SVC EEG

August 23, 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 coeficients 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
```

```python
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]:
```python
data=pd.read_csv("Data_medians_4.csv")
```

[3]:
```python
del data['Unnamed: 0']
del data['38']
```

[4]:
```python
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
```

[5]:
```python
data_2=data.dropna()
```

[6]:
```python
data_2
```

[6]:
```
             0          1          2          3          4          5  \
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

              6           7           8           9  …          29  \
0     58.638571   60.644444   61.956667   57.580000  …  210.934721
1    148.707143  114.740000  116.255556  180.642222  …  601.949326
2    104.157619   78.117778   77.450000  141.416667  …  395.701329
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   55.311111   62.484444   65.027778  …  233.876713
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    13.241111    14.298889  …    41.261791

                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   835.901439   759.237127   474.306587
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

                35            36        37     39
0       495.039453  4.422272e+07  0.001152  Awake
1      1750.616297  2.508360e+06  0.002201     N2
2      1170.567469  1.469640e+06  0.001673    REM
3       787.208156  5.040967e+06  0.002785     N2
4       465.555425  9.224363e+06  0.001658     N3
..             …            …        …     …
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     N3
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]
```

[8]:
```
X_train, X_test, y_train, y_test = train_test_split(X, Y, train_size=0.75,␣
 ↪random_state=100)
```

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
    coef0=0.0,                        # If kernel = 'poly'/'sigmoid'
    shrinking=True,                   # To use shrinking heuristic
    probability=False,                # Enable probability estimates
    tol=0.001,                        # Stopping crierion
    cache_size=200,                   # Size of kernel cache
    class_weight=None,                # The weight of each class
    verbose=False,                    # Enable verbose output
    max_iter=- 1,                     # Hard limit on iterations
    decision_function_shape='ovr',    # One-vs-rest or one-vs-one
    break_ties=False,                 # How to handle breaking ties
    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.

[9]:
```
weights = {
  "Awake": 1,
  "N1": 0.5,
  "N2": 0.5,
  "N3": 0.5,
  "REM": 1
}
```

1.2.2 kernel and degree:

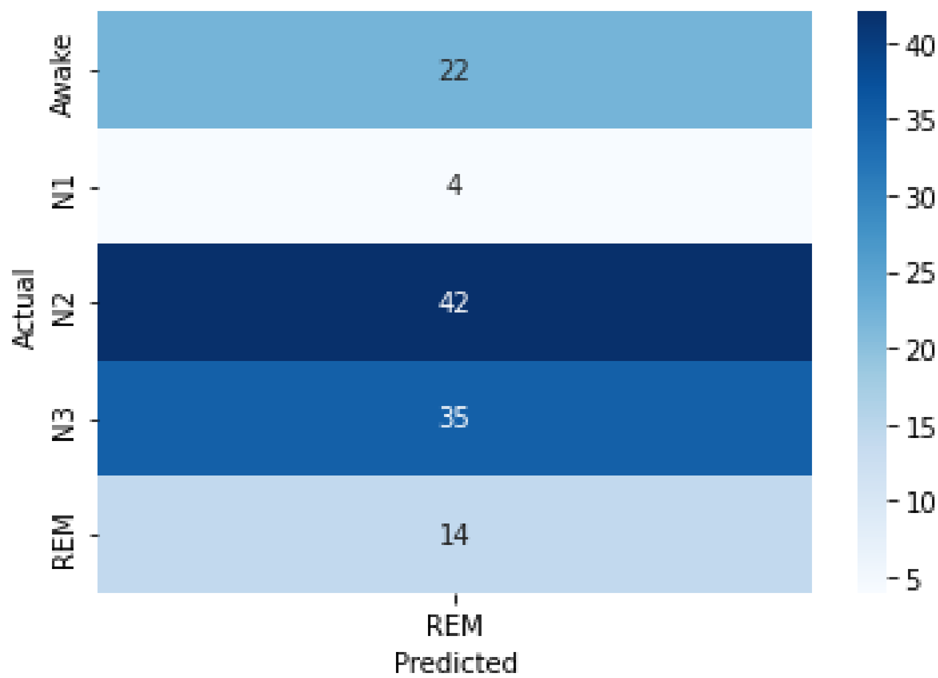
We will use a polynomial kernel of 3rd degree

[ ]:
```
clf = SVC(kernel='poly', degree=5, gamma='auto', C=1.0,class_weight=weights)
clf.fit(X_train, y_train)
```

[11]:
```
predictions_2 = clf.predict(X_train)
```

[12]:
```
confusion_matrix = pd.crosstab(y_train, predictions_2, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

heatmap(confusion_matrix, annot=True, cmap="Blues")
plt.show()
```

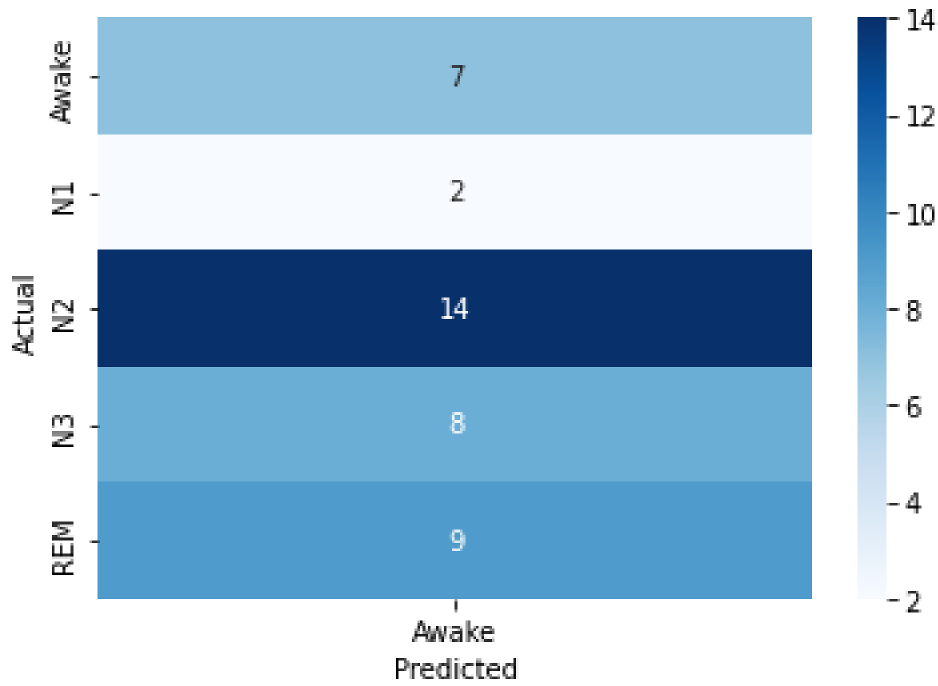


[111]:
```
predictions = clf.predict(X_test)
print(predictions)
```

```
['Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake'
 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake'
 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake'
 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake' 'Awake'
 'Awake' 'Awake' 'Awake' 'Awake']
```

[112]:
```
confusion_matrix = pd.crosstab(y_test, predictions, rownames=['Actual'],
 ↪colnames=['Predicted'])

heatmap(confusion_matrix, annot=True, cmap="Blues")
plt.show()
```



[65]:
```
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
```

[66]:
```
gauss=GaussianProcessClassifier(1.0 * RBF(1.0),random_state=0)
```

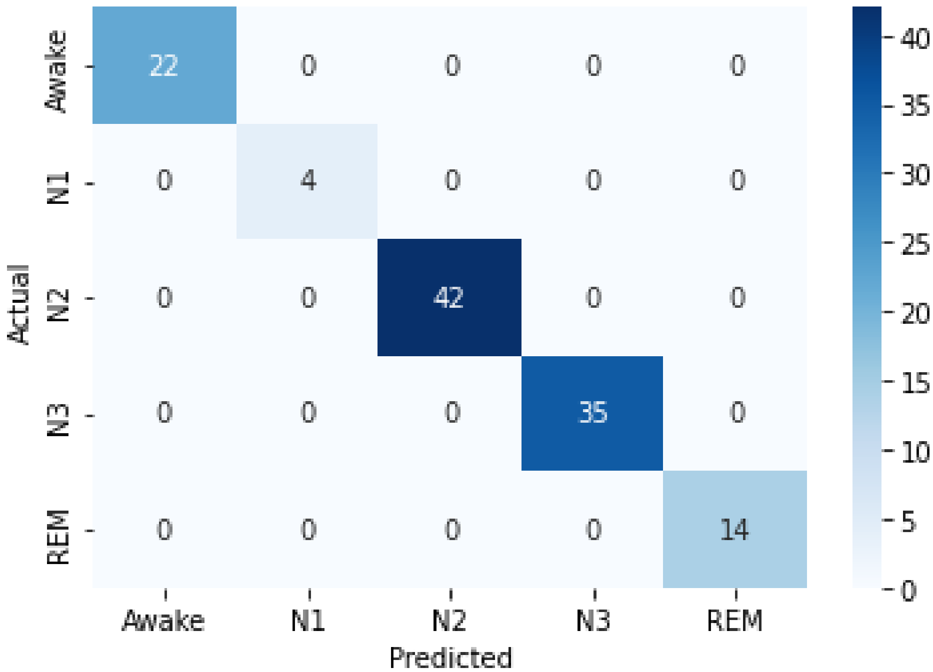
[67]:
```
gauss.fit(X_train, y_train)
```

[67]:
```
GaussianProcessClassifier(kernel=1**2 * RBF(length_scale=1), random_state=0)
```

[70]:
```
predictions_4 = gauss.predict(X_train)
```

[74]:
```
confusion_matrix = pd.crosstab(y_train, predictions_4, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

heatmap(confusion_matrix, annot=True, cmap="Blues")
plt.show()
```

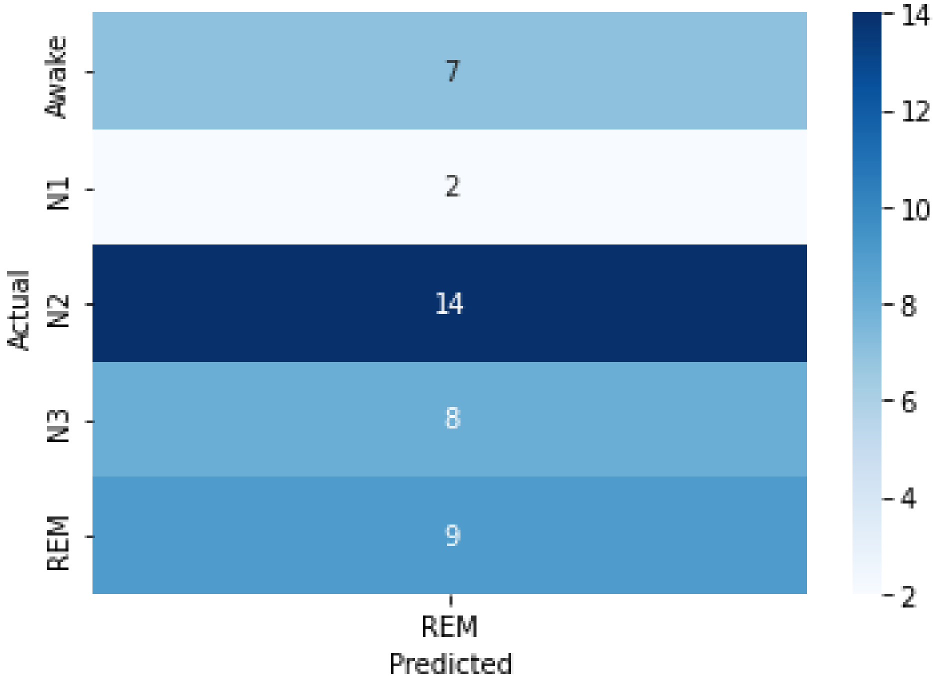


[75]:
```
predictions_3 = gauss.predict(X_test)
print(predictions_3)
```

```
['REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM'
 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM'
 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM' 'REM'
 'REM' 'REM' 'REM' 'REM']
```

[76]:
```
confusion_matrix = pd.crosstab(y_test, predictions_3, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

heatmap(confusion_matrix, annot=True, cmap="Blues")
plt.show()
```



Observations:

- Note that the training set has a 100% accuracy, however the test set lets us know that all the data is being classified as REM. This means that the input data is biased and the algorithm tends to overfit the training set.
- To avoid this we must use a simpler algorithm

```
[ ]:
```