## Background and Goals of the Project

The goal of the project is to produce a classifier, with acceptable precision and recall levels, to identify persons of interest (POI) based on data extracted from public materials associated from the Enron case.

Briefly, the data derives from three sources:

* Fourteen financial features extracted from a *Payments to Insiders* document which contains an itemized record of payments from Enron Corp. to its insiders in both cash and stock.
* Six email features extracted from the Enron Corpus, a database of email of all Enron Corp. employees, as related to the insiders named in the Financial data. For the purposes of this project, the data points include the total number of emails sent and received by the person in question, and how many of them were sent to, received from, or have shared receipt with a POI.
* A list of POI.

This, in total, contains a dataset involving 146 insiders with 21 features for each insider.

## Outlier investigation

During the course, it has already been noted that a grand total line from the *Payments to Insiders* document was inadvertently included into the dataset. This is removed from the dataset immediately.

Due to the large level of intra-individual variances within the data set, and the fact that some high-deviation data points within the data set cannot be excluded just because of this (as mentioned in the class, this would have removed the infamous Kenneth Lay and Jeffrey Skilling owing to the fact they were paid highly), no unsupervised outlier identification has been performed. Instead, I check for the sanity of several data points, for example, restricted\_stock must be larger than restricted\_stock\_deferred, as no person can defer something that don’t own. Similarly, all financial features are either positive or ‘NaN’ except for those ending with “\_deferred,” which are always negative.

Through this, I have identified two suspicious data points. Sanjay Bhatnagar is recorded to have $-2,604,490 in restricted stock, of which $15,459,290 was deferred, which is absurd, as there stocks does not negative value. Similarly, Robert Belfer has a total stock value of $-4,4093, which is similarly absurd. Cross-checking with the *Payments to Insiders* document indicates these are errors potentially introduced by the dataset by the OCR software that digitalized the document by left or right-shifting several fields. The financial data for these two people were corrected.

## Other investigations of the data

While this data set includes data from 146 insiders, only 18 of them has been identified as a POI, which indicates an unbalanced response label.

On the other hand, many features have missing values for more than half of the insiders. In descending order, these fields include loan\_advances (>98%), directors\_fees (>90%), restricted\_stock\_deferred (>88%), deferral\_payments (74%), deferred\_income (36%), and long\_term\_incentive (55%). However, these do not appear to be essential features for an employee’s remuneration package, so I decided to not act on those except treating them as zeroes.

## Feature Processing

Field “email\_address” was never imported in any analysis, due to the fact that I do not plan to perform any text analyses on the email messages, and its string nature poses problems for the other algorithms used in machine learning.

I added five new features to this data set:

|  |  |  |
| --- | --- | --- |
| Feature Name | Definition | Justification |
| proportion\_from\_this\_to\_poi | The proportion of emails from this person to one or more POI to all emails he sent | The level of email communication between an insider to a known POI is indicative of that insider’s involvement of the fraud in question. However, I consider the proportional email communication to POI relative to the person’s total email count to be more predictive than the raw email number. |
| proportion\_from\_poi\_to\_this | The proportion of emails from one or more POI to this person to all emails he received |
| proportion\_shared\_receipt\_with\_poi | The proportion of emails to one or more POI and this person to all emails he received |
| proportion\_of\_stock | The proportion of stock for that person’s remuneration package. | The use of stock options is seen by critics to encourage risk-taking behavior. On the other hand, deferred compensation has the effect of increasing company debt[[1]](#footnote-1). It is curious to see if these factors would be associated to corporate criminality. |
| proportion\_payments\_deferred | The proportion of payments this person was entitled to received, but was deferred. |

Due to the choice of these features, the original email features (to\_messages, from\_messages, from\_poi\_to\_this\_person, from\_this\_person\_to\_poi and shared\_receipt\_with\_poi) were removed from the data set prior to feature selection.

Feature selection was performed using sklearn.linear\_model.RandomizedLasso. Based on the lasso model, RandomizedLasso, in the default setting, performs 200 of 75% stratified subsets of the normalized data, ran Lasso on each subset, and counts the frequency a feature has a non-zero coefficient. Features having a non-zero coefficient in more than 25% of the subsets were selected for further algorithm testing and training. Eleven features were eventually selected, including salary, deferral\_payments, bonus, restricted\_stock\_deferred, deferred\_income, total\_stock\_value, expenses, exercised\_stock\_options, other, long\_term\_incentive, and proportion\_from\_this\_to\_poi.

Features were normalized by Normalize if they were used as an input for algorithms that are sensitive to unscaled features, such as SVC and Naïve Bayes. Otherwise, algorithms were trained with unscaled data.

## Algorithm Selection and Tuning

All algorithms mentioned in the course, including Gaussian Naïve Bayes, SVM (using sklearn.SVM.SVC), Decision Tree, AdaBoost and Random Forest were tuned and tested using GridSearchCV.

First, 40% of the data set was set aside for testing using train\_test\_split. Bearing in mind of the imbalance of the response variable, the stratify parameter is used to ensure the composition of the response labels is the same between training and testing groups.

All the algorithms listed above were tuned using GridSearchCV using a large variety of parameters, with the exception of Naïve Bayes, which doesn’t have parameters; the F1 score were used as the scoring function.

The F1 scores from the best model for each algorithm are:

|  |  |
| --- | --- |
| Algorithm | F1 score |
| Random Forest | 0.586 |
| Decision Tree | 0.578 |
| AdaBoost | 0.485 |
| SVC | 0.239 |
| Naïve Bayes | 0.195[[2]](#footnote-2) |

Based on these results, the model based on Decision Tree algorithm was selected for having the highest score of the five used.

The chosen Random Tree classifier assigned zero importance to most of the features used with the exception of the following five:

| Feature | Importance |
| --- | --- |
| Other | 0.4581 |
| Expenses | 0.2387 |
| Total\_stock\_value | 0.1432 |
| Deferred\_income | 0.0983 |
| proportion\_from\_this\_to\_poi | 0.0617 |

## Algorithm Validation

Classifier models were trained for a subset of all data points, and thus, logically speaking, applicable only for that particular subset and not necessarily for the entire data set. As a result, validation is required to ensure the models’ general applicability for all data points to be predicted using the same model.

The most common validation metrics for classifier models that predict discrete class labels are precision and recall. Precision is defined as the probability that a data point predicted by model to be a member of class *x* actually belongs to class *x*, while recall is defined as the probability that a member of class *x* is predicted by the model as class *x*.

On the other hand, due to the fact that the response variable is highly imbalanced in this data set, the standard metric of accuracy score would be considered inappropriate. For example, if all the POI in this data set were misclassified as non-POI were correctly classified as such, the accuracy score would still be 0.855, because 124 of 145 points were predicted correctly. However, in this case the recall is 0 and the precision undefined.

In this instance, I used the test\_classifier subroutine from tester.py to perform validation. This subroutine performs 1,000 rounds of train-test splitting with 90% used for training and ensures the POI label ratios in each subset is roughly equal to the POI/non-POI ratio in the original dataset. Precision and recall metrics were calculated from the aggregated results from the 1,000 bootstrap trials. This subroutine estimated the precision and recall of this model to be 0.31965 and 0.47500 respectively.

1. https://www.newyorkfed.org/medialibrary/media/research/staff\_reports/sr445.pdf [↑](#footnote-ref-1)
2. Since GridSearchCV cannot be applied on the Gaussian Naïve Bayes algorithm, this F1 score calculated by comparing the predicted and true POI labels from the testing set. [↑](#footnote-ref-2)