Assignment 2

David Gyaraki, Thao Le

Contents

```r
# load packages
if(!require(pacman)){install.packages("pacman")}

p_load(devtools,tidyverse,dplyr,ggplot2,latex2exp,
       sampleSelection, quantreg)
```

```
  There is a binary version available but the source version is later:
         binary source needs_compilation
devtools  2.4.4  2.4.5             FALSE
```

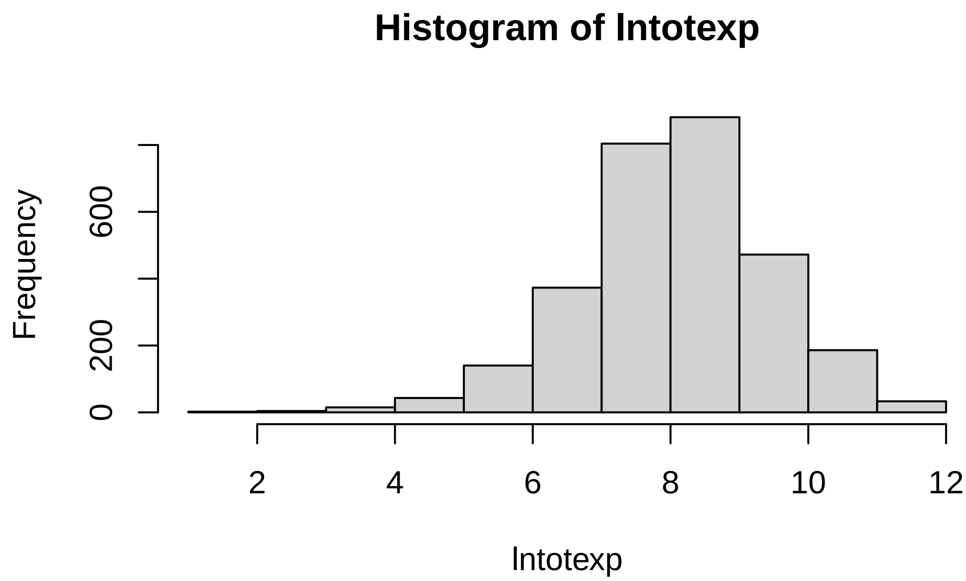
```r
#load data
dfData = read.csv("assignment2a_2023.csv")
attach(dfData)
```

1 Question 1

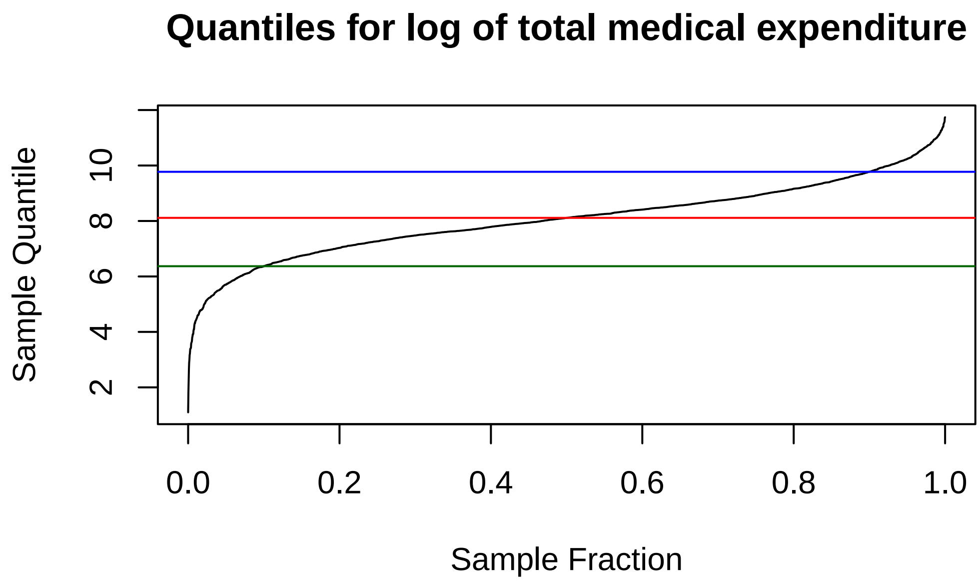
1.1 (i)

```r
# Get the quantile values
quant=quantile(lntotexp, seq(0.1, 0.9, by=.4))

# Histogram of log of total medical expenditure
hist(lntotexp)
```




```r
# Quantile plot of log of total medical expenditure
n = length(lntotexp)
plot((1:n - 1)/(n - 1), sort(lntotexp), type="l",
main = "Quantiles for log of total medical expenditure",
xlab = "Sample Fraction",
ylab = "Sample Quantile")
abline(h=quant, col = c("dark green","red", "blue"))
```



In the quantile plot, the median is indicated by the red line, the 10^{th} and 90^{th} quantile are indicated by the blue and green lines.

We can see from the distribution of log of total medical expenditure that there are few values from 0 to 4. Thus, the quantile plot increases quickly in this region. From 4 to 6, we see an increase frequencies of observations, thus, the quantile plot increases slower. The most rapid increase in the quantile plot is observed between 6 and 10, which makes sense because that is the region where most observations lie. After 10, there are less observations and the quantile plot increases rapidly again.

Although the quantile plot increases rapidly in both regions from 0 to 4 and 10 to 12, we observed a much steeper increase from 0 to 4, thus, we can say that the distribution of log total medical expenditure is left-skewed. This is confirmed by looking at its histogram.

1.2 (ii)

```r
# Quantile regression
q= c(0.1,0.25,0.5,0.75,0.9)
quant_reg = rq(lntotexp ~ . , tau = q, data = dfData)
summary(quant_reg)
```

```
Call: rq(formula = lntotexp ~ ., tau = q, data = dfData)

tau: [1] 0.1

Coefficients:
            Value    Std. Error t value  Pr(>|t|)
(Intercept)  3.86704  0.48065    8.04549  0.00000
age          0.01927  0.00601    3.20732  0.00135
female      -0.01273  0.07579   -0.16794  0.86664
white        0.07344  0.19533    0.37597  0.70697
totchr       0.53919  0.02534   21.27920  0.00000
suppins      0.39572  0.07851    5.04027  0.00000

Call: rq(formula = lntotexp ~ ., tau = q, data = dfData)

tau: [1] 0.25

Coefficients:
            Value    Std. Error t value  Pr(>|t|)
(Intercept)  4.74732  0.30724   15.45160  0.00000
age          0.01551  0.00399    3.88410  0.00010
female      -0.01623  0.05328   -0.30462  0.76068
white        0.33775  0.09662    3.49570  0.00048
totchr       0.45918  0.01833   25.04804  0.00000
suppins      0.38584  0.05992    6.43964  0.00000

Call: rq(formula = lntotexp ~ ., tau = q, data = dfData)

tau: [1] 0.5

Coefficients:
            Value    Std. Error t value  Pr(>|t|)
(Intercept)  5.61116  0.35187   15.94656  0.00000
age          0.01487  0.00406    3.66512  0.00025
female      -0.08810  0.05406   -1.62961  0.10329
white        0.53648  0.19319    2.77697  0.00552
totchr       0.39427  0.01846   21.35942  0.00000
suppins      0.27698  0.05347    5.18025  0.00000

Call: rq(formula = lntotexp ~ ., tau = q, data = dfData)

tau: [1] 0.75
```

```
Coefficients:
            Value    Std. Error t value  Pr(>|t|)
(Intercept)  6.59997  0.42690   15.46027  0.00000
age          0.01825  0.00475    3.83862  0.00013
female      -0.12194  0.06060   -2.01231  0.04428
white        0.19319  0.25684    0.75219  0.45200
totchr       0.37354  0.02286   16.33884  0.00000
suppins      0.14885  0.06203    2.39991  0.01646

Call: rq(formula = lntotexp ~ ., tau = q, data = dfData)

tau: [1] 0.9

Coefficients:
            Value    Std. Error t value  Pr(>|t|)
(Intercept)  8.32264  0.54599   15.24309  0.00000
age          0.00592  0.00651    0.91022  0.36278
female      -0.15763  0.08914   -1.76831  0.07711
white        0.30522  0.24260    1.25811  0.20845
totchr       0.35795  0.03310   10.81289  0.00000
suppins     -0.01428  0.08642   -0.16527  0.86874
```

Looking at the results, we observe different coefficients across the different quantiles. Quite expectedly, we have increasing intercept coefficients, however the interesting part is the different significance of the coefficients in the different quantile regressions. We observe that for the 0.1 quantile, the female and white dummies are insignificant, for the 0.25 and 0.5 quantiles only the female dummy is insignificant, for the 0.75, interestingly the white dummy is insignificant while the female dummy turns out to be significant, and for the 0.9 quantile, only the chronic illness variable seems to be strongly significant with the female dummy slightly (at 10% level) significant too. These trends will lead to the conclusion that the different predictors likely have different dynamics across the groups of patients when ordered by medical expenditure. Being white significantly increases medical expenditure in the mid-groups but not in the tails of the expenditure distribution. Age and extra insurance are associated with significant increase in costs for low spending groups but not for the highest spenders, and gender comes into influence for the highest spenders only. Let us then look at the OLS results, coefficients and their significance levels.

```r
# OLS Regression
OLS_reg = lm(lntotexp ~ . , data = dfData)
summary(OLS_reg)
```

```
Call:
```

```
lm(formula = lntotexp ~ ., data = dfData)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.2474 -0.7666 -0.0032  0.7827  3.8516 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  5.898155   0.295694  19.947  < 2e-16 ***
age          0.012656   0.003595   3.520 0.000437 ***
female      -0.076517   0.046110  -1.659 0.097132 .  
white        0.317811   0.141360   2.248 0.024635 *  
totchr       0.445272   0.017549  25.374  < 2e-16 ***
suppins      0.256811   0.046450   5.529 3.51e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.227 on 2949 degrees of freedom
Multiple R-squared:  0.1969,	Adjusted R-squared:  0.1955 
F-statistic: 144.6 on 5 and 2949 DF,  p-value: < 2.2e-16
```

When one looks at the OLS regression results, the model shows that most variables are statistically significant for explaining the logarithm of medical expenditure, except for the female dummy variable. The variables *age*, *totchr* and *suppins* all have positive effect on medical expenditure with less than 0.001 significance, and the variable *white* has a positive effect as well on 5% significance level. The interpretation of the coefficients can also be given as one unit increase in the independent variables (keeping all else equal) increases the medical expenditure by $(exp(\beta_k) - 1) * 100)$ percentage. We can see below, that a year of age increase will result in an estimated 1.274% increase in medical expenses. Similarly, being female reduces the expenses by -7.366% (although this is only significant at 10% level in the OLS model), being white is associated with 37.412% increase in medical expenses, an additional chronic illness will increase expenditure by 56.091% and having a supplementary private insurance will result in 29.280% increase in medical expenses.

```r
(exp(OLS_reg$coefficients)-1)*100
```

```
 (Intercept)          age       female        white       totchr      suppins 
36336.450509     1.273661    -7.366254    37.411599    56.091416    29.280045 
```

1.3 (iii)