Final Presentation - 4381 - Restaurant Health Violations (SFO)

Thao Wells

	business_id	business_name	business_address	business_city	business_state	business_postal_code	business_latitude	business_longitude	business_location
0	85936	Laurel Court	950 Mason St	San Francisco	CA	94108	NaN	NaN	NaN
1	5827	HILLCREST ELEMENTARY SCHOOL	810 SILVER Ave	San Francisco	CA	94134	37.729016	-122.419253	POINT (-122.419253 37.729016)
2	94910	lke's Kitchen	800 Van Ness Ave	San Francisco	CA	94109	NaN	NaN	NaN
3	64667	Jasmine Rae Bakery	1890 Bryant St #309	San Francisco	CA	94110	37.763156	-122.410351	POINT (-122.410351 37.763156)
4	97722	THE CHURRO FACTORY	PIER 39 K-01	San Francisco	CA	94133	NaN	NaN	NaN
	***	***	344		112	344	(815)	344	18mg
53968	70220	Trader Joe's #200	1095 Hyde St	San Francisco	CA	94109	NaN	NaN	NaN
53969	95021	Wing Wings	422 Haight St	San Francisco	CA	94117	NaN	NaN	NaN
53970	78289	Sam Jordans Bar	4004 03rd St	San Francisco	CA	94124	NaN	NaN	NaN
53971	100887	ASIA CHINESE FOOD	350 BAY ST.	San Francisco	CA	94133	NaN	NaN	NaN
53972	15120	Nordstrom Espresso Bar	865 Market Street	San Francisco	CA	94103	37.784317	-122.407563	POINT (-122.407563 37.784317)

business_phone_number		inspection_score	inspection_type	violation_id	violation_description	risk_category	Neighborhoods	SF Find Neighborhoods	Current Police Districts	Current Supervisor Districts	Analysis Neighborhoods
1.415578e+10	373	100.0	Routine - Unscheduled	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1.415546e+10	1775	NaN	Reinspection/Followup	NaN	NaN	NaN	92.0	92.0	2.0	2.0	7.0
NaN		NaN	New Ownership - Followup	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN		NaN	Reinspection/Followup	NaN	NaN	NaN	53.0	53.0	3.0	2.0	20.0
NaN		96.0	Routine - Unscheduled	97722_20181217_103154	Unclean or degraded floors walls or ceilings	Low Risk	NaN	NaN	NaN	NaN	NaN
9,555	***	8999	***		1777		***	***		(500)	1000
1.415530e+10	***	NaN	Complaint	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1.415584e+10		92.0	Routine - Unscheduled	95021_20190228_103119	Inadequate and inaccessible handwashing facili	Moderate Risk	NaN	NaN	NaN	NaN	NaN
NaN		NaN	Reinspection/Followup	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1.415582e+10		NaN	New Ownership - Followup	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN	***	NaN	Non-inspection site visit	NaN	NaN	NaN	32.0	32.0	5.0	10.0	34.0

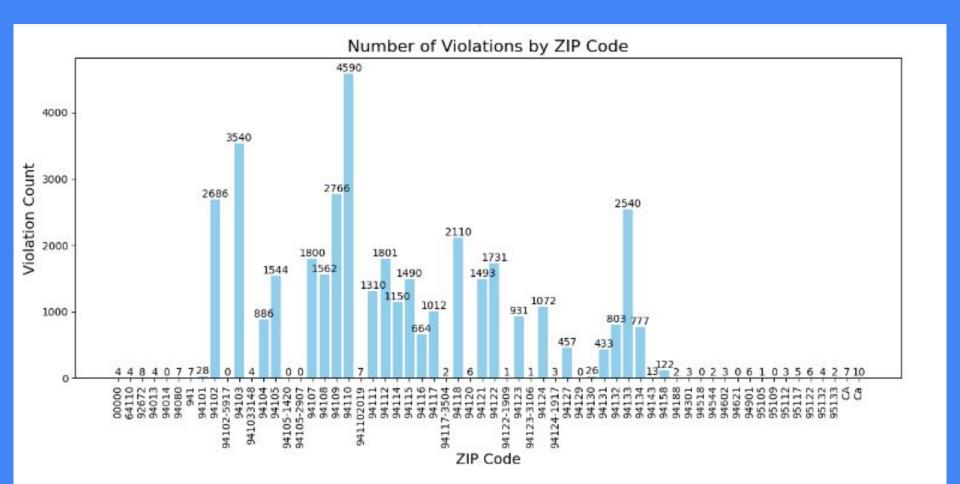
Models:

- Random Forest (was working, needs to be redone)
- Gradient Boosting Machines (was working, needs to be redone)
- Support Vector Machines (SVM) (unfinished)
- Baseline: Logistic Regression (done, will be redone when secondary datasets are added)

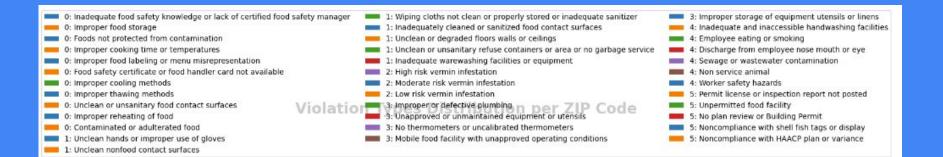
Evaluation Metrics:

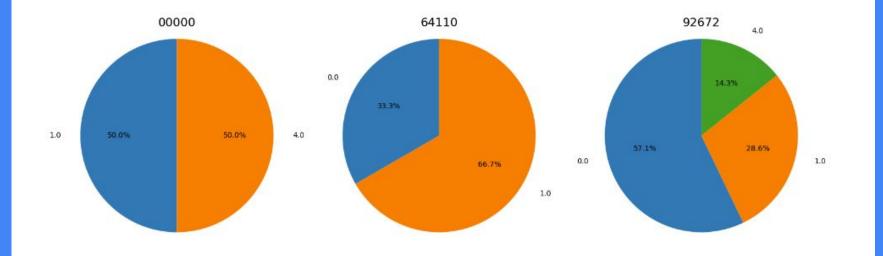
- Accuracy, Precision, Recall, F1-Score, ROC-AUC.
- Special focus on precision/recall for high-risk violations.

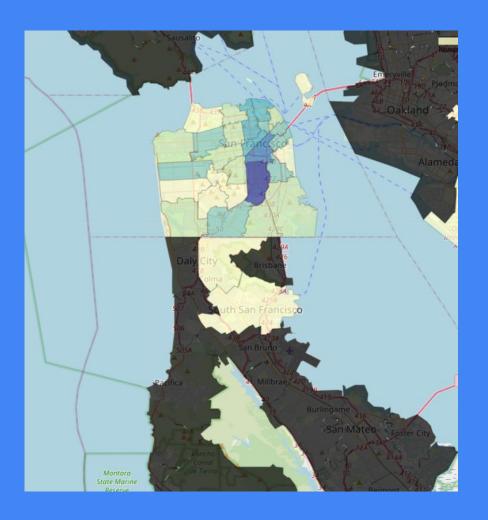
Analysis of Violations and Highway Proximity



violation_description	00000		92672	94013	94080	941	94101	94102	94103	941033148	94104	94105	94107	94108	94109	941
Consumer advisory not provided for raw or undercooked foods	0	0	0	0	0	0	0	4	1	0	0	0	1	1	1	0
Contaminated or adulterated food	0	0	0	0	0	0	0	11	11	0	0	3	6	8	14	20
Discharge from employee nose mouth or eye	0	0	0	0	0	0	0	0	0	0	1	0	1 1	0	0	1
Employee eating or smoking	0	0	0	0	0	0	0	10	20	0	4	2	7	4	7	53
Food in poor condition	0	0	0	0	0	0	0	8	9	0	1	2	6	1	3	7
Food safety certificate or food handler card not available	0	1	0	0	0	1	2	80	100	0	21	20	51	47	97	123
Foods not protected from contamination	0	0	1	0	0	0	0	129	184	0	40	87	103	85	160	157
High risk food holding temperature	0	1	0	0	0	0	2	116	171	0	52	89	61	72	119	182
High risk vermin infestation	0	0	0	0	0	0	0	50	88	0	9	14	31	49	88	107
Improper cooking time or temperatures	0	1 0	0	0	0	0	0	0	0	0	0	0	0	2	2	1 0
Improper cooling methods	0	0	0	0	0	0	0	67	104	0	10	98	43	36	43	148
Improper food labeling or menu misrepresentation	0	0	0	0	0	0	0	12	14	0	7	6	6	5	20	24
Improper food storage	0	0	1	0	0	1	1	129	124	0	29	35	54	88	115	170
Improper or defective plumbing	0	i ø	0	0	0	0	1	54	64	0	35	43	23	44	57	69
Improper reheating of food	0	i 0	0	0	0	0	0	11	15	0	7	9	7	3	6	1 13
Improper storage of equipment utensils or linens	0	i 0	0	1	0	1	1	66	66	0	28	22	30	44	64	108
Improper storage use or identification of toxic substances	0	0	0	0	0	1	1	40	26	0	15	10	17	14	33	26
Improper thawing methods	0	0	0	0	1	0	1	44	48	0	9	9	30	36	45	57
Improperly displayed mobile food permit or signage	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
Improperly washed fruits and vegetables	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	2
Inadequate HACCP plan record keeping	0	1 0	0	0	0	0	0	4	3	0	1	2	3	1	0	3
Inadequate and inaccessible handwashing facilities	2	0	1	0	0	0	1	194	242	1	38	128	171	102	174	254
Inadequate dressing rooms or improper storage of personal items	0	0	0	0	0	0	0	13	43	1 0	6	31	22	6	13	44
Inadequate food safety knowledge or lack of certified food safety manager	0	0	0	0	0	0	2	54	86	1	42	54	49	29	49	162
Inadequate or unsanitary refuse containers or area or no garbage service	0	0	0	0	0	0	1 0	10	3	i a	0	2	2	4	8	20
Inadequate procedures or records for time as a public health control	0	0	0	1 0	0	0	0	7	31	1 0	3	10	11	3	7	1 15
Inadequate sewage or wastewater disposal	0	1 0	0	1 0	0	0	1 0	5	1 13	0	1 1	8	1	2	8	4
Inadequate ventilation or lighting	0	0	0	0	0	0	0	27	15	0	6	11	16	18	33	32
Inadequate warewashing facilities or equipment	0	0	1 0	1 0	0	0	2	34	45	1 0	1 33	11	9	17	33	1 16
Inadequately cleaned or sanitized food contact surfaces	1 1	1 1	0	1	1	0	1 1	181	310	1 1	81	137	142	123	154	303
Insufficient hot water or running water	0	0	0	1 0	0	0	1 2	59	48	1 0	49	37	35	43	78	51
Low risk vermin infestation	0	0	0	1 0	0	0	1 0	82	82	0	1 15	34	40	44	102	175
Mobile food facility not operating with an approved commissary	1 0	1 0	1 0	1 0	0	1 0	1 0	0 0	1 10		1 0	0	0	0	2	0
Mobile food facility not operating with an approved commissary Mobile food facility stored in unapproved location	0	1 0	1 0	1 0	0	1 0	1 0	1 0	1 0	1 0	1 0	1 0	0	0	0	0
Mobile food facility with unapproved operating conditions	0	1 0	1 0	1 0	0	0	1 0	1 2	1 0		1 0	1 1	0	0	0	0
Moderate risk food holding temperature		1 0	0	0	0		0	1 163	231	0	0 59	109	173	96	151	292







Exploring Correlations Between Business Locations, Violations, and Highway Distance

Investigate the relationship between business location, violation codes, and proximity to highways.

Examine whether being closer to highways affects the frequency and type of violations.

*Initially, I was working on models that were just based off of a geographical data set and the restaurant dataset, but I wanted to analyse it compared against proximity to a highway (implying traffic)

Overview

Data Sources:

- Violation data (Business postal codes, violation codes, and counts of violations).
- Geographic data (Highway shapefiles for the San Francisco area).

Key Variables:

- business_postal_code: Location of businesses.
- violation_code: Type of violation (e.g., parking violations).
- Count: Number of violations.
- distance_to_highway: Proximity of each business to the nearest highway.

Issues

Problem: Unable to parse the HTML file (violations_by_zip.html) containing the relevant data.

Attempted Solutions:

Tried reading the file using pd.read_html(), but no tables were found in the HTML.

Tried extracting JSON data from the HTML using BeautifulSoup, but the data format was not as expected.

Solution: Reached out to various methods, including examining the raw HTML content and adjusting the extraction code, but failed to get usable data directly from the HTML file.

Issues

GeoJSON File for Map Visualization:

Problem: GeoJSON data used for Choropleth mapping needed to match ZIP codes in violation data.

Issue with handling mismatched formats.

Solution: Successfully created Choropleth maps after resolving format issues, and a separate readable file as the html file did not have tables

Issues

Issues with Correlation Matrix:

Data Preprocessing Challenges:

Issue: Some columns contained non-numeric data, making it impossible to compute a correlation matrix directly.

Solution: Dropped non-numeric columns and encoded categorical features using One-Hot Encoding.

Key Takeaways

Importance of data format consistency (JSON, CSV, GeoJSON).

Careful preprocessing is essential before performing statistical analyses like PCA and correlation matrices.

Handling missing values and non-numeric data is crucial for generating meaningful insights.

preprocessing

- Cleaned and merged violation data with geographic coordinates.
- Used geographic shapefiles for highway data.
- Calculated the distance of each business from the nearest highway using GeoPandas.
- Re-projected spatial data to ensure matching CRS (Coordinate Reference System).

	business_postal_code	violation_code	Count	1
business_postal_code	1.000000	-0.024614	0.737425	
violation_code	-0.024614	1.000000	-0.693375	
Count	0.737425	-0.693375	1.000000	
distance_to_highway	-0.976476	0.239595	-0.865718	
	distance_to_highway			
business_postal_code	-0.976476			
violation_code	0.239595			
Count	-0.865718			
distance_to_highway	1.000000			

Correlation Analysis

Key Findings from Correlation Matrix:

- Business postal code vs. distance to highway: Strong negative correlation (-0.98), indicating that businesses further from city centers tend to be closer to highways.
- **Violation code vs. distance to highway**: Weak positive correlation (0.24), suggesting some types of violations are slightly more frequent near highways.
- Count vs. distance to highway: Strong negative correlation (-0.87), suggesting that higher numbers of violations tend to occur near highways.

Proximity to highways plays a significant role in the occurrence of violations, with more violations occurring closer to highways.

Certain violation types may be more associated with locations near highways.

Further Analysis

Further Analysis:

- Explore more advanced modeling techniques (e.g., regression analysis or spatial clustering) to predict violations based on proximity to highways.
- Investigate the spatial distribution of violations to identify specific patterns and trends.

Potential Applications:

- Urban planning and traffic management.
- Policy development for improved enforcement and safety measures.

