## COMPUTER EXERCISE 1 NHUT CAO – 906939

#### 1.2 Homework

a) Read file "tobacco.txt", set seed

Fit1 is the linear regression model. Summary(fit1) returns the summary as in the console Constant term is the Intercept

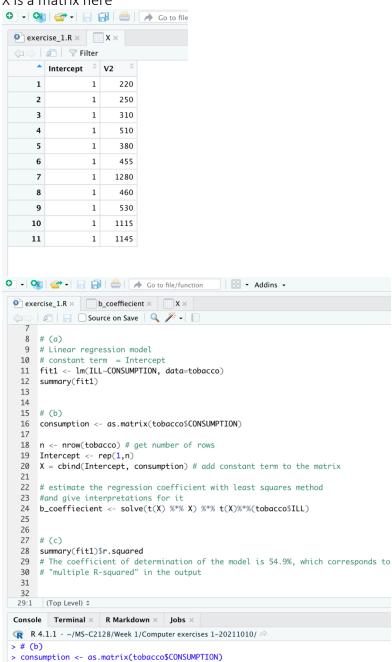
```
tobacco = read.table("tobacco.txt", header=T, sep = "\t")
tobacco.matrix <- as.matrix(tobacco)

# colnames(tobacco)
set.seed(123)

# (a)
# Linear regression model
# constant term = Intercept
fit1 <- lm(ILL~CONSUMPTION, data=tobacco)
summary(fit1)</pre>
```

```
Residuals:
              1Q Median
                               30
    Min
                                      Max
-169.016 -32.813 0.004 45.804 136.914
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 65.74886 48.95871 1.343 0.21217
CONSUMPTION 0.22912 0.06921
                               3.310 0.00908 **
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 84.13 on 9 degrees of freedom
Multiple R-squared: 0.549, Adjusted R-squared: 0.4989
F-statistic: 10.96 on 1 and 9 DF, p-value: 0.009081
· Wi auch
```

### X is a matrix here



> n <- nrow(tobacco) # get number of rows

> X = cbind(Intercept, consumption) # add constant term to the matrix
> # estimate the regression coefficient with least squares method
> #and give interpretations for it
> b\_coefficient <- solve(t(X) %\*% X) %\*% t(X)%\*%(tobacco\$ILL)</pre>

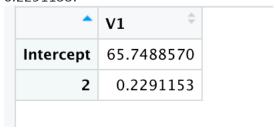
> Intercept <- rep(1.n)</pre>

> summary(fit1)\$r.squared

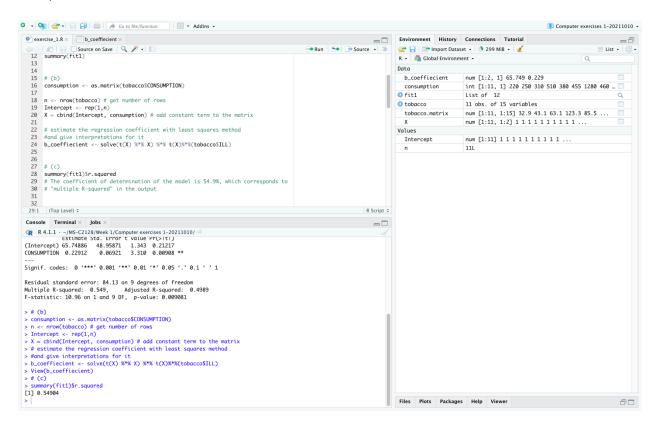
> # (c)

[1] 0.54904 > View(b\_coefficient)

We got "coefficient" by least squares method, Which is similar to what we got from the summary function, the intercept is the constant term, value of 2 is the coefficient, which is 0.2291153:



c) The coefficient of determination of the model: 54.9%



## d) & e)

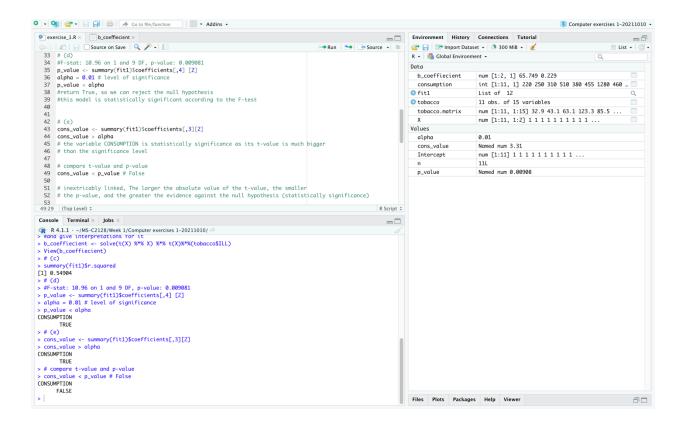
Here the level of significance is 1% = 0.01

For F-test: the p-value is less than the significance level, therefore we can reject the null hypothesis and conclude that this model is statistically significant.

For t-test: the CONSUMPTION variable has t-value much bigger than the level of significance, therefore it is statistically significant.

Compare the t-value and p-value, we see that t-value is much bigger than p-value, and these two values are inextricably linked. The larger the absolute value of the t-value, the smaller the p-value, and the greater the evidence against the null hypothesis

=> Statistically significance.

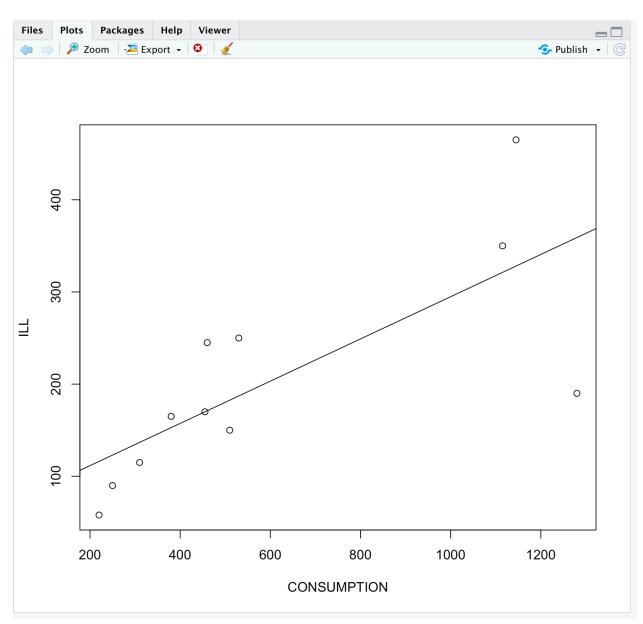


```
f)
Response variable ILL, explanatory variable CONSUMPTION

53
54 # (f)
55 plot(tobacco[,5], tobacco[,14], xlab = "CONSUMPTION", ylab = "ILL")
56 abline(fit1)

57
```

# Below is the scatterplot:



g)

Concept of confidence interval:

Confidence interval displays the probability that a parameter may fall between a pair of values around the mean. It measures the degree of uncertainty or certainty in a sampling method.

FACT: "A level  $(1 - \alpha)$  confidence interval for a parameter  $\theta$  is a random interval that contains the true (non-random) parameter value  $\theta$  with probability  $(1 - \alpha)$ ."

h) For the 99%, the value of the constant term is much wider as it allows one to be more confident that the unknown population parameter is contained within the interval.

```
58 # (h)
59 confint(fit1,level=0.95)
60
61 confint(fit1,level=0.99)
```

```
> confint(fit1,level=0.95)

2.5 % 97.5 %

(Intercept) -45.00344053 176.5011546

CONSUMPTION 0.07254024 0.3856904

> confint(fit1,level=0.99)

0.5 % 99.5 %

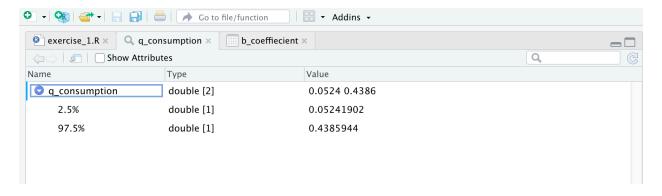
(Intercept) -93.358900306 224.8566143

CONSUMPTION 0.004178126 0.4540525

> |
```

i)

```
63 # (i)
64
65 k <- 2000
66 bootmat <- matrix(NA, nrow=k,ncol=2)
67 y <- tobacco$ILL
68
69 set.seed(123)
70 * for(i in 1:(k-1)){
71 ind <- sample(1:n,replace = TRUE)
72 Xtmp <- X[ind,]
73 ytmp <- y[ind]
74
      btmp <- solve(t(Xtmp)%*%Xtmp)%*%t(Xtmp)%*%ytmp</pre>
75
      bootmat[i,] <- t(btmp)</pre>
76 - }
77
78  #b_original <- solve(t(X)%*%X)%*%t(X)%*%y
79 bootmat[k,] <- t(b_coefficient)</pre>
80
81 q_consumption <- quantile(bootmat[,2], probs = c(0.025,0.975))
82
83
84
```



Compare this to h), we see that this confidence intervals is quite close from those two intervals, especially with the 99% confidence intervals.

j)

Bootstrap approach is a useful alternative to the traditional method of hypothesis testing as it is quite simple, and it mitigates some of the pitfalls encountered within the traditional approach. If the sample size is really large, it cannot necessarily be assumed that the theoretical sampling distribution is normal. This then makes it difficult to determine the standard error of the estimate, and harder to draw reasonable conclusions from the data in the traditional way.

The bootstrapping approach will always work because it does not assume any underlying distribution of the data.

Bootstrapping is a straightforward way to derive the estimates of standard errors and confidence intervals, and it is convenient since it avoids the cost of repeating the experiment to get other groups of sampled data.