A Bayesian Perspective on Race and Traffic Stops

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Have you ever got pulled over by police?

The average driver drives more than 14,000 miles per year and has a 1% chance of being stopped anywhere in the country.

The Odds of Being Pulled Over: Race, Traffic Stops, and Bayes' Theorem

https://oag.ca.gov/sites/all/files/agweb/pdfs/ripa/ripa-board-report-2020.pdf

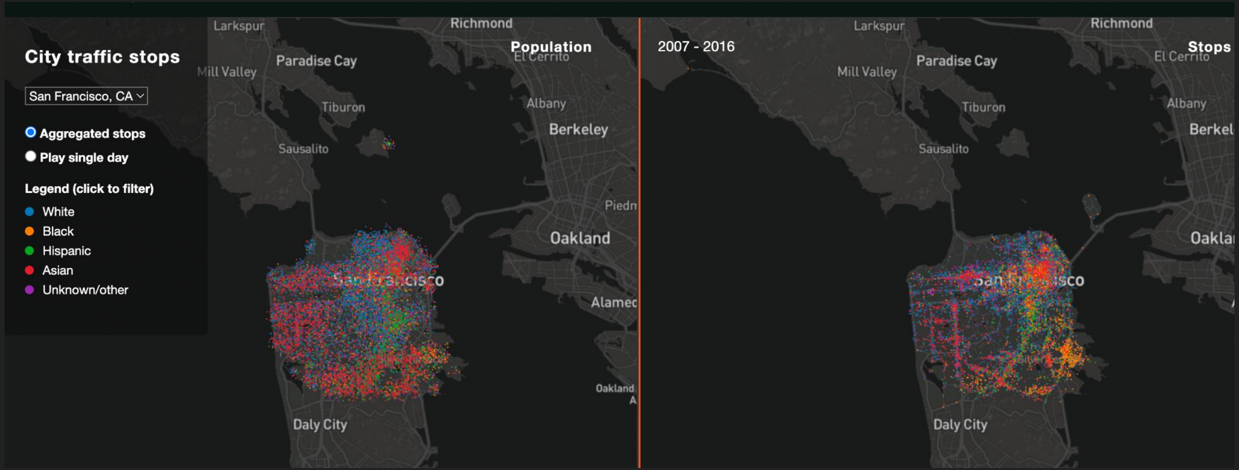
Part II: Dataset & Model inputs

Objective: How race impact police's decision after pull over?

What data we use: The data we use comes from The Stanford Open Policing Project data (https://openpolicing.stanford.edu/data/). Stanford Open Policing Project analyzed data from nearly 100 million traffic stops in the US..

Location: San Francisco

Parameter:
Race, Gender,
arrest_made
citation_issued
Warning_issued
Outcome



source : https://openpolicing.stanford.edu/explore/

Part II: The quality of data

After clean the data, we get the database with 900,000 rows

Accuracy: Errors or inaccuracies in the data, such as inconsistencies, outliers, or data entry mistakes, have been cleaned. However, there is a possibility that some data reported by policemen could be fake or intentionally misrepresented, which could impact the accuracy of the analysis.

Completeness: Blank data that may affect the quality of analysis has been deleted, indicating efforts to ensure data completeness.

Reliability: The data is described as original and collected by Stanford University and the California Racial and Identity Profiling Advisory Board, which suggests a certain level of reliability in terms of the data source.

Relevance: The data includes information such as reason for stop, search conducted, which are relevant for analyzing racial and gender disparities in policing practices.

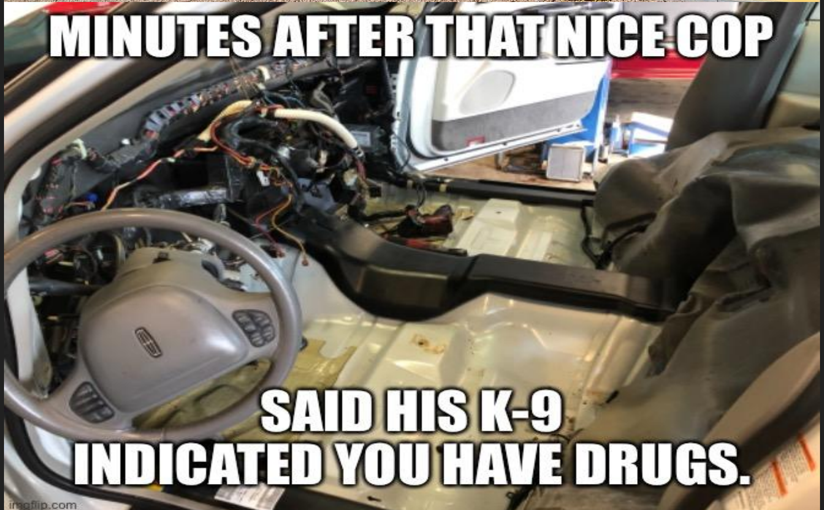
Timeliness: The data is reported to be from 2014-2016, and it's mentioned that the project was stopped in 2016 but resumed recently due to BLM. The timeliness of the data may impact its relevance to current circumstances and the ability to draw up-to-date conclusions.

	A	B	C	D	E	F	G	H
1	date	district	subject_race	subject_sex	arrest_made	citation_issued	warning_issued	outcome
2	8/1/14	NA	api	female	FALSE	FALSE	TRUE	warning
3	8/1/14	NA	black	male	FALSE	TRUE	FALSE	citation
4	8/1/14	NA	hispanic	male	FALSE	TRUE	FALSE	citation
5	8/1/14	NA	hispanic	male	FALSE	FALSE	TRUE	warning
6	8/1/14	NA	white	male	FALSE	TRUE	FALSE	citation
7	8/1/14	NA	black	male	FALSE	TRUE	FALSE	citation
8	8/1/14	NA	hispanic	male	FALSE	TRUE	FALSE	citation
9	8/1/14	NA	black	female	FALSE	TRUE	FALSE	citation
10	8/1/14	NA	black	male	FALSE	TRUE	FALSE	citation
11	8/1/14	NA	white	female	FALSE	TRUE	FALSE	citation
12	8/1/14	NA	white	female	FALSE	TRUE	FALSE	citation
13	8/1/14	NA	white	male	FALSE	TRUE	FALSE	citation
14	8/1/14	NA	white	male	FALSE	TRUE	FALSE	citation
15	8/1/14	NA	hispanic	male	FALSE	FALSE	TRUE	warning
16	8/1/14	NA	white	male	FALSE	FALSE	TRUE	warning
17	8/1/14	NA	white	male	FALSE	FALSE	TRUE	warning
18	8/1/14	NA	api	male	FALSE	FALSE	TRUE	warning
19	8/1/14	NA	black	male	FALSE	FALSE	TRUE	warning
20	8/1/14	NA	other	male	FALSE	FALSE	TRUE	warning
21	8/1/14	NA	white	male	FALSE	TRUE	FALSE	citation
22	8/1/14	NA	white	male	FALSE	TRUE	FALSE	citation
23	8/1/14	NA	api	female	FALSE	TRUE	FALSE	citation
24	8/1/14	NA	white	male	FALSE	TRUE	FALSE	citation
25	8/1/14	NA	white	male	FALSE	TRUE	FALSE	citation
26	8/1/14	NA	black	male	FALSE	TRUE	FALSE	citation
27	8/1/14	NA	white	male	FALSE	FALSE	TRUE	warning
28	8/1/14	NA	black	male	FALSE	FALSE	TRUE	warning
29	8/1/14	NA	white	male	FALSE	TRUE	FALSE	citation
30	8/1/14	NA	other	male	FALSE	TRUE	FALSE	citation
31	8/1/14	NA	api	male	TRUE	FALSE	FALSE	arrest
32	8/1/14	NA	hispanic	male	FALSE	FALSE	TRUE	warning

Part II: Assumption of Model

There is one assumption based on our model.

We assume that policeman does not know your race before stop and stops you only because of traffic violation. Then, we analyze the penalty result from police.



Part III: Model Design & Result

$$P(Y|\beta) * P(\beta) = P(\beta|Y) * P(Y)$$
$$P(\beta|Y) = P(Y|\beta) * P(\beta) \;/\; P(Y)$$

- $P(Y)$, is the normalizer, is difficult to compute but is built into Markov-Chain Monte-Carlo simulation. This term ensures that the posterior density integrates to 1.
- $P(Y|\beta)$ is our observation. This is the data from our dataset which is used to fit our model.
- $P(\beta|Y)$ is the posterior distribution. From this, we can gain knowledge of β from the evidence (ie. our dataset). Samples of β can be obtained by simulating our JAGS model, which then can be used for comparison.
- $P(\beta)$ is our prior distribution. We provide a probability density function for β, and through the training process, $P(\beta|Y)$ (ie. the posterior) is estimated by fitting the dataset. In other words, we come up with an initial guess for β, and then update our knowledge about β by fitting our observation Y.

Implementation of Bayesian Model:

We implemented Bayesian logistic regression using a Bayesian hierarchical model through R and RJAGS. The response variable represents the number of times an incident occurs, which is defined as an arrest or a citation.

The inputs are races involved, number of incidents, and stops. The hyperparameter is betarace, sampled from a normal distribution. Racial group is treated as random effects.

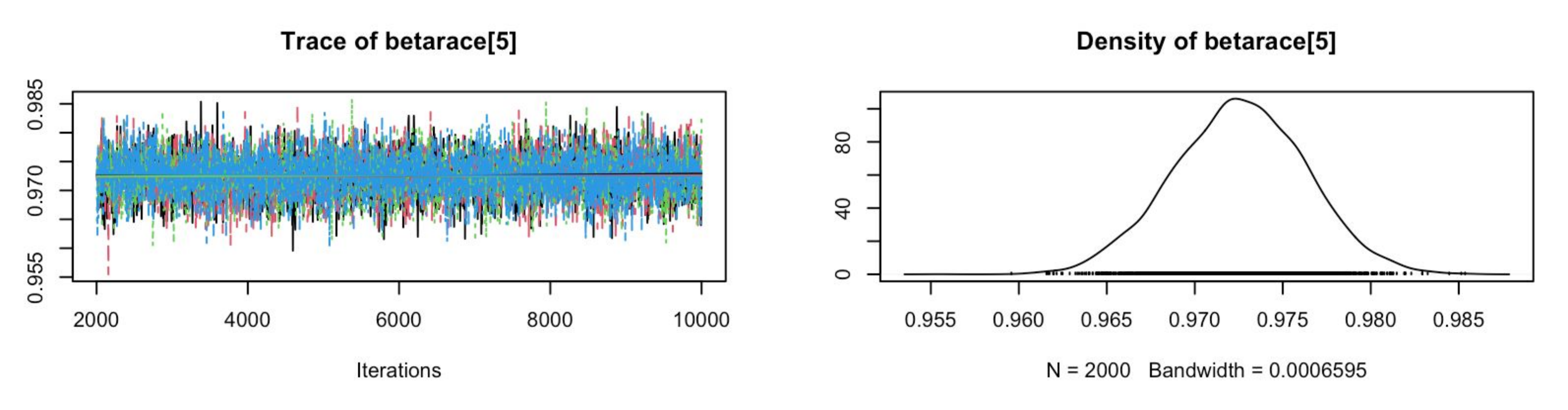
Markov-Chain Monte-Carlo (MCMC) simulation is used to generate samples.

We define the prior for β to be a normal distribution. Each race has its own corresponding β value which is used as a logistic regression coefficient for determining if an incident happens to a subject.

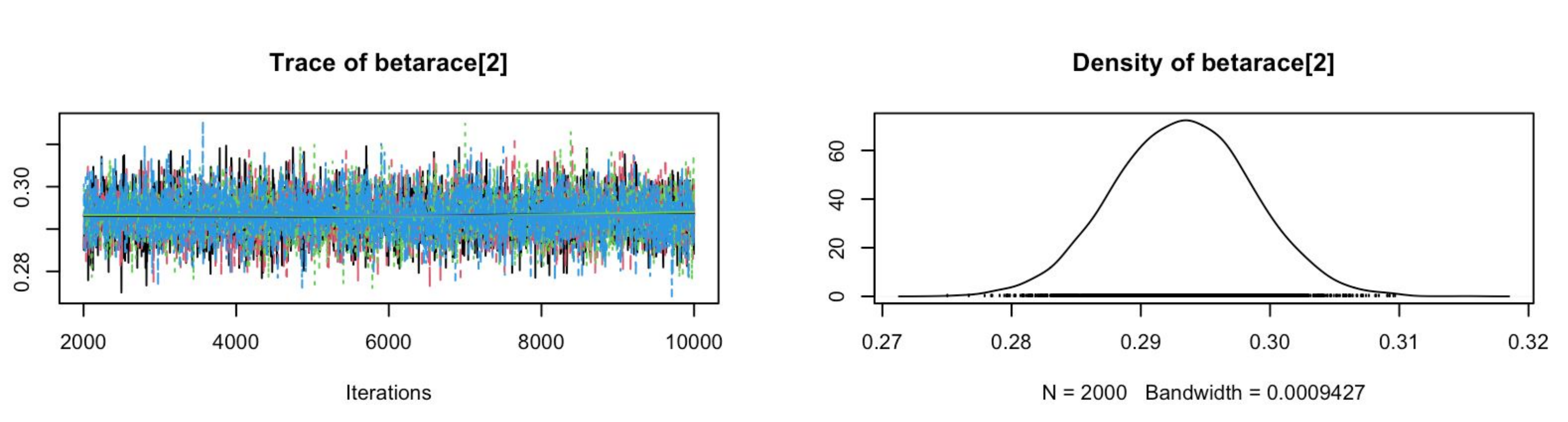
We define an incident to be either an arrest or a citation. (A warning is not considered as an incident.)

Model Results

White

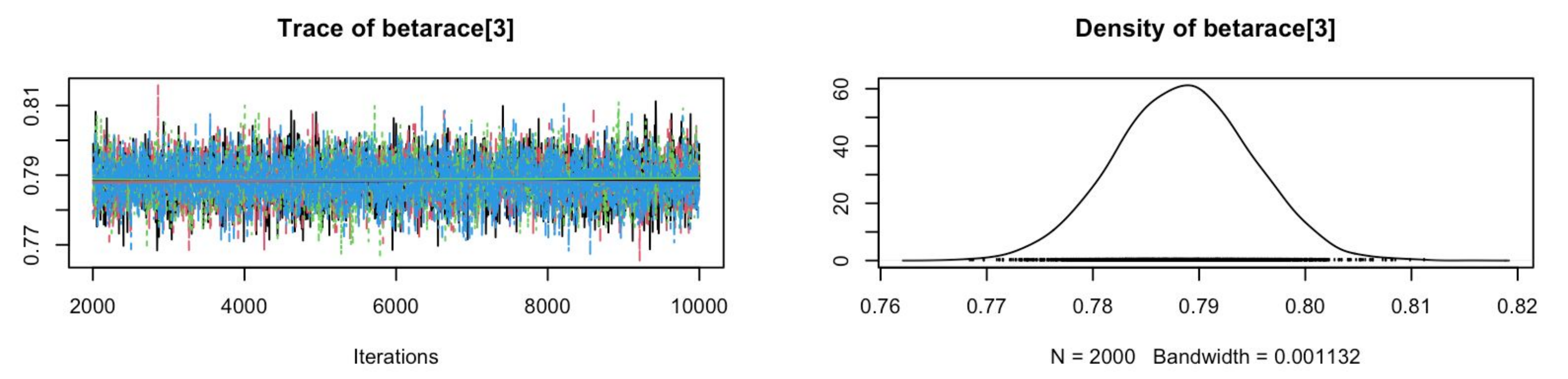


Black

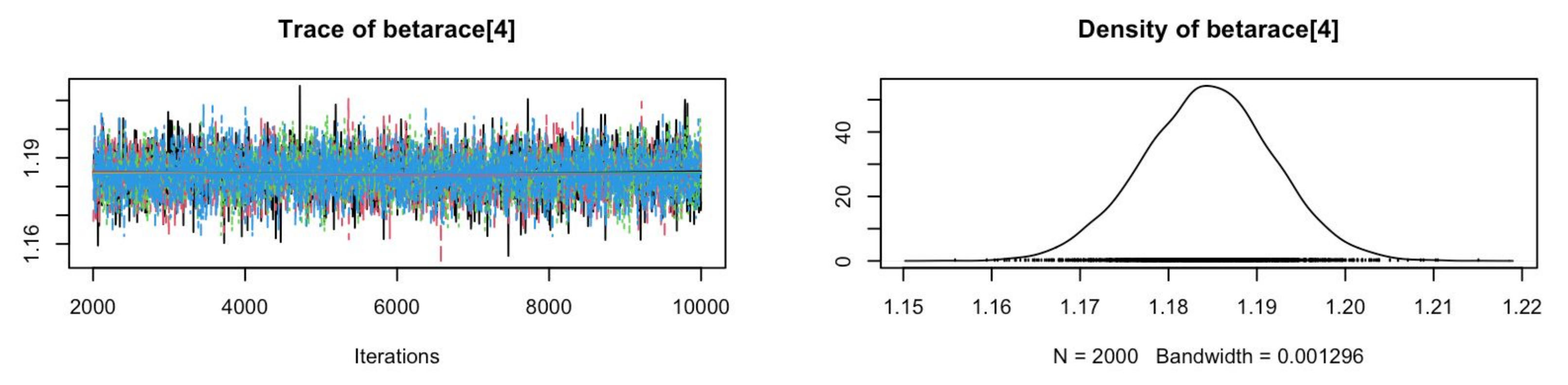


Model Results

Hispanic

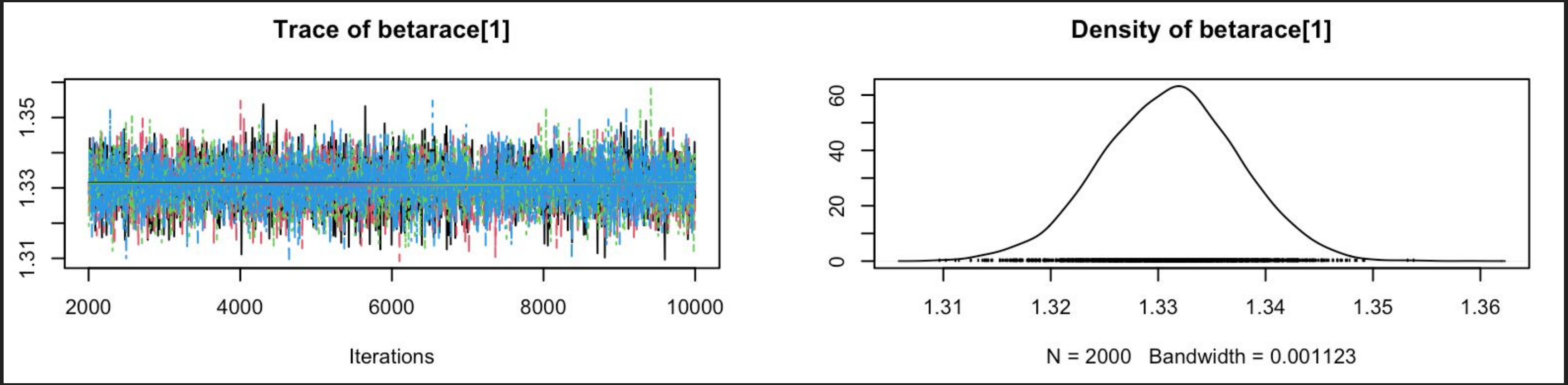


Others



Model Results

Asian Pacific Islander




```
[1] "====================="
[1] white    api      hispanic black    other
Levels: api black hispanic other white
[1] 1.331128
[1] 0.2932641
[1] 0.7885007
[1] 1.184448
[1] 0.9725466
[1] "====================="
[1] "percentage samples where bete_api greater than beta_white"
[1] 1
[1] "====================="
```

$\beta\_api = 1.331128$

$\beta\_other = 1.184448$

$\beta\_white = 0.9725466$

$\beta\_hispanic = 0.7885007$

$\beta\_\ black = 0.2932641$

Evaluate our model using simple statistics:

Race	Incidents	Stops	Incident/ Stops	Rank by %	Beta from Simulation	Rank by Beta
white	256729	353802	73%	3	0.9725837	3
api	116924	147813	79%	1	1.331179	1
hispanic	74980	109054	69%	4	0.7886193	4
black	82439	143923	57%	5	0.2933018	5
other	75266	98291	77%	2	1.184477	2

Conclusion:

Discrimination against Asian in driving does exist.

Part IV: Model limitations

Potential Bias in Police Officer Behavior

One limitation here would be related to the assumption that the model makes regarding the police officer's behavior. Our model assumes that police officers do not have prior knowledge of a driver's race before pulling them over. However, in reality, some officers may use prior biases or assumptions to target certain racial groups. For example, a police officer who has previously worked in a predominantly Asian neighborhood may assume that Asian drivers are more likely to be involved in criminal activity and may pull them over more frequently than other drivers.

These biases or assumptions can be conscious or unconscious, and they can have a significant impact on the accuracy and fairness of the model's predictions. Additionally, if the model is used to inform decision-making in law enforcement, it may perpetuate these biases or lead to further discrimination against certain racial groups.

Part IV: Model limitations

Limitations of Generalizability

It is important to note that the findings of the analysis may not be representative of other time periods or locations, especially those with different demographics or cultural factors that could affect the behavior of police officers and drivers.

Additionally, it is also important to note that the data used in the analysis is limited to California, which is just one state in the United States. Other states may have different laws, regulations, and cultural factors that could affect the results of the analysis. Thus, generalizing the findings of this analysis to the entire United States could be misleading and potentially harmful.

Part IV: Model limitations

Influence of unmeasured factors

This limitation refers to the fact that the model may not be able to capture all of the information that can impact traffic stops and incidents. For example, the model may not consider the specific location where the traffic stop occurred, which could affect the likelihood of the stop and the outcome. It may also not consider the time of day or other situational factors that could influence the behavior of the driver or the officer.

Moreover, the behavior of the driver, which could be a significant factor in determining the outcome of the traffic stop. For instance, if the driver is acting suspiciously or aggressively, the officer may be more likely to conduct a search or make an arrest, regardless of the driver's race or ethnicity. Similarly, if the driver is cooperative and respectful, the officer may be more likely to let them go with a warning or a citation.

Part V: Unlocking the Mysteries of Mathematics: *Project Achievements, Learning Outcomes and Acknowledgement*

- Project Achievements:
    - Conclusion: police’s decision after pull over are racially impacted.
    - Utilized a Bayesian hierarchical model through R and RJags to analyze and draw conclusions.
    - Hope to raise social awareness of racial issues and contribute to create a more equitable society.
- Learning Outcomes:
    - Applied probability knowledge and Bayesian modeling skills to social science topics.
    - Deeper understanding about probability, Bayesian Inference and MCMC.
    - Knowing other applications of Bayesian model.
- Acknowledgement:
    - *To Prof. Mayram*
    - *To teammates*

References and codes:

[1] Pierson, Emma, Camelia Simoiu, Jan Overgoor, Sam Corbett-Davies, Daniel Jenson, Amy Shoemaker, Vignesh Ramachandran et al. "A large-scale analysis of racial disparities in police stops across the United States." N*ature human behaviour* 4, no. 7 (2020): 736-745.

[2] Albert, Jim, and Jingchen Hu. *Probability and Bayesian modeling*. CRC press, 2019.

JAGS Model:

```
model {

  for (i in 1:length(stops)) {

    incidents[i] ~ dbin(prob[i], stops[i])

    logit(prob[i]) <- betarace[race[i]]

  }

  for (j in 1:max(race)) {

    betarace[j] ~ dnorm(0, 0.1)

  }

}
```

R Codes:

```
library(rjags)

police <-
read.csv("ca_san_francisco_2020_04_01-cleaned_dataset
.csv", header=TRUE)

police_sub <- subset(police, district != 'N/A')

police_sub$incidents <- police_sub$arrest_made |
police_sub$citation_issued

df <- data.frame(matrix(ncol = 4, nrow = 0))

names(df) <- c("race", "sex", "incidents", "stops")

for (race in unique(police_sub$subject_race)) {

  rows = police_sub[(police_sub$subject_race == race), ]

  stops = nrow(as.matrix(rows))

}
```

```
rows = police_sub[(police_sub$subject_race ==
race &

               police_sub$incidents == TRUE), ]

 incidents = nrow(as.matrix(rows))


 row = data.frame(race = race,

               incidents = incidents,

              stops = stops)

 df = rbind(df, row)

d1 <- list(stops=df$stops, incidents=df$incidents,

              race=unclass(factor(df$race)))


inits1 <- list(list(betarace=c(10,10,10,10,10)),

               list(betarace=c(10,-10,10,-10,10)),

               list(betarace=c(-10,10,-10,10,-10)),

               list(betarace=c(-10,-10,-10,-10,-10)))
```

```
m1<-jags.model("model.bug",d1,inits1,n.chains=4,n.ad
apt=1000)

update(m1, 1000)

x0 <- coda.samples(m1, c("betarace"), n.iter=8000,
thin=4)
print(gelman.diag(x0, autoburnin = FALSE))

plot(x0)

print("=====================")
print(mean(as.matrix(x0[,"betarace[2]"]) >
as.matrix(x0[,"betarace[1]"])))
print("=====================")

x1 <- coda.samples(m1, c("prob", "incidents"),
n.iter=8000)

probs <- as.matrix(x1)[, paste("prob[", 1:nrow(df),"]",
sep="")]
incidents <- as.matrix(x1)[, paste("incidents[",
1:nrow(df),"]", sep="")]

Tchi <- numeric(nrow(incidents))
Tchirep <- numeric(nrow(incidents))

for (s in 1:nrow(incidents)) {
  Tchi[s] <- sum((df$incidents     -
df$stops*probs[s,])^2/(df$stops*probs[s,]*(1-probs[s,])))
  Tchirep[s] <- sum((incidents[s,] -
df$stops*probs[s,])^2/(df$stops*probs[s,]*(1-probs[s,])))
}

print(mean(Tchirep))
print(mean(Tchi))
```

Thank you and Safe driving!