

Preface

While the proliferation of sensors being deployed in cell phones, vehicles, buildings, roadways, and computers allows for larger and more diverse information to be collected, the cost of acquiring labels for all these data remains extremely high. To overcome the burden of annotation, alternative solutions have been proposed in the literature to learn decision making models by exploiting unlabeled data from the same domain (data acquired in similar conditions as the targeted data) or also data from related but different domains (different datasets due to different conditions or provided by different customers). In many real-world machine learning scenarios, using only the data from the same domain might be insufficient and data or models borrowed from similar domains can significantly improve the learning process. Such a process, referred to as *domain adaptation*, aims to leverage labeled data in one or more related domains (sources), in order to build models for a target domain.

Domain adaptation is particularly critical for service companies, where all machine learning components deployed in a given service solution should be customized for a new customer either by annotating new data or, preferably, by calibrating the models in order to achieve a contractual performance in the new environment. While adaptation across domains is a challenging task for many applications, in this book, we focus on solutions for *visual applications*.

The aim of the book is to give a relatively broad view of the field by selecting a diverse set of methods which made different advances in the field. The book begins with a comprehensive survey of domain adaptation and transfer learning, including historical shallow methods, more recent methods using deep architectures, and methods addressing computer vision tasks beyond image categorization, such as detection, segmentation or visual attributes. Then, Chap. 2 gives a deeper look at dataset bias in existing datasets when different representations including features extracted from deep architectures are used. The rest of the book is divided into four main parts, following the same structure as the survey presented in Chap. 1.

Part I is dedicated to shallow domain adaptation methods, beginning with the widely used Geodesic Flow Kernel (Chap. 3) and Subspace Alignment (Chap. 4). Both chapters propose solutions for selecting landmark samples in the source dataset. Chapter 5 presents domain-invariant embedding methods and Chap. 6

describes the Transductive Transfer Machine, a method that combines local feature space transformation with classifier selection and parameter adaptation. The first part ends with Chap. 7 that addresses domain adaptation cases where the access to the source data is constrained.

Part II is dedicated to deep adversarial discriminative domain adaptation methods. The first two methods presented use a confusion loss as an adversarial objective to adapt the source network towards the target data. The deep CORAL (Chap. 8) learns a nonlinear transformation that aligns correlations of activation layers of the deep model. The Deep Domain Confusion network (Chap. 9) uses a Maximum Mean Discrepancy based domain confusion loss to induce domain invariant representations. In contrast, Chap. 10 presents the domain-adversarial neural network that integrates a Gradient Reversal Layer to promote the emergence of features discriminative for the main learning task and non-discriminate with respect to the domain shift.

Part III is a collection of contributions addressing domain adaptation problems different from classical image categorization. As such, Chap. 11 focuses on Fisher vector based patch encoding adaptation in the context of vehicle re-identification. Chapter 12 explores the adaptation of semantic segmentation models trained on synthetic images to correctly operate in real scenarios. Chapter 13 addresses the challenge of pedestrian detection by adapting a Deformable Part-Based Model trained on virtual-world data to real world data using structure-aware adaptive structural SVMs. Finally, Chap. 14 proposes a method to generalize semantic part detectors across domains.

Part IV concludes the book with unifying perspectives. On the one hand, Chap. 15 proposes to use multi-source domain generalization techniques for the purpose of learning cross-category generalizable attribute detectors. On the other hand, Chap. 16 proposes a common framework that unifies multi-domain and multi-task learning which can be flexibly applied also to zero-shot learning and zero-shot domain adaptation.

Overall, this comprehensive volume, designed to form and inform professionals, young researchers, and graduate students, is the first collection dedicated to domain adaptation for visual applications. In this book I wanted not only to address historically shallow and recent deep domain adaptation methods, but also contributions focused on object or object part detection, re-identification, image segmentation, attribute detection as well to present generic frameworks that unify domain adaptation with multi-domain, multi-task and zero-shot learning.

To give such a broad view, I brought together leading experts in the field to showcase their techniques. I would like to thank them specially for accepting my invitation and for their dedicated effort to share in this book their valuable experiences in the various chapters. Finally, I would also like to thank our Springer editors, Wayne Wheeler and Simon Rees, for their advice and their help in guiding me through the book production process.

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