

# Prevalence of Having Contraband among Pulled-over Drives

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## Background and Introduction

To be done.

## Causal Roadma

### Scientific Question:

What is the prevalence of having contraband if all drives are searched.

### Causal Model

$W_1$  : age

$W_2$  : race: black or not

$W_3$  : gender : female or male

$W_4$  : Speed or not

$W = (W_1, W_2, W_3, W_4)$

$\Delta$  : if search is conducted

$Y^*$  : Underlying contraband status

$Y$  : if contraband is found

- Endogenous variables:  $X = (W_1, W_2, W_3, W_4, \Delta, Y)$
- Exogenous variables:  $U \sim \mathbb{P}_U$  (to be determined).

Structral equation  $F$ :

$$\begin{aligned}W_1 &= f_{W_1}(U_{W_1}) \\W_2 &= f_{W_2}(U_{W_2}) \\W_3 &= f_{W_3}(U_{W_3}) \\W_4 &= f_{W_4}(W_1, W_2, W_3, U_{W_4}) \\ \Delta &= f_{\Delta}(W_1, W_2, W_3, W_4, U_{\Delta}) \\Y^* &= f_{Y^*}(W_1, W_2, W_3, W_4, U_{Y^*}) \\Y &= \Delta \times Y^*\end{aligned}$$

### Causal Parameter

$$\Psi^*(\mathbb{P}^*) = \mathbb{P}^*(Y^* = 1) = \mathbb{P}^*(Y_{\Delta=1})$$

## Observed data and its link to causal model

Observed data are randomly generated from the structural causal model.

## Identifiability

Lest's assume all  $U$ s are independent.

## Statistical estimand

$$\Psi^*(\mathbb{P}^*) = \Psi(\mathbb{P}_0) = \mathbb{E}_W\{\mathbb{P}_0(Y = 1|\Delta = 1, W)\}$$

## Estimate

Parametric G-computation (simple substitution estimator), IPTW, TMLE. Use super learner during the estimating procedure. Don't forget to talk about the positivity assumptions.

Present a detailed plan for statistical inference/variance estimation based on the non-parametric bootstrap and implement it.

## Data preprocessing

```
# packages
library(tidyverse)
library(lubridate)
library(SuperLearner)
library(boot)
library(ltmle)

# load dataset
dat <- readRDS("data/MAStatePatrol.rds")
# take a look at the variables we have
colnames(dat)

## [1] "raw_row_number"      "date"
## [3] "location"            "county_name"
## [5] "subject_age"         "subject_race"
## [7] "subject_sex"         "type"
## [9] "arrest_made"         "citation_issued"
## [11] "warning_issued"      "outcome"
## [13] "contraband_found"    "contraband_drugs"
## [15] "contraband_weapons"  "contraband_alcohol"
## [17] "contraband_other"    "frisk_performed"
## [19] "search_conducted"    "search_basis"
## [21] "reason_for_stop"     "vehicle_type"
## [23] "vehicle_registration_state" "raw_Race"

table(year(dat$date)) # the dataset is balanced over years

##
## 2007 2008 2009 2010 2011 2012 2013 2014 2015
## 247357 468131 428714 388280 335974 418846 400931 384468 343537

dat_prep <- function(dat, loc, years){
  datBos <- dat %>%
```

```

filter(location == loc) %>% # select location
filter(year(date) == years) %>% # select year
filter(vehicle_type == 'Passenger') %>% # passenger vehicle only
# delete missing values
filter(!is.na(subject_age) & !is.na(subject_sex) &
       !is.na(subject_race) & !is.na(reason_for_stop) &
       !is.na(search_conducted)) %>%
mutate(subject_race = as.character(subject_race)) %>% # change subject_race to string
# select following variables
select(subject_age,
       subject_race,
       subject_sex,
       reason_for_stop,
       contraband_found,
       search_conducted)

# drop unused levels from the dataframe
datBos <- droplevels(datBos)
# subject_race represents black or not
datBos$subject_race[datBos$subject_race != 'black'] = 'others'
# reason_for_stop represents speed or not
datBos$reason_for_stop[datBos$reason_for_stop == 'Speed' &
                      datBos$reason_for_stop == 'Speed,SearBelt' &
                      datBos$reason_for_stop == 'Speed,ChildRest' &
                      datBos$reason_for_stop == 'Speed,SeatBelt,ChildRest'] = 'Speed'
datBos$reason_for_stop[datBos$reason_for_stop != 'Speed'] = 'Not Speed'
return(datBos)
}

for (i in 2007:2015){
  datBos <- dat_prep(dat, 'BOSTON', i)
  print(table(datBos$contraband_found, useNA = 'ifany'))
}

```

```

##
## FALSE TRUE <NA>
## 207 79 15747
##
## FALSE TRUE <NA>
## 159 77 28235
##
## FALSE TRUE <NA>
## 74 40 26541
##
## FALSE TRUE <NA>
## 76 62 23201
##
## FALSE TRUE <NA>
## 50 45 19649
##
## FALSE TRUE <NA>
## 75 48 22270
##
## FALSE TRUE <NA>

```

```

##      46      29 24071
##
## FALSE  TRUE  <NA>
##      32      27 14082
##
## FALSE  TRUE  <NA>
##      31      22 17055

datBos <- dat_prep(dat, 'BOSTON', 2007)

# show summary and check positivity assumptions
summary(datBos$search_conducted)

##      Mode  FALSE      TRUE
## logical  15747      286

summary(datBos$contraband_found)

##      Mode  FALSE      TRUE  NA's
## logical    207      79  15747

summary(datBos$subject_age)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      11.00  26.00   35.00   36.45  45.00   87.00

summary(datBos$subject_sex)

##      male female
##      11698   4335

table(datBos$subject_race)

##
##      black others
##      2385  13648

table(datBos$reason_for_stop)

##
##      Not Speed      Speed
##           2294     13739

# check positivity assumption
table(datBos$subject_race, datBos$subject_sex, datBos$reason_for_stop, datBos$search_conducted)

## , , = Not Speed, = FALSE
##
##
##           male female
##      black   580    141
##      others 1150    302
##
## , , = Speed, = FALSE
##
##
##           male female
##      black  1134    453
##      others 8606   3381

```

```
##
## , , = Not Speed, = TRUE
##
##
##      male female
##  black    35    10
##  others   58    18
##
## , , = Speed, = TRUE
##
##
##      male female
##  black    27     5
##  others  108    25
```

Following are some attempts of estimation, I'll consider more parametric models and super learner and put all of them in R functions.

## G-computation

$$\hat{\Psi}_{SS}(\hat{\mathbb{P}}) = \frac{1}{n} \sum_{i=1}^n \left( \hat{\mathbb{E}}(Y|A_i = 1, W_i) - \hat{\mathbb{E}}(Y|\Delta_i = 0, W_i) \right)$$

We consider following parametric models of  $\mathbb{E}(Y|\Delta, W)$ :

$$\mathbb{E}(Y|\Delta, W) = \text{logit}^{-1}(\beta_0 + \beta_1 W_1 + \beta_2 W_2 + \beta_3 W_3 + \beta_4 W_4 + \beta_5 \Delta)$$

$$\mathbb{E}(Y|\Delta, W) = \text{logit}^{-1}(\beta_0 + \beta_1 W_1 + \beta_2 W_2 + \beta_3 W_3 + \beta_4 W_4 + \beta_5 \Delta + \beta_6 W_1 * W_4 + \beta_7 W_2 * W_4 + \beta_8 W_3 * W_4)$$

```
# G-computation
# reference: RCT_MissingData.pdf

# only drives are searched
datBos.searched <- datBos %>% filter(search_conducted == TRUE)
datBos.intervene <- datBos %>% mutate(search_conducted = TRUE)
# 10 fold cross validation/Discrete super learner
set.seed(2019)
cv.error.1 <- cv.error.2 <- 0
for (i in 1:10){
  # model 1
  fit.g1 <- glm(contraband_found ~
    subject_age +
    subject_race +
    subject_sex +
    reason_for_stop,
    family = 'binomial', data = datBos.searched)
  cv.error.1[i] <- cv.glm(datBos.searched, fit.g1, K = 10)$delta[1]
  # model 2
  fit.g2 <- glm(contraband_found ~
    subject_age*reason_for_stop +
    subject_race*reason_for_stop +
    subject_sex*reason_for_stop,
    family = 'binomial', data = datBos.searched)
```

```

  cv.error.2[i] <- cv.glm(datBos.searched, fit.g2, K = 10)$delta[1]
}
c(mean(cv.error.1), mean(cv.error.2)) # model 1 is better

## [1] 0.1771311 0.1791976

# model 1 function
gcomp.1 <- function(dat.s, dat.i){
  fit.gcomp.1 <- glm(contraband_found ~
    subject_age +
    subject_race +
    subject_sex +
    reason_for_stop,
    family = 'binomial', data = dat.s)
  EY.gcomp.1 <- predict(fit.gcomp.1, newdata = dat.i, type = 'response')
  est.gcomp.1 <- mean(EY.gcomp.1)
  est.gcomp.1
}

dat.intervene <- datBos %>% mutate(search_conducted = TRUE)
est.gcomp <- gcomp.1(datBos.searched, dat.intervene) # point estimate
est.gcomp

## [1] 0.163418

# Nonparametric bootstrap 500 times
n <- nrow(datBos)
est.g1 <- 0
for (k in 1:500){
  dat.bp <- datBos[sample(1:n, n, replace = TRUE), ]
  dat.s<- dat.bp %>% filter(search_conducted == TRUE)
  dat.i <- dat.bp %>% mutate(search_conducted = TRUE)
  est.g1[k] <- gcomp.1(dat.s, dat.i)
}
# mean
mean(est.g1)

## [1] 0.1636413

# standard error
sd(est.g1)

## [1] 0.0240266

# confidence interval 5%
c(est.gcomp - 1.96*sd(est.g1), est.gcomp + 1.96*sd(est.g1))

## [1] 0.1163259 0.2105102

```

## IPTW

$$\hat{\Psi}_{IPTW}(\hat{\mathbb{P}}) = \frac{1}{n} \sum_{i=1}^n \left( \frac{\mathbb{I}(\Delta_i = 1)}{\hat{\mathbb{P}}(\Delta = 1|W_i)} - \frac{\mathbb{I}(\Delta_i = 0)}{\hat{\mathbb{P}}(\Delta = 0|W_i)} \right) Y_i$$

Parametric models of  $\mathbb{P}(A|W)$ :

$$\mathbb{P}(\Delta|W) = \text{logit}^{-1}(\beta_0 + \beta_1 W_1 + \beta_2 W_2 + \beta_3 W_3 + \beta_4 W_4)$$

$$\mathbb{E}(\Delta|W) = \text{logit}^{-1}(\beta_0 + \beta_1 W_1 + \beta_2 W_2 + \beta_3 W_3 + \beta_4 W_4 + \beta_5 W_1 * W_4 + \beta_6 W_2 * W_4 + \beta_7 W_3 * W_4)$$

```
# IPTW # reference : RLab3.pdf

# 10 fold cross validation/Discrete super learner
set.seed(2019)
cv.error.1 <- cv.error.2 <- 0
for (i in 1:10){
  # model 1
  fit.prob.D.1 <- glm(search_conducted ~
    subject_age +
    subject_race +
    subject_sex +
    reason_for_stop,
    family = 'binomial', data = datBos)
  cv.error.1[i] <- cv.glm(datBos, fit.prob.D.1, K = 10)$delta[1]
  # model 2
  fit.prob.D.2 <- glm(search_conducted ~
    subject_age*reason_for_stop +
    subject_race*reason_for_stop +
    subject_sex*reason_for_stop,
    family = 'binomial', data = datBos)
  cv.error.2[i] <- cv.glm(datBos, fit.prob.D.2, K = 10)$delta[1]
}
c(mean(cv.error.1), mean(cv.error.2)) # performace are close, model 1 is simpler

## [1] 0.01725586 0.01724772

# model 1 function
iptw.1 <- function(dat){
  fit.prob.D.1 <- glm(search_conducted ~
    subject_age +
    subject_race +
    subject_sex +
    reason_for_stop,
    family = 'binomial', data = dat)
  prob.D1 <- predict(fit.prob.D.1, type = 'response')
  # calculate weights
  wt1 <- as.numeric(datBos$search_conducted == 1)/prob.D1
  # estimate
  est.IPTW.1 <- mean(wt1*dat$contraband_found, na.rm = TRUE)
  # Stabelized IPTW
  wt1.mean <- mean(wt1[!is.na(datBos$contraband_found)])
  est.sIPTW.1 <- mean(wt1*datBos$contraband_found, na.rm = TRUE)/wt1.mean
  list(est.IPTW.1, est.sIPTW.1, wt1)
}

est.IPTW <- iptw.1(datBos)
# IPTW point estimate
est.IPTW[[1]]

## [1] 9.49691
```

```

# standardized IPTW point estimate
est.IPTW[[2]]

## [1] 0.1633454

# distribution of weight
summary(est.IPTW[[3]]) # large variation

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.000  0.000  0.000  1.037  0.000 317.227

# We adopt standardized IPTW estimator
# Nonparametric bootstrap 500 times
est.IPTW1 <- 0
for (k in 1:500){
  dat.bp <- datBos[sample(1:n, n, replace = TRUE), ]
  est.IPTW1[k] <- iptw.1(dat.bp)[[2]]
}
# mean
mean(est.IPTW1)

## [1] 0.2763022

# standard error
sd(est.IPTW1)

## [1] 0.01743561

# confidence interval 5%
c(est.IPTW[[2]] - 1.96*sd(est.IPTW1), est.IPTW[[2]] + 1.96*sd(est.IPTW1))

## [1] 0.1291716 0.1975192

```

## TMLE

$$\Psi_{TMLE}(\hat{\mathbb{P}}) = \frac{1}{n} \sum_{i=1}^n \left[ \hat{\mathbb{E}}^*(Y|A_i = 1, W_i) - \hat{\mathbb{E}}^*(Y|A_i = 0, W_i) \right]$$

Here we use super learner.

```

# TMLE
set.seed(2019)
# specify the library
SL.library<- c("SL.mean", "SL.glm", "SL.glm.interaction")

# G-spomputation with Super Learner
# Estimate E_0(Y|A,W)
X <- subset(datBos.searched, select = c(subject_age, subject_race,
                                         subject_sex, reason_for_stop))
X1 <- subset(datBos.intervene, select = c(subject_age, subject_race,
                                          subject_sex, reason_for_stop))
fit.SL.1 <- SuperLearner(Y=as.numeric(datBos.searched$contraband_found),
                        X=X, SL.library=SL.library, family='binomial')
# performace of superlearner
CV.fit.SL.1 <- CV.SuperLearner(Y=as.numeric(datBos.searched$contraband_found),
                              X=X, SL.library=SL.library, family='binomial')
summary(CV.fit.SL.1) # superlearner is not the best!!!!!!!!!!!!

```



```
##
## Call:
## CV.SuperLearner(Y = as.numeric(datBos.searched$contraband_found), X = X,
##   family = "binomial", SL.library = SL.library)
##
## Risk is based on: Mean Squared Error
##
## All risk estimates are based on V = 10
##
##           Algorithm      Ave      se      Min      Max
## Super Learner 0.17976 0.011913 0.13459 0.24143
## Discrete SL 0.17878 0.012243 0.13442 0.24354
## SL.mean_All 0.20161 0.011942 0.15603 0.26601
## SL.glm_All 0.17638 0.011954 0.13442 0.24354
## SL.glm.interaction_All 0.17941 0.012501 0.13719 0.23968
EY.1W <- predict(fit.SL.1, newdata = X1)$pred
est.gcomp.SL <- mean(EY.1W)
est.gcomp.SL

## [1] 0.1689822
# IPTW with Super Learner
X <- subset(datBos, select = c(subject_age, subject_race,
                               subject_sex, reason_for_stop))
fit.SL.2 <- SuperLearner(Y=as.numeric(datBos$search_conducted),
                        X=X, SL.library=SL.library, family='binomial')
# performace of superlearner
CV.fit.SL.2 <- CV.SuperLearner(Y=as.numeric(datBos$search_conducted),
                              X=X, SL.library=SL.library, family='binomial')
summary(CV.fit.SL.2) # superlearner is not the best!!!!!!!!!!!!

##
## Call:
## CV.SuperLearner(Y = as.numeric(datBos$search_conducted), X = X, family = "binomial",
##   SL.library = SL.library)
##
## Risk is based on: Mean Squared Error
##
## All risk estimates are based on V = 10
##
##           Algorithm      Ave      se      Min      Max
## Super Learner 0.017257 0.00097881 0.014284 0.020591
## Discrete SL 0.017285 0.00097900 0.014285 0.020614
## SL.mean_All 0.017521 0.00100814 0.014157 0.020774
## SL.glm_All 0.017254 0.00097845 0.014273 0.020614
## SL.glm.interaction_All 0.017265 0.00097726 0.014293 0.020571
PA1.W <- fit.SL.2$SL.predict
H.AW <- as.numeric(datBos$search_conducted == 1)/PA1.W
H.AW.mean.s <- mean(H.AW[!is.na(datBos$contraband_found)])
# standardized IPTW
est.sIPTW.SL <- mean(H.AW*datBos$contraband_found, na.rm = TRUE)/H.AW.mean.s
est.sIPTW.SL

## [1] 0.1641883
```

```

# TMLE estimate
# one-step update initial estimator of EY.AW
H.AW.std.s <- H.AW[!is.na(datBos$contraband_found)]/H.AW.mean.s
EY.1W.s <- EY.1W[!is.na(datBos$contraband_found)]
logitUpdate <- glm(datBos$searched$contraband_found ~ -1 + offset(qlogis(EY.1W.s)) + H.AW.std.s,
                    family='binomial')
epsilon <- logitUpdate$coefficients
H.1W <- 1/PA1.W
H.1W.std <- H.1W/mean(H.1W)
EY.1W.star <- plogis(qlogis(EY.1W) + epsilon*H.1W.std)
est.TLME <- mean(EY.1W.star)
est.TLME

```

```
## [1] 0.1673682
```

```

# use ltmle package
#####
# if we use dataset which only includes searched cases,
# then all search_conducted is 1, model cannot fit
# if we use dataset with all cases,
# then contraband_found has missing value, model cannot fit wither.
# Conclusion: we must update by hard coding.
#####

# datBos.searched.new <- datBos.searched %>%
#   mutate(search_conducted = as.numeric(search_conducted),
#           contraband_found = as.numeric(contraband_found))
# ltmle.SL<- ltmle(data=datBos.searched.new, Anodes='search_conducted',
#                 Ynodes='contraband_found', abar=1, SL.library=SL.library)

```

```
# nonparametric bootstrap for variance estimation
```

```

# hard code function
est.all <- function(dat.bp){
  # Simple substitution
  dat.s<- dat.bp %>% filter(search_conducted == TRUE)
  dat.i <- dat.bp %>% mutate(search_conducted = TRUE)

  X <- subset(dat.s, select = c(subject_age, subject_race,
                                subject_sex, reason_for_stop))
  X1 <- subset(dat.i, select = c(subject_age, subject_race,
                                subject_sex, reason_for_stop))
  fit.SL.1 <- SuperLearner(Y=as.numeric(dat.s$contraband_found),
                          X=X, SL.library=SL.library, family='binomial')
  EY.1W <- predict(fit.SL.1, newdata = X1)$pred
  est.gcomp.SL <- mean(EY.1W)

  # IPTW
  X <- subset(dat.bp, select = c(subject_age, subject_race,
                                subject_sex, reason_for_stop))
  fit.SL.2 <- SuperLearner(Y=as.numeric(dat.bp$search_conducted),
                          X=X, SL.library=SL.library, family='binomial')

  PA1.W <- fit.SL.2$SL.predict
  H.AW <- as.numeric(dat.bp$search_conducted == 1)/PA1.W

```

```

H.AW.mean.s <- mean(H.AW[!is.na(dat.bp$contraband_found)])
# standardized IPTW
est.sIPTW.SL <- mean(H.AW*dat.bp$contraband_found, na.rm = TRUE)/H.AW.mean.s

# TMLE
H.AW.std.s <- H.AW[!is.na(dat.bp$contraband_found)]/H.AW.mean.s
EY.1W.s <- EY.1W[!is.na(dat.bp$contraband_found)]
logitUpdate <- glm(dat.s$contraband_found ~ -1 + offset(qlogis(EY.1W.s)) + H.AW.std.s,
  family='binomial')
epsilon <- logitUpdate$coefficients
H.1W <- 1/PA1.W
H.1W.std <- H.1W/mean(H.1W)
EY.1W.star <- plogis(qlogis(EY.1W) + epsilon*H.1W.std)
est.TLME <- mean(EY.1W.star)
c(est.gcomp.SL, est.sIPTW.SL, est.TLME)
}

# bootstrap
set.seed(2019)
est.results <- matrix(NA, ncol = 3, nrow = 500)
for (k in 1:500){
  dat.bp <- datBos[sample(1:n, n, replace = TRUE), ]
  est.results[k,] <- est.all(dat.bp)
}

```

```

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

```



[illegible]

[illegible]

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[illegible]





[illegible]

[illegible]







[illegible]

[illegible]





[illegible]





[illegible]

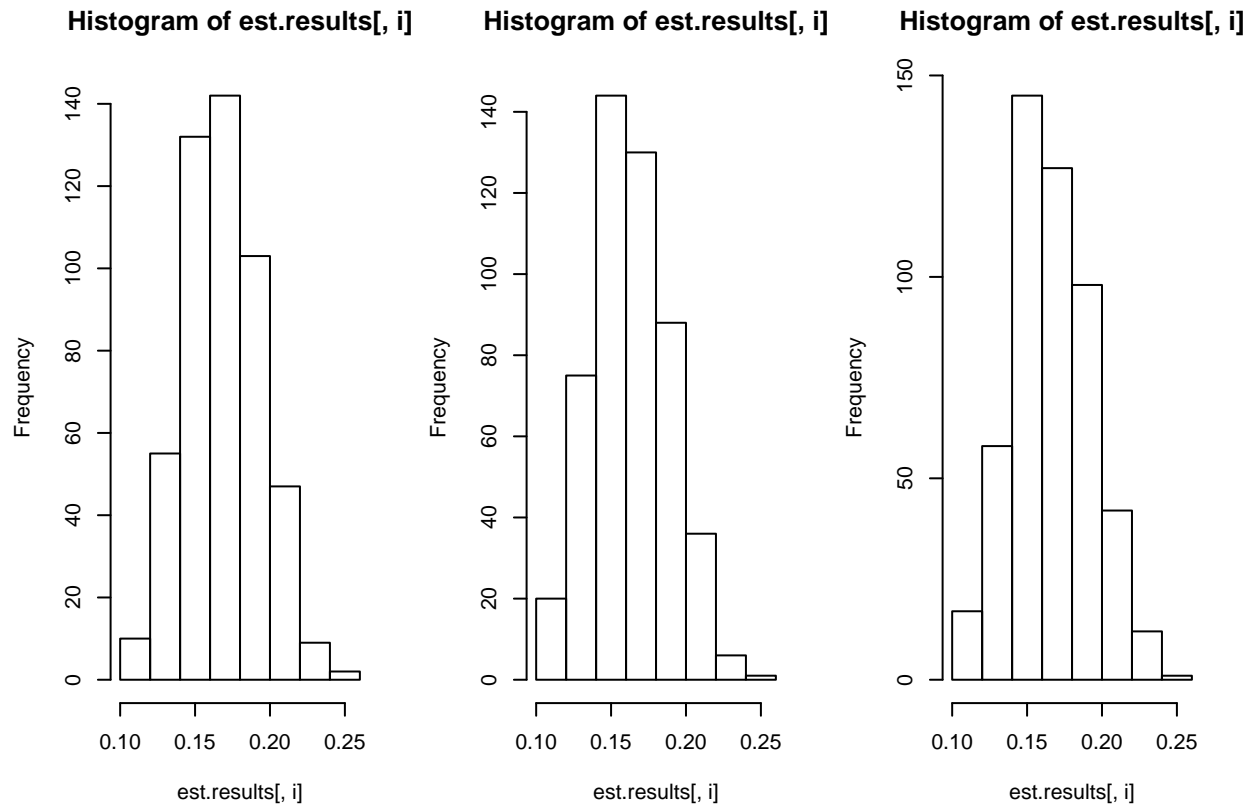
```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
# plot histograms
par(mfrow = c(1,3))
for(i in 1:3){
  print(hist(est.results[,i]))
}
```

```
## $breaks
## [1] 0.10 0.12 0.14 0.16 0.18 0.20 0.22 0.24 0.26
##
## $counts
## [1] 10 55 132 142 103 47 9 2
##
## $density
## [1] 1.0 5.5 13.2 14.2 10.3 4.7 0.9 0.2
##
## $mids
## [1] 0.11 0.13 0.15 0.17 0.19 0.21 0.23 0.25
##
## $xname
## [1] "est.results[, i]"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"

## $breaks
## [1] 0.10 0.12 0.14 0.16 0.18 0.20 0.22 0.24 0.26
##
## $counts
## [1] 20 75 144 130 88 36 6 1
##
## $density
## [1] 2.0 7.5 14.4 13.0 8.8 3.6 0.6 0.1
##
## $mids
## [1] 0.11 0.13 0.15 0.17 0.19 0.21 0.23 0.25
##
## $xname
```

```
## [1] "est.results[, i]"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
```



```
## $breaks
## [1] 0.10 0.12 0.14 0.16 0.18 0.20 0.22 0.24 0.26
##
## $counts
## [1] 17 58 145 127 98 42 12 1
##
## $density
## [1] 1.7 5.8 14.5 12.7 9.8 4.2 1.2 0.1
##
## $mids
## [1] 0.11 0.13 0.15 0.17 0.19 0.21 0.23 0.25
##
## $xname
## [1] "est.results[, i]"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
```

```

# point estimate
est.pt <- est.all(datBos)

# confidence interval
est.sd <- apply(est.results, 2, sd)
cbind(est.pt - 1.96*est.sd, est.pt + 1.96*est.sd)

##           [,1]      [,2]
## [1,] 0.1137243 0.2137579
## [2,] 0.1123482 0.2148759
## [3,] 0.1139156 0.2180133

# save all results
save.image(file = "envir_1207_v1.Rdata")

```