Final Project Code

Kunwu Lyu and Evan Hart

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Data Wrangling

```r
## Data from ICPSR
survey <- read_tsv("data/ICPSR_37143/DS0001/37143-0001-Data.tsv") %>%
  janitor::clean_names() # To all lower case
receipt <- read_tsv("data/ICPSR_37143/DS0002/37143-0002-Data.tsv") %>%
  janitor::clean_names()
fast_food <- read_tsv("data/ICPSR_37143/DS0003/37143-0003-Data.tsv") %>%
  janitor::clean_names()
grocery <- read_tsv("data/ICPSR_37143/DS0004/37143-0004-Data.tsv") %>%
  janitor::clean_names()
recall <- read_tsv("data/ICPSR_37143/DS0005/37143-0005-Data.tsv") %>%
  janitor::clean_names()

## Combine multiple surveys
full_data <- survey %>%
  full_join(receipt, relationship = "many-to-many") %>%
  full_join(fast_food, relationship = "many-to-many") %>%
  full_join(grocery, relationship = "many-to-many") %>%
  full_join(recall, relationship = "many-to-many")

## Mutating
full_data <- full_data %>%
  mutate(limit = ordered(q75, levels = c("Never", "Seldom", "Sometimes",
                                         "Often", "Always"))) %>% # for ordinal
  mutate(age = as.numeric(q76),
         gender = if_else(q77 == 0, "M", "F"),
         race = case_when(
           !is.na(q79_1) ~ "Native",
           !is.na(q79_2) ~ "Black",
           !is.na(q79_3) ~ "Asian",
           !is.na(q79_4) ~ "White",
           !is.na(q79_a) ~ "Other"
         ),
         edu = as.numeric(q80),
         location = nemslocationindicator,
         city = q1,
         num_kids = q44,
         surveydate = dmy(surveydate)) %>%
  mutate(days_since_ban =
           as.numeric(interval(as.Date("2013-03-12"), surveydate) / days(1))) %>%
  filter(age > 0)
```

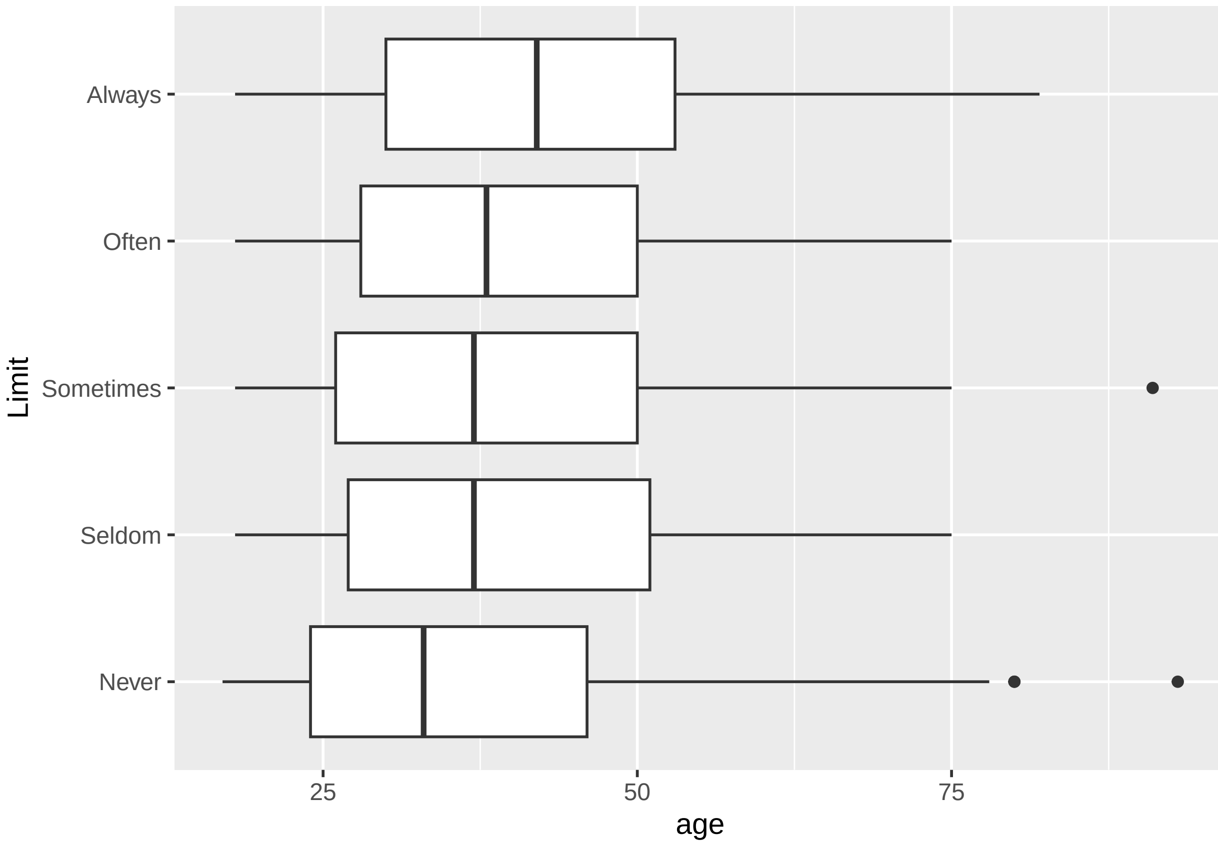
```r
# Standardize numerical for prediction
standardize <- function(x, na.rm = TRUE) {
  (x - mean(x, na.rm = na.rm)) /
    sd(x, na.rm = na.rm)
}

# subset of complete dataset
reduced_data <- full_data %>%
  mutate(age_std = standardize(as.numeric(q76))) %>%
  select(c("receiptid", "person_id", "limit", "age", "age_std", "gender",
           "race", "edu", "city", "caff", "location", "round", "nsigns_ssb",
           "num_kids", "surveydate", "days_since_ban", "kcal", "f_total",
           "v_total")) %>%
  group_by(receiptid) %>%
  mutate(caff = mean(caff, na.rm = T), # across each receipt
         f_total = mean(f_total, na.rm = T),
         v_total = mean(v_total, na.rm = T),
         kcal = mean(kcal, na.rm = T)) %>%
  drop_na() %>%
  distinct() %>% # Remove duplicate rows because multiple items are on a receipt
  mutate(receiptid = as.factor(receiptid),
         person_id = as.factor(person_id),
         location = as.factor(location),
         round = as.factor(round),
         edu = case_when(
           edu == 1 ~ "Less than High School",
           edu == 2 ~ "Some High School",
           edu == 3 ~ "High School",
           edu == 4 ~ "Some College",
           edu == 5 ~ "Associates Degree",
           edu == 6 ~ "College Degree",
           edu == 7 ~ "Graduate Degree"
         )) %>%
  ungroup() %>%
  mutate(f_std = standardize(f_total),
         v_std = standardize(v_total),
         caff_std = standardize(caff),
         nsigns_ssb_std = standardize(nsigns_ssb),
         days_since_ban_std = standardize(days_since_ban),
         kcal_std = standardize(kcal)
         ) %>%
  mutate(fv = f_std + v_std) %>%
  mutate(fv_std = standardize(fv),
         log_age = log(age),
         exp_age = exp(age))

# Cleaned data
write_csv(reduced_data, "dietControl.csv")

# One receipt can't appear in multiple locations
multi_receipt_locations <- reduced_data %>%
  group_by(receiptid) %>%
  summarize(n_rounds = n_distinct(location)) %>%
```

```
  filter(n_rounds > 1) %>%
  pull(receiptid)

reduced_data %>%
  filter(receiptid %in% multi_receipt_locations) %>%
  count(receiptid, location)
```

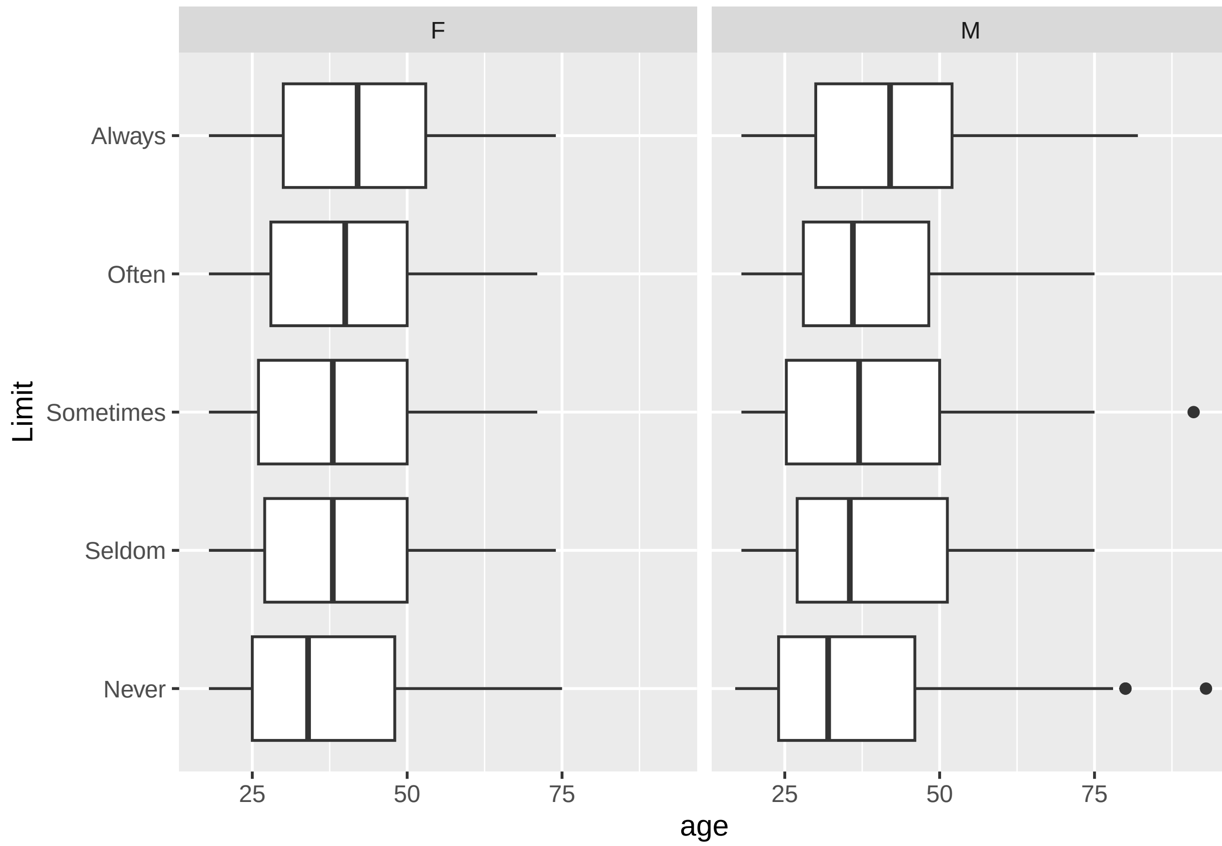
```
## # A tibble: 0 x 3
## # i 3 variables: receiptid <fct>, location <fct>, n <int>
```

EDA

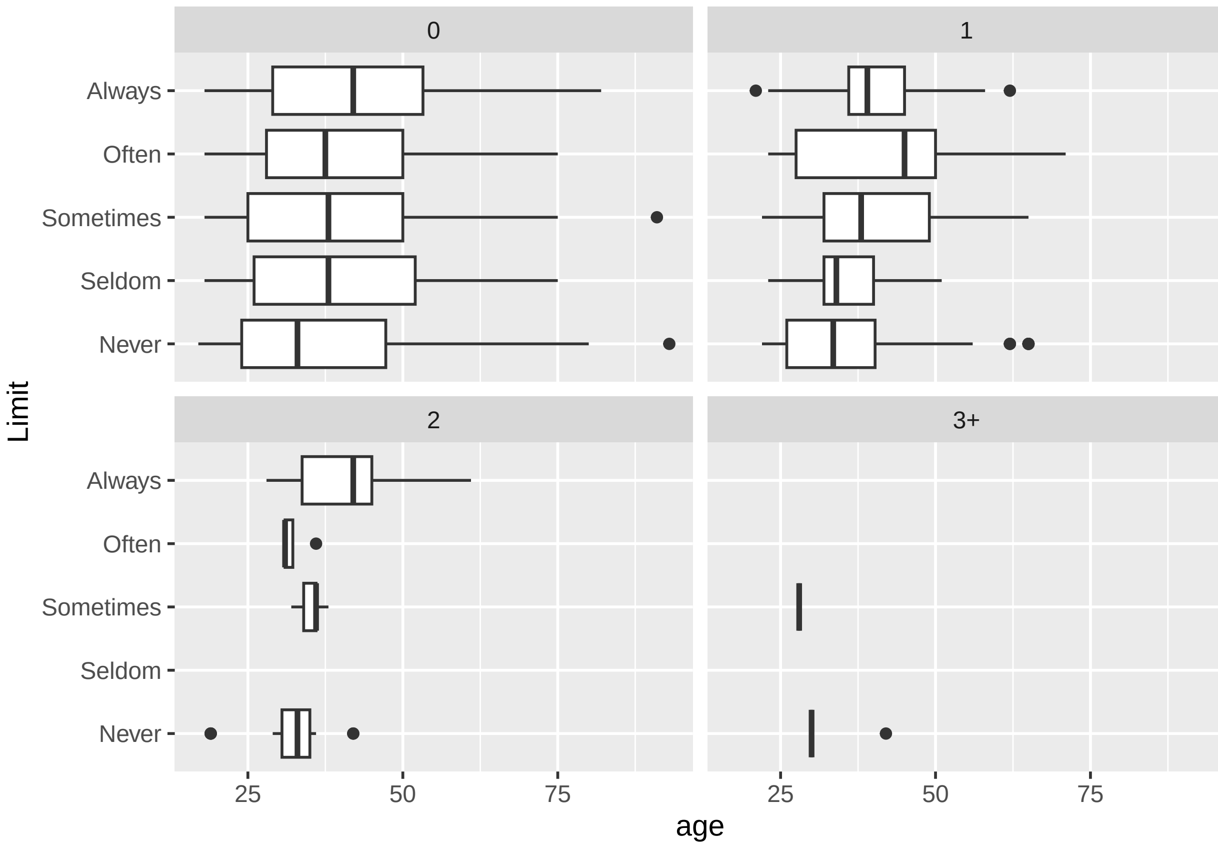
```
# Single variables, interactions plotted against limit

# Age
ggplot(data = reduced_data, aes(x = age , y = limit)) +
  geom_boxplot() +
  labs(x = "age", y = "Limit")
```



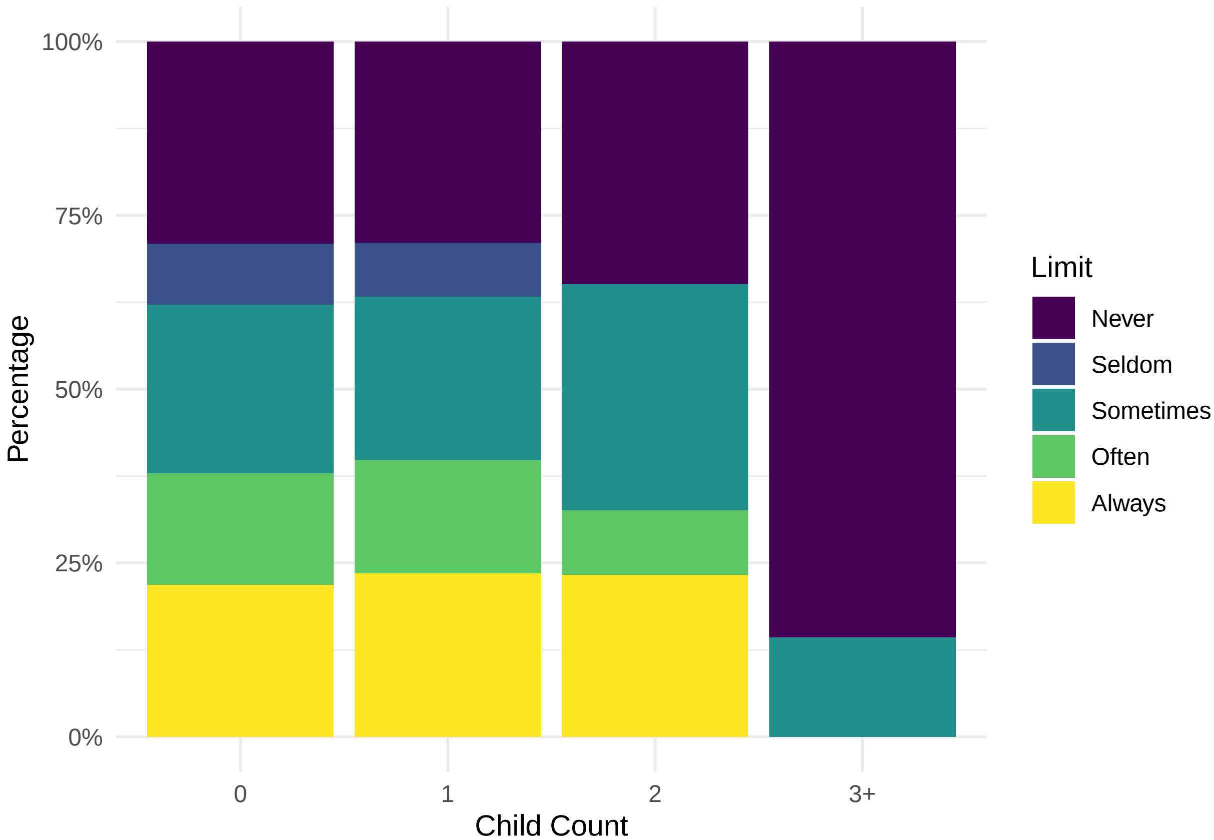

```
# Age faceted by gender
ggplot(data = reduced_data, aes(x = age , y = limit)) +
  geom_boxplot() +
  facet_wrap(~gender) +
  labs(x = "age", y = "Limit")
```



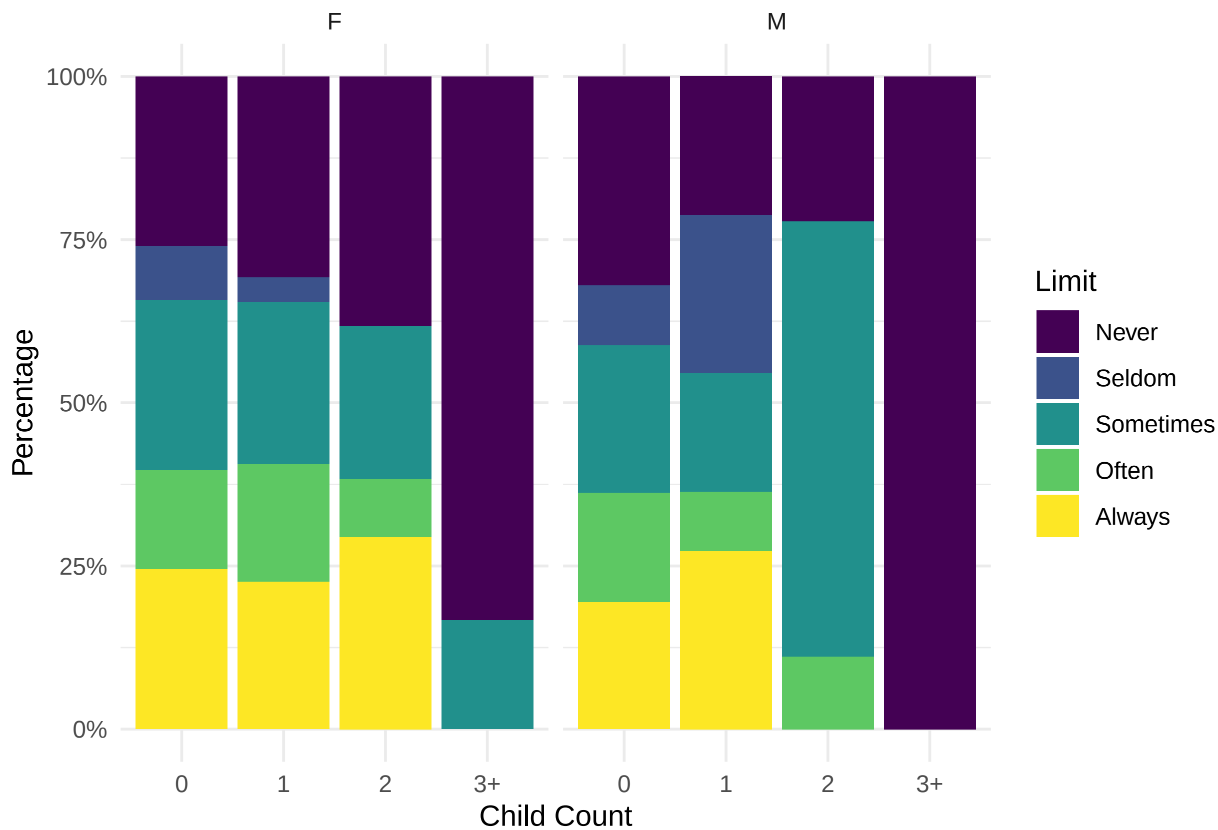

```r
# Age faceted by child count
ggplot(data = reduced_data, aes(x = age , y = limit)) +
  geom_boxplot() +
  facet_wrap(~num_kids) +
  labs(x = "age", y = "Limit")
```



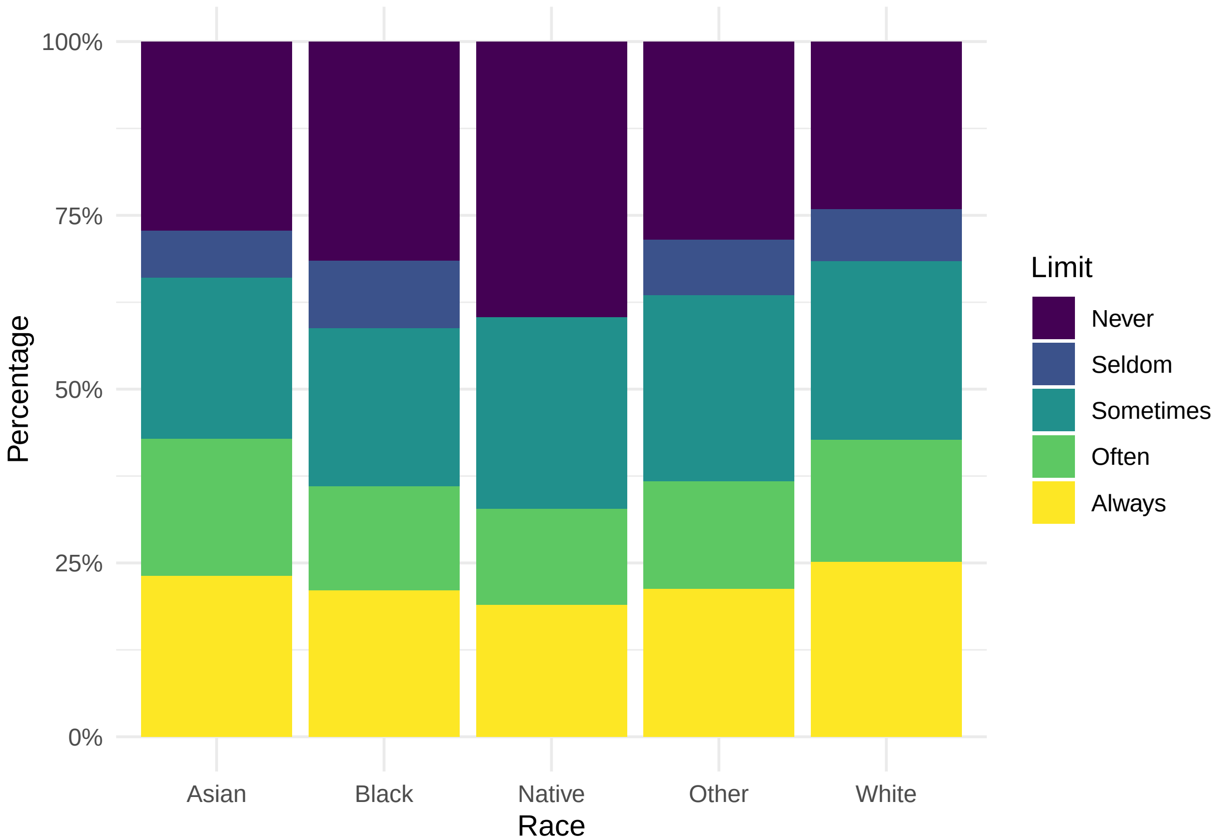

```r
# Child count
ggplot(data = reduced_data, aes(x = num_kids, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Child Count", y = "Percentage", fill = "Limit") +
  theme_minimal()
```



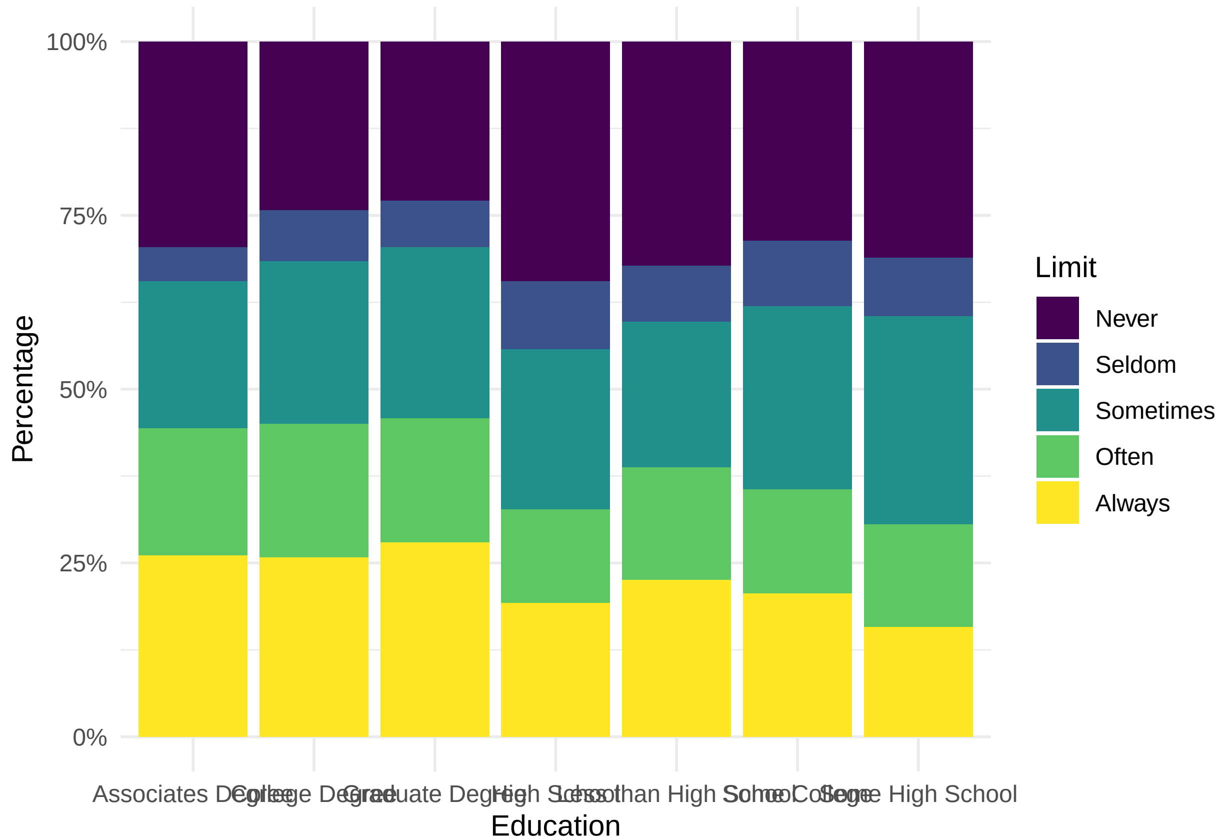

```r
# Child count / gender interaction
ggplot(data = reduced_data, aes(x = num_kids, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Child Count", y = "Percentage", fill = "Limit") +
  facet_wrap(~gender) +
  theme_minimal()
```




```
# Race
ggplot(data = reduced_data, aes(x = race, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Race", y = "Percentage", fill = "Limit") +
  theme_minimal()
```

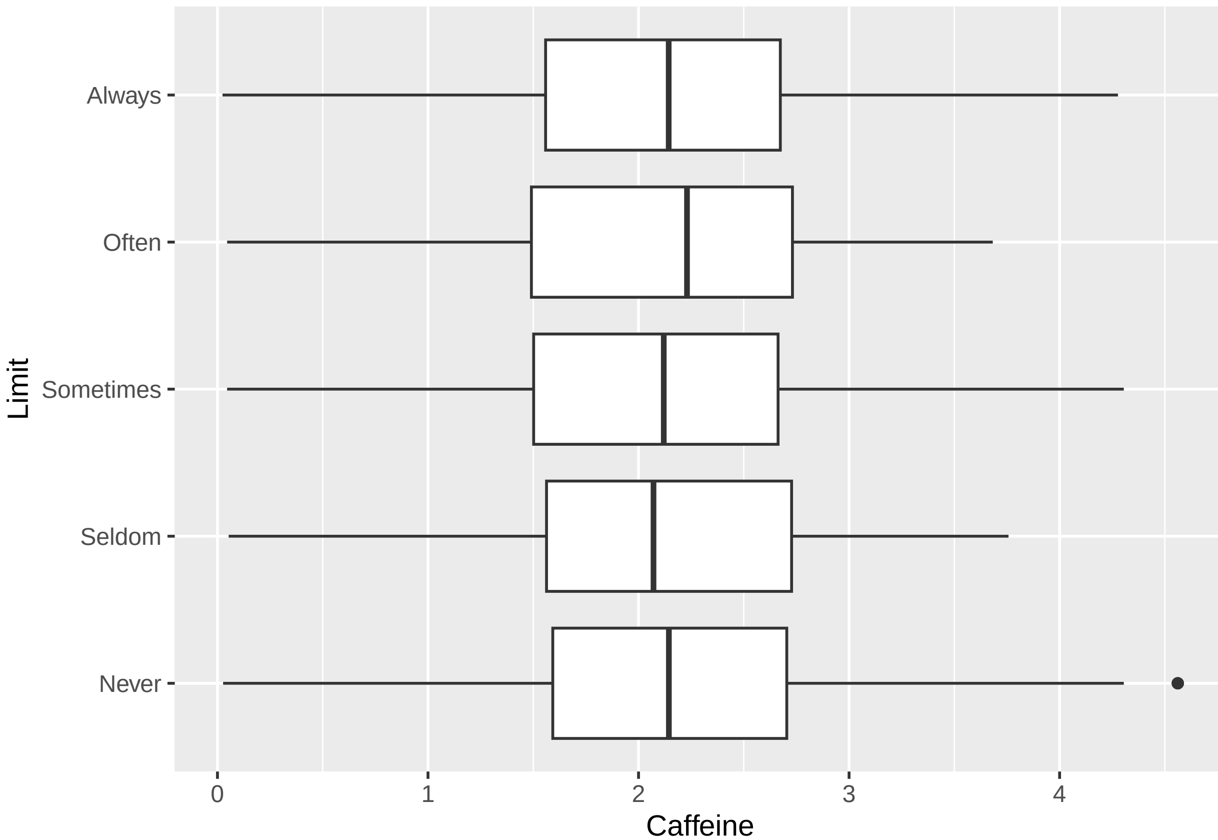



```r
# Education
ggplot(data = reduced_data, aes(x = edu, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Education", y = "Percentage", fill = "Limit") +
  theme_minimal()
```

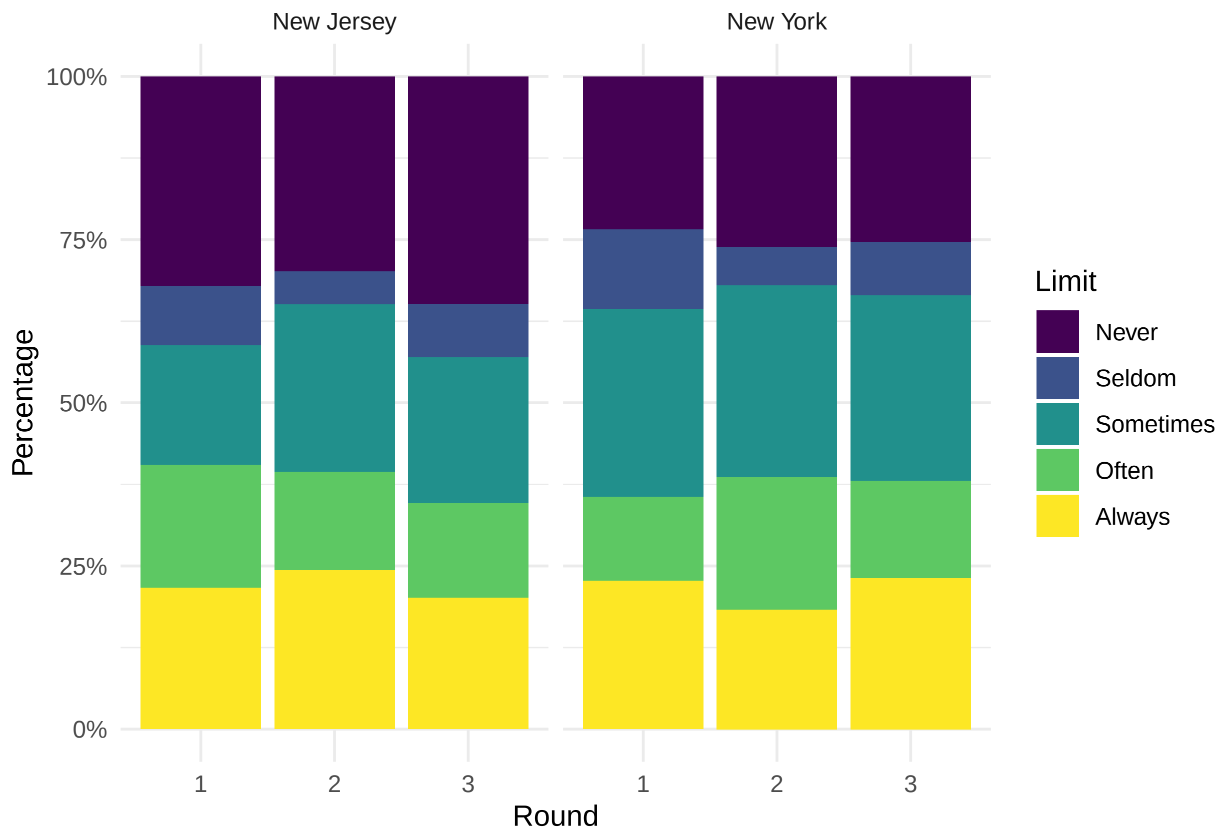



```r
# City
ggplot(data = reduced_data, aes(x = city, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "City", y = "Percentage", fill = "Limit") +
  theme_minimal()
```

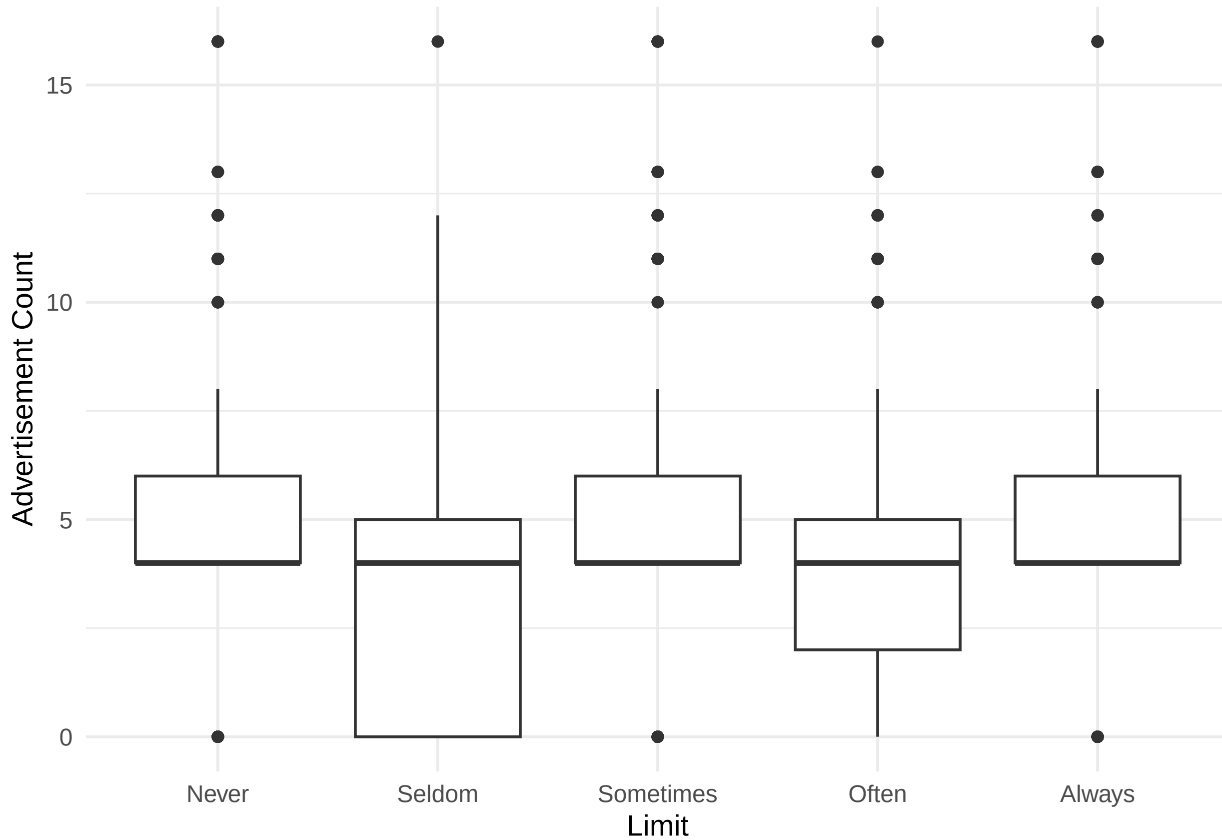

```r
# Caffeine
ggplot(data = reduced_data %>% filter(caff > 0), aes(x = log(caff + 1) , y = limit)) +
  geom_boxplot() +
  labs(x = "Caffeine", y = "Limit")
```




```r
# Survey round
ggplot(data = reduced_data, aes(x = round, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Round", y = "Percentage", fill = "Limit") +
  facet_wrap(~city) +
  theme_minimal()
```



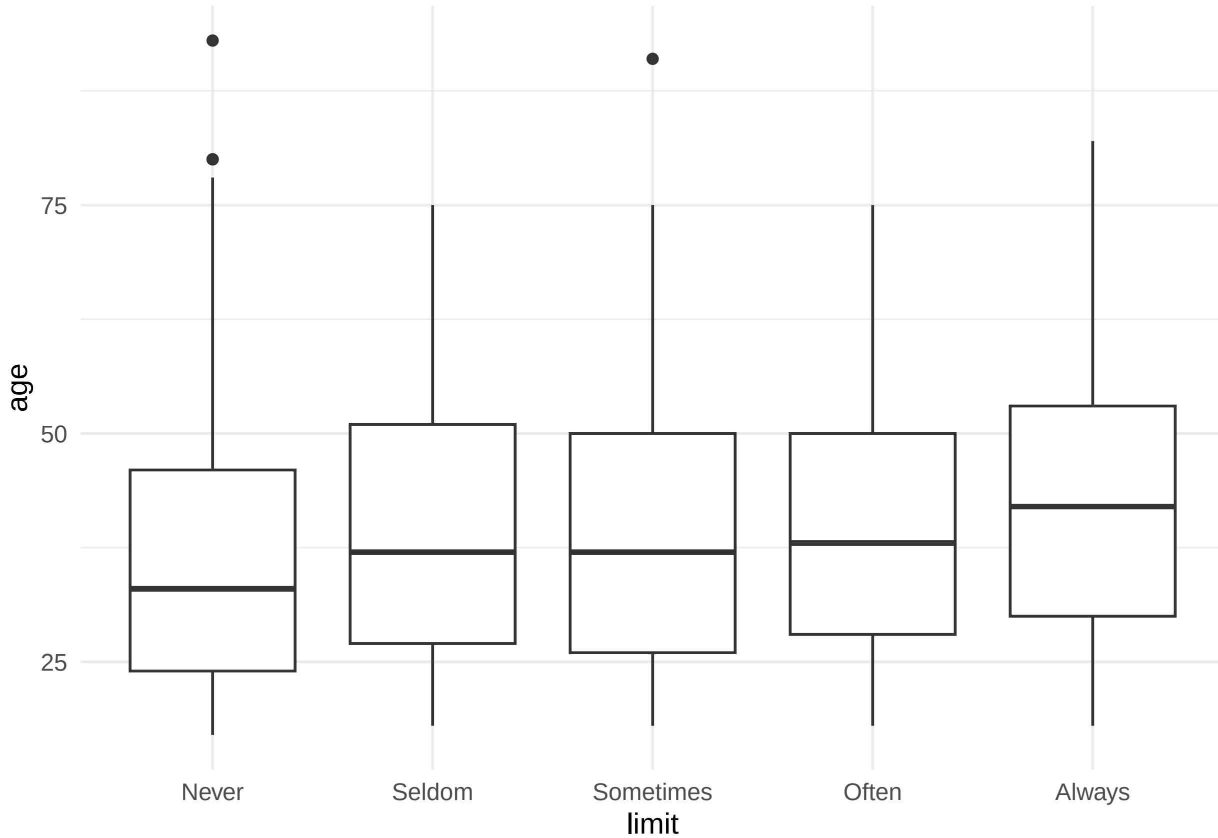

```r
# Advertisement count
ggplot(data = reduced_data, aes(y = nsigns_ssb, x = limit)) +
  geom_boxplot() +
  labs(y = "Advertisement Count", x = "Limit") +
  theme_minimal()
```

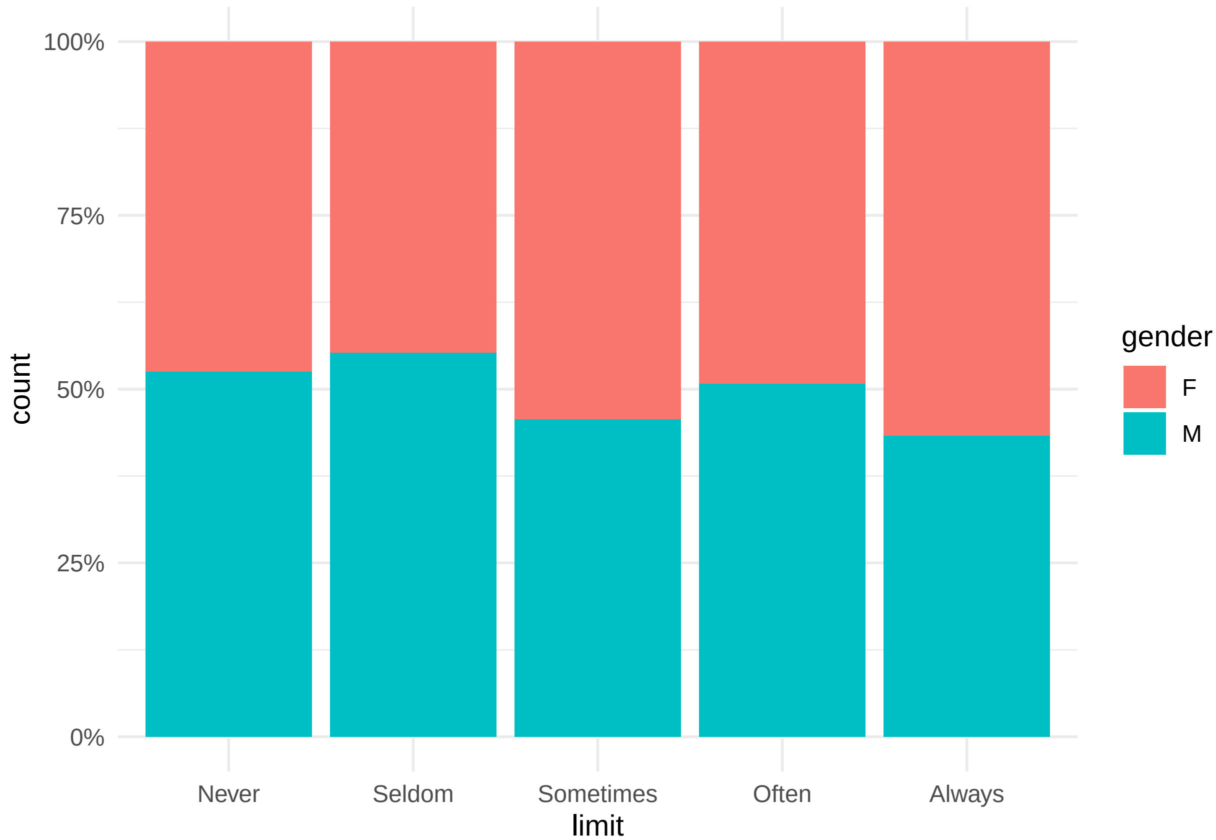


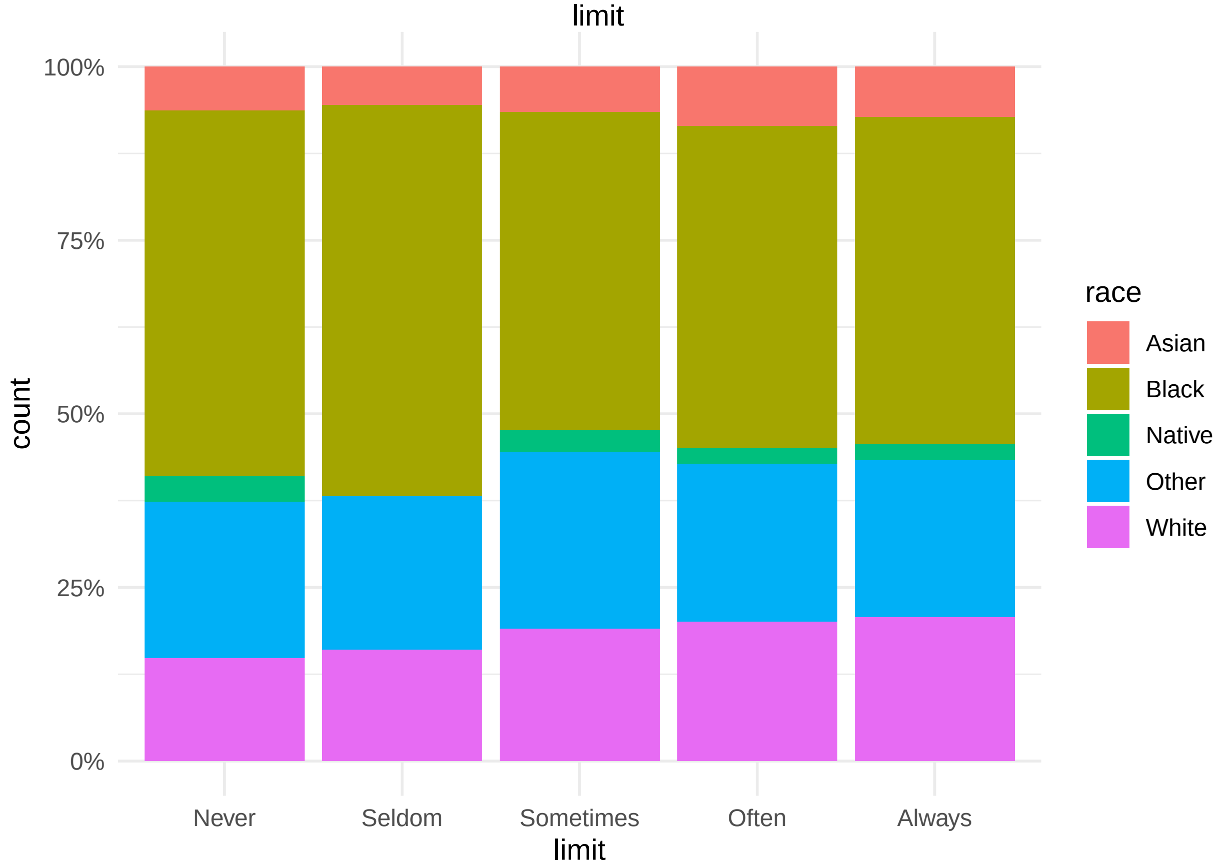

```r
# Plot function for interactions

plot_cats <- c("limit", "gender", "race", "city", "round", "num_kids", "edu", "diet")
plot_nums <- c("age", "caff", "nsigns_ssb", "days_since_ban")

library(rlang)

make_plot <- function(var1, var2){
  if(var1 %in% plot_cats & var2 %in% plot_cats){
    print(ret_plot <- ggplot(data =reduced_data, aes(x = !!sym(var1), fill = !!sym(var2))) +
      geom_bar(position = "fill") +
      scale_y_continuous(labels = scales::percent) +
      theme_minimal())
  }

  if(var1 %in% plot_cats & var2 %in% plot_nums){
    print(ret_plot <- ggplot(data = reduced_data, aes(x = !!sym(var1), y = !!sym(var2))) +
      geom_boxplot() +
      theme_minimal())
  }

  if(var1 %in% plot_nums & var2 %in% plot_cats){
    print(ret_plot <- ggplot(data = reduced_data, aes(x = !!sym(var2), y = !!sym(var1))) +
       geom_boxplot() +
       theme_minimal())
  }
```

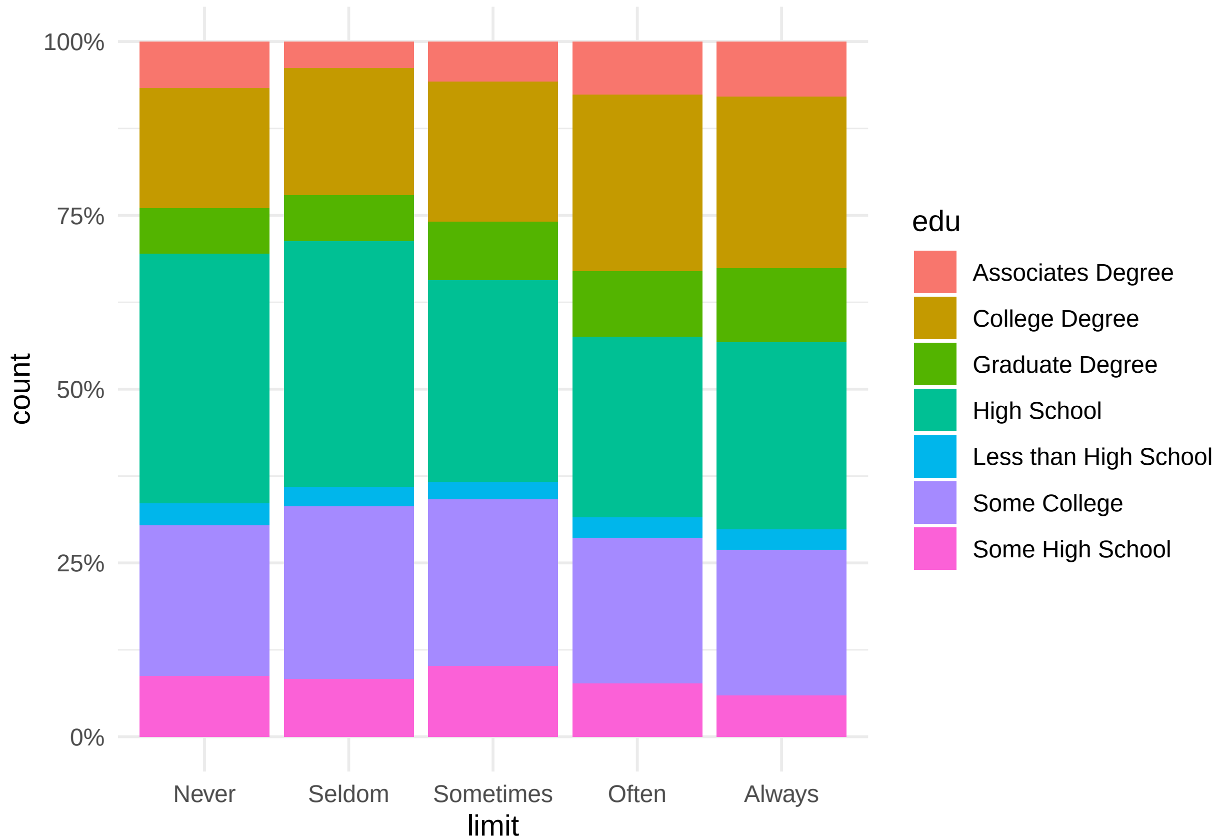
```
  if(var1 %in% plot_nums & var2 %in% plot_nums){
    print(ggplot(data = reduced_data, aes(x = !!sym(var2), y = !!sym(var1))) +
      geom_point() +
      theme_minimal())
  }
}
```

```
for(i in 1:length(names(reduced_data))){
  if(i != length(reduced_data)){
    for(j in (i+1):length(reduced_data)){
      make_plot(names(reduced_data)[i], names(reduced_data)[j])
    }
  }
}
```

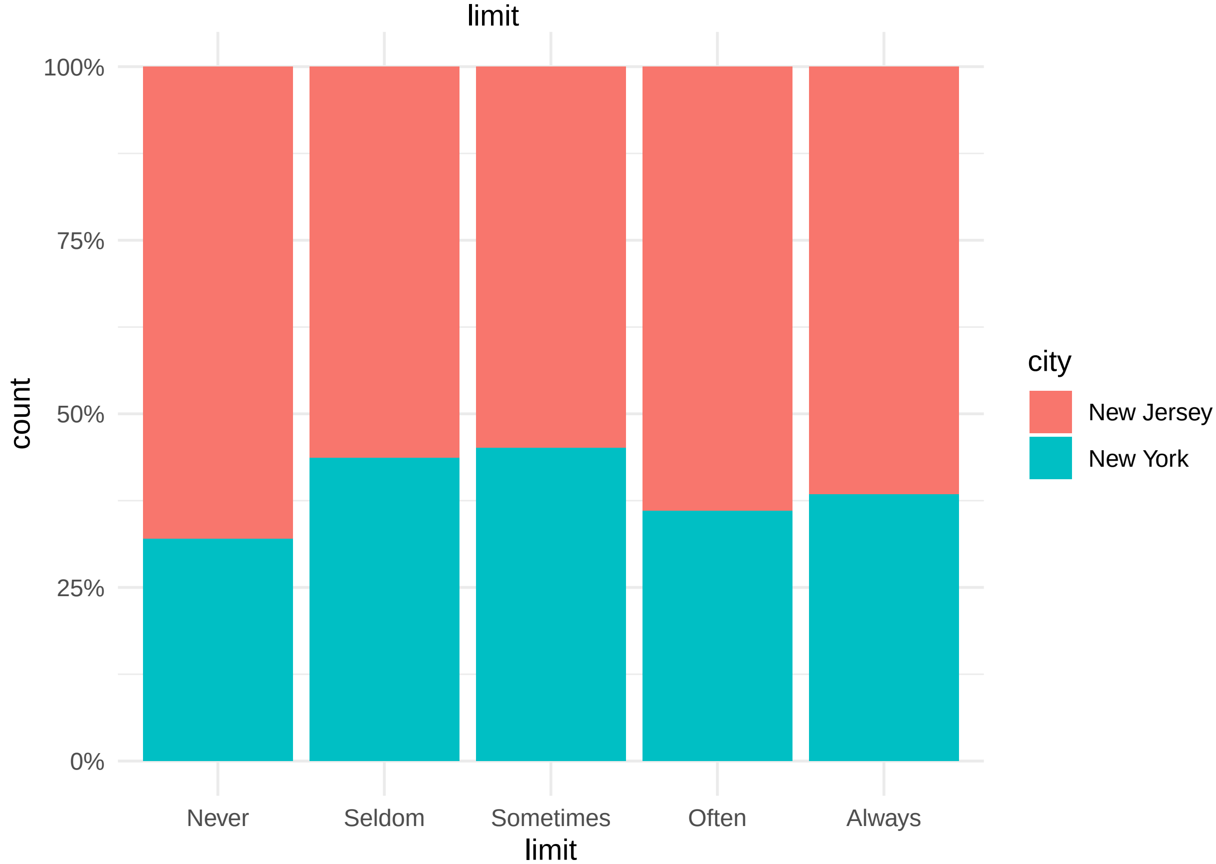



100%
75%
50%
25%
0%
count
Never
Seldom
Sometimes
Often
Always
limit
gender
F
M

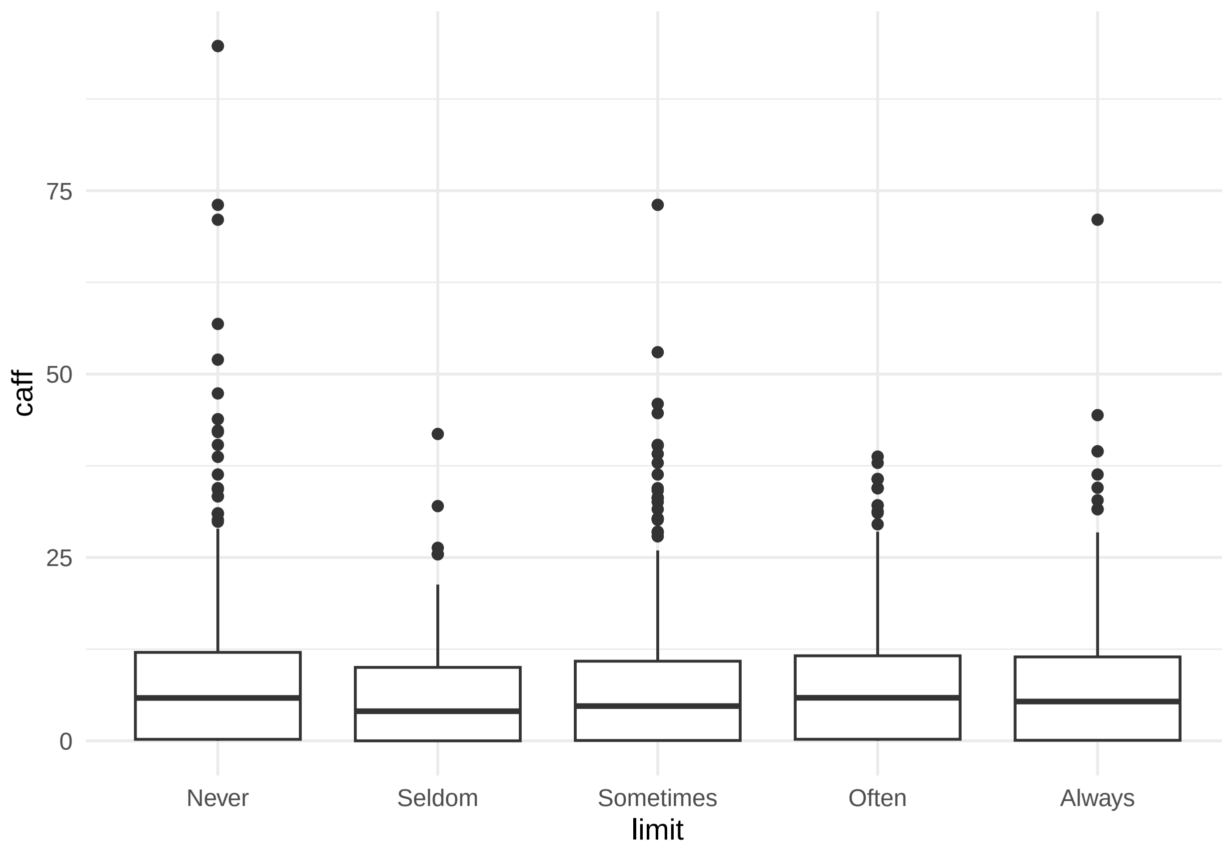

100%
75%
50%
25%
0%
count
Never
Seldom
Sometimes
Often
Always
limit
race
Asian
Black
Native
Other
White

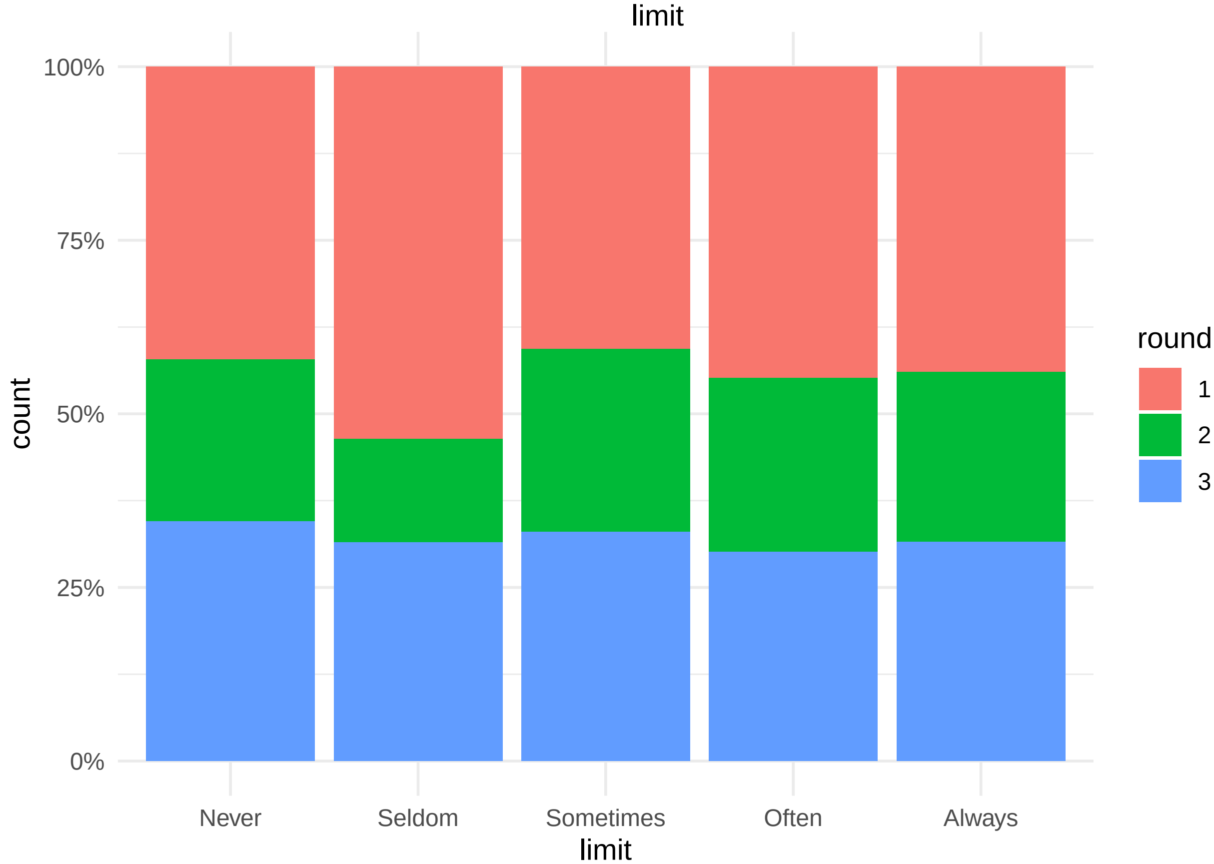


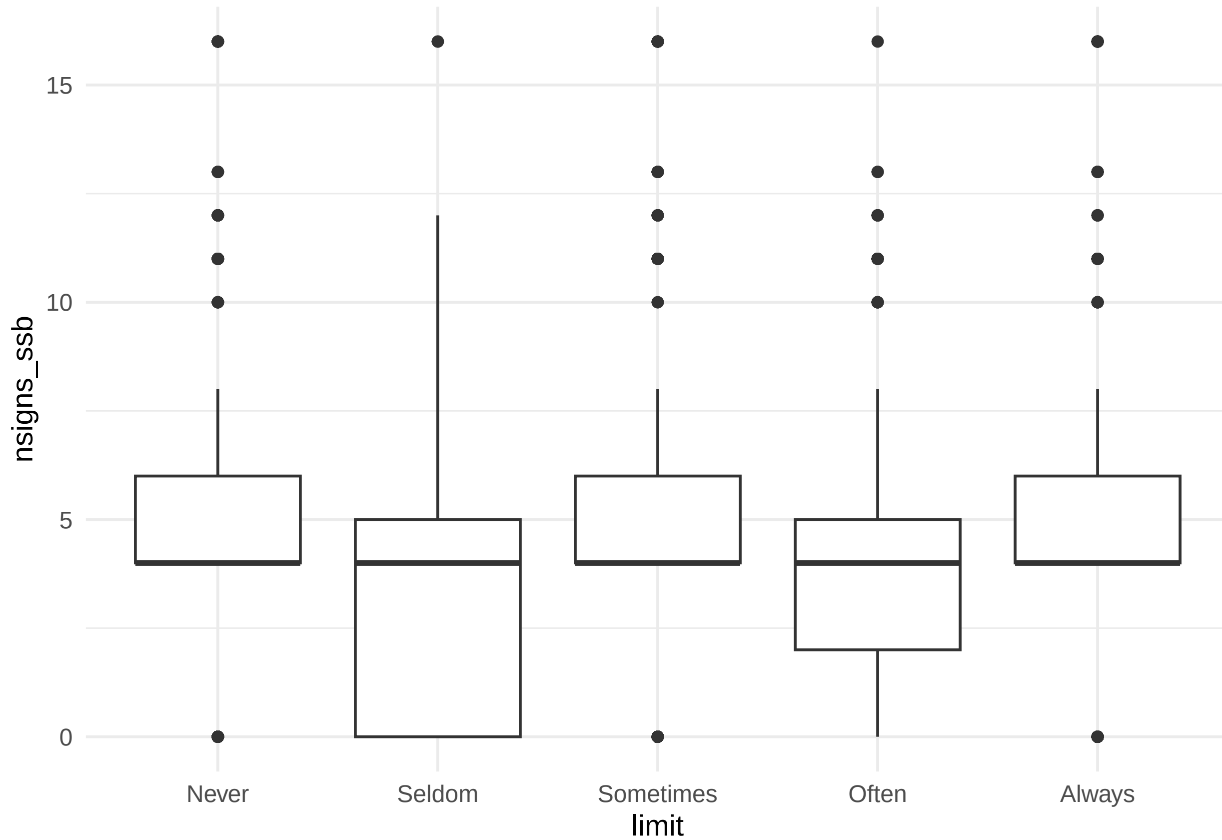
100%
75%
50%
25%
0%
count
Never
Seldom
Sometimes
Often
Always
limit
edu
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School



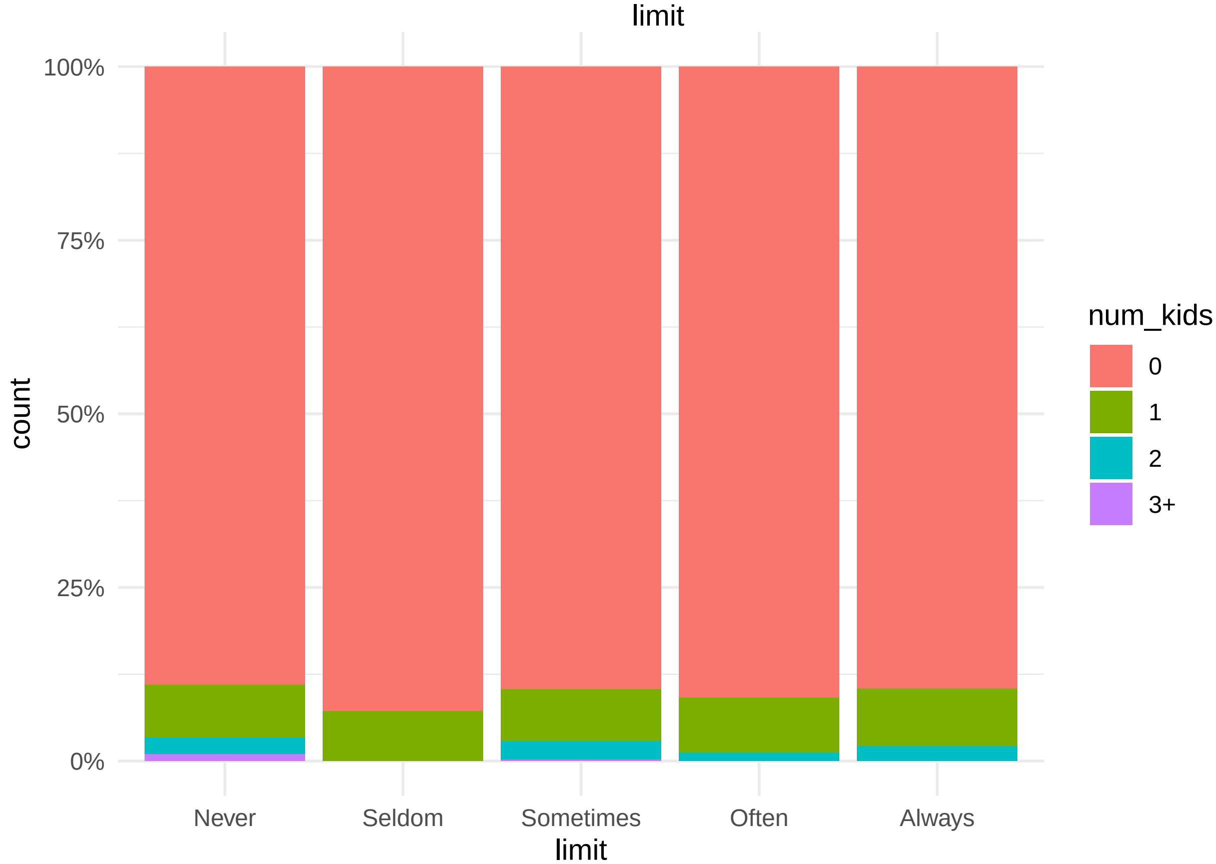
100%
75%
50%
25%
0%
count
Never
Seldom
Sometimes
Often
Always
limit
city
New Jersey
New York


caff
75
50
25
0
Never
Seldom
Sometimes
Often
Always
limit

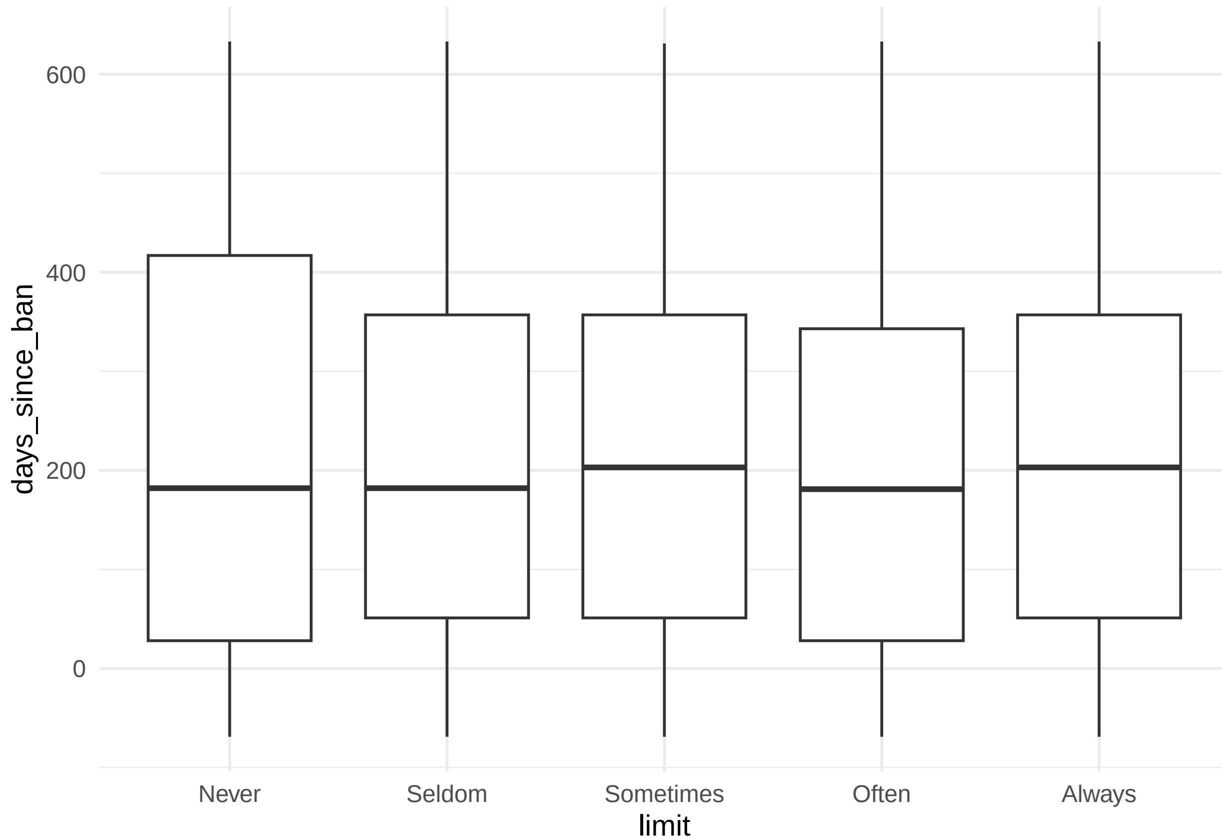

count
100%
75%
50%
25%
0%
Never
Seldom
Sometimes
Often
Always
limit
round
1
2
3



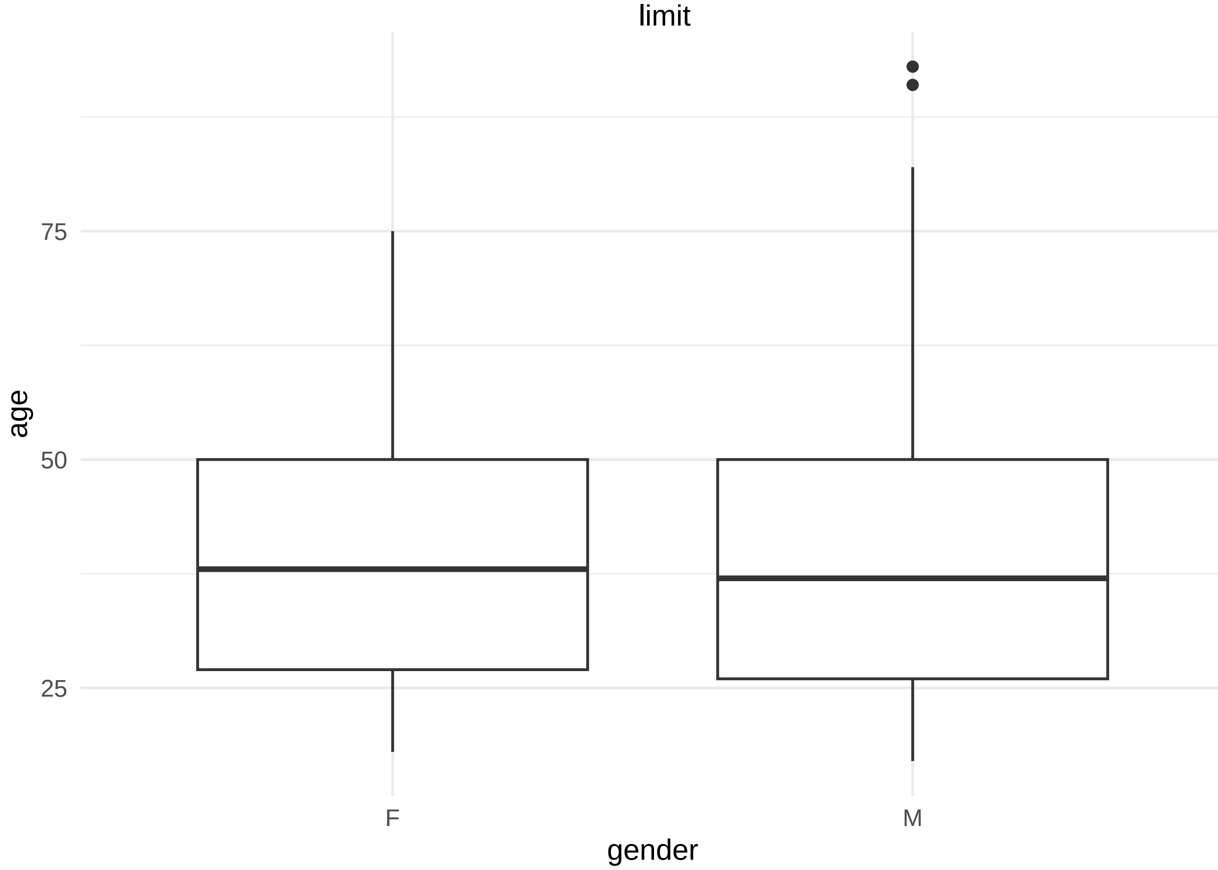
nsigns_ssb
15
10
5
0
Never
Seldom
Sometimes
Often
Always
limit



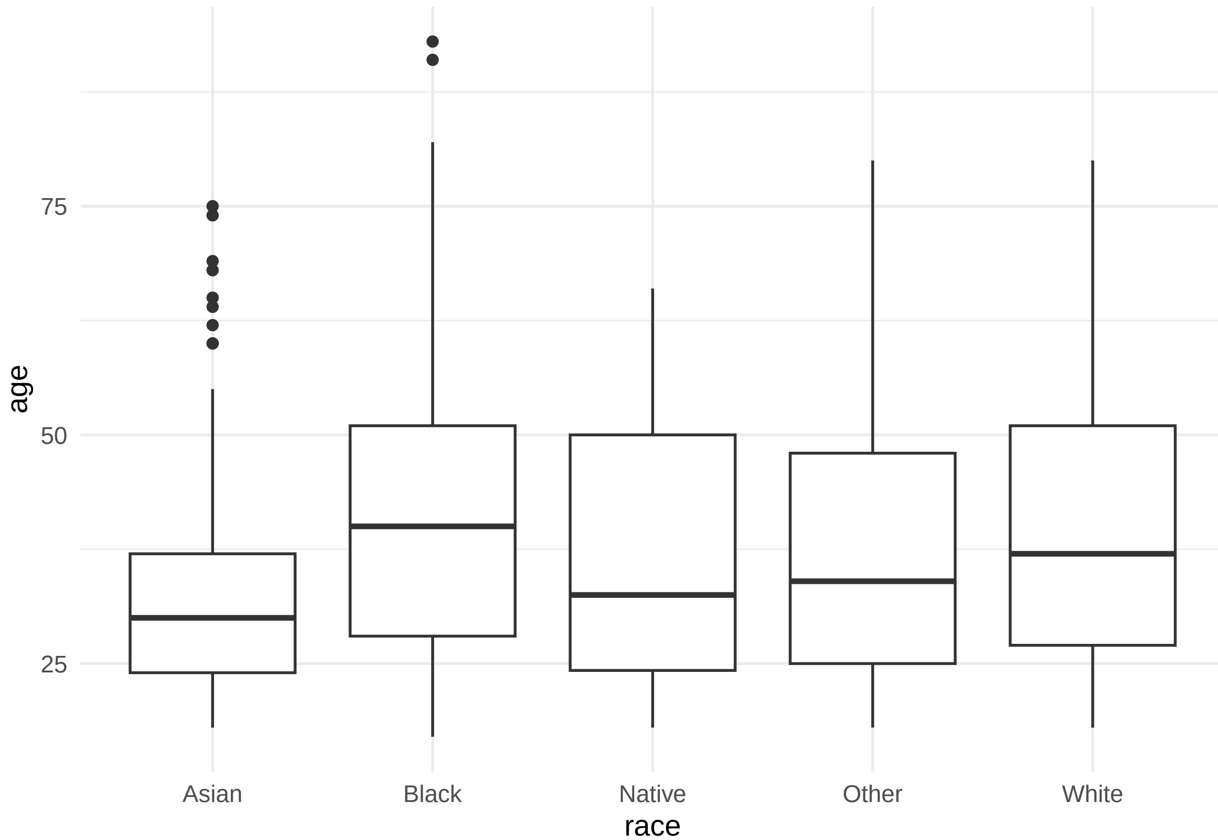
count
100%
75%
50%
25%
0%
Never
Seldom
Sometimes
Often
Always
limit
num_kids
0
1
2
3+

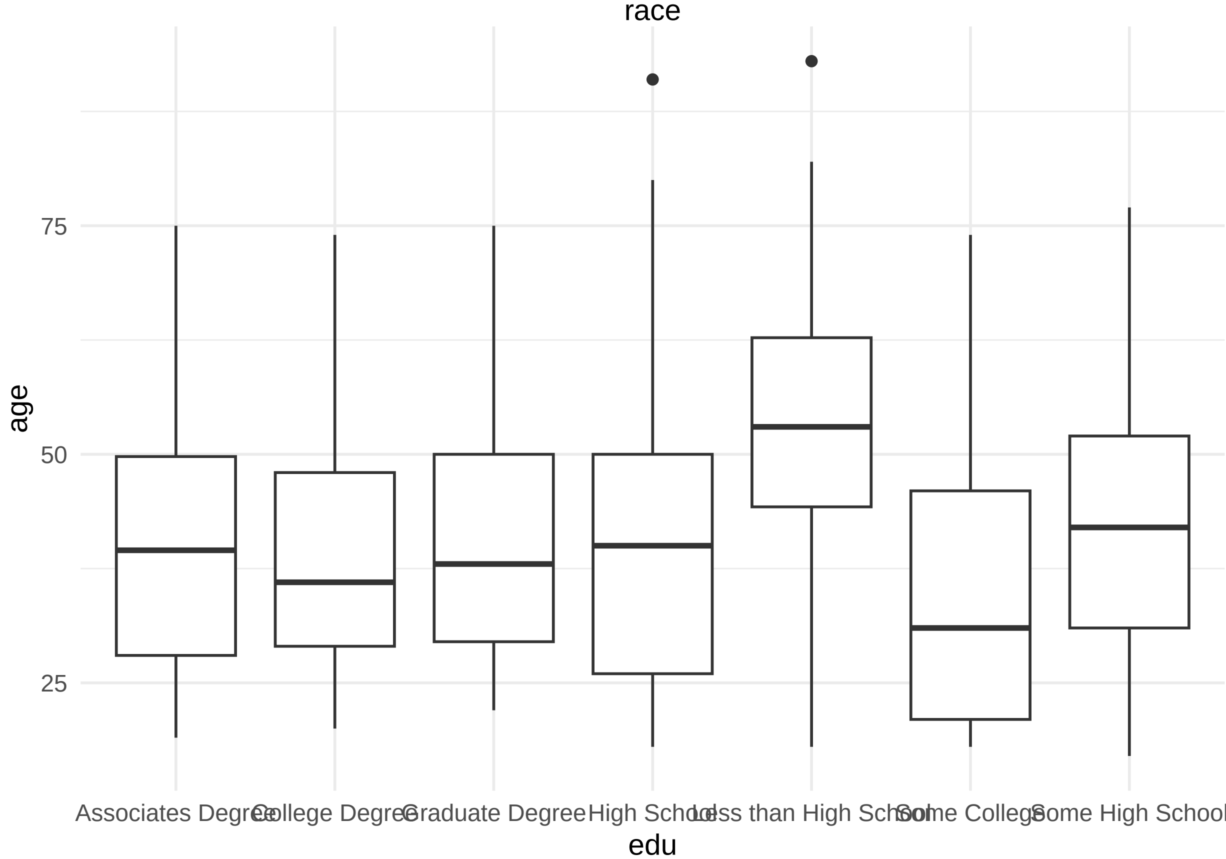


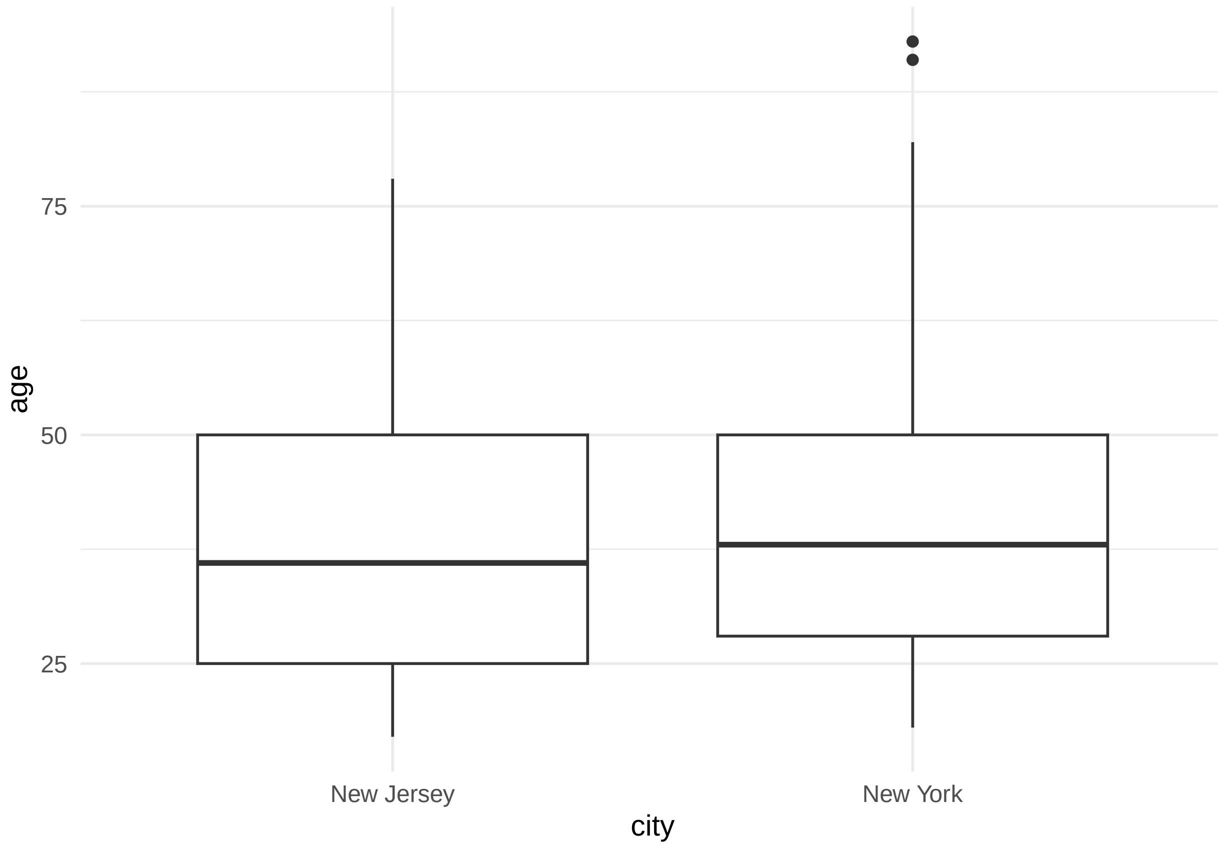
600
400
200
0
days_since_ban
Never
Seldom
Sometimes
Often
Always
limit

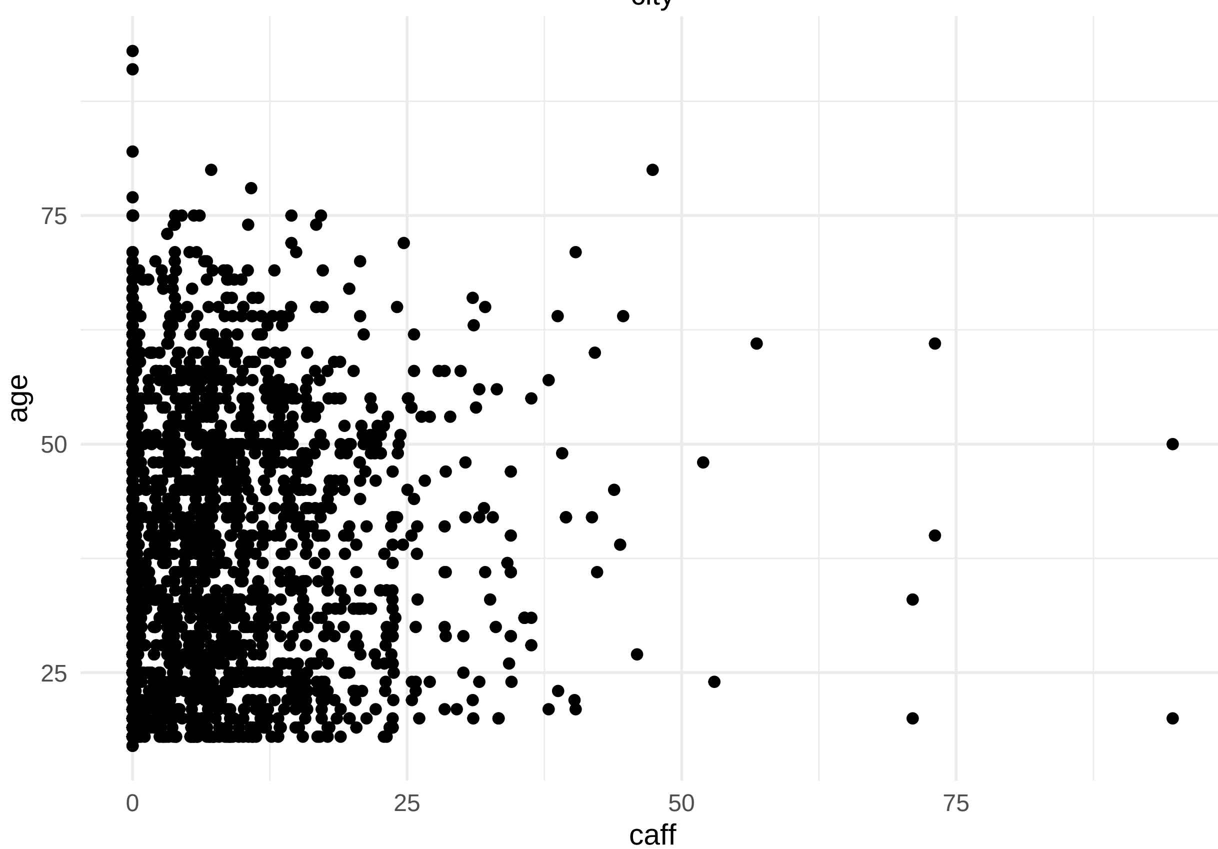


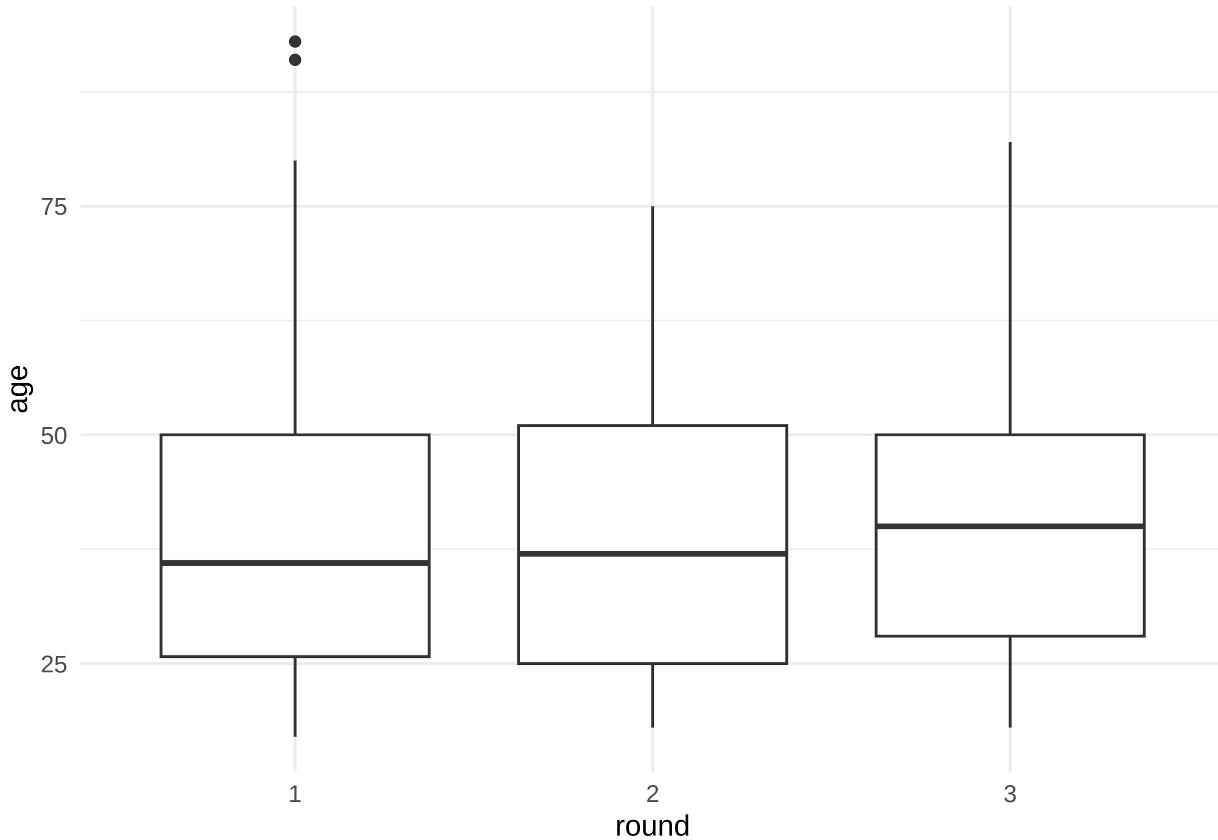
75
50
25
age
F
M
gender


75
50
25
age
Asian
Black
Native
Other
White
race

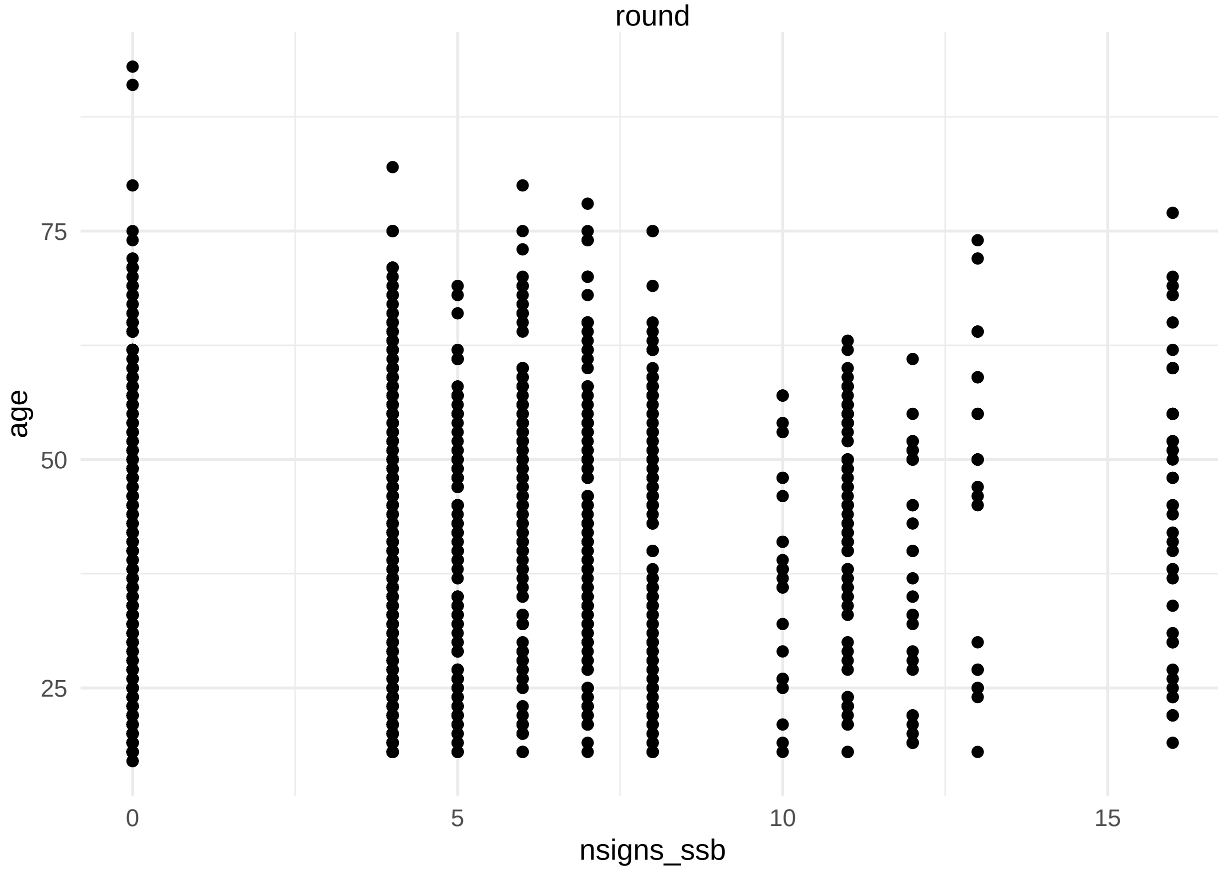

75
50
25
age
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu


age
75
50
25
New Jersey
New York
city

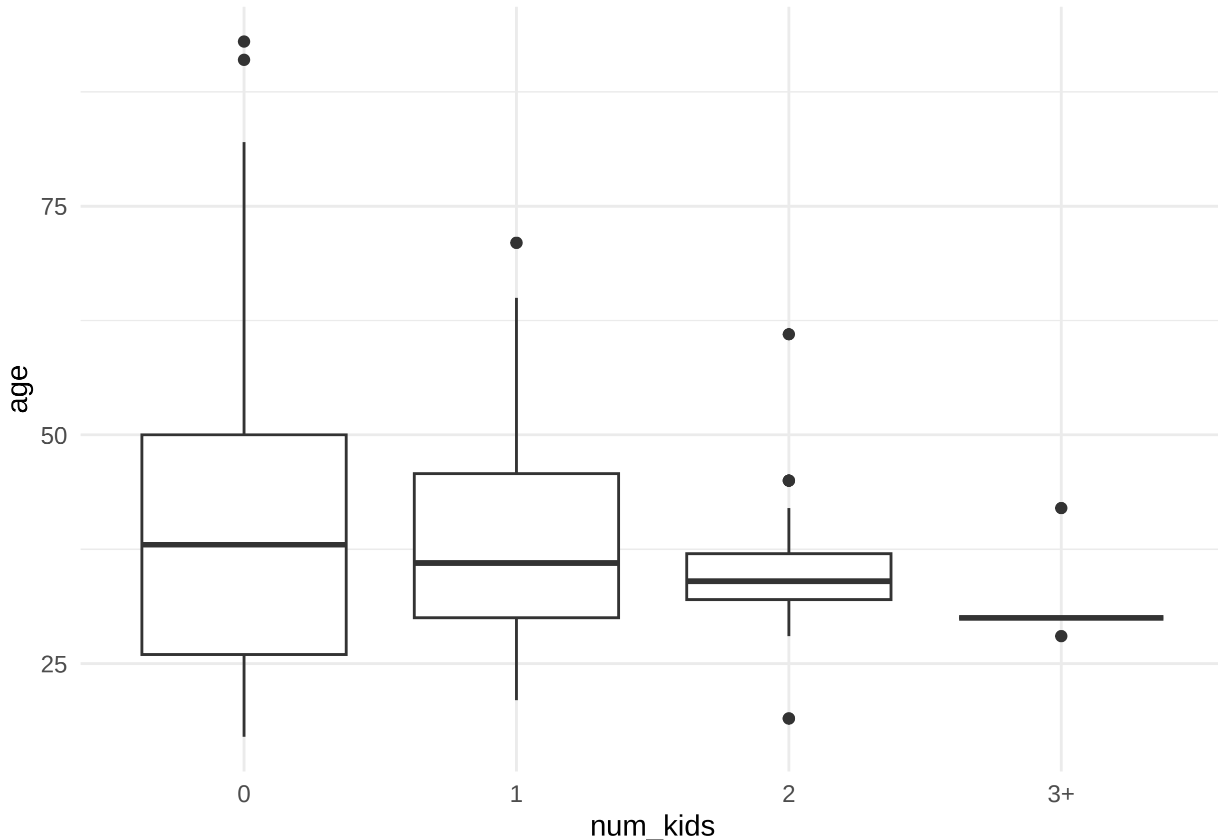

age
75
50
25
0
25
50
75
caff

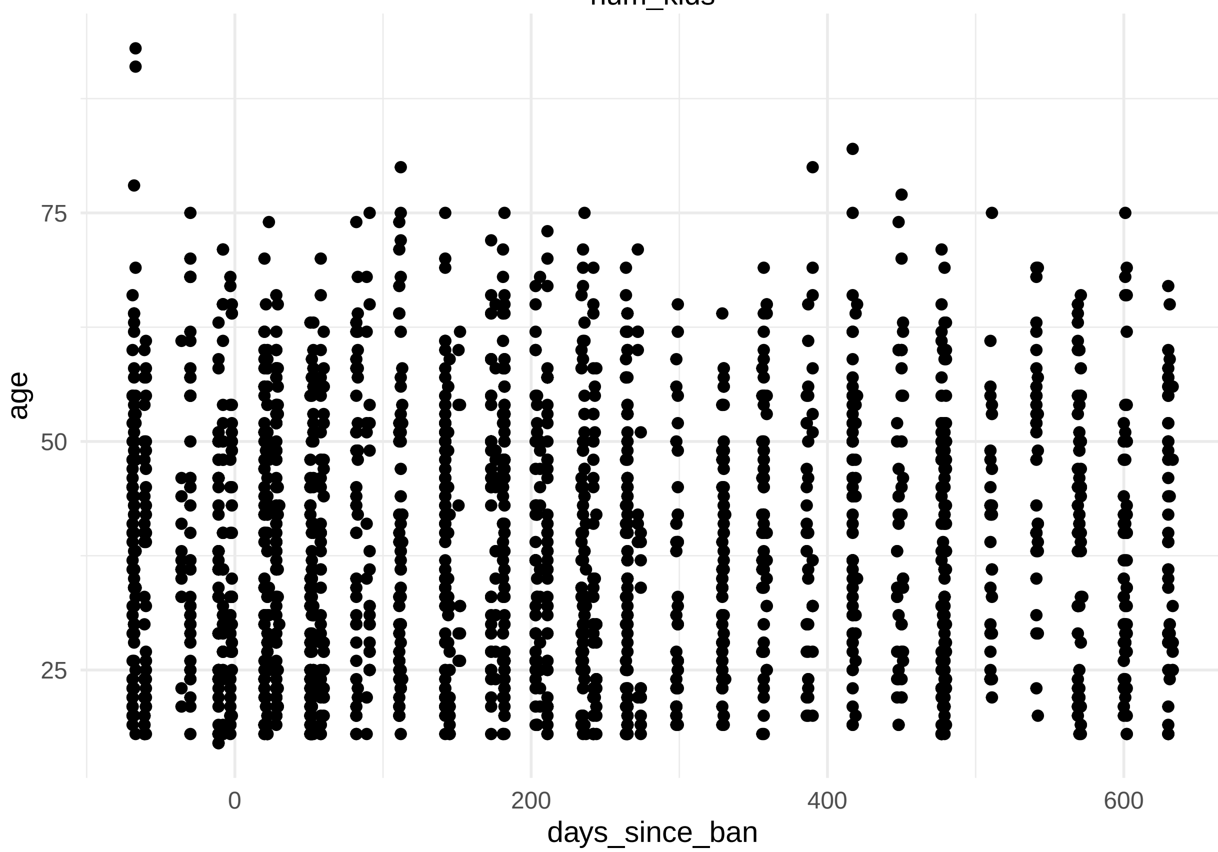


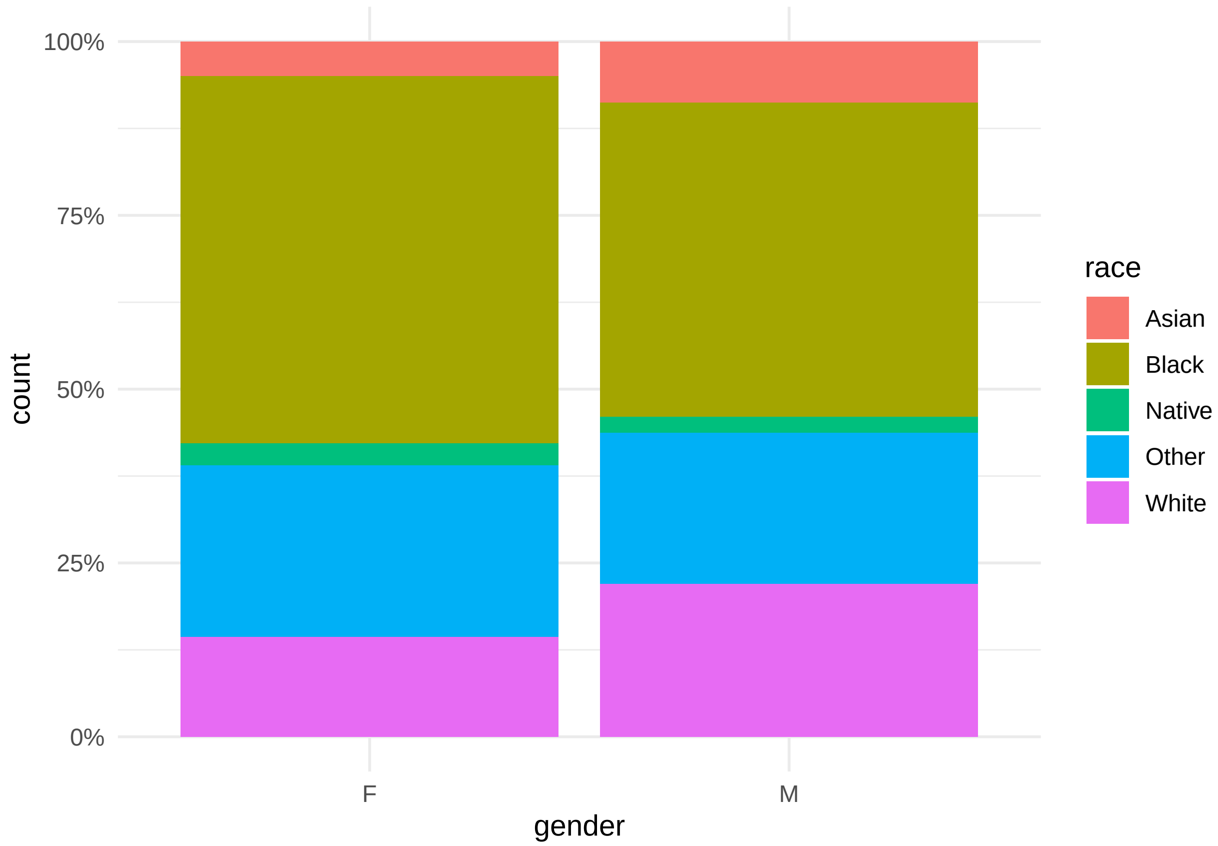
age
75
50
25
1
2
3
round

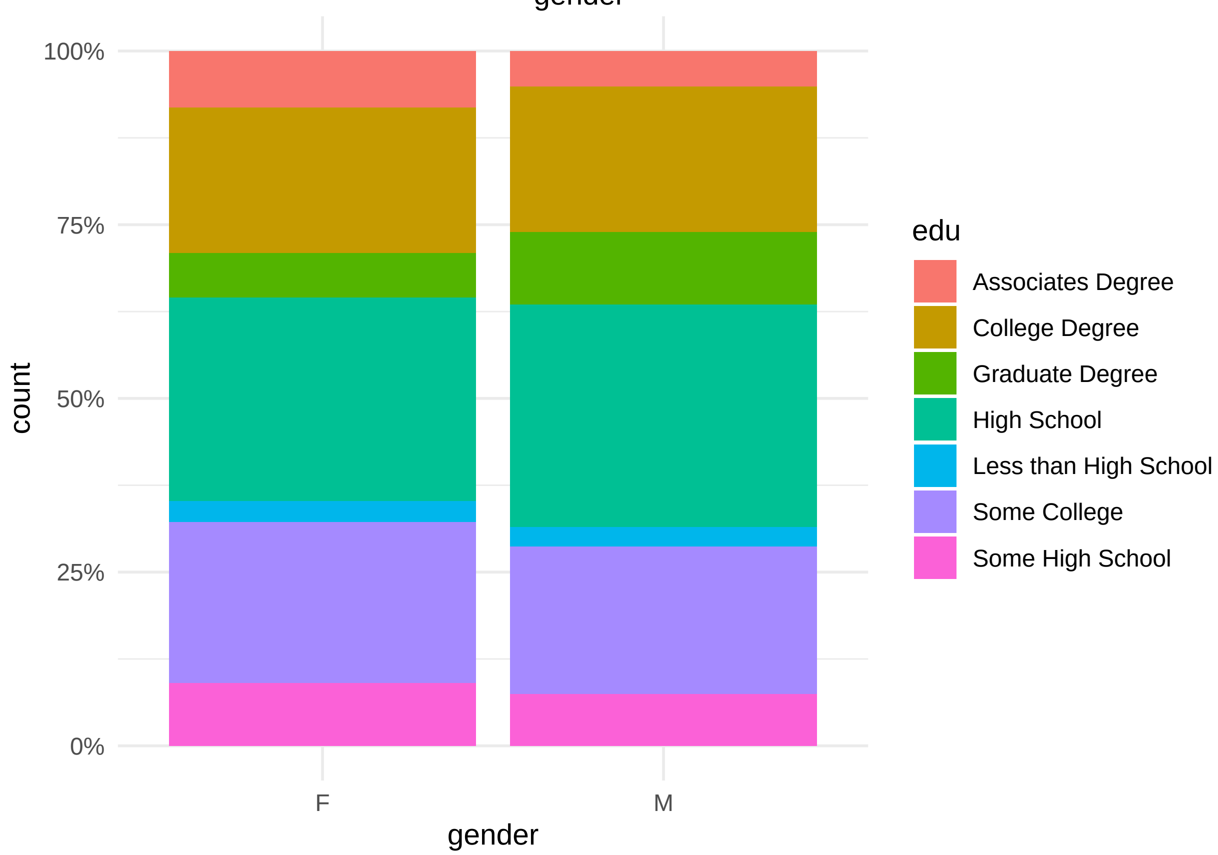


age
75
50
25
0
5
10
15
nsigns_ssb

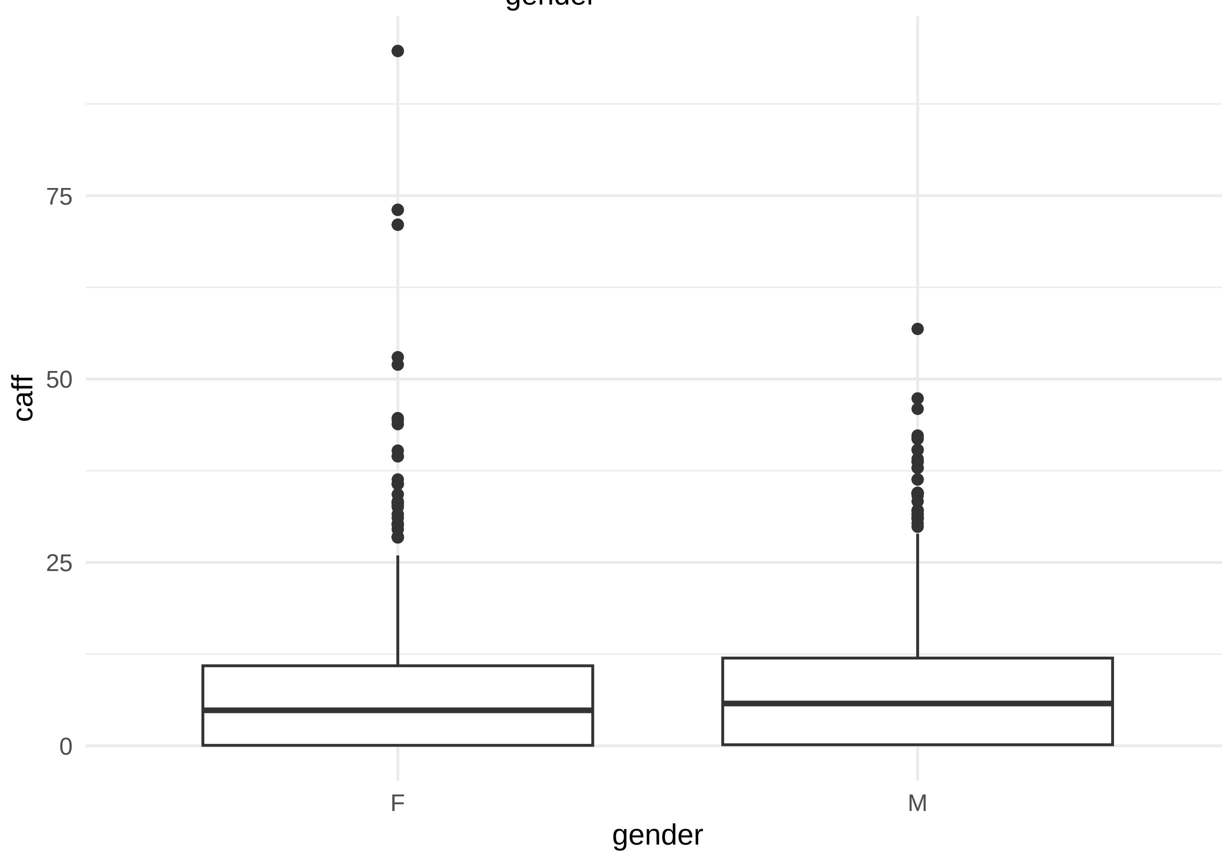

age
75
50
25
0
1
2
3+
num_kids

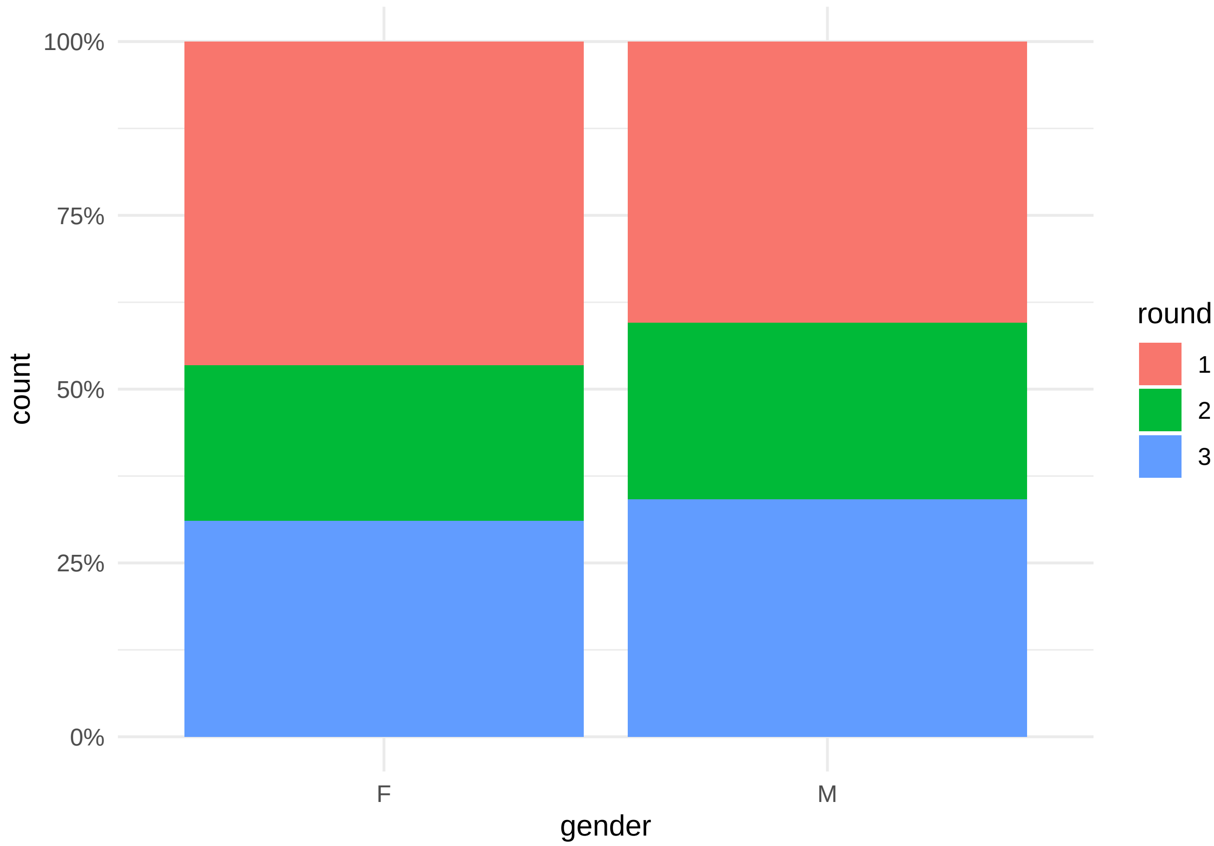

age
75
50
25
0
200
400
600
days_since_ban

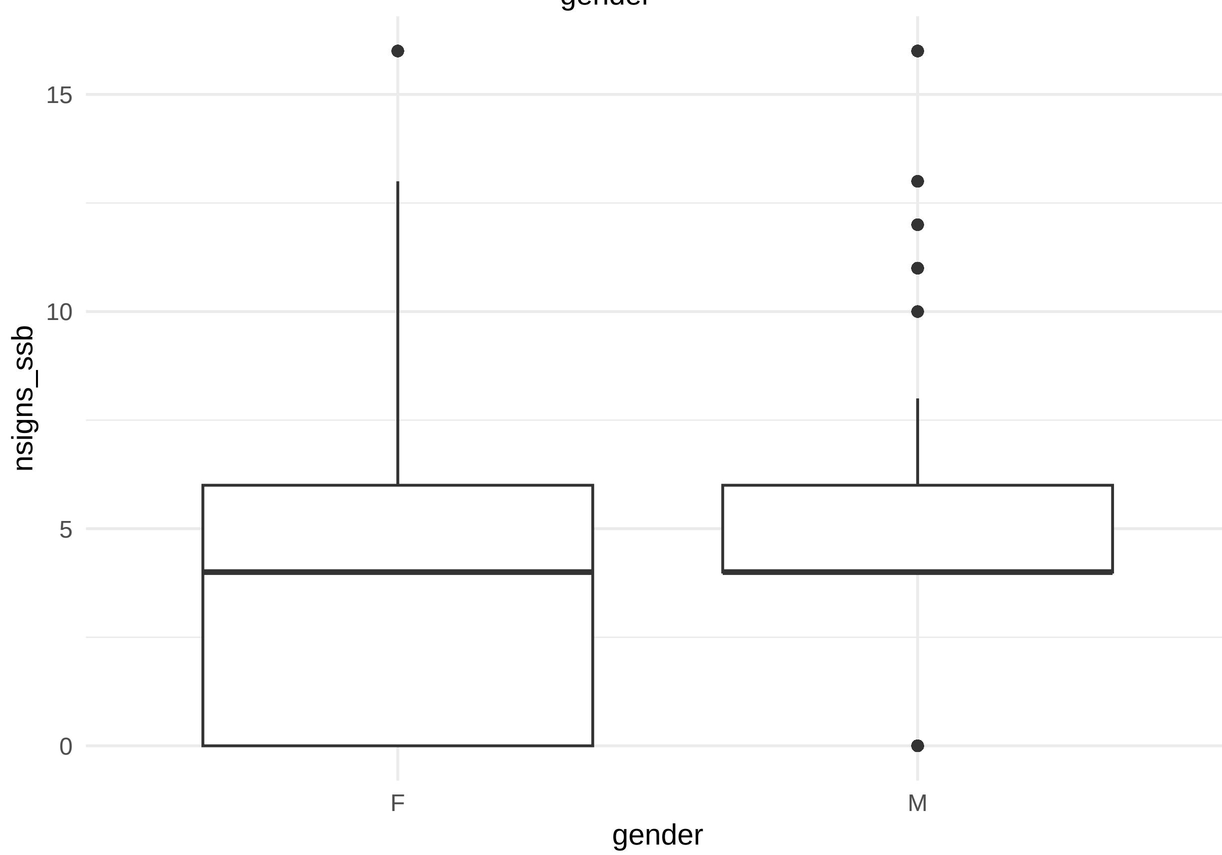

100%
75%
50%
25%
0%
count
F
M
gender
race
Asian
Black
Native
Other
White

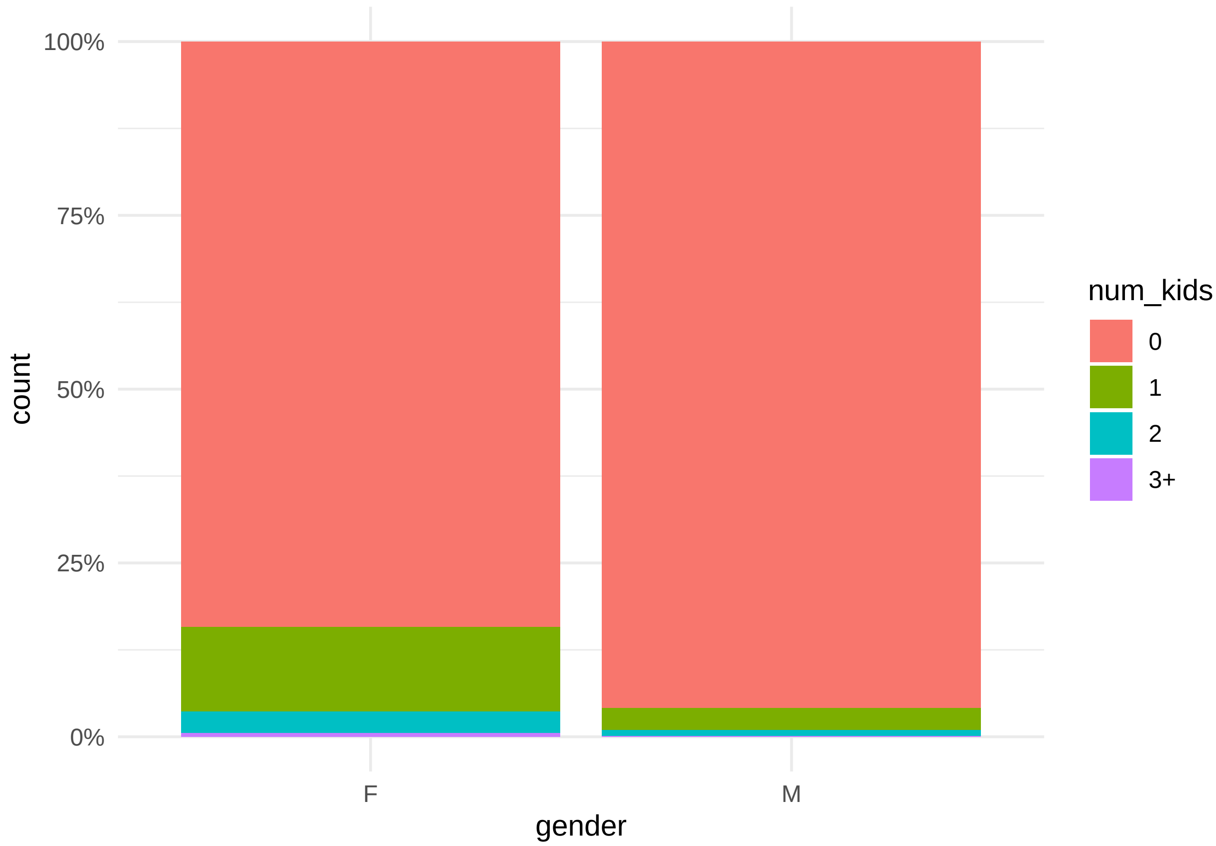

100%
75%
50%
25%
0%
count
F
M
gender
edu
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School

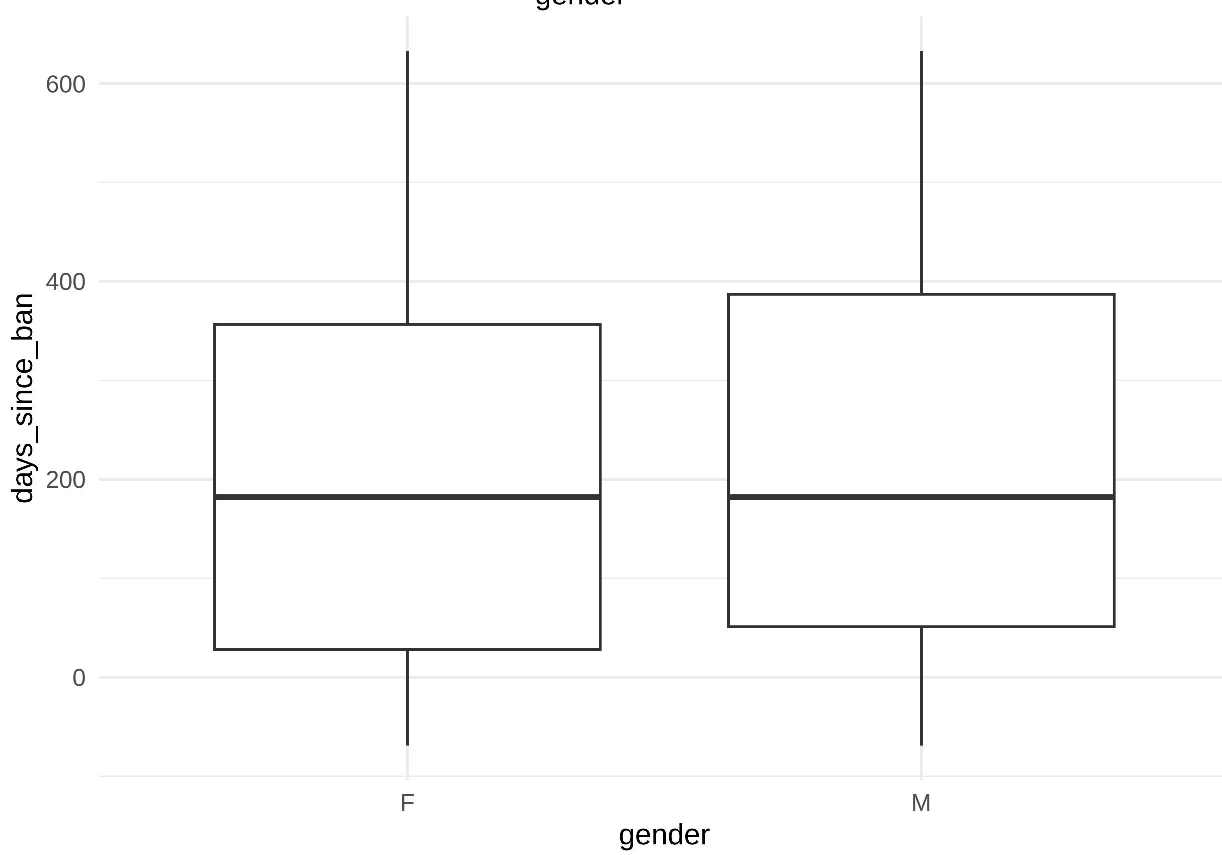

100%
75%
50%
25%
0%
count
F
M
gender
city
New Jersey
New York

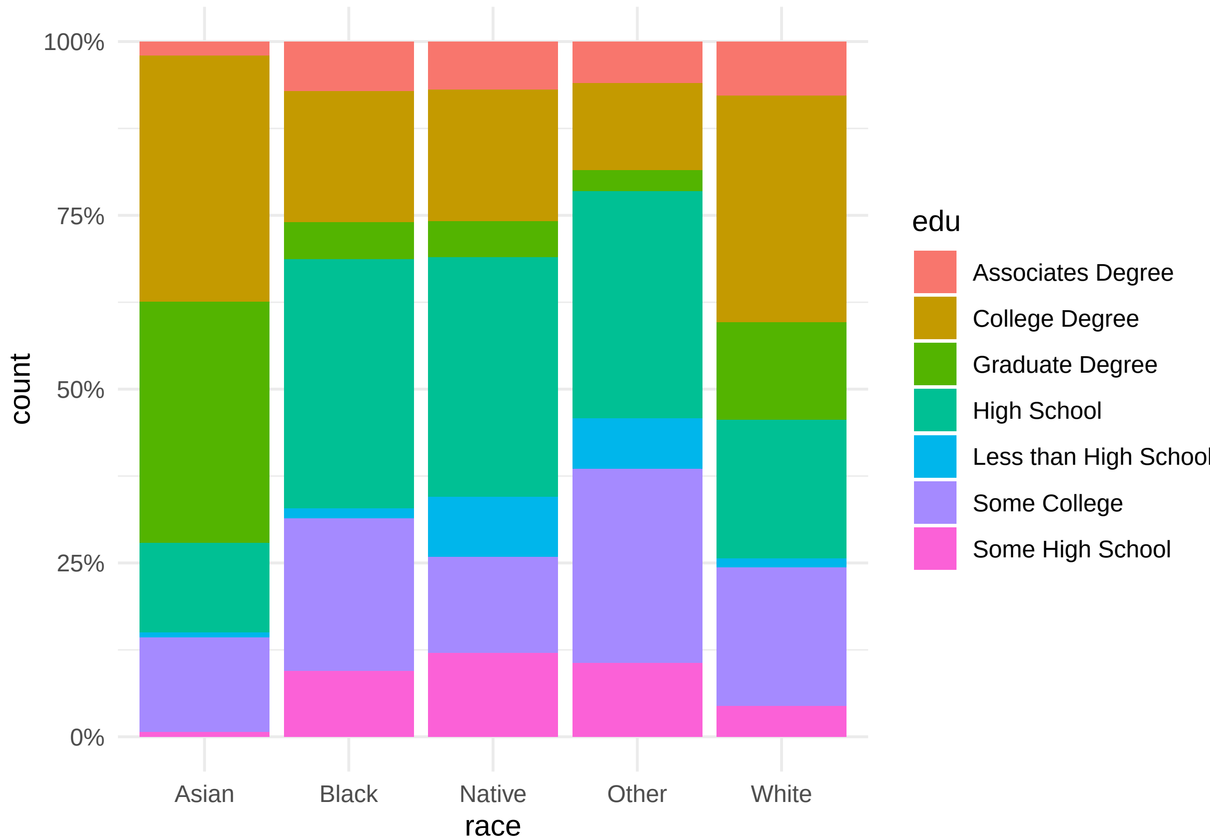

75
50
25
0
caff
F
M
gender

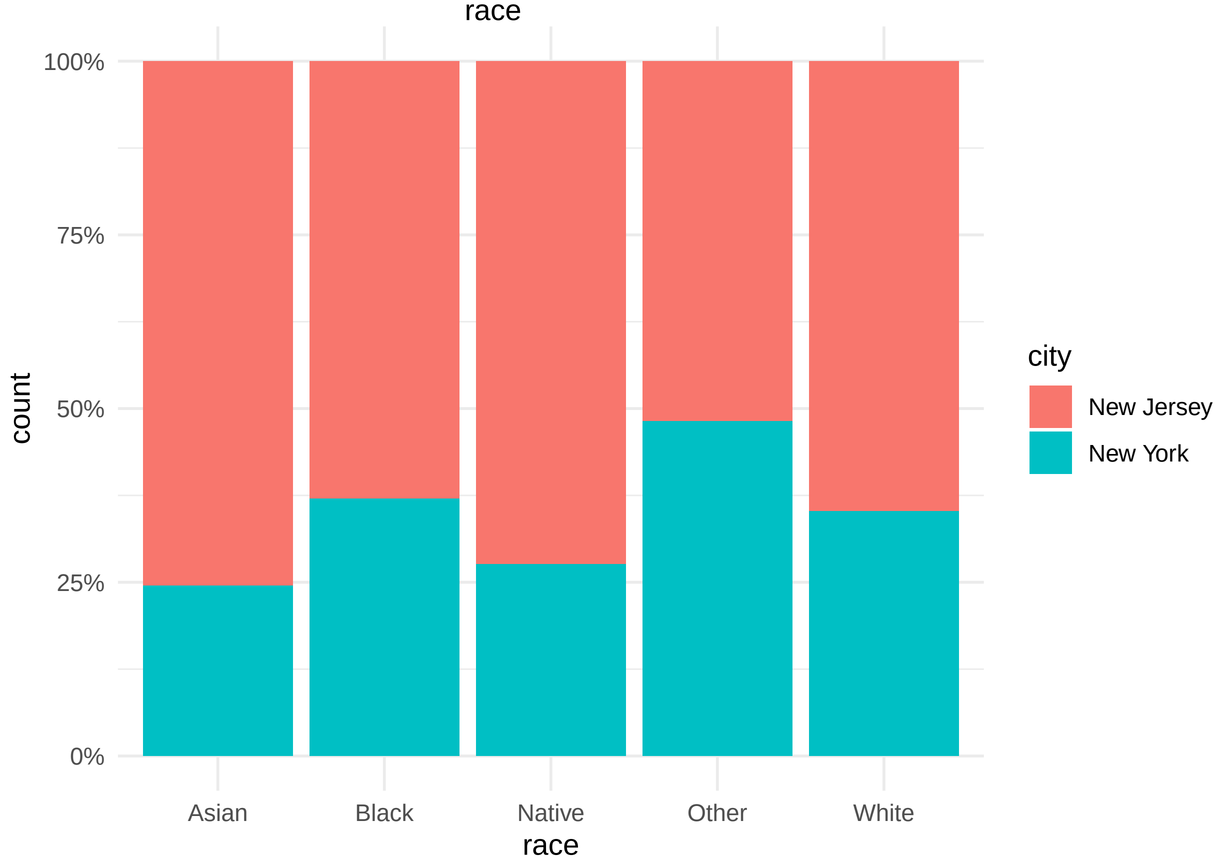

100%
75%
50%
25%
0%
count
F
M
gender
round
1
2
3

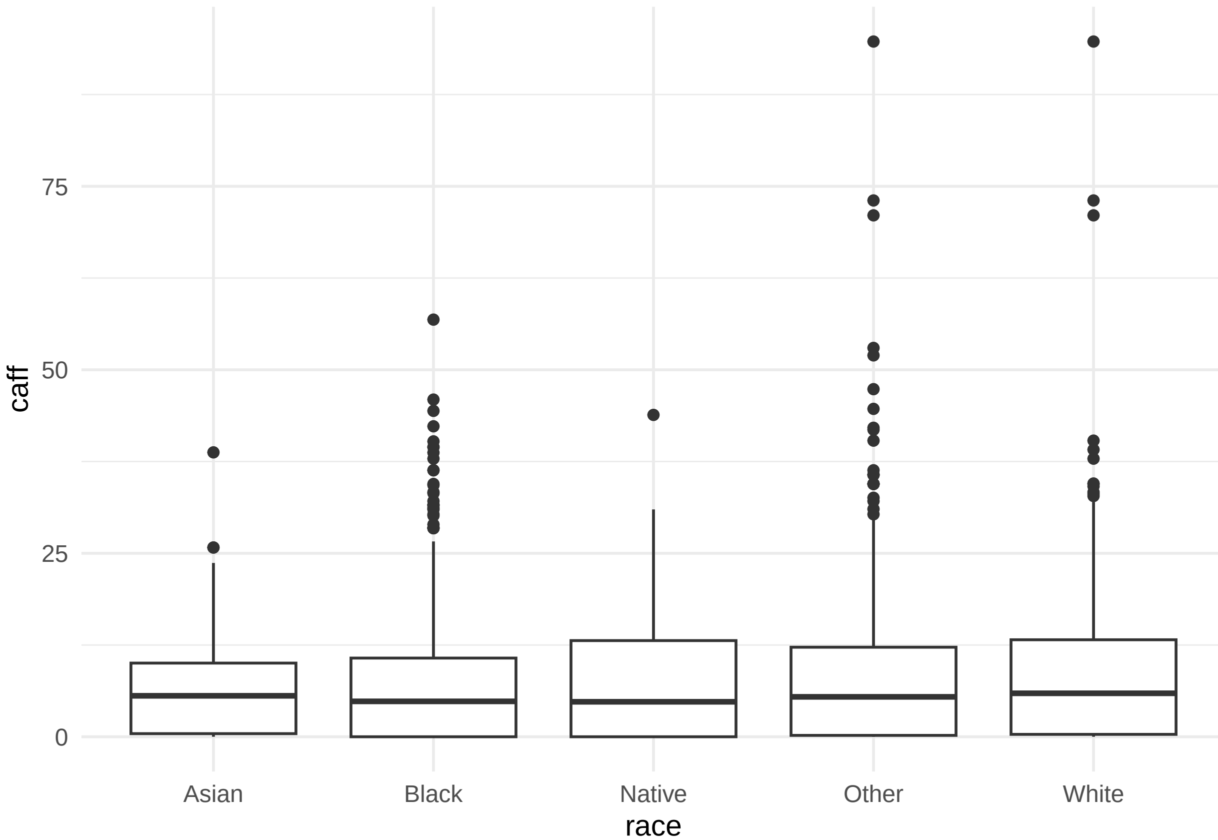

15
10
5
0
nsigns_ssb
F
M
gender


100%
75%
50%
25%
0%
count
F
M
gender
num_kids
0
1
2
3+

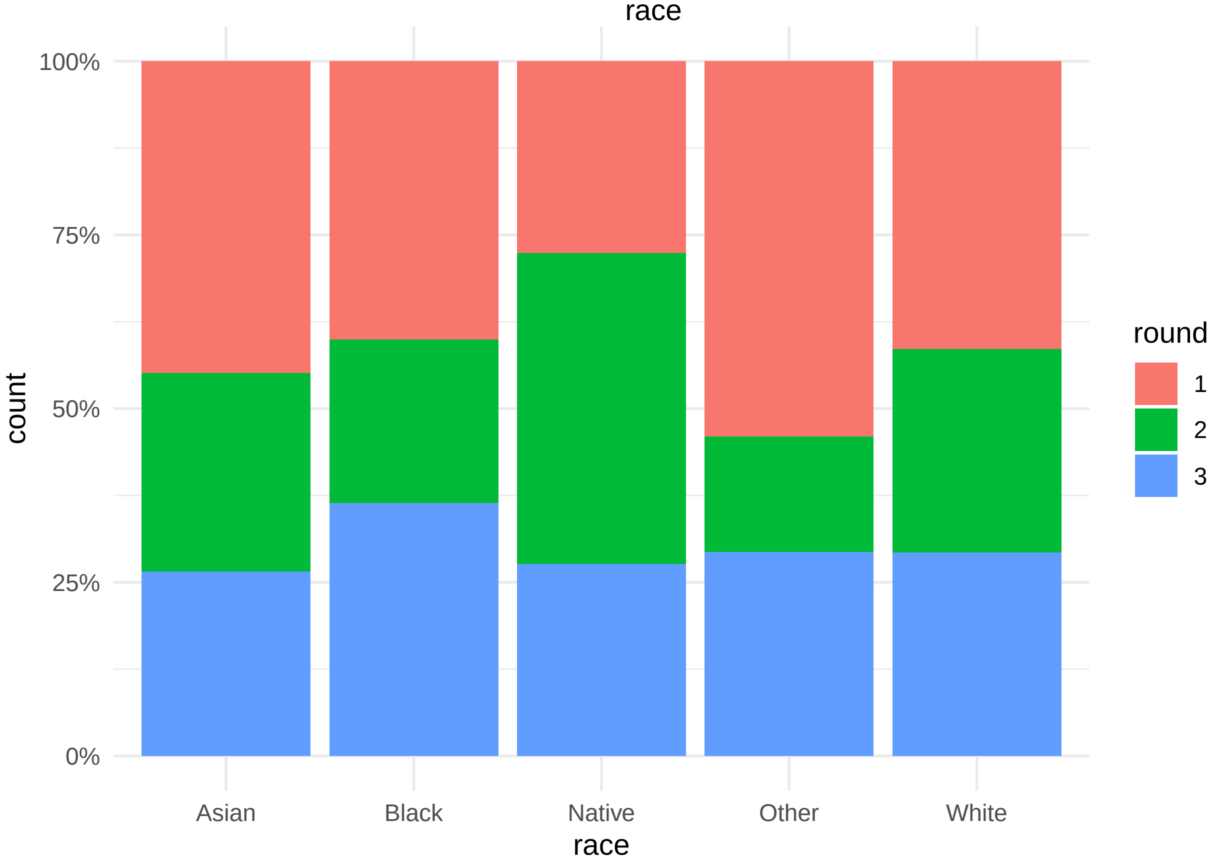

600
400
200
0
days_since_ban
F
M
gender


100%
75%
50%
25%
0%
count
Asian
Black
Native
Other
White
race
edu
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School

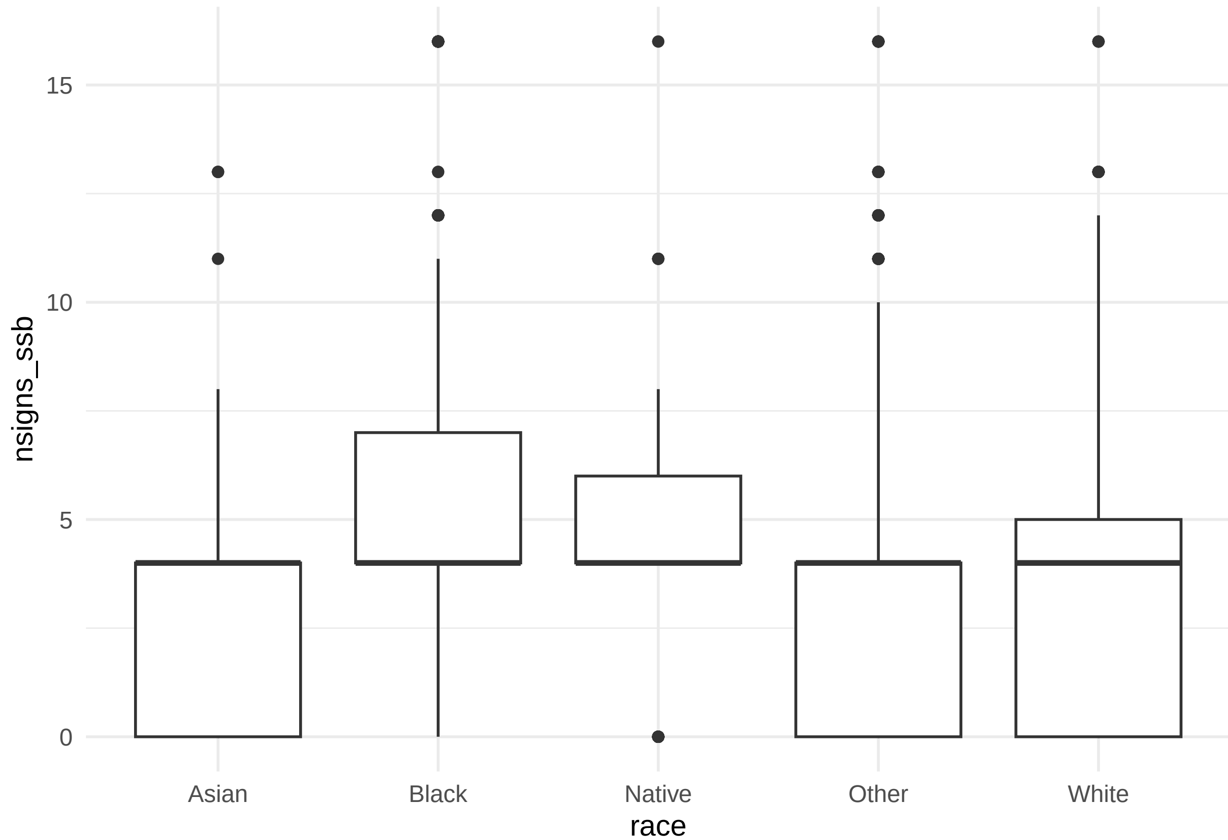

100%
75%
50%
25%
0%
count
Asian
Black
Native
Other
White
race
city
New Jersey
New York

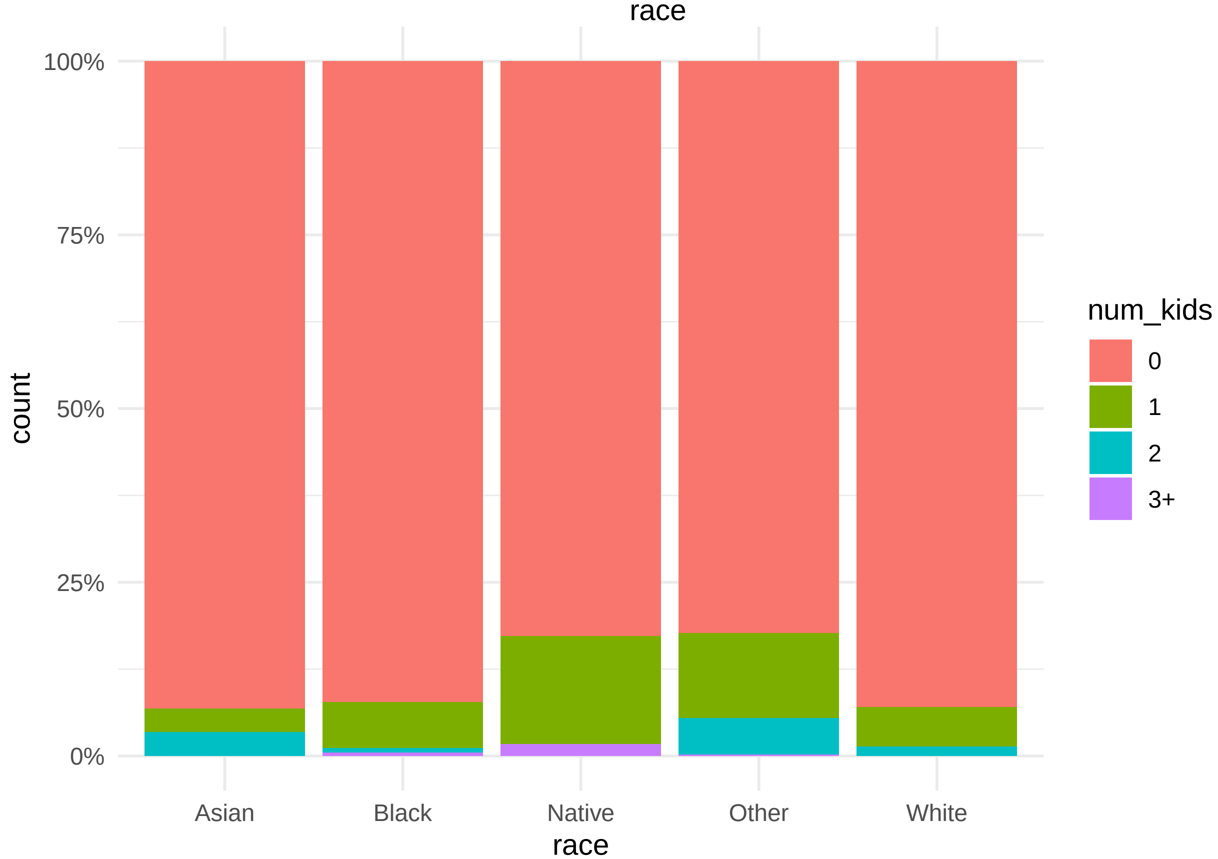


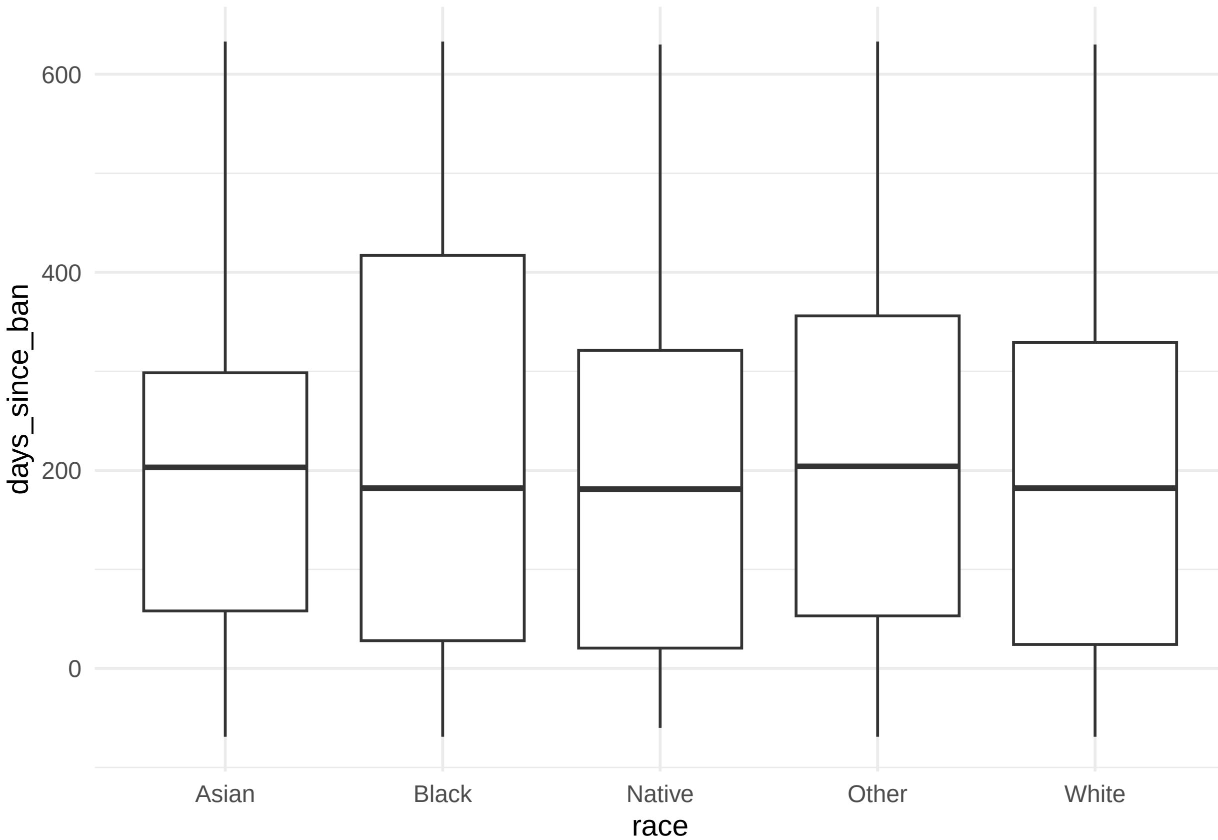
caff
75
50
25
0
Asian
Black
Native
Other
White
race

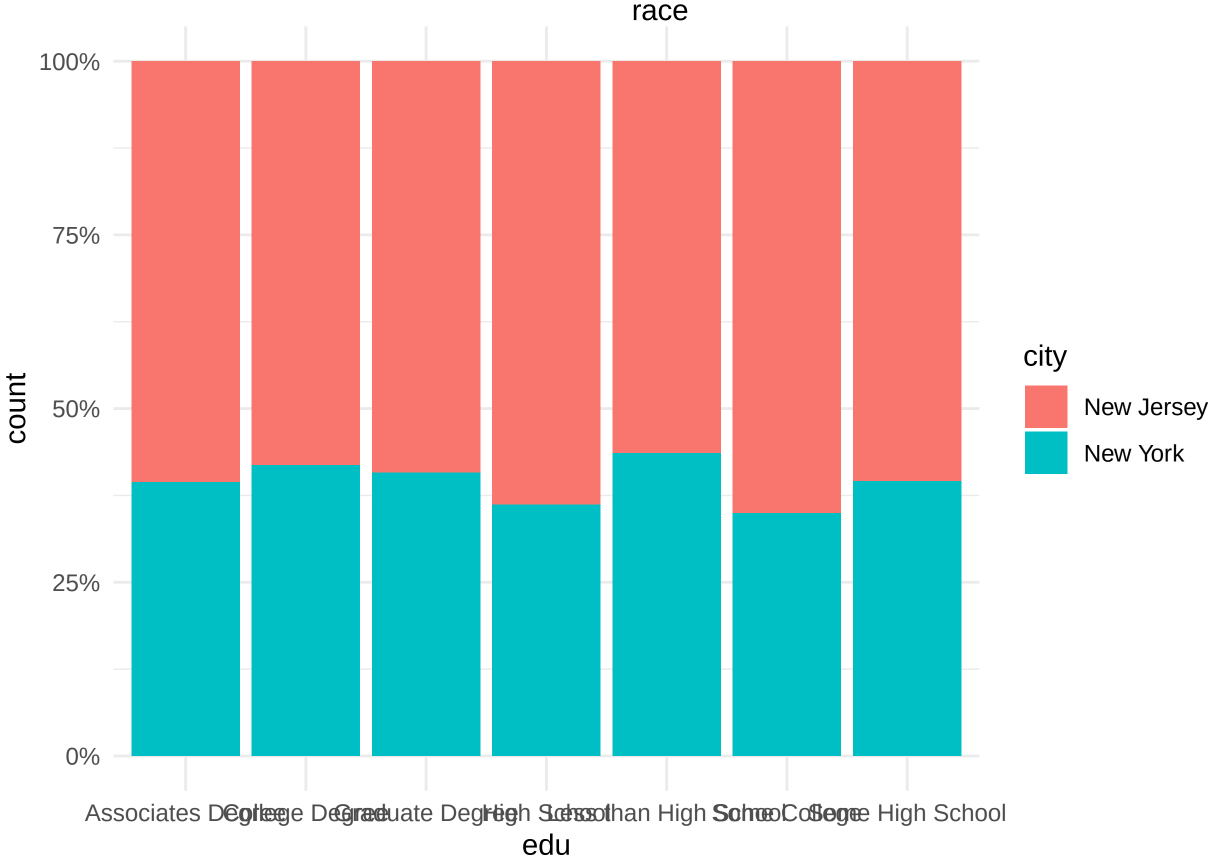


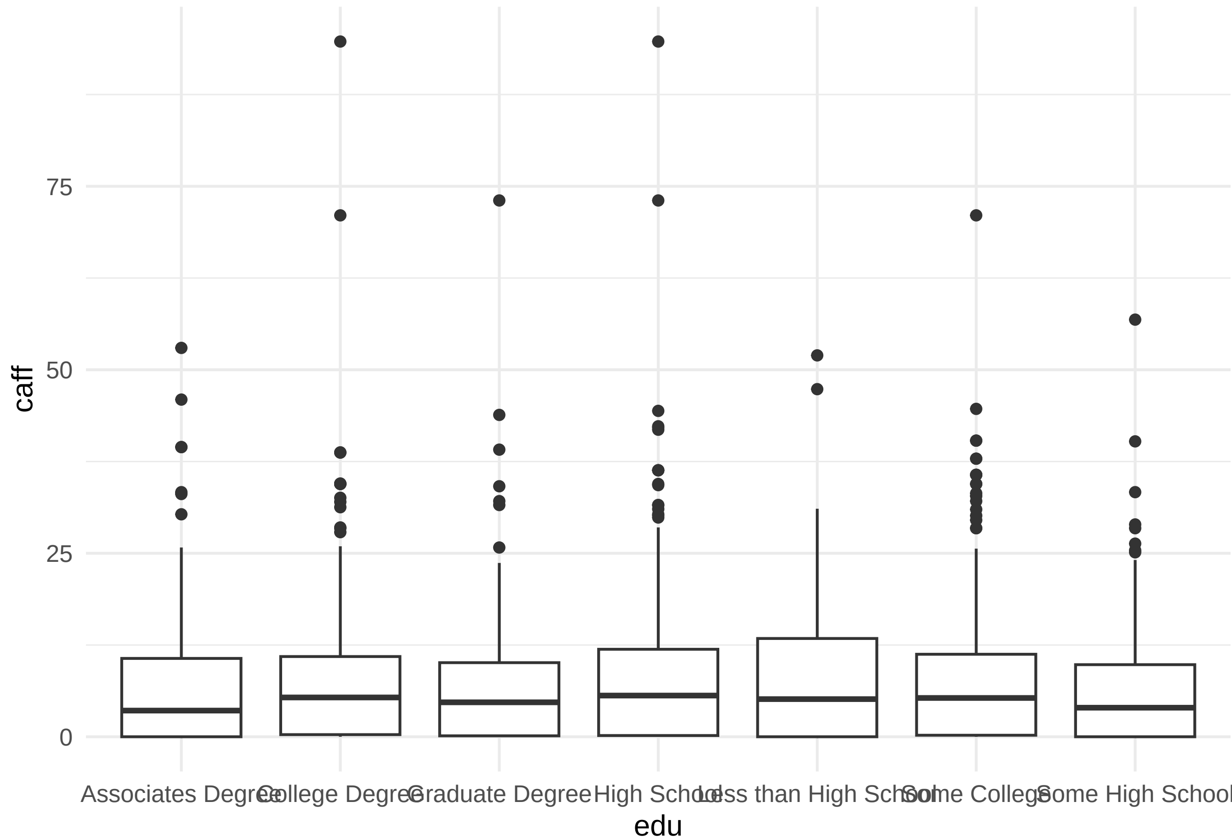
count
100%
75%
50%
25%
0%
Asian
Black
Native
Other
White
race
round
1
2
3

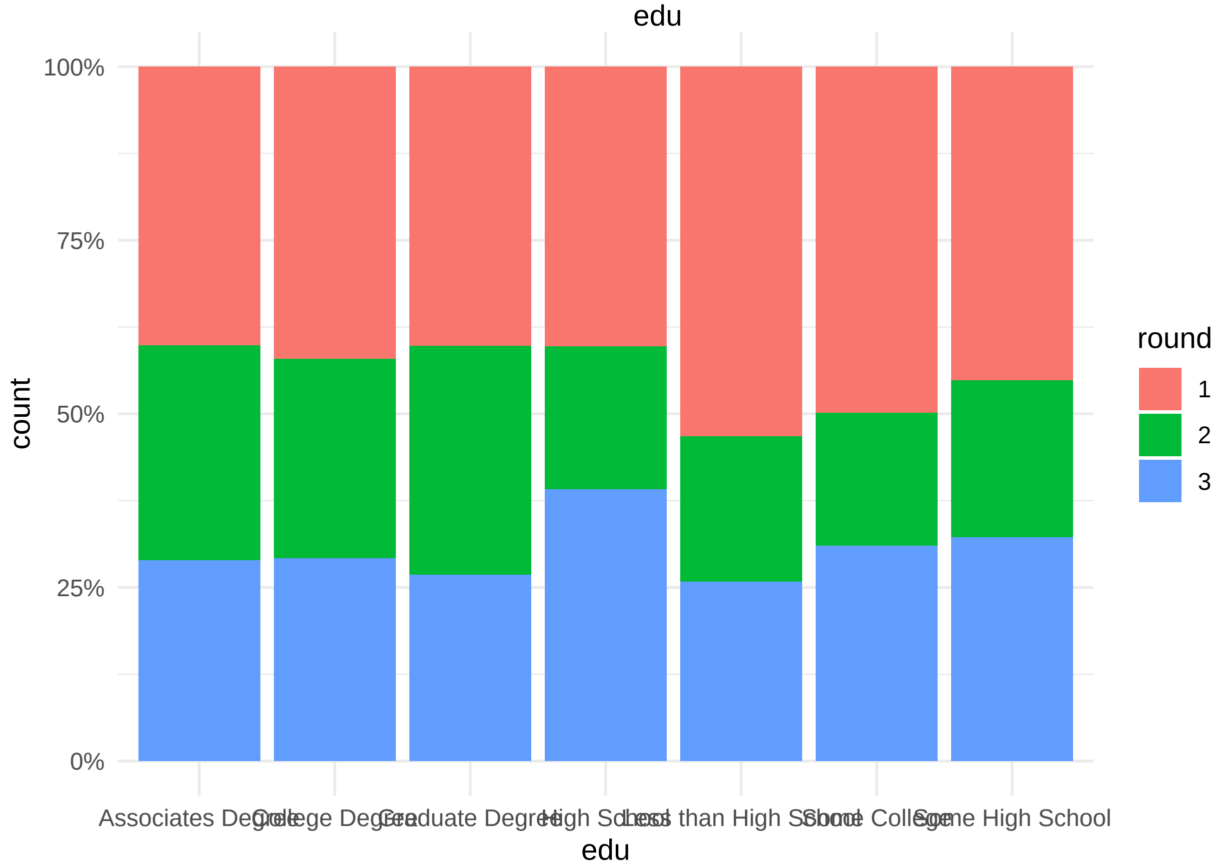

nsigns_ssb
15
10
5
0
Asian
Black
Native
Other
White
race

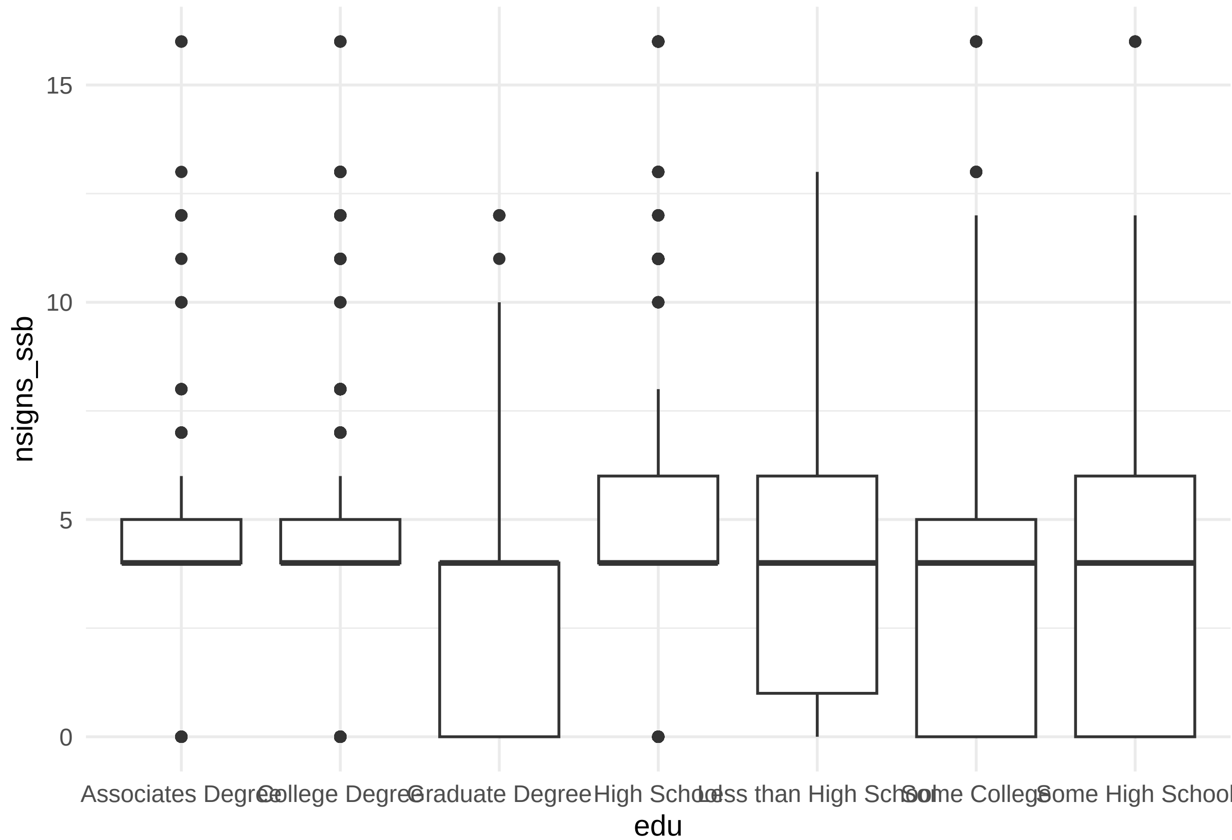

count
100%
75%
50%
25%
0%
Asian
Black
Native
Other
White
race
num_kids
0
1
2
3+

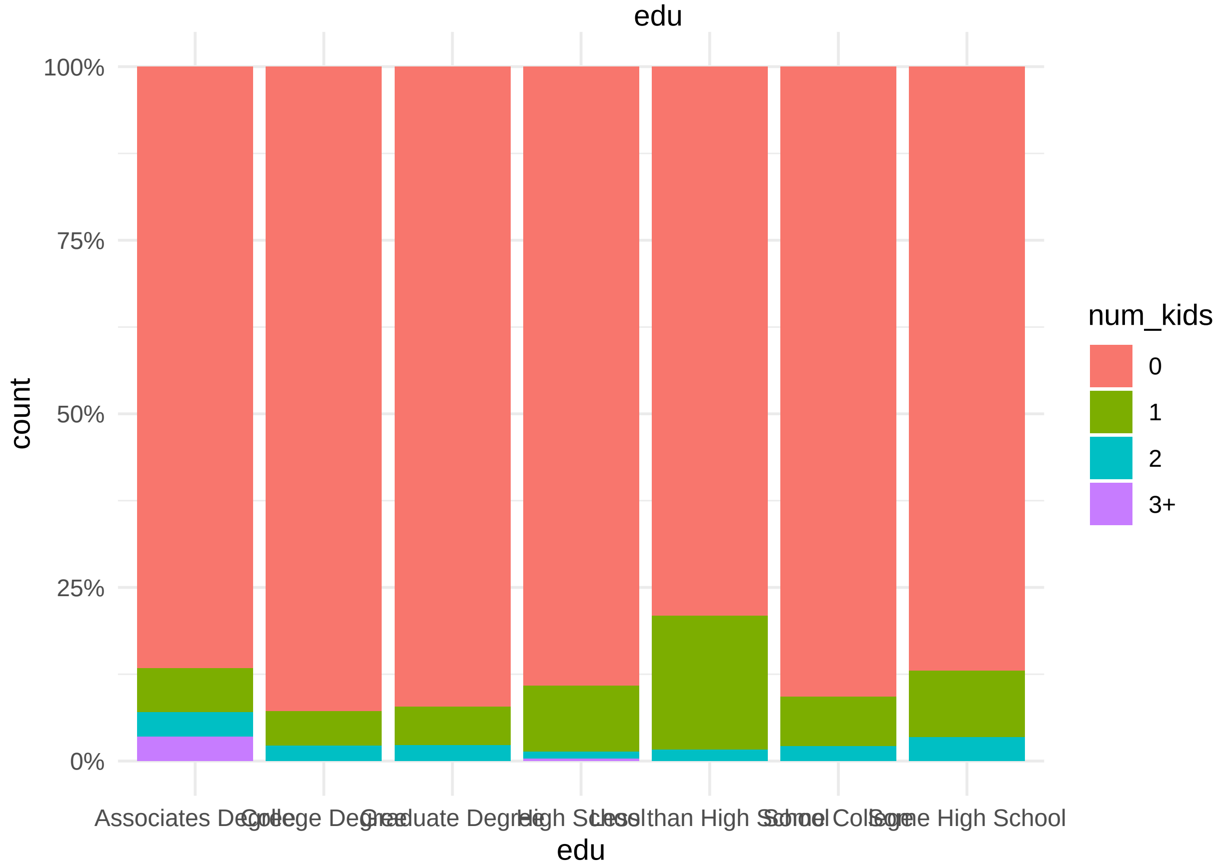

600
400
200
0
days_since_ban
Asian
Black
Native
Other
White
race

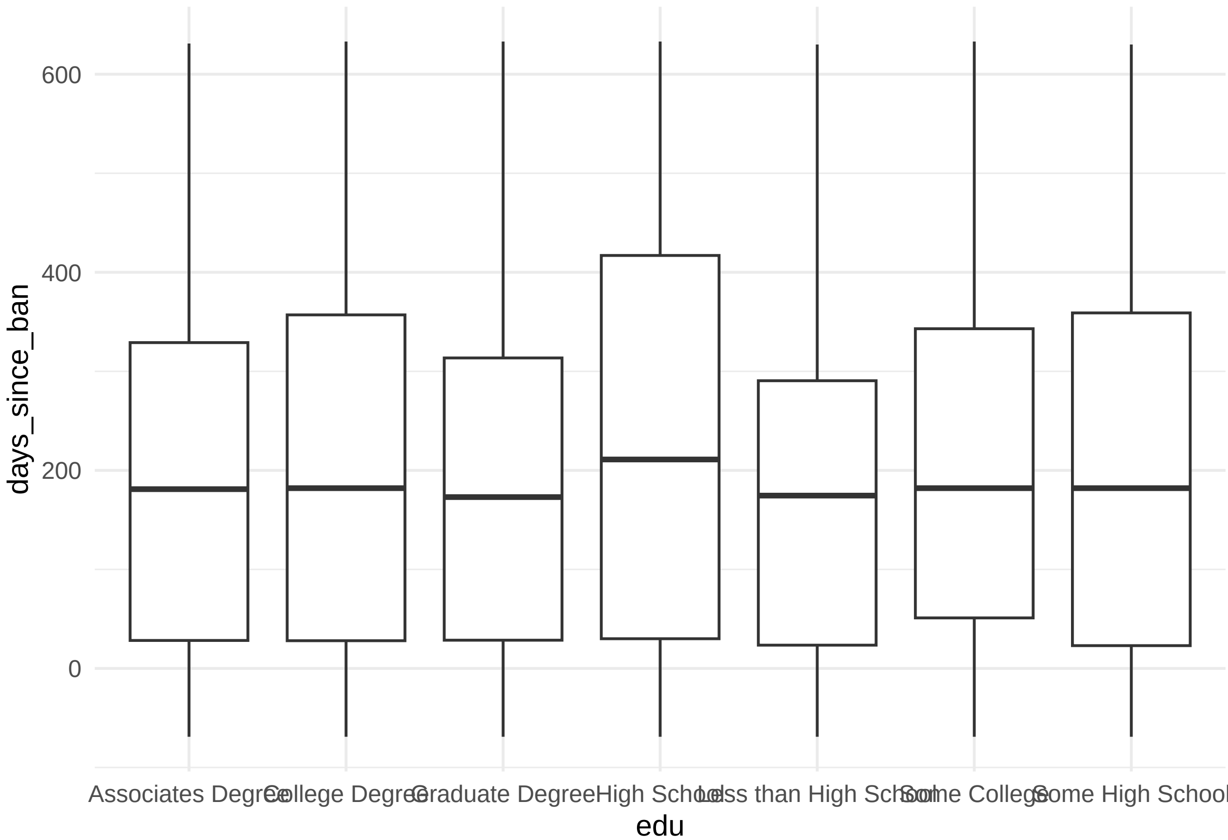

100%
75%
50%
25%
0%
count
edu
city
New Jersey
New York

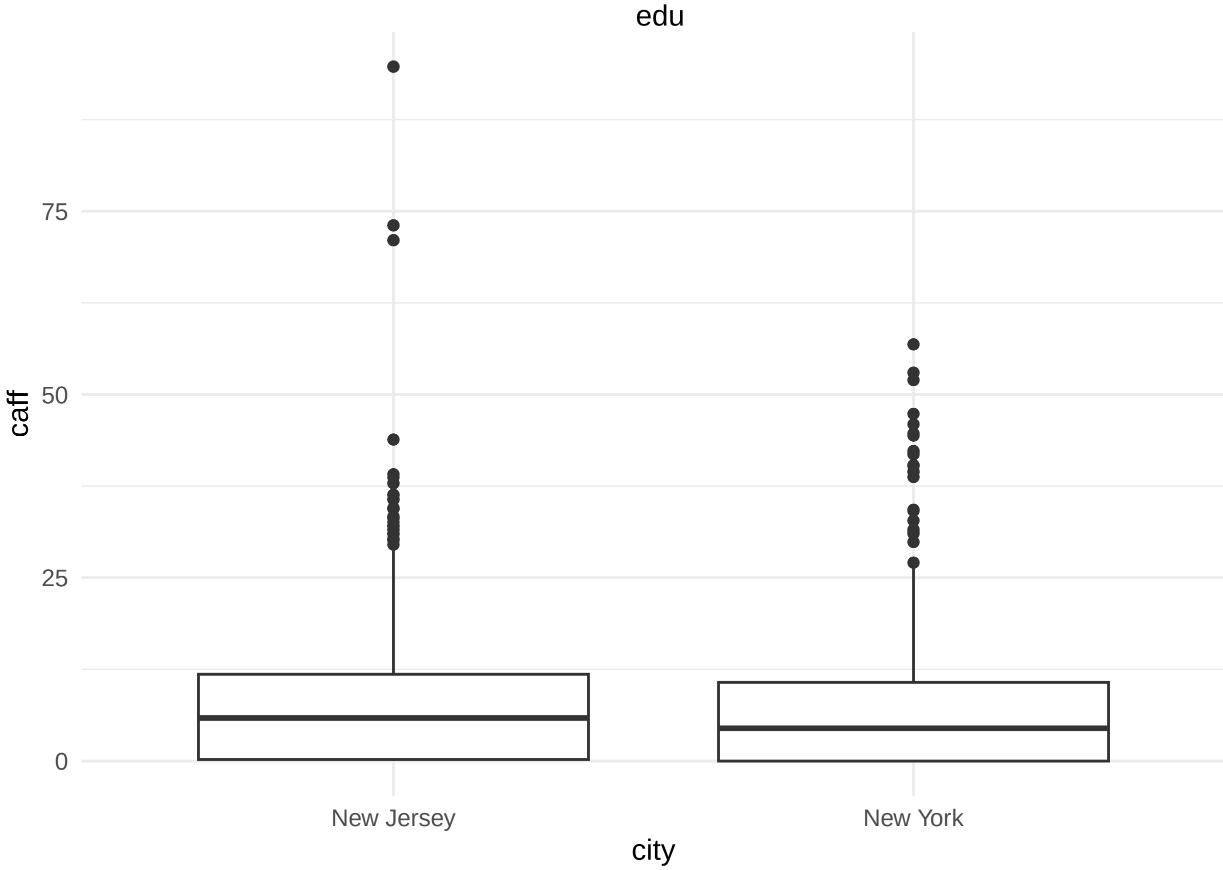

caff
75
50
25
0
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu

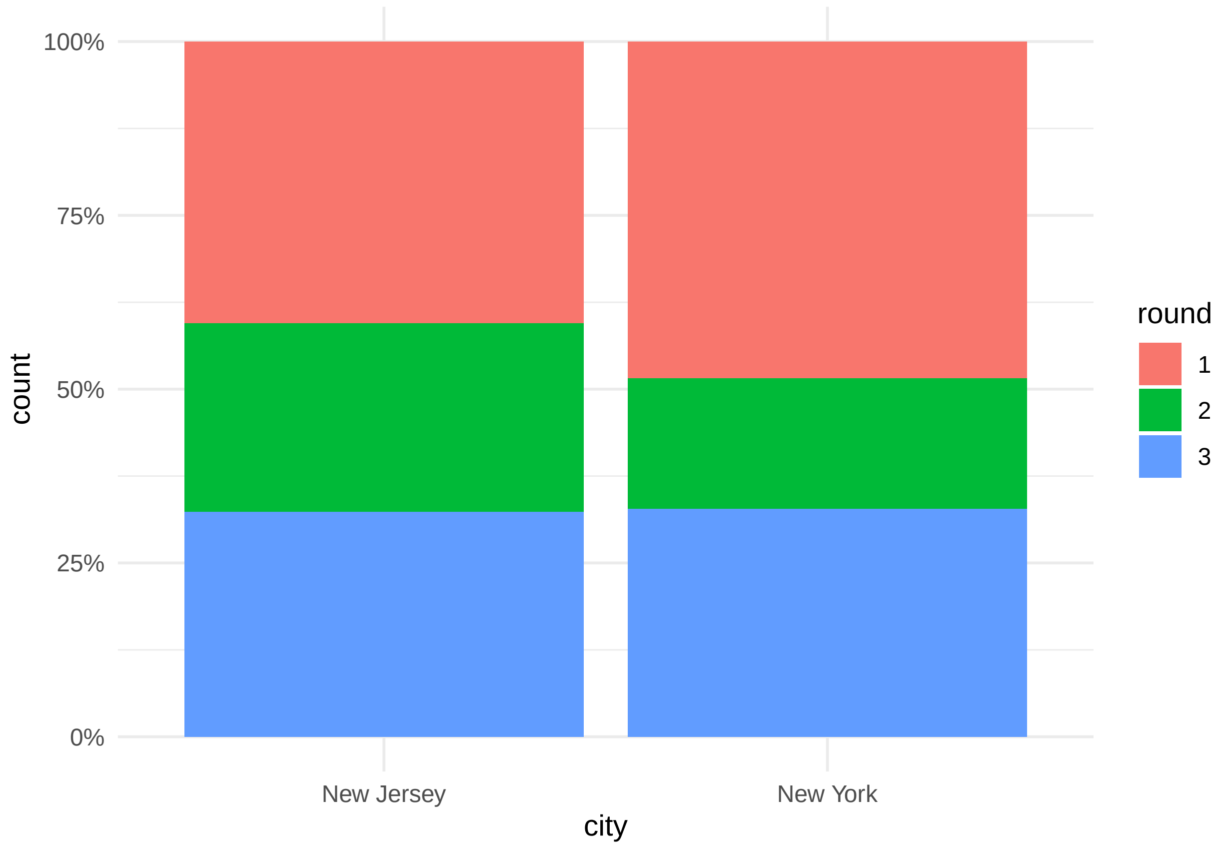

100%
75%
50%
25%
0%
count
round
1
2
3
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu

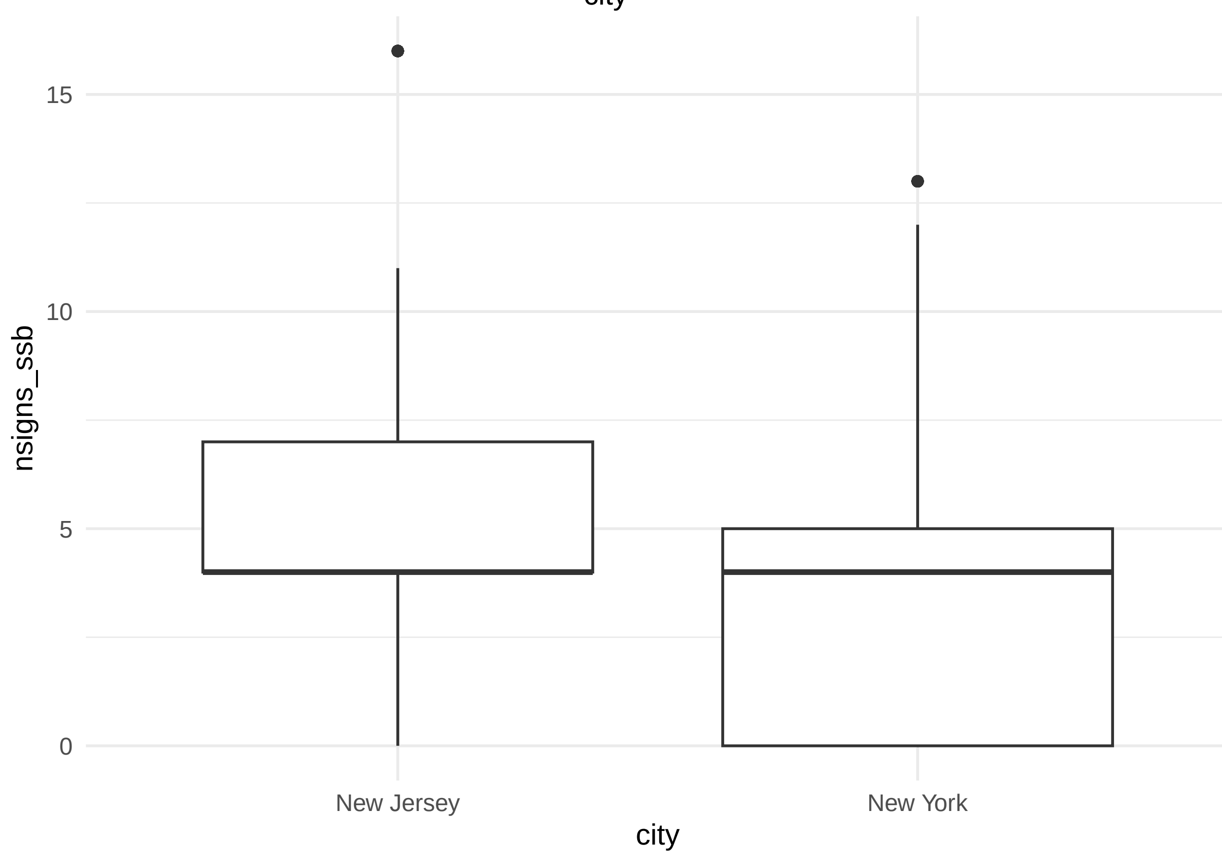

15
10
5
0
nsigns_ssb
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu

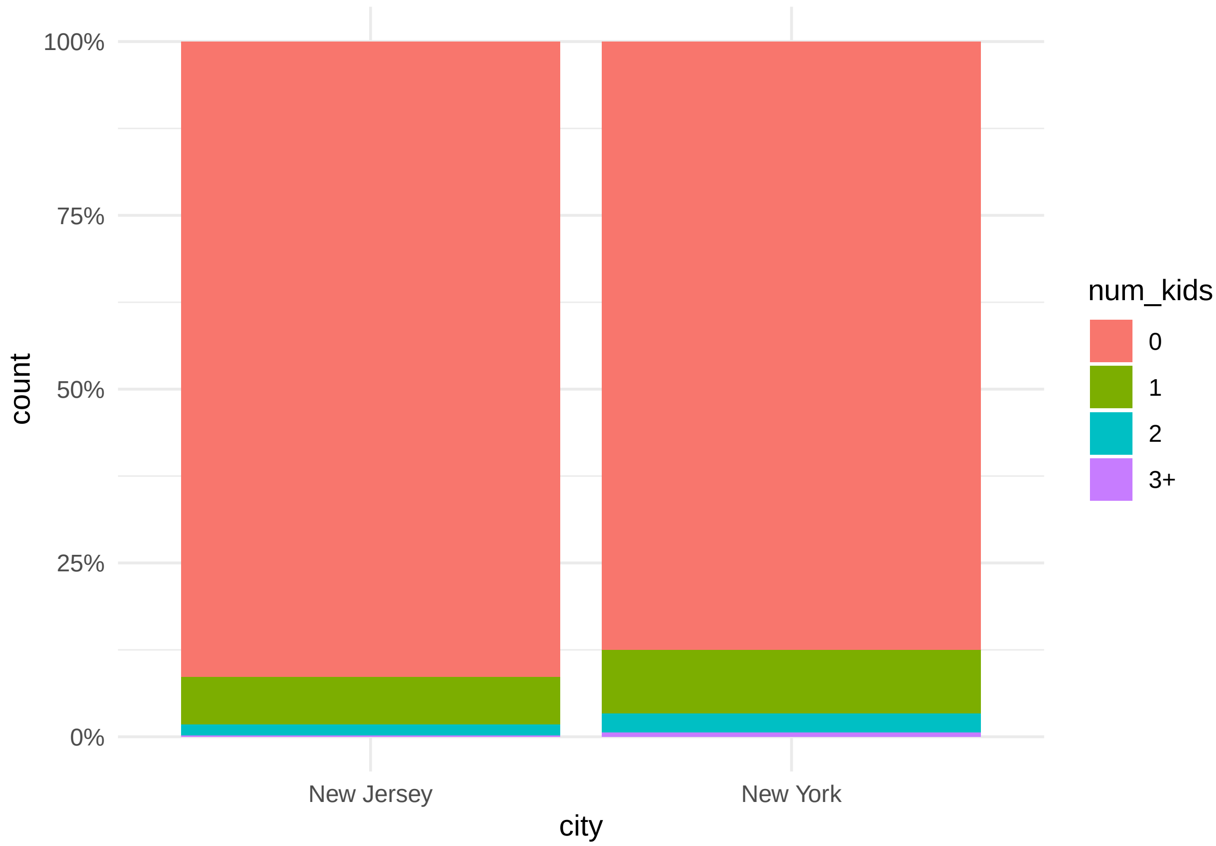

100%
75%
50%
25%
0%
count
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu
num_kids
0
1
2
3+

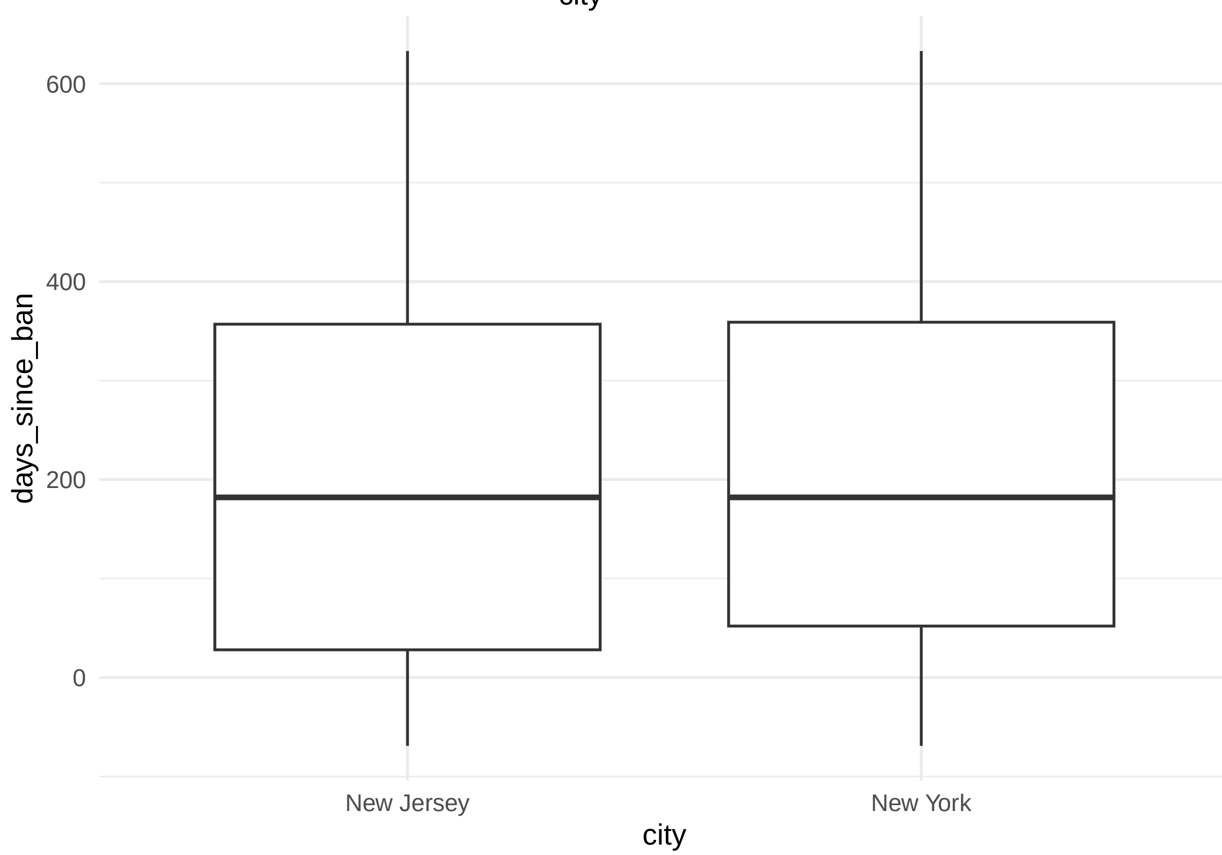

600
400
200
0
days_since_ban
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu

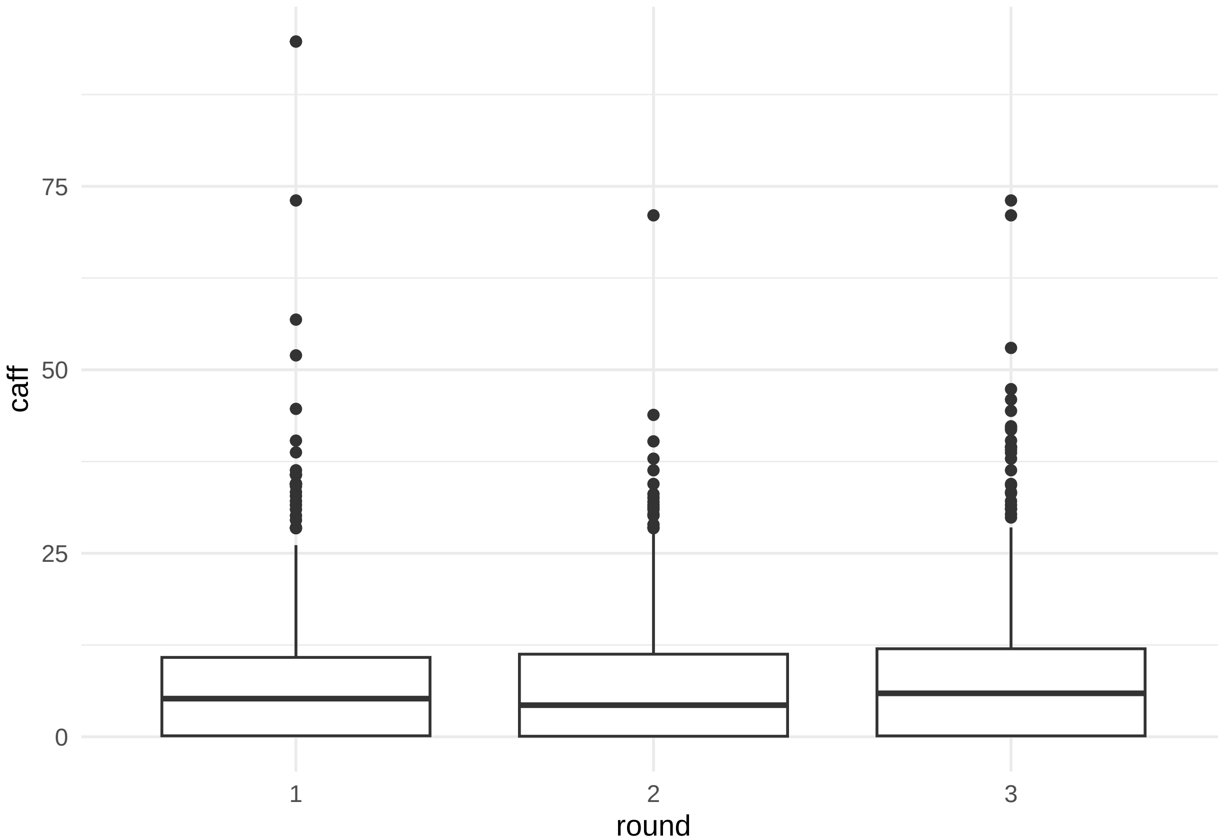

75
50
25
0
caff
New Jersey
New York
city

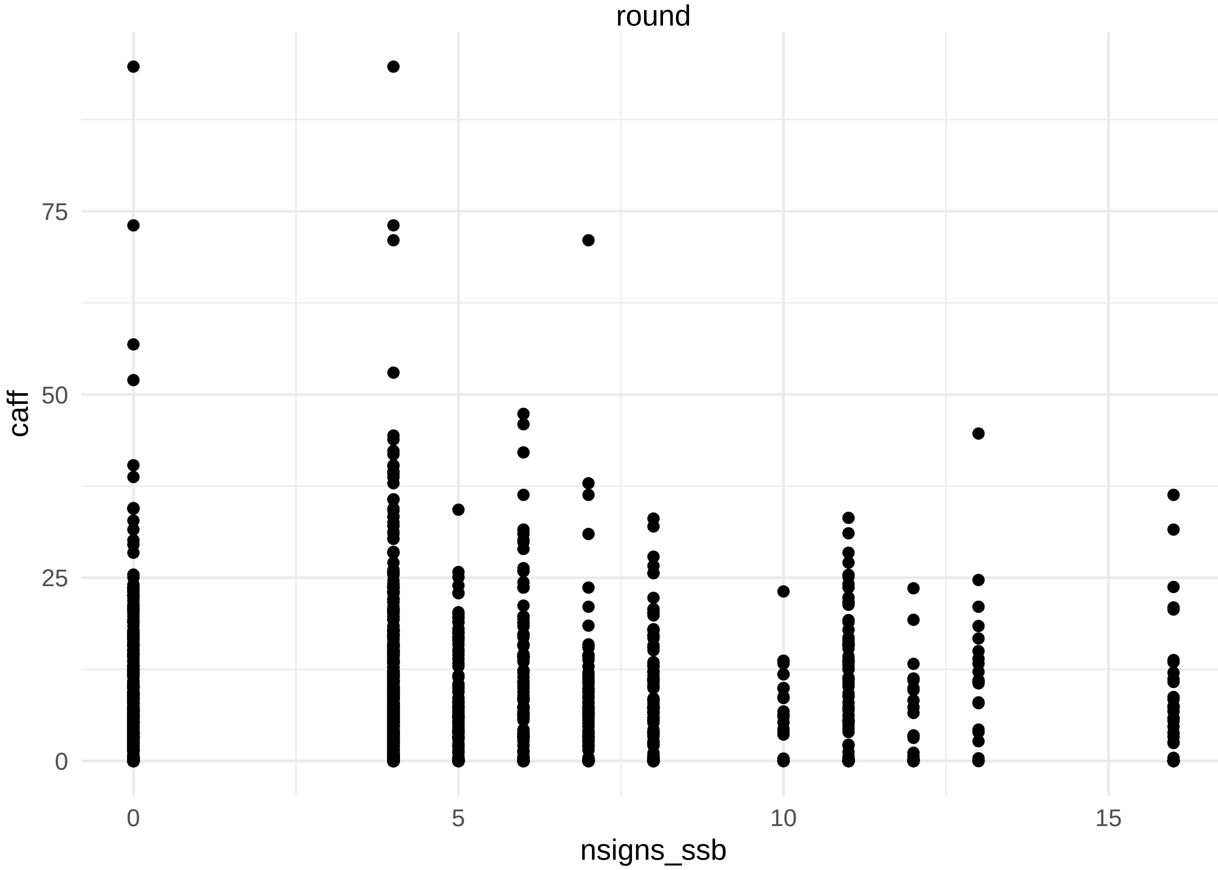

100%
75%
50%
25%
0%
count
round
1
2
3
New Jersey
New York
city

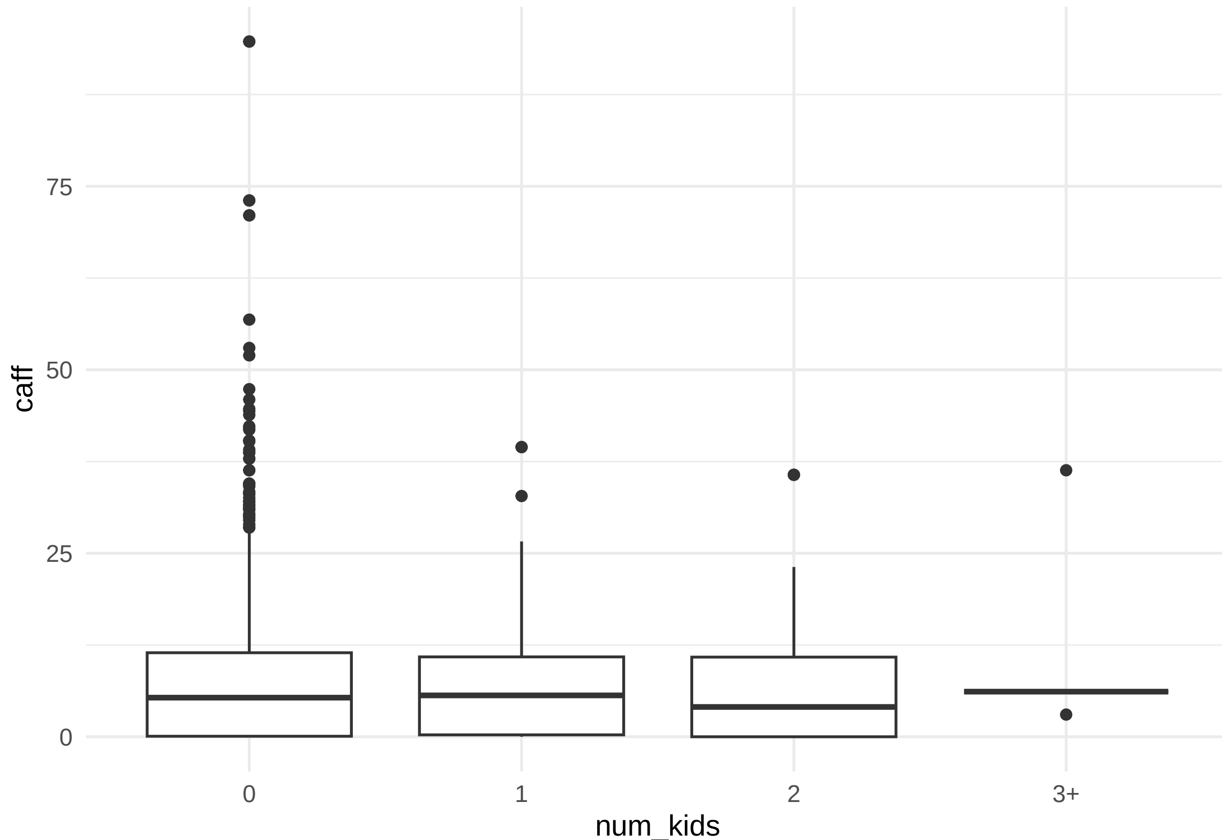

15
10
5
0
nsigns_ssb
New Jersey
New York
city

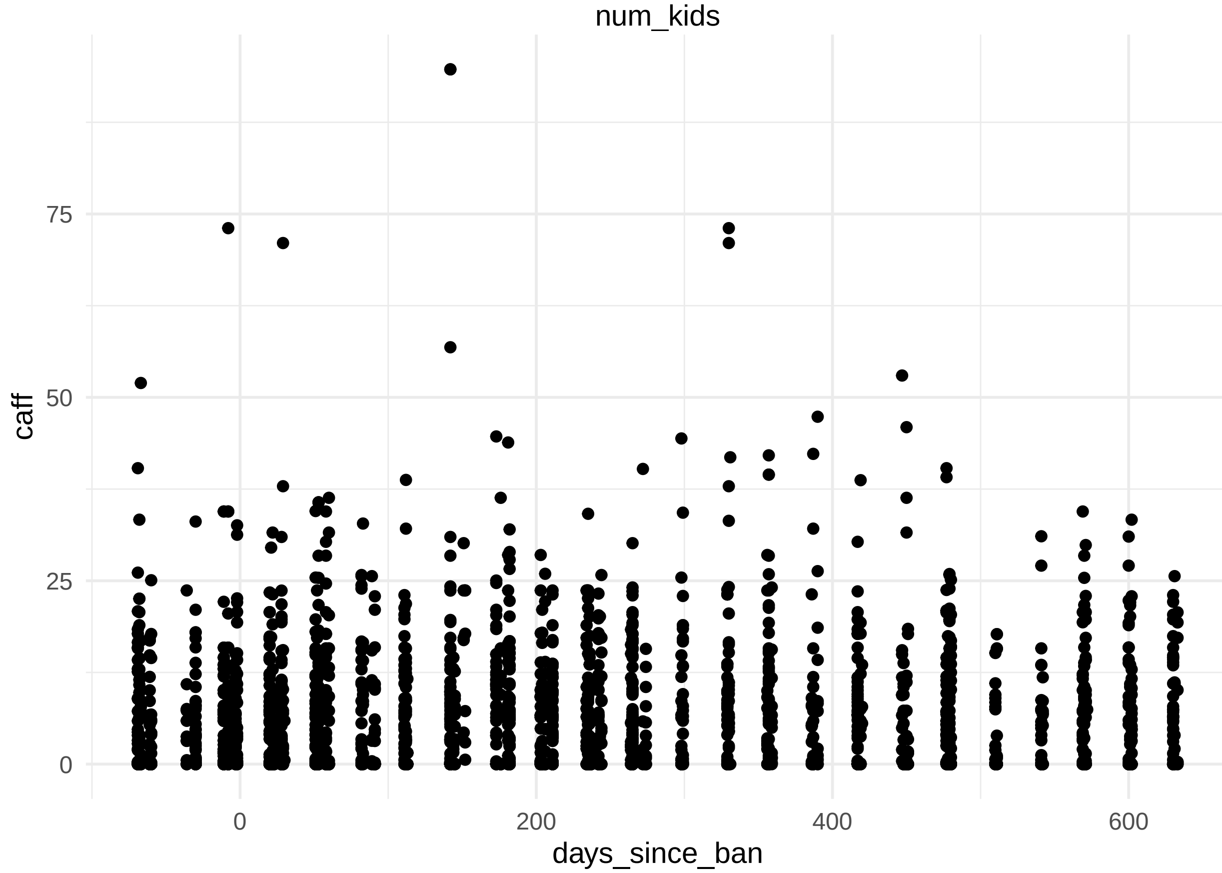

100%
75%
50%
25%
0%
count
New Jersey
New York
city
num_kids
0
1
2
3+

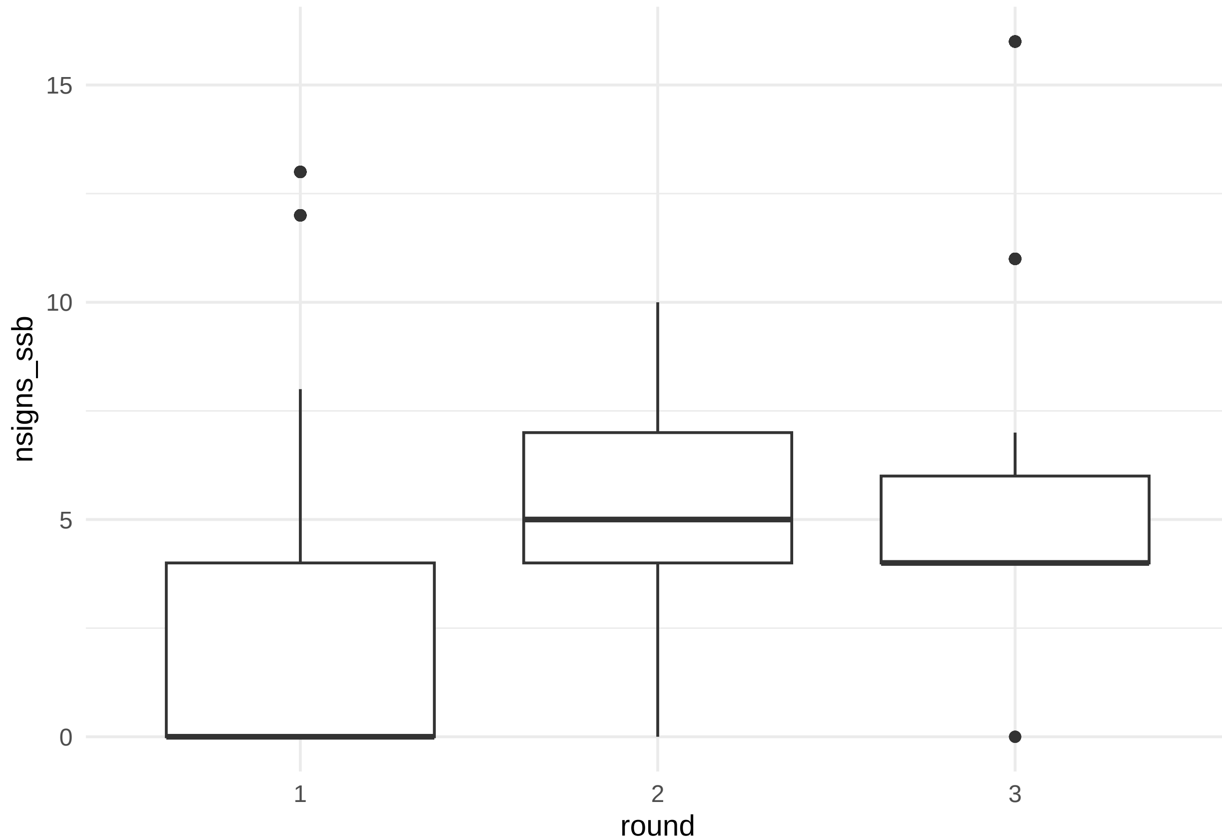

600
400
200
0
days_since_ban
New Jersey
New York
city


caff
75
50
25
0
1
2
3
round

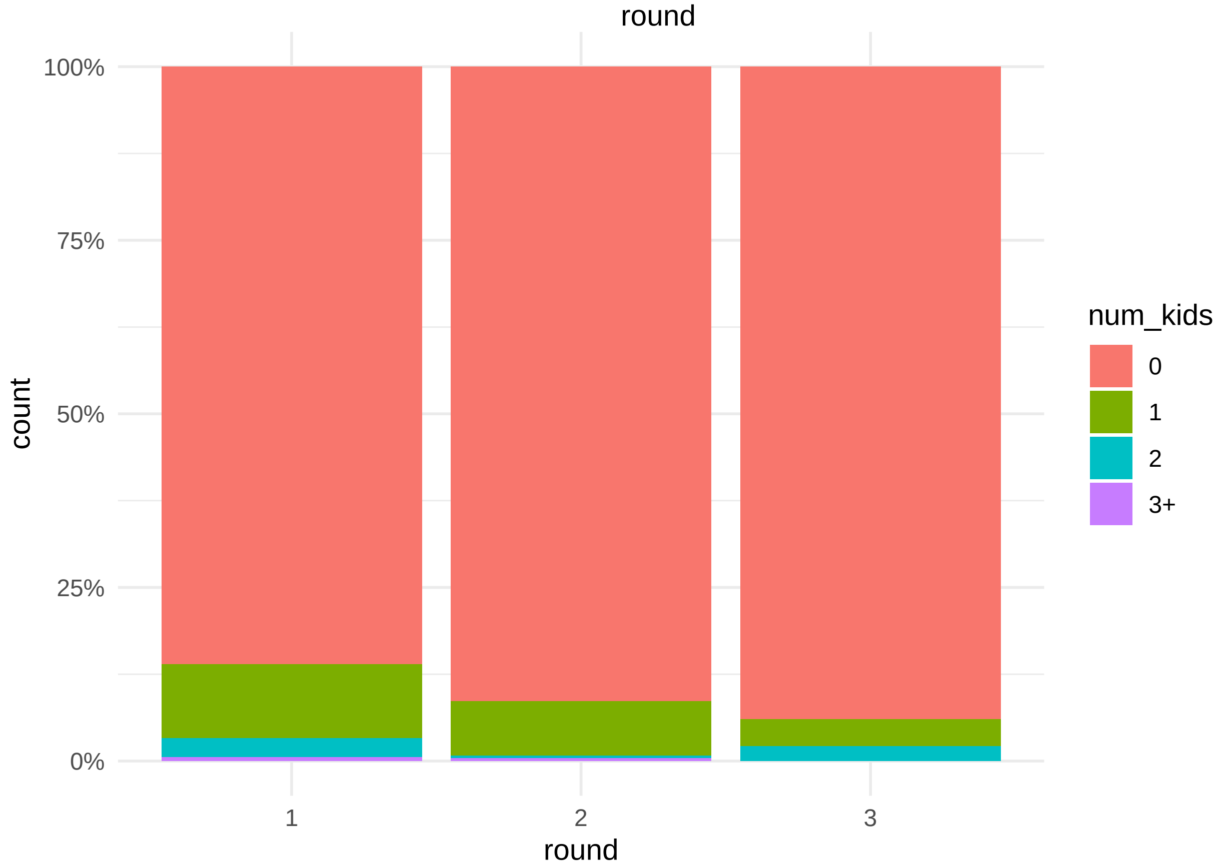

caff
75
50
25
0
0
5
10
15
nsigns_ssb


caff
0
25
50
75
0
1
2
3+
num_kids

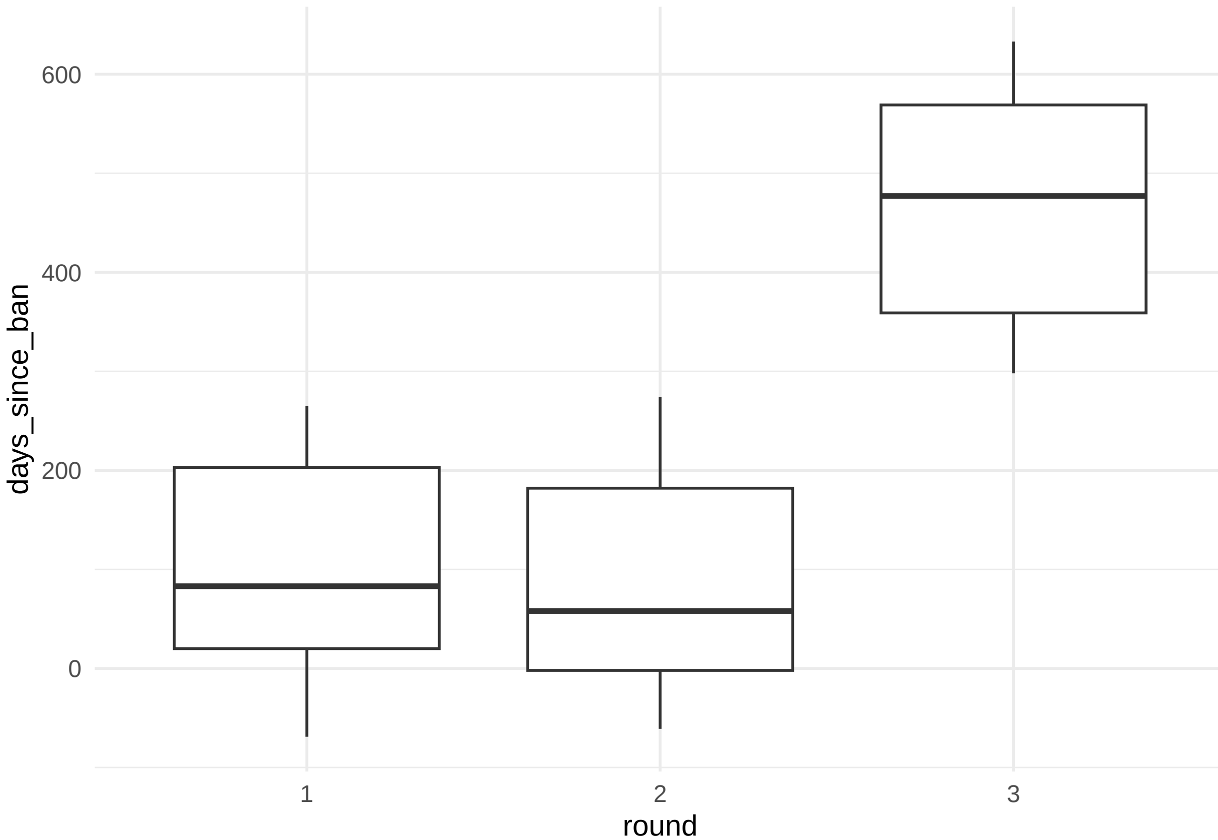

caff
0
25
50
75
0
200
400
600
days_since_ban

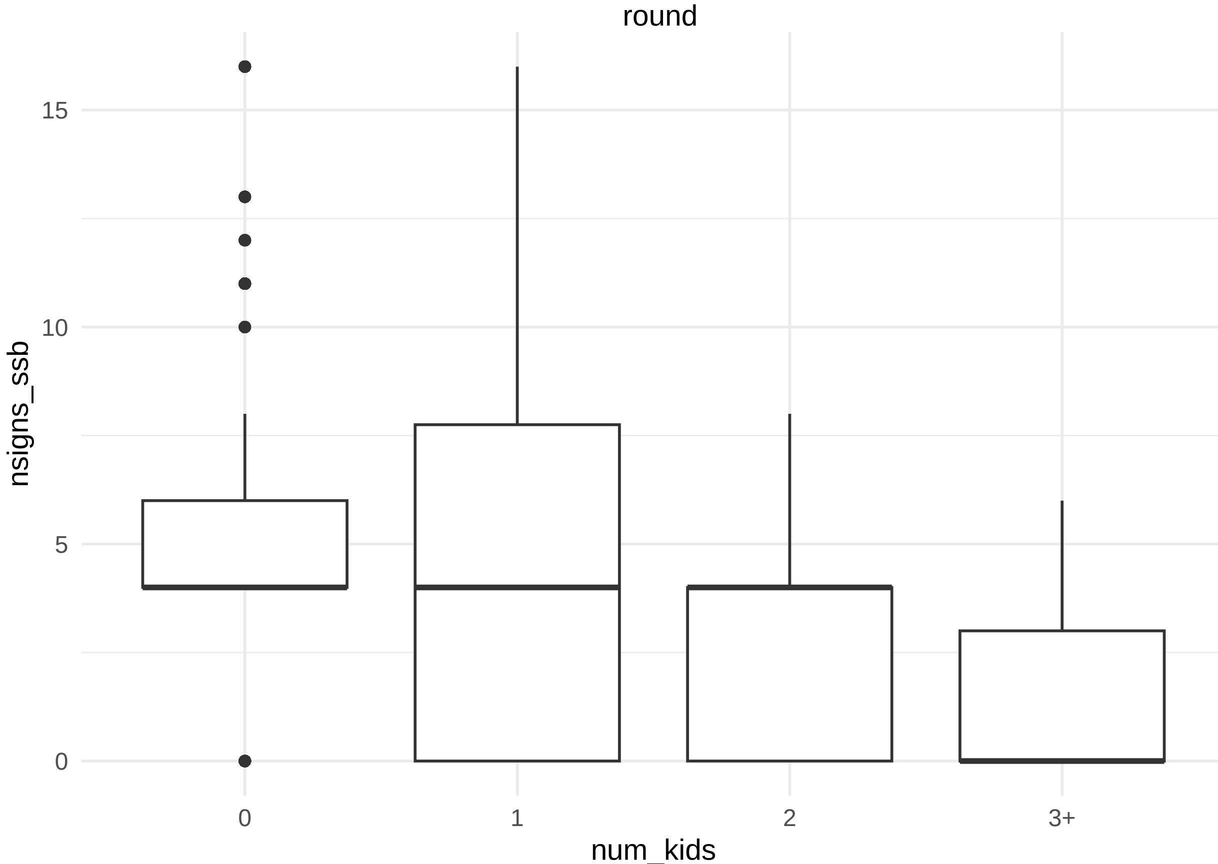


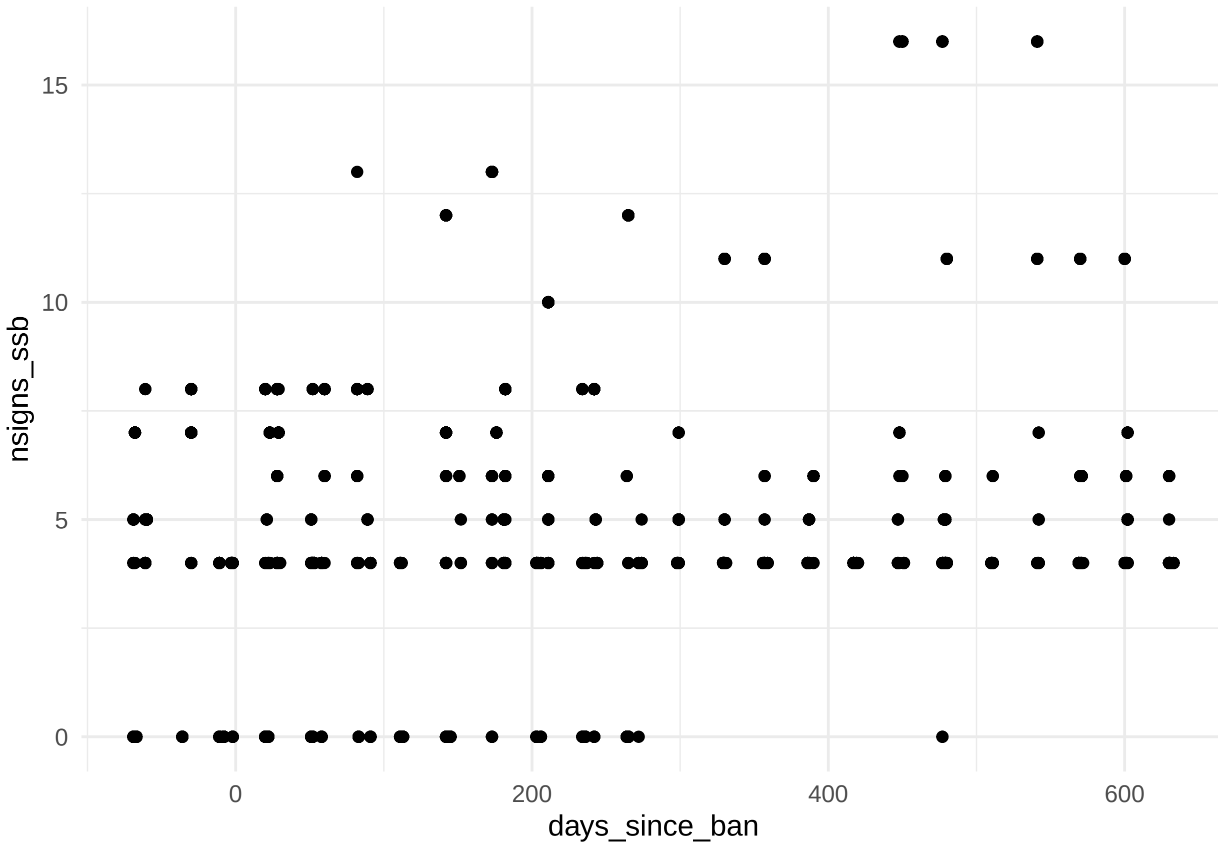
15
10
5
0
nsigns_ssb
1
2
3
round

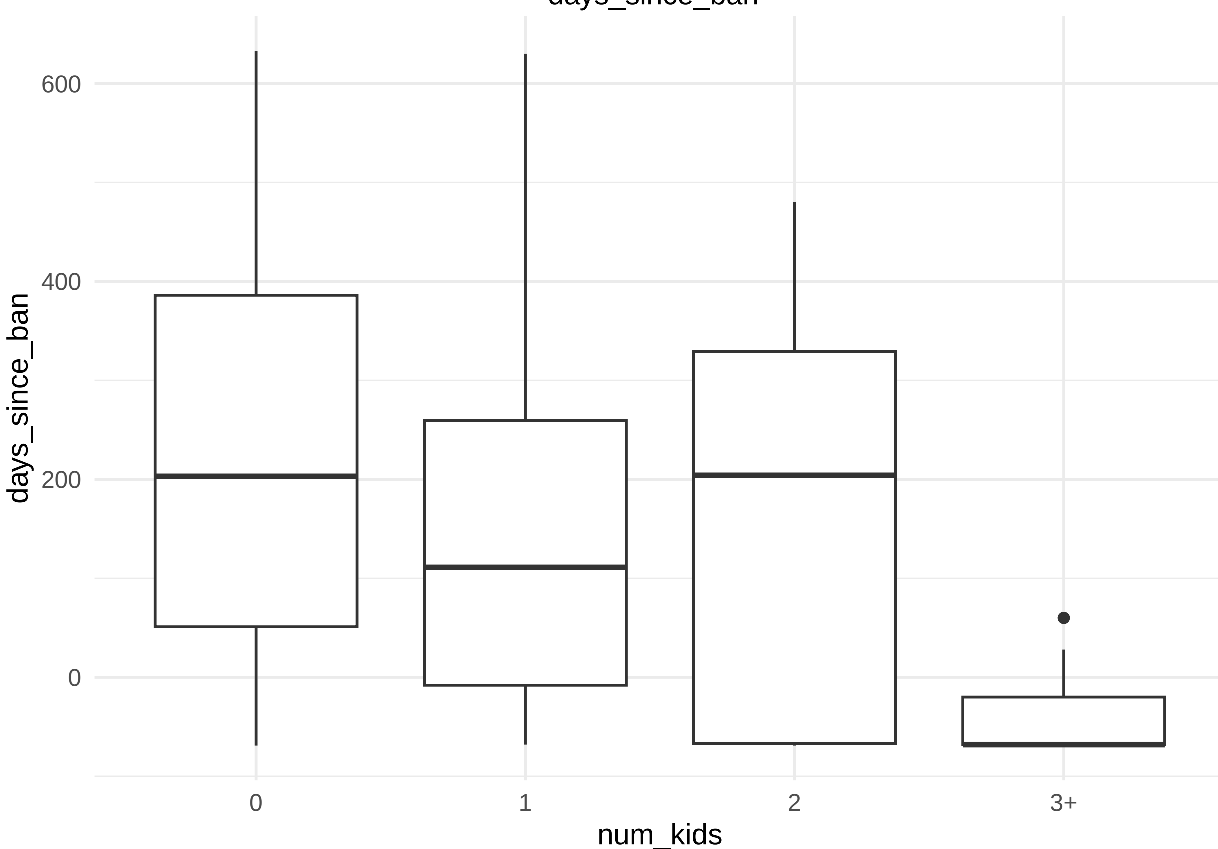


100%
75%
50%
25%
0%
count
1
2
3
round
num_kids
0
1
2
3+


600
400
200
0
days_since_ban
1
2
3
round


15
10
5
0
nsigns_ssb
0
1
2
3+
num_kids


nsigns_ssb
15
10
5
0
0
200
400
600
days_since_ban


days_since_ban
600
400
200
0
0
1
2
3+
num_kids

Modeling Process

Testing Different Optimization Methods

For models with no random effects, best to use Newton's approximation. For models with random effects, best to use `nlminb`, which is the default.

```
# No random effects
control_clm_full <- clm(limit ~ 1 + age + gender + race + edu + caff +
                          nsigns_ssb + num_kids + days_since_ban,
                   data = reduced_data, control = list(
  maxIter = 10000,
  maxLineIter = 2000,
  maxModIter = 2000,
  method = "Newton",
  trace = 1))
control_clm <- clm(limit ~ 1 + age + gender + race + edu + caff +
                     nsigns_ssb + num_kids + days_since_ban, data = reduced_data, control = list(
  method = "ucminf",
  stepmax = 1,
  grad = "central",
  maxeval = 500000,
  gradstep = c(1e-10, 1e-12),
  trace = 1))
control_clm <- clm(limit ~ 1 + age + gender + race + edu + caff +
                     nsigns_ssb + num_kids + days_since_ban, data = reduced_data, control = list(
  method = "nlminb",
  eval.max = 2000,
  iter.max = 1500,
  abs.tol = 1e-20,
  trace = 1))
control_clm <- clm(limit ~ 1 + age + gender + race + edu + caff +
                     nsigns_ssb + num_kids + days_since_ban, data = reduced_data, control = list(
  method = "optim",
  tmax = 100,
  maxit = 100000,
  type = 1,
  ndeps = 1e-10,
  REPORT = 1,
  trace = 1))

## Check with alternative packages. Produced the same intercepts
control_vglm <- vglm(limit ~ 1 + age + gender + race + edu + caff +
                       nsigns_ssb + num_kids + days_since_ban,
                     data = reduced_data, family = cumulative(parallel = TRUE))

## Random effects. Omit the rest for brevity
control_clmm_full <- clmm(limit ~ 1 + age + gender + race + edu + city + caff +
                            nsigns_ssb + num_kids + days_since_ban +
                            (1 | location) + (1 | round),
                          control = list(method = "nlminb",
                                         useMatrix = T,
                                         maxIter = 200,
                                         gradTol = 1e-4,
                                         maxLineIter = 200,
```

```r
                                          trace = 1),
                      data = reduced_data, link = "logit")

# Same intercepts
summary(control_clm)
summary(control_vglm)
coef(control_vglm, matrix = T)

summary(control_clmm_full)
coef(control_clmm_full, matrix = T)
```

Full Model

Note that we also tested the non-standardized model. They both produced the similar conclusions. However, the non-standardized model couldn't fit properly because of the `kcal` variable. We proceeded with the standardized model for predictions.

```r
control_clmm_full_std <- clmm(limit ~ 1 + age_std + gender + race + edu + city + caff_std +
                                nsigns_ssb_std + num_kids + days_since_ban_std + kcal_std + fv_std +
                                (1 | location) + (1 | round),
                            control = list(method = "nlminb",
                                          useMatrix = T,
                                          maxIter = 200,
                                          gradTol = 1e-4,
                                          maxLineIter = 200),
                      data = reduced_data, link = "logit")

summary(control_clmm_full_std)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: limit ~ 1 + age_std + gender + race + edu + city + caff_std +
##     nsigns_ssb_std + num_kids + days_since_ban_std + kcal_std +
##     fv_std + (1 | location) + (1 | round)
## data:    reduced_data
##
##  link  threshold nobs logLik   AIC     niter       max.grad cond.H
##  logit flexible  2139 -3233.83 6521.66 5501(11142) 4.76e-03 3.3e+03
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  location (Intercept) 0.01099  0.1048
##  round    (Intercept) 0.00000  0.0000
## Number of groups:  location 53,  round 3
##
## Coefficients:
##                           Estimate Std. Error z value Pr(>|z|)
## age_std                    0.265459   0.042249   6.283 3.32e-10 ***
## genderM                   -0.251753   0.080889  -3.112  0.00186 **
## raceBlack                 -0.273282   0.171503  -1.593  0.11106
## raceNative                -0.345505   0.292339  -1.182  0.23726
## raceOther                 -0.075643   0.182247  -0.415  0.67810
## raceWhite                  0.008450   0.178180   0.047  0.96217
## eduCollege Degree         -0.007903   0.178483  -0.044  0.96468
```

```
## eduGraduate Degree        0.027508   0.211106   0.130  0.89633
## eduHigh School           -0.434245   0.171244  -2.536  0.01122 *
## eduLess than High School -0.522547   0.285267  -1.832  0.06698 .
## eduSome College          -0.180833   0.176061  -1.027  0.30437
## eduSome High School      -0.457062   0.204394  -2.236  0.02534 *
## cityNew York              0.109383   0.090114   1.214  0.22481
## caff_std                 -0.050834   0.040937  -1.242  0.21432
## nsigns_ssb_std            0.048602   0.050292   0.966  0.33384
## num_kids1                 0.033589   0.150270   0.224  0.82313
## num_kids2                -0.176070   0.288405  -0.610  0.54153
## num_kids3+               -2.603060   1.097924  -2.371  0.01775 *
## days_since_ban_std       -0.034499   0.041755  -0.826  0.40868
## kcal_std                 -0.070073   0.046496  -1.507  0.13179
## fv_std                    0.019100   0.043636   0.438  0.66159
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##                  Estimate Std. Error z value
## Never|Seldom      -1.4020     0.2310  -6.069
## Seldom|Sometimes  -1.0052     0.2301  -4.369
## Sometimes|Often    0.0283     0.2287   0.124
## Often|Always       0.8239     0.2296   3.589
```

```
## Non-standardized model
# control_clmm_full_non <- clmm(limit ~ 1 + age + gender + race + edu + city + caff +
# nsigns_ssb + num_kids + days_since_ban + kcal + fv +
# (1 | location) + (1 | round),
#                            control = list(method = "nlminb",
#                                           useMatrix = T,
#                                           maxIter = 200,
#                                           gradTol = 1e-4,
#                                           maxLineIter = 200,
#                                           trace = 1),
#                       data = reduced_data, link = "logit")
```

Fixed Effects

```
control_clmm_red <- clmm(limit ~ 1 + age_std + gender + edu + num_kids +
                           (1 | location) + (1 | round),
                         data = reduced_data, link = "logit")
anova(control_clmm_red, control_clmm_full_std)
```

```
## Likelihood ratio tests of cumulative link models:
##
##                       formula:
## control_clmm_red      limit ~ 1 + age_std + gender + edu + num_kids + (1 | location) + (1 | round)
## control_clmm_full_std limit ~ 1 + age_std + gender + race + edu + city + caff_std + nsigns_ssb_std +
##                       link: threshold:
## control_clmm_red      logit flexible
## control_clmm_full_std logit flexible
##
##                       no.par    AIC  logLik LR.stat df Pr(>Chisq)
## control_clmm_red          17 6517.6 -3241.8
```

```
## control_clmm_full_std     27 6521.7 -3233.8  15.906 10     0.1024
```

```r
summary(control_clmm_red)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: limit ~ 1 + age_std + gender + edu + num_kids + (1 | location) +
##     (1 | round)
## data:    reduced_data
##
##  link  threshold nobs logLik   AIC     niter      max.grad cond.H
##  logit flexible  2139 -3241.79 6517.57 2305(4611) 8.85e-03 3.3e+03
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  location (Intercept) 0.01383  0.1176
##  round    (Intercept) 0.00000  0.0000
## Number of groups:  location 53,  round 3
##
## Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## age_std                   0.26272    0.04138   6.349 2.17e-10 ***
## genderM                  -0.23320    0.08001  -2.915  0.00356 **
## eduCollege Degree         0.03361    0.17735   0.190  0.84969
## eduGraduate Degree        0.10987    0.20602   0.533  0.59384
## eduHigh School           -0.44955    0.17085  -2.631  0.00851 **
## eduLess than High School -0.48726    0.28066  -1.736  0.08254 .
## eduSome College          -0.17665    0.17566  -1.006  0.31459
## eduSome High School      -0.46652    0.20405  -2.286  0.02224 *
## num_kids1                 0.05817    0.14888   0.391  0.69601
## num_kids2                -0.07592    0.28532  -0.266  0.79018
## num_kids3+               -2.65571    1.09340  -2.429  0.01515 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##                  Estimate Std. Error z value
## Never|Seldom      -1.2616     0.1637  -7.706
## Seldom|Sometimes  -0.8676     0.1625  -5.340
## Sometimes|Often    0.1617     0.1610   1.005
## Often|Always       0.9553     0.1624   5.883
```

Random Effects

Note that we couldn't perform bootstrap because the `simulate` command is not implemented in `ordinal`, but the effects are fairly marginal and not significant.

```r
control_clmm_loc <- clmm(limit ~ 1 + age_std + gender + edu + num_kids +
                           (1 | location),
                         data = reduced_data, link = "logit")

lrt_obs_round <- as.numeric(2*(logLik(control_clmm_red) -
                               logLik(control_clmm_loc)))
.5*(1 - pchisq(lrt_obs_round, 0)) + .5*(1 - pchisq(lrt_obs_round, 1))
```

Level 3 Random Intercept

```
## [1] 0.4986052
```

```
control_clm <- clm(limit ~ 1 + age_std + gender + edu + num_kids,
                   data = reduced_data, link = "logit")
lrt_obs_loc <- as.numeric(2*(logLik(control_clmm_loc) - logLik(control_clm)))
.5*(1 - pchisq(lrt_obs_loc, 0)) + .5*(1 - pchisq(lrt_obs_loc, 1))
```

Level 2 Random Intercept

```
## [1] 0.108981
```

Separate slopes for each level

Ordinal provides two built-in commands for testing whether we need separate slopes for predictors of each level and whether we need to scale our response by each predictors. None of them showed significance.

```
nominal_test(control_clm)
```

```
## Tests of nominal effects
##
## formula: limit ~ 1 + age_std + gender + edu + num_kids
##          Df  logLik    AIC     LRT Pr(>Chi)
## <none>      -3242.5 6515.1
## age_std   3 -3240.1 6516.2  4.8521  0.18295
## gender    3 -3239.4 6514.8  6.2676  0.09929 .
## edu      18 -3237.3 6540.6 10.4781  0.91518
## num_kids
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
scale_test(control_clm)
```

```
## Tests of scale effects
##
## formula: limit ~ 1 + age_std + gender + edu + num_kids
##          Df  logLik    AIC    LRT Pr(>Chi)
## <none>      -3242.5 6515.1
## age_std   1 -3242.3 6516.6 0.5204   0.4707
## gender    1 -3242.2 6516.4 0.6724   0.4122
## edu       6 -3239.8 6521.7 5.4054   0.4930
## num_kids  3 -3242.5 6521.0 0.1380   0.9869
```

Overall fit Compared to the only intercept model.

```
control_null <- clm(limit ~ 1, data = reduced_data, link = "logit")
# Overall fit
anova(control_null, control_clm)
```

```
## Likelihood ratio tests of cumulative link models:
##
##              formula:                                      link: threshold:
## control_null limit ~ 1                                     logit flexible
## control_clm  limit ~ 1 + age_std + gender + edu + num_kids logit flexible
##
##              no.par    AIC  logLik LR.stat df Pr(>Chisq)
```

```
## control_null      4 6585.7 -3288.9
## control_clm      15 6515.1 -3242.5  92.658 11  5.015e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(control_clm)
```

```
## formula: limit ~ 1 + age_std + gender + edu + num_kids
## data:    reduced_data
##
##  link  threshold nobs logLik   AIC     niter max.grad cond.H
##  logit flexible  2139 -3242.54 6515.09 5(1)  8.30e-08 3.3e+03
##
## Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## age_std                   0.25824    0.04080   6.329 2.47e-10 ***
## genderM                  -0.22566    0.07934  -2.844  0.00445 **
## eduCollege Degree         0.05809    0.17564   0.331  0.74083
## eduGraduate Degree        0.12832    0.20481   0.627  0.53095
## eduHigh School           -0.45328    0.17019  -2.663  0.00774 **
## eduLess than High School -0.49043    0.28007  -1.751  0.07992 .
## eduSome College          -0.17911    0.17514  -1.023  0.30648
## eduSome High School      -0.47485    0.20317  -2.337  0.01943 *
## num_kids1                 0.05314    0.14774   0.360  0.71909
## num_kids2                -0.11298    0.28131  -0.402  0.68797
## num_kids3+               -2.73734    1.08823  -2.515  0.01189 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##                  Estimate Std. Error z value
## Never|Seldom      -1.2434     0.1615  -7.700
## Seldom|Sometimes  -0.8507     0.1603  -5.306
## Sometimes|Often    0.1746     0.1591   1.098
## Often|Always       0.9657     0.1606   6.013
```

Model Diagnostics

Accuracy Metrics

Because residual analysis are not well understood in ordinal models, we opted for accuracy metrics. Note that our model doesn't predict well.

```r
library(tidymodels)
library(workflows)
# Predict response
control_pred <- predict(control_clm, type = "class")

control_results <- reduced_data %>%
  bind_cols(control_pred)

# Confusion matrix
# table(control_results$limit, control_results$fit)
conf_mat(control_results, truth = limit, estimate = fit)
```

```
##            Truth
```

```
## Prediction  Never Seldom Sometimes Often Always
##   Never       493    131       367   229    288
##   Seldom        0      0         0     0      0
##   Sometimes     0      0         0     0      0
##   Often         0      0         0     0      0
##   Always      136     50       154   110    181
```

```r
# accuracy metrics
accuracy(control_results, truth = limit, estimate = fit)
```

```
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy multiclass     0.315
```

```r
sensitivity(control_results, truth = limit, estimate = fit)
```

```
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 sensitivity macro          0.234
```

```r
specificity(control_results, truth = limit, estimate = fit)
```

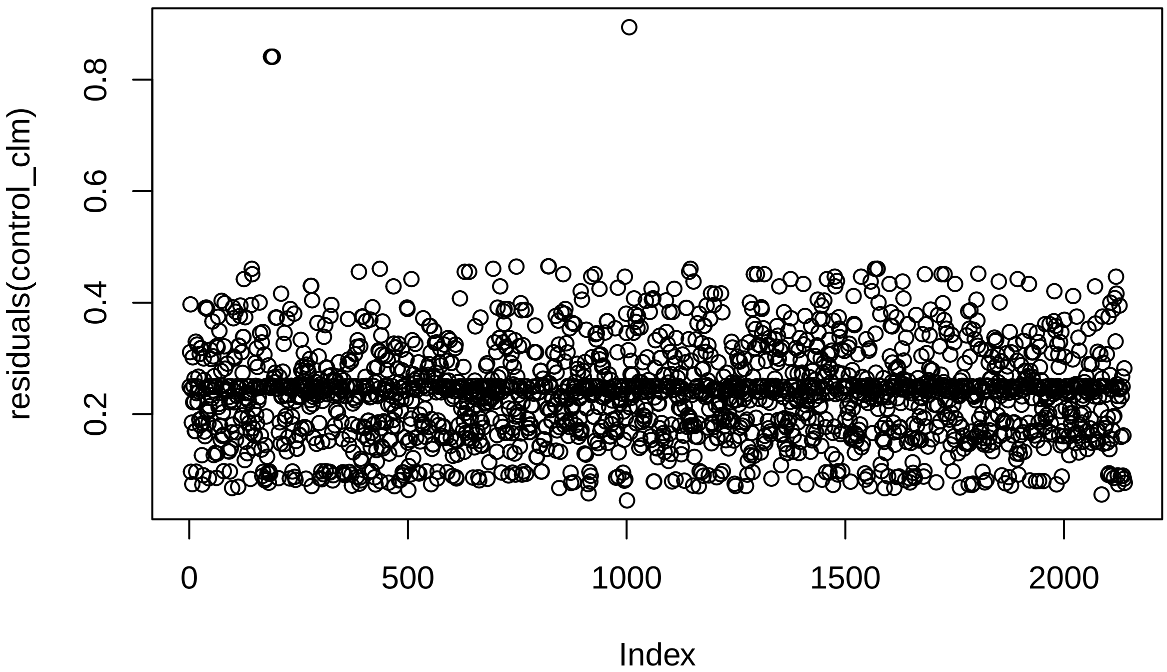
```
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 specificity macro          0.812
```

```r
# ppv(control_results, truth = limit, estimate = fit)
```

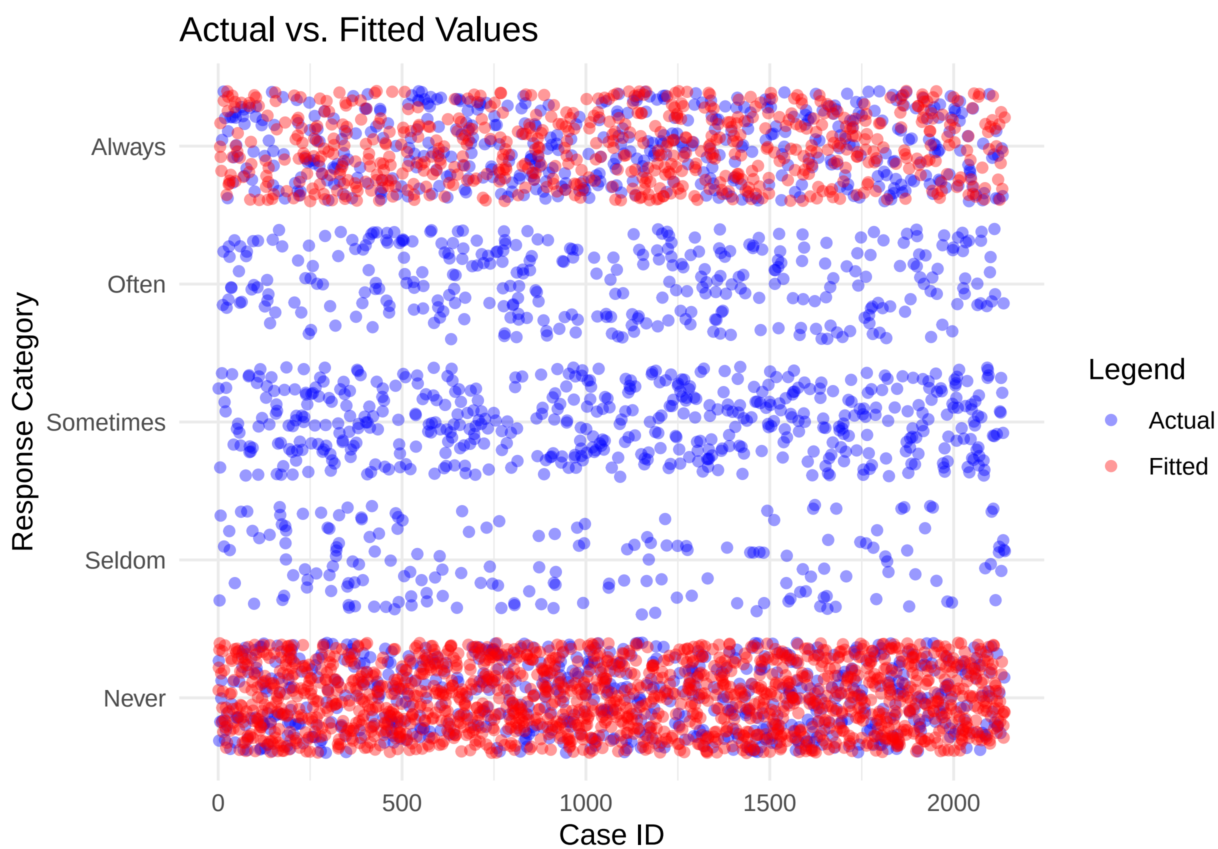
```r
# Goodness of fit
chisq.test(control_results$limit, control_results$fit)
```

```
##
##  Pearson's Chi-squared test
##
## data:  control_results$limit and control_results$fit
## X-squared = 39.141, df = 4, p-value = 6.515e-08
```

```r
plot(fitted(control_clm), residuals(control_clm))
```




```
control_resid <- control_results %>%
  mutate(
    case_id = row_number(),
    fit = ordered(fit, levels = c("Never", "Seldom", "Sometimes", "Often", "Always"))
  ) %>%
  select(case_id, limit, fit)

ggplot(control_resid, aes(x = case_id)) +
  geom_jitter(aes(y = limit, color = "Actual"), alpha = 0.4) +
  geom_jitter(aes(y = fit, color = "Fitted"), alpha = 0.4) +
  scale_color_manual(values = c("Actual" = "blue", "Fitted" = "red")) +
  labs(
    x = "Case ID",
    y = "Response Category",
    title = "Actual vs. Fitted Values",
    color = "Legend"
  ) +
  theme_minimal()
```



Effects Interpretation

Confidence Intervals

```r
confint(control_clm) %>% kable(digits = 3)
```

	2.5 %	97.5 %
age_std	0.178	0.338
genderM	-0.381	-0.070
eduCollege Degree	-0.286	0.403
eduGraduate Degree	-0.273	0.530
eduHigh School	-0.787	-0.119
eduLess than High School	-1.041	0.058
eduSome College	-0.523	0.165
eduSome High School	-0.874	-0.077
num_kids1	-0.237	0.343
num_kids2	-0.669	0.438
num_kids3+	-5.685	-0.956

```r
exp(confint(control_clm)) %>% kable(digits = 3)
```

	2.5 %	97.5 %
age_std	1.195	1.403
genderM	0.683	0.932

	2.5 %	97.5 %
eduCollege Degree	0.751	1.496
eduGraduate Degree	0.761	1.699
eduHigh School	0.455	0.887
eduLess than High School	0.353	1.060
eduSome College	0.593	1.179
eduSome High School	0.417	0.926
num_kids1	0.789	1.409
num_kids2	0.512	1.549
num_kids3+	0.003	0.384

```
(100*(exp(confint(control_clm))-1)) %>% kable(digits = 3)
```

	2.5 %	97.5 %
age_std	19.533	40.270
genderM	-31.701	-6.782
eduCollege Degree	-24.891	49.594
eduGraduate Degree	-23.895	69.930
eduHigh School	-54.483	-11.259
eduLess than High School	-64.695	5.983
eduSome College	-40.698	17.881
eduSome High School	-58.255	-7.386
num_kids1	-21.083	40.891
num_kids2	-48.790	54.893
num_kids3+	-99.660	-61.557