# **Chapter 2 Example**

Andaleeb Hassan

# Computing using user defined function

#### Forbes's data

User defined function:

```
SLR <- function(x,y) {</pre>
  n <- length(x)</pre>
  x_bar <- mean(x)</pre>
  y_bar <- mean(y)</pre>
  SXX \leftarrow sum((x-x_bar)**2)
  SXY \leftarrow sum((x-x_bar)*(y-y_bar))
  SYY <- sum((y-y_bar)**2)</pre>
  beta_1_hat <- SXY/SXX
  beta_0_hat <- y_bar-(x_bar*beta_1_hat)</pre>
  RSS <- SYY-(beta_1_hat)^2*SXX
  RMS <- RSS/(n-2)
  se_beta1 <- sqrt(RMS/SXX)</pre>
  se_beta0 \leftarrow sqrt(RMS*((1/n)+(x_bar^2/SXX)))
   R_2 \leftarrow 1-(RSS/SYY)
   cov \leftarrow -RMS * (x_bar/SXX)
  return(list(x_bar = x_bar,
                 y_bar = y_bar,
                 SXX = SXX,
                 SXY = SXY,
```

```
SYY = SYY,
               beta_1_hat = beta_1_hat,
               beta_0_hat= beta_0_hat,
               RSS = RSS,
               RMS = RMS,
               se_beta1 = se_beta1,
               se_beta0 = se_beta0,
               n = n,
               R_2 = R_2,
               cov = cov
  ))
}
result <- SLR(Forbes$bp,Forbes$lpres)</pre>
result[c(6,7)]
$beta_1_hat
[1] 0.8954937
$beta_0_hat
[1] -42.13778
                           \hat{E}(lpres|bp) = -42.138 + 0.895bp
result$RSS
[1] 2.154927
result$RMS
[1] 0.1436618
confidence interval for \beta_0:
```

result\$se\_beta0

#### [1] 3.340199

 $round(c(result\$beta\_0\_hat-(qt(.95,result\$n-2)*result\$se\_beta0),result\$beta\_0\_hat+(qt(.95,result\$n-2)*result\$se\_beta0),result\$beta\_0\_hat+(qt(.95,result\$n-2)*result\$se\_beta0),result\$beta\_0\_hat+(qt(.95,result\$n-2)*result\$se\_beta0),result\$se\_beta0),result\$se\_beta0),result\$se\_beta0]$ 

[1] -47.99 -36.28

The 90% confidence interval is  $-48.35 \le \beta_0 \le -35.93$ .

$$H_0: \beta_0 = -35$$
  
 $H_1: \beta_0 \neq -35$ 

The test statistic:

$$t = \frac{\hat{\beta}_0 - \beta_0}{se(\hat{\beta}_0 | x_1, x_2, \cdots, x_n)}$$

t = (result\$beta\_0\_ha+35)/result\$se\_beta0
min(2\*pt(abs(t),result\$n-2,lower.tail = FALSE),1)

[1] 0.04948427

Here, for the two sided test the p-value is  $p = min\{1, p(t > |t_{cal}|)\}$ . The p-value is approximately 0.05, providing evidence against the null hypothesis.

Slope:

$$\hat{\beta}_1 - t_{\frac{\alpha}{\alpha}, n-2} \ se(\hat{\beta}_1 | x_1, x_2, \cdots, x_n) \le \beta_1 \le \hat{\beta}_1 + t_{\frac{\alpha}{\alpha}, n-2} \ se(\hat{\beta}_1 | x_1, x_2, \cdots, x_n)$$

## Predicted value and Fitted value

Prediction of value  $y_*$  corresponding to  $x_*$  which is yet to be observed. With assumption that the fitted model to the observed data can be used to predict for the new case. The point prediction would be:

$$\tilde{y}_* = \hat{\beta}_0 + \hat{\beta}_1 x_*$$
  $x_*$  is a new data point

The true value of  $y_*$  is:

$$y_* = \beta_0 + \beta_1 x_* + \epsilon_* \qquad \qquad \epsilon \sim N(0, \sigma^2)$$

The variance of  $\tilde{y}_*$  would be the sum of variance due to random error  $\epsilon$  and variance of the predicted parameters.

$$Var(\tilde{y}_{*}|x_{*}) = \sigma^{2} + \sigma^{2}(\frac{1}{n} + \frac{(x_{*} - \bar{x})^{2}}{SXX})$$

The standard error of prediction:

$$se(\tilde{y_*}|x_*) = \hat{\sigma}(1 + \frac{1}{n} + \frac{(x_* - \bar{x})^2}{SXX})^{\frac{1}{2}}$$

For  $x_*=200$ , we have,  $\tilde{y_*}=136.961$  and  $se(\tilde{y_*}|x_*=200)=0.393$ 

[1] 135.803 138.120

## Heights data

SLR(Heights\$mheight, Heights\$dheight)[c(6,7)]

\$beta\_1\_hat [1] 0.541747

\$beta\_0\_hat [1] 29.91744

For the model:

$$\widetilde{dheight}_* = E(dheight_*|mheight_*) = \beta_0 + \beta_1 mheight_*$$

Similarly, 95% confidence interval for daughter's height for given mother's height can be calculated as following.

$$\hat{\beta}_0 + \hat{\beta}_1 x_* \pm t_{.025 \ n-2} \times se(dheight_*|mheight_*)$$

## In built function:

```
model <- lm(lpres~bp,Forbes)</pre>
```

```
summary(model)[6]
```

#### \$sigma

[1] 0.3790275

Table 1: Estimate of the model

term	estimate	std.error	statistic	p.value
(Intercept) bp	-42.138 $0.895$	3.340 0.016	-12.615 54.431	<0.001 <0.001

Similarly,

$$\hat{E}(lpres|bp) = -42.138 + 0.895bp$$

The Confidence interval:

```
confint(model,level = .9)
```

```
5 % 95 % (Intercept) -47.9933161 -36.2822424 bp 0.8666529 0.9243344
```

prediction:

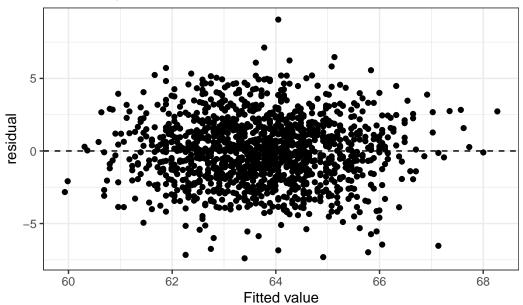
```
data <- tibble(bp = c(200))
predict(model, newdata = data, level = .99,interval = "prediction")</pre>
```

```
fit lwr upr
1 136.961 135.8028 138.1191
```

## Residuals

Residual analysis is used for model adequacy checking.

## Residual plot



There is no pattern visible in the plot. Thus the assumptions are not violated.

```
model1 <- lm(lpres~bp, data = Forbes)
model2 <- lm(lpres~bp, data = Forbes[-12,])

tidy(model1)%>%
  select(1:2) %>%
  mutate(type = "model1")%>%
  bind_rows(tidy(model2)%>%
```

```
select(1:2)%>%
    mutate(type = "model2"))%>%
    pivot_wider(id_cols = term, names_from = type, values_from = estimate) %>%
    kbl(format = "latex", booktabs = TRUE, digits = 3, caption = "Model comparisons") %>%
    kable_styling(latex_options = "hold_position")
```

Table 2: Model comparisons

term	model1	model2
(Intercept)	-42.138	-41.308
bp	0.895	0.891

```
`model-1` <- lapply(SLR(Forbes$bp,Forbes$lpres),round,digit = 3 )
`model-2` <- lapply(SLR(Forbes[-12,]$bp,Forbes[-12,]$lpres),round,digit = 3)

cbind(`model-1`,`model-2`) %>%
  kbl(format = "latex", booktabs = TRUE, digits = 3, caption = "Model comparisons") %>%
  kable_styling(latex_options = "hold_position")
```

Table 3: Model comparisons

	model-1	model-2
x_bar	202.953	202.85
y_bar	139.605	139.428
SXX	530.782	527.9
SXY	475.312	470.351
SYY	427.794	419.256
beta_1_hat	0.895	0.891
$beta_0_hat$	-42.138	-41.308
RSS	2.155	0.18
RMS	0.144	0.013
$se\_beta1$	0.016	0.005
$se\_beta0$	3.34	1.001
n	17	16
R_2	0.995	1
cov	-0.055	-0.005