U6614: Assignment 3: Subway Fare Evasion Microdata

Sample Solution

2021-01-22

Please submit your knitted .pdf file along with the corresponding R markdown (.rmd) via Courseworks by 11:59pm on Monday, February 1st.

Before knitting your rmd file as a pdf, you will need to install TinyTex for Latex distribution by running the following code:

`tinytex::install_tinytex()`

Please visit this link for more information on TinyTex installation.

1 Load libraries

```
#remember to make sure these packaged are installed before trying to load
library(tidyverse)
library(fastDummies)
```

2 Load and inspect the two public defender client datasets (BDS & LAS).

```
arrests_bds <- read_csv("microdata_BDS_inclass.csv", na = "")
arrests_las <- read_csv("microdata_LAS_inclass.csv", na = "")

str(arrests_bds)
```

```
## tibble [2,246 x 8] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ client_zip: num [1:2246] 11205 11385 11226 11207 11225 ...
##  $ age       : num [1:2246] 25 20 19 17 21 52 59 32 22 19 ...
##  $ ethnicity : chr [1:2246] "Hispanic" "Hispanic" "Non-Hispanic" "Non-Hispanic" ...
##  $ race      : chr [1:2246] "White" "Black" "Black" "Black" ...
##  $ male      : num [1:2246] 1 1 0 1 1 1 1 1 0 1 ...
##  $ loc2      : chr [1:2246] "jefferson st l line station" "myrtle - wyckoff avs station" "winthrop s
##  $ st_id     : num [1:2246] 100 119 156 156 156 156 156 156 156 156 ...
##  $ year      : num [1:2246] 2016 2016 2016 2016 2016 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   client_zip = col_double(),
##   ..   age = col_double(),
##   ..   ethnicity = col_character(),
##   ..   race = col_character(),
##   ..   male = col_double(),
```

```
##   ..   loc2 = col_character(),
##   ..   st_id = col_double(),
##   ..   year = col_double()
##   .. )
```

```r
str(arrests_las)
```

```
## tibble [1,965 x 9] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ client_zip   : num [1:1965] 11222 10016 11236 11236 NA ...
##  $ las_race_key : chr [1:1965] "Black" "Asian or Pacific Islander" "Black" "Black" ...
##  $ hispanic_flag: chr [1:1965] "N" "N" "N" "N" ...
##  $ age          : num [1:1965] 32 47 20 64 23 29 26 52 52 22 ...
##  $ year         : num [1:1965] 2016 2016 2016 2016 2016 ...
##  $ male         : num [1:1965] 1 0 1 1 1 1 0 1 1 1 ...
##  $ dismissal    : num [1:1965] 0 1 0 0 0 0 1 0 0 1 ...
##  $ loc2         : chr [1:1965] "kingston - throop avs" "avenue h q subway" "nostrand ave and fulton s
##  $ st_id        : num [1:1965] 106 28 131 150 131 27 68 44 85 31 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   client_zip = col_double(),
##   ..   las_race_key = col_character(),
##   ..   hispanic_flag = col_character(),
##   ..   age = col_double(),
##   ..   year = col_double(),
##   ..   male = col_double(),
##   ..   dismissal = col_double(),
##   ..   loc2 = col_character(),
##   ..   st_id = col_double()
##   .. )
```

2.1 Give a brief overview of the data. The aim is not be exhaustive, but to paint a picture of they key features of the data with respect to the policy questions you'll be exploring.

The BDS data includes 2246 observations (client arrest records), and the LAS data includes another 1965 observations. Both datasets include basic demographic information on age, sex, race, ethnicity (coded differently in each dataset), as well as information on the location/subway station where the arrest occurred.

The LAS data also includes information on case dismissal rates.

2.2 For each dataset, what is the unit of observation and population represented by this "sample"? Do you think this sample does a good job representing the population of interest?

In each raw dataset, the unit of observation is the arrested individual (client). On the surface, the representative population is all individuals arrested by the NYPD for subway fare evasion in Brooklyn during 2016 who are represented by public defenders. If nearly all individuals arrested for fare evasion are represented by public defenders, then this sample comes close to the universe of subway fare evasion arrests in Brooklyn in 2016. This is difficult to argue convincingly without additional information, but is supported anecdotally by court observers.

2.3 Inspect and describe the coding of race/ethnicity in each dataset.

```r
#recode race/ethnicity information from character to factors
arrests_bds <- arrests_bds %>% mutate(race = as.factor(race),
                                      ethnicity = as.factor(ethnicity) )
arrests_las <- arrests_las %>% mutate(race = as.factor(las_race_key),
                                      ethnicity = as.factor(hispanic_flag) )
#compare race coding
  summary(arrests_bds$race)
```

```
##                       0               Am Indian Asian/Pacific Islander
##                      35                       1                     21
##                   Black                   Other                Unknown
##                    1465                      32                      2
##                   White                    NA's
##                     533                     157
```

```r
  summary(arrests_las$race)
```

```
## Asian or Pacific Islander                     Black                  Hispanic
##                        11                      1247                        21
##                    Latino                     Other                   Unknown
##                         2                        20                        10
##                     White                      NA's
##                       426                       228
```

```r
#compare Hispanic/ethnicity coding
  summary(arrests_bds$ethnicity)
```

```
##            0     Hispanic Non-Hispanic        Other         NA's
##           33          493         1558            5          157
```

```r
  summary(arrests_las$ethnicity)
```

```
##    N    Y NA's
## 1619  189  157
```

Race information is generally stored in one variable, Hispanic identity in a second variable. To work towards consistent variable names and coding in both datasets, let's first recode the raw race and ethnicity information into two separate columns of data (factors) named `race` and `ethnicity`.

While each dataset refers to similar race and ethnicity categories, there are different category names in each (including some slightly different spellings).

We also note that Hispanic identity factors into both race and Hispanic variables in the Legal Aid Society (LAS) data; in the BDS data, information on Hispanic identity is only included in the ethnicity variable.

Each dataset also contains a different set of values that seem to convey unknown race/ethnicity information, in addition to true missings (e.g. "0" and "Unknown" in addition to blank entries).

2.4 From the outset, are there any data limitations you think are important to note?

It's unclear what processes are used to code race and ethnicity at each public defender group. How much does the information reflect client self-identification rather than identity assigned by police and entered into arrest reports?

It's also important to emphasize what information this data does **not** include that might be relevant to the question of biased fare evasion enforcement:

- fare evasion that resulted in a summons (ticket + fine) rather than an arrest

- fare evasion enforcement on buses

3 Clean BDS race and ethnicity data (insert code chunks that only include code you used to recode and very briefly validate your recoding)

3.1 BDS: race data (generate column `race_clean`).

```
#identify every combination of race-ethnicity in the raw data
table(arrests_bds$race, arrests_bds$ethnicity, useNA = "always")
```

```
##
##                           0 Hispanic Non-Hispanic Other <NA>
##   0                      31        1            3     0    0
##   Am Indian               0        0            1     0    0
##   Asian/Pacific Islander  0        0           21     0    0
##   Black                   2      104         1358     1    0
##   Other                   0       20           11     1    0
##   Unknown                 0        0            0     2    0
##   White                   0      368          164     1    0
##   <NA>                    0        0            0     0  157
```

```
#recode as factor in an internally consistent manner (address NAs, specify levels)
arrests_bds.clean <- arrests_bds %>%
  mutate(race_clean = recode(race, "0" = "NA",
                                   "Unknown" = "NA",
                                   "Am Indian" = "Other" ) )  %>%
  mutate(race_clean = factor(race_clean,
                            levels = c("Black", "White", "Asian/Pacific Islander", "Other")))

#validation: confirm the recode worked as intended
arrests_bds.clean %>% count(race_clean, sort = TRUE)
```

```
## # A tibble: 5 x 2
##   race_clean                 n
##   <fct>                  <int>
## 1 Black                   1465
## 2 White                    533
## 3 <NA>                     194
## 4 Other                     33
## 5 Asian/Pacific Islander    21
```

```
table(arrests_bds.clean$race_clean, arrests_bds.clean$race, useNA = "always")
```

```
##
##                           0 Am Indian Asian/Pacific Islander Black Other
##   Black                   0         0                      0  1465     0
##   White                   0         0                      0     0     0
##   Asian/Pacific Islander  0         0                     21     0     0
##   Other                   0         1                      0     0    32
##   <NA>                   35         0                      0     0     0
##
```

```
##                             Unknown White <NA>
##   Black                           0     0    0
##   White                           0   533    0
##   Asian/Pacific Islander          0     0    0
##   Other                           0     0    0
##   <NA>                            2     0  157
```

3.2 BDS: ethnicity data (generate column `ethnicity_clean`).

```
#ok now let's recode to Hispanic, Non-Hispanic, and NA
arrests_bds.clean <- arrests_bds.clean %>%
  mutate(hispanic = recode(ethnicity, "0" = "NA", "Other" = "Non-Hispanic") ) %>%
  mutate(hispanic = factor(hispanic, levels = c("Hispanic", "Non-Hispanic")))

#validation: confirm the recode worked as intended
  summary(arrests_bds.clean$hispanic)
```

```
##     Hispanic Non-Hispanic         NA's
##          493         1563          190
```

```
  table(arrests_bds.clean$race_clean, arrests_bds.clean$hispanic, useNA = "always")
```

```
##
##                             Hispanic Non-Hispanic <NA>
##   Black                          104         1359    2
##   White                          368          165    0
##   Asian/Pacific Islander           0           21    0
##   Other                           20           13    0
##   <NA>                             1            5  188
```

3.3 Generate a single race/ethnicity factor variable `race_eth` with mutually exclusive categories.

```
#let's investigate a bit
table(arrests_bds.clean$race_clean, arrests_bds.clean$hispanic, useNA = "always")
```

```
##
##                             Hispanic Non-Hispanic <NA>
##   Black                          104         1359    2
##   White                          368          165    0
##   Asian/Pacific Islander           0           21    0
##   Other                           20           13    0
##   <NA>                             1            5  188
```

```
#generate race_eth column (as a factor) in steps
arrests_bds.clean <- arrests_bds.clean %>%
  mutate(race_clean_char = as.character(race_clean)) %>% #work with characters
  mutate(hispanic_char = as.character(hispanic))     %>% #work with characters
  mutate(race_eth = ifelse(hispanic_char == "Hispanic",
                           hispanic_char,
                           race_clean_char) ) %>%
  mutate(race_eth = as.factor(recode(race_eth, "White" = "Non-Hispanic White"))) %>%
  select(-race_clean_char, -hispanic_char)

#validate results: joint distribution of race_eth and hispanic
```

```r
table(arrests_bds.clean$race_eth, arrests_bds.clean$hispanic, useNA = "always")
```

```
##
##                           Hispanic Non-Hispanic <NA>
##   Asian/Pacific Islander         0           21    0
##   Black                          0         1359    0
##   Hispanic                     493            0    0
##   Non-Hispanic White             0          165    0
##   Other                          0           13    0
##   <NA>                           0            5  190
```

```r
arrests_bds.clean %>% count(race_eth, sort = TRUE)
```

```
## # A tibble: 6 x 2
##   race_eth                   n
##   <fct>                  <int>
## 1 Black                   1359
## 2 Hispanic                 493
## 3 <NA>                     195
## 4 Non-Hispanic White       165
## 5 Asian/Pacific Islander    21
## 6 Other                     13
```

Note that `race_eth` assigns individuals who identify as both Hispanic and a race other than white as Hispanic. This means, for example, that an individual who identifies as both Black and Hispanic appears as Hispanic in the `race_eth` column.

4 Clean LAS race and ethnicity data

4.1 Follow your own steps to end up at a `race_eth` variable for the LAS data that is coded in a comparable manner as in the BDS data.

NOTE: you may be able to do everything in a single pipe, depending on your approach (but you certainly don't have to).

```r
#inspect LAS data
table(arrests_las$las_race_key, arrests_las$hispanic_flag, useNA = "always")
```

```
##
##                                N    Y <NA>
##   Asian or Pacific Islander   11    0    0
##   Black                     1201   46    0
##   Hispanic                    20    1    0
##   Latino                       2    0    0
##   Other                       11    9    0
##   Unknown                     10    0    0
##   White                      294  132    0
##   <NA>                        70    1  157
```

```r
#generate race_eth column as a factor
arrests_las.clean <- arrests_las %>%
  mutate(race_eth = recode(las_race_key, "Asian or Pacific Islander" = "Asian/Pacific Islander",
                                         "Unknown" = "NA",
                                         "Latino" = "Hispanic",
```

```r
                                          "White" = "Non-Hispanic White")) %>%
  mutate(race_eth = ifelse(hispanic_flag == "Y", "Hispanic", race_eth) ) %>%
  mutate(race_eth = factor(race_eth,
                            levels = c("Black", "Hispanic", "Non-Hispanic White", "Asian/Pacific Islande

#validate
arrests_las.clean %>% count(race_eth, sort = TRUE)
```

```
## # A tibble: 6 x 2
##   race_eth                   n
##   <fct>                  <int>
## 1 Black                   1201
## 2 Non-Hispanic White       294
## 3 <NA>                     237
## 4 Hispanic                 211
## 5 Asian/Pacific Islander    11
## 6 Other                     11
```

```r
table(arrests_las.clean$race_eth, arrests_las.clean$hispanic_flag, useNA = "always")
```

```
##
##                              N    Y <NA>
##   Black                   1201    0    0
##   Hispanic                  22  189    0
##   Non-Hispanic White       294    0    0
##   Asian/Pacific Islander    11    0    0
##   Other                     11    0    0
##   <NA>                      80    0  157
```

5 Combining (appending) the BDS and LAS microdata

5.1 Create a column (pd) to identify public defender data source.

```r
arrests_bds.clean <- arrests_bds.clean %>% mutate(pd = "bds")
arrests_las.clean <- arrests_las.clean %>% mutate(pd = "las")
```

5.2 Append `arrests_bds.clean` and `arrests_las.clean` using `rbind()`. Store as new data frame `arrests_all` and inspect for consistency/accuracy.

```r
  arrests.clean <- plyr::rbind.fill(arrests_las.clean, arrests_bds.clean) %>%
    mutate(pd = as.factor(pd),
           st_id = as.factor(st_id),
           loc2 = as.factor(loc2)) %>% #station/location info is not continuous
    select(pd, race_eth, age, male, dismissal, st_id, loc2)
  summary(arrests.clean)
```

```
##    pd                        race_eth         age              male
##  bds:2246   Black                 :2560   Min.   : 0.00   Min.   :0.0000
##  las:1965   Hispanic              : 704   1st Qu.:20.00   1st Qu.:1.0000
##             Non-Hispanic White    : 459   Median :26.00   Median :1.0000
##             Asian/Pacific Islander:  32   Mean   :29.18   Mean   :0.8748
##             Other                 :  24   3rd Qu.:35.00   3rd Qu.:1.0000
```

```
##             NA's                  : 432   Max.   :71.00   Max.   :1.0000
##                                          NA's   :317     NA's   :314
##    dismissal          st_id                                          loc2
##   Min.   :0.0000   66      : 223   coney island-stillwell ave           : 223
##   1st Qu.:0.0000   99      : 198   jay st - metrotech                   : 198
##   Median :1.0000   150     : 143   utica ave and fulton st              : 143
##   Mean   :0.5392   70      : 142   utica ave and eastern parkway        : 142
##   3rd Qu.:1.0000   114     : 141   marcy ave j m z line                 : 141
##   Max.   :1.0000   131     : 141   nostrand ave and fulton st a c station: 141
##   NA's   :2529     (Other):3223   (Other)                              :3223
```

5.3 What is the total number of subway fare evasion arrest records?

The total number of subway fare evasion arrest records from both BDS and LAS is 4211.

5.4 Export `arrests_all` as .csv, and save as .rds file.

```
write_csv(arrests.clean, "arrests_all.csv")
saveRDS(arrests.clean, "../Lecture4/arrests.clean.rds")
```

6 Descriptive statistics by race/ethnicity

6.1 Print the number of arrests for each race/ethnicity category (a frequency table).

```
arrests.clean %>% count(race_eth, sort = TRUE)
```

```
##                 race_eth    n
## 1                  Black 2560
## 2               Hispanic  704
## 3     Non-Hispanic White  459
## 4                   <NA>  432
## 5 Asian/Pacific Islander   32
## 6                  Other   24
```

6.2 Print the proportion of total arrests for each race/ethnicity category.

```
#including NAs
prop.table(table(arrests.clean$race_eth, useNA = "always")) %>%
  round(2) %>%
  as.data.frame() %>%
  arrange(desc(Freq)) %>%
  rename(race_eth = Var1)
```

```
##                 race_eth Freq
## 1                  Black 0.61
## 2               Hispanic 0.17
## 3     Non-Hispanic White 0.11
## 4                   <NA> 0.10
## 5 Asian/Pacific Islander 0.01
## 6                  Other 0.01
```

```r
#excluding NAs
prop.table(table(arrests.clean$race_eth)) %>%
  round(2) %>%
  as.data.frame() %>%
  arrange(desc(Freq)) %>%
  rename(race_eth = Var1)
```

```
##                 race_eth Freq
## 1                  Black 0.68
## 2               Hispanic 0.19
## 3     Non-Hispanic White 0.12
## 4 Asian/Pacific Islander 0.01
## 5                  Other 0.01
```

6.3 Show the average age, share male, and dimissal rate for each race/ethnicity category. Describe any noteworthy findings.

```r
arrests.clean %>%
  group_by(race_eth) %>%
  summarise(n = n(),
            mean_age = mean(age, na.rm = TRUE),
            mean_male = mean(male, na.rm = TRUE),
            mean_dism = mean(dismissal, na.rm = TRUE))
```

```
## # A tibble: 6 x 5
##   race_eth                   n mean_age mean_male mean_dism
##   <fct>                  <int>    <dbl>     <dbl>     <dbl>
## 1 Black                   2560     29.1     0.875     0.514
## 2 Hispanic                 704     29.7     0.901     0.538
## 3 Non-Hispanic White       459     29.7     0.898     0.587
## 4 Asian/Pacific Islander    32     28.9     0.938     0.636
## 5 Other                     24     28.3     0.833     0.444
## 6 <NA>                     432     25.9     0.610     0.75
```

7 Subway-station level analysis

7.1 Create dummy variables for each race/ethnicity category and show summary statistics only for these dummy variables.

```r
arrests.clean <- dummy_cols(arrests.clean, select_columns = "race_eth")
arrests.clean %>%
  summarise(mean_black = round(mean(race_eth_Black, na.rm = TRUE), 2),
            mean_hisp = round(mean(race_eth_Hispanic, na.rm = TRUE), 2),
            mean_nhw  = round(mean(`race_eth_Non-Hispanic White`, na.rm = TRUE), 2),
            mean_api  = round(mean(`race_eth_Asian/Pacific Islander`, na.rm = TRUE), 2),
            mean_oth  = round(mean(race_eth_Other, na.rm = TRUE), 2),
            mean_NA   = round(mean(race_eth_NA, na.rm = TRUE), 2)  )
```

```
##   mean_black mean_hisp mean_nhw mean_api mean_oth mean_NA
## 1       0.68      0.19     0.12     0.01     0.01     0.1
```

7.2 Aggregate to station-level observations and show a table with the top 10 stations by arrest totals, including the following information for each station:

- *station name (given by loc2)*
- *st_id*
- *total number of arrests at each station*
- *total number of arrests for each race_eth category at each station*
- *sort in descending order of total number of arrests*
- *remember to only show the top 10 stations*
- *use kable() in the knitr package for better formatting*

```
arrests_stations <- arrests.clean %>%
  group_by(loc2) %>%
  summarise(st_id = first(st_id),
            n = n(),
            n_black = sum(race_eth_Black, na.rm = TRUE),
            n_hisp  = sum(race_eth_Hispanic, na.rm = TRUE),
            n_api   = sum(`race_eth_Asian/Pacific Islander`, na.rm = TRUE),
            n_nhw   = sum(`race_eth_Non-Hispanic White`, na.rm = TRUE),
            n_oth   = sum(race_eth_Other, na.rm = TRUE) )   %>%
  arrange(desc(n))
knitr::kable(head(arrests_stations, n = 10))
```

loc2	st_id	n	n_black	n_hisp	n_api	n_nhw	n_oth
coney island-stillwell ave	66	223	124	48	5	35	1
jay st - metrotech	99	198	112	43	3	29	0
utica ave and fulton st	150	143	111	19	0	7	0
utica ave and eastern parkway	70	142	118	13	0	5	0
marcy ave j m z line	114	141	55	42	3	34	0
nostrand ave and fulton st a c station	131	141	107	20	0	7	1
canarsie rockaway pkwy	54	133	109	4	1	11	2
sutter avenue station l line	147	102	79	12	0	6	0
kingston - throop avs	106	90	69	12	0	6	0
nevins st 2 3 4 5 lines	123	86	63	11	0	6	1

7.3 Aggregate to station-level observations (group by loc2), and show a table of stations with at least 50 arrests along with the following information:

- *station name (loc2)*
- *station arrest total*
- *combined total number of Black and Hispanic arrests*
- *total number of arrests with race/ethnicity coded as NA*
- *share of arrests that are Black and Hispanic (excluding race_eth = NA from denominator)*
- *sorted in ascending order above Black and Hispanic arrest share*
- *remember to only show stations with at least 50 total arrests*
- *use kable() in the knitr package for better formatting*

```
arrests_stations_top <- arrests.clean %>%
  group_by(loc2)    %>%
  summarise(st_id = first(st_id),
            n = n(),
            n_black = sum(race_eth_Black, na.rm = TRUE),
            n_hisp  = sum(race_eth_Hispanic, na.rm = TRUE),
```

```r
            n_api   = sum(`race_eth_Asian/Pacific Islander`, na.rm = TRUE),
            n_nhw   = sum(`race_eth_Non-Hispanic White`, na.rm = TRUE),
            n_oth   = sum(race_eth_Other, na.rm = TRUE),
            n_bh    = sum(race_eth_Black, race_eth_Hispanic, na.rm = TRUE),
            n_na    = sum(race_eth_NA))  %>%
  mutate(sh_bh = round(n_bh / (n - n_na), 2)) %>%
  select(loc2, n, n_bh, n_na, sh_bh) %>%
  filter(n >= 50) %>%
  arrange(sh_bh)
knitr::kable(arrests_stations_top)
```

loc2	n	n_bh	n_na	sh_bh
marcy ave j m z line	141	97	7	0.72
myrtle av and broadway station	69	53	3	0.80
coney island-stillwell ave	223	172	10	0.81
graham ave l line	54	39	6	0.81
broadway and lorimer st j m station	70	56	2	0.82
clinton - washington avs station	63	48	5	0.83
jay st - metrotech	198	155	11	0.83
hoyt-schermerhorn a c g line	71	55	6	0.85
myrtle - willoughby avs g line	50	39	5	0.87
canarsie rockaway pkwy	133	113	6	0.89
nevins st 2 3 4 5 lines	86	74	5	0.91
hoyt st 2 3	77	70	2	0.93
kingston - throop avs	90	81	3	0.93
nostrand ave and fulton st a c station	141	127	6	0.94
sutter avenue station l line	102	91	5	0.94
utica ave and fulton st	143	130	6	0.95
court st r subway/borough hall 2 subway 3 subway 4 subway 5 subway	59	53	4	0.96
junius st 3 line	75	70	2	0.96
livonia ave l line	75	69	3	0.96
utica ave and eastern parkway	142	131	6	0.96
rockaway ave c line	61	57	3	0.98
sutter av - rutland rd 3 line	68	64	3	0.98
rockaway ave 3 line	61	57	4	1.00

7.4 Briefly summarize any noteworthy findings from the table you just generated.

At every single high-arrest subway station, the majority of arrested individuals are Black or Hispanic. This isn't surprising, given that 87 percent of *all* arrested individuals with coded race/ethnicity are Black or Hispanic.

8 (OPTIONAL) Visualize the distribution of arrests by race/ethnicity at stations with > 100 arrests.

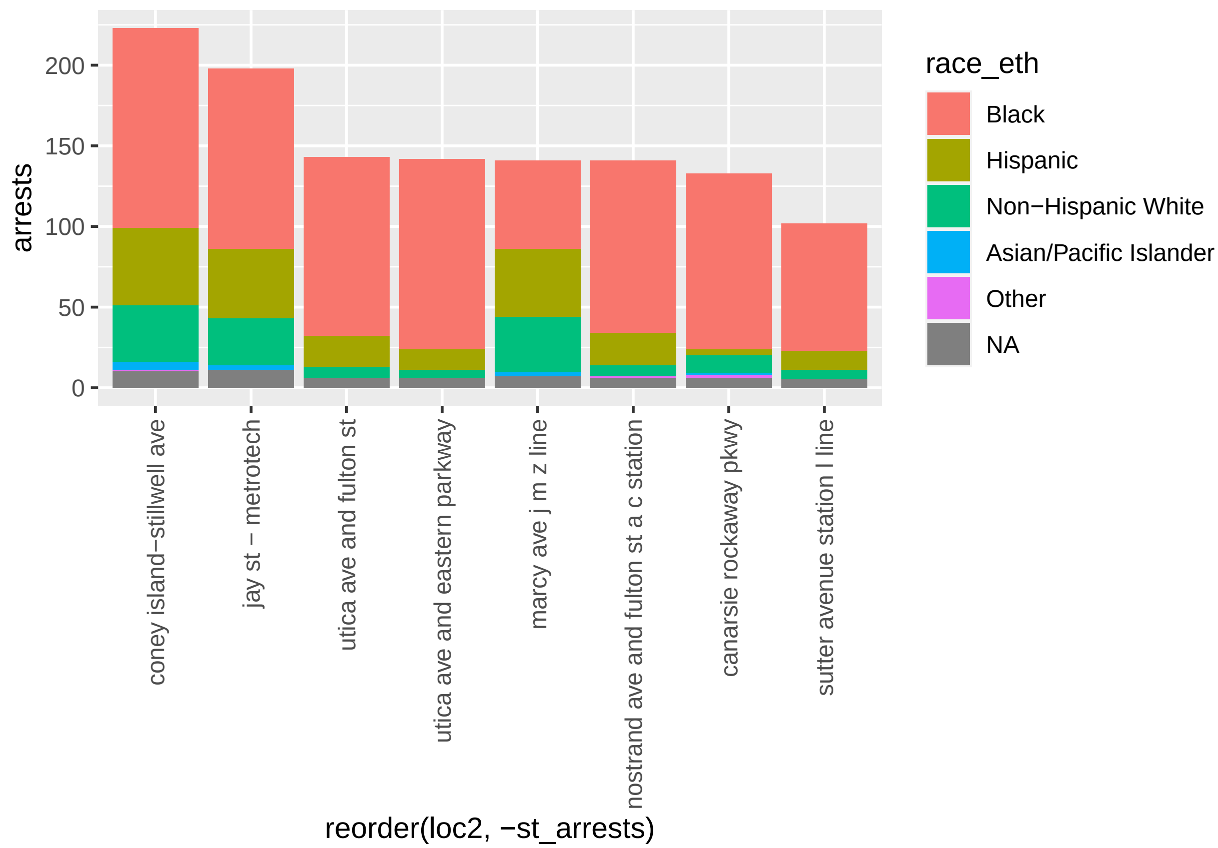
Hint: see R code from class, section 8

```r
#get data frame with obs for every station-race_eth pairings on arrest counts
arrests_stations_race <- arrests.clean %>%
  group_by(loc2) %>%
```

```r
  mutate(st_arrests = n()) %>%
  ungroup() %>%
  group_by(loc2, race_eth)  %>%
  summarise(arrests = n(), st_arrests = first(st_arrests)) %>%
  arrange(desc(st_arrests)) %>%
  filter(st_arrests > 100)
arrests_stations_race
```

```
## # A tibble: 39 x 4
## # Groups:   loc2 [8]
##    loc2                        race_eth               arrests st_arrests
##    <fct>                       <fct>                    <int>      <int>
##  1 coney island-stillwell ave Black                      124        223
##  2 coney island-stillwell ave Hispanic                    48        223
##  3 coney island-stillwell ave Non-Hispanic White          35        223
##  4 coney island-stillwell ave Asian/Pacific Islander       5        223
##  5 coney island-stillwell ave Other                        1        223
##  6 coney island-stillwell ave <NA>                        10        223
##  7 jay st - metrotech         Black                      112        198
##  8 jay st - metrotech         Hispanic                    43        198
##  9 jay st - metrotech         Non-Hispanic White          29        198
## 10 jay st - metrotech         Asian/Pacific Islander       3        198
## # ... with 29 more rows
```

```r
ggplot(arrests_stations_race,
       aes(x = reorder(loc2, -st_arrests), y = arrests, fill = race_eth)) +
  geom_bar(stat = "identity") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```


arrests
200
150
100
50
0
race_eth
Black
Hispanic
Non−Hispanic White
Asian/Pacific Islander
Other
NA
coney island−stillwell ave
jay st − metrotech
utica ave and fulton st
utica ave and eastern parkway
marcy ave j m z line
nostrand ave and fulton st a c station
canarsie rockaway pkwy
sutter avenue station l line
reorder(loc2, −st_arrests)