cs109a Final Project, Milestone 3

Project C: Predicting Types of Crime

Project team #109

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PLEASE NOTE: Besides any sample notebooks submitted with this milestone, all project work completed to-date by our team (including all notebooks in progress and supporting materials) can be viewed directly on GitHub in our shared project repository located here: https://github.com/sedelmeyer/predicting-crime

Contents

Description of the data

Data sources used

Below is a list of Boston.gov data sources investigated as part of our initial EDA and used to assist in feature engineering for our baseline model. For a complete list of URLs for the below listed datasets, and to see all other datasets we have found and are investigating to-date (including data from additional sources), please see the “data-inventory.csv” file in our GitHub repository.

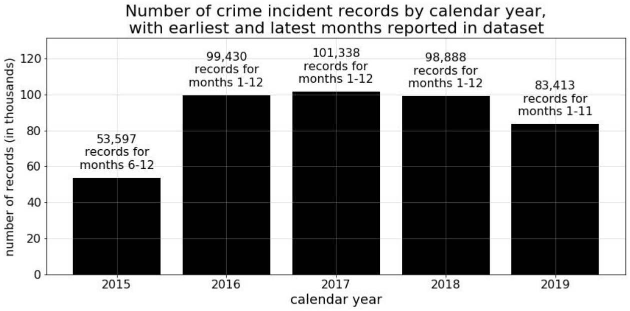
1. Crime incident data
2. Property assessment data
3. Streetlight location data
4. Street Address Management (SAM) system data
5. Neighborhood demographics data
6. Liquor licensing data
7. Public and non-public schools data
8. Universities and colleges data
9. Property violations
10. Various City of Boston shape files
    - These include Census tracts, Boston neighborhoods, Zip codes, Street segments, and Open spaces

Noteworthy EDA findings

Crime incident data

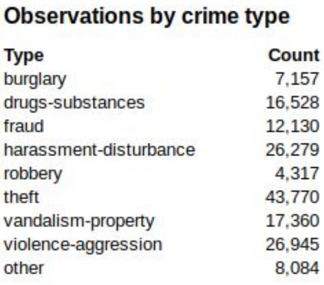
EDA notebook:
https://github.com/sedelmeyer/predicting-crime/blob/master/notebooks/009_EDA_crime_incident_reports.ipynb

The City of Boston's crime incident reports (August 2015 - to date) data is the source data for the parameter of interest in our analysis, crime type. The original data contained 436,666 crime incident observations, spanning 66 different crime "offense code groups" across the City of Boston.



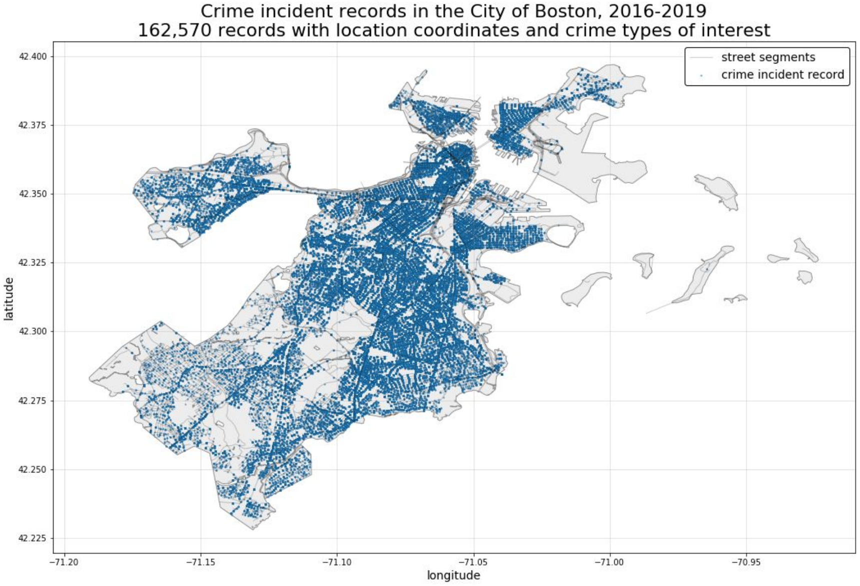
Due to limitations imposed by years of available property assessment data (see next section), and the limited number of 2015 observations, we decided to use incident reports for just the 2016-2019 calendar years. Because of the geospatial nature of our analysis, we also excluded 35,785 additional records with missing latitude and longitude coordinates. And, due to a disproportionately large proportion of records during the final 3 months of observations (Sep.-Nov 2019) missing coordinates, those three months were excluded as well. By subsetting of our data to Jan. 2016 through Aug. 2019, and excluding observations with missing coordinates, we were left with 347,284 crime incident observations.

Because we are dealing with a classification challenge, we also felt it was important to consolidate our 66 offense code groups into a smaller subset of "crime types" to generate more meaningful results later in our analysis. To accomplish this, we (a) removed incident categories of little interest that might otherwise obscure trends in more important areas of crime (for instance ambiguous categories like "investigations" or non-crime categories like "motor vehicle accident response") and (b) consolidated the remaining categories into a set of 9 different "crime types": burglary, drugs-substances, fraud, harassment-disturbance, robbery, theft, vandalism-property, violence-aggression, and other. Once we dropped unused offense codes and were able to tie each record to its corresponding census tract shape (the geospatial unit of analysis used to summarize our property-related features), we were left with 151,072 records for our analysis, distributed as shown below:

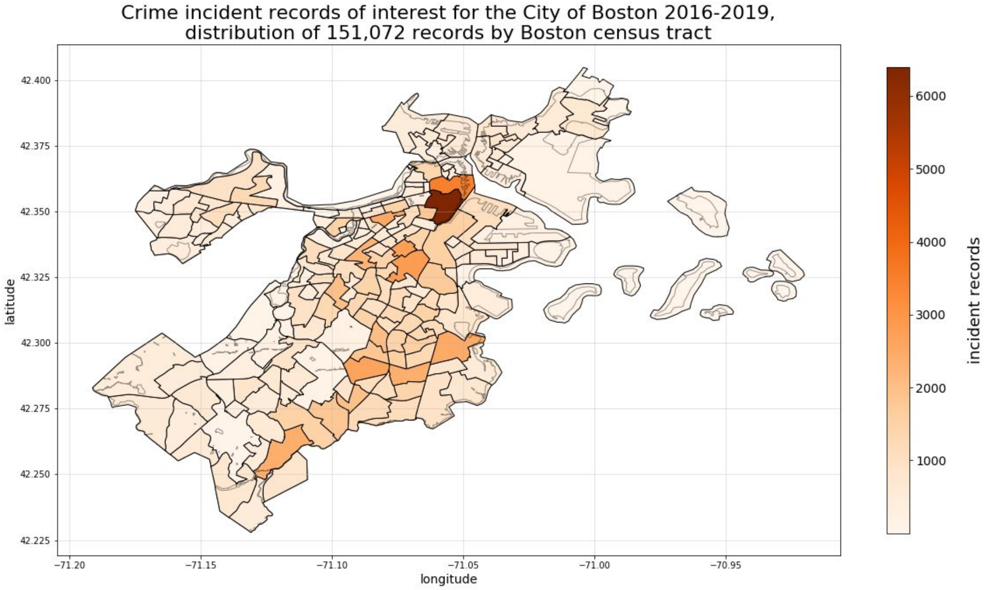


Observations by crime type

Type	Count
burglary	7,157
drugs-substances	16,528
fraud	12,130
harassment-disturbance	26,279
robbery	4,317
theft	43,770
vandalism-property	17,360
violence-aggression	26,945
other	8,084



Crime incident records in the City of Boston, 2016-2019
162,570 records with location coordinates and crime types of interest



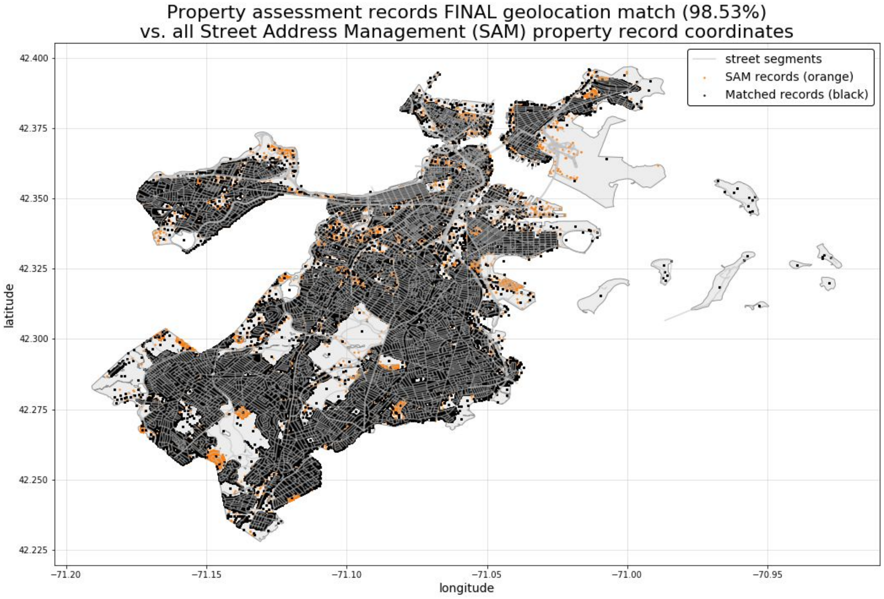
Crime incident records of interest for the City of Boston 2016-2019,
distribution of 151,072 records by Boston census tract

By referring to our accompanying notebook, you can also view additional EDA steps such as our investigation of potential observation bias in the observations with missing location coordinates.

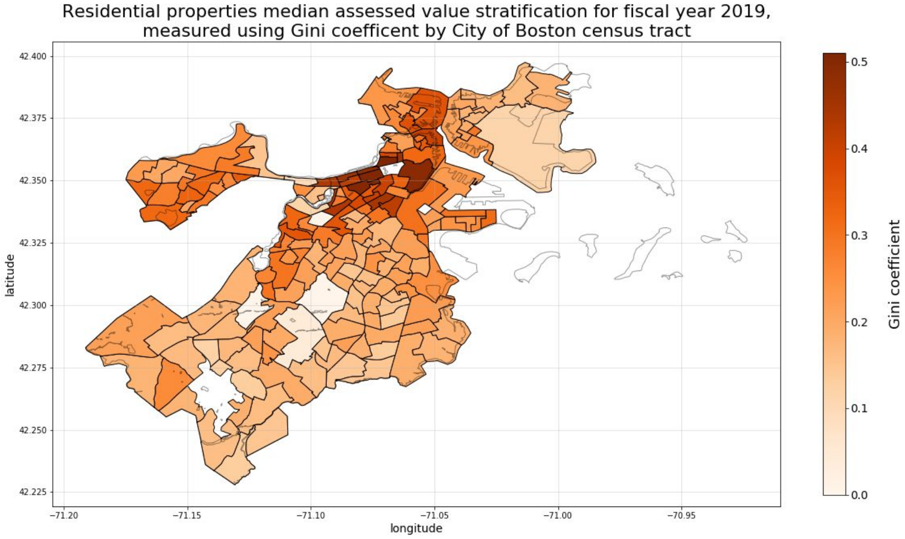
Property assessment data

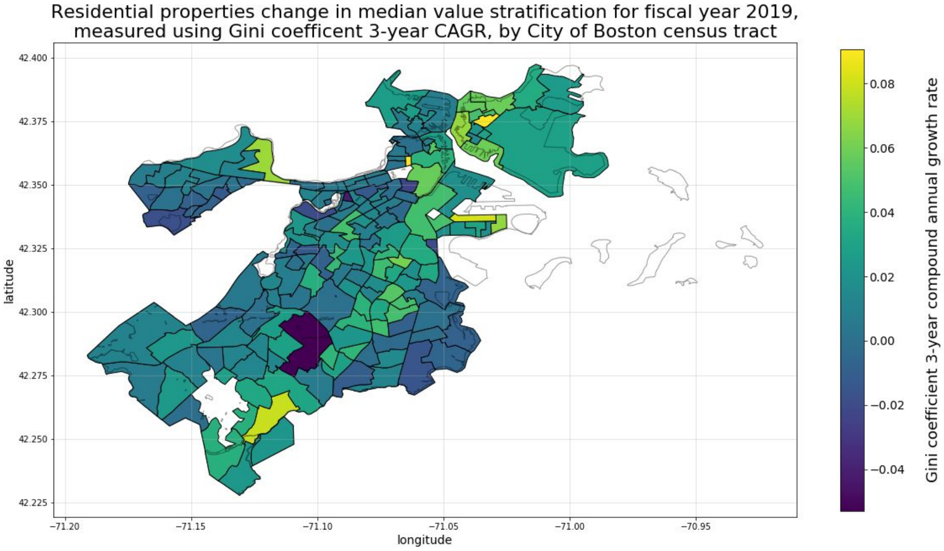
EDA notebook:
https://github.com/sedelmeyer/predicting-crime/blob/master/notebooks/010_EDA_boston_property_assessments.ipynb

The City of Boston's property assessment records provided data we used to engineer several features for our baseline model. The records used for our analysis can be found on the Boston Analyze website and included all Boston properties, by Parcel ID (PID) and address, from fiscal years 2013 to 2019. This consolidated dataset included 1,185,432 total property assessment records and the largest challenge associated with this data was matching location coordinates to years of data with no recorded location coordinates (approx. 1,083,590 records). By matching PIDs for years with reporting coordinates, the vast majority of these missing coordinates were matched. For the remaining 78,018 unmatched records, the City of Boston's Live Street Address Management (SAM) System parcel dataset was used for matching. With the SAM dataset, we were able to match coordinates to all but 32,297 assessment records for a 98.5% total match rate (see plot below).



With these matched coordinates, we were able to explore the dataset for features of interest that we could aggregate within geospatial regions. From this, we engineered a set of 10 property-based predictors, each providing a census tract-level metric per-year to give (1) a point in time measure for that geographic area, as well as (2) a 3-year average annual change rate to measure shifting property demographics for the area. The full set of features are described below in the “Baseline Model” section of this report (listed as predictors 4 through 13). Here are two plots illustrating a sample of these engineered features:

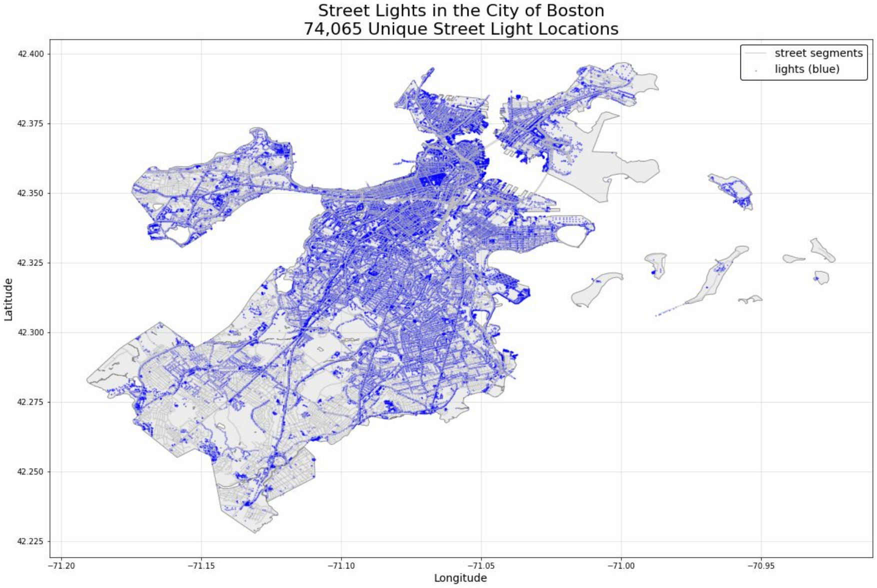

Residential properties median assessed value stratification for fiscal year 2019,
measured using Gini coefficent by City of Boston census tract
latitude
longitude
Gini coefficient
42.400
42.375
42.350
42.325
42.300
42.275
42.250
42.225
−71.20
−71.15
−71.10
−71.05
−71.00
−70.95
0.5
0.4
0.3
0.2
0.1
0.0

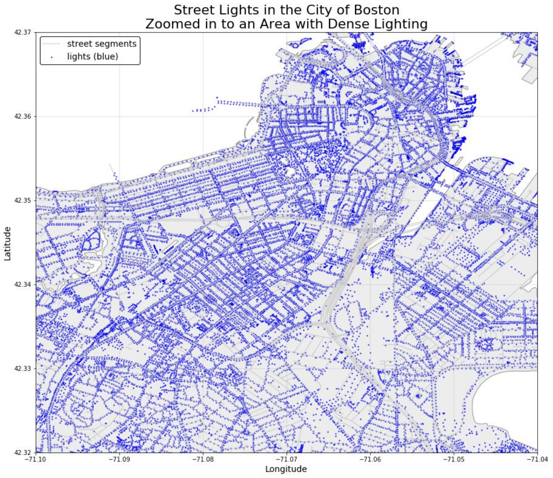

Residential properties change in median value stratification for fiscal year 2019,
measured using Gini coefficent 3-year CAGR, by City of Boston census tract
latitude
longitude
42.400
42.375
42.350
42.325
42.300
42.275
42.250
42.225
−71.20
−71.15
−71.10
−71.05
−71.00
−70.95
Gini coefficient 3-year compound annual growth rate
0.08
0.06
0.04
0.02
0.00
−0.02
−0.04

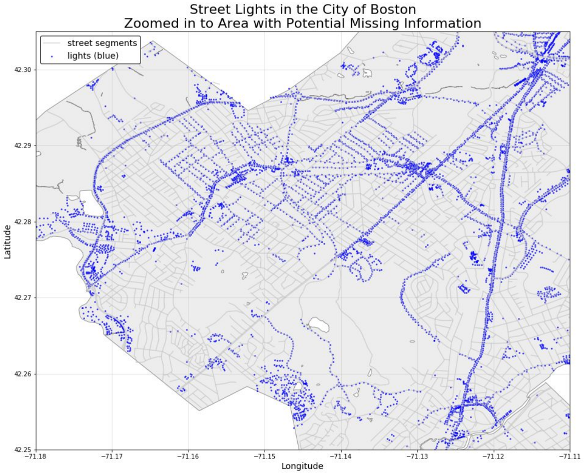
Streetlight location data

EDA notebook:
https://github.com/sedelmeyer/predicting-crime/blob/master/notebooks/017_EDA_street_lights.ipynb

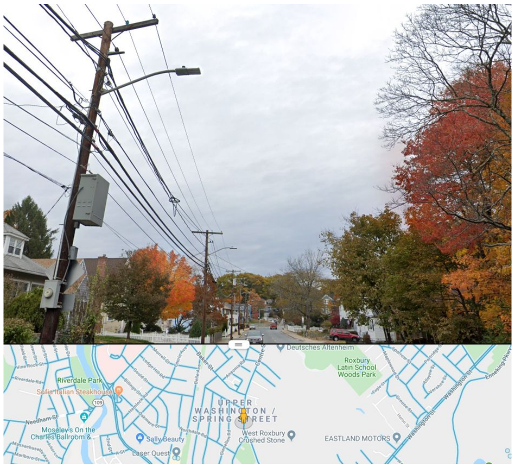
There are 74,065 streetlights listed by their lat and long in this dataset. All records are of type LIGHT so the only useful information in this dataset is the location of the light. Given this we first plotted out each of the lights on a map of the city of Boston. The map shows a sparse distribution of light locations in the lower-left corner of the map. This is shown more clearly by comparing the middle two figures below. The middle right figure indicates that there are multiple streets with no lights in zip code 02132 (West Roxbury). To explore whether this sparsity was in fact missing data, we investigated Google Street View to explore some of these West Roxbury streets. We found that these streets do indeed have streetlights (as is shown in the photograph below) confirming that this dataset is not a complete representation of streetlights in Boston.







Google Street View image of a West Roxbury Street


Deutsches Altenheim
Roxbury Latin School Woods Park
Riverdale Park
UPPER WASHINGTON / SPRING STREET
West Roxbury Crushed Stone
EASTLAND MOTORS
Sally Beauty
Laser Quest

This missing streetlight data has the potential of skewing any model that uses this information as a predictor. However, to further explore the usefulness of this data and any effect of this missing data, we have begun work on engineering a model feature that measures streetlight density within 100 meters (configurable) of each crime in the crime dataset. For example, here are the number of streetlights within 100 meter proximity of the first twenty observations in the crime dataset:
[0, 4, 8, 55, 43, 37, 53, 33, 33, 27, 28, 54, 54, 28, 33, 2, 26, 19, 22, 31]. More analysis is still required for this feature set.

Neighborhood demographics data

EDA notebook:
https://github.com/sedelmeyer/predicting-crime/blob/master/notebooks/015_EDA_neighborhood_demographics.ipynb

By Boston neighborhood we have successfully pulled together demographic data in the following categories:

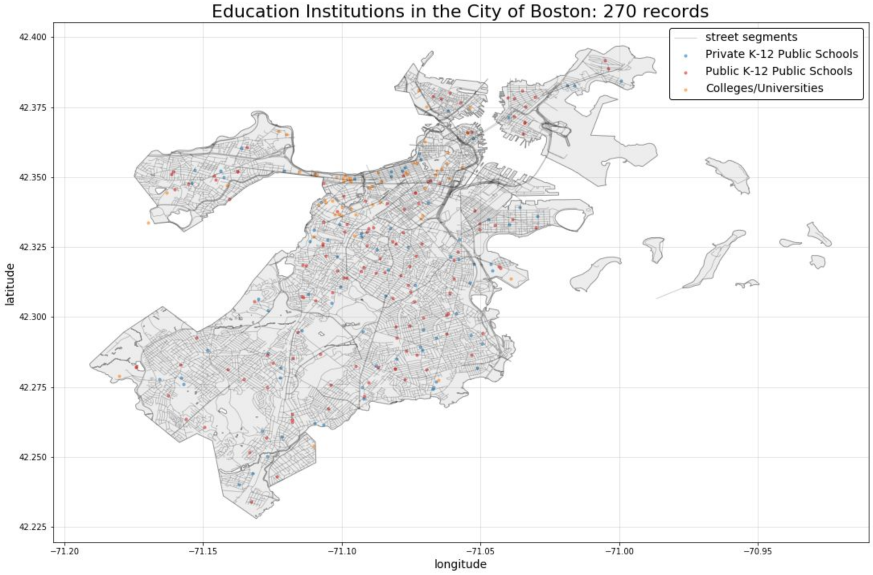
- Age
- Housing Tenure
- Household Income
- Poverty Rate
- Educational Attainment | School Enrollment

For our 17 identified neighborhoods we have created one master data frame including over 70 features granting us flexibility for model experimentation. Given that the demographics data is at an aggregated neighborhood level (rather than by census tract) further discussion is needed around model implementation.

Education institutions

EDA notebook:
https://github.com/sedelmeyer/predicting-crime/blob/master/notebooks/014_EDA_schools_and_universities.ipynb

We have examined public K-12 schools, non-public K-12 schools, as well as colleges and universities in the Boston area. We've cleaned and prepared 131 Public K-12 Boston area schools, 82 non-public schools, and 57 colleges/universities. The plot below illustrates the combined 270 education institutions differentiated by color. All education institutions include geographical coordinates and are ready to be utilized within our models.



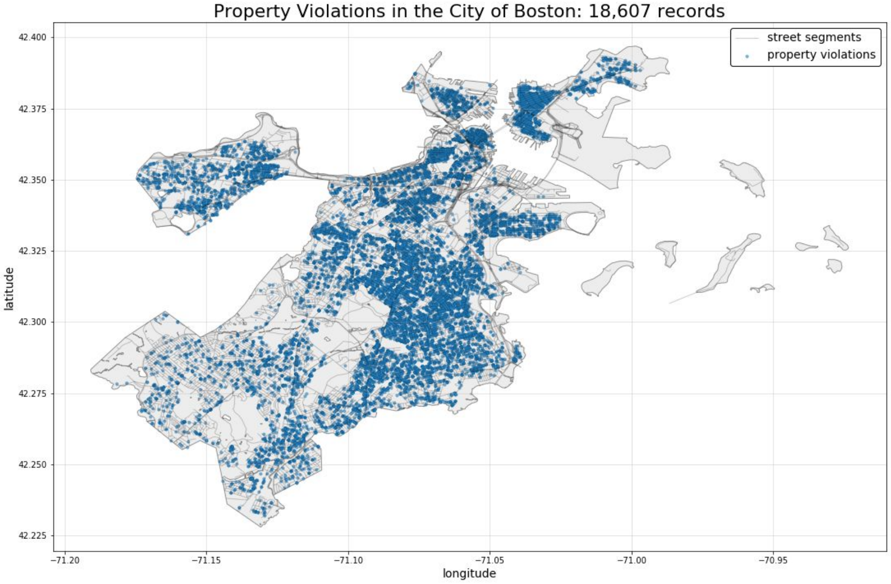
Property violations

EDA notebook:
https://github.com/sedelmeyer/predicting-crime/blob/master/notebooks/016_EDA_property_violations.ipynb

Over 18,000 property violations in the Boston area have been analyzed across 453 property violation types. The most common property violation types include:

1. "Unsafe and Dangerous" (17%)
2. "Failure to Obtain Permit" (14%)
3. "Owners Responsibility to Maintain Structural Elements" (8%)

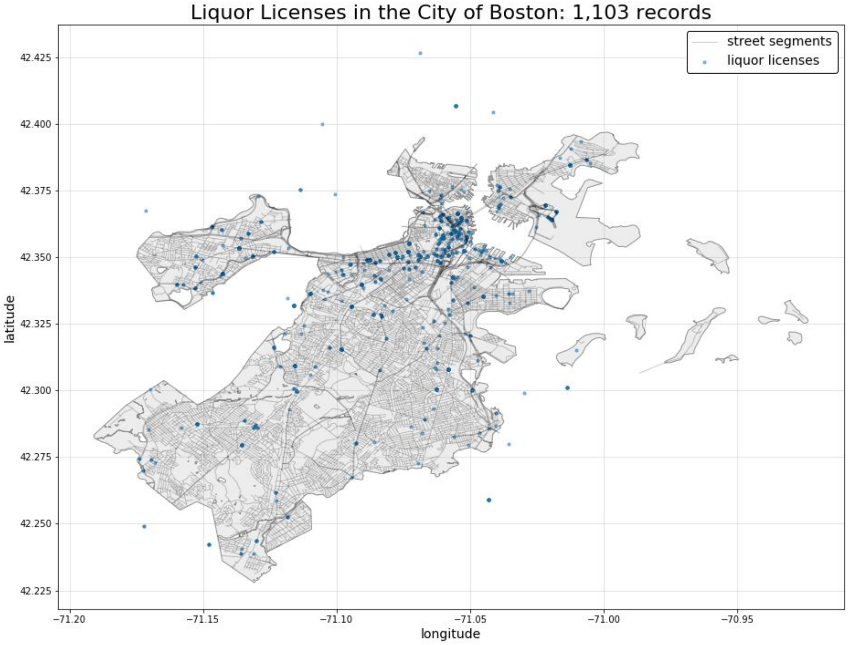
Given that the remaining 450 property violations cover the remaining 69% of all violations we may consider further feature engineering to simplify our violation types or exclude property violations from our models. The plot below illustrates all property violations in the city of Boston.



Liquor license data

EDA notebooks:
https://github.com/sedelmeyer/predicting-crime/blob/master/notebooks/012_liquor_data_prep.ipynb
https://github.com/sedelmeyer/predicting-crime/blob/master/notebooks/013_EDA_liquor_data.ipynb

Examining liquor licenses in Boston took a fair amount of data cleansing efforts to transform incomplete addresses to latitude and longitude. We have successfully processed over 1,100 liquor license records and plotted them in the figure below:



What we’ve found a bit peculiar is that several of our data points fall outside our map. Digging a bit deeper we’ve found that over 85% of our liquor license categories belong to “Common Victualler" which represents “any establishment that has on its premises the ability to assemble, prepare, or cook food”. We would not expect such an unequal distribution of liquor license types which raises concern towards the completeness of our dataset. Given these concerns we may decide to exclude the presence of liquor licenses in our final model.

Revised project questions

Given the (1) variety preliminary datasets we were able to find, (2) the results of our initial EDA on a subset of those datasets, and (3) the number of additional predictors we currently have under development (see the Next Steps section of this document), we have decided to define our project questions in fairly broad terms similar to how they were proposed in the original project description :

- Given environmental and demographic features of a specific location in the City of Boston, can we predict (from a defined subset of crime types), which type of crime is most likely to occur at that location?

- What effects do specific location-based features have on the type of crime most likely to occur at that location?

Baseline model

Baseline model notebook:
https://github.com/sedelmeyer/predicting-crime/blob/master/notebooks/021_MODEL_baseline_logistic_classifier.ipynb

As an initial baseline model, we ran several multi-class Logistic Regression models on a version of our predictors outlined below, in which all non-binary predictors were standardized to adjust for variability in scale among predictors. Variations attempted while building our baseline model included both one-vs-rest and multinomial versions of the model. In addition, we ran the versions of the models without regularization and then with L1 Lasso-like regularization (but without cross-validation) to ultimately examine coefficient shrinkage and to begin understanding relationships between our response classes and each individual predictor.

For reference, the best baseline model reported here was specified with the following parameters::

```
LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=10000,
                   multi_class='multinomial', n_jobs=None, penalty='l1',
                   random_state=20, solver='saga', tol=0.0001, verbose=0,
                   warm_start=False)
```

Response variable

The response variable for our model is **“type of crime,"** defined as a set of 9 crime-type categories consolidated from a subset of the 66 available OFFENSE_CODE_GROUP categories in the raw crime incidents dataset over the years 2016-2019.

The 9 crime-type categories are:

1. Burglary
2. Drugs-substances
3. Fraud
4. Harassment-disturbance
5. Robbery
6. Theft
7. Vandalism-property
8. Violence-aggression
9. Other

Predictors

Listed below are the predictors used in our baseline model. Additional predictors still under development for future iterations of our model are listed separately in Appendix 1 of this document.

1. ***Day of week***
   - This is a one-hot-encoded categorical variable for Tue, Wed, Thu, Fri, Sat, and Sun, indicating the day of the week during which the incident occurred.
2. ***Month of year***
   - This is a one-hot-encoded categorical variable for Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, and Dec indicating the month of the incident.
3. ***Night***
   - This is a binary variable indicating whether the crime occurred between the hours of 8pm and 4am.
   - The next iteration of this model will use actual sunset/sunrise times (as recorded by local NOAA weather stations) for the date the incident occurred to specify this predictor.
4. ***Median residential property value***
   - This is measured by census tract area in which and year when the observation occurred.
5. ***Median residential value, 3-year CAGR***
   - This provides a measure of gentrification/development trend activity in the observation's census tract area and year of occurrence.
6. ***Disparity of residential property values (Gini coefficient)***
   - For this feature "disparity" is measured using the Gini coefficient as a measure of economic inequality in the observation's census tract and year.
7. ***Disparity change trend for residential property values (Gini 3-year CAGR)***
   - This provides a measure of growing or shrinking inequality in the observation's census tract area and year of occurrence.
8. ***Commercial properties mix ratio***
   - This provides a measure as to how "commercial" the corresponding census tract is, as measured by total assessed commercial property value in the tract divided by the total assessed value for all property in the tract during the given observation year.
9. ***Commercial properties mix ratio, 3-year CAGR***
   - Provides a measure of how much more or less commercial the tract is becoming at the time of the observation.
10. ***Industrial properties mix ratio***
    - This provides a measure as to how "industrial" the corresponding census tract is, as measured by total assessed industrial property value in the tract divided by the total assessed value for all property in the tract during the given observation year.
11. ***Industrial properties mix ratio, 3-year CAGR***
    - Provides a measure of how much more or less industrial the tract is becoming at the time of the observation.
12. ***Owner-occupied residential property ratio***
    - What proportion of the residential and mixed-use properties are owner-occupied in the corresponding census tract during the given observation year.
    - To a degree this acts as a measure of local ownership as well as a potential indicator of absentee property ownership.
13. ***Owner-occupied residential property ratio, 3-year CAGR***
    - Measures trend changes in local ownership for the census tract at the time of observation.

Model results

While we still have some issues with missingness and collinearity in several of our features (collinearity information is included in Appendix 2) to resolve in future iterations of our predictive model, our best baseline model, which used lasso regularized logistic regression with multinomial classification, resulted in a training accuracy score of 0.2733 and TEST score of 0.2730. Given the geographical inter-mixing of our response classes and the high bias of these results, we suspect that the linear decision boundaries of a logistic function are not expressive enough for accurately defining our feature space and predicting results. For that reason, we expect to see better accuracy results in future iterations of the model wherein we plan to first use non-parametric methods such as k-Nearest Neighbors and Decision Tree ensembles, and then later Artificial Neural Networks trained on our soon to be expanded feature set.

Even if a logistic function does not provide sufficient expressiveness for our classification problem, it does provide the benefit of interpretable results, from which we can begin to develop a better understanding of the relationships between specific predictors and response classes. For an overview of our estimated coefficients (as well as an indication of which predictors are found to be “not important” via lasso coefficient shrinkage to zero for certain response classes), please see the figures provided in Appendix 3.

Appendices

Below are several additional items referenced in our write-up above that we moved to the end of this report to allow for better flow while reading the document.

Appendix 1: Predictors still under development

The following several predictors were not yet ready for inclusion in our baseline model, but are still being sorted out and will likely be incorporated into our next versions of the model:

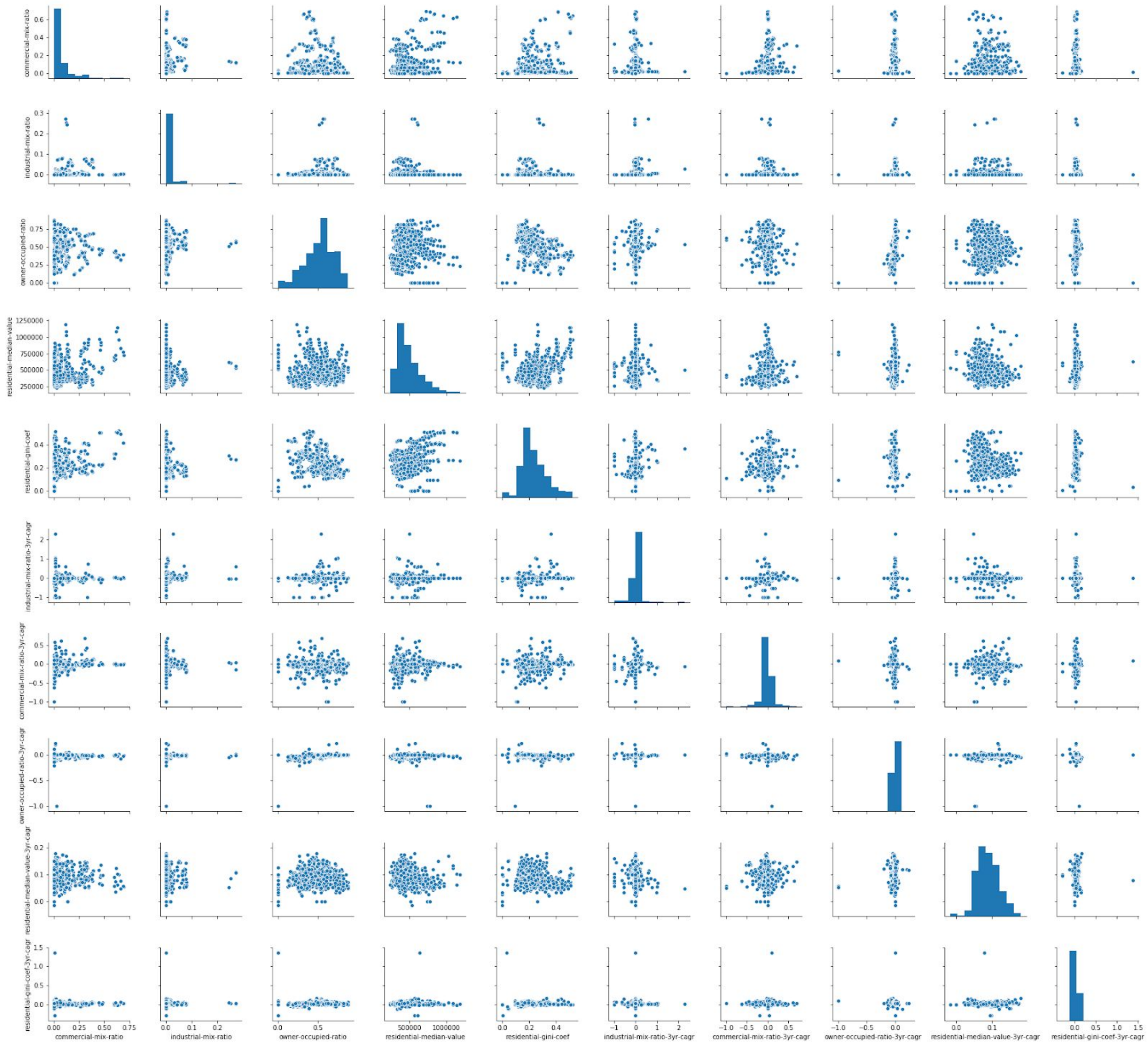
- ***Streetlight lighting density at location of crime***
    - This feature is still being developed and further analysis is needed to determine whether density provides a more meaningful metric when measured by tract, nearest street segment, or within some threshold proximity to a crime observation.
- ***Proximity to university / college campus***
    - Indicates whether the the crime occur on or within close proximity to a university or college campus (categorical predictor).
- ***Proximity to high school campus***
    - Indicates whether the the crime occur on or within close proximity to a high school campus (categorical predictor).
- ***Liquor license density by tract of observation***
    - We are still considering the inclusion of a census tract liquor license density predictor, however, early EDA indicates that the licensing dataset may not include enough valid data for engineering a reliable feature
- ***Property violations density by tract of observation***
    - We are still considering the inclusion of a property violations density predictor.
- ***Census demographics by neighborhood of observation***
    - We still have some consideration to give as to what demographic features we wish to include. Options include features related to age, poverty, income, and education.

Appendix 2: Overview of predictor collinearity

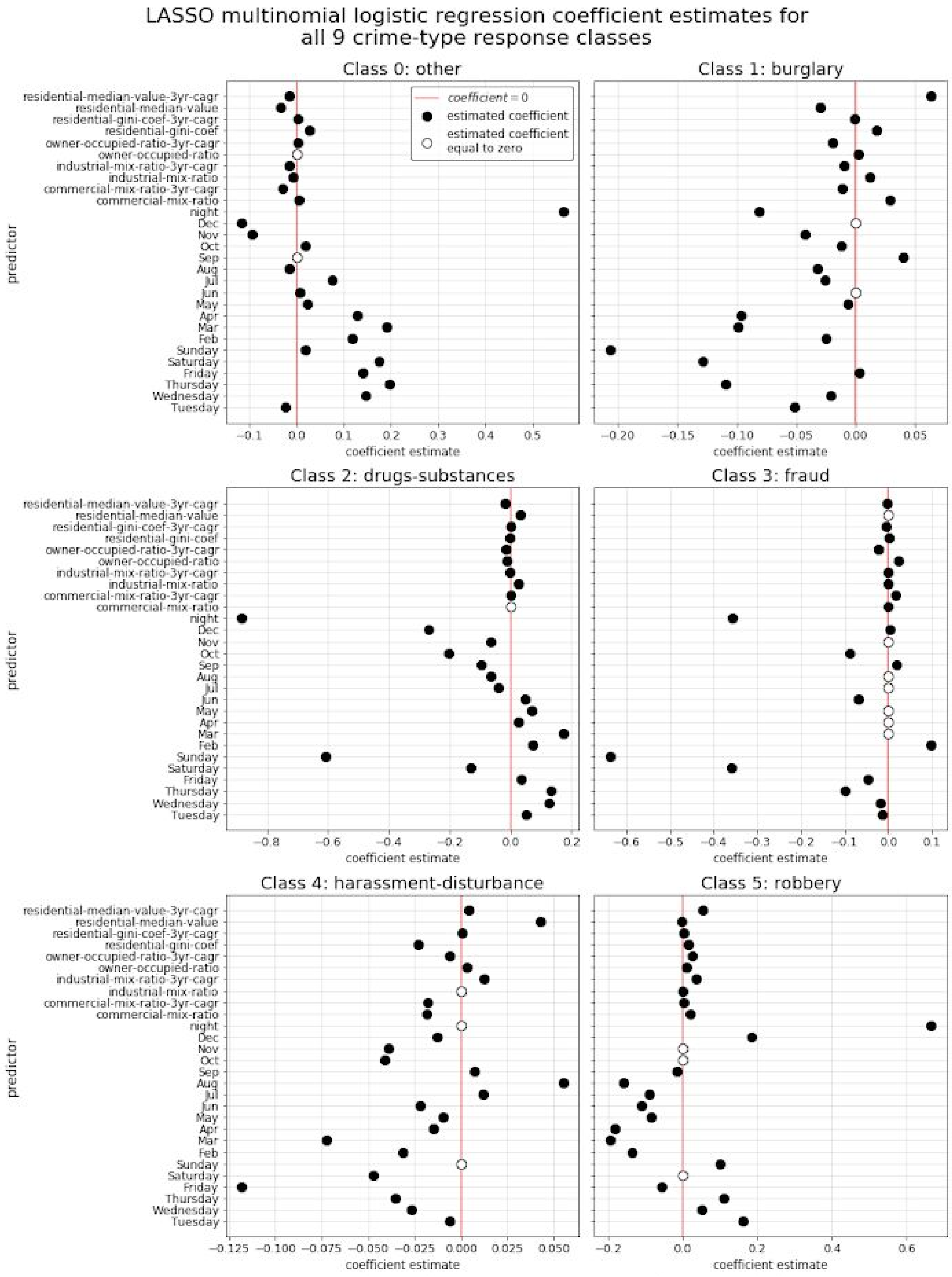
The most strongly correlated predictors (correlation > 0.20) in our baseline model predictor training set and their corresponding correlation values are:

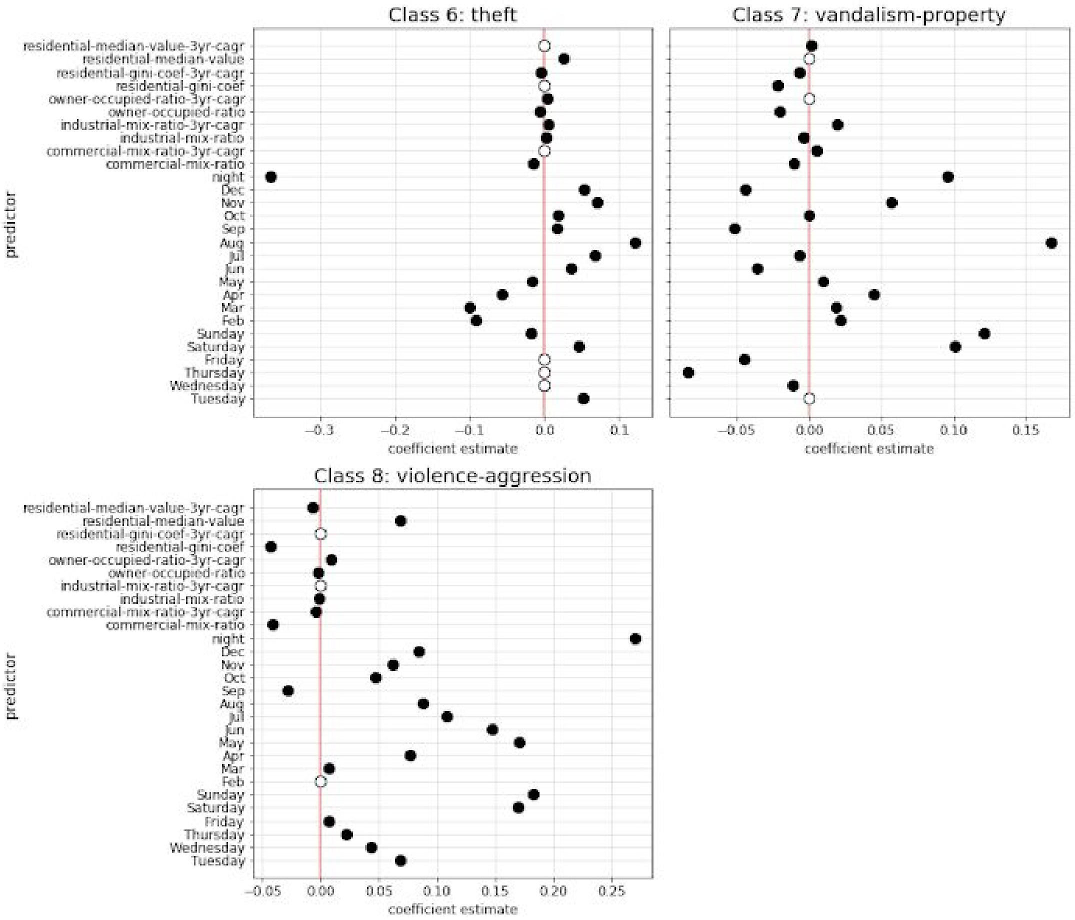
Predictor 1	Predictor 2	Pairwise correlation
residential-median-value	residential-gini-coef	0.68
residential-median-value	commercial-mix-ratio	0.58
commercial-mix-ratio	residential-gini-coef	0.57
owner-occupied-ratio	residential-gini-coef	0.42
owner-occupied-ratio	owner-occupied-ratio-3yr-cagr	0.41
residential-gini-coef	residential-median-value-3yr-cagr	0.34
owner-occupied-ratio	commercial-mix-ratio	0.31
residential-median-value	residential-median-value-3yr-cagr	0.28
residential-median-value	owner-occupied-ratio	0.27
owner-occupied-ratio-3yr-cagr	residential-gini-coef	0.26
residential-median-value-3yr-cagr	commercial-mix-ratio	0.24

Pairwise relationships of all numeric (non-binary) predictors in the crime-type training set



Appendix 3: Lasso regularized multinomial logistic regression model coefficients by response class





Class 6: theft

Class 7: vandalism-property

Class 8: violence-aggression