classifier

March 17, 2019

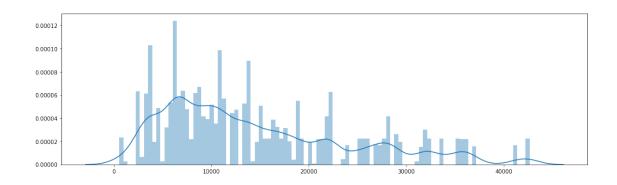
```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import matplotlib.path as mpath
        plt.rcParams['figure.figsize'] = [17, 5]
        from sklearn.linear_model import LogisticRegression
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.model_selection import train_test_split, cross_val_score
        from sklearn.grid_search import GridSearchCV
        from sklearn.metrics import precision_recall_curve, average_precision_score
        from scipy import stats
        import seaborn as sns
/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41: DeprecationWarning: This
  "This module will be removed in 0.20.", DeprecationWarning)
/anaconda3/lib/python3.6/site-packages/sklearn/grid_search.py:42: DeprecationWarning: This modul
  DeprecationWarning)
In [2]: # load data
        df_sub1 = pd.read_csv('./labeled_data/sub1label.csv')
        df_sub2 = pd.read_csv('./labeled_data/sub2label.csv')
        df_sub3 = pd.read_csv('./labeled_data/sub3label.csv')
        # drop unneccessary columns
        df_sub1.drop('Unnamed: 0', axis=1, inplace=True)
        df_sub2.drop('Unnamed: 0', axis=1, inplace=True)
        df_sub3.drop('Unnamed: 0', axis=1, inplace=True)
        df_subjects = pd.concat([df_sub1, df_sub2, df_sub3], keys=['s1', 's2', 's3'])
        df_true = df_subjects.loc[df_subjects['label'] == 1]
        df_false = df_subjects.loc[df_subjects['label'] == 0]
        df_subjects.head(10)
```

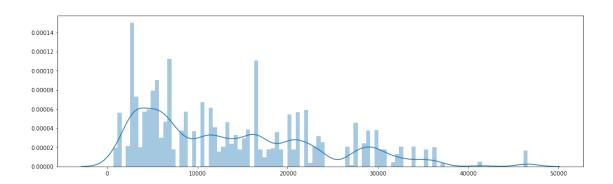
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Out [2]:
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\#df\_false = df\_false[np.abs(df\_false['high\_beta']-df\_false['high\_beta'].mean()) <= (3*df\_false[np.abs(df\_false['high\_beta']-df\_false['high\_beta'].mean()) <= (3*df\_false[np.abs(df\_false['high\_beta']-df\_false['high\_beta'].mean()) <= (3*df\_false[np.abs(df\_false['high\_beta']-df\_false['high\_beta'].mean()) <= (3*df\_false[np.abs(df\_false['high\_beta']-df\_false['high\_beta'].mean()) <= (3*df\_false['high\_beta']-df\_false['high\_beta'].mean()) <= (3*df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df\_false['high\_beta']-df
                            cols = list(df_subjects)
                            for c in cols:
                                          df_true = df_true[np.abs(df_true[c]-df_true[c].mean())<=(3*df_true[c].std())]
                                          df_false = df_false[np.abs(df_false[c]-df_false[c].mean())<=(3*df_false[c].std())]</pre>
                                          df_subjects = df_subjects[np.abs(df_subjects[c]-df_subjects[c].mean())<=(3*df_subjects[c]-df_subjects[c].mean())<=(3*df_subjects[c]-df_subjects[c]-df_subjects[c].mean())<=(3*df_subjects[c]-df_subjects[c]-df_subjects[c].mean())<=(3*df_subjects[c]-df_subjects[c]-df_subjects[c].mean())<=(3*df_subjects[c]-df_subjects[c]-df_subjects[c].mean())<=(3*df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-df_subjects[c]-d
In [4]: print(df_subjects.shape)
```

(109057, 14)

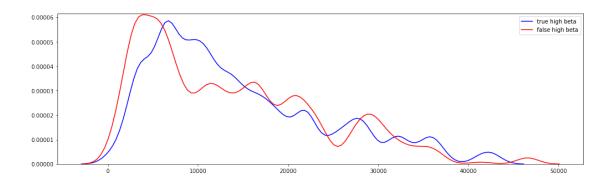
```
In [5]: sns.distplot(df_true['high_beta'].values, bins=100);
    plt.show()
    sns.distplot(df_false['high_beta'].values, bins=100);
    plt.show()
```

/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1633: FutureWarning: Using a non-tup return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval

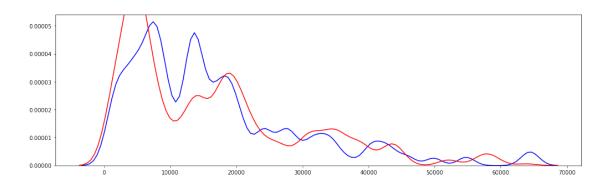




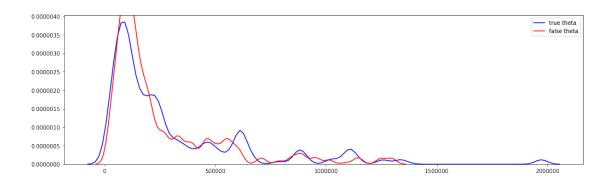
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1633: FutureWarning: Using a non-tup return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval



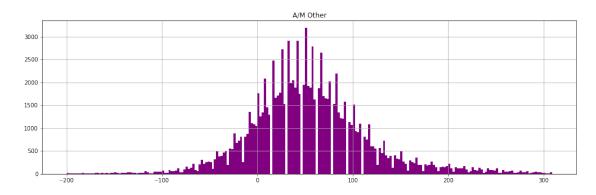
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1633: FutureWarning: Using a non-tup return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval

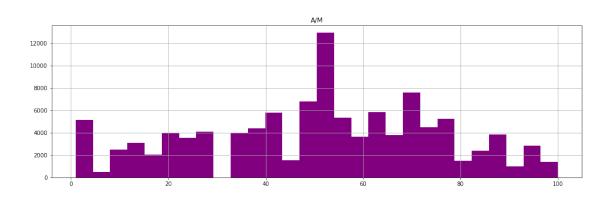


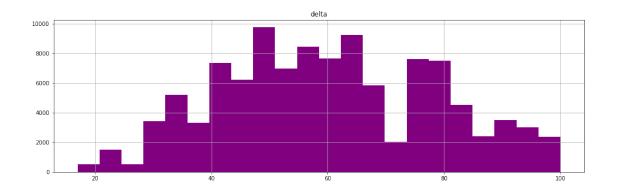
/anaconda3/lib/python3.6/site-packages/scipy/stats/stats.py:1633: FutureWarning: Using a non-tup return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval

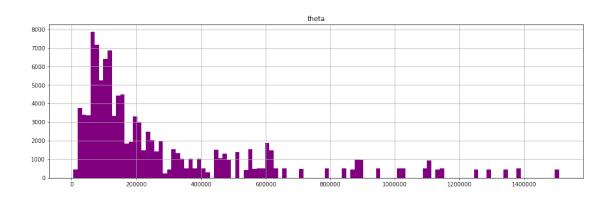


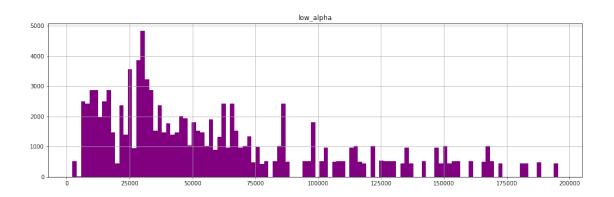
```
In [9]: # plot all features vs time
    cols = list(df_subjects)
    for c in cols:
        if (c == "Time") or (c == "label"):
            continue
        else:
            unique = df_subjects[c].nunique()
            unique /= 2
            df_subjects.hist(column=c, bins=round(unique), color="purple")
        plt.show()
```

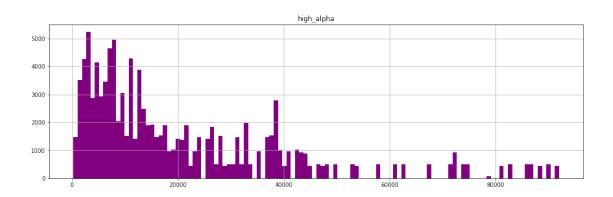


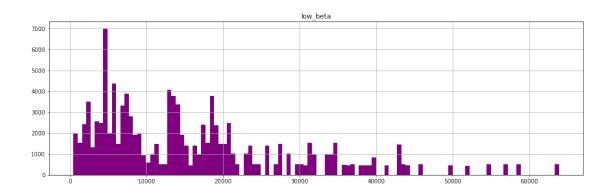


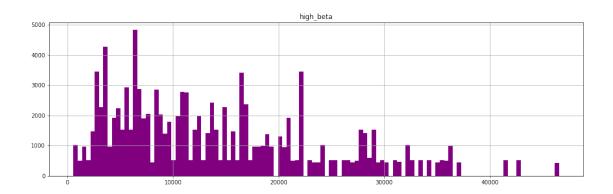


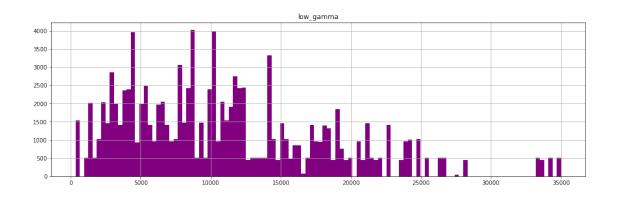


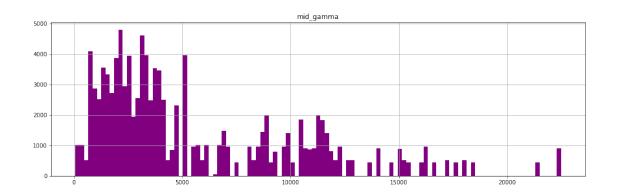


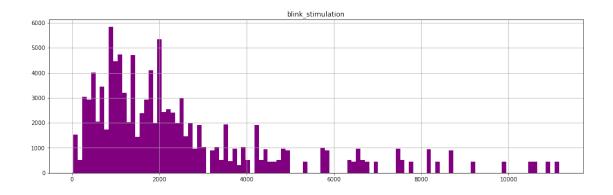


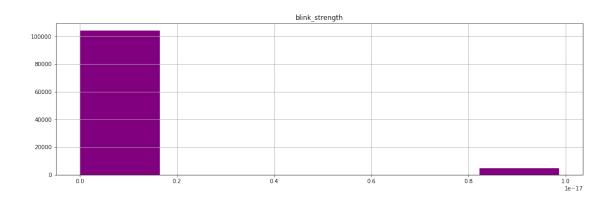


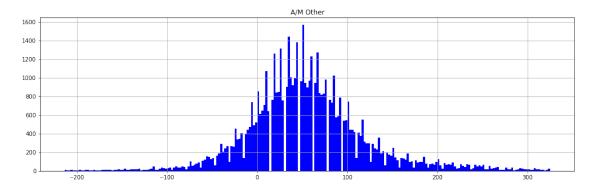


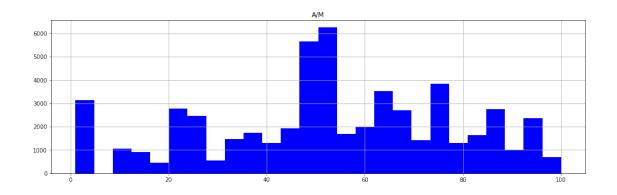


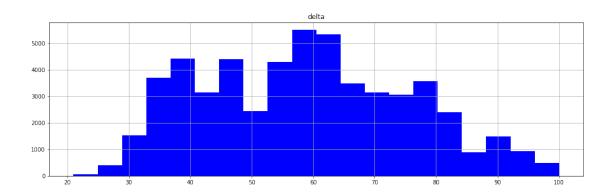


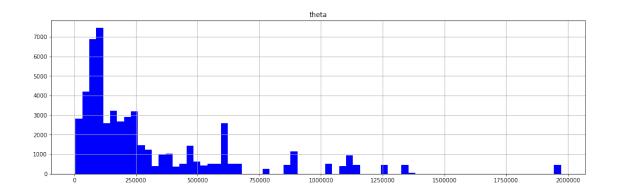


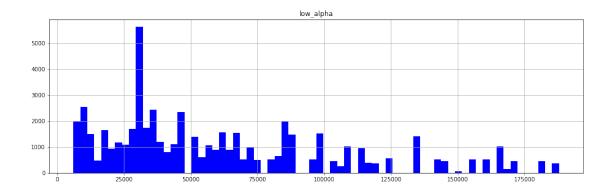


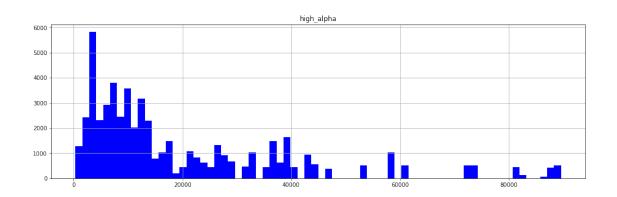


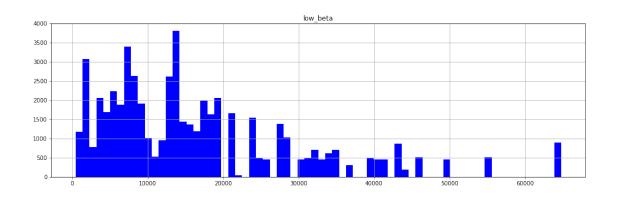


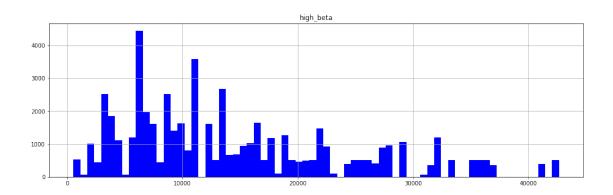


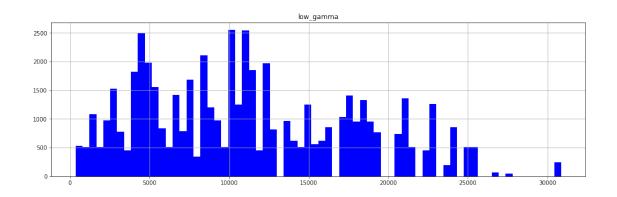


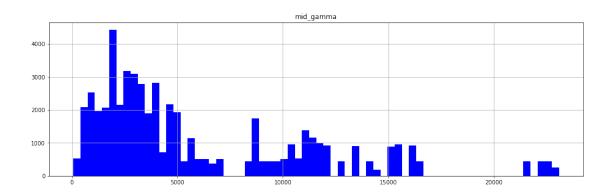


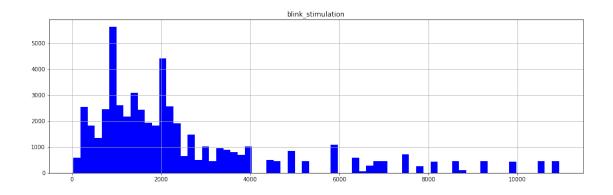


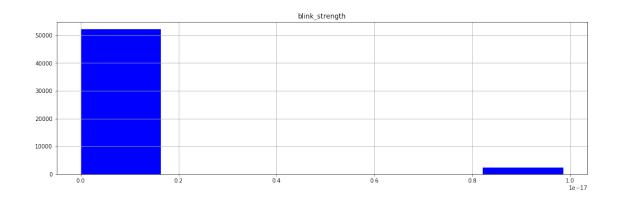


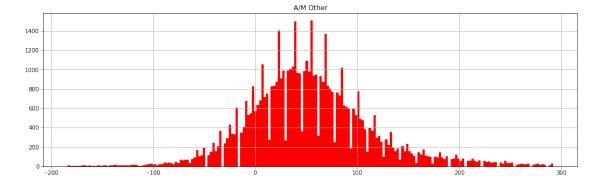


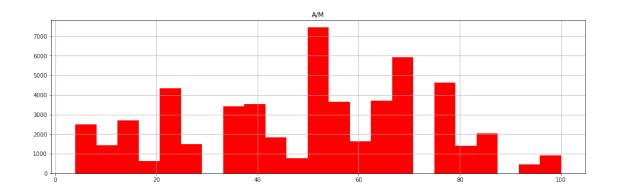


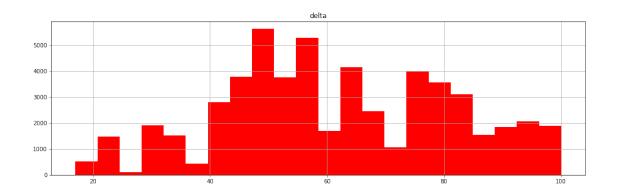


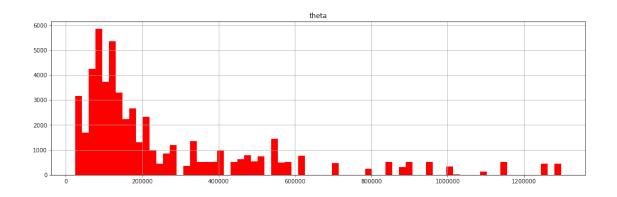


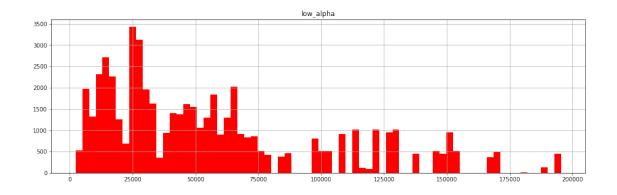


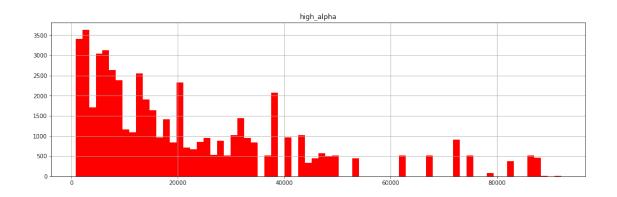


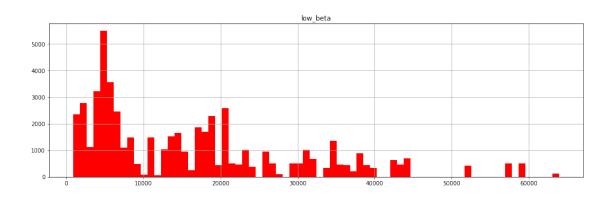


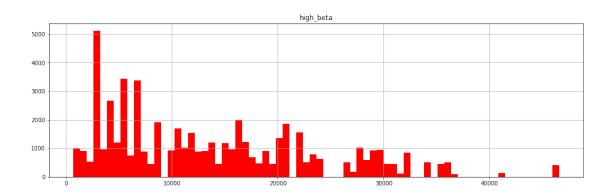


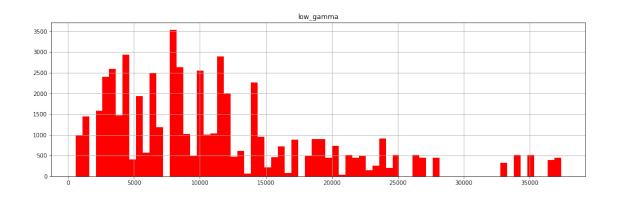


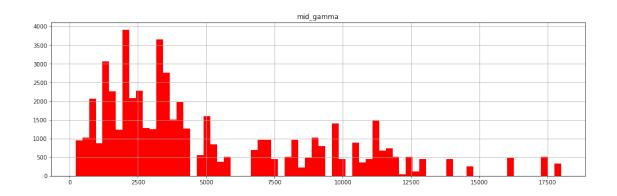


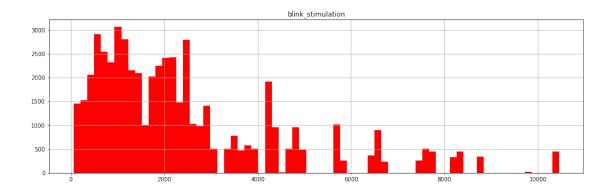


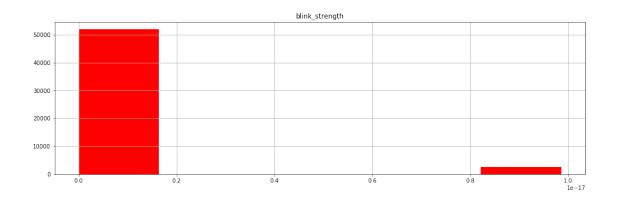










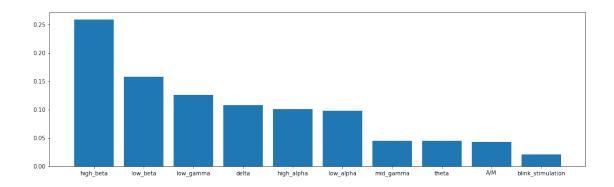


```
In [12]: # remove time from dfs
         df_subjects.drop('Time', axis=1, inplace=True)
         #df_sub2.drop('Time', axis=1, inplace=True)
         cols = list(df_subjects)
         df_subjects.head()
Out[12]:
                            A/M delta
               A/M Other
                                           theta
                                                   low_alpha high_alpha low_beta \
         s1 0
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                                                                     blink_strength
               high_beta
                           low_gamma
                                      mid_gamma
                                                 blink_stimulation
         s1 0
                  9837.0
                             10228.0
                                         1916.0
                                                              849.0
                                                                        3.783506e-44
                  9837.0
                             10228.0
                                                              849.0
                                                                        4.764415e-43
            1
                                         1916.0
            2
                  9837.0
                             10228.0
                                                              849.0
                                                                        3.363116e-44
                                         1916.0
            3
                  9837.0
                             10228.0
                                         1916.0
                                                              849.0
                                                                        4.203895e-44
            4
                                                                        0.00000e+00
                  9837.0
                             10228.0
                                         1916.0
                                                              849.0
               label
         s1 0
                   0
            1
                   0
            2
                   0
                   0
            3
            4
                    0
```

Out[13]: <pandas.io.formats.style.Styler at 0x1a103a42b0>

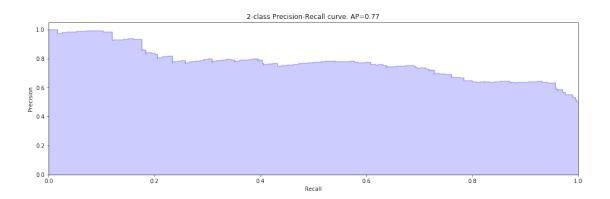
0.1 Random Forest

```
In [14]: # random forest
         train, test = train_test_split(df_subjects, test_size=0.2)
         X = train.values[:,0:12]
         Y = train.values[:,12]
         X_test = test.values[:,0:12]
         Y_test = test.values[:,12]
         clf = RandomForestClassifier(n_estimators=200, max_depth=2, random_state=0)
         clf.fit(X, Y)
         # feature importance
         features = []
         importances = []
         for importance, feature in reversed(sorted(zip(clf.feature_importances_, cols))):
             print(feature, importance)
             if (importance > 0):
                 features.append(feature)
                 importances.append(importance)
         y_pos = np.arange(len(importances))
         # Create bars
         plt.bar(y_pos, importances)
         plt.xticks(y_pos, features)
         plt.show()
high_beta 0.25836055359698246
low_beta 0.15715450200659462
low_gamma 0.12537139999102379
delta 0.10744481345125945
high_alpha 0.10077402623846263
low_alpha 0.0974421656418545
mid_gamma 0.044939941848689734
theta 0.04451182924990966
A/M 0.04275744019694354
blink_stimulation 0.02124332777827959
blink_strength 0.0
A/M Other 0.0
```



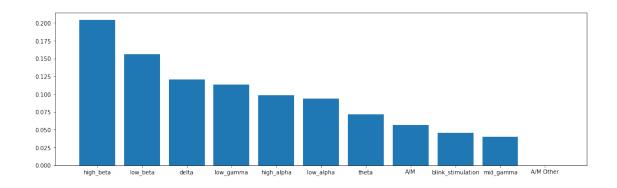
```
In [15]: # accuracy
         print("mean accuracy: ", clf.score(X_test, Y_test))
         Y_scores = []
         Y_scores = clf.predict_proba(X_test)[:,-1]
         #print(Y_scores)
         # cross validation
         #scores = cross_val_score(clf, X, Y, cv=5)
         #print("CV score:", scores)
         # precision recall
         precision, recall, thresholds = precision_recall_curve(Y_test, Y_scores)
         average_precision = average_precision_score(Y_test, Y_scores)
         plt.step(recall, precision, color='b', alpha=0.2,
                  where='post')
         plt.fill_between(recall, precision, step='post', alpha=0.2,
                          color='b')
         plt.xlabel('Recall')
         plt.ylabel('Precision')
        plt.ylim([0.0, 1.05])
         plt.xlim([0.0, 1.0])
         plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precision))
         plt.show()
```

mean accuracy: 0.6825600586832936

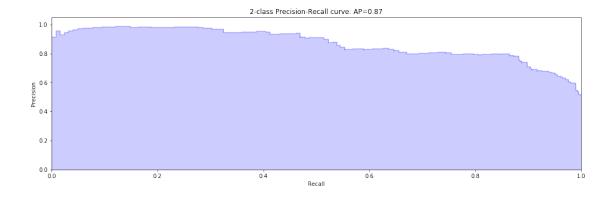


```
In [16]: # perform grid search for best hyperparams (DO NOT UNCOMMENT UNLESS GRID SEARCH IS NEEL
         #param_grid = {
              'n_estimators': [200, 500, 800],
              'max_features': ['sqrt', 'log2', 'auto'],
              'max_depth': [1, 2, 3]
         #}
         #CV_rfc = GridSearchCV(estimator=clf, param_grid=param_grid, cv=5)
         \#CV\_rfc.fit(X, Y)
         #print(CV_rfc.best_params_)
In [17]: # random forest with grid searched hyperparams
         clf = RandomForestClassifier(n_estimators=200, max_depth=3, max_features="auto", random
         clf.fit(X, Y)
         print("mean accuracy: ", clf.score(X_test, Y_test))
         # feature importance
         features = []
         importances = []
         for importance, feature in reversed(sorted(zip(clf.feature_importances_, cols))):
             print(feature, importance)
             if (importance > 0):
                 features.append(feature)
                 importances.append(importance)
         y_pos = np.arange(len(importances))
         # Create bars
         plt.bar(y_pos, importances)
         plt.xticks(y_pos, features)
         plt.show()
mean accuracy: 0.815193471483587
high_beta 0.2041092358230558
low_beta 0.15571194278913486
```

```
delta 0.1204588670482259
low_gamma 0.113303324019169
high_alpha 0.09860168961649275
low_alpha 0.09402905512898525
theta 0.07167617507125773
A/M 0.056332333290639136
blink_stimulation 0.045648813308566814
mid_gamma 0.04008999479913835
A/M Other 3.8569105334336756e-05
blink_strength 0.0
```

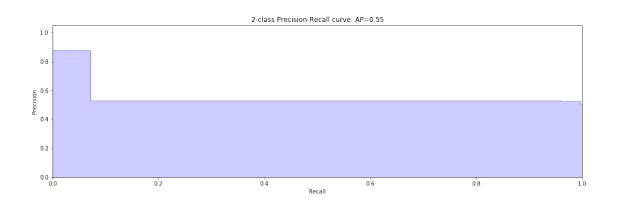


```
In [18]: # accuracy
         print("mean accuracy: ", clf.score(X_test, Y_test))
         Y_scores = []
         Y_scores = clf.predict_proba(X_test)[:,-1]
         #print(Y_scores)
         # cross validation
         #scores = cross_val_score(clf, X, Y, cv=5)
         #print("CV score:", scores)
         # precision recall
         precision, recall, thresholds = precision_recall_curve(Y_test, Y_scores)
         average_precision = average_precision_score(Y_test, Y_scores)
         plt.step(recall, precision, color='b', alpha=0.2, where='post')
         plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')
         plt.xlabel('Recall')
         plt.ylabel('Precision')
         plt.ylim([0.0, 1.05])
         plt.xlim([0.0, 1.0])
         plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precision))
         plt.show()
```



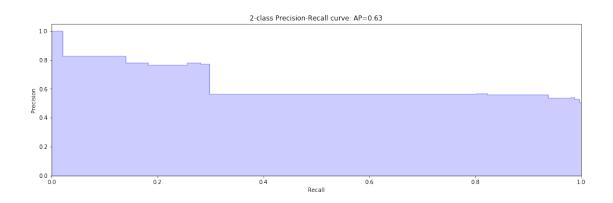
```
In [19]: # random forest on beta waves
         df_beta = df_subjects[['high_beta', 'label']]
         print(df_beta.head())
         train, test = train_test_split(df_beta, test_size=0.2)
         X = train.values[:,0:1]
         Y = train.values[:,1]
         X_test = test.values[:,0:1]
         Y_test = test.values[:,1]
         clf = RandomForestClassifier(n_estimators=200, max_depth=2, random_state=0)
         clf.fit(X, Y)
         # accuracy
         print("mean accuracy: ", clf.score(X_test, Y_test))
         Y_scores = []
         Y_scores = clf.predict_proba(X_test)[:,-1]
         #print(Y_scores)
         # cross validation
         #scores = cross_val_score(clf, X, Y, cv=5)
         #print("CV score:", scores)
         # precision recall
         precision, recall, thresholds = precision_recall_curve(Y_test, Y_scores)
         average_precision = average_precision_score(Y_test, Y_scores)
         plt.step(recall, precision, color='b', alpha=0.2, where='post')
         plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')
         plt.xlabel('Recall')
         plt.ylabel('Precision')
```

```
plt.ylim([0.0, 1.05])
         plt.xlim([0.0, 1.0])
         plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precision))
         plt.show()
      high_beta label
s1 0
         9837.0
   1
         9837.0
                     0
   2
         9837.0
                     0
   3
         9837.0
                     0
   4
         9837.0
                     0
mean accuracy: 0.549193104713002
```



```
In [20]: # random forest on beta waves
         df_beta = df_subjects[['high_beta', 'low_alpha', 'label']]
         print(df_beta.head())
         train, test = train_test_split(df_beta, test_size=0.2)
         X = train.values[:,0:2]
         Y = train.values[:,2]
         X_test = test.values[:,0:2]
         Y_test = test.values[:,2]
         clf = RandomForestClassifier(n_estimators=200, max_depth=2, random_state=0)
         clf.fit(X, Y)
         # accuracy
         print("mean accuracy: ", clf.score(X_test, Y_test))
         Y_scores = []
         Y_scores = clf.predict_proba(X_test)[:,-1]
         #print(Y_scores)
         # cross validation
         #scores = cross_val_score(clf, X, Y, cv=5)
```

```
#print("CV score:", scores)
         # precision recall
         precision, recall, thresholds = precision_recall_curve(Y_test, Y_scores)
         average_precision = average_precision_score(Y_test, Y_scores)
         plt.step(recall, precision, color='b', alpha=0.2, where='post')
         plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')
         plt.xlabel('Recall')
         plt.ylabel('Precision')
         plt.ylim([0.0, 1.05])
         plt.xlim([0.0, 1.0])
         plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precision))
         plt.show()
      high_beta low_alpha
                            label
s1 0
         9837.0
                   74006.0
                                0
   1
         9837.0
                   74006.0
                   74006.0
                                0
   2
         9837.0
   3
         9837.0
                   74006.0
                                0
         9837.0
                   74006.0
   4
                                0
mean accuracy: 0.5923803410966441
```



1 testing on subject 2

```
train2, test2 = train_test_split(df_sub2, test_size=0.2) X2 = train2.values[:,0:12] Y2 =
train2.values[:,12]
  X_test2 = test2.values[:,0:12] Y_test2 = test2.values[:,12]
  clf.fit(X2, Y2)
```

2 accuracy

3 cross validation

scores = cross_val_score(clf, X, Y, cv=5) print("CV score:", scores)

precision, recall, thresholds = precision_recall_curve(Y_test2, Y_scores2) average_precision = average_precision_score(Y_test2, Y_scores2)

plt.step(recall, precision, color='b', alpha=0.2, where='post') plt.fill_between(recall, precision, step='post', alpha=0.2, color='b')

plt.xlabel('Recall') plt.ylabel('Precision') plt.ylim([0.0, 1.05]) plt.xlim([0.0, 1.0]) plt.title('2-class Precision-Recall curve: AP={0:0.2f}'.format(average_precision)) plt.show()