Project 1: Wrangling, Exploration, Visualization

SDS322E

Data Wrangling, Exploration, Visualization

Shilpi Karan sk46966

Introduction The two data sets used in this project are the U.S. State Public School Expenditures dataset and the Violent Crime Rates by US State dataset. The common ID variable that they share is states. Other variables that are in the data sets include murder, assault, urbanpop, and rape in dataset 1 and education, income, young, and urban in dataset2. The variables were acquired by looking at per-capital values and by collecting data from populations of 1,000 or 100,000 people and creating a proportion from that. These data sets and variables were interesting for me because I wanted to know if there is a correlation between education/income and crime rates in America.

```
library(tidyverse)

data1 <- read_csv("https://vincentarelbundock.github.io/Rdatasets/csv/datasets/USArrests.csv")
data2 <- read_csv("https://vincentarelbundock.github.io/Rdatasets/csv/carData/Anscombe.csv")
```

Tidying: Reshaping If your datasets are tidy already, demonstrate that you can reshape data with pivot wider/longer here (e.g., untidy and then retidy). Alternatively, it may be easier to wait until the wrangling section so you can reshape your summary statistics. Note here if you are going to do this.

```
data1
```

```
## # A tibble: 50 x 5
##    X1          Murder Assault UrbanPop  Rape
##    <chr>        <dbl>   <dbl>    <dbl> <dbl>
##  1 Alabama       13.2     236       58  21.2
##  2 Alaska        10       263       48  44.5
##  3 Arizona        8.1     294       80  31
##  4 Arkansas       8.8     190       50  19.5
##  5 California     9       276       91  40.6
##  6 Colorado       7.9     204       78  38.7
##  7 Connecticut    3.3     110       77  11.1
##  8 Delaware       5.9     238       72  15.8
##  9 Florida       15.4     335       80  31.9
## 10 Georgia       17.4     211       60  25.8
## # ... with 40 more rows
```

```
data2
```

```
## # A tibble: 51 x 5
##    X1    education income young urban
##    <chr>     <dbl>  <dbl> <dbl> <dbl>
##  1 ME          189   2824  351.   508
##  2 NH          169   3259  346.   564
```

```
##   3 VT          230   3072  348.   322
##   4 MA          168   3835  335.   846
##   5 RI          180   3549  327.   871
##   6 CT          193   4256  341    774
##   7 NY          261   4151  326.   856
##   8 NJ          214   3954  334.   889
##   9 PA          201   3419  326.   715
##  10 OH          172   3509  354.   753
## # ... with 41 more rows
```

```r
# UNTIDY
data1 <- data1 %>% pivot_wider(names_from = X1, values_from = Murder)
data2 <- data2 %>% pivot_wider(names_from = X1, values_from = education)

data1
```

```
## # A tibble: 50 x 53
##    Assault UrbanPop  Rape Alabama Alaska Arizona Arkansas California Colorado
##      <dbl>    <dbl> <dbl>   <dbl>  <dbl>   <dbl>    <dbl>      <dbl>    <dbl>
##  1     236       58  21.2    13.2     NA    NA       NA           NA     NA
##  2     263       48  44.5    NA       10    NA       NA           NA     NA
##  3     294       80  31      NA       NA     8.1     NA           NA     NA
##  4     190       50  19.5    NA       NA    NA        8.8         NA     NA
##  5     276       91  40.6    NA       NA    NA       NA            9     NA
##  6     204       78  38.7    NA       NA    NA       NA           NA      7.9
##  7     110       77  11.1    NA       NA    NA       NA           NA     NA
##  8     238       72  15.8    NA       NA    NA       NA           NA     NA
##  9     335       80  31.9    NA       NA    NA       NA           NA     NA
## 10     211       60  25.8    NA       NA    NA       NA           NA     NA
## # ... with 40 more rows, and 44 more variables: Connecticut <dbl>,
## #   Delaware <dbl>, Florida <dbl>, Georgia <dbl>, Hawaii <dbl>, Idaho <dbl>,
## #   Illinois <dbl>, Indiana <dbl>, Iowa <dbl>, Kansas <dbl>, Kentucky <dbl>,
## #   Louisiana <dbl>, Maine <dbl>, Maryland <dbl>, Massachusetts <dbl>,
## #   Michigan <dbl>, Minnesota <dbl>, Mississippi <dbl>, Missouri <dbl>,
## #   Montana <dbl>, Nebraska <dbl>, Nevada <dbl>, `New Hampshire` <dbl>, `New
## #   Jersey` <dbl>, `New Mexico` <dbl>, `New York` <dbl>, `North
## #   Carolina` <dbl>, `North Dakota` <dbl>, Ohio <dbl>, Oklahoma <dbl>,
## #   Oregon <dbl>, Pennsylvania <dbl>, `Rhode Island` <dbl>, `South
## #   Carolina` <dbl>, `South Dakota` <dbl>, Tennessee <dbl>, Texas <dbl>,
## #   Utah <dbl>, Vermont <dbl>, Virginia <dbl>, Washington <dbl>, `West
## #   Virginia` <dbl>, Wisconsin <dbl>, Wyoming <dbl>
```

```r
data2
```

```
## # A tibble: 51 x 54
##    income young urban    ME    NH    VT    MA    RI    CT    NY    NJ    PA
##     <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
##  1   2824  351.   508   189    NA    NA    NA    NA    NA    NA    NA    NA
##  2   3259  346.   564    NA   169    NA    NA    NA    NA    NA    NA    NA
##  3   3072  348.   322    NA    NA   230    NA    NA    NA    NA    NA    NA
##  4   3835  335.   846    NA    NA    NA   168    NA    NA    NA    NA    NA
##  5   3549  327.   871    NA    NA    NA    NA   180    NA    NA    NA    NA
##  6   4256  341    774    NA    NA    NA    NA    NA   193    NA    NA    NA
##  7   4151  326.   856    NA    NA    NA    NA    NA    NA   261    NA    NA
##  8   3954  334.   889    NA    NA    NA    NA    NA    NA    NA   214    NA
##  9   3419  326.   715    NA    NA    NA    NA    NA    NA    NA    NA   201
```

```
## 10   3509  354.   753    NA    NA    NA    NA    NA    NA    NA    NA    NA
## # ... with 41 more rows, and 42 more variables: OH <dbl>, IN <dbl>, IL <dbl>,
## #   MI <dbl>, WI <dbl>, MN <dbl>, IO <dbl>, MO <dbl>, ND <dbl>, SD <dbl>,
## #   NE <dbl>, KA <dbl>, DE <dbl>, MD <dbl>, DC <dbl>, VA <dbl>, WV <dbl>,
## #   NC <dbl>, SC <dbl>, GA <dbl>, FL <dbl>, KY <dbl>, TN <dbl>, AL <dbl>,
## #   MS <dbl>, AR <dbl>, LA <dbl>, OK <dbl>, TX <dbl>, MT <dbl>, ID <dbl>,
## #   WY <dbl>, CO <dbl>, NM <dbl>, AZ <dbl>, UT <dbl>, NV <dbl>, WA <dbl>,
## #   OR <dbl>, CA <dbl>, AK <dbl>, HI <dbl>
```

```r
# TIDY
data1 <- data1 %>% pivot_longer(cols = Alabama:Wyoming, names_to = "X1",
    values_to = "Murder", values_drop_na = TRUE)
data2 <- data2 %>% pivot_longer(cols = ME:HI, names_to = "X1",
    values_to = "education", values_drop_na = TRUE)

data1
```

```
## # A tibble: 50 x 5
##    Assault UrbanPop  Rape X1          Murder
##      <dbl>    <dbl> <dbl> <chr>        <dbl>
##  1     236       58  21.2 Alabama       13.2
##  2     263       48  44.5 Alaska        10
##  3     294       80  31   Arizona        8.1
##  4     190       50  19.5 Arkansas       8.8
##  5     276       91  40.6 California     9
##  6     204       78  38.7 Colorado       7.9
##  7     110       77  11.1 Connecticut    3.3
##  8     238       72  15.8 Delaware       5.9
##  9     335       80  31.9 Florida       15.4
## 10     211       60  25.8 Georgia       17.4
## # ... with 40 more rows
```

```r
data2
```

```
## # A tibble: 51 x 5
##    income young urban X1    education
##     <dbl> <dbl> <dbl> <chr>     <dbl>
##  1   2824  351.   508 ME          189
##  2   3259  346.   564 NH          169
##  3   3072  348.   322 VT          230
##  4   3835  335.   846 MA          168
##  5   3549  327.   871 RI          180
##  6   4256  341    774 CT          193
##  7   4151  326.   856 NY          261
##  8   3954  334.   889 NJ          214
##  9   3419  326.   715 PA          201
## 10   3509  354.   753 OH          172
## # ... with 41 more rows
```

```r
data1 <- data1 %>% relocate(X1, .before = Assault)
data2 <- data2 %>% relocate(X1, .before = income)

data1
```

```
## # A tibble: 50 x 5
##    X1          Assault UrbanPop  Rape Murder
##    <chr>         <dbl>    <dbl> <dbl>  <dbl>
```

```
##   1 Alabama         236       58  21.2   13.2
##   2 Alaska          263       48  44.5   10
##   3 Arizona         294       80  31       8.1
##   4 Arkansas        190       50  19.5     8.8
##   5 California      276       91  40.6     9
##   6 Colorado        204       78  38.7     7.9
##   7 Connecticut     110       77  11.1     3.3
##   8 Delaware        238       72  15.8     5.9
##   9 Florida         335       80  31.9    15.4
##  10 Georgia         211       60  25.8    17.4
## # ... with 40 more rows
```

```
data2
```

```
## # A tibble: 51 x 5
##     X1    income young urban education
##     <chr>  <dbl> <dbl> <dbl>     <dbl>
##   1 ME      2824  351.   508       189
##   2 NH      3259  346.   564       169
##   3 VT      3072  348.   322       230
##   4 MA      3835  335.   846       168
##   5 RI      3549  327.   871       180
##   6 CT      4256  341    774       193
##   7 NY      4151  326.   856       261
##   8 NJ      3954  334.   889       214
##   9 PA      3419  326.   715       201
##  10 OH      3509  354.   753       172
## # ... with 41 more rows
```

```
library(dplyr)

data2[1, 1] <- "Alaska"
data2[2, 1] <- "Alabama"
data2[3, 1] <- "Arkansas"
data2[4, 1] <- "Arizona"
data2[5, 1] <- "California"
data2[6, 1] <- "Colorado"
data2[7, 1] <- "Connecticut"
data2[8, 1] <- "Delaware"
data2[9, 1] <- "Florida"
data2[10, 1] <- "Georgia"
data2[11, 1] <- "Hawaii"
data2[12, 1] <- "Idaho"
data2[13, 1] <- "Illinois"
data2[14, 1] <- "Indiana"
data2[15, 1] <- "Iowa"
data2[16, 1] <- "Kansas"
data2[17, 1] <- "Kentucky"
data2[18, 1] <- "Louisiana"
data2[19, 1] <- "Massachusetts"
data2[20, 1] <- "Maryland"
data2[21, 1] <- "Maine"
data2[22, 1] <- "Michigan"
```

```r
data2[23, 1] <- "Minnesota"
data2[24, 1] <- "Missouri"
data2[25, 1] <- "Mississippi"
data2[26, 1] <- "Montana"
data2[27, 1] <- "North Carolina"
data2[28, 1] <- "North Dakota"
data2[29, 1] <- "Nebraska"
data2[30, 1] <- "New Hampshire"
data2[31, 1] <- "New Jersey"
data2[32, 1] <- "New Mexico"
data2[33, 1] <- "Nevada"
data2[34, 1] <- "New York"
data2[35, 1] <- "Ohio"
data2[36, 1] <- "Oklahoma"
data2[37, 1] <- "Oregon"
data2[38, 1] <- "Pennsylvania"
data2[39, 1] <- "Rhode Island"
data2[40, 1] <- "South Carolina"
data2[41, 1] <- "South Dakota"
data2[42, 1] <- "Tennessee"
data2[43, 1] <- "Texas"
data2[44, 1] <- "Utah"
data2[45, 1] <- "Virginia"
data2[46, 1] <- "Vermont"
data2[47, 1] <- "Washington"
data2[48, 1] <- "Wisconsin"
data2[49, 1] <- "West Virginia"
data2[50, 1] <- "Wyoming"

data2 <- data2 %>% arrange(data2)
data2
```

Joining/Merging

```
## # A tibble: 51 x 5
##    X1           income young urban education
##    <chr>         <dbl> <dbl> <dbl>     <dbl>
##  1 Alabama        3259  346.   564       169
##  2 Alaska         2824  351.   508       189
##  3 Arizona        3835  335.   846       168
##  4 Arkansas       3072  348.   322       230
##  5 California     3549  327.   871       180
##  6 Colorado       4256  341    774       193
##  7 Connecticut    4151  326.   856       261
##  8 Delaware       3954  334.   889       214
##  9 Florida        3419  326.   715       201
## 10 Georgia        3509  354.   753       172
## # ... with 41 more rows
```

```r
data3 <- full_join(data1, data2)
data3
```

```
## # A tibble: 51 x 9
##    X1           Assault UrbanPop  Rape Murder income young urban education
##    <chr>          <dbl>    <dbl> <dbl>  <dbl>  <dbl> <dbl> <dbl>     <dbl>
```

```
##  1 Alabama         236       58  21.2    13.2     3259  346.    564        169
##  2 Alaska          263       48  44.5    10       2824  351.    508        189
##  3 Arizona         294       80  31       8.1     3835  335.    846        168
##  4 Arkansas        190       50  19.5     8.8     3072  348.    322        230
##  5 California      276       91  40.6     9       3549  327.    871        180
##  6 Colorado        204       78  38.7     7.9     4256  341     774        193
##  7 Connecticut     110       77  11.1     3.3     4151  326.    856        261
##  8 Delaware        238       72  15.8     5.9     3954  334.    889        214
##  9 Florida         335       80  31.9    15.4     3419  326.    715        201
## 10 Georgia         211       60  25.8    17.4     3509  354.    753        172
## # ... with 41 more rows
```

```r
# data1 <- data1 %>% rename(States = X1) data2 <- data2 %>%
# rename(States = X1)
data1
```

```
## # A tibble: 50 x 5
##    X1          Assault UrbanPop  Rape Murder
##    <chr>         <dbl>    <dbl> <dbl>  <dbl>
##  1 Alabama         236       58  21.2   13.2
##  2 Alaska          263       48  44.5   10
##  3 Arizona         294       80  31      8.1
##  4 Arkansas        190       50  19.5    8.8
##  5 California      276       91  40.6    9
##  6 Colorado        204       78  38.7    7.9
##  7 Connecticut     110       77  11.1    3.3
##  8 Delaware        238       72  15.8    5.9
##  9 Florida         335       80  31.9   15.4
## 10 Georgia         211       60  25.8   17.4
## # ... with 40 more rows
```

```r
data2
```

```
## # A tibble: 51 x 5
##    X1          income young urban education
##    <chr>        <dbl> <dbl> <dbl>     <dbl>
##  1 Alabama       3259  346.   564       169
##  2 Alaska        2824  351.   508       189
##  3 Arizona       3835  335.   846       168
##  4 Arkansas      3072  348.   322       230
##  5 California    3549  327.   871       180
##  6 Colorado      4256  341    774       193
##  7 Connecticut   4151  326.   856       261
##  8 Delaware      3954  334.   889       214
##  9 Florida       3419  326.   715       201
## 10 Georgia       3509  354.   753       172
## # ... with 41 more rows
```

```r
dim(data1)
```

```
## [1] 50  5
```

```r
dim(data2)
```

```
## [1] 51  5
```

```r
dim(data3)
```

```
## [1] 51  9
```

```r
colnames(data1)
```

```
## [1] "X1"       "Assault"  "UrbanPop" "Rape"     "Murder"
```

```r
colnames(data2)
```

```
## [1] "X1"        "income"    "young"     "urban"     "education"
```

Datasets 1 and 2 were full joined. I used full join because both datasets have the same matching rows so it would make no difference and thus be of no use to do inner, left, or right join. There are 50 observations/rows in each dataset. The ID that the datasets have in common is states. The unique IDs in dataset 1 that are not in dataset 2 are murder, assault, urbanpop, and rape. The other IDs are unique to dataset 2, and they are education, income, young, and urban. The size of the joined dataset is larger than the individual datasets. It has 9 variables/columns while the individual datasets had 5 columns/variables each. There were no observations dropped, and so there is also no problem associated with it.

```r
data3 %>% arrange(income)
```

Wrangling

```
## # A tibble: 51 x 9
##    X1             Assault UrbanPop  Rape Murder income young urban education
##    <chr>            <dbl>    <dbl> <dbl>  <dbl>  <dbl> <dbl> <dbl>     <dbl>
##  1 New York           254       86  26.1   11.1   2081  385.   445       130
##  2 Ohio               120       75  21.4    7.3   2322  352.   500       134
##  3 Nevada             252       81  46     12.2   2337  362.   584       112
##  4 North Dakota        45       44   7.3    0.8   2380  377.   476       149
##  5 Montana            109       53  16.4    6     2470  329.   390       149
##  6 New Mexico         285       70  32.1   11.4   2579  343.   588       137
##  7 Oklahoma           151       68  20      6.6   2634  390.   661       162
##  8 New Jersey         159       89  18.8    7.4   2645  349.   523       140
##  9 Texas              201       80  25.5   12.7   2651  422.   698       227
## 10 North Carolina     337       45  16.1   13     2664  354.   450       155
## # ... with 41 more rows
```

```r
data3 %>% filter(str_detect(Rape, "17.4"))
```

```
## # A tibble: 0 x 9
## # ... with 9 variables: X1 <chr>, Assault <dbl>, UrbanPop <dbl>, Rape <dbl>,
## #   Murder <dbl>, income <dbl>, young <dbl>, urban <dbl>, education <dbl>
```

```r
data3 %>% filter(urban >= 500)
```

```
## # A tibble: 43 x 9
##    X1          Assault UrbanPop  Rape Murder income young urban education
##    <chr>         <dbl>    <dbl> <dbl>  <dbl>  <dbl> <dbl> <dbl>     <dbl>
##  1 Alabama         236       58  21.2   13.2   3259  346.   564       169
##  2 Alaska          263       48  44.5   10     2824  351.   508       189
##  3 Arizona         294       80  31      8.1   3835  335.   846       168
##  4 California      276       91  40.6    9     3549  327.   871       180
##  5 Colorado        204       78  38.7    7.9   4256  341    774       193
##  6 Connecticut     110       77  11.1    3.3   4151  326.   856       261
##  7 Delaware        238       72  15.8    5.9   3954  334.   889       214
##  8 Florida         335       80  31.9   15.4   3419  326.   715       201
##  9 Georgia         211       60  25.8   17.4   3509  354.   753       172
```

```
## 10 Hawaii           46       83  20.2    5.3   3412  359.   649       194
## # ... with 33 more rows
```

```
data3 %>% select(X1, Murder, income)
```

```
## # A tibble: 51 x 3
##    X1          Murder income
##    <chr>        <dbl>  <dbl>
##  1 Alabama       13.2   3259
##  2 Alaska        10     2824
##  3 Arizona        8.1   3835
##  4 Arkansas       8.8   3072
##  5 California     9     3549
##  6 Colorado       7.9   4256
##  7 Connecticut    3.3   4151
##  8 Delaware       5.9   3954
##  9 Florida       15.4   3419
## 10 Georgia       17.4   3509
## # ... with 41 more rows
```

```
data3 %>% mutate(ratio = Murder/income)
```

```
## # A tibble: 51 x 10
##    X1         Assault UrbanPop  Rape Murder income young urban education   ratio
##    <chr>        <dbl>    <dbl> <dbl>  <dbl>  <dbl> <dbl> <dbl>     <dbl>   <dbl>
##  1 Alabama        236       58  21.2   13.2   3259  346.   564       169 4.05e-3
##  2 Alaska         263       48  44.5   10     2824  351.   508       189 3.54e-3
##  3 Arizona        294       80  31      8.1   3835  335.   846       168 2.11e-3
##  4 Arkansas       190       50  19.5    8.8   3072  348.   322       230 2.86e-3
##  5 California     276       91  40.6    9     3549  327.   871       180 2.54e-3
##  6 Colorado       204       78  38.7    7.9   4256  341    774       193 1.86e-3
##  7 Connectic~     110       77  11.1    3.3   4151  326.   856       261 7.95e-4
##  8 Delaware       238       72  15.8    5.9   3954  334.   889       214 1.49e-3
##  9 Florida        335       80  31.9   15.4   3419  326.   715       201 4.50e-3
## 10 Georgia        211       60  25.8   17.4   3509  354.   753       172 4.96e-3
## # ... with 41 more rows
```

```
data3$lh_UrbanPop <- as.factor(ifelse(data3$UrbanPop < 50, "low",
    "high"))
data3
```

```
## # A tibble: 51 x 10
##    X1     Assault UrbanPop  Rape Murder income young urban education lh_UrbanPop
##    <chr>    <dbl>    <dbl> <dbl>  <dbl>  <dbl> <dbl> <dbl>     <dbl> <fct>
##  1 Alaba~     236       58  21.2   13.2   3259  346.   564       169 high
##  2 Alaska     263       48  44.5   10     2824  351.   508       189 low
##  3 Arizo~     294       80  31      8.1   3835  335.   846       168 high
##  4 Arkan~     190       50  19.5    8.8   3072  348.   322       230 high
##  5 Calif~     276       91  40.6    9     3549  327.   871       180 high
##  6 Color~     204       78  38.7    7.9   4256  341    774       193 high
##  7 Conne~     110       77  11.1    3.3   4151  326.   856       261 high
##  8 Delaw~     238       72  15.8    5.9   3954  334.   889       214 high
##  9 Flori~     335       80  31.9   15.4   3419  326.   715       201 high
## 10 Georg~     211       60  25.8   17.4   3509  354.   753       172 high
## # ... with 41 more rows
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(counts = n())
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop counts
##   <fct>        <int>
## 1 high            42
## 2 low              8
## 3 <NA>             1
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(mean(education,
    na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `mean(education, na.rm = T)`
##   <fct>                              <dbl>
## 1 high                                196.
## 2 low                                 197.
## 3 <NA>                                212
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(sd(education, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `sd(education, na.rm = T)`
##   <fct>                            <dbl>
## 1 high                              47.9
## 2 low                               43.7
## 3 <NA>                              NA
```

```r
data3 %>% summarize(max(education, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `max(education, na.rm = T)`
##                         <dbl>
## 1                         372
```

```r
data3 %>% summarize(min(education, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `min(education, na.rm = T)`
##                         <dbl>
## 1                         112
```

```r
data3 %>% summarize(median(education, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `median(education, na.rm = T)`
##                            <dbl>
## 1                            192
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(mean(Murder, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `mean(Murder, na.rm = T)`
##   <fct>                           <dbl>
## 1 high                             7.7
## 2 low                              8.25
## 3 <NA>                           NaN
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(sd(Murder, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `sd(Murder, na.rm = T)`
##   <fct>                         <dbl>
## 1 high                           4.08
## 2 low                            5.90
## 3 <NA>                          NA
```

```r
data3 %>% summarize(max(Murder, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `max(Murder, na.rm = T)`
##                      <dbl>
## 1                     17.4
```

```r
data3 %>% summarize(min(Murder, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `min(Murder, na.rm = T)`
##                      <dbl>
## 1                      0.8
```

```r
data3 %>% summarize(median(Murder, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `median(Murder, na.rm = T)`
##                         <dbl>
## 1                        7.25
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(mean(income, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `mean(income, na.rm = T)`
##   <fct>                           <dbl>
## 1 high                            3244.
## 2 low                             3090.
## 3 <NA>                            3513
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(sd(income, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `sd(income, na.rm = T)`
##   <fct>                         <dbl>
## 1 high                           562.
## 2 low                            594.
## 3 <NA>                            NA
```

```r
data3 %>% summarize(max(income, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `max(income, na.rm = T)`
##                      <dbl>
## 1                     4425
```

```r
data3 %>% summarize(min(income, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `min(income, na.rm = T)`
```

```
##                        <dbl>
## 1                       2081
```

```r
data3 %>% summarize(median(income, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `median(income, na.rm = T)`
##                           <dbl>
## 1                          3257
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(mean(UrbanPop,
    na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `mean(UrbanPop, na.rm = T)`
##   <fct>                             <dbl>
## 1 high                               69.8
## 2 low                                43.1
## 3 <NA>                              NaN
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(sd(UrbanPop, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `sd(UrbanPop, na.rm = T)`
##   <fct>                           <dbl>
## 1 high                            11.4
## 2 low                              5.30
## 3 <NA>                            NA
```

```r
data3 %>% summarize(max(UrbanPop, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `max(UrbanPop, na.rm = T)`
##                          <dbl>
## 1                           91
```

```r
data3 %>% summarize(min(UrbanPop, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `min(UrbanPop, na.rm = T)`
##                          <dbl>
## 1                           32
```

```r
data3 %>% summarize(median(UrbanPop, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `median(UrbanPop, na.rm = T)`
##                             <dbl>
## 1                              66
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(mean(Assault, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `mean(Assault, na.rm = T)`
##   <fct>                            <dbl>
## 1 high                              170
## 2 low                               175.
## 3 <NA>                              NaN
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(sd(Assault, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `sd(Assault, na.rm = T)`
##   <fct>                          <dbl>
## 1 high                            76.3
## 2 low                            121.
## 3 <NA>                            NA
```

```r
data3 %>% summarize(max(Assault, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `max(Assault, na.rm = T)`
##                       <dbl>
## 1                       337
```

```r
data3 %>% summarize(min(Assault, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `min(Assault, na.rm = T)`
##                       <dbl>
## 1                        45
```

```r
data3 %>% summarize(median(Assault, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `median(Assault, na.rm = T)`
##                          <dbl>
## 1                          159
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(mean(young, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `mean(young, na.rm = T)`
##   <fct>                          <dbl>
## 1 high                            358.
## 2 low                             363.
## 3 <NA>                            383.
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(sd(young, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `sd(young, na.rm = T)`
##   <fct>                        <dbl>
## 1 high                          25.5
## 2 low                           13.4
## 3 <NA>                          NA
```

```r
data3 %>% summarize(max(young, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `max(young, na.rm = T)`
##                     <dbl>
## 1                    440.
```

```r
data3 %>% summarize(min(young, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `min(young, na.rm = T)`
```

```
##                        <dbl>
## 1                       326.
```

```
data3 %>% summarize(median(young, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `median(young, na.rm = T)`
##                           <dbl>
## 1                          354.
```

```
data3 %>% group_by(lh_UrbanPop) %>% summarize(mean(Rape, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `mean(Rape, na.rm = T)`
##   <fct>                             <dbl>
## 1 high                               21.9
## 2 low                                17.6
## 3 <NA>                              NaN
```

```
data3 %>% group_by(lh_UrbanPop) %>% summarize(sd(Rape, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `sd(Rape, na.rm = T)`
##   <fct>                           <dbl>
## 1 high                             8.81
## 2 low                             11.9
## 3 <NA>                            NA
```

```
data3 %>% summarize(max(Rape, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `max(Rape, na.rm = T)`
##                      <dbl>
## 1                       46
```

```
data3 %>% summarize(min(Rape, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `min(Rape, na.rm = T)`
##                      <dbl>
## 1                      7.3
```

```
data3 %>% summarize(median(Rape, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `median(Rape, na.rm = T)`
##                          <dbl>
## 1                         20.1
```

```
data3 %>% group_by(lh_UrbanPop) %>% summarize(mean(urban, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `mean(urban, na.rm = T)`
##   <fct>                              <dbl>
## 1 high                                670.
## 2 low                                 616.
## 3 <NA>                                831
```

```
data3 %>% group_by(lh_UrbanPop) %>% summarize(sd(urban, na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `sd(urban, na.rm = T)`
##   <fct>                        <dbl>
## 1 high                          149.
## 2 low                           164.
## 3 <NA>                           NA
```

```r
data3 %>% summarize(max(urban, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `max(urban, na.rm = T)`
##                     <dbl>
## 1                    1000
```

```r
data3 %>% summarize(min(urban, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `min(urban, na.rm = T)`
##                     <dbl>
## 1                     322
```

```r
data3 %>% summarize(median(urban, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `median(urban, na.rm = T)`
##                        <dbl>
## 1                        664
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(mean(education/income,
    na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `mean(education/income, na.rm = T)`
##   <fct>                                     <dbl>
## 1 high                                     0.0605
## 2 low                                      0.0638
## 3 <NA>                                     0.0603
```

```r
data3 %>% group_by(lh_UrbanPop) %>% summarize(sd(education/income,
    na.rm = T))
```

```
## # A tibble: 3 x 2
##   lh_UrbanPop `sd(education/income, na.rm = T)`
##   <fct>                                   <dbl>
## 1 high                                  0.0109
## 2 low                                   0.00608
## 3 <NA>                                 NA
```

```r
data3 %>% summarize(max(education/income, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `max(education/income, na.rm = T)`
##                                <dbl>
## 1                             0.0897
```

```r
data3 %>% summarize(min(education/income, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `min(education/income, na.rm = T)`
##                                <dbl>
```

```
## 1                              0.0438
```

```r
data3 %>% summarize(median(education/income, na.rm = T))
```

```
## # A tibble: 1 x 1
##   `median(education/income, na.rm = T)`
##                                   <dbl>
## 1                                0.0599
```

```r
percent_decimal <- function(UrbanPop) {
    DecUrbanPop <- (UrbanPop/100)
    return(DecUrbanPop)
}

data3 %>% summarize(percent_decimal(max(UrbanPop, na.rm = T)))
```

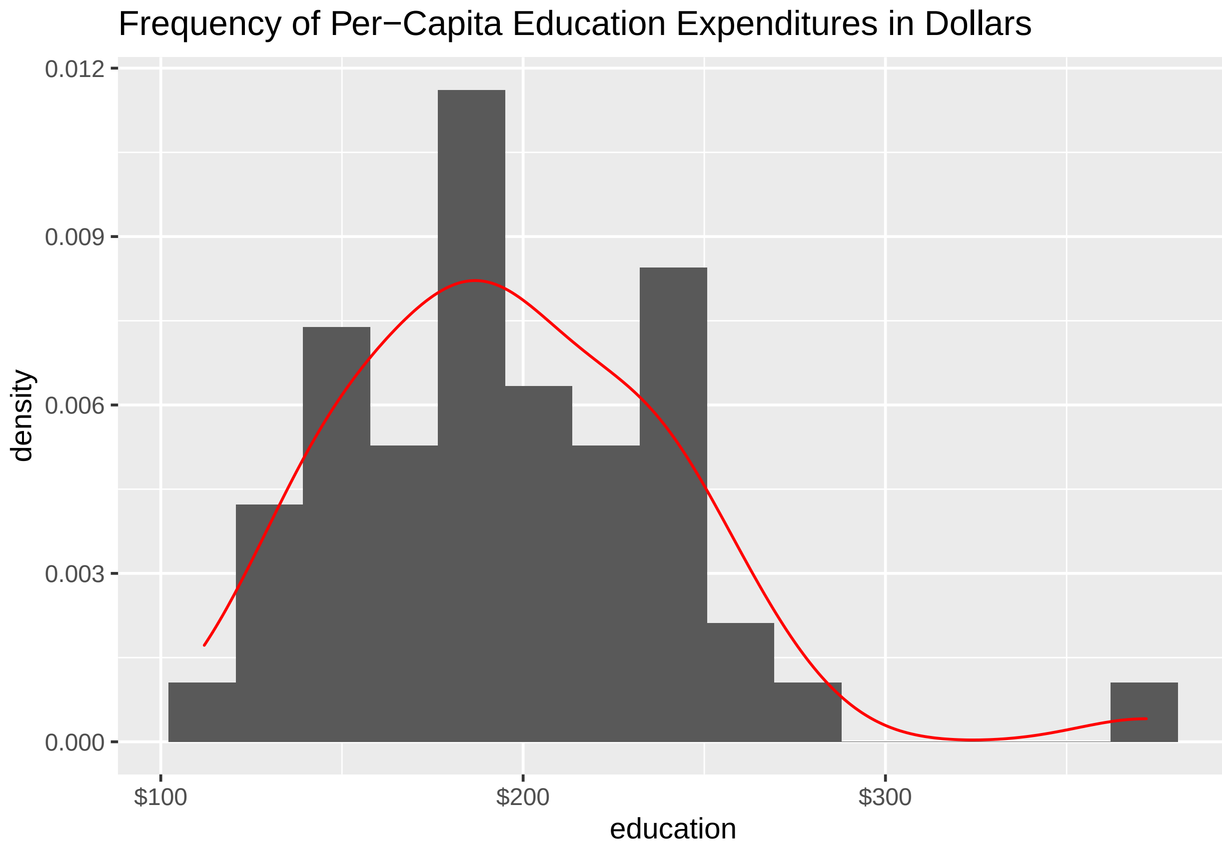
```
## # A tibble: 1 x 1
##   `percent_decimal(max(UrbanPop, na.rm = T))`
##                                         <dbl>
## 1                                        0.91
```

```r
# gt_tbl <- gt(data3 %>% group_by(lh_UrbanPop) %>%
# summarize(counts=n())) gt_tbl
```

To start off, the data was arranged based on income. Then, it was filtered for certain variables, selected for other variables, and mutated for certain values. All of this was done to better understand the relationship (and if there was one or not) between crime rates and income/education. A new categorical variable was created that sorted the data into high and low urbanpop percentages. Later, the data was grouped by the new categorical variable that was created and it was also used in the summaries in which, mean, median, max, min, and standard deviation values were determined for each variable. The counts for the low and high urbanpop was also determined. One table was also styled with a gt package. A new function was also created to help with making sense of the data more. Byfar, the most interesting finding was that a larger than expected amount of the U.S. population lived in urban areas). Another interesting finding was that, there is one state where .91 out of 1 of the population lives in Urban areas (noted as a decimal), and this is indicated by the function that was created.

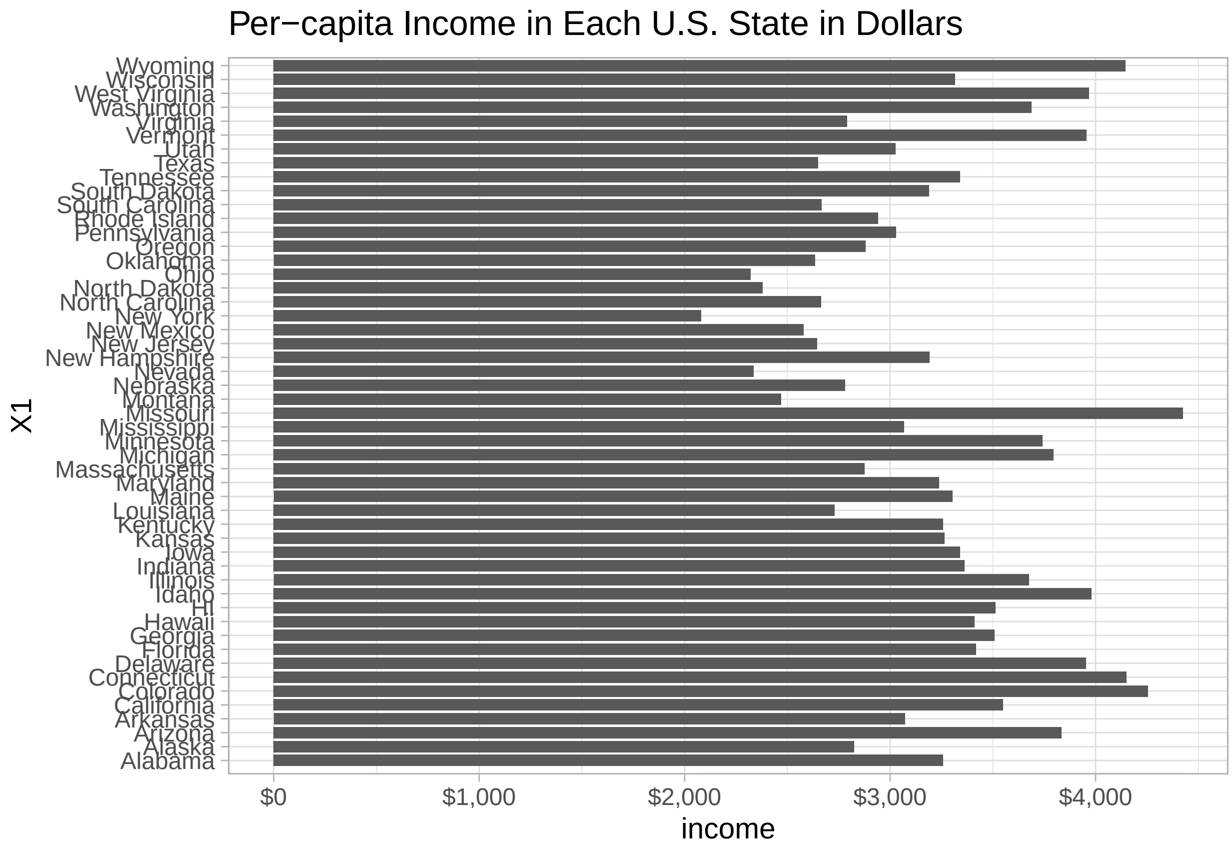
```r
ggplot(data3, aes(x = education)) + geom_histogram(aes(y = ..density..),
    bins = 15) + geom_density(color = "red") + theme_grey() +
    scale_x_continuous(labels = scales::dollar) + ggtitle("Frequency of Per-Capita Education Expenditure
```

Visualizing



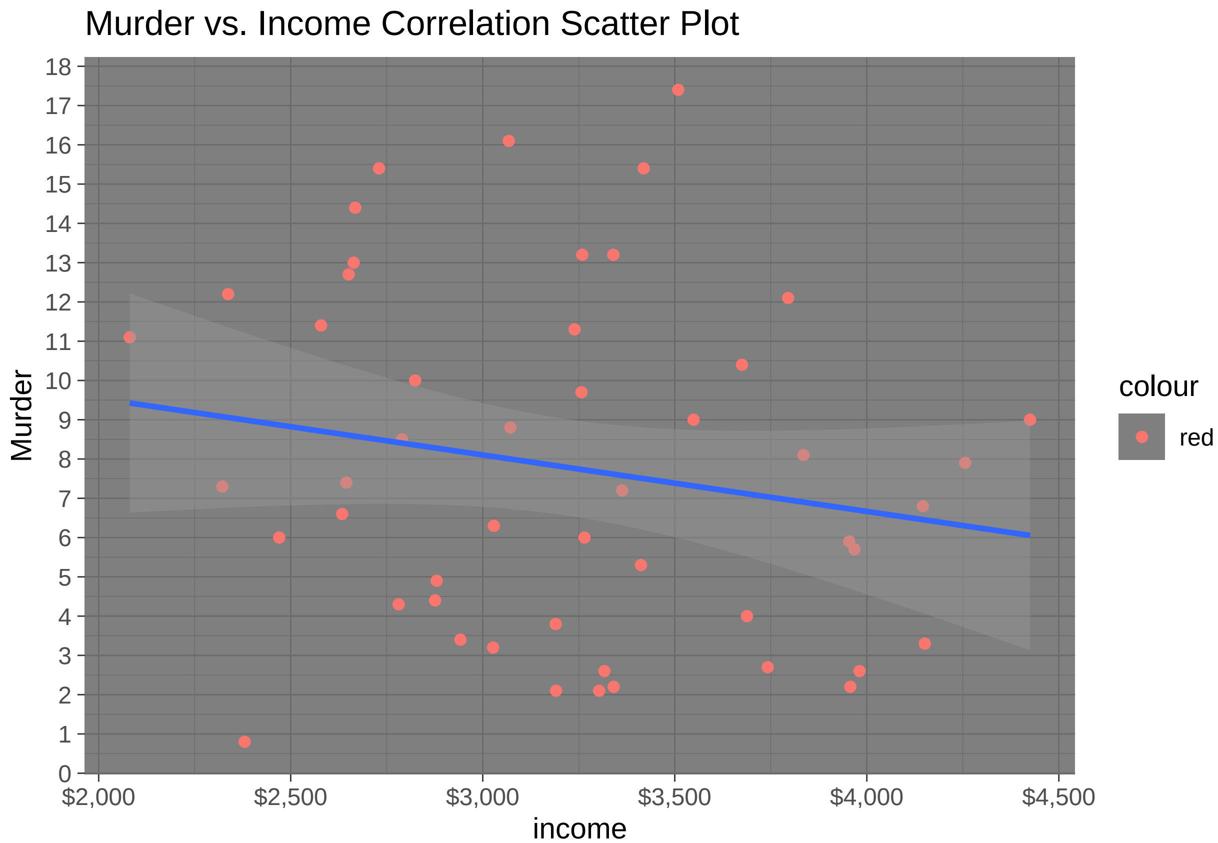
The plot depicts the amount of money that was spent per-capita on education in dollars. The relationships/trends that are apparent from this histograpm and density line is that most people did not spend as much on education and that the majority spent around $180. The plot shows mainly a normal distribution bell curve with a potential outlier to the far right. Overall, this plot indicates that the majority of the population spends similar amounts of money towards education relative to one another.

```
ggplot(data3, aes(x = income)) + geom_bar(aes(y = X1), stat = "summary",
    width = 0.8) + geom_density() + theme_light() + scale_x_continuous(labels = scales::dollar) +
    ggtitle("Per-capita Income in Each U.S. State in Dollars")
```



The barplot shown above depicts income per-capita, in dollars, in each U.S. state. There is no apparent trend or relationship shown from this plot. It is only apparent that some states have a much higher per-capita income than other states. This just shows the variations of incomes between different states.

```
ggplot(data = data3, aes(x = income, y = Murder)) + geom_point(aes(color = "red")) +
    geom_smooth(method = "lm") + theme_dark() + scale_x_continuous(labels = scales::dollar) +
    scale_y_continuous(breaks = seq(0, 18, 1)) + ggtitle("Murder vs. Income Correlation Scatter Plot")
```



The scatterplot above shows the correlation between murder and income. Based on the plot, it is apparent that there is no correlation between the two variables. There is no obvious relationship as the values for income and murder for each state is mainly scattered. The trendline also shows that there is no positive or negative linear relationship.

Concluding Remarks We cannot conclude anything from this data in regards to the relation between education/income values and crime rates. There does not seem to be an apparent relationship from the data that was collected, so there cannot be a conclusion or generalization made from it.