Machine Learning A Probabilistic Perspective Kevin P Murphy

Machine Learning Probabilistic Machine Learning Study Guide for Machine Learning Probabilistic Deep Learning Probabilistic Machine Learning for Civil Engineers Learning Probabilistic Graphical Models in R Probabilistic Graphical Models Deep Learning *Machine Learning, second edition* **Hardware-Aware Probabilistic Machine Learning Models** *Foundations of Probabilistic Logic Programming* **Probabilistic Deep Learning Machine Learning Research on Teaching and Learning Probability** A Probabilistic Theory of Pattern Recognition *Probability for Statistics and Machine Learning* **Bayesian Reasoning and Machine Learning Probability for Machine Learning** *Probabilistic Machine Learning* Mastering Probabilistic Graphical Models Using Python **Teaching and Learning Stochastics** Probabilistic Graphical Models *Foundations of Probabilistic Programming Machine Learning for Probabilistic Prediction* **Mathematics for Machine Learning** *Exploring Probability in School* **Game-Theoretic Learning and Distributed Optimization in Memoryless Multi-Agent Systems Artificial Intelligence** Generative Deep Learning **PAGODA Information Theory, Inference and Learning Algorithms** Practical Probabilistic Programming **Bayesian Methods for Hackers** Graphical Models for Machine Learning and Digital Communication **Bayesian Learning of Probabilistic Language Models Foundations of Machine Learning, second edition** Handbook of Probabilistic Models **An Introduction to Probabilistic Modeling** Logical and Relational Learning Pattern Recognition and Machine Learning

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Foundations of Probabilistic Logic Programming Dec 22 2021

Probabilistic Machine Learning Apr 13 2021 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.

Machine Learning, second edition Feb 21 2022 The second and expanded edition of a comprehensive introduction to machine learning that uses probabilistic models and inference as a unifying approach. This textbook offers a comprehensive and self-contained introduction to the field of machine learning, including deep learning, viewed through the lens of probabilistic modeling and Bayesian decision theory. This second edition has been substantially expanded and revised, incorporating many recent developments in the field. It has new chapters on linear algebra, optimization, implicit generative models, reinforcement learning, and causality; and other chapters on such topics as variational inference and graphical models have been significantly updated. The software for the book (hosted on github) is now implemented in Python rather than MATLAB, and uses state-of-the-art libraries including as scikit-learn, Tensorflow 2, and JAX.

Learning Probabilistic Graphical Models in R May 27 2022 Familiarize yourself with probabilistic graphical models through real-world problems and illustrative code examples in R About This Book Predict and use a probabilistic graphical models (PGM) as an expert system Comprehend how your computer can learn Bayesian modeling to solve real-world problems Know how to prepare data and feed the models by using the appropriate algorithms from the appropriate R package Who This Book Is For This book is for anyone who has to deal with lots of data and draw conclusions from it, especially when the data is noisy or uncertain. Data scientists, machine learning enthusiasts, engineers, and those who curious about the latest advances in machine learning will find PGM interesting. What You Will Learn Understand the concepts of PGM and which type of PGM to use for which problem Tune the model's parameters and explore new models automatically Understand the basic principles of Bayesian models, from simple to advanced Transform the old linear regression model into a powerful probabilistic model Use standard industry models but with the power of PGM Understand the advanced models used throughout today's industry See how to compute posterior distribution with exact and approximate inference algorithms In Detail Probabilistic graphical models (PGM, also known as graphical models) are a marriage between probability theory and graph theory. Generally, PGMs use a graph-based representation. Two branches of graphical representations of distributions are commonly used, namely Bayesian networks and Markov networks. R has many packages to implement graphical models. We'll start by showing you how to transform a classical statistical model into a modern PGM and then look at how to do exact inference in graphical models. Proceeding, we'll introduce you to many modern R packages that will help you to perform inference on the models. We will then run a Bayesian linear regression and you'll see the advantage of going probabilistic when you want to do prediction. Next, you'll master using R packages and implementing its techniques. Finally, you'll be presented with machine learning applications that have a direct impact in many fields. Here, we'll cover clustering and the discovery of hidden information in big data, as well as two important methods, PCA and ICA, to reduce the size of big problems. Style and approach This book gives you a detailed and step-by-step explanation of each mathematical concept, which will help you build and analyze your own machine learning models and apply them to real-world problems. The mathematics is kept simple and each formula is explained thoroughly.

Mathematics for Machine Learning Oct 08 2020 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.

Mastering Probabilistic Graphical Models Using Python Mar 13 2021 Master probabilistic graphical models by learning through real-world problems and illustrative code examples in Python About This Book Gain in-depth knowledge of Probabilistic Graphical Models Model time-series problems using Dynamic Bayesian Networks A practical guide to help you apply PGMs to real-world problems Who This Book Is For If you are a researcher or a machine learning enthusiast, or are working in the data science field and have a basic idea of Bayesian Learning or Probabilistic Graphical Models, this book will help you to understand the details of Graphical Models and use it in your data science problems. This book will also help you select the appropriate model as well as the appropriate algorithm for your problem. What You Will Learn Get to know the basics of Probability theory and Graph Theory Work with Markov Networks Implement Bayesian Networks Exact Inference Techniques in Graphical Models such as the Variable Elimination Algorithm Understand approximate Inference Techniques in Graphical Models such as Message Passing Algorithms Sample algorithms in Graphical Models Grasp details of Naive Bayes with real-world examples Deploy PGMs using various libraries in Python Gain working details of Hidden Markov Models with real-world examples In Detail Probabilistic Graphical Models is a technique in machine learning that uses the concepts of graph theory to compactly represent and optimally predict values in our data problems. In real world problems, it's often difficult to select the appropriate graphical model as well as the appropriate inference algorithm, which can make a huge difference in computation time and accuracy. Thus, it is crucial to know the working details of these algorithms. This book starts with the basics of probability theory and graph theory, then goes on to discuss various models and inference algorithms. All the different types of models are discussed along with code examples to create and modify them, and also to run different inference algorithms on them. There is a complete chapter devoted to the most widely used networks Naive Bayes Model and Hidden Markov Models (HMMs). These models have been thoroughly discussed using real-world examples. Style and approach An easy-to-follow guide to help you understand Probabilistic Graphical Models using simple examples and numerous code examples, with an emphasis on more widely used models.

Foundations of Machine Learning, second edition Oct 27 2019 A new edition of a graduate-level machine learning textbook that focuses on the analysis and theory of algorithms. This book is a general introduction to machine learning that can serve as a textbook for graduate students and a reference for researchers. It covers fundamental modern topics in machine learning while providing the theoretical basis and conceptual tools needed for the discussion and justification of algorithms. It also describes several key aspects of the application of these algorithms. The authors aim to present novel theoretical tools and concepts while giving concise proofs even for relatively advanced topics. Foundations of Machine Learning is unique in its focus on the analysis and theory of algorithms. The first four chapters lay the theoretical foundation for what follows; subsequent chapters are mostly self-contained. Topics covered include the Probably Approximately Correct (PAC) learning framework; generalization bounds based on Rademacher complexity and VC-dimension; Support Vector Machines (SVMs); kernel methods; boosting; on-line learning; multi-class classification; ranking; regression; algorithmic stability; dimensionality reduction; learning automata and languages; and reinforcement learning. Each chapter ends with a set of exercises. Appendixes provide additional material including concise probability review. This second edition offers three new chapters, on model selection, maximum entropy models, and conditional entropy models. New material in the appendixes includes a major section on Fenchel duality, expanded coverage of concentration inequalities, and an entirely new entry on information theory. More than half of the exercises are new to this edition.

Bayesian Learning of Probabilistic Language Models Nov 28 2019

Game-Theoretic Learning and Distributed Optimization in Memoryless Multi-Agent Systems Aug 06 2020 This book presents new efficient methods for optimization in realistic large-scale, multi-agent systems. These methods do not require the agents to have the full information about the system, but instead allow them to make their local decisions based only on the local information, possibly obtained during communication with their local neighbors. The book, primarily aimed at researchers in optimization and control, considers three different information settings in multi-agent systems: oracle-based, communication-based, and payoff-based. For each of these information types, an efficient optimization algorithm is developed, which leads the system to an optimal state. The optimization problems are set without such restrictive assumptions as convexity of the objective functions, complicated communication topologies, closed-form expressions for costs and utilities, and finiteness of the system's state space.

Probabilistic Machine Learning for Civil Engineers Jun 27 2022 An introduction to key concepts and techniques in probabilistic machine learning for civil engineering students and professionals; with many step-by-step examples, illustrations, and exercises. This book introduces probabilistic machine learning concepts to civil engineering students and professionals, presenting key approaches and techniques in a way that is accessible to readers without a specialized background in statistics or computer science. It presents different methods clearly and directly, through step-by-step examples, illustrations, and exercises. Having mastered the material, readers will be able to understand the more advanced machine learning literature from which this book draws. The book presents key approaches in the three subfields of probabilistic machine learning: supervised learning, unsupervised learning, and reinforcement learning. It first covers the background knowledge required to understand machine learning, including linear algebra and probability theory. It goes on to present Bayesian estimation, which is behind the formulation of both supervised and unsupervised learning methods, and Markov chain Monte Carlo methods, which enable Bayesian estimation in certain complex cases. The book then covers approaches associated with supervised learning, including regression methods and classification methods, and notions associated with unsupervised learning, including clustering, dimensionality reduction, Bayesian networks, state-space models, and model calibration. Finally, the book introduces fundamental concepts of rational decisions in uncertain contexts and rational decision-making in uncertain and sequential contexts. Building on this, the book describes the basics of reinforcement learning, whereby a virtual agent learns how to make optimal decisions through trial and error while interacting with its environment.

Probabilistic Deep Learning Jul 29 2022 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

PAGODA May 03 2020

Exploring Probability in School Sep 06 2020 Exploring Probability in School provides a new perspective into research on the teaching and learning of probability. It creates this perspective by recognizing and analysing the special challenges faced by teachers and learners in contemporary classrooms where probability has recently become a mainstream part of the curriculum from early childhood through high school. The authors of the book discuss the nature of probability, look at the meaning of probabilistic literacy, and examine student access to powerful ideas in probability during the elementary, middle, and high school years. Moreover, they assemble and analyse research-based pedagogical knowledge for teachers that can enhance the learning of probability throughout these school years. With the book's rich application of probability research to classroom practice, it will not only be essential reading for researchers and graduate students involved in probability education; it will also capture the interest of educational policy makers, curriculum personnel, teacher educators, and teachers.

Logical and Relational Learning Jul 25 2019 This first textbook on multi-relational data mining and inductive logic programming provides a complete overview of the field. It is self-contained and easily accessible for graduate students and practitioners of data mining and machine learning.

Probabilistic Graphical Models Apr 25 2022 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.

Hardware-Aware Probabilistic Machine Learning Models Jan 23 2022 This book proposes probabilistic machine learning models that represent the hardware properties of the device hosting them. These models can be used to evaluate the impact that a specific device configuration may have on resource consumption and performance of the machine learning task, with the overarching goal of balancing the two optimally. The book first motivates extreme-edge computing in the context of the Internet of Things (IoT) paradigm. Then, it briefly reviews the steps involved in the execution of a machine learning task and identifies the implications associated with implementing this type of workload in resource-constrained devices. The core of this book focuses on augmenting and exploiting the properties of Bayesian Networks and Probabilistic Circuits in order to endow them with hardware-awareness. The proposed models can encode the properties of various device sub-systems that are typically not considered by other resource-aware strategies, bringing about resource-saving opportunities that traditional approaches fail to uncover. The performance of the proposed models and strategies is empirically evaluated for several use cases. All of the considered examples show the potential of attaining significant resource-saving opportunities with minimal accuracy losses at application time. Overall, this book constitutes a novel approach to hardware-algorithm co-optimization that further bridges the fields of Machine Learning and Electrical Engineering.

Practical Probabilistic Programming Mar 01 2020 Summary Practical Probabilistic Programming introduces the working programmer to probabilistic programming. In it, you'll learn how to use the PP paradigm to model application domains and then express those probabilistic models in code. Although PP can seem abstract, in this book you'll immediately work on practical examples, like using the Figaro language to build a spam filter and applying Bayesian and Markov networks, to diagnose computer system data problems and recover digital images. Purchase of the print book includes a free eBook in PDF, Kindle, and ePub formats from Manning Publications. About the Technology The data you accumulate about your customers, products, and website users can help you not only to interpret your past, it can also help you predict your future! Probabilistic programming uses code to draw probabilistic inferences from data. By applying specialized algorithms, your programs assign degrees of probability to conclusions. This means you can forecast future events like sales trends, computer system failures, experimental outcomes, and many other critical concerns. About the Book Practical Probabilistic Programming introduces the working programmer to probabilistic programming. In this book, you'll immediately work on practical examples like building a spam filter, diagnosing computer system data problems, and recovering digital images. You'll discover probabilistic inference, where algorithms help make extended predictions about issues like social media usage. Along the way, you'll learn to use functional-style programming for text analysis, object-oriented models to predict social phenomena like the spread of tweets, and open universe models to gauge real-life social media usage. The book also has chapters on how probabilistic models can help in decision making and modeling of dynamic systems. What's Inside Introduction to probabilistic modeling Writing probabilistic programs in Figaro Building Bayesian networks Predicting product lifecycles Decision-making algorithms About the Reader This book assumes no prior exposure to probabilistic programming. Knowledge of Scala is helpful. About the Author Avi Pfeffer is the principal developer of the Figaro language for probabilistic programming. Table of Contents PART 1 INTRODUCING PROBABILISTIC PROGRAMMING AND FIGARO Probabilistic programming in a nutshell A quick Figaro tutorial Creating a probabilistic programming application PART 2 WRITING PROBABILISTIC PROGRAMS Probabilistic models and probabilistic programs Modeling dependencies with Bayesian and Markov networks Using Scala and Figaro collections to build up models Object-oriented probabilistic modeling Modeling dynamic systems PART 3 INFERENCE The three rules of probabilistic inference Factored inference algorithms Sampling algorithms Solving other inference tasks Dynamic reasoning and parameter learning

Handbook of Probabilistic Models Sep 26 2019 Handbook of Probabilistic Models carefully examines the application of advanced probabilistic models in conventional engineering fields. In this comprehensive handbook, practitioners, researchers and scientists will find detailed explanations of technical concepts, applications of the proposed methods, and the respective scientific approaches needed to solve the problem. This book provides an interdisciplinary approach that creates advanced probabilistic models for engineering fields, ranging from conventional fields of mechanical engineering and civil engineering, to electronics, electrical, earth sciences, climate, agriculture, water resource, mathematical sciences and computer sciences. Specific topics covered include minimax probability machine regression, stochastic finite element method, relevance vector machine, logistic regression, Monte Carlo simulations, random matrix, Gaussian process regression, Kalman filter, stochastic optimization, maximum likelihood, Bayesian inference, Bayesian update, kriging, copula-statistical models, and more. Explains the application of advanced probabilistic models encompassing multidisciplinary research Applies probabilistic modeling to emerging areas in engineering Provides an interdisciplinary approach to probabilistic models and their applications, thus solving a wide range of practical problems

Artificial Intelligence Jul 05 2020 Artificial Intelligence presents a practical guide to AI, including agents, machine learning and problem-solving simple and complex domains.

Graphical Models for Machine Learning and Digital Communication Dec 30 2019 Content Description. #Includes bibliographical references and index.

Foundations of Probabilistic Programming Dec 10 2020 This book provides an overview of the theoretical underpinnings of modern probabilistic programming and presents applications in e.g., machine learning, security, and approximate computing. Comprehensive survey chapters make the material accessible to graduate students and non-experts. This title is also available as Open Access on Cambridge Core.

Probabilistic Graphical Models Jan 11 2021 This fully updated new edition of a uniquely accessible textbook/reference provides a general introduction to probabilistic graphical models (PGMs) from an engineering perspective. It features new material on partially observable Markov decision processes, graphical models, and deep learning, as well as an even greater number of exercises. The book covers the fundamentals for each of the main classes of PGMs, including representation, inference and learning principles, and reviews real-world applications for each type of model. These applications are drawn from a broad range of disciplines, highlighting the many uses of Bayesian classifiers, hidden Markov models, Bayesian networks, dynamic and temporal Bayesian networks, Markov random fields, influence diagrams, and Markov decision processes. Topics and features: Presents a unified framework encompassing all of the main classes of PGMs Explores the fundamental aspects of representation, inference and learning for each technique Examines new material on partially observable Markov decision processes, and graphical models Includes a new chapter introducing deep neural networks and their relation with probabilistic graphical models Covers multidimensional Bayesian classifiers, relational graphical models, and causal models Provides substantial chapter-ending exercises, suggestions for further reading, and ideas for research or programming projects Describes classifiers such as Gaussian Naive Bayes, Circular Chain Classifiers, and Hierarchical Classifiers with Bayesian Networks Outlines the practical application of the different techniques Suggests possible course outlines for instructors This classroom-tested work is suitable as a textbook for an advanced undergraduate or a graduate course in probabilistic graphical models for students of computer science, engineering, and physics. Professionals wishing to apply probabilistic graphical models in their own field, or interested in the basis of these techniques, will also find the book to be an invaluable reference. Dr. Luis Enrique Sucar is a Senior Research Scientist at the National Institute for Astrophysics, Optics and Electronics (INAOE), Puebla, Mexico. He received the National Science Prize en 2016.

Bayesian Reasoning and Machine Learning Jun 15 2021 A practical introduction perfect for final-year undergraduate and graduate students without a solid background in linear algebra and calculus.

Generative Deep Learning Jun 03 2020 Generative modeling is one of the hottest topics in AI. It's now possible to teach a machine to excel at human endeavors such as painting, writing, and composing music. With this practical book, machine-learning engineers and data scientists will discover how to re-create some of the most impressive examples of generative deep learning models, such as variational autoencoders,generative adversarial networks (GANs), encoder-decoder models and world models. Author David Foster demonstrates the inner workings of each technique, starting with the basics of deep learning before advancing to some of the most cutting-edge algorithms in the field. Through tips and tricks, you'll understand how to make your models learn more efficiently and become more creative. Discover how variational autoencoders can change facial expressions in photos Build practical GAN examples from scratch, including CycleGAN for style transfer and MuseGAN for music generation Create recurrent generative models for text generation and learn how to improve the models using attention Understand how generative models can help agents to accomplish tasks within a reinforcement learning setting Explore the architecture of the Transformer (BERT, GPT-2) and image generation models such as ProGAN and StyleGAN

Machine Learning Nov 01 2022 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.

Study Guide for Machine Learning Aug 30 2022 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 Oct 20 2021 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

Probability for Statistics and Machine Learning Jul 17 2021 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.

Probabilistic Deep Learning Nov 20 2021 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

A Probabilistic Theory of Pattern Recognition Aug 18 2021 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.

Bayesian Methods for Hackers Jan 29 2020 Master Bayesian Inference through Practical Examples and Computation–Without Advanced Mathematical Analysis Bayesian methods of inference are deeply natural and extremely powerful. However, most discussions of Bayesian inference rely on intensely complex mathematical analyses and artificial examples, making it inaccessible to anyone without a strong mathematical background. Now, though, Cameron Davidson-Pilon introduces Bayesian inference from a computational perspective, bridging theory to practice–freeing you to get results using computing power. Bayesian Methods for Hackers illuminates Bayesian inference through probabilistic programming with the powerful PyMC language and the closely related Python tools NumPy, SciPy, and Matplotlib. Using this approach, you can reach effective solutions in small increments, without extensive mathematical intervention. Davidson-Pilon begins by introducing the concepts underlying Bayesian inference, comparing it with other techniques and guiding you through building and training your first Bayesian model. Next, he introduces PyMC through a series of detailed examples and intuitive explanations that have been refined after extensive user feedback. You'll learn how to use the Markov Chain Monte Carlo algorithm, choose appropriate sample sizes and priors, work with loss functions, and apply Bayesian inference in domains ranging from finance to marketing. Once you've mastered these techniques, you'll constantly turn to this guide for the working PyMC code you need to jumpstart future projects. Coverage includes • Learning the Bayesian "state of mind" and its practical implications • Understanding how computers perform Bayesian inference • Using the PyMC Python library to program Bayesian analyses • Building and debugging models with PyMC • Testing your model's "goodness of fit" • Opening the "black box" of the Markov Chain Monte Carlo algorithm to see how and why it works • Leveraging the power of the "Law of Large Numbers" • Mastering key concepts, such as clustering, convergence, autocorrelation, and thinning • Using loss functions to measure an estimate's weaknesses based on your goals and desired outcomes • Selecting appropriate priors and understanding how their influence changes with dataset size • Overcoming the "exploration versus exploitation" dilemma: deciding when "pretty good" is good enough • Using Bayesian inference to improve A/B testing • Solving data science problems when only small amounts of data are available Cameron Davidson-Pilon has worked in many areas of applied mathematics, from the evolutionary dynamics of genes and diseases to stochastic modeling of financial prices. His contributions to the open source community include lifelines, an implementation of survival analysis in Python. Educated at the University of Waterloo and at the Independent University of Moscow, he currently works with the online commerce leader Shopify.

Teaching and Learning Stochastics Feb 09 2021 This book presents a collection of selected papers that represent the current variety of research on the teaching and learning of probability. The respective chapters address a diverse range of theoretical, empirical and practical aspects underpinning the teaching and learning of probability, curricular issues, probabilistic reasoning, misconceptions and biases, as well as their pedagogical implications. These chapters are divided into THREE main sections, dealing with: TEACHING PROBABILITY, STUDENTS' REASONING AND LEARNING AND EDUCATION OF TEACHERS. In brief, the papers presented here include research dealing with teachers and students at different levels and ages (from primary school to university) and address epistemological and curricular analysis, as well as the role of technology, simulations, language and visualisation in teaching and learning probability. As such, it offers essential information for teachers, researchers and curricular designers alike.

An Introduction to Probabilistic Modeling Aug 25 2019 Introduction to the basic concepts of probability theory: independence, expectation, convergence in law and almost-sure convergence. Short expositions of more advanced topics such as Markov Chains, Stochastic Processes, Bayesian Decision Theory and Information Theory.

Machine Learning for Probabilistic Prediction Nov 08 2020

Research on Teaching and Learning Probability Sep 18 2021 This book summarizes the vast amount of research related to teaching and learning probability that has been conducted for more than 50 years in a variety of disciplines. It begins with a synthesis of the most important probability interpretations throughout history: intuitive, classical, frequentist, subjective, logical propensity and axiomatic views. It discusses their possible applications, philosophical problems, as well as their potential and the level of interest they enjoy at different educational levels. Next, the book describes the main features of probabilistic thinking and reasoning, including the contrast to classical logic, probability language features, the role of intuitions, as well as paradoxes and the relevance of modeling. It presents an analysis of the differences between conditioning and causation, the variability expression in data as a sum of random and causal variations, as well as those of probabilistic versus statistical thinking. This is followed by an analysis of probability's role and main presence in school curricula and an outline of the central expectations in recent curricular guidelines at the primary, secondary and high school level in several countries. This book classifies and discusses in detail the three different research periods on students' and people's intuitions and difficulties concerning probability: early research focused on cognitive development, a period of heuristics and biases programs, and the current period marked by a multitude of foci, approaches and theoretical frameworks.

Probability for Machine Learning May 15 2021 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.

Pattern Recognition and Machine Learning Jun 23 2019 This is the first textbook on pattern recognition to present the Bayesian viewpoint. The book presents approximate inference algorithms that permit fast approximate answers in situations where exact answers are not feasible. It uses graphical models to describe probability distributions when no other books apply graphical models to machine learning. No previous knowledge of pattern recognition or machine learning concepts is assumed. Familiarity with multivariate calculus and basic linear algebra is required, and some experience in the use of probabilities would be helpful though not essential as the book includes a self-contained introduction to basic probability theory.

Information Theory, Inference and Learning Algorithms Apr 01 2020 Table of contents

Deep Learning Mar 25 2022 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 Machine Learning Sep 30 2022 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.