Enron Submission Free-Response Questions and Answers

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? [relevant rubric items: “data exploration”, “outlier investigation”]

   The goal of this project is to choose a combination of features of former Enron employees and choose an appropriate machine learning algorithm to predict whether that person is considered a person of interest (POI) or not. This is considered a Supervised Classification problem as we are trying to predict the discrete outcome, which is binary (2 options only), and we are actually given a data set that contains the right “answers” (whether the person is actually a POI or not). The goal will be to get the most accurate predictions when we apply our ML algorithm to test this model. For example, if we correctly predicted all the POIs in the test data set we would get an accuracy of 1.0.

   This dataset is from Enron, which is an infamous American company known for its extensive fraud. The actual dataset itself consists of email metadata and financial data for created by about 150 employees of Enron (mostly senior management).

   I initially thought about using a strategy of removing the top 10% of values with the largest residual errors (as highlighted in the instructor videos). However, that strategy seemed appropriate for a regression problem where we are trying to arrive at a predicted quantitative value vs this problem which is a classification problem with only two results: Non-POI or POI.

   Using a more manual strategy of inspection, I found that there were actually just two outliers. ‘Total’ was definitely not a valid person which was found in the dataset after exploring all the employee names. The second invalid record was for a travel agency called ‘THE TRAVEL AGENCY IN THE PARK’. Most of the values for each field were invalid (‘NaN’) and thus this record was also removed. The final count of records in this relatively small dataset was 144.

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 doesn’t 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.) If you used an algorithm like a decision tree, please also give the feature importances of the features that you use. [relevant rubric items: “create new features”, “properly scale features”, “intelligently select feature”]

   I used ‘domain knowledge’ to select the features for the model. After watching the film “Enron: The Smartest Guys in the Room”, I became somewhat knowledgeable about the features found in a few of the people of interest such as Lou Pai, Jeff

Skilling, Ken Lay, and Andy Fastow. I noticed that Lou had a really large expense account; he was known to spend a lot of the company's money on corporate jet trips and strip clubs for example. Another thing that was frequently mentioned in the movie was that a lot of the POIs exercised a lot of options as they knew that the company's fortunes were bound to eventually turn around due to the fraudulent activities that were commonplace. So for the initial feature selection process, I chose actually 6 features which I hypothesized would give me a good starting model.

The new feature I generated was restricted_stock_ratio (restricted_stock/total_stock_value). I originally noticed that a lot of the POIs had a 1/1 ratio (more than 50%) and when doing more research on restricted stock I learned this was a popular form of compensation to executives due to its favorable tax consequences. In the end, I didn't need to add this model because my simpler model with only 3 features (salary','exercised_stock_options', 'bonus') was able to predict POIs accurately with just over 86 % accuracy.

In regards to feature scaling, since my K nearest neighbor's model used Euclidean distance to calculate the nearest neighbors, I thought feature scaling would indeed improve my model. However, after writing a function to calculate NaNs, I noticed that a large percentage of my data was NaN for the features I had chosen (salary, exercised_stock_options,bonus); the percentages of NaN respectively were (35%, 30%, 44%). Nonetheless, I tried an imputation strategy of using the median values to replace NaNs and then reran the model. I was shocked to see that accuracy, precision, and recall all went down when I used rescaled features. My hypothesis was that the imputation strategy could have affected the model too much since there were so many NaNs that were imputed with the median. Ultimately, I decided against using any scaled features.

3. What algorithm did you end up using? What other one(s) did you try? [relevant rubric item: "pick an algorithm"]

   I ended up using the k Nearest Neighbors (kNN) algorithm in a supervised classification context. I considered the more complicated DecisionTree and the RandomForest algorithms. On my first run, I actually got better results with k Nearest Neighbors and, from my perspective; it is also the simpler model to interpret as well.

   As I learned in an earlier Statistics course, it is always best to choose the parsimonious model when there are similar alternatives with similar results (in fact this case this simple model also performed better for accuracy, precision, and recall).

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"]

   Tuning the parameters of an algorithm means to pull some of the 'levers' to influence the results of the model. If you don't tune your parameters appropriately, you will end up using the defaults, which will likely not result in an optimized model. This means the accuracy, precision, recall or other performance measure is not as good as it could be because the model was not customized to the particular dataset's features (in this case features is not referring to the predictor variables).

In this case, I tuned the parameters manually by trying some different combinations as I figured it was simple enough without having to use more complicated methods such as GridSearchCV. The main parameter I played with was actually k itself. k refers to the number of surrounding nearest neighbors to look at when voting on the majority class. I found that the optimal number to get the accuracy, precision, and recall I wanted was k = 5. This means if my predicted data point was close to 3 POI and 2 non-POI (the 5 closest neighbors) it would be classified itself as POI because the majority rules. I also found that instead of giving a uniform weight to all neighbors, I decided to weigh the value of each neighbor based on how far away from the data point they were (weights= 'distance'). This means that neighbors that were further away are weighted less than closer points.

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 is a strategy to separate your data into training and testing dataset initially. This allows you to train your model on a training set and then test that model on an independent test dataset. This reduces the problem of over fitting your model to the dataset that you initially trained it on. If you only tested the model on your training dataset you would be shooting yourself in the foot because you would not know how well your model would perform on a new, unknown dataset. While validating on a test set, if you got much poorer results you would know that there is a chance you over fitted your model to the training dataset.

I validated my dataset with the help of the test_classifier () function that used the sklearn StratifiedShuffleSplit () function to do the splitting of the data into a training set and test set. The parameter for n_iter (represented by the folds variable) was 1000. That means the model is run 1000 different times and for each iteration a random test data set is used (this test dataset still comes from the original dataset and is usually different from previous test data sets).

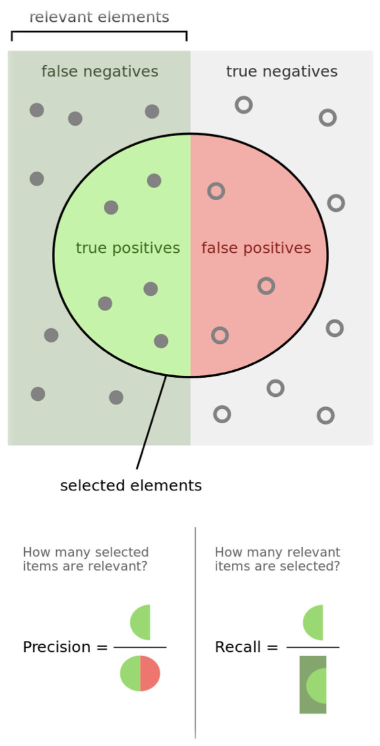
6. Give at least 2 evaluation metrics, and your average performance for each of them. Explain an interpretation of your metrics that says something human-understandable about your algorithm's performance. [relevant rubric item: "usage of evaluation metrics"]

Accuracy: Accuracy refers to the ratio of correct predictions out of the total predictions made. In this context, it means how many POIs the model was able to correctly predict. The average performance for the kNN model I tuned was 0.86969. This means nearly 87% of predictions the model made were correct.

Precision: Precision refers to the ratio of correct **positive** predictions made out of the total **positive** predictions made (Positive predictions means predicting that the employee is a POI). 1156 total positive predictions were made by the model on the test data and the amount of these positive predictions that was were correct was 731. This is why the precision of the model was just over 63%.

Recall: Recall is a more difficult thing to conceptualize for many (I have attached an image from Wikipedia below that should help). Recall refers to the ratio of correct **positive** predictions made out of the actual total that were indeed positive (correct **positive** predictions + incorrect false **negative** predictions). We are basically looking only at the actual POIs in the test data set and seeing what proportion of them were correctly identified. The model was able to achieve a recall of about 37%.

You can see that there is a tradeoff between precision and recall which needs to be balanced in all models depending on what is more important for the model. However, in cases such as this which contains a lot more of one class over another class (way more non-POI than POI), recall and precision are both better measures than accuracy. Just predicting that everyone is not a POI would get a pretty high accuracy due to the fact there are just a lot more non-POIs in the dataset. This is a very important takeaway I learned from this entire process; just because a model has a very high accuracy doesn't necessarily mean it is a great model.


relevant elements
false negatives
true negatives
true positives
false positives
selected elements
How many selected items are relevant?
How many relevant items are selected?
Precision =
Recall =