Enron Summary Report

1. **Summarize for us the goal of this project and how machine learning is useful in trying to accomplish it. As part of your answer, give some background on the dataset and how it can be used to answer the project question. Were there any outliers in the data when you got it, and how did you handle those?**

In 2000, Enron was one of the largest companies in the United States. By 2002, it had collapsed into bankruptcy due to widespread corporate fraud. In the resulting Federal investigation, a significant amount of typically confidential information entered into the public record, including tens of thousands of emails and detailed financial data for top executives. The goal of this project is to create a prediction model to check whether an Enron employee is a "Person of Interest (POI)", i.e. whether an employee was involved in the fraud. By applying machine learning skills, I am trying to better a model which would serve for the goal for the project.

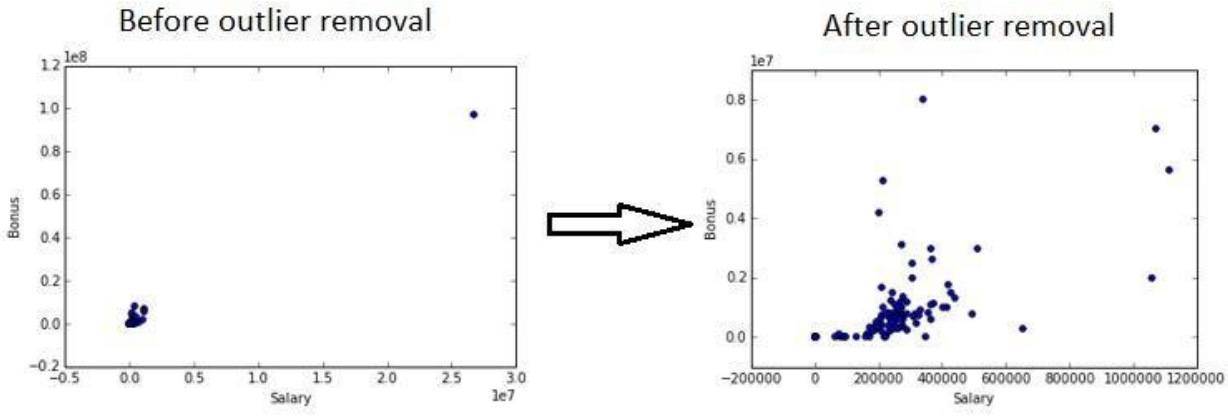
The data combines the Enron email and financial data into a dictionary, where each key-value pair in the dictionary corresponds to one person. The dictionary key is the person's name, and the value is another dictionary, which contains the names of all the features and their values for that person. The features in the data fall into three major types: 14 financial features, 6 email features and POI labels.

Financial_features: ['salary', 'deferral_payments', 'total_payments', 'loan_advances', 'bonus', 'restricted_stock_deferred', 'deferred_income', 'total_stock_value', 'expenses', 'exercised_stock_options', 'other', 'long_term_incentive', 'restricted_stock', 'director_fees'] (all units are in US dollars)

Email_features: ['to_messages', 'email_address', 'from_poi_to_this_person', 'from_messages', 'from_this_person_to_poi', 'shared_receipt_with_poi'] (units are generally number of emails messages; notable exception is 'email_address', which is a text string)

POI label: ['poi'] (boolean, represented as integer)

There was a total of 146 observations (i.e. employees) with each observation having 21 features (14 financial + 6 email + POI label). Out of the 146 observations, 18 employees have the POI label. This is relatively a small sample size for a prediction model which could present a challenge in the analysis. Making a scatterplot with the features, "salary" vs "bonus", gave out a outlier, very far away from the rest of the data as seen in the below figure.



A review of the financial information found that this outlier corresponds to the "TOTAL" line item in the financial information, so it was removed by deleting it immediately after loading the dataset.

Taking in analysis, with a percentile of values, to remove outliers is not something to be done with the data and the question in hand, because the particular interest of this project is to find those high values so as to investigate the person in question with whether that employee was involved in the fraud or not.

Reviewing the file, line by line, also showed an observation for ""THE TRAVEL AGENCY IN THE PARK". Since this does not correspond to an individual, it was also removed, leaving 144 individuals for the analysis.

2. **What features did you end up using in your POI identifier, and what selection process did you use to pick them? Did you have to do any scaling? Why or why not? As part of the assignment, you should attempt to engineer your own feature that does not come ready-made in the dataset -- explain what feature you tried to make, and the rationale behind it. (You do not necessarily have to use it in the final analysis, only engineer and test it.) In your feature selection step, if you used an algorithm like a decision tree, please also give the feature importances of the features that you use, and if you used an automated feature selection function like SelectKBest, please report the feature scores and reasons for your choice of parameter values.**

Next step in my analysis, was to look out for missing values, i.e NaN values for the entries in the column values missing. The table with each feature's percentage of values missing is shown below. If the percentage is too high, I might as well drop that feature since the high percentage NaN values feature may not be that helpful with its importance when the model is constructed as most of its values would be missing.

Then I created, three new features, two of these new features were calculated by finding the fraction of emails a person received (or sent) that involved a POI out of the total emails a person received (or sent). If a high percentage of an employee's emails involved a POI, it may be more likely that they are also a POI. I named these two features as: "sent_to_poi_percent" and "rec_from_poi_percent." The third feature I created determined the ratio of total payments to total stock value: "payments_to_stocks." This could contribute to find patterns between payments and stocks if there is an POI. I indicated the new created features in bold in the table.

Feature	**% NaN out of 144**
salary	35%
deferral_payments	74%
total_payments	15%
loan_advances	98%
bonus	44%

restricted_stock_deferred	88%
deferred_income	67%
total_stock_value	13%
expenses	35%
exercised_stock_options	30%
other	37%
long_term_incentive	55%
restricted_stock	24%
director_fees	89%
to_messages	40%
from_poi_to_this_person	40%
from_messages	40%
from_this_person_to_poi	40%
shared_receipt_with_poi	40%
sent_to_poi_percent	40%
rec_from_poi_percent	40%
payments_to_stocks	26%

After creating the new features, I selected the SelectKBest tool to rank my features by their predictive ability percentage.

Feature	% NaN out of 144	Importance (High to Low)
exercised_stock_options	30%	24.82
total_stock_value	13%	24.18
bonus	44%	20.79
salary	35%	18.29
sent_to_poi_percent	40%	16.41
deferred_income	67%	11.46
long_term_incentive	55%	9.92
restricted_stock	24%	9.21
total_payments	15%	8.77
shared_receipt_with_poi	40%	8.59
loan_advances	**98%**	**7.18**
expenses	35%	6.09
from_poi_to_this_person	40%	5.24
other	37%	4.19
rec_from_poi_percent	40%	3.13
from_this_person_to_poi	40%	2.38
director_fees	**89%**	**2.13**
to_messages	40%	1.65
payments_to_stocks	26%	0.63
deferral_payments	74%	0.22
from_messages	40%	0.17
restricted_stock_deferred	**88%**	**0.07**

The black ones are the features which I created. And the yellow ones are the features which had very high missing values % which I won't be using for developing the predictive model.

Next thing I did was to scale my features using MinMaxScaler. Algorithms that depend on the distance between data points (e.g. SVM) rely on feature scaling because the financial data can be orders of magnitude larger than the number of emails. Other algorithms, such as Decision Trees, do not require scaling since the features are divided into categories. Feature scaling does not adversely affect algorithms that do not require it, so I went ahead and applied scaling upfront.

I decided to use the top 8 features in my final POI classifier (rank 1 to 8 in the chart above). These features achieve solid performance based on metric evaluation (see section 3). I also considered the Bias-Variance dilemma in my feature selection. Even though the model has acceptable performance with as few as 3 features, I am a little concerned that only 3 features would over-simplify and lead to high bias. Also, only using the top 3 features would exclude any of the email features, which I believe should be a factor in classifying POIs. Alternatively, I did not want to include more features than necessary, or I would have issues with high variance and overfitting. Using 8 features is the right balance between selecting a model that passes the performance requirements and does not have too much bias or variance. It also maximizes the recall (see section 6).

3. What algorithm did you end up using? What other one(s) did you try? How did model performance differ between algorithms?

I applied several algorithms , with features selection with "GridSearchCV" to my dataset using different numbers of features and decided to use GaussianNB with the top 8 features. I applied an exhaustive approach to determine the best number of features and the best algorithm. The chart below reflects my analysis using precision and recall, with the green cells showing every scenario that had greater than 0.3 for both metrics.

Classifier:	**GaussianNB**		**DecisionTree**		**Kneighbors**		**RandomForest**		**AdaBoost**	
# of Features	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
2	0.46889	0.2675	0.22396	0.201	0.68929	0.193	0.30727	0.169	0.39952	0.2515
3	0.48581	0.351	0.3606	0.3835	0.63795	0.2555	0.59617	0.296	0.34211	0.299
4	0.50312	0.323	0.32189	0.333	0.65971	0.2685	0.50416	0.2425	0.31411	0.207
5	0.45558	0.3	0.29325	0.3365	0.64164	0.282	0.4644	0.225	0.27734	0.227
6	0.47723	0.351	0.28292	0.289	0.68675	0.2565	0.47776	0.188	0.33575	0.2545
7	0.46376	0.3615	0.28541	0.268	0.60926	0.2105	0.47301	0.1665	0.31565	0.238

8	0.4537	0.365	0.26786	0.255	0.68883	0.259	0.43296	0.155	0.31357	0.238
9	0.37697	0.311	0.27655	0.293	0.63878	0.168	0.39038	0.138	0.29742	0.225
10	0.35801	0.3095	0.33105	0.314	0.63878	0.168	0.42574	0.1505	0.35567	0.268
11	0.35949	0.3115	0.30016	0.285	0.63878	0.168	0.45633	0.1515	0.37814	0.2785
12	0.35378	0.3085	0.30451	0.287	0.63878	0.168	0.45789	0.1495	0.37977	0.2835
13	0.3562	0.296	0.33436	0.327	0.64636	0.191	0.44113	0.1405	0.39677	0.3075
14	0.34965	0.2965	0.33452	0.329	0.64636	0.191	0.45526	0.145	0.38526	0.298
15	0.31643	0.287	0.31844	0.31	0.64636	0.191	0.41571	0.127	0.38263	0.282

The GaussianNB and DecisionTree classifiers clearly performed better than the other models, at least with the default parameters. This was interesting to me because GaussianNB is one of the simplest machine learning algorithms, and it does not even have parameters to tune. I also attempted an SVC classifier, but it took too long to train so I abandoned that route.

The reason that I chose the GaussianNB classifier with 8 features is that GaussianNB consistently performed the best and 8 features gave the highest recall. I felt it was important to maximize the recall in this exercise (see section 6).

4) What does it mean to tune the parameters of an algorithm, and what can happen if you don't do this well? How did you tune the parameters of your particular algorithm? (Some algorithms don't have parameters that you need to tune--if this is the case for the one you picked, identify and briefly explain how you would have done it if you used, say, a decision tree classifier). [relevant rubric item: "tune the algorithm"]

Most machine learning algorithms have parameters that can be tuned to improve the performance of the model. Tuning requires a knowledge of the dataset and an understanding of how the algorithms operate, and it helps improve predictive ability by slightly adjusting how the algorithm finds the optimal model. For example, one of the parameters for the DecisionTree algorithm is min_samples_split. This parameter determines whether there are enough samples to continue to split the decision tree further. If min_samples_split is too low, the classifier has the potential to overfit on the training data.

My final classifier (GaussianNB) does not have any parameters. However, I applied parameter tuning to my DecisionTree classifier to see if I could improve its performance. I used GridSearchCV to iterate through several combinations of parameters and find the optimal settings. Based on that analysis, the best combination of parameters was a min_samples_split of 5 and criterion equal to entropy. While this did improve the accuracy from 0.82367 to 0.85127, the precision/recall performance still did not exceed the performance of the GaussianNB classifier.

5) What is validation, and what's a classic mistake you can make if you do it wrong? How did you validate your analysis? [relevant rubric item: "validation strategy"]

Validation in machine learning tests the accuracy of the predictive model. This is a crucial aspect of creating a good predictive model because I need to understand how well the model performs when applied to new data. A classic mistake when applying validation is using the entire dataset to train the algorithm. This can cause overfitting and there is no way to test how the model performs when applied to new data. So, the dataset should always be split into training and testing data.

In my analysis, I used the tester.py script that was provided with the project. This guaranteed that my algorithm will pass the required metrics and streamlines my efforts so that I can focus on feature and algorithm selection. The testing script generates training and testing data using StratifiedShuffleSplit with 1,000 folds, which is effective for a small sample size. The script also calculates several important metrics that are used to evaluate the performance of the model, including F1 score, precision, recall, and the underlying calculations.

6) Give at least 2 evaluation metrics, and your average performance for each of them. Explain an interpretation of your metrics that says something human-understandable about your algorithm's performance. [relevant rubric item: "usage of evaluation metrics"]

The main metrics that I considered when evaluating my model were precision and recall. Precision is the number of correctly-identified POIs (true positives) divided by the number of predicted POIs (true positives plus false positives). Recall is the number of correctly-identified POIs (true positives) divided by the number of actual POIs (true positives plus false negatives). Part of the requirements for completing this project was to achieve precision and recall above 0.3. My chart in section 3 clearly shows that precision and recall stayed above 0.3 consistently for my chosen algorithm and features.

One key point when applying my metric evaluation is that maximizing the recall is more relevant to this project, because getting a higher recall minimizes the false negatives. A false negative is when my model incorrectly does not label an individual as a POI, so low recall makes it more likely that POIs "escape" scrutiny. That's why in this particular scenario, a high recall is much important than a high precision. It is not as important to maximize precision, because false positives can still be found innocent after further inspection. In other words, maximizing recall will cast a wider net for potential POI.

Reflection

Completing this project taught me how to apply machine learning to a real-world example. I found success through ranking features and testing them with different supervised learning algorithms. Even though my model reached the required thresholds, there is still room for improvement. One area that I did not address was the huge library of emails. In a more advanced model, I could have parsed out the text in all these emails and tested for word patterns amongst POIs. This likely could increase both precision and recall. Also, it would be interesting to have a larger dataset of Enron employees, because 144 is only a small sample of all Enron employees. I look forward to applying my new knowledge to other areas to see what insights and predictive ability I can uncover.