## rf trials

May 26, 2020

```
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
from sklearn import preprocessing
```

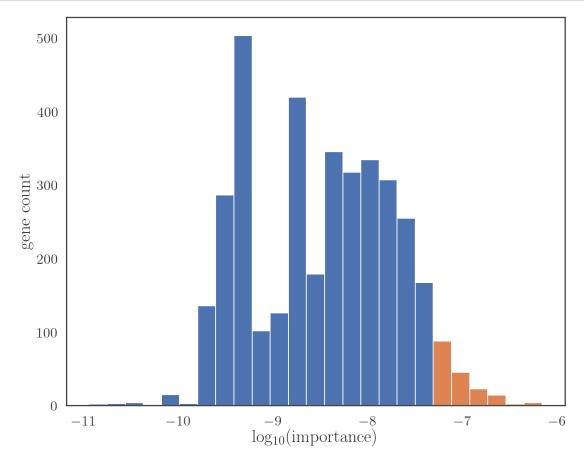
### 1 Transforming and Splitting Data

```
[357]: df = pd.read_csv("data/combined_expression.csv")
       df.head()
[358]:
[358]:
          CELL_LINE_NAME
                          classification
                                             TSPAN6
                                                          TNMD
                                                                     DPM1
                                                                               SCYL3 \
                 1240121
       0
                                           6.419526
                                                      3.182094
                                                                 9.320548
                                                                           3.759654
                                        1
       1
                 1240122
                                        2
                                           7.646494
                                                      2.626819
                                                                10.153853
                                                                           3.564755
       2
                                           8.319417
                                                      3.111183
                 1240123
                                                                 9.643558
                                                                           4.757258
       3
                 1240124
                                           9.006994
                                                      3.028173
                                                                 9.686700
                                                                           4.280504
       4
                 1240127
                                           7.985676
                                                      2.694729
                                                                10.676134
                                                                           4.159685
          C1orf112
                         FGR
                                    CFH
                                            FUCA2
                                                        COL15A1
                                                                  C6orf10
                                                                             TMEM225
       0 3.802619
                    3.215753
                               4.698729
                                         7.873672
                                                       3.245454
                                                                 2.953508
                                                                           3.543429
       1 3.942749
                    3.290760
                              3.551675
                                         8.252413
                                                       2.786709
                                                                 3.077382
                                                                           3.728232
       2 3.919757
                                                                 3.085394
                    3.602185
                               3.329644
                                         9.076950
                                                       3.459089
                                                                           3.462811
                                         8.678790
       3 3.147646
                    3.188881
                               3.293807
                                                       2.835403
                                                                 2.960303
                                                                           3.415083
       4 3.804637
                    3.481942
                               3.111261
                                         7.555407
                                                       2.896523
                                                                 2.849899
                                                                           3.480114
            NOTCH4
                        PBX2
                                   AGER
                                             RNF5
                                                      AGPAT1
                                                                DFNB59
                                                                            PRRT1
          3.352022
                    4.672310
                               3.641128
                                         3.135310
                                                    3.737072
                                                              3.450927
                                                                        3.168800
       1 3.208882
                    4.586840
                               3.395654
                                         3.586800
                                                   3.519128
                                                              3.115323
                                                                        3.051645
       2 3.339030
                    4.614897
                                                              3.729310
                               3.395845
                                         3.419193
                                                    3.971646
                                                                        3.320022
       3 3.290171
                    4.770123
                               3.400821
                                         3.383734
                                                   3.798107
                                                              2.822404
                                                                        3.297547
       4 3.226128
                    5.832710
                                                              5.198524
                              3.612179
                                         3.347095
                                                   4.457963
                                                                        4.553586
```

[5 rows x 16383 columns]

```
y = df['classification']
       feat_labels = list(X.columns)
[360]: min max scaler = preprocessing.MinMaxScaler()
       x_scaled = min_max_scaler.fit_transform(X)
       X = pd.DataFrame(x scaled)
[361]: # 20% test, 80% train
       X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,_
        →random state=0)
          Creating the Classifier With All Features
[362]: # create and train the classifier
       clf = RandomForestClassifier(n_estimators=100, random_state=0, n_jobs=-1)
       clf.fit(X_train, y_train)
[362]: 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=100,
                              n_jobs=-1, oob_score=False, random_state=0, verbose=0,
                              warm_start=False)
[363]: # 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)
[366]: # plotting the feature importances
       import matplotlib.pyplot as plt
       plt.tight_layout()
       indices = np.arange(len(feat_importances))
       x, y = zip(*feat importances)
       y = [i \text{ for } i \text{ in } y \text{ if } i > 0]
      <Figure size 720x720 with 0 Axes>
[398]: ax1 = plt.subplot(111)
       _, _, bars = plt.hist(np.log(y), bins=25, color='CO')
       for bar in bars:
```

[359]: X = df.drop(columns=['CELL\_LINE\_NAME', 'classification'])



# 3 Testing Various Thresholds

#### 3.1 Defining Functions for Multiple Iterations

```
[345]: def sfm_transforms(sfm, X_train, X_test):
    X_important_train = sfm.transform(X_train)
    X_important_test = sfm.transform(X_test)
    return X_important_train, X_important_test
```

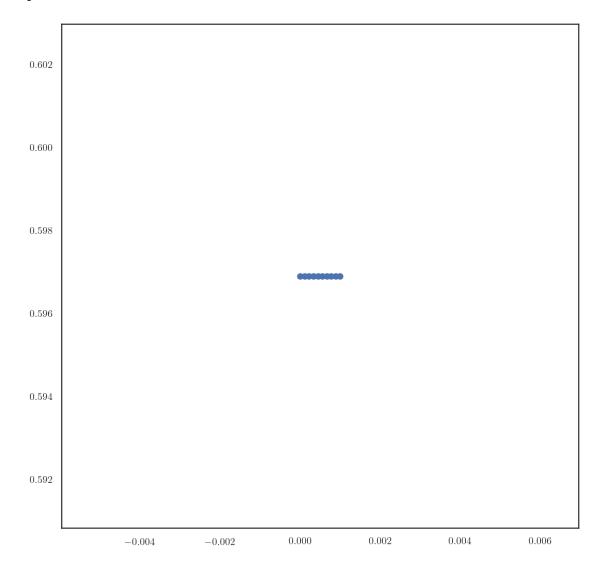
```
[346]: def det_accuracy(clf, X_test, y_test):
    y_pred = clf.predict(X_test)
    return accuracy_score(y_test, y_pred)
```

```
3.2 Testing Multiple Iterations
[381]: thresholds = np.linspace(1e-7, 1e-3, 10)
     thresholds
[381]: array([1.000e-07, 1.112e-04, 2.223e-04, 3.334e-04, 4.445e-04, 5.556e-04,
           6.667e-04, 7.778e-04, 8.889e-04, 1.000e-03])
[382]: 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=100, random_state=0,_
      \rightarrown_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: 1e-07
     Iteration: 3; threshold: 0.000222299999999998
     Iteration: 4; threshold: 0.0003333999999999997
     Iteration: 5; threshold: 0.0004444999999999996
     Iteration: 6; threshold: 0.0005556
     Iteration: 8; threshold: 0.00077779999999998
     Iteration: 9; threshold: 0.000888899999999999
     Iteration: 10; threshold: 0.001
[383]: thresh_accuracy
[383]: [(1e-07, 0.5968992248062015),
      (0.0003333999999999999997, 0.5968992248062015),
```

```
(0.0005556, 0.5968992248062015),
(0.000666699999999999, 0.5968992248062015),
(0.000777799999999998, 0.5968992248062015),
(0.000888899999999999, 0.5968992248062015),
(0.001, 0.5968992248062015)]
```

```
[384]: # testList2 = [(np.log(elem1), elem2) for elem1, elem2 in thresh_accuracy] plt.scatter(*zip(*thresh_accuracy))
```

[384]: <matplotlib.collections.PathCollection at 0x1a2c3065f8>



```
[385]: len(thresh_accuracy) thresh_accuracy
```

```
[385]: [(1e-07, 0.5968992248062015), (0.0001111999999999999, 0.5968992248062015), (0.0002222999999999999, 0.5968992248062015), (0.00033339999999999999, 0.5968992248062015), (0.0004444999999999996, 0.5968992248062015), (0.0005556, 0.5968992248062015), (0.00066669999999999, 0.5968992248062015), (0.000777799999999999, 0.5968992248062015), (0.00088889999999999, 0.5968992248062015), (0.001, 0.5968992248062015)]
```

#### 4 Threshold to Choose

The accuracy does not significantly differ across the thresholds chosen. Therefore, a threshold of 1e-3 of importance will be used as the cutoff as it provides a relatively small subset of the 16833 genes. This gives 40 genes as the subset to analyze.