### Investigating Racial Profiling

MCMC Modeling for the NYC Stop-and-Frisk Policy

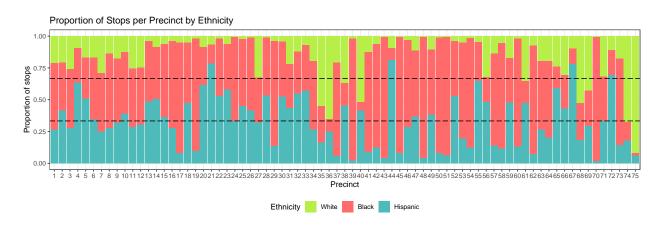
Chen Shi, Belle Xu

4/21/2021

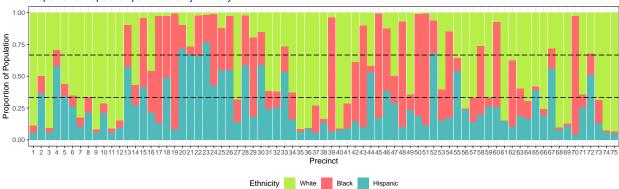
```
stop <- read.table("stop-and-frisk.dat", header = TRUE)</pre>
```

### **Exploratory Data Analysis**

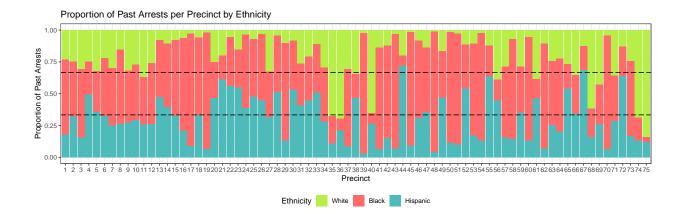
```
# Proportion of stops for each ethnicity in each precinct
stop %>%
  mutate(eth = factor(eth, levels = c("3", "1", "2")),
         precinct = factor(precinct)) %>%
  group_by(eth, precinct) %>%
  mutate(stop_eth = sum(stops)) %>%
  ggplot(mapping = aes(x = precinct, y = stop_eth, fill = eth)) +
  geom_bar(position = "fill", stat = "identity") +
  geom_hline(yintercept = 1/3, linetype=5) +
  geom_hline(yintercept = 2/3, linetype=5) +
  labs(y = "Proportion of stops", x = "Precinct",
       title = "Proportion of Stops per Precinct by Ethnicity")+
  theme_bw() +
  theme(legend.position = "bottom") +
  scale_fill_discrete(name = "Ethnicity",
                      labels=c("White", "Black", "Hispanic"),
                      type = c("#b7ee47","#ff6b6b","#4ebaba"))
```



### Proportion of Population per Precinct by Ethnicity



```
stop %>%
  mutate(eth = factor(eth, levels = c("3", "1", "2")),
         precinct = factor(precinct)) %>%
  group by(eth, precinct) %>%
  mutate(crime_eth = sum(past.arrests)) %>%
  ggplot(mapping = aes(x = precinct, y = crime_eth, fill = eth)) +
  geom_bar(position = "fill", stat = "identity") +
  geom_hline(yintercept = 1/3, linetype=5) +
  geom hline(yintercept = 2/3, linetype=5) +
  labs(title = "Proportion of Past Arrests per Precinct by Ethnicity",
      y = "Proportion of Past Arrests", x = "Precinct") +
  theme_bw() +
  theme(legend.position = "bottom") +
  scale_fill_discrete(name = "Ethnicity",
                      labels=c("White", "Black", "Hispanic"),
                      type = c("#b7ee47","#ff6b6b","#4ebaba"))
```



# Proportion of Past Arrests (Black) per Precinct by Crime Type 1.00 0.5

# Proportion of Stops (Black) per Precinct by Crime Type 1.00 90,75 0.25 0.25 1.00 1.0

```
Proportion of Past Arrests (Hispanic) per Precinct by Crime Type

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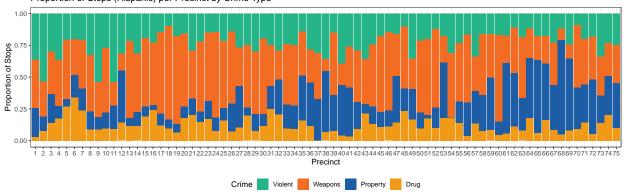
1.00

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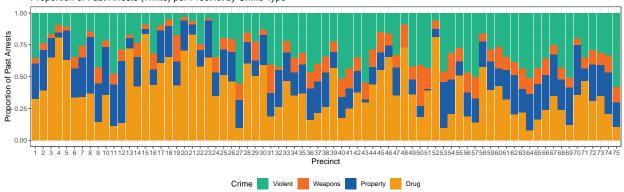
1.00
```

```
stop %>%
mutate(eth = factor(eth, levels = c("3", "1", "2")),
    precinct = factor(precinct),
    crime = factor(crime)) %>%
```

### Proportion of Stops (Hispanic) per Precinct by Crime Type







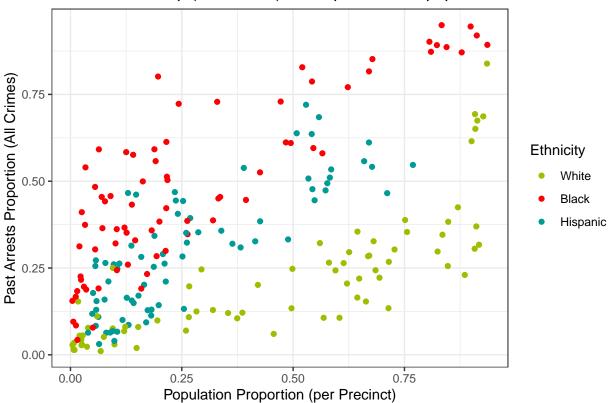
### 1.00 - sd 0.75 - sd 0.75 - sd 0.25 -

Proportion of Stops (White) per Precinct by Crime Type



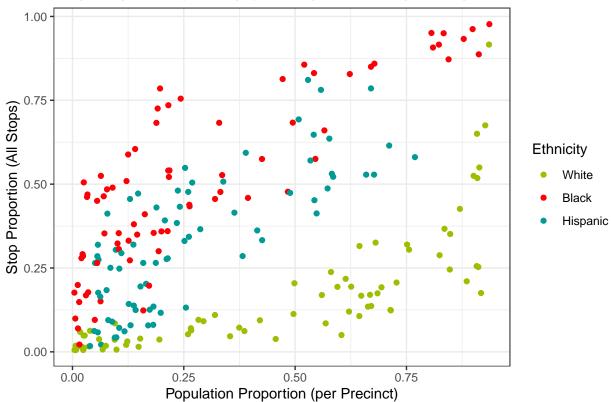
```
stop %>%
  mutate(eth = factor(eth, levels = c("3", "1", "2")),
         precinct = factor(precinct),
         crime = factor(crime)) %>%
  group by(precinct) %>%
  mutate(total_pop = sum(pop) / 4,
         pop_prop = pop / total_pop,
         total_arrest = sum(past.arrests),
         crime_prop = past.arrests / total_arrest) %>%
  group by(eth, precinct) %>%
  mutate(eth_crime = sum(crime_prop)) %>%
  filter(crime == 1) %>%
  ggplot(mapping = aes(x = pop_prop, y = eth_crime, color = eth)) +
  geom_point() + theme_bw()+
  labs(title="Past Arrests Prop.(All Crimes) vs. Population Prop. per Precinct",
       x = "Population Proportion (per Precinct)",
      y = "Past Arrests Proportion (All Crimes)") +
  scale_colour_discrete(name = "Ethnicity",
                      labels=c("White", "Black", "Hispanic"),
                      type = c("#9EBE00","#FD0006","#009B95"))
```

### Past Arrests Prop.(All Crimes) vs. Population Prop. per Precinct



```
stop %>%
  mutate(eth = factor(eth, levels = c("3", "1", "2")),
         precinct = factor(precinct),
         crime = factor(crime)) %>%
  group_by(precinct) %>%
  mutate(total_pop = sum(pop) / 4,
         pop_prop = pop / total_pop,
         total_stop = sum(stops),
         stop_prop = stops / total_stop) %>%
  group_by(eth, precinct) %>%
  mutate(eth_stop = sum(stop_prop)) %>%
  filter(crime == 1) %>%
  ggplot(mapping = aes(x = pop_prop, y = eth_stop, color = eth)) +
  geom_point() + theme_bw()+
  labs(title = "Stop Proportion (All Stops) vs. Population Proportion per Precinct",
       x = "Population Proportion (per Precinct)", y = "Stop Proportion (All Stops)") +
  scale_colour_discrete(name = "Ethnicity",
                      labels=c("White", "Black", "Hispanic"),
                      type = c("#9EBE00","#FD0006","#009B95"))
```

### Stop Proportion (All Stops) vs. Population Proportion per Precinct



mean(total\_crime\$stops)

## [1] 146.0222

var(total\_crime\$stops)

## [1] 47254.93

### Modeling

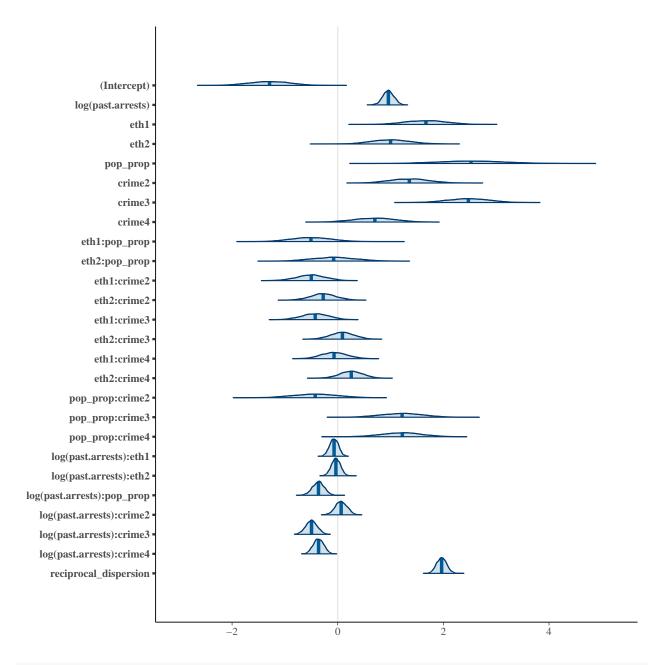
```
model.1 <- stan_glm(data = total_crime,</pre>
                    formula = stops ~ eth * (pop_prop + crime) + pop_prop * crime,
                    family = neg_binomial_2(link = "log"),
                    offset = log(past.arrests),
                    seed = 360,
                    prior = cauchy(0, 2.5),
                    prior_intercept = cauchy(0, 2.5),
                    refresh = 0,
                   diagnostic_file = file.path(tempdir(), "glm1.csv"))
model.2 <- stan_glm(data = total_crime,</pre>
                    formula = stops ~ eth * (crime_prop + pop_prop + crime) +
                      pop_prop * crime_prop + pop_prop * crime +
                      crime_prop * crime,
                    family = neg_binomial_2(link = "log"),
                    prior = cauchy(0, 2.5),
                    prior_intercept = cauchy(0, 2.5),
                    seed = 360,
                    refresh = 0,
                   diagnostic_file = file.path(tempdir(), "glm2.csv"))
model.3 <- stan_glm(data = total_crime,</pre>
                    formula = stops ~ log(past.arrests)+
                      eth * (pop_prop + crime) + pop_prop * crime,
                    family = neg_binomial_2(link = "log"),
                    prior = cauchy(0, 2.5),
                    prior_intercept = cauchy(0, 2.5),
                    seed = 360,
                    refresh = 0,
                   diagnostic_file = file.path(tempdir(), "glm3.csv"))
rstanarm::loo_compare(loo(model.1), loo(model.2), loo(model.3))
           elpd_diff se_diff
##
## model.3 0.0
                     0.0
## model.2 -43.9
                     14.5
## model.1 -81.1
                     15.6
model.3.full <- stan_glm(data = total_crime,</pre>
                    formula = stops ~ log(past.arrests)+
                      eth * (pop_prop + crime) + pop_prop * crime+
                      eth*log(past.arrests) + pop_prop*log(past.arrests) +
                      crime*log(past.arrests),
                    family = neg_binomial_2(link = "log"),
                    prior = cauchy(0, 2.5),
                    prior_intercept = cauchy(0, 2.5),
                    seed = 360,
                    refresh = 0,
                   diagnostic file = file.path(tempdir(), "glm3full.csv"))
```

```
bayesfactor_models(model.3, model.3.full, denominator = model.3.full)
## Warning: Bayes factors might not be precise.
## For precise Bayes factors, it is recommended sampling at least 40,000 posterior samples.
## Computation of Bayes factors: estimating marginal likelihood, please wait...
## Bayes Factors for Model Comparison
##
##
       Model
                                                                             BF
## [1] log(past.arrests) + eth * (pop_prop + crime) + pop_prop * crime < 0.001</pre>
##
## * Against Denominator: [2] log(past.arrests) + eth * (pop_prop + crime) + pop_prop * crime + eth * 1
       Bayes Factor Type: marginal likelihoods (bridgesampling)
rstanarm::loo_compare(loo(model.3), loo(model.3.full))
                elpd_diff se_diff
## model.3.full 0.0
                            0.0
## model.3
                -23.2
                            9.7
```

See diagnostic plots in the pdf file Diagnostic-Plots within this GitHub Repository.

### Results

```
mcmc_areas(as.matrix(model.3.full), prob = 0.95, prob_outer = 1)
```



### round(coef(model.3.full), 3)

<pre>log(past.arrests)</pre>	(Intercept)	##
0.959	-1.291	##
eth2	eth1	##
1.000	1.671	##
crime2	pop_prop	##
1.356	2.525	##
crime4	crime3	##
0.703	2.473	##
eth2:pop_prop	eth1:pop_prop	##
-0.077	-0.507	##
eth2:crime2	eth1:crime2	##

```
-0.501
                                                     -0.275
##
##
                   eth1:crime3
                                               eth2:crime3
                        -0.426
                                                      0.089
##
##
                   eth1:crime4
                                               eth2:crime4
##
                        -0.070
                                                      0.257
##
              pop_prop:crime2
                                           pop_prop:crime3
##
                        -0.426
                                                      1.218
##
              pop_prop:crime4
                                    log(past.arrests):eth1
##
                         1.222
                                                     -0.069
##
       log(past.arrests):eth2 log(past.arrests):pop_prop
##
                        -0.035
                                                     -0.365
##
                                 log(past.arrests):crime3
     log(past.arrests):crime2
##
                         0.065
                                                     -0.496
##
     log(past.arrests):crime4
##
                        -0.363
```

### round(posterior\_interval(model.3.full, prob = 0.95), 3)

```
##
                               2.5% 97.5%
## (Intercept)
                             -2.045 -0.538
## log(past.arrests)
                              0.751 1.165
## eth1
                              0.911 2.437
## eth2
                              0.295 1.755
                              1.339 3.809
## pop_prop
                              0.659 2.056
## crime2
## crime3
                              1.709 3.232
## crime4
                             -0.034 1.432
                             -1.208 0.243
## eth1:pop_prop
                             -0.843 0.749
## eth2:pop_prop
## eth1:crime2
                             -1.051 0.013
                             -0.744 0.205
## eth2:crime2
## eth1:crime3
                             -0.920 0.054
## eth2:crime3
                             -0.347 0.511
## eth1:crime4
                             -0.532 0.414
                             -0.179 0.679
## eth2:crime4
## pop_prop:crime2
                             -1.240 0.412
## pop_prop:crime3
                              0.432 2.000
## pop_prop:crime4
                              0.423 1.960
## log(past.arrests):eth1
                             -0.234 0.089
## log(past.arrests):eth2
                             -0.199 0.127
## log(past.arrests):pop_prop -0.591 -0.154
                             -0.154 0.282
## log(past.arrests):crime2
## log(past.arrests):crime3
                             -0.709 -0.286
## log(past.arrests):crime4
                             -0.547 -0.177
## reciprocal_dispersion
                              1.790 2.156
```