

## Baseball Data Salary

1.

(a) In this section, I have chosen a Stepwise Procedure:

Forward Addition

```
#SELECTING STEPWISE PROCEDURE: FORWARD ADDITION

fit.forward <- step(fit.null, scope=list(lower=fit.null, upper=fit.whole),
                    direction="forward", k = 2 )

fit.forward$anova
summary(fit.forward)
fit <- lm(fit.forward)
```

```
> fit.forward$anova
  Step Df      Deviance Resid. Df Resid. Dev      AIC
1      NA          NA      336 0.52547467 -2176.212
2 + x2 -1 0.3413313278      335 0.18414334 -2527.586
3 + x9 -1 0.0309893461      334 0.15315400 -2587.685
4 + x4 -1 0.0842436539      333 0.06891034 -2854.826
5 + x10 -1 0.0009680921      332 0.06794225 -2857.594
6 + x13 -1 0.0006421774      331 0.06730007 -2858.794
7 + x8 -1 0.0006093884      330 0.06669068 -2859.859
8 + x15 -1 0.0004417272      329 0.06624896 -2860.099
> summary(fit.forward)

Call:
lm(formula = x1 ~ x2 + x9 + x4 + x10 + x13 + x8 + x15, data = dat)

Residuals:
    Min       1Q   Median       3Q      Max
-0.064046 -0.005495 -0.000792  0.005048  0.073422

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.061e-03  6.646e-03   0.762  0.44687
x2           7.805e-01  2.183e-02  35.757 < 2e-16 ***
x9          -1.049e-03  5.841e-05 -17.964 < 2e-16 ***
x4           4.404e-04  3.071e-05  14.341 < 2e-16 ***
x10         -1.125e-04  3.812e-05  -2.951  0.00339 **
x13         -4.616e-03  1.931e-03  -2.391  0.01737 *
x8           1.053e-04  5.818e-05   1.811  0.07110 .
x15         -3.404e-03  2.298e-03  -1.481  0.13954
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01419 on 329 degrees of freedom
Multiple R-squared:  0.8739,    Adjusted R-squared:  0.8712
F-statistic: 325.8 on 7 and 329 DF,  p-value: < 2.2e-16
```

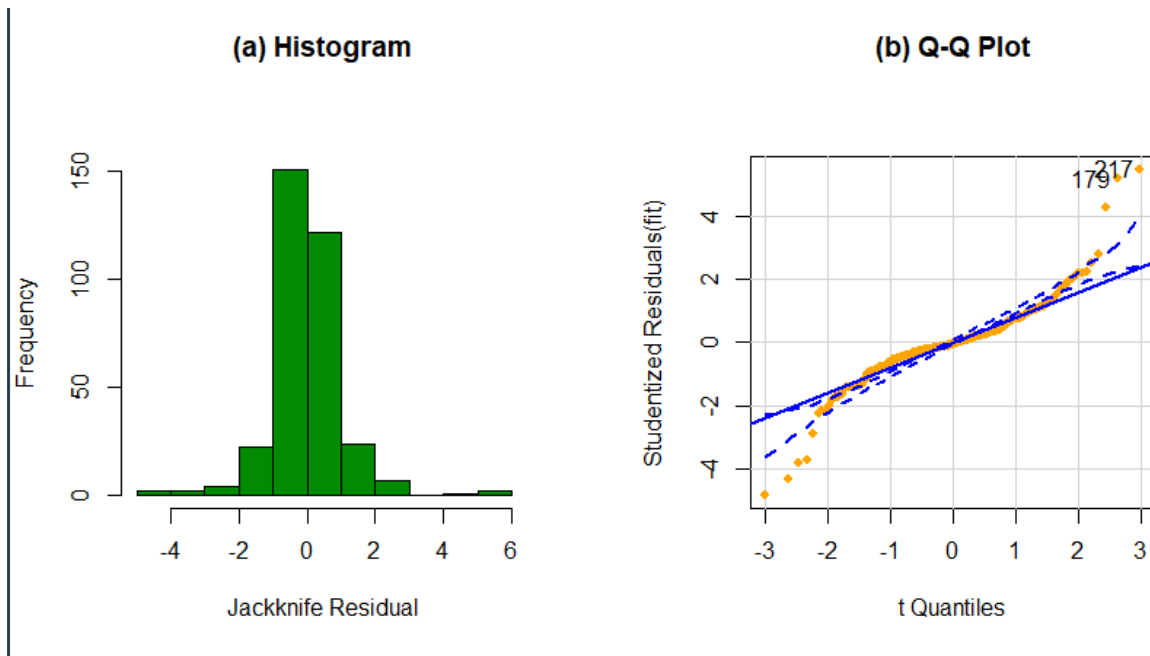
- Based on low values of AIC, one can conclude that forward addition model will provide a parsimonious model of the data.

(b).  $R^2$ : .87 this means that 87% of the data is represented by the best model in this situation.

- Looking at the summary of parameter estimates, it shows that most of the predictors are meaningful addition to the model, except for x8 and x15 due to the fact that the p-values here are higher than .05.

1. (a)

i.



Shapiro-Wilk normality test

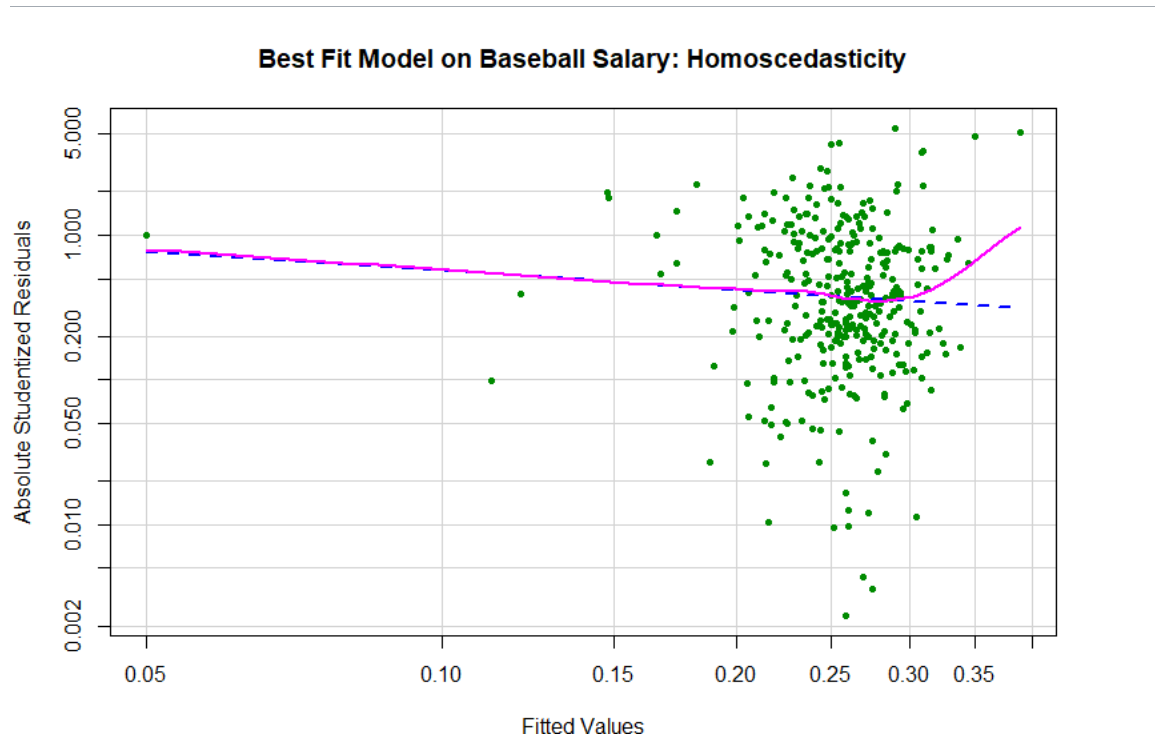
```
data: r.jack  
W = 0.8749, p-value = 6.591e-16
```

-When looking at the histogram, we can see that there is a bell shaped curve, which looks relatively normal, however, there are a few outliers which are influencing the data on both ends of the curve.

- The Q-Q plot shows us that there are quantities outside of the bounds, which can cause concern when it comes to normality. These points are outliers.

-Shapiro-Wilk test shows that the p-value =  $6.59e-16$ , which indicates that this value is smaller than .05. In this case we reject Normality.

ii.



- Based on this graph, both lines should be straight, but there is actually a curve towards the end of this graph. This indicates that there is a violation on equal variance. After running the program, there is a suggested power transformation which will allow for a better fit.

```
Suggested power transformation: 1.444162
> par(mfrow=c(1,1),mar=c(4, 4, 4, 4))
> spreadLevelPlot(fit, pch=20, cex=0.5, col="green4",
+                 main="Best Fit Model on Baseball Salary: Homoscedasticity")
```

iii.

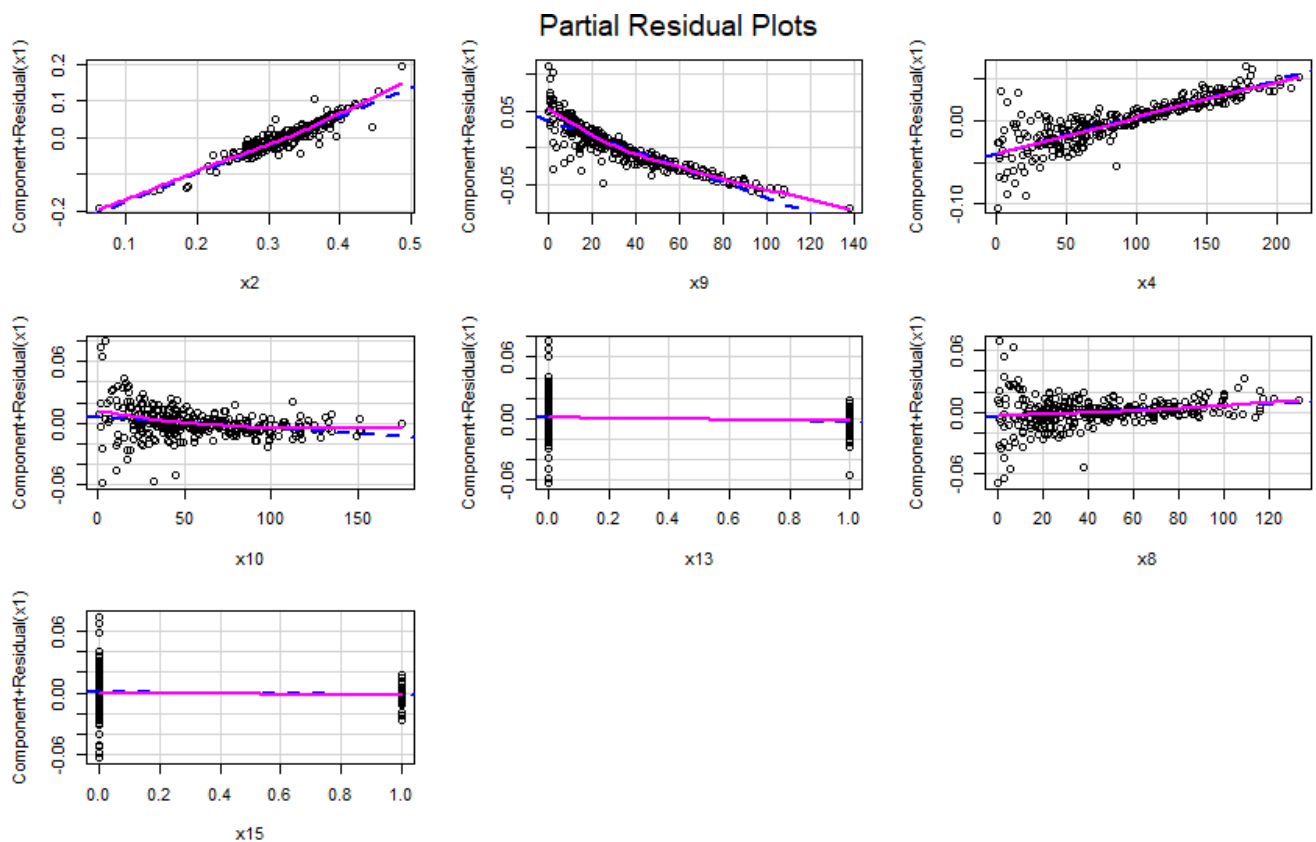
```
> #INDEPENDENCE
> durbinWatsonTest(fit)
lag Autocorrelation D-W Statistic p-value
1 -0.03081245 2.020839 0.888
Alternative hypothesis: rho != 0
> # LARGE P-VALUE (>0.05) JUSTIFIES INDEPENDENCE
>
```

- When running the Durbin Watson test, one gets a value of:

.888.

.888 > .05, hence this value justifies independence.

iv.



- When analyzing these partial residual plots, we can see that the smooth line is mostly in line with our model, therefore linearity is justified. The lines are mostly straight in all of the plots except for plot two, the line is a bit curved, but for the most part all of the lines are aligned with the blue line.

2b.

Potentially influential observations of												
lm(formula = fit.forward) :												
	dfb.1_	dfb.x2	dfb.x9	dfb.x4	dfb.x10	dfb.x13	dfb.x8	dfb.x15	dfit	cov.r	cook.d	hat
7	0.39	-0.43	0.45	-0.01	-0.16	-0.34	0.01	-0.06	-0.62_*	0.74_*	0.05	0.03
21	0.01	-0.03	0.13	0.04	0.16	-0.10	-0.16	-0.05	0.30	1.08_*	0.01	0.07_*
52	0.03	-0.02	0.17	-0.15	-0.15	-0.07	0.17	0.08	0.30	1.10_*	0.01	0.09_*
102	0.02	0.06	-0.07	-0.05	-0.02	-0.07	-0.01	-0.07	0.30	0.86_*	0.01	0.01
115	0.02	-0.05	0.27	0.22	-0.01	0.02	-0.33	-0.03	0.46	1.06	0.03	0.08_*
122	0.06	0.00	-0.02	-0.06	-0.05	-0.07	0.03	-0.06	0.24	0.92_*	0.01	0.01
124	0.11	-0.21	-0.10	0.15	-0.10	0.15	0.17	0.08	-0.56_*	0.67_*	0.04	0.02
134	0.95	-1.15_*	0.55	0.36	-0.19	0.02	-0.06	0.02	-1.29_*	0.63_*	0.20	0.07
151	-0.10	0.09	-0.05	0.01	0.04	0.02	-0.01	0.02	-0.10	1.09_*	0.00	0.06
176	0.14	-0.08	-0.02	0.00	-0.08	-0.09	0.02	-0.09	0.27	0.89_*	0.01	0.01
179	-1.34_*	1.57_*	-0.82	-0.37	0.24	-0.03	0.12	-0.04	1.69_*	0.61_*	0.33	0.10_*
192	0.00	0.00	0.00	-0.02	0.01	0.00	0.03	0.00	0.05	1.08_*	0.00	0.05
196	0.00	-0.01	0.10	-0.17	0.21	0.07	-0.04	0.05	0.33	1.11_*	0.01	0.10_*
201	0.00	0.00	0.01	0.00	-0.02	0.01	0.00	0.01	-0.02	1.07_*	0.00	0.05
217	-0.42	0.61	-0.32	-0.29	0.01	-0.09	0.10	-0.08	0.90_*	0.52_*	0.09	0.03
230	0.04	0.10	-0.05	-0.17	-0.15	-0.12	0.10	-0.11	0.52_*	0.68_*	0.03	0.01
234	-0.01	0.00	-0.01	0.01	0.02	0.01	-0.02	0.00	0.03	1.08_*	0.00	0.05
251	-0.02	-0.06	-0.01	0.10	0.03	0.09	0.01	0.07	-0.32	0.85_*	0.01	0.01
261	0.01	-0.02	0.45	-0.14	-0.16	-0.32	0.11	-0.17	0.64_*	1.03	0.05	0.09_*
303	0.38	-0.36	0.17	-0.01	-0.15	0.08	0.03	0.01	0.40	1.17_*	0.02	0.14_*
333	-0.03	0.02	-0.01	0.00	0.01	0.01	0.00	0.00	-0.03	1.10_*	0.00	0.07
337	0.43	-0.56	0.24	0.26	-0.06	0.07	-0.08	0.05	-0.71_*	0.76_*	0.06	0.04

Important outliers:

> infl.sum											
	dfb.1_	dfb.x2	dfb.x9	dfb.x4	dfb.x10	dfb.x13	dfb.x8	dfb.x15	dfit	cov.r	cook.d
7	0.389995723	-0.4264355569	0.446562148	-0.0145343166	-0.161132777	-0.344951274	0.011235305	-0.059571883	-0.62085185	0.7438331	4.628049e-02
21	0.008493499	-0.0287339538	0.132495836	0.0350860699	0.157862100	-0.100487903	-0.163371563	-0.053863049	0.29689704	1.0764519	1.101477e-02
52	0.029525529	-0.0238868411	0.169603891	-0.1510352822	-0.145019986	-0.069866393	0.168729202	0.075835682	0.29868060	1.0992552	1.115401e-02
102	0.018253719	0.0569400212	-0.066145727	-0.0453093165	-0.016659885	-0.074248537	-0.005973737	-0.074666958	0.30101265	0.8594099	1.109751e-02
115	0.019459671	-0.0526711135	0.270221030	0.2159409337	-0.008284744	0.018113491	-0.327726008	-0.033615670	0.45692766	1.0559968	2.599403e-02
122	0.059753476	0.0015767282	-0.017842059	-0.0574602416	-0.052646434	-0.065329429	0.029428800	-0.061067425	0.23684279	0.9241216	6.932806e-03
124	0.110401130	-0.2132902403	-0.099938374	0.1495274280	-0.097191016	0.147079512	0.167171486	0.084667515	-0.55723352	0.6661960	3.681692e-02
134	0.946686175	-1.1460204594	0.548529842	0.3583796492	-0.190243106	0.024702228	-0.061960837	0.021796167	-1.29365147	0.6340432	1.959052e-01
151	-0.099095563	0.0896857071	-0.045835347	0.0059566716	0.043359851	0.019795675	-0.012616821	0.016860728	-0.10163219	1.0896829	1.294470e-03
176	0.140926851	-0.0812842051	-0.016807022	0.0031554311	-0.076310601	-0.091320189	0.018224961	-0.094079683	0.27354088	0.8905306	9.204903e-03
179	-1.344768055	1.5678508737	-0.815038266	-0.3654402449	0.242251704	-0.027198988	0.118258447	-0.040393616	1.69448223	0.6060888	3.328625e-01
192	-0.003295289	0.0007404214	-0.003848104	-0.0228838575	0.010024679	0.003858830	0.029293693	-0.002883989	0.04546873	1.0769015	2.591821e-04
196	-0.003315265	-0.0110305532	0.099203785	-0.1738280788	0.209030824	0.068156292	-0.035643762	0.053903723	0.33194235	1.1116741	1.377367e-02
201	0.003464739	-0.0022716973	0.010381717	-0.0002263683	-0.015546038	0.008195010	-0.003143824	0.007113748	-0.02403142	1.0749664	7.240618e-05
217	-0.418073625	0.6129039222	-0.319267055	-0.2906528217	0.006973057	-0.088956439	0.097504037	-0.084271468	0.89745260	0.5235272	9.254604e-02
230	0.037856778	0.0993891804	-0.053828533	-0.1659329843	-0.146952457	-0.116173046	0.102828695	-0.106095060	0.51637893	0.6755073	3.167814e-02
234	-0.007027221	0.0038237010	-0.007732400	0.0140896067	0.018157344	0.005959760	-0.016886290	-0.001342567	0.02521361	1.0801569	7.970521e-05
251	-0.022280598	-0.0575932353	-0.014743511	0.0975618844	0.028809650	0.087955751	0.009614324	0.068127398	-0.31660327	0.8469752	1.225408e-02
261	0.012747480	-0.0172698534	0.453283675	-0.1422688029	-0.159260702	-0.324825206	0.107500663	-0.174548763	0.64297190	1.0259622	5.120931e-02
303	0.377903583	-0.3645547606	0.167245354	-0.0149414794	-0.151119785	0.079882972	0.028056540	0.012849551	0.40345062	1.1652648	2.034735e-02
333	-0.026559207	0.0242699408	-0.012387069	0.0010577188	0.011096607	0.005112707	-0.002722924	0.004362686	-0.02707477	1.1008184	9.190700e-05
337	0.427624696	-0.5615144019	0.242786065	0.2572248766	-0.060610012	0.065215457	-0.078305132	0.047155675	-0.71059747	0.7624009	6.074204e-02

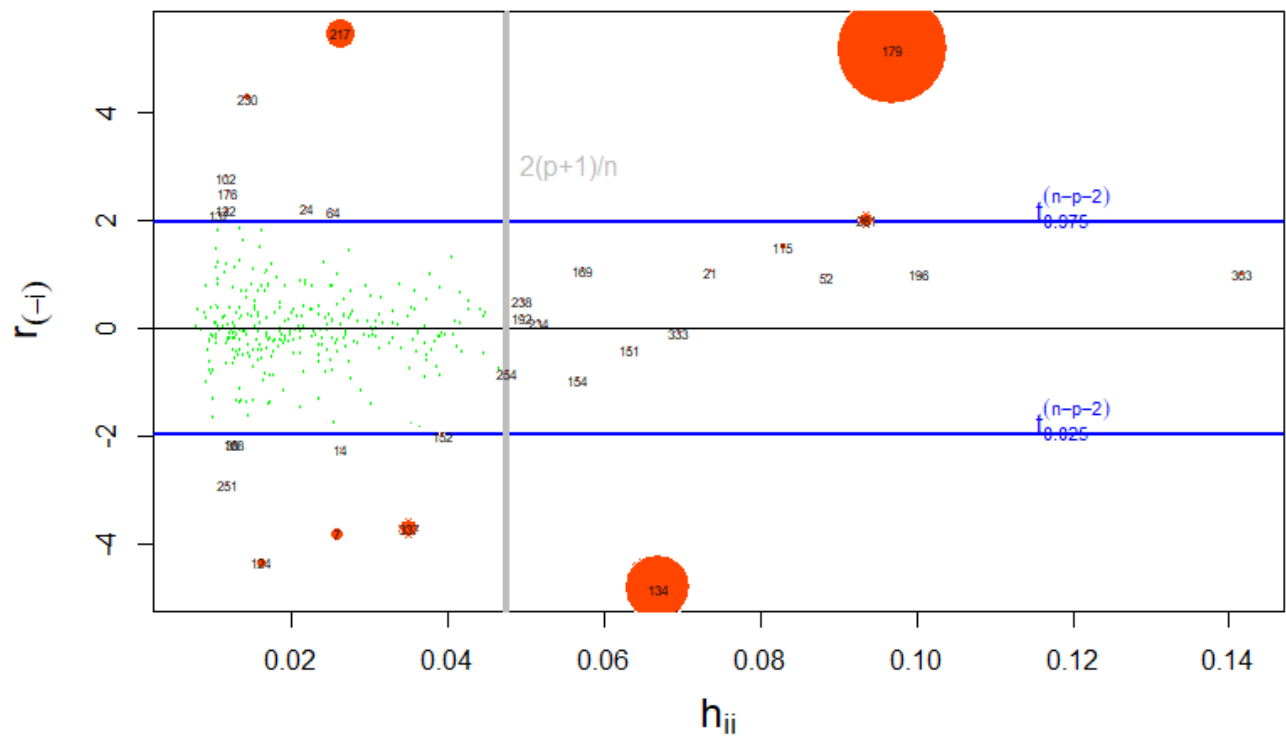
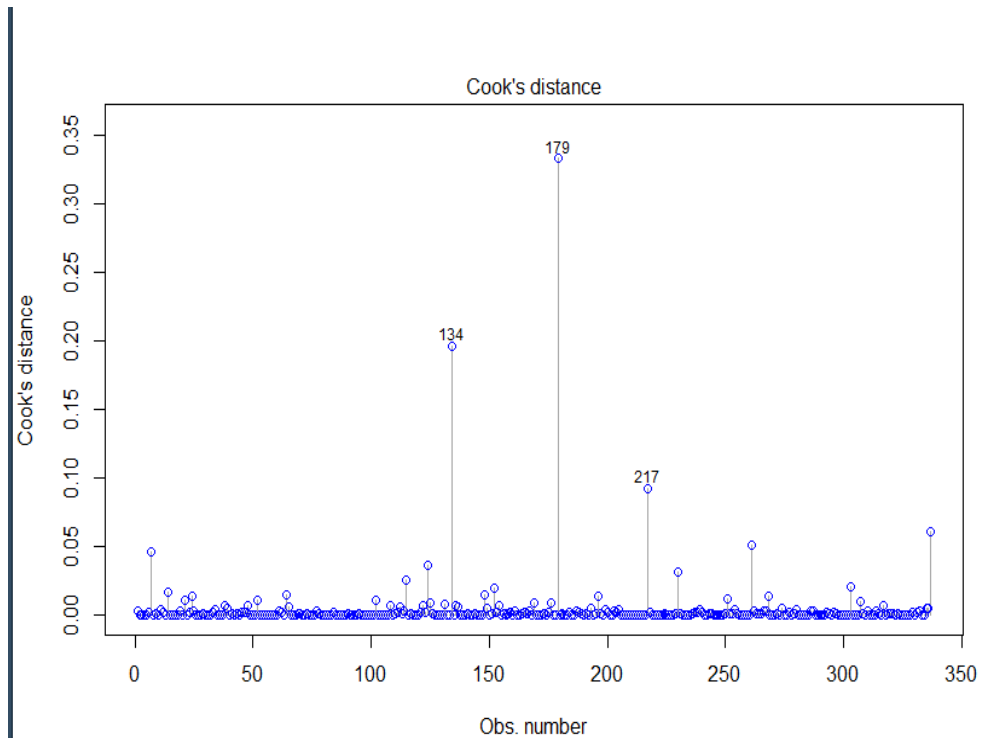
hat	
7	0.02586285
21	0.07352117
52	0.08849620
102	0.01151800
115	0.08275233
122	0.01167317
124	0.01621161
134	0.06697686
151	0.06318368
176	0.01174491
179	0.09695241
192	0.04944026
196	0.10022057
201	0.04707716
217	0.02622397
230	0.01446676
234	0.05165585
251	0.01179228
261	0.09362491
303	0.14155675
333	0.06941372
337	0.03512142

	rstudent	unadjusted p-value	Bonferroni p
217	5.468798	8.9974e-08	3.0321e-05
179	5.171458	4.0494e-07	1.3647e-04
134	-4.828376	2.1147e-06	7.1267e-04
124	-4.340852	1.8932e-05	6.3800e-03
230	4.262049	2.6509e-05	8.9334e-03

```
> # Cook's Distance
[1] 3.428251e-03 2.481798e-08 4.789807e-04 2.541485e-07 7.128498e-07 1.660096e-03 4.628049e-02 1.182988e-05 7.328436e-04 3.623249e-04
[11] 4.321672e-03 2.143798e-03 5.575290e-05 1.668970e-02 2.012447e-04 1.934399e-04 2.066900e-04 1.948460e-04 3.049215e-03 6.060846e-05
[21] 1.101477e-02 4.051989e-04 2.200583e-03 1.390030e-02 2.819766e-03 1.860651e-05 1.115596e-04 5.682811e-04 1.151797e-03 8.110243e-05
[31] 2.185384e-08 1.415936e-04 2.276641e-03 4.417753e-03 1.297592e-04 6.170737e-05 1.044773e-05 7.162437e-03 4.916026e-03 4.692957e-05
[41] 7.610083e-04 1.610731e-05 9.979372e-04 7.422803e-06 2.030649e-03 1.714701e-03 2.130398e-03 6.554321e-03 1.188880e-04 1.394549e-04
[51] 5.280179e-05 1.115401e-02 2.993721e-04 4.664407e-05 2.313736e-04 3.225186e-04 1.217999e-04 8.643652e-05 2.039750e-04 1.835116e-05
[61] 3.110138e-03 2.083221e-03 3.044664e-08 1.514156e-02 5.562295e-03 7.547050e-05 1.979002e-04 4.178000e-04 6.362479e-04 1.385289e-03
[71] 7.690182e-05 1.140687e-05 8.690381e-04 5.040992e-07 1.216183e-04 1.420685e-04 3.489237e-03 7.299398e-04 1.704087e-04 4.871876e-04
[81] 5.315334e-05 1.393957e-04 4.533872e-04 1.945185e-03 3.209389e-04 3.716076e-04 3.513061e-04 6.017130e-05 4.746942e-04 1.199965e-03
[91] 8.232436e-05 4.531868e-05 1.217393e-04 2.453838e-04 1.101937e-03 2.153299e-04 8.611619e-06 1.058709e-04 1.170284e-04 1.253610e-04
[101] 7.316698e-06 1.109751e-02 5.748774e-04 6.427017e-05 3.237819e-04 9.535880e-05 1.855902e-06 7.252132e-03 5.617621e-05 6.441428e-04
[111] 2.191370e-05 5.850574e-03 6.337661e-04 3.172601e-03 2.599403e-02 9.497698e-05 1.178377e-03 2.699755e-05 1.743121e-06 1.371558e-04
[121] 2.369439e-03 6.932806e-03 1.945869e-03 3.681692e-02 8.775536e-03 1.067404e-03 3.037528e-05 1.089081e-04 8.255154e-05 1.557733e-04
[131] 7.553663e-03 5.177491e-04 3.988195e-04 1.959052e-01 1.001008e-04 7.146617e-03 5.930847e-03 3.198069e-05 2.098361e-04 3.718852e-04
[141] 1.276205e-03 3.765677e-05 4.894603e-06 1.198385e-03 1.657074e-05 5.023486e-05 3.995610e-06 1.527406e-02 4.956714e-03 7.611639e-05
[151] 1.294470e-03 2.014951e-02 1.941662e-03 6.714554e-03 7.854733e-05 1.292575e-03 5.774596e-05 9.343386e-04 1.799285e-03 1.416536e-05
[161] 3.429379e-03 2.086357e-05 1.477952e-05 1.070518e-03 1.619679e-03 9.545779e-04 2.792318e-03 3.747001e-05 8.824365e-03 1.156553e-04
[171] 5.116703e-05 3.073223e-04 6.297294e-04 1.671036e-04 1.746086e-03 9.204903e-03 1.006275e-05 2.122129e-04 3.328625e-01 1.783623e-05
[181] 8.181923e-04 3.069742e-05 1.497456e-05 1.982388e-03 1.195032e-05 3.614812e-05 3.318697e-03 1.936450e-03 7.052122e-04 9.527009e-06
[191] 8.659887e-04 2.591821e-04 4.737324e-03 2.811022e-04 1.404238e-03 1.377367e-02 9.095602e-04 7.080448e-05 4.179762e-03 2.195191e-03
[201] 7.240618e-05 6.344668e-05 2.698050e-03 1.988798e-03 3.911801e-03 1.170721e-04 2.102019e-07 8.677168e-05 4.736738e-06 1.191446e-04
[211] 1.493537e-06 8.722601e-06 5.217655e-05 1.543391e-04 3.216406e-04 1.436451e-04 9.254604e-02 1.666984e-03 5.056771e-04 1.416832e-04
[221] 3.158635e-04 1.111328e-04 1.075427e-05 6.841249e-04 4.943655e-04 9.800860e-05 5.781315e-05 1.005284e-06 7.331811e-04 3.167814e-02
[231] 1.449000e-06 6.510105e-05 2.282379e-04 7.970521e-05 1.093156e-04 6.343210e-04 2.083607e-03 1.599809e-03 4.199374e-03 1.736035e-03
[241] 5.315661e-04 5.238665e-05 7.308174e-04 7.834138e-04 6.612895e-05 6.187331e-05 3.166388e-04 1.213943e-04 2.594375e-04 9.949821e-04
[251] 1.225408e-02 1.457806e-03 6.210506e-04 4.319977e-03 6.009819e-04 4.451961e-07 1.512839e-04 4.387588e-04 3.401960e-05 9.726536e-05
[261] 5.120931e-02 2.627321e-03 7.658791e-04 1.219903e-03 1.522231e-03 2.950603e-03 3.013276e-03 1.395624e-02 4.092455e-05 1.477634e-04
[271] 1.792710e-04 1.287597e-03 3.141972e-04 4.501672e-03 3.023288e-04 1.942800e-04 1.889718e-03 2.056897e-06 1.549983e-03 3.937179e-03
[281] 4.994443e-04 8.823175e-08 1.552935e-07 4.669797e-04 2.387253e-05 2.644244e-03 3.271656e-03 1.177105e-04 2.998526e-04 4.461541e-04
[291] 3.511973e-05 8.498584e-05 2.082669e-03 1.186530e-03 3.488432e-04 1.989187e-03 8.903605e-04 1.833569e-04 2.718209e-04 2.840674e-06
[301] 7.889183e-05 4.698860e-04 2.034735e-02 1.070434e-05 8.549526e-06 2.233192e-04 9.827976e-03 8.650494e-04 2.206026e-06 2.638270e-03
[311] 3.486841e-04 2.728600e-04 8.994041e-06 3.237919e-03 1.365135e-03 3.359904e-04 7.032374e-03 2.828365e-04 6.407341e-04 6.547888e-04
[321] 6.251743e-04 9.390103e-06 6.113018e-04 1.251517e-04 9.947106e-05 6.552539e-05 2.375062e-04 6.265204e-05 1.762888e-03 1.996794e-04
[331] 2.149555e-03 3.435186e-03 9.190700e-05 1.684836e-04 5.306631e-03 4.510433e-03 6.074204e-02
```

```
> # EXTRACT INFLUENTIAL POINTS
> baseball[cook.d > 0.05, ] # HIGH COOK'S DISTANCE
      x1    x2    x3    x4    x5    x6    x7    x8    x9   x10   x11   x12   x13   x14   x15   x16  logsalary
134  0.286  0.444    0     2    0    0    0     0     2     3     0     0     0     0     0     0     4.867534
179  0.457  0.486    6    16    4    2    0     7     2     2     0     2     0     0     0     0     4.976734
217  0.364  0.364    2     4     1    0    1     1     0     4     0     0     0     0     0     0     4.691348
261  0.318  0.453   104   178   31     2   32   109   138   112     1     2     0     0     0     0     6.429719
337  0.258  0.395     6     8     1    0    1     6     7    11     0     0     0     0     0     0     4.691348
```





Based on these values and the graph generated we see that our biggest outliers are 134, 179 and 217. These points are also highly influential on the data. The number 363 has the greatest leverage in this graph and the outliers under and over the bands are also considered outliers. Two of our greatest influencers also have high leverage as well.

2C.

```
> fitUpdate <- update(fit, ~. -1, data = dat);  
>  
> kappa(lm(fitUpdate, x=TRUE)$x);  
[1] 632.4887
```

632.4887 > 100

-Based on this answer, we can see that the number we got is larger than the cut-off point of 100. It is actually a very serious concern in this case based on this number, as it is very big. There may be predictors that may be collinear with other predictors in this case.

```
> vif(fit)  
      x2      x9      x4      x10     x13      x8      x15  
1.766046 3.513289 4.237453 2.775130 1.493984 4.935015 1.376195
```

-When we look at VIF, we can see that all of our numbers are below ten, so there may not be an issue with multicollinearity.

3.

```
> ##95% interval  
> player.new <- baseball[1, ]  
> predict(fit, newdata=data.frame(player.new), se.fit=TRUE, interval="prediction", level=0.95);  
$fit  
      fit      lwr      upr  
1 0.2824034 0.2538479 0.3109589  
  
$se.fit  
[1] 0.00305672  
  
$df  
[1] 329  
  
$residual.scale  
[1] 0.0141903
```

-Based on my best fit model, we can assume that there is a 95% chance the salary of this baseball player with the same stats as Andre Dawson, will fall between [.2538479, .3109589] in thousands of dollars.

## Index

### 1. Set-up:

```
library(car)
```

```
baseball <- read.table(file=  
  "http://www.amstat.org/publications/jse/datasets/baseball.dat.txt", header  
  = F,  
  col.names=c("salary", "x1", "x2", "x3", "x4", "x5", "x6", "x7", "x8", "x9",  
  "x10", "x11", "x12", "x13", "x14", "x15", "x16", "ID"))  
baseball$logsalary <- log(baseball$salary);  
baseball <- baseball[, -c(1, 18)] # REMOVE salary AND ID dim(baseball);  
head(baseball)  
dat <- baseball  
logsalary <- baseball$logsalary
```

```
fit.null <- lm(x1 ~ 1, data = dat)  
fit.whole <- lm(baseball, data = dat, x = TRUE, y = TRUE)
```

```
n <- NROW(dat);  
p <- length(coef(fit))-1 # NUMBER OF SLOPES
```

#### (a). #SELECTING STEPWISE PROCEDURE: BACKWARD DELETION

```
fit.forward <- step(fit.null, scope=list(lower=fit.null, upper=fit.whole),  
  direction="forward", k = 2 )  
fit.forward$anova  
summary(fit.forward)  
fit <- lm(fit.forward)
```

### 2.

#### (ai).

#CHECKING NORMALITY: SHAPIRO, HISTOGRAM AND JACK RESIDUALS

```
r.jack <- rstudent(fit)
```

```
par(mfrow=c(1,2),mar=c(8,4,8,4))
```

```
# The first plot: Histogram
hist(r.jack, xlab="Jackknife Residual", col="green4",
     main="(a) Histogram")
# FUNCION
qqPlot() in {car}: A fancier qq plot for studentized jackknife residuals
qqPlot(fit, pch=19, cex=.8, col="orange", main="(b) Q-Q Plot")
# ?qqPlot
shapiro.test(r.jack)
```

(aii).  
#HOMOSCEDASTICITY

```
# Plot Absolute Jackknife Residuals vs. Fitted values
# Power Box-Cox Transformation on the response Y is suggested
# library(car)
par(mfrow=c(1,1),mar=c(4, 4, 4, 4))
spreadLevelPlot(fit, pch=20, cex=0.5, col="green4",
                main="Best Fit Model on Baseball Salary: Homoscedasticity")
# IF THE LINES ARE FLAT, THEN EQUAL VARIANCE IS JUSTIFIED
```

(aiii).  
#INDEPENDENCE  
durbinWatsonTest(fit)  
# LARGE P-VALUE ( $>0.05$ ) JUSTIFIES INDEPENDENCE

(aiv).  
#LINEARITY  
crPlots(fit, main="Partial Residual Plots")

2B.  
infl <- influence.measures(fit);  
infl.mat <- as.data.frame(infl\$inflmat)  
infl.sum <- summary(influence.measures(fit));  
infl.sum  
write.csv(infl.sum, file="Influence-Mat.csv", row.names=TRUE)

# Cook's Distance  
cook.d <- infl.mat\$cook.d; cook.d

# library(car)  
outlierTest(fit) # Bonferonni p-value for most extreme obs

# Plot of Cook's Distance

```
cutoff <- 4/(n-p-2)
plot(fit, which=4, cook.levels=cutoff, col="gray65", lwd=1.5)
points(1:n, cook.d, pch=1, cex=1, col="blue")
```

```
# EXTRACT INFLUENTIAL POINTS
baseball[cook.d > 0.05, ] # HIGH COOK'S DISTANCE
```

```
# Interactive Plot for Identifying Influential Points
# Press ESC to stop when you are done with identification
influencePlot(fit, id=list(method="identify"),
              col="blue",
              main="Influence Plot",
              sub="Circle size is proportional to Cook's d")
```

```
2C.
# CONDITION NUMBER (> 15, 30, 100?);
```

```
#WITH INTERCEPT
fitIntercept <- lm(fit, x=TRUE)
kappa(fitIntercept$x);
```

```
# WITHOUT INTERCEPT
```

```
fitUpdate <- update(fit, ~. -1, data = dat);

kappa(lm(fitUpdate, x=TRUE)$x);
```

```
# COMPUTE VIF USING FUNCTION vif DIRECTLY (> 10?)
vif(fit)
```

```
3.
```

```
##95% interval
```

```
player.new <- baseball[1, ]

predict(fit, newdata=data.frame(player.new), se.fit=TRUE,interval="prediction",
level=0.95);
```