Fast Generalized Distillation for Semi-supervised Domain Adaptation

Abstract

Semi-supervised domain adaptation (SDA) is a typical setting when we face the problem of domain adaptation in the real applications. In this paper, we propose a new paradigm, called *Generalized Distillation Semi-supervised Domain Adaptation* (GDSDA), that uses the recently proposed framework *Generalized Distillation* (Lopez-Paz et al. 2016) to solve the SDA problem. We first demonstrate the reason why GDSDA can work for SDA problem and show that the imitation parameter can greatly affect the performance of the target model. Then to make GDSDA more practical for real applications, we propose a novel parameter estimation method, called GDSDA-SVM which uses SVM as the base classifier for GDSDA and can effectively estimate the imitation parameter. Specifically, we use mean square loss in GDSDA-SVM and show that we can effectively estimate the imitation parameter by minimizing the Leave-one-out loss of the target model on the training data. Experiment results show that our method can effectively transfer the knowledge between different domains and estimate the imitation parameter for SDA problem.

Introduction

Domain adaptation can be used in many real applications, which addresses the problem of learning a target domain with the help of a different but related source domain. Previous methods show that carefully modeling the source data to compensate for the domain shift between different domains can significantly improve the performance on the target domain (Donahue et al. 2013). In real applications, it can be very expensive to obtain sufficient labeled examples while there are abundant unlabeled examples in the target domain. *Semi-supervised domain adaptation* (SDA) tries to use some unlabeled examples as well as a few labeled ones from the target domain to compensate for the domain shift(Karl, Bidigare, and Letelier 2001). Typically, the labeled examples are too few to construct a good classifier alone. How to effectively utilize the unlabeled examples is an important issue in SDA.

Recently, a framework called *Generalized Distillation* (**GD**) (Lopez-Paz et al. 2016) was proposed, which allows the knowledge to be transferred between the teacher and student models effectively. GD can be considered as a hybrid framework of two popular paradigms, *Distillation* (Hinton, Vinyals, and Dean 2014) and *Privileged Information* (Vapnik and Izmailov 2015). In GD, the student learner tries to distill the knowledge from the teacher model trained with the privileged information, and mimick the outputs of the teacher model on the training data. Remarkably, GD can be applied in many learning scenarios such as unsupervised, semi-supervised and multitask learning (Lopez-Paz et al. 2016). Given that GD has such ability in various learning scenarios, it is natural to ask the following two questions: (1) Can GD be applied to solve the SDA problem? (2) Is there any obstacle when we apply GD to real SDA applications?

To answer these two questions, in this paper, we first propose a new paradigm, called *Generalized Distillation Semi-supervised Domain Adaptation* (**GDSDA**), and illustrate how it can solve the SDA problem. Secondly, we propose a novel algorithm GDSDA-SVM, that makes GDSDA more effective for real applications. Specifically, to answer the first question, we demonstrate that the target model trained with our GDSDA framework can effectively exploit the knowledge from the source domain and the unlabeled data of the target domain under the SDA setting. Specifically, we show that the knowledge transfer process is so effective that the target model can outperform the source model it learned from even without using any ground truth label. Different from many other paradigms which requires to access every single example of the source domain, GDSDA only requires the predicted class probabilities of the target domain examples from the source model. Therefore, GDSDA is more efficient especially when the source domain is relatively large and there is a well-trained source model.

Then we argue that the imitation parameter of GDSDA which controls the amount of knowledge transferred from the source can greatly affect the performance of the target model in prediction. However, according to previous works (Lopez-Paz et al. 2016; Tzeng et al. 2015), the imitation parameter can only be determined by either brute force search or background knowledge. It would be ideal to find a method that can determine the imitation parameter automatically, especially when there are multiple source domains and imitation parameters.

Therefore, we propose a novel imitation parameter estimation method for GDSDA, called GDSDA-SVM that uses SVM as the base classifier and can determine the imitation parameter automatically. In particular, inspired by (Cawley 2006), we use mean square loss for GDSDA-SVM and show that the Leave-one-out cross validation (LOOCV) loss can be calculated in a closed form. By minimizing the LOOCV loss on the target training data, we can find the optimal imitation parameter for the target model. In our experiments, we show that GDSDA-SVM can effectively find the optimal imitation parameter and achieve competitive performance compared to methods using brutal force search. To summarize, the main contributions of this paper include: (1) We propose the framework GDSDA for domain adaptation and show that GDSDA can be used in many real SDA problems. (2) We propose the GDSDA-SVM that can effectively find the optimal imitation parameter for GDSDA.

Related Work

As we use GD to solve SDA problem, we will introduce the related work on both GD and SDA areas.

In SDA, many works have been proposed to utilize the unlabeled data. (Yao et al. 2015) proposed a framework named Semi-supervised Domain Adaptation with Subspace Learning (SDASL) to correct data distribution mismatch and leverage unlabeled data. (Donahue et al. 2013) proposed a framework for adapting classifiers by "borrowing" the source data to the target domain using a combination of available labeled and unlabeled examples. (Daumé III, Kumar, and Saha 2010) proposed a method by augmenting the feature space to compensate the domain shift. (Duan et al. 2012) proposed a method using the unlabeled data to measure the mismatch between the domains based on the maximum mean discrepancy.

There are also many works related to GD for computer vision tasks. (Sharmanska, Quadrianto, and Lampert 2013) proposed a Rank Transfer method that uses attributes, annotator rationales, object bounding boxes, and textual descriptions as the privileged information for object recognition. (Motiian et al. 2016) proposed the information bottleneck method with privileged information (IBPI) that leverage the auxiliary information such as supplemental visual features, bounding box annotations and 3D skeleton tracking data to improve visual recognition performance. (Tzeng et al. 2015) proposed a CNN architecture for domain adaptation to leverage the knowledge from limited or no labeled data using the soft label. (Urban et al. 2016) used a small shallow net to mimick the output of a large deep net while using layerwised distillation with ℓ_2 loss of the outputs of student and teacher net. Similarly, (Luo et al. 2016) used ℓ_2 loss to train a compressed student model from the teacher model for face recognition. (Gupta, Hoffman, and Malik 2016) used supervision transfer to distill the knowledge from a trained CNN with unlabeled data or just a few labeled data.

Generalized Distillation for Semi-supervised Domain Adaptation

As we mentioned, GDSDA is a paradigm using generalized distillation for semi-supervised domain adaptation. In this section, we first give a brief review of generalized distillation. Then we show the process of GDSDA and demonstrate the reason why GDSDA can work for the SDA problem. Finally, we show the importance of the imitation parameter.

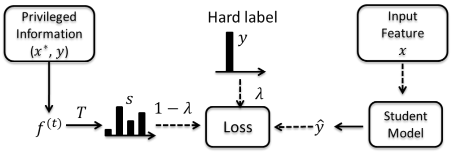


Figure 1: Illustration of Generalized Distillation training process.

An overview of Generalized Distillation and GDSDA

Distillation (Hinton, Vinyals, and Dean 2014) and *Learning Using Privileged Information* (LUPI) (Vapnik and Izmailov 2015) are two paradigms that enable machines to learn from other machines. Both methods address the problem of how to build a student model that can learn from the advanced teacher models. Recently, Lopez et al. (Lopez-Paz et al. 2016) proposed a framework called *generalized distillation* that unifies both methods and show that it can be applied in many scenarios.

In GD, the training data can be represented as a collection of the triples:

$$\{(x_1, x_1^*, y_1), (x_2, x_2^*, y_2) \ldots (x_n, x_n^*, y_n)\}$$

x^* is the privileged information for data x, which is only available in the training set and y is the corresponding label. Therefore, the goal of GD is to train a model, called student model with the guidance of the privileged information to predict the unseen example pair (x, y).

The process of generalized distillation is as follows: in step 1, a teacher model $f^{(t)}$ is trained using the input-output pairs $\{x_i^*, y_i\}_{i=1}^n$. In step 2, use $f^{(t)}$ to generate the soft label s_i for each training example x_i using the softmax function σ:

$$s_i = \sigma(f^{(t)}(x_i)/T) \tag{1}$$

where T is a parameter called temperature to control the smoothness of the soft label. In step 3, learn the student $f^{(s)}$ from the pairs $\{(x_i, y_i), (x_i, s_i)\}_{i=1}^n$ using:

$$\begin{aligned} f^{(s)} = & \underset{f^{(s)} \in \mathcal{F}^{(s)}}{\arg\min} \frac{1}{n} \sum_{i=1}^{n} \Big[\lambda \ell \left(y_i, \sigma(f^{(s)}(x_i)) \right) \\ & + (1-\lambda) \ell \left(s_i, \sigma(f^{(s)}(x_i)) \right) \Big] \end{aligned} \tag{2}$$

Here, $\ell(\cdot, \cdot)$ is the loss function and λ is the imitation parameter to balance the importance between the hard label y_i and the soft label s_i.

GD can be used in many scenarios such as multi-task learning, semi-supervised learning, and reinforcement learning. As generalized distillation only requires the training inputs $\{x_i, y_i\}_{i=1}^n$ and the output s_i from the teacher function $f^{(t)}$, it can be naturally applied to SDA. This leads to

Generalized Distillation Semi-supervised Domain Adaptation (**GDSDA**), where the source model can be used as the teacher to output the soft labels and the student model is the target model. To be consistent with other works in domain adaptation, we use source model and target model to denote the teacher model and the student model in the rest of our paper.

An important issue of applying GD to SDA is that, in Eq. (2), each example is assigned with a hard label y (true label) and a soft label s (class probabilities from the teacher). However, in SDA, we are not able to obtain the hard labels of the unlabeled data. Here we follow the GD work(Lopez-Paz et al. 2016) and use the "fake label" strategy to label the unlabeled data: for the labeled examples, we use *one-hot* strategy to encode their labels while using the *gray code* (all 0s) as the label of the unlabeled examples. Thus, each example in the target domain is assigned with a label. It is arguable that the "fake label" strategy would introduce extra noise and degrade the performance. However, we will show in our experiment that this noise can be well controlled by setting a proper value to the imitation parameter and we can still achieve improved performance (See the single source experiment).

Suppose we have $M-1$ source domains denoted as $D_s^{(j)} = \{X^{(j)}, Y^{(j)}\}_{j=1}^{M-1}$ and the target domain $D_t = \{X, Y\}$ encoded with the "fake label" strategy. Similar to GD, the process of GDSDA is as follows:

1. Train the source models f_j^* for each of the $M-1$ domain with $\{X^{(j)}, Y^{(j)}\}$.
2. For each of the training example x_i in the target domain, computer the corresponding soft label y_{ij}^* with each of the source model f_j^* and the temperature $T > 0$.
3. Learn the target model f_t using the $(M+1)$-tuples $\{x_i, y_i, y_{i1}^*, \ldots, y_{i(M-1)}^*\}_{i=1}^{L}$ with the imitation parameters $\{\lambda_i\}_{i=1}^{M}$ using (3):

$$\begin{aligned} f_t(\lambda) =& \arg\min_{f_t \in \mathcal{F}} \frac{1}{L} \sum_{i=1}^{L} \Bigg[\lambda_1 \ell\left(y_i, f_t(x_i)\right) + \\ & \sum_{j=1}^{M-1} \lambda_{j+1} \ell\left(y_{ij}^*, f_t(x_i)\right) \Bigg] \qquad \text{s.t.} \qquad \sum_i \lambda_i = 1 \end{aligned} \tag{3}$$

Compared to other works of SDA which require to use each example of the source domain, by either re-weighting (Donahue et al. 2013; Duan et al. 2012) or augmentation (Daumé III, Kumar, and Saha 2010), GDSDA only requires the trained model from the source domain to generate the soft labels. Considering the fact that it is more convenient to access the source model than each of the examples of the source domain, GDSDA can be more useful than those previous methods. For example, if we want to use ImageNet (Deng et al. 2009) as the source domain, it is almost impossible to access each of the millions of the examples while there are many well trained models publicly available online that can be used for GDSDA. Also, GDSDA is able to handle the multi-class scenario while some previous works, such as SHFA(Duan, Xu, and Tsang 2012) can only solve the binary classification problem in SSDA. Moreover, GDSDA is compatible with any type of source model that is able to output the soft label (i.e. class probabilities).

Why does GDSDA work

In this part, we provide demonstrate the scenarios where GDSDA would work. Before we provide our analysis, we first introduce the two basic assumptions for GDSDA to work well in domain adaptation: the *assumption of distillation and the assumption of the source model.*

Assumption of Distillation: The capacity (or VC dimension) of the target model f_t is smaller than the capacity of source model f^*. This assumption is inherited from distillation. **Assumption of the source model:** The source model f^* should work better than a target model f_t' trained only with the hard labels. For example, when we only have a single labeled example for each class in the target training set, it is reasonable to assume that the source model trained from another domain could perform better than any model trained only with the target training data on the target task. Based on this two assumptions, we will show that GDSDA can effectively leverage the source model and transfer the knowledge between different domains under the SDA setting.

According to ERM principle(Vapnik 1999), the simple model has better generalization ability than the complex one if they both have the same training error. As long as the target model f_t can achieve similar training error to the training error of the source model f^* on the target domain, considering the fact that the VC dimension of f_t is smaller than f^*, we can expect that the target model has better generalization ability. This process can be achieved by letting the target model mimick the output of the source model on the training data.

It is worthy to notice that in this process, the target model only has to mimick the output of the source model (soft label) without considering the hard labels of the examples. In another word, GDSDA provide an effective way to utilize the unlabeled data.

Arguably, because of the domain shift, the source model is biased towards the source domain when applying on the target task. However, as it is suggested in (Hinton, Vinyals, and Dean 2014), we can use a few labeled data from the target domain to compensate for the domain shift and achieve a better performance on the target task with Eq. (3). Specifically, we use the imitation parameter λ to control the relative importance of the soft label from the source model and the hard label, which in turn reflects the similarity between the source and target tasks. For example, in Figure **??**, when we set $\lambda_2 = 0$, we actually ignore the knowledge from source domain 1. As a result, GDSDA can compensate for the domain shift under the setting of SDA (for more details, please see the experiment section).

Key parameter: the imitation parameter

From above we can see that GDSDA can effectively transfer the knowledge between source and target domains. In this part, we demonstrate that the imitation parameter can greatly affect the performance of the target model.

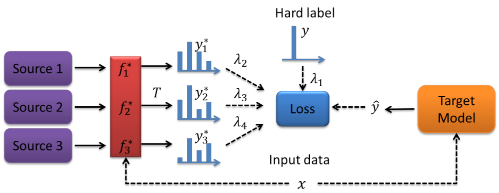


Figure 2: Illustration of GDSDA training process.

In GDSDA, we have to decide the values of 2 parameters, the temperature T and the imitation parameter λ. The temperature T controls the smoothness of the soft label and the imitation parameter λ controls how much knowledge can be transferred from the source model. Many previous works have addressed the importance of knowledge control in domain adaptation (Duan, Xu, and Tsang 2012; Duan et al. 2012). Without carefully controlling the amount of knowledge transferred from the source domain, it is easy for the target model to get degraded performance or even suffer from negative transfer (Pan and Yang 2010). How to choose the imitation parameter is essential for GDSDA. In the previous works, the imitation parameter can only be determined by either brute force search (Lopez-Paz et al. 2016) or background knowledge (Tzeng et al. 2015). On the other hand, in real applications, it is common that there could be multiple source domains to be exploited. As it is suggested in (Tommasi, Orabona, and Caputo 2014), learning from multiple related sources simultaneously can significantly improve the performance of the target model. However, these previous works become more difficult to apply when there are multiple sources and imitation parameters to be determined. For these reasons, it is ideal to find a method that can determine the imitation parameter automatically.

GDSDA-SVM

As we mentioned, it is important to find a method that can determine the imitation parameter effectively. In this section, we propose our method GDSDA-SVM that uses SVM as the base classifier and can effectively estimate the imitation parameter by minimizing the training error on the target domain.

Distillation with multiple sources

As it is suggested in (Vapnik and Izmailov 2015), the optimal imitation parameter should be the one that can minimize the training error on the target domain. Based on that, we propose our method GDSDA-SVM that can estimate the imitation parameter effectively.

In our GDSDA-SVM, instead of using hinge loss, we use Mean Squared Error (MSE) as our loss function for the following two reasons: (1) Several recently works (Ba and Caruana 2014; Luo et al. 2016; Romero et al. 2015; Urban et al. 2016) show that MSE is also an efficient measurement for the target model to mimick the behavior of the source model. (2) MSE can provide a closed form cross-validation error estimation. Thus we can effectively estimate the imitation parameter.

Suppose we have L examples $\{\mathbf{x}_j, \mathbf{y}_j\}_{j=1}^{L}$ from and N classes in the target domain where $X \in R^{L\times d}, Y \in R^{L\times N}$. Meanwhile, there are $M-1$ the source (teacher) models providing the soft labels $Y^* = \{\mathbf{y}^*_{ij} | j = 1, ..., L; i = 1, ..., M-1\}$ for each of the L examples. For simplicity, we combine the hard label Y and soft label Y^* and use new label matrix: $S \in R^{M\times L\times N}$ to denote them. To solve this N-class classification problem, we adopt the One-vs-All strategy to build N binary SVMs. To obtain the nth binary SVM, we have to solve the following optimization problem:

$$\begin{aligned} \min \quad & \frac{1}{2}||\mathbf{w}_n||^2 + C\sum_{i,j}\lambda_i e^2_{ijn} \\ s.t. \quad & e_{ijn} = s_{ijn} - \mathbf{w}_n\mathbf{x}_j \\ & \sum_i \lambda_i = 1; \lambda_i \in [0,1]; i \in M; j \in L \end{aligned} \tag{4}$$

To solve this optimization problem, we use KKT theorem (Cristianini and Shawe-Taylor 2000) and add the dual sets of variables to the Lagrangian of the optimization problem:

$$\begin{aligned} \mathcal{L} =& \frac{1}{2}||\mathbf{w}_n||^2 + C\sum_{i,j}\lambda_i e^2_{ijn} + \sum_{i,j}\alpha^{(n)}_{ij}\left(s_{ij} - \mathbf{w}_n\mathbf{x}_j - e_{ij}\right) \\ & + \beta^{(n)}\left(\sum_i \lambda_i - 1\right) \end{aligned} \tag{5}$$

To find the saddle point,

$$\begin{aligned} \frac{\partial L}{\partial \mathbf{w}_n} &= \mathbf{w}_n - \sum_j \alpha^{(n)}_{ij}\mathbf{x}_j = 0 \rightarrow \mathbf{w}_n = \sum_j \alpha^{(n)}_{ij}\mathbf{x}_j \\ \frac{\partial L}{\partial e_{ijn}} &= 2C\lambda_i e_{ijn} - \alpha^{(n)}_{ij} = 0 \rightarrow \alpha^{(n)}_{ij} = 2C\lambda_i e_{ijn} \end{aligned} \tag{6}$$

For each example $\mathbf{x}_j$ and its constraint of label s_{ijn}, we have $e_{ijn} + \mathbf{w}_n\mathbf{x}_j = s_{ijn}$. Replacing $\mathbf{w}_n$ and e_{ijn}, we have:

$$\lambda_i\mathbf{x}_j\sum_k \alpha^{(n)}_{ik}\mathbf{x}_k + \frac{\alpha^{(n)}_{ij}}{2C} = \lambda_i s_{ijn} \tag{7}$$

Summing over each constraint of example x_j, we have:

$$\underbrace{\sum_i \lambda_i}_{=1}\mathbf{x}_j\sum_k \alpha^{(n)}_{ik}\mathbf{x}_k + \sum_i \frac{\alpha^{(n)}_{ij}}{2C} = \sum_i \lambda_i s_{ijn} \tag{8}$$

Let $\eta_{jn} = \sum_i \alpha^{(n)}_{ij}$, we have:

$$\sum_j \eta_{jn}\mathbf{x}_j x_i + \frac{\eta_{in}}{2C} = \sum_i \lambda_i s_{ijn} \tag{9}$$

This implies that solving the optimization problem (4) is equivalent to solve a standard LS-SVM (Suykens and Vandewalle 1999) whose the target is the weighted sum of each label $\sum_i \lambda_i s_{ijn}$.

Here we use Ω to denote the matrix $\Omega = [K + \frac{\mathbf{I}}{2C}]$ where K is the kernel matrix $K = \{\mathbf{x}_i\mathbf{x}_j | i, j \in 1 \ldots L\}$. To simplify our notation, let $\eta'_n = M^{-1}S_n$ where S_n is the matrix

$S_n = \{s_{ijn}|i \in M; j \in L\}$ and Ω^{-1} is the inverse of matrix Ω.

Let $\eta_{jn} = \sum_i \lambda_i \eta'_{ijn}$. The Leave-one-out estimation of the example $\mathbf{x}_j$ for the nth binary SVM can be written as (Cawley 2006):

$$\sum_i \lambda_i s_{ijn} - \hat{y}_{jn} = \frac{\eta_{jn}}{\Omega^{-1}_{jj}} = \frac{\sum_i \lambda_i \eta'_{ijn}}{\Omega^{-1}_{jj}}$$

$$\hat{y}_{jn} = \sum_i \lambda_i \left(s_{ijn} - \frac{\eta'_{ijn}}{\Omega^{-1}_{jj}} \right) \tag{10}$$

where Ω^{-1}_{jj} is the jth diagonal element of Ω^{-1}. Now for any given λ, we have found an efficient way to estimate the LOO of each binary target model for example $\mathbf{x}_j$. In the following part, we will introduce how to find the optimal λ_i for each of the source models.

Cross-entropy loss for imitation parameter estimation

From the previous part, we have already found a effective way to estimate the output of the SVM. The optimal imitation parameters, can be found by solving the following optimization problem:

$$\begin{aligned} \min \quad & L_c(\lambda) = \frac{1}{2}\sum_i^M ||\lambda_i||^2 + \frac{1}{L}\sum_{j,n} \ell\left(y_{in}, \hat{y}_{jn}(\lambda)\right) \\ s.t. \quad & \sum \lambda_i = 1 \end{aligned} \tag{11}$$

Here we use the ℓ-2 regularization term to control the complexity of λs so that the target model can achieve better generalization performance. For the loss function $\ell(\cdot,\cdot)$, We use the cross-entropy loss function.

$$\begin{aligned} \ell\left(y_{in}, \hat{y}_{jn}(\lambda)\right) =& y_{in}\log(P_{jn}) \\ P_{jn} =& \frac{e^{\hat{y}_{jn}}}{\sum_h e^{\hat{y}_{jh}}} \end{aligned} \tag{12}$$

Cross-entropy pays less attention to a single incorrect prediction which reduces the affect of the outliers in the training data. Moreover, cross-entropy works better for the unlabeled data with our ”fake label” strategy. As we mentioned in our ”fake label” strategy, we use one-hot strategy to encode the hard labels of the labeled examples while encoding the unlabeled examples with gray code. When we use cross-entropy, it can automatically ignore penalties of the unlabeled examples and reduce the noise introduced by our ”fake label” strategy. Let:

$$\mu_{ijn} = s_{ijn} - \frac{\eta'_{ijn}}{\Omega^{-1}_{jj}} \tag{13}$$

The derivative can be written as:

$$\frac{\partial \ell(\lambda)}{\partial \lambda_i} = \sum_n \mu_{ijn}\left(P_{jn} - y_{jn}\right) \tag{14}$$

To summarize, we describe GDSDA-SVM in Algorithm 1. As the optimization problem (11) is strongly convex, it is easy to prove that Algorithm 2 can converge to the optimal λ with the rate of $O(\log(t)/t)$ where t is the optimization iteration (The proof is shown in Supplemental Material).

Algorithm 1 GDSDA-SVM

```
Input: Input examples $X = \{\mathbf{x}_1, ..., \mathbf{x}_L\}$, number of
    classes $N$, number of sources $M$, 3D label matrix, $S =$
    $[Y_1, Y_2, ..., Y_M]$ with size $L \times M \times N$, temperature $T$
Output: Target model $f_t = Wx$
    Compute $\Omega = [K + \frac{\mathbf{I}}{2C}]$
    Compute imitation parameter $\lambda$ with Algorithm 2
    Compute new label $Y_{new} = \sum_i \lambda_i Y_i$
    Compute $\eta = \Omega^{-1} Y_{new}$
    Compute $w_n = \sum_j \eta_{jn} x_j$
```

Algorithm 2 λ Optimization

```
Input: Input examples $X$, number of classes $N$, size of
    sources $M$, 3D label matrix $S$, temperature $T$, optimization
    iteration $iter$, Kernel matrix $\Omega$
Output: Imitation parameter $\lambda$
    Initialize $\lambda = \frac{1}{M}$,
    Let $S_n$ be the label matrix of $S$ for class $n$
    for Each label $S_n$ do
        Compute $\eta'_n = \Omega^{-1} S_n$
    end for
    Compute $\mu$ using (13)
    for $it \in \{1, ..., iter\}$ do
        Compute $\hat{y}_{jn}$ and $P_{jn}$ with (10) and (12)
        $\Delta_\lambda \leftarrow 0$
        for each $\mathbf{x}_j$ in $X$ do
            $\Delta_\lambda = \Delta_\lambda + \sum_n \mu_{ijn}(P_{jn} - y_{jn})$
        end for
        $\Delta_\lambda = \Delta_\lambda / L$, $\lambda = \lambda - \frac{1}{it}(\Delta_\lambda + \lambda)$
        $\lambda = \lambda / \sum \lambda_i$
    end for
```

Experiments

In this section, we demonstrate the empirical performance of our algorithm GDSDA-SVM on the benchmark dataset Office. Specifically, we provide two different settings: single source and multi-source transfer scenarios for GDSDA-SVM.

Dataset: There are 3 subsets in Office datasets, Webcam (795 examples), Amazon (2817 examples) and DSLR (498 examples), sharing 31 classes. In our experiments, we use DSLR and Webcam as the source domain and Amazon as the target domain. We use the features extracted from Alexnet (Krizhevsky, Sutskever, and Hinton 2012) FC7 as the input features for both source and target domain. The source models are trained with multi-layer perception (MLP) on the whole source dataset.

Single Source for Office datasets

In this experiment, we compare our algorithm under the setting where there is just one source model. Specifically, we perform two groups of experiment using Amazon dataset as the target domain and DSLR and Webcam datasets as the source domains respectively. As we mentioned, there are significantly fewer labeled examples than unlabeled ones in real SDA applications. Therefore, in each group of experiment, we just use 1 labeled example per class with 3 different sizes of unlabeled example (10, 15 and 20 per class).

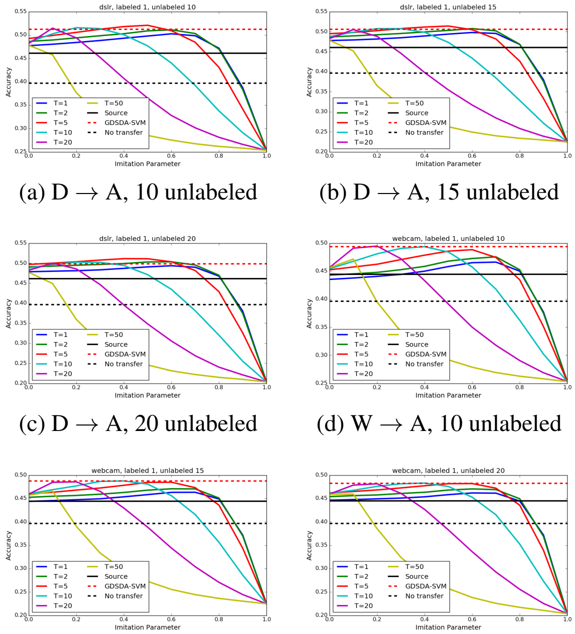
To show the effectiveness of GDSDA-SVM, we show the performance of GDSDA using brute force to search the imitation parameter λ in the range $[0, 0.1, ..., 1]$ with different temperature T as the baselines. Meanwhile, we show the performance of the source model on the target task, denoted as "Source" and the performance of a target model (using LIBLINEAR(Fan et al. 2008)) trained with only labeled examples in the target domain denoted as "No transfer". To avoid the randomness, we perform each experiment 10 times and report the average result. For GDSDA-SVM, we use temperature $T = 20$ for all experiments in this part. The experimental results are shown in Figure 3.

From the results of brutal force search, it is clear that the value of imitation parameter can greatly affect the performance of the target model. Also, we can see that, when we only use the unlabeled data for distillation, i.e. $\lambda = 0$, as we expected, GDSDA can still slightly outperform the source model. This means GDSDA can effectively transfer the knowledge between different domains even merely with the unlabeled data. As we increase the value of imitation parameter, i.e. introducing the hard labels from the target domain, the performance of GDSDA can be further improved. As we mentioned before, even though our "fake label" strategy would introduce extra noise, the noise can be limited by setting the proper value to imitation parameter and the target model can still get improved performance compared to the baselines. More importantly, we can see that GDSDA-SVM can achieve the competitive results compared to baselines using brutal force search in D→A experiments. In W→A experiments, it achieves the best performance among all methods. This indicates that we can effectively (about 6 times faster than brutal force search) obtain a good target model with our imitation parameter estimation method.

Multi-Source for Office datasets

In this experiment, we train the target model for the Amazon dataset and adapt the knowledge from the rest of two source domains, Webcam and DSLR. We use the similar settings as our single source experiment and perform 2 groups of experiments using 1 labeled and 2 labeled examples per class respectively. We use temperature $T = 5$ and the results of multi-source GDSDA-SVM are denoted as SVM_Multi. Here we use two single source GDSDA-SVMs (SVM_w and SVM_d trained with Webcam and DSLR respectively) as the baselines. We also show the best performance of the brutal force search model (SVM_BF). We search temperature in range $T = [1, 2, 5, 10, 20, 50]$ and each imitation parameter in range $[0, 0.1, ..., 1]$, making sure that their sum equals to 1. The experiment results are shown in Figure 4.

From the results, we can see that, when we have 2 source domains, SVM_Multi can still leverage the knowledge effectively and outperform any single source model trained with GDSDA. This shows that the imitation parameter estimated by our method can effectively balance the importance of each source to achieve improved performance. SVM_Multi performs slightly worse than the best result found by brutal force search in some experiments. However, considering their time complexity (GDSDA-SVM is around 30 times faster than brutal force search), SVM_Multi still has its advantage in real applications.



(a) D → A, 10 unlabeled (b) D → A, 15 unlabeled

(c) D → A, 20 unlabeled (d) W → A, 10 unlabeled

(e) W → A, 15 unlabeled (f) W → A, 20 unlabeled

Figure 3: Experiment results on DSLR→Amazon and Webcam→Amazon when there are just a few labeled examples. The experiments use only 1 labeled example per class. The results of DSLR→Amazon and Webcam→Amazon are shown in figure (a)-(c) and (d)-(e) respectively. GDSDA-SVM is trained with temperature $T = 20$. λ on the X-axis denotes the imitation parameter for the hard label and the corresponding imitation parameter for the soft label is set to $1 - \lambda$.

Conclusion

In this paper, we propose a framework called *Generalized Distillation Semi-supervised Domain Adaptation* (GDSDA) that can effectively leverage the knowledge from the source domain for SDA problem. To make GDSDA more effective in real applications, we proposed a method called GDSDA-SVM and show that GDSDA-SVM can effectively determine the imitation parameter for GDSDA.

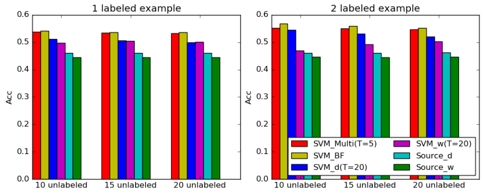


Figure 4: D+W→A, Multi-source results comparison.

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