

Statistical Learning for Biomedical Data

This book is for anyone who has biomedical data and needs to identify variables that predict an outcome, for two-group outcomes such as tumor/not tumor, survival/death, or response from treatment. Statistical learning machines are ideally suited to these types of prediction problems, especially if the variables being studied may not meet the assumptions of traditional techniques.

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Coverage includes single decision trees, multiple-tree techniques such as Random Forests™, neural nets, support vector machines, nearest neighbors, and boosting.

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Preface

Statistical learning machines live at the triple-point of statistical data analysis, pure mathematics, and computer science. Learning machines form a still rapidly expanding family of technologies and strategies for analyzing an astonishing variety of data. Methods include pattern recognition, classification, and prediction, and the discovery of networks, hidden structure, or buried relationships. This book focuses on the problem of using biomedical data to classify subjects into just two groups. Connections are drawn to other topics that arise naturally in this setting, including how to find the most important predictors in the data, how to validate the results, how to compare different prediction models (“engines”), and how to combine models for better performance than any one model can give. While emphasis is placed on the core ideas and strategies, keeping mathematical gadgets in the background, we provide extensive plain-text translations of recent important mathematical and statistical results. Important learning machine topics that we don’t discuss, but which are being studied actively in the research literature, are described in Chapter 13: Summary and conclusions.

Acknowledgments

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We dedicate this book to Leo Breiman (1928–2005).