# The Potential Relationship between Foodborne Illness and Restaurant Inspection Result in New York City

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September 12, 2020

#### Abstract

In New York City, cultural diversity has promoted the growing number of restaurants. However, food sanitation has always been a concern for public health. The project focuses on discovering whether violation results from restaurants inspections would have any strong correlations with food poisoning. Restaurants inspection results from DOHMH as well 311 complains are used and analyzed through random forest ensemble learning method. The results indicates that violations found in food sourcing and restaurant facility design have stronger correlation than other factors with regards to foodborne illness incidents.

## Introduction

The very fast-pace lifestyle of New York City has stimulated the trend of dinning out. In New York City, there are over 24,000 food services providers which include restaurants and street food vendors. The great number of food services embraces the cultural diversity and attracts more tourists to enjoy their time in this city.

In recent years, the increasing use of social media has directed public attention to the sanitation of food services. Many foodborne illness, incidents, and unregulated food preparation processes have been exposed through social media by consumers as well as many food services providers. In addition, with the convenience of 311 hotline, many food poisoning incidents have been reported accordingly and brought to the attention to corresponding department. Throughout years, the Department of Health and Mental Hygiene has been working on regulating the sanitation of food services providers. On a regular basis, sanitation inspections are performed at all the food services provides. From the inspection results, different types of violations are discovered and restaurants are urged to make changes and improve their environmental hygiene. However, with large numbers of food poisoning cases reported regularly, it is of great concern that what types of sanitary violation would be related to such incidents.

# **Data Selection and Processing**

To find out which type of sanitation violation has the strongest correlation with foodborne illness, the inspection results published by DOHMH is used as detecting the types of violations. At the same time, 311 complaints under the category of food poisoning are used as the sources of locating foodborne illness.

Under the inspection results dataset, every restaurant's violation type is listed. Each record has been processed to demonstrate whether violations has been identified from this restaurant in the following 5 categories: food source violation (code 03), food storage and protection violation (code 02 or 04), services and preparation violation (code 06), facility design and maintenance violation (code 05 and 10), vermin and waste violation (code 08). On the other side, the complaints from 311 are processed first by eliminating unnecessary columns (for example, Park Borough). Then, the number of food poisoning cases are aggregated based the address of the incidents.

Due to the recording issues of 311 data, the addresses of incidents could not be matched directly with the inspection results as the dataset includes missing unit numbers, spelling, and formatting errors. To be able to merge the two datasets for further analysis, PLUTO data were imported and aggregated which then merged with the inspections data.

# Methodology and Data Analysis

As a result of data processing, the food poisoning cases of each BBL is recorded as boolean value (True or False, corresponding to incidents or no incidents). The inspection violation results are processed and under each category, are recorded as boolean value (True or False, corresponding to violation found or not). The data used in this project are categorical data.

Instead of using regular regression correlation for comparing 5 different violation types, the random forest ensemble has been selected to evaluate which violation issue discovered would demonstrate strong relationship with or have strong impacts on the foodborne illness incidents. Through building random forest, more than one tree will be generated and therefore, comparing to the single decision tree model, there can be less variances and bias. The random forest was set at maximum depth of 3, applying Gini Impurity as criterion. Fig. 1 below shows one of the decision tree built by the Random Forest model. In total, there are 10 decision trees created by the random forest model. Looking at each tree, not essentially the top split feature would be the most important feature but the feature or features tend to appear more.



Figure 1: One decision tree generated by the Random Forest (tree no.0)

A feature importance table has been generated summarized with regards to the random forest model. Demonstrated in Fig. 2 below, food source demonstrate the highest importance followed by Facility Design and Maintenance. Vermin protection and waste management violations, among all five categories, are the least important feature when it comes to predicting food poisioning cases.

To test the effectiveness of the random forest model, 33% of the data has been selected as the testing sample after shuffling the dataset. The random forest model first build on the 67% of training dataset. The score for the training model was 0.633 whereas the score for the testing set was 0.601. The scores of the random forest model demonstrate a moderate predicting power as the scores are relatively close to each other. Therefore, the model is possibly not behaving in a over predicting manner.

The sample predicting results are summarized in the follow table (Table 1) and a confusion matrix

	Importance
Food Protection	0.133945
Food Source	0.356935
Food Preparation	0.165726
Facility Design Maintenance	0.215187
Vermin and Waste	0.128208

Figure 2: Feature Importance Summary Table

below demonstrates the testing result (Fig.3). The result shows that when conducting the prediction, the model predicted almost all the sample incidents results to be TRUE which is too extreme. The accuracy of the model is 62.01% while the precision of the model is 62% as well. The sensitivity of the model is very high, 99.9% but the specificity is around 0.3%. With such high sensitivity, the model can be overestimating the possibility of food poisoning.

		Predict Food Poision Incidents	
		TRUE	FALSE
Actual Food Poisoning Incidents	TRUE	1020	1
	FALSE	625	2



Table 1: Data of Confusion Matrix

Figure 3: Confusion matrix of test result (data spilt = 0.33, Random Forest build at depth of 3)

### Conclusion

Five types of violations were selected for determine which category tend to have the strongest correlation with regards to foodborne illness incidents. The result shows that food sources and restaurant's facility design and maintenance may have the relatively stronger impacts (accounts for more than 50% feature importance).

Food sources violations include unknown origins, present of unpasteurized source, and water potability. Facility design and maintenance violations involve lack of on-site sanitation and protection structure and utensils as well as evidences of lack of hygiene maintenance. However, considering the moderate accuracy and very high sensitivity of the model, violation inspection results can be used as reference for identifying potential contributors of food poisoning but not direct cause.

As a result, restaurant inspector might need to stress more on regulating the food sources in the food vending industry. At the meantime, when it comes of building permit process, restaurant safety specialist should contribute their opinions into validating a design of a new restaurant.

### Weaknesses and Issues

During the data processing procedures, it was found that the incidents locations were not recorded with very accurate location. Therefore, BBL was selected as the main location merge method. However, in reality, there are more than one restaurant can be found under the same BBL. Therefore, the result accuracy is compromised to certain extend.

In the meantime, the random forest model demonstrate a high sensitivity when it comes to predicting incidents which lead to many non-incidents records were predicted as incidents. The way how data was processed and recorded for fitting model might need certain reconsiderations. Meanwhile, this can also be due the selection of training set.

#### **Future Work Potential**

With regard to the inspection result, there is a column listed whether the inspection violation results are critical or non-critical. Potential works can be considered to separate critical results and non-critical results. Similar methodology can be applied to test the two groups. However, the Inspection Procedures does not demonstrate the division between critical and non-critical. Therefore, more clarification is need to explain whether violation score or condition level would affect the criticalness. In addition, due to different types of cuisine involves various cook methods, a further study can look into if any particular cuisine demonstrate higher foodborne illness incidents. The results from this potential study might be helpful to improve the standards of violation code.

#### **Reference:**

1. Firestone M.J., Hedberg C.W. (2018). Restaurant inspection letter grades and Salmonella infections. Emerging Infectious Disease, 24(12). DOI: 10.3201/eid2412.180544

2. Jones, T. F., Pavlin, B. I., LaFleur, B. J., Ingram, L. A., & Schaffner, W. (2004). Restaurant inspection scores and foodborne disease. Emerging Infectious Diseases, 10(4), 688.

3. New York City Department of Health and Mental Hygiene.(2010). Chapter 23: Food Service Establishment Inspection Procedures. Retrieved from: https://www1.nyc.gov/assets/doh/downloads/pdf/ about/healthcode/health-code-chapter23.pdf

#### Extra Note:

All the supporting material can be located: https://github.com/sz2404/PUI2018\_sz2404/tree/master/ Extra\_Credit\_Project