model_combined

November 6, 2017

1 The Very Best Model

1.0.1 Combined warbler acoustic parameters and audio descriptors on gradient boosted trees

In [1]:
```
import sklearn
import numpy as np
import pandas as pd
import xgboost as xg
import seaborn as sns
# import matplotlib
# matplotlib.use('Agg')
import matplotlib.pyplot as plt

from sklearn import metrics
from sklearn.model_selection import train_test_split

%matplotlib inline
```

Load both data sets

In [2]:
```
descriptors_path = '/home/tracek/Data/gender/gender_descriptors.csv'
warbler_path = '/home/tracek/Data/gender/gender_warbler.csv'
seed = 42

params = {'max_depth': 13,
          'n_estimators': 1000,
          'objective': 'binary:logistic',
          'eval_metric': ['auc', 'error'],
          'gamma': 0.1}

test_fraction = 0.1
val_fraction = 0.2
```

Concatenate the two. Since they were produced on identical data sets and nothing is missing, we can simply sort data by filename and concatenate horizontally - no joins required.

In [3]:
```
warbler_df = pd.read_csv(warbler_path).sort_values('filename').drop(['filename', 'centro
descriptors_df = pd.read_csv(descriptors_path).sort_values('filename').drop(['filename',
data = pd.concat([warbler_df, descriptors_df], axis=1)
y = data.pop('label')
```

1.0.2 Train - Validation (Development) - Test split

I divide my data into three sets to prevent information leakage when tuning any hyperparameters.

```
In [4]: if test_fraction > 0.0:
            X_train, X_test, y_train, y_test = train_test_split(data, y, test_size=test_fraction
            X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=val_fr
            dtest = xg.DMatrix(X_test, label=y_test)
        else:
            X_train, X_val, y_train, y_val = train_test_split(data, y, test_size=val_fraction, r
```

1.1 Train!

```
In [5]: dtrain = xg.DMatrix(X_train, label=y_train)
        dval = xg.DMatrix(X_val, label=y_val)
        evallist = [(dval, 'eval'), (dtrain, 'train')]
        model = xg.train(params=params, dtrain=dtrain, num_boost_round=100, evals=evallist, earl
```

```
[0]        eval-auc:0.990664        eval-error:0.022722        train-auc:0.993535        train-e
Multiple eval metrics have been passed: 'train-error' will be used for early stopping.

Will train until train-error hasn't improved in 5 rounds.
[1]        eval-auc:0.992364        eval-error:0.019645        train-auc:0.995143        train-e
[2]        eval-auc:0.992999        eval-error:0.017751        train-auc:0.995605        train-e
[3]        eval-auc:0.995294        eval-error:0.017041        train-auc:0.997063        train-e
[4]        eval-auc:0.996245        eval-error:0.016805        train-auc:0.99868        train-er
[5]        eval-auc:0.996757        eval-error:0.015385        train-auc:0.998968        train-e
[6]        eval-auc:0.997089        eval-error:0.015444        train-auc:0.999565        train-e
[7]        eval-auc:0.997237        eval-error:0.01503        train-auc:0.999762        train-er
[8]        eval-auc:0.997232        eval-error:0.01432        train-auc:0.999877        train-er
[9]        eval-auc:0.997403        eval-error:0.01355        train-auc:0.999932        train-er
[10]        eval-auc:0.997594        eval-error:0.013195        train-auc:0.999947        train-
[11]        eval-auc:0.997821        eval-error:0.012485        train-auc:0.999963        train-
[12]        eval-auc:0.997884        eval-error:0.011834        train-auc:0.999968        train-
[13]        eval-auc:0.99822        eval-error:0.011953        train-auc:0.999979        train-e
[14]        eval-auc:0.998347        eval-error:0.011538        train-auc:0.999989        train-
[15]        eval-auc:0.998492        eval-error:0.011479        train-auc:0.999993        train-
[16]        eval-auc:0.998587        eval-error:0.011479        train-auc:0.999995        train-
[17]        eval-auc:0.998669        eval-error:0.011183        train-auc:0.999997        train-
[18]        eval-auc:0.998766        eval-error:0.010888        train-auc:0.999998        train-
[19]        eval-auc:0.998827        eval-error:0.010651        train-auc:0.999998        train-
[20]        eval-auc:0.998902        eval-error:0.010355        train-auc:0.999999        train-
[21]        eval-auc:0.998936        eval-error:0.010355        train-auc:0.999999        train-
[22]        eval-auc:0.998998        eval-error:0.010237        train-auc:0.999999        train-
[23]        eval-auc:0.999026        eval-error:0.010059        train-auc:0.999999        train-
[24]        eval-auc:0.999033        eval-error:0.01        train-auc:1        train-error:7.4e-
[25]        eval-auc:0.999044        eval-error:0.010178        train-auc:1        train-error:5
[26]        eval-auc:0.999051        eval-error:0.009941        train-auc:1        train-error:4
[27]        eval-auc:0.999074        eval-error:0.010059        train-auc:1        train-error:4
```

```
[28]	eval-auc:0.999088	eval-error:0.009822	train-auc:1	train-error:4
[29]	eval-auc:0.999093	eval-error:0.009882	train-auc:1	train-error:1
[30]	eval-auc:0.999122	eval-error:0.009704	train-auc:1	train-error:1
[31]	eval-auc:0.999153	eval-error:0.009645	train-auc:1	train-error:1
[32]	eval-auc:0.999158	eval-error:0.009467	train-auc:1	train-error:1
[33]	eval-auc:0.999194	eval-error:0.009467	train-auc:1	train-error:1
[34]	eval-auc:0.999214	eval-error:0.009349	train-auc:1	train-error:1
Stopping. Best iteration:
[29]	eval-auc:0.999093	eval-error:0.009882	train-auc:1	train-error:1
```

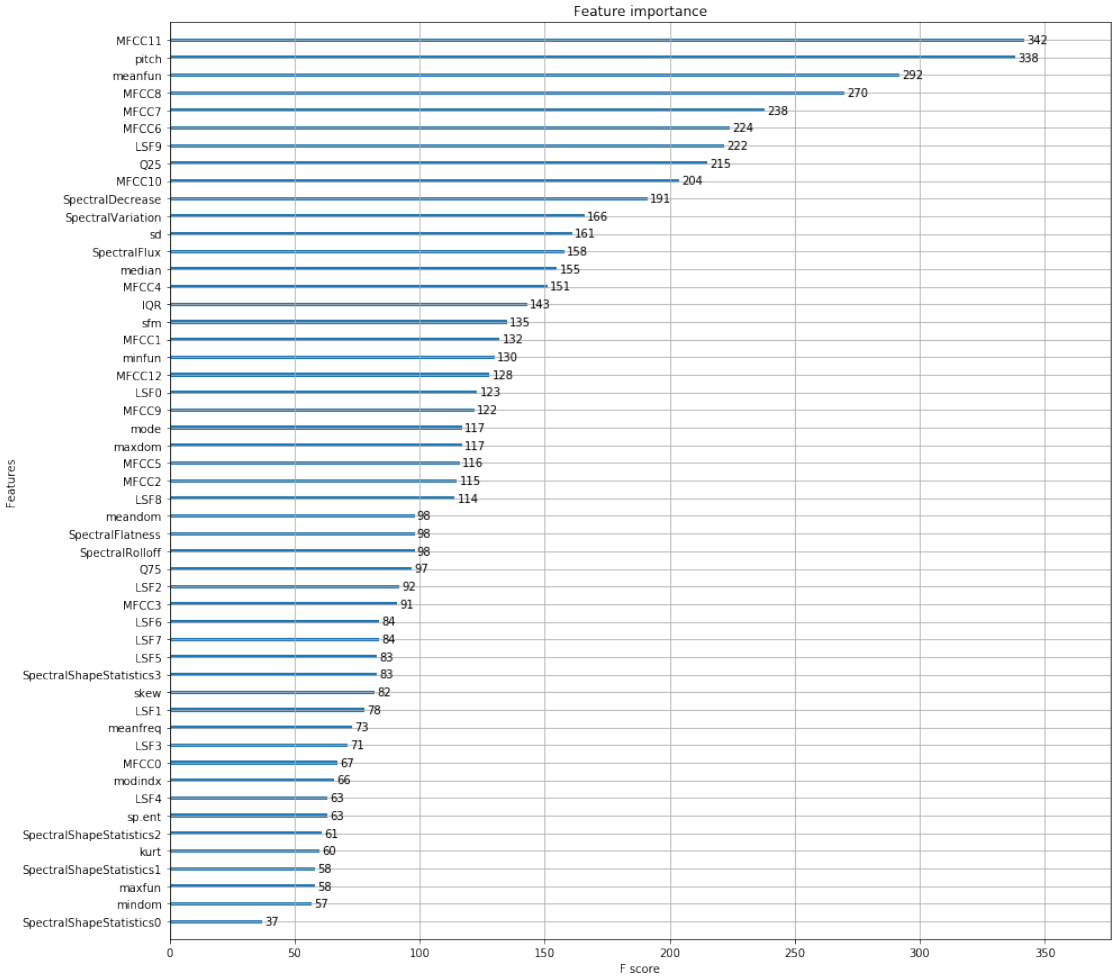
Looks great, beats the two separately (no surprises here). The model converges significantly faster then warbler alone and only a bit slower than descriptors alone. Yay.

```
In [6]: y_pred_prob = model.predict(dtest)
        y_pred = (y_pred_prob > 0.5).astype(int)

In [7]: r = metrics.classification_report(y_true=y_test, y_pred=y_pred)
        acc = metrics.accuracy_score(y_true=y_test, y_pred=y_pred)

In [8]: print(r)

             precision    recall  f1-score   support

          0       0.99      1.00      1.00      7882
          1       0.98      0.97      0.97      1507

avg / total       0.99      0.99      0.99      9389


In [9]: print('Accuracy: ', acc)

Accuracy:  0.991692406007
```

1.1.1 Excellent

The score on test set beats significantly the warbler and improves over descriptors alone.

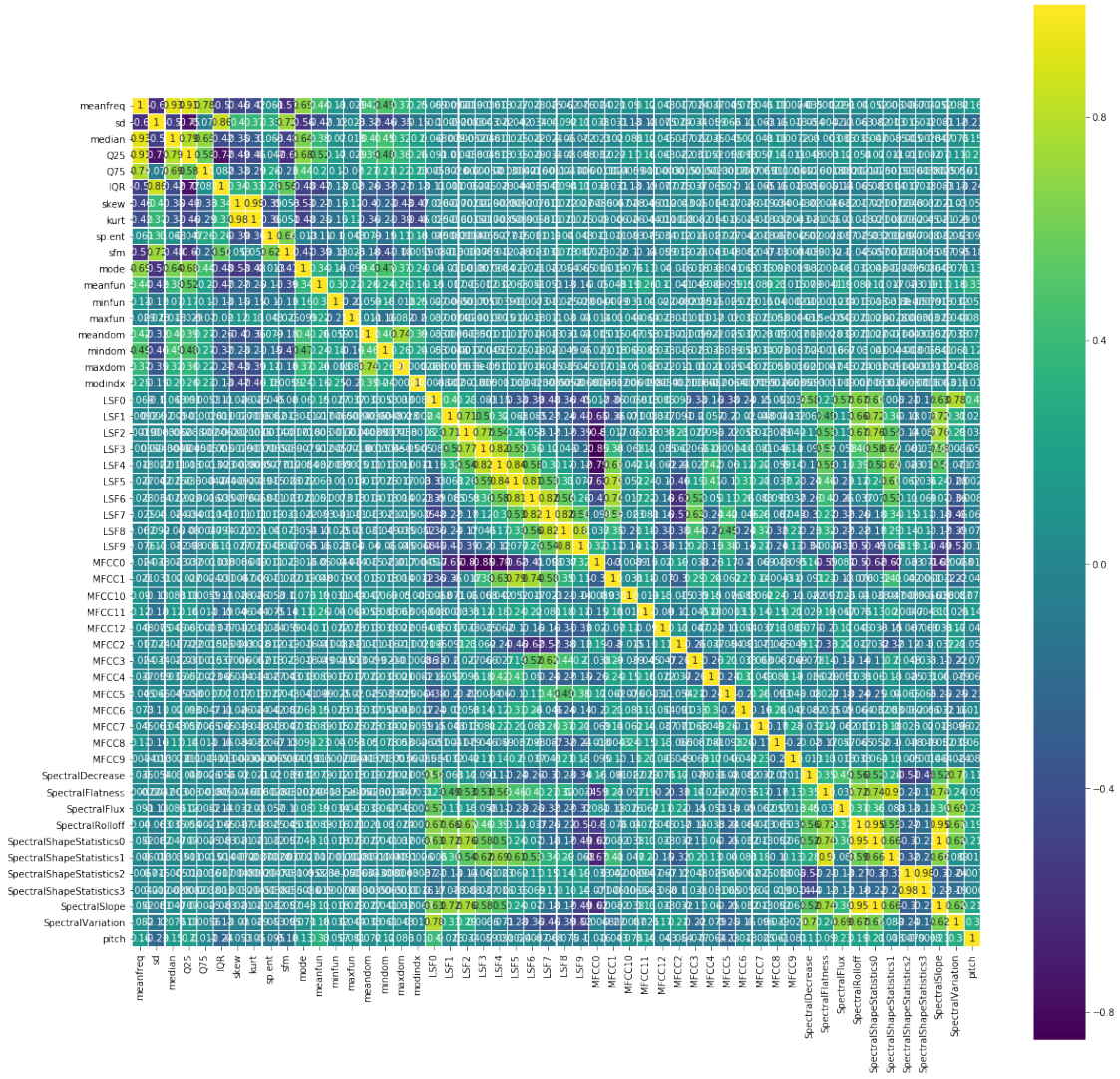
```
In [10]: model.feature_names = [name.replace(' ', '') for name in model.feature_names]
         fig, ax = plt.subplots(figsize=(15, 15))
         xg.plot_importance(model, ax)

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f0591963748>
```



What is striking is that the pitch I am calculating (with aubio!) beats what warbleR delivers. Also, somewhat less surprisingly, mel-frequencies cepstrum coefficients are doing amazingly well. Curious, since aggregated I did not think they will be THAT informative (at least some). On the other hand, these are meant to capture voice characteristic.

Let's see how these features correlate with each other.

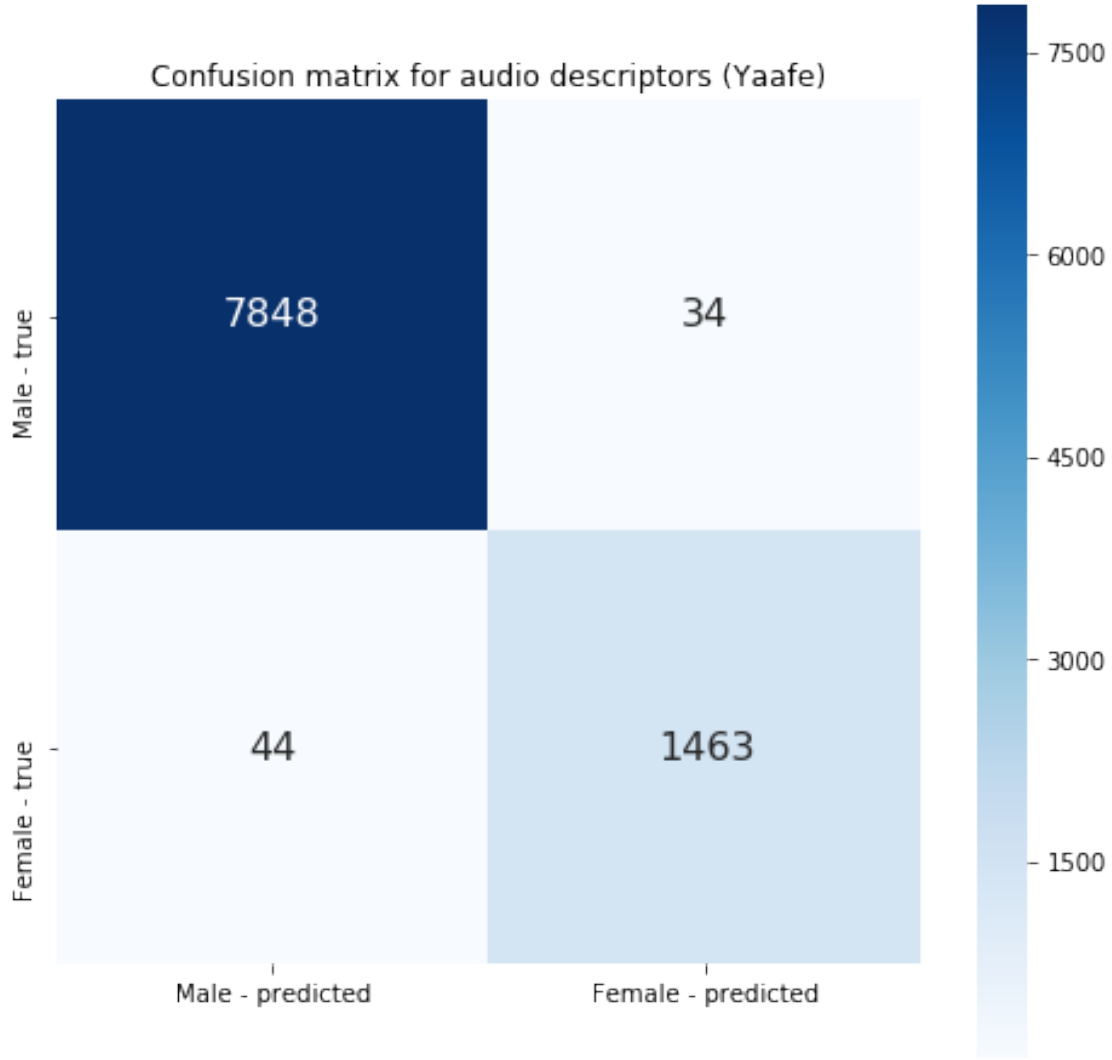
```
In [11]: data_corr = data.corr()
         plt.figure(figsize=(20, 20))
         sns.heatmap(data_corr,
                     xticklabels=data_corr.columns.values,
                     yticklabels=data_corr.columns.values,
                     linewidths=0.2,
                     vmax=1.0,
                     square=True,
                     cmap=plt.cm.viridis,
                     linecolor='white',
                     annot=True)
         plt.savefig('combined_cm.png')
```



Interestingly, we don't get that high correlation on features that were computed from both approaches, like e.g. spectral flatness.

```
In [12]: plt.figure(figsize=(8, 8))
         plt.title('Confusion matrix for audio descriptors (Yaafe)')
         cm = metrics.confusion_matrix(y_true=y_test, y_pred=y_pred)
         sns.heatmap(cm, annot=True, annot_kws={"size": 16}, cmap='Blues', fmt='g', square=True,
                     xticklabels=['Male - predicted', 'Female - predicted'], yticklabels=['Male
```

```
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f058ff86b38>
```



1.2 Discussion of errors

The mistakes are truly marginal. Model does not represent any strong bias. Frankly, I would easily confuse 1% of time a person on a phone. On top of that, the data set contains also recording of youth, meaning also people before voice change - or ongoing change. This will also confuse the model. Last, but not least...

2 Data lies!

(mo surprises here) Here are two examples of incorrectly labelled recordings: *male* labelled as *female*: - Anniepoo-20140308-bft - male - abc-20091120-mfr - male