Heterogeneous Transfer Learning with Weighted Instance-Correspondence Data

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Abstract

Instance-correspondence (IC) data are potent resources for heterogeneous transfer learning (HeTL) due to the capability of bridging the source and the target domains at the instance-level. To this end, people tend to use machine-generated IC data, because manually establishing IC data is expensive and primitive. However, existing IC data machine generators are not perfect and always produce the data that are not of high quality, thus hampering the performance of domain adaptation. In this paper, instead of improving the IC data generator, which might not be an optimal way, we accept the fact that data quality variation does exist but find a better way to use the data. Specifically, we propose a novel heterogeneous transfer learning method named Transfer Learning with Weighted Correspondence (TLWC), which utilizes IC data to adapt the source domain to the target domain. Rather than treating IC data equally, TLWC can assign solid weights to each IC data pair depending on the quality of the data. We conduct extensive experiments on HeTL datasets and the state-of-the-art results verify the effectiveness of TLWC.

Introduction

Transfer learning or domain adaptation builds machine learners that can be generalized across different domains, and is capable of leveraging rich label information from the source domain to the target domain. Transfer learning can effectively ease the manual effort of labeling data for the target domain (Pan and Yang 2010).

Different from homogeneous transfer learning (HoTL), where the source and the target domain share the same feature space, heterogeneous transfer learning (HeTL) allows the data in two domains to be represented with different feature spaces (Weiss, Khoshgoftaar, and Wang 2016). Therefore, how to unify the feature spaces of the two domains is a bottleneck of HeTL.

For HeTL, instance-correspondence (IC) data are valuable mediums to unify the feature spaces (i.e. a document presented both in English and French) (Zhu et al. 2011; Zhou et al. 2014). These data can be utilized to either

Figure 1: Framework of TLWC. IC data points sizes are proportional to their weights.
Transfer learning or domain adaptation aims at transferring rich label information from a source domain to a target domain. The main problem of transfer learning is how to reduce the data discrepancy between the two domains (Pan and Yang 2010; Weiss, Khosgoftaar, and Wang 2016).

Depending on whether the feature spaces of the two domains are the same, transfer learning is divided into two categories: homogeneous transfer learning (HoTL) and heterogeneous transfer learning (HeTL). Different from HoTL, where the domain shift can be reduced by directly minimizing the data distribution discrepancy (Tzeng et al. 2015; Long et al. 2017), HeTL must unify the feature spaces of the two domains. For HeTL, there are two groups of methods for feature unification: (1) Projecting data from the two domains into a common feature space (Wang and Mahadevan 2011; Hoffman et al. 2014; Yang et al. 2015; Herath, Harandi, and Porikli 2017); (2) Mapping data from one domain to another one (Li et al. 2013; Hoffman et al. 2014; Xiao and Guo 2015; Tsai, Yeh, and Wang 2016).

For the first group, for example, Li et al. (2013) proposed a semi-supervised heterogeneous domain adaptation (SFHA), which transforms data from two domains into an augmented feature space. Herath et al. (2017) considered an invariant latent space (ILS) and they established a common Hilbert space for both domains.

For the second group, for example, Tsai et al. (2016) mapped the labeled source-domain data to the dimension-reduced target domain. And the mapped data are assigned with different weights. Hoffman et al. (2014) proposed a max-margin domain transformation (MMDT). With MMDT, the data in the target domain are projected to the source domain, while the projected data are classified by maximizing the margins.

The above HeTL methods bridge two domains by matching either the marginal or conditional distributions at the domain-level and the category-level respectively. With instance-correspondence (IC) data, the two domains can be bridged at the instance-level, which will boost the unification and adaptation of the two heterogeneous domains. According to the above two groups of feature unification methods, IC data can be utilized in various ways. For the first group of methods, which learns a common feature space for the two domains, IC data can be taken as the equivalent data in the common feature space. For example, Xiao and Guo (2013) proposed a two-step learning method which turns feature space learning into a matrix completion problem. The combined IC data are complete data in the matrix and they are employed to complete the unobserved data in the matrix. Zhou et al. (2015) designed a subspace for both domains and the projected IC data in the subspace are the same. For the second group of methods, which maps data from one domain to another, IC data are applied to learn the feature transformations. For example, Zhou et al. (2014) proposed a hybrid heterogeneous transfer learning (HHTL), which learns several transformation matrices with high-level features of IC data. Wang et al. (2018) applied deep autoencoder to embed the shallow representations of both domains and learned a feature transformation with IC data features at the top embedding layer.

However, all of the above methods consider the IC data to be equally important, which is not reliable. The IC data with low quality will hamper the domain adaptation procedure. Although there are existing instance weighting strategies (Chu, La Torre, and Cohn 2013; Long et al. 2014), they are only designed for HoTL. Zhou et al. (2016) selectively labeled IC data with active learning, but manually labeling IC data is prohibitive and informative machine-generated data are given up.
We assigned different weights to all the IC data pairs and optimized these weights as well as feature transformation with meta-learning. Meta-learning aims at optimizing parameter or hyper-parameter of a learner by establishing a high-level learner. The high-level learner can be divided into two groups: 1. Learner based on hyper-network (Andrychowicz et al. 2016; Snell, Swersky, and Zemel 2017; Jin et al. 2018); 2 Learner based on gradient descent (Finn, Abbeel, and Levine 2017; Ren et al. 2018). For the first group, a hyper-network, such as LSTM, is constructed to guide the parameter updating of the original learner. For the second group, a meta-objective is established, which is derivable to the parameters to be updated. The meta-objective can be validation loss of the original learner. In the beginning, meta-learning aims to supervise the updating procedure of the original learner and guide it to learn to better (Andrychowicz et al. 2016; Finn, Abbeel, and Levine 2017). Recently, instance weights are also considered to be updated with a meta-learner (Jin et al. 2018; Ren et al. 2018).

**Proposed Method**

**Problem Formulation**

Our problem is to establish a classifier for a target domain with limited labeled data. To achieve this goal, we need to transfer knowledge from a source domain with rich label information to the target domain. The given data are: sufficient labeled data \( \{X_{s,l}, y_{s,l}\}_{i=1}^{n_{s,l}} \) and unlabeled data \( \{X_{s,u}\}_{i=1}^{n_{s,u}} \) in the source domain; a set of labeled data \( \{X_{t,l}, y_{t,l}\}_{i=1}^{n_{t,l}} \) and unlabeled data \( \{X_{t,u}\}_{i=1}^{n_{t,u}} \) in the target domain, where \( n_{s,l} \gg n_{t,l} \); a set of unlabeled IC data \( \{X_{s,c}^{T,l}, X_{t,c}^{T,l}\}_{i=1}^{n_{c}} \) across the two domains. \( X_{s,l}^{T,l}, X_{s,u}^{T,l} \) and \( X_{t,l}^{T,l}, X_{t,u}^{T,l} \) are in \( \mathbb{R}^{d_{s}} \) while \( X_{s,c}^{T,l}, X_{t,c}^{T,l} \) are in \( \mathbb{R}^{d_{t}} \), where \( d_{s} \neq d_{t} \). \( n_{s} = n_{s,l} + n_{s,u} + n_{c} \) and \( n_{t} = n_{t,l} + n_{t,u} + n_{c} \).

To solve the problem, we propose a HeTL method named **Transfer Learning with Weighted Correspondence** (TLWC), which consists of two components: (1) High-level feature learning; (2) IC data weights and transformation updating. For the first component, we learn high-level features for both domains with a marginalized stacked denoised autoencoder (mSDA). For the second component, we establish a meta-learner to optimize the weights of IC data and utilize weighted IC data to learn feature transformations to bridge two domains. Then the feature transformations are updated further by the meta-learner. When the optimization procedure is finished, the classifier for the target domain in the meta-learner is what we need.

**High-Level Feature Learning**

We employ a marginalized stacked denoised autoencoder (mSDA) on both to learn high-level features (Chen et al. 2012; Zhou et al. 2014). mSDA simplifies SDA from feature reconstruction to feature mapping, which makes the computation much more efficient.

Denoting \( \star \in \{S, T\} \), to learn the feature mapping matrix \( W^{\star} \in \mathbb{R}^{d_{s} \times (d_{t}+1)} \), which is used to generate high-level features, we minimize the overall squared loss:

\[
L_{sq}(W) = \sum_{i=1}^{n_{s}} \|x_{s}^{i} - W^{\star}[x_{s}^{i}; 1]\|^2.
\]  
(1)

Each dimension of \( x_{s}^{i} \) is corrupted to 0 with a probability \( p \), and \( x_{s}^{i} \) is the expected version of corrupted \( x_{s}^{i} \). To incorporate the bias term, we absorb 1 into \( x_{s}^{i} \). Defining a surviving feature vector \( q = [1 - p, ..., 1 - p, 1] \in \mathbb{R}^{d_{t}+1} \) and \( X^{\star} = [X^{\star}; 1^{\top}] \in \mathbb{R}^{(d_{t}+1) \times n_{s}} \), we can write the analytic solution of \( W^{\star} \) as:

\[
W^{\star} = PQ^{-1},
\]  
(2)

where \( P_{ij} = (X^{\star}X^{\star\top})_{ij}q_{i}q_{j} \), and

\[
Q_{ij} = \begin{cases} 
(X^{\star}X^{\star\top})_{ij}q_{i}q_{j}, & \text{if } i \neq j \\
(X^{\star}X^{\star\top})_{ij}q_{i}, & \text{otherwise}
\end{cases}
\]  
(3)

With the reconstruction weights \( W^{\star} \), we can generate nonlinear features \( H^{\star} \), where \( H^{\star} = \tanh(W^{\star}X^{\star}) \). After recursively doing the procedure by replacing \( X^{\star} \) with \( H^{\star} \) for \( K - 1 \) times, we can obtain \( K \) layers of high-level features, where \( H_{k}^{\star} \) is the features at the \( k^{th} \) layer and \( H_{1}^{\star} = X^{\star} \).

**Weights and Transformation Updating**

We define a weight vector \( \epsilon \in \mathbb{R}^{n_{r}} \) for IC data features, which can be applied to establish feature transformations \( G_{k} \in \mathbb{R}^{d_{x} \times (d_{x}+1)} \) for each layer of two domains. To optimize \( \epsilon \) and learn more solid feature transformations for domain adaptation, we construct a meta-learner for \( \epsilon \) and \( G_{k} \). The meta-objective of the learner consists of two terms: (1) Small classification loss on \( \{X_{T,l}, y_{T,l}\} \). (2) Acceptable distribution discrepancy between the two domains. The meta-learner is a computation graph w.r.t. \( \epsilon \). We denote \( \epsilon = \epsilon_{t} \) at each training step and \( \epsilon_{1} = 1 \).

To establish the meta-learner, at each training step \( t \), we first learn the feature transformation \( G_{k} \), which maps features from the source to the target domain at \( k^{th} \) layer. \( G_{k} \) is learned with IC data features \( \tilde{H}_{k}^{S,c}, H_{k}^{T,c} \) and the objective function to be minimized is:

\[
L_{p,k}(\epsilon_{t}, G_{k}) = \|H_{k}^{T,c}Y_{s} - G_{k}H_{k}^{S,c}Y_{s}\|_{F}^{2} + \lambda\|G_{k}\|_{F}^{2},
\]  
(4)

where \( H_{k}^{S,c} = [H_{k}^{S,c}; 1_{T_{c}}^{\top}] \in \mathbb{R}^{(d_{x}+1) \times n_{c}} \), \( \epsilon \) is a diagonal matrix and \( Y_{s} = \text{diag}(\epsilon) \), \( \lambda \) is the parameter of the regularization term. The closed form solution for Eq. 4 can be written as:

\[
G_{k}(\epsilon_{t}) = (H_{k}^{S,c}Y_{s}^{\top}H_{k}^{T,c})^{-1}(H_{k}^{T,c}Y_{s}^{\top}Y_{s}H_{k}^{T,c} + \lambda I)^{-1}.
\]  
(5)

To measure the classification loss on \( \{X_{T,l}, y_{T,l}\} \), which is the first term of the meta-objective, we establish a classifier \( f_{0} \) for the target domain, which requires the outputs to be derivable to the inputs, such as a logistic regression classifier or a neural network model. Let \( \theta \) be the model
parameters and $f(x, y, \theta)$ be the classification loss for example x. The inputs of $f_\theta$ are the concatenated high-level features in the target domain. For an instance $x^T$, its features vector for $f_\theta$ is $z^T = [h_1^T; \ldots; h_K^T] \in \mathbb{R}^{T \times D}^K$, where $h_k^T$ is the corresponding features of $x^t$ at $k^{th}$ layer and $h_1^T = x^T$. And for an instance $x^S$, its features vector for $\delta_f$ is $z^S(\epsilon) = \{g_1(\epsilon)h_1^S; \ldots; g_K(\epsilon)h_K^S\} \in \mathbb{R}^{S \times D}^K$. We denote $z_\delta^S = \{z^S(\epsilon)\}_{\epsilon=1}^n$ and $Z^T = \{z^T\}_{\epsilon=1}^n$.

At each training step $t$, we take a one-step batch gradient descent with $z_i^{S,t}(\epsilon_i), y_i^{S,t} \in T$ to update $\theta_t$:

$$L_S(\epsilon_t, \theta_t, Z_t) = \frac{1}{n_{i,s}} \sum_{i=1}^{n_{i,s}} f\left(z_i^{S,t}(\epsilon_t), y_i^{S,t}, \theta_t \right),$$

$$\theta_t' = \theta_t - \alpha \nabla L_S(\epsilon_t, \theta_t, Z_t).$$

Now the two terms of the meta-objective can be formed. The first term, which aims at minimizing the classification loss of $\delta_f$ on $z_i^{T,t}, y_i^{T,t} \in T$, is written as:

$$L_T(\epsilon_t, \theta_t') = \frac{1}{n_{T,t}} \sum_{i=1}^{n_{T,t}} f\left(z_i^{T,t}, y_i^{T,t}, \theta_t' \right).$$

The second term is the transformation loss in Eq. 4, which prevents $\epsilon_t$ from overfitting to the limited labeled target-domain data. The two terms are utilized to update both IC weights $\epsilon_t$ and transformations $\{g_k\}_{k=1}^K$.

### Data Weights Updating
To optimize $\epsilon_t$ with the meta-objective, we take a single gradient descent step w.r.t. $\epsilon_t$:

$$\nabla \epsilon_t = \frac{\partial}{\partial \epsilon_t} \left( L_T(\epsilon_t, \theta_t') + \eta \sum_{k=1}^K L_{p,k}(1, g_k(\epsilon_t)) \right).$$

Before updating $\epsilon$ with $\nabla \epsilon$, we normalize the $\nabla (\epsilon_t)$ with

$$\nabla \epsilon_t = \frac{\nabla \epsilon_t}{\|\nabla \epsilon_t\|_\infty + \delta(\|\nabla \epsilon_t\|_\infty)}.$$
We compare TLWC with previous HeTL methods on 3 HeTL datasets and conduct a series of experiments to verify its effectiveness on IC data weighting.

Datasets and Parameters

Webis-CLS-10 (Prettenhofer and Stein 2010) is a cross-language sentiment classification dataset, which consists of Amazon product reviews of three product categories: book (B), DVD (D) and music (M). The reviews are written in four languages: English (EN), German (GE), French (FR), and Japanese (JP). For each category in a non-English language, 2000 data are translated into English with Google Translate. We adopt the widely used 9 HeTL tasks of this dataset: EFB, EFD, EFM, EGB, EGD, EGM, EJB, EJD, EJM. EFB means, for example, taking book reviews in English as the source domain and those in French as the target domain. The documents are represented with TF-IDF and 2000 most frequent words are selected.

Multilingual Reuters Collection (MRC) is a news dataset with five languages (English (EN), French (FR), German (GE), Italian(IT) and Spanish(SP)), where each article is represented by TF-IDF. The news articles in this dataset share 6 topics (C15, CCAT, E21, ECAT, GCAT and M11). Following (Zhou et al. 2016), we take English as the source domain and other languages as target domains, which forms 4 topic classification tasks.

Finally, we can apply \( \{z_i^T, y_i^T\}_{i=1}^{n_T} \) to fine-tune \( f_\theta \) to improve its performance further, then \( f_{\theta_M} \) is the classifier we need. We summarize TWLC in Algorithm 1.

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NUS-WIDE (Chua et al. 2009) contains 269,648 images from Flickr and their corresponding text-tag. Follow Wang et al. (2018) we conduct experiments on 10 categories: birds, buildings, car, cat, dog, fish, horses, flowers, mountain and plane. The source domain data are texts represented by 4096-dimensional tags. The target-domain data are images represented both by 1000-dimensional DeCAF (Donahue et al. 2014) and 500-dimensional SIFT (Lowe 1999) respectively.

The detailed data volume and parameter settings for our experiments are shown in Table 1 and 2.

Baselines

We compare TLWC with the following state-of-the-art HeTL methods based on IC data.

- **TSL** (Xiao and Guo 2013): TSL converts domain bridging into a matrix completion problem. In the matrix, each instance is completed based on IC data. Then a classifier can be employed on the completed matrix.

- **DMMC** (Zhou et al. 2016): DMMC is an extension on TSL. Besides matrix completion, DMMC considers the distribution discrepancy of the two domains.

- **HHTL** (Zhou et al. 2014): HHTL first extracts high-level
features for both domains with mSDA and learns feature transformations with IC data features, which projects the features from the target domain to the corresponding layer in the source domain.

- **DHFM** (Guntuku et al. 2016): DHFM also applies high-level-features of IC data to bridge the two domains, while it learns feature transformations in a cross-layer pattern.

- **DATN** (Wang, Cui, and Zhu 2018): DATN establishes two deep autoencoders to learn hidden features for the two domains. Then a feature transformation at top layer is learned to match the two domains.

In addition, to demonstrates the effectiveness of each component, we consider a variant version of TLWC (denoted as TLWC\textsubscript{sup}), which does not update the feature transformation with the meta-learner. The experimental results are shown in Figure 3, Table 3 and Table 4. On NUS-WIDE, we do not report the results of TSL and DMMC in Figure 3 because they do not achieve comparable results with other baselines, a possible reasons is that they are designed for cross-language tasks.

We have made significant test in our experiment and the p values for all the tasks are less than 0.01. From the experimental results, we have the following observations: (1) HHTL, DFHM and DATN outperform TSL and DMMC, which demonstrates that high-level features extracted by deep models are more transferable between two domains. (2) HHTL, DFHM perform better than DATN, which shows that the features in middle layers still contain domain-invariant factors. (3) TLWC performs better than all of the state-of-the-art IC data based HeTL methods, which verifies the effectiveness of TLWC on domain adaptation. (4) TLWC\textsubscript{sup} does not outperforms the baselines on some categories of NUS-WIDE, the possible explantation is that compared with machine-translated IC data in Webis, the qualities of tag-image IC data of NUS-WIDE are much higher, which reduces the necessity to reweight the IC data. In order to verify our guess, we will manually add some noise to these data in the next section. (5) The improvement of TLWC over TLWC\textsubscript{sup} demonstrates that the meta-optimization over the feature transformation is effective.

**Empirical Analysis**

**Feature Visualization.** To validate the transferability of the features learned by TLWC, we randomly select 50 examples from each category of both domains and plot their t-SNE embeddings (van der Maaten and Hinton 2008) learned by HHTL and TLWC in Figure 4. The embedding tasks are EFB and text $\rightarrow$ DeCAF\textsubscript{6}. From Figure 4, we have the following observations: (1) The points with TLWC features are more discriminative than points with HHTL features. (2) With TLWC learned features, the points in one category from the two domains are aligned better.

**Noisy Weights Distribution.** To statistically prove the effectiveness of TLWC on reweighting IC data, we manually add quantified artificial noise to IC data. In detail, for task text $\rightarrow$ DeCAF\textsubscript{6}, partial IC data are mismatched to other documents and the mismatched number in each category is $n^e$ in average. The performances w.r.t. $n^e$ are shown in Figure 5. To demonstrate the advantage on IC data reweighting of TLWC, we apply TLWC\textsubscript{sup} to compare with baseline methods.

From Figure 5 we find that the performance gap between the methods is relatively small. However, the performances of previous HeTL methods drop significantly when $n^e$ increases, while the performance of TLWC maintains at a relatively stable level. We plot the weights distribution when
1. It should be a positive tone. 2. It should be an negative tone.

... étalés étaient pas mal du tout. ... de mon mieux fin ... 
... stars were not all bad ... the design is so good, the humor less fine ...

1. Inaccurate phrase. 2. Personal pronouns cannot be judged.

... Alors je me suis obligée d’aller jusqu’au bout. Il m’a... 
... so i forced myself for going through. He was...

1. Lack possessive case. 2. The translation exists grammatical problem.

...roman de Julie Wolkenstein, Colloque sentimental, que certains rapprochaient volontiers de David Lodge, mais là, j’avoue que je n’ai pas jusqu’au bout. ...
...previous novel julie wolkenstein, colloque sentimental, some willingly approached by david lodge ... but then, i confess that i will not go through. ...

1. The clause structure is not translated, and the translation exists grammatical problem.

...ne reconnais même plus les personnages. Quant à l’intrigue ............... C’est à se ... 
...i do not even recognize the characters. as for the plot ............... one wonders if the same person who wrote this book!

Figure 7: IC documents examples of EFB task. 4 pairs with minimum weights are on the left and 4 pairs with maximum weights are on the right.

Figure 8: Feature visualization with t-SNE on EFB and text→DeCAF6.

\( n^c = 16 \) and \( n^c = 32 \) in Figure 6, which illustrates that the weights of the mismatched IC data are mostly pushed to zeros. The experimental results prove that TLWC is able to learn reliable IC data weights according to data qualities, which can advance the domain adaptation of HeTL.

**IC Samples Display.** To intuitively realize the effectiveness of TLWC on weights learning, we display the 4 pairs of IC documents with minimum weights and 4 pairs with maximum weights of EFB task respectively. The documents are displayed in Figure 7. We invite a volunteer to mark the inappropriate translation in each pair of documents and explained the error above the pair. The volunteer is not told the experimental purpose as well as the data weights. From the figure, we find that there are more translation mistakes in the documents with minimum weights and some mistakes are even on emotions, which is detrimental to the sentiment classification task.

**Parameter Sensitivity.** We investigate the effects of the parameter \( \alpha \) in Eq. 7, \( \beta \) in Eq. 15, \( \gamma \) in Eq. 11 and \( \eta \) in Eq. 9, 14 on tasks based on NUS-WIDE. Figure 8 shows the performance variations w.r.t. \( \alpha \in \{10^{-7}, 10^{-6}, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}\} \), \( \beta \in \{10^{0}, 10^{1}, 10^{2}, 10^{3}, 10^{4}, 10^{5}\} \), \( \eta \in \{0, 0.5, 1, 2, 4, 8\} \) and \( \gamma \in \{2^{-5}, 2^{-4}, 2^{-2}, 1, 2^{2}, 2^{4}, 2^{5}\} \). The figure shows that the performances w.r.t. \( \alpha \) and \( \beta \) exhibit bell-shaped curves. And the choice of \( \alpha = 10^{5} \) and \( \beta = 10^{4} \) would be reasonable in our experiment. Compared with \( \alpha \) and \( \beta \), The accuracies are not so sensitive to the \( \eta \) and \( \gamma \). For task text → SIFT, accuracy w.r.t. \( \gamma \) decreases when \( \gamma \) increases. As the weights tend to be zeros or ones when \( \gamma \) is large, this result illustrates that IC data weights with floating values are more robust to learn feature transformations.

**Conclusion**

In this paper, we proposed a novel Transfer Learning with Weighted Correspondence (TLWC) to perform heterogeneous transfer learning with instance-correspondence (IC) data. Different from previous methods that assumed all the IC data are equally important, we construct a meta-learner that utilizes the classification loss in the target domain to guide the IC data weights learning and feature transformation optimization. Based on this framework, the transformed feature space learned by TLWC is more adaptive to the task in the target domain. Extensive experiments on 3 datasets demonstrate the effectiveness of TLWC on IC data weights updating and domain adaptation.
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