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Machine Learning Cambridge University Press Probabilistic Deep Learning is a hands-on guide to the principles that support neural networks. Learn to improve network performance with the right distribution for different data types, and discover Bayesian variants that can state their own uncertainty to increase accuracy. This book provides easy-to-apply code and uses popular frameworks to keep you focused on practical applications. Summary Probabilistic Deep Learning: With Python, Keras and TensorFlow Probability teaches the increasingly popular probabilistic approach to deep learning that allows you to refine your results more quickly and accurately without much trial-and-error testing. Emphasizing practical techniques that use the Python-based Tensorflow Probability Framework, you'll learn to build highly-performant deep learning applications that can reliably handle the noise and uncertainty of real-world data. Purchase of the print book includes a free eBook in

PDF, Kindle, and ePub formats from Manning Publications. About the technology The world is a noisy and uncertain place. Probabilistic deep learning models capture that noise and uncertainty, pulling it into real-world scenarios. Crucial for self-driving cars and scientific testing, these techniques help deep learning engineers assess the accuracy of their results, spot errors, and improve their understanding of how algorithms work. About the book Probabilistic Deep Learning is a hands-on guide to the principles that support neural networks. Learn to improve network performance with the right distribution for different data types, and discover Bayesian variants that can state their own uncertainty to increase accuracy. This book provides easy-to-apply code and uses popular frameworks to keep you focused on practical applications. What's inside Explore maximum likelihood and the statistical basis of deep learning Discover probabilistic models that can indicate possible outcomes

Learn to use normalizing flows for modeling and generating complex distributions Use Bayesian neural networks to access the uncertainty in the model About the reader For experienced machine learning developers. About the author Oliver Dürr is a professor at the University of Applied Sciences in Konstanz, Germany. Beate Sick holds a chair for applied statistics at ZHAW and works as a researcher and lecturer at the University of Zurich. Elvis Murina is a data scientist. Table of Contents PART 1 - BASICS OF DEEP LEARNING 1 Introduction to probabilistic deep learning 2 Neural network architectures 3 Principles of curve fitting PART 2 - MAXIMUM LIKELIHOOD APPROACHES FOR PROBABILISTIC DL MODELS 4 Building loss functions with the likelihood approach 5 Probabilistic deep learning models with TensorFlow Probability 6 Probabilistic deep learning models in the wild PART 3 - BAYESIAN APPROACHES FOR PROBABILISTIC DL MODELS 7 Bayesian learning 8 Bayesian neural networks

Game-Theoretic Learning and Distributed

Optimization in Memoryless Multi-Agent Systems MIT Press

An introduction to a broad range of topics in deep learning, covering mathematical and conceptual background, deep learning techniques used in industry, and research perspectives. “Written by three experts in the field, Deep Learning is the only comprehensive book on the subject.” —Elon Musk, cochair of OpenAI; cofounder and CEO of Tesla and SpaceX Deep learning is a form of machine learning that enables computers to learn from experience and understand the world in terms of a hierarchy of concepts. Because the computer gathers knowledge from experience, there is no need for a human computer operator to formally specify all the knowledge that the computer needs. The hierarchy of concepts allows the computer to learn complicated concepts by building them out of simpler ones; a graph of these hierarchies would be many layers deep. This book introduces a broad range of topics in deep learning. The text offers mathematical and conceptual background, covering relevant concepts in linear algebra, probability theory and information theory, numerical computation, and machine learning. It describes deep learning techniques used by practitioners in industry, including deep feedforward networks, regularization, optimization algorithms, convolutional networks, sequence modeling, and practical methodology; and it surveys such applications as natural language processing, speech recognition, computer vision, online recommendation systems, bioinformatics, and videogames. Finally, the book offers research perspectives, covering such theoretical topics as linear factor models, autoencoders, representation learning, structured probabilistic models, Monte Carlo methods, the partition function, approximate inference, and deep generative models. Deep Learning can be used by undergraduate or graduate students planning careers in either industry or research, and by software engineers who want to begin using deep learning in their products or platforms. A website offers supplementary material for both readers and instructors.

Probabilistic Graphical Models Morgan & Claypool Publishers

This book provides a versatile and lucid treatment of classic as well as modern probability theory, while integrating them with core topics in statistical theory and also some key tools in machine learning. It is written in an extremely accessible style, with elaborate motivating discussions and numerous worked out examples and exercises. The book has 20 chapters on a wide range of topics, 423 worked out examples, and 808 exercises. It is unique in its unification of probability and statistics, its coverage and its superb exercise sets, detailed bibliography, and in its substantive treatment of many topics of current importance. This book can be used as a text for a year long graduate course in statistics, computer science, or mathematics, for self-study, and as an invaluable research reference on probabiliity and its applications. Particularly worth mentioning are the treatments of distribution theory, asymptotics, simulation and Markov Chain Monte Carlo, Markov chains and martingales, Gaussian processes, VC theory, probability metrics, large deviations, bootstrap, the EM algorithm, confidence intervals, maximum likelihood and Bayes estimates, exponential families, kernels, and Hilbert spaces, and a self contained complete review of univariate probability.

Chance Encounters: Probability in Education Springer Science & Business Media

Introduction -- Supervised learning -- Bayesian decision theory -- Parametric methods -- Multivariate methods -- Dimensionality reduction -- Clustering -- Nonparametric methods -- Decision trees -- Linear discrimination -- Multilayer perceptrons -- Local models -- Kernel machines -- Graphical models -- Brief contents -- Hidden markov models -- Bayesian estimation -- Combining multiple learners -- Reinforcement learning -- Design and analysis of machine learning experiments.

Essentials of Economics MIT Press
A comprehensive and self-contained introduction to Gaussian processes, which provide a principled, practical, probabilistic approach to learning in kernel machines. Gaussian processes (GPs) provide a principled, practical, probabilistic approach to learning in kernel machines. GPs have received increased attention in the machine-learning community over the past decade, and this book provides a long-needed systematic and unified treatment of theoretical and practical aspects of GPs in machine learning. The treatment is comprehensive and self-contained, targeted at researchers and students in machine learning and applied statistics. The book deals with the supervised-learning problem for both regression and classification, and includes detailed algorithms. A wide variety of covariance (kernel) functions are presented and their properties discussed. Model selection is discussed both from a Bayesian and a classical perspective. Many connections to other well-known techniques from

machine learning and statistics are discussed, including support-vector machines, neural networks, splines, regularization networks, relevance vector machines and others. Theoretical issues including learning curves and the PAC-Bayesian framework are treated, and several approximation methods for learning with large datasets are discussed. The book contains illustrative examples and exercises, and code and datasets are available on the Web. Appendixes provide mathematical background and a discussion of Gaussian Markov processes.

Machine Learning Springer

Probability is the bedrock of machine learning. You cannot develop a deep understanding and application of machine learning without it. Cut through the equations, Greek letters, and confusion, and discover the topics in probability that you need to know. Using clear explanations, standard Python libraries, and step-by-step tutorial lessons, you will discover the importance of probability to machine learning, Bayesian probability, entropy, density estimation, maximum likelihood, and much more.

Gaussian Process Regression Analysis for Functional Data Abhishek Thakur

A general framework for constructing and using probabilistic models of complex systems that would enable a computer to use available information for making decisions. Most tasks require a person or an automated system to reason—to reach conclusions based on available information. The framework of probabilistic graphical models, presented in this book, provides a general approach for this task. The approach is model-based, allowing interpretable models to be constructed and then manipulated by reasoning algorithms. These models can also be learned automatically from data, allowing the approach to be used in cases where manually constructing a model is difficult or even impossible. Because uncertainty is an inescapable aspect of most real-world applications, the book focuses on probabilistic models, which make the uncertainty explicit and provide models that are more faithful to reality. Probabilistic Graphical Models discusses a variety of models, spanning Bayesian networks, undirected Markov networks, discrete and continuous models, and extensions to deal with dynamical systems and relational data. For each class of models, the text describes the three fundamental cornerstones: representation, inference, and learning, presenting both basic concepts and advanced techniques. Finally, the book considers the use of the proposed framework for causal reasoning and decision making under uncertainty. The main text in each chapter provides the detailed technical development of the key ideas. Most chapters also include boxes with additional material: skill boxes, which describe techniques; case study boxes, which discuss empirical cases related to the approach described in the text, including applications in computer vision, robotics, natural language understanding, and computational biology; and concept boxes, which present significant concepts drawn from the material in the chapter. Instructors (and readers) can group chapters in various combinations, from core topics to more technically advanced material, to suit their particular needs.

Graphical Models for Machine Learning and Digital Communication

MIT Press

If you ' re an experienced programmer interested in crunching data, this book will get you started with machine learning—a toolkit of algorithms that enables computers to train themselves to automate useful tasks. Authors Drew Conway and John Myles White help you understand machine learning and statistics tools through a series of hands-on case studies, instead of a traditional math-heavy presentation. Each chapter focuses on a specific problem in machine learning, such as classification, prediction, optimization, and recommendation. Using the R programming language, you ' ll learn how to analyze sample datasets and write simple machine learning algorithms. Machine Learning for Hackers is ideal for programmers from any background, including business, government, and academic research. Develop a na ï ve Bayesian classifier to determine if an email is spam, based only on its text Use linear regression to predict the number of page views for the top 1,000 websites Learn optimization techniques by attempting to break a simple letter cipher Compare and contrast U.S. Senators statistically, based on their voting records Build a “ whom to follow ” recommendation system from Twitter data

Bayesian Probability Theory Academic Press

Machine Learning: A Bayesian and Optimization Perspective, 2nd edition, gives a unified perspective on machine learning by covering both pillars of supervised learning, namely regression and classification. The book starts with the basics, including mean square, least squares and maximum likelihood methods, ridge regression, Bayesian decision theory classification, logistic regression, and decision trees. It then progresses to more recent techniques, covering sparse modelling methods, learning in reproducing kernel Hilbert spaces and support vector machines, Bayesian inference with a focus on the EM algorithm and its approximate inference variational versions, Monte Carlo methods, probabilistic graphical models focusing on Bayesian networks, hidden Markov models and particle filtering. Dimensionality reduction and latent variables modelling are also considered in depth. This palette of techniques concludes with an extended chapter on neural networks and deep learning architectures. The book also covers the fundamentals of statistical parameter estimation, Wiener and Kalman filtering, convexity and convex optimization, including a chapter on stochastic approximation and the gradient descent family of algorithms, presenting related online learning techniques as well as concepts and algorithmic versions for distributed optimization. Focusing on the physical reasoning behind the mathematics, without sacrificing rigor, all the various methods and techniques are explained in depth, supported by examples and problems, giving an invaluable resource to the student and researcher for understanding and applying machine learning concepts. Most of the chapters include typical case studies and computer exercises, both in MATLAB and Python. The chapters are written to be as self-contained as possible, making the text suitable for different courses: pattern recognition, statistical/adaptive signal processing, statistical/Bayesian learning, as well as courses on sparse modeling, deep learning, and probabilistic graphical models. New to this edition: Complete re-write of the chapter on Neural Networks and Deep Learning to reflect the latest advances since the 1st edition. The chapter, starting from the basic perceptron and feed-forward neural networks concepts, now presents an in depth treatment of deep networks, including recent optimization algorithms, batch normalization, regularization techniques such as the dropout method, convolutional neural networks, recurrent neural networks, attention mechanisms, adversarial examples and training, capsule networks and generative architectures, such as restricted Boltzman machines (RBMs), variational autoencoders and generative adversarial networks (GANs). Expanded treatment of Bayesian learning to include nonparametric Bayesian methods, with a focus on the Chinese restaurant and the Indian buffet processes. Presents the physical reasoning, mathematical modeling and algorithmic implementation of each method Updates on the latest trends, including sparsity, convex analysis and optimization, online distributed algorithms, learning in RKH spaces, Bayesian inference, graphical and hidden Markov models, particle filtering, deep learning, dictionary learning and latent variables modeling Provides case studies on a variety of topics, including protein folding prediction, optical character recognition, text authorship identification, fMRI data analysis, change point detection, hyperspectral image unmixing, target localization, and more

Machine Learning, Second Edition: A Probabilistic Perspective "O'Reilly Media, Inc."

A self-contained and coherent account of probabilistic techniques, covering: distance measures, kernel rules, nearest neighbour rules, Vapnik-Chervonenkis theory, parametric classification, and feature extraction. Each chapter concludes with problems and exercises to further the readers understanding. Both research workers and graduate students will benefit from this wide-ranging and up-to-date account of a fast- moving field.

Machine Learning Cambridge University Press

A detailed and up-to-date introduction to machine learning, presented through the unifying lens of probabilistic modeling and Bayesian decision theory. This book offers a detailed and up-to-date introduction to machine learning (including deep learning) through the unifying lens of probabilistic modeling and Bayesian decision theory. The book covers mathematical background (including linear algebra and optimization), basic supervised learning (including linear and logistic regression and deep neural networks), as well as more advanced topics (including transfer learning and unsupervised learning). End-of-chapter exercises allow students to apply what they have learned, and an appendix covers notation. Probabilistic Machine Learning grew out of the author ’ s 2012 book, Machine Learning: A Probabilistic Perspective. More than just a simple update, this is a completely new book that reflects the dramatic developments in the field since 2012, most notably deep learning. In addition, the new book is accompanied by online Python code, using libraries such as scikit-learn, JAX, PyTorch, and Tensorflow, which can be used to reproduce nearly all the figures; this code can be run inside a web browser using cloud-based notebooks, and provides a practical complement to the theoretical topics discussed in the book. This introductory text will be followed by a sequel that covers more advanced topics, taking the same probabilistic approach.

Bayesian Multiple Target Tracking, Second Edition Springer

This second edition has undergone substantial revision from the 1999 first edition, recognizing that a lot has changed in the multiple target tracking field. One of the most dramatic changes is in the widespread use of particle filters to implement nonlinear, non-Gaussian Bayesian trackers. This book views multiple target tracking as a Bayesian inference problem. Within this framework it develops the theory of single target tracking, multiple target tracking, and likelihood ratio detection and tracking. In addition to providing a detailed description of a basic particle filter that implements the Bayesian single target recursion, this resource provides numerous examples that involve the use of particle filters. With these examples illustrating the developed concepts, algorithms, and approaches -- the book helps radar engineers develop tracking solutions when observations are non-linear functions of target state, when the target state distributions or measurement error distributions are not Gaussian, in low data rate and low signal to noise ratio situations, and when notions of contact and association are merged or unresolved among more than one target.

Probabilistic Machine Learning Simon and Schuster

A comprehensive introduction to machine learning that uses probabilistic models and inference as a unifying approach. Today's Web-enabled deluge of electronic data calls for automated methods of data analysis. Machine learning provides these, developing methods that can automatically detect patterns in data and then use the uncovered patterns to predict future data. This textbook offers a comprehensive and self-contained introduction to the field of machine learning, based on a unified, probabilistic approach. The coverage combines breadth and depth, offering necessary background material on such topics as probability, optimization, and linear algebra as well as discussion of recent developments in the field, including conditional random fields, L1 regularization, and deep learning. The book is written in an informal, accessible style, complete with pseudo-code for the most important algorithms. All topics are copiously illustrated with color images and worked examples drawn from such application domains as biology, text processing, computer vision, and robotics. Rather than providing a cookbook of different heuristic methods, the book stresses a principled model-based approach, often using the language of graphical models to specify models in a concise and intuitive way. Almost all the models described have been implemented in a MATLAB software package—PMTK (probabilistic modeling toolkit)—that is freely available online. The book is suitable for upper-level undergraduates with an introductory-level college math background and beginning graduate students.

Approaching (Almost) Any Machine Learning Problem MIT Press

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

Modeling and Reasoning with Bayesian Networks Springer Science & Business Media

Never HIGHLIGHT a Book Again! Virtually all of the testable terms, concepts, persons, places, and events from the textbook are included. Cram101 Just the FACTS101 studyguides give all of the outlines, highlights, notes, and quizzes for your textbook with optional online comprehensive practice tests. Only Cram101 is Textbook Specific. Accompanys: 9780262018029 .

Machine Learning, second edition Springer

A practical introduction perfect for final-year undergraduate and graduate students without a solid background in linear algebra and calculus.

Machine Learning for Hackers Morgan & Claypool Publishers

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.

A First Course in Machine Learning CRC Press

Gaussian Process Regression Analysis for Functional Data presents nonparametric statistical methods for functional regression analysis, specifically the methods based on a Gaussian process prior in a functional space. The authors focus on problems involving functional response variables and mixed covariates of functional and scalar variables. Covering the basics of Gaussian process regression, the first several chapters discuss functional data analysis, theoretical aspects based on the asymptotic properties of Gaussian process regression models, and new methodological developments for high dimensional data and variable selection. The remainder of the text explores advanced topics of functional regression analysis, including novel nonparametric statistical methods for curve prediction, curve clustering, functional ANOVA, and functional regression analysis of batch data, repeated curves, and non-Gaussian data. Many flexible models based on Gaussian processes provide efficient ways of model learning, interpreting model structure, and carrying out inference, particularly when dealing with large dimensional functional data. This book shows how to use these Gaussian process regression models in the analysis of functional data. Some MATLAB® and C codes are available on the first author ' s website.

Mathematics for Machine Learning Springer Science & Business Media

Covering all aspects of probability theory, statistics and data analysis from a Bayesian perspective for graduate students and researchers.

A Probabilistic Theory of Pattern Recognition CRC Press

This book has been written to fIll a substantial gap in the current literature in mathemat ical education. Throughout the world, school mathematical curricula have incorporated probability and statistics as new topics. There have been many research papers written on specifIc aspects of teaching, presenting novel and unusual approaches to introducing ideas in the classroom; however, there has been no book giving an overview. Here we have decided to focus on probability, making reference to inferential statistics where appropriate; we have deliberately avoided descriptive statistics as it is a separate area and would have made ideas less coherent and the book excessively long. A general lead has been taken from the fIrst book in this series written by the man who, probably more than everyone else, has established mathematical education as an aca demic discipline. However, in his exposition of didactical phenomenology, Freudenthal does not analyze probability. Thus, in this book, we show how probability is able to organize the world of chance and idealized chance phenomena based on its development and applications. In preparing these chapters we and our co-authors have reflected on our own acquisition of probabilistic ideas, analyzed textbooks, and observed and reflect ed upon the learning processes involved when children and adults struggle to acquire the relevant concepts.