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Zhengming Ding · Handong Zhao Yun Fu

Learning Representation for Multi-View Data Analysis

Models and Applications



Zhengming Ding Indiana University-Purdue University Indianapolis Indianapolis, IN, USA

Handong Zhao Adobe Research San Jose, CA, USA Yun Fu Northeastern University Boston, MA, USA

ISSN 1610-3947 ISSN 2197-8441 (electronic) Advanced Information and Knowledge Processing ISBN 978-3-030-00733-1 ISBN 978-3-030-00734-8 (eBook) https://doi.org/10.1007/978-3-030-00734-8

Library of Congress Control Number: 2018961715

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Preface

This book equips readers to handle complex multi-view data representation, centered around several major visual applications, sharing many tips and insights through a unified learning framework. This framework is able to model most existing multi-view learning and domain adaptation, enriching readers' understanding from their similarity and differences based on data organization and problem settings, as well as the research goal.

A comprehensive review exhaustively provides the key recent research on multi-view data analysis, i.e., multi-view clustering, multi-view classification, zero-shot learning, and domain adaption. More practical challenges in multi-view data analysis are discussed including incomplete, unbalanced, and large-scale multi-view learning. Learning representation for multi-view data analysis covers a wide range of applications in the research fields of big data, human-centered computing, pattern recognition, digital marketing, Web mining, and computer vision.

This book consists of ten chapters. Chapter 1 introduces the background and unified model of multi-view data representations. Part I, which includes Chaps. 2–4, introduces the unsupervised learning for multi-view data analysis. Chapter 2 presents the unsupervised representation learning methods for two multi-view scenarios. One is considering various data sources as multiple views. The other is considering different splits of one source data as multiple views. Chapter 3 addresses the more challenging and practical incomplete multi-view clustering problem. Chapter 4 introduces a novel outlier detection problem in multi-view setting and correspondingly proposes a multi-view outlier detection framework.

Part II, which includes Chaps. 5 and 6, presents the multi-view data analysis for supervised multi-view classification. Chapter 5 presents two multi-view classification models—one is dual low-rank decomposition multi-view subspace and the other is cross-view auto-encoder. Chapter 6 shows an adaptive latent semantic representation model in a sparse dictionary learning scheme for zero-shot learning (a special case of multi-view classification problem). Part III, which includes Chaps. 7–10, presents the multi-view data analysis for domain adaptation. Chapter 7 lists the missing modality transfer learning model to solve the problem when target modality is not available in the training stage. Chapter 8 discusses the multi-source

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transfer learning problem when all the sources are incomplete. Chapter 9 proposes three deep domain adaptation models to address the challenge where target data has limited or no label. Following this, Chap. 10 provides a deep domain generalization model aiming to deal with the target domain that is not available in the training stage while only with multiple related sources at hand.

In particular, this book can be used by these audiences in the background of computer science, information systems, data science, statistics, and mathematics. Other potential audiences can be attracted from broad fields of science and engineering since this topic has potential applications in many disciplines.

We would like to thank our collaborators Ming Shao, Hongfu Liu, and Shuyang Wang. We would also like to thank editor Helen Desmond from Springer for the help and support.

Indianapolis, IN, USA San Jose, CA, USA Boston, MA, USA September 2018 Zhengming Ding Handong Zhao Yun Fu

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