Machine_learining_EEG

September 5, 2022

0.1 Machine learning with the extracted EEG parameters

0.1.1 Importing the packagery:

[1]:
```
#Python3.7
#Numpy version:
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn.cluster import KMeans, SpectralClustering
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_samples, silhouette_score

%matplotlib inline
```

Now we will try different combinations of parameters and evaluate the accuracy of a cluster based analysis. Lets remember that we have two main types of parameters: the ones extracted from the bipolar derivations and the ones extracted from the original chanels.

0.2 Standard deviation_ vertical_bipolar

This first derivation contain the standard deviation of the vertical bipolar chains obtained from the double banana. Each row of the CSV data represents a segment of the recording. The lenght of each segment depends on the duration of the sleep stage. Each segment is then subdivided into sub-segments of 10 seconds.

Then a PSD plot is obtained from each sub-segment and divided into 5 frequency bands: Delta waves(0.2-4 Hz), theta waves(4-8 Hz), alpha(8-12 Hz), beta(12-30 Hz) and gamma(30-90 Hz).

Finaly a standard deviation of the relative power of a frequency band is calculated. The standard deviations that correspond to a same segment and a same shain are averaged and recorded. This means that for a single segment we have 7 chains, each with 5 bands. This results in an array of 35 dependent variables. The last variable in the array is the independent variable: the sleep stage.

Importing the data

[3]:
```
data=pd.read_csv("Extracted_data/Data_medians_vert_STD.csv")
```

Adapting the data

[4]:
```
del data['Unnamed: 0']
```

[5]:
```
# 0: Awake
# 1: N1
# 2: N2
# 3: N3
# 4: REM

for i in range(0,len(data)):
    if data.iloc[i,-1]=='Awake':
        data.iloc[i,-1]=0
    elif data.iloc[i,-1]=='N1':
        data.iloc[i,-1]=1
    elif data.iloc[i,-1]=='N2':
        data.iloc[i,-1]=2
    elif data.iloc[i,-1]=='N3':
        data.iloc[i,-1]=3
    elif data.iloc[i,-1]=='REM':
        data.iloc[i,-1]=4
    else:
        data.iloc[i,-1]=np.nan
```

[6]:
```
data_2=data.dropna()
```

[7]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_2.iloc[:,:35])
```

[8]:
```
Y=data_2.iloc[:,-1].to_numpy()
```

[9]:
```
# Train-test split
X_train=X[:int(len(X)*0.9)]
X_test=X[int(len(X)*0.9):]
```

[10]:
```
Y_train=Y[:int(len(X)*0.9)]
Y_test=Y[int(len(X)*0.9):]
```

Defining a Kmeans model The KMeans algorithm clusters the data by attempting to divide the samples into n groups of equal variance. The mean is commonly called the "centroid" of the cluster. Note that these are typically not points from the dataset.

The k-means algorithm aims to choose centroids that minimize the in-cluster inertia or sum of squares criterion. The first step is to select the first centroid. The kmeans algorithm consists in 3 basic steps. First a number of points of the dataset are selected as the first centroids. Then the rest of the points are clasified according to the nearest centroid. The new centroid is the mean value of the points in each class. The difference between the old and new centroids is calculated and the algorithm repeats these last two steps until this value is below the threshold. For more information visit the documentation site.

[11]:
```python
# Run local implementation of kmeans
model = KMeans(n_clusters=6, max_iter=100, init='random',n_init=10)
```

[12]:
```python
model.fit(X_train)
```

[12]:
```
KMeans(init='random', max_iter=100, n_clusters=6)
```

[13]:
```python
#Obtaining clusters centroid
centroids = model.cluster_centers_

#To obtain the labels of each cluster
labels = model.labels_
```

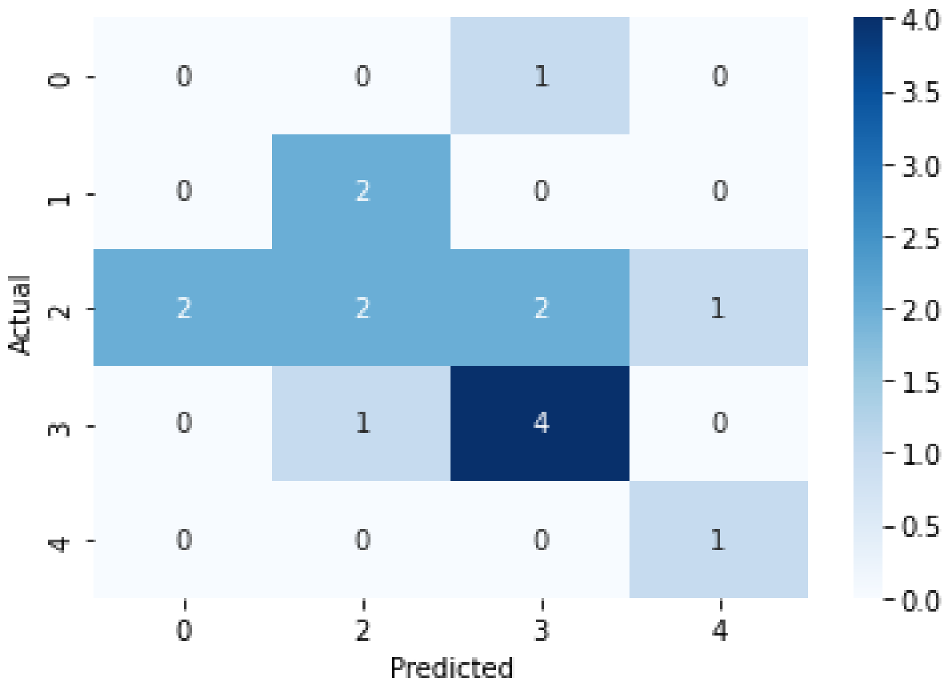
Train values

[14]:
```python
confusion_matrix = pd.crosstab(Y_train, labels, rownames=['Actual'],␣
↪colnames=['Predicted'])

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

Test values

[15]:
```python
y_pred=model.predict(X_test)
```

```
[16]: confusion_matrix = pd.crosstab(Y_test, y_pred, rownames=['Actual'],␣
       ↪colnames=['Predicted'])

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



Observations:

- STD works great to identify the N3 segments
- STD works fairly well to identify periods awake and N2
- STD doesn't seem to be working on REM idenntification
- The low count of N1 segments makes it difficult to assess its accuracy.
- It should be considered that it is possible that the third group of STD corresponds to epileptic seizures.

0.3 Medians: Lobes

Now we will obtain the average value for each band dividing each chanel into lobes. The lobes taken into account were: Frontal, occipital, parietal, temporal and central(even though it isn't a cerebral lobe, it doesn't share the same characheristics as the frontal or parietal lobes).

Importing the data

```
[19]: data=pd.read_csv("Extracted_data/Data_medians_lobes.csv")
```

```
[20]: del data['Unnamed: 0']
```

[21]:
```
# 0: Awake
# 1: N1
# 2: N2
# 3: N3
# 4: REM

for i in range(0,len(data)):
    if data.iloc[i,-1]=='Awake':
        data.iloc[i,-1]=0
    elif data.iloc[i,-1]=='N1':
        data.iloc[i,-1]=1
    elif data.iloc[i,-1]=='N2':
        data.iloc[i,-1]=2
    elif data.iloc[i,-1]=='N3':
        data.iloc[i,-1]=3
    elif data.iloc[i,-1]=='REM':
        data.iloc[i,-1]=4
    else:
        data.iloc[i,-1]=np.nan
```

Adapting the data

[22]:
```
data_2=data.dropna()
```

[23]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_2.iloc[:,:35])

Y=data_2.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.9)]
X_test=X[int(len(X)*0.9):]

Y_train=Y[:int(len(X)*0.9)]
Y_test=Y[int(len(X)*0.9):]
```

Defining a Kmeans model

[24]:
```
# Run local implementation of kmeans
model = KMeans(n_clusters=6, max_iter=100, init='random',n_init=10)
```

[25]:
```
model.fit(X_train)
```

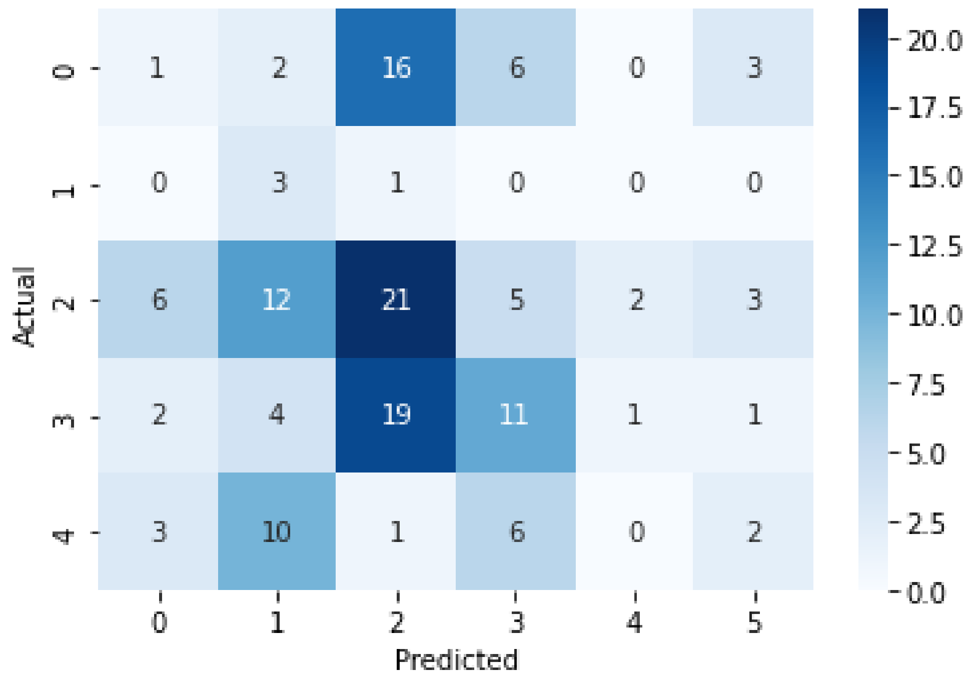
[25]:
```
KMeans(init='random', max_iter=100, n_clusters=6)
```

[26]:
```
#Obtaining clusters centroid
centroids = model.cluster_centers_
```

```
#To obtain the labels of each cluster
labels = model.labels_
```

Train values

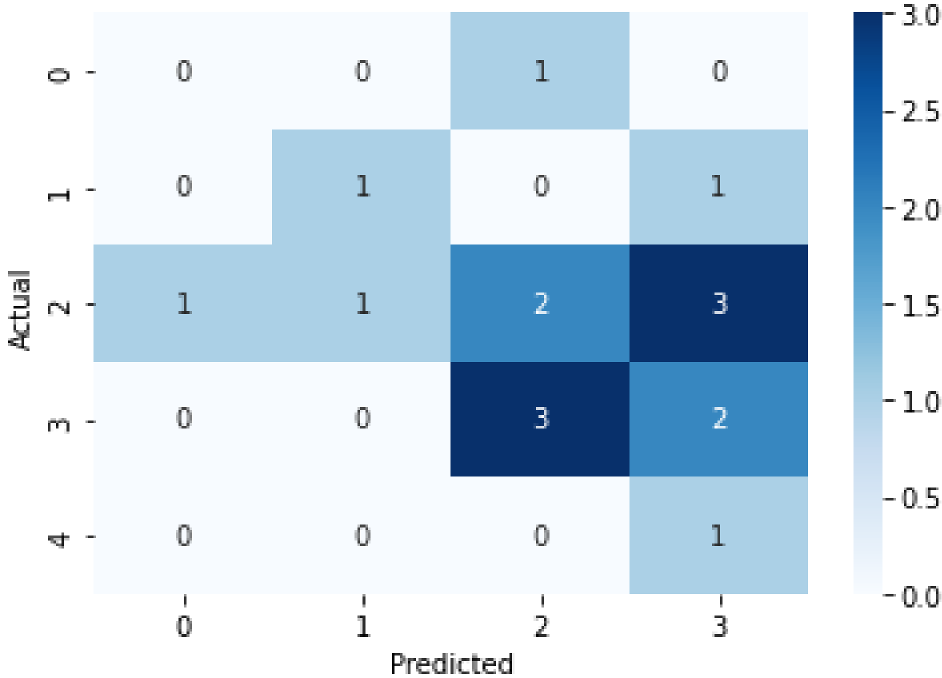
[27]:
```
confusion_matrix = pd.crosstab(Y_train, labels, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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



Test values

[28]:
```
y_pred=model.predict(X_test)
```

[29]:
```
confusion_matrix = pd.crosstab(Y_test, y_pred, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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



Observations: * Lobe method confuses N2 with N3 * Moderately defined awake periods * First and last group very similar: One may correspond to epilepsy

[ ]:

```

```

0.4 Data_medians_horizontal

This data consist on horizontal bipolar derivations, simlar to the double bannana, but in a perpendicular direction.

Importing the data

[30]:
```
data=pd.read_csv("Extracted_data/Data_medians_horizontal.csv")
```

Adapting the data

[31]:
```
del data['Unnamed: 0']
```

[32]:
```
# 0: Awake
# 1: N1
# 2: N2
# 3: N3
# 4: REM

for i in range(0,len(data)):
```

```
    if data.iloc[i,-1]=='Awake':
        data.iloc[i,-1]=0
    elif data.iloc[i,-1]=='N1':
        data.iloc[i,-1]=1
    elif data.iloc[i,-1]=='N2':
        data.iloc[i,-1]=2
    elif data.iloc[i,-1]=='N3':
        data.iloc[i,-1]=3
    elif data.iloc[i,-1]=='REM':
        data.iloc[i,-1]=4
    else:
        data.iloc[i,-1]=np.nan
```

[33]:
```
data_2=data.dropna()
```

[34]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_2.iloc[:,:35])

Y=data_2.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.9)]
X_test=X[int(len(X)*0.9):]

Y_train=Y[:int(len(X)*0.9)]
Y_test=Y[int(len(X)*0.9):]
```

Defining a Kmeans model

[35]:
```
# Run local implementation of kmeans
model = KMeans(n_clusters=6, max_iter=100, init='random',n_init=10)
```

[36]:
```
model.fit(X_train)
```

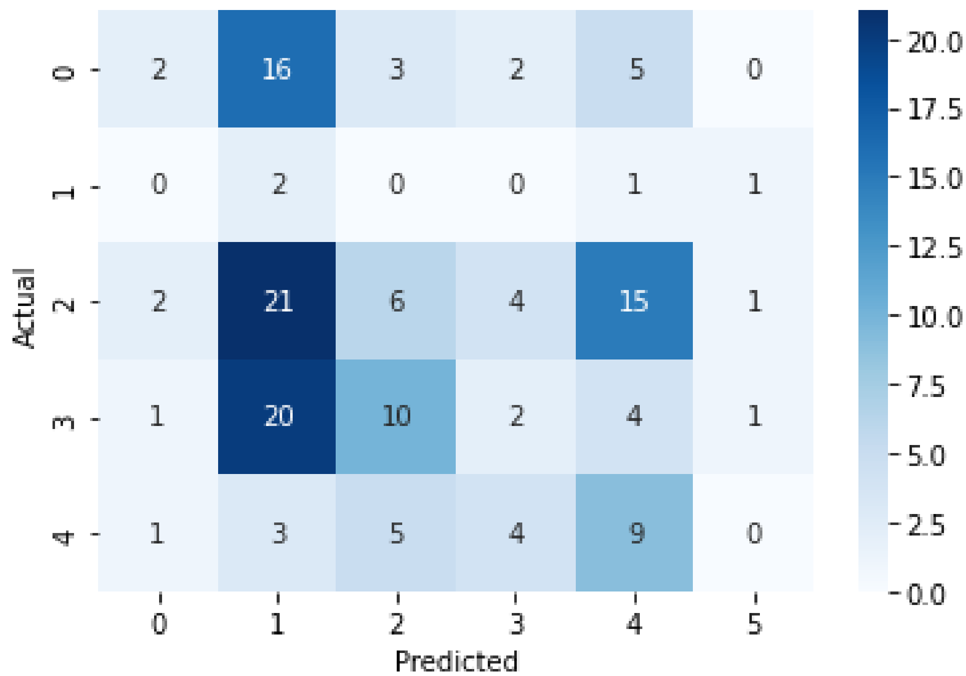
[36]:
```
KMeans(init='random', max_iter=100, n_clusters=6)
```

[37]:
```
#Obtaining clusters centroid
centroids = model.cluster_centers_

#To obtain the labels of each cluster
labels = model.labels_
```

Train values

[38]:
```
confusion_matrix = pd.crosstab(Y_train, labels, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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

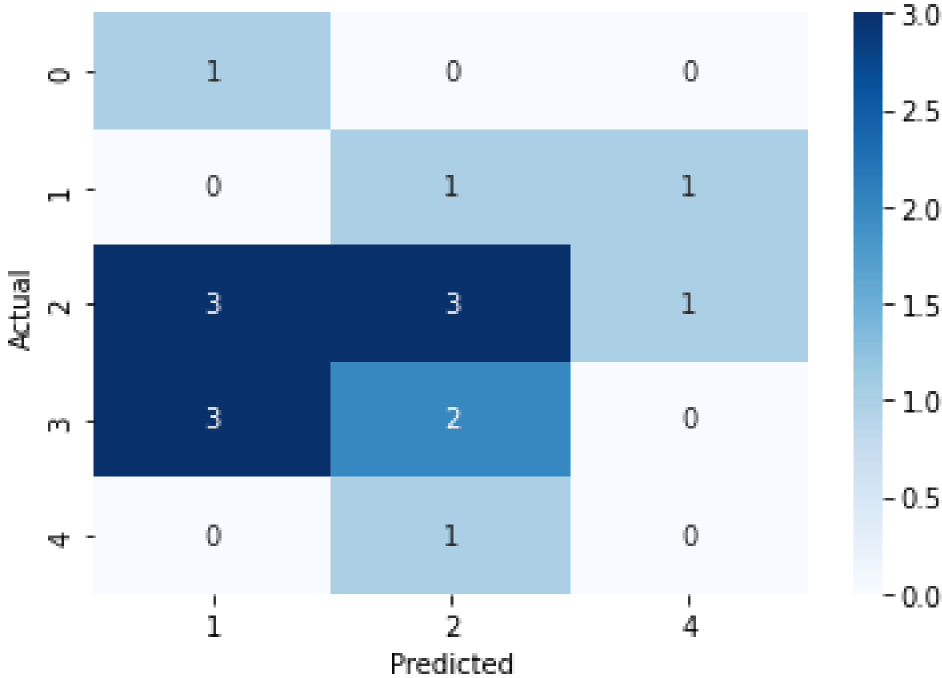
```
plt.show()
```



Test values

[39]:
```
y_pred=model.predict(X_test)
```

[40]:
```
confusion_matrix = pd.crosstab(Y_test, y_pred, rownames=['Actual'],␣
↪colnames=['Predicted'])

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



Observations: * Two groups correspond to N2 and N3. Possibly one corresponds to segments with attacks * No group is particularly defined

0.5 Data_medians_vertical

Median values of the vertical bipolar derivations. Very similar to the first test but instead of using the standard derivation among the values, we will use the mean value of medians.

Importing the data

[41]:
```
data=pd.read_csv("Extracted_data/Data_medians_vertical.csv")
```

Adapting the data

[42]:
```
del data['Unnamed: 0']
```

[43]:
```
# 0: Awake
# 1: N1
# 2: N2
# 3: N3
# 4: REM

for i in range(0,len(data)):
    if data.iloc[i,-1]=='Awake':
        data.iloc[i,-1]=0
    elif data.iloc[i,-1]=='N1':
```

```
        data.iloc[i,-1]=1
    elif data.iloc[i,-1]=='N2':
        data.iloc[i,-1]=2
    elif data.iloc[i,-1]=='N3':
        data.iloc[i,-1]=3
    elif data.iloc[i,-1]=='REM':
        data.iloc[i,-1]=4
    else:
        data.iloc[i,-1]=np.nan
```

[44]:
```
data_2=data.dropna()
```

[45]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_2.iloc[:,:35])

Y=data_2.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.9)]
X_test=X[int(len(X)*0.9):]

Y_train=Y[:int(len(X)*0.9)]
Y_test=Y[int(len(X)*0.9):]
```

Defining a Kmeans model

[46]:
```
# Run local implementation of kmeans
model = KMeans(n_clusters=6, max_iter=100, init='random',n_init=10)
```

[47]:
```
model.fit(X_train)
```

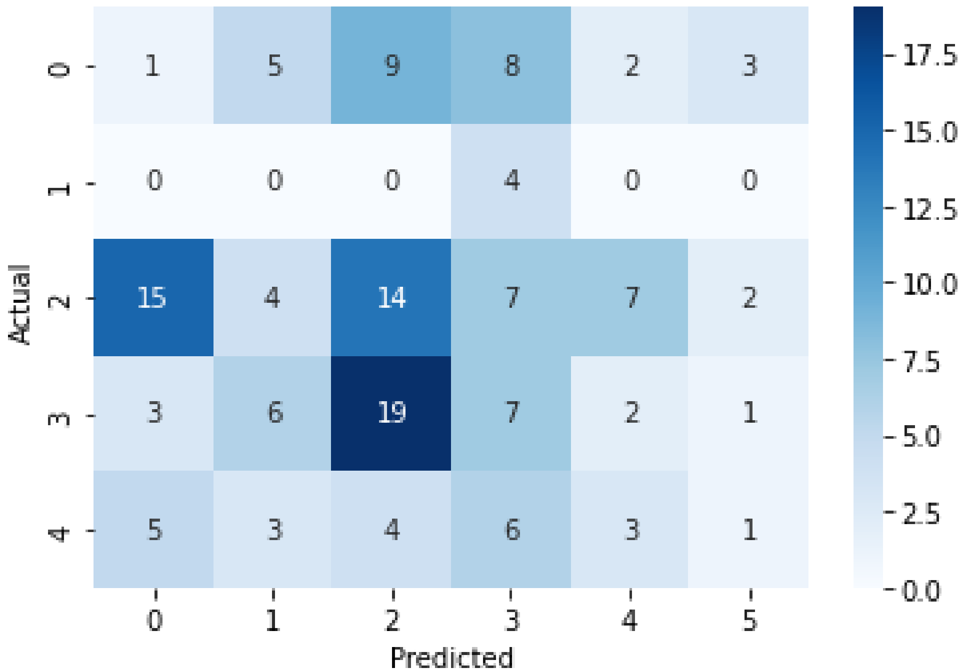
[47]:
```
KMeans(init='random', max_iter=100, n_clusters=6)
```

[48]:
```
data_2=data.dropna()
```

Train values

[49]:
```
#Obtaining clusters centroid
centroids = model.cluster_centers_

#To obtain the labels of each cluster
labels = model.labels_
```

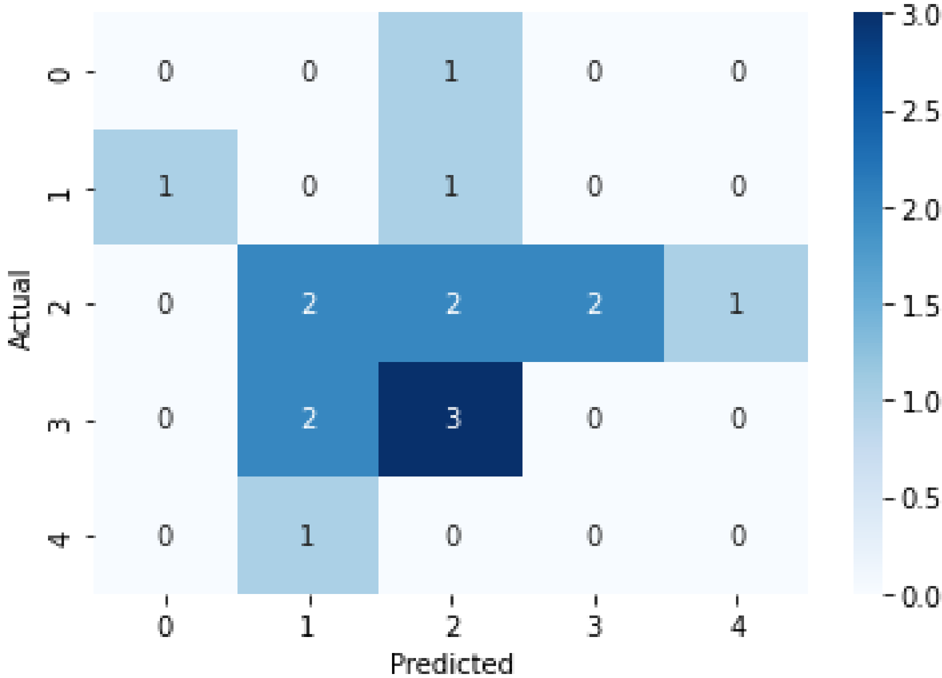
[50]:
```
confusion_matrix = pd.crosstab(Y_train, labels, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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



Test values

[51]:
```
y_pred=model.predict(X_test)
```

[52]:
```
confusion_matrix = pd.crosstab(Y_test, y_pred, rownames=['Actual'],␣
↪colnames=['Predicted'])

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



0.6 Data_lobes_std

Single electrode recordings with the electrodes classified into lobes. The value of intrest here is the standard derivation in a single class of electodes. Lets remember that the median value wasn't very accurate in the correct classification of N2 and N3 fragments. We hope that the electrophisiological properties of each stage are more distinguishable by using the standard derivation.

Importing the data

[53]:
```
data=pd.read_csv("Extracted_data/Data_medians_3.csv")
```

Adapting the data

[54]:
```
del data['Unnamed: 0']
```

[55]:
```
# 0: Awake
# 1: N1
# 2: N2
# 3: N3
# 4: REM

for i in range(0,len(data)):
    if data.iloc[i,-1]=='Awake':
        data.iloc[i,-1]=0
    elif data.iloc[i,-1]=='N1':
```

```
        data.iloc[i,-1]=1
    elif data.iloc[i,-1]=='N2':
        data.iloc[i,-1]=2
    elif data.iloc[i,-1]=='N3':
        data.iloc[i,-1]=3
    elif data.iloc[i,-1]=='REM':
        data.iloc[i,-1]=4
    else:
        data.iloc[i,-1]=np.nan
```

[56]:
```
data_2=data.dropna()
```

[57]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_2.iloc[:,:25])

Y=data_2.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.9)]
X_test=X[int(len(X)*0.9):]

Y_train=Y[:int(len(X)*0.9)]
Y_test=Y[int(len(X)*0.9):]
```

Defining a Kmeans model

[58]:
```
# Run local implementation of kmeans
model = KMeans(n_clusters=6, max_iter=100, init='random',n_init=10)
```

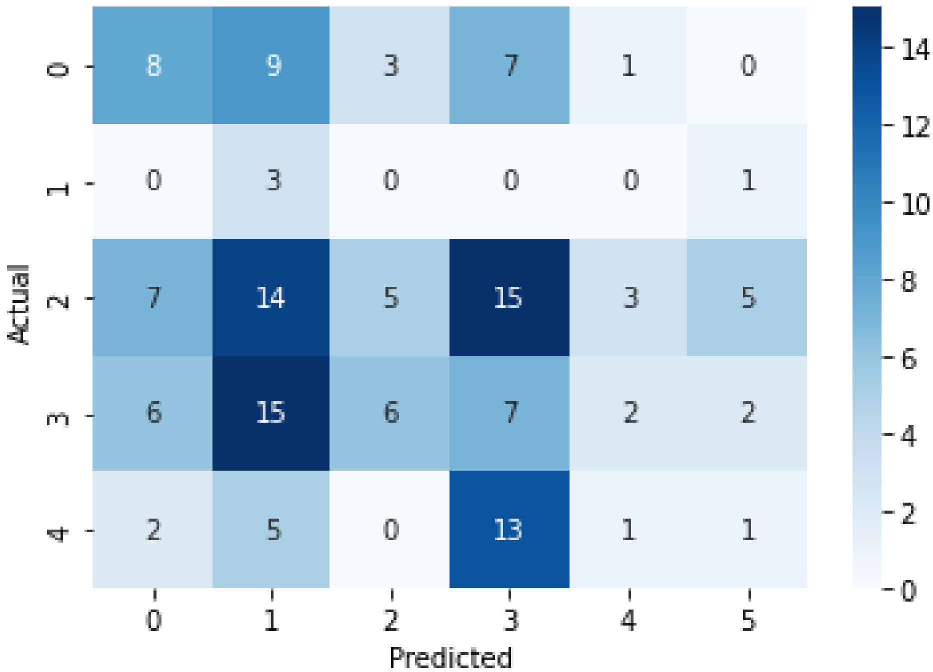
[59]:
```
model.fit(X_train)
```

[59]:
```
KMeans(init='random', max_iter=100, n_clusters=6)
```

Train values

[60]:
```
#Obtaining clusters centroid
centroids = model.cluster_centers_

#To obtain the labels of each cluster
labels = model.labels_
```

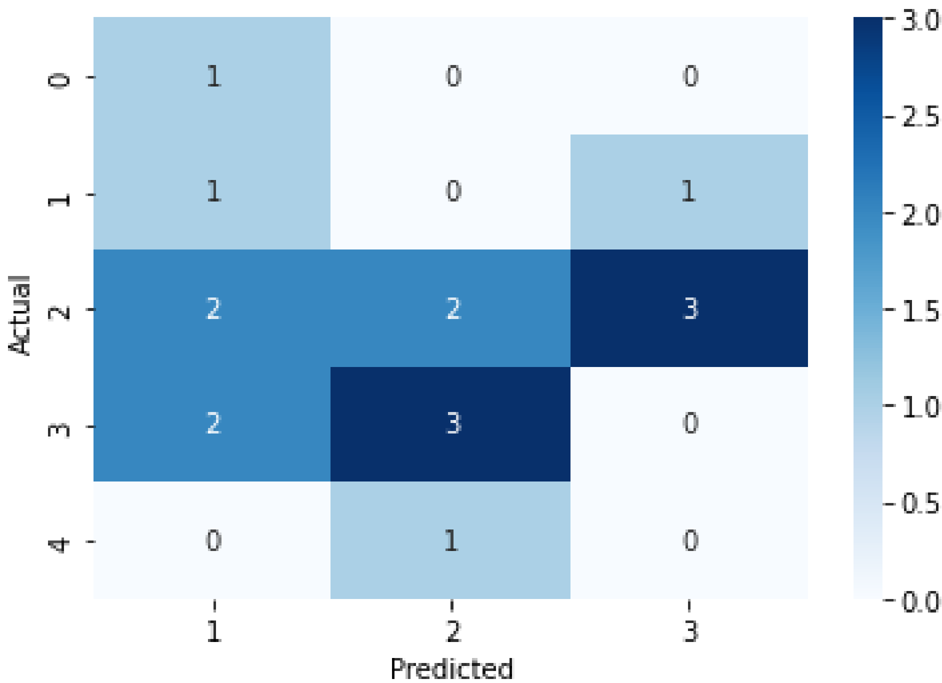
[61]:
```
confusion_matrix = pd.crosstab(Y_train, labels, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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



Test values

[62]:
```
y_pred=model.predict(X_test)
```

[63]:
```
confusion_matrix = pd.crosstab(Y_test, y_pred, rownames=['Actual'],␣
↪colnames=['Predicted'])

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



[64]:
```
np.std(centroids,axis=0)
```

[64]:
```
array([1.10639682, 1.15550397, 1.19108799, 1.1278308 , 1.13799211,
       1.20562992, 1.22571886, 1.30946676, 1.29401192, 1.2754787 ,
       1.29055034, 1.35164439, 1.11808464, 1.15387115, 1.14641472,
       1.20852432, 1.26136467, 1.22864774, 0.18717068])
```

Observations: * Even though the correct classification of N2 and N3 fragments improved, the REM stage accuracy greatly decreased. * Awake periods also experienced a decreased accuracy.

0.7 Data_lobes_mean

We already tried the median value and the standard deviation for the lobe analysis. Each had it's strenghts and weaknesses. We hope the mean value is able to provide information both about the skewness of the PSD and the main frequency.

Importing the data

[65]:
```
data=pd.read_csv("Extracted_data/Data_medians_lobe_STD.csv")
```

Adapting the data

[66]:
```
del data['Unnamed: 0']
```

[67]:
```
# 0: Awake
# 1: N1
# 2: N2
# 3: N3
# 4: REM

for i in range(0,len(data)):
    if data.iloc[i,-1]=='Awake':
        data.iloc[i,-1]=0
    elif data.iloc[i,-1]=='N1':
        data.iloc[i,-1]=1
    elif data.iloc[i,-1]=='N2':
        data.iloc[i,-1]=2
    elif data.iloc[i,-1]=='N3':
        data.iloc[i,-1]=3
    elif data.iloc[i,-1]=='REM':
        data.iloc[i,-1]=4
    else:
        data.iloc[i,-1]=np.nan
```

[68]:
```
data_2=data.dropna()
```

[69]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_2.iloc[:,:25])

Y=data_2.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.9)]
X_test=X[int(len(X)*0.9):]

Y_train=Y[:int(len(X)*0.9)]
Y_validate=Y[int(len(X)*0.9):]
```

Defining a Kmeans model

[70]:
```
# Run local implementation of kmeans
model = KMeans(n_clusters=6, max_iter=100, init='random',n_init=10)
```

[71]:
```
model.fit(X_train)
```

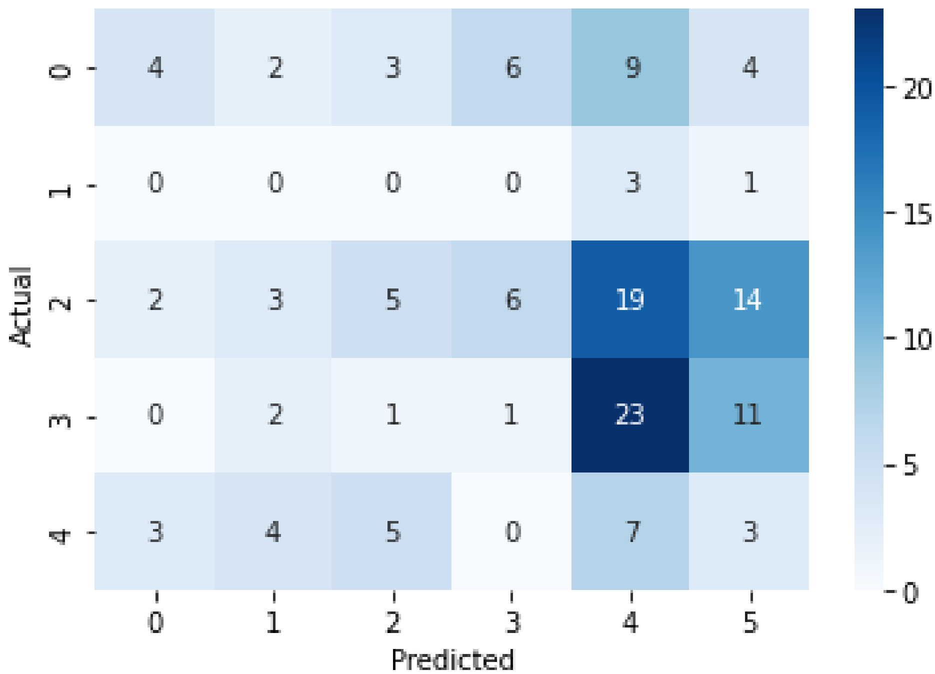
[71]:
```
KMeans(init='random', max_iter=100, n_clusters=6)
```

[72]:
```
#Obtaining clusters centroid
centroids = model.cluster_centers_

#To obtain the labels of each cluster
labels = model.labels_
```

Train values

[73]:
```
#Obtaining clusters centroid
centroids = model.cluster_centers_

#To obtain the labels of each cluster
labels = model.labels_
```

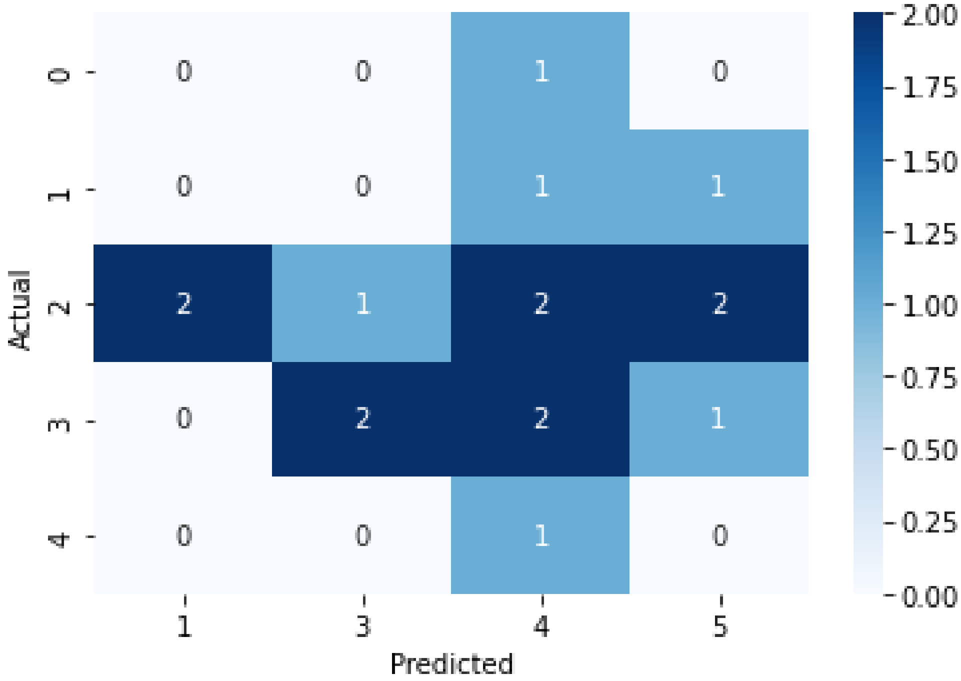
[74]:
```
confusion_matrix = pd.crosstab(Y_train, labels, rownames=['Actual'],␣
↪colnames=['Predicted'])

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



Test values

[75]:
```
y_pred=model.predict(X_test)
```

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

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



Observations: * Somehow we have worse results than with the median and with the STD. * Maybe the best parameter group includes both the median and the STD, but with a generalized version of parameters.

0.8 Data_lobes_std+medians

Now we will try to use the two best parameter groups and hope that the algorithm won't be over adjusted to the data.

Importing the data

[78]:
```
data=pd.read_csv("Extracted_data/Data_medians_4.csv")
```

Adapting the data

[79]:
```
del data['Unnamed: 0']
```

[80]:
```
del data['38']
```

[81]:
```
# 0: Awake
# 1: N1
# 2: N2
# 3: N3
# 4: REM

for i in range(0,len(data)):
```

```
    if data.iloc[i,-1]=='Awake':
        data.iloc[i,-1]=0
    elif data.iloc[i,-1]=='N1':
        data.iloc[i,-1]=1
    elif data.iloc[i,-1]=='N2':
        data.iloc[i,-1]=2
    elif data.iloc[i,-1]=='N3':
        data.iloc[i,-1]=3
    elif data.iloc[i,-1]=='REM':
        data.iloc[i,-1]=4
    else:
        data.iloc[i,-1]=np.nan
```

[82]:
```
data_2=data.dropna()
```

[83]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_2.iloc[:,:17])

Y=data_2.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.85)]
X_test=X[int(len(X)*0.85):]

Y_train=Y[:int(len(X)*0.85)]
Y_test=Y[int(len(X)*0.85):]
```

Defining a Kmeans model

[84]:
```
# Run local implementation of kmeans
model = KMeans(n_clusters=6, max_iter=100, init='random',n_init=10)
```

[85]:
```
model.fit(X_train)
```

[85]:
```
KMeans(init='random', max_iter=100, n_clusters=6)
```

[86]:
```
#Obtaining clusters centroid
centroids = model.cluster_centers_

#To obtain the labels of each cluster
labels = model.labels_
```

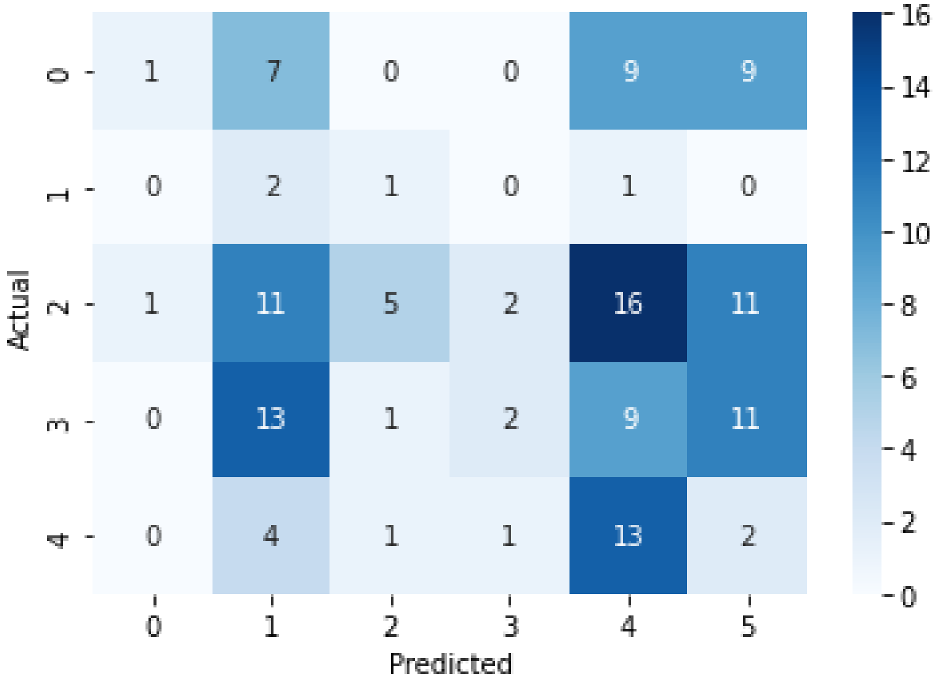
Train values

[87]:
```
y_pred=model.predict(X_train)
```

[88]:
```
np.shape(Y)
```

[88]: (157,)

[89]:
```
confusion_matrix = pd.crosstab(Y_train, y_pred, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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



[90]:
```
np.shape(centroids)
```

[90]: (6, 17)

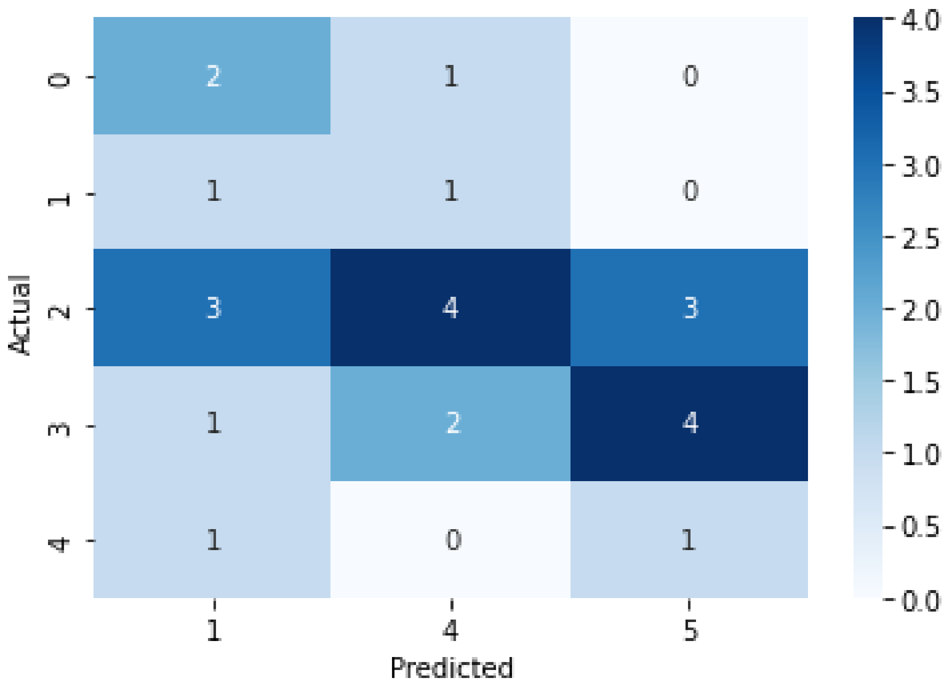
[91]:
```
np.std(centroids,axis=0)
```

[91]:
```
array([1.31508141, 1.44789848, 1.4518577 , 1.50542897, 1.74182931,
       1.68103272, 1.43457101, 1.64228555, 1.57416316, 1.62400309,
       1.85653065, 1.81386237, 1.35501158, 1.47113136, 1.41265323,
       1.41818002, 1.65714423])
```

Test values

[92]:
```
y_pred=model.predict(X_test)
```

[93]:
```
confusion_matrix = pd.crosstab(Y_test, y_pred, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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



0.9 Keras

[94]:
```
from sklearn.neighbors import KNeighborsClassifier
```

The following series of experiments take means and standard deviations of the 6 main areas: Frontal, left temporal, right temporal, central, parietal and occipital. 10-second segments were taken that were not on the border of a sleep stage. A PSD was obtained for each segment and for each electrode. The first three quintiles were calculated for each PSD (ie when the area under the curve corresponded to 20%, 40% and 60% of the total area). Finally, the average of each quintile was obtained for each area and for all the segments of the same sleep phase, as well as the standard deviation.

Finally, the activity and mobility of each stage were calculated. These two values are two of the Hjorth parameters and are calculated as:

Activity $\rightarrow A = \sigma_0^2$

Mobility $\rightarrow M = \frac{\sigma_1}{\sigma_0}$

Where σ_i represents the variance of the ith derivative of the EEG recording. That is, σ_0 is the variance of the raw EEG values. For the Hjorth parameters, all available electrodes were collapsed.

[128]:
```
data=pd.read_csv("Extracted_data/Data_medians_4.csv")
del data['Unnamed: 0']
del data['38']
```

[129]:
```
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
```

[130]:
```
data
```

[130]:
```
             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

[165 rows x 39 columns]
```

[131]:
```python
data_2=data.dropna()
```

[132]:
```python
# Standardize the data
X = StandardScaler().fit_transform(data_2.iloc[:,:35])

Y=data_2.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.75)]
X_test=X[int(len(X)*0.75):]

Y_train=Y[:int(len(X)*0.75)]
Y_test=Y[int(len(X)*0.75):]
```

[102]:
```python
k_neighbor=KNeighborsClassifier(5)
```

[103]:
```python
print(np.shape(X_train))
print(np.shape(Y_train))
```

```
(117, 35)
(117,)
```

[104]:
```python
Y_train
```

[104]: array(['Awake', 'N2', 'REM', 'N2', 'N3', 'REM', 'N3', 'REM', 'N2', 'N3',
       'REM', 'Awake', 'N2', 'N2', 'N3', 'REM', 'Awake', 'N2', 'N2', 'N3',
       'N3', 'Awake', 'REM', 'N2', 'Awake', 'N2', 'N3', 'REM', 'N3',
       'REM', 'Awake', 'REM', 'Awake', 'Awake', 'N2', 'Awake', 'N3',
       'Awake', 'N2', 'N3', 'REM', 'N2', 'N3', 'N2', 'N1', 'N2', 'N3',
       'N2', 'N1', 'N3', 'N3', 'N2', 'N2', 'REM', 'N2', 'Awake', 'N3',
       'N2', 'N3', 'N2', 'Awake', 'N2', 'N3', 'Awake', 'N2', 'Awake',
       'REM', 'N2', 'Awake', 'N2', 'N3', 'N2', 'N3', 'N2', 'N2', 'N3',
       'Awake', 'N1', 'Awake', 'Awake', 'N2', 'N3', 'REM', 'N2', 'N3',
       'N2', 'Awake', 'N3', 'N2', 'N3', 'N2', 'N3', 'REM', 'N2', 'N2',
       'N3', 'N2', 'N2', 'REM', 'N3', 'REM', 'N2', 'Awake', 'N2', 'N3',
       'N2', 'N3', 'N2', 'N3', 'REM', 'Awake', 'N2', 'N3', 'REM', 'N3',
       'REM', 'N2'], dtype=object)

[105]:
```
k_neighbor.fit(X_train,Y_train)
```

[105]: KNeighborsClassifier()

[106]:
```
y_pred=k_neighbor.predict(X_train)
```

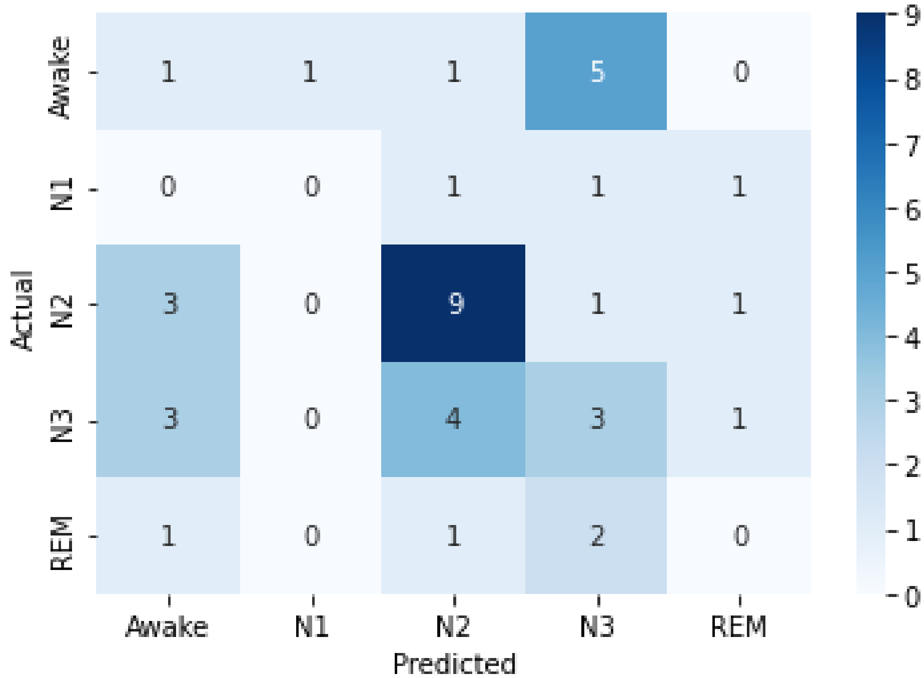
[107]:
```
confusion_matrix = pd.crosstab(Y_train, y_pred, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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

```
[108]: sum(confusion_matrix.iloc[i,i] for i in range(0,len(confusion_matrix)))/
         ↪len(Y_train)
```

```
[108]: 0.4188034188034188
```

```
[109]: y_pred=k_neighbor.predict(X_test)
```

```
[110]: confusion_matrix = pd.crosstab(Y_test, y_pred, rownames=['Actual'],␣
         ↪colnames=['Predicted'])

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




```
[111]: sum(confusion_matrix.iloc[i,i] for i in range(0,len(confusion_matrix)))/
         ↪len(Y_test)
```

```
[111]: 0.325
```

0.10 Comparison between sections

From the last lesson we learned that epileptic attacks occur mostly in the N2 and N3 sleep stages. So now we will try to split the sub-segemnts of each stage into two clusters. We expect that, with the correct set of paramteters, one of the clusters will correspond to epileptic seizures and the other will correspond to normal recordings.

Please note that this classification can't be evaluated and validated because there are not markings that allow us to compare the results to a gold standard.

0.10.1 N2

[112]:
```
data_c=data
```

[113]:
```
for i in range(0,len(data)):
    if data.iloc[i,-1]!="N2":
        data_c.iloc[i,-1]=np.nan
```

[114]:
```
data_c=data_c.dropna()
```

[115]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_c.iloc[:,:37])

X_train=X[:int(len(X)*0.75)]
```

[116]:
```
# Run local implementation of kmeans
model = KMeans(n_clusters=2, max_iter=100, init='random',n_init=10)
```

[117]:
```
model.fit(X)
```

[117]:
```
KMeans(init='random', max_iter=100, n_clusters=2)
```

[118]:
```
#Obtaining clusters centroid
centroids = model.cluster_centers_
```

[119]:
```
centroids
```

[119]:
```
array([[-0.61783467, -0.62070957, -0.61891999, -0.62231813, -0.59319319,
        -0.58682692, -0.58719187, -0.59447495, -0.57491152, -0.58687597,
        -0.55478317, -0.55559992, -0.54025856, -0.6013481 , -0.56503859,
        -0.55747612, -0.56713299, -0.56355206, -0.61688024, -0.62213048,
        -0.62049631, -0.6234374 , -0.59625971, -0.59148912, -0.58258563,
        -0.59645084, -0.57565797, -0.58404583, -0.5579193 , -0.56066686,
        -0.52861544, -0.60169546, -0.55909407, -0.55051283, -0.56889795,
        -0.56726235,  0.03406   ],
       [ 1.11210241,  1.11727723,  1.11405598,  1.12017263,  1.06774773,
         1.05628846,  1.05694536,  1.07005492,  1.03484073,  1.05637674,
         0.99860971,  1.00007986,  0.9724654 ,  1.08242657,  1.01706945,
         1.00345702,  1.02083938,  1.0143937 ,  1.11038443,  1.11983486,
         1.11689335,  1.12218731,  1.07326748,  1.06468042,  1.04865413,
         1.07361151,  1.03618435,  1.0512825 ,  1.00425474,  1.00920034,
         0.95150778,  1.08305183,  1.00636933,  0.99092309,  1.02401631,
```

```
         1.02107224, -0.06130801]])
```

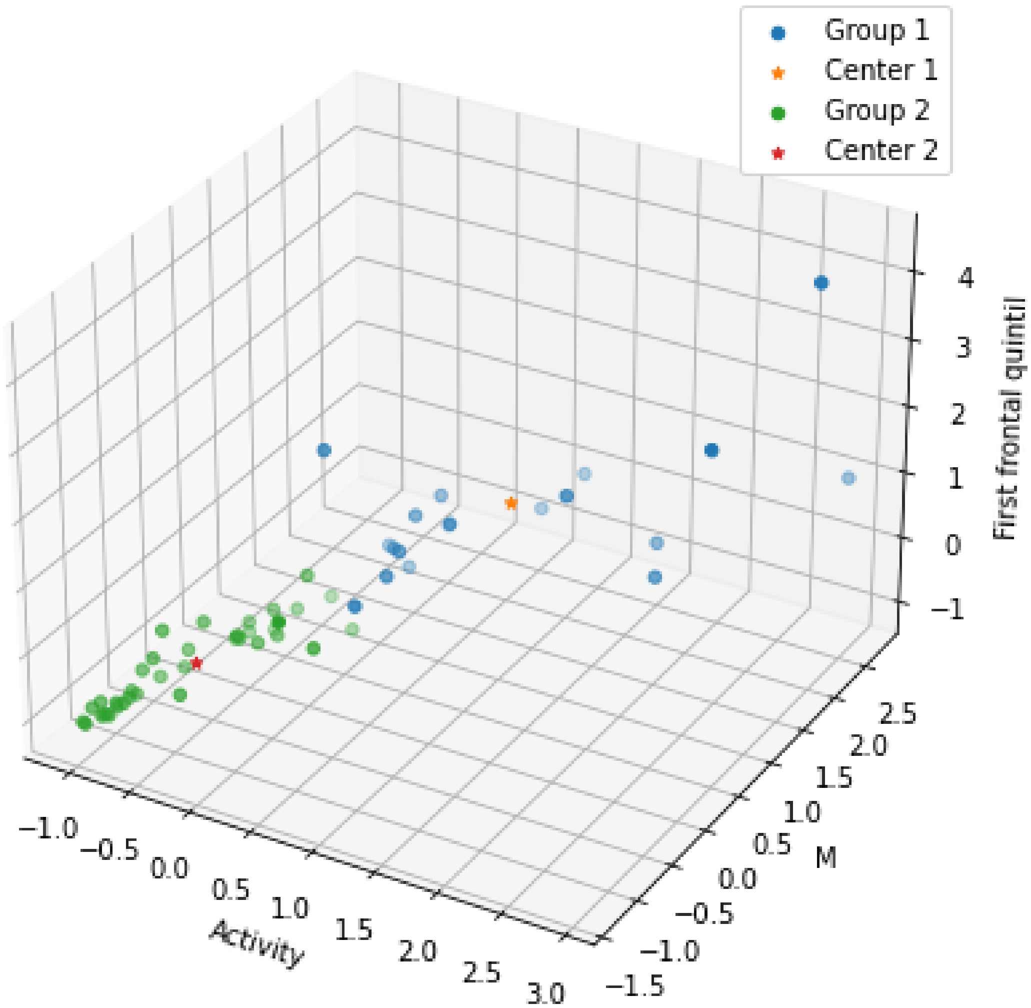
[120]:
```
centroids[0]-centroids[1]
```

[120]:
```
array([-1.72993707, -1.7379868 , -1.73297596, -1.74249076, -1.66094092,
       -1.64311539, -1.64413722, -1.66452987, -1.60975225, -1.64325271,
       -1.55339288, -1.55567978, -1.51272396, -1.68377467, -1.58210804,
       -1.56093315, -1.58797237, -1.57794576, -1.72726467, -1.74196534,
       -1.73738966, -1.74562471, -1.66952719, -1.65616955, -1.63123976,
       -1.67006235, -1.61184232, -1.63532833, -1.56217404, -1.5698672 ,
       -1.48012322, -1.68474729, -1.56546341, -1.54143592, -1.59291426,
       -1.58833459,  0.09536801])
```

[121]:
```
#To obtain the labels of each cluster
labels = model.labels_
```

[122]:
```
# Creating figure
fig = plt.figure(figsize = (10, 7))
ax = plt.axes(projection ="3d")
x=-2
y=1
z=30
ax.scatter3D(X[labels>0][:,x],X[labels>0][:,y],X[labels>0][:,z],label="Group 1")
ax.scatter3D(centroids[1,x],centroids[1,y],centroids[1,0],label="Center␣
 ↪1",marker='*')
ax.scatter3D(X[labels<1][:,x],X[labels<1][:,y],X[labels<1][:,z],label="Group 2")
ax.scatter3D(centroids[0,x],centroids[0,y],centroids[0,z],label="Center␣
 ↪2",marker='*')
ax.set_ylabel("M")
ax.set_xlabel("Activity")
ax.set_zlabel("First frontal quintil")
ax.legend()
```

[122]:
```
<matplotlib.legend.Legend at 0x7fa2bda879d0>
```



Observations:

- The first group has the mayority of points and is more compact than the second group.
- The sub-segments that are classified in the second group have more extreme parameters. This might be due to the precence of an artifact or because it corresponds to a epileptic seizure.
- Based on the positions of the centroids we can infer that, if the clasification is correct, the first group corresponds to epileptic seizures and the second group to normal recodings.
- Every single parameter is higher in the first group except the movility.

0.10.2 N3

[133]:
```
data_c=data
```

[134]:
```
for i in range(0,len(data)):
    if data.iloc[i,-1]!="N3":
        data_c.iloc[i,-1]=np.nan
```

[135]:
```
data_c=data_c.dropna()
```

[136]:
```
data_c
```

[136]:
```
             0          1          2          3          4          5  \
4    11.339524  10.327778  11.073333   9.653333  12.070000  10.046667
6    26.998571  26.215556  29.127778  29.162222  28.964444  28.295000
9    10.481905  10.418889  11.724444  11.373333  10.986667  10.811667
14   34.483810  39.271111  39.704444  42.848889  52.626667  48.441667
20   12.452381  13.240000  13.191111  12.627778  13.446667  12.915000
22   19.874286  17.511111  15.896667  18.567778  17.408889  16.461667
29   31.032857  29.833333  29.096667  26.802222  27.352222  28.403333
32   20.797619  19.597778  19.213333  17.788889  17.948889  18.641667
41   17.056190  15.736667  17.441111  18.685556  18.053333  16.200000
44   22.938571  20.206667  24.743333  23.447778  24.880000  20.580000
47   13.509524  12.738889  15.117778  14.091111  14.761111  12.363333
52   27.002857  30.531111  27.175556  30.455556  23.521111  30.885000
55    6.249524   6.042222   6.161111   6.868889   5.803333   5.753333
56   30.269524  27.227778  27.304444  31.934444  29.443333  27.925000
63   22.354286  22.023333  19.170000  21.132222  20.140000  20.373333
65   12.850476  12.911111  11.314444  12.953333  12.010000  12.263333
69   21.699048  16.857778  16.901111  14.498889  19.883333  12.946667
77    3.702857   3.464444   3.512222   3.314444   3.535556   3.431667
79   26.012857  25.021111  25.410000  25.485556  24.295556  20.575000
82   26.410952  23.981111  25.848889  26.752222  24.001111  23.941667
88   14.148571  12.938889  11.632222  13.528889  12.736667  12.380000
91   31.956667  27.707778  18.122222  29.747778  27.568889  23.048333
94   22.989524  20.058889  14.544444  20.261111  18.684444  15.398333
96    8.130476   7.284444   6.515556   7.003333   6.388889   5.288333
98   11.078571  13.480000   9.510000  12.590000  10.761111   8.158333
102  48.024286  45.288889  56.105556  38.996667  42.208889  46.661667
106  16.691905  17.795556  17.750000  13.072222  15.040000  13.595000
111  39.234762  38.838889  38.456667  38.068889  36.417778  33.683333
113  26.122381  24.840000  25.090000  25.616667  24.204444  21.866667
115  30.772857  37.638889  40.477778  30.845556  33.401111  35.395000
119  20.350000  18.946667  27.378889  18.882222  21.194444  15.316667
121   7.587619   7.875556  10.221111   6.840000   7.737778   5.386667
126  17.987619  15.767778  16.215556  18.902222  16.343333  15.956667
130   4.200000   3.641111   3.693333   4.238889   3.674444   3.561667
132  16.167619  28.574444  30.382222  23.164444  25.064444  23.246667
137   2.534286   2.466667   2.526667   2.556667   2.502222   2.265000
140  15.134286  15.461111  15.403333  16.684444  15.866667  14.901667
145  27.841429  29.337778  29.293333  27.997778  25.055556  25.330000
149  12.059524  12.661111  12.512222  12.027778  10.525556  10.926667
153  34.179524  33.141111  31.646667  33.260000  31.634444  29.551667
154  26.902381  27.300000  25.703333  26.954444  25.543333  24.010000
158  28.656190  26.148889  28.142222  29.854444  25.000000  23.476667
```

163	10.816190	9.702222	10.213333	10.985556	9.072222	8.145000

	6	7	8	9	…	29 \
4	42.745238	33.640000	34.700000	37.300000	…	156.242749
6	61.641429	60.512222	82.962222	74.073333	…	399.858713
9	25.147143	24.993333	33.655556	28.965556	…	144.186463
14	87.269048	112.805556	105.626667	113.292222	…	660.603977
20	25.688571	26.050000	26.112222	24.443333	…	129.994494
22	44.143333	35.455556	31.470000	38.522222	…	168.509782
29	58.532857	54.425556	53.760000	52.906667	…	279.149177
32	39.318571	36.075556	35.627778	35.066667	…	183.913391
41	38.504286	36.480000	38.413333	39.751111	…	173.948698
44	58.670000	48.557778	63.928889	59.466667	…	262.032101
47	34.662381	30.922222	40.020000	36.181111	…	158.756784
52	53.664286	67.217778	57.476667	63.621111	…	383.438299
55	11.253333	10.975556	11.208889	12.394444	…	48.283386
56	61.611429	56.700000	51.467778	63.308889	…	295.746814
63	55.316667	51.916667	40.483333	48.080000	…	221.670005
65	32.771905	31.150000	24.155556	31.478889	…	133.566442
69	60.640952	49.612222	47.582222	43.042222	…	184.263274
77	7.904286	7.245556	7.262222	6.896667	…	21.421253
79	65.421429	70.426667	62.573333	68.556667	…	266.678385
82	63.301905	59.346667	62.635556	59.471111	…	273.349123
88	28.691905	26.242222	24.961111	27.225556	…	126.354677
91	91.949048	63.400000	50.353333	66.278889	…	244.080074
94	73.354762	48.211111	37.993333	46.555556	…	162.397470
96	25.550476	17.801111	19.468889	15.501111	…	49.980521
98	33.675714	41.008889	29.511111	37.497778	…	106.413721
102	172.341905	156.258889	187.771111	129.700000	…	756.633924
106	44.405714	50.278889	47.530000	29.537778	…	140.196937
111	75.847619	76.986667	76.892222	72.163333	…	313.933238
113	48.101905	45.718889	47.163333	46.223333	…	206.259057
115	102.132381	124.227778	131.256667	109.773333	…	605.024322
119	63.618095	64.472222	85.874444	60.328889	…	244.212924
121	23.472381	26.840000	35.091111	21.463333	…	71.407751
126	32.170000	29.741111	30.374444	36.917778	…	151.865404
130	7.272857	6.743333	6.746667	8.026667	…	28.214914
132	38.160476	72.165556	75.347778	48.813333	…	263.592880
137	4.841429	4.704444	4.878889	4.747778	…	13.632215
140	34.830952	37.225556	37.133333	41.551111	…	179.454228
145	53.556667	58.505556	58.205556	54.065556	…	253.110709
149	25.241905	28.402222	27.533333	25.598889	…	113.256666
153	76.524762	73.398889	66.352222	67.616667	…	285.148926
154	61.178571	67.254444	59.908889	59.874444	…	250.997183
158	71.534286	65.567778	72.303333	75.062222	…	290.153260
163	27.838095	24.458889	27.936667	28.534444	…	99.599288

	30	31	32	33	34 \
4	587.817203	465.337699	467.104798	546.078070	612.918988
6	875.714794	795.695026	1081.203383	976.650182	1007.277740
9	329.504906	299.966163	400.458743	347.526865	350.097442
14	810.729764	1178.118628	1073.187894	1112.275571	1286.495199
20	235.258307	273.743060	243.592546	257.479009	283.038934
22	466.936157	369.663944	313.986636	401.507249	355.099730
29	601.866864	564.956831	556.644310	581.754025	529.543763
32	396.192725	369.603986	365.086165	380.098674	346.435712
41	390.992855	354.784589	378.417194	408.356892	385.593292
44	660.175106	555.743070	728.627763	655.188247	701.497471
47	389.865403	345.386991	449.811277	390.568133	418.003661
52	662.537763	1230.418855	798.101891	925.404313	537.842633
55	98.718814	93.877851	96.610335	116.956018	94.046291
56	636.094697	524.642010	493.004100	610.609312	542.743026
63	657.426995	563.646951	401.770693	631.536068	495.514555
65	393.295247	350.744256	242.966376	477.452683	294.922349
69	727.622711	573.013377	546.437332	516.997233	558.992780
77	47.885933	44.538181	42.768123	44.231258	48.017281
79	981.816777	1021.609019	811.503872	1061.325166	649.918134
82	718.692429	688.950026	721.330118	642.779865	529.542734
88	327.491416	300.667696	288.439385	309.124707	293.245258
91	1986.062811	1082.466498	879.061319	1003.909821	766.299146
94	1703.199243	884.173153	865.625408	752.394480	543.215938
96	579.800415	370.898427	527.854273	242.218301	161.193851
98	438.797076	484.642007	377.384311	415.397009	354.127376
102	3039.386077	2380.556244	2878.895408	1864.050784	1554.563101
106	744.050453	741.812404	684.449737	414.872184	479.822748
111	783.234271	785.081986	834.365976	736.142512	695.171512
113	508.891489	507.931461	540.571387	478.699402	447.418727
115	1928.838600	1911.900744	1976.685758	1885.518235	1451.778778
119	807.615376	834.401797	1621.700797	786.025970	754.618554
121	295.966877	361.806818	743.585816	275.536118	265.440138
126	308.896578	287.130775	293.200326	444.668751	292.554209
130	54.663652	49.433609	49.256356	71.999100	50.639364
132	448.815948	1578.282792	1730.909541	506.564951	566.225446
137	29.314164	27.933372	28.957759	28.136708	29.234411
140	456.293709	496.922674	482.631157	540.505234	437.217073
145	671.441757	742.741410	737.986796	650.834585	573.037639
149	310.814455	348.890665	340.459252	299.829648	258.393600
153	1049.807550	1083.384077	932.847137	859.836816	730.518049
154	794.803224	1074.479630	890.432675	792.040132	675.661065
158	1118.145036	1082.963101	1274.547841	1167.185522	768.765636
163	449.385031	411.347601	560.246779	459.417619	270.892424

	35	36	37	39
4	465.555425	9.224363e+06	0.001658	N3

```
6     1048.574140  2.324112e+07  0.000369  N3
9      367.198218  3.268244e+07  0.000392  N3
14    1287.632856  4.220465e+07  0.001066  N3
20     254.441075  1.402703e+08  0.000571  N3
22     326.303332  3.574233e+08  0.000113  N3
29     548.070935  2.867187e+08  0.000065  N3
32     360.993817  2.020305e+08  0.000056  N3
41     350.101424  3.644143e+08  0.000212  N3
44     598.048333  9.533055e+07  0.000159  N3
47     363.520168  6.683818e+07  0.000195  N3
52    1396.628739  1.886213e+07  0.000228  N3
55      92.639052  1.967117e+07  0.000181  N3
56     533.690439  9.170754e+07  0.000226  N3
63     447.726223  1.532783e+09  0.000261  N3
65     291.012161  3.030377e+08  0.000256  N3
69     427.396602  9.360937e+06  0.000407  N3
77      43.032654  5.721059e+07  0.000639  N3
79     565.242040  3.889402e+07  0.000400  N3
82     546.895263  4.879537e+07  0.000291  N3
88     288.084486  1.020876e+07  0.000219  N3
91     617.692599  1.250906e+07  0.000206  N3
94     427.940223  2.291153e+07  0.000121  N3
96     129.802689  1.167292e+07  0.000173  N3
98     286.121791  2.376138e+07  0.000372  N3
102   1766.158443  4.743891e+05  0.000940  N3
106    307.205007  7.949271e+06  0.000346  N3
111    657.977234  5.047649e+06  0.003162  N3
113    424.540621  2.048876e+08  0.000277  N3
115   1591.044722  5.051843e+06  0.000230  N3
119    663.226873  2.203814e+06  0.000565  N3
121    216.778679  2.882108e+06  0.000623  N3
126    302.807136  1.635488e+08  0.000204  N3
130     51.094968  4.744499e+08  0.000126  N3
132    555.668905  4.273410e+07  0.000158  N3
137     25.364101  3.148235e+07  0.000190  N3
140    459.117927  2.925963e+07  0.000163  N3
145    577.772239  3.294283e+07  0.000260  N3
149    266.383254  4.062186e+07  0.000196  N3
153    677.864444  1.908625e+07  0.000203  N3
154    623.961387  2.925272e+07  0.000156  N3
158    805.499974  1.381545e+07  0.000045  N3
163    296.452757  6.754039e+06  0.000063  N3

[43 rows x 39 columns]
```

[137]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_c.iloc[:,:37])
```

```python
X_train=X[:int(len(X)*0.75)]
```

[138]:
```python
# Run local implementation of kmeans
model = KMeans(n_clusters=2, max_iter=100, init='random',n_init=10)
```

[139]:
```python
model.fit(X)
```

[139]:
```
KMeans(init='random', max_iter=100, n_clusters=2)
```

[140]:
```python
#Obtaining clusters centroid
centroids = model.cluster_centers_
```

[141]:
```python
centroids
```

[141]:
```
array([[ 0.9022813 ,  0.94666278,  0.94364226,  0.96600637,  0.92142726,
         0.91359058,  0.78781903,  0.86812783,  0.84073075,  0.91252208,
         0.83504189,  0.84035134,  0.64084523,  0.83582256,  0.78937134,
         0.83271777,  0.82464295,  0.82983492,  0.89916541,  0.94996185,
         0.94533212,  0.96746171,  0.92697076,  0.91912787,  0.77404641,
         0.86492543,  0.83912937,  0.91035214,  0.84266109,  0.84449831,
         0.61796436,  0.83180087,  0.77590607,  0.83014204,  0.83089472,
         0.83230979, -0.28308837],
       [-0.64964254, -0.6815972 , -0.67942243, -0.69552458, -0.66342762,
        -0.65778521, -0.5672297 , -0.62505204, -0.60532614, -0.65701589,
        -0.60123016, -0.60505296, -0.46140856, -0.60179224, -0.56834737,
        -0.5995568 , -0.59374292, -0.59748114, -0.64739909, -0.68397253,
        -0.68063912, -0.69657243, -0.66741894, -0.66177207, -0.55731341,
        -0.62274631, -0.60417314, -0.65545354, -0.60671598, -0.60803878,
        -0.44493434, -0.59889663, -0.55865237, -0.59770227, -0.5982442 ,
        -0.59926305,  0.20382363]])
```

[142]:
```python
centroids[0]-centroids[1]
```

[142]:
```
array([ 1.55192384,  1.62825998,  1.62306469,  1.66153095,  1.58485488,
        1.57137579,  1.35504874,  1.49317986,  1.44605689,  1.56953797,
        1.43627205,  1.44540431,  1.10225379,  1.43761481,  1.35771871,
        1.43227457,  1.41838587,  1.42731607,  1.5465645 ,  1.63393438,
        1.62597124,  1.66403414,  1.5943897 ,  1.58089994,  1.33135982,
        1.48767174,  1.44330251,  1.56580567,  1.44937707,  1.45253709,
        1.0628987 ,  1.4306975 ,  1.33455845,  1.42784432,  1.42913892,
        1.43157284, -0.486912  ])
```

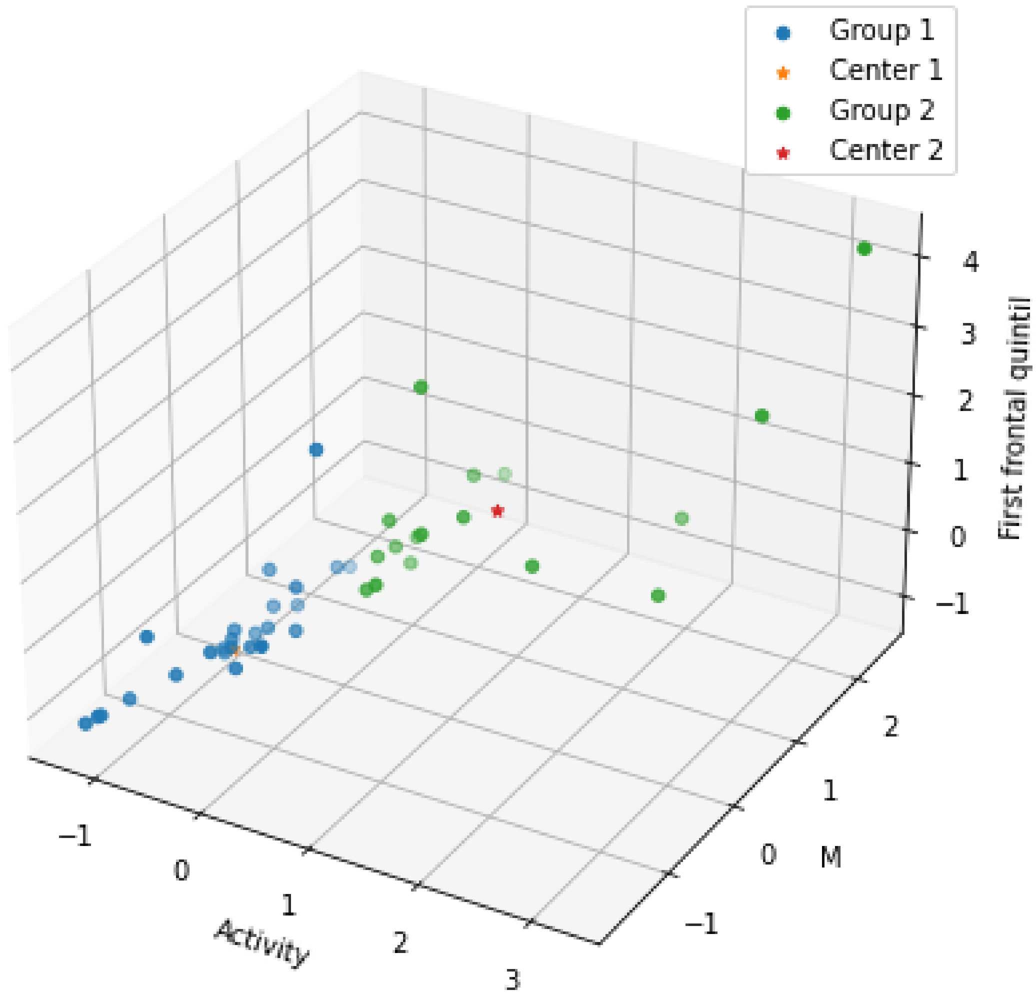
[143]:
```python
#To obtain the labels of each cluster
labels = model.labels_
```

[144]:

```
# Creating figure
fig = plt.figure(figsize = (10, 7))
ax = plt.axes(projection ="3d")
x=-2
y=1
z=30
ax.scatter3D(X[labels>0][:,x],X[labels>0][:,y],X[labels>0][:,z],label="Group 1")
ax.scatter3D(centroids[1,x],centroids[1,y],centroids[1,0],label="Center␣
 ↪1",marker='*')
ax.scatter3D(X[labels<1][:,x],X[labels<1][:,y],X[labels<1][:,z],label="Group 2")
ax.scatter3D(centroids[0,x],centroids[0,y],centroids[0,z],label="Center␣
 ↪2",marker='*')
ax.set_ylabel("M")
ax.set_xlabel("Activity")
ax.set_zlabel("First frontal quintil")
ax.legend()
```

[144]:

```
<matplotlib.legend.Legend at 0x7fa2be9241f0>
```



Observations:

- The results are very similar to the ones obtained in the N2 stage
- The first group corresponds to the more extreme data while the second one has the mayority of the sub-segments
- All the parameters expect the mobility are higher in the first goup

0.11 Temporal lobe collapse

In order to reduce the number of parameters we will colapse the parameters of the two two temporal lobes into a single group.

[168]:
```
data=pd.read_csv("Extracted_data/Data_medians_4.csv")
del data['Unnamed: 0']
del data['38']
```

[169]:

```
data_t=data
```

[170]:

```
data_t
```

[170]:

```
             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

[165 rows x 39 columns]
```

To collapse the values of both temporal lobes, we must find a way to calculate averages and standard deviations of two groups of the same size. Average is pretty straightforward. Just remember the equations:

$M_1 = \frac{1}{n_1}\sum_{n=1}^{n_1} X_n$

$M_2 = \frac{1}{n_2}\sum_{n=1}^{n_2} Y_n$

$M_t = \frac{1}{n_1+n_2}(\sum_{n=1}^{n_1} X_n + \sum_{n=1}^{n_2} Y_n)$

Note that $n_1 = n_2 = N$, so:

$M_t = \frac{1}{2N}(\sum_{n=1}^{N} X_n + \sum_{n=1}^{N} Y_n)$

$\therefore M_t = \frac{M_1+M_2}{2}$

[148]:
```
for i in range(0,len(data_t)):
     #We collapse the averages of the first quintile
    data_t.iloc[i,1]=(data.iloc[i,1]+data.iloc[i,2])/2
     # We collapse the averages of the second quintile
    data_t.iloc[i,7]=(data.iloc[i,7]+data.iloc[i,8])/2
     # We collapse the averages of the third quintile
    data_t.iloc[i,13]=(data.iloc[i,13]+data.iloc[i,14])/2

#Remove collapsed data columns
del data_t['2']
del data_t["8"]
del data_t["14"]
```

Now we are going to collapse the standard deviations. Let us remember that:

$S_1 = \sqrt{\frac{1}{n_1}\sum_{i=1}^{n_1}(x_i - \bar{x}_1)^2}$

$S_2 = \sqrt{\frac{1}{n_2}\sum_{i=1}^{n_2}(y_i - \bar{y}_2)^2}$

$S_t = \sqrt{\frac{1}{2N}\sum_{i=1}^{N}(x_i - \bar{y})^2 + (y_i - \bar{y})^2}$

En donde $\bar{y} = \frac{\bar{x}_1+\bar{y}_2}{2}$

$$\rightarrow S_t = \sqrt{\frac{1}{2N}\sum_{i=1}^{N}(x_i - \frac{\bar{x}_1+\bar{y}_2}{2})^2 + (y_i - \frac{\bar{x}_1+\bar{y}_2}{2})^2}$$

$$\rightarrow S_t = \sqrt{\frac{1}{2N}\sum_{i=1}^{N} x_i^2 - x_i(\bar{x}_1+\bar{y}_2) + \frac{(\bar{x}_1+\bar{y}_2)^2}{4} + y_i^2 - y_i(\bar{x}_1+\bar{y}_2) + \frac{(\bar{x}_1+\bar{y}_2)^2}{4}}$$

$$\rightarrow S_t = \sqrt{\frac{1}{2N}\sum_{i=1}^{N} x_i^2 - (x_i+y_i)(\bar{x}_1+\bar{y}_2) + \frac{(\bar{x}_1+\bar{y}_2)^2}{2} + y_i^2}$$

$$\rightarrow S_t = \sqrt{\frac{1}{2N}\sum_{i=1}^{N} x_i^2 - (x_i\bar{x}_1 + x_i\bar{y}_2 + y_i\bar{x}_1 + y_i\bar{y}_2) + \frac{(\bar{x}_1+\bar{y}_2)^2}{2} + y_i^2}$$

From the standard deviations of the individual groups we can derive that:

$$n_1 S_1^2 = \sum_{i=1}^{n_1}(x_i - \bar{x})^2$$

$$n_2 S_2^2 = \sum_{i=1}^{n_2}(y_i - \bar{y})^2$$

$$S_t = \sqrt{\frac{1}{2N}(NS_1^2 + NS_2^2 + N(\bar{y}_1 - \bar{y})^2 + N(\bar{y}_2 - \bar{y})^2)}$$

$$\therefore S_t = \sqrt{\frac{1}{2}(S_1^2 + S_2^2 + (\bar{y}_1 - \bar{y})^2 + (\bar{y}_2 - \bar{y})^2)}$$

[149]:
```
data_t.loc[0,'1']
```

[149]: 20.863888888888887

[150]:
```
for i in range(0,len(data_t)):
     #We collapse the standard deviations of the first quintile
    data_t.iloc[i,19]=((data.iloc[i,19]**2+data.iloc[i,20]**2+(data.
 ↪iloc[i,1]-data_t.loc[i ,'1'])**2+(data.iloc[i,2]-data_t.loc[i,'1'])**2)/
 ↪2)**0.5
     # We collapse the standard deviations of the second quintile
    data_t.iloc[i,25]=((data.iloc[i,25]**2+data.iloc[i,26]**2+(data.
 ↪iloc[i,7]-data_t.loc[i ,'7'])**2+(data.iloc[i,8]-data_t.loc[i,'7'])**2)/
 ↪2)**0.5
     # We collapse the standard deviations of the third quintile
    data_t.iloc[i,31]=((data.iloc[i,31]**2+data.iloc[i,32]**2+(data.
 ↪iloc[i,13]-data_t.loc[i ,'13'])**2+(data.iloc[i,14]-data_t.loc[i,'13'])**2)/
 ↪2)**0.5

#Remove collapsed data columns
del data_t['20']
del data_t['26']
del data_t['32']
```

[151]:
```
np.shape(data_t)
```

[151]: (165, 33)

Notice that we managed to go down 6 dimensions.

0.11.1 K means

[152]:
```
# 0: Awake
# 1: N1
# 2: N2
# 3: N3
# 4: REM

for i in range(0,len(data_t)):
    if data_t.iloc[i,-1]=='Awake':
        data_t.iloc[i,-1]=0
    elif data_t.iloc[i,-1]=='N1':
        data_t.iloc[i,-1]=1
    elif data_t.iloc[i,-1]=='N2':
        data_t.iloc[i,-1]=2
    elif data_t.iloc[i,-1]=='N3':
        data_t.iloc[i,-1]=3
    elif data_t.iloc[i,-1]=='REM':
        data_t.iloc[i,-1]=4
    else:
        data_t.iloc[i,-1]=np.nan
```

[153]:
```
data_t2=data_t.dropna()
```

[154]:
```
data_t2
```

[154]:
```
             0          1          3          4          5           6  \
0    19.911429  20.863889  19.076667  21.918889  14.850000   58.638571
1    40.660000  37.111111  42.591111  40.958889  37.191667  148.707143
2    28.203333  25.277222  33.302222  28.286667  24.416667  104.157619
3    18.286190  16.874444  22.212222  18.586667  15.928333   72.619048
4    11.339524  10.700556   9.653333  12.070000  10.046667   42.745238
..         …          …          …          …        …          …
160  23.572857  21.947778  24.652222  19.970000  18.556667   62.023810
161  18.736190  17.328333  19.476667  16.011111  14.800000   47.885238
162  14.926190  13.982222  15.434444  12.957778  11.726667   37.418571
163  10.816190   9.957778  10.985556   9.072222   8.145000   27.838095
164   4.886190   4.542778   4.972222   4.191111   3.780000   12.803333

              7           9          10          11  …         28  \
0     61.300556   57.580000   54.570000   43.411667  …  240.741312
1    115.497778  180.642222  136.624444  117.346667  …  663.806544
2     77.783889  141.416667   91.605556   77.440000  …  439.829679
3     55.201111   98.113333   65.053333   53.331667  …  293.769864
4     34.170000   37.300000   41.403333   33.041667  …  179.658886
..          …          …          …          …  …          …
160   58.897778   65.027778   46.384444   46.100000  …  235.548155
```

```
161   45.166667   49.993333   35.975556   35.510000  …  180.235205
162   35.437222   38.766667   28.706667   27.921667  …  139.774550
163   26.197778   28.534444   20.034444   19.595000  …  101.098596
164   12.726667   14.298889   10.335556    9.438333  …   43.916360

             29           30           31           33           34  \
0    210.934721   627.235043   648.175431   643.377231   518.721683
1    601.949326  2122.510839  1710.063114  3062.885569  1934.006195
2    395.701329  1433.984345  1147.643210  2268.983257  1277.791388
3    258.530174   951.861362   774.702891  1493.072896   868.889384
4    156.242749   587.817203   465.337699   546.078070   544.583428
..          …            …            …            …            …
160  233.876713   956.606279   901.840306  1000.445620   648.364502
161  179.285611   731.916047   694.028468   759.237127   494.270849
162  137.755238   558.178258   505.701924   566.989604   378.484287
163   99.599288   449.385031   411.347601   459.417619   285.576327
164   41.261791   165.142991   188.748088   206.167366   116.909527

              35            36        37  39
0     495.039453  4.422272e+07  0.001152   0
1    1750.616297  2.508360e+06  0.002201   2
2    1170.567469  1.469640e+06  0.001673   4
3     787.208156  5.040967e+06  0.002785   2
4     465.555425  9.224363e+06  0.001658   3
..           …             …         …  ..
160   663.898963  1.033058e+05  0.000996   4
161   509.926345  3.701008e+04  0.000528   1
162   390.608436  9.521701e+04  0.000363   2
163   296.452757  6.754039e+06  0.000063   3
164   109.744217  2.577399e+06  0.000092   2

[157 rows x 33 columns]
```

[155]:
```
# Standardize the data
X = StandardScaler().fit_transform(data_t2.iloc[:,:32])

Y=data_t2.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.85)]
X_test=X[int(len(X)*0.85):]

Y_train=Y[:int(len(X)*0.85)]
Y_test=Y[int(len(X)*0.85):]
```

[156]:
```
# Run local implementation of kmeans
model = KMeans(n_clusters=5, max_iter=100, init='random',n_init=10)
```

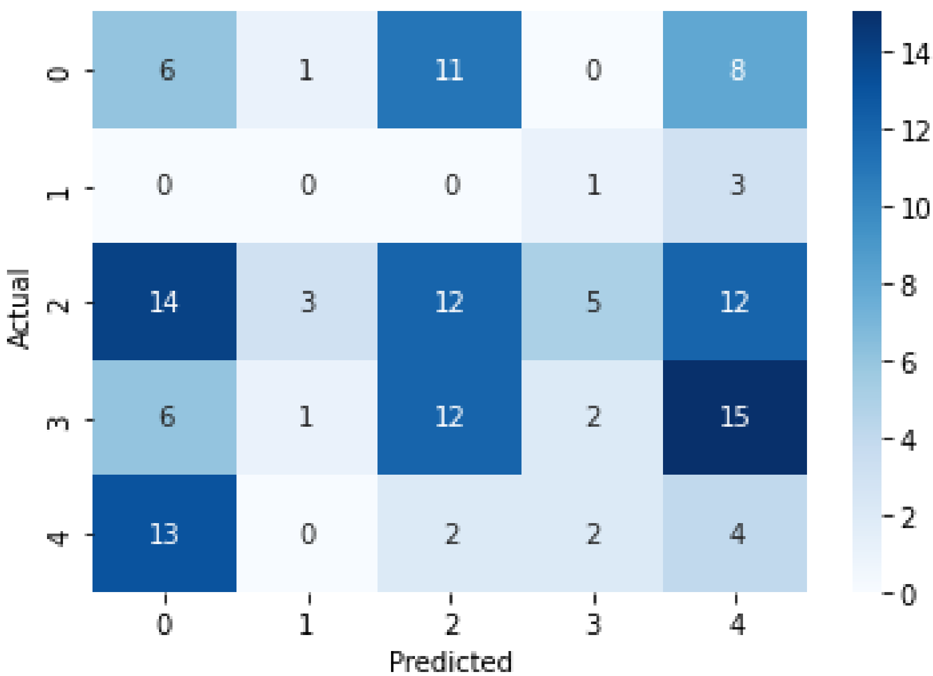
[157]:
```
model.fit(X_train)
```

[157]: KMeans(init='random', max_iter=100, n_clusters=5)

[158]:
```
#Obtaining clusters centroid
centroids = model.cluster_centers_

#To obtain the labels of each cluster
labels = model.labels_
```

[159]:
```
y_pred=model.predict(X_train)
```

[160]:
```
confusion_matrix = pd.crosstab(Y_train, y_pred, rownames=['Actual'],
↪colnames=['Predicted'])

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



Observations:

- By adding the Hjorth parameters the accuracy to identify REM stages increased, however the N2 segment indentifiaction is worse.
- Some N2 and N3 segments have similar properties to the awake class.
- Other N2 segments were misidentified as REM.

0.11.2 K neighbors

Now we will try a clustering by neighbors method. By using this type of algorithm we hope to be able to find a big difference between the awake, NREM and REM segments. Classification between NREM stages (N1, N2, N3) might not be accurate because they correspond to a gradual progress. This means that some points of a N2 stage might be closer to a N3 segment than another N2 segment.

[171]:
```
for i in range(0,len(data_t)):
    if data_t.iloc[i,-1]!='Awake':
        if data_t.iloc[i,-1]!='N2':
            if data_t.iloc[i,-1]!='N3':
                if data_t.iloc[i,-1]!='REM':
                    data_t.iloc[i,-1]=np.nan
```

[172]:
```
data_t
```

[172]:
```
             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    NaN
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

[165 rows x 39 columns]
```

[173]:
```python
data_t3=data_t.dropna()
```

[174]:
```python
# Standardize the data
X = StandardScaler().fit_transform(data_t3.iloc[:,:32])

Y=data_t3.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.75)]
X_test=X[int(len(X)*0.75):]

Y_train=Y[:int(len(X)*0.75)]
Y_test=Y[int(len(X)*0.75):]
```

[175]:
```python
k_neighbor=KNeighborsClassifier(5)
```

[176]:
```python
print(np.shape(X_train))
print(np.shape(Y_train))
```

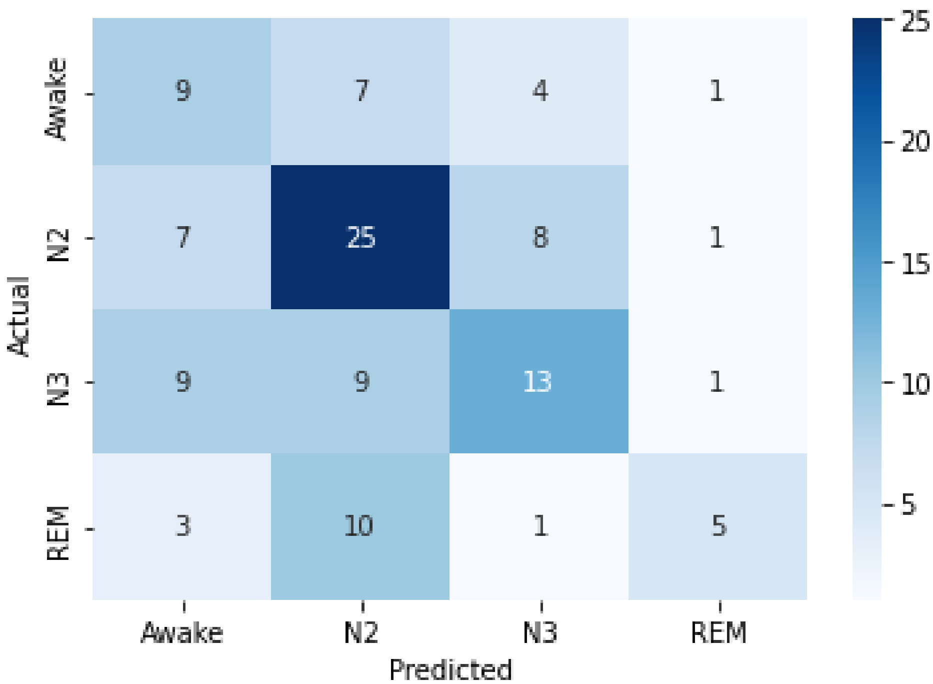
```
(113, 32)
(113,)
```

[177]:
```python
k_neighbor.fit(X_train,Y_train)
```

[177]:
```
KNeighborsClassifier()
```

[178]:
```
y_pred=k_neighbor.predict(X_train)
```

[179]:
```
confusion_matrix = pd.crosstab(Y_train, y_pred, rownames=['Actual'],␣
↪colnames=['Predicted'])

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

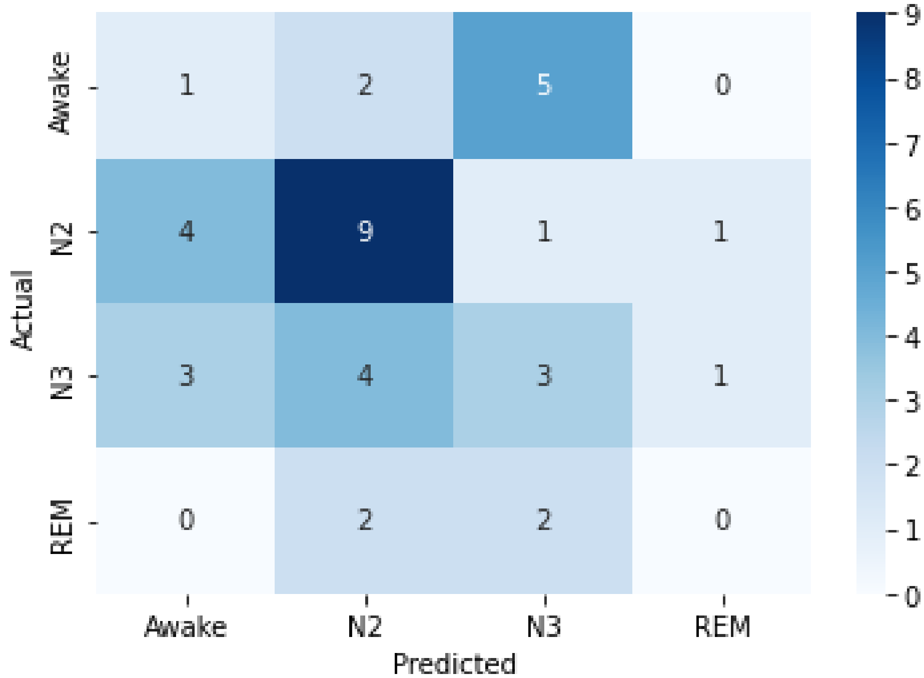


[180]:
```
sum(confusion_matrix.iloc[i,i] for i in range(0,len(confusion_matrix)))/
↪len(Y_train)
```

[180]: 0.46017699115044247

[181]:
```
y_pred=k_neighbor.predict(X_test)
```

[182]:
```
confusion_matrix = pd.crosstab(Y_test, y_pred, rownames=['Actual'],␣
↪colnames=['Predicted'])

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




```
[183]: sum(confusion_matrix.iloc[i,i] for i in range(0,len(confusion_matrix)))/
       ↪len(Y_test)
```

```
[183]: 0.34210526315789475
```

Observations: * Our initial hypothesis proved to be completely wrong. The results concluded the opposite to what we expected. * Differences beween N2 and N3 segments was outstanding. The identification of REM and Awake segments was an absolute caos. Most of the REM segments were classified as N2 and most of the awake sagments were classified as N3.

0.11.3 N1 vs N2 vs REM

Now we will try the same neighbors clustering analysis but excluding the awake segments. To distinguish between awake and asleep an ECG is a far better method than an EEG.

```
[184]: for i in range(0,len(data_t)):
           if data_t.iloc[i,-1]!='N2':
               if data_t.iloc[i,-1]!='N3':
                   if data_t.iloc[i,-1]!='REM':
                       data_t.iloc[i,-1]=np.nan
```

```
[185]: data_t4=data_t.dropna()
```

```
[186]: # Standardize the data
       X = StandardScaler().fit_transform(data_t4.iloc[:,:32])
```

```
Y=data_t4.iloc[:,-1].to_numpy()

X_train=X[:int(len(X)*0.75)]
X_test=X[int(len(X)*0.75):]

Y_train=Y[:int(len(X)*0.75)]
Y_test=Y[int(len(X)*0.75):]
```

[187]:
```
k_neighbor=KNeighborsClassifier(3)
```

[188]:
```
print(np.shape(X_train))
print(np.shape(Y_train))
```

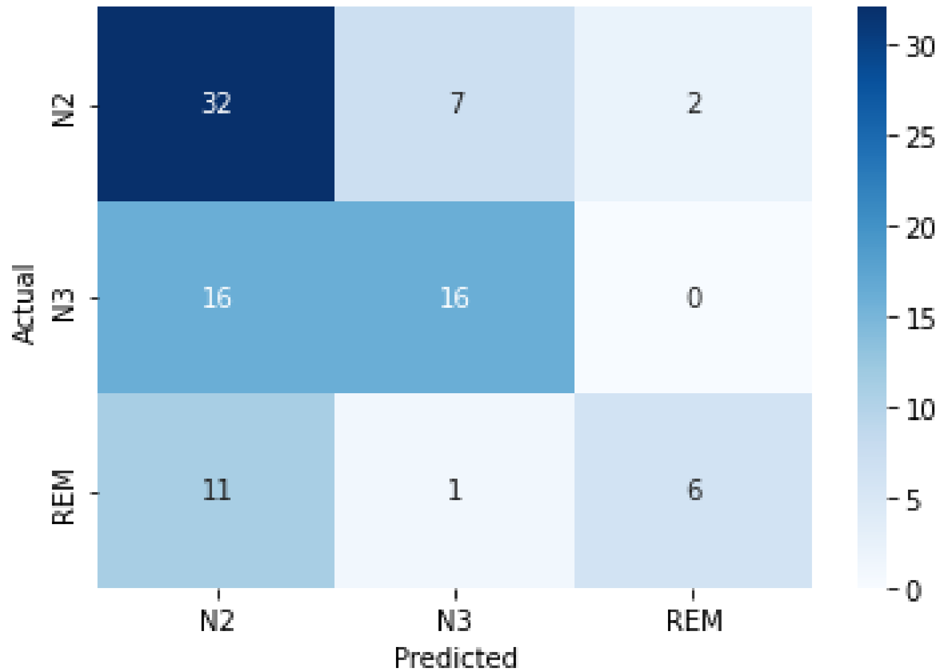
```
(91, 32)
(91,)
```

[189]:
```
k_neighbor.fit(X_train,Y_train)
```

[189]:
```
KNeighborsClassifier(n_neighbors=3)
```

[190]:
```
y_pred=k_neighbor.predict(X_train)
```

[191]:
```
confusion_matrix = pd.crosstab(Y_train, y_pred, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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

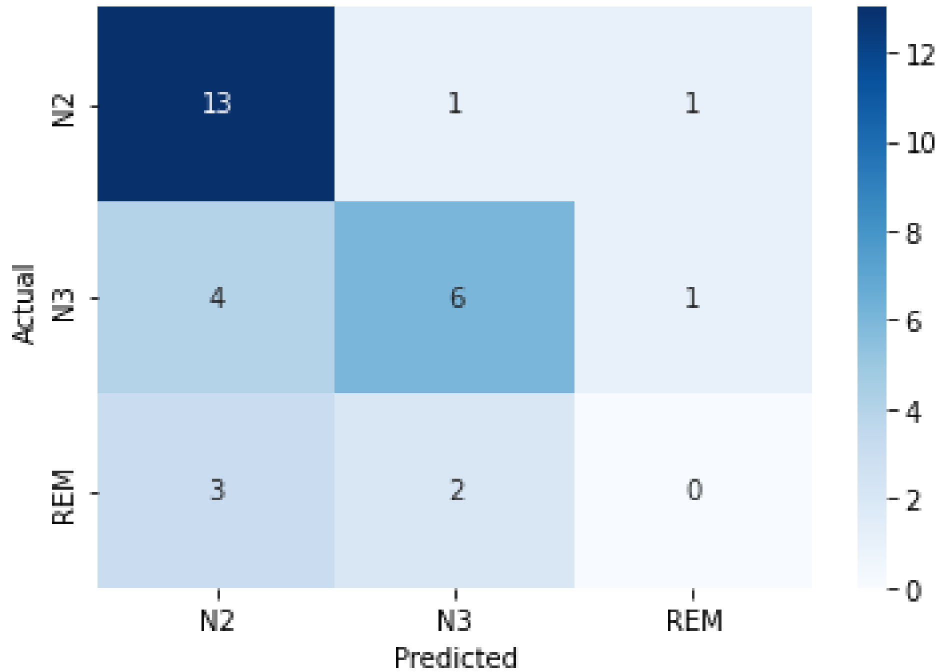


[192]:
```
sum(confusion_matrix.iloc[i,i] for i in range(0,len(confusion_matrix)))/
 ↪len(Y_train)
```

[192]: 0.5934065934065934

[193]:
```
y_pred=k_neighbor.predict(X_test)
```

[194]:
```
confusion_matrix = pd.crosstab(Y_test, y_pred, rownames=['Actual'],␣
 ↪colnames=['Predicted'])

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




```
[195]: sum(confusion_matrix.iloc[i,i] for i in range(0,len(confusion_matrix)))/
       ↪len(Y_test)
```

```
[195]: 0.6129032258064516
```

Observations: * This has been the best algorithm so far. * It has a general accuracy of 61.29% * There is a slight bias in the training because most of the segments correspond to the N2 stage. * REM identification isn't accurate

Sensibility and accuracy: * N2: * Sensitivity: 13/15=86.66% * PPV: 13/20=65% * N3: * Sensitivity: 6/11= 54.54% * PPV: 6/9= 66.66% * REM: * Sensitivity: 0% * PPV: 0%

```
[ ]:
```