Chapter 16 Logistic Regression

Chapter Table of Contents

DISPLAYING THE LOGISTIC REGRESSION ANALYSIS
Model Equation
Summary of Fit
Analysis of Deviance
Type III (Wald) Tests
Parameter Estimates Table
Residuals-by-Predicted Plot
MODIFYING THE MODEL
REFERENCES

Part 2. Introduction

Chapter 16 Logistic Regression

In the last two chapters, you used least-squares methods to fit linear models. In this chapter, you use maximum-likelihood methods to fit *generalized* linear models. You can choose **Analyze:Fit (Y X)** to carry out a logistic regression analysis. You can use the fit variables and method dialogs to specify generalized linear models and to add and delete variables from the model.

SAS: Fit SASUSER.PATIENT										
<u>File</u> Edit	Analyze	<u>T</u> ables <u>G</u> r	aphs <u>Curves</u>	<u>Vars</u> <u>H</u> elp						
						Δ				
🕨 REMIS	s =	CELL LI 1	TEMP							
Response	e Distribu	ution: Bino	mial							
Link Fu	Link Function: Logit									
Model Equation										
Logit	(REMIS	6) = 6	7.6339 + 9.	6521 CELL	+ 3.8671 LI -	82.0737 TEMP				
	Summary of Fit									
Mean of	Response	0.3333	Deviance	21.9534	Pearson ChiSq	20.4234				
SCHLE		1.0000	Deviance / DF Scaled Dev	0.9545 21.9534	Pearson ChiSq / DF Scaled ChiSg	0.8880 20.4234				
L				L110001	course survey					
		A	nalysis of Devi	lance						
Source	DF	Deviance	Deviance / DF	Scaled De	<pre>v Pr > Scaled Dev</pre>					
Model Error	3 23	12.4184 21.9534	4.1395 0.9545	12.418	• 0.0061 •					
C Total	26	34.3718								
]							
Sourco	Type II	L (Wald) Te	sts P» > ChiSa							
CELL	1	1.5507	0.2130							
LI	ĩ	4.7290	0.0297							
TEMP	1	1.7687	0.1835							
		Para	meter Estimate	5						
Variabl	e DF	Estimate	Std Error	ChiSq	Pr → ChiSq					
Interce	ot I	67.633	9 56.8875	1.4135	0.2345					
		1 9.652 1 3.867	1 7.7511	1.5507	0.2130 0.0297					
TEMP	1	-82.073	7 61.7124	1.7687	0.1835					
	-									
	-	•								
0.5										
R		-								
R										
E 0.0 -			•							
Ï	· .									
5										
5										
		••								
	0 ['] 2	0'4 0'S								
	V.L	P_REMISS	0.0							
1										

Figure 16.1. Logistic Regression Analysis

Displaying the Logistic Regression Analysis

The **PATIENT** data set, described by Lee (1974), contains data collected on 27 cancer patients. The response variable, **REMISS**, is binary and indicates whether cancer remission occurred:

REMISS = 1 indicates success (remission occurred)

REMISS = 0 indicates failure (remission did not occur)

Several other variables containing patient characteristics thought to affect cancer remission were also included in the study. For this example, consider the following three explanatory variables: **CELL**, **LI**, and **TEMP**. (You may want to carry out a more complete analysis on your own.)

 \implies Open the PATIENT data set.

	SAS: SASUSER.PATIENT 🗾 🗖							
<u>File Edit Analyze Tables Graphs Curves Vars Help</u>								
► 7	Int	Int	Int	Int	Int	Int	Int	
27	REMISS	CELL	SMEAR	INFIL	LI	BLAST	TEMP	
– 1	1	0.80	0.83	0.66	1.9	1.100	0.996	
■ 2	1	0.90	0.36	0.32	1.4	0.740	0.992	
• 3	0	0.80	0.88	0.70	0.8	0.176	0.982	
• 4	0	1.00	0.87	0.87	0.7	1.053	0.986	
5	1	0.90	0.75	0.68	1.3	0.519	0.980	
6	0	1.00	0.65	0.65	0.6	0.519	0.982	
<u> </u>	1	0.95	0.97	0.92	1.0	1.230	0.992	
• 8	0	0.95	0.87	0.83	1.9	1.354	1.020	
9	0	1.00	0.45	0.45	0.8	0.322	0.999	
I	0	0.95	0.36	0.34	0.5	0.000	1.038	

Figure 16.2. Data Window

The generalized linear model has three components:

• a linear predictor function constructed from explanatory variables. For this example, the function is

$$\theta_i = \beta_0 + \beta_1 \mathsf{CELL}_i + \beta_2 \mathsf{LI}_i + \beta_3 \mathsf{TEMP}_i$$

where $\beta_0, \beta_1, \beta_2$ and β_3 are coefficients (parameters) for the linear predictor, and CELL_i, Ll_i, and TEMP_i are the values of the explanatory variables.

• a distribution or probability function for the response variable that depends on the mean μ and sometimes other parameters as well. For this example, the probability function is binomial.

• a link function, g(.), that relates the mean to the linear predictor function. For logistic regression, the link function is the logit

$$g(p_i) = \text{logit}(\mathbf{p_i}) = \log(\frac{\mathbf{p_i}}{1-\mathbf{p_i}}) = \theta_{\mathbf{i}}$$

where $p_i = \Pr(\text{REMISS}=1 \mid x_i)$ is the response probability to be modeled, and x_i is the set of explanatory variables for the *i*th patient.

You can specify these three components to fit a generalized linear model by following these steps.

 \implies Choose Analyze:Fit (Y X) to display the fit variables dialog.

 \implies Select **REMISS** in the list at the left, then click the Y button.

 \implies Select CELL, LI, and TEMP in the variables list, then click the X button.

Your variables dialog should now appear, as shown in Figure 16.3.

		SAS: Fit (Y \times)		/
PATIENT REMISS CELL SMEAR INFIL LI BLAST TEMP	¥ REMISS	X Eross Nost Expand	CELL LI TEMP	
- App 1y	Group OK Ca	Label 	Freq od Output	Height

Figure 16.3. Fit Variables Dialog with Variable Roles Assigned

To specify the probability distribution for the response variable and the link function, follow these steps.

 \implies Click the Method button in the variables dialog to display the method dialog.

	SAS: Fi	t(YX)	
PRTIENT REMISS Cell Smear INFIL LI BLAST TEMP	Response Dist.: Vormal Inv. Gaussian Gamma Poisson Binomial	Link Function: Canonical Identity Log Logit Probit Comp. Log-Log Power	Scale: MLE Deviance Pearson Constant Power: 1
	Binomial 04	Co Ifset Quasi Exact Fishe	nstant: <u>1</u> i-Likelihood t Distribution er's Scoring



 \implies Click on Binomial under Response Dist to specify the probability distribution.

You do not need to specify a **Link Function** for this example. **Canonical**, the default, allows **Fit (YX)** to choose a link dependent on the probability distribution. For the binomial distribution, as in this example, it is equivalent to choosing **Logit**, which yields a logistic regression.

 \implies Click the OK button to close the method dialog.

\implies Click the Apply button in the variables dialog.

This creates the analysis shown in Figure 16.5. Recall that the **Apply** button causes the variables dialog to stay on the screen after the fit window appears. This is convenient for adding and deleting variables from the model.

By default, the fit window displays tables for model information, **Model Equation**, **Summary of Fit**, **Analysis of Deviance**, **Type III (Wald) Tests**, and **Parameter Estimates**, and a residual-by-predicted plot. You can control the tables and graphs displayed by clicking on the **Output** button in the fit variables dialog or by choosing from the **Tables** and **Graphs** menus.

The first table displays the model information. The first line gives the model specification. The second and third lines give the error distribution and the link function you specified in the Method dialog.



Figure 16.5. Fit Window

Model Equation

The **Model Equation** table writes out the fitted model using the estimated regression coefficients:

logit(Prob(REMISS = 1))= 67.6399 + 9.6521*CELL + 3.8671*LI - 82.0737*TEMP

Summary of Fit

The **Summary of Fit** table contains summary statistics for the fit of the model including values for **Deviance** and **Pearson's Chi-Squared** statistics. These values contrast the fit of your model to that of a saturated model that allows a different fit for each observation. If the data are sparse in the sense that most observations have a different set of explanatory variables, as in this set of data, then the quality of these measures is likely to be poor. Inferences drawn from these measures should be treated cautiously.

Analysis of Deviance

The **Analysis of Deviance** table summarizes information about the variation in the response for the set of data. Some of the variation can be explained by the **Model**. The **Error** is the remainder that is not systematically explained. **C Total** (the total corrected or adjusted for the mean) is the sum of **Model** and **Error**. The probability values give a measure of whether the amount of variation is consistent with chance alone or whether there is evidence of additional variation. In this case the **Deviance** associated with the **Model** shows a significant effect for the model, (p = 0.0061).

Type III (Wald) Tests

Wald tests are Chi-square statistics that test the null hypothesis that a parameter is 0; in other words, that the corresponding variable has no effect given that the other variables are in the model. These are approximate tests that are more accurate with larger sample sizes. In this example, only the coefficient for **LI** is statistically significant (p = 0.0297).

Parameter Estimates Table

The **Parameter Estimates** table shows the estimate, standard error, Chi-square statistic and associated degrees of freedom, and *p*-value for each of the parameters estimated.

Residuals-by-Predicted Plot

In the diagnostic plot of residuals versus predicted values, you can examine residuals for the model. You can point and click to identify individual observations. Because the observed response must either be 0 or 1, the plot of the residuals versus predicted values must lie along two straight lines. Plots of residuals versus the independent variables and other possible explanatory variables may be more useful. You can create scatter plots by selecting the response and explanatory variables in the data window and choosing **Analyze:Scatter Plot (Y X)**.

Modifying the Model

Plots of the residuals against other variables may suggest extensions of the model. Alternatively you may be able to remove some variables and thus simplify the model without losing explanatory power. The **Type III (Wald) Tests** table or the possibly more accurate **Type III (LR) Tests** table contains statistics that can help you decide whether to remove an effect. If the *p*-value associated with the test is large, then there is little evidence for any explanatory value of the corresponding variable.

 \implies Choose Tables:Type III (LR) Tests.

<u>F</u> ile <u>E</u> dit <u>A</u> nalyze	Tables Graphs Curves Vars Help
	 Model Equation
	X'X Matrix
	 Summary of Fit
	 Analysis of Variance/Deviance
	Type I/I (LR) Tests
	✓ Type III (Wald) Tests
	Type III (LR) Tests
	✓ Parameter Estimates
	C.I. (Wald) for Parameters
	C.I. (LR) for Parameters
	Collinearity Diagnostics
	Estimated Cov Matrix
	Estimated Corr Matrix

Figure 16.6. Tables Menu

This displays the table shown in Figure 16.7.

	SAS: Fit SASUSER.PATIENT										
E	ile <u>E</u> dit	<u>A</u> nalyze	<u>T</u> ables <u>G</u>	graphs	Curves	Vars	<u>H</u> elp				
		Type I	II (LR) Te	sts			Δ				
	Source DF		ChiSq	Pr >	ChiSq						
	CELL	1	2.6945	0	. 1007						
	LI 1		8.8752	0	.0029						
	TEMP	1	2.3874	0	.1223						
							∇				
⊴.											

Figure 16.7. Likelihood Ratio Type III Tests

The *p*-values for **TEMP** and **CELL** are relatively large, suggesting these effects could be removed. Although the numbers are different, the same conclusions would be reached from the corresponding **Wald** tests. In the Fit Variables dialog, follow these steps to request a new model with **TEMP** removed.

- \implies Select TEMP in the effects list, then click the Remove button. TEMP disappears from the effects list.
- \implies Click on Apply, and a new fit window appears, as shown in Figure 16.8.



Figure 16.8. Fit Window with CELL and LI as Explanatory Variables

 \implies Choose Tables:Type III (LR) Tests in the new fit window. This displays a Type III (LR) Tests table in the window.

-	SAS: Fit 1 SASUSER.PATIENT								
E	File Edit Analyze Tables Graphs Curves Vars								
) Source	Type DF	III (LR) Te ChiSa	sts Pr > ChiSa		Δ			
	CELL	1 1	1.7322 7.4511	0.1881 0.0063					
<u> </u>									

Figure 16.9. Likelihood Ratio Type III Tests

The *p*-value for **CELL** in the LR test suggests that this effect could also be removed.

- \implies Click on the variable CELL in the effects list in the Fit Dialog. Then click on **Remove**. CELL disappears from the effects list.
- ⇒ Click on Apply, and a new Fit window appears, as shown in Figure 16.10. Since the new model contains only one X variable, the fit window displays a plot of REMISS versus CELL.

Using the **Apply** button, you have quickly created three logistic regression models. Logistic regression is only one special case of the generalized linear model. Another case, Poisson regression, is described in the next chapter.

Related Reading: Generalized Linear Models, Chapter 39.



Figure 16.10. Fit Window with LI as the Only Explanatory Variable

References

- Lee, E.T. (1974), "A Computer Program for Linear Logistic Regression Analysis," *Computer Programs in Biomedicine*, 80–92.
- McCullagh, P. and Nelder, J.A. (1989), *Generalized Linear Models*, Second Edition, London: Chapman and Hall.

The correct bibliographic citation for this manual is as follows: SAS Institute Inc., SAS/ INSIGHT User's Guide, Version 8, Cary, NC: SAS Institute Inc., 1999. 752 pp.

SAS/INSIGHT User's Guide, Version 8

Copyright © 1999 by SAS Institute Inc., Cary, NC, USA.

ISBN 1-58025-490-X

All rights reserved. Printed in the United States of America. No part of this publication may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, or otherwise, without the prior written permission of the publisher, SAS Institute Inc.

U.S. Government Restricted Rights Notice. Use, duplication, or disclosure of the software by the government is subject to restrictions as set forth in FAR 52.227–19 Commercial Computer Software-Restricted Rights (June 1987).

SAS Institute Inc., SAS Campus Drive, Cary, North Carolina 27513.

1st printing, October 1999

 SAS^{\circledast} and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. $^{\circledast}$ indicates USA registration.

Other brand and product names are registered trademarks or trademarks of their respective companies.

The Institute is a private company devoted to the support and further development of its software and related services.