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.

I normalized emails sent to persons of interest by dividing by total number of emails sent; similarly for emails received from POI and emails received that were also sent to a person of interest. 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. Although the orders varied between the two methods, compensation was ranked as more important that the email count ratios. I take a subset of features, as I will use Principle Component Analysis (PCA) to reduce the dimensions of the features.

I compared the final model with and without derived email features. I found that removing email features and relying only on the compensation data gives us a higher precision but lower recall, and slightly lower F1 score. One interpretation is that including both compensation and email features help us cast a wider net, which improves recall by increasing the number of true positive predictions, but could hurt precision by predicting more false positives. Conversely, by excluding email features, we cast a smaller net, and make fewer positive predictions, improving precision but hurting recall.

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 Adaboost, with SVM as the base estimator, and also used PCA to reduce the feature dimensions from 11 to 5. The F1 score, which is higher when there are more true positives and fewer false classifications (false positive, false negative), is slightly above 0.3 for most tests with varying parameters, and as high as 0.34. At the same time, both precision (true positive divided by all predicted positives) and recall (true positives divided by all actual positives) are above 0.30.

I first tried non-ensemble estimators with and without PCA, including Naive Bayes, Support Vector Machines (SVM), and Decision Trees. By varying the number of components used, I generally saw that, of 11 features, using between 5 and 9 dimensions yielded higher precision, recall and F1 scores. Best F1 scores were .27 (trees), .30 (Bayes) .36 (SVM using grid search to optimize parameters). However, when varying parameters and number of PCA components, F1 scores for any non-ensemble algorithm could dip below 0.30, and often one of either precision or recall would be below 0.30 despite an F1 above 0.30.

Next, I tried Adaboost with Bayes, SVM, trees, and logistic regression as base estimators. Adaboost with Bayes did worse than Bayes alone (F1 at most 0.23). Adaboost with SVM did better than SVM alone in that all three of F1, precision, and recall were above 0.30 for a variety of PCA components, variety of base estimator iterations (each iteration puts more weight on incorrectly classified observations). Adaboost with decision trees had its highest F1 at .33, but recall was consistently below 0.30. I also tried a random forest (an average of multiple decision trees). It had its highest F1 of .32 but recall was consistently below 0.30. I tried Adaboost with logistic regression as the base estimator, and using grid search to vary parameters, got an F1 of .35, precision of .83, but recall of 0.22.

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 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, as well as 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. I used for loops to vary the parameters so that I could run the test and compare validation scores for each combination of parameter values. I also used Grid Search to see how the model performs on validation testing. If I understand Grid Search correctly, it tunes the parameters each time it fits to a training set. So when testing validation uses cross-validation and fits to multiple training sets, the tuned parameters can change each time. That is why I wanted to use for loops to fix a combination of parameter values for cross validation, to see how the test scores compare for those parameter values.

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)](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 gives us a numerical measure of how well the model would perform when using inputs that were not used to train the model. In other words, validation lets us state how well the model might do when it is being used to make new predictions. Validation must use 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. 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 positive predictions are correct (true positives divided by all predictions of the positive class). The precision can be 0 at worst and 1 at best. Using Adaboost with SVM as a base estimator, I got a precision of 0.36.

The recall score measures what fraction of all actual positives are correctly discovered (true positives divided by all actual positives). The recall can be 0 at worst and 1 at best. The tuned adaboost had a recall of 0.36.

An F1 score equally weighs the precision and recall (true positives are in the numerator, and false negatives and false positives are in the denominator). F1 can be 0 at worst and 1 at best. A model with more false predictions than another model, given the same number of true positives, will have a lower F1 score. The adaboost had an F1 of 0.36.

I used the cross validation method provided, with 100 folds instead of 1,000 to compare the F1, precision, and recall scores. If I run the validation method with 1,000 folds, the final Adaboost with SVM classifier still has F1, precision and recall at 0.30 or above.

Appendix: steps taken to select features and choose algorithm

In [423]:
```
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
```

In [371]:
```
### Load the dictionary containing the dataset
with open("final_project_dataset.pkl", "r") as data_file:
    data_dict = pickle.load(data_file)
```

In [372]:
```
len(data_dict)
```

Out[372]:
```
146
```

In [373]:
```
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 [374]:
```
feature_l.keys()
```

Out[374]:
```
['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 [375]:
```
feature_l['name']
```

Out[375]:

```
['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 [408]:
```
data_dict.pop('THE TRAVEL AGENCY IN THE PARK')
```

Out[408]:
```
{'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)))
```

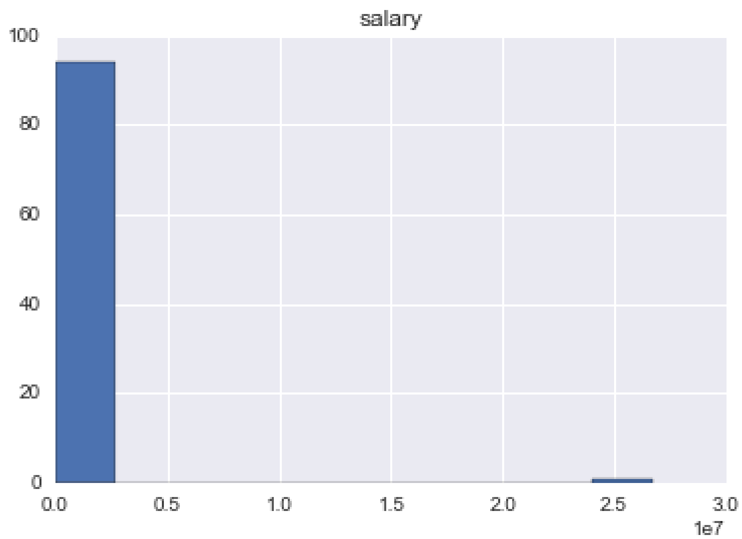
In [378]:
```
salary_c.describe()
```

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 [393]:
```
#data_dict.pop('TOTAL')
data_df = data_df[data_df['name'] != 'TOTAL']
```

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

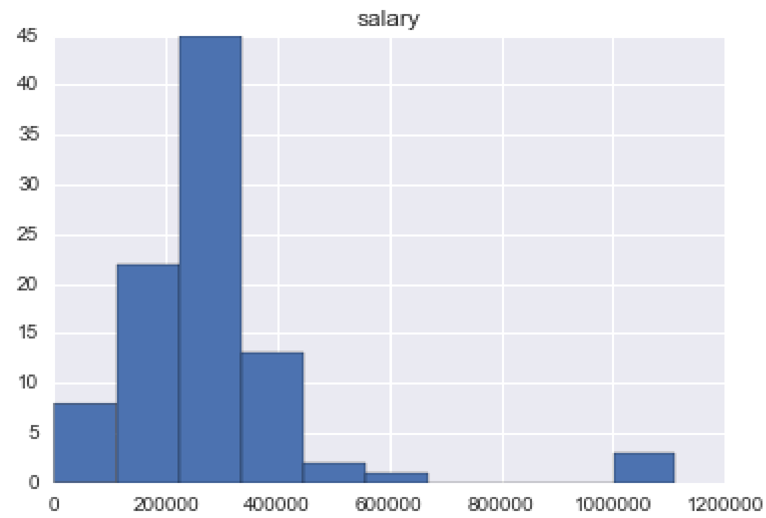
In [443]:
```
poi = data_df['poi']
poi = poi.apply(lambda x: 1 if x else 0)
```

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']
```

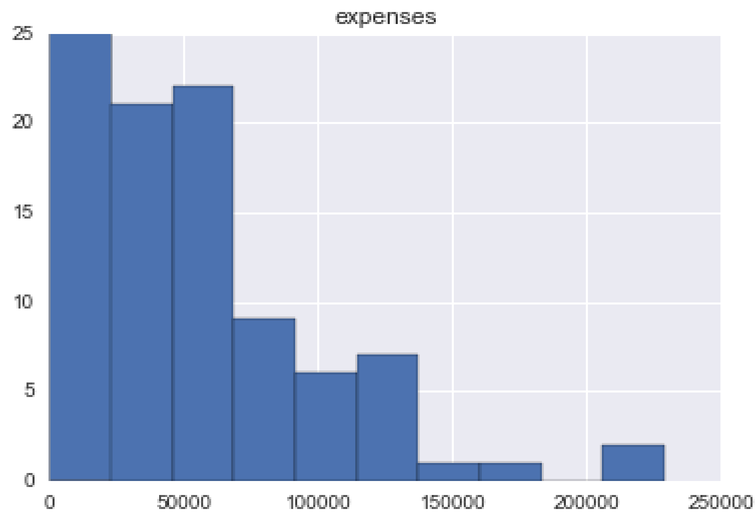
Out[398]:
```
95    SKILLING JEFFREY K
Name: name, dtype: object
```

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

In [47]:
```
#Task 2 Remove outliers
data_dict.pop('THE TRAVEL AGENCY IN THE PARK')
```

Out[47]:
```
{'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 [48]:
```
data_dict.pop('TOTAL')
```

Out[48]:
```
{'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}
```

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 [81]:
```
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[feature]]]))[0][0]
    return data_dict
```

In [89]:
```
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 [90]:
```
#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 [98]:
```
#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 [452]:
```
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 [101]:
```
### Store to my_dataset for easy export below.
my_dataset = data_dict
```

In [453]:
```
### 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 importance

I'll try both Random Forest and selectkbest method to rank features

In [459]:
```
from sklearn.ensemble import RandomForestRegressor
clf = RandomForestRegressor()
clf.fit(features, labels)
print sorted (zip (map(lambda x: round(x,2),clf.feature_importances_) ,
feature_list), reverse=True)
```

```
[(0.17, 'expenses_scaled'), (0.15, 'exercised_stock_options_scaled'),
 (0.12, 'restricted_stock_scaled'), (0.11, 'other_scaled'), (0.11, 'bon
us_scaled'), (0.1, 'salary_scaled'), (0.08, 'from_poi_ratio_scaled'),
 (0.06, 'total_payments_scaled'), (0.04, 'total_stock_value_scaled'),
 (0.03, 'to_poi_ratio_scaled'), (0.02, 'poi')]
```

Rank feature using selectKBest

In [468]:
```
from sklearn.feature_selection import SelectKBest
clf = SelectKBest(k=11)
clf.fit(features, labels)
print sorted (zip (map(lambda x: round(x,0),clf.scores_), feature_list),
 reverse = True)
```

```
[(24.0, 'salary_scaled'), (24.0, 'restricted_stock_scaled'), (20.0, 'ot
her_scaled'), (18.0, 'poi'), (16.0, 'expenses_scaled'), (11.0, 'total_p
ayments_scaled'), (9.0, 'total_stock_value_scaled'), (9.0, 'from_poi_ra
tio_scaled'), (6.0, 'bonus_scaled'), (4.0, 'exercised_stock_options_sca
led'), (3.0, 'to_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 with and without PCA

If I vary the components for each test, I find the best F1 score of 0.30151 at 9 components. Whereas if I run grid search, it gives 4 as the best number of components; but this gives me lower precision and recall when I run it through the test. So will try using and not using GridSearch when trying to find the best parameters.

In [265]:
```
from sklearn.decomposition import PCA
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.naive_bayes import GaussianNB
for n_components in [None,3,4,5,6,7,8,9,10]:

    if n_components == None:
        print "Naive Bayes without PCA"
        gnb = GaussianNB()
        test_classifier(clf=gnb, dataset=my_dataset, feature_list=featur
e_list, folds=1000)
    else:
        print "Naive Bayes with PCA using {} components".format(n_compon
ents)
        pca = PCA(n_components=n_components)
        gnb = GaussianNB()
        pipe = make_pipeline(pca, gnb)
        test_classifier(clf=pipe, dataset=my_dataset, feature_list=featu
re_list, folds=1000)
```

```
Using PCA with None components
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

Using PCA with 3 components
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=3, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gaussiannb', GaussianNB
(priors=None))])
        Accuracy: 0.84833       Precision: 0.35167      Recall: 0.16300
        F1: 0.22275     F2: 0.18259
        Total predictions: 15000        True positives:  326    False p
ositives:  601  False negatives: 1674   True negatives: 12399

Using PCA with 4 components
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=4, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gaussiannb', GaussianNB
(priors=None))])
        Accuracy: 0.84440       Precision: 0.32384      Recall: 0.15350
        F1: 0.20828     F2: 0.17155
        Total predictions: 15000        True positives:  307    False p
ositives:  641  False negatives: 1693   True negatives: 12359

Using PCA with 5 components
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gaussiannb', GaussianNB
(priors=None))])
        Accuracy: 0.83947       Precision: 0.32322      Recall: 0.18650
        F1: 0.23653     F2: 0.20374
        Total predictions: 15000        True positives:  373    False p
ositives:  781  False negatives: 1627   True negatives: 12219

Using PCA with 6 components
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=6, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gaussiannb', GaussianNB
(priors=None))])
        Accuracy: 0.82007       Precision: 0.27082      Recall: 0.20650
        F1: 0.23433     F2: 0.21680
        Total predictions: 15000        True positives:  413    False p
ositives: 1112  False negatives: 1587   True negatives: 11888

Using PCA with 7 components
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gaussiannb', GaussianNB
(priors=None))])
        Accuracy: 0.82240       Precision: 0.31115      Recall: 0.27350
        F1: 0.29111     F2: 0.28028
        Total predictions: 15000        True positives:  547    False p
ositives: 1211  False negatives: 1453   True negatives: 11789
```

```
Using PCA with 8 components
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=8, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gaussiannb', GaussianNB
(priors=None))])
        Accuracy: 0.82193       Precision: 0.31474      Recall: 0.28500
        F1: 0.29913     F2: 0.29049
        Total predictions: 15000        True positives:  570    False p
ositives: 1241  False negatives: 1430   True negatives: 11759

Using PCA with 9 components
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gaussiannb', GaussianNB
(priors=None))])
        Accuracy: 0.81220       Precision: 0.29907      Recall: 0.30400
        F1: 0.30151     F2: 0.30300
        Total predictions: 15000        True positives:  608    False p
ositives: 1425  False negatives: 1392   True negatives: 11575

Using PCA with 10 components
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=10, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gaussiannb', GaussianNB
(priors=None))])
        Accuracy: 0.80087       Precision: 0.25139      Recall: 0.24950
        F1: 0.25044     F2: 0.24987
        Total predictions: 15000        True positives:  499    False p
ositives: 1486  False negatives: 1501   True negatives: 11514
```

I tried using GridSearch to use either no PCA or PCA with varying components, but the results have a lower precision/accuracy than when I use a loop to vary the use of PCA. The F1 score is 0.27257

In [277]:
```
#Pipeline PCA and Naive Bayes and GridSearch
pca = PCA()
gnb = GaussianNB()
estimators = [('pca', pca),
              ('gnb', gnb)]
pipe = Pipeline(estimators)
params = dict(pca = [None,
                     PCA(n_components=8),
                     PCA(n_components=9)
                    ])
clf = GridSearchCV(pipe, param_grid=params)

test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=1000)
```

```
GridSearchCV(cv=None, error_score='raise',
       estimator=Pipeline(steps=[('pca', PCA(copy=True, iterated_power
='auto', n_components=None, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gnb', GaussianNB(priors
=None))]),
       fit_params={}, iid=True, n_jobs=1,
       param_grid={'pca': [None, PCA(copy=True, iterated_power='auto',
 n_components=8, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False), PCA(copy=True, iterated_po
wer='auto', n_components=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring=None, verbose=0)
        Accuracy: 0.83027       Precision: 0.31800      Recall: 0.23850
        F1: 0.27257     F2: 0.25105
        Total predictions: 15000        True positives:  477    False p
ositives: 1023  False negatives: 1523   True negatives: 11977
```

Support Vector Machine with and without PCA

The best F1 score I see is .28289 for when I don't use PCA, C is 10000.0, gamma is either 0.0005 or 0.001.

In [284]:
```
from sklearn.svm import SVC
print "Support Vector Machines with PCA with different components"

for n_components in [None,5,7]:
    for C in [5e3, 1e4, 5e4]:
        for gamma in [0.0005, 0.001, 0.005]:

            if n_components == None:
                print "SVC without PCA, C {} gamma {}".format(C,gamma)
                clf = SVC(kernel='rbf', C=C, gamma=gamma)
                test_classifier(clf=clf, dataset=my_dataset, feature_lis
t=feature_list, folds=100)
            else:
                print "SVC with PCA & {} components, C {}, gamma {}".for
mat(n_components,

       C, gamma)
                pca = PCA(n_components=n_components)
                svc = SVC(kernel='rbf', C=C, gamma=gamma)
                clf = make_pipeline(pca, svc)
                test_classifier(clf=clf, dataset=my_dataset, feature_lis
t=feature_list, folds=100)
```

```
Support Vector Machines with PCA with different components
SVC without PCA, C 5000.0 gamma 0.0005
SVC(C=5000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.0005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.88400       Precision: 0.86111      Recall: 0.15500
        F1: 0.26271     F2: 0.18541
        Total predictions: 1500 True positives:   31    False positive
s:    5 False negatives:  169   True negatives: 1295

SVC without PCA, C 5000.0 gamma 0.001
SVC(C=5000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.88733       Precision: 0.89744      Recall: 0.17500
        F1: 0.29289     F2: 0.20858
        Total predictions: 1500 True positives:   35    False positive
s:    4 False negatives:  165   True negatives: 1296

SVC without PCA, C 5000.0 gamma 0.005
SVC(C=5000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.87933       Precision: 0.77143      Recall: 0.13500
        F1: 0.22979     F2: 0.16168
        Total predictions: 1500 True positives:   27    False positive
s:    8 False negatives:  173   True negatives: 1292

SVC without PCA, C 10000.0 gamma 0.0005
SVC(C=10000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.0005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.88733       Precision: 0.89744      Recall: 0.17500
        F1: 0.29289     F2: 0.20858
        Total predictions: 1500 True positives:   35    False positive
s:    4 False negatives:  165   True negatives: 1296

SVC without PCA, C 10000.0 gamma 0.001
SVC(C=10000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.88333       Precision: 0.83784      Recall: 0.15500
        F1: 0.26160     F2: 0.18519
        Total predictions: 1500 True positives:   31    False positive
s:    6 False negatives:  169   True negatives: 1294

SVC without PCA, C 10000.0 gamma 0.005
SVC(C=10000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.87667       Precision: 0.71429      Recall: 0.12500
```

```
        F1: 0.21277     F2: 0.14970
        Total predictions: 1500 True positives:   25    False positive
s:   10 False negatives:  175   True negatives: 1290

SVC without PCA, C 50000.0 gamma 0.0005
SVC(C=50000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.0005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.88000       Precision: 0.76316      Recall: 0.14500
        F1: 0.24370     F2: 0.17303
        Total predictions: 1500 True positives:   29    False positive
s:    9 False negatives:  171   True negatives: 1291

SVC without PCA, C 50000.0 gamma 0.001
SVC(C=50000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.87800       Precision: 0.71795      Recall: 0.14000
        F1: 0.23431     F2: 0.16687
        Total predictions: 1500 True positives:   28    False positive
s:   11 False negatives:  172   True negatives: 1289

SVC without PCA, C 50000.0 gamma 0.005
SVC(C=50000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
        Accuracy: 0.86200       Precision: 0.42222      Recall: 0.09500
        F1: 0.15510     F2: 0.11243
        Total predictions: 1500 True positives:   19    False positive
s:   26 False negatives:  181   True negatives: 1274

SVC with PCA & 5 components, C 5000.0, gamma 0.0005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=5000.0, cac
he_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.0005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86800       Precision: 0.75000      Recall: 0.01500
        F1: 0.02941     F2: 0.01866
        Total predictions: 1500 True positives:    3    False positive
s:    1 False negatives:  197   True negatives: 1299

SVC with PCA & 5 components, C 5000.0, gamma 0.001
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=5000.0, cac
he_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86800       Precision: 0.66667      Recall: 0.02000
        F1: 0.03883     F2: 0.02481
```

```
        Total predictions: 1500 True positives:    4    False positive
s:    2 False negatives:  196   True negatives: 1298

SVC with PCA & 5 components, C 5000.0, gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=5000.0, cac
he_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86667       Precision: 0.50000      Recall: 0.02000
        F1: 0.03846     F2: 0.02475
        Total predictions: 1500 True positives:    4    False positive
s:    4 False negatives:  196   True negatives: 1296

SVC with PCA & 5 components, C 10000.0, gamma 0.0005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=10000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.0005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86800       Precision: 0.66667      Recall: 0.02000
        F1: 0.03883     F2: 0.02481
        Total predictions: 1500 True positives:    4    False positive
s:    2 False negatives:  196   True negatives: 1298

SVC with PCA & 5 components, C 10000.0, gamma 0.001
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=10000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86733       Precision: 0.57143      Recall: 0.02000
        F1: 0.03865     F2: 0.02478
        Total predictions: 1500 True positives:    4    False positive
s:    3 False negatives:  196   True negatives: 1297

SVC with PCA & 5 components, C 10000.0, gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=10000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86800       Precision: 0.56250      Recall: 0.04500
        F1: 0.08333     F2: 0.05515
        Total predictions: 1500 True positives:    9    False positive
s:    7 False negatives:  191   True negatives: 1293

SVC with PCA & 5 components, C 50000.0, gamma 0.0005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
```

```
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=50000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.0005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86667       Precision: 0.50000      Recall: 0.02000
        F1: 0.03846     F2: 0.02475
        Total predictions: 1500 True positives:    4    False positive
s:    4 False negatives:  196   True negatives: 1296

SVC with PCA & 5 components, C 50000.0, gamma 0.001
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=50000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86600       Precision: 0.44444      Recall: 0.02000
        F1: 0.03828     F2: 0.02472
        Total predictions: 1500 True positives:    4    False positive
s:    5 False negatives:  196   True negatives: 1295

SVC with PCA & 5 components, C 50000.0, gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=50000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86400       Precision: 0.41667      Recall: 0.05000
        F1: 0.08929     F2: 0.06068
        Total predictions: 1500 True positives:   10    False positive
s:   14 False negatives:  190   True negatives: 1286

SVC with PCA & 7 components, C 5000.0, gamma 0.0005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=5000.0, cac
he_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.0005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.87000       Precision: 0.69231      Recall: 0.04500
        F1: 0.08451     F2: 0.05535
        Total predictions: 1500 True positives:    9    False positive
s:    4 False negatives:  191   True negatives: 1296

SVC with PCA & 7 components, C 5000.0, gamma 0.001
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=5000.0, cac
he_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
```

```
  tol=0.001, verbose=False))])
        Accuracy: 0.87000       Precision: 0.66667      Recall: 0.05000
        F1: 0.09302     F2: 0.06135
        Total predictions: 1500 True positives:   10    False positive
s:    5 False negatives:  190   True negatives: 1295

SVC with PCA & 7 components, C 5000.0, gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=5000.0, cac
he_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.87133       Precision: 0.70588      Recall: 0.06000
        F1: 0.11060     F2: 0.07344
        Total predictions: 1500 True positives:   12    False positive
s:    5 False negatives:  188   True negatives: 1295

SVC with PCA & 7 components, C 10000.0, gamma 0.0005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=10000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.0005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.87000       Precision: 0.66667      Recall: 0.05000
        F1: 0.09302     F2: 0.06135
        Total predictions: 1500 True positives:   10    False positive
s:    5 False negatives:  190   True negatives: 1295

SVC with PCA & 7 components, C 10000.0, gamma 0.001
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=10000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.87200       Precision: 0.72222      Recall: 0.06500
        F1: 0.11927     F2: 0.07946
        Total predictions: 1500 True positives:   13    False positive
s:    5 False negatives:  187   True negatives: 1295

SVC with PCA & 7 components, C 10000.0, gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=10000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.87067       Precision: 0.66667      Recall: 0.06000
        F1: 0.11009     F2: 0.07335
        Total predictions: 1500 True positives:   12    False positive
s:    6 False negatives:  188   True negatives: 1294
```

```
SVC with PCA & 7 components, C 50000.0, gamma 0.0005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=50000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.0005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.87200       Precision: 0.72222      Recall: 0.06500
        F1: 0.11927     F2: 0.07946
        Total predictions: 1500 True positives:   13    False positive
s:    5 False negatives:  187   True negatives: 1295

SVC with PCA & 7 components, C 50000.0, gamma 0.001
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=50000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.87200       Precision: 0.72222      Recall: 0.06500
        F1: 0.11927     F2: 0.07946
        Total predictions: 1500 True positives:   13    False positive
s:    5 False negatives:  187   True negatives: 1295

SVC with PCA & 7 components, C 50000.0, gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('svc', SVC(C=50000.0, ca
che_size=200, class_weight=None, coef0=0.0,
  decision_function_shape=None, degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
        Accuracy: 0.86533       Precision: 0.46667      Recall: 0.07000
        F1: 0.12174     F2: 0.08434
        Total predictions: 1500 True positives:   14    False positive
s:   16 False negatives:  186   True negatives: 1284
```

When using GridSearch, each time I run fit, it will look for the best parameter, which may not be the same whenever the training data changes. So when I pass the grid search to the test method, since it runs fit multiple times as it re-shuffles the data to create mutiple training sets, I'm ending up with higher precision, recall and F1 scores.

The highest F1 score I see is 0.35951, when there are 4 PCA components.

In [285]:
```
print "Support Vector Machines with PCA with different components"
for n_components in [4,5,6,7,8]:
    pca = PCA(n_components=n_components)
    param_grid = {
          'C': [1e3, 5e3, 1e4, 5e4, 1e5],
          'gamma': [0.0001, 0.0005, 0.001, 0.005, 0.01, 0.1],
          }
    grid_svc = GridSearchCV(SVC(kernel='rbf', class_weight='balanced'),
param_grid)
    clf = make_pipeline(pca,grid_svc)
    print "PCA with {} components, SVC grid search".format(n_components)
    test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_li
st, folds=100)
    print "\n"
```

```
Support Vector Machines with PCA with different components
PCA with 4 components, SVC grid search
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=4, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gridsearchcv', GridSear
chCV(cv=None, error_score='raise',
       estimator=SVC(C=1.0, cache_size=200, class_weight='balanced', co
ef0=0.0,
  decision_function_shape=...     pre_dispatch='2*n_jobs', refit=True,
 return_train_score=True,
       scoring=None, verbose=0))])
        Accuracy: 0.75533       Precision: 0.27614      Recall: 0.51500
        F1: 0.35951     F2: 0.43905
        Total predictions: 1500 True positives:  103    False positive
s:  270 False negatives:   97   True negatives: 1030

PCA with 5 components, SVC grid search
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gridsearchcv', GridSear
chCV(cv=None, error_score='raise',
       estimator=SVC(C=1.0, cache_size=200, class_weight='balanced', co
ef0=0.0,
  decision_function_shape=...     pre_dispatch='2*n_jobs', refit=True,
 return_train_score=True,
       scoring=None, verbose=0))])
        Accuracy: 0.75733       Precision: 0.25152      Recall: 0.41500
        F1: 0.31321     F2: 0.36726
        Total predictions: 1500 True positives:   83    False positive
s:  247 False negatives:  117   True negatives: 1053

PCA with 6 components, SVC grid search
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=6, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gridsearchcv', GridSear
chCV(cv=None, error_score='raise',
       estimator=SVC(C=1.0, cache_size=200, class_weight='balanced', co
ef0=0.0,
  decision_function_shape=...     pre_dispatch='2*n_jobs', refit=True,
 return_train_score=True,
       scoring=None, verbose=0))])
        Accuracy: 0.79533       Precision: 0.28163      Recall: 0.34500
        F1: 0.31011     F2: 0.33014
        Total predictions: 1500 True positives:   69    False positive
s:  176 False negatives:  131   True negatives: 1124

PCA with 7 components, SVC grid search
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gridsearchcv', GridSear
chCV(cv=None, error_score='raise',
       estimator=SVC(C=1.0, cache_size=200, class_weight='balanced', co
ef0=0.0,
  decision_function_shape=...     pre_dispatch='2*n_jobs', refit=True,
 return_train_score=True,
       scoring=None, verbose=0))])
        Accuracy: 0.77933       Precision: 0.24111      Recall: 0.30500
```

```
        F1: 0.26932     F2: 0.28965
        Total predictions: 1500 True positives:   61    False positive
s:  192 False negatives:  139   True negatives: 1108

PCA with 8 components, SVC grid search
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=8, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gridsearchcv', GridSear
chCV(cv=None, error_score='raise',
       estimator=SVC(C=1.0, cache_size=200, class_weight='balanced', co
ef0=0.0,
  decision_function_shape=...     pre_dispatch='2*n_jobs', refit=True,
 return_train_score=True,
       scoring=None, verbose=0))])
        Accuracy: 0.78000       Precision: 0.22458      Recall: 0.26500
        F1: 0.24312     F2: 0.25579
        Total predictions: 1500 True positives:   53    False positive
s:  183 False negatives:  147   True negatives: 1117
```

Decision Trees

The highest F1 I see is 0.24157 when PCA is used with 5 components and min samples to split is 20. But F1 scores are generally low.

In [289]:
```
from sklearn.tree import DecisionTreeClassifier

for n_components in [None,5,7,9]:
    for min_samples_split in [20,50,70]:
        if n_components == None:
            print "Decision Tree min samples to split {} without PCA".fo
rmat(min_samples_split)
            clf = DecisionTreeClassifier(min_samples_split=min_samples_s
plit)
            test_classifier(clf=clf, dataset=my_dataset, feature_list=fe
ature_list, folds=100)

        else:
            print "PCA {}, Decision Tree min_samples_split {} PCA".forma
t(n_components,

        min_samples_split)
            pca = PCA(n_components=n_components)
            dtc = DecisionTreeClassifier(min_samples_split=min_samples_s
plit)
            clf = make_pipeline(pca, dtc)
            test_classifier(clf=clf, dataset=my_dataset, feature_list=fe
ature_list, folds=100)
```

```
Decision Tree min samples to split 20 without PCA
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: 0.81800       Precision: 0.22137      Recall: 0.14500
        F1: 0.17523     F2: 0.15575
        Total predictions: 1500 True positives:   29    False positive
s:  102 False negatives:  171   True negatives: 1198

Decision Tree min samples to split 50 without PCA
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=50, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best')
        Accuracy: 0.83333       Precision: 0.14286      Recall: 0.05000
        F1: 0.07407     F2: 0.05747
        Total predictions: 1500 True positives:   10    False positive
s:   60 False negatives:  190   True negatives: 1240

Decision Tree min samples to split 70 without PCA
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=70, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best')
        Accuracy: 0.83333       Precision: 0.14286      Recall: 0.05000
        F1: 0.07407     F2: 0.05747
        Total predictions: 1500 True positives:   10    False positive
s:   60 False negatives:  190   True negatives: 1240

PCA 5, Decision Tree min_samples_split 20 PCA
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('decisiontreeclassifie
r', DecisionTreeClassifier(class_weight=None, criterion='gini', max_dep
th=None,
            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: 0.82000       Precision: 0.27564      Recall: 0.21500
        F1: 0.24157     F2: 0.22490
        Total predictions: 1500 True positives:   43    False positive
s:  113 False negatives:  157   True negatives: 1187

PCA 5, Decision Tree min_samples_split 50 PCA
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('decisiontreeclassifie
r', DecisionTreeClassifier(class_weight=None, criterion='gini', max_dep
th=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'))])
        Accuracy: 0.83600       Precision: 0.12903      Recall: 0.04000
        F1: 0.06107     F2: 0.04640
        Total predictions: 1500 True positives:    8    False positive
s:   54 False negatives:  192   True negatives: 1246

PCA 5, Decision Tree min_samples_split 70 PCA
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('decisiontreeclassifie
r', DecisionTreeClassifier(class_weight=None, criterion='gini', max_dep
th=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'))])
        Accuracy: 0.83600       Precision: 0.12903      Recall: 0.04000
        F1: 0.06107     F2: 0.04640
        Total predictions: 1500 True positives:    8    False positive
s:   54 False negatives:  192   True negatives: 1246

PCA 7, Decision Tree min_samples_split 20 PCA
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('decisiontreeclassifie
r', DecisionTreeClassifier(class_weight=None, criterion='gini', max_dep
th=None,
            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: 0.81000       Precision: 0.22222      Recall: 0.17000
        F1: 0.19263     F2: 0.17838
        Total predictions: 1500 True positives:   34    False positive
s:  119 False negatives:  166   True negatives: 1181

PCA 7, Decision Tree min_samples_split 50 PCA
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('decisiontreeclassifie
r', DecisionTreeClassifier(class_weight=None, criterion='gini', max_dep
th=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'))])
        Accuracy: 0.82867       Precision: 0.13924      Recall: 0.05500
        F1: 0.07885     F2: 0.06257
        Total predictions: 1500 True positives:   11    False positive
s:   68 False negatives:  189   True negatives: 1232

PCA 7, Decision Tree min_samples_split 70 PCA
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
```

```
  svd_solver='auto', tol=0.0, whiten=False)), ('decisiontreeclassifie
r', DecisionTreeClassifier(class_weight=None, criterion='gini', max_dep
th=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'))])
        Accuracy: 0.83133       Precision: 0.15584      Recall: 0.06000
        F1: 0.08664     F2: 0.06842
        Total predictions: 1500 True positives:   12    False positive
s:   65 False negatives:  188   True negatives: 1235

PCA 9, Decision Tree min_samples_split 20 PCA
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('decisiontreeclassifie
r', DecisionTreeClassifier(class_weight=None, criterion='gini', max_dep
th=None,
            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: 0.80067       Precision: 0.20359      Recall: 0.17000
        F1: 0.18529     F2: 0.17580
        Total predictions: 1500 True positives:   34    False positive
s:  133 False negatives:  166   True negatives: 1167

PCA 9, Decision Tree min_samples_split 50 PCA
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('decisiontreeclassifie
r', DecisionTreeClassifier(class_weight=None, criterion='gini', max_dep
th=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'))])
        Accuracy: 0.82400       Precision: 0.14444      Recall: 0.06500
        F1: 0.08966     F2: 0.07303
        Total predictions: 1500 True positives:   13    False positive
s:   77 False negatives:  187   True negatives: 1223

PCA 9, Decision Tree min_samples_split 70 PCA
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('decisiontreeclassifie
r', DecisionTreeClassifier(class_weight=None, criterion='gini', max_dep
th=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'))])
        Accuracy: 0.82467       Precision: 0.14607      Recall: 0.06500
        F1: 0.08997     F2: 0.07312
        Total predictions: 1500 True positives:   13    False positive
s:   76 False negatives:  187   True negatives: 1224
```

For Decision Tree with GridSearch, accuracy was lower than when I did not use grid search.

In [290]:
```
for n_components in [None, 5, 7, 9]:
    if n_components == None:
        print "Decision Tree grid search, no PCA"
        dtc = DecisionTreeClassifier()
        param_grid = {'min_samples_split': [20,50,70]}
        clf = GridSearchCV(dtc, param_grid)
        test_classifier(clf=clf, dataset=my_dataset, feature_list=featur
e_list, folds=100)
    else:
        print "Decision Tree, PCA {} grid search".format(n_components)
        pca = PCA(n_components)
        param_grid = {'min_samples_split': [20,50,70]}
        grid_dtc = GridSearchCV(dtc, param_grid)
        clf = make_pipeline(pca, grid_dtc)
        test_classifier(clf=clf, dataset=my_dataset, feature_list=featur
e_list, folds=100)
```

```
Decision Tree grid search, no PCA
GridSearchCV(cv=None, 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, 50, 70]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
       scoring=None, verbose=0)
        Accuracy: 0.82867       Precision: 0.16471      Recall: 0.07000
        F1: 0.09825     F2: 0.07910
        Total predictions: 1500 True positives:   14    False positive
s:   71 False negatives:  186   True negatives: 1229

Decision Tree, PCA 5 grid search
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gridsearchcv', GridSear
chCV(cv=None, error_score='raise',
       estimator=DecisionTreeClassifier(class_weight=None, criterion='g
ini', max_depth=None,
            m...     pre_dispatch='2*n_jobs', refit=True, return_train_
score=True,
       scoring=None, verbose=0))])
        Accuracy: 0.83000       Precision: 0.20430      Recall: 0.09500
        F1: 0.12969     F2: 0.10638
        Total predictions: 1500 True positives:   19    False positive
s:   74 False negatives:  181   True negatives: 1226

Decision Tree, PCA 7 grid search
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gridsearchcv', GridSear
chCV(cv=None, error_score='raise',
       estimator=DecisionTreeClassifier(class_weight=None, criterion='g
ini', max_depth=None,
            m...     pre_dispatch='2*n_jobs', refit=True, return_train_
score=True,
       scoring=None, verbose=0))])
        Accuracy: 0.81867       Precision: 0.18966      Recall: 0.11000
        F1: 0.13924     F2: 0.12009
        Total predictions: 1500 True positives:   22    False positive
s:   94 False negatives:  178   True negatives: 1206

Decision Tree, PCA 9 grid search
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gridsearchcv', GridSear
chCV(cv=None, error_score='raise',
       estimator=DecisionTreeClassifier(class_weight=None, criterion='g
ini', max_depth=None,
            m...     pre_dispatch='2*n_jobs', refit=True, return_train_
score=True,
       scoring=None, verbose=0))])
```

```
                Accuracy: 0.81267       Precision: 0.18110      Recall: 0.11500
                F1: 0.14067     F2: 0.12406
                Total predictions: 1500 True positives:   23    False positive
        s:  104 False negatives:  177   True negatives: 1196
```

Adaboost with Naive Bayes and PCA

I will try Adaboost with Naive Bayes as the base estimator, and use PCA with 9 components. The highest F1 score I see is 0.23110, using 10 estimators

In [299]:
```
for n_estimators in [2,5,10]:
    n_components = 9
    pca = PCA(n_components)
    gnb = GaussianNB()
    ada = AdaBoostClassifier(base_estimator=gnb,
                                     n_estimators=n_estimators,
                                     algorithm = algorithm)
    clf = make_pipeline(pca,ada)
    print "Adaboost {}, Naive Bayes, PCA {}".format(n_estimators, n_comp
onents)
    test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_li
st, folds=100)
    print "\n"
```

```
Adaboost 2, Naive Bayes, PCA 9
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME.R',
          base_estimator=GaussianNB(priors=None), learning_rate=1.0,
          n_estimators=2, random_state=None))])
        Accuracy: 0.19400       Precision: 0.12210      Recall: 0.81500
        F1: 0.21238     F2: 0.38173
        Total predictions: 1500 True positives:  163    False positive
s: 1172 False negatives:   37   True negatives:  128



Adaboost 5, Naive Bayes, PCA 9
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME.R',
          base_estimator=GaussianNB(priors=None), learning_rate=1.0,
          n_estimators=5, random_state=None))])
        Accuracy: 0.68267       Precision: 0.16827      Recall: 0.35000
        F1: 0.22727     F2: 0.28783
        Total predictions: 1500 True positives:   70    False positive
s:  346 False negatives:  130   True negatives:  954



Adaboost 10, Naive Bayes, PCA 9
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME.R',
          base_estimator=GaussianNB(priors=None), learning_rate=1.0,
          n_estimators=10, random_state=None))])
        Accuracy: 0.64067       Precision: 0.16168      Recall: 0.40500
        F1: 0.23110     F2: 0.31130
        Total predictions: 1500 True positives:   81    False positive
s:  420 False negatives:  119   True negatives:  880
```

Adaboost with SVM and PCA

Given that I got better results using SVM with PCA, I will try to use this within Adaboost, and fix SVM parameters C = 5000, gamma = .005

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.

http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.AdaBoostClassifier.html (http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.AdaBoostClassifier.html)

Also, I cannot use grid search as the base_estimator because it does not support sample weights.

Using AdaBoost with SVM, the highest F1 score I see is 0.34270 when there are either 5 or 10 estimators, PCA 5 components, (C is 5000, gamma is .005 were set for all iterations).

In [294]:
```
from sklearn.ensemble import AdaBoostClassifier

for n_estimators in [2, 5, 10]:
    for n_components in [5, 7, 9]:
        C = 5000
        gamma = .005
        algorithm = 'SAMME'
        print "estimators {} PCA {}, Adaboost using SVC C {} gamma {}".f
ormat(n_estimators,

             n_components,

             C,

             gamma)
        pca = PCA(n_components=n_components)
        base_estimator = svc = SVC(kernel='rbf',
class_weight='balanced', C=C, gamma=gamma)
        ada = AdaBoostClassifier(base_estimator=base_estimator,
                                 n_estimators=n_estimators,
                                 algorithm = algorithm)
        clf = make_pipeline(pca,ada)
        test_classifier(clf=clf, dataset=my_dataset, feature_list=featur
e_list, folds=100)
        print "\n"
```

```
estimators 2 PCA 5, Adaboost using SVC C 5000 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000, cache_size=200, class_weight='bala
nced', coef0=0.0,
  decision_funct...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=2, random_state=None))])
        Accuracy: 0.83067       Precision: 0.34483      Recall: 0.30000
        F1: 0.32086     F2: 0.30801
        Total predictions: 1500 True positives:   60    False positive
s:  114 False negatives:  140   True negatives: 1186

estimators 2 PCA 7, Adaboost using SVC C 5000 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000, cache_size=200, class_weight='bala
nced', coef0=0.0,
  decision_funct...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=2, random_state=None))])
        Accuracy: 0.82800       Precision: 0.32738      Recall: 0.27500
        F1: 0.29891     F2: 0.28409
        Total predictions: 1500 True positives:   55    False positive
s:  113 False negatives:  145   True negatives: 1187

estimators 2 PCA 9, Adaboost using SVC C 5000 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000, cache_size=200, class_weight='bala
nced', coef0=0.0,
  decision_funct...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=2, random_state=None))])
        Accuracy: 0.82867       Precision: 0.34078      Recall: 0.30500
        F1: 0.32190     F2: 0.31154
        Total predictions: 1500 True positives:   61    False positive
s:  118 False negatives:  139   True negatives: 1182

estimators 5 PCA 5, Adaboost using SVC C 5000 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000, cache_size=200, class_weight='bala
nced', coef0=0.0,
  decision_funct...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.84400       Precision: 0.39103      Recall: 0.30500
        F1: 0.34270     F2: 0.31904
```

```
        Total predictions: 1500 True positives:   61    False positive
s:   95 False negatives:  139   True negatives: 1205

estimators 5 PCA 7, Adaboost using SVC C 5000 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000, cache_size=200, class_weight='bala
nced', coef0=0.0,
  decision_funct...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.83267       Precision: 0.33962      Recall: 0.27000
        F1: 0.30084     F2: 0.28154
        Total predictions: 1500 True positives:   54    False positive
s:  105 False negatives:  146   True negatives: 1195

estimators 5 PCA 9, Adaboost using SVC C 5000 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000, cache_size=200, class_weight='bala
nced', coef0=0.0,
  decision_funct...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.83467       Precision: 0.35714      Recall: 0.30000
        F1: 0.32609     F2: 0.30992
        Total predictions: 1500 True positives:   60    False positive
s:  108 False negatives:  140   True negatives: 1192

estimators 10 PCA 5, Adaboost using SVC C 5000 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000, cache_size=200, class_weight='bala
nced', coef0=0.0,
  decision_funct...rue,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=10, random_state=None))])
        Accuracy: 0.84400       Precision: 0.39103      Recall: 0.30500
        F1: 0.34270     F2: 0.31904
        Total predictions: 1500 True positives:   61    False positive
s:   95 False negatives:  139   True negatives: 1205

estimators 10 PCA 7, Adaboost using SVC C 5000 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=7, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000, cache_size=200, class_weight='bala
nced', coef0=0.0,
  decision_funct...rue,
  tol=0.001, verbose=False),
```

```
              learning_rate=1.0, n_estimators=10, random_state=None))])
            Accuracy: 0.83267       Precision: 0.33962      Recall: 0.27000
            F1: 0.30084     F2: 0.28154
            Total predictions: 1500 True positives:   54    False positive
s:  105 False negatives:  146   True negatives: 1195

estimators 10 PCA 9, Adaboost using SVC C 5000 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=9, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000, cache_size=200, class_weight='bala
nced', coef0=0.0,
  decision_funct...rue,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=10, random_state=None))])
        Accuracy: 0.83467       Precision: 0.35714      Recall: 0.30000
        F1: 0.32609     F2: 0.30992
        Total predictions: 1500 True positives:   60    False positive
s:  108 False negatives:  140   True negatives: 1192
```

I'll try Adaboost again with 5 estimators 5 PCA components. I'll use loops to vary C and gamma.
Using SVC C 10000.0 gamma 0.005, I get an F1 of .36, precision of .36, and recall of .36

In [420]:
```
n_estimators = 5
n_components = 5
algorithm = 'SAMME'
for C in [5e3, 1e4, 5e4]:
    for gamma in [0.0005, 0.001, 0.005]:

        print "estimators {} PCA {}, Adaboost using SVC C {} gamma {}".f
ormat(n_estimators,

             n_components,

             C,

             gamma)
        pca = PCA(n_components=n_components)
        base_estimator = svc = SVC(kernel='rbf',
class_weight='balanced', C=C, gamma=gamma)
        ada = AdaBoostClassifier(base_estimator=base_estimator,
                                 n_estimators=n_estimators,
                                 algorithm = algorithm)
        clf = make_pipeline(pca,ada)
        test_classifier(clf=clf, dataset=my_dataset, feature_list=featur
e_list, folds=100)
        print "\n"
```

```
estimators 5 PCA 5, Adaboost using SVC C 5000.0 gamma 0.0005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000.0, cache_size=200, class_weight='ba
lanced', coef0=0.0,
  decision_fun...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.86600       Precision: 0.49587      Recall: 0.30000
        F1: 0.37383     F2: 0.32573
        Total predictions: 1500 True positives:   60    False positive
s:   61 False negatives:  140   True negatives: 1239



estimators 5 PCA 5, Adaboost using SVC C 5000.0 gamma 0.001
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000.0, cache_size=200, class_weight='ba
lanced', coef0=0.0,
  decision_fun...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.87667       Precision: 0.74194      Recall: 0.11500
        F1: 0.19913     F2: 0.13839
        Total predictions: 1500 True positives:   23    False positive
s:    8 False negatives:  177   True negatives: 1292



estimators 5 PCA 5, Adaboost using SVC C 5000.0 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=5000.0, cache_size=200, class_weight='ba
lanced', coef0=0.0,
  decision_fun...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.84400       Precision: 0.39103      Recall: 0.30500
        F1: 0.34270     F2: 0.31904
        Total predictions: 1500 True positives:   61    False positive
s:   95 False negatives:  139   True negatives: 1205



estimators 5 PCA 5, Adaboost using SVC C 10000.0 gamma 0.0005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=10000.0, cache_size=200, class_weight='b
```

```
alanced', coef0=0.0,
  decision_fu...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.87667       Precision: 0.74194      Recall: 0.11500
        F1: 0.19913     F2: 0.13839
        Total predictions: 1500 True positives:   23    False positive
s:    8 False negatives:  177   True negatives: 1292



estimators 5 PCA 5, Adaboost using SVC C 10000.0 gamma 0.001
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=10000.0, cache_size=200, class_weight='b
alanced', coef0=0.0,
  decision_fu...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.86267       Precision: 0.46739      Recall: 0.21500
        F1: 0.29452     F2: 0.24103
        Total predictions: 1500 True positives:   43    False positive
s:   49 False negatives:  157   True negatives: 1251



estimators 5 PCA 5, Adaboost using SVC C 10000.0 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=10000.0, cache_size=200, class_weight='b
alanced', coef0=0.0,
  decision_fu...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.83000       Precision: 0.36181      Recall: 0.36000
        F1: 0.36090     F2: 0.36036
        Total predictions: 1500 True positives:   72    False positive
s:  127 False negatives:  128   True negatives: 1173



estimators 5 PCA 5, Adaboost using SVC C 50000.0 gamma 0.0005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=50000.0, cache_size=200, class_weight='b
alanced', coef0=0.0,
  decision_fu...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.84400       Precision: 0.39103      Recall: 0.30500
        F1: 0.34270     F2: 0.31904
```

```
        Total predictions: 1500 True positives:   61    False positive
s:   95 False negatives:  139   True negatives: 1205



estimators 5 PCA 5, Adaboost using SVC C 50000.0 gamma 0.001
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=50000.0, cache_size=200, class_weight='b
alanced', coef0=0.0,
  decision_fu...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.83267       Precision: 0.36788      Recall: 0.35500
        F1: 0.36132     F2: 0.35750
        Total predictions: 1500 True positives:   71    False positive
s:  122 False negatives:  129   True negatives: 1178



estimators 5 PCA 5, Adaboost using SVC C 50000.0 gamma 0.005
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=50000.0, cache_size=200, class_weight='b
alanced', coef0=0.0,
  decision_fu...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.80067       Precision: 0.29960      Recall: 0.37000
        F1: 0.33110     F2: 0.35339
        Total predictions: 1500 True positives:   74    False positive
s:  173 False negatives:  126   True negatives: 1127
```

Adaboost SVM with GridSearch doesn't appear to work, because it says that the result is worse than random, and cannot be fit.

In [470]:
```
n_estimators = 5
n_components = 5
algorithm = 'SAMME'
param_grid = {
         'base_estimator__C': [5e3, 1e4, 5e4, 1e5],
          'base_estimator__gamma': [0.0005, 0.001, 0.005, 0.01, 0.1],
          }
pca = PCA(n_components=n_components)
base_estimator = SVC(kernel='rbf', class_weight='balanced')
ada = AdaBoostClassifier(base_estimator=base_estimator,
                                 n_estimators=n_estimators,
                                 algorithm = algorithm)
grid = GridSearchCV(ada, param_grid)
clf = grid
clf = make_pipeline(pca, grid)

#this gives the error :
#ValueError: BaseClassifier in AdaBoostClassifier ensemble is worse than
 random, ensemble can not be fit.

#test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
 folds=100)
```

Adaboost with Decision Tree

Since the decision tree did better without PCA, I'll try Adaboost using Decision Tree as the base estimator, and using original features without PCA.

The highest F1 score I see here is 0.33429, when n_estimators for Adaboost is 5, and min samples for a split in the tree is 70. This seems to change each time i run the test, but generally, with 10 estimators, for min sample split of 20, 50 or 70, the F1 is .30 or higher.

In [303]:
```
from sklearn.ensemble import AdaBoostClassifier

algorithm = 'SAMME.R' #default
for n_estimators in [5,10,20]:
    for min_samples_split in [20,50,70]:
        base_estimator = DecisionTreeClassifier(min_samples_split=min_sa
mples_split)
        clf = AdaBoostClassifier(base_estimator=base_estimator,
                                 n_estimators=n_estimators,
                                 algorithm = algorithm)
        print "AdaBoost w/ Decision Tree; n_estimators {}, min_samples
 {}".format(n_estimators,

         min_samples_split)
        test_classifier(clf=clf, dataset=my_dataset, feature_list=featur
e_list, folds=100)
        print "\n"
```

```
AdaBoost w/ Decision Tree; n_estimators 5, min_samples 20
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=20, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
          learning_rate=1.0, n_estimators=5, random_state=None)
        Accuracy: 0.84467       Precision: 0.37594      Recall: 0.25000
        F1: 0.30030     F2: 0.26795
        Total predictions: 1500 True positives:   50    False positive
s:   83 False negatives:  150   True negatives: 1217



AdaBoost w/ Decision Tree; n_estimators 5, min_samples 50
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: 0.83333       Precision: 0.34756      Recall: 0.28500
        F1: 0.31319     F2: 0.29564
        Total predictions: 1500 True positives:   57    False positive
s:  107 False negatives:  143   True negatives: 1193



AdaBoost w/ Decision Tree; n_estimators 5, min_samples 70
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=5, random_state=None)
        Accuracy: 0.84600       Precision: 0.39456      Recall: 0.29000
        F1: 0.33429     F2: 0.30623
        Total predictions: 1500 True positives:   58    False positive
s:   89 False negatives:  142   True negatives: 1211



AdaBoost w/ Decision Tree; n_estimators 10, min_samples 20
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=20, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
          learning_rate=1.0, n_estimators=10, random_state=None)
```

```
        Accuracy: 0.84533       Precision: 0.38889      Recall: 0.28000
        F1: 0.32558     F2: 0.29661
        Total predictions: 1500 True positives:   56    False positive
s:   88 False negatives:  144   True negatives: 1212



AdaBoost w/ Decision Tree; n_estimators 10, min_samples 50
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=10, random_state=None)
        Accuracy: 0.84000       Precision: 0.36301      Recall: 0.26500
        F1: 0.30636     F2: 0.28013
        Total predictions: 1500 True positives:   53    False positive
s:   93 False negatives:  147   True negatives: 1207



AdaBoost w/ Decision Tree; n_estimators 10, min_samples 70
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=10, random_state=None)
        Accuracy: 0.84467       Precision: 0.38129      Recall: 0.26500
        F1: 0.31268     F2: 0.28222
        Total predictions: 1500 True positives:   53    False positive
s:   86 False negatives:  147   True negatives: 1214



AdaBoost w/ Decision Tree; n_estimators 20, min_samples 20
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=20, min_weight_fraction_leaf=0.0,
            presort=False, random_state=None, splitter='best'),
          learning_rate=1.0, n_estimators=20, random_state=None)
        Accuracy: 0.84600       Precision: 0.37795      Recall: 0.24000
        F1: 0.29358     F2: 0.25890
        Total predictions: 1500 True positives:   48    False positive
s:   79 False negatives:  152   True negatives: 1221



AdaBoost w/ Decision Tree; n_estimators 20, min_samples 50
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=20, random_state=None)
        Accuracy: 0.84600       Precision: 0.38519      Recall: 0.26000
        F1: 0.31045     F2: 0.27807
        Total predictions: 1500 True positives:   52    False positive
s:   83 False negatives:  148   True negatives: 1217



AdaBoost w/ Decision Tree; n_estimators 20, min_samples 70
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=20, random_state=None)
        Accuracy: 0.83467       Precision: 0.32857      Recall: 0.23000
        F1: 0.27059     F2: 0.24468
        Total predictions: 1500 True positives:   46    False positive
s:   94 False negatives:  154   True negatives: 1206
```

Random Forest

With Random Forest, the highest F1 I see is 0.32117, with 5 estimators and 20 min sample size for a split. This is better than using the decision tree by itself, for which the highest F1 score I found was .24

In [301]:
```
from sklearn.ensemble import RandomForestClassifier
for n_estimators in [5,10]:
    for min_samples_split in [20, 50, 70]:
        clf = RandomForestClassifier(n_estimators=n_estimators,
                                     min_samples_split=min_samples_split)
        print "Random Forest n_estimators {}, min_samples {}".format(n_e
stimators,
                                                                     min
_samples_split)
        test_classifier(clf=clf, dataset=my_dataset, feature_list=featur
e_list, folds=100)
        print "\n"
```

```
Random Forest n_estimators 5, min_samples 20
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=20, min_weight_fraction_leaf=0.0,
            n_estimators=5, n_jobs=1, oob_score=False, random_state=Non
e,
            verbose=0, warm_start=False)
        Accuracy: 0.86067       Precision: 0.45161      Recall: 0.21000
        F1: 0.28669     F2: 0.23516
        Total predictions: 1500 True positives:   42    False positive
s:   51 False negatives:  158   True negatives: 1249



Random Forest n_estimators 5, min_samples 50
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=5, n_jobs=1, oob_score=False, random_state=Non
e,
            verbose=0, warm_start=False)
        Accuracy: 0.86733       Precision: 0.50847      Recall: 0.15000
        F1: 0.23166     F2: 0.17462
        Total predictions: 1500 True positives:   30    False positive
s:   29 False negatives:  170   True negatives: 1271



Random Forest n_estimators 5, min_samples 70
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=70, min_weight_fraction_leaf=0.0,
            n_estimators=5, n_jobs=1, oob_score=False, random_state=Non
e,
            verbose=0, warm_start=False)
        Accuracy: 0.87333       Precision: 0.62500      Recall: 0.12500
        F1: 0.20833     F2: 0.14881
        Total predictions: 1500 True positives:   25    False positive
s:   15 False negatives:  175   True negatives: 1285



Random Forest n_estimators 10, min_samples 20
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=20, min_weight_fraction_leaf=0.0,
            n_estimators=10, n_jobs=1, oob_score=False, random_state=No
ne,
            verbose=0, warm_start=False)
```

```
        Accuracy: 0.87600       Precision: 0.59459      Recall: 0.22000
        F1: 0.32117     F2: 0.25172
        Total predictions: 1500 True positives:   44    False positive
s:   30 False negatives:  156   True negatives: 1270



Random Forest n_estimators 10, min_samples 50
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=10, n_jobs=1, oob_score=False, random_state=No
ne,
            verbose=0, warm_start=False)
        Accuracy: 0.87200       Precision: 0.60000      Recall: 0.12000
        F1: 0.20000     F2: 0.14286
        Total predictions: 1500 True positives:   24    False positive
s:   16 False negatives:  176   True negatives: 1284



Random Forest n_estimators 10, min_samples 70
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=70, min_weight_fraction_leaf=0.0,
            n_estimators=10, n_jobs=1, oob_score=False, random_state=No
ne,
            verbose=0, warm_start=False)
        Accuracy: 0.87667       Precision: 0.80000      Recall: 0.10000
        F1: 0.17778     F2: 0.12121
        Total predictions: 1500 True positives:   20    False positive
s:    5 False negatives:  180   True negatives: 1295
```

Adaboost with logistic regression

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 [422]:
```
from sklearn.linear_model import LogisticRegression
n_estimators = 5
n_components = 5
param_grid = {
    'base_estimator__C' : [1e3, 5e3, 1e4, 5e4, 1e5],
    'n_estimators' : [5, 10]
}

pca = PCA(n_components=n_components)
base_estimator = LogisticRegression()
ada = AdaBoostClassifier(base_estimator=base_estimator,
                                 n_estimators=n_estimators,
                                 algorithm = algorithm)
grid = GridSearchCV(ada, param_grid)
clf = make_pipeline(pca, grid)
test_classifier(clf=clf, dataset=my_dataset, feature_list=feature_list,
folds=100)
```

```
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('gridsearchcv', GridSear
chCV(cv=None, error_score='raise',
       estimator=AdaBoostClassifier(algorithm='SAMME',
          base_estimator=LogisticRegression(C=1.0, ...     pre_dispatch
='2*n_jobs', refit=True, return_train_score=True,
       scoring=None, verbose=0))])
        Accuracy: 0.89000       Precision: 0.83019      Recall: 0.22000
        F1: 0.34783     F2: 0.25791
        Total predictions: 1500 True positives:   44    False positive
s:    9 False negatives:  156   True negatives: 1291
```

Effects of created features

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

Adaboost SVM with email ratio features

In [447]:
```
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'
               ]
n_estimators = 5
n_components = 5
algorithm = 'SAMME'
C = 1e4
gamma = 0.005
pca = PCA(n_components=n_components)
base_estimator = svc = SVC(kernel='rbf',
                           class_weight='balanced',
                           C=C,
                           gamma=gamma)
ada = AdaBoostClassifier(base_estimator=base_estimator,
                         n_estimators=n_estimators,
                         algorithm = algorithm)
clf = make_pipeline(pca,ada)
test_classifier(clf=clf,
                dataset=my_dataset,
                feature_list=feature_list,
                folds=100)
```

```
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=10000.0, cache_size=200, class_weight='b
alanced', coef0=0.0,
  decision_fu...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.83000       Precision: 0.36181      Recall: 0.36000
        F1: 0.36090     F2: 0.36036
        Total predictions: 1500 True positives:   72    False positive
s:  127 False negatives:  128   True negatives: 1173
```

Adaboost SVM with absolute email counts

This doesn't get a result, possibly because it gives no positive predictions. So absolute email counts are not helpful.

In [449]:
```
feature_to_scale = ['salary',
                    'total_stock_value',
                     'total_payments',
                     'restricted_stock',
                     'exercised_stock_options',
                     'other',
                     'bonus',
                     'expenses',
                     'from_this_person_to_poi',
                     'from_poi_to_this_person',
                     'shared_receipt_with_poi'
                    ]

for feature in feature_to_scale:
    data_dict = scale_feature(data_dict, feature, feature + '_scaled')

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',
                 'from_this_person_to_poi',
                 'from_poi_to_this_person',
                 'shared_receipt_with_poi'
                ]

n_estimators = 5
n_components = 5
algorithm = 'SAMME'
C = 1e4
gamma = 0.005
pca = PCA(n_components=n_components)
base_estimator = svc = SVC(kernel='rbf',
                           class_weight='balanced',
                           C=C,
                           gamma=gamma)
ada = AdaBoostClassifier(base_estimator=base_estimator,
                         n_estimators=n_estimators,
                         algorithm = algorithm)
clf = make_pipeline(pca,ada)
test_classifier(clf=clf,
                dataset=my_dataset,
                feature_list=feature_list,
                folds=100)
```

```
Got a divide by zero when trying out: Pipeline(steps=[('pca', PCA(copy=
True, iterated_power='auto', n_components=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=10000.0, cache_size=200, class_weight='b
alanced', coef0=0.0,
  decision_fu...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
Precision or recall may be undefined due to a lack of true positive pre
dicitons.
```

Adaboost SVM with without email data

With only compensation data, the precision is higher, at .45, but recall is lower at .275. This makes sense, in that with only compensation features, we cast a narrower net, and predict fewer false positives (and probably fewer true positives as well). Moreover, without the email features, we miss more cases and have a lower recall. The F1 score was 0.34.

In [450]:
```
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'
                ]

n_estimators = 5
n_components = 5
algorithm = 'SAMME'
C = 1e4
gamma = 0.005
pca = PCA(n_components=n_components)
base_estimator = svc = SVC(kernel='rbf',
                           class_weight='balanced',
                           C=C,
                           gamma=gamma)
ada = AdaBoostClassifier(base_estimator=base_estimator,
                         n_estimators=n_estimators,
                         algorithm = algorithm)
clf = make_pipeline(pca,ada)
test_classifier(clf=clf,
                dataset=my_dataset,
                feature_list=feature_list,
                folds=100)
```

```
Pipeline(steps=[('pca', PCA(copy=True, iterated_power='auto', n_compone
nts=5, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)), ('adaboostclassifier', Ad
aBoostClassifier(algorithm='SAMME',
          base_estimator=SVC(C=10000.0, cache_size=200, class_weight='b
alanced', coef0=0.0,
  decision_fu...True,
  tol=0.001, verbose=False),
          learning_rate=1.0, n_estimators=5, random_state=None))])
        Accuracy: 0.85933       Precision: 0.45455      Recall: 0.27500
        F1: 0.34268     F2: 0.29859
        Total predictions: 1500 True positives:   55    False positive
s:   66 False negatives:  145   True negatives: 1234
```

In [ ]: