# poi_id

November 14, 2015

In [12]:
```
#!/usr/bin/python

import sys
import pickle
sys.path.append("../tools/")

from feature_format import featureFormat, targetFeatureSplit
from tester import test_classifier, dump_classifier_and_data
%matplotlib inline
import matplotlib.pyplot
from time import time

from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif

from sklearn.preprocessing import MinMaxScaler

from sklearn.decomposition import PCA

from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.pipeline import Pipeline

from sklearn.cross_validation import StratifiedShuffleSplit

from sklearn.grid_search import GridSearchCV
```

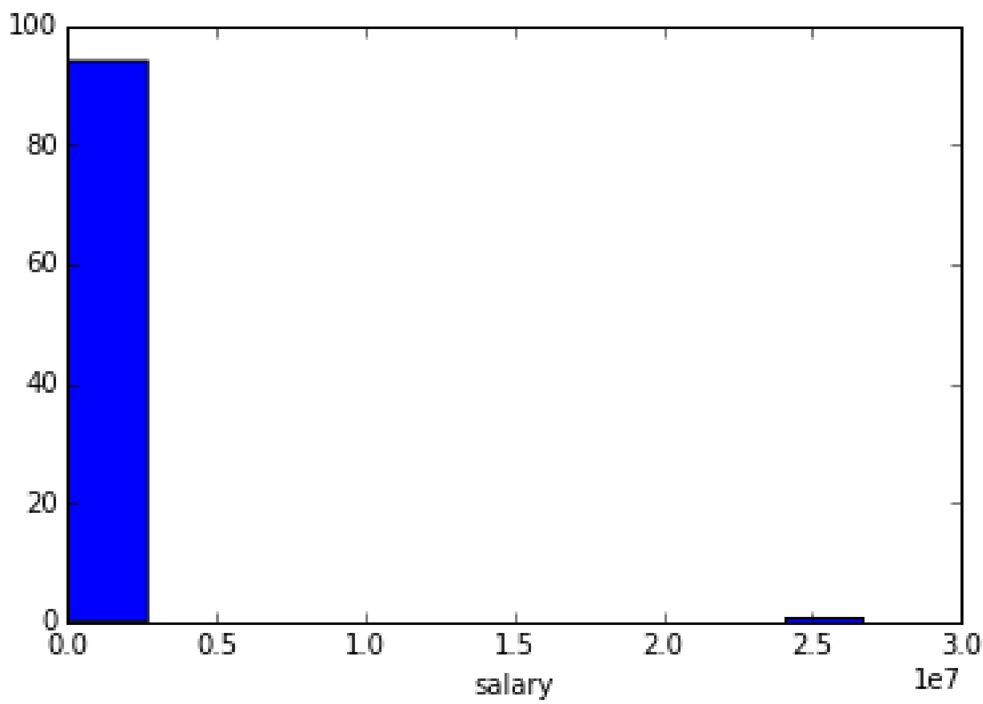
In [13]:
```
### Task 1: Select what features you'll use.
### features_list is a list of strings, each of which is a feature name.
### The first feature must be "poi".
features_list = ['poi','salary'] # You will need to use more features

### Load the dictionary containing the dataset
data_dict = pickle.load(open("final_project_dataset.pkl", "r") )

# The data_dict is organized as a list of people, each containing a dictionary of features
# Display general information about the dataset...
print "Total Number of data points:", len(data_dict)
print data_dict.keys(), "\n"
```

```
poi=0
npoi=0
for person in data_dict:
    if data_dict[person]["poi"] == 0:
        npoi += 1
    else:
        poi += 1

print "There are", npoi, "non-POI records and", poi, "POI records.\n"

print "All Features:", data_dict[data_dict.keys()[0]].keys(), "\n"

print "Number of Features:", len(data_dict[data_dict.keys()[0]].keys())

for feature in data_dict[data_dict.keys()[0]].keys():
    nan=0
    for person in data_dict:
        if data_dict[person][feature] == 'NaN':
            nan += 1

    print feature, "has", nan, "records with missing values."
```

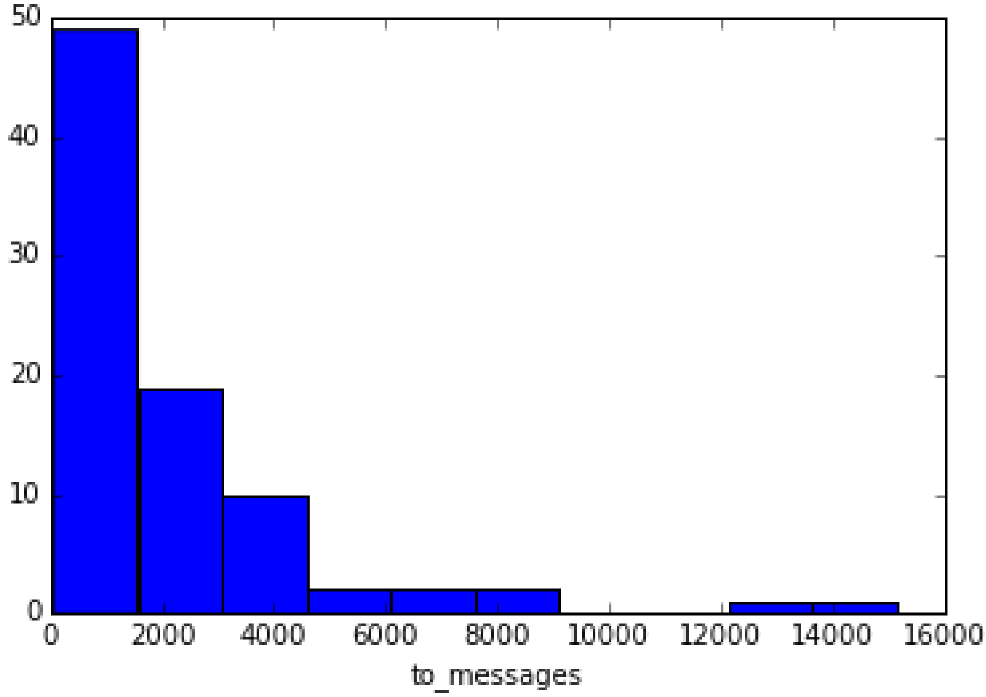
```
Total Number of data points: 146
['METTS MARK', 'BAXTER JOHN C', 'ELLIOTT STEVEN', 'CORDES WILLIAM R', 'HANNON KEVIN P', 'MORDAUNT KRISTI

There are 128 non-POI records and 18 POI records.

All Features: ['salary', 'to_messages', 'deferral_payments', 'total_payments', 'exercised_stock_options',

Number of Features: 21
salary has 51 records with missing values.
to_messages has 60 records with missing values.
deferral_payments has 107 records with missing values.
total_payments has 21 records with missing values.
exercised_stock_options has 44 records with missing values.
bonus has 64 records with missing values.
restricted_stock has 36 records with missing values.
shared_receipt_with_poi has 60 records with missing values.
restricted_stock_deferred has 128 records with missing values.
total_stock_value has 20 records with missing values.
expenses has 51 records with missing values.
loan_advances has 142 records with missing values.
from_messages has 60 records with missing values.
other has 53 records with missing values.
from_this_person_to_poi has 60 records with missing values.
poi has 0 records with missing values.
director_fees has 129 records with missing values.
deferred_income has 97 records with missing values.
long_term_incentive has 80 records with missing values.
email_address has 35 records with missing values.
from_poi_to_this_person has 60 records with missing values.
```

In [14]:
```
### Task 2: Remove outliers
#
# Identify possible outliers by looking at a histogram for each field.
# Identify the person with the max value for each field.

for feature in data_dict[data_dict.keys()[0]].keys():
    if feature == "email_address" or feature == 'poi':
        continue
    data = featureFormat(data_dict, [feature])
    for person in data_dict:
        if data_dict[person][feature] == max(data):
            print "Possible Outlier for", feature, ":", person
    matplotlib.pyplot.hist(data, bins=10)
    matplotlib.pyplot.xlabel(feature)
    matplotlib.pyplot.show()
```

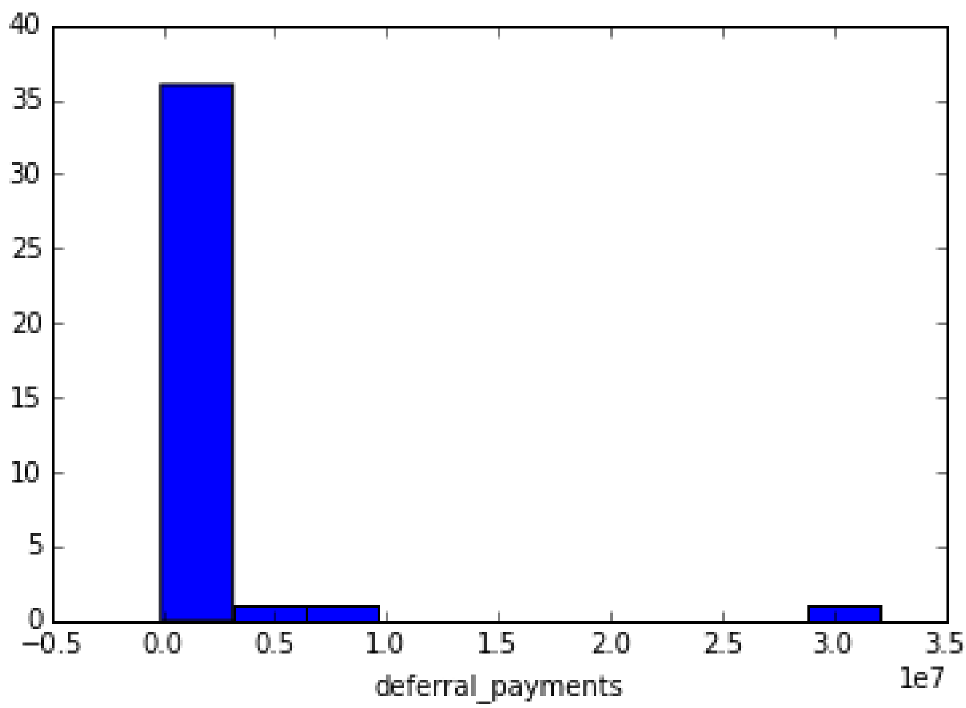
```
Possible Outlier for salary : TOTAL
```



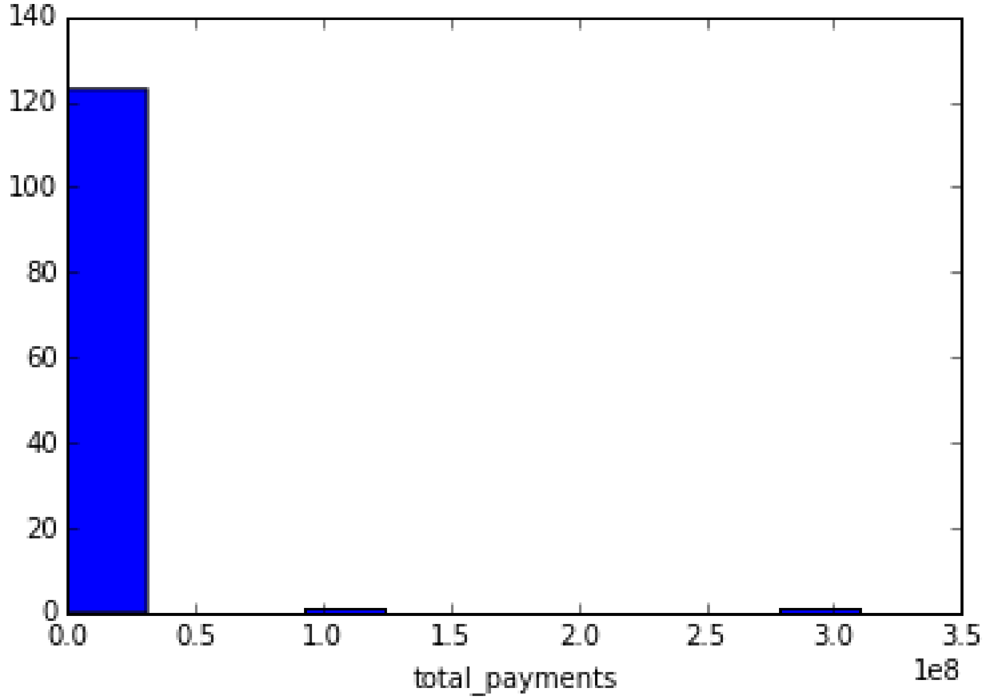

```
Possible Outlier for to_messages : SHAPIRO RICHARD S
```



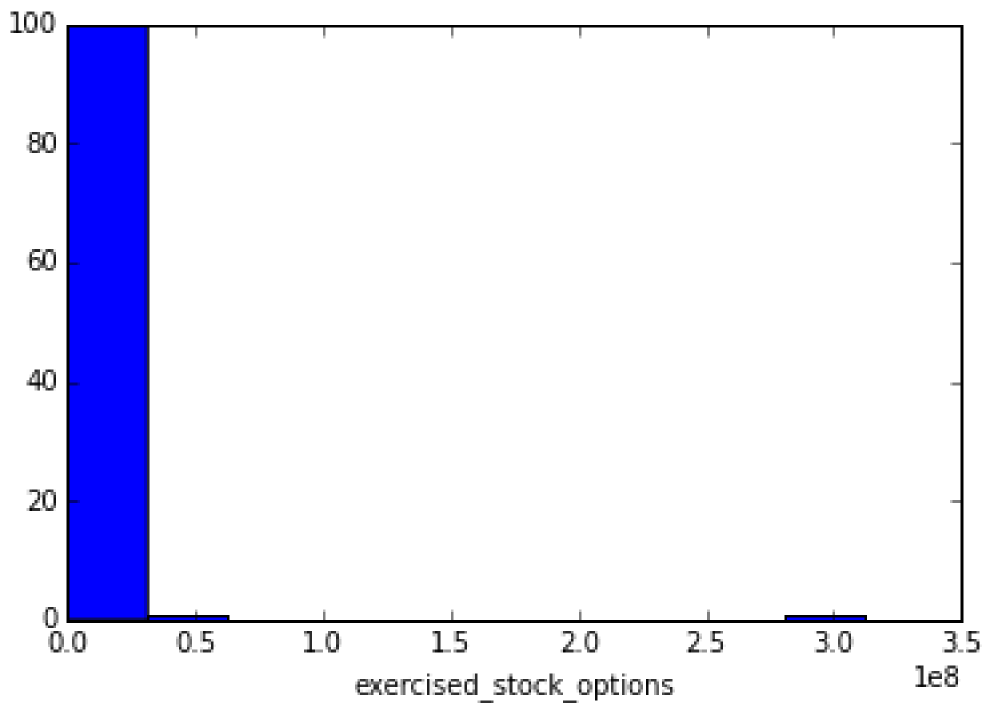

Possible Outlier for deferral_payments : TOTAL



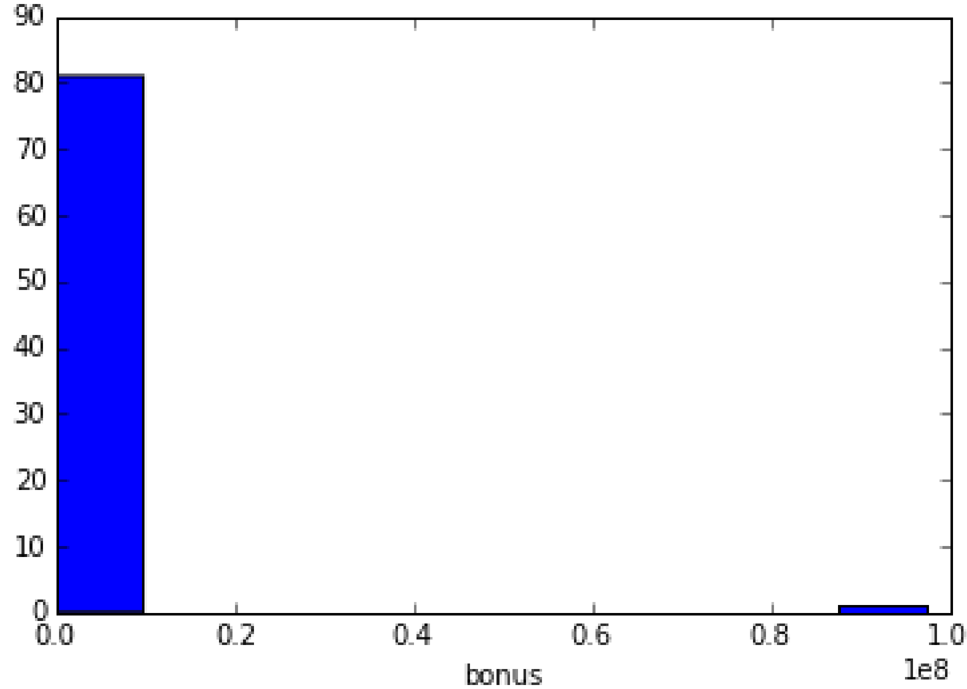
Possible Outlier for total_payments : TOTAL



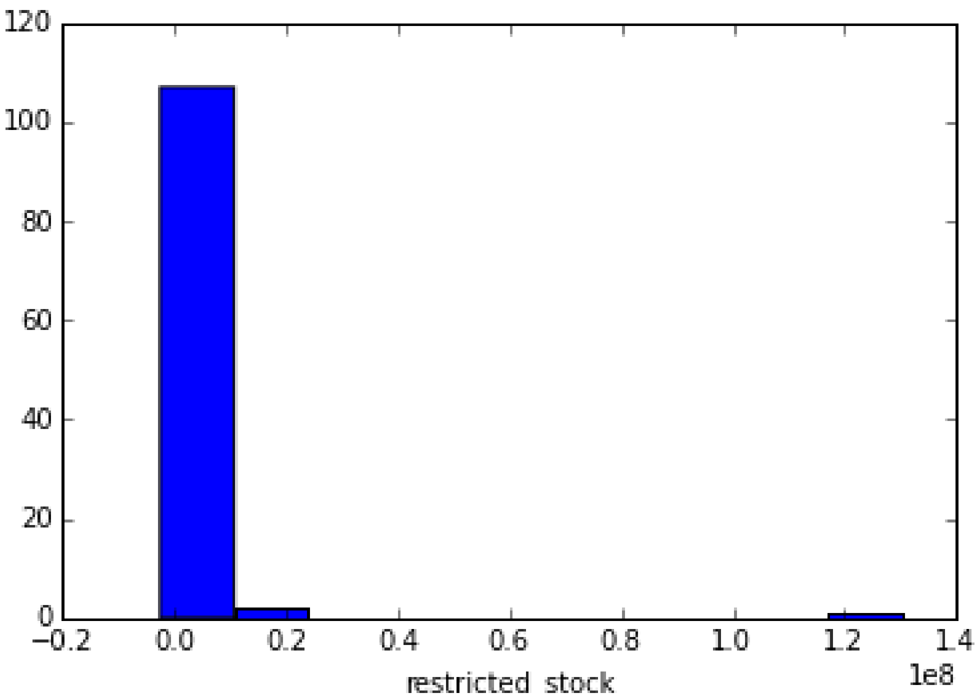

Possible Outlier for exercised_stock_options : TOTAL



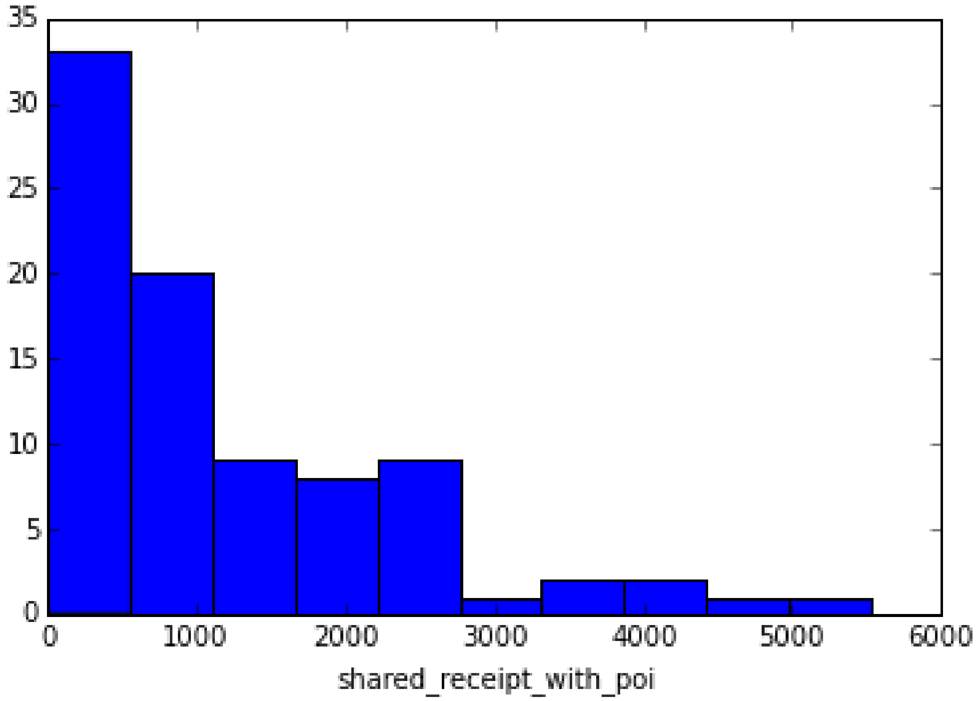
```
Possible Outlier for bonus : TOTAL
```



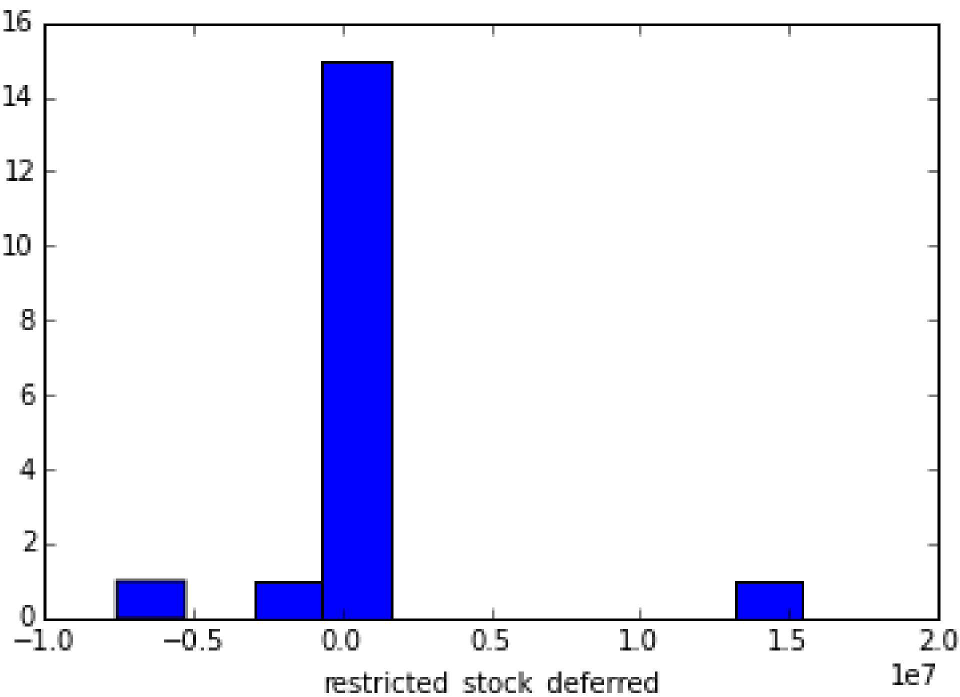

```
Possible Outlier for restricted_stock : TOTAL
```



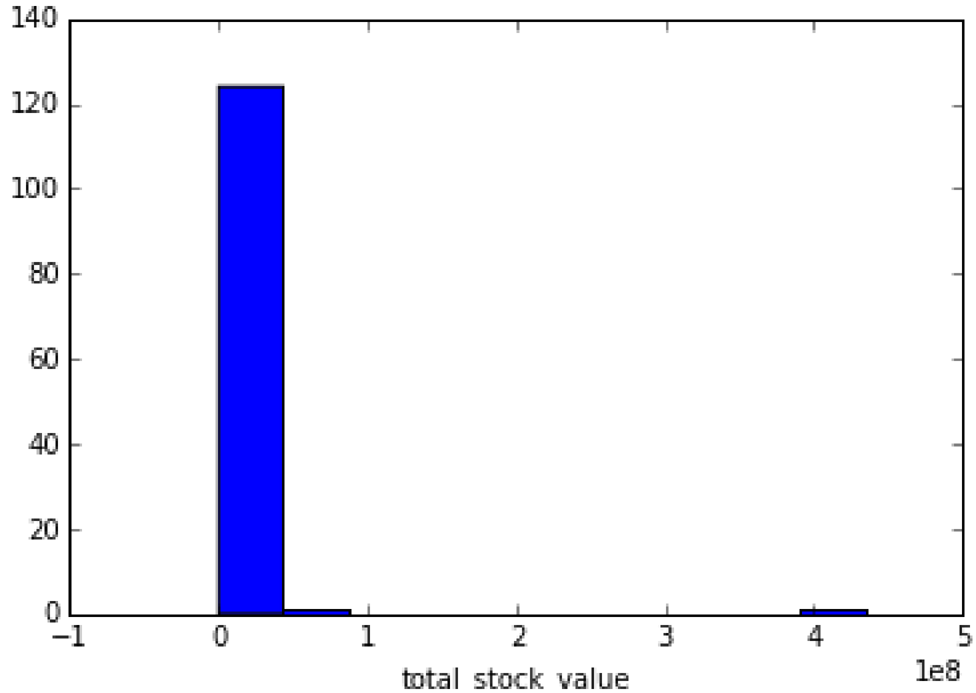
Possible Outlier for shared_receipt_with_poi : BELDEN TIMOTHY N



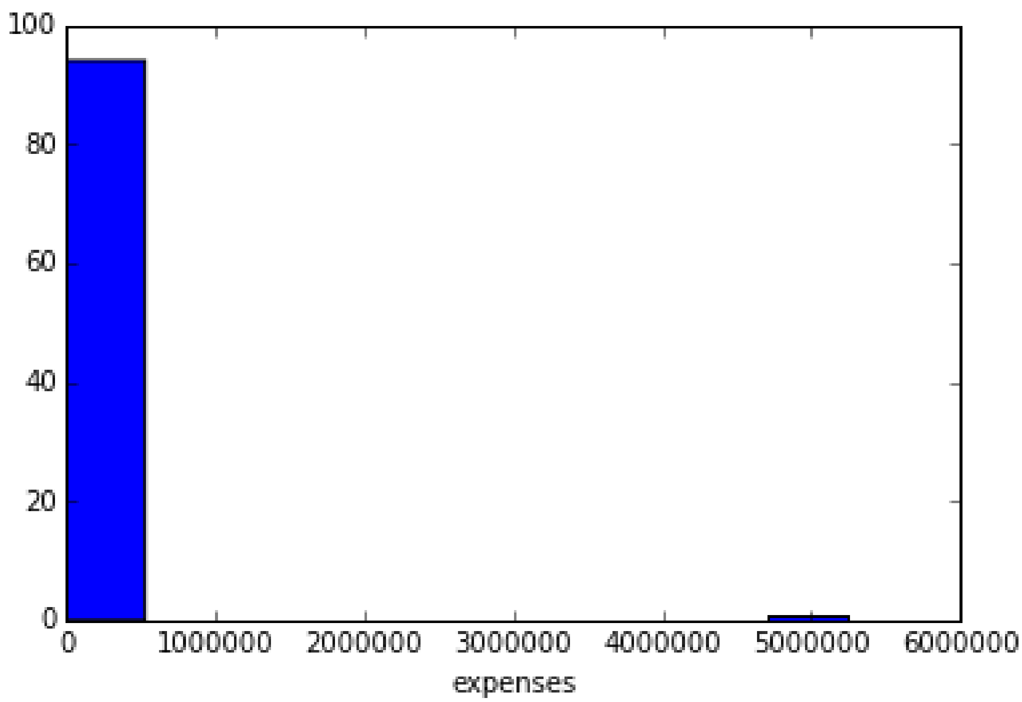

Possible Outlier for restricted_stock_deferred : BHATNAGAR SANJAY



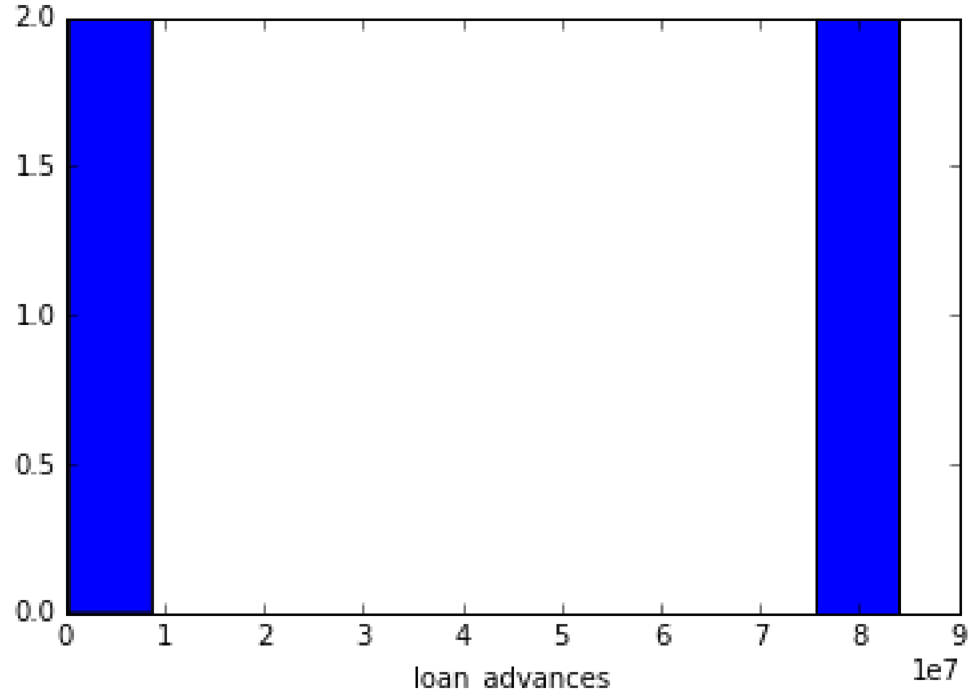
Possible Outlier for total_stock_value : TOTAL



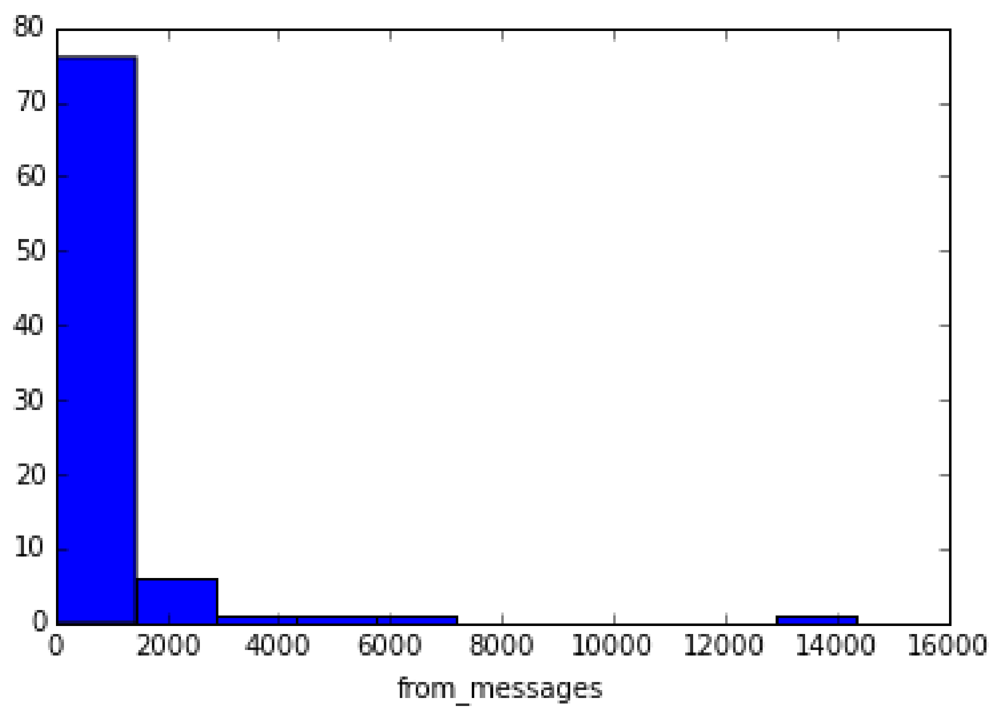

Possible Outlier for expenses : TOTAL



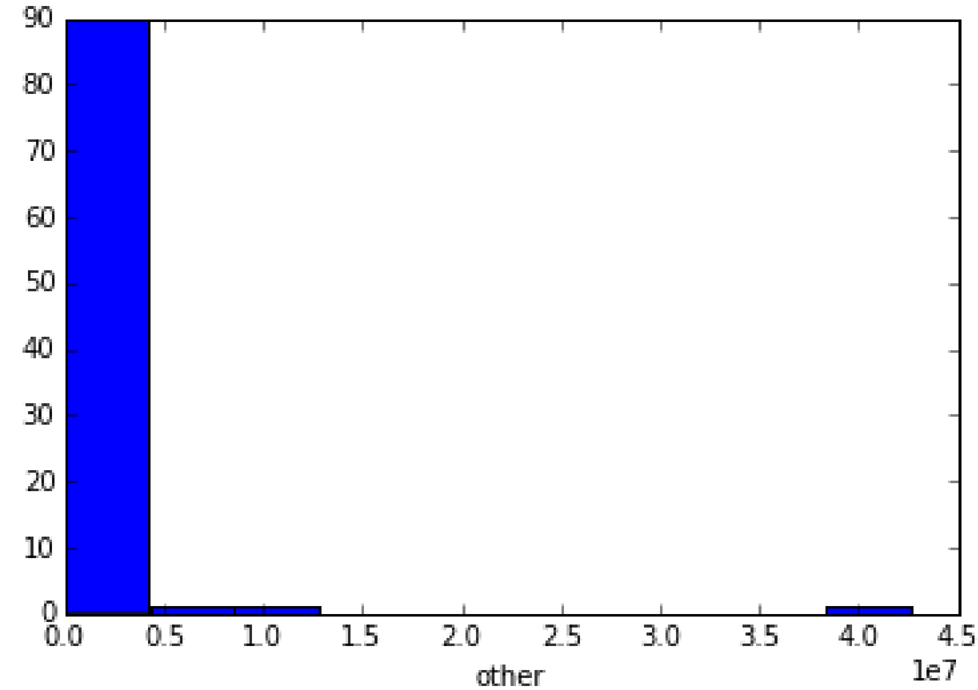
Possible Outlier for loan_advances : TOTAL



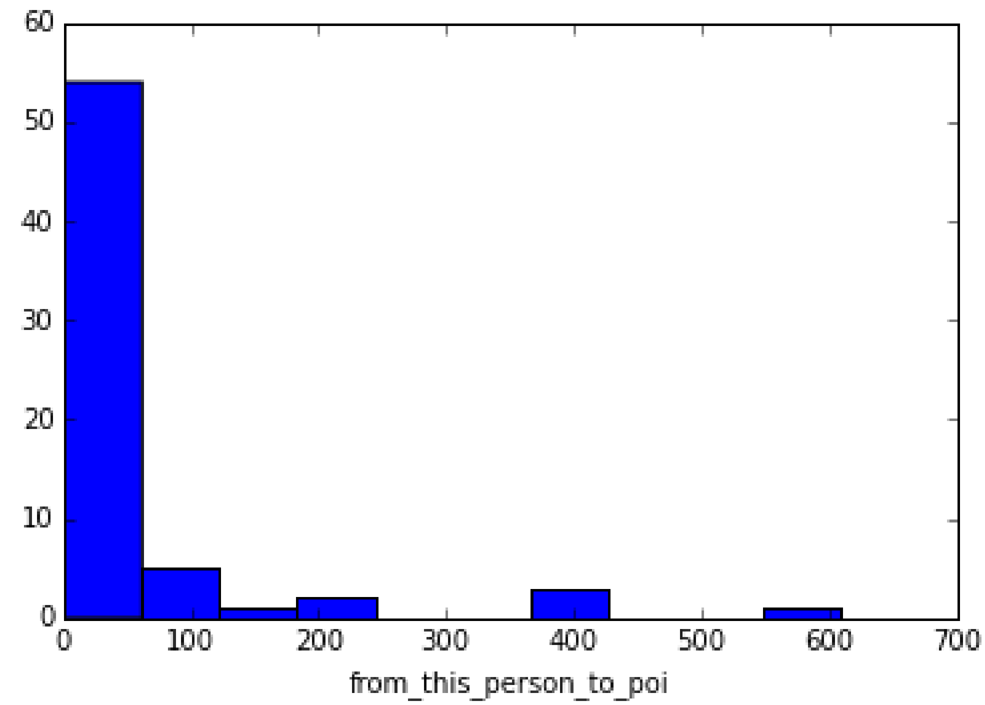

Possible Outlier for from_messages : KAMINSKI WINCENTY J



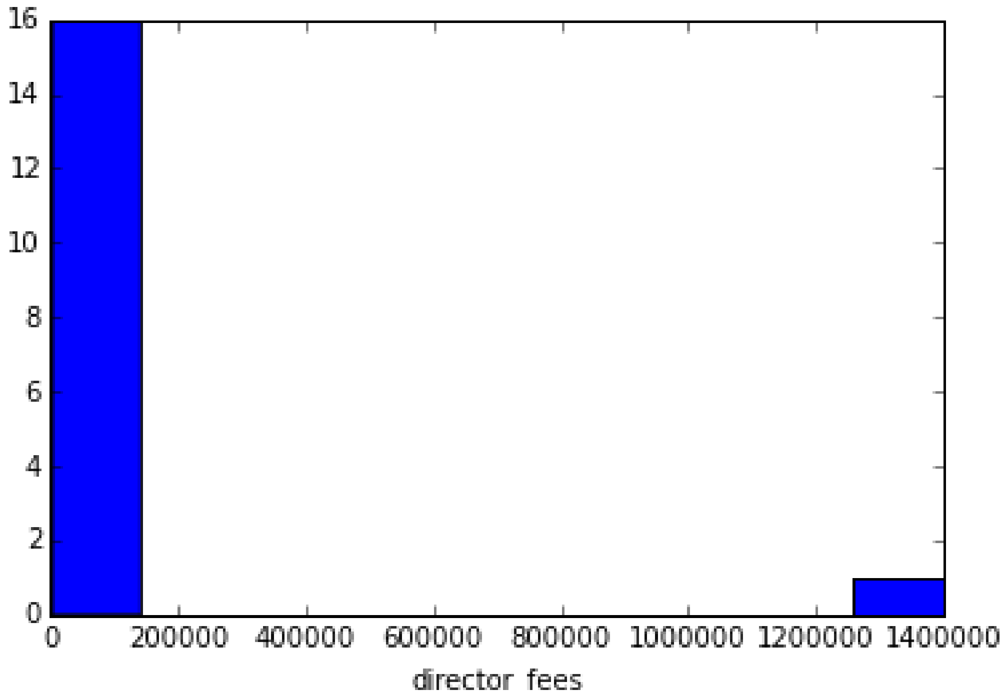
Possible Outlier for other : TOTAL



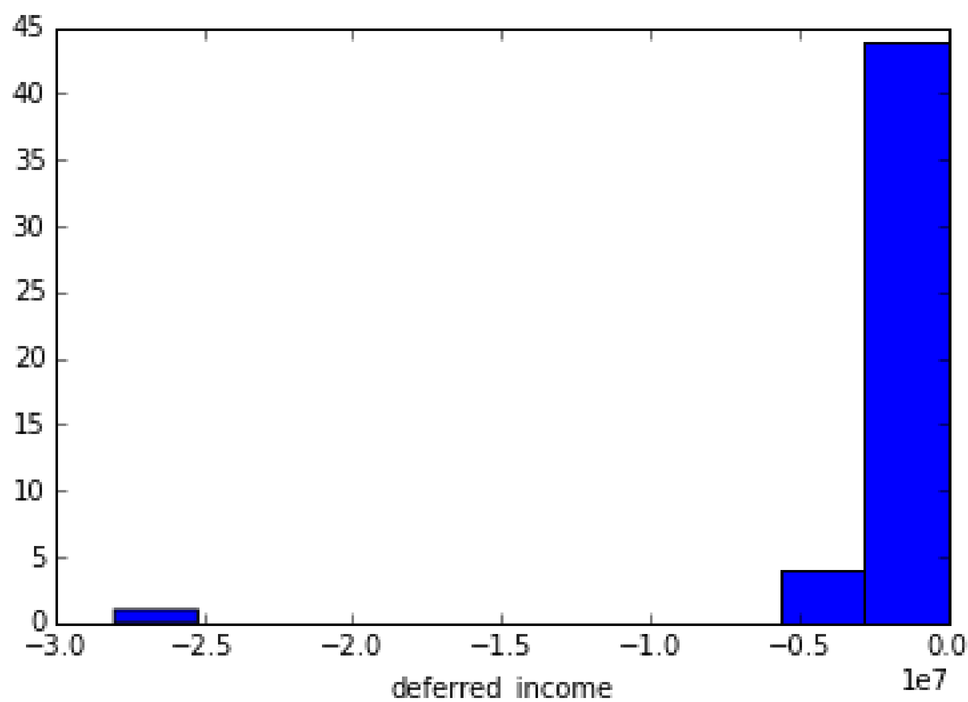

Possible Outlier for from_this_person_to_poi : DELAINEY DAVID W



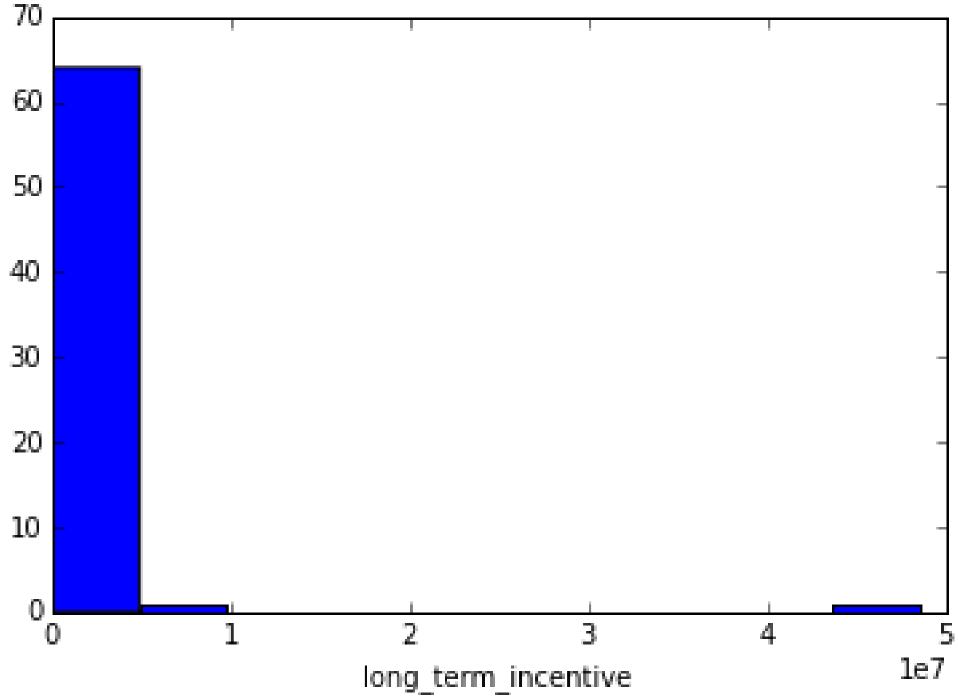
Possible Outlier for director_fees : TOTAL



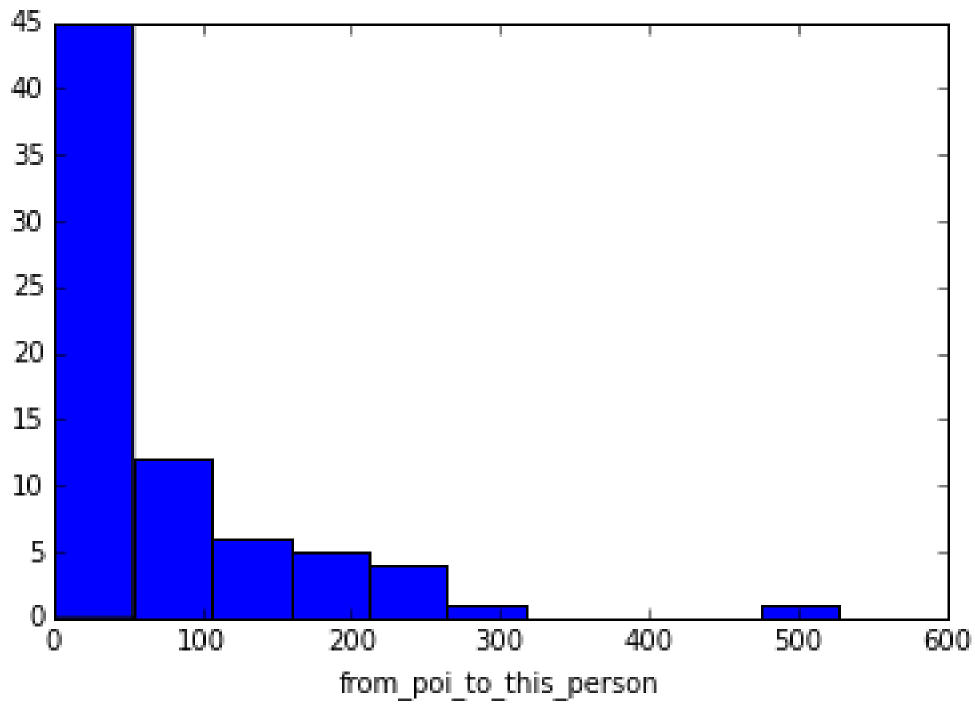

Possible Outlier for deferred_income : BOWEN JR RAYMOND M



Possible Outlier for long_term_incentive : TOTAL




Possible Outlier for from_poi_to_this_person : LAVORATO JOHN J



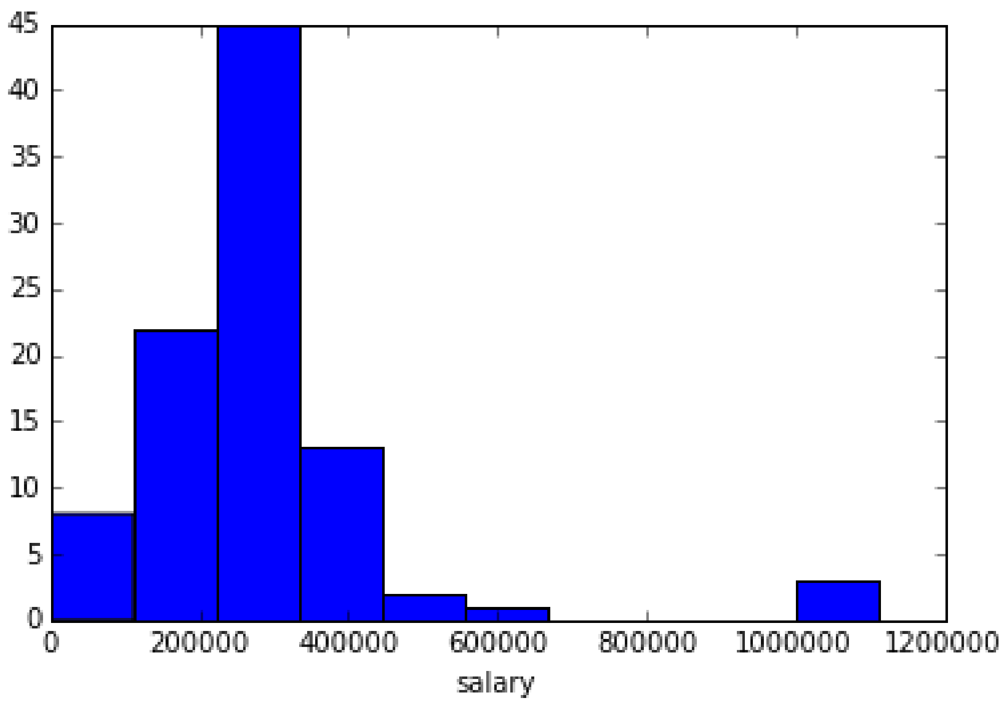
In [15]:
```
# Locate bad data (if any)
for person in data_dict:
    delete = True
    for feature in data_dict[person]:
        if feature == "email_address" or feature == 'poi':
            continue
        if data_dict[person][feature] == 'NaN':
            continue
        if data_dict[person][feature] > 0:
            delete = False  #If any field is positive, then keep the record...
    if delete:
        print person
        for feature in data_dict[person]:
            print feature, data_dict[person][feature]  # something is wrong with the data.
```

```
LOCKHART EUGENE E
salary NaN
to_messages NaN
deferral_payments NaN
total_payments NaN
exercised_stock_options NaN
bonus NaN
restricted_stock NaN
shared_receipt_with_poi NaN
restricted_stock_deferred NaN
total_stock_value NaN
expenses NaN
loan_advances NaN
from_messages NaN
other NaN
from_this_person_to_poi NaN
poi False
director_fees NaN
deferred_income NaN
long_term_incentive NaN
email_address NaN
from_poi_to_this_person NaN
```

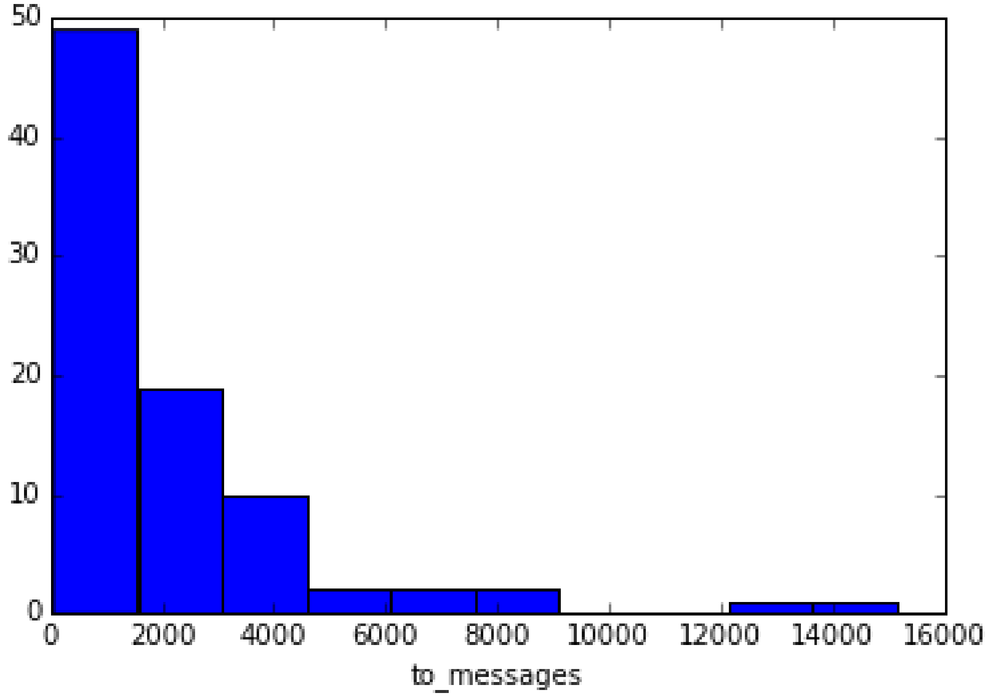
In [16]:
```
# By looking at the historgrams and and the "person" with the max value,
# it becomes obvious that "TOTAL" is a sum of the data and not a valid person.
# Remove TOTAL from the data.  Additionally, by since there are only 146 total
# records, a visual inspection of the names reveals not only the "TOTAL" person,
# but also a person named "THE TRAVEL AGENCY IN THE PARK".  Upon reviewing the
# accompanying pdf from FindLaw, we learn that "Payments were made by Enron
# employees on account of business-related travel" to this "person".  Since this
# is not a POI and not a real person, I decided it should also be exluded.
# Additionally, all the values for "LOCKHART EUGENE E" are NaN, so I excluded this
# record as well.
data_dict.pop('TOTAL', 0 )
data_dict.pop('THE TRAVEL AGENCY IN THE PARK', 0 )
data_dict.pop('LOCKHART EUGENE E', 0 )
```

```python
# Reproduce the historgrams and look for possibly other outliers...
for feature in data_dict[data_dict.keys()[0]].keys():
    if feature == "email_address" or feature == 'poi':
        continue
    data = featureFormat(data_dict, [feature])
    for person in data_dict:
        if data_dict[person][feature] == max(data):
            print "Possible Outlier for", feature, ":", person
    matplotlib.pyplot.hist(data, bins=10)
    matplotlib.pyplot.xlabel(feature)
    matplotlib.pyplot.show()

###
# After reviewing the new historgrams, while some people appear more than others
# with large values, these are persons of interest and should remain in the dataset.
# No further cleaning is required.
```

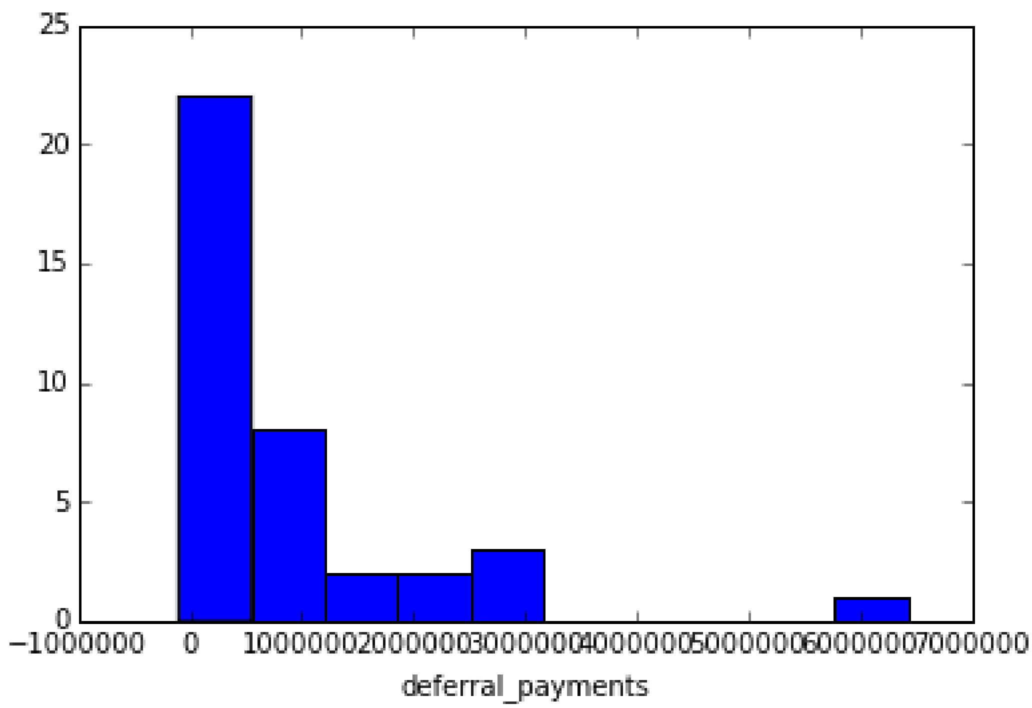
```
Possible Outlier for salary : SKILLING JEFFREY K
```



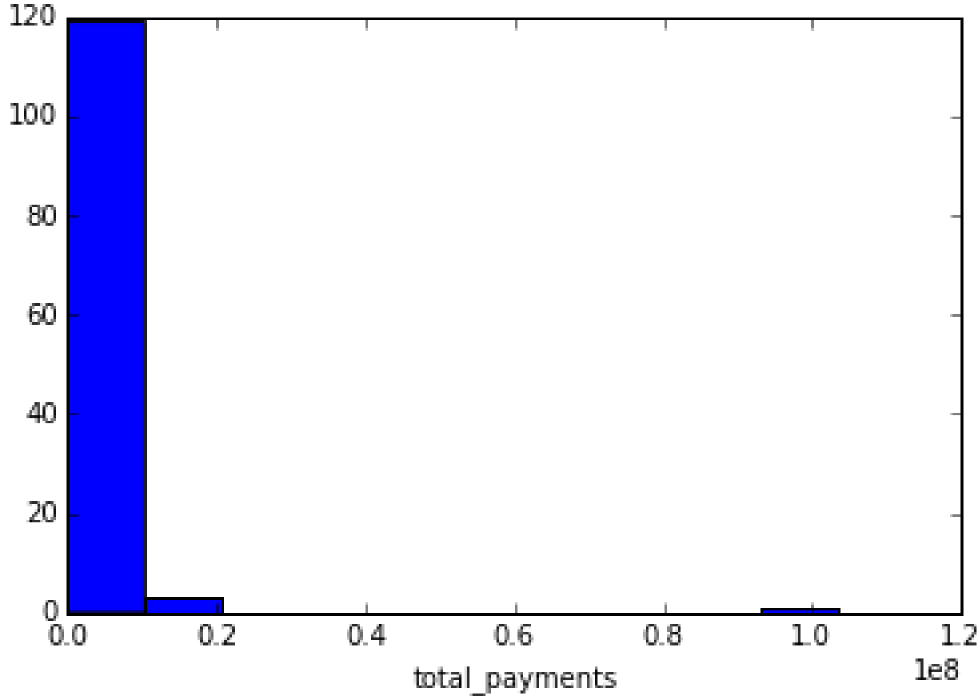

```
Possible Outlier for to_messages : SHAPIRO RICHARD S
```



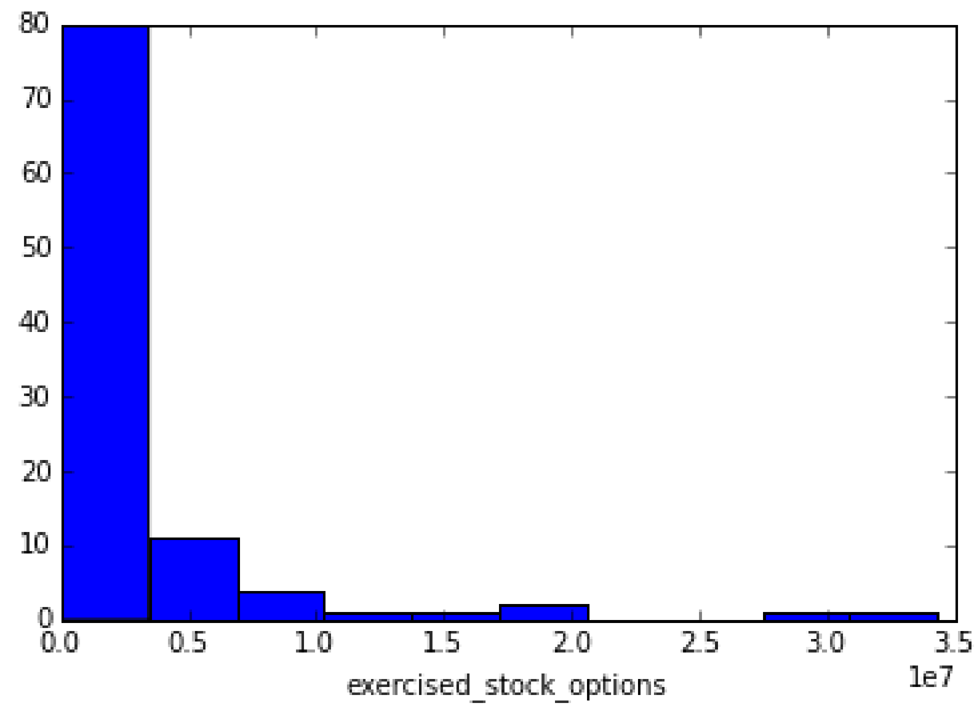

`Possible Outlier for deferral_payments : FREVERT MARK A`



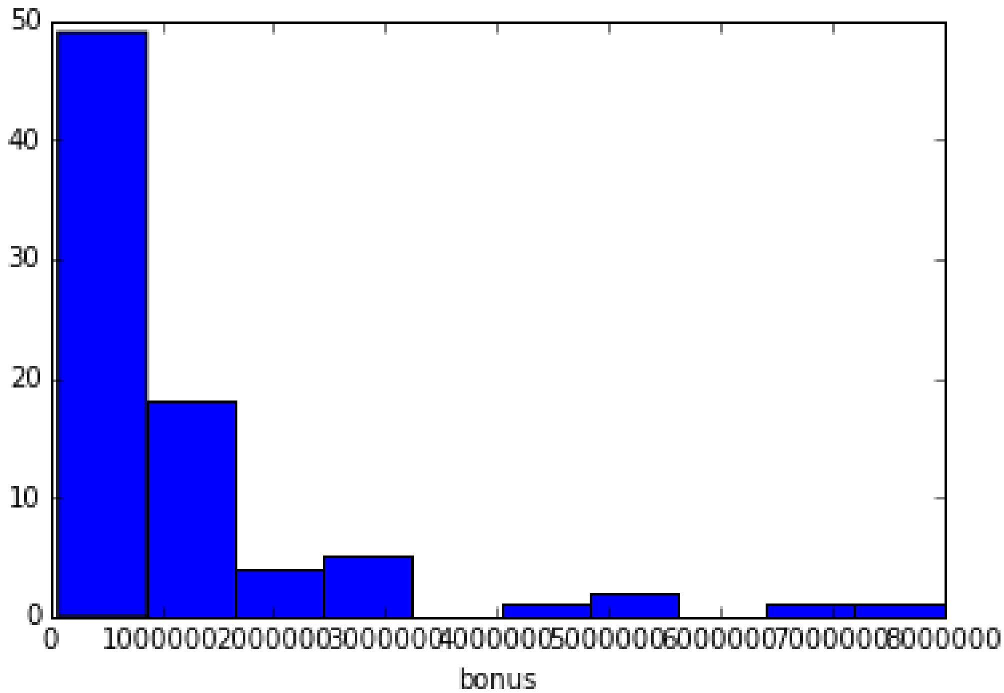
Possible Outlier for total_payments : LAY KENNETH L



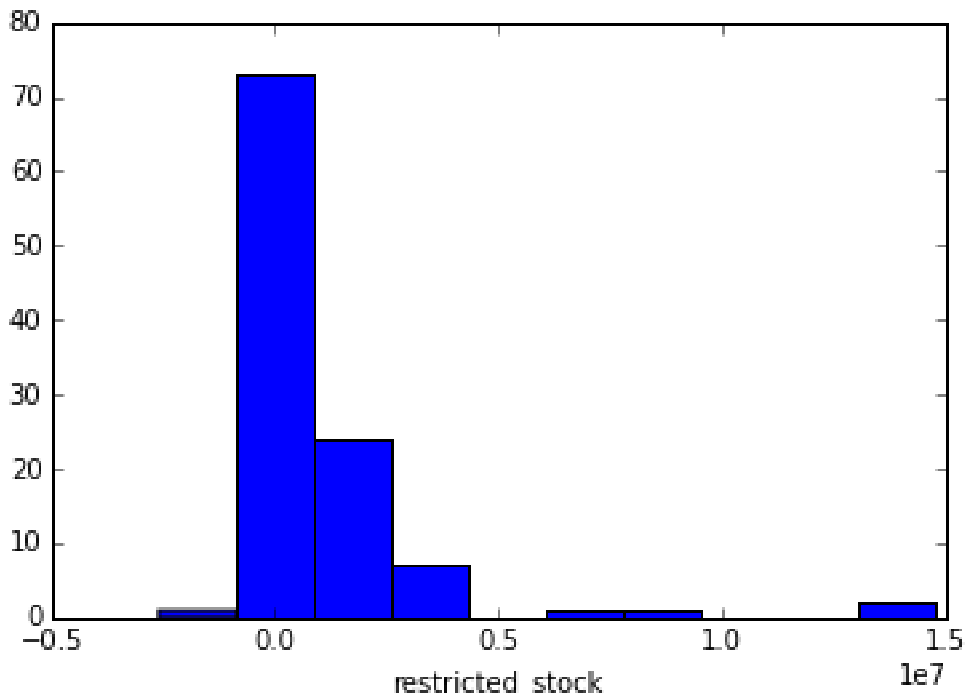

Possible Outlier for exercised_stock_options : LAY KENNETH L



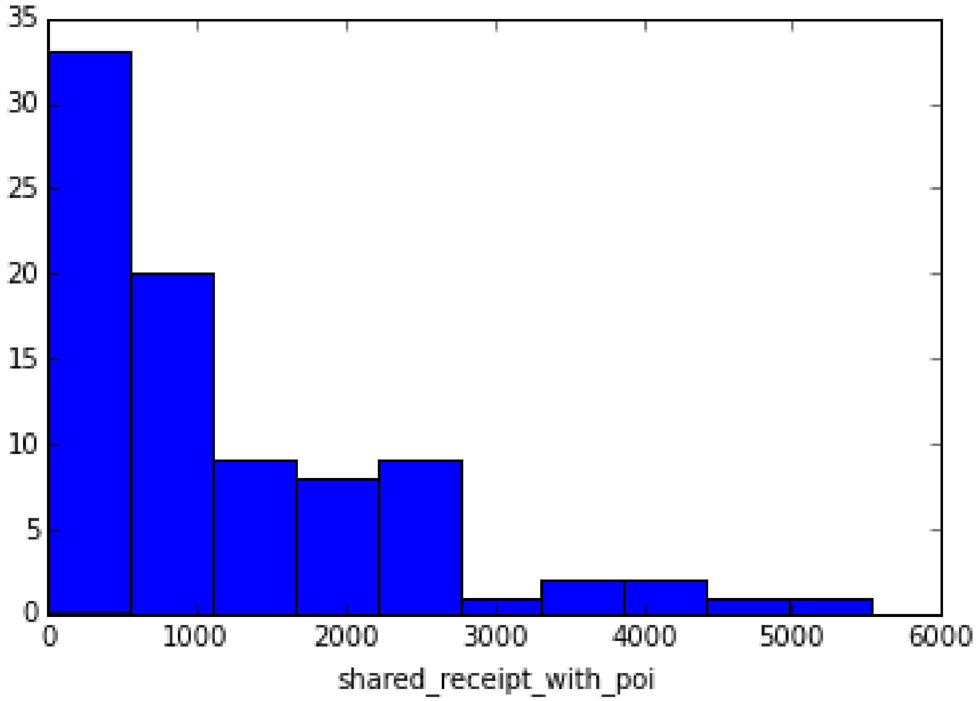
Possible Outlier for bonus : LAVORATO JOHN J



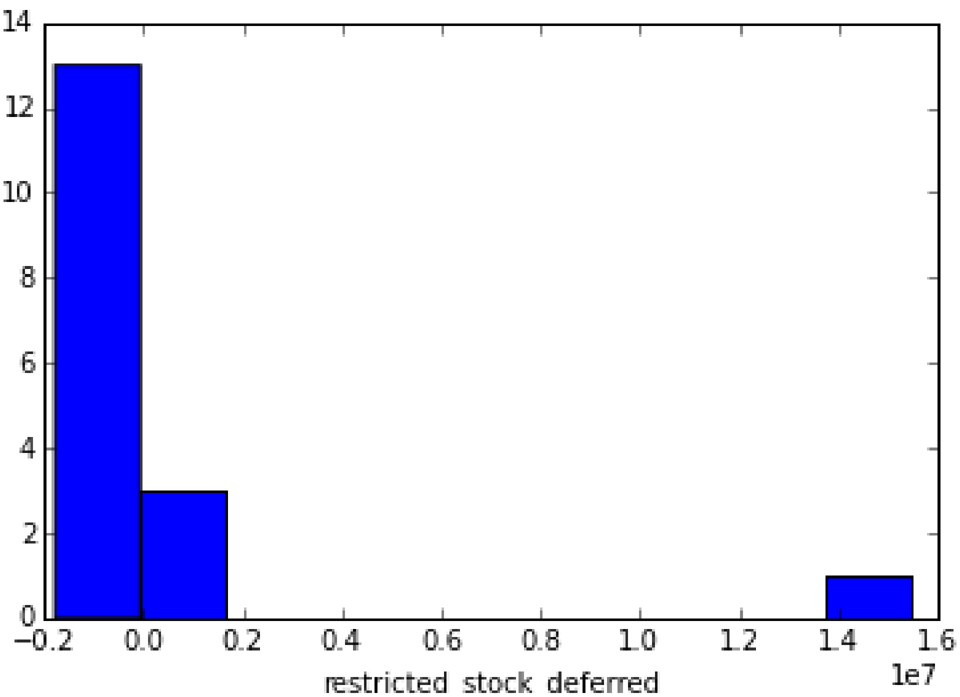

Possible Outlier for restricted_stock : LAY KENNETH L



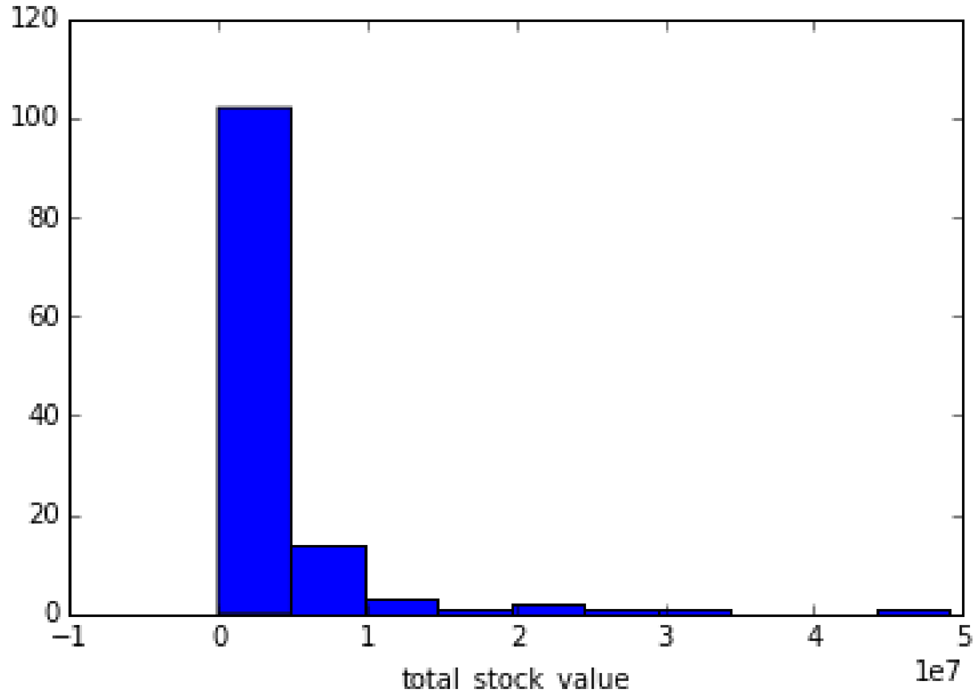
Possible Outlier for shared_receipt_with_poi : BELDEN TIMOTHY N



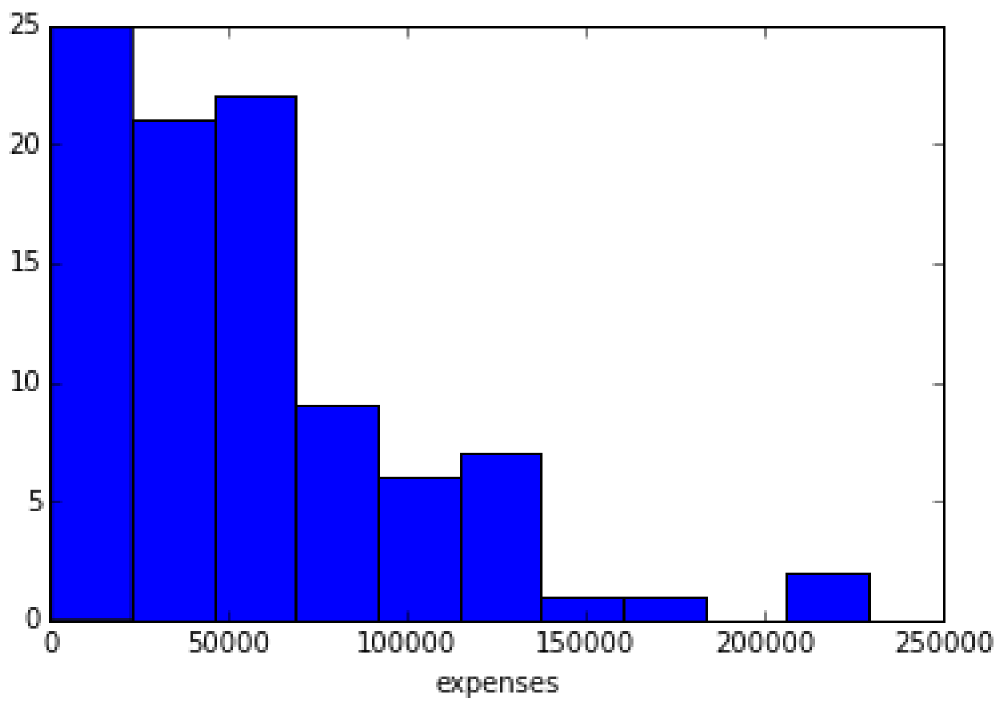

Possible Outlier for restricted_stock_deferred : BHATNAGAR SANJAY



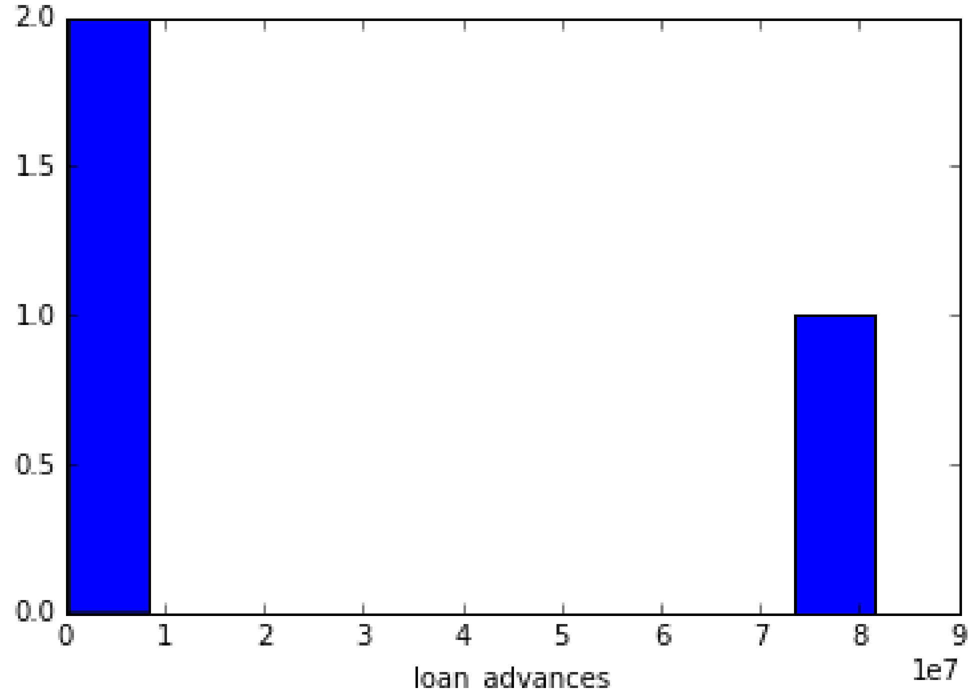
`Possible Outlier for total_stock_value : LAY KENNETH L`



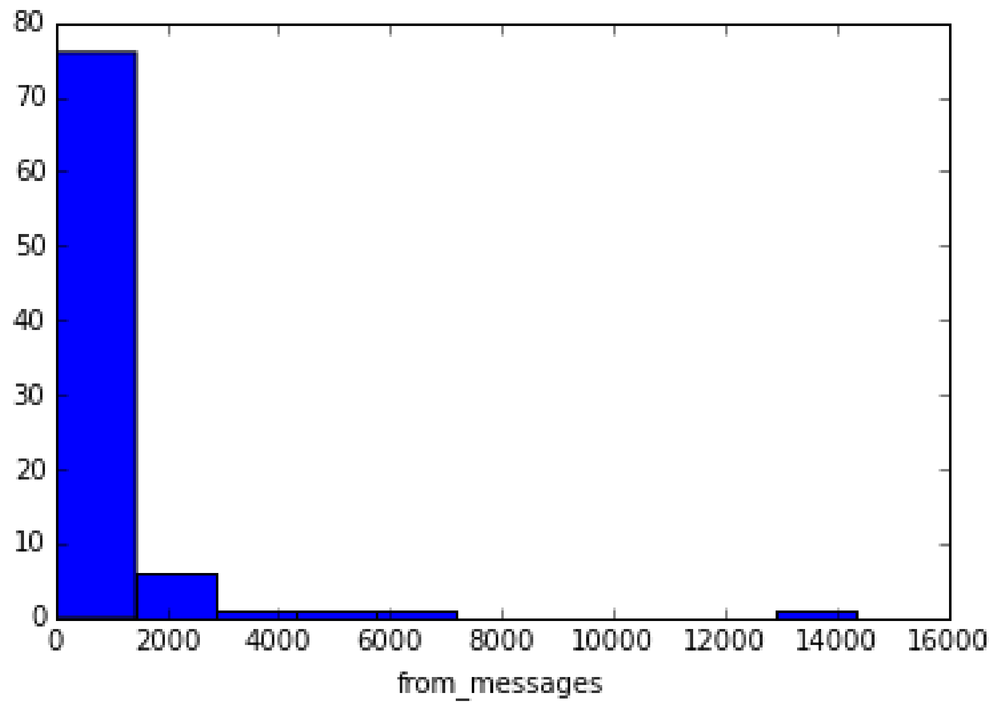

`Possible Outlier for expenses : MCCLELLAN GEORGE`



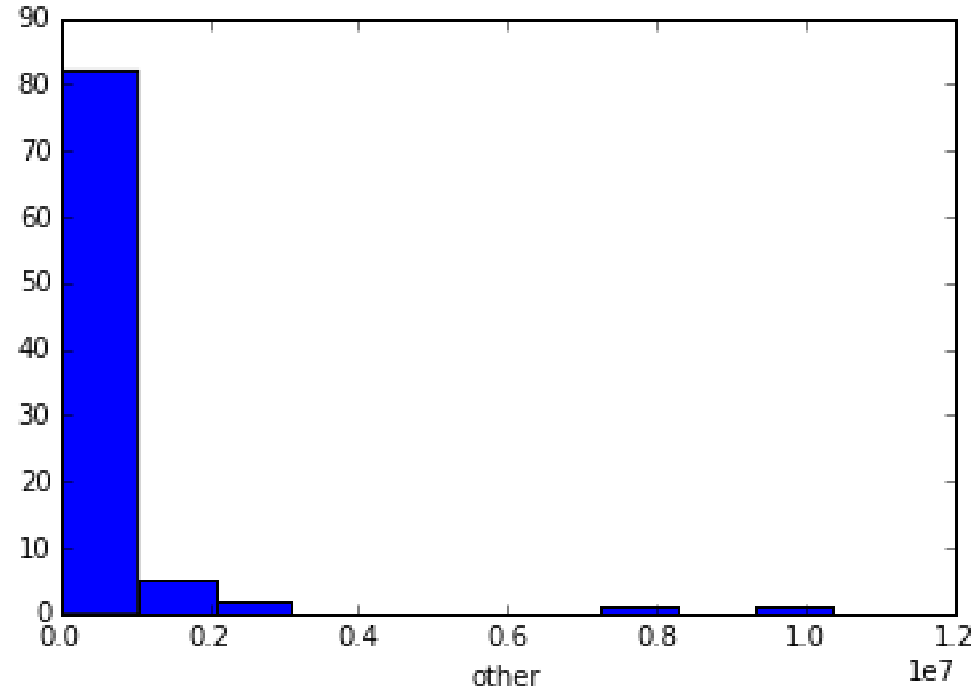
Possible Outlier for loan_advances : LAY KENNETH L



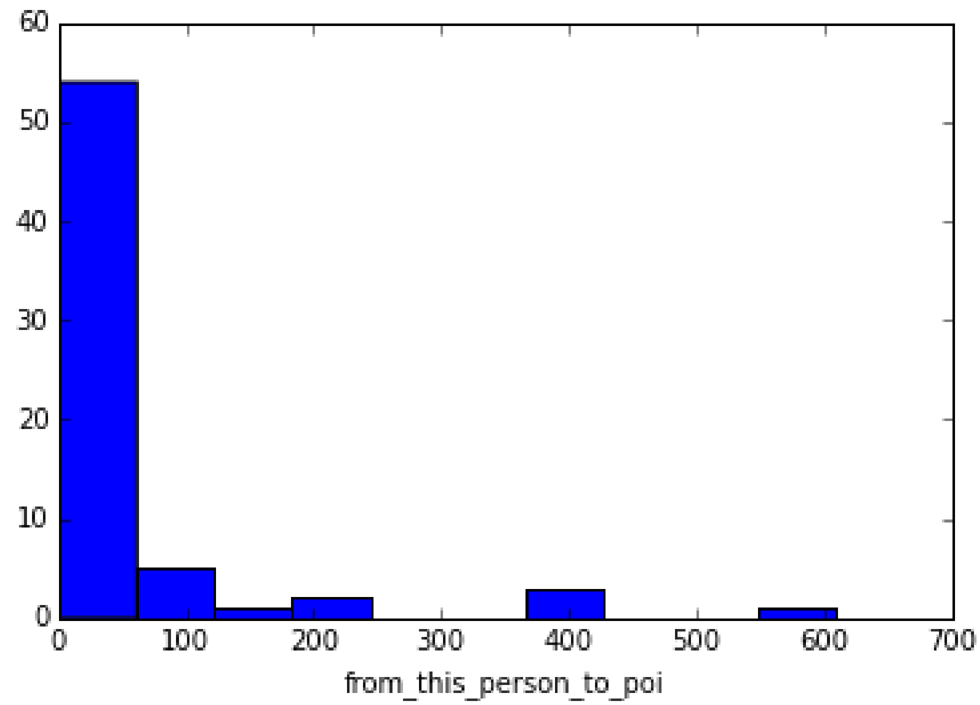

Possible Outlier for from_messages : KAMINSKI WINCENTY J



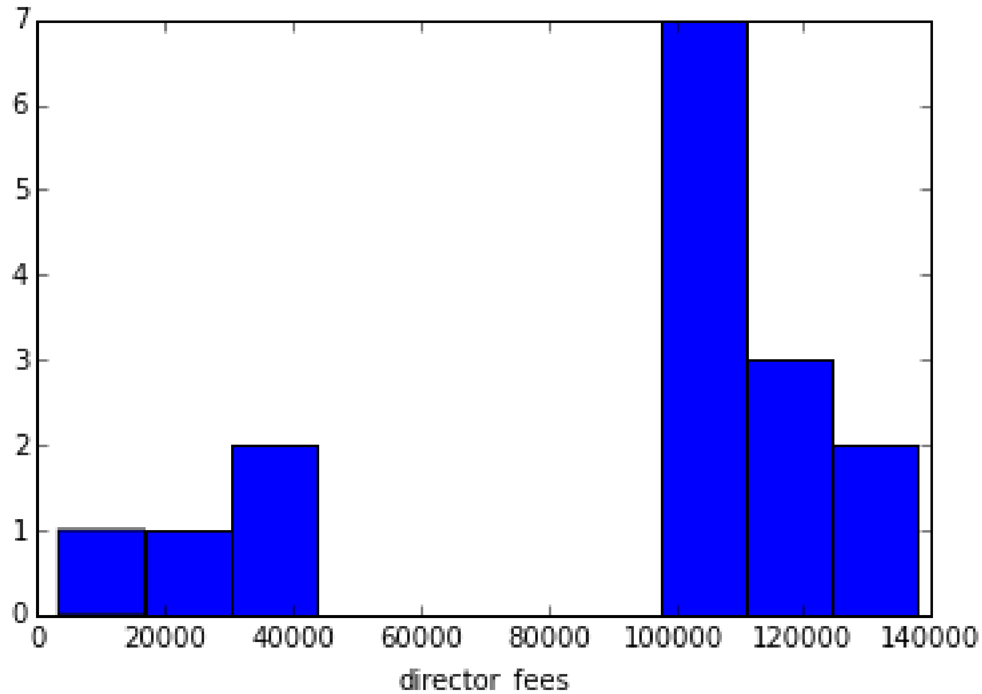
Possible Outlier for other : LAY KENNETH L



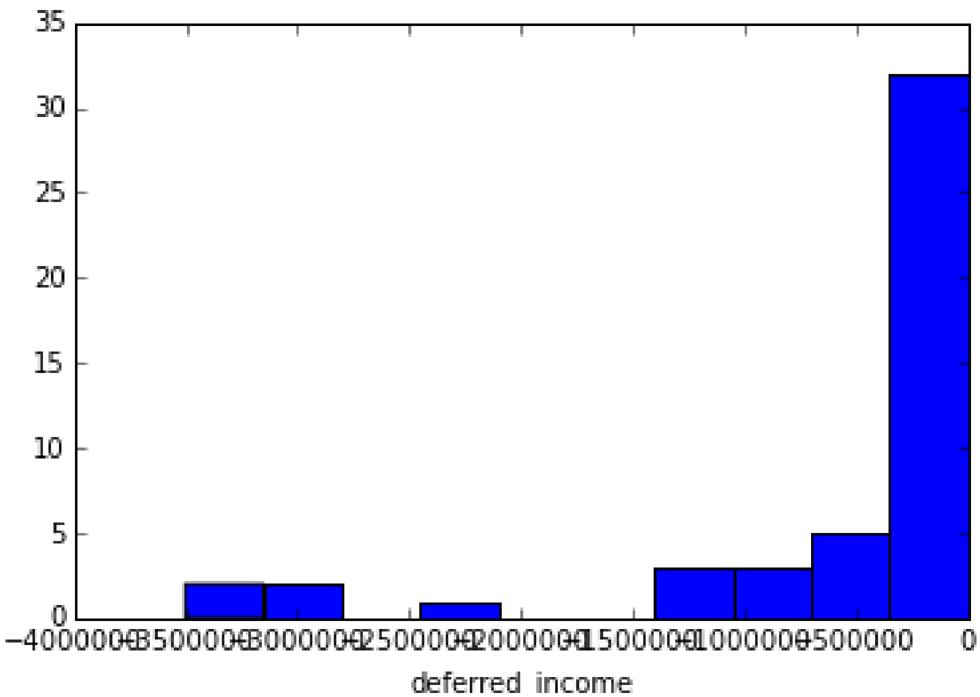

Possible Outlier for from_this_person_to_poi : DELAINEY DAVID W



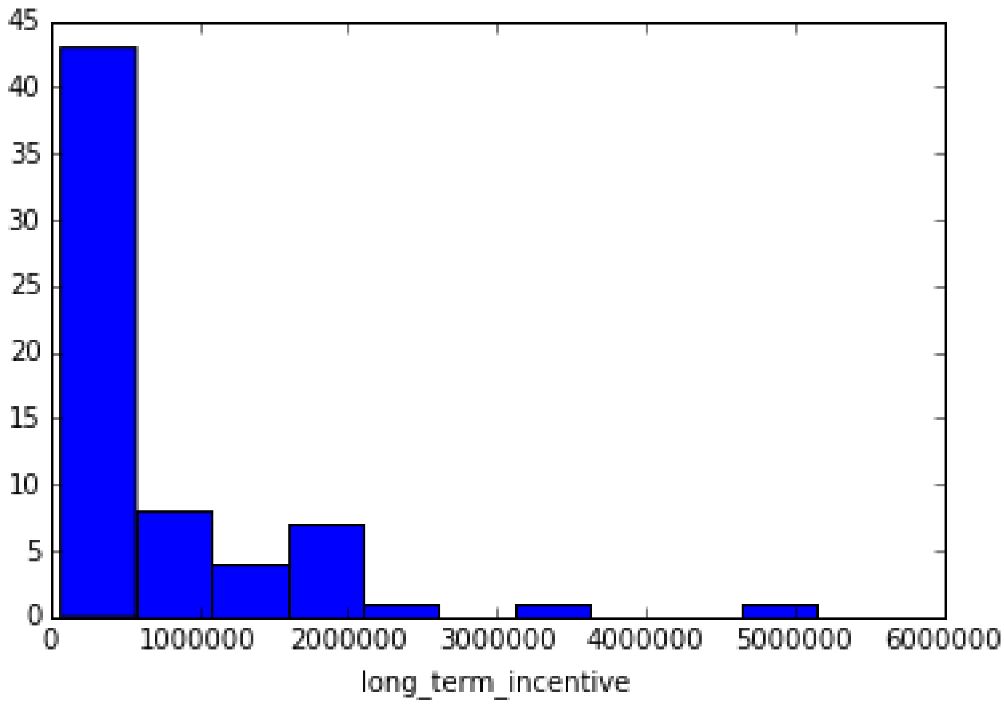
Possible Outlier for director_fees : BHATNAGAR SANJAY



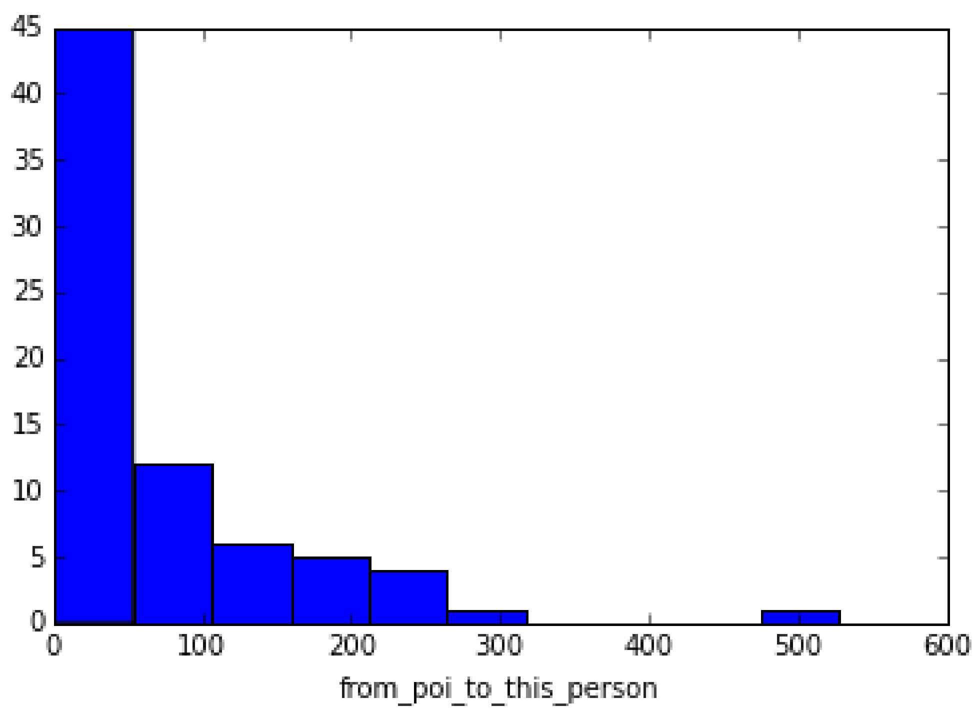

Possible Outlier for deferred_income : BOWEN JR RAYMOND M



Possible Outlier for long_term_incentive : MARTIN AMANDA K




Possible Outlier for from_poi_to_this_person : LAVORATO JOHN J



In [17]:
```
### Task 3: Create new feature(s)
### Store to my_dataset for easy export below.
my_dataset = data_dict

# Add ratio of bonus to pay
for person in my_dataset:
    if my_dataset[person]['salary'] > 0 and \
    my_dataset[person]['salary'] != 'NaN' and \
    my_dataset[person]['bonus'] != 'NaN':
        my_dataset[person]['bonusratio'] = 1.0 * \
        my_dataset[person]['bonus'] / my_dataset[person]['salary']
    else:
        my_dataset[person]['bonusratio'] = 'NaN'

# Add ratio of poi email messages (higher percentage of email
# to/from a poi could indicate also a poi)
for person in my_dataset:
    if my_dataset[person]['to_messages'] != 'NaN' and \
    my_dataset[person]['from_messages'] != 'NaN' and \
    my_dataset[person]['from_this_person_to_poi'] != 'NaN' and \
    my_dataset[person]['from_poi_to_this_person'] != 'NaN':
        poi_email = my_dataset[person]['from_this_person_to_poi'] + \
        my_dataset[person]['from_poi_to_this_person']
        all_email = my_dataset[person]['to_messages'] + my_dataset[person]['from_messages']
        my_dataset[person]['poi_email_ratio'] = 1.0 * poi_email / all_email
    else:
        my_dataset[person]['poi_email_ratio'] = 'NaN'
```

In [18]:
```
### 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

# Below are the classifiers that were tried.  Pipelines were used in order to easily setup
# the flow.  A MinMaxScaler was used in the pipeline because some pipelines included PCA,
# which  has been results when used on scaled values.
# 1: MinMaxScaler, SelectKBest(score_func=f_classif), PCA, GaussianNB
#   {'kbest__k': [5, 10, 15, 20], 'pca__n_components': [2, 3, 4],
#       'pca__whiten': [True, False]}
#   fit time: 83.653 s
#   Best Params: {'kbest__k': 10, 'pca__n_components': 4, 'pca__whiten': True}
#   Accuracy: 0.83227, Precision: 0.34877, Recall: 0.29750, F1: 0.32110, F2: 0.30651
#
# 2: SelectKBest(score_func=f_classif), GaussiabNB
#   {'kbest__k': [5, 10, 15, 20]}
#   pipeline 1 fit time: 10.282 s
#   Best Params: {'kbest__k': 5}
#   Accuracy: 0.84653, Precision: 0.41322, Recall: 0.35950, F1: 0.38449, F2: 0.36910
#
# 3: MinMaxScaler, SelectKBest(score_func=f_classif), PCA, LogisticRegression
```

```
#   {'kbest__k': [5, 10, 15, 20], 'pca__n_components': [2, 3, 4],
#      'pca__whiten': [True, False], clf__C': [1, 10, 100, 1000],
#       'clf__solver': ['liblinear', 'newton-cg']}
#   fit time: 1083.793 s
#   Best Params: {'pca__n_components': 4, 'kbest__k': 10, 'clf__C': 100,
#      'clf__solver': 'liblinear', 'pca__whiten': True}
#   Accuracy: 0.85933, Precision: 0.42188, Recall: 0.14850, F1: 0.21967, F2: 0.17061
#
# 4: MinMaxScaler, SelectKBest(score_func=f_classif), PCA,  SVC(random_state =42)
#   {'kbest__k': [5, 10, 15, 20], 'pca__n_components': [2, 3, 4],
#       'pca__whiten': [True, False], 'clf__C': [1, 10, 100, 1000],
#       'clf__kernel': ['rbf', 'linear']}
#   fit time: 5934.505 s
#   Best Params: {'kbest__k': 15, 'clf__C': 1000, 'pca__n_components': 4,
#        'pca__whiten': True, 'clf__kernel': 'rbf'}
#   Accuracy: 0.81840, Precision: 0.31146, Recall: 0.29900, F1: 0.30510, F2: 0.30141
#
# 5: MinMaxScaler, SelectKBest(score_func=f_classif), PCA,
#        DecisionTreeClassifier(random_state =42)
#   {'kbest__k': [5, 10, 15, 20], 'pca__n_components': [2, 3, 4],
#        'pca__whiten': [True, False], 'clf__criterion': ['gini', 'entropy'],
#        'clf__max_depth': [10, 100, 1000, 10000]}
#   fit time: 711.177 s
#   Best Params: {'pca__n_components': 3, 'clf__criterion': 'entropy',
#       'clf__max_depth': 100, 'kbest__k': 10, 'pca__whiten': True}
#   Accuracy: 0.79760, Precision: 0.23161, Recall: 0.22350, F1: 0.22748, F2: 0.22508
#
# 6: MinMaxScaler, SelectKBest(score_func=f_classif), GaussiabNB
#   {'kbest__k': [5, 10, 15, 20]}
#   fit time: 11.212 s
#   Best Params: {'kbest__k': 5}
#   Accuracy: 0.84653, Precision: 0.41322, Recall: 0.35950, F1: 0.38449, F2: 0.36910
#
# 7: MinMaxScaler, SelectKBest(score_func=f_classif), LogisticRegression
#   {'kbest__k': [5, 10, 15, 20], 'clf__C': [1, 10, 100, 1000],
#         'clf__solver': ['liblinear', 'newton-cg']}
#   fit time: 213.16 s
#   Best Params: {'kbest__k': 20, 'clf__C': 1000, 'clf__solver': 'liblinear'}
#   Accuracy: 0.81933, Precision: 0.21371, Recall: 0.13250, F1: 0.16358, F2: 0.14340
#
# 8: MinMaxScaler, SelectKBest(score_func=f_classif),
#         DecisionTreeClassifier(random_state =42)
#   {'kbest__k': [5, 10, 15, 20], 'clf__criterion': ['gini', 'entropy'],
#         'clf__max_depth': [10, 100, 1000, 10000]}
#   fit time: 104.541 s
#   Best Params: {'clf__criterion': 'entropy', 'clf__max_depth': 100, 'kbest__k': 15}
#   Accuracy: 0.80153, Precision: 0.23494, Recall: 0.21650, F1: 0.22534, F2: 0.21995
#
# 9: MinMaxScaler, SelectKBest(score_func=f_classif), LogisticRegression
#   {'kbest__k': [5, 10, 15, 20], 'clf__C': [1000, 10000, 100000, 1000000],
#         'clf__solver': ['liblinear', 'newton-cg']}
#   fit time: 403.069 s
#   Best Params: {'kbest__k': 20, 'clf__C': 1000000, 'clf__solver': 'newton-cg'}
#   Accuracy: 0.81647, Precision: 0.26336, Recall: 0.20950, F1: 0.23336, F2: 0.21843
```

```
#
# 10: MinMaxScaler, SelectKBest(score_func=f_classif), PCA,  SVC(random_state =42)
#   {'kbest__k': [5, 10, 15, 20], 'clf__C': [1000, 10000, 100000, 1000000],
#       'clf__kernel': ['rbf', 'linear']}
#   fit time: 42313.693 s
#   Best Params: {'kbest__k': 20, 'clf__C': 100000, 'clf__kernel': 'rbf'}
#   Accuracy: 0.81113, Precision: 0.29018, Recall: 0.28800, F1: 0.28908, F2: 0.28843
#
# 11: MinMaxScaler, SelectKBest(score_func=f_classif), PCA,
#        RandomForestClassifier(random_state =42)
#   {'kbest__k': [5, 10, 15, 20], 'clf__criterion': ['gini', 'entropy'],
#        'clf__n_estimators': [10, 100, 1000, 10000]}
#   fit time: 66037.228 s
#   Best Params: {'clf__criterion': 'gini', 'kbest__k': 5, 'clf__n_estimators': 100}
#   Accuracy: 0.85973, Precision: 0.44503, Recall: 0.21050, F1: 0.28581, F2: 0.23530

# The best classifier turned out the be the GaussianNB when run with
# SelectKBest(k=5, score_func=f_classif).  The pipeline fit was about 10 seconds.  Adding in
# scaling made no change to the accuracy or presicion, which was expected.

# Setup the pipeline
# GaussianNB gave the best results with no scaler and no PCA.  This is the classifer that
# will be used to generate the project pickle files.  All the above tests were performed in
# the same manner by modifying the pipeline.
pipeline = Pipeline(steps=[('kbest', SelectKBest(score_func=f_classif)),
                           ('clf', GaussianNB())
                           ])
p_params = {'kbest__k': [5, 10, 15, 20]}
```

In [19]:
```
### Task 5: Tune your classifier to achieve better than .3 precision and recall
### using our testing script. Check the tester.py script in the final project
### folder for details on the evaluation method, especially the test_classifier
### function. Because of the small size of the dataset, the script uses
### stratified shuffle split cross validation. For more info:
### http://scikit-learn.org/stable/modules/generated/sklearn.cross_validation.StratifiedShuffl

# Example starting point. Try investigating other evaluation techniques!
# Create a feature_list that has all features on it.  We will use selectKBest to determine the
all_features = data_dict[my_dataset.keys()[0]].keys()
all_features.remove('poi')
all_features.remove('email_address')
features_list = ['poi']
features_list.extend(all_features)

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

# Create 1000 random test sets to go over...
shuffle = StratifiedShuffleSplit(labels, n_iter=1000, test_size=0.3, random_state=42)

#Select a scoring function.  Turns out recall is not so good...
#scorer = 'recall'
scorer = 'f1'
```

```
In [20]: # Find the best classifer
         t0 = time()
         p_grid = GridSearchCV(pipeline, param_grid=p_params, cv=shuffle,
                               scoring=scorer, verbose=0)
         p_grid.fit(features, labels)
         print "fit time:", round(time()-t0, 3), "s"
```

```
fit time: 9.98 s
```

```
In [21]: # Results....
         features_selected = p_grid.best_estimator_.named_steps['kbest'].get_support()
         x=0
         print "Feature(Score) Selected:"
         for feat in features_list:
             if feat == "poi":
                 continue
             if features_selected[x] == True:
                 print '   %s(%f)' % (feat, p_grid.best_estimator_.named_steps['kbest'].scores_[x])
             x += 1
         print "Score:", p_grid.best_score_
         print "Params:", p_grid.best_params_

         clf = p_grid.best_estimator_
         test_classifier(clf, my_dataset, features_list)
```

```
Feature(Score) Selected:
   deferred_income(11.458477)
   bonus(20.792252)
   total_stock_value(24.182899)
   salary(18.289684)
   exercised_stock_options(24.815080)
Score: 0.309143105476
Params: {'kbest__k': 5}
Pipeline(steps=[('kbest', SelectKBest(k=5, score_func=<function f_classif at 0x000000001AD2F668>)), ('cl
        Accuracy: 0.84653       Precision: 0.41322      Recall: 0.35950     F1: 0.38449     F2
        Total predictions: 15000        True positives:  719        False positives: 1021       False 
```

```
In [22]: ### Task 6: Dump your classifier, dataset, and features_list so anyone can
         ### check your results. You do not need to change anything below, but make sure
         ### that the version of poi_id.py that you submit can be run on its own and
         ### generates the necessary .pkl files for validating your results.

         dump_classifier_and_data(clf, my_dataset, features_list)
```