Domain Transfer Multiple Kernel Learning

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Abstract—Cross-domain learning methods have shown promising results by leveraging labeled patterns from the auxiliary domain to learn a robust classifier for the target domain which has only a limited number of labeled samples. To cope with the considerable change between feature distributions of different domains, we propose a new cross-domain kernel learning framework into which many existing kernel methods can be readily incorporated. Our framework, referred to as Domain Transfer Multiple Kernel Learning (DTMKL), simultaneously learns a kernel function and a robust classifier by minimizing both the structural risk functional and the distribution mismatch between the labeled and unlabeled samples from the auxiliary and target domains. Under the DTMKL framework, we also propose two novel methods by using SVM and prelearned classifiers, respectively. Comprehensive experiments on three domain adaptation data sets (i.e., TRECVID, 20 Newsgroups, and email spam data sets) demonstrate that DTMKL-based methods outperform existing cross-domain learning and multiple kernel learning methods.

Index Terms—Cross-domain learning, domain adaptation, transfer learning, support vector machine, multiple kernel learning.

1 Introduction

The conventional machine learning methods usually assume that the training and test data are drawn from the same data distribution. In many applications, it is expensive and time consuming to collect labeled training samples. Meanwhile, classifiers trained with only a limited number of labeled patterns are usually not robust for pattern recognition tasks. Recently, there has been increasing research interest in developing new transfer learning (or cross-domain learning/domain adaptation) methods which can learn robust classifiers with only a limited number of labeled patterns from the target domain by leveraging a large amount of labeled training data from other domains (referred to as auxiliary/source domains). In practice, cross-domain learning methods have been successfully used in many real-world applications, such as sentiment classification [2], natural language processing [11], text categorization [9], [21], information extraction [9], WiFi localization [21], and visual concept classification [16], [17], [36].

Recall that the feature distributions of training samples from different domains change tremendously, and the training samples from multiple sources also have very different statistical properties (such as mean, intraclass, and interclass variance). Though a large number of training data are available in the auxiliary domain, the classifiers trained from those data or the combined data from both the auxiliary and target domains may perform poorly on the test data from the target domain [16], [36].

To take advantage of all labeled patterns from both auxiliary and target domains, Daumé III [11] proposed a so-called Feature Replication (FR) method to augment features for cross-domain learning. The augmented features are then used to construct a kernel function for Support Vector Machine (SVM) training. Yang et al. [36] proposed Adaptive SVM (A-SVM) for visual concept classification, in which the new SVM classifier $f^T(\mathbf{x})$ is adapted from an existing classifier $f^A(\mathbf{x})$ (referred to as auxiliary classifier) trained from the auxiliary domain. Cross-domain SVM (CD-SVM) proposed by Jiang et al. [16] used k-nearest neighbors from the target domain to define a weight for each auxiliary pattern, and then the SVM classifier was trained with the reweighted auxiliary patterns. More recently, Jiang et al. [17] proposed mining the relationship among different visual concepts for video concept detection. They first built a semantic graph and the graph can then be adapted in an online fashion to fit the new knowledge mined from the test data. However, all these methods [11], [16], [17], [31], [36] did not utilize unlabeled patterns from the target domain. Such unlabeled patterns can also be used to improve the classification performance [3], [37].

When there are only a few or even no labeled patterns available in the target domain, the auxiliary patterns or the unlabeled target patterns can be used to train the target classifier. Several cross-domain learning methods [15], [29] were proposed to cope with the inconsistency of data distributions (such as covariate shift [29] or sampling selection bias [15]). These methods reweighted the training samples from the auxiliary domain by using unlabeled data from the target domain such that the statistics of samples from both domains are matched. Very recently, Bruzzone and Marconcini [6] proposed Domain Adaptation Support Vector Machine (DASVM), which extended Transductive SVM (T-SVM) to label unlabeled target patterns progressively and simultaneously remove some auxiliary labeled patterns. Interested readers may refer to [22] for the more complete survey of cross-domain learning methods.

The common observation is that most of these cross-domain learning methods are either variants of SVM or in tandem with SVM or other kernel methods. The prediction performances of these kernel methods heavily depend on the choice of the kernel. To obtain the optimal kernel,

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Lanckriet et al. [18] proposed to learn a nonparametric kernel matrix by solving an expensive semidefinite programming (SDP) problem. However, the time complexity is $O(n^{6.5})$, which is computationally prohibitive for many real-world applications. Instead of directly learning the kernel matrix, many efficient Multiple Kernel Learning (MKL) methods [1], [18], [28], [24] have been proposed to learn the kernel function in which the kernel function is assumed to be a linear combination of multiple predefined kernel functions (referred to as base kernel functions). And these methods simultaneously learn the decision function as well as the kernel. In practice, MKL has been successfully employed in many computer vision applications, such as action recognition [30], [32], object detection [33], and so on. However, these methods commonly assume that both training data and test data are drawn from the same domain. As a result, MKL methods cannot learn the optimal kernel with the combined data from the auxiliary and target domains for the cross-domain problem. Therefore, the training data from the auxiliary domain may degrade the performance of MKL algorithms in the target domain.

In this paper, we propose a unified cross-domain kernel learning framework, referred to as Domain Transfer Multiple Kernel Learning (DTMKL), for several challenging domain adaptation tasks. The main contributions of this paper include:

- To deal with the considerable change between feature distributions of different domains, DTMKL minimizes the structural risk functional and Maximum Mean Discrepancy (MMD) [4], a criterion to evaluate the distribution mismatch between the auxiliary and target domains. In practice, DTMKL provides a unified framework to simultaneously learn an optimal kernel function as well as a robust classifier.
- Many existing kernel methods, including SVM, Support Vector Regression (SVR), Kernel Regularized Least Squares (KRLS), and so on, can be incorporated into the framework of DTMKL to tackle cross-domain learning problems. Moreover, we propose a reduced gradient descent procedure to efficiently and effectively learn the linear combination coefficients of multiple base kernels as well as the target classifier.
- Under the DTMKL framework, we propose two methods on the basis of SVM and prelearned classifiers, respectively. The first method, *DTMKL_AT*, directly utilizes the training data from the auxiliary and target domain. The second method, *DTMKL_f*, makes use of the labeled target training data as well as the decision values from the existing base classifiers on the unlabeled data from the target domain. And, these base classifiers can be prelearned by using any method (e.g., SVM and SVR).
- To the best of our knowledge, DTMKL is the first semi-supervised cross-domain kernel learning framework for the single auxiliary domain problem which can incorporate many existing kernel methods. In contrast to the traditional kernel learning methods, DTMKL does not assume that the training and test data are drawn from the same domain.
- Comprehensive experiments on TRECVID, 20 Newsgroups, and email spam data sets demonstrate the effectiveness of the DTMKL framework in real-world applications.

The rest of the paper is organized as follows: We briefly review the related work in Section 2. We then introduce our framework Domain Transfer Multiple Kernel Learning in Section 3. In particular, we present two methods DTMKL_AT and DTMKL_*f* to tackle the single auxiliary domain problem by using SVM and prelearned classifiers, respectively. We experimentally compare the two proposed methods with other SVM-based cross-domain learning methods on the TRECVID data set for video concept detection, as well as on the 20 Newsgroups and email spam data sets for text classification in Section 4. Finally, conclusive remarks are presented in Section 5.

2 Brief Review of Related Work

Let us denote the data set of labeled and unlabeled patterns from the target domain as $D_l^T = (\mathbf{x}_i^T, y_i^T)|_{i=1}^{n_l}$ and $D_u^T = \mathbf{x}_i^T|_{i=n_l+1}^{n_l+n_u}$, respectively, where y_i^T is the label of $\mathbf{x}_i^T$. We also define $D^T = D_l^T \cup D_u^T$ as the data set from the target domain with the size $n_T = n_l + n_u$ under the marginal data distribution $\mathcal{P}$, and $D^A = (\mathbf{x}_i^A, y_i^A)|_{i=1}^{n_A}$ as the data set from the auxiliary domain under the marginal data distribution $\mathcal{Q}$. Let us also represent the labeled training data set as $D = (\mathbf{x}_i, y_i)|_{i=1}^{n}$, where n is the total number of labeled patterns. The labeled training data can be from the target domain (i.e., $D = D_l^T$) or from both domains (i.e., $D = D_l^T \cup D^A$).

In this work, the transpose of vector/matrix is denoted by the superscript $'$ and the trace of a matrix $\mathbf{A}$ is represented as $\mathrm{tr}(\mathbf{A})$. Let us also define $\mathbf{I}_n$ as the n-by-n identity matrix. $\mathbf{0}_n$ and $\mathbf{1}_n$ are n-by-1 vectors of all zeros and ones, respectively. The inequality $\mathbf{u} = [u_1, \ldots, u_n]' \geq \mathbf{0}_n$ means that $u_i \geq 0$ for $i = 1, \ldots, n$. And the element-wise product between vectors $\mathbf{u}$ and $\mathbf{v}$ is represented as $\mathbf{u} \circ \mathbf{v} = [u_1 v_1, \ldots, u_n v_n]'$. $\mathbf{A} \succ \mathbf{0}$ means that the matrix $\mathbf{A}$ is symmetric and positive definite (pd).

In the following sections, we will briefly review two major paradigms of cross-domain learning. The first is to directly learn the decision function for the target domain (also known as *target classifier*) based on the labeled data from the target domain or two domains by minimizing the mismatch of data distribution between two domains. The second is to make use of the existing *auxiliary classifiers* trained based on the auxiliary domain patterns for cross-domain learning.

2.1 Reducing Mismatch of Data Distribution

In cross-domain learning, it is crucial to reduce the difference between the data distributions of the auxiliary and target domains. Many parametric criteria (e.g., Kullback-Leibler (KL) divergence) have been used to measure the distance between data distributions. However, an intermediate density estimate process is usually required. To avoid such a nontrivial task, Borgwardt et al. [4] proposed an effective nonparametric criterion, referred to as Maximum Mean Discrepancy, to compare data distributions based on the distance between the means of samples from two domains in a kernel k induced Reproducing Kernel Hilbert Space (RKHS) $\mathcal{H}$, namely,

$$\begin{aligned}\mathrm{DIST}_k(D^A, D^T) &= \sup_{\|f\|_{\mathcal{H}}\leq 1}\left(\mathrm{E}_{\mathbf{x}^A\sim\mathcal{Q}}[f(\mathbf{x}^A)] - \mathrm{E}_{\mathbf{x}^T\sim\mathcal{P}}[f(\mathbf{x}^T)]\right)\\ &= \sup_{\|f\|_{\mathcal{H}}\leq 1}\left\langle f, \left(\mathrm{E}_{\mathbf{x}^A\sim\mathcal{Q}}[\phi(\mathbf{x}^A)] - \mathrm{E}_{\mathbf{x}^T\sim\mathcal{P}}[\phi(\mathbf{x}^T)]\right)\right\rangle_{\mathcal{H}}\\ &= \left\|\mathrm{E}_{\mathbf{x}^A\sim\mathcal{Q}}[\phi(\mathbf{x}^A)] - \mathrm{E}_{\mathbf{x}^T\sim\mathcal{P}}[\phi(\mathbf{x}^T)]\right\|_{\mathcal{H}},\end{aligned} \tag{1}$$

where $\mathrm{E}_{\mathbf{x}\sim\mathcal{U}}[\cdot]$ denotes the expectation operator under the data distribution $\mathcal{U}$ and $f(\mathbf{x})$ is any function in $\mathcal{H}$. The second equality holds as $f(\mathbf{x}) = \langle f, \phi(\mathbf{x})\rangle_{\mathcal{H}}$ by the property of RKHS [25], where $\phi(\cdot)$ is the nonlinear feature mapping of the kernel k. Note that the inner product of $\phi(\mathbf{x}_i)$ and $\phi(\mathbf{x}_j)$ equals to the kernel function k (or $k(\cdot,\cdot)$) on $\mathbf{x}_i$ and $\mathbf{x}_j$, namely, $k(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)'\phi(\mathbf{x}_j)$. Asymptotically, the empirical measure of MMD in (1) can be well estimated by

$$\mathrm{DIST}_k(D^A, D^T) = \left\|\frac{1}{n_A}\sum_{i=1}^{n_A}\phi\left(\mathbf{x}_i^A\right) - \frac{1}{n_T}\sum_{i=1}^{n_T}\phi\left(\mathbf{x}_i^T\right)\right\|_{\mathcal{H}}. \tag{2}$$

To capture higher order statistics of the data (e.g., higher order moments of probability distribution), the samples in (2) are transformed into a higher dimensional or even infinite dimensional space through the nonlinear feature mapping $\phi(\cdot)$. When $\mathrm{DIST}_k(D^A, D^T)$ is close to zero, the higher order moments of the data from the two domains become matched, and so their data distributions are also close to each other [4]. The MMD criterion was successfully used to integrate biological data from multiple sources in [4].

Due to the change of data distributions from different domains, training with samples only from the auxiliary domain may degrade the classification performance in the target domain. To reduce the mismatch between two different domains, Huang et al. [15] proposed a two-step approach called Kernel Mean Matching (KMM). The first step is to diminish the mismatch between means of samples in RKHS from the two domains by reweighting the samples $\phi(\mathbf{x}_i)$ in the auxiliary domain as $\beta_i\phi(\mathbf{x}_i)$, where β_i is learned by using the square of the MMD criterion in (2). Then, the second step is to learn a decision function $f(\mathbf{x}) = \mathbf{w}'\phi(\mathbf{x}) + b$ that separates patterns from two opposite classes in D using the loss function reweighted by β_i.

Recently, Pan et al. [21] proposed an unsupervised kernel learning method, referred to as Maximum Mean Discrepancy Embedding (MMDE), by minimizing the square of the MMD criterion in (2) as well, and then applied the learned kernel matrix to train an SVM classifier for WiFi localization and text categorization.

2.2 Learning from Existing Auxiliary Classifiers

Instead of learning the target classifier directly from the labeled data in both auxiliary and target domains, some researchers make use of the prelearned classifiers trained from the auxiliary domain to learn the target classifier. Yang et al. [36] proposed Adaptive SVM, in which a new SVM classifier $f^T(\mathbf{x})$ is adapted from an existing auxiliary classifier $f^A(\mathbf{x})$ trained with the patterns from the auxiliary domain.[1] Specifically, the new decision function is formulated as $f^T(\mathbf{x}) = f^A(\mathbf{x}) + \Delta f(\mathbf{x})$, where the perturbation function $\Delta f(\mathbf{x})$ is learned by using the labeled data D_l^T from the target domain. As shown in [36], $f^A(\mathbf{x})$ can be deemed as a pattern-dependent bias, and then the perturbation function $\Delta f(\mathbf{x})$ can be easily learned.

Besides A-SVM, Schweikert et al. [26] proposed to use the linear combination of the decision values from the auxiliary SVM classifier and the target SVM classifier for the prediction in the target domain. It is noteworthy that both this method and A-SVM do not utilize the abundant and useful unlabeled data D_u^T in the target domain for cross-domain learning.

1. Yang et al. [36] also proposed a formulation to solve the multiple auxiliary domain problem. This paper mainly focuses on single auxiliary domain setting. We therefore briefly introduce their work under this setting.

3 Domain Transfer Multiple Kernel Learning Framework

In this section, we introduce our proposed unified cross-domain learning framework, referred to as Domain Transfer Multiple Kernel Learning. And we also present a unified learning algorithm for DTMKL. Based on the proposed framework, we further propose two methods using SVM and the existing classifiers, respectively.

3.1 Proposed Framework

In previous cross-domain learning methods [15], [21], the weights or the kernel matrix of samples are learned separately using the MMD criterion in (2) without considering any label information. However, it is usually beneficial to utilize label information during kernel learning. Instead of using the two-step approaches as in [15], [21], we propose a unified cross-domain learning framework, DTMKL, to learn the decision function for the target domain:

$$f(\mathbf{x}) = \mathbf{w}'\phi(\mathbf{x}) + b = \sum_{i=1}^{n}\alpha_i k(\mathbf{x}_i, \mathbf{x}) + b, \tag{3}$$

as well as the kernel function k simultaneously, where $\mathbf{w}$ is the weight vector in the feature space and b is the bias term. Notice that α_is are the coefficients of the kernel expansion for the decision function $f(\mathbf{x})$ using Representer Theorem [25]. In practice, DTMKL minimizes the distance between the data distributions of the auxiliary and target domains, as well as the structural risk functional of any kernel method. The learning framework of DTMKL is then formulated as

$$[k, f] = \arg\min_{k,f}\ \Omega\left(\mathrm{DIST}_k^2(D^A, D^T)\right) + \theta R(k, f, D), \tag{4}$$

where $\Omega(\cdot)$ is any monotonic increasing function and $\theta > 0$ is a tradeoff parameter to balance the mismatch between data distributions of two domains and the structural risk functional $R(k, f, D)$ defined on the labeled patterns.

3.1.1 Minimizing Data Distribution Mismatch

The first objective in DTMKL is to minimize the mismatch between data distributions of two domains using the MMD criterion defined in (2). We define a column vector $\mathbf{s}$ with $n_A + n_T$ entries, in which the first n_A entries are set as $1/n_A$ and the remaining entries are set as $-1/n_T$, respectively. Let $\Phi = [\phi(\mathbf{x}_1^A), \ldots, \phi(\mathbf{x}_{n_A}^A), \phi(\mathbf{x}_1^T), \ldots, \phi(\mathbf{x}_{n_T}^T)]$ be the kernel

matrix after feature mapping, and then $\frac{1}{n_A}\sum_{i=1}^{n_A}\phi(\mathbf{x}_i^A) - \frac{1}{n_T}\sum_{i=1}^{n_T}\phi(\mathbf{x}_i^T)$ in (2) is simplified as $\Phi\mathbf{s}$. Thus, the criterion in (2) can be rewritten as

$$\mathrm{DIST}_k^2(D^A, D^T) = \|\Phi\mathbf{s}\|^2 = \mathrm{tr}(\Phi'\Phi\mathbf{S}) = \mathrm{tr}(\mathbf{KS}),$$

where

$$\mathbf{S} = \mathbf{s}\mathbf{s}' \in \Re^{(n_A+n_T)\times(n_A+n_T)}, \quad \mathbf{K} = \Phi'\Phi = \begin{bmatrix} \mathbf{K}^{A,A} & \mathbf{K}^{A,T} \\ \mathbf{K}^{T,A} & \mathbf{K}^{T,T} \end{bmatrix} \in \Re^{(n_A+n_T)\times(n_A+n_T)}, \quad \mathbf{K}^{A,A} \in \Re^{n_A\times n_A}, \quad \mathbf{K}^{T,T} \in \Re^{n_T\times n_T},$$

and $\mathbf{K}^{A,T} \in \Re^{n_A\times n_T}$ are the kernel matrices defined for the auxiliary domain, the target domain, and the cross domain from the auxiliary domain to the target domain, respectively.

3.1.2 Minimizing Structural Risk Functional

The second objective in DTMKL is to minimize the structural risk functional $R(k, f, D)$ defined on the labeled patterns in D. Note that the structural risk functional of many existing kernel methods, including SVM, SVR, KRLS, and so on, can be used here. Without using the first term in (4), the resultant optimization problem becomes a standard kernel learning problem [18] to learn the kernel k and the decision function f for the corresponding kernel method.

3.1.3 Multiple Base Kernels

Instead of learning a nonparametric kernel matrix $\mathbf{K}$ in (4) for cross-domain learning as in [21], following [18], [24], [28] we assume the kernel k is a linear combination of a set of base kernels k_ms, namely,

$$k = \sum_{m=1}^{M} d_m k_m,$$

where $d_m \geq 0$, $\sum_{m=1}^{M} d_m = 1$. We further assume the first objective $\Omega(\mathrm{tr}(\mathbf{KS}))$ in (4) is

$$\Omega(\mathrm{tr}(\mathbf{KS})) = \frac{1}{2}(\mathrm{tr}(\mathbf{KS}))^2 = \frac{1}{2}\left(\mathrm{tr}\left(\sum_{m=1}^{M} d_m\mathbf{K}_m\mathbf{S}\right)\right)^2 = \frac{1}{2}\mathbf{d}'\mathbf{p}\mathbf{p}'\mathbf{d},$$

where

$$\mathbf{p} = [p_1, \ldots, p_M]', p_m = \mathrm{tr}(\mathbf{K}_m\mathbf{S}), \mathbf{K}_m = [k_m(\mathbf{x}_i, \mathbf{x}_j)] \in \Re^{(n_A+n_T)\times(n_A+n_T)},$$

and $\mathbf{d} = [d_1, \ldots, d_M]'$. Moreover, from (3), we have $f(\mathbf{x}) = \sum_{m=1}^{M} d_m\mathbf{w}_m'\phi_m(\mathbf{x}) + b$, where $\mathbf{w}_m = \sum_{i=1}^{n}\alpha_i\phi_m(\mathbf{x}_i)$.

Thus, the optimization problem in (4) can be rewritten as

$$\min_{\mathbf{d}\in\mathcal{D}} \min_{f} \frac{1}{2}\mathbf{d}'\mathbf{p}\mathbf{p}'\mathbf{d} + \theta\, R(\mathbf{d}, f, D), \tag{5}$$

where $\mathcal{D} = \{\mathbf{d}|\mathbf{d} \geq 0, \mathbf{d}'\mathbf{1}_M = 1\}$ is the feasible set of $\mathbf{d}$ and f is the target decision function. Note that we have only M variables in $\mathbf{d}$, which is much smaller than the total number of variables $(n_A + n_T)^2$ in $\mathbf{K}$. Thus, the resultant optimization problem is much simpler than that of the nonparametric kernel matrix learning in MMDE [21].

3.1.4 Learning Algorithm

Let us define

$$J(\mathbf{d}) = \min_{f} R(\mathbf{d}, f, D). \tag{6}$$

Then, the optimization problem (5) can be rewritten as

$$\min_{\mathbf{d}\in\mathcal{D}} \; h(\mathbf{d}) = \min_{\mathbf{d}\in\mathcal{D}} \; \frac{1}{2}\mathbf{d}'\mathbf{p}\mathbf{p}'\mathbf{d} + \theta\, J(\mathbf{d}). \tag{7}$$

It is worth mentioning that the traditional MKL methods suffer from the nonsmooth problem on the linear kernel combination coefficient $\mathbf{d}$, and thus the simple coordinate descent algorithms such as SMO may not lead to the global solution [1]. As shown in the literature, the global optimum of MKL can be achieved by using the reduced gradient descent method [24] or semi-infinite linear programming [28], [38]. Following [24], we develop an efficient and effective reduced gradient descent procedure to iteratively update different variables (e.g., $\mathbf{d}$ and f) in (5) to obtain the optimal solution. The algorithm is detailed as follows:

Updating the decision function f. With the fixed $\mathbf{d}$, only the structural risk functional $R(\mathbf{d}, f, D)$ in (5) depends on f. We can solve the decision function f by minimizing $R(\mathbf{d}, f, D)$.

Updating kernel coefficients $\mathbf{d}$. When the decision function f is fixed, (7) can be updated using the reduced gradient descent method as suggested in [24]. Specifically, the gradient of h in (7) is

$$\nabla h = \mathbf{p}\mathbf{p}'\mathbf{d} + \theta\nabla J,$$

where ∇J is the gradient of J in (6). Furthermore, the Hessian matrix can be derived as

$$\nabla^2 h = \mathbf{p}\mathbf{p}' + \theta\nabla^2 J.$$

Note that $\mathbf{p}\mathbf{p}' + \theta\nabla^2 J$ may not be full rank. Thus, to avoid numerical instability, we replace $\mathbf{p}\mathbf{p}'$ by $\mathbf{p}\mathbf{p}' + \varepsilon\mathbf{I}$ to make sure $\nabla^2 h = \mathbf{p}\mathbf{p}' + \varepsilon\mathbf{I} + \theta\nabla^2 J \succ \mathbf{0}$, where ε is set to 10^{-2} in the experiments. Compared with first-order gradient-based methods, second-order derivative-based methods usually converge faster. So, we use $\mathbf{g} = (\nabla^2 h)^{-1}\nabla h$ as the updating direction. To maintain $\mathbf{d} \in \mathcal{D}$, the updating direction $\mathbf{g}$ is reduced as in [24], so the updated weight of multiple base kernels is

$$\mathbf{d}_{t+1} = \mathbf{d}_t - \eta_t\mathbf{g}_t \in \mathcal{D}, \tag{8}$$

where $\mathbf{d}_t$ and $\mathbf{g}_t$ are the linear combination coefficient vector $\mathbf{d}$ and the reduced updating direction $\mathbf{g}$ at the tth iteration, respectively, and η_t is the learning rate. The overall procedure of the proposed DTMKL is summarized in Algorithm 1.

Algorithm 1. DTMKL Algorithm.

1: Initialize $\mathbf{d} = \frac{1}{M}\mathbf{1}_M$.
2: For $t = 1, \ldots, T_{\max}$
3: Solve the target classifer f in the objective function in (6).

4: Update the linear combination coefficient vector $\mathbf{d}$ of multiple base kernels using (8).
5: End.

As mentioned before, one can employ any structural risk functional of kernel methods in the learning framework of DTMKL. In the preliminary conference version of this paper[2] [13], we proposed to use the hinge loss in SVM. Then, the structural risk functional becomes SVM, which is the first formulation in this paper. Moreover, inspired by the utilization of auxiliary classifiers for cross-domain learning, we also propose another formulation which considers the decision values from the base classifiers on the unlabeled patterns in the target domain.

3.2 DTMKL Using Hinge Loss

SVM is used to model the second objective $R(\mathbf{d}, f, D)$ in (5), that is,

$$\min_{\mathbf{d}\in\mathcal{D}} \min_{f} \ \frac{1}{2}\mathbf{d}'\mathbf{p}\mathbf{p}'\mathbf{d} + \theta \, \mathrm{SVM}^{primal}(\mathbf{d}, f, D), \tag{9}$$

which employs the hinge loss, i.e., $\ell_h(t) = \max(0, 1-t)$. Here, we use the regularizer $\frac{1}{2}\sum_{m=1}^{M} d_m \|\mathbf{w}_m\|^2$ for multiple kernel learning introduced in [38]. Then, the corresponding constrained optimization problem in (9) can be rewritten as

$$\min_{\mathbf{d}\in\mathcal{D}} \min_{\mathbf{w}_m, b, \xi_i} \frac{1}{2}\mathbf{d}'\mathbf{p}\mathbf{p}'\mathbf{d} + \theta\left(\frac{1}{2}\sum_{m=1}^{M} d_m \|\mathbf{w}_m\|^2 + C\sum_{i=1}^{n}\xi_i\right), \tag{10}$$

$$\text{s.t.} \quad y_i\left(\sum_{m=1}^{M} d_m \mathbf{w}_m'\phi_m(\mathbf{x}_i) + b\right) \geq 1 - \xi_i, \xi_i \geq 0, \tag{11}$$

where $C > 0$ is the regularization parameter and ξ_is are the slack variables for the corresponding constraints. However, (10) in general is nonconvex due to the product of d_m and $\mathbf{w}_m$ in the inequality constraints of (10). Following [38], we introduce a transformation $\mathbf{v}_m = d_m\mathbf{w}_m$, and (10) can be then rewritten as

$$\min_{\mathbf{d}\in\mathcal{D}} \min_{\mathbf{v}_m, b, \xi_i} \frac{1}{2}\mathbf{d}'\mathbf{p}\mathbf{p}'\mathbf{d} + \theta \underbrace{\left(\frac{1}{2}\sum_{m=1}^{M}\frac{\|\mathbf{v}_m\|^2}{d_m} + C\sum_{i=1}^{n}\xi_i\right)}_{J(\mathbf{d})}, \tag{12}$$

$$\text{s.t.} \quad y_i\left(\sum_{m=1}^{M} \mathbf{v}_m'\phi_m(\mathbf{x}_i) + b\right) \geq 1 - \xi_i, \xi_i \geq 0. \tag{13}$$

In the following theorem, we prove that the optimization problem (12) is convex.

Theorem 1. *The optimization problem (12) is jointly convex with respect to* $\mathbf{d}$, $\mathbf{v}_m$, b, *and* ξ_i.

Proof. The first term $\frac{1}{2}\mathbf{d}'\mathbf{p}\mathbf{p}'\mathbf{d}$ in the objective function (12) is a convex quadratic term. Other terms in the objective function and constraints are linear except the term $\frac{1}{2}\sum_{m=1}^{M}\frac{\|\mathbf{v}_m\|^2}{d_m}$ in (12). As shown in [24], this term is also jointly convex with respect to $\mathbf{d}$ and $\mathbf{v}_m$. Therefore, the optimization problem in (12) is jointly convex with respect to $\mathbf{d}$, $\mathbf{v}_m$, b, and ξ_i. □

Therefore, (12) can converge to the global minimum using the reduced gradient descent procedure described in Algorithm 1. Note that when one of the linear combination coefficients (say, d_m) is zero, the corresponding $\mathbf{v}_m$ at the optimality must be zero as well [24]. In other cases (i.e., the corresponding $\mathbf{v}_m$ is nonzero), the corresponding descent direction is nonzero, and so d_m will be updated again by using the reduced descent direction in the subsequent iteration until the objective function in (12) cannot be decreased.

Recall that the constrained optimization problem of SVM is usually solved by its dual problem, which is in the form of a quadratic programming (QP) problem:

$$\max_{\boldsymbol{\alpha}\in\mathcal{A}} \mathbf{1}_n'\boldsymbol{\alpha} - \frac{1}{2}(\boldsymbol{\alpha}\circ\mathbf{y})'\mathbf{K}(\boldsymbol{\alpha}\circ\mathbf{y}).$$

Similarly, one can show that $J(\mathbf{d})$ in (12) can be written as follows [38]:

$$J(\mathbf{d}) = \max_{\boldsymbol{\alpha}\in\mathcal{A}} \mathbf{1}_n'\boldsymbol{\alpha} - \frac{1}{2}(\boldsymbol{\alpha}\circ\mathbf{y})'\left(\sum_{m=1}^{M} d_m\mathbf{K}_m\right)(\boldsymbol{\alpha}\circ\mathbf{y}), \tag{14}$$

where $J(\mathbf{d})$ is linear in $\mathbf{d}\in\mathcal{D}$, $\mathcal{A} = \{\boldsymbol{\alpha}|\boldsymbol{\alpha}'\mathbf{y} = 0, \mathbf{0}_n \leq \boldsymbol{\alpha} \leq C\mathbf{1}_n\}$ is the feasible set of the dual variables $\boldsymbol{\alpha}$, $\mathbf{y} = [y_1, \ldots, y_n]'$ is the label vector, and $\mathbf{K}_m = [k_m(\mathbf{x}_i, \mathbf{x}_j)] = [\phi_m(\mathbf{x}_i)'\phi_m(\mathbf{x}_j)] \in \Re^{n\times n}$ is the mth base kernel matrix of the labeled patterns.

With the optimal $\mathbf{d}$ and the dual variables $\boldsymbol{\alpha}$, the prediction of any test data $\mathbf{x}$ using the target decision function can be obtained:

$$\begin{aligned} f^T(\mathbf{x}) &= \sum_{m=1}^{M} d_m\mathbf{w}_m'\phi_m(\mathbf{x}) + b \\ &= \sum_{i:\,\alpha_i\neq 0} \alpha_i y_i \sum_{m=1}^{M} d_m k_m(\mathbf{x}_i, \mathbf{x}) + b. \end{aligned}$$

In this method, the labeled samples from the **A**uxiliary domain and the **T**arget domain can be directly used to improve the classification performance of the classifier in the target domain. In this case, we term this method as *DTMKL_AT*. It is worth mentioning that the unlabeled target data D_u^T can be used for the calculation of the MMD values in (2), which does not require label information.

3.3 DTMKL Using Existing Base Classifiers

In this section, we extend our proposed DTMKL by defining the structural risk functional of SVR on both labeled and unlabeled data in the target domain. There are no input labels for the unlabeled target patterns. Inspired by the use of base classifiers, we introduce a regularization term (i.e., the last term in (15)) to enforce that the decision values from the target classifier and the existing base classifiers are similar on the unlabeled target patterns. Moreover, we further introduce another penalty term (i.e., the fourth term in (15)) for the labeled target patterns to ensure that the decision values from the target classifier are close to the true labels. Note that the labeled training data can be from the target domain (i.e., $D = D_l^T$) or from both

2. The corresponding cross-domain learning method is referred to as Domain Transfer SVM (DTSVM) in [13].

domains (i.e., $D = D_l^T \cup D^A$). Let us denote $f^{T,m}$ and $f^{B,m}$ as the target classifier and the base classifier with the mth base kernel, respectively. For simplicity, we define $f_i^{T,m}$ and $f_i^{B,m}$ as the decision values on any data $\mathbf{x}_i$, respectively. Similarly to (10), we also assume that the regularizer is $\frac{1}{2}\sum_{m=1}^{M} d_m \|\mathbf{w}_m\|^2$. Then, we present another formulation of DTMKL as follows:

$$\begin{aligned}\min_{\substack{\mathbf{d}\in\mathcal{D},\mathbf{w}_m,b,\xi_i,\\ \xi_i^*,f_l^{T,m},f_u^{T,m}}} & \frac{1}{2}\mathbf{d}'\mathbf{p}\mathbf{p}'\mathbf{d} + \theta\left\{\frac{1}{2}\sum_{m=1}^{M} d_m\|\mathbf{w}_m\|^2 + C\sum_{i=1}^{n+n_u}(\xi_i+\xi_i^*)\right.\\ & \left. + \frac{\zeta}{2}\left(\sum_{m=1}^{M}\left\|\boldsymbol{f}_l^{T,m}-\mathbf{y}\right\|^2 + \lambda\sum_{m=1}^{M}\left\|\boldsymbol{f}_u^{T,m}-\boldsymbol{f}_u^{B,m}\right\|^2\right)\right\},\\ \text{s.t.} \quad & \sum_{m=1}^{M} d_m\mathbf{w}_m'\phi_m(\mathbf{x}_i) + b - \sum_{m=1}^{M} d_m f_i^{T,m} \le \epsilon+\xi_i, \xi_i \ge 0,\\ & \sum_{m=1}^{M} d_m f_i^{T,m} - \sum_{m=1}^{M} d_m\mathbf{w}_m'\phi_m(\mathbf{x}_i) - b \le \epsilon+\xi_i^*, \xi_i^* \ge 0,\end{aligned} \tag{15}$$

where $\lambda > 0$ is the balance parameter, $C, \zeta > 0$ are the regularization parameters, $\mathbf{y} = [y_1, \ldots, y_n]'$ is the label vector of the labeled training data from D, ξ_is and ξ_i^*s are slack variables for ϵ-insensitive loss, $\boldsymbol{f}_l^{T,m} = [f_1^{T,m}, \ldots, f_n^{T,m}]'$ is the decision value vector of the labeled training data D from the target classifier, and $\boldsymbol{f}_u^{T,m} = [f_{n+1}^{T,m}, \ldots, f_{n+n_u}^{T,m}]'$ and $\boldsymbol{f}_u^{B,m} = [f_{n+1}^{B,m}, \ldots, f_{n+n_u}^{B,m}]'$ are the decision value vectors of the unlabeled target data D_u^T from the target classifier $f^{T,m}$ and the base classifier $f^{B,m}$, respectively. While the objective function in (15) is not jointly convex with respect to the variables d_m and $\mathbf{w}_m$, our iterative approach listed in Algorithm 1 can still reach the local minimum.

We denote the objective inside $\{\}$ of (15) as $J(\mathbf{d})$. The dual of $J(\mathbf{d})$ (see the supplemental material for the detailed derivation, which can be found in the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TPAMI.2011.114) can be derived by introducing the Lagrangian multipliers $\boldsymbol{\alpha}$ and $\boldsymbol{\alpha}^*$:

$$\begin{aligned}J(\mathbf{d}) = \max_{(\boldsymbol{\alpha},\boldsymbol{\alpha}^*)\in\mathcal{A}} & -\frac{1}{2}(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*)'\tilde{\mathbf{K}}(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*)\\ & -\tilde{\mathbf{y}}'(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*) - \epsilon\mathbf{1}_{n+n_u}'(\boldsymbol{\alpha}+\boldsymbol{\alpha}^*),\end{aligned} \tag{16}$$

where

$$\tilde{\mathbf{K}} = \sum_{m=1}^{M} d_m\tilde{\mathbf{K}}_m = \sum_{m=1}^{M} d_m\mathbf{K}_m + \frac{1}{\zeta}\sum_{m=1}^{M} d_m^2\begin{bmatrix}\mathbf{I}_n & \\ & \frac{1}{\lambda}\mathbf{I}_{n_u}\end{bmatrix}, \tag{17}$$

$$\tilde{\mathbf{y}} = \sum_{m=1}^{M} d_m\tilde{\mathbf{y}}_m = \begin{bmatrix}\mathbf{y}\\ \sum_{m=1}^{M} d_m\boldsymbol{f}_u^{B,m}\end{bmatrix}, \tag{18}$$

$\mathcal{A} = \{(\boldsymbol{\alpha},\boldsymbol{\alpha}^*)|\boldsymbol{\alpha}'\mathbf{1}_{n+n_u} = \boldsymbol{\alpha}^{*\prime}\mathbf{1}_{n+n_u}, \mathbf{0}_{n+n_u} \le \boldsymbol{\alpha},\boldsymbol{\alpha}^* \le C\mathbf{1}_{n+n_u}\}$ is the feasible set of the dual variables $\boldsymbol{\alpha}$ and $\boldsymbol{\alpha}^*$, and $\mathbf{K}_m = [k_m(\mathbf{x}_i,\mathbf{x}_j)] \in \Re^{(n+n_u)\times(n+n_u)}$ is the kernel matrix of both the labeled patterns from D and unlabeled patterns from D_u^T.

Recall that the dual form of the standard ϵ-SVR is as follows:

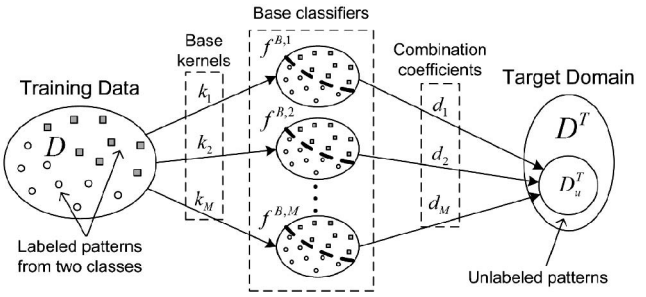


Fig. 1. Illustration of virtual labels. The base classifier $f^{B,m}$ is learned with the base kernel function k_m and the labeled training data from D, where $m = 1, \ldots, M$. For each of the unlabeled target pattern $\mathbf{x}$ from D_u^T, we can obtain its decision value $f^{B,m}(\mathbf{x})$ from each base classifier. Then, the virtual label $\tilde{y}$ of $\mathbf{x}$ is defined as the linear combination of its decision values $f^{B,m}(\mathbf{x})$s weighted by the coefficients d_ms, i.e., $\tilde{y} = \sum_{m=1}^{M} d_m f^{B,m}(\mathbf{x})$.

$$\begin{aligned}\max_{(\boldsymbol{\alpha},\boldsymbol{\alpha}^*)\in\mathcal{A}} & -\frac{1}{2}(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*)'\hat{\mathbf{K}}(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*)\\ & -\hat{\mathbf{y}}'(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*) - \epsilon\mathbf{1}_{n+n_u}'(\boldsymbol{\alpha}+\boldsymbol{\alpha}^*).\end{aligned} \tag{19}$$

Surprisingly, (16) is very similar to (19) except for some minor changes, that is, the kernel matrices $\hat{\mathbf{K}}$ and $\hat{\mathbf{y}}$ are replaced by $\tilde{\mathbf{K}}$ and $\tilde{\mathbf{y}}$, respectively. Therefore, (16) can be efficiently solved by using the state-of-the-art SVM solver (e.g., LIBSVM [7]). The kernel matrix $\tilde{\mathbf{K}}$ is similar to Automatic Relevance Determination (ARD) kernel used in Gaussian Process, and the second term in (17) is to control the noise of output. Interestingly, each of the last n_u entries of $\tilde{\mathbf{y}}$ in (18) can be considered as a so-called virtual label $\tilde{y} = \sum_{m=1}^{M} d_m f^{B,m}(\mathbf{x})$ composed by the linear combination of the decision values from the base classifiers $f^{B,m}$s on the unlabeled target pattern $\mathbf{x}$ (see Fig. 1 for illustration).

With the optimal $\mathbf{d}$ and the dual variables $\boldsymbol{\alpha}$ and $\boldsymbol{\alpha}^*$, the target decision function can be found as

$$\begin{aligned}f(\mathbf{x}) &= \sum_{m=1}^{M} d_m\mathbf{w}_m'\phi_m(\mathbf{x}) + b\\ &= \sum_{i:\,\alpha_i-\alpha_i^*\neq 0}(\alpha_i-\alpha_i^*)\sum_{m=1}^{M} d_m k_m(\mathbf{x}_i,\mathbf{x}) + b.\end{aligned}$$

Because of the use of the existing base classification functions, we then refer to this method as *DTMKL_f*.

3.4 Computational Complexity of DTMKL

Recall that DTMKL adopts the reduced gradient descent scheme as in [24] to iteratively update the coefficients of base kernels and learn the target classifier. For DTMKL_AT, the overall optimization procedure is dominated by a series of the kernel classifier training.[3] For example, at each iteration of DTMKL_AT, the cost is essentially the same as the SVM training. Empirically, the SVM training complexity is $O(n^{2.3})$ [23]. And so the training cost for our proposed DTMKL_AT is $O(T_{\max} \times n^{2.3})$, where $T_{\max}$ is the number of iterations in DTMKL. As shown in Section 4.5, our DTMKL_AT generally converges after less than five

3. Here, we suppose multiple base kernels can be precomputed and loaded into memory before the DTMKL training. Then, the computational cost for the calculation of the learned kernel $\mathbf{K} = \sum_{m=1}^{M} d_m\mathbf{K}_m$, which takes $O(Mn^2)$ time can be ignored.

iterations. For DTMKL_f, we use multiple base classifiers. For example, the base classifiers SVM_AT can be prelearned and adapted from the existing classifier SVM_A at very little computational cost by using warm start strategy or using A-SVM. Thus, the cost of the calculation of the virtual labels for DTMKL_f is not significant. Recall that DTMKL_f incorporates both labeled and unlabeled patterns in the training stage. Therefore, the training complexity of DTMKL_f is $O(T_{\max} \times (n + n_u)^{2.3})$.

The testing complexity of DTMKL_AT and DTMKL_f depends on the number of support vectors learned from the training stage. And we show in Table 3 that our methods DTMKL_AT and DTMKL_f take less than 1 minute to finish the whole prediction process for about 21,213 test samples from each of 36 concepts on the TRECVID data set, which are as fast as the MKL algorithm.

3.5 Discussions with Related Work

Our work is different from prior cross-domain learning methods such as [6], [11], [15], [16], [31], [36]. These methods use standard kernel functions for SVM training, in which the kernel parameters are usually determined through cross validation. Recall that the kernel function plays a crucial role in SVM. When the labeled data from the target domain are limited, the cross-validation approach may not choose the optimal kernel, which significantly degrades the generalization performance of SVM. Moreover, most existing cross-domain learning algorithms [11], [16], [31], [36] do not explicitly consider any specific criterion to measure the distribution mismatch of samples between different domains. As demonstrated in the previous work [12], [19], [26], [36], the auxiliary classifiers (i.e., the base classifiers trained with the data from one or multiple auxiliary domains) can be used to learn a robust target classifier. Again, there is no specific criterion used to minimize the distribution mismatch between the auxiliary and target domains in these methods. In addition, the work in [12] focuses on the setting with *multiple auxiliary domains* and the Domain Adaptation Machine (DAM) algorithm was specifically proposed for multiple auxiliary domain adaptation problem. The algorithm Cross-Domain Regularized Regression (CDRR) and its incremental version Incremental CDRR (ICDRR) in [19] were specifically designed for large-scale image retrieval applications. In order to achieve real-time retrieval performance on the large image data set with about 270,000 images, a linear regression function is used as the target function in [19]. Also, in the previous work [12], [19], [26], [36], only one kernel is used in the target decision function. In contrast to these methods [11], [12], [16], [19], [26], [31], [36], DTMKL is a unified cross-domain kernel learning framework in which the optimal kernel is learned by explicitly minimizing the distribution mismatch between the auxiliary and target domains by using both labeled and unlabeled patterns. Most importantly, many kernel learning methods (e.g., SVM, SVR, KRLS, etc.) can be readily embedded into our DTMKL framework to solve cross-domain learning problems.

The work most closely related to DTMKL was proposed by Pan et al. [21] in which a two-step approach is used for cross-domain learning. The first step is to learn a kernel matrix of samples using the MMD criterion, and the second step is to apply the learned kernel matrix to train an SVM classifier. DTMKL is different from [21] in the following aspects:

1. A kernel matrix is learned in an unsupervised setting in [21] without using any label information, which is not as effective as our semi-supervised learning method DTMKL.
2. In contrast to the two-step approach in [21], DTMKL simultaneously learns a kernel function and SVM classifier.
3. The learned kernel matrix in [21] is nonparametric; thus, it cannot be applied to unseen data. Instead, DTMKL can handle any new test data.
4. The optimization problem in [21] is in the form of expensive semidefinite programming [5], the time complexity of which is $O(n^{6.5})$.

As a result, it can only handle several hundred patterns. Therefore, it cannot be applied to medium or large-scale applications such as video concept detection. Another related work is Adaptive Multiple Kernel Learning (A-MKL) [14] in which the target classifier is constrained as the linear combination of a set of prelearned classifiers and the perturbation function learned by multiple kernel learning. A-MKL can be considered as an extension of DTMKL_AT. In A-MKL, the unlabeled target patterns are only used to measure the distribution mismatch between the two domains in the Maximum Mean Discrepancy criterion, which is similar as in DTMKL_AT and DTMKL_f. In contrast, in DTMKL_f, the decision values from the prelearned base classifiers on the unlabeled target patterns are used as virtual labels in a new regularizer (i.e., the last term in (15)) in order to enforce that the decision values from the target classifier and the existing base classifiers are similar on the unlabeled target patterns. Moreover, A-MKL classifier can also be used as one base classifier in DTMKL_f.

Multiple Kernel Learning methods [18], [24], [28] also simultaneously learn the decision function and the kernel in an inductive setting. However, the default assumption of MKL is that the training data and the test data are drawn from the same domain. When the training data and the test data come from different distributions, MKL methods cannot learn the optimal kernel with the combined training data from the auxiliary and target domains. Therefore, the training data from the auxiliary domain may degrade the classification performances of MKL algorithms in the target domain. In contrast, DTMKL can utilize the patterns from both domains for better classification performances.

4 Experiments

In this section, we evaluate our methods DTMKL_AT and DTMKL_f for two cross-domain learning related applications: 1) video concept detection on the challenging TRECVID video corpus and 2) text classification on the 20 Newsgroups data set and the email spam data set.

4.1 Descriptions of Data Sets and Features

4.1.1 TRECVID Data Set

The TRECVID video corpus[4] is one of the largest annotated video benchmark data sets for research purposes. The TRECVID 2005 data set contains 61,901 keyframes extracted from 108 hours of video programs from six broadcast channels (in English, Arabic, and Chinese), and the TRECVID 2007 data set contains 21,532 keyframes extracted

4. http://www-nlpir.nist.gov/projects/trecvid.

TABLE 1
Description of the 20 Newsgroups Data Set

Setting	Auxiliary Domain	Target Domain
comp vs rec	comp.windows.x & rec.sport.hockey	comp.sys.ibm.pc.hardware & rec.motorcycles
comp vs sci	comp.windows.x & sci.crypt	comp.sys.ibm.pc.hardware & sci.med
comp vs talk	comp.windows.x & talk.politics.mideast	comp.sys.ibm.pc.hardware & talk.politics.guns

from 60 hours of news magazine, science news, documentaries, and educational programming videos. As shown in [16], TRECVID data sets are challenging for cross-domain learning methods due to the large difference between TRECVID 2007 data set and TRECVID 2005 data set in terms of program structure and production values. Thirty-six semantic concepts are chosen from the LSCOM-lite lexicon [20], a preliminary version of LSCOM, which covers 36 dominant visual concepts present in broadcast news videos, including objects, scenes, locations, people, events, and programs. The 36 concepts have been manually annotated to describe the visual content of the keyframes in both TRECVID 2005 and 2007 data sets.

In this work, we focus on the single auxiliary domain and single target domain setting. To evaluate the performances of all the methods, we choose one Chinese channel, *CCTV4*, from TRECVID 2005 data set as the auxiliary domain, and use the TRECVID 2007 data set as the target domain. The auxiliary data set D^A consists of all the labeled samples from the auxiliary domain (i.e., 10,896 keyframes in CCTV4 channel). We randomly select 10 positive samples per concept from the TRECVID 2007 data set as the labeled target training data set D_l^T. Considering that it is computationally prohibitive to compare all the methods over multiple random training and testing splits, we report results from one split. In order to facilitate other researchers to repeat the results, we have made the selected 355 positive samples[5] publicly available at http://www.ntu.edu.sg/home/dongxu/sampled_keyframes.txt. And, for each of the 36 concepts, we have 21,213 test samples on average.

Three low-level global features Grid Color Moment (225 dim.), Gabor Texture (48 dim.), and Edge Direction Histogram (73 dim.) are extracted to represent the diverse content of keyframes because of their consistent good performances reported in TRECVID [16], [36]. Moreover, the three types of global features can be efficiently extracted and the previous work [16], [36] also shows that the cross-domain issue exists when using these global features. Yanagawa et al. have made the three types of features extracted from the keyframes of TRECVID data sets publicly available (see [35] for more details). We further concatenate the three types of features to form a 346-dimensional feature vector for each keyframe.

4.1.2 20 Newsgroups Data Set

The 20 Newsgroups data set[6] is a collection of 18,774 news documents. This data set is organized in a hierarchical structure which consists of six main categories and 20 subcategories. Some of the subcategories (from the same category) are related to each other while others (from different categories) are not related, making this data set suitable to evaluate cross-domain learning algorithms.

In the experiments, the four largest main categories (i.e., "comp," "rec," "sci," and "talk") are chosen for evaluation. Specifically, for each main category, the largest subcategory is selected as the target domain, while the second largest subcategory is chosen as the auxiliary domain. Moreover, we consider the largest category "comp" as the positive class and one of the three other categories as the negative class for each setting. Table 1 provides the detailed information of all three settings. To construct the training data set, we use all labeled samples from the auxiliary domain, as well as randomly choose m positive and m negative samples from the target domain. And the remaining samples in the target domain are considered as the test data which are also used as the unlabeled data for training. In the experiments, m is set as 0, 1, 3, 5, 7, and 10. For any given m, we randomly sample the training data from the target domain five times and report the means and the standard deviations of all methods. Moreover, the word-frequency feature is used to represent each document.

4.1.3 Email Spam Data Set

There are three email subsets (denoted by User1, User2, and User3, respectively) annotated by three different users in the email spam data set.[7] The task is to classify spam and nonspam emails. Since the spam and nonspam emails in the subsets have been differentiated by different users, the data distributions of the three subsets are related but different. Each subset has 2,500 emails, in which one half of the emails are *nonspam* (labeled as 1) and the other half of them are *spam* (labeled as -1).

On this data set, we consider three settings: 1) User1 (auxiliary domain) and User2 (target domain); 2) User2 (auxiliary domain) and User3 (target domain); and 3) User3 (auxiliary domain) and User1 (target domain). For each setting, the training data set contains all labeled samples from the auxiliary domain as well as the labeled samples from the target domain in which five positive and five negative samples are randomly chosen. And the remaining samples in the target domain are used as the unlabeled training data and the test data as well. We randomly sample the training data from the target domain for five times and report the means and the standard deviations of all methods. Again, the word-frequency feature is used to represent each document.

5. A large portion of keyframes in TRECVID 2007 data set have multiple labels. We therefore only have 355 unique labeled target training samples. For each concept, we make sure that there are only 10 positive samples from the target domain when training one-versus-all classifiers. It is worth noting that for some concepts (e.g., "Person"), we have fewer than 345 negative samples for model learning after excluding some training samples that are selected from other non-"Person" concepts but also positively labeled as "Person."

6. http://people.csail.mit.edu/jrennie/20Newsgroups.

7. http://www.ecmlpkdd2006.org/challenge.html.

4.2 Experimental Setup

We systematically compare our proposed methods DTMKL_AT and DTMKL_f with the baseline SVM and other cross-domain learning algorithms including Feature Replication [11], Adaptive SVM [36], Cross-Domain SVM [16], and Kernel Mean Matching [15]. We also report the results of the Multiple Kernel Learning algorithm in which the optimal kernel combination coefficients are learned by only minimizing the second part of DTMKL_AT in (10) corresponding to the structural risk functional of SVM. Note that we do not compare with [21] because their work cannot cope with thousands of training and test samples.

For all methods, we train one-versus-all classifiers. Note that the standard SVM can use the labeled training data set D_l^T from the target domain, the labeled training data set D^A from the auxiliary domain, or the combined training data set $D^A \cup D_l^T$ from both auxiliary and target domains. We then refer to SVM in the above three cases as SVM_T, SVM_A, and SVM_AT, respectively. We also report the results of MKL_AT by employing the combined training data from two domains. The cross-domain learning methods FR, A-SVM, CD-SVM, and KMM also make use of the combined training data set $D^A \cup D_l^T$ for model learning.

MKL_AT and our DTMKL-based methods can make use of multiple base kernels. For fair comparison, we use the same kernels for other methods, including SVM_T, SVM_A, SVM_AT, FR, A-SVM, CD-SVM, and KMM. Specifically, for each method we train multiple classifiers using the same kernels and then equally fuse the decision values to obtain the final prediction results.

Note that we make use of the unlabeled target training data from D_u^T in KMM and our DTMKL-based methods. For KMM and DTMKL_AT, the labeled and unlabeled training data are employed to measure the data distribution mismatch between two domains using the MMD criterion in (2). We additionally make use of the virtual labels for DTMKL_f, which are the linear combination of the decision values from multiple base classifiers on the unlabeled training data from D_u^T. In this work, we employ SVM_AT from multiple base kernels as the base classifiers in DTMKL_f.

With our experimental setting, cross validation is not suitable to automatically tune the optimal parameters for the target classifier because we only have a limited number of labeled samples or even no labeled samples from the target domain. For the two text data sets, we vary the regularization parameter C for all methods and report the best result of each method with the optimal C, where $C \in \{0.1, 0.2, 0.5, 1, 2, 5, 10, 20, 50\}$. We fix the regularization parameter C as the default value 1 in LIBSVM for the large TRECVID data set, because it is time consuming to run the experiments multiple times using different C.

4.2.1 Details on the TRECVID Data Set

Four thousand unlabeled samples from the target domain are randomly selected as the unlabeled training data set D_u^T for model learning in KMM and our DTMKL methods. Moreover, for DTMKL_f, only the labeled and unlabeled samples $D_l^T \cup D_u^T$ from the target domain are used as the training data. For KMM, the parameter B is empirically set as 0.99. And for our methods, the parameter θ in DTMKL_AT and DTMKL_f and the parameters λ, ζ in DTMKL_f need to be determined beforehand. We empirically set $\zeta = 0.1$ and $\theta = 10^{-5}$. Recall that the parameter λ in DTMKL_f is used to balance the costs from labeled data and unlabeled data. Considering that the total number of unlabeled target samples is roughly 10 times more than that of the labeled target samples, we fix $\lambda = 0.1$ in our experiments.

Base kernels are predetermined for all methods. Specifically, we use four types of kernels: Gaussian kernel (i.e., $k(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2)$), Laplacian kernel (i.e., $k(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\sqrt{\gamma}\|\mathbf{x}_i - \mathbf{x}_j\|)$), inverse square distance kernel (i.e., $k(\mathbf{x}_i, \mathbf{x}_j) = \frac{1}{\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2 + 1}$), and inverse distance kernel (i.e., $k(\mathbf{x}_i, \mathbf{x}_j) = \frac{1}{\sqrt{\gamma}\|\mathbf{x}_i - \mathbf{x}_j\| + 1}$), where the kernel parameter γ is set as the default value $\frac{1}{d} = 0.0029$ ($d = 346$ is the feature dimension) in LIBSVM. And for each type of kernels, we use 13 kernel parameters $1.2^{\delta+3}\gamma$, $\delta \in \{-3, -2.5, \ldots, 2.5, 3\}$. In total, we have 52 base kernels for all methods.

Note that our framework can readily incorporate other methods such as FR. Therefore, we introduce another approach (referred to as $\mathrm{DTMKL\_AT_{FR}}$) by replacing SVM with FR in DTMKL_AT, in which we employ the kernel proposed in the FR method [11] to form the base kernels for $\mathrm{DTMKL\_AT_{FR}}$.

For performance evaluation, we use noninterpolated Average Precision (AP) [8], [27], [34], which has been used as the official performance metric in TRECVID since 2001. AP is related to the multipoint average precision value of a precision-recall curve and incorporates the effect of recall when AP is computed over the entire classification results.

4.2.2 Details on the 20 Newsgroups and Email Spam Data Sets

On two text data sets, all the test data in the target domain are also considered as the unlabeled data in the training stage. And for our proposed method DTMKL_f, the unlabeled data from the target domain as well as the labeled data from both the auxiliary and target domains are used to construct the training data set, i.e., $D^A \cup D_l^T \cup D_u^T$. For DTMKL_f, we set $\lambda = 1$ in the experiments because the total number of unlabeled target samples is roughly the same with that of the labeled training samples from both domains.

We consider two types of base kernels: linear kernel (i.e., $k(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i' \mathbf{x}_j$) and polynomial kernel (i.e., $k(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i' \mathbf{x}_j + 1)^a$), where $a = 1.5, 1.6, \ldots, 2.0$. Then, we have, in total, seven base kernels for all methods. Classification accuracy is adopted as the performance evaluation metric for text classification.

4.3 Results of Video Concept Detection

We compare our DTMKL methods with other algorithms on the challenging TRECVID data set for the video concept detection task. For each concept, we count the frequency (referred to as positive frequency) of positive samples in the auxiliary domain. According to the positive frequency, we partition all 36 concepts into three groups (i.e., Group_High, Group_Med, and Group_Low), with 12 concepts for each group. The concepts in Group_High, Group_Med, and Group_Low are with high, moderate, and low positive

TABLE 2
Mean Average Precisions (Percent) of All Methods on the TRECVID Data Set

	SVM_T	SVM_A	SVM_AT	MKL_AT	FR	A-SVM	CD-SVM	KMM	DTMKL_AT	DTMKL_AT$_{FR}$	DTMKL_f
MAP_High	39.6	39.4	44.1	42.1	45.7	45.4	43.8	44.0	45.0	**46.7**	46.5
MAP_Med	12.0	9.2	12.7	11.7	13.1	13.1	12.1	12.7	12.9	13.7	**15.1**
MAP_Low	15.3	2.5	14.5	14.4	15.4	15.3	14.9	14.5	14.6	15.8	**16.4**
MAP_ALL	22.3	17.0	23.8	22.7	24.7	24.6	23.6	23.7	24.2	25.4	**26.0**

MAPs are from concepts of three individual groups and all 36 concepts.

frequencies, respectively. And the average results of all methods are presented in Table 2, where Mean Average Precisions (MAPs) of the concepts in three groups and all 36 concepts are referred to as MAP_High, MAP_Med, MAP_Low, and MAP_ALL, respectively. Fig. 2 plots the per-concept APs of all 36 concepts using different methods. From Table 2 and Fig 2, we have the following observations:

1. SVM_A is much worse than SVM_T according to the MAPs over all 36 concepts, which demonstrates that the SVM classifier learned with the training data from the auxiliary domain performs poorly on the target domain. The explanation is that the data distributions of TRECVID data sets collected in different years are quite different. It is interesting to observe that SVM_AT outperforms SVM_T and SVM_A in terms of MAP_High, but SVM_T is better than SVM_AT and SVM_A in terms of MAP_Low. The explanation is that the concepts in Group_High generally have a large number of positive patterns in both auxiliary and target domains. Intuitively, when sufficient positive samples exist in both domains, the samples distribute densely in the feature space. In this case, the distributions of samples from two domains may overlap between each other [16], and thus, the data from the auxiliary domain may be helpful for video concept detection in the target domain. On the other hand, for the concepts in Group_Low, the positive samples from both domains distribute sparsely in the feature space. It is more likely that there is less overlap between the data distributions of two domains. Therefore, for the concepts in Group_Low, the data from the auxiliary

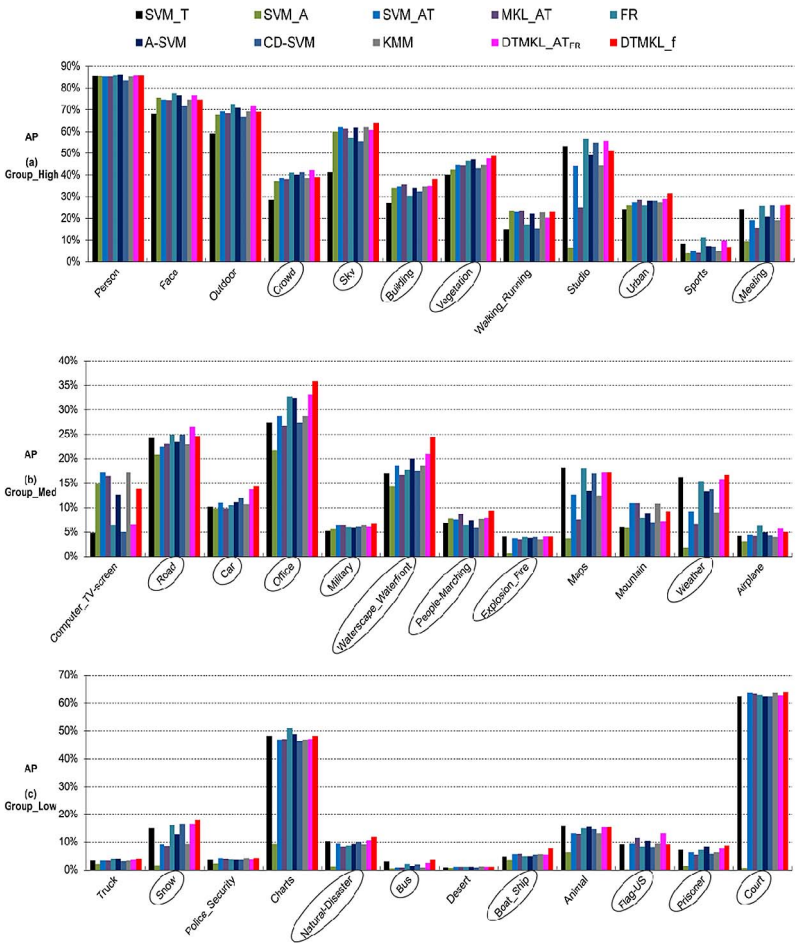


Fig. 2. Per-concept APs of all 36 concepts using different methods. The concepts are divided into three groups according to the positive frequency. Our methods achieve the best performances for the circled concepts.

TABLE 3
Average Training and Testing Time (in Seconds) Comparisons of All Methods on the TRECVID Data Set

	SVM_T	SVM_A	SVM_AT	MKL_AT	FR	A-SVM	CD-SVM	KMM	DTMKL_AT	DTMKL_AT$_{FR}$	DTMKL_*f*
TR	1	1576	1618	686	1636	1576+32	2287	4218	639	688	1618+186
TE	31	475	509	34	523	511	485	508	41	43	52

For A-SVM and DTMKL_f, the two numbers represent the average training time for the learning of the prelearned classifiers and the learning of the target classifier.

domain may degrade the performance for video concept detection in the target domain.

2. MKL_AT is worse than SVM_AT. The assumption in MKL is the training data and the test data come from the same domain. When the data distributions of different domains change considerably in cross-domain learning, the optimal kernel combination coefficients may not be effectively learned by using MKL methods based on the combined data set from two domains.
3. FR and A-SVM outperform SVM_AT in terms of MAPs from all the three groups, which demonstrates that the information from the auxiliary domain can be effectively used in FR and A-SVM to improve the classification performance in the target domain. We also observe that KMM and CD-SVM are slightly worse than SVM_AT in terms of MAP_ALL. A possible explanation is that in CD-SVM, k-nearest neighbors from the target domain are used to define the weights for the auxiliary patterns. When the total number of positive training samples in the target domain is very limited (e.g., 10 positive samples per concept in this work), the learned weights for the auxiliary patterns are not reliable, which may degrade the performance of CD-SVM. Similarly, KMM learns the weights for the auxiliary samples in an unsupervised setting without using any label information, which may not be as effective as other cross-domain learning methods (e.g., FR and A-SVM).
4. DTMKL_AT is better than SVM_AT and MKL_AT in terms of MAPs over all 36 concepts. Moreover, $\mathrm{DTMKL\_AT_{FR}}$ and DTMKL_*f* outperform all other methods in terms of MAPs from all three groups. These results clearly demonstrate that the DTMKL methods can successfully minimize the data distribution mismatch between two domains and the structural risk functional through effective combination of multiple base kernels. DTMKL_*f* is better than $\mathrm{DTMKL\_AT_{FR}}$ in terms of MAP_ALL because of the additional utilization of the base classifiers. $\mathrm{DTMKL\_AT_{FR}}$ or DTMKL_*f* achieves the best results in 21 out of 36 concepts. In addition, some concepts enjoy large performance gains. For instance, the AP for the concept "Waterscape_Waterfront" significantly increases from 20.0 (A-SVM) to 24.5 percent (DTMKL_*f*), equivalent to a 22.5 percent relative improvement; and the AP for the concept "Car" is improved from 11.9 (CD-SVM) to 14.3 percent (DTMKL_*f*), equivalent to a 20.2 percent relative improvement. Compared with the best results from the existing methods, DTMKL_*f* (15.1 percent) enjoys a relative improvement 15.3 percent over FR and A-SVM (13.1 percent) in terms of MAP_Med, DTMKL_*f* (16.4 percent) enjoys a relative improvement 6.5 percent over FR (15.4 percent) in terms of MAP_Low. Moreover, compared with FR (24.7 percent), A-SVM (24.6 percent), KMM (23.7 percent), CD-SVM (23.6 percent), MKL_AT (22.7 percent), SVM_AT (23.8 percent), and SVM_T (22.3 percent), the relative MAP improvements of DTMKL_*f* (26.0 percent) over all 36 concepts are 5.3, 5.7, 9.7, 10.2, 14.5, 9.2, and 16.6 percent, respectively.
5. We also observe that $\mathrm{DTMKL\_AT_{FR}}$ is slightly better than DTMKL_*f* in terms of MAP_High, possibly because the distributions of samples from two domains overlap between each other in this case. We therefore propose a simple predicting method by using $\mathrm{DTMKL\_AT_{FR}}$ for the concepts in Group_High and DTMKL_*f* for the rest concepts in Group_Med and Group_Low. The MAP of the predicting method over all 36 concepts is 26.1 percent, with the relative improvements over FR, A-SVM, KMM, CD-SVM, MKL_AT, SVM_AT, and SVM_T as 5.7, 6.1, 10.1, 10.6, 15.0, 9.7, and 17.0 percent, respectively.

We additionally report the average training (TR) and testing (TE) time of all the methods for each concept in Table 3. All the experiments are performed on an IBM workstation (2.66 GHz CPU with 32 Gbyte RAM) with LIBSVM [7]. From Table 3, we observe that SVM_T is quite fast because it only utilizes the labeled training data from the target domain. We also observe that some MKL-based methods (i.e., MKL_AT, DTMKL_AT, and $\mathrm{DTMKL\_AT_{FR}}$) are much faster than the late-fusion-based methods except SVM_T in the training phase. For A-SVM and DTMKL_*f*, the most time-consuming part in the training phase is from the learning of the prelearned classifiers, while it is very fast to learn the target classifier. Moreover, all the MKL-based methods are also much faster than the late-fusion-based methods except SVM_T in the testing phase. On average, our DTMKL methods take less than 1 minute to finish the whole prediction phase for about 21,213 test samples from each concept, which is still acceptable in the real-world applications.

4.4 Results of Text Classification

For the text classification task, we focus the comparisons between DTMKL_*f* and other related methods using two text data sets. For each setting, we report the results of all methods obtained by using the training data from the auxiliary domain as well as m positive and m negative training samples randomly selected from the target domain, where we set $m = 0, 1, 3, 5, 7$, and 10 for the 20 Newsgroups data set and $m = 5$ for the email spam data set. We randomly sample the training data from the target domain

TABLE 4
Means and Standard Deviations (Percent) of Classification Accuracies of All Methods with Different Number of Positive and Negative Training Samples (i.e., m) from the Target Domain on the 20 Newsgroups Data Set

(a) comp vs. rec

m	SVM_T	SVM_A	SVM_AT	MKL_AT	FR	A-SVM	CD-SVM	KMM	A-MKL	DTMKL_f
0	–	89.0±0.0	–	–	–	–	–	89.2±0.0	–	**91.8±0.0**
1	52.9±5.9	89.0±0.0	89.3±0.2	89.4±0.4	86.6±2.2	88.2±1.6	88.8±0.3	89.6±0.3	89.0±0.2	**92.3±0.3**
3	64.0±5.8	89.0±0.0	90.0±0.2	90.2±0.4	85.7±3.9	88.2±1.4	89.5±0.6	90.3±0.5	89.8±0.3	**92.8±0.4**
5	76.8±10.9	89.0±0.0	90.6±0.4	90.9±0.1	88.9±3.1	89.5±2.0	90.6±0.7	91.4±0.7	91.0±0.5	**93.3±0.5**
7	80.6±9.1	89.0±0.0	91.0±0.1	91.1±0.0	89.5±2.5	90.2±1.6	90.9±0.1	91.1±0.1	91.2±0.9	**93.6±0.5**
10	84.8±6.2	89.0±0.0	91.7±0.1	91.7±0.1	91.3±2.2	91.1±1.5	91.5±0.1	91.8±0.1	92.1±0.9	**94.2±0.4**

(b) comp vs. sci

m	SVM_T	SVM_A	SVM_AT	MKL_AT	FR	A-SVM	CD-SVM	KMM	A-MKL	DTMKL_f
0	–	70.7±0.0	–	–	–	–	–	70.2±0.0	–	**72.9±0.0**
1	51.6±3.7	70.7±0.0	70.8±0.1	71.1±0.1	70.5±1.6	70.3±0.5	69.5±1.0	70.3±0.1	70.3±0.2	**73.1±0.1**
3	57.8±8.9	70.7±0.0	72.0±0.7	71.8±0.8	69.6±1.8	70.4±0.4	72.0±0.8	72.0±0.5	72.0±0.7	**74.8±0.6**
5	63.8±13.0	70.7±0.0	74.1±3.1	74.1±3.2	71.3±7.7	71.3±2.8	74.1±3.1	74.0±3.0	74.2±3.0	**77.0±2.9**
7	73.8±4.3	70.7±0.0	75.6±2.7	75.8±2.7	76.0±4.5	73.4±3.3	75.8±2.7	75.8±2.6	75.7±2.7	**78.3±2.7**
10	76.6±3.9	70.7±0.0	78.1±2.7	77.9±2.7	78.4±3.4	74.8±2.4	78.1±2.7	78.1±2.8	78.1±2.7	**80.5±2.8**

(c) comp vs. talk

m	SVM_T	SVM_A	SVM_AT	MKL_AT	FR	A-SVM	CD-SVM	KMM	A-MKL	DTMKL_f
0	–	92.9±0.0	–	–	–	–	–	92.2±0.0	–	**94.3±0.0**
1	56.7±7.1	92.9±0.0	93.1±0.2	93.2±0.3	91.4±3.9	92.3±1.5	93.1±0.3	92.3±0.1	94.3±0.1	**94.6±0.2**
3	72.4±8.4	92.9±0.0	93.4±0.4	93.6±0.4	91.7±3.0	93.7±0.6	93.4±0.3	92.5±0.5	94.4±0.3	**94.9±0.2**
5	81.9±2.1	92.9±0.0	93.6±0.3	93.7±0.4	93.1±0.6	94.0±0.6	93.7±0.3	92.8±0.5	94.4±0.2	**95.0±0.3**
7	83.5±2.0	92.9±0.0	93.7±0.3	93.8±0.3	93.3±1.0	93.7±0.7	93.8±0.4	93.7±0.3	94.5±0.2	**95.1±0.3**
10	93.5±2.0	92.9±0.0	94.0±0.4	94.1±0.4	93.6±1.0	94.0±0.4	94.0±0.3	93.9±0.8	94.6±0.4	**95.2±0.4**

Each result in the table is the best among all the results obtained by using different regularization parameters $C \in \{0.1, 0.2, 0.5, 1, 2, 5, 10, 20, 50\}$. The results shown in boldface are significantly better than the others, judged by the t-test with a significance level of 0.1.

for five times. In Tables 4 and 5, we report the means and standard deviations of classification accuracies (ACC) for all methods on the 20 Newsgroups and email spam data sets, respectively. It is worth noting that when there are no training samples from the target domain, DTMKL_f can employ the base SVM classifiers learned from the auxiliary data only. But other methods, like SVM_T, SVM_AT, MKL_AT, FR, A-SVM, CD-SVM, and A-MKL [14], cannot work in this case. Also note that for all methods, each result in Tables 4 and 5 is the best among all the results obtained by using different regularization parameters $C \in \{0.1, 0.2, 0.5, 1, 2, 5, 10, 20, 50\}$. From Tables 4 and 5, we have the following observations:

1. On both data sets, MKL_AT is comparable with SVM_AT, which shows that the auxiliary domain is relevant to the target domain. The performances of SVM_T and SVM_AT become better on the 20 Newsgroups data set, when the number of labeled positive and negative training samples (i.e., m) increases. And SVM_AT outperforms SVM_T and SVM_A on both data sets, which demonstrates that it is beneficial to utilize the data from the auxiliary domain to improve the performance in the target domain.
2. Some cross-domain learning methods (i.e., CD-SVM and KMM) generally achieve similar performances when compared with SVM_AT. The explanation is that the data distributions of two domains are quite

TABLE 5
Means and Standard Deviations (Percent) of Classification Accuracies of All Methods with Five Positive and Five Negative Training Samples from the Target Domain on the EMail Spam Data Set

(a) User1 (auxiliary domain) & User2 (target domain)

	SVM_T	SVM_A	SVM_AT	MKL_AT	FR	A-SVM	CD-SVM	KMM	A-MKL	DTMKL_f
ACC	80.2±3.5	96.1±0.0	96.2±0.1	96.2±0.0	92.5±2.8	95.4±0.9	96.2±0.2	96.2±0.1	96.3±0.3	**96.9±0.1**

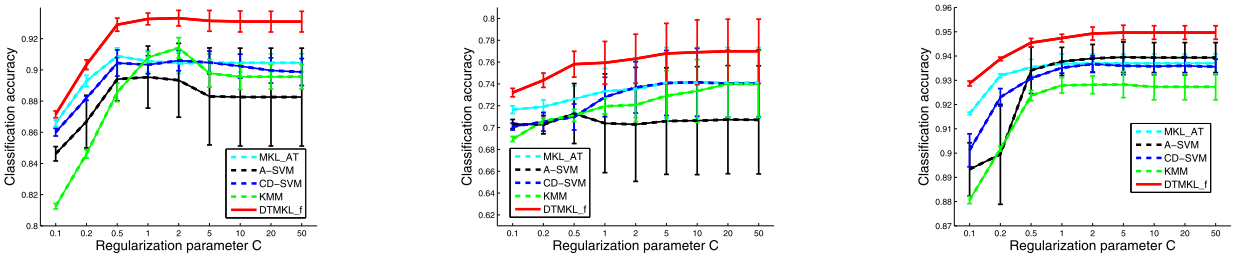
(b) User2 (auxiliary domain) & User3 (target domain)

	SVM_T	SVM_A	SVM_AT	MKL_AT	FR	A-SVM	CD-SVM	KMM	A-MKL	DTMKL_f
ACC	82.0±2.6	96.9±0.0	97.0±0.1	97.0±0.1	92.1±2.4	96.0±1.3	97.0±0.1	97.0±0.1	97.3±0.0	**97.7±0.1**

(c) User3 (auxiliary domain) & User1 (target domain)

	SVM_T	SVM_A	SVM_AT	MKL_AT	FR	A-SVM	CD-SVM	KMM	A-MKL	DTMKL_f
ACC	79.1±1.9	91.7±0.0	91.8±0.1	91.4±0.1	91.8±2.5	92.4±1.2	91.8±0.1	91.8±0.1	92.8±0.5	**94.0±0.4**

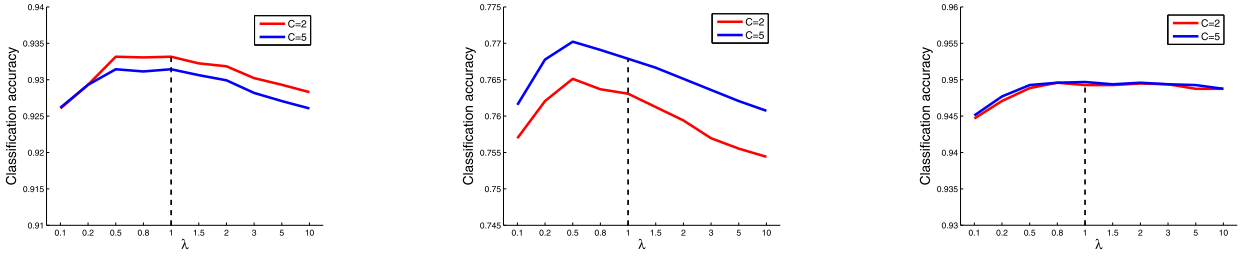
Each result in the table is the best among all the results obtained by using different regularization parameters $C \in \{0.1, 0.2, 0.5, 1, 2, 5, 10, 20, 50\}$. The results shown in boldface are significantly better than the others, judged by the t-test with a significance level of 0.1.



(a) comp vs. rec ($m = 5$) (b) comp vs. sci ($m = 5$) (c) comp vs. talk ($m = 5$)

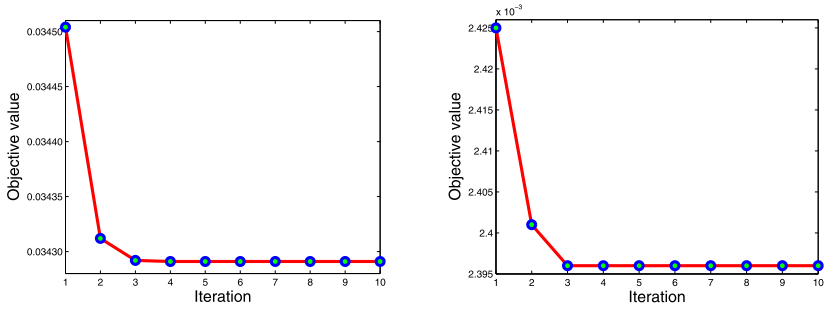
(d) comp vs. rec ($m = 10$) (e) comp vs. sci ($m = 10$) (f) comp vs. talk ($m = 10$)

Fig. 3. Performance comparisons of DTMKL_*f* with other methods in terms of the means and standard deviations of classification accuracies on the 20 Newsgroups data set by using different regularization parameters $C \in \{0.1, 0.2, 0.5, 1, 2, 5, 10, 20, 50\}$. We set $m = 5$ (top) and $m = 10$ (bottom).



(a) comp vs. rec (b) comp vs. sci (c) comp vs. talk

Fig. 4. Performance (i.e., the means of classification accuracies) variation of DTMKL_*f* with respect to the balance parameter $\lambda \in [0.1, 10]$ on the 20 Newsgroups data set. We set the regularization parameter $C = 2$ and $C = 5$.



(a) Person (b) Airplane

Fig. 5. Illustration of the convergence of DTMKL_AT.

related, making it difficult for the existing cross-domain learning methods to further improve the performances in the target domain. We also observe that A-SVM is worse than SVM_AT in most settings on the two text data sets. It seems that the limited number of labeled training samples from the target domain are not sufficient to facilitate robust adaptation for A-SVM. And it is interesting to observe that FR is generally worse than SVM_AT on the email spam data set in terms of the means of classification accuracies. A possible explanation is that the kernel of FR, which is constructed based on the augmented features, is less effective on this data set. Moreover, in most cases, A-MKL [14] outperforms other methods except DTMKL_*f* in terms of the means of classification accuracies.

3. Our proposed method DTMKL_*f* is consistently better than all other methods in terms of the means of classification accuracies on both data sets, thanks to the explicit modeling of the data distribution mismatch as well as the successful utilization of the unlabeled data and the base classifiers. As shown in Table 4, when the number of labeled positive and negative training samples (i.e., m) from the target

domain increases, DTMKL_f becomes better on the 20 Newsgroups data set. Moreover, judged by the t-test with a significance level of 0.1, DTMKL_f is significantly better than other methods in all settings.

We also compare our proposed method DTMKL_f with the competitive methods, including MKL_AT, A-SVM, CD-SVM, and KMM, by using different regularization parameters $C \in \{0.1, 0.2, 0.5, 1, 2, 5, 10, 20, 50\}$. The results of all methods are obtained by using m positive and m negative training samples from the target domain as well as the training data from the auxiliary domain, in which we set $m = 5$ and 10 for the 20 Newsgroups data set in Fig. 3. From the figure, we observe that when C becomes larger, all methods tend to have better performances. In addition, our method DTMKL_f consistently outperforms other methods in terms of the means of classification accuracies. Moreover, DTMKL_f is also relatively stable according to the standard deviations of classification accuracies. We have similar observations on this data set when using different m and also on the email spam data set.

Recall that the parameter λ in DTMKL_f balances the costs from the labeled and unlabeled samples (see (15)). In Fig. 4, we take the 20 Newsgroups data set as an example to investigate the performance variation of DTMKL_f with respect to the parameter λ, in which we set $m = 5$ and the regularization parameter $C = 2$ and 5. Note the total number of labeled samples from two domains and the number of unlabeled samples from the target domain are almost the same on the 20 Newsgroups data set. From Fig. 4, we have the following observations: 1) The performance of DTMKL_f changes with different λ in a large range (i.e., $\lambda \in [0.1, 10]$); 2) when λ is quite small or quite large (i.e., the cost from labeled data or unlabeled data is more important), the performances of DTMKL_f generally degrade a bit; and 3) when we set $\lambda \in [0.5, 1.5]$, DTMKL_f achieves the best results and is not sensitive to the parameter λ as well. In this case, both the labeled data and the unlabeled data from the target domain can be effectively utilized to learn a robust classifier. We have similar observations on this data set when using different C and m, and on the email spam data set as well.

4.5 Convergence

In Theorem 1, we theoretically prove that DTMKL_AT is jointly convex with respect to $\mathbf{d}$, $\mathbf{v}_m$, b, and ξ_i. Here, we take two concepts "Person" and "Airplane" from the TRECVID data set as examples to experimentally demonstrate the convergence of DTMKL_AT. As shown in Fig. 5, the objective values of DTMKL_AT converge after less than five iterations. We have similar observations for other concepts as well.

5 Conclusions and Future Work

In this work, we have proposed a unified cross-domain learning framework Domain Transfer Multiple Kernel Learning to explore the single auxiliary domain and single target domain problem. DTMKL simultaneously learns a kernel function and a target classifier by minimizing the structural risk functional as well as the distribution mismatch between the samples from the auxiliary and target domains. By assuming that the kernel function is a linear combination of multiple base kernels, we also develop a unified learning algorithm by using the second-order derivatives to accelerate the convergence of the proposed framework. Most importantly, many existing kernel methods, including SVM, SVR, KRLS, and so on, can be readily incorporated into the framework of DTMKL to tackle cross-domain learning problems.

Based on the DTMKL framework, we propose two methods DTMKL_AT and DTMKL_f by using SVM and existing classifiers, respectively. For DTMKL_f, many machine learning methods (e.g., SVM and SVR) can be used to learn the base classifiers. Specifically, in DTMKL_f, we enforce that 1) for the unlabeled target data, the target classifier produces similar decision values with those obtained from the base classifiers; and 2) for the labeled target data, the decision values obtained from the target classifier are close to the true labels. Experimental results show that DTMKL_f outperforms existing cross-domain learning and multiple kernel learning methods on the challenging TRECVID data set for video concept detection as well as on the 20 Newsgroups and email spam data sets for text classification.

In this work, we randomly select a number of unlabeled target patterns as the training data for DTMKL_f. Considering that it is beneficial to establish the optimal balance between the labeled and unlabeled patterns [10], we will investigate how to determine such optimal balance in the future. Moreover, we will also study how to automatically determine the optimal parameters for DTMKL_AT and DTMKL_f.

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