

STAT 3008: Applied Linear Regression
2019-20 Term 2
Assignment #3 Solutions

Problem 1: (a) $\hat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} = \begin{pmatrix} 62.74663 \\ 10.54172 \\ -1.394128 \end{pmatrix}$

(b) $RSS = \mathbf{Y}'\mathbf{Y} - \mathbf{Y}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y} = 4107.409$, $\hat{\sigma}^2 = RSS/(n-3) = 195.5909$, $\hat{\sigma} = 13.9854$ (12.65 ok)

(c) Optimal $x = -\hat{\beta}_1/(2\hat{\beta}_2) = 3.7808$.

(d) From part (b), $SS_{\text{res}} = 4107.409$. $SS_{\text{total}} = \mathbf{Y}'\mathbf{Y} - n\bar{y}^2 = 89882.2642 - 24(56.6275)^2 = 12922.09$.

The ANOVA Table is given by:

	df	SS	MS	F-stat	p-value
Regression	2	8814.68	4407.34	22.533	5.94E-06
Residuals	21	4107.41	195.591		
Total	23	12922.09			

(e) (Section 4.3: x -values should be scattered like normal distribution in order to obtain a balance between goodness-of-fit and locating the center).

Compared with linear regression, quadratic regression should rely on more data points on the two sides to provide better information about the curvature. The problem setup, however, have only one data point in the middle – which is difficult to locate the optimal value of x easily.

Suggestion: Allocate 1/4 to 1/3 of the data points in the middle of the x range [1,10], and the rest are evenly spread on the two sides.

Problem 2: (a) $\hat{Y} = 15952.1 + 244.5s + 409.9x + 4383.11U_2 + 8975.97U_3 - 1059.19U_2s + 1582.95U_3s$

(a) $\hat{\sigma}^2 \approx 2432^2 = 5,914,624$

```
fit0<-lm(Salary~ Sex +Year+ factor(Rank) + Sex:factor(Rank),data=salary); summary(fit0)
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	15952.10	855.91	18.638	< 2e-16 ***
Sex	244.50	1159.16	0.211	0.833894
Year	409.90	78.21	5.241	4.10e-06 ***
factor(Rank)2	4383.11	1063.99	4.119	0.000161 ***
factor(Rank)3	8975.97	1133.16	7.921	4.49e-10 ***
Sex:factor(Rank)2	-1059.19	2188.78	-0.484	0.630791
Sex:factor(Rank)3	1582.95	1836.99	0.862	0.393417

Residual standard error: 2432 on 45 degrees of freedom
Multiple R-squared: 0.8509, Adjusted R-squared: 0.831
F-statistic: 42.8 on 6 and 45 DF, p-value: < 2.2e-16
sum(fit0\$res^2)
[1] 266244659

(b) Put $U_2 = U_3 = x = 0$ and $s=1 \Rightarrow \hat{Y} = 15952.1 + 244.5(1) = \$16,196.6$

(c) $RSS = 266,244,659$ (or $2432^2(45)=266,158,080$)

	df	SS	MS	F-stat	p-value
Regression	4	642,448,811	160,612,203	27.146	1.708E-11
Residuals	45	266,244,659	5,916,548		
Total	49	908,693,470			

(d)

```
fit1<-lm(Salary~Sex+Year,data=salary)
```

```
anova(fit1,fit0)
```

Model 1: Salary ~ Sex + Year

Model 2: Salary ~ Sex + Year + factor(Rank) + Sex:factor(Rank)

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	49	908693470				
2	45	266244659	4	642448811	27.146	1.708e-11 ***

(e) Since $p\text{-value} = 1.708 \times 10^{-11} < \alpha = 0.05$, we reject H_o at $\alpha=0.05$

We have sufficient evidence that rank is an important term to explain the salary.

(f)
$$E(Y | R = j, X = x) = \eta_0 + \beta x + \sum_{j=2}^3 \eta_{0j} U_j$$

(g)
$$E(Y | S = s, R = j, X = x) = \eta_0 + \eta_1 s + \beta x + \sum_{j=2}^3 (\eta_{0j} U_j + \eta_{1j} U_{js})$$

	df	SS	MS	F-stat	p-value
Regression	3	10,748,075	3,582,692	0.6055	0.6148
Residuals	45	266,244,659	5,916,548		
Total	48	276,992,734			

(h)

```
fit2<-lm(Salary~ Year+ factor(Rank),data=salary); summary(fit2)
```

```
anova(fit2,fit0)
```

Analysis of Variance Table

Model 1: Salary ~ Year + factor(Rank)

Model 2: Salary ~ Sex + Year + factor(Rank) + Sex:factor(Rank)

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	48	276992734				
2	45	266244659	3	10748075	0.6055	0.6148

(i) Since $p\text{-value} = 0.6148 > 0.05$, we do not reject H_o at $\alpha=0.05$.

We do have sufficient evidence that the salary for male and female are different for some of the 3 ranks.

(We do not have sufficient evidence that sex is important to explain the annual salary)

Problem 3:

(a) Based on Step $i = 1, 2, 3$ and 4 below, the terms added from the intercept model are in the sequence of x_1, x_2, x_4 and x_3 . Therefore, parsimonious model is

$$\text{Model 16: } y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + e$$

Step	Start					
i=1	Models	y~1	y~x1	y~x2	y~x3	y~x4
	AIC	-68.1	-151	-121.8	-148.8	-66.7
i=2	Models	y~x1	y~x1+x2	y~x1+x3	y~x1+x4	
	AIC	-151	-609.1	-149.3	-150.9	
i=3	Models	y~x1+x2	y~x1+x2+x3	y~x1+x2+x4		
	AIC	-609.1	-608.2	-7317.1		
i=4	Models	y~x1+x2+x4	y~x1+x2+x4+x3			
	AIC	-7317.1	-7317.6			

(b) Based on Step $i = 1$ and 2 below, the only term being removed from the full model is x_3 .

Therefore, parsimonious model is Model 12: $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_4 x_4 + e$

Step	Start					
i=1	Models	y~x1+x2+x3+x4	y~x1+x2+x3	y~x1+x2+x4	y~x1+x3+x4	y~x2+x3+x4
	BIC	-7304.6	-597.8	-7306.7	-138.6	-449.1
i=2	Models	y~x1+x2+x4	y~x1+x2	y~x1+x4	y~x2+x4	
	BIC	-7306.7	-601.3	-143.1	-112.5	

(c) Let p_c to be the # of parameters in Model 16.

Based on the AIC and BIC of Model 16, $p_c(\log(n)-2) = -7304.6 - (-7317.6) = 13.0$

Based on the AIC and BIC of Model 12, $(p_c-1)(\log(n)-2) = -7306.7 - (-7317.1) = 10.4$

Hence $\log(n)-2 = 13.0-10.4 = 2.6 \Rightarrow n = \exp(4.6) = 99.484 \Rightarrow n = 99 \text{ or } 100$

(d) Yes, x_3 is likely to be highly collinear with x_1 because the AIC for (i) Model #2 and #6 are similar, but (ii) AIC for Model #5 is comparable to the AIC for Model #2.

Problem 4: (a) Based on the R outputs, the parsimonious models for both forward and backward selection methods are $y \sim x_4 + x_3 + x_6$

```
> AIC.F<-stepAIC(fit0,scope=list(lower=fit0, upper=fit1),direction="forward",trace=1) # forward selection
Start:  AIC=253.58
y ~ 1
      Df Sum of Sq  RSS   AIC
+ x4   1   1661.66 884.73 181.57
+ x2   1   1120.45 1425.95 214.99
+ x1   1    504.47 2041.92 240.12
+ x3   1    462.22 2084.18 241.55
+ x6   1    360.22 2186.17 244.90
+ x5   1    281.47 2264.92 247.38
<none>          2546.39 253.58

Step:  AIC=181.58
y ~ x4
      Df Sum of Sq  RSS   AIC
+ x3   1   141.523 743.21 171.37
+ x5   1    90.016 794.72 176.06
+ x6   1    49.592 835.14 179.54
+ x2   1    25.046 859.69 181.56
<none>          884.73 181.57

> AIC.B<-stepAIC(fit1,scope=list(lower=fit0, upper=fit1),direction="backward",trace=1) # backward selection
Start:  AIC=172.67
y ~ x1 + x2 + x3 + x4 + x5 + x6
      Df Sum of Sq  RSS   AIC
- x2   1      2.93  678.29 170.98
- x5   1      2.95  678.31 170.98
- x1   1      7.01  682.38 171.40
<none>          675.36 172.67
- x6   1     44.82  720.18 175.17
- x3   1     59.18  734.54 176.55
- x4   1    646.12 1321.48 217.66
Step:  AIC=170.98
y ~ x1 + x3 + x4 + x5 + x6
      Df Sum of Sq  RSS   AIC
- x5   1      4.34  682.64 169.42
- x1   1     15.22  693.52 170.53
<none>          678.29 170.98
- x6   1     54.83  733.12 174.42
- x3   1     74.01  752.30 176.22
- x4   1    1190.09 1868.39 239.90
Step:  AIC=169.42

Step:  AIC=171.37
y ~ x4 + x3
      Df Sum of Sq  RSS   AIC
+ x6   1    45.431 697.78 168.96
+ x2   1    21.519 721.69 171.32
<none>          743.21 171.37
+ x1   1     8.535 734.68 172.56
+ x5   1     1.637 741.57 173.22
Step:  AIC=168.96
y ~ x4 + x3 + x6
      Df Sum of Sq  RSS   AIC
<none>          697.78 168.96
+ x1   1    15.1423 682.64 169.42
+ x2   1    13.2307 684.55 169.62
+ x5   1     4.2635 693.52 170.53

y ~ x1 + x3 + x4 + x6
      Df Sum of Sq  RSS   AIC
- x1   1     15.14  697.78 168.96
<none>          682.64 169.42
- x6   1     52.04  734.68 172.56
- x3   1    148.70  831.34 181.22
- x4   1    1222.35 1904.99 239.26
Step:  AIC=168.96
y ~ x3 + x4 + x6
      Df Sum of Sq  RSS   AIC
<none>          697.78 168.96
- x6   1     45.43  743.21 171.37
- x3   1    137.36  835.14 179.54
- x4   1    1278.97 1976.75 239.85
```

(b) Based on the R outputs, the parsimonious models for both forward and backward selection methods are $y \sim x_4 + x_3 + x_6$, which is the same as that for part (a).

```
> BIC.F<-stepAIC(fit0,scope=list(lower=fit0, upper=fit1),direction="forward",trace=1,k=log(n)) # forward selection
Start:  AIC=254.06
y ~ 1
      Df Sum of Sq  RSS   AIC
+ x4   1   1661.66 884.73 182.54
+ x2   1   1120.45 1425.95 215.96
+ x1   1    504.47 2041.92 241.09
+ x3   1    462.22 2084.18 242.52
+ x6   1    360.22 2186.17 245.87
+ x5   1    281.47 2264.92 248.35
<none>          2546.39 254.06

Step:  AIC=182.55
y ~ x4
      Df Sum of Sq  RSS   AIC
+ x3   1   141.523 743.21 172.83
+ x5   1    90.016 794.72 177.52
+ x6   1    49.592 835.14 180.99
<none>          884.73 182.54
+ x2   1    25.046 859.69 183.02
+ x1   1     8.291 876.44 184.37

Step:  AIC=172.83
y ~ x4 + x3
      Df Sum of Sq  RSS   AIC
+ x6   1    45.431 697.78 170.90
<none>          743.21 172.83
+ x2   1    21.519 721.69 173.26
+ x1   1     8.535 734.68 174.50
+ x5   1     1.637 741.57 175.16
Step:  AIC=170.9
y ~ x4 + x3 + x6
      Df Sum of Sq  RSS   AIC
<none>          697.78 170.90
+ x1   1    15.1423 682.64 171.85
+ x2   1    13.2307 684.55 172.04
+ x5   1     4.2635 693.52 172.95
```

```
> BIC.B<-stepAIC(fit1,scope=list(lower=fit0, upper=fit1),direction="backward",trace=1,k=log(n)) # backward selection
```

```
Start:  AIC=176.07
y ~ x1 + x2 + x3 + x4 + x5 + x6
      Df Sum of Sq  RSS   AIC
- x2   1      2.93 678.29 173.88
- x5   1      2.95 678.31 173.89
- x1   1      7.01 682.38 174.31
<none>                  675.36 176.07
- x6   1     44.82 720.18 178.08
- x3   1     59.18 734.54 179.46
- x4   1    646.12 1321.48 220.57
Step:  AIC=173.89
y ~ x1 + x3 + x4 + x5 + x6
      Df Sum of Sq  RSS   AIC
- x5   1      4.34 682.64 171.85
- x1   1     15.22 693.52 172.95
<none>                  678.29 173.88
- x6   1     54.83 733.12 176.84
- x3   1     74.01 752.30 178.65
```

```
- x4   1    1190.09 1868.39 242.33
Step:  AIC=171.85
y ~ x1 + x3 + x4 + x6
      Df Sum of Sq  RSS   AIC
- x1   1     15.14 697.78 170.90
<none>                  682.64 171.85
- x6   1     52.04 734.68 174.50
- x3   1    148.70 831.34 183.16
- x4   1   1222.35 1904.99 241.20
Step:  AIC=170.9
y ~ x3 + x4 + x6
      Df Sum of Sq  RSS   AIC
<none>                  697.78 170.90
- x6   1     45.43 743.21 172.83
- x3   1    137.36 835.14 180.99
- x4   1   1278.97 1976.75 241.31
```

(c) From the R-output, $VIR_5 = 1/(1 - R^2_5) = 1/(1 - 0.8343) = 6.0346$

```
> fitx5<-lm(x5~x1+x2+x3+x4+x6); 1/(1-summary(fitx5)$r.squared)
```

```
[1] 6.034562
```