Algebraic Geometry And Statistical Learning Theory Cambridge Monographs On Applied And Computational Mathematics

Several years ago our statistical friends and relations introduced us to the work of Amari and Barndorff-Nielsen on applications of differential geometry to statistics. This book has arisen because we believe that there is a deep relationship between statistics and differential geometry and moreoever that this relationship uses parts of differential geometry, particularly its 'higher-order' aspects not readily accessible to a statistical audience from the existing literature. It is, in part, a long reply to the frequent requests we have had for references on differential geometry! While we have not gone beyond the path-breaking work of Amari and Barndorff- Nielsen in the realm of applications, our book gives some new explanations of their ideas from a first principles point of view as far as geometry is concerned. In particular it seeks to explain why geometry should enter into parametric statistics, and how the theory of asymptotic expansions involves a form of higher-order differential geometry. The first chapter of the book explores exponential families as flat geometries. Indeed the whole notion of using log-likelihoods amounts to exploiting a particular form of flat space known as an affine geometry, in which straight lines and planes make sense, but lengths and angles are absent. We use these geometric ideas to introduce the notion of the second fundamental form of a family whose vanishing characterises precisely the exponential families.

In a world where we are constantly being asked to make decisions based on incomplete information, facility with basic probability is an essential skill. This book provides a solid foundation in basic probability theory designed for intellectually curious readers and those new to the subject. Through its conversational tone and careful pacing of mathematical development, the book balances a charming style with informative discussion. This text will immerse the reader in a mathematical view of the world, giving them a glimpse into what attracts mathematicians to the subject in the first place. Rather than simply writing out and memorizing formulas, the reader will come out with an understanding of what those formulas mean, and how and when to use them. Readers will also encounter settings where probabilistic reasoning does not apply or where intuition can be misleading. This book establishes simple principles of counting collections and sequences of alternatives, and elaborates on these techniques to solve real world problems both inside and outside the casino. Pair this book with the HarvardX online course for great videos and interactive learning: https://harvardx.link/fat-chance.

The fundamental mathematical tools needed to understand machine learning include linear algebra, analytic geometry, matrix decompositions, vector calculus, optimization, probability and statistics. These topics are traditionally taught in disparate courses, making it hard for data science or computer science students, or professionals, to efficiently learn the mathematics. This self-contained textbook bridges the gap between mathematical and machine learning texts, introducing the mathematical concepts with a minimum of prerequisites. It uses these concepts to derive four central machine learning methods: linear regression, principal component analysis, Gaussian mixture models and support vector machines. For students and others with a mathematical background, these derivations provide a starting point to machine learning texts. For those learning the mathematics for the first time, the methods help build intuition and practical experience with applying mathematical concepts. Every chapter includes worked examples and exercises to test understanding. Programming tutorials are offered on the book's web site.

At the crossroads of representation theory, algebraic geometry and finite group theory, this 2004 book blends together many of the main concerns of modern algebra, with full proofs of some of the most remarkable achievements in the area. Cabanes and Enguehard follow three main themes: first, applications of étale cohomology, leading to the proof of the recent Bonnafé–Rouquier theorems. The second is a straightforward and simplified account of the Dipper–James theorems relating irreducible characters and modular representations. The final theme is local representation theory. One of the main results here is the authors' version of Fong–Srinivasan theorems. Throughout the text is illustrated by many examples and background is provided by several introductory chapters on basic results and appendices on algebraic geometry and derived categories. The result is an essential introduction for graduate students and reference for all algebraists.

An accessible introduction to convex algebraic geometry and semidefinite optimization. For graduate students and researchers in mathematics and computer science.

The purpose of this unique book is to establish purely algebraic foundations for the development of certain parts of topology. Some topologists seek to understand geometric properties of solutions to finite systems of equations or inequalities and configurations which in some sense actually occur in the real world. Others study spaces constructed more abstractly using infinite limit processes. Their goal is to determine just how similar or different these abstract spaces are from those which are finitely described. However, as topology is usually taught, even the first, more concrete type of problem is approached using the language and methods of the second type. Professor Brumfiel's thesis is that this is unnecessary and, in fact, misleading philosophically. He develops a type of algebra, partially ordered rings, in which it makes sense to talk about solutions of equations and inequalities and to compare geometrically the resulting spaces. The importance of this approach is primarily that it clarifies the sort of geometrical questions one wants to ask and answer about those spaces which might have physical significance.

This book presents algorithmic tools for algebraic geometry, with experimental applications. It also introduces Macaulay 2, a computer algebra system supporting research in algebraic geometry, commutative algebra, and their applications. The algorithmic tools presented here are designed to serve readers wishing to bring such tools to bear on their own problems. The first part of the book covers Macaulay 2 using concrete applications; the second emphasizes details of the mathematics.

This is the first comprehensive book on information geometry, written by the founder of the field. It begins with an elementary introduction to dualistic geometry and proceeds to a wide range of applications, covering information science, engineering, and neuroscience. It consists of four parts, which on the whole can be read independently. A manifold with a divergence function is first introduced, leading directly to dualistic structure, the heart of information geometry. This part (Part I) can be apprehended without any knowledge of differential geometry. An intuitive explanation of modern differential geometry then follows in Part II, although the book is for the most part understandable without modern differential geometry. Information geometry of statistical inference, including time series analysis and semiparametric estimation (the Neyman–Scott problem), is demonstrated concisely in Part III. Applications addressed in Part IV include hot current topics in machine learning, signal processing, optimization, and neural networks. The book is interdisciplinary, connecting mathematics, information sciences, physics, and neurosciences, inviting readers to a new world of information and geometry. This book is highly recommended to graduate students and researchers who seek new mathematical methods and tools useful in their own fields.

A traditional approach to developing multivariate statistical theory is algebraic. Sets of observations are represented by matrices, linear combinations are formed from these matrices by multiplying them by coefficient matrices, and useful statistics are found by imposing various criteria of optimization on these combinations. Matrix algebra is the vehicle for these calculations. A second approach is computational. Since many users find that they do not need to know the mathematical basis of the techniques as long as they have a way to transform data into results, the computation can be done by a package of computer programs that somebody else has written. An approach from this perspective emphasizes how the computer packages are used, and is usually coupled with rules that allow one to extract the most important numbers from the output and interpret them. Useful as both approaches are--particularly when combined--they can overlook an important aspect of multivariate analysis. To apply it correctly, one needs a way to conceptualize the multivariate relationships that exist among variables. This book is designed to help the reader develop a way of thinking about multivariate statistics, as well as to understand in a broader and more intuitive sense what the procedures do and how their results are interpreted. Presenting important procedures of multivariate statistical theory geometrically, the author hopes that this emphasis on the geometry will give the reader a coherent picture into which all the multivariate techniques fit.

A handbook of key articles providing both an introduction and reference for newcomers and experts alike.

A rigorous introduction to geometric and topological inference, for anyone interested in a geometric approach to data science.

Doing Math with Python shows you how to use Python to delve into high school–level math topics like statistics, geometry, probability, and calculus. You'll start with simple projects, like a factoring program and a quadratic-equation solver, and then create more complex projects once you've gotten the hang of things. Along the way, you'll discover new ways to explore math and gain valuable programming skills that you'll use throughout your study of math and computer science. Learn how to: -Describe your data with statistics, and visualize it with line graphs, bar charts, and scatter plots -Explore set theory and probability with programs for coin flips, dicing, and other games of chance -Solve algebra problems using Python's symbolic math functions -Draw geometric shapes and explore fractals like the Barnsley fern, the Sierpinski triangle, and the Mandelbrot set -Write programs to find derivatives and integrate functions Creative coding challenges and applied examples help you see how you can put your new math and coding skills into practice. You'll write an inequality solver, plot gravity's effect on how far a bullet will travel, shuffle a deck of cards, estimate the area of a circle by throwing 100,000 "darts" at a board, explore the relationship between the Fibonacci sequence and the golden ratio, and more. Whether you're interested in math but have yet to dip into programming or you're a teacher looking to bring programming into the classroom, you'll find that Python makes programming easy and practical. Let Python handle the grunt work while you focus on the math.

The aim of this book is to discuss the fundamental ideas which lie behind the statistical theory of learning and generalization. It considers learning as a general problem of function estimation based on empirical data. Omitting proofs and technical details, the author concentrates on discussing the main results of learning theory and their connections to fundamental problems in statistics. This second edition contains three new chapters devoted to further development of the learning theory and SVM techniques. Written in a readable and concise style, the book is intended for statisticians, mathematicians, physicists, and computer scientists.

Sure to be influential, Watanabe's book lays the foundations for the use of algebraic geometry in statistical learning theory. Many models/machines are singular: mixture models, neural networks, HMMs, Bayesian networks, stochastic context-free grammars are major examples. The theory achieved here underpins accurate estimation techniques in the presence of singularities.

The book provides a comprehensive introduction and a novel mathematical foundation of the field of information geometry with complete proofs and detailed background material on measure theory, Riemannian geometry and Banach space theory. Parametrised measure models are defined as fundamental geometric objects, which can be both finite or infinite dimensional. Based on these models, canonical tensor fields are introduced and further studied, including the Fisher metric and the Amari-Chentsov tensor, and embeddings of statistical manifolds are investigated. This novel foundation then leads to application highlights, such as generalizations and extensions of the classical uniqueness result of Chentsov or the Cramér-Rao inequality. Additionally, several new application fields of information geometry are highlighted, for instance hierarchical and graphical models, complexity theory, population genetics, or Markov Chain Monte Carlo. The book will be of interest to mathematicians who are interested in geometry, information theory, or the foundations of statistics, to statisticians as well as to scientists interested in the mathematical foundations of complex systems.

This book explains deep learning concepts and derives semi-supervised learning and nuclear learning frameworks based on cognition mechanism and Lie group theory. Lie group machine learning is a theoretical basis for brain intelligence, Neuromorphic learning (NL), advanced machine learning, and advanced artifi cial intelligence. The book further discusses algorithms and applications in tensor learning, spectrum estimation learning, Finsler geometry learning, Homology boundary learning, and prototype theory. With abundant case studies, this book can be used as a reference book for senior college students and graduate students as well as college teachers and scientific and technical personnel involved in computer science, artifi cial intelligence, machine learning, automation, mathematics, management science, cognitive science, financial management, and data analysis. In addition, this text can be used as the basis for teaching the principles of machine learning. Li Fanzhang is professor at the Soochow University, China. He is director of network security engineering laboratory in Jiangsu Province and is also the director of the Soochow Institute of industrial large data. He published more than 200 papers, 7 academic monographs, and 4 textbooks. Zhang Li is professor at the School of Computer Science and Technology of the Soochow University. She published more than 100 papers in journals and conferences, and holds 23 patents. Zhang Zhao is currently an associate professor at the School of Computer Science and Technology of the Soochow University. He has authored and co-authored more than 60 technical papers.

The theory of elliptic curves involves a blend of algebra, geometry, analysis, and number theory. This book stresses this interplay as it develops the basic theory, providing an opportunity for readers to appreciate the unity of modern mathematics. The book's accessibility, the informal writing style, and a wealth of exercises make it an ideal introduction for those interested in learning about Diophantine equations and arithmetic geometry.

This book describes how neural networks operate from the mathematical point of view. As a result, neural networks can be interpreted both as function universal approximators and information processors. The book bridges the gap between ideas and concepts of neural networks, which are used nowadays at an intuitive level, and the precise modern mathematical language, presenting the best practices of the former and enjoying the robustness and elegance of the latter. This book can be used in a graduate course in deep learning, with the first few parts being accessible to senior undergraduates. In addition, the book will be of wide interest to machine learning researchers who are interested in a theoretical understanding of the subject.

The problem of enumerating maps (a map is a set of polygonal "countries" on a world of a certain topology, not necessarily the plane or the sphere) is an important problem in mathematics and physics, and it has many applications ranging from statistical physics, geometry, particle physics, informatics, biology, ... etc. This problem has been studied by many communities of researchers, mostly combinatorists, probabilists, and physicists. In 1978+, physicists have invented a method called "matrix models" to address that problem, and many results have been obtained. Besides, another important problem in mathematics and physics (in particular string theory), is to count Riemann surfaces. Riemann surfaces of a given topology are parametrized by a finite number of real parameters (called moduli), and the moduli space is a finite dimensional compact manifold of complicated topology. The number of Riemann surfaces is the volume of that moduli space. More generally, an important problem in algebraic geometry is to characterize the moduli spaces, by computing not only their volumes, but also their intersection numbers. The so called Witten's conjecture (which was first proved by Kontsevich), was the assertion that Riemann surfaces can be obtained as limits of polygonal surfaces (maps), made of a very large number of very small polygons. In other words, the number of maps in a certain limit, should give the intersection numbers of moduli spaces. In this book, we show how that limit takes place. The goal of this book is to explain the "matrix model" method, to show the main results obtained with it, and to compare it with methods used in combinatorics (bijective proofs, Tutte's equations), or algebraic geometry (Mirzakhani's recursions). The book intends to be self-contained and pedagogical, and will provide comprehensive proofs, several examples, and will give the general formula for the enumeration of maps on surfaces of any topology. In the end, the link with more general topics such as algebraic geometry, string theory, will be discussed, and in particular we give a proof of the Witten-Kontsevich conjecture.

The Contemporary Introduction to Deep Reinforcement Learning that Combines Theory and Practice Deep reinforcement learning (deep RL) combines deep learning and reinforcement learning, in which artificial agents learn to solve sequential decision-making problems. In the past decade deep RL has achieved remarkable results on a range of problems, from single and multiplayer games—such as Go, Atari games, and DotA 2—to robotics. Foundations of Deep Reinforcement Learning is an introduction to deep RL that uniquely combines both theory and implementation. It starts with intuition, then carefully explains the theory of deep RL algorithms, discusses implementations in its companion software library SLM Lab, and finishes with the practical details of getting deep RL to work. This guide is ideal for both computer science students and software engineers who are familiar with basic machine learning concepts and have a working understanding of Python. Understand each key aspect of a deep RL problem Explore policy- and value-based algorithms, including REINFORCE, SARSA, DQN, Double DQN, and Prioritized Experience Replay (PER) Delve into combined algorithms, including Actor-Critic and Proximal Policy Optimization (PPO) Understand how algorithms can be parallelized synchronously and asynchronously Run algorithms in SLM Lab and learn the practical implementation details for getting deep RL to work Explore algorithm benchmark results with tuned hyperparameters Understand how deep RL environments are designed Register your book for convenient access to downloads, updates, and/or corrections as they become available. See inside book for details.

The book developed from the need to teach a linear algebra course to students focused on data science and bioinformatics programs. These students tend not to realize the importance of linear algebra in applied sciences since traditional linear algebra courses tend to cover mathematical contexts but not the computational aspect of linear algebra or its applications to data science and bioinformatics. The author presents the topics in a traditional course yet offers lectures as well as lab exercises on simulated and empirical data sets. This textbook provides students a theoretical basis which can then be applied to the practical R and Python problems, providing the tools needed for real-world applications. Each section starts with working examples to demonstrate how tools from linear algebra can help solve problems in applied science. These exercises start from easy computations, such as computing determinants of matrices, to practical applications on simulated and empirical data sets with R so that students learn how to get started with R along with computational examples in each section and then they learn how to apply what they learn to problems in applied sciences. This book is designed from first principles to demonstrate the importance of linear algebra through working computational examples with R and python including tutorials on how to install R in the Appendix. If a student has never seen R, they can get started without any additional help. Since Python is one of the most popular languages in data science, optimization, and computer science, code supplements are available for students who feel more comfortable with Python. R is used primarily for computational examples to develop student's practical computational skills. Table of Contents Preface List of Figures List of Tables 1. Systems of Linear Equations and Matrices 2. Matrix Arithmetic 3. Deteminants 4. Vector Spaces 5. Inner Product Space 6. Eigen values and Eigen vectors 7. Linear Regression 8. Linear Programming Network Analysis Appendices A) Introduction to RStudio via Amazon Web Service (AWS) B) Introduction to R Bibliography Index Biography Dr. Ruriko Yoshida is an Associate Professor of Operations Research at the Naval Postgraduate School. She received her Ph.D. in Mathematics from the University of California, Davis. Her research topics cover a wide variety of areas: applications of algebraic combinatorics to statistical problems such as statistical learning on non-Euclidean spaces, sensor networks, phylogenetics, and phylogenomics. She teaches courses in statistics, stochastic models, probability, and data science.

An up-to-date account of algebraic statistics and information geometry, which also explores the emerging connections between these two disciplines.

Now that people are aware that data can make the difference in an election or a business model, data science as an occupation is gaining ground. But how can you get started working in a wide-ranging, interdisciplinary field that's so clouded in hype? This insightful book, based on Columbia University's Introduction to Data Science class, tells you what you need to know. In many of these chapter-long lectures, data scientists from companies such as Google, Microsoft, and eBay share new algorithms, methods, and models by presenting case studies and the code they use. If you're familiar with linear algebra, probability, and statistics, and have programming experience, this book is an ideal introduction to data science. Topics include: Statistical inference, exploratory data analysis, and the data science process Algorithms Spam filters, Naive Bayes, and data wrangling Logistic regression Financial modeling Recommendation engines and causality Data visualization Social networks and data journalism Data engineering, MapReduce, Pregel, and Hadoop Doing Data Science is collaboration between course instructor Rachel Schutt, Senior VP of Data Science at News Corp, and data science consultant Cathy O'Neil, a senior data scientist at Johnson Research Labs, who attended and blogged about the course.

Algebraic Geometry and Statistical Learning TheoryCambridge University Press

Results from national and international assessments indicate that school children in the United States are not learning mathematics well enough. Many students cannot correctly apply computational algorithms to solve problems. Their understanding and use of decimals and fractions are especially weak. Indeed, helping all children succeed in mathematics is an imperative national goal. However, for our youth to succeed, we need to change how weâ€™re teaching this discipline. Helping Children Learn Mathematics provides comprehensive and reliable information that will guide efforts to improve school mathematics from pre--kindergarten through eighth grade. The authors explain the five strands of mathematical proficiency and discuss the major changes that need to be made in mathematics instruction, instructional materials, assessments, teacher education, and the broader educational system and answers some of the frequently asked questions when it comes to mathematics instruction. The book concludes by providing recommended actions for parents and caregivers, teachers, administrators, and policy makers, stressing the importance that everyone work together to ensure a mathematically literate society.

This book, first published in 2005, offers an introduction to the application of algebraic statistics to computational biology.

A classic problem in mathematics is solving systems of polynomial equations in several unknowns. Today, polynomial models are ubiquitous and widely used across the sciences. They arise in robotics, coding theory, optimization, mathematical biology, computer vision, game theory, statistics, and numerous other areas. This book furnishes a bridge across mathematical disciplines and exposes many facets of systems of polynomial equations. It covers a wide spectrum of mathematical techniques and algorithms, both symbolic and numerical.The set of solutions to a system of polynomial equations is an algebraic variety - the basic object of algebraic geometry. The algorithmic study of algebraic varieties is the central theme of computational algebraic geometry. Exciting recent developments in computer software for geometric calculations have revolutionized the field. Formerly inaccessible problems are now tractable, providing fertile ground for experimentation and conjecture. The first half of the book gives a snapshot of the state of the art of the topic. Familiar themes are covered in the first five chapters, including polynomials in one variable, Grobner bases of zero-dimensional ideals, Newton polytopes and Bernstein's Theorem, multidimensional resultants, and primary decomposition.The second half of the book explores polynomial equations from a variety of novel and unexpected angles. It introduces interdisciplinary connections, discusses highlights of current research, and outlines possible future algorithms. Topics include computation of Nash equilibria in game theory, semidefinite programming and the real Nullstellensatz, the algebraic geometry of statistical models, the piecewise-linear geometry of valuations and amoebas, and the Ehrenpreis-Palamodov theorem on linear partial differential equations with constant coefficients.Throughout the text, there are many hands-on examples and exercises, including short but complete sessions in MapleR, MATLABR, Macaulay 2, Singular, PHCpack, CoCoA, and SOSTools software. These examples will be particularly useful for readers with no background in algebraic geometry or commutative algebra. Within minutes, readers can learn how to type in polynomial equations and actually see some meaningful results on their computer screens. Prerequisites include basic abstract and computational algebra. The book is designed as a text for a graduate course in computational algebra.

Written by pioneers in this exciting new field, Algebraic Statistics introduces the application of polynomial algebra to experimental design, discrete probability, and statistics. It begins with an introduction to Gröbner bases and a thorough description of their applications to experimental design. A special chapter covers the binary case with new application to coherent systems in reliability and two level factorial designs. The work paves the way, in the last two chapters, for the application of computer algebra to discrete probability and statistical modelling through the important concept of an algebraic statistical model. As the first book on the subject, Algebraic Statistics presents many opportunities for spin-off research and applications and should become a landmark work welcomed by both the statistical community and its relatives in mathematics and computer science.

How does an algebraic geometer studying secant varieties further the understanding of hypothesis tests in statistics? Why would a statistician working on factor analysis raise open problems about determinantal varieties? Connections of this type are at the heart of the new field of "algebraic statistics". In this field, mathematicians and statisticians come together to solve statistical inference problems using concepts from algebraic geometry as well as related computational and combinatorial techniques. The goal of these lectures is to introduce newcomers from the different camps to algebraic statistics. The introduction will be centered around the following three observations: many important statistical models correspond to algebraic or semi-algebraic sets of parameters; the geometry of these parameter spaces determines the behaviour of widely used statistical inference procedures; computational algebraic geometry can be used to study parameter spaces and other features of statistical models.

Sure to be influential, Watanabe s book lays the foundations for the use of algebraic geometry in statistical learning theory. Many models/machines are singular: mixture models, neural networks, HMMs, Bayesian networks, stochastic context-free grammars are major examples. The theory achieved here underpins accurate estimation techniques in the presence of singularities.

Introduces cutting-edge research on machine learning theory and practice, providing an accessible, modern algorithmic toolkit.

Machine learning allows computers to learn and discern patterns without actually being programmed. When Statistical techniques and machine learning are combined together they are a powerful tool for analysing various kinds of data in many computer science/engineering areas including, image processing, speech processing, natural language processing, robot control, as well as in fundamental sciences such as biology, medicine, astronomy, physics, and materials. Introduction to Statistical Machine Learning provides a general introduction to machine learning that covers a wide range of topics concisely and will help you bridge the gap between theory and practice. Part I discusses the fundamental concepts of statistics and probability that are used in describing machine learning algorithms. Part II and Part III explain the two major approaches of machine learning techniques; generative methods and discriminative methods. While Part III provides an in-depth look at advanced topics that play essential roles in making machine learning algorithms more useful in practice. The accompanying MATLAB/Octave programs provide you with the necessary practical skills needed to accomplish a wide range of data analysis tasks. Provides the necessary background material to understand machine learning such as statistics, probability, linear algebra, and calculus. Complete coverage of the generative approach to statistical pattern recognition and the discriminative approach to statistical machine learning. Includes MATLAB/Octave programs so that readers can test the algorithms numerically and acquire both mathematical and practical skills in a wide range of data analysis tasks Discusses a wide range of applications in machine learning and statistics and provides examples drawn from image processing, speech processing, natural language processing, robot control, as well as biology, medicine, astronomy, physics, and materials.

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Algebraic geometry, central to pure mathematics, has important applications in such fields as engineering, computer science, statistics and computational biology, which exploit the computational algorithms that the theory provides. Users get the full benefit, however, when they know something of the underlying theory, as well as basic procedures and facts. This book is a systematic introduction to the central concepts of algebraic geometry most useful for computation. Written for advanced undergraduate and graduate students in mathematics and researchers in application areas, it focuses on specific examples and restricts development of formalism to what is needed to address these examples. In particular, it introduces the notion of Gröbner bases early on and develops algorithms for almost everything covered. It is based on courses given over the past five years in a large interdisciplinary programme in computational algebraic geometry at Rice University, spanning mathematics, computer science, biomathematics and bioinformatics.

This book provides a comprehensive introduction to the latest advances in the mathematical theory and computational tools for modeling high-dimensional data drawn from one or multiple low-dimensional subspaces (or manifolds) and potentially corrupted by noise, gross errors, or outliers. This challenging task requires the development of new algebraic, geometric, statistical, and computational methods for efficient and robust estimation and segmentation of one or multiple subspaces. The book also presents interesting real-world applications of these new methods in image processing, image and video segmentation, face recognition and clustering, and hybrid system identification etc. This book is intended to serve as a textbook for graduate students and beginning researchers in data science, machine learning, computer vision, image and signal processing, and systems theory. It contains ample illustrations, examples, and exercises and is made largely self-contained with three Appendices which survey basic concepts and principles from statistics, optimization, and algebraic-geometry used in this book. René Vidal is a Professor of Biomedical Engineering and Director of the Vision Dynamics and Learning Lab at The Johns Hopkins University. Yi Ma is Executive Dean and Professor at the School of Information Science and Technology at ShanghaiTech University. S. Shankar Sastry is Dean of the College of Engineering, Professor of Electrical Engineering and Computer Science and Professor of Bioengineering at the University of California, Berkeley.

An introduction to computational complexity theory, its connections and interactions with mathematics, and its central role in the natural and social sciences, technology, and philosophy Mathematics and Computation provides a broad, conceptual overview of computational complexity theory—the mathematical study of efficient computation. With important practical applications to computer science and industry, computational complexity theory has evolved into a highly interdisciplinary field, with strong links to most mathematical areas and to a growing number of scientific endeavors. Avi Wigderson takes a sweeping survey of complexity theory, emphasizing the field’s insights and challenges. He explains the ideas and motivations leading to key models, notions, and results. In particular, he looks at algorithms and complexity, computations and proofs, randomness and interaction, quantum and arithmetic computation, and cryptography and learning, all as parts of a cohesive whole with numerous cross-influences. Wigderson illustrates the immense breadth of the field, its beauty and richness, and its diverse and growing interactions with other areas of mathematics. He ends with a comprehensive look at the theory of computation, its methodology and aspirations, and the unique and fundamental ways in which it has shaped and will further shape science, technology, and society. For further reading, an extensive bibliography is provided for all topics covered. Mathematics and Computation is useful for undergraduate and graduate students in mathematics, computer science, and related fields, as well as researchers and teachers in these fields. Many parts require little background, and serve as an invitation to newcomers seeking an introduction to the theory of computation. Comprehensive coverage of computational complexity theory, and beyond High-level, intuitive exposition, which brings conceptual clarity to this central and dynamic scientific discipline Historical accounts of the evolution and motivations of central concepts and models A broad view of the theory of computation's influence on science, technology, and society Extensive bibliography

Introduces machine learning and its algorithmic paradigms, explaining the principles behind automated learning approaches and the considerations underlying their usage.

In this ambitious study, David Corfield attacks the widely held view that it is the nature of mathematical knowledge which has shaped the way in which mathematics is treated philosophically and claims that contingent factors have brought us to the present thematically limited discipline. Illustrating his discussion with a wealth of examples, he sets out a variety of approaches to new thinking about the philosophy of mathematics, ranging from an exploration of whether computers producing mathematical proofs or conjectures are doing real mathematics, to the use of analogy, the prospects for a Bayesian confirmation theory, the notion of a mathematical research programme and the ways in which new concepts are justified. His inspiring book challenges both philosophers and mathematicians to develop the broadest and richest philosophical resources for work in their disciplines and points clearly to the ways in which this can be done.

Introductory account of commutative algebra, aimed at students with a background in basic algebra.

This open access textbook provides the background needed to correctly use, interpret and understand statistics and statistical data in diverse settings. Part I makes key concepts in statistics readily clear. Parts I and II give an overview of the most common tests (t-test, ANOVA, correlations) and work out their statistical principles. Part III provides insight into meta-statistics (statistics of statistics) and demonstrates why experiments often do not replicate. Finally, the textbook shows how complex statistics can be avoided by using clever experimental design. Both non-scientists and students in Biology, Biomedicine and Engineering will benefit from the book by learning the statistical basis of scientific claims and by discovering ways to evaluate the quality of scientific reports in academic journals and news outlets.

Mathematical Theory of Bayesian Statistics introduces the mathematical foundation of Bayesian inference which is well-known to be more accurate in many real-world problems than the maximum likelihood method. Recent research has uncovered several mathematical laws in Bayesian statistics, by which both the generalization loss and the marginal likelihood are estimated even if the posterior distribution cannot be approximated by any normal distribution. Features Explains Bayesian inference not subjectively but objectively. Provides a mathematical framework for conventional Bayesian theorems. Introduces and proves new theorems. Cross validation and information criteria of Bayesian statistics are studied from the mathematical point of view. Illustrates applications to several statistical problems, for example, model selection, hyperparameter optimization, and hypothesis tests. This book provides basic introductions for students, researchers, and users of Bayesian statistics, as well as applied mathematicians. Author Sumio Watanabe is a professor of Department of Mathematical and Computing Science at Tokyo Institute of Technology. He studies the relationship between algebraic geometry and mathematical statistics.