Raleigh Restaurant Inspections

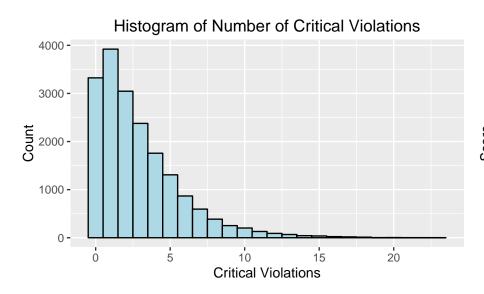
JHUAPL

November 17, 2016

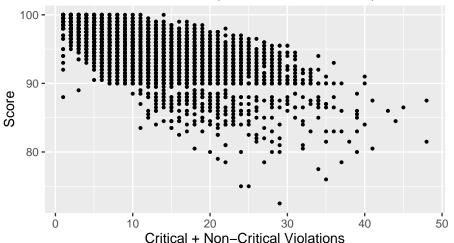
Data Description

- Data from 9/21/2012 to 11/03/2016.
- 2,809 facilities (1,867 are restaurants)
- 18.469 inspections
- Cities in Wake County
 - ► top 5: Raleigh, Cary, Wake Forest, Apex, Morrisville

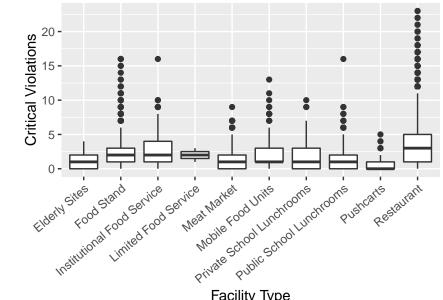
Number of Critical Violations



Score vs. Number of All (Critical+Non–Critical) Violations

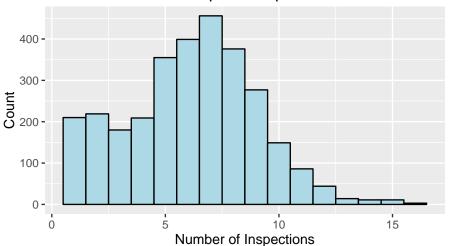


Critical Violations by Facility Type



Facility Type

Number of Inspections per Restaurant

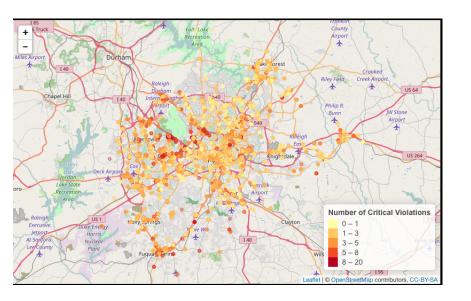


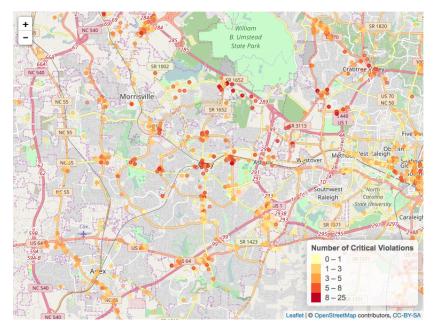
Other Variables in Model / Other Data Sources

Besides number of previous critical violations, days from last inspection, and days since opening (extracted from inspections), other variables include:

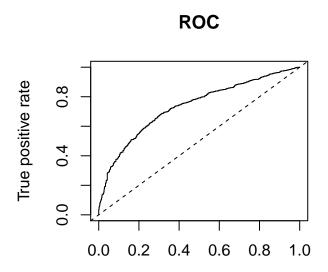
- Geographical Information
 - Average Number of Critical Violations for all Prior Inspections of Nearest 5 Neighbors
- Census data: extracted income information by ZIP
 - ► Median Household Income
 - ► Percent below Poverty Line
- Yelp data: extracted information on restaurants
 - Rating (out of 5 stars)
 - ► Price (\$-\$\$\$)
 - ► Restaurant Category (top 20, e.g. Mexican, Sushi, Chinese, Coffee)

What is NOT in model: Inspector information, ZIP code





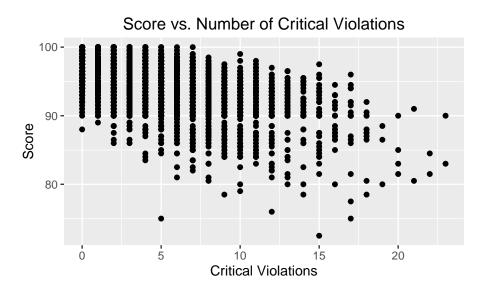
Logistic regression model trained on 2012-2015, tested on 2016 (Jan-Nov), approx. 70/30 split. The AUC on test-set is 0.734.



Next Steps

- For binary response, what threshold would be most useful?
 - Results for cutoffs of 2, 3, 4, or 5 are similar (AUC 0.73-0.77) beyond that gets rare
- Class imbalance
- To model counts, use a different model and performance measure
- How to make use of items that don't match from Yelp, Google Places
- Previous values seem quite useful: can me model those better (not just use one previous but all previous)

Appendix A



Appendix B

Variable Importance Plot (Random Forest)



