INFORMAC: Analytics Data Science Challenge

•••

Placed Runner Up in University
 Challenge

Overview

The city of Los Angeles publishes data on Environment Health inspection and enforcement results from restaurants in the Los Angeles county. These data cover 85 of 88 cities and all unincorporated areas in the LA county.

There are two datasets available: (i) market inspection dataset: contains results of inspection; and (ii) market violations dataset: contains information on health code violations in restaurants. These data were last updated on January 16, 2019. Data dictionaries for the above two data sets are included below. Feel free to supplement the above information with other publicly-available information.

Understanding the problem: Problem Statement

Q 1 03 Q 2 04 Are there any Are there any patterns What are the most What are the key relationships between in terms of how health important factors in factors in predicting various types of health scores of restaurants classifying health "scores" of the code violations and change over time? restaurants into restaurants in Los scores/grades of a different "grades"? Angeles county? restaurant?

Approach:

Timeline

Data Preprocessing

- Removing NaN, duplicates
- Transforming categorical into one hot encoding

Visualize data for Anomalies

Heatmap for correlation | box plots for outliers

Ensemble Learning

- Random Forest Feature Importance
- Chi Square for categorical variable comparison

Understanding important aspects of Dataset

Date of health inspection First inspection date taken as 1, and every month **Activity Date** followed with increment of 1, including the year Foreign key - used to join inspection and Serial Number violation datasets Calculate distance (in miles) from one reference Zip Code /Location lat long Correlated variables Score - Grade Score used for regression; Grade for classification

Pre-Processing

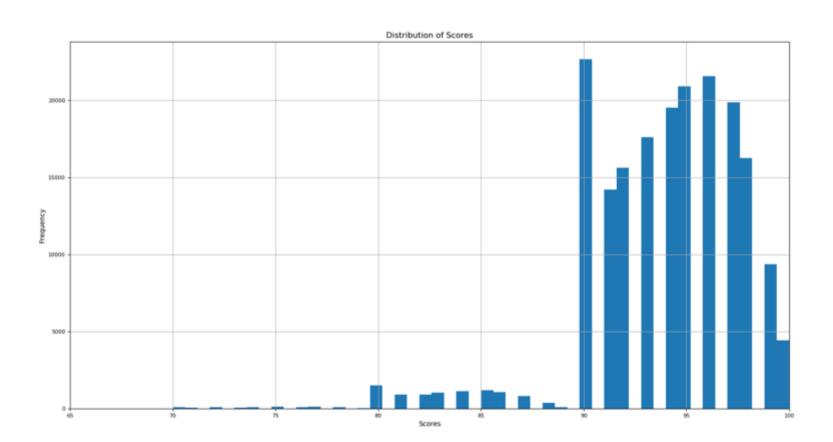
Calculated relative distance (in miles) of the restaurants and used them as interval data for modeling.

Program description is parsed to get establishment type, seating capacity and the risk factor, used regex in python

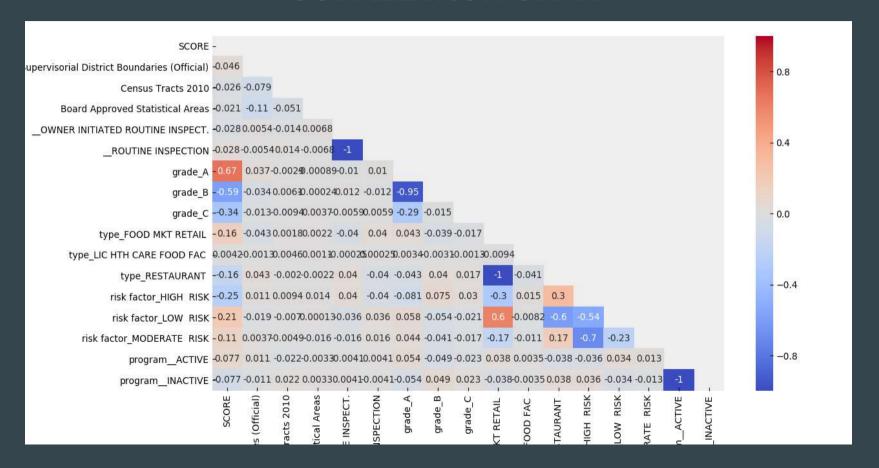
Longitude	Latitude	Distance in miles
-118.295	34.04771	0
-118.326	34.098	3.906000639
-118.233	33.94311	8.05014473
-118.536	34.1935	17.0901967
-118.3	34.17459	8.773421187
-118.311	34.0617	1.351031373
-118.078	33.90229	15.98451445
-118.102	34.07957	11.24438867
-118.369	34.06378	4.374914302
-118.255	34.04535	2.28303536
-118.236	34.22171	12.48491766
-118.352	33.89278	11.20538452
-118.091	33.91717	14.75363495
-118.48	33.99446	11.24842351
-117.89	34.07505	23.23861435
-118.26	34.07317	2.673523817
-118.015	34.09101	16.27768292
-118.288	34.09816	3.505837149

PE DESCRIPTION	type	seating size	risk factor
RESTAURANT (0-30) SEATS HIGH RISK	1	0-30	1
RESTAURANT (0-30) SEATS HIGH RISK	1	0-30	1
FOOD MKT RETAIL (1-1,999 SF) LOW RISK			-
RESTAURANT (61-150) SEATS MODERATE RISK	2	1-1,999 SF	3
RESTAURANT (0-30) SEATS HIGH RISK	1	0-30	1
RESTAURANT (31-60) SEATS MODERATE RISK	1	31-60	2
RESTAURANT (61-150) SEATS HIGH RISK	1	61-150	1
FOOD MKT RETAIL (1-1,999 SF) MODERATE RISK			_
RESTAURANT (0-30) SEATS HIGH RISK	1	0-30	1
RESTAURANT (0-30) SEATS MODERATE RISK	1	0-30	2
RESTAURANT (31-60) SEATS MODERATE RISK	1	31-60	2
RESTAURANT (0-30) SEATS HIGH RISK	1	0-30	1
RESTAURANT (0-30) SEATS MODERATE RISK			2
FOOD MKT RETAIL (2,000+ SF) LOW RISK	1	0-30	_
FOOD MKT RETAIL (2,000+ SF) MODERATE RISK	2	2,000+ SF	2
FOOD MKT RETAIL (1-1,999 SF) LOW RISK	2	1-1,999 SF	3
RESTAURANT (151 +) SEATS HIGH RISK	1	151+	1
RESTAURANT (61-150) SEATS MODERATE RISK	1	61-150	2
RESTAURANT (0-30) SEATS HIGH RISK			_
RESTAURANT (31-60) SEATS HIGH RISK	1	0-30	1
RESTAURANT (0-30) SEATS HIGH RISK	1	31-60	1

EXPLANATORY DATA ANALYSIS



CORRELATION CHART



RESTAURANT COUNT ACCORDING TO RISK FACTOR

risk fact	tor	
HIGH RIS	SK	119771
LOW RISE	Х	28414
MODERATE	RISK	43703

TOP 10 RESTAURANTS WITH HIGH SCORE

	FACILITY NAME	SCORE
101592	IHOP	100
147153	COSTCO WHOLESALE #117	100
125832	LOS ANGELES CITY COLLEGE BO	100
90194	PRIME LIQUOR MARKET	100
111703	NORTHGATE MARKET #4	100
24335	STARBUCKS COFFEE #5708	100
66397	GRIFFIN CLUB LOS ANGELES	100
184881	SUPER VALUE + EXPRESS	100
111656	BAJA FRESH #130	100
66423	POMONA FISH MARKET	100

BOTTOM 10 RESTAURANTS

	FACILITY NAME	SCORE
183329	CAFE CON LECHE BAKERY AND CAFE	70
99056	MARISCOS CHENTE	70
41351	MANDARIN DISH	70
55449	GOLD HIBACHI BUFFET	70
153624	EL OAXAQUENO BAKERY	70
33689	PONCE'S BAKERY	70
124683	LIVE BASIL PIZZA-SMASH BURGER-TOM'S URBAN	70
20633	SPARE TIRE	70
28960	PALETERIA Y NEVERIA FIESTA MICHOACAN	70
135318	GARAGE KITCHEN	70

AVERAGE SCORE PER FACILITY TYPE



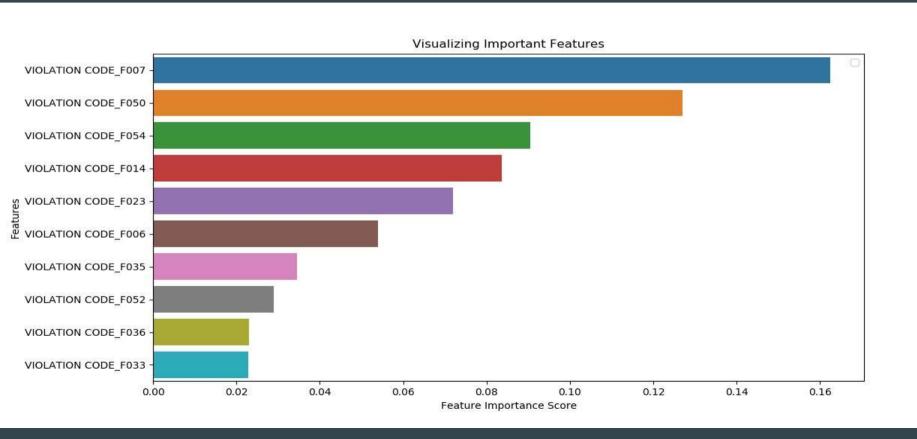
Top 15 violation codes

		200000000000000000000000000000000000000
		Count
VIOLATION DESCRIPTION	VIOLATION CODE	
# 44. Floors, walls and ceilings: properly buil	F044	106608
# 33. Nonfood-contact surfaces clean and in goo	F033	103926
# 35. Equipment/Utensils - approved; installed;	F035	83417
# 40. Plumbing: Plumbing in good repair, proper	F040	52977
# 36. Equipment, utensils and linens: storage a	F036	52451
# 37. Adequate ventilation and lighting; design	F037	50165
# 43. Premises; personal/cleaning items; vermin	F043	45496
# 07. Proper hot and cold holding temperatures	F007	42511
# 30. Food properly stored; food storage contai	F030	40213
# 14. Food contact surfaces: clean and sanitized	F014	38802
# 39. Wiping cloths: properly used and stored	F039	36336
# 06. Adequate handwashing facilities supplied	F006	35572
# 23. No rodents, insects, birds, or animals	F023	32734
# 34. Warewashing facilities: Adequate, maintai	F034	20760
# 29. Toxic substances properly identified, sto	F029	19902

Q1:

- Problem Statement: to predict the scores of the restaurants using random forest regression.
- Target Variable : Score
- Predictors: 'PROGRAM STATUS', 'SERVICE CODE', 'Distance in miles', '2011
 Supervisorial District Boundaries Official', 'Census Tracts 2010', 'Board
 Approved Statistical Areas', 'type', 'risk factor', 'month', and all one-hot encoded violation codes
- Accuracy : 94.32%
- Used bagging regressor and classifier random forest feature selection to display top 10 features

Key Factors In predicting health scores.



Q2:

- Problem statement : to classify the restaurants based on grade
- Model: Building a classifier using Random Forest
- Target Variable : Grade
- Predictors: 'PROGRAM STATUS', 'SERVICE CODE', 'Distance in miles', '2011
 Supervisorial District Boundaries Official', 'Census Tracts 2010', 'Board
 Approved Statistical Areas', 'type', 'risk factor', 'month', and all one-hot encoded violation codes
- Accuracy : 96.70 %

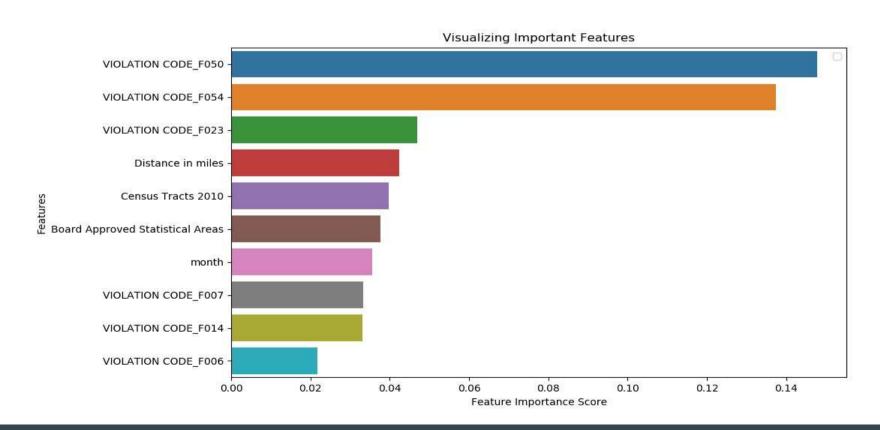
```
inf x

"C:\Users\Amit Mutgi\AppData\Local\Programs\Python\Python37\python.exe" "C:/Users/Amit Mutgi/Documents/informac/inf.py"

Accuracy: 0.9670277989174584

Process finished with exit code 0
```

Key Factors In classifying restaurants into grades.



- Selecting the top 10 features based on importance score
- Re-generating the model on selected features :
- Accuracy: 97.56 %

```
"C:\Users\Amit Mutgi\AppData\Local\Programs\Python\Python37\python.exe" "C:/Users/Amit Mutgi/Documents/informac/inf.py"
Accuracy: 0.9756983240223464

Process finished with exit code 0
```

 Removing the least important features results increased the accuracy. This is because of removal of misleading data and noise. Also, reduced training time increases the efficiency.

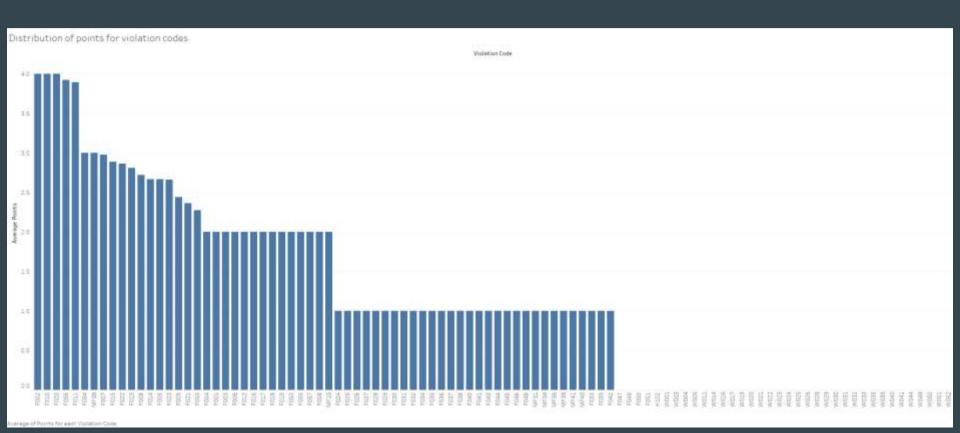
Q3.

```
Count of restaurant grade totals
GRADE
A 182171
B 8986
C 880
```

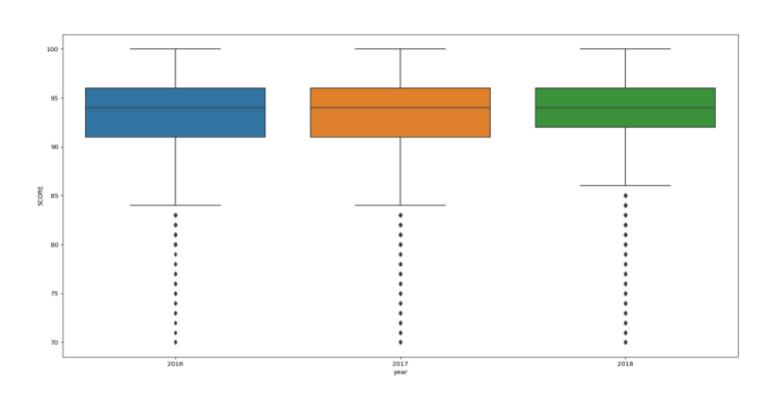
```
Chi Square State for Grade of restaurant;
Power divergenceResult(statistic=1341701.079781985, pvalue=0.0)
Chi Square State for Violation Codes :
Power divergenceResult(statistic=4295120.612272515, pvalue=0.0)
Chi Square State
54918,0092155784
[[3,46873205e+03 3,11038356e+01 3,11038356e+01 3,17822665e+03
  4.44788559e+03 3.19184462e+04 3.78691937e+04 4.81316139e+03
  6.91831498e+03 2.13381387e+01 6.59394954e+02 2.13281387e+01
  4.25052020e+03 3.50732354e+04 6.62060971e+02 1.10373118e+03
  3.91015876e+01 7.10937956e+01 1.06640693e+02 8.88672445e-01
  1,29746177e+03 1,58094828e+03 2,72742460e+04 7,39375474e+03
  1.10455645e+04 7.36620590e+03 1.62644531e+04 1.70625109e+02
  1,79556367e+04 3,586665199e+04 5,74063399e+02 5,87501353e+03
  9.25010953e+04 1.07207737e+04 7.41020405e+04 4.71476279e+04
  4.50148140e+04 1.00348892e+04 3.18669052e+04 4.74871008e+04
  4,17587182e+03 1.55642092e+04 4,07634050e+04 9.51803735e+04
  4.35449498e+02 1.56735159e+04 6.62949644e+02 5.45111670e+03
  0.53036600e+03 2.57004071e+03 4.35440400e+01 1.51190730e+04
  6.62367741e+03 2.39497224e+03 4.59687990e+03 4.26562774e+01
  1.89287231e+03 7.37598129e+03 8.88672445e-01 1.77734489e+00
  1.77754489m+00 0.88672445e-01 8.88672445e-01 4.44336222e+00
  8.00672445e-01 8.00672445e-01 4.44336222e+00 8.00672445e-01
  1,77734489e+00 1,77734489e+00 5,33203467e+00 1,77734489e+00
  1,77734465e+00 6,68673445e-01 2,66601733e+00 4,44236232e+00
  2.66601733e+00 2.66601733e+00 8.85672445e-01 1.06640693e+01
  0.00672445e-01 0.00672445e-01 2.66601733e+00 0.00672445e-01
  0.00672445e-01 0.00672445e-01 2.66601733e+00 0.00672445e-01
  0.80672445e-01 0.80672445e-01 0.08672445e-01 0.08672445e-01
  0.80672445e-01 2.66601733e+00 0.88672445e-01 3.55468978e+00
  7.99805200m+00 8.88672445m+00]
 [2,72031586e+02 3.42732379e+00 3.42732379e+00 3.49880798e+02
  4.90107302e+03 3.51711968e+03 4.00468450e+03 5.30255953e+02
  7.62334735e+02 2.350164e9e+00 7.26592644e+01 2.350164e9e+00
  4,60360277e+02 3,86474023e+03 7,29530350e+01 1,21621033e+02
```

- Chi square statistical test used since we are dealing with categorical variables
- The results of the test will help us to understand whether a relation exists between the grades of the restaurant and violation codes.
- Hypothesis:
 - Null hypothesis: Grades of the restaurant and violation codes are not related Alternate hypothesis: There exists a relation between the grades & violation codes
- The chi square statistic value compares the counts of categorical responses between the two independent group.
- Considering 5% significance level, p value has a value less than 0.05, showing that it is significant and null hypothesis can be rejected.
- We can conclude that there is a relationship between grades of the restaurant and violation codes.

Distribution of points for violation codes

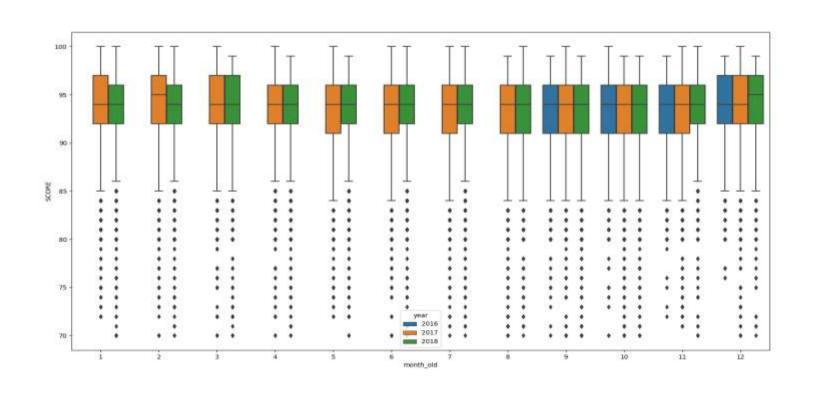


Q4. Variation of Score across Years



- 1. The scores have remained constant over the three years.
- 2. However in the year 2018 ,the restaurants having lower scored have improved .
- 3. This can be due to the fact that people prefer more hygienic restaurants.

Variation of Scores Across Months and Year



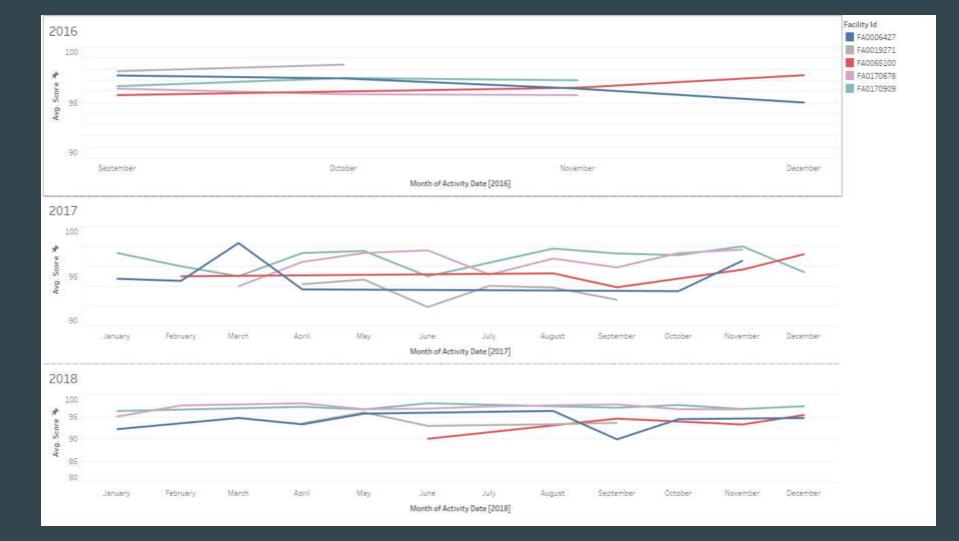
1. January and February has seen a decline in score as compared to the previous year.

2. This can be due to weather changes in Los Angeles during January and February in the year 2018.

3. The median of score in December for 2018 has seen an increase.

Variation of score in Top 5 Facilities over the years.

FACILITY ID	FACILITY NAME
FA0006427	LEVY PREMIUM FOODSERVICE LIMITED PARTNERSHIP
FA0019271	LEVY Premium foodservice ,LP
FA0065100	Legends Hospitality ,LLC
FA0170678	Magic Mountain ,LLC
FA0170909	Universal City Studios ,LLC



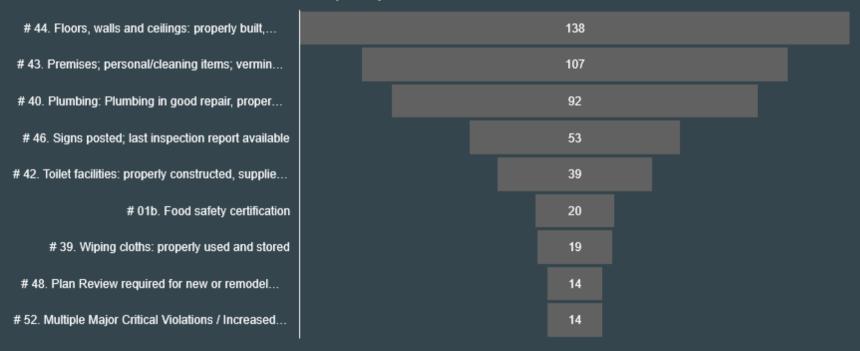
- 1.In the year 2016 Legends Hospitality, LLC has seen a continuous increase in Score over the year and Levy Premium foodservice Limited Partnership has seen a decrease in the score.
- 2. Most of the Facilities see a dip of score in the month of June and July.
- 3. The scores have remained constant across the different facilities in the year 2018.

Avg Score across Different areas



Business Recommendations for Avalon

Frequency of violations in Avalon



General Recommendations

- If your establishment receives a poor health inspection score, you can schedule a re-inspection in 5 - 45 days. This will give you time to correct the violations.
- Figure out how each violation occurred and how you can prevent it from happening again.
- Just like with your own self-inspection, review any violations and their proper corrective action with your staff.

Thank You