Identify Persons of Interest using Machine Learning

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Summary of project goal

Summarize for us the goal of this project and how machine learning is useful in trying to accomplish it. As part of your answer, give some background on the dataset and how it can be used to answer the project question. Were there any outliers in the data when you got it, and how did you handle those? [relevant rubric items: “data exploration”, “outlier investigation”]

Given information about Enron employees and whether they are persons of interest (POI) in fraud, we use machine learning to predict whether employees are persons of interest or not. The data is primarily numerical, and either compensation related data (salary, bonus, stock options) or email count data (messages sent to persons of interest, all messages sent, etc). There are 144 persons in the dataset (after removing two non-person records), of which 18 are person of interest and the rest are not. Some features have 100 or more missing values (deferral_payments, restricted_stock_deferred, director_fees, loan_advances), so we'll focus on features that have fewer missing values. Compensation and email data can represent latent features, such as how similar a person is to a POI, or how professionally connected one is to a POI. We will be using 11 features, 8 related to compensation, and 3 features related to email counts.

Each record should represent a person. Using a histogram of salary, I found an outlier named "TOTAL", which I removed, since it is not a person. I also removed "The Travel Agency in the Park" because it also does not represent a person. Outliers that represent persons are kept (for example, Jeff Skilling's salary was an outlier that was kept).

Feature Selection

What features did you end up using in your POI identifier, and what selection process did you use to pick them? Did you have to do any scaling? Why or why not? As part of the assignment, you should attempt to engineer your own feature that does not come ready-made in the dataset -- explain what feature you tried to make, and the rationale behind it. (You do not necessarily have to use it in the final analysis, only engineer and test it.) In your feature selection step, if you used an algorithm like a decision tree, please also give the feature importances of the features that you use, and if you used an automated feature selection function like SelectKBest, please report the feature scores and reasons for your choice of parameter values. [relevant rubric items: “create new features”, “properly scale features”, “intelligently select feature”]

I chose features that represent compensation and email counts, and excluded features that had more than a threshold of missing values. When a feature has too many missing values, it can unintentionally associate missing values to a particular class. When choosing the threshold, I wanted to include features that had fewer missing values than the core features that I wanted to keep (email counts), which was 60 missing values out of 144 total records. The "bonus" feature was close enough to the threshold that I kept it as well. So I selected 11 features, 8 that are compensation-related, and 3 that are email-related.

I normalized emails sent to persons of interest (POI) by dividing by total number of emails sent; similarly for emails received from POI and emails received that were also sent to a POI. This represents the fraction of each person's emails that were associated with a POI. The latent feature I think that this represents is how close the professional relationship was with POIs. I scaled all of the compensation and email count ratios to range from 0 to 1, to accommodate algorithms that calculate distances using features, such as SVM.

I used a random forest regression and also selectKBest algorithm to rank features by importance (highest importance first).

feature rank using random forest

[(0.16, 'expenses_scaled'), (0.16, 'exercised_stock_options_scaled'), (0.14, 'to_poi_ratio_scaled'), (0.1, 'shared_poi_ratio_scaled'), (0.1, 'other_scaled'), (0.09, 'salary_scaled'), (0.09, 'bonus_scaled'), (0.07, 'total_payments_scaled'), (0.04, 'total_stock_value_scaled'), (0.04, 'from_poi_ratio_scaled'), (0.02, 'restricted_stock_scaled')]

feature rank using SelectKBest

[(16.18, 'to_poi_ratio_scaled'), (9.02, 'shared_poi_ratio_scaled'), (3.05, 'from_poi_ratio_scaled'), (0.33, 'total_payments_scaled'), (0.21, 'exercised_stock_options_scaled'), (0.15, 'total_stock_value_scaled'), (0.11, 'restricted_stock_scaled'), (0.06, 'other_scaled'), (0.06, 'bonus_scaled'), (0.02, 'expenses_scaled'), (0.0, 'salary_scaled')]

For random forest feature ranking, I used the top 1 through 6 features (top 1, top 2, top 3 etc). I used SVM to test. The best F1 score was from using the top three features: to poi ratio, bonus, and shared poi ratio.

For selectKbest ranking, I used the top 4,5,6 features, and SVM to test. The best F1 score was from using the top 4 features: to poi ratio; shared poi ratio, from poi ratio, total payments.

Since I got the highest score using the top three features found by random forest ranking, I used either the top three features (to poi email ratio, bonus, shared email ratio), as well as all 11 features when comparing algorithms. This is because decision trees and random forest performed better with all 11 features.

I also used SVM to test whether the new features improve prediction.

SVM with top 3 features including email ratio:

Precision: 0.44888 Recall: 0.73100 F1: 0.55621

Features used are: to poi ratio, bonus, shared poi ratio

SVM without new features

Precision: 0.18282 Recall: 0.11600 F1: 0.14194

Features used are bonus, exercised stock options, from poi email count, salary

I used original features, ranked them using random forest, and used the top four from the ranking:

[(0.16, 'bonus_scaled'), (0.14, 'exercised_stock_options_scaled'), (0.11, 'from_poi_to_this_person'), (0.1, 'salary_scaled'), (0.08, 'shared_receipt_with_poi'), (0.08, 'other_scaled'), (0.08, 'from_messages'), (0.07, 'expenses_scaled'), (0.05, 'total_payments_scaled'), (0.05, 'from_this_person_to_poi'), (0.03, 'restricted_stock_scaled'), (0.02, 'to_messages'), (0.01, 'total_stock_value_scaled')]

I tuned parameters for SVM and tested. The model performs worse without the new email ratio features.

Algorithm selection

What algorithm did you end up using? What other one(s) did you try? How did model performance differ between algorithms? [relevant rubric item: "pick an algorithm"]

I chose SVM, as it had the highest F1 score. SVM had the highest recall, so it would be good for casting a wider net to find more potential POIs. Adaboost with logistic regression had the highest precision, so it would be good for trying to label only the actual POIs as POIs.

I tried the following algorithms, using grid search to tune parameters and try with or without PCA. The results are:

SVM

Precision: 0.44614 Recall: 0.82000 F1: 0.57787

SVM does better with the top 3 features rather than all 11

Adaboost and SVM

Precision: 0.43168 Recall: 0.65400 F1: 0.52008

Like SVM, Adaboost using SVM does best with the top selected features. Adaboost with SVM does slightly worse than SVM alone.

Adaboost Decision Tree

Precision: 0.40729 Recall: 0.31850 F1: 0.35746

Similar to decision trees, adaboost using decision trees performs better using 11 features rather than the top 2

Naive Bayes

Precision: 0.39823 Recall: 0.24750 F1: 0.30527

Naive Bayes performs better with selected features rather than all of them

Adaboost with logistic regression

Precision: 0.48645 Recall: 0.18850 F1: 0.27171

Adaboost with logistic regression does a little bit better when using just the top 3 features as opposed to 11. The three algorithms that had precision, recall and F1 above 0.30 are SVM, Adaboost with SVM, and Adaboost with decision trees.

Adaboost with Naive Bayes

Precision: 0.31329 Recall: 0.22400 F1: 0.26122

Adaboost with Naive Bayes did a little better with all 11 features rather than the top 3 features.

Random Forest

Precision: 0.38034 Recall: 0.14700 F1: 0.21204 Random forest with 11 features does worse than Adaboost with decision trees and 11 features, but better than decision trees alone.

Decision Trees

Precision: 0.21442 Recall: 0.16650 F1: 0.18745

Decision tree appears to do worse with just the top features, and when using PCA. Decision trees did better when I included all features.

Parameter tuning

What does it mean to tune the parameters of an algorithm, and what can happen if you don't do this well? How did you tune the parameters of your particular algorithm? (Some algorithms do not have parameters that you need to tune -- if this is the case for the one you picked, identify and briefly explain how you would have done it for the model that was not your final choice or a different model that does utilize parameter tuning, e.g. a decision tree classifier). [relevant rubric item: "tune the algorithm"]

An algorithm's parameters are constants that can be altered to change the bias and variance of the model. For instance, the SVM's C "penalty" can be increased to penalize mis-classifying each data point. A higher penalty would make the model fit the training data more accurately, but also increase the variance of the model (a different training set would likely change the model significantly). The SVM's gamma can be increased to reduce the influence of a data point in determining the classification of other points that are far away; this increases the model's bias, so that a different training set is not likely to result in a different model.

When using PCA, I varied the number of components used, and also tested on the original features without PCA. For Adaboost, I varied the number of estimator iterations. For SVM, I varied the C (penalty) and gamma. For decision trees, I varied the minimum number of samples to allow a split. For random forest, I varied the number of trees. For logistic regression, I varied the penalty parameter.

Reference:

https://www.quora.com/What-are-C-and-gamma-with-regards-to-a-support-vector-machine (https://www.quora.com/What-are-C-and-gamma-with-regards-to-a-support-vector-machine)

Validation

What is validation, and what’s a classic mistake you can make if you do it wrong? How did you validate your analysis? [relevant rubric item: “validation strategy”]

Validation measures how well the model would perform when making new predictions. Validation uses test data that is not part of the training data. If the same data is used to train and validate a model, then the parameters that give the best validation score will also cause the model to overfit the data, resulting in a high variance model. A high variance model would change significantly each time it is given a different data set to train on. Another requirement is for the training and test data to be chosen randomly, so that both sets are representative of the whole data set. If training and test data are not representative of the whole set, then the model will perform poorly when validated against the test data. For example, if all training data are of POI and all test data are of non-POIs, then the model will make poor predictions when faced with the test data.

Evaluation metrics

Give at least 2 evaluation metrics and your average performance for each of them. Explain an interpretation of your metrics that says something human-understandable about your algorithm’s performance. [relevant rubric item: “usage of evaluation metrics”]

The precision score measures what fraction of all predictions of POI are actually POI.

The recall score measures what fraction of all actual POIs are correctly predicted as POI.

An F1 score equally weighs the precision and recall as one score. So a model has a higher F1 score when more of its predictions of POI are actually POI, and also when more of the actual POI are predicted as POI.

The cross validation method used is stratified shuffle split. Stratified validation is useful when the number of POIs and non-POIs are very different as a fraction of the available data (for example, we have few POIs and many non-POIs). When dividing the data into several folds (some of which are assigned to training, the rest for testing), each fold is stratified, meaning that the fraction of POIs in each fold is the same as the fraction in the whole data set. The data is also shuffled before it is divided into folds. Shuffling data also helps to make the training and test set more representative of the whole data set.

Reference

[http://scikit-learn.org/stable/modules/cross_validation.html (http://scikit-learn.org/stable/modules/cross_validation.html)](http://scikit-learn.org/stable/modules/cross_validation.html)

Appendix: steps taken to select features and choose algorithm

In [3]:
```
import sys
import pickle
from time import time
import math
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.pipeline import Pipeline
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn.model_selection import GridSearchCV
sys.path.append("../tools/")
from collections import defaultdict
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from feature_format import featureFormat, targetFeatureSplit
from tester import dump_classifier_and_data
from tester import test_classifier
```

```
/Users/edude/anaconda/lib/python2.7/site-packages/sklearn/cross_validat
ion.py:44: DeprecationWarning: This module was deprecated in version 0.
18 in favor of the model_selection module into which all the refactored
 classes and functions are moved. Also note that the interface of the n
ew CV iterators are different from that of this module. This module wil
l be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [205]:
```
### Load the dictionary containing the dataset
with open("final_project_dataset.pkl", "r") as data_file:
    data_dict = pickle.load(data_file)
```

In [201]:
```
len(data_dict)
```

Out[201]:
```
146
```

In [206]:
```
feature_l = defaultdict(list)
for name, content in data_dict.iteritems():
    feature_l['name'].append(name)
    for feature, value in content.iteritems():
        feature_l[feature].append(value)
```

In [203]:
```
feature_l.keys()
```

Out[203]:
```
['to_messages',
 'deferral_payments',
 'expenses',
 'poi',
 'long_term_incentive',
 'email_address',
 'from_poi_to_this_person',
 'deferred_income',
 'restricted_stock_deferred',
 'shared_receipt_with_poi',
 'loan_advances',
 'from_messages',
 'other',
 'director_fees',
 'bonus',
 'total_stock_value',
 'from_this_person_to_poi',
 'restricted_stock',
 'salary',
 'name',
 'total_payments',
 'exercised_stock_options']
```

In [204]:
```
feature_l['name']
```

Out[204]:

```
['METTS MARK',
 'BAXTER JOHN C',
 'ELLIOTT STEVEN',
 'CORDES WILLIAM R',
 'HANNON KEVIN P',
 'MORDAUNT KRISTINA M',
 'MEYER ROCKFORD G',
 'MCMAHON JEFFREY',
 'HORTON STANLEY C',
 'PIPER GREGORY F',
 'HUMPHREY GENE E',
 'UMANOFF ADAM S',
 'BLACHMAN JEREMY M',
 'SUNDE MARTIN',
 'GIBBS DANA R',
 'LOWRY CHARLES P',
 'COLWELL WESLEY',
 'MULLER MARK S',
 'JACKSON CHARLENE R',
 'WESTFAHL RICHARD K',
 'WALTERS GARETH W',
 'WALLS JR ROBERT H',
 'KITCHEN LOUISE',
 'CHAN RONNIE',
 'BELFER ROBERT',
 'SHANKMAN JEFFREY A',
 'WODRASKA JOHN',
 'BERGSIEKER RICHARD P',
 'URQUHART JOHN A',
 'BIBI PHILIPPE A',
 'RIEKER PAULA H',
 'WHALEY DAVID A',
 'BECK SALLY W',
 'HAUG DAVID L',
 'ECHOLS JOHN B',
 'MENDELSOHN JOHN',
 'HICKERSON GARY J',
 'CLINE KENNETH W',
 'LEWIS RICHARD',
 'HAYES ROBERT E',
 'MCCARTY DANNY J',
 'KOPPER MICHAEL J',
 'LEFF DANIEL P',
 'LAVORATO JOHN J',
 'BERBERIAN DAVID',
 'DETMERING TIMOTHY J',
 'WAKEHAM JOHN',
 'POWERS WILLIAM',
 'GOLD JOSEPH',
 'BANNANTINE JAMES M',
 'DUNCAN JOHN H',
 'SHAPIRO RICHARD S',
 'SHERRIFF JOHN R',
 'SHELBY REX',
 'LEMAISTRE CHARLES',
 'DEFFNER JOSEPH M',
 'KISHKILL JOSEPH G',
```

```
                  'WHALLEY LAWRENCE G',
                  'MCCONNELL MICHAEL S',
                  'PIRO JIM',
                  'DELAINEY DAVID W',
                  'SULLIVAN-SHAKLOVITZ COLLEEN',
                  'WROBEL BRUCE',
                  'LINDHOLM TOD A',
                  'MEYER JEROME J',
                  'LAY KENNETH L',
                  'BUTTS ROBERT H',
                  'OLSON CINDY K',
                  'MCDONALD REBECCA',
                  'CUMBERLAND MICHAEL S',
                  'GAHN ROBERT S',
                  'MCCLELLAN GEORGE',
                  'HERMANN ROBERT J',
                  'SCRIMSHAW MATTHEW',
                  'GATHMANN WILLIAM D',
                  'HAEDICKE MARK E',
                  'BOWEN JR RAYMOND M',
                  'GILLIS JOHN',
                  'FITZGERALD JAY L',
                  'MORAN MICHAEL P',
                  'REDMOND BRIAN L',
                  'BAZELIDES PHILIP J',
                  'BELDEN TIMOTHY N',
                  'DURAN WILLIAM D',
                  'THORN TERENCE H',
                  'FASTOW ANDREW S',
                  'FOY JOE',
                  'CALGER CHRISTOPHER F',
                  'RICE KENNETH D',
                  'KAMINSKI WINCENTY J',
                  'LOCKHART EUGENE E',
                  'COX DAVID',
                  'OVERDYKE JR JERE C',
                  'PEREIRA PAULO V. FERRAZ',
                  'STABLER FRANK',
                  'SKILLING JEFFREY K',
                  'BLAKE JR. NORMAN P',
                  'SHERRICK JEFFREY B',
                  'PRENTICE JAMES',
                  'GRAY RODNEY',
                  'PICKERING MARK R',
                  'THE TRAVEL AGENCY IN THE PARK',
                  'NOLES JAMES L',
                  'KEAN STEVEN J',
                  'TOTAL',
                  'FOWLER PEGGY',
                  'WASAFF GEORGE',
                  'WHITE JR THOMAS E',
                  'CHRISTODOULOU DIOMEDES',
                  'ALLEN PHILLIP K',
                  'SHARP VICTORIA T',
                  'JAEDICKE ROBERT',
                  'WINOKUR JR. HERBERT S',
                  'BROWN MICHAEL',
```

```
              'BADUM JAMES P',
              'HUGHES JAMES A',
              'REYNOLDS LAWRENCE',
              'DIMICHELE RICHARD G',
              'BHATNAGAR SANJAY',
              'CARTER REBECCA C',
              'BUCHANAN HAROLD G',
              'YEAP SOON',
              'MURRAY JULIA H',
              'GARLAND C KEVIN',
              'DODSON KEITH',
              'YEAGER F SCOTT',
              'HIRKO JOSEPH',
              'DIETRICH JANET R',
              'DERRICK JR. JAMES V',
              'FREVERT MARK A',
              'PAI LOU L',
              'BAY FRANKLIN R',
              'HAYSLETT RODERICK J',
              'FUGH JOHN L',
              'FALLON JAMES B',
              'KOENIG MARK E',
              'SAVAGE FRANK',
              'IZZO LAWRENCE L',
              'TILNEY ELIZABETH A',
              'MARTIN AMANDA K',
              'BUY RICHARD B',
              'GRAMM WENDY L',
              'CAUSEY RICHARD A',
              'TAYLOR MITCHELL S',
              'DONAHUE JR JEFFREY M',
              'GLISAN JR BEN F']
```

Looking at the names, 'The Travel Agency in the Park' is not a person, so we'll remove this. We are trying to identify persons of interest, so we only want to train and test on person data.

In [207]:
```
data_dict.pop('THE TRAVEL AGENCY IN THE PARK')
```

Out[207]:
```
{'bonus': 'NaN',
 'deferral_payments': 'NaN',
 'deferred_income': 'NaN',
 'director_fees': 'NaN',
 'email_address': 'NaN',
 'exercised_stock_options': 'NaN',
 'expenses': 'NaN',
 'from_messages': 'NaN',
 'from_poi_to_this_person': 'NaN',
 'from_this_person_to_poi': 'NaN',
 'loan_advances': 'NaN',
 'long_term_incentive': 'NaN',
 'other': 362096,
 'poi': False,
 'restricted_stock': 'NaN',
 'restricted_stock_deferred': 'NaN',
 'salary': 'NaN',
 'shared_receipt_with_poi': 'NaN',
 'to_messages': 'NaN',
 'total_payments': 362096,
 'total_stock_value': 'NaN'}
```

In [376]:
```
#Convert dict to a data frame to describe data and plot it
data_df = pd.DataFrame(feature_l)
```

In [377]:
```
#remove NaN from each col and plot it for outliers
salary = data_df['salary']
salary_c = salary[salary.apply(lambda x: not math.isnan(float(x)))]
salary_c = pd.DataFrame(salary_c.apply(lambda x: float(x)))
```

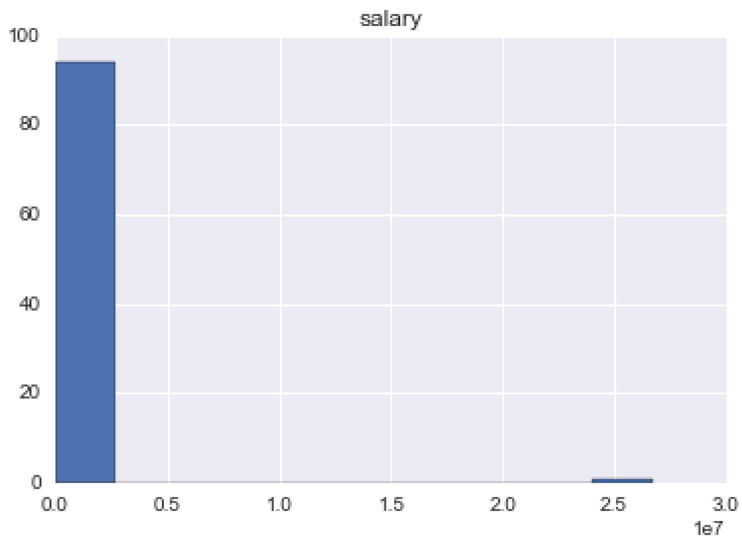
In [378]:
```
salary_c.describe()
```

Out[378]:

	salary
count	9.500000e+01
mean	5.621943e+05
std	2.716369e+06
min	4.770000e+02
25%	2.118160e+05
50%	2.599960e+05
75%	3.121170e+05
max	2.670423e+07

Histogram shows an outlier

In [379]:
```
salary_c.hist();
```



In [384]:
```
salary_c.max()[0]
```

Out[384]:
```
26704229.0
```

In [385]:
```
data_df[data_df['salary']==salary_c.max()[0]]['name']
```

Out[385]:
```
104    TOTAL
Name: name, dtype: object
```

Remove the 'TOTAL' record from data_dict and the data frame

In [208]:
```
data_dict.pop('TOTAL')
```

Out[208]:
```
{'bonus': 97343619,
 'deferral_payments': 32083396,
 'deferred_income': -27992891,
 'director_fees': 1398517,
 'email_address': 'NaN',
 'exercised_stock_options': 311764000,
 'expenses': 5235198,
 'from_messages': 'NaN',
 'from_poi_to_this_person': 'NaN',
 'from_this_person_to_poi': 'NaN',
 'loan_advances': 83925000,
 'long_term_incentive': 48521928,
 'other': 42667589,
 'poi': False,
 'restricted_stock': 130322299,
 'restricted_stock_deferred': -7576788,
 'salary': 26704229,
 'shared_receipt_with_poi': 'NaN',
 'to_messages': 'NaN',
 'total_payments': 309886585,
 'total_stock_value': 434509511}
```

In [393]:
```
data_df = data_df[data_df['name'] != 'TOTAL']
```

In [435]:
```
data_df = data_df[data_df['name'] != 'THE TRAVEL AGENCY IN THE PARK']
```

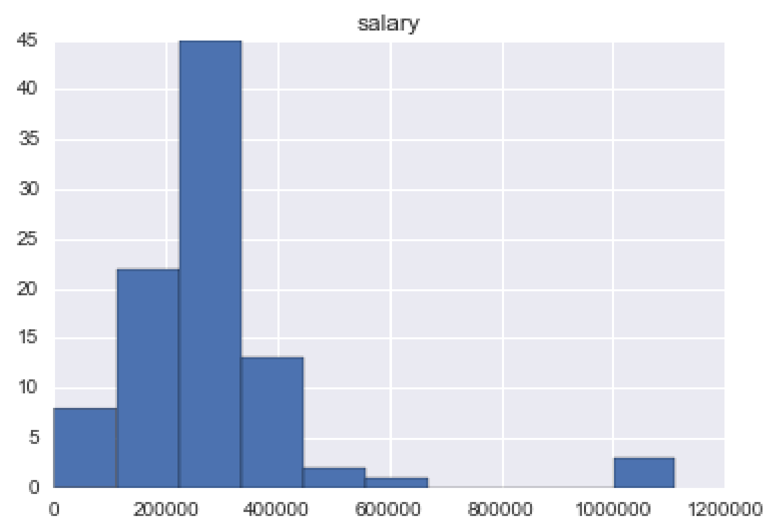
In [443]:
```
poi = data_df['poi']
poi = poi.apply(lambda x: 1 if x else 0)
```

In [446]:
```
sum(poi)
```

Out[446]:
```
18
```

In [394]:
```
#remove max from from salary_c and check again
salary_c = salary_c[ salary_c['salary'] != salary_c['salary'].max()]
```

In [396]:
```
salary_c.hist();
```



In [397]:
```
salary_c['salary'].max()
```

Out[397]:
```
1111258.0
```

In [398]:
```
data_df[ data_df['salary'] == salary_c['salary'].max() ]['name']
```

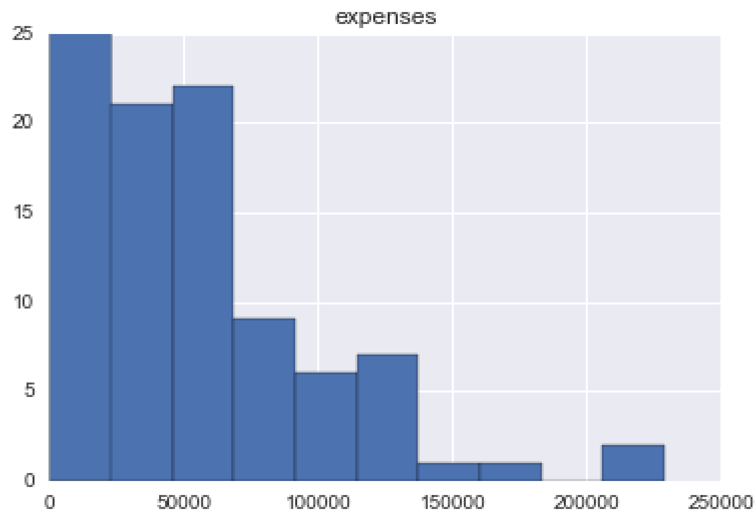
Out[398]:
```
95    SKILLING JEFFREY K
Name: name, dtype: object
```

Since this second 'outlier' is a person, we'll keep this data.

Looking for other outliers

In [402]:
```
expenses = data_df['expenses']
expenses_c = expenses[expenses.apply(lambda x: not
math.isnan(float(x)))]
expenses_c = pd.DataFrame(expenses_c.apply(lambda x: float(x)))
```

In [403]:
```
expenses_c.hist();
```



In [406]:
```
expenses_c.describe()
```

Out[406]:

	expenses
count	94.000000
mean	54192.010638
std	46108.377454
min	148.000000
25%	22479.000000
50%	46547.500000
75%	78408.500000
max	228763.000000

In [407]:
```
data_df[ data_df['expenses'] == expenses_c['expenses'].max() ]['name']
```

Out[407]:
```
71    MCCLELLAN GEORGE
Name: name, dtype: object
```

The max expense is from a person; we'll keep this as well.

In [409]:
```
nan_count = defaultdict(list)
for k, v in feature_l.iteritems():
    num_nan = sum([1 for e in v if e == 'NaN'] )
    nan_count['feature'].append(k)
    nan_count['nan_count'].append(num_nan)

nan_count = pd.DataFrame(nan_count)
```

In [410]:
```
nan_count.sort_values('nan_count')
```

Out[410]:

	feature	nan_count
19	name	0
3	poi	0
15	total_stock_value	20
20	total_payments	21
5	email_address	35
17	restricted_stock	36
21	exercised_stock_options	44
2	expenses	51
18	salary	51
12	other	53
16	from_this_person_to_poi	60
0	to_messages	60
9	shared_receipt_with_poi	60
6	from_poi_to_this_person	60
11	from_messages	60
14	bonus	64
4	long_term_incentive	80
7	deferred_income	97
1	deferral_payments	107
8	restricted_stock_deferred	128
13	director_fees	129
10	loan_advances	142

I prefer features that have more data as opposed to missing data. Since I plan to use the email data, which have 60 NaNs per feature at most, I'll use that as the cut-off point. Since 'bonus' is close to that cut-off at 64 NaNs, I'll also include 'bonus' and all features with fewer NaNs. I'll exclude 'email address', since it is not numerical.

In [237]:
```
### Task 1: Select what features you'll use.
### feature_list is a list of strings, each of which is a feature name.
### The first feature must be "poi".

#The features are either related to compensation/expenses or to emails
feature_list = ['poi',
                 'salary',
                 'total_stock_value',
                 'total_payments',
                 'restricted_stock',
                 'exercised_stock_options',
                 'other',
                 'bonus',
                 'expenses',
                 'to_messages',
                 'from_messages',
                 'from_this_person_to_poi',
                 'from_poi_to_this_person',
                 'shared_receipt_with_poi'
                ]
```

Two members appear not to be persons, so I'll remove these from the data

Create new features

I can scale the compensation data to be between 0 and 1. This is helpful if using SVM or K-means which calculate a distance based on more than one dimension.

For emails, I can get a ratio of poi emails received divided by all emails received, and similarly for other poi_emails.

In [209]:
```
def scale_feature(data_dict, feature, feature_scaled):
    feature_l = [v[feature] for v in data_dict.values() if v[feature] !=
 'NaN']
    scaler = MinMaxScaler()
    scaler.fit(np.array(feature_l).reshape(len(feature_l),1))

    for name, data in data_dict.iteritems():
        if data[feature] == 'NaN':
            data[feature_scaled] = 'NaN'
        else:
            data[feature_scaled] = scaler.transform(np.array([[data[feat
ure]]]))[0][0]
    return data_dict
```

In [210]:
```
def compute_ratio(data_dict, numerator, denominator, ratio):
    for k, v in data_dict.iteritems():
        n = v[numerator]
        d = v[denominator]
        if n == 'NaN' or d == 'NaN' or d == 0:
            data_dict[k][ratio] = 'NaN'
        else:
            data_dict[k][ratio] = float(n) / float(d)
```

In [211]:
```
#first compute email ratios
ratios_to_compute = [('from_this_person_to_poi', 'from_messages', 'to_po
i_ratio'),
                     ('from_poi_to_this_person', 'to_messages', 'from_po
i_ratio'),
                     ('shared_receipt_with_poi', 'to_messages', 'shared_
poi_ratio')
                    ]

for numerator, denominator, ratio in ratios_to_compute:
    compute_ratio(data_dict, numerator, denominator, ratio)
```

In [212]:
```
#then scale compensation, expense, and email ratios
feature_to_scale = ['salary',
                    'total_stock_value',
                     'total_payments',
                     'restricted_stock',
                     'exercised_stock_options',
                     'other',
                     'bonus',
                     'expenses',
                     'to_poi_ratio',
                     'from_poi_ratio',
                     'shared_poi_ratio'
                    ]
for feature in feature_to_scale:
    data_dict = scale_feature(data_dict, feature, feature + '_scaled')
```

In [21]:
```
data_dict[data_dict.keys()[0]]
```

Out[21]:
```
{'bonus': 600000,
 'bonus_scaled': 0.0054485481824213819,
 'deferral_payments': 'NaN',
 'deferred_income': 'NaN',
 'director_fees': 'NaN',
 'email_address': 'mark.metts@enron.com',
 'exercised_stock_options': 'NaN',
 'exercised_stock_options_scaled': 'NaN',
 'expenses': 94299,
 'expenses_scaled': 0.017984737490568382,
 'from_messages': 29,
 'from_poi_ratio': 0.04708798017348203,
 'from_poi_ratio_scaled': 0.21665480239394658,
 'from_poi_to_this_person': 38,
 'from_this_person_to_poi': 1,
 'loan_advances': 'NaN',
 'long_term_incentive': 'NaN',
 'other': 1740,
 'other_scaled': 4.0733496365754174e-05,
 'poi': False,
 'restricted_stock': 585062,
 'restricted_stock_deferred': 'NaN',
 'restricted_stock_scaled': 0.023994802131269415,
 'salary': 365788,
 'salary_scaled': 0.013680137532733229,
 'shared_poi_ratio': 0.8698884758364313,
 'shared_poi_ratio_scaled': 0.86644162302202699,
 'shared_receipt_with_poi': 702,
 'to_messages': 807,
 'to_poi_ratio': 0.034482758620689655,
 'to_poi_ratio_scaled': 0.034482758620689655,
 'total_payments': 1061827,
 'total_payments_scaled': 0.0034260260315942775,
 'total_stock_value': 585062,
 'total_stock_value_scaled': 0.0014478190819469075}
```

In [213]:
```
feature_list = ['poi',
                 'salary_scaled',
                 'total_stock_value_scaled',
                 'total_payments_scaled',
                 'restricted_stock_scaled',
                 'exercised_stock_options_scaled',
                 'other_scaled',
                 'bonus_scaled',
                 'expenses_scaled',
                 'to_poi_ratio_scaled',
                 'from_poi_ratio_scaled',
                 'shared_poi_ratio_scaled'
                ]
```

In [221]:
```
### Store to my_dataset for easy export below.
my_dataset = data_dict
```

In [222]:
```
### Extract features and labels from dataset for local testing
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)
```

Rank features by random forest

In [29]:
```
feature_only = feature_list[1:]
```

In [327]:
```
from sklearn.ensemble import RandomForestRegressor
clf = RandomForestRegressor()
clf.fit(features, labels)
feature_rank = sorted (zip (map(lambda x: round(x,2),clf.feature_importa
nces_) , feature_only), reverse=True)
print "feature rank using random forest"
print feature_rank
```

```
feature rank using random forest
[(0.18, 'to_poi_ratio_scaled'), (0.14, 'bonus_scaled'), (0.12, 'shared_
poi_ratio_scaled'), (0.11, 'total_stock_value_scaled'), (0.1, 'exercise
d_stock_options_scaled'), (0.09, 'total_payments_scaled'), (0.09, 'othe
r_scaled'), (0.09, 'expenses_scaled'), (0.05, 'restricted_stock_scale
d'), (0.02, 'from_poi_ratio_scaled'), (0.01, 'salary_scaled')]
```

In [328]:
```
#test with top 1 feature of random forest ranking
feature_list = ['poi',
                'to_poi_ratio_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.61657       Precision: 0.26894      Recall: 0.98000
        F1: 0.42205     F2: 0.64103
        Total predictions: 7000 True positives:  980    False positive
s: 2664 False negatives:   20   True negatives: 3336
```

In [329]:
```
#test with top 2 features of random forest ranking
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.72020       Precision: 0.40527      Recall: 0.85350
        F1: 0.54958     F2: 0.69890
        Total predictions: 10000        True positives: 1707    False p
ositives: 2505  False negatives:  293   True negatives: 5495
```

In [330]:
```
#test with top 3 features of random forest ranking
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.78218       Precision: 0.44614      Recall: 0.82000
        F1: 0.57787     F2: 0.70230
        Total predictions: 11000        True positives: 1640    False p
ositives: 2036  False negatives:  360   True negatives: 6964
```

In [344]:
```
#test with top 4 features
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled',
                'total_stock_value_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.76469       Precision: 0.35959      Recall: 0.67800
        F1: 0.46994     F2: 0.57599
        Total predictions: 13000        True positives: 1356    False p
ositives: 2415  False negatives:  644   True negatives: 8585
```

In [343]:
```
#test with top 5 features
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled',
                'total_stock_value_scaled',
                'exercised_stock_options_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.76131       Precision: 0.35634      Recall: 0.68400
        F1: 0.46857     F2: 0.57775
        Total predictions: 13000        True positives: 1368    False p
ositives: 2471  False negatives:  632   True negatives: 8529
```

In [345]:
```
#test with top 6 features
feature_list = ['poi',
                'shared_poi_ratio_scaled',
                'bonus_scaled',
                'expenses_scaled',
                'exercised_stock_options_scaled',
                'total_stock_value_scaled',
                'total_payments_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.75893       Precision: 0.31583      Recall: 0.58950
        F1: 0.41130     F2: 0.50243
        Total predictions: 14000        True positives: 1179    False p
ositives: 2554  False negatives:  821   True negatives: 9446
```

Rank feature using selectKBest

In [193]:
```
feature_list = ['poi',
                 'salary_scaled',
                 'total_stock_value_scaled',
                 'total_payments_scaled',
                 'restricted_stock_scaled',
                 'exercised_stock_options_scaled',
                 'other_scaled',
                 'bonus_scaled',
                 'expenses_scaled',
                 'to_poi_ratio_scaled',
                 'from_poi_ratio_scaled',
                 'shared_poi_ratio_scaled'
                ]

from sklearn.feature_selection import SelectKBest
clf = SelectKBest(k=11)
clf.fit(features, labels)
feature_rank = sorted (zip (map(lambda x: round(x,2),clf.scores_), featu
re_only), reverse = True)
print "feature rank using SelectKBest"
print feature_rank
```

```
feature rank using SelectKBest
[(16.18, 'to_poi_ratio_scaled'), (9.02, 'shared_poi_ratio_scaled'), (3.
05, 'from_poi_ratio_scaled'), (0.33, 'total_payments_scaled'), (0.21,
 'exercised_stock_options_scaled'), (0.15, 'total_stock_value_scaled'),
 (0.11, 'restricted_stock_scaled'), (0.06, 'other_scaled'), (0.06, 'bon
us_scaled'), (0.02, 'expenses_scaled'), (0.0, 'salary_scaled')]
```

Test with top 4 features

In [346]:
```
#test with top 3 features
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'shared_poi_ratio_scaled',
                'from_poi_ratio_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.67544       Precision: 0.24744      Recall: 0.94100
        F1: 0.39184     F2: 0.60297
        Total predictions: 9000 True positives:  941    False positive
s: 2862 False negatives:   59   True negatives: 5138
```

In [347]:
```
#test with top 4 features
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'shared_poi_ratio_scaled',
                'from_poi_ratio_scaled',
                'total_payments_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.75836       Precision: 0.33794      Recall: 0.72100
        F1: 0.46019     F2: 0.58776
        Total predictions: 14000        True positives: 1442    False p
ositives: 2825  False negatives:  558   True negatives: 9175
```

In [348]:
```
#test with top 5 features
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'shared_poi_ratio_scaled',
                'from_poi_ratio_scaled',
                'total_payments_scaled',
                'exercised_stock_options_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.75386       Precision: 0.32245      Recall: 0.65650
        F1: 0.43248     F2: 0.54382
        Total predictions: 14000        True positives: 1313    False p
ositives: 2759  False negatives:  687   True negatives: 9241
```

In [349]:
```
#test with top 6 features
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'shared_poi_ratio_scaled',
                'from_poi_ratio_scaled',
                'total_payments_scaled',
                'exercised_stock_options_scaled',
                'total_stock_value_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.73950       Precision: 0.29920      Recall: 0.61350
        F1: 0.40223     F2: 0.50698
        Total predictions: 14000        True positives: 1227    False p
ositives: 2874  False negatives:  773   True negatives: 9126
```

Given the results, I'll use the top 3 feaures as ranked by random forest:

to poi ratio

bonus

shared poi ratio

In [244]:
```
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
```

Try classifiers

In [103]:
```
### Task 4: Try a varity of classifiers
### Please name your classifier clf for easy export below.
### Note that if you want to do PCA or other multi-stage operations,
### you'll need to use Pipelines. For more info:
### http://scikit-learn.org/stable/modules/pipeline.html
```

In [105]:
```
features_train, features_test, labels_train, labels_test = \
    train_test_split(features, labels, test_size=0.3, random_state=42)
```

Naive Bayes

Precision: 0.39823 Recall: 0.24750 F1: 0.30527

Naive Bayes performs better with selected features rather than all of them

In [350]:
```
from sklearn.decomposition import PCA
from sklearn.naive_bayes import GaussianNB
from sklearn.cross_validation import StratifiedShuffleSplit

feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
clf = GaussianNB()
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
GaussianNB(priors=None)
        Accuracy: 0.79518       Precision: 0.39823      Recall: 0.24750
        F1: 0.30527     F2: 0.26777
        Total predictions: 11000        True positives:  495    False p
ositives:  748  False negatives: 1505   True negatives: 8252
```

In [265]:
```
feature_list = ['poi',
                 'salary_scaled',
                 'total_stock_value_scaled',
                 'total_payments_scaled',
                 'restricted_stock_scaled',
                 'exercised_stock_options_scaled',
                 'other_scaled',
                 'bonus_scaled',
                 'expenses_scaled',
                 'to_poi_ratio_scaled',
                 'from_poi_ratio_scaled',
                 'shared_poi_ratio_scaled'
                ]
clf = GaussianNB()
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
GaussianNB(priors=None)
        Accuracy: 0.83867       Precision: 0.33465      Recall: 0.21250
        F1: 0.25994     F2: 0.22923
        Total predictions: 15000        True positives:  425    False p
ositives:  845  False negatives: 1575   True negatives: 12155
```

Support Vector Machine

Precision: 0.44614 Recall: 0.82000 F1: 0.57787

SVM does better with the top 3 features rather than all 11

In [340]:
```
from sklearn.svm import SVC

feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]

data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)

svc = SVC(kernel='rbf', class_weight='balanced')
n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
param_grid = {'C': [5e2, 1e3, 5e3, 1e4, 1e4],
              'gamma': [.05, 0.1, 0.5, 1]
             }
grid = GridSearchCV(estimator=svc, param_grid=param_grid, cv=cv, scoring=
)
grid.fit(features,labels)
```

Out[340]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  0.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=SVC(C=1.0, cache_size=200, class_weight='balanced', co
ef0=0.0,
  decision_function_shape=None, degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'C': [500.0, 1000.0, 5000.0, 10000.0, 10000.0], 'gam
ma': [0.05, 0.1, 0.5, 1]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [341]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'C': 1000.0, 'gamma': 0.1} with a score of 0.5
70071428571
```

In [338]:
```
#test with top 3 features of random forest ranking
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.78218       Precision: 0.44614      Recall: 0.82000
        F1: 0.57787     F2: 0.70230
        Total predictions: 11000        True positives: 1640    False p
ositives: 2036  False negatives:  360   True negatives: 6964
```

In [266]:
```
#test with 11 features
feature_list = ['poi',
                 'salary_scaled',
                 'total_stock_value_scaled',
                 'total_payments_scaled',
                 'restricted_stock_scaled',
                 'exercised_stock_options_scaled',
                 'other_scaled',
                 'bonus_scaled',
                 'expenses_scaled',
                 'to_poi_ratio_scaled',
                 'from_poi_ratio_scaled',
                 'shared_poi_ratio_scaled'
                ]
C = 10000
gamma = 0.5
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=10000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.5, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.80960       Precision: 0.26940      Recall: 0.25000
        F1: 0.25934     F2: 0.25365
        Total predictions: 15000        True positives:  500    False p
ositives: 1356  False negatives: 1500   True negatives: 11644
```

Decision Trees

Precision: 0.21442 Recall: 0.16650 F1: 0.18745

Decision tree appears to do worse with just the top features, and when using PCA. Decision trees did better when I included all features.

In [351]:

```
from sklearn.tree import DecisionTreeClassifier

feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)

dtc = DecisionTreeClassifier()
n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
param_grid = {'min_samples_split' : [20, 40, 60, 80]
             }
grid = GridSearchCV(estimator=dtc, param_grid=param_grid, cv=cv, scoring=
)
grid.fit(features, labels)
```

Out[351]:

```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  0.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=DecisionTreeClassifier(class_weight=None, criterion='g
ini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'min_samples_split': [20, 40, 60, 80]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [352]:

```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'min_samples_split': 20} with a score of 0.247
428571429
```

In [353]:
```
feature_list = ['poi',
                'shared_poi_ratio_scaled',
                'bonus_scaled'
                ]
clf = DecisionTreeClassifier(min_samples_split=20)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=N
one,
            max_features=None, max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=20, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best')
        Accuracy: 0.77945       Precision: 0.20251      Recall: 0.07250
        F1: 0.10677     F2: 0.08318
        Total predictions: 11000        True positives:  145    False p
ositives:  571  False negatives: 1855   True negatives: 8429
```

In [324]:
```
#tune parameters with 11 features
from sklearn.tree import DecisionTreeClassifier

feature_list = ['poi',
                'salary_scaled',
                'total_stock_value_scaled',
                'total_payments_scaled',
                'restricted_stock_scaled',
                'exercised_stock_options_scaled',
                'other_scaled',
                'bonus_scaled',
                'expenses_scaled',
                'to_poi_ratio_scaled',
                'from_poi_ratio_scaled',
                'shared_poi_ratio_scaled'
               ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)

dtc = DecisionTreeClassifier()
n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
param_grid = {'min_samples_split' : [20, 40, 60, 80]
             }
grid = GridSearchCV(estimator=dtc, param_grid=param_grid, cv=cv, scoring=
)
grid.fit(features, labels)
```

Out[324]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  1.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=DecisionTreeClassifier(class_weight=None, criterion='g
ini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'min_samples_split': [20, 40, 60, 80]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [325]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'min_samples_split': 20} with a score of 0.135
904761905
```

In [326]:
```
#try again with 11 features
feature_list = ['poi',
                  'salary_scaled',
                  'total_stock_value_scaled',
                  'total_payments_scaled',
                  'restricted_stock_scaled',
                  'exercised_stock_options_scaled',
                  'other_scaled',
                  'bonus_scaled',
                  'expenses_scaled',
                  'to_poi_ratio_scaled',
                  'from_poi_ratio_scaled',
                  'shared_poi_ratio_scaled'
                 ]
clf = DecisionTreeClassifier(min_samples_split=20)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=N
one,
            max_features=None, max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=20, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best')
        Accuracy: 0.80753       Precision: 0.21442      Recall: 0.16650
        F1: 0.18745     F2: 0.17429
        Total predictions: 15000        True positives:  333    False p
ositives: 1220  False negatives: 1667   True negatives: 11780
```

Adaboost with Naive Bayes

Precision: 0.31329 Recall: 0.22400 F1: 0.26122

Adaboost with Naive Bayes did a little better with all 11 features rather than the top 3 features.

In [354]:
```
from sklearn.ensemble import AdaBoostClassifier

feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)

gnb = GaussianNB()
ada = AdaBoostClassifier(base_estimator=gnb, algorithm='SAMME')
n_iter=100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
param_grid={'n_estimators': [5,10]
            }
grid = GridSearchCV(estimator=ada, param_grid=param_grid, cv=cv, scoring=
)
grid.fit(features, labels)
```

Out[354]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  0.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=AdaBoostClassifier(algorithm='SAMME', base_estimator=G
aussianNB(priors=None),
          learning_rate=1.0, n_estimators=50, random_state=None),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'n_estimators': [5, 10]}, pre_dispatch='2*n_jobs',
       refit=True, return_train_score=True, scoring='f1', verbose=0)
```

In [355]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'n_estimators': 5} with a score of 0.212547619
048
```

In [356]:
```
#test with select features
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]

gnb = GaussianNB()
clf = AdaBoostClassifier(base_estimator=gnb, algorithm='SAMME', n_estima
tors=5)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
AdaBoostClassifier(algorithm='SAMME', base_estimator=GaussianNB(priors=
None),
          learning_rate=1.0, n_estimators=5, random_state=None)
        Accuracy: 0.80045       Precision: 0.39617      Recall: 0.18600
        F1: 0.25315     F2: 0.20808
        Total predictions: 11000        True positives:  372    False p
ositives:  567  False negatives: 1628   True negatives: 8433
```

In [270]:
```
#test with 11 features
feature_list = ['poi',
                 'salary_scaled',
                 'total_stock_value_scaled',
                 'total_payments_scaled',
                 'restricted_stock_scaled',
                 'exercised_stock_options_scaled',
                 'other_scaled',
                 'bonus_scaled',
                 'expenses_scaled',
                 'to_poi_ratio_scaled',
                 'from_poi_ratio_scaled',
                 'shared_poi_ratio_scaled'
                ]
gnb = GaussianNB()
clf = AdaBoostClassifier(base_estimator=gnb, algorithm='SAMME', n_estima
tors=5)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
AdaBoostClassifier(algorithm='SAMME', base_estimator=GaussianNB(priors=
None),
          learning_rate=1.0, n_estimators=5, random_state=None)
        Accuracy: 0.83107       Precision: 0.31329      Recall: 0.22400
        F1: 0.26122     F2: 0.23754
        Total predictions: 15000        True positives:  448    False p
ositives:  982  False negatives: 1552   True negatives: 12018
```

Adaboost and SVM

Precision: 0.43168 Recall: 0.65400 F1: 0.52008

Like SVM, Adaboost using SVM does best with the top selected features. Adaboost with SVM does slightly worse than SVM alone.

Note that if adaboost algorithm is set to the default SAMME.R, then it requires the weak learner (base estimator) to support calculation of class probabilities (it needs the base estimator to have the attribute 'predict_proba'.

Since SVM does not have this, I need to set algorithm to SAMME.

In [357]:
```
from sklearn.cross_validation import StratifiedShuffleSplit
from sklearn.svm import SVC
from sklearn.ensemble import AdaBoostClassifier

feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)

n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)

svc = SVC(kernel='rbf', class_weight='balanced')
ada = AdaBoostClassifier(base_estimator=svc, algorithm = 'SAMME')

param_grid = {
    'base_estimator__C': [1e3, 5e3, 1e4, 5e4],
    'base_estimator__gamma': [0.25, 0.5, 0.75],
    'n_estimators' : [5, 10]
          }
grid = GridSearchCV(estimator=ada, param_grid=param_grid, cv = cv, scori
ng='f1')
grid.fit(features, labels)
```

Out[357]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  0.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=AdaBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=1.0, cache_size=200, class_weight='balan
ced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=50, random_state=None),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'base_estimator__C': [1000.0, 5000.0, 10000.0, 5000
0.0], 'n_estimators': [5, 10], 'base_estimator__gamma': [0.25, 0.5, 0.7
5]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [358]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'base_estimator__C': 10000.0, 'n_estimators':
 5, 'base_estimator__gamma': 0.25} with a score of 0.516777777778
```

In [359]:
```
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
C = 10000
gamma = 0.25
n_estimators = 5
svc = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
clf = AdaBoostClassifier(base_estimator=svc, algorithm = 'SAMME', n_esti
mators=n_estimators)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
AdaBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=10000, cache_size=200, class_weight='bal
anced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.25, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None)
        Accuracy: 0.78055       Precision: 0.43168      Recall: 0.65400
        F1: 0.52008     F2: 0.59293
        Total predictions: 11000        True positives: 1308    False p
ositives: 1722  False negatives:  692   True negatives: 7278
```

Adaboost Decision Tree

Precision: 0.40729 Recall: 0.31850 F1: 0.35746

Similar to decision trees, adaboost using decision trees performs better using 11 features rather than the top 2

In [360]:
```
from sklearn.tree import DecisionTreeClassifier

feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)


base_estimator = DecisionTreeClassifier()
ada = AdaBoostClassifier(base_estimator=base_estimator, algorithm = 'SAM
ME')
param_grid = {'base_estimator__min_samples_split' : [50,60,70],
              'n_estimators' : [2,3,5]
             }
n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
grid = GridSearchCV(estimator=ada, param_grid=param_grid, cv = cv, scori
ng='f1')
grid.fit(features, labels)
```

Out[360]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  0.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=AdaBoostClassifier(algorithm='SAMME',
          base_estimator=DecisionTreeClassifier(class_weight=None, crit
erion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
          learning_rate=1.0, n_estimators=50, random_state=None),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'n_estimators': [2, 3, 5], 'base_estimator__min_samp
les_split': [50, 60, 70]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [361]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'n_estimators': 3, 'base_estimator__min_sample
s_split': 70} with a score of 0.476
```

In [364]:
```
#test with best features
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
min_samples_split = 70
n_estimators = 3
dtc = DecisionTreeClassifier(min_samples_split=min_samples_split)
clf = AdaBoostClassifier(base_estimator=dtc, n_estimators=n_estimators)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
AdaBoostClassifier(algorithm='SAMME.R',
          base_estimator=DecisionTreeClassifier(class_weight=None, crit
erion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=70, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
          learning_rate=1.0, n_estimators=3, random_state=None)
        Accuracy: 0.79736       Precision: 0.34075      Recall: 0.12250
        F1: 0.18021     F2: 0.14050
        Total predictions: 11000        True positives:  245    False p
ositives:  474  False negatives: 1755   True negatives: 8526
```

In [294]:
```
#grid search using 11 features
feature_list = ['poi',
                'salary_scaled',
                'total_stock_value_scaled',
                'total_payments_scaled',
                'restricted_stock_scaled',
                'exercised_stock_options_scaled',
                'other_scaled',
                'bonus_scaled',
                'expenses_scaled',
                'to_poi_ratio_scaled',
                'from_poi_ratio_scaled',
                'shared_poi_ratio_scaled'
               ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)


base_estimator = DecisionTreeClassifier()
ada = AdaBoostClassifier(base_estimator=base_estimator, algorithm = 'SAM
ME')
param_grid = {'base_estimator__min_samples_split' : [40,50,60,70],
              'n_estimators' : [3,5,7]
             }
n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
grid = GridSearchCV(estimator=ada, param_grid=param_grid, cv = cv, scori
ng='f1')
grid.fit(features, labels)
```

Out[294]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  1.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=AdaBoostClassifier(algorithm='SAMME',
          base_estimator=DecisionTreeClassifier(class_weight=None, crit
erion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
          learning_rate=1.0, n_estimators=50, random_state=None),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'n_estimators': [3, 5, 7], 'base_estimator__min_samp
les_split': [40, 50, 60, 70]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [295]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'n_estimators': 5, 'base_estimator__min_sample
s_split': 50} with a score of 0.393666666667
```

In [293]:
```
#test with 11 features
feature_list = ['poi',
                  'salary_scaled',
                  'total_stock_value_scaled',
                  'total_payments_scaled',
                  'restricted_stock_scaled',
                  'exercised_stock_options_scaled',
                  'other_scaled',
                  'bonus_scaled',
                  'expenses_scaled',
                  'to_poi_ratio_scaled',
                  'from_poi_ratio_scaled',
                  'shared_poi_ratio_scaled'
                 ]
min_samples_split = 50
n_estimators=5
dtc = DecisionTreeClassifier(min_samples_split=min_samples_split)
clf = AdaBoostClassifier(base_estimator=dtc, n_estimators=n_estimators)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
AdaBoostClassifier(algorithm='SAMME.R',
          base_estimator=DecisionTreeClassifier(class_weight=None, crit
erion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=50, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
          learning_rate=1.0, n_estimators=5, random_state=None)
        Accuracy: 0.84733       Precision: 0.40729      Recall: 0.31850
        F1: 0.35746     F2: 0.33302
        Total predictions: 15000        True positives:  637    False p
ositives:  927  False negatives: 1363   True negatives: 12073
```

Random Forest

Precision: 0.38034 Recall: 0.14700 F1: 0.21204 Random forest with 11 features does worse than Adaboost with decision trees and 11 features

In [300]:
```
from sklearn.ensemble import RandomForestClassifier

#grid search using 11 features
feature_list = ['poi',
                 'salary_scaled',
                 'total_stock_value_scaled',
                 'total_payments_scaled',
                 'restricted_stock_scaled',
                 'exercised_stock_options_scaled',
                 'other_scaled',
                 'bonus_scaled',
                 'expenses_scaled',
                 'to_poi_ratio_scaled',
                 'from_poi_ratio_scaled',
                 'shared_poi_ratio_scaled'
                ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)

rfc = RandomForestClassifier()
n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
param_grid = {'min_samples_split' : [40, 50, 60],
              'n_estimators' : [2,3,4]
             }
grid = GridSearchCV(estimator=rfc, param_grid=param_grid, cv = cv, scori
ng='f1')
grid.fit(features, labels)
```

Out[300]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  1.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=RandomForestClassifier(bootstrap=True, class_weight=No
ne, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=10, n_jobs=1, oob_score=False, random_state=No
ne,
            verbose=0, warm_start=False),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'min_samples_split': [40, 50, 60], 'n_estimators':
 [2, 3, 4]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [301]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'min_samples_split': 50, 'n_estimators': 2} wi
th a score of 0.198333333333
```

In [302]:
```
#run test on best parameters
feature_list = ['poi',
                  'salary_scaled',
                  'total_stock_value_scaled',
                  'total_payments_scaled',
                  'restricted_stock_scaled',
                  'exercised_stock_options_scaled',
                  'other_scaled',
                  'bonus_scaled',
                  'expenses_scaled',
                  'to_poi_ratio_scaled',
                  'from_poi_ratio_scaled',
                  'shared_poi_ratio_scaled'
                 ]
min_samples_split = 50
n_estimators = 2
clf = RandomForestClassifier(min_samples_split=min_samples_split,
                             n_estimators=n_estimators)
test_classifier(clf=clf,dataset=my_dataset, feature_list=feature_list, f
olds=1000)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gi
ni',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=50, min_weight_fraction_leaf=0.0,
            n_estimators=2, n_jobs=1, oob_score=False, random_state=Non
e,
            verbose=0, warm_start=False)
        Accuracy: 0.85433       Precision: 0.38034      Recall: 0.14700
        F1: 0.21204     F2: 0.16756
        Total predictions: 15000        True positives:  294    False p
ositives:  479  False negatives: 1706   True negatives: 12521
```

Adaboost with logistic regression

Precision: 0.48645 Recall: 0.18850 F1: 0.27171

Adaboost with logistic regression does a little bit better when using just the top 3 features as opposed to 11.

This posting pointed out that the Adaboost's base estimator should support class probabilities, and gave logistic regression as an example.

Reference

[http://stackoverflow.com/questions/27107205/sklearn-ensemble-adaboostclassifier-cannot-accecpt-svm-as-base-estimator (http://stackoverflow.com/questions/27107205/sklearn-ensemble-adaboostclassifier-cannot-accecpt-svm-as-base-estimator)](http://stackoverflow.com/questions/27107205/sklearn-ensemble-adaboostclassifier-cannot-accecpt-svm-as-base-estimator)

In [365]:
```
from sklearn.linear_model import LogisticRegression
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)

algorithm = 'SAMME'
reg = LogisticRegression()
ada = AdaBoostClassifier(base_estimator=reg,
                         algorithm = 'SAMME')
n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
param_grid = {
    'base_estimator__C' : [2.25e4, 5e4, 7.5e4],
    'n_estimators' : [2,3,4]
}
grid = GridSearchCV(estimator=ada, param_grid=param_grid, cv=cv, scoring=
)
grid.fit(features, labels)
```

Out[365]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  0.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=AdaBoostClassifier(algorithm='SAMME',
          base_estimator=LogisticRegression(C=1.0, class_weight=None, d
ual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False),
          learning_rate=1.0, n_estimators=50, random_state=None),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'base_estimator__C': [22500.0, 50000.0, 75000.0], 'n
_estimators': [2, 3, 4]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [366]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'base_estimator__C': 22500.0, 'n_estimators':
 4} with a score of 0.207666666667
```

In [367]:
```
#test with top features
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
base_estimator = LogisticRegression(C=22500)
clf = AdaBoostClassifier(base_estimator=base_estimator,
                         n_estimators=4,
                         algorithm = 'SAMME')
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
AdaBoostClassifier(algorithm='SAMME',
          base_estimator=LogisticRegression(C=22500, class_weight=None,
 dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False),
          learning_rate=1.0, n_estimators=4, random_state=None)
        Accuracy: 0.81627       Precision: 0.48645      Recall: 0.18850
        F1: 0.27171     F2: 0.21481
        Total predictions: 11000        True positives:  377    False p
ositives:  398  False negatives: 1623   True negatives: 8602
```

In [313]:
```
feature_list = ['poi',
                'salary_scaled',
                'total_stock_value_scaled',
                'total_payments_scaled',
                'restricted_stock_scaled',
                'exercised_stock_options_scaled',
                'other_scaled',
                'bonus_scaled',
                'expenses_scaled',
                'to_poi_ratio_scaled',
                'from_poi_ratio_scaled',
                'shared_poi_ratio_scaled'
               ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)

algorithm = 'SAMME'
reg = LogisticRegression()
ada = AdaBoostClassifier(base_estimator=reg,
                         algorithm = 'SAMME')
n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
param_grid = {
    'base_estimator__C' : [2.25e4, 5e4, 7.5e4],
    'n_estimators' : [2,3,4]
}
grid = GridSearchCV(estimator=ada, param_grid=param_grid, cv=cv, scoring=
)
grid.fit(features, labels)
```

Out[313]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  1.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=AdaBoostClassifier(algorithm='SAMME',
          base_estimator=LogisticRegression(C=1.0, class_weight=None, d
ual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False),
          learning_rate=1.0, n_estimators=50, random_state=None),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'base_estimator__C': [22500.0, 50000.0, 75000.0], 'n
_estimators': [2, 3, 4]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [314]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'base_estimator__C': 75000.0, 'n_estimators':
 4} with a score of 0.251857142857
```

In [316]:
```
#test
feature_list = ['poi',
                  'salary_scaled',
                  'total_stock_value_scaled',
                  'total_payments_scaled',
                  'restricted_stock_scaled',
                  'exercised_stock_options_scaled',
                  'other_scaled',
                  'bonus_scaled',
                  'expenses_scaled',
                  'to_poi_ratio_scaled',
                  'from_poi_ratio_scaled',
                  'shared_poi_ratio_scaled'
                 ]
base_estimator = LogisticRegression(C=75000)
clf = AdaBoostClassifier(base_estimator=base_estimator,
                         n_estimators=4,
                         algorithm = 'SAMME')
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
AdaBoostClassifier(algorithm='SAMME',
          base_estimator=LogisticRegression(C=75000, class_weight=None,
 dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.00
01,
          verbose=0, warm_start=False),
          learning_rate=1.0, n_estimators=4, random_state=None)
        Accuracy: 0.83167       Precision: 0.28216      Recall: 0.17000
        F1: 0.21217     F2: 0.18468
        Total predictions: 15000        True positives:  340    False p
ositives:  865  False negatives: 1660   True negatives: 12135
```

Effects of created features

Compare SVM with the email ratio features, with just the email counts, and without the email data

SVM with email ratio features

Precision: 0.44888 Recall: 0.73100 F1: 0.55621

In [368]:
```
feature_list = ['poi',
                'to_poi_ratio_scaled',
                'bonus_scaled',
                'shared_poi_ratio_scaled'
                ]
C = 1000
gamma = 0.1
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=1000, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.78218       Precision: 0.44614      Recall: 0.82000
        F1: 0.57787     F2: 0.70230
        Total predictions: 11000        True positives: 1640    False p
ositives: 2036  False negatives:  360   True negatives: 6964
```

SVM without new features

Precision: 0.18282 Recall: 0.11600 F1: 0.14194

I used original features, ran feature ranking using random forest, and used the top four from the ranking:

[(0.16, 'bonus_scaled'), (0.14, 'exercised_stock_options_scaled'), (0.11, 'from_poi_to_this_person'), (0.1, 'salary_scaled'), (0.08, 'shared_receipt_with_poi'), (0.08, 'other_scaled'), (0.08, 'from_messages'), (0.07, 'expenses_scaled'), (0.05, 'total_payments_scaled'), (0.05, 'from_this_person_to_poi'), (0.03, 'restricted_stock_scaled'), (0.02, 'to_messages'), (0.01, 'total_stock_value_scaled')]

I tuned parameters for SVM and tested. The model performs worse without the new email ratio features.

In [370]:
```
#first use random forest to rank all original features

feature_list = ['poi',
                'salary_scaled',
                'total_stock_value_scaled',
                'total_payments_scaled',
                'restricted_stock_scaled',
                'exercised_stock_options_scaled',
                'other_scaled',
                'bonus_scaled',
                'expenses_scaled',
                'to_messages',
                'from_messages',
                'from_this_person_to_poi',
                'from_poi_to_this_person',
                'shared_receipt_with_poi'
               ]

feature_only = feature_list[1:]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)

from sklearn.ensemble import RandomForestRegressor
clf = RandomForestRegressor()
clf.fit(features, labels)
feature_rank = sorted (zip (map(lambda x: round(x,2),clf.feature_importa
nces_) , feature_only), reverse=True)
print "feature rank using random forest"
print feature_rank
```

```
feature rank using random forest
[(0.16, 'bonus_scaled'), (0.14, 'exercised_stock_options_scaled'), (0.1
1, 'from_poi_to_this_person'), (0.1, 'salary_scaled'), (0.08, 'shared_r
eceipt_with_poi'), (0.08, 'other_scaled'), (0.08, 'from_messages'), (0.
07, 'expenses_scaled'), (0.05, 'total_payments_scaled'), (0.05, 'from_t
his_person_to_poi'), (0.03, 'restricted_stock_scaled'), (0.02, 'to_mess
ages'), (0.01, 'total_stock_value_scaled')]
```

In [372]:
```
from sklearn.svm import SVC
feature_list = ['poi',
                'bonus_scaled',
                'exercised_stock_options_scaled',
                'from_poi_to_this_person',
                'salary_scaled'
                ]
data = featureFormat(my_dataset, feature_list, sort_keys = True)
labels, features = targetFeatureSplit(data)
svc = SVC(kernel='rbf', class_weight='balanced')
n_iter = 100
cv = StratifiedShuffleSplit(y=labels, n_iter=n_iter, random_state=42)
param_grid = {'C': [5e2, 1e3, 5e3, 1e4],
              'gamma': [0.5, 1, 1.5, 2]
             }
grid = GridSearchCV(estimator=svc, param_grid=param_grid, cv=cv, scoring=
)
grid.fit(features, labels)
```

Out[372]:
```
GridSearchCV(cv=StratifiedShuffleSplit(labels=[ 0.  0. ...,  1.  0.], n
_iter=100, test_size=0.1, random_state=42),
       error_score='raise',
       estimator=SVC(C=1.0, cache_size=200, class_weight='balanced', co
ef0=0.0,
  decision_function_shape=None, degree=3, gamma='auto', kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'C': [500.0, 1000.0, 5000.0, 10000.0], 'gamma': [0.
5, 1, 1.5, 2]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring='f1', verbose=0)
```

In [373]:
```
print "The best parameters are {} with a score of {}".format(grid.best_p
arams_, grid.best_score_)
```

```
The best parameters are {'C': 500.0, 'gamma': 0.5} with a score of 0.12
7523809524
```

In [374]:
```
# test with parameters tuned for the two best non-email features
feature_list = ['poi',
                'bonus_scaled',
                'exercised_stock_options_scaled',
                'from_poi_to_this_person',
                'salary_scaled'
                ]
C = 500
gamma = 0.5
clf = SVC(kernel='rbf', class_weight='balanced', C=C, gamma=gamma)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
SVC(C=500, cache_size=200, class_weight='balanced', coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.5, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.78423       Precision: 0.18282      Recall: 0.11600
        F1: 0.14194     F2: 0.12515
        Total predictions: 13000        True positives:  232    False p
ositives: 1037  False negatives: 1768   True negatives: 9963
```