Abstract—Instance transfer approaches consider source and target data together during the training process, and borrow examples from the source domain to augment the training data, when there is limited or no label in the target domain. Among them, boosting-based transfer learning methods (e.g., TrAdaBoost) are most widely used. When dealing with more complex data, we may consider the more complex hypotheses (e.g., a decision tree with deeper layers). However, with the fixed and high complexity of the hypotheses, TrAdaBoost and its variants may face the overfitting problems. Even worse, in the transfer learning scenario, a decision tree with deep layers may overfit different distribution data in the source domain. In this paper, we propose a new instance transfer learning method, i.e., Deep Decision Tree Transfer Boosting (DTTrBoost), whose weights are learned and assigned to base learners by minimizing the data-dependent learning bounds across both source and target domains in terms of the Rademacher complexities. This guarantees that we can learn decision trees with deep layers without overfitting. The theorem proof and experimental results indicate the effectiveness of our proposed method.

Index Terms—Decision tree, deep boosting (DeepBoost), instance transfer learning, transfer boosting.

I. INTRODUCTION

TRANSFER learning is a hot research topic in neural networks and learning systems, which shows effective performance in visual categorization, face recognition, saliency detection, and so on [1]–[7]. Usually, the prediction performance of a learned model degrades if the number of training data is very limited. Transfer learning algorithms target at extracting the knowledge from one or more source domains and applying the knowledge to a target domain [1], [8]–[10]. Although the training data are more or less out-dated or in a different domain, some parts of the data could still be reused. For instance transfer approaches, both source and target data are considered during the training process [11]–[13]. A small amount of labeled same-distributed training data in the target domain are applied to vote the usefulness of each instance of the source domain. Since some of the source-domain training data might be under a different distribution from the target domain, they are called diff-distributed training data.

One major challenge of transfer learning lies in formulating an approach that makes full use of the available source-domain data. Instance transfer learning algorithms address this challenge by identifying the relevant instances that would be useful in learning a tuned classifier that classifies target data points correctly [14]–[18]. It is widely used in pedestrian detector [19], head pose classification [20], facial expression recognition [21], and so on. Among them, TrAdaBoost [14] is the most widely used method. In TrAdaBoost, AdaBoost [22] is applied to same-distributed training data to learn the base classifiers of the model. The weights of diff-distributed training instances, which are wrongly predicted due to the dissimilarity to the same-distributed instances, would be decreased to weaken their impacts.

However, for some difficult tasks in computer vision or image processing, simple boost stumps (e.g., one layer decision tree) may be not sufficient to model the data distribution to achieve high accuracy. Then, it attempts to apply a more complex hypothesis set, for example, decision trees with deep layers. However, in transfer learning scenario, it might not work, which is mainly because target-domain and source-domain samples are from different distributions. Directly adapting more complex base learners in TrAdaBoost, for example, the ensemble of deep layer decision trees with the same depth, may result in overfitting because it probably will overfit some diff-distributed data in the source domain. For example, gradient boosting methods [23] try to compute the optimal gradient direction to fit the training data to minimize the loss function. However, in transfer learning scenario, the optimal gradient directions of source- and target-domain data are different if their distributions are different. If we directly train a gradient tree with high depth to fit the whole data (i.e., both source- and target-domain data), the gradient tree may overfit some source-domain data with different distributions as the target-domain data.

To address the above-mentioned challenge, we propose a Deep Decision Tree Transfer Boosting (DTTrBoost) approach, which is enlightened by DeepBoost [24], to improve the instance transfer learning when facing more complex data. DeepBoost proposes the learning bounds for convex ensembles of the base classifier set formulated in terms of the Rademacher complexities [25]. Like Vapnik–Chervonenkis (VC)-dimension, Rademacher complexity is a data-dependent
II. RELATED WORK

In this section, we first briefly describe the related works of ensemble learning methods. Second, we introduce the related works of transfer learning methods, especially the instance transfer learning ones.

A. Ensemble Learning

Ensemble learning methods (e.g., boosting, bagging, Bayesian averaging, and stacking) combine several learning algorithms to create one with higher prediction accuracy [22], [26]–[28].

Ensemble methods are widely applied in practice, due to the significant improvement in terms of performance [29]–[32]. Ditzler et al. [29] developed an ensemble of online linear models using bagging and boosting for online feature selection. Li et al. [30] integrated $L_p$-norm into the bag scores to localize the witness instances for multinstance classification. Ensemble algorithms have also been introduced in semisupervised classification (SSC) with improved generalization performance when compared to single classifiers. For example, Soares et al. [31] proposed a cluster-based boosting method for multiclass SSC. They integrated cluster-based regularization into boosting to avoid generating decision boundaries in high-density regions [31]. Zhang et al. [32] proposed a multi-objective deep belief networks ensemble method for estimating the remaining useful life.

In particular, AdaBoost, short for Adaptive Boosting, is based on a rich theoretical analysis, which guarantees the performance in terms of the margins of the training samples [33], [34]. AdaBoost and its variants have been widely applied to regression and classification problems. Bjurgert et al. [35] used AdaBoot to estimate dynamical systems and explored the connection between AdaBoost and system identification. Qi et al. [36] applied ensemble learning strategy for the learning problem with label proportions (LLPs). They proposed an Adaboost-based loss function according to different weights for LLP and named as Adaboost-LLP. Adaboost-LLP exploits extra weight information and ensembles multiple weak classifiers into a strong one. However, AdaBoost and its variants [16], [37] may face the overfitting problem with more complex data. Deep boosting (DeepBoost) decomposes a set of base classifiers into subfamilies according to, for example, the depth of the decision tree. It adopts new data-dependent learning bounds for convex ensemble expressed in terms of the Rademacher complexities of the subfamilies [24].

B. Transfer Learning

In recent years, transfer learning is widely used in neural networks and learning systems [1]–[7]. For example, Zhang et al. [3] applied a deep learning model with deep intersaliency mining and intrasaliency prior transfer for cosaliency detection among multiple related images. Sequence transfer learning methods have also attracted a lot of attentions due to the large amounts of text and video data from social media such as Twitter and Facebook [6].
Transfer learning approaches fall into three categories: inductive, transductive, and unsupervised transfer learning [8].

Inductive transfer learning focuses on the scenario that the target task is different from the source task, while two domains can be either the same or not. The tasks of source and target domain of the transductive transfer learning are the same while two domains are different. In unsupervised transfer learning approaches, the target-domain learning tasks are unsupervised, such as dimensionality reduction, clustering, and density estimation.

Instance transfer learning belongs to the transductive transfer learning setting. Instance transfer approaches take both source and target data into consideration during the training process [8]. TrAdaBoost [14] paved the way of instance transfer learning, which adopts AdaBoost [22] algorithm as a best-fit instance transfer learner. We will provide more detailed introduction of TrAdaBoost in Section III-B. TrAdaBoost is extended to many transfer learning tasks such as regression transfer [37] and multisource learning [17], [38]. For example, TransferBoost [17] calculates the error difference between only the target task or the integrate of the target and each source task as the aggregate transfer term for each source task. The weights of instances that belong to a positive transferable source task to the target task are boosted. Recently, Huang et al. [39] proposed a topic-related TrAdaBoost for cross-domain sentiment classification. They first extracted the topic distribution for each document. Then, they constructed the new representation for each document by appending the topic distribution to the original model.

A few efforts have been done to improve the performance of TrAdaBoost by modifying the weight updating strategy. For example, in cost-sensitive boosting approaches [17], a fixed cost is incorporated, via AdaCost [15], to the source strategy. For example, in cost-sensitive boosting approaches [17], performance of TrAdaBoost by modifying the weight updating strategy. For example, in cost-sensitive boosting approaches [17], the performance of TrAdaBoost by modifying the weight updating strategy. For example, in cost-sensitive boosting approaches [17], the performance of TrAdaBoost by modifying the weight updating strategy. For example, in cost-sensitive boosting approaches [17], the performance of TrAdaBoost by modifying the weight updating strategy. For example, in cost-sensitive boosting approaches [17], the performance of TrAdaBoost by modifying the weight updating strategy. 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For example, in cost-sensitive boosting approaches [17], the performance of TrAdaBoost by modifying the weight estimating as the cost. Recently, Ryu et al. [40] also applied the cost-sensitive boosting approach to predict the cross-project defect. In dynamic- TrAdaBoost, a dynamic factor was incorporated to meet the intended design of both AdaBoost and the “weighted majority algorithm” [16]. However, none of them focused on the overfitting problems when the hypotheses become more complex, for example, deeper decision trees. TrAdaBoost and the extension methods are with complexity-fixed hypotheses, which may bring overfitting problems when facing more complex data.

Recently, deep transfer learning algorithms generalize deep structures into the transfer learning scenario, in order to reduce the domain discrepancy and improve the transferability of feature representation [41]–[47]. For example, Zhou et al. [46] proposed a deep learning transfer hashing framework that incorporates transfer learning and hashing to address the data sparsity problem in hashing. Ding and Fu [47] investigated low-rank coding at top task-specific layers and proposed a deep transfer low-rank coding neural network framework. However, although those works can mitigate the marginal distribution divergence between the target and the source domain, they may fail to uncover the intrinsic classwise structure of two domains. Meanwhile, a huge number of labeled data are usually needed to estimate a mass of parameters in deep convolutional neural network framework.

Specifically, our method is in the line of instance transfer learning. Compared with TrAdaBoost and the extension methods with complexity-fixed hypotheses, DTrBoost adds the complexity penalty on the hypotheses. It means a hypothesis with the higher complexity (e.g., a deeper decision tree) is penalized and allocated lower weights. DTrBoost ensembles different complexity hypotheses families learning from both source-domain data and target-domain data, and allocates more weights on hypotheses from less complexity hypotheses families to avoid overfitting.

III. PROPOSED METHOD

In this section, we first give the problem formulation. Second, we introduce the preliminary knowledge: Boosting-based transfer learning (i.e., TrAdaBoost) [14] and DeepBoost [24]. Third, we describe our DTrBoost algorithm in detail. The theorem proof of the convergence property is also provided.

A. Problem Formulation

For the instance transfer learning scenario, let \( X = X_s \cup X_d \) be the instance space, where \( X_s \) is the target-domain instance space and \( X_d \) is the source-domain instance space, which is with different distributions as the target domain. \( Y = \{1, -1\} \) denotes the set of category labels. A concept is a Boolean function \( c \), mapping from \( X \) to \( Y \). The test data set is with the same distribution as the target domain, denoted as \( U \). We partition the training data set \( L \subseteq \{X \times Y\} \) into two labeled sets \( L_d \) and \( L_s \). \( L_d \) denotes the diff-distributed training data that \( L_d = \{(x^d_i, c(x^d_i))\} \), where \( x^d_i \in \{X_d(i = 1, \ldots, n) \} \). \( L_s \) denotes the same-distributed training data that \( L_s = \{(x^s_i, c(x^s_i))\} \), where \( x^s_i \in \{X_s(i = 1, \ldots, m) \} \). \( L = \{(x_i, c(x_i))\} \), where \( x_i \) is defined as

\[
\begin{align*}
  x_i &= x^d_i, \quad i = 1, \ldots, n \\
  x_i &= x^s_i, \quad i = n + 1, \ldots, n + m.
\end{align*}
\]

The problem is that, given a small number of labeled target-domain training data \( L_s \) and a large number of labeled source-domain training data \( L_d \), we aim to learn a Boolean function \( c \) from \( X \) to \( Y \) to minimize the prediction error on the unlabeled test data \( U \).

B. Boosting-Based Transfer Learning

In this section, we briefly describe the algorithm of TrAdaBoost [14]. TrAdaBoost paved the way of boosting-based transfer learning algorithms [15], [37], [38], [48], and it is one of the most representative methods in the transfer learning scenario [8].

The input of TrAdaBoost consists of labeled source- and target-domain training data \( L_d \) and \( L_s \); a base “learner” such as a decision tree with one or two stumps; the maximum number of iterations \( T \). TrAdaBoost iteratively trains a set of base classifiers based on the weighted target and source training samples. At the end of each boosting iteration, we increase...
the weights of misclassified target instances and decrease the weights of misclassified source instances. The weights of correctly classified instances are unchanged. The weight of each hypothesis depends on the training error of the target domain in each iteration. Thus, the impacts of diff-distributed instances in the source domain gradually decrease. After all $T$ iterations, TrAdaBoost ensembles the weighted hypotheses learned from $[T/2+1, T]$ as the final classifier.

This updating mechanism is adapted from the AdaBoost [22] algorithm. The algorithm of TrAdaBoost is given in Algorithm 1 and more detailed descriptions could be referred in [14].

C. Deep Boosting

Our work is enlightened by DeepBoost [24]. Here, we briefly introduce the basic idea and the objective function of DeepBoost.

Assume that $p$ disjoint families $H_1, ..., H_p$ are decomposed from a set of base classifiers $H_t$, mapping from $X$ to $\mathbb{R}$, ordered by an increasing complexity. Each family $H_k$, $k \in [1, p]$ can be a set of functions based on monomials of degree $k$ or a set of decision trees of depth $k$.

The core of the DeepBoost is a capacity-conscious criterion for the hypotheses $h_t$ selection. A learning bound for the convex ensembles formulated using the Rademacher complexities [25] of the subfamilies, and the weights are assigned to each subfamily. It is beneficial and guaranteed that DeepBoost seeks $\alpha$ to minimize the learning bound, which is

$$G(\alpha) = \frac{1}{m} \sum_{i=1}^{m} \left( y_i \sum_{t=1}^{T} a_t h_t(x_i) \leq \rho \right) + \frac{4}{\rho} \sum_{t=1}^{T} a_t r_t$$

where $x_i$ denotes the target domain instance, $i \in [1, ..., m]$. $y_i$ denotes the label of $x_i$, $T$ denotes the number of iterations. $h_t$ denotes the selected hypothesis at $t$th iteration. $a_t$ denotes the weight assigned to the corresponding $h_t$. Let $\rho > 0$ while $\sum_{t=1}^{T} a_t h_t(x_i) \leq \rho$ is the $\rho$-margin error, and $r_t = \Phi_m(H_{d(h_t)})$ is the standard Rademacher complexity. $d(h_t)$ is an index function that maps $h_t$ to its hypotheses subfamily $H_k$. More descriptions of DeepBoost could be referred to [24].

D. Deep Decision Tree Boosting

TrAdaBoost and its variants may face overfitting problem when it comes to more complex data. In the transfer learning scenario, even worse, a more complex hypothesis set is likely to not only overfit the target-domain training samples but also the useless source-domain training samples, which are lying in different distributions. In order to solve this problem, we propose a DTrBoost algorithm.

We first introduce the hypotheses generation using decision tree. It is treated as a process of parameter estimation. We mainly follow the idea of the gradient boost tree to learn the parameters of hypotheses [23]. The objective function of gradient boost [23] of both the target domain and the source domain is as

$$\min_{a_t \geq 0} \frac{1}{n + m} \sum_{i=1}^{n+m} \Phi(1 - y_i \sum_{t=1}^{T} a_t h_t(x_i, a_t))$$

where $x_i$ denotes the input instance and $i \in [1, \ldots, n, \ldots, n + m]$. $y_i$ denotes the label of $x_i$. $t \in [1, 2, \ldots, T]$ denotes the index of iteration. $T$ denotes the total number of iterations. $h_t(x_i, a_t)$ denotes the hypothesis in the iteration $t$, where $a_t$ is the model parameters of $h_t$. $a_t$ denotes the weight of $h_t$. Let $\Phi$ be a nonincreasing convex function. For example, in AdaBoost, $\Phi$ is selected as the exponential function.

In $t$th iteration, gradient boosting chooses a new function $h_t(x_i, a_t)$ to be the most parallel to the negative gradient $\{d_t^{w}(x_i)\}_{t=1}^{n+m}$ along the observed data

$$d_t^{w}(x_i) = \nabla \Phi(y_i, f(x))$$

where $f_t \leftarrow f_{t-1} + a_t h_t(x, a_t)$. Here, $d_t^{w}$ denotes the gradient calculated with both source and target domains. $w$ notifies whole data including the source domain and the target domain.

However, as discussed above, in the source domain, some data are useless and with different distributions as the target domain. Thus, the gradient directions are different between whole data and data in the target domain. We could not directly apply the hypotheses learned in the whole data for target-domain classification.

Our main idea is to decrease the weights of the diff-distributed samples in the source domain, so that the gradient direction would become very close when the weighted data in two domains are from the same distribution. Meanwhile, we consider the complexity penalty enlightened by DeepBoost to avoid overfitting.

Suppose $H = \{h_1, \ldots, h_j, \ldots, h_N\}$ are $N$ different hypotheses. $e_j$ is the direction of the $j$th hypothesis. $F_w$ is the loss function of gradient boosting of data in both the source
and the target domain, and \( F_s \) is the loss function of gradient boosting of data in the target domain as

\[
F'_w = \frac{1}{n+m} \sum_{i=1}^{n+m} \Phi(1 - y_i \sum_{j=1}^{N} a_{t,j} h_j(x_i, a_j)) + \sum_{j=1}^{N} (\lambda r_t + \beta) a_{t,j} \\
F'_s = \frac{1}{m} \sum_{i=1}^{m} \Phi(1 - y_i \sum_{j=1}^{N} a_{t,j} h_j(x_i, a_j)) + \sum_{j=1}^{N} (\lambda r_t + \beta) a_{t,j}
\]

where \( a_{t,j} \) denotes the weight of hypothesis \( j \) in the \( t \)th iteration. The second part in (4) and (5) is the regularization of the hypothesis Rademacher complexity, where \( \lambda \) and \( \beta \) are the parameters, \( r_t = \mathbb{9}_m(H_j(h_t)) \) is the standard Rademacher complexity. This term is introduced in DeepBoost but not for transfer learning scenario [24]. \( d(h_t) \) denotes the index of the hypothesis set which \( h_t \) belong to, and that is \( h_t \in H_{d(h_t)} \).

Our objective function is to minimize the derivative of \( F'_w \) and \( F'_s \) in direction \( e_j \) as

\[
\min_{a_{t,j}} G = \min_{a_{t,j}} \left| F'_w(a_{t-1,j,j}, e_j) - F'_s(a_{t-1,j}, e_j) \right|
\]

where \( F'_w(a_{t-1,j,j}, e_j) \) and \( F'_s(a_{t-1,j,j}, e_j) \) are the derivative of \( F'_w \) and \( F'_s \) in direction \( e_j \), respectively. By minimizing the derivative of \( F'_w \) and \( F'_s \), the weights of the distributed samples in the source domain would be declassified at each iteration. Thus, the distributions of the weighted samples in source and target domain gradually get similar to each other. When learning the weights of hypotheses, by adding the complexity penalty, the objective function can punish more of complex hypotheses. Thus, the hypotheses families with less complexity would be allocated more weights to avoid overfitting.

\[E. Optimization\]

Our optimization mainly consists of three parts. The first is to learn a series of hypotheses with different complexities (e.g., decision trees with different depths) on both target-domain data and source-domain data. The second is to select the local best hypothesis from different complexity hypotheses families only based on target-domain data, and update the weights of the best hypothesis set. The third is to update weights of both source and target domains.

1) Learning Hypothesis: We apply both \( n \) source-domain data \( L_d \) and \( m \) target-domain data \( L_s \) to learn hypothesis as (4). We take the derivative of (4) in direction \( e_j \) in iteration \( t \) toward all the weighted samples according to [24]

\[
d^u_{t,j} = F'_w(a_{t-1,j,j}, e_j) = -\frac{1}{n+m} \sum_{i=1}^{n+m} y_i h_j(x_i) \Phi'(1 - y_i f_{t-1}(x_i)) + a_{t-1,j} \Lambda^u_t
\]

where \( \Lambda^u_t \) is the derivative of \( F^u_t \) toward direction \( e_j \) in the \( t \)th iteration. \( \Lambda^u_t \) is calculated as \( \Lambda^u_t = \lambda r_t + \beta. \lambda r_t + \beta \) is the complexity penalty in (4), \( S^u_t \) is the normalizer of the weights of \( L_s \) and \( L_d \) in iteration \( t \) [24]. \( D^u_t(i) \) denotes the sample weight of each \( x_i \). \( e^u_{t,j} \) denotes the estimated error.

After calculating the gradient \( d^u_{t,j} \), gradient boost tree chooses the new function \( h_j(x_i, a_j) \) incrementally to the most correlated with \( -d^u_{t,j} \)

\[
a_j = \arg\min_{a_j} \sum_{i=1}^{n+m} \left[ -d^u_{t,j}(x_i) - h_j(x_i, a_j) \right]^2
\]

Thus, we obtain the hypothesis set \( H = \{h_1, \ldots, h_t, \ldots, h_N \} \) after \( t \)-iterations, \( N \leq t < T \).

2) Search and Update Local Best Hypothesis: In order to minimize the derivative of \( F^u_t \) and \( F^s_t \), after getting \( H = \{h_1, \ldots, h_t, \ldots, h_N \} \), we find and update the local best hypothesis \( h_k \) among \( H \) in each iteration.

First, we calculate the derivative of \( F_s \) in each direction \( e_j \) of \( h_j \) toward weighted target-domain samples with the same strategy as (7) as

\[
d^s_{t,j} = F'_s(a_{t-1,j,j}, e_j) = -\frac{1}{m} \sum_{i=1}^{m} y_i h_j(x_i) \Phi'(1 - y_i f_{t-1}(x_i)) + a_{t-1,j} \Lambda^s_t
\]

where \( \Lambda^s_t \) is the derivative of \( F^s_t \) toward direction \( e_j \) in the \( t \)th iteration. Similar as (7), \( S^s_t \) is the normalizer of the weights of \( L_s \) in iteration \( t \). \( D^s_t(i) \) denotes the sample weight. \( e^s_{t,j} \) denotes the estimated error. \( \lambda \) is the complexity penalty.

Then, we choose \( h_j \) with the largest \( d^s_{t,j} \) as the local best learner, denoted as \( h_k \). In this way, we find the direction \( e_j \) that is most parallel to the gradients of \( F_s \) of the weighted target-domain samples.

The basic idea of updating the weights of hypothesis is that, in each iteration \( t \), we only update the weight \( a_{t,k} \) of local best hypothesis \( h_k \) and keeps other \( a_{t,j} (j \neq k) \) unchanged. This idea could be formalized as \( a_{t,j} = a_{t-1,j} + \eta e_k \), where \( a_{t,j} \) is the set of \( a_{t,j} \), \( a_{t,j} = \{a_{t,1}, \ldots a_{t,N} \} \). \( e_k \) denotes that direction of \( h_k \). \( \eta \) could be calculated as [24].

3) Update Weights of Training Samples: We introduce the strategy of updating the weights of both target-domain training samples \( L_s \) and source-domain training samples \( L_d \).

Target-domain training data \( L_s \) are updated according to the derivative of target-domain data [24]

\[
D^s_{t+1}(i) \leftarrow \frac{\Phi'(1 - y_i \sum_{j=1}^{N} a_{t,j} h_j(x_i))}{S^s_{t+1}}, \quad n+1 \leq i \leq n+m.
\]
The source-domain training data \( L_d \) are updated as
\[
D^d_{t+1}(i) \leftarrow D^d_t(i)^{\gamma} \left( \sum_{j=1}^N \alpha_{t,j} h_j(x_i) \right)^{1-\gamma}, \quad 1 \leq i \leq n
\]
where \( \gamma = \exp \left( -0.5 \times \log(1 + 2 \ln n / T^{1/2}) \right) \) and \( c(x_i) \) is the class label of \( x_i \) [14].

4) Ensemble Local Best Hypotheses: After \( T \) iterations, DTrBoost ensembles all the \( N \) local best hypotheses together as
\[
f = \sum_{j=1}^N (a_{T,j} - a_{T/2,j}) h_j.
\]
f is the final output of the algorithm. The weight of the \( r \)th hypothesis is \((a_{T,r} - a_{T/2,r})\), meaning we only consider the weight \( a_{t,j} \), \( t \in [2T + 1, T] \). We exclude the weights learned from the first \( T/2 \) iterations.

Because in the first certain number of iterations (i.e., \( T/2 \)), the weights of diff-distributed data in the source domain have not been decreased to a very small number. It will largely hold back learning the same gradient direction comparing to the gradient direction only learning from the target domain. In the theoretical analysis, we will prove that after \( T/2 \) iterations, the differences of the gradient direction in the whole data and the target-domain data would be a very small number.

Algorithm 2 DTrBoost

INPUT:
1. Source and target domain data \( L_d, L_s \).
2. Maximum depth of decision tree,
3. Maximum number of iterations \( T \).

1: Initialize the weights of source domain samples \( D^d_1 \), and target domain samples \( D^s_1 \).
2: for \( t = 1, 2, \cdots, T \) do
3: \hspace{1em} Calculate the derivative \( d^w_{t,j} \) as Eq. (7) and learn \( h_t \).
4: \hspace{1em} Calculate the number of different hypotheses \( N \).
5: \hspace{1em} for \( j = 1, 2, \cdots, N \) do
6: \hspace{2em} Calculate the derivative \( d^s_{t,j} \) of Eq. (9).
7: \hspace{1em} end for
8: \hspace{1em} \( k = \arg \max |d^s_{t,j}|_{j \in [1,N]} \).
9: \hspace{1em} Update \( \alpha_t \) by \( \alpha_{t} = \alpha_{t-1} + \eta_t e_k \).
10: \hspace{1em} Update target domain data weight \( D^s_{t+1} \) as Eq. (10).
11: \hspace{1em} Update source domain data weight \( D^d_{t+1} \) as Eq. (11).
2: end for

OUTPUT: \( f = \sum_{j=1}^N (a_{T,j} - a_{T/2,j}) h_j \).

Algorithm 2 presents the algorithm of DTrBoost. The inputs of the algorithm are the labeled source-domain (diff-distributed) training data \( L_d \) and labeled target-domain (same-distributed) training data \( L_s \). The output of DTrBoost is \( f = \sum_{j=1}^N (a_{T,j} - a_{T/2,j}) h_j \), where \( N \) is the number of different hypotheses, \( N \leq T \).

5) Discussion: Here, we analyze the relationship between our DTrBoost and TrAdaBoost. When \( \lambda = 0 \) and \( \beta = 0 \), the complexity term of the bound of DTrBoost and the control of the sum of the mixture weights are ignored. It coincides with TrAdaBoost with precisely the same direction.

IV. THEORETICAL ANALYSIS OF DTrBOOST

In this section, we theoretically analyze our framework in terms of the convergence property. We prove that after several iterations, the difference between \( F^u_t \) and \( F^t_t \) in (6) is within a certain small number.

Lemma 1: In the source domain \( \forall \epsilon \), \( \exists T_0, t \geq T_0, S^d_t \leq \exp(-1 - \gamma \eta) \), where \( t \) is a small number and convergent after \( t \geq T_0 \). We follow [14] and set \( T_0 \) as \( T/2. \) \( \gamma \) is a weight updated root and \( c(x_i) = \exp(-0.5 \times \log(1 + 2 \ln n / T^{1/2})) \).

Theorem 2: \( \forall \epsilon_j \), \( T \). \( |F^u_{t}(a_{t-1,j}, e_j) - F^s_{t}(a_{t-1,j}, e_j)| \leq (2\epsilon_j \eta_t)(S_t^d/m) \leq (2\epsilon_j \eta_t)(\exp(-1 - \gamma \eta \eta_t)/m) \), where \( F^u_{t}(a_{t-1,j}, e_j) \) is the derivative of the loss function toward the \( j \)th direction on whole data in the \( t \)th iteration, and \( F^s_{t}(a_{t-1,j}, e_j) \) is the derivative of the loss function toward the \( j \)th direction on target-domain data in the \( t \)th iteration. \( (2\epsilon_j \eta_t)(\exp(-1 - \gamma \eta \eta_t)/m) \) is a certain small number.

Theorem 2 substantiates that after \( T/2 \) iterations, the derivative of the loss function between whole data and target-domain data toward the same direction is within a certain small value. As described above, the difference of the derivative is mainly caused by the difference of the distribution of source and target-domain data. During the optimization, the weights of the diff-distributed source-domain data are gradually decreasing and loosing impact. After \( T/2 \) iterations, the difference of the derivative is within a certain small number. It shows that DTrBoost is able to decrease the impact of diff-distributed source-domain data, and augment the knowledge learning from same-distributed source-domain data.

The proof of Lemma 1 and Theorem 2 could be found in the Appendix.

V. EXPERIMENT

In this section, first at all, we introduce the data set and experimental settings. Second, we present the experimental results of both our method and the state-of-the-art methods. Third, we discuss the impact of the depth of the decision tree and the overfitting problem.

A. Data Sets

To evaluate the effectiveness of DTrBoost, we conduct the experiments on seven data sets, including three image data sets and four UCI data sets, following the data sets used by our comparison methods. Table I summarizes the description of seven data sets.

Office+Caltech and CMU PIE are the two benchmark transfer learning data sets. Office+Caltech has four domains: Caltech-256 (C), Amazon (A), Webcam (W), and digital single-lens reflex camera (DSLR) (D). It is released in [49].

The office data set contains 4,652 images, 31 categories and three domains, Amazon, Webcam, and DSLR. Caltech-256 contains 30,607 images and 256 categories. It is a standard object recognition database. For Office+Caltech data set, we apply two kinds of feature representations to conduct the experiments: speeded-up robust features (SURF) and convolution neural network (CNN). For better comparison with previously reported performance, we first use the SURF descriptors provided in [49]. SURF descriptors are encoded with the codebook which is from a subset of Amazon

1https://archive.ics.uci.edu/ml/data sets.html
images. The histograms are with 800-bin and standardized by z-score. Following [50], we also apply DeCaf's features. DeCaf is a convolutional network framework which is trained on imageNet [51], [52]. DeCaf's features are the activations of the sixth fully connected layer of the network and with 4096-dimension features.

PIE, which stands for “Pose, Illumination, Expression,” is a benchmark face database. Each subset of PIE is with different poses and we follow [53] and choose PIE05 (left pose), PIE07 (upward pose), PIE09 (downward pose), PIE27 (frontal pose), and PIE29 (right pose) as five domains in the experiments. In each domain, face images are taken with different illuminations and expression conditions. In CMU PIE, the faces are cropped into the size of 32×32 and adopt the gray-scale raw pixel value as the input, which leads to 1024-dimension features.

In the experiments, we pick one domain as the target domain, the others as the source domain. In CUM PIE, the PIE05 means we take PIE05 as the target domain and combine the rest as the source domain. As we deal with the binary classification problem, we average the pairwise binary classification accuracy.

VLCSI [54], [55] consists of 18 070 images from PASCAL VOC2007 (V), LabelMe (L), Caltech-101 (C), SUN09 (S), and ImageNet (I) data sets, each of which represents one domain. C and I are the object-centric data sets, while V, L, and S are scene-centric. The five domains share five object categories: “bird,” “car,” “chair,” “dog,” and “person.”

For four UCI data sets, we apply the original attributes of the data as feature representation. As these four UCI data sets are not originally used for transfer learning purpose, we follow TrAdaBoost [14] to use KL-divergence (Kullback and Leibler, 1951) as the criterion to separate the data set into two domains of different distributions. For example, for Mushroom data set, we split the data set based on the feature “stalk-shape” following TrAdaBoost. Table II summarizes the KL-divergence and size of source-domain training data $L_d$, and target-domain training and test data $L_s \cup U$.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Type</th>
<th>#Sample</th>
<th>Descriptor</th>
<th>#Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Office + Caltech</td>
<td>Object</td>
<td>2,533</td>
<td>SURF</td>
<td>800</td>
</tr>
<tr>
<td>PIE</td>
<td>Face</td>
<td>11,554</td>
<td>Raw pixel</td>
<td>1,024</td>
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<td>VLCSI</td>
<td>Object</td>
<td>18,070</td>
<td>CNN</td>
<td>4,096</td>
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<tr>
<td>Mushroom</td>
<td>Life</td>
<td>8,416</td>
<td>Attributes</td>
<td>22</td>
</tr>
<tr>
<td>OCR</td>
<td>Computer</td>
<td>5,620</td>
<td>Attributes</td>
<td>64</td>
</tr>
<tr>
<td>Ionosphere</td>
<td>Physical</td>
<td>351</td>
<td>Attributes</td>
<td>34</td>
</tr>
<tr>
<td>BreastCancer</td>
<td>Life</td>
<td>699</td>
<td>Attributes</td>
<td>10</td>
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</table>

<table>
<thead>
<tr>
<th>Dataset</th>
<th>KL-divergence</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mushroom</td>
<td>0.5086</td>
<td>4,864, 3,552</td>
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<tr>
<td>OCR17</td>
<td>23.01</td>
<td>776, 358</td>
</tr>
<tr>
<td>OCR49</td>
<td>24.88</td>
<td>362, 769</td>
</tr>
<tr>
<td>Ionosphere</td>
<td>16.36</td>
<td>204, 147</td>
</tr>
<tr>
<td>BreastCancer</td>
<td>5.808</td>
<td>292, 407</td>
</tr>
</tbody>
</table>

**TABLE I**

**DATA SET DESCRIPTION.** We show the type of the task (Type), number of samples (#Sample), feature descriptor (Descriptor), feature dimensions (#Feature) of each data set.

**TABLE II**

**DESCRIPTION OF UCI DATA SETS MUSHROOM, OCR17, OCR49, IONOSPHERE, AND BREAST CANCER. FOR EACH DATA SET, WE PRESENT THE KL-DIVERGENCE AND THE SIZE OF SOURCE-DOMAIN TRAINING DATA $L_d$, AND TARGET-DOMAIN TRAINING AND TEST DATA $L_s \cup U$.**

**B. Compared Methods**

We compare our method with three state-of-the-art instance transfer learning methods: boosting for transfer learning (TrAdaBoost), cost-sensitive boosting (Cost-TrAdaBoost), adaptive boosting for transfer learning using dynamic updates (Dynamic-TrAdaBoost). Although there are other state-of-the-art related works [4], [37]–[39], they are not working on the same scenario as ours.

In order to show the effectiveness of transfer learning, we also compare boosting based methods but without transfer learning: AdaBoost and DeepAdaBoost (i.e., the AdaBoost setting for DeepBoost). For transfer learning methods, both the target- and source-domain training data are used. For these two nontransfer learning methods, only target-domain training data are used.

The brief introduction of five methods is listed as follows.

1) **TrAdaBoost** [14]: TrAdaBoost is the most popular boosting-based transfer learning algorithm, which extends boosting-based learning algorithms [22] to the transfer learning scenario. The description of TrAdaBoost is presented in Section III-B “boosting-based transfer learning.”

2) **Cost-TrAdaBoost** [15]: Ashok et al. extended the cost-sensitive boosting method [48] to transfer learning scenario for concept drift. In Cost-TrAdaBoost, a fixed cost is incorporated into the source-domain weight updating strategy. This cost is precalculated according to the relevance between source and target distributions by probability estimates. Recently, Ryu et al [40] also applied the cost-sensitive boosting approach for cross-project defect prediction.

3) **Dynamic-TrAdaBoost** [16]: Al-Stouhi and Reddy [16] extended TrAdaBoost by incorporating a dynamic factor in order to meet the intended design of both AdaBoost and the “weighted majority algorithm.”

4) **AdaBoost** [22]: AdaBoost ensembles a base classifier hypothesis set. In each iteration, Adaboost increases the weight of wrongly classified samples and decreases the weight for correctly classified samples.

5) **DeepAdaBoost** [24]: DeepBoost investigates a capacity-conscious criterion for the hypotheses selection. A complexity penalty is added to prevent overfitting. In this paper, we adopt the exponential function-based DeepBoost and name it as DeepAdaBoost.
TABLE III
ERROR RATES UNDER OFFICE+CALTECH-256 DATA SET USING SURF DESCRIPTORS AND CMU PIE DATA SET USING THE RAW PIXEL DESCRIPTOR UNDER THE RATIO OF 0.05. \( H_1 \) AND \( H_2 \) DENOTE \( H_1^{\text{stumps}} \) AND \( H_2^{\text{stumps}} \), RESPECTIVELY. THE BEST AND SECOND BEST PERFORMANCES ARE WITH BOLD FONTS AND UNDERLINE, RESPECTIVELY.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>AdaBoost ( H_1 )</th>
<th>AdaBoost ( H_2 )</th>
<th>Deep AdaBoost ( H_1 )</th>
<th>Deep AdaBoost ( H_2 )</th>
<th>TrAdaBoost ( H_1 )</th>
<th>TrAdaBoost ( H_2 )</th>
<th>Cost-TrAdaBoost ( H_1 )</th>
<th>Cost-TrAdaBoost ( H_2 )</th>
<th>Dynamic-TrAdaBoost ( H_1 )</th>
<th>Dynamic-TrAdaBoost ( H_2 )</th>
<th>Ours ( H_1 )</th>
<th>Ours ( H_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>C.D,W-&gt;A</td>
<td>0.1824</td>
<td>0.2340</td>
<td>0.1622</td>
<td>0.1482</td>
<td>0.1527</td>
<td>0.1436</td>
<td>0.1448</td>
<td>0.1743</td>
<td>0.2100</td>
<td>0.1366</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.D,W-&gt;C</td>
<td>0.3200</td>
<td>0.3462</td>
<td>0.3143</td>
<td>0.3123</td>
<td>0.3018</td>
<td>0.3123</td>
<td>0.3018</td>
<td>0.3123</td>
<td>0.3123</td>
<td>0.2942</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.C,W-&gt;D</td>
<td>0.2431</td>
<td>0.2333</td>
<td>0.2235</td>
<td>0.2152</td>
<td>0.2064</td>
<td>0.2011</td>
<td>0.1972</td>
<td>0.2023</td>
<td>0.1988</td>
<td>0.1924</td>
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<tr>
<td>A,C,D-&gt;W</td>
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<td>0.2982</td>
<td>0.2755</td>
<td>0.1850</td>
<td>0.1750</td>
<td>0.1850</td>
<td>0.1750</td>
<td>0.1850</td>
<td>0.1750</td>
<td>0.1635</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PIE05</td>
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<td>0.1326</td>
<td>0.1135</td>
<td>0.1287</td>
<td>0.1224</td>
<td>0.1326</td>
<td>0.1048</td>
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<td>PIE27</td>
<td>0.2832</td>
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<td>0.1357</td>
<td>0.1542</td>
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<td>0.1233</td>
<td>0.1246</td>
<td>0.1183</td>
<td>0.0781</td>
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TABLE IV
ERROR RATES UNDER MUSHROOM, OCR17&19, IONOSPHERE, AND BREAST CANCER DATA SETS UNDER THE RATIO OF 0.1. \( H_1 \) AND \( H_2 \) DENOTE \( H_1^{\text{stumps}} \) AND \( H_2^{\text{stumps}} \), RESPECTIVELY. THE BEST AND SECOND BEST PERFORMANCES ARE SHOWN WITH BOLD FONTS AND UNDERLINE, RESPECTIVELY.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>AdaBoost ( H_1 )</th>
<th>AdaBoost ( H_2 )</th>
<th>Deep AdaBoost ( H_1 )</th>
<th>Deep AdaBoost ( H_2 )</th>
<th>TrAdaBoost ( H_1 )</th>
<th>TrAdaBoost ( H_2 )</th>
<th>Cost-TrAdaBoost ( H_1 )</th>
<th>Cost-TrAdaBoost ( H_2 )</th>
<th>Dynamic-TrAdaBoost ( H_1 )</th>
<th>Dynamic-TrAdaBoost ( H_2 )</th>
<th>Ours ( H_1 )</th>
<th>Ours ( H_2 )</th>
</tr>
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<tbody>
<tr>
<td>Mushroom</td>
<td>0.0071</td>
<td>0.0071</td>
<td>0.0091</td>
<td>0.0091</td>
<td>0.00440</td>
<td>0.0087</td>
<td>0.00440</td>
<td>0.0076</td>
<td>0.0049</td>
<td>0.0041</td>
<td>0.0037</td>
<td></td>
</tr>
<tr>
<td>OCR17</td>
<td>0.0513</td>
<td>0.0613</td>
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<td>0.0247</td>
<td>0.0253</td>
<td>0.0238</td>
<td>0.0267</td>
<td>0.0247</td>
<td>0.0453</td>
<td>0.0387</td>
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<tr>
<td>OCR49</td>
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<td>0.0636</td>
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<td>0.0447</td>
<td>0.0451</td>
<td>0.0447</td>
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<td>0.0562</td>
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</tr>
<tr>
<td>Ionsosphere</td>
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<td>0.2800</td>
<td>0.3520</td>
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<td>0.3520</td>
<td>0.2268</td>
<td>0.2132</td>
<td>0.1925</td>
<td>0.2631</td>
<td>0.2075</td>
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<tr>
<td>BreastCancer</td>
<td>0.1476</td>
<td>0.1360</td>
<td>0.1148</td>
<td>0.1060</td>
<td>0.1152</td>
<td>0.1060</td>
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<td>0.1100</td>
<td>0.1589</td>
<td>0.0960</td>
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</table>

TABLE V
ERROR RATES UNDER OFFICE+CALTECH-256 DATA SET USING CNN DESCRIPTORS UNDER THE RATIO OF 0.05. \( H_1 \) AND \( H_2 \) DENOTE \( H_1^{\text{stumps}} \) AND \( H_2^{\text{stumps}} \), RESPECTIVELY. THE BEST AND SECOND BEST PERFORMANCES ARE SHOWN WITH BOLD FONTS AND UNDERLINE, RESPECTIVELY.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>AdaBoost ( H_1 )</th>
<th>AdaBoost ( H_2 )</th>
<th>Deep AdaBoost ( H_1 )</th>
<th>Deep AdaBoost ( H_2 )</th>
<th>TrAdaBoost ( H_1 )</th>
<th>TrAdaBoost ( H_2 )</th>
<th>Cost-TrAdaBoost ( H_1 )</th>
<th>Cost-TrAdaBoost ( H_2 )</th>
<th>Dynamic-TrAdaBoost ( H_1 )</th>
<th>Dynamic-TrAdaBoost ( H_2 )</th>
<th>DAN</th>
<th>Ours</th>
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</thead>
<tbody>
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<td>C.D,W-&gt;A</td>
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<td>0.0614</td>
<td>0.0614</td>
<td>0.0526</td>
<td>0.0441</td>
<td>0.0418</td>
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<tr>
<td>A.D,W-&gt;C</td>
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<td>0.1346</td>
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<td>0.0831</td>
<td>0.0851</td>
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</tr>
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<td>0.0165</td>
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<tr>
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<td>0.0331</td>
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<td>0.0232</td>
<td>0.0232</td>
<td>0.0252</td>
<td>0.0252</td>
<td>0.0192</td>
<td>0.0192</td>
<td></td>
</tr>
</tbody>
</table>

6) \( \text{DTTrAdaBoost(Ours)} \): This method contains the full pipeline of our method. We adopt the exponential function-based \( \text{DTTrBoost} \) and name it as Deep\( \text{DTTrAdaBoost} \).

C. Experimental Settings

We use decision tree as the basic learner for all the methods. As AdaBoost, TrAdaBoost, Cost-TrAdaBoost, and Dynamic-TrAdaBoost are with the fixed depth of decision tree, we follow the depth setting (i.e., 1 or 2 depth) in this paper for better comparison, named \( H_1^{\text{stumps}} \) and \( H_2^{\text{stumps}} \). Note that in existing instance transfer learning approaches, deep decision tree is not considered.

To fairly compare our method (depth adaptive) and existing instance transfer learning methods (depth fixed), in Tables III and IV, we set the maximum depth as 2. We aim at evaluating whether our method could adaptively select the depth between 1 and 2, and outperform existing methods under their depth settings. Then, in Section V-E, we discuss each method under deeper layer settings and show the effectiveness of our method toward the overfitting problem.

We set the number of iterations as 100 and the loss of boosting with the exponential function for all the methods. We test the ratio of the number of target- and source-domain training data from 0.01 to 0.5 as [14]. We conduct the experiments under each setting for 10 times and report and averaged error rates.

D. Experimental Result

We compare our method with both nontransfer learning methods, AdaBoost and DeepAdaBoost, and instance transfer learning methods, TrAdaBoost, Cost-TrAdaBoost, and Dynamic-TrAdaBoost. In Section V-D1, we show results based on low-level feature under Office+Caltech-256 and CMU PIE data sets given in Table III and under Mushroom, OCR17&19, Ionsosphere, and Breast Cancer data sets given in Table IV. In Section V-D2, we show the results based on deep learning-based feature. We show the results based on
CNN feature under Office+Caltech-256 given in Table IV and under VLCSI data set [54], [55] in Fig. 2. We further compare with one typical deep transfer learning method, i.e., deep adaptation networks (DAN) [44] in Office+Caltech-256 and VLCSI data set.

For four nondeep methods, AdaBoost, TrAdaBoost, Cost-TrAdaBoost, and Dynamic-TrAdaBoost, we present the results under the depth of decision tree as 1 ($H_1^{\text{stumps}}$) and 2 ($H_2^{\text{stumps}}$). As discussed in experimental settings, in order to fairly compare the performance of deep and nondeep methods, we set the maximum depth of decision tree of DeepAdaBoost and our method as 2.

The ratio of the number of training samples in the target and the source domain given in Tables III and V and Fig. 2 is 0.05 and in Table IV is 0.1. λ and β in (4) and (5) are set in the range of $\lambda \in (10^{-4} : i = 0, \cdots, 7)$ and $\beta \in (2^{-4} : i = 0, \cdots, 13)$ according to cross validation.

1) Low-Level Feature-Based Results: Tables III and IV show the error rate of each method using low-level or raw feature descriptors. First, we could see that transfer learning methods achieve a much higher performance than nontransfer learning methods. In all the data sets, TrAdaBoost gets the lower error rate than AdaBoost, and DTrAdaBoost (ours) gets lower error rate than DeepAdaBoost. It shows the effectiveness of transfer learning methods compared to nontransfer learning methods with limited target-domain training data.

Second, when comparing DTrAdaBoost (ours) with other three instance transfer learning methods, in Table III, DTrAdaBoost achieves the lowest error rate on all data sets of both $H_1^{\text{stumps}}$ and $H_2^{\text{stumps}}$. In Table IV, DTrAdaBoost achieves the lowest error rate on all the settings, except for Ionosphere data set where our performance achieves the second best, which 1.5% higher error rate than Dynamic-TrAdaBoost with base hypotheses $H_2^{\text{stumps}}$. We analyze that it is mainly because the overfitting problem in the transfer scenario in Ionosphere is not serious under $H_2^{\text{stumps}}$. We could see that in three transfer learning methods TrAdaBoost, Cost-TrAdaBoost, and Dynamic-TrAdaBoost, the error rates under $H_2^{\text{stumps}}$ are all lower than $H_1^{\text{stumps}}$. Thus, the DTrAdaBoost does not show significant advantages on preventing the overfitting in this setting. Furthermore, the Dynamic-TrAdaBoost does show effective performance under Ionosphere data set.

We could also observe in Tables III and IV that $H_2^{\text{stumps}}$ does not necessarily achieve the lower error rate than $H_1^{\text{stumps}}$, which demonstrates that with fixed depth, a deeper hypothesis may perform worse than a lower hypothesis, which may be caused by overfitting. However, as DeepAdaBoost and DTrAdaBoost (ours) could adaptively adjust the depth of hypotheses while training, DeepAdaBoost achieves better performances than AdaBoost and our method achieves better performances than other three boosting-based transfer learning methods of both $H_1^{\text{stumps}}$ and $H_2^{\text{stumps}}$.

2) Deep Learning-Based Results: We also conduct experiments based on the deep learning feature descriptor. We adopt the CNN DeCAF5 features as inputs, with the representations’ dimensionality of 4096. We further compare with one typical deep transfer learning method, i.e., DAN [44] in Office+Caltech-256 and VLCSI data set [54], [55], and given in Table V and Fig. 2. Since DAN is an end-to-end deep model, we directly train on the raw images.

Table VI shows the error rate of nontransfer learning methods, AdaBoost and DeepAdaBoost, and instance-based transfer learning methods, TrAdaBoost, Cost-TrAdaBoost, and Dynamic-TrAdaBoost, using CNN feature descriptor, and deep transfer learning model DAN. First, the results show that transfer learning-based models (TrAdaBoost, Cost-TrAdaBoost, Dynamic-TrAdaBoost, DAN, and ours) achieve lower error rates than nontransfer learning-based methods (AdaBoost and DeepAdaBoost). Second, the results demonstrate that our method achieves the lowest error rate among all the instance transfer learning methods. These two observations are the same as in Tables III and IV, which are based on low-level-based feature descriptors. Third, when comparing with DAN, our method outperforms DAN over all the four scenarios, which further shows the effectiveness of our method. Fourth, when comparing results given in Tables III and V, CNN feature-based results outperform SURF based results, which show the effectiveness of applying deep learning-based features.

Fig. 2 shows the accuracy of classification results by “target only,” “DAN [44],” and “Ours.” Specifically, “target only” means we only apply labeled target-domain data to recognize the test target data. The x-axis presents the name of the target domain, and the rest four domains are combined as the source domain.
TABLE VII
ERROR RATES UNDER THE DEPTH OF DECISION TREE FROM 1 TO 5 IN OFFICE+CALTECH-256 DATA SET A,D,W→C SCENARIO USING CNN FEATURES AT THE RATIO OF 0.05

<table>
<thead>
<tr>
<th>Depth</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>0.4324</td>
<td>0.4168</td>
<td>0.4264</td>
<td>0.4278</td>
<td>0.4276</td>
</tr>
<tr>
<td>AdaBoost</td>
<td>0.3140</td>
<td>0.3140</td>
<td>0.3145</td>
<td>0.3267</td>
<td>0.3215</td>
</tr>
<tr>
<td>DeepAdaBoost</td>
<td>0.3154</td>
<td>0.3096</td>
<td>0.3075</td>
<td>0.3063</td>
<td>0.3065</td>
</tr>
<tr>
<td>TrAdaBoost</td>
<td>0.3060</td>
<td>0.3011</td>
<td>0.3068</td>
<td>0.3116</td>
<td>0.3115</td>
</tr>
<tr>
<td>Cost</td>
<td>0.3012</td>
<td>0.3012</td>
<td>0.3022</td>
<td>0.3107</td>
<td>0.3108</td>
</tr>
<tr>
<td>Dynamic</td>
<td>0.3042</td>
<td>0.3052</td>
<td>0.3050</td>
<td>0.3068</td>
<td>0.3066</td>
</tr>
<tr>
<td>Ours</td>
<td>0.2984</td>
<td>0.2832</td>
<td>0.2829</td>
<td>0.2827</td>
<td>0.2827</td>
</tr>
</tbody>
</table>

TABLE VIII
ERROR RATES UNDER THE DEPTH OF DECISION TREE FROM 1 TO 5 IN MUSHROOM DATA SET AT THE RATIO OF 0.1

<table>
<thead>
<tr>
<th>Depth</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>0.2059</td>
<td>0.0900</td>
<td>0.0423</td>
<td>0.0294</td>
<td>0.0313</td>
</tr>
<tr>
<td>AdaBoost</td>
<td>0.0071</td>
<td>0.0071</td>
<td>0.0061</td>
<td>0.0064</td>
<td>0.0064</td>
</tr>
<tr>
<td>TrAdaBoost</td>
<td>0.0091</td>
<td>0.0044</td>
<td>0.0048</td>
<td>0.0055</td>
<td>0.0070</td>
</tr>
<tr>
<td>Cost</td>
<td>0.0087</td>
<td>0.0044</td>
<td>0.0050</td>
<td>0.0057</td>
<td>0.0067</td>
</tr>
<tr>
<td>Dynamic</td>
<td>0.0076</td>
<td>0.0049</td>
<td>0.0049</td>
<td>0.0055</td>
<td>0.0063</td>
</tr>
<tr>
<td>DeepAdaBoost</td>
<td>0.0044</td>
<td>0.0041</td>
<td>0.0054</td>
<td>0.0059</td>
<td>0.0042</td>
</tr>
<tr>
<td>Ours</td>
<td>0.0072</td>
<td>0.0037</td>
<td>0.0037</td>
<td>0.0037</td>
<td>0.0034</td>
</tr>
</tbody>
</table>

We could see that the error rate of the depth-fixed methods increases when the “Depth” increases. It shows that when directly using a more complex basic learner (i.e., a deeper layer decision tree) to fit the training data, the model is easily getting overfitting. It is corresponding to our motivation to solve the overfitting problem when using a deeper decision tree in the transfer learning scenario.

However, for depth-adaptive methods (i.e., DeepAdaBoost and Ours), when the “Depth” increases, the error rate keeps decreasing, meaning facing a less serious overfitting problem. We analyze that it is because the model could penalize the complexity of the decision tree in the objective function. Thus, the actual layers of the decision tree are learned adaptively to avoid the model to be too complex and overfitting.

### Discussion of the Ratio in Transfer Learning

In this section, we discuss the impact of the ratio of number of target-domain samples to source-domain samples. We compare both nontransfer learning methods Adaboost and DeepAdaBoost, and instance transfer learning methods TrAdaBoost, Cost-TrAdaBoost, and Dynamic-TrAdaBoost with our method. Adaboost, TrAdaBoost, Cost-TrAdaBoost, Dynamic-TrAdaBoost are with base hypotheses $H_{stumps}^2$. We also conduct experiments with the ratio from 0.01 to 0.1 in Mushroom and Ionosphere data sets. Adaboost, TrAdaBoost, Cost-TrAdaBoost, Dynamic-TrAdaBoost are with $H_{stumps}^2$. Fig. 3 shows the curves of error rates under the ratio from 0.01 to 0.1 in Mushroom and Ionosphere data sets. Adaboost, TrAdaBoost, Cost-TrAdaBoost, Dynamic-TrAdaBoost are with $H_{stumps}^2$. We also conduct experiments with the ratio from
0.2 to 0.5 and we observe that there is no significant difference between transfer methods under the ratio from 0.2 to 0.5.

First, we could see that when the ratio is very small such as 0.01, all the transfer learning methods are with the lower error rates compared to nontransfer learning methods. It shows that with limited number of training data, nontransfer learning methods are failed to learn good hypotheses, which is known as the data sparsity problem.

Second, when the ratio increases, the error rates of all the methods decrease. Meanwhile, the difference of the error rate between transfer and nontransfer learning methods decreases. When the ratio is 0.1, the difference between transfer and nontransfer learning methods is very small. We also conduct experiments with the ratio from 0.2 to 0.5 and we observe that the difference between transfer methods is not significant under the ratio from 0.2 to 0.5. This phenomenon is similar as the observation in [14].

Third, in Fig. 3, we could see that under the ratio from 0.01 to 0.1, our method achieves the lowest error rate of nontransfer learning methods is very small. We also conduct when the ratio is 0.1, the difference between transfer and nontransfer learning methods is very small. We also conduct experiments with the ratio from 0.2 to 0.5 and we observe that the difference between transfer methods is not significant under the ratio from 0.2 to 0.5. This phenomenon is similar as the observation in [14].

VI. CONCLUSION

In this paper, we proposed a novel instance transfer learning method, DTrBoost. Compared with existing boosting-based transfer learning methods of complexity-fixed hypotheses, DTrBoost ensemble different complexity hypotheses families and added the complexity penalty on the hypotheses. It allocated larger weights to the hypotheses drawn from less complexity families and smaller weights to the hypotheses drawn from higher complexity families. In this way, DTrBoost could avoid overfitting when applying more complex hypotheses (e.g., deep decision tree) to deal with more complex cases such as computer vision data. In each iteration, a depth adaptive hypothesis was learned with the complexity penalty from both the source-domain and the target-domain data and then DTrBoost choose the direction with the largest gradient to optimize the objective function. We theoretically analyzed our algorithm in terms of the convergence property. Experimental results demonstrated the effectiveness of our method. In the future, we plan to extend DTrBoost to multisource and multiclass scenarios.

APPENDIX A

PROOF OF LEMMA 1 AND THEOREM 2

A. Proof of Lemma 1

Lemma 1 could be proved according to Lemma 1 in Adaboost [22] and Theorem 2 in TrAdaboost [14]. It means that after $t$ iterations ($t \geq T_0$), the normalizer of the source domain becomes a very small number. We follow [14] and set $T_0$ as $T/2$. The proof of Lemma 1 is as following.

Proof: As shown in Lemma 1 in Adaboost [22], for any sequence of loss vectors $\ell^1, \ldots, \ell^t$, in each iteration $t$, we have

$$S^d_t \leq \exp\left(-\left(1 - \gamma\right)\sum_{t=1}^{t} p^t_i \cdot \ell^t_i\right)$$

where $S^d_t$ denotes the normalizer of the source domain in the $t$th iteration. $\ell^t_i$ denotes the loss of the training instance $x_i$ in the $t$th iteration and $p^t_i$ denotes the weight of $x_i$. $\gamma$ denotes a weight updated root and $\gamma = \exp(-0.5 \times \log(1 + (2 \times \ln n/T)^{(1/2)})$, and $n$ denotes the number of source-domain data.

According to Theorem 2 in TrAdaboost [14]

$$\lim_{T \to \infty} \left(\sum_{t=[T/2]}^{T} \sum_{i=1}^{n} p^t_i \cdot \ell^t_i / (T - [T/2])\right) = 0$$

which means that after $t \geq T_0$ iteration ($T_0$ as $T/2$), $\sum_{t=1}^{T} \sum_{i=1}^{n} p^t_i \cdot \ell^t_i$ is convergent. Thus, we have $S^d_t \leq \exp\left(-(1 - \gamma) t\right)$, where $t$ is a small number and convergent after ($t \geq T_0$). To this end, we have proved the Lemma 1.

B. Proof of Theorem 2

Here, we provide the proof of Theorem 2 that, $\exists T_0$, $t \geq T_0$, $|F'_w(a_{t-1,j}, e_j) - F'_s(a_{t-1,j}, e_j)| \leq (2\epsilon^s_{t,j}) \left(S^d_t / m\right) \leq (2\epsilon^s_{t,j}) \exp\left(-(1 - \gamma) t\right) / m)$. $F'_w(a_{t-1,j}, e_j)$ and $F'_s(a_{t-1,j}, e_j)$ have been described in (7) and (9) in Section III-E. To simplify, we write $|F'_w(a_{t-1,j}, e_j) - F'_s(a_{t-1,j}, e_j)|$ as $|F'_{w} - F'_{s}|$. The proof of Theorem 2 is as.

Proof: We could easily calculate $|F'_w - F'_{s}|$ according to (7) and (9) as

$$|F'_w - F'_{s}| = \left|\frac{1}{m + n} \sum_{i=1}^{m+n} y_i h(x_i) \Phi'\left(1 - y_i f_{r-1}(x_i)\right)\right. - \left.\frac{1}{m} \sum_{i=n+1}^{m+n} y_i h(x_i) \Phi'\left(1 - y_i f_{r-1}(x_i)\right)\right|$$

$$= \left|\frac{1}{m} \left(S^w_{t,j} + S^d_t\right) - \frac{2\epsilon^s_{t,j}}{m} + \frac{(S^w_{t,j} - 1) S^s_{t,j}}{m}\right|$$

where $m$ and $n$ denote the number of target- and source-domain data, $y_i$ denotes the label of $x_i$, $S^d_t$ and $S^s_t$ denote the normalizer of target- and source-domain data, respectively. $\epsilon^w_{t,j}$ and $\epsilon^s_{t,j}$ denote the training error of target-domain data and whole data in the $r$th iteration and $j$th direction, respectively.

With the increase in iterations, the weights of the wrongly classified source-domain data are gradually decreased.
When $t \geq T_0$, we have $S_t^d e^d_{i,j} \ll S_t^e e^e_{i,j}$. Then, we have

$$e^w_{i,j} = \frac{S_t^d e^d_{i,j} + S_t^e e^e_{i,j}}{S_t^d + S_t^e} \leq \frac{S_t^e e^e_{i,j} + S_t^e e^e_{i,j}}{S_t^d + S_t^e} \leq 2e^e_{i,j}. \quad (13)$$

Thus, (14) would be written as

$$|F_{i,j}^w - F_{i,j}^e| = \left| (4e^e_{i,j} - 1) \frac{S_t^e + S_t^d}{m+n} - (2e^e_{i,j} - 1) \frac{S_t^e}{m} \right| \leq \frac{(2e^e_{i,j} - 1) S_t^e}{m+n} - \frac{(2e^e_{i,j} - 1) S_t^e}{m} + 2e^e_{i,j} \frac{S_t^d + S_t^e}{m+n}.$$  

(14)

Since $m \ll n$, $S_t^e < n$, $S_t^d < n$, and according to the Lemma 1, we have

$$|F_{i,j}^w - F_{i,j}^e| \leq \left| (2e^e_{i,j} - 1) \left( \frac{S_t^d}{m} + 2e^e_{i,j} \right) \right| \leq \frac{(2e^e_{i,j} - 1) \exp \left( -\left(1 - \frac{1}{m} \right) \right)}{m} + 2e^e_{i,j} e^e_{i,j}. \quad (15)$$

To this end, we have proved the Theorem 2.

REFERENCES


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