Modeling Housing Violations in New York City

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Introduction

Question

What is the relationship between the number of 311 calls from geographic area and the number of housing violations that occur within it?

311

311 is a phone number in New York City that allows citizens can to report civil, non-emergency events, e.g., graffiti or noise complaints

Goal

- The end goal is to build a model to predict housing violations
- A successful model could potentially
  - Allow the city government to plan and target housing inspections faster and more efficiently
  - Help civil rights to detect potential discrimination

Data

311 Calls

- NYC Open Data web site: data.cityofnewyork.us houses a log of every 311 call made since 2010, and updated daily
- Accessible via API endpoint
- Millions of 311 calls are made each year, so I limit this project to the year 2014 only
- Records contain geographic information (address, borough, latitude and longitude), creation and close date, and compaint type

Housing Violations

- Also archived by NYC Open Data, and accessible by API endpoint
- 23 thousand housing violations reported in 2014
- Important columns here include various dates (of inspection, certification, etc.), geographic information (address, lat/long, Census tract, etc.), a description of the violation, and violation status

Demographic Data

- Available via an easy-to-use R package called `tidycensus`: https://walkerke.github.io/tidycensus/ – which wraps the Census Bureau's API (requires token)
- Census data can be aggregated at various geographical levels – I chose zip code
- There are hundreds of possible variables from the Census, but to keep it simple, I focused on measures of a zip code's:
  - Education
  - Language
  - Income
  - Age
  - Race/ethnicity

Demographic Data

- Beware of multicollinearity: Most of these variables are related to eachother

Dependent Variable

- The number of housing violations per zip code per month

zip	epoch	violations
10001	2014-01-01	4
10001	2014-02-01	10
10001	2014-03-01	0
10001	2014-04-01	0
10001	2014-05-01	1
⋮	⋮	⋮

Independent Variable: 311 Calls

- Aggregated to number of 311 calls per zip code per month

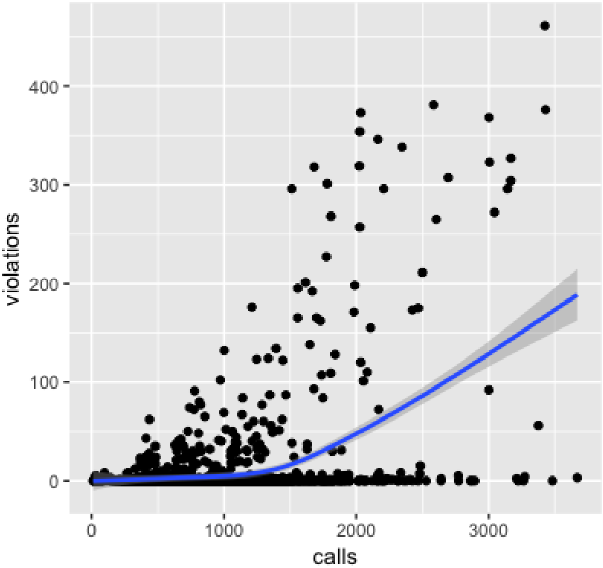
zip	epoch	calls
00083	2014-01-01	2
00083	2014-02-01	5
00083	2014-03-01	8
00083	2014-04-01	14
00083	2014-05-01	9
⋮	⋮	⋮

Independent Variables: Demographics

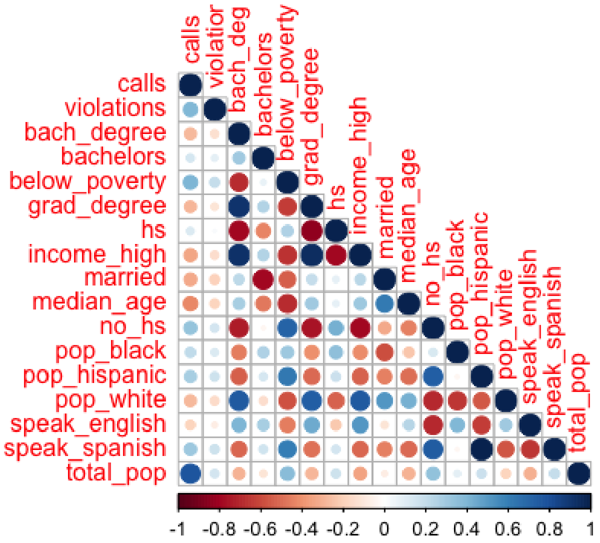
- Transform to percentage of total population per zip code
- E.g., 27.7 percent of residents in zip code have a bachelors degree, and 73 percent speak English

Exploratory Data Analysis

Scatterplot of (`calls`, `violations`)



Correlations



Models

Evaluation

- Split into train and test sets (70 percent, 30 percent)
- Evaluate on mean squared error *MSE* (and R^2)

```r
mse <- function(m) mean(resid(m)^2)

calc_r2 <- function(y, y_hat) {
    rss <- sum((y_hat - y)^2)
    tss <- sum((y - mean(y_hat))^2)
    return(1 - (rss/tss))
}
```

M_0: Dummy Model

- Predicts the mean of `violations`
- Useful to establish a baseline

```
m0 <- lm(violations ~ 1, train)
```

M_1: Simple Linear Regression

- Use all variables to predict `violations` in straight forward model

```
m1 <- lm(violations ~ calls + bach_degree +
             bachelors + below_poverty +
             grad_degree + hs + income_high +
             married + median_age + no_hs +
             pop_black + pop_hispanic + pop_white +
             speak_english + speak_spanish +
             total_pop, train)
```

M_2: Regression + Month

- Examining the residuals, it became clear the observations this model had the most trouble with were in the winter—January and February
- Remedy by adding a `month` factor variabel

M_3: Mixed Effects Panel Model

- In fact, linear regression is inappopriate for this data set
- Linear regression assumes each observation is independent of eachother
- Because each subject (zip code) is sampled numerous times, this assumption is violated

M_3: Mixed Effects Panel Model

- This can be remedied by using a mixed effects model via R package lmer4

```
library(lmer4)
m3 <- lmer(violations ~ calls + bach_degree +
             bachelors + below_poverty +
             grad_degree + hs + income_high +
             married + median_age + no_hs +
             pop_black + pop_hispanic + pop_white +
             speak_english + speak_spanish +
             total_pop + (1 | zip) + (1 | month),
           data=train)
```

M_4: Dealing with Multicollinearity

- Including so many variables that are correlated to eachother can cause the model to misestimate parameter values, reducing its predictive capability
- M_4 is also a mixed effects model, but eliminates some of the most correlated independent variables

M_5: Zero-Inflated Poisson Regression

NOTE: This is new territory for me, just trying it out for the first time!

- The dependant variable `violations` is actually a count, suggesting a Poisson regression may be more appropriate
- `violations` has a lot of zeros, so use this this special Poisson model

```
library(pscl)
m5 <- zeroinfl(violations ~ calls + bach_degree +
               bachelors + below_poverty +
               grad_degree + hs + income_high +
               married + median_age + no_hs +
               pop_black + pop_hispanic + pop_white +
               speak_english + speak_spanish +
               total_pop + | month, train)
```

Model Evaluation

Test Set *MSE*

	Type	MSE
M_0	Dummy	2657
M_1	Simple LR	1849
M_2	LR + Month	1305
M_3	Mixed Effects	1306
M_4	Mixed Effects -	1303
M_5	0-Inflated Poisson	758

Test Set R^2

	Type	R^2
M_0	Dummy	0
M_1	Simple LR	0.30
M_2	LR + Month	0.51
M_3	Mixed Effects	0.51
M_4	Mixed Effects -	0.51
M_5	0-Inflated Poisson	0.72

Conclusion

Lessons

- Examining a model's residuals can suggest simple ways to greatly improve the model, as with the `month` variable that increased R^2 by 70 percent
- Even though M_4 and M_3 had the same performance, their parameter estimates were very different because of the adjustments I made to counter multicollinearity
- It is important to understand your data and pick the appropriate modelling framework

Findings

- Every model found a highly significant and positive relationship between the number of calls to 311 and housing violations in New York City zip codes
- The best model, the zero-inflated Poisson model M_5, estimates that every 1175 calls to 311 is associated with one housing violation
- The proportion of residents living below the poverty line is also positively and significantly associated with housing violations
- A big thank you to whomever made `tidycensus` for making this project immensely easier

The End