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Nota di contenuto	Intro -- Preface -- Contents -- About the Editors -- 1 Machine Learning in Computer Aided Engineering -- 1.1 Introduction -- 1.2 Machine Learning Procedures Employed in CAE -- 1.2.1 Machine Learning Aspects and Classification of Procedures -- 1.2.2 Overview of Classical Machine Learning Procedures Used in CAE -- 1.3 Constraining to, and Incorporating Physics in, Data-Driven Methods -- 1.3.1 Incorporating Physics in, and Learning Physics From, the Dataset -- 1.3.2 Incorporating Physics in the Design of a ML Method -- 1.3.3 Data Assimilation and Correction Methods -- 1.3.4 ML Methods Designed to Learn Physics -- 1.4 Applications of Machine Learning in Computer Aided Engineering -- 1.4.1 Constitutive Modeling and Multiscale Applications -- 1.4.2 Fluid Mechanics Applications -- 1.4.3 Structural Mechanics Applications -- 1.4.4 Machine Learning Approaches Motivated in Structural Mechanics and by Finite Element Concepts -- 1.4.5 Multiphysics Problems -- 1.4.6 Machine Learning in Manufacturing and Design -- 1.5 Conclusions -- References -- 2 Artificial Neural Networks -- 2.1 Introduction -- 2.2 Biological Motivation and Pre-history -- 2.2.1 Memory -- 2.2.2 Learning -- 2.2.3 Parallel Distributed Processing Paradigm -- 2.2.4 The Artificial Neuron -- 2.2.5 The Perceptron -- 2.3 The First Age-The Multi-layer Perceptron -- 2.3.1 Existence of Solutions -- 2.3.2 Uniqueness of

Solutions -- 2.3.3 Generalization and Regularization -- 2.3.4 Choice of Output Activations Functions -- 2.4 A First-Age Case Study: Structural Monitoring of an Aircraft Wing -- 2.5 The Second Age-Deep Learning -- 2.5.1 Convolutional Neural Networks (CNNs) -- 2.5.2 A Little More History -- 2.5.3 Other Recent Developments -- 2.6 Conclusions -- References -- 3 Gaussian Processes -- 3.1 Introduction -- 3.1.1 A Visual Introduction To Gaussian Processes -- 3.1.2 Gaussian Process Regression. 3.1.3 Implementation and Learning of the GP -- 3.2 Beyond the Gaussian Process -- 3.2.1 Large Training Data -- 3.2.2 Non-Gaussian Likelihoods -- 3.2.3 Multiple-Output GPs -- 3.3 A Case Study with Wind Turbine Power Curves -- 3.4 Conclusions -- References -- 4 Machine Learning Methods for Constructing Dynamic Models From Data -- 4.1 Introduction -- 4.2 Modeling Viewpoints -- 4.3 Learning Paradigms: Burgers' Equation -- 4.4 Dynamic Models From Data -- 4.4.1 Dynamic Mode Decomposition -- 4.4.2 Sparse Identification of Nonlinear Dynamics -- 4.4.3 Neural Networks -- 4.5 Joint Discovery of Coordinates and Models -- 4.6 Conclusions -- References -- 5 Physics-Informed Neural Networks: Theory and Applications -- 5.1 Introduction -- 5.2 Basics of Artificial Neural Networks -- 5.2.1 Feed-Forward Neural Networks -- 5.2.2 Activation Functions -- 5.2.3 Training -- 5.2.4 Testing and Validation -- 5.2.5 Optimizers -- 5.3 Physics-Informed Neural Networks -- 5.3.1 Collocation Method -- 5.3.2 Energy Minimization Method -- 5.4 Numerical Applications -- 5.4.1 Forward Problems -- 5.4.2 Inverse Problems -- 5.5 Conclusions -- References -- 6 Physics-Informed Deep Neural Operator Networks -- 6.1 Introduction -- 6.2 DeepONet and Its Extensions -- 6.2.1 Feature Expansion in DeepONet -- 6.2.2 Multiple Input DeepONet -- 6.2.3 Physics-Informed DeepONet -- 6.3 FNO and Its Extensions -- 6.3.1 Feature Expansion in FNO -- 6.3.2 Implicit FNO -- 6.3.3 Physics-Informed FNO -- 6.4 Graph Neural Operators -- 6.4.1 Graph Neural Networks -- 6.4.2 Integral Neural Operators Through Graph Kernel Learning -- 6.5 Neural Operator Theory -- 6.6 Applications -- 6.6.1 Data-Driven Neural Operators -- 6.6.2 Physics-Informed Neural Operators -- 6.7 Summary and Outlook -- References -- 7 Digital Twin for Dynamical Systems -- 7.1 Introduction -- 7.2 Building Blocks and Nominal Model in Digital Twin. 7.3 Physics-Based Digital Twin for SDOF System -- 7.3.1 Nominal Model -- 7.3.2 The Digital Twin Framework -- 7.3.3 Formulating the Digital Twin -- 7.3.4 Numerical Experiment -- 7.4 Physics ML Fusion: Towards a Predictive Digital Twin -- 7.4.1 Gaussian Process -- 7.4.2 Numerical Experiment -- 7.5 Digital Twin for Nonlinear Stochastic Dynamical Systems -- 7.5.1 Stochastic Nonlinear MDOF System: The Nominal Model -- 7.5.2 Problem Statement -- 7.5.3 The Digital Twin Framework -- 7.5.4 Numerical Examples -- 7.6 Digital Twin for Systems with Misspecified Physics -- 7.6.1 Model Updating Using Input-Output Measurement -- 7.6.2 Model Updating Using Output-Only Measurements -- 7.6.3 Sparse Bayesian Regression -- 7.6.4 Numerical Examples -- 7.7 Conclusions -- References -- 8 Reduced Order Modeling -- 8.1 Introduction -- 8.2 Proper Orthogonal Decomposition -- 8.2.1 Proper Orthogonal Decomposition Applied to Partial Differential Equations -- 8.2.2 Singular Value Decomposition -- 8.3 Reduced Order Modeling Using Proper Orthogonal Decomposition -- 8.3.1 Galerkin Projection -- 8.3.2 Hyperreduction -- 8.3.3 Stabilization Using Variational Multiscale Methods -- 8.4 Non-intrusive Reduced Order Models -- 8.4.1 The General Concept -- 8.4.2 Dynamic Mode Decomposition -- 8.5 Parametric Reduced Order Models -- 8.5.1 Global Basis -- 8.5.2 Local Basis with Interpolation -- 8.6 Machine

Learning-Based Reduced Order Models -- 8.6.1 Nonlinear Dimension Reduction -- 8.6.2 Machine Learning Based Non-intrusive Reduced Order Models -- 8.6.3 Closure Modeling -- 8.6.4 Correction Based on Fine Solutions -- 8.6.5 Machine Learning Applied to Parametric Reduced Order Models -- 8.6.6 Physics Informed Machine Learning for Reduced Order Models -- 8.6.7 Reduced System Identification -- 8.7 Concluding Remarks -- References -- 9 Regression Models for Machine Learning -- 9.1 Introduction. 9.2 Parametric Regression: A Non-Bayesian Perspective -- 9.2.1 Least Square Regression -- 9.2.2 Support Vector Regression -- 9.2.3 Kernel Trick -- 9.3 Regression: A Bayesian Perspective -- 9.3.1 Gaussian Process Regression: A Parametric Space Perspective -- 9.3.2 Gaussian Process Regression: A Functional Space Perspective -- 9.4 Active Learning -- 9.4.1 Active Learning for Bayesian Cubature -- 9.4.2 Active Learning for Bayesian Reliability Assessment -- 9.5 Conclusions -- References -- 10 Overview on Machine Learning Assisted Topology Optimization Methodologies -- 10.1 Introduction -- 10.2 Background -- 10.2.1 Topology Optimization -- 10.2.2 Artificial Intelligence and Neural Networks -- 10.3 Literature Survey -- 10.3.1 Density-Based Methods -- 10.3.2 Image-Based Methods -- 10.4 Conclusions -- References -- 11 Mixed-Variable Concurrent Material, Geometry, and Process Design in Integrated Computational Materials Engineering -- 11.1 Introduction -- 11.2 Mixed-Variable and Constrained Bayesian Optimization -- 11.2.1 Gaussian Processes and Bayesian Optimization -- 11.2.2 Latent Variable Gaussian Process (LVGP) Modeling -- 11.2.3 Constrained Bayesian Optimization -- 11.3 Application to Concurrent Structure and Material Design -- 11.3.1 The Integrated Material-Structure Model -- 11.3.2 Design Variables, Constraints, and Objectives -- 11.3.3 LVGP Modeling and Validation -- 11.3.4 LVGP-CBO Setup and Design Results -- 11.4 Application to Concurrent Material and Process Design -- 11.4.1 The Integrated Process-Structure-Property Model -- 11.4.2 Design Variables, Constraints, and Objectives for SFRP Design -- 11.4.3 LVGP Modeling and Validation -- 11.4.4 LVGP-CBO Setup and Design Results -- 11.5 Conclusions -- References -- 12 Machine Learning Interatomic Potentials: Keys to First-Principles Multiscale Modeling -- 12.1 Introduction. 12.2 Methods for Exploring Interatomic Forces -- 12.2.1 Quantum Mechanics -- 12.2.2 Empirical Interatomic Potentials -- 12.2.3 Machine Learning Interatomic Potentials -- 12.3 Developing a Machine Learning Interatomic Potential -- 12.3.1 Popular Machine Learning Interatomic Potentials -- 12.3.2 Training of Machine Learning Interatomic Potentials -- 12.3.3 Passive or Active Fitting -- 12.3.4 Current Challenges of MLIPs -- 12.4 Quantum Mechanics and Empirical Interatomic Potentials Challenges -- 12.4.1 Thermal Transport -- 12.4.2 Mechanical Properties -- 12.5 First-Principles Multiscale Modeling -- 12.6 Concluding Remark -- References.

Sommario/riassunto

This book focuses on the application of machine learning techniques in engineering and the sciences, emphasizing their role in modeling and simulation. Edited by Timon Rabczuk and Klaus-Jürgen Bathe, it covers a wide range of topics including solid structural mechanics, fluid dynamics, heat transfer, and more. The book highlights the potential of machine learning to solve complex engineering problems, reduce computational costs, and innovate in fields like digital twins and new material design. This comprehensive volume is intended for professionals and researchers in engineering and applied sciences, offering both theoretical insights and practical applications.
