Final Project Code

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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", "caloriescal", "fatg",
           "sugarg")) %>%
  group_by(receiptid) %>%
  mutate(black = if_else(race == "Black", "Black", "non-Black")) %>%
  mutate(caff = sum(caff, na.rm = T), # across each receipt
         caloriescal = sum(caloriescal, na.rm = T),
         fatg = sum(fatg, na.rm = T),
         sugarg = sum(sugarg, 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(
         caff_std = standardize(caff),
         nsigns_ssb_std = standardize(nsigns_ssb),
         days_since_ban_std = standardize(days_since_ban),
         caloriescal_std = standardize(caloriescal),
         fatg_std = standardize(fatg),
         sugarg_std = standardize(sugarg)
         )

# 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)
```

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

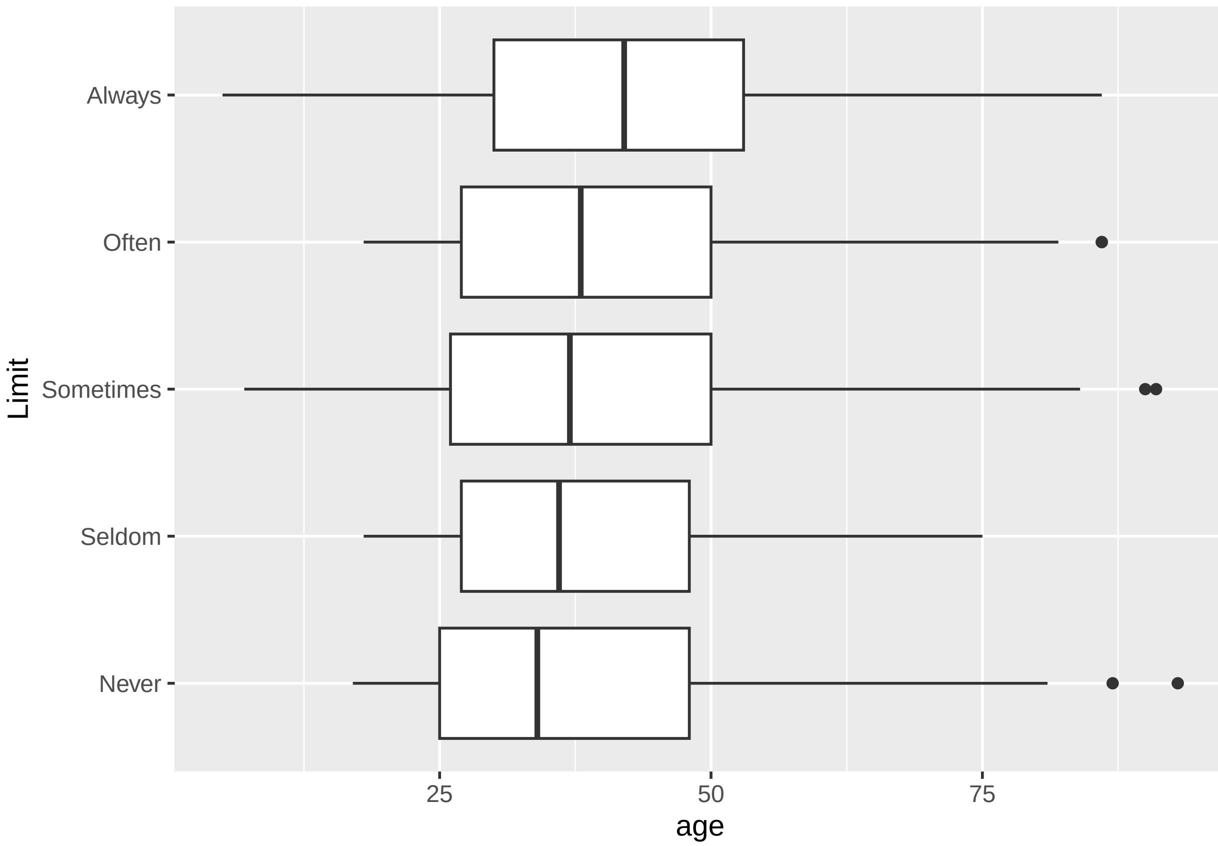
```
## # A tibble: 0 x 3
## # i 3 variables: receiptid <fct>, location <fct>, n <int>
```

```r
## But not all stores have been surveyed three times
multi_round_locations <- reduced_data %>%
  group_by(location) %>%
  summarize(n_rounds = n_distinct(round)) %>%
  filter(n_rounds < 3) %>%
  pull(location)

reduced_data %>%
  filter(location %in% multi_round_locations) %>%
  count(location, round)
```

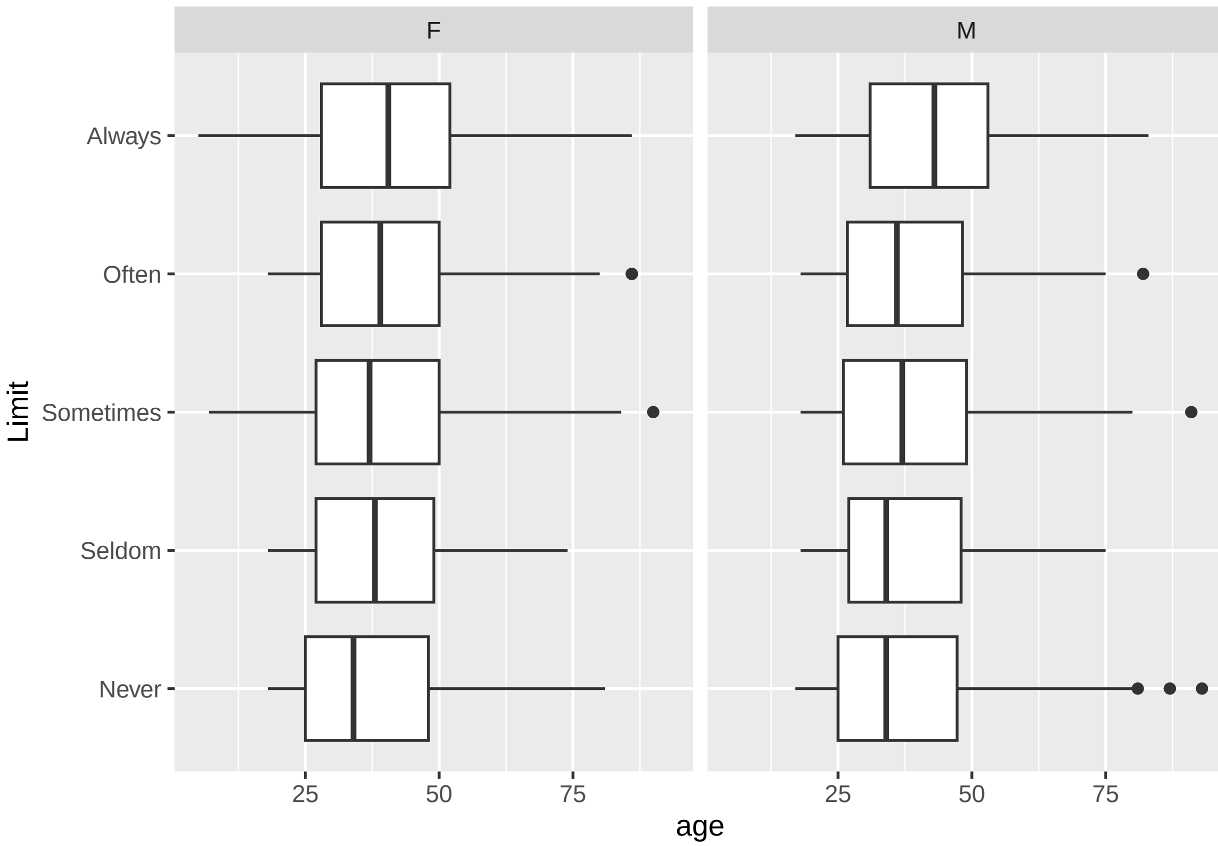
```
## # A tibble: 47 x 3
##    location round     n
##    <fct>    <fct> <int>
##  1 B105     1        11
##  2 B127A    1         2
##  3 B127B    1         8
##  4 B127B    3        22
##  5 B205     1         8
##  6 B217     1        16
##  7 B227     1        25
##  8 B227     3        31
##  9 K234     2         7
## 10 K234     3        34
## # i 37 more rows
```

EDA

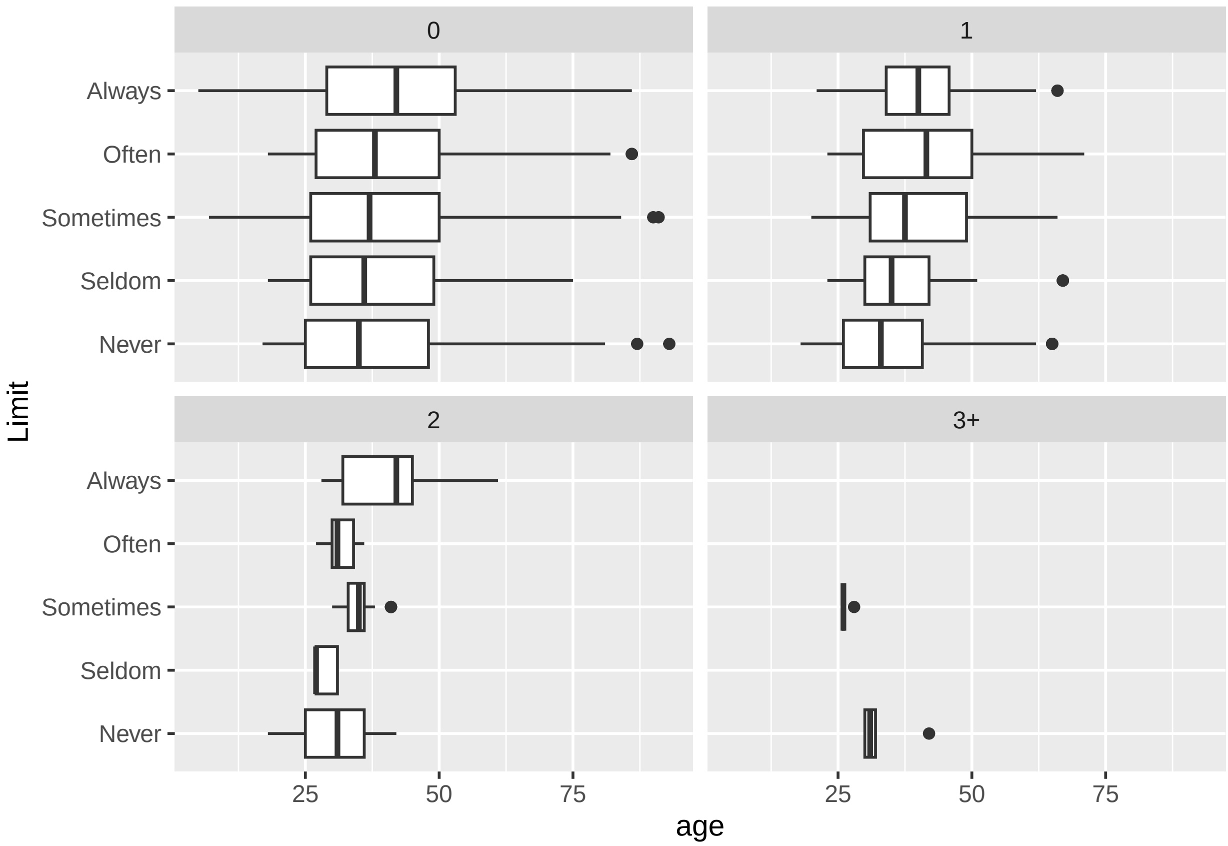
```r
# Single variables, interactions plotted against limit

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



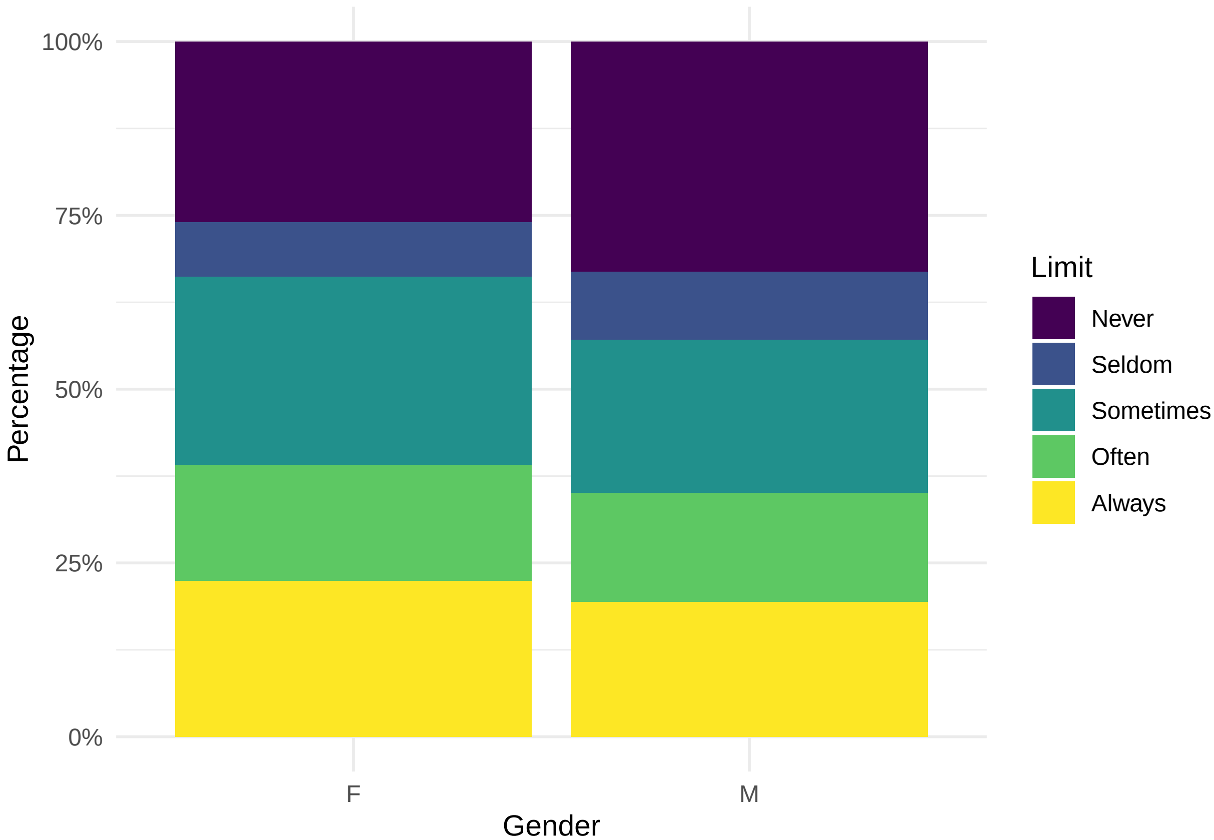

```r
# Age faceted by gender
ggplot(data = reduced_data, aes(x = age , y = limit)) +
  geom_boxplot() +
  facet_wrap(~gender) +
  labs(x = "age", y = "Limit")
```



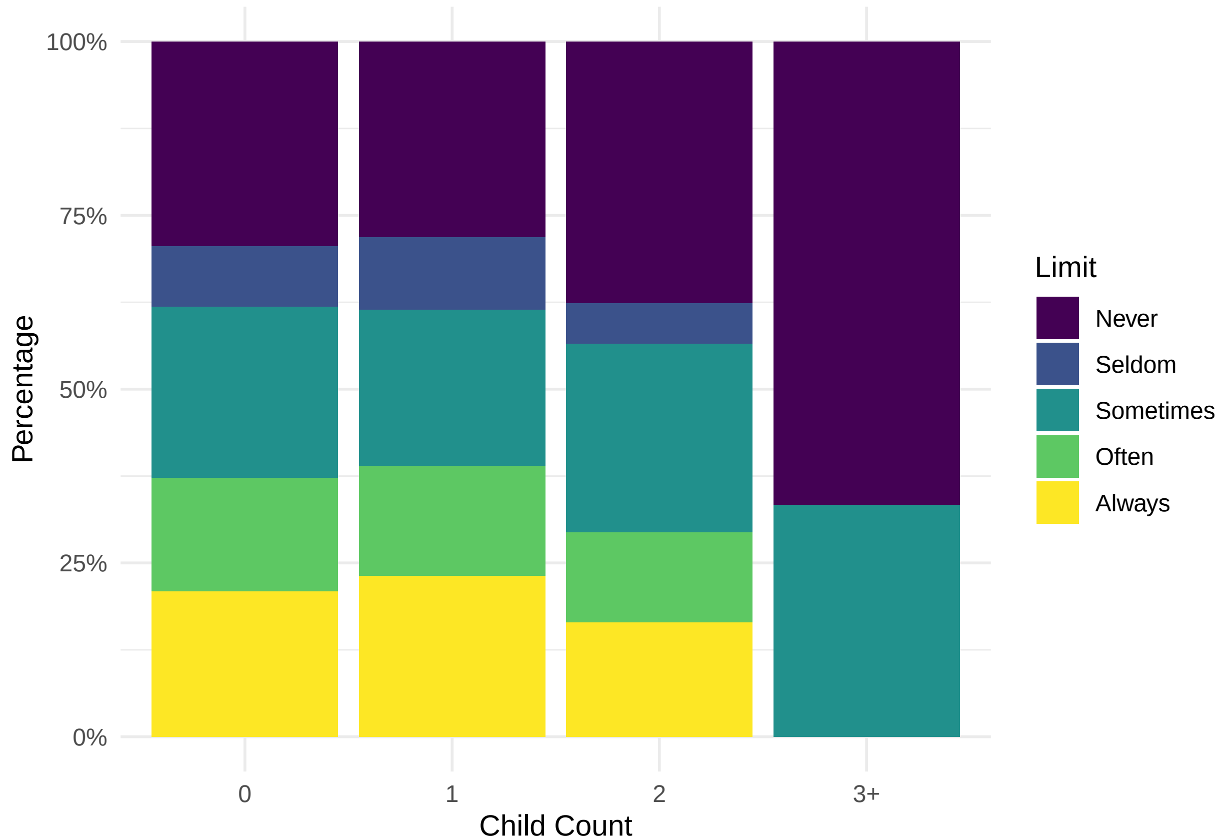

```r
# Age faceted by child count
ggplot(data = reduced_data, aes(x = age , y = limit)) +
  geom_boxplot() +
  facet_wrap(~num_kids) +
  labs(x = "age", y = "Limit")
```



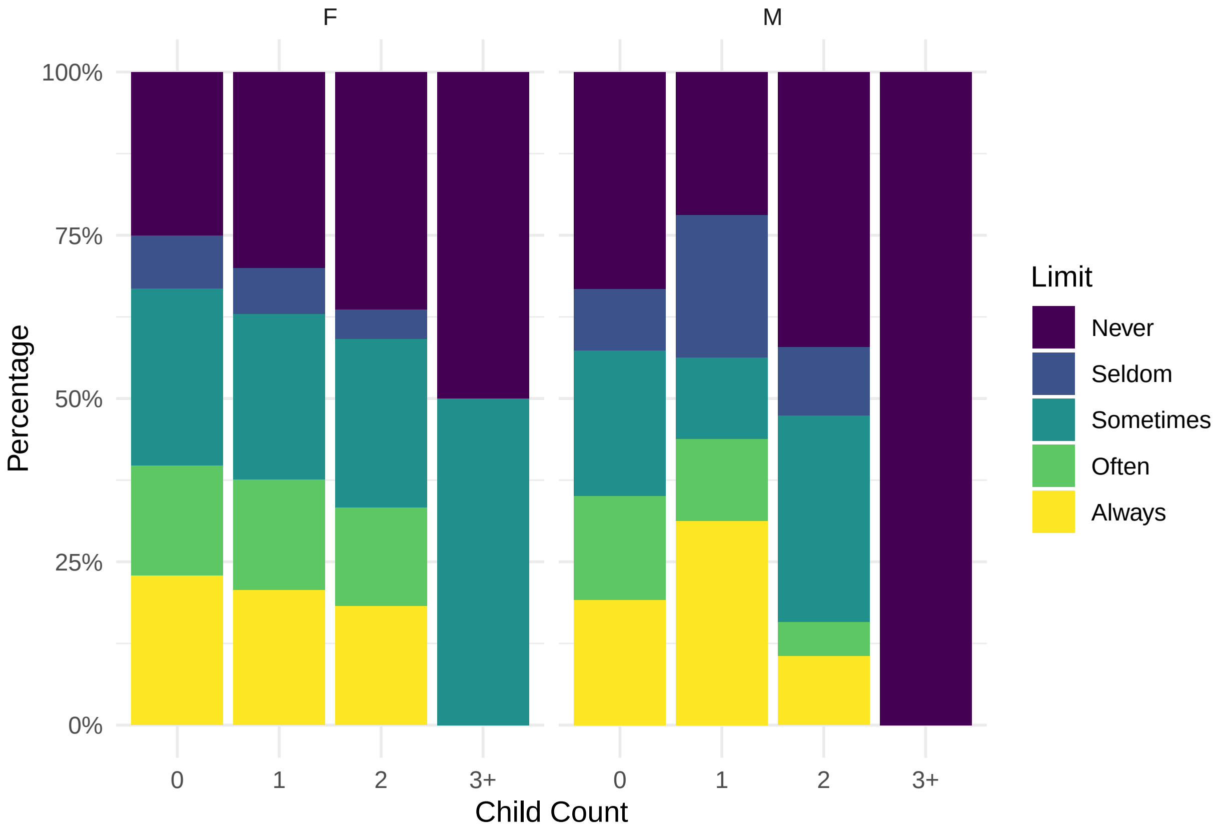

```
# Gender
ggplot(data = reduced_data, aes(x = gender, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Gender", y = "Percentage", fill = "Limit") +
  theme_minimal()
```



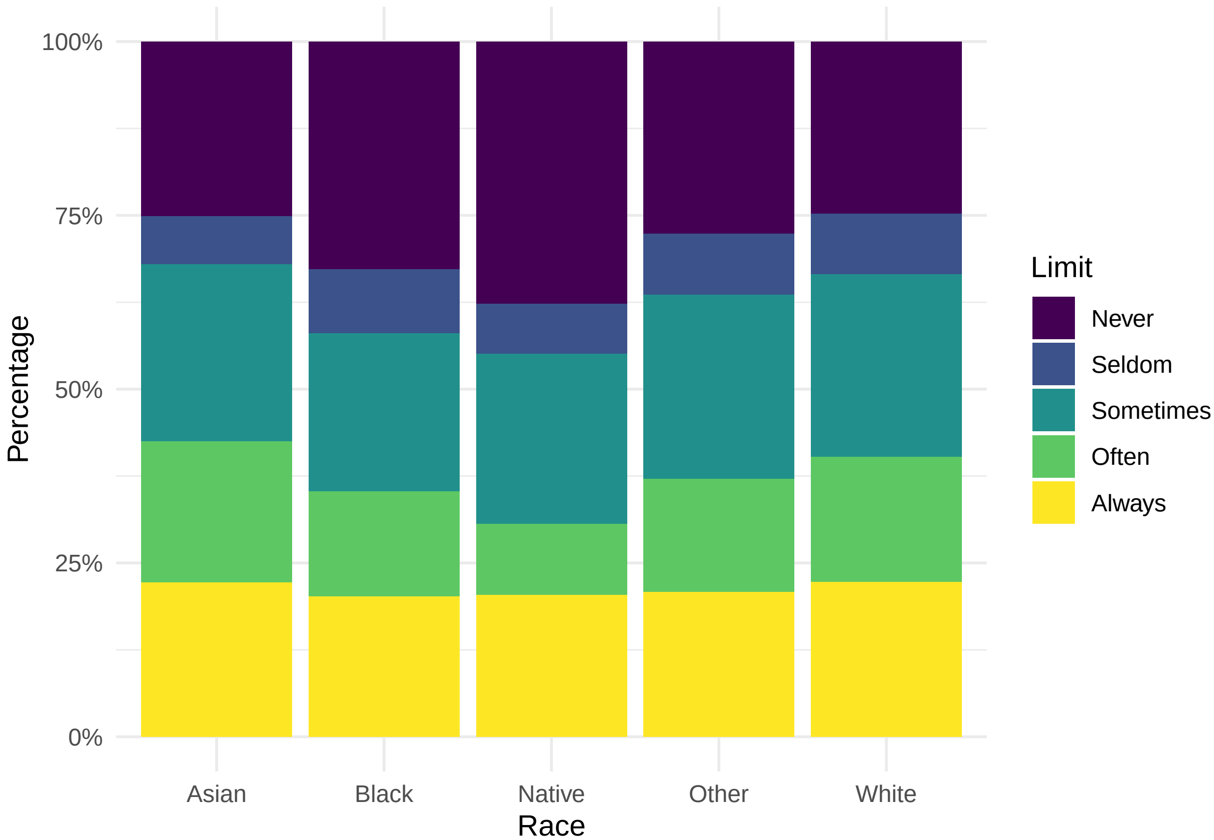

```r
# Child count
ggplot(data = reduced_data, aes(x = num_kids, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Child Count", y = "Percentage", fill = "Limit") +
  theme_minimal()
```



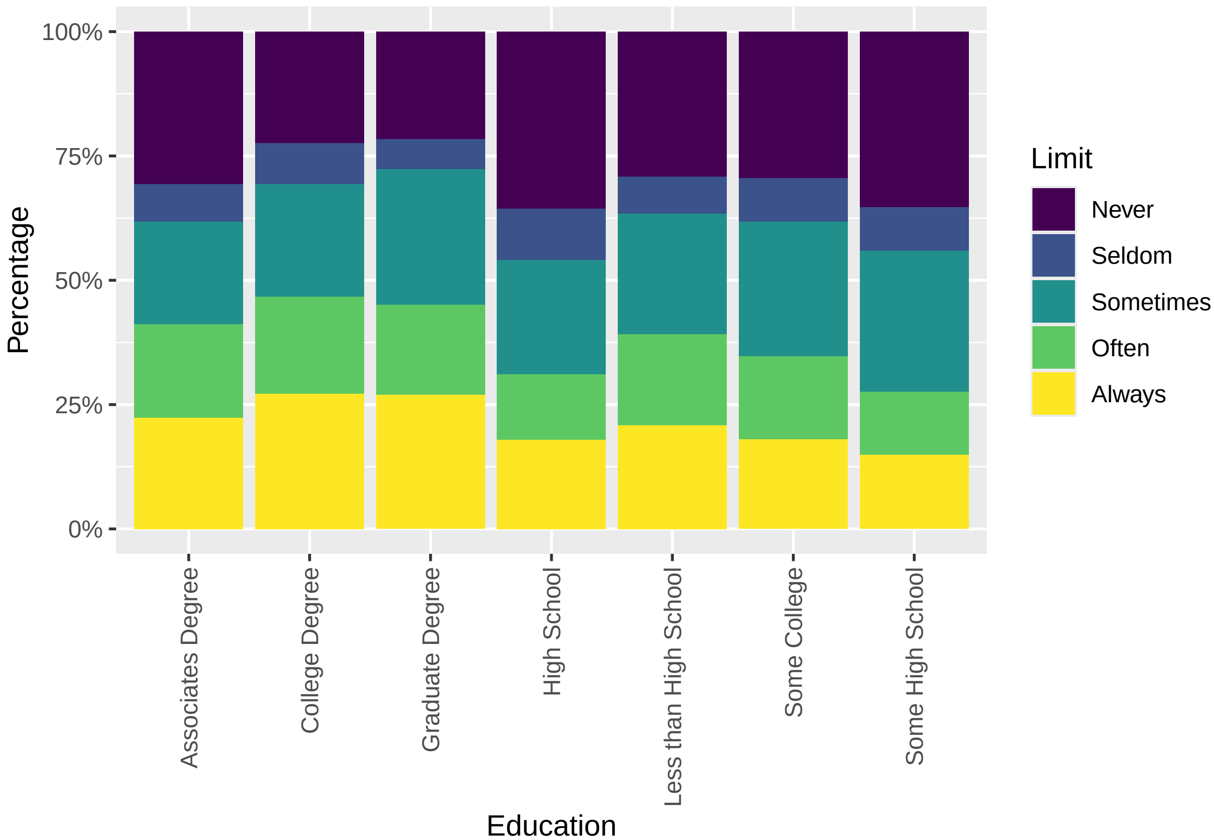

```
# Child count / gender interaction
ggplot(data = reduced_data, aes(x = num_kids, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Child Count", y = "Percentage", fill = "Limit") +
  facet_wrap(~gender) +
  theme_minimal()
```



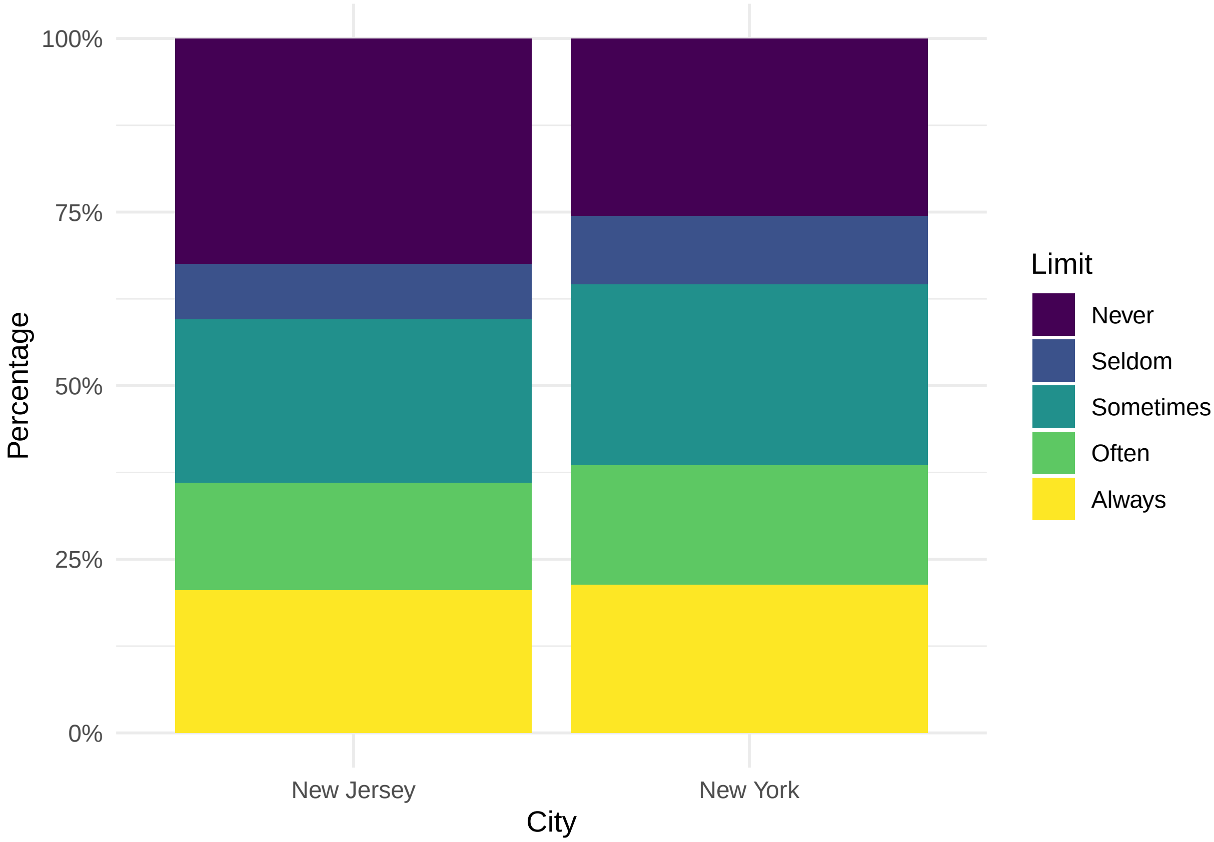

```r
# Race
ggplot(data = reduced_data, aes(x = race, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Race", y = "Percentage", fill = "Limit") +
  theme_minimal()
```



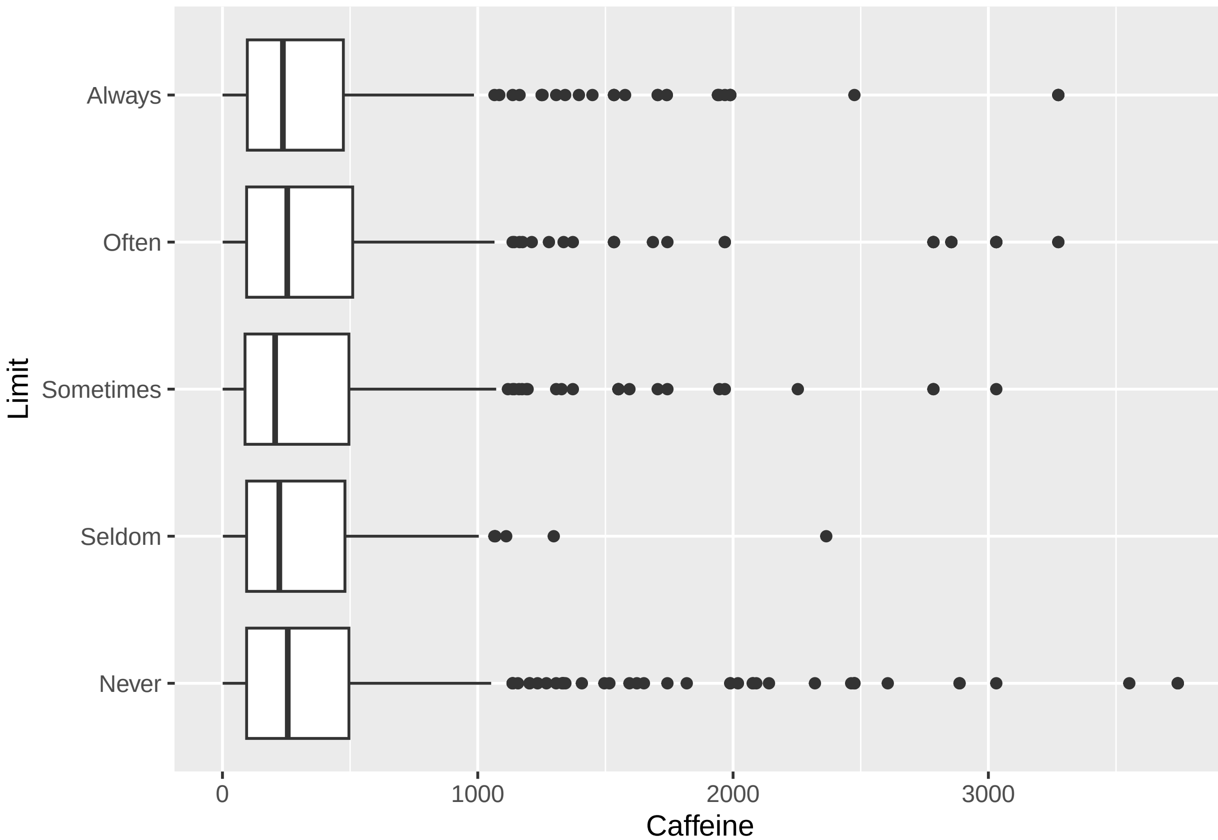

```r
# Education
ggplot(data = reduced_data, aes(x = edu, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "Education", y = "Percentage", fill = "Limit") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```



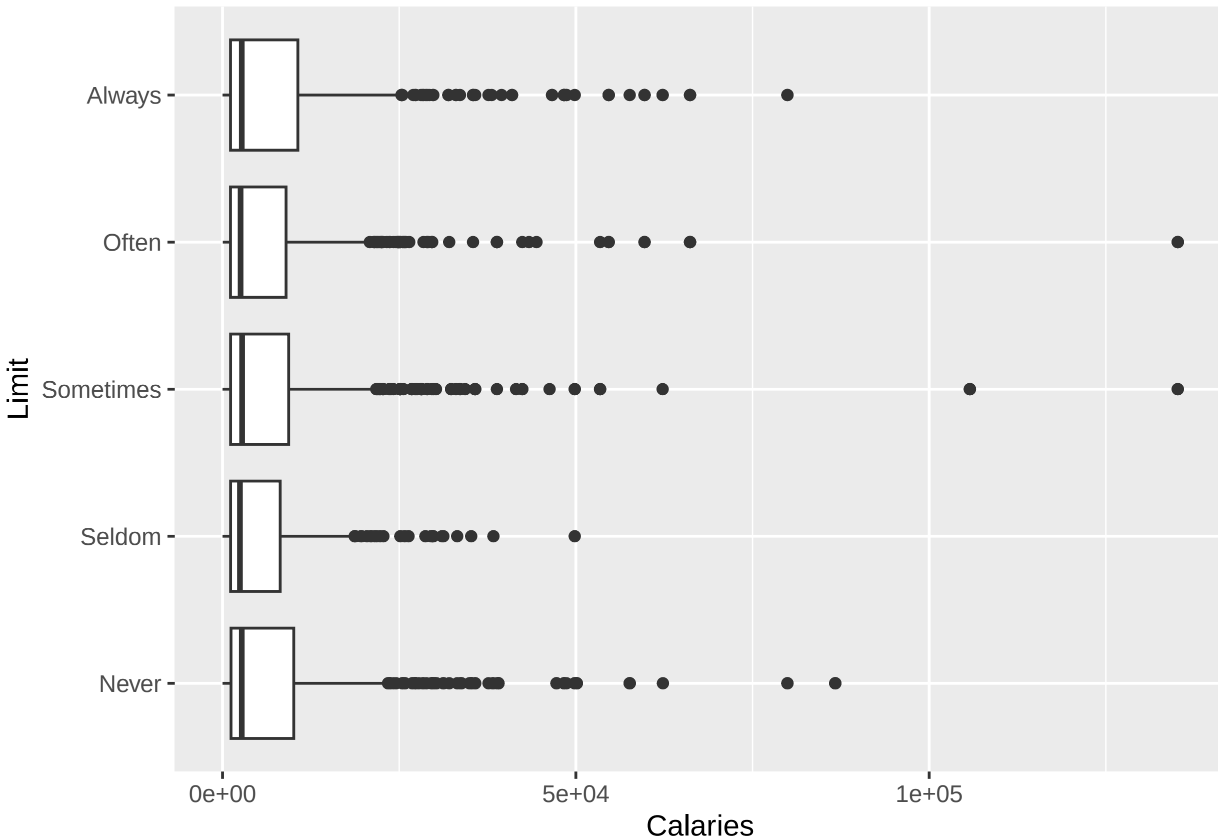

```r
# City
ggplot(data = reduced_data, aes(x = city, fill = limit)) +
  geom_bar(position = "fill") +
  scale_y_continuous(labels = scales::percent) +
  labs(x = "City", y = "Percentage", fill = "Limit") +
  theme_minimal()
```



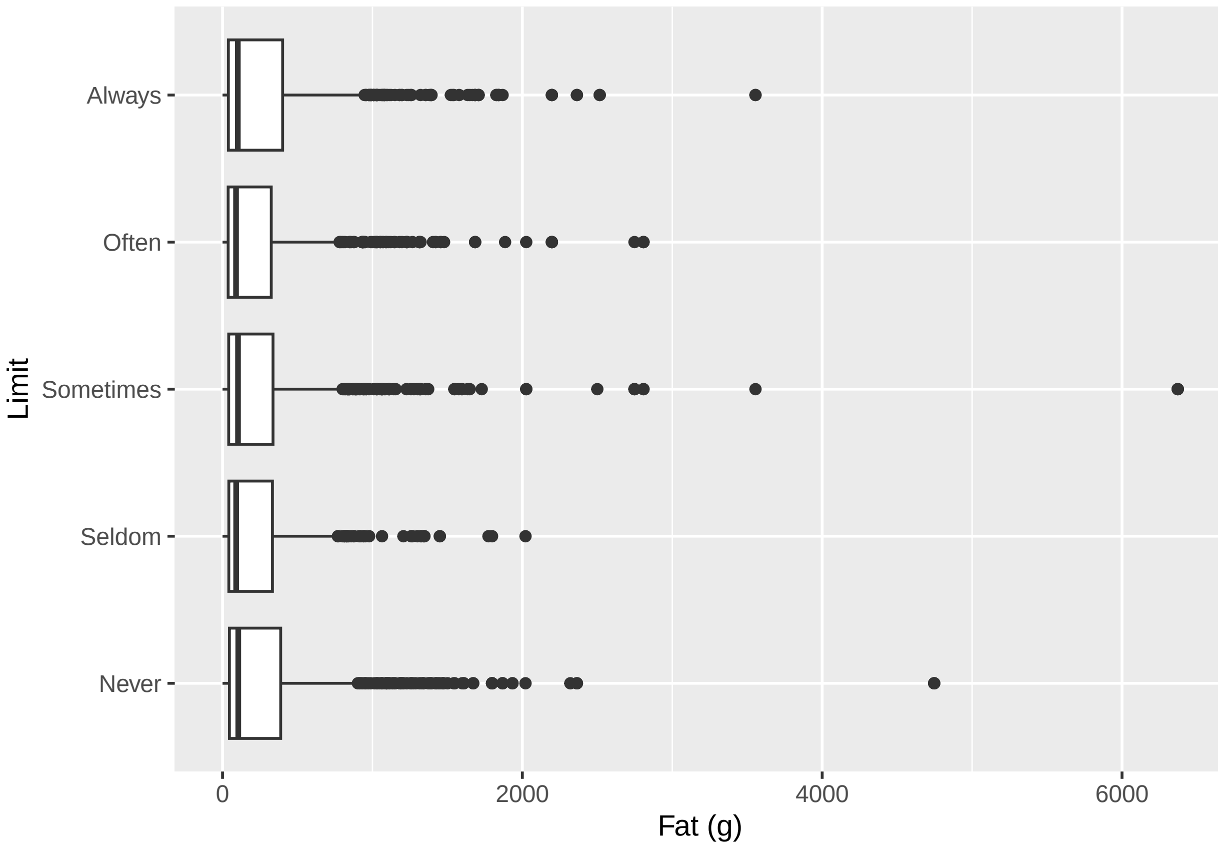

```r
# Caffeine
ggplot(data = reduced_data %>% filter(caff > 0), aes(x = caff , y = limit)) +
  geom_boxplot() +
  labs(x = "Caffeine", y = "Limit")
```



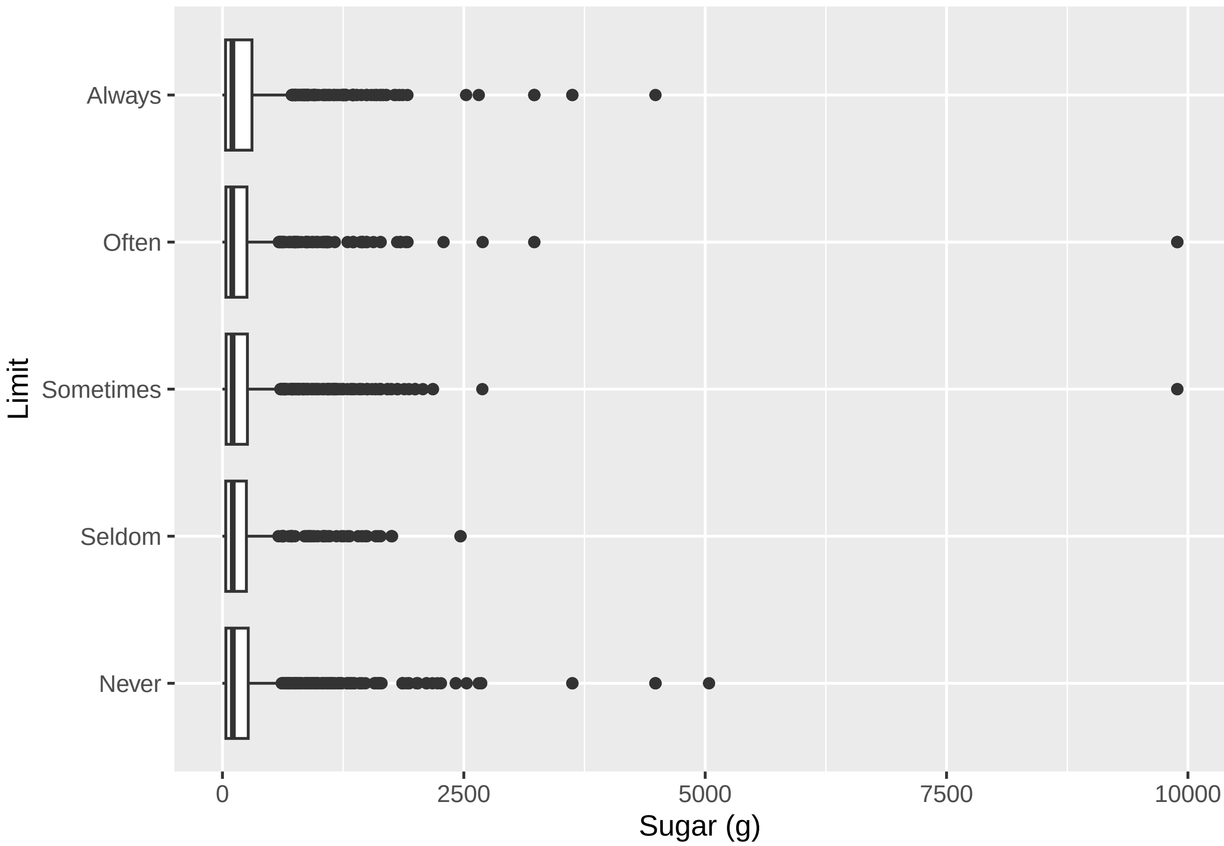

```
# Kcal
ggplot(data = reduced_data, aes(x = caloriescal, y = limit)) +
  geom_boxplot() +
  labs(x = "Calaries", y = "Limit")
```



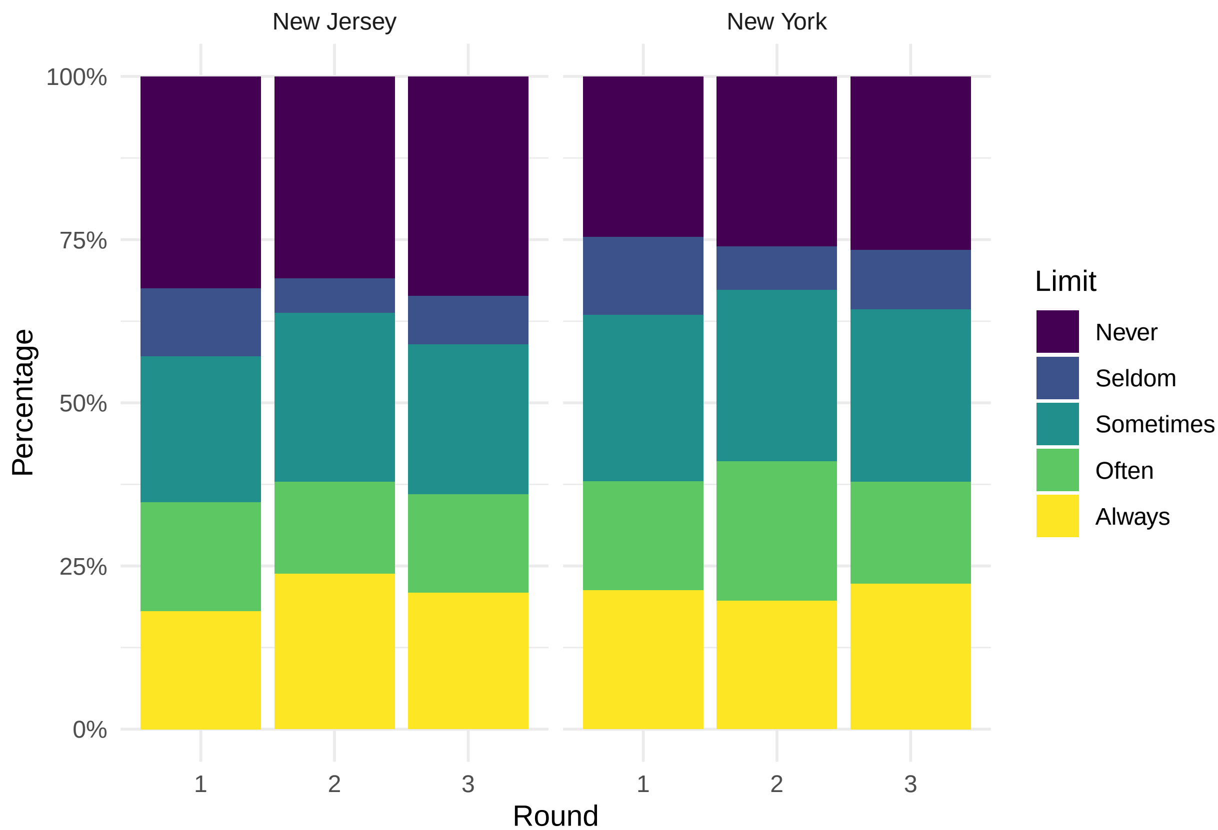

```r
# fat
ggplot(data = reduced_data, aes(x = fatg, y = limit)) +
  geom_boxplot() +
  labs(x = "Fat (g)", y = "Limit")
```



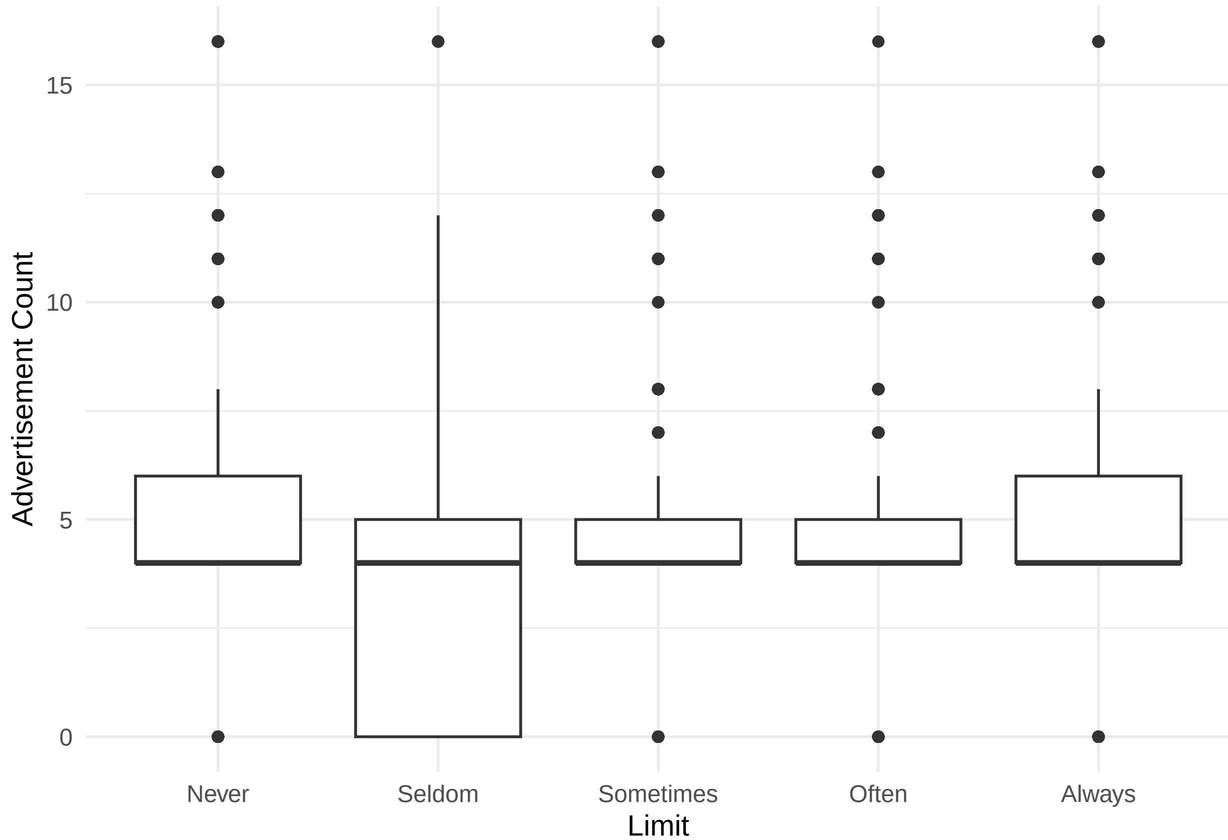

```r
# sugar
ggplot(data = reduced_data, aes(x = sugarg, y = limit)) +
  geom_boxplot() +
  labs(x = "Sugar (g)", y = "Limit")
```




```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()
```



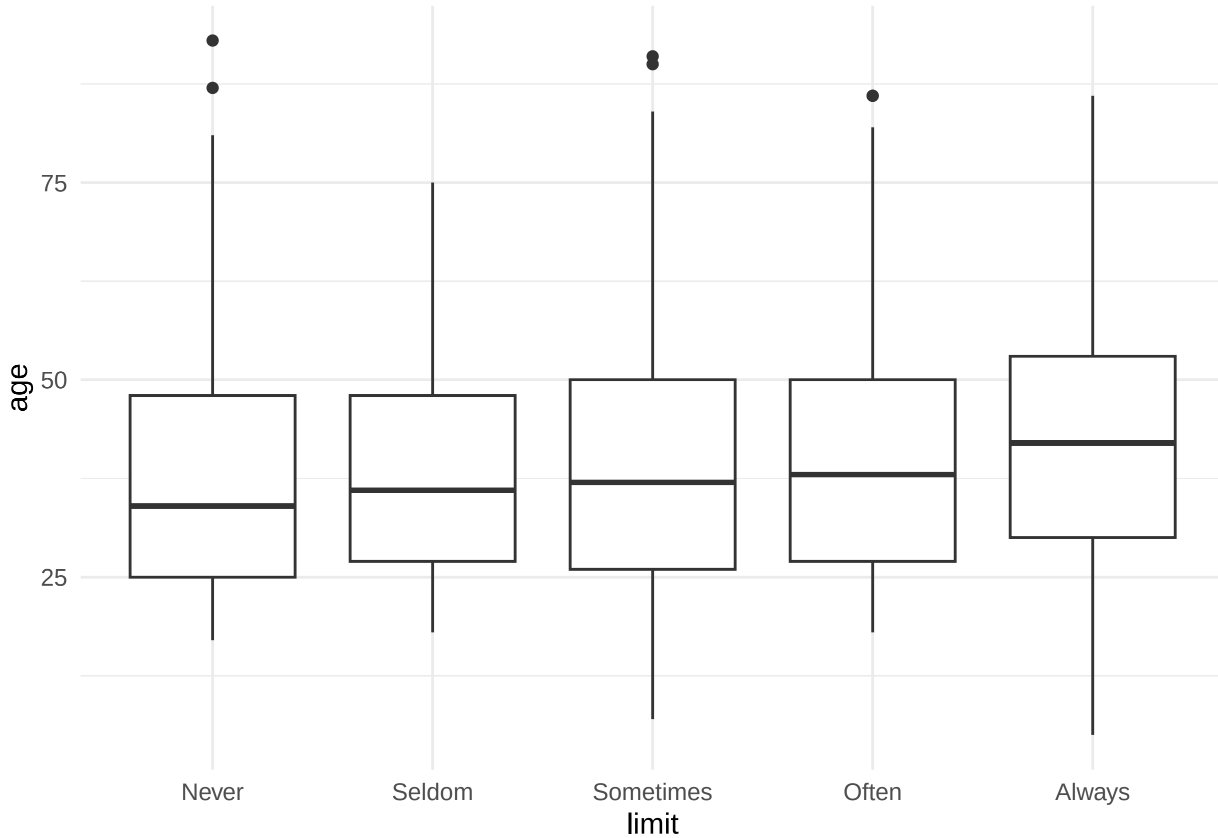

```r
# Advertisement count
ggplot(data = reduced_data, aes(y = nsigns_ssb, x = limit)) +
  geom_boxplot() +
  labs(y = "Advertisement Count", x = "Limit") +
  theme_minimal()
```

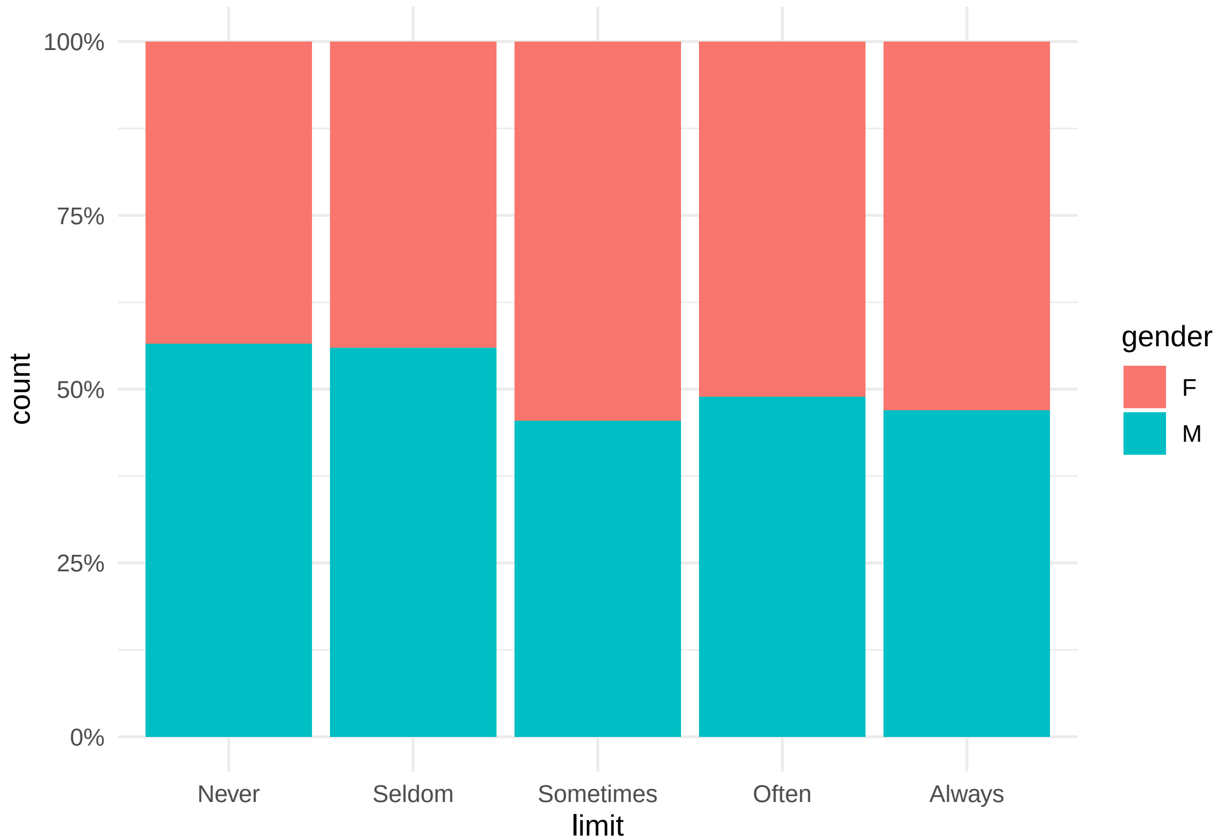


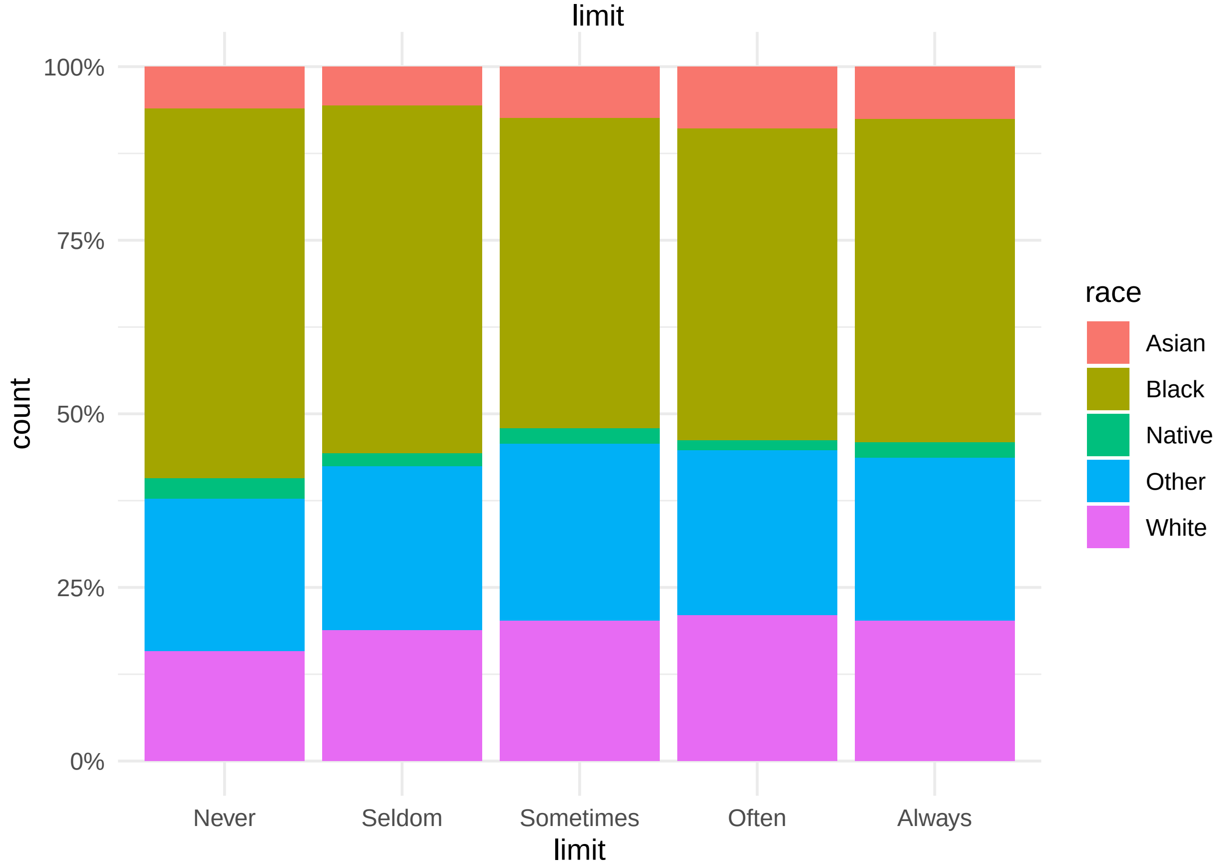

```r
# Plot function for interactions

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

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())
  }
```

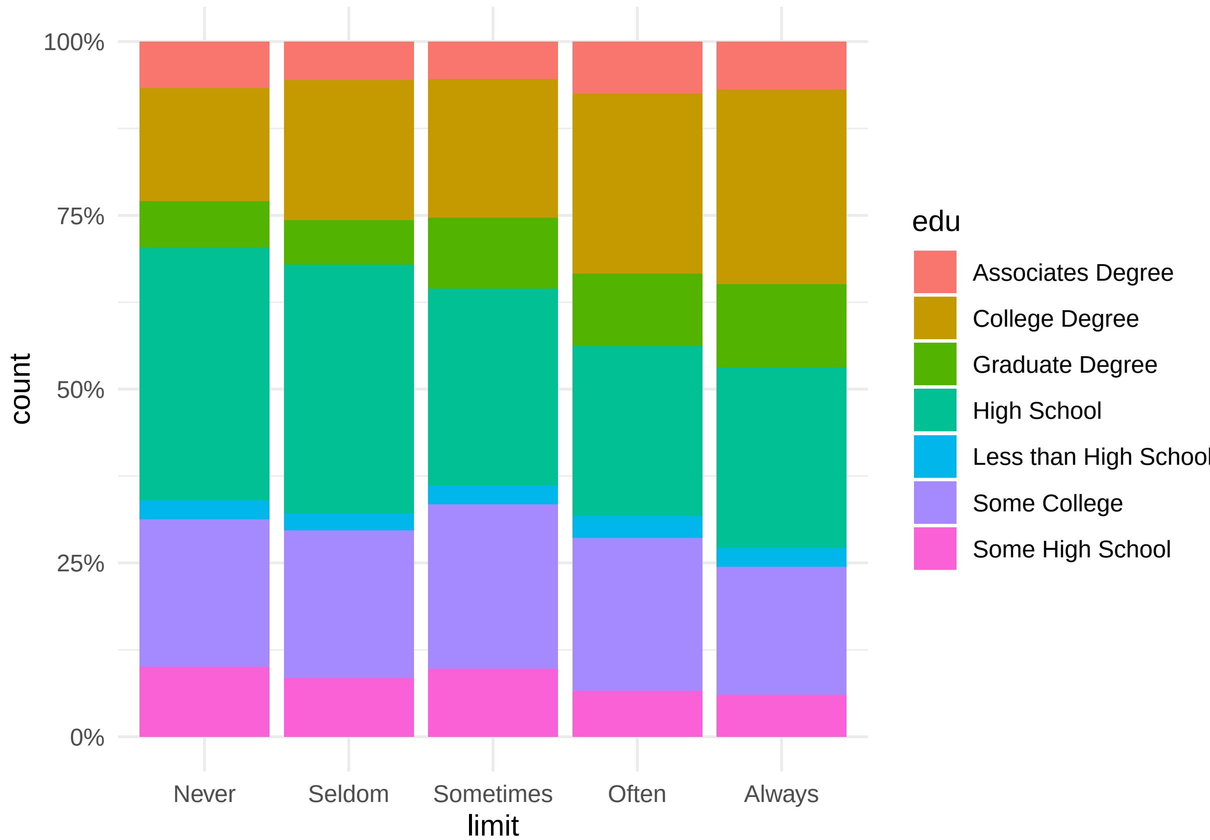
```
  if(var1 %in% plot_nums & var2 %in% plot_nums){
    print(ggplot(data = reduced_data, aes(x = !!sym(var2), y = !!sym(var1))) +
      geom_point() +
      theme_minimal())
  }
}
```

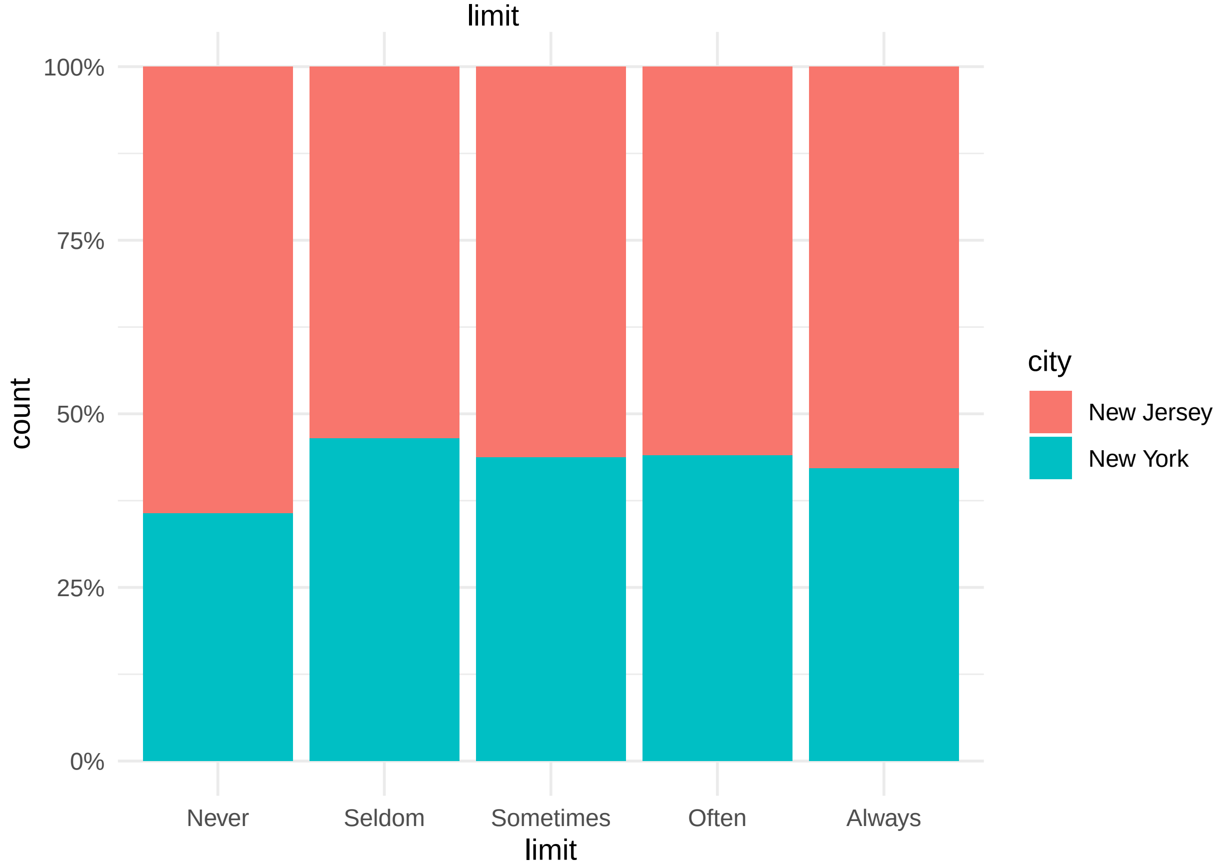
```
for(i in 1:length(names(reduced_data))){
  if(i != length(reduced_data)){
    for(j in (i+1):length(reduced_data)){
      make_plot(names(reduced_data)[i], names(reduced_data)[j])
    }
  }
}
```

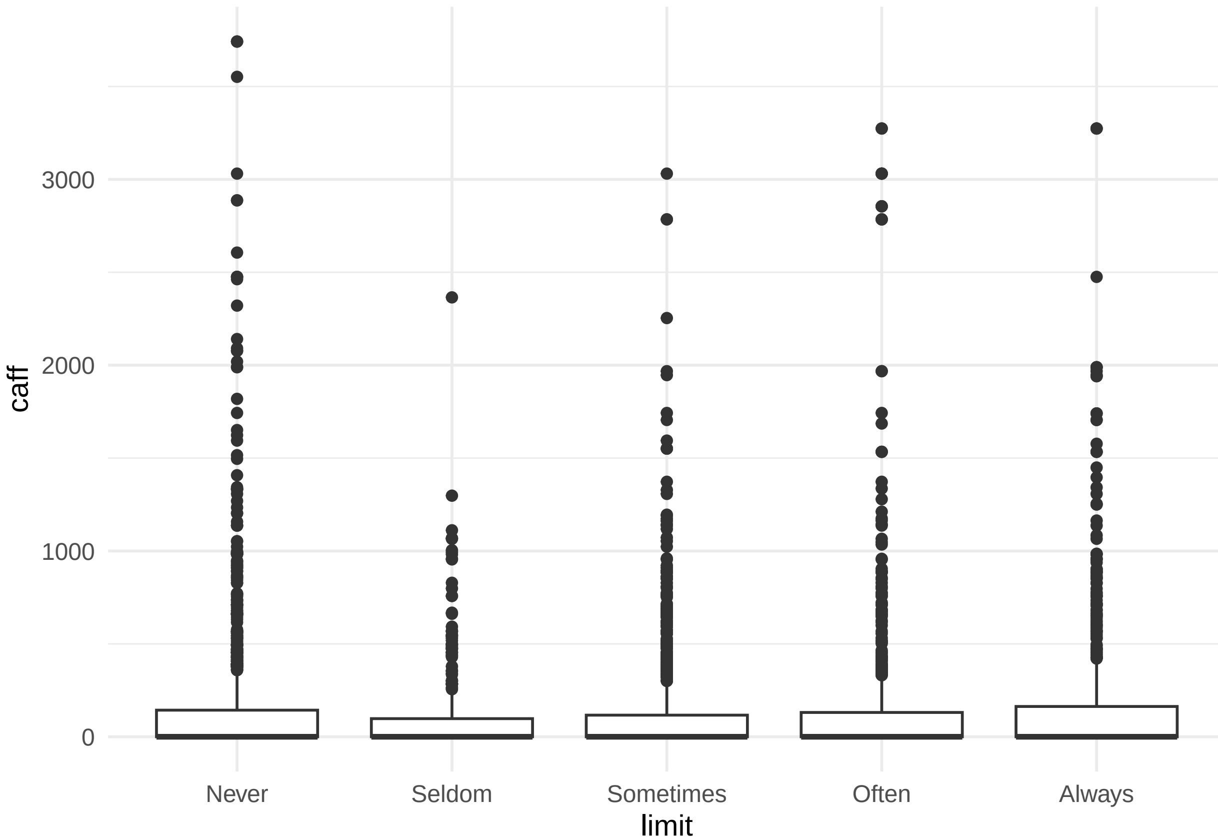


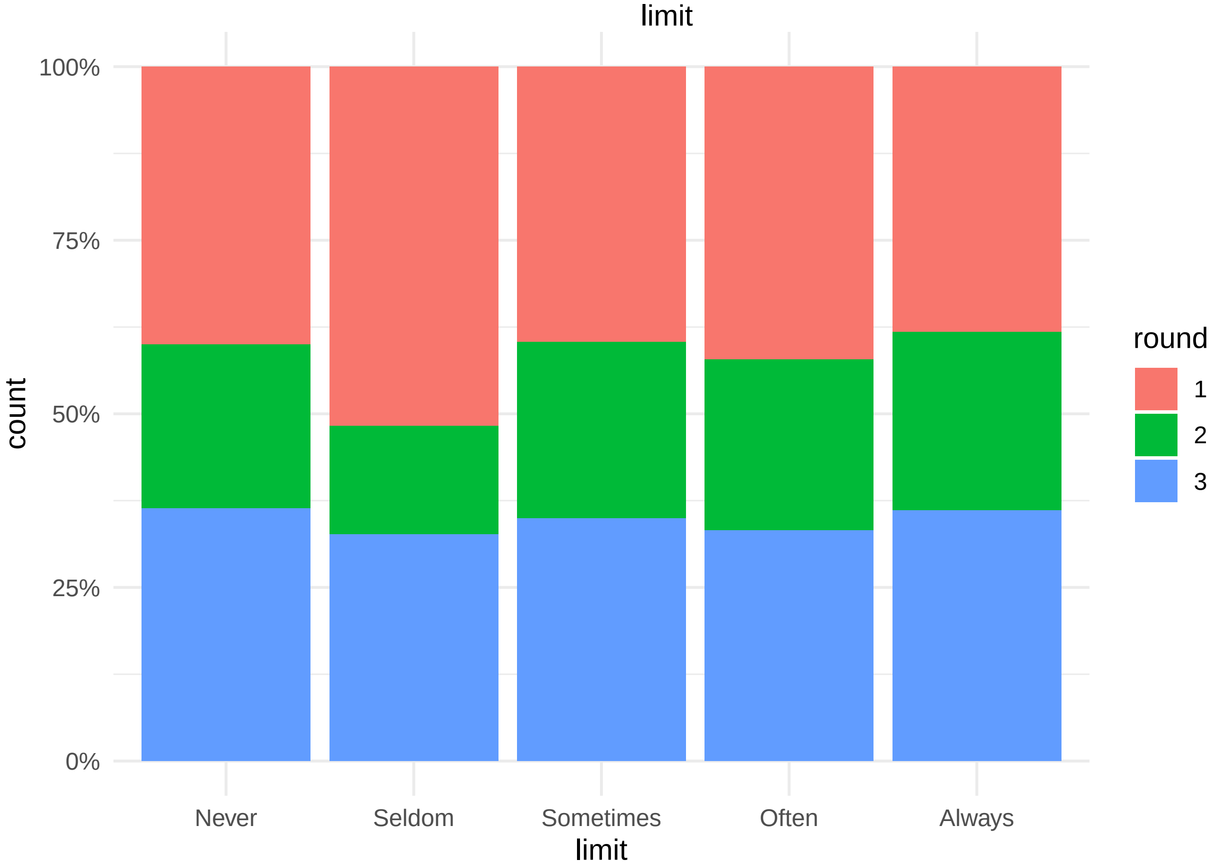

100%
75%
50%
25%
0%
count
Never
Seldom
Sometimes
Often
Always
limit
gender
F
M

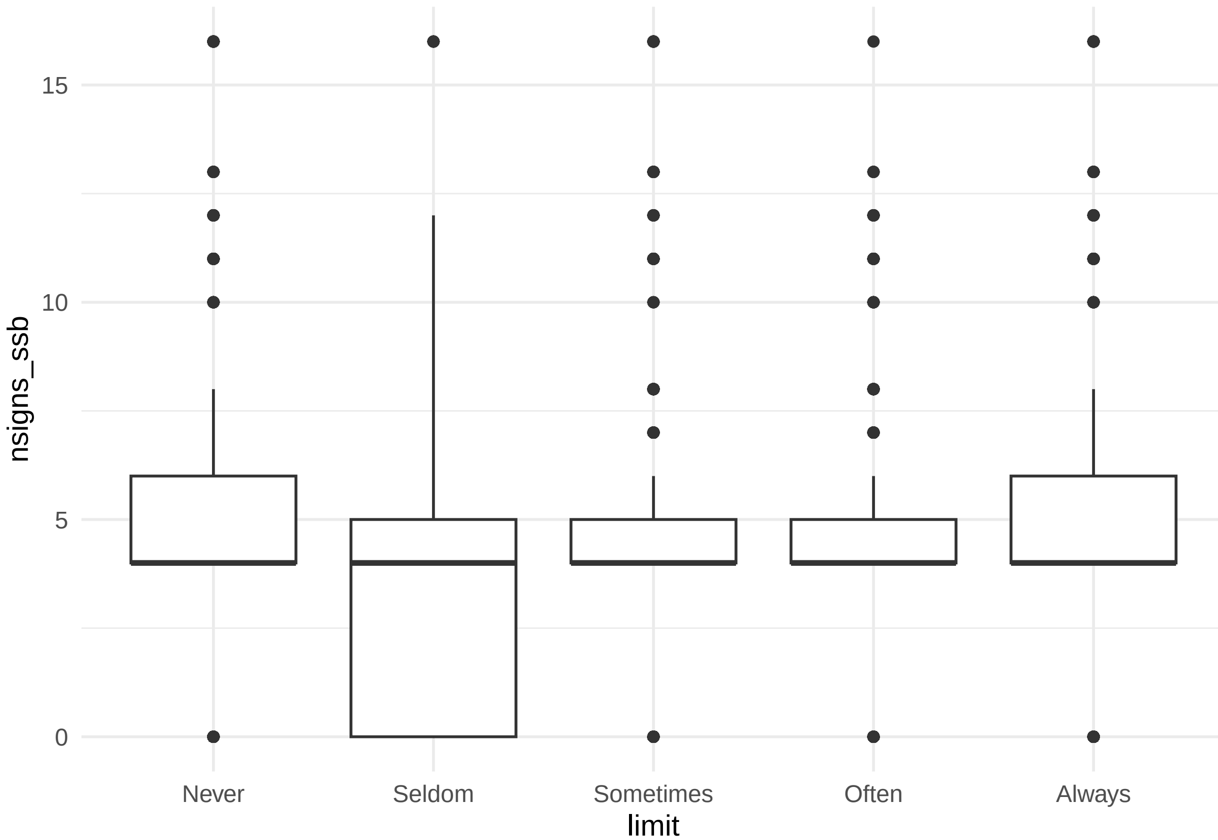

100%
75%
50%
25%
0%
count
Never
Seldom
Sometimes
Often
Always
limit
race
Asian
Black
Native
Other
White


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

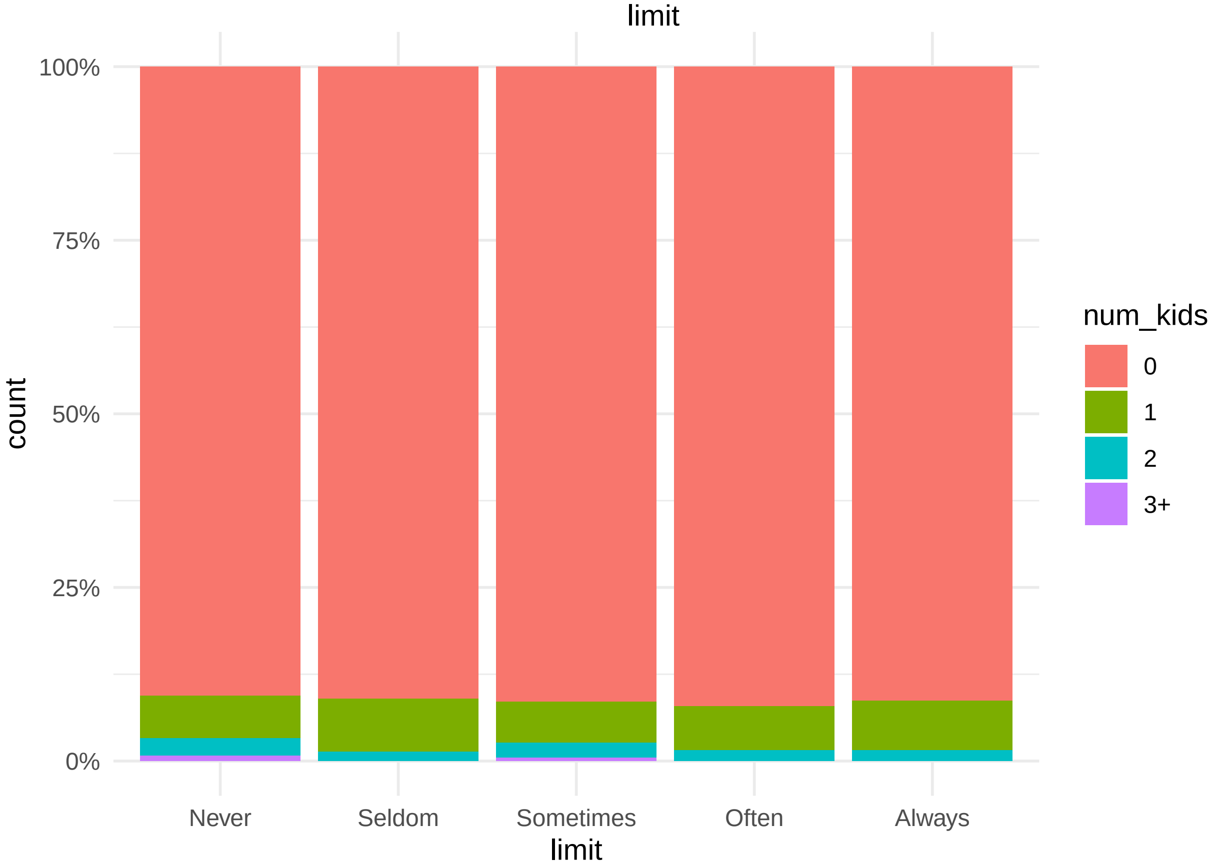

100%
75%
50%
25%
0%
count
Never
Seldom
Sometimes
Often
Always
limit
city
New Jersey
New York


caff
3000
2000
1000
0
Never
Seldom
Sometimes
Often
Always
limit

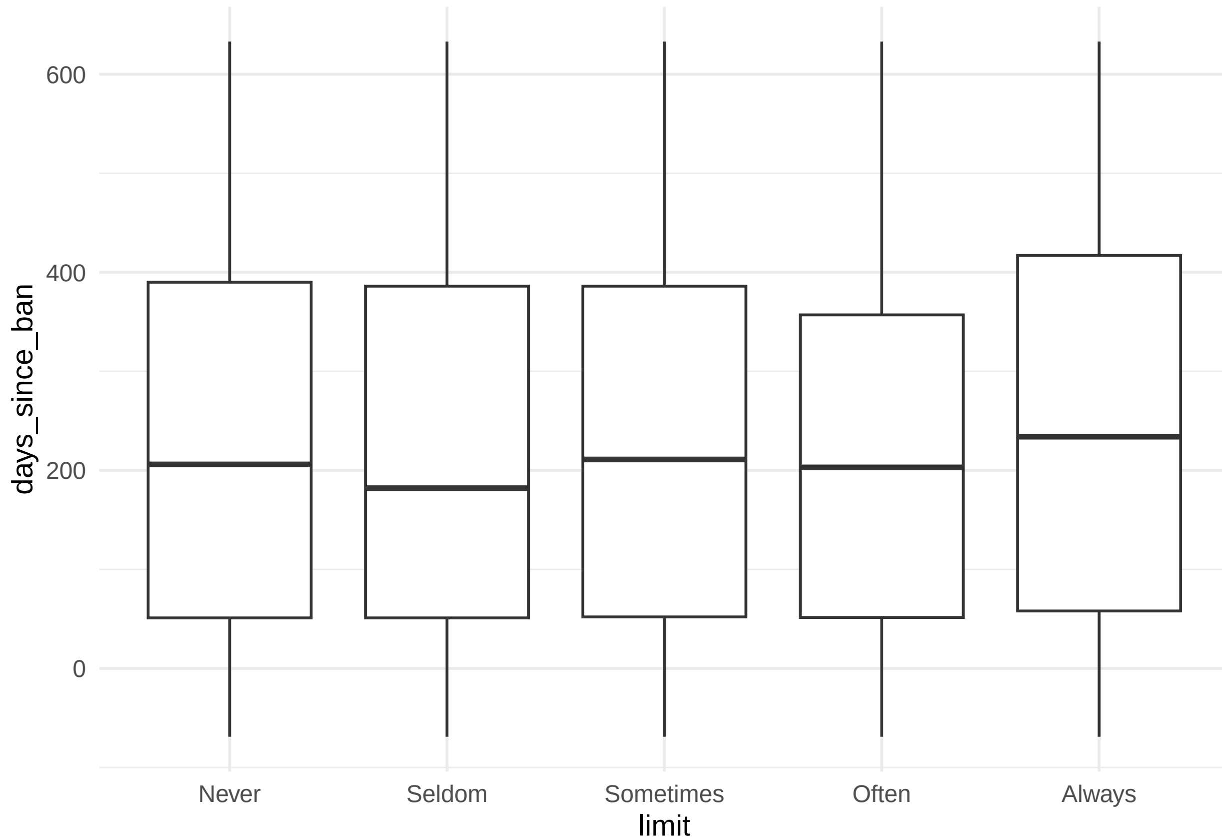

count
100%
75%
50%
25%
0%
Never
Seldom
Sometimes
Often
Always
limit
round
1
2
3



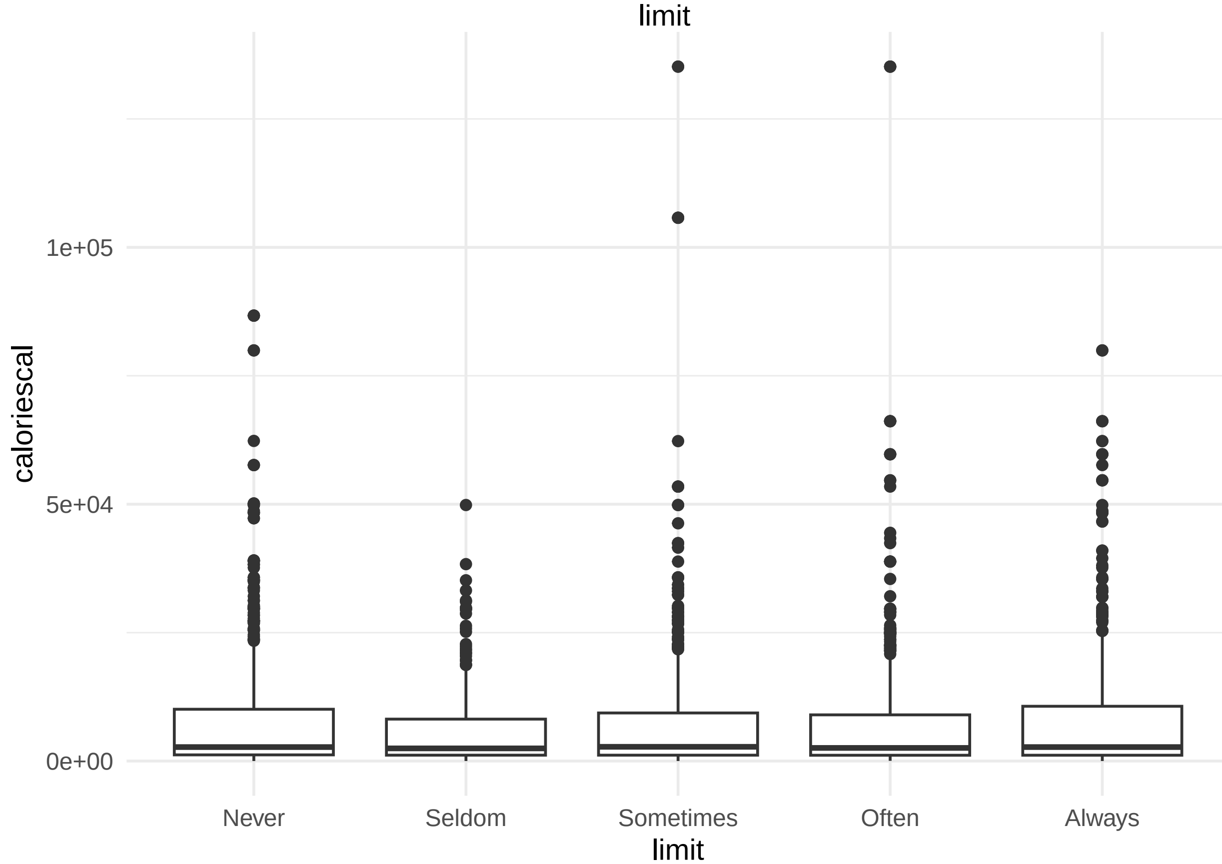
15
10
5
0
nsigns_ssb
Never
Seldom
Sometimes
Often
Always
limit



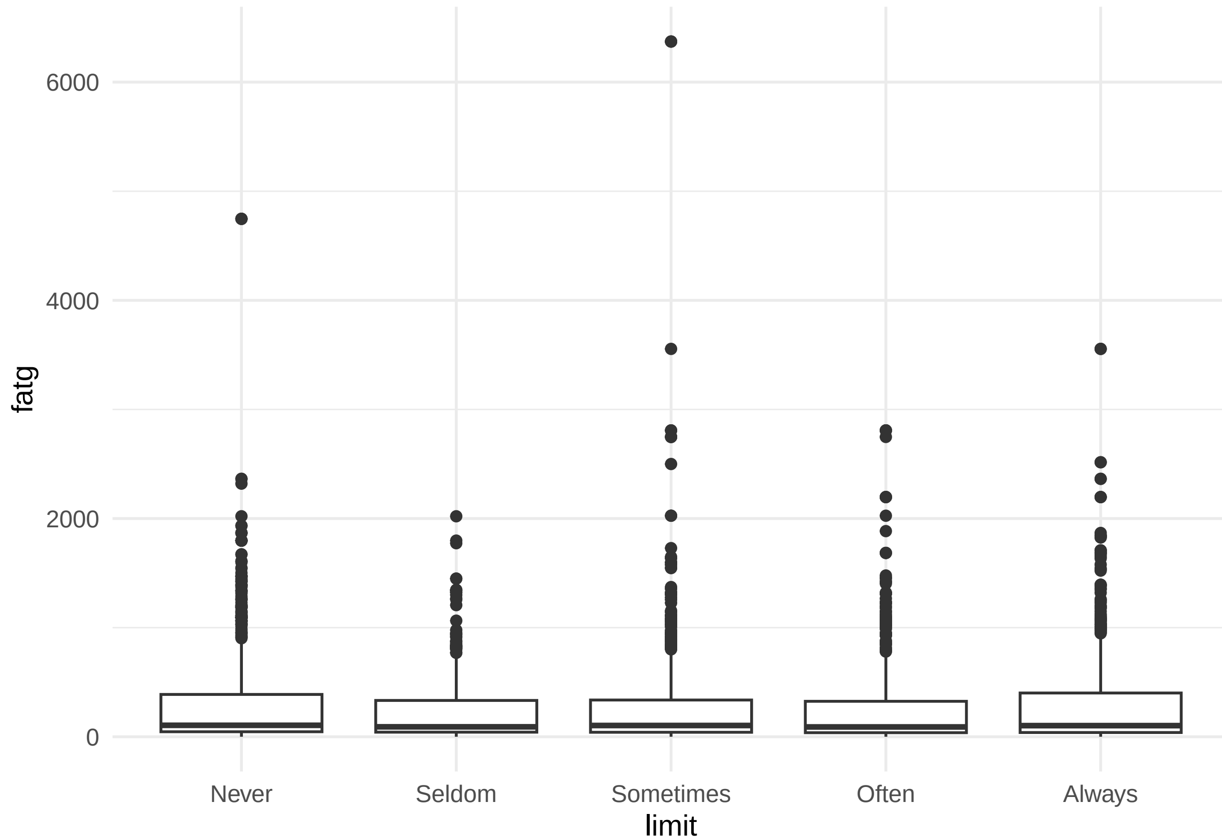
100%
75%
50%
25%
0%
count
Never
Seldom
Sometimes
Often
Always
limit
num_kids
0
1
2
3+

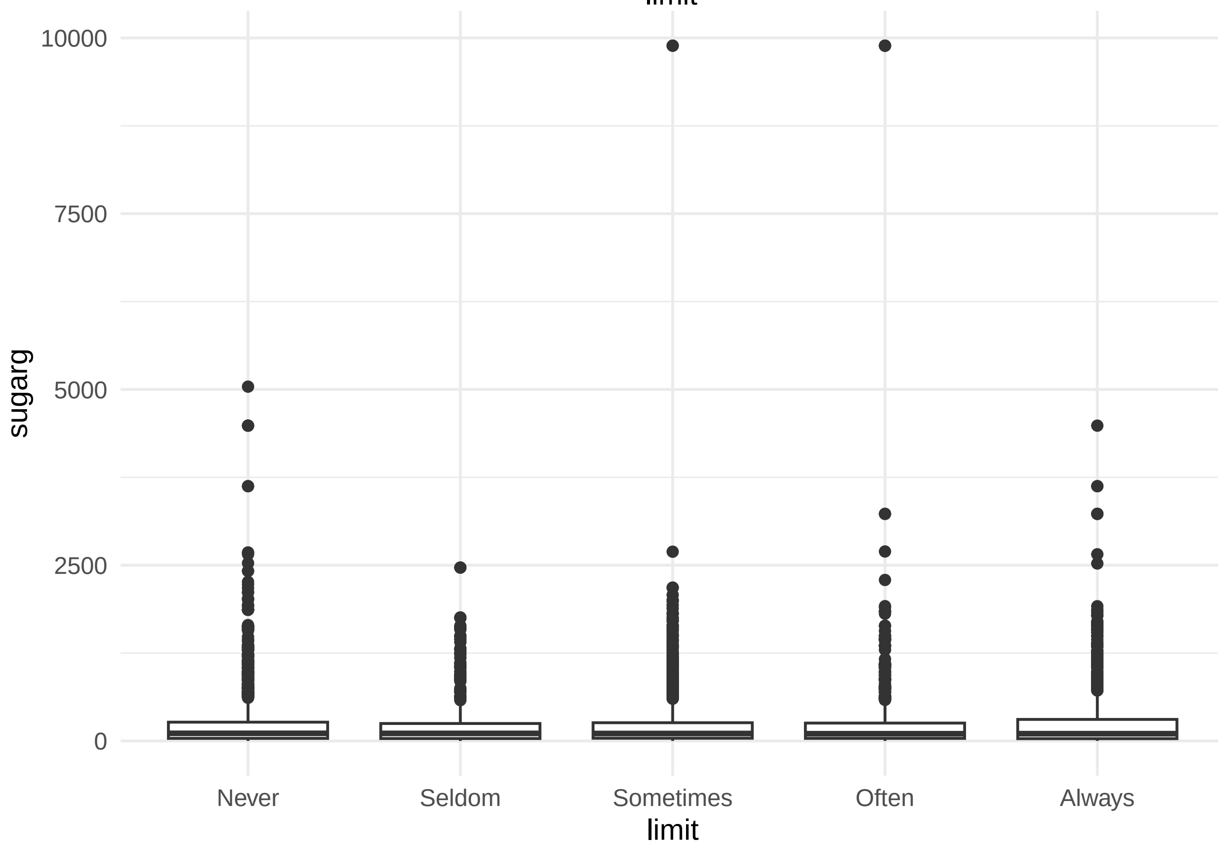


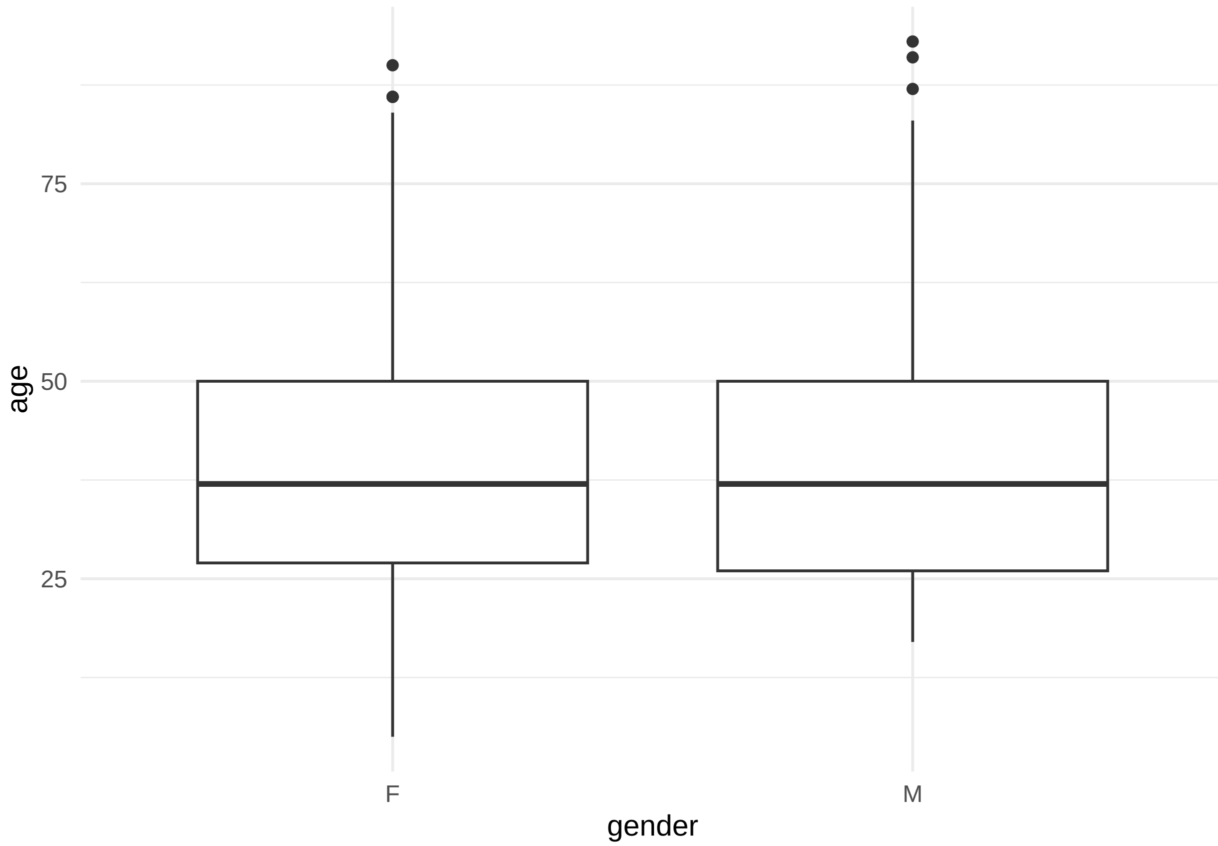
600
400
200
0
days_since_ban
Never
Seldom
Sometimes
Often
Always
limit



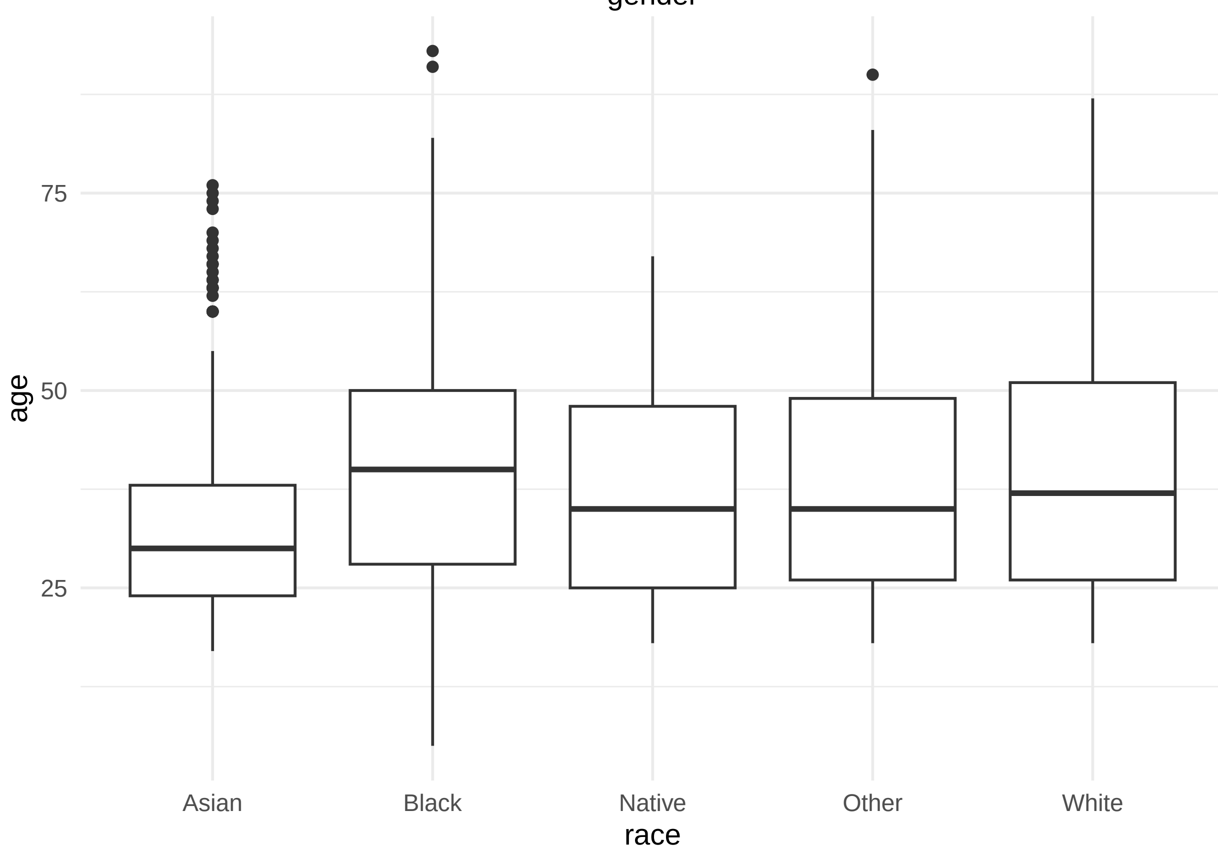
1e+05
5e+04
0e+00
caloriescal
Never
Seldom
Sometimes
Often
Always
limit


6000
4000
2000
0
fatg
Never
Seldom
Sometimes
Often
Always
limit

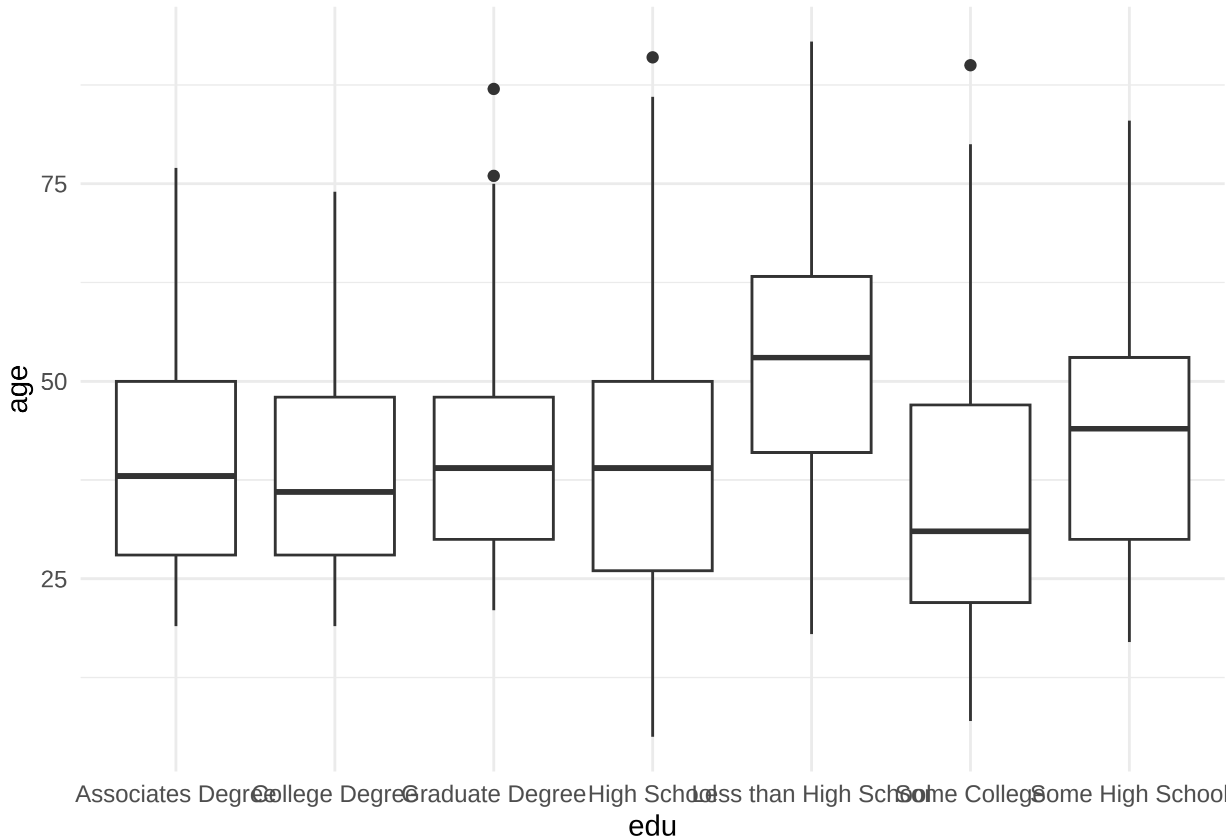

10000
7500
5000
2500
0
sugarg
Never
Seldom
Sometimes
Often
Always
limit



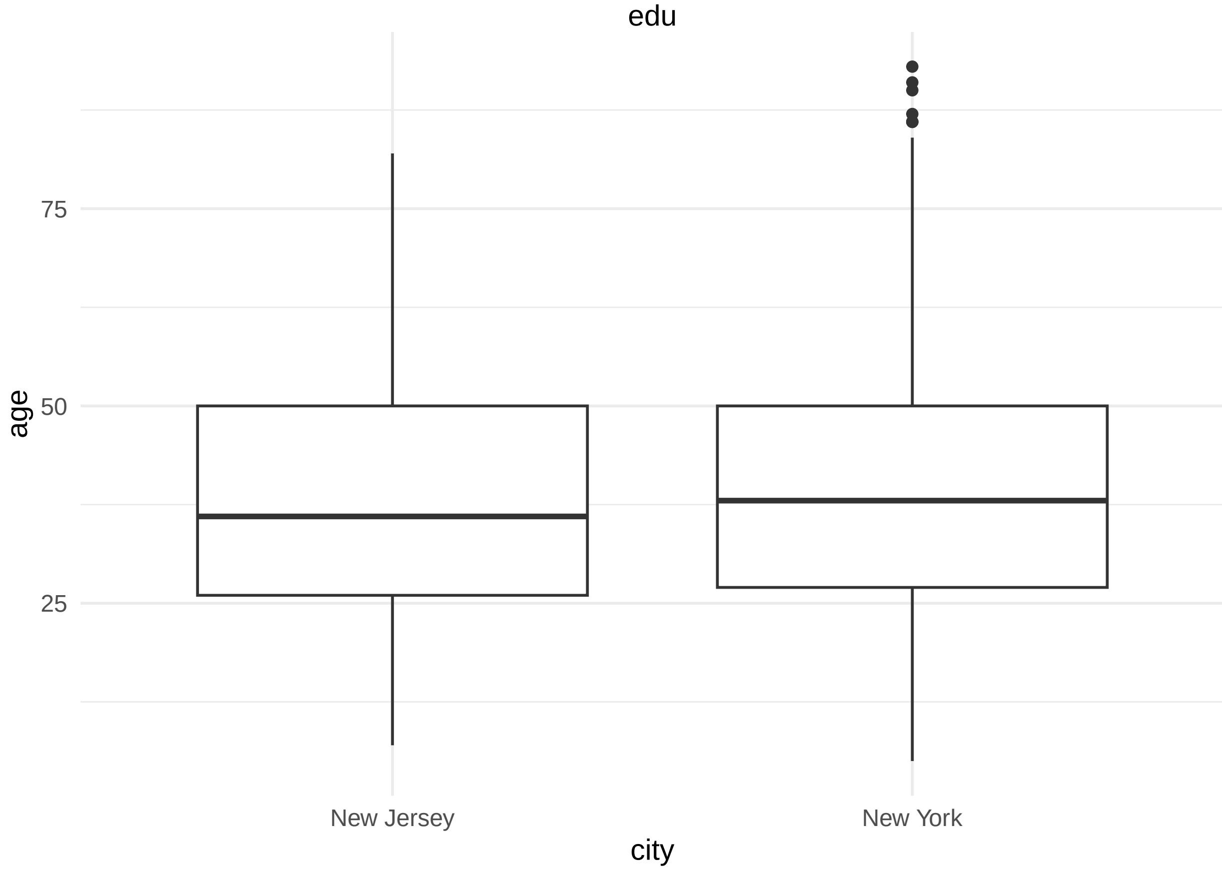
75
50
25
age
F
M
gender



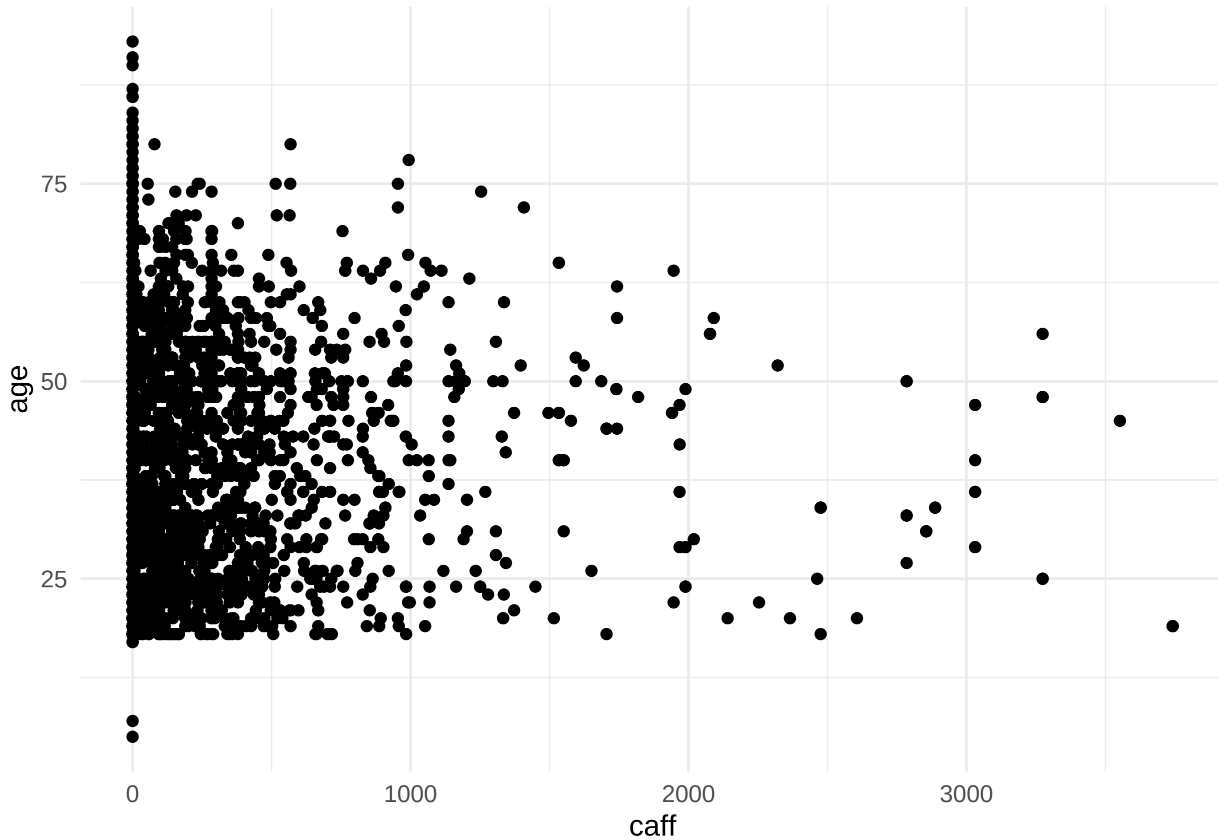
75
50
25
age
Asian
Black
Native
Other
White
race



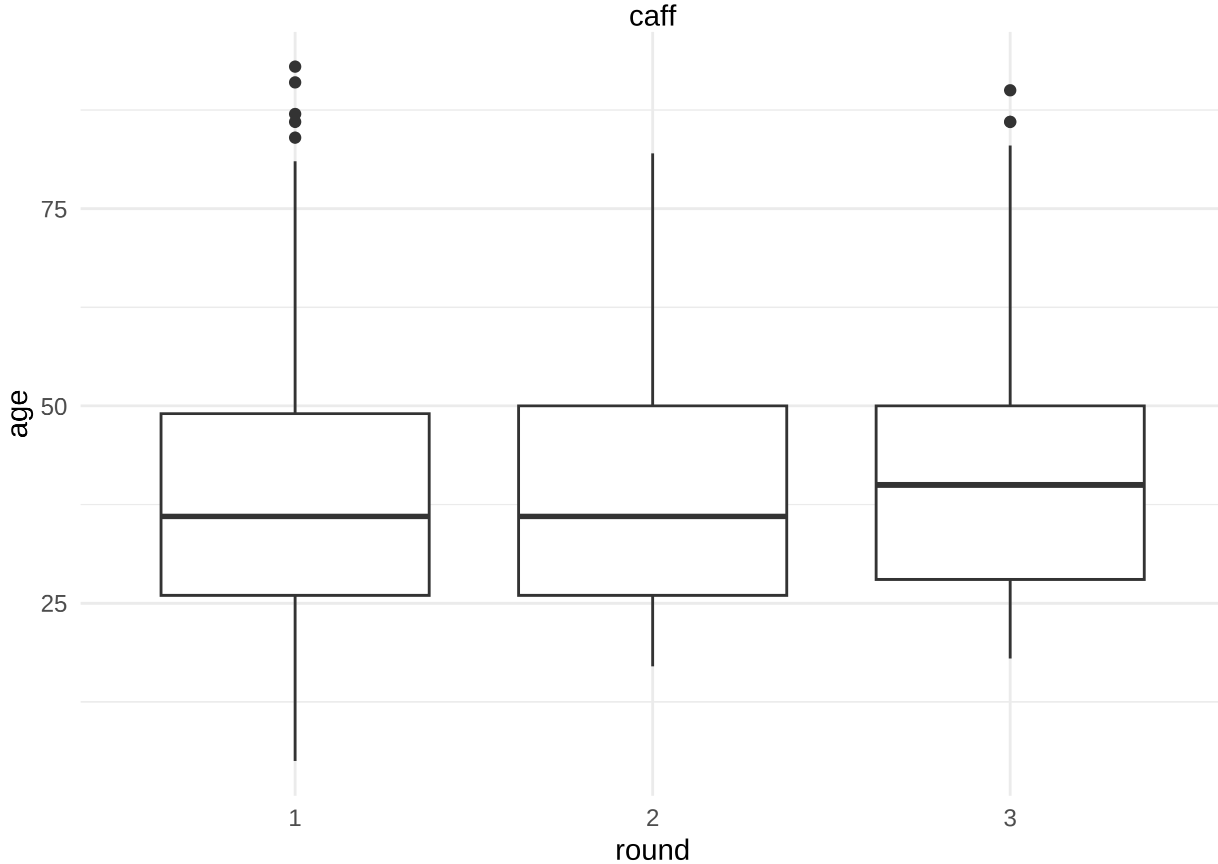
age
75
50
25
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu



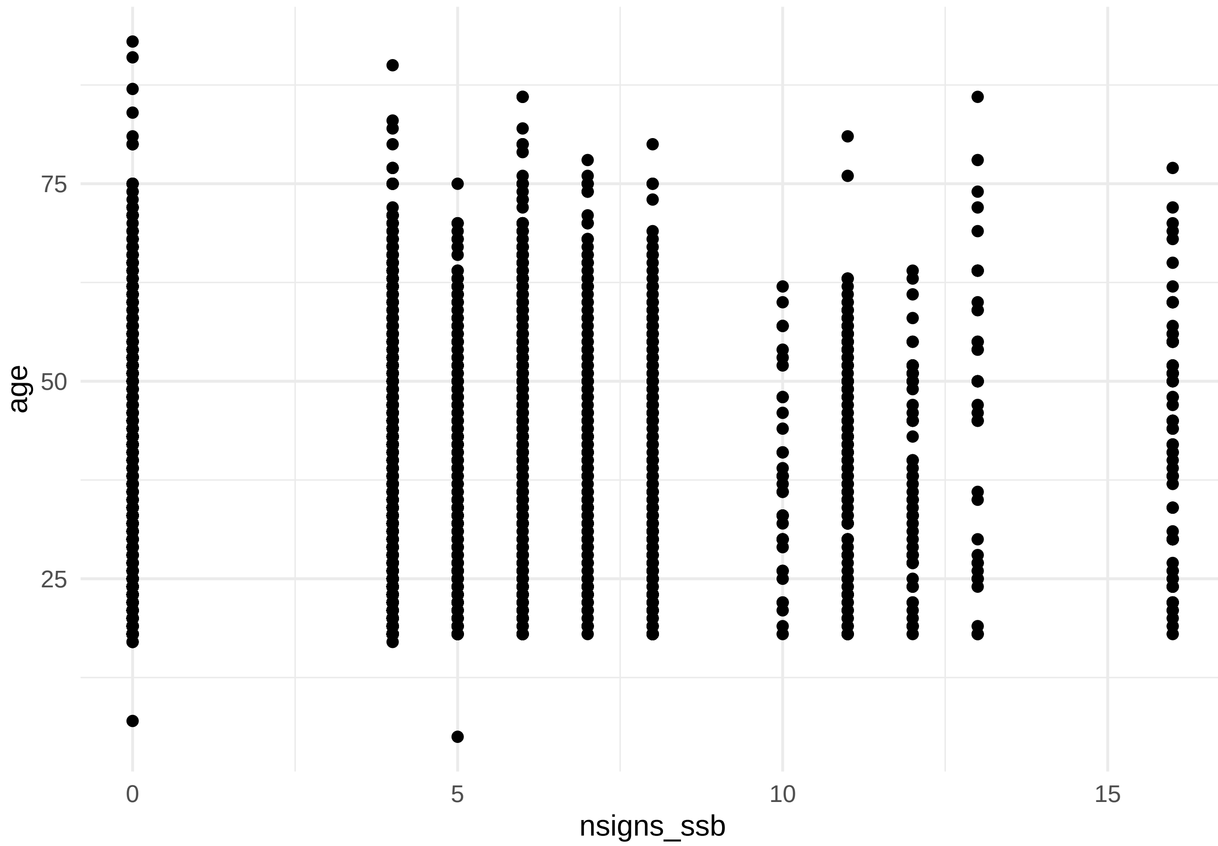
age
75
50
25
New Jersey
New York
city

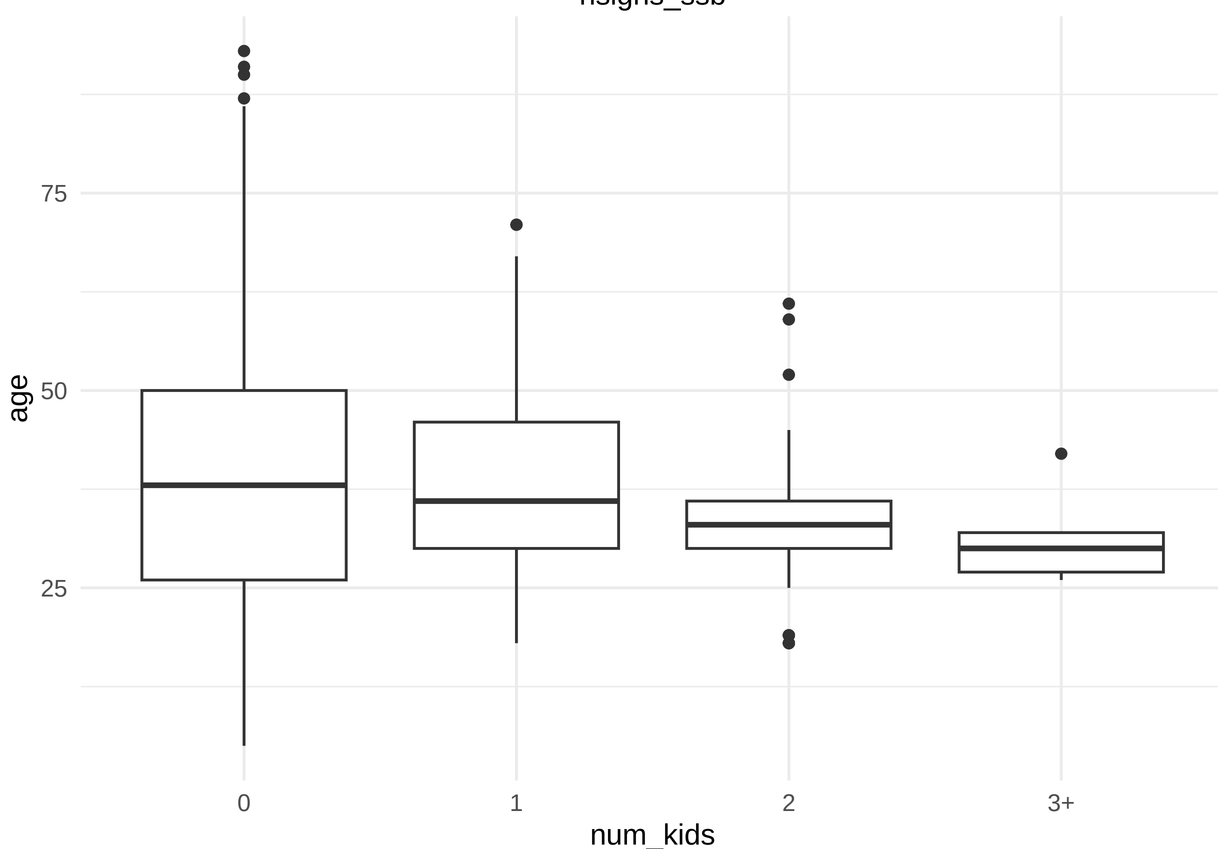


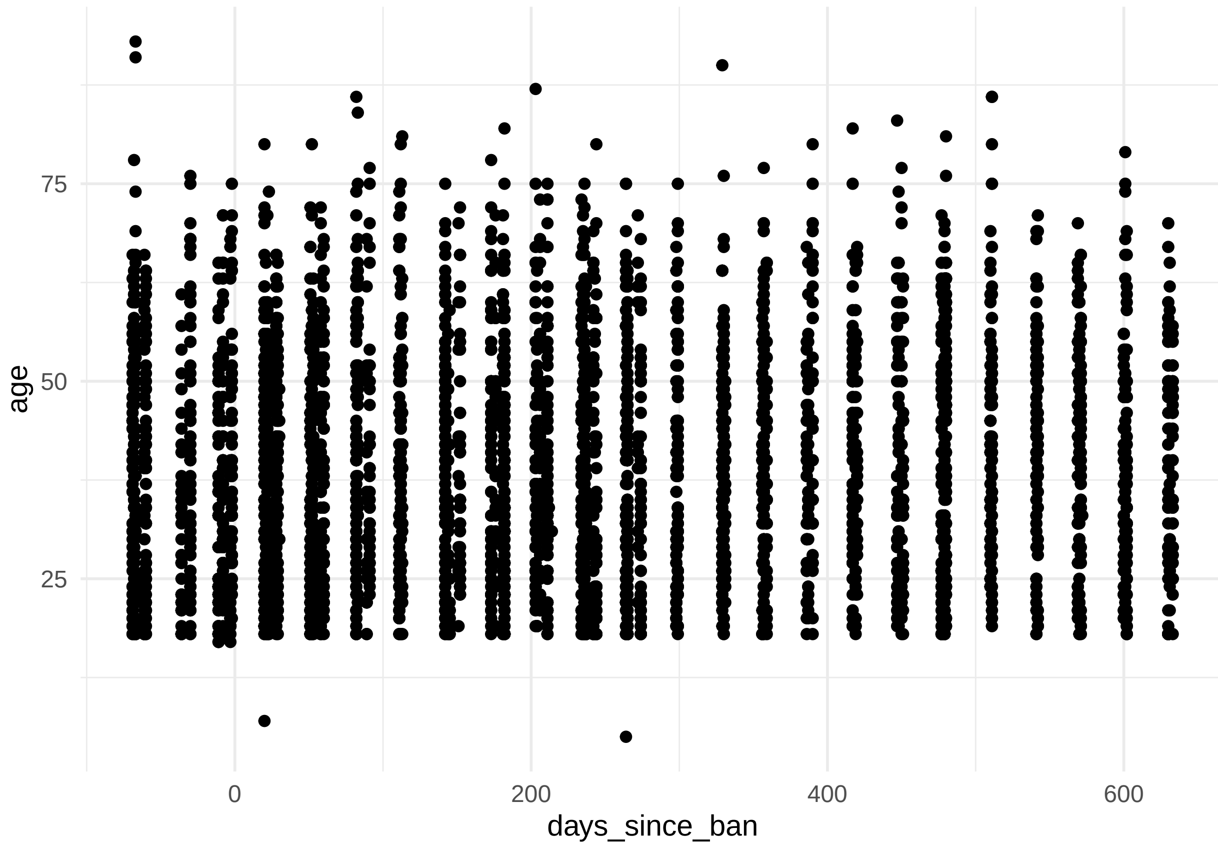
75
50
25
age
0
1000
2000
3000
caff



75
50
25
age
1
2
3
round


age
75
50
25
0
5
10
15
nsigns_ssb


age
75
50
25
0
1
2
3+
num_kids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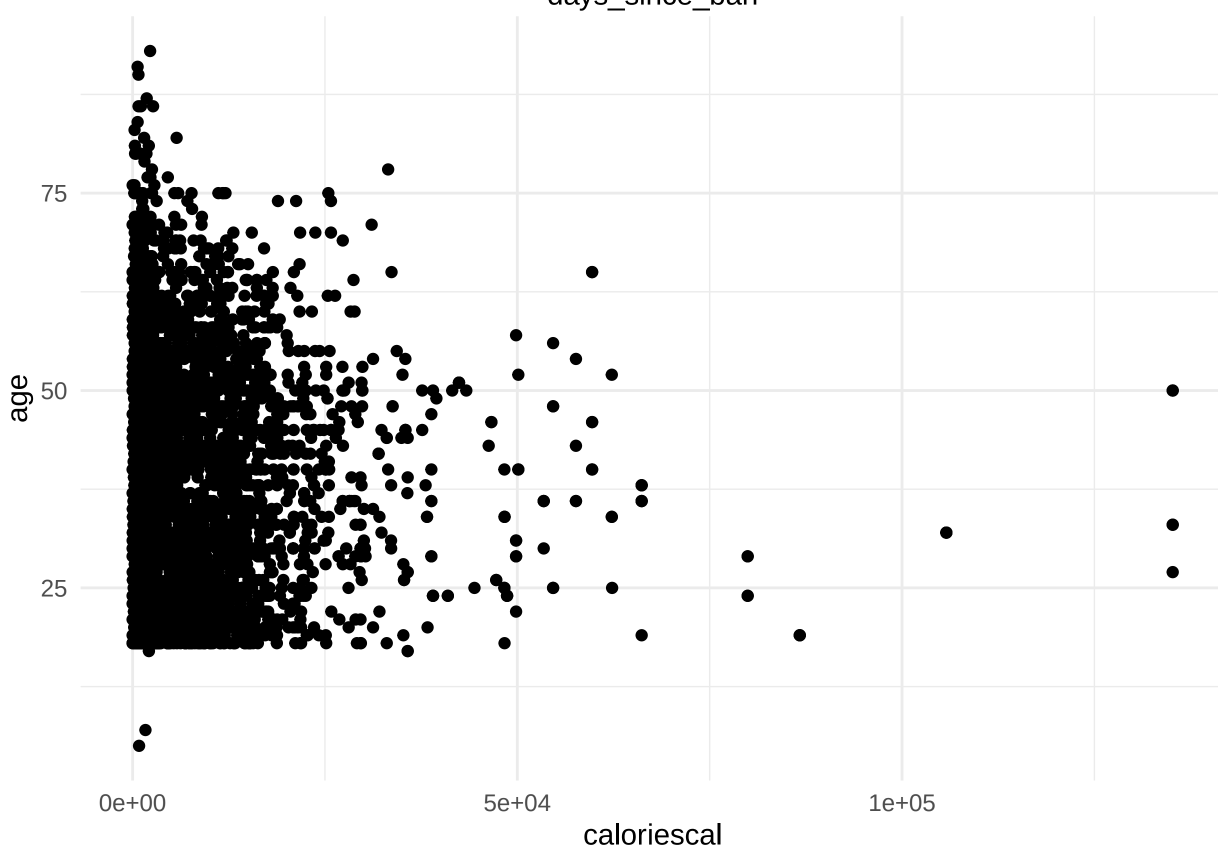
600
days_since_ban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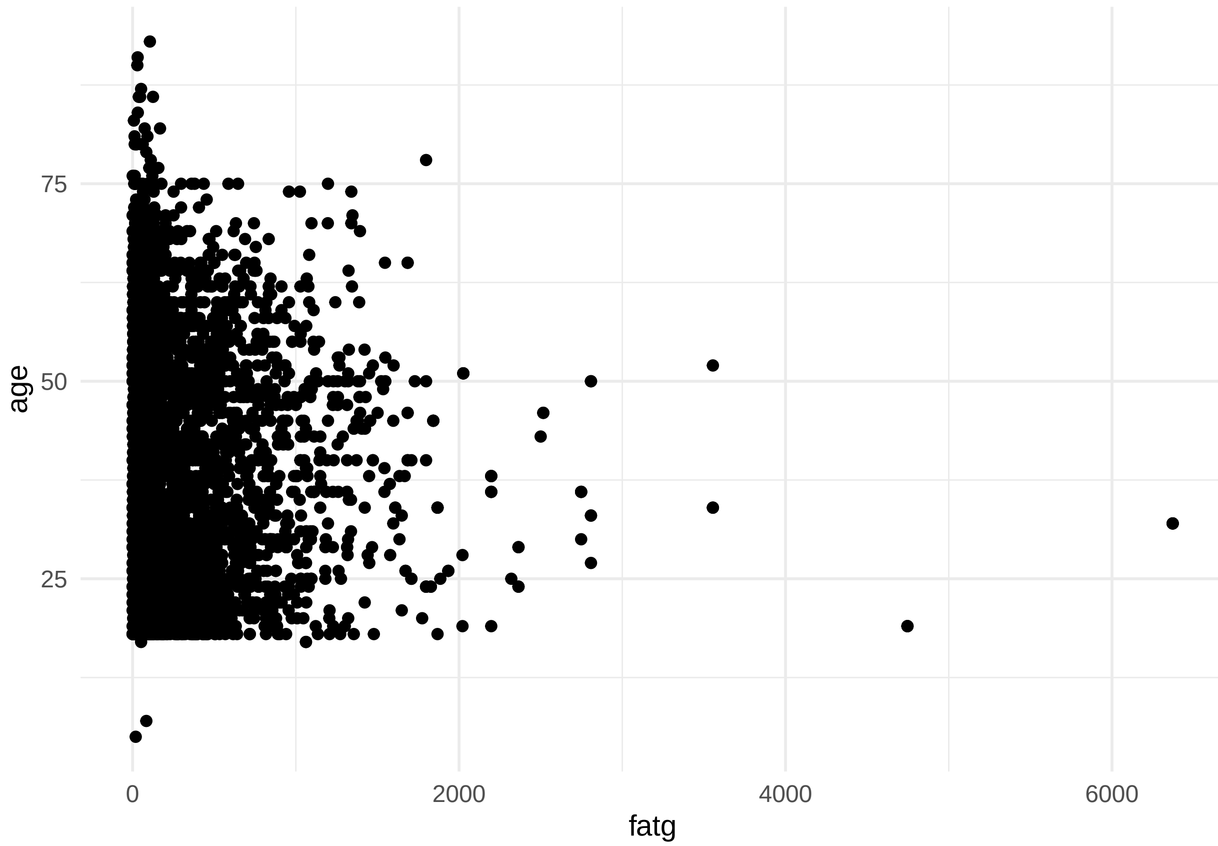
1e+05
caloriescal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6000
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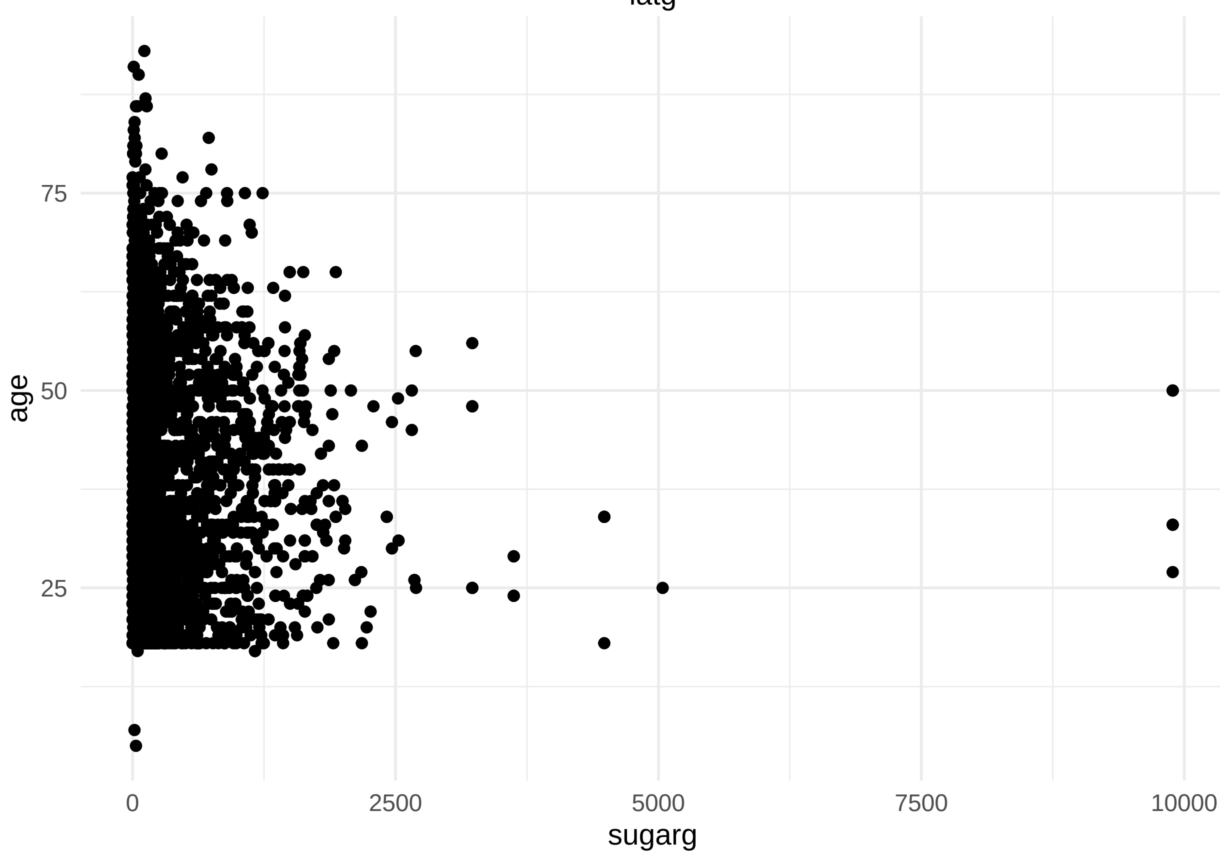
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7500
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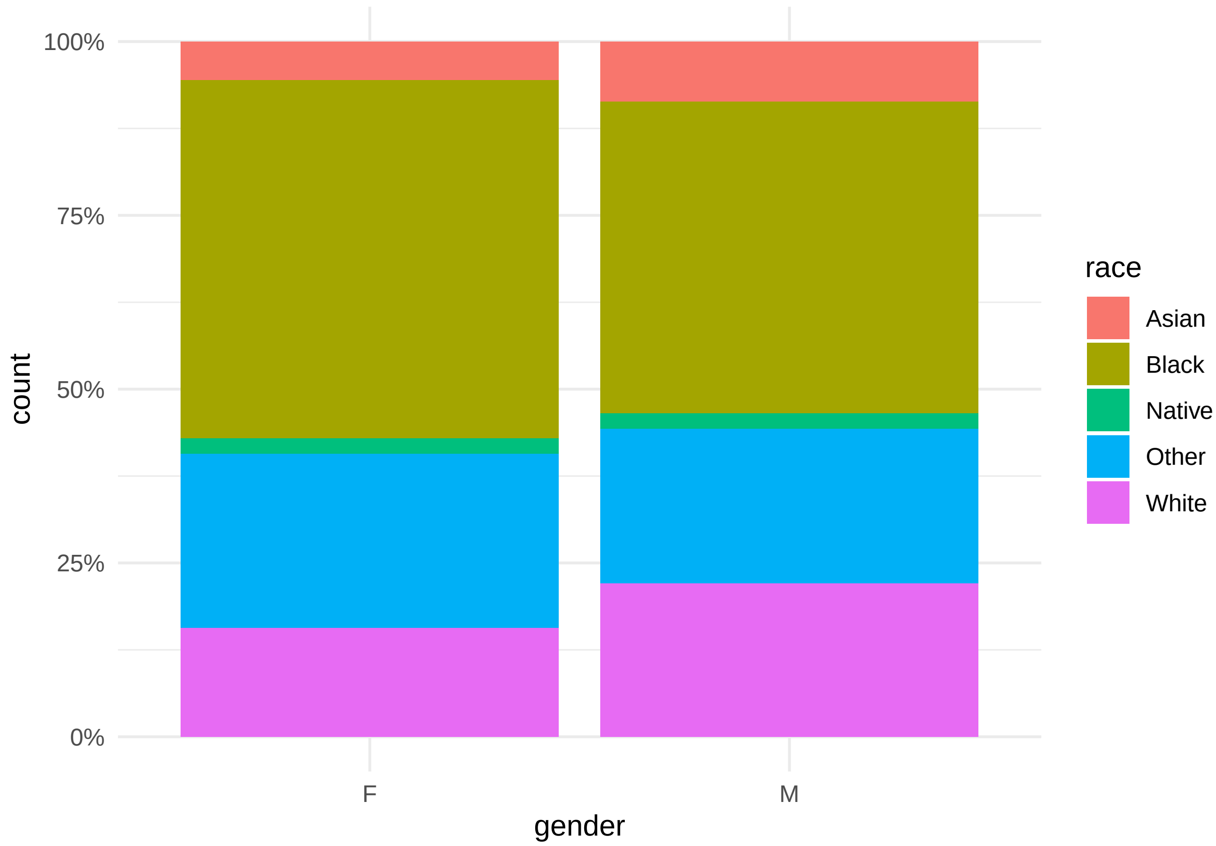
sugarg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count
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M
gender
race
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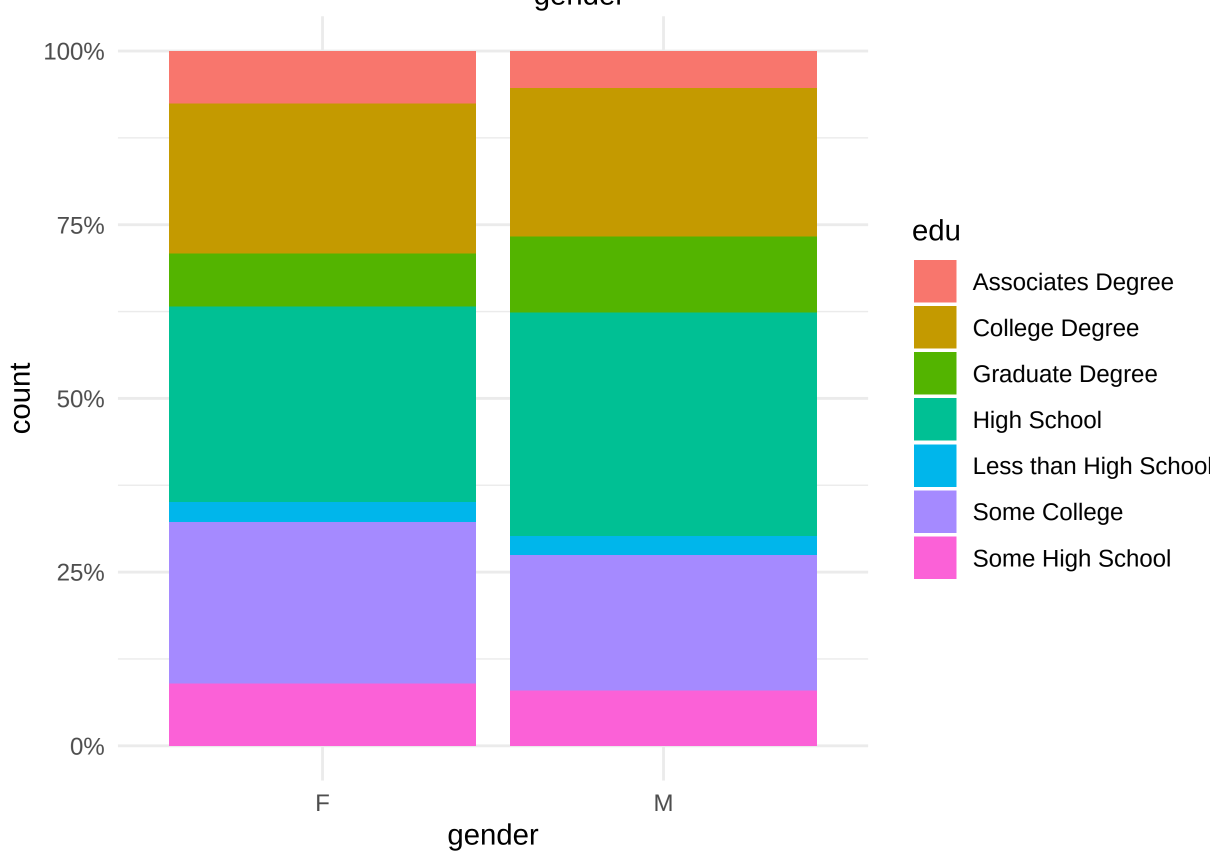
Black
Native
Other
White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count
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M
gender
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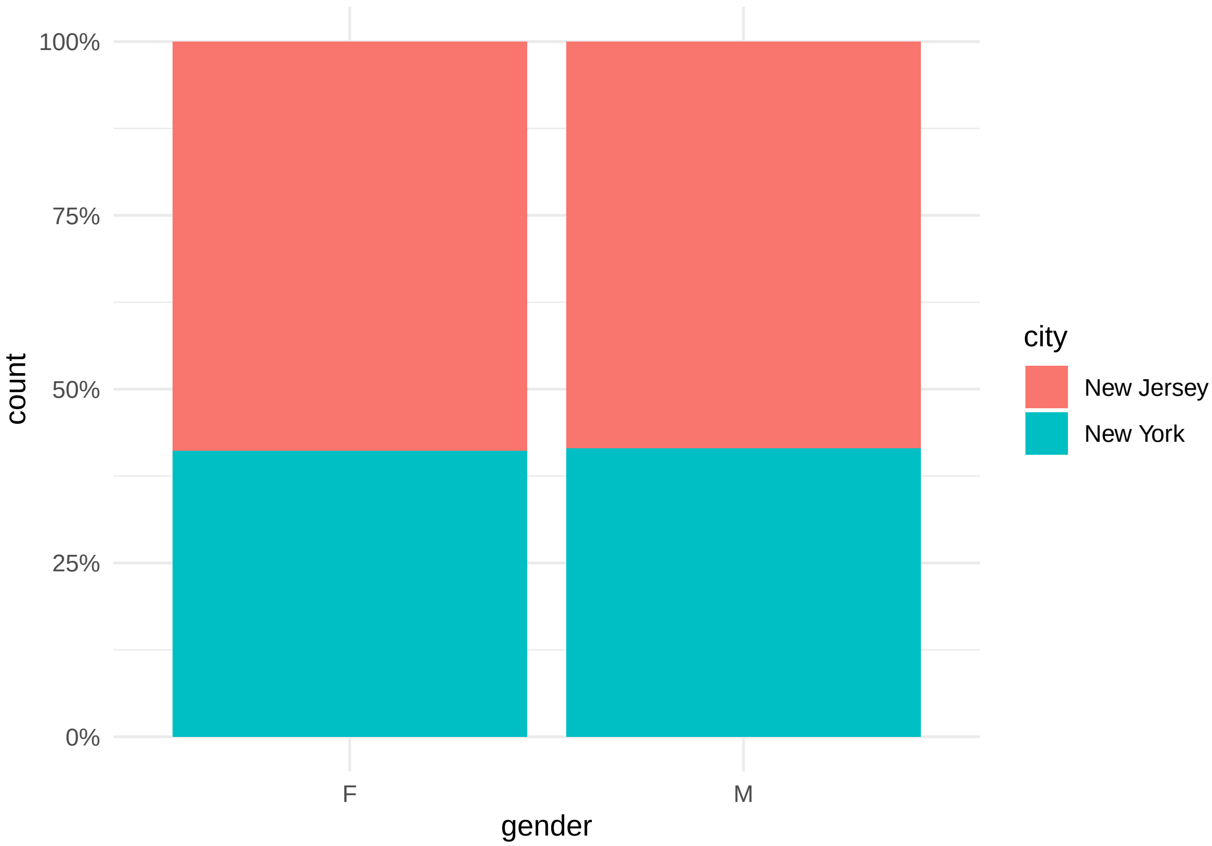
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School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count
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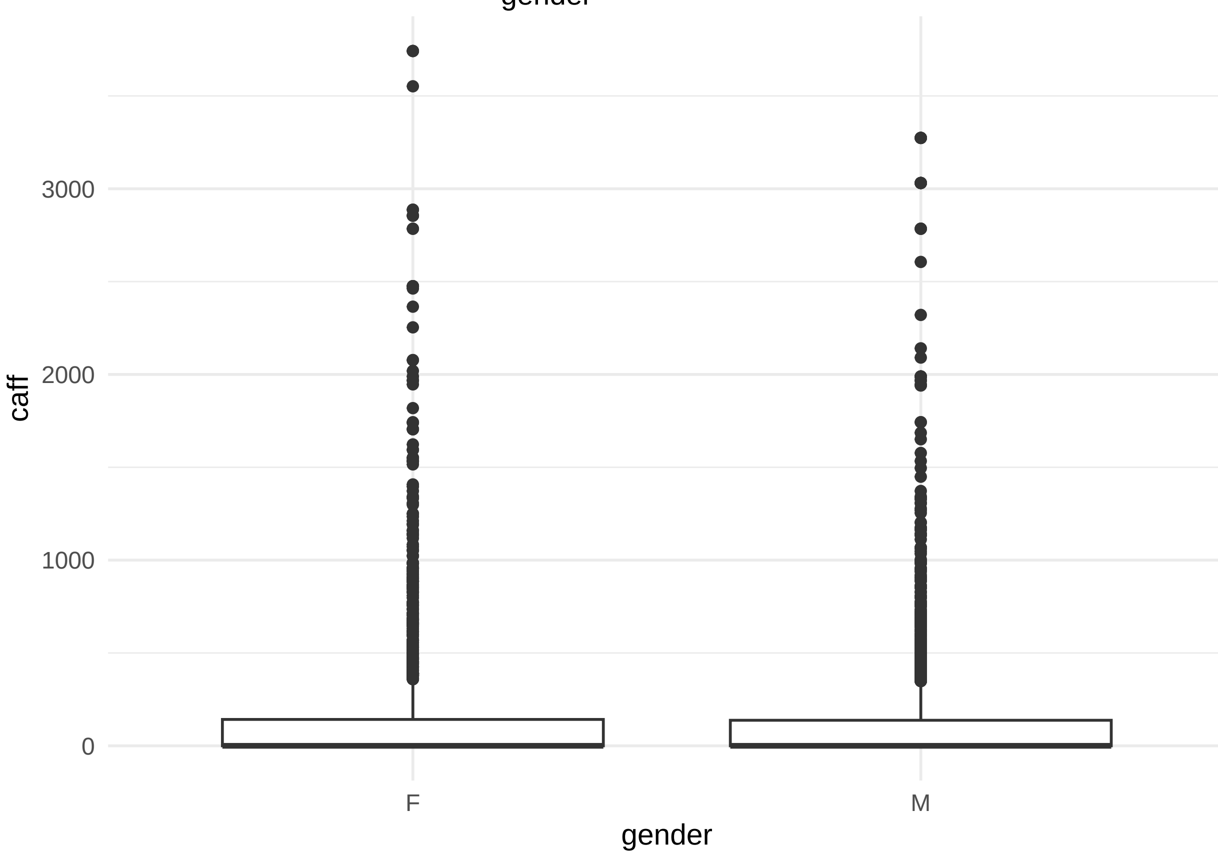
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caff
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M
gender


100%
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count
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gender
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2
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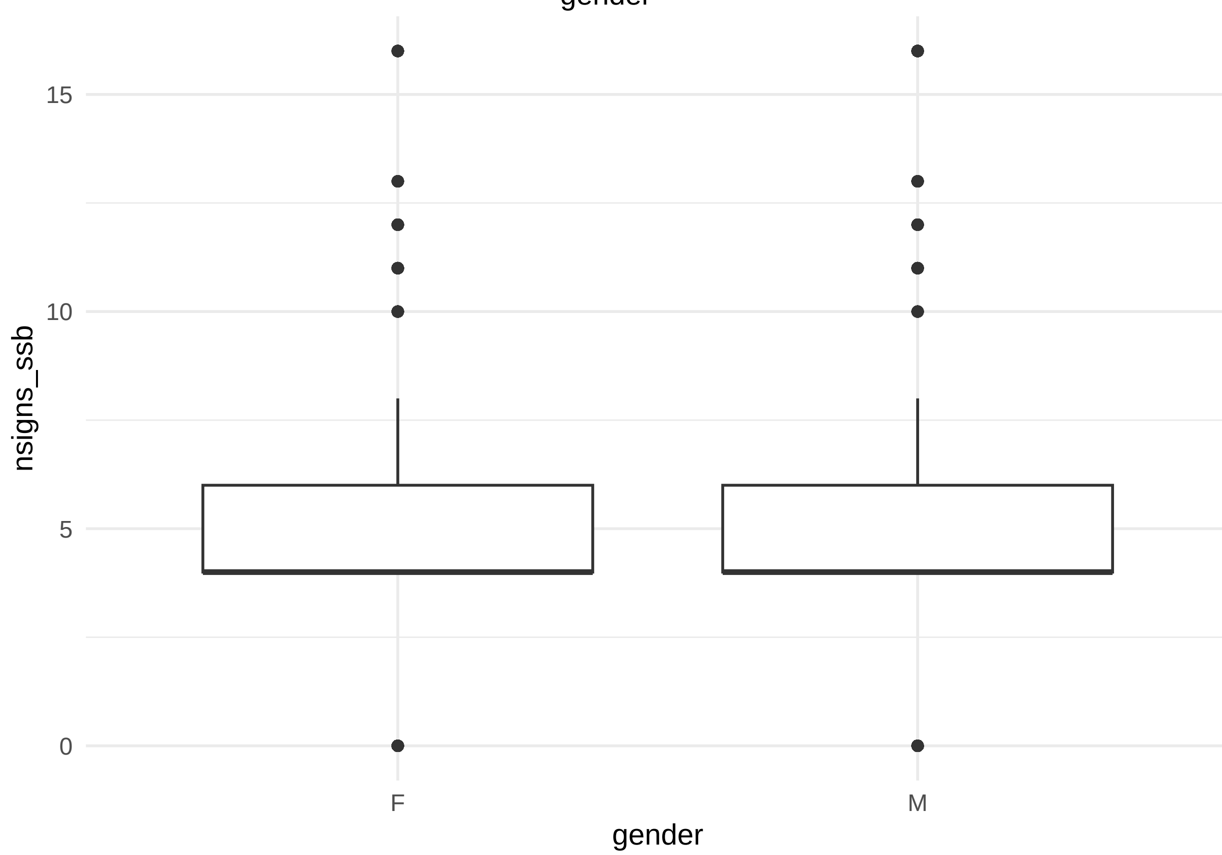
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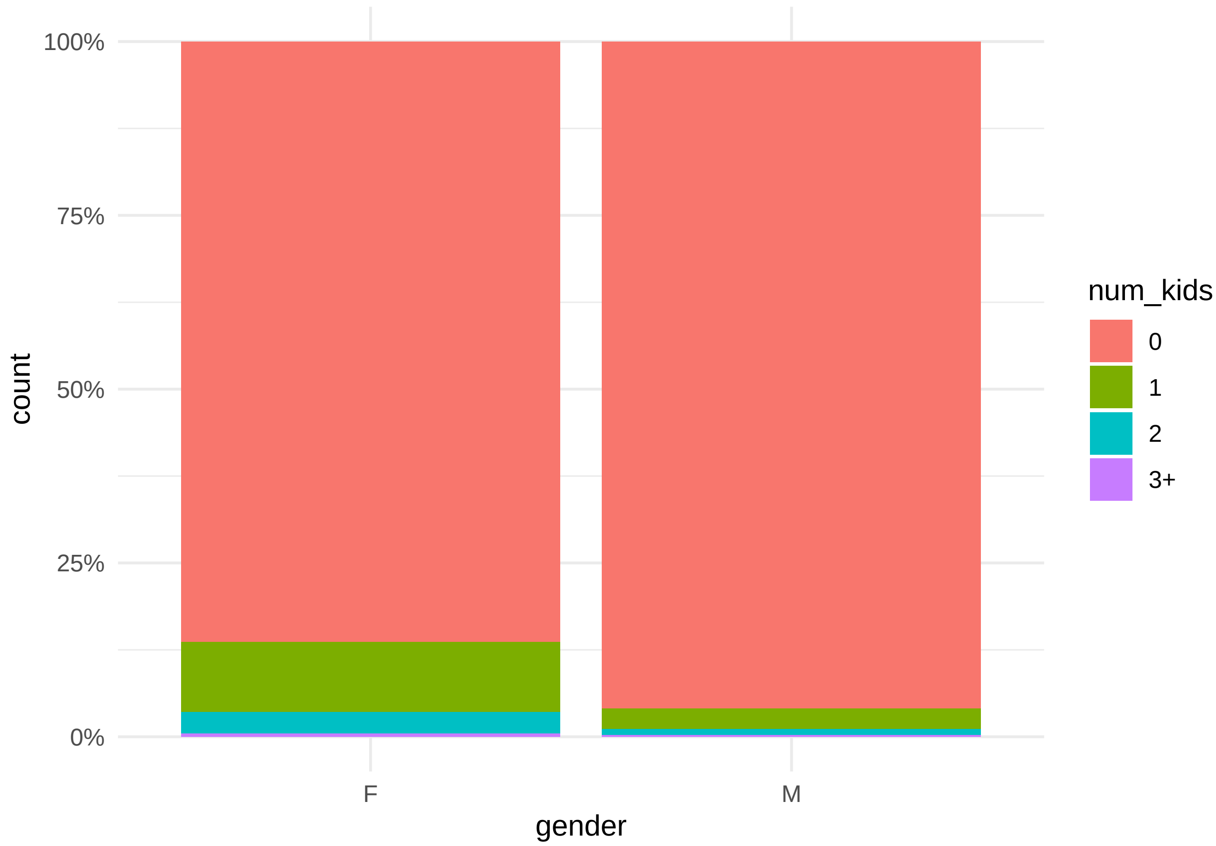
M
gender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M
gender
num_kids
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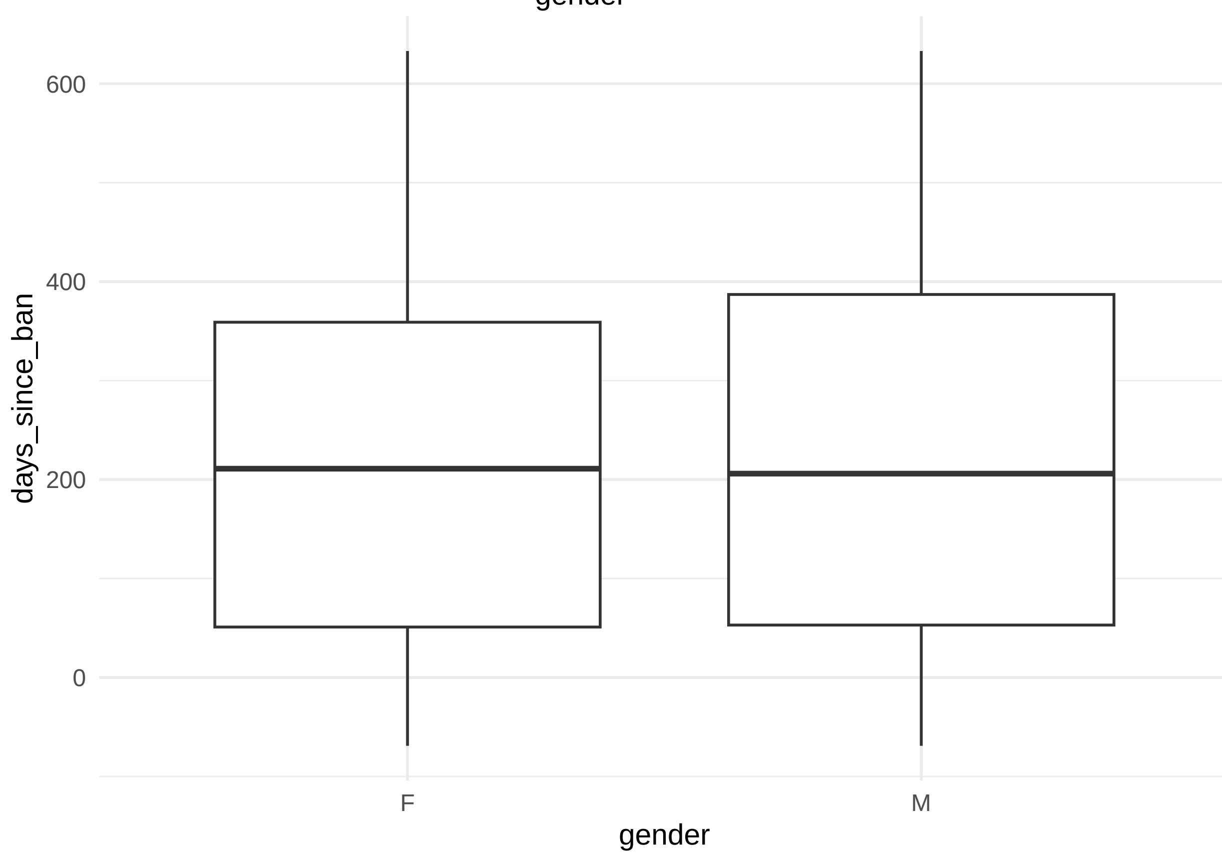
1
2
3+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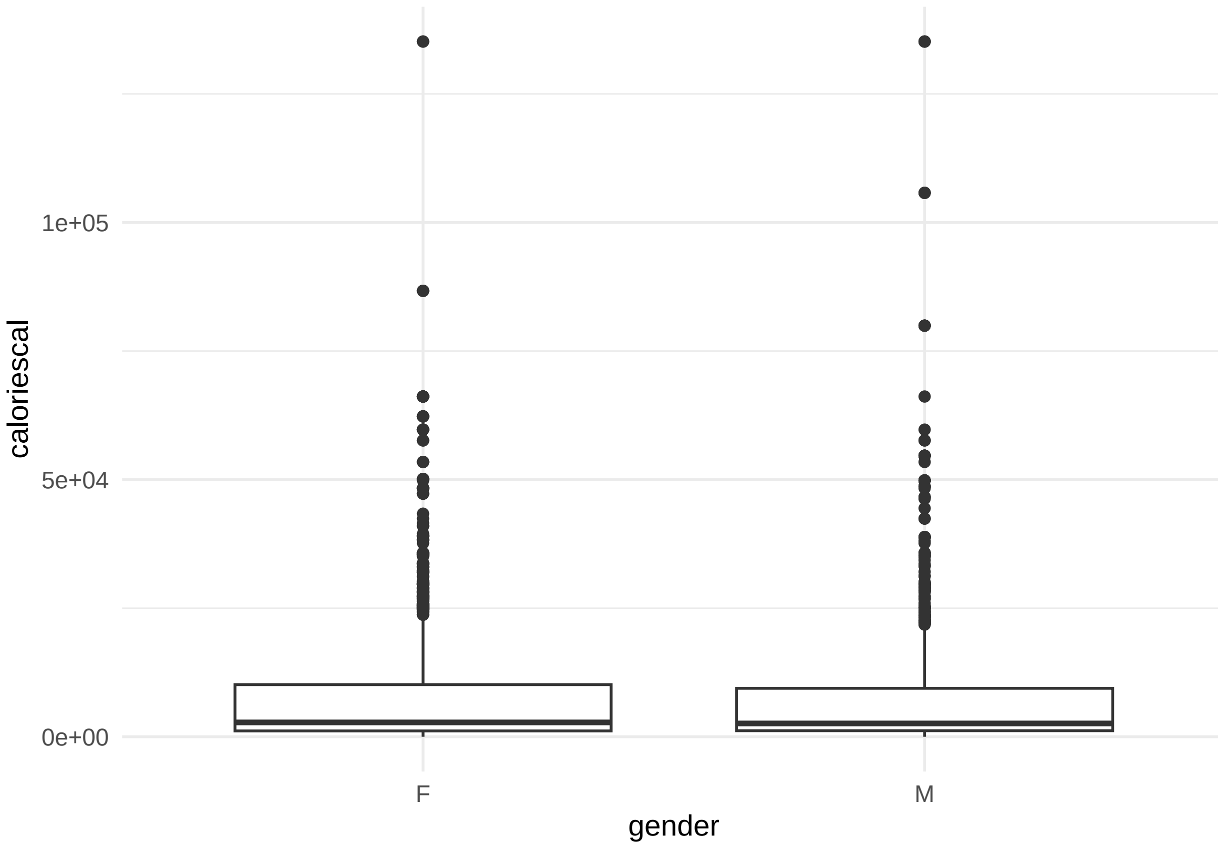
gender



caloriescal
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5e+04
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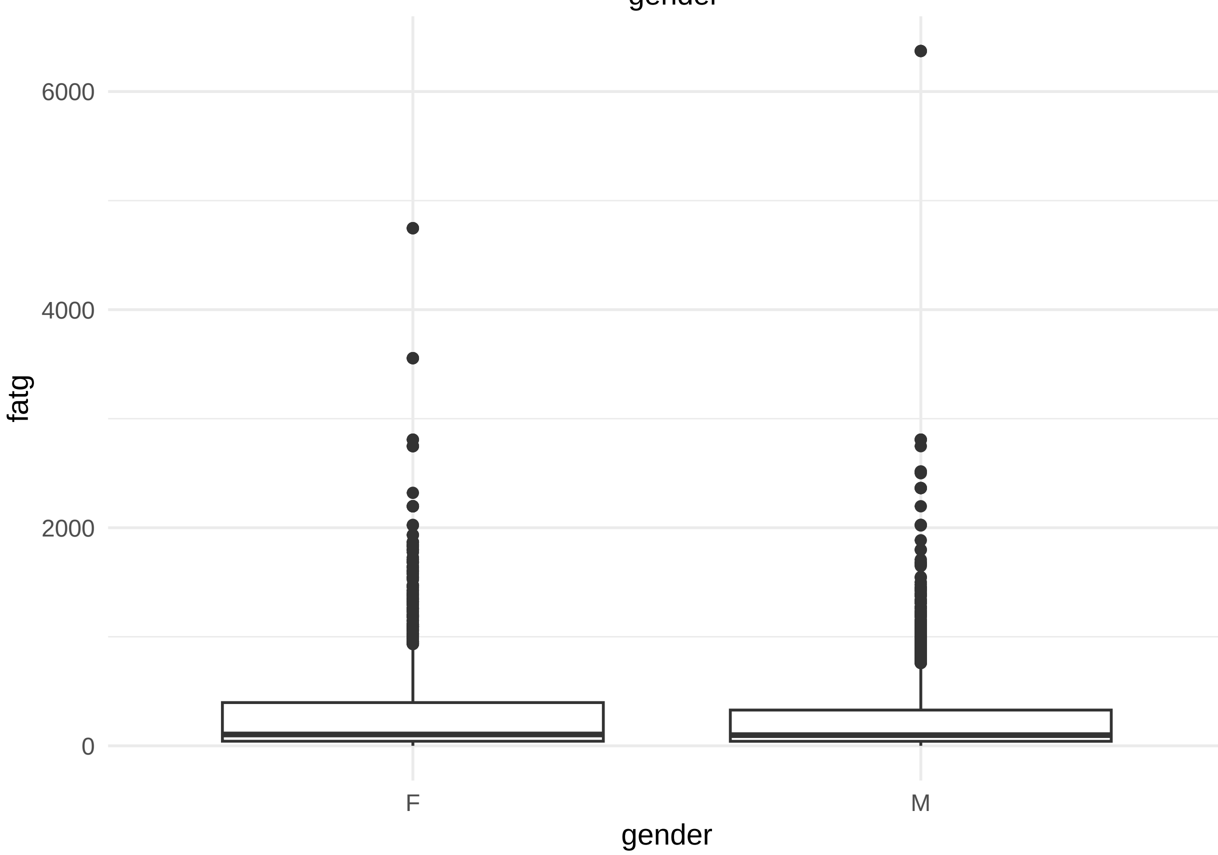
gender



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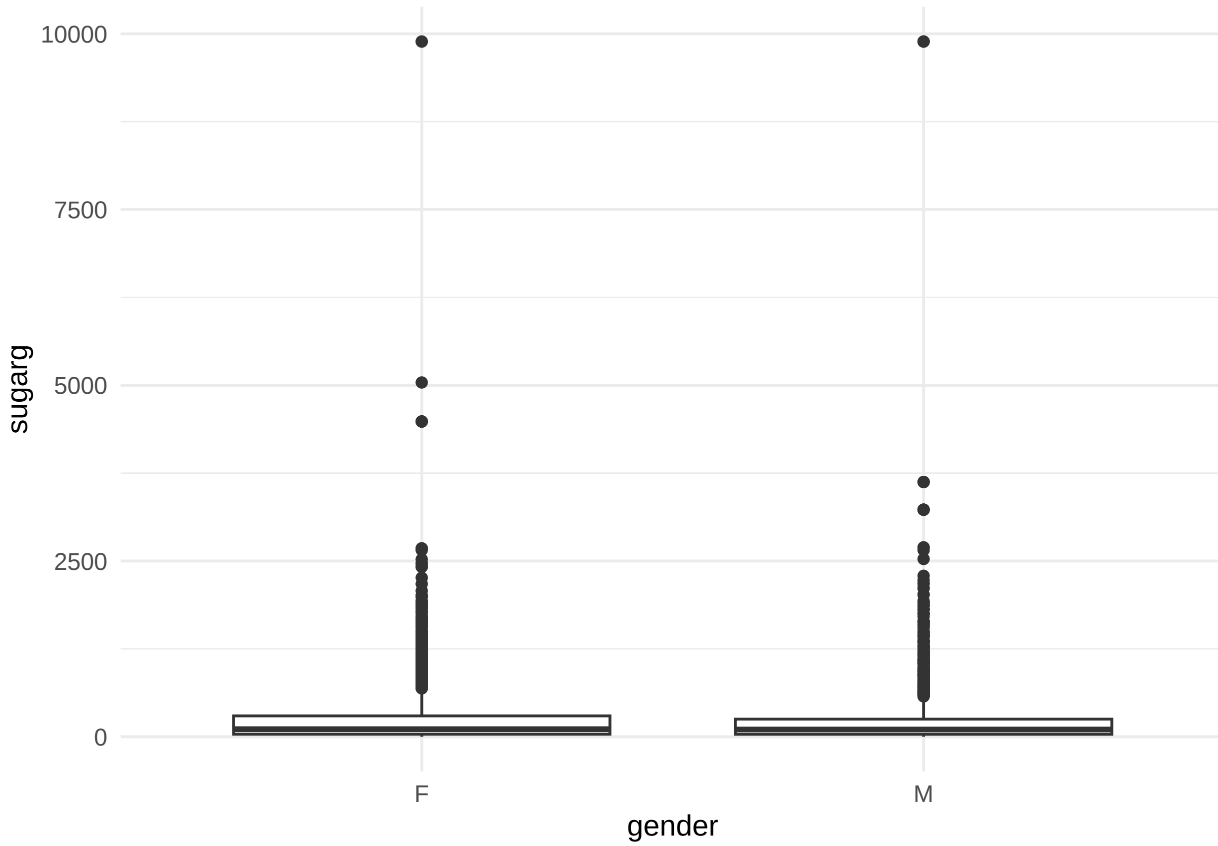
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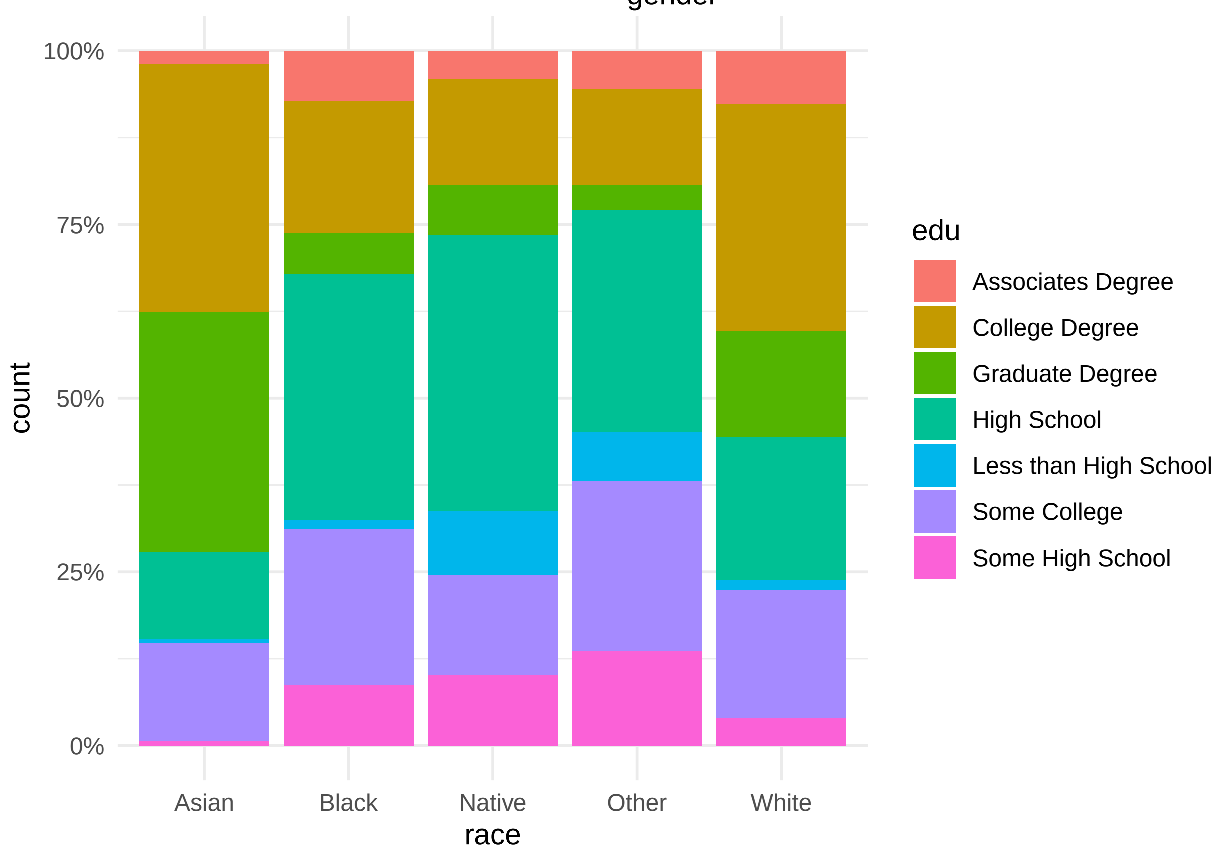
M
gender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count
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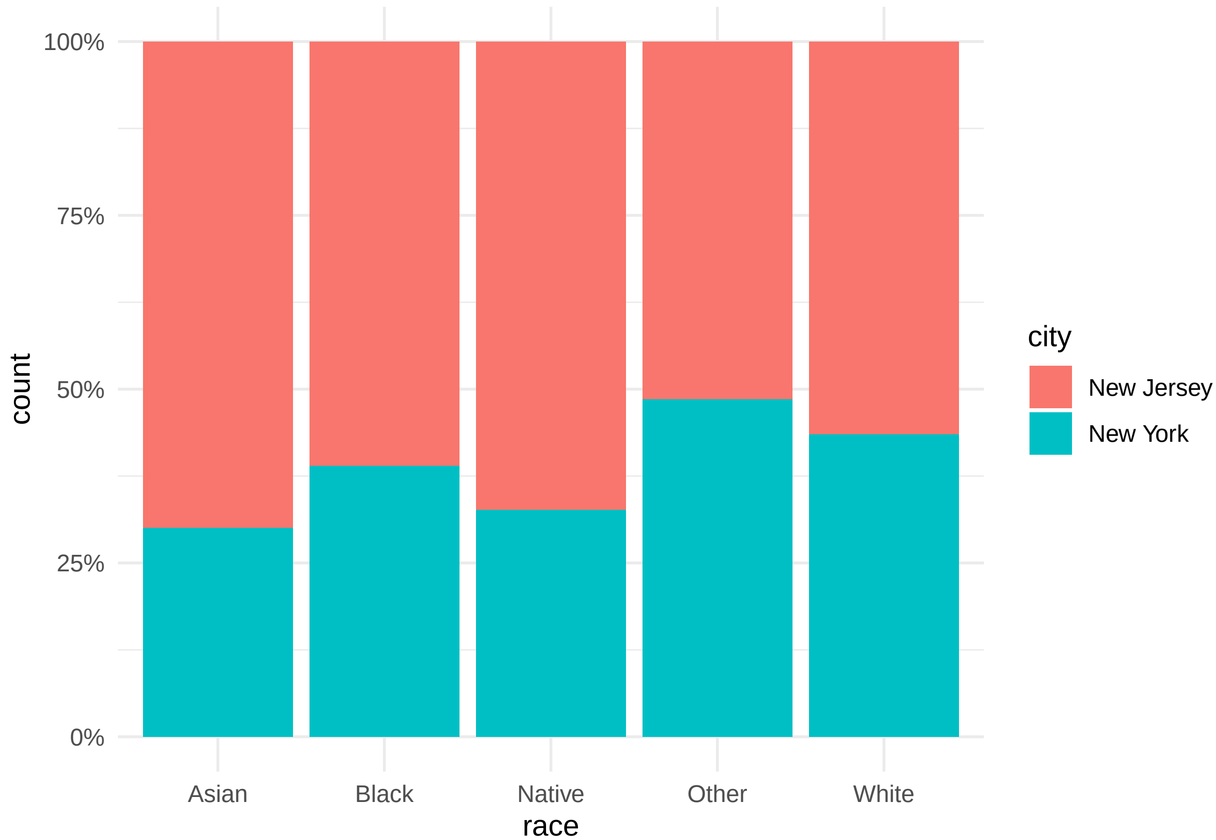
Native
Other
White
race
edu
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School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count
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Black
Native
Other
White
race
city
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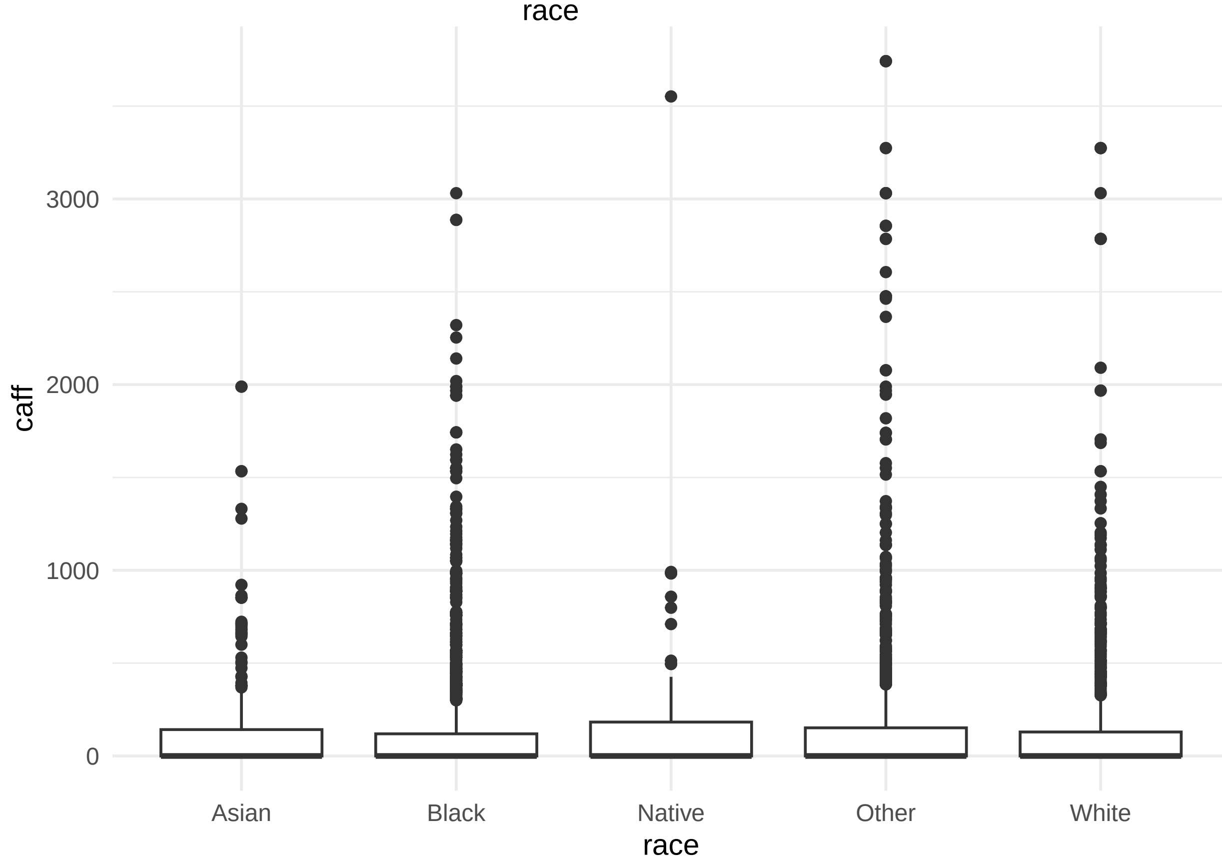
New York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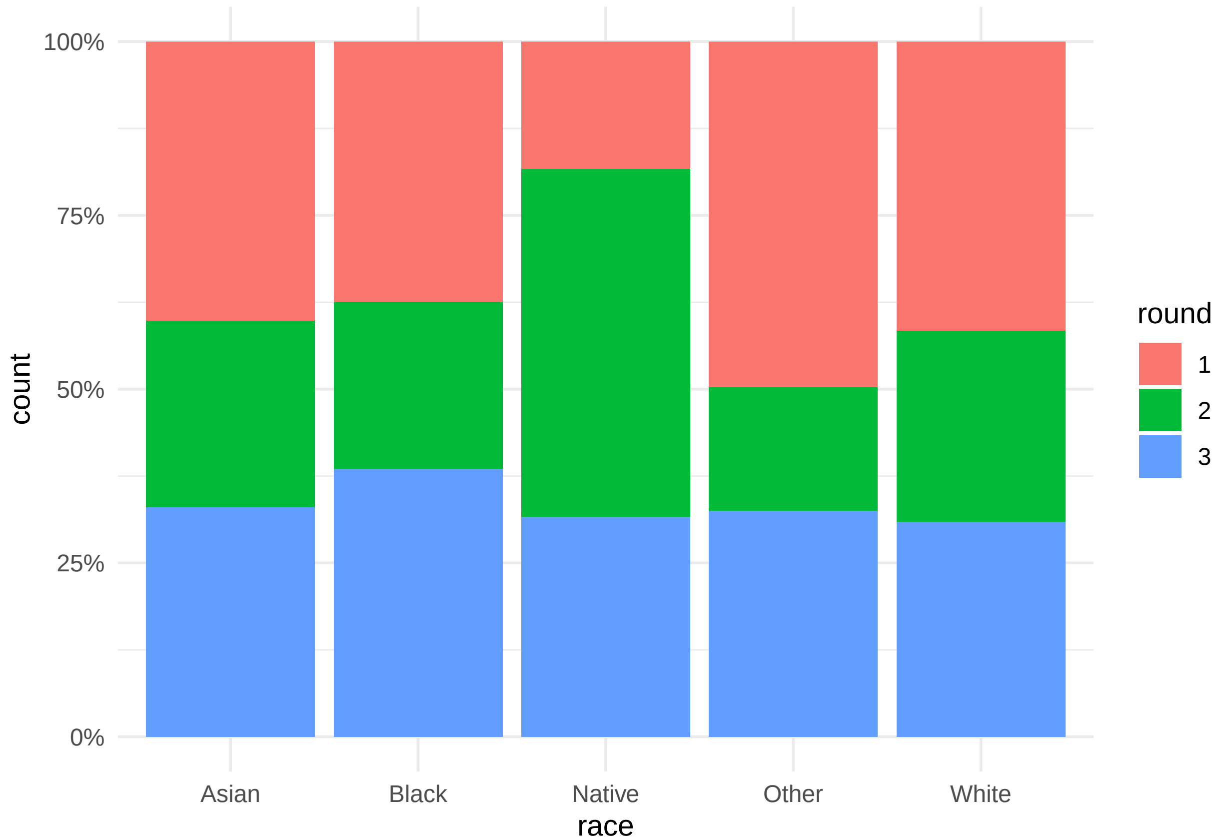
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count
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Native
Other
White
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round
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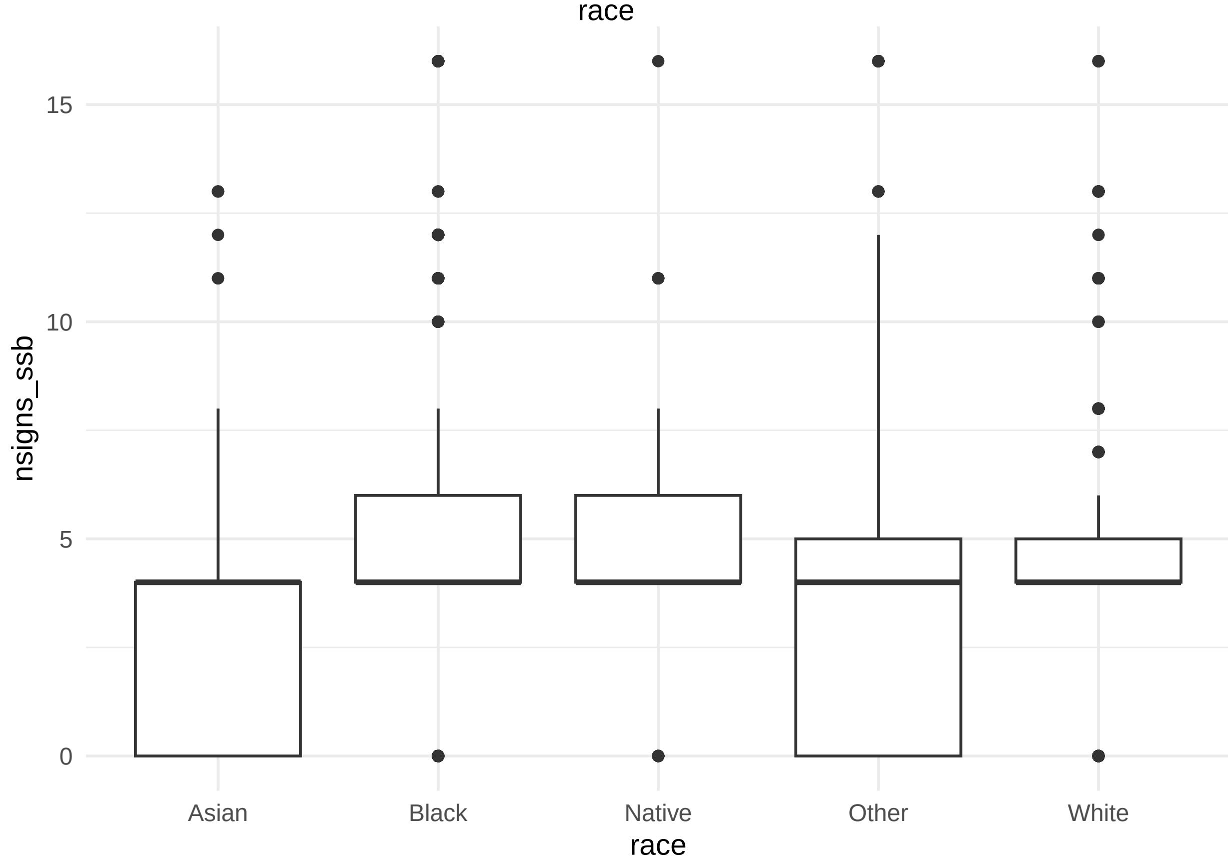
3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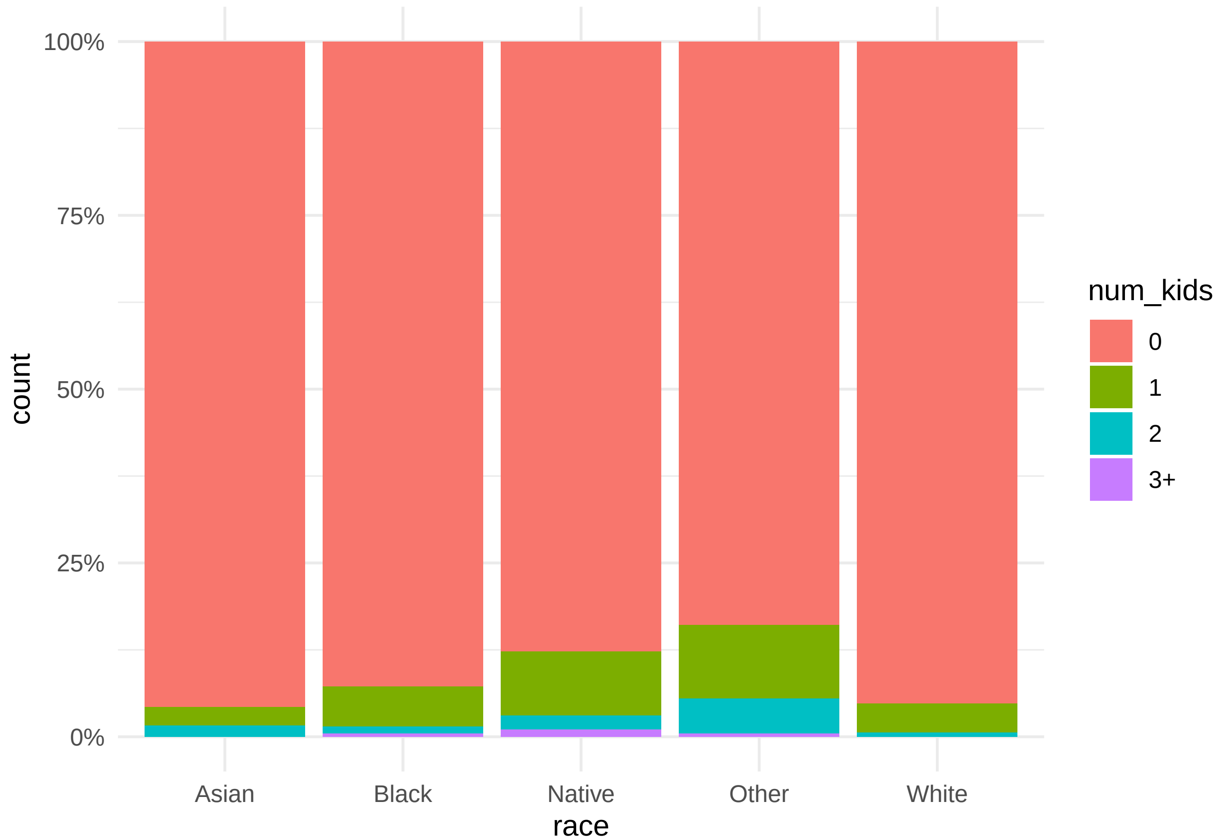
Native
Other
White
race



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count
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Black
Native
Other
White
race
num_kids
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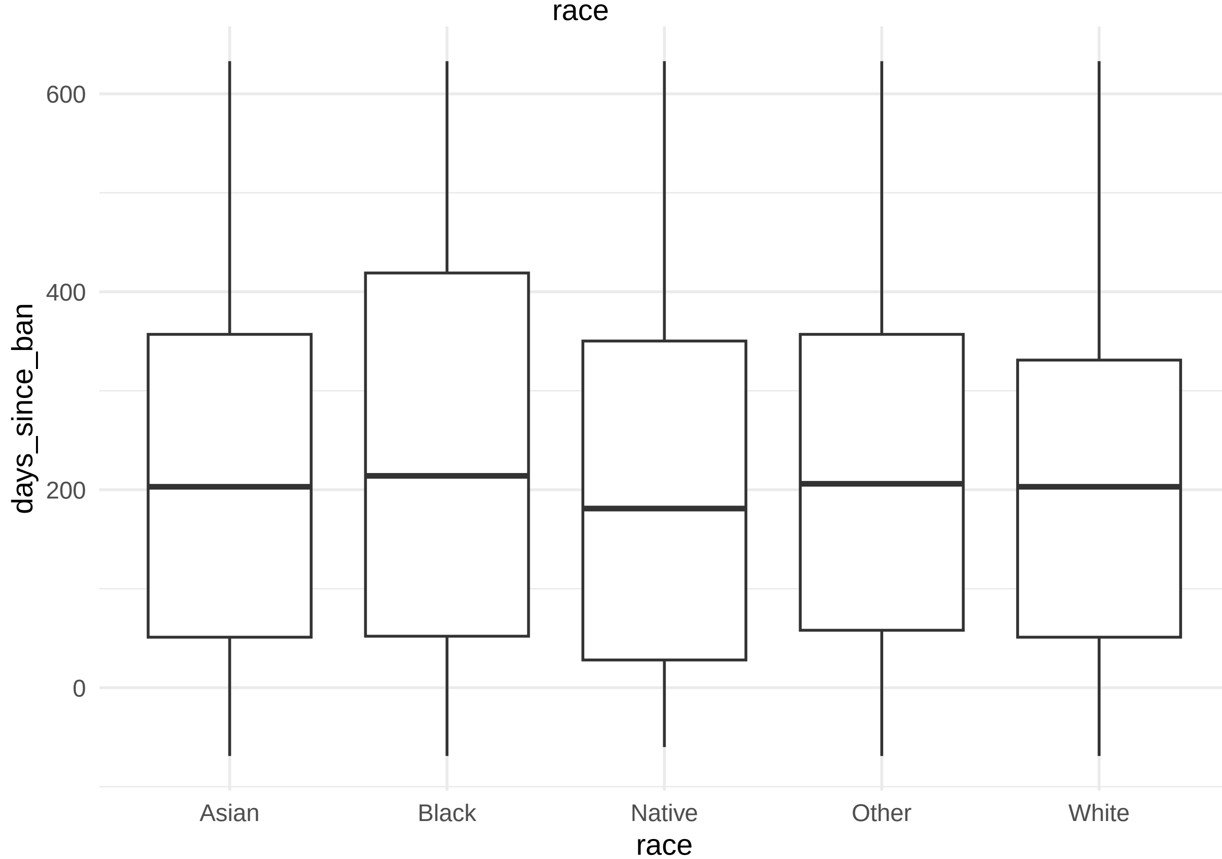
1
2
3+



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days_since_ban
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Other
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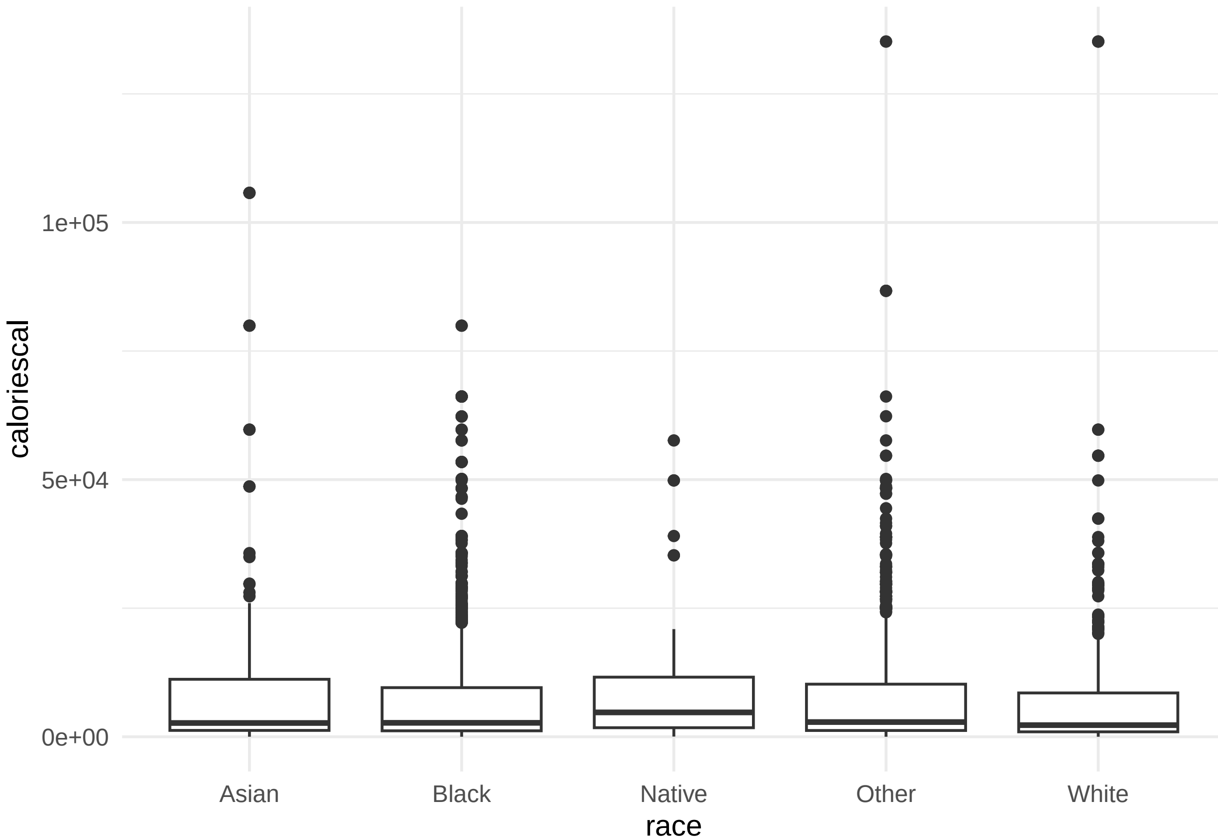

caloriescal
1e+05
5e+04
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Native
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White
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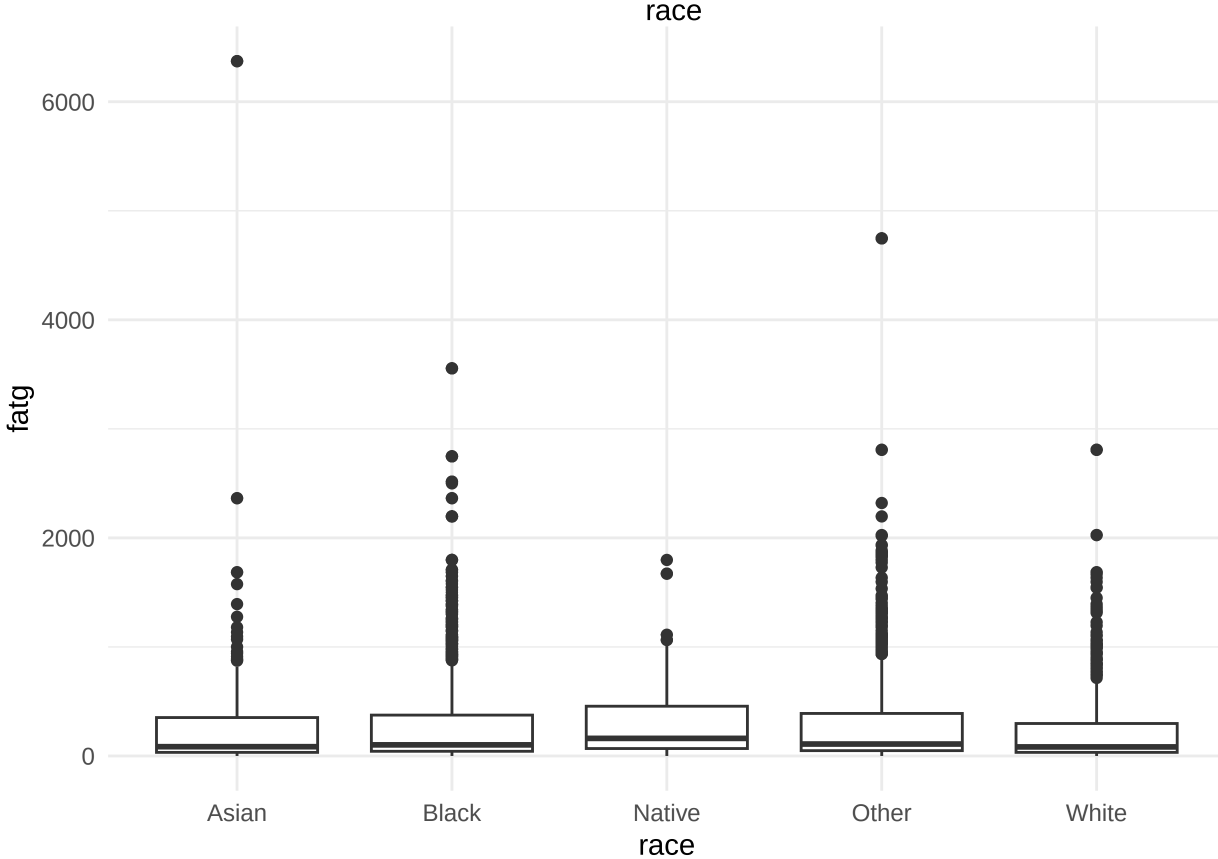

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2000
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Native
Other
White
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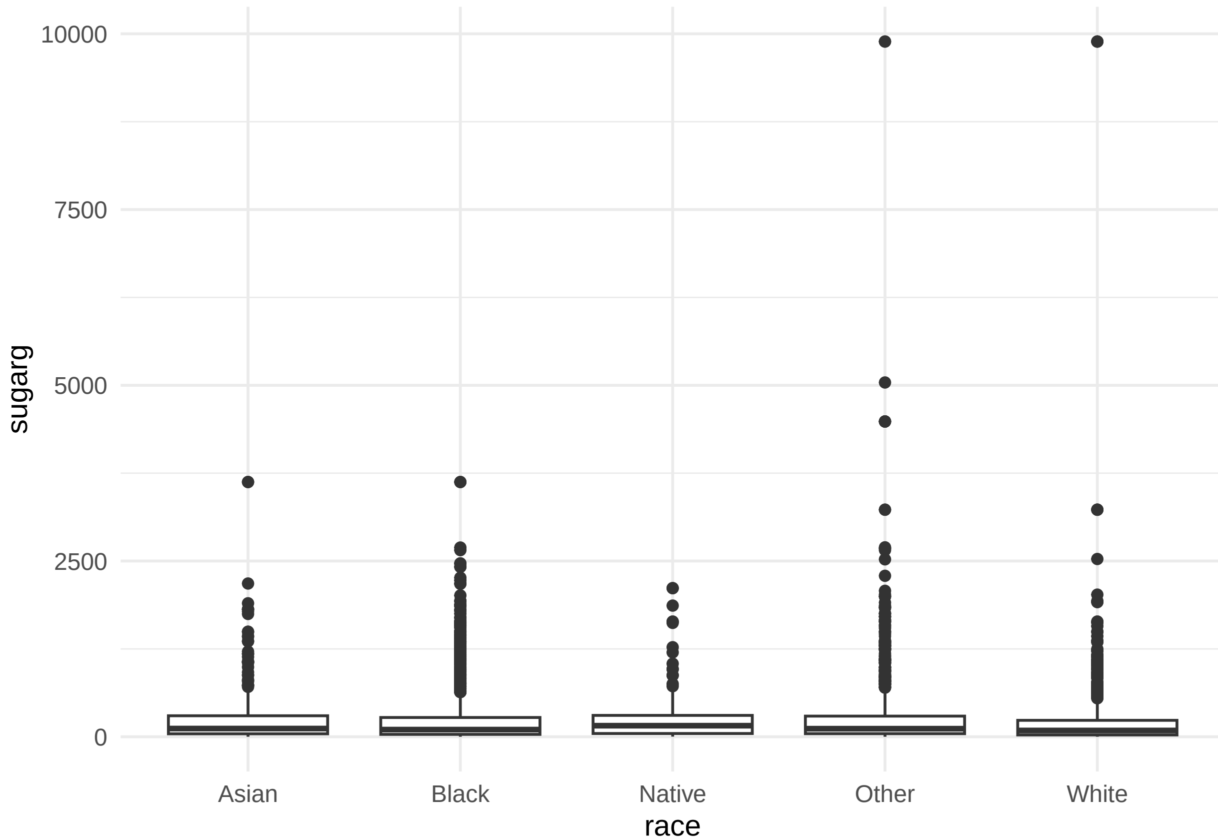
sugarg
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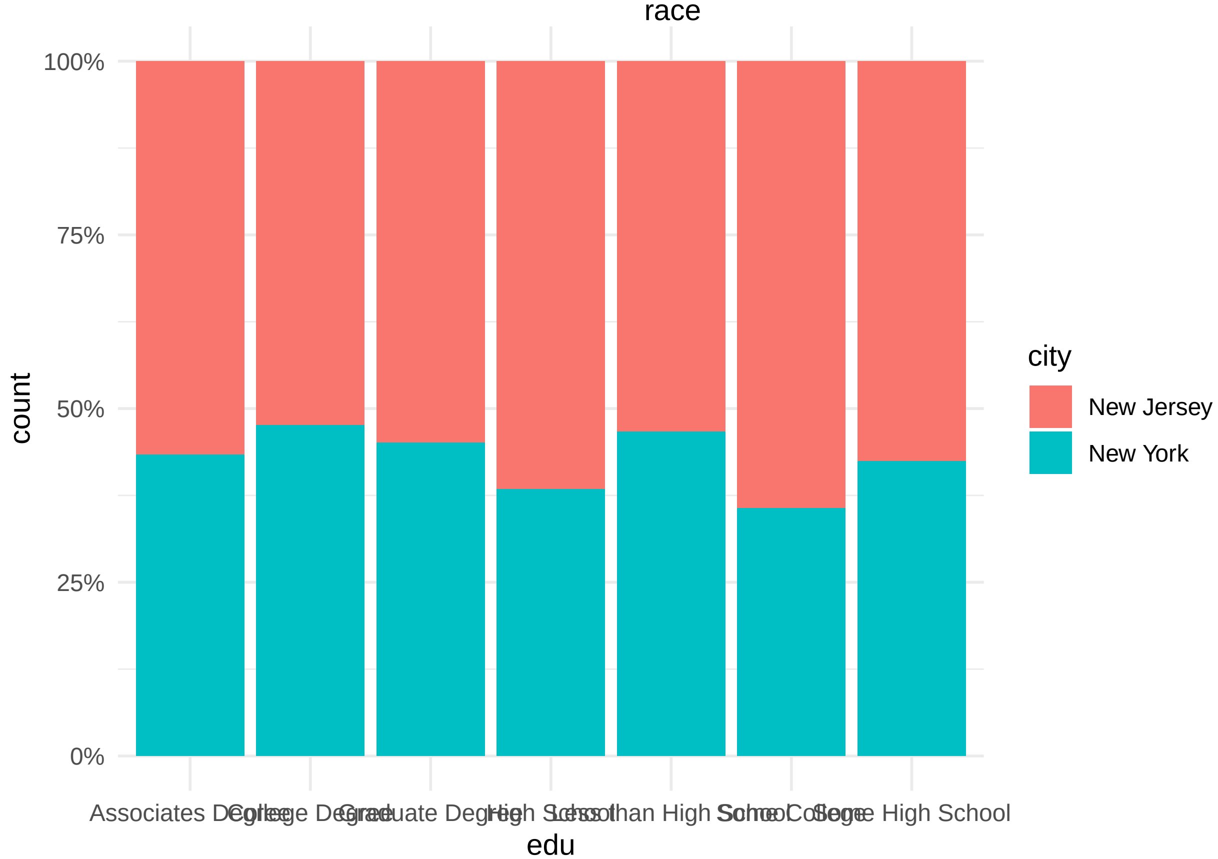
Native
Other
White
race


count
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Associates Degree
College Degree
Graduate Degree
High School
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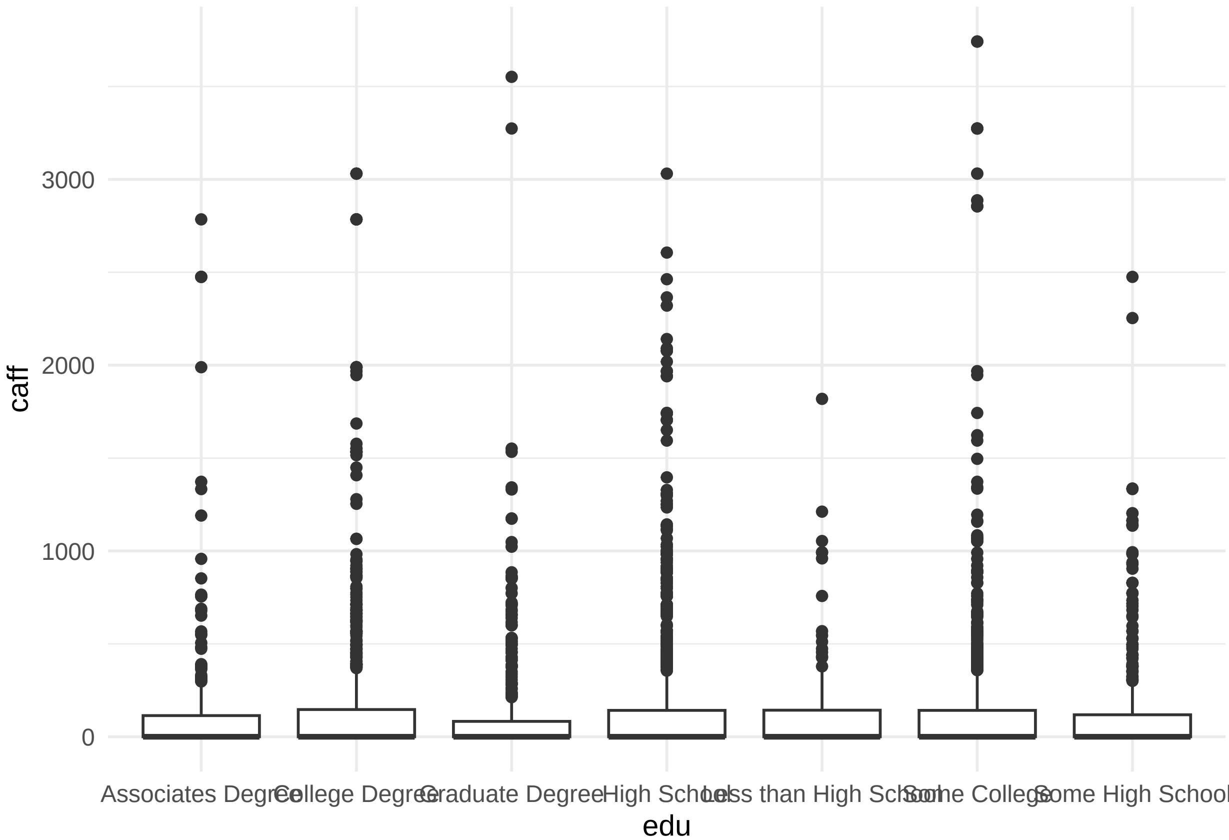
New York



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College Degree
Graduate Degree
High School
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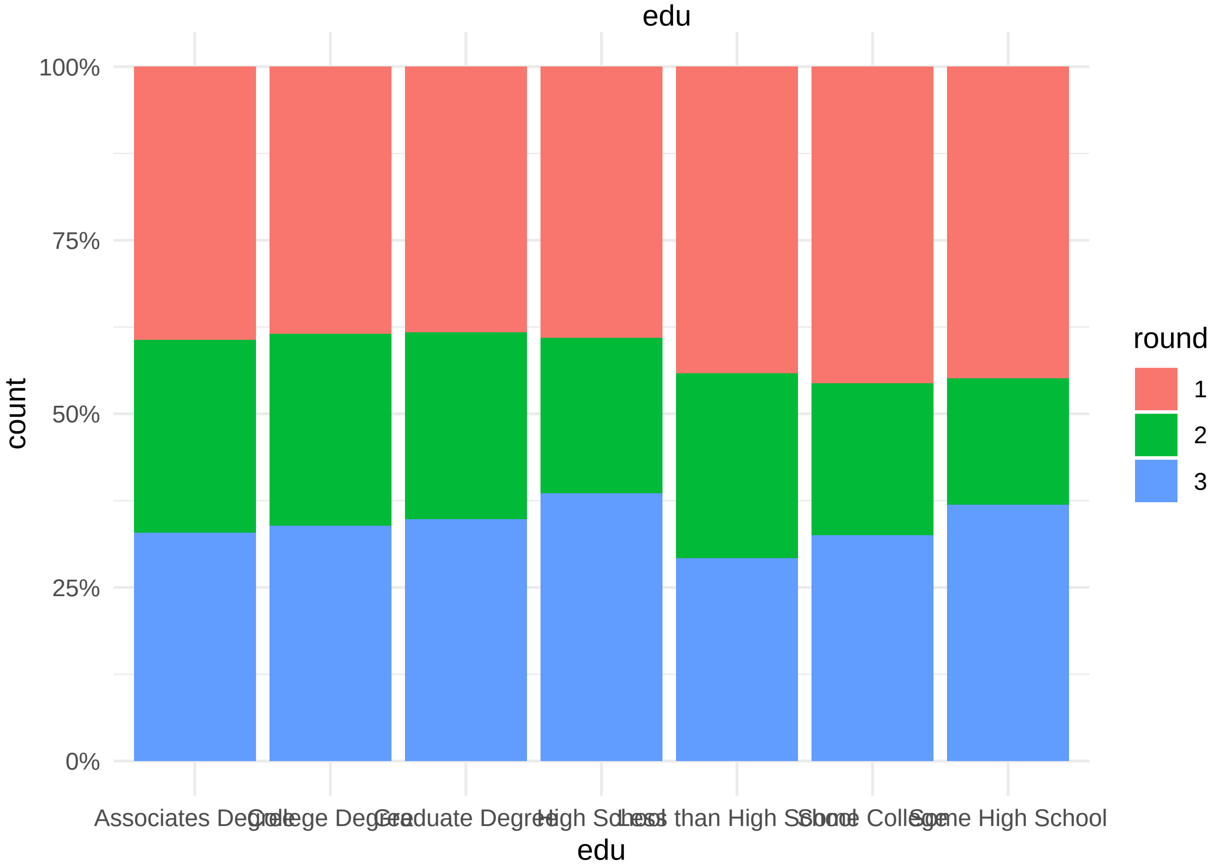
Some College
Some High School
edu



count
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Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu
round
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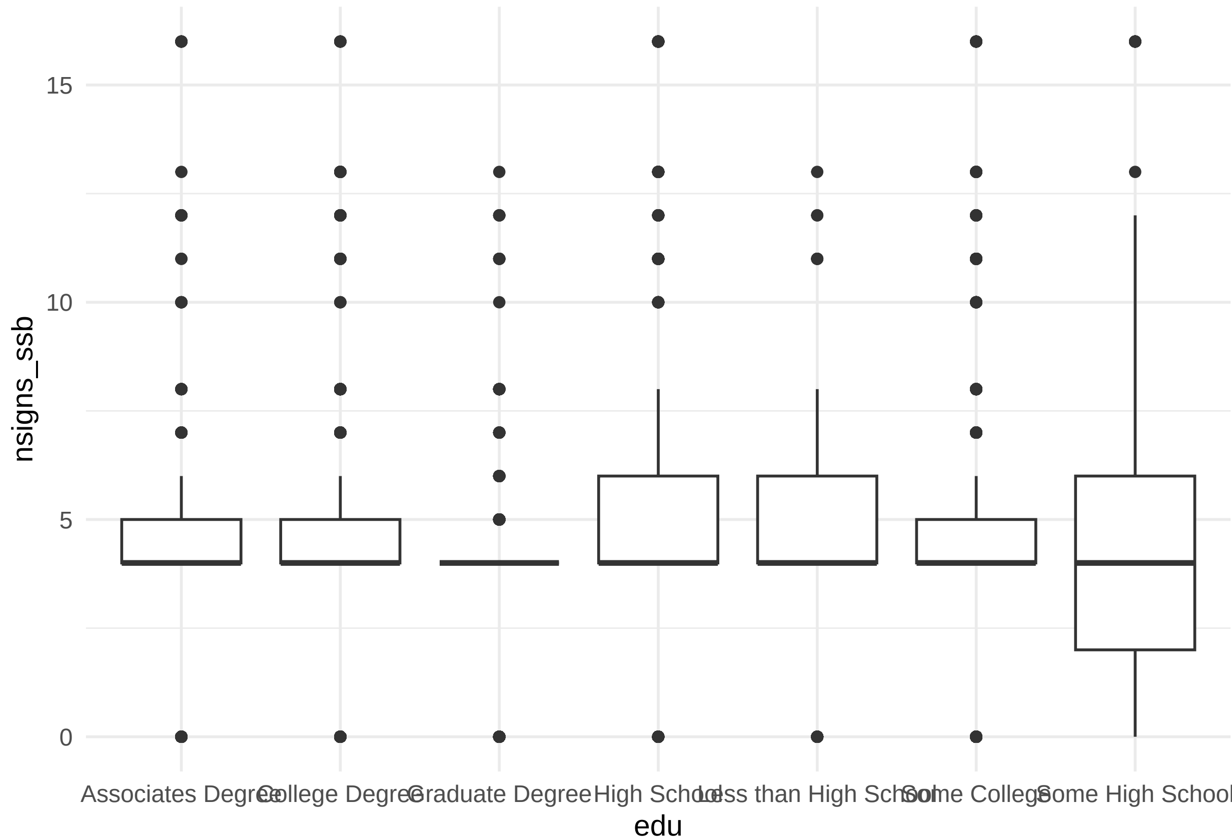
2
3


nsigns_ssb
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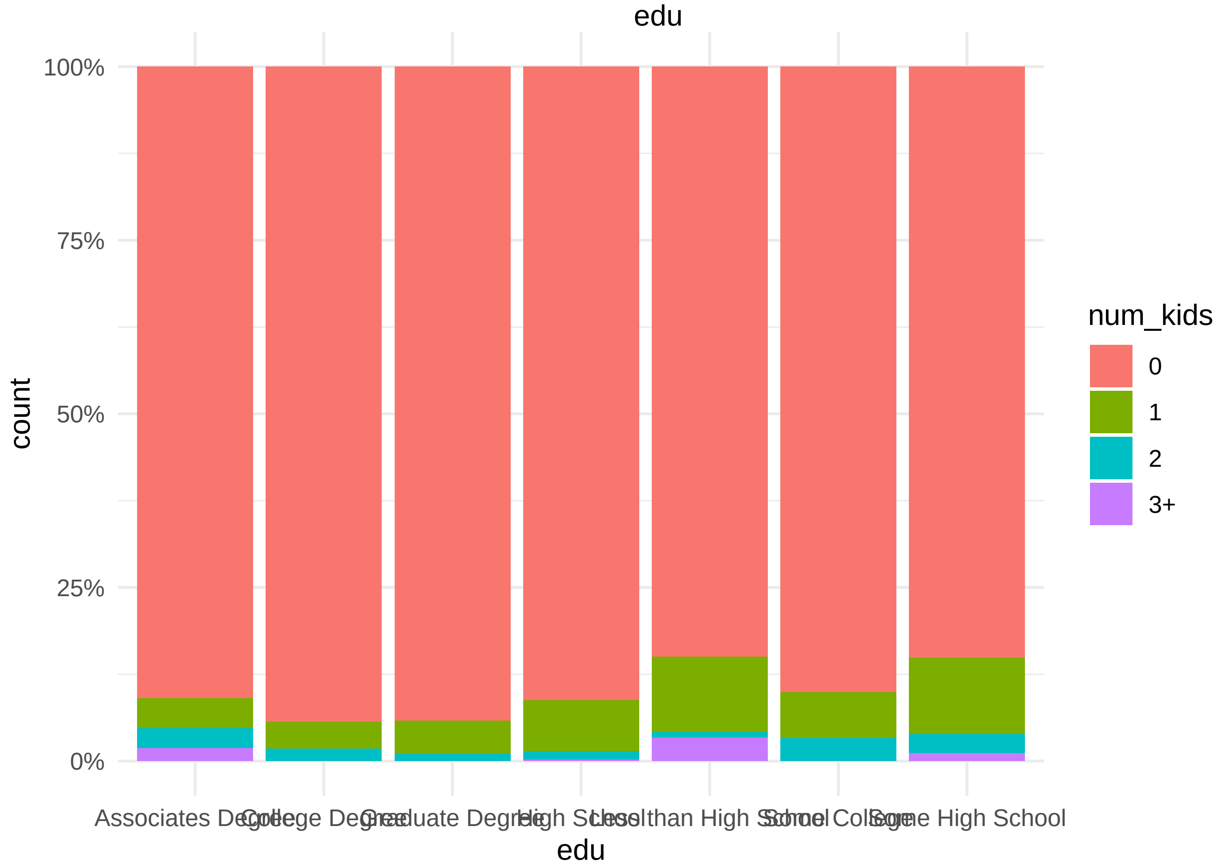
Associates Degree
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu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College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
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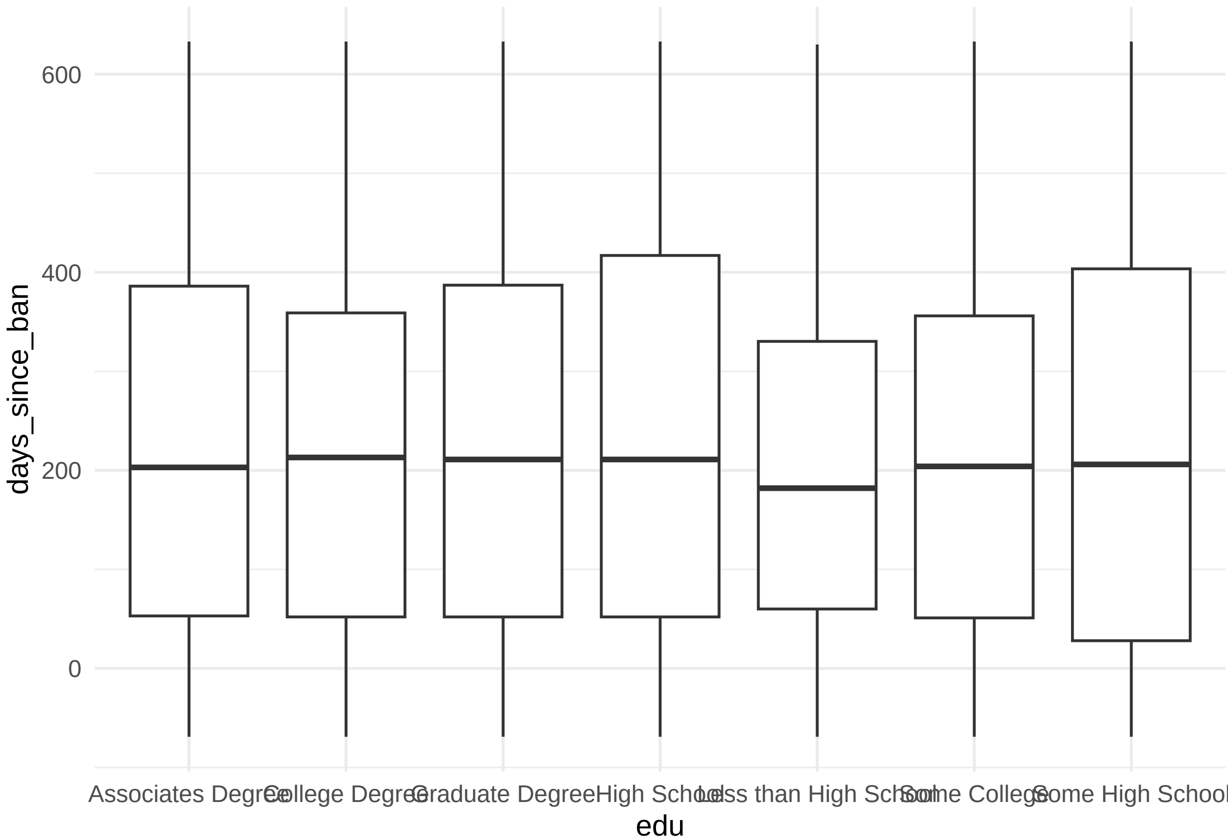
1
2
3+



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days_since_ban
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College Degree
Graduate Degree
High School
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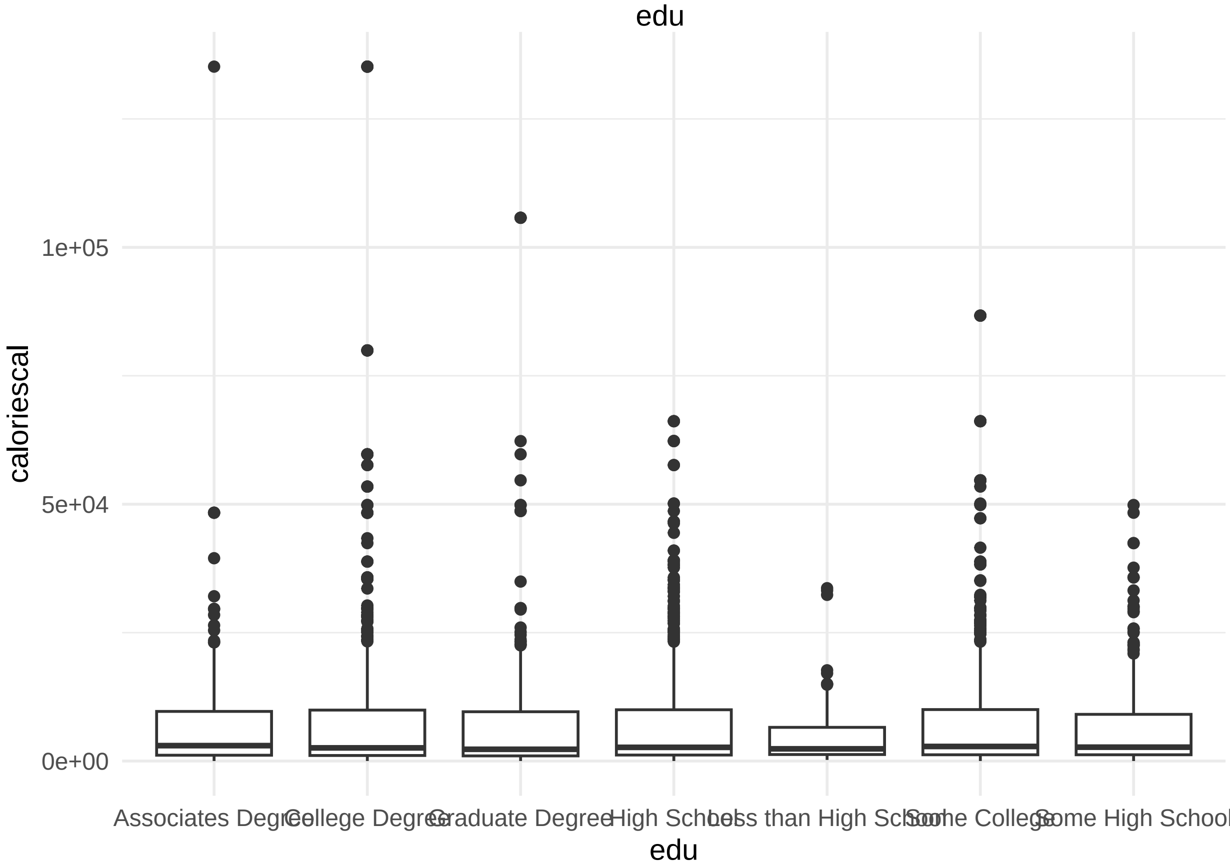
Some College
Some High School
edu



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caloriescal
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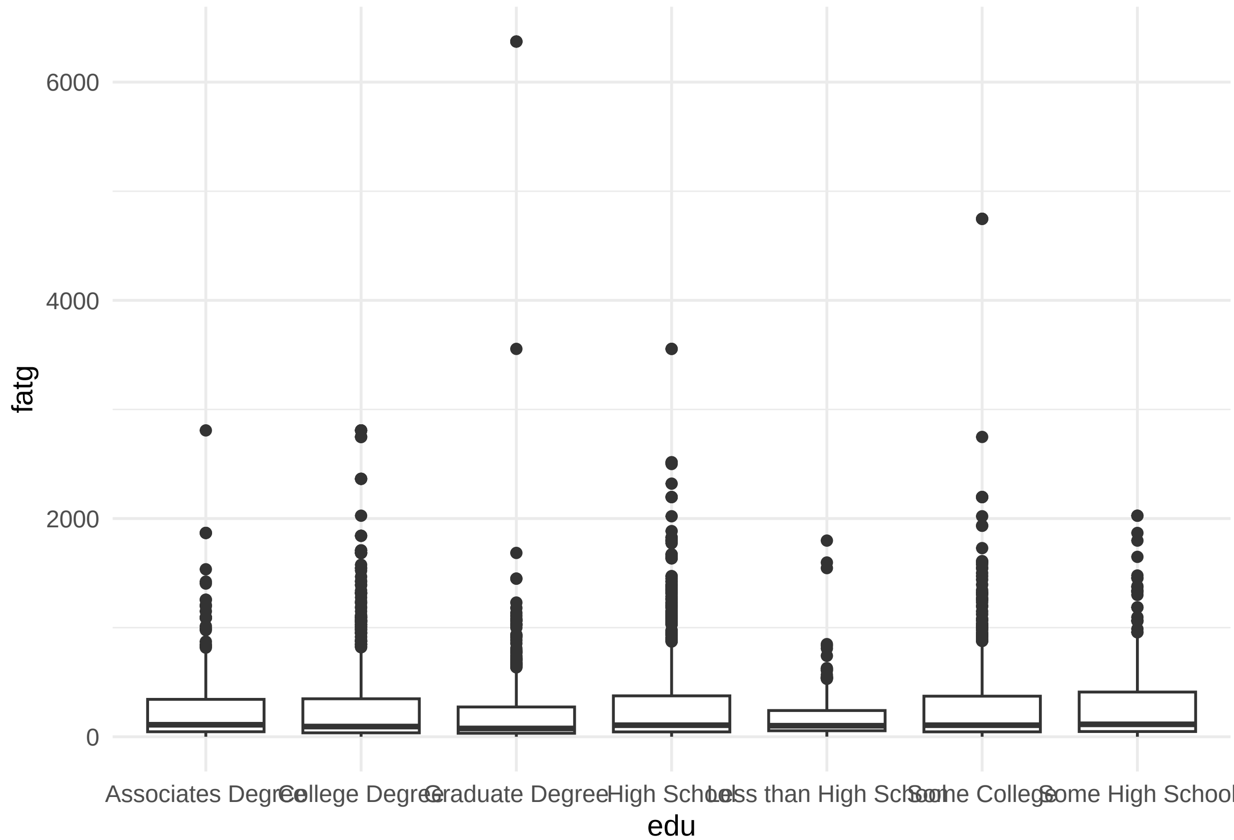
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu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Graduate Degree
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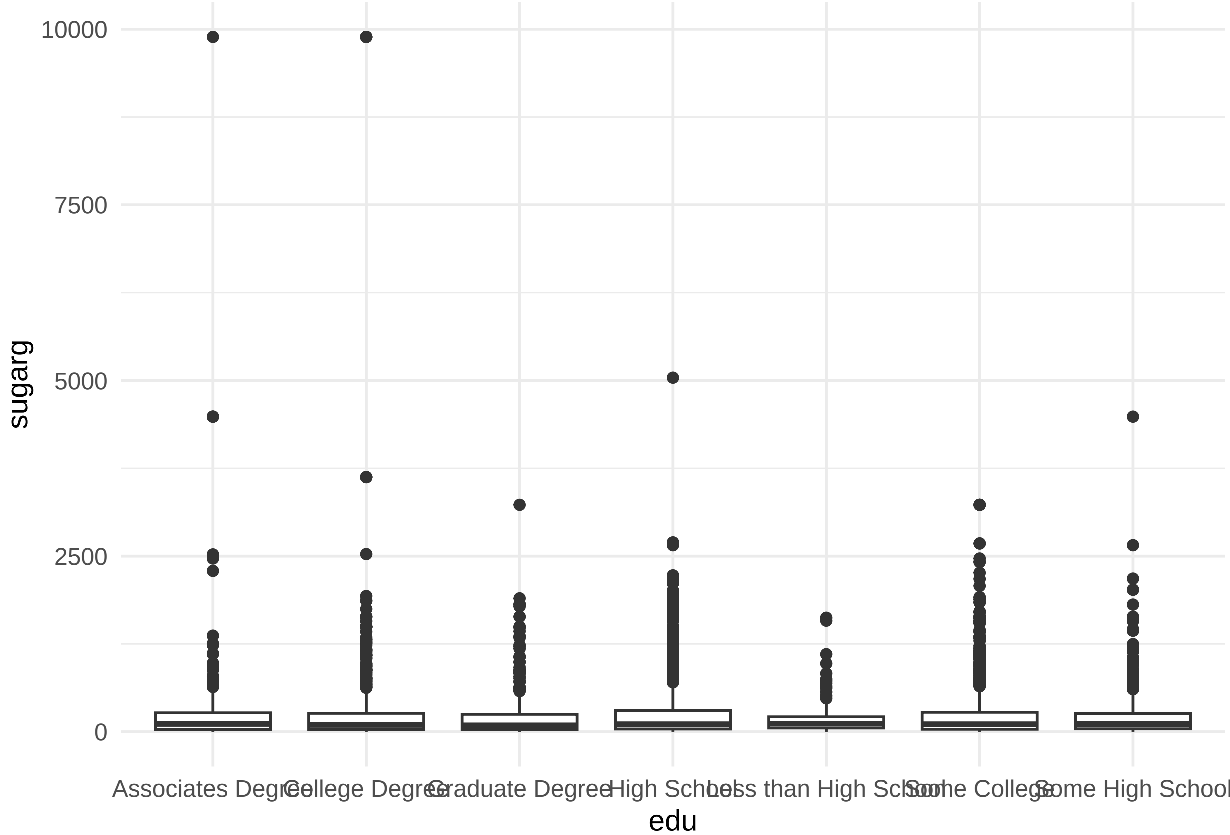
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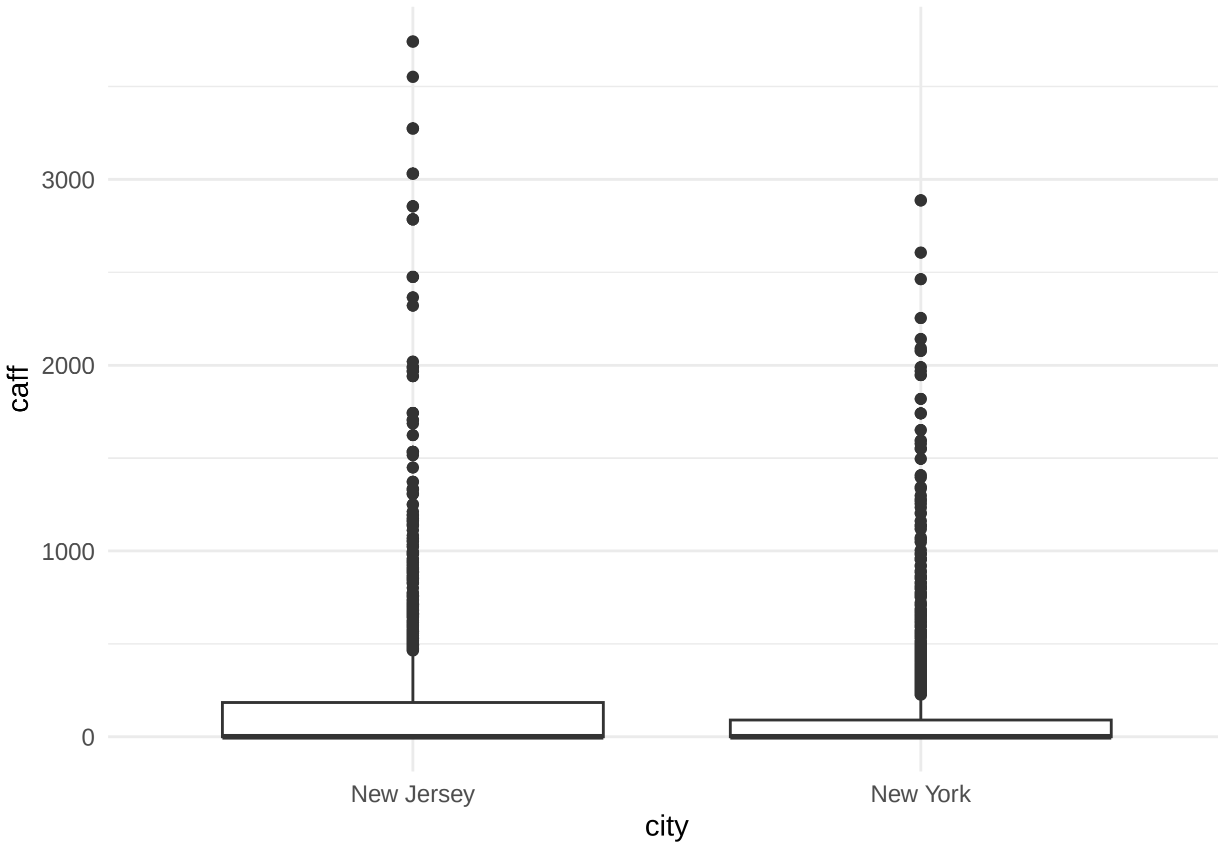
College Degree
Graduate Degree
High School
Less than High School
Some College
Some High School
edu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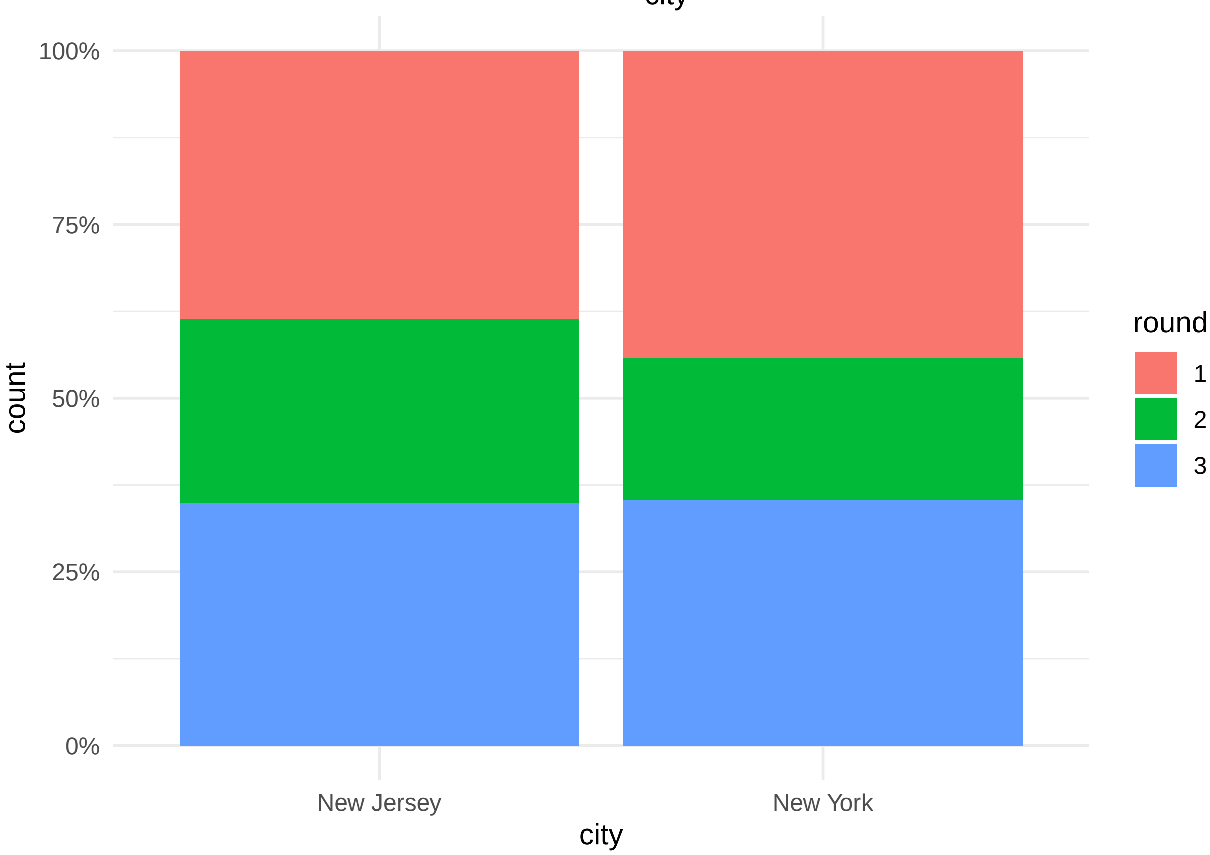
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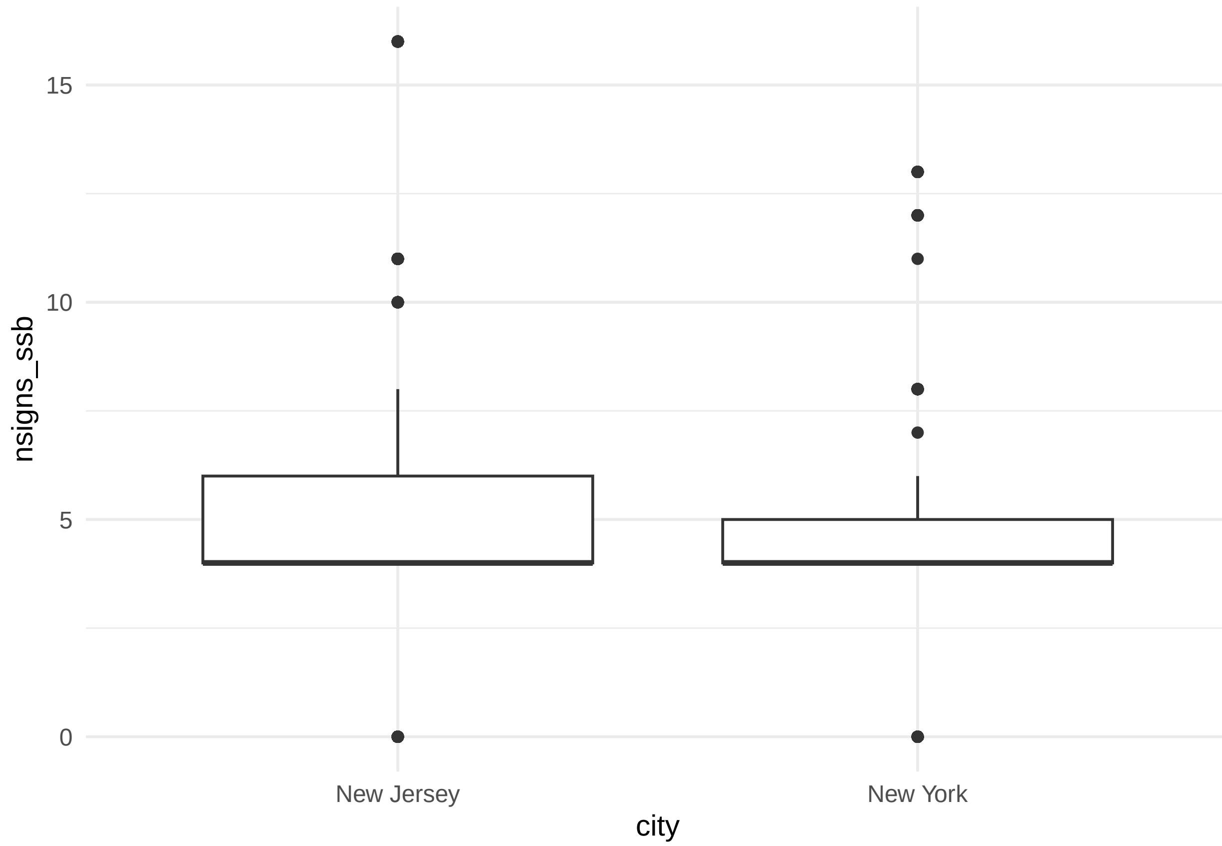
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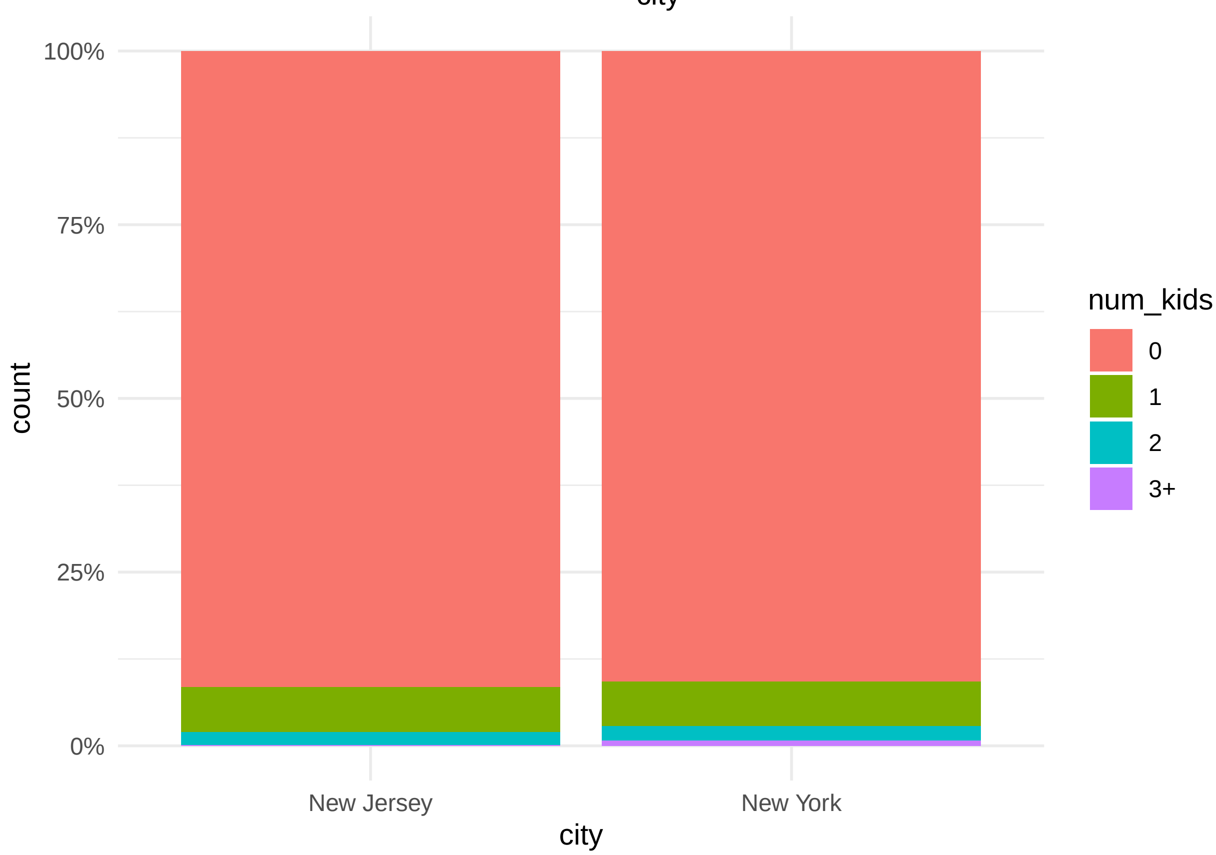
city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num_kids
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2
3+


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200
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days_since_ban
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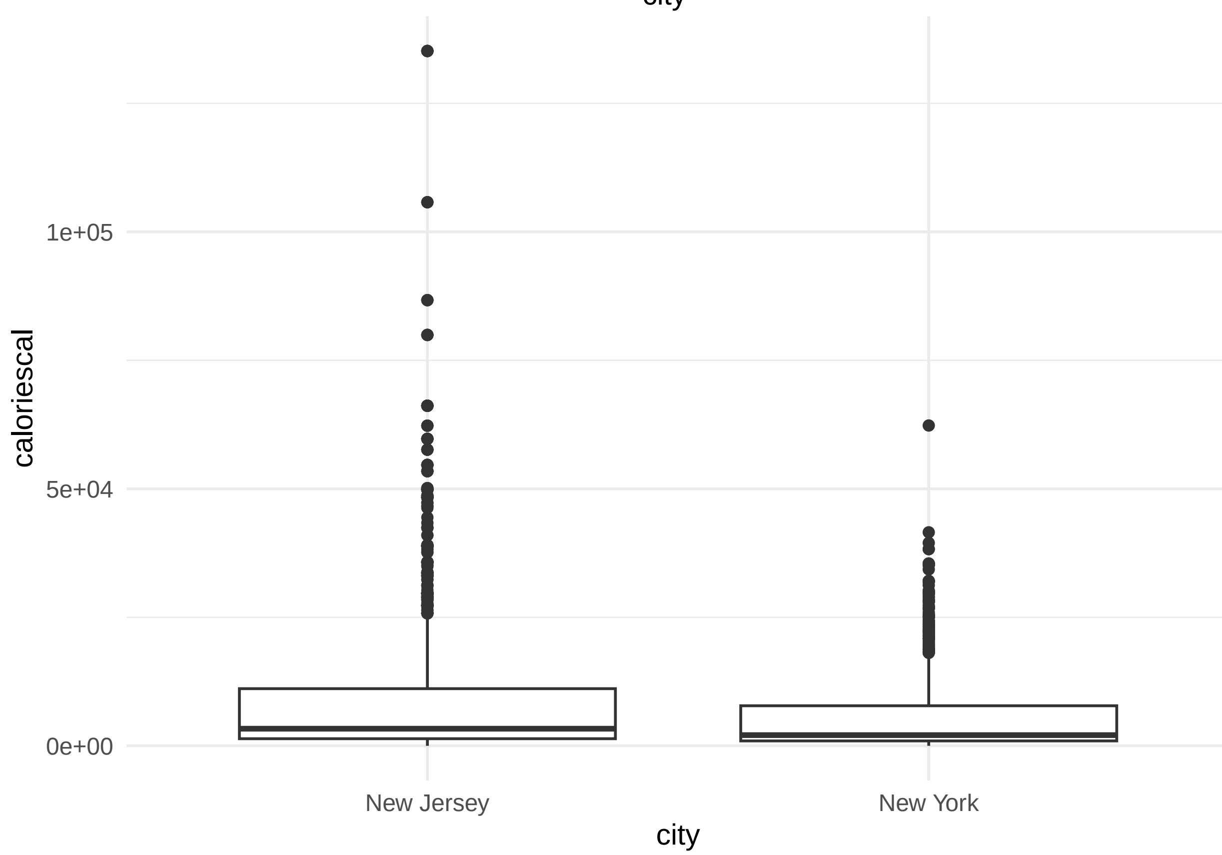
New York
city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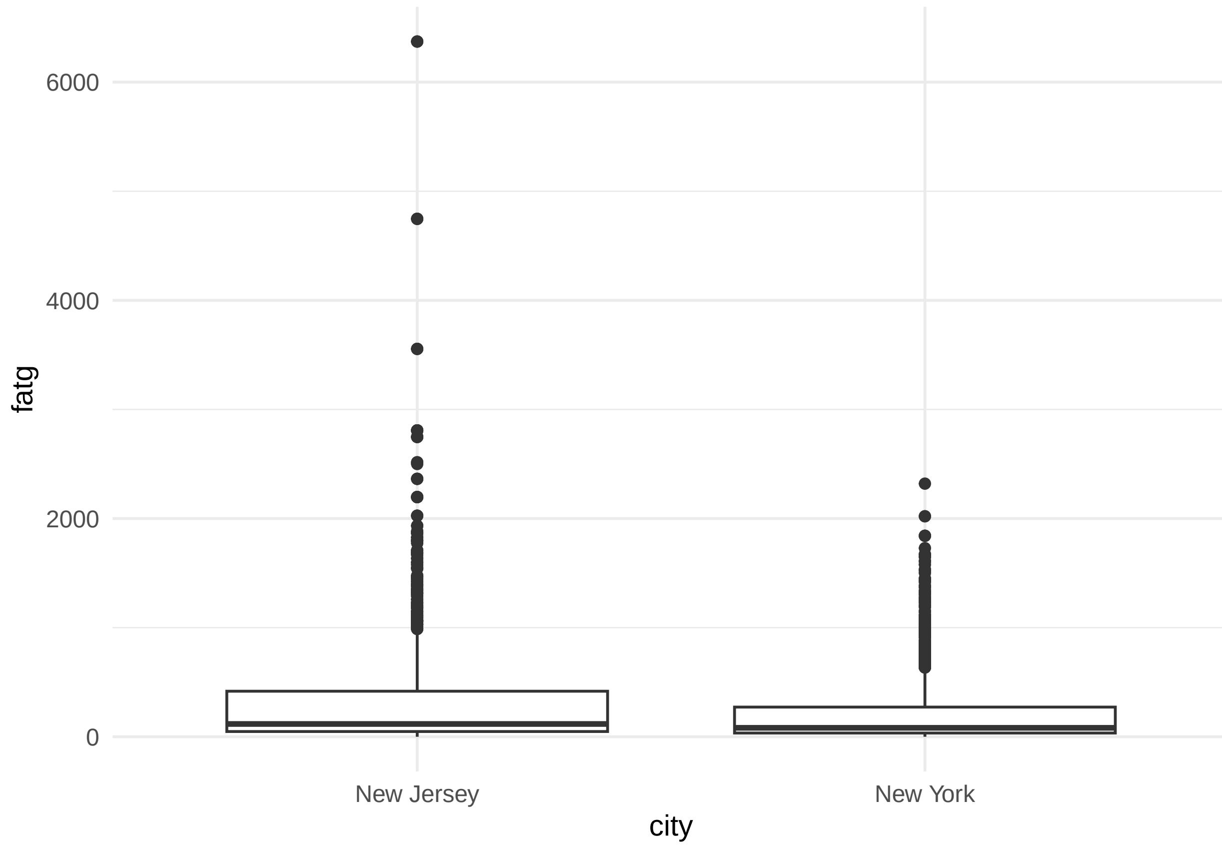
city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New York
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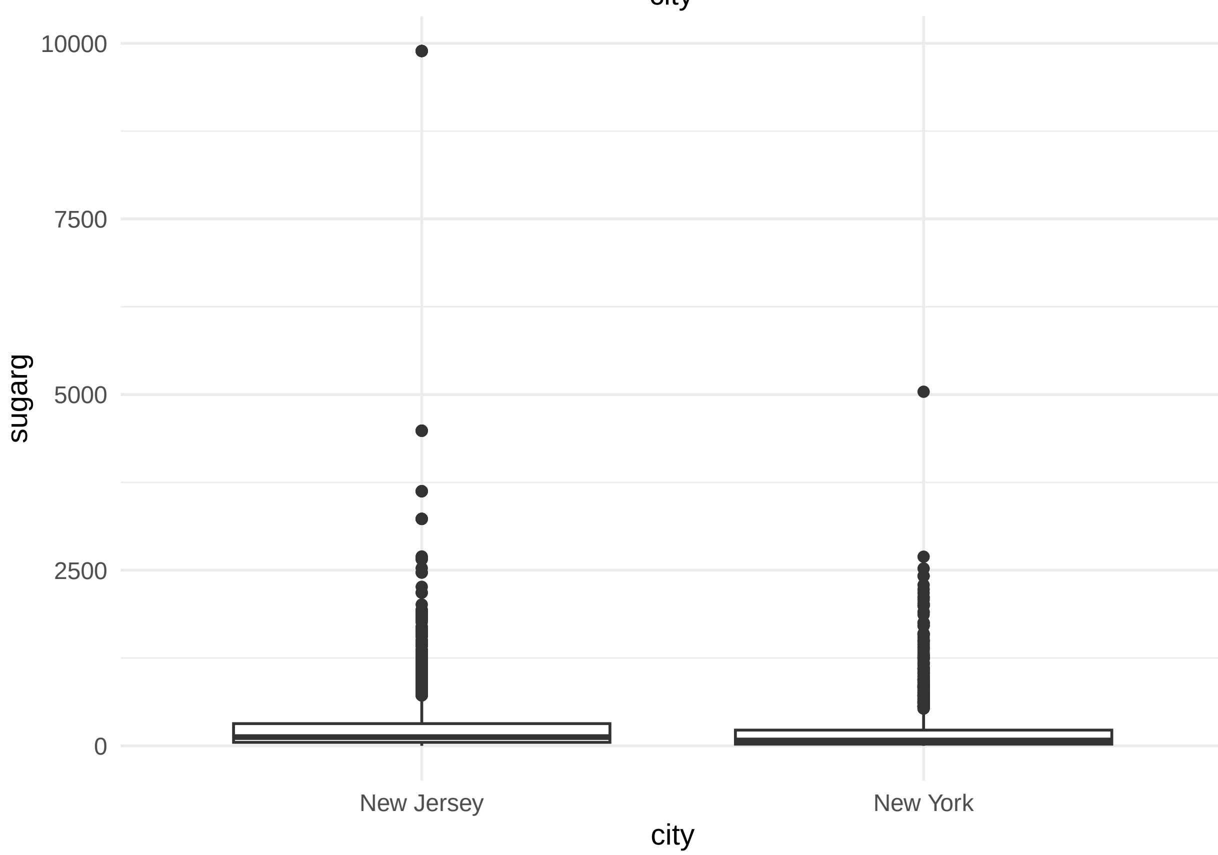
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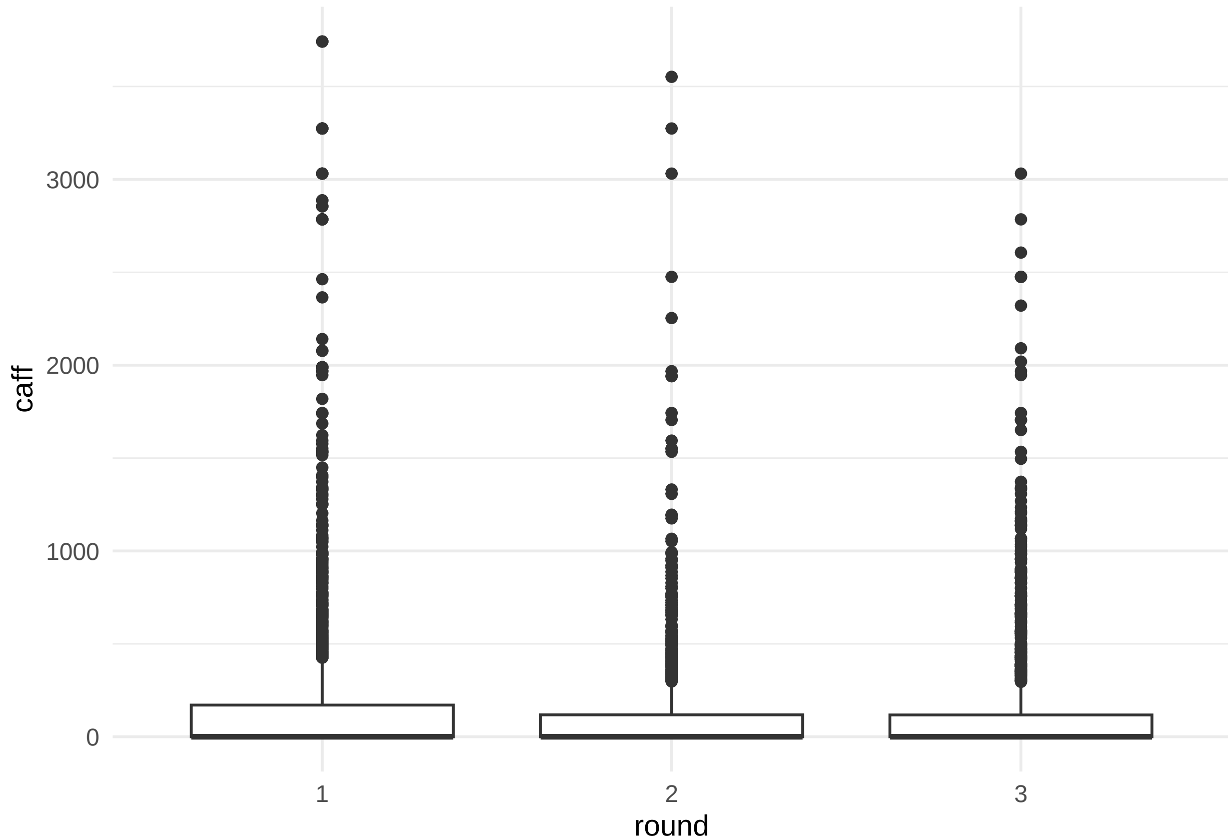
city



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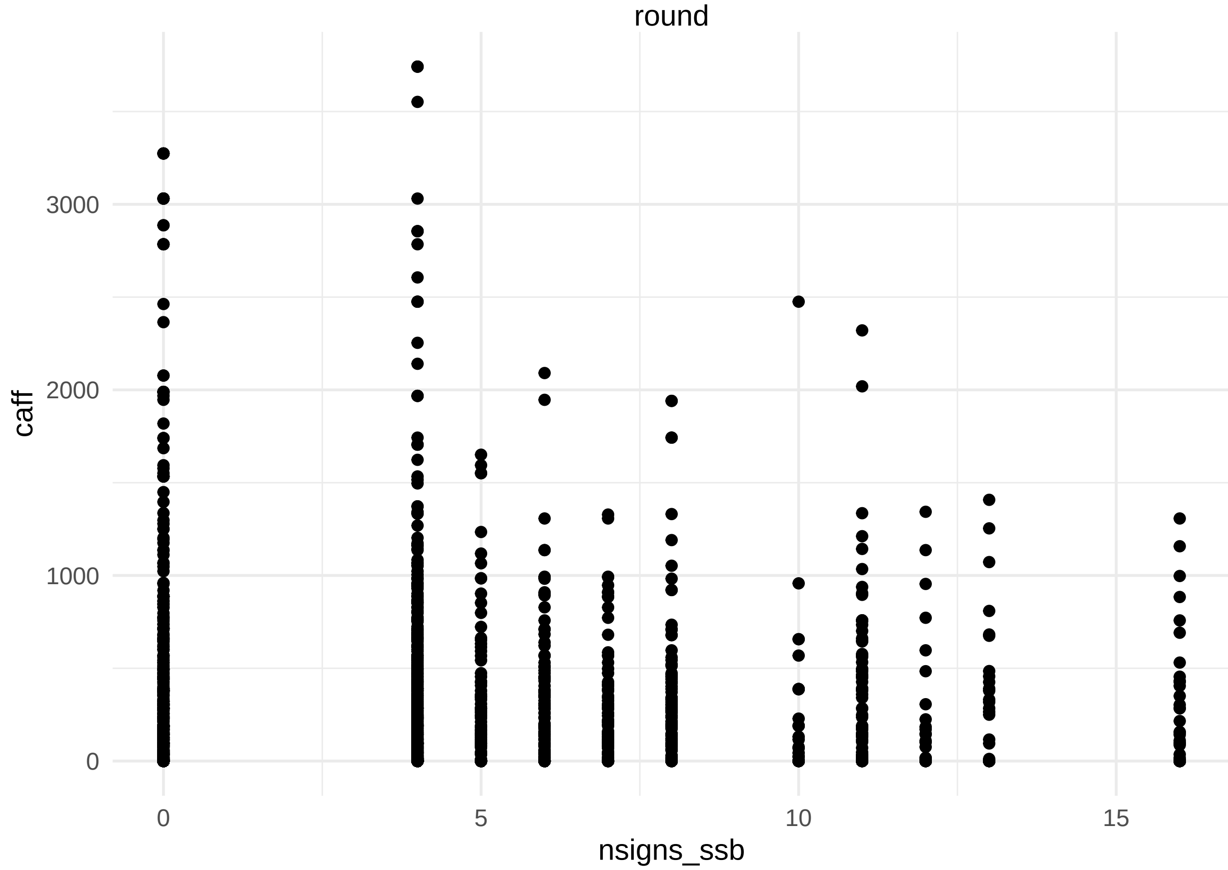
round



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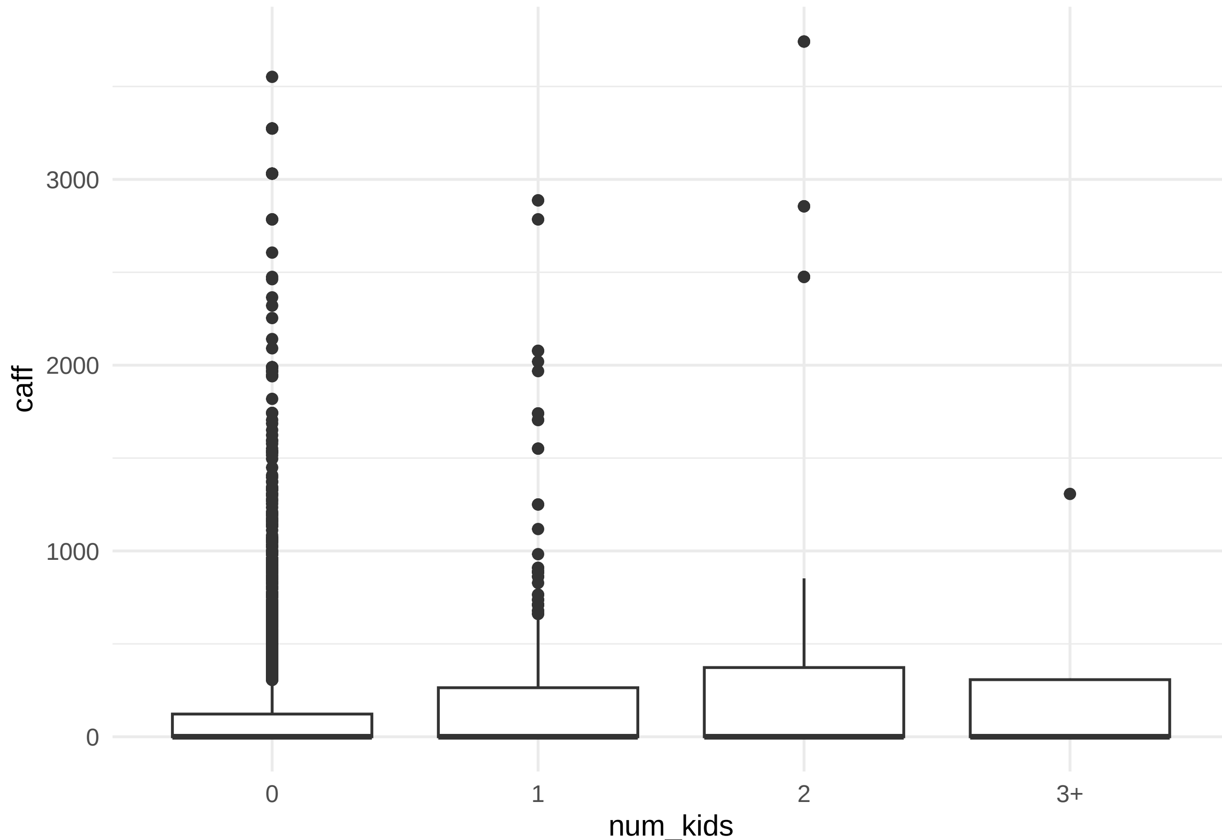
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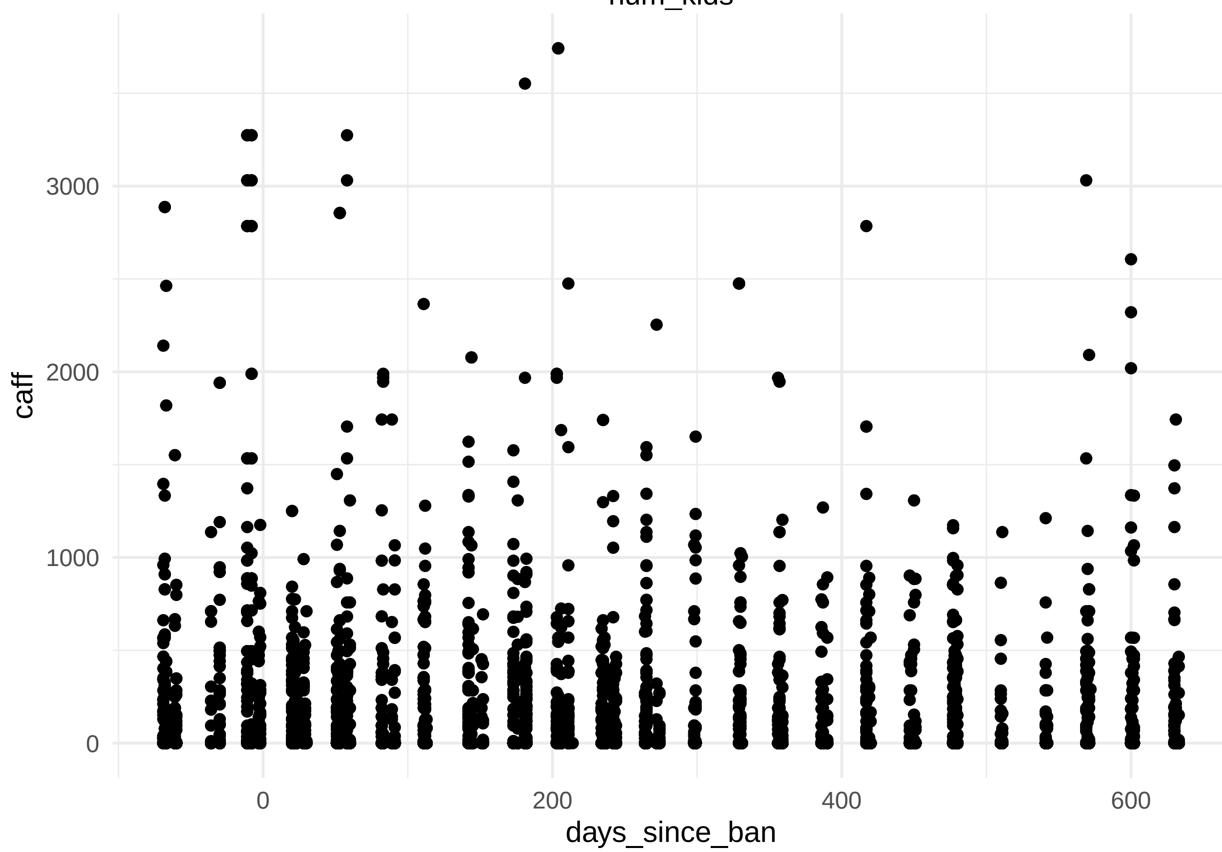
num_kids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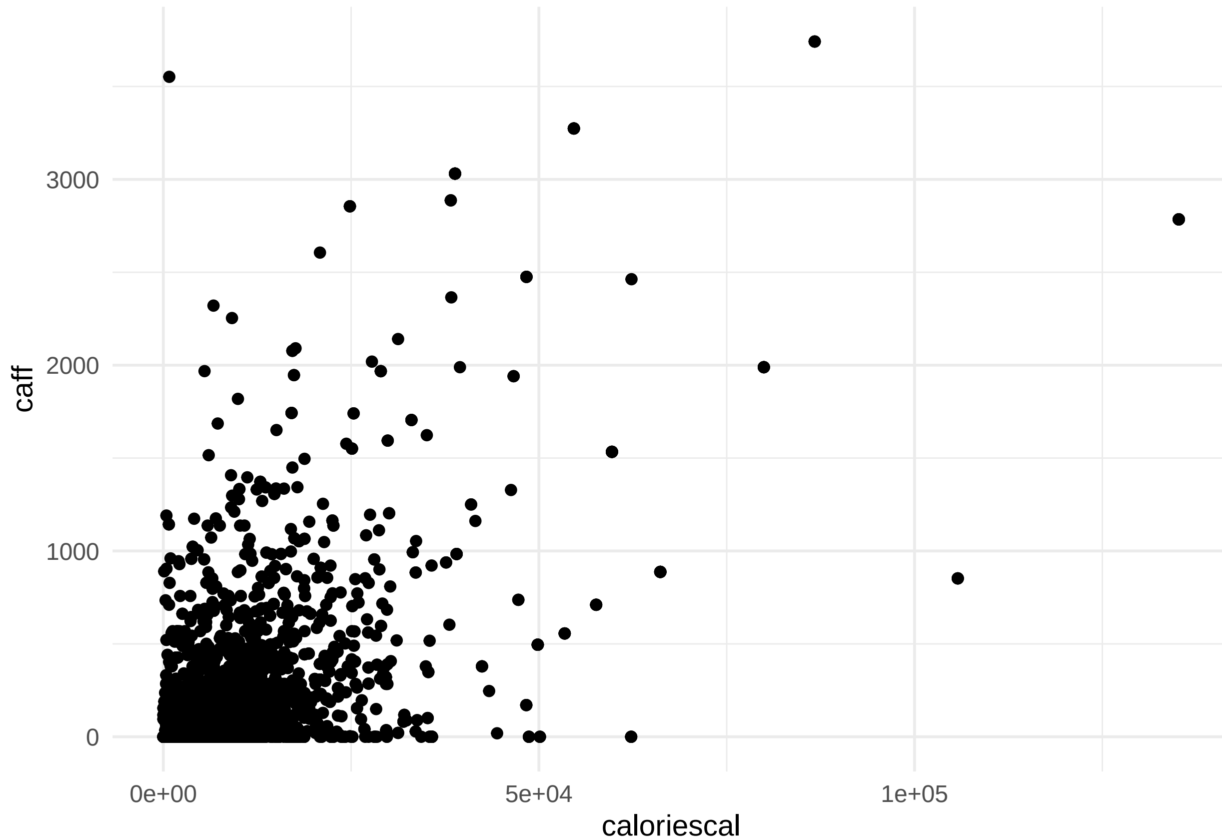
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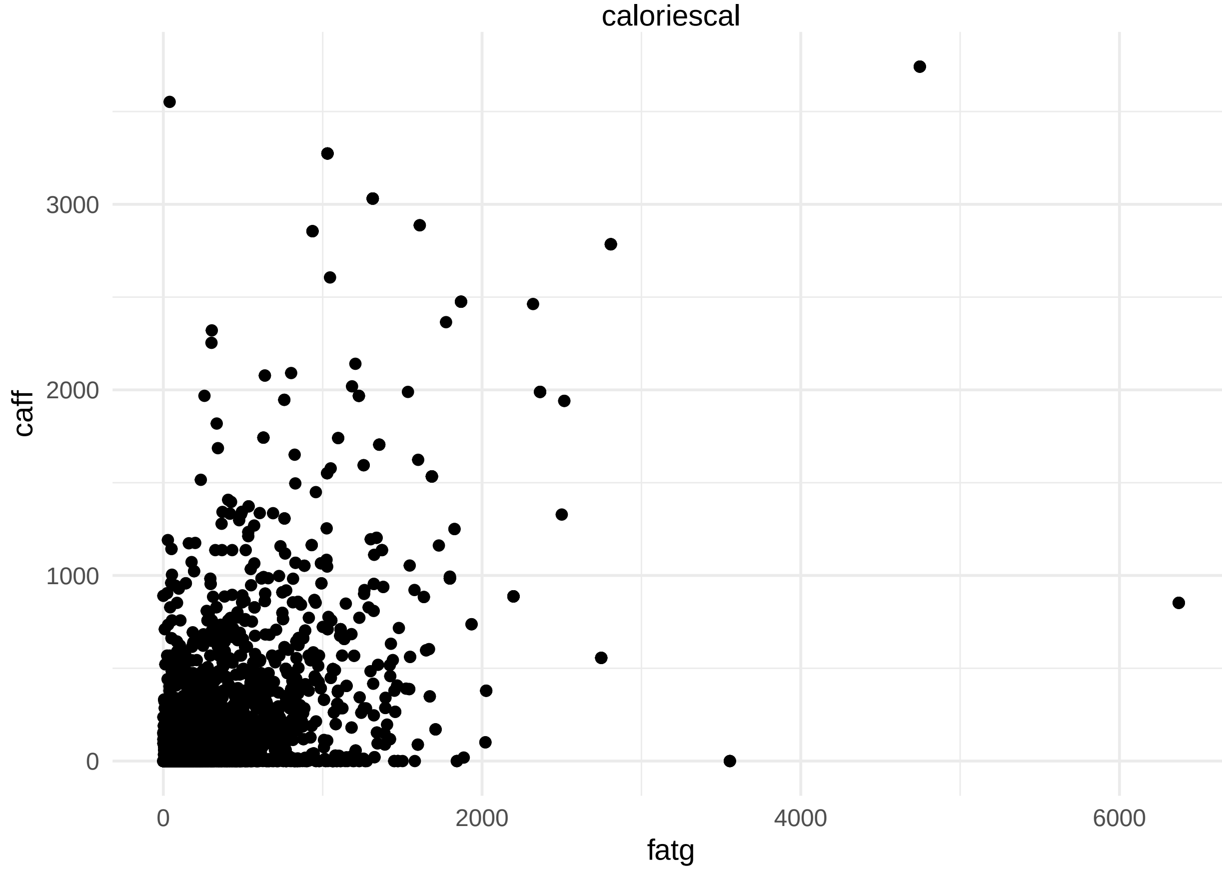
caloriescal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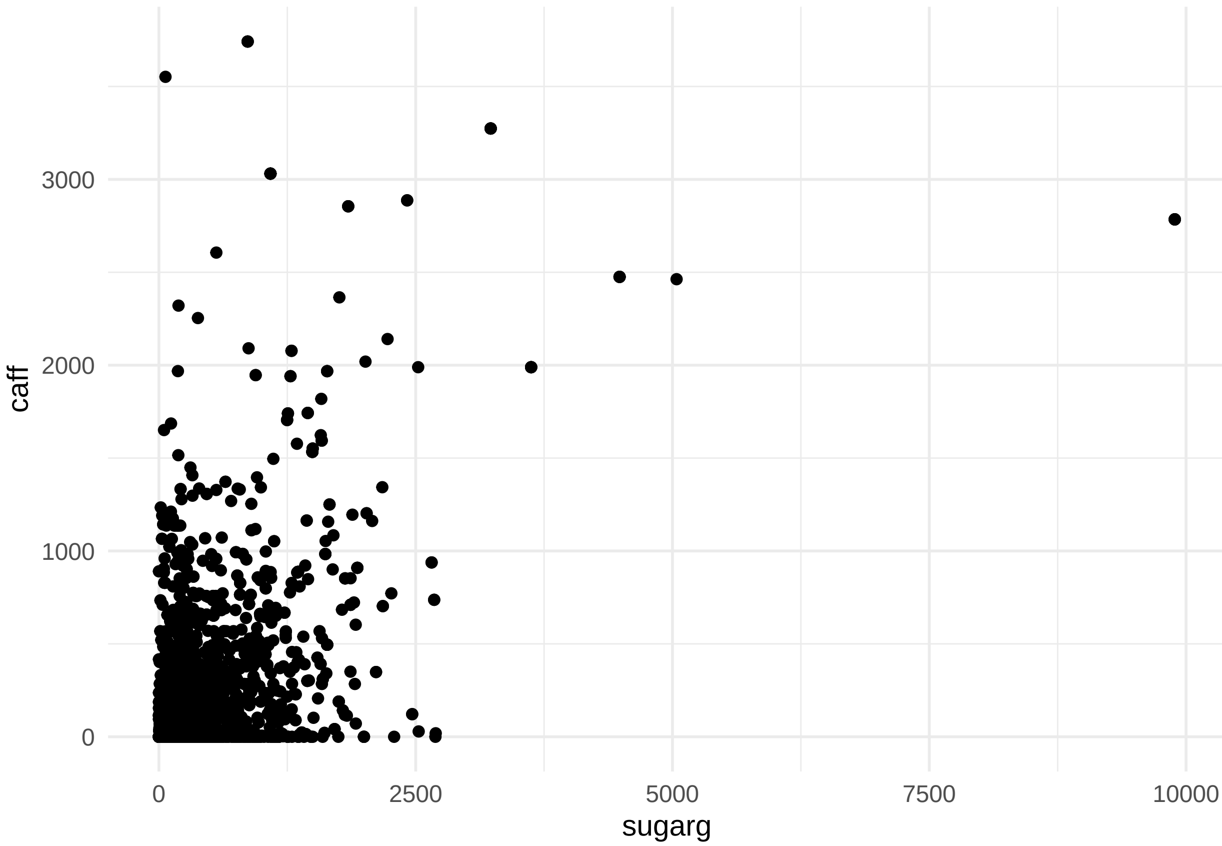

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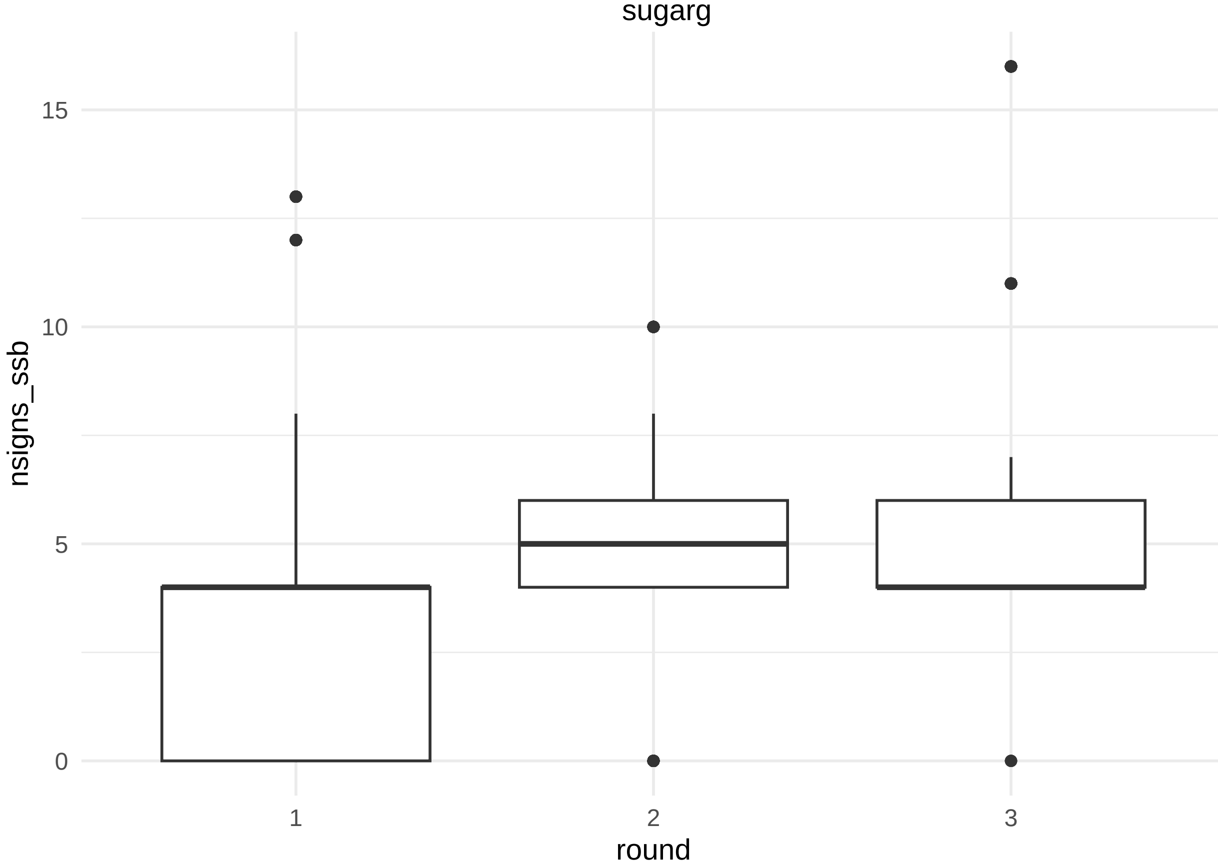

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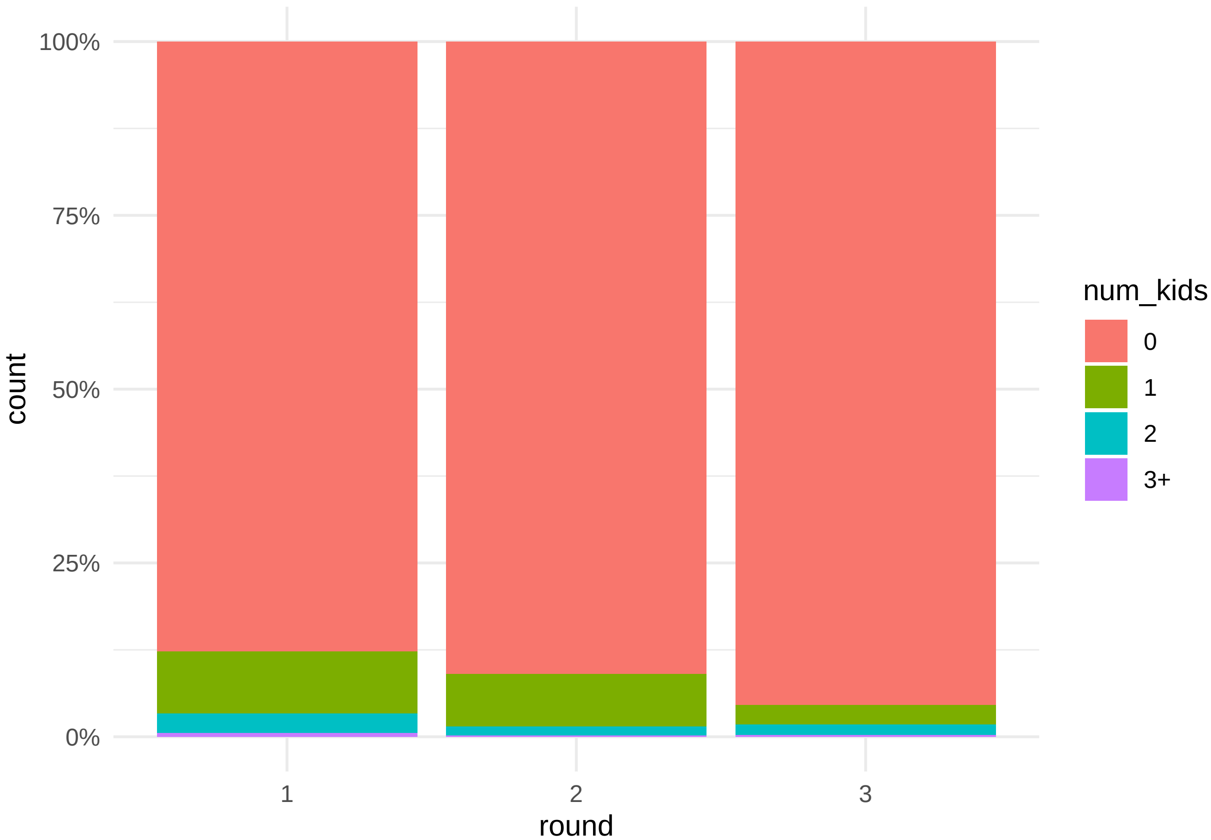
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count
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3
round
num_kids
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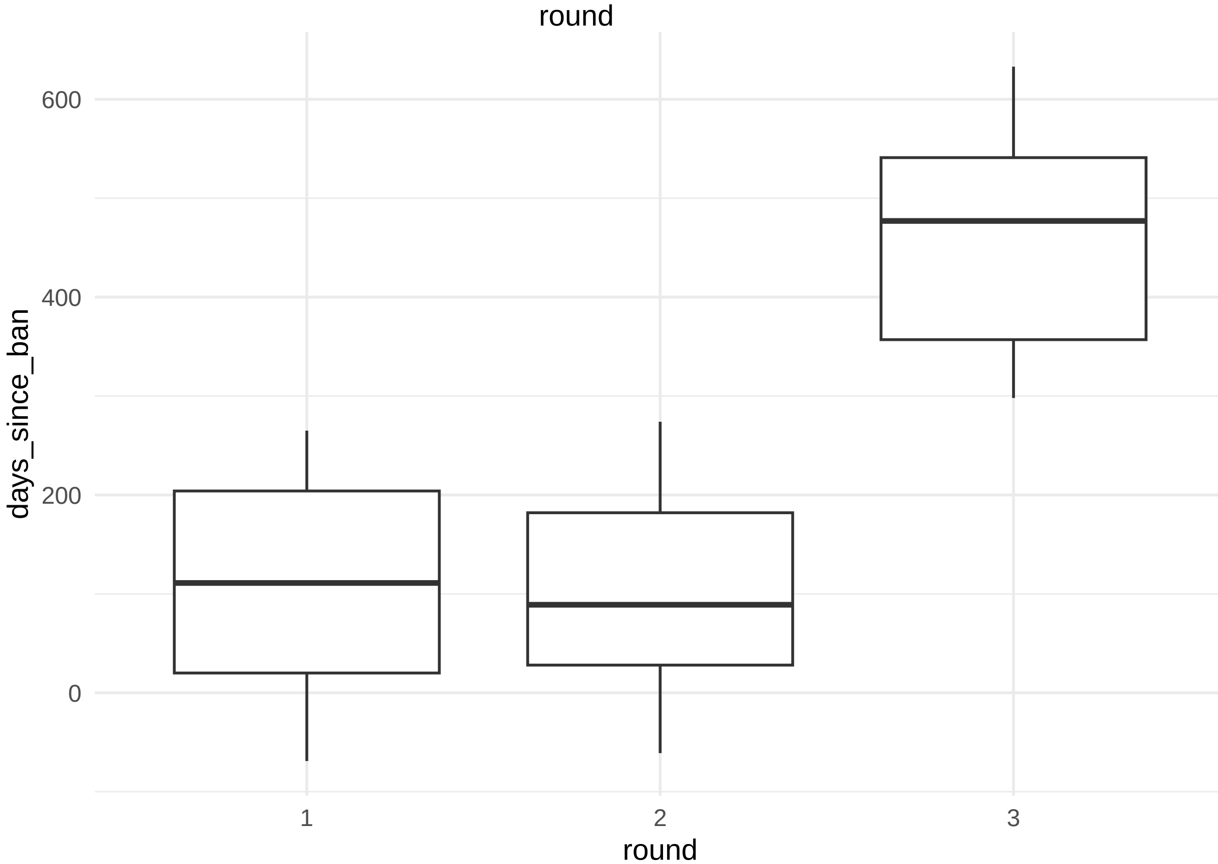
2
3+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days_since_ban
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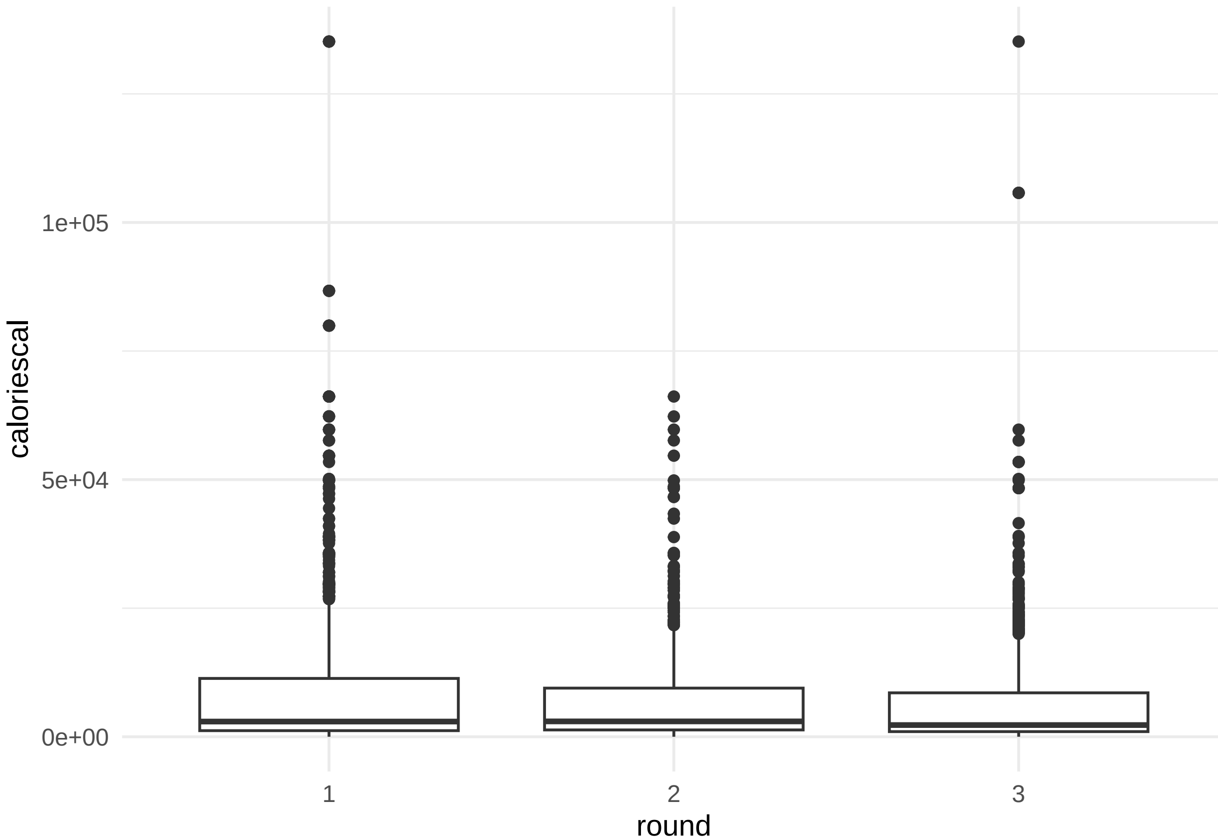
round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5e+04
0e+00
caloriescal
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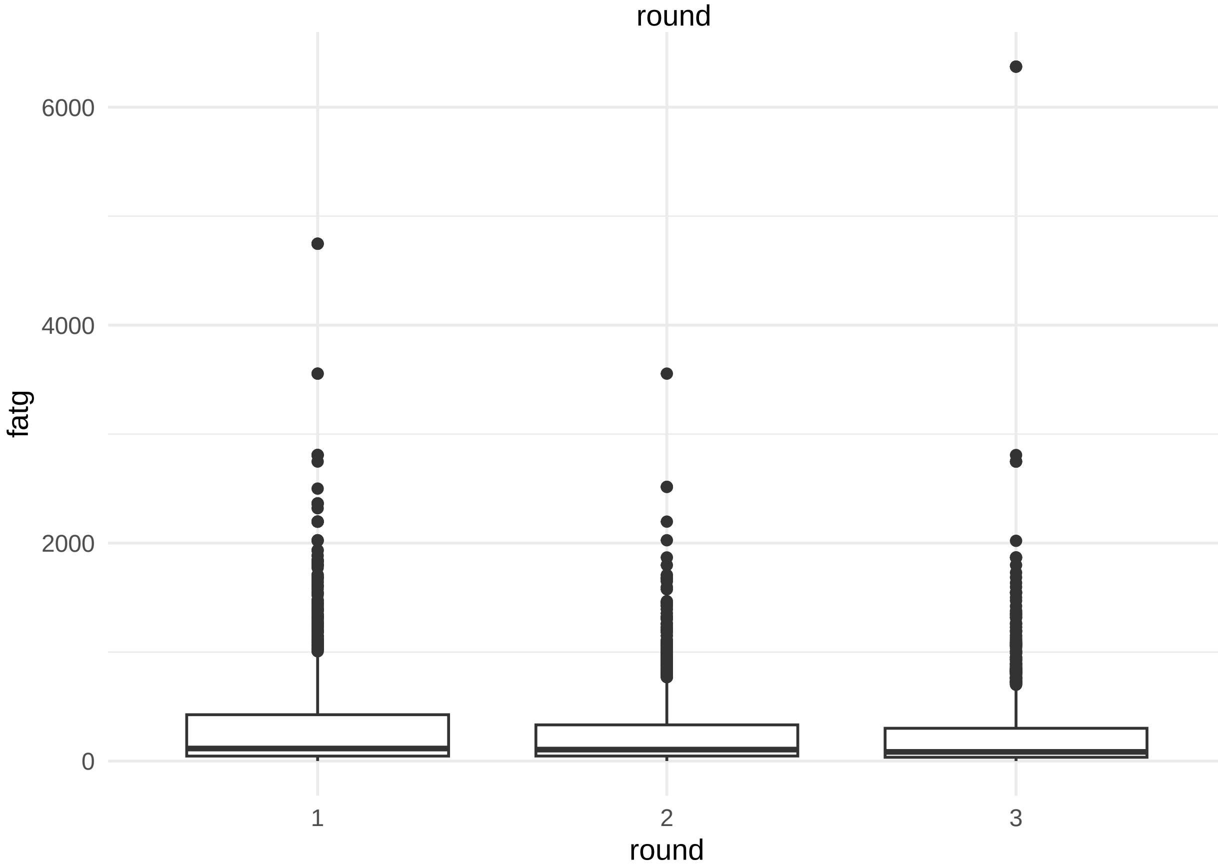
round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fatg
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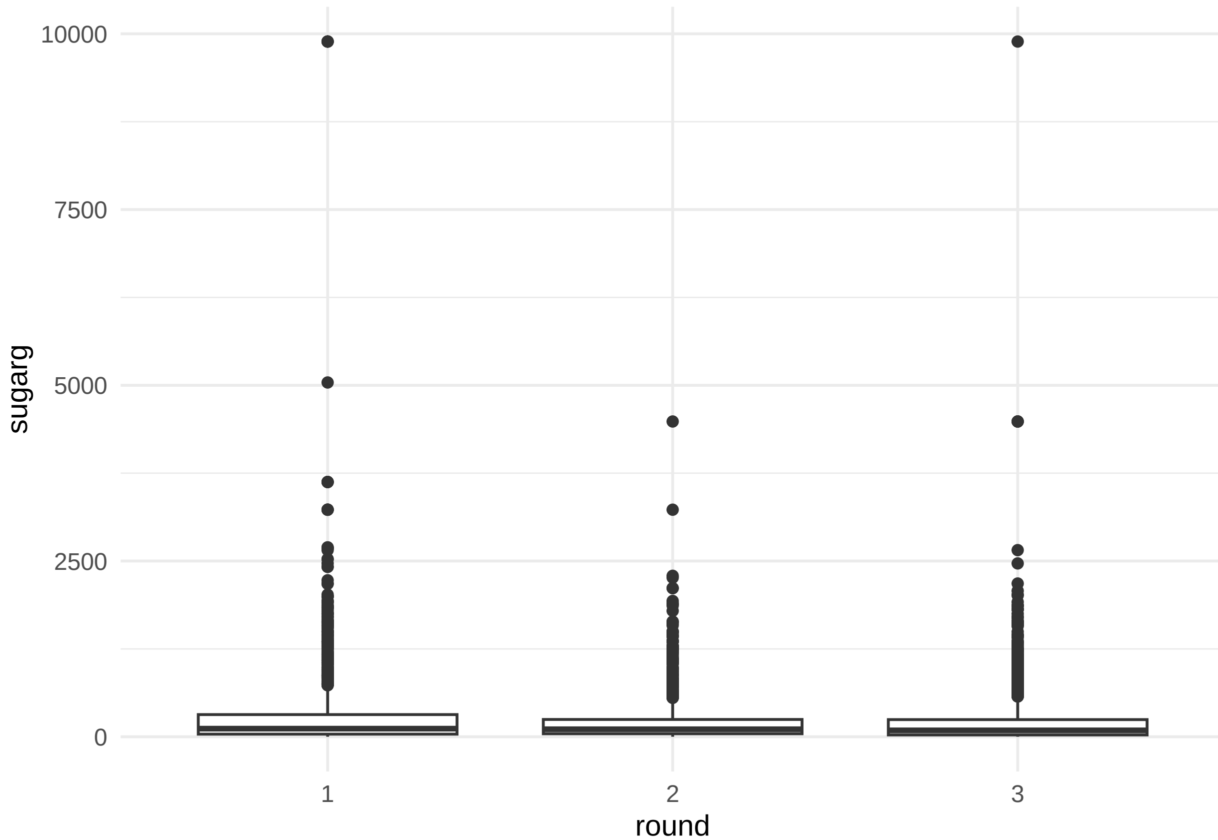
3
round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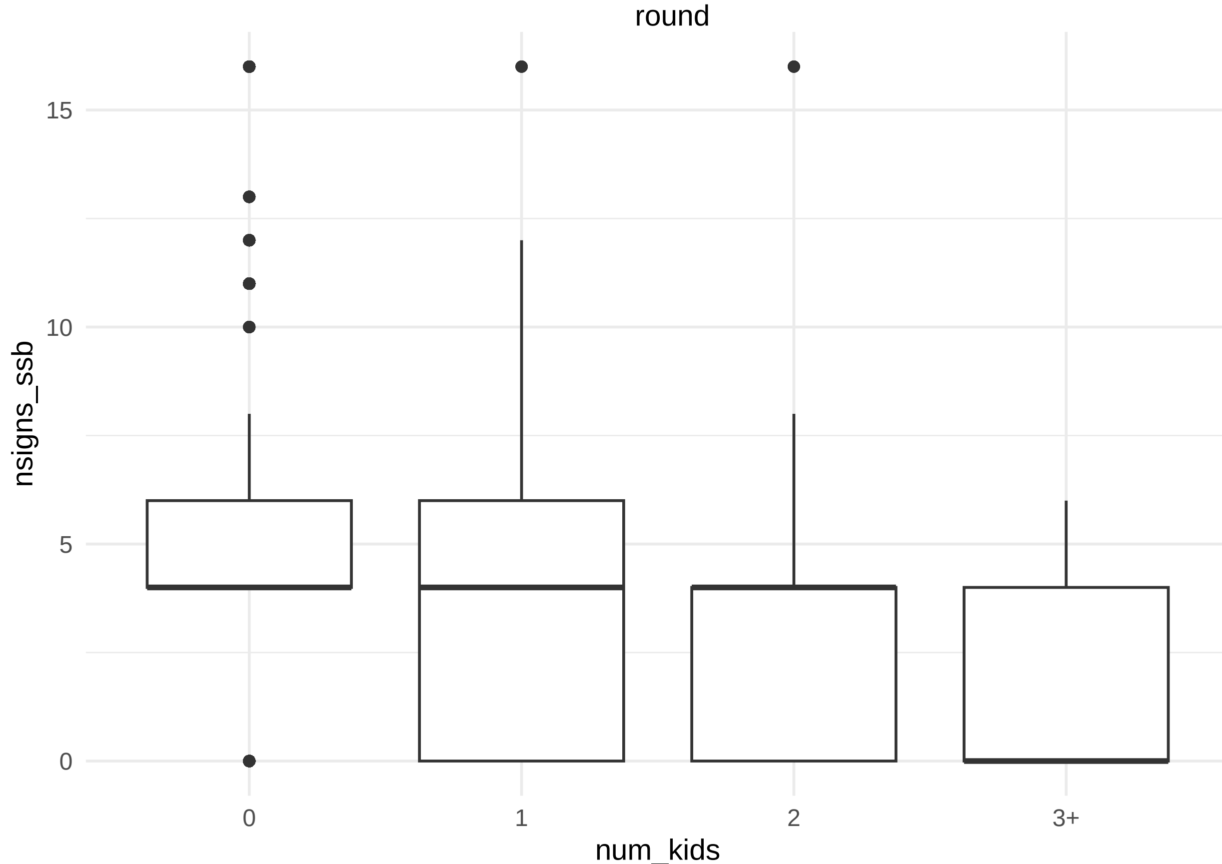
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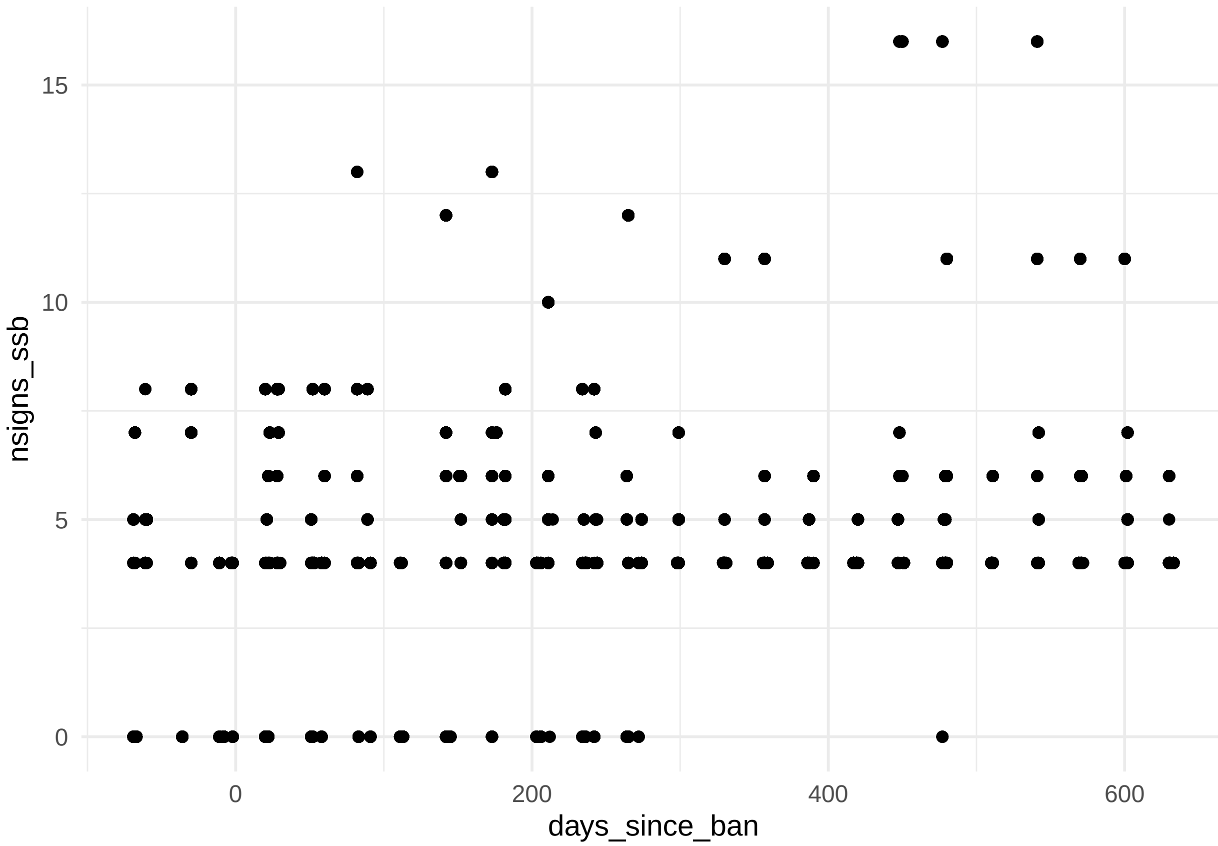
num_kids



nsigns_ssb
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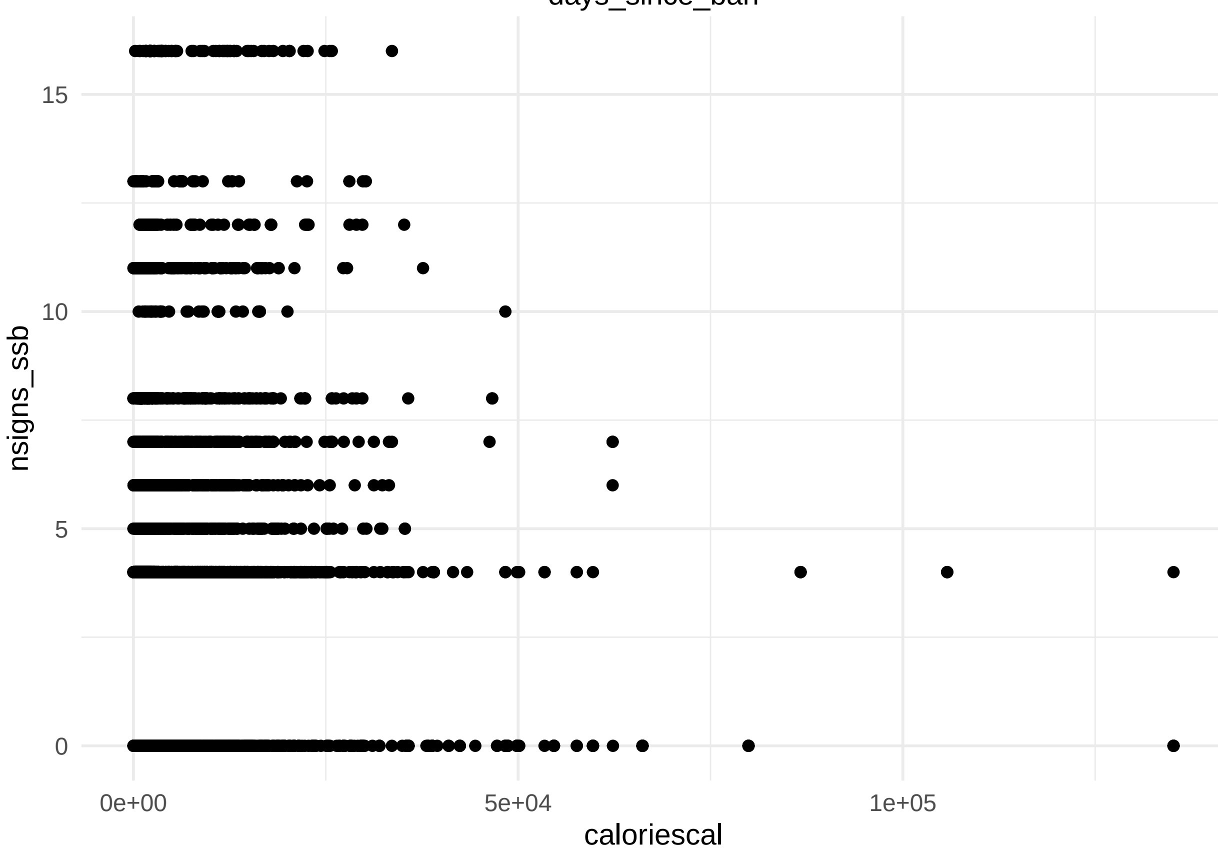
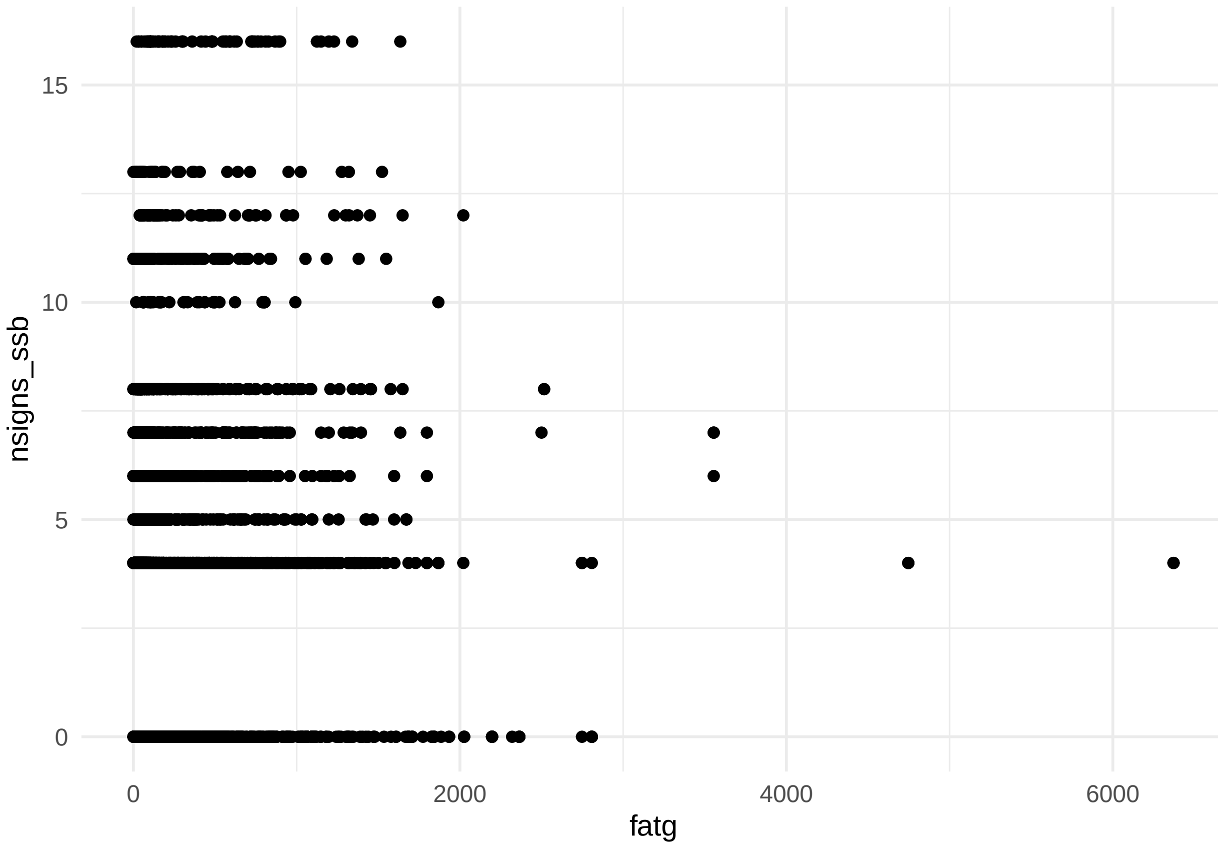
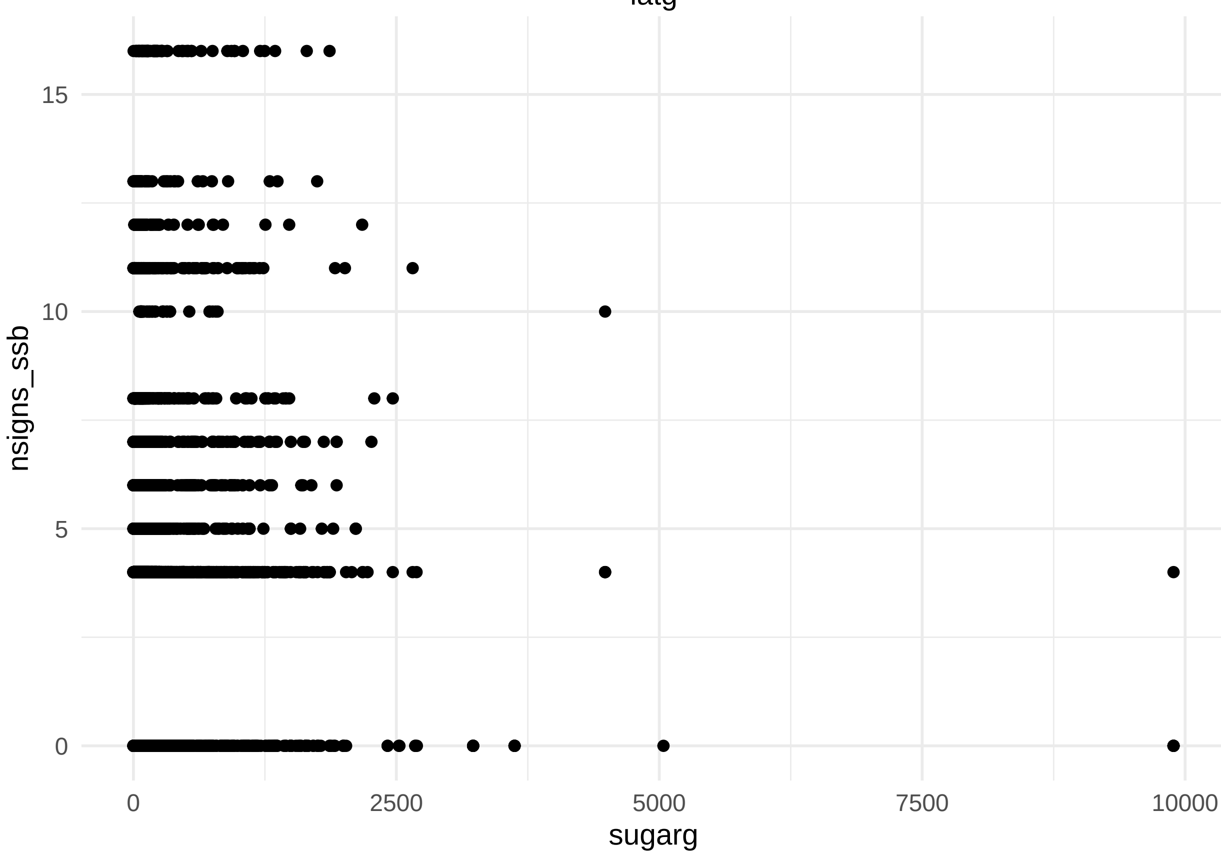
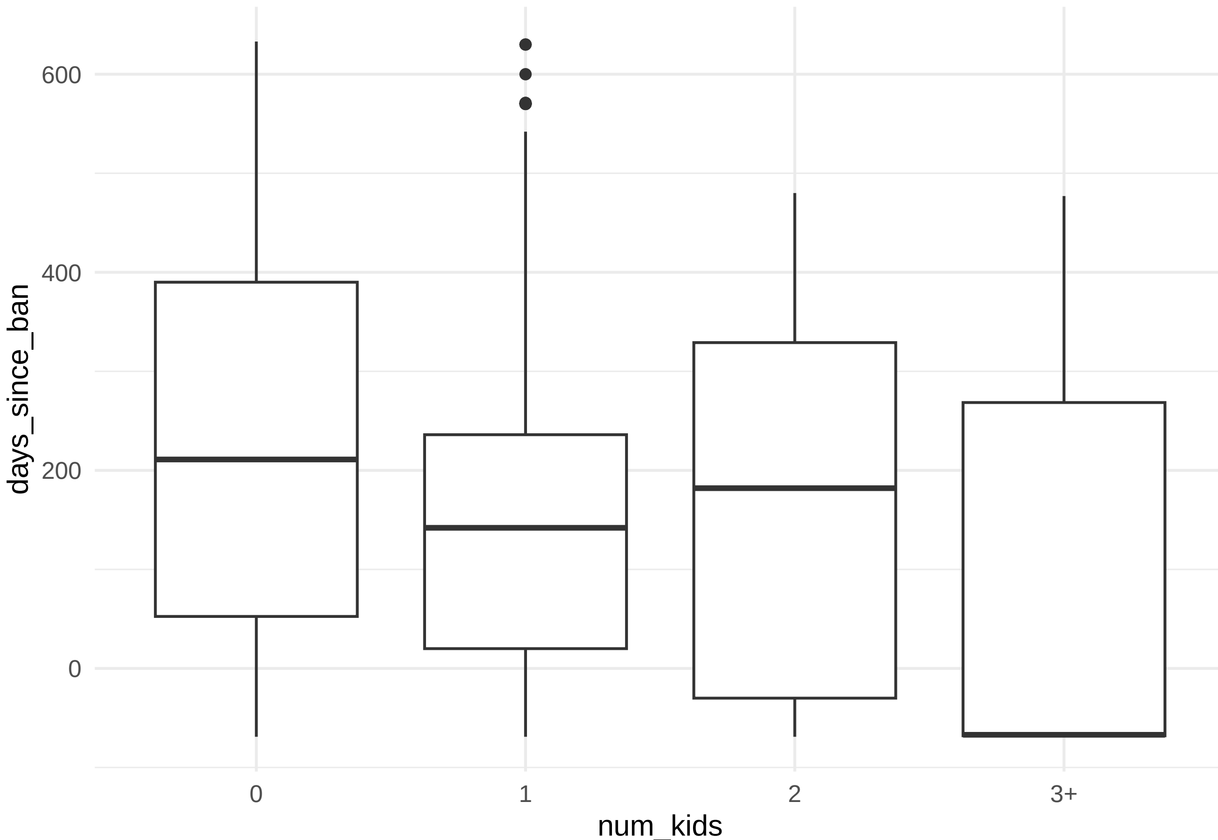
600
days_since_ban

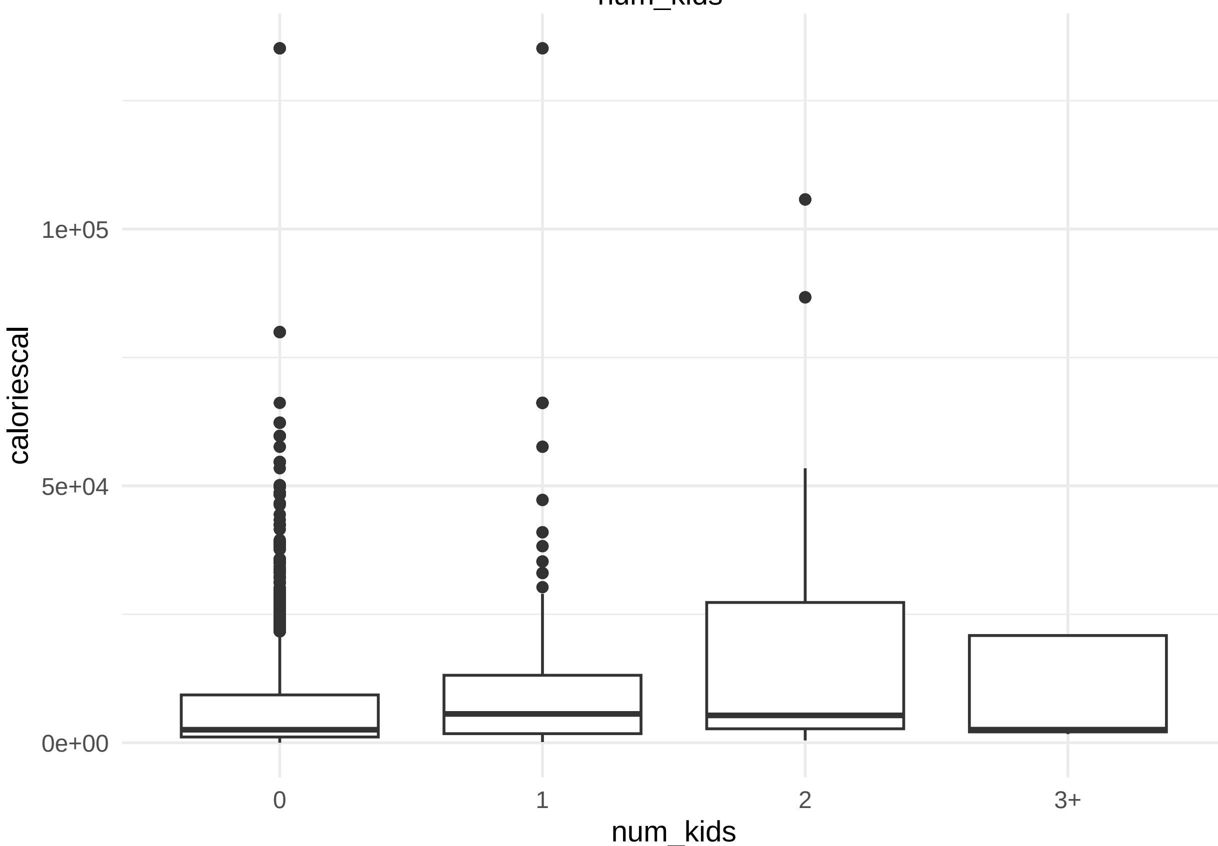


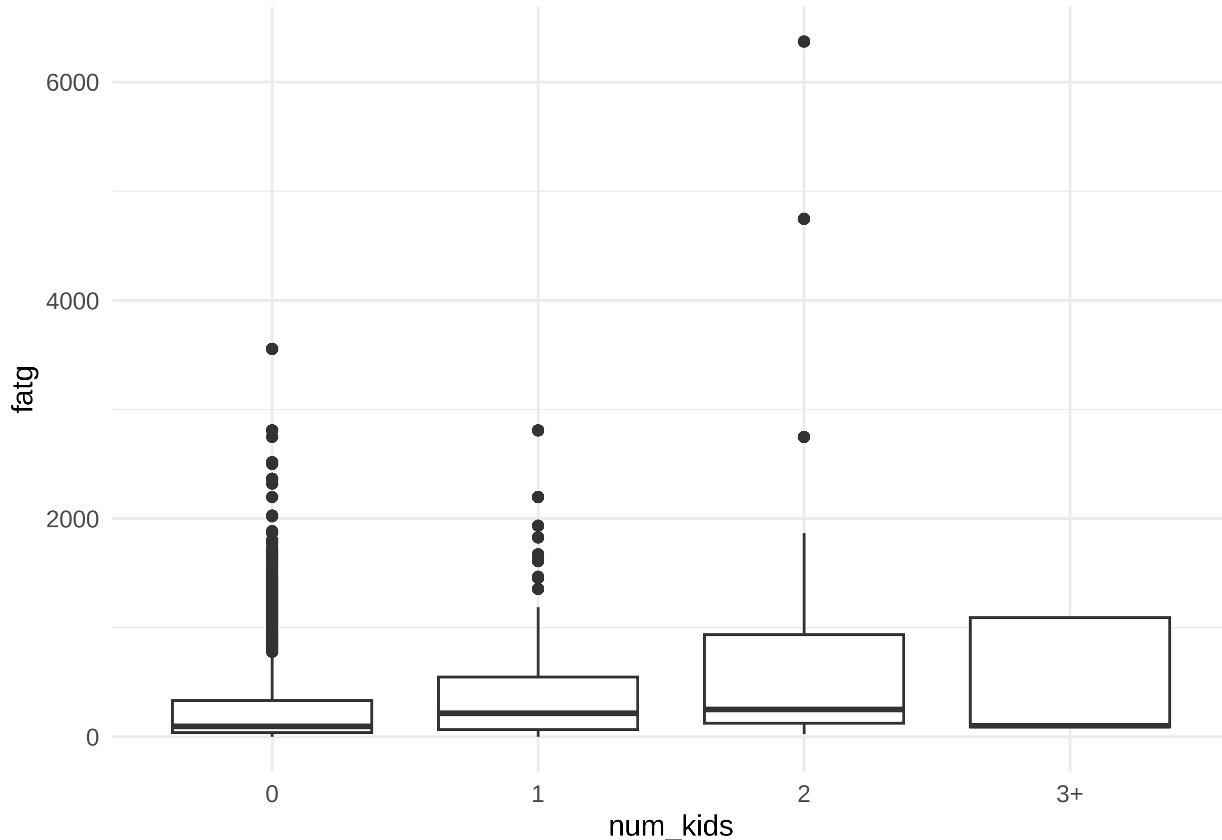
nsigns_ssb
15
10
5
0
0e+00
5e+04
1e+05
caloriescal

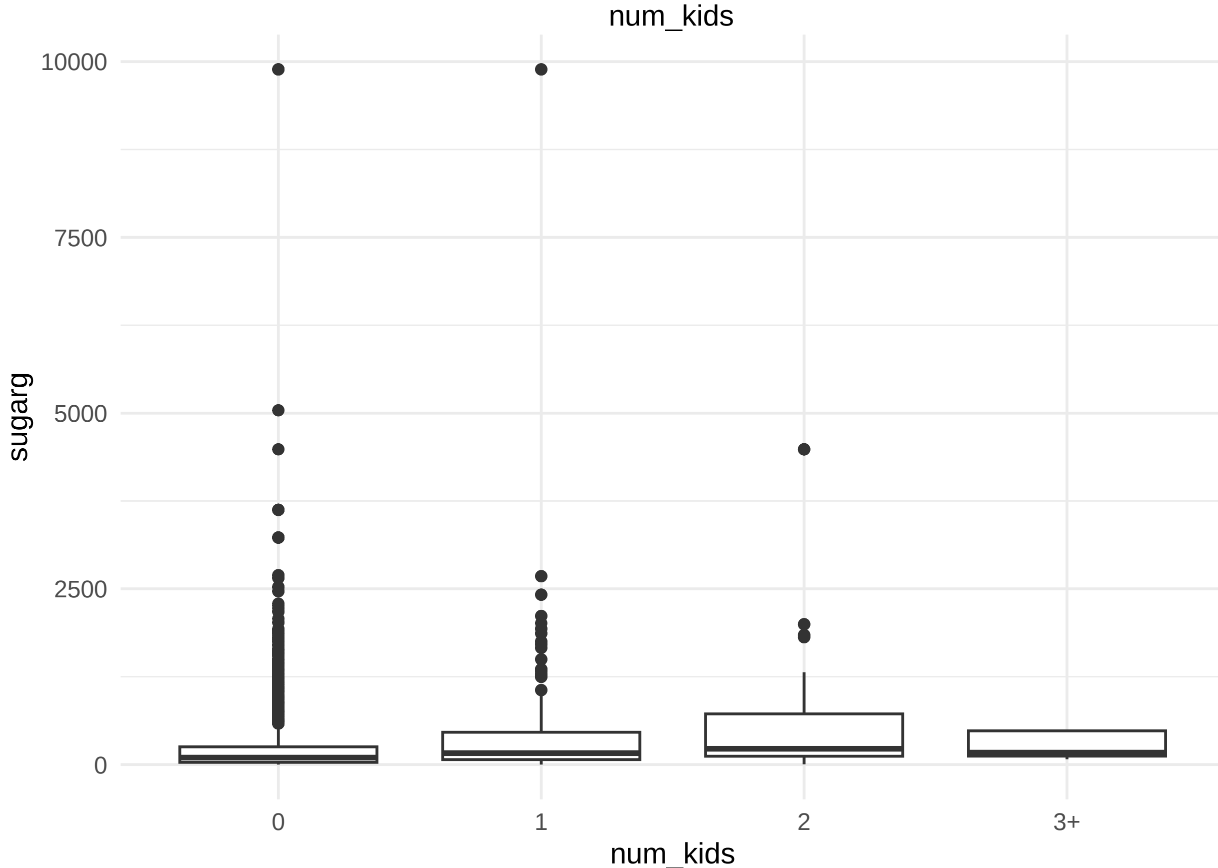

15
10
5
0
nsigns_ssb
0
2000
4000
6000
fatg

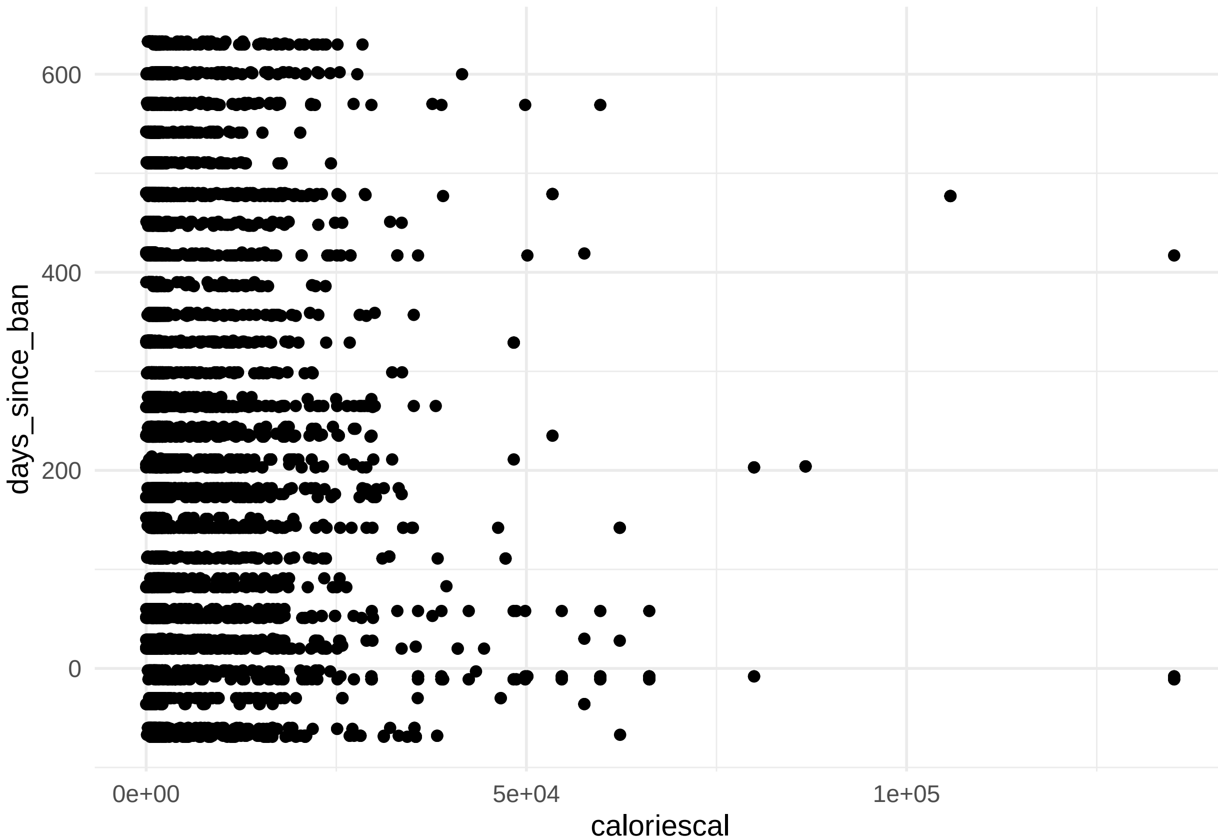

15
10
5
0
nsigns_ssb
0
2500
5000
7500
10000
sugarg

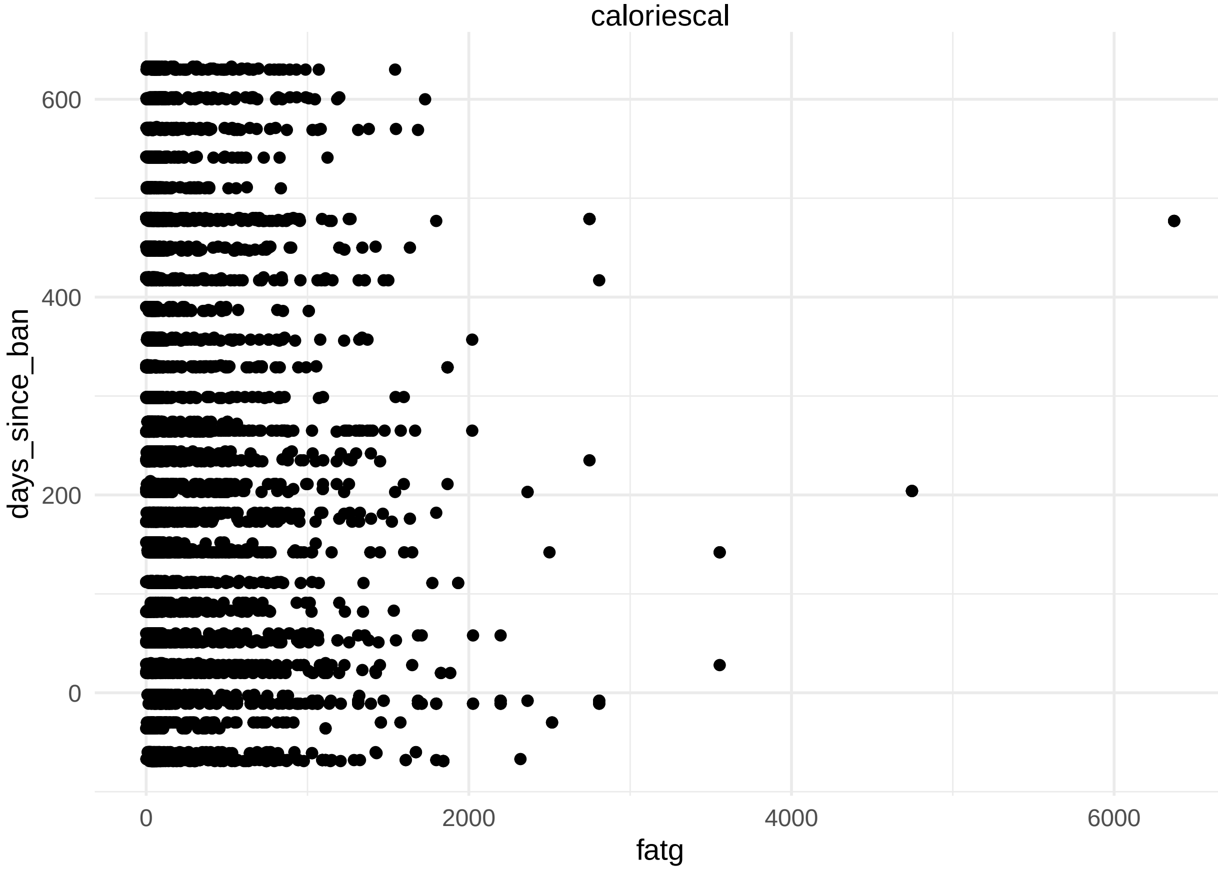

600
400
200
0
days_since_ban
0
1
2
3+
num_kids

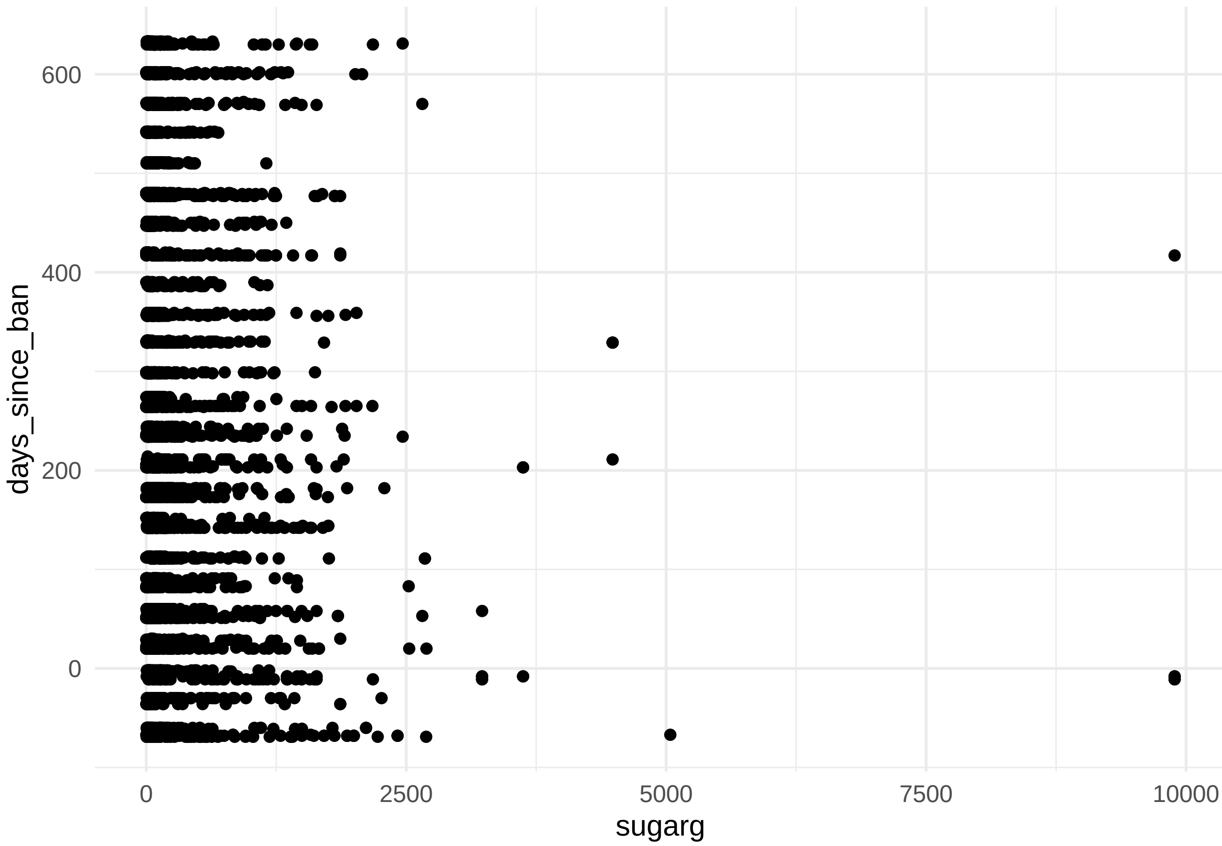

1e+05
5e+04
0e+00
caloriescal
0
1
2
3+
num_kids


6000
4000
2000
0
fatg
0
1
2
3+
num_kids

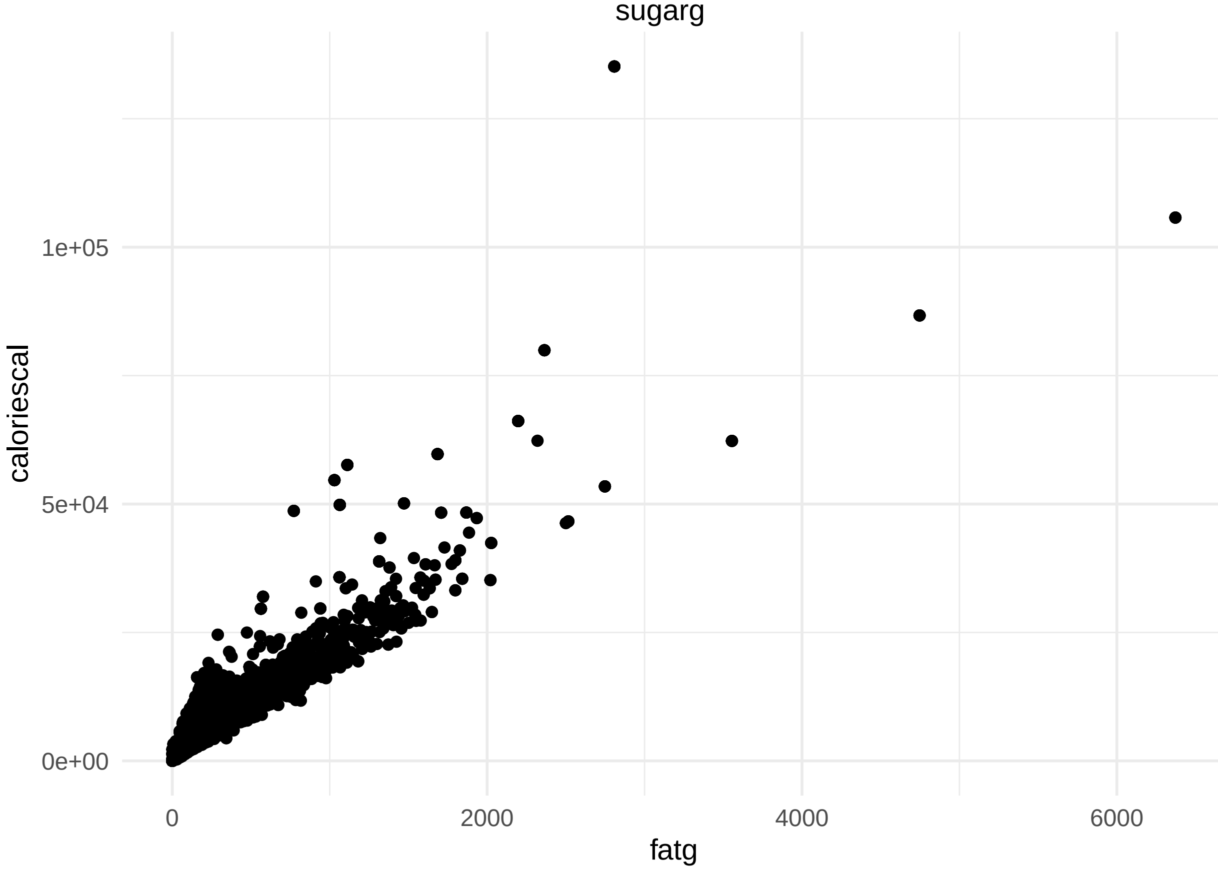

10000
7500
5000
2500
0
sugarg
0
1
2
3+
num_kids


600
400
200
0
days_since_ban
0e+00
5e+04
1e+05
caloriescal

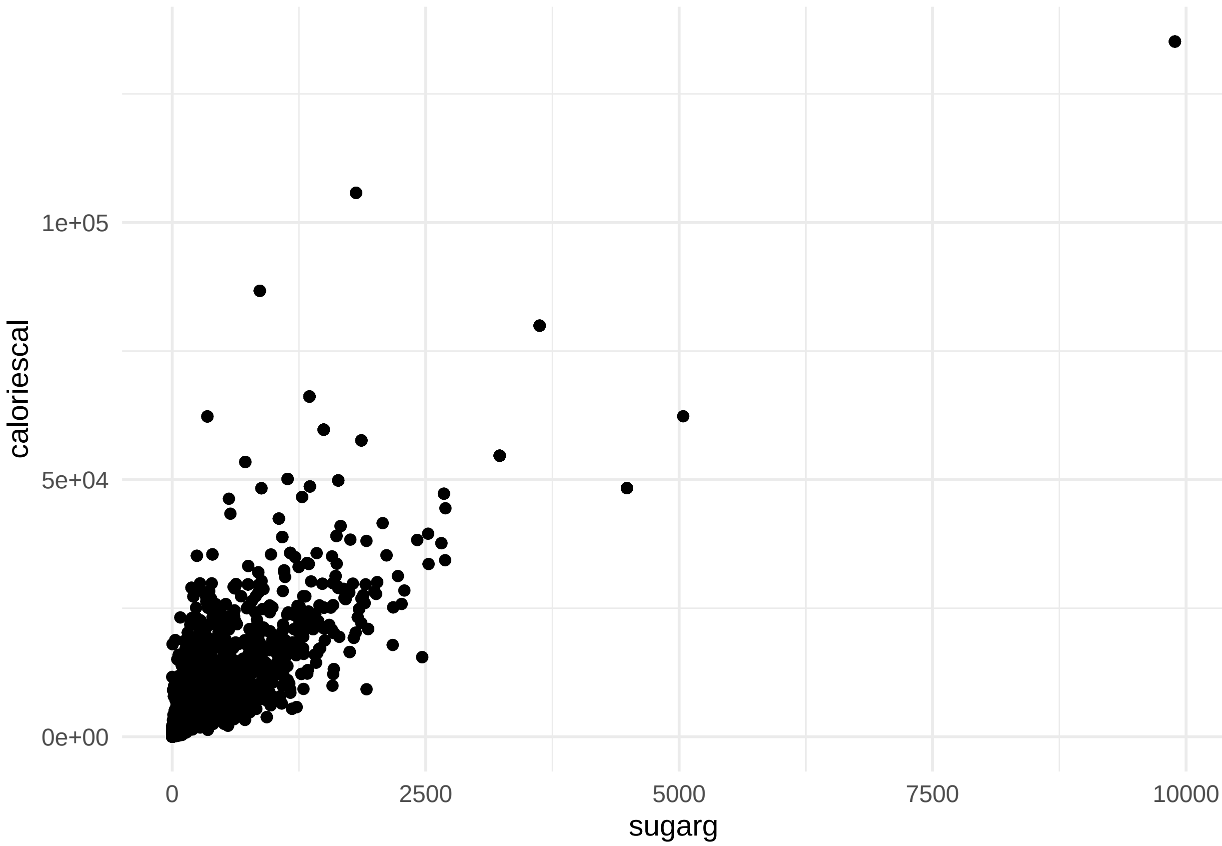

600
400
200
0
days_since_ban
0
2000
4000
6000
fatg

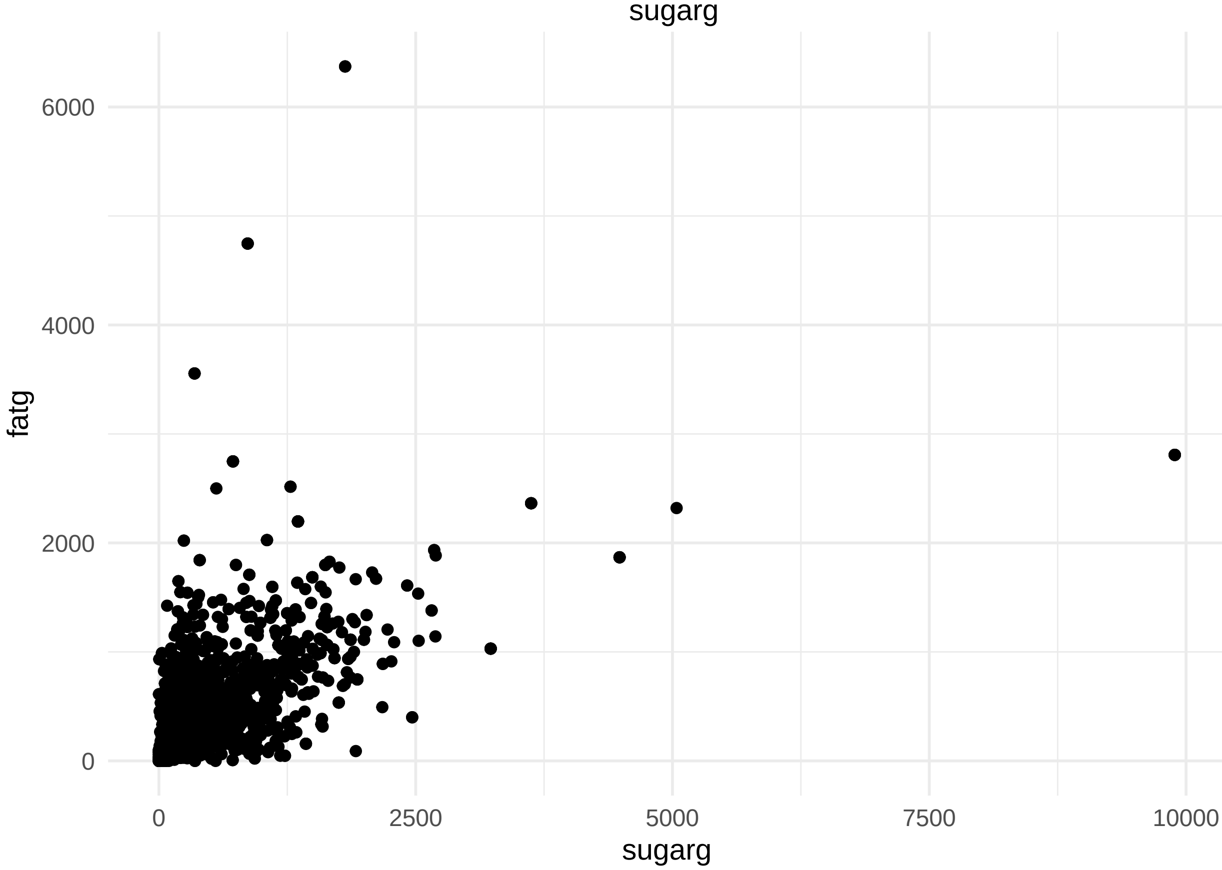


days_since_ban
600
400
200
0
0
2500
5000
7500
10000
sugarg



caloriescal
1e+05
5e+04
0e+00
0
2000
4000
6000
fatg


1e+05
5e+04
0e+00
caloriescal
0
2500
5000
7500
10000
sugarg


6000
4000
2000
0
fatg
0
2500
5000
7500
10000
sugarg

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 +
                                caloriescal_std + fatg_std + sugarg_std +
                                (1 | location) + (1 | round),
                          control = list(method = "nlminb",
                                          useMatrix = T,
                                          maxIter = 200,
                                          gradTol = 1e-4,
                                          maxLineIter = 200
                                          # , trace = 1
                                          ),
                      data = reduced_data, link = "logit")
control_clmm_full_std_int <- clmm(limit ~ age_std + gender*num_kids + race + edu + city + caff_std +
                                nsigns_ssb_std + days_since_ban_std +
                                caloriescal_std + fatg_std + sugarg_std +
                                (1 | location) + (1 | round),
                          control = list(method = "nlminb",
                                          useMatrix = T,
                                          maxIter = 200,
                                          gradTol = 1e-4,
                                          maxLineIter = 200
                                          # , trace = 1
                                          ),
                      data = reduced_data, link = "logit")
```

```
## Warning: (1) Hessian is numerically singular: parameters are not uniquely determined
## In addition: Absolute convergence criterion was met, but relative criterion was not met
```

```r
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 + caloriescal_std +
##     fatg_std + sugarg_std + (1 | location) + (1 | round)
## data:    reduced_data
##
##  link  threshold nobs logLik   AIC      niter       max.grad cond.H
```

```
##  logit flexible  4296 -6498.59 13053.18 6481(13170) 3.83e-03 1.6e+03
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  location (Intercept) 0.02328  0.1526
##  round    (Intercept) 0.00000  0.0000
## Number of groups:  location 57,  round 3
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## age_std                   0.2259749  0.0296596   7.619 2.56e-14 ***
## genderM                  -0.2933068  0.0566808  -5.175 2.28e-07 ***
## raceBlack                -0.1940720  0.1185131  -1.638  0.10151
## raceNative               -0.2588840  0.2185724  -1.184  0.23624
## raceOther                 0.0470979  0.1266716   0.372  0.71003
## raceWhite                -0.0452073  0.1228145  -0.368  0.71280
## eduCollege Degree         0.2579721  0.1262403   2.044  0.04100 *
## eduGraduate Degree        0.2480524  0.1462447   1.696  0.08986 .
## eduHigh School           -0.3044348  0.1217535  -2.500  0.01240 *
## eduLess than High School -0.1760818  0.2027481  -0.868  0.38513
## eduSome College          -0.0670136  0.1251944  -0.535  0.59246
## eduSome High School      -0.4089046  0.1461276  -2.798  0.00514 **
## cityNew York              0.1652177  0.0735426   2.247  0.02467 *
## caff_std                 -0.0220947  0.0368587  -0.599  0.54888
## nsigns_ssb_std            0.0679932  0.0383321   1.774  0.07610 .
## num_kids1                 0.0732200  0.1159336   0.632  0.52767
## num_kids2                -0.2779861  0.2079258  -1.337  0.18124
## num_kids3+               -1.4221950  0.5391322  -2.638  0.00834 **
## days_since_ban_std       -0.0003282  0.0304117  -0.011  0.99139
## caloriescal_std           0.2954583  0.1209173   2.443  0.01455 *
## fatg_std                 -0.1628537  0.0902732  -1.804  0.07123 .
## sugarg_std               -0.1083325  0.0567918  -1.908  0.05645 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##                  Estimate Std. Error z value
## Never|Seldom      -1.1865     0.1641  -7.230
## Seldom|Sometimes  -0.7759     0.1635  -4.745
## Sometimes|Often    0.2743     0.1630   1.683
## Often|Always       1.1073     0.1640   6.751
```

```
## 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

```r
control_clmm_red <- clmm(limit ~ 1 + age_std + gender + race + edu + city +
                           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 + race + edu + city + num_kids + (1 | location) +
## 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          22 13052 -6504.0
## control_clmm_full_std     28 13053 -6498.6  10.854  6    0.09301 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(control_clmm_red)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: limit ~ 1 + age_std + gender + race + edu + city + num_kids +
##     (1 | location) + (1 | round)
## data:    reduced_data
##
##  link  threshold nobs logLik   AIC      niter       max.grad cond.H
##  logit flexible  4296 -6504.02 13052.03 5022(10163) 5.34e-03 1.6e+03
##
## Random effects:
##  Groups   Name        Variance  Std.Dev.
##  location (Intercept) 2.309e-02 1.520e-01
##  round    (Intercept) 1.743e-11 4.175e-06
## Number of groups:  location 57,  round 3
##
## Coefficients:
##                           Estimate Std. Error z value Pr(>|z|)
## age_std                    0.22618    0.02964   7.630 2.35e-14 ***
## genderM                   -0.28895    0.05662  -5.103 3.34e-07 ***
## raceBlack                 -0.18659    0.11856  -1.574  0.11553
## raceNative                -0.24327    0.21806  -1.116  0.26458
## raceOther                  0.04228    0.12649   0.334  0.73817
## raceWhite                 -0.04580    0.12264  -0.373  0.70884
## eduCollege Degree          0.27544    0.12607   2.185  0.02890 *
## eduGraduate Degree         0.25296    0.14599   1.733  0.08316 .
## eduHigh School            -0.30598    0.12168  -2.515  0.01192 *
## eduLess than High School -0.18646    0.20259  -0.920  0.35739
## eduSome College           -0.06847    0.12512  -0.547  0.58420
## eduSome High School       -0.41383    0.14602  -2.834  0.00460 **
## cityNew York               0.13928    0.07279   1.914  0.05568 .
```

```
## num_kids1                 0.07677    0.11518   0.667  0.50508
## num_kids2                -0.28274    0.20261  -1.395  0.16287
## num_kids3+               -1.43678    0.53843  -2.668  0.00762 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##                    Estimate Std. Error z value
## Never|Seldom        -1.1827     0.1640  -7.211
## Seldom|Sometimes    -0.7726     0.1634  -4.727
## Sometimes|Often      0.2750     0.1629   1.688
## Often|Always         1.1059     0.1640   6.743
```

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 + race + edu + city +
                           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 2 Round Random Intercept

```
## [1] 0.496914
```

```r
control_clm <- clm(limit ~ 1 + age_std + gender + race + edu + city +
                           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 Location Random Intercept

```
## [1] 0.000985921
```

```r
summary(control_clmm_loc)
```

```
## Cumulative Link Mixed Model fitted with the Laplace approximation
##
## formula: limit ~ 1 + age_std + gender + race + edu + city + num_kids +
##     (1 | location)
## data:    reduced_data
##
##  link  threshold nobs logLik   AIC      niter      max.grad cond.H
##  logit flexible  4296 -6504.02 13050.03 3688(7515) 4.27e-03 1.6e+03
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
```

```
##  location (Intercept) 0.02309  0.152
## Number of groups:  location 57
##
## Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## age_std                   0.22617    0.02964   7.630 2.35e-14 ***
## genderM                  -0.28895    0.05663  -5.103 3.35e-07 ***
## raceBlack                -0.18656    0.11859  -1.573  0.11568
## raceNative               -0.24324    0.21811  -1.115  0.26476
## raceOther                 0.04231    0.12652   0.334  0.73806
## raceWhite                -0.04576    0.12267  -0.373  0.70909
## eduCollege Degree         0.27547    0.12610   2.185  0.02892 *
## eduGraduate Degree        0.25300    0.14602   1.733  0.08317 .
## eduHigh School           -0.30595    0.12171  -2.514  0.01194 *
## eduLess than High School -0.18644    0.20260  -0.920  0.35744
## eduSome College          -0.06844    0.12515  -0.547  0.58445
## eduSome High School      -0.41381    0.14605  -2.833  0.00461 **
## cityNew York              0.13928    0.07279   1.913  0.05569 .
## num_kids1                 0.07678    0.11519   0.667  0.50508
## num_kids2                -0.28275    0.20261  -1.396  0.16285
## num_kids3+               -1.43677    0.53839  -2.669  0.00762 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Threshold coefficients:
##                  Estimate Std. Error z value
## Never|Seldom      -1.1826     0.1641  -7.208
## Seldom|Sometimes  -0.7725     0.1635  -4.725
## Sometimes|Often    0.2751     0.1630   1.688
## Often|Always       1.1060     0.1641   6.741
```

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 + race + edu + city + num_kids
##          Df  logLik   AIC     LRT Pr(>Chi)
## <none>      -6508.8 13058
## age_std   3 -6504.2 13054  9.1575 0.027269 *
## gender    3 -6501.7 13050 14.1251 0.002740 **
## race     12 -6501.2 13066 15.2722 0.226885
## edu      18 -6498.2 13072 21.2215 0.268386
## city      3 -6500.9 13048 15.8213 0.001234 **
## 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 + race + edu + city + num_kids
##          Df  logLik   AIC     LRT  Pr(>Chi)
## <none>       -6508.8 13058
## age_std   1 -6505.5 13053  6.5930 0.0102379 *
## gender    1 -6506.9 13056  3.8980 0.0483442 *
## race      4 -6502.7 13054 12.1205 0.0164771 *
## edu       6 -6505.6 13063  6.4472 0.3749976
## city      1 -6503.2 13048 11.2105 0.0008134 ***
## num_kids  3 -6507.2 13060  3.1636 0.3670831
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
control_clm_nom <- clm(limit ~ 1 + race + edu + num_kids,
                       nominal = ~ age_std + gender + city,
                   data = reduced_data, link = "logit")
anova(control_clm_nom, control_clm)
```

```
## Likelihood ratio tests of cumulative link models:
##
##                 formula:
## control_clm     limit ~ 1 + age_std + gender + race + edu + city + num_kids
## control_clm_nom limit ~ 1 + race + edu + num_kids
##                 nominal:                  link: threshold:
## control_clm     ~1                        logit flexible
## control_clm_nom ~age_std + gender + city logit flexible
##
##                 no.par   AIC  logLik LR.stat df Pr(>Chisq)
## control_clm         20 13058 -6508.8
## control_clm_nom     29 13035 -6488.6  40.311  9  6.674e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Overall fit Compared to the only intercept model.

```r
control_null <- clm(limit ~ 1, data = reduced_data, link = "logit")
```

```
## Warning: (-1) Model failed to converge with max|grad| = 5.30767e-06 (tol = 1e-06)
## In addition: iteration limit reached
```

```r
# Overall fit
anova(control_null, control_clm_nom)
```

```
## Likelihood ratio tests of cumulative link models:
##
##                 formula:
## control_null    limit ~ 1
## control_clm_nom limit ~ 1 + race + edu + num_kids + caloriescal_std
##                 nominal:                             link: threshold:
## control_null    ~1                                   logit flexible
## control_clm_nom ~age_std + gender + city + caff_std logit flexible
##
##                 no.par   AIC  logLik LR.stat df Pr(>Chisq)
## control_null         4 13243 -6617.6
## control_clm_nom     34 13029 -6480.5  274.31 30  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
control_null_re <- clmm(limit ~ 1 + (1 | location), data = reduced_data, link = "logit")
```

```
## Warning: (-1) Model failed to converge with max|grad| = 5.30767e-06 (tol = 1e-06)
## In addition: iteration limit reached
```

```r
anova(control_null, control_clmm_loc)
```

```
## Likelihood ratio tests of cumulative link models:
##
##                  formula:
## control_null     limit ~ 1
## control_clmm_loc limit ~ 1 + age_std + gender + race + edu + city + caff_std + num_kids + caloriescal
##                  link: threshold:
## control_null     logit flexible
## control_clmm_loc logit flexible
##
##                  no.par   AIC  logLik LR.stat df Pr(>Chisq)
## control_null          4 13243 -6617.6
## control_clmm_loc     23 13051 -6502.7  229.99 19  < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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)

model_accuracy <- function(model = control_clm, adj = F) {
    comp_metrics <- function(model = model, predict) {
      control_results <- reduced_data %>%
      bind_cols(fit = predict)


    # Confusion matrix
    # table(control_results$limit, control_results$fit)
    conf_mat(control_results, truth = limit, estimate = fit) -> conf

    # accuracy metrics
    accuracy(control_results, truth = limit, estimate = fit) -> acc
    precision(control_results, truth = limit, estimate = fit) -> pre
    sensitivity(control_results, truth = limit, estimate = fit) -> sen
    specificity(control_results, truth = limit, estimate = fit) -> spe

    # Goodness of fit
    chisq.test(control_results$limit, control_results$fit) -> gof

    return(list(control_results = control_results, conf = conf, acc = acc, pre = pre, sen = sen, spe = s
    }
  if (adj) {
    # Predict response
```

```r
    control_vglm_pred <- predict(model, type = "response")
    level_counts <- table(reduced_data$limit)
    total_counts <- sum(level_counts)
    proportions <- as.numeric(level_counts / total_counts)
    names(proportions) <- names(level_counts)

    adjusted_probs <- control_vglm_pred / proportions[colnames(control_vglm_pred)]
    adjusted_probs <- adjusted_probs / rowSums(adjusted_probs)
    fit <- ordered(colnames(adjusted_probs)[max.col(adjusted_probs)],
                   levels = c("Never", "Seldom", "Sometimes",
                              "Often", "Always"))
    comp_metrics(model = model, predict = fit) -> result
  } else {
    # Predict response
    control_pred <- predict(model, type = "class")
    comp_metrics(model = model, control_pred) -> result
  }
  return(result)
}

model_accuracy(control_clm_nom)
```

```
## Warning: While computing multiclass `precision()`, some levels had no predicted events
## (i.e. `true_positive + false_positive = 0`).
## Precision is undefined in this case, and those levels will be removed from the
## averaged result.
## Note that the following number of true events actually occurred for each
## problematic event level:
## 'Seldom': 377, 'Often': 695

## $control_results
## # A tibble: 4,296 x 27
##    receiptid person_id limit       age age_std gender race  edu     city    caff
##    <fct>     <fct>     <ord>     <dbl>   <dbl> <chr>  <chr> <chr>   <chr>  <dbl>
##  1 B103-098  900563    Sometimes    30 -0.670  F      Black Associ~ New ~     0
##  2 B103-022  900076    Sometimes    22 -1.22   F      Other Some C~ New ~     0
##  3 B103-091  900582    Never        40  0.0172 F      White High S~ New ~ 1137.
##  4 B103-081  900569    Never        20 -1.36   F      Other Some H~ New ~     0
##  5 B103-080  900568    Sometimes    34 -0.395  M      Other High S~ New ~     0
##  6 B103-090  900578    Seldom       19 -1.43   F      Other High S~ New ~  101.
##  7 B103-024  900078    Sometimes    61  1.46   M      Black Some C~ New ~   75.8
##  8 B103-067  900021    Always       51  0.773  F      Black Colleg~ New ~     0
##  9 B103-086  900574    Never        58  1.25   F      Black Some C~ New ~     0
## 10 B103-023  900077    Never        50  0.704  F      Black Colleg~ New ~     0
## # i 4,286 more rows
## # i 17 more variables: location <fct>, round <fct>, nsigns_ssb <dbl>,
## #   num_kids <chr>, surveydate <date>, days_since_ban <dbl>, caloriescal <dbl>,
## #   fatg <dbl>, sugarg <dbl>, black <chr>, caff_std <dbl>,
## #   nsigns_ssb_std <dbl>, days_since_ban_std <dbl>, caloriescal_std <dbl>,
## #   fatg_std <dbl>, sugarg_std <dbl>, fit <fct>
##
## $conf
##             Truth
## Prediction  Never Seldom Sometimes Often Always
```

```
##   Never       893    234       591   358    436
##   Seldom        0      0         0     0      0
##   Sometimes   193     70       250   158    204
##   Often         0      0         0     0      0
##   Always      187     73       213   179    257
##
## $acc
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy multiclass     0.326
##
## $pre
## # A tibble: 1 x 3
##   .metric   .estimator .estimate
##   <chr>     <chr>          <dbl>
## 1 precision macro          0.308
##
## $sen
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 sensitivity macro          0.245
##
## $spe
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 specificity macro          0.816
##
## $gof
##
##  Pearson's Chi-squared test
##
## data:  control_results$limit and control_results$fit
## X-squared = 136.94, df = 8, p-value < 2.2e-16
```

```r
model_accuracy(control_clm)
```

```
## Warning: While computing multiclass `precision()`, some levels had no predicted events
## (i.e. `true_positive + false_positive = 0`).
## Precision is undefined in this case, and those levels will be removed from the
## averaged result.
## Note that the following number of true events actually occurred for each
## problematic event level:
## 'Seldom': 377, 'Often': 695

## $control_results
## # A tibble: 4,296 x 27
##    receiptid person_id limit       age age_std gender race  edu     city    caff
##    <fct>     <fct>     <ord>     <dbl>   <dbl> <chr>  <chr> <chr>   <chr>  <dbl>
##  1 B103-098  900563    Sometimes    30 -0.670  F      Black Associ~ New ~     0
##  2 B103-022  900076    Sometimes    22 -1.22   F      Other Some C~ New ~     0
##  3 B103-091  900582    Never        40  0.0172 F      White High S~ New ~ 1137.
##  4 B103-081  900569    Never        20 -1.36   F      Other Some H~ New ~     0
```

```
##  5 B103-080  900568    Sometimes    34 -0.395  M      Other High S~ New ~    0
##  6 B103-090  900578    Seldom       19 -1.43   F      Other High S~ New ~  101.
##  7 B103-024  900078    Sometimes    61  1.46   M      Black Some C~ New ~   75.8
##  8 B103-067  900021    Always       51  0.773  F      Black Colleg~ New ~    0
##  9 B103-086  900574    Never        58  1.25   F      Black Some C~ New ~    0
## 10 B103-023  900077    Never        50  0.704  F      Black Colleg~ New ~    0
## # i 4,286 more rows
## # i 17 more variables: location <fct>, round <fct>, nsigns_ssb <dbl>,
## #   num_kids <chr>, surveydate <date>, days_since_ban <dbl>, caloriescal <dbl>,
## #   fatg <dbl>, sugarg <dbl>, black <chr>, caff_std <dbl>,
## #   nsigns_ssb_std <dbl>, days_since_ban_std <dbl>, caloriescal_std <dbl>,
## #   fatg_std <dbl>, sugarg_std <dbl>, fit <fct>
##
## $conf
##            Truth
## Prediction  Never Seldom Sometimes Often Always
##   Never       983    254       685   423    492
##   Seldom        0      0         0     0      0
##   Sometimes    67     35        97    70     78
##   Often         0      0         0     0      0
##   Always      223     88       272   202    327
##
## $acc
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy multiclass     0.328
##
## $pre
## # A tibble: 1 x 3
##   .metric   .estimator .estimate
##   <chr>     <chr>          <dbl>
## 1 precision macro          0.307
##
## $sen
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 sensitivity macro          0.246
##
## $spe
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 specificity macro          0.816
##
## $gof
##
##  Pearson's Chi-squared test
##
## data:  control_results$limit and control_results$fit
## X-squared = 139.67, df = 8, p-value < 2.2e-16
```

```r
## Similar results under different model specifications
control_clm_probit <- clm(limit ~ 1 + age_std + gender + race + edu + city +
                           num_kids,
                   data = reduced_data, link = "probit")
model_accuracy(control_clm_probit)
```

```
## Warning: While computing multiclass `precision()`, some levels had no predicted events
## (i.e. `true_positive + false_positive = 0`).
## Precision is undefined in this case, and those levels will be removed from the
## averaged result.
## Note that the following number of true events actually occurred for each
## problematic event level:
## 'Seldom': 377, 'Often': 695
```

```
## $control_results
## # A tibble: 4,296 x 27
##    receiptid person_id limit       age age_std gender race  edu     city    caff
##    <fct>     <fct>     <ord>     <dbl>   <dbl> <chr>  <chr> <chr>   <chr>  <dbl>
##  1 B103-098  900563    Sometimes    30 -0.670  F      Black Associ~ New ~     0
##  2 B103-022  900076    Sometimes    22 -1.22   F      Other Some C~ New ~     0
##  3 B103-091  900582    Never        40  0.0172 F      White High S~ New ~ 1137.
##  4 B103-081  900569    Never        20 -1.36   F      Other Some H~ New ~     0
##  5 B103-080  900568    Sometimes    34 -0.395  M      Other High S~ New ~     0
##  6 B103-090  900578    Seldom       19 -1.43   F      Other High S~ New ~  101.
##  7 B103-024  900078    Sometimes    61  1.46   M      Black Some C~ New ~   75.8
##  8 B103-067  900021    Always       51  0.773  F      Black Colleg~ New ~     0
##  9 B103-086  900574    Never        58  1.25   F      Black Some C~ New ~     0
## 10 B103-023  900077    Never        50  0.704  F      Black Colleg~ New ~     0
## # i 4,286 more rows
## # i 17 more variables: location <fct>, round <fct>, nsigns_ssb <dbl>,
## #   num_kids <chr>, surveydate <date>, days_since_ban <dbl>, caloriescal <dbl>,
## #   fatg <dbl>, sugarg <dbl>, black <chr>, caff_std <dbl>,
## #   nsigns_ssb_std <dbl>, days_since_ban_std <dbl>, caloriescal_std <dbl>,
## #   fatg_std <dbl>, sugarg_std <dbl>, fit <fct>
##
## $conf
##            Truth
## Prediction  Never Seldom Sometimes Often Always
##   Never       991    260       701   437    499
##   Seldom        0      0         0     0      0
##   Sometimes    53     23        67    49     54
##   Often         0      0         0     0      0
##   Always      229     94       286   209    344
##
## $acc
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy multiclass     0.326
##
## $pre
## # A tibble: 1 x 3
##   .metric   .estimator .estimate
##   <chr>     <chr>          <dbl>
```

```
## 1 precision macro          0.304
##
## $sen
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 sensitivity macro          0.245
##
## $spe
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 specificity macro          0.815
##
## $gof
##
##  Pearson's Chi-squared test
##
## data:  control_results$limit and control_results$fit
## X-squared = 133.99, df = 8, p-value < 2.2e-16
```

```
control_clm_sym <- clm(limit ~ 1 + age_std + gender + race + edu + city +
                           num_kids,
                   data = reduced_data,
                   link = "probit", threshold = "equidistant")
model_accuracy(control_clm_sym)
```

```
## Warning: While computing multiclass `precision()`, some levels had no predicted events
## (i.e. `true_positive + false_positive = 0`).
## Precision is undefined in this case, and those levels will be removed from the
## averaged result.
## Note that the following number of true events actually occurred for each
## problematic event level:
## 'Seldom': 377, 'Sometimes': 1054, 'Often': 695
```

```
## $control_results
## # A tibble: 4,296 x 27
##    receiptid person_id limit       age age_std gender race  edu     city    caff
##    <fct>     <fct>     <ord>     <dbl>   <dbl> <chr>  <chr> <chr>   <chr>  <dbl>
##  1 B103-098  900563    Sometimes    30 -0.670  F      Black Associ~ New ~     0
##  2 B103-022  900076    Sometimes    22 -1.22   F      Other Some C~ New ~     0
##  3 B103-091  900582    Never        40  0.0172 F      White High S~ New ~ 1137.
##  4 B103-081  900569    Never        20 -1.36   F      Other Some H~ New ~     0
##  5 B103-080  900568    Sometimes    34 -0.395  M      Other High S~ New ~     0
##  6 B103-090  900578    Seldom       19 -1.43   F      Other High S~ New ~  101.
##  7 B103-024  900078    Sometimes    61  1.46   M      Black Some C~ New ~   75.8
##  8 B103-067  900021    Always       51  0.773  F      Black Colleg~ New ~     0
##  9 B103-086  900574    Never        58  1.25   F      Black Some C~ New ~     0
## 10 B103-023  900077    Never        50  0.704  F      Black Colleg~ New ~     0
## # i 4,286 more rows
## # i 17 more variables: location <fct>, round <fct>, nsigns_ssb <dbl>,
## #   num_kids <chr>, surveydate <date>, days_since_ban <dbl>, caloriescal <dbl>,
## #   fatg <dbl>, sugarg <dbl>, black <chr>, caff_std <dbl>,
## #   nsigns_ssb_std <dbl>, days_since_ban_std <dbl>, caloriescal_std <dbl>,
## #   fatg_std <dbl>, sugarg_std <dbl>, fit <fct>
```

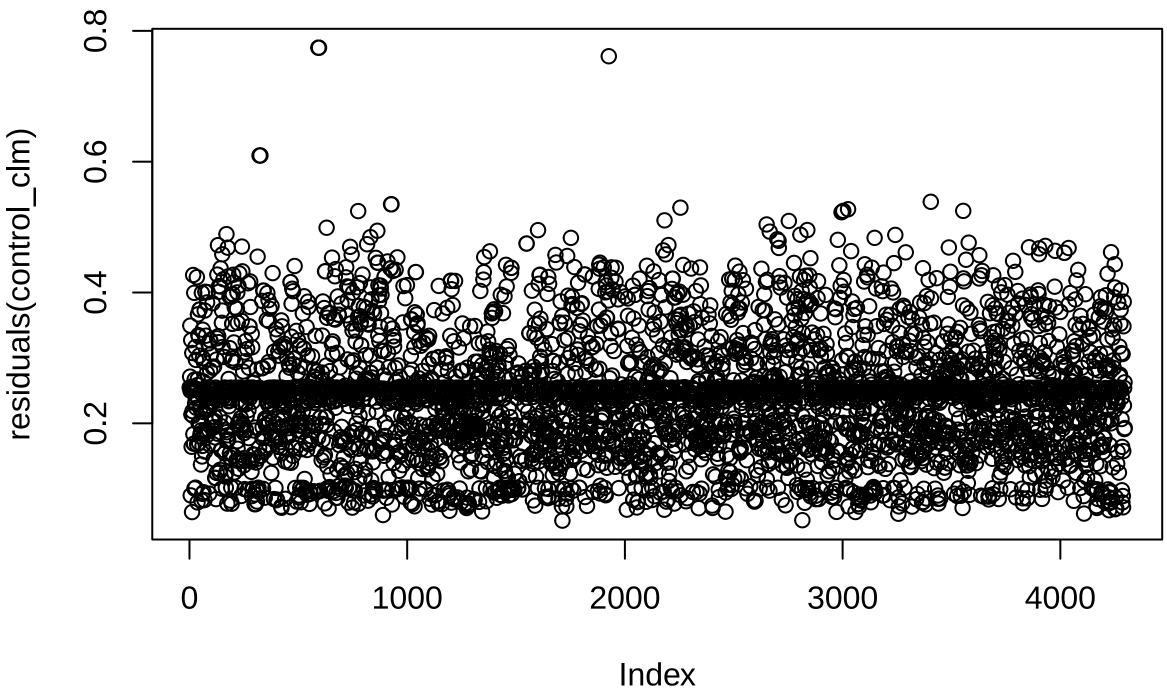
```
##
## $conf
##             Truth
## Prediction  Never Seldom Sometimes Often Always
##   Never       951    248       656   403    470
##   Seldom        0      0         0     0      0
##   Sometimes     0      0         0     0      0
##   Often         0      0         0     0      0
##   Always      322    129       398   292    427
##
## $acc
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy multiclass     0.321
##
## $pre
## # A tibble: 1 x 3
##   .metric   .estimator .estimate
##   <chr>     <chr>          <dbl>
## 1 precision macro          0.310
##
## $sen
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 sensitivity macro          0.245
##
## $spe
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 specificity macro          0.815
##
## $gof
##
##  Pearson's Chi-squared test
##
## data:  control_results$limit and control_results$fit
## X-squared = 127.36, df = 4, p-value < 2.2e-16
```

```
## Use VGAM to get prob for each level of resp, not implemented in Ordinal
## Similarly inaccurate model
control_vglm_sig <- vglm(limit ~ 1 + age_std + gender + race + edu + city +
                           num_kids,
                     data = reduced_data,
                     family = cumulative(parallel = TRUE))
model_accuracy(control_vglm_sig, adj = T)
```

```
## $control_results
## # A tibble: 4,296 x 27
##    receiptid person_id limit       age age_std gender race  edu     city    caff
##    <fct>     <fct>     <ord>     <dbl>   <dbl> <chr>  <chr> <chr>   <chr>  <dbl>
##  1 B103-098  900563    Sometimes    30  -0.670 F      Black Associ~ New ~     0
##  2 B103-022  900076    Sometimes    22  -1.22  F      Other Some C~ New ~     0
```

```
##   3 B103-091  900582    Never        40  0.0172 F      White High S~ New ~ 1137.
##   4 B103-081  900569    Never        20 -1.36   F      Other Some H~ New ~    0
##   5 B103-080  900568    Sometimes    34 -0.395  M      Other High S~ New ~    0
##   6 B103-090  900578    Seldom       19 -1.43   F      Other High S~ New ~  101.
##   7 B103-024  900078    Sometimes    61  1.46   M      Black Some C~ New ~   75.8
##   8 B103-067  900021    Always       51  0.773  F      Black Colleg~ New ~    0
##   9 B103-086  900574    Never        58  1.25   F      Black Some C~ New ~    0
##  10 B103-023  900077    Never        50  0.704  F      Black Colleg~ New ~    0
## # i 4,286 more rows
## # i 17 more variables: location <fct>, round <fct>, nsigns_ssb <dbl>,
## #   num_kids <chr>, surveydate <date>, days_since_ban <dbl>, caloriescal <dbl>,
## #   fatg <dbl>, sugarg <dbl>, black <chr>, caff_std <dbl>,
## #   nsigns_ssb_std <dbl>, days_since_ban_std <dbl>, caloriescal_std <dbl>,
## #   fatg_std <dbl>, sugarg_std <dbl>, fit <ord>
##
## $conf
##             Truth
## Prediction  Never Seldom Sometimes Often Always
##   Never       587    152       427   279    266
##   Seldom       22      8        26    11     16
##   Sometimes   272     66       220   150    193
##   Often       116     37       129    95    138
##   Always      276    114       252   160    284
##
## $acc
## # A tibble: 1 x 3
##   .metric  .estimator .estimate
##   <chr>    <chr>          <dbl>
## 1 accuracy multiclass     0.278
##
## $pre
## # A tibble: 1 x 3
##   .metric   .estimator .estimate
##   <chr>     <chr>          <dbl>
## 1 precision macro          0.226
##
## $sen
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 sensitivity macro          0.229
##
## $spe
## # A tibble: 1 x 3
##   .metric     .estimator .estimate
##   <chr>       <chr>          <dbl>
## 1 specificity macro          0.809
##
## $gof
##
##  Pearson's Chi-squared test
##
## data:  control_results$limit and control_results$fit
## X-squared = 88.466, df = 16, p-value = 4.791e-12
```

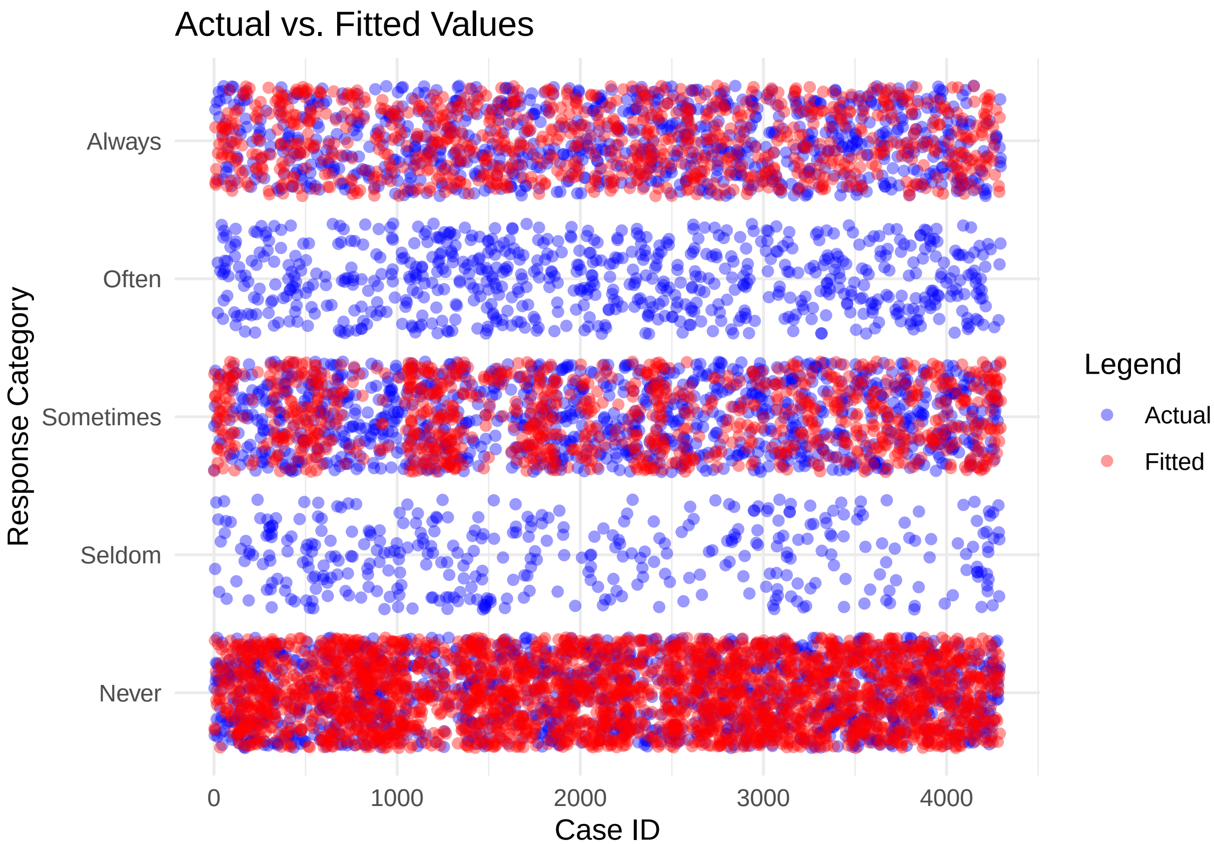
```r
plot(fitted(control_clm), residuals(control_clm))
```



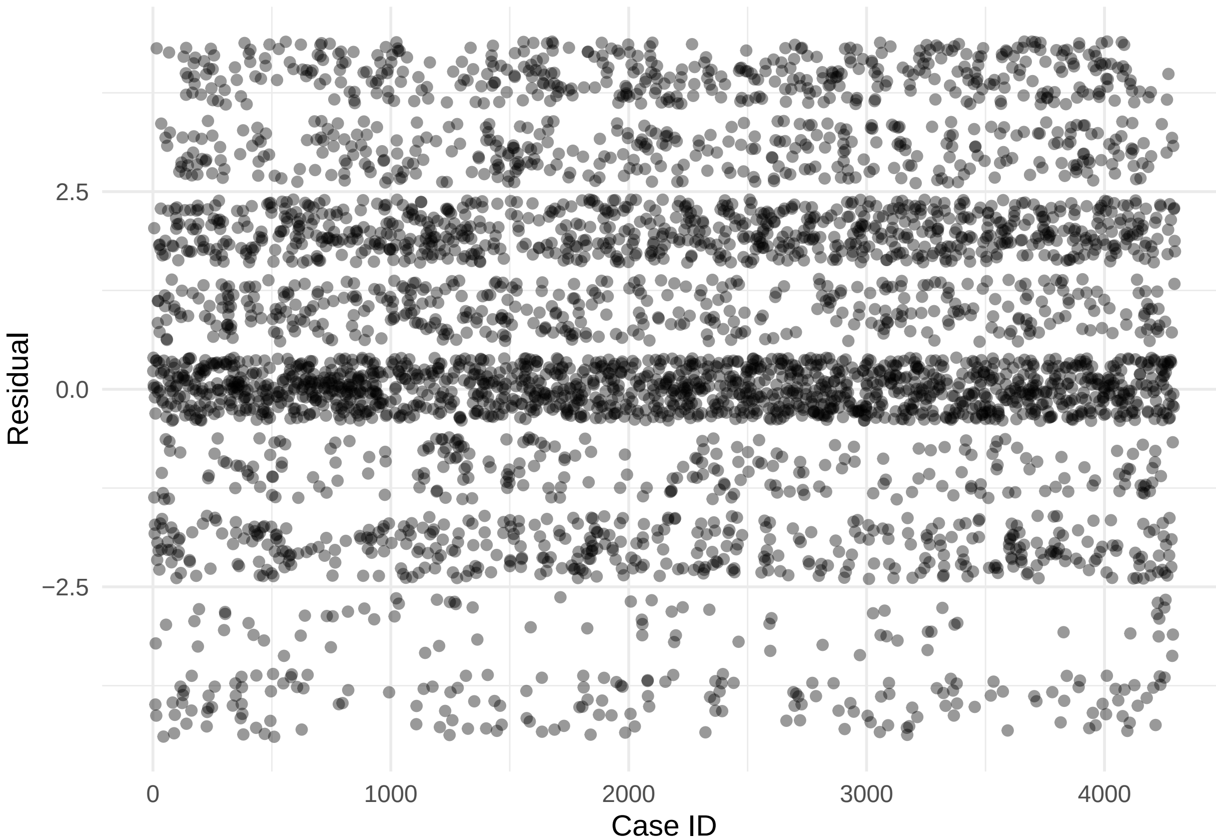

```r
control_resid <- model_accuracy(control_clm_nom)$control_results %>%
  mutate(
    case_id = row_number(),
    fit = ordered(fit, levels = c("Never", "Seldom", "Sometimes", "Often", "Always"))
  ) %>%
  select(case_id, limit, fit) %>%
  mutate(
    limit_num = case_when(
      limit == "Never" ~ 0,
      limit == "Seldom" ~ 1,
      limit == "Sometimes" ~ 2,
      limit == "Often" ~ 3,
      limit == "Always" ~ 4),
    fit_num = case_when(
      fit == "Never" ~ 0,
      fit == "Seldom" ~ 1,
      fit == "Sometimes" ~ 2,
      fit == "Often" ~ 3,
      fit == "Always" ~ 4),
    ) %>%
  mutate(resid = limit_num - fit_num)

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()
```




```
ggplot(control_resid, aes(x = case_id, y = resid)) +
  geom_jitter(alpha = 0.4) +
  labs(
    x = "Case ID",
    y = "Residual"
  ) +
  theme_minimal()
```



Effects Interpretation

Confidence Intervals

```r
summary(control_clmm_loc)$coefficients %>%
  bind_cols(confint(control_clmm_loc)) %>%
  kable(digits = 2)
```

Estimate	Std. Error	z value	Pr(>|z|)	2.5 %	97.5 %
-1.18	0.16	-7.21	0.00	-1.50	-0.86
-0.77	0.16	-4.73	0.00	-1.09	-0.45
0.28	0.16	1.69	0.09	-0.04	0.59
1.11	0.16	6.74	0.00	0.78	1.43
0.23	0.03	7.63	0.00	0.17	0.28
-0.29	0.06	-5.10	0.00	-0.40	-0.18
-0.19	0.12	-1.57	0.12	-0.42	0.05
-0.24	0.22	-1.12	0.26	-0.67	0.18
0.04	0.13	0.33	0.74	-0.21	0.29
-0.05	0.12	-0.37	0.71	-0.29	0.19
0.28	0.13	2.18	0.03	0.03	0.52
0.25	0.15	1.73	0.08	-0.03	0.54
-0.31	0.12	-2.51	0.01	-0.54	-0.07
-0.19	0.20	-0.92	0.36	-0.58	0.21
-0.07	0.13	-0.55	0.58	-0.31	0.18
-0.41	0.15	-2.83	0.00	-0.70	-0.13
0.14	0.07	1.91	0.06	0.00	0.28

Estimate	Std. Error	z value	Pr(>|z|)	2.5 %	97.5 %
0.08	0.12	0.67	0.51	-0.15	0.30
-0.28	0.20	-1.40	0.16	-0.68	0.11
-1.44	0.54	-2.67	0.01	-2.49	-0.38

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

	2.5 %	97.5 %
Never|Seldom	-1.504	-0.861
Seldom|Sometimes	-1.093	-0.452
Sometimes|Often	-0.044	0.595
Often|Always	0.784	1.428
age_std	0.168	0.284
genderM	-0.400	-0.178
raceBlack	-0.419	0.046
raceNative	-0.671	0.184
raceOther	-0.206	0.290
raceWhite	-0.286	0.195
eduCollege Degree	0.028	0.523
eduGraduate Degree	-0.033	0.539
eduHigh School	-0.544	-0.067
eduLess than High School	-0.584	0.211
eduSome College	-0.314	0.177
eduSome High School	-0.700	-0.128
cityNew York	-0.003	0.282
num_kids1	-0.149	0.303
num_kids2	-0.680	0.114
num_kids3+	-2.492	-0.382

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

	2.5 %	97.5 %
Never|Seldom	0.222	0.423
Seldom|Sometimes	0.335	0.636
Sometimes|Often	0.957	1.812
Often|Always	2.191	4.168
age_std	1.183	1.329
genderM	0.670	0.837
raceBlack	0.658	1.047
raceNative	0.511	1.202
raceOther	0.814	1.337
raceWhite	0.751	1.215
eduCollege Degree	1.029	1.686
eduGraduate Degree	0.967	1.715
eduHigh School	0.580	0.935
eduLess than High School	0.558	1.234
eduSome College	0.731	1.193
eduSome High School	0.497	0.880
cityNew York	0.997	1.326
num_kids1	0.862	1.353

	2.5 %	97.5 %
num_kids2	0.507	1.121
num_kids3+	0.083	0.683

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

	2.5 %	97.5 %
Never|Seldom	-77.780	-57.728
Seldom|Sometimes	-66.476	-36.369
Sometimes|Often	-4.335	81.219
Often|Always	119.107	316.830
age_std	18.302	32.880
genderM	-32.964	-16.303
raceBlack	-34.229	4.694
raceNative	-48.866	20.231
raceOther	-18.589	33.680
raceWhite	-24.888	21.489
eduCollege Degree	2.873	68.644
eduGraduate Degree	-3.266	71.463
eduHigh School	-41.986	-6.519
eduLess than High School	-44.208	23.448
eduSome College	-26.928	19.344
eduSome High School	-50.345	-11.975
cityNew York	-0.338	32.570
num_kids1	-13.842	35.329
num_kids2	-49.331	12.116
num_kids3+	-91.725	-31.720