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Domain adaptation via Multi-Layer Transfer Learning

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ABSTRACT

Transfer learning, which leverages labeled data in a source domain to train an accurate classifier for classification tasks in a target domain, has attracted extensive research interests recently for its effectiveness proven by many studies. Previous approaches adopt a common strategy that models the shared structure as a bridge across different domains by reducing distribution divergences. However, those approaches totally ignore specific latent spaces, which can be utilized to learn non-shared concepts. Only specific latent spaces contain specific latent factors, lacking which will lead to ineffective distinct concept learning. Additionally, only learning latent factors in one latent feature space layer may ignore those in the other layers. The missing latent factors may also help us to model the latent structure shared as the bridge. This paper proposes a novel transfer learning method Multi-Layer Transfer Learning (MLTL). MLTL first generates specific latent feature spaces. Second, it combines these specific latent feature spaces with common latent feature space into one latent feature space layer. Third, it generates multiple layers to learn the corresponding distributions on different layers with their pluralism simultaneously. Specifically, the pluralism of the distributions on different layers means that learning the distributions on one layer can help us to learn the distributions on the others. Furthermore, an iterative algorithm based on Non-Negative Matrix Tri-Factorization is proposed to solve the optimization problem. Comprehensive experiments demonstrate that MLTL can significantly outperform the state-of-the-art learning methods on topic and sentiment classification tasks.

1. Introduction

Traditional machine learning classification algorithms implicitly assume that the training and test data are drawn from the same distribution. However, this assumption seldom holds in reality. To tackle the challenge of different data distributions, many transfer learning methods have been proposed recently for real-world applications, such as computational biology [11], image classification [12] and text classification [3–7,13,14]. Transfer learning or domain adaptation aims to exploit the labeled examples in the source domain to model a better classifier for predicting the classes of the test examples in the target domain, where there are less or no labeled examples. Some of these previous approaches show that the latent high-level concepts, which are related to feature clusters extracted on the raw features, are more appropriate for the text classification across domains than learning from the original features [7]. In [3], CoCC (Co-clustering based classification for out-of-domain documents) transfers the identical concepts. MTrick [4] exploits the associations between the homogeneous concepts and the example classes as the bridge across domains. DTL (Dual transfer learning) [5] uses the identical and homogeneous concepts as the shared concepts to establish the bridge. In addition, HIDC (Concept Learning for Cross-Domain Text Classification: A General Probabilistic Framework) [7] and Tri-TL [6] exploit the distinct concepts for classification learning besides the shared concepts.

To model the latent structure shared for knowledge transfer, these previous methods usually construct one latent feature space layer to learn the corresponding distributions. We represent such method as the single layer transfer learning. The limitation of these approaches is two-fold:

(1) To build a more effective bridge across domains, some previous methods such as Tri-TL [6] and HIDC [7] learn the shared concepts (including identical and homogeneous concepts) and non-shared concepts (including distinct concepts) simultaneously. Additionally, these approaches construct one common latent feature space and two random latent spaces for

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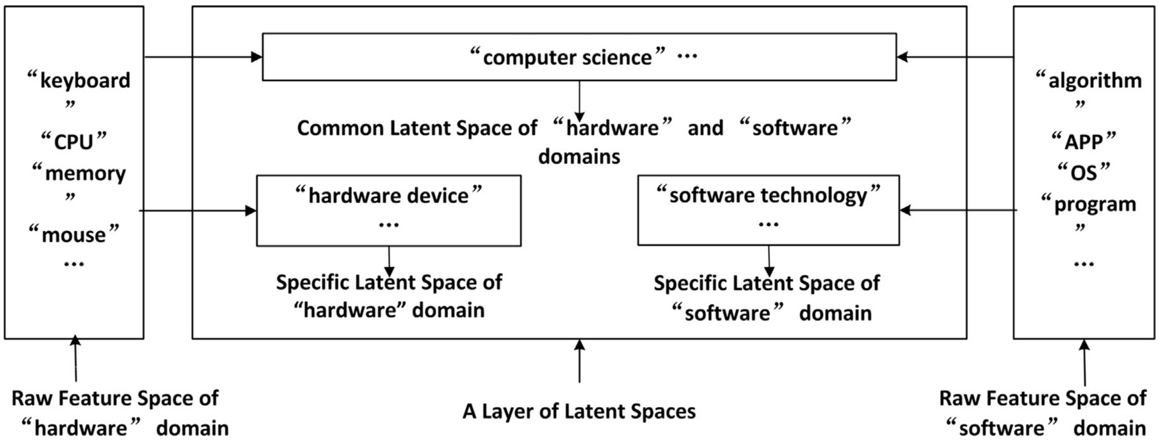

Fig. 1. A latent feature space layer.

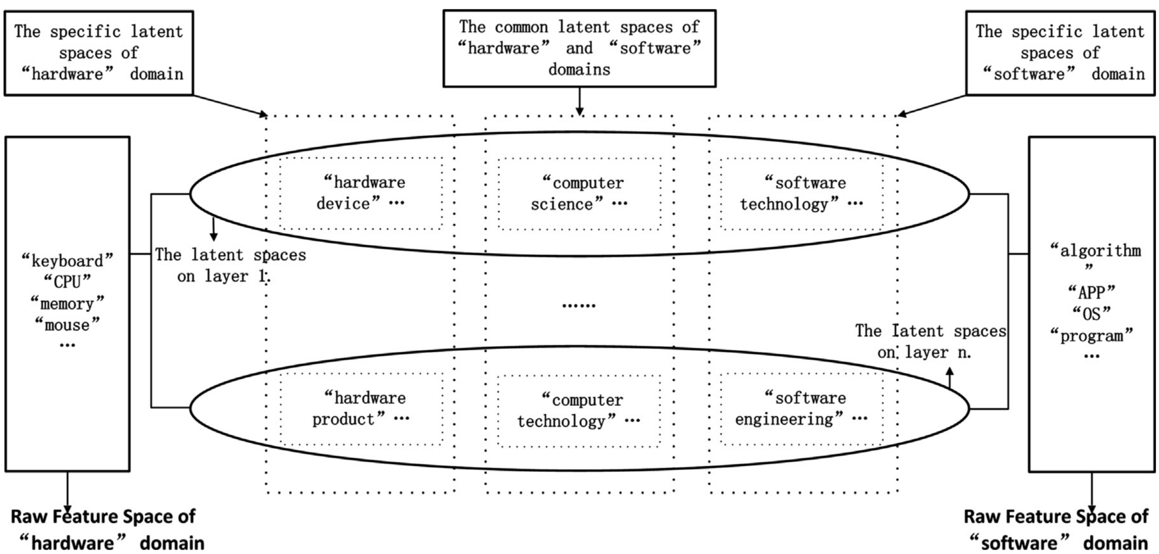

Fig. 2. Learning the distributions on different latent feature space layers.

learning the shared and non-shared concepts respectively (one of the random latent spaces is constructed for learning the distinct concepts in the source domain, and the other one is for the learning in target domain). These latent spaces constitute a latent space layer. The common latent space is composed of feature clusters, which are extracted on the common raw feature space, and the random latent spaces are composed of the random-number clusters. The ideal model should learn the shared concepts on the common latent space, and learn the non-shared concepts on the specific latent spaces. However, these methods did not construct the specific latent spaces for learning non-shared concepts, and using the random latent spaces instead. Actually, the common and random latent space contains few specific latent factors, which are related to the distinct concepts, to discriminate domains.
For example, words like “CPU” and “keyboard”, which are drawn from *hardware* domain, as well as “APP” and “algorithm”, which are drawn from *software* domain, can be indicated to the distinct concepts “hardware device” and “software technology” respectively. These distinct concepts are among the most discriminative latent concepts. In Fig. 1, we can find that these distinct concepts only can be obtained from the corresponding specific latent spaces respectively. Therefore, lack of specific latent factors leads to ineffective distinct concepts learning.

(2) These methods only construct one latent space layer and implicitly assume that all the useful latent factors can be obtained from this latent space layer. However, this assumption seldom holds in reality. The set of the latent factors in one latent space layer is just a subset of all the latent factors. For example, words like “CPU”, “keyboard”, “APP” and “algorithm” can be indicated to the shared concept “computer science”, which exists in a latent space layer. In Fig. 2, we can see that these words can be also indicated to the shared concept “computer technology”, which may exist in another layer. Both of these shared concepts can help us to model the shared structure as the bridge across domain. Therefore, it will ignore some other latent factors to construct the single latent space layer. At worst, when the distribution is dominated by these latent factors and the distribution divergences among domains are so large, this strict assumption will cause negative transfer.

In this paper, we propose Multi-Layer Transfer Learning (MLTL), a novel transfer learning method based on Non-Negative Matrix Tri-Factorization (NMTF) techniques, which constructs specific latent feature spaces and integrates them with the common latent