# Regression Analysis (I)

Kutner's Applied Linear Statistical Models (5/E)

## Chapter 9: Model Selection and Validation

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# 9.1 Overview of Model-Building Process

A strategy for the building of a regression model:

1.	Data collection and	
2.	Reduction of explanatory orstudies)	variables (for exploratory observational
3.	Model refinement and	
4.	Model	

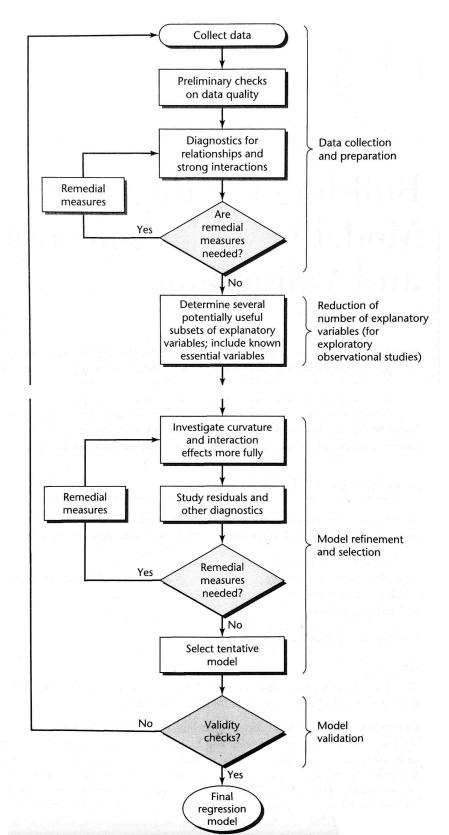


FIGURE 9.1 Strategy for

**Building** a

Regression

Model.



## 9.2 Surgical Unit Example

1. A hospital surgical unit was interested in predicting survival in patients undergoing a particular type of liver operation. A random selection of 108 patients was available for analysis. From each patient record, the following information was extracted from the pre-operation evaluation:

```
X_1 blood clotting score (血栓分數)
X_2 prognostic index (預後指數)
X_3 enzyme function test score (酶功能)
X_4 liver function test score (肝功能)
X_5 age, in years
X_6 indicator variable for gender (0 = \text{male}, 1 = \text{female})
X_7, X_8 indicator variables for history of alcohol use:

None: X_7 = 0, X_8 = 0, Moderate: X_7 = 1, X_8 = 0, Severe: X_7 = 0, X_8 = 1
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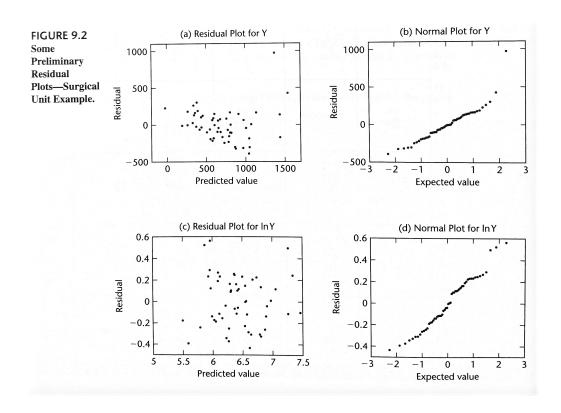
- 2. These constitute the pool of \_\_\_\_\_ or predictor variables for a predictive regression model.
- 3. (Table 9.1) The response variable Y is \_\_\_\_\_\_\_, which was ascertained in a follow-up study. A portion of the data on the potential predictor variables and the response variable is presented in Table 9.1. These data have already been \_\_\_\_\_ and properly \_\_\_\_\_\_ for errors.

TABLE 9.1 Potential Predictor Variables and Response Variable—Surgical Unit Example.

Case Number i	Blood- Clotting Score X <sub>i1</sub>	Prognostic Index X <sub>12</sub>	Enzyme Test X <sub>i3</sub>	Liver Test X <sub>14</sub>	Age X <sub>i5</sub>	Gender X <sub>i6</sub>	Alc. Use: Mod. X <sub>17</sub>	Alc. Use: Heavy X <sub>i8</sub>	Survival Time Y <sub>i</sub>	$Y_i' = \ln Y_i$
1	6.7	62	81	2.59	50	0	1	0	695	6.544
2	5.1	59	66	1.70	39	0	0	0	403	5.999
3	7.4	57	83	2.16	55	. 0	0	0	710	6.565
						•••				
52	6.4	85	40	1.21	58	0	0	1	579	6.361
53	6.4	59	85	2.33	63	0	1	0	550	6.310
54	8.8	78	72	3.20	56	0	0	0	651	6.478

4. To illustrate the model-building procedures discussed in this and the next section, we will use only the first four explanatory variables. We will also use only the first 54 of the 108 patients.

- 5. Since the pool of predictor variables is small, a reasonably \_\_\_\_\_ of relationships and of possible strong interaction effects is possible at this stage of data preparation.
  - (a) <u>Stem-and-leaf plots</u> for each of the predictor variables (not shown). These high-lighted several cases as \_\_\_\_\_ with respect to the explanatory variables. The investigator was thereby alerted to examine later the \_\_\_\_\_ of these cases.
  - (b) A scatter plot matrix and the correlation matrix (not shown)
- 6. A first-order regression model based on all predictor variables was fitted to serve as a starting point.
  - (a) (Figure 9.2a) A plot of residuals against predicted values suggests that both and are apparent.
  - (b) (Figure 9.2b) the normal probability plot suggests some \_\_\_\_\_ from normality.



- 7. Transformation: To make the distribution of the error terms more nearly normal and to see if the same transformation would also reduce the apparent curvature, the investigator examined the transformation .
  - (a) (Figure 9.2c) A plot of residuals against fitted values when Y' is regressed on all four predictor variables in a first-order model;
  - (b) (Figure 9.2d) The normal probability plot of residuals for the transformed data shows that the distribution of the error terms is more  $\cdot$ .
- 8. (Figure 9.3) A scatter plot matrix and the correlation matrix with the transformed Y variable.

**Multivariate Correlations** FIGURE 9.3 Liver Progindex Enzyme **JMP Scatter** LnSurvival Bloodclot **Plot Matrix** 0.6493 0.6539 LnSurvival 1.0000 0.2462 0.4699 0.5024 and 0.0901 -0.1496Bloodclot 0.2462 1.0000 Correlation 0.3690 1.0000 -0.0236Progindex 0.4699 0.0901 Matrix when 0.4164 0.6539 -0.02361.0000 -0.1496Enzyme Response 0.4164 1.0000 0.5024 0.3690 0.6493 Liver Variable Is Y'—Surgical **Scatterplot Matrix** Unit Example. 7.5 6.5 LnSurvival 5.5 Bloodclot 90 70 **Progindex** 50 30 10 90 70 Enzyme 50 30 Liver 5.5 6 6.5 7 7.5 8 3 4 5 6 7 8 9 11 10 30 50 70 90 30 50 70 90 110 1 2 3 4 5 6 7

	(a) Each of the predic	ctor variables is		with $Y'$ , with $X_3$
	and $X_4$ showing the	ne highest degrees of	association and $X_1$	the lowest.
	(b) Show	among the	e potential predictor	r variables. In par-
	ticular, $X_4$ has mo	derately high pairwis	se correlations with	$X_1, X_2, \text{ and } X_3$
9.	Various an	d	were obtained (not	shown here).
10.	On the basis of these a	nalyses, the investiga	ator concluded to u	se, at this stage of
	the model-building pro-	cess,	as the response va	riable, to represent
	the predictor variables	in linear terms, and r	not to include any in	nteraction terms.
11.	The next stage is to ex	amine whether all of	the	variables
	are needed or whether a	a subset of them is ac	lequate.	

### 9.3 Criteria for Model Selection

- 1. From any set of \_\_\_\_\_ predictors, \_\_\_\_\_ alternative models can be constructed. This calculation is based on the fact that each predictor can be either included or excluded from the model.
- 2. (Table 9.2) the \_\_\_\_\_ different possible subset models that can be formed from the pool of four X variables in The Surgical Unit Example.

X Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables in Model	p	$SSE_p$	$R_p^2$	$R_{a,p}^2$	$C_p$	AIC,	SBCp	PRESS,
None	1	12.808	0.000	0.000	151.498	-75.703	-73.714	13.296
<i>X</i> <sub>1</sub>	2	12.031	0.061	0.043	141.164	-77.079	-73.101	13.512
$X_2$	2	9.979	0.221	0.206	108.556	-87.178	-83.200	10.744
$X_3$	2	7.332	0.428	0.417	66.489	-103.827	-99.849	8.327
$X_4$	2	7.409	0.422	0.410	67.715	-103.262	-99.284	8.025
$X_1, X_2$	3	9.443	0.263	0.234	102.031	-88.162	-82.195	11.062
$X_1, X_3$	3	5.781	0.549	0.531	43.852	-114.658	-108.691	6.988
$X_1, X_4$	3	7.299	0.430	0.408	67.972	-102.067	-96.100	8.472
$X_2, X_3$	3	4.312	0.663	0.650	20.520	-130.483	-124.516	5.065
$X_2, X_4$	3	6.622	0.483	0.463	57.215	-107.324	-101.357	7.476
$X_3, X_4$	3	5.130	0.599	0.584	33.504	-121.113	-115,146	6.12
$X_1, X_2, X_3$	4	3.109	0.757	0.743	3.391	-146.161	-138,205	3.914
$X_1, X_2, X_4$	4	6.570	0.487	0.456	58.392	-105,748	-97.792	7.903
$X_1, X_3, X_4$	4	4.968	0.612	0.589	32.932	-120.844	-112.888	6.207
$X_2, X_3, X_4$	4	3.614	0.718	0.701	11.424	-138.023	-130.067	4.597
$X_1, X_2, X_3, X_4$	5	3.084	0.759	0.740	5.000	-144.590	-134.645	4.069

3.	procedures, also known as subset selection or
	procedures, have been developed to identify a small group of regression models that
	are according to a specified criterion.
4.	While many criteria for comparing the regression models have been developed, we
	will focus on six:
5.	We shall denote the number of potential $X$ variables in the pool by We assume throughout this chapter that all regression models contain an intercept term Hence, the regression function containing all potential $X$ variables contains parameters, and the function with no $X$ variables contains one parameter $(\beta_0)$ .
6.	The number of $X$ variables in a subset will be denoted by, as always, so that there are parameters in the regression function for this subset of $X$ variables. Thus, we have: $1 \le p \le P$ .
7.	We will assume that the number of observations exceeds the maximum number of potential parameters:
$R_p^2$	or $SSE_p$ Criterion
_	$R_p^2$ criterion calls for the use of the coefficient of:
	$R_p^2 = \underline{\hspace{1cm}}$
2.	$R_p^2$ indicates that there are p parameters, or $X$ variables, in the regres-
	sion function on which $R_p^2$ is based.
3.	The $R_p^2$ criterion is equivalent to using the error sum of squares as the criterion (we again show the number of parameters in the regression model as a subscript).
4.	The $\mathbb{R}^2_p$ criterion is not intended to identify the subsets that maximize this criterion.
5.	We know that $\mathbb{R}^2_p$ can never decrease as variables are included in
	the model. Hence, $R_p^2$ will be a when potential $X$
	variables are included in the regression model.

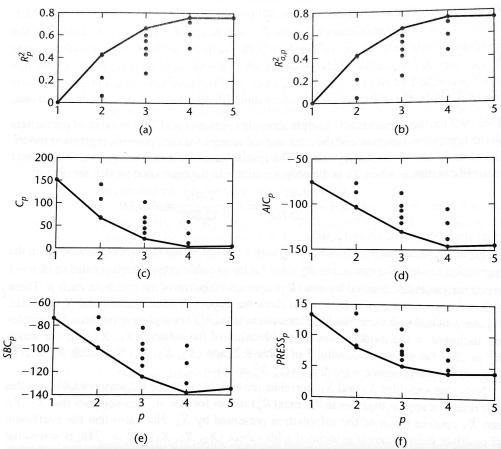
- 6. The intent in using the  $R_p^2$  criterion is to find the point where \_\_\_\_\_\_\_ variables is not worthwhile because it leads to a very \_\_\_\_\_\_ .
- 7. Example The Surgical Unit Example
  - (a) (Table 9.2, column 3) the  $\mathbb{R}_p^2$  values were obtained from a series of computer runs.
  - (b) For instance, when  $X_4$  is the only X variable in the regression model, we obtain:

$$R_2^2 = 1 - \frac{SSE(X_4)}{SSTO} =$$

Note that  $SSTO = SSE_1 = 12.808$ 

(c) (Figure 9.4a) a plot of the  $\mathbb{R}_p^2$  values against p, the number of parameters in the regression model.

FIGURE 9.4 Plot of Variables Selection Criteria—Surgical Unit Example.

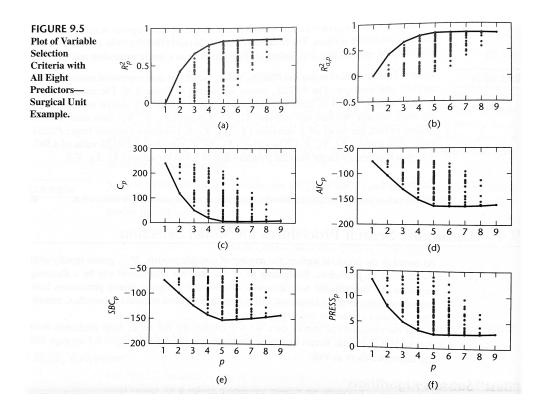


	d) The maximum $R_p^2$ value for the possible subsets each consist dictor variables, denoted by, appears at the for each $p$ . These points are connected by solid lines to sh	top of the graph
	ior each p. These points are connected by solid lines to sh	ow the impact of
	e) (Figure 9.4a) little increase in $\max(R_p)$ takes place after three included in the model.	ee $X$ variables are
	(f) Hence, consideration of the subsets for whi	ich $R_4^2 = 0.757$ (as
	shown in column 3 of Table 9.2) and for appears to be reasonable according to the $\mathbb{R}^2_p$ criterion.	which $R_4^2 = 0.718$
	g) Note that variables $X_3$ and $X_4$ , correlate most	with the response
	variable, yet this pair does not appear together in the $\max(R_p^2)$	(3) model for $p = 4$ .
$R_{a,p}^2$	$r$ $MSE_p$ Criterion	
1.	nce $R_p^2$ does not take account of the	in the regression
	odel and since $\max(R_p^2)$ can never decrease as $p$ increases, the	
	multiple determination $R_{a,p}^2$ in (6.42) has been suggested as an	alternative crite-
	on:	
	$R_{a,p}^2 =$	(9.4)
2.	can be seeg from (9.4) that $R_{a,p}^2$ increases if and only if nee $SSTO/(n-1)$ is fixed for the given Y observations. Hence	decreases $R_{a,p}^2$ and $MSE_p$
	rovide information.	_
3.	he largest $R_{a,p}^2$ for a given number of parameters in the model	$, \max(R_{a,p}^2), \text{ can},$
	deed,	
4.	nd a few subsets for which $R_{a,p}^2$ is at the or so	the
	aximum that more variables is not worthwhile.	
5.	Example The Surgical Unit Example	
	a) (Table 9.2, column 4). For instance, we have for the regression ing only $X_4$ :	on model contain-
	$R_{a,2}^2 = $	

(b) (Figure 9.4b) The story told by the	<del></del>	
to that told by the $R_p^2$ plot in Fig. (c) Consideration of the subsets	and	appears
to be reasonable according to the		
	maximized for subset	, and
that adding to this subse	et - thus using all four predictors	ors – decreases
the criterion slightly:		
Mallows' $C_p$ Criterion* $AIC_p$ and $SBC_p$ Criteria		
1. Two popular alternatives that also prov		tors are
	and	
2. We search for models that have small		
$AIC_p = $	(9.14)	
$AIC_p =                                   $	(9.	15)
3. Notice that for both of these measures,		ch
as, The second term		
the third term with the	e number of parameters,	
4. Models with will do	well by these criteria as long a	s the penalties
$-2p$ for $AIC_p$ and $(\ln n)p$ for $SBC_p$	– are	
5. If the penalty for $SBC_p$ is	s larger than that for $AIC_p$ .	
6. Example The Surgical Unit Example	3	
(a) (Table 9.2, columns 6 and 7) Who model:	en $X_4$ is the only $X$ variable in	the regression
$AIC_2 = n \ln SSE_2 - n \ln SSE_$	$n \ln n + 2p$	
=		
$SBC_2 = n \ln SSE_2 - n \ln SSE_$	$n\ln n + (\ln n)p$	
=		

1. Th		criterion is a measure of how we
the	a riga of the	
	e use of the	_ for a subset model can predict the
a n	measure.	m of squares,, is also suc
. Th	he $PRESS$ measure differs from	om $SSE$ in that each fitted value $Y_i$ for the $PRES_i$
cri	iterion is obtained by	from the data set, estimating th
reg	gression function for the subs	
	en using the fitted regression e $i$ th case.	function to obtain the predicted value for
. We	Te use the notation	now for the fitted value to indicate, by the first
sul	bscript $i$ , that it is a	for the $i$ th case and, by the secon
	bscript $(i)$ , that the $i$ th case ited.	was when the regression function wa
. Th	he $PRESS$ prediction error for	or the $i$ th case then is:
		(9.16)
	ad the $PRESS_p$ criterion is tases:	the sum of the squared prediction errors over all
	$PRESS_p =$	(9.17)
Th		are considered good candidate models ediction errors $Y_i - \hat{Y}_{i(i)}$ are small, so are the square of the squared prediction errors.
Ex	Example The Surgical Unit E	xample
and cas  5. Mo Th pre 6. Ex	and the $PRESS_p$ criterion is to see: $PRESS_p = \begin{bmatrix} & & & & & & & & & & & & & & & & & &$	(9.16)  The sum of the squared prediction errors of $(9.17)$ are considered good candidate ediction errors $Y_i - \hat{Y}_{i(i)}$ are small, so are the of the squared prediction errors.

	(b) We find that sul	osets	and	have small $PRESS$
	values;			
		$X$ variables $(X_1, X_2, X_3)$ .	$(X_2, X_3, X_4)$ involve	s a slightly larger <i>PRESS</i>
			a <i>PRESS</i> value of 3.914 for subset (	$(X_1, X_2, X_3)$ .
9.4	Automatic	Search P	rocedures f	or Model Selec-
	$\mathbf{tion}$			
1.	The number of possidictors.	ble models,	, grows rapid	ly with the number of pre-
2.	A variety of "best" subsets regres	sion and stepwis		s have been developed, e.g.,
"Be	st" Subsets Alg	m corithms		
1.	Time-saving algorith possible regression m		alculation of only	a of all
2.		es using much les	s computational e	absets of $X$ variables with fort than when all possible
3.	When the pool of porthe "best" subset alg		v 0, v	greater than 30 or 40, even
4.	As previously empha	sized, our objecti	ve at this stage is no	ot to identify
	; we hop study.	e to identify a sr	mall set of	for further
5.	Example The Surgion possible models.	cal Unit Example	(eight predictors),	we know there are $2^8 = 256$



- (a) (Figure 9.5) Plots of the six model selection criteria. The best values of each criterion for each p have been connected with lines.
- (b) (Table 9.3) The overall \_\_\_\_\_ criterion values have been underlined in each column of the table.

TABLE 9.3 (1) (2) (4) C<sub>p</sub> (3)Best Variable-PRESS,  $SSE_p$  $R_p^2$  $R_{a,p}^2$ AIC, SBCp Selection 12.808 0.000 -75.703 -73.714 Criterion 0.000 240.452 13.296 Values-7.332 0.428 -99.849 0.417 117.409 -103.8278.025 Surgical Unit 3 4.312 0.663 0.650 50.472 -130.483-124.5165.065 4 5 6 2.843 Example. 0.778 0.765 18.914 -150.985 -143.0293,469 2.179 0.830 0.816 5.751 -163.351153.406 2.738 2.082 0.837 -163.805-151.871 2.739 0.821 5.541 2.005 0.843 5.787 -163.834 -149.9110.823 2.772 8 1.972 0.846 0.823 7.029 -162.736 -146.8242.809 1.971 9.000 0.846 0.819 -160.771-142.8702.931

- (c) For example
  - i. a 7-or 8-parameter model is identified as best by the  $R_{a,p}^2$  criterion (both have
  - ii. a 6-parameter model is identified by the  $C_p$  criterion (
  - iii. a 7-parameter model is identified by the  $AIC_p$  criterion (

	iv. Both the $SI$	$BC_p$ ar	dPI	$RESS_p$ crit	eria poir	nt to 5-pa	arameter models
	(			and			).
(d)	(Figure 9.6) MI	NITAE	outp	out for the	"best" s	ubsets al	lgorithm. We specified
	that the			be iden	ntified fo	or each i	number of variables in
	the regression m	odel.					
	FIGURE 9.6 MINITAB Output for "Best" Two Subsets for Each Subset Size—Surgical Unit Example.	Vars	R-Sq 42.8 42.2 66.3	R-Sq(adj) 41.7 41.0 65.0	C-p 117.4 119.2 50.5	S 0.37549 0.37746 0.29079	BP H lr Hi ooE Gis ognL est dizi nth cnyvAdme ldmegeoa oeererdv  X X
	entra el arembion cultingua paración non general paración con unio aversación con unio aversación con con entración	2 3 4 4 5 6 6 7 7 8	59.9 77.8 75.7 83.0 81.4 83.7 83.6 84.3 83.9 84.6 84.4	58.4 76.5 74.3 81.6 79.9 82.1 81.9 82.3 81.9 82.3 82.0 81.9	69.1 18.9 25.0 5.8 10.3 5.5 6.0 5.8 7.0 7.7	0.31715 0.23845 0.24934 0.21087 0.22023 0.20827 0.20931 0.20655 0.20934 0.20705 0.20867 0.20927	X X X X X X X X X X X X X X X X X X X
(e)	The MINITAB a of the "best" sub most columns of	sets tl	ne $R_{a}^{2}$	$_{p}, C_{p}, $ and	$\sqrt{M}SE_{p}$		out also shows for each d S) values. The righting in the subset.
(f)	except	$(X_4)$	) and	l	(hi	istory of	based on all predictors moderate alcohol use except $\underline{\hspace{1cm}}(X_4)$
(g)	The $R_{a,p}^2$ criterio	n valu	e for	both of the	ese mode	els is	·
The	ber of subsets that	at are	"good	l" according			entification of a small criterion.
Cons	sequently, one ma	ay wis	h at t	times to co	nsider		in
	nating possible su				_		

6.

7.

8.	8. Once the investigator has identified a few "good" subsets for	intensive examina-					
	tion, a final choice of the model variables must be made. This	choice is aided by					
	(and other to be cover	red in Chapter 10)					
	and by the investigator's of the subject under s						
	confirmed through studies.						
Ste	tepwise Regression Methods						
1.	1. When the pool of potential $X$ variables contains 30 to 40 or $e^{-x}$	ven more variables,					
	use of a "best" subsets algorithm may not be						
2.	2. An search procedure that develops the "best"	subset of $X$ vari-					
	ables may then be helpful. The						
	procedure is probably the most widely used of the automatic se	arch methods.					
0							
პ.	3. Essentially, the forward stepwise search method develops	1 1					
	·	variable. The cri-					
	terion for adding or deleting an $X$ variable can be stated equiv	· ·					
	, coefficient of partial correla	tion,statis-					
	tic, or statistic.						
4.	4. An essential difference between stepwise procedures and the "	best" subsets algo-					
	rithm is that stepwise search procedures end with the identification of a						
	regression model as "best." With the "best" subsets algorithm,	regres-					
	sion models can be identified as "good" for final consideration.						
For	orward Stepwise Regression						
We s	Ve shall describe the forward stepwise regression search algorithm in te	rms of the					
(2.17)	2.17) and their associated for the usual tests of regres	sion parameters.					
1.	1. The stepwise regression routine first fits a	model for					
	each of the $p-1$ potential X variables. For each SLR model,						
	testing whether or not the slope is zero is obtained:						

(a) '	The $X$ with the va	alue is the candidate for first
		, or if the corresponding
		$\alpha$ , the X variable is
		es with considered suffi-
(	ciently helpful to enter the regress	sion moder.
		step 1. The stepwise regression routine now
fits al	ll regression models with	, where $X_7$ is one of the pair.
	For each such regression model, the newly added predictor $X_k$ is obtain	he corresponding to the ined.
	This is the statistic for testing whe are the variables in the model.	ther or not when
	The $X$ variable with the the candidate for addition at the	value-or equivalently, thesecond stage.
]		ermined level (i.e., the $P$ -value falls below a $X$ variable is Otherwise, the
		variables should
` '	There is at this stage only one oth one $t^*$ test statistic is obtained:	her $X$ variable in the model, $X_7$ , so that only
	$t_7^st$ =	=
	At later stages, there would be a the variables in the model	number of these $t^*$ statistics, one for each of
		est) is the candidate for
	If this $t^*$ value falls below-or the variable is dropped from the mode	P-value exceeds-a predetermined limit, the el; otherwise, it is

- 4. Suppose  $X_7$  is retained so that both  $X_3$  and  $X_7$  are now in the model.
  - (a) The stepwise regression routine now examines which X variable is the next candidate for \_\_\_\_\_.
  - (b) Then examines whether any of the variables \_\_\_\_\_ should now be dropped.
  - (c) And so on until no further X variables can either be added or deleted, at which point the search .
- 5. Note that the stepwise regression algorithm allows an X variable, brought into the model at an \_\_\_\_\_ stage, to be dropped subsequently if it is \_\_\_\_\_ in conjunction with variables added at later stages.

#### Example

(Figure 9.7) MINITAB computer printout for the forward stepwise regression procedure for The Surgical Unit Example. The maximum acceptable a limit for \_\_\_\_\_ a variable is 0.10 and the minimum acceptable a limit for a variable is 0.15.

Forward	Response i	s lnSurvi	v on 8	predicto	ors, with	N =	54	
Stepwise	•							
Regression	Step	1	2	3	4			
Output—	Constant	5.264	4.351	4.291	3.852			
Surgical Unit								
Example.	Enzyme	0.0151	0.0154	0.0145	0.0155			
	T-Value	6.23	8.19	9.33	11.07			
	P-Value	0.000	0.000	0.000	0.000			
	ProgInde		0.0141	0.0149	0.0142			
	T-Value		5.98	7.68	8.20			
	P-Value		0.000	0.000	0.000			
	Histheav			0.429	0.353			
	T-Value			5.08	4.57			
	P-Value			0.000	0.000			
	Bloodclo				0.073			
	T-Value				3.86			
	P-Value				0.000			
	S	0.375	0.291	0.238	0.211			
	R-Sq	42.76	66.33	77.80	82.99			
	R-Sq(adj)	41.66	65.01	76.47	81.60			
	С-р	117.4	50.5	18.9	5.8			

- 1. At the start of the stepwise search, \_\_\_\_\_ is in the model so that the model to be fitted is  $Y_i = \beta_0 + \epsilon_i$ ;
  - (a) (Step 1), the \_\_\_\_\_ statistics and corresponding P-values are calculated for each potential X variable, and the predictor having the \_\_\_\_\_
    ( ) is chosen to enter the equation.
  - (b) Enzyme  $(X_3)$  had the largest test statistic:

$$t_3^* = \frac{b_3}{s\{b_3\}} = \frac{0.015124}{0.002427} = \underline{\hspace{1cm}}.$$

- (c) The P-value for this test statistic is \_\_\_\_\_, which falls below the maximum acceptable  $\alpha$ -to-enter value of 0.10; hence Enzyme  $(X_3)$  is added to the model.
- (d) The current regression model contains Enzyme  $(X_3)$ , "Step 1": the regression coefficient for Enzyme (0.0151).
- (e) At the bottom of column 1, a number of variables-selection criteria, including  $R_1^2(42.76)$ ,  $R_{a,1}^2(41.66)$ , and  $C_1(117.4)$  are also provided.
- 2. Next, all regression models containing  $X_3$  and \_\_\_\_\_\_ variable are fitted, and the  $t^*$  statistics calculated:

$$t_k^* =$$
 , since ,

Progindex  $(X_2)$  has the highest  $t^*$  value, and its P-value (0.000) falls below 0.10, so that  $X_2$  now enters the model.

- 3. Enzyme and Progindex  $(X_3 \text{ and } X_2)$  are now in the model. At this point, a test whether \_\_\_\_\_ should be dropped is undertaken, but because the \_\_\_\_\_ (0.000) corresponding to  $X_3$  is not above 0.15, this variable is \_\_\_\_\_.
- 4. Next, all regression models containing  $X_2$ ,  $X_3$ , and one of the remaining potential X variables are fitted. The appropriate  $t^*$  statistics:

$$t_k^* =$$

The predictor labeled Histheavy  $(X_8)$  had the largest  $t^*$  value, (P-value = 0.000) and was next added to the model.  $X_2, X_3$ , and  $X_8$  are now in the model.

5.	Next, a test is undertaken to determine whether					
	Since both of the corresponding $P$ -values are less than 0.15, neither predictor is dropped from the model.					
6.	Step 4) Bloodclot $(X_1)$ is added, and no terms previously included were dropped. The right-most column of Figure 9.7 summarizes the addition of variable $X_1$ into the model containing variables $X_2$ , $X_3$ , and $X_8$ .					
7.	Next, a test is undertaken to determine whether either should be dropped. Since all $P$ -values are less than 0.15 (all are 0.0(0), all variables are retained.					
8.	Finally, the stepwise regression routine considers adding one of $X_4$ , $X_5$ , $X_6$ , or $X_7$ to the model containing $X_1$ , $X_2$ , $X_3$ , and $X_8$ . In each case, the $P$ -values are greater than 0.10 (not shown); therefore, no additional variables can be added to the model and the search process is terminated.					
9.	Thus, the stepwise search algorithm identifies as the "best" subset of $X$ variables. This model also happens to be the model identified by both the and criteria in our previous analyses based on an assessment of "best" subset selection.					
Oth	er Stepwise Procedures					
1.	<u>Forward Selection</u> . The forward selection search procedure is a simplified version of forward stepwise regression, whether a variable once entered into the model should be					
2.	Backward Elimination. The backward elimination search procedure is the selection.					
	(a) It begins with the model containing $\_$ potential $X$ variables and identifies the one with the largest $P$ -value.					
	(b) If the maximum $P$ -value is greater than a predetermined limit, that $X$ variable is dropped.					

- (c) The model with the remaining (P-2) X variables is then fitted, and the next candidate for dropping is identified.
- (d) This process continues until no further X variables can be dropped.

# 9.5 Some Final Comments on Automatic Model Selection Procedures\*

#### 9.6 Model Validation

2. Model validation usually i	involves checking a	against
Three basic ways of valid	ating a regression model are:	
(a) Collection of	to check the model an	nd its predictive ability.
(b) of sults, and simulation	results with theoretical expect results.	cations, earlier empirical re-
(c) Use of a	to check the model and	d its
set is for	en: training set, testing set and (100%): e.g, training set (75%)	, , ,
	t (100%): $k$ -fold cross validation "testing set (25%), training set	
(c) A observed data set 4-fold CV)	t (100%): hold-out set (20%),	Not hold-out set (80% for
ollection of New Dat	a to Check Model	
1. The means of m	nodel validation is through the _	
	new data is to be able to exam	
model developed from th	e earlier data is still	. If

	so, one has assurance about the	of the model to	data beyond				
	tho, se on which the model is based.						
	Methods of Checking Validity. A means of measuring the						
	of the selected regression model is to use this model to predict each case in the new						
	data set and then to calculate the mean of the squared prediction errors, to be						
denoted by $MSPR$ , which stands for mean squared prediction error:							
	MSPR =						
	where:						
	• $Y_i$ is the value of the response variable in the $i$ th						
	$ullet$ $\hat{Y}_i$ is the for the $i$ th validation case based on the model-						
building dataset.							
	• $n^*$ is the number of cases in the validation data	a set.					
2.	If the mean squared prediction error $MSPR$ is fairly	y close to	based on				
	the regression fit to the	_, then the error	mean square				
	MSE for the selected regression model is		and gives an				
	appropriate indication of the predictive ability of th	e model.					
3.	If the mean squared prediction error is		, one should				
	ely on the mean squared prediction error as an indicator of how well the selected						
	regression model will predict in the future.						

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• **Problems**: 9.6, 9.11, 9.18, 9.21

• Exercises: none

• Projects: none