

5-1-2002

Modeling Strategies In Logistic Regression With *SAS, SPSS, Systat, BMDP, Minitab, And STATA*

Chao-Ying Joanne Peng
Indiana University, peng@indiana.edu

Tak-Shing Harry So
Indiana University

 Part of the [Applied Statistics Commons](#), [Social and Behavioral Sciences Commons](#), and the [Statistical Theory Commons](#)

Recommended Citation

Peng, Chao-Ying Joanne and So, Tak-Shing Harry (2002) "Modeling Strategies In Logistic Regression With *SAS, SPSS, Systat, BMDP, Minitab, And STATA*," *Journal of Modern Applied Statistical Methods*: Vol. 1 : Iss. 1 , Article 21.

STATISTICAL SOFTWARE APPLICATIONS & REVIEW

Modeling Strategies In Logistic Regression With *SAS, SPSS, Systat, BMDP, Minitab, And STATA*

Chao-Ying Joanne Peng
School of Education
Indiana University

Tak-Shing Harry So
School of Education
Indiana University

This paper addresses modeling strategies in logistic regression within the context of a real-world data set. Six commercially available statistical packages were evaluated in how they addressed modeling issues and in the accuracy of their regression results. Recommendations are offered for data analysts in terms of each package's strengths and weaknesses.

Keywords: Logistic regression, Analysis issues, Statistical packages, Binary outcome, Categorical variables, Statistical computing

Introduction

Among the variety of statistical methods that are employed to analyze social science data, regression methods are widely used in examining the relationship between an outcome variable and one or more predictor variables. One class of regression methods, logistic regression, is well suited for studying categorical or qualitative outcome variables. This technique is increasingly applied in social science research, especially in higher education (Austin, Yaffee, & Hinkle, 1992; Cabrera, 1994). Logistic regression textbooks by Hosmer and Lemeshow (2000), Kleinbaum (1994), McCullagh and Nelder (1989), and Menard (1995) have been published within the last thirteen years. Other textbooks of multivariate statistics (e.g., Afifi & Clark, 1990; Ryan, 1997; Tabachnick & Fidell, 1996) have begun to include chapters on logistic regression in their recent editions. Because logistic regression does not assume that data are drawn from a multivariate normal distribution with equal variances and covariances for all variables (Efron, 1975; Lei & Koehly, 2000; Press & Wilson, 1978), it is less restrictive than linear discriminant function analysis. Thus, social science researchers have recognized logistic regression as a viable method for handling categorical outcome variables.

Despite the simplicity of logistic regression and the ease with which researchers are able to implement this technique using statistical software, most researchers are unaware how a number of modeling issues are dealt with by statistical software. This paper addresses these issues within

the context of a real-world data set. Six statistical packages were compared and contrasted in how they addressed these issues and in the accuracy of logistic regression results. We conclude this paper by offering evaluations of the six packages for logistic regression.

Statistical Packages

Six logistic regression procedures/commands implemented in *SAS*, *SPSS*, *SYSTAT*, *BMDP*, *MINITAB*, and *STATA* were reviewed in order to understand how these popular and accessible packages handled logistic regression models:

- I. the LOGISTIC procedure in *SAS* Release 8,
- II. the LOGISTIC REGRESSION command in *SPSS* Release 10,
- III. the LOGIT command in *SYSTAT* Release 9,
- IV. the LR command in *BMDP* Release 7.1,
- V. the BLOGISTIC command in *MINITAB* Release 13, and
- VI. the LOGISTIC command in *STATA* Release 6.

For the purpose of discussion, statistical packages refer to *SAS*, *SPSS*, *SYSTAT*, *BMDP*, *MINITAB*, and *STATA* software. Procedure refers to a procedure or main command in a statistical package that performs logistic regression, such as the LOGISTIC procedure in *SAS*, the LOGISTIC REGRESSION command in *SPSS*, etc. (For clarity, variable names are written with an underscore, e.g., labor force paid = lfp.)

Two types of logistic regression models (direct and stepwise) were fit to these data. Direct modeling permits researchers to specify predictors that represent main effects and interactions according to a theory-based proposition. Stepwise modeling yields best models according to statistical software's internal criteria and restrictions. This modeling approach is largely atheoretical; its use is popular among researchers, yet controversial among methodologists.

Chao-Ying Joanne Peng, Counseling & Educational Psychology, School of Education, #4050, 201 N. Rose Ave., Indiana University, Bloomington, IN, 47405. Email: peng@indiana.edu. Tak-Shing Harry So is at Indiana University. The authors acknowledge Gary M. Ingersoll, Lisa Kurtz, Dan J. Mueller, Edward St. John, Dale Weigel, Jim Zhu, and Larry Hoezee for helpful comments.

Data

The “married women labor force participation” data (hereafter abbreviated as MWLFP) were provided by Mroz (1987). The data set contains profiles of 752 married white women who were recruited in 1975 for the Panel Study of Income Dynamics conducted at the University of Michigan. We were interested in explaining women’s decision to enter the paid labor force in 1975 with their demographic information. The outcome variable (*lfp*) was coded 1 for women who worked for pay in 1975 and 0 otherwise. The predictors were: the age of women (*age*), number of children under the age of 5 (*k5*), number of children between ages 6 and 18 (*k618*), the household’s total income minus the wife’s labor income (*inc*), the wife’s estimated wage rate (*wg*) plus two dichotomous variables indicating, respectively, whether the wife (*wc*) and the husband (*hc*) spent at least one year in college. Table 1 presents descriptive information of the eight variables.

Direct Modeling

A direct model (Model 1) was fit to the MWLFP data to explain the predicted odds of women entering the paid labor force (i.e., *lfp*=1) in 1975. This model included four main effects—*k5*, *k618*, *hc*, *wc*—plus one categorical variable (*newage*) and its interaction with *wc*.

Model 1:

$$\text{predicted logit (lfp=1)} = \alpha + \beta_1 \times k5 + \beta_2 \times k618 + \beta_3 \times \text{newage1} + \beta_4 \times \text{newage2} + \beta_5 \times \text{newage3} + \beta_6 \times \text{newage4} + \beta_7 \times \text{newage5} + \beta_8 \times hc + \beta_9 \times wc + \beta_{10} \times (wc * \text{newage1}) + \beta_{11} \times (wc * \text{newage2}) + \beta_{12} \times (wc * \text{newage3}) + \beta_{13} \times (wc * \text{newage4}) + \beta_{14} \times (wc * \text{newage5}).$$

The variable *newage* was transformed from the continuous variable *age* according to a 5-year increment (i.e., 30 to 34, 35 to 39, ..., and 55 to 60) with the last category (women older than 54 years old) designated as the reference group.

After specifying Model 1 into the six statistical packages, we obtained very similar estimates for parameters and standard errors. All predictors reached the significance level of 0.05, except for *k618*, *hc*, and the interactions of *wc* with *newage1* through *newage5* (Table 2). The result implied that the odds for married women to enter the paid labor force in 1975 were related to the number of young children (5 years old or under), their age groups, and whether women had some college education.

Tests of individual parameter estimates are performed either by the likelihood ratio test, the Wald statistic, or the Score test. According to Jennings (1986), Long (1997), and Tabachnick and Fidell (1996), the likelihood ratio test is more powerful than the Wald test while the Score test is a normal approximation to the likelihood ratio test. *BMDP*

is the only package that computes the likelihood ratio test. The other five perform the Wald test [Table 3 (III) Results]. For categorical predictors, *SAS*, *SPSS*, and *MINITAB* automatically perform an overall test of design variables transformed from the same categorical predictor. In *SYSTAT*, this test is requested by the *CONSTRAINT* subcommand. This subcommand may also be applied to test two or more slope parameters simultaneously against zero. An equivalent option (the *TEST* statement) is available in *SAS LOGISTIC*. Both *CONSTRAINT* and *TEST* work in stepwise modeling only if the multiple predictors, to be tested simultaneously, are already selected into the model.

Stepwise Modeling

As stated earlier, the application of stepwise modeling is controversial among methodologists since the inclusion or removal of predictors is based entirely on statistical criteria. The substantive importance of predictors is often overlooked in the process. Small differences in the criteria can have a great impact on those marginally significant predictors. Furthermore, any model determined by the stepwise algorithm is sample-bound and atheoretical. The most serious of all problems is the positive bias introduced into parameter estimates, as with the stepwise discriminant function analysis (Kromrey, Foster-Johnson, & Yi, 1997). Despite these criticisms, stepwise logistic modeling is a flourishing practice among higher education researchers (Peng, So, Stage, & St. John, 2002). As Tabachnick and Fidell (1996) explain, it can assist researchers in generating and screening hypotheses.

Forward stepwise, or simply stepwise, modeling is one of four model selection methods available in five statistical packages we examined [Table 3 (II) Model Specification]. *MINITAB* was excluded because it does not provide a selection method. The stepwise method begins with only a constant in the model. At each subsequent step, the most important+ predictor is added to the model. A predictor’s importance is determined by its criterion statistic. Only when the largest criterion statistic is tested to be significant according to a preset entry p-level, will its corresponding predictor be selected into the model. Otherwise, the selection process stops. As a predictor is added to the model, all predictors already in the model are simultaneously reassessed to determine if any of them meets the criterion for removal, again according to a preset removal p-level.

To implement stepwise modeling, we considered all effects already contained in Model 1, plus additional main effects and interactions: *inc*, *wg*, *wg2* (the squared value of *wg*), *wc*wg*, and *wc*wg2*. These interactions were included for the illustration of stepwise modeling only. Following suggestions from Hosmer and Lemeshow (2000), we adopted 0.15 and 0.20 as entry and removal p-levels,

respectively. Two models (2 and 3) were identified by five packages. Model 2—the model identified by *SAS* and *BMDP*—contained ten predictors while *SPSS*, *SYSTAT*, and *STATA* selected Model 3 with eleven predictors (Table 2). Nine predictors in both models were identical: *k5*, *newage1-newage5*, *inc*, *wg*, and *wg2*. Two predictors, *wc*wg* and *wc*wg2*, appeared only in Model 3, whereas *hc* appeared only in Model 2. The difference between these two models was caused by a modeling restriction imposed by *SAS* and *BMDP*. This restriction requires that all main-effects and lower-order interaction(s) be included in the model before a higher-order interaction is entered into the model. *SAS* and *BMDP* enforce this definition for hierarchical modeling during the model selection process while *MINITAB* and *STATA* do so only in direct modeling.

Which model, 2 or 3, is a better model for the data? To answer this question fully, one needs to examine multiple descriptive as well as inferential statistics. They are described below:

Descriptive statistics. The Akaike Information Criterion (AIC) and the Schwarz Criterion (SC) provided by *SAS* were used to compare different models derived from the same sample. A smaller value indicates a better fit. The AIC and SC values for Model 2 (787.446 and 838.296), Model 3 (719.743 and 775.216), and Model 1 (966.078 and 1035.238) indicated that either Model 2 or 3 outperformed Model 1. Furthermore, Model 3 was a better model than Model 2. Other measures, such as R^2 , Somers' D_{xy} , Gamma, Tau-a, and c statistics, also supported the same conclusions. Because Model 3 did not satisfy the hierarchical modeling restriction, we constructed one additional model—Model 4—for comparison with Model 3. Model 4 contained all predictors from Model 3 plus *wc*; it yielded similar values as Model 3 on all descriptive indices (Table 2).

Inferential statistics. Because Model 3 was nested in Model 4, we used the likelihood ratio test to test if the additional predictor (i.e., *wc*) had a zero coefficient (i.e., $H_0: \beta_{wc} = 0$). The likelihood ratio test is based on the difference (G) in the log-likelihood (LL) of both models. Under the null hypothesis that coefficients of additional predictors equal zero, the G statistic follows a chi-square distribution with degree(s) of freedom equal to the number of additional predictors. To test $H_0: \beta_{wc} = 0$, the G statistic equals $-2[-347.8715 - (-347.4725)] = 0.789$. Because the G statistic did not exceed the χ^2 critical value of 3.841 with 1 degree of freedom and alpha of 0.05, the null hypothesis was not rejected. We concluded that *wc* in Model 4 did not significantly improve the prediction. Hence, Model 3 was considered as good as Model 4 and better than either Model 1 or 2.

Evaluations of Six Logistic Regression Procedures

An ideal statistical package for logistic regression should be user-friendly and comprehensive in its options and output. Each package we examined possesses certain features of this ideal package. Table 3 summarizes features and options available in all six procedures. An evaluation of each is given below:

- I. *SAS* LOGISTIC is the most versatile procedure. Several selection methods are provided. Its ability to fit a broad class of binary response models, plus its provision to correct for over-sampling, over-dispersion, and bias introduced into predicted probabilities, sets it apart from the other five.
- II. With dazzling graphic interfaces, *SPSS* LOGISTIC REGRESSION and *SYSTAT* LOGIT are user-friendly. They provide several selection methods, yet their goodness-of-fit statistics and diagnostic statistics are calculated from individual observations. Hence, they should not be interpreted as chi-square values.
- III. *BMDP* LR performs logistic regression on covariate patterns. It is a stepwise procedure that provides the greatest flexibility in selecting the "best" set of predictors, under the hierarchical modeling restriction. Unfortunately, it does not compute diagnostic statistics recommended by Hosmer and Lemeshow (2000), such as change in Pearson chi-square, change in deviance, or change in parameter estimates.
 - I. *MINITAB* BLOGISTIC is the simplest to use. It adopts the hierarchical modeling restriction in direct modeling. However, the absence of predictor selection methods may make it less appealing to some researchers.
 - II. *STATA* LOGISTIC provides the most detailed information on parameter estimates, yet its goodness-of-fit indices are limited. Its command language is easy to learn. It generates high quality graphics with a single command. Model selections are carried out in two procedures: SW for stepwise selection and LOGISTIC for logistic regression modeling. Multicollinearity among predictors is examined automatically during stepwise modeling.

In sum, we recommend *MINITAB* and *STATA* for beginners. If either *SPSS* or *SYSTAT* is the only package available, researchers must be aware that both compute the goodness-of-fit and diagnostic statistics from individual observations. Consequently, these statistics are inappropriate for statistical tests. *SAS* and *BMDP* are more suitable for experienced researchers. Their options are versatile and

results are comprehensive and accurate. Last but not the least, researchers should always check default settings of a statistical package when performing logistic regression. Variations in results may be due to different defaults.

With the wide availability of sophisticated statistical software installed on high-speed computers, the anticipated use of logistic regression appears to be increasing. Researchers in social sciences are encouraged to apply this versatile technique fully to their data and evaluate competing models with supplementary statistics provided by statistical software.

References

- Afifi, A. A., & Clark, V. (1990). *Computer-aided multivariate analysis* (2nd ed.). New York, NY: Van Nostrand Reinhold.
- Austin, J. T., Yaffee, R. A., & Hinkle, D. E. (1992). Logistic regression for research in higher education. In J. C. Smart (ed.), *Higher education: Handbook of theory and research, Vol. VIII*, 379-410.
- BMDP (1992). *BMDP statistical software manual* (Vol. 2). Los Angeles, CA: BMDP Statistical Software, Inc.
- Cabrera, A. F. (1994). Logistic regression analysis in higher education: An applied perspective. In J. C. Smart (ed.), *Higher Education: Handbook of theory and research, Vol. X*, 225-256.
- Efron, B. (1975). The efficiency of logistic regression compared to normal discriminant analysis. *Journal of the American Statistical Association*, 70, 892-898.
- Homer, D. W., Jr., & Lemeshow, S. (2000). *Applied logistic regression* (2nd ed.). New York, NY: John Wiley & Sons, Inc.
- Jennings, D. E. (1986). Judging inference adequacy in logistic regression. *Journal of the American Statistical Association*, 81, 471-476.
- Kleinbaum, D. G. (1994). *Logistic regression: A self-learning text*. New York, NY: Springer-Verlag.
- Kromrey, J. D., Foster-Johnson, L., & Yi, Q. (1997, March). Statistical bias resulting from the use of variables selection algorithms in discriminant function analysis: What do stepwise-built models represent? Paper presented at the Annual Meeting of American Educational Research Association, Chicago, IL.
- Lei, P.-W., & Koehly, L. M. (April, 2000). Linear discriminant analysis versus logistic regression: A comparison of classification errors. Paper presented at the Annual Meeting of American Educational Research Association, New Orleans, LO.
- Long, J. S. (1997). *Regression models for categorical and limited dependent variables*. Thousand Oaks, CA: Sage.
- McCullagh, P., & Nelder, J. A. (1989). *Generalized linear models* (2nd ed.). London: Chapman & Hall.
- Menard, S. (1995). *Applied logistic regression analysis*. Sage University paper series on quantitative applications in the social sciences, 07-106. Thousand Oaks, CA: Sage.
- Minitab (2000). *MINITAB user's guide 2: Data analysis and quality tools, Release 13*. State College, PA: Minitab Inc.
- Mroz, T. A. (1987). The sensitivity of an empirical model of married women's hours of work to economic and statistical assumptions. *Econometrica*, 55, 765-799.
- Peng, C. Y., So, T. S., Stage, F. K., & St. John, E. P. (2002). The use and interpretation of logistic regression in higher education journals: *Research in Higher Education*, 43(3), 259-293.
- Press, S. J., & Wilson, S. (1978). Choosing between logistic regression and discriminant analysis. *Journal of the American Statistical Association*, 73, 699-705.
- Ryan, T. P. (1997). *Modern regression methods*. New York, NY: John Wiley & Son, Inc.
- SAS (1999). *SAS/STAT user's guide, version 8, volume 2*. Cary, NC: SAS Institute Inc.
- SPSS (1999a). *SPSS regression models 10*. Chicago, IL: SPSS Inc.
- SPSS (1999b). *SYSTAT 9.0 Statistics I*. Chicago, IL: SPSS Inc.
- Stata (1999). *STATA reference manual release 6* (Vols. 1-4). College Station, TX: Stata Press.
- Tabachnick, B. G., & Fidell, L. S. (1996). *Using multivariate statistics* (3rd ed.). New York, NY: Harper Collins.

Table 1

Descriptive Statistics for the Married Women Labor Force Participation Data

Variable Name	Mean	Standard Deviation	Minimum	Maximum	Description
<u>Lfp</u>					1 if wife is in the paid labor force; else=0
Full Sample	0.567	0.496	0	1	
<u>k5</u>					Number of children ages 5 or younger
Full Sample	0.238	0.524	0	3	
Working Women	0.141	0.392	0	2	
Non-working Women	0.366	1.327	0	3	
<u>k618</u>					Number of children ages 6 to 18
Full Sample	1.352	1.321	0	8	
Working Women	1.349	1.317	0	8	
Non-working Women	1.357	1.327	0	7	
<u>Age</u>					Wife's age in years
Full Sample	42.547	8.073	30	60	
Working Women	41.988	7.722	30	60	
Non-working Women	43.283	8.468	30	60	
<u>Wc</u>					1 if wife attended college; else 0
Full Sample	0.281	0.450	0	1	
Working Women	0.335	0.473	0	1	
Non-working Women	0.209	0.407	0	1	
<u>Hc</u>					1 if husband attended college; else 0
Full Sample	0.392	0.489	0	1	
Working Women	0.415	0.493	0	1	
Non-working Women	0.363	0.482	0	1	
<u>Wg</u>					Wife's estimated wage rate
Full Sample	3.56	2.64	0.13	25.00	
Working Women	4.17	3.31	0.13	25.00	
Non-working Women	2.76	0.81	0.99	5.80	
<u>Inc</u>					Family income excluding wife's wages (in \$1,000)
Full Sample	20.156	11.619	1.120	96	
Working Women	18.981	10.564	1.120	91	
Non-working Women	21.698	12.728	1.500	96	

Note. Full Sample: N=752. Working Women Sample: n=427. Non-working Women Sample: n=325

Table 2

Summary of Models 1, 2, 3, and 4

	Model 1	Model 2 ^a	Model 3 ^b	Model 4
CONSTANT	-0.5935 (0.3325) ^c	3.4100 (0.7113) ^c	7.0724 (1.0463) ^c	6.5700 (1.1705) ^c
<u>k5</u>	-1.3710** (0.1955) ^c	-1.5196** (0.2300) ^c	-1.3861** (0.2290) ^c	-1.4038** (0.2319) ^c
<u>k618</u>	-0.1097 (0.0703) ^c	--	--	--
<u>age</u>				
<u>newage1 (age<=34)</u>	1.8425** (0.4271) ^c	1.7787** (0.4096) ^c	1.8844** (0.4348) ^c	1.8582** (0.4348) ^c
<u>newage2 (34<age<=39)</u>	1.6956** (0.4331) ^c	1.3882** (0.3947) ^c	1.5615** (0.4210) ^c	1.5391** (0.4205) ^c
<u>newage3 (39<age<=44)</u>	1.1662** (0.4175) ^c	1.0839** (0.3888) ^c	1.0523** (0.4132) ^c	1.0289* (0.4128) ^c
<u>newage4 (44<age<=49)</u>	0.9405* (0.3854) ^c	1.0950** (0.3761) ^c	1.1647** (0.4030) ^c	1.1401** (0.4026) ^c
<u>newage5 (49<age<=54)</u>	0.4613 (0.3999) ^c	0.5016 (0.3937) ^c	0.3819 (0.4216) ^c	0.3669 (0.4207) ^c
<u>hc</u>	-0.1205 (0.1938) ^c	0.3230 (0.2083) ^c	--	--
<u>inc</u>	--	-0.0372** (0.00967) ^c	-0.0325** (0.00931) ^c	-0.0359** (0.01) ^c
<u>wc</u>	1.3834* (0.6541) ^c	--	--	2.1547 (2.5187) ^c
<u>wg</u>	--	-2.9908** (0.4517) ^c	-6.6937** (0.8214) ^c	-6.2739** (0.9306) ^c
<u>wg2</u>	--	0.5473** (0.0747) ^c	1.3500** (0.1614) ^c	1.2723** (0.1800) ^c
<u>wc*wg</u>	--	--	2.6923** (0.3925) ^c	1.4177 (1.5160) ^c
<u>wc*wg2</u>	--	--	-0.8025** (0.1150) ^c	-0.6186** (0.2373) ^c
<u>wc*age</u>				
<u>wc*newage1</u>	-0.5837 (0.7544) ^c	--	--	--
<u>wc*newage2</u>	-0.7515 (0.7788) ^c	--	--	--
<u>wc*newage3</u>	-0.9163 (0.7637) ^c	--	--	--
<u>wc*newage4</u>	-0.0448	--	--	--

<u>wc*newage5</u>	(0.7769) ^c -0.4655 (0.7934) ^c	--	--	--
Likelihood Ratio Test	92.538** (<u>df</u> = 14)	263.1693** (<u>df</u> = 10)	332.8725** (<u>df</u> = 11)	333.671** (<u>df</u> = 12)
Score Test	87.547** (<u>df</u> = 14)	136.975** (<u>df</u> = 10)	137.0647** (<u>df</u> = 11)	147.8995** (<u>df</u> = 12)
Wald Test	76.838** (<u>df</u> = 14)	108.2304** (<u>df</u> = 10)	120.1213** (<u>df</u> = 11)	118.6195** (<u>df</u> = 12)
Akaike's Criterion (AIC)	966.078	787.446	719.743	720.945
Schwarz Criterion (SC)	1035.238	838.296	775.216	781.041
Somers' <u>D</u> _{xy}	0.397	0.638	0.688	0.687
Gamma	0.405	0.639	0.689	0.688
Kendall's Tau- <u>a</u>	0.195	0.314	0.338	0.338
<u>c</u> statistic	0.698	0.819	0.844	0.844

Note. Results were reported by SAS LOGISTIC unless noted otherwise.

^aBased on a stepwise model suggested by SAS and BMDP.

^bBased on a stepwise model suggested by SPSS, SYSTAT, and STATA.

^cThe number in parentheses is the standard error for the parameter.

* $p < 0.05$. ** $p < 0.01$.

Table 3.

Options and Features Available in Six Statistical Packages for Logistic Regression (Continued)

Features		Diagnostic statistics calculation depends on data formats	Diagnostic statistics calculation based on observations		Diagnostic statistics calculation based on covariate patterns		
		SAS LOGISTIC	SPSS LOGISTIC REGRESSION	SYSTAT LOGIT	BMDP LR	MINITAB BLOGISTIC	STATA LOGISTIC
Selection of predictors							
Selection methods—	1. Forward 2. Backward	1, 2	NA	NA	1, 2	NA	1, 2
Stepwise methods—	1. Forward stepwise (Fstep) 2. Backward stepwise (Bstep)	1	1, 2	1, 2	1, 2	NA	1, 2
Selection criteria—	Stepwise based on 1. Conditional 2. Likelihood ratio 3. Wald statistic 4. Score statistic 5. Maximum likelihood ratio 6. ACE (Est. asymptotic covariance matrix of β 's)	1	1, 2, 3	4. for Fstep 3. for Bstep	5, 6	NA	2, 3
	Probability enter (default)	0.05	0.05	0.05	0.10	NA	No default
	Probability remove (default)	0.05	0.10	0.10	0.15	NA	No default
Other modeling methods—	Force entry of selected predictors	Yes	Yes	Yes	Yes	NA	Yes
	The best k-predictors model	Yes	No	No	No	NA	No
	Sequential modeling	Yes	Yes	No	No	NA	Yes (HIER)
	Hierarchical modeling	Yes	No	No	Yes	NA	No
	Starting and stopping with k-predictors in selection	Yes	No	No	No	NA	No
(III) Results							
Evaluations of the model	Log-likelihood (LL) or -2 Log-likelihood (-2LL) for intercept-only model	-2LL	-2LL	LL	No	No	No
	Log-likelihood (LL) or -2 Log-likelihood (-2LL) for intercept with predictors model	-2LL	-2LL	LL	LL	LL	LL
	Akaike Information Criterion (AIC)	Yes	No	No	No	No	No
	Score Statistic	Yes	Yes	No	No	No	No
	Schwartz Criterion (SC)	Yes	No	No	No	No	No
	Wald test	Yes	No	No	No	No	No
	Residual chi-square performed for selection methods only	Yes	Yes	No	No	NA	No
	Test of variable not in the model performed for selection methods only	Score test	Score test	Score test	App. χ^2 or F	NA	z-test
	Test of variable in the model performed for the full model and stepwise models	Wald test	Wald test	t-ratio	Coeff/SE	NA	z-test

Table 3

Options and Features Available in Six Statistical Packages for Logistic Regression (Continued)

Features		Diagnostic statistics calculation depends on data formats	Diagnostic statistics calculation based on observations		Diagnostic statistics calculation based on covariate patterns		
		SAS LOGISTIC	SPSS LOGISTIC REGRESSION	SYSTAT LOGIT	BMDP LR	MINITAB BLOGISTIC	STATA LOGISTIC
Selection of predictors							
Selection methods—	Forward Backward		NA	NA		NA	
Stepwise methods—	Forward stepwise (Fstep) Backward stepwise (Bstep)					NA	
Selection criteria—	Stepwise based on Conditional Likelihood ratio Wald statistic Score statistic Maximum likelihood ratio ACE (Est. asymptotic covariance matrix of β 's)			for Fstep for Bstep		NA	
	Probability enter (default)	0.05	0.05	0.05	0.10	NA	No default
	Probability remove (default)	0.05	0.10	0.10	0.15	NA	No default
Other modeling methods—	Force entry of selected predictors	Yes	Yes	Yes	Yes	NA	Yes
	The best k-predictors model	Yes	No	No	No	NA	No
	Sequential modeling	Yes	Yes	No	No	NA	Yes (HIER)
	Hierarchical modeling	Yes	No	No	Yes	NA	No
	Starting and stopping with n-predictors in selection	Yes	No	No	No	NA	No
(III) Results							
Evaluations of the model	Log-likelihood (LL) or -2 Log-likelihood (-2LL) for intercept-only model	-2LL	-2LL	LL	No	No	No
	Log-likelihood (LL) or -2 Log-likelihood (-2LL) for intercept with predictors model	-2LL	-2LL	LL	LL	LL	LL
	Akaike Information Criterion (AIC)	Yes	No	No	No	No	No
	Score Statistic	Yes	No	No	No	No	No
	Schwartz Criterion (SC)	Yes	No	No	No	No	No
	Wald test	Yes	No	No	No	No	No
	Residual chi-square performed for selection methods only	Yes	Yes	No	No	NA	No
	Test of variable not in the model performed for selection methods only	Score test	Score test	Score test	App. χ^2 or F	NA	z-test
	Test of variable in the model performed for the full model and stepwise models	Wald test	Wald test	t-ratio	Coeff/SE	NA	z-test

Table 3

Options and Features Available in Six Statistical Packages for Logistic Regression (Continued)

Features		Diagnostic statistics calculation depends on data formats	Diagnostic statistics calculation based on observations		Diagnostic statistics calculation based on covariate patterns		
		SAS LOGISTIC	SPSS LOGISTIC REGRESSION	SYSTAT LOGIT	BMDP LR	MINITAB BLOGISTIC	STATA LOGISTIC
(III) Results (Continued)							
Statistics related to regression coefficient estimates	Standard error of the regression coefficient	Yes	Yes	Yes	Yes	Yes	Yes
	Robust estimate of variance for the coefficients	No	No	No	No	No	Yes
	Goodness-of-fit chi-square test for individual predictor in the specified model	No	Yes (LR)	No	Yes	No	No
	Can perform a combined test on design variables	Yes	Yes	Yes	Yes	Yes	No
	Can perform a combined test on two or more predictors	Yes	No	Yes	No	No	No
	Regression coefficient divided by standard error	Wald Chi-square	Wald Chi-square	t-ratio	Coeff/SE	z-ratio	z-ratio
	Probability value of coefficient divided by standard error	Yes	Yes	Yes	No	Yes	Yes
	Confidence interval of the regression coefficient	Yes (CLPARM=)	No	No	No	No	Yes
	Odds ratio or exp(β)	Odds ratio	exp(β)	Odds ratio	exp(β)	Odds ratio	Odds ratio
	Confidence interval of the odds ratio or exp(β)	Yes (CLODDS=)	Yes	Yes	Yes	Yes	Yes
	Can set the significant level for the confidence intervals	Yes (ALPHA=)	Yes (CI(#))	No	Yes (CONF=#)	No	Yes (LEVEL(#))
	Partial correlation between outcome and each predictor	No	Yes	No	No	No	No
	Correlations among regression coefficients	Yes (CORRB)	Yes	No	Yes	No	Yes (VCE, CORR)
	Covariances among regression coefficients	Yes (COVB)	No	No	Yes	Yes	Yes (VCE)
Confidence interval displacement diagnostics for each observation	Yes	No	No	No	No	No	