

# Regression Diagnostics

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While studying whether any of these 3 “possible” outliers may be influential, we found

- (i) on DFFits, observation **5 and 28** seems to be influential
- (ii) on DFBetas, observation **5** seems to be influential
- (iii) What happens on Cook's distance?

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**We are going to learn 7 new things today; from each of the 7 rows.**

# Question 1: Judging based on Cook's Distance

Cook's:

$$D_i = \frac{\sum_{j=1}^n (\hat{Y}_j - \hat{Y}_{j(i)})^2}{pMSE} = \frac{e_i^2}{pMSE} \left\{ \frac{h_{ii}}{(1-h_{ii})^2} \right\}$$

Rule of thumb:

Calculate the percentile of  $F_{(p,n-p)}$ . If the percentile value is less than 20th percentile, then no serious departure. If more than 50th percentile, then definitely an outlier.

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So, we don't consider even observation 5 as an outlier.

## Question 2: How to judge multicollinearity

Multicollinearity is a way to see if the independent variables are correlated with each other.

$$(VIF)_k = \frac{1}{1-R_k^2}; k = 1, \dots, p-1.$$

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$VIF > 10$  serious multicollinearity;  $2 < VIF \leq 10$  intermediate

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`modx = lm(x2 ~ x1 + x3 + x4 + x5 + x6 + x7 + x8)`

`summary(modx)$r.squared` = 0.2370387

`1/(1-0.2370387)` = 1.310682

No serious multicollinearity.



### Question 3: Model Selection using AIC criterion and through forward, backward and stepwise methods

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mod= lm(lnY ~ x1+x2+x3+x4+x5+x6+x7+x8)
step(mod, direction="both", k=2)
step(mod, direction= "backward", k=2)
step(mod, direction="forward", k=2)
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## Question 4: Model Selection using SBC criterion

$$(SBC)_p = n\log(SSE_p) - n\log(n) + \log(n)p$$

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mod= lm(lnY ~ x1+x2+x3+x4+x5+x6+x7+x8)
step(mod, direction="both", k=log(nrow(data)))
step(mod, direction= "backward", k=log(nrow(data)))
step(mod, direction="forward", k=log(nrow(data)))
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## Question 5: Model Selection using $C_p$ criterion

$$C_p = \frac{SSE_p}{MSE(X_1, \dots, X_{p-1})} - (n - 2p)$$

Rule of thumb:

The model with smaller  $C_p$  and  $C_p$  close to  $p$  are better.

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```
step(mod, direction="both", scale=(summary(mod)$sigma)^2)
library(leaps)
x<-model.matrix(mod)[-1]
y<-data$lnY
leaps(x,y,nbest=3)
matrix(c(a$size-1,a$Cp, a$which),ncol=10)
```

## Question 6: Model Selection using adjusted R-squared, R-squared, PRESS criteria

$$R_{a,p}^2 = 1 - \frac{n-1}{n-p} \frac{SSE_p}{SSTO}$$

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The model with higher  $R^2$ ,  $R_{a,p}^2$  and lower  $PRESS_p$  are better.

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library(leaps)
x<-model.matrix(mod)[-1]
leaps(x, lny, method="adjr2",nbest=3)
leaps(x, lny, method="r2",nbest=3)
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x<-model.matrix(mod)[-1]
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mod2= lm(lny~ x1+x2+x3+x8)
h2ii=ls.diag(mod2)$hat
PRESS2=sum(((mod2$residual/(1-h2ii))^2) 2.737771
```

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mod= lm(lny ~ x1+x2+X3+X4+x5+x6+x7+x8)
predict(mod, data2)
data2=read.table("CH09TA05.txt", header=T)
modv1= lm(data2$lny ~
data2$x1+data2$x2+data2$x3+data2$x5+data2$x6
+data2$x8)
summary(modv1)
summary(mod1)
```