ENRON PERSON OF INTEREST DETECTOR

Himanshu Maurya
2013089
(himanshumaurya@iiitdmj.ac.in)

Kunal Deshwal
2013107
(kunaldeshwal24@gmail.com)

1.ABSTRACT

This report describes our efforts to detect the fraudents in one of the largest companies in United States Enron in 2000. This report provides the insights into how the data was analyzed and cleaned to apply different machine learning algorithms. We have used Naive Bayes & Decision Tree Classifier to train and predict Enron Dataset and compared the result from both the algrithms.We have used 3-fold cross validation and establised the why accuracy is not the correct method to find out goodness of our result and provided the appropriate method to do so. We have also concluded why is Naive Bayes algorithm fails to give good results on this dataset and provided the future areas in which the work can be extended.

2.INTRODUCTION

In 2000, Enron was one of the largest companies in the United States. By 2002, it hadcollapsed into bankruptcy due to widespread corporate fraud. In the resulting Federal investigation, there was a significant amount of typically confidential information entered into public record, including tens of thousands of emails and detailed financial data for top executives. In this project, you will play detective, and put your new skills to use by building a person of interest identifier based on financial and email data made public as a result of the Enron scandal. To assist you in your detective work, we've combined this data with a hand-generated list of persons of interest in the fraud case, which means individuals who were indicted, reached a settlement, or plea deal with the government, or testified in exchange for prosecution immunity.

We have investigated the Enron email corpus together with employee financial data to identify employees' involved in the fraud (hereto referred as a person of interest or poi).

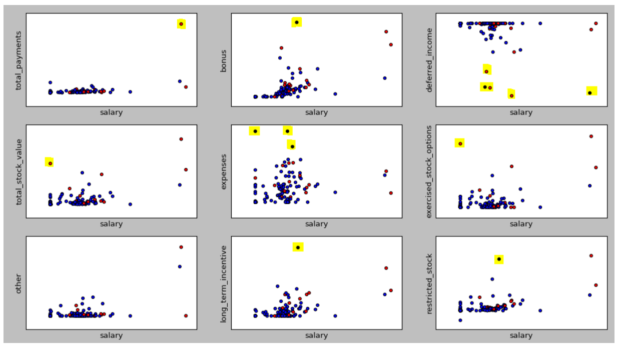
3.DATASET

Measurement	Value
Total Data Points	146
Point of Interest Data points	18
Non Point of Interest Data points	128
Number of Features	21

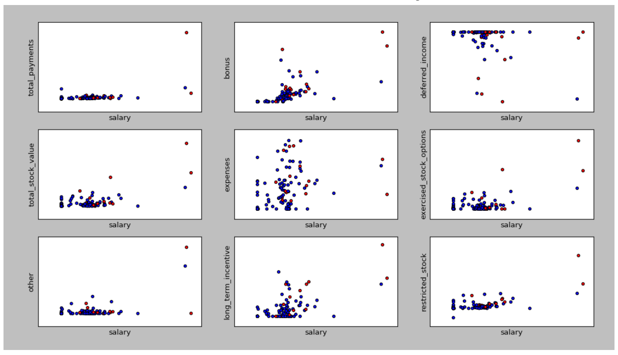
Handling missing values:

Features with more than 50% missing values:
deferral_payments, loan_advances,restricted_stock_deferred, deferred_income, long_term_incentive, director_fees
POI's with more than 50% missing values:
deferral_payments, loan_advances,restricted_stock_deferred, director_fees
Conclusion:
The features restricted_stock_deferred, director_fees, loan_advances have both a large number of missing non-poi(>110) and poi(>17); therefore it would be imprudent to use them as features.

Initial Dataset:



Dataset after financial features were adjusted:



4.RELATED WORK

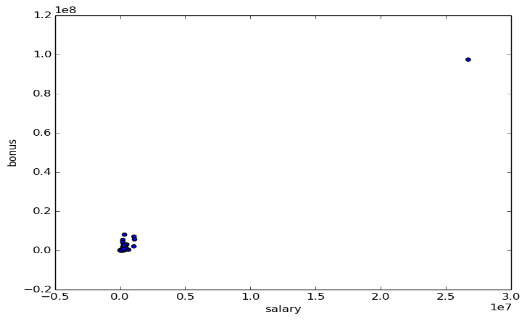
- A paper describing the Enron data was presented at the 2004 CEAS conference.
- Some experiments associated with this data are described on Ron Bekkerman's home page.
- Structure of data in enron dataset http://research.cs.queensu.ca/~skill/enron.pdf

5.APPROCH

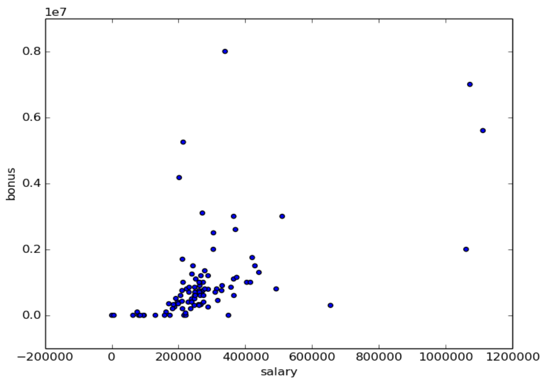
There are four major steps in our project:

1. Enron dataset
2. Feature processing
3. Algorithm
4. Validation

First of all We'd like to have a look at my data and check it for outliers. We plot salaries and bonuses on Enron employees and see an outlier in the data



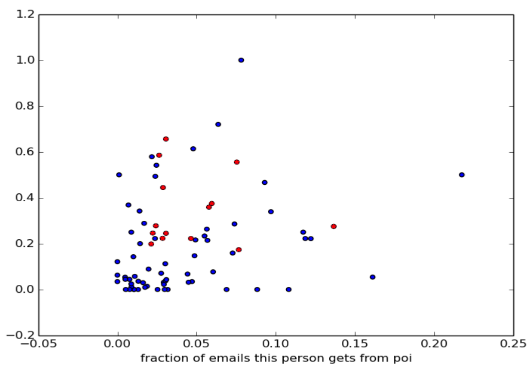
When We checked it We see this is a number of total salary and bonus. As this is not sensible information for our analyss. We removed it manually. Two more outliers (SKILLING JEFFREJ and LAY KENNETH) We kept in dataset as these values are real and actually they are already a sign of these two managers being involved in the fraud. Now dataset looks like this:



5.1 Feature Processing

After cleaning the data from outliers We had to pick the most sensible features to use. First We picked 'from_poi_this_person' and 'from_this_person_to_poi' but there was no strong pattern when We plotted the data so We used fractions for both features of 'from/to poi messages' and 'total from/to messages'.

POI's in the dataset. There were 35 people who were



Two new features were created and tested for this project. These were:

- the fraction of all emails to a person that were sent from a person of interest.
- The fraction of all emails that a person sent that were addressed to persons of interest.

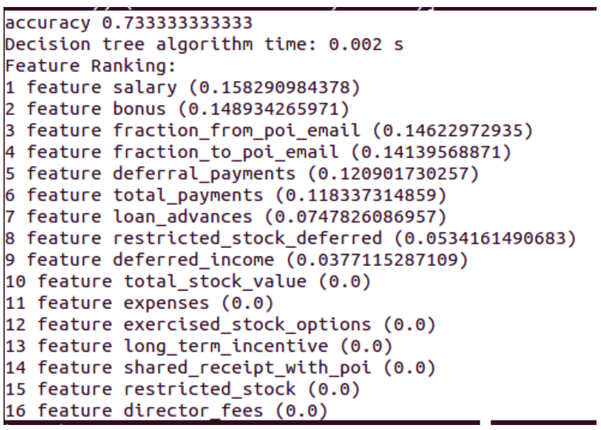
Our hypothesis was that there is stronger connection between POI's via email that between POI's and non-POI's. When we look at scatterplot we can agree that the data pattern confirms said above, eg. There is no POI below 0.2 in 'y' axis.

In order to find the most effective features for classification, feature selection using "Decision Tree" was deployed to rank the features. Selection features was half manual iterative process. First We put all the possible features into features_list and then started deleting them one by one using score value and human intuition.

We picked 10 features which are:
[**"salary", "bonus", "fraction_from_poi_email", "fraction_to_poi_email", deferral_payments", "total_payments", "loan_advances", "restricted_stock_deferred", "deferred_income", "total_stock_value"**]

Accuracy for this feature set is around 0.8
Approximate **feature ranking**:

It



```
accuracy 0.733333333333
Decision tree algorithm time: 0.002 s
Feature Ranking:
1 feature salary (0.158290984378)
2 feature bonus (0.148934265971)
3 feature fraction_from_poi_email (0.14622972935)
4 feature fraction_to_poi_email (0.14139568871)
5 feature deferral_payments (0.120901730257)
6 feature total_payments (0.118337314859)
7 feature loan_advances (0.0747826086957)
8 feature restricted_stock_deferred (0.0534161490683)
9 feature deferred_income (0.0377115287109)
10 feature total_stock_value (0.0)
11 feature expenses (0.0)
12 feature exercised_stock_options (0.0)
13 feature long_term_incentive (0.0)
14 feature shared_receipt_with_poi (0.0)
15 feature restricted_stock (0.0)
16 feature director_fees (0.0)
```

But with these features our precision and recall were too low(less than 0.3) so We had to change my strategy and manually pick features which gave me precision and recall values over 0.3 . In this dataset We cannot use accuracy for evaluating my algorithm because there are few POI's and in dataset and the best evaluator are precision and recall. There were only 18 examples of

POIs in “real life”, but for various reasons, half of those are not present in this dataset.

Finally We picked the following features:
[**“fraction_from_poi_email”,”fraction_to_poi_email”,” shared_receipt_with_poi”**]

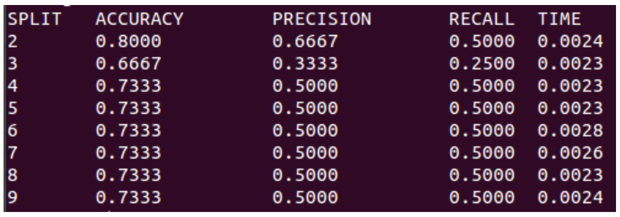
5.2 Algorithm selection and Tuning

Firstly We tried Naive Bayes, accuracy was lower than with Decision Tree(0.267 and 0.92 respectively). We made a conclusion that the feature set We used does not suit the distributional and interactive assumptions of Naive Bayes well.

We selected Decision Tree Algorithm for the POI identifier. It gave me accuracy before tuning parameter in range 0.69-0.83 and after tuning to 0.89-0.93.

No feature scaling was deployed, as it's not necessary when using a decision tree.

After selecting features and algorithm We manually tuned parameters **min_samples_split**.

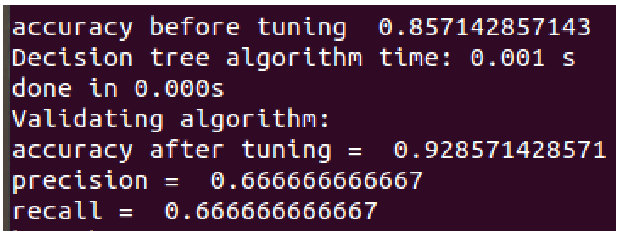


```
SPLIT   ACCURACY             PRECISION            RECALL   TIME
2       0.8000               0.6667               0.5000   0.0024
3       0.6667               0.3333               0.2500   0.0023
4       0.7333               0.5000               0.5000   0.0023
5       0.7333               0.5000               0.5000   0.0023
6       0.7333               0.5000               0.5000   0.0028
7       0.7333               0.5000               0.5000   0.0026
8       0.7333               0.5000               0.5000   0.0023
9       0.7333               0.5000               0.5000   0.0024
```

It turned out that the best value for min_split_value are 5 and 6.

5.3 Analysis Validation and Performance

This process was validated using 3-fold cross-validation, precision and recall scores. First We used accuracy to evaluate my algorithm. It was a mistake because in this case we have a class imbalance problem- the number of POIs is small compared to the total number of examples in the dataset. So We had to use precision and recall for these activities instead.
We was able to reach average value of **precision=0.667** and **recall=0.667**



```
accuracy before tuning  0.857142857143
Decision tree algorithm time: 0.001 s
done in 0.000s
Validating algorithm:
accuracy after tuning =  0.928571428571
precision =  0.666666666667
recall =  0.666666666667
```

6.RESULTS AND DISCUSSION

The precision can be interpreted as the likelihood that a person who is identified as a POI is actually a true POI; the fact that this is 0.67 means that using the identifier to flag POIs would result in 32% of the positive flags being false alarm. Recall measures how likely it is that identifier will flag a POI in the test set. 67% of the times it would catch the person and 33% of the time it wouldn't.

7.CONCLUSION AND FUTURE DIRECTION

These numbers are quite good but we still can improve the strategy. One of the possible paths to improvement is digging in to the emails data more. The email features in the started dataset were aggregated over all the messages for a given person. By digging in the starter dataset we aggregated over all the messages, it's possible that more detailed patterns(say, messages to/from a specific address, rather than just messages to/from any POI address, or the usage of specific vocabulary terms) might emerge. Since we live in a world in which more POI finance data might not be easy to find, the next realistic thing to try might be to extract more data from the emails.

ACKNOWLEDGEMENT

We thank Dr. Atul Gupta for getting us started, and helping us along the way.
We would along like to acknowledge CMU for providing the Enron Data Set.

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