

Problem 1

```
> library(faraway)
> data(longley)
> nrow(longley)
[1] 16
> longley[1:3, ]
      GNP.deflator      GNP Unemployed Armed.Forces Population Year Employed
1947      83.0 234.289      235.6      159.0    107.608 1947    60.323
1948      88.5 259.426      232.5      145.6    108.632 1948    61.122
1949      88.2 258.054      368.2      161.6    109.773 1949    60.171
> attach(longley)
```

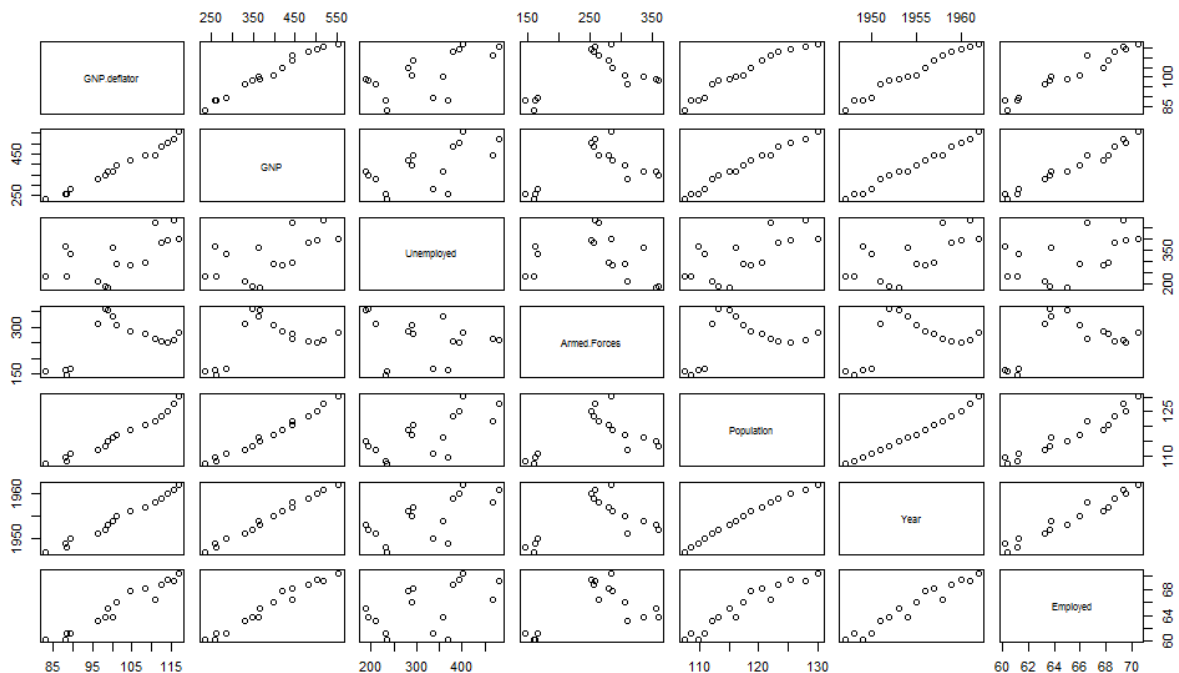
(a)

```
> options(digits=3)
> round(cor(longley), 2)
```

	GNP.deflator	GNP	Unemployed	Armed.Forces	Population	Year	Employed
GNP.deflator	1.00	0.99	0.62	0.46	0.98	0.99	0.97
GNP	0.99	1.00	0.60	0.45	0.99	1.00	0.98
Unemployed	0.62	0.60	1.00	-0.18	0.69	0.67	0.50
Armed.Forces	0.46	0.45	-0.18	1.00	0.36	0.42	0.46
Population	0.98	0.99	0.69	0.36	1.00	0.99	0.96
Year	0.99	1.00	0.67	0.42	0.99	1.00	0.97
Employed	0.97	0.98	0.50	0.46	0.96	0.97	1.00

(b)

```
> pairs(longley)
```



From the scatter plots and the correlation matrix from part (a), these pairs of variables seems to probably linearly related:

GNP.deflator & GNP (cor=0.99)	GNP.deflator & Population (cor=0.98)
GNP.deflator & Year (cor=0.99)	GNP.deflator & Employed (cor=0.97)
GNP & Population (cor=0.99)	GNP & Year (cor=1.00)
GNP & Employed (cor=0.98)	Population & Year (cor=0.99)
Population & Employed (cor=0.96)	Year & Employed (cor=0.97)

Especially, “GNP” and “Year” has a correlation 1.00 that indicates highly linear relationship.

(c)

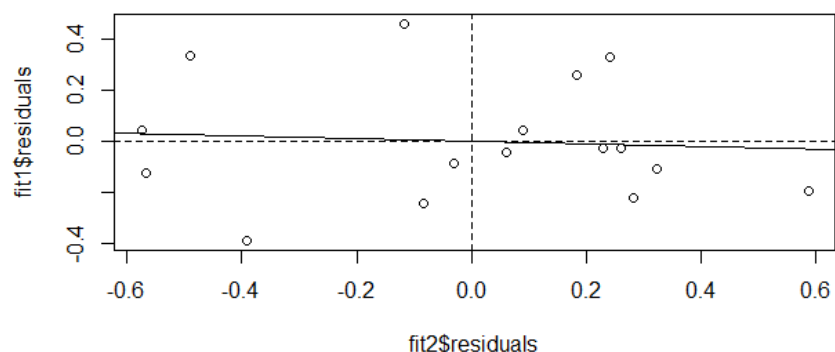
```
> options(digits=5)
> fit = lm(Employed~., data = longley)
> vif(fit)
```

GNP. deflator	GNP	Unemployed	Armed. Forces	Population	Year
135.5324	1788.5135	33.6189	3.5889	399.1510	758.9806

Variance inflation factor that is greater than 5 is problematic. In this full model, only one VIF of “Armed.Forces” is smaller than 5, and all the others are extremely large, which suggests a huge multicollinearity issue.

(d)

```
> fit1 = lm(Employed~. - Population, data = longley)
> fit2 = lm(Population~. - Employed, data = longley)
> cor(fit2$residuals, fit1$residuals)
[1] -0.075137
> plot(fit2$residuals, fit1$residuals)
> abline(h=0, lty=2)
> abline(v=0, lty=2)
> abline(lm(fit1$residuals ~ fit2$residuals))
```



The partial correlation is very low, and the variable added plot almost shows no linear relationship, thus “Population” should not remain in the full model.

(e)

```
> summary(fit)
```

Call:

```
lm(formula = Employed ~ ., data = longley)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.4101	-0.1577	-0.0282	0.1016	0.4554

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-3.48e+03	8.90e+02	-3.91	0.00356	**
GNP. deflator	1.51e-02	8.49e-02	0.18	0.86314	
GNP	-3.58e-02	3.35e-02	-1.07	0.31268	
Unemployed	-2.02e-02	4.88e-03	-4.14	0.00254	**
Armed. Forces	-1.03e-02	2.14e-03	-4.82	0.00094	***
Population	-5.11e-02	2.26e-01	-0.23	0.82621	
Year	1.83e+00	4.55e-01	4.02	0.00304	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.305 on 9 degrees of freedom

Multiple R-squared: 0.995, Adjusted R-squared: 0.992

F-statistic: 330 on 6 and 9 DF, p-value: 4.98e-10

In the full model, the predictors “Unemployed”, “Armed.Forces” and “Year” are significant.

Fit a new model with these three predictors.

```
> fit_new = lm(Employed~Unemployed+Armed. Forces+Year)
```

```
> vif(fit_new)
```

Unemployed	Armed. Forces	Year
3.3179	2.2233	3.8909

All the variance inflation factors are smaller than 5, thus none of them suggests multicollinearity.

(f)

```
> anova(fit_new, fit)
```

Analysis of Variance Table

Model 1: Employed ~ Unemployed + Armed. Forces + Year

Model 2: Employed ~ GNP. deflator + GNP + Unemployed + Armed. Forces + Population +

	Res. Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	12	1.323				
2	9	0.836	3	0.487	1.75	0.23

F test statistic = 1.75, and p-value = 0.23 > 0.1.

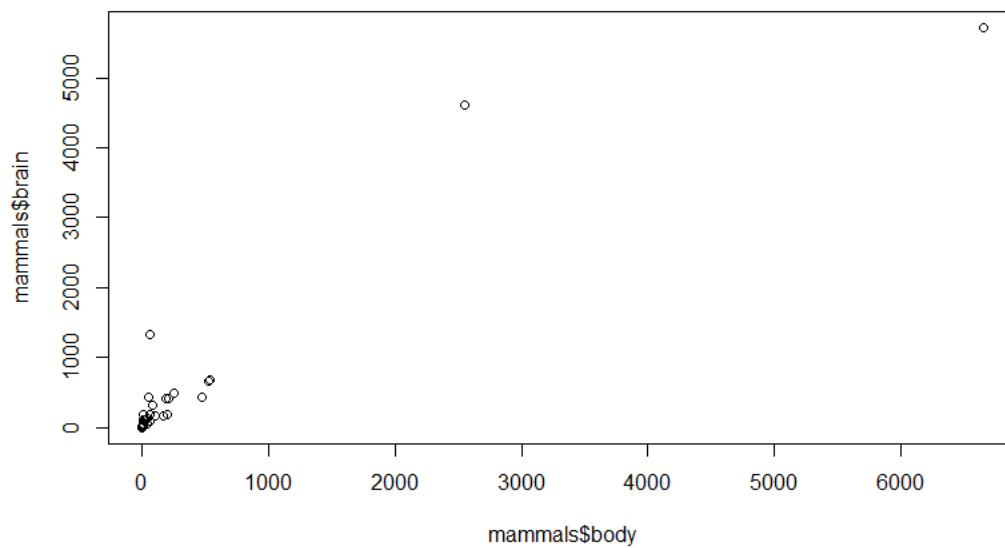
Therefore, **Do not Reject Ho** (Null Model) at $\alpha = 10\%$ or smaller significance level. **The new, smaller model is preferred**, which is only explained by predictors “Unemployed”, “Armed.Forces” and “Year”.

Problem 2

```
> library(MASS)
> data(mammals)
> nrow(mammals)
[1] 62
> mammals[1:3, ]
      body brain
Arctic fox  3.385  44.5
Owl monkey  0.480  15.5
Mountain beaver 1.350   8.1
> attach(mammals)
```

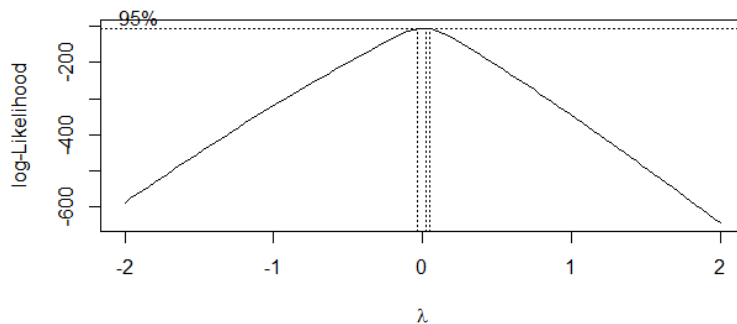
(a)

```
> plot(mammals$body, mammals$brain)
```



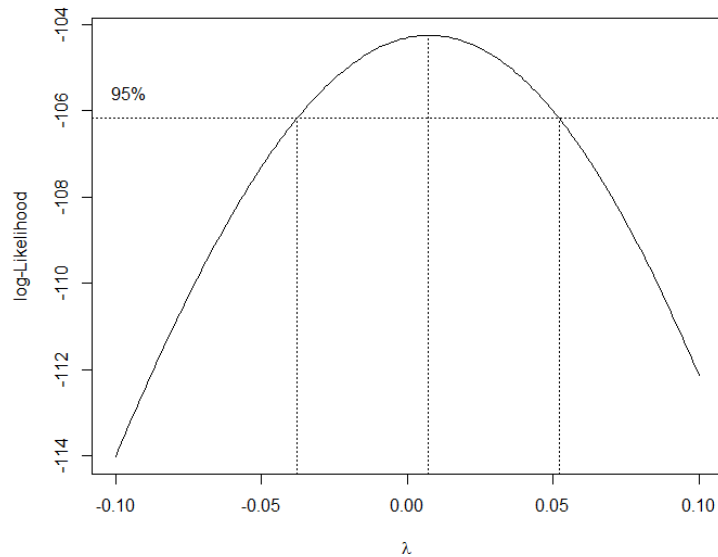
(b)

```
> fit = lm(brain~log(body), data = mammals)
> boxcox(fit, plotit = TRUE)
```



Then adjust the zoom.

```
> boxcox(fit, plotit = TRUE, lambda = seq(-0.1, 0.1, by=0.001))
```

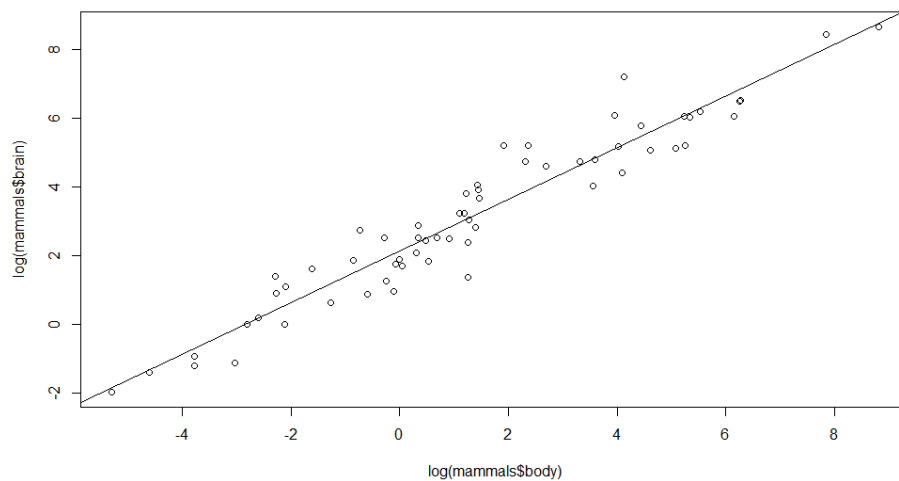


The Box-Cox result shows that $\lambda = 0$ is covered in the 95% confidence interval.

Therefore, $\log(\text{brain weight})$ is the appropriate transformation of the response variable.

(c)

```
> plot(log(mammals$body), log(mammals$brain))
> fit_log = lm(log(brain) ~ log(body), data = mammals)
> abline(fit_log)
```



The plot of this new model suggests that this transformed linear model is appropriate.

```

> new=data.frame(body=254)
> predict.lm(fit_log, new, interval=c("prediction"), level=0.95)
      fit      lwr      upr
1 6.2971 4.8769 7.7174
> exp(predict.lm(fit_log, new, interval=c("prediction"), level=0.95))
      fit      lwr      upr
1 543.01 131.22 2247

```

The prediction of the average brain weight of a Siberian tiger is **543.01 g**, of which the average body weight is 254 kg.

And the 95% prediction interval of its average brain weight is **(131.22, 2247) g**.