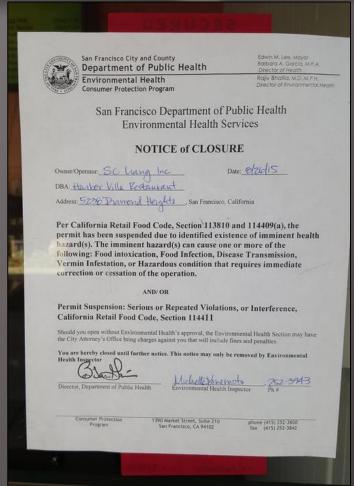


Background



- The Food Safety Program enforces health code regulations, which may result in administrative actions and suspension or revocation of the Permit to Operate when violations are identified.
- To enforce the health code regulations, Environmental Health Inspectors inspect over 7,000 locations in San Francisco that serves food to the public including restaurants, bars, markets, bakeries, pushcarts, and stadium food.
 - Inspection score > 80: requires 2 routine inspections per year
 - Inspection score < 80: requires 3 routine inspections per year
- Recent articles have pointed out that San Francisco, as well as other cities, have shortages of health (food/restaurant) inspectors.
- Many establishments have not received a single follow-up inspection in over 2 years.



Objective



- Determine if SF health department food inspection scores can be predicted based on Yelp data.
- This could allow better resource allocation for health inspectors.



Data Sources



- 1. SF Public Health Department (SFPHD): Inspection data
 - https://extxfer.sfdph.org/food/SFBusinesses.zip [last accessed 8/23/2016]
 - Businesses.csv: list of business ids (primary key), name, location, phone
 - Inspections.csv: score, date



2. Yelp

- Used Yelp API's to 'manually' assemble the Yelp dataset
- Two different versions of the API had to be run
 - Version 2 required to return the 'neighborhood' feature
 - Version 3 (in beta) required to return the 'price' feature
- At least 2 different implementations of each had to be used to collect all the data (phone & location via latitude/longitude) making for 2x2 = 4 calls over all the businesses



Process



Data collection

- Obtained SFDPH inspection data set straightforward
- Created a database linking SFDPH data to generate list of query criteria for Yelp APIs
- Programmed Yelp API queries
- Two different versions of the API had to be run to obtain desired features
 - V2 required to return the 'neighborhood' feature
 - V3 (in beta) required to return the 'price' feature
- At least 2 different implementations of each version had to be used to collect all the data (phone & location) making for 2x2 = 4x calls per business ($\sim 4k+$) = 16k+ calls
- Yelp JSON data parsed to Pandas DataFrames
- Yelp data added to database

Process



- Cleaning
 - Businesses with less than 10 Yelp reviews were dropped Yelp data likely not meaningful
 - Businesses operating at AT&T Park (SF Giants) were dropped too difficult to find via Yelp APIs
 - Businesses with SFDPH name and Yelp API return name that do not match were dropped
 - Initial # of rows 3418 -> cleaning -> 2997 (88% remained)
- Data split into training and testing sets
- Exploratory data analysis
- Model development

Data

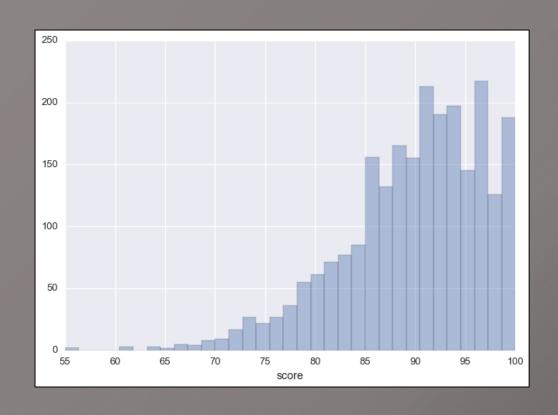


- Inspection score
 - 0-100, integer
- Rating (Yelp)
 - Categorical, 1-5 in 0.5 steps
- Counts
 - # Ratings, integer # of Yelp ratings
 - # Inspections, integer # of health inspections
- Chain
 - Binary, O not a chain, 1 chain
 - Calculated defined as having more than 1 duplicate business name
- Price
 - Categorical, 1 to 4 (\$ to \$\$\$\$)
- · Category, type of establishment
 - Categorical, condensed from a list of 152 down to 25
- Neighborhood, location of establishment
 - Categorical, condensed from a list of 63 down to 21

- Totals
 - # of features: 60
 - # of samples (after cleaning): 2998

Inspection Score

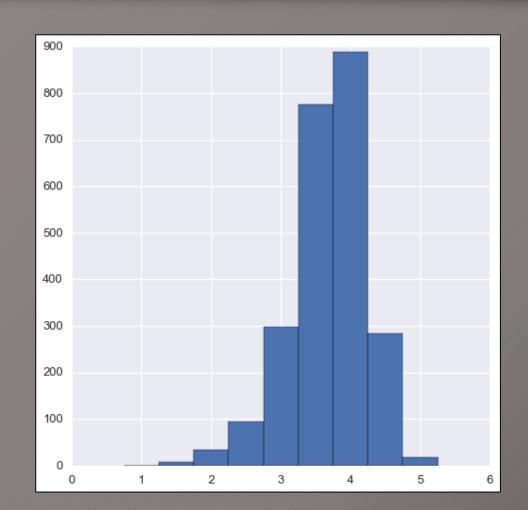


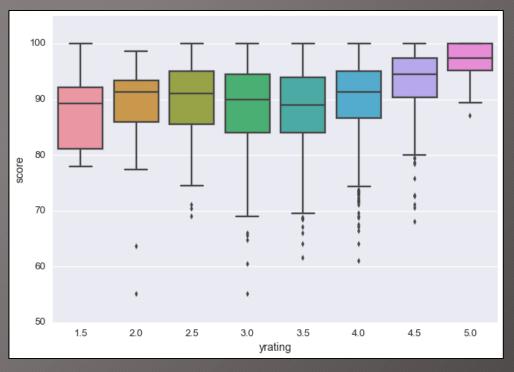


Count	2997
Mean	90
Std	7.1
Min	55
25%	86
50%	91
75%	95
Max	100

Yelp Rating

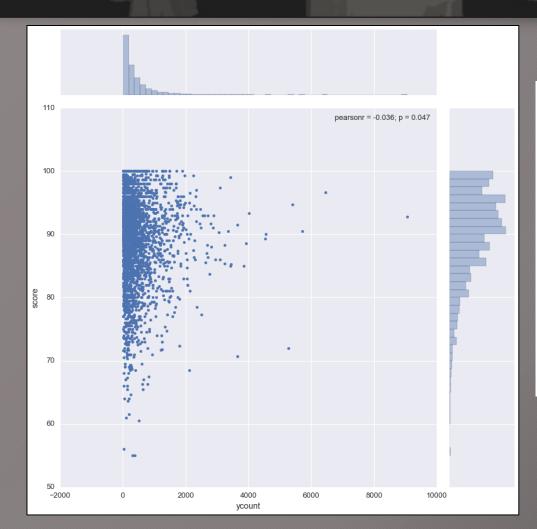






of Yelp Reviews

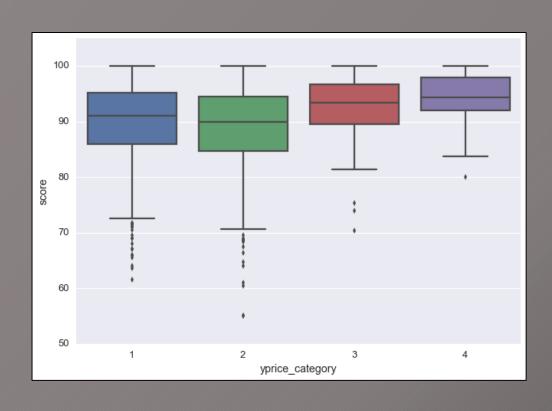


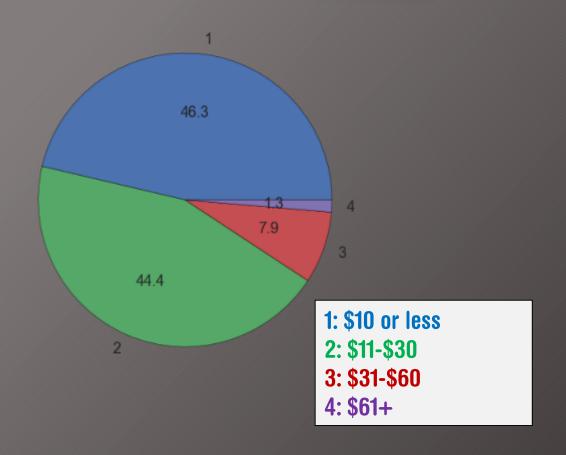


	yname	score	ycount	ccategory	cneighborhood	yrating	yprice_category	chain
1564	bi rite creamery	92.75	9051	desserts	mission	4.5	1	0
898	tartine bakery and cafe	96.67	6450	bakeries	mission	4.0	2	0
454	burma superstar	90.50	5715	asian	richmond	4.0	2	0
825	house of prime rib	94.67	5403	american	nobhill	4.0	3	0
2559	san tung	72.00	5267	chinese	sunset	4.0	2	0
817	gary danko	90.00	4559	american	russianhill	4.5	4	0
1391	the slanted door	89.25	4533	vietnamese	northbeach	3.5	3	0
698	foreign cinema	93.33	4015	american	mission	4.0	3	0
559	el farolito	88.60	3925	mexican	mission	4.0	1	1
121	the house	85.00	3847	asian	northbeach	4.5	3	0

Price

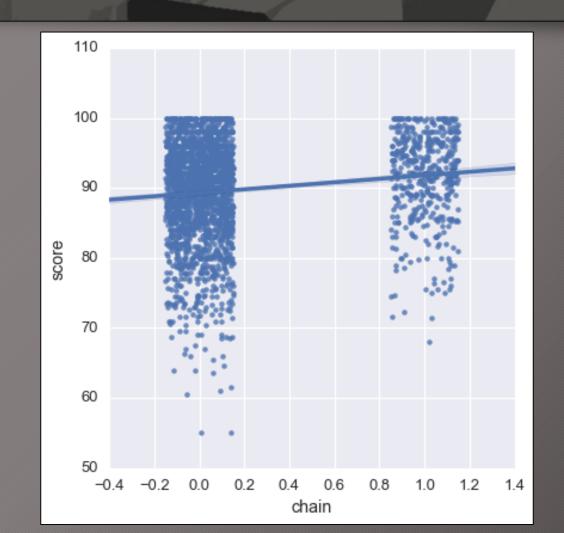






Chain

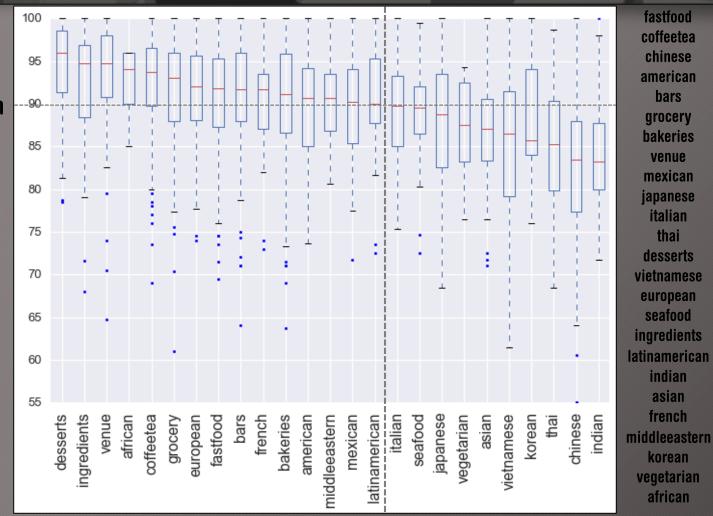




Category



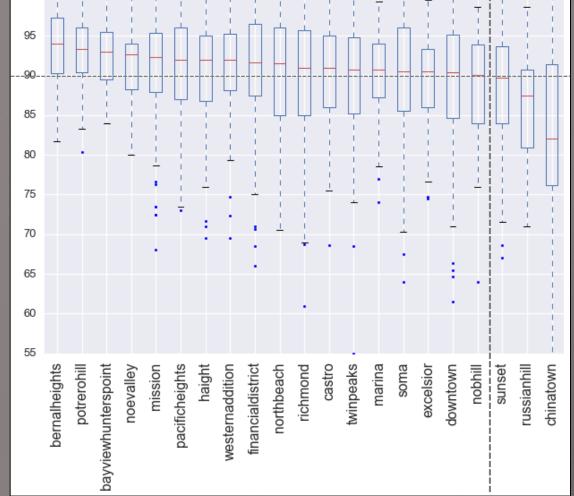




Neighborhood

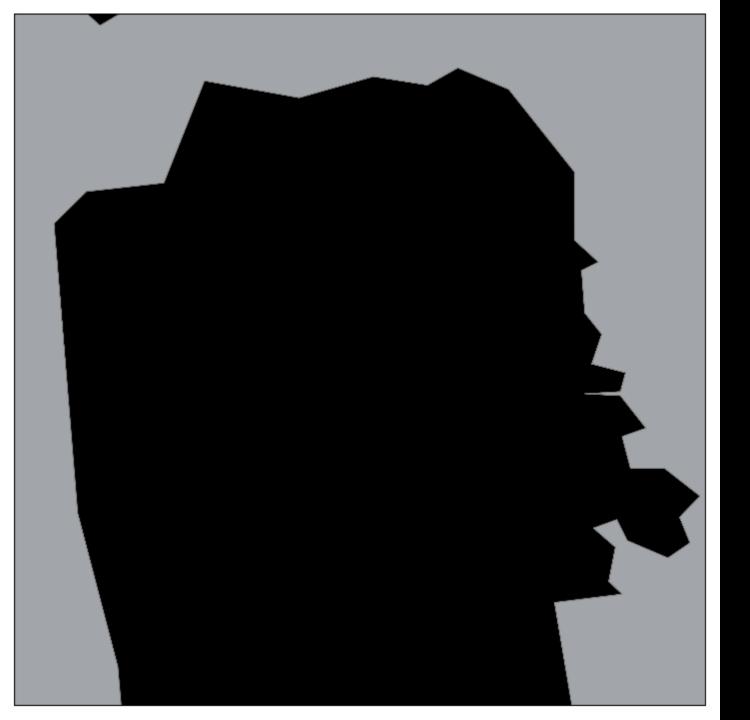


Mean



mission 356 financialdistrict 305 downtown 257 253 sunset richmond 229 soma 192 northbeach 172 pacificheights 152 nobhill 142 marina haight 108 russianhill 105 chinatown 98 excelsior 94 88 castro twinpeaks westernaddition bernalheights 63 noevalley 51 bayviewhunterspoint 39 potrerohill





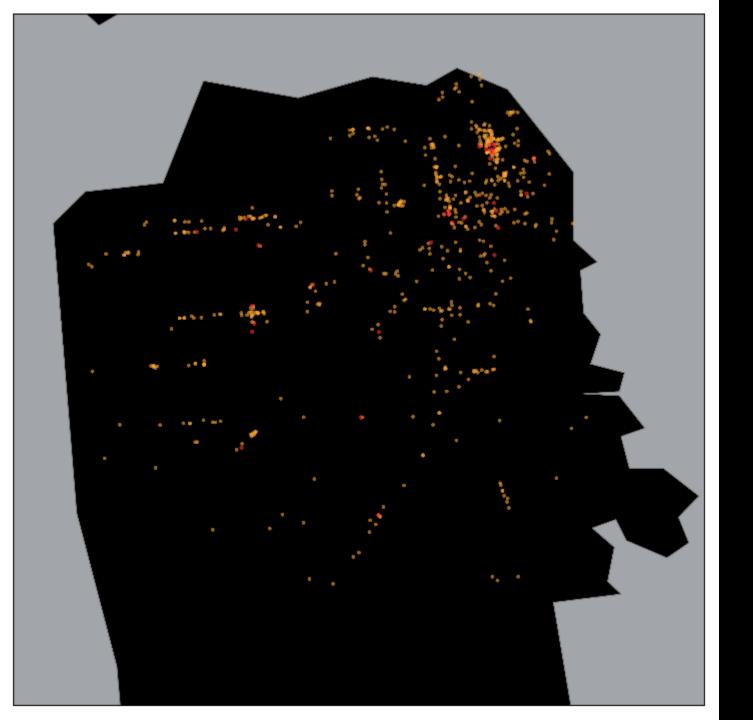


Score	Operating Condition Categor	y	Inspection Findings
>90	Good	•	Typically, only lower-risk health and safety violations observed May have high-risk violations
86-90	Adequate	•	Several violations observed May have high-risk violations
71-85	Needs Improvement	•	Multiple violations observed Typically, several high-risk violations
Less than or equal to 70	Poor		Multiple violations observed Typically, several high-risk violations



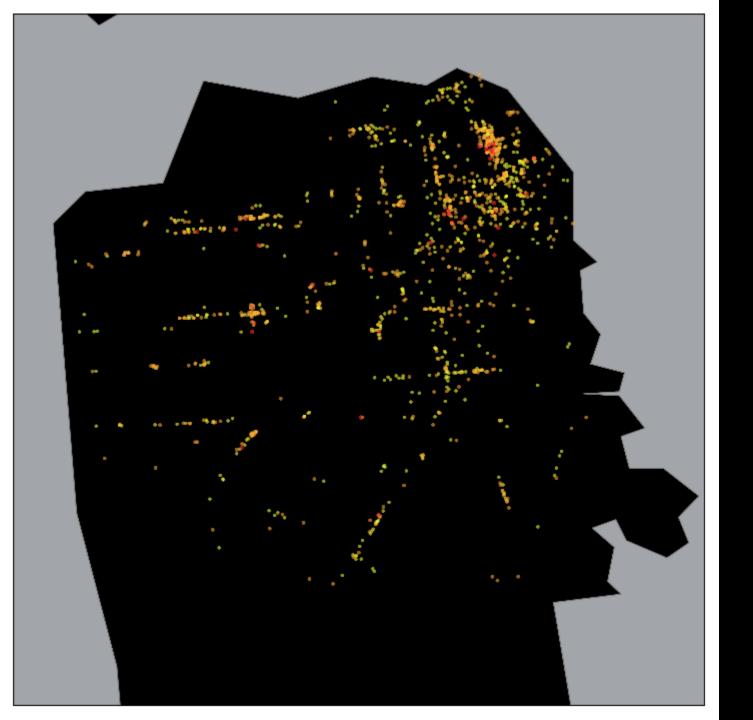


Score	Operating Condition Categor	y	Inspection Findings
>90	Good	•	Typically, only lower-risk health and safety violations observed May have high-risk violations
86-90	Adequate	•	Several violations observed May have high-risk violations
71-85	Needs Improvement	•	Multiple violations observed Typically, several high-risk violations
Less than or equal to 70	Poor		Multiple violations observed Typically, several high-risk violations



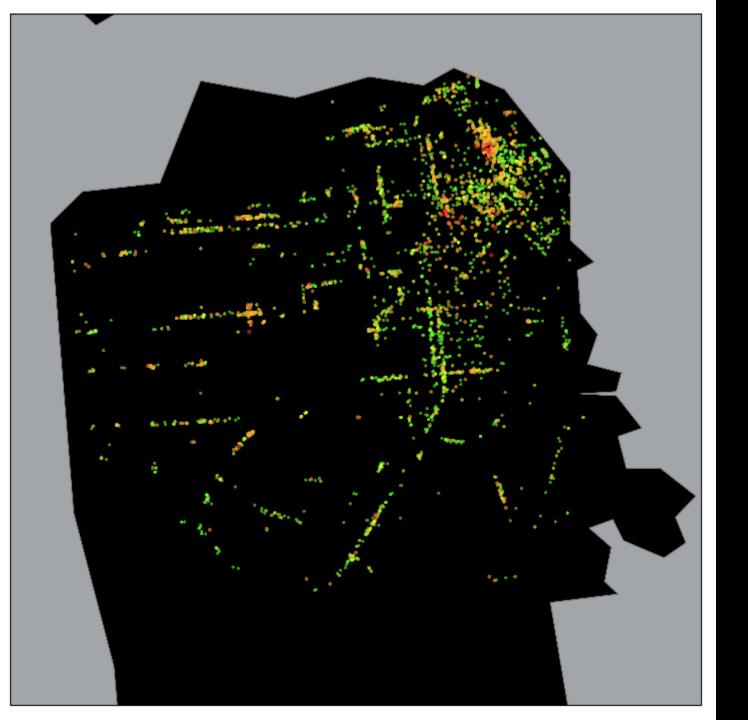


Score	Operating Condition Categor	Inspection Findings	
>90	Good	 Typically, only lower-risk health and safety violations observed May have high-risk violations 	
86-90	Adequate	Several violations observedMay have high-risk violations	
71-85	Needs Improvement	Multiple violations observedTypically, several high-risk violations	3
Less than or equal to 70	Poor	Multiple violations observedTypically, several high-risk violations	





Score	Operating Condition Categor	y	Inspection Findings
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Less than or equal to 70	Poor		Multiple violations observed Typically, several high-risk violations

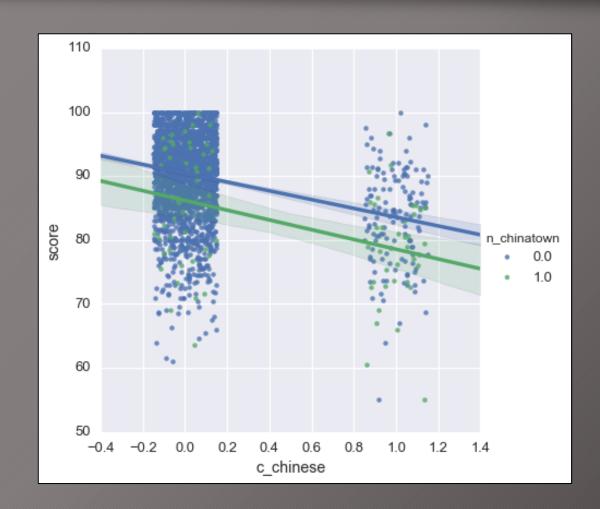




Score	Operating Condition Categor	Inspection Findings
>90	Good	 Typically, only lower-risk health and safety violations observed May have high-risk violations
86-90	Adequate	Several violations observedMay have high-risk violations
71-85	Needs Improvement	Multiple violations observedTypically, several high-risk violations
Less than or equal to 70	Poor	Multiple violations observedTypically, several high-risk violations

Combined Effects





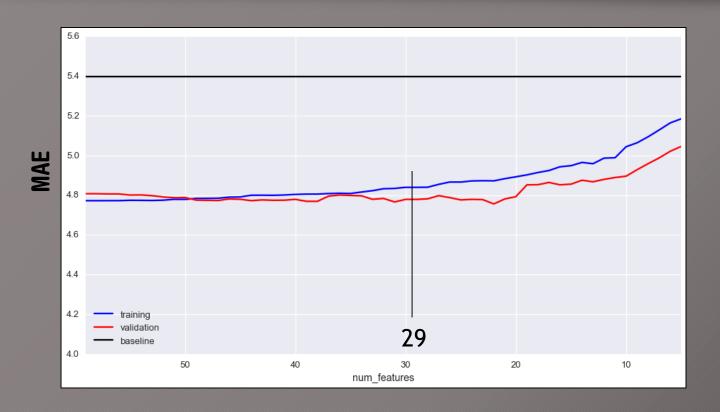
Modeling Approach



- Optimizing for Mean Absolute Error
 - The average of the absolute errors, where f_i is the predicted value (yhat) and y_i is the actual value.
- Data split
 - 80% training/validation, 20% test
 - Of the training set: 70% model training, 30% model validation
- 60 features -> All-in approach
 - All features fit
 - Ranked
 - Lowest contributor tossed out
 - · Re-fit
 - Repeat until all features are exhausted or the training MAE is > the baseline MAE
- The feature set to use is where the test/training MAE starts to significantly deviate

$$igg| \mathrm{MAE} = rac{1}{n} \sum_{i=1}^n |f_i - y_i| = rac{1}{n} \sum_{i=1}^n |e_i| \, .$$

Linear Regression

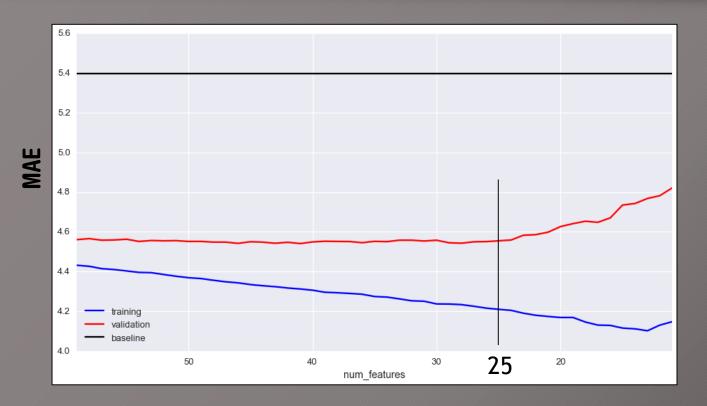


```
1.810894717139152e-46, 'c chinese'
         7.2285477679285451e-20, 'n_chinatown'
         3.0320814941594692e-18, 'rating_4.5'
4.
         3.9937047952153105e-14, 'c coffeetea'
          1.0833529253459801e-11, 'chain'
         3.7961835364454637e-11, 'rating 3.5'
         2.8215529367003095e-10, 'c venue'
          1.005588355444725e-09, 'c_thai'
          1.0717760243754801e-09, 'price 3'
10.
          1.5998268265255936e-08, 'c vietnamese'
11.
          9.006843133751674e-08, 'price 2'
12.
         1.3686555097935e-06, 'c indian'
13.
         2.0700553858507486e-06, 'c desserts'
14.
         4.0915394735824555e-06, 'n russianhill'
15.
         7.5880180054662327e-05, 'rating_5.0'
16.
         0.00023091715880025794, 'n_mission'
         0.00040909974942875712, 'n_bernalheights'
18.
         0.00064214295416450951, 'n_financialdistrict'
19.
         0.00076069604792101497, 'price 4'
20.
         0.0011117470575030132, 'c_japanese'
21.
         0.001319635793739738, 'c fastfood'
23.
         0.0038915225910515867, 'rating_3.0'
24.
         0.005914424290869965, 'c asian'
25.
         0.014441365848194495, 'c_grocery'
26.
         0.015171515966960245, 'c bars'
28.
         0.023421443595428235, 'n_potrerohill'
29.
         0.27815701064558435, 'n haight'
count 2398
```

count 2398
mean 4.795664
std 3.799989
min 0.002107
25% 1.815817
50% 4.087439
75% 6.792585
max 27.895557



Random Forest Regression



n_features = 10, min_samples_leaf = 5

```
0.1536387867101322, 'c chinese'
         0.049499623659676265, 'n chinatown'
         0.048760944031403734, 'rating_4.5'
         0.039798033848302279, 'chain'
         0.031893551363132648, 'rating_3.5'
         0.030674919560013794, 'c_thai'
         0.030343857314512959, 'c coffeetea'
         0.028910887586159912, 'c vietnamese'
12.
         0.024836747237302611, 'price 2'
13.
         0.0239275656249869, 'c_venue'
14.
         0.019494771910807007, 'price_1'
15.
         0.018774190011046427, 'n_sunset'
16.
         0.018043212903155997, 'n russianhill'
         0.016353538501653223, 'n downtown'
18.
         0.01601880840380349, 'price_3'
19.
         0.015660240587556988, 'n mission'
20.
         0.015472136326288662, 'c_japanese'
21.
         0.014890384430931297, 'rating 3.0'
22.
         0.013798707580006769, 'c fastfood'
23.
         0.01291440092037606, 'n financialdistrict'
24.
         0.011315910083317615, 'c_bakeries'
25.
         0.0084804066433696538, 'n_richmond'
count 2398
        4.114636
mean
std
        3.300645
min
        0.001760
25%
         1.609043
50%
         3.507397
```

75%

max

5.758480

27.902103



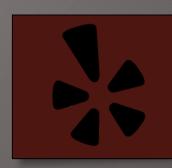
Linear Regression: Outliers

Under-predicted

		yname	score	score_test	ycount	ccategory	cneighborhood	yrating	yprice_category	chain
45	9	panda express	100.00	85.387588	57	chinese	sunset	2.5	1	1
24	30	aslams rasoi	99.00	84.732348	810	indian	mission	4.0	2	0
23	15	thai cottage restaurant	98.67	84.417342	179	thai	sunset	4.0	2	0
86	6	oriental pearl restaurant	92.75	78.686799	303	chinese	chinatown	3.5	2	0
27	95	backroom dining	98.00	83.983648	12	asian	twinpeaks	3.0	2	0

Over-predicted

	yname	score	score_test	ycount	ccategory	cneighborhood	yrating	yprice_category	chain
273	taqueria la paz	56.00	88.767174	26	mexican	downtown	4.0	1	0
1588	bristol farms	66.33	91.057225	793	grocery	downtown	3.5	3	0
2563	roxies market and deli	69.33	89.934308	259	fastfood	sunset	4.0	1	0
1257	el chico produce no 2	74.00	94.499435	21	ingredients	mission	4.5	1	1
785	happy garden	65.50	82.891191	148	chinese	richmond	2.5	1	0
1273	rjs market levi plaza	73.00	90.388670	203	grocery	northbeach	3.0	3	0
951	cove on castro cafe	71.00	88.371984	222	american	castro	3.5	2	0
2893	sa beang thai	67.33	84.612201	133	thai	haight	3.5	2	0
2199	gateway croissant	73.00	90.152401	102	coffeetea	downtown	3.5	1	0
7	oasis grill	77.00	92.451744	1046	european	financialdistrict	4.0	1	1



Random Forest: Outliers



Under-predicted

	yname	score	score_test	ycount	ccategory	cneighborhood	yrating	yprice_category	chain
540	gold mirror italian restaurant	100.0	84.038106	213	italian	sunset	3.5	2	0
3338	t 28 bakery and cafe	94.0	80.552224	197	chinese	sunset	3.0	1	0
3398	yans kitchen	98.0	84.911949	392	chinese	financialdistrict	4.0	1	0
500	b and m mei sing restaurant	96.0	83.204686	228	chinese	financialdistrict	3.0	1	0
459	panda express	100.0	87.531577	57	chinese	sunset	2.5	1	1

Over-predicted

	yname	score	score_test	ycount	ccategory	cneighborhood	yrating	yprice_category	chain
273	taqueria la paz	56.00	91.054029	26	mexican	downtown	4.0	1	0
1588	bristol farms	66.33	90.093305	793	grocery	downtown	3.5	3	0
2893	sa beang thai	67.33	87.705460	133	thai	haight	3.5	2	0
2563	roxies market and deli	69.33	88.694850	259	fastfood	sunset	4.0	1	0
951	cove on castro cafe	71.00	89.435155	222	american	castro	3.5	2	0
785	happy garden	65.50	82.802818	148	chinese	richmond	2.5	1	0
1273	rjs market levi plaza	73.00	90.064174	203	grocery	northbeach	3.0	3	0
1257	el chico produce no 2	74.00	91.051120	21	ingredients	mission	4.5	1	1
2199	gateway croissant	73.00	89.348069	102	coffeetea	downtown	3.5	1	0
3192	wei lee chinese food and donuts	76.00	91.754760	59	fastfood	richmond	2.5	1	0

Model Comparison



N = 599	Baseline	Linear (OLS)	Random Forest
Improvement (mean/mean)	-	8.3%	11.5%
mean	5.40	4.95	4.78
std	4.43	3.98	3.94
25%	2.06	2.01	1.84
50%	4.39	4.05	4.00
75%	7.94	6.87	6.47

Model Comparison



N = 599	Baseline	Linear (OLS)	Random Forest
Improvement (mean/mean)	-	8.3%	11.5%
mean	5.40	4.95	4.78
std	4.43	3.98	3.94
25%	2.06	2.01	1.84
50%	4.39	4.05	4.00
75%	7.94	6.87	6.47

High Risk

- -7 pts
- Violations that directly relate to the transmission of food borne illnesses, the adulteration of food products and the contamination of food-contact surfaces.
- Moderate Risk
 - - 4 pts
 - Violations that are of a moderate risk to the public health and safety.
- Low Risk
 - -2 pts
 - Violations that are low risk or have no immediate risk to the public health and safety.

Conclusions



- Be careful eating Chinese in Chinatown
- Exploratory data analysis was really interesting
 - What is the highest rated & most reviewed business with the lowest inspection score?
 - Arizmendi Bakery, 4.5 Yelp rating and 1682 ratings, w/ mean score of 78.5 over 2 inspections
 - What is the most expensive business with the lowest inspection score?
 - Campton Place (2 Michelin Stars!!) w/ mean score of 80 over 4 inspections
- Model could be useful for resource allocation but it is not good at capturing extremes

Conclusions



- High degree of variability in scores due to the random nature of violations
 - Off/busy day
 - Bad employees
 - Lack of training
 - Age/condition of kitchen
- All of the factors above would likely not be apparent to Yelp reviewers
 - It would be interesting to add a feature if the kitchen is visible to patrons (an open kitchen); currently doesn't exist in Yelp data but could possibly be text mined from reviews

Next Steps



- Cleaner data = More data
 - Need a better link between SFDPH and Yelp data
 - It would be best if the Yelp ID was imbedded in the SFDPH dataset
 - The Yelp ID (their primary key) is the only real unique way to identify a business in Yelp
- NLP / latent variable
 - Analysis of inspection violation types
 - Sentiment analysis in Yelp reviews
- Collect new data over fixed time intervals
 - New Yelp data + historical inspection and Yelp data -> predict new inspection score
 - This type of model would likely be more useful for better resource allocation of inspectors



Sample Data: SF Health Department



business_id	name
10	TIRAMISU KITCHEN
19	NRGIZE LIFESTYLE CAFE
24	OMNI S.F. HOTEL - 2ND FLOOR PANTRY
31	NORMAN'S ICE CREAM AND FREEZES
45	CHARLIE'S DELI CAFE
48	ART'S CAFE
50	SUSHI ZONE
54	RHODA GOLDMAN PLAZA
56	CAFE X + 0

address
033 BELDEN PL
1200 VAN NESS AVE, 3RD FLOOR
500 CALIFORNIA ST, 2ND FLOOR
2801 LEAVENWORTH ST
3202 FOLSOM ST
747 IRVING ST
1815 MARKET ST.
2180 POST ST
1799 CHURCH ST

city	state	postal_code	latitude	longitude	phone_number
San Francisco	CA	94104	37.791116	-122.403816	14154217044
San Francisco	CA	94109	37.786848	-122.421547	14157763262
San Francisco	CA	94104	37.792888	-122.403135	14156779494
San Francisco	CA	94133	37.807155	-122.419004	
San Francisco	CA	94110	37.747114	-122.413641	14156415051
San Francisco	CA	94122	37.764013	-122.465749	14156657440
San Francisco	CA	94103	37.771437	-122.423892	14156211114
San Francisco	CA	94115	37.784626	-122.437734	14153455060
San Francisco	CA	94131	37.742325	-122.426476	14158263535

business_id	score	date	type	
10	82	20160503	routine	
10	94	20140729	routine	
10	92	20140114	routine	
19	94	20160513	routine	
19	94	20141110	routine	
19	94	20140214	routine	
19	96	20130904	routine	
24	96	20160311	routine	
24	96	20141124	routine	
24	96	20140612	routine	
24	100	20131118	routine	

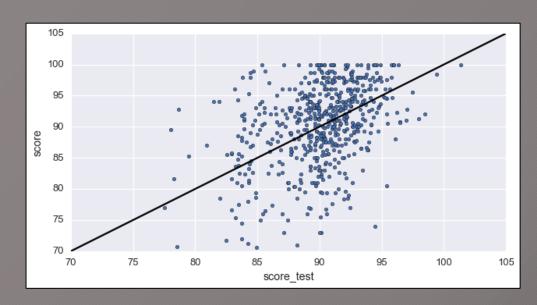
Sample Data: Yelp API's

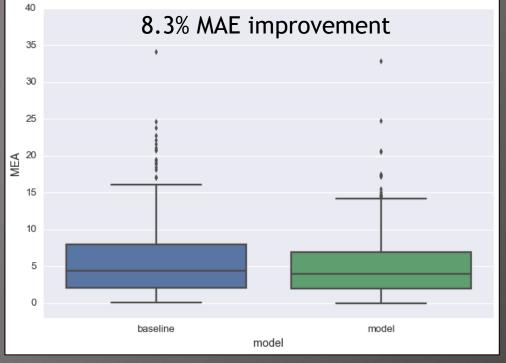


- JSON output
- [{"rating": 4.0, "review_count": 1046, "name": "Oasis Grill", "photos": ["https://s3-media3.fl.yelpcdn.com/bphoto/ct6p78k0Uf6u6JVES6dTN0/o.jpg", "https://s3-media4.fl.yelpcdn.com/bphoto/Sg5cz9hi_p6G22TFja2xRA/o.jpg", "https://s3-media2.fl.yelpcdn.com/bphoto/FlbKcFrbuwyqSgs0A2_4PA/o.jpg"], "url": "https://www.yelp.com/biz/oasis-grill-san-francisco?adjust_creative=wXkLRioDMWxUkNynLkngJg&utm_campaign=yelp_api_v3&utm_medium=api_v3_bu siness lookup&utm_source=wXkLRioDMWxUkNynLkngJg", "price": "\$", "coordinates": {"latitude": 37.7944464239893, "longitude": -122.396736520868}, "hours": [{"hours_type": "REGULAR", "open": [{"is_overnight": false, "end": "2200", "day": 0, "starf": "0900"}, {"is_overnight": false, "end": "2200", "day": 1, "start": "0900"}, {"is_overnight": false, "end": "2200", "day": 1, "start": "0900"}, {"is_overnight": false, "end": "2200", "day": 5, "start": "1000"}, {"is_overnight": false, "end": "2200", "day": 6, "start": "1000"}, "is_open_now": true}, "phone": "+14157810313", "image_url": "https://s3-media4.fl.yelpcdn.com/bphoto/ct6p78k0Uf6u6JVES6dTNO/o.jpg", "location": {"city": "San Francisco", "address1": "91 Drumm St", "address2": ", "address3": ", "state": "CA", "country": "US", "zip_code": "94111"}, "id": "oasis-grill-san-francisco", "categories": [{"alias": "greek", "title": "Greek"}, {"alias": "mediterranean", "title": "Mediterranean"}, ""ittle": "Mediterranean"}, ""

Results: Linear Regression

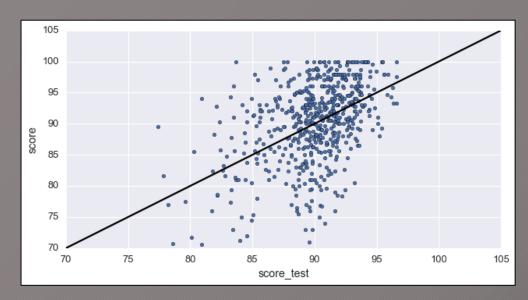


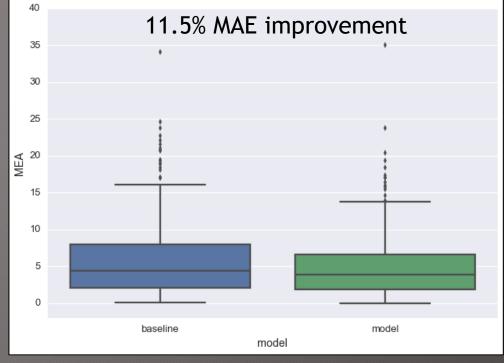




Results: Random Forest Regression







Interesting Data



Total Yelp reviews by neighborhood Mean Ye	elp r	'eviews i	oy nei	gnbor	nood
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		-	7
mission	168495	westernaddition	680
financialdistrict	116963	northbeach	629
downtown	108509	russianhill	552
northbeach	108137	haight	485
richmond	99474	soma	479
sunset	97861	potrerohill	475
soma	91942	mission	473
pacificheights	66837	nobhill	466
nobhill	66135	marina	446
russianhill	57943	pacificheights	440
haight	52343	richmond	434
marina	49518	downtown	422
westernaddition	42838	castro	409
castro	36007	sunset	387
chinatown	31163	financialdistrict	383
twinpeaks	21677	noevalley	367
noevalley	18706	chinatown	318
potrerohill	18513	bernalheights	290
bernalheights	18287	twinpeaks	285
excelsior	12163	excelsior	129
bayviewhunterspoint	3781	bayviewhunterspoint	88

