Analyzing Chicago
Food Inspections Data
to Predict Inspection
Results

Capstone Project

Yelena Zadoyan

The Problem

- Health and Safety Issues
- Resource Allocation Issues
- Legal and Regulatory Compliance Issues
- Problem Solving Steps
 - data preprocessing,
 - EDA,
 - feature engineering,
 - model building,
 - model evaluation,
 - inspection result prediction.

The Dataset

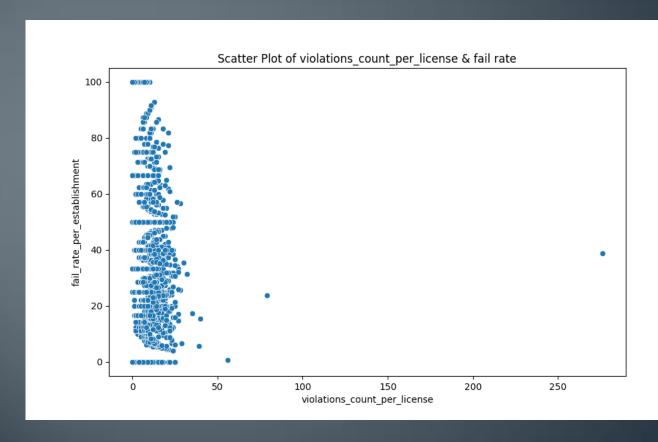
- Dataset food inspections conducted in Chicago.
- Attributes the ID of the inspection, the name of the establishment, the type of establishment, the risk level, the address, the date of the inspection, the type of inspection, the results, and any violations found.
- AIM predict the results of food inspections in the city of Chicago – the possible failure.

Data Preprocessing

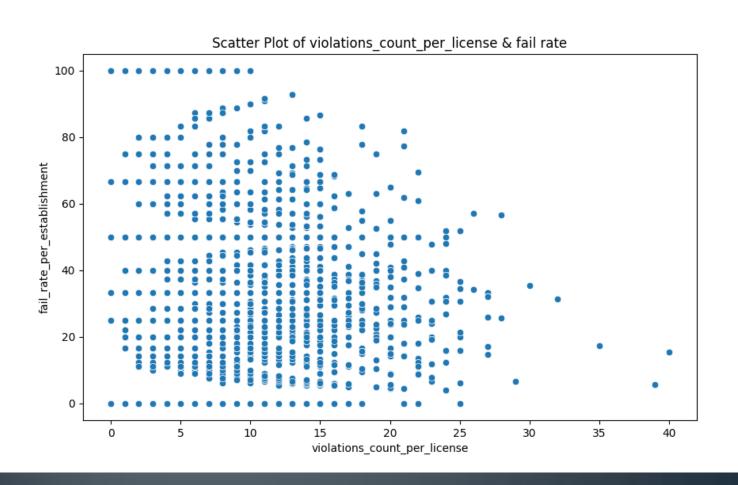
- As we deal with categorical data the missing values can be replaced by the mode. But in our case, as the data refers to the safety standards, the rows containing missing values are dropped. The high weight of missing values has the Violations feature, for which the replacement by the model could impact significantly the results without increasing the accuracy.
- Only the inspections with Pass and Fail results are left by dropping the other rows.
- Those categorical variables that are considered in the scope of model building (have impact on failure rate and/or high weight in the dataset) are transformed into dummies.

Data Preprocessing

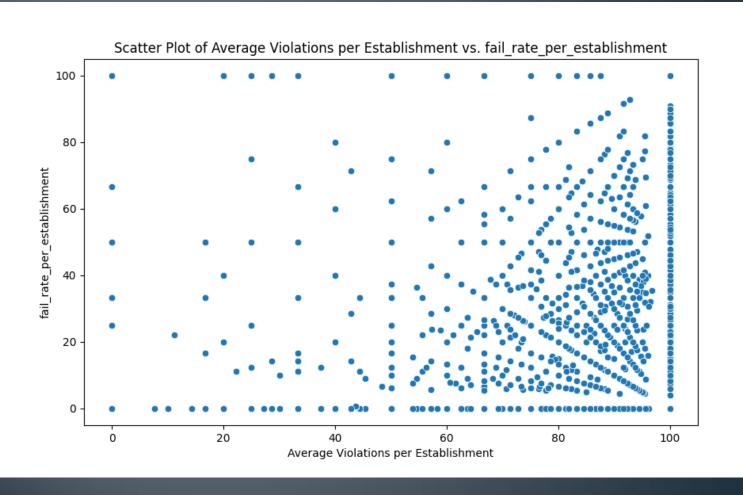
Dropping outliers with high violation rate (>50)

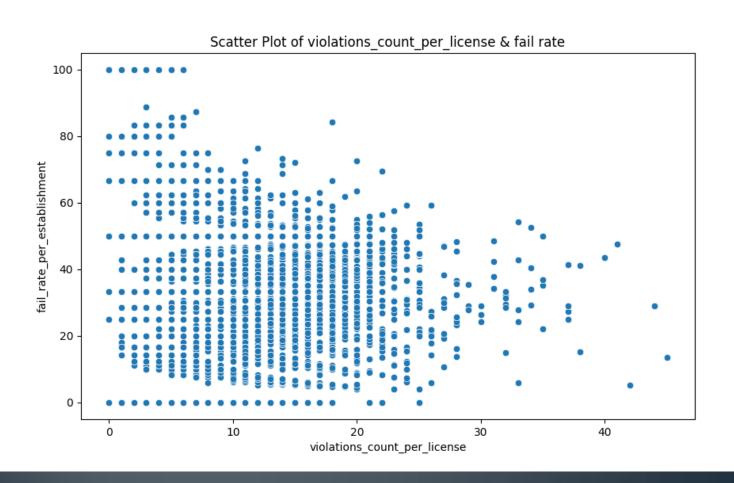


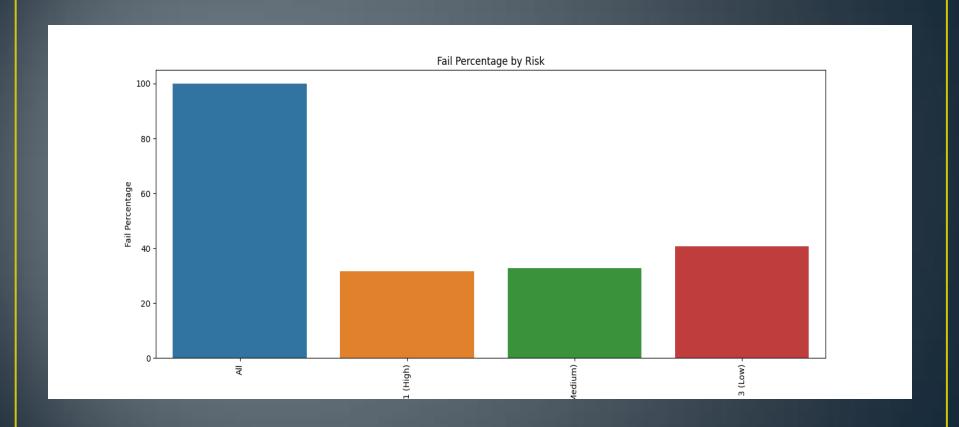
Data Preprocessing

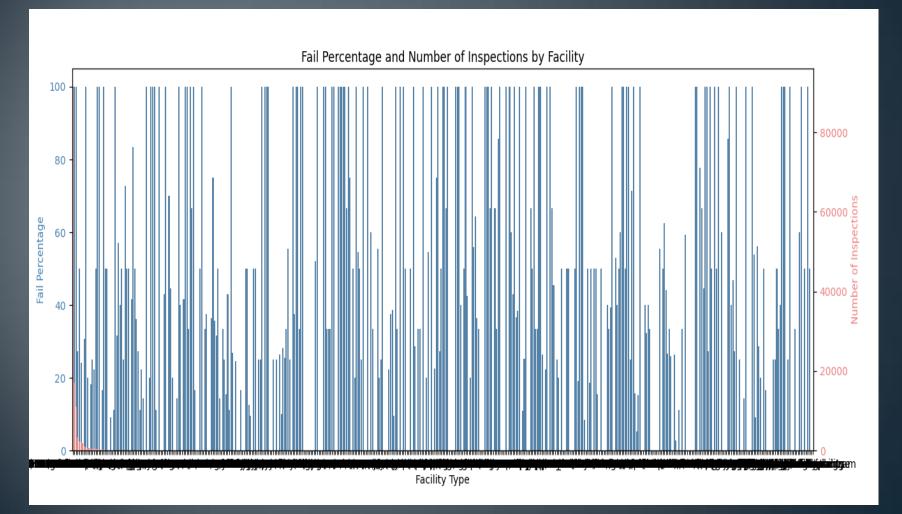


Feature engineering & EDA









From Facility type feature
 only those types are transformed
 into dummies, which have

>5% weight.

Facility Type	Weight
Restaurant	66.090488
Grocery Store	12.360622
School	7.989421
Children's Services Facility	2.409255

Daycare Above and Under 2 Years

1	.5	9	4	1	2	6

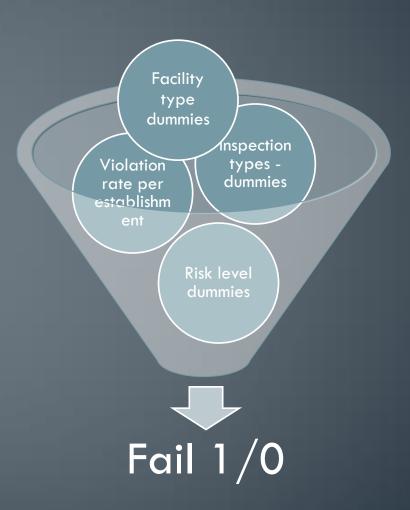
PALETERIA /ICECREAM SHOP	0.000723
GROCERY/LIQUOR	0.000723
PRODUCE STAND	0.000723
RESTAURANT/GROCERY	0.000723
Kids Cafe'	0.000723

EDA

Fail rate analysis by inspection types

Inspection_Canvass	28.42%
Inspection_Suspect	37.02%
Inspection_Task	57.99 %
Inspection_Consultation	20.57%
Inspection_Complaint	37.41 %
Inspection_other inf	24.10%

Data selection for model estimation

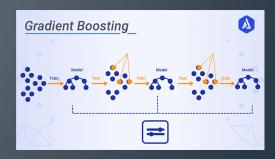


Model building









Four types of binary classification models considered.

Model Evaluation

Train 70%

Validation 15%

Test 15%

Model Evaluation

Model Group #1

ALL Data:

 Inspection and re-inspection categories

Model Group #2

 Cutting the results from the re-inspection

No over-fit possibility

Model Results - Group #1

Logit Train RF Train

Accuracy **0.7268**

Precision: **0.6398**

Recall: **0.0142**

F1: **0.0278**

Train Accuracy 0.7289

Precision: **0.7060**

Recall: **0.0236**

F1: **0.0458**

Val Accuracy: 0.7279

Precision: 0.6446

Recall: **0.0145**

F1: **0.0283**

Val Accuracy 0.7293

RF

Precision: **0.6629**

Recall: **0.0237**

F1: **0.0457**

DF
Train Accuracy
0.7288

Precision 0.6641

Recall: **0.0276**

F1: **0.0530**

Train Accuracy 0.7268

GB

Precision **0.8114**

Recall: **0.0082**

F1: **0.0162**

Val Accuracy 0.7293

Precision: **0.6250**

Recall: **0.0284**

F1: **0.0544**

Val Accurac

GB

Precision: **0.8171**

0.7281

Recall: **0.0091**

F1: **0.0179**

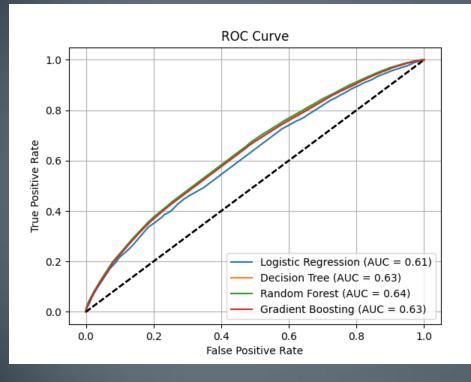
Over-fit possibility

Model Results - Group #2

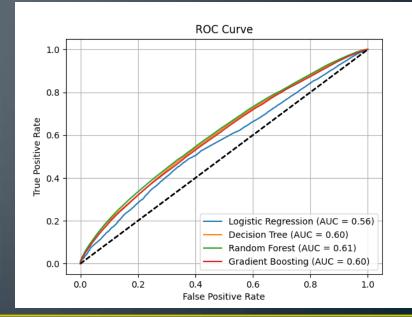
Logit DF DF Logit Val Val Train Train 0.6736 0.6771 0.6846 0.6882 0.6012 0.5931 0.5757 0.5677 Recall: Recall: Recall: Recall: 0.0628 0.0599 0.1218 0.1221 F1: F1: F1: F1: 0.1089 0.2011 0.2010 0.1137 RF RF GB GB Val Val Train Train 0.6774 0.6755 0.6885 0.6867 0.5809 0.5817 0.5727 Recall: Recall: Recall: Recall: 0.1191 0.1182 0.0978 0.0965 F1: F1: F1: F1: 0.1977 0.1959 0.1651 0.1675

Model Evaluation

Model Group #2



Model Group #1



Hyper-parameter optimization

```
Logistic Regression - Best Parameters: {'C': 10, 'penalty': '12'}

Decision Tree - Best Parameters: {'max_depth': 10, 'min_samples_split': 10}

Random Forest - Best Parameters: {'max_depth': 10, 'n_estimators': 50}

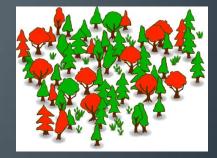
Gradient Boosting - Best Parameters: {'learning_rate': 0.1, 'n_estimators': 200}
```

Model Selection Models #1

Models #2

- Higher Accuracy & Precision
- Lower Recall & F1, ROC-AUC
- No over-fit possibility

- Lower Accuracy & Precision
- Higher Recall & F1, ROC-AUC
- Over-fit possibility



Model Result prediction

Logit Accuracy 0.6784

Precisions 0.5929

Recall: 0.0591

F1: 0.1074

DT test Accuracy: 0.6789

Precision:

Recall: 0.1173

F1: 0.1931

RF
test Accuracy
0.6797

Precision:
0.5550

Recall:
0.1149

F1:
0.1905

GB
test Accuracy:
0.6776

Precision:
0.5490

Recall:
0.0921

F1:
0.1578

Testing sample

Conclusion

• All the models have high accuracy and precision rates and very low recall and F1 score. Thus, the results can be used mostly in case of **Resource Allocation issues**, when limited resources are directed toward inspections that are more likely to identify actual failures, reducing unnecessary inspections on compliant establishments, and for **Legal and Regulatory compliance** issues, when precision might be prioritized to minimize the risk of wrongly penalizing compliant establishments. But the model cannot be considered in case of Health and Safety concerns.



