Enron Submission Free-Response Questions

A critical part of machine learning is making sense of your analysis process and communicating it to others. The questions below will help us understand your decision-making process and allow us to give feedback on your project. Please answer each question; your answers should be about 1-2 paragraphs per question. If you find yourself writing much more than that, take a step back and see if you can simplify your response!

When your evaluator looks at your responses, he or she will use a specific list of rubric items to assess your answers. Here is the link to that rubric: [[Link](https://www.google.com/url?q=https://review.udacity.com/%23%21/projects/3174288624/rubric&sa=D&ust=1499048292730000&usg=AFQjCNE66YlXRMP7OiPb6R3sW39ugPYcwg)] Each question has one or more specific rubric items associated with it, so before you submit an answer, take a look at that part of the rubric. If your response does not meet expectations for all rubric points, you will be asked to revise and resubmit your project. Make sure that your responses are detailed enough that the evaluator will be able to understand the steps you took and your thought processes as you went through the data analysis.

Once you’ve submitted your responses, your coach will take a look and may ask a few more focused follow-up questions on one or more of your answers.

We can’t wait to see what you’ve put together for this project!

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”]

Goal of this project is to predict persons of interest for the Enron scandal using Machine learning techniques. The given dataset has both financial and e-mail information of various people connected to Enron. Initial analysis of the data using Pandas and visual inspection showed couple of outliers. One is Total and the other one is THE TRAVEL AGENCY IN THE PARK. Since we are only focused on Persons of Interest, these two outliers should be removed.

I removed these two outliers from the dictionary.

1. 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.  [relevant rubric items: “create new features”, “intelligently select features”, “properly scale features”]

I created the following two new features and used both of them in the initial analysis -

ratio\_of\_messages\_received\_from\_poi – which is a ratio of number of messages received from poi to total no of messages received by the individual

Ratio\_of\_messages\_sent\_to\_poi - which is a ratio of a number of messages sent to poi to total number of messages sent out by the individual.

I thought about these features thinking that the ratio of communications with POIs to the overall communication a person does might be valuable for this analysis. My hunch proved correct and ration\_of\_meesges\_sent\_to\_poi was selected as one of the important feature by kbest.

For the initial analysis I have used most of the given features except the ones with too many missing values. I started the analysis with the following list.

From\_messages, from\_poi\_to\_this\_person, form\_this\_person\_to\_poi, shared\_receipt\_with\_poi, to\_messages, ratio\_of\_messages\_received\_from\_poi, ratio\_of\_message\_sent\_to\_poi, bonus,deferred\_income, exercised\_stock\_options, expenses, long\_term\_incentive, other, restricted\_stock, salary, total\_payments, total\_stock\_value

In the later steps, in an effort to fine tune, I have used skbest to select features Also I have used feature scaling to give equal weightage to both email features and financial features. A pipeline was used to scale the features, put them through selection process using skbest and create a classifier using decision tree.

Here is the feature ranking and importance

feature no. 1: ratio\_of\_messages\_sent\_to\_poi (0.60047554673)

feature no. 2: bonus (0.221674010171)

feature no. 3: total\_stock\_value (0.177850443099)

feature no. 4: salary (0.0)

feature no. 5: long\_term\_incentive (0.0)

feature no. 6: exercised\_stock\_options (0.0)

feature no. 7: deferred\_income (0.0)

1. What algorithm did you end up using? What other one(s) did you try? How did model performance differ between algorithms?  [relevant rubric item: “pick an algorithm”]

I ended up using Decision Tree. Both Naïve Bayes and SVM also had high accuracy in the initial analysis, when trained and tested using Train/Test split cross validation method. I explored NaiveBayes and Decision Tree further with feature scaling, feature selection and parameter tuning. Decision Tree gave better result at the end and I chose to go with Decision Tree as the final classifier.

1. 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? What parameters did you tune? (Some algorithms do not 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 for the model that was not your final choice or a different model that does utilize parameter tuning, e.g. a decision tree classifier).  [relevant rubric items: “discuss parameter tuning”, “tune the algorithm”]

Parameter turning means optimizing the parameters used in the classifier for the given data to improve prediction accuracy. I have used GridSearchCV function to tune the parameters for the Decision Tree classifier. If the parameters are not tuned properly, it will impact accuracy, precision and recall scores. The following parameters were tuned

parameters = {'kbest\_\_k': [1,2,3,4,5,6,7],

'DTC\_\_criterion': ['gini', 'entropy'],

'DTC\_\_min\_samples\_split': [2, 10, 20],

'DTC\_\_max\_depth': [None, 2, 5, 10],

'DTC\_\_min\_samples\_leaf': [1, 5, 10],

'DTC\_\_max\_leaf\_nodes': [None, 5, 10, 20

1. 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 items: “discuss validation”, “validation strategy”]

Validation is a way of verifying the accuracy of your trained classifier. In the initial analysis I have used train/test split method for validation. Since we have a very limited data, Train/Test is not most effective. For the final chosen classifier, I have used StratifiedShuffleSplit method for validation. If the proper validation techniques are not used, it will impact prediction accuracy.

1. Give at least two 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 following evaluation metrics were used:

Precision score for a class is the *number of true positives* (i.e. the number of items correctly labeled as belonging to the positive class) *divided by the total number of elements labeled as belonging to the positive class* (i.e. the sum of true positives and [false positives](https://en.wikipedia.org/wiki/Type_I_and_type_II_errors), which are items incorrectly labeled as belonging to the class).

Recall score Recall in this context is defined as the *number of true positives divided by the total number of elements that actually belong to the positive class* (i.e. the sum of true positives and [false negatives](https://en.wikipedia.org/wiki/Type_I_and_type_II_errors), which are items which were not labeled as belonging to the positive class but should have been).

Simply put

Precision is - How many selected items are relevant?

Recall is – How many relevant items are selected?