**Draft:**

Title: Investigating Racial Bias in Surveillance Requests: A Poisson Regression Approach

**Introduction:**

In collaboration with the Tarak Shah of the Human Rights Data Analysis Group, we conducted an analysis on public records data to investigate potential racial bias in surveillance requests by the New Orleans Police Department (NOPD) to the Real Time Crime Center (RTCC). Our central question was: In an investigation for a given criminal charge, is a Black suspect more likely to be the subject of a surveillance request than a non-Black suspect?

**Methodology:**

Initially, the analysis employed a Chi-Squared test to answer the question, but we decided to use a Poisson regression instead to model all the charges. We used R packages tidyverse, brms, and tidybayes to read in the data, manipulate it, and fit the model.

We joined the police report data with the surveillance requests dataset, and modeled the counts of RTCC requests as a binomial distribution. The binomial probability depends on the race of the suspect and the charge description, with a varying intercept for the latter. We used a normal(0,5) prior for the coefficient on the race\_BLACK indicator and the default student\_t(3, 0, .25) prior for the standard deviation of the varying intercept distribution.

**Results:**

After fitting the model and examining the summary, we found that a significant portion of the variation in surveillance requests was explained by the criminal charge. Importantly, even after accounting for the charge, there was a positive coefficient for race\_BLACK (0.34), indicating that Black suspects were more likely to be the subject of a surveillance request.

In exploring the charges most and least likely to result in surveillance requests, we found that "Littering from motor vehicle" was a surprising entry in the top 10, while charges like "CDC WARRANT#" and "WARRANT ISSUED BY" were among the least likely to prompt surveillance requests.

We also made predictions for surveillance footage requests for a hypothetical new charge that was not part of the dataset. The results suggested that there is still a difference in the number of requests based on the race of the suspect:

Non-Black suspect: Median of 28.5 requests (95% CI: 2 to 279)

Black suspect: Median of 39.5 requests (95% CI: 3 to 335)

This finding indicates that even for an unseen charge, the race of the suspect may play a role in the likelihood of a surveillance request.

**Conclusion:**

Our analysis revealed that there is a higher likelihood of surveillance requests for Black suspects compared to non-Black suspects, even after accounting for the type of criminal charge. This finding raises important questions about potential racial bias in the use of surveillance technology by law enforcement agencies. Further research is needed to explore the underlying causes of this disparity and to develop strategies for ensuring equitable treatment in the criminal justice system

Original email from TS:

**Interesting bit of analysis**

Working with local (NOLA) group [eye on surveillance](https://eyeonsurveillance.org/), Ayyub has been analyzing some [public records data on requests for surveillance data from the NOPD to the Real Time Crime Center (RTCC)](https://github.com/ayyubibrahimi/eos-cameras). [This notebook](https://github.com/ayyubibrahimi/eos-cameras/blob/main/notebooks_epr/rtcc_police_reports_regression_race_and_crime_type.ipynb) joins police report data to the surveillance requests to try in order to answer a question about bias in surveillance requests: in an investigation for a given criminal charge, is a Black suspect more likely to be the subject of a surveillance request than a non-Black suspect? Interesting question! Originally AI answered this question with a Chi-Squared test, but I find the named statistical tests very confusing and suggested a poisson regression. I continued to be kind of curious though. There are a lot of charges, it would be interesting to model all of them. So I cloned the repo and tried fitting my own model. We start the same as AI, reading in the data and joining the two tables. I’m sort of mindlessly dropping records with missing data here for the sake of a quick example, and I’m also assuming that the two datasets refer to the same time period:

library(tidyverse)

library(brms)

library(tidybayes)

pr <- read\_csv("../data/police\_reports/electronic\_police\_report\_2018\_2022.csv",

               guess\_max = 20000) %>%

    mutate(race\_black = offender\_race == "BLACK")

rtcc <- read\_csv("../data/real\_time\_crime\_center/rtcc.csv",

                 guess\_max = 20000) %>%

    distinct(item\_number) %>%

    mutate(rtcc\_requested = 1)

rc <- pr %>%

    filter(![is.na](http://is.na/)(offender\_race),

           ![is.na](http://is.na/)(charge\_description)) %>%

    select(item\_number, race\_black, charge\_description) %>%

    left\_join(rtcc, by = "item\_number") %>%

    replace\_na(list(rtcc\_requested = 0)) %>%

    group\_by(race\_black, charge\_description) %>%

    summarise(n = n(), rtcc = sum(rtcc\_requested), .groups = "drop")

From there I modeled the counts of RTCC requests as a binomial distribution, with the binomial probability depending on race and charge description (using a varying intercept for the latter):

spec <- bf(rtcc | trials(n) ~ race\_black + (1 | charge\_description),

           family = "binomial", center = TRUE)

model <- brm(spec,

             prior = set\_prior("normal(0, 5)", class = "b"),

             data = rc, chains = 4, iter = 5000)

The normal(0,5) prior is for the coefficient on the race\_BLACK indicator, given centered data this is a wide, not very informative prior. We stick with the default student\_t(3, 0, .25) prior for the standard deviation of the varying intercept distribution.

I was thinking of useful ways to check this model. We could e.g. fit the model using all but one of the charges and then compare the posterior distribution of counts for an unseen charge with the actual counts from the held-out charge, and repeat this for each of the charges.

And what does the model tell us? In the summary of the resulting model, we see as we might have predicted that a lot of variation is explained by the charge, and that even accounting for that, there is a positive coefficient for when race\_BLACK is 1:

Group-Level Effects:

~charge\_description (Number of levels: 620)

              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS Tail\_ESS

sd(Intercept)     1.61      0.08     1.46     1.79 1.00      876     1512

Population-Level Effects:

               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS Tail\_ESS

Intercept         -3.58      0.10    -3.79    -3.39 1.01      567      989

race\_blackTRUE     0.34      0.03     0.29     0.40 1.00    13138     7181

Out of curiosity, I wanted to know the most and least likely charges to result in a surveillance request, so I sampled from the appropriate coefficients in the model:

coef\_summaries <- spread\_draws(model, r\_charge\_description[charge,b]) %>%

    group\_by(charge) %>%

    summarise(q05 = quantile(r\_charge\_description, .05),

              median = median(r\_charge\_description),

              q95 = quantile(r\_charge\_description, .95))

First we look at the charges that were most likely to trigger surveillance footage requests. “Littering from motor vehicle” is an interesting appearance in this top 10:

> arrange(coef\_summaries, desc(median))

# A tibble: 619 × 4

   charge                                        q05 median   q95

   <chr>                                       <dbl>  <dbl> <dbl>

1 PRINCIPAL.TO.2ND.DEGREE.MURDER               3.28   4.34  5.58

2 FIRST.DEGREE.MURDER                          3.61   3.92  4.24

3 RELATIVE.TO.PRINCIPAL.TO.ATTEMPTED.HOMICIDE  2.89   3.81  4.80

4 ILLEGAL.DUMPING                              3.32   3.72  4.13

5 SECOND.DEGREE.MURDER                         3.32   3.57  3.82

6 ACCESSORY.-.AGG..BATTERY                     2.66   3.50  4.35

7 RELATIVE.TO.INSURANCE.FRAUD                  1.84   3.48  5.21

8 ASSAULT.BY.DRIVE.BY.SHOOTING                 2.99   3.38  3.78

9 LITTERING.FROM.MOTOR.VEHICLE                 2.33   3.37  4.43

10 ATTEMPT.-.SECOND.DEGREEMURDER                2.82   3.09  3.36

#  609 more rows

At the other end, charges that don’t often lead to surveillance requests:

> arrange(coef\_summaries, median)

# A tibble: 619 × 4

   charge                                                    q05 median    q95

   <chr>                                                   <dbl>  <dbl>  <dbl>

1 CDC.WARRANT#                                            -4.65  -3.44 -2.51

 2 [WARRANT.ISSUED.BY](http://warrant.issued.by/)                                       -3.97  -3.37 -2.86

 3 OUT.OF.STATE.FUGITIVE                                   -4.84  -3.17 -2.00

 4 TELEPHONE.COMMUNICATIONS;.IMPROPER.LANGUAGE;.HARASSMENT -4.57  -3.02 -1.82

 5 VIOLATION#                                              -4.65  -3.02 -1.83

 6 LOOTING                                                 -4.22  -2.41 -1.13

 7 HARASSING.PHONE.CALLS                                   -4.10  -2.27 -0.947

8 STALKING                                                -4.03  -2.25 -0.898

9 DOMESTIC.ABUSE.BATTERY(CHILD.ENDANGERMENT).-.SIMPLE     -3.15  -2.20 -1.45

10 POSSESSION.OF.MARIJUANA.(1ST.OFFENSE)                   -2.64  -2.16 -1.73

I can look at predicted requests for surveillance footage given a new charge that we don’t have a fit parameter for, to compare the marginal differences based on the race of the suspect:

tibble(race\_black = c(T, F), charge\_description = "XXXX", n = 1000) %>%

    add\_predicted\_draws(model, allow\_new\_levels = TRUE, ndraws = 200) %>%

    summarise(q\_05 = quantile(.prediction, .05),

              median = median(.prediction),

              q95 = quantile(.prediction, .95),

              .groups = "drop") %>%

    select(race\_black, q\_05, median, q95)

Which shows:

# A tibble: 2 × 4

  race\_black  q\_05 median   q95

  <lgl>      <dbl>  <dbl> <dbl>

1 FALSE          2   28.5  279.

2 TRUE           3   39.5  335.

But I assume the charge is also influenced by the person’s race? Hmmn . . ..