

The Statistical Sleuth in R:

Chapter 12

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1 Introduction

This document is intended to help describe how to undertake analyses introduced as examples in the Third Edition of the *Statistical Sleuth* (2013) by Fred Ramsey and Dan Schafer. More information about the book can be found at <http://www.proaxis.com/~panorama/home.htm>. This file as well as the associated **knitr** reproducible analysis source file can be found at <http://www.math.smith.edu/~nhorton/sleuth3>.

This work leverages initiatives undertaken by Project MOSAIC (<http://www.mosaic-web.org>), an NSF-funded effort to improve the teaching of statistics, calculus, science and computing in the undergraduate curriculum. In particular, we utilize the **mosaic** package, which was written to simplify the use of R for introductory statistics courses. A short summary of the R needed to teach introductory statistics can be found in the mosaic package vignette (<http://cran.r-project.org/web/packages/mosaic/vignettes/MinimalR.pdf>).

To use a package within R, it must be installed (one time), and loaded (each session). The package can be installed using the following command:

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```
> install.packages('mosaic') # note the quotation marks
```

Once this is installed, it can be loaded by running the command:

```
> require(mosaic)
```

This needs to be done once per session.

In addition the data files for the *Sleuth* case studies can be accessed by installing the **Sleuth3** package.

```
> install.packages('Sleuth3') # note the quotation marks
```

```
> require(Sleuth3)
```

We also set some options to improve legibility of graphs and output.

```
> trellis.par.set(theme=col.mosaic()) # get a better color scheme for lattice
> options(digits=4)
```

The specific goal of this document is to demonstrate how to calculate the quantities described in Chapter 12: Strategies for Variable Selection using R.

2 State Average SAT Scores

What variables are associated with state SAT scores? This is the question addressed in case study 12.1 in the *Sleuth*.

2.1 Summary statistics

We begin by reading the data and summarizing the variables.

```
> summary(case1201)
```

State	SAT	Takers	Income
Alabama : 1	Min. : 790	Min. : 2.00	Min. :208
Alaska : 1	1st Qu.: 889	1st Qu.: 6.25	1st Qu.:262
Arizona : 1	Median : 966	Median :16.00	Median :295
Arkansas : 1	Mean : 948	Mean :26.22	Mean :294
California: 1	3rd Qu.: 998	3rd Qu.:47.75	3rd Qu.:325
Colorado : 1	Max. :1088	Max. :69.00	Max. :401
(Other) :44			
Years	Public	Expend	Rank
Min. :14.4	Min. :44.8	Min. :13.8	Min. :69.8
1st Qu.:15.9	1st Qu.:76.9	1st Qu.:19.6	1st Qu.:74.0

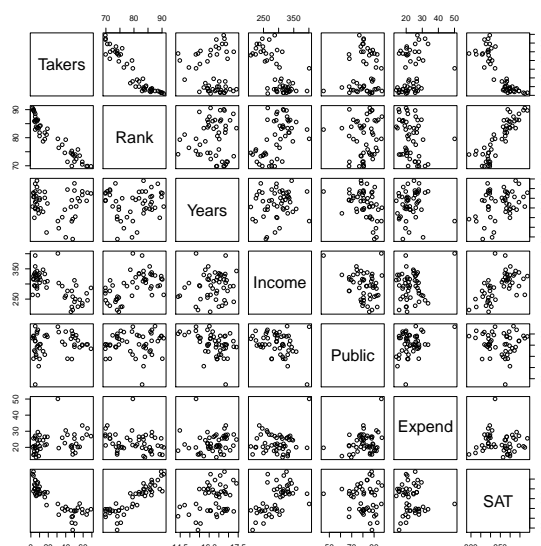
Median :16.4	Median :80.8	Median :21.6	Median :80.8
Mean :16.2	Mean :81.2	Mean :23.0	Mean :80.0
3rd Qu.:16.8	3rd Qu.:88.2	3rd Qu.:26.4	3rd Qu.:85.8
Max. :17.4	Max. :97.0	Max. :50.1	Max. :90.6

The data are shown on page 347 (display 12.1). A total of 50 state average SAT scores are included in this data.

2.2 Dealing with Many Explanatory Variables

The following graph is presented as Display 12.4, page 356.

```
> pairs(~ Takers+Rank+Years+Income+Public+Expend+SAT, data=case1201)
```

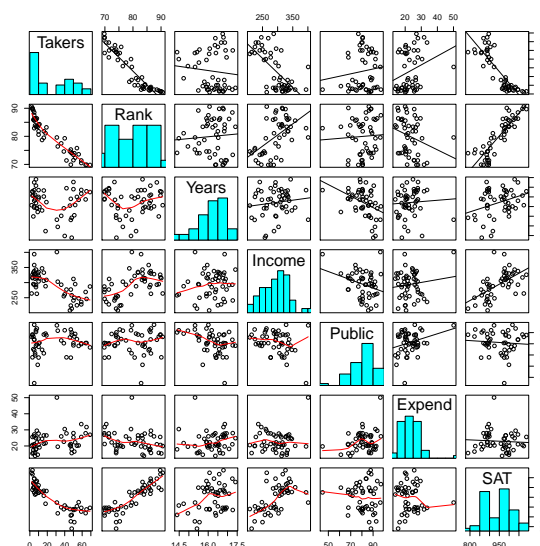


We can get a fancier graph using following code:

```
> panel.hist = function(x, ...)
+ {
+   usr = par("usr"); on.exit(par(usr))
+   par(usr = c(usr[1:2], 0, 1.5) )
+   h = hist(x, plot=FALSE)
+   breaks = h$breaks; nB = length(breaks)
+   y = h$counts; y = y/max(y)
+   rect(breaks[-nB], 0, breaks[-1], y, col="cyan", ...)
+ }
>
> panel.lm = function(x, y, col=par("col"), bg=NA,
+   pch=par("pch"), cex=1, col.lm="red", ...)
```

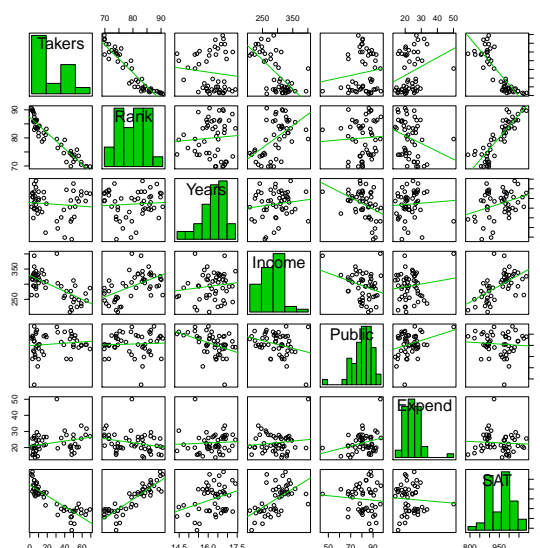
```
+ {
+   points(x, y, pch=pch, col=col, bg=bg, cex=cex)
+   ok = is.finite(x) & is.finite(y)
+   if (any(ok))
+     abline(lm(y[ok] ~ x[ok]))
+ }
```

```
> pairs(~ Takers+Rank+Years+Income+Public+Expend+SAT,
+       lower.panel=panel.smooth, diag.panel=panel.hist,
+       upper.panel=panel.lm, data=case1201)
```



An alternative graph can be generated using the `car` package.

```
> require(car)
> scatterplotMatrix(~ Takers+Rank+Years+Income+Public+Expend+SAT, diagonal="histogram", smooth=
```



Based on the scatterplot, we choose the logarithm of percentage of SAT takers and median class rank to fit our first model (page 355-357):

```
> lm1 = lm(SAT ~ Rank+log(Takers), data=case1201)
> summary(lm1)
```

Call:

```
lm(formula = SAT ~ Rank + log(Takers), data = case1201)
```

Residuals:

Min	1Q	Median	3Q	Max
-94.46	-17.31	5.32	22.82	48.47

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	882.08	224.13	3.94	0.00027
Rank	2.40	2.33	1.03	0.30898
log(Takers)	-45.19	14.06	-3.21	0.00236

Residual standard error: 31.1 on 47 degrees of freedom

Multiple R-squared: 0.815, Adjusted R-squared: 0.807

F-statistic: 103 on 2 and 47 DF, p-value: <2e-16

From the regression output, we observe that these two variables can explain 81.5% of the variation.

Next we fit a linear regression model using all variables and create the partial residual plot presented on page 357 as Display 12.5:

```
> lm2 = lm(SAT ~ log2(Takers)+Income+Years+Public+Expend+Rank, data=case1201)
> summary(lm2)
```

Call:

```
lm(formula = SAT ~ log2(Takers) + Income + Years + Public + Expend +
    Rank, data = case1201)
```

Residuals:

Min	1Q	Median	3Q	Max
-61.11	-8.60	2.86	14.77	53.40

Coefficients:

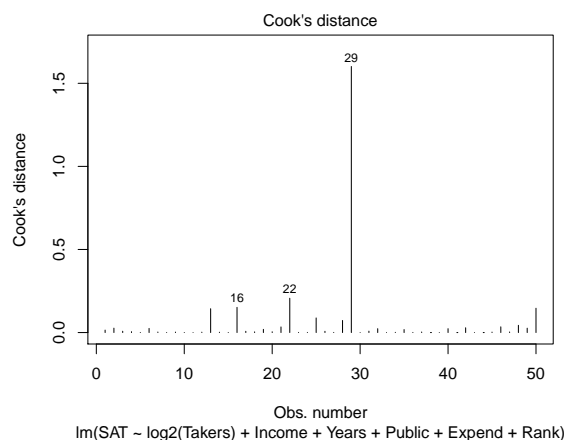
	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	407.5399	282.7633	1.44	0.1567
log2(Takers)	-26.6429	11.0572	-2.41	0.0203
Income	-0.0359	0.1301	-0.28	0.7841
Years	17.2181	6.3201	2.72	0.0093
Public	-0.1130	0.5624	-0.20	0.8417
Expend	2.5669	0.8064	3.18	0.0027
Rank	4.1143	2.5017	1.64	0.1073

Residual standard error: 24.9 on 43 degrees of freedom

Multiple R-squared: 0.892, Adjusted R-squared: 0.877

F-statistic: 59.2 on 6 and 43 DF, p-value: <2e-16

```
> plot(lm2, which=4)
```



According to the Cook's distance plot, obs 29 (Alaska) seems to be an influential outlier. We may consider removing this observation from the dataset.

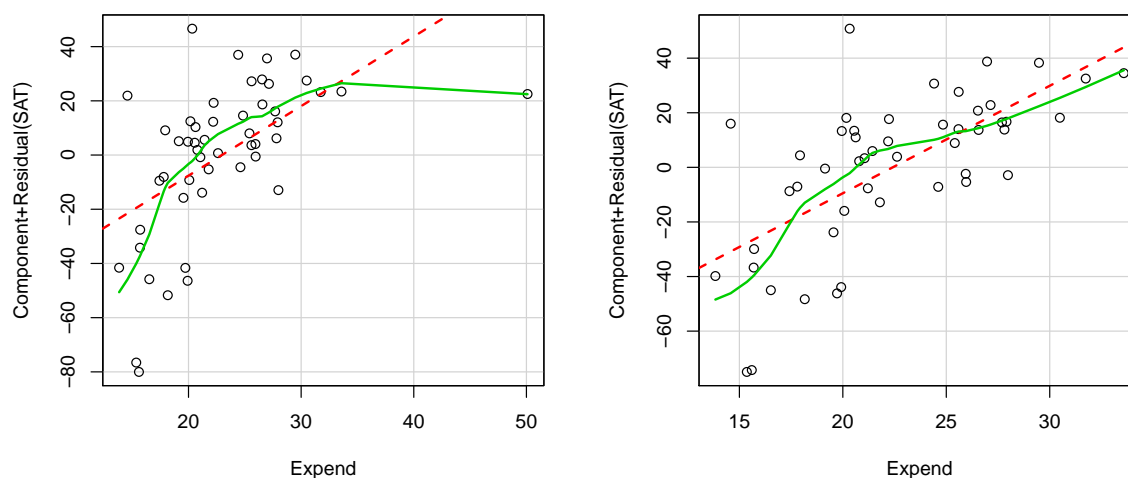
```
> case1201r = case1201[-c(29),]
> lm3 = lm(SAT ~ log2(Takers) + Income+ Years + Public + Expend + Rank, data=case1201r)
> anova(lm3)
```

Analysis of Variance Table

Response: SAT

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
log2(Takers)	1	199007	199007	390.63	< 2e-16
Income	1	785	785	1.54	0.2214
Years	1	5910	5910	11.60	0.0015
Public	1	5086	5086	9.98	0.0029
Expend	1	10513	10513	20.64	4.6e-05
Rank	1	2679	2679	5.26	0.0269
Residuals	42	21397	509		

```
> crPlots(lm2, term = ~ Expend) # with Alaska
> crPlots(lm3, term = ~ Expend) # without Alaska
```



The difference between these two slopes indicates that Alaska is an influential observation. We decide to remove it from the original dataset.

2.3 Sequential Variable Selection

The book uses F-statistics as the criterion to perform the procedures of forward selection and backward elimination presented on page 359. As mentioned on page 359, the entire forward selection procedure required the fitting of only 16 of the 64 possible models presented on Display 12.6 (page 360). These 16 models utilized Expenditure and log(Takers) to predict SAT scores. Further, as mentioned on page 359, the entire backward selection procedure required the fitting of only 3

models of the 64 possible models. These 3 models used Year, Expenditure, Rank and $\log(\text{Takers})$ to predict SAT scores.

To the best of our knowledge, RStudio is not equipped to perform stepwise regressions using F-statistics. Instead, we demonstrate this proceduring using AIC criterion and get the final model using the following code. Note that we choose $\log(\text{Taker})$ as our preliminary predictor for forward selection, because it has the largest F-value when we fitted `lm3`.

```
> # Forward Selection
> lm4 = lm(SAT ~ log2(Takers), data=case1201r)
> stepAIC(lm4, scope=list(upper=lm3, lower=~1),
+   direction="forward", trace=FALSE)$anova
```

Stepwise Model Path
Analysis of Deviance Table

Initial Model:
SAT ~ log2(Takers)

Final Model:
SAT ~ log2(Takers) + Expend + Years + Rank

	Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
1				47	46369	339.8
2	+ Expend	1	20523	46	25846	313.1
3	+ Years	1	1248	45	24598	312.7
4	+ Rank	1	2676	44	21922	309.1

```
> # Backward Elimination
> stepAIC(lm3, direction="backward", trace=FALSE)$anova
```

Stepwise Model Path
Analysis of Deviance Table

Initial Model:
SAT ~ log2(Takers) + Income + Years + Public + Expend + Rank

Final Model:
SAT ~ log2(Takers) + Years + Expend + Rank

	Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
1				42	21397	311.9
2	- Public	1	20.0	43	21417	309.9
3	- Income	1	505.4	44	21922	309.1


```
> # Stepwise Regression
> stepAIC(lm3, direction="both", trace=FALSE)$anova
```

Stepwise Model Path
Analysis of Deviance Table

Initial Model:
SAT ~ log2(Takers) + Income + Years + Public + Expend + Rank

Final Model:
SAT ~ log2(Takers) + Years + Expend + Rank

	Step	Df	Deviance	Resid. Df	Resid. Dev	AIC
1				42	21397	311.9
2 - Public	1	20.0		43	21417	309.9
3 - Income	1	505.4		44	21922	309.1

Thus, the final model includes log(Takers), Expenditure, Years and Rank.

```
> lm5 = lm(SAT ~ log2(Takers) + Expend + Years + Rank, data=case1201r)
> summary(lm5)
```

Call:
lm(formula = SAT ~ log2(Takers) + Expend + Years + Rank, data = case1201r)

Residuals:

Min	1Q	Median	3Q	Max
-52.30	-9.92	0.60	11.88	59.20

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	399.115	232.372	1.72	0.0929
log2(Takers)	-26.409	8.259	-3.20	0.0026
Expend	3.996	0.764	5.23	4.5e-06
Years	13.147	5.478	2.40	0.0207
Rank	4.400	1.899	2.32	0.0252

Residual standard error: 22.3 on 44 degrees of freedom
Multiple R-squared: 0.911, Adjusted R-squared: 0.903
F-statistic: 112 on 4 and 44 DF, p-value: <2e-16

The final model can explain 91.1% percent or the variation of SAT. All of the explanatory variables are statistically significant at the $\alpha = .05$ level.

2.4 Model Selection Among All Subsets

The Cp-statistic can be an useful criterion to select model among all subsets. We'll give an example about how to calculate this statistic for one model, which includes log(Takers), Expenditure, Years and Rank.

```
> sigma5 = summary(lm5)$sigma^2 # sigma-squared of chosen model
> sigma3 = summary(lm3)$sigma^2 # sigma-squared of full model
> n = 49 # sample size
> p = 4+1 # number of coefficients in model
> Cp=(n-p)*sigma5/sigma3+(2*p-n)
> Cp

[1] 4.031
```

The Cp statistic for this model is 4.0312.

Alternatively, the Cp statistic can be calculated using the following command:

```
> require(leaps)
> explanatory = with(case1201r, cbind(log(Takers), Income, Years, Public, Expend, Rank))
> with(case1201r, leaps(explanatory, SAT, method="Cp"))$which[27,]

      1      2      3      4      5      6
TRUE FALSE TRUE FALSE TRUE TRUE
```

This means that the 27th fitting model includes log(Takers), Years and Expend.

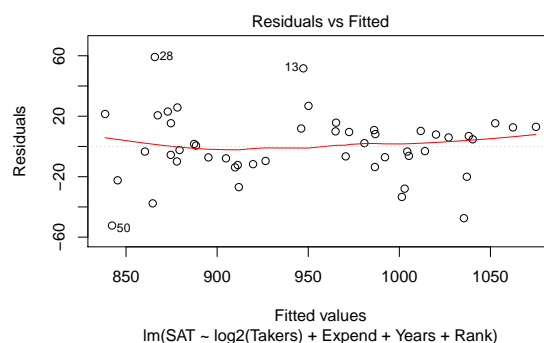
```
> with(case1201r, leaps(explanatory, SAT, method="Cp"))$Cp[27]

[1] 4.031
```

The Cp statistic for this model is 4.0312. This will be the the "tyer" point on the Display 12.9, page 365.

We use the following code to generate the graph presented as Display 12.14 on page 372.

```
> plot(lm5, which=1)
```



From the scatterplot, we see that obs 28 (New Hampshire) has the largest residual, while obs 50 (South Carolina) has the smallest.

2.5 Contribution of Expend

Display 12.13 (page 363) shows the contribution of Expend to the model.

```
> lm7 = lm(SAT ~ Expend, data=case1201r)
> summary(lm7)
```

Call:
lm(formula = SAT ~ Expend, data = case1201r)

Residuals:

Min	1Q	Median	3Q	Max
-162.5	-57.7	17.0	46.6	141.4

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	961.724	49.888	19.28	<2e-16
Expend	-0.592	2.178	-0.27	0.79

Residual standard error: 72.2 on 47 degrees of freedom
Multiple R-squared: 0.00157, Adjusted R-squared: -0.0197
F-statistic: 0.074 on 1 and 47 DF, p-value: 0.787

```
> lm8 = lm(SAT ~ Income + Expend, data=case1201r)
> summary(lm8)
```

Call:
lm(formula = SAT ~ Income + Expend, data = case1201r)

Residuals:

Min	1Q	Median	3Q	Max
-91.15	-38.41	-2.58	27.29	159.52

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	604.682	73.209	8.26	1.2e-10
Income	1.127	0.196	5.73	7.2e-07
Expend	0.672	1.695	0.40	0.69

Residual standard error: 55.7 on 46 degrees of freedom
Multiple R-squared: 0.418, Adjusted R-squared: 0.392
F-statistic: 16.5 on 2 and 46 DF, p-value: 3.95e-06

3 Sex Discrimination in Employment

Do females receive lower starting salaries than similarly qualified and similarly experience males and did females receive smaller pay increases than males? These are the questions explored in case 12.2 in the *Sleuth*.

3.1 Summary Statistics

We begin by summarizing the data.

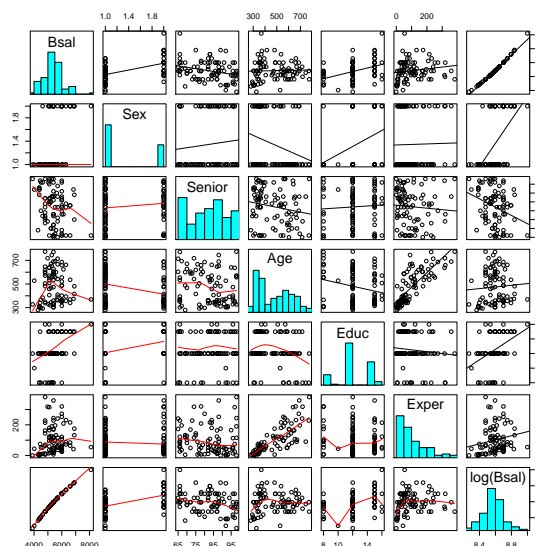
```
> summary(case1202)
```

Bsal		Sal77	Sex	Senior	Age
Min.	:3900	Min. : 7860	Female:61	Min. :65.0	Min. :280
1st Qu.:	4980	1st Qu.: 9000	Male :32	1st Qu.:74.0	1st Qu.:349
Median	:5400	Median :10020		Median :84.0	Median :468
Mean	:5420	Mean :10393		Mean :82.3	Mean :474
3rd Qu.:	6000	3rd Qu.:11220		3rd Qu.:90.0	3rd Qu.:590
Max.	:8100	Max. :16320		Max. :98.0	Max. :774
Educ		Exper			
Min.	: 8.0	Min. : 0.0			
1st Qu.:	12.0	1st Qu.: 35.5			
Median	:12.0	Median : 70.0			
Mean	:12.5	Mean :100.9			
3rd Qu.:	15.0	3rd Qu.:144.0			
Max.	:16.0	Max. :381.0			

The data is shown on page 350-351 as display 12.3. A total of 93 employee salaries are included: 61 females and 32 males.

Next we present a full graphical display for the variables within the dataset and the log of the beginning salary variable.

```
> pairs(~ Bsal+Sex+Senior+Age+Educ+Exper+log(Bsal),
+       lower.panel=panel.smooth, diag.panel=panel.hist,
+       upper.panel=panel.lm, data=case1202)
```



Through these scatterplots it appears that beginning salary should be on the log scale and the starting model without the effects of gender will be a saturated second-order model with 14 variables including Seniority, Age, Education, Experience, as main effects, quadratic terms, and their full interactions.

3.2 Model Selection

To determine the best subset of these variables we first compared Cp statistics. Display 12.11 shows the Cp statistics for models that meet ‘good practice’ and have small Cp values. We will demonstrate how to calculate the Cp statistics for the two models with the lowest Cp statistics discussed in “Identifying Good Subset Models” on pages 367-368.

The first model includes Seniority, Age, Education, Experience, and the interactions between Seniority and Education, Age and Education, and Age and Experience. The second model includes Seniority, Age, Education, Experience, and the interactions between Age and Education and Age and Experience.

```
> require(leaps)
> explanatory1 = with(case1202, cbind(Senior, Age, Educ, Exper, Senior*Educ, Age*Educ, Age*Exp
> # First model (saexnck)
> with(case1202, leaps(explanatory1, log(Bsal), method="Cp"))$which[55,]

  1    2    3    4    5    6    7
TRUE TRUE TRUE TRUE TRUE TRUE TRUE

> with(case1202, leaps(explanatory1, log(Bsal), method="Cp"))$Cp[55]

[1] 8

> # second model (saexck)
> with(case1202, leaps(explanatory1, log(Bsal), method="Cp"))$which[49,]
```

```

      1      2      3      4      5      6      7
TRUE TRUE TRUE TRUE FALSE TRUE TRUE

> with(case1202, leaps(explanatory1, log(Bsal), method="Cp"))$Cp[49]

[1] 8.124

```

This first model has a Cp statistic of 8. Compared to the second model with a Cp statistic of 8.12.

We can also compare models using the BIC, we will next compare the second model with a third model defined as $saeryc = \text{Seniority} + \text{Age} + \text{Education} + \text{Experience} + \text{Experience}^2 + \text{Age} * \text{Education}$.

```

> BIC(lm(log(Bsal) ~ Senior+Age+Educ+Exper+Age*Educ+Age*Exper, data=case1202))

[1] -140.2

> BIC(lm(log(Bsal) ~ Senior+Age+Educ+Exper+(Exper)^2+Age*Educ, data=case1202))

[1] -131.3

```

Thus our final model is the second model, summarized below.

```

> lm1 = lm(log(Bsal) ~ Senior + Age + Educ + Exper + Age*Educ + Age*Exper, data=case1202)
> summary(lm1)

Call:
lm(formula = log(Bsal) ~ Senior + Age + Educ + Exper + Age *
    Educ + Age * Exper, data = case1202)

Residuals:
    Min       1Q   Median       3Q      Max
-0.2817 -0.0476  0.0132  0.0605  0.2341

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   7.89e+00   2.45e-01  32.21  < 2e-16
Senior        -3.15e-03   1.04e-03  -3.04  0.00313
Age           1.24e-03   4.02e-04   3.09  0.00270
Educ          7.20e-02   1.67e-02   4.31  4.3e-05
Exper         2.86e-03   6.67e-04   4.28  4.8e-05
Age:Educ      -1.02e-04   3.15e-05  -3.25  0.00166
Age:Exper     -3.72e-06   1.02e-06  -3.65  0.00044

Residual standard error: 0.0974 on 86 degrees of freedom

```

```
Multiple R-squared: 0.469, Adjusted R-squared: 0.431
F-statistic: 12.6 on 6 and 86 DF, p-value: 3.58e-10
```

3.3 Evaluating the Sex Effect

After selecting the model $saexck = \text{Seniority} + \text{Age} + \text{Education} + \text{Experience} + \text{Age} \times \text{Education} + \text{Age} \times \text{Experience}$ we can add the sex indicator variable as summarized on page 360.

```
> lm2 = lm(log(Bsal) ~ Senior + Age + Educ + Exper + Age*Educ + Age*Exper + Sex, data=case1202)
> summary(lm2)
```

Call:

```
lm(formula = log(Bsal) ~ Senior + Age + Educ + Exper + Age *
    Educ + Age * Exper + Sex, data = case1202)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-0.17822	-0.05197	-0.00203	0.05301	0.20466

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	8.16e+00	2.21e-01	36.99	< 2e-16
Senior	-3.48e-03	9.09e-04	-3.83	0.00024
Age	9.15e-04	3.57e-04	2.56	0.01218
Educ	4.23e-02	1.57e-02	2.70	0.00836
Exper	2.18e-03	5.98e-04	3.65	0.00045
SexMale	1.20e-01	2.29e-02	5.22	1.3e-06
Age:Educ	-5.46e-05	2.91e-05	-1.88	0.06402
Age:Exper	-3.23e-06	8.96e-07	-3.61	0.00052

Residual standard error: 0.0853 on 85 degrees of freedom

Multiple R-squared: 0.598, Adjusted R-squared: 0.564

F-statistic: 18 on 7 and 85 DF, p-value: 1.79e-14

In contrast to the book, our reference group is Male, therefore the median male salary is estimated to be 1.13 times as large as the median female salary, adjusted for the other variables.