Assignment2

2025-02-07

```
flint <- read.csv(file = "flint.csv")

#1b
mean(flint$Pb >= 15)
```

```
## [1] 0.04436229
```

```
#1c
mean(flint$Cu[flint$Region == "North"])
```

```
## [1] 44.6424
```

```
#1d
mean(flint$Cu[flint$Pb >= 15])
```

```
## [1] 305.8333
```

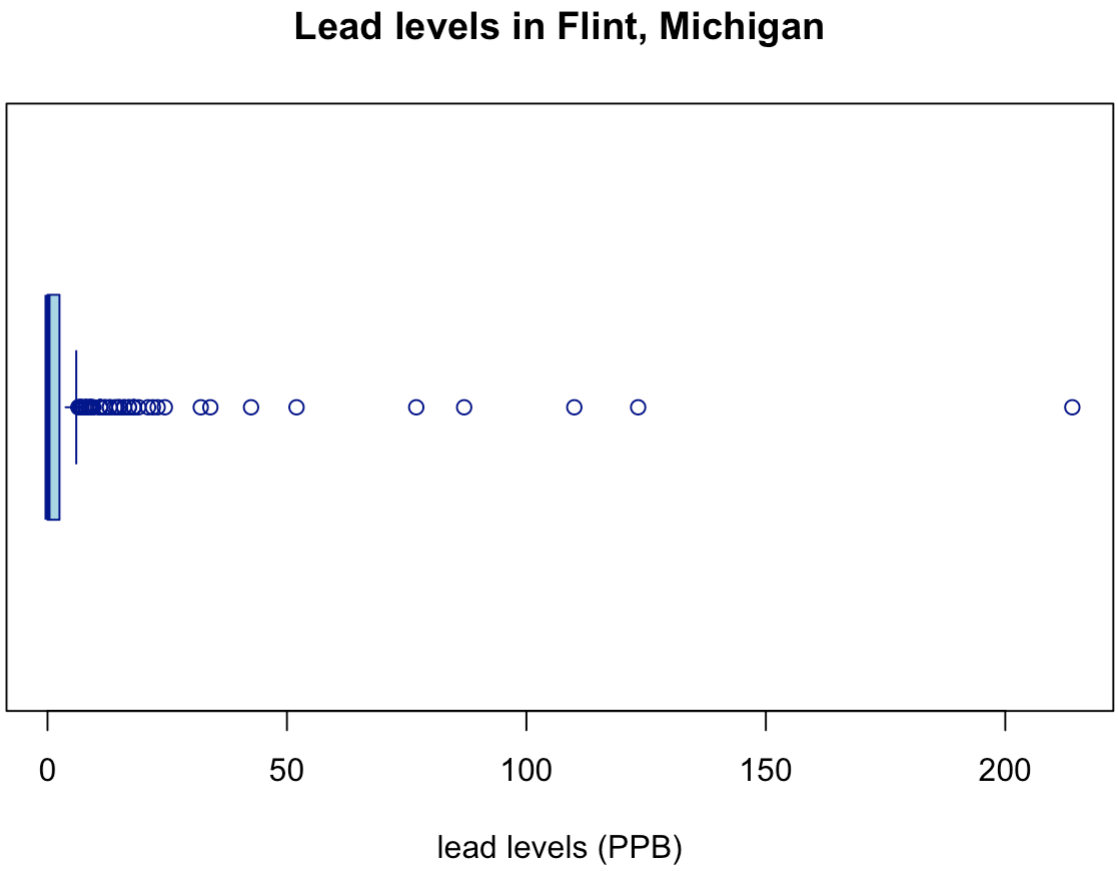
```
#1e
mean(flint$Pb)
```

```
## [1] 3.383272
```

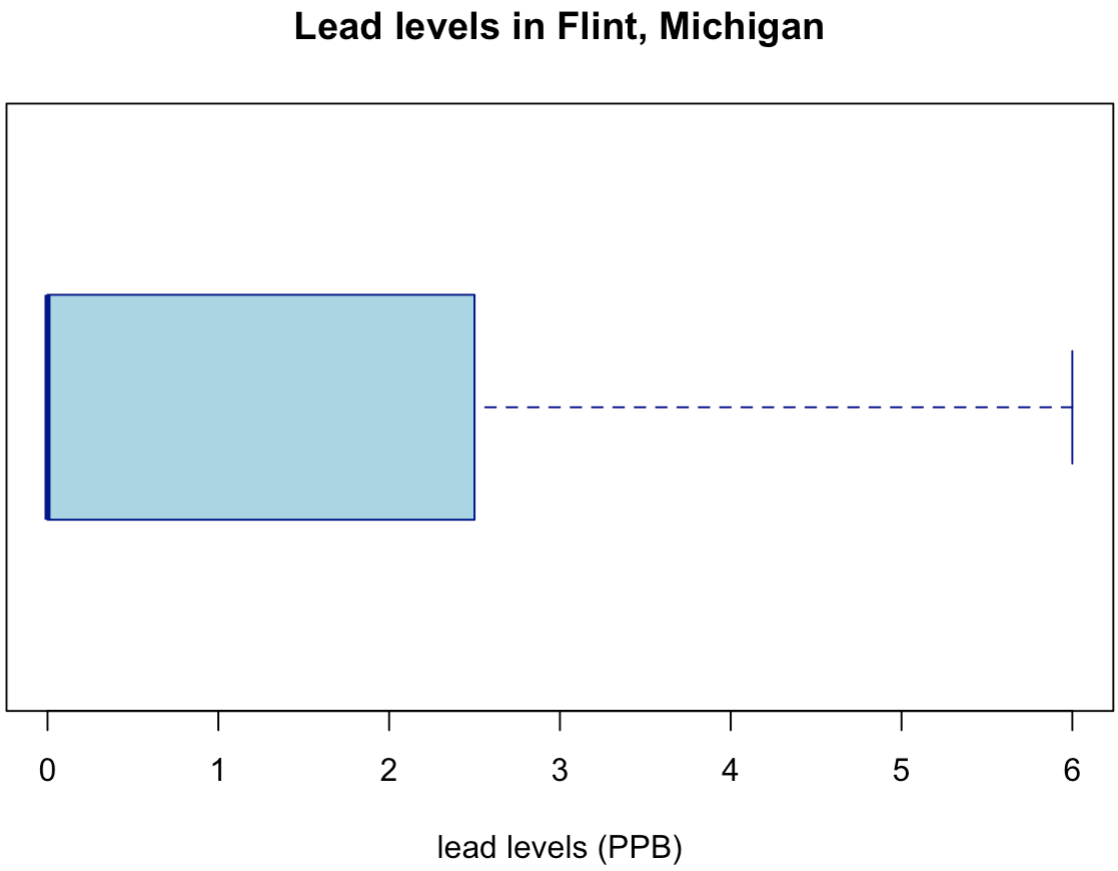
```
mean(flint$Cu)
```

```
## [1] 54.58102
```

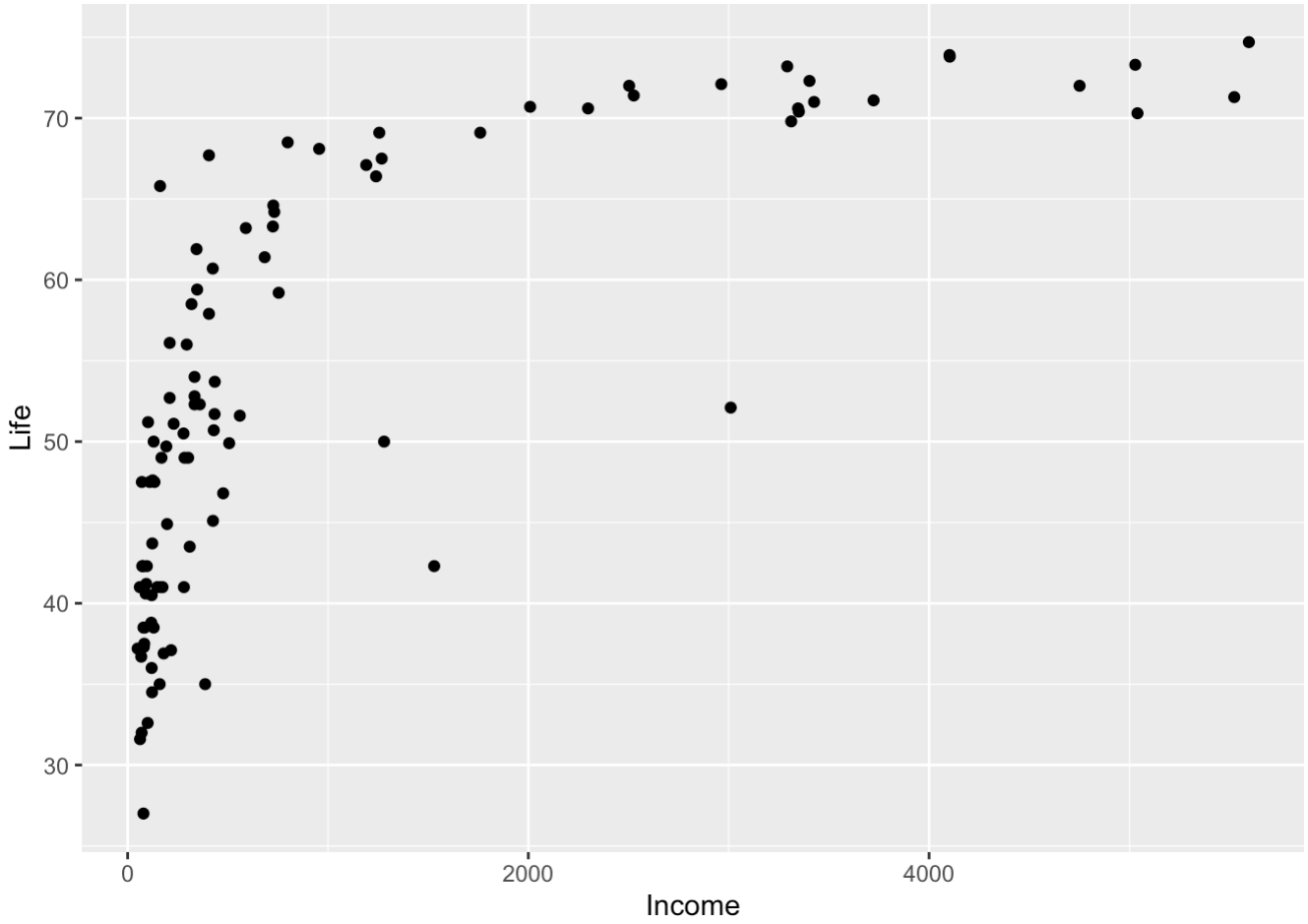
```
#1f
boxplot(flint$Pb,
        main="Lead levels in Flint, Michigan",
        xlab="lead levels (PPB)",
        col="lightblue",
        border="darkblue", outline=TRUE, horizontal=TRUE)
```



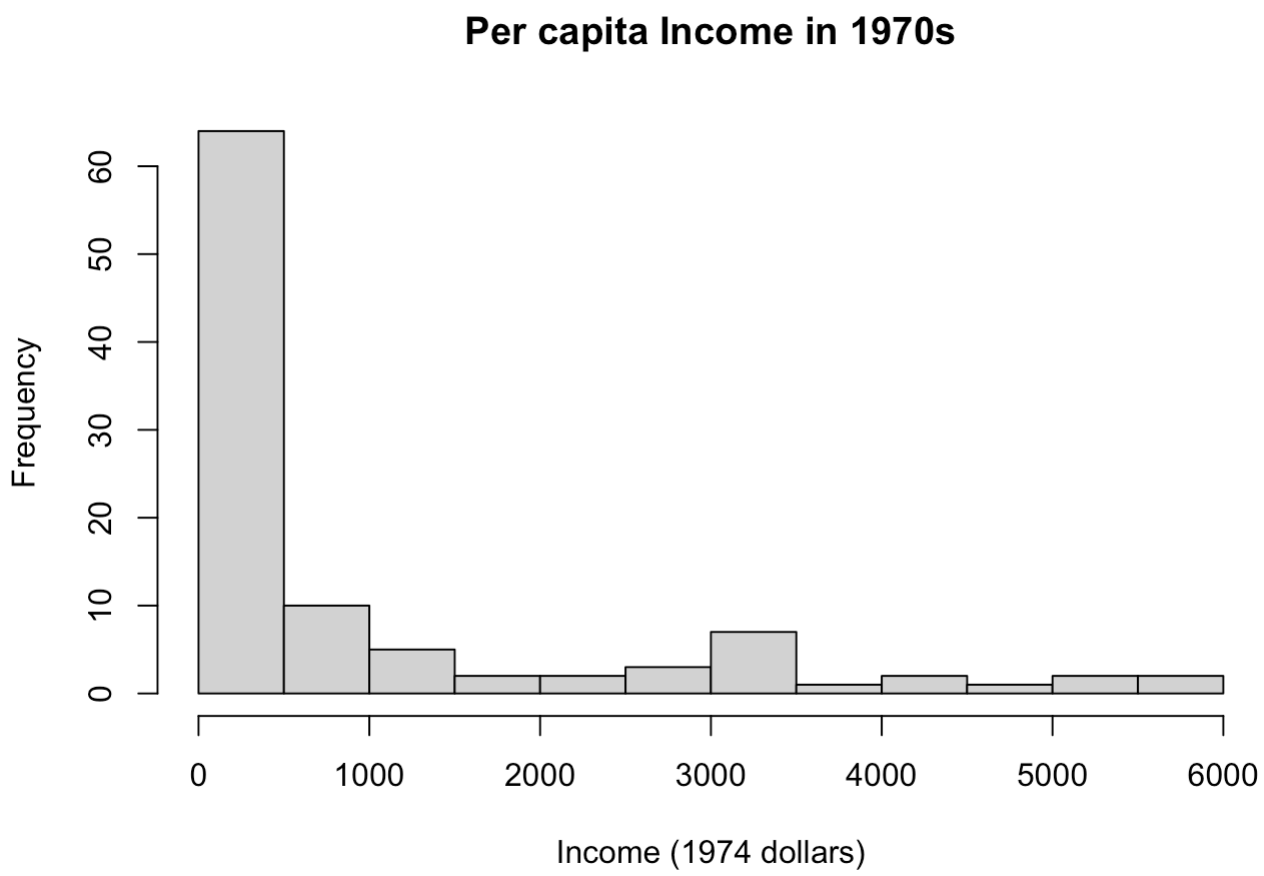

```
#checking the boxplot without the outliers to get a clearer picture
boxplot(flint$Pb,
        main="Lead levels in Flint, Michigan",
        xlab="lead levels (PPB)",
        col="lightblue",
        border="darkblue", outline=FALSE, horizontal=TRUE)
```



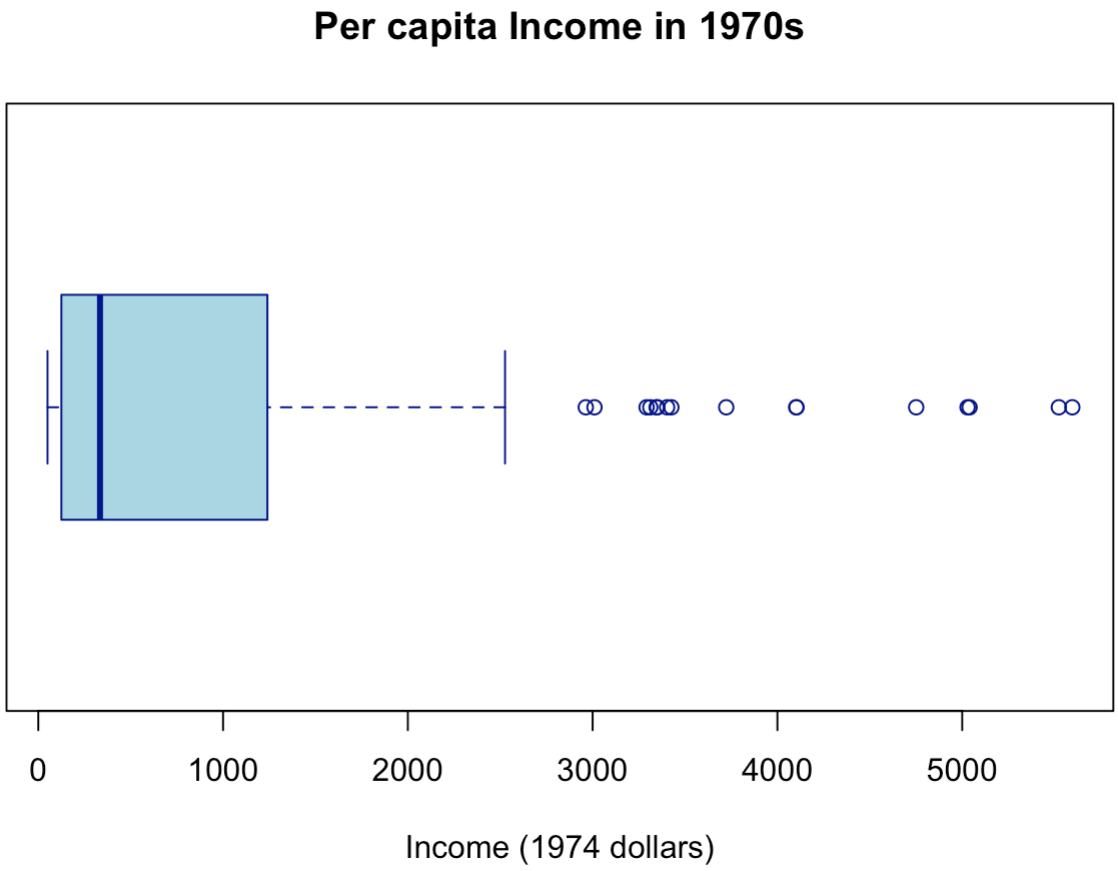

```
#1g
# As we can see in the boxplot the data contains a lot of outliers, i.e. areas
# with a much higher lead level so the mean might not be suitable way to
# measure the data. For skewed data distributions such as this the median tends
# to be a better measure to see the center of the data



#2
life <-read.table(
  "https://ucla.box.com/shared/static/rqk4lc030pabv30wknx2ft9jy848ub9n.txt",
  header = TRUE)
library(ggplot2)

#2a
ggplot(life, aes(x=Income, y=Life)) + geom_point()
```



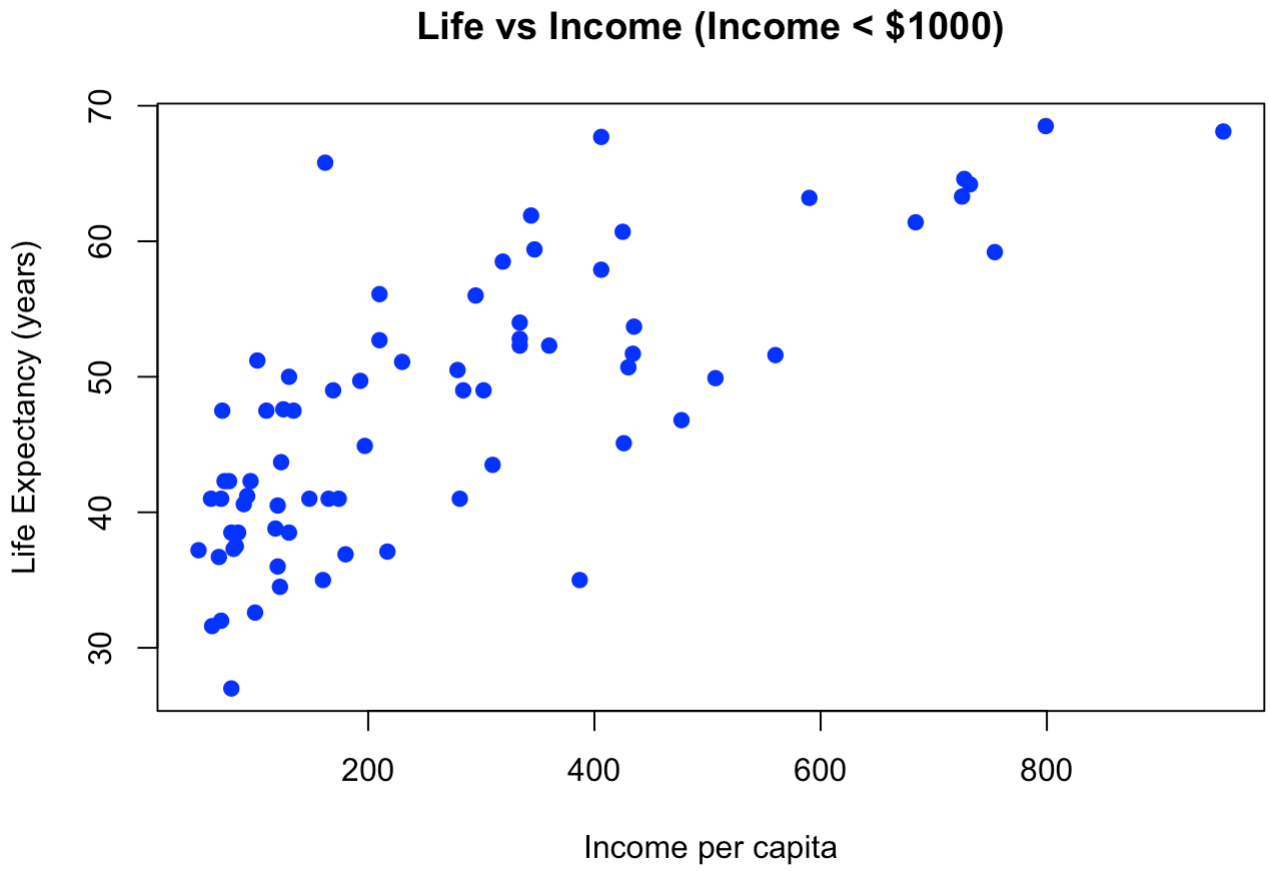

```
# as expected as income increases initially, life expectancy rises very rapidly
# but at a certain point the rate of increase plateaus and as income increases
# life expectancy increases at a much slower rate (this is almost an
# exponential growth)

#2b
hist(life$Income, xlab="Income (1974 dollars)",
     main="Per capita Income in 1970s")
```




```
boxplot(life$Income,
        main="Per capita Income in 1970s",
        xlab="Income (1974 dollars)",
        col="lightblue",
        border="darkblue", outline=TRUE, horizontal=TRUE)
```




```
# as we can see the income levels are highly right skewed. Most of the data
# lies between the 0-500 range but there are a lot of outliers with a much
# higher per capita income () (larger variability)

#2c
income_below_1000 <- life[life$Income < 1000, ]
income_atleast_1000 <- life[life$Income >= 1000, ]

#2d
plot(income_below_1000$Income, income_below_1000$Life,
     main="Life vs Income (Income < $1000)",
     xlab="Income per capita", ylab="Life Expectancy (years)",
     pch=19, col="blue")
```




```
correlation <- cor(income_below_1000$Income, income_below_1000$Life)
correlation
```

```
## [1] 0.752886
```

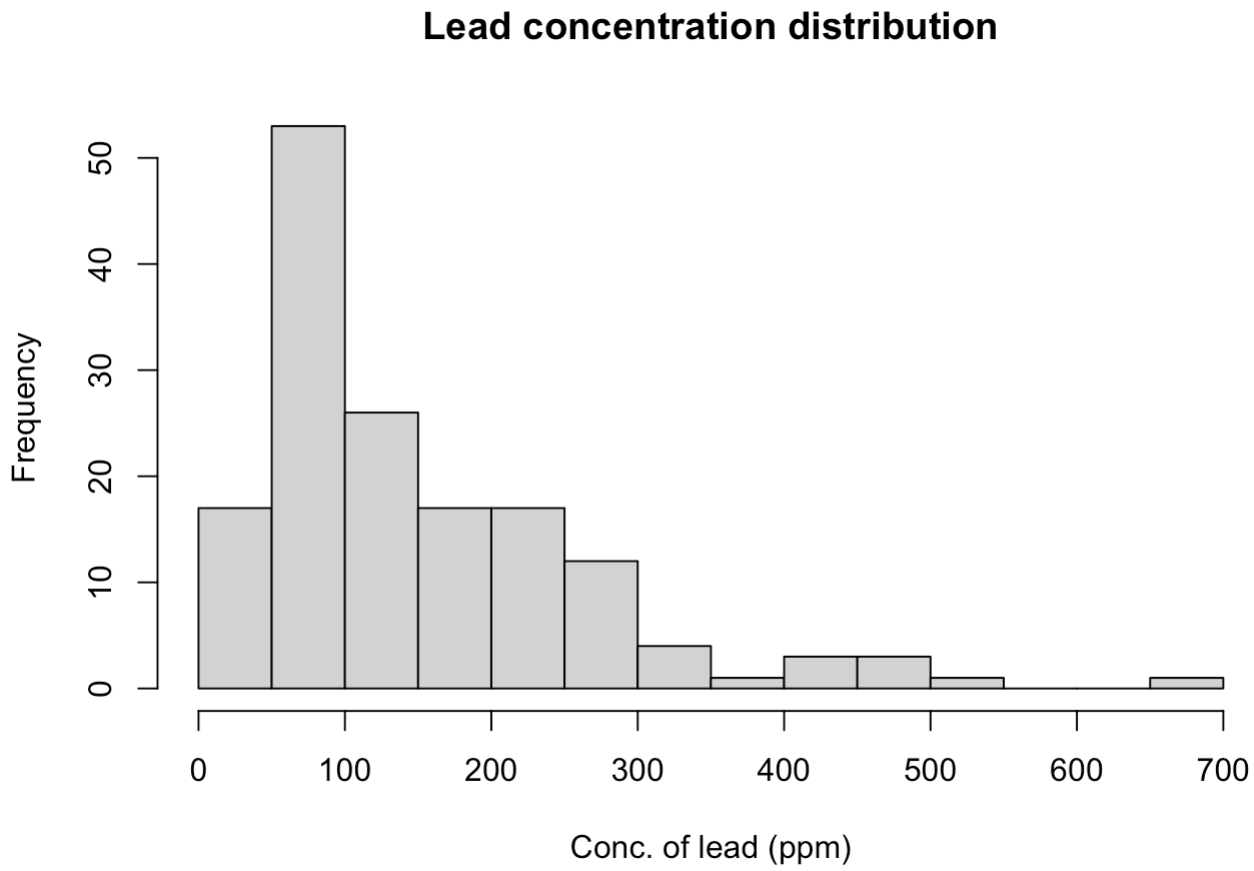
```
#3
maas <- read.table(
  "https://ucla.box.com/shared/static/tv3cxooyp6y8fh6gb0qj2cxihj8klg1h.txt",
  header = TRUE)

#3a
summary(maas$lead)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    37.0    72.5   123.0   153.4   207.0   654.0
```

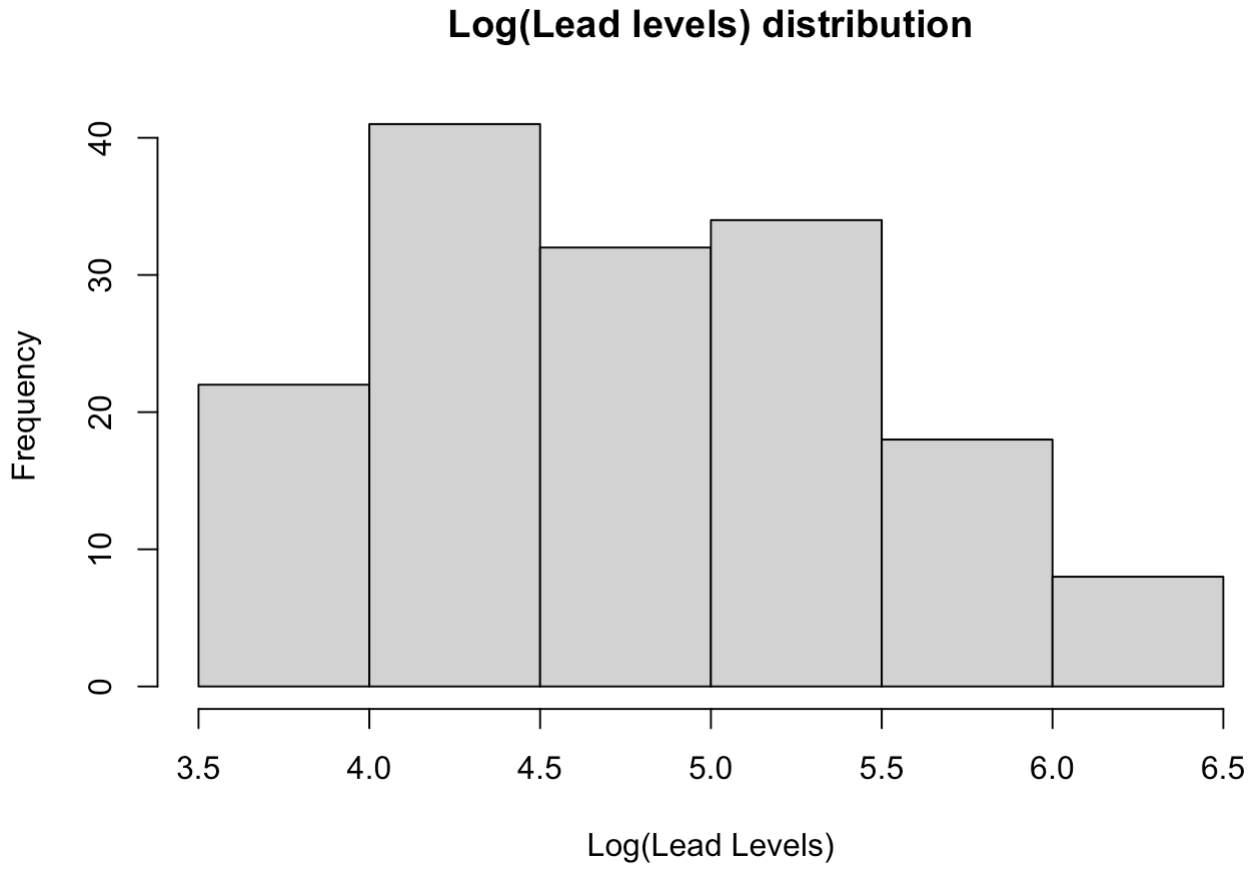
```
summary(maas$zinc)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   113.0   198.0   326.0   469.7   674.5  1839.0
```

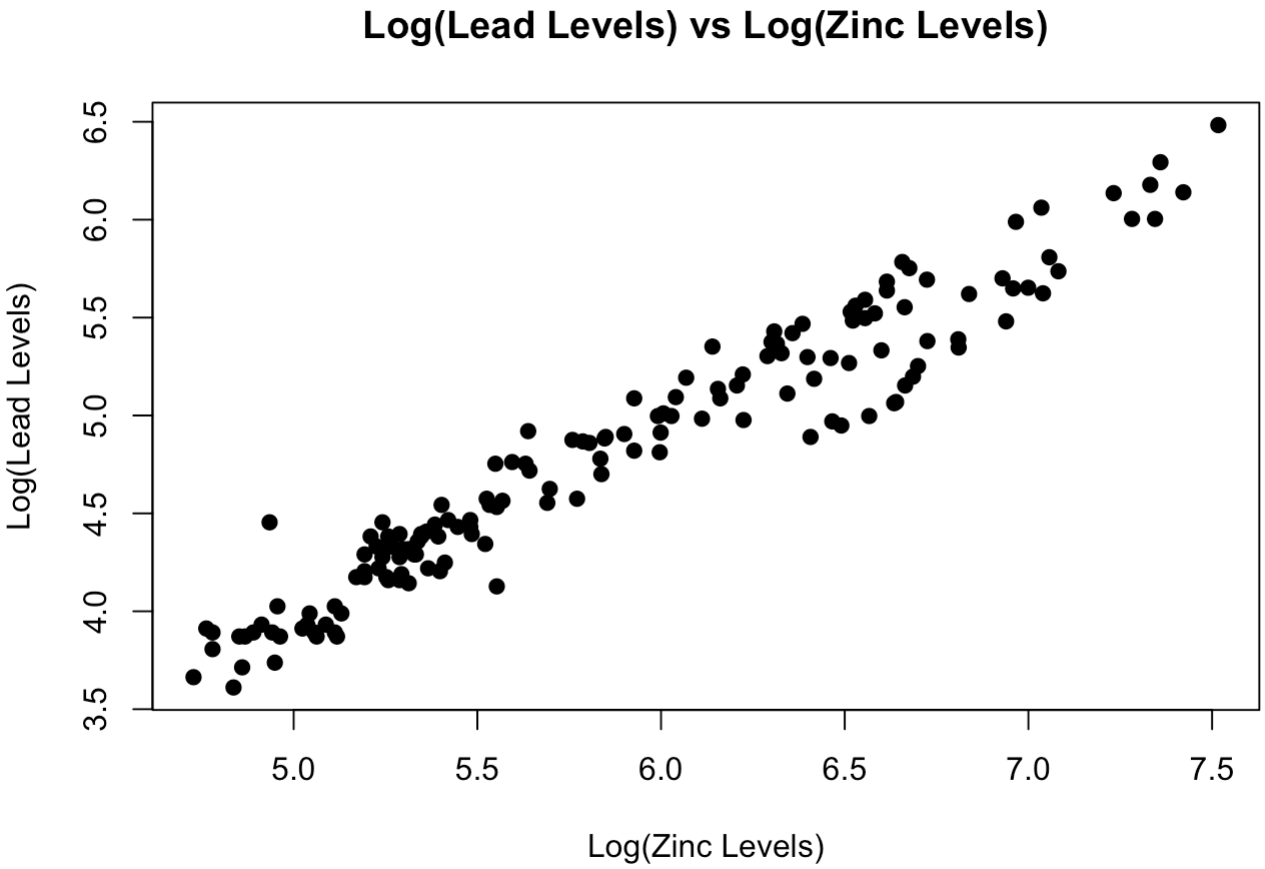
```
#3b
hist(maas$lead, xlab="Conc. of lead (ppm)",
     main="Lead concentration distribution")
```



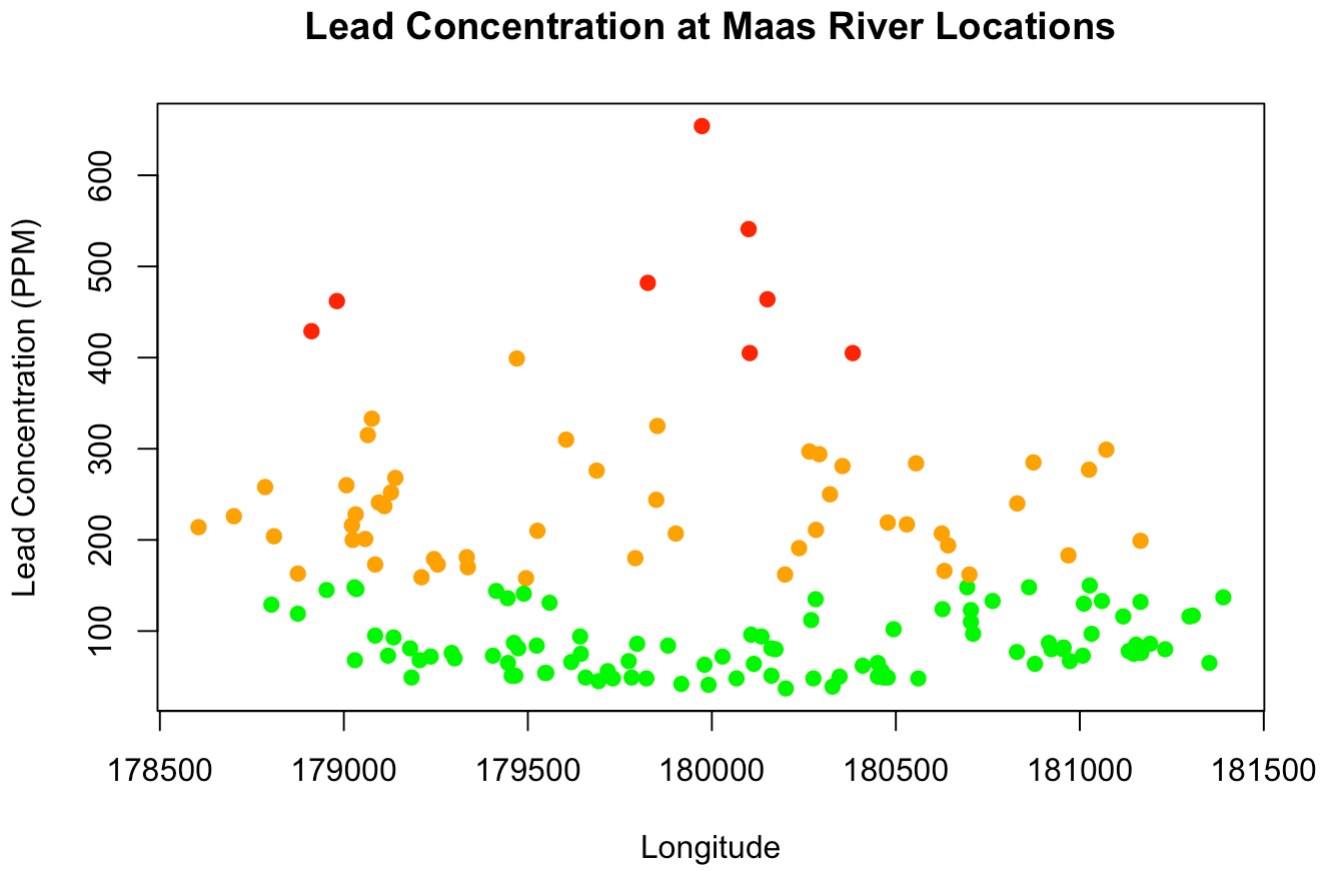

```
hist(log(maas$lead), xlab="Log(Lead Levels)",
     main="Log(Lead levels) distribution")
```



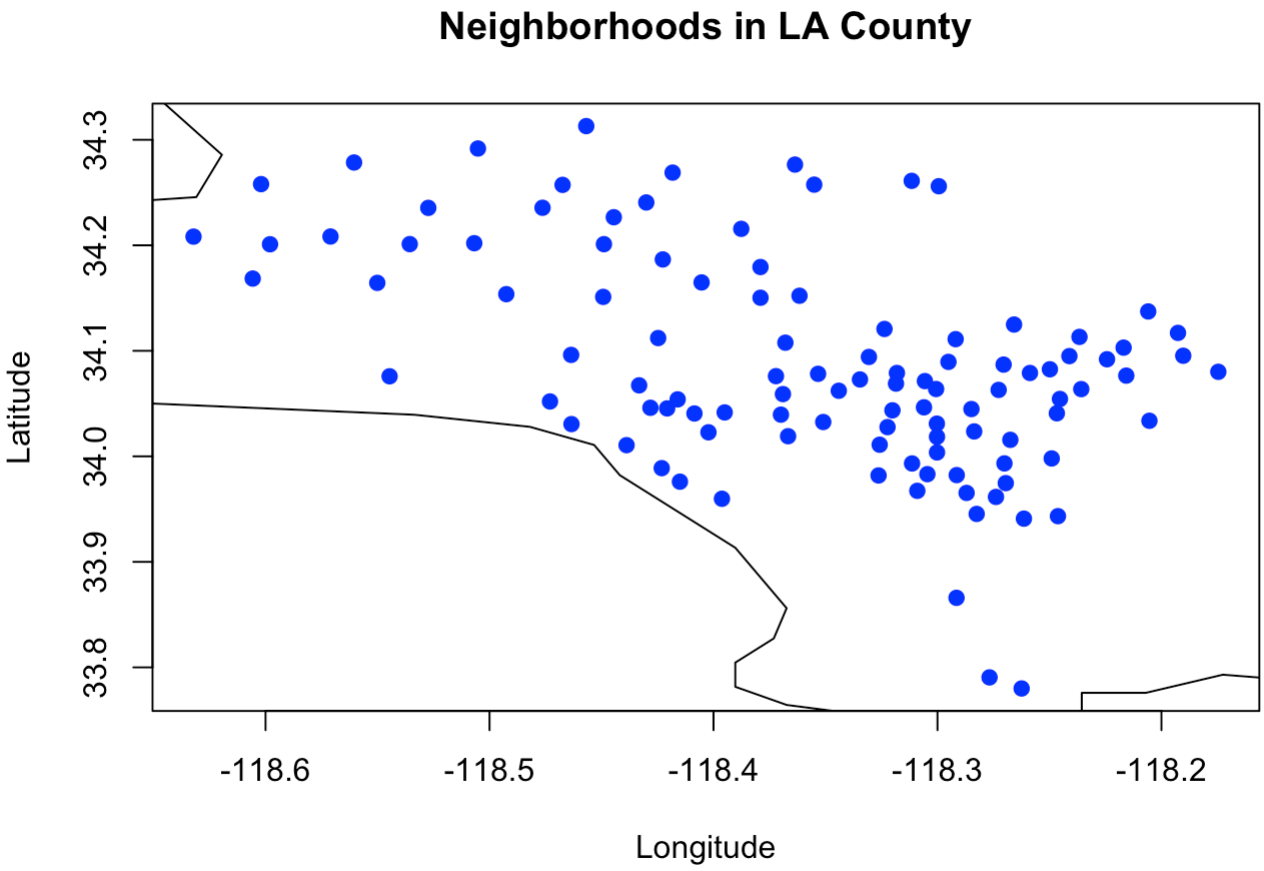
```
#3c
plot(log(maas$zinc), log(maas$lead), pch=19,
     xlab="Log(Zinc Levels)", ylab="Log(Lead Levels)",
     main="Log(Lead Levels) vs Log(Zinc Levels)")
```



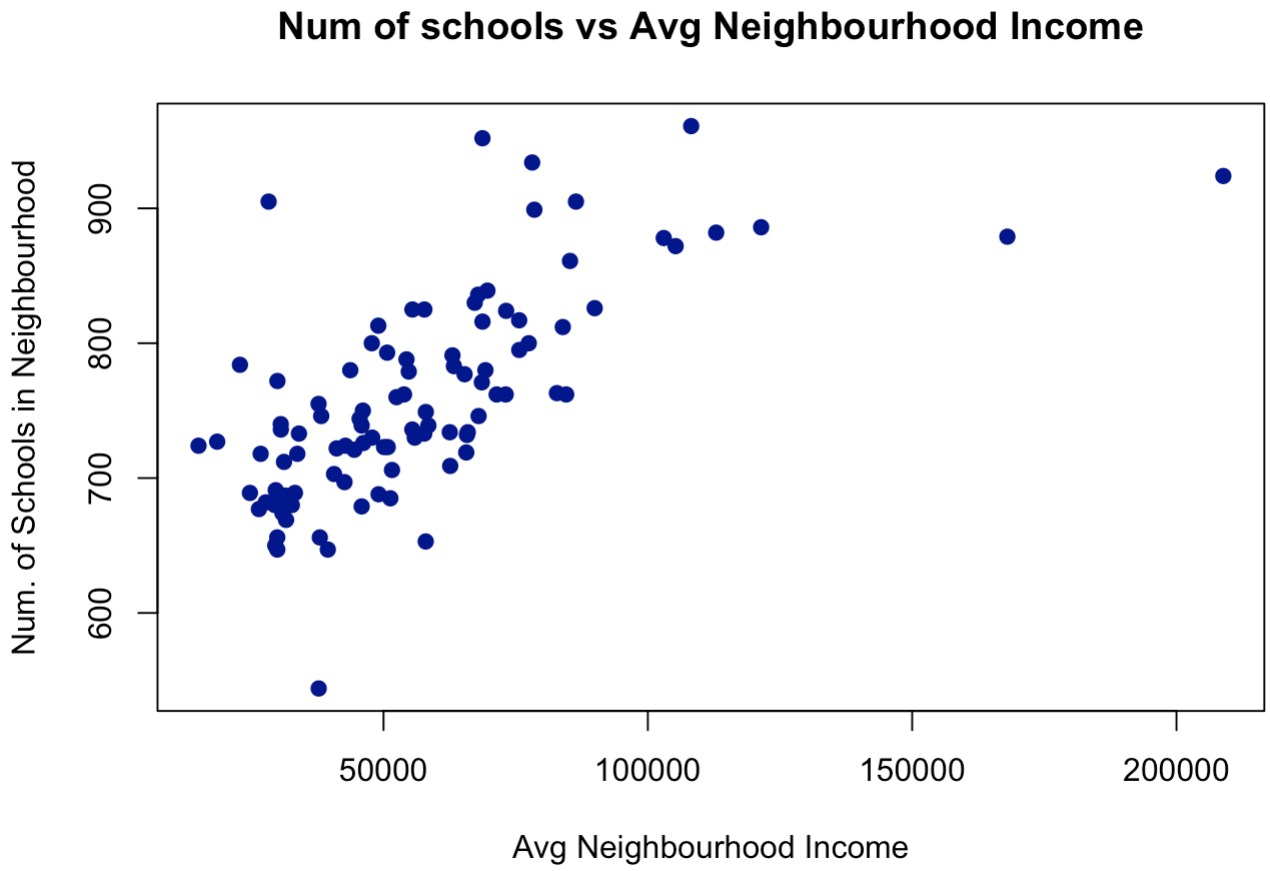

```
# the graph shows us a strong positive linear relationship between
# log(lead) and log(zinc)

#3d
x <- maas$x
y <- maas$lead

mycolors <- c("green", "orange", "red") #can be changed to other colors
mylevels <- cut(y, c(0, 150, 400, Inf))

plot(x, y,
     col=mycolors[as.numeric(mylevels)],
     pch= 19,
     main="Lead Concentration at Maas River Locations",
     xlab="Longitude",
     ylab="Lead Concentration (PPM)")
```




```
#4
LA <- read.table(
  "https://ucla.box.com/shared/static/d189x2gn5xfmcic0dmnhj2cw94jwvqpa.txt",
  header=TRUE)
library(maps)
library(mapdata)

#4a
#install.packages("maps")
#library(maps)

plot(x = LA$Longitude, y = LA$Latitude, pch=19,
     xlab="Longitude", ylab="Latitude",
     main="Neighborhoods in LA County",
     col="blue")
map("county", "california", add = TRUE)
```




```
#4b
LA_neighbourhoods_with_schools <- LA[LA$Schools > 0, ]
plot(LA_neighbourhoods_with_schools$Income,
     LA_neighbourhoods_with_schools$Schools,
     xlab="Avg Neighbourhood Income", ylab="Num. of Schools in Neighbourhood",
     main="Num of schools vs Avg Neighbourhood Income",
     pch=19, col="darkblue")
```




```
# There's a moderate positive linear relationship between income and LA school
# performance. That means that neighbourhoods with higher incomes tend to have
# better performing schools.

#5
customer_data <- read.csv(
  "https://ucla.box.com/shared/static/y2y8rcie7mjw2h5t92x9dfcp133tc90h.csv")

#5a
colSums(is.na(customer_data))
```

```
##        cust_id            age         gender         income      education
##              0             10              0              5              0
## marital_status   purchase_amt
##              0              7
```

```
# there are 22 missing values
# age, income, and purchase_amt have missing values 10, 5, and 7 respectively

#5b
class(customer_data$cust_id) #character
```

```
## [1] "character"
```

```
class(customer_data$age) #integer
```

```
## [1] "integer"
```

```
class(customer_data$gender) #character
```

```
## [1] "character"
```

```
class(customer_data$income) #integer
```

```
## [1] "integer"
```

```
class(customer_data$education) #character
```

```
## [1] "character"
```

```
class(customer_data$marital_status) #character
```

```
## [1] "character"
```

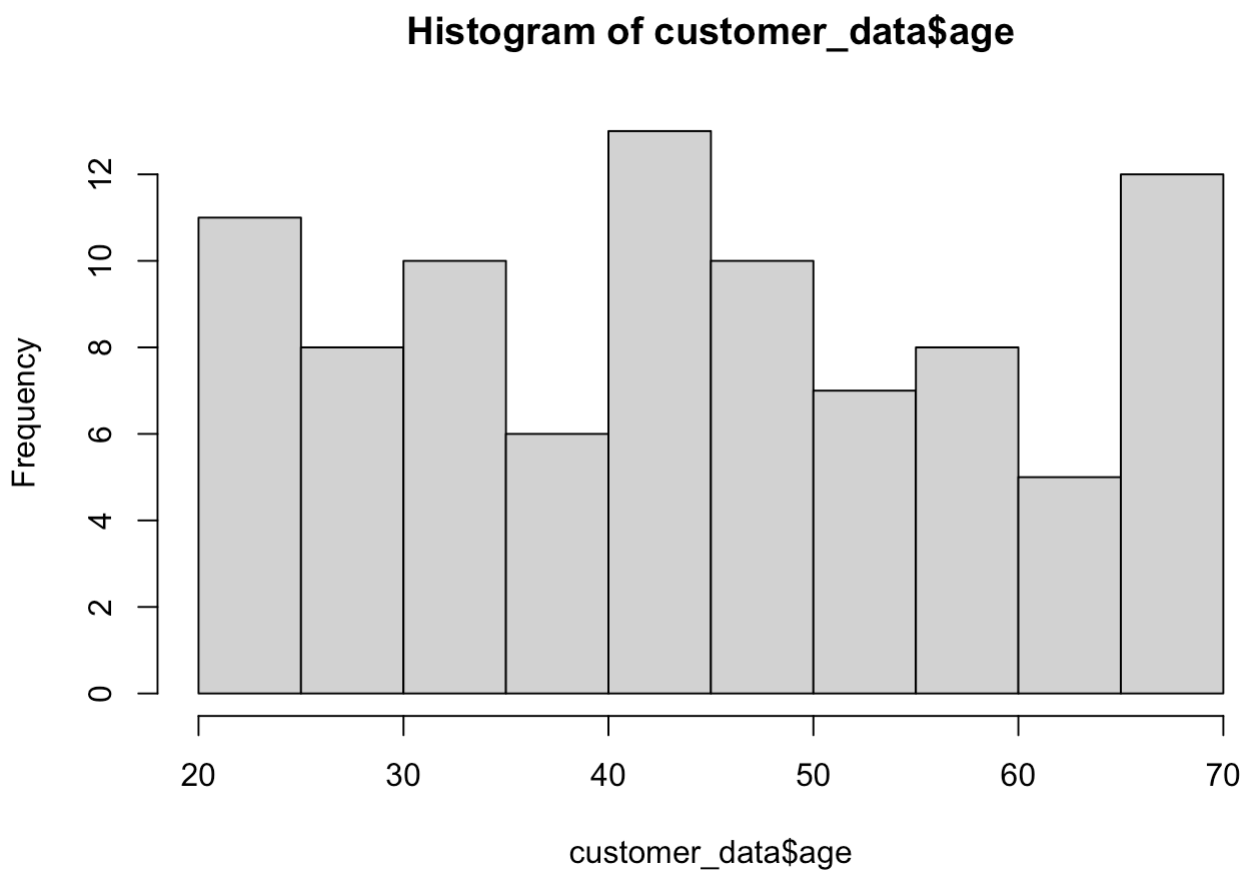
```
class(customer_data$purchase_amt) #integer
```

```
## [1] "integer"
```

```
# as gender, education, and marital_status have limited options as to what
# they could be it might be better to convert them to factor

customer_data$gender <- as.factor(customer_data$gender)
customer_data$education <- as.factor(customer_data$education)
customer_data$marital_status <- as.factor(customer_data$marital_status)

#5c
summary(customer_data$age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   20.00   32.00   44.00   44.99   56.75   70.00      10
```

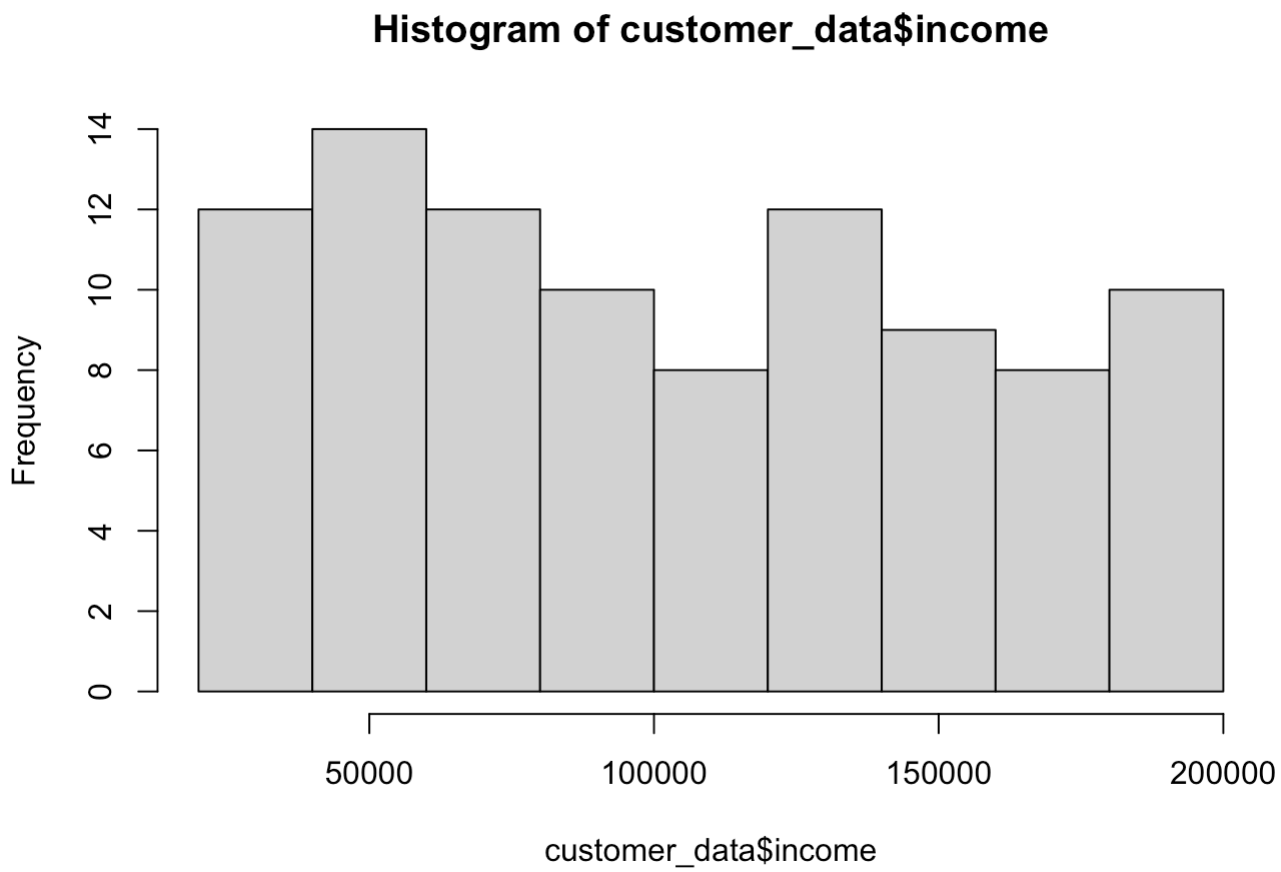
```
hist(customer_data$age)
```



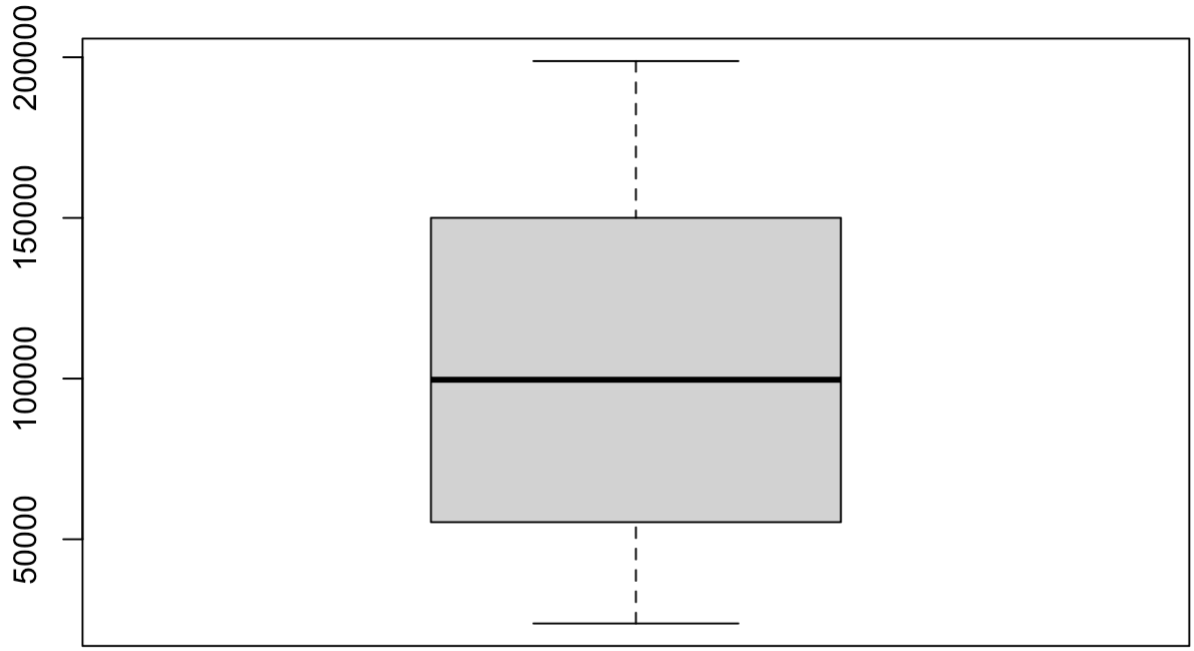

```
# a pretty even spread with seemingly no outliers

summary(customer_data$income)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   23798   55320   99637  103425  150030  198808       5
```

```
hist(customer_data$income)
```



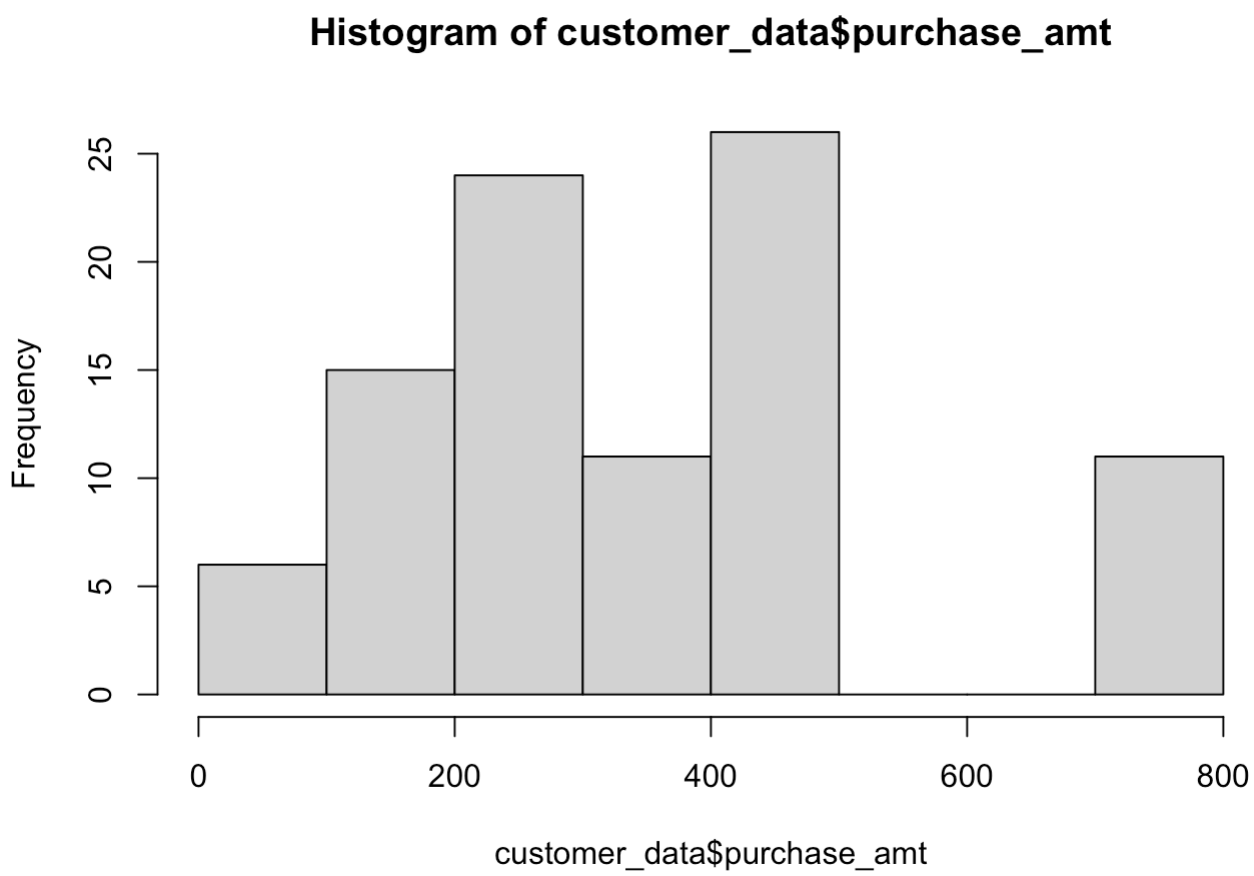

```
boxplot(customer_data$income)
```



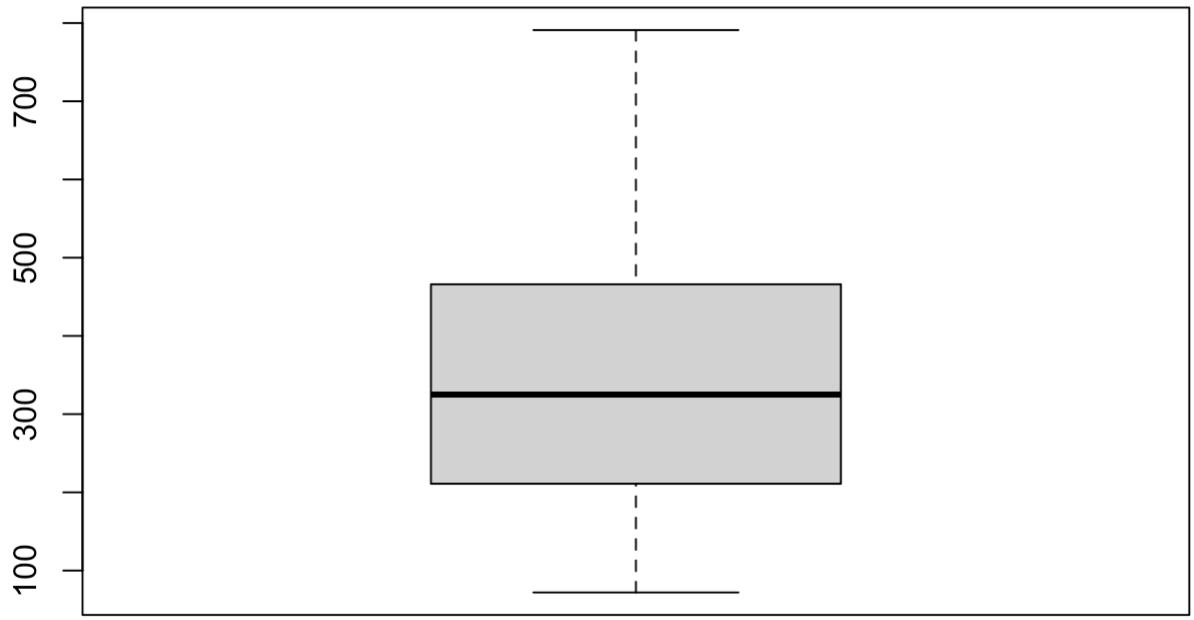
```
# a pretty even spread with seemingly no outliers

summary(customer_data$purchase_amt)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    72.0   211.0   325.0   356.2   466.0   791.0       7
```

```
hist(customer_data$purchase_amt)
```




```
boxplot(customer_data$purchase_amt)
```




```
# the histogram shows us there are some gaps in the distribution but
# the boxplot shows us that there are no outliers and all the values lie within
# 1.5IQR above and below the 3rd and 1st upper quartile
```

Part II

Ex1.

a. I think it's safe to say most students are happy with their body weight as the largest proportion of women and men fall in the "about right" category. More specifically ⅔ of all students sampled responded with "about right".
b. A stacked bar chart would be effective for this comparison, as it can show the distribution of body image responses for each gender. We could also use pie charts and compare so we can see the differences in percentages of answers for men and women.
c. The proportion of female students who responded with "about right" is 0.66, and the proportion of male students with the same answer is 0.67. As we can see proportion of male students who think theyre "about right" is equal if not higher than the female students so female students are not more likely to feel "about right" than male.
d. Proportion of female students who don't feel "about right" feel overweight = (130/160) = 0.**8125**. The proportion of male students who don't feel "about right" feel overweight = (68/140) = 0.**4857**. The proportion of female students who don't feel "about right" feel underweight = (30/160) % = 0.**1875**. Percentage of male students who don't feel "about right" feel underweight = (72/140) = 0.**5143**

   Female students are more likely to feel "Overweight" than male students, while male students are slightly more likely to feel "Underweight" than female students.

Ex2.

a. We can see a strong/moderate positive linear correlation. States with higher percentages of college-educated populations tend to have higher median family incomes, suggesting education level is associated with earning potential. There could be one potential outlier state where percentage of residents with a BA is 30

but the median family income is only $60K/yr. There could be various different reasons for this outlier.

b. This is clearly a non linear relationship. We can see a strong curved or parabolic (U shaped) relation between the variables which shows us fuel consumption is highest at very low and very high speeds, with an optimal (minimum) fuel usage at moderate speeds. No data points look like outliers.

Ex3.

a. Explanatory variable: Starting median salary. Response variable: Mid-career median salary.
b. Median salary could be used instead of mean for various different reasons. We know the median is less sensitive to extreme values/outliers so to account for that or to account for the fact that salary distributions are typically right-skewed.
c. Yes, 60k starting salary can be estimated because: It falls within the range of the data shown in the scatterplot and using the regression line we can provide a reliable estimate which is -7.699 + 1.989(60) = $111.6k/yr
d. No, 100k starting salary cannot be estimated because it falls outside the range of the observed data and we dont know if the line of best fit would still be the best estimate because we don't know if the relation between the variables changes. But if we were still to approximate it, the mid-career median would be −7.699 + 1.989 × 100 = −7.699 + 198.9 = $191.2k/yr

Ex4.

a. b = r x (SD of y / SD of x) = 0.95 x (46.34/2.32) ≈ 19 . The intercept = Mean of y – b x Mean of x = 141.67 – (19 x 11.03) ≈ -68
b. Regression equation: Calories = -67.77 + 19.0(% alcohol). For each additional percentage point of alcohol, the calories are expected to increase by 19.0 units, starting from a base of -67.77 calories. It suggests that when the % alcohol is zero, the expected calories are approximately -68, which doesn't make sense. However,

this suggests a positive relationship or association between alcohol content and calorific content of wine.

c. The coefficient of determination $r^2 = (0.95)2 = 0.9025$. About 90.25% of the variation in calories can be explained by the linear relationship with alcohol percentage.
d. The point (20, 0) lies far from the pattern of the other points so it would decrease the correlation coefficient r. The slope would become less steep (more negative) due to this outlier

Ex 5.

a. Yes, if the doctor places the most severe patients in the antidepressants group, it will affect his ability to compare the effectiveness of the antidepressants and the "talk therapy." This is because the initial severity of the patients' conditions can be a confounding variable. It can create selection bias and make the comparison of treatment effectiveness of the groups invalid because we cannot determine if differences are due to treatment or initial severity
b. The doctor knowing treatment assignments can be problematic because it creates potential for observer bias and could unconsciously influence evaluation scores. Doctors may treat patients differently based on treatment group and this would compromise the objectivity of the study
c. Several improvements can be made to the plan.
    i. First, patients should be randomly assigned to each treatment group. This randomization ensures that both observed and unobserved confounding variables are equally distributed between the groups, which helps to reduce bias.
    ii. Second, the study should ideally be conducted as a double-blind trial, meaning that neither the patients nor the doctors know which treatment each patient is receiving. This design minimizes bias in both the administration of treatment and the assessment of outcomes.

iii. Third, if there is a concern that the severity of depression might affect the outcomes, patients can be matched based on the severity of their depression. For every severely depressed patient in one group, a patient with a similar level of depression should be identified in the other group to ensure that the comparison is fair and balanced.