Predicting Building Permit Issuance Times

Project Report by

Aparna Shastry

Orange County,
California, USA

Content

1. Introduction

A building permit is an official approval document issued by a governmental agency that allows you or your contractor to proceed with a construction or remodeling project on one's property. For more details click here. Each city or county has its own office related to buildings, that can do multiple functions like issuing permits, inspecting buildings to enforce safety measures, modifying rules to accommodate needs of the growing population etc. The delays in permit issuance pose serious problems to construction industries and later on real estate agencies.Read this Trulia study and Vancouver city article. We are set out to conduct an analysis and modeling of certain data related building permits.

1.1 Possible Clients and the benefits

Most significant outcome of this study is a tool to have a better idea on within which window a certain building permit is expected to be issued. Thus this project can benefit builders, planners and real estate industry. Planners can have reduced uncertainty and more concrete dates for several phases of their construction projects, builders can accordingly streamline their various constructions and finally real estate industry can keep up better with the demand, due to reduced delays in projects.

1.2 Scope of this Project

Primary objective of this Data Science Project is design a machine learning model that learns using historical building permit data and predicts the time delay in days between permit application and permit issuance. Here, as an example, it is done for the data set obtained for the city of San Francisco, California, USA. The process is similar for other cities, although there might be slight differences in the attributes of data. For the city of San Francisco, permit issuing is taken care by Permit Services wing of Department of Building Inspection (henceforth called DBI). Since it is not possible to accurately predict the delay in resolution of days, the problem is limited to predicting if a permit will be issued in a week, or in 3 months or beyond 3 months.

Apart from this, a few insights are drawn from the data to answer a few questions that might interest the applicants, or those who want to apply.

2. Data Description / Data Wrangling

2.1 Data retrieval

Data used to get the results explained in next sections is available in San Francisco city open data portal. It is updated every Saturday.

Step by step process to download:

- Go to the link: SF data portal.

- Click on Filter and "Add a Filter Condition". A drop down menu appears.
- Select, "Filed Date" and "is after".
- Enter date as 12/31/2012, because I wanted to do analysis of last 4-5 years. I think most recent data is important in matters such as this, the city council policies could change, there might be new rules, new employers to expedite process etc. Old data may not be too useful in modeling.

CSV format is chosen because it is less than 100MB size and easy to load into notebook. There are other methods like downloading json, or using socrata. This is found to be more reliable and less dependent on any extra libraries.

Date of download for this analysis: The file as of Feb 25, 2018 (Sunday) has been downloaded and kept locally for easy access. Size is about 75MB. The results of this analysis can be reproduced only if one more filter is used in the second step above, to select “Filed Date” “is before” and put Feb 26th, 2018.

2.2 Data Attributes

The data downloaded for 5+ years has close to 198,900 records and 43 columns. Here is the table containing the column names.

Sl No	Column name	Description	Number of unique values In case of categories, Also mention if < 100 non-null entries
1	Permit Number	Number assigned while filing	198900
2	Permit Type	Type of the permit represented numerically.	8
3	Permit Type Definition	Description of the Permit type, for example new construction, alterations	8
4	Permit Creation Date	Date on which permit created, later than or same as filing date	N.A.
5	Block	Related to address	4896
6	Lot	Related to address	1055
7	Street Number	Related to address	5099

8	Street Number Suffix	Related to address	18
9	Street Name	Related to address	1704
10	Street Name Suffix	Related to address	21
11	Unit	Unit of a building	660
12	Unit suffix	Suffix if any, for the unit	164
13	Description	Details about purpose of the permit. Example: reroofing, bathroom renovation	134272
14	Current Status	Current status of the permit application. This can have “filed”, “issued”,”completed”, and also many more, like “withdrawn”, “plancheck”, “cancelled”	14
15	Current Status Date	Date at which current status was entered	N.A
16	Filed Date	Filed date for the permit	N.A
17	Issued Date	Issued date for the permit	N.A
18	Completed Date	The date on which project was completed, applicable if Current Status = “completed”	N.A
19	First Construction Document Date	Date on which construction was documented	N.A
20	Structural Notification	Notification to meet some legal need, given or not	1 (it is either Y or blank)
21	Number of Existing Stories	Number of existing stories in the building. Not applicable for certain permit types	64
22	Number of Proposed Stories	Number of proposed stories for the construction/alteration	64

23	Voluntary Soft-Story Retrofit	Soft story to meet earth quake regulations	1 (it is either Y or blank) 35 Y only.
24	Fire Only Permit	Fire hazard prevention related permit	1 (it is either Y or blank)
25	Permit Expiration Date	Expiration date related to issued permit.	N.A
26	Estimated Cost	Initial estimation of the cost of the project	N.A
27	Revised Cost	Revised estimation of the cost of the project	N.A
28	Existing Use	Existing use of the building	93
29	Existing Units	Existing number of units	348
30	Proposed Use	Proposed use of the building	94
31	Proposed Units	Proposed number of units	368
32	Plansets	Plan set type for the construction.	8
33	TIDF Compliance	TIDF compliant or not, this is a new legal requirement	2 types, 2 non-null entries only
34	Existing Construction Type	Construction type, existing,as categories represented numerically	5
35	Existing Construction Type Description	Description of the above, for example, wood or other construction types	5
36	Proposed Construction Type	Construction type, proposed, as categories represented numerically	5
37	Proposed Construction Type Description	Description of the above	5

38	Site Permit	Permit for site	1, Y or blank
39	Supervisor District	Supervisor District to which the building location belongs to	11
40	Neighborhoods - Analysis Boundaries	Neighborhood to which the building location belongs to	41
41	Zipcode	Zipcode of building address	27
42	Location	Location in latitude, longitude pair.	57604
43	Record ID	Some ID, not useful for this	As many as permit numbers

As obvious from the table, not all 43 attributes are useful for learning from the data. This leaves us with a lot of scope for data munging.

2.3 Cleaning up

Columns to Retain: A few columns have numeric and text versions both. Only numerics were retained. Location information is in many columns, like Block, lot, street number, name, unit, Zipcode, neighborhood, supervisor district and Location. Location is numerical and more precise. Hence retained only Location. Permit Number and Record ID are not useful to analysis and prediction, so dropped. Permit Creation date, current status date, expiry date, First construction document date are irrelevant to the problem. TIDF Compliance, Voluntary soft-story retrofit suffer from lack of non-null entries, not even 100. Hence dropped. Estimated Cost is not necessary, as there is Revised cost, which is more meaningful and recent.
We are left with the following subset to do the EDA:

1. Permit Type
2. Permit Type Definition (Duplicate, but retained for meaning)
3. Plansets
4. Fire Only Permit
5. Revised Cost
6. Current Status
7. Filed Date
8. Issued Date
9. Structural Notification

10. Number of Existing Stories
11. Number of proposed Stories
12. Existing use
13. Proposed Use
14. Existing Construction Type
15. Proposed Construction Type
16. Site permit
17. Location

Rows to Retain:

a) Current Status had 14 types, of which withdrawn, cancelled and disapproved status and not having issue dates are not relevant for further study. Hence rows corresponding to these records are dropped. This was about 2k in total. After doing this Current Status column is eliminated.
b) Records corresponding to no location also had to be dropped, as it made no sense in the next stages.

Cleaning the NaNs:

a) Fire Only Permit, Site Permit and Structural Notification had only Y and blank entries. Blanks are interpreted as N, and replaced with N.
b) Revised cost NaNs were filled with 0's initially and at EDA stage all zeros are filled with 10^(-5) to avoid underflow while taking logarithm.
c) Blanks in existing use and proposed use are filled with strings 'Unknown'
d) All other NaN are left as they are, because it means "Not applicable" and the categories will be handled as such by the models.

Invalid weekdays:

The DBI is open only from Monday to Friday. Saturday, Sundays are replaced by the nearer weekday to avoid anomalies in EDA.

2.4 Other potential Data set

The process followed in this project can be generalized with minor modifications, for any city's building permit data, provided that it has at least permit filing date and issue date attributes. It is not always guaranteed that both will be there in the database. For example, Los Angeles city data or Chicago did not have application filing date.
Another dataset that has similar attributes to that of SFO is New York city building permit data. This can be used for studying and coming up with model for permit issue delays.

3. Exploratory Data Analysis (EDA)

The project notebook BuildingPermitSFO.ipynb explains all the details of exploratory data analysis. We will highlight some key findings here, with assumptions made.

3.1 Assumptions made on "time taken" variable:

Firstly, the main variable of interest, *"time_taken"-that is the time difference between issue date and filed date in number of days,* revealed some interesting insights. As some of the permits were not assigned during the download time, we had to do some approximations for the EDA and inferential statistics to work more realistic. Without doing any approximations, the time taken had the following statistics: Note that, the count doesn't include rows without issue dates

Count	183960
Mean	26.05
Std	91.06
Min	0
50%	0
75%	6
Max	1740

1. We had the option of dropping the rows with no issue date, or put a hypothetical date. Dropping would introduce bias and make the mean wait time appear smaller than it is. Not only mean, the median, 75% percentile and the max wait time also be smaller number than it would be compared to assuming an issue date at least as late as the download date. Hence issue date was fixed at download date. This imputation was done in EDA part, after looking at the difference it would make.
2. We dropped the records corresponding to file date after September 30th 2017, so that whatever records with hypothetical issue dates had surely wait time of at least 150 days. This was a good approximation, looking at the outliers of the data. Later on while modeling, this will be brought up again.

The modified statistics after these two approximations:

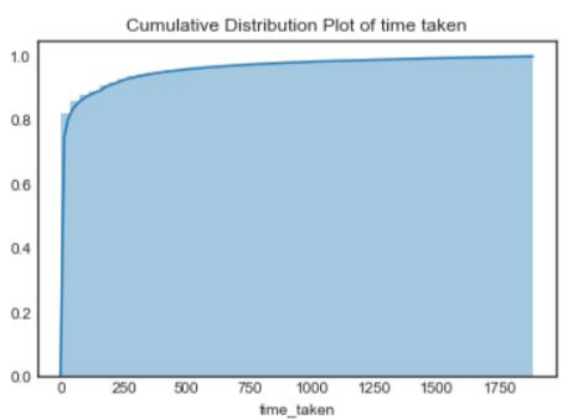
Count	180811
Mean	66.20
Std	217.54
Min	0
50%	0
75%	13
Max	1880

Now the problem became slightly more interesting with at least 75 percentile having a value of 13. The following table gives a better split on the percentage permits issued with dropping NaTs and without dropping NaT's, records for file dates Jan 2013 - Sept 2017:

```
Number of records: 170832 for first column and 180811 for second column
```

	Percentage with dropping	Percentage with hypothetical issue date
same day	62.21	58.77
less than 15 days	80.74	76.29
less than 3 months	91.97	86.90
less than 6 months	95.19	90.61
less than a year	98.26	94.64

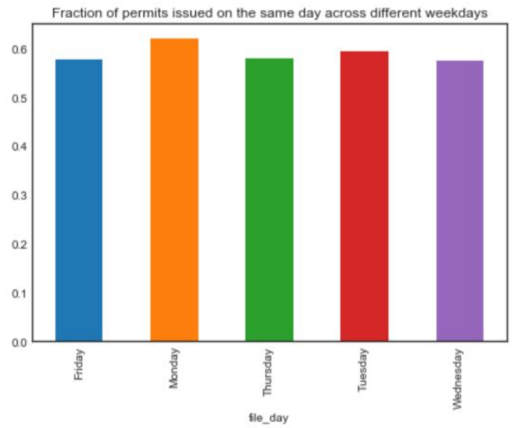
This is the cumulative distribution function of time_taken variable, after filling NaT in issue dates and taking the difference

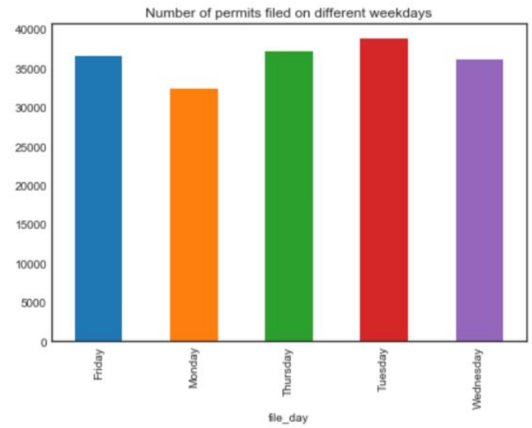


3.2 What is the best day of the week to visit DBI?

General belief is that Wednesday being the middle of the week is least crowded. Is that true?

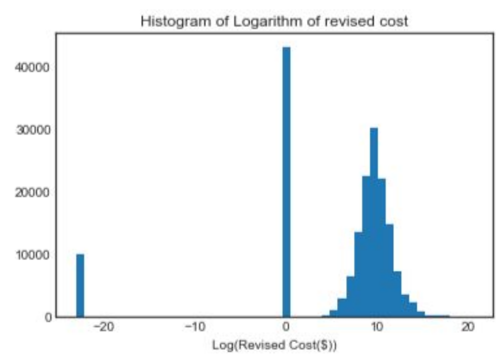
It is found that Monday is the least crowded day and also on Mondays mean wait times are lower than other days, and also the probability of permits getting processed same day is highest.

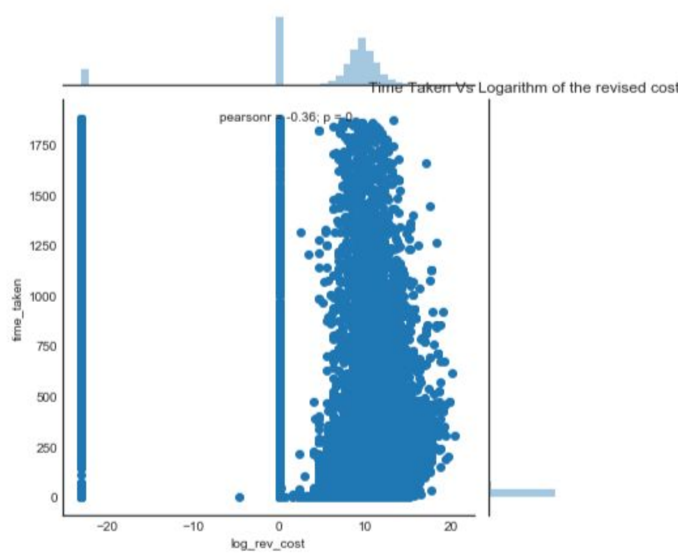




3.3 How does the histogram of Revised Cost look? How is it related to "time_taken"?

The plain scatter plot of Revised cost is rather messy. Hence we took logarithm. Many applicants do not prefer to reveal the cost. There are about 28-29% entries which are less than 10$. This can not be accident. The following plots clearly show it: First one is histogram of logarithm of revised cost, second is scatter plot against time_taken.





It is also found that when revised cost is put as 0 or NaN, except for permit type OTC alterations, none of them get issued the same day, and the minimum delay is around 5 months for all except demolitions, even that has minimum delay of 39 days. **<u>It is recommended to put a realistic number in revised cost field of the application.</u>**

3.4 How does the time taken vary across permit types?

This is the descriptive statistics table for time taken Vs permit types. Notice that the plain new construction applications take minimum 2 months, although they are very small portion of the total applications. OTC alterations permits dominate with more than 80% representation and as the name OTC (Over the counter) suggests, they are supposed to be issued the same day. But some are not!

perm_typ_def	count	mean	std	min	25%	50%	75%	max
new construction	301.0	570.810631	344.639562	60.0	329.00	460.0	762.00	1745.0
new construction wood frame	873.0	507.321879	380.214589	2.0	221.00	409.0	763.00	1837.0
demolitions	516.0	463.164729	387.444375	0.0	159.00	368.0	706.50	1824.0
additions alterations or repairs	12597.0	345.122728	329.004391	0.0	135.00	240.0	436.00	1875.0
wall or painted sign	433.0	253.092379	439.792013	0.0	3.00	30.0	231.00	1859.0
grade or quarry or fill or excavate	88.0	203.784091	387.183833	0.0	44.75	81.0	156.25	1803.0
sign - erect	2587.0	153.627754	334.840111	0.0	2.00	15.0	126.00	1878.0
otc alterations permit	163416.0	38.200904	176.576709	0.0	0.00	0.0	5.00	1880.0

These are the ones that matter the most for modeling. Rest can be referred to in notebook.

4. Inferential Statistics

A few statistical tests were conducted to check some of the assumptions/(hypothetical) claims and below is a summary. Details are available in the Inferential Statistics Report.

4.1. Is the DBI's (hypothetical) claim that on an average 65% of the applicants receive the permits same day true?

There is no sufficient statistical evidence to believe the DBI's claim that on an average it processes 65% of the permit applications the same day. A one sample population proportion test with a significance level of 0.01, on a randomly drawn sample of size 7500 records resulted in alternate hypothesis to be accepted in place of null (default) hypothesis.

1.a What is the mean wait time observed? Give the 95% confidence interval.

A randomly drawn sample of size 7500 records revealed that one can expect DBI to process 58.83% applications the same day, with 95% confidence being [57.71, 59.94]

4.2. Is there any difference in mean wait times of fire only permit or non fire only permits? Is this statistically significant?

There is enough statistical evidence to believe that average wait times for fire only permit and the normal permits are not the same. A 2 sample z-test for mean wait times for a significance level 0.01 on sample sizes of 700+ (fire only), 6700+ (not fire only) revealed statistically significance results to believe that mean wait times are different.

4.3. Was there a scope to conduct ANOVA test to compare statistics across various populations like mean time across weekdays or permit types?

We could not conduct statistical tests to compare the average wait times across various permit types because conditions required for ANOVA test were not satisfied

5. Modeling and Predicting

5.01 Machine Learning Problem in the context of Building business:

We defined the problem as classifying time taken variable into one of the three classes using the independent variables that influence it. There are several categories of permits/permit applicants. Some of them will be interested to know if permit will be issued the same day, some will be interested to know if it will be within a week, or within 2 weeks or within 3 months or beyond 3 months. Recall that new building permits take minimum 2 months. Hence the binary classification of within a week or after a week, or within 2 weeks or after 2 weeks, is not of any value to this category, where in fact stakes are very high.

5.02 Target and Predictor Variables

Let us call our target variable as y and define,
y = 0, if time_taken < 8 days
= 1, if time_taken > 7 days, < 92 days
= 2 else

Predictors are,

1. Revised Cost
2. Latitude
3. Longitude
4. Permit Type
5. Plansets

6. Fire Only Permit
7. Site Permit
8. Structural Notification
9. Existing Use
10. Proposed Use
11. Existing Construction Type
12. Proposed Construction Type
13. Existing number of stories
14. Proposed number of stories
15. File day (Day of the week extracted from file date)
16. File month (Month in which application was filed)

Out of 43 columns in the data downloaded, we are left with 16 useful features! Welcome to the real data science world!

5.03: Train/Dev/Test set split:

There were 180000+ clean records, which is quite a lot. This was split as Train: Dev: Test set in the ratio 60:20:20. Further the train set was used in K-fold cross validation to tune hyperparameters.

5.04: Metrics:

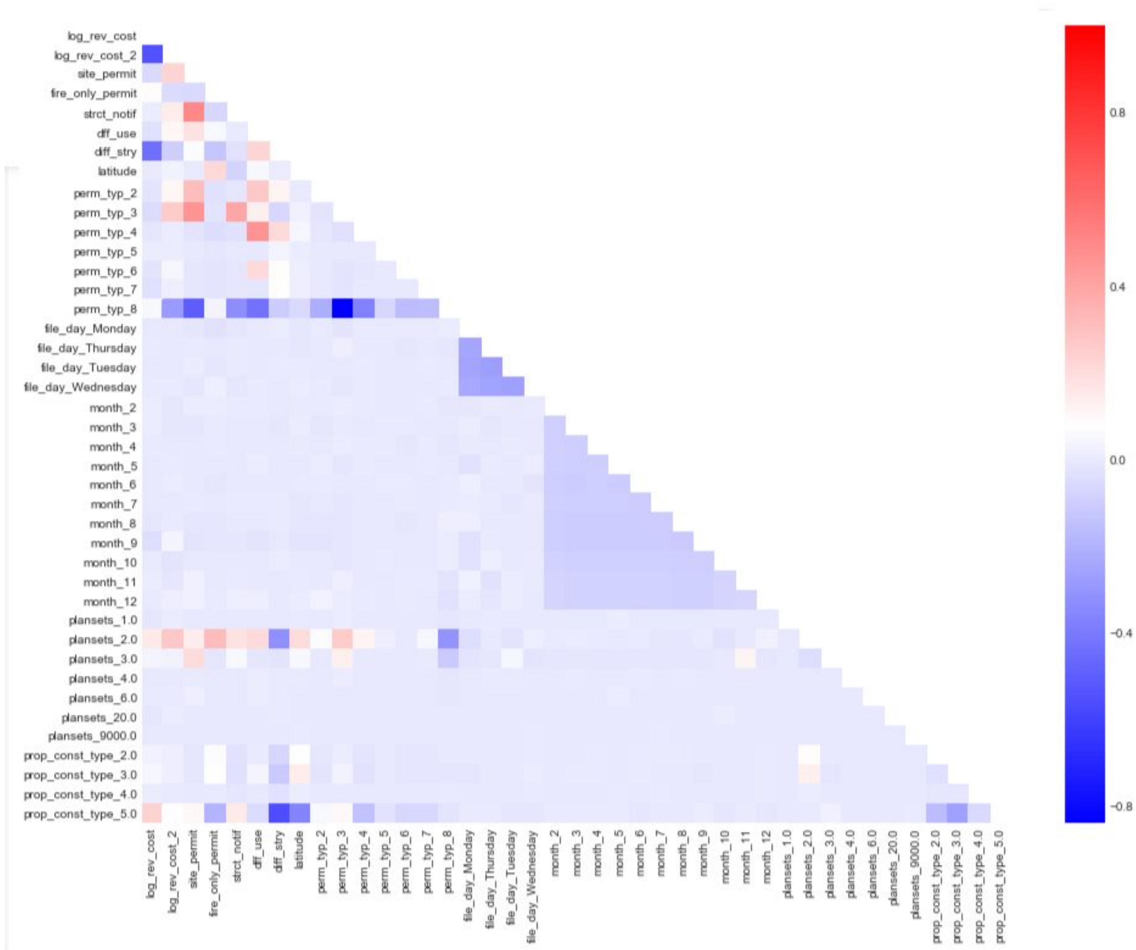
Before diving into models, a note on metrics used:

To know which is a better classifier, Area under ROC curve for development set were compared. But since we did not prefer one class over the other, we also looked at overall accuracy numbers to see if improvement in AUC is of any value to the problem at hand.

5.05: Feature Engineering:

a) Some predictors like Existing use and proposed use have too many categories to be really useful. Also, it is likely that many of them are equal and hence correlated, because as we saw, most permit types are alteration permits. Instead of dealing with numerous categorical variables, we chose to generate 2 new predictors, diff_use = existing_use != proposed_use, and diff_story = existing_use != proposed_story
b) Log of revised cost was not correlated to time_taken by a great extent. Hence tried to take square and cube of log of revised cost and these became 2 more features. These are all quantitative variables.
c) Week day of the filing and month of filing were not explicitly in data set, they were extracted from the filing date.
d) Location was opened up into Latitude and Longitude. These are numeric (quantitative) variables

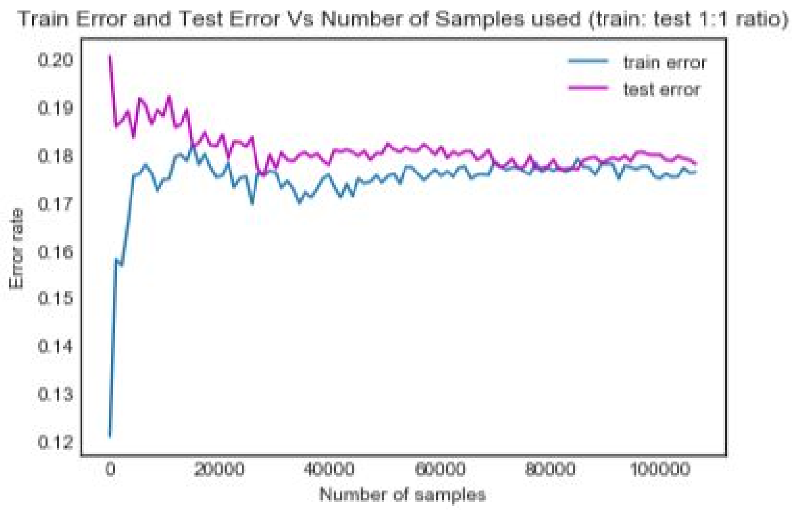
5.06: One hot encoding: One hot encoding was done for all categorical predictor variables, before feeding it to Logistic Regression model. The correlation was examined and some redundant ones were dropped. This is the heatmap after dropping redundant categories.



From the above correlation heatmap, it is observed that predictors do not suffer from multicollinearity. There are 41 predictors.

5.07: Checking for bias in Data set

To examine the bias in the samples, a logistic regression model was trained and tested with varying number of training samples. The training samples were shuffled to introduce random ordering. Number of training samples increased from a small number like total samples / 100, in steps of total samples / 100. Very soon, the train and development sample error curves met and reached steady state. This shows that there’s bias. One way to overcome is by adding more features, or creating/engineering more features from the existing. Already explained in section 5.05

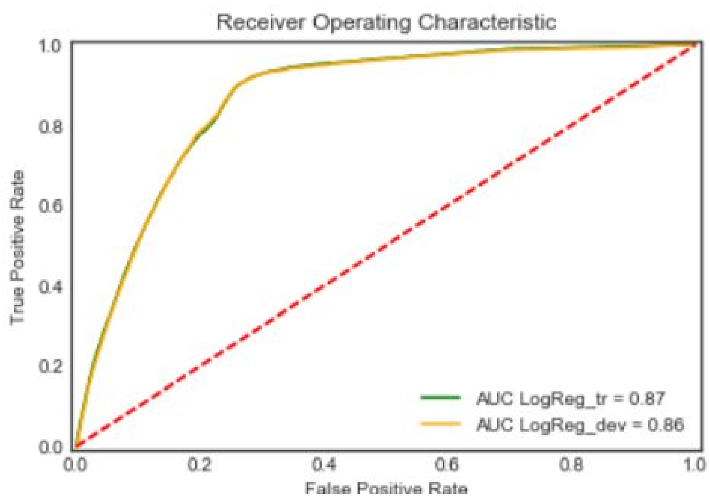


Now let us look at results of fitting and predicting the class y using a few well known machine learning models.

5.1 Logistic Regression Results:

parameters = {"C":[10,1000,100000]}

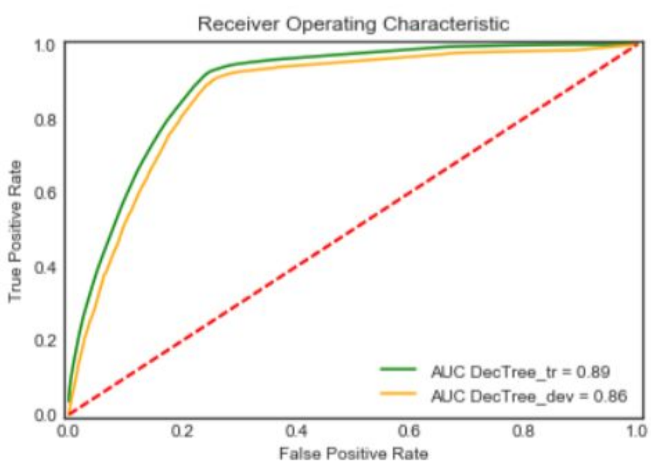
```
BEST {'C': 1000} 0.8049459986855289
############# based on standard predict ################
Accuracy on training data: 82.20%
Accuracy on test data:     82.02%
confusion_matrix on dev data
[[24584  1124    16]
 [ 3330  1691   413]
 [ 1047   517  3127]]
classification report on dev data
             precision    recall  f1-score   support

          0       0.85      0.96      0.90     25724
          1       0.51      0.31      0.39      5434
          2       0.88      0.67      0.76      4691

avg / total       0.80      0.82      0.80     35849

########################################################
Wall time: 48.3 s
```



5.2 Decision Tree Classifier Results

parameters = {"max_depth": [6,8,12,14], 'min_samples_leaf': [1,2,4,6]}

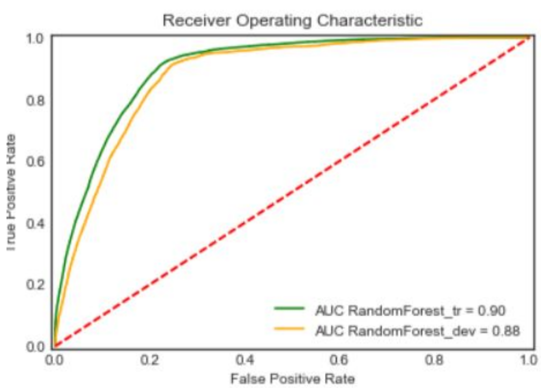
```
BEST {'max_depth': 12, 'min_samples_leaf': 1} 0.8174973970017702
############# based on standard predict ################
Accuracy on training data: 83.91%
Accuracy on test data:     82.54%
confusion_matrix on dev data
[[24347  1294    83]
 [ 2998  2075   361]
 [  846   678  3167]]
classification report on dev data
             precision    recall  f1-score   support

          0       0.86      0.95      0.90     25724
          1       0.51      0.38      0.44      5434
          2       0.88      0.68      0.76      4691

avg / total       0.81      0.83      0.81     35849

########################################################
Wall time: 50.3 s
```



5.3 Random Forest Classifier Results

The features were added one by one and AUC of train and dev set was examined. Some features were not adding any value to dev set AUC, but they were not hurting it as well. The train set AUC reached the maximum only when all features were present. Hence they were all retained.
Parameter tuning:
parameters = {"max_depth": [6,8,12], 'min_samples_leaf': 1,2,4,6],"n_estimators":[20,30,40,50]}

```
BEST {'max_depth': 12, 'min_samples_leaf': 1, 'n_estimators': 40} 0.8221987737486058
############# based on standard predict ################
Accuracy on training data: 84.39%
Accuracy on test data:     82.98%
confusion_matrix on dev data
[[24407  1299    18]
 [ 2940  2200   294]
 [  875   677  3139]]
classification report on dev data
             precision    recall  f1-score   support

          0       0.86      0.95      0.90     25724
          1       0.53      0.40      0.46      5434
          2       0.91      0.67      0.77      4691

avg / total       0.82      0.83      0.82     35849

########################################################
Wall time: 9min 37s
```

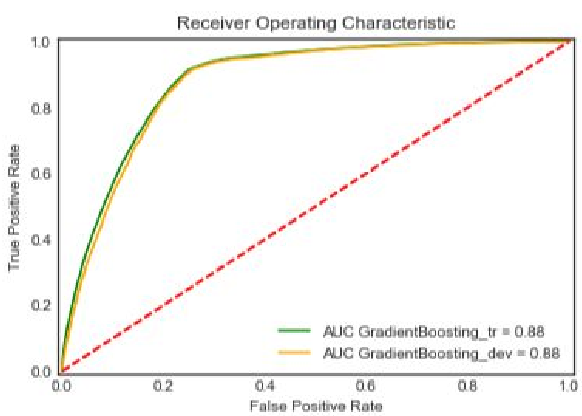


5.4 Gradient Boosting Classifier Results

Gradient Boosting was taking a long time to execute, and yet giving suboptimal AUC numbers than random forest for the same max_depth and min_leaf parameters. Hence not much time was invested on it.

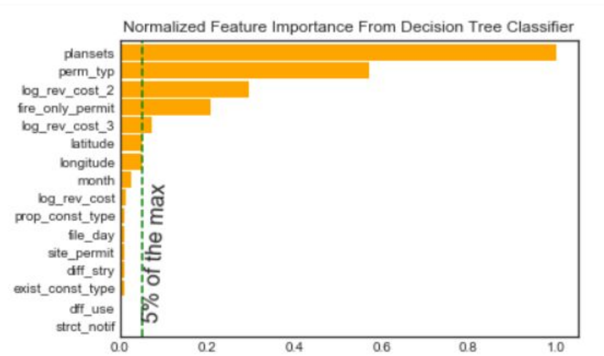
Parameter tuning: parameters = {"n_estimators":[50,100,200]}

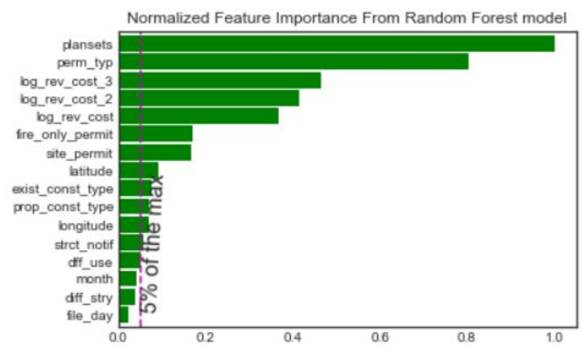
```
BEST {'n_estimators': 200} 0.8210361537618411
############# based on standard predict ################
Accuracy on training data: 83.48%
Accuracy on test data:     82.73%
confusion_matrix on dev data
[[24327  1383    14]
 [ 2900  2233   301]
 [  853   740  3098]]
classification report on dev data
             precision    recall  f1-score   support

          0       0.87      0.95      0.90     25724
          1       0.51      0.41      0.46      5434
          2       0.91      0.66      0.76      4691

avg / total       0.82      0.83      0.82     35849

########################################################
Wall time: 8min 56s
```

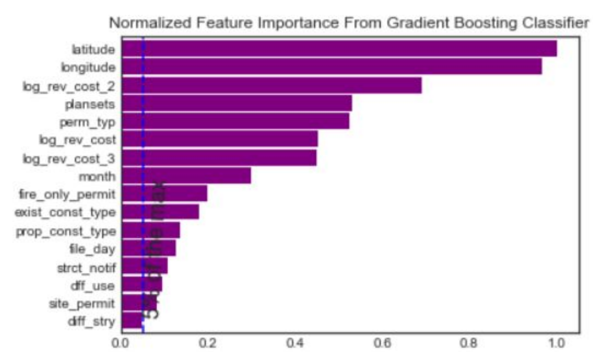


5.5 Comparison of Feature importance in tree methods:

Feature Importance (Normalized to make max = 1)







Decision Tree needs least number of features, yet does a good job!
Only 7 are above 5% line of the feature with maximum importance.

5.6 Additional models tried/parameters tuned:

1. Support Vector Classifier was tried: It was too slow, did not give good results
2. Bagging Classifier was tried: It did not give as good AUC as Random Forest (expected observation)
3. All models were tried with cross validation of default score function (accuracy) as well. Did not see any difference in overall accuracy
4. Class weight argument was also a hyperparameter to tune at one point. It chose balanced, for logistic regression and None for tree methods. Hence for ease of comparison, even logistic regression was not given this option. We do not prefer one class over the others anyway.

6. Conclusion / Work Remaining

We did Data cleaning, EDA and inferential statistics on the data. Defined the time taken variable as a 3 - class classification problem, fitted a few models, did hyperparameter tuning and evaluated the performance. It was pretty OK, but we could do more.

6.1 Model Chosen

Both Logistic Regression and Decision Tree look fine because they perform similarly on the dev data even though they have lower AUC than the other two models. Decision Tree looks slightly better in accuracy and f1-score, but that could just be chance. They are a lot faster and less memory/CPU time consuming than the other two. Also, Decision Tree in this case needs just about 7 features to attain the same accuracy as Random Forest does with more than 10 features. Decision Tree is more straightforward and interpretable than Logistic regression, because logistic regression suffers from sparsity and abundance introduced by one-hot encoding.

6.2 Work Remaining

1. Can we take out some OTC permit applications, as they dominate the data and even the commonsense says the word OTC itself means on the counter and hence the same day. We may be taking a wise decision by doing this
2. We should look at metrics/scoring function to see if these are the right ones to use for hyperparameter tuning. We didn’t see much difference in accuracy/AUC of label 1, when the scoring function was f1_micro/f1_weighted or default (accuracy)
3. Gradient Boosting is not fully explored yet. Perhaps not needed.
4. If everything is done, evaluate the models on test (hold out) set discussed in 5.03

Author	Revision History Version / Date	Comments
Aparna Shastry	0.1/03.05.2018	Initial Draft