Udacity Course: Data Science II

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Enron Scandal

Final Project Report

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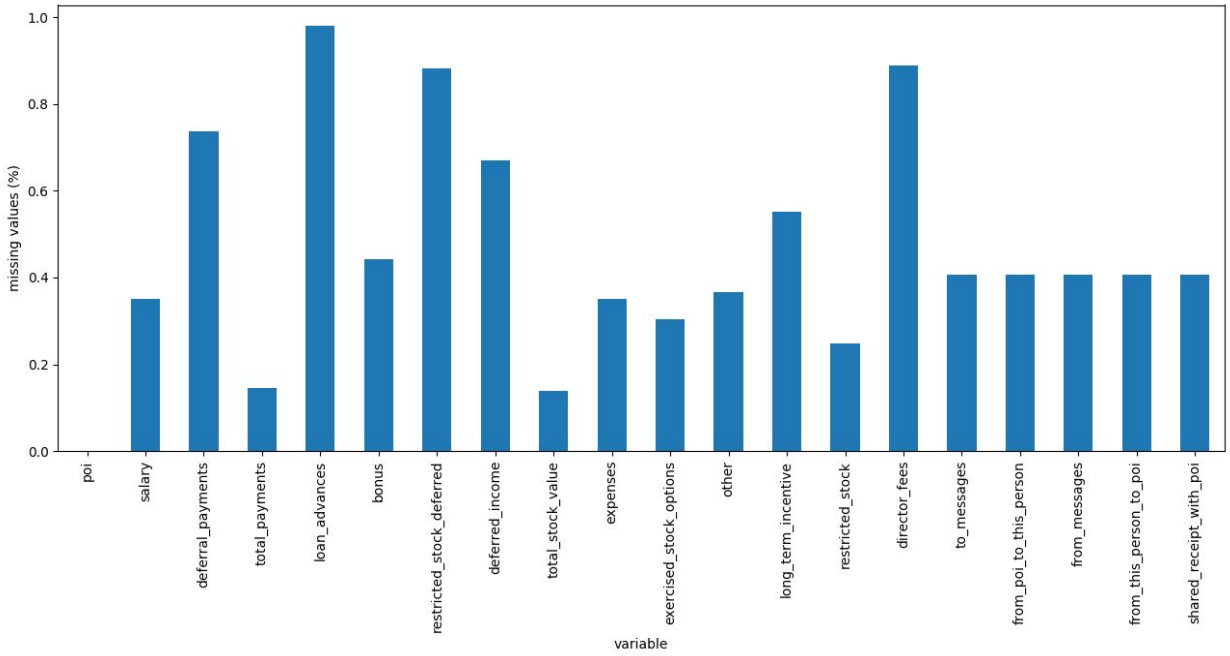
Introduction

In this project, we are going to use the power of machine learning to try to predict who was involved in the famous Enron' Scandal. This scandal refers to a series of unethical practices, mostly from managers, including changes in the balance sheett of the company to change its performance. These practices were later discovered and led the company to its bankruptcy, and many senior managers were found guilty in some degree.

Our goal here is to try to predict who was involved in this schema looking at individual attributes that may reveal their roles in the scandal. For instance, for a matter of fact, people involved in these bad practices earned a lot more money than regular employees. Then, we can use a machine learning classification model in order to understand this implied relationship.

Data Exploration

The dataset contains 146 data points, from only 18 people have "poi" allocation (the classed are highly non balanced). We have a significant percentage of missing data, as seen in the graph below, specially for total_advances, restricted_stick_deferred and director_fees. In our model, we decided to convert NaN values to 0.0, and remove data points whenever all entries are zero. After making that process, it was not necessary to remove any data entry.



Outliers were investigated in the following way:.

1. Salary: there is a value of 26.704.229,0 USD that seems an outlier, standing very far from the others in boxplot view. Investigating the person associated with this data point, we noticed that it says 'TOTAL', which points out to be the sum of all salaries in the Enron dataset, which we confirmed in the "enron61702insiderpay.pdf" document. After that removal, we can still see maybe 4 outliers in boxplot view, but investigation showed that these points are real persons, like the "POI" LAY KENNETH L (Enron's CEO from 1995 to 2001) and SKILLING JEFFREY K (Enron's after Kenneth), so we definitely should not remove them from the dataset.
2. total_payments: looks like it shows an outlier too, but investigation also shows that this point is Kenneth Lay too. While all other data points had total_payments below 20 millions USD, with most of these below 1 million USD, Lay had over 100 million USD in total payments. Same happens for bonus feature: highest values correspond to real cases.

Features Selection

Between features that show emails information, it's clear that 'from_poi_to_this_person' and 'from_this_person_to_poi' are the principal ones, because they show the relationship between a person in the dataset and a POI. In the image below (already without the outlier), we see that a POI does not used to email other POI as much as the non POI did, which raises a hypothesis that POI could use other medias to chat information, specially about the scandal (this hypothesis is not explored here). The "shared_receipt_with_poi" also can show a relationship with poi, so we kept these 3 email features.

About the financial features, it not difficult to see, intuitively, that "salary", "total_payments", "bonus" are the most likely related with a chance to be a poi (poi earned much more money due to the scandal).

In order to follow a systematic feature selection, we kept all of numeric features, which excludes only the "email_address" feature. This feature is obviously not useful for classification since everyone should have a unique email address. By using PCA inside our pipeline for finding the best tuning for our classifier and parameters, we will get the components that explain the variance in our data and also which features are more intrinsic related with PCA components.

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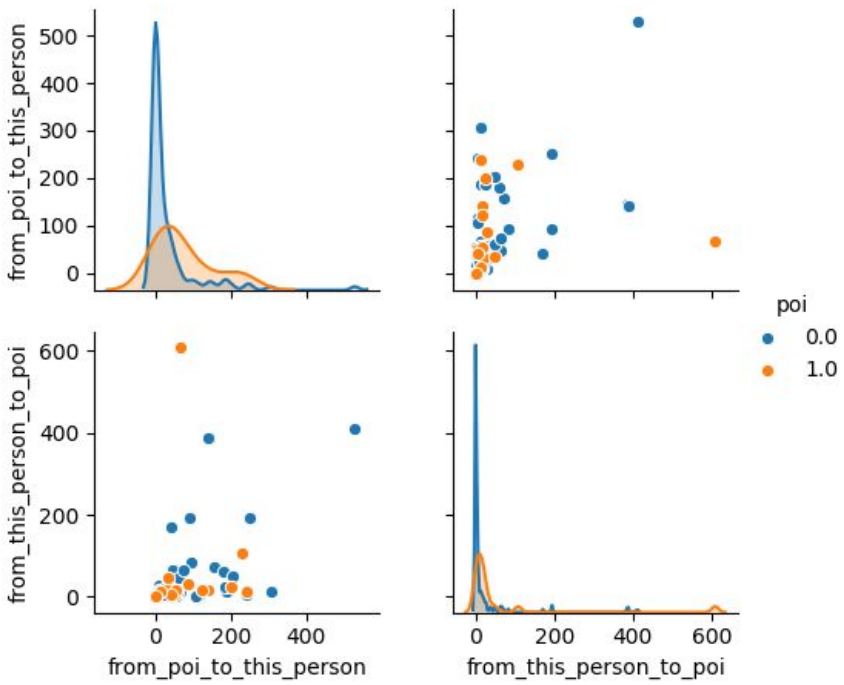

messages between poi and non-poi.

New Features

We also created a new feature to test in our model, which is the ratio between “total_payments” and “salary”, in order to try to detect big differences between the current salary and all the money paid to someone. The result in the best classifier found ahead was not significant, however, probably because it is a combination that can be detected by the original classifier, when looking to both features separately. The results with this new feature is presented in the Evaluation Metrics section.

Pipeline Structure

In order to find the best model, we chose to build a pipeline using the previous features selected (we've fit the pipeline for more financial features, but then we removed some that did not lower our scores). This pipeline is based on the following steps:

- Scalar;
- PCA;
- Classifier.

For the scalar, we chose StandardScaler(), a very common one, but for PCA and Classifier we've tried several options. The classifiers analyzed were: Gaussian Naive Bayes, Decision Trees, Random Forests and Support Vector Machines.

For the pipeline models, we also used GridSearchCV for cross-validation, for which we could pass a variety of parameters to tune our classifiers. The tuning of classifiers is a fundamental step in a classification problem in order to avoid overfitting or underfitting our model. An example of that is with the Support Vector Machines. They try to fin the best hyperplane that separates classes. For that objective, it can use different types of hyperplanes (Kernel parameter as 'linear', "poly" or "rbf") and different degrees of non-linearity ("gamma" parameter as a positive float number). Higher numbers of "C" makes high non-linear hyperplanes that try to fit all the training data, which is dangerous for predicting new data, for example (overfitting). The opposite is also true: if the parameters make the classifier a very bad predictor of training data, it will probably fail to predict new data as well (underfitting).

In that way, the tuning of parameters during the train-test step is fundamental to build a solid classifier that can avoid the extremes of underfitting and overfitting.

As we are going to see, the best classifier found was the **Naive Bayes**. The following topics resume the best parameters found for each classifier under this pipeline, as well as the main scores for these best parameters (all of them referencing the same set of features) when we used tester.py to test the classifier:

1. SVM
    best params:
        PCA_components: 4
        SVM_C: 0.001
        SVM_gamma: 0,1
    tester.py results
        accuracy: 0.86870
        precision: 0.11012
        recall: 0.00671
        F1: 0.01265
        F2: 0.00826

2. NB
    best params:
        PCA_components: 4
        NB__priors: None
    tester.py results
        accuracy: 0.84216
        precision: 0.31544
        recall: 0.22158
        F1: 0.26030
        F2: 0.23560

3. Decision Tree (DT)
    best params:
        PCA_components: 2
        DT_criterion: 'entropy', DT_splitter: 'random'
    tester.py results
        accuracy: 0.80955
        precision: 0.24802
        recall: 0.25567
        F1: 0.25179
        F2: 0.02541

4. Random Forest Classifier (RFC)
    best params:
        PCA_components: 2
        RFC_criterion: 'entropy'
    tester.py results
        accuracy: 0.83195
        precision: 0.02531

recall: 0.17461
F1: 0.20665
F2: 0.18616

We see that for the NB classifier, we could only set options for “priors” parameter, but for the other ones we could vary some parameters, such as “criterion” for Decision Trees and Random Forest, or “C” and “gamma” for the SVM.

For the best classifier, Naive Bayes, we found that the best number of components are 2, which answer for 81,3% and 14,2%. Looking at the features most related with principal components, we found (see lines 147 to 152 in poi_id.py) the following matrix:

[[7.82354422e-03 6.27847066e-03 6.84724238e-01 5.19989408e-01

5.16982795e-02 4.52726253e-03 5.99700187e-03 3.96997566e-01

5.68864753e-04 2.86262778e-01 7.36148821e-02 2.64579236e-02

1.10729288e-01 1.28212642e-04 2.65194166e-05 1.00019893e-06

2.33333648e-06 1.00054241e-07 1.69919106e-05]

[5.12137210e-03 8.72267098e-03 3.79704393e-01 3.26232928e-01

7.14963750e-03 3.36868230e-02 2.90183962e-02 6.55699910e-01

5.51789301e-04 5.52976583e-01 1.69880419e-02 1.61735377e-03

1.06060359e-01 7.49520404e-04 2.40294298e-05 5.43488135e-08

1.08953510e-05 5.31516439e-07 7.32839172e-06]]

That matrix has shape (2,19), 2 PCA components and 19 features. For the first row (main PCA) we note that the higher values appears for the features total_payments (nº 3), loan_advances (nº 4), total_stock_value (nº 8), exercised_stock_options (nº 10) and restricted_stock (nº 13). The rest of the features have variance by at least 10 times smaller, so we can stay with the cited

ones as most relevant features in explaining the data. Intuitively, these are features would be higher for people involved in the scandal. Email informations had the worst relation in explaining the problem of predicting poi.

Validation

In the section before, the validation that generated the score metrics was done using the tester.py script, even though a prior validation is done in poi_id.py. Both validations have the main ideia: it is fundamental to separate the training set from the testing set. If one does not do that, he incurs in a big risk of biasing the model a lot, in a sense that it will have a great performance for the dataset studied but will not be able to predict well new data. The separation step avoid this, forcing the data to really learn patterns of training set that also apply to the test set, and then the model will predict better new data.

Particularly, the tester.py uses StratifiedShuffleSplit() to separate 30% of the data to testing, and for training set it creates 1000 folds of same size were the percentages of each class are maintained on each fold.

Evaluation Metrics

Finally, as seen in the Pipeline Structure section, we obtained the best performance of 0.32 for precision, 0.22 for recall and 0.84 for accuracy. While the last shows a got fit for the whole model, we did not get recall over 0.30. A variety of grids were tested but we could not get a higher recall. For the new feature implemented, when included in feature_list, shown the following results: Accuracy: 0.83605, Precision: 0.28957, Recall: 0.21197, F1: 0.24477, and F2: 0.22397. Hence, it diminished precision by almost 0.30, but elevated recall by only 0.39 points, which shows that the feature does not boost the classifier performance.

The precision show us the ability of the model not to label as positive a sample that is negative, and the recall shows the ability not to label as negative a sample that is actually positive . In the context of Enron's emails, we rather prefer a good recall over precision, because we can guarantee that we are not labeling a true poi as negative. A false poi, labeled by the clf as poi, can be taken out from investigation after later parts in the process, but we do not want to "lose" a true poi. to find all positives samples, or not labeling as negative a sample that is positive. Then, we got the classifier with the best accuracy and recall.