

Topic 14 - Regression Diagnostics

STAT 525 - Fall 2013

Outline

- Partial Regression Plots
- Residuals
 - Studentized
 - Studentized Deleted
- Identifying outlying X 's
- Identifying influential cases

Example Page 386

- Surveyed 18 managers age 30-39. Interested in relating the amount of life insurance carried to risk aversion and salary.
- Y is dollar amount of life insurance carried (thousands)
- Two predictor variables
 - X_1 average annual income in past two years (thousands)
 - X_2 risk aversion score (higher \rightarrow more averse)

Partial Regression Plots

- Also called added variable plots or adjusted variable plots
- Recall partial correlation / coefficient of determination
- These provide visual display of that relationship
- One plot for each X_i
- Allows check of “adjusted” relationship

Partial Regression Plots

- Procedure for X_i vs Y
 - Predict Y using other X 's
 - Predict X_i using other X 's
 - Plot residuals from first regression vs residuals from the second regression
- Shows the **strength** of the marginal relationship in terms of the **full** model
- Can detect:
 - Nonlinear relationship
 - Heterogeneous variance
 - Unusual observations

SAS Commands

```
proc reg data=a1;
  model insur=income risk/r partial influence tol;
  id income risk; plot r.*(p. risk income);

proc reg data=a1;
  model insur risk = income;
  output out=a2 r=resins resris;
proc sort data=a2; by resris;
proc gplot data=a2;
  plot resins*resris;
proc reg data=a2; model resins = resris;
  output out=new1 r=res p=pred;
proc gplot data=new1;
  plot res*pred;
run;
```

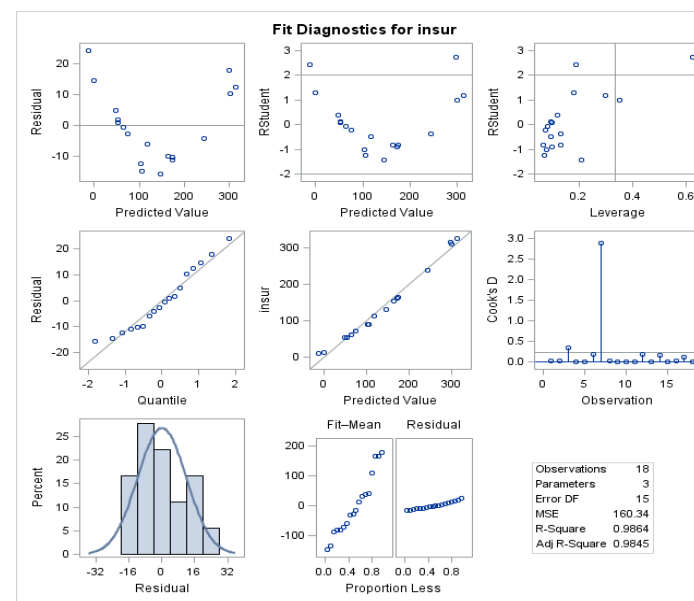
Generates added variable
plot for risk. Similar
approach for income

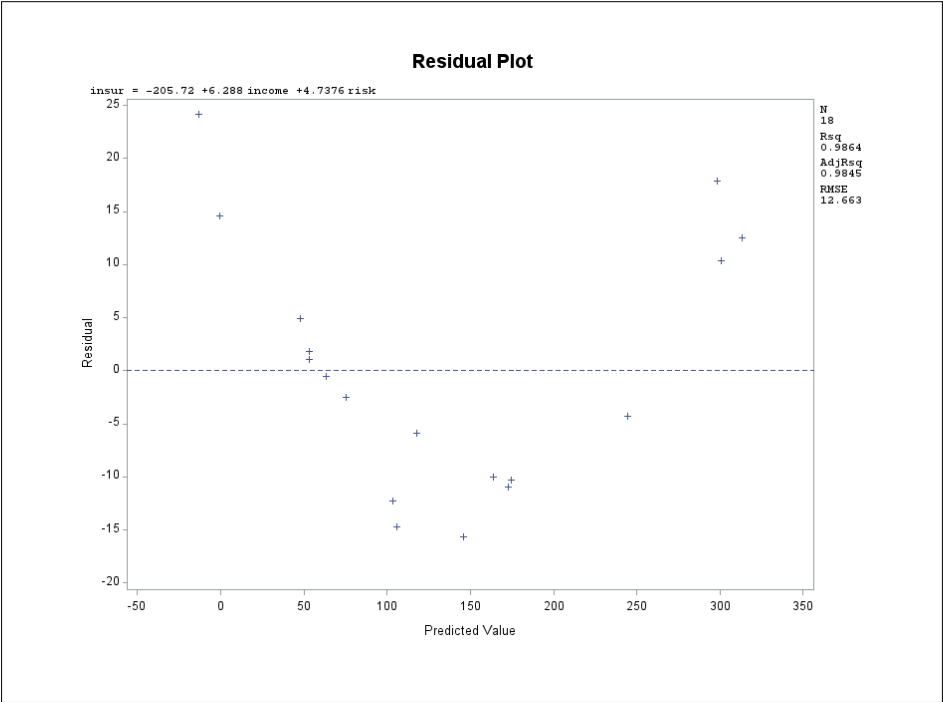
Output

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	173919	86960	542.33	<.0001
Error	15	2405.14763	160.34318		
Corrected Total	17	176324			

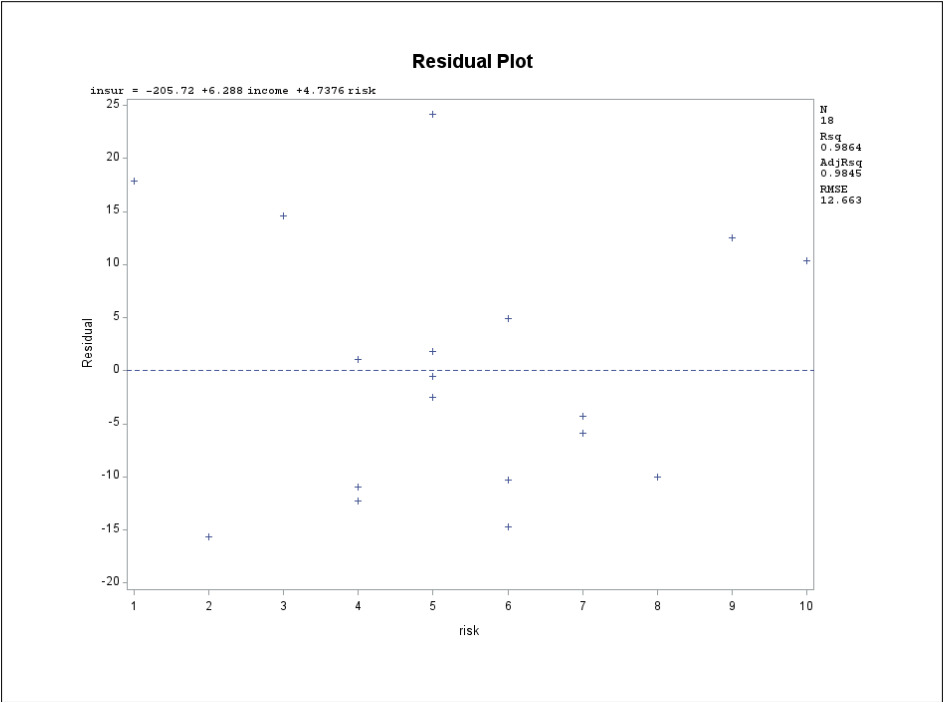
Root MSE	12.66267	R-Square	0.9864
Dependent Mean	134.44444	Adj R-Sq	0.9845
Coeff Var	9.41851		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-205.71866	11.39268	-18.06	<.0001
income	1	6.28803	0.20415	30.80	<.0001
risk	1	4.73760	1.37808	3.44	0.0037

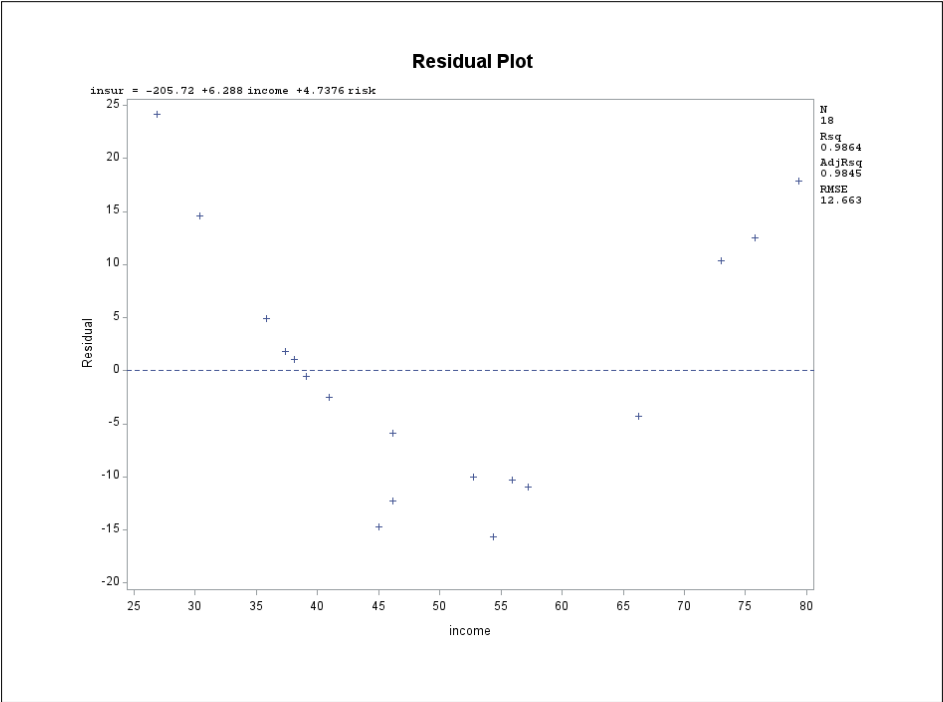




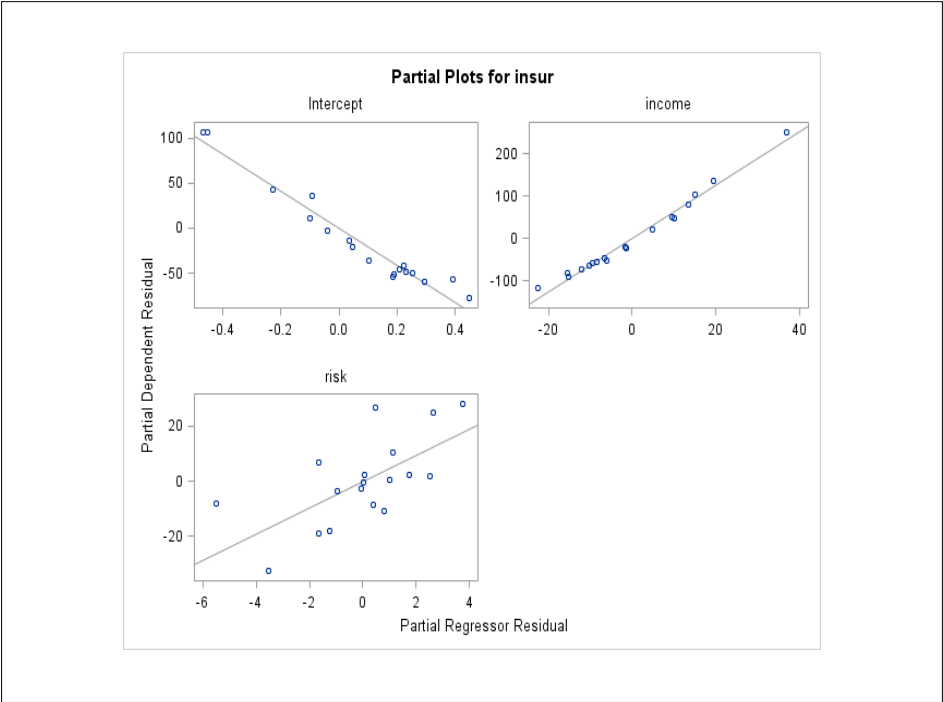
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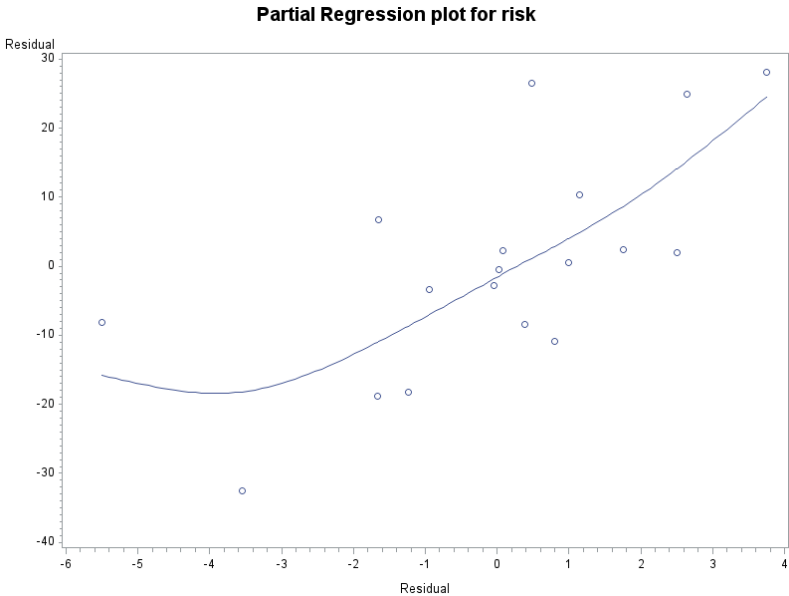
Output

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	1895.04339	1895.04339	12.61	0.0027
Error	16	2405.14763	150.32173		
Corrected Total	17	4300.19102			

Root MSE	12.26058	R-Square	0.4407	**Partial R-Square
Dependent Mean	-1.204E-14	Adj R-Sq	0.4057	
Coeff Var	-1.01834E17			

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	-9.4683E-15	2.88985	-0.00	1.0000
resris	1	4.73760	1.33432	3.55	0.0027

**Note that the parameter estimate for the slope is the same as the parameter estimate for RISK in the full model



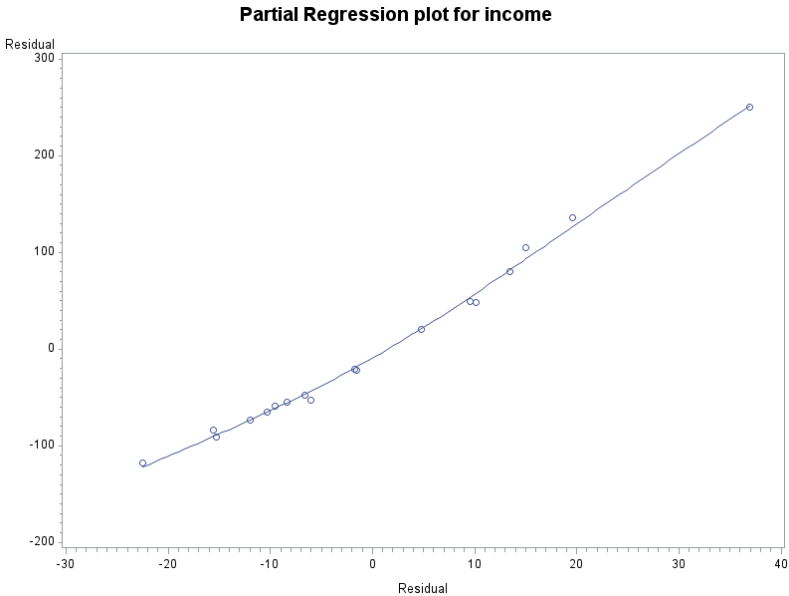
Output

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	152119	152119	1011.96	<.0001
Error	16	2405.14763	150.32173		
Corrected Total	17	154524			

Root MSE	12.26058	R-Square	0.9844	**Partial R-squar
Dependent Mean	-6.3159E-15	Adj R-Sq	0.9835	
Coeff Var	-1.94121E17			

Variable	DF	Parameter Estimate	Std Error	t Value	Pr > t
Intercept	1	1.10593E-14	2.88985	0.00	1.0000
resinc	1	6.28803	0.19767	31.81	<.0001

**Note that the parameter estimate for the slope is the same as the parameter estimate for INCOME in the full model

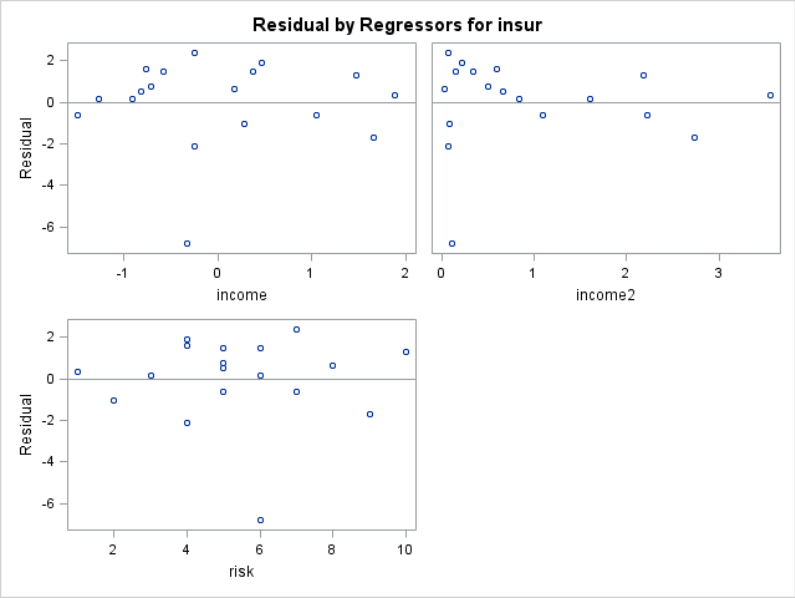
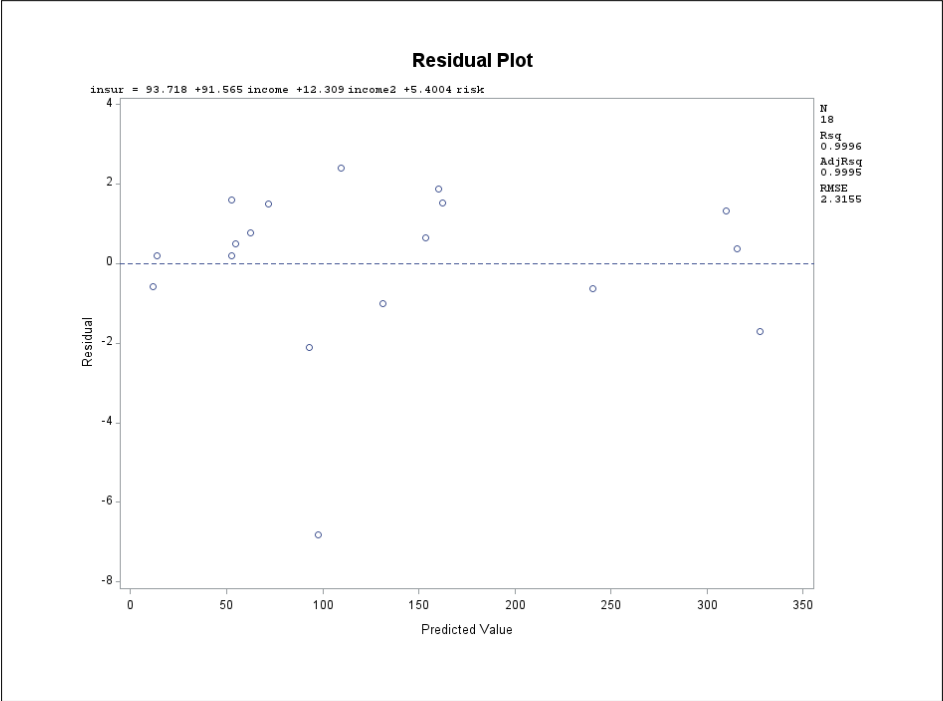
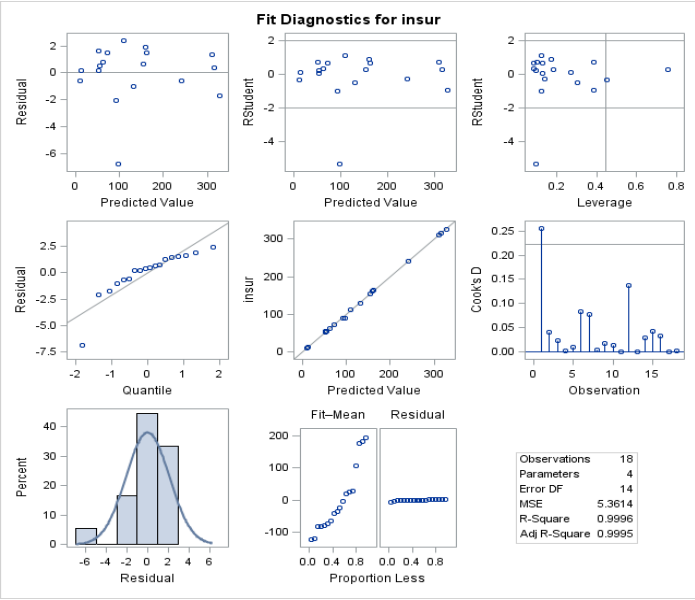


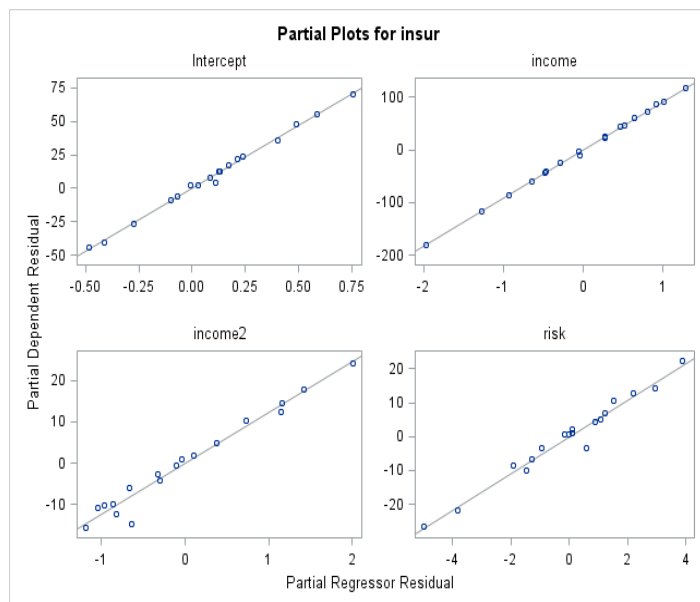
Output - Adding Income²

Analysis of Variance					
		Sum of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
Model	3	176249	58750	10958.0	<.0001
Error	14	75.05895	5.36135		
Corrected Total	17	176324			

Root MSE	2.31546	R-Square	0.9996
Dependent Mean	134.44444	Adj R-Sq	0.9995
Coeff Var	1.72224		

		Parameter	Standard			
Variable	DF	Estimate	Error	t Value	Pr > t	
Intercept	1	93.71759	1.63501	57.32	<.0001	
income	1	91.56523	0.65352	140.11	<.0001	
income2	1	12.30855	0.59042	20.85	<.0001	
risk	1	5.40039	0.25399	21.26	<.0001	





Residuals

- Standard residual

$$e_i = Y_i - \hat{Y}_i \rightarrow \mathbf{e} \sim \text{MVN}(\mathbf{0}, (\mathbf{I} - \mathbf{H})\sigma^2)$$

- Studentized residual

$$r_i = \frac{e_i}{\sqrt{\text{MSE}(1 - h_{ii})}}$$

- Studentized deleted residual

$$\begin{aligned} t_i &= \frac{Y_i - \hat{Y}_{i(i)}}{\sqrt{\text{MSE}_{(i)}/(1 - h_{ii})}} \sim t(n - p - 1) \\ &= e_i \left[\frac{n - p - 1}{\text{SSE}(1 - h_{ii}) - e_i^2} \right]^{1/2} \end{aligned}$$

Studentized Deleted Residual

- Can express deleted residual as

$$Y_i - \hat{Y}_{i(i)} = \frac{e_i}{1 - h_{ii}}$$

- Based on following identity (Gauss 1821)

$$(\mathbf{X}'_{(i)} \mathbf{X}_{(i)})^{-1} = (\mathbf{X}' \mathbf{X})^{-1} + \frac{(\mathbf{X}' \mathbf{X})^{-1} X_i X_i' (\mathbf{X}' \mathbf{X})^{-1}}{1 - h_{ii}}$$

- Relationship between $\text{MSE}_{(i)}$ and MSE

$$(n - p) \text{MSE} = (n - p - 1) \text{MSE}_{(i)} + \frac{e_i^2}{1 - h_{ii}}$$

Output

Output Statistics					
Obs	income	risk	Residual	Std Error Residual	Student Residual
1	-0.323145222	6	-6.8164	2.201	-3.097
2	0.4607431878	4	1.8799	2.108	0.892
3	-1.490427964	5	-0.5901	1.713	-0.344
4	1.0448345518	7	-0.6278	2.151	-0.292
5	-0.583241377	5	1.4981	2.218	0.675
6	1.4759281779	10	1.3223	1.816	0.728
7	1.8863221101	1	0.3641	1.150	0.317
8	0.175447406	8	0.6355	2.096	0.303
9	0.377944412	6	1.5153	2.165	0.700
10	-0.765938675	4	1.5932	2.196	0.726
11	-0.912636506	6	0.1940	2.160	0.0898
12	1.6559255166	9	-1.6975	1.815	-0.935
13	-0.811837997	5	0.5043	2.203	0.229
14	0.2789458757	2	-1.0179	1.935	-0.526
15	-0.24754634	7	2.3920	2.166	1.104
16	-0.251146287	4	-2.0992	2.169	-0.968
17	-1.264531303	3	0.1865	1.978	0.0943
18	-0.705639567	5	0.7637	2.214	0.345

Output

Output Statistics								Cook's	
Obs	income	risk	-2	-1	0	1	2	D	RStudent
1	-0.323145222	6	*****					0.255	-5.3155
2	0.4607431878	4		*				0.041	0.8848
3	-1.490427964	5						0.025	-0.3333
4	1.0448345518	7						0.003	-0.2822
5	-0.583241377	5		*				0.010	0.6618
6	1.4759281779	10		*				0.083	0.7153
7	1.8863221101	1						0.077	0.3063
8	0.175447406	8						0.005	0.2931
9	0.377944412	6		*				0.018	0.6866
10	-0.765938675	4		*				0.015	0.7127
11	-0.912636506	6						0.000	0.0866
12	1.6559255166	9		*				0.137	-0.9308
13	-0.811837997	5						0.001	0.2210
14	0.2789458757	2		*				0.030	-0.5120
15	-0.24754634	7		**				0.044	1.1138
16	-0.251146287	4		*				0.033	-0.9653
17	-1.264531303	3						0.001	0.0909
18	-0.705639567	5						0.003	0.3338

With 18 observations and 3 predictors, the df for the studentized deleted residuals are 13. The P-value associated with Obs #1 is 0.00014. Using Bonferroni, we'd compare this to $.05/18 = 0.00278$. Conclusion: observation does appear to be unusual.

Hat Matrix Diagonals

- Used to identify outlying X observations
- Diagonals $0 \leq h_{ii} \leq 1$ and sum to p
- Also known as the leverage of i th case
- Is a measure of distance between the X value and the mean of the X values for all n cases ($\bar{X}_1, \bar{X}_2, \dots, \bar{X}_{p-1}$)
- Since $\hat{\mathbf{Y}} = \mathbf{H}\mathbf{Y}$

$$\hat{Y}_i = h_{i1}Y_1 + h_{i2}Y_2 + \dots + h_{in}Y_n$$

- Thus h_{ii} is a measure of how much Y_i is contributing to the prediction of \hat{Y}_i

Hat Matrix Diagonals

- Residual $e_i = (1 - h_{ii})Y_i$
- $\text{Var}(e_i) = \sigma^2(1 - h_{ii})$
- If h_{ii} large, small residual variance
- This implies \hat{Y}_i will be close to Y_i (i.e., model forced to fit observation closely)
- Look for large h_{ii} : usually considered large if it is more than double the mean leverage value (p/n)
- When predicting, can compute $\mathbf{X}'_{i(\text{new})}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}_{i(\text{new})}$ to see if there is the danger of extrapolating

Output

Obs	income	risk	Hat Diag		Cov	
			H	Ratio	DFFITS	
1	-0.323145222	6	0.0962	0.0147	-1.7339	
2	0.4607431878	4	0.1711	1.2842	0.4020	
3	-1.490427964	5	0.4524	2.3742	-0.3029	
4	1.0448345518	7	0.1373	1.5215	-0.1126	
5	-0.583241377	5	0.0826	1.2842	0.1986	
6	1.4759281779	10	0.3848	1.8735	0.5656	
7	1.8863221101	1	0.7535	5.3027	0.5356	
8	0.175447406	8	0.1802	1.5981	0.1374	
9	0.377944412	6	0.1258	1.3342	0.2604	
10	-0.765938675	4	0.1006	1.2830	0.2384	
11	-0.912636506	6	0.1297	1.5420	0.0334	
12	1.6559255166	9	0.3856	1.6912	-0.7373	
13	-0.811837997	5	0.0951	1.4643	0.0717	
14	0.2789458757	2	0.3018	1.7786	-0.3366	
15	-0.24754634	7	0.1249	1.0675	0.4209	
16	-0.251146287	4	0.1222	1.1616	-0.3601	
17	-1.264531303	3	0.2705	1.8390	0.0553	
18	-0.705639567	5	0.0856	1.4216	0.1022	

The critical value in this case would be if a diagonal value was greater than $2(4)/18 = 0.44$. It does appear that there are some outlying X observations (Obs #3 and #7). For Obs #7, the largest income and lowest risk. For Obs #3, the smallest income.

DFFITS

- Measures influence of case i on \hat{Y}_i
- Closely related to h_{ii}

$$\text{DFFITS}_i = \frac{\hat{Y}_i - \hat{Y}_{i(i)}}{\sqrt{\text{MSE}_{(i)} h_{ii}}} = t_i \sqrt{\frac{h_{ii}}{1 - h_{ii}}}$$

- Adjusts studentized deleted residual by function of h_{ii}
- Concern if absolute value greater than 1 for small data sets or greater than $2\sqrt{p/n}$ for large data sets

Output

Obs	income	risk	Hat	Diag	Cov	DFFITS
			H	Ratio		
1	-0.323145222	6	0.0962	0.0147		-1.7339
2	0.4607431878	4	0.1711	1.2842		0.4020
3	-1.490427964	5	0.4524	2.3742		-0.3029
4	1.0448345518	7	0.1373	1.5215		-0.1126
5	-0.583241377	5	0.0826	1.2842		0.1986
6	1.4759281779	10	0.3848	1.8735		0.5656
7	1.8863221101	1	0.7535	5.3027		0.5356
8	0.175447406	8	0.1802	1.5981		0.1374
9	0.377944412	6	0.1258	1.3342		0.2604
10	-0.765938675	4	0.1006	1.2830		0.2384
11	-0.912636506	6	0.1297	1.5420		0.0334
12	1.6559255166	9	0.3856	1.6912		-0.7373
13	-0.811837997	5	0.0951	1.4643		0.0717
14	0.2789458757	2	0.3018	1.7786		-0.3366
15	-0.24754634	7	0.1249	1.0675		0.4209
16	-0.251146287	4	0.1222	1.1616		-0.3601
17	-1.264531303	3	0.2705	1.8390		0.0553
18	-0.705639567	5	0.0856	1.4216		0.1022

This is a small data set, so we'll be concerned about values greater than 1. In this case, Obs #1 has strong influence. Recall this observation had a very large studentized deleted residual. None of the others are a concern.

Cook's Distance

- Measures influence of case i on all \hat{Y}_i 's
- Standardized version of sum of squared differences between fitted values with and without case i

$$D_i = \frac{\sum (\hat{Y}_j - \hat{Y}_{j(i)})^2}{p \text{MSE}}$$

- Compare with $F(p, n - p)$
- Concern if D_i above the 50%-tile
- Can show $D_i = \text{MSE}_{(i)}(\text{DFFITS}_i)^2 / (p \text{MSE})$...Thus another cutoff is $4/n$ provided $\text{MSE}_{(i)} / \text{MSE} \approx 1$

Output

Output Statistics								Cook's	
Obs	income	risk	-2	-1	0	1	2	D	RStudent
1	-0.323145222	6	*****					0.255	-5.3155
2	0.4607431878	4			*			0.041	0.8848
3	-1.490427964	5						0.025	-0.3333
4	1.0448345518	7						0.003	-0.2822
5	-0.583241377	5			*			0.010	0.6618
6	1.4759281779	10			*			0.083	0.7153
7	1.8863221101	1						0.077	0.3063
8	0.175447406	8						0.005	0.2931
9	0.377944412	6			*			0.018	0.6866
10	-0.765938675	4			*			0.015	0.7127
11	-0.912636506	6						0.000	0.0866
12	1.6559255166	9			*			0.137	-0.9308
13	-0.811837997	5						0.001	0.2210
14	0.2789458757	2			*			0.030	-0.5120
15	-0.24754634	7			**			0.044	1.1138
16	-0.251146287	4			*			0.033	-0.9653
17	-1.264531303	3						0.001	0.0909
18	-0.705639567	5						0.003	0.3338

With 18 observations and 3 predictors, the df for the F are 4 and 14. The 30, 40, and 50%-tiles are 0.553, 0.707, and 0.881 respectively. None of the observations appear to have an undue amount of influence.

DFBETAS

- Measures influence of case i on each of the regression coefficients
- Standardized version of the difference between regression coefficient computed with and without case i

$$\text{DFBETAS}_{k(i)} = \frac{b_k - b_{k(i)}}{\sqrt{\text{MSE}_{(i)} c_{kk}}}$$

where c_{kk} is from $(\mathbf{X}'\mathbf{X})^{-1}$

- Concern if greater than 1 for small data sets or greater than $2/\sqrt{n}$ for large data sets

Output

Output Statistics

-----DFBETAS-----						
Obs	income	risk	Intercept	income	income2	risk
1	-0.323145222	6	-0.4440	0.0662	0.9168	-0.3686
2	0.4607431878	4	0.3372	0.2513	-0.2579	-0.2064
3	-1.490427964	5	0.0874	0.2513	-0.2312	-0.0525
4	1.0448345518	7	-0.0067	-0.0692	0.0230	-0.0299
5	-0.583241377	5	0.0831	-0.0566	-0.0580	-0.0108
6	1.4759281779	10	-0.3129	0.1183	0.1704	0.3901
7	1.8863221101	1	0.2554	0.2235	0.2233	-0.3381
8	0.175447406	8	-0.0162	0.0245	-0.0712	0.0788
9	0.377944412	6	0.1121	0.1333	-0.1799	0.0084
10	-0.765938675	4	0.1267	-0.0988	-0.0084	-0.0773
11	-0.912636506	6	-0.0064	-0.0244	0.0091	0.0126
12	1.6559255166	9	0.3453	-0.1728	-0.3486	-0.3821
13	-0.811837997	5	0.0137	-0.0427	0.0063	0.0030
14	0.2789458757	2	-0.3279	-0.1746	0.1861	0.2583
15	-0.24754634	7	-0.0046	-0.0195	-0.2036	0.2003
16	-0.251146287	4	-0.2937	-0.0774	0.2177	0.1654
17	-1.264531303	3	0.0101	-0.0383	0.0317	-0.0150
18	-0.705639567	5	0.0310	-0.0471	-0.0097	-0.0003

Nothing looks real troubling here except for Obs #1 and its influence on the quadratic coefficient. Since this had such a large residual, we will remove it and refit the model.

Output

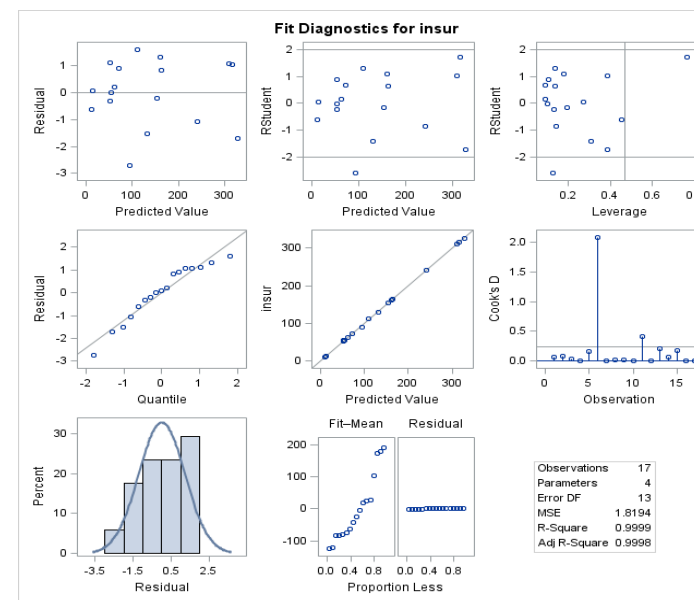
Analysis of Variance

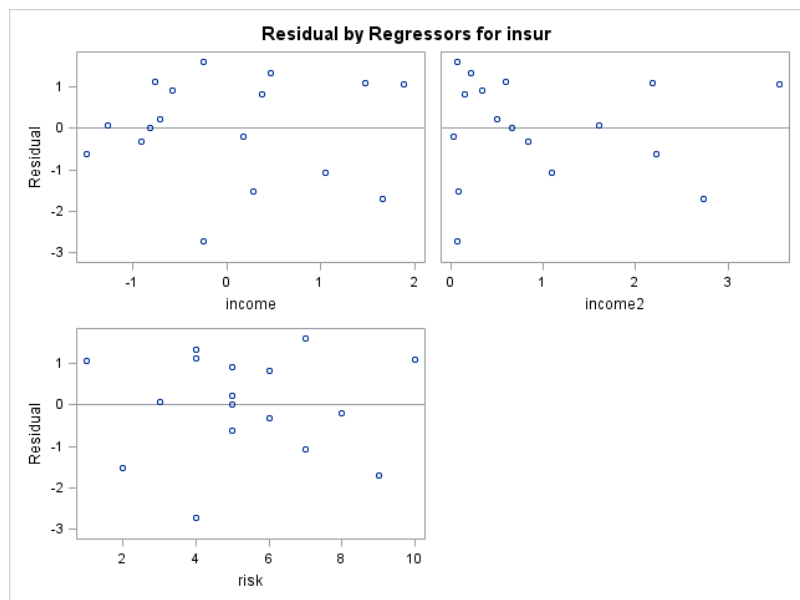
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	174302	58101	31934.2	<.0001
Error	13	23.65205	1.81939		
Corrected Total	16	174326			

Root MSE	1.34885	R-Square	0.9999
Dependent Mean	137.00000	Adj R-Sq	0.9998
Coeff Var	0.98456		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t
Intercept	1	94.14049	0.95577	98.50	<.0001
income	1	91.54004	0.38073	240.43	<.0001
income2	1	11.99324	0.34902	34.36	<.0001
risk	1	5.45493	0.14831	36.78	<.0001





Output

```
-----DFBETAS-----
Obs income      risk Intercept  income  income2  risk
1  0.4607431878    4   0.4210   0.3079  -0.3285  -0.2467
2 -1.490427964    5   0.1587   0.4590  -0.4154  -0.0960
3  1.0448345518    7  -0.0246  -0.2058   0.0768  -0.0927
4  -0.583241377    5   0.0906  -0.0592  -0.0692  -0.0069
5  1.4759281779   10  -0.4422   0.1685   0.2325   0.5595
6  1.8863221101    1   1.4336   1.2882   1.3223  -1.9612
7   0.175447406    8   0.0074  -0.0138   0.0439  -0.0465
8   0.377944412    6   0.1100   0.1238  -0.1770   0.0124
9  -0.765938675    4   0.1591  -0.1213  -0.0204  -0.0899
10 -0.912636506    6   0.0163   0.0690  -0.0221  -0.0367
11  1.6559255166    9   0.6402  -0.3214  -0.6388  -0.7095
12 -0.811837997    5  -0.0002   0.0006  -0.0000  -0.0001
13  0.2789458757    2  -0.9070  -0.4778   0.5234   0.6995
14  -0.24754634    7   0.0076  -0.0251  -0.2646   0.2479
15 -0.251146287    4  -0.8138  -0.2068   0.6230   0.4303
16 -1.264531303    3   0.0068  -0.0254   0.0205  -0.0098
17 -0.705639567    5   0.0155  -0.0221  -0.0066   0.0007
```

Now Obs #6 is influential. This was Obs #7 before we discarded the first observation. It would be worth investigating how much the model changes with and without this observation.

Variance Inflation Factor

- The VIF is related to the variance of the estimated regression coefficients
- Looks at standardized model using correlation transformation
- Can show $\sigma^2(\mathbf{b}) = (\sigma')^2 r_{XX}^{-1}$
- VIF_k is the the k th diagonal element of r_{XX}^{-1}
- Can show $VIF_k = (1 - R_k^2)^{-1}$

Variance Inflation Factor

- VIF of 10 or more suggests strong multicollinearity
- Also compare mean VIF to 1

$$\overline{VIF} = \frac{\sum VIF_k}{p-1}$$

- Tolerance(TOL) = $1/VIF$
- SAS gives TOL results for each predictor
- Trouble if TOL < .1

Output						
Analysis of Variance						
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F	
Model	3	174302	58101	31934.2	<.0001	
Error	13	23.65205	1.81939			
Corrected Total	16	174326				
Root MSE		1.34885	R-Square	0.9999		
Dependent Mean		137.00000	Adj R-Sq	0.9998		
Coeff Var		0.98456				
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > t	Tolerance
Intercept	1	94.14049	0.95577	98.50	<.0001	.
income	1	91.54004	0.38073	240.43	<.0001	0.74314
income2	1	11.99324	0.34902	34.36	<.0001	0.79731
risk	1	5.45493	0.14831	36.78	<.0001	0.92021

Background Reading	
<ul style="list-style-type: none">• KNNL Chapter 10• knnl386.sas• KNNL Sections 11.1, 11.5, 11.6	