Example 2 – Subset Selection

This section presents an example of how to conduct a subset selection. The data used are stored in the Leukemia dataset. This analysis will search for the best model from among a pool of the six numeric variables.

Setup

To run this example, complete the following steps:

1 Open the Leukemia example dataset

- From the File menu of the NCSS Data window, select **Open Example Data**.
- Select **Leukemia** and click **OK**.

2 Specify the Logistic Regression procedure options

- Find and open the **Logistic Regression** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 2a** settings template. To load this template, click **Open Example Template** in the Help Center or File menu.

<u>Option</u>	<u>Value</u>
Variables, Model Tab Y Numeric X's Terms.	Cell, Smear, Infil, LI, Blast, Temp
Subset Selection Tab Search for the Best Subset from the X's	
Search Method Stop search when number of terms reaches	Hierarchical Forward Selection 6
Reports Tab	
Run Summary	Checked
Subset Summary	Checked
Subset Detail	Checked
Coefficient Significance Tests	Checked
All Other Reports	Unchecked
Plots Tab All Plots	Unchecked
Report Options (in the Toolbar) Variable Labels	Column Names

3 Run the procedure

• Click the **Run** button to perform the calculations and generate the output.

Run Summary

'Variable Reference Value	Remiss		
Reference Value		Rows Processed	29
	0	Rows Used	27
Number of Y-Values	2	Rows for Validation	0
requency Variable	None	Rows X's Missing	2
Numeric X Variables	6	Rows Freq Miss. or 0	0
Categorical X Variables	0	Rows Prediction Only	0
inal Log Likelihood	-10.87752	Unique Rows (Y and X's)	27
Model R ²	0.36707	Sum of Frequencies	27
Actual Convergence	2.081623E-06	Likelihood Iterations	9
arget Convergence	1E-06	Maximum Iterations	20
Model D.F.	6	Completion Status	Quasi-Separation
Priors	Equal		
Subset Selection Method	Hierarchical Forwa	rd Selection	

The first thing we notice is the warning message about quasi-separation. If quasi-separation occurs, the maximum likelihood estimates do not exist and all results are suspect. We note that 9 likelihood iterations occurred and the Actual Convergence is near the Target Convergence. We decide to rerun the analysis after resetting the Max Terms in Subset box from 6 to 5. Note that this error message often occurs when a small set of data is fit with a model with too many terms.

At this point, reset the value for **Stop search when number of terms reaches** (on the Subset Selection tab) to **5** manually or load the template **Example2b**. Now, rerun the analysis.

Run Summary

Item	Value	Item	Value
Y Variable	Remiss	Rows Processed	29
Reference Value	0	Rows Used	27
Number of Y-Values	2	Rows for Validation	0
Frequency Variable	None	Rows X's Missing	2
Numeric X Variables	6	Rows Freq Miss. or 0	0
Categorical X Variables	0	Rows Prediction Only	0
Final Log Likelihood	-10.92900	Unique Rows (Y and X's)	27
Model R ²	0.36407	Sum of Frequencies	27
Actual Convergence	7.136538E-07	Likelihood Iterations	7
Target Convergence	1E-06	Maximum Iterations	20
Model D.F.	5	Completion Status	Normal Completion
Priors	Equal		
Subset Selection Method	Hierarchical Forwar	d Selection	

The warning message has disappeared and the algorithm finished normally.

Subset Selection Summary

Subset Selection Summary ——

Subset Selection Method = Hierarchical Forward Selection

No. Terms	No. X's	Log Likelihood	R² Value	R² Change
1	1	-17.18588	0.00000	0.00000
2	2	-13.03648	0.24144	0.24144
3	3	-12.17036	0.29184	0.05040
4	4	-10.97669	0.36130	0.06946
5	5	-10.92900	0.36407	0.00277

This report shows the best log-likelihood value for each subset size. In this example, it appears that four terms (the intercept and three variables) provides the best model. Note that adding the fifth variable does not increase the R-squared value very much.

No. Terms

The number of terms. Note that this includes the intercept.

No. X's

The number of *X*'s that were included in the model. Note that in this case, the number of terms matches the number of *X*'s. This would not be the case if some of the terms were categorical variables.

Log Likelihood

This is the value of the log likelihood function evaluated at the maximum likelihood estimates. Our goal is to find a subset size above which little is gained by adding more variables.

R² Value

This is the value of R^2 calculated using the formula

$$R_L^2 = \frac{L_p - L_0}{L_0 - L_S}$$

as discussed in the introduction. We are looking for the subset size at which this value does not increase by a meaningful amount.

R²

This is the increase in R^2 that occurs when each new subset size is reached. Search for the subset size below which the R^2 value does not increase by more than 0.02 for small samples or 0.01 for large samples.

In this example, the optimum subset size appears to be four terms.

Subset Selection Detail

	Selection I		archical For	ward Selection		
Step	Action	No. of Terms	No. of X's	Log Likelihood	Term Entered	Term Removed
1	Add	1	1	-17.18588	Intercept	
2	Add	2	2	-13.03648	LI .	
3	Add	3	3	-12.17036	Cell	
4	Add	4	4	-10.97669	Temp	
5	Add	5	5	-10.92900	Smear	

This report shows the highest log likelihood for each subset size. In this example, it appears that four terms (the intercept and three variables) provide the best model. Note that adding the fifth variable does not increase the *R*-squared value very much.

Action

This item identifies the action that was taken at this step. A term was added, removed, or two were switched.

No. Terms

The number of terms. Note that this includes the intercept.

No. X's

The number of *X*'s that were included in the model. Note that in this case, the number of terms matches the number of *X*'s. This would not be the case if some of the terms were categorical variables.

Log Likelihood

This is the value of the log likelihood function after the completion of this step. Our goal is to find a subset size above which little is gained by adding more variables.

Terms Entered and Removed

These columns identify the terms added, removed, or switched.

Discussion of Example 2

After considering these reports, it was decided to include Cell, LI, and Temp in the final logistic regression model. Another run should now take place using only these independent variables. A complete residual analysis is necessary before the equation is finally adopted.

Example 3 - One Categorical X Variable

The independent variables in logistic regression may be categorical as well as numerical. This example is of the simplest categorical case of a binary response and a binary independent variable. More complicated examples will be shown below.

In this example, a simple yes-no question is asked of each member of two groups. The following two-by-two table presents the results. The analyst wants to understand the relationship between group membership and response to the question.

	Resp	onse	
Group	Yes	No	Total
Α	91	9	100
В	93	27	120
Total	184	36	220

These data would normally be analyzed using the methods for comparing two proportions such as Fisher's exact test or the chi-square test for independence in a contingency table. The following table presents the results of this analysis.

Two Proportions Output

Counts and Proportion	ns					
	Respons	<u>e</u>				
Group No Count 9 B 27	Yes Count 91 93	100	Proportion* p1 = 0.0900 p2 = 0.2250			
* Proportion = No / Tota	ıl					
Proportions Analysis						
Statistic Group 1 Event Rate (p1 Group 2 Event Rate (p2 Absolute Risk Difference Number Needed to Trea Relative Risk Reduction Relative Risk p1/p2 Odds Ratio o1/o2	t) e p1 - p2 at 1/ p1 - p2 ı p1 - p2 /p2	Value 0.0900 0.2250 0.1350 7.41 0.60 0.40 0.34				
Two-Sided Tests of the H0: P1 = P2 vs. Ha: P1		P1 - P2)				
Test Statistic Name Wald Z 0.09 Fisher's Exact 0.09		0 -0.1350	Value -2.695	Prob Level 0.0070 0.0097	Reject H0 at α = 0.05? Yes Yes	

The conclusion of this analysis is to reject the null hypothesis that the two proportions are equal. The significance levels are 0.0097 using Fisher's exact test and 0.0070 using the normal approximation which is equivalent to the chi-square test for independence. Note that the odds ratio is 0.34.

We will now see how to analyze these data using logistic regression. The data must be entered into a database so that they can be processed. The following table shows how these data are rearranged and entered. These data have been entered into a database named 2BY2.

2By2 dataset (subset)

Group	Response	Count
Α	No	9
Α	Yes	91
В	No	27
В	Yes	93

Setup

To run this example, complete the following steps:

1 Open the 2By2 example dataset

- From the File menu of the NCSS Data window, select **Open Example Data**.
- Select 2By2 and click OK.

2 Specify the Logistic Regression procedure options

- Find and open the **Logistic Regression** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 3** settings template. To load this template, click **Open Example Template** in the Help Center or File menu.

<u>Option</u>	<u>Value</u>
Variables, Model Tab	
Υ	. Response
Categorical X's	. Group
Default Recoding Scheme	. Binary
Frequencies	. Count
Priors	Equal across Y Values
Reports Tab	
Run Summary	. Checked
Y Variable Summary	. Checked
Coefficient Significance Tests	. Checked
Odds Ratios	. Checked
Analysis of Deviance	. Checked
Log-Likelihood and R ²	
All Other Reports	District and and

3 Run the procedure

• Click the **Run** button to perform the calculations and generate the output.

Logistic Regression Output

Run Summar	у							
Item Y Variable Reference Val Number of Y-V Frequency Val Numeric X Van Categorical X Final Log Likel Model R ² Actual Conver Target Conver Model D.F. Priors	Values riable riables Variables lihood	No 2 Col 0 1 -94 0.0	.23344 6908 59022E-11	Row Row Row Row Uniq Sum Likel	s Processed s Used s for Validat s X's Missin s Freq Miss s Prediction ue Rows (Y of Frequen ihood Iterati mum Iterati pletion Stat	cion g . or 0 Only and X's) cies ions ons	Val 4 4 0 0 0 0 0 4 220 6 20 Not	
Y Variable Su	ımmary —			 				
Y Response No Yes Total	Count 36 184 220		ique ows X's) Pro 2 2 4	Y oportion 0.16364 0.83636	Y Prior 0.50000 0.50000			Percent Correctly Classified 75.000 49.457 53.636
Coefficient Si	ignificanc	e Tests -						
Independent Variable X Intercept (Group="B")	Coeff 0.	ession ficient b(i) 68222 .07687	Standard Error Sb(i) 0.29814 0.41218	Z-Value H0: β=0 2.288	P-Val	.12 1.	Odds Ratio p(b(i)) 97826 34066	
Independent Variable X Intercept (Group="B")	Coeff 0.	ession ficient b(i) .68222 .07687	Odds Ratio Exp(b(i)) 1.97826 0.34066	Lower 99 Confiden Lin 1.102 0.151	nce Co mit 182	oper 95% nfidence Limit 3.54863 0.76413		
Analysis of D	eviance -							
Term Omitted All Group None(Model)	DF 1 1 1	Deviar 196.086 196.086 188.466	Fro E 10ce 1640 1640	Increase m Model Deviance (Chi²) 7.61951 7.61951	P-Value 0.00577 0.00577			
Log Likelihoo	od & R² —							
Term(s) Omitted All Group None(Model) None(Saturate	DF 1 1 1 ed) 4	-9 -9 -9	Log relihood 8.04320 8.04320 4.23344 2.89226	R ² of Remaining Term(s) 0.00000 0.00000 0.06908 1.00000	Moc 0 0 0 0 0 0	ction From Iel R ² 06908 00000	Satura 1 0	Juction From ated R ² .00000 .93092 .00000

Although a casual comparison between this report and that of the Two Proportion procedure shows little in common, a more detailed report shows many similarities. First of all, notice that the significance level of the test of GROUP in the Analysis of Deviance Section of 0.00577 compares very closely with the 0.007037 from the

NCSS Statistical Software Logistic Regression

chi-square test. Also notice that the odds ratios from both reports round to 0.34066. The confidence limits of these two reports are not exactly the same, but they are close.

To summarize the logistic regression analysis, we can conclude that there is a significant relationship between response and group.

This example has shown the similarities between these two approaches to the analysis of two proportions. Usually, you would analyze these data using the two proportions approach. However, that approach is not as easily extended to the case of several independent variables including a mixture of categorical and numeric.

Example 4 - Logit Model Validation with BMDP PR

This example will serve three purposes. First of all, it will be the first example of a dataset whose Y variable has more than two outcomes. Second, it will be an example of what the output looks like when all of the independent variables are categorical. And finally, it will validate the procedure by allowing the comparison of the **NCSS** output with that of the **BMDP PR** program which also performs multiple-group logistic regression. This example comes from the **BMDP** manual. The database containing the data used in this example is named NC Criminal

The NC Criminal dataset contains data that will be used to study the relationship between a cases verdict and three factors: race, county, and type of offense. The variables that are on the database are as follows.

Count contains the number of individuals with the characteristics specified on that row.

Verdict is the response variable. Three outcomes are given in the database: *G* for guilty, *NG* for not guilty, and *NP* for not prosecuted.

Race gives the race of the individual. It has two values: A and B.

County refers to county in North Carolina in which the offense was considered. The possible values are: *Durham* and *Orange*.

Offense contains the particular offense that the individual was accused of. These are *Drunk*, *Violence*, *Property*, *Major Traffic*, and *Speeding*.

You can view the data by loading the NC Criminal dataset, so they will not be displayed here.

Setup

To run this example, complete the following steps:

1 Open the NC Criminal example dataset

- From the File menu of the NCSS Data window, select Open Example Data.
- Select NC Criminal and click OK.

2 Specify the Logistic Regression procedure options

- Find and open the **Logistic Regression** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 4** settings template. To load this template, click **Open Example Template** in the Help Center or File menu.

<u>Option</u>	<u>Value</u>
Variables, Model Tab	
Υ	. Verdict
Reference Value	. NP
Categorical X's	. Race(B;A) County(B;Durham) Offense(B;Drunk)
Frequencies	. Count
Priors	. Ni/N (Y-Value Proportions)
Reports Tab	
Run Summary	. Checked
Y Variable Summary	. Checked
Coefficient Significance Tests	. Checked
Analysis of Deviance	. Checked
Log-Likelihood and R ²	. Checked
All Other Reports	. Unchecked

3 Run the procedure

• Click the **Run** button to perform the calculations and generate the output.

Logistic Regression Output

tem	Value		Item		Value	
Y Variable	Verdic		Rows Process	ed	60	
Reference Value	NP	,,	Rows Used	eu	57	
Number of Y-Values	3		Rows for Valid	ation	0	
Frequency Variable	Count		Rows X's Miss		0	
Numeric X Variables	0		Rows Freq Mis	U	3	
Categorical X Variable	-		Rows Prediction		0	
Final Log Likelihood	-408.2	0185	Unique Rows (60	
Model R ²	0.6977		Sum of Freque		615	
Actual Convergence		915E-11	Likelihood Itera		6	
Farget Convergence	1E-06		Maximum Itera		20	
Model D.F.	14		Completion Sta			I Completion
Priors	Ni/N		Completion St	atus	Noma	Completion
۲ Variable Summarر	<i>1</i>					
Turidoic Gariniar	, Unique				R²	Percent
Y	Rows		Y Y	(Y vs Pr		Correctly
ı ∕erdict Count	(Y and X's)		-	Probabil		Classified
G 445	20			0.17		93.933
NG 123	20			0.10		20.325
	20	0.200	0.20000	0.10	001	20.020
√P 47	20	0.076	42 0.07642	0.06	628	0.000
Total 615	20 60		0.07642	0.06	628	0.000 72.033
Total 615 Coefficient Significandependent Rough	60		Wald Z-Value	0.06	628 Odc Rati	72.033 ds
Total 615 Coefficient Significandependent Rough	60 ance Tests — egression	Standard	Wald		Odd	72.033 ds io
Coefficient Significandependent Royariable Coefficient Coefficient Significant Royariable Coefficient Royariable C	egression coefficient b(i)	Standard Error	Wald Z-Value	Wald	Odo Rati Exp(b(i	72.033 ds io i))
Fotal 615 Coefficient Significate Independent Row Variable Communication Kuntercept G	60 ance Tests — egression Coefficient	Standard Error	Wald Z-Value	Wald	Odc Rati	72.033 ds io i))
Fotal 615 Coefficient Significate Independent Row Variable Coefficient K ntercept G NG	egression coefficient b(i)	Standard Error Sb(i)	Wald Z-Value H0: β=0	Wald P-Value	Odo Rati Exp(b(i	72.033 ds io ii))
Fotal 615 Coefficient Significate Independent Row Variable Coefficient K ntercept G NG	egression Coefficient b(i) 2.82983	Standard Error Sb(i) 0.44457	Wald Z-Value H0: β=0 6.365	Wald P-Value 0.00000	Odo Rati Exp(b(i	72.033 ds io ii))
Coefficient Significandependent Royariable Coefficient G NG (Race="B")	egression Coefficient b(i) 2.82983	Standard Error Sb(i) 0.44457	Wald Z-Value H0: β=0 6.365	Wald P-Value 0.00000	Odo Rati Exp(b(i	72.033 ds io ii)) 53
Coefficient Significandependent Royariable Coefficient G NG Race="B")	egression Coefficient b(i) 2.82983 1.24012	Standard Error Sb(i) 0.44457 0.48781	Wald Z-Value H0: β=0 6.365 2.542	Wald P-Value 0.00000 0.01102	Odc Rati Exp(b(i 16.9425 3.4560	72.033 ds io ii)) 53 04
Coefficient Significandependent Royariable Coefficient G NG (Race="B") G NG	egression coefficient b(i) 2.82983 1.24012 0.26083	Standard Error Sb(i) 0.44457 0.48781 0.33984	Wald Z-Value H0: β=0 6.365 2.542 0.767	Wald P-Value 0.00000 0.01102 0.44279	Odc Rati Exp(b(i 16.9425 3.4560	72.033 ds io ii)) 53 04
Coefficient Significandependent Royariable Coefficient G NG (Race="B")	egression coefficient b(i) 2.82983 1.24012 0.26083	Standard Error Sb(i) 0.44457 0.48781 0.33984	Wald Z-Value H0: β=0 6.365 2.542 0.767	Wald P-Value 0.00000 0.01102 0.44279	Odc Rati Exp(b(i 16.9425 3.4560	72.033 ds iio ii)) 53 04
Coefficient Significandependent Revariable Coefficient Significander Coefficient Signification Coefficient Coeffic	egression Coefficient b(i) 2.82983 1.24012 0.26083 -0.10324	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285	Wald P-Value 0.00000 0.01102 0.44279 0.77579	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019	72.033 ds io ii) 53 04 00 91
Coefficient Significandependent Revariable Coefficient Significand Revariable Coefficient Significand Revariable Coefficient Significant Revariable Coefficient Significant Revariable Reva	egression coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285	Wald P-Value 0.00000 0.01102 0.44279 0.77579	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019	72.033 ds io ii) 53 04 00 91
Coefficient Significandependent Revariable Coefficient Significand Revariable Coefficient Significand Revariable Coefficient Significant Revariable Revari	egression coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285	Wald P-Value 0.00000 0.01102 0.44279 0.77579	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019	72.033 ds io io ii)) 53 04 00 91 23 37
Coefficient Significand Protection Coefficient Significand Protect Coefficient	egression Coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719 0.36036	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285 -2.657 -0.338	Wald P-Value 0.00000 0.01102 0.44279 0.77579 0.00788 0.73547	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019 0.4082 0.8853	72.033 ds io io i)) 53 04 00 91 23 37
Coefficient Significand Processing Coefficient Significand Processing Coefficient Signification Coefficient Coefficient Signification Coefficient Coef	egression Coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175 -0.21380	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719 0.36036 0.62893	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285 -2.657 -0.338 -0.340	Wald P-Value 0.00000 0.01102 0.44279 0.77579 0.00788 0.73547 0.73390	Oddc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019 0.4082 0.8853 0.8075	72.033 ds io io i)) 53 04 00 91 23 37
Coefficient Significat Independent Rowariable Coefficient Significat Independent Rowariable Coefficient Signification Co	egression Coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175 -0.21380	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719 0.36036 0.62893	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285 -2.657 -0.338 -0.340	Wald P-Value 0.00000 0.01102 0.44279 0.77579 0.00788 0.73547 0.73390	Oddc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019 0.4082 0.8853 0.8075	72.033 ds io ii)) 53 04 00 91 23 37 51 27
Coefficient Significat Independent Roward R	egression coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175 -0.21380 0.48012	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719 0.36036 0.62893 0.67038	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285 -2.657 -0.338 -0.340 0.716	Wald P-Value 0.00000 0.01102 0.44279 0.77579 0.00788 0.73547 0.73390 0.47387	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019 0.4082 0.8853 0.8075 1.6162	72.033 ds io ii)) 53 04 00 91 23 37 51 27
Total 615 Coefficient Significat Independent Independ	egression coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175 -0.21380 0.48012 -0.91853	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719 0.36036 0.62893 0.67038	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285 -2.657 -0.338 -0.340 0.716 -1.590	Wald P-Value 0.00000 0.01102 0.44279 0.77579 0.00788 0.73547 0.73390 0.47387 0.11193	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019 0.4082 0.8853 0.8075 1.6162	72.033 ds io ii)) 53 04 00 91 23 37 51 27
Coefficient Signification of the coefficient Signification of the coefficient Signification of the coefficient Signification of the coefficient of	egression coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175 -0.21380 0.48012 -0.91853	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719 0.36036 0.62893 0.67038	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285 -2.657 -0.338 -0.340 0.716 -1.590	Wald P-Value 0.00000 0.01102 0.44279 0.77579 0.00788 0.73547 0.73390 0.47387 0.11193	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019 0.4082 0.8853 0.8075 1.6162	72.033 ds io ii) 53 04 00 91 23 37 51 27 11 32
Coefficient Significand Property (Coefficient Significand Property (Coeffi	egression coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175 -0.21380 0.48012 -0.91853 0.00928	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719 0.36036 0.62893 0.67038 0.57784 0.61911	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285 -2.657 -0.338 -0.340 0.716 -1.590 0.015	Wald P-Value 0.00000 0.01102 0.44279 0.77579 0.00788 0.73547 0.73390 0.47387 0.11193 0.98804	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019 0.4082 0.8853 0.8075 1.6162 0.3991 1.0093	72.033 ds io i)) 53 04 00 91 23 37 51 27 11 32 26
Coefficient Significandependent Refariable Coefficient Significandependent Refariable Coefficient Significandependent Refariable Coefficient Significant Significa	egression Coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175 -0.21380 0.48012 -0.91853 0.00928 0.49546 -0.26697	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719 0.36036 0.62893 0.67038 0.57784 0.61911	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285 -2.657 -0.338 -0.340 0.716 -1.590 0.015 0.967	Wald P-Value 0.00000 0.01102 0.44279 0.77579 0.00788 0.73547 0.73390 0.47387 0.11193 0.98804 0.33361	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019 0.4082 0.8853 0.8075 1.6162 0.3991 1.0093	72.033 ds io i)) 53 04 00 91 23 37 51 27 11 32 26
Coefficient Significat Independent	egression Coefficient b(i) 2.82983 1.24012 0.26083 -0.10324 -0.89593 -0.12175 -0.21380 0.48012 -0.91853 0.00928 0.49546 -0.26697	Standard Error Sb(i) 0.44457 0.48781 0.33984 0.36248 0.33719 0.36036 0.62893 0.67038 0.57784 0.61911	Wald Z-Value H0: β=0 6.365 2.542 0.767 -0.285 -2.657 -0.338 -0.340 0.716 -1.590 0.015 0.967	Wald P-Value 0.00000 0.01102 0.44279 0.77579 0.00788 0.73547 0.73390 0.47387 0.11193 0.98804 0.33361	Odc Rati Exp(b(i 16.9425 3.4560 1.2980 0.9019 0.4082 0.8853 0.8075 1.6162 0.3991 1.0093	72.033 ds io io ii)) 53 04 00 91 23 37 51 27 11 32 26 70

Torm			From I					
Term Omitted	DF	Deviance		iance (Chi²)	P-Va	ш		
All	12	925.59805		01434	0.000			
Race	2	819.21845		63475	0.000			
County	2	832.03780		45409	0.207			
Offense	8	898.18115		59744	0.000			
None(Model)	12	816.58371	01.	001 44	0.000	.00		
1 1 10 - 10	0.02							
Log Likelihood	& R ² —			R²	of	Reduction	Reduction	n
Term(s)			Log	Remaini	ng	From	Fron	m
Term(s) Omitted	D	F Likelih	_		ng			m
Term(s) Omitted All	D	F Likelih 2 -462.79	ood 1903	Remainin Term 0.000	ng (s)	From Model R ²	Fron Saturated R	m R²
J	D	F Likelih 2 -462.79 2 -409.60	ood 9903 923	Remaini Term 0.000 0.680	ng (s) 000	From Model R ² 0.01686	Fron Saturated R	m R² 07
Term(s) Omitted All Race	D	F Likelih 2 -462.79 2 -409.60 2 -416.01	ood 9903 923	Remainin Term 0.000	ng (s) 000	From Model R ²	Fron Saturated R	m R ²
Term(s) Omitted All Race County Offense	D	F Likelih 2 -462.79 2 -409.60 2 -416.01 8 -449.09	ood 9903 9923 890	Remainin Term 0.000 0.680 0.598 0.175	ng (s) 000 93 87	From Model R ² 0.01686 0.09892 0.52230	Fron Saturated R 0.31907 0.40113 0.8245	m R ² 07 13
Term(s) Omitted All	D	F Likelih 2 -462.79 2 -409.60 2 -416.01 8 -449.09 2 -408.29	ood 1903 1923 890 1057 1185	Remainin Term 0.000 0.680 0.598	ng (s) 000 93 87 449	From Model R ² 0.01686 0.09892	Fron Saturated R 0.31907 0.40113	m R ² 07 13 51 21

The output format is similar to previous examples. Notice in the analysis of deviance section that the variable *Race* is not significant. That is, in these data, the race of the defendant is not related to the verdict.

The *Coefficient Significance Tests* report combines the two logistic regression equations on one report. This makes it a bit more complicated to read, but it allows a quick comparison to be made of the corresponding regression coefficients. For each independent variable, the regression coefficient from each equation is shown. Thus, 2.82983 is the intercept for the *G* equation and 1.24012 is the intercept for the *NG* equation. No coefficient is shown for *NP* because it is the reference value.

Also note that the definition of the binary variables is as before. Thus the independent variable *County="Orange"* refers to a binary variable that was generated from the *County* variable. This binary variable is one when the county value is *Orange* and zero otherwise.

Validation

In order to validate this module, the estimated regression coefficients and the log likelihood generated by the *BMDP* (refer to page 1165 of version 7.0 of the *BMDP* manual) are displayed below.

Outcome: G 1 RACE 2 COUNTY 3 OFFENSE(1) 4 OFFENSE(2) 5 OFFENSE(3) 6 OFFENSE(4) 7 CONST1	Coefficient 0.2608 -0.8959 -2.230 -0.9185 -0.2138 0.4955 2.830	Std Error 0.340 0.337 0.514 0.578 0.629 0.512 0.445
Outcome: NG 8 RACE 9 COUNTY 10 OFFENSE(1) 11 OFFENSE(2) 12 OFFENSE(3) 13 OFFENSE(4) 14 CONST1	Coefficient -0.1032 -0.1218 -0.5786 0.9281E-02 0.4801 -0.2670 1.240	Std Error 0.362 0.360 0.537 0.619 0.670 0.576

As you can see, these results match those displayed by **NCSS** exactly.

Example 5 – Logit Model with Interaction

This example continues with the analysis of the data given in Example 4. In that example, no interactions were included in the model. This example will include the two-way interactions in the model.

Setup

To run this example, complete the following steps:

1 Open the NC Criminal example dataset

- From the File menu of the NCSS Data window, select **Open Example Data**.
- Select **NC Criminal** and click **OK**.

2 Specify the Logistic Regression procedure options

- Find and open the **Logistic Regression** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 5** settings template. To load this template, click **Open Example Template** in the Help Center or File menu.

<u>Option</u>	Value
Variables, Model Tab	
Υ	. Verdict
Reference Value	. NP
Categorical X's	. Race(B;A) County(B;Durham) Offense(B;Drunk)
Frequencies	Count
Terms	. Up to 2-Way
Priors	Ni/N (Y-Value Proportions)
Reports Tab	
Run Summary	. Checked
Y Variable Summary	. Checked
Coefficient Significance Tests	. Checked
Analysis of Deviance	. Checked
Log-Likelihood and R ²	. Checked
All Other Reports	. Unchecked

3 Run the procedure

• Click the **Run** button to perform the calculations and generate the output.

Logistic Regression Output

Independent Variable X	Regression Coefficient b(i)	Standard Error Sb(i)	Wald Z-Value H0: β=0	Wald P-Value	Odds Ratio Exp(b(i))
Intercept	0.00500	0.50400		0.00007	
G	2.00583	0.50400	3.980	0.00007	7.43225
NG (Race="B")	0.72258	0.57465	1.257	0.20860	2.05975
G (Nace= B)	1.44835	0.86924	1.666	0.09567	4.25608
NG	-1.10628	1.08369	-1.021	0.30733	0.33079
(County="Orang					
`G ´	0.14731	1.15368	0.128	0.89840	1.15871
NG	1.83395	1.18755	1.544	0.12251	6.25854
(Offense="MjTra					
G	-0.30745	1.10221	-0.279	0.78029	0.73532
NG (Offense-"Brone	-0.25450	1.23436	-0.206	0.83665	0.77531
(Offense="Prope G	-0.72178	0.83542	-0.864	0.38760	0.48589
NG	0.35757	0.89267	0.401	0.68874	1.42985
(Offense="Spee		0.50201	3.101	0.0001	2000
G	1.93682	1.08041	1.793	0.07303	6.93666
NG	0.87254	1.19650	0.729	0.46586	2.39297
(Offense="Viole	nce")				
G	-0.15836	0.87409	-0.181	0.85624	0.85354
NG	1.07460	0.91294	1.177	0.23916	2.92882
(Race="B")*(Co		0.04547	0.240	0.04067	1.04500
G NG	0.19528 0.83286	0.81517 0.85899	0.240 0.970	0.81067 0.33225	1.21566 2.29990
	0.63266 ense="MjTraffic")		0.570	0.00220	2.23330
G (Nace- B) (OII	-1.17876	1.35078	-0.873	0.38285	0.30766
NG	1.16592	1.50638	0.774	0.43894	3.20886
(Race="B")*(Off	ense="Property")				
G	-0.83367	1.27452	-0.654	0.51305	0.43445
NG	1.35214	1.42888	0.946	0.34400	3.86569
(Race="B")*(Off		4.05551	4 400	0.45000	0.40000
G	-1.78987	1.25551	-1.426	0.15398	0.16698
NG (Race="R")*(Off	0.24862 ense="Violence")	1.45010	0.171	0.86387	1.28225
G (Race= B) (Oil	-2.31322	1.19041	-1.943	0.05199	0.09894
NG	0.51640	1.30133	0.397	0.69150	1.67598
	je")*(Offense="Mj				
G	0.45137	1.52019	0.297	0.76653	1.57046
NG	-0.53668	1.61710	-0.332	0.73998	0.58469
	je")*(Offense="Pr		0.004	0.07050	4.04000
G	0.04871	1.41697	0.034	0.97258	1.04992
NG	-2.10279 -"*(Offense="Sr	1.47544	-1.425	0.15410	0.12212
G G County= Orang	e")*(Offense="Sp -1.39431	1.37573	-1.014	0.31082	0.24800
NG NG	-2.66093	1.48387	-1.793	0.07294	0.24600
	je")*(Offense="Vi		00	3.37 204	2.00000
G	-2.42314	1.36627	-1.774	0.07614	0.08864
NG	-3.93664	1.38198	-2.849	0.00439	0.01951
Analysis of Dev	viance				
			Increase		
			From Model		
Term			Deviance		
Omitted	DF D	Deviance	(Chi²)	P-Value	
All		25.59805	146.82239	0.00000	
Race		97.83870	19.06304	0.00007	
	2 78	88.31126	9.53560	0.00850	
County		00.00011			
County Offense	8 80	02.98614	24.21048	0.00211	
County Offense Race*County	8 80 2 78	80.53878	1.76312	0.41414	
County Offense Race*County Race*Offense	8 80 2 78 8 79	80.53878 95.98619	1.76312 17.21053	0.41414 0.02799	
County Offense Race*County	8 80 2 78 8 79 8 79	80.53878	1.76312	0.41414	

NCSS Statistical Software Logistic Regression

Term(s)		Log	R ² of Remaining	Reduction From	Reduction From
Omitted	DF	Likelihood	Term(s)	Model R ²	Saturated R ²
All	2	-462.79903	0.00000	inouoi it	outuratou it
Race	2	-398.91935	0.81778	0.12202	0.18222
County	2	-394.15563	0.87877	0.06104	0.12123
Offense	8	-401.49307	0.78483	0.15497	0.21517
Race*County	2	-390.26939	0.92852	0.01129	0.07148
Race*Offense	8	-397.99309	0.82964	0.11016	0.17036
County*Offense	8	-399.40586	0.81155	0.12825	0.18845
None(Model)	30	-389.38783	0.93980	0.00000	0.06020
None(Saturated)	120	-384.68554	1.00000		0.00000

Notice how the interactions are labeled. For example, the variable labeled (*Race="B"*)*(*Offense="Violence"*) is the interaction variable is generated by multiplying the binary variable defined by (Race="B") with the binary variable defined by (Offense="Violence"). The resulting variable is one if both of these conditions are true and zero otherwise.

Note that the R^2 is now 0.93980, so this model is almost as good as the saturated model.

Looking at the analysis of deviance table, we note that all terms are significant except for the Race*County interaction.

Example 6 - Odds Ratios for Categorical X's

Lachin (2000) pages 90, 91, and 257 presents an analysis of hypothetical data from an ulcer healing clinical trial conducted to study the effectiveness of a drug over a placebo. There were 100 patients assigned to the group receiving the drug and another 100 patients assigned to the group receiving the placebo. The ulcers were stratified into one of three types: 1. Acid-dependent, 2. Drug dependent, and 3. Intermediate. Each ulcer was followed for a period of time after which it was considered healed or not. The data for this experiment are given below. These data have been entered into a database named **Lachin91**.

Lachin91 dataset (subset)

Count	Ulcer	Drug	Healed
16	1	1	1
26	1	1	0
20	1	0	1
27	1	0	0
9	2	1	1
3	2	1	0
4	2	0	1
5	2	0	0
28	3	1	1
18	3	1	0
16	3	0	1
28	3	0	0

Setup

To run this example, complete the following steps:

1 Open the Lachin91 example dataset

- From the File menu of the NCSS Data window, select Open Example Data.
- Select Lachin91 and click OK.

2 Specify the Logistic Regression procedure options

- Find and open the **Logistic Regression** procedure using the menus or the Procedure Navigator.
- The settings for this example are listed below and are stored in the **Example 6** settings template. To load this template, click **Open Example Template** in the Help Center or File menu.

<u>Option</u>	<u>Value</u>
Variables, Model Tab	
Υ	Healed
Categorical X's	Ulcer Drug
Frequencies	Count
Priors	Equal across Y Values
Reports Tab	
Run Summary	Checked
Coefficient Significance Tests	Checked
Odds Ratios	Checked
Analysis of Deviance	Checked
All Other Reports	Unchecked

3 Run the procedure

• Click the **Run** button to perform the calculations and generate the output.

Logistic Regression Output

			_					
Run Summary								
Item Y Variable Reference Value Number of Y-Va Frequency Varia Numeric X Varia Categorical X Va Final Log Likelih Model R ² Actual Converge Actual Converge Model D.F. Priors	lues able ables ariables aood	Value Healed 0 2 Count 0 2 -134.84 0.5410 1.1027 1E-06 4 Equal	4531 6	Rows Proces Rows Used Rows for Val Rows X's Mir Rows Freq N Rows Predic Unique Rows Sum of Freq Likelihood Ite Maximum Ite Completion S	lidation ssing Miss. or 0 tion Only s (Y and X uencies erations erations	1. 0 0 0 0 0 0 ('s) 1. 2 4	2 2 00	n
Coefficient Sign								
Independent Variable X Intercept (Ulcer=2) (Ulcer=3) (Drug=1) Odds Ratios —	0.8 0.3		Standard Error Sb(i) 0.21833 0.50247 0.30424 0.28845	Wald Z-Value H0: β=0 -2.242 1.662 1.077 1.742	Wald P-Value 0.02496 0.09645 0.28132 0.08159	Ex 0. 2. 1.	Odds Ratio p(b(i)) 61293 30543 38787 65259	
Independent Variable X Intercept (Ulcer=2) (Ulcer=3) (Drug=1)	0.8 0.3		Odds Ratio Exp(b(i)) 0.61293 2.30543 1.38787 1.65259	Lower 95% Confidence Limit 0.39955 0.86109 0.76451 0.93894	Con	per 95% fidence Limit 0.94027 6.17243 2.51949 2.90864		
Analysis of Dev	/iance —							
Term Omitted All Ulcer Drug None(Model)	DF 3 2 1 3	Deviance 276.27807 272.87155 272.7452 269.6906	From Dev 9 7 6. 5 3. 1 3.	.58746 0. .18094 0.	-Value 08628 20383 08051			

Note that neither Drug nor Ulcer is statistically significant at the 0.05 level using either the deviance tests in the *Analysis of Deviance* table or the Wald tests in the *Coefficient Significance Tests* section. From the *Odds Ratios* section, we see that the odds of healing are increased 1.65259 when the drug is administered.