Response Analysis

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Read in packages and saved data from the email scripts:

Also have a bit of code to pull in segregation data:

```
segregation <- read.csv("../../data/raw/Segregation_by_metro_areas_2021-10.csv")
# Obtained via curl  https://belonging.berkeley.edu/sites/default/files/2021-10/Segregation%20by%20metr

# TKTK: match our 20 Craigslist region names to these metro regions
# TKTK: Write up a short justification for this matching, citing e.g.
# https://geoffboeing.com/publications/craigslist-rental-housing-markets/ :
# "Craigslist geographies are not always a perfect match for census geographies
# [...] but the vast majority of listings are far from these gray-area boundaries
# and the geographies do generally correspond well."

df <- segregation %>% mutate(City = NA) %>% filter(Metro=='Clear')
for (city in unique(rental_response_data$city)) {

    row <- segregation[grepl(toupper(city), toupper(segregation$Metro)),]

    if (nrow(row) != 1) {

      if (city == 'washingtondc') {
            row <- segregation[grepl(toupper('Washington'), toupper(segregation$Metro)),]
        } else if (city == 'sfbay') {
            row <- segregation[grepl(toupper('San Francisco'), toupper(segregation$Metro)),]
        } else if (city == 'inlandempire') {
            row <- segregation[grepl(toupper('Riverside'), toupper(segregation$Metro)),]
        } else if (city == 'sandiego') {
            row <- segregation[grepl(toupper('San Diego'), toupper(segregation$Metro)),]
        } else if (city == 'newyork') {
            row <- segregation[grepl(toupper('New York'), toupper(segregation$Metro)),]
        } else if (city == 'losangeles') {
            row <- segregation[grepl(toupper('Los Angeles'), toupper(segregation$Metro)),]
        } else if (city == 'atlanta') {
            row <- segregation[grepl(toupper(city), toupper(segregation$Metro)),]
        } else if (city == 'baltimore') {
            row <- segregation[grepl(toupper(city), toupper(segregation$Metro)),]
        }
    }

    row$city <- city
    df <- rbind(df, row)
```

```
}

rental_response_data <- rental_response_data %>% merge(df)
```

This script will use the saved rental response data once that is is fully populated. In the meantime, artificial data will need to be generated:

```
# predicted response ratios by group
rr_white_male = .5
rr_white_female = .7
rr_black_male = .3
rr_black_female = .35
white_male_names = c("Brad Anderson","Steven Smith","Luke Mitchell","Brian Bailey")
white_female_names = c("Hilary Roberts", "Amy Morgan", "Stephanie Nelson", "Kristen Hall")
black_male_names = c("Jamal Jefferson", "DeAndre Jackson", "Terell Robinson", "Jayvon Carter")
black_female_names = c("Shanice Thomas", "Tionna Wilson" , "Ebony Williams", "Tyra Booker")

# to have fake data to work with:
rental_response_data <- rental_response_data %>%
  filter(city != 'test') %>%
  mutate(response = ifelse(!is.na(response_timestamp), 1, 0))

# comment this out once data pipeline fully working:
rental_response_data$response <- NA
rental_response_data$sending_name <- NA
for (i in 1:nrow(rental_response_data)) {

  female = rental_response_data$female[i]
  black = rental_response_data$black[i]

  rental_response_data$response[i] = ifelse(female == 1 & black == 1, sample(0:1, 1,
                                                    prob = c(1-rr_black_female, rr_black_female)),
                                     ifelse(female == 1 & black == 0, sample(0:1, 1,
                                                    prob = c(1-rr_white_female, rr_white_female)),
                                     ifelse(female == 0 & black == 0, sample(0:1, 1,
                                                    prob = c(1-rr_white_male, rr_white_male)),
                                            sample(0:1, 1, prob = c(1-rr_black_male, rr_black_male)))))

  rental_response_data$sending_name[i] = ifelse(female == 1 & black == 1, sample(black_female_names),
                                         ifelse(female == 1 & black == 0, sample(white_female_names),
                                         ifelse(female == 0 & black == 0, sample(white_male_names),
                                            sample(black_male_names))))

}
```

Here we add indicator variables for each of the name effects, and build each model.

We'll be using models ranging from a more simple model with 3 terms:

$$Response = \alpha + \beta_1 Female + \beta_2 Black + \beta_3 Female * Black$$

To models with controls for cities and names:

$$Response = \alpha + \beta_1 Female + \beta_2 Black + \beta_3 Female * Black + \beta_i City_{Chicago} + ... + B_n Name_{BrianBailey} + ...$$

```r
d <- as.data.table(rental_response_data)
d <- d[, Brian_Bailey := ifelse(sending_name == 'Brian Bailey', 1, 0)]
d <- d[, Steven_Smith := ifelse(sending_name == 'Steven Smith', 1, 0)]
d <- d[, Luke_Mitchell := ifelse(sending_name == 'Luke Mitchell', 1, 0)]
d <- d[, Kristen_Hall := ifelse(sending_name == 'Kristen Hall', 1, 0)]
d <- d[, Stephanie_Nelson := ifelse(sending_name == 'Stephanie Nelson', 1, 0)]
d <- d[, Amy_Morgan := ifelse(sending_name == 'Amy Morgan', 1, 0)]
d <- d[, DeAndre_Jackson := ifelse(sending_name == 'DeAndre Jackson', 1, 0)]
d <- d[, Terell_Robinson := ifelse(sending_name == 'Terell Robinson', 1, 0)]
d <- d[, Jayvon_Carter := ifelse(sending_name == 'Jayvon Carter', 1, 0)]
d <- d[, Tionna_Wilson := ifelse(sending_name == 'Tionna Wilson', 1, 0)]
d <- d[, Ebony_Williams := ifelse(sending_name == 'Ebony Williams', 1, 0)]
d <- d[, Tyra_Booker := ifelse(sending_name == 'Tyra Booker', 1, 0)]

mod_simple <-  d[,lm(response ~ female + black + female:black)]

mod_city_controls <- d[,lm(response ~ female + black + female:black + city)]
mod_city_segregation_1 <- d[,lm(response ~ female + black + female:black + Divergence)]
mod_city_segregation_2 <- d[,lm(response ~ female + black + female:black + Segregation.Category)]

mod_name_controls  <- d[,lm(response ~ female + black + female:black + city +
                                       Brian_Bailey + Steven_Smith + Luke_Mitchell +
                                       DeAndre_Jackson + Terell_Robinson + Jayvon_Carter +
                                       Tionna_Wilson + Ebony_Williams + Tyra_Booker)]
```

Now can render the stargazer table and a plot if desired:

```r
stargazer(mod_simple, mod_city_controls, mod_city_segregation_1,
          mod_city_segregation_2, mod_name_controls,
          type = 'text',
          font.size = "small",
          align = TRUE,
          omit.stat=c("f", "ser")
          )
```

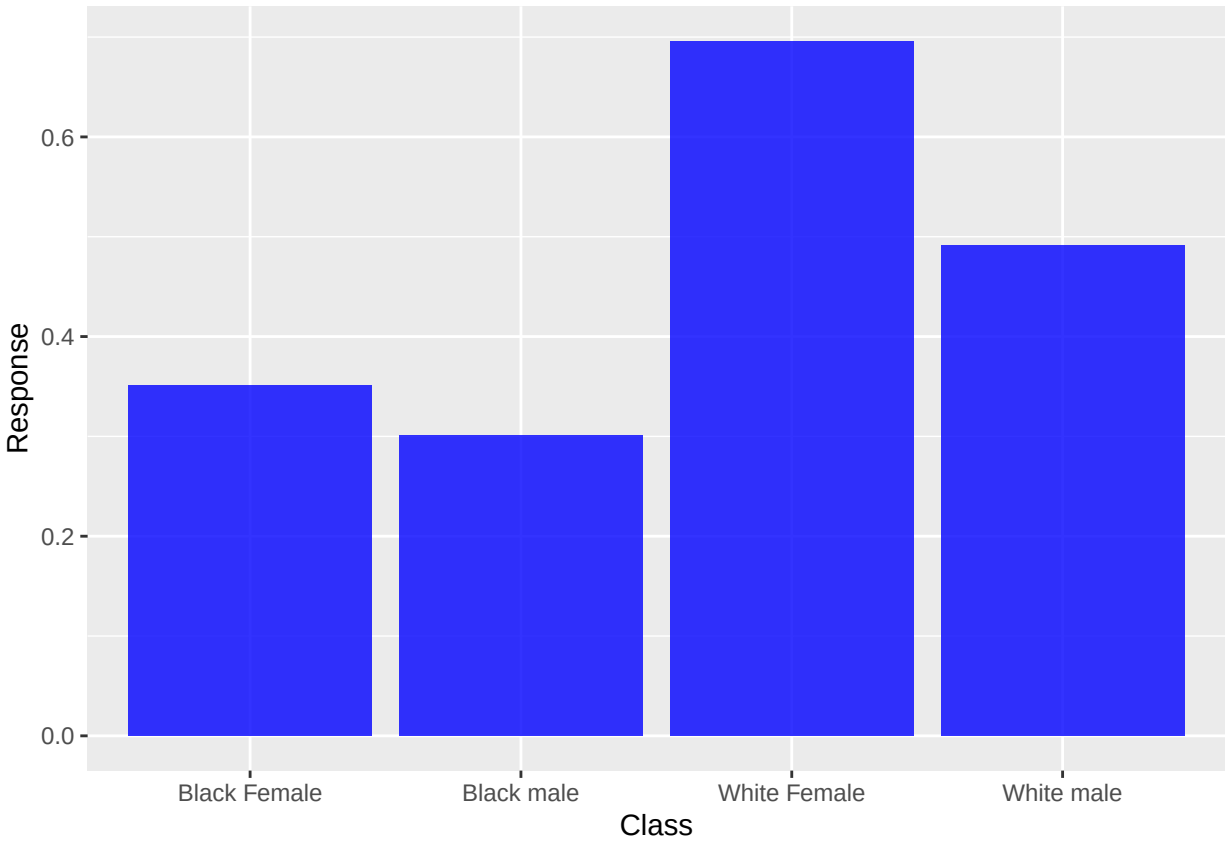
```
##
## ===========================================================================================
##                                                           Dependent variable:
##                                              ----------------------------------------------
##                                                               response
##                                                 (1)      (2)      (3)      (4)      (5)
## -------------------------------------------------------------------------------------------
## female                                       0.204*** 0.205*** 0.204*** 0.204*** 0.220***
##                                               (0.014)  (0.014)  (0.014)  (0.014)  (0.023)
##
## black                                        -0.191*** -0.191*** -0.191*** -0.191*** -0.154***
##                                               (0.014)  (0.014)  (0.014)  (0.014)  (0.028)
##
## citybaltimore                                          -0.034                     -0.036
```

```
##                                                 (0.030)                 (0.030)
##
## cityboston                                      -0.025                  -0.025
##                                                 (0.030)                 (0.030)
##
## citychicago                                      0.009                   0.007
##                                                 (0.030)                 (0.030)
##
## citydallas                                      -0.031                  -0.032
##                                                 (0.030)                 (0.030)
##
## citydenver                                       0.011                   0.008
##                                                 (0.030)                 (0.030)
##
## citydetroit                                     -0.029                  -0.031
##                                                 (0.030)                 (0.030)
##
## cityhouston                                     -0.008                  -0.010
##                                                 (0.030)                 (0.030)
##
## cityinlandempire                                -0.038                  -0.040
##                                                 (0.030)                 (0.030)
##
## citymiami                                       -0.043                  -0.044
##                                                 (0.030)                 (0.030)
##
## cityminneapolis                                 -0.013                  -0.014
##                                                 (0.030)                 (0.030)
##
## cityphiladelphia                                -0.007                  -0.008
##                                                 (0.030)                 (0.030)
##
## cityphoenix                                     -0.002                  -0.003
##                                                 (0.030)                 (0.030)
##
## citysandiego                                    -0.028                  -0.029
##                                                 (0.030)                 (0.030)
##
## cityseattle                                     -0.022                  -0.024
##                                                 (0.030)                 (0.030)
##
## citysfbay                                       -0.029                  -0.030
##                                                 (0.030)                 (0.030)
##
## citytampa                                       -0.013                  -0.016
##                                                 (0.030)                 (0.030)
##
## citywashingtondc                                -0.015                  -0.016
##                                                 (0.030)                 (0.030)
##
## Divergence                                                0.003
##                                                          (0.066)
##
## Segregation.CategoryLow-Medium Segregation                                0.0001
```

```
##                                                                          (0.016)
##
## Brian_Bailey                                                                      0.002
##                                                                                  (0.028)
##
## Steven_Smith                                                                      0.022
##                                                                                  (0.028)
##
## Luke_Mitchell                                                                     0.037
##                                                                                  (0.028)
##
## DeAndre_Jackson                                                                  -0.019
##                                                                                  (0.029)
##
## Terell_Robinson                                                                  -0.042
##                                                                                  (0.029)
##
## Jayvon_Carter                                                                    -0.027
##                                                                                  (0.028)
##
## Tionna_Wilson                                                                    0.070**
##                                                                                  (0.028)
##
## Ebony_Williams                                                                   0.050*
##                                                                                  (0.028)
##
## Tyra_Booker                                                                      0.059**
##                                                                                  (0.028)
##
## female:black                                 -0.154*** -0.155*** -0.154*** -0.154*** -0.236***
##                                               (0.020)   (0.020)   (0.020)   (0.020)   (0.036)
##
## Constant                                     0.492***  0.509***  0.491***  0.492***  0.495***
##                                               (0.010)   (0.023)   (0.019)   (0.010)   (0.029)
##
## -------------------------------------------------------------------------------------------
## Observations                                   9,000     9,000     9,000     9,000     9,000
## R2                                             0.094     0.095     0.094     0.094     0.096
## Adjusted R2                                    0.094     0.093     0.094     0.094     0.093
## ===========================================================================================
## Note:                                                        *p<0.1; **p<0.05; ***p<0.01
```

```
plot_data <- data.frame('Class' = c('White male', 'Black male', 'White Female', 'Black Female'),
                        'Response' = c(coef(mod_simple)[1],
                                       coef(mod_simple)[1] + coef(mod_simple)[3],
                                       coef(mod_simple)[1] + coef(mod_simple)[2],
                                       coef(mod_simple)[1] + coef(mod_simple)[2] + coef(mod_simple)[3] +

ggplot(plot_data) +
  geom_bar( aes(x=Class, y=Response), stat="identity", fill="blue", alpha=0.8)
```



By looking at the terms for female, black and the female:black interaction term, we can assess the hypotheses of whether racial/ethnic minorities in the US subject to bias when seeking housing, and whether such bias vary by gender.