DOCTORAL THESIS

Distribution alignment for unsupervised domain adaptation: cross-domain feature learning and synthesis

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Abstract

In recent years, many machine learning algorithms have been developed and widely applied in various practical applications. However, most of them have considered the data distributions of the training and test datasets to be similar. This thesis concerns on the decrease of generalization ability in a test dataset when the data distribution is different from that of the training dataset. In some applications, labels are unavailable in the test dataset, so we follow the effective approach of unsupervised domain adaptation to improve the generalization ability of models learned from the training dataset in the test dataset. In unsupervised domain adaptation, the data distribution mismatch between the source and target domains is the main reason for the performance drop of a source model in the target domain. Therefore, in this thesis, distribution alignment methods for unsupervised domain adaptation are proposed.

In unsupervised domain adaptation, joint distribution alignment across the source and target domains is a key research problem. However, direct alignment of the source and target joint distributions is infeasible, because the target conditional distribution cannot be known without target labels. Instead of estimating target labels for target conditional distribution approximation, a new criterion of domain-shared group sparsity is proposed, which is an equivalent condition for conditional distribution alignment. We develop a domain-shared group-sparse dictionary learning model, together with marginal distribution alignment, to learn domain-shared representations with aligned joint distributions. A cross-domain label propagation method is then proposed to train a classifier for the target domain using the domain-

shared group-sparse representations and the target-specific information from the target data. The proposed method outperforms eight state-of-the-art unsupervised domain adaptation algorithms for cross-domain face recognition and cross-dataset object recognition with hand-drafted and deep features. Experimental results across multiple sub-domains show that the proposed method also performs well across datasets with large variance. Our results are quantitatively and qualitatively analyzed, and parameter sensitivity and convergence analysis experiments are conducted to show the effectiveness of the proposed method.

On the other hand, although many distribution alignment methods have been proposed to solve the problem of distribution mismatch, most of these alignment methods have not considered the difference in distribution structures that also needs to be aligned across the source and target domains. This can result in poor alignment across domains. Therefore a novel graph alignment method is proposed in this thesis, which aligns both data representations and distribution structural information across the source and target domains. An adversarial network is developed for graph alignment, which maps both source and target data to a feature space where the data are distributed with unified structure criteria. The results of the experiments on cross-dataset digit and object recognition show that the proposed method achieves good performance compared with state-of-the-art unsupervised domain adaptation methods.

Furthermore, the problem of dataset bias also exists in the task of human pose estimation across datasets with different image qualities. Experiments show that the performance of pose estimators may degrade dramatically when the image quality differs between training and testing datasets. Thus, this thesis also addresses problems in cross-image-quality human pose estimation. To achieve this, we follow the unsupervised domain adaptation approach, in which labels in the target domain are unavailable. Unlike existing unsupervised domain adaptation methods that find label information from unlabeled data, the target pose information (label) is instead generated by synthesizing body parts with similar image quality to the

target domain. A translative dictionary is learned to associate the source and target domains, and a cross-quality adaptation model is developed to refine the source pose estimator using the synthesized target body parts. We perform cross-quality experiments on three datasets with different image quality by using two state-of-the-art pose estimators, and compare the proposed method with five unsupervised domain adaptation methods. Our experimental results show that the proposed method outperforms not only the source pose estimators, but also other unsupervised domain adaptation methods.

The main contributions of this thesis are as follows.

- A domain-shared group-sparse dictionary learning model is developed with a constraint derived from equal conditional distribution, to align joint distributions across the source and target domains for unsupervised domain adaptation.

- An adversarial network with graph alignment losses is developed to align the structural information of distributions across the source and target domains for unsupervised domain adaptation.

- We propose an Image Quality Translative Dictionary Learning model to synthesize target body parts, and refine the source pose estimator to the target domain with the synthesized target body parts for cross-quality pose estimation.

Keywords: domain adaptation, distribution alignment, pose estimation

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