1. INTRODUCTION

This document describes the different steps and thought when performing the P5 project.

For the second submission, added text is in Italic. Removed text has been strike though.

You can customize the way the poi_id.py script behave by settings some Boolean variables.

- showunivariate: will display histogram chart for all features if set to True
- showheatmap: will display the correlation heatmap if set to True
- *showboxplot: will display the correlation bloxplot if set to True*
- showcorrelation: will display correlation scatter plot between features if set to True
- performalltunings: will perform the algorithm tuning is set to True

By default, all these parameters are set to True.

2. DESCRIPTIVE STATISTICS, OUTLIERS MGT, FEATURES SELECTION

We use all features and retrieve associated descriptive statistics

	salary
count	95.000000
mean	562194.294737
std	2716369.154553
min	477.000000
25%	211816.000000
50%	259996.000000
75%	312117.000000
max	26704229.000000

If I look to the maximum value of salary, I see it corresponds to the total value of salaries from the enron61702insiderpay.pdf. I will delete the TOTAL values and re-compute descriptive statistics.

	salary	bonus	long_term_incentive	deferred_income	\
count	94.000000	81.000000	65.000000	48.000000	
mean	284087.542553	1201773.074074	746491.200000	-581049.812500	
std	177131.115377	1441679.438330	862917.421568	942076.402972	
min	477.000000	70000.000000	69223.000000	-3504386.000000	
25%	211802.000000	425000.000000	275000.000000	-611209.250000	
50%	258741.000000	750000.000000	422158.000000	-151927.000000	
75%	308606.500000	1200000.000000	831809.000000	-37926.000000	
max	1111258.000000	8000000.000000	5145434.000000	-833.000000	

	deferral_payments	loan_advances	other	expenses	\
count	38.000000	3.000000	92.000000	94.000000	
mean	841602.526316	27975000.000000	465276.663043	54192.010638	
std	1289322.626180	46382560.030684	1389719.064851	46108.377454	
min	-102500.000000	400000.000000	2.000000	148.000000	
25%	79644.500000	1200000.000000	1209.000000	22479.000000	
50%	221063.500000	2000000.000000	51984.500000	46547.500000	
75%	867211.250000	41762500.000000	357577.250000	78408.500000	
max	6426990.000000	81525000.000000	10359729.000000	228763.000000	

```
       director_fees  total_payments  exercised_stock_options  \
count      16.000000    1.240000e+02               101.000000
mean    89822.875000    2.623421e+06           2959559.257426
std     41112.700735    9.488106e+06           5499449.598994
min      3285.000000    1.480000e+02              3285.000000
25%     83674.500000    3.863802e+05            506765.000000
50%    106164.500000    1.100246e+06           1297049.000000
75%    112815.000000    2.084663e+06           2542813.000000
max    137864.000000    1.035598e+08          34348384.000000

       restricted_stock  restricted_stock_deferred  total_stock_value  \
count        109.000000                  17.000000         125.000000
mean     1147424.091743             621892.823529     3352073.024000
std      2249770.356903            3845528.349509     6532883.097201
min     -2604490.000000           -1787380.000000      -44093.000000
25%       252055.000000            -329825.000000      494136.000000
50%       441096.000000            -140264.000000     1095040.000000
75%       985032.000000             -72419.000000     2606763.000000
max     14761694.000000           15456290.000000    49110078.000000

        to_messages  from_poi_to_this_person  from_messages  \
count     86.000000                86.000000      86.000000
mean    2073.860465                64.895349     608.790698
std     2582.700981                86.979244    1841.033949
min       57.000000                 0.000000      12.000000
25%      541.250000                10.000000      22.750000
50%     1211.000000                35.000000      41.000000
75%     2634.750000                72.250000     145.500000
max    15149.000000               528.000000   14368.000000

       from_this_person_to_poi  shared_receipt_with_poi         poi
count                86.000000                86.000000  145.000000
mean                 41.232558              1176.465116    0.124138
std                 100.073111              1178.317641    0.330882
min                   0.000000                 2.000000    0.000000
25%                   1.000000               249.750000    0.000000
50%                   8.000000               740.500000    0.000000
75%                  24.750000              1888.250000    0.000000
max                 609.000000              5521.000000    1.000000
```

I can see that:

- There are 145 peoples in the dataset (there are 18 POIs within this set of 145 peoples).
- Only the POI feature has been fully set (all other feature have missing values)
- Emails data is filled for only 86 peoples.
- The deferral_payments, restricted_stock, restricted_stock_deferred , total_stock_value have positive values and negative values in it.
- There are a very small number of information for features loan_advances, director_fees and restricted_stock_deferred.

As a consequence, I decide to:

- Remove features loan_advances, director_fees and restricted_stock_deferred from the dataset and analysis.
- Delete negative values for features: deferral_payments, restricted_stock, total_stock_value

I decide then to have a look on data distribution using a histogram chart.

I see that a lot of feature distributions are skewed: bonus, long_term_incentive, deferred_income, deferral_payments, other, expenses, total_payments, exercised_stock_options, restricted_stock, total_stock_value, to_messages, from_poi_to_this_person, from_messages, from_this_person_to_poi, shared_receipt_with_poi. In the machine learning algorithm, I will check if applying a log transformation on these feature values helps.

I can also find some outliers values, but I decide to keep these values as they are real values.

I now want to have a look on possible correlated data in my dataset.

We can find some strong correlations, for instance between deferral_payments and deferred_income, total_stock_value and restricted_stock, to_message and from_this_person_to_poi, to_message and shared_receipt_with_poi.

On the other hand, I notice there is not strong between poi and all other variables.

When looking to the variables scatter plots, I decided not to perform any data transformation based on these correlations. I prefer to rely on the principal component algorithm with prior Min/Max scaling.

When looking to the correlation matrix, we identify 3 groups of data:

- Salary related information
- Stock related information
- Email related information.

When doing the machine learning algorithm tweak, I will evaluate performance using:

- All selected features
- Only the total_payments, total_stock_value and all emails features.

Missing values will be replaced with 0. I think that other standard strategies (Mean, Median, Most frequent) proposed in sklearn are not relevant in our case.

3. ADDITIONAL FEATURES CREATION

We can reasonably think that email exchange between POIs may be greater than between POIs and non POIs.

Instead of working with absolute values, I decide to create two additional ratios:

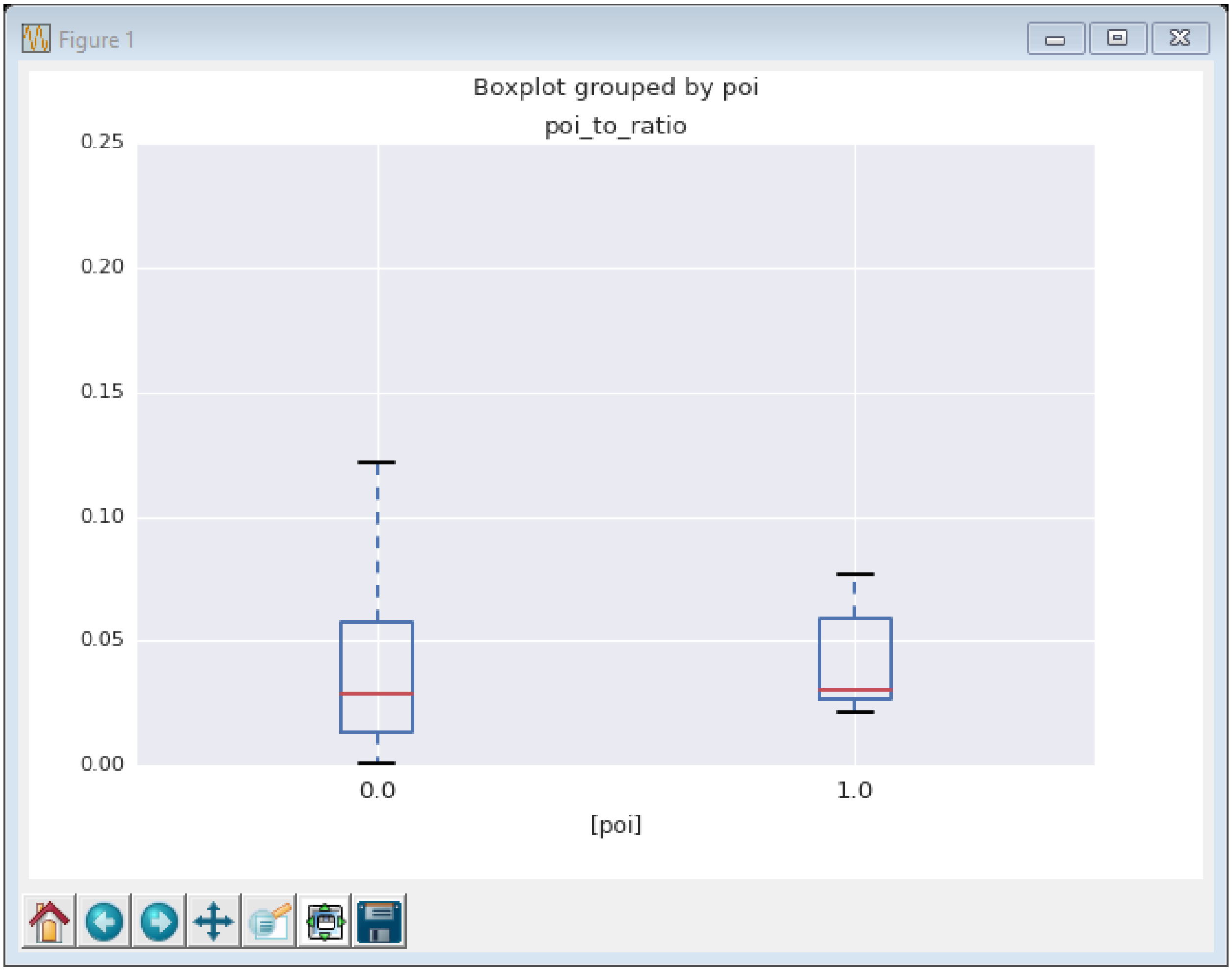
- poi_to_ratio = from_poi_to_this_person / to_messages
- poi_from_ratio = from_this_person_to_poi / from_messages

~~If we look to correlation, I cannot see a real correlation between POIs and these 2 new ratios.~~

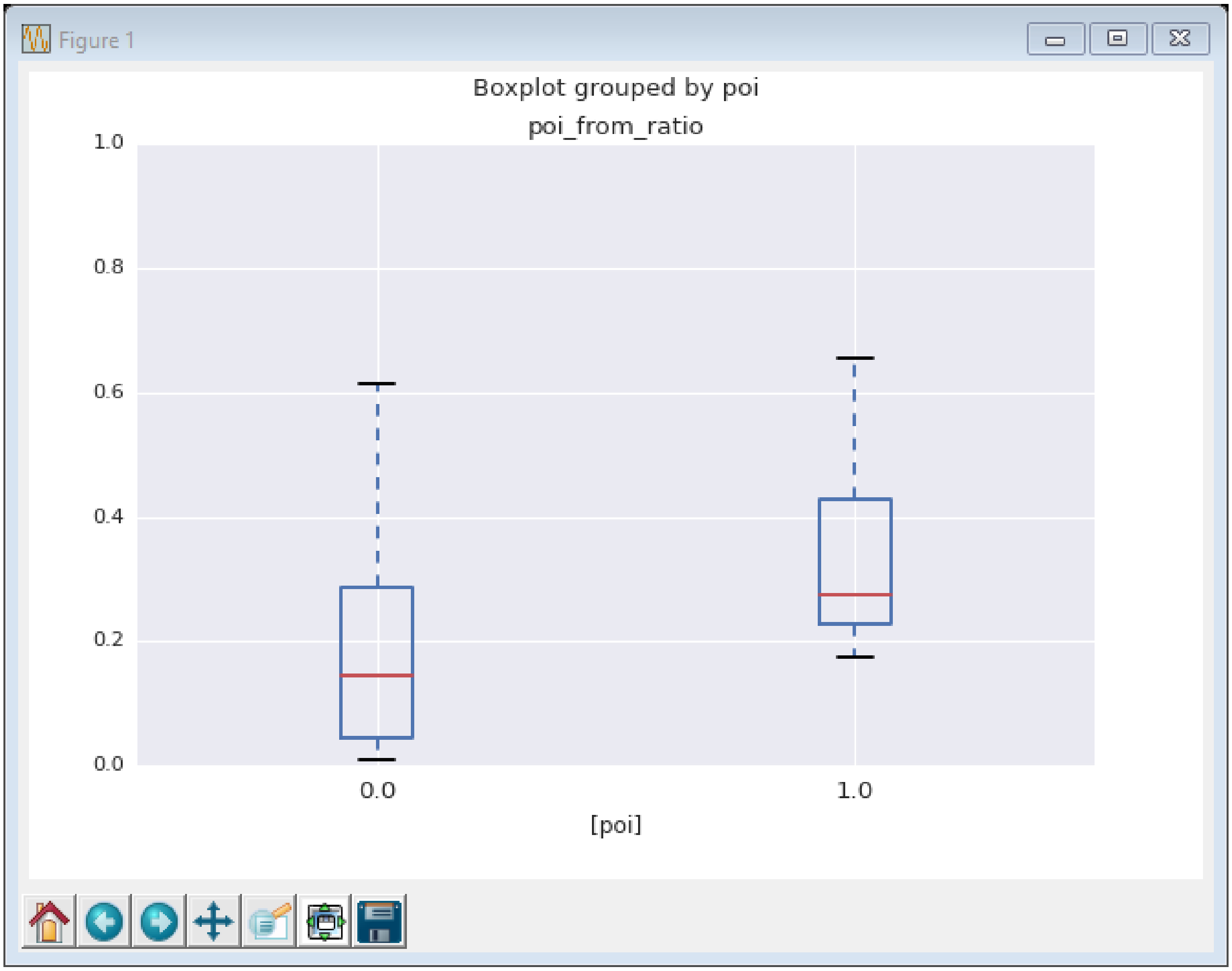
	~~poi_to_ratio~~	~~poi_from_ratio~~	~~poi~~
~~poi_to_ratio~~	~~1.000000~~	~~0.245350~~	~~0.059688~~

~~poi_from_ratio 0.245350 1.000000 0.312483~~
~~poi 0.059688 0.312483 1.000000~~

The two-following chart shows the distribution of the two created ratio per poi value.



I can see that the values range for poi and non-poi are not exclusive. This ratio shall not provide additional information to solve our problem.



Even if for POI, the poi_from_ratio is a little bit greater, this new figures does not provide much additional information.

The final algorithm selection test will be performed on the standard dataset but also on the standard dataset with these two-additional ratios. Analysis of the machine learning with and without these ratios will be described.

Please, see my question about your comment at the end of this document.

4. MACHINE LEARNING ALGORITHM SELECTION AND TUNING

<u>What is parameter tuning and importance of this activity:</u>
Each machine learning algorithm have 0 or several parameters. When a machine learning algorithm has on or several parameters, the combination of these parameters values have a significant impact on the capacity of the algorithm to answer our problem. This is the reason why we need to find the best set of parameters values. This is activity is known as parameter

tuning. Without this activity, we have a high probability to have a very poor machine learning algorithm.

I will perform a benchmarking analysis using:
- 3 differents supervised classification machine learning algorithm (Naïve Bayes, Support Vector Machine, Decision Tree).
- Each algorithm will be preceded by a scaling activity (Min/Max) and a principal component anlaysis.
- 3 differents datasets: all features except new ratios, all features including ratios, restricted features excluding ratio. Each time, we will evaluate the algorithm with unchanged information and log changed information.
- 2 differents validation strategies: use of a basic sample of the data set, use of a KFold sets of the data set.
- For SVM algorithm and decision tree algorithms, a random selection based tuning will be used to limit computer CPU usage.

For the PCA algorithm, the number of final component is part of the tuning activity.
For the SVM algorithm, the kernel, C and gamma parameters are part of the tuning activity. The possible values will be:
- C=[1,10,100,1000],
- gamma=[0.01,0.001, 0.0001],
- kernel=['rbf','linear','poly']

For the decision tree algorithm, the criterion and max features parameters are part of the tuning activity. The possible values will be:
- criterion=['gini','entropy'],
- max_features=['sqrt','log2',None])

Algorithm validation and importance of this phase:
The validation phase consists of using a test dataset in order to evaluate the different performances of our machine learning algorithm. In order to avoid any bias, the test dataset has to be different from the learning dataset. This validation phase is important in order to know the performances of our machine learning algorithm, and to detect any possible misbehavior due to overfitting for instance.

For each of this test, we will use the f1 scoring function as value to be optimized. This metrics offer a good balance between precision and recall. We will have a look to precision and recall metrics for the selected algorithm.

We use two f1 computation. The one based on estimator.best_score_ value (directly provided by sklearn), and a second computed using a modified version of the test_classifier function from the tester.py.

The results are provided in the following table:

Data set	Log values	Val strategy	Algo	F1	F1

				(computed)	(best_score_)
Full	Yes	Basic	Naïve Bayes	0.31	0.39
Full	Yes	Basic	SVM	0.03	0.61
Full	Yes	Basic	Decision tree	0.27	0.61
Full	Yes	KFold	Naïve Bayes	0.43	0.47
Full	Yes	KFold	SVM	0.19	0.42
Full	Yes	KFold	Decision tree	0.28	0.38
Full	No	Basic	Naïve Bayes	0.19	0.46
Full	No	Basic	SVM	0.20	0.60
Full	No	Basic	Decision tree	0.28	0.52
Full	No	KFold	Naïve Bayes	0.43	0.47
Full	No	KFold	SVM	0.20	0.42
Full	No	KFold	Decision tree	0.29	0.32
Full with ratio	Yes	Basic	Naïve Bayes	0.27	0.39
Full with ratio	Yes	Basic	SVM	0.02	0.62
Full with ratio	Yes	Basic	Decision tree	0.28	0.46
Full with ratio	Yes	KFold	Naïve Bayes	0.27	0.4
Full with ratio	Yes	KFold	SVM	0.02	0.47
Full with ratio	Yes	KFold	Decision tree	0.28	0.48
Full with ratio	No	Basic	Naïve Bayes	0.27	0.39
Full with ratio	No	Basic	SVM	0.02	0.62
Full with ratio	No	Basic	Decision tree	0.28	0.42
Full with ratio	No	KFold	Naïve Bayes	0.27	0.4
Full with ratio	No	KFold	SVM	0.02	0.47
Full with ratio	No	KFold	Decision tree	0.28	0.5
Limited	Yes	Basic	Naïve Bayes	0.37	0.35
Limited	Yes	Basic	SVM	0	0
Limited	Yes	Basic	Decision tree	0.22	0.28
Limited	Yes	KFold	Naïve Bayes	0.35	0.32
Limited	Yes	KFold	SVM	0	0
Limited	Yes	KFold	Decision tree	0.22	0.26
Limited	No	Basic	Naïve Bayes	0.38	0.35
Limited	No	Basic	SVM	0	0
Limited	No	Basic	Decision tree	0.22	0.28
Limited	No	KFold	Naïve Bayes	0.35	0.32
Limited	No	KFold	SVM	0	0
Limited	No	KFold	Decision tree	0.21	0.22

Interpretation

Validation strategy

We see that when tuned, the SVM algorithm including all features (+ additional ratios) is the better performance using a basic validation strategy.

Data set	Log	Val	Algo	F1	F1

	values	strategy		(computed)	(best_score_)
Full with ratio	Yes	Basic	SVM	0.02	0.62
Full with ratio	No	Basic	SVM	0.02	0.62

But we see that when applying the Udacity validation strategy, this algorithm behave badly.

This is clearly important to perform validation in the way the algorithm will be used in operation condition.

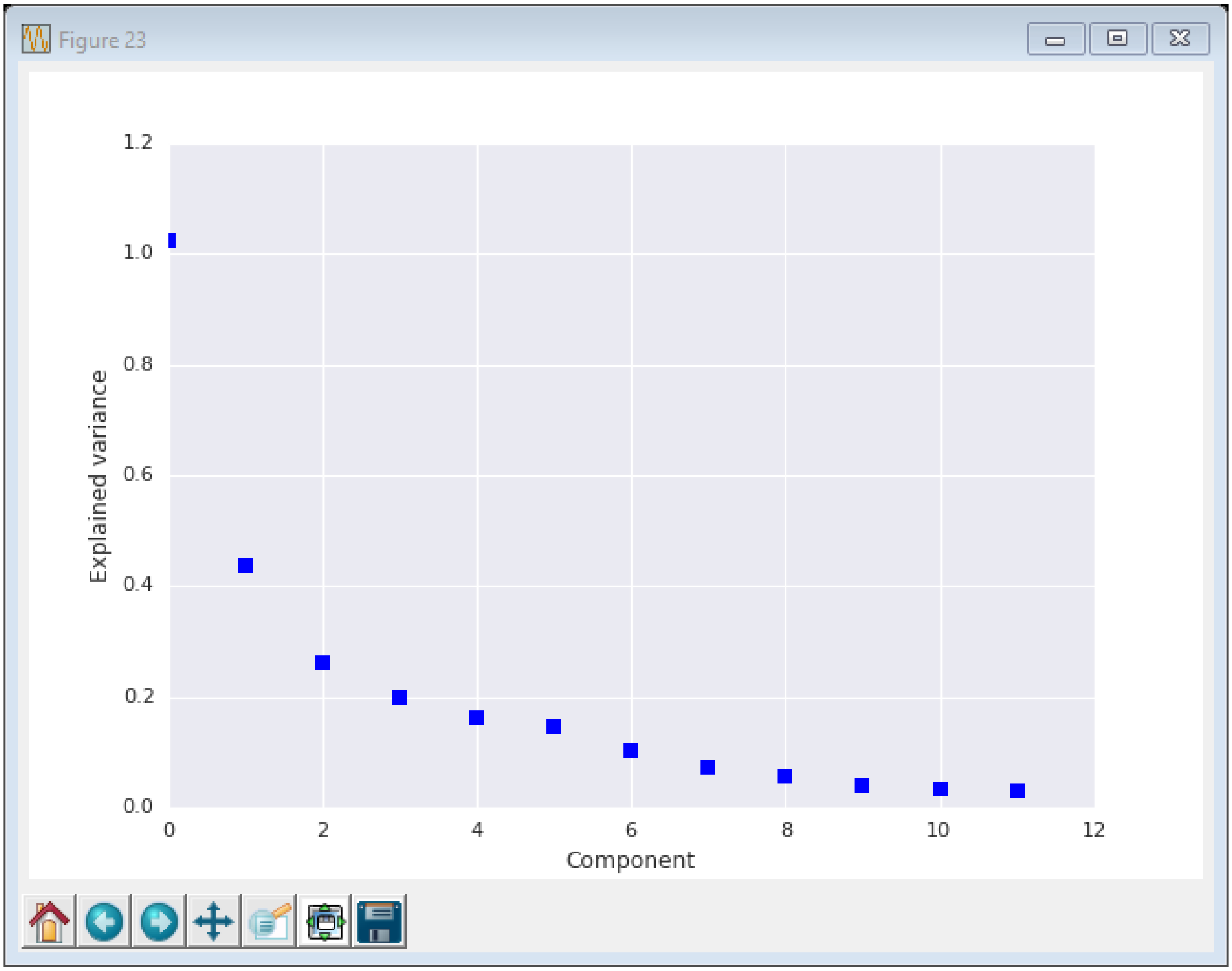
At the end, the best algorithm is not the one providing the best tuned result.

Data set	Log values	Val strategy	Algo	F1 (computed)	F1 (best_score_)
Full	Yes	KFold	Naïve Bayes	0.43	0.47
Full	No	KFold	Naïve Bayes	0.43	0.47

The final selected algorithm is a pipeline of:

- Min Max scaler
- PCA with 12 components
- Naïve Bayes classifier

The following chart shows the explained variance for the 12 components:



Output from the tester.py script are:

```
Accuracy: 0.83440      Precision: 0.39702     Recall: 0.46650        F1: 0.42897     F2: 0.45072
Total predictions: 15000
True positives:  933   False positives: 1417  False negatives: 1067  True negatives: 11583
```

POIs were identified in 47% of the cases, and when identified, we were right in 40% of cases.

http://www.h5.com/document-review-accuracy-the-recall-precision-tradeoff/

Globally, I consider this algorithm a bit weak.

When we run a simple test strategy, we can find results looking like the following one:

```
             precision    recall  f1-score   support

        0.0       0.89      1.00      0.94        39
        1.0       0.00      0.00      0.00         5

avg / total       0.79      0.89      0.83        44
```

The algorithm behave pretty good, but it is very efficient identifying non POIs. He is totally week for detecting POIs.

This may come from our initial dataset with a lot of missing values.

As a conclusion, I see that the algorithm validation phase is crucial and has to be well thought.

Log transformation of feature

Row Labels	Average of F1 (computed)	Average of F1 (best_score_)
No	0.216111111	0.375555556
Yes	0.211666667	0.383888889
Grand Total	**0.213888889**	**0.379722222**

We see that the log transformation of features values has no real impact on the algorithm performances.

Inclusion of new features

Row Labels	Average of F1 (computed)	Average of F1 (best_score_)
Full	0.258333333	0.4725
Full with ratio	0.19	0.468333333
Limited	0.193333333	0.198333333
Grand Total	**0.213888889**	**0.379722222**

We see that inclusion of the two new ratios does not provide a significant impact on the performances of the algorithm. It even tends to decrease it performance.

I applied the PCA algorithm prior to the final machine learning algorithm tuning. If the new ratios do not add new information, they will not be considered (or weakly considered) by PCA algorithm.

Feedback about 1st review:

At least one new feature is implemented. Justification for that feature is provided in the written response, and the effect of that feature on the final algorithm performance is tested. The student is not required to include their new feature in their final feature set.

Good work engineering your features, including your reasons and testing their impact over your classifier, however correlation is not an appropriate test to determine their importance since POI is a categorical variable, you can find more info here on this topic . An appropriate analysis to estimate the relevance of these features would be to calculate the proportions of each value of the independent variable (`POI`) vs all the values of the dependent variable and then use a test that takes into account these proportions. A Contingency Table is an excellent tool for this purpose and Chi Squared Test is the right test to choose since it will test the observed values of each cell against the expected value of each cell in the contingency table and return a test result with a p-value. For your reference, have a look at this link where it is explained the Chi-Squared test and Contingency tables.

Another option is to simply test your classifiers with/without these features.

My answer:

I have some difficulties to understand your comment. I understand that correlation computation was not the right way to check for correlation, as POI is a categorical variable.

But, I am not sure the method you propose can be applied to my new features. I think the method you mention can be applied if my new features are categorical also. In my case, I created two ratios with contiguous values.

There is maybe something wrong in my analysis. Can you provide me with more details for me to understand better?