

Computational Modeling of Cognition and Behavior

Computational modelling is now ubiquitous in psychology, and researchers who are not modellers may find it increasingly difficult to follow the theoretical developments in their field. This book presents an integrated framework for the development and application of models in psychology and related disciplines. Researchers and students are given the knowledge and tools to interpret models published in their area, as well as to develop, fit, and test their own models.

Both the development of models and key features of any model are covered, as are the applications of models in a variety of domains across the behavioural sciences. A number of chapters are devoted to fitting models using maximum likelihood and Bayesian estimation, including fitting hierarchical and mixture models. Model comparison is described as a core philosophy of scientific inference, and the use of models to understand theories and advance scientific discourse is explained.

Simon Farrell is a professor in the School of Psychological Science at the University of Western Australia. He uses computational modelling and experiments to understand memory, judgement, choice, and the role of memory in decision-making. He is the co-author of *Computational Modeling in Cognition: Principles and Practice* (2011) and has published numerous papers on the application of models to psychological data. Simon was Associate Editor of the *Journal of Memory and Language* (2009–11) and the *Quarterly Journal of Experimental Psychology* (2011–16). In 2009 Farrell was awarded the Bertelson Award by the European Society for Cognitive Psychology for his outstanding early career contribution to European Cognitive Psychology.

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Computational Modeling of Cognition and Behavior

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To Jodi, Alec, and Sylvie, with love (S.F.)

To Annie and the tribe (Ben, Rachel, Thomas, Jess, and Zachary) with love (S.L.)

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Preface

This book presents an integrated approach to the application of computational and mathematical models in psychology. Computational models have been extensively applied to better understand many domains of human behavior, such as perception, memory, reasoning, decision-making, communicating, and deciding. Modeling is often applied in these areas to different purposes – measurement, prediction, and model testing. Our major goal here is to provide a unified view on the interface between theories, simulations, and data, with a view to answering the central question: how can we learn from models of behavior?

We cover several topics. Part I of the book explains what a computational model is and gives a general overview of models that have been applied to understanding human behavior. We also examine the process of converting theoretical statements into simulation code and give an overview of the various concepts required to understand modeling. Part II examines one use of models: parameter estimation. By fitting models to data, inferences can be made from the resulting parameter estimates, and statements made about the psychological mechanism(s) or representations that generated those data. We cover maximum likelihood estimation and Bayesian estimation, including estimation across multiple participants and hierarchical estimation. Part III explores how inferences can be made from models by using model comparison. We consider under what conditions statements of sufficiency and necessity can be made from data, and how model complexity can be conceptualized and quantified. Part III examines several approaches to accounting for complexity in model comparison, including information criteria and Bayes Factors. Part IV considers the role of computational modeling in advancing psychological theory. We explore use of models as adjuncts to human reasoning, and the interaction between human and artificial intelligence to guide theorizing and generation of conceptual insights. We also consider the use of models as tools to arrive at shared understanding between researchers (i.e. the use of models as common terms of reference), and practices for communicating and sharing models. We finish by giving an overview of the application of models in several popular areas: neural network models, models of choice response time, and the application of models to understand neural data.

To accomplish all this, we use a freely available computer language, called R, which was initially developed for statistical data analysis but has broad applicability and is now used by many modellers.

Some readers may know that we wrote a seemingly similar book some time ago (Lewandowsky and Farrell, 2011). The present book retains some of the features of the earlier book that seemed to be appreciated by readers – for example, we try to explain the important features in all our snippets of source code. Thus, while this is not a textbook in R programming, the book does point to the most important aspects of our programs that are relevant to the task at hand, namely how to understand the human mind by computational means. Beyond that, however, the present book is very different from our earlier volume. Whereas the earlier book was an introductory textbook, the present volume aspires to more lofty goals: we want to take the reader to the leading edge of current modeling practice, and we introduce several novel developments in the course of doing so.

As well as providing simulation code in the R language to complement the equations and descriptions in the text, each chapter ends with an *in vivo* section. For each *in vivo* example, we asked a researcher to share their experiences in working on that topic or method, some consideration of the philosophy of science in that area, or a counterpoint to our own views. We think these sections are insightful and illuminating (and amusing!), and we are very grateful to other members of the field for giving us the opportunity to share their thoughts with you.

As well as the authors of the *in vivo* sections throughout the book, we would like to thank the numerous friends and colleagues with whom we have discussed many issues in preparing this book. In particular, we thank Henrik Singmann and Benjamin Vincent for their comments on drafts of chapters in which their work was cited and used. We would also like to thank the instructors (Gordon Brown, Amy Criss, Adele Diederich, Chris Donkin, Bob French, Cas Ludwig, Klaus Oberauer, Jörg Rieskamp, Lael Schooler, Joachim Vandekerckhove, and Eric-Jan Wagenmakers) and students of the four European Summer Schools on Computational and Mathematical Modeling of Cognition that we have conducted over the past eight years, and that have attracted more than 120 students to date. Their feedback on drafts of this book have been invaluable and we thank students and instructors for many enthusiastic discussions. One thing that has been affirmed for us through these discussions is that models are used in many different ways in psychology. In presenting a unified and integrative theoretical framework for modeling, we have attempted to capture this variance, but recognize that there are many models and points of view that we could not explore here. We would also like to thank Janka Romero and her predecessor, Hetty Marx, at Cambridge University Press for their help and encouragement whilst proposing and writing the book, and Adam Hooper, Anup Kumar, Christina Taylor, and Sindhujaa Ayyappan for their help during production.