

Assignment 5 Chunlei Zhou

Q1

(a)

Continuity of $g(x)$ and continuity of the first derivative each represent a single linear constraint at each knot, so there are 6 linear constraints. These are

$$b_1 + 2c_1\eta_1 + 3d_1\eta_1^2 = 0$$

$$b_1 + 2c_1\eta_2 + 3d_1\eta_2^2 = b_2 + 2c_2\eta_2 + 3d_2\eta_2^2$$

$$b_2 + 2c_2\eta_3 + 3d_2\eta_3^2 = 0$$

for continuity of the first derivative, and

$$a_1 + b_1\eta_1 + c_1\eta_1^2 + d_1\eta_1^3 = a_0$$

$$a_1 + b_1\eta_2 + c_1\eta_2^2 + d_1\eta_2^3 = a_2 + b_2\eta_2 + c_2\eta_2^2 + d_2\eta_2^3$$

$$a_2 + b_2\eta_3 + c_2\eta_3^2 + d_2\eta_3^3 = a_3$$

for continuity.

(b)

Since the total order of all polynomials is 10, and the total constraints we have is 6, we can denote that the degrees of freedom equal to $10 - 6 = 4$.

Q2

(a)

> table_a

	SSE	AIC	BIC	DF
Model1	2.055594	-350.5192	-345.4540	2
Model2	1.671742	-367.7422	-360.1444	3
Model3	1.778792	-363.9699	-358.9047	2
Model4	1.722704	-366.9495	-361.8843	2
Model5	1.873968	-357.1224	-349.5246	3
Model6	1.638056	-367.6353	-357.5049	4

(b)

> table_b

	SSE	AIC	BIC	DF
Model1	2.055594	-86.59667	-81.53147	2
Model2	1.671742	-103.81961	-96.22181	3
Model3	1.778792	-100.04730	-94.98210	2
Model4	1.722704	-103.02694	-97.96174	2
Model5	1.873968	-93.19980	-85.60200	3
Model6	1.638056	-103.71272	-93.58232	4

(c)

> table_c

	SSE	AIC	BIC	DF
Model1	2.055594	-84.59667	-76.99887	2
Model2	1.671742	-101.81961	-91.68921	3
Model3	1.778792	-98.04730	-90.44950	2
Model4	1.722704	-101.02694	-93.42914	2
Model5	1.873968	-91.19980	-81.06940	3
Model6	1.638056	-101.71272	-89.04973	4

(d)

Standardized table for part(a):

> s_table_a

	SSE	AIC	BIC	DF
Model1	2.055594	17.2229379	16.430268	2
Model2	1.671742	0.0000000	1.739929	3
Model3	1.778792	3.7723093	2.979639	2
Model4	1.722704	0.7926700	0.000000	2
Model5	1.873968	10.6198113	12.359741	3
Model6	1.638056	0.1068864	4.379415	4

Standardized table for part(b):

> s_table_b

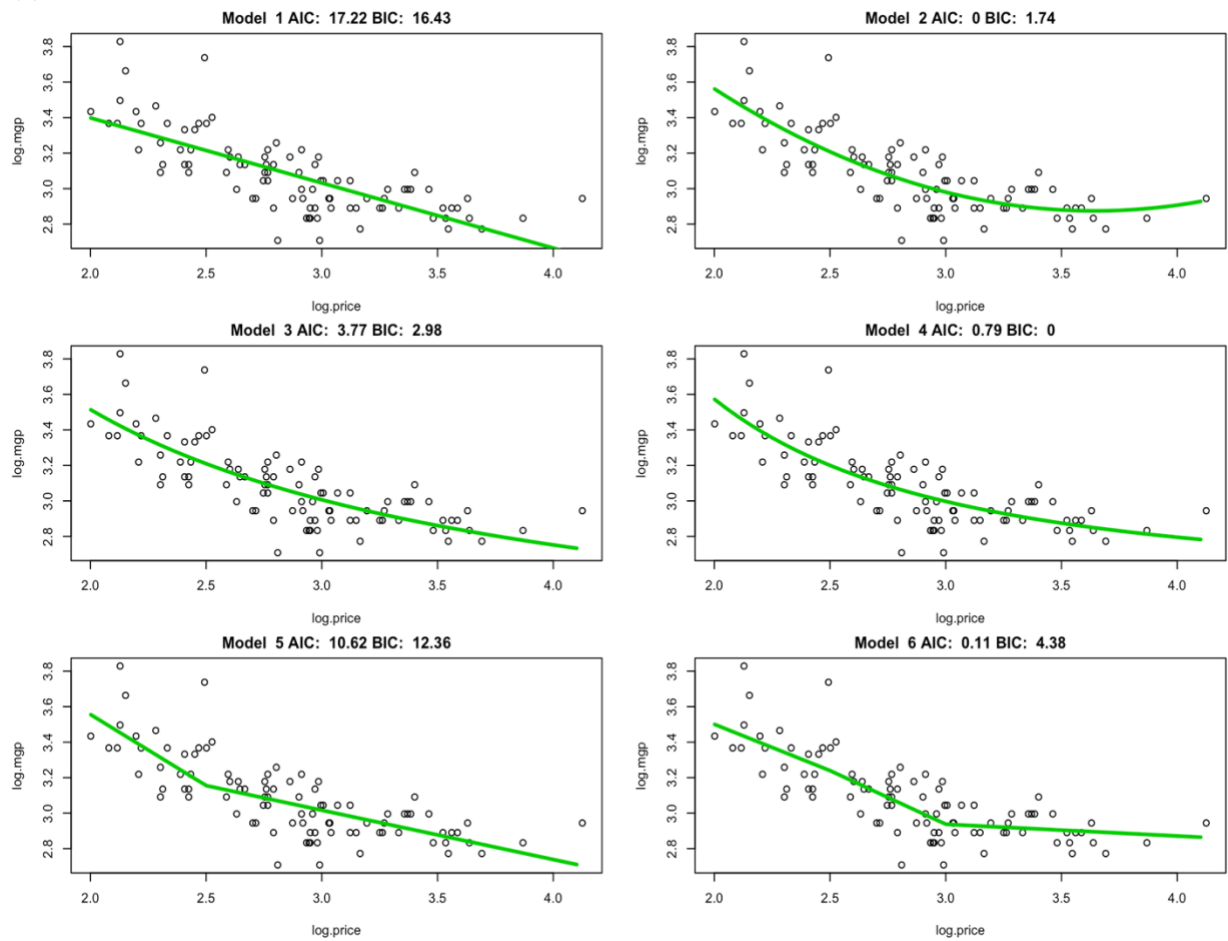
	SSE	AIC	BIC	DF
Model1	2.055594	17.2229379	16.430268	2
Model2	1.671742	0.0000000	1.739929	3
Model3	1.778792	3.7723093	2.979639	2
Model4	1.722704	0.7926700	0.000000	2
Model5	1.873968	10.6198113	12.359741	3
Model6	1.638056	0.1068864	4.379415	4

Standardized table for part(c):

> s_table_c

	SSE	AIC	BIC	DF
Model1	2.055594	17.2229379	16.430268	2
Model2	1.671742	0.0000000	1.739929	3
Model3	1.778792	3.7723093	2.979639	2
Model4	1.722704	0.7926700	0.000000	2
Model5	1.873968	10.6198113	12.359741	3
Model6	1.638056	0.1068864	4.379415	4

(e)



(f)

If the model selection application is based on AIC scores, then Model 2 has the optimal AIC and BIC scores (AIC = 0, which is the smallest among all six models). However, Model 2 is overfitting, because it fits the outlier. While Model 6 and Model 4, with the second and third smallest AIC scores respectively, are not overfitting, there is a distinct reason that models with the second or third lowest AIC might be used in place of the optimal AIC model.

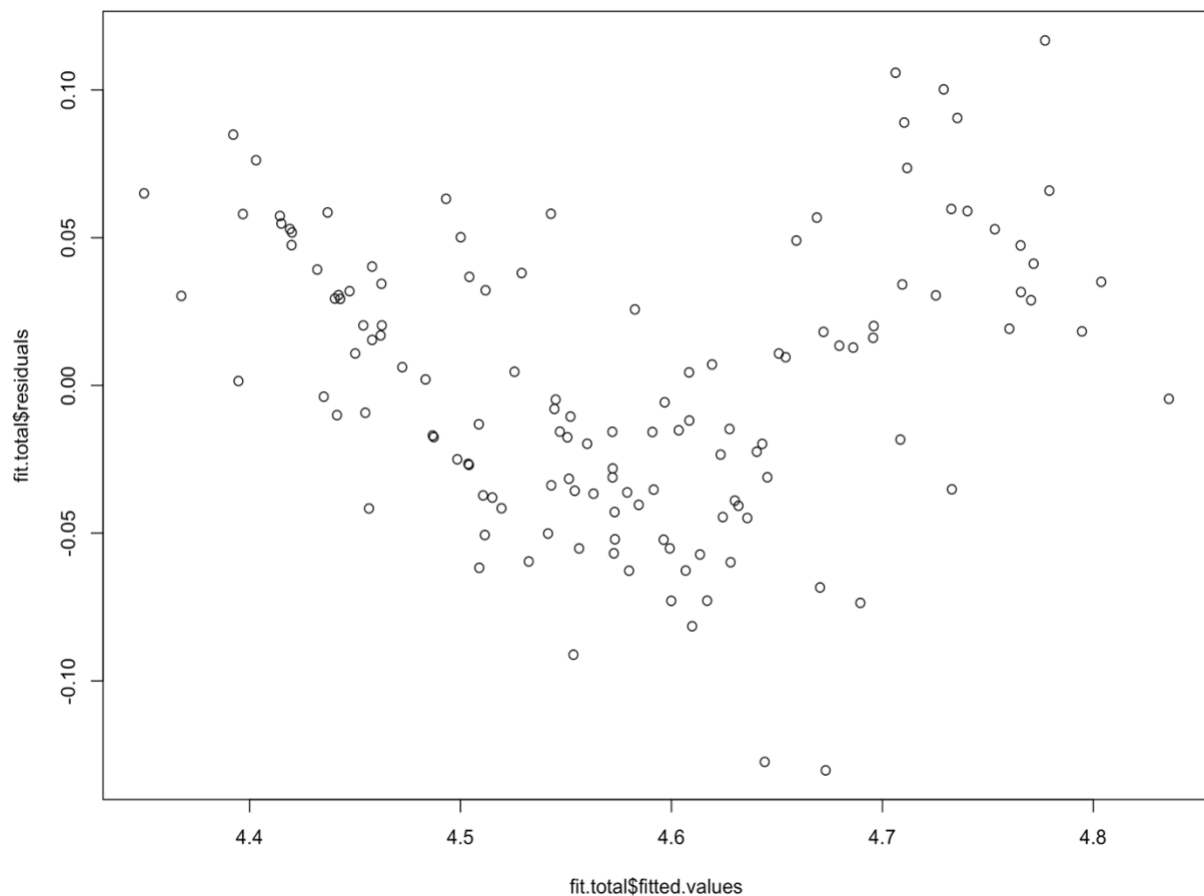
Q3

(a)

R^2 for each predictor:

[1] "R-square for predictor = rank is 0.906048203507413"
[1] "R-square for predictor = LSAT is 0.617296896570578"
[1] "R-square for predictor = GPA is 0.586749347746426"
[1] "R-square for predictor = faculty is 0.128602021730388"
[1] "R-square for predictor = clsize is 0.0629362367654693"
[1] "R-square for predictor = studfac is 0.0377271898430339"
[1] "R-square for predictor = llibvol is 0.520850141125811"
[1] "R-square for predictor = lcost is 0.253040457876905"

Predictor rank appears to be most informative of salary.



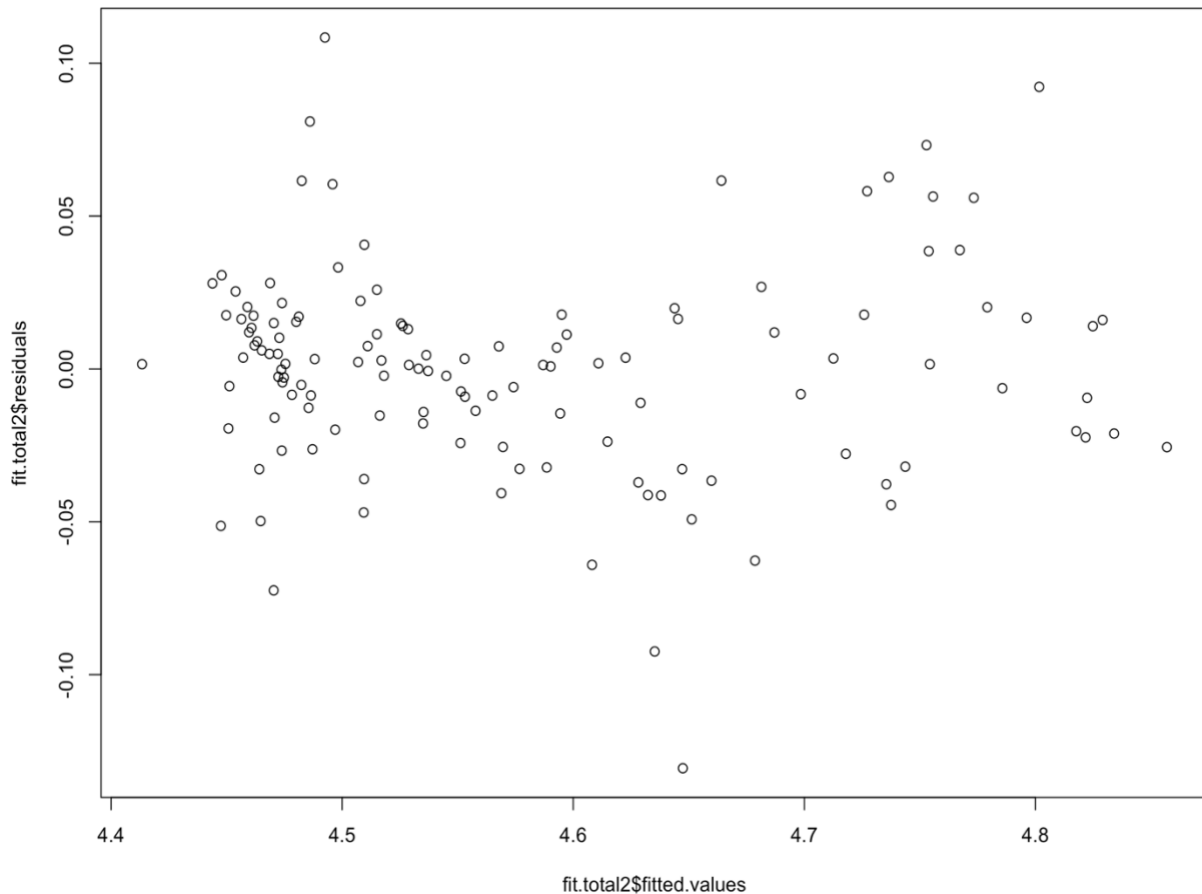
I noticed that this is a megaphone shaped scatter plot, which indicates that the model might not be suitable.

(b)

```
> apply(xs, 2, var)
```

rank	rank2	LSAT	LSAT2	GPA	GPA2
0.007692308	0.007692308	0.007692308	0.007692308	0.007692308	0.007692308
faculty	faculty2	clsize	clsize2	studfac	studfac2
0.007692308	0.007692308	0.007692308	0.007692308	0.007692308	0.007692308
llibvol	llibvol2	lcost	lcosr2		
0.007692308	0.007692308	0.007692308	0.007692308		

It is obvious that all column variances are equal.



It seems that variables are much more random compared to those in part (a).

(c)

```
> coef.1se.lasso[,1][which(coef.1se.lasso[,1] !=0)]
```

(Intercept)	rank	rank2	LSAT	GPA	llibvol
4.57751884	-0.98047207	0.27602144	0.10377027	0.02742180	0.01957966

The above listed variables are included in the 1se solution.

(d)

Ranking is from high to low with 1 representing the largest value.

```
> abs.coef.1se.ridge = abs(coef.1se.ridge[,1][which(coef.1se.ridge[,1] !=0)])  
> rank(-abs.coef.1se.ridge)
```

(Intercept)	rank	rank2	LSAT	LSAT2	GPA
1	2	4	5	14	3
GPA2	faculty	faculty2	clsize	clsize2	studfac
8	10	9	12	15	16
studfac2	llibvol	llibvol2	lcost	lcosr2	
11	6	17	7	13	

```
> abs.coef.1se.lasso = abs(coef.1se.lasso[,1][which(coef.1se.lasso[,1] !=0)])  
> rank(-abs.coef.1se.lasso)
```

(Intercept)	rank	rank2	LSAT	GPA	llibvol
1	2	3	4	5	6

The ranks of those coefficients selected by the LASSO model of Part (c) is:

Variable name	Ranks
rank	1
rank2	3
LSAT	4
GPA	2
llibvol	5

(e)

For forward model, the included variables, their values, and their ranks are as bellow:
(Ranking is from high to low with 1 representing the largest absolute value.)

```
> coef(fit.stepaicf)[which(coef(fit.stepaicf) !=0)]  
(Intercept)      rank      rank2      LSAT      LSAT2  
4.577518837 -1.117582256  0.404255775  0.148780040 -0.033026242  
      GPA      GPA2      faculty      faculty2      clsize  
0.078167265  0.062324420  0.138273116  0.032697006  0.002092815  
      clsize2      studfac      studfac2      llibvol      llibvol2  
0.029783741  0.072780553 -0.045937763 -0.045803915  0.001250647  
      lcost      lcosr2  
-0.060717584  0.003852739
```

```
> rank(-coef.stepaicf)
```

(Intercept)	rank	rank2	LSAT	LSAT2	GPA
1	2	3	4	12	6
GPA2	faculty	faculty2	clsize	clsize2	studfac
8	5	13	16	14	7
studfac2	llibvol	llibvol2	lcost	lcosr2	
10	11	17	9	15	

For backward model, the included variables, their values, and their ranks are as bellow:
(Ranking is from high to low with 1 representing the largest absolute value.)

```
> coef(fit.stepaib)[which(coef(fit.stepaib) !=0)]
(Intercept)      rank      rank2      LSAT      faculty      faculty2
  4.57751884 -1.11854248  0.42132919  0.15337353  0.06796724  0.07139841
> rank(-coef.stepaib)
(Intercept)      rank      rank2      LSAT      faculty      faculty2
           1           2           3           4           6           5
```

For all subset model, the included variables, their values, and their ranks are as bellow:
(Ranking is from high to low with 1 representing the largest absolute value.)

```
> coef(allsub.bestmodelbyaic)[which(coef(allsub.bestmodelbyaic) !=0)]
(Intercept)      rank      rank2      LSAT      faculty2      clsize
  4.57751884 -1.10979722  0.41860566  0.17069993  0.07579634  0.08026534
> rank(-coef.allsub)
(Intercept)      rank      rank2      LSAT      faculty2      clsize
           1           2           3           4           6           5
```

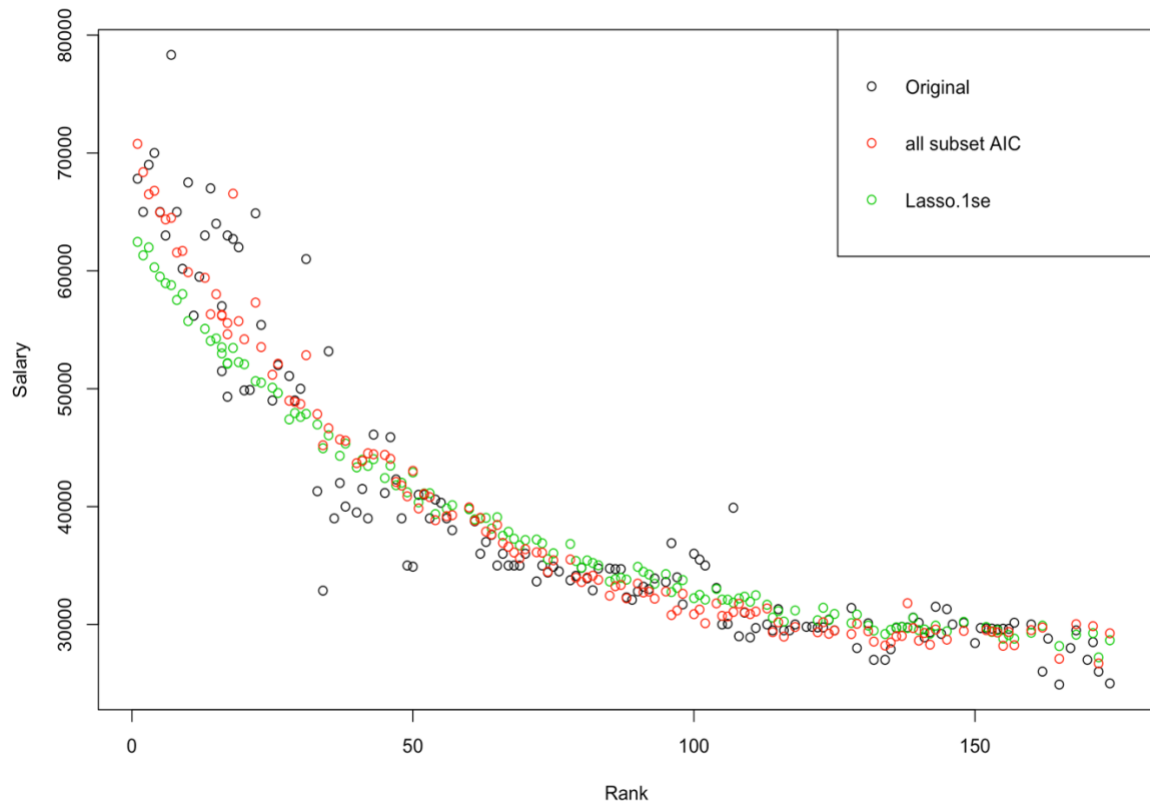
The computation time of AIC forward (st1), AIC backward (st1), all subset model (st3), and LASSO model (st4) are listed in the photo below:

```
> st1
      user  system elapsed
    0.003    0.000    0.002
> st2
      user  system elapsed
    0.081    0.003    0.082
> st3
      user  system elapsed
   77.176    1.548    79.703
> st4
      user  system elapsed
    0.053    0.000    0.053
```

Considering the elapsed time, AIC forward model is the fastest while all subset model is the slowest. The LASSO model is faster than AIC backward model.

Variables rank, rank2 and LAST are included in all four models. This makes sense considering the R^2 in part(a).

(f)



It seems that all subset model has some shrinkage effect.

Q4

The log likelihood function $l(\theta; \xi)$ after some math is:

$$l(\theta; \xi) = -\frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n \epsilon_i^2$$

$$= -\frac{n}{2} \log(2\pi) - \frac{n}{2} \log(\sigma^2) - \frac{1}{2\sigma^2} SSE$$

$$-2 \times l(\theta; \xi) = n \log(2\pi) + n \log(\sigma^2) + \frac{1}{\sigma^2} SSE$$

since we have $\sigma_{MLE}^2 = \frac{SSE}{n}$, we can denote that

$$-2 \times l(\theta; \xi) = n \log(2\pi) + n \log\left(\frac{SSE}{n}\right) + n$$

$$n \log\left(\frac{SSE}{n}\right) - (-2 \times l(\theta; \xi))$$

$$= n \log\left(\frac{SSE}{n}\right) - n \log(2\pi) - n \log\left(\frac{SSE}{n}\right) - n$$

$$= n \log(2\pi) - n$$

It is obvious that the for a Gaussian multiple regression model the quantities $n \log\left(\frac{SSE}{n}\right)$ and $-2 \times l(\theta; \xi)$ differ by a constant $n \log(2\pi) - n$ which depends only on n. Therefore, the AIC and BIC evaluation methods of Parts (a) and (b) in Q2 are equivalent from the point of view of model selection.