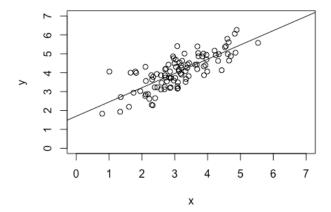
HW#2, Nan Deng

```
(1)
library(MASS)
mu < -c(3,4)
sigma <- matrix(c(1.0,0.8,0.8,1.0),nrow=2)</pre>
set.seed(123)
datam <- data.frame(mvrnorm(100,mu,sigma))</pre>
colnames(datam) <- c("x","y")</pre>
(a)
library(faraway)
fit_line <- lm(y \sim x, data=datam)
summary(fit_line)
##
## Call:
## lm(formula = y \sim x, data = datam)
##
## Residuals:
##
        Min
                  1Q
                       Median
                                     3Q
                                             Max
## -1.18120 -0.44633 -0.01159 0.36843 1.60020
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
                           0.19998
                                      8.486 2.31e-13 ***
## (Intercept) 1.69698
## x
                0.75479
                            0.06144 12.285 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5701 on 98 degrees of freedom
## Multiple R-squared: 0.6063, Adjusted R-squared: 0.6023
## F-statistic: 150.9 on 1 and 98 DF, p-value: < 2.2e-16
plot(datam$x,datam$y,xlab="x",ylab="y",xlim=c(0,7),ylim=c(0,7))
abline(fit_line)
```



```
## (Intercept)
##
     1.6969772
                  0.7547914
summary(fit_line)$sigma
## [1] 0.5701041
summary(fit_line)$r.squared
## [1] 0.606287
(b) \alpha = 1.6969772; \beta = 0.7547914; \sigma = 0.5701041; R^2 = 0.606287
(c)
t.test(datam, mu=0, alternative="greater", conf.level=0.95)
    One Sample t-test
##
##
## data: datam
## t = 49.314, df = 199, p-value < 2.2e-16
## alternative hypothesis: true mean is greater than 0
## 95 percent confidence interval:
## 3.465606
## sample estimates:
## mean of x
## 3.585767
```

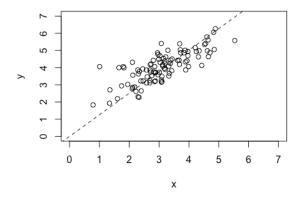
Considering that p-value in this model is less than 2.2e-16 and definitely less than 0.05, H_0 should be rejected.

```
(d)
fit_line1 <- lm(y ~ offset(0.9*x),data=datam)</pre>
anova(fit_line,fit_line1)
## Analysis of Variance Table
##
## Model 1: y ~ x
## Model 2: y \sim offset(0.9 * x)
     Res.Df RSS Df Sum of Sq
                                     F Pr(>F)
##
## 1
         98 31.852
         99 33.667 -1
                      -1.8154 5.5854 0.02008 *
## 2
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

Since p-value of this model is around 0.02, which is less than 0.05, H₀ should also be rejected.

```
(2)
m0 <- lm(y ~ x -1 , data=datam)
summary(m0)
##
## Call:
## lm(formula = y ~ x - 1, data = datam)
##
## Residuals:
## Min 1Q Median 3Q Max</pre>
```

```
## -1.4258 -0.3656 0.1252 0.5823 2.7931
##
## Coefficients:
     Estimate Std. Error t value Pr(>|t|)
## x 1.25453
                0.02295
                          54.66
                                 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7471 on 99 degrees of freedom
## Multiple R-squared: 0.9679, Adjusted R-squared: 0.9676
## F-statistic: 2987 on 1 and 99 DF, p-value: < 2.2e-16
(a)
plot(datam$x,datam$y,xlab="x",ylab="y",xlim=c(0,7),ylim=c(0,7))
abline(m0,lty=2)
```



```
(b)
sum(summary(m0)$resid)
## [1] 13.79104
```

No, the sum of residuals is about 13.8 rather than 0.

```
(c)
sum(datam$x * residuals(m0))
## [1] -4.010681e-15
sum(fitted.values(m0) * residuals(m0))
## [1] -4.458239e-15
```

$$\frac{\partial}{\partial \beta} \Xi (9i - \beta xi)^{2} = 0 \implies \beta = \frac{\Xi xi yi}{\Xi (xi)^{2}}$$

$$\Xi xi ei = \Xi xi (yi - \beta xi)$$

$$= \Xi xi (yi - \frac{\Xi xi yi}{\Xi (xi)^{2}} \cdot xi)$$

$$= 0$$

$$\Xi \hat{g} i ei = \hat{\beta} \Xi xi ei = 0$$

(3)

(a)

$$\hat{\beta} = \frac{\sum (x_i - \overline{x}) y_i}{\sum (x_i - \overline{x})^2} = \frac{g_{xy}}{g_{xx}} \implies g_{xy} = \hat{\beta} \cdot g_{xx}$$

$$\hat{\beta} = \frac{g_{xy}}{\sqrt{g_{xx}g_{yy}}} = \frac{\hat{\beta} \cdot g_{xx}}{\sqrt{g_{xx}g_{yy}}} = \hat{\beta} \cdot \frac{g_{xx}}{g_{yy}}$$

In this equation, r and β have the same sign.

(b)

$$SSE = \sum (y_i - \hat{y}_i)^2 = \sum [y_i - \hat{y}_i) - \hat{p}(x_i - \bar{x}_i)^2$$

$$= \sum (y_i - \hat{y}_i)^2 - 2\hat{p} \sum (y_i - \bar{y}_i)(x_i - \bar{x}_i)$$

$$+ \hat{p}^2 \sum (x_i - \bar{x}_i)^2$$

$$= \sum y_i - 2\hat{p} \sum y_i + \hat{p}^2 \sum x_i$$

$$= \sum y_i - 2\hat{p} \sum y_i + \hat{p}^2 \sum x_i$$

$$= \sum y_i - 2\hat{p} \sum y_i$$

$$= \sum y_i - 2\hat{y} \sum y_i$$

$$= \sum y$$