SVC EEG

August 9, 2022

1 Support Vector Machine: EEG of pediatric subjects with epilepsy

Support Vector Machine or SVM is a type of algorithms that establish continious functions that create a surface in the space of the input data and optimize the classification of labeled data. In order to do this several hyperparameters are needed. We must define what type of function will be optimized(e.g. polinomial), the starting coefficients and the weights of each class.

The advantages of support vector machines are:

- Effective in high dimensional spaces.
- Still effective in cases where number of dimensions is greater than the number of samples.
- Uses a subset of training points in the decision function (called support vectors), so it is also memory efficient.
- Versatile: different Kernel functions can be specified for the decision function. Common kernels are provided, but it is also possible to specify custom kernels.

The disadvantages of support vector machines include: * If the number of features is much greater than the number of samples, avoid over-fitting in choosing Kernel functions and regularization term is crucial. * SVMs do not directly provide probability estimates, these are calculated using an expensive five-fold cross-validation (see Scores and probabilities).

1.0.1 Importing the packagery:

```
[1]: from seaborn import load_dataset, pairplot, heatmap import pandas as pd import numpy as np import matplotlib.pyplot as plt from matplotlib.colors import ListedColormap from sklearn.model_selection import train_test_split from sklearn.preprocessing import StandardScaler from sklearn.datasets import make_moons, make_circles, make_classification from sklearn.neural_network import MLPClassifier from sklearn.neighbors import KNeighborsClassifier from sklearn.svm import SVC from sklearn.gaussian_process import GaussianProcessClassifier from sklearn.gaussian_process.kernels import RBF from sklearn.tree import DecisionTreeClassifier from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
```

```
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

1.0.2 Imprting the data:

```
[2]: data=pd.read_csv("Data_medians_4.csv")
[3]: del data['Unnamed: 0']
     del data['38']
[4]: for i in range(0,len(data)):
         if data.iloc[i,-1]!='Awake':
             if data.iloc[i,-1]!='N1':
                  if data.iloc[i,-1]!='N2':
                      if data.iloc[i,-1]!='N3':
                          if data.iloc[i,-1]!='REM':
                              data.iloc[i,-1]=np.nan
     data_2=data.dropna()
[6]:
     data_2
[6]:
                  0
     0
          19.911429
                     21.826667
                                 19.901111
                                             19.076667
                                                        21.918889
                                                                    14.850000
     1
          40.660000
                      35.816667
                                 38.405556
                                             42.591111
                                                        40.958889
                                                                    37.191667
     2
          28.203333
                     24.951111
                                 25.603333
                                             33.302222
                                                        28.286667
                                                                    24.416667
     3
          18.286190
                      16.575556
                                 17.173333
                                             22.212222
                                                        18.586667
                                                                    15.928333
     4
          11.339524
                      10.327778
                                 11.073333
                                              9.653333
                                                        12.070000
                                                                    10.046667
     160
         23.572857
                      21.060000
                                 22.835556
                                             24.652222
                                                        19.970000
                                                                    18.556667
     161
          18.736190
                      16.664444
                                 17.992222
                                             19.476667
                                                        16.011111
                                                                    14.800000
     162
          14.926190
                     13.685556
                                 14.278889
                                             15.434444
                                                        12.957778
                                                                    11.726667
     163
         10.816190
                       9.702222
                                 10.213333
                                             10.985556
                                                         9.072222
                                                                     8.145000
     164
           4.886190
                       4.464444
                                  4.621111
                                              4.972222
                                                         4.191111
                                                                     3.780000
                                7
                    6
                                             8
                                                         9
                                                                        29
     0
                        60.644444
                                                                210.934721
           58.638571
                                    61.956667
                                                 57.580000
     1
          148.707143
                       114.740000
                                   116.255556
                                                180.642222
                                                                601.949326
                                                                395.701329
     2
          104.157619
                        78.117778
                                                141.416667
                                    77.450000
     3
           72.619048
                        55.015556
                                    55.386667
                                                 98.113333
                                                                258.530174
     4
           42.745238
                        33.640000
                                    34.700000
                                                 37.300000
                                                                156.242749
     160
           62.023810
                                                                233.876713
                        55.311111
                                    62.484444
                                                 65.027778
     161
           47.885238
                        42.373333
                                    47.960000
                                                 49.993333
                                                                179.285611
     162
           37.418571
                        33.524444
                                    37.350000
                                                 38.766667
                                                                137.755238
```

```
163
      27.838095
                  24.458889
                               27.936667
                                            28.534444 ...
                                                           99.599288
164
      12.803333
                   12.212222
                                            14.298889
                                                           41.261791
                               13.241111
              30
                            31
                                         32
                                                       33
                                                                     34
0
      627.235043
                   648.175431
                                 626.022091
                                               643.377231
                                                            540.470154
1
     2122.510839
                  1710.063114
                               1684.448166
                                              3062.885569
                                                           2100.222584
2
     1433.984345
                  1147.643210
                                1131.199674
                                              2268.983257
                                                           1375.903119
3
      951.861362
                   774.702891
                                 776.389821
                                              1493.072896
                                                            943.001124
4
      587.817203
                   465.337699
                                 467.104798
                                               546.078070
                                                            612.918988
. .
160
      956.606279
                   901.840306
                                1079.626406
                                              1000.445620
                                                            627.724242
161
      731.916047
                   694.028468
                                               759.237127
                                                            474.306587
                                 835.901439
162
      558.178258
                   505.701924
                                 648.375509
                                               566.989604
                                                            363.330987
163
      449.385031
                   411.347601
                                 560.246779
                                               459.417619
                                                            270.892424
164
      165.142991
                   188.748088
                                 225.965814
                                               206.167366
                                                            122.058242
                                       37
                                               39
              35
                             36
0
      495.039453
                  4.422272e+07
                                 0.001152
                                           Awake
1
     1750.616297
                  2.508360e+06
                                 0.002201
                                               N2
2
                                              R.E.M
     1170.567469
                  1.469640e+06
                                 0.001673
3
      787.208156
                  5.040967e+06
                                 0.002785
                                               N2
      465.555425
4
                  9.224363e+06
                                 0.001658
                                               ΝЗ
160
      663.898963
                  1.033058e+05
                                 0.000996
                                              REM
161
      509.926345
                  3.701008e+04
                                 0.000528
                                               N1
162
      390.608436
                  9.521701e+04
                                 0.000363
                                               N2
163
      296.452757
                  6.754039e+06
                                 0.000063
                                               ΝЗ
164
      109.744217
                  2.577399e+06 0.000092
                                               N2
```

[157 rows x 39 columns]

1.0.3 Splitting the data

```
[7]: X=data_2.iloc[:,:-1]
Y=data_2.iloc[:,-1]
```

1.1 Meaning of each hyperparameter:

Warning: DO NOT RUN THE NEXT LINE OF CODE

```
[9]: # The SVC Class from Sklearn
SVC(C=1.0,  # The regularization parameter
    kernel='rbf',  # The kernel type used
    degree=3,  # Degree of polynomial function
```

```
gamma='scale',
                                # The kernel coefficient
                                # If kernel = 'poly'/'sigmoid'
coef0=0.0,
shrinking=True,
                                # To use shrinking heuristic
                                # Enable probability estimates
probability=False,
tol=0.001,
                               # Stopping crierion
                               # Size of kernel cache
cache_size=200,
class_weight=None,
                               # The weight of each class
                                # Enable verbose output
verbose=False,
                                # Hard limit on iterations
max iter=- 1,
decision_function_shape='ovr', # One-vs-rest or one-vs-one
                                # How to handle breaking ties
break ties=False,
random_state=None
                                # Random state of the model
```

[9]: SVC()

1.2 Defining the model

1.2.1 Wheights:

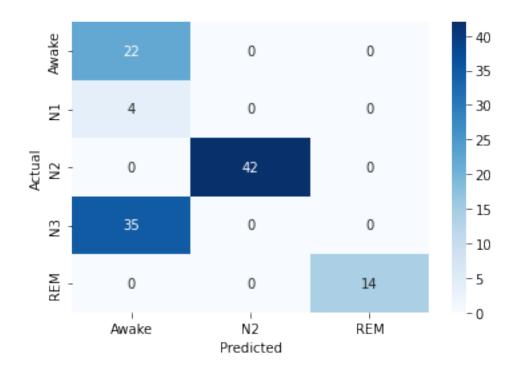
We expect the algorithm to have difficulties to distinguish bewteen N2 and N3 segments due to the epileptic "noise". To avoid an overfitting of the data, we will lower the weight of this two classes.

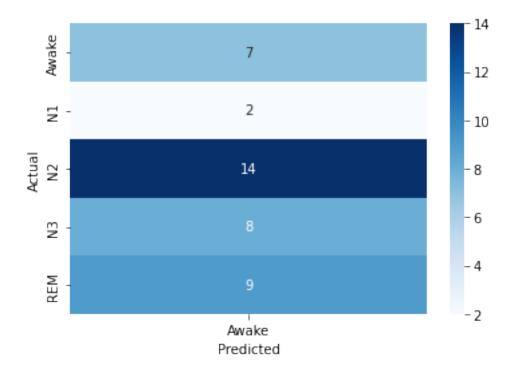
```
[103]: weights = {
    "Awake": 1,
    "N1": 0.5,
    "N2": 0.5,
    "N3": 0.5,
    "REM": 1
}
```

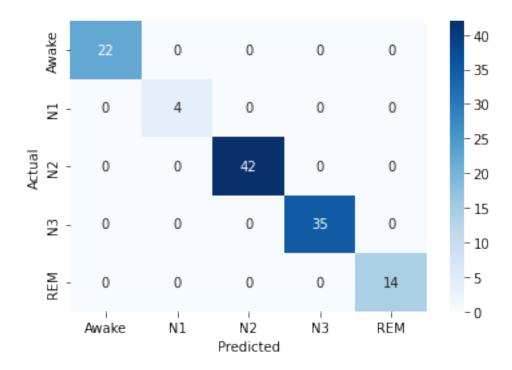
1.2.2 kernel and degree:

plt.show()

We will use a polynomial kernel of 3rd degree

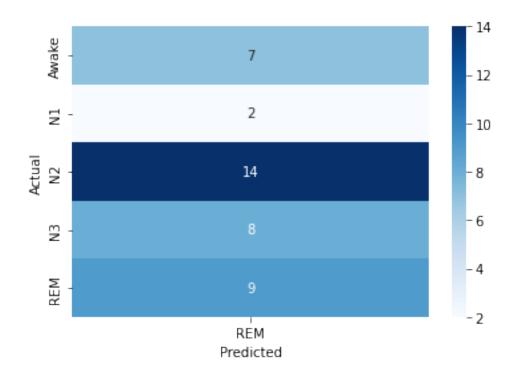






```
[75]: predictions_3 = gauss.predict(X_test)
    print(predictions_3)

['REM' 'REM' 'R
```



[]: