

TOPIC3: Model selection

Multiple Linear Regression

Part III: Model Selection

© Thuntida Ngamkham 2022 modified by Paul Galpern

Model Selection

One of the biggest problem in building a model to describe a response variable (Y) is choosing the important independent variables to be included. The list of potentially important independent variables is extremely long and we need some objective methods of screening out those which are not important. The problem of deciding which of a large set of independent variables to include in a model is a common one.

For example: Independent Variables in the Executive Salary

Independent Variable and Description

- x_1 : Experience (years)-quantitative
- x_2 : Education (years)-quantitative
- x_3 : Bonus eligibility (1 if yes, 0 if no)-qualitative
- x_4 : Number of employees supervised-quantitative
- x_5 : Corporate assets (millions of dollars)-quantitative
- x_6 : Board member (1 if yes, 0 if no)-qualitative
- x_7 : Age (years)-quantitative
- x_8 : Company profits (past 12 months, millions of dollars)-quantitative
- x_9 : Has international responsibility (1 if yes, 0 if no)-qualitative
- x_{10} : Company's total sales (past 12 months, millions of dollars)-quantitative

Steps in Selecting the Best Regression Equation

To select the best regresson equation, carry out the following steps

1. Specify the maximum model to be considered.
2. Specify a strategy for selecting a model
3. Evaluate the reliability of the model chosen.

By following theses steps, you can convert the fuzzy idea of finding the best predictors of Y into simple, concrete action. Each step helps to ensure reliability and to reduce the work required.

Step 1: Specifying the Maximum Model

The maximum model is defined to be the largest model (the one having the most predictor variables) considered at any point in the process of model selection. A model created by deleting predictors from the maximum model is called *a restriction of the maximum model*.

Step 2: Specify a strategy for selecting a model

A systematic approach to building a restriction model from a large number of independent variables is difficult because the interpretation of multivariable interactions is complicated. We therefore turn to a screening procedure, available in most statistical software packages, objectively determine which independent variables in the list are the most important predictors of Y and which are the least important predictors. The most widely used method is **stepwise regression**, while another popular method, **backward** and **forward regression**, also are provided in this section.

Stepwise Regression Procedure

The user first identifies the response y and the set of potentially important independent variables x_1, x_2, \dots, x_p , where p is generally large. However, we often **include only the main effects** of both quantitative variables (first-order terms) and qualitative variables (dummy variables). The response and independent variables are then entered into the computer software, and the stepwise procedure begins.

Step 1 The software program fits all possible one-variable models of the form

$$E(Y) = \beta_0 + \beta_1 X_i$$

to the data, where X_i is the i th independent variable, $i = 1, 2, \dots, p$. For each model, the t-test for a single β_1 parameter is conducted to test the null hypothesis

$$H_0: \beta_1 = 0$$

against the alternative hypothesis

$$H_a: \beta_1 \neq 0$$

The independent variable that produces the largest (absolute) t-value is then declared the best one-variable predictor of Y . Call this independent variable X_1 .

```
library(olsrr)#need to install the package olsrr
```

```
##
```

```
## Attaching package: 'olsrr'
```

```
## The following object is masked from 'package:datasets':
```

```
##
```

```
## rivers
```

```
salary=read.csv("EXECSAL2.csv", header = TRUE)
```

```
model1<-lm(Y~X1, data = salary)
```

```
summary(model1)
```

```
##
```

```
## Call:
```

```
## lm(formula = Y ~ X1, data = salary)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.51010 -0.08148  0.01533  0.09007  0.34663
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.090887   0.033055  335.52  <2e-16 ***
## X1           0.027839   0.002206   12.62  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1612 on 98 degrees of freedom
## Multiple R-squared:  0.619, Adjusted R-squared:  0.6151
## F-statistic: 159.2 on 1 and 98 DF,  p-value: < 2.2e-16
```

```
model2<-lm(Y~X2, data = salary)
summary(model2)
```

```
##
## Call:
## lm(formula = Y ~ X2, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.69058 -0.17417  0.01475  0.14929  0.60722
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.05594   0.17971  61.520  <2e-16 ***
## X2           0.02491   0.01110   2.243   0.0271 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2547 on 98 degrees of freedom
## Multiple R-squared:  0.04884, Adjusted R-squared:  0.03914
## F-statistic: 5.032 on 1 and 98 DF,  p-value: 0.02713
```

```
model3<-lm(Y~X3, data = salary)
summary(model3)
```

```
##
## Call:
## lm(formula = Y ~ X3, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.64801 -0.17344  0.02863  0.18306  0.53486
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.31231   0.04112  275.116  < 2e-16 ***
## X3yes        0.21623   0.05061   4.272 4.49e-05 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2398 on 98 degrees of freedom
## Multiple R-squared:  0.157, Adjusted R-squared:  0.1484
## F-statistic: 18.25 on 1 and 98 DF, p-value: 4.487e-05
```

```
model4<-lm(Y~X4, data = salary)
summary(model4)
```

```
##
## Call:
## lm(formula = Y ~ X4, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.79069 -0.16613 -0.01677  0.18069  0.53399
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.134e+01  5.813e-02 195.157  <2e-16 ***
## X4           3.236e-04  1.535e-04   2.107   0.0376 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2554 on 98 degrees of freedom
## Multiple R-squared:  0.04335, Adjusted R-squared:  0.03359
## F-statistic: 4.441 on 1 and 98 DF, p-value: 0.03763
```

```
model5<-lm(Y~X5, data = salary)
summary(model5)
```

```
##
## Call:
## lm(formula = Y ~ X5, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.70447 -0.17997 -0.00744  0.17354  0.57667
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.853365  0.293139  37.02  <2e-16 ***
## X5           0.003436  0.001668   2.06   0.042 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2557 on 98 degrees of freedom
## Multiple R-squared:  0.04152, Adjusted R-squared:  0.03174
## F-statistic: 4.245 on 1 and 98 DF, p-value: 0.04202
```

```
model6<-lm(Y~X6, data = salary)
summary(model6)
```

```
##
## Call:
## lm(formula = Y ~ X6, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.77744 -0.18580 -0.00297  0.15596  0.59563
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.46777    0.03652 314.017  <2e-16 ***
## X6yes       -0.02603    0.05217  -0.499   0.619
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2608 on 98 degrees of freedom
## Multiple R-squared:  0.002533, Adjusted R-squared:  -0.007645
## F-statistic: 0.2489 on 1 and 98 DF, p-value: 0.619
```

```
model7<-lm(Y~X7, data = salary)
summary(model7)
```

```
##
## Call:
## lm(formula = Y ~ X7, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.52333 -0.13687  0.02306  0.13711  0.49733
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.682669    0.098393 108.571  < 2e-16 ***
## X7           0.018029    0.002247   8.022 2.28e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2029 on 98 degrees of freedom
## Multiple R-squared:  0.3964, Adjusted R-squared:  0.3902
## F-statistic: 64.35 on 1 and 98 DF, p-value: 2.277e-12
```

```
model8<-lm(Y~X8, data = salary)
summary(model8)
```

```
##
## Call:
## lm(formula = Y ~ X8, data = salary)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.78463 -0.17565  0.00108  0.14772  0.62316
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.388078   0.132479  85.961  <2e-16 ***
## X8           0.008693   0.016868   0.515   0.607
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2608 on 98 degrees of freedom
## Multiple R-squared:  0.002703, Adjusted R-squared: -0.007474
## F-statistic: 0.2656 on 1 and 98 DF, p-value: 0.6075
```

```
model9<-lm(Y~X9, data = salary)
summary(model9)
```

```
##
## Call:
## lm(formula = Y ~ X9, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.79002 -0.17332  0.00838  0.15368  0.60908
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.45432    0.02884 397.211  <2e-16 ***
## X9yes        0.00386    0.06797   0.057   0.955
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2611 on 98 degrees of freedom
## Multiple R-squared:  3.291e-05, Adjusted R-squared: -0.01017
## F-statistic: 0.003225 on 1 and 98 DF, p-value: 0.9548
```

```
model10<-lm(Y~X10, data = salary)
summary(model10)
```

```
##
## Call:
## lm(formula = Y ~ X10, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.7916 -0.1661  0.0035  0.1677  0.5867
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.325878   0.238765  47.435  <2e-16 ***
## X10          0.005201   0.009558   0.544   0.588
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2607 on 98 degrees of freedom
## Multiple R-squared:  0.003012,    Adjusted R-squared:  -0.007161
## F-statistic: 0.2961 on 1 and 98 DF,  p-value: 0.5876
```

Step 2 The stepwise program now begins to search through the remaining $(p - 1)$ independent variables for the best two-variable model of the form

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_i$$

This is done by fitting all two-variable models containing X_1 and each of the other $(p - 1)$ options for the second variable X_i . The t-values for the test $H_0 : \beta_2 = 0$ are computed for each of the $p - 1$ models (corresponding to the remaining independent variables, $X_i, i = 2, 3, \dots, p - 1$), and the variable having the largest t is retained. Call this variable X_2 .

Before proceeding to Step 3, the stepwise routine will go back and check the t-value of $\hat{\beta}_1$ after $\hat{\beta}_2 X_2$ has been added to the model. If the t-value has become nonsignificant at some specified α level (say $\alpha = 0.3$), the variable X_1 is removed and a search is made for the independent variable with a β parameter that will yield the most significant t-value in the presence of $\hat{\beta}_2 X_2$.

The reason the t-value for X_1 may change from step 1 to step 2 is that the meaning of the coefficient $\hat{\beta}_1$ changes. In step 2, we are approximating a complex response surface in two variables with a plane. The best-fitting plane may yield a different value for $\hat{\beta}_1$ than that obtained in step 1. Thus, both the value of $\hat{\beta}_1$ and its significance usually changes from step 1 to step 2. For this reason, stepwise procedures that recheck the t-values at each step are preferred.

```
library(olsrr)#need to install the package olsrr
salary=read.csv("EXECSAL2.csv", header = TRUE)
model1<-lm(Y~X1+X2, data = salary)
summary(model1)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X2, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.41018 -0.08883 -0.00270  0.08998  0.35311
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.692577   0.110148  97.075  < 2e-16 ***
## X1           0.027835   0.002071  13.439  < 2e-16 ***
## X2           0.024866   0.006598   3.769 0.000282 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1513 on 97 degrees of freedom
## Multiple R-squared:  0.6676, Adjusted R-squared:  0.6608
## F-statistic: 97.43 on 2 and 97 DF,  p-value: < 2.2e-16
```

```
model2<-lm(Y~X1+X3, data = salary)
summary(model2)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X3, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.38585 -0.08612  0.00136  0.09114  0.27781
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.968372   0.032010 342.659 < 2e-16 ***
## X1           0.027258   0.001801  15.134 < 2e-16 ***
## X3yes        0.197135   0.027777   7.097 2.1e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1314 on 97 degrees of freedom
## Multiple R-squared:  0.7492, Adjusted R-squared:  0.744
## F-statistic: 144.9 on 2 and 97 DF,  p-value: < 2.2e-16
```

```
model3<-lm(Y~X1+X4, data = salary)
summary(model3)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X4, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.50928 -0.08646  0.01543  0.10257  0.29984
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.098e+01  4.414e-02 248.645 < 2e-16 ***
## X1           2.792e-02  2.077e-03  13.439 < 2e-16 ***
## X4           3.361e-04  9.123e-05   3.684 0.000378 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1517 on 97 degrees of freedom
## Multiple R-squared:  0.6657, Adjusted R-squared:  0.6589
## F-statistic: 96.6 on 2 and 97 DF,  p-value: < 2.2e-16
```

```
model4<-lm(Y~X1+X5, data = salary)
summary(model4)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X5, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.42563 -0.08619  0.00795  0.08695  0.30373
```



```
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.050e+01  1.777e-01  59.077 < 2e-16 ***
## X1          2.781e-02  2.098e-03  13.256 < 2e-16 ***
## X5          3.378e-03  9.997e-04   3.379  0.00105 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1533 on 97 degrees of freedom
## Multiple R-squared:  0.6591, Adjusted R-squared:  0.6521
## F-statistic: 93.77 on 2 and 97 DF,  p-value: < 2.2e-16
```

```
model5<-lm(Y~X1+X6, data = salary)
summary(model5)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X6, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.48700 -0.08907  0.00752  0.09016  0.34976
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.110322   0.036001 308.609 <2e-16 ***
## X1           0.027960   0.002199  12.712 <2e-16 ***
## X6yes        -0.042898   0.032144  -1.335   0.185
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1606 on 97 degrees of freedom
## Multiple R-squared:  0.6258, Adjusted R-squared:  0.6181
## F-statistic: 81.13 on 2 and 97 DF,  p-value: < 2.2e-16
```

```
model6<-lm(Y~X1+X7, data = salary)
summary(model6)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X7, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.49375 -0.08082  0.02015  0.08661  0.33368
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.042344   0.091739 120.367 < 2e-16 ***
## X1           0.026315   0.003480   7.562 2.26e-11 ***
## X7           0.001598   0.002816   0.568   0.572
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1617 on 97 degrees of freedom
## Multiple R-squared:  0.6202, Adjusted R-squared:  0.6124
## F-statistic: 79.21 on 2 and 97 DF,  p-value: < 2.2e-16
```

```
model7<-lm(Y~X1+X8, data = salary)
summary(model7)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X8, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.50473 -0.08487  0.02426  0.08717  0.36774
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.030724   0.086844 127.018  <2e-16 ***
## X1           0.027828   0.002211  12.584  <2e-16 ***
## X8           0.007832   0.010450   0.749    0.455
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1616 on 97 degrees of freedom
## Multiple R-squared:  0.6212, Adjusted R-squared:  0.6134
## F-statistic: 79.53 on 2 and 97 DF,  p-value: < 2.2e-16
```

```
model8<-lm(Y~X1+X9, data = salary)
summary(model8)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X9, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.51268 -0.07828  0.01660  0.09221  0.34383
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.093365   0.033831 327.909  <2e-16 ***
## X1           0.027871   0.002218  12.568  <2e-16 ***
## X9yes        -0.016080   0.042170  -0.381    0.704
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1619 on 97 degrees of freedom
## Multiple R-squared:  0.6195, Adjusted R-squared:  0.6117
## F-statistic: 78.98 on 2 and 97 DF,  p-value: < 2.2e-16
```

```
model9<-lm(Y~X1+X10, data = salary)
summary(model9)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X10, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.50403 -0.06077  0.00449  0.08415  0.35693
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11.272380   0.147215  76.571  <2e-16 ***
## X1           0.028314   0.002231  12.689  <2e-16 ***
## X10          -0.007560   0.005976  -1.265    0.209
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1607 on 97 degrees of freedom
## Multiple R-squared:  0.6252, Adjusted R-squared:  0.6174
## F-statistic: 80.89 on 2 and 97 DF,  p-value: < 2.2e-16
```

Step 3 The stepwise regression procedure now checks for a third independent variable to include in the model with X_1 and X_2 . That is, we seek the best model of the form

$$E(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_i$$

To do this, the computer fits all the $(p-2)$ models using X_1, X_2 , and each of the $(p-2)$ remaining variables, X_i , as a possible X_3 . The criterion is again to include the independent variable with the largest (significant) t-value. Call this best third variable X_3 . The better programs now recheck the t-values corresponding to the X_1 and X_2 coefficients, replacing the variables that yield nonsignificant t-values.

This procedure is continued until no further independent variables can be found that yield significant t-values (at the specified α level) in the presence of the variables already in the model.

Refer to the Executive Salary Example. A preliminary step in the construction of this model is the determination of the most important independent variables. For one firm, 10 potential independent variables (seven quantitative and three qualitative) were measured in a sample of 100 executives. The data are saved in the **EXECSAL2.CSV** file. Since it would be very difficult to construct a complete first-order model with all of the 10 independent variables, use stepwise regression to decide which of the 10 variables should be included in the building of the final model.

```
library(olsrr)#need to install the package olsrr
salary=read.csv("EXECSAL2.csv", header = TRUE)
fullmodel<-lm(Y~X1+X2+factor(X3)+X4+X5+factor(X6)+X7+X8+factor(X9)+X10, data = salary)
summary(fullmodel)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X2 + factor(X3) + X4 + X5 + factor(X6) +
##      X7 + X8 + factor(X9) + X10, data = salary)
##
## Residuals:
```

```
##           Min           1Q       Median           3Q           Max
## -0.201770 -0.050464  0.004435  0.046826  0.185952
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.002e+01  1.481e-01  67.692 < 2e-16 ***
## X1            2.792e-02  1.773e-03  15.745 < 2e-16 ***
## X2            2.903e-02  3.426e-03   8.475 4.57e-13 ***
## factor(X3)yes 2.243e-01  1.708e-02  13.135 < 2e-16 ***
## X4            5.140e-04  4.922e-05  10.443 < 2e-16 ***
## X5            2.048e-03  5.250e-04   3.901 0.000186 ***
## factor(X6)yes -1.538e-02  1.686e-02  -0.912 0.364124
## X7            -5.097e-04  1.438e-03  -0.355 0.723795
## X8            -2.633e-03  5.128e-03  -0.513 0.608896
## factor(X9)yes -2.656e-02  2.037e-02  -1.304 0.195613
## X10           -9.774e-04  2.959e-03  -0.330 0.741955
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07608 on 89 degrees of freedom
## Multiple R-squared:  0.9229, Adjusted R-squared:  0.9142
## F-statistic: 106.5 on 10 and 89 DF,  p-value: < 2.2e-16
```

```
stepmod=ols_step_both_p(fullmodel,pent = 0.1, prem = 0.3, details=TRUE)
```

```
## Stepwise Selection Method
## -----
##
## Candidate Terms:
##
## 1. X1
## 2. X2
## 3. factor(X3)
## 4. X4
## 5. X5
## 6. factor(X6)
## 7. X7
## 8. X8
## 9. factor(X9)
## 10. X10
##
## We are selecting variables based on p value...
##
## Stepwise Selection: Step 1
##
## - X1 added
##
##               Model Summary
## -----
## R              0.787          RMSE              0.161
## R-Squared      0.619          Coef. Var          1.407
## Adj. R-Squared 0.615          MSE              0.026
## Pred R-Squared 0.601          MAE              0.122
```

```

## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
## ANOVA
## -----
## Sum of
## Squares      DF      Mean Square      F      Sig.
## -----
## Regression    4.136      1      4.136    159.204    0.0000
## Residual      2.546     98      0.026
## Total         6.683     99
## -----
##
## Parameter Estimates
## -----
## model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept) 11.091      0.033           335.524    0.000      11.025     11.156
## X1          0.028      0.002           0.787     12.618    0.000      0.023     0.032
## -----
##
## Stepwise Selection: Step 2
##
## - factor(X3) added
##
## Model Summary
## -----
## R              0.866      RMSE          0.131
## R-Squared      0.749      Coef. Var     1.147
## Adj. R-Squared 0.744      MSE           0.017
## Pred R-Squared 0.732      MAE           0.104
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
## ANOVA
## -----
## Sum of
## Squares      DF      Mean Square      F      Sig.
## -----
## Regression    5.007      2      2.503    144.887    0.0000
## Residual      1.676     97      0.017
## Total         6.683     99
## -----
##
## Parameter Estimates
## -----
## model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----

```

```

##      (Intercept)    10.968      0.032      342.659    0.000    10.905    11.032
##            X1       0.027      0.002      0.770     15.134    0.000     0.024     0.031
## factor(X3)yes     0.197      0.028      0.361      7.097    0.000     0.142     0.252
## -----
##
##
##
##                      Model Summary
## -----
## R                0.866      RMSE                0.131
## R-Squared         0.749      Coef. Var            1.147
## Adj. R-Squared    0.744      MSE                0.017
## Pred R-Squared    0.732      MAE                0.104
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                      ANOVA
## -----
##              Sum of      DF      Mean Square      F      Sig.
##              Squares
## -----
## Regression      5.007        2          2.503    144.887    0.0000
## Residual        1.676       97          0.017
## Total           6.683       99
## -----
##
##                      Parameter Estimates
## -----
##      model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
##      (Intercept)  10.968      0.032      342.659    0.000    10.905    11.032
##            X1     0.027      0.002      0.770     15.134    0.000     0.024     0.031
## factor(X3)yes    0.197      0.028      0.361      7.097    0.000     0.142     0.252
## -----
##
##
##
## Stepwise Selection: Step 3
##
## - X4 added
##
##                      Model Summary
## -----
## R                0.916      RMSE                0.106
## R-Squared         0.839      Coef. Var            0.924
## Adj. R-Squared    0.834      MSE                0.011
## Pred R-Squared    0.825      MAE                0.082
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##

```

```

##                                ANOVA
## -----
##                                Sum of
##                                Squares      DF      Mean Square      F      Sig.
## -----
## Regression      5.607      3      1.869      166.873      0.0000
## Residual        1.075      96      0.011
## Total           6.683      99
## -----
##
##                                Parameter Estimates
## -----
##                                model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)      10.783      0.036      298.170      0.000      10.711      10.854
## X1                0.027      0.001      0.771      18.801      0.000      0.024      0.030
## factor(X3)yes     0.233      0.023      0.427      10.170      0.000      0.187      0.278
## X4                0.000      0.000      0.307      7.323      0.000      0.000      0.001
## -----
##
##                                Model Summary
## -----
## R                0.916      RMSE      0.106
## R-Squared         0.839      Coef. Var      0.924
## Adj. R-Squared    0.834      MSE      0.011
## Pred R-Squared    0.825      MAE      0.082
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                                ANOVA
## -----
##                                Sum of
##                                Squares      DF      Mean Square      F      Sig.
## -----
## Regression      5.607      3      1.869      166.873      0.0000
## Residual        1.075      96      0.011
## Total           6.683      99
## -----
##
##                                Parameter Estimates
## -----
##                                model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)      10.783      0.036      298.170      0.000      10.711      10.854
## X1                0.027      0.001      0.771      18.801      0.000      0.024      0.030
## factor(X3)yes     0.233      0.023      0.427      10.170      0.000      0.187      0.278
## X4                0.000      0.000      0.307      7.323      0.000      0.000      0.001
## -----
##
##
##

```

```
##
## Stepwise Selection: Step 4
##
## - X2 added
```

```
##
##           Model Summary
## -----
```

## R	0.953	RMSE	0.081
## R-Squared	0.907	Coef. Var	0.704
## Adj. R-Squared	0.904	MSE	0.007
## Pred R-Squared	0.896	MAE	0.062

```
## -----
```

```
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
```

```
##
##           ANOVA
## -----
```

##	Sum of	DF	Mean Square	F	Sig.
##	Squares				
## Regression	6.064	4	1.516	232.936	0.0000
## Residual	0.618	95	0.007		
## Total	6.683	99			

```
## -----
```

```
##
##           Parameter Estimates
## -----
```

##	model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
##	(Intercept)	10.278	0.066		155.154	0.000	10.146	10.409
##	X1	0.027	0.001	0.771	24.677	0.000	0.025	0.029
##	factor(X3)yes	0.232	0.017	0.425	13.297	0.000	0.197	0.267
##	X4	0.001	0.000	0.354	10.920	0.000	0.000	0.001
##	X2	0.030	0.004	0.266	8.379	0.000	0.023	0.037

```
## -----
```

```
##
##           Model Summary
## -----
```

## R	0.953	RMSE	0.081
## R-Squared	0.907	Coef. Var	0.704
## Adj. R-Squared	0.904	MSE	0.007
## Pred R-Squared	0.896	MAE	0.062

```
## -----
```

```
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
```

```
##
##           ANOVA
## -----
```

##	Sum of	DF	Mean Square	F	Sig.
##	Squares				


```

## -----
## Regression      6.064      4      1.516    232.936    0.0000
## Residual       0.618     95      0.007
## Total          6.683     99
## -----
##
##                               Parameter Estimates
## -----
##      model      Beta    Std. Error    Std. Beta      t      Sig      lower    upper
## -----
##      (Intercept)  10.278      0.066              155.154    0.000    10.146    10.409
##      X1           0.027      0.001      0.771      24.677    0.000     0.025     0.029
##      factor(X3)yes 0.232      0.017      0.425      13.297    0.000     0.197     0.267
##      X4           0.001      0.000      0.354      10.920    0.000     0.000     0.001
##      X2           0.030      0.004      0.266       8.379    0.000     0.023     0.037
## -----
##
##
##
## Stepwise Selection: Step 5
##
## - X5 added
##
##                               Model Summary
## -----
## R                0.959      RMSE              0.075
## R-Squared         0.921      Coef. Var        0.656
## Adj. R-Squared    0.916      MSE              0.006
## Pred R-Squared    0.909      MAE              0.059
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                               ANOVA
## -----
##      Sum of
##      Squares      DF      Mean Square      F      Sig.
## -----
## Regression      6.152      5      1.230    218.061    0.0000
## Residual        0.530     94      0.006
## Total           6.683     99
## -----
##
##                               Parameter Estimates
## -----
##      model      Beta    Std. Error    Std. Beta      t      Sig      lower    upper
## -----
##      (Intercept)  9.962      0.101              98.578    0.000     9.761    10.163
##      X1           0.027      0.001      0.771     26.501    0.000     0.025     0.029
##      factor(X3)yes 0.225      0.016      0.412     13.742    0.000     0.192     0.257
##      X4           0.001      0.000      0.337     11.064    0.000     0.000     0.001
##      X2           0.029      0.003      0.258      8.719    0.000     0.022     0.036
##      X5           0.002      0.000      0.116      3.947    0.000     0.001     0.003

```

```

## -----
##
##
##
##
##           Model Summary
## -----
## R                0.959          RMSE                0.075
## R-Squared        0.921          Coef. Var            0.656
## Adj. R-Squared   0.916          MSE                  0.006
## Pred R-Squared   0.909          MAE                  0.059
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##
##           ANOVA
## -----
##              Sum of
##              Squares      DF      Mean Square      F      Sig.
## -----
## Regression      6.152        5          1.230    218.061    0.0000
## Residual        0.530       94          0.006
## Total           6.683       99
## -----
##
##
##           Parameter Estimates
## -----
##      model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)    9.962        0.101          98.578    0.000    9.761    10.163
## X1              0.027        0.001          26.501    0.000    0.025    0.029
## factor(X3)yes  0.225        0.016          13.742    0.000    0.192    0.257
## X4              0.001        0.000          11.064    0.000    0.000    0.001
## X2              0.029        0.003          8.719    0.000    0.022    0.036
## X5              0.002        0.000          3.947    0.000    0.001    0.003
## -----
##
##
##
## No more variables to be added/removed.
##
##
## Final Model Output
## -----
##
##           Model Summary
## -----
## R                0.959          RMSE                0.075
## R-Squared        0.921          Coef. Var            0.656
## Adj. R-Squared   0.916          MSE                  0.006
## Pred R-Squared   0.909          MAE                  0.059
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error

```

```
## MAE: Mean Absolute Error
##
##
## ANOVA
## -----
##          Sum of
##          Squares      DF      Mean Square      F      Sig.
## -----
## Regression      6.152        5          1.230    218.061    0.0000
## Residual        0.530       94          0.006
## Total           6.683       99
## -----
##
##
## Parameter Estimates
## -----
##          model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)      9.962        0.101          98.578    0.000      9.761    10.163
## X1                0.027        0.001          26.501    0.000      0.025     0.029
## factor(X3)yes     0.225        0.016          13.742    0.000      0.192     0.257
## X4                0.001        0.000          11.064    0.000      0.000     0.001
## X2                0.029        0.003           8.719    0.000      0.022     0.036
## X5                0.002        0.000           3.947    0.000      0.001     0.003
## -----
```

```
summary(stepmod$model)
```

```
##
## Call:
## lm(formula = paste(response, "~", paste(preds, collapse = " + ")),
##     data = 1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.201219 -0.056016 -0.003581  0.053656  0.187251
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  9.9619345  0.1010567  98.578 < 2e-16 ***
## X1           0.0272762  0.0010293  26.501 < 2e-16 ***
## factor(X3)yes 0.2246932  0.0163503  13.742 < 2e-16 ***
## X4           0.0005244  0.0000474   11.064 < 2e-16 ***
## X2           0.0290921  0.0033367   8.719 9.71e-14 ***
## X5           0.0019623  0.0004972   3.947 0.000153 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07512 on 94 degrees of freedom
## Multiple R-squared:  0.9206, Adjusted R-squared:  0.9164
## F-statistic: 218.1 on 5 and 94 DF,  p-value: < 2.2e-16
```

R functions ols_step_both_p(): Build regression model from a set of candidate predictor variables by entering and removing predictors based on p values

Note!

pent: variables with p value less than pent will enter into the model.

prem: variables with p value more than prem will be removed from the model.

details: print the regression result at each step.

From the output, the regression model is $Y = X_1 + X_2 + X_3 + X_4 + X_5 + \epsilon$. Is this model the best fit for predicting executive salary?

Inclass Practice Problem 10

From the credit example in MLR Modelling Part 2, use **Stepwise Regression Procedure** to find the potentially important independent variables for predicting credit card balance.

Backward Elimination Procedure

The Backward procedure initially fits a model containing terms for all potential independent variables. That is, for p independent variables, the model $E(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p$ is fit in step 1. The variable with the smallest t (or F) statistic for testing $H_0 : \beta_i = 0$ is identified and dropped from the model if the t-value is less than some specified critical value or p-value more than a cut-off. The model with the remaining $(p-1)$ independent variables is fit in step 2, and again, the variable associated with the smallest nonsignificant t-value is dropped. This process is repeated until no further nonsignificant independent variables can be found.

```
library(olsrr) #need to install the package olsrr
salary=read.csv("EXECSAL2.csv", header = TRUE)
fullmodel<-lm(Y~X1+X2+factor(X3)+X4+X5+factor(X6)+X7+X8+factor(X9)+X10, data = salary)
backmodel=ols_step_backward_p(fullmodel, prem = 0.3, details=TRUE)
```

```
## Backward Elimination Method
## -----
##
## Candidate Terms:
##
## 1 . X1
## 2 . X2
## 3 . factor(X3)
## 4 . X4
## 5 . X5
## 6 . factor(X6)
## 7 . X7
## 8 . X8
## 9 . factor(X9)
## 10 . X10
##
## We are eliminating variables based on p value...
##
## - X10
##
## Backward Elimination: Step 1
##
## Variable X10 Removed
##
```

```

##                               Model Summary
## -----
## R                0.961          RMSE                0.076
## R-Squared        0.923          Coef. Var            0.661
## Adj. R-Squared   0.915          MSE                 0.006
## Pred R-Squared   0.904          MAE                 0.058
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                               ANOVA
## -----
##                Sum of
##                Squares      DF      Mean Square      F      Sig.
## -----
## Regression      6.167        9          0.685    119.551    0.0000
## Residual        0.516       90          0.006
## Total          6.683       99
## -----
##
##                               Parameter Estimates
## -----
##                model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)    9.995        0.123              81.304    0.000      9.751    10.239
## X1              0.028        0.002              16.329    0.000      0.024     0.031
## X2              0.029        0.003              8.519    0.000      0.022     0.036
## factor(X3)yes   0.225        0.017              13.430    0.000      0.192     0.259
## X4              0.001        0.000              10.557    0.000      0.000     0.001
## X5              0.002        0.001              3.911    0.000      0.001     0.003
## factor(X6)yes  -0.015        0.017              -0.884    0.379     -0.048     0.018
## X7              0.000        0.001              -0.296    0.768     -0.003     0.002
## X8             -0.003        0.005              -0.509    0.612     -0.013     0.008
## factor(X9)yes  -0.027        0.020              -1.316    0.192     -0.067     0.014
## -----
##
##
## - X7
##
## Backward Elimination: Step 2
##
## Variable X7 Removed
##
##                               Model Summary
## -----
## R                0.961          RMSE                0.075
## R-Squared        0.923          Coef. Var            0.658
## Adj. R-Squared   0.916          MSE                 0.006
## Pred R-Squared   0.906          MAE                 0.058
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error

```

```

##
## ANOVA
## -----
## Sum of
## Squares DF Mean Square F Sig.
## -----
## Regression 6.166 8 0.771 135.846 0.0000
## Residual 0.516 91 0.006
## Total 6.683 99
## -----
##
## Parameter Estimates
## -----
## model Beta Std. Error Std. Beta t Sig. lower upper
## -----
## (Intercept) 9.978 0.108 92.466 0.000 9.764 10.192
## X1 0.027 0.001 0.773 26.473 0.000 0.025 0.029
## X2 0.029 0.003 0.259 8.648 0.000 0.022 0.036
## factor(X3)yes 0.225 0.017 0.411 13.605 0.000 0.192 0.257
## X4 0.001 0.000 0.331 10.607 0.000 0.000 0.001
## X5 0.002 0.001 0.122 3.978 0.000 0.001 0.003
## factor(X6)yes -0.013 0.016 -0.026 -0.839 0.404 -0.045 0.018
## X8 -0.003 0.005 -0.015 -0.509 0.612 -0.013 0.007
## factor(X9)yes -0.026 0.020 -0.039 -1.302 0.196 -0.066 0.014
## -----
##
##
## - X8
##
## Backward Elimination: Step 3
##
## Variable X8 Removed
##
## Model Summary
## -----
## R 0.960 RMSE 0.075
## R-Squared 0.923 Coef. Var 0.655
## Adj. R-Squared 0.917 MSE 0.006
## Pred R-Squared 0.907 MAE 0.058
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
## ANOVA
## -----
## Sum of
## Squares DF Mean Square F Sig.
## -----
## Regression 6.165 7 0.881 156.475 0.0000
## Residual 0.518 92 0.006
## Total 6.683 99
## -----
##
##

```

```

##                                     Parameter Estimates
## -----
##      model      Beta      Std. Error      Std. Beta      t      Sig      lower      upper
## -----
##      (Intercept)      9.966      0.105      94.885      0.000      9.758      10.175
##      X1      0.027      0.001      0.773      26.575      0.000      0.025      0.029
##      X2      0.029      0.003      0.258      8.669      0.000      0.022      0.036
##      factor(X3)yes      0.224      0.016      0.411      13.652      0.000      0.192      0.257
##      X4      0.001      0.000      0.332      10.680      0.000      0.000      0.001
##      X5      0.002      0.001      0.119      3.966      0.000      0.001      0.003
##      factor(X6)yes      -0.012      0.016      -0.023      -0.768      0.444      -0.043      0.019
##      factor(X9)yes      -0.025      0.020      -0.037      -1.254      0.213      -0.064      0.015
## -----
##
##
## - factor(X6)
##
## Backward Elimination: Step 4
##
## Variable factor(X6) Removed
##
##                                     Model Summary
## -----
##      R      0.960      RMSE      0.075
##      R-Squared      0.922      Coef. Var      0.653
##      Adj. R-Squared      0.917      MSE      0.006
##      Pred R-Squared      0.909      MAE      0.058
## -----
##      RMSE: Root Mean Square Error
##      MSE: Mean Square Error
##      MAE: Mean Absolute Error
##
##                                     ANOVA
## -----
##      Sum of
##      Squares      DF      Mean Square      F      Sig.
## -----
##      Regression      6.162      6      1.027      183.264      0.0000
##      Residual      0.521      93      0.006
##      Total      6.683      99
## -----
##
##                                     Parameter Estimates
## -----
##      model      Beta      Std. Error      Std. Beta      t      Sig      lower      upper
## -----
##      (Intercept)      9.946      0.101      98.028      0.000      9.745      10.147
##      X1      0.027      0.001      0.772      26.623      0.000      0.025      0.029
##      X2      0.029      0.003      0.260      8.807      0.000      0.023      0.036
##      factor(X3)yes      0.223      0.016      0.409      13.667      0.000      0.191      0.256
##      X4      0.001      0.000      0.337      11.071      0.000      0.000      0.001
##      X5      0.002      0.001      0.122      4.112      0.000      0.001      0.003
##      factor(X9)yes      -0.025      0.020      -0.038      -1.287      0.201      -0.065      0.014
## -----

```

```
##
##
##
## No more variables satisfy the condition of p value = 0.3
##
##
## Variables Removed:
##
## - X10
## - X7
## - X8
## - factor(X6)
##
##
## Final Model Output
## -----
##
##                               Model Summary
## -----
## R                0.960          RMSE                0.075
## R-Squared        0.922          Coef. Var            0.653
## Adj. R-Squared   0.917          MSE                 0.006
## Pred R-Squared   0.909          MAE                 0.058
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                               ANOVA
## -----
##                Sum of
##                Squares      DF      Mean Square      F      Sig.
## -----
## Regression      6.162        6          1.027      183.264    0.0000
## Residual        0.521       93          0.006
## Total          6.683       99
## -----
##
##                               Parameter Estimates
## -----
##                model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)      9.946        0.101          0.772      98.028    0.000      9.745     10.147
## X1                0.027        0.001          0.260     26.623    0.000      0.025      0.029
## X2                0.029        0.003          0.260      8.807    0.000      0.023      0.036
## factor(X3)yes    0.223        0.016          0.409     13.667    0.000      0.191      0.256
## X4                0.001        0.000          0.337     11.071    0.000      0.000      0.001
## X5                0.002        0.001          0.122      4.112    0.000      0.001      0.003
## factor(X9)yes   -0.025        0.020         -0.038     -1.287    0.201     -0.065      0.014
## -----
```

```
summary(backmodel$model)
```

```
##
```



```
## Call:
## lm(formula = paste(response, "~", paste(preds, collapse = " + ")),
##     data = l)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.20278 -0.05332 -0.00050  0.05115  0.18286
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   9.946e+00  1.015e-01  98.028 < 2e-16 ***
## X1            2.733e-02  1.027e-03  26.623 < 2e-16 ***
## X2            2.933e-02  3.330e-03   8.807 6.82e-14 ***
## factor(X3)yes 2.232e-01  1.633e-02  13.667 < 2e-16 ***
## X4            5.230e-04  4.724e-05  11.071 < 2e-16 ***
## X5            2.062e-03  5.014e-04   4.112 8.46e-05 ***
## factor(X9)yes -2.549e-02  1.980e-02  -1.287  0.201
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07486 on 93 degrees of freedom
## Multiple R-squared:  0.922, Adjusted R-squared:  0.917
## F-statistic: 183.3 on 6 and 93 DF,  p-value: < 2.2e-16
```

R functions `ols_step_backward_p()`: Build regression model from a set of candidate predictor variables by removing predictors based on p values

From the output, the first order regression model by using Backward Regression Procedure is $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_9 X_9 + \epsilon$. Consider the predictor X9 has $t_{cal} = -1.287$ with the p -value = 0.201, this predictor should be dropped out from the output. Therefore, $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon$ is the first order model to predict salary by using For Backward Regression Procedure.

Inclass Practice Problem 11

From the credit example in MLR Modelling Part 2, use **Backward Regression Procedure** to find the potentially important independent variables for predicting credit card balance.

Forward selection procedure

This method is nearly identical to the stepwise procedure previously outlined. The only difference is that the forward selection technique provides no option for rechecking the t-values corresponding to the X 's that have entered the model in an earlier step.

```
library(olsrr) #need to install the package olsrr
salary=read.csv("EXECSAL2.csv", header = TRUE)
fullmodel<-lm(Y~X1+X2+factor(X3)+X4+X5+factor(X6)+X7+X8+factor(X9)+X10, data = salary)
formodel=ols_step_forward_p(fullmodel,penter = 0.1, details=TRUE)
```

```
## Forward Selection Method
## -----
##
## Candidate Terms:
```

```
##
## 1. X1
## 2. X2
## 3. factor(X3)
## 4. X4
## 5. X5
## 6. factor(X6)
## 7. X7
## 8. X8
## 9. factor(X9)
## 10. X10
##
## We are selecting variables based on p value...
##
##
## Forward Selection: Step 1
##
## - X1
##
##
##                               Model Summary
## -----
## R                               0.787          RMSE              0.161
## R-Squared                      0.619          Coef. Var        1.407
## Adj. R-Squared                 0.615          MSE              0.026
## Pred R-Squared                 0.601          MAE              0.122
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##
##                               ANOVA
## -----
##                               Sum of
##                               Squares      DF      Mean Square      F      Sig.
## -----
## Regression      4.136           1           4.136      159.204    0.0000
## Residual        2.546          98           0.026
## Total           6.683          99
## -----
##
##
##                               Parameter Estimates
## -----
## model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept) 11.091      0.033           335.524    0.000      11.025    11.156
## X1          0.028      0.002           0.787     12.618    0.000      0.023     0.032
## -----
##
##
## Forward Selection: Step 2
##
## - factor(X3)
##
```

```

##                               Model Summary
## -----
## R                0.866          RMSE                0.131
## R-Squared        0.749          Coef. Var            1.147
## Adj. R-Squared   0.744          MSE                 0.017
## Pred R-Squared   0.732          MAE                 0.104
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                               ANOVA
## -----
##                Sum of
##                Squares      DF      Mean Square      F      Sig.
## -----
## Regression      5.007         2          2.503    144.887    0.0000
## Residual        1.676        97          0.017
## Total           6.683        99
## -----
##
##                               Parameter Estimates
## -----
##                model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)    10.968         0.032              342.659    0.000    10.905    11.032
## X1              0.027         0.002              15.134    0.000     0.024     0.031
## factor(X3)yes  0.197         0.028              7.097    0.000     0.142     0.252
## -----
##
##
## Forward Selection: Step 3
##
## - X4
##
##                               Model Summary
## -----
## R                0.916          RMSE                0.106
## R-Squared        0.839          Coef. Var            0.924
## Adj. R-Squared   0.834          MSE                 0.011
## Pred R-Squared   0.825          MAE                 0.082
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                               ANOVA
## -----
##                Sum of
##                Squares      DF      Mean Square      F      Sig.
## -----
## Regression      5.607         3          1.869    166.873    0.0000
## Residual        1.075        96          0.011

```

```

## Total          6.683          99
## -----
##
##                                     Parameter Estimates
## -----
##      model      Beta      Std. Error      Std. Beta      t      Sig      lower      upper
## -----
##      (Intercept)  10.783          0.036              298.170    0.000      10.711    10.854
##      X1           0.027          0.001           0.771      18.801    0.000       0.024     0.030
## factor(X3)yes    0.233          0.023           0.427      10.170    0.000       0.187     0.278
##      X4           0.000          0.000           0.307       7.323    0.000       0.000     0.001
## -----
##
##
##
## Forward Selection: Step 4
##
## - X2
##
##                                     Model Summary
## -----
## R              0.953      RMSE              0.081
## R-Squared       0.907      Coef. Var        0.704
## Adj. R-Squared  0.904      MSE              0.007
## Pred R-Squared  0.896      MAE              0.062
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                                     ANOVA
## -----
##      Sum of
##      Squares      DF      Mean Square      F      Sig.
## -----
## Regression      6.064        4          1.516    232.936    0.0000
## Residual         0.618       95          0.007
## Total           6.683       99
## -----
##
##                                     Parameter Estimates
## -----
##      model      Beta      Std. Error      Std. Beta      t      Sig      lower      upper
## -----
##      (Intercept)  10.278          0.066          155.154    0.000      10.146    10.409
##      X1           0.027          0.001           0.771     24.677    0.000       0.025     0.029
## factor(X3)yes    0.232          0.017           0.425     13.297    0.000       0.197     0.267
##      X4           0.001          0.000           0.354     10.920    0.000       0.000     0.001
##      X2           0.030          0.004           0.266      8.379    0.000       0.023     0.037
## -----
##
##
##
## Forward Selection: Step 5

```

```

##
## - X5
##
##
##           Model Summary
## -----
## R                0.959      RMSE                0.075
## R-Squared         0.921      Coef. Var           0.656
## Adj. R-Squared    0.916      MSE                0.006
## Pred R-Squared    0.909      MAE                0.059
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##
##           ANOVA
## -----
##           Sum of
##           Squares      DF      Mean Square      F      Sig.
## -----
## Regression        6.152        5          1.230    218.061    0.0000
## Residual           0.530       94          0.006
## Total              6.683       99
## -----
##
##
##           Parameter Estimates
## -----
##           model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)      9.962        0.101          98.578      0.000      9.761     10.163
## X1                0.027        0.001          26.501      0.000      0.025      0.029
## factor(X3)yes     0.225        0.016          13.742      0.000      0.192      0.257
## X4                0.001        0.000          11.064      0.000      0.000      0.001
## X2                0.029        0.003          8.719      0.000      0.022      0.036
## X5                0.002        0.000          3.947      0.000      0.001      0.003
## -----
##
##
##
## No more variables to be added.
##
## Variables Entered:
##
## + X1
## + factor(X3)
## + X4
## + X2
## + X5
##
##
## Final Model Output
## -----
##
##           Model Summary
## -----

```

```
## R              0.959      RMSE              0.075
## R-Squared      0.921      Coef. Var         0.656
## Adj. R-Squared 0.916      MSE              0.006
## Pred R-Squared 0.909      MAE              0.059
```

```
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
```

ANOVA

```
## -----
##              Sum of
##              Squares      DF      Mean Square      F      Sig.
## -----
## Regression    6.152        5          1.230    218.061    0.0000
## Residual      0.530       94          0.006
## Total         6.683       99
```

```
## -----
##
```

Parameter Estimates

```
## -----
##              model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)    9.962        0.101          98.578      0.000      9.761      10.163
## X1              0.027        0.001          26.501      0.000      0.025      0.029
## factor(X3)yes  0.225        0.016          13.742      0.000      0.192      0.257
## X4              0.001        0.000          11.064      0.000      0.000      0.001
## X2              0.029        0.003          8.719      0.000      0.022      0.036
## X5              0.002        0.000          3.947      0.000      0.001      0.003
## -----
```

```
summary(formodel$model)
```

```
##
## Call:
## lm(formula = paste(response, "~", paste(preds, collapse = " + ")),
##     data = l)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.201219 -0.056016 -0.003581  0.053656  0.187251
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  9.9619345  0.1010567  98.578 < 2e-16 ***
## X1           0.0272762  0.0010293  26.501 < 2e-16 ***
## factor(X3)yes 0.2246932  0.0163503  13.742 < 2e-16 ***
## X4           0.0005244  0.0000474  11.064 < 2e-16 ***
## X2           0.0290921  0.0033367   8.719 9.71e-14 ***
## X5           0.0019623  0.0004972   3.947 0.000153 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07512 on 94 degrees of freedom
```

```
## Multiple R-squared:  0.9206, Adjusted R-squared:  0.9164
## F-statistic: 218.1 on 5 and 94 DF,  p-value: < 2.2e-16
```

R functions ols_step_forward_p(): Build regression model from a set of candidate predictor variables by entering predictors based on p values penter: p value; variables with p value less than penter will enter into the model. By default, penter=0.3

From the output, we specified our penter = 0.1 to follow the same procedure of Stepwise regression. Therefore, the regression model by using Forward Regression Procedure is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon.$$

Inclass Practice Problem 12

From the credit example in MLR Modelling Part 2, use **Forward Regression Procedure** to find the potentially important independent variables for predicting credit card balance.

Note!

R also provides a function for selecting a subset of predictors from a larger set. You can use stepwise selection (backward, forward, both) by using the stepAIC() function from the MASS package. This function will select variable by extracting AIC (AIC value is explained in the next topic).

CAUTION Be aware of using the results of stepwise regression to make inferences about the relationship between $E(Y)$ and the independent variables in the first order model.

First, an extremely large number of t-tests have been conducted, leading to a high probability of making more Type I errors.

Second, stepwise regression should be used only when necessary- that is when you want to determine which of a large number of potentially important independent variables should be used in the model building process.

All-Possible-Regressions Selection Procedure

We presented stepwise regression as an objective screening procedure. Stepwise does not only provide the largest t-value, but also the techniques differ with respect to the criteria for selecting the “best” subset of variables. In this section, we describe four criteria widely used in practice,

1. R^2 Criterion the multiple coefficient of determination

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$$

will increase when independent variables are added to the model. Therefore, the model that includes all p independent variables $E(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p$ will yield the largest R^2 .

2. **Adjusted R^2 or RMSE Criterion**

We can use the adjusted R^2 instead of R^2 . It is easy to show that R_{adj}^2 is related to MSE as follows:

$$\begin{aligned} R_{adj}^2 &= 1 - \frac{\frac{SSE}{n-p-1}}{\frac{SST}{n-1}} \\ R_{adj}^2 &= 1 - (n-1) \frac{MSE}{SST} \\ s &= RMSE = \sqrt{\frac{1}{n-p-1} SSE} \end{aligned}$$

Note that R_{adj}^2 increases only if RMSE decreases [since SST remains constant for all models]. Thus, an equivalent procedure is to search for the model with the minimum, or near minimum, RMSE.

3. Mallows's Cp Criterion

The Cp criterion, named for Colin Lingwood Mallow, selects as the best subset model with

- (1) a small value of Cp (i.e., a small total mean square error), means that the model is relatively precise.
- (2) a value of Cp near $p + 1$, a property that indicates that slight (or no) bias exists in the subset regression model.

Thus, the Cp criterion focuses on minimizing total mean square error and the regression bias. If we are mainly concerned with minimizing total mean square error, we will want to choose the model with the smallest Cp value, as long as the bias is not large. On the other hand, we may prefer a model that yields a Cp value slightly larger than the minimum but that has slight (or no) bias.

4. AIC (Akaike's information criterion)

When using the model to predict Y , some information will be lost. Akaike's information criterion estimates the relative information lost by a given model. It is defined as

$$AIC = n \ln\left(\frac{SSE}{n}\right) + 2p$$

The formula is formulated by the statistician **Hirotsugu Akaike**. Models with smaller values of AIC are preferred.

Where

n : the number of observations in the dataset

p : the number of parameters in the model

5. BIC (Bayesian information criteria)

Bayesian information criterion (BIC) is another criterion for model selection. It is based, in part, on the likelihood function, and it is closely related to Akaike information criterion (AIC). The models can be tested using corresponding BIC values. Lower BIC value indicates a better model.²

$$BIC = n \ln\left(\frac{SSE}{n}\right) + (p) \ln(n)$$

Note!

n : the number of observations in the dataset

p : the number of parameters in the model

In this class, we are going to use R software package to calculate all values.

```
# Option 1
library(olsrr)
salary=read.csv("EXECSAL2.csv", header = TRUE)
firstordermodel<-lm(Y~X1+X2+X3+X4+X5+X6+X7+X8+X9+X10, data= salary)
#Select the subset of predictors that do the best at meeting some well-defined objective
criterion, such ks=ols_step_best_subset(firstordermodel, details=TRUE)
# for the output interpretation
rsquare<-c(ks$rsquare)
AdjustedR<-c(ks$adjr)
```



```

cp<-c(ks$cp)
AIC<-c(ks$aic)
cbind(rsquare,AdjustedR,cp,AIC)

```

```

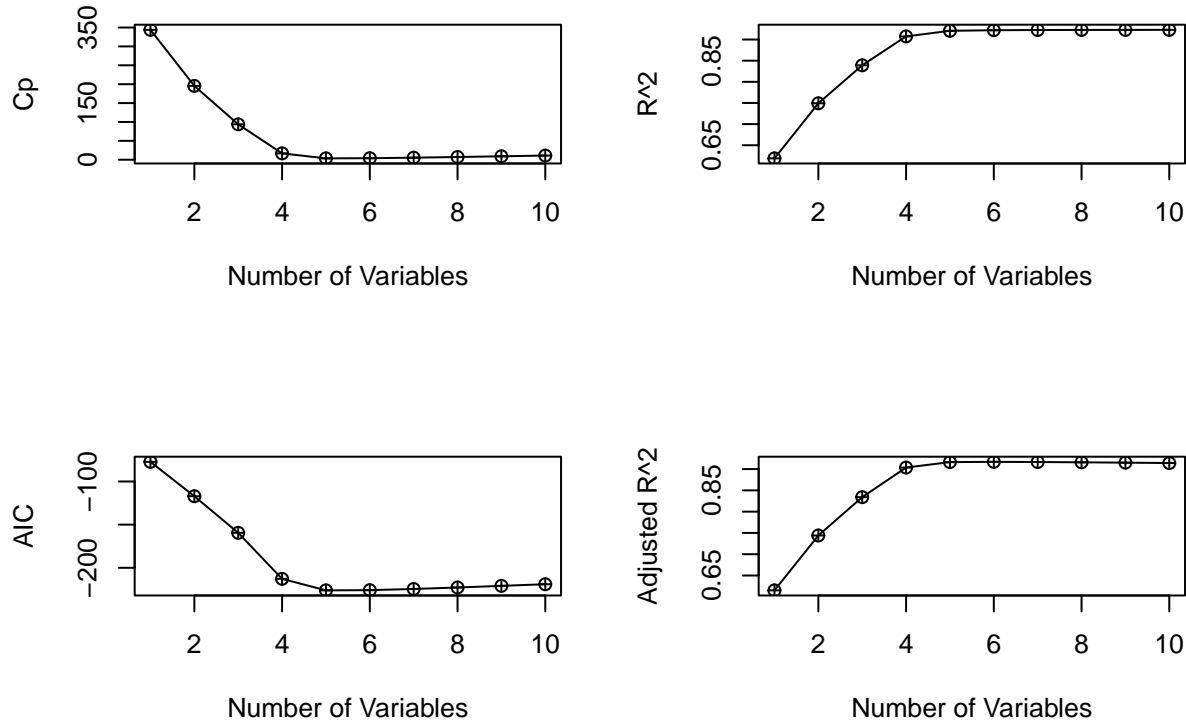
##          rsquare AdjustedR          cp          AIC
## [1,] 0.6189795 0.6150915 343.856582 -77.26778
## [2,] 0.7492075 0.7440365 195.519164 -117.09051
## [3,] 0.8390930 0.8340647  93.753768 -159.47046
## [4,] 0.9074746 0.9035788  16.812839 -212.80484
## [5,] 0.9206284 0.9164065   3.627915 -226.13906
## [6,] 0.9220182 0.9169871   4.023513 -225.90557
## [7,] 0.9225151 0.9166195   5.449923 -224.54476
## [8,] 0.9227354 0.9159429   7.195556 -222.82953
## [9,] 0.9228103 0.9150913   9.109093 -220.92652
## [10,] 0.9229048 0.9142424  11.000000 -219.04902

```

```

par(mfrow=c(2,2)) # split the plotting panel into a 2 x 2 grid
plot(ks$cp,type = "o",pch=10, xlab="Number of Variables",ylab= "Cp")
plot(ks$rsq,type = "o",pch=10, xlab="Number of Variables",ylab= "R^2")
plot(ks$aic,type = "o",pch=10, xlab="Number of Variables",ylab= "AIC")
plot(ks$adjr,type = "o",pch=10, xlab="Number of Variables",ylab= "Adjusted R^2")

```



R functions

ols_step_best_subset: Best subsets regression, select the subset of predictors that do the best at meeting some

well-defined objective criterion, such as having the largest $adjR^2$ value or the smallest MSE, Mallows's Cp or AIC.¹ BIC values are not provided

```
# Option 2
library(olsrr)
salary=read.csv("EXECSAL2.csv", header = TRUE)
firstordermodel<-lm(Y~X1+X2+X3+X4+X5+X6+X7+X8+X9+X10, data= salary)

library(leaps) #need to install the package leaps for regsubsets() function
```

```
## Warning: package 'leaps' was built under R version 4.2.2
```

```
best.subset<-regsubsets(Y~X1+X2+X3+X4+X5+X6+X7+X8+X9+X10, data= salary, nv=10 )
#by default, regsubsets() only reports results up to the best 8-variable model
#Model selection by exhaustive search, forward or backward stepwise, or sequential replacement
#The summary() command outputs the best set of variables for each model size using RMSE.
summary(best.subset)
```

```
## Subset selection object
## Call: regsubsets.formula(Y ~ X1 + X2 + X3 + X4 + X5 + X6 + X7 + X8 +
##      X9 + X10, data = salary, nv = 10)
## 10 Variables (and intercept)
##      Forced in Forced out
## X1          FALSE      FALSE
## X2          FALSE      FALSE
## X3yes        FALSE      FALSE
## X4          FALSE      FALSE
## X5          FALSE      FALSE
## X6yes        FALSE      FALSE
## X7          FALSE      FALSE
## X8          FALSE      FALSE
## X9yes        FALSE      FALSE
## X10         FALSE      FALSE
## 1 subsets of each size up to 10
## Selection Algorithm: exhaustive
##      X1 X2 X3yes X4 X5 X6yes X7 X8 X9yes X10
## 1 ( 1 ) "*" " " " " " " " " " " " " " "
## 2 ( 1 ) "*" " " "*" " " " " " " " " " "
## 3 ( 1 ) "*" " " "*" "*" " " " " " " " "
## 4 ( 1 ) "*" "*" "*" "*" " " " " " " " "
## 5 ( 1 ) "*" "*" "*" "*" "*" " " " " " "
## 6 ( 1 ) "*" "*" "*" "*" "*" "*" " " " "
## 7 ( 1 ) "*" "*" "*" "*" "*" "*" "*" " " "
## 8 ( 1 ) "*" "*" "*" "*" "*" "*" "*" "*" " "
## 9 ( 1 ) "*" "*" "*" "*" "*" "*" "*" "*" "*"
## 10 ( 1 ) "*" "*" "*" "*" "*" "*" "*" "*" "*" *
```

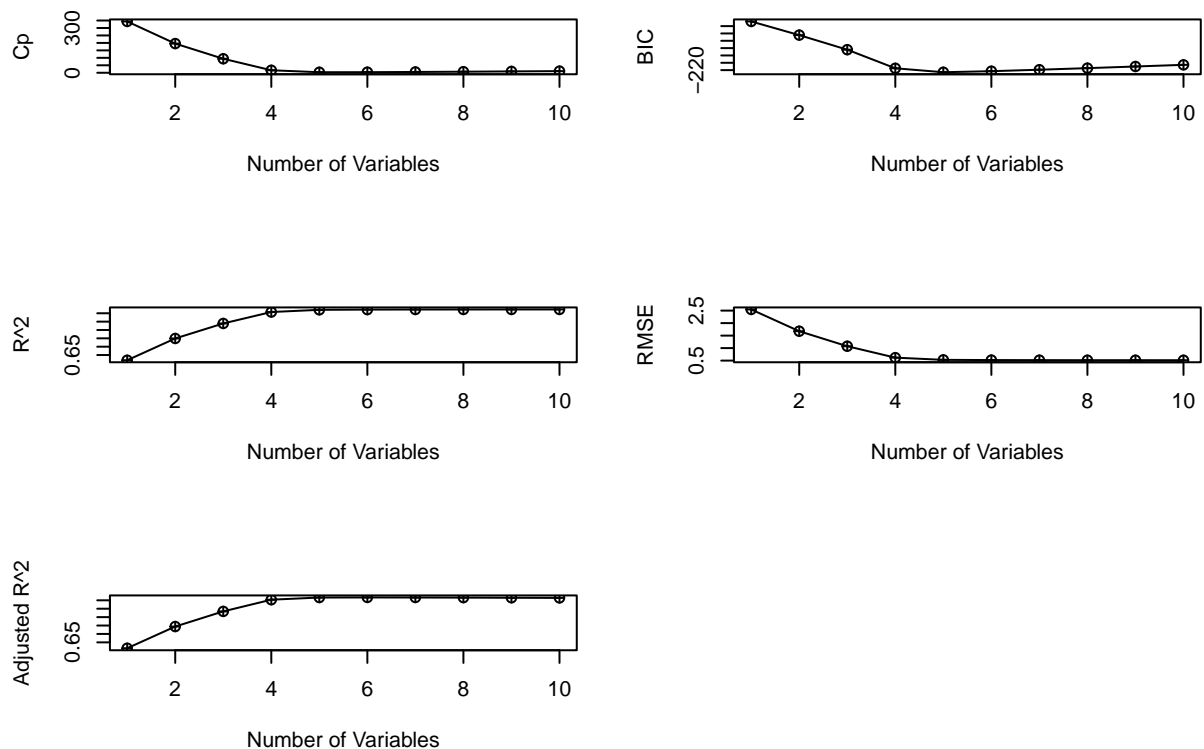
```
reg.summary<-summary(best.subset)
```

```
# for the output interpretation
rsquare<-c(reg.summary$rsq)
cp<-c(reg.summary$cp)
```

```
AdjustedR<-c(reg.summary$adjr2)
RMSE<-c(reg.summary$rss)
BIC<-c(reg.summary$bic)
cbind(rsquare,cp,BIC,RMSE,AdjustedR)
```

```
##      rsquare      cp      BIC      RMSE AdjustedR
## [1,] 0.6189795 343.856582 -87.27986 2.5462337 0.6150915
## [2,] 0.7492075 195.519164 -124.49741 1.6759632 0.7440365
## [3,] 0.8390930  93.753768 -164.27219 1.0752880 0.8340647
## [4,] 0.9074746  16.812839 -215.00141 0.6183162 0.9035788
## [5,] 0.9206284   3.627915 -225.73045 0.5304140 0.9164065
## [6,] 0.9220182   4.023513 -222.89179 0.5211265 0.9169871
## [7,] 0.9225151   5.449923 -218.92582 0.5178061 0.9166195
## [8,] 0.9227354   7.195556 -214.60542 0.5163336 0.9159429
## [9,] 0.9228103   9.109093 -210.09723 0.5158331 0.9150913
## [10,] 0.9229048 11.000000 -205.61456 0.5152016 0.9142424
```

```
par(mfrow=c(3,2)) # split the plotting panel into a 3 x 2 grid
plot(reg.summary$cp,type = "o",pch=10, xlab="Number of Variables",ylab= "Cp")
plot(reg.summary$bic,type = "o",pch=10, xlab="Number of Variables",ylab= "BIC")
plot(reg.summary$rsq,type = "o",pch=10, xlab="Number of Variables",ylab= "R^2")
plot(reg.summary$rss,type = "o",pch=10, xlab="Number of Variables",ylab= "RMSE")
plot(reg.summary$adjr2,type = "o",pch=10, xlab="Number of Variables",ylab= "Adjusted R^2")
```



R functions

regsubsets() :performs best sub- set selection by identifying the best model that contains a given number of predictors. No AIC values are provided

From the output, the first order regression model is $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon$. Is this model the best fitted model for predicting executive salary?

Inclass practice Problem 13

From the credit card example, using **All Possible Regressions Selection Procedure** to analyse which independent predictors should be used in the model.

3. Evaluate the reliability of the model chosen.

After using model selection by automatic methods or all possible regression methods, we might not have the best fit model yet, as we consider only main effects on independent variables. After eliminating some variables that are not important out of the model, we consider interaction terms and/or high order multiple regression model to improve the model.

```
salary=read.csv("EXECSAL2.csv", header = TRUE )

firstordermodel<-lm(Y~X1+X2+factor(X3)+X4+X5,data=salary)
summary(firstordermodel)

##
## Call:
## lm(formula = Y ~ X1 + X2 + factor(X3) + X4 + X5, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.201219 -0.056016 -0.003581  0.053656  0.187251
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   9.9619345   0.1010567   98.578 < 2e-16 ***
## X1             0.0272762   0.0010293   26.501 < 2e-16 ***
## X2             0.0290921   0.0033367    8.719 9.71e-14 ***
## factor(X3)yes  0.2246932   0.0163503   13.742 < 2e-16 ***
## X4             0.0005244   0.0000474   11.064 < 2e-16 ***
## X5             0.0019623   0.0004972    3.947 0.000153 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07512 on 94 degrees of freedom
## Multiple R-squared:  0.9206, Adjusted R-squared:  0.9164
## F-statistic: 218.1 on 5 and 94 DF,  p-value: < 2.2e-16

# building the best model with interation term
interacmodel<-lm(Y~(X1+X2+factor(X3)+X4+X5)^2,data = salary)
summary(interacmodel)
```

```
##
## Call:
## lm(formula = Y ~ (X1 + X2 + factor(X3) + X4 + X5)^2, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.174954 -0.051664 -0.001672  0.047063  0.163348
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    9.467e+00  7.451e-01  12.705 < 2e-16 ***
## X1              4.238e-02  1.514e-02   2.798  0.00637 **
## X2              7.323e-02  3.893e-02   1.881  0.06344 .
## factor(X3)yes  -1.140e-01  2.029e-01  -0.562  0.57564
## X4              6.225e-04  6.279e-04   0.991  0.32436
## X5              3.466e-03  4.453e-03   0.778  0.43858
## X1:X2          -7.848e-04  4.976e-04  -1.577  0.11850
## X1:factor(X3)yes 7.695e-04  2.271e-03   0.339  0.73556
## X1:X4          -2.135e-07  6.283e-06  -0.034  0.97298
## X1:X5          -1.804e-05  6.987e-05  -0.258  0.79686
## X2:factor(X3)yes -5.825e-03  7.254e-03  -0.803  0.42424
## X2:X4          -8.966e-06  2.151e-05  -0.417  0.67785
## X2:X5          -1.430e-04  2.260e-04  -0.633  0.52853
## factor(X3)yes:X4 2.346e-04  1.076e-04   2.179  0.03211 *
## factor(X3)yes:X5 1.898e-03  1.096e-03   1.732  0.08703 .
## X4:X5          -6.789e-07  3.275e-06  -0.207  0.83627
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07333 on 84 degrees of freedom
## Multiple R-squared:  0.9324, Adjusted R-squared:  0.9203
## F-statistic: 77.25 on 15 and 84 DF, p-value: < 2.2e-16
```

```
bestinteracmodel<-lm(Y~X1+X2+factor(X3)+X4+X5+factor(X3)*X4,data=salary)
summary(bestinteracmodel)
```

```
##
## Call:
## lm(formula = Y ~ X1 + X2 + factor(X3) + X4 + X5 + factor(X3) *
##      X4, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.210078 -0.052939  0.003473  0.046302  0.155280
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.002e+01  1.001e-01 100.096 < 2e-16 ***
## X1              2.690e-02  1.006e-03  26.741 < 2e-16 ***
## X2              2.977e-02  3.240e-03   9.189 1.06e-14 ***
## factor(X3)yes  1.234e-01  4.071e-02   3.032 0.003150 **
## X4              3.263e-04  8.655e-05   3.770 0.000286 ***
## X5              2.043e-03  4.823e-04   4.236 5.34e-05 ***
## factor(X3)yes:X4 2.744e-04  1.016e-04   2.700 0.008249 **
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07273 on 93 degrees of freedom
## Multiple R-squared:  0.9264, Adjusted R-squared:  0.9216
## F-statistic: 195.1 on 6 and 93 DF,  p-value: < 2.2e-16

#considering high order model between Xs and Y to improve the model
library(GGally) # need to install the GGally package for ggpairs function

## Warning: package 'GGally' was built under R version 4.2.2

## Loading required package: ggplot2

## Registered S3 method overwritten by 'GGally':
##   method from
##   +.gg      ggplot2

#option 1: using function ggpairs()
salarydata <-data.frame(salary$Y,salary$X1,salary$X2,salary$X3,salary$X4,salary$X5)
salarydata
```

	salary.Y	salary.X1	salary.X2	salary.X3	salary.X4	salary.X5
## 1	11.6009	17	16	no	520	180
## 2	11.0837	2	17	no	590	190
## 3	11.2159	2	18	no	600	190
## 4	11.2810	13	12	no	390	170
## 5	11.3218	11	14	no	440	150
## 6	10.9819	4	18	no	70	150
## 7	11.3964	13	16	no	420	170
## 8	11.5973	25	19	no	150	200
## 9	11.1732	2	17	no	430	190
## 10	11.4648	13	13	no	570	180
## 11	10.8493	3	12	no	440	190
## 12	11.5991	22	17	no	370	200
## 13	11.1065	9	12	no	180	160
## 14	11.3278	10	18	no	90	180
## 15	11.4917	16	17	no	380	160
## 16	11.9621	24	12	yes	530	200
## 17	11.5703	9	13	yes	560	170
## 18	11.5768	14	18	yes	110	170
## 19	11.5750	18	13	yes	190	190
## 20	11.2567	10	14	yes	110	160
## 21	11.7707	21	13	yes	430	190
## 22	11.7448	26	15	yes	210	190
## 23	11.7110	22	18	yes	320	160
## 24	11.4742	3	16	yes	560	180
## 25	11.7668	17	18	yes	450	190
## 26	11.1872	2	16	yes	410	180
## 27	11.2810	8	17	yes	90	190
## 28	11.4731	13	15	yes	290	160
## 29	11.4606	3	18	yes	530	180

## 30	11.4648	11	15	yes	500	190
## 31	12.0634	26	17	yes	570	190
## 32	11.5806	20	20	yes	90	150
## 33	11.5129	19	12	yes	340	160
## 34	11.5199	12	13	yes	440	170
## 35	11.9369	22	18	yes	500	160
## 36	11.2554	2	15	yes	560	190
## 37	11.6639	23	19	yes	130	150
## 38	11.5759	13	19	yes	310	150
## 39	11.6182	7	19	yes	520	200
## 40	11.9798	25	18	yes	590	160
## 41	11.7159	10	19	yes	480	200
## 42	11.1169	3	19	yes	80	160
## 43	11.3874	20	14	no	370	170
## 44	11.1619	14	13	no	420	160
## 45	11.2292	10	19	no	300	170
## 46	11.3794	23	14	no	220	170
## 47	11.4175	15	16	no	300	150
## 48	11.5560	18	19	no	350	160
## 49	11.3998	12	17	no	480	190
## 50	10.6643	3	12	no	340	150
## 51	11.5815	20	17	no	490	160
## 52	11.0186	1	15	no	570	180
## 53	11.3574	11	17	no	190	160
## 54	11.3953	21	13	no	500	160
## 55	11.4436	12	15	yes	240	170
## 56	11.7753	25	14	yes	510	160
## 57	11.2172	3	19	yes	170	170
## 58	11.6553	19	12	yes	520	150
## 59	11.6457	18	18	yes	290	170
## 60	11.1927	2	17	yes	200	180
## 61	11.5954	14	13	yes	560	180
## 62	11.1360	4	16	yes	230	160
## 63	11.8629	21	16	yes	410	180
## 64	11.4175	10	13	yes	370	190
## 65	11.2037	11	12	yes	180	170
## 66	11.5229	12	19	yes	60	200
## 67	11.3551	10	19	yes	60	180
## 68	11.8372	26	17	yes	110	200
## 69	11.3181	7	15	yes	280	190
## 70	11.3563	7	19	yes	110	180
## 71	11.7527	12	15	yes	570	200
## 72	11.2910	6	16	yes	240	180
## 73	11.6046	15	18	yes	260	170
## 74	11.1662	8	13	yes	150	160
## 75	11.1732	2	13	yes	370	190
## 76	11.3551	13	14	yes	150	160
## 77	11.7345	21	15	yes	310	180
## 78	11.7361	20	16	yes	520	160
## 79	11.7134	20	19	yes	200	170
## 80	10.9988	2	17	yes	70	160
## 81	11.4690	9	17	yes	300	160
## 82	11.8706	20	20	yes	390	170
## 83	11.3609	13	19	no	370	200

```
## 84 11.2910      8      17      no      560      170
## 85 11.6448     21      20      no      590      180
## 86 11.3771      9      18      no      440      180
## 87 11.5415     19      15      no      480      190
## 88 11.3457     15      14      yes     160      170
## 89 11.4360     12      13      yes     390      190
## 90 11.2823      5      17      yes     330      160
## 91 11.2709      5      16      yes     290      200
## 92 10.9526      5      15      no      470      150
## 93 11.4109     24      14      no      160      180
## 94 11.5327      8      18      yes     540      150
## 95 11.5268     19      15      yes      90      180
## 96 11.9144     23      16      yes     560      180
## 97 11.3783      3      16      yes     340      190
## 98 11.7830     22      17      yes      70      200
## 99 11.6579     22      16      yes     160      190
## 100 11.5405     13      18      yes     110      180
```

```
#ggpairs(salarydata)
#LOESS or LOWESS: LOcally WEighted Scatter-plot Smoother
#ggpairs(salarydata,lower = list(continuous = "smooth_loess", combo =
# "facethist", discrete = "facetbar", na = "na"))
#option2: using function pairs()
#pairs(~Y+X1+X2+factor(X3)+X4+X5,data=salary,panel = panel.smooth)

bestmodel<-lm(Y~X1+I(X1^2)+X2+factor(X3)+X4+X5+factor(X3)*X4,data=salary)
summary(bestmodel)
```

```
##
## Call:
## lm(formula = Y ~ X1 + I(X1^2) + X2 + factor(X3) + X4 + X5 + factor(X3) *
##     X4, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.163466 -0.048971 -0.001111  0.041345  0.124534
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   9.862e+00  9.703e-02 101.634 < 2e-16 ***
## X1             4.364e-02  3.761e-03  11.604 < 2e-16 ***
## I(X1^2)       -6.347e-04  1.384e-04  -4.588 1.41e-05 ***
## X2            3.094e-02  2.950e-03  10.487 < 2e-16 ***
## factor(X3)yes  1.166e-01  3.696e-02   3.155 0.00217 **
## X4            3.259e-04  7.850e-05   4.152 7.36e-05 ***
## X5            2.391e-03  4.439e-04   5.386 5.49e-07 ***
## factor(X3)yes:X4 3.020e-04  9.239e-05   3.269 0.00152 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.06596 on 92 degrees of freedom
## Multiple R-squared:  0.9401, Adjusted R-squared:  0.9355
## F-statistic: 206.3 on 7 and 92 DF,  p-value: < 2.2e-16
```



```
bestmodel1<-lm(Y~X1+I(X1^2)+I(X1^3)+X2+factor(X3)+X4+X5+factor(X3)*X4,data=salary)
summary(bestmodel1)
```

```
##
## Call:
## lm(formula = Y ~ X1 + I(X1^2) + I(X1^3) + X2 + factor(X3) + X4 +
##     X5 + factor(X3) * X4, data = salary)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.163271 -0.048191 -0.000127  0.040151  0.122471
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    9.854e+00  9.980e-02  98.737  < 2e-16 ***
## X1              4.742e-02  1.057e-02   4.485 2.12e-05 ***
## I(X1^2)        -9.854e-04  9.277e-04  -1.062 0.290972
## I(X1^3)         8.853e-06  2.316e-05   0.382 0.703128
## X2              3.094e-02  2.964e-03  10.439  < 2e-16 ***
## factor(X3)yes   1.198e-01  3.805e-02   3.148 0.002222 **
## X4              3.352e-04  8.249e-05   4.063 0.000103 ***
## X5              2.367e-03  4.504e-04   5.256 9.64e-07 ***
## factor(X3)yes:X4 2.921e-04  9.633e-05   3.033 0.003158 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.06627 on 91 degrees of freedom
## Multiple R-squared:  0.9402, Adjusted R-squared:  0.9349
## F-statistic: 178.8 on 8 and 91 DF,  p-value: < 2.2e-16
```

R Functions ggpairs(): look at all pairwise combinations of continuous variables in scatterplots. pairs(): optional function for pairwise combinations panel.smooth: add a smooth loess curve on the scatters

From the output, you can see that after including an interaction term ($X_3 * X_4$) and quadratic term X_1^2 , they led to such a big improvement in the model as following,

1. all the p-values < 0.05 , which means that all regression coefficients were significantly non-zero.
2. R_{adj}^2 increases from 0.9164 to 0.9355
3. Standard error of residuals (RMSE) decreases from 0.07512 to 0.06596

Therefore, it is clear that adding the additional terms really has led to a better fit to the data.

Inclass practice Problem 14

From the credit card example, when we investigate the scatter plots for all pairwise combinations between variables, find the best fitted model to predict balance. You may include interaction terms and higher order terms to improve the model.

Inclass Practice Problem 15

Clerical staff work hours. In any production process in which one or more workers are engaged in a variety of tasks, the total time spent in production varies as a function of the size of the work pool and the level of output of the various activities.

For example, in a large metropolitan department store, the number of hours worked (Y) per day by the clerical staff may depend on the following

variables:

X1 = Number of pieces of mail processed (open, sort, etc.)

X2 = Number of money orders and gift certificates sold,

X3 = Number of window payments (customer charge accounts) transacted ,

X4 = Number of change order transactions processed ,

X5 = Number of checks cashed ,

X6 =Number of pieces of miscellaneous mail processed on an ‘as available’ basis , and

X7 =Number of bus tickets sold

The data are provided in **CLERICAL.csv** file count for these activities on each of 52 working days. Conduct a Stepwise Regression Procedure and All-Possible-Regressions procedure of the data using R software package.

¹https://www.rdocumentation.org/packages/olsrr/versions/0.5.3/topics/ols_step_best_subset

²<https://medium.com/@analyttica/what-is-bayesian-information-criterion-bic-b3396a894be6>

References

-Gareth James & Daniela Witten & Trevor Hastie Robert Tibshirani, *An Introduction to Statistical Learning with Applications in R: Springer New York Heidelberg Dordrecht London*.

-Wickham and Grolemund, *R for Data Science: O'Reilly Media*