Problem Set 7

Daniel Shapiro

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Question 1 Background:

Download the dataset `quartet.dta` *from the course website.*

1a) Load the dataset. The file is in a format compatible with Stata, but not with base R. Google how to load .dta files in R.

```
dataset <- read_dta("quartet.dta")
```

1b) Regress each y on its corresponding x (e.g., $y1$ on $x1$, $y2$ on $x2$) using the `lm()` command. Using stargazer, present the results in a nicely formatted table. Interpret the regression coefficients.

```
reg1 <- lm(`y1` ~ `x1`, data = dataset)
reg2 <- lm(`y2` ~ `x2`, data = dataset)
reg3 <- lm(`y3` ~ `x3`, data = dataset)
reg4 <- lm(`y4` ~ `x4`, data = dataset)

sum1 <- summary(reg1)
sum2 <- summary(reg2)
sum3 <- summary(reg3)
sum4 <- summary(reg4)

stargazer(reg1, reg2, reg3, reg4, type = "text")
```

```
##
## ====================================================================
##                                        Dependent variable:
##                              ---------------------------------------
##                                 y1        y2        y3        y4
##                                 (1)       (2)       (3)       (4)
## --------------------------------------------------------------------
## x1                           0.500***
##                               (0.118)
##
## x2                                     0.500***
##                                         (0.118)
```

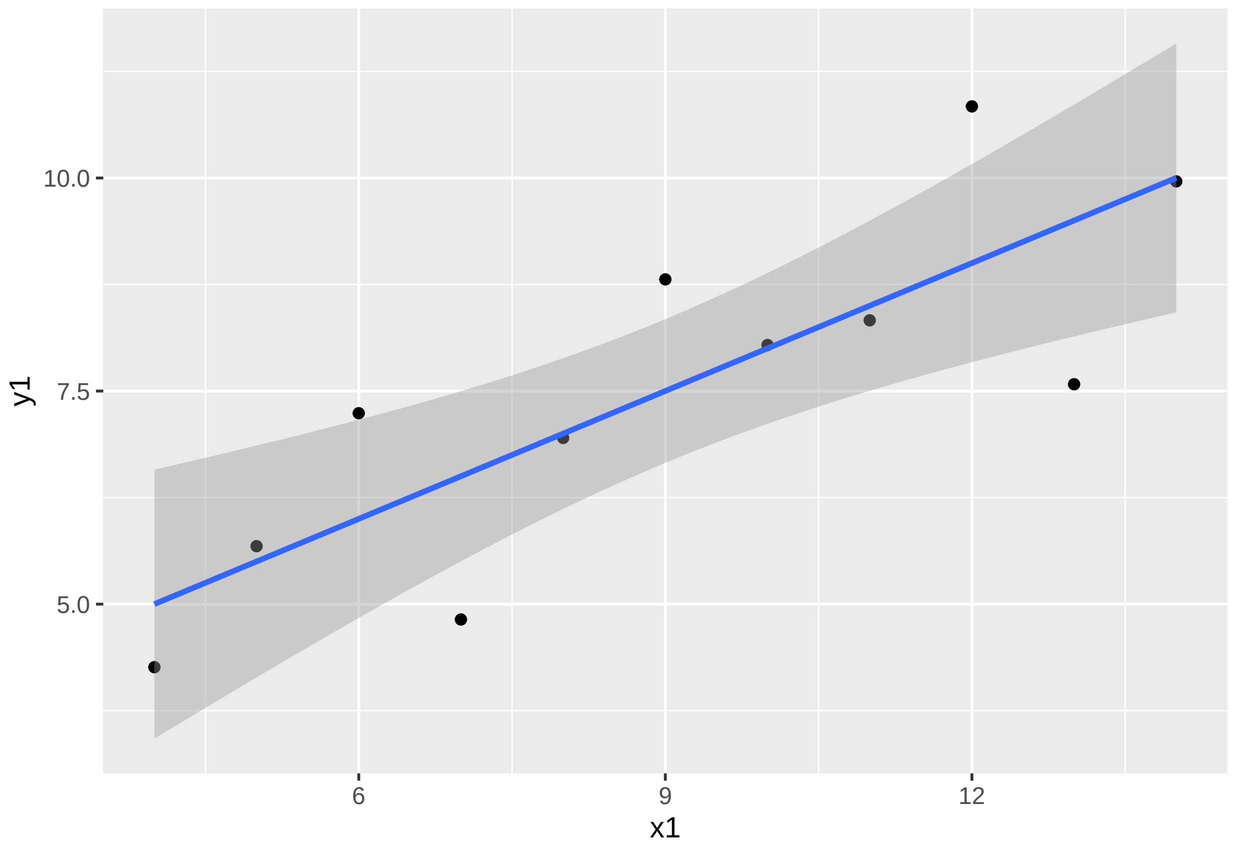
```
##
## x3                                               0.500***
##                                                   (0.118)
##
## x4                                                         0.500***
##                                                             (0.118)
##
## Constant                      3.000**   3.001**   3.002**   3.002**
##                               (1.125)   (1.125)   (1.124)   (1.124)
##
## --------------------------------------------------------------------
## Observations                    11        11        11        11
## R2                             0.667     0.666     0.666     0.667
## Adjusted R2                    0.629     0.629     0.629     0.630
## Residual Std. Error (df = 9)   1.237     1.237     1.236     1.236
## F Statistic (df = 1; 9)      17.990*** 17.966*** 17.972*** 18.003***
## ====================================================================
## Note:                                    *p<0.1; **p<0.05; ***p<0.01
```

This output looks very strange at first glance, given that each relationship has identical coefficients, but it actually ends up making sense once you look at the graphs produced below. Basically, the coefficients indicate that for each unit that x1 increases, y1 increases by around 0.5, and so on and so forth for x2/y2, x3/y3, and x4/y4.

1c) Using ggplot(), produce scatterplots of each y on its corresponding x and add both a linear regression line.

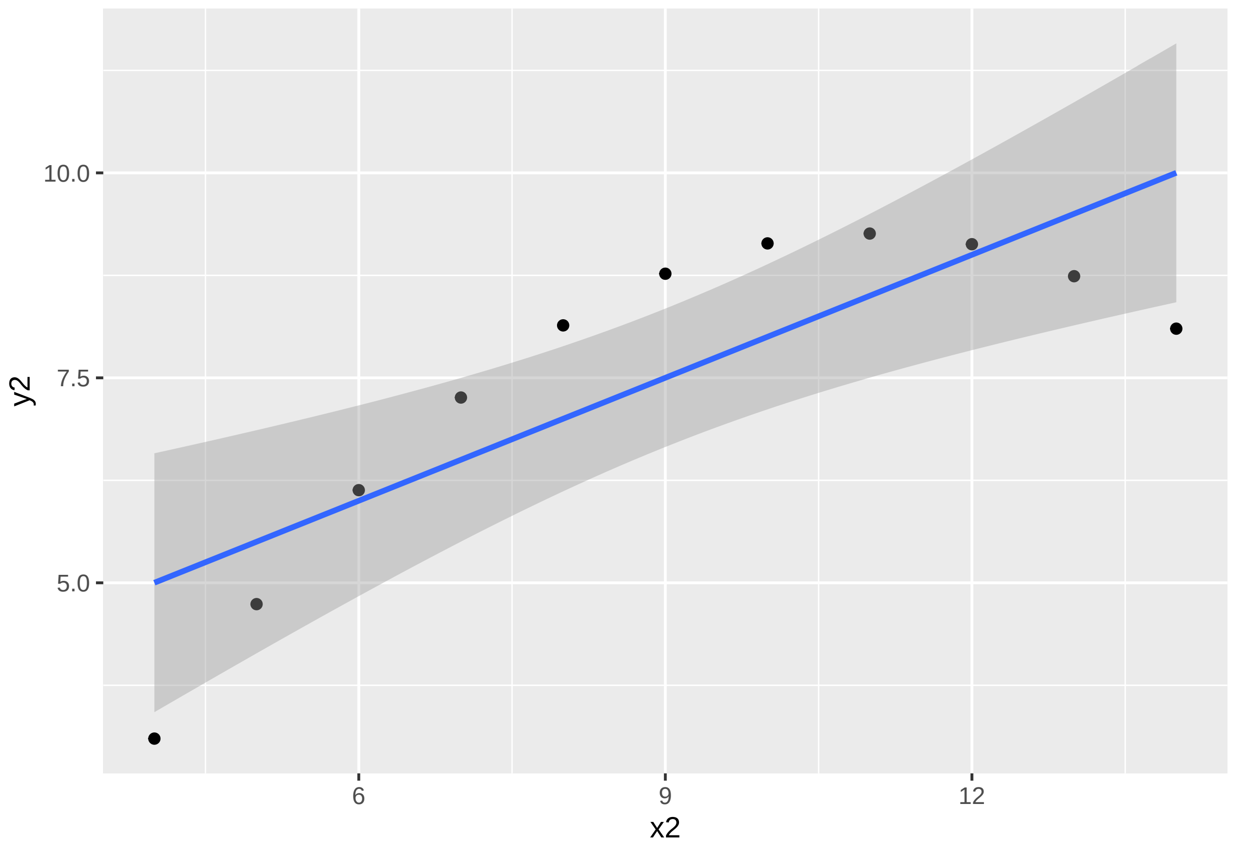
```
ggplot(dataset, aes(x = x1, y = y1)) +
  geom_point() +
  geom_smooth(method = "lm")
```

```
## ‘geom_smooth()‘ using formula ’y ~ x’
```



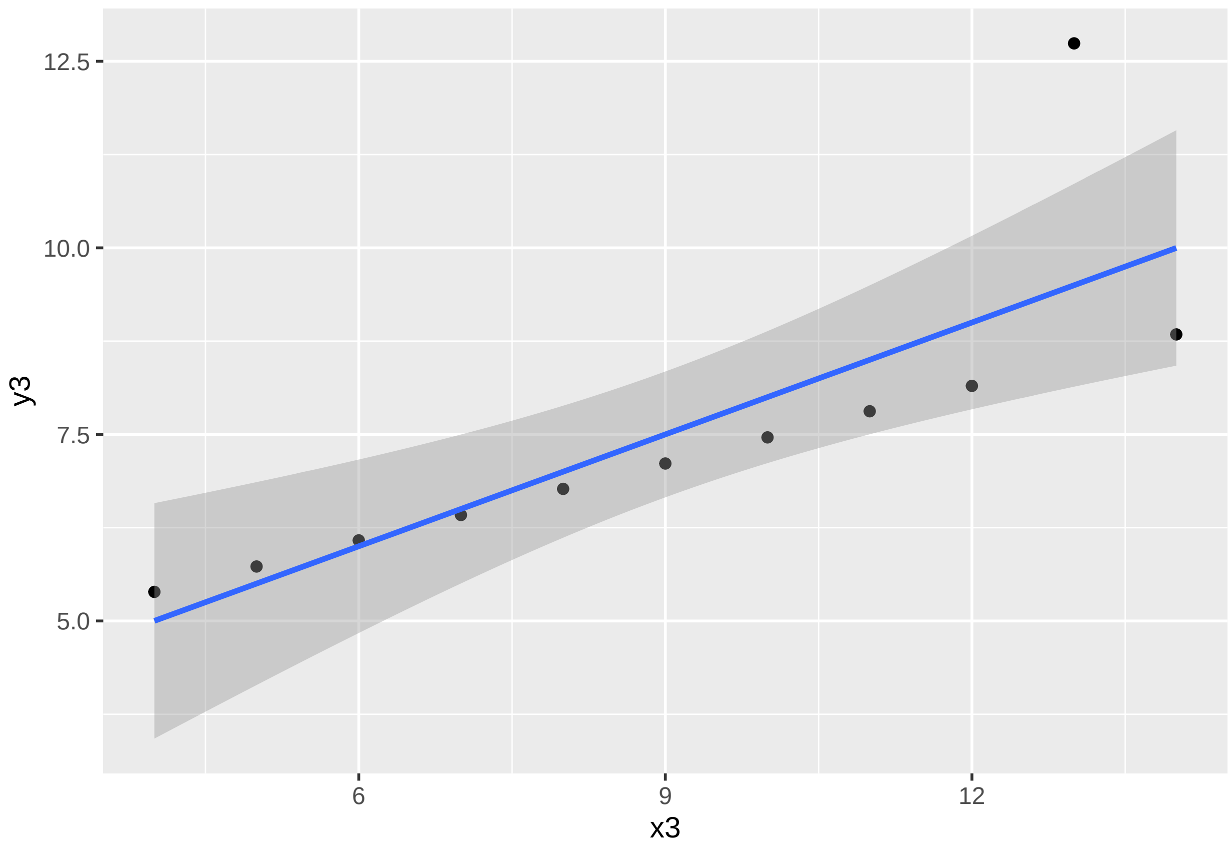
```
ggplot(dataset, aes(x = x2, y = y2)) +
  geom_point() +
  geom_smooth(method = "lm")
```

```
## ‘geom_smooth()‘ using formula ’y ~ x’
```



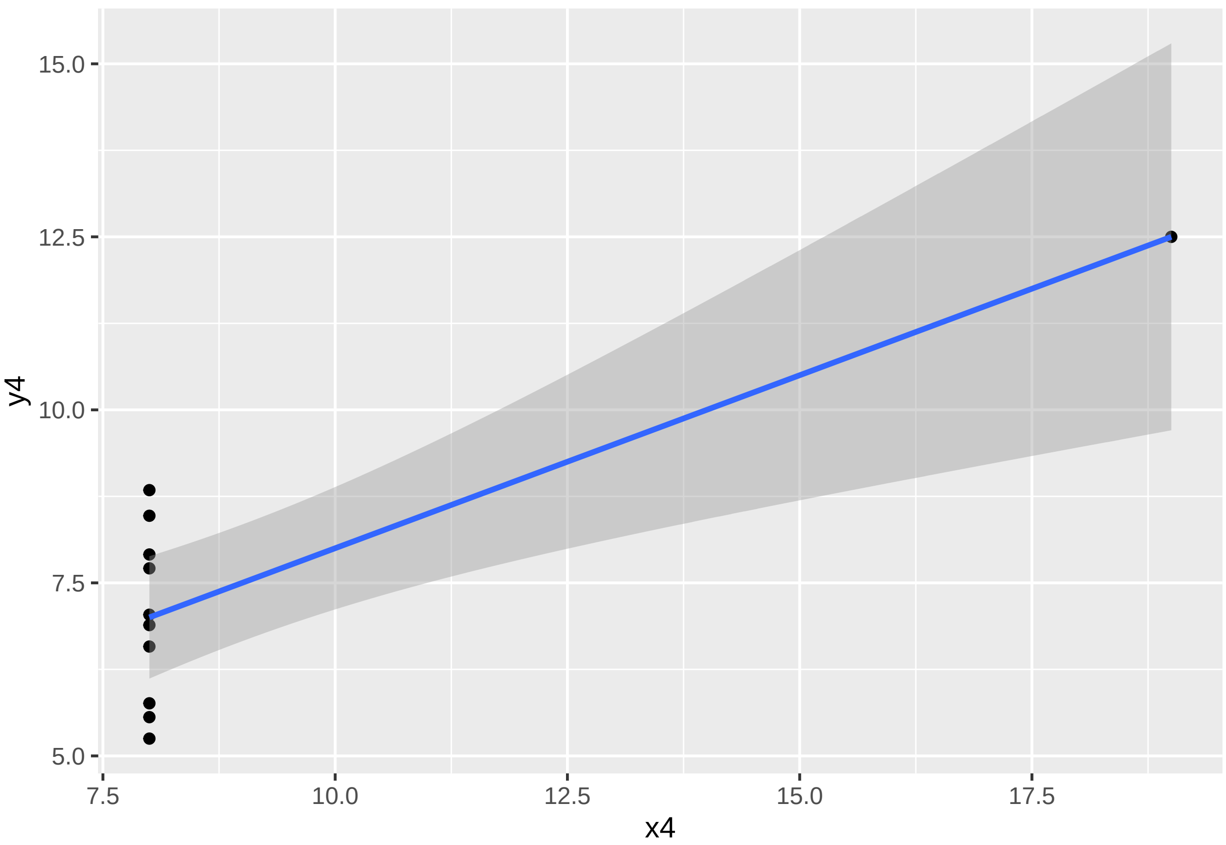
```
ggplot(dataset, aes(x = x3, y = y3)) +
  geom_point() +
  geom_smooth(method = "lm")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



```r
ggplot(dataset, aes(x = x4, y = y4)) +
  geom_point() +
  geom_smooth(method = "lm")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



1d) What can you conclude about the use of regression (or other fancy statistical techniques) from this example?

Well, it's certainly not an infallible technique. These regressions technically all have the same coefficient, but the respective graphs of the variables' relationships look completely different from one another. In order to truly understand the nature of the data and the relationship between two variables, you need to do some additional analysis and remember that even if some relationships have the same coefficients, it doesn't necessarily mean that the relationship truly looks the same.

Question 2 Background:

Let's explore some data on expenditures for households in Pakistan. The data in `pakistan.dta` *on the course website come from a nationally representative sample of households in Pakistan in 1995. Each of the n observations pertainst to a household i. Variable definitions are as follows (all monetary figures are in 1995 rupees):*

- totexp: Total monthly household expenditures (in rupees)
- food: Total monthly household expenditures on food (in rupees)
- hhincome: Total monthly household income (in thousands of rupees)
- nfkids: number of female children in the household
- nmkids: number of male kids in the household

- nfadult: number of female adults in the household
- nmadult: number of male adults in the household

2a) Engel's Law states that as households become richer, they spend a smaller percent of their total budget on food. Run a regression of the percent of total household expenditure on food (call it y) on household income per capita (call it x) using the `lm` command (see help file for how to structure your argument). Use `stargazer` to present your results in a nicely formatted table.

```
seconddata <- read_dta("pakistan.dta")
```

```
# First, I need to make a new data column with the percentage.

seconddata <- seconddata %>%
  mutate(pctfood = food/totexp * 100) %>%

# I divided my totexp by 1000 to make the results more usable.

  mutate(totexp = totexp/1000) %>%

# I have to make a new "percapita" column that takes into account all family members.

  mutate(percapita = hhincome/(nfadult + nmadult + nfkids + nmkids))

percentfood <- lm(pctfood ~ percapita, data = seconddata)

stargazer(percentfood, type = "text")
```

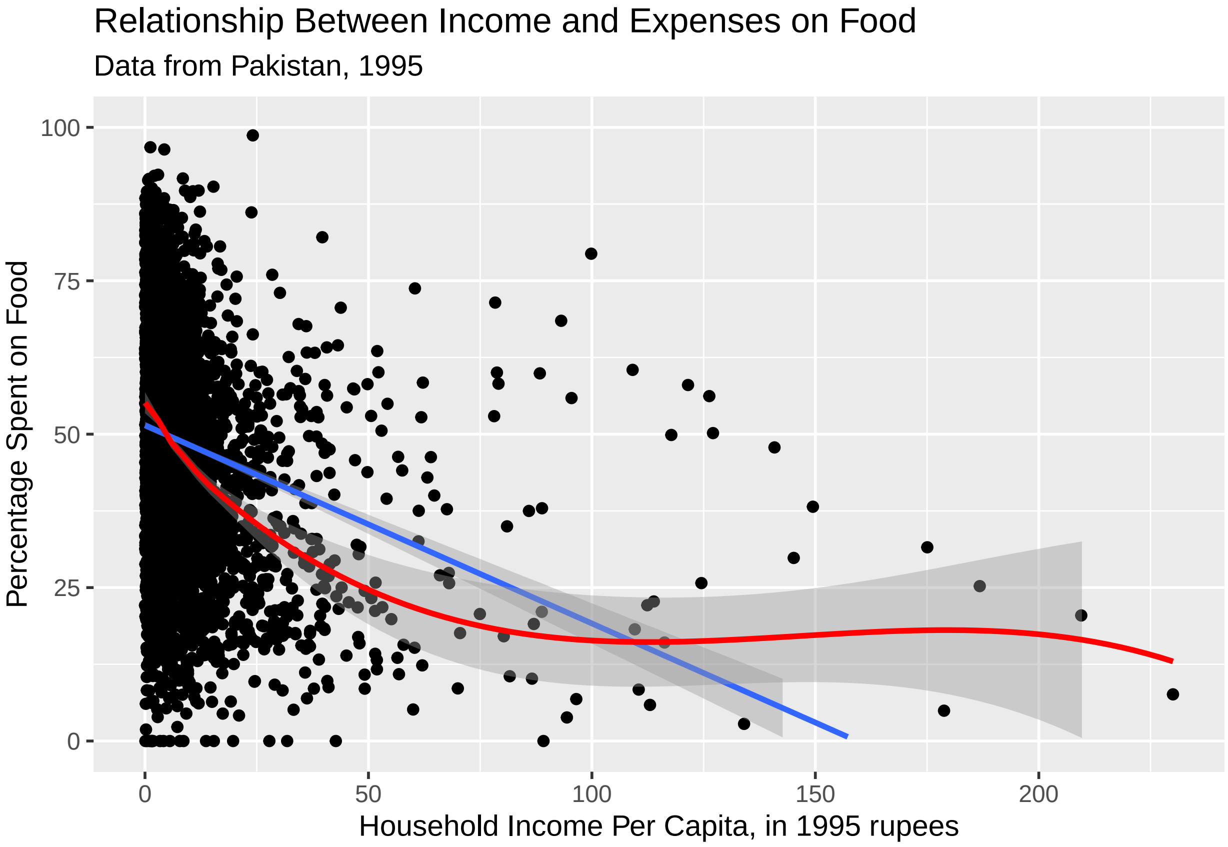
```
##
## ===============================================
##                         Dependent variable:
##                     ---------------------------
##                               pctfood
## -----------------------------------------------
## percapita                    -0.323***
##                               (0.018)
##
## Constant                     51.454***
##                               (0.286)
##
## -----------------------------------------------
## Observations                   4,720
## R2                             0.064
## Adjusted R2                    0.063
## Residual Std. Error     16.950 (df = 4718)
## F Statistic          320.686*** (df = 1; 4718)
## ===============================================
## Note:               *p<0.1; **p<0.05; ***p<0.01
```

2b) Produce a scatterplot of y and x, with a superimposed linear regression line, using ggplot(). Also add a more flexible loess line, in a different color or line style.

```
ggplot(seconddata, aes(x = percapita, y = pctfood)) +
  geom_point() +
  geom_smooth(method = "lm") +
  ylim(0, 100) +
  stat_smooth(method = "loess", color = "red") +
  labs(title = "Relationship Between Income and Expenses on Food",
       subtitle = "Data from Pakistan, 1995",
       x = "Household Income Per Capita, in 1995 rupees",
       y = "Percentage Spent on Food")
```

```
## 'geom_smooth()' using formula 'y ~ x'
## 'geom_smooth()' using formula 'y ~ x'
```

```
## Warning: Removed 25 rows containing missing values (geom_smooth).
```



2c) Interpret the slope coefficient. Does Engel's Law seem to hold?

It does, the slope is negative. In this case, as income increases, the percentage spent on food (in general) decreases.

2d) Interpret the intercept coefficient. Do you have a lot of confidence in this finding? Why or why not?

First, I’m going to pull up the summary of the regression, so that we can see the intercept coefficient.

```
summary(percentfood)
```

```
##
## Call:
## lm(formula = pctfood ~ percapita, data = seconddata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -51.423 -11.708   0.487  12.126  60.200
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 51.45394    0.28642  179.64   <2e-16 ***
## percapita   -0.32296    0.01803  -17.91   <2e-16 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## Residual standard error: 16.95 on 4718 degrees of freedom
## Multiple R-squared:  0.06364,    Adjusted R-squared:  0.06345
## F-statistic: 320.7 on 1 and 4718 DF,  p-value: < 2.2e-16
```

I have no confidence in this finding, because it does not make logical sense. Essentially, the intercept tells us that when a household has a per capita income of 0, they can be expected to spend 50% of their income on food. Needless to say, this makes no logical sense. We should not look at the intercept value as a key part of the model here.

Question 3 Background:

We’re going to look at the relationship between age and income, using the dataset `vote.csv` *from the course website.*

3a) First, run a simple regression of income (y) on age (x) using the `lm` command. What do the results tell you? Briefly, how would you interpret the intercept and slope coefficients?

```
vote <- read.csv("vote.csv")
```

```
aregression <- lm(income ~ age, data = vote)
summary(aregression)
```

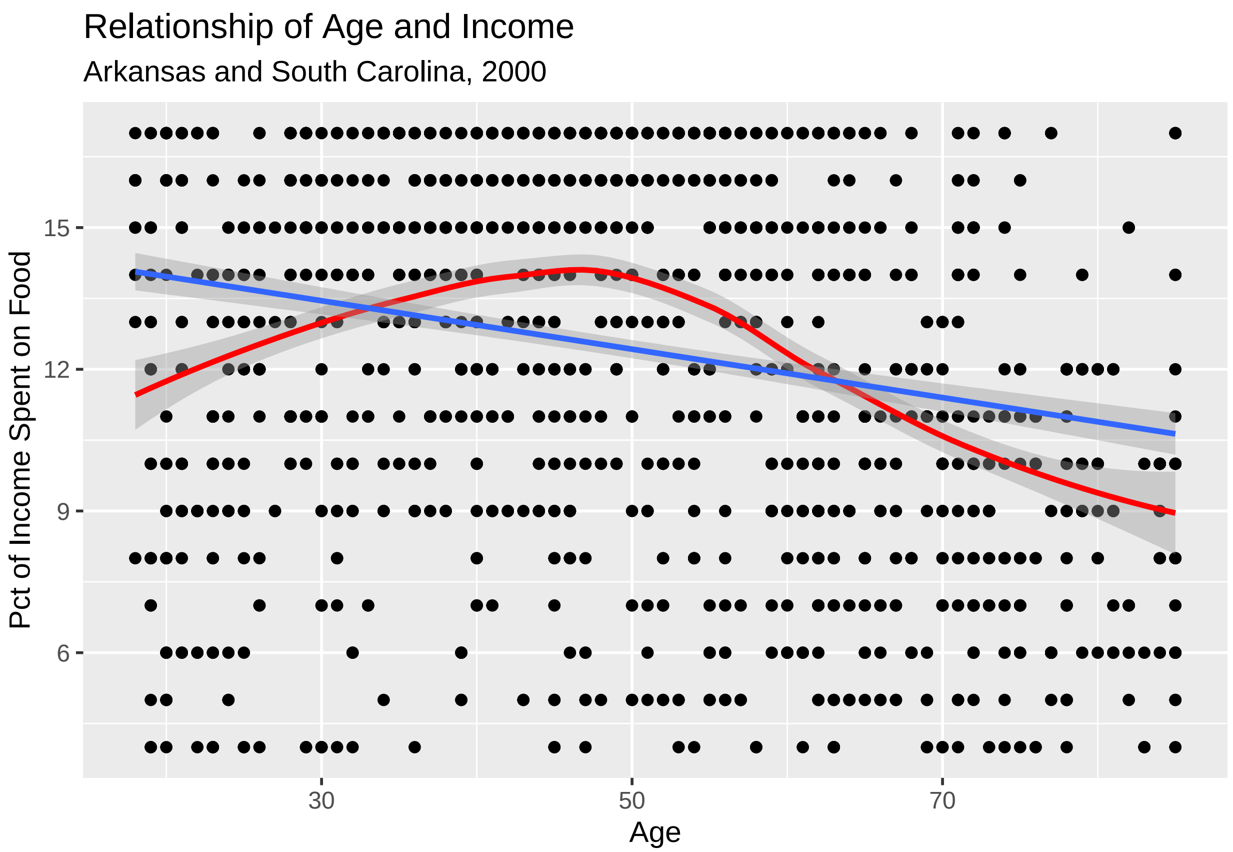
```
##
## Call:
## lm(formula = income ~ age, data = vote)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.0149  -2.7149   0.6514   3.2151   6.3676
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 14.988661   0.294633  50.872   <2e-16 ***
## age         -0.051250   0.005637  -9.091   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.813 on 1498 degrees of freedom
## Multiple R-squared:  0.05229,    Adjusted R-squared:  0.05166
## F-statistic: 82.65 on 1 and 1498 DF,  p-value: < 2.2e-16
```

First, it's worth pointing out that the income variable seems to be some sort of categorical variable that divides income into different levels, which we can't really tell exactly from these data. So we should analyze our results with this factor in mind. The intercept here really isn't helpful, because age is on the x-axis, meaning that this is the value when x = 0, or when age = 0. Presumably, no baby has an income, unless they are very precocious and Arkansas and South Carolina are ignoring their child labor laws. The slope coefficient (-0.051250) essentially means that for each additional year, people in this dataset tend to make about .05% of an income level less, with a high degree of significance.

3b) Create a scatterplot of the data, where age is on the x-axis and income is on the y-axis. Add a line representing the regression line found in part (a), and a more flexibly-fit loess line. What does this tell you about the relationship between age and income?

```
ggplot(vote, aes(x = age, y = income)) +
  geom_point() +
  geom_smooth(method = "loess", color = "red") +
  geom_smooth(method = "lm") +
  labs(x = "Age",
       y = "Pct of Income Spent on Food",
       title = "Relationship of Age and Income",
       subtitle = "Arkansas and South Carolina, 2000")
```

```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```



Including the loess line helps us see a more accurate picture of the trends in this data. Here we see that on average, people don't make too much money when they're 20, but that number gradually increases until they hit about 45 (as they get promoted, advance in their careers, etc.), after which it steadily drops. The relationship between the age and income variables is definitely not linear. I mean, a linear regression line can be fit to it and we can see a general pattern, but it doesn't show us the "true nature" of the data as well as this loess line does.

3c) Let's analyze the data using a different way of presenting the results. First, convert the age variable from a continuous variable into a categorical or factor variable, with the following bins: $18 - 35, 36 - 50, 51 - 65, 66 - 85$**. Produce histograms of the relationship between each age bin and the percent of income spent on food. What do your results suggest?**

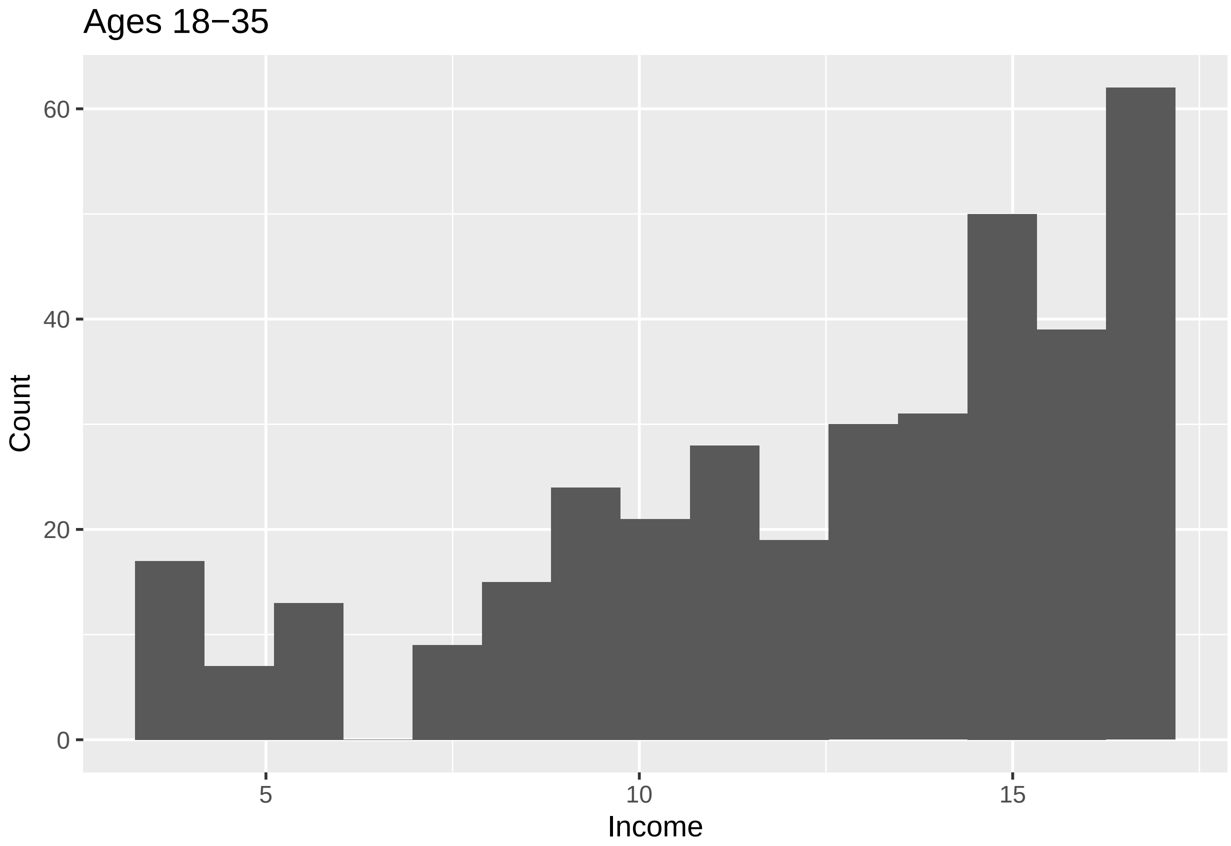
```
# Here, I can use a for loop. First, I have to create a new column.

vote3c <- vote %>%
  mutate(age_categorical = 1)

for(i in 1:1500){
  if(vote3c$age[i] %in% c(66:85)){vote3c$age_categorical[i] <- 4}
  else if(vote3c$age[i] %in% c(51:65)){vote3c$age_categorical[i] <- 3}
  else if(vote3c$age[i] %in% c(36:50)){vote3c$age_categorical[i] <- 2}
  else(vote3c$age_categorical[i] <- 1)
}
```

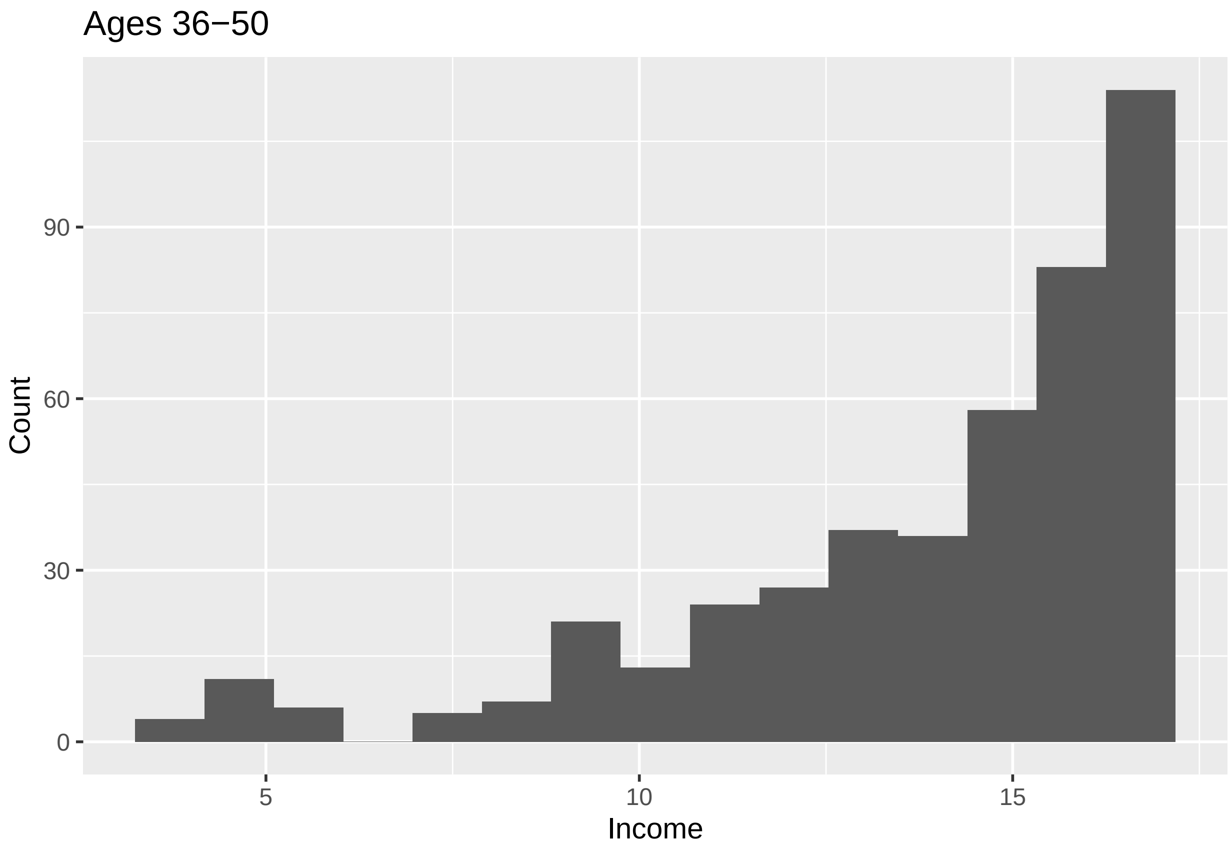
```r
first_histdata <- vote3c %>%
  filter(age_categorical == 1)

ggplot(first_histdata, aes(x = income)) +
  geom_histogram(bins = 15) +
  labs(x = "Income",
       y = "Count",
       title = "Ages 18-35")
```



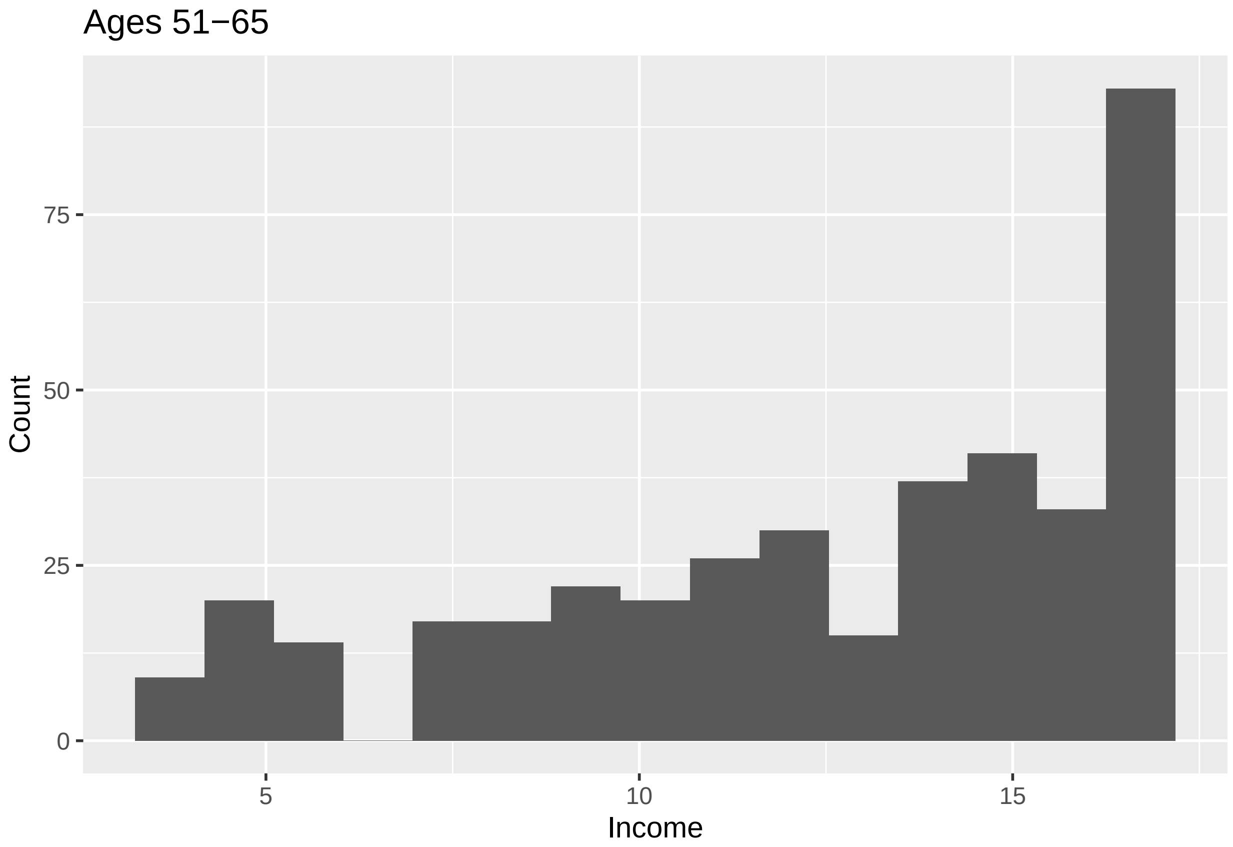
```r
second_histdata <- vote3c %>%
  filter(age_categorical == 2)

ggplot(second_histdata, aes(x = income)) +
  geom_histogram(bins = 15) +
  labs(x = "Income",
       y = "Count",
       title = "Ages 36-50")
```



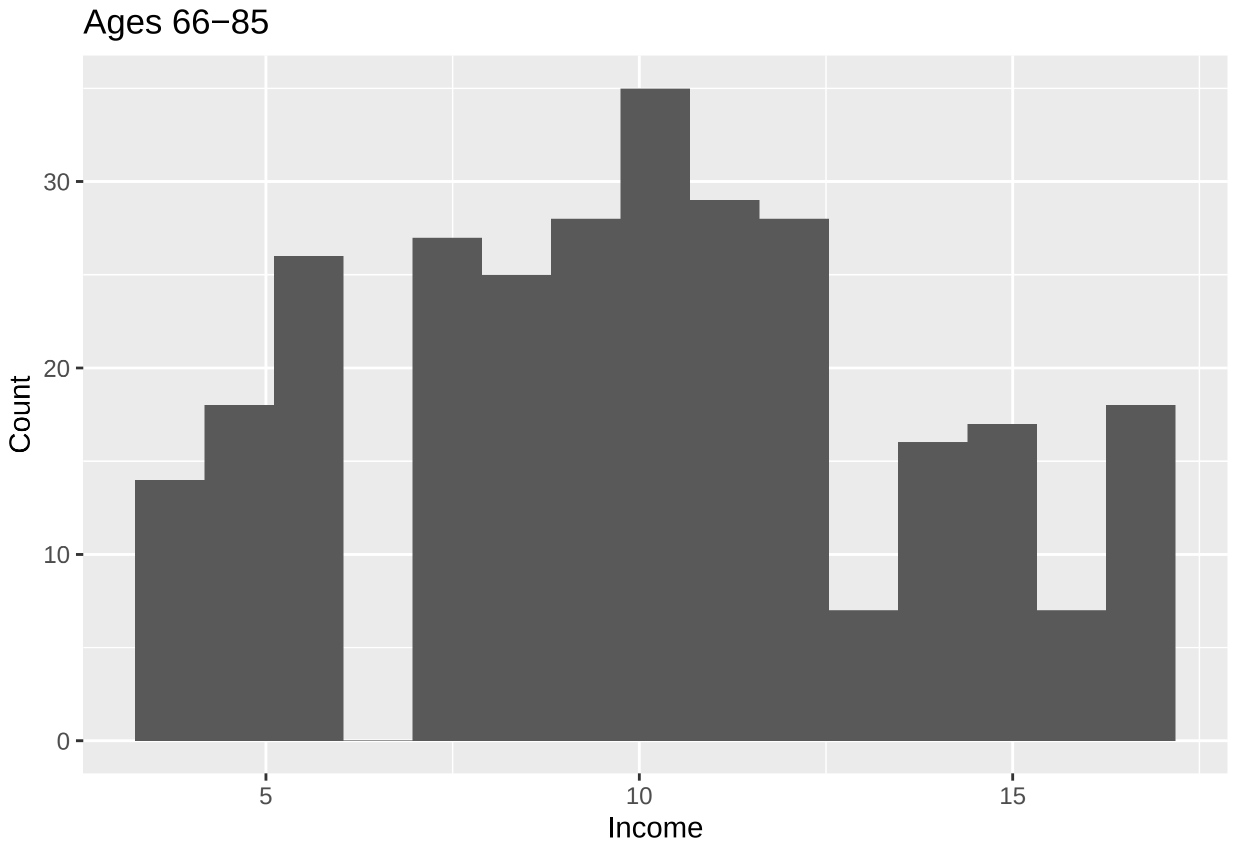
```r
third_histdata <- vote3c %>%
  filter(age_categorical == 3)

ggplot(third_histdata, aes(x = income)) +
  geom_histogram(bins = 15) +
  labs(x = "Income",
       y = "Count",
       title = "Ages 51-65")
```



```
fourth_histdata <- vote3c %>%
  filter(age_categorical == 4)

ggplot(fourth_histdata, aes(x = income)) +
  geom_histogram(bins = 15) +
  labs(x = "Income",
       y = "Count",
       title = "Ages 66-85")
```



This is some interesting data. Generally speaking, people from ages 36-65, the graphs look similar – the quantity of people rises gradually per category until it gets to a certain point and spikes upward. The spike is more dramatic for these two age groups than for people between 18-35, although that age group does have a relatively similar-looking graph to the next two age groups. For people from 66-85, though, the graph looks completely different. The pattern looks more centered around 10 than 15 like in the preceding graphs, and there are results to both the left and right of the maximum. It seems that in general, people ages 66 and above earn less money than others, which makes a certain amount of sense, given that a lot of them are most likely retired.