PREDICTING HEALTH CODE VIOLATIONS IN BOSTON RESTAURANTS

Capstone Project by Roy Wright – August 2016

CLIENT AND PROBLEM

The City of Boston, like many others, conducts health inspections of food service establishments in a largely random pattern of visits. With a model for predicting where and when health code violations might be expected, the inspections can be carried out in a targeted way. This could make more efficient use of inspectors' time and, more importantly, increase the chances of detecting violations.

Our aim is to find restaurants that are likely to fail an unannounced health inspection — that is, we will develop the capability of predicting whether a health code violation would be found at a given food service establishment, if it were chosen to be inspected, without prior notice, right now. The main factors to be used in predicting an inspection outcome will be the urban conditions near the restaurant in the weeks leading up to the inspection.

DATA TO BE USED

DATASET: CITY OF BOSTON HEALTH INSPECTION RECORDS

Detailed records of health inspections throughout Boston, from 2006 to present, can be obtained from data.cityofboston.gov. Each inspection record includes the following pieces of information, among others:

- Food service establishment's name
- Category
    - category "FS" stands for "Eating & Drinking"
    - category "FT" stands for "Eating & Drinking w/ Take Out"
    - category "MFW" stands for "Mobile Food Walk On"
    - category "RF" stands for "Retail Food"
- The result of the inspection
    - "HE_Fail" when an establishment's first inspection (or first yearly inspection) is unsatisfactory
    - "HE_FailExt" when an establishment is re-inspected within a few weeks after a failure, and fails again
    - "HE_Pass" when an establishment passes an inspection with no violations (either its first yearly inspection or a re-inspection a few weeks after failure)
    - "HE_Filed" for the first inspection of an opening establishment
    - other result codes are much less common
- The date of the inspection
- Description of each violation found, along with its severity, rated as * or ** or *** (one star, two stars, or three stars)
- Written comments

- Business address
- Latitude/longitude coordinates – but only sometimes!

Dataset: Condensed Health Inspection Records

Yelp.com published academic datasets for the 2015 “Keeping it Fresh: Predict Restaurant Inspections” contest, hosted by DrivenData.org. At the heart of these datasets is a list of inspection results. Each row gives the inspection date, a “restaurant ID” for the establishment inspected, and tallies of the violations found at each severity level (*, **, and ***). Another dataset gives a summary of Yelp-provided information for each business, including its name, address, “Yelp ID” number (which is distinct from its “restaurant ID”), number of Yelp reviews available, average rating, and latitude/longitude coordinates. Lastly, a table is provided for matching Yelp ID’s to restaurant ID’s.

Two Sets of Inspection Records: What is the Difference?

As can be seen above, we have two separate datasets that provide records of past health inspections. To compare these datasets, let’s take a look at the contents of each one for a single day. Below, we display part of the contents of the City of Boston’s records for August 12, 2014. This date is chosen mostly arbitrarily.

name	**category**	**result**	**level**	**description**	**comments**	**latitude**	**longitude**
A C Farm Market	RF	HE_Pass	*	Non-Food Contact Surfaces	Repair rusty shelving below prep table.	42.302302	-71.059800
A C Farm Market	RF	HE_Pass	*	Food Protection	Discontinue store vegetables in stagnant wate...	42.302302	-71.059800
A C Farm Market	RF	HE_Pass	**	Insects Rodents Animals	Evidence of fruit flies provide exterminators ...	42.302302	-71.059800
A C Farm Market	RF	HE_Pass	*	Dishwashng Facilities	Replace missing sink plugs.	42.302302	-71.059800
A C Farm Market	RF	HE_Pass	*	Food Container Labels	Provide labels for all packaged foods.	42.302302	-71.059800
Choice's by Au Bon Pain	FT	HE_Fail	*	Non-Food Contact Surfaces	bakery/replace worn door gasket to 1 door reac...	NaN	NaN
Choice's by Au Bon Pain	FT	HE_Fail	***	Cold Holding	salad bar/carrot and raisin salad 49 degrees/c...	NaN	NaN
Choice's by Au Bon Pain	FT	HE_Fail	*	Equipment Thermometers	front line/ 2 door drawer/provide internal the...	NaN	NaN
Choice's by Au Bon Pain	FT	HE_Fail	*	Non-Food Contact Surfaces Clean	salad bar/clean interior cabinets	NaN	NaN

name	category	result	level	description	comments	latitude	longitude
Choice's by Au Bon Pain	FT	HE_Fail	*	Improper Maintenance of Floors	replace damaged floor tile in front of proof b...	NaN	NaN
City Sports	RF	HE_Fail	*	Hand Cleaner Drying Tissue Signage	restroom/provide employee must wash hands signage	42.350722	-71.073709
City Sports	RF	HE_Fail	*	Installed and Maintained	repair hot water faucet handle in restroom	42.350722	-71.073709
DUNKIN DONUTS(FRANKLIN)	FT	HE_Pass	NaN	NaN	NaN	42.356510	-71.053320
Foumami	FT	HE_Pass	NaN	NaN	NaN	NaN	NaN
Great Chef	FT	HE_Pass	*	Equipment Thermometers	Provide visible thermometers where necessary.	42.379493	-71.027910
Great Chef	FT	HE_Pass	*	Soiled Linen Storage	Basement -Cover dirty laundry container	42.379493	-71.027910
Great Chef	FT	HE_Pass	*	Improper Maintenance of Walls/Ceilings	Clean cooking vent hood.	42.379493	-71.027910
Great Chef	FT	HE_Pass	*	Wiping Cloths Clean Sanitize	Keep wiping cloths in sanitizer	42.379493	-71.027910
Great Chef	FT	HE_Pass	*	Food Protection	Elevate food containers 6" off floor in walk in.	42.379493	-71.027910
Great Chef	FT	HE_Pass	*	Non-Food Contact Surfaces	Defrost french fry freezer	42.379493	-71.027910
Great Chef	FT	HE_Pass	*	Non-Food Contact Surfaces Clean	Clean underside of shelving over prep tables.	42.379493	-71.027910
Great Chef	FT	HE_Pass	*	Food Protection	Cover all open foods in reach ins.	42.379493	-71.027910
Great Chef	FT	HE_Pass	*	Non-Food Contact Surfaces Clean	Clean and refinish rusted Can opener.	42.379493	-71.027910
KANTIN	FT	HE_Fail	***	PIC Performing Duties	The time as a public health control logs are n...	42.352411	-71.125329
KANTIN	FT	HE_Fail	*	Installed and Maintained	The cold water at the back handwash sink is no...	42.352411	-71.125329

name	category	result	level	description	comments	latitude	longitude
KANTIN	FT	HE_Fail	*	Non-Food Contact Surfaces	There is duct tape on the handle of the rice c...	42.352411	-71.125329
KANTIN	FT	HE_Fail	*	Premises Maintained	There is excess clutter in the upstairs storag...	42.352411	-71.125329
...	...	...	...	...	...	...	...
Samurai Kuang Eatery	FT	HE_Pass	***	Cold Holding	Sushi grade salmon 51F White fish 50F / Provi...	42.355795	-71.058451
Samurai Kuang Eatery	FT	HE_Pass	*	Equipment Thermometers	Dish machine gauge is broken / Repair.	42.355795	-71.058451
Samurai Kuang Eatery	FT	HE_Pass	*	Improper Maintenance of Floors	Floors under cookline around handsink heavily...	42.355795	-71.058451
Samurai Kuang Eatery	FT	HE_Pass	*	Non-Food Contact Surfaces	Back door opened without screen / Provide scr...	42.355795	-71.058451
Samurai Kuang Eatery	FT	HE_Pass	*	Improper Maintenance of Walls/Ceilings	Hood vents with visible grease build up / Clea...	42.355795	-71.058451
Shaw's Supermarket No. 586	RF	HE_Fail	*	Food Contact Surfaces Design	Sponge being used at the 3 bay sink in the pro...	42.271930	-71.069700
Shaw's Supermarket No. 586	RF	HE_Fail	*	Non-Food Contact Surfaces Clean	Interior of the chicken freezer near the rotis...	42.271930	-71.069700
Shaw's Supermarket No. 586	RF	HE_Fail	*	Improper Maintenance of Floors	Floor under the storage cabinet near the rotti...	42.271930	-71.069700
Shaw's Supermarket No. 586	RF	HE_Fail	*	Improper Maintenance of Walls/Ceilings	Portion of the wall in the meat walk-in cooler...	42.271930	-71.069700
Shaw's Supermarket No. 586	RF	HE_Fail	*	Installed and Maintained	Pipe under the hand sink in the meat preparati...	42.271930	-71.069700
Shaw's Supermarket No. 586	RF	HE_Fail	*	Non-Food Contact Surfaces	Salad bar unit operating at around 50F. PIC (B...	42.271930	-71.069700
Shaw's Supermarket No. 586	RF	HE_Fail	***	Cold Holding	All foods inside of the salad bar withg temper...	42.271930	-71.069700

name	category	result	level	description	comments	latitude	longitude
WORLD TRADE CENTER	FT	HE_Fail	*	Walls/Ceilings Designed Constructed Installed	replace stained and heavily soiled ceiling til...	NaN	NaN
WORLD TRADE CENTER	FT	HE_Fail	*	Floors Designed Constructed Installed	clean floor of paper goods storage room. also ...	NaN	NaN
WORLD TRADE CENTER	FT	HE_Fail	*	Non-Food Contact Surfaces	remove ice buildup from pipes inside walk i8n ...	NaN	NaN
WORLD TRADE CENTER	FT	HE_Fail	*	Premises Maintained	remove shoes from tops of lockers in both chan...	NaN	NaN

By contrast, here are Yelp's condensed records for August 12, 2014, once they have been assembled from the three sources mentioned before.

date	restaurant_id	violations			name	latitude	longitude
		*	**	***			
2014-08-12	we39j9ok	4	0	0	Dunkin' Donuts	42.349264	-71.042474
2014-08-12	lnORdd3N	0	0	0	Dunkin' Donuts	42.356527	-71.053353
2014-08-12	KAoK8ZOg	0	0	0	Fóumami	42.356039	-71.053455
2014-08-12	0ZEDGWOD	9	0	0	Great Chef Chinese Food Day Square	42.379525	-71.027940
2014-08-12	njoZ1D3r	3	0	1	Kantin	42.352744	-71.125447
2014-08-12	eVOBLr3j	1	0	1	Lollicup	42.352444	-71.125403
2014-08-12	B1oXNlEV	11	1	3	Max Brenner	42.349491	-71.080588
2014-08-12	B1oX4boV	4	0	1	Samurai Kuang Eatery	42.355741	-71.058335
2014-08-12	8xExZeo0	4	1	1	South Boston Chinese Restaurant	42.336483	-71.047309

At a glance, we can see that the inspection records maintained by the City of Boston are more detailed than those provided by Yelp. It is easier to compare the two if we regroup the city's records in a way more like Yelp's version, as shown below.

Note that some businesses present in the city's records do not appear in Yelp's data. In fact, it seems that no business of the "retail food" type appears in Yelp's data. On the other hand, every inspection listed in Yelp's data can be seen represented in the city's data, although not always clearly. For example, the first Dunkin' Donuts inspection listed above, with four 1-star violations and no 2- or 3-star violations, is listed at the bottom of the table below, with the name "WORLD TRADE CENTER" (which is actually the location of that particular Dunkin' Donuts). But aside from that, each of the other inspections shown above can be found without much difficulty in the table below.

name	level	count	result	category
A C Farm Market	*	4	HE_Pass	Retail Food
	**	1	HE_Pass	Retail Food
Choice's by Au Bon Pain	*	4	HE_Fail	Eating & Drinking w/ Take Out
	***	1	HE_Fail	Eating & Drinking w/ Take Out
City Sports	*	2	HE_Fail	Retail Food
DUNKIN DONUTS(FRANKLIN)	none		HE_Pass	Eating & Drinking w/ Take Out
Foumami	none		HE_Pass	Eating & Drinking w/ Take Out
Great Chef	*	9	HE_Pass	Eating & Drinking w/ Take Out
KANTIN	*	3	HE_Fail	Eating & Drinking w/ Take Out
	***	1	HE_Fail	Eating & Drinking w/ Take Out
LOLLICUP TEA ZONE	*	1	HE_Fail	Eating & Drinking w/ Take Out
	***	1	HE_Fail	Eating & Drinking w/ Take Out
Max Brenner	*	11	HE_Fail	Eating & Drinking
	**	1	HE_Fail	Eating & Drinking
	***	3	HE_Fail	Eating & Drinking
Pho Viets	*	1	HE_Filed	Eating & Drinking w/ Take Out
Pollos A La Brasa Beto's	*	7	HE_Filed	Eating & Drinking w/ Take Out
SOUTH BOSTON CHINESE	*	4	HE_Pass	Eating & Drinking w/ Take Out
	**	1	HE_Pass	Eating & Drinking w/ Take Out
	***	1	HE_Pass	Eating & Drinking w/ Take Out
Samurai Kuang Eatery	*	4	HE_Pass	Eating & Drinking w/ Take Out
	***	1	HE_Pass	Eating & Drinking w/ Take Out
Shaw's Supermarket No. 586	*	6	HE_Fail	Retail Food
	***	1	HE_Fail	Retail Food
WORLD TRADE CENTER	*	4	HE_Fail	Eating & Drinking w/ Take Out

There are some important mistakes in Yelp's condensed records. To see why, note for example that in the city records above, the inspection of Samurai Kuang Eatery is marked as passing. For that inspection, four 1-star and one 3-star violations are noted, but this is only because that inspection was a follow-up to an inspection from one week before, which found those violations. Unfortunately, the Yelp data treats these inspections identically, marking four 1-star and one 3-star violations for each of the two inspections, which is quite misleading. This mistaken double-entry of health violations happens frequently throughout the Yelp dataset. We will see later that this issue, once we make an appropriate correction for it, will not impede the central purpose of this project.

In light of the comparison above, we can now consider the advantages of each dataset of inspection results. The City of Boston's dataset is kept continually up-to-date, with new results being entered as they occur, while Yelp's data ends in mid 2015. Boston's dataset is also more complete in the sense that each violation is categorized in much finer detail than a simple a three-level severity rating. However, it should be noted that Yelp’s condensed dataset was developed with the express support of the City of Boston, working toward a purpose very similar to the purpose of the present project. Most crucially, this dataset provides latitude/longitude coordinates for *every* inspection location listed.

DATASET: SERVICE REQUEST CALLS

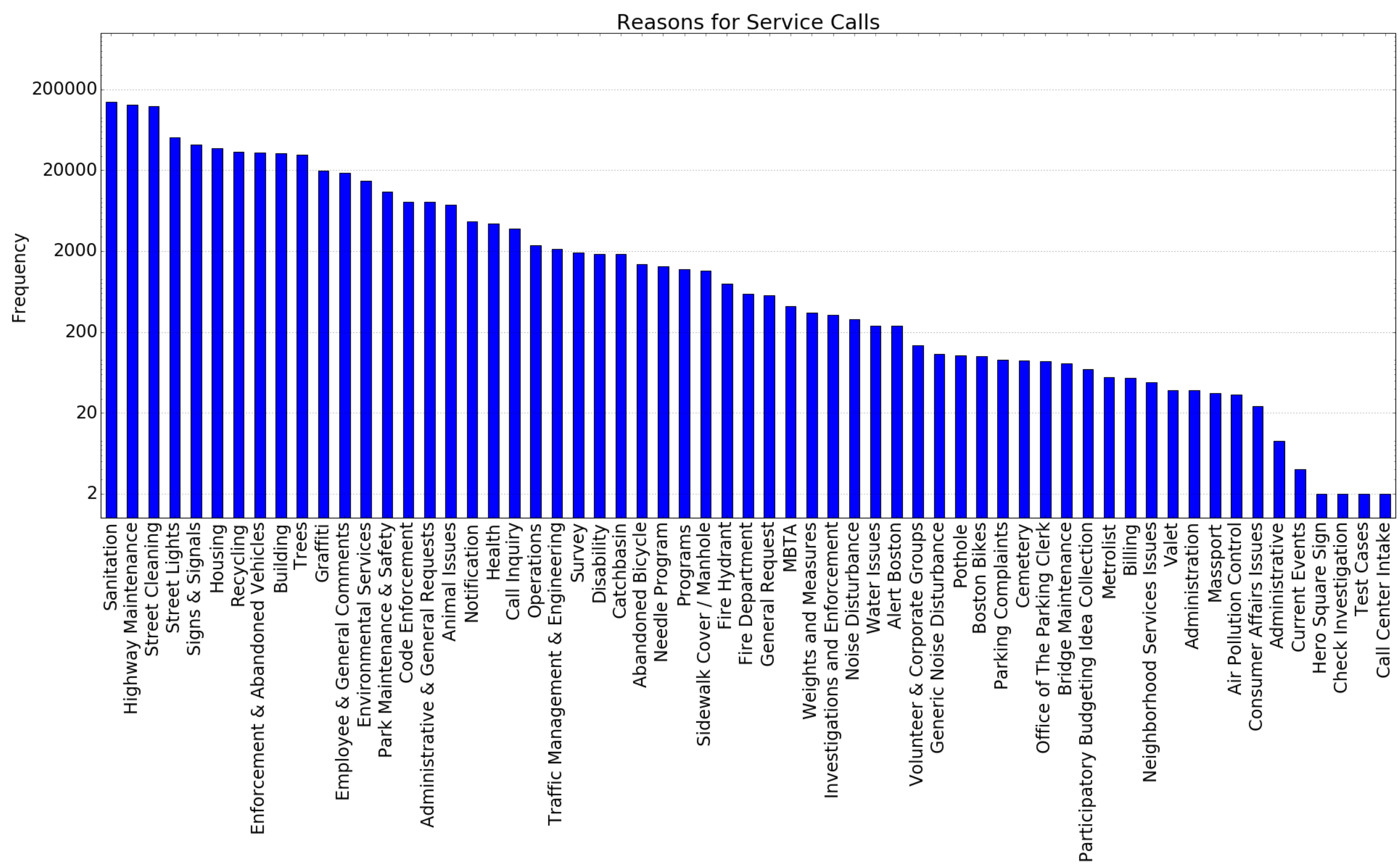
Boston residents are able to dial "311" and report public property issues such as rodent sightings, unsanitary conditions, streetlight outages, and so forth. Records of these 311 service requests, from July 2011 to present, are available from data.cityofboston.gov.

Each call record includes the following relevant information:

- The date the complaint was made
- Various descriptions of the nature of the complaint
- Latitude/longitude coordinates of the issue

Each complaint is described, often redundantly, by a "title," a "subject," a "reason," and a "type." In the dataset, there are 7837 different titles, 18 different subjects, 61 different reasons, and 215 different types. We will find it convenient to use "reasons" as a natural way to categorize complaints in our later work, since they strike a balance between being overly specific (as in the thousands of different "titles") and not being descriptive enough (like the handful of vague "subjects").

The following graph shows the prevalence of each of the various service call "reasons." Note that there is a swift decline in the frequencies of the least common reasons, with a handful of the very least common reasons only appearing in the dataset a few times. Because of this, in the work that follows we will disregard these extremely rare service reasons.



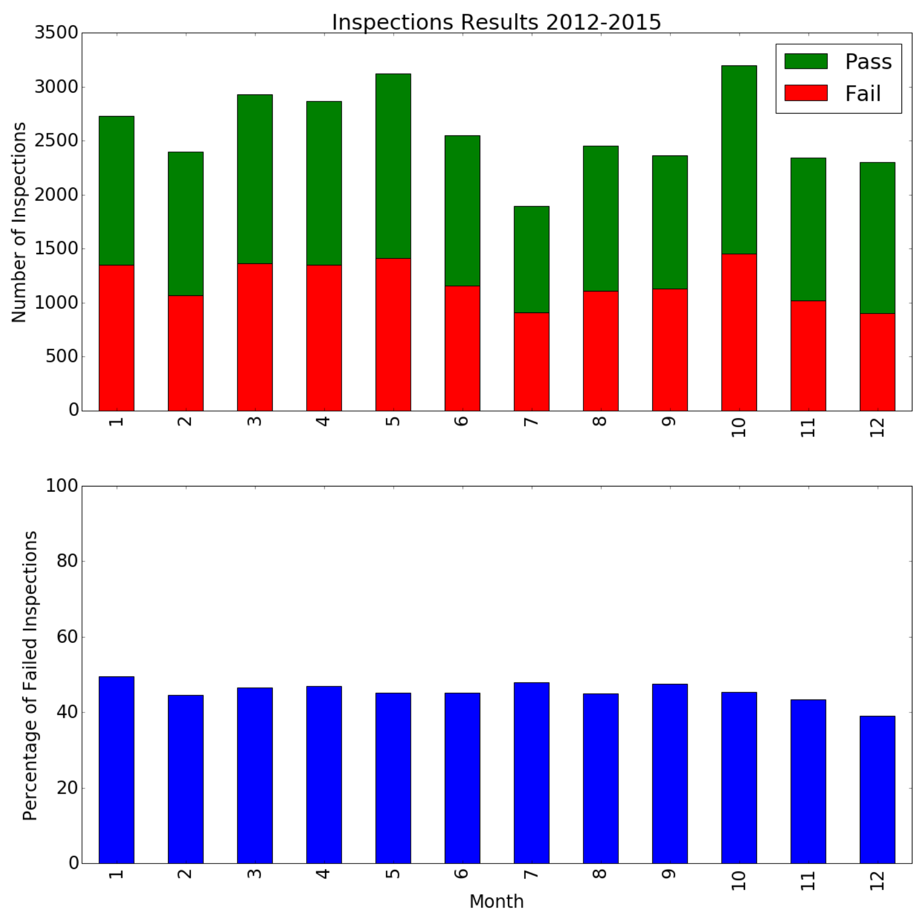
This dataset provides a wealth of details about reported environmental conditions near restaurant inspections. From these details we can derive a model for predicting the outcomes of those inspections.

Data Analysis

Preliminary Exploration

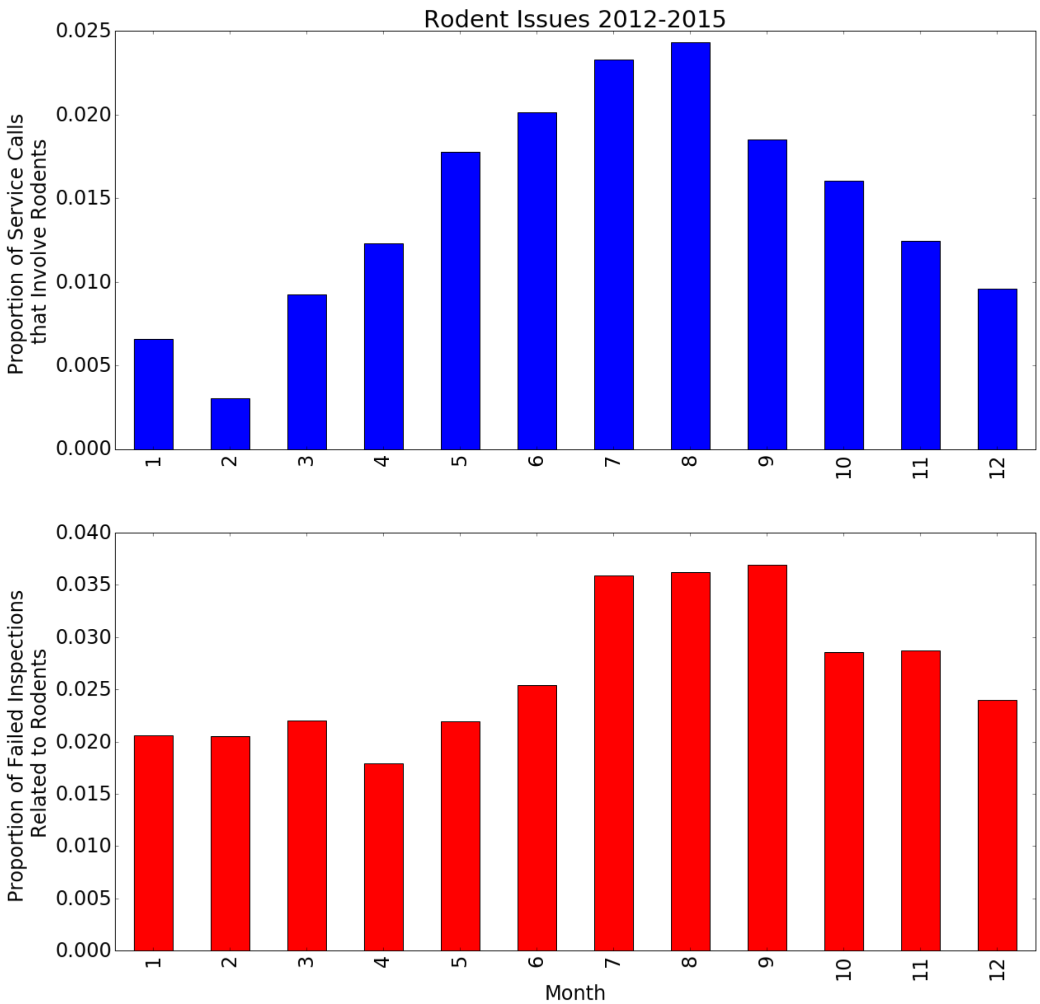
Since service call data is only available from July 2011 onward, we will only consider inspection results from August 2011 onward. In the condensed inspection results data, 1634 different businesses were inspected in total, and 1327 of them experienced a failed inspection at some point. Meanwhile, in the more complete raw inspection data from the City of Boston, 5604 businesses were inspected, with 3876 of them experiencing at least one failed inspection. For this first exploration, we will focus on the raw City of Boston dataset, since it can provide us with some interesting insights not available from the more condensed and selective Yelp dataset.

Looking at the years 2012 through 2015, the number of inspections performed varies a great deal from month to month, but the *percentage of inspections that fail* is consistently between about 40 and 50 percent.



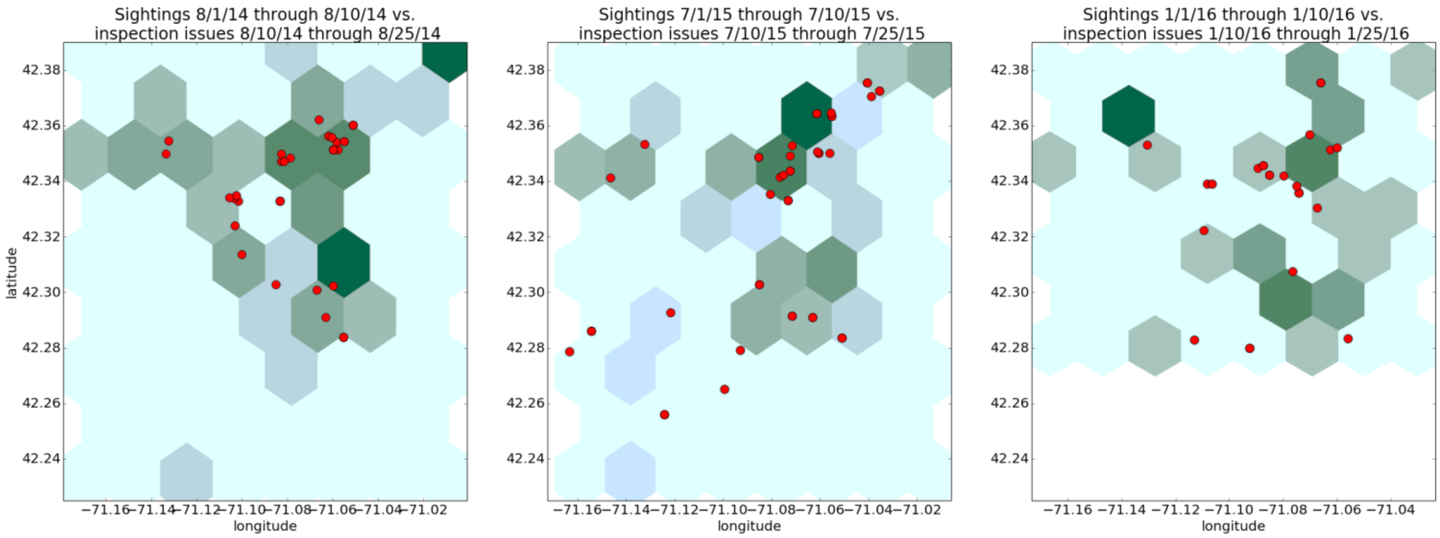
Our overall goal is to be able to predict the outcome (pass or fail) of a given health inspection, regardless of the specific underlying causes for a failure. However, we will be building our predictions upon environmental conditions near each inspected business, so it is worthwhile to consider some possible relationships between specific types of environmental issues and the reported causes of inspection failures. One aspect of food safety that often inspires public interest is the presence of rodents in food service establishments.

The dataset reveals that over 20% of inspected businesses have experienced inspection failures related to rodents. Inspections with rodent-related issues are an interesting subset of all inspections because we can investigate, relatively easily, whether citizens' reports of rodent sightings (through 311 service calls) are good predictors of subsequent rodent-related issues during health inspections of nearby food service establishments. Intriguingly, based on service call data, rodents are reported via 311 most commonly around June to August, and are detected in health inspections most commonly shortly thereafter, in July to September.



The pattern above shows an unmistakable correlation between the *timing* of rodent sightings and rodent-related inspection issues. With more difficulty, we can use visuals to explore whether there might be a correlation between the *locations* of sightings and inspection issues. For the graphs below, three different 10-day periods are selected (more or less at random) and service calls involving rodent activity during those periods are mapped. This reported rodent activity is indicated in green, with darker green corresponding to more activity. Then, rodent-related health inspections during an immediately subsequent

15-day period are shown in red. In each case, the distributions of sightings and rodent-related inspection results do appear to be roughly similar, although this conclusion is admittedly subjective.



Such patterns in both time and space lend some weak support to the idea that a restaurant that is near increased reported rodent activity might be at an increased risk of rodent-related issues during a health inspection. Soon, we will see firm statistical evidence that this is indeed the case.

Again, rodent-related issues are just one particularly interesting subset of public health challenges, serving here as a microcosm of the possible predictive relationship between service call data and inspection outcomes. Extending this beyond rodents, by combining other aspects of the available service call data, we will construct a model for predicting the timing and location of a much broader variety of health inspection failures.

Extracting Features

In attempting to predict the outcome of a given restaurant inspection, we will primarily look to conditions in the city near that restaurant in the recent past, as reflected in service calls. For each of the service call "reasons" discussed before, we count the number of times that particular issue has been reported near the inspected business, between 5 and 15 days before the inspection. Nearness is judged in terms of distance in latitude/longitude coordinates; roughly speaking, we count any reports that have occurred within about 3 miles of the inspected business. These choices for the time window and distance are arbitrary, to some extent. Systematic experimentation with other choices reveals that the accuracy of our predictive models is not very sensitive to these values, within reason.

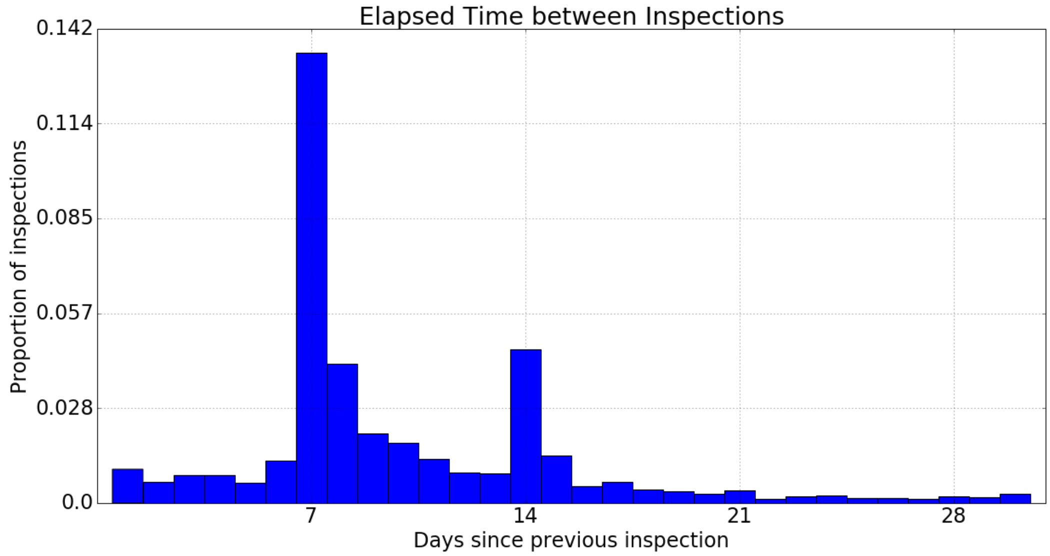
Because the features we will use are mostly derived from location information, for the remainder of this report, we will use only the condensed inspection dataset provided by Yelp, which provides latitude and longitude coordinates for every inspection. Another somewhat less important reason for using this dataset will also be seen later.

In addition to the features explained above, for each business inspected we also measure the length of time that has passed since its previous inspection, along with the results of the previous inspection, in the form of 1-star, 2-star, and 3-star violation counts.

Below, for demonstration purposes, we display the extracted information for some of the inspections that occurred on July 22, 2014. With any one of these, we can illustrate the meaning of the features described above. For example, an inspection occurred at Penguin Pizza that day. This inspection was a failure, since some violations were found. Between 5 and 15 days prior to this inspection, there were 699 complaints related to "sanitation" in the area around Pengin Pizza, 455 complaints related to "highway maintenance," 180 related to "street cleaning," and so on. It had been 208 days since Penguin Pizza's last inspection. (For the sake of space, the results of the previous inspection are not shown here.)

violations			**name**	**Sanitation**	**Highway Maintenance**	**Street Cleaning**	**...**	**Valet**	**Administration**	**Massport**	**Air Pollution Control**	**delay**
*	**	***										
13	0	0	My Thai Vegan Cafe	587.0	382.0	137.0	...	1.0	0.0	0.0	0.0	204.0
8	0	1	Penguin Pizza	699.0	455.0	180.0	...	1.0	0.0	0.0	0.0	208.0
0	0	0	Rebecca's Cafe	521.0	318.0	114.0	...	1.0	0.0	0.0	0.0	194.0
22	2	12	New Saigon Sandwich	587.0	384.0	137.0	...	1.0	0.0	0.0	0.0	186.0
6	2	2	Anh Hong	669.0	359.0	210.0	...	0.0	0.0	0.0	0.0	166.0
3	0	0	Starbucks	628.0	408.0	148.0	...	1.0	0.0	0.0	0.0	148.0
9	2	1	Al Dente Restaurant	444.0	304.0	101.0	...	1.0	0.0	0.0	0.0	140.0
4	0	0	Chipotle Mexican Grill	656.0	415.0	133.0	...	1.0	0.0	0.0	0.0	273.0
2	1	0	Boloco	519.0	320.0	114.0	...	1.0	0.0	0.0	0.0	141.0
7	2	2	Benevento's	444.0	304.0	101.0	...	1.0	0.0	0.0	0.0	140.0

As mentioned before, there are systematic mistakes in the condensed inspection records, with a kind of double-entry of health violations happening frequently throughout the dataset. While most inspections repeat after a period of about one year, we should be suspicious of any inspection results that supposedly took place within a few weeks of a previous inspection at the same business. With the “delay” feature of the data extracted (as seen above), we can take a closer look at such results. The graph below shows that quickly repeated inspections are overwhelmingly repeated after either exactly one week or exactly two weeks. Because of this, we will make one final correction to the data by dropping any inspection with a calculated delay of 14 or fewer days.



SOME INSIGHTS FROM INFERENTIAL STATISTICS

Once we have extracted a set of environmental features as explained above, we can attempt to construct a predictive model using modern machine learning techniques. But before moving to that stage, let's briefly investigate the relationship (if any) between our features and the outcomes of health inspections using elementary statistical methods.

Since the question we wish to answer – will a given establishment fail an unannounced health inspection or not? – is binary in nature, we will test the influence that our environmental features have on the proportion of failed inspections. For each kind of common issue (or "reason") that may be reported through service calls, we can use a permutation approach to test hypotheses of the following general form:

> **Null hypothesis:** Establishments where the issue has been reported frequently, recently, and nearby will fail health inspections at the *same* rate as establishments where the issue has not been reported frequently, recently, and nearby.
>
> **Alternative hypothesis:** Establishments where the issue has been reported frequently, recently, and nearby will fail health inspections at a *different* rate than establishments where the issue has not been reported frequently, recently, and nearby.

For example, we can test whether businesses that are near the sites of more than a few recent complaints related to "environmental services" are more likely than other businesses to fail a health inspection. Note that "environmental services" complaints largely consist of rodent sightings, and most inspected businesses are near at least 10 such recent complaints. Using our dataset, a hypothesis test indicates a statistically significant difference in the inspection failure rates of businesses that are near at least 10 recent "environmental services" complaints, compared to other businesses (simulated p-value less than 0.001). In our dataset, these establishments fail inspections at a rate about 20% higher than others, which seems to be useful information in predicting inspection failures!

As another example, there is a significant difference in failure rates between businesses that are near very few (less than 3) recent "health" complaints and other businesses. The simulated p-value is less than 0.001, and in the dataset, businesses that are near at least 3 recent "health" complaints have a failure rate about

26% higher than others. Note that complaints with the reason "health" are mostly reports of "unsanitary conditions" in food establishments.

Similar results can be found for many of the other environmental features, which suggests that these features will indeed be directly useful in developing a model to fulfill our stated purpose.

Developing a Predictive Model

Overview

We aim to devise a means for predicting the outcomes of future health inspections. To this end, we have a list of 9641 previous inspections and their outcomes. For each of these inspections (or any hypothetical future inspection), we have calculated (or can calculate) 60 numerical features. Of these features, 54 measure the recent and nearby occurrences of various kinds of city service complaints, while 4 of the features relate to the outcome of the restaurant's previous inspection, and 2 of the features are simply the latitude and longitude of the restaurant.

To develop a model for classifying inspections as failing or passing, we will take the following general steps:

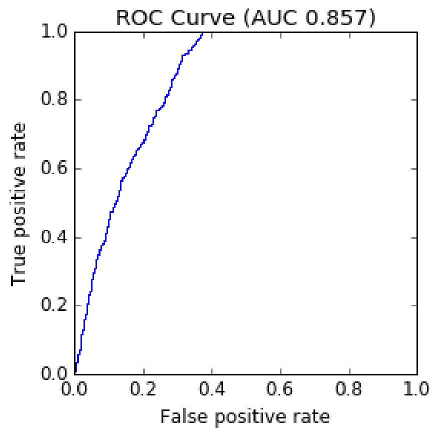
- Partition the data into a training set and a test set. We will randomly assign 80% of the data to the training set, in a "stratified" scheme that preserves the relative frequencies of failed and passed inspections.
- Use 3-fold cross-validation on the training set to search for hyperparameter values to maximize accuracy, and use those best values to create the model.
- Use the previously untouched test set the check the model's accuracy, along with other measures of performance.

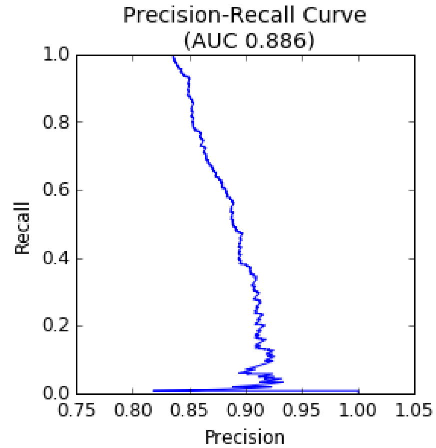
These steps have been applied to create a variety of predictive models for restaurant inspections, using the concepts of logistic regression, decision trees, support vector machines, and ensemble techniques. The performance of each type of model has been fairly comparable, but we will now detail two of the most successful.

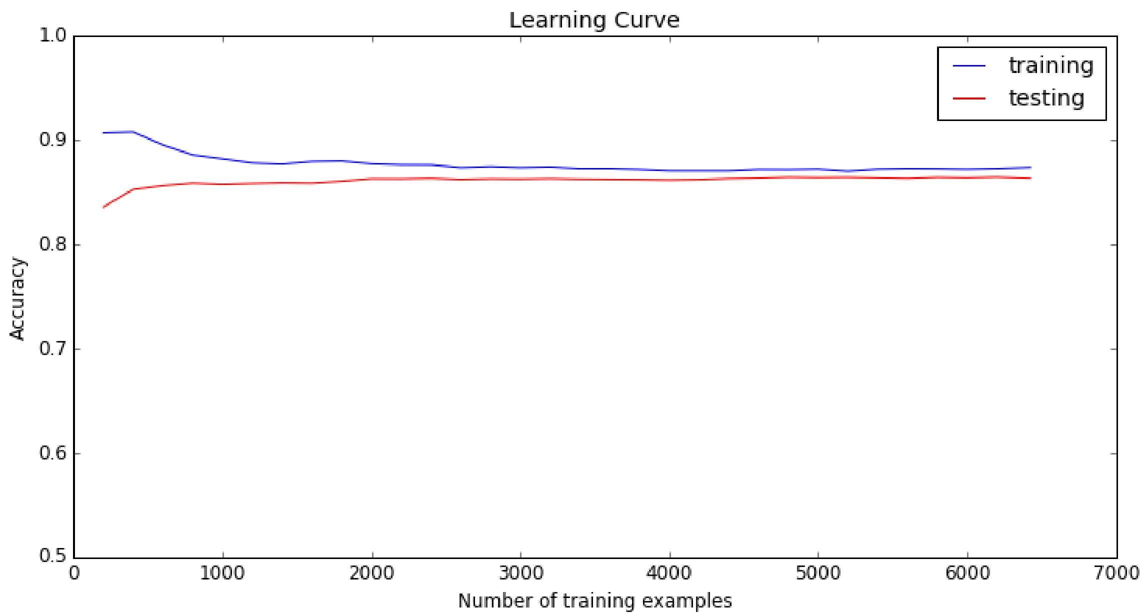
Support Vector Machine

Using the features and general steps described previously, a support vector machine classifier can be constructed. We first standardize the feature values, then search for optimal values of the regularization hyperparameter and the coefficient of the radial basis function kernel. Once the model is created, its accuracy on the test set is typically 0.86 or 0.87.

Below we have the receiver operating characteristic (ROC) curve for a typical SVM classifier. Since the classes in our problem are slightly unbalanced, we also show the precision-recall curve, which may be a better indicator of the classifier's performance. The learning curve is also shown.



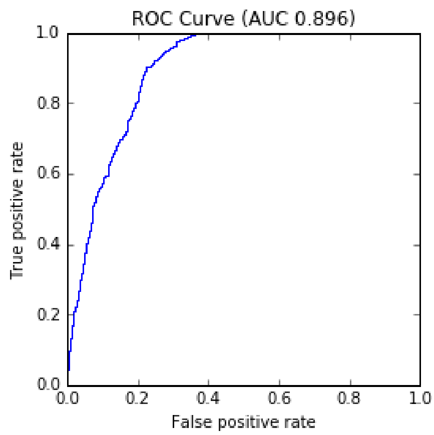


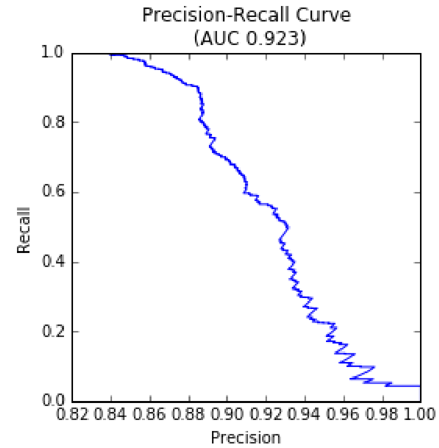


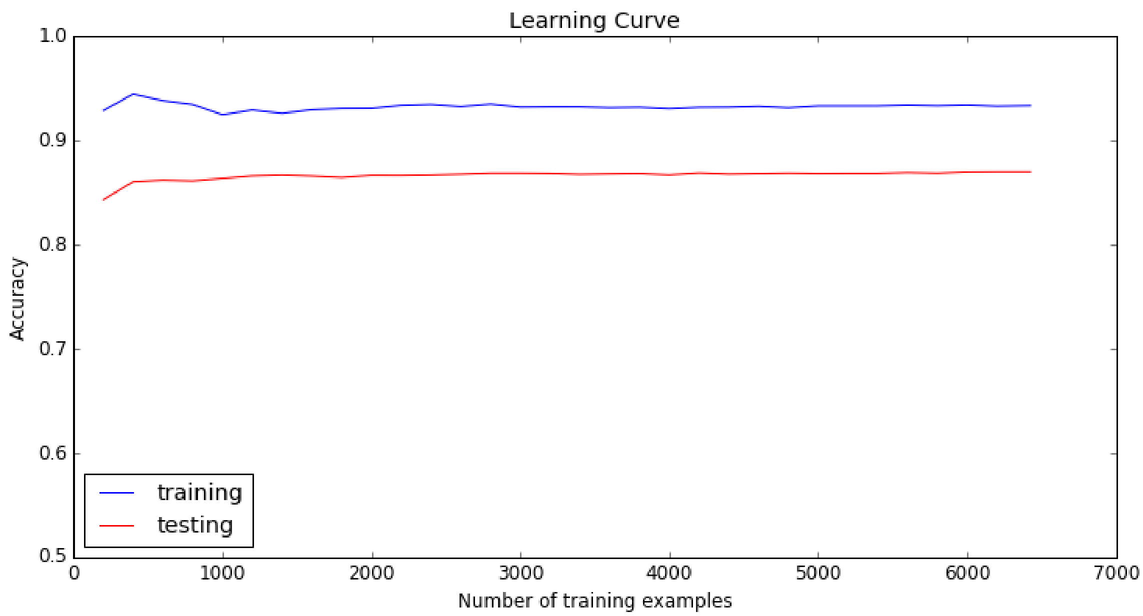
RANDOM FOREST

Using the same features and general steps again, we construct a random forest classifier. We attempt to optimize for the following hyperparameters: the maximum depth of trees in the forest, the number of features to consider when splitting, the minimum number of samples allowed in a new leaf, and the minimum number of samples required when splitting a node. Once created, a random forest model typically achieves an accuracy of around 0.87 or 0.88 on the test set.

Below, we have the ROC curve, precision-recall curve, and learning curve for a typical random forest classifier.

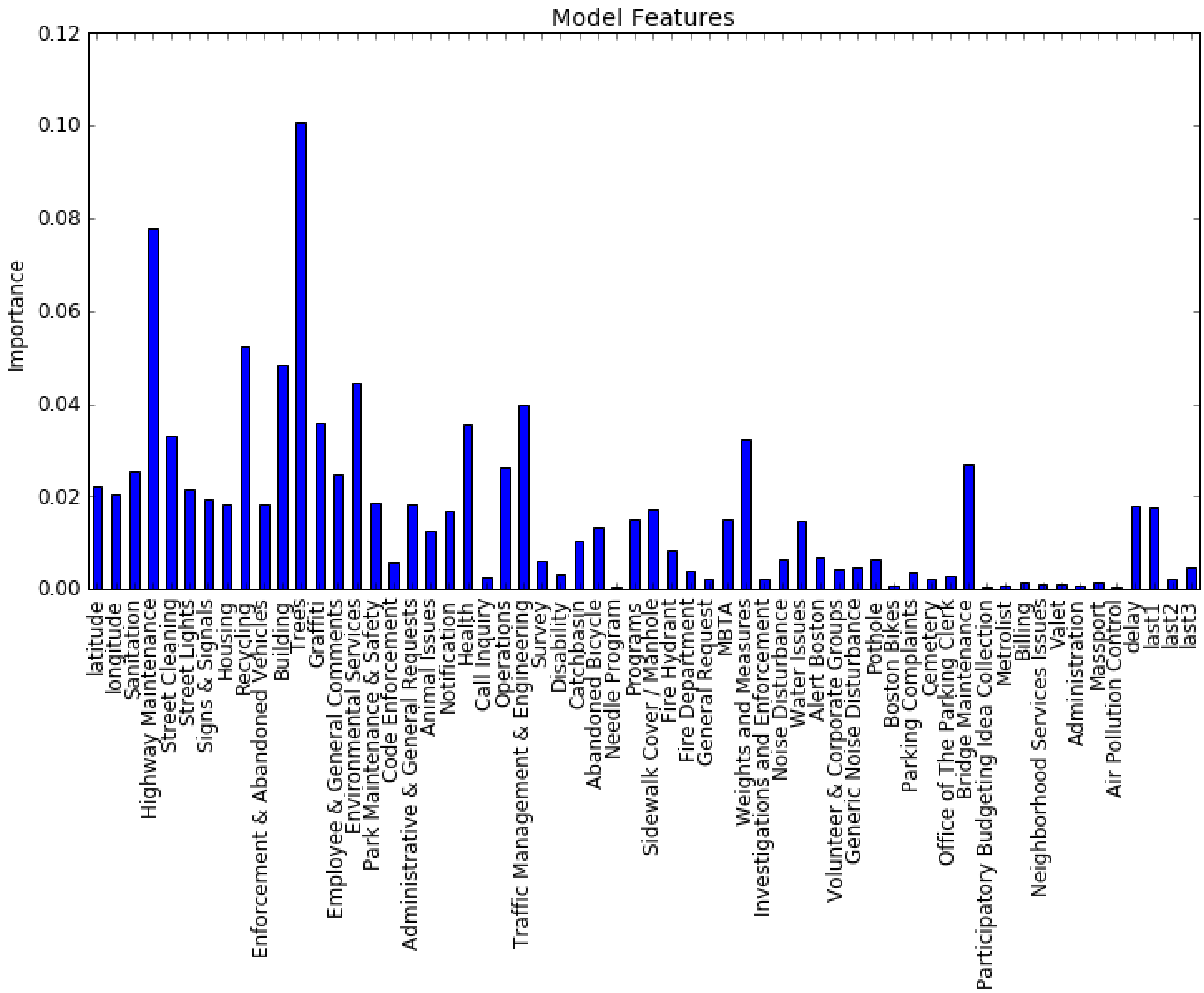






The use of a tree-based classifier provides a straightforward measure of the importances of the model's features. For the random forest with the results shown above, the most important features were the service call reasons of "Trees," "Highway Maintenance," "Recycling," "Building," and "Environmental Services." The features that are ranked as the most important in one random forest model may vary somewhat when a new forest is constructed – even if the same data and hyperparameters are used – but in the present situation, the set of most important features is fairly consistent from one forest to another.

In the graph below, we visualize the importances of all 60 features used. Note that other than the first 2 features on the left, and the last 4 features on the right, the rest of the features are related to service requests. Note also that these features are listed in order of decreasing frequency (just as they were listed in a previous graph). Unsurprisingly, we can see that the more prevalent service call reasons tend to have higher importance than the less prevalent ones.



Comparison to Previous Contest Results

As mentioned before, the condensed health inspections dataset that has been used here, primarily as a target for classifiers, was released as part of the "Keeping it Fresh: Predict Restaurant Inspections" contest at DrivenData.org in 2015. The goal of that contest was to be able to predict the number of one-star, two-star, and three-star violations found at each health inspection during a six-week period after the closing of contest submissions. So, in contrast to our present goal of simple classification, the DrivenData contest involved a problem of regression. The correctness of contestants' predictions was judged using the following weighted root mean square log error formula:

$$\text{WRMSLE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[\log(y_i \cdot W + 1) - \log(\hat{y}_i \cdot W + 1)]^2}$$

In the notation used for this scoring function, there are N inspections, y_i represents the results (a vector of three integers) of the i^{th} inspection, W is the weighting vector $(1, 2, 5)$, and $\hat{y}_i$ represents the predicted results of the i^{th} inspection. The winning contestant's error score, as reported at DrivenData.org, was 0.8901.

Contestants extracted features mainly from the text of customer reviews and other information provided through Yelp, in addition to details from past inspection outcomes. In the present project, we have taken a very different approach, using features related to reported environmental conditions near upcoming restaurant inspections. It would be interesting to compare the predictive ability of our features with those used in the contest. To make a somewhat fair comparison, using the same set of 60 features upon which we built our previous classification models, we take the following steps:

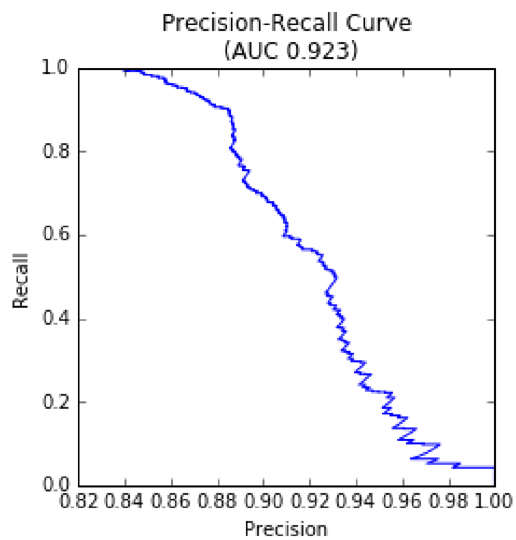
- Set aside the last 6 weeks of available data as a test set, with the rest of the data as a training set.
- Use cross-validation on the training set to search for hyperparameter values to minimize the WRMSLE score, and use those best values to create a regression model.
- Use the previously untouched test set to calculate the regression model's WRMSLE score.

A random forest regression model created in this way typically achieves a WRMSLE score of around 0.85 on the test data – a level of error quite comparable to the leading results of the DrivenData competition.

RECOMMENDATIONS

Given our successful development of an accurate predictor for health inspection failures, the City of Boston is advised to make use of such a predictor in planning upcoming inspections, in order to make more efficient use of inspectors' time.

While a randomly-selected restaurant has around a 64% chance of failing an unexpected inspection, a restaurant identified by our random forest predictor will have an 84% or higher chance of failure. If desired, this precision can be increased, at the cost of decreasing recall. For example, if the City is willing to accept only 50% recall (i.e. only 50% of failed inspections are foreseen), then the precision of predictions could be increased to about 93%. This trade-off should be calibrated in consultation with the Inspectional Services Department of Boston.



The models developed in this project have been based on a limited record of past health inspection results, for the principal reason that the City of Boston's live records lack latitude and longitude information for many inspections. As such, our models can be seen as a proof of concept; a fully operational model for ongoing use would need incorporate the City's live records. Therefore the City is advised to require all health inspections to include location data. Alternatively, missing location data for past and future inspections may be generated rather inexpensively through the use of the [Google Maps Geocoding API](). The [code included with this report]() already gives some indication as to how this would be done.

Possible Directions for Future Study

The environmental features we have extracted provide enough information for a successful classifier, but there is likely room for improvement. We have used the same time window and nearness threshold in the calculation of each of those features. Perhaps some variation in these choices from feature to feature would lead to a better-performing model, since some environmental factors might have influence at different distances, or on different timescales, than others.

When the City of Boston's more detailed inspection records are used, we may incorporate new features based on the fine details of past inspections, such as the exact reasons for past failures. After all, it seems plausible that some health issues are more prone to repeat offense than others.

Lastly, given the success of the DrivenData contestants in using customer reviews to predict inspection outcomes, our model might benefit from an incorporation of features derived from textual and other data provided by Yelp and Google restaurant reviews.