# rf trials

May 26, 2020

```
[4]: import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectFromModel
from sklearn.metrics import accuracy_score
```

## 1 Transforming and Splitting Data

```
[5]: df = pd.read_csv("data/combined_expression.csv")
     df.head()
[6]:
        CELL_LINE_NAME
                         classification
                                            TSPAN6
                                                         TNMD
                                                                    DPM1
                                                                              SCYL3
                1240121
                                          6.419526
                                                     3.182094
                                                                9.320548
                                                                           3.759654
     0
     1
                1240122
                                       6
                                          7.646494
                                                     2.626819
                                                               10.153853
                                                                           3.564755
     2
                1240123
                                       5
                                          8.319417
                                                     3.111183
                                                                9.643558
                                                                           4.757258
     3
                1240124
                                          9.006994
                                                     3.028173
                                                                9.686700
                                                                           4.280504
                                       1
     4
                                          7.985676
                                                    2.694729
                                                                           4.159685
                1240127
                                                               10.676134
        C1orf112
                                           FUCA2
                        FGR
                                  CFH
                                                       COL15A1
                                                                 C6orf10
                                                                            TMEM225
        3.802619
                  3.215753
                             4.698729
                                        7.873672
                                                      3.245454
                                                                2.953508
                                                                           3.543429
        3.942749
                  3.290760
                             3.551675
                                        8.252413
                                                      2.786709
                                                                3.077382
                                                                           3.728232
     2 3.919757
                  3.602185
                             3.329644
                                        9.076950
                                                      3.459089
                                                                3.085394
                                                                           3.462811
                                                      2.835403
                                                                2.960303
     3
        3.147646
                  3.188881
                             3.293807
                                        8.678790
                                                                           3.415083
        3.804637
                  3.481942
                                                      2.896523
                                                                2.849899
                                                                           3.480114
                             3.111261
                                        7.555407
          NOTCH4
                                  AGER
                       PBX2
                                            RNF5
                                                     AGPAT1
                                                               DFNB59
                                                                           PRRT1
        3.352022
                  4.672310
                             3.641128
                                        3.135310
                                                   3.737072
                                                             3.450927
                                                                        3.168800
        3.208882
                  4.586840
                             3.395654
                                        3.586800
                                                   3.519128
                                                             3.115323
                                                                        3.051645
     2 3.339030
                  4.614897
                             3.395845
                                        3.419193
                                                   3.971646
                                                             3.729310
                                                                        3.320022
        3.290171
                  4.770123
                             3.400821
                                                             2.822404
                                        3.383734
                                                   3.798107
                                                                        3.297547
        3.226128
                  5.832710
                             3.612179
                                                             5.198524
                                        3.347095
                                                  4.457963
                                                                        4.553586
```

[5 rows x 16383 columns]

```
[7]: X = df.drop(columns=['CELL_LINE_NAME', 'classification'])
y = df['classification']
feat_labels = list(X.columns)
```

```
[8]: # 20% test, 80% train
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, □
→random_state=0)
```

### 2 Creating the Classifier With All Features

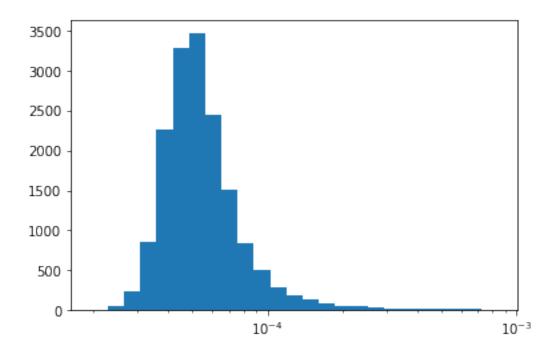
```
[9]: # create and train the classifier
clf = RandomForestClassifier(n_estimators=X.shape[1], random_state=0, n_jobs=-1)
clf.fit(X_train, y_train)
```

```
[9]: RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None, criterion='gini', max_depth=None, max_features='auto', max_leaf_nodes=None, max_samples=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, n_estimators=16381, n_jobs=-1, oob_score=False, random_state=0, verbose=0, warm_start=False)
```

```
[10]: # associating each feature with its relative importance
feat_importances = list(zip(feat_labels, clf.feature_importances_))
feat_importances.sort(key = lambda x: x[1], reverse=True)
```

```
[11]: # plotting the feature importances
import matplotlib.pyplot as plt
indices = np.arange(len(feat_importances))
x, y = zip(*feat_importances)

def plot_loghist(x, bins):
    hist, bins = np.histogram(x, bins=bins)
    logbins = np.logspace(np.log10(bins[0]), np.log10(bins[-1]), len(bins))
    plt.hist(x, bins=logbins)
    plt.xscale('log')
plot_loghist(y, 25)
```



## 3 Testing Various Thresholds

#### 3.1 Defining Functions for Multiple Iterations

#### 3.2 Testing Multiple Iterations

```
[72]: hist, bins = np.histogram(y, bins=25)
    thresholds = np.logspace(np.log10(bins[0]), np.log10(bins[-1]), len(y))
    thresholds = sorted(thresholds, reverse=True)
    thresholds = list(filter(lambda x: x >= 8.25e-4, thresholds))
    len(thresholds)
```

[72]: 80

```
[73]: thresh_accuracy = list()

j=1
for i in thresholds:
    sfm = SelectFromModel(clf, i)
    sfm.fit(X_train, y_train)
    X_important_train, X_important_test = sfm_transforms(sfm, X_train, X_test)

clf_important = RandomForestClassifier(n_estimators=X.shape[1],u
    random_state=0, n_jobs=-1)
    clf_important.fit(X_important_train, y_train)

thresh_accuracy.append((i, det_accuracy(clf, X_test, y_test)))

print(f'Iteration: {j}; threshold: {i}')
    j += 1
```

```
Iteration: 1; threshold: 0.0008402505637710409
Iteration: 2; threshold: 0.0008400578348545766
Iteration: 3; threshold: 0.0008398651501444916
Iteration: 4; threshold: 0.0008396725096306465
Iteration: 5; threshold: 0.0008394799133029039
Iteration: 6; threshold: 0.0008392873611511286
Iteration: 7; threshold: 0.0008390948531651882
Iteration: 8; threshold: 0.0008389023893349522
Iteration: 9; threshold: 0.0008387099696502934
Iteration: 10; threshold: 0.0008385175941010836
Iteration: 11; threshold: 0.0008383252626772029
Iteration: 12; threshold: 0.0008381329753685267
Iteration: 13; threshold: 0.0008379407321649397
Iteration: 14; threshold: 0.0008377485330563222
Iteration: 15; threshold: 0.0008375563780325633
Iteration: 16; threshold: 0.0008373642670835479
Iteration: 17; threshold: 0.00083717220019917
Iteration: 18; threshold: 0.0008369801773693199
Iteration: 19; threshold: 0.0008367881985838937
Iteration: 20; threshold: 0.0008365962638327886
Iteration: 21; threshold: 0.0008364043731059048
Iteration: 22; threshold: 0.0008362125263931442
Iteration: 23; threshold: 0.0008360207236844113
Iteration: 24; threshold: 0.0008358289649696127
Iteration: 25; threshold: 0.0008356372502386578
Iteration: 26; threshold: 0.0008354455794814586
Iteration: 27; threshold: 0.0008352539526879264
Iteration: 28; threshold: 0.0008350623698479805
Iteration: 29; threshold: 0.0008348708309515358
Iteration: 30; threshold: 0.0008346793359885166
```

```
Iteration: 31; threshold: 0.0008344878849488421
Iteration: 32; threshold: 0.0008342964778224413
Iteration: 33; threshold: 0.0008341051145992391
Iteration: 34; threshold: 0.0008339137952691661
Iteration: 35; threshold: 0.0008337225198221547
Iteration: 36; threshold: 0.0008335312882481393
Iteration: 37; threshold: 0.0008333401005370568
Iteration: 38; threshold: 0.0008331489566788462
Iteration: 39; threshold: 0.0008329578566634491
Iteration: 40; threshold: 0.000832766800480809
Iteration: 41; threshold: 0.000832575788120873
Iteration: 42; threshold: 0.000832384819573587
Iteration: 43; threshold: 0.0008321938948289047
Iteration: 44; threshold: 0.000832003013876776
Iteration: 45; threshold: 0.0008318121767071593
Iteration: 46; threshold: 0.0008316213833100091
Iteration: 47; threshold: 0.0008314306336752883
Iteration: 48; threshold: 0.000831239927792956
Iteration: 49; threshold: 0.0008310492656529799
Iteration: 50; threshold: 0.0008308586472453243
Iteration: 51; threshold: 0.000830668072559959
Iteration: 52; threshold: 0.0008304775415868556
Iteration: 53; threshold: 0.0008302870543159876
Iteration: 54; threshold: 0.000830096610737331
Iteration: 55; threshold: 0.0008299062108408643
Iteration: 56; threshold: 0.0008297158546165679
Iteration: 57; threshold: 0.0008295255420544247
Iteration: 58; threshold: 0.0008293352731444208
Iteration: 59; threshold: 0.0008291450478765409
Iteration: 60; threshold: 0.0008289548662407785
Iteration: 61; threshold: 0.000828764728227122
Iteration: 62; threshold: 0.0008285746338255693
Iteration: 63; threshold: 0.0008283845830261137
Iteration: 64; threshold: 0.0008281945758187573
Iteration: 65; threshold: 0.0008280046121934992
Iteration: 66; threshold: 0.0008278146921403434
Iteration: 67; threshold: 0.0008276248156492959
Iteration: 68; threshold: 0.000827434982710365
Iteration: 69; threshold: 0.0008272451933135608
Iteration: 70; threshold: 0.0008270554474488961
Iteration: 71; threshold: 0.0008268657451063861
Iteration: 72; threshold: 0.0008266760862760479
Iteration: 73; threshold: 0.000826486470947902
Iteration: 74; threshold: 0.0008262968991119676
Iteration: 75; threshold: 0.0008261073707582724
Iteration: 76; threshold: 0.0008259178858768395
Iteration: 77; threshold: 0.0008257284444577008
Iteration: 78; threshold: 0.000825539046490884
```

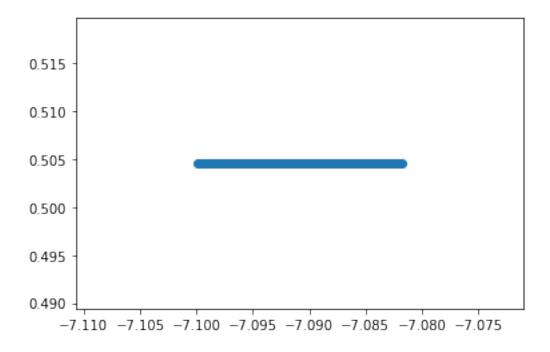
Iteration: 79; threshold: 0.000825349691966426 Iteration: 80; threshold: 0.0008251603808743588

#### [74]: thresh\_accuracy

```
[74]: [(0.0008402505637710409, 0.5045871559633027),
       (0.0008400578348545766, 0.5045871559633027),
       (0.0008398651501444916, 0.5045871559633027),
       (0.0008396725096306465, 0.5045871559633027),
       (0.0008394799133029039, 0.5045871559633027),
       (0.0008392873611511286, 0.5045871559633027),
       (0.0008390948531651882, 0.5045871559633027),
       (0.0008389023893349522, 0.5045871559633027),
       (0.0008387099696502934, 0.5045871559633027),
       (0.0008385175941010836, 0.5045871559633027),
       (0.0008383252626772029, 0.5045871559633027),
       (0.0008381329753685267, 0.5045871559633027),
       (0.0008379407321649397, 0.5045871559633027),
       (0.0008377485330563222, 0.5045871559633027),
       (0.0008375563780325633, 0.5045871559633027),
       (0.0008373642670835479, 0.5045871559633027),
       (0.00083717220019917, 0.5045871559633027),
       (0.0008369801773693199, 0.5045871559633027),
       (0.0008367881985838937, 0.5045871559633027),
       (0.0008365962638327886, 0.5045871559633027),
       (0.0008364043731059048, 0.5045871559633027),
       (0.0008362125263931442, 0.5045871559633027),
       (0.0008360207236844113, 0.5045871559633027),
       (0.0008358289649696127, 0.5045871559633027),
       (0.0008356372502386578, 0.5045871559633027),
       (0.0008354455794814586, 0.5045871559633027),
       (0.0008352539526879264, 0.5045871559633027),
       (0.0008350623698479805, 0.5045871559633027),
       (0.0008348708309515358, 0.5045871559633027),
       (0.0008346793359885166, 0.5045871559633027),
       (0.0008344878849488421, 0.5045871559633027),
       (0.0008342964778224413, 0.5045871559633027),
       (0.0008341051145992391, 0.5045871559633027),
       (0.0008339137952691661, 0.5045871559633027),
       (0.0008337225198221547, 0.5045871559633027),
       (0.0008335312882481393, 0.5045871559633027),
       (0.0008333401005370568, 0.5045871559633027),
       (0.0008331489566788462, 0.5045871559633027),
       (0.0008329578566634491, 0.5045871559633027),
       (0.000832766800480809, 0.5045871559633027),
       (0.000832575788120873, 0.5045871559633027),
       (0.000832384819573587, 0.5045871559633027),
```

```
(0.000832003013876776, 0.5045871559633027),
       (0.0008318121767071593, 0.5045871559633027),
       (0.0008316213833100091, 0.5045871559633027),
       (0.0008314306336752883, 0.5045871559633027),
       (0.000831239927792956, 0.5045871559633027),
       (0.0008310492656529799, 0.5045871559633027),
       (0.0008308586472453243, 0.5045871559633027),
       (0.000830668072559959, 0.5045871559633027),
       (0.0008304775415868556, 0.5045871559633027),
       (0.0008302870543159876, 0.5045871559633027),
       (0.000830096610737331, 0.5045871559633027),
       (0.0008299062108408643, 0.5045871559633027),
       (0.0008297158546165679, 0.5045871559633027),
       (0.0008295255420544247, 0.5045871559633027),
       (0.0008293352731444208, 0.5045871559633027),
       (0.0008291450478765409, 0.5045871559633027),
       (0.0008289548662407785, 0.5045871559633027),
       (0.000828764728227122, 0.5045871559633027),
       (0.0008285746338255693, 0.5045871559633027),
       (0.0008283845830261137, 0.5045871559633027),
       (0.0008281945758187573, 0.5045871559633027),
       (0.0008280046121934992, 0.5045871559633027),
       (0.0008278146921403434, 0.5045871559633027),
       (0.0008276248156492959, 0.5045871559633027),
       (0.000827434982710365, 0.5045871559633027),
       (0.0008272451933135608, 0.5045871559633027),
       (0.0008270554474488961, 0.5045871559633027),
       (0.0008268657451063861, 0.5045871559633027),
       (0.0008266760862760479, 0.5045871559633027),
       (0.000826486470947902, 0.5045871559633027),
       (0.0008262968991119676, 0.5045871559633027),
       (0.0008261073707582724, 0.5045871559633027),
       (0.0008259178858768395, 0.5045871559633027),
       (0.0008257284444577008, 0.5045871559633027),
       (0.000825539046490884, 0.5045871559633027),
       (0.000825349691966426, 0.5045871559633027),
       (0.0008251603808743588, 0.5045871559633027)]
[87]: testList2 = [(np.log(elem1), elem2) for elem1, elem2 in thresh_accuracy]
      plt.scatter(*zip(*testList2))
[87]: <matplotlib.collections.PathCollection at 0x1ab24bbe48>
```

(0.0008321938948289047, 0.5045871559633027),



[]: