Udacity: Machine Learning Final Project

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Project Goal

The goal of this project is to identify Enron Employees who may have committed fraud based on the public Enron financial and email dataset.

Dataset Exploration

Machine learning is useful to comb and refine the dataset that consists of **146 data points** with **21 features** with **18 Persons of Interest (POI)**.

This is especially true when there are a large number of missing values represented as "NaNs" in each feature. To analyse the data, I've replaced NaNs with 0.

Observations

- The loan advances, deferral_payments, director_fees and restricted_stock_deferred columns have the highest number of missing values
- Out of the set, total_payments and total_stock_value have the lowest amount of missing values

Feature	No. of NaNs	Mean	Max.	Min.
bonus	64	1,333,474.23	97,343,619	0
deferral_payments	107	438,796.52	32,083,396	-102,500
deferred_income	97	-382,762.21	0	-27,992,891
director_fees	129	19,422.49	1,398,517	0
email_address	35	N/A	N/A	N/A
exercised_stock_options	44	4,182,736.2	311,764,000	0
expenses	51	70,748.27	5,235,198	0
from_messages	60	358.6	14,368	0
from_poi_to_this_person	60	38.23	528	0
from_this_person_to_poi	60	24.29	609	0
loan_advances	142	1,149,657.53	83,925,000	0
long_term_incentive	80	664,683.95	48,521,928	0
other	53	585,431.79	42,667,589	0
poi	0	0.12	1	0
restricted_stock	36	1,749,257.02	130,322,299	-2,604,490
restricted_stock_deferred	128	20,516.37	15,456,290	-7,576,788
salary	51	365,811.36	26,704,229	0
shared_receipt_with_poi	60	692.99	5,521	0
to_messages	60	1,221.59	15,149	0
total_payments	21	4,350,621.99	309,886,585	0
total_stock_value	20	5,846,018.08	434,509,511	-44,093

Through this simple table, it's easy to hypothesise that the POIs are essentially skewing the Max values. When we isolate the 18 POIs, we see a different story.

POIs generally average higher in all values. It's strange to see that the Max values don't match the Max values earlier observed; which subsequently means that the outliers in the data are not all coming from POIs.

Feature	No. of NaNs	Mean	Max.	Min.
poi	0	1.0	1	1
total_payments	0	7,913,589.78	103,559,793	91,093
total_stock_value	0	9,165,670.94	49,110,078	126,027
salary	1	362,142.39	1,111,258	0
deferral_payments	13	144,415.06	2,144,013	0
exercised_stock_options	6	6,975,862.44	34,348,384	0
bonus	2	1,844,444.39	7,000,000	0
restricted_stock	1	2,189,808.5	14,761,694	0
restricted_stock_deferred	18	0.0	0	0
expenses	0	59,873.83	127,017	16,514
loan_advances	17	4,529,166.67	81,525,000	0
other	0	802,997.39	10,359,729	486
director_fees	18	0.0	0	0
deferred_income	7	-632,691.56	0	-3,504,386
long_term_incentive	6	803,241.61	3,600,000	0

Outliers

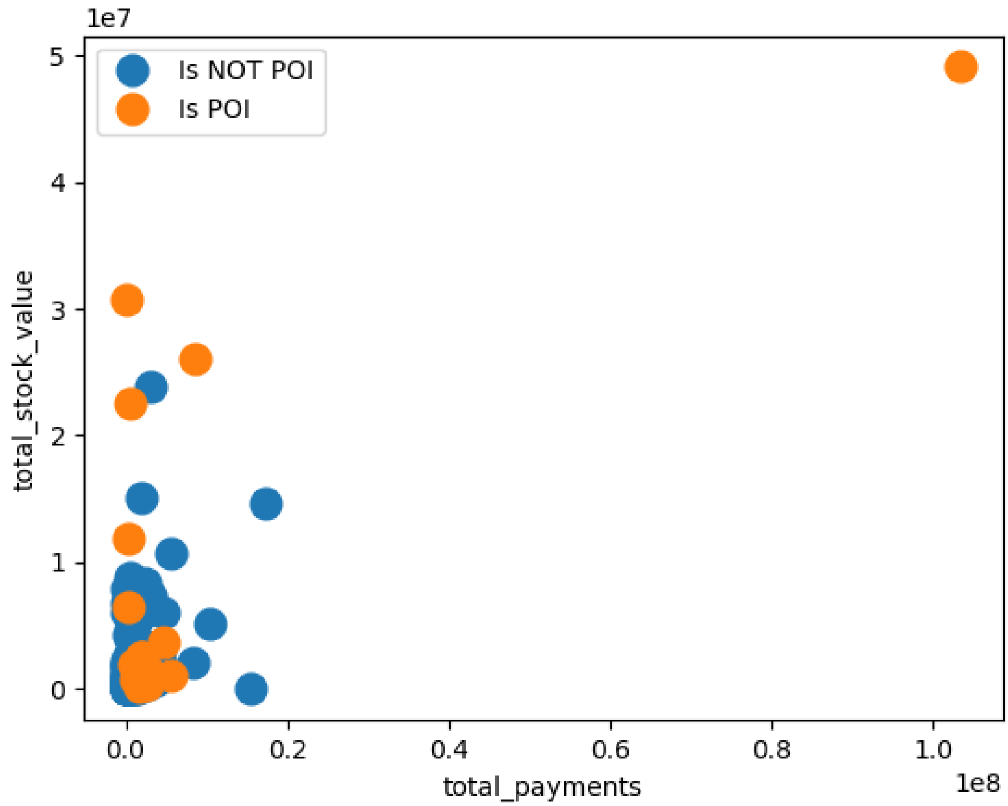
When we dig deeper into the Max. values, we find that the email address which has the Max Value for total_payments is actually the "TOTAL" value for all columns. When we remove the outlier, the Max values now match the POI values and the total means are lower.

While removing "TOTAL" helped in reconciling the differences between the POI and both POI and non-POI values, when we plot the two features for totals together, we find that there are still a couple of Outliers, especially one POI; namely **"LAY KENNETH L"**. (the top right orange dot in the scatter plot)

In [1]:

```
from IPython.display import Image
Image("Outlier1.png")
```

Out[1]:

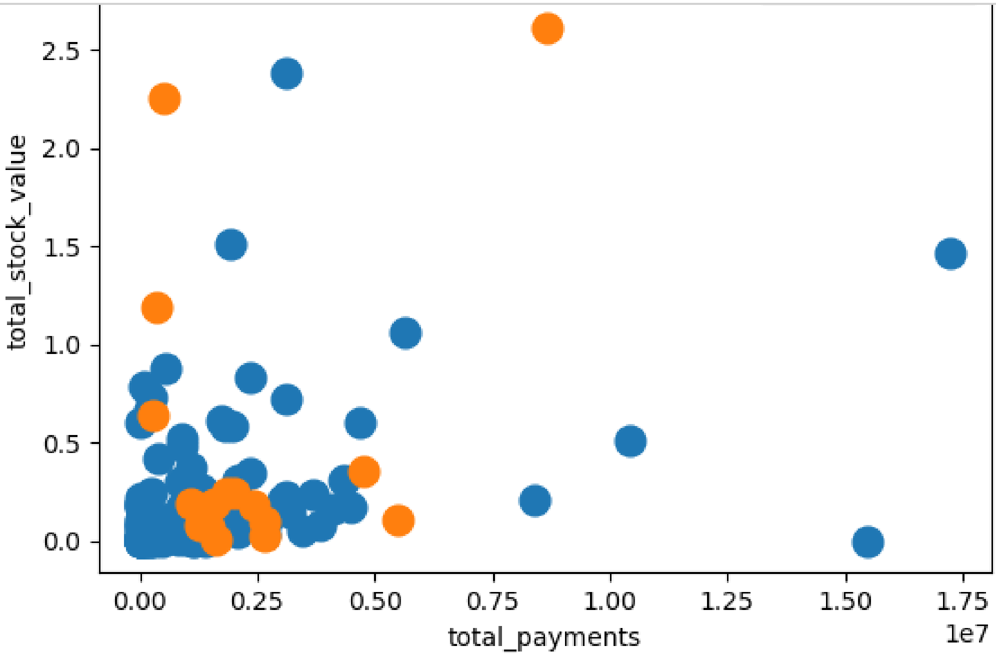


By removing "LAY KENNETH L" and by removing a non-POI "THE TRAVEL AGENCY IN THE PARK" who is listed in the PDF, we get really different results.

While there seems to be a positive correlation between the two features, we can clearly see it is weak even without calculating the correlation coeff.

In [2]:

```
Image("Outlier2.png")
```



Feature	No. of NaNs	Mean	Max.	Min.
poi	0	0.12	1	0
total_payments	21	1,548,128.23	17,252,530	0
total_stock_value	19	2,586,706.64	30,766,064	-44,093
salary	50	179,244.11	1,111,258	0
deferral_payments	106	222,223.67	6,426,990	-102,500
exercised_stock_options	43	1,850,119.59	30,766,064	0
bonus	63	631,773.56	8,000,000	0
restricted_stock	35	771,381.34	13,847,074	-2,604,490
restricted_stock_deferred	126	73,931.31	15,456,290	-1,787,380
expenses	50	34,924.59	228,763	0
loan_advances	141	16,783.22	2,000,000	0
other	53	224,361.03	7,427,621	0
director_fees	127	10,050.11	137,864	0
deferred_income	96	-192,939.8	0	-3,504,386
long_term_incentive	79	314,139.36	5,145,434	0

POI numbers without Kenneth Lay are also lower and some Max. values are starting to match the non-POI numbers.

Now that we have cleaned up our data and it makes a lot more sense, we can finally move on to creating a model to detect POIs.

Feature	No. of NaNs	Mean	Max.	Min.
poi	0	1.0	1	1
total_payments	0	2,287,342.53	8,682,716	91,093
total_stock_value	0	6,815,999.94	30,766,064	126,027
salary	1	320,367.18	1,111,258	0
deferral_payments	13	140,974.12	2,144,013	0
exercised_stock_options	6	5,365,714.12	30,766,064	0

```
bonus                                 2  1,541,176.41  5,600,000   0
restricted_stock                      1  1,450,285.82  6,843,672   0
restricted_stock_deferred            17  0.0           0           0
expenses                              0  57,523.35     127,017     16,514
loan_advances                        17  0.0           0           0
other                                 0  240,836.71    1,573,324   486
director_fees                        17  0.0           0           0
deferred_income                       7  -652,261.65   0           -3,504,386
long_term_incentive                   6  638,726.41    1,920,000   0
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Feature Engineering

New Feature: % of Stock Value over Payments

At this point, while total_payments and total_stock_value have a low level of missing values and therefore one would assume a better fit for the data, it's all because these features happen to be totals of all the other features.

However this pair makes for a good feature. When comparing averages of total stock value over payments, POI seem to have a higher total stock value per total payment ratio. We can use feature selection tools to evaluate this hypothesis. I've named the new feature "stock_value_ratio". I will test this once we've determined the best feature algorithm and parameters for the original dataset.

Feature Selection

In order to better evaluate prediction of the POI by their monetary activity and attributes, I have removed all features that look at the email activity from and between poi and sender (email_address, from_messages, from_poi_to_this_person, from_this_person_to_poi, shared_receipt_with_poi). This is to also ensure the variance in the data makes sense before applying feature reduction techniques.

After removing these features, the final feature list (without the new, untested feature) is:

- 'total_payments'
- 'total_stock_value'
- 'salary'
- 'deferral_payments'
- 'exercised_stock_options'
- 'bonus'
- 'restricted_stock'
- 'restricted_stock_deferred'
- 'expenses'
- 'loan_advances'
- 'other'
- 'director_fees'
- 'deferred_income'
- 'long_term_incentive'

Feature Scaling

In order to use GridSearchCV, non-negative values need to be excluded. So I've used MinMaxScaler() to scale the features and standardize the features for validation.

Cross-Validation: Feature Reduction and Classifier Algorithm on Original Dataset

Next, in order to appropriate the best method for identifying POIs, we need to validate all methods. This is necessary because we need to discover the best model fit that can be applied for other samples.

To validate the best combination of feature selection, classifiers and its parameters, I've used GridSearchCV with the StratifiedShuffleSplit module (to be in line with test CV module) that passes the combination into the tester file's testing module.

In order to achieve the possibility of a higher score, it's best to tune the parameters of the algorithm. If I don't do this well, I'll miss out on that opportunity and could possibly overfit the data.

To sync with the tester.py random state, I have left the random state at 42 wherever possible in the algorithms.

The comparisons between each part of the combo is as such

- **Feature Selection**: Comparing between SelectKBest, SelectPercentile and PCA
- **Classifier Algorithn**: Comparing between LinearSVC, SVC, GaussianNB, KNeighborsClassifier and DecisionTreeClassifier

After validating, the combo that **GridSearchCV** determined was best was

- **Feature Selection**: SelectKBest
- **Classifier Algorithn**: GaussianNB with an Accuracy score of 0.7, Precision score of 0.2 and Recall of 0.6.

A higher precision score would mean that when a POI gets flagged in my test set, I know with confidence that it's a real POI and not a false alarm. However I would probably miss the real POIs since I'm effectively reluctant to pull the trigger on edge cases.

A higher recall score would mean that whenever a POI shows up in the test set, I am able to identify him/her. The cost of this is that sometimes I get some false positives where non-POIs get flagged.

Further Tuning and Validation Needed

Evaluating Feature Scaling

Because Precision is below 0.3, we'll need to see if other methods work as well. Using MinMaxScaler() to scale the features as it's perfect for handling negative values, I ran the validation code again.

This time Accuracy and Precision scores were slightly lower. Not ideal for this project.

Evaluating the new feature

I then tested out the new feature (stock_value_ratio) to see if it helps in gaining a higher score with any of the combos.

Unfortunately, both Precision and Recall scores were lower. Because this isn't ideal we will need to go ahead without the new feature and try to tune the parameters to achieve a higher score.

Parameter Tuning

Because SelectKBest and GaussianNB came out as the best performing feature reduction model and classifier respectively, I then proceeded with trying to fine tune the parameters for SelectKBest by tuning the k parameter.

As it turns out, k=9 produced an **Accuracy score of 0.8, Precision of 0.3, Recall of 0.5**. Definitely an improvement to where we were before. Perfect!

The final combo is as below:

- SelectKBest(k=9, score_func=f_classif),
- GaussianNB(priors=None)

produced ...

- Accuracy: 0.76880
- Precision: 0.29195
- Recall: 0.51500
- F1: 0.37265
- F2: 0.44674
- Total predictions: 15000
- True positives: 1030
- False positives: 2498
- False negatives: 970
- True negatives: 10502