Machine Learning And Causal Inference A Modular Approach

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GIOVANNA ROJAS

An Introduction to Causal Inference Springer
In science, business, and policymaking -- anywhere data are used in prediction -- two sorts of problems requiring very different methods of analysis often arise. The first, problems of recognition and classification, concerns learning how to use some features of a system to accurately predict other features of that system. The second, problems of causal discovery, concerns learning how to predict those changes to some features of a system that will result if an intervention changes other features. This book is about the second -- much more difficult -- type of problem. Typical problems of causal discovery are: How will a change in commission rates affect the total sales of a company? How will a reduction in cigarette smoking among older smokers affect their life expectancy? How will a change in the formula a college uses to award scholarships affect its dropout rate? These sorts of changes are interventions that directly alter some features of the system and perhaps -- and this is the question -- indirectly alter others. The contributors discuss recent research and applications using Bayes nets or directed graphic representations, including representations of feedback or recursive systems. The book contains a thorough discussion of foundational issues, algorithms, proof techniques, and applications to economics, physics, biology, educational research, and other areas.
Trustworthy Online Controlled Experiments CRC Press
This text presents statistical methods for studying causal effects and discusses how readers can assess such effects in simple randomized experiments.
Handbook of Big Data Cambridge University Press
Causality offers the first comprehensive coverage of causal analysis in many sciences, including recent advances using graphical methods. Pearl presents a unified account of the probabilistic, manipulative, counterfactual and structural approaches to causation, and devises simple mathematical tools for analyzing the relationships between causal connections, statistical associations, actions and observations. The book will open the way for including causal analysis in the standard curriculum of statistics, artificial intelligence ...
Causal Inference in Econometrics CreateSpace
In recent years, interest in rigorous impact evaluation has grown tremendously in policy-making, economics, public health, social sciences and international relations. Evidence-based policy-making has become a recurring theme in public policy, alongside greater demands for accountability in public policies and public spending, and requests for independent and rigorous impact evaluations for policy evidence. Frlich and Sperlich offer a comprehensive and up-to-date approach to quantitative impact evaluation analysis, also known as causal inference or treatment effect analysis, illustrating the main approaches for identification and estimation: experimental studies, randomization inference and randomized control trials (RCTs), matching and propensity score matching and weighting, instrumental variable estimation, difference-in-differences, regression discontinuity designs, quantile treatment effects, and evaluation of dynamic treatments. The book is designed for economics graduate courses but can also serve as a manual for professionals in research institutes, governments, and international organizations, evaluating the impact of a wide range of public policies in health, environment, transport and economic development.
A New Framework for Machine Learning and the Social Sciences Grand Central Publishing
Big Data in Omics and Imaging: Integrated Analysis and Causal Inference addresses the recent development of integrated genomic, epigenomic and imaging data analysis and causal inference in big data era. Despite significant progress in dissecting the genetic architecture of complex diseases by genome-wide association studies (GWAS), genome-wide expression studies (GWES), and epigenome-wide association studies (EWAS), the overall contribution of the new identified genetic variants is small and a large fraction of genetic variants is still hidden. Understanding the etiology and causal chain of mechanism underlying complex diseases remains elusive. It is time to bring big data, machine learning and causal revolution to developing a new generation of genetic analysis for shifting the current paradigm of genetic analysis from shallow association analysis to deep causal inference and from genetic analysis alone to integrated omics and imaging data analysis for unraveling the mechanism of complex diseases. FEATURES Provides a natural extension and companion volume to Big Data in Omic and Imaging: Association Analysis, but can be read independently. Introduce causal inference theory to genomic, epigenomic and imaging data analysis Develop novel statistics for genome-wide causation studies and epigenome-wide causation studies. Bridge the gap between the traditional association analysis and modern causation analysis Use combinatorial optimization methods and various causal models as a general framework for inferring multilevel omic and image causal networks Present statistical methods and computational algorithms for searching causal paths from genetic variant to disease Develop causal machine learning methods integrating causal inference and machine learning Develop statistics for testing significant difference in directed edge, path, and graphs, and for assessing causal relationships between two networks The book is designed for graduate students and researchers in genomics, epigenomics, medical image, bioinformatics, and data science. Topics covered are: mathematical formulation of causal inference, information geometry for causal inference, topology group and Haar measure, additive noise models, distance correlation, multivariate causal inference and causal networks, dynamic causal networks, multivariate and functional structural equation

models, mixed structural equation models, causal inference with confounders, integer programming, deep learning and differential equations for wearable computing, genetic analysis of function-valued traits, RNA-seq data analysis, causal networks for genetic methylation analysis, gene expression and methylation deconvolution, cell –specific causal networks, deep learning for image segmentation and image analysis, imaging and genomic data analysis, integrated multilevel causal genomic, epigenomic and imaging data analysis.

Causality Cambridge University Press

A Turing Award-winning computer scientist and statistician shows how understanding causality has revolutionized science and will revolutionize artificial intelligence "Correlation is not causation." This mantra, chanted by scientists for more than a century, has led to a virtual prohibition on causal talk. Today, that taboo is dead. The causal revolution, instigated by Judea Pearl and his colleagues, has cut through a century of confusion and established causality -- the study of cause and effect -- on a firm scientific basis. His work explains how we can know easy things, like whether it was rain or a sprinkler that made a sidewalk wet; and how to answer hard questions, like whether a drug cured an illness. Pearl's work enables us to know not just whether one thing causes another: it lets us explore the world that is and the worlds that could have been. It shows us the essence of human thought and key to artificial intelligence. Anyone who wants to understand either needs The Book of Why.

Impact Evaluation Aaai Press

The statistics profession is at a unique point in history. The need for valid statistical tools is greater than ever; data sets are massive, often measuring hundreds of thousands of measurements for a single subject. The field is ready to move towards clear objective benchmarks under which tools can be evaluated. Targeted learning allows (1) the full generalization and utilization of cross-validation as an estimator selection tool so that the subjective choices made by humans are now made by the machine, and (2) targeting the fitting of the probability distribution of the data toward the target parameter representing the scientific question of interest. This book is aimed at both statisticians and applied researchers interested in causal inference and general effect estimation for observational and experimental data. Part I is an accessible introduction to super learning and the targeted maximum likelihood estimator, including related concepts necessary to understand and apply these methods. Parts II-IX handle complex data structures and topics applied researchers will immediately recognize from their own research, including time-to-event outcomes, direct and indirect effects, positivity violations, case-control studies, censored data, longitudinal data, and genomic studies.

The Economics of Artificial Intelligence Springer Science & Business Media

This textbook for graduate students in statistics, data science, and public health deals with the practical challenges that come with big, complex, and dynamic data. It presents a scientific roadmap to translate real-world data science applications into formal statistical estimation problems by using the general template of targeted maximum likelihood estimators. These targeted machine learning algorithms estimate quantities of interest while still providing valid inference. Targeted learning methods within data science area critical component for solving scientific problems in the modern age. The techniques can answer complex questions including optimal rules for assigning treatment based on longitudinal data with time-dependent confounding, as well as other estimands in dependent data structures, such as networks. Included in Targeted Learning in Data Science are demonstrations with soft ware packages and real data sets that present a case that targeted learning is crucial for the next generation of statisticians and data scientists. Th is book is a sequel to the first textbook on machine learning for causal inference, Targeted Learning, published in 2011. Mark van der Laan, PhD, is Jiann-Ping Hsu/Karl E. Peace Professor of Biostatistics and Statistics at UC Berkeley. His research interests include statistical methods in genomics, survival analysis, censored data, machine learning, semiparametric models, causal inference, and targeted learning. Dr. van der Laan received the 2004 Mortimer Spiegelman Award, the 2005 Van Dantzig Award, the 2005 COPSS Snedecor Award, the 2005 COPSS Presidential Award, and has graduated over 40 PhD students in biostatistics and statistics. Sherri Rose, PhD, is Associate Professor of Health Care Policy (Biostatistics) at Harvard Medical School. Her work is centered on developing and integrating innovative statistical approaches to advance human health. Dr. Rose’s methodological research focuses on nonparametric machine learning for causal inference and prediction. She co-leads the Health Policy Data Science Lab and currently serves as an associate editor for the Journal of the American Statistical Association and Biostatistics.

Integrated Analysis and Causal Inference Princeton University Press

The application of causal inference methods is growing exponentially in fields that deal with observational data. Written by pioneers in the field, this practical book presents an authoritative yet accessible overview of the methods and applications of causal inference. With a wide range of detailed, worked examples using real epidemiologic data as well as software for replicating the analyses, the text provides a thorough introduction to the basics of the theory for non-time-varying treatments and the generalization to complex longitudinal data.

Actual Causality CRC Press

Statistical Methods for Dynamic Treatment Regimes shares state of the art of statistical methods developed to address questions of estimation and inference for dynamic treatment regimes, a branch of personalized medicine. This volume demonstrates these methods with their conceptual underpinnings and illustration through analysis of real and simulated data. These methods are immediately applicable to the practice of personalized medicine, which is a medical paradigm that emphasizes the systematic use of individual patient information to optimize patient health care. This is the first single source to provide an overview of methodology and results gathered from journals, proceedings, and technical reports with the goal of orienting researchers to the field. The first chapter establishes context for the statistical reader in the landscape of personalized medicine. Readers need only have familiarity with elementary calculus, linear algebra, and basic large-sample theory to use this text. Throughout the text, authors direct readers to available code or packages in different statistical languages to facilitate implementation. In cases where code does not already exist, the authors provide analytic approaches in sufficient detail that any researcher with knowledge of statistical programming could implement the methods from scratch. This will be an important volume for a wide range of researchers, including statisticians, epidemiologists, medical researchers, and machine learning researchers interested in medical applications. Advanced graduate students in statistics and biostatistics will also find material in Statistical Methods for Dynamic Treatment Regimes to be a critical part of their studies.

Causation, Prediction, and Search Elements of Causal InferenceFoundations and Learning Algorithms

Machine learning tools are well known for their success in prediction. But prediction is not causation, and causal discovery is at the core of most questions concerning economic policy. Recently, however, the literature has focused more on issues of causality. This paper gently introduces some leading work in this area, using a concrete example—assessing the impact of a hypothetical banking crisis on a country's growth. By enabling consideration of a rich set of potential nonlinearities, and by allowing individually-tailored policy assessments, machine learning can provide an invaluable complement to the skill set of economists within the Fund and beyond.

A Practical Guide to A/B Testing Academic Press

This book is devoted to the analysis of causal inference which is one of the most difficult tasks in data analysis: when two phenomena are observed to be related, it is often difficult to decide whether one of them causally influences the other one, or whether these two phenomena have a common cause. This analysis is the main focus of this volume. To get a good understanding of the causal inference, it is important to have models of economic phenomena which are as accurate as possible. Because of this need, this volume also contains papers that use non-traditional economic models, such as fuzzy models and models obtained by using neural networks and data mining techniques. It also contains papers that apply different econometric models to analyze real-life economic dependencies.

Semi-Supervised Learning Springer Science & Business Media

Many of the concepts and terminology surrounding modern causal inference can be quite intimidating to the novice. Judea Pearl presents a book ideal for beginners in statistics, providing a comprehensive introduction to the field of causality. Examples from classical statistics are presented throughout to demonstrate the need for causality in resolving decision-making dilemmas posed by data. Causal methods are also compared to traditional statistical methods, whilst questions are provided at the end of each section to aid student learning.

Cause Effect Pairs in Machine Learning Springer Science & Business Media

This book presents ground-breaking advances in the domain of causal structure learning. The problem of distinguishing cause from effect ("Does altitude cause a change in atmospheric pressure, or vice versa?") is here cast as a binary classification problem, to be tackled by machine learning algorithms. Based on the results of the ChaLearn Cause-Effect Pairs Challenge, this book reveals that the joint distribution of two variables can be scrutinized by machine learning algorithms to reveal the possible existence of a "causal mechanism", in the sense that the values of one variable may have been generated from the values of the other. This book provides both tutorial material on the state-of-the-art on cause-effect pairs and exposes the reader to more advanced material, with a collection of selected papers. Supplemental material includes videos, slides, and code which can be found on the workshop website. Discovering causal relationships from observational data will become increasingly important in data science with the increasing amount of available data, as a means of detecting potential triggers in epidemiology, social sciences, economy, biology, medicine, and other sciences.

Robust Causal Inference and Machine Learning with Clinical Applications MIT Press

As healthcare data becomes increasingly ubiquitous, improving data-driven biomedical research is timely and important. There is a rush to learn from these new sources of data, and to implement research findings into clinical practice. While machine learning methods provide compelling examples of recognizing sophisticated patterns in data, their impact rests heavily on their ability to use data to influence decision making, especially in healthcare. The relationship between machine learning and decision making becomes particularly clear through the lens of causal inference. In general, the harm and benefit attributed to a medical decision depends on the causal treatment effect of the decision in the appropriate population, beyond their baseline risk of poor outcomes. In precision medicine research, the goal is to develop treatment decisions for individual patients by considering the sub-population of individuals with similar covariates to each patient. This thesis advances methodology and practice for applying machine learning to learn better decision-making rules that influence clinical practice, and understanding the fundamental possibilities and limitations of using data to learn to make optimal decisions. First, we develop an approach for personalized treatment effect estimation based on the relative ratio of treatment outcomes. Second, we study when we can trust causal results learned from data, and develop a sensitivity analysis for conditional and average treatment effects to bound the bias created from unobserved confounding. Third, noting that treatment benefit is highly correlated with baseline risk for preventative treatments for atherosclerotic cardiovascular disease (ASCVD), we use machine learning approaches to improve ASCVD risk predictions from longitudinal cohort data that affect clinical prescribing practice, particularly among under-represented minorities.

Three Essays on Causal Inference with High-dimensional Data and Machine Learning Methods CRC Press

A comprehensive review of an area of machine learning that deals with the use of unlabeled data in classification problems: state-of-the-art algorithms, a taxonomy of the field, applications, benchmark experiments, and directions for future research. In the field of machine learning, semi-supervised learning (SSL) occupies the middle ground, between supervised learning (in which all training examples are labeled) and unsupervised learning (in which no label data are given). Interest in SSL has increased in recent years, particularly because of application domains in which unlabeled data are plentiful, such as images, text, and bioinformatics. This first comprehensive overview of SSL presents state-of-the-art algorithms, a taxonomy of the field, selected applications, benchmark experiments, and perspectives on ongoing and future research.Semi-Supervised Learning first presents the key assumptions and ideas underlying the field: smoothness, cluster or low-density separation, manifold structure, and transduction. The core of the book is the presentation of SSL methods, organized according to algorithmic strategies. After an examination of generative models, the book describes algorithms that implement the low-density separation assumption, graph-based methods, and algorithms that perform two-step learning. The book then discusses SSL applications and offers guidelines for SSL practitioners by analyzing the results of extensive benchmark experiments. Finally, the book looks at interesting directions for SSL research. The book closes with a discussion of the relationship between semi-supervised learning and transduction.

Causal Inference for Complex Longitudinal Studies MIT Press

Causal inference -- the process of drawing a conclusion about the impact of an exposure on an outcome -- is foundational to biomedicine, where it is used to guide intervention. The current gold-standard approach for causal inference is randomized experimentation, such as randomized controlled trials (RCTs). Yet, randomized experiments, including RCTs, often enforce strict eligibility criteria that impede the generalizability of causal knowledge to the real world. Observational data, such as the electronic health record (EHR), is often regarded as a more representative source from which to generate causal knowledge. However, observational data is non-randomized, and therefore causal estimates from this source are susceptible to bias from confounders. This weakness complicates two central tasks of causal inference: the replication or evaluation of existing causal knowledge and the generation of new causal knowledge. In this dissertation I (i) address the feasibility of observational data to replicate existing causal knowledge and (ii) present new methods for the generation of causal knowledge with observational data, with a focus on the causal tasks of comparing an outcome between two cohorts and the estimation of attributable risks of exposures in a causal system.

The Book of Why Cambridge University Press

Big Data in Omics and Imaging: Integrated Analysis and Causal Inference addresses the recent development of integrated genomic, epigenomic and imaging data analysis and causal inference in big data era. Despite significant progress in dissecting the genetic architecture of complex diseases by genome-wide association studies (GWAS), genome-wide expression studies (GWES), and epigenome-wide association studies (EWAS), the overall contribution of the new identified genetic variants is small and a large fraction of genetic variants is still hidden. Understanding the etiology and causal chain of mechanism underlying complex diseases remains elusive. It is time to bring big data, machine learning and causal revolution to developing a new generation of genetic analysis for shifting the current paradigm of genetic analysis from shallow association analysis to deep causal inference and from genetic analysis alone to integrated omics and imaging data analysis for unraveling the mechanism of complex diseases. FEATURES Provides a natural extension and companion volume to Big Data in Omic and Imaging: Association Analysis, but can be read independently. Introduce causal inference theory to genomic, epigenomic and imaging data analysis Develop novel statistics for genome-wide causation studies and epigenome-wide causation studies. Bridge the gap between the traditional association analysis and modern causation analysis Use combinatorial optimization methods and various causal models as a general framework for inferring multilevel omic and image causal networks Present statistical methods and computational algorithms for searching causal paths from genetic variant to disease Develop causal machine learning methods integrating causal inference and machine learning Develop statistics for testing significant difference in directed edge, path, and graphs, and for assessing causal relationships between two networks The book is designed for graduate students and researchers in genomics, epigenomics, medical image, bioinformatics, and data science. Topics covered are: mathematical formulation of causal inference, information geometry for causal inference, topology group and Haar measure, additive noise models, distance correlation, multivariate causal inference and causal networks, dynamic causal networks, multivariate and functional structural equation models, mixed structural equation models, causal inference with confounders, integer programming, deep learning and differential equations for wearable computing, genetic analysis of function-valued traits, RNA-seq data analysis, causal networks for genetic methylation analysis, gene expression and methylation deconvolution, cell –specific causal networks, deep learning for image segmentation and image analysis, imaging and genomic data analysis, integrated multilevel causal genomic, epigenomic and imaging data analysis.

Machine Learning and Causality: The Impact of Financial Crises on Growth Basic Books

This book honours the outstanding contributions of Vladimir Vapnik, a rare example of a scientist for whom the following statements hold true simultaneously: his work led to the inception of a new field of research, the theory of statistical learning and empirical inference; he has lived to see the field blossom; and he is still as active as ever. He started analyzing learning algorithms in the 1960s and he invented the first version of the generalized portrait algorithm. He later developed one of the most successful methods in machine learning, the support vector machine (SVM) – more than just an algorithm, this was a new approach to learning problems, pioneering the use of functional analysis and convex optimization in machine learning. Part I of this book contains three chapters describing and witnessing some of Vladimir Vapnik's contributions to science. In the first chapter, Léon Bottou discusses the seminal paper published in 1968 by Vapnik and Chervonenkis that lay the foundations of statistical learning theory, and the second chapter is an English-language translation of that original paper. In the third chapter, Alexey Chervonenkis presents a first-hand account of the early history of SVMs and valuable insights into the first steps in the development of the SVM in the framework of the generalised portrait method. The remaining chapters, by leading scientists in domains such as statistics, theoretical computer science, and mathematics, address substantial topics in the theory and practice of statistical learning theory, including SVMs and other kernel-based methods, boosting, PAC-Bayesian theory, online and transductive learning, loss functions, learnable function classes, notions of complexity for function classes, multitask learning, and hypothesis selection. These contributions include historical and context notes, short surveys, and comments on future research directions. This book will be of interest to researchers, engineers, and graduate students engaged with all aspects of statistical learning.

A Primer International Monetary Fund

Random forests are a powerful method for non-parametric regression, but are limited in their ability to fit smooth signals. Taking the perspective of random forests as an adaptive kernel method, we pair the forest kernel with a local linear regression adjustment to better capture smoothness. The resulting procedure, local linear forests, enables us to improve on asymptotic rates of convergence for random forests with smooth signals, and provides substantial gains in accuracy on both real and simulated data. We prove a central limit theorem valid under regularity conditions on the forest and smoothness constraints, propose a computationally efficient construction for confidence intervals, and discuss an extension to local linear causal forests for learning heterogeneous treatment effects. Following this deep dive into local linear forests, we discuss two applications of machine learning for causal inference. The first is a retirement reform in Denmark, in which shifting eligibility ages for an early retirement program provide an opportunity to analyze heterogeneous treatment effects of the age of retirement eligibility. The second is a randomized controlled trial in Nairobi, Kenya, aiming to lower rates of gender-based violence against adolescent students living in informal settlements. In the latter example, we explore how local linear causal forests help to uncover and emphasize trends in marginalized student responses to the intervention. In both cases, we address how machine learning and causal inference are powerful tools to discover patterns in individual treatment effects, and to advocate for marginalized groups when estimates reveal troubling patterns in the data.