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Label Space Driven Heterogeneous Transfer Learning with Web Induced Alignment

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Abstract

Heterogeneous Transfer Learning (HTL) algorithms leverage knowledge from a heterogeneous source domain to perform a task in a target domain. We present a novel HTL algorithm that works even where there are no shared features, instance correspondences and further, the two domains do not have identical labels. We utilize the label relationships via web-distance to align the data of the domains in the projected space, while preserving the structure of the original data.

Introduction

Traditional supervised algorithms require sufficient labeled data to learn a computational model for making reliable predictions. Often, obtaining labeled training data is expensive and time consuming. Transfer learning algorithms overcome this limitation for a target domain by leveraging labeled knowledge from related domains (often termed as the source domains) that can have different distributions, different feature spaces and even different label spaces (Sukhija, Krishnan, and Singh 2016). Knowledge transfer between domains with heterogeneous feature spaces is widely known as Heterogeneous Transfer Learning (HTL). As the feature spaces are heterogeneous, the first task of any HTL approach is to identify a common feature space for the source and target domain that can be used for adaptation. Based on this common space, the HTL literature can be categorized into two groups. The HTL methods belonging to the first group (also known as Feature Space Remapping (FSR) methods) learn a single transformation that maps source features to target features. With the help of this learned transformation, the data from the source domain can be projected to the target domain and vice-versa. The approaches associated with the second group (also known as Latent Space Transformation (LST) methods) learn a pair of mappings, one for each domain, to project the data onto a shared subspace for adaptation. The second task is to bridge the gap between the data differences that arise when the data from both the domains is projected onto the common space. For compensating these differences, some shared information can be leveraged to maximize the similarity of the source and target domain data in the common space. The shared information can be present in the form of instance correspondences, overlapping features, shared label space, common meta-features/latent space or any task specific/independent information. Some HTL approaches also leverage domain-specific knowledge by utilizing external sources such as oracles/dictionary, social media or web to reduce the domain differences.

The proposed algorithm utilizes the inter-label space semantic similarities to improve the joint alignment of the data from the source and target domains in the common space. Our approach is motivated by the cross-domain activity recognition task where the label spaces are semantically related. Learning a robust activity recognition model requires manually annotating large amounts of sensor observations, which is an expensive task. Cross-domain activity recognition leverages labeled data from existing smart homes to a target smart home to circumvent the annotation effort. The presence of different sensor modalities across the different smart home layouts leads to heterogeneous feature spaces. Differences in the daily routine of the residents in different smart homes results in differences in the marginal and conditional distribution of the data. However, the daily activities of different smart home residents lead to semantically related label spaces. The proposed approach learns a mapping between the heterogeneous sensors to enable knowledge transfer. We conducted experiments to test the transfer efficiency of our proposed approach on three single-resident smart homes from the CASAS datasets (Cook et al. 2013).

Proposed approach

The primary limitation with state-of-the-art LST approaches is that they rely on implicit feature relationships to find a lower dimensional optimal shared subspace that will be used for adaptation. Learning the optimal shared subspace is an expensive task as it involves a grid-search on the dimension of the shared subspace. In order to circumvent this inherent limitation of LST approaches, the proposed HTL algorithm is conceived as a FSR minimization objective that bridges the heterogeneous feature and output spaces of the source and target domains without relying on instance or feature correspondences. Our novel approach, Label Space Driven Heterogeneous Transfer Learning with Web Induced Alignment (LSDHTL-WIA), aligns the data from the source and

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Table 1: Transfer performance comparison of state-of-the-art algorithms is shown in terms of mean error and standard deviation (%) over 4 folds. The best performance has been highlighted in bold.

CASAS horizon house datasets									
	Baseline Results		Transfer Results						
S→T	BRF	SVM ECOC	SHFR ECOC	HFA	HeMap	SHDA-RF	SHFR-RF	Co-HTL	LSDHTL WIA
hh102→hh113	29.67±2.51	34.58±2.20	28.25±2.86	36.31±2.35	35.51±3.50	26.37±2.23	27.98±2.51	28.32±2.38	**25.19±2.49**
hh102→hh118	36.41±2.42	43.51±3.01	33.14±2.82	32.99±3.41	41.08±3.33	31.50±2.01	32.01±2.09	31.09±2.66	**28.30±2.80**
hh113→hh102	36.70±1.95	41.23±2.93	31.58±2.41	41.28±2.65	38.05±3.71	29.88±1.76	32.81±2.38	33.52±2.47	**28.97±2.78**
hh113→hh118	32.35±2.56	39.41±1.89	31.02±2.16	38.52±2.07	38.04±2.68	28.0±2.02	30.15±2.44	30.06±1.97	**27.28±2.46**
hh118→hh102	38.95±2.57	41.80±2.21	36.51±2.31	43.51±2.75	41.08±2.72	33.02±2.13	35.40±2.35	36.32±2.28	**32.54±2.10**
hh118→hh113	31.01±1.80	34.73±3.39	29.27±3.44	31.09±3.67	35.89±3.61	27.73±1.08	30.46±2.95	31.53±2.55	**27.42±2.73**

target domain in the projected space taking into consideration the semantic relationship between the labels while preserving the original structure of data.

The proposed minimization objective is shown in Equation 1. Given the source domain data $S \in \mathbb{R}^{n_S \times d_S}$ and target domain data $T \in \mathbb{R}^{n_T \times d_T}$, the proposed optimization framework iteratively minimizes the overall loss $J(.)$ incurred by jointly aligning the data of the source and target domain for learning the optimal transformation $P \in \mathbb{R}^{d_S \times d_T}$, the optimal projected source data $B_S \in \mathbb{R}^{n_S \times d_T}$ and the optimal projected target data $B_T \in \mathbb{R}^{n_T \times d_S}$.

$$
\begin{aligned}
J(.) = &\min_{B_S, B_T, P} || \; S - B_S P^{'} \; ||^2 + || \; T - B_T P \; ||^2 \; + \\
&\beta (\sum_{i=1}^{n_S} \sum_{j=1}^{n_T} W_{ij} \; || \; x_i^S - B_{T_j} \; ||^2 + \\
&\sum_{i=1}^{n_S} \sum_{j=1}^{n_T} W_{ij} \; || \; B_{S_i} - x_j^T \; ||^2) \\
&+ \; \lambda (|| \; B_S \; ||^2 + || \; B_T \; ||^2 + || \; P \; ||^2)
\end{aligned} \tag{1}
$$

The first two terms represent the individual reconstruction loss functions for the source and target domain. A linear reconstruction helps to preserve the original structure of data in the projected space. However, there can still be significant distribution differences in the projected space even after preserving the original topology. Hence, in order to add more discriminating information to the learned transformation, the proposed optimization framework constrains the instances from the source and target domains with the same or related labels to be closer to each other in the projected space. This can be viewed as minimizing the conditional distribution differences in the projected space. The similarity between the labeled data across the domains is defined using the Normalized Google Distance (NGD) (Cilibrasi and Vitanyi 2007) on the associated labels. NGD is a well known semantic similarity measure that returns the web distance between any two keywords. We transform NGD into a similarity measure $W \in [0, 1]^{n_S \times n_T}$ for every labeled instance pair in the source and target domain.

Using the similarity matrix W, the third term induces semantic co-alignment in our framework by penalizing for semantic data misalignment between the source and target data points in the projected space. While minimizing the inter-domain differences using the label information, there is a significant risk of over-fitting on source training data. Hence, we adopt a regularizer in the objective function (the fourth term) to penalize over-fitting. The hyper-parameter β regulates the importance of label space induced alignment while λ controls the importance of the regularization term. The proposed optimization problem is not jointly convex with respect to the three variables B_S, B_T and P. However, it is convex with respect to any one of them while the other two have been fixed. Consequently, we utilize an alternating algorithm for solving the unconstrained optimization, by iteratively fixing two out of the three variables to estimate the remaining one until convergence.

Results and Discussion

We report the performance of LSDHTL-WIA against several baselines and state-of-the-art transfer approaches on six cross-domain activity recognition tasks in Table 1. It can be seen that our algorithm outperforms all the baseline and transfer approaches on all transfer tasks. Kindly refer the supplementary material[1] for detailed experimental results. A limitation of the proposed approach is that it requires some amount of labeled data in the target domain. Consequently, if labeled data is absent in the target domain, annotating relatively small number of unlabeled data becomes an inescapable task.

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[1]https://drive.google.com/open?id=1Ay7oF2NYz58ZgN-OrdvFFpjR5dR_DRUW