ML results_231

August 6, 2018

```
In [1]: patid = '231'
```

```
In [4]: import pandas as pd
        import logging
        import numpy as np
        import sys
        import matplotlib.pyplot as plt
        import time
        import operator

        from sklearn.cross_validation import train_test_split
        from random import shuffle
        from sklearn.base import BaseEstimator, RegressorMixin
        from scipy.optimize import minimize
        from sklearn.model_selection import GridSearchCV, PredefinedSplit
        from sklearn.model_selection import ParameterGrid
        from sklearn.metrics import mean_squared_error, make_scorer

        from sklearn.model_selection import train_test_split
        from sklearn.model_selection import StratifiedKFold
        from sklearn.model_selection import GridSearchCV
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import confusion_matrix
        from sklearn.externals import joblib
        import jj_basic_fn as JJ
        from sklearn import ensemble
        import seaborn as sns
        %matplotlib inline

        #PLOT CONFUSION MATRIX
        from sklearn.metrics import confusion_matrix
        import itertools

        #matrix inverse
        from numpy.linalg import inv

        #default size of the graph
        plt.rcParams['figure.figsize'] = (10.0, 8.0)
```

```
%load_ext autoreload
%autoreload 2

pd.set_option('display.max_rows', 10)
pd.set_option('display.max_columns', 10)
pd.set_option('display.max_colwidth', -1)

n_classifier = 7
```

In [5]:
```
features_list = ['theta', 'alpha','beta', 'high_gamma']
plot_3d_var_list = ['high_gamma3', 'high_gamma4','beta4']
```

0.1 1. Data loading

0.1.1 What the data looks like

In [19]:
```
import pickle
data = pickle.load( open( "../data/ml_ready_data.p", "rb" ) )
# remove outliers
data = JJ.remove_outliers(data)
pd.set_option('display.max_rows', 10)
pd.set_option('display.max_columns', 10)

data
```

Out[19]:
```
          filename           region_start_time      delta1      delta2  \
86   1.309997e+17 2016-02-14 03:59:36.960000   61.166778  273.677298
87   1.310015e+17 2016-02-15 20:59:18.960000   40.548973  773.155101
88   1.310019e+17 2016-02-16 20:59:12.998400   41.771439  172.179808
89   1.310032e+17 2016-02-18 03:58:56.006400   42.171886  290.146546
90   1.310041e+17 2016-02-19 03:58:42.960000   45.669293  290.906731
..            ...                        ...         ...         ...
884  1.316288e+17 2018-02-11 15:51:35.971200  104.142656   43.925946
885  1.316296e+17 2018-02-11 21:51:24.998400  113.162000   50.395396
886  1.316296e+17 2018-02-12 03:51:23.011200  225.536331  153.708886
887  1.316296e+17 2018-02-12 09:51:21.974400   85.753303   34.006378
888  1.316296e+17 2018-02-12 15:51:21.024000   78.690558   35.500397

         delta3      ...         i34  epoch  label  patid  if_stimulated
86    33.567358      ...         0.0      0   True  222_1          False
87    25.976912      ...         0.0      0   True  222_1          False
88    32.841170      ...         0.0      0   True  222_1          False
89    36.623015      ...         0.0      0   True  222_1          False
90    25.191819      ...         0.0      0   True  222_1          False
..          ...      ...         ...    ...    ...    ...            ...
884  121.402267      ...         1.0     11  False    231           True
885   91.166914      ...         1.0     11  False    231           True
886  189.820605      ...         8.0     11  False    231           True
```

```
887  103.498303     ...       0.0      11  False    231            True
888   83.216243     ...       0.0      11  False    231            True

[2153 rows x 36 columns]
```

In [7]:
```python
pd.set_option('display.max_colwidth', 10000)
data_sp = JJ.select_data(data,select_dict = {'patid':'231'}, keep_list = ['patid','file
a = np.array(data_sp.sort_values(by=['high_gamma4']).filename)
#for i in range():
#    print('{:f}'.format(a[i]))
```

0.2 2. Building Classifiers

0.2.1 Fitting 7 classfier to the training data and tune the hyperparameter using 10-fold cross-validation. Evaluate the performance of each classifier using test data

0.2.2 1:'Logistic Regression' (regulation type, regulation parameter)

0.2.3 2: 'SVM' (kernel type, degreee, regulation type, regulation parameter)

0.2.4 3: 'Gaussian Naive Bayes classifier'

0.2.5 4:'Linear Discriminant Analysis'

0.2.6 5:'Decision Tree' (criterion for splliting, max depth, min sample per leaf)

0.2.7 6:'Random Forest' (criterion for splliting, number of trees, number of features used in each tree, max depth, min sample per leaf)

0.2.8 7:'Gradient Boosting' (number of estimator, number of samples used in each estimator, max depth, min sample per leaf, learning rate)

0.3 3. Classifier Performance

0.3.1 Performace Overview of each Classifier

In [11]:
```python
X_train, X_test, y_train, y_test = JJ.get_ml_data(data, patid, if_scaler = 1, if_remo

JJ.scores_estimators(X_test, y_test, patid = patid)
```

```
            Classifier       AUC
0    gradient boosting  0.842561
1        random forest  0.831488
2                  SVM  0.827957
3        decision tree  0.808538
4  Logistic Regression  0.793773


            Classifier  Accuracy
0    gradient boosting   0.82500
1        random forest   0.78750
2                  SVM   0.78125
3  Logistic Regression   0.76250
```

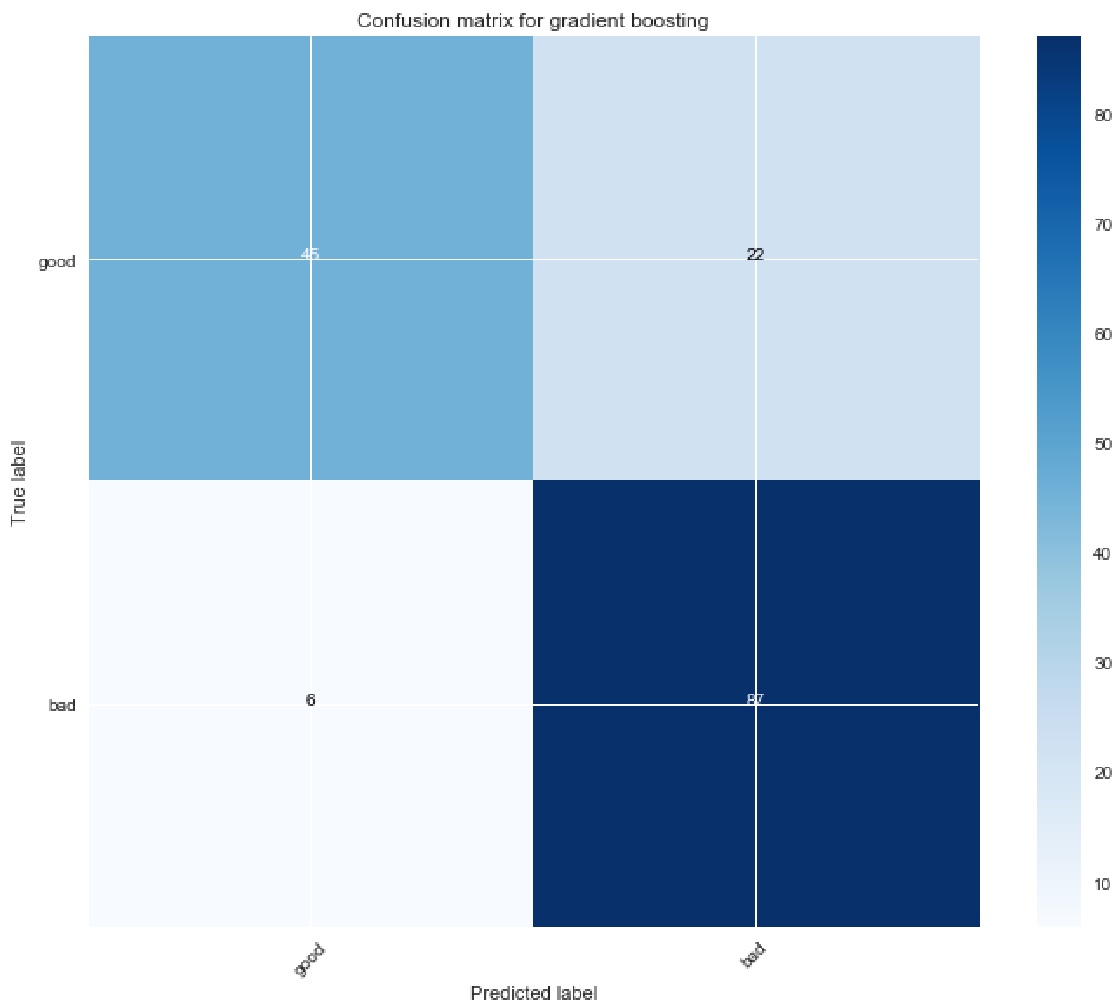
```
4        decision tree   0.75000
```

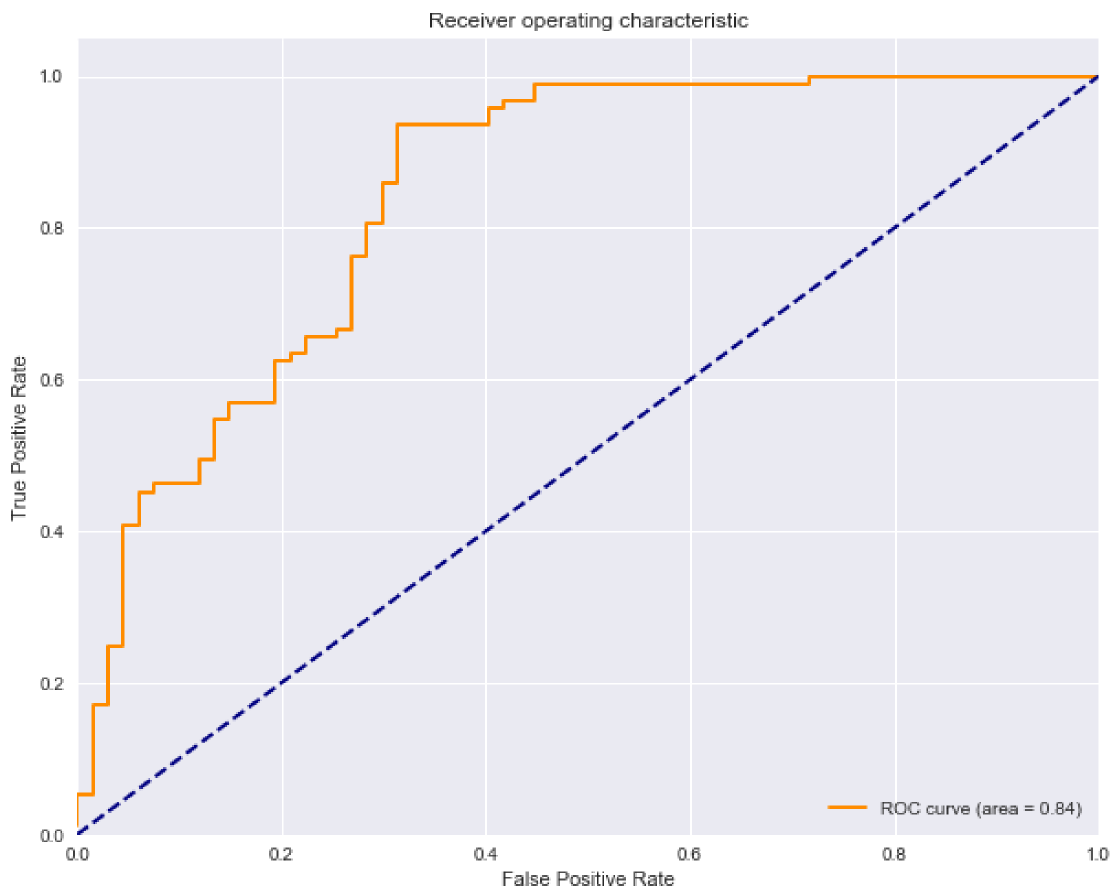
0.3.2 The confusion matrix and ROC of Gradient Boosting (the best classifier in this case)

```
In [12]: X_train, X_test, y_train, y_test = JJ.get_ml_data(data, patid, if_scaler = 1, if_remov

         JJ.estimator_performance(7, X_test, y_test, patid = patid, if_plot_c = 1, if_plot_roc
```

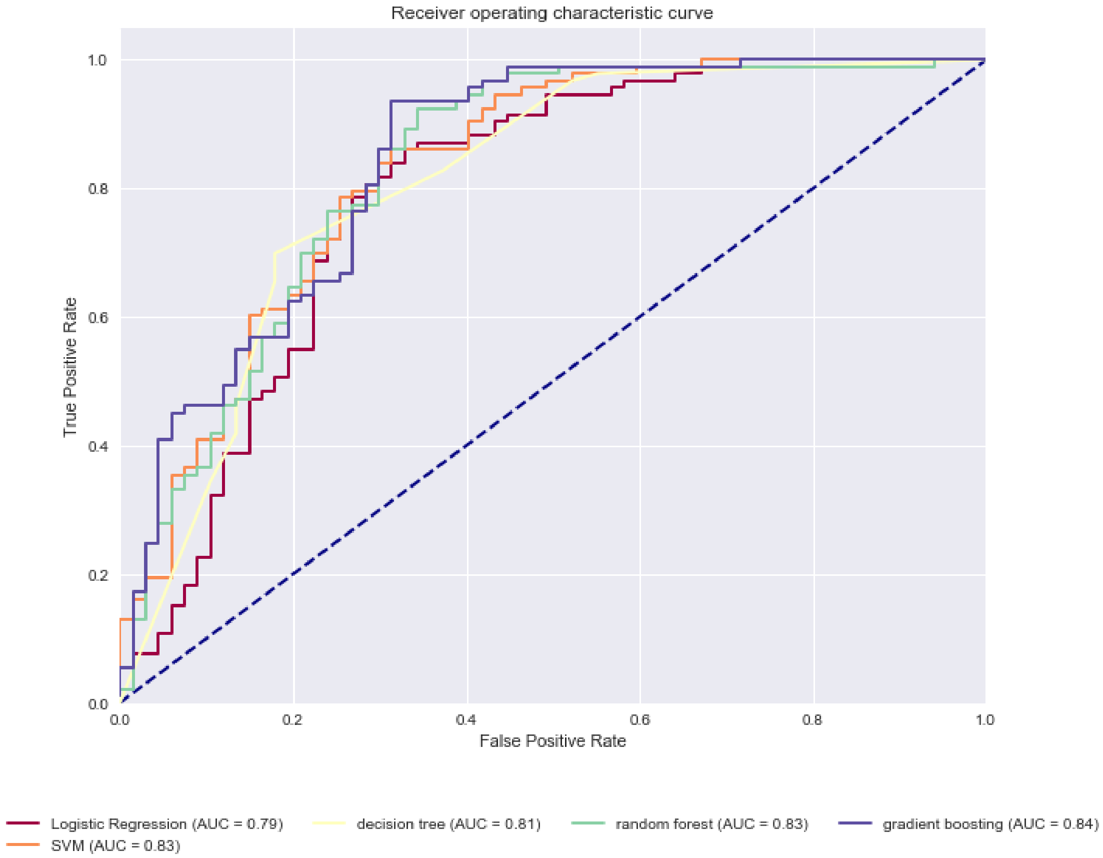
```
Confusion matrix, without normalization
```





0.3.3 ROC curve for all classifiers

```
In [13]: JJ.plot_roc_all(X_test, y_test, patid = patid)
```



0.3.4 Ensemble SVM, Logistic Regression, Random Forest and Gradient Boosting using hard vote

In [15]:
```
X_train, X_test, y_train, y_test = JJ.get_ml_data(data, patid, if_scaler = 1, if_remov
#parameter_tuning(X_train, X_test, y_train, y_test, classifier = 1, C_range_num = 100

print("The accuracy for ensemble model is")
JJ.ensemble_model(X_train, y_train, X_test, y_test, patid = patid,if_save = 0)
```

```
The accuracy for ensemble model is
0.825
```

0.4 4. Feature Importance

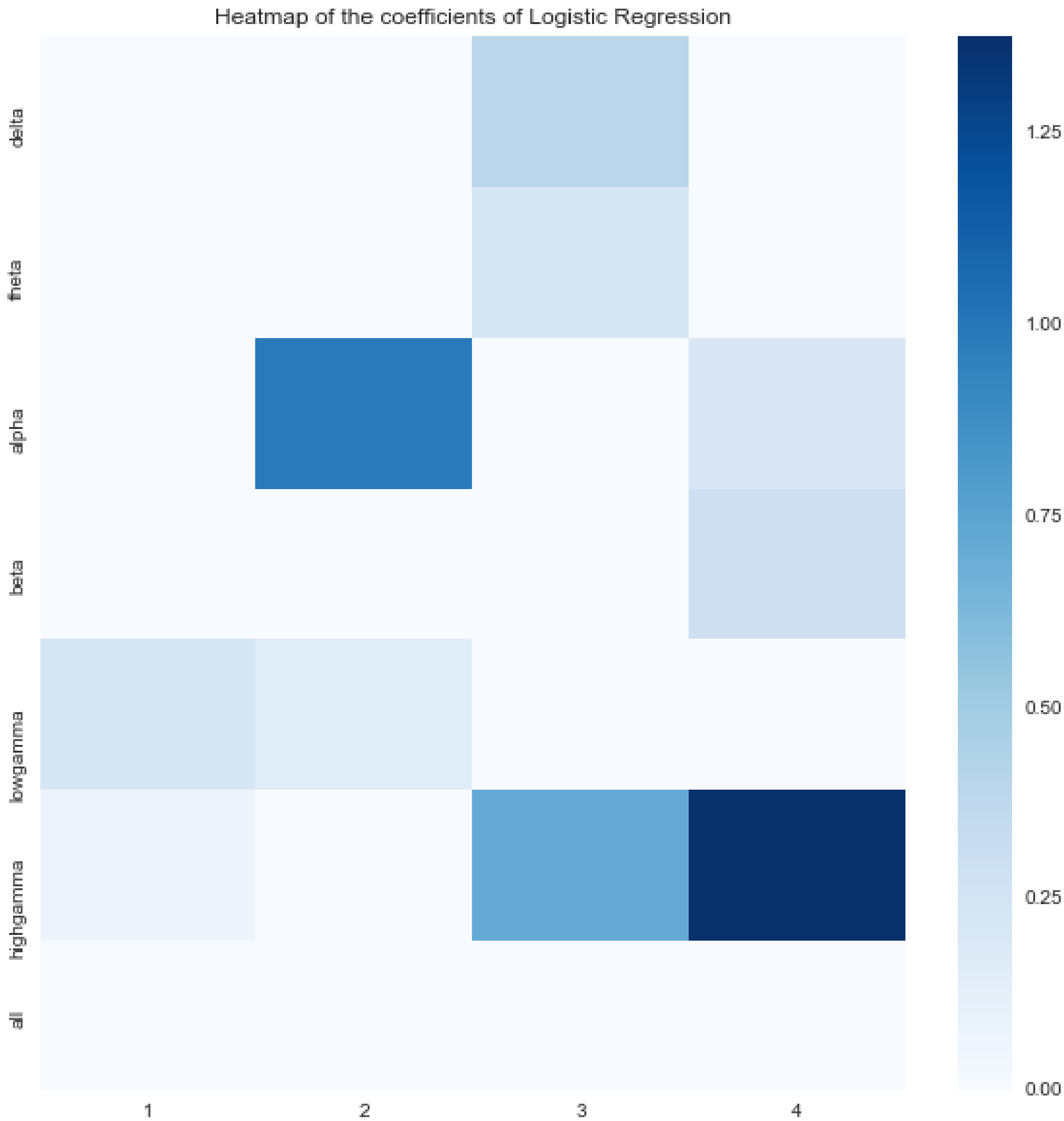
0.4.1 Feature Importance for Logistic regression

In [16]:
```
import matplotlib.pyplot as plt

prepath = '../estimators/'+patid + '/'
classifier_int = 1
```

```
int2name = {1:'Logistic Regression', 2: 'SVM', 3: 'Gaussian Naive Bayes classifier', 4
clf_name = int2name[classifier_int]
clf = pickle.load(open(prepath + 'best_estimator_for_' + str(clf_name) + '.p', "rb" ))
coef = np.abs(clf.coef_.reshape(7,4))
powerband = ['delta', 'theta', 'alpha', 'beta', 'lowgamma', 'highgamma', 'all'][::-1]
channel = ['1', '2', '3', '4']
df = pd.DataFrame(coef, index = powerband, columns = channel)
import seaborn as sns
fig = plt.figure()
fig, ax = plt.subplots(1,1, figsize=(10,10))
r = sns.heatmap(coef, cmap = "Blues")
r.set_title("Heatmap of the coefficients of {}".format(clf_name))
ax.set_yticklabels(df.index)
ax.set_xticklabels(df.columns)
plt.show()
```

```
<matplotlib.figure.Figure at 0x1a15880080>
```

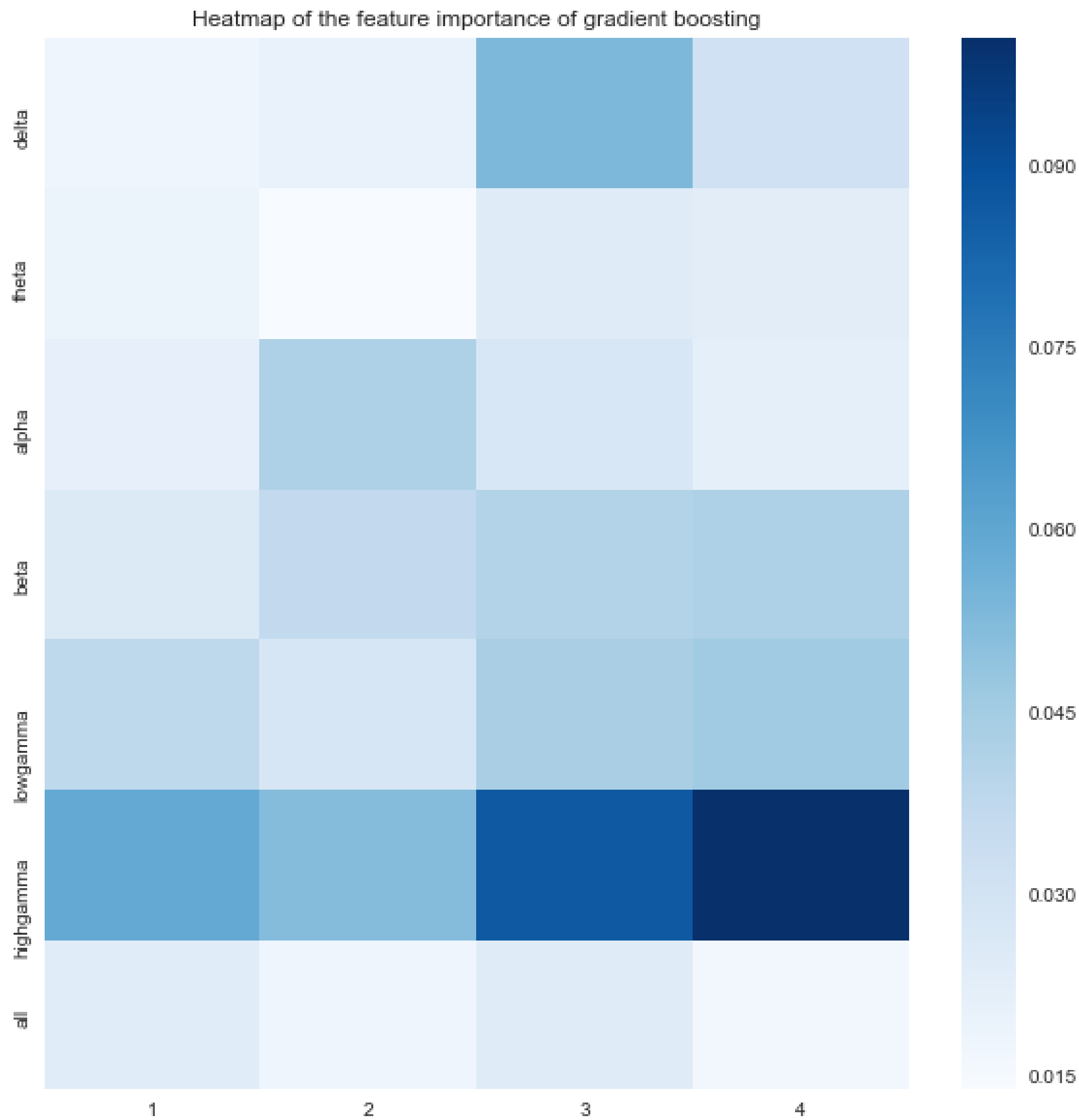


0.4.2 Feature Importance for Gradient Boosting

```
In [17]: import matplotlib.pyplot as plt
         %matplotlib inline
         prepath = '../estimators/'+patid + '/'
         classifier_int = 7
         int2name = {1:'Logistic Regression', 2: 'SVM', 3: 'Gaussian Naive Bayes classifier',
         clf_name = int2name[classifier_int]
         clf = pickle.load(open(prepath + 'best_estimator_for_' + str(clf_name) + '.p', "rb" ))
         coef = np.abs(clf.feature_importances_.reshape(7,4))
         powerband = ['delta', 'theta', 'alpha', 'beta', 'lowgamma', 'highgamma', 'all'][::-1]
```

```
channel = ['4', '3', '2', '1'][::-1]
df = pd.DataFrame(coef, index = powerband, columns = channel)
import seaborn as sns
fig = plt.figure()
fig, ax = plt.subplots(1,1, figsize=(10,10))
r = sns.heatmap(coef, cmap = "Blues")
r.set_title("Heatmap of the feature importance of {}".format(clf_name))
ax.set_yticklabels(df.index)
ax.set_xticklabels(df.columns)
sns.plt.show()
```

```
<matplotlib.figure.Figure at 0x1a15180cc0>
```



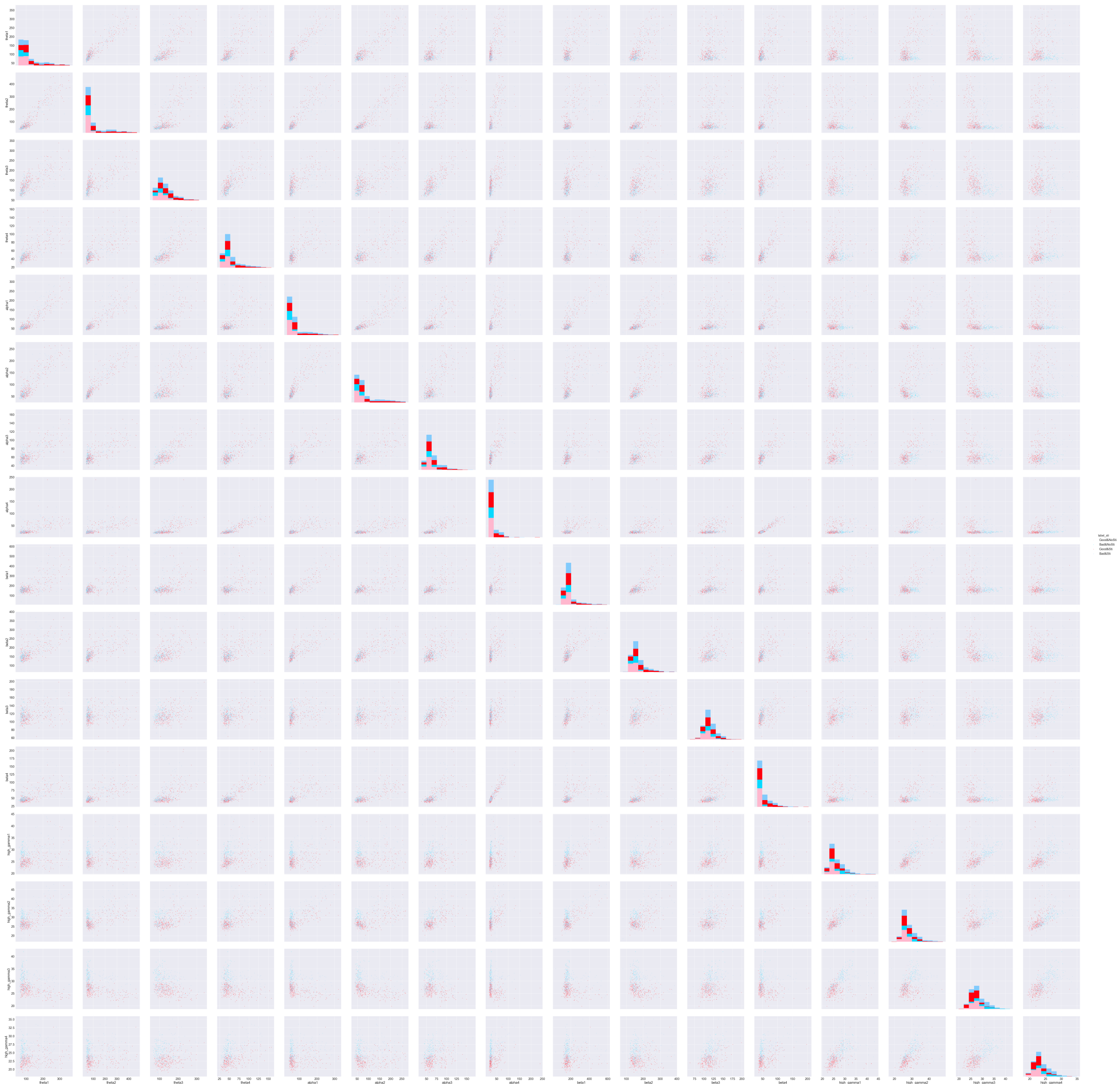
0.5 5. Data visualization

0.6 Pairwise features scatter plot

0.6.1 Each data point corresponds to a .dat file. Red points means it is in a good epoch, and blue points means it is in a bad epoch.

In [18]:
```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

data_ml = JJ.get_scatter_plot_data(data, patid)
sns.set(font_scale=2)
colors = ["baby pink", "neon blue", "bright red", "sky"]
#sns.pairplot(data_ml, hue="label_sti", size = 5, vars=JJ.get_variable_name(features_
g = sns.pairplot(data_ml, hue="label_sti", size = 6, vars=JJ.get_variable_name(feature
plt.savefig('../fig/scatter_231.png')
plt.show()
```



0.6.2 3D scatter plot

```
In [12]: %matplotlib notebook

         JJ.scatter_plot_3d(data,patid, var_list = plot_3d_var_list)
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

```
<IPython.core.display.HTML object>
```

```
In [ ]:
```