poi_id

September 1, 2018

This project is to identify Enron employees who may have committed fraud based on the public Enron financial and email dataset. The machine learning algorithms are suitable to detect implicit patterns in a large amount of data without explicit methodology. With given the data on which the fraud is marked, we have to classify unknown fraud from the data. This corresponds to the supervised machine learning.

0.0.1 Task 1: Select what features you'll use.

```
In [2]: import sys
        import pickle
        sys.path.append("../tools/")

        from feature_format import featureFormat, targetFeatureSplit
        from tester import dump_classifier_and_data

        ### Load the dictionary containing the dataset
        with open("final_project_dataset.pkl", "rb") as data_file:
            data_dict = pickle.load(data_file)
```

There are 146 data points with 21 features. The data consists of integers and string.

```
In [102]: import pandas as pd
          %matplotlib inline

          data_df = pd.DataFrame.from_dict(data_dict, orient='index')
          data_df.shape

Out[102]: (146, 21)

In [103]: data_df.head()

Out[103]:                     salary to_messages deferral_payments total_payments  \
          ALLEN PHILLIP K     201955        2902            2869717        4484442
          BADUM JAMES P          NaN         NaN             178980         182466
          BANNANTINE JAMES M     477         566                NaN         916197
          BAXTER JOHN C       267102         NaN            1295738        5634343
          BAY FRANKLIN R      239671         NaN             260455         827696
```

```
                     loan_advances    bonus                email_address  \
ALLEN PHILLIP K                NaN  4175000     phillip.allen@enron.com
BADUM JAMES P                  NaN      NaN                          NaN
BANNANTINE JAMES M             NaN      NaN  james.bannantine@enron.com
BAXTER JOHN C                  NaN  1200000                          NaN
BAY FRANKLIN R                 NaN   400000         frank.bay@enron.com

                     restricted_stock_deferred deferred_income  \
ALLEN PHILLIP K                      -126027        -3081055
BADUM JAMES P                            NaN             NaN
BANNANTINE JAMES M                   -560222           -5104
BAXTER JOHN C                            NaN        -1386055
BAY FRANKLIN R                        -82782         -201641

                     total_stock_value      ...      from_poi_to_this_person  \
ALLEN PHILLIP K                1729541      ...                           47
BADUM JAMES P                   257817      ...                          NaN
BANNANTINE JAMES M             5243487      ...                           39
BAXTER JOHN C                 10623258      ...                          NaN
BAY FRANKLIN R                   63014      ...                          NaN

                     exercised_stock_options from_messages    other  \
ALLEN PHILLIP K                      1729541          2195      152
BADUM JAMES P                         257817           NaN      NaN
BANNANTINE JAMES M                   4046157            29   864523
BAXTER JOHN C                        6680544           NaN  2660303
BAY FRANKLIN R                           NaN           NaN       69

                     from_this_person_to_poi    poi  long_term_incentive  \
ALLEN PHILLIP K                           65  False                304805
BADUM JAMES P                            NaN  False                   NaN
BANNANTINE JAMES M                         0  False                   NaN
BAXTER JOHN C                            NaN  False               1586055
BAY FRANKLIN R                           NaN  False                   NaN

                     shared_receipt_with_poi restricted_stock director_fees
ALLEN PHILLIP K                         1407           126027           NaN
BADUM JAMES P                            NaN              NaN           NaN
BANNANTINE JAMES M                       465          1757552           NaN
BAXTER JOHN C                            NaN          3942714           NaN
BAY FRANKLIN R                           NaN           145796           NaN

[5 rows x 21 columns]
```

The string 'NaN' values are replaced with NumPy NaN for the sake of convenience.

```
In [105]: import numpy as np
          data_df = data_df.replace('NaN', np.nan)
          data_df.describe()
```

Out[105]:

	salary	to_messages	deferral_payments	total_payments
count	9.500000e+01	86.000000	3.900000e+01	1.250000e+02
mean	5.621943e+05	2073.860465	1.642674e+06	5.081526e+06
std	2.716369e+06	2582.700981	5.161930e+06	2.906172e+07
min	4.770000e+02	57.000000	-1.025000e+05	1.480000e+02
25%	2.118160e+05	541.250000	8.157300e+04	3.944750e+05
50%	2.599960e+05	1211.000000	2.274490e+05	1.101393e+06
75%	3.121170e+05	2634.750000	1.002672e+06	2.093263e+06
max	2.670423e+07	15149.000000	3.208340e+07	3.098866e+08

	loan_advances	bonus	restricted_stock_deferred
count	4.000000e+00	8.200000e+01	1.800000e+01
mean	4.196250e+07	2.374235e+06	1.664106e+05
std	4.708321e+07	1.071333e+07	4.201494e+06
min	4.000000e+05	7.000000e+04	-7.576788e+06
25%	1.600000e+06	4.312500e+05	-3.896218e+05
50%	4.176250e+07	7.693750e+05	-1.469750e+05
75%	8.212500e+07	1.200000e+06	-7.500975e+04
max	8.392500e+07	9.734362e+07	1.545629e+07

	deferred_income	total_stock_value	expenses
count	4.900000e+01	1.260000e+02	9.500000e+01
mean	-1.140475e+06	6.773957e+06	1.087289e+05
std	4.025406e+06	3.895777e+07	5.335348e+05
min	-2.799289e+07	-4.409300e+04	1.480000e+02
25%	-6.948620e+05	4.945102e+05	2.261400e+04
50%	-1.597920e+05	1.102872e+06	4.695000e+04
75%	-3.834600e+04	2.949847e+06	7.995250e+04
max	-8.330000e+02	4.345095e+08	5.235198e+06

	from_poi_to_this_person	exercised_stock_options	from_messages
count	86.000000	1.020000e+02	86.000000
mean	64.895349	5.987054e+06	608.790698
std	86.979244	3.106201e+07	1841.033949
min	0.000000	3.285000e+03	12.000000
25%	10.000000	5.278862e+05	22.750000
50%	35.000000	1.310814e+06	41.000000
75%	72.250000	2.547724e+06	145.500000
max	528.000000	3.117640e+08	14368.000000

	other	from_this_person_to_poi	long_term_incentive
count	9.300000e+01	86.000000	6.600000e+01
mean	9.190650e+05	41.232558	1.470361e+06
std	4.589253e+06	100.073111	5.942759e+06
min	2.000000e+00	0.000000	6.922300e+04
25%	1.215000e+03	1.000000	2.812500e+05
50%	5.238200e+04	8.000000	4.420350e+05
75%	3.620960e+05	24.750000	9.386720e+05

```
max    4.266759e+07                609.000000         4.852193e+07

       shared_receipt_with_poi  restricted_stock  director_fees
count                86.000000      1.100000e+02   1.700000e+01
mean               1176.465116      2.321741e+06   1.668049e+05
std                1178.317641      1.251828e+07   3.198914e+05
min                   2.000000     -2.604490e+06   3.285000e+03
25%                 249.750000      2.540180e+05   9.878400e+04
50%                 740.500000      4.517400e+05   1.085790e+05
75%                1888.250000      1.002370e+06   1.137840e+05
max                5521.000000      1.303223e+08   1.398517e+06
```

All data points have at least one 'NaN' in their features. Also, all features, except 'poi', have at least one 'NaN' through their data points. The lack of value may cause bad effect on the result. As a rule of thumb, I'll use features with at least 100 non-NA values for finalcial data.

```
In [7]: data_df.count()
```

```
Out[7]: salary                       95
        to_messages                  86
        deferral_payments            39
        total_payments              125
        loan_advances                 4
        bonus                        82
        email_address               111
        restricted_stock_deferred    18
        deferred_income              49
        total_stock_value           126
        expenses                     95
        from_poi_to_this_person      86
        exercised_stock_options     102
        from_messages                86
        other                        93
        from_this_person_to_poi      86
        poi                         146
        long_term_incentive          66
        shared_receipt_with_poi      86
        restricted_stock            110
        director_fees                17
        dtype: int64
```

```
In [88]: financial_features_list = ['total_payments','total_stock_value',
                                    'exercised_stock_options','restricted_stock']
```

If the data points are insufficient or need another feature, try to add up normalized financial features.

There are 18 POIs in the dataset. The dataset is skewed, and accuracy may not be the correct metric.

```
In [11]: len(data_df[data_df['poi']==1])
```

```
Out[11]: 18
```

0.0.2 Task 2: Remove outliers

The maximum values of financial features are two orders of magnitude greater than most of the other value.

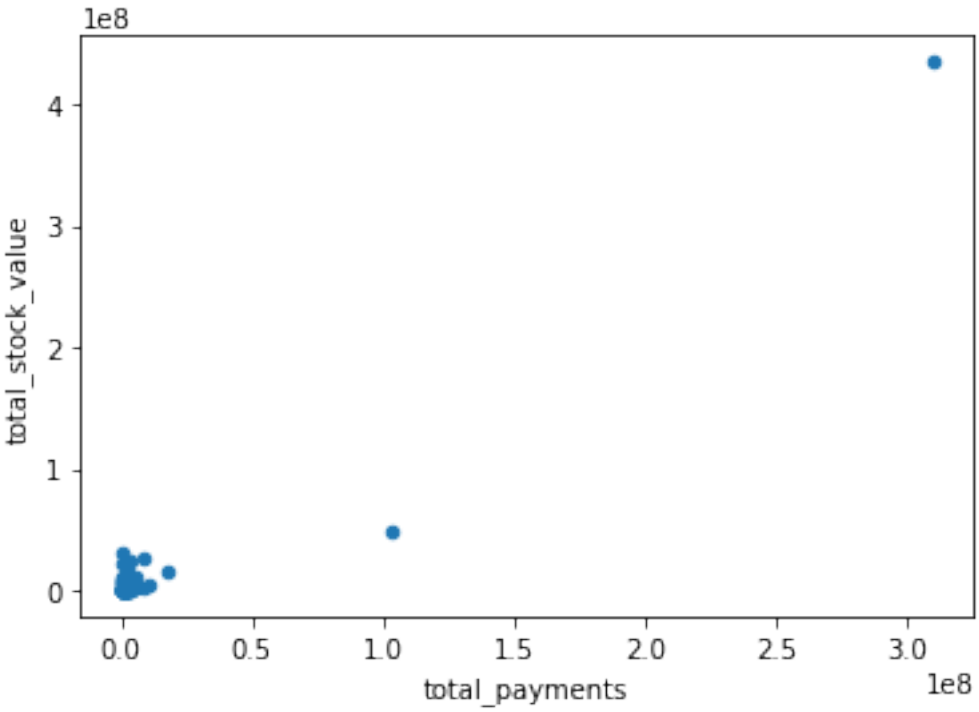
```
In [101]: data_df[financial_features_list].describe()
```

```
Out[101]:        total_payments  total_stock_value  exercised_stock_options  \
          count    1.250000e+02       1.260000e+02             1.020000e+02
          mean     5.081526e+06       6.773957e+06             5.987054e+06
          std      2.906172e+07       3.895777e+07             3.106201e+07
          min      1.480000e+02      -4.409300e+04             3.285000e+03
          25%      3.944750e+05       4.945102e+05             5.278862e+05
          50%      1.101393e+06       1.102872e+06             1.310814e+06
          75%      2.093263e+06       2.949847e+06             2.547724e+06
          max      3.098866e+08       4.345095e+08             3.117640e+08

                 restricted_stock
          count      1.100000e+02
          mean       2.321741e+06
          std        1.251828e+07
          min       -2.604490e+06
          25%        2.540180e+05
          50%        4.517400e+05
          75%        1.002370e+06
          max        1.303223e+08
```

```
In [14]: data_df.plot.scatter(x='total_payments', y='total_stock_value')
```

```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x11d24e1d0>
```



The data point turns out 'TOTAL,' so that should be removed.

```
In [15]: data_df[data_df['total_payments'] > 1e8]
```

```
Out[15]:                   salary  to_messages  deferral_payments  total_payments  \
         LAY KENNETH L   1072321.0       4273.0           202911.0     103559793.0
         TOTAL          26704229.0          NaN         32083396.0     309886585.0

                        loan_advances       bonus          email_address  \
         LAY KENNETH L     81525000.0   7000000.0  kenneth.lay@enron.com
         TOTAL             83925000.0  97343619.0                    NaN

                        restricted_stock_deferred  deferred_income  total_stock_value  \
         LAY KENNETH L                        NaN        -300000.0         49110078.0
         TOTAL                         -7576788.0      -27992891.0        434509511.0

                             ...        from_poi_to_this_person  \
         LAY KENNETH L       ...                          123.0
         TOTAL               ...                            NaN

                        exercised_stock_options  from_messages       other  \
         LAY KENNETH L              34348384.0           36.0  10359729.0
         TOTAL                     311764000.0            NaN  42667589.0

                        from_this_person_to_poi    poi  long_term_incentive  \
```

```
LAY KENNETH L                        16.0   True            3600000.0
TOTAL                                 NaN  False           48521928.0

                shared_receipt_with_poi  restricted_stock  director_fees
LAY KENNETH L                    2411.0        14761694.0            NaN
TOTAL                               NaN       130322299.0      1398517.0

[2 rows x 21 columns]
```

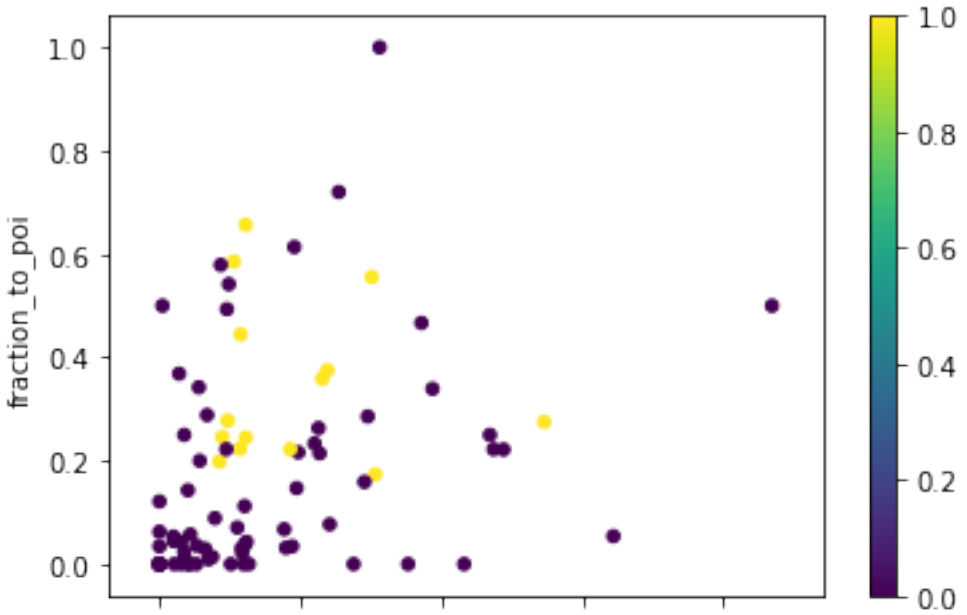
```
In [106]: data_df = data_df.drop('TOTAL')
```

0.0.3 Task 3: Create new feature(s)

Though the higher value of 'from_poi_to_this_person' and 'from_this_person_to_poi' indicates the data point is POI, it may be originated from the fact that he/she treated many emails. So the message ratio related to the POI, rather than the absolute number of the message, will be a more adequate feature.

```
In [113]: data_df['fraction_from_poi'] = (data_df['from_poi_to_this_person']) / data_df['to_mes
          data_df['fraction_to_poi'] = data_df['from_this_person_to_poi'] / data_df['from_messa
          data_df.plot.scatter(x='fraction_from_poi', y='fraction_to_poi',
                               c=data_df['poi'].replace(True,1).replace(False,0),
                               colormap='viridis')
```

```
Out[113]: <matplotlib.axes._subplots.AxesSubplot at 0x11f2dc080>
```



```
In [109]: ### Store to my_dataset for easy export below.
          my_dataset = data_df.replace(np.nan, 'NaN').to_dict('index')

          features_list = ['poi', 'salary', 'total_payments', 'total_stock_value', 'exercised_s
                           'restricted_stock', 'fraction_from_poi', 'fraction_to_poi']

          ### Extract features and labels from dataset for local testing
          data = featureFormat(my_dataset, features_list, sort_keys = True)
          labels, features = targetFeatureSplit(data)
```

0.0.4 Task 4: Try a varity of classifiers

Because the data points are small and skewed, it is better to use Stratified ShuffleSplit cross-validator which returns stratified randomized folds with the percentage of samples for each class.

```
In [22]: from sklearn.model_selection import StratifiedShuffleSplit

         cv = StratifiedShuffleSplit(n_splits = 1000, random_state = 42)
         for train_idx, test_idx in cv.split(features, labels):
             features_train = []
             features_test  = []
             labels_train   = []
             labels_test    = []
             for ii in train_idx:
                 features_train.append(features[ii])
                 labels_train.append(labels[ii])
             for jj in test_idx:
                 features_test.append(features[jj])
                 labels_test.append(labels[jj])
```

I'll try the tree supervised classifiers. They are Gaussian Naive Bayes, C-Support Vector Classification, and decision tree classifier. The first trial of C-Support Vector Classification with default parameters produces zero score for precision and accuracy. However, it may be possible to get a better result by tuning the parameters.

```
In [115]: from sklearn.preprocessing import MinMaxScaler
          from sklearn.decomposition import PCA
          from sklearn.svm import SVC
          from sklearn.naive_bayes import GaussianNB
          from sklearn.pipeline import Pipeline, make_pipeline
          from sklearn.metrics import precision_score, recall_score, f1_score
          from tempfile import mkdtemp
          from shutil import rmtree

          cachedir = mkdtemp()
          pipe = make_pipeline(MinMaxScaler(), PCA(n_components=5), GaussianNB(), memory=cache
          pipe.fit(features_train, labels_train)
          labels_pred = pipe.predict(features_test)
          print("accuracy:", pipe.score(features_test, labels_test))
```

```
          print("precision:", precision_score(labels_test, labels_pred))
          print("recall:", recall_score(labels_test, labels_pred))
          print("f1:", f1_score(labels_test, labels_pred))
          rmtree(cachedir)
```

```
accuracy: 0.8
precision: 0.3333333333333333
recall: 0.5
f1: 0.4
```

```
In [90]: from sklearn.preprocessing import MinMaxScaler
         from sklearn.decomposition import PCA
         from sklearn.svm import SVC
         from sklearn.naive_bayes import GaussianNB
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.pipeline import Pipeline, make_pipeline
         from sklearn.metrics import precision_score, recall_score, f1_score
         from tempfile import mkdtemp
         from shutil import rmtree

         cachedir = mkdtemp()
         pipe = make_pipeline(SVC(), memory=cachedir)
         pipe.fit(features_train, labels_train)
         labels_pred = pipe.predict(features_test)
         print("accuracy:", pipe.score(features_test, labels_test))
         print("precision:", precision_score(labels_test, labels_pred))
         print("recall:", recall_score(labels_test, labels_pred))
         print("f1:", f1_score(labels_test, labels_pred))
         rmtree(cachedir)
```

```
accuracy: 0.8666666666666667
precision: 0.0
recall: 0.0
f1: 0.0
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```

```
In [91]: from sklearn.preprocessing import MinMaxScaler
         from sklearn.decomposition import PCA
         from sklearn.svm import SVC
         from sklearn.naive_bayes import GaussianNB
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.pipeline import Pipeline, make_pipeline
```

```
        from sklearn.metrics import precision_score, recall_score, f1_score
        from tempfile import mkdtemp
        from shutil import rmtree

        cachedir = mkdtemp()
        pipe = make_pipeline(DecisionTreeClassifier(), memory=cachedir)
        pipe.fit(features_train, labels_train)
        labels_pred = pipe.predict(features_test)
        print("accuracy:", pipe.score(features_test, labels_test))
        print("precision:", precision_score(labels_test, labels_pred))
        print("recall:", recall_score(labels_test, labels_pred))
        print("f1:", f1_score(labels_test, labels_pred))
        rmtree(cachedir)
```

```
accuracy: 0.8666666666666667
precision: 0.5
recall: 0.5
f1: 0.5
```

```
In [24]: from sklearn.preprocessing import MinMaxScaler
         from sklearn.decomposition import PCA
         from sklearn.svm import SVC
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.pipeline import Pipeline, make_pipeline
         from sklearn.metrics import precision_score, recall_score, f1_score
         from tempfile import mkdtemp
         from shutil import rmtree

         cachedir = mkdtemp()
         pipe = make_pipeline(MinMaxScaler(), PCA(n_components=7), KNeighborsClassifier(), mem
         pipe.fit(features_train, labels_train)
         labels_pred = pipe.predict(features_test)
         print("accuracy:", pipe.score(features_test, labels_test))
         print("precision:", precision_score(labels_test, labels_pred))
         print("recall:", recall_score(labels_test, labels_pred))
         print("f1:", f1_score(labels_test, labels_pred))
         rmtree(cachedir)
```

```
accuracy: 0.8666666666666667
precision: 0.0
recall: 0.0
f1: 0.0
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetric
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetric
```

```
  'precision', 'predicted', average, warn_for)
```

```
In [33]: from sklearn.preprocessing import MinMaxScaler
         from sklearn.decomposition import PCA
         from sklearn.svm import SVC
         from sklearn.ensemble import AdaBoostClassifier
         from sklearn.pipeline import Pipeline, make_pipeline
         from sklearn.metrics import precision_score, recall_score, f1_score
         from tempfile import mkdtemp
         from shutil import rmtree

         cachedir = mkdtemp()
         pipe = make_pipeline(MinMaxScaler(), PCA(n_components=7), AdaBoostClassifier(), memory
         pipe.fit(features_train, labels_train)
         labels_pred = pipe.predict(features_test)
         print("accuracy:", pipe.score(features_test, labels_test))
         print("precision:", precision_score(labels_test, labels_pred))
         print("recall:", recall_score(labels_test, labels_pred))
         print("f1:", f1_score(labels_test, labels_pred))
         rmtree(cachedir)
```

```
accuracy: 0.9333333333333333
precision: 1.0
recall: 0.5
f1: 0.6666666666666666
```

```
In [28]: from sklearn.preprocessing import MinMaxScaler
         from sklearn.decomposition import PCA
         from sklearn.svm import SVC
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.pipeline import Pipeline, make_pipeline
         from sklearn.metrics import precision_score, recall_score, f1_score
         from tempfile import mkdtemp
         from shutil import rmtree

         cachedir = mkdtemp()
         pipe = make_pipeline(MinMaxScaler(), PCA(n_components=7), RandomForestClassifier(), me
         pipe.fit(features_train, labels_train)
         labels_pred = pipe.predict(features_test)
         print("accuracy:", pipe.score(features_test, labels_test))
         print("precision:", precision_score(labels_test, labels_pred))
         print("recall:", recall_score(labels_test, labels_pred))
         print("f1:", f1_score(labels_test, labels_pred))
         rmtree(cachedir)
```

```
accuracy: 0.8666666666666667
precision: 0.0
```

```
recall: 0.0
f1: 0.0


/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetric
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetric
  'precision', 'predicted', average, warn_for)
```

0.0.5 Task 5: Tune your classifier

GaussianNB does not have any parameter to adjust. However, we can enhance the result by normalization. Also, reducing the dimension helps to prevent overfitting of the classifier.

```
In [117]: from sklearn.preprocessing import MinMaxScaler
          from sklearn.decomposition import PCA
          from sklearn.naive_bayes import GaussianNB
          from sklearn.pipeline import make_pipeline
          from sklearn.model_selection import GridSearchCV
          from sklearn.metrics import classification_report
          from tempfile import mkdtemp
          from shutil import rmtree

          cachedir = mkdtemp()
          pipe = make_pipeline(MinMaxScaler(), PCA(), GaussianNB(), memory=cachedir)
          tuned_parameters = [{'pca__n_components': [2, 3, 4, 5, 6, 7]}]
          scores = ['precision', 'recall']

          for score in scores:
              print("# Tuning hyper-parameters for %s" % score)
              print()

              clf = GridSearchCV(pipe, tuned_parameters, cv=5,
                                 scoring='%s_macro' % score)
              clf.fit(features_train, labels_train)

              print("Best parameters set found on development set:")
              print()
              print(clf.best_params_)
              print()
              print("Grid scores on development set:")
              print()
              means = clf.cv_results_['mean_test_score']
              stds = clf.cv_results_['std_test_score']
              for mean, std, params in zip(means, stds, clf.cv_results_['params']):
                  print("%0.3f (+/-%0.03f) for %r"
                        % (mean, std * 2, params))
```

```
                print()

                print("Detailed classification report:")
                print()
                print("The model is trained on the full development set.")
                print("The scores are computed on the full evaluation set.")
                print()
                labels_true, labels_pred = labels_test, clf.predict(features_test)
                print(classification_report(labels_true, labels_pred))
                print()

            rmtree(cachedir)

# Tuning hyper-parameters for precision

Best parameters set found on development set:

{'pca__n_components': 5}

Grid scores on development set:

0.672 (+/-0.490) for {'pca__n_components': 2}
0.670 (+/-0.492) for {'pca__n_components': 3}
0.621 (+/-0.398) for {'pca__n_components': 4}
0.679 (+/-0.484) for {'pca__n_components': 5}
0.625 (+/-0.397) for {'pca__n_components': 6}
0.628 (+/-0.291) for {'pca__n_components': 7}

Detailed classification report:

The model is trained on the full development set.
The scores are computed on the full evaluation set.

              precision    recall  f1-score   support

         0.0       0.92      0.85      0.88        13
         1.0       0.33      0.50      0.40         2

avg / total       0.84      0.80      0.82        15


# Tuning hyper-parameters for recall

Best parameters set found on development set:

{'pca__n_components': 7}

Grid scores on development set:
```

```
0.584 (+/-0.227) for {'pca__n_components': 2}
0.575 (+/-0.246) for {'pca__n_components': 3}
0.570 (+/-0.221) for {'pca__n_components': 4}
0.579 (+/-0.255) for {'pca__n_components': 5}
0.566 (+/-0.243) for {'pca__n_components': 6}
0.625 (+/-0.275) for {'pca__n_components': 7}

Detailed classification report:

The model is trained on the full development set.
The scores are computed on the full evaluation set.

             precision    recall  f1-score   support

        0.0       0.92      0.92      0.92        13
        1.0       0.50      0.50      0.50         2

avg / total       0.87      0.87      0.87        15
```

The minimum sampling limit helps to prevent overfitting of the decision tree.

```
In [116]: from sklearn.preprocessing import MinMaxScaler
          from sklearn.decomposition import PCA
          from sklearn.tree import DecisionTreeClassifier
          from sklearn.pipeline import make_pipeline
          from sklearn.metrics import classification_report
          from tempfile import mkdtemp
          from shutil import rmtree

          cachedir = mkdtemp()
          pipe = make_pipeline(PCA(), DecisionTreeClassifier(), memory=cachedir)
          tuned_parameters = [{'pca__n_components': [2,3,4,5,7],
                               'decisiontreeclassifier__min_samples_split': [2,4,6,8,10]
                               }]
          scores = ['precision', 'recall']

          for score in scores:
              print("# Tuning hyper-parameters for %s" % score)
              print()

              clf = GridSearchCV(pipe, tuned_parameters, cv=5,
                                 scoring='%s_macro' % score)
              clf.fit(features_train, labels_train)
```

```
        print("Best parameters set found on development set:")
        print()
        print(clf.best_params_)
        print()
        print("Grid scores on development set:")
        print()
        means = clf.cv_results_['mean_test_score']
        stds = clf.cv_results_['std_test_score']
        for mean, std, params in zip(means, stds, clf.cv_results_['params']):
            print("%0.3f (+/-%0.03f) for %r"
                  % (mean, std * 2, params))
        print()

        print("Detailed classification report:")
        print()
        print("The model is trained on the full development set.")
        print("The scores are computed on the full evaluation set.")
        print()
        labels_true, labels_pred = labels_test, clf.predict(features_test)
        print(classification_report(labels_true, labels_pred))
        print()
```

```
# Tuning hyper-parameters for precision



/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: UndefinedMetricW
  'precision', 'predicted', average, warn_for)


Best parameters set found on development set:

{'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 7}

Grid scores on development set:

0.495 (+/-0.176) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 2}
0.533 (+/-0.210) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 3}
0.478 (+/-0.120) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 4}
0.545 (+/-0.212) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 5}
0.607 (+/-0.337) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 7}
0.524 (+/-0.165) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 2}
0.550 (+/-0.214) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 3}
0.522 (+/-0.145) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 4}
0.559 (+/-0.210) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 5}
0.597 (+/-0.290) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 7}
0.527 (+/-0.164) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 2}
0.547 (+/-0.223) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 3}
0.549 (+/-0.204) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 4}
0.566 (+/-0.221) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 5}
0.635 (+/-0.249) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 7}
0.527 (+/-0.164) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 2}
0.533 (+/-0.210) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 3}
0.548 (+/-0.218) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 4}
0.549 (+/-0.216) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 5}
0.629 (+/-0.302) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 7}
0.531 (+/-0.163) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 2}
0.533 (+/-0.210) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 3}
0.549 (+/-0.217) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 4}
0.558 (+/-0.223) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 5}
0.573 (+/-0.316) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 7}

Detailed classification report:
```

```
The model is trained on the full development set.
The scores are computed on the full evaluation set.

             precision    recall  f1-score   support

        0.0       0.92      0.92      0.92        13
        1.0       0.50      0.50      0.50         2

avg / total       0.87      0.87      0.87        15


# Tuning hyper-parameters for recall

Best parameters set found on development set:

{'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 7}

Grid scores on development set:

0.512 (+/-0.198) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 2}
0.567 (+/-0.232) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 3}
0.508 (+/-0.135) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 4}
0.548 (+/-0.127) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 5}
0.522 (+/-0.166) for {'decisiontreeclassifier__min_samples_split': 2, 'pca__n_components': 7}
0.543 (+/-0.130) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 2}
0.593 (+/-0.231) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 3}
0.548 (+/-0.163) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 4}
0.583 (+/-0.172) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 5}
0.646 (+/-0.243) for {'decisiontreeclassifier__min_samples_split': 4, 'pca__n_components': 7}
0.548 (+/-0.124) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 2}
0.576 (+/-0.236) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 3}
0.553 (+/-0.168) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 4}
0.579 (+/-0.174) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 5}
0.613 (+/-0.367) for {'decisiontreeclassifier__min_samples_split': 6, 'pca__n_components': 7}
0.552 (+/-0.120) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 2}
0.567 (+/-0.232) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 3}
0.587 (+/-0.264) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 4}
0.596 (+/-0.249) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 5}
0.665 (+/-0.382) for {'decisiontreeclassifier__min_samples_split': 8, 'pca__n_components': 7}
0.548 (+/-0.124) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 2}
0.567 (+/-0.232) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 3}
0.587 (+/-0.255) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 4}
0.596 (+/-0.249) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 5}
0.585 (+/-0.235) for {'decisiontreeclassifier__min_samples_split': 10, 'pca__n_components': 7}

Detailed classification report:

The model is trained on the full development set.
```

```
The scores are computed on the full evaluation set.

             precision    recall  f1-score   support

        0.0       0.92      0.92      0.92        13
        1.0       0.50      0.50      0.50         2

avg / total       0.87      0.87      0.87        15
```

0.0.6 Task 6: Dump your classifier, dataset, and features_list

The Gaussian Naive Bayes and decision tree classifier show a good performance at the same level. Tuning strategy of these algorithms for the Enron data is to prevent the overfitting. For the Gaussian Naive Bayes, reduction of the feature dimensionality works well. For the decision tree classifier, the minimum splitting limit helps to fit well. The best case of both models shows 0.5 for precision and recall. When I tested the algorithm using tester.py, the decision tree classifier gives higher scores more often. Therefore my pick of the algorithm is the decision tree classifier.

```
In [114]: from sklearn.decomposition import PCA
          from sklearn.tree import DecisionTreeClassifier
          from sklearn.naive_bayes import GaussianNB
          from sklearn.pipeline import Pipeline, make_pipeline
          from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

          clf = make_pipeline(PCA(n_components=7), DecisionTreeClassifier(min_samples_split=4))
          clf.fit(features_train, labels_train)
          labels_pred = clf.predict(features_test)
          print("accuracy:", accuracy_score(labels_test, labels_pred))
          print("precision:", precision_score(labels_test, labels_pred))
          print("recall:", recall_score(labels_test, labels_pred))
          print("f1:", f1_score(labels_test, labels_pred))
```

```
accuracy: 0.8666666666666667
precision: 0.5
recall: 0.5
f1: 0.5
```

```
In [71]: dump_classifier_and_data(clf, my_dataset, features_list)
```