"Building" a Regression Model I: Selection of X's

## Preamble and 8.1

## Types of Application and Role of X's

• <u>Controlled Expt's</u> ... Factors(s) manipulated by investigator

( authors' use of term "control variables" here is confusing)

without /

with supplemental X variables

- may be 'imbalanced' w.r.t. the (primary) factor of interest, and thus need to be 'adjusted for';

- (even if balanced) are a source of additional variation (noise) that one wishes to remove, in order to see the 'signal' more clearly

• Non-exp'tl studies (all data are "observational")

Primary variable(s), other explanatory variables

or

Search for explanatory variables

Might also categorize applications into predictive (focus on  $\hat{Y}$ 's) vs. descriptive (focus on individual  $\hat{Y}$ 's)

## **Reduction of No. of Explanatory Variables**

• Controlled Expt's with supplemental X variables

<u>if n small</u>, imbalances with respect to other important X's are possible (making for a biased comparison); this bias can be synthetically "removed" by including these important X variables (the objective is to make the comparison over the level(s) of the primary variable "**fairer**").

no matter whether n is large or small, and even if other important X's are well balanced over the levels of the primary X, (i.e. even if other X's are *"orthogonal"* to the primary X), supplementary variables that explain a lot of the extraneous 'noise' in Y should be included in order to remove this extraneous variation (a matter of making comparison "**sharper**").

(These objectives are the subject of the later Chapter on Analysis of Covariance)

Usually, the number of such variables is small, and their influence is known a priori.

See "Making comparisons <u>sharper</u> and <u>fairer</u>" in article "Appropriate Uses of Multivariate Analysis" by JH under "articles" at top of www material for this Course (697)

See also article "Modeling and Variable Selection in Epidemiology" by S. Greenland under "Chapter 16" in www material for Course 678

# **Reduction of No. of Explanatory Variables**

• Non-Expt'l Data

# Focus on a "Primary" X

other X's retained for comparability with other investigations even if they don't substantially reduce the variability in Y, or even if they are not highly correlated with the Primary X. (provided they aren't so many, and that the number of observations so few, that they create rather than eliminate, noise in the  $^\circ$  of interest. Their use for bias-reduction and noise-reduction is no different than their use in the "Controlled Exp't" situation above.

# Search for Explanatory X's

- helpful to have 'hierarchy' of X's
- ask if the objective is focus is on good  $\hat{Y}$ 's or good  $\hat{Y}$ 's [conditional on other X's]
- no one "best" model.

no matter whether n is large or small, and even if other important X's are well balanced over

# 8.2 Surgical Unit Example ... general comments

[I would have preferred the title "prediction of survival following a liver operation"]

- Essentially a prognostic application
  - [notice that there is no examination of specific  $^{\prime}$ 's, their magnitudes, or even their signs!!]

? Wonder if  $X_2$  (prognostic score that includes age") also includes parts of  $X_1, X_3$ , and  $X_4$  as well.

? Wouldn't a histogram of the 54 Y's (survival times) be helpful before starting out?

Distribution of survival data often has a long right tail, corresponding to "cures".

Also, survival times often "censored" -- if analysis performed before everyone has reached endpoint of interest, and so not amenable to parameter estimation by the LS criterion.

A bit surprising that post-surgery course was "uniformly fatal" and that the survival times were all within such a narrow interval. The text does not even give the (1 mo.- 27 mo.) range of Y's!

# ? Why did authors choose log[Y] transform, rather than say $Y^{1/2}$ or other Y transform ?

## 8.2 Surgical Unit Example ... "Log-Normal" Distributions

Note: an important distinction and a connection to generalized linear models.

To keep example simple,  $X = the X_4$  variable dichotomized at approximately its median. Also, take logs to base e to correspond with generalized linear model.

7	Variable	N	Mean	Std Dev	Minimum	Maximum
X=0 X=1	Y Y <b>rati</b>	28 26 . <b>0</b>	132.75 <u>266.54</u> <b>2.01</b>	55.13 178.39	34 72	217 (days) 830 (days)
	LOG <sub>e</sub> Y LOG <sub>e</sub> Y <i>differ</i>	28 26	4.79 <u>5.39</u> 0.60	0.49 0.69	3.53 4.28	5.38 (log days) 6.72 (log days)

Notice that, on average, survival is twice as long when X = 1 i.e. when  $X_4 >$  median.

### •1• When fit model to Y using a log link with (constant) Gaussian errors

i.e.  $\log_{e} \left[ \mu_{Y} \mid X \right] = 0 + 1 X$ ; SD[Y | X] same for both X=0 and X=1

in generalized linear model, we obtain

 $\log_e average(survival | X) = 4.89 + 0.70 X$ ; SD(survival | X) = 127 days

with the model:  $Y | X \sim Gaussian(exp[4.89 + 0.70 X]; SD = 127 days)$ 

### •2• When fit to log Y using the identity link and Gaussian errors

i.e.  $\mu_{\log Y | X} = 0 + 1 X$ 

in ("regular") linear model], we obtain

average(log survival | X) = 4.79 + 0.60 X; SD(log survival | X) = .56

This latter is modeling **survival** in the 2 X-groups as **log-normal**,

i.e.  $\log(Y \mid X) \sim \text{Gaussian}(4.79 + 0.60 \text{ X}, \text{SD} = .56)$ 

exp[0.60] = 1.82 the 2.01 ratio in average survival when we model survival directly -- we lose something in trying to go back from log[survival] to survival.

Remember from mathematical-statistics courses: If log Y ~ Gaussian[mu, sigma], then

E[Y]	$= \exp[mu + sigma^2/2]$	exp[mu] if sigma > 0
Var[Y]	$= \exp[2 \operatorname{mu} + \operatorname{sigma}^2] (\operatorname{Exp}[\operatorname{sigma}^2] - 1)$	

It is difficult to get <u>all</u> aspects to be correct & useful: Within-X variation in actual Y's is neither constant or Gaussian so model  $\bullet 1 \bullet$  has trouble reflecting the actual distribution of the Y's around each  $\mu$ .

One should ask what <u>the important parameters</u> are in each specific application. If the objective is communication with the patient, then compare this prognosis example with a chest physician's use of say a patient's age, gender, height and weight to estimate the average FEV (Forced Expiratory Volume) in patients with these "X" values, and to express this patient's FEV in relation to that average. Does it matter if the chest physician models the log of FEV?

# 8.3 ALL POSSIBLE REGRESSIONS

"Pool" of **P - 1** possible **terms** + the "1" term implicit in the  $_0 = \mathbf{P}$  possible terms in all. Reduce to **p - 1 terms** + the "1" term implicit in the  $_0 = \mathbf{p}$  terms in all.

Try to find a few (3-6) "good" subsets for closer examination - can specify target p in many software packages

Principle / Comments
$R^{2} = 1 - \frac{SSE}{SS_{total}}$ - increases with p - over-optimistic if p -> n
$R^{2}_{adjusted} = 1 - \frac{SSE / (n-p)}{SS_{total} / (n-1)}$ does not continue to increase with p - at some point, SSR(extra term) < MSE <sub>p</sub>
idea of "bias" or error in fitted model <u>Total Mean Squared Error</u> True Error Variance
Uses the assumption that error variance estimated from model with all P terms is an unbiased estimate (i.e. that the P terms contain all the important ones and that no important ones were overlooked)
how well does prediction based on n-1 of the observations do in predicting the omitted observation?
PRESS <sub>p</sub> = $(Y - \hat{Y} \text{ from other } n-1 \text{ X's })^2$ cf. SSE <sub>p</sub> = $(Y - \hat{Y} \text{ from same } n \text{ X's })^2$

## More details on C<sub>p</sub>

 $\underline{X}$  is a P-dimensional vector  $(1, X_1, X_2, ..., X_{P-1})$  at which one of the n Y's is observed.

 $\underline{x}$  is a p-dimensional vector (1, ... ), a subset of  $\underline{X}$ .

If a particular model, based on a subset  $\underline{x}$  with p < P components, is not "correct" (some important components of  $\underline{X}$  omitted), then, over all possible datasets with same set of n  $\underline{X}$ 's,

the average  $\hat{Y} \mid \underline{x}$  the "correct"  $E[Y \mid \underline{X}] = \mu[Y \mid \underline{X}]$ 

i.e.  $\hat{Y} \mid \underline{x}$  is a biased estimator of  $\mu[Y \mid \underline{X}]$ ; denote the difference as "bias[P,p] ".

In any one application (dataset) ...

$$\hat{Y} \mid \underline{x} = \mu[Y \mid \underline{X}] + \text{bias}[P,p] + \text{random sampling error in } \hat{Y} \mid \underline{x}$$

(random sampling error is around  $\mu[Y | X]$  + bias[P,p])

 $average \; [\; \{ \stackrel{A}{Y} \mid \underline{x} \; - \; \mu[Y \mid \underline{X} \;] \; \} \;^2 \; ] \; = \{ \; bias[P,p] \; \}^2 + variance \; \{ \; \stackrel{A}{Y} \mid \underline{x} \; \; \}$ 

Sum these biases over all n  $\underline{X}$ 's

average squared error = { bias[P,p] }<sup>2</sup> + { variance { 
$$\hat{Y} | \underline{x} }$$
 }

Scale this sum by dividing by "true" error variance []<sup>2</sup>.

$$p = \frac{\{ \text{ bias}[\text{using p rather than P}] \}^2 + \{ \text{ variance } \{ \hat{\mathbf{Y}} \mid \underline{\mathbf{x}} \} \}}{[1]^2}$$

Estimate this by substituting MSE<sub>P</sub> for []<sup>2</sup> and MSE<sub>p</sub> for the variance term in var {  $\hat{Y} | \underline{x}$  } <sup>†</sup>

$$C_p = \frac{SSE_p}{MSE_P} - (n - 2p).$$

If model with p variables is <u>unbiased</u>, then  $E[C_p] = p$ . Otherwise,  $C_p$  will <u>tend to be</u> > p

# So, look for "elbow" in "C<sub>p</sub> vs p" plot.

**† Note 3** (p344):

- (a) why  $\operatorname{var}[\hat{\mathbf{Y}} | \underline{\mathbf{x}}] = p^{-2}$ : The n × 1 vector  $\hat{\mathbf{Y}} = \mathbf{H}_p \mathbf{Y}$ , where  $\mathbf{H}_p$  is the n × n hat matrix  $X(X^TX)^{-1}X^T$ , so  $\operatorname{var}[\hat{\mathbf{Y}}] = \mathbf{H}_p({}^{2}\mathbf{I})\mathbf{H}_p = {}^{2}\mathbf{H}_p$ ; thus  $\operatorname{var}(\hat{\mathbf{Y}}) = {}^{2}(\operatorname{trace} \mathbf{H}_p) = {}^{2}p$ .
- (b) why E[SSE<sub>p</sub>] = bias<sup>2</sup> + (n p)<sup>2</sup>:  $\mathbf{e}_p = (\mathbf{I}-\mathbf{H}_p)\mathbf{Y}$ ; SSE<sub>p</sub> =  $\mathbf{e}_p^T \mathbf{e}_p$ . The ith element of  $\mathbf{e}_p$  has expectation = bias<sub>i</sub>, and variance = (1-h<sub>ii</sub>)<sup>2</sup> where h<sub>ii</sub> is the ith diagonal entry of H. The expected squared residual = bias<sup>2</sup> + var, so their over n = bias<sup>2</sup> + <sup>2</sup> (trace [I-H<sub>p</sub>]) = bias<sup>2</sup> + (n p)<sup>2</sup>.

8.3	"Bes	t'' Suk	osets	<b>REGRESSION</b> (Text p 346)	
	proc	reg;	mod	el l_100km = Cylinder EngSize rpm do sporty front_dr allwh_d	<pre>mestic van r /selection = cp best = 5 ;</pre>
	<u>C(p)</u>	R-sq	# Va	ars in Model	
	2.51	0.684	4	CYLINDER ENGSIZE VAN ALLWH_DR	
	2.93	0.675	3	CYLINDER ENGSIZE VAN	
	3.33			CYLINDER ENGSIZE VAN FRONT_DR	
	3.49			CYLINDER ENGSIZE DOMESTIC VAN ALLWH_DR	
	4.00	0.678	4	CYLINDER ENGSIZE DOMESTIC VAN	
	<u>C(p)</u>	R-sq		<i>Vars in Model</i>	<pre>/selection = cp stop = 3 ;</pre>
		0.67		CYLINDER ENGSIZE VAN	
		0.670		—	
		0.66		CYLINDER VAN ALLWH_DR CYLINDER VAN	
	5.853			CYLINDER RPM VAN	
		0.663		ENGSIZE VAN ALLWH_DR	
		0.65		ENGSIZE VAN	
		0.661		CYLINDER VAN SPORTY	
		0.659		CYLINDER DOMESTIC VAN	
		0.659			
		0.658			
	7.899	0.650	53	ENGSIZE VAN SPORTY	
	8.681	0.654	43	ENGSIZE RPM VAN	
	27.976	0.582	23	RPM VAN FRONT_DR	
	31.649	0.560	02	RPM VAN	
	32.308			RPM VAN ALLWH_DR	
	32.345				
		0.563			
		0.54		—	
		0.533		—	
		0.52		CYLINDER ALLWH_DR	
	42.050			ENGSIZE DOMESTIC ALLWH_DR	
	42.689	0.52		CYLINDER SPORTY ALLWH_DR	
	42.098			ENGSIZE ALLWH_DR CYLINDER DOMESTIC ALLWH DR	
	43.160			—	
		0.52			
		0.520			
	44.648				
		0.473		CYLINDER ENGSIZE FRONT_DR	
	57.654	0.463	32	CYLINDER FRONT_DR	
	58.346	0.468	83	CYLINDER RPM FRONT_DR	
	58.707	0.46	73	CYLINDER SPORTY FRONT_DR	
		0.464		CYLINDER DOMESTIC FRONT_DR	
	61.597			CYLINDER ENGSIZE	
	61.991			CYLINDER ENGSIZE DOMESTIC	
	63.522			CYLINDER ENGSIZE SPORTY	
	63.559			CYLINDER ENGSIZE RPM	
	64.440			CYLINDER	
	64.456	0.438		ENGSIZE FRONT_DR CYLINDER RPM	
	64.619			ENGSIZE DOMESTIC FRONT_DR	
	65.306			CYLINDER RPM DOMESTIC	
	66.048			ENGSIZE SPORTY FRONT_DR	
	66.124			CYLINDER DOMESTIC	
	66.254			ENGSIZE RPM FRONT_DR	
	66.279			CYLINDER SPORTY	
	66.378			CYLINDER RPM SPORTY	
		0.43		VAN FRONT_DR ALLWH_DR	
	67.494			ENGSIZE DOMESTIC	
	67.997	0.432	23	CYLINDER DOMESTIC SPORTY	
	68.148	0.41	7 1	ENGSIZE	

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Highlights / Key Concepts in NKNW4 Chapter 8

### 8.3 "Best" Subsets REGRESSION (Text p 346)

/selection = adjrsq best = 5;

# Vars in Model Adj. R-sq R-sq 0.670 0.688 5 CYLINDER ENGSIZE DOMESTIC VAN ALLWH\_DR 0.670 0.684 4 CYLINDER ENGSIZE VAN ALLWH\_DR 0.668 0.689 CYLINDER ENGSIZE DOMESTIC VAN SPORTY ALLWH\_DR 6 CYLINDER ENGSIZE VAN SPORTY ALLWH DR 0.667 0.685 5 0.666 0.681 4 CYLINDER ENGSIZE VAN FRONT\_DR /selection = maxr stop = 4; <u>Step 1</u> CYLINDER Entered <u>R-sq = 0.431</u> C(p) = 64.44DF MS Prob>F SS F 76.11 76.11 68.17 0.0001 Regression 1 Error 90 100.47 1.11 Total 91 176.58 Step 2 VAN Entered R-sq = 0.659C(p) = 5.20DF SS MS F Prob>F 2 58.23 86.23 Regression 116.47 0.0001 Error 89 60.11 0.67 91 Total 176.58 Step 3 ENGSIZE Entered R-sq = 0.675C(p) = 2.93DF Sum of Sq MS F Prob>F 39.76 3 119.28 61.06 0.0001 Regression Error 88 57.30 0.65 Total 91 176.58 <u>Step 4</u> ALLWH\_DR Entered R-sq = 0.684 C(p) = 2.51 DF Sum of Sq MS F Prob>F 30.22 47.20 0.0001 Regression 4 120.88 87 55.70 0.64 Error Total 91 176.58 Parameter Standard Type II Error Variable Estimate SS Prob>F F 0.365 135.02 210.88 INTERCEP 5.30 0.0001 0.34 0.141 3.78 5.91 0.0171 CYLINDER ENGSIZE 0.39 0.179 3.08 4.81 0.0309 2.00 0.326 24.16 37.75 0.0001 VAN 1.59 ALLWH\_DR 0.48 0.306 2.49 0.1181

# 8.4 Forward, Forward Stepwise, and Backward Elimination Search Procedures

[ if large ( > a dozen, say ) terms ... each produces a single "best" model]

# **Forward Stepwise Procedure**

Terms In Model {in}	Terms Not In Model {out}.		
cycle (i)	From (out) identify <b>V</b> with may <b>F</b> *		
Add X <sub>max</sub> if F*> "F-to-Enter"	From {out}, identify $X_{max}$ with max F*		
From {in}, identify $X_{min}$ with min F*	Take out X <sub>min</sub> if F*< "F-to-Stay"		

N.B. Set F-to-Enter (or P-to-Enter) <u>more extreme</u> than F-to-Stay (or P-to-Stay). (Also, meaning of P-values not exact with with repeat testing)

# **Forward Selection Procedure**

Add  $X_{max}$  if > "F-to-Enter"

•••

•••

•••

From {out}, identify  $X_{max}$ 

**Backward Elimination Procedure** 

From {in}, identify X<sub>min</sub>

Take out  $X_{min}$  if  $F^* < "F-to-Stay"$ 

# **Backward Stepwise Procedure**

From {in}, identify X <sub>min</sub>	
· · ·	Take out $X_{min}$ if $F^* < "F-to-Stay"$
	From {out}, identify $X_{max}$ (has max $F^*$ )
Add $X_{max}$ if $F^* >$ "F-to-Enter"	

### / selection = stepwise slentry=0.05 slstay=0.10 details

Stepwise Procedure for Dependent Variable L\_100KM

#### Statistics for Entry: Step 1 DF = 1,90

r = 1,90

Variable	Tolerance	Model R**2	F	Prob>F
CYLINDER ENGSIZE RPM DOMESTIC VAN SPORTY	1.000000 1.000000 1.000000 1.000000 1.000000 1.000000	0.4310 0.4172 0.3001 0.0258 0.3446 0.0011	68.1748 64.4188 38.5971 2.3814 47.3186 0.1017	0.0001 0.0001 0.1263 0.0001 0.7505
FRONT_DR ALLWH_DR	1.000000 1.000000	0.1441 0.0871	15.1564 8.5871	0.0002

Step 1 CYLINDER Entered R-square = 0.431 C(p) = 64.44

#### Statistics for Entry: Step 2 DF = 1,89

		Model		
Variable	Tolerance	R**2	F	Prob>F
ENGSIZE	0.206596	0.4491	2.9201	0.0910
RPM	0.436376	0.4379	1.0966	0.2978
DOMESTIC	0.913235	0.4322	0.1849	0.6682
VAN	0.968509	0.6596	59.7628	0.0001
SPORTY	0.999808	0.4316	0.0941	0.7598
FRONT_DR	0.899742	0.4638	5.4432	0.0219
ALLWH_DR	0.999671	0.5253	17.6810	0.0001

### Step 2 VAN Entered R-square = 0.659 C(p) = 5.20

Statistics for Removal: Step 3 DF = 1,89

Variable	Partial R**2	Model R**2
CYLINDER	0.3150	0.3446

VAN 0.2286 0.4310

### Statistics for Entry: Step 3 DF = 1,88

=	1,8	8	

	Variable	Tolerance	Model R**2	F	Prob>F
	ENGSIZE	0.206534	0.6755	4.3171	0.0406
	RPM	0.436085	0.6646	1.3192	0.2538
	DOMESTIC	0.912307	0.6600	0.0946	0.7591
	SPORTY	0.982056	0.6612	0.4062	0.5255
	FRONT_DR	0.875287	0.6703	2.8699	0.0938
	ALLWH_DR	0.765756	0.6671	1.9836	0.1625
Step 3	ENGSIZE En	tered R-squ	<u>are = 0.675</u>	C(p) = 2.93	

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## / selection = stepwise slentry=0.05 slstay=0.10 details CONTINUED

### Statistics for Removal: Step 4

DF = 1,88

Variable	Partial R**2	Model R**2
CYLINDER ENGSIZE	$0.0215 \\ 0.0159$	0.6540 0.6596
VAN	0.0159	0.4491

#### Statistics for Entry: Step 4 DF = 1,87

		Model		
Variable	Tolerance	R**2	F	Prob>F
RPM	0.306882	0.6755	0.0019	0.9654
DOMESTIC	0.832604	0.6790	0.9450	0.3337
SPORTY	0.978957	0.6777	0.5890	0.4449
FRONT_DR	0.830951	0.6815	1.6310	0.2050
ALLWH_DR	0.762499	0.6845	2.4920	0.1181

All variables left in the model are significant at the 0.10 level. No other variable met the 0.05 significance level for entry into the model.

#### Summary of Stepwise Procedure for Dependent Variable L\_100KM

Step	Variable Entered Ro	Number emoved In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	CYLINDER	1	0.431	0.4310	64.4402	68.174	8 0.0001
2	VAN	2	0.228	0.6596	5.2001	59.762	28 0.0001
3	ENGSIZE	3	0.015	0.6755	2.9352	4.317	1 0.0406

# selection = backward slentry=0.05 slstay=0.10 details

Backward Elimination Procedure for Dependent Variable L\_100KM

Step 0	All	Variables	Entered	R-squar	e =	0.69019826	C(p)	= 9	.00	000000
		DF	Sum	of Squares		Mean Square			F	Prob>F
Regressio Error Total	on	8 83 91	Ę	21.87968268 54.70679842 76.58648111		15.23496034 0.65911805		23.1	1	0.0001
Variable		Paramet Estima		Standard Error	Sı	Type II um of Squares			F	Prob>F
INTERCEP CYLINDER ENGSIZE		5.627298 0.318209 0.428164	12 11	1.23885070 0.14663650 0.23612525		13.59957045 3.10387561 2.16719942		20.6 4.7 3.2	1 9	0.0001 0.0329 0.0734
RPM DOMESTIC VAN		-0.000082 -0.210095 2.028352	30	0.00031917 0.19595870 0.34330399		0.04375972 0.75764680 23.00871758		0.0 1.1 34.9	5	0.7973 0.2868 0.0001
SPORTY FRONT_DR _ALLWH_DR		0.157555 -0.010482 0.455570	77	0.25574944 0.28485068 0.41213654		0.25015032 0.00089265 0.80536392		0.3 0.0 <u>1.2</u>	0	0.5395 0.9707 0.2722

### Statistics for Removal: Step 1

DF = 1,83

Variable	Partial R**2	Model R**2
CYLINDER	0.0176	0.6726
ENGSIZE	0.0123	0.6779
RPM	0.0002	0.6900
DOMESTIC	0.0043	0.6859
VAN	0.1303	0.5599
SPORTY	0.0014	0.6888
FRONT_DR	0.0000	0.6902
ALLWH_DR	0.0046	0.6856

Step 1 Variable FRONT\_DR Removed R-square = 0.69019321 C(p) = 7.00135431

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression Error Total	7 84 91	121.87879003 54.70769107 176.58648111	17.41125572 0.65128204	26.73	0.0001
Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP CYLINDER ENGSIZE RPM DOMESTIC VAN	5.61220184 0.31756644 0.43138882 -0.00008156 -0.21143635 2.02598220	1.16198895 0.14472481 0.21795704 0.00031673 0.19139269 0.33519684	15.19258476 3.13582849 2.55132087 0.04318430 0.79483632 23.79252403	23.33 4.81 3.92 0.07 1.22 36.53	0.0001 0.0310 0.0511 0.7974 0.2724 0.0001
SPORTY ALLWH_DR	0.15958308 0.46537255	0.24825546 0.31262849	0.26911950 1.44315684	0.41 2.22	0.5221 0.1403

selection =		Statistic		<b>0 details CON</b> noval: Step 2	TINUED	
		Variable	Partial R**2	Model R**2		
		CYLINDER ENGSIZE RPM DOMESTIC VAN SPORTY ALLWH_DR	0.0178 0.0144 0.0002 0.0045 0.1347 0.0015 0.0082	0.6724 0.6757 0.6899 0.6857 0.5555 0.6887 0.6820		
Step 2 Va	ariable RPM Ren	moved	R-square	= 0.68994866	C(p) = 5.0	5687261
Regression Error Total	DF 6 85 91	121.8 54.7	Squares 83560574 75087537 58648111	Mean Square 20.30593429 0.64412795		Prob>F 0.0001
Variable INTERCEP CYLINDER ENGSIZE DOMESTIC VAN SPORTY ALLWH_DR	Paramete Estima 5.328602 0.319988 0.459059 -0.199369 2.029298 0.163759 0.464535	te 10 0.1 73 0.1 89 0.1 82 0.1 57 0.1 42 0.1	Standard Error 36841192 14362339 18858048 18454546 33310460 24636075 31088987	Type II Sum of Squares 134.75080686 3.19735729 3.81695798 0.75176871 23.90577213 0.28460444 1.43812271	5.93 1.17 37.11	Prob>F 0.0001 0.0285 0.0170 0.2831 0.0001 0.5080 0.1388
	1			noval: Step 3		
		Variable CYLINDER ENGSIZE DOMESTIC VAN SPORTY ALLWH_DR	DF = 1,85 Partial R**2 0.0181 0.0216 0.0043 0.1354 0.0016 0.0081	Model R**2 0.6718 0.6683 0.6857 0.5546 0.6883 0.6818		
Step 3 Va	ariable SPORTY	Removed	R-square	= 0.68833696	C(p) = 3.4	9866847
Regression Error Total	DF 5 86 91	121.! 55.0	Squares 55100129 03547981 58648111	Mean Square 24.31020026 0.63994744	F 37.99	Prob>F 0.0001
Variable INTERCEP CYLINDER ENGSIZE	Paramete Estima 5.339753 0.326362 0.4496653	te 49 0.1 22 0.1 81 0.1	Standard Error 36683352 14283718 18743894	Type II Sum of Squares 135.59656477 3.34088490 3.68302269	F 211.89 5.22 5.76	Prob>F 0.0001 0.0248 0.0186

0.18304191

0.32665239

0.30696596

0.66953176

1.64935958

23.74220664

1.05

2.58

37.10

-0.18722506

1.98963874

0.49280572

DOMESTIC

ALLWH\_DR

VAN

0.3092

0.0001

0.1121

## selection = backward slentry=0.05 slstay=0.10 details CONTINUED

Statistics for Removal: Step 4 DF = 1,86

Variable	Partial R**2	Model R**2
CYLINDER	0.0189	0.6694
ENGSIZE	0.0209	0.6675
DOMESTIC	0.0038	0.6845
VAN	0.1345	0.5539
ALLWH_DR	0.0093	0.6790

Step 4 Variable DOMESTIC Removed R-square = 0.68454544 C(p) = 2.51446793

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression Error Total	4 87 91	120.88146953 55.70501157 176.58648111	30.22036738 0.64028749	47.20	0.0001
Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP CYLINDER ENGSIZE VAN ALLWH DR	5.30355882 0.34456671 0.39280256 2.00521810 0.48453473	0.36521981 0.14176168 0.17905259 0.32638377 0.30694096	135.02094830 3.78271792 3.08150191 24.16802325 1.59556738	210.88 5.91 4.81 37.75 2.49	0.0001 0.0171 0.0309 0.0001 0.1181

### Statistics for Removal: Step 5

DF = 1,87

Variable	Partial R**2	Model R**2	
CYLINDER	0.0214	0.6631	
ENGSIZE	0.0175	0.6671	
VAN	0.1369	0.5477	
ALLWH_DR	0.0090	0.6755	

Step 5 Variable ALLWH\_DR Removed R-square = 0.67550982 C(p) = 2.93522907

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression Error Total	3 88 91	119.28590216 57.30057895 176.58648111	39.76196739 0.65114294	61.06	0.0001

Variable	Parameter Estimate	Standard Error	Type II Sum of Sq	F	Prob>F
INTERCEP	5.37	0.365	141.14122366	216.76	0.0001
CYLINDER	0.34	0.142	3.79891080	5.83	0.0178
ENGSIZE	0.37	0.180	2.81103746	4.32	0.0406
VAN	2.25	0.287	39.98361647	61.41	0.0001

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## selection = backward slentry=0.05 slstay=0.10 details CONTINUED

Statistics for Removal: Step 6 DF = 1,88

Variable	Partial R**2	Model R**2
CYLINDER	0.0215	0.6540
ENGSIZE	0.0159	0.6596
VAN	0.2264	0.4491

All variables left in the model are significant at the 0.1000 level.

Summary of Backward Elimination Procedure for Dependent Variable L\_100KM

Step	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	FRONT_DR	7	0.0000	0.6902	7.0014	0.0014	0.9707
2	RPM	б	0.0002	0.6899	5.0669	0.0663	0.7974
3	SPORTY	5	0.0016	0.6883	3.4987	0.4418	0.5080
4	DOMESTIC	4	0.0038	0.6845	2.5145	1.0462	0.3092
5	ALLWH_DR	3	0.0090	0.6755	2.9352	2.4920	0.1181