Identifying Fraud from Enron Emails using Machine Learning

Enron was one of the prosperous companies in the United States in 2000. However, it had gone bankruptcy due to frauds committed by some of its CIOs by 2002. Therefore, a federal investigation was carried out to find the corruption in the company. As a result, a large amount of confidential details including email and financial details of top executives became public records. In this project, the machine learning algorithms along with Python data handling techniques used to identify persons of interests (POI) by analyzing financial and email data made public as a result of the Enron scandal.

Overview of the dataset

In the preprocessed dataset, the email and financial information are confined into 21 features for each person investigated. Among them for the preliminary exploration, following list of features selected based on intuition. The number of features will be further reduced in a later stage.

features\_list = ['poi','salary', 'deferral\_payments', 'total\_payments', 'loan\_advances', 'bonus', 'deferred\_income', 'total\_stock\_value','expenses', 'long\_term\_incentive', 'to\_messages', from\_poi\_to\_this\_person', 'from\_messages', 'from\_this\_person\_to\_poi', 'shared\_receipt\_with\_poi']

The dataset contains records of 146 persons (thus 146 records of for each feature (including missing values)). However, after running ‘featureFormat’ function, the total number of rocords redused down to 136, after removing missing values. In the dataset, there are 18 pois and 118 nonpois. There are considerable amount of missing values can be observable in all most every feature (for example: the feature salary, bonus and to\_messages have 51, 64 and 50 missing values, respectively).

Handling outliers

During the preliminary examination of the financial data in the dataset, some calculated values were identified. For example, the totals of the entire columns observed as records(that might have calculated when the dataset was in spreadsheet format). The totals of columns were shown in the main dictionary as ‘TOTAL’. The ‘TOTAL’ field deviate all the data because the total values are very high compare to other values. Therefore, the ‘TOTAL’ field removed form the dictionary using following Python code.

data\_dict.pop('TOTAL', None)

To identify whether there are outliers, boxplots were generated for each numerical feature in the dataset. The example boxplots are shown in Figure 1 and Figure 2. Based on the boxplots results, there are more potential outliers. However, these outliers maybe valid data points and can be helpful to identify a fraud if any. Therefore, these data points were kept in the dataset.

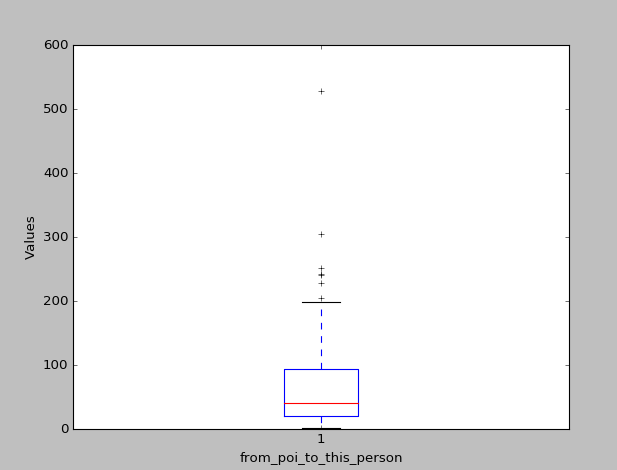


Figure 1: Boxplot for form\_poi\_to\_this\_person vs values. (The black crosses are potential outliers)

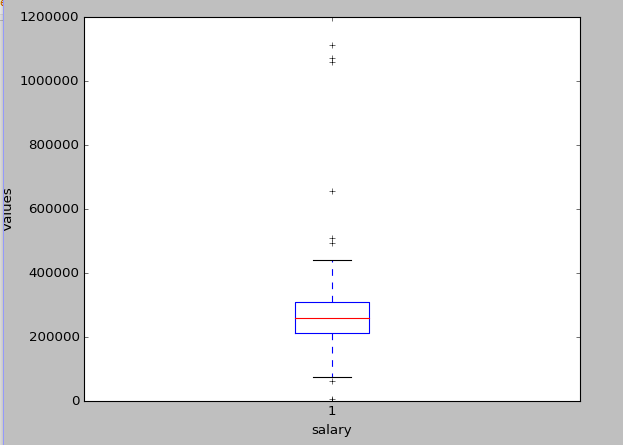


Figure 2: Boxplot for salary vs values. (The black crosses are potential outliers)

Fracture selection and reduction

The selected features (see the feature-list above) can be further reduced. Therefore, in order to reduce number of features and standardized the features, two new features were created (see the following equations) using four features of incoming and outgoing emails.

from\_this\_person\_to\_poi \_ratio = from\_this\_person\_to\_poi / from\_messages

from\_poi\_to\_this\_person \_ratio = from\_poi\_to\_this\_person / to\_messages

The engineered two features are explaining how the relationship between two people involved is. Higher the value of new features represent a higher the relationship between persons. However, the prediction is accurate if the persons have higher email exchange rate.

After this adjustment following is the new list of features.

features\_list = ['poi', 'salary', 'total\_payments', 'bonus', 'deferred\_income', 'expenses', 'shared\_receipt\_with\_poi', **from\_this\_person\_to\_poi \_ratio’, ‘from\_poi\_to\_this\_person \_ratio’**]

In order to compare features, the selected features were scaled using StandardScaler function from sklearn.preprocessing module. After this step, the relative importance of features was calculated using sklearn.ensemble.ExtraTreesClassifier module.

Following lists shows four consecutive relative importance results for the features in features\_list.

[0.1273601, 0.1069279, 0.1280600, 0.1378528, 0.1201878, 0.1037098, 0.18176876, 0.09413255]

[0.1411725, 0.1529980, 0.1301091, 0.1367751, 0.1252963, 0.08735614, 0.1489267, 0.07736584]

[0.1245838, 0.1348846, 0.1115029, 0.1137376, 0.1516839, 0.0888458, 0.1911254, 0.08363575]

[0.1646108, 0.1211031, 0.1308363, 0.1280421, 0.1279375, 0.0920179, 0.17591885, 0.05953318]

The relative importance results show that all the features selected are almost equally important. However, the average values of relative importance for the features at the position 5 and 7 (based on 0 list indexing and ignoring ‘poi’) are relatively low. Therefore, the features at position 5 and 7 were removed and the final feature list is as follows.

features\_list = ['poi', 'salary', 'total\_payments', 'bonus', 'deferred\_income', 'expenses', 'std\_from\_this\_person\_to\_poi']

As shown in the final feature list, a newly engineered feature is also relatively important. The final features\_list contains six different features and this amount of features can be considered reasonable for a study like this.