

vector space training

vector space training is a fundamental concept in various fields such as machine learning, data science, and applied mathematics. This training involves understanding and utilizing vector spaces to enhance data representation, improve algorithmic efficiency, and optimize model performance. By mastering vector space concepts, professionals can better handle high-dimensional data, perform accurate similarity measurements, and develop more effective predictive models. This article explores the core principles of vector space training, its practical applications, and the methodologies involved. Additionally, it addresses the challenges, tools, and techniques that facilitate effective learning and implementation of vector space concepts. The comprehensive overview will provide readers with a solid foundation in vector space training and its significance in modern computational tasks.

- Understanding Vector Spaces in Machine Learning
- Core Concepts of Vector Space Training
- Applications of Vector Space Training
- Techniques and Tools for Vector Space Training
- Challenges and Best Practices in Vector Space Training

Understanding Vector Spaces in Machine Learning

Vector spaces are mathematical structures formed by vectors, which are objects that can be added together and multiplied by scalars while satisfying certain axioms. In machine learning, vector spaces provide a framework for representing data points, features, and transformations. Vector representations enable algorithms to perform operations such as distance calculations, projections, and dimensionality reduction, which are crucial for pattern recognition and classification.

Definition and Properties of Vector Spaces

A vector space is defined over a field, usually the real numbers, and consists of a set of vectors equipped with two operations: vector addition and scalar multiplication. Key properties include closure, associativity, distributivity, existence of an additive identity (zero vector), and the existence of additive inverses. These properties ensure that vectors can be manipulated consistently within the space for analytical and computational

purposes.

Importance in Data Representation

Representing data as vectors in a vector space allows for the use of geometric and algebraic methods to analyze relationships between data points. Feature vectors can encode attributes of data instances, enabling similarity measures such as cosine similarity or Euclidean distance. Vector space models facilitate the handling of large datasets and support operations like clustering, classification, and regression.

Core Concepts of Vector Space Training

Vector space training encompasses the processes and methodologies used to develop an understanding and practical skills in manipulating vector spaces. This training emphasizes the theoretical foundations and applied techniques necessary for effective use in computational tasks.

Basis and Dimension

A fundamental aspect of vector spaces is the concept of a basis, a set of linearly independent vectors that span the entire space. The number of vectors in a basis defines the dimension of the space. Training in vector spaces involves learning how to identify bases, understand dimensionality, and perform coordinate transformations relative to different bases.

Vector Space Models and Embeddings

Vector space training includes mastering vector space models such as word embeddings in natural language processing or feature embeddings in recommendation systems. These models transform discrete data into continuous vector representations, capturing semantic or structural relationships. Understanding how to generate, interpret, and optimize embeddings is a critical part of vector space training.

Linear Transformations and Projections

Linear transformations map vectors from one vector space to another while preserving vector addition and scalar multiplication. Training covers concepts such as matrix multiplication, eigenvalues, eigenvectors, and projections, which are essential for tasks like dimensionality reduction (e.g., PCA) and feature extraction.

Applications of Vector Space Training

Vector space training has widespread applications across multiple domains, leveraging vector representations to solve complex problems efficiently.

Natural Language Processing (NLP)

In NLP, vector space training is used to develop word embeddings and document representations that capture linguistic semantics. Techniques like Word2Vec, GloVe, and BERT rely on vector spaces to perform tasks such as sentiment analysis, machine translation, and information retrieval.

Image and Signal Processing

Vector space concepts underpin image feature extraction, compression, and recognition. Training in vector spaces enables the development of algorithms that represent images as feature vectors, facilitating operations like classification, clustering, and anomaly detection.

Recommendation Systems

Recommendation engines utilize vector embeddings of users and items to predict preferences and generate personalized suggestions. Vector space training helps in understanding collaborative filtering and matrix factorization techniques that improve recommendation accuracy.

Data Mining and Pattern Recognition

Vector spaces provide a mathematical framework for identifying patterns, trends, and clusters in large datasets. Training covers methods like k-means clustering, support vector machines, and other algorithms that rely on vector representations for efficient computation.

Techniques and Tools for Vector Space Training

Effective vector space training involves a combination of theoretical study and practical implementation using specialized tools and techniques.

Mathematical Foundations and Tutorials

Training begins with building a strong foundation in linear algebra, including vector operations, matrix theory, and eigen decomposition. Educational resources such as textbooks, online courses, and tutorials

provide structured learning paths for mastering these concepts.

Programming Libraries and Frameworks

Several software libraries facilitate vector space computations and model training:

- **NumPy:** Provides support for multidimensional arrays and linear algebra operations.
- **scikit-learn:** Offers tools for dimensionality reduction, clustering, and classification using vector spaces.
- **TensorFlow and PyTorch:** Enable the creation and training of neural networks that generate vector embeddings.
- **Gensim:** Specialized in topic modeling and vector space modeling for text data.

Best Practices in Model Training

Vector space training emphasizes best practices such as normalization of vectors, regularization to prevent overfitting, and validation to ensure model robustness. Understanding hyperparameter tuning and optimization techniques is essential for improving vector space models.

Challenges and Best Practices in Vector Space Training

While vector space training provides powerful tools for data representation, it also presents challenges that practitioners must address to ensure successful outcomes.

Handling High Dimensionality

High-dimensional vector spaces can lead to the "curse of dimensionality," where increased dimensions cause sparsity and degrade model performance. Techniques like dimensionality reduction (PCA, t-SNE) and feature selection are critical components of vector space training to mitigate these issues.

Interpretability of Vector Representations

Interpreting the meaning of vectors, especially in complex embeddings, can be difficult. Training involves learning methods to visualize and analyze vector spaces to better understand the relationships encoded in the data.

Scalability and Computational Efficiency

Training and utilizing vector space models on large datasets require scalable algorithms and efficient computation. Techniques such as approximate nearest neighbor search and distributed computing are often incorporated into vector space training programs.

Ensuring Data Quality and Preprocessing

Quality of input data significantly impacts vector space models. Proper preprocessing steps, including cleaning, normalization, and handling missing values, form an integral part of vector space training to maximize model accuracy and reliability.

Frequently Asked Questions

What is vector space training in machine learning?

Vector space training refers to the process of training machine learning models using data represented in vector space, where each data point is encoded as a vector of numerical features to enable mathematical operations and pattern recognition.

How does vector space training improve natural language processing models?

Vector space training improves NLP models by representing words, sentences, or documents as vectors in a continuous vector space, allowing models to capture semantic relationships and perform tasks like similarity measurement, clustering, and classification more effectively.

What are common techniques used in vector space training?

Common techniques include word embeddings (e.g., Word2Vec, GloVe), TF-IDF vectorization, and dimensionality reduction methods like PCA and t-SNE, which help transform raw data into meaningful vector representations for training.

Can vector space training be applied to image recognition?

Yes, vector space training is applied in image recognition by representing images as vectors of pixel values or feature embeddings extracted using convolutional neural networks, enabling effective training and classification of visual data.

What role does vector normalization play in vector space training?

Vector normalization scales vectors to have a consistent length, which improves the stability and performance of machine learning algorithms by ensuring that differences in vector magnitude do not unduly influence similarity measures or model training.

How do embedding layers contribute to vector space training?

Embedding layers learn dense vector representations of categorical data or tokens during training, mapping discrete inputs into continuous vector spaces that capture semantic and syntactic information useful for downstream tasks.

What challenges are associated with vector space training?

Challenges include handling high dimensionality, ensuring meaningful vector representations, avoiding overfitting, managing computational complexity, and addressing bias in training data that can be reflected in the learned vector spaces.

Additional Resources

1. Linear Algebra and Its Applications

This comprehensive book covers the fundamental concepts of vector spaces, linear transformations, and matrix theory. It provides numerous examples and exercises that help readers develop a deep understanding of vector space structures. The book is suitable for both beginners and those looking to reinforce their linear algebra skills.

2. Introduction to Vector Spaces and Linear Transformations

Focused on the theoretical underpinnings of vector spaces, this text offers detailed explanations of key concepts such as basis, dimension, and linear mappings. It balances rigorous proofs with intuitive insights, making it ideal for students in mathematics and engineering. The book also includes practical applications to illustrate abstract ideas.

3. *Applied Linear Algebra and Matrix Analysis*

This book emphasizes the practical aspects of vector spaces and linear algebra in applied sciences and engineering. It explores topics like eigenvalues, eigenvectors, and orthogonality with real-world problems. Readers will find it useful for developing computational skills alongside theoretical knowledge.

4. *Vector Spaces: An Introduction to Linear Algebra*

Designed for those new to the subject, this introductory text breaks down vector spaces into accessible sections. It introduces vectors, subspaces, and span with clear examples and visual aids. The book also includes exercises that reinforce learning and encourage problem-solving.

5. *Advanced Linear Algebra*

Targeting more experienced readers, this book delves into complex topics such as inner product spaces, tensor products, and canonical forms. It provides rigorous proofs and detailed discussions to deepen understanding of vector space theory. Ideal for graduate students and researchers in mathematics.

6. *Computational Linear Algebra and Vector Space Methods*

This title focuses on algorithmic approaches to vector spaces, including numerical methods for solving linear systems and eigenvalue problems. It covers software tools and programming techniques to implement vector space computations. Suitable for computer scientists and applied mathematicians.

7. *Geometry of Vector Spaces*

Bridging algebra and geometry, this book explores the geometric interpretation of vector spaces and linear transformations. Topics include affine spaces, projections, and geometric transformations in multiple dimensions. The book is rich with diagrams and geometric intuition to aid comprehension.

8. *Functional Analysis and Vector Space Theory*

Integrating vector space concepts with functional analysis, this text introduces normed spaces, Banach spaces, and Hilbert spaces. It is aimed at readers interested in advanced mathematical analysis and its applications in physics and engineering. The book combines theory with examples from real-world problems.

9. *Vector Spaces in Data Science and Machine Learning*

This contemporary book applies vector space theory to data science, focusing on high-dimensional data representation, feature extraction, and dimensionality reduction techniques. It explains how vector spaces underpin algorithms such as PCA and support vector machines. Ideal for practitioners and students in AI and machine learning fields.

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vector space training: Kernel Methods and Machine Learning S. Y. Kung, 2014-04-17 Covering the fundamentals of kernel-based learning theory, this is an essential resource for graduate students and professionals in computer science.

vector space training: Basic Training in Mathematics R. Shankar, 2013-12-20 Based on course material used by the author at Yale University, this practical text addresses the widening gap found between the mathematics required for upper-level courses in the physical sciences and the knowledge of incoming students. This superb book offers students an excellent opportunity to strengthen their mathematical skills by solving various problems in differential calculus. By covering material in its simplest form, students can look forward to a smooth entry into any course in the physical sciences.

vector space training: Federated Learning Heiko Ludwig, Nathalie Baracaldo, 2022-07-07 Federated Learning: A Comprehensive Overview of Methods and Applications presents an in-depth discussion of the most important issues and approaches to federated learning for researchers and practitioners. Federated Learning (FL) is an approach to machine learning in which the training data are not managed centrally. Data are retained by data parties that participate in the FL process and are not shared with any other entity. This makes FL an increasingly popular solution for machine learning tasks for which bringing data together in a centralized repository is problematic, either for privacy, regulatory or practical reasons. This book explains recent progress in research and the state-of-the-art development of Federated Learning (FL), from the initial conception of the field to first applications and commercial use. To obtain this broad and deep overview, leading researchers address the different perspectives of federated learning: the core machine learning perspective, privacy and security, distributed systems, and specific application domains. Readers learn about the challenges faced in each of these areas, how they are interconnected, and how they are solved by state-of-the-art methods. Following an overview on federated learning basics in the introduction, over the following 24 chapters, the reader will dive deeply into various topics. A first part addresses algorithmic questions of solving different machine learning tasks in a federated way, how to train efficiently, at scale, and fairly. Another part focuses on providing clarity on how to select privacy and security solutions in a way that can be tailored to specific use cases, while yet another considers the pragmatics of the systems where the federated learning process will run. The book also covers other important use cases for federated learning such as split learning and vertical federated learning. Finally, the book includes some chapters focusing on applying FL in real-world enterprise settings.

vector space training: Course In Linear Algebra With Applications, A (2nd Edition) Derek J S Robinson, 2006-08-15 This is the second edition of the best-selling introduction to linear algebra. Presupposing no knowledge beyond calculus, it provides a thorough treatment of all the basic concepts, such as vector space, linear transformation and inner product. The concept of a quotient space is introduced and related to solutions of linear system of equations, and a simplified treatment of Jordan normal form is given. Numerous applications of linear algebra are described, including systems of linear recurrence relations, systems of linear differential equations, Markov processes,

and the Method of Least Squares. An entirely new chapter on linear programming introduces the reader to the simplex algorithm with emphasis on understanding the theory behind it. The book is addressed to students who wish to learn linear algebra, as well as to professionals who need to use the methods of the subject in their own fields.

vector space training: Software Engineering, Business Continuity, and Education

Tai-hoon Kim, Hojjat Adeli, Haeng-Kon Kim, Heau-jo Kang, Kyung Jung Kim, Akingbehin Kiumi, Byeong-Ho Kang, 2011-12-02 This book comprises selected papers of the International Conferences, ASEA, DRBC and EL 2011, held as Part of the Future Generation Information Technology Conference, FGIT 2011, in Conjunction with GDC 2011, Jeju Island, Korea, in December 2011. The papers presented were carefully reviewed and selected from numerous submissions and focus on the various aspects of advances in software engineering and its Application, disaster recovery and business continuity, education and learning.

vector space training: Similarity-Based Pattern Analysis and Recognition

Marcello Pelillo, 2013-11-26 This accessible text/reference presents a coherent overview of the emerging field of non-Euclidean similarity learning. The book presents a broad range of perspectives on similarity-based pattern analysis and recognition methods, from purely theoretical challenges to practical, real-world applications. The coverage includes both supervised and unsupervised learning paradigms, as well as generative and discriminative models. Topics and features: explores the origination and causes of non-Euclidean (dis)similarity measures, and how they influence the performance of traditional classification algorithms; reviews similarity measures for non-vectorial data, considering both a "kernel tailoring" approach and a strategy for learning similarities directly from training data; describes various methods for "structure-preserving" embeddings of structured data; formulates classical pattern recognition problems from a purely game-theoretic perspective; examines two large-scale biomedical imaging applications.

vector space training: Conceptual Modeling

Paolo Atzeni, David Cheung, Sudha Ram, 2012-10-14 This book constitutes the refereed proceedings of the 31st International Conference on Conceptual Modeling, ER 2012, held in Florence, Italy, in October 2012. The 24 regular papers presented together with 13 short papers, 6 poster papers and 3 keynotes were carefully reviewed and selected from 141 submissions. The papers are organized in topical sections on understandability and cognitive approaches; conceptual modeling for datawarehousing and business intelligence; extraction, discovery and clustering; search and documents; data and process modeling; ontology based approaches; variability and evolution; adaptation, preferences and query refinement; queries, matching and topic search; and conceptual modeling in action.

vector space training: A First Course in Sobolev Spaces

Giovanni Leoni, 2024-04-17 This book is about differentiation of functions. It is divided into two parts, which can be used as different textbooks, one for an advanced undergraduate course in functions of one variable and one for a graduate course on Sobolev functions. The first part develops the theory of monotone, absolutely continuous, and bounded variation functions of one variable and their relationship with Lebesgue-Stieltjes measures and Sobolev functions. It also studies decreasing rearrangement and curves. The second edition includes a chapter on functions mapping time into Banach spaces. The second part of the book studies functions of several variables. It begins with an overview of classical results such as Rademacher's and Stepanoff's differentiability theorems, Whitney's extension theorem, Brouwer's fixed point theorem, and the divergence theorem for Lipschitz domains. It then moves to distributions, Fourier transforms and tempered distributions. The remaining chapters are a treatise on Sobolev functions. The second edition focuses more on higher order derivatives and it includes the interpolation theorems of Gagliardo and Nirenberg. It studies embedding theorems, extension domains, chain rule, superposition, Poincaré's inequalities and traces. A major change compared to the first edition is the chapter on Besov spaces, which are now treated using interpolation theory.

vector space training: A Course in Ordinary Differential Equations

Stephen A. Wirkus, Randall J. Swift, 2014-12-15 A Course in Ordinary Differential Equations, Second Edition teaches

students how to use analytical and numerical solution methods in typical engineering, physics, and mathematics applications. Lauded for its extensive computer code and student-friendly approach, the first edition of this popular textbook was the first on ordinary differential equations.

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vector space training: Linear Algebra and Optimization for Machine Learning Charu C. Aggarwal, 2025-09-23 This textbook is the second edition of the linear algebra and optimization book that was published in 2020. The exposition in this edition is greatly simplified as compared to the first edition. The second edition is enhanced with a large number of solved examples and exercises. A frequent challenge faced by beginners in machine learning is the extensive background required in linear algebra and optimization. One problem is that the existing linear algebra and optimization courses are not specific to machine learning; therefore, one would typically have to complete more course material than is necessary to pick up machine learning. Furthermore, certain types of ideas and tricks from optimization and linear algebra recur more frequently in machine learning than other application-centric settings. Therefore, there is significant value in developing a view of linear algebra and optimization that is better suited to the specific perspective of machine learning. It is common for machine learning practitioners to pick up missing bits and pieces of linear algebra and optimization via "osmosis" while studying the solutions to machine learning applications. However, this type of unsystematic approach is unsatisfying because the primary focus on machine learning gets in the way of learning linear algebra and optimization in a generalizable way across new situations and applications. Therefore, we have inverted the focus in this book, with linear algebra/optimization as the primary topics of interest, and solutions to machine learning problems as the applications of this machinery. In other words, the book goes out of its way to teach linear algebra and optimization with machine learning examples. By using this approach, the book focuses on those aspects of linear algebra and optimization that are more relevant to machine learning, and also teaches the reader how to apply them in the machine learning context. As a side benefit, the reader will pick up knowledge of several fundamental problems in machine learning. At the end of the process, the reader will become familiar with many of the basic linear-algebra- and optimization-centric algorithms in machine learning. Although the book is not intended to provide exhaustive coverage of machine learning, it serves as a "technical starter" for the key models and optimization methods in machine learning. Even for seasoned practitioners of machine learning, a systematic introduction to fundamental linear algebra and optimization methodologies can be useful in terms of providing a fresh perspective. The chapters of the book are organized as follows.

1-Linear algebra and its applications: The chapters focus on the basics of linear algebra together with their common applications to singular value decomposition, matrix factorization, similarity matrices (kernel methods), and graph analysis. Numerous machine learning applications have been used as examples, such as spectral clustering, kernel-based classification, and outlier detection. The tight integration of linear algebra methods with examples from machine learning differentiates this book from generic volumes on linear algebra. The focus is clearly on the most relevant aspects of linear algebra for machine learning and to teach readers how to apply these concepts.

2-Optimization and its applications: Much of machine learning is posed as an optimization problem in which we try to maximize the accuracy of regression and classification models. The “parent problem” of optimization-centric machine learning is least-squares regression. Interestingly, this problem arises in both linear algebra and optimization and is one of the key connecting problems of the two fields. Least-squares regression is also the starting point for support vector machines, logistic regression, and recommender systems. Furthermore, the methods for dimensionality reduction and matrix factorization also require the development of optimization methods. A general view of optimization in computational graphs is discussed together with its applications to backpropagation in neural networks. The primary audience for this textbook is graduate level students and professors. The secondary audience is industry. Advanced undergraduates might also be interested, and it is possible to use this book for the mathematics requirements of an undergraduate data science course.

vector space training: Machine Learning with Spark Rajdeep Dua, Manpreet Singh Ghotra, Nick Pentreath, 2017-04-28 Create scalable machine learning applications to power a modern data-driven business using Spark 2.x About This Book Get to the grips with the latest version of Apache Spark Utilize Spark's machine learning library to implement predictive analytics Leverage Spark's powerful tools to load, analyze, clean, and transform your data Who This Book Is For If you have a basic knowledge of machine learning and want to implement various machine-learning concepts in the context of Spark ML, this book is for you. You should be well versed with the Scala and Python languages. What You Will Learn Get hands-on with the latest version of Spark ML Create your first Spark program with Scala and Python Set up and configure a development environment for Spark on your own computer, as well as on Amazon EC2 Access public machine learning datasets and use Spark to load, process, clean, and transform data Use Spark's machine learning library to implement programs by utilizing well-known machine learning models Deal with large-scale text data, including feature extraction and using text data as input to your machine learning models Write Spark functions to evaluate the performance of your machine learning models In Detail This book will teach you about popular machine learning algorithms and their implementation. You will learn how various machine learning concepts are implemented in the context of Spark ML. You will start by installing Spark in a single and multinode cluster. Next you'll see how to execute Scala and Python based programs for Spark ML. Then we will take a few datasets and go deeper into clustering, classification, and regression. Toward the end, we will also cover text processing using Spark ML. Once you have learned the concepts, they can be applied to implement algorithms in either green-field implementations or to migrate existing systems to this new platform. You can migrate from Mahout or Scikit to use Spark ML. By the end of this book, you will acquire the skills to leverage Spark's features to create your own scalable machine learning applications and power a modern data-driven business. Style and approach This practical tutorial with real-world use cases enables you to develop your own machine learning systems with Spark. The examples will help you combine various techniques and models into an intelligent machine learning system.

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Google Cloud

vector space training: *Leveraging Applications of Formal Methods, Verification, and Validation* Reiner Hähnle, Jens Knoop, Tiziana Margaria, Dietmar Schreiner, Bernhard Steffen, 2012-10-12 This volume contains a selection of revised papers that were presented at the Software Aspects of Robotic Systems, SARS 2011 Workshop and the Machine Learning for System Construction, MLSC 2011 Workshop, held during October 17-18 in Vienna, Austria, under the auspices of the International Symposium Series on Leveraging Applications of Formal Methods, Verification, and Validation, ISOFA. The topics covered by the papers of the SARS and the MLSC workshop demonstrate the breadth and the richness of the respective fields of the two workshops stretching from robot programming to languages and compilation techniques, to real-time and fault tolerance, to dependability, software architectures, computer vision, cognitive robotics, multi-robot-coordination, and simulation to bio-inspired algorithms, and from machine learning for anomaly detection, to model construction in software product lines to classification of web service interfaces. In addition the SARS workshop hosted a special session on the recently launched KOROS project on collaborating robot systems that is borne by a consortium of researchers of the faculties of architecture and planning, computer science, electrical engineering and information technology, and mechanical and industrial engineering at the Vienna University of Technology. The four papers devoted to this session highlight important research directions pursued in this interdisciplinary research project.

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vector space training: *Learning Modern Algebra* Albert Cuoco, Joseph Rotman, 2013 Much of modern algebra arose from attempts to prove Fermat's Last Theorem, which in turn has its roots in Diophantus' classification of Pythagorean triples. This book, designed for prospective and practising mathematics teachers, makes explicit connections between the ideas of abstract algebra and the mathematics taught at high-school level. Algebraic concepts are presented in historical order, and the book also demonstrates how other important themes in algebra arose from questions related to teaching. The focus is on number theory, polynomials, and commutative rings. Group theory is introduced near the end of the text to explain why generalisations of the quadratic formula do not exist for polynomials of high degree, allowing the reader to appreciate the work of Galois and Abel. Results are motivated with specific examples, and applications range from the theory of repeating decimals to the use of imaginary quadratic fields to construct problems with rational solutions.

vector space training: *Deep Learning Applications in Medical Imaging* Saxena, Sanjay, Paul, Sudip, 2020-10-16 Before the modern age of medicine, the chance of surviving a terminal disease such as cancer was minimal at best. After embracing the age of computer-aided medical analysis technologies, however, detecting and preventing individuals from contracting a variety of life-threatening diseases has led to a greater survival percentage and increased the development of algorithmic technologies in healthcare. Deep Learning Applications in Medical Imaging is a pivotal reference source that provides vital research on the application of generating pictorial depictions of the interior of a body for medical intervention and clinical analysis. While highlighting topics such as artificial neural networks, disease prediction, and healthcare analysis, this publication explores image acquisition and pattern recognition as well as the methods of treatment and care. This book is ideally designed for diagnosticians, medical imaging specialists, healthcare professionals, physicians, medical researchers, academicians, and students.

vector space training: *War Narratives in Post-Conflict Societies* Michal Mochtak, 2024-02-29 This book studies war narratives and their role in the political arenas of post-conflict societies, with a focus on the former Yugoslavia. How do politicians in postwar societies talk about the past war? How do they discursively represent vulnerable social groups created by the conflict? Does the nature of this representation depend on the politicians' ideology, personal characteristics, or their record of

combat service? The book answers these questions by pairing natural language processing tools and large corpora of parliamentary debates collected in three southeast European post-conflict societies (Bosnia-Herzegovina, Croatia, and Serbia). Using the latest advances in computer science, the book explores patterns in the war discourse of the political elites of these countries and discusses how politicians talk about war in terms of common narratives and shared frameworks. Mapping over 20 years of parliamentary debates, the book presents a new perspective on the role of the legacies of war in public space and develops theoretical arguments about reconciliation in post-conflict societies. The wars of the 1990s and the breakup of Yugoslavia have created three totally different settings for remembering the past conflicts in these countries, despite their common history. It is a story of victorious battles (Croatia), past grievances (Bosnia-Herzegovina), and denial (Serbia), showing the different flavors of past wars in various national contexts that are symptomatic of many post-conflict societies in different parts of the world. This book will be of much interest to students of war and conflict studies, southeastern European politics, discourse analysis, and international relations.

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