Identifying Fraud from Enron Emails

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What's new :
- First release

Introduction

A critical part of machine learning is making sense of your analysis process and communicating it to others. The questions below will help us understand your decision-making process and allow us to give feedback on your project. Please answer each question; your answers should be about 1-2 paragraphs per question. If you find yourself writing much more than that, take a step back and see if you can simplify your response!

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.

The goal of this project is to determine who are the person of interest in the Enron Fraud case based on the provided data : financial and email.

In 2000, Enron was one of the top company in the united states but in 2002, due to a fraud, the company bankrupted.

Today, we have the data, including the results of the investigation, to use machine learning in order to detect who can be related to the fraud.

I'll try to follow my analysis. Beginning in python, I know I can optimise the code, create functions instead of copy/paste. But when I get something working I prefer not to touch it.

Data exploration

Data Exploration (related lesson: "Datasets and Questions")
Student response addresses the most important characteristics of the dataset and uses these characteristics to inform their analysis. Important characteristics include:
total number of data points
allocation across classes (POI/non-POI)
number of features used
are there features with many missing values? etc.

At this stage, I get some of the characteristics of the dataset we have.

Total People number : 146

Number of features : 21

features names:

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

POIs list :

HANNON KEVIN P
COLWELL WESLEY
RIEKER PAULA H
KOPPER MICHAEL J
SHELBY REX
DELAINEY DAVID W
LAY KENNETH L
BOWEN JR RAYMOND M
BELDEN TIMOTHY N
FASTOW ANDREW S
CALGER CHRISTOPHER F
RICE KENNETH D
SKILLING JEFFREY K
YEAGER F SCOTT
HIRKO JOSEPH
KOENIG MARK E
CAUSEY RICHARD A
GLISAN JR BEN F

Total POIs : 18

Here are the management of the NaN and Zero data in the dataset :

At first, it seemed there was no NaN but in reality it was not a real NaN.
So I had to convert it, especially when I tried to use dataframe conversion and plotting.

(Also, I discovered later, I needed to convert negative values into absolute ones.)

```
Value/Nan check :
---------------
---------------
NaN conversion : done
---------------
---------------
Value/Zero check :
---------------
Zero number for each feature:
from_poi_to_this_person  :  12
from_this_person_to_poi  :  20
poi  :  128
---------------
Zero check : done
---------------
```

Concerning the zero value, it makes sense for these three features :

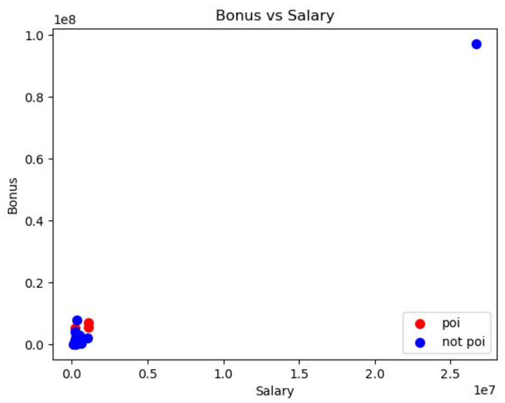
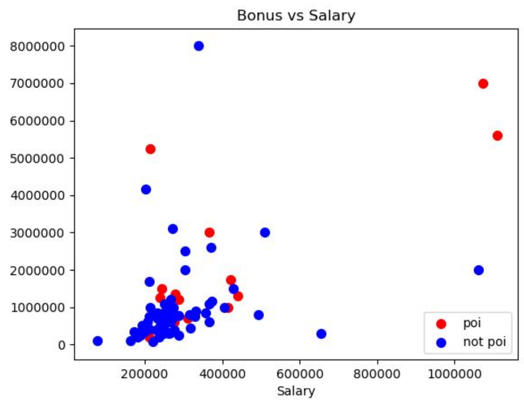
- from_poi_to_this_person : 12
- from_this_person_to_poi : 20
- poi : 128

Outliers management

Outlier Investigation (related lesson: "Outliers")
Student response identifies outlier(s) in the financial data, and explains how they are removed or otherwise handled.

As part of the training, we got a lesson about outliers management dedicated to Enron database.

As in the lesson outlier detection :

	
We clearly see an outlier when checking Bonus vs Salary relationship	SPOIL : after analysis and outlier removal, we see a more consistent pack of data

For sure it works, but it does not come from me, it was part of the lessons.
Also I tried several relationship between several data, to me it was too much about luck than a real analysis, so I tried another one.

I tried to apply the InterQuartileRange IQR analysis manually :

Beginning in python, it is always several hours step by step to compile data into one table. So, before going further into the kind of work, I took two features and check what I got with the IQR calculation.

```
---------------
IQR salary
---------------

salary  to_messages  deferral_payments  total_payments  exercised_stock_options
TOTAL              26704229.0         NaN        32083396.0     309886585.0
SKILLING JEFFREY K    1111258.0       3627.0              NaN       8682716.0
LAY KENNETH L         1072321.0       4273.0          202911.0     103559793.0
FREVERT MARK A        1060932.0       3275.0         6426990.0      17252530.0
PICKERING MARK R       655037.0        898.0              NaN       1386690.0
WHALLEY LAWRENCE G     510364.0       6019.0              NaN       4677574.0
DERRICK JR. JAMES V    492375.0       2181.0              NaN        550981.0
FASTOW ANDREW S        440698.0         NaN              NaN       2424083.0
SHERRIFF JOHN R        428780.0       3187.0              NaN       4335388.0
RICE KENNETH D         420636.0        905.0              NaN        505050.0

[10 rows x 21 columns]
(95, 21)

---------------


---------------
IQR to_messages
---------------

salary  to_messages  deferral_payments  total_payments  exercised_stock_options
SHAPIRO RICHARD S      269076.0      15149.0              NaN       1057548.0
KEAN STEVEN J          404338.0      12754.0              NaN       1747522.0
KITCHEN LOUISE         271442.0       8305.0              NaN       3471141.0
BELDEN TIMOTHY N       213999.0       7991.0         2144013.0       5501630.0
BECK SALLY W           231330.0       7315.0              NaN        969068.0
LAVORATO JOHN J        339288.0       7259.0              NaN      10425757.0
WHALLEY LAWRENCE G     510364.0       6019.0              NaN       4677574.0
KAMINSKI WINCENTY J    275101.0       4607.0              NaN       1086821.0
LAY KENNETH L         1072321.0       4273.0          202911.0     103559793.0
HAEDICKE MARK E        374125.0       4009.0         2157527.0       3859065.0

[10 rows x 21 columns]
(86, 21)
```

For sure, I can exploit them but I understood this method should be an automatic one used in huge dataset.

So I tried another method to detect the outliers.

Visual boxplot(IQR) method :
Looking for outliers management into google, I saw the visual IQR boxplot method !
This one seemed really interesting and full of sense to me.
During my first try, I noticed, I should check who is the max outlier.
So I put the ID of the person who’s outlying most.

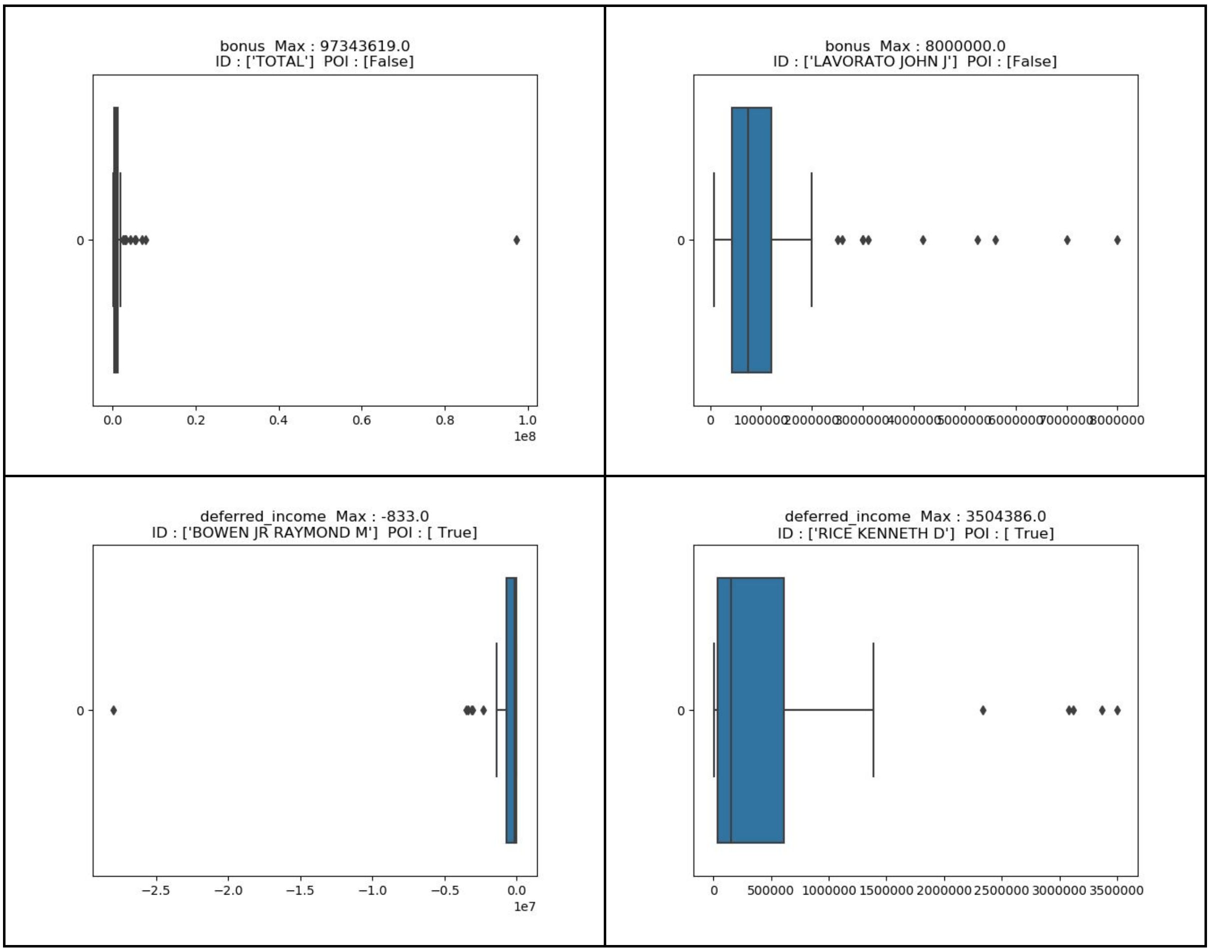
As I saw the boxplot, I decided to not analyse the lower outliers, to me it was not relevant.

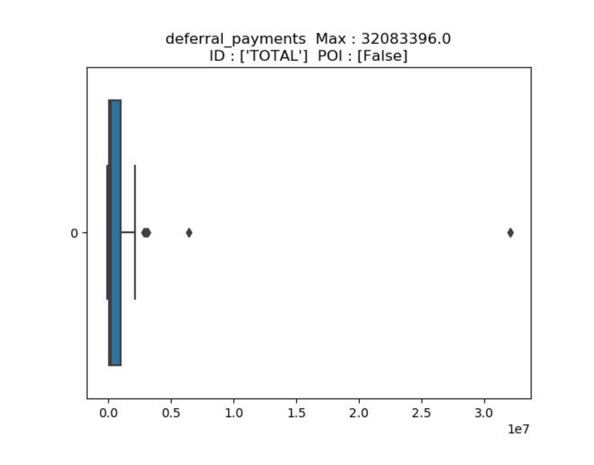
I decided to managed the outliers detecting who’s the most outlying, analysing it, dropping it if necessary and checking again.

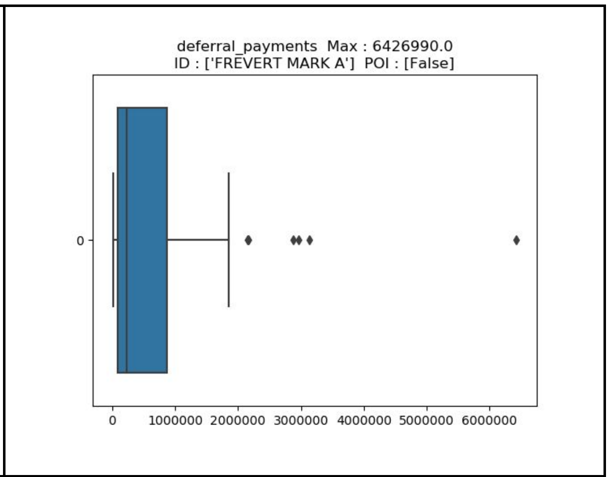
Analysing the outlier highlighted by the boxplot is depending of :

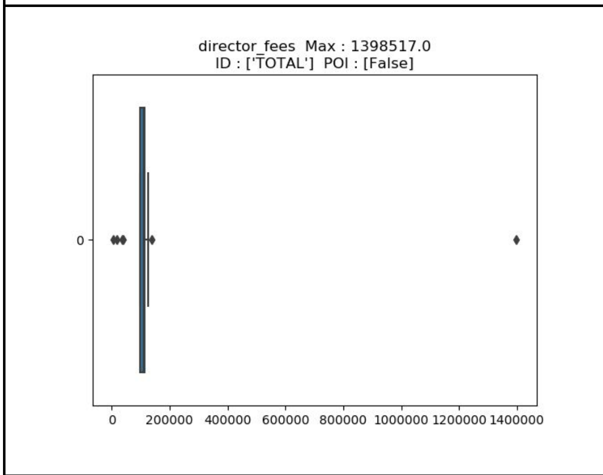
- What is inside the data source, PDF file
    - If it an error of the retrieving of the data
- If the person is a POI or not
    - A POI may be an outlier

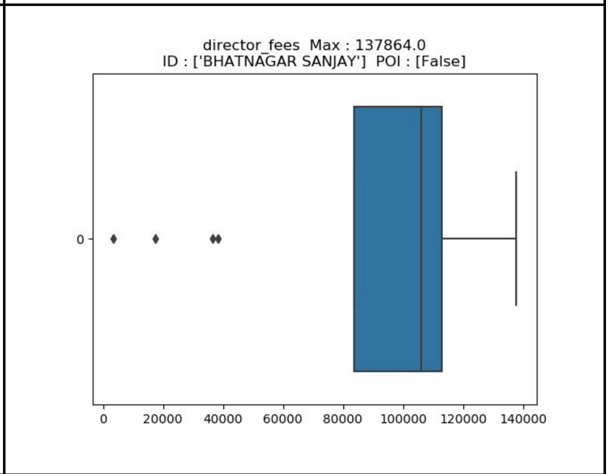
Here is the result before and after :

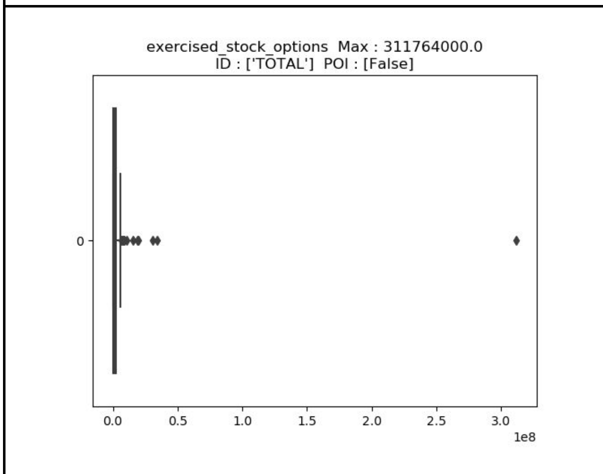


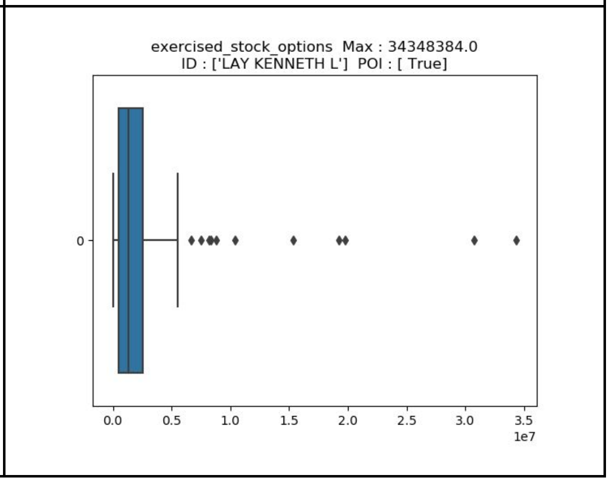

deferral_payments Max : 32083396.0
ID : ['TOTAL'] POI : [False]
0
0.0 0.5 1.0 1.5 2.0 2.5 3.0
1e7

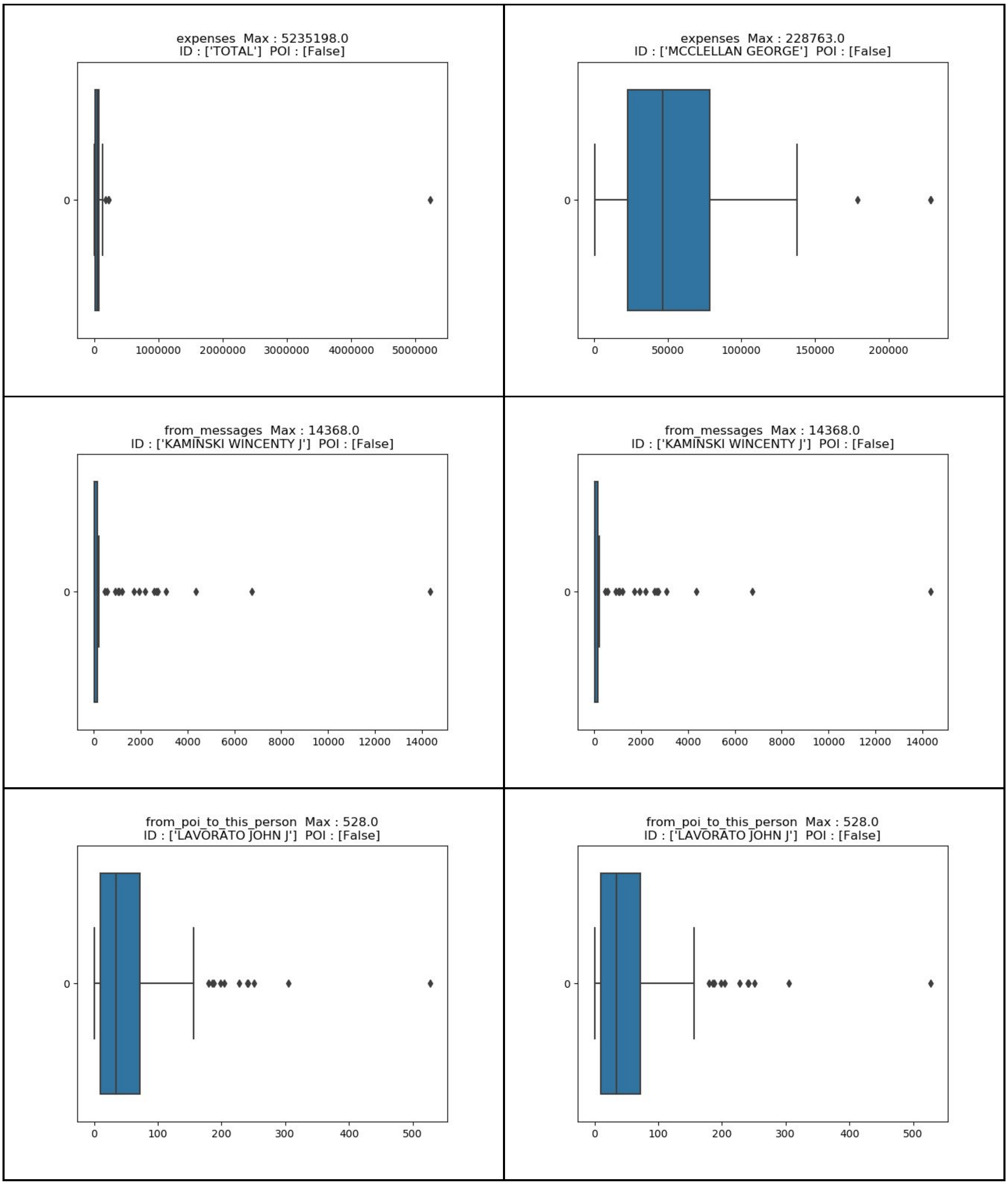

deferral_payments Max : 6426990.0
ID : ['FREVERT MARK A'] POI : [False]
0
0 1000000 2000000 3000000 4000000 5000000 6000000

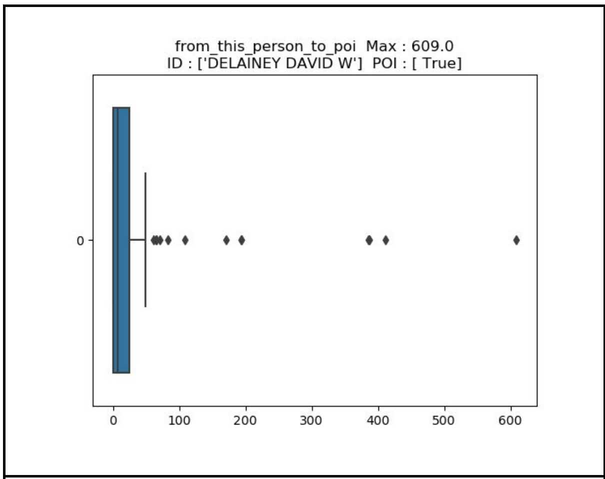

director_fees Max : 1398517.0
ID : ['TOTAL'] POI : [False]
0
0 200000 400000 600000 800000 1000000 1200000 1400000

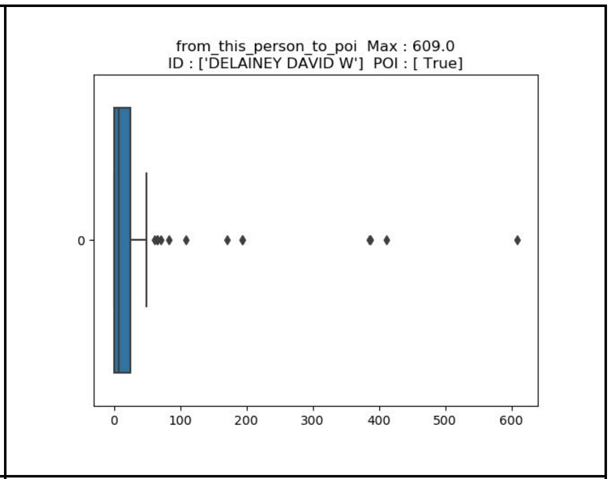

director_fees Max : 137864.0
ID : ['BHATNAGAR SANJAY'] POI : [False]
0
0 20000 40000 60000 80000 100000 120000 140000

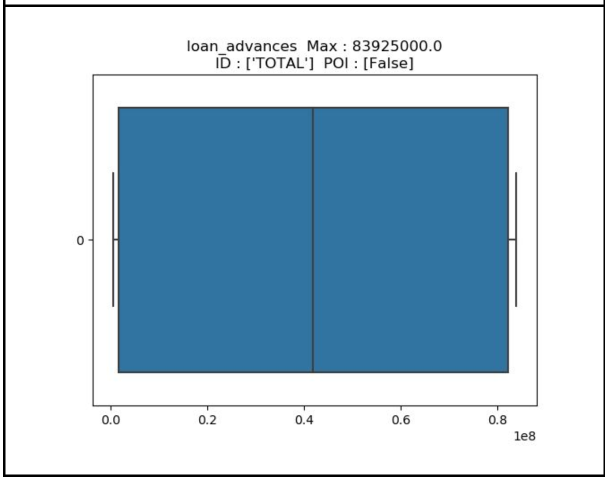

exercised_stock_options Max : 311764000.0
ID : ['TOTAL'] POI : [False]
0
0.0 0.5 1.0 1.5 2.0 2.5 3.0
1e8

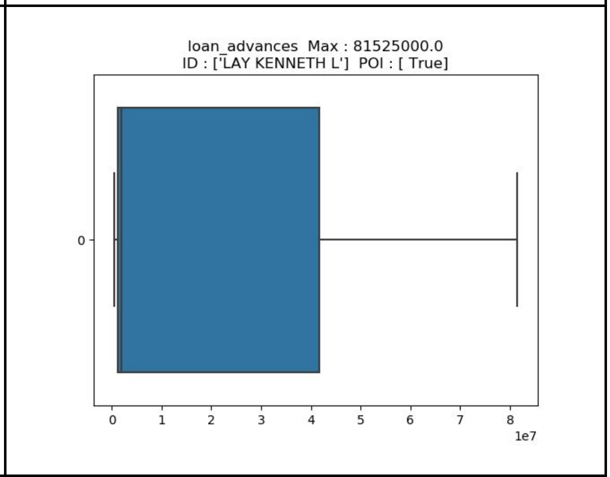

exercised_stock_options Max : 34348384.0
ID : ['LAY KENNETH L'] POI : [True]
0
0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5
1e7

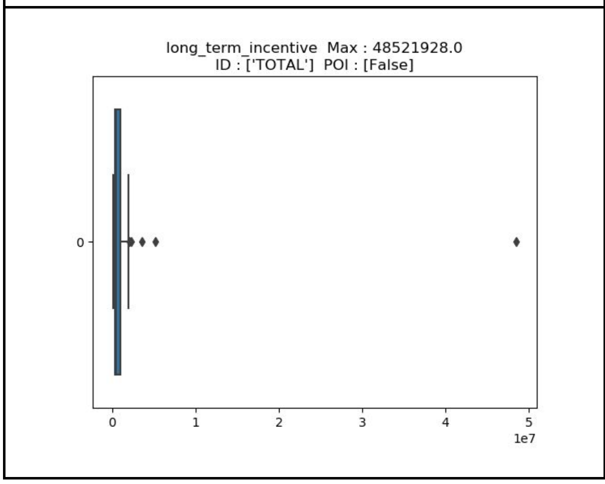

expenses Max : 5235198.0
ID : ['TOTAL'] POI : [False]
expenses Max : 228763.0
ID : ['MCCLELLAN GEORGE'] POI : [False]
from_messages Max : 14368.0
ID : ['KAMINSKI WINCENTY J'] POI : [False]
from_messages Max : 14368.0
ID : ['KAMINSKI WINCENTY J'] POI : [False]
from_poi_to_this_person Max : 528.0
ID : ['LAVORATO JOHN J'] POI : [False]
from_poi_to_this_person Max : 528.0
ID : ['LAVORATO JOHN J'] POI : [False]

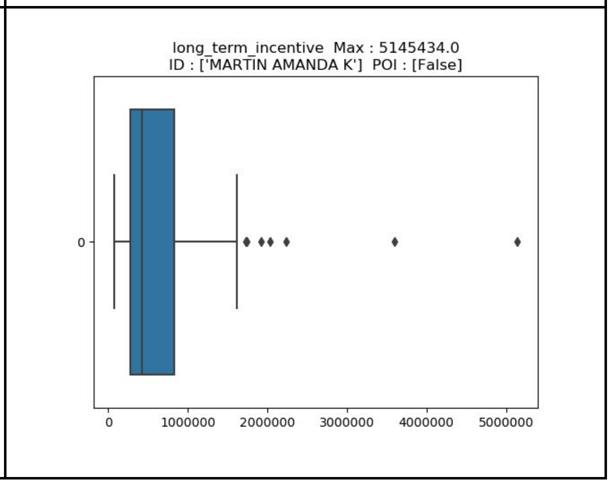

from_this_person_to_poi Max : 609.0
ID : ['DELAINEY DAVID W'] POI : [True]
0
0 100 200 300 400 500 600

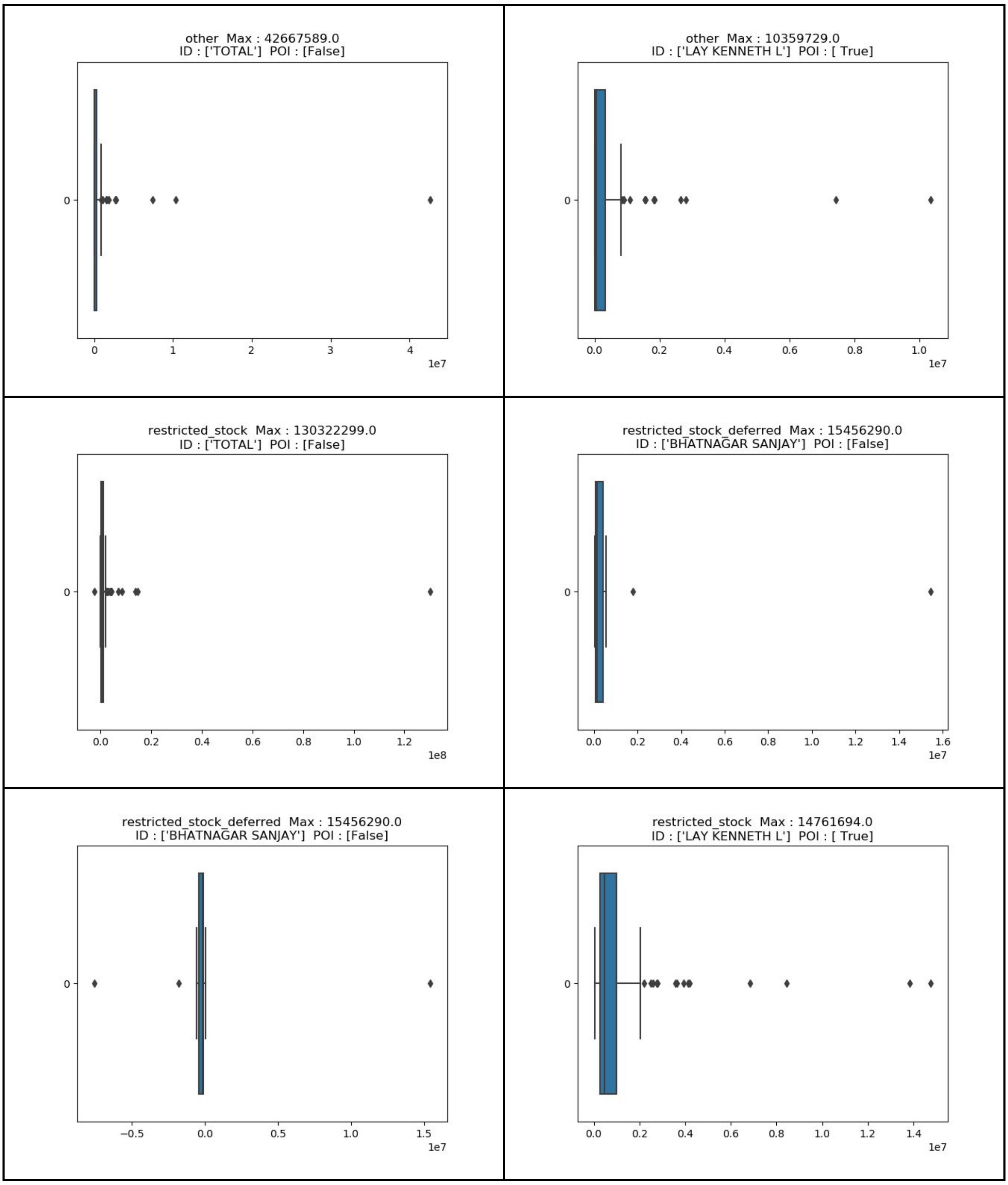

from_this_person_to_poi Max : 609.0
ID : ['DELAINEY DAVID W'] POI : [True]
0
0 100 200 300 400 500 600

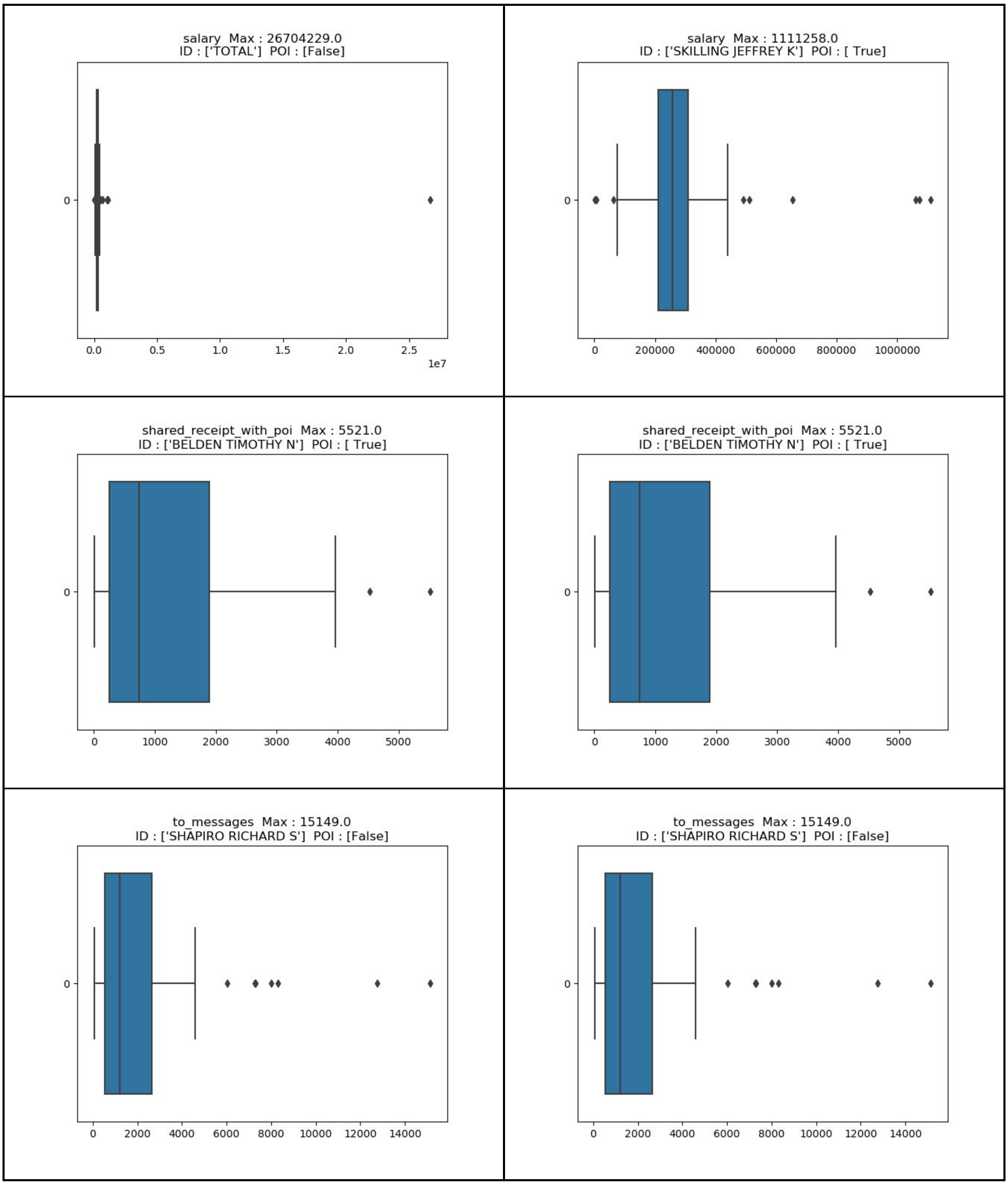

loan_advances Max : 83925000.0
ID : ['TOTAL'] POI : [False]
0
0.0 0.2 0.4 0.6 0.8
1e8

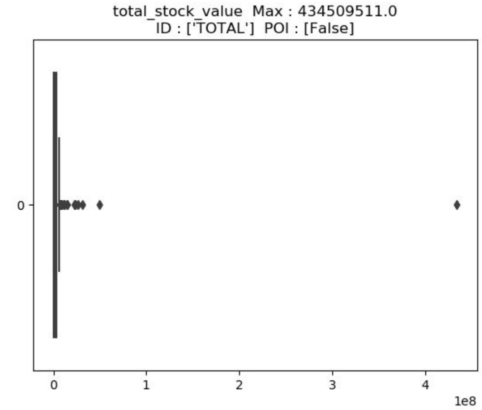

loan_advances Max : 81525000.0
ID : ['LAY KENNETH L'] POI : [True]
0
0 1 2 3 4 5 6 7 8
1e7

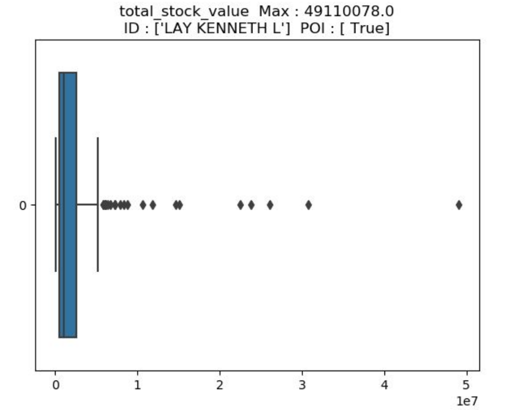

long_term_incentive Max : 48521928.0
ID : ['TOTAL'] POI : [False]
0
0 1 2 3 4 5
1e7

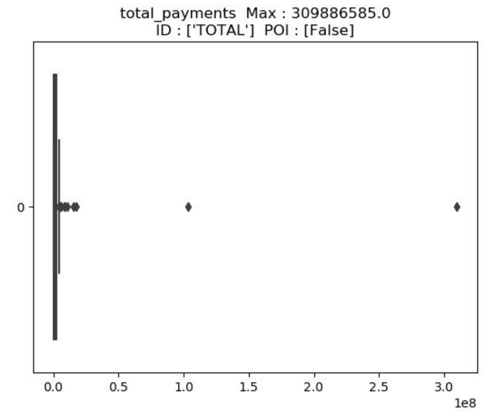

long_term_incentive Max : 5145434.0
ID : ['MARTIN AMANDA K'] POI : [False]
0
0 1000000 2000000 3000000 4000000 5000000

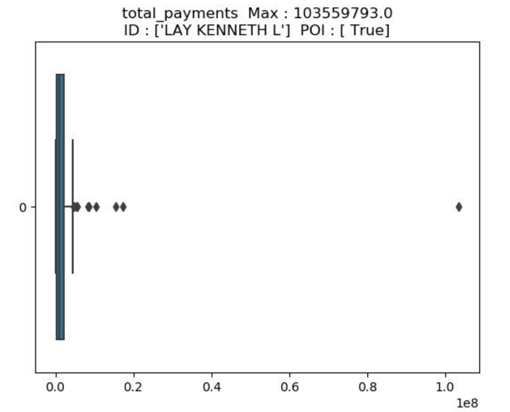

other Max : 42667589.0
ID : ['TOTAL'] POI : [False]
0
0 1 2 3 4
1e7
other Max : 10359729.0
ID : ['LAY KENNETH L'] POI : [True]
0
0.0 0.2 0.4 0.6 0.8 1.0
1e7
restricted_stock Max : 130322299.0
ID : ['TOTAL'] POI : [False]
0
0.0 0.2 0.4 0.6 0.8 1.0 1.2
1e8
restricted_stock_deferred Max : 15456290.0
ID : ['BHATNAGAR SANJAY'] POI : [False]
0
0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6
1e7
restricted_stock_deferred Max : 15456290.0
ID : ['BHATNAGAR SANJAY'] POI : [False]
0
−0.5 0.0 0.5 1.0 1.5
1e7
restricted_stock Max : 14761694.0
ID : ['LAY KENNETH L'] POI : [True]
0
0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4
1e7


salary Max : 26704229.0
ID : ['TOTAL'] POI : [False]
0
0.0 0.5 1.0 1.5 2.0 2.5
1e7
salary Max : 1111258.0
ID : ['SKILLING JEFFREY K'] POI : [True]
0
0 200000 400000 600000 800000 1000000
shared_receipt_with_poi Max : 5521.0
ID : ['BELDEN TIMOTHY N'] POI : [True]
0
0 1000 2000 3000 4000 5000
shared_receipt_with_poi Max : 5521.0
ID : ['BELDEN TIMOTHY N'] POI : [True]
0
0 1000 2000 3000 4000 5000
to_messages Max : 15149.0
ID : ['SHAPIRO RICHARD S'] POI : [False]
0
0 2000 4000 6000 8000 10000 12000 14000
to_messages Max : 15149.0
ID : ['SHAPIRO RICHARD S'] POI : [False]
0
0 2000 4000 6000 8000 10000 12000 14000









In the end of this outliers analysis, I dropped :
‘TOTAL’ which is the total of the columns of the different features.
And I also saw during the check of the boxplot 'THE TRAVEL AGENCY IN THE PARK' which is not a person although linked to a person.

I was thinking, the more relevant data we have, the best performance in term of quality we’ll have to classify them. If I understood well, we check for error visualizing disparity of the data.

Features management

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", "intelligently select features", "properly scale features"]

The first thing concerning the features was to identify which data may be in relation with the fraud.
So, it is not about computer science but really about real life.
The scope of the data we have is financial and some relation between people with their mail.
As the goal of a fraud is about money, I suppose money data is pretty important.
In a company, the most used communication channel is the email.

So, I added 5 features calculated by already known features :

In the order of relevance in my mind :

['ratio_to_poi'] = Percentage of mail sent to POI
['ratio_from_poi'] = Percentage of mail received from POI

['total_mail'] = total mail of a person
['total_mail_poi'] = Number of mail related to POI (sent and received)
['total_ratio_mail_poi'] = percentage of mail related to POI (sent and received)

I did not feel any need of scaling at this step.

Then, I decided to use scikit-learn Univariate feature selection "**selectKBest**".

My goal was to confront my vision to the computer vision, I found a code on google, displaying the result in a table :

Warning : Spoil : these results are bad !

feature	score
total_mail	25.097542
bonus	24.464726
director_fees	21.060002
restricted_stock	18.575703
from_poi_to_this_person	16.641707
expenses	11.595548
deferred_income	10.072455
from_this_person_to_poi	8.961784
salary	8.866722
restricted_stock_deferred	8.746486
shared_receipt_with_poi	7.242730
deferral_payments	6.234201
ratio_from_poi	5.518506
total_stock_value	5.344942
exercised_stock_options	4.955198
from_messages	4.204971
total_mail_poi	3.210762
ratio_to_poi	2.426508
other	2.107656
poi	1.698824
total_payments	0.515192
long_term_incentive	0.245090
to_messages	0.225355
loan_advances	0.164164

After these first results, I tried the the classifiers as is to check how they perform :

KNeighborsClassifier(algorithm='auto', leaf_size=30,
metric='minkowski',metric_params=None, n_jobs=1, n_neighbors=5, p=2,weights='uniform')
Precision: 0.04852
Recall: 0.01150

GaussianNB(priors=None)
Precision: 0.17341
Recall: 0.95100

The results were so bad, we wanted a precision and recall of 0.3 minimum.

I tried to select the features manually : selecting only a few and it worked, so I checked my selectKbest code and saw I should have removed POI from the display list, the label shifted…

With a better code, I used selectKbest again and got these good results :
in bold, the features I kept.

features	**score**
exercised_stock_options	**24.815080**
total_stock_value	**24.179972**
bonus	**20.792252**
salary	**18.289684**
ratio_to_poi	**16.409713**
deferred_income	**11.458477**
long_term_incentive	**9.922186**
restricted_stock	**8.828679**
total_payments	**8.772778**
shared_receipt_with_poi	**8.589421**
loan_advances	**7.184056**
expenses	**6.094173**
total_ratio_mail_poi	**5.399370**
from_poi_to_this_person	**5.243450**
total_mail_poi	*4.863682*
other	*4.187478*
ratio_from_poi	*3.128092*
from_this_person_to_poi	*2.382612*
director_fees	*2.126328*
to_messages	*1.646341*
total_mail	*0.490666*
restricted_stock_deferred	*0.247053*
deferral_payments	*0.233091*
from_messages	*0.169701*

Time to check how well these new parameters performed :

GaussianNB(priors=None)
Precision: 0.32480
Recall: 0.31100

KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski', metric_params=None, n_jobs=1, n_neighbors=5, p=2, weights='uniform')
Precision: 0.63878
Recall: 0.16800

I already reach the wanted results with Naive Bayes algorithm with my features selection :

My features list will be :

```
['poi',
 'exercised_stock_options',
 'total_stock_value',
 'bonus',
 'salary',
 'ratio_to_poi',
 'deferred_income',
 'long_term_incentive',
 'restricted_stock',
 'total_payments',
 'shared_receipt_with_poi',
 'loan_advances',
 'expenses',
 'total_ratio_mail_poi',
 'from_poi_to_this_person']
```

end of features list

Algorithm benchmarking

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”]

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? What parameters did you tune? (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 items: “discuss parameter tuning”, “tune the algorithm”]

At first I used these 2 algorithms as they are the ones I understood really well during the lessons, also, Naive Bayes doesn’t require any hyper-parameters.

- GaussianNB
- KNeighborsClassifier

The first thing I can say is : **the feature selection is part of the parameters.**

Although I got the desired score, I decided to check more algorithms and also I’ll train myself to use scikit learn.

My second step was to launch with default hyper-parameters the following algorithms using the test_classifier() function provided :

GaussianNB(priors=None)
Accuracy: 0.82193 **Precision: 0.32480** **Recall: 0.31100** F1: 0.31775 F2: 0.31367
Total predictions: 15000 True positives: 622 False positives: 1293 False negatives: 1378 True negatives: 11707

KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski', metric_params=None, n_jobs=1, n_neighbors=5, p=2, weights='uniform')
Accuracy: 0.87640 **Precision: 0.63878** Recall: 0.16800 F1: 0.26603 F2: 0.19704
Total predictions: 15000 True positives: 336 False positives: 190 False negatives: 1664 True negatives: 12810

LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True, intercept_scaling=1, loss='squared_hinge', max_iter=1000, multi_class='ovr', penalty='l2', random_state=None, tol=0.0001, verbose=0)
Accuracy: 0.68300 Precision: 0.13335 Recall: 0.25050 F1: 0.17405 F2: 0.21306
Total predictions: 15000 True positives: 501 False positives: 3256 False negatives: 1499 True negatives: 9744

LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True, intercept_scaling=1, loss='hinge', max_iter=1000, multi_class='ovr', penalty='l2', random_state=None, tol=0.0001, verbose=0)

```
Accuracy: 0.69147       Precision: 0.13090      Recall: 0.23300 F1: 0.16763     F2: 0.20156
Total predictions: 15000        True positives:  466    False positives: 3094   False negatives:
1534   True negatives: 9906

LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True,intercept_scaling=1,
loss='squared_hinge', max_iter=1000, multi_class='ovr', penalty='l2', random_state=None,
tol=0.0001, verbose=0)
Accuracy: 0.69073       Precision: 0.13070      Recall: 0.23350 F1: 0.16759     F2: 0.20176
Total predictions: 15000        True positives:  467    False positives: 3106   False negatives:
1533   True negatives: 9894

DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
max_features=None, max_leaf_nodes=None, min_impurity_decrease=0.0,
min_impurity_split=None, min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, presort=False, random_state=None, splitter='best')
Accuracy: 0.81380       Precision: 0.29509      Recall: 0.28550 F1: 0.29022     F2: 0.28737
Total predictions: 15000        True positives:  571    False positives: 1364   False negatives:
1429   True negatives: 11636

AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None, learning_rate=1.0,
n_estimators=50, random_state=None)
Accuracy: 0.83247       Precision: 0.34293      Recall: 0.28000 F1: 0.30829     F2: 0.29067
Total predictions: 15000        True positives:  560    False positives: 1073   False negatives:
1440   True negatives: 11927
```

As previously, Naive Bayes performed well.

I decided to go more in depth and tried to use **GridSearchCV** on **DecisionTreeClassifier**

I use a parameters table mixing :

- 'max_features'
- 'splitter'
- 'criterion''

It ended the best parameters were :

- max_features= 'sqrt'
- splitter= 'best'
- criterion= 'gini'

```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=None,
            max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
	Accuracy: 0.83553	Precision: 0.37107	Recall: 0.33600	F1: 0.35266	F2: 0.34247
	Total predictions: 15000	True positives:  672	False positives: 1139	False negatives: 1328	True negatives: 11861	0.561000108719  secs
```

These results are slightly better than Naive Bayes. I am sure if I spend more time and testing with different features, we can reach a better score.

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 items: "discuss validation", "validation strategy"]

Validation is the method you use to determine if the algorithm is well performing or not.
The classic mistake is to use the same data to train the algorithm and to test it.
In this case, we talk about overfitting.

In sci-kit learn, there are several validation tools.

As the provided code kindly includes the test_classifier() function using stratified shuffle split cross validation method, I did not use another one and stick with it.

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"]

As the performance requested were :

- Precision >=0.3
- Recall >=0.3

I'll talk about these two.

About my performance :

	Precision	**recall**
GaussianNB	0,3248	**0,311**
KNeighborsClassifier	**0,63878**	0,168
LinearSVC(squared_hinge)	0,13335	0,2505
LinearSVC(hinge)	0,1309	0,233
LinearSVC	0,1307	0,2335
DecisionTreeClassifier	0,29509	0,2855
AdaBoostClassifier	0,34293	0,28
average	0,29	0,25
maximum	0,64	0,31

About their meaning :

Precision is the algorithm performance to classify correctly.
In our case, the precision is the real POI detected divided by the right or wrong POI detected by the algorithm.
How many POI detected are true POI.

Recall is the algorithm capacity to detect correct data.
In our case, the recall is the number of real POI detected divided by the real number of POI.

Conclusion

Here is the algorithm I choose : simple and working

GaussianNB(priors=None)
Accuracy: 0.82193 **Precision: 0.32480** **Recall: 0.31100** F1: 0.31775 F2: 0.31367
Total predictions: 15000 True positives: 622 False positives: 1293 False negatives: 1378 True negatives: 11707