
                                     16.0
                                         2978.0 205.0 230.0
          2
             2962.0
                   276.0 7.0
                               497.0
                                     47.0
                                          3610.0 201.0 242.0
                                                            179.0 5658.0
             2759.0
          2
                   160.0 12.0
                              120.0
                                     35.0
                                          2782.0 233.0 242.0
                                                            139.0 2462.0
          2
             2646.0 9.0
                          33.0
                               60.0
                                     9.0
                                          1771.0 165.0 156.0
                                                            112.0 1518.0
                                     ...
                                                 ...
             2982.0 10.0
                          18.0
                               30.0
                                     7.0
                                          4562.0 197.0 200.0 136.0 2538.0
             3032.0 339.0 14.0
                               95.0
                                     23.0 4710.0 189.0 219.0 169.0 518.0
             2896.0 72.0
                          16.0 319.0
                                    44.0
                                          3294.0 236.0 208.0
                                                            98.0
                                                                   2726.0
             2846.0 135.0
                         2.0
                               0.0
                                          3056.0 222.0 238.0
                                                            152.0 2349.0
                                     0.0
             2995.0 39.0
                          18.0 0.0
                                          4472.0 218.0 198.0
                                     0.0
                                                            109.0 2609.0
         500 rows × 10 columns
```

```
In [17]:
             %%time
             tsne = TSNE(random_state=17)
          3
             tsne_representation = tsne.fit_transform(B)
             plt.rcParams['figure.figsize'] = (10, 10)
         Wall time: 2.79 s
In [18]:
             plt.scatter(tsne_representation[:, 0], tsne_representation[:, 1]);
           15
           10
            5
            0
           -5
          -10
          -15
          -20
                       -20
                                -10
                                                    10
                                                             20
                                                                       30
                                                                                40
In [19]:
          1 B.index.unique()
          Int64Index([2, 1, 5], dtype='int64')
```

```
In [20]:
            plt.scatter(tsne_representation[:, 0], tsne_representation[:, 1],
         2
                         c=B.index.map({ 1: 'blue', 2: 'orange', 3: 'red', 4: 'green', 5: 'bl
          15
          10
           5
           0
          -5
         -10
         -15
         -20
                     -20
                              -10
                                        ò
                                                 10
                                                          20
                                                                   30
                                                                            40
            -30
In [ ]:
In [ ]:
In [21]:
            def predict(train, test, n):
         2
                 distances = [(train.columns[k], (np.linalg.norm(train.iloc[:,k] - test))) fo
         3
                 distances.sort(key=lambda tup: tup[1])
         4
                 neighbours = [distances[i][0] for i in range(n)]
         5
                 prediction = max(set(neighbours), key=neighbours.count)
         6
                 return(prediction)
```

```
[n [22]:
            def knn(train, test, n):
         2
                TrainIndexNames, TestIndexNames = train.index.values, test.index.values
         3
                A scaled = min max scaler.fit transform(train)
                B scaled = min max scaler.fit transform(test)
         4
                train df, test df = pd.DataFrame(data = A scaled, index = TrainIndexNames),
         5
                test_predict = [predict(train_df.T, test_df.T[k], n) for k in test_df.T.colu
         6
                return(test predict, TestIndexNames)
In [23]:
            %load ext memory profiler
In [ ]:
In [ ]:
In [24]:
            def knn descr():
                prediction, test labels = knn(A, B, 1) #n
         3
                print(prediction[:10])
                print(list(test labels[:10]))
         4
         5
                display(accuracy score(test labels, prediction, normalize=True))
         6
                display(confusion matrix(test labels, prediction))
In [25]:
            def knn descr scipy():
         2
                knn = KNeighborsClassifier(n_neighbors=1) #n
         3
                knn.fit(A, A.index.values)
                knn pred = knn.predict(B)
         5
                accuracy score (B.index.values, knn pred)
         6
                display(accuracy score(B.index.values, knn pred))
                display(confusion matrix(B.index.values, knn_pred))
         7
```

```
In [26]:
             %%time
             %memit knn_descr_scipy()
          0.402
          array([[ 43, 45, 0],
               [127, 158, 18],
                [ 64, 45, 0]], dtype=int64)
          0.402
          array([[ 43, 45, 0],
               [127, 158, 18],
                [ 64, 45, 0]], dtype=int64)
          0.402
          array([[ 43, 45, 0],
               [127, 158, 18],
                [ 64, 45, 0]], dtype=int64)
          peak memory: 727.54 MiB, increment: 0.14 MiB
          Wall time: 2.19 s
In [27]:
             %%time
          2 knn_descr()
          3 %memit knn_descr()
          [2, 1, 2, 2, 2, 2, 2, 2, 2, 2]
          [2, 2, 2, 2, 2, 2, 1, 2, 2]
          0.488
          array([[ 55, 33, 0],
                [102, 189, 12],
                [ 56, 53, 0]], dtype=int64)
          [2, 1, 2, 2, 2, 2, 2, 2, 2, 2]
          [2, 2, 2, 2, 2, 2, 1, 2, 2]
          0.488
          array([[ 55, 33, 0],
                [102, 189, 12],
                [ 56, 53, 0]], dtype=int64)
          peak memory: 727.73 MiB, increment: 0.00 MiB
          Wall time: 2min 7s
```

```
In [ ]:
            1
In [ ]:
            Część 1 - NM
In [28]:
               features df
                         1
                  0
                              2
                                     3
                                                  5
                                                         6
                                                               7
                                                                      8
                                                                             9 10
                                                                                    11 12 13
                                                                                                 14 15 16
                                                                                                              17
              2596.0 51.0
                            3.0
                                 258.0 0.0
                                              510.0
                                                     221.0
                                                            232.0
                                                                 148.0 6279.0
                                                                               1.0
                                                                                    0.0 0.0
                                                                                             0.0
                                                                                                  0.0 0.0
                                                                                                          0.0
                                                                                                               0.0
                                                                                                                   0.0 0.0
           5
              2590.0 56.0
                            2.0
                                 212.0
                                       -6.0
                                              390.0
                                                     220.0
                                                           235.0 151.0 6225.0 1.0
                                                                                    0.0 0.0
                                                                                             0.0
                                                                                                 0.0 0.0
                                                                                                          0.0
                                                                                                              0.0
                                                                                                                  0.0 0.0
              2804.0
                    139.0
                           9.0
                                 268.0
                                        65.0
                                              3180.0
                                                     234.0
                                                            238.0
                                                                 135.0 6121.0
                                                                               1.0
                                                                                    0.0 0.0
                                                                                             0.0
                                                                                                 0.0
                                                                                                     0.0
                                                                                                          0.0
                                                                                                               0.0
              2785.0 155.0
                            18.0 242.0
                                        118.0
                                              3090.0
                                                     238.0
                                                            238.0 122.0
                                                                        6211.0
                                                                                    0.0 0.0
                                                                                                  0.0
                                                                                                      0.0
                                                                                1.0
                                                                                             0.0
                                                                                                                   0.0 0.0
           5
              2595.0 45.0
                            2.0
                                 153.0
                                       -1.0
                                              391.0
                                                      220.0 234.0 150.0 6172.0 1.0
                                                                                    0.0 0.0 0.0 0.0 0.0
                                                                                                              0.0 0.0 0.0
                                                                                                          0.0
           3
              2396.0 153.0
                           20.0
                                 85.0
                                        17.0
                                              108.0
                                                      240.0
                                                           237.0 118.0
                                                                         837.0
                                                                                0.0
                                                                                    0.0 1.0
                                                                                             0.0
                                                                                                 0.0 1.0
                                                                                                          0.0
                                                                                                               0.0 0.0 0.0
              2391.0 152.0
                           19.0
                                 67.0
                                        12.0
                                              95.0
                                                      240.0 237.0
                                                                 119.0
                                                                         845.0
                                                                                    0.0
                                                                                             0.0
                                                                                                 0.0
                                                                                0.0
                                                                                         1.0
                                                                                                      1.0
                                                           241.0
           3
              2386.0 159.0
                           17.0
                                 60.0
                                        7.0
                                              90.0
                                                                 130.0
                                                                        854.0
                                                                                0.0
                                                                                    0.0
                                                                                                 0.0
                                                                                                          0.0
                                                                                                               0.0 0.0 0.0
                                                      236.0
                                                                                        1.0
                                                                                             0.0
                                                                                                      1.0
              2384.0 170.0 15.0 60.0
                                        5.0
                                              90.0
                                                      230.0 245.0 143.0 864.0
                                                                                0.0
                                                                                    0.0 1.0 0.0 0.0 1.0
                                                                                                          0.0
                                                                                                              0.0 0.0 0.0
                                                                                0.0 0.0 1.0 0.0 0.0 1.0 0.0 0.0 0.0 0.0
              2383.0 165.0 13.0 60.0
                                        4.0
                                              67.0
                                                      231.0 244.0 141.0 875.0
          581012 \text{ rows} \times 54 \text{ columns}
In [29]:
                A = features droped[:500]
            2
               B = features droped[500:1000] #test
In [30]:
            1
               Α
                  0
                         1
                              2
                                     3
                                                  5
                                                         6
                                                               7
                                                                      8
                                                                             9
                                                     221.0 232.0 148.0 6279.0
              2596.0 51.0
                                              510.0
           5
                            3.0
                                 258.0 0.0
              2590.0 56.0
                            2.0
                                 212.0 -6.0
                                              390.0
                                                     220.0 235.0 151.0 6225.0
           2
              2804.0
                    139.0
                           9.0
                                 268.0 65.0
                                              3180.0
                                                     234.0
                                                            238.0
                                                                 135.0
              2785.0 155.0
                           18.0
                                 242.0 118.0
                                              3090.0
                                                     238.0
                                                            238.0 122.0 6211.0
           5
              2595.0 45.0
                            2.0
                                 153.0 -1.0
                                              391.0
                                                     220.0 234.0 150.0 6172.0
              2909.0 72.0
                            5.0
                                 324.0 5.0
                                              4554.0 226.0 230.0 138.0 5006.0
              2909.0 0.0
                            3.0
                                 350.0 5.0
                                              4582.0 215.0
                                                           233.0 156.0 4985.0
           2
              2900.0 180.0 3.0
                                 300.0 -2.0
                                              4725.0 220.0
                                                           241.0 156.0 4880.0
              2867.0 143.0
                           12.0 437.0 114.0
                                             3363.0 237.0
                                                           237.0
                                                                 129.0
                                              5664.0 204.0 222.0 156.0 3811.0
              3047.0 356.0 10.0 618.0 75.0
          500 rows × 10 columns
```

```
[n [31]:
    1 pd.DataFrame(data = features df.index.to series(), index = target)
    5
   5
   5 5
   2
    2
   2 2
   5
    5
   3
    3
   3
    3
   3 3
   3 3
   581012 \text{ rows} \times 1 \text{ columns}
In [104]
     df_1 = features_df.loc[1,:]
    2
     df 1
                5
                   6
                     7
                       8
                          9 10 11 12 13 14 15 16 17 18 19
    2699.0 347.0 3.0 0.0 0.0
               2696.0 72.0
           30.0 0.0
               2.0
    13.0 90.0 6.0
               2919.0 13.0
       ...
             ...
                 ...
                    ...
                      ...
                        ...
                           ...
                              ...
    2826.0 72.0
         2820.0 69.0
         2925.0 234.0 206.0 99.0
                        2812.0 67.0
         16.0 30.0 0.0
         2832.0 45.0
    2827.0 43.0
         211840 rows × 54 columns
```

```
[n [32]:
            def NM():
         2
                df 1 = features df.loc[1,:]
         3
                df 2 = features df.loc[2,:]
                df 3 = features df.loc[3,:]
         4
                df 4 = features df.loc[4,:]
         5
         6
                df 5 = features df.loc[5,:]
         7
                df 6 = features df.loc[6,:]
         8
                df 7 = features df.loc[7,:]
         9
                df 1 mean = df 1.mean(axis=0)
        10
        11
                df 2 mean = df 2.mean(axis=0)
                df 3 mean = df 3.mean(axis=0)
        12
                df 4 mean = df 4.mean(axis=0)
        13
                df 5 mean = df 5.mean(axis=0)
        14
                df 6 mean = df 6.mean(axis=0)
        15
                df 7 mean = df 7.mean(axis=0)
        16
        17
                frames = [df 1 mean, df 2 mean, df 3 mean, df 4 mean, df 5 mean, df 6 mean, df 7 m
        18
                meansy = pd.concat(frames, axis=1, join='outer', ignore index=False)
        19
                meansy = meansy.transpose()
        20
        21
        22
        23
                meansy dropped = meansy.iloc[:,[0,1,2,3,4,5,6,7,8,9]] #bo 10 cech ma A,B
        24
                distanceNM = scipy.spatial.distance.cdist(meansy dropped, B, metric='euclide
        25
                Dist df = pd.DataFrame(data = distanceNM)
                dist df min = pd.DataFrame(data = Dist df.idxmin(axis=0, skipna=True))
        26
        27
                dist z bledem = dist df min.values
                dist = ( dist z bledem +1)
        28
                Truth = pd.DataFrame(data = B.index.to series())
        29
                display(accuracy score(Truth.values, dist, normalize=True))
        31
                display(confusion matrix(Truth.values, dist))
In [33]:
            NM()
         0.152
         array([[ 4, 19, 1, 7,
                               1, 56],
              [ 26, 58, 16, 53, 25, 125],
              [ 0,
                    0,
                        0,
                            Ο,
                                 Ο,
                                    0],
              [ 2, 33,
                        0, 14,
                                0, 60],
              [ 0,
                   0,
                        0, 0,
                                0,
                                    0],
              [ 0,
                   Ο,
                        0, 0,
                                0, 0]], dtype=int64)
```

```
In [34]:
            %%time
         2
            NM()
         3 %memit NM()
         0.152
         array([[ 4, 19, 1, 7, 1, 56],
              [ 26, 58, 16, 53, 25, 125],
              [ 0, 0, 0, 0, 0, 0],
              [ 2, 33, 0, 14, 0, 60],
              [ 0, 0, 0, 0, 0, 0],
               [ 0, 0, 0, 0, 0, 0]], dtype=int64)
         0.152
         array([[ 4, 19, 1, 7, 1, 56],
              [ 26, 58, 16, 53, 25, 125],
               [ 0, 0, 0, 0, 0, 0],
               [ 2, 33, 0, 14, 0, 60],
               [ 0, 0, 0, 0, 0, 0],
               [ 0, 0, 0, 0, 0, 0]], dtype=int64)
         peak memory: 980.29 MiB, increment: 243.17 MiB
         Wall time: 1.56 s
In [35]:
            %%time
            %memit knn descr()
         [2, 1, 2, 2, 2, 2, 2, 2, 2, 2]
         [2, 2, 2, 2, 2, 2, 1, 2, 2]
         0.488
         array([[ 55, 33, 0],
              [102, 189, 12],
               [ 56, 53, 0]], dtype=int64)
         peak memory: 737.12 MiB, increment: 0.00 MiB
         Wall time: 1min 5s
In [ ]:
```

```
In [36]:
             %%time
             %memit knn_descr_scipy()
          0.402
          array([[ 43, 45, 0],
               [127, 158, 18],
               [ 64, 45, 0]], dtype=int64)
          0.402
          array([[ 43, 45, 0],
              [127, 158, 18],
               [ 64, 45, 0]], dtype=int64)
          0.402
          array([[ 43, 45, 0],
               [127, 158, 18],
                [ 64, 45, 0]], dtype=int64)
         peak memory: 737.12 MiB, increment: 0.00 MiB
         Wall time: 1.92 s
```

Część 1 - Podsumowanie

Algorytmy scipy są zdecydowanie szybsze(2s vs minuta), jednak dla grup testowych, algorytm własny wydaje się bardziej dokładny. Algo zdecydowniae szybszy, na poziomie scipy KNN, jednak jego precyz bardzo nikła oraz posiada on najwyższe zużycie pamięci

In []:

Część 2

```
n [38]:
           import matplotlib.pyplot as plt
           import numpy as np
        3
           import csv
        4
        5
           # function for reading the images
        6
           # arguments: path to the traffic sign data, for example './GTSRB/Training'
        7
           # returns: list of images, list of corresponding labels
        8
           def readTrafficSigns(rootpath):
        9
               "''Reads traffic sign data for German Traffic Sign Recognition Benchmark.
       10
       11
               Arguments: path to the traffic sign data, for example './GTSRB/Training'
               Returns: list of images, list of corresponding labels'''
       12
               images = [] # images
       13
               labels = [] # corresponding labels
       14
               # loop over all 42 classes
       15
               for c in range (0,43):
       16
       17
                   prefix = rootpath + '/' + format(c, '05d') + '/' # subdirectory for clas
                   qtFile = open(prefix + 'GT-'+ format(c, '05d') + '.csv') # annotations f
       18
                   gtReader = csv.reader(gtFile, delimiter=';') # csv parser for annotation
       19
                   next(gtReader) # skip header !!!!!!!!!!!!!!!!!!!!!!!!!!!!!! XALEŻY KONIECZKIE Z
       20
                   # loop over all images in current annotations file
       21
       22
                   for row in gtReader:
        23
                       x1, y1, x2, y2 = map(int, row[3:7])
                       images.append(np.array(plt.imread(prefix + row[0]))[y1:y2,x1:x2]) #
        24
        25
                       labels.append(int(row[7])) # the 8th column is the label# TU ZMIENIĆ
       26
                   gtFile.close()
       27
               return np.array(images), np.array(labels)# I TU JESZCZE TROCHĘ
In [39]:
           path = r"C:\Users\sticz\Desktop\Magisterka sezon drugi\Podstawy Uczenia Maszynow
           images, labels = readTrafficSigns(path)
In [40]:
           class names=["zakazu", "ostrzegawcze", "informacyjne", "nakazu"]
           labels groups = np.array([sign groups[cls] for cls in labels])
```

```
In [119]
             lg = pd.DataFrame(data =labels_groups)
          2 lg
               0
         0
         1
               0
         2
               0
         3
               0
         4
               0
         39204 0
         39205 0
         39206 0
         39207 0
         39208 0
        39209 rows × 1 columns
```

```
In [41]:
            plt.figure()
            plt.imshow(images[100])
            plt.show()
          0
          5
         10
         15
         20
                                       10
                                                    15
                                                                  20
In [42]:
             img=images[100]
             features = np.array([np.sum(img[:,:,0]), np.sum(img[:,:,1]), np.sum(img[:,:,2])])
         3
             features=features/np.sum(features)
            features
         array([0.41163983, 0.30225772, 0.28610245])
In [43]:
             from sklearn.mode
                                  1 lection import train_test_split
             training_set, tes
                                  2 t, training_labels, test_labels = train_test_split(images,
In [44]:
            def convertToRelativeRGB(arr):
         2
                 result = [np.array([np.sum(img[:,:,0]),np.sum(img[:,:,1]),np.sum(img[:,:,2])
         3
                 result = result/np.sum(result,axis=1)[:,None]
         4
                 return result
```

```
In [45]:
             image features = convertToRelativeRGB(images)
             training vec = convertToRelativeRGB(training set)
             test vec = convertToRelativeRGB(test set)
In [46]:
             print(np.shape(training vec))
          2 print(np.shape(test vec))
          (31367, 3)
          (7842, 3)
In [125]
              training df = pd.DataFrame(data = training_vec,index = training_labels)
In [126]
             training df[3] = training df[0] / (training df[1])
          2
             training df[4] = training df[1] / (training df[2])
In [127]
             training df
                  0
                          1
                                  2
                                           3
                                                   4
         5 0.381992 0.307066 0.310942 1.244005 0.987536
         25  0.377253  0.320273  0.302474  1.177913  1.058841
         35  0.261371  0.318120  0.420509  0.821610  0.756514
         13  0.334737  0.316305  0.348958  1.058275  0.906427
         15  0.377899  0.315657  0.306444  1.197181  1.030065
                     ...
                                     ...
                             ...
         42 0.293942 0.311669 0.394390 0.943122 0.790256
         18  0.390866  0.308146  0.300988  1.268442  1.023784
         7 0.335223 0.304185 0.360593 1.102037 0.843568
         1 0.347016 0.304401 0.348583 1.139997 0.873251
         3 0.318040 0.304606 0.377354 1.044105 0.807215
         31367 rows × 5 columns
In [122]
             test df = pd.DataFrame(data = test vec, index = test labels)
In [123]
             test df[3] = test df[0] / (test df[1])
             test df[4] = test df[1] / (test df[2])
In [170]
              image features df = pd.DataFrame(data = image features, index = labels)
In [171]
              image features df[3] = image features df[0] / (image features df[1])
              image features df[4] = image features df[1] / (image features <math>df[2])
```

```
n [172]
            image features df
                                2
            0.388223  0.299714  0.312063  1.295310  0.960430
         0 0.384023 0.302212 0.313765 1.270710 0.963178
         0 0.381788 0.300540 0.317672 1.270343 0.946068
          42 0.287313 0.321295 0.391392 0.894235 0.820902
         42 0.287875 0.320836 0.391289 0.897264 0.819947
         42 0.287277 0.320460 0.392263 0.896451 0.816952
         42 0.287722 0.320912 0.391366 0.896578 0.819978
        42 0.284333 0.321476 0.394191 0.884462 0.815533
        39209 rows \times 5 columns
In [128]
            def knn descr():
         2
                 prediction, test labels = knn(training df, test df, 1) #n
          3
                 print(prediction[:10])
                 print(list(test labels[:10]))
          4
                 display(accuracy score(test labels, prediction, normalize=True))
                 display(confusion matrix(test_labels, prediction))
          6
In [139]
         1
             def knn descr scipy():
         2
                 knn = KNeighborsClassifier(n neighbors=1) #n
         3
                 knn.fit(training_df, training_labels)
          4
                 knn_pred = knn.predict(test_df)
         5
                 accuracy_score(test_labels, knn_pred)
          6
                 display(accuracy_score(test_labels, knn_pred))
                 display(confusion matrix(test labels, knn pred))
In [140]
         1
            %%time
            %memit knn descr scipy()
         0.19867380770211682
         array([[ 2, 4, 3, ..., 0, 0, 0],
              [ 5, 72, 39, ..., 0, 1, 0],
               [ 2, 34, 73, ..., 0, 1, 0],
               [ 0, 1, 0, ..., 17, 0, 1],
               [ 0, 1, 0, ..., 0, 11, 0],
               [ 0, 1, 0, ..., 0, 0, 11]], dtype=int64)
         peak memory: 1215.25 MiB, increment: 1.20 MiB
         Wall time: 1 s
```

```
In [97]:
            #%%time
            #%memit knn descr()
In [ ]:
In [185]
         1
            def NM():
         2
                meansy = []
         3
                for i in range (0,42):
                    df x = image features df.loc[i,:]
         4
                    df x mean = df x.mean(axis=0)
         5
                    meansy.append(df x mean)
         6
         7
                    meansy df = pd.DataFrame(data=meansy)
         8
         9
                 #meansy = meansy.transpose()
        10
        11
        12
                 \#meansy dropped = meansy df.iloc[:,[0,1,2,3,4]] \#bo 5 cech ma
        13
                distanceNM = scipy.spatial.distance.cdist(meansy df, test df, metric='euclid
        14
        15
                Dist df = pd.DataFrame(data = distanceNM)
                dist df min = pd.DataFrame(data = Dist df.idxmin(axis=0, skipna=True))
        16
                dist z bledem = dist df min.values
        17
        18
                dist = (dist z bledem +1)
        19
                display(accuracy score(test labels, dist, normalize=True))
        20
                display(confusion matrix(test labels, dist))
In [180]
In [ ]:
In [ ]:
```

```
In [186]
             %%time
          2
             NM()
          3 %memit NM()
         0.04106095383830655
         array([[ 0, 0, 0, ..., 0, 0, 0],
               [ 0, 9, 2, ..., 0, 7, 3],
               [ 0, 14, 1, ..., 0, 0, 3],
               [ 0, 0, 0, ..., 18, 14, 0],
               [ 0, 0, 0, ..., 0, 3, 8],
                [ 0, 0, 0, ..., 0, 15, 2]], dtype=int64)
         0.04106095383830655
         array([[ 0, 0, 0, ..., 0, 0],
               [0, 9, 2, \ldots, 0, 7, 3],
               [ 0, 14, 1, ..., 0, 0, 3],
               . . . ,
               [ 0, 0, 0, ..., 18, 14, 0],
               [ 0, 0, 0, ..., 0, 3, 8],
               [ 0, 0, 0, ..., 0, 15, 2]], dtype=int64)
         0.04106095383830655
         array([[ 0, 0, 0, ..., 0, 0, 0],
               [ 0, 9, 2, ..., 0, 7, 3],
               [ 0, 14, 1, ..., 0, 0, 3],
               [ 0, 0, 0, ..., 18, 14, 0],
               [ 0, 0, 0, ..., 0, 3, 8],
                [ 0, 0, 0, ..., 0, 15, 2]], dtype=int64)
         peak memory: 1271.50 MiB, increment: 2.52 MiB
         Wall time: 1.91 s
In [187]
             %%time
             tsne = TSNE(random state=17)
          3 tsne representation = tsne.fit transform(test df, train df)
             plt.rcParams['figure.figsize'] = (10, 10)
         Wall time: 1min 21s
```

