

# Springer Series in Statistics

*Advisors:*

P. Bickel, P. Diggle, S.E. Feinberg, U. Gather,  
I. Olkin, S. Zeger

More information about this series at <http://www.springer.com/series/692>



Frank E. Harrell, Jr.

# Regression Modeling Strategies

With Applications to Linear Models,  
Logistic and Ordinal Regression,  
and Survival Analysis

Second Edition

 Springer

Frank E. Harrell, Jr.  
Department of Biostatistics  
School of Medicine  
Vanderbilt University  
Nashville, TN, USA

ISSN 0172-7397                      ISSN 2197-568X (electronic)  
Springer Series in Statistics  
ISBN 978-3-319-19424-0              ISBN 978-3-319-19425-7 (eBook)  
DOI 10.1007/978-3-319-19425-7

Library of Congress Control Number: 2015942921

Springer Cham Heidelberg New York Dordrecht London

© Springer Science+Business Media New York 2001

© Springer International Publishing Switzerland 2015

This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.

The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, express or implied, with respect to the material contained herein or for any errors or omissions that may have been made.

Printed on acid-free paper

Springer International Publishing AG Switzerland is part of Springer Science+Business Media ([www.springer.com](http://www.springer.com))

*To the memories of Frank E. Harrell, Sr.,  
Richard Jackson, L. Richard Smith, John  
Burdeshaw, and Todd Nick, and with  
appreciation to Liana and Charlotte  
Harrell, two high school math teachers:  
Carolyn Wailes (née Gaston) and Floyd  
Christian, two college professors: David  
Hurst (who advised me to choose the field  
of biostatistics) and Doug Stocks, and my  
graduate advisor P. K. Sen.*



# Preface

There are many books that are excellent sources of knowledge about individual statistical tools (survival models, general linear models, etc.), but the art of data analysis is about choosing and using multiple tools. In the words of Chatfield [100, p. 420] “. . . students typically know the technical details of regression for example, but not necessarily when and how to apply it. This argues the need for a better balance in the literature and in statistical teaching between *techniques* and problem solving *strategies*.” Whether analyzing risk factors, adjusting for biases in observational studies, or developing predictive models, there are common problems that few regression texts address. For example, there are missing data in the majority of datasets one is likely to encounter (other than those used in textbooks!) but most regression texts do not include methods for dealing with such data effectively, and most texts on missing data do not cover regression modeling.

This book links standard regression modeling approaches with

- methods for relaxing linearity assumptions that still allow one to easily obtain predictions and confidence limits for future observations, and to do formal hypothesis tests,
- non-additive modeling approaches not requiring the assumption that interactions are always linear  $\times$  linear,
- methods for imputing missing data and for penalizing variances for incomplete data,
- methods for handling large numbers of predictors without resorting to problematic stepwise variable selection techniques,
- data reduction methods (unsupervised learning methods, some of which are based on multivariate psychometric techniques too seldom used in statistics) that help with the problem of “too many variables to analyze and not enough observations” as well as making the model more interpretable when there are predictor variables containing overlapping information,
- methods for quantifying predictive accuracy of a fitted model,

- powerful model validation techniques based on the bootstrap that allow the analyst to estimate predictive accuracy nearly unbiasedly without holding back data from the model development process, and
- graphical methods for understanding complex models.

On the last point, this text has special emphasis on what could be called “presentation graphics for fitted models” to help make regression analyses more palatable to non-statisticians. For example, nomograms have long been used to make equations portable, but they are not drawn routinely because doing so is very labor-intensive. An R function called `nomogram` in the package described below draws nomograms from a regression fit, and these diagrams can be used to communicate modeling results as well as to obtain predicted values manually even in the presence of complex variable transformations.

Most of the methods in this text apply to all regression models, but special emphasis is given to some of the most popular ones: multiple regression using least squares and its generalized least squares extension for serial (repeated measurement) data, the binary logistic model, models for ordinal responses, parametric survival regression models, and the Cox semiparametric survival model. There is also a chapter on nonparametric transform-both-sides regression. Emphasis is given to detailed case studies for these methods as well as for data reduction, imputation, model simplification, and other tasks. Except for the case study on survival of Titanic passengers, all examples are from biomedical research. However, the methods presented here have broad application to other areas including economics, epidemiology, sociology, psychology, engineering, and predicting consumer behavior and other business outcomes.

This text is intended for Masters or PhD level graduate students who have had a general introductory probability and statistics course and who are well versed in ordinary multiple regression and intermediate algebra. The book is also intended to serve as a reference for data analysts and statistical methodologists. Readers without a strong background in applied statistics may wish to first study one of the many introductory applied statistics and regression texts that are available. The author’s course notes *Biostatistics for Biomedical Research* on the text’s web site covers basic regression and many other topics. The paper by Nick and Hardin [476] also provides a good introduction to multivariable modeling and interpretation. There are many excellent intermediate level texts on regression analysis. One of them is by Fox, which also has a companion software-based text [200, 201]. For readers interested in medical or epidemiologic research, Steyerberg’s excellent text *Clinical Prediction Models* [586] is an ideal companion for *Regression Modeling Strategies*. Steyerberg’s book provides further explanations, examples, and simulations of many of the methods presented here. And no text on regression modeling should fail to mention the seminal work of John Nelder [450].

The overall philosophy of this book is summarized by the following statements.

- Satisfaction of model assumptions improves precision and increases statistical power.
- It is more productive to make a model fit step by step (e.g., transformation estimation) than to postulate a simple model and find out what went wrong.
- Graphical methods should be married to formal inference.
- Overfitting occurs frequently, so data reduction and model validation are important.
- In most research projects, the cost of data collection far outweighs the cost of data analysis, so it is important to use the most efficient and accurate modeling techniques, to avoid categorizing continuous variables, and to not remove data from the estimation sample just to be able to validate the model.
- The bootstrap is a breakthrough for statistical modeling, and the analyst should use it for many steps of the modeling strategy, including derivation of distribution-free confidence intervals and estimation of optimism in model fit that takes into account variations caused by the modeling strategy.
- Imputation of missing data is better than discarding incomplete observations.
- Variance often dominates bias, so biased methods such as penalized maximum likelihood estimation yield models that have a greater chance of accurately predicting future observations.
- Software without multiple facilities for assessing and fixing model fit may only seem to be user-friendly.
- Carefully fitting an improper model is better than badly fitting (and overfitting) a well-chosen one.
- Methods that work for all types of regression models are the most valuable.
- Using the data to guide the data analysis is almost as dangerous as not doing so.
- There are benefits to modeling by deciding how many degrees of freedom (i.e., number of regression parameters) can be “spent,” deciding where they should be spent, and then spending them.

On the last point, the author believes that significance tests and  $P$ -values are problematic, especially when making modeling decisions. Judging by the increased emphasis on confidence intervals in scientific journals there is reason to believe that hypothesis testing is gradually being de-emphasized. Yet the reader will notice that this text contains many  $P$ -values. How does that make sense when, for example, the text recommends against simplifying a model when a test of linearity is not significant? First, some readers may wish to emphasize hypothesis testing in general, and some hypotheses have special interest, such as in pharmacology where one may be interested in whether the effect of a drug is linear in log dose. Second, many of the more interesting hypothesis tests in the text are tests of complexity (nonlinearity, interaction) of the overall model. Null hypotheses of linearity of effects in particular are

frequently rejected, providing formal evidence that the analyst's investment of time to use more than simple statistical models was warranted.

The rapid development of Bayesian modeling methods and rise in their use is exciting. Full Bayesian modeling greatly reduces the need for the approximations made for confidence intervals and distributions of test statistics, and Bayesian methods formalize the still rather ad hoc frequentist approach to penalized maximum likelihood estimation by using skeptical prior distributions to obtain well-defined posterior distributions that automatically deal with shrinkage. The Bayesian approach also provides a formal mechanism for incorporating information external to the data. Although Bayesian methods are beyond the scope of this text, the text is Bayesian in spirit by emphasizing the careful use of subject matter expertise while building statistical models.

The text emphasizes predictive modeling, but as discussed in Chapter 1, developing good predictions goes hand in hand with accurate estimation of effects and with hypothesis testing (when appropriate). Besides emphasis on multivariable modeling, the text includes a Chapter 17 introducing survival analysis and methods for analyzing various types of single and multiple events. This book does not provide examples of analyses of one common type of response variable, namely, cost and related measures of resource consumption. However, least squares modeling presented in Chapter 15.1, the robust rank-based methods presented in Chapters 13, 15, and 20, and the transform-both-sides regression models discussed in Chapter 16 are very applicable and robust for modeling economic outcomes. See [167] and [260] for example analyses of such dependent variables using, respectively, the Cox model and nonparametric additive regression. The central Web site for this book (see the Appendix) has much more material on the use of the Cox model for analyzing costs.

This text does not address some important study design issues that if not respected can doom a predictive modeling or estimation project to failure. See Laupacis, Sekar, and Stiell [378] for a list of some of these issues.

Heavy use is made of the S language used by R. R is the focus because it is an elegant object-oriented system in which it is easy to implement new statistical ideas. Many R users around the world have done so, and their work has benefited many of the procedures described here. R also has a uniform syntax for specifying statistical models (with respect to categorical predictors, interactions, etc.), no matter which type of model is being fitted [96].

The free, open-source statistical software system R has been adopted by analysts and research statisticians worldwide. Its capabilities are growing exponentially because of the involvement of an ever-growing community of statisticians who are adding new tools to the base R system through contributed packages. All of the functions used in this text are available in R. See the book's Web site for updated information about software availability.

Readers who don't use R or any other statistical software environment will still find the statistical methods and case studies in this text useful, and it is hoped that the code that is presented will make the statistical methods more

concrete. At the very least, the code demonstrates that all of the methods presented in the text are feasible.

This text does not teach analysts how to use R. For that, the reader may wish to see reading recommendations on [www.r-project.org](http://www.r-project.org) as well as Venables and Ripley [635] (which is also an excellent companion to this text) and the many other excellent texts on R. See the Appendix for more information.

In addition to powerful features that are built into R, this text uses a package of freely available R functions called `rms` written by the author. `rms` tracks modeling details related to the expanded  $X$  or design matrix. It is a series of over 200 functions for model fitting, testing, estimation, validation, graphics, prediction, and typesetting by storing enhanced model design attributes in the fit. `rms` includes functions for least squares and penalized least squares multiple regression modeling in addition to functions for binary and ordinal regression, generalized least squares for analyzing serial data, quantile regression, and survival analysis that are emphasized in this text. Other freely available miscellaneous R functions used in the text are found in the `Hmisc` package also written by the author. Functions in `Hmisc` include facilities for data reduction, imputation, power and sample size calculation, advanced table making, recoding variables, importing and inspecting data, and general graphics. Consult the Appendix for information on obtaining `Hmisc` and `rms`.

The author and his colleagues have written SAS macros for fitting restricted cubic splines and for other basic operations. See the Appendix for more information. It is unfair not to mention some excellent capabilities of other statistical packages such as Stata (which has also been extended to provide regression splines and other modeling tools), but the extendability and graphics of R makes it especially attractive for all aspects of the comprehensive modeling strategy presented in this book.

Portions of Chapters 4 and 20 were published as reference [269]. Some of Chapter 13 was published as reference [272].

The author may be contacted by electronic mail at [f.harrell@vanderbilt.edu](mailto:f.harrell@vanderbilt.edu) and would appreciate being informed of unclear points, errors, and omissions in this book. Suggestions for improvements and for future topics are also welcome. As described in the Web site, instructors may contact the author to obtain copies of quizzes and extra assignments (both with answers) related to much of the material in the earlier chapters, and to obtain full solutions (with graphical output) to the majority of assignments in the text.

Major changes since the first edition include the following:

1. Creation of a now mature R package, `rms`, that replaces and greatly extends the `Design` library used in the first edition
2. Conversion of all of the book's code to R
3. Conversion of the book source into `knitr` [677] reproducible documents
4. All code from the text is executable and is on the web site
5. Use of color graphics and use of the `ggplot2` graphics package [667]
6. Scanned images were re-drawn

7. New text about problems with dichotomization of continuous variables and with classification (as opposed to prediction)
8. Expanded material on multiple imputation and predictive mean matching and emphasis on multiple imputation (using the Hmisc `aregImpute` function) instead of single imputation
9. Addition of redundancy analysis
10. Added a new section in Chapter 5 on bootstrap confidence intervals for rankings of predictors
11. Replacement of the U.S. presidential election data with analyses of a new diabetes dataset from NHANES using ordinal and quantile regression
12. More emphasis on semiparametric ordinal regression models for continuous  $Y$ , as direct competitors of ordinary multiple regression, with a detailed case study
13. A new chapter on generalized least squares for analysis of serial response data
14. The case study in imputation and data reduction was completely reworked and now focuses only on data reduction, with the addition of sparse principal components
15. More information about indexes of predictive accuracy
16. Augmentation of the chapter on maximum likelihood to include more flexible ways of testing contrasts as well as new methods for obtaining simultaneous confidence intervals
17. Binary logistic regression case study 1 was completely re-worked, now providing examples of model selection and model approximation accuracy
18. Single imputation was dropped from binary logistic case study 2
19. The case study in transform-both-sides regression modeling has been reworked using simulated data where true transformations are known, and a new example of the smearing estimator was added
20. Addition of 225 references, most of them published 2001–2014
21. New guidance on minimum sample sizes needed by some of the models
22. De-emphasis of bootstrap bumping [610] for obtaining simultaneous confidence regions, in favor of a general multiplicity approach [307].

## Acknowledgments

A good deal of the writing of the first edition of this book was done during my 17 years on the faculty of Duke University. I wish to thank my close colleague Kerry Lee for providing many valuable ideas, fruitful collaborations, and well-organized lecture notes from which I have greatly benefited over the past years. Terry Therneau of Mayo Clinic has given me many of his wonderful ideas for many years, and has written state-of-the-art R software for survival analysis that forms the core of survival analysis software in my `rms` package. Michael Symons of the Department of Biostatistics of the University of North

Carolina at Chapel Hill and Timothy Morgan of the Division of Public Health Sciences at Wake Forest University School of Medicine also provided course materials, some of which motivated portions of this text. My former clinical colleagues in the Cardiology Division at Duke University, Robert Califf, Phillip Harris, Mark Hlatky, Dan Mark, David Pryor, and Robert Rosati, for many years provided valuable motivation, feedback, and ideas through our interaction on clinical problems. Besides Kerry Lee, statistical colleagues L. Richard Smith, Lawrence Muhlbaier, and Elizabeth DeLong clarified my thinking and gave me new ideas on numerous occasions. Charlotte Nelson and Carlos Alzola frequently helped me debug S routines when they thought they were just analyzing data.

Former students Bercedis Peterson, James Herndon, Robert McMahon, and Yuan-Li Shen have provided many insights into logistic and survival modeling. Associations with Doug Wagner and William Knaus of the University of Virginia, Ken Offord of Mayo Clinic, David Naftel of the University of Alabama in Birmingham, Phil Miller of Washington University, and Phil Goodman of the University of Nevada Reno have provided many valuable ideas and motivations for this work, as have Michael Schemper of Vienna University, Janez Stare of Ljubljana University, Slovenia, Ewout Steyerberg of Erasmus University, Rotterdam, Karel Moons of Utrecht University, and Drew Levy of Genentech. Richard Goldstein, along with several anonymous reviewers, provided many helpful criticisms of a previous version of this manuscript that resulted in significant improvements, and critical reading by Bob Edson (VA Cooperative Studies Program, Palo Alto) resulted in many error corrections. Thanks to Brian Ripley of the University of Oxford for providing many helpful software tools and statistical insights that greatly aided in the production of this book, and to Bill Venables of CSIRO Australia for wisdom, both statistical and otherwise. This work would also not have been possible without the S environment developed by Rick Becker, John Chambers, Allan Wilks, and the R language developed by Ross Ihaka and Robert Gentleman.

Work for the second edition was done in the excellent academic environment of Vanderbilt University, where biostatistical and biomedical colleagues and graduate students provided new insights and stimulating discussions. Thanks to Nick Cox, Durham University, UK, who provided from his careful reading of the first edition a very large number of improvements and corrections that were incorporated into the second. Four anonymous reviewers of the second edition also made numerous suggestions that improved the text.

Nashville, TN, USA  
July 2015

Frank E. Harrell, Jr.



# Contents

<b>Typographical Conventions</b> .....	xxv
<b>1 Introduction</b> .....	1
1.1 Hypothesis Testing, Estimation, and Prediction .....	1
1.2 Examples of Uses of Predictive Multivariable Modeling .....	3
1.3 Prediction vs. Classification .....	4
1.4 Planning for Modeling .....	6
1.4.1 Emphasizing Continuous Variables .....	8
1.5 Choice of the Model .....	8
1.6 Further Reading .....	11
<b>2 General Aspects of Fitting Regression Models</b> .....	13
2.1 Notation for Multivariable Regression Models .....	13
2.2 Model Formulations .....	14
2.3 Interpreting Model Parameters .....	15
2.3.1 Nominal Predictors .....	16
2.3.2 Interactions .....	16
2.3.3 Example: Inference for a Simple Model .....	17
2.4 Relaxing Linearity Assumption for Continuous Predictors ..	18
2.4.1 Avoiding Categorization .....	18
2.4.2 Simple Nonlinear Terms .....	21
2.4.3 Splines for Estimating Shape of Regression Function and Determining Predictor Transformations .....	22
2.4.4 Cubic Spline Functions .....	23
2.4.5 Restricted Cubic Splines .....	24
2.4.6 Choosing Number and Position of Knots .....	26
2.4.7 Nonparametric Regression .....	28
2.4.8 Advantages of Regression Splines over Other Methods .....	30

2.5	Recursive Partitioning: Tree-Based Models . . . . .	30
2.6	Multiple Degree of Freedom Tests of Association . . . . .	31
2.7	Assessment of Model Fit . . . . .	33
	2.7.1 Regression Assumptions . . . . .	33
	2.7.2 Modeling and Testing Complex Interactions . . . . .	36
	2.7.3 Fitting Ordinal Predictors . . . . .	38
	2.7.4 Distributional Assumptions . . . . .	39
2.8	Further Reading . . . . .	40
2.9	Problems . . . . .	42
<b>3</b>	<b>Missing Data</b> . . . . .	<b>45</b>
	3.1 Types of Missing Data . . . . .	45
	3.2 Prelude to Modeling . . . . .	46
	3.3 Missing Values for Different Types of Response Variables . . . . .	47
	3.4 Problems with Simple Alternatives to Imputation . . . . .	47
	3.5 Strategies for Developing an Imputation Model . . . . .	49
	3.6 Single Conditional Mean Imputation . . . . .	52
	3.7 Predictive Mean Matching . . . . .	52
	3.8 Multiple Imputation . . . . .	53
	3.8.1 The <code>aregImpute</code> and Other Chained Equations Approaches . . . . .	55
	3.9 Diagnostics . . . . .	56
	3.10 Summary and Rough Guidelines . . . . .	56
	3.11 Further Reading . . . . .	58
	3.12 Problems . . . . .	59
<b>4</b>	<b>Multivariable Modeling Strategies</b> . . . . .	<b>63</b>
	4.1 Prespecification of Predictor Complexity Without Later Simplification . . . . .	64
	4.2 Checking Assumptions of Multiple Predictors Simultaneously . . . . .	67
	4.3 Variable Selection . . . . .	67
	4.4 Sample Size, Overfitting, and Limits on Number of Predictors . . . . .	72
	4.5 Shrinkage . . . . .	75
	4.6 Collinearity . . . . .	78
	4.7 Data Reduction . . . . .	79
	4.7.1 Redundancy Analysis . . . . .	80
	4.7.2 Variable Clustering . . . . .	81
	4.7.3 Transformation and Scaling Variables Without Using $Y$ . . . . .	81
	4.7.4 Simultaneous Transformation and Imputation . . . . .	83
	4.7.5 Simple Scoring of Variable Clusters . . . . .	85
	4.7.6 Simplifying Cluster Scores . . . . .	87
	4.7.7 How Much Data Reduction Is Necessary? . . . . .	87

4.8	Other Approaches to Predictive Modeling . . . . .	89
4.9	Overly Influential Observations . . . . .	90
4.10	Comparing Two Models . . . . .	92
4.11	Improving the Practice of Multivariable Prediction . . . . .	94
4.12	Summary: Possible Modeling Strategies . . . . .	94
	4.12.1 Developing Predictive Models . . . . .	95
	4.12.2 Developing Models for Effect Estimation . . . . .	98
	4.12.3 Developing Models for Hypothesis Testing . . . . .	99
4.13	Further Reading . . . . .	100
4.14	Problems . . . . .	102
<b>5</b>	<b>Describing, Resampling, Validating, and Simplifying the Model . . . . .</b>	<b>103</b>
5.1	Describing the Fitted Model . . . . .	103
	5.1.1 Interpreting Effects . . . . .	103
	5.1.2 Indexes of Model Performance . . . . .	104
5.2	The Bootstrap . . . . .	106
5.3	Model Validation . . . . .	109
	5.3.1 Introduction . . . . .	109
	5.3.2 Which Quantities Should Be Used in Validation? . . . . .	110
	5.3.3 Data-Splitting . . . . .	111
	5.3.4 Improvements on Data-Splitting: Resampling . . . . .	112
	5.3.5 Validation Using the Bootstrap . . . . .	114
5.4	Bootstrapping Ranks of Predictors . . . . .	117
5.5	Simplifying the Final Model by Approximating It . . . . .	118
	5.5.1 Difficulties Using Full Models . . . . .	118
	5.5.2 Approximating the Full Model . . . . .	119
5.6	Further Reading . . . . .	121
5.7	Problem . . . . .	124
<b>6</b>	<b>R Software . . . . .</b>	<b>127</b>
6.1	The R Modeling Language . . . . .	128
6.2	User-Contributed Functions . . . . .	129
6.3	The <code>rms</code> Package . . . . .	130
6.4	Other Functions . . . . .	141
6.5	Further Reading . . . . .	142
<b>7</b>	<b>Modeling Longitudinal Responses using Generalized Least Squares . . . . .</b>	<b>143</b>
7.1	Notation and Data Setup . . . . .	143
7.2	Model Specification for Effects on $E(Y)$ . . . . .	144
7.3	Modeling Within-Subject Dependence . . . . .	144
7.4	Parameter Estimation Procedure . . . . .	147
7.5	Common Correlation Structures . . . . .	147
7.6	Checking Model Fit . . . . .	148

7.7	Sample Size Considerations . . . . .	148
7.8	R Software . . . . .	149
7.9	Case Study . . . . .	149
	7.9.1 Graphical Exploration of Data . . . . .	150
	7.9.2 Using Generalized Least Squares . . . . .	151
7.10	Further Reading . . . . .	158
<b>8</b>	<b>Case Study in Data Reduction . . . . .</b>	<b>161</b>
8.1	Data . . . . .	161
8.2	How Many Parameters Can Be Estimated? . . . . .	164
8.3	Redundancy Analysis . . . . .	164
8.4	Variable Clustering . . . . .	166
8.5	Transformation and Single Imputation Using <code>transcan</code> . . . . .	167
8.6	Data Reduction Using Principal Components . . . . .	170
	8.6.1 Sparse Principal Components . . . . .	175
8.7	Transformation Using Nonparametric Smoothers . . . . .	176
8.8	Further Reading . . . . .	177
8.9	Problems . . . . .	178
<b>9</b>	<b>Overview of Maximum Likelihood Estimation . . . . .</b>	<b>181</b>
9.1	General Notions—Simple Cases . . . . .	181
9.2	Hypothesis Tests . . . . .	185
	9.2.1 Likelihood Ratio Test . . . . .	185
	9.2.2 Wald Test . . . . .	186
	9.2.3 Score Test . . . . .	186
	9.2.4 Normal Distribution—One Sample . . . . .	187
9.3	General Case . . . . .	188
	9.3.1 Global Test Statistics . . . . .	189
	9.3.2 Testing a Subset of the Parameters . . . . .	190
	9.3.3 Tests Based on Contrasts . . . . .	192
	9.3.4 Which Test Statistics to Use When . . . . .	193
	9.3.5 Example: Binomial—Comparing Two Proportions . . . . .	194
9.4	Iterative ML Estimation . . . . .	195
9.5	Robust Estimation of the Covariance Matrix . . . . .	196
9.6	Wald, Score, and Likelihood-Based Confidence Intervals . . . . .	198
	9.6.1 Simultaneous Wald Confidence Regions . . . . .	199
9.7	Bootstrap Confidence Regions . . . . .	199
9.8	Further Use of the Log Likelihood . . . . .	203
	9.8.1 Rating Two Models, Penalizing for Complexity . . . . .	203
	9.8.2 Testing Whether One Model Is Better than Another . . . . .	204
	9.8.3 Unitless Index of Predictive Ability . . . . .	205
	9.8.4 Unitless Index of Adequacy of a Subset of Predictors . . . . .	207
9.9	Weighted Maximum Likelihood Estimation . . . . .	208
9.10	Penalized Maximum Likelihood Estimation . . . . .	209

9.11	Further Reading . . . . .	213
9.12	Problems . . . . .	216
<b>10</b>	<b>Binary Logistic Regression . . . . .</b>	<b>219</b>
10.1	Model . . . . .	219
10.1.1	Model Assumptions and Interpretation of Parameters . . . . .	221
10.1.2	Odds Ratio, Risk Ratio, and Risk Difference . . . . .	224
10.1.3	Detailed Example . . . . .	225
10.1.4	Design Formulations . . . . .	230
10.2	Estimation . . . . .	231
10.2.1	Maximum Likelihood Estimates . . . . .	231
10.2.2	Estimation of Odds Ratios and Probabilities . . . . .	232
10.2.3	Minimum Sample Size Requirement . . . . .	233
10.3	Test Statistics . . . . .	234
10.4	Residuals . . . . .	235
10.5	Assessment of Model Fit . . . . .	236
10.6	Collinearity . . . . .	255
10.7	Overly Influential Observations . . . . .	255
10.8	Quantifying Predictive Ability . . . . .	256
10.9	Validating the Fitted Model . . . . .	259
10.10	Describing the Fitted Model . . . . .	264
10.11	R Functions . . . . .	269
10.12	Further Reading . . . . .	271
10.13	Problems . . . . .	273
<b>11</b>	<b>Binary Logistic Regression Case Study 1 . . . . .</b>	<b>275</b>
11.1	Overview . . . . .	275
11.2	Background . . . . .	275
11.3	Data Transformations and Single Imputation . . . . .	276
11.4	Regression on Original Variables, Principal Components and Pretransformations . . . . .	277
11.5	Description of Fitted Model . . . . .	278
11.6	Backwards Step-Down . . . . .	280
11.7	Model Approximation . . . . .	287
<b>12</b>	<b>Logistic Model Case Study 2: Survival of Titanic Passengers . . . . .</b>	<b>291</b>
12.1	Descriptive Statistics . . . . .	291
12.2	Exploring Trends with Nonparametric Regression . . . . .	294
12.3	Binary Logistic Model With Casewise Deletion of Missing Values . . . . .	296
12.4	Examining Missing Data Patterns . . . . .	302
12.5	Multiple Imputation . . . . .	304
12.6	Summarizing the Fitted Model . . . . .	307

<b>13 Ordinal Logistic Regression</b> . . . . .	311
13.1 Background . . . . .	311
13.2 Ordinality Assumption . . . . .	312
13.3 Proportional Odds Model . . . . .	313
13.3.1 Model . . . . .	313
13.3.2 Assumptions and Interpretation of Parameters . . . . .	313
13.3.3 Estimation . . . . .	314
13.3.4 Residuals . . . . .	314
13.3.5 Assessment of Model Fit . . . . .	315
13.3.6 Quantifying Predictive Ability . . . . .	318
13.3.7 Describing the Fitted Model . . . . .	318
13.3.8 Validating the Fitted Model . . . . .	318
13.3.9 R Functions . . . . .	319
13.4 Continuation Ratio Model . . . . .	319
13.4.1 Model . . . . .	319
13.4.2 Assumptions and Interpretation of Parameters . . . . .	320
13.4.3 Estimation . . . . .	320
13.4.4 Residuals . . . . .	321
13.4.5 Assessment of Model Fit . . . . .	321
13.4.6 Extended CR Model . . . . .	321
13.4.7 Role of Penalization in Extended CR Model . . . . .	322
13.4.8 Validating the Fitted Model . . . . .	322
13.4.9 R Functions . . . . .	323
13.5 Further Reading . . . . .	324
13.6 Problems . . . . .	324
<b>14 Case Study in Ordinal Regression, Data Reduction, and Penalization</b> . . . . .	327
14.1 Response Variable . . . . .	328
14.2 Variable Clustering . . . . .	329
14.3 Developing Cluster Summary Scores . . . . .	330
14.4 Assessing Ordinality of $Y$ for each $X$ , and Unadjusted Checking of PO and CR Assumptions . . . . .	333
14.5 A Tentative Full Proportional Odds Model . . . . .	333
14.6 Residual Plots . . . . .	337
14.7 Graphical Assessment of Fit of CR Model . . . . .	339
14.8 Extended Continuation Ratio Model . . . . .	340
14.9 Penalized Estimation . . . . .	342
14.10 Using Approximations to Simplify the Model . . . . .	348
14.11 Validating the Model . . . . .	353
14.12 Summary . . . . .	355
14.13 Further Reading . . . . .	356
14.14 Problems . . . . .	357

**15 Regression Models for Continuous  $Y$  and Case Study in Ordinal Regression** . . . . . 359

15.1 The Linear Model . . . . . 359

15.2 Quantile Regression . . . . . 360

15.3 Ordinal Regression Models for Continuous  $Y$  . . . . . 361

15.3.1 Minimum Sample Size Requirement . . . . . 363

15.4 Comparison of Assumptions of Various Models . . . . . 364

15.5 Dataset and Descriptive Statistics . . . . . 365

15.5.1 Checking Assumptions of OLS and Other Models . . . . . 368

15.6 Ordinal Regression Applied to  $HbA_{1c}$  . . . . . 370

15.6.1 Checking Fit for Various Models Using Age . . . . . 370

15.6.2 Examination of BMI . . . . . 374

15.6.3 Consideration of All Body Size Measurements . . . . . 375

**16 Transform-Both-Sides Regression** . . . . . 389

16.1 Background . . . . . 389

16.2 Generalized Additive Models . . . . . 390

16.3 Nonparametric Estimation of  $Y$ -Transformation . . . . . 390

16.4 Obtaining Estimates on the Original Scale . . . . . 391

16.5 R Functions . . . . . 392

16.6 Case Study . . . . . 393

**17 Introduction to Survival Analysis** . . . . . 399

17.1 Background . . . . . 399

17.2 Censoring, Delayed Entry, and Truncation . . . . . 401

17.3 Notation, Survival, and Hazard Functions . . . . . 402

17.4 Homogeneous Failure Time Distributions . . . . . 407

17.5 Nonparametric Estimation of  $S$  and  $\Lambda$  . . . . . 409

17.5.1 Kaplan–Meier Estimator . . . . . 409

17.5.2 Altschuler–Nelson Estimator . . . . . 413

17.6 Analysis of Multiple Endpoints . . . . . 413

17.6.1 Competing Risks . . . . . 414

17.6.2 Competing Dependent Risks . . . . . 414

17.6.3 State Transitions and Multiple Types of Nonfatal Events . . . . . 416

17.6.4 Joint Analysis of Time and Severity of an Event . . . . . 417

17.6.5 Analysis of Multiple Events . . . . . 417

17.7 R Functions . . . . . 418

17.8 Further Reading . . . . . 420

17.9 Problems . . . . . 421

**18 Parametric Survival Models** . . . . . 423

18.1 Homogeneous Models (No Predictors) . . . . . 423

18.1.1 Specific Models . . . . . 423

18.1.2 Estimation . . . . . 424

18.1.3 Assessment of Model Fit . . . . . 426

18.2	Parametric Proportional Hazards Models . . . . .	427
18.2.1	Model . . . . .	427
18.2.2	Model Assumptions and Interpretation of Parameters . . . . .	428
18.2.3	Hazard Ratio, Risk Ratio, and Risk Difference . . . .	430
18.2.4	Specific Models . . . . .	431
18.2.5	Estimation . . . . .	432
18.2.6	Assessment of Model Fit . . . . .	434
18.3	Accelerated Failure Time Models . . . . .	436
18.3.1	Model . . . . .	436
18.3.2	Model Assumptions and Interpretation of Parameters . . . . .	436
18.3.3	Specific Models . . . . .	437
18.3.4	Estimation . . . . .	438
18.3.5	Residuals . . . . .	440
18.3.6	Assessment of Model Fit . . . . .	440
18.3.7	Validating the Fitted Model . . . . .	446
18.4	Buckley–James Regression Model . . . . .	447
18.5	Design Formulations . . . . .	447
18.6	Test Statistics . . . . .	447
18.7	Quantifying Predictive Ability . . . . .	447
18.8	Time-Dependent Covariates . . . . .	447
18.9	R Functions . . . . .	448
18.10	Further Reading . . . . .	450
18.11	Problems . . . . .	451
<b>19</b>	<b>Case Study in Parametric Survival Modeling and Model Approximation . . . . .</b>	<b>453</b>
19.1	Descriptive Statistics . . . . .	453
19.2	Checking Adequacy of Log-Normal Accelerated Failure Time Model . . . . .	458
19.3	Summarizing the Fitted Model . . . . .	466
19.4	Internal Validation of the Fitted Model Using the Bootstrap . . . . .	466
19.5	Approximating the Full Model . . . . .	469
19.6	Problems . . . . .	473
<b>20</b>	<b>Cox Proportional Hazards Regression Model . . . . .</b>	<b>475</b>
20.1	Model . . . . .	475
20.1.1	Preliminaries . . . . .	475
20.1.2	Model Definition . . . . .	476
20.1.3	Estimation of $\beta$ . . . . .	476
20.1.4	Model Assumptions and Interpretation of Parameters . . . . .	478
20.1.5	Example . . . . .	478

20.1.6	Design Formulations . . . . .	480
20.1.7	Extending the Model by Stratification . . . . .	481
20.2	Estimation of Survival Probability and Secondary Parameters . . . . .	483
20.3	Sample Size Considerations . . . . .	486
20.4	Test Statistics . . . . .	486
20.5	Residuals . . . . .	487
20.6	Assessment of Model Fit . . . . .	487
20.6.1	Regression Assumptions . . . . .	487
20.6.2	Proportional Hazards Assumption . . . . .	494
20.7	What to Do When PH Fails . . . . .	501
20.8	Collinearity . . . . .	503
20.9	Overly Influential Observations . . . . .	504
20.10	Quantifying Predictive Ability . . . . .	504
20.11	Validating the Fitted Model . . . . .	506
20.11.1	Validation of Model Calibration . . . . .	506
20.11.2	Validation of Discrimination and Other Statistical Indexes . . . . .	507
20.12	Describing the Fitted Model . . . . .	509
20.13	R Functions . . . . .	513
20.14	Further Reading . . . . .	517
<b>21</b>	<b>Case Study in Cox Regression . . . . .</b>	<b>521</b>
21.1	Choosing the Number of Parameters and Fitting the Model . . . . .	521
21.2	Checking Proportional Hazards . . . . .	525
21.3	Testing Interactions . . . . .	527
21.4	Describing Predictor Effects . . . . .	527
21.5	Validating the Model . . . . .	529
21.6	Presenting the Model . . . . .	530
21.7	Problems . . . . .	531
<b>A</b>	<b>Datasets, R Packages, and Internet Resources . . . . .</b>	<b>535</b>
	<b>References . . . . .</b>	<b>539</b>
	<b>Index . . . . .</b>	<b>571</b>



# Typographical Conventions

Boxed numbers in the margins such as  $\boxed{1}$  correspond to numbers at the end of chapters in sections named “Further Reading.” Bracketed numbers and numeric superscripts in the text refer to the bibliography, while alphabetic superscripts indicate footnotes.

R language commands and names of R functions and packages are set in `typewriter font`, as are most variable names.

R code blocks are set off with a shadowbox, and R output that is not directly using  $\LaTeX$  appears in a box that is framed on three sides.

In the S language upon which R is based,  $x \leftarrow y$  is read “ $x$  gets the value of  $y$ .” The assignment operator  $\leftarrow$ , used in the text for aesthetic reasons (as are  $\leq$  and  $\geq$ ), is entered by the user as `<-`. Comments begin with `#`, subscripts use brackets (`[ ]`), and the missing value is denoted by `NA` (not available).

In ordinary text and mathematical expressions, `[logical variable]` and `[logical expression]` imply a value of 1 if the logical variable or expression is true, and 0 otherwise.