Detroit Blight

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url: https://notebooks.azure.com/n/fw1h9ATbKck/notebooks/DetroitBlightReport.ipynb (https://notebooks.azure.com/n/fw1h9ATbKck/notebooks/DetroitBlightReport.ipynb)

Introduction

A blighted building is a property that has been abandoned, deteriorated, and/or unsafe to the public. Many buildings of this state leads to urban decay - where an otherwise functioning area becomes non-functional or dysfunctional.
Blighted buildings have been a well documented issue in the Detroit area. If blighted buildings could be predicted before they happen and spreads broadly, government officials could step into provide funding or solutions to prevent or slow down the decay.

In the following analysis, we'll examine crime, demolition, 311 incidents, and blight violations in the Detroit muncipal area and attempt to predict blight. More specifically, we'll ask does criminal, demolition, and 311 incidents at specific GPS locations in 2016 predict blight violations in those same locations YTD 2017? If so, what is the accuracy and performance of the model. To perform this analysis, we'll join several datasets from Open Data site www.data.detroitmi.gov and run a few models on the final dataset.

Data Preparation and Working Dataset

One of the main challenges with this project was obtaining, cleaning, and merging the data from four different data repositories. The following section summaraizes the steps we took to prepare the data for exploration and model construction, but this section won't provide cleaning details. While these steps are important and necessary to perform the analysis, a lengthy discussion isn't needed to inform the analysis and conclusions. Specific details and supporting code are discussed in the Appendix. If you wish to execute the code in this notebook from scratch, please start with the Appendix - Data Cleaning section. Here we'll show the final product of the data preparation (i.e. the final working dataset).

In [ ]:
```
# load enviornment variables for analysis. This shorcuts the data prep s
teps in the Appendix
load("~/Dropbox/UW_DS/DS450_DetroitBlight/envDataPS.RData")
```

The working data set - detAll contains 71 variables and 144820 unique gps locations in Detroit. The criminal offense and 311 issue type factors are stretched out to individual columns with frequencies of each type at a specific location. The blight violation count, neighborhood, and any demolition permit data is also included with the unique location. The total counts in each of the four groups are represented with an n+"group" variable name.

In [10]:

```
# Examine structure of final data
str(detAll)
```

```
'data.frame':	148820 obs. of  73 variables:
 $ loc.id                             : chr  "400984831213" "414841818" 
"4173583529" "417938866098" ...
 $ lat                                : num  40.1 41.5 41.7 41.8 41.9 
...
 $ long                               : num  -83.1 -81.8 -83.5 -86.6 -8
3.4 ...
 $ n                                  : num  1 1 1 1 1 1 1 1 1 1 ...
 $ Abandoned Vehicle                  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Blocked Catch Basin                : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Curbside Solid Waste Issue         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Dead Animal Removal                : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Debris Removal                     : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Detroit Land Bank Referral         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Fire Hydrant Issue                 : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Illegal Dump Sites                 : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Manhole Cover Issue                : num  0 0 0 0 0 0 0 0 0 0 ...
 $ New LED Street Light Out           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Other environmental                : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Park Issue                         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Potholes                           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Residential Snow Removal Issue     : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Running Water in a Home or Building: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Street Light Pole Down             : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Traffic Sign Issue                 : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Traffic Signal Issue               : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Tree Issue                         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Water Main Break                   : num  0 0 0 0 0 0 0 0 0 0 ...
 $ n311                               : num  0 0 0 0 0 0 0 0 0 0 ...
 $ AGGRAVATED ASSAULT                 : num  0 0 1 0 0 0 0 0 0 0 ...
 $ ARSON                              : num  0 0 0 0 0 0 0 0 0 0 ...
 $ ASSAULT                            : num  0 0 0 0 0 0 0 0 0 0 ...
 $ BRIBERY                            : num  0 0 0 0 0 0 0 0 0 0 ...
 $ BURGLARY                           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ CIVIL                              : num  0 0 0 0 0 0 0 0 0 0 ...
 $ DAMAGE TO PROPERTY                 : num  0 0 0 0 0 0 0 0 0 0 ...
 $ DANGEROUS DRUGS                    : num  0 0 0 0 0 0 0 0 0 0 ...
 $ DISORDERLY CONDUCT                 : num  0 0 0 0 0 0 0 0 0 0 ...
 $ DRUNKENNESS                        : num  0 0 0 0 0 0 0 0 0 0 ...
 $ EMBEZZLEMENT                       : num  0 0 0 0 0 0 0 0 0 0 ...
 $ ENVIRONMENT                        : num  0 0 0 0 0 0 0 0 0 0 ...
 $ ESCAPE                             : num  0 0 0 0 0 0 0 0 0 0 ...
 $ EXTORTION                          : num  0 0 0 0 0 0 0 0 0 0 ...
 $ FAMILY OFFENSE                     : num  0 0 0 0 0 0 0 0 0 0 ...
 $ FORGERY                            : num  0 0 0 0 0 1 0 0 0 0 ...
 $ FRAUD                              : num  1 0 0 0 0 0 0 0 0 0 ...
 $ GAMBLING                           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ HOMICIDE                           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ IMMIGRATION                        : num  0 0 0 0 0 0 0 0 0 0 ...
 $ JUSTIFIABLE HOMICIDE               : num  0 0 0 0 0 0 0 0 0 0 ...
 $ KIDNAPPING                         : num  0 0 0 0 0 0 0 0 0 0 ...
 $ LARCENY                            : num  0 0 0 1 0 0 0 0 0 0 ...
 $ LIQUOR                             : num  0 0 0 0 0 0 0 0 0 0 ...
 $ MISCELLANEOUS                      : num  0 0 0 0 0 0 1 0 1 1 ...
 $ MISCELLANEOUS ARREST               : num  0 0 0 0 0 0 0 0 0 0 ...
 $ NEGLIGENT HOMICIDE                 : num  0 0 0 0 0 0 0 0 0 0 ...
 $ OBSCENITY                          : num  0 0 0 0 0 0 0 0 0 0 ...
```

```
 $ OBSTRUCTING JUDICIARY             : num  0 1 0 0 0 0 0 0 0 0 ...
 $ OBSTRUCTING THE POLICE            : num  0 0 0 0 0 0 0 0 0 0 ...
 $ OTHER                             : num  0 0 0 0 0 0 0 0 0 0 ...
 $ OTHER BURGLARY                    : num  0 0 0 0 0 0 0 0 0 0 ...
 $ OUIL                              : num  0 0 0 0 0 0 0 0 0 0 ...
 $ ROBBERY                           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ RUNAWAY                           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ SEX OFFENSES                      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ SOLICITATION                      : num  0 0 0 0 0 0 0 0 0 0 ...
 $ STOLEN PROPERTY                   : num  0 0 0 0 0 0 0 0 0 0 ...
 $ STOLEN VEHICLE                    : num  0 0 0 0 0 0 0 0 0 0 ...
 $ TRAFFIC                           : num  0 0 0 0 1 0 0 1 0 0 ...
 $ VAGRANCY (OTHER)                  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ WEAPONS OFFENSES                  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ nCrime                            : num  1 1 1 1 1 1 1 1 1 1 ...
 $ d.price                           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ commercial                        : Factor w/ 3 levels "No","unknow
n",..: 2 2 2 2 2 2 2 2 2 2 ...
 $ nBlight                           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ ng.hood                           : Factor w/ 158 levels "ARDEN PAR
K/EAST BOSTON",..: 146 146 146 146 146 146 146 146 146 146 ...
 $ nDemo                             : num  0 0 0 0 0 0 0 0 0 0 ...
```

In [11]:

```
# summary stats for detAll
summary(detAll)
```

```
   loc.id               lat             long              n          
 Length:148820      Min.   :40.10   Min.   :-86.61   Min.   :  1.000  
 Class :character   1st Qu.:42.36   1st Qu.:-83.20   1st Qu.:  1.000  
 Mode  :character   Median :42.39   Median :-83.12   Median :  1.000  
                    Mean   :42.39   Mean   :-83.11   Mean   :  1.283  
                    3rd Qu.:42.42   3rd Qu.:-83.03   3rd Qu.:  1.000  
                    Max.   :42.96   Max.   :-81.80   Max.   :318.000  

 Abandoned Vehicle   Blocked Catch Basin Curbside Solid Waste Issue
 Min.   : 0.000000   Min.   :0.0000      Min.   : 0.00000          
 1st Qu.: 0.000000   1st Qu.:0.0000      1st Qu.: 0.00000          
 Median : 0.000000   Median :0.0000      Median : 0.00000          
 Mean   : 0.007378   Mean   :0.0209      Mean   : 0.03953          
 3rd Qu.: 0.000000   3rd Qu.:0.0000      3rd Qu.: 0.00000          
 Max.   :26.000000   Max.   :7.0000      Max.   :29.00000          

 Dead Animal Removal Debris Removal     Detroit Land Bank Referral
 Min.   :0.000000    Min.   : 0.00000   Min.   :0.0000000         
 1st Qu.:0.000000    1st Qu.: 0.00000   1st Qu.:0.0000000         
 Median :0.000000    Median : 0.00000   Median :0.0000000         
 Mean   :0.004085    Mean   : 0.04737   Mean   :0.0002486         
 3rd Qu.:0.000000    3rd Qu.: 0.00000   3rd Qu.:0.0000000         
 Max.   :4.000000    Max.   :24.00000   Max.   :2.0000000         

 Fire Hydrant Issue Illegal Dump Sites Manhole Cover Issue
 Min.   :0.000000   Min.   : 0.00000   Min.   :0.000000   
 1st Qu.:0.000000   1st Qu.: 0.00000   1st Qu.:0.000000   
 Median :0.000000   Median : 0.00000   Median :0.000000   
 Mean   :0.004643   Mean   : 0.02865   Mean   :0.002842   
 3rd Qu.:0.000000   3rd Qu.: 0.00000   3rd Qu.:0.000000   
 Max.   :4.000000   Max.   :33.00000   Max.   :4.000000   

 New LED Street Light Out Other environmental   Park Issue       
 Min.   :0.000000         Min.   : 0.00000    Min.   :0.0000000  
 1st Qu.:0.000000         1st Qu.: 0.00000    1st Qu.:0.0000000  
 Median :0.000000         Median : 0.00000    Median :0.0000000  
 Mean   :0.001949         Mean   : 0.04768    Mean   :0.0001075  
 3rd Qu.:0.000000         3rd Qu.: 0.00000    3rd Qu.:0.0000000  
 Max.   :3.000000         Max.   :41.00000    Max.   :1.0000000  

    Potholes         Residential Snow Removal Issue
 Min.   :  0.00000   Min.   :0.000000              
 1st Qu.:  0.00000   1st Qu.:0.000000              
 Median :  0.00000   Median :0.000000              
 Mean   :  0.01794   Mean   :0.001331              
 3rd Qu.:  0.00000   3rd Qu.:0.000000              
 Max.   :134.00000   Max.   :2.000000              

 Running Water in a Home or Building Street Light Pole Down Traffic Sig
n Issue
 Min.   :0.00e+00                    Min.   :0.000000       Min.   :0.0
00000
 1st Qu.:0.00e+00                    1st Qu.:0.000000       1st Qu.:0.0
00000
 Median :0.00e+00                    Median :0.000000       Median :0.0
00000
 Mean   :7.81e-03                    Mean   :0.001015       Mean   :0.0
```

```
09784
 3rd Qu.:0.00e+00                     3rd Qu.:0.000000       3rd Qu.:0.0
00000
 Max.   :1.60e+02                     Max.   :4.000000       Max.   :5.0
00000


 Traffic Signal Issue   Tree Issue       Water Main Break       n311

 Min.   :0.000000     Min.   : 0.00000   Min.   :0.000000   Min.   :
0.0000
 1st Qu.:0.000000     1st Qu.: 0.00000   1st Qu.:0.000000   1st Qu.:
0.0000
 Median :0.000000     Median : 0.00000   Median :0.000000   Median :
0.0000
 Mean   :0.004227     Mean   : 0.01619   Mean   :0.008151   Mean   :
0.2718
 3rd Qu.:0.000000     3rd Qu.: 0.00000   3rd Qu.:0.000000   3rd Qu.:
0.0000
 Max.   :6.000000     Max.   :12.00000   Max.   :6.000000   Max.   :31
8.0000


 AGGRAVATED ASSAULT     ARSON              ASSAULT            BRIBERY

 Min.   :0.0000      Min.   :0.00000   Min.   :0.0000   Min.   :0.00e+00

 1st Qu.:0.0000      1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.00e+00

 Median :0.0000      Median :0.00000   Median :0.0000   Median :0.00e+00

 Mean   :0.0572      Mean   :0.00631   Mean   :0.1189   Mean   :2.02e-05

 3rd Qu.:0.0000      3rd Qu.:0.00000   3rd Qu.:0.0000   3rd Qu.:0.00e+00

 Max.   :3.0000      Max.   :2.00000   Max.   :4.0000   Max.   :1.00e+00



    BURGLARY             CIVIL            DAMAGE TO PROPERTY DANGEROUS DRUG
S
 Min.   :0.00000   Min.   :0.00e+00   Min.   :0.00000    Min.   :0.0000
0
 1st Qu.:0.00000   1st Qu.:0.00e+00   1st Qu.:0.00000    1st Qu.:0.0000
0
 Median :0.00000   Median :0.00e+00   Median :0.00000    Median :0.0000
0
 Mean   :0.05282   Mean   :5.38e-05   Mean   :0.06713    Mean   :0.0189
7
 3rd Qu.:0.00000   3rd Qu.:0.00e+00   3rd Qu.:0.00000    3rd Qu.:0.0000
0
 Max.   :5.00000   Max.   :1.00e+00   Max.   :3.00000    Max.   :6.0000
0


 DISORDERLY CONDUCT  DRUNKENNESS       EMBEZZLEMENT       ENVIRONMENT
```

```
 Min.   :0.00000    Min.   :0.0e+00   Min.   :0.000000   Min.   :0.0000
00
 1st Qu.:0.00000    1st Qu.:0.0e+00   1st Qu.:0.000000   1st Qu.:0.0000
00
 Median :0.00000    Median :0.0e+00   Median :0.000000   Median :0.0000
00
 Mean   :0.00592    Mean   :6.7e-06   Mean   :0.000215   Mean   :0.0010
75
 3rd Qu.:0.00000    3rd Qu.:0.0e+00   3rd Qu.:0.000000   3rd Qu.:0.0000
00
 Max.   :3.00000    Max.   :1.0e+00   Max.   :1.000000   Max.   :2.0000
00


     ESCAPE             EXTORTION         FAMILY OFFENSE        FORGERY

 Min.   :0.000000   Min.   :0.000000   Min.   :0.000000   Min.   :0.000
000
 1st Qu.:0.000000   1st Qu.:0.000000   1st Qu.:0.000000   1st Qu.:0.000
000
 Median :0.000000   Median :0.000000   Median :0.000000   Median :0.000
000
 Mean   :0.004804   Mean   :0.001129   Mean   :0.002742   Mean   :0.001
062
 3rd Qu.:0.000000   3rd Qu.:0.000000   3rd Qu.:0.000000   3rd Qu.:0.000
000
 Max.   :3.000000   Max.   :1.000000   Max.   :2.000000   Max.   :1.000
000


     FRAUD             GAMBLING          HOMICIDE          IMMIGRATION

 Min.   :0.00000   Min.   :0.0e+00   Min.   :0.000000   Min.   :0.00e+0
0
 1st Qu.:0.00000   1st Qu.:0.0e+00   1st Qu.:0.000000   1st Qu.:0.00e+0
0
 Median :0.00000   Median :0.0e+00   Median :0.000000   Median :0.00e+0
0
 Mean   :0.03004   Mean   :6.7e-06   Mean   :0.001962   Mean   :7.39e-0
5
 3rd Qu.:0.00000   3rd Qu.:0.0e+00   3rd Qu.:0.000000   3rd Qu.:0.00e+0
0
 Max.   :3.00000   Max.   :1.0e+00   Max.   :2.000000   Max.   :1.00e+0
0


 JUSTIFIABLE HOMICIDE   KIDNAPPING          LARCENY            LIQUOR

 Min.   :0.00e+00     Min.   :0.000000   Min.   : 0.00000   Min.   :0.0
000000
 1st Qu.:0.00e+00     1st Qu.:0.000000   1st Qu.: 0.00000   1st Qu.:0.0
000000
 Median :0.00e+00     Median :0.000000   Median : 0.00000   Median :0.0
000000
 Mean   :2.69e-05     Mean   :0.001055   Mean   : 0.09408   Mean   :0.0
006988
 3rd Qu.:0.00e+00     3rd Qu.:0.000000   3rd Qu.: 0.00000   3rd Qu.:0.0
```

```
000000
 Max.   :1.00e+00     Max.   :1.000000   Max.   :11.00000   Max.   :1.0
000000


 MISCELLANEOUS     MISCELLANEOUS ARREST NEGLIGENT HOMICIDE    OBSCENITY

 Min.   : 0.0000   Min.   :0.0e+00      Min.   :0.0000000   Min.   :0.0
0e+00
 1st Qu.: 0.0000   1st Qu.:0.0e+00      1st Qu.:0.0000000   1st Qu.:0.0
0e+00
 Median : 0.0000   Median :0.0e+00      Median :0.0000000   Median :0.0
0e+00
 Mean   : 0.2185   Mean   :6.7e-06      Mean   :0.0001142   Mean   :6.0
5e-05
 3rd Qu.: 0.0000   3rd Qu.:0.0e+00      3rd Qu.:0.0000000   3rd Qu.:0.0
0e+00
 Max.   :14.0000   Max.   :1.0e+00      Max.   :1.0000000   Max.   :1.0
0e+00


 OBSTRUCTING JUDICIARY OBSTRUCTING THE POLICE     OTHER
 Min.   :0.00000       Min.   :0.000000       Min.   :0.000000
 1st Qu.:0.00000       1st Qu.:0.000000       1st Qu.:0.000000
 Median :0.00000       Median :0.000000       Median :0.000000
 Mean   :0.01086       Mean   :0.002137       Mean   :0.002527
 3rd Qu.:0.00000       3rd Qu.:0.000000       3rd Qu.:0.000000
 Max.   :3.00000       Max.   :1.000000       Max.   :2.000000

 OTHER BURGLARY           OUIL               ROBBERY           RUNAWAY

 Min.   :0.000000   Min.   :0.000000   Min.   :0.00000   Min.   : 0.000
000
 1st Qu.:0.000000   1st Qu.:0.000000   1st Qu.:0.00000   1st Qu.: 0.000
000
 Median :0.000000   Median :0.000000   Median :0.00000   Median : 0.000
000
 Mean   :0.001727   Mean   :0.003138   Mean   :0.01955   Mean   : 0.006
027
 3rd Qu.:0.000000   3rd Qu.:0.000000   3rd Qu.:0.00000   3rd Qu.: 0.000
000
 Max.   :1.000000   Max.   :2.000000   Max.   :2.00000   Max.   :14.000
000


  SEX OFFENSES       SOLICITATION       STOLEN PROPERTY    STOLEN VEHICL
E
 Min.   :0.00e+00   Min.   :0.000000   Min.   :0.000000   Min.   :0.000
00
 1st Qu.:0.00e+00   1st Qu.:0.000000   1st Qu.:0.000000   1st Qu.:0.000
00
 Median :0.00e+00   Median :0.000000   Median :0.000000   Median :0.000
00
 Mean   :5.38e-05   Mean   :0.002258   Mean   :0.002426   Mean   :0.054
11
 3rd Qu.:0.00e+00   3rd Qu.:0.000000   3rd Qu.:0.000000   3rd Qu.:0.000
00
```

```
 Max.   :2.00e+00   Max.   :3.000000   Max.   :1.000000   Max.   :3.000
00


    TRAFFIC         VAGRANCY (OTHER)   WEAPONS OFFENSES      nCrime

 Min.   : 0.00000   Min.   :0.000000   Min.   :0.00000   Min.   : 0.000
0
 1st Qu.: 0.00000   1st Qu.:0.000000   1st Qu.:0.00000   1st Qu.: 0.000
0
 Median : 0.00000   Median :0.000000   Median :0.00000   Median : 1.000
0
 Mean   : 0.04552   Mean   :0.001808   Mean   :0.01134   Mean   : 0.848
5
 3rd Qu.: 0.00000   3rd Qu.:0.000000   3rd Qu.:0.00000   3rd Qu.: 1.000
0
 Max.   :32.00000   Max.   :6.000000   Max.   :3.00000   Max.   :40.000
0


    d.price             commercial        nBlight                    ng.h
ood
 Min.   :       0.0   No      :  3111   Min.   : 0.000   unknown
:45072
 1st Qu.:       0.0   unknown:145618   1st Qu.: 0.000   GREENFIELD
: 3693
 Median :       0.0   Yes     :    91   Median : 0.000   STATE FAIR-NOLA
N: 3545
 Mean   :     306.4                     Mean   : 0.141   WARRENDALE
: 3246
 3rd Qu.:       0.0                     3rd Qu.: 0.000   DENBY
: 3150
 Max.   :1270930.0                      Max.   :58.000   PERSHING
: 2673
                                                         (Other)
:87441
     nDemo
 Min.   :0.00000
 1st Qu.:0.00000
 Median :0.00000
 Mean   :0.02152
 3rd Qu.:0.00000
 Max.   :1.00000
```

Data Exploration

The first thing that we want understand the relationship between location and frequencies of incidents and if we see any visual trends we can see. Note, the code below executes a raster plot overlayed on a map file. (Note, due to updates with ggplot2 this code didn't work in jupyter on OSx where this report is written, but did work in Windows where some analysis was conducted). Also, only relevant visuals are shown here, rather than all exploraratory attempts.

In [ ]:

```
# Add column for demolition count
library(dplyr)
detAll <- detAll %>% mutate(nDemo = ifelse(commercial != "unknown", 1, 0
))
```

In [ ]:

```
load("meltData.RData")
library(dplyr)
```

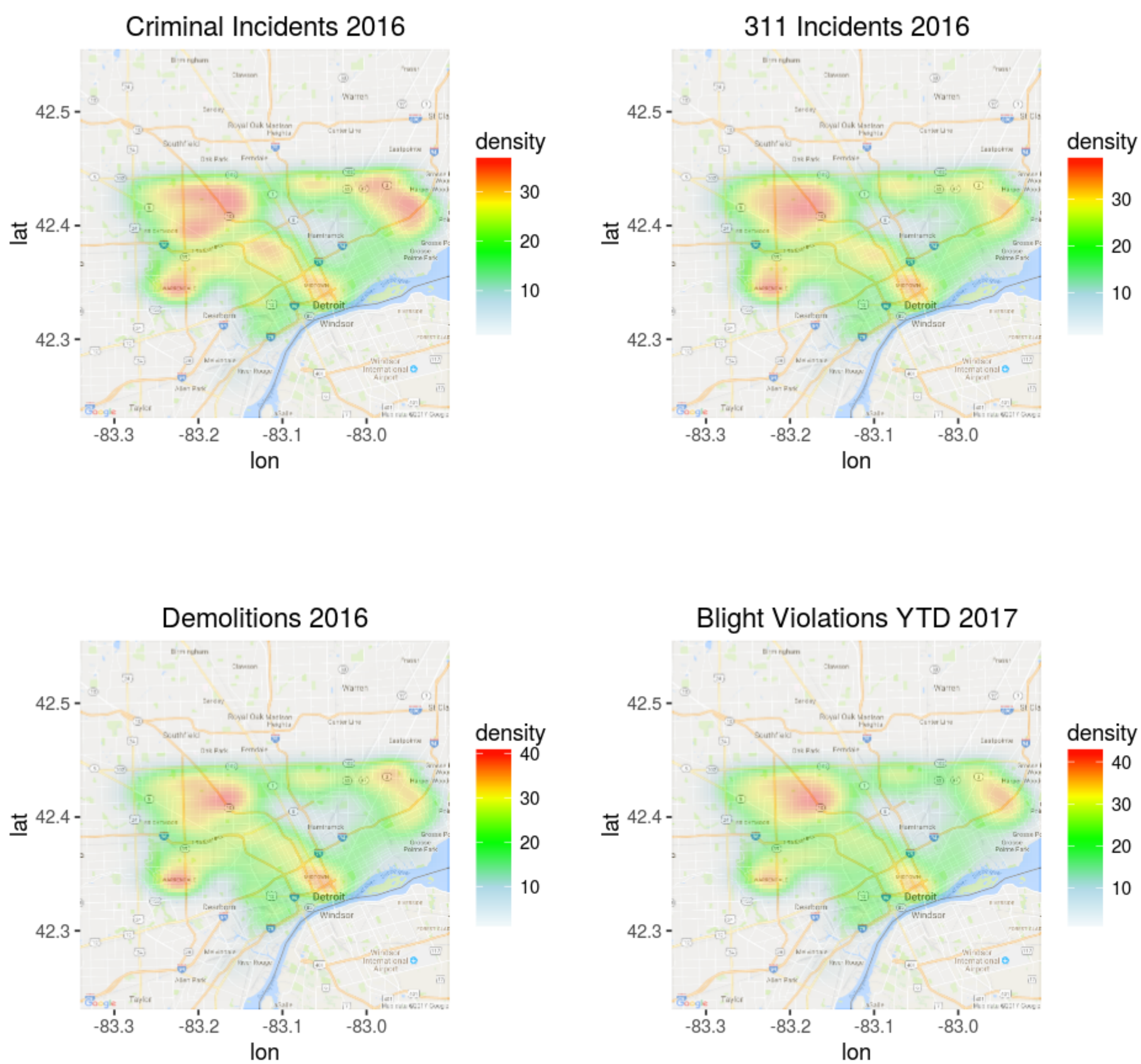
In [ ]:

```
# get google map
library(ggplot2)
library(ggmap)
library(reshape2)
library(gridExtra)


#  citation:
#  D. Kahle and H. Wickham. ggmap: Spatial Visualization with ggplot2. T
he R Journal, 5(1), 144-161. URL
#  http://journal.r-project.org/archive/2013-1/kahle-wickham.pdf

centers <- lapply(detAll[, c("lat", "long")], median)
detMap <- get_googlemap(center = c(lon = centers$long, lat = centers$lat
),
                        size = c(640, 640),
                        scale = 1,
                        zoom = 11,
                        maptype = "roadmap")

# melt frequencies for plotting
melt.detAll <- melt(detAll[, c("lat", "long", "nCrime", "n311", "nDemo",
 "nBlight")], id = c("lat", "long"))

# plot raster
# set color ramp
colfunc <- colorRampPalette(c("white", "lightblue", "green", "yellow",
"red"))

detMap.den.crime <- ggmap(detMap) + stat_density2d(data = sample_n(melt.
detAll %>% filter(variable == "nCrime"), 5000),
                                                   aes(x = long, y = lat
, fill = ..density..),
                                                   geom = "tile", contou
r = FALSE, alpha = 0.3) +
                                    scale_fill_gradientn(colours=colfunc
(400)) + ggtitle("Criminal Incidents 2016")

detMap.den.311 <- ggmap(detMap) + stat_density2d(data = sample_n(melt.de
tAll %>% filter(variable == "n311"), 5000),
                                                 aes(x = long, y = lat,
 fill = ..density..),
                                                 geom = "tile", contour
= FALSE, alpha = 0.3) +
                                  scale_fill_gradientn(colours=colfunc(4
00)) + ggtitle("311 Incidents 2016")

detMap.den.demo <- ggmap(detMap) + stat_density2d(data = sample_n(melt.d
```

```
etAll %>% filter(variable == "nDemo"), 5000),
                                                  aes(x = long, y = lat,
 fill = ..density..),
                                                  geom = "tile", contour
= FALSE, alpha = 0.3) +
                                    scale_fill_gradientn(colours=colfunc
(400)) + ggtitle("Demolitions 2016")

detMap.den.blight <- ggmap(detMap) + stat_density2d(data = sample_n(mel
t.detAll %>% filter(variable == "nBlight"), 5000),
                                                   aes(x = long, y = lat,
 fill = ..density..),
                                                   geom = "tile", contour
 = FALSE, alpha = 0.3) +
                                   scale_fill_gradientn(colours=colfunc(
400)) + ggtitle("Blight Violations YTD 2017")


# detMap.den.crime
# detMap.den.311
# detMap.den.demo
# detMap.den.blight

grid.arrange(detMap.den.crime, detMap.den.311, detMap.den.demo, detMap.d
en.blight, nrow = 2, ncol = 2)
```

In [8]:
```
require(repr)
options(repr.plot.width=8, repr.plot.height=8)

grid.arrange(detMap.den.crime, detMap.den.311, detMap.den.demo, detMap.d
en.blight, nrow = 2, ncol = 2)
```

```
Loading required package: repr
Warning message:
"Removed 3 rows containing non-finite values (stat_density2d)."Warning
message:
"Removed 3 rows containing non-finite values (stat_density2d)."Warning
message:
"Removed 4 rows containing non-finite values (stat_density2d)."Warning
message:
"Removed 3 rows containing non-finite values (stat_density2d)."
```

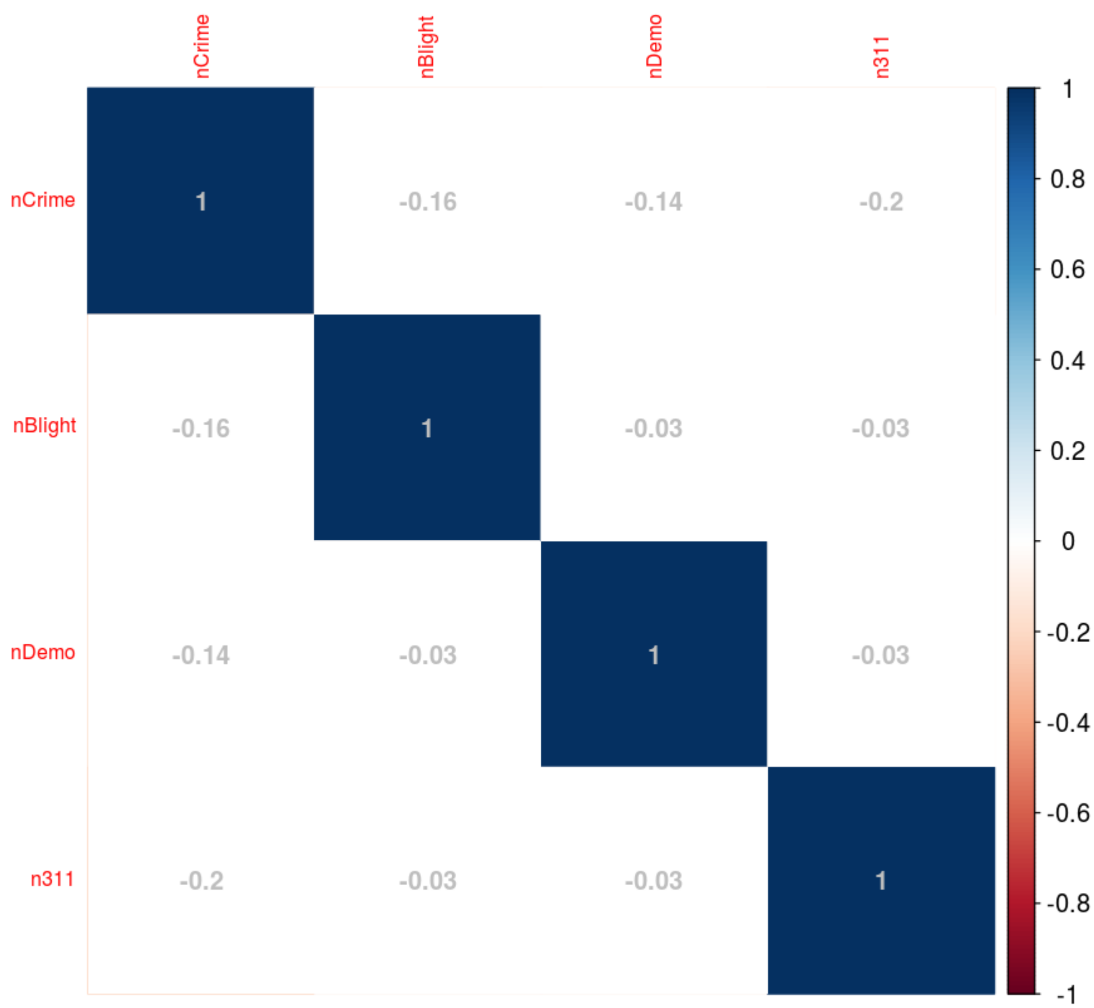


There are several areas in the Detroit area that stand out in this visual. First the northwest and west parts of Detroit had high criminal, 311, and demolition incidents, which overlaps with high 2017 blight violations in the same quadrants of the city. The East and South Central areas show the same. Next we want to understand if there are any correlations between crime, 311 incidents, demolitions and blight violations.

In [9]:

```
# correlation plot
# is there a correlation between frequency of crime, 311, demos, and bli
ght?
# There doesn't seem to be much correlation.

library(corrplot)

cors <- cor(detAll %>% select(nCrime, n311, nDemo, nBlight), method = 'p
earson')

source('cormtest.R', echo=TRUE)
corm <- cor.mtest.2(cors)

# add cor.mtest for p.value matrix.... look in help

corrplot(cors,  p.mat = corm[[1]], insig = "blank", method = "color",
         addCoef.col="grey",
         order = "AOE", tl.cex = 0.8,
         cl.cex = 1/par("cex"), addCoefasPercent = FALSE)
```

```
> cor.mtest <- function(mat, ...) {
+     mat <- as.matrix(mat)
+     n <- ncol(mat)
+     p.mat <- matrix(NA, n, n)
+     diag(p.mat) <- 0
+     for  .... [TRUNCATED]

> cor.mtest.2 <- function(mat, conf.level = 0.95) {
+     mat <- as.matrix(mat)
+     n <- ncol(mat)
+     p.mat <- lowCI.mat <- uppCI.mat <- matrix(N .... [TRUNCATED]
```



It looks like there are not any significant correlations between the four frequencies.

Model Construction and Evaluation

In the following section we will look at three models - a baseline logistic classifier, a regularized logistic classifier, and a tree based model (CART). The last two models were cross validated to 10 folds.

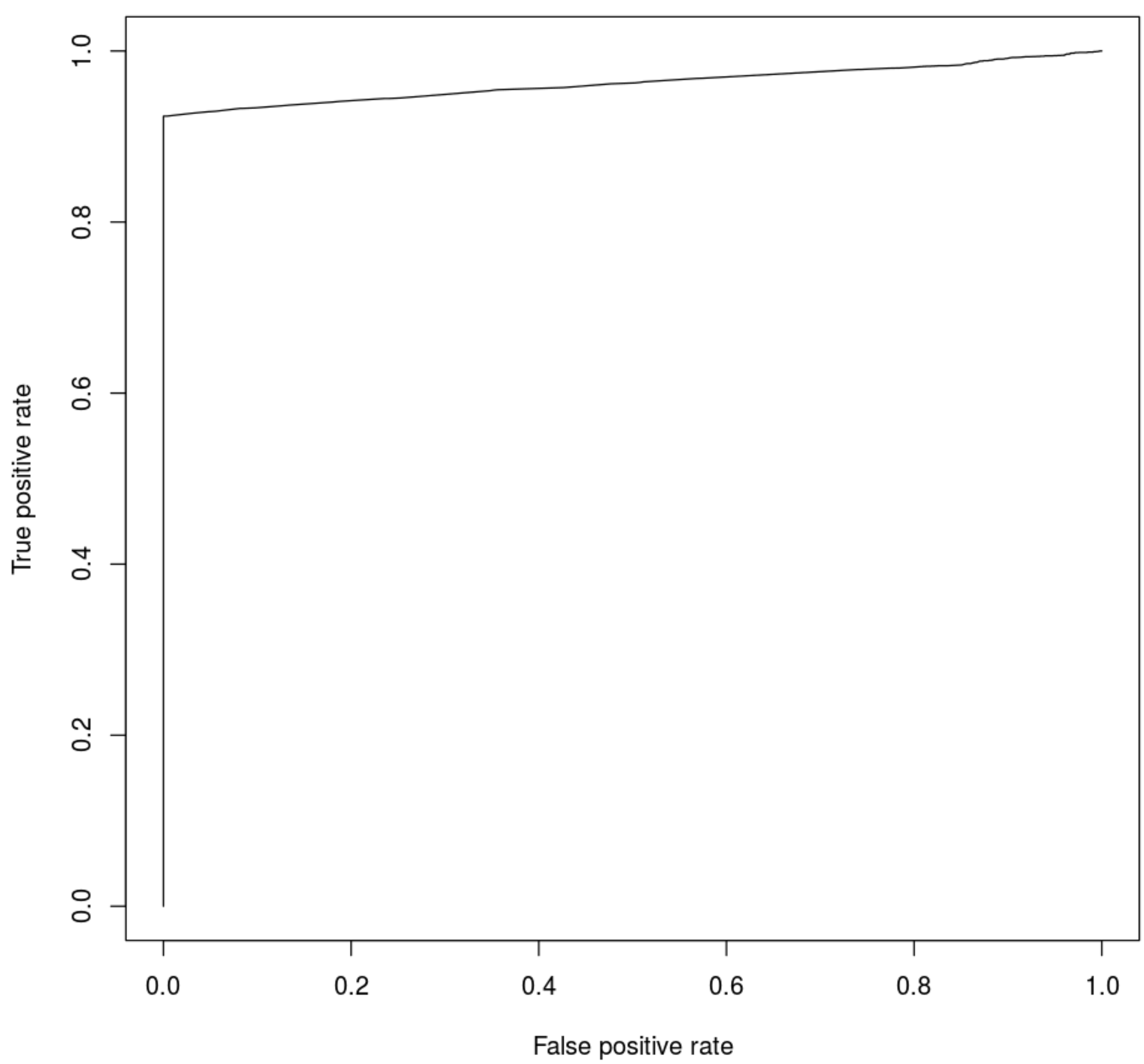
Baseline logistic on all non-count data

Before running the baseline logistic model, we created a labled column - simply if a location had any blight violations. Next we split the data into a training and testing set. Then we selected the relevant columns we wanted in the model, in this case the offense and issue type categories and demolition data. Because the neighborhood factor was proving complex in the models we left it out (this is likely because many of the neighboorhoods were "unknown").

In [12]:

```
# Build several models and compare performance
# 1. Add blight classification column
# 2. split data into training and testing set
# 3. Baseline model logistic regression with K-fold cross validation
# 4. CART with K-fold cross validation

library(caret)
library(ROCR)

# add a classification column for blight
detAll$blight <- as.factor(ifelse(detAll$nBlight > 0, "Yes", "No"))

# split data
set.seed(36924)
perc.split <- 0.5
row.samp <- sample(1:nrow(detAll), perc.split*nrow(detAll))
detAll.train <- detAll[row.samp, ]
detAll.test <- detAll[-row.samp, ]

# select data for the model
detAll.train.trim <- detAll.train %>% select(-nCrime, -n311, -nBlight, -
nDemo, -n, -loc.id, - lat, -long, -ng.hood)
detAll.test.trim <- detAll.test %>% select(-nCrime, -n311, -nBlight, - n
Demo, -n, -loc.id, - lat, -long, -ng.hood)

# baseline regression

logit.base <- glm(blight ~ ., data = detAll.train.trim, family = "binomi
al")

logit.base.pred <- predict(logit.base, detAll.test.trim %>% select(-blig
ht))
pred <- prediction(as.numeric(logit.base.pred), as.numeric(detAll.test.t
rim$blight))

prf <- performance(pred, measure = "tpr", x.measure = "fpr")
plot(prf)

auc <- performance(pred, "auc")
print(paste("AUC=", auc@y.values[[1]], sep=""))
```

```
Loading required package: lattice
Loading required package: gplots

Attaching package: 'gplots'

The following object is masked from 'package:stats':

    lowess

Warning message:
"glm.fit: fitted probabilities numerically 0 or 1 occurred"Warning mess
age in predict.lm(object, newdata, se.fit, scale = 1, type = ifelse(typ
e == :
"prediction from a rank-deficient fit may be misleading"
[1] "AUC=0.962377037582919"
```



In the baseline model we find that the AUC is above 0.96, but this is misleading as the model seems to be rank deficient. Or the predictor variable data doesn't seem to be doing a good job of reliably predicting blight at specific locations. This is an issue we will see in other models.

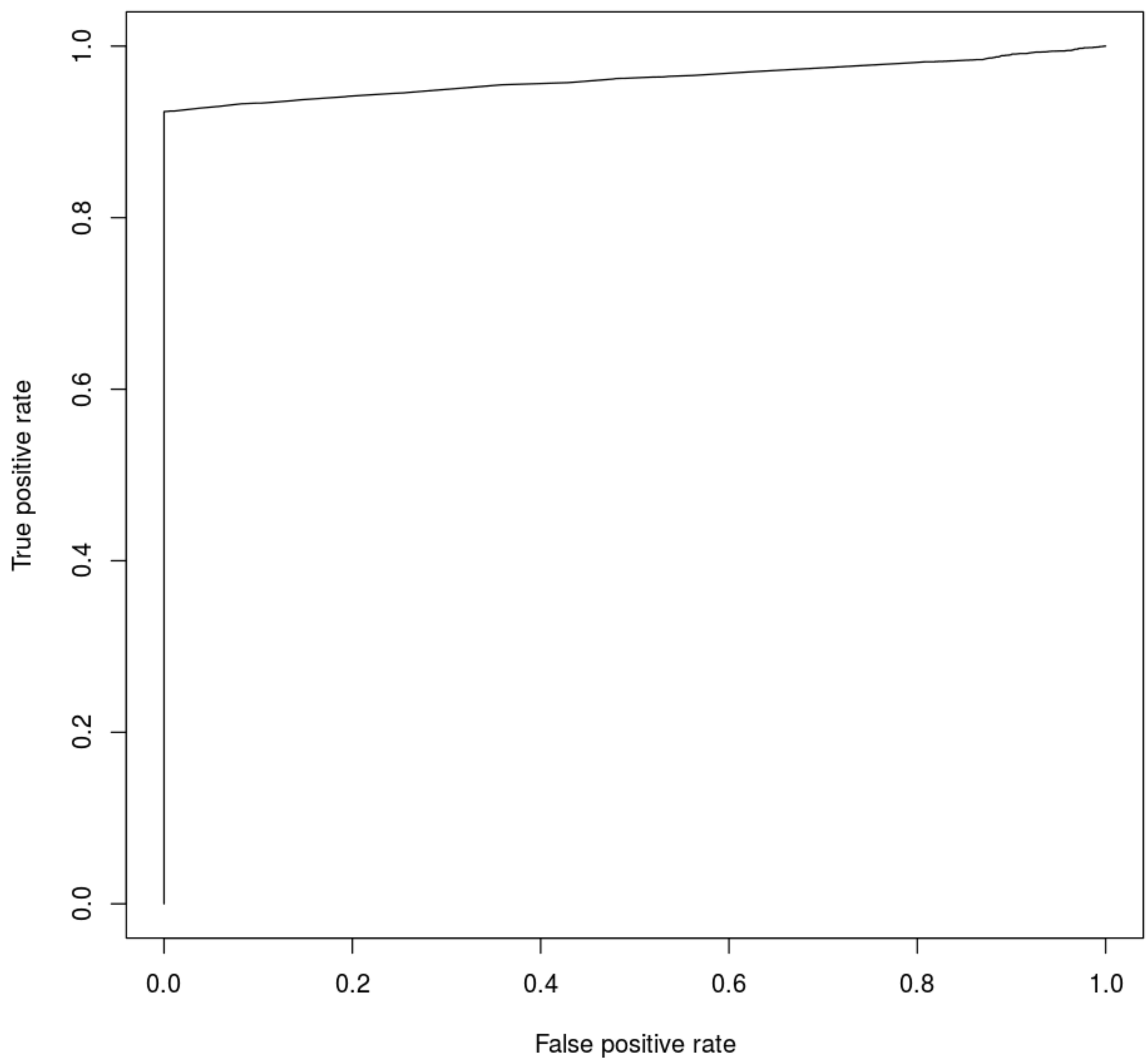
Regularized Logistic with 10-fold CV

Next we try a logistic classifier with L1 and L2 penalization. Once again we see some issues with this model in that the accuracy measure AUC is high, but seems too good to be true.

In [13]:

```
# k fold glmnet logistic, with constant L1 nad L2
library(glmnet)
# create model matrix
mod.train <- model.matrix(blight ~ . -1, data = detAll.train.trim)
# setup glmnet with alpha = 0.5 and nlambda =20
logit.reg <- cv.glmnet(mod.train, detAll.train.trim$blight, nfolds = 10,
 family = "binomial", nlambda = 20, alpha = 0.5)

logit.reg.pred <- predict(logit.reg, model.matrix(blight ~. -1, detAll.t
est.trim))
pred <- prediction(as.numeric(logit.reg.pred), as.numeric(detAll.test.tr
im$blight))

prf <- performance(pred, measure = "tpr", x.measure = "fpr")
plot(prf)

auc <- performance(pred, "auc")
print(paste("AUC=", auc@y.values[[1]], sep=""))
```

```
Loading required package: Matrix
Loading required package: foreach
Loaded glmnet 2.0-5

[1] "AUC=0.961923865413854"
```



CART - Tree based model

Again we will use 10 fold cross validation but with an regression tree for this model. After several tests we control the max depth of the tree to 10 branches. This model predicts as good as a guess with an AUC of 0.5.

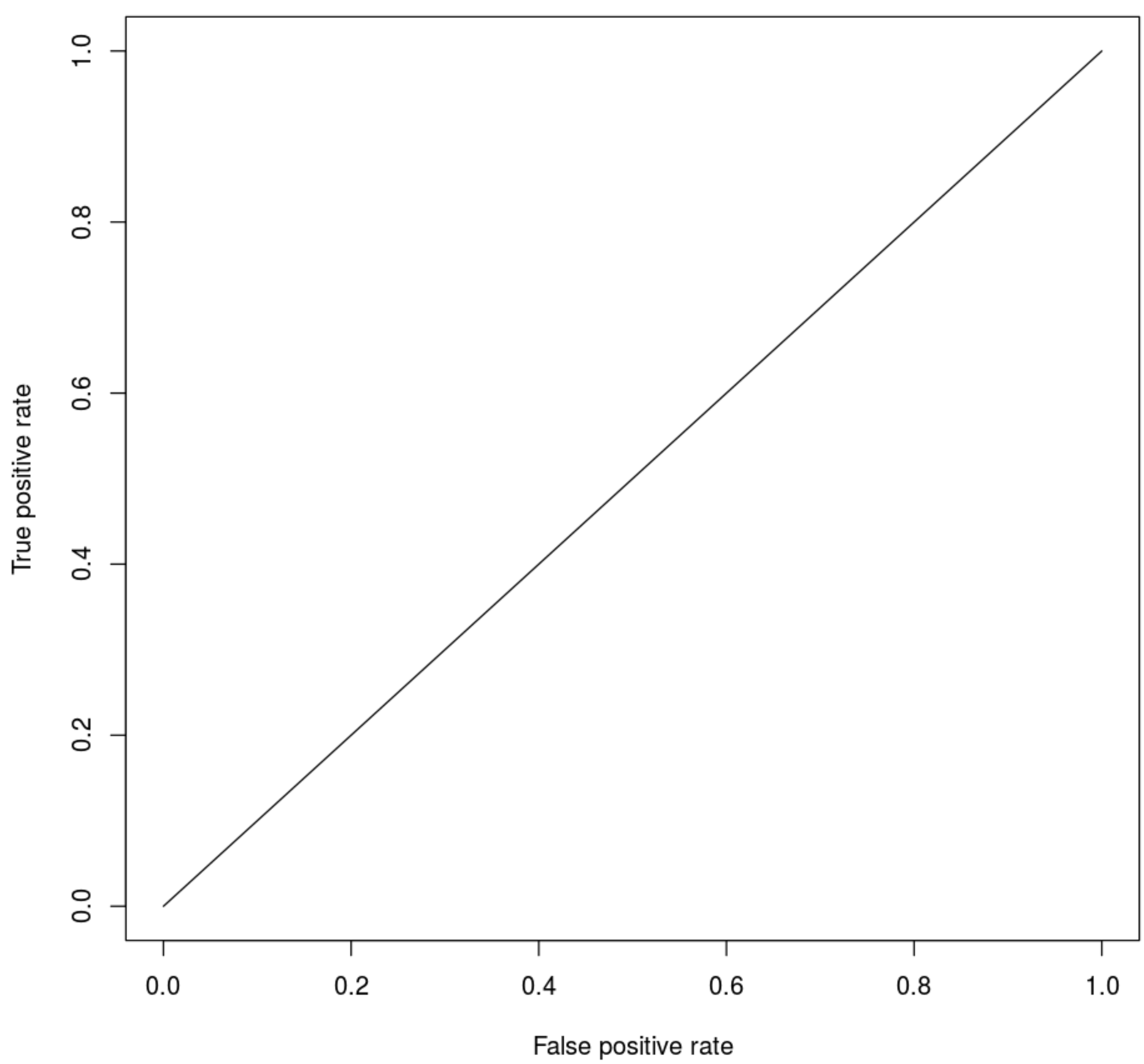
In [15]:

```
# regression tree
library(rpart)
library(rpart.plot)

fitControl <- trainControl(## 5-fold CV
                           method = "cv",
                           number = 10,
                           classProbs = TRUE,
                           summaryFunction = twoClassSummary)

rpart.model <- train(x = detAll.train.trim[, 1:64],
                     y = detAll.train.trim[, 65],
                     method = "rpart1SE",
                     trControl = fitControl,
                     control = rpart.control(maxdepth = 10),
                     metric = "ROC")

print(rpart.model$finalModel)
rpart.plot(rpart.model$finalModel)
```

```
n= 74410

node), split, n, loss, yval, (yprob)
      * denotes terminal node

1) root 74410 4734 No (0.93637952 0.06362048) *
```

In [16]:
```
rpart.pred <- predict(rpart.model$finalModel, detAll.test.trim %>% selec
t(-blight))
pred <- prediction(as.numeric(rpart.pred[,2]), as.numeric(detAll.test.tr
im$blight))

prf <- performance(pred, measure = "tpr", x.measure = "fpr")
plot(prf)

auc <- performance(pred, "auc")
print(paste("AUC=", auc@y.values[[1]], sep=""))
```

```
[1] "AUC=0.5"
```



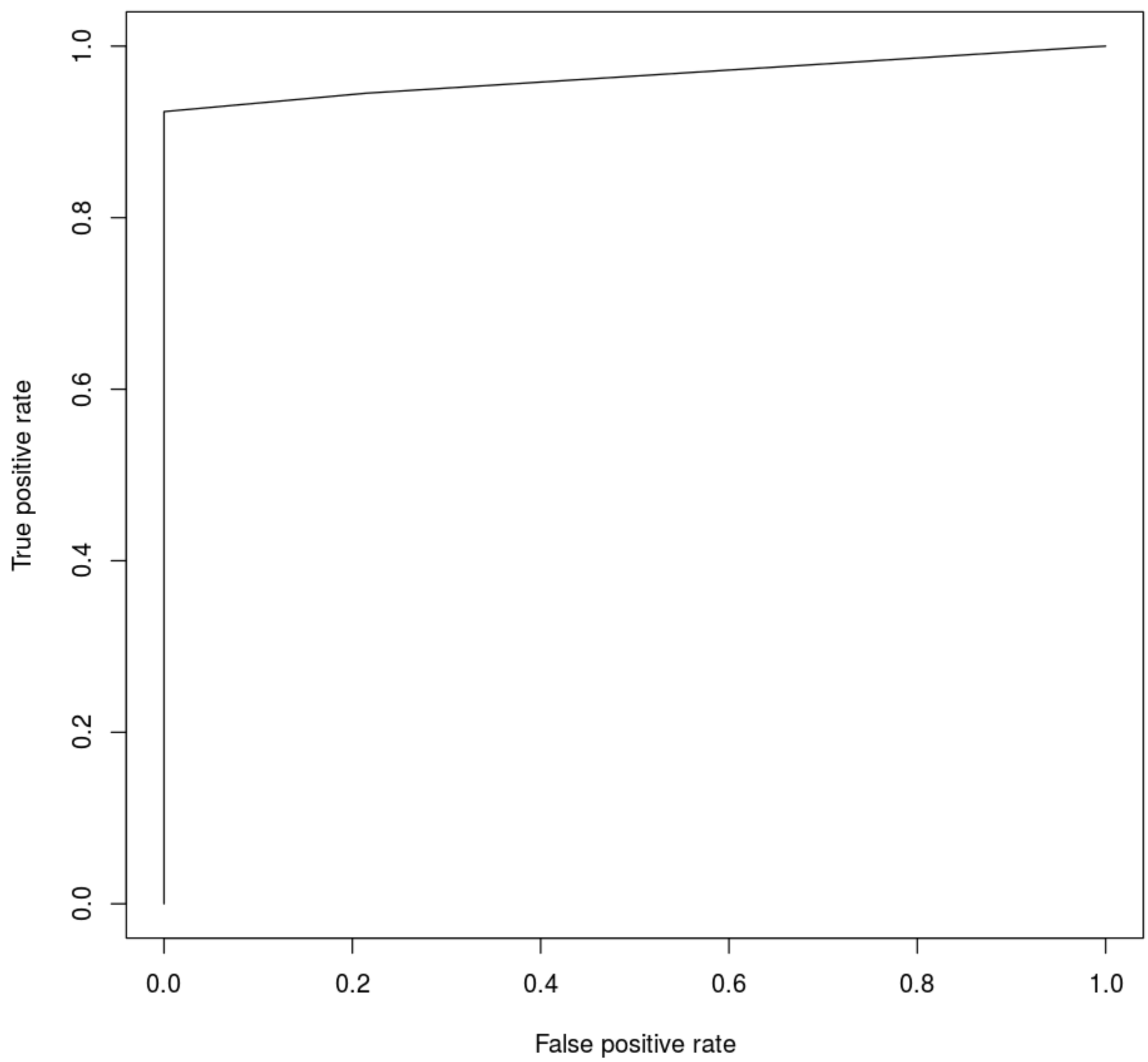
Adjustments to CART with nCount data

Because we are not seeing reliable prediction with the above models we can try using n+"groupings" features in the tree. Even using just the count data, we see some too good to be true results - an AUC of 0.96. This suggests that the features we've created and are using in the models are not really predicting anything. Additionally, blight violations only make up 6% of the observations in the working data set, so the dataset may suffer from minority imbalance and SMOTEing or another sampling method may be required.

In [17]:

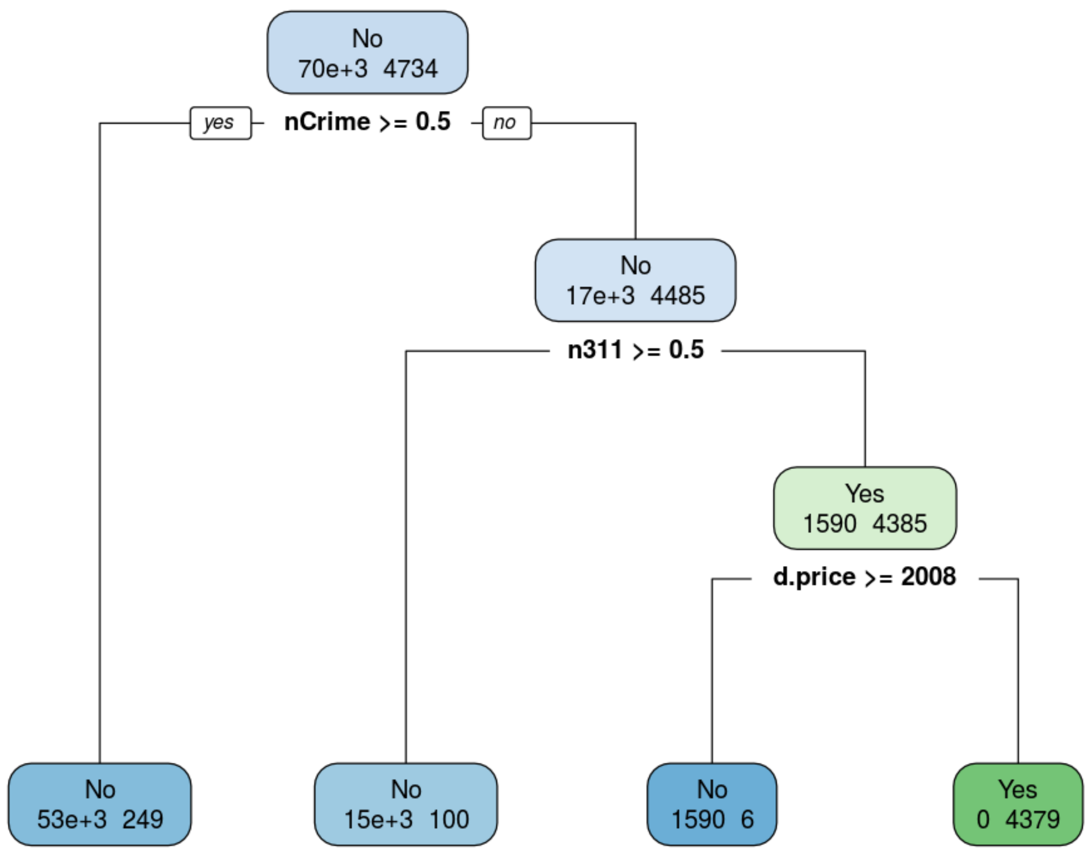
```
# select data for the model
detAll.train.trim <- detAll.train %>% select(nCrime, n311, d.price, blig
ht)
detAll.test.trim <- detAll.test %>% select(nCrime, n311, d.price, blight
)

#setup control
fitControl <- trainControl(## 10-fold CV
  method = "cv",
  number = 10,
  classProbs = TRUE,
  summaryFunction = twoClassSummary)

#run rpart
rpart.model <- train(x = detAll.train.trim[, 1:3],
                     y = detAll.train.trim[, 4],
                     method = "rpart1SE",
                     trControl = fitControl,
                     control = rpart.control(maxdepth = 10),
                     metric = "ROC")

# predict and evaluate AUC on test set
rpart.pred <- predict(rpart.model$finalModel, detAll.test.trim %>% selec
t(-blight))
pred <- prediction(as.numeric(rpart.pred[,2]), as.numeric(detAll.test.tr
im$blight))

prf <- performance(pred, measure = "tpr", x.measure = "fpr")
plot(prf)

auc <- performance(pred, "auc")
print(paste("AUC=", auc@y.values[[1]], sep=""))
```

```
[1] "AUC=0.964477068048075"
```



In [18]:
```
# print and plot tree
print(rpart.model$finalModel)
rpart.plot(rpart.model$finalModel,  extra = 1)
```

```
n= 74410

node), split, n, loss, yval, (yprob)
      * denotes terminal node

 1) root 74410 4734 No (0.936379519 0.063620481)
   2) nCrime>=0.5 53235  249 No (0.995322626 0.004677374) *
   3) nCrime< 0.5 21175 4485 No (0.788193625 0.211806375)
     6) n311>=0.5 15200  100 No (0.993421053 0.006578947) *
     7) n311< 0.5 5975 1590 Yes (0.266108787 0.733891213)
      14) d.price>=2008 1596    6 No (0.996240602 0.003759398) *
      15) d.price< 2008 4379    0 Yes (0.000000000 1.000000000) *
```



In [19]:
```
# blight count
summary(detAll$blight)
```

No	139316
Yes	9504

Conclusions

Based on the map visual, we can definitely see some areas on the map that have high crime, 311 incidents, and demos that overlap with blight violations. Unfortunately the dataset with the mostly frequency features don't really do a good job of predicting blight. The models seem to be rank defecient, meaning the data we are using to predict blight in the following year doesn't have enough strong information to create a good model. Some reasons for this include:

- Location resolution is to fine and may need to expanded to a greater radius. In our analysis, locations were rounded to a 1e-4 resolution.
- There may be a minority imbalance. Another sampling method to correct this imbalance may be required for better model results.
- Predicting blight in the following year (i.e. 2016 incidents predicting 2017 blight) isn't the right question. Potential looking at shorter time frames (next month(s)) or overlapping time frames (within the same quarter) may produce better results.

Going forward it may

Appendix - Data Cleaning and Preparation

Get Data

We obtained data from Detroit's open source data repository.

In [ ]:

```
# Get Detroit Map Data
# download csvs from https://data.detroitmi.gov/

# Note this takes a long time...

# Detroit crime data from Dec 6th 2016 to present
detCrime1216_pres <- read.csv("https://data.detroitmi.gov/api/views/6gdg
-y3kf/rows.csv?accessType=DOWNLOAD")

# Detroit crime data from Jan 1, 2009 to Dec 6th 2016
detCrime1909_1216 <- read.csv("https://data.detroitmi.gov/api/views/invm
-th67/rows.csv?accessType=DOWNLOAD&bom=true&format=true")

# 311 issues submission from Dec 3rd 2014 to present
det311 <- read.csv("https://data.detroitmi.gov/api/views/fwz3-w3yn/rows.
csv?accessType=DOWNLOAD")

# Demolition permits from Jan 1st 2014 to present
detDemolitions <- read.csv("https://data.detroitmi.gov/api/views/rv44-e9
di/rows.csv?accessType=DOWNLOAD")

# Blight violations (tickets) from 2006 - present
detBlight <- read.csv("https://data.detroitmi.gov/api/views/ti6p-wcg4/ro
ws.csv?accessType=DOWNLOAD")
```

Initial Summary of Raw Data Objects

Here we look at the raw data obtained from Detroit's website.

In [ ]:

```
# Source getDetroitData
# source("getDetroitData.r") #run this to get data

# intitial summary of data - 311 issues
head(det311)
str(det311)
summary(det311)

# initial summary of data - Crime
head(detCrime1216_pres)
str(detCrime1216_pres)
summary(detCrime1216_pres)

# initial summary of data - Crime pre 12/6/16
head(detCrime1909_1216)
str(detCrime1909_1216)
summary(detCrime1909_1216)

# initial summary of data - Demolitions
head(detDemolitions)
str(detDemolitions)
summary(detDemolitions)

# initial summary of data - Blight
head(detBlight)
str(detBlight)
summary(detBlight)
```

Clean Data

In this step we:

1. Filter raw data in criminal, demolitions, and 311 incidents to dates between 1/1/16 to 12/31/16. Note Criminal activity only goes to 12/6/16, because of a system change to Detroit's data collection process. Criminal data from 12/6/16 to 12/31/16 is not included in the final data set.
2. Filter raw data in Blight to dates between 1/1/17 to YTD 2017 (11/13/17, at the time of coding)
3. Parse GPS location data in criminal data. See gpsParse function.
4. Include only latitude, longitude, criminal offense category, 311 category, neighborhood, commercial building, and demolition price in final data.
5. Omit data NA location data from Blight
6. Round latitude and longitude to 4 sig figs.
7. Save raw data to enviornment, if needed later.

In [ ]:

```
# The following code is based on the following report:
# https://rstudio-pubs-static.s3.amazonaws.com/194529_5b7aff21a29541fb94
b8f4176e42abf2.html
# by Paulo Cardso

gpsParse <- function(loc.txt, p="\\(.*\\)"){
  r <- regexpr(p, loc.txt)
  out <- rep(NA, length(r))
  out[r != -1] <- regmatches(loc.txt, r)
  out <- gsub("[()]", "", out)
  lat <- unlist(lapply(out, function(x) as.numeric(strsplit(x, split=","
)[[1]][1])))
  long <- unlist(lapply(out, function(x) as.numeric(strsplit(x, split=
",")[[1]][2])))
  list(lat=lat, long=long)
}
```

In [ ]:

```
# clean data
# 1. To limit scope of this activity - filter out incidents that happene
d before 1.1.17
# 2. Strip out columns that are not necessary for this analysis

# source("getDetroitData.R")

library(dplyr)

# Filter dates > 1/1/17
# Blight violations
detBlightDate <- detBlight
detBlightDate$Violation.Date <- as.Date(detBlightDate$Violation.Date, "%
m/%d/%Y")
detBlightDate <- detBlightDate %>% filter(Violation.Date >= '2017-01-01'
)

# demolitions
detDemDate <- detDemolitions
detDemDate$Demolition.Date <- as.Date(detDemDate$Demolition.Date, "%m/%
d/%Y")
detDemDate <- detDemDate %>% filter(Demolition.Date >= '2016-01-01' & De
molition.Date < '2017-01-01')

# 311 incidents
det311Date <- det311
det311Date$ticket_created_date_time <- as.character(det311Date$ticket_cr
eated_date_time)
det311Date$ticket_created_date_time <- as.POSIXct(strptime(det311Date$ti
cket_created_date_time, "%m/%d/%Y %H:%M:%S %p"))
det311Date$ticket_created_date <- as.Date(det311Date$ticket_created_date
_time)
det311Date <- det311Date %>% filter(ticket_created_date >= '2016-01-01'
& ticket_created_date < '2017-01-01')

# Crime incidents post 12/6/16
detCrimeDate <- detCrime1216_pres
detCrimeDate$Incident.Date...Time <- as.character(detCrimeDate$Incident.
Date...Time)
```

```
detCrimeDate$Incident.Date...Time <- as.POSIXct(strptime(detCrimeDate$In
cident.Date...Time, "%m/%d/%Y %H:%M:%S %p"))
detCrimeDate$Incident.Date <- as.Date(detCrimeDate$Incident.Date...Time)
detCrimeDate <- detCrimeDate %>% filter(Incident.Date >= '2017-01-01')

# Crime incidents pre 12/6/16, note this was added later because once al
l data was merged
# it was determined that blight violations didn't overlap with crime and
 311 locations in 2017...
detCrimeDate <- detCrime1909_1216
detCrimeDate$Incident.Date...Time <- as.character(detCrimeDate$INCIDENTD
ATE)
detCrimeDate$Incident.Date...Time <- as.POSIXct(strptime(detCrimeDate$In
cident.Date...Time, "%m/%d/%Y %H:%M:%S %p"))
detCrimeDate$Incident.Date <- as.Date(detCrimeDate$Incident.Date...Time)
detCrimeDate <- detCrimeDate %>% filter(Incident.Date >= '2016-01-01' &
 Incident.Date < '2017-01-01')

# Need to string split location in pre 12/6/17 crime data
source("gpsParse.R")
t.loc <- gpsParse(loc.txt = detCrimeDate$LOCATION)
detCrimeDate$Latitude <- t.loc$lat
detCrimeDate$Longitude <- t.loc$long

# Remove columns that are not needed for analysis
dBlight <- detBlightDate %>% select(Violation.Latitude, Violation.Longit
ude)
dDemo <- detDemDate %>% select(Price, Commercial.Building, Latitude, Lon
gitude)
d311 <- det311Date %>% select(issue_type, lat, lng)
dCrime <- detCrimeDate %>% select(CATEGORY, NEIGHBORHOOD, Latitude, Long
itude)

# verify structures
str(dBlight)
str(dDemo)
str(d311)
str(dCrime)

summary(dBlight) # contains NA lats and longs that will need omission.
summary(dDemo)
summary(d311)
summary(dCrime)


# remove date data
rm(det311Date, detBlightDate, detDemDate) #detCrimeDate
# remove origin data -- only do this if sure
rm(detCrime1909_1216, detCrime1216_pres, detDemolitions, detBlight, det3
11)

# rename columns
colnames(dBlight) <- c("lat", "long")
colnames(dDemo) <- c("d.price","commercial", "lat", "long")
colnames(d311) <- c("inc.type", "lat", "long")
colnames(dCrime) <- c("crm.type", "ng.hood", "lat", "long")
```

```
# round lat long to 4 sig figs
dBlight[,sapply(dBlight, is.numeric)] <- as.data.frame(sapply(dBlight[,s
apply(dBlight, is.numeric)], round, digits = 4))
dDemo[,sapply(dDemo, is.numeric)] <- as.data.frame(sapply(dDemo[,sapply(
dDemo, is.numeric)], round, digits = 4))
d311[,sapply(d311, is.numeric)] <- as.data.frame(sapply(d311[,sapply(d31
1, is.numeric)], round, digits = 4))
dCrime[,sapply(dCrime, is.numeric)] <- as.data.frame(sapply(dCrime[,sapp
ly(dCrime, is.numeric)], round, digits = 4))

# omit blight violations without gps lat and long
dBlight <- na.omit(dBlight)

# change dDemo$d.price to numeric
dDemo$d.price <- as.numeric(sub('$', "", as.character(dDemo$d.price), fi
xed = TRUE))

# remove "DPW - " and " - DPW USE ONLY" from incident factors in d311
a <- gsub("DPW - ", "", as.character(d311$inc.type))
a <- gsub(" - DPW USE ONLY", "", as.character(a))
a <- as.factor(a)
d311$inc.type <- a

# keep raw data from 2016 on
det311.2016 <- det311
det311.2016$ticket_created_date_time <- as.character(det311.2016$ticket_
created_date_time)
det311.2016$ticket_created_date_time <- as.POSIXct(strptime(det311.2016$
ticket_created_date_time, "%m/%d/%Y %H:%M:%S %p"))
det311.2016$ticket_created_date <- as.Date(det311.2016$ticket_created_da
te_time)
det311.2016 <- det311.2016 %>% filter(ticket_created_date >= '2016-01-0
1')

detCrime.2017 <- detCrime1216_pres
detCrime.2017 $Incident.Date...Time <- as.character(detCrime.2017 $Incid
ent.Date...Time)
detCrime.2017 $Incident.Date...Time <- as.POSIXct(strptime(detCrime.2017
 $Incident.Date...Time, "%m/%d/%Y %H:%M:%S %p"))
detCrime.2017 $Incident.Date <- as.Date(detCrime.2017 $Incident.Date...T
ime)
detCrime.2017  <- detCrime.2017  %>% filter(Incident.Date >= '2016-12-0
1')

detDem.2016 <- detDemolitions
detDem.2016$Demolition.Date <- as.Date(detDem.2016$Demolition.Date, "%
m/%d/%Y")
detDem.2016 <- detDem.2016 %>% filter(Demolition.Date >= '2016-01-01')

detBlight.2016 <- detBlight
detBlight.2016$Violation.Date <- as.Date(detBlight.2016$Violation.Date,
"%m/%d/%Y")
detBlight.2016 <- detBlight.2016 %>% filter(Violation.Date >= '2016-01-0
1')
```

Mutate Data

In this set of code we further prepare the data for exploratory and model consumption

In this step we:

1. Create a location charater id column, which we use to join data sets together.
2. Extend out criminal offense factor to individual columns
3. Extend out 311 issue types to individual columns
4. Get frequencies at specific locations for each data object through location id groupings
5. Create a master list of unique locations
6. Merge the four data files together on unique location character ids
7. Clean up final data set - fill in NAs in numerics and factors

In [ ]:

```
# Mutate data
# 1. Add character id column
# 2. Group and count by character id
# 3. Join data sets on id
# 4. Add blight classification on id

# source("cleanData.R")

# add loc character id column for each data set

d311$loc.id <- gsub("[^0-9]", "", paste(d311$lat, d311$long, sep = ""))
dBlight$loc.id <- gsub("[^0-9]", "", paste(dBlight$lat, dBlight$long, se
p = ""))
dCrime$loc.id <- gsub("[^0-9]", "", paste(dCrime$lat, dCrime$long, sep =
 ""))
dDemo$loc.id <- gsub("[^0-9]", "", paste(dDemo$lat, dDemo$long, sep = ""
))

# extend out factors to dummy variables for counting

# d311

library(dummies)
a <- dummy(d311$inc.type, sep = "")
colnames(a) <- gsub("inc.type", "", colnames(a), fixed = TRUE)
d311 <- cbind(d311, a)

# dCrime
a <- dummy(dCrime$crm.type, sep = "")
colnames(a) <- gsub("crm.type", "", colnames(a), fixed = TRUE)
dCrime <- cbind(dCrime, a)

# group columns on location id and sum incidents
temp.gr.311 <- d311[, 4:ncol(d311)] %>% group_by(loc.id) %>% summarise_a
ll(funs(sum))
temp.gr.Crime <- dCrime[, 5:ncol(dCrime)] %>% group_by(loc.id) %>% summa
rise_all(funs(sum))
temp.gr.Blight <- dBlight %>% group_by(loc.id) %>% summarise(nBlight = n
())
```