

HW1 TJ Jiang

Load necessary libraries

```
library(fields)
```

```
## Warning: package 'fields' was built under R version 3.2.5
## Loading required package: spam
## Warning: package 'spam' was built under R version 3.2.5
## Loading required package: grid
## Spam version 1.4-0 (2016-08-29) is loaded.
## Type 'help( Spam)' or 'demo( spam)' for a short introduction
## and overview of this package.
## Help for individual functions is also obtained by adding the
## suffix '.spam' to the function name, e.g. 'help( chol.spam)'.
##
## Attaching package: 'spam'
## The following objects are masked from 'package:base':
##
##      backsolve, forwardsolve
## Loading required package: maps
## Warning: package 'maps' was built under R version 3.2.5
```

```
library(SpatialTools)
```

```
## # This research was partially supported under NSF Grant ATM-0534173
```

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.2.5
```

Problem 1

Chapter 2 problem 2

a)

Regression, inference, $n = 500$, $p = 3$

b)

Classification, prediction, $n = 20$, $p = 13$

c)

Regression, prediction, $p = 3$, $n = 52$

Problem 2

Exercise 3 from section 2.4 (p. 52)

a)

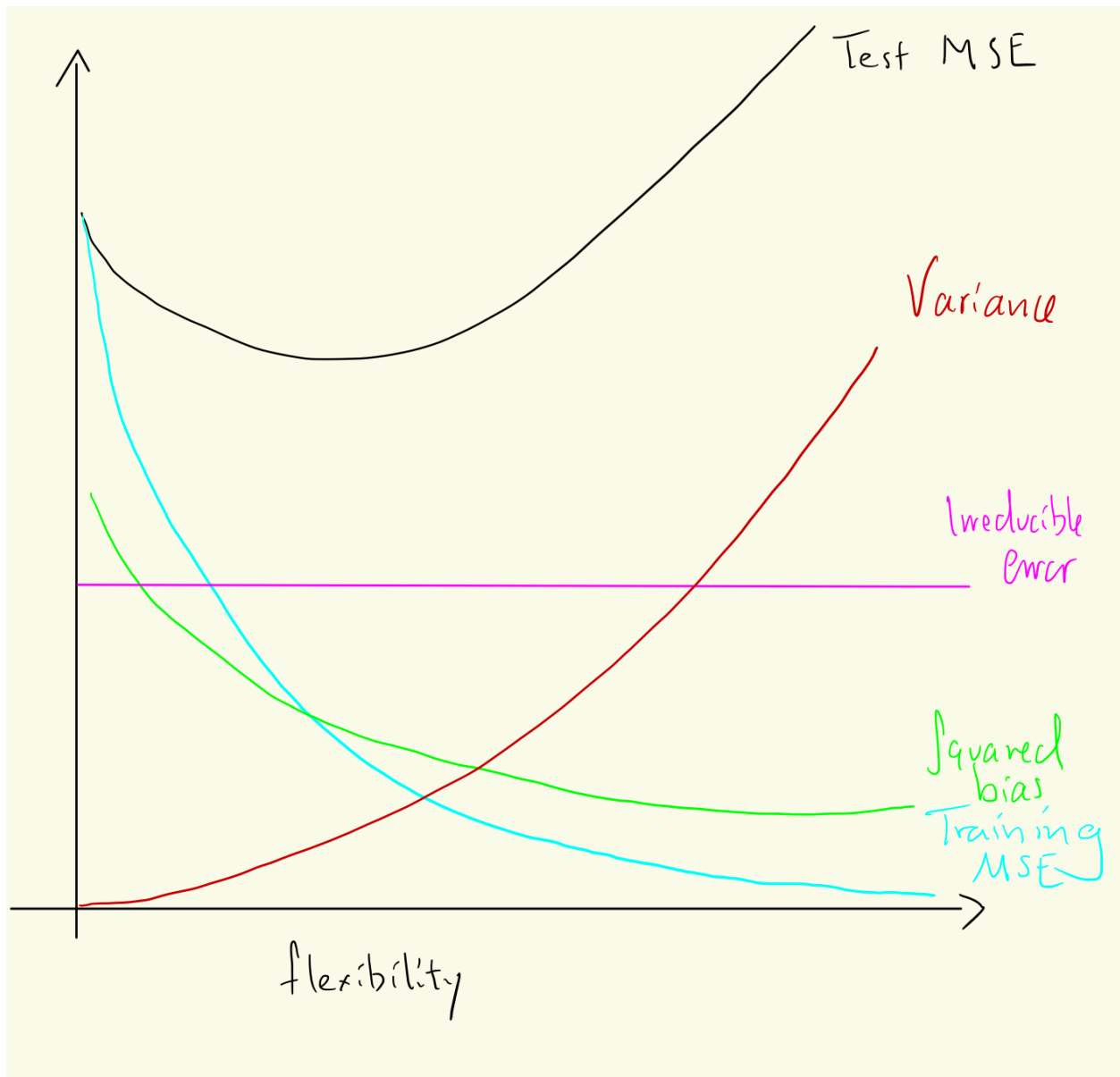


Figure 1: Problem 2a Sketch

b)

Irreducible error cannot be predicted using the input predictor variables. No matter how well the model fits it will not be attenuated. This term could be due to unmeasured quantities or unmeasurable variation. Training error will always decrease as the model becomes more flexible, but will eventually lead to detriment

in generalizability Test error curve goes from an underfit model to a minima where the model fit well with low variance and low bias, but as flexibility increases more the model becomes overfit Variance will increase as model becomes more flexible as overfitting becomes an issue and small changes in predictor variables leads to potentially large changes in prediced response Bias will decrease as model becomes more flexible but will reach an asymptote (diminishing returns) at some point depending on the true model coefficients

Problem 3

Complete Exercise 7 from section 2.4 of the textbook (p. 53).

```
Obs <- seq(1,6,length=6)
X1 <- c(0,2,0,0,-1,1)
X2 <- c(3,0,1,1,0,1)
X3 <- c(0,0,3,2,1,1)
Y <- c('Red', 'Red', 'Red', 'Green', 'Green', 'Red')
df <- data.frame(Obs, X1, X2, X3, Y)
(df)
```

```
##   Obs X1 X2 X3   Y
## 1   1  0  3  0  Red
## 2   2  2  0  0  Red
## 3   3  0  1  3  Red
## 4   4  0  1  2 Green
## 5   5 -1  0  1 Green
## 6   6  1  1  1  Red
```

```
coords_mat <- data.matrix(df[2:4])
coords_mat
```

```
##      X1 X2 X3
## [1,]  0  3  0
## [2,]  2  0  0
## [3,]  0  1  3
## [4,]  0  1  2
## [5,] -1  0  1
## [6,]  1  1  1
```

a)

```
dist <- NULL
for(i in 1:nrow(coords_mat)) {
  dist[i] <- dist(rbind(coords_mat[i,], c(0,0,0)))
}
df$dist <- dist
```

```
df
```

```
##   Obs X1 X2 X3   Y   dist
## 1   1  0  3  0  Red 3.000000
## 2   2  2  0  0  Red 2.000000
## 3   3  0  1  3  Red 3.162278
## 4   4  0  1  2 Green 2.236068
## 5   5 -1  0  1 Green 1.414214
## 6   6  1  1  1  Red 1.732051
```

b)

If the only datapoint we care about is the one nearest neighbor, then the prediction will be Green (Obs 5)

c)

Obs 2, 5, 6 are the closest 3 neighbors for $[0,0,0]$, which corresponds with a Y of Red, Green and Red respectively; thus the prediction would be red.

d)

If the actual Bayes decision boundary is highly non-linear, we would want a small k allowing a more flexible decision boundary. This corresponds to a classifier with low bias but high variance.

Problem 4: Exercise 1 (p. 413)

a)

$$\begin{aligned}
 & \frac{1}{|C_k|} \sum_{i, i' \in C_k} \sum_{j=1}^p (x_{ij} - x_{i'j})^2 = \frac{1}{|C_k|} \sum_{i, i' \in C_k} \sum_{j=1}^p ((x_{ij} - \bar{x}_{kj}) - (x_{i'j} - \bar{x}_{kj}))^2 \\
 & \quad \text{subtract and add } \bar{x}_{kj} \text{ term, net 0} \\
 & = \frac{1}{|C_k|} \sum_{i, i' \in C_k} \sum_{j=1}^p ((x_{ij} - \bar{x}_{kj})^2 - 2(x_{ij} - \bar{x}_{kj})(x_{i'j} - \bar{x}_{kj}) + (x_{i'j} - \bar{x}_{kj})^2) \\
 & \quad \text{multiply out} \\
 & \text{Summing over } i \text{ and } i'; \text{ expressions w/o } i' \text{ will be repeated for each } i', \text{ gaining a } C_k \text{ term.} \\
 & = \sum_{i \in C_k} \sum_{j=1}^p (x_{ij} - \bar{x}_{kj})^2 - \frac{2}{|C_k|} \sum_{i \in C_k} \sum_{j=1}^p (x_{ij} - \bar{x}_{kj})(x_{i'j} - \bar{x}_{kj}) + \sum_{i \in C_k} \sum_{j=1}^p (x_{i'j} - \bar{x}_{kj})^2 \\
 & \text{As } \bar{x}_{kj} = \frac{1}{|C_k|} \sum_{i \in C_k} x_{ij} \text{ e.g. mean for feature } j \text{ in cluster } C_k \\
 & = 2 \sum_{i \in C_k} \sum_{j=1}^p (x_{ij} - \bar{x}_{kj})^2
 \end{aligned}$$

Figure 2: Proof of 10.12

b)

On the basis of this identity, argue that the K-means clustering algorithm (Algorithm 10.1) decreases the objective (10.11) at each iteration.

The left hand term (10.10) defines the within-cluster variation using squared Euclidian distance. In k-means clustering, we want to partition the observations into k clusters such that the total within-cluster variation summed over all clusters is minimized. 10.12 shows that as we minimize 10.10 we also minimize the within-cluster variation for each cluster.

Problem 5

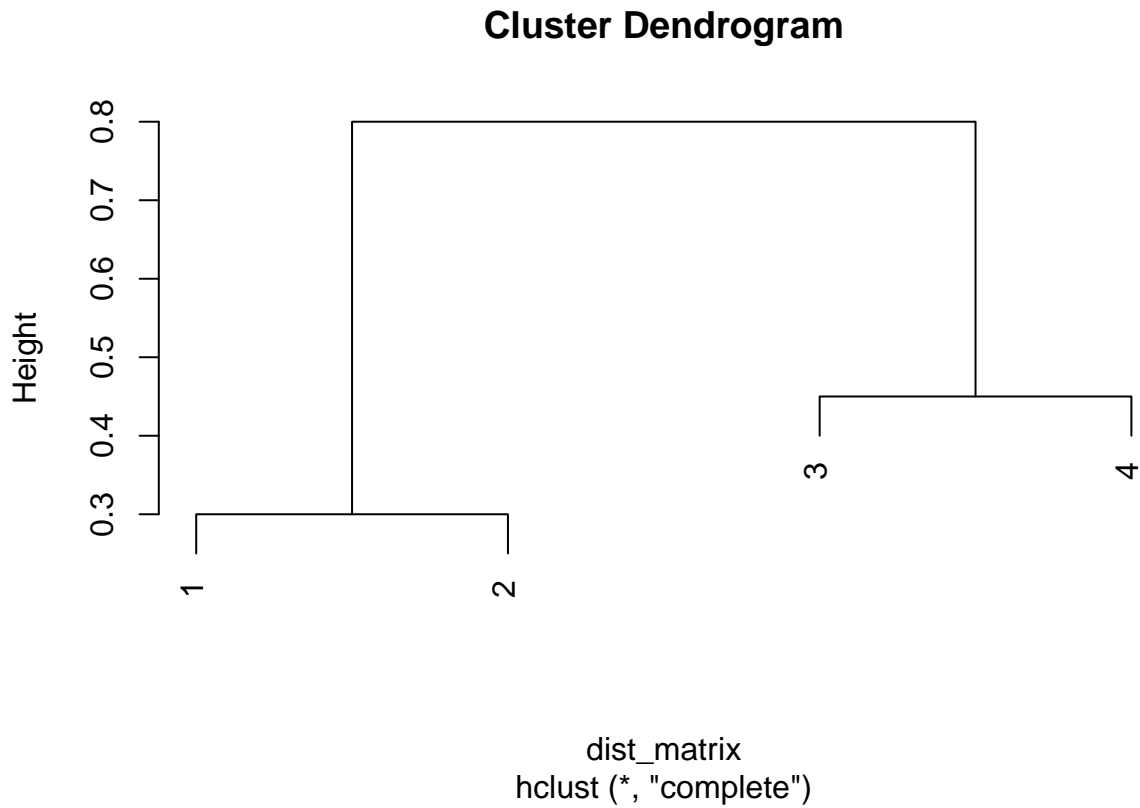
Exercise 2 (p. 413)

a)

On the basis of this dissimilarity matrix, sketch the dendrogram that results from hierarchically clustering these four observations using complete linkage. Be sure to indicate on the plot the height at which each

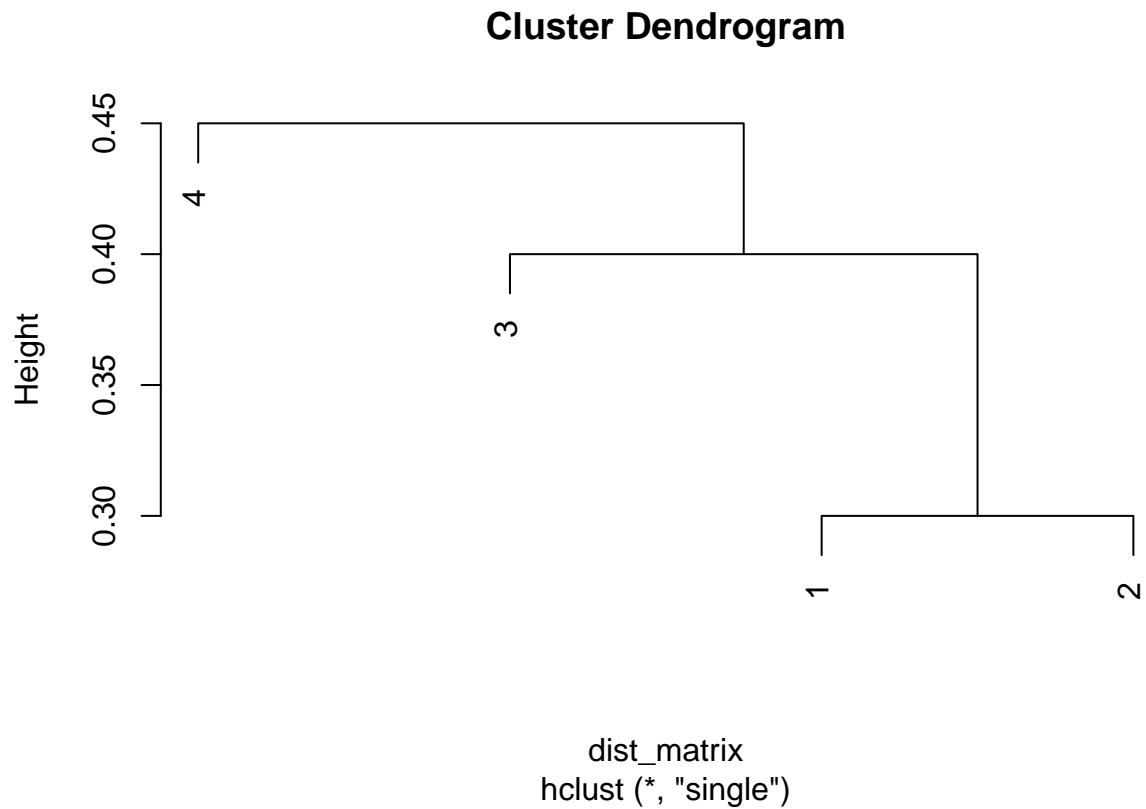
fusion occurs, as well as the observations corresponding to each leaf in the dendrogram.

```
data <-c (0, 0.3, 0.4, 0.7, 0.3, 0, 0.5, 0.8, 0.4, 0.5, 0.0, 0.45, 0.7, 0.8, 0.45, 0.0)
data_mat <- matrix(data, nrow=4)
dist_matrix <- as.dist(data_mat)
plot(hclust(dist_matrix, method="complete"))
```



b)

```
plot(hclust(dist_matrix, method="single"))
```



c)

Cluster1: Observations 1 and 2; Cluster2: Observations 3 and 4

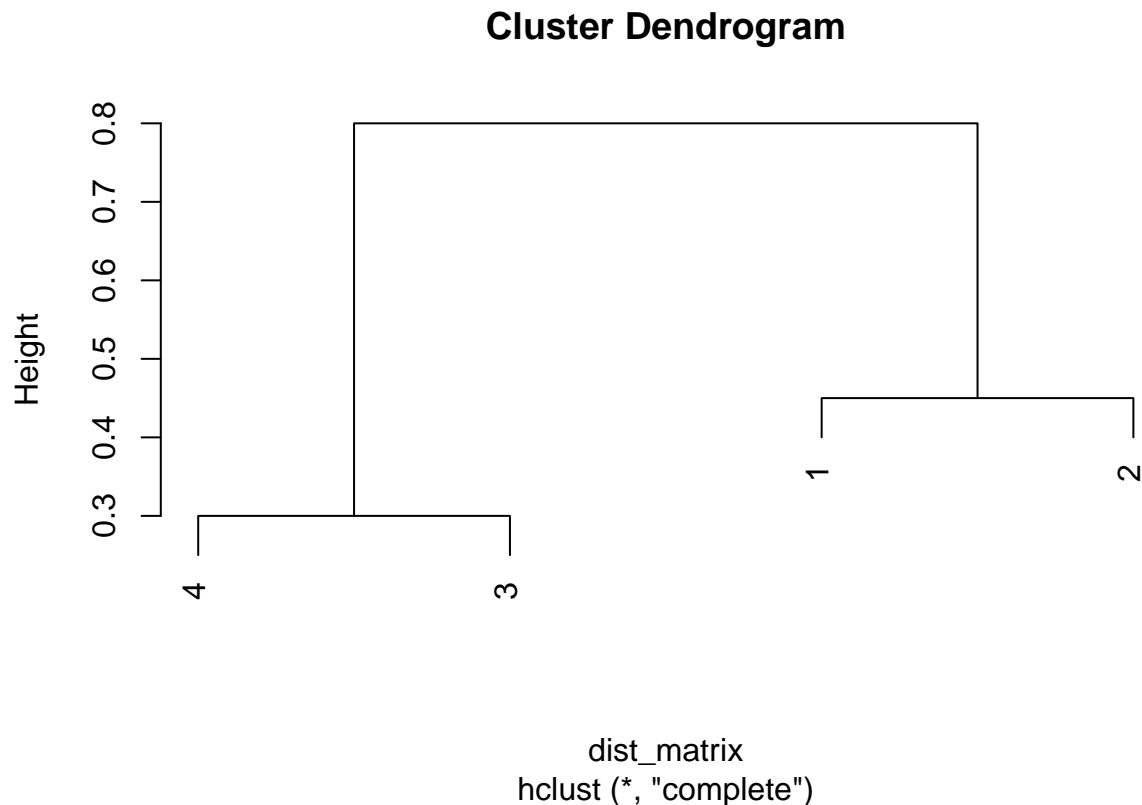
d)

Cluster1: Observations 1,2, and 3; Cluster2: Observation 4

e)

The following dendrogram swaps positions of the two clusters without changing the meaning

```
plot(hclust(dist_matrix, method="complete"), labels=c(4,3,1,2))
```

Problem 6

Exercise 4 (p. 414)

Suppose that for a particular data set, we perform hierarchical clustering using single linkage and using complete linkage. We obtain two dendrograms.

a)

At a certain point on the single linkage dendrogram, the clusters $\{1,2,3\}$ and $\{4,5\}$ fuse. On the complete linkage dendrogram, the clusters $\{1, 2, 3\}$ and $\{4, 5\}$ also fuse at a certain point. Which fusion will occur higher on the tree, or will they fuse at the same height, or is there not enough information to tell?

This question requires more information to answer and is dependent on both the organization of information as well as the dissimilarity measure (euclidian distance, correlation etc). Complete linkage joins on maximal intercluster dissimilarity, while single linkage joins on minimal intercluster dissimilarity; were these to be equal, then the two clusters in question would fuse at the same height. Otherwise, a dendrogram formed with complete linkage would fuse them at a greater height than a dendrogram formed with single linkage.

b)

At a certain point on the single linkage dendrogram, the clusters $\{5\}$ and $\{6\}$ fuse. On the complete linkage dendrogram, the clusters $\{5\}$ and $\{6\}$ also fuse at a certain point. Which fusion will occur higher on the tree, or will they fuse at the same height, or is there not enough information to tell?

They would fuse at the same height because the choice of complete vs single linkage operates on observations between two clusters instead of the clustering of two individual observations that are not yet clustered.

Problem 7

Exercise 9 (p. 416)

```
data("USArrests")
names(USArrests)
```

```
## [1] "Murder" "Assault" "UrbanPop" "Rape"
```

```
dim(USArrests)
```

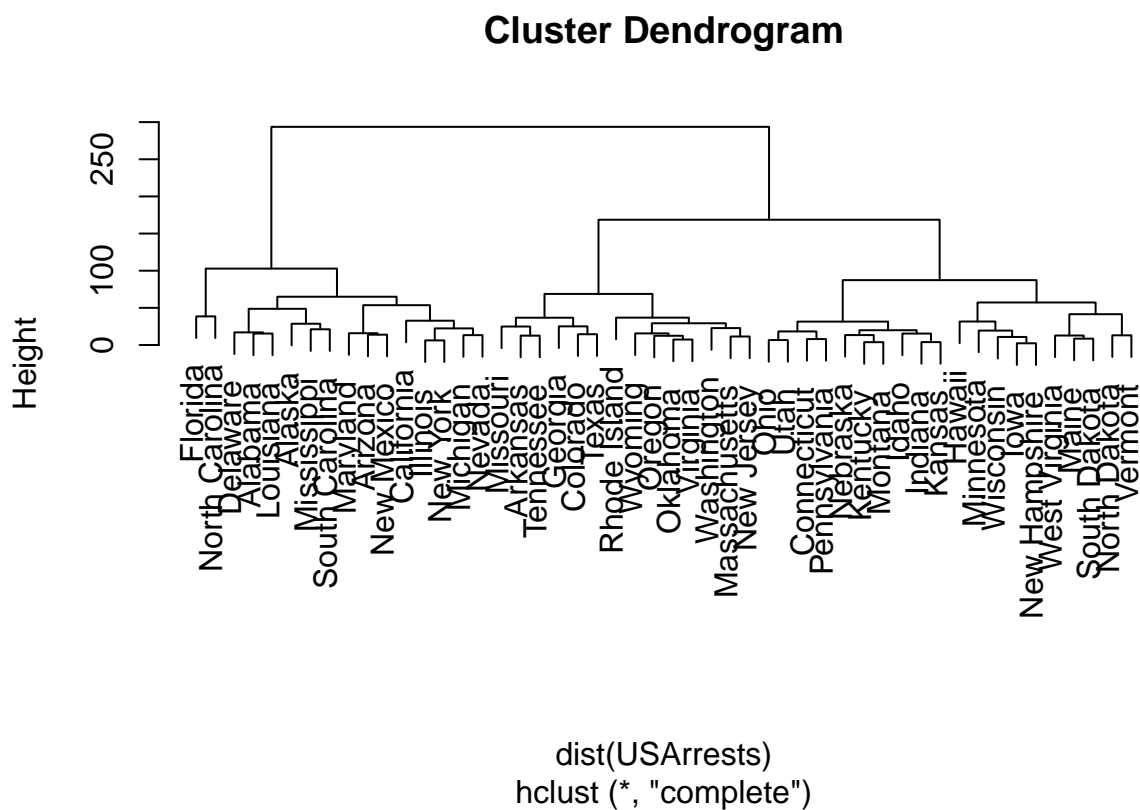
```
## [1] 50 4
```

```
class(USArrests)
```

```
## [1] "data.frame"
```

a)

```
cluster_USArrests <- hclust(dist(USArrests), method="complete")
plot(cluster_USArrests)
```



b)

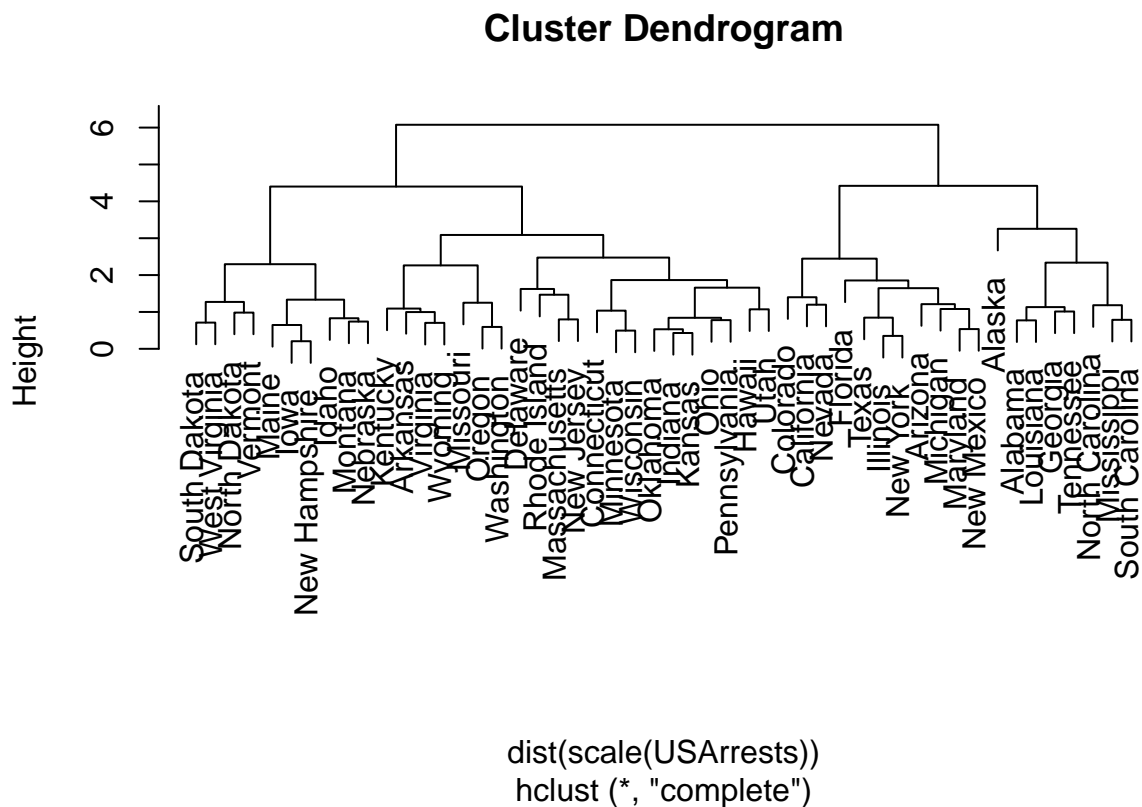
```
cutree(cluster_USArrests, 3)
```

```
##      Alabama      Alaska      Arizona      Arkansas      California
##           1           1           1           2           1
##      Colorado      Connecticut      Delaware      Florida      Georgia
```

##	2	3	1	1	2
##	Hawaii	Idaho	Illinois	Indiana	Iowa
##	3	3	1	3	3
##	Kansas	Kentucky	Louisiana	Maine	Maryland
##	3	3	1	3	1
##	Massachusetts	Michigan	Minnesota	Mississippi	Missouri
##	2	1	3	1	2
##	Montana	Nebraska	Nevada	New Hampshire	New Jersey
##	3	3	1	3	2
##	New Mexico	New York	North Carolina	North Dakota	Ohio
##	1	1	1	3	3
##	Oklahoma	Oregon	Pennsylvania	Rhode Island	South Carolina
##	2	2	3	2	1
##	South Dakota	Tennessee	Texas	Utah	Vermont
##	3	2	2	3	3
##	Virginia	Washington	West Virginia	Wisconsin	Wyoming
##	2	2	3	3	2

c)

```
cluster_USArrests_scaled = hclust(dist(scale(USArrests)), method="complete")
plot(cluster_USArrests_scaled)
```



d)

Number of states in each cluster without scaling USArrests:

```
table(cutree(cluster_USArrests, 3))
```

```
##  
##  1  2  3  
## 16 14 20
```

Number of states in each cluster after scaling USArrests:

```
table(cutree(cluster_USArrests_scaled, 3))
```

```
##  
##  1  2  3  
##  8 11 31
```

The overall height and spread of the dendrogram was not dramatically altered after scaling the input dataset. The states that ended up in each 3 cluster did change. In general, scaling each variable vector to standardize variance makes sense. The variables in USArrests dataset have different units with different inherent variance. Units with a larger variance has a greater effect on euclidian distance, and thus have a greater influence on how clusters are formed.

Problem 8

Exercise 4 (p. 120)

I collect a set of data ($n = 100$ observations) containing a single predictor and a quantitative response. I then fit a linear regression model to the data, as well as a separate cubic regression, i.e. $Y = 0 + 1X + 2X^2 + 3X^3 + \epsilon$.

a)

Suppose that the true relationship between X and Y is linear, i.e. $Y = 0 + 1X + \epsilon$. Consider the training residual sum of squares (RSS) for the linear regression, and also the training RSS for the cubic regression. Would we expect one to be lower than the other, would we expect them to be the same, or is there not enough information to tell? Justify your answer.

Adding more variables to the least squares equations always improves the fit to the training data; thus, the RSS to training data should decrease

b)

Answer (a) using test rather than training RSS.

test RSS should decrease due to the overfitting and failing to generalize overfit model to test dataset

c)

Suppose that the true relationship between X and Y is not linear, but we don't know how far it is from linear. Consider the training RSS for the linear regression, and also the training RSS for the cubic regression. Would we expect one to be lower than the other, would we expect them to be the same, or is there not enough information to tell? Justify your answer.

The increased flexibility from polynomial regression will lead to a better fit to training data over a linear regression.

d)

Answer (c) using test rather than training RSS.

Since the true relationship is not known, there is not enough information to exactly tell whether test dataset RSS will be better with a polynomial fit

Problem 9

Exercise 9 (p. 122). In parts (e) and (f), you need only try a few interactions and transformations.

```
Auto = na.omit(read.csv("Auto.csv", na.strings="?")) #message out question marks and lists with missing
Auto
```

##	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
## 1	18.0	8	307.0	130	3504	12.0	70	1
## 2	15.0	8	350.0	165	3693	11.5	70	1
## 3	18.0	8	318.0	150	3436	11.0	70	1
## 4	16.0	8	304.0	150	3433	12.0	70	1
## 5	17.0	8	302.0	140	3449	10.5	70	1
## 6	15.0	8	429.0	198	4341	10.0	70	1
## 7	14.0	8	454.0	220	4354	9.0	70	1
## 8	14.0	8	440.0	215	4312	8.5	70	1
## 9	14.0	8	455.0	225	4425	10.0	70	1
## 10	15.0	8	390.0	190	3850	8.5	70	1
## 11	15.0	8	383.0	170	3563	10.0	70	1
## 12	14.0	8	340.0	160	3609	8.0	70	1
## 13	15.0	8	400.0	150	3761	9.5	70	1
## 14	14.0	8	455.0	225	3086	10.0	70	1
## 15	24.0	4	113.0	95	2372	15.0	70	3
## 16	22.0	6	198.0	95	2833	15.5	70	1
## 17	18.0	6	199.0	97	2774	15.5	70	1
## 18	21.0	6	200.0	85	2587	16.0	70	1
## 19	27.0	4	97.0	88	2130	14.5	70	3
## 20	26.0	4	97.0	46	1835	20.5	70	2
## 21	25.0	4	110.0	87	2672	17.5	70	2
## 22	24.0	4	107.0	90	2430	14.5	70	2
## 23	25.0	4	104.0	95	2375	17.5	70	2
## 24	26.0	4	121.0	113	2234	12.5	70	2
## 25	21.0	6	199.0	90	2648	15.0	70	1
## 26	10.0	8	360.0	215	4615	14.0	70	1
## 27	10.0	8	307.0	200	4376	15.0	70	1
## 28	11.0	8	318.0	210	4382	13.5	70	1
## 29	9.0	8	304.0	193	4732	18.5	70	1
## 30	27.0	4	97.0	88	2130	14.5	71	3
## 31	28.0	4	140.0	90	2264	15.5	71	1
## 32	25.0	4	113.0	95	2228	14.0	71	3
## 34	19.0	6	232.0	100	2634	13.0	71	1
## 35	16.0	6	225.0	105	3439	15.5	71	1
## 36	17.0	6	250.0	100	3329	15.5	71	1
## 37	19.0	6	250.0	88	3302	15.5	71	1
## 38	18.0	6	232.0	100	3288	15.5	71	1
## 39	14.0	8	350.0	165	4209	12.0	71	1
## 40	14.0	8	400.0	175	4464	11.5	71	1
## 41	14.0	8	351.0	153	4154	13.5	71	1

## 42	14.0	8	318.0	150	4096	13.0	71	1
## 43	12.0	8	383.0	180	4955	11.5	71	1
## 44	13.0	8	400.0	170	4746	12.0	71	1
## 45	13.0	8	400.0	175	5140	12.0	71	1
## 46	18.0	6	258.0	110	2962	13.5	71	1
## 47	22.0	4	140.0	72	2408	19.0	71	1
## 48	19.0	6	250.0	100	3282	15.0	71	1
## 49	18.0	6	250.0	88	3139	14.5	71	1
## 50	23.0	4	122.0	86	2220	14.0	71	1
## 51	28.0	4	116.0	90	2123	14.0	71	2
## 52	30.0	4	79.0	70	2074	19.5	71	2
## 53	30.0	4	88.0	76	2065	14.5	71	2
## 54	31.0	4	71.0	65	1773	19.0	71	3
## 55	35.0	4	72.0	69	1613	18.0	71	3
## 56	27.0	4	97.0	60	1834	19.0	71	2
## 57	26.0	4	91.0	70	1955	20.5	71	1
## 58	24.0	4	113.0	95	2278	15.5	72	3
## 59	25.0	4	97.5	80	2126	17.0	72	1
## 60	23.0	4	97.0	54	2254	23.5	72	2
## 61	20.0	4	140.0	90	2408	19.5	72	1
## 62	21.0	4	122.0	86	2226	16.5	72	1
## 63	13.0	8	350.0	165	4274	12.0	72	1
## 64	14.0	8	400.0	175	4385	12.0	72	1
## 65	15.0	8	318.0	150	4135	13.5	72	1
## 66	14.0	8	351.0	153	4129	13.0	72	1
## 67	17.0	8	304.0	150	3672	11.5	72	1
## 68	11.0	8	429.0	208	4633	11.0	72	1
## 69	13.0	8	350.0	155	4502	13.5	72	1
## 70	12.0	8	350.0	160	4456	13.5	72	1
## 71	13.0	8	400.0	190	4422	12.5	72	1
## 72	19.0	3	70.0	97	2330	13.5	72	3
## 73	15.0	8	304.0	150	3892	12.5	72	1
## 74	13.0	8	307.0	130	4098	14.0	72	1
## 75	13.0	8	302.0	140	4294	16.0	72	1
## 76	14.0	8	318.0	150	4077	14.0	72	1
## 77	18.0	4	121.0	112	2933	14.5	72	2
## 78	22.0	4	121.0	76	2511	18.0	72	2
## 79	21.0	4	120.0	87	2979	19.5	72	2
## 80	26.0	4	96.0	69	2189	18.0	72	2
## 81	22.0	4	122.0	86	2395	16.0	72	1
## 82	28.0	4	97.0	92	2288	17.0	72	3
## 83	23.0	4	120.0	97	2506	14.5	72	3
## 84	28.0	4	98.0	80	2164	15.0	72	1
## 85	27.0	4	97.0	88	2100	16.5	72	3
## 86	13.0	8	350.0	175	4100	13.0	73	1
## 87	14.0	8	304.0	150	3672	11.5	73	1
## 88	13.0	8	350.0	145	3988	13.0	73	1
## 89	14.0	8	302.0	137	4042	14.5	73	1
## 90	15.0	8	318.0	150	3777	12.5	73	1
## 91	12.0	8	429.0	198	4952	11.5	73	1
## 92	13.0	8	400.0	150	4464	12.0	73	1
## 93	13.0	8	351.0	158	4363	13.0	73	1
## 94	14.0	8	318.0	150	4237	14.5	73	1
## 95	13.0	8	440.0	215	4735	11.0	73	1

## 96	12.0	8	455.0	225	4951	11.0	73	1
## 97	13.0	8	360.0	175	3821	11.0	73	1
## 98	18.0	6	225.0	105	3121	16.5	73	1
## 99	16.0	6	250.0	100	3278	18.0	73	1
## 100	18.0	6	232.0	100	2945	16.0	73	1
## 101	18.0	6	250.0	88	3021	16.5	73	1
## 102	23.0	6	198.0	95	2904	16.0	73	1
## 103	26.0	4	97.0	46	1950	21.0	73	2
## 104	11.0	8	400.0	150	4997	14.0	73	1
## 105	12.0	8	400.0	167	4906	12.5	73	1
## 106	13.0	8	360.0	170	4654	13.0	73	1
## 107	12.0	8	350.0	180	4499	12.5	73	1
## 108	18.0	6	232.0	100	2789	15.0	73	1
## 109	20.0	4	97.0	88	2279	19.0	73	3
## 110	21.0	4	140.0	72	2401	19.5	73	1
## 111	22.0	4	108.0	94	2379	16.5	73	3
## 112	18.0	3	70.0	90	2124	13.5	73	3
## 113	19.0	4	122.0	85	2310	18.5	73	1
## 114	21.0	6	155.0	107	2472	14.0	73	1
## 115	26.0	4	98.0	90	2265	15.5	73	2
## 116	15.0	8	350.0	145	4082	13.0	73	1
## 117	16.0	8	400.0	230	4278	9.5	73	1
## 118	29.0	4	68.0	49	1867	19.5	73	2
## 119	24.0	4	116.0	75	2158	15.5	73	2
## 120	20.0	4	114.0	91	2582	14.0	73	2
## 121	19.0	4	121.0	112	2868	15.5	73	2
## 122	15.0	8	318.0	150	3399	11.0	73	1
## 123	24.0	4	121.0	110	2660	14.0	73	2
## 124	20.0	6	156.0	122	2807	13.5	73	3
## 125	11.0	8	350.0	180	3664	11.0	73	1
## 126	20.0	6	198.0	95	3102	16.5	74	1
## 128	19.0	6	232.0	100	2901	16.0	74	1
## 129	15.0	6	250.0	100	3336	17.0	74	1
## 130	31.0	4	79.0	67	1950	19.0	74	3
## 131	26.0	4	122.0	80	2451	16.5	74	1
## 132	32.0	4	71.0	65	1836	21.0	74	3
## 133	25.0	4	140.0	75	2542	17.0	74	1
## 134	16.0	6	250.0	100	3781	17.0	74	1
## 135	16.0	6	258.0	110	3632	18.0	74	1
## 136	18.0	6	225.0	105	3613	16.5	74	1
## 137	16.0	8	302.0	140	4141	14.0	74	1
## 138	13.0	8	350.0	150	4699	14.5	74	1
## 139	14.0	8	318.0	150	4457	13.5	74	1
## 140	14.0	8	302.0	140	4638	16.0	74	1
## 141	14.0	8	304.0	150	4257	15.5	74	1
## 142	29.0	4	98.0	83	2219	16.5	74	2
## 143	26.0	4	79.0	67	1963	15.5	74	2
## 144	26.0	4	97.0	78	2300	14.5	74	2
## 145	31.0	4	76.0	52	1649	16.5	74	3
## 146	32.0	4	83.0	61	2003	19.0	74	3
## 147	28.0	4	90.0	75	2125	14.5	74	1
## 148	24.0	4	90.0	75	2108	15.5	74	2
## 149	26.0	4	116.0	75	2246	14.0	74	2
## 150	24.0	4	120.0	97	2489	15.0	74	3

## 151 26.0	4	108.0	93	2391	15.5	74	3
## 152 31.0	4	79.0	67	2000	16.0	74	2
## 153 19.0	6	225.0	95	3264	16.0	75	1
## 154 18.0	6	250.0	105	3459	16.0	75	1
## 155 15.0	6	250.0	72	3432	21.0	75	1
## 156 15.0	6	250.0	72	3158	19.5	75	1
## 157 16.0	8	400.0	170	4668	11.5	75	1
## 158 15.0	8	350.0	145	4440	14.0	75	1
## 159 16.0	8	318.0	150	4498	14.5	75	1
## 160 14.0	8	351.0	148	4657	13.5	75	1
## 161 17.0	6	231.0	110	3907	21.0	75	1
## 162 16.0	6	250.0	105	3897	18.5	75	1
## 163 15.0	6	258.0	110	3730	19.0	75	1
## 164 18.0	6	225.0	95	3785	19.0	75	1
## 165 21.0	6	231.0	110	3039	15.0	75	1
## 166 20.0	8	262.0	110	3221	13.5	75	1
## 167 13.0	8	302.0	129	3169	12.0	75	1
## 168 29.0	4	97.0	75	2171	16.0	75	3
## 169 23.0	4	140.0	83	2639	17.0	75	1
## 170 20.0	6	232.0	100	2914	16.0	75	1
## 171 23.0	4	140.0	78	2592	18.5	75	1
## 172 24.0	4	134.0	96	2702	13.5	75	3
## 173 25.0	4	90.0	71	2223	16.5	75	2
## 174 24.0	4	119.0	97	2545	17.0	75	3
## 175 18.0	6	171.0	97	2984	14.5	75	1
## 176 29.0	4	90.0	70	1937	14.0	75	2
## 177 19.0	6	232.0	90	3211	17.0	75	1
## 178 23.0	4	115.0	95	2694	15.0	75	2
## 179 23.0	4	120.0	88	2957	17.0	75	2
## 180 22.0	4	121.0	98	2945	14.5	75	2
## 181 25.0	4	121.0	115	2671	13.5	75	2
## 182 33.0	4	91.0	53	1795	17.5	75	3
## 183 28.0	4	107.0	86	2464	15.5	76	2
## 184 25.0	4	116.0	81	2220	16.9	76	2
## 185 25.0	4	140.0	92	2572	14.9	76	1
## 186 26.0	4	98.0	79	2255	17.7	76	1
## 187 27.0	4	101.0	83	2202	15.3	76	2
## 188 17.5	8	305.0	140	4215	13.0	76	1
## 189 16.0	8	318.0	150	4190	13.0	76	1
## 190 15.5	8	304.0	120	3962	13.9	76	1
## 191 14.5	8	351.0	152	4215	12.8	76	1
## 192 22.0	6	225.0	100	3233	15.4	76	1
## 193 22.0	6	250.0	105	3353	14.5	76	1
## 194 24.0	6	200.0	81	3012	17.6	76	1
## 195 22.5	6	232.0	90	3085	17.6	76	1
## 196 29.0	4	85.0	52	2035	22.2	76	1
## 197 24.5	4	98.0	60	2164	22.1	76	1
## 198 29.0	4	90.0	70	1937	14.2	76	2
## 199 33.0	4	91.0	53	1795	17.4	76	3
## 200 20.0	6	225.0	100	3651	17.7	76	1
## 201 18.0	6	250.0	78	3574	21.0	76	1
## 202 18.5	6	250.0	110	3645	16.2	76	1
## 203 17.5	6	258.0	95	3193	17.8	76	1
## 204 29.5	4	97.0	71	1825	12.2	76	2

## 205	32.0	4	85.0	70	1990	17.0	76	3
## 206	28.0	4	97.0	75	2155	16.4	76	3
## 207	26.5	4	140.0	72	2565	13.6	76	1
## 208	20.0	4	130.0	102	3150	15.7	76	2
## 209	13.0	8	318.0	150	3940	13.2	76	1
## 210	19.0	4	120.0	88	3270	21.9	76	2
## 211	19.0	6	156.0	108	2930	15.5	76	3
## 212	16.5	6	168.0	120	3820	16.7	76	2
## 213	16.5	8	350.0	180	4380	12.1	76	1
## 214	13.0	8	350.0	145	4055	12.0	76	1
## 215	13.0	8	302.0	130	3870	15.0	76	1
## 216	13.0	8	318.0	150	3755	14.0	76	1
## 217	31.5	4	98.0	68	2045	18.5	77	3
## 218	30.0	4	111.0	80	2155	14.8	77	1
## 219	36.0	4	79.0	58	1825	18.6	77	2
## 220	25.5	4	122.0	96	2300	15.5	77	1
## 221	33.5	4	85.0	70	1945	16.8	77	3
## 222	17.5	8	305.0	145	3880	12.5	77	1
## 223	17.0	8	260.0	110	4060	19.0	77	1
## 224	15.5	8	318.0	145	4140	13.7	77	1
## 225	15.0	8	302.0	130	4295	14.9	77	1
## 226	17.5	6	250.0	110	3520	16.4	77	1
## 227	20.5	6	231.0	105	3425	16.9	77	1
## 228	19.0	6	225.0	100	3630	17.7	77	1
## 229	18.5	6	250.0	98	3525	19.0	77	1
## 230	16.0	8	400.0	180	4220	11.1	77	1
## 231	15.5	8	350.0	170	4165	11.4	77	1
## 232	15.5	8	400.0	190	4325	12.2	77	1
## 233	16.0	8	351.0	149	4335	14.5	77	1
## 234	29.0	4	97.0	78	1940	14.5	77	2
## 235	24.5	4	151.0	88	2740	16.0	77	1
## 236	26.0	4	97.0	75	2265	18.2	77	3
## 237	25.5	4	140.0	89	2755	15.8	77	1
## 238	30.5	4	98.0	63	2051	17.0	77	1
## 239	33.5	4	98.0	83	2075	15.9	77	1
## 240	30.0	4	97.0	67	1985	16.4	77	3
## 241	30.5	4	97.0	78	2190	14.1	77	2
## 242	22.0	6	146.0	97	2815	14.5	77	3
## 243	21.5	4	121.0	110	2600	12.8	77	2
## 244	21.5	3	80.0	110	2720	13.5	77	3
## 245	43.1	4	90.0	48	1985	21.5	78	2
## 246	36.1	4	98.0	66	1800	14.4	78	1
## 247	32.8	4	78.0	52	1985	19.4	78	3
## 248	39.4	4	85.0	70	2070	18.6	78	3
## 249	36.1	4	91.0	60	1800	16.4	78	3
## 250	19.9	8	260.0	110	3365	15.5	78	1
## 251	19.4	8	318.0	140	3735	13.2	78	1
## 252	20.2	8	302.0	139	3570	12.8	78	1
## 253	19.2	6	231.0	105	3535	19.2	78	1
## 254	20.5	6	200.0	95	3155	18.2	78	1
## 255	20.2	6	200.0	85	2965	15.8	78	1
## 256	25.1	4	140.0	88	2720	15.4	78	1
## 257	20.5	6	225.0	100	3430	17.2	78	1
## 258	19.4	6	232.0	90	3210	17.2	78	1

## 259	20.6	6	231.0	105	3380	15.8	78	1
## 260	20.8	6	200.0	85	3070	16.7	78	1
## 261	18.6	6	225.0	110	3620	18.7	78	1
## 262	18.1	6	258.0	120	3410	15.1	78	1
## 263	19.2	8	305.0	145	3425	13.2	78	1
## 264	17.7	6	231.0	165	3445	13.4	78	1
## 265	18.1	8	302.0	139	3205	11.2	78	1
## 266	17.5	8	318.0	140	4080	13.7	78	1
## 267	30.0	4	98.0	68	2155	16.5	78	1
## 268	27.5	4	134.0	95	2560	14.2	78	3
## 269	27.2	4	119.0	97	2300	14.7	78	3
## 270	30.9	4	105.0	75	2230	14.5	78	1
## 271	21.1	4	134.0	95	2515	14.8	78	3
## 272	23.2	4	156.0	105	2745	16.7	78	1
## 273	23.8	4	151.0	85	2855	17.6	78	1
## 274	23.9	4	119.0	97	2405	14.9	78	3
## 275	20.3	5	131.0	103	2830	15.9	78	2
## 276	17.0	6	163.0	125	3140	13.6	78	2
## 277	21.6	4	121.0	115	2795	15.7	78	2
## 278	16.2	6	163.0	133	3410	15.8	78	2
## 279	31.5	4	89.0	71	1990	14.9	78	2
## 280	29.5	4	98.0	68	2135	16.6	78	3
## 281	21.5	6	231.0	115	3245	15.4	79	1
## 282	19.8	6	200.0	85	2990	18.2	79	1
## 283	22.3	4	140.0	88	2890	17.3	79	1
## 284	20.2	6	232.0	90	3265	18.2	79	1
## 285	20.6	6	225.0	110	3360	16.6	79	1
## 286	17.0	8	305.0	130	3840	15.4	79	1
## 287	17.6	8	302.0	129	3725	13.4	79	1
## 288	16.5	8	351.0	138	3955	13.2	79	1
## 289	18.2	8	318.0	135	3830	15.2	79	1
## 290	16.9	8	350.0	155	4360	14.9	79	1
## 291	15.5	8	351.0	142	4054	14.3	79	1
## 292	19.2	8	267.0	125	3605	15.0	79	1
## 293	18.5	8	360.0	150	3940	13.0	79	1
## 294	31.9	4	89.0	71	1925	14.0	79	2
## 295	34.1	4	86.0	65	1975	15.2	79	3
## 296	35.7	4	98.0	80	1915	14.4	79	1
## 297	27.4	4	121.0	80	2670	15.0	79	1
## 298	25.4	5	183.0	77	3530	20.1	79	2
## 299	23.0	8	350.0	125	3900	17.4	79	1
## 300	27.2	4	141.0	71	3190	24.8	79	2
## 301	23.9	8	260.0	90	3420	22.2	79	1
## 302	34.2	4	105.0	70	2200	13.2	79	1
## 303	34.5	4	105.0	70	2150	14.9	79	1
## 304	31.8	4	85.0	65	2020	19.2	79	3
## 305	37.3	4	91.0	69	2130	14.7	79	2
## 306	28.4	4	151.0	90	2670	16.0	79	1
## 307	28.8	6	173.0	115	2595	11.3	79	1
## 308	26.8	6	173.0	115	2700	12.9	79	1
## 309	33.5	4	151.0	90	2556	13.2	79	1
## 310	41.5	4	98.0	76	2144	14.7	80	2
## 311	38.1	4	89.0	60	1968	18.8	80	3
## 312	32.1	4	98.0	70	2120	15.5	80	1

## 313 37.2	4	86.0	65	2019	16.4	80	3
## 314 28.0	4	151.0	90	2678	16.5	80	1
## 315 26.4	4	140.0	88	2870	18.1	80	1
## 316 24.3	4	151.0	90	3003	20.1	80	1
## 317 19.1	6	225.0	90	3381	18.7	80	1
## 318 34.3	4	97.0	78	2188	15.8	80	2
## 319 29.8	4	134.0	90	2711	15.5	80	3
## 320 31.3	4	120.0	75	2542	17.5	80	3
## 321 37.0	4	119.0	92	2434	15.0	80	3
## 322 32.2	4	108.0	75	2265	15.2	80	3
## 323 46.6	4	86.0	65	2110	17.9	80	3
## 324 27.9	4	156.0	105	2800	14.4	80	1
## 325 40.8	4	85.0	65	2110	19.2	80	3
## 326 44.3	4	90.0	48	2085	21.7	80	2
## 327 43.4	4	90.0	48	2335	23.7	80	2
## 328 36.4	5	121.0	67	2950	19.9	80	2
## 329 30.0	4	146.0	67	3250	21.8	80	2
## 330 44.6	4	91.0	67	1850	13.8	80	3
## 332 33.8	4	97.0	67	2145	18.0	80	3
## 333 29.8	4	89.0	62	1845	15.3	80	2
## 334 32.7	6	168.0	132	2910	11.4	80	3
## 335 23.7	3	70.0	100	2420	12.5	80	3
## 336 35.0	4	122.0	88	2500	15.1	80	2
## 338 32.4	4	107.0	72	2290	17.0	80	3
## 339 27.2	4	135.0	84	2490	15.7	81	1
## 340 26.6	4	151.0	84	2635	16.4	81	1
## 341 25.8	4	156.0	92	2620	14.4	81	1
## 342 23.5	6	173.0	110	2725	12.6	81	1
## 343 30.0	4	135.0	84	2385	12.9	81	1
## 344 39.1	4	79.0	58	1755	16.9	81	3
## 345 39.0	4	86.0	64	1875	16.4	81	1
## 346 35.1	4	81.0	60	1760	16.1	81	3
## 347 32.3	4	97.0	67	2065	17.8	81	3
## 348 37.0	4	85.0	65	1975	19.4	81	3
## 349 37.7	4	89.0	62	2050	17.3	81	3
## 350 34.1	4	91.0	68	1985	16.0	81	3
## 351 34.7	4	105.0	63	2215	14.9	81	1
## 352 34.4	4	98.0	65	2045	16.2	81	1
## 353 29.9	4	98.0	65	2380	20.7	81	1
## 354 33.0	4	105.0	74	2190	14.2	81	2
## 356 33.7	4	107.0	75	2210	14.4	81	3
## 357 32.4	4	108.0	75	2350	16.8	81	3
## 358 32.9	4	119.0	100	2615	14.8	81	3
## 359 31.6	4	120.0	74	2635	18.3	81	3
## 360 28.1	4	141.0	80	3230	20.4	81	2
## 361 30.7	6	145.0	76	3160	19.6	81	2
## 362 25.4	6	168.0	116	2900	12.6	81	3
## 363 24.2	6	146.0	120	2930	13.8	81	3
## 364 22.4	6	231.0	110	3415	15.8	81	1
## 365 26.6	8	350.0	105	3725	19.0	81	1
## 366 20.2	6	200.0	88	3060	17.1	81	1
## 367 17.6	6	225.0	85	3465	16.6	81	1
## 368 28.0	4	112.0	88	2605	19.6	82	1
## 369 27.0	4	112.0	88	2640	18.6	82	1

##	370	34.0	4	112.0	88	2395	18.0	82	1
##	371	31.0	4	112.0	85	2575	16.2	82	1
##	372	29.0	4	135.0	84	2525	16.0	82	1
##	373	27.0	4	151.0	90	2735	18.0	82	1
##	374	24.0	4	140.0	92	2865	16.4	82	1
##	375	36.0	4	105.0	74	1980	15.3	82	2
##	376	37.0	4	91.0	68	2025	18.2	82	3
##	377	31.0	4	91.0	68	1970	17.6	82	3
##	378	38.0	4	105.0	63	2125	14.7	82	1
##	379	36.0	4	98.0	70	2125	17.3	82	1
##	380	36.0	4	120.0	88	2160	14.5	82	3
##	381	36.0	4	107.0	75	2205	14.5	82	3
##	382	34.0	4	108.0	70	2245	16.9	82	3
##	383	38.0	4	91.0	67	1965	15.0	82	3
##	384	32.0	4	91.0	67	1965	15.7	82	3
##	385	38.0	4	91.0	67	1995	16.2	82	3
##	386	25.0	6	181.0	110	2945	16.4	82	1
##	387	38.0	6	262.0	85	3015	17.0	82	1
##	388	26.0	4	156.0	92	2585	14.5	82	1
##	389	22.0	6	232.0	112	2835	14.7	82	1
##	390	32.0	4	144.0	96	2665	13.9	82	3
##	391	36.0	4	135.0	84	2370	13.0	82	1
##	392	27.0	4	151.0	90	2950	17.3	82	1
##	393	27.0	4	140.0	86	2790	15.6	82	1
##	394	44.0	4	97.0	52	2130	24.6	82	2
##	395	32.0	4	135.0	84	2295	11.6	82	1
##	396	28.0	4	120.0	79	2625	18.6	82	1
##	397	31.0	4	119.0	82	2720	19.4	82	1
##									
##						name			
##	1					chevrolet chevelle malibu			
##	2					buick skylark 320			
##	3					plymouth satellite			
##	4					amc rebel sst			
##	5					ford torino			
##	6					ford galaxie 500			
##	7					chevrolet impala			
##	8					plymouth fury iii			
##	9					pontiac catalina			
##	10					amc ambassador dpl			
##	11					dodge challenger se			
##	12					plymouth 'cuda 340			
##	13					chevrolet monte carlo			
##	14					buick estate wagon (sw)			
##	15					toyota corona mark ii			
##	16					plymouth duster			
##	17					amc hornet			
##	18					ford maverick			
##	19					datsum pl510			
##	20					volkswagen 1131 deluxe sedan			
##	21					peugeot 504			
##	22					audi 100 ls			
##	23					saab 99e			
##	24					bmw 2002			
##	25					amc gremlin			

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## 26          ford f250
## 27          chevy c20
## 28          dodge d200
## 29          hi 1200d
## 30          datsun pl510
## 31          chevrolet vega 2300
## 32          toyota corona
## 34          amc gremlin
## 35          plymouth satellite custom
## 36          chevrolet chevelle malibu
## 37          ford torino 500
## 38          amc matador
## 39          chevrolet impala
## 40          pontiac catalina brougham
## 41          ford galaxie 500
## 42          plymouth fury iii
## 43          dodge monaco (sw)
## 44          ford country squire (sw)
## 45          pontiac safari (sw)
## 46          amc hornet sportabout (sw)
## 47          chevrolet vega (sw)
## 48          pontiac firebird
## 49          ford mustang
## 50          mercury capri 2000
## 51          opel 1900
## 52          peugeot 304
## 53          fiat 124b
## 54          toyota corolla 1200
## 55          datsun 1200
## 56          volkswagen model 111
## 57          plymouth cricket
## 58          toyota corona hardtop
## 59          dodge colt hardtop
## 60          volkswagen type 3
## 61          chevrolet vega
## 62          ford pinto runabout
## 63          chevrolet impala
## 64          pontiac catalina
## 65          plymouth fury iii
## 66          ford galaxie 500
## 67          amc ambassador sst
## 68          mercury marquis
## 69          buick lesabre custom
## 70          oldsmobile delta 88 royale
## 71          chrysler newport royal
## 72          mazda rx2 coupe
## 73          amc matador (sw)
## 74          chevrolet chevelle concours (sw)
## 75          ford gran torino (sw)
## 76          plymouth satellite custom (sw)
## 77          volvo 145e (sw)
## 78          volkswagen 411 (sw)
## 79          peugeot 504 (sw)
## 80          renault 12 (sw)

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## 81          ford pinto (sw)
## 82          datsun 510 (sw)
## 83      toyouta corona mark ii (sw)
## 84          dodge colt (sw)
## 85      toyota corolla 1600 (sw)
## 86          buick century 350
## 87          amc matador
## 88          chevrolet malibu
## 89          ford gran torino
## 90          dodge coronet custom
## 91      mercury marquis brougham
## 92      chevrolet caprice classic
## 93          ford ltd
## 94      plymouth fury gran sedan
## 95      chrysler new yorker brougham
## 96      buick electra 225 custom
## 97      amc ambassador brougham
## 98          plymouth valiant
## 99      chevrolet nova custom
## 100          amc hornet
## 101          ford maverick
## 102          plymouth duster
## 103      volkswagen super beetle
## 104          chevrolet impala
## 105          ford country
## 106      plymouth custom suburb
## 107      oldsmobile vista cruiser
## 108          amc gremlin
## 109          toyota carina
## 110          chevrolet vega
## 111          datsun 610
## 112          maxda rx3
## 113          ford pinto
## 114      mercury capri v6
## 115      fiat 124 sport coupe
## 116      chevrolet monte carlo s
## 117      pontiac grand prix
## 118          fiat 128
## 119          opel manta
## 120          audi 100ls
## 121          volvo 144ea
## 122      dodge dart custom
## 123          saab 99le
## 124          toyota mark ii
## 125      oldsmobile omega
## 126      plymouth duster
## 127          amc hornet
## 128          chevrolet nova
## 129          datsun b210
## 130          ford pinto
## 131      toyota corolla 1200
## 132          chevrolet vega
## 133      chevrolet chevelle malibu classic
## 134          amc matador

```

```

## 136      plymouth satellite sebring
## 137      ford gran torino
## 138      buick century luxus (sw)
## 139      dodge coronet custom (sw)
## 140      ford gran torino (sw)
## 141      amc matador (sw)
## 142      audi fox
## 143      volkswagen dasher
## 144      opel manta
## 145      toyota corona
## 146      datsun 710
## 147      dodge colt
## 148      fiat 128
## 149      fiat 124 tc
## 150      honda civic
## 151      subaru
## 152      fiat x1.9
## 153      plymouth valiant custom
## 154      chevrolet nova
## 155      mercury monarch
## 156      ford maverick
## 157      pontiac catalina
## 158      chevrolet bel air
## 159      plymouth grand fury
## 160      ford ltd
## 161      buick century
## 162      chevrolet chevelle malibu
## 163      amc matador
## 164      plymouth fury
## 165      buick skyhawk
## 166      chevrolet monza 2+2
## 167      ford mustang ii
## 168      toyota corolla
## 169      ford pinto
## 170      amc gremlin
## 171      pontiac astro
## 172      toyota corona
## 173      volkswagen dasher
## 174      datsun 710
## 175      ford pinto
## 176      volkswagen rabbit
## 177      amc pacer
## 178      audi 100ls
## 179      peugeot 504
## 180      volvo 244dl
## 181      saab 99le
## 182      honda civic cvcc
## 183      fiat 131
## 184      opel 1900
## 185      capri ii
## 186      dodge colt
## 187      renault 12tl
## 188      chevrolet chevelle malibu classic
## 189      dodge coronet brougham

```

```

## 190             amc matador
## 191             ford gran torino
## 192             plymouth valiant
## 193             chevrolet nova
## 194             ford maverick
## 195             amc hornet
## 196             chevrolet chevette
## 197             chevrolet woody
## 198             vw rabbit
## 199             honda civic
## 200             dodge aspen se
## 201             ford granada ghia
## 202             pontiac ventura sj
## 203             amc pacer d/l
## 204             volkswagen rabbit
## 205             datsun b-210
## 206             toyota corolla
## 207             ford pinto
## 208             volvo 245
## 209             plymouth volare premier v8
## 210             peugeot 504
## 211             toyota mark ii
## 212             mercedes-benz 280s
## 213             cadillac seville
## 214             chevy c10
## 215             ford f108
## 216             dodge d100
## 217             honda accord cvcc
## 218             buick opel isuzu deluxe
## 219             renault 5 gtl
## 220             plymouth arrow gs
## 221             datsun f-10 hatchback
## 222             chevrolet caprice classic
## 223             oldsmobile cutlass supreme
## 224             dodge monaco brougham
## 225             mercury cougar brougham
## 226             chevrolet concours
## 227             buick skylark
## 228             plymouth volare custom
## 229             ford granada
## 230             pontiac grand prix lj
## 231             chevrolet monte carlo landau
## 232             chrysler cordoba
## 233             ford thunderbird
## 234             volkswagen rabbit custom
## 235             pontiac sunbird coupe
## 236             toyota corolla liftback
## 237             ford mustang ii 2+2
## 238             chevrolet chevette
## 239             dodge colt m/m
## 240             subaru dl
## 241             volkswagen dasher
## 242             datsun 810
## 243             bmw 320i

```



```

## 244                mazda rx-4
## 245      volkswagen rabbit custom diesel
## 246                ford fiesta
## 247                mazda glc deluxe
## 248                datsun b210 gx
## 249                honda civic cvcc
## 250      oldsmobile cutlass salon brougham
## 251                dodge diplomat
## 252      mercury monarch ghia
## 253      pontiac phoenix lj
## 254      chevrolet malibu
## 255      ford fairmont (auto)
## 256      ford fairmont (man)
## 257      plymouth volare
## 258                amc concord
## 259      buick century special
## 260      mercury zephyr
## 261      dodge aspen
## 262      amc concord d/l
## 263      chevrolet monte carlo landau
## 264      buick regal sport coupe (turbo)
## 265                ford futura
## 266      dodge magnum xe
## 267      chevrolet chevette
## 268      toyota corona
## 269      datsun 510
## 270      dodge omni
## 271      toyota celica gt liftback
## 272      plymouth sapporo
## 273      oldsmobile starfire sx
## 274      datsun 200-sx
## 275      audi 5000
## 276      volvo 264gl
## 277      saab 99gle
## 278      peugeot 604sl
## 279      volkswagen scirocco
## 280      honda accord lx
## 281      pontiac lemans v6
## 282      mercury zephyr 6
## 283      ford fairmont 4
## 284      amc concord dl 6
## 285      dodge aspen 6
## 286      chevrolet caprice classic
## 287      ford ltd landau
## 288      mercury grand marquis
## 289      dodge st. regis
## 290      buick estate wagon (sw)
## 291      ford country squire (sw)
## 292      chevrolet malibu classic (sw)
## 293 chrysler lebaron town @ country (sw)
## 294                vw rabbit custom
## 295      mazda glc deluxe
## 296      dodge colt hatchback custom
## 297      amc spirit dl

```

```

## 298         mercedes benz 300d
## 299         cadillac eldorado
## 300         peugeot 504
## 301 oldsmobile cutlass salon brougham
## 302         plymouth horizon
## 303         plymouth horizon tc3
## 304         datsun 210
## 305         fiat strada custom
## 306         buick skylark limited
## 307         chevrolet citation
## 308 oldsmobile omega brougham
## 309         pontiac phoenix
## 310         vw rabbit
## 311         toyota corolla tercel
## 312         chevrolet chevette
## 313         datsun 310
## 314         chevrolet citation
## 315         ford fairmont
## 316         amc concord
## 317         dodge aspen
## 318         audi 4000
## 319         toyota corona liftback
## 320         mazda 626
## 321         datsun 510 hatchback
## 322         toyota corolla
## 323         mazda glc
## 324         dodge colt
## 325         datsun 210
## 326         vw rabbit c (diesel)
## 327         vw dasher (diesel)
## 328         audi 5000s (diesel)
## 329         mercedes-benz 240d
## 330         honda civic 1500 gl
## 332         subaru dl
## 333         vokswagen rabbit
## 334         datsun 280-zx
## 335         mazda rx-7 gs
## 336         triumph tr7 coupe
## 338         honda accord
## 339         plymouth reliant
## 340         buick skylark
## 341         dodge aries wagon (sw)
## 342         chevrolet citation
## 343         plymouth reliant
## 344         toyota starlet
## 345         plymouth champ
## 346         honda civic 1300
## 347         subaru
## 348         datsun 210 mpg
## 349         toyota tercel
## 350         mazda glc 4
## 351         plymouth horizon 4
## 352         ford escort 4w
## 353         ford escort 2h

```

```

## 354          volkswagen jetta
## 356          honda prelude
## 357          toyota corolla
## 358          datsun 200sx
## 359          mazda 626
## 360      peugeot 505s turbo diesel
## 361          volvo diesel
## 362          toyota cressida
## 363          datsun 810 maxima
## 364          buick century
## 365      oldsmobile cutlass ls
## 366          ford granada gl
## 367      chrysler lebaron salon
## 368          chevrolet cavalier
## 369      chevrolet cavalier wagon
## 370      chevrolet cavalier 2-door
## 371      pontiac j2000 se hatchback
## 372          dodge aries se
## 373          pontiac phoenix
## 374          ford fairmont futura
## 375          volkswagen rabbit l
## 376          mazda glc custom l
## 377          mazda glc custom
## 378      plymouth horizon miser
## 379          mercury lynx l
## 380          nissan stanza xe
## 381          honda accord
## 382          toyota corolla
## 383          honda civic
## 384          honda civic (auto)
## 385          datsun 310 gx
## 386          buick century limited
## 387      oldsmobile cutlass ciera (diesel)
## 388          chrysler lebaron medallion
## 389          ford granada l
## 390          toyota celica gt
## 391      dodge charger 2.2
## 392          chevrolet camaro
## 393          ford mustang gl
## 394          vw pickup
## 395          dodge rampage
## 396          ford ranger
## 397          chevy s-10

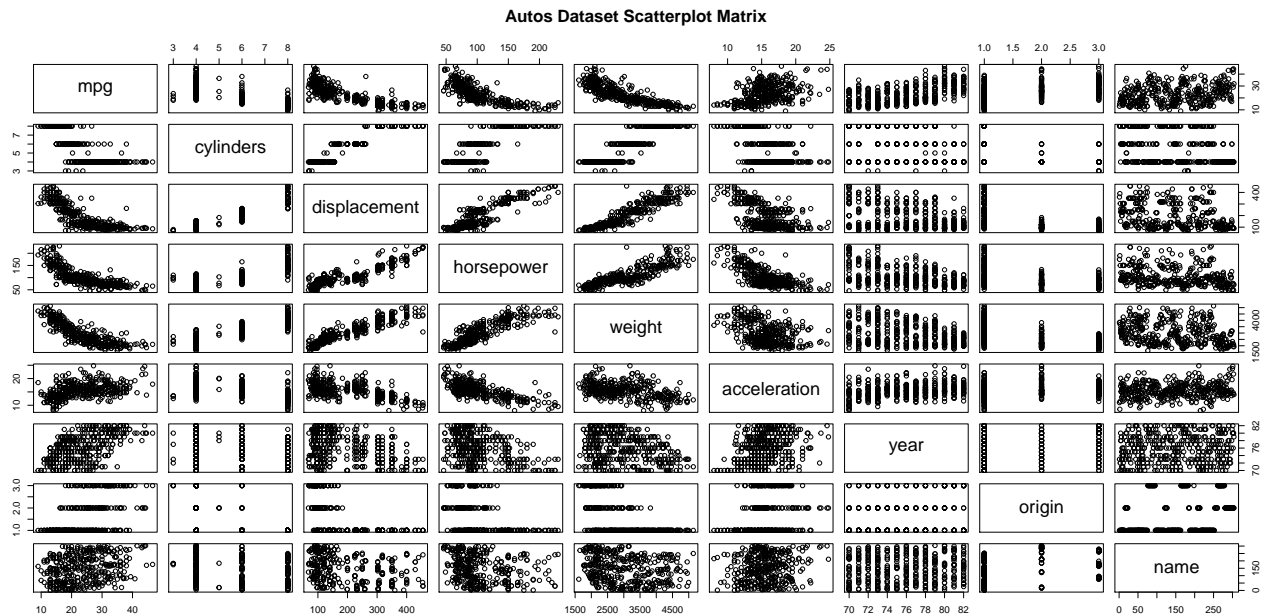
```

a)

```

pairs(Auto, main="Autos Dataset Scatterplot Matrix")

```



b)

```
cor(data.matrix(Auto[, -length(Auto)]))
```

```
##               mpg  cylinders displacement horsepower    weight
## mpg           1.0000000 -0.7776175  -0.8051269 -0.7784268 -0.8322442
## cylinders     -0.7776175  1.0000000   0.9508233  0.8429834  0.8975273
## displacement -0.8051269  0.9508233   1.0000000  0.8972570  0.9329944
## horsepower   -0.7784268  0.8429834   0.8972570  1.0000000  0.8645377
## weight        -0.8322442  0.8975273   0.9329944  0.8645377  1.0000000
## acceleration  0.4233285 -0.5046834  -0.5438005 -0.6891955 -0.4168392
## year          0.5805410 -0.3456474  -0.3698552 -0.4163615 -0.3091199
## origin        0.5652088 -0.5689316  -0.6145351 -0.4551715 -0.5850054
##
##      acceleration      year      origin
## mpg           0.4233285  0.5805410  0.5652088
## cylinders     -0.5046834 -0.3456474 -0.5689316
## displacement  -0.5438005 -0.3698552 -0.6145351
## horsepower    -0.6891955 -0.4163615 -0.4551715
## weight        -0.4168392 -0.3091199 -0.5850054
## acceleration  1.0000000  0.2903161  0.2127458
## year          0.2903161  1.0000000  0.1815277
## origin        0.2127458  0.1815277  1.0000000
```

c)

```
df <- Auto[, -length(Auto)]
# help(lm)
model <- lm(mpg ~ ., data=df)
summary(model)
```

```
##
## Call:
## lm(formula = mpg ~ ., data = df)
##
## Residuals:
```

```
##      Min      1Q  Median      3Q      Max
## -9.5903 -2.1565 -0.1169  1.8690 13.0604
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -17.218435  4.644294  -3.707  0.00024 ***
## cylinders    -0.493376  0.323282  -1.526  0.12780
## displacement  0.019896  0.007515   2.647  0.00844 **
## horsepower   -0.016951  0.013787  -1.230  0.21963
## weight       -0.006474  0.000652  -9.929 < 2e-16 ***
## acceleration  0.080576  0.098845   0.815  0.41548
## year          0.750773  0.050973  14.729 < 2e-16 ***
## origin        1.426141  0.278136   5.127 4.67e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.328 on 384 degrees of freedom
## Multiple R-squared:  0.8215, Adjusted R-squared:  0.8182
## F-statistic: 252.4 on 7 and 384 DF,  p-value: < 2.2e-16
```

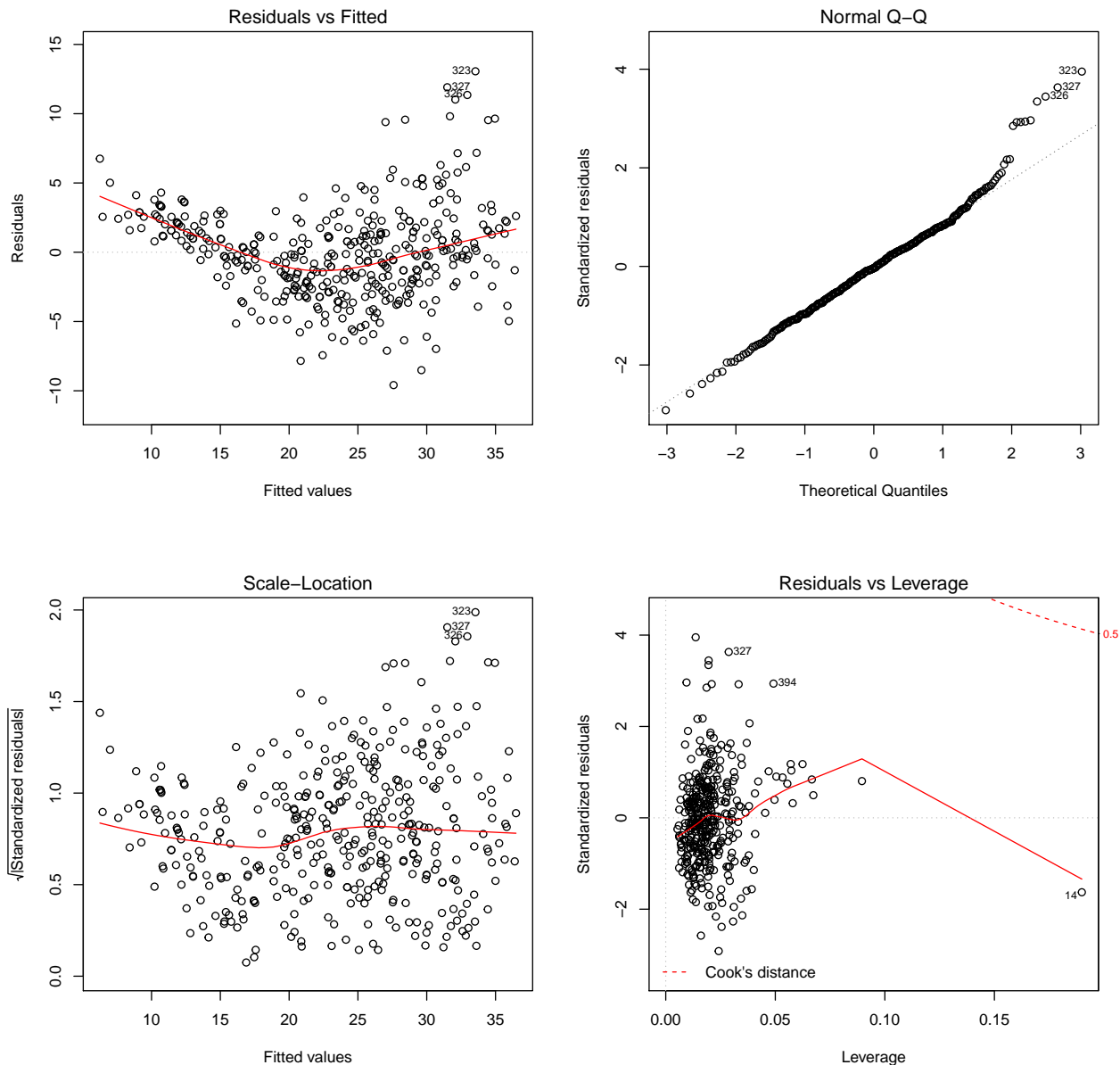
c.i) The model does predict a relationship between the predictors and response; R^2 at 0.903 is high, expressing that the model fits training data well. The F-statistic is high (considering the number of observations is much larger than our number of predictors) and p value is very low, thus the null-hypothesis can be rejected.

c.ii) Based on their low p values (highlighted by the 2-3 stars next to each p-value), displacement, weight, year and origin appear to have a statistically significant relationship to the response

c.iii) With each passing year, mpg increases by ~0.75 mpg

d)

```
par(mfrow=c(2,2))
plot(model)
```



```
par(mfrow=c(1,1)) # Change back to 1 x 1
```

The residuals vs fitted plot can be used to diagnose non-linear behavior in residuals. There appears to be a parabolic shape to the residuals curves, where non-linear relationship that was not explained by the model was left out in the residuals. The Normal Q-Q plot shows if residuals are normally distributed; there is some deviation in the points that have gained labels: 326, 327 and 323. The Scale-Location plot shows that the residuals are randomly spread and homoscedastic. The residuals vs leverage plot shows that residual 14 has leverage, but all points are within cook's distance, meaning there aren't any particular residual that is highly influential to regression results.

e)

with some car knowledge that engine performance depends on an interaction of number of cylinders and total displacement, I believed it would be interesting to see whether this can influence our model:

```
model_interaction <- lm(mpg~cylinders*displacement, data=df)
summary(model_interaction)
```

```
##
## Call:
## lm(formula = mpg ~ cylinders * displacement, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.0432  -2.4308  -0.2263   2.2048  20.9051
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    48.22040     2.34712  20.545 < 2e-16 ***
## cylinders      -2.41838     0.53456  -4.524 8.08e-06 ***
## displacement  -0.13436     0.01615  -8.321 1.50e-15 ***
## cylinders:displacement  0.01182     0.00207   5.711 2.24e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.454 on 388 degrees of freedom
## Multiple R-squared:  0.6769, Adjusted R-squared:  0.6744
## F-statistic: 271 on 3 and 388 DF, p-value: < 2.2e-16
```

Cylinders, displacement as well as their interaction proved to be very statistically significant in predicting mpg, which makes sense from a mechanical standpoint; more cylinders should allow for a more stable engine and higher RPMs, coupled with greater displacement fuel use can increase very quickly

Next I wondered whether there were strong interactions between year and origin, i.e. whether some countries of origin made great improvements overtime or vice versa

```
model_interaction <- lm(mpg~year*origin, data=df)
summary(model_interaction)
```

```
##
## Call:
## lm(formula = mpg ~ year * origin, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.3141  -3.7120  -0.6513   3.3621  15.5859
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -83.3809    12.0000  -6.948 1.57e-11 ***
## year           1.3089     0.1576   8.305 1.68e-15 ***
## origin        17.3752     6.8325   2.543  0.0114 *
## year:origin   -0.1663     0.0889  -1.871  0.0621 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.199 on 388 degrees of freedom
## Multiple R-squared:  0.5596, Adjusted R-squared:  0.5562
## F-statistic: 164.4 on 3 and 388 DF, p-value: < 2.2e-16
```

However, here the significance is rather weak

Finally, knowing that acceleration can have a very high penalty on fuel usage, and that horsepower is a function of RPM:

```
model_interaction <- lm(mpg~acceleration*horsepower, data=df)
summary(model_interaction)
```

```
##
## Call:
## lm(formula = mpg ~ acceleration * horsepower, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.3442  -2.7324  -0.4049   2.4210  15.8840
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    33.51244    3.420187   9.798 < 2e-16 ***
## acceleration     0.800296    0.211899   3.777 0.000184 ***
## horsepower      0.017590    0.027425   0.641 0.521664
## acceleration:horsepower -0.015698    0.002003  -7.838 4.45e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.426 on 388 degrees of freedom
## Multiple R-squared:  0.6809, Adjusted R-squared:  0.6784
## F-statistic: 275.9 on 3 and 388 DF,  p-value: < 2.2e-16
```

It turns out that a fast moving, high revving powerhouse consumes a ton of fuel: the interaction is statistically significant.

f)

```
model_transform <- lm(log(mpg)~cylinders+exp(displacement)+log(horsepower)+log(weight)+log(acceleration)
summary(model_transform)
```

```
##
## Call:
## lm(formula = log(mpg) ~ cylinders + exp(displacement) + log(horsepower) +
##      log(weight) + log(acceleration) + I(year^2) + origin, data = Auto)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.40259 -0.07022 -0.00125  0.06176  0.38161
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    8.278e+00    3.461e-01  23.921 < 2e-16 ***
## cylinders      -1.515e-02    7.799e-03  -1.942  0.05284 .
## exp(displacement) 1.922e-199    0.000e+00      Inf < 2e-16 ***
## log(horsepower)  -3.069e-01    5.805e-02  -5.287 2.09e-07 ***
## log(weight)      -5.475e-01    6.743e-02  -8.119 6.46e-15 ***
## log(acceleration) -1.846e-01    5.754e-02  -3.208 0.00145 **
## I(year^2)        1.959e-04    1.127e-05  17.385 < 2e-16 ***
## origin          2.401e-02    9.074e-03   2.646 0.00847 **
## ---
```

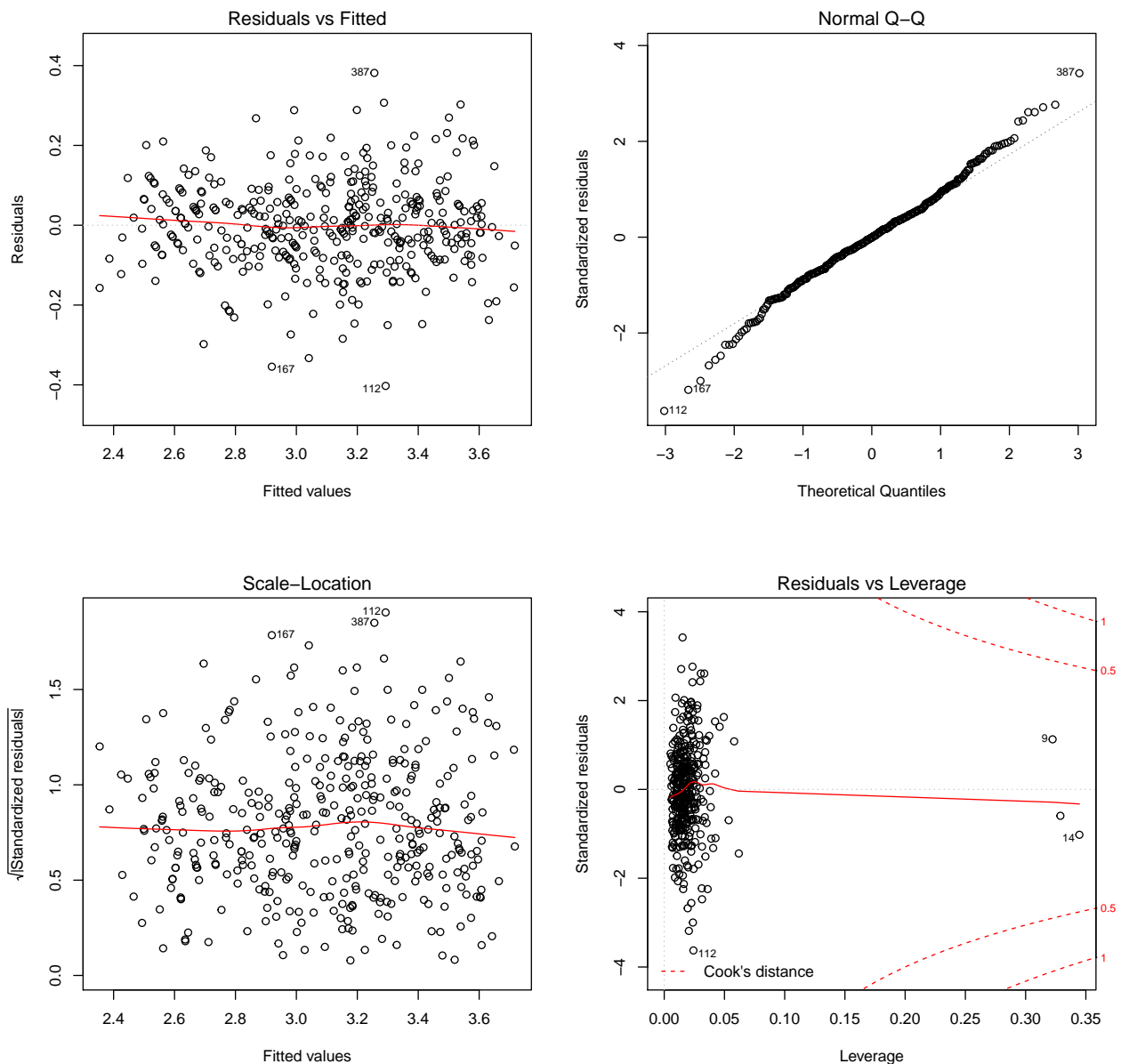


```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1124 on 384 degrees of freedom
## Multiple R-squared:  0.8927, Adjusted R-squared:  0.8908
## F-statistic: 456.5 on 7 and 384 DF,  p-value: < 2.2e-16
```

Using a log transform of mpg proved a much better fit on its own; making additional transforms on predictor vectors, especially `exp()` on displacement and `log()` on horsepower, weight and acceleration further improved adjusted R^2 and reduced RSE

And now looking at the diagnostic plots:

```
par(mfrow=c(2,2))
plot(model_transform)
```



```
par(mfrow=c(1,1)) # Change back to 1 x 1
```

We see that with the aforementioned transforms on our response and predictor variables, the non-linear

patterns on residuals greatly decreased (on the residuals vs fitted plot). Deviation of residuals from the straight line on Normal Q-Q plot also decreased, signifying more normally distributed residuals

Problem 10

Exercise 14 (p. 125)

a)

```
set.seed(1)
x1 <- runif(100)
x2 <- 0.5 * x1 + rnorm(100)/10
y = 2 + 2*x1 + 0.3*x2 + rnorm(100)
```

Form of the model and regression coefficients

$$Y = 2 + 2X_1 + 0.3X_2 + \varepsilon$$

$$\beta_0 = 2$$

$$\beta_1 = 2$$

$$\beta_2 = 0.3$$

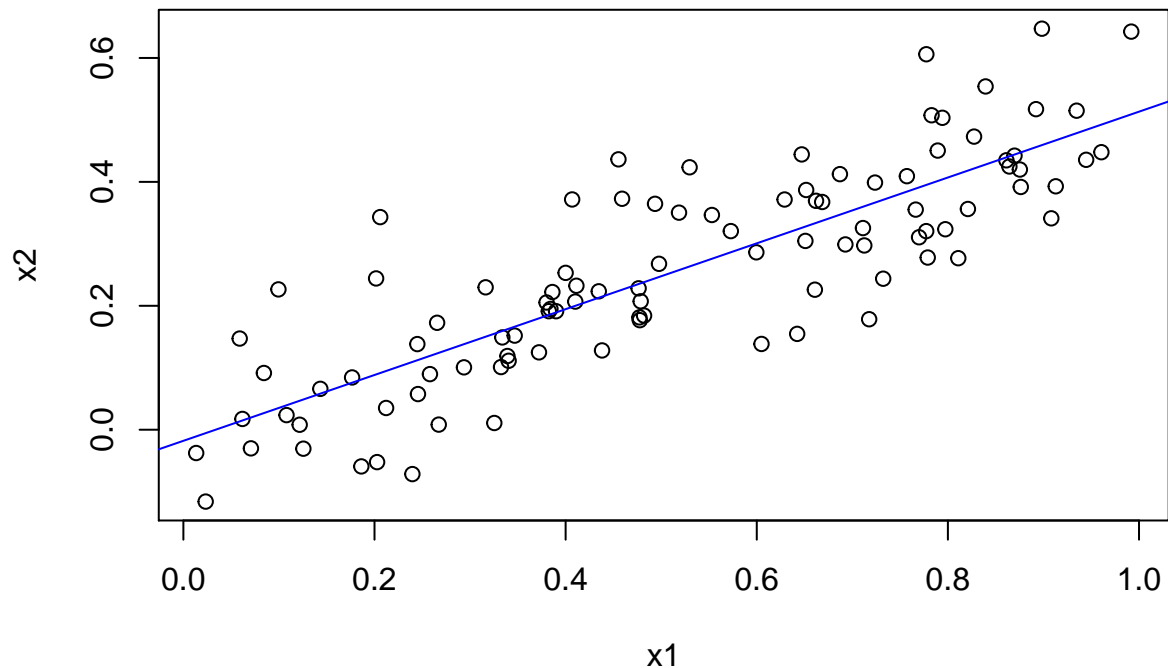
Figure 3: problem 10a

Per 3.36 in the book, the form has a quadratic shape but model is still linear

b)

```
print(cor(x1, x2))

## [1] 0.8351212
model <- lm(x2~x1)
plot(x1, x2)
abline(model, col='blue')
```



c)

```
model <- lm(y~x1+x2)
coef(model)
```

```
## (Intercept)      x1      x2
##    2.130500    1.439555    1.009674
```

```
summary(model)
```

```
##
## Call:
## lm(formula = y ~ x1 + x2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.8311 -0.7273 -0.0537  0.6338  2.3359
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.1305     0.2319   9.188 7.61e-15 ***
## x1             1.4396     0.7212   1.996  0.0487 *
## x2             1.0097     1.1337   0.891  0.3754
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.056 on 97 degrees of freedom
## Multiple R-squared:  0.2088, Adjusted R-squared:  0.1925
## F-statistic: 12.8 on 2 and 97 DF,  p-value: 1.164e-05
```

Only B0 is close to the true coefficients. B1 and B2 are nontrivially divergent from true coefficient values, with large std. error. We can marginally reject the null hypothesis for B1 as its p-value is below 5%. However, the p-value for B2 is quite high, so we cannot reject the null hypothesis.

d)

```
model_x1only <- lm(y~x1)
summary(model_x1only)
```

```
##
## Call:
## lm(formula = y ~ x1)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.89495 -0.66874 -0.07785  0.59221  2.45560
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.1124     0.2307   9.155 8.27e-15 ***
## x1             1.9759     0.3963   4.986 2.66e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.055 on 98 degrees of freedom
## Multiple R-squared:  0.2024, Adjusted R-squared:  0.1942
## F-statistic: 24.86 on 1 and 98 DF,  p-value: 2.661e-06
```

Std error is relatively low here as a ratio of the coefficient estimate compared to the multiple linear regression case in 10.c. P-value is very low, thus we can reject the null-hypothesis of $B_1=0$.

e)

```
model_x2only <- lm(y~x2)
summary(model_x2only)
```

```
##
## Call:
## lm(formula = y ~ x2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.62687 -0.75156 -0.03598  0.72383  2.44890
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.3899     0.1949  12.26 < 2e-16 ***
## x2             2.8996     0.6330   4.58 1.37e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.072 on 98 degrees of freedom
## Multiple R-squared:  0.1763, Adjusted R-squared:  0.1679
## F-statistic: 20.98 on 1 and 98 DF,  p-value: 1.366e-05
```

Again, std error is relatively low here as a ratio of the coefficient estimate compared to the multiple linear regression case in 10.c. P-value is very low, thus we can reject the null-hypothesis of $B_2=0$.

f)

The results do not contradict each other. From 10.b, we can see that x_1 and x_2 have significant collinearity and increase together. In a regression problem, this can cause problems due to the difficulty of separating out the individual effects of collinear predictors on the response.

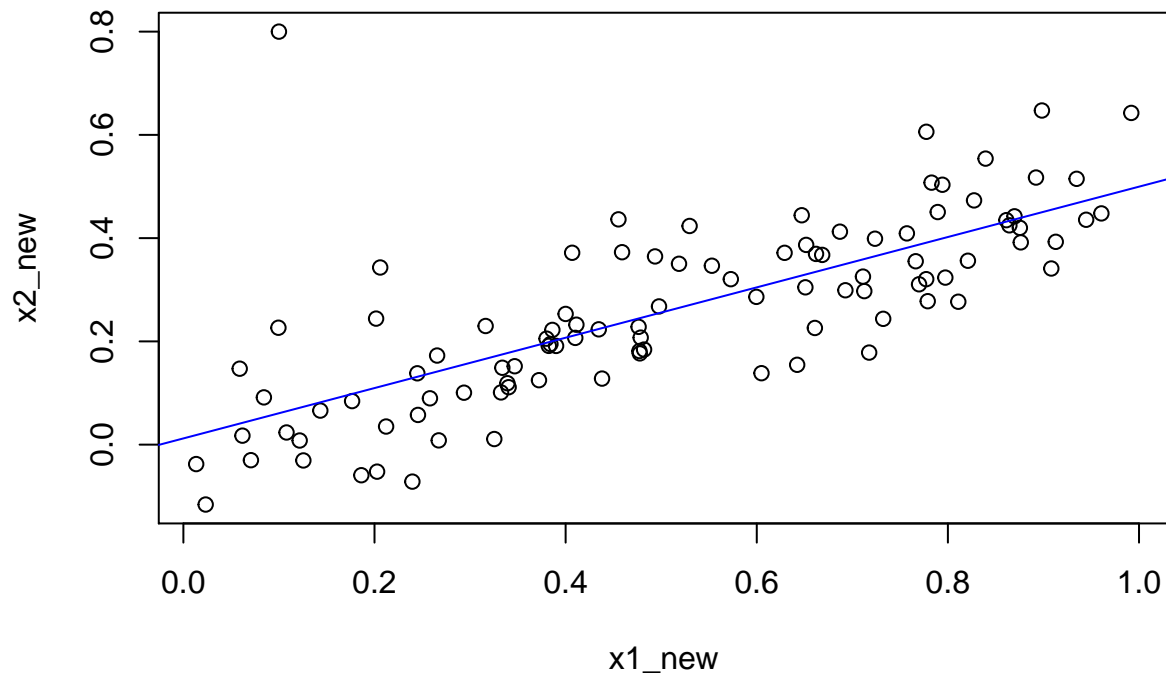
g)

```
x1_new <- c(x1, 0.1)
x2_new <- c(x2, 0.8)
y_new <- c(y, 6)

print(cor(x1_new, x2_new))
```

```
## [1] 0.7392279
```

```
model = lm(x2_new~x1_new)
plot(x1_new, x2_new)
abline(model, col='blue')
```



```
model <- lm(y_new~x1_new+x2_new)
summary(model)
```

```
##
## Call:
## lm(formula = y_new ~ x1_new + x2_new)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.73348 -0.69318 -0.05263  0.66385  2.30619
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
##
```

```
## (Intercept)  2.2267      0.2314   9.624 7.91e-16 ***
## x1_new       0.5394      0.5922   0.911  0.36458
## x2_new       2.5146      0.8977   2.801  0.00614 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.075 on 98 degrees of freedom
## Multiple R-squared:  0.2188, Adjusted R-squared:  0.2029
## F-statistic: 13.72 on 2 and 98 DF,  p-value: 5.564e-06

model_x1only <- lm(y_new~x1_new)
summary(model_x1only)
```

```
##
## Call:
## lm(formula = y_new ~ x1_new)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.8897 -0.6556 -0.0909  0.5682  3.5665
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.2569     0.2390   9.445 1.78e-15 ***
## x1_new         1.7657     0.4124   4.282 4.29e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.111 on 99 degrees of freedom
## Multiple R-squared:  0.1562, Adjusted R-squared:  0.1477
## F-statistic: 18.33 on 1 and 99 DF,  p-value: 4.295e-05

model_x2only <- lm(y_new~x2_new)
summary(model_x2only)
```

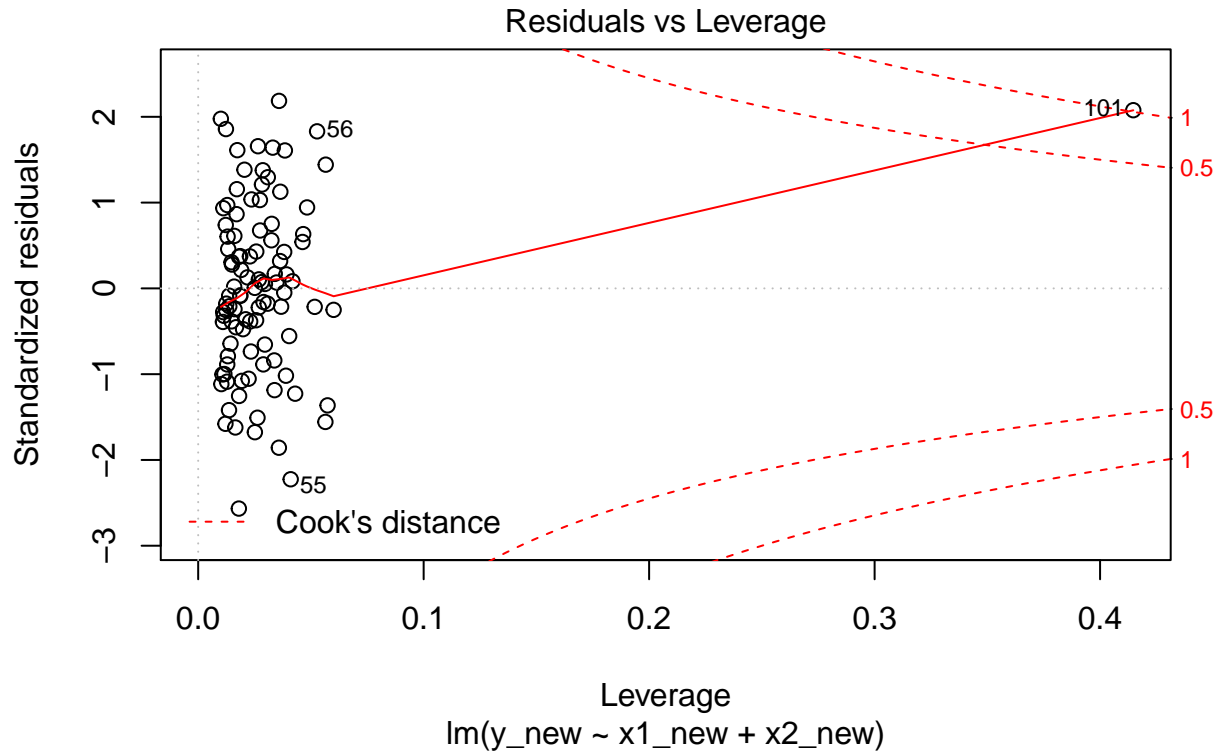
```
##
## Call:
## lm(formula = y_new ~ x2_new)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.64729 -0.71021 -0.06899  0.72699  2.38074
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.3451     0.1912  12.264 < 2e-16 ***
## x2_new         3.1190     0.6040   5.164 1.25e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.074 on 99 degrees of freedom
## Multiple R-squared:  0.2122, Adjusted R-squared:  0.2042
## F-statistic: 26.66 on 1 and 99 DF,  p-value: 1.253e-06
```

By adding this point, the amount of response variability explained by the multiple linear regression model improves: adjusted R^2 went from 0.21 to 0.27. Here $x1_new$ is no longer a statistically significant predictor.

The p-value for $x2_new$ shifts down and we can reject the null hypothesis that $B2=0$.

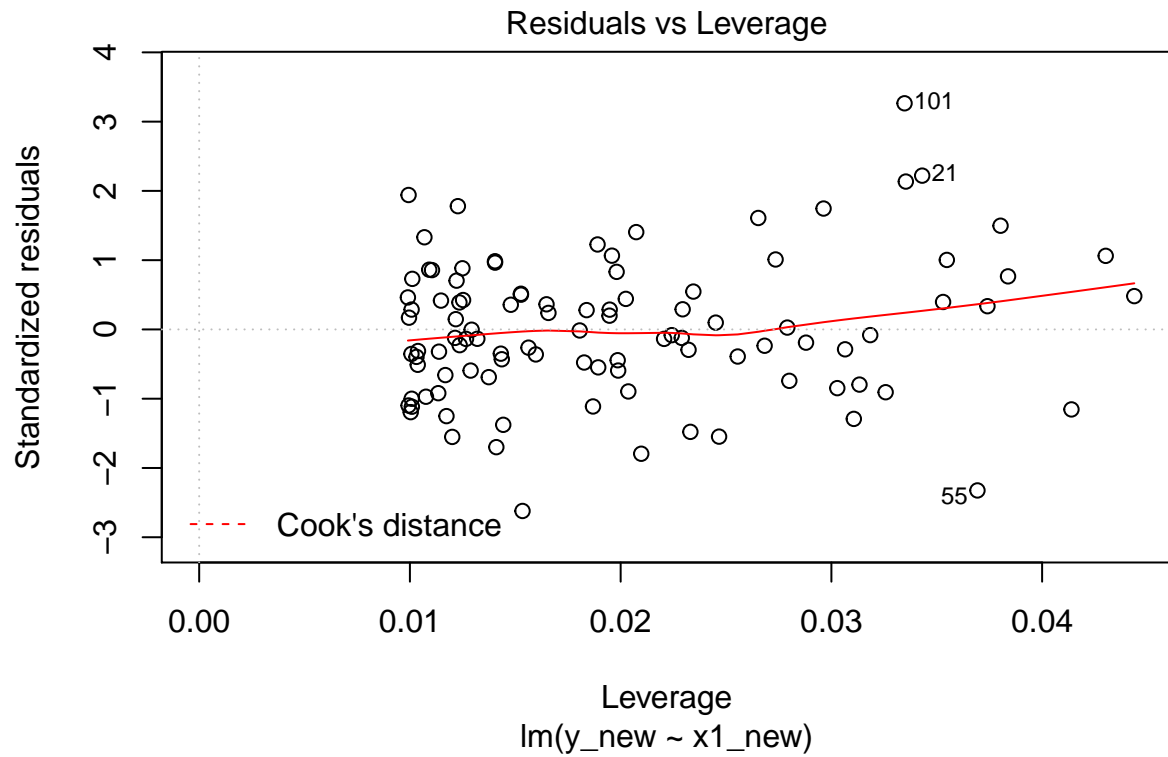
In the both cases of simple linear regression using only either $x1_new$ or $x2_new$ as predictor, the null hypothesis can be rejected based on p-value.

```
plot(model, which=5)
```



The new point, labeled 101, becomes a high leverage point in the first model using multiple linear regression with both $x1$ and $x2$ as predictors.

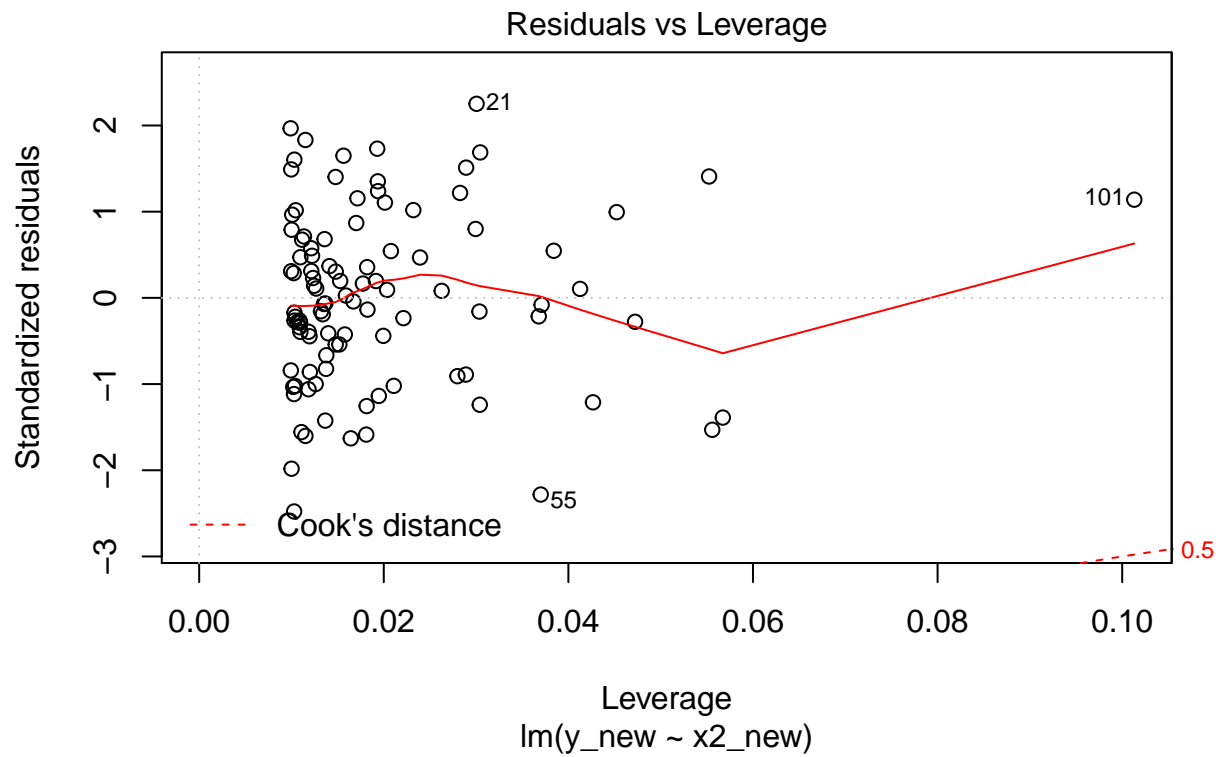
```
plot(model_x1only, which=5)
```

No

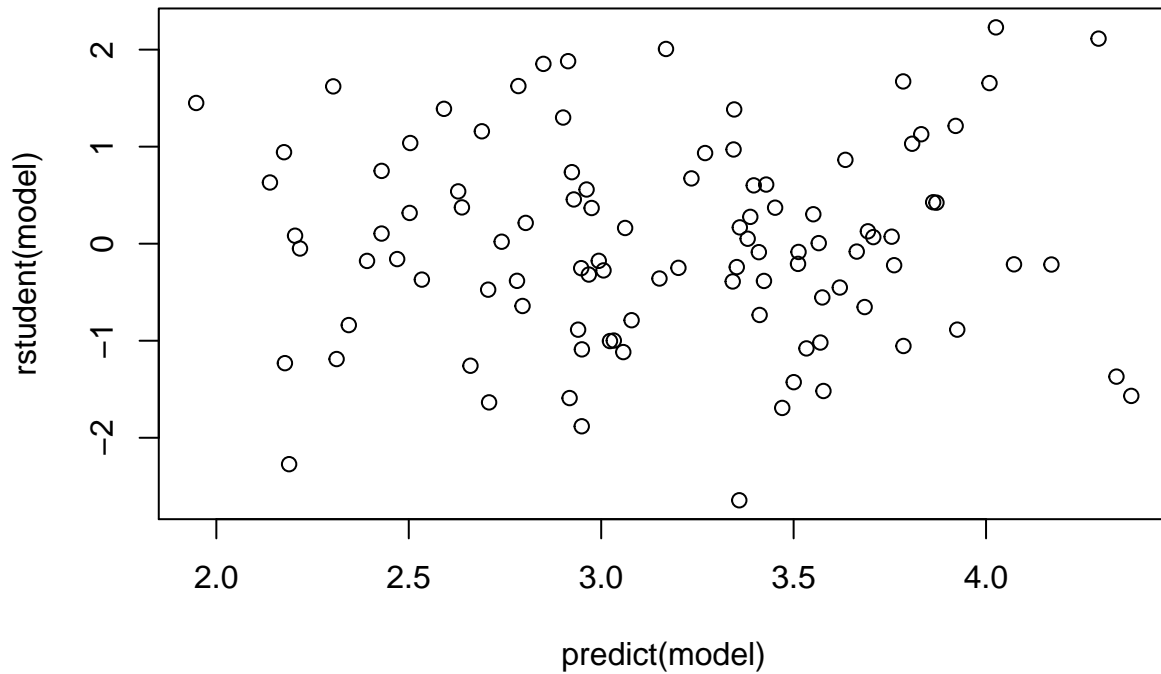
high leverage points found

```
plot(model_x2only, which=5)
```



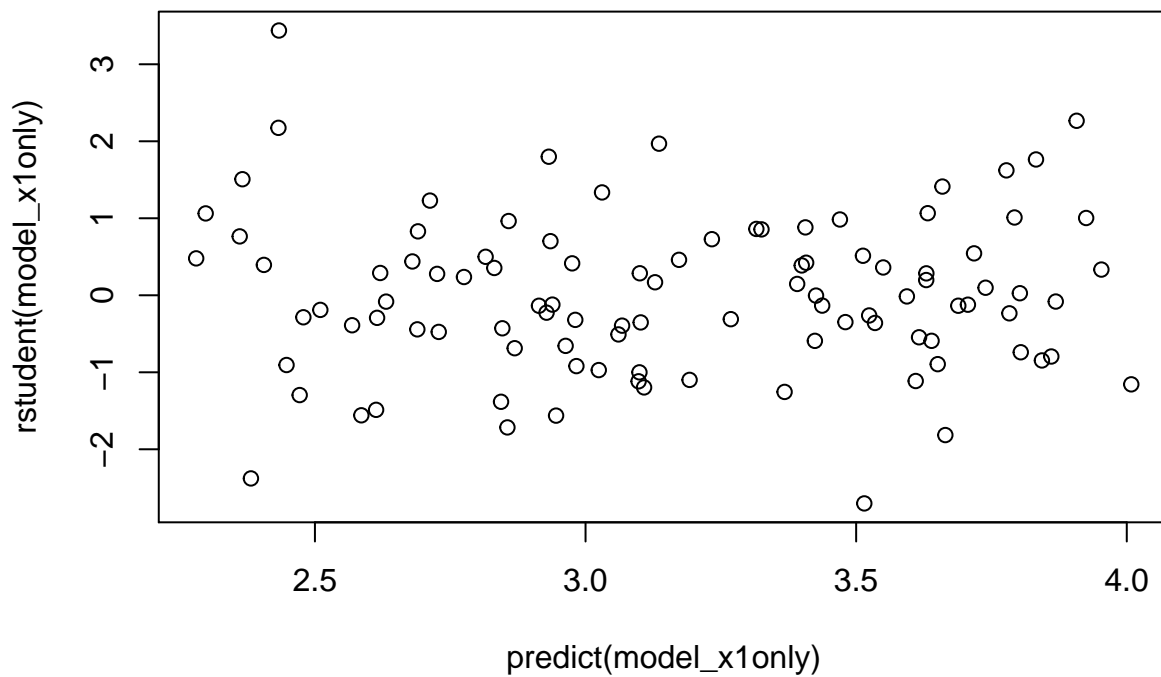
Point 101 is also relatively high leverage in the x2 only model, but is still within Cook's distance.

```
plot(predict(model), rstudent(model))
```



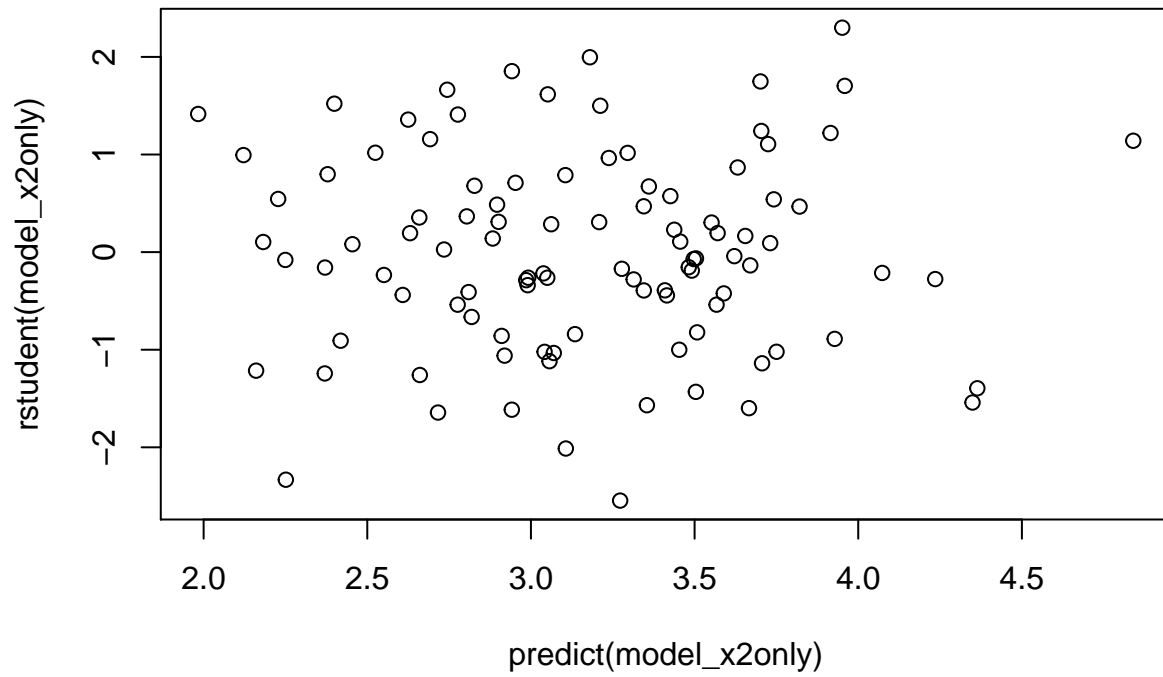
No possible outliers in multiple linear regression model using both x1 and x2

```
plot(predict(model_x1only), rstudent(model_x1only))
```



Possible outlier lying outside of +3 studentised residual in simple linear regression model using x1

```
plot(predict(model_x2only), rstudent(model_x2only))
```



No outliers detected for simple linear regression model using x2