Capstone Project

Predicting Health Code Violations in Boston Restaurants

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.

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, measured 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
Choice's by Au Bon Pain	FT	HE_Fail	*	Improper Maintenance of Floors	replace damaged floor tile in front of proof b...	NaN	NaN

name	category	result	level	description	comments	latitude	longitude
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
KANTIN	FT	HE_Fail	*	Non-Food Contact Surfaces	There is duct tape on the handle of the rice c...	42.352411	-71.125329

name	category	result	level	description	comments	latitude	longitude
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
WORLD TRADE CENTER	FT	HE_Fail	*	Walls/Ceilings Designed Constructed Installed	replace stained and heavily soiled ceiling til...	NaN	NaN

name	category	result	level	description	comments	latitude	longitude
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

name	level	count	result	category
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 measurement. 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

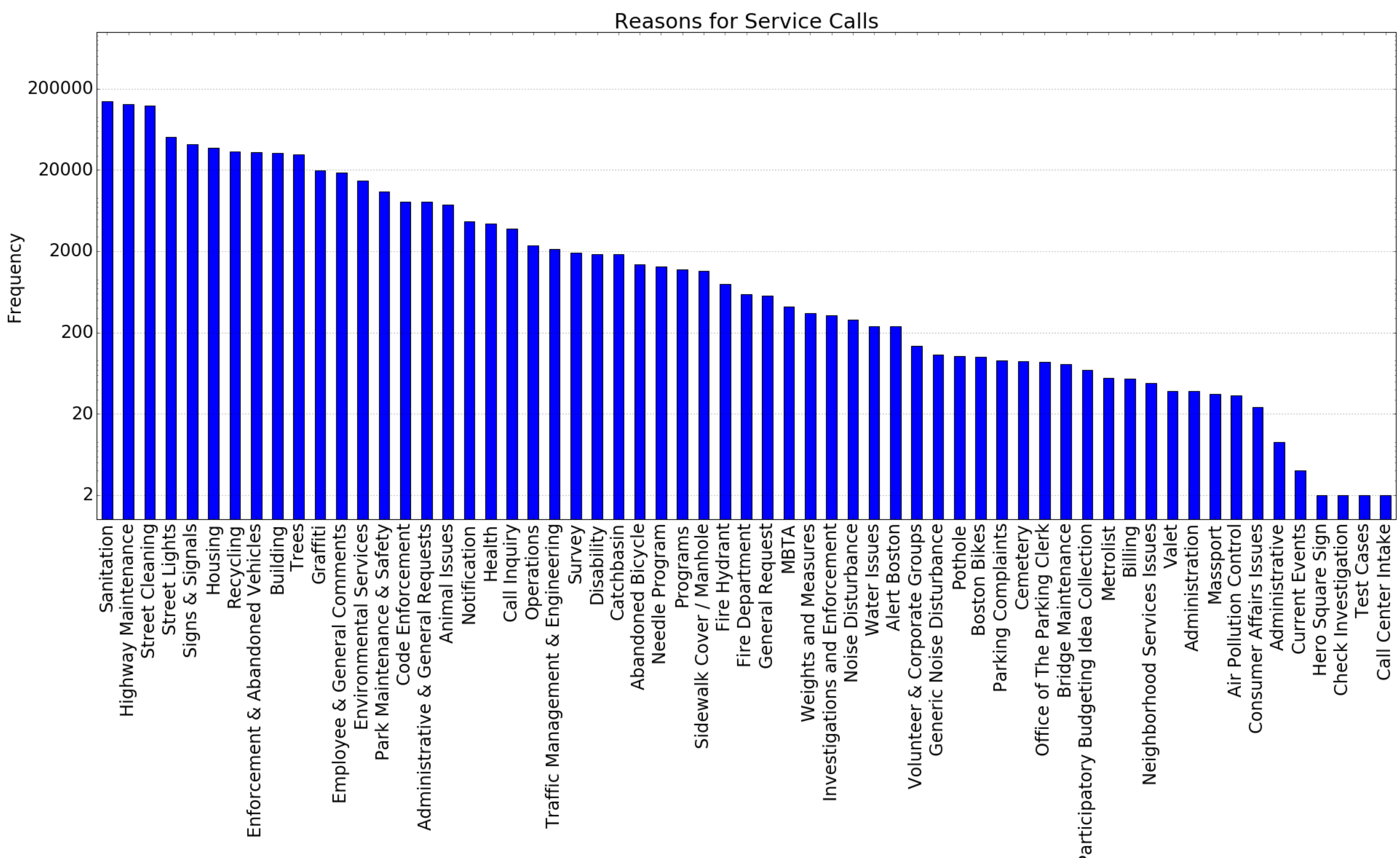
Boston residents are able to dial "311" and report public property issues such as rodent sightings, unsanitary conditions, streetlight outages, and so forth. Records of these 311 service requests, from July 2011 to present, are available from data.cityofboston.gov.

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.



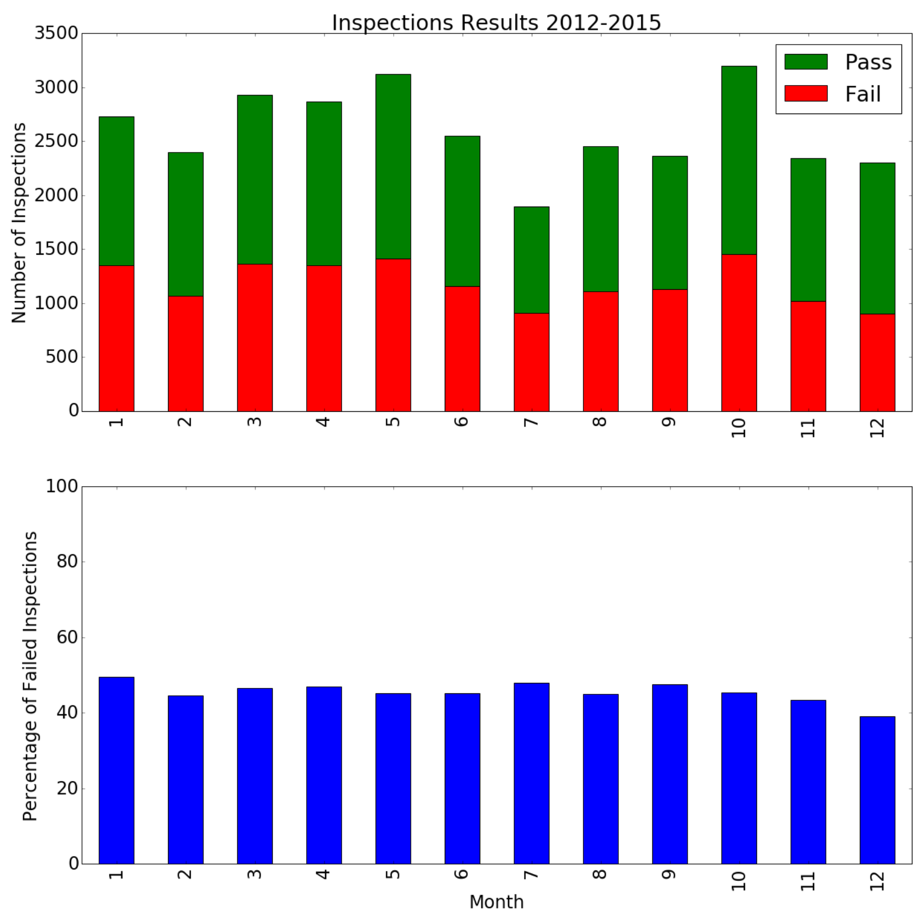
This dataset provides a wealth of details about reported environmental conditions near restaurant inspections. From these details we can derive a model for predicting the outcomes of those inspections.

Data Analysis

Preliminary Exploration

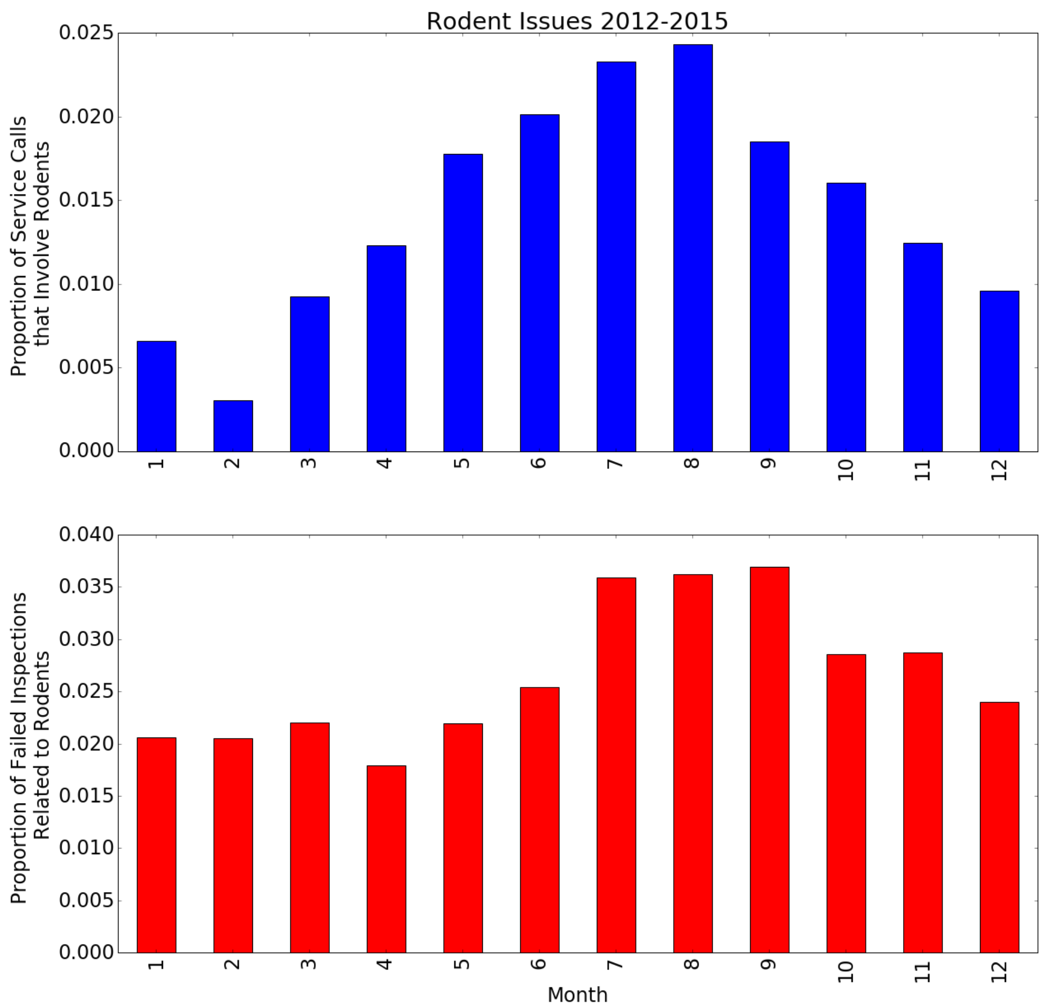
Since service call data is only available from July 2011 onward, we will only consider inspection results from August 2011 onward. In the condensed inspection results data, 1634 different businesses were inspected in total, and 1327 of them experienced a failed inspection at some point. Meanwhile, in 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.

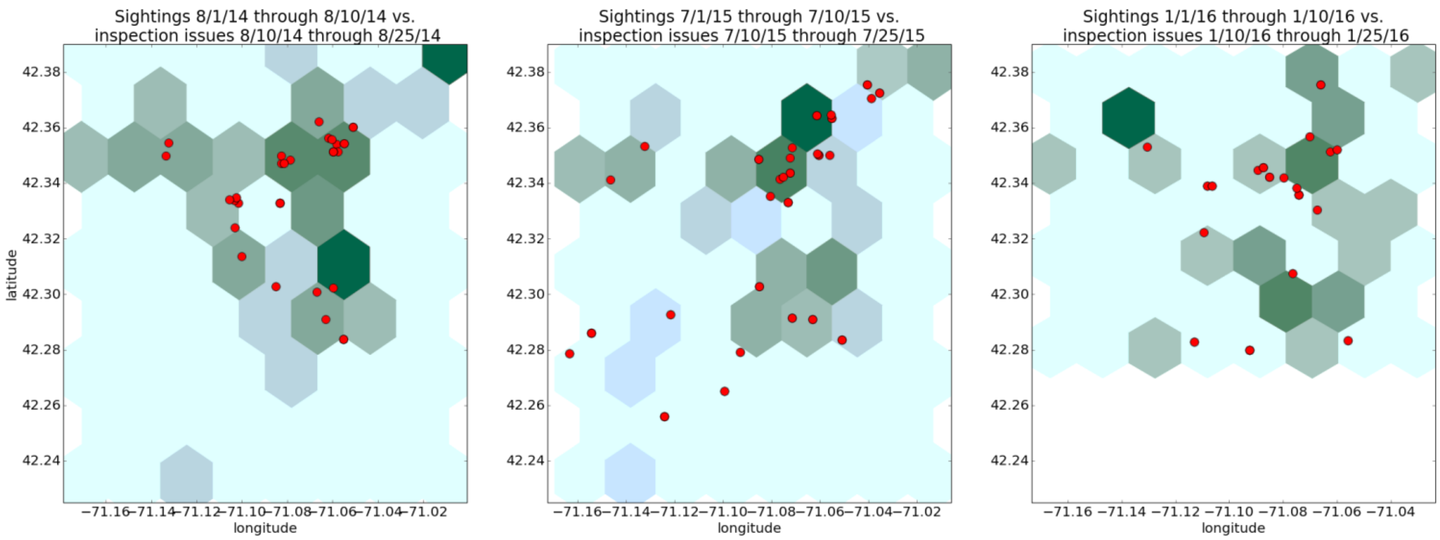


Our overall goal is to be able to predict the outcome (pass or fail) of a given health inspection, regardless of the specific underlying causes for a failure. However, we will be building our predictions upon environmental conditions near each inspected business, so it is worthwhile to consider some 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 somewhat arbitrary. Systematic experimentation with other choices reveals that the accuracy of our predictive models is not very sensitive to these values, within reason.

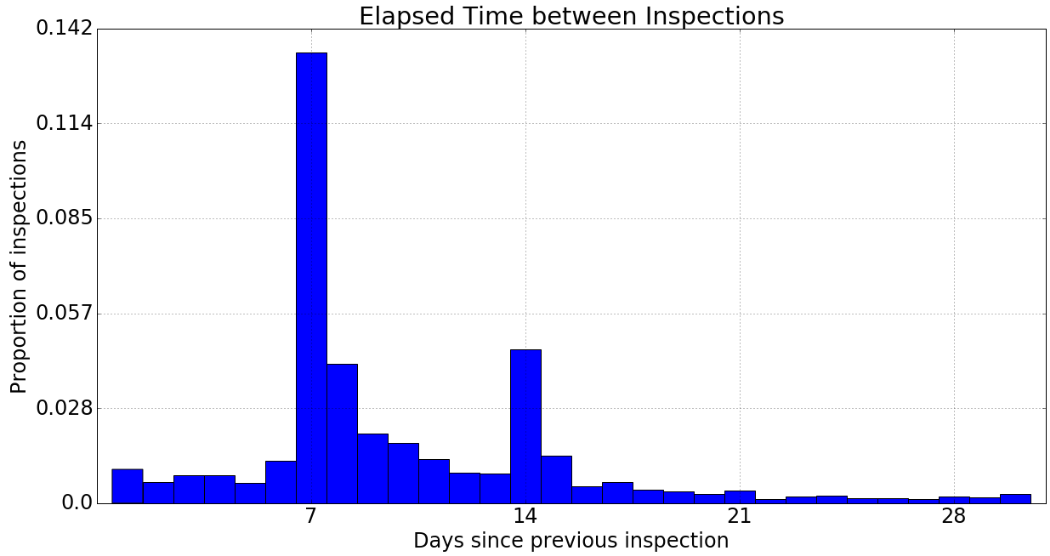
Because the features we will use are mostly derived from location information, for the remainder of this report, we will use only the condensed inspection dataset provided by Yelp, which provides latitude and longitude coordinates for every inspection. Another somewhat less important reason for using 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 the final correction of dropping any inspection with a calculated delay of 14 or fewer days.



Some Insights from Inferential Statistics

[[contents of this subsection will be similar to my "milestone report" from before, illustrating statistically significant correlations between features and inspection outcomes]]

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

[[specifics of this model, performance, etc.]]

RANDOM FOREST

[[specifics of this model, performance, feature importances, etc.]]

COMPARISON TO PREVIOUS CONTEST RESULTS

CONCLUSIONS