Project Report

Note : All the steps described below are shown in more detail in Enron Email POI Classification notebook . The file is named as Enron Email POI Classification.ipynb

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?

Background to the dataset

Enron was an American Organization based in Houston, Texas . Founded in 1985 , this ompany employed 20,000 employees towards the end in 2001 . In December , it was revealed that its reported financial condition was sustained by institutionalized, systematic, and creatively planned accounting fraud, known since as the Enron scandal.

This dataset basically contains information regarding the email sent by it's employees . There are certain people who are marked as Person of Interest (POI) . A person of interest (POI) is someone who was indicted for fraud, settled with the government, or testified in exchange for immunity. This dataset contains over 600,000 emails sent by 158 employees . It was released after the company declared bankruptcy . Detailed financial records of the said employees was also released as part of the dataset .

Goal of the project and How machine Learning can help

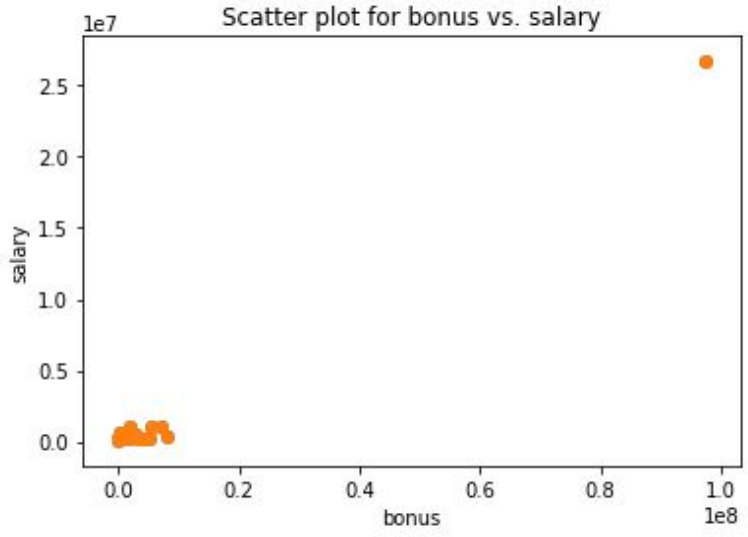
The goal of the project is to identify POI from the dataset using Predictive Machine Learning Models . Machine Learning allows us to build mathematical models that use the features present in a dataset to make future predictions when it encounter real world data .

The dataset contains financial information and emails of 146 people in our datatset . There are total 35 POI's out of which we have information of about 18 of them . The financial data is missing for the remaining POIs .

The dataset also suffers from class imbalance problem since there are only 18 POIs agains 128 non-POIs.

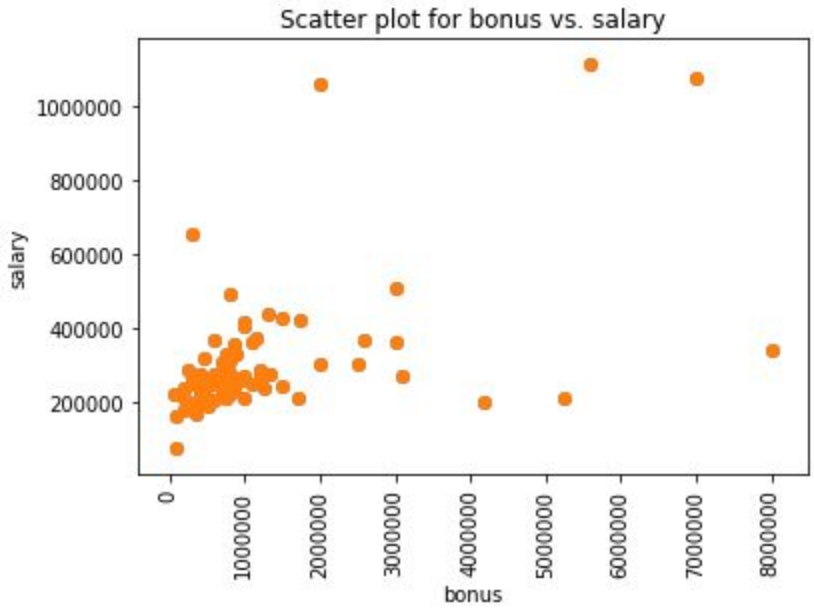
Outlier Detection

Below is the scatter plot for salary vs bonus .



The outlier has the name ‘TOTAL’ , suggesting that it is basically a sum of all the values . Since it does not make any sense for our analysis I have removed it .

After removing the above outlier, we get the following following plot .



After examining the outliers I came to the conclusion that we do not delete the the outliers since these are valid data points .

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.**

Dealing with NaN values .

In the initial dataset we had the following NaN values in each columns .

```
Count of NaNs in each column after cleaning

bonus                       64
deferral_payments          107
deferred_income             97
director_fees              129
exercised_stock_options     44
expenses                    51
from_messages               60
from_poi_to_this_person     60
from_this_person_to_poi     60
loan_advances              142
long_term_incentive         80
other                       53
poi                          0
restricted_stock            36
restricted_stock_deferred  128
salary                      51
shared_receipt_with_poi     60
to_messages                 60
total_payments              21
total_stock_value           20
dtype: int64
```

Let's get convert the above values into percentage :

```
Percentage of NaNs in each column

bonus                      43.835616
deferral_payments          73.287671
deferred_income            66.438356
director_fees              88.356164
exercised_stock_options    30.136986
expenses                   34.931507
from_messages              41.095890
from_poi_to_this_person    41.095890
from_this_person_to_poi    41.095890
loan_advances              97.260274
long_term_incentive        54.794521
other                      36.301370
poi                         0.000000
restricted_stock           24.657534
restricted_stock_deferred  87.671233
salary                     34.931507
shared_receipt_with_poi    41.095890
to_messages                41.095890
total_payments             14.383562
total_stock_value          13.698630
dtype: float64
```

One more thing to taken into consideration before deleting any column is that we need to check is that if the count of NaNs is not specific for POI or non-POI . If that is the case the the machine learning algorithm will use NaN to make prediction for POI or non-POI . So I have included the further analysis based on the label associated with each row .
This table shows % of NaNs in each column grouped by label :

	Not POI %	POI %
bonus	48.43750	11.111111
deferral_payments	73.43750	72.222222
deferred_income	70.31250	38.888889
director_fees	86.71875	100.000000
exercised_stock_options	29.68750	33.333333
expenses	39.84375	0.000000
from_messages	43.75000	22.222222
from_poi_to_this_person	43.75000	22.222222
from_this_person_to_poi	43.75000	22.222222
loan_advances	97.65625	94.444444
long_term_incentive	57.81250	33.333333
other	41.40625	0.000000
restricted_stock	27.34375	5.555556
restricted_stock_deferred	85.93750	100.000000
salary	39.06250	5.555556
shared_receipt_with_poi	43.75000	22.222222
to_messages	43.75000	22.222222
total_payments	16.40625	0.000000
total_stock_value	15.62500	0.000000

After observing the above table , I decided to remove columns which had more than 70% NaNs in them .

So I removed the following columns :

- Deferred Payments
- Deferred Income
- Director Fees
- Loan advances
- Restricted Stock Deferred

Next , I removed up those rows which had more than 70% NaN values .

Note : To be sure I did not delete any row with POI labels , I double checked among the rows that were to be deleted whether they were POI or not . After inspection I found out that they were all non-POI rows. So I deleted them .

After all this cleaning of NaN values, The % reduction in NaN values is as follows :

```
Reduction in percentage of NaNs in each column after cleaning

bonus                      40.625000
exercised_stock_options    34.090909
expenses                   37.254902
from_messages              43.333333
from_poi_to_this_person    43.333333
from_this_person_to_poi    43.333333
long_term_incentive        32.500000
other                      45.283019
poi                              NaN
restricted_stock           52.777778
salary                     50.980392
shared_receipt_with_poi    43.333333
to_messages                43.333333
total_payments             47.619048
total_stock_value          65.000000
dtype: float64
```

Feature Engineering

The following features were created from the existing dataset :

- **Fraction_from_poi** : fraction of from_messages received that were from POI
    - It is calculated as : (from_poi_to_this_person/from messages)
- **Fraction_to_poi :** fraction of to_messages sent to POI
    - It is calculated as : (from_poi_to_this_person/from messages)
- **Related to poi :** fraction of all messages (sent+received) that were related to POI
    - ((from_poi_to_this_person+from_this person to POI)/(to msgs+from messages))
- **Effective salary :** This is basically calculated as salary+bonus+long term incentive - expenses .

Feature Selection :

I used sklearn's selectKBest function to select the features with highest ranking . The ranking is as follows :

Ranking of new featrues:

```
Ranking of features is as follows
1 . Score for  exercised_stock_options  is  23.6138062092
2 . Score for  total_stock_value  is  16.7366284243
3 . Score for  Effective Salary  is  11.5559727014
4 . Score for  related_to_poi  is  7.72312955873
5 . Score for  total_payments  is  5.75730233923
6 . Score for  restricted_stock  is  5.34226430067
7 . Score for  long_term_incentive  is  5.07283618479
8 . Score for  shared_receipt_with_poi  is  4.87403011599
9 . Score for  fraction_from_poi  is  3.11963598574
10 . Score for  from_poi_to_this_person  is  2.58082108539
11 . Score for  fraction_to_poi  is  1.99020062202
12 . Score for  other  is  1.59257036438
13 . Score for  from_this_person_to_poi  is  1.15629869907
14 . Score for  from_messages  is  0.497759385305
15 . Score for  expenses  is  0.496738048357
16 . Score for  to_messages  is  0.312817105062
```

As you can see clearly , the new features show up in the ranking (Effective salary and related_to_poi)

I decided to make 3 sets of features , each containing Top 5 , Top 7 and Top 10 features from the above ranking .

After performing analysis with the above 3 sets using different machine learning algorithms, I decide to use the following 5 features which gave the most optimum results :

- **Exercised Stock Options**
- **Total Stock values**
- **Effective Salary**
- **Related to POI**
- **Total Payments**
- **Restricted Stock**
- **Long term incentive**

Note : The above mentioned Analysis is shown in detail in the notebook .

[**Changes suggested by reviewer**]

Old set of features

I also ranked the old set of features :

```
Ranking of features is as follows
1 . Score for  exercised_stock_options  is  23.6138062092
2 . Score for  total_stock_value  is  16.7366284243
3 . Score for  bonus  is  9.73938229385
4 . Score for  salary  is  7.99996454308
5 . Score for  total_payments  is  5.75730233923
6 . Score for  restricted_stock  is  5.34226430067
7 . Score for  long_term_incentive  is  5.07283618479
8 . Score for  shared_receipt_with_poi  is  4.87403011599
9 . Score for  from_poi_to_this_person  is  2.58082108539
10 . Score for  other  is  1.59257036438
11 . Score for  from_this_person_to_poi  is  1.15629869907
12 . Score for  from_messages  is  0.497759385305
13 . Score for  expenses  is  0.496738048357
14 . Score for  to_messages  is  0.312817105062
```

I also saved the top 7 features from the old dataset before feature engineering :

- Exercised stock options
- Total Stock value
- Bonus
- Salary
- Total Payments
- Restricted Stock
- Long term incentive

Note: The comparison with the old features is done at the end of the notebook . The old set of features gave worse results than the new features .

Comparison of classifier on old and new dataset .

After performing parameter tuning and stratified cross-validation on old and new set of features , I trained different models of Logistic Regression on both set of features and compared the results.

Metric	**New Features**	**Old Features**
Accuracy	79.158%	70.85%
Precision	37.668%	28.465%
Recall	38.25%	49.5%
F1 score	37.956%	36.145%
F2 score	38.132%	43.126%

As you can see clearly, the new set of features perform better than the old set of features . Additional analysis can be viewed in the notebook .

Feature Scaling

I used sklearn's Standard Scalar function to scale the feature . This was added as a step in the machine learning pipeline . The main idea behind feature scaling is to ensure that all features are to be treated equally regardless of the values that they contain, i.e. one feature should not affect the other feature just because the former one had larger values , etc. For more on Standard Scalar function check this link .

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

I tried various machine learning algortihms and compared their accuracies, recall and precision :

```
Using Top 7 fetaures
```

Classifier	Accuracy	Precision	Recall
KNN	0.166666666667	0.0666666666667	0.861111111111
Decision Tree	0.419312169312	0.466666666667	0.805555555556
SVM_rbf	0.235338345865	0.666666666667	0.648148148148
Gaussian Naive Bayes	0.361111111111	0.266666666667	0.833333333333
SVM_linear	0.323232323232	0.6	0.768518518519
Logistic Regrssion	0.308913308913	0.666666666667	0.740740740741
SVM_sigmoid	0.224937343358	0.733333333333	0.611111111111
Random Forest	0.0833333333333	0.0666666666667	0.833333333333

Now out of the above algorithms I decided to select SVM with sigmoid kernel , Logistic Regression and Decision trees for parameter tuning .

Note : Random Forest was not chosen because grid search over Random Forest was taking a lot of time and I did not have the necessary computing resources to do it quickly .

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 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)

Most of the machine learning algorithms have different parameter that control it's performance and are needed to be tuned according the data . This requires running the algorithms multiple times using different sets of parameter and finally selecting the one with the best performance . This also ensures that our algorithm do not overfit on the training data .

I have used sklearn's GridSearchCV to perfrom parameter tuning of the selected machine learning algorithm . Check out this link for more info .
I also used startified train/test split to perfrom cross validation over the dataset . Check out this link for more info .

The features tuned for Logistic Regression were

- Tolerance : [1.0,0.1,0.01,0.001]
- C (Inverse of regularization Stregth) : [0.001, 0.01, 0.1, 1.0, 10.0]
- Solver : ['newton-cg', 'lbfgs', 'liblinear', 'sag']

The features tuned for SVM with sigmoid kernel were

- Tolerance : [1.0,0.1,0.01,0.001]
- C (Inverse of regularization Stregth) : [0.01, 0.1, 1.0, 10.0]
- Gamma (Kernel Coefficient) : [1,0.5,0.33,0.25,0.2]

The features tuned for Decision Tree were min_samples_split, max depth and max_leaf_nodes .

- Min Sample Split : [2 , 7 , 12 , 17]
- Max depth : [1 , 3 , 5 , 7 , 9]
- Max leaf nodes : [50 , 70 , 90]

Also note that class-weight was set to 'balanced' to account for class imbalance and random state was set to 0 for all the classifiers .

Note : The performance metric chosen to compare algorithms was F1 score with average parameter set to 'weighted' to account for class imbalance **.** This choice will be explained in the next section . You can check about sklearn's implementation of F1 score on this link .

The performance of the three algorithms after parameter tuning is as follows :

Classifier	F1 score
SVM with sigmoid kernel	0.658785332315
Logistic Regression	0.769213139801
Decision Tree	0.534759358289

The final algorithm chosen was Logistic Regression with the following configuration :
LogisticRegression(C=0.001, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=500,
multi_class='ovr', n_jobs=1, penalty='l2', random_state=0,
solver='sag', tol=0.01, verbose=0, warm_start=False))])

5. What is validation, and what's a classic mistake you can make if you do it wrong? How did you validate your analysis?

Validation is basically a measure to check how well our model performs before using it on real world data . It can also be used to check if our model does not overfit over the training dataset .

Generally , we use accuracy as a measure to check how well our algorithms performs . Since our data suffers from class imbalance problem , i.e. out of the 146 people only 18 are POI . So even if we marked all points as non-POI , we would get an accuracy of 128/146 , i.e. approx 87% . To rectify this error , we use precision , recall , F1 score , F2 score and area under ROC curve which are explained below :

- **Precision :** If our algorithm identifies a person as POI, the probability that the person is actually a POI
- **Recall :** Probability of identifying a POI , given that the person is actually a POI.
- **F1 score :** 2.0 * true_positives/(2*true_positives + false_positives+false_negatives)
- **F2 score :** (1+2.0*2.0) * precision*recall/(4*precision + recall)

The file tester.py is used to analyse the performance of the final model . It uses 1000 randomized stratified splits of our dataset to evaluate our model and returns the accuracy,precision, recall, F1 score and F2 score averaged over the 1000 splits . The tester.py file uses Stratified split to perform splits over the dataset . When dealing with small imbalanced datasets, it is possible that some folds contain almost none instances of the minority class because of class imbalance . The idea behind stratification is to keep the percentage of the target class as close as possible to the one we have in the complete dataset.

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.

I have used precision and recall as the final measure to evaluate the performance of the final model .
The final Logistic Regression model reported the following results :

- **Precision of 37 .668% :** If our algorithm predicts that a person is POI, then there is 34.168% chance that he/she is actually a POI .
- **Recall of 38.25% :** There is 49.15% chance of identifying a person as POI, given that that person is actually a POI .

Our final model reported the final results over the different evaluation metrics :

Metric	**Value**
Accuracy	79.158%
Precision	37.668%
Recall	38.25%
F1 score	37.956%

F2 score	38.132%