Learning Transferable Features with Deep Adaptation Networks

Mingsheng Long†‡
Jianmin Wang†
†Department of EECS, University of California, Berkeley
‡School of Software, Tsinghua University, Beijing, China

Abstract
Recent studies reveal that a deep neural network can learn transferable features which generalize well to novel tasks for domain adaptation. However, as deep features eventually transition from general to specific along the network, the feature transferability drops significantly in higher layers with increasing domain discrepancy. Hence, it is critical to formally reduce the domain bias and enhance the transferability in task-specific layers. In this paper, we propose a new Deep Adaptation Network (DAN) architecture, which generalizes deep convolutional neural network to the domain adaptation scenario. In DAN, hidden representations of all task-specific layers are embedded to a reproducing kernel Hilbert space where the mean embeddings of different domain distributions can be explicitly matched. The domain discrepancy is further reduced using an optimal multi-kernel selection method for mean embedding matching. DAN can learn invariant features with enhanced transferability, and can scale linearly by unbiased estimate of kernel embedding. Extensive empirical evidence demonstrates the proposed architecture significantly outperforms state-of-the-art results on standard domain adaptation benchmarks.

1. Introduction
The generalization error of supervised learning machines with limited training samples will be unsatisfactorily large, while manual labeling of sufficient training data for diverse application domains may be prohibitive. Therefore, there is incentive to establishing effective algorithms to reduce the labeling cost, typically by leveraging off-the-shelf labeled data from relevant source domains to the target domains. Domain adaptation addresses the problem that we have data from two related domains but under different distributions.

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crimination, enlarged domain discrepancy may deteriorate domain adaptation performance (Ben-David et al., 2010).

Inspired by the literature’s latest understanding about the transferability of deep neural networks, we propose in this paper a new Deep Adaptation Network (DAN) architecture, which generalizes deep convolutional neural network to the domain adaptation scenario. The main idea of this work is to enhance the feature transferability in the task-specific layers of the deep neural network by explicitly reducing the domain discrepancy. To establish this goal, the hidden representations of all the task-specific layers are embedded to a reproducing kernel Hilbert space where the mean embeddings of different domain distributions can be explicitly matched. As mean embedding matching is sensitive to the kernel choices, an optimal multi-kernel selection procedure is devised to further reduce the domain discrepancy. In addition, we implement a linear-time unbiased estimate of the kernel mean embedding to enable scalable training, which is very desirable for deep learning. Finally, as deep models pre-trained with large-scale repositories such as ImageNet (Russakovsky et al., 2014) are representative for general-purpose tasks (Yosinski et al., 2014; Hoffman et al., 2014), the proposed DAN model is trained by fine-tuning from the AlexNet model (Krizhevsky et al., 2012) pre-trained on ImageNet, which is implemented in Caffe (Jia et al., 2014). Comprehensive empirical evidence demonstrates that the proposed architecture outperforms state-of-the-art results evaluated on the standard domain adaptation benchmarks.

The contributions of this paper are summarized as follows. 1) We propose a novel deep neural network architecture for domain adaptation, in which all the layers corresponding to task-specific features are adapted in a layerwise manner, hence benefiting from “deep adaptation” besides the deep representation. 2) We explore multiple kernels for adapting deep representations, which substantially enhances adaptation effectiveness than conventional single kernel methods.

The remainder of this paper is organized as follows. We begin by reviewing the related works in Section 2. Then we formally present the proposed model and algorithm in Section 3. Empirical evaluations are reported in Section 4, while conclusion and future work are enclosed in Section 5.

2. Related Work

Deep neural networks learn nonlinear representations that disentangle and hide different explanatory factors of variation behind data samples (Bengio et al., 2013). The learned deep representations manifest invariant factors underlying different populations and are transferable from the original tasks to similar novel tasks (Yosinski et al., 2014). Hence, deep neural networks have been explored for domain adaptation (Glorot et al., 2011; Chen et al., 2012), multimodal and multi-source learning problems (Ngiam et al., 2011; Ge et al., 2013), where significant performance gains have been witnessed. However, all these methods depend on the assumption that deep neural networks can learn invariant representations that are transferable across different tasks. As revealed by (Yosinski et al., 2014), deep features in the lower layers of the networks are general Gabor filters that are transferable to novel tasks, however, the features in the higher layers of the networks are tailored to the original tasks and cannot be safely transferred to novel tasks when the novel tasks are distant from the original tasks. In other words, the domain discrepancy can be alleviated, but not removed, by deep neural networks. Hence, domain bias has posed a bottleneck to the transferability of deep networks.

A related literature is transfer learning (Pan & Yang, 2010), which learns a representation or classification model to bridge different domains or tasks, explicitly taking domain discrepancy into consideration. It has been explored to save the manual labeling efforts for machine learning (Pan et al., 2011; Zhang et al., 2013; Wang & Schneider, 2014) and computer vision (Gong et al., 2012; Baktashmotlagh et al., 2013; Long et al., 2013), etc. It is widely recognized that the domain discrepancy in the probability distributions of different domains should be formally measured and explicitly reduced. Hence the major bottleneck is how to match different domain distributions effectively. Most of existing methods learn a new shallow representation model in which the domain discrepancy can be reduced. However, without learning deep features which can suppress domain-specific exploratory factors, the transferability of shallow features could be limited by the task-specific variational structures.

There are several very recent works on learning domain-invariant features in the context of shallow neural networks (Ajakan et al., 2014; Ghifary et al., 2014). Due to limited capacity of shallow architecture, the performance of these works cannot surpass deep CNN (Krizhevsky et al., 2012). To address this limitation, (Tzeng et al., 2014) proposed a DDC model that adds an adaptation layer and a domain discrepancy loss to deep CNN architecture for learning a representation that is semantically meaningful and domain invariant. While significant performance gain was shown, DDC adapts only a single layer of the network, which may be limited in that there are multiple layers where the hidden features are not transferable (Yosinski et al., 2014). DDC is also limited by suboptimal kernel embedding of probability distributions (Gretton et al., 2012), which could further degrade its transferability. In this paper, we have proposed a new deep adaptation network to address these limitations.

3. Deep Adaptation Networks

In unsupervised domain adaptation, we are given a source domain $D_s = \{(x^s_i, y^s_i)\}_{i=1}^{n_s}$ with $n_s$ labeled examples, and
a target domain \( D_t = \{ x_t^j \}_{j=1}^{n_t} \) with \( n_t \) unlabeled examples. The source domain and target domain follow different probability distributions \( p \) and \( q \), respectively. Hence, we are targeting a deep neural network which is able to learn transferable features to bridge the domain discrepancy, and build a classifier \( y = \theta(x) \) which minimizes target risk \( R_{D_t}(\theta) = \Pr_{(x,y)\sim q}[\theta(x) \neq y] \) using source supervision. In semi-supervised adaptation where the target has a small amount of labeled examples, we denote \( D_o = \{ (x_o^a, y_o^a) \} \) as the \( n_a \) annotated examples of source and target domains.

3.1. The Model

MK-MMD Domain adaptation is challenging in that the target domain has no (or only limited) labeled information. To approach this problem, many existing methods aimed to bound the target error by the source error plus a discrepancy metric between the source and the target (Ben-David et al., 2010). Two classes of statistics have been explored for the two-sample testing, which makes acceptance or rejection decision to the null hypothesis \( p = q \), given two samples generated respectively from \( p \) and \( q \). On the one hand, the energy distances are derived from the statistical literature, and on the other hand, the maximum mean discrepancies (MMD) are established in the machine learning literature (Sejdinovic et al., 2013). In this paper, we will focus on the multiple kernel variant of MMD (MK-MMD) proposed by (Gretton et al., 2012), which is formalized to jointly maximize the two-sample test power and minimize the Type II error, i.e. failure of rejecting a false null hypothesis \( p = q \).

Denote \( H_k \) the reproducing kernel Hilbert space (RKHS) endowed with a characteristic kernel \( k \). Then the mean embedding of probability \( p \) in \( H_k \) is a unique element \( \mu_k(p) \) such that \( E_{x \sim p} f(x) = \langle f(x), \mu_k(p) \rangle_{H_k} \) for all \( f \in H_k \). The MK-MMD between probability distributions \( p \) and \( q \) is defined as the RKHS-distance between the mean embeddings of \( p \) and \( q \). A formulation of squared MK-MMD is

\[
d_k^2(p, q) = \| E_p [\phi(x)] - E_q [\phi(x)] \|^2_{H_k}. \tag{1}
\]

The most important property is that \( p = q \) iff \( d_k^2(p, q) = 0 \). The characteristic kernel \( k(x^s, x^t) = \langle \phi(x^s), \phi(x^t) \rangle \) is defined as the convex combination of \( m \) PSD kernels \( \{ k_u \} \),

\[
\mathcal{K} = \left\{ k = \sum_{u=1}^{m} \beta_u k_u : \sum_{u=1}^{m} \beta_u = 1, \beta_u \geq 0, \forall u \right\}, \tag{2}
\]

where the constraints on coefficients \( \{ \beta_u \} \) are imposed to guarantee that the derived multi-kernel \( k \) is characteristic. As studied theoretically in (Gretton et al., 2012), the kernel adopted for the mean embeddings of \( p \) and \( q \) is critical in ensuring the test power and low test error. The multi-kernel \( k \) can leverage different kernels to enhance MK-MMD test, leading to a principled method for optimal kernel selection.

As revealed by (Ben-David et al., 2010), a good strategy to control the domain discrepancy is to find an abstract feature representation through which the source and target domains are similar. Note that MMD has been extensively explored in this line of works (Pan et al., 2011; Zhang et al., 2013; Wang & Schneider, 2014). However, there is no attempt in enhancing the transferability of feature representation via MK-MMD in deep networks, hence prior methods may be limited by either the representation or adaptation weakness.

**Deep Adaptation Networks (DAN)** In this paper, we will explore the idea of MK-MMD based distribution adaptation for learning transferable features in the deep networks. We start with deep convolutional neural networks (CNN) (Krizhevsky et al., 2012), a strong model when it is adapted to novel tasks (Donahue et al., 2014; Hoffman et al., 2014). However, the main challenge lies in that the target domain has no or just limited labeled information, hence adapting CNN to the target domain via fine-tuning is impossible or is easily over-fitted. With the idea of domain adaptation, we are targeting a deep adaptation network (DAN) that can explore both source labeled data and target unlabeled data. Figure 1 gives an illustration of the proposed DAN model.

We extend AlexNet (Krizhevsky et al., 2012) architecture, which consists of 5 convolutional layers (conv1-conv5) and 3 fully connected layers (fc6-fc8). Each fc layer \( \ell \) learns a nonlinear mapping \( h^\ell_i = f^\ell(W^\ell h^{\ell-1}_i + b^\ell_i) \), where \( h^{\ell}_i \) is the \( i \)th hidden representation of point \( x \), \( W^\ell \) and \( b^\ell \) are the weights and bias of the \( \ell \)th layer, and \( f^\ell \) is the activation, taking as rectifier units \( f^\ell(x) = \max(0, x) \) for hidden layers or softmax units \( f^\ell(x) = e^x / \sum_{j=1}^{\ell} e^{x_j} \) for output layer. Denote \( \Theta = \{ W^\ell, b^\ell \}_{\ell=1}^{L} \) the set of all CNN parameters, then the overall empirical risk of CNN is

\[
\min_{\Theta} \frac{1}{n_a} \sum_{i=1}^{n_a} J(\theta(x^a_i), y^a_i), \tag{3}
\]

where \( J \) is the cross-entropy loss function, and \( \theta(x^a_i) \) is
In our implemented DAN, we set layer indices between which the regularizer are effective. The reason is due to (Yosinski et al., 2014) in that the convolutional layers can learn generic features that are sufficiently transferable in conv1–conv3 and slightly domain-biased in conv4–conv5. Hence, when adapting the pre-trained AlexNet to the target, we opt to frozen conv1–conv3 due to limited supervision in domain adaptation and fine-tune conv4–conv5 to preserve the efficacy of fragile co-adaptation (Hinton et al., 2012).

In standard CNN, deep features must eventually transition from general to specific by the last layer of the network, and the transferability gap grows with the domain discrepancy and becomes particularly large when transferring the higher layers fc6–fc8 (Yosinski et al., 2014). In other words, the fc layers are tailored to their original task at the expense of degraded performance on the target task, hence they cannot be directly transferred to the target domain via fine-tuning with limited target supervision. In this paper, we fine-tune CNN on the source labeled examples and require the probabilities of the source and target become similar under the hidden representations of fully connected layers fc6–fc8. This can be established by introducing an MK-MMD (1) based multi-layer adaptation regularizer to CNN risk (3) as

\[
\min_{\Theta} \frac{1}{n_a} \sum_{i=1}^{n_a} J(\theta(x_i^s), y_i^t) + \lambda \sum_{\ell=1}^{\ell_2} d_k(D^s_\ell, D^t_\ell),
\]

where \( \lambda > 0 \) is a penalty parameter to trade off the weights between CNN risk and MK-MMD regularizer, \( \ell_1 \) and \( \ell_2 \) are layer indices between which the regularizer are effective. In our implemented DAN, we set \( \ell_1 = 6 \) and \( \ell_2 = 8 \), while a different configuration is also possible, depending on the size of the labeled source dataset and the number of parameters in the layers that are to be fine-tuned. \( D^s_\ell = \{h^s_\ell\} \) is the \( \ell \)th layer hidden representation for the source and target examples, and \( d_k(D^s_\ell, D^t_\ell) \) is the MK-MMD between the source and target evaluated on the \( \ell \)th layer representation.

Training deep CNN requires large amount of labeled data, which is prohibitive for many domain adaptation problems, hence we start by AlexNet model pre-trained on ImageNet 2012 and fine-tune it to our tasks as (Tzeng et al., 2014). With the proposed DAN optimization framework (4), we are able to learn transferable features from a source domain to a related target domain. The learned representation can both be salient benefiting from CNN, and unbiased thanks to MK-MMD. Two important advantages that distinguish DAN from relevant literature are: 1) multi-layer adaptation. As revealed by (Yosinski et al., 2014), feature transferability gets worse on conv4–conv5 and significantly drops on fc6–fc8, hence it is crucial to adapt multiple layers instead of only one layer that was studied in (Tzeng et al., 2014). In other words, adapting a single layer cannot undo the dataset bias between the source and the target, since there are other layers that are not transferable. Another benefit of multi-layer adaptation is that by jointly adapting representation layers and classifier layer, we could essentially bridge the domain discrepancy underlying both marginal distribution and conditional distribution, which is crucial for domain adaptation (Zhang et al., 2013), 2) multi-kernel adaptation. As pointed out by (Gretton et al., 2012), kernel choice is critical to the testing power of MMD since different kernels may embed probability distributions into different RKHS where different orders of the sufficient statistics could be emphasized. This is important for moment matching, while it is not well explored by prior domain adaptation methods.

### 3.2. Algorithm

**Learning \( \Theta \)** Using the kernel trick, MK-MMD (1) can be computed as the expectation of kernel functions \( d_k^2(p, q) = E_{x \sim x^s} k(x, x^t) + E_{x \sim x^t} k(x^t, x^t) - 2E_{x \sim x^s} k(x^s, x^t) \), where \( x^s, x^t \sim id p, x^t, x^t \sim id q \), and \( k \in K \). However, this computation incurs a complexity of \( O(n^2) \), which is rather undesirable for deep CNN, as the power of deep neural networks largely rely on the learning from large-scale datasets. Moreover, the summation over pairwise similarity between data points makes mini-batch stochastic gradient descent (SGD) more difficult, whereas mini-batch SGD is crucial to the training effectiveness of deep networks. While prior works based on MMD (Pan et al., 2011; Tzeng et al., 2014) rarely address this issue, we believe it is more critical in the context of deep learning. In this paper, we adopt the unbiased estimate of MK-MMD (Gretton et al., 2012) which can be computed with linear complexity. More specifically, \( d_k^2(p, q) = \frac{1}{n} \sum_{i=1}^{n} g_k(z_i) \), where for notation clarity, we denote quad-tuple \( z_i := (x_i^{s_{2i-1}}, x_i^{s_{2i}}, x_i^{t_{2i-1}}, x_i^{t_{2i}}) \), and evaluate multi-kernel function \( k \) on each quad-tuple \( z_i \) by \( g_k(z_i) := k(x_i^{s_{2i-1}}, x_i^{s_{2i}}) + k(x_i^{t_{2i-1}}, x_i^{t_{2i}}) - k(x_i^{s_{2i-1}}, x_i^{t_{2i}}) - k(x_i^{s_{2i}}, x_i^{t_{2i-1}}) \). This arrangement of examples computes an expectation of independent variables as (1) with cost \( O(n) \).

As we train deep CNN by mini-batch SGD, we only need to consider the gradient of objective (4) with respect to each data point \( x_i \). As linear-time MK-MMD takes a summation form that can be readily decoupled into the sum of \( g_k(z_i) \)'s, we only need compute gradient \( \frac{\partial g_k(z_i)}{\partial \theta(x_i^s)} \) for the quad-tuple \( z_i = (h_i^{s_{2i-1}}, h_i^{s_{2i}}, h_i^{t_{2i-1}}, h_i^{t_{2i}}) \) of \( \ell \)th layer hidden representation. To be consistent with the gradient of MK-MMD, we compute the corresponding gradient of CNN risk \( \frac{\partial J(z_i)}{\partial \theta} \), where \( J(z_i) = \sum_{s,t} J(\theta(x_i^s), y_i^t) \), and \( \{x_i^s, y_i^t\} \) indicates the labeled examples in quad-tuple \( z_i \)—for instance, in unsupervised adaptation the target domain has no labeled data and hence \( \{x_i^s, y_i^t\} = \{x_i^{s_{2i-1}}, y_i^{t_{2i-1}}, x_i^{s_{2i}}, y_i^{t_{2i}}\} \). To perform mini-batch update, we compute the gradient of
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objective (4) with respect to the \( \ell \)th layer parameter \( \Theta^\ell \) as

\[
\nabla_{\Theta^\ell} = \frac{\partial J (x_i)}{\partial \Theta^\ell} + \lambda \frac{\partial g_k (z_i^\ell)}{\partial \Theta^\ell}.
\]

(5)

Such a mini-batch SGD can be easily implemented based on the Caffe framework (Jia et al., 2014) for CNN. Given kernel \( k \) as the linear combination of \( m \) Gaussian kernels \( \{k_u (x_i, x_j) = e^{-\|x_i - x_j\|^2 / \tau_u^2}\} \), the gradient \( \frac{\partial g_k (z_i^\ell)}{\partial \Theta^\ell} \) can be readily computed based on the chain rule. For instance, \( \frac{\partial k (h_{2i-1}^\ell, h_{2i}^\ell)}{\partial W} = -\sum_{u=1}^{m} 2\beta_u \sum_{d=1}^{D} k_u \left(h_{2i-1}^\ell, h_{2i}^\ell \right) \times 

(\text{6})

\[
\text{where the last row computes the gradient of the \ell \text{th layer rectifier units, with } I \text{ being defined as an indicator such that } I (h_{ji}^{\ell-1}) = h_{ji}^{\ell-1} \text{ if } W h_{j}^{\ell-1} + b_{j} \geq 0, \text{ else } I (h_{ji}^{\ell-1}) = 0.}
\]

Learning \( \beta \) The proposed multi-layer adaptation regularizer performs layerwise matching by MK-MMD, hence we seek to learn optimal kernel parameter \( \beta \) for MK-MMD by jointly maximizing the test power and minimizing the Type II error (Gretton et al., 2012), leading to an optimization as

\[
\max_{k \in K} d_k^2 (D_s^\ell, D_t^\ell) \sigma_k^{-2};
\]

(7)

where \( \sigma_k^2 = E_{x} g_k^2 (z) - E_{x} g_k (z)^2 \) is estimation variance. Denote \( d = (d_1, d_2, \ldots, d_m)^T \), each \( d_k \) is MMD via kernel \( k_u \). Covariance \( Q = \text{cov} (g_k) \in \mathbb{R}^{m \times m} \) can be computed in \( O(m^2n) \) cost, i.e., \( Q_{uw} = \frac{1}{m} \sum_{i=1}^{n} g_k (z_i) g_k (z_i') \), where \( z_i' := (z_{2i-1}, z_{2i}) \) and \( g_k (z_i') := g_k (z_{2i-1}) - g_k (z_{2i}) \). Hence (7) is reduced to quadratic program (QP),

\[
\min_{\beta \geq 0} \beta^T (Q + \varepsilon I) \beta,
\]

where \( \varepsilon = 10^{-3} \) is a small regularizer to make the problem well-defined. By solving (8), we can attain a multi-kernel \( k = \sum_{u=1}^{m} \beta_u k_u \) that jointly maximizes the test power and minimizes the Type II error. While our purpose is to apply optimal kernel selection on the \( \ell \)th layer hidden representation, we refer readers to (Gretton et al., 2012) for more details.

We have to note that the DAN objective (4) is essentially a minimax problem, i.e., we target \( \min_{\Theta} \max_{\ell} d_k^2 (D_s^\ell, D_t^\ell) \sigma_k^{-2} \). CNN parameter \( \Theta \) is learned by minimizing MK-MMD as a domain discrepancy, while MK-MMD parameter \( \beta \) is learned by minimizing the Type II error. Both criteria are dedicated to an effective adaptation of domain discrepancy, targeting to consolidate the transferability of DAN features. Hence, we adopt an alternating optimization that updates \( \Theta \) by mini-batch SGD (5) and \( \beta \) by QP (8) iteratively. Both updates cost \( O(n) \) epochs and scale well to large datasets.

3.3. Relations to Prior Work

Our work is primarily motivated by (Yosinski et al., 2014), which comprehensively explores the feature transferability of deep convolutional neural networks. To transfer the features learned from a source domain to the target domain, the method requires sufficient labeled target examples such that the source network can be fine-tuned to the target task. In many real problems, labeled data is usually limited especially for a novel target task, which hinders the applicability of (Yosinski et al., 2014). Hence, in this work, we propose to transfer the knowledge of both features and categories, from a related labeled source domain to the target domain.

In context of our paradigm, the most related work is DDC (Tzeng et al., 2014), which also generalizes a pre-trained deep CNN network to the target task by exploring a related labeled source task as the supervision for fine-tuning. To make the source task useful for the target task, DDC adds an adaptation layer to CNN, between \( fc7 \) and \( fc8 \), which minimizes the single-kernel MMD between the source and target. Several crucial improvements distinguish our work from DDC. 1) As supervision is usually limited in domain adaptation, a network with more layers is more prone to over-fitting. Hence, imposing a regularizer to the existing CNN network as our work may be more robust than adding a new layer that complicates the network architecture. 2) As revealed by (Yosinski et al., 2014), the transferability of features in the \( fc6 – fc8 \) layers drops significantly. Hence, jointly adapting multiple layers as our work can remove the dataset bias more effectively than using a single adaptation layer. 3) Two-sample matching has long been the major bottleneck of domain adaptation which heavily relies on the optimal characteristic kernel in an RKHS. Hence, matching the distributions using an optimal kernel via multi-kernel learning can significantly enhance adaptation effectiveness. 4) DAN adopts unbiased linear-time MK-MMD and scales linearly to large datasets, while DDC incurs quadratic cost. The above advantages of the proposed DAN model against DDC would be extensively evaluated in the empirical study.

4. Experiments

We evaluate the DAN approach to state-of-the-art transfer learning and deep learning methods on both unsupervised and semi-supervised adaptation problems, and focus on the efficacy of multi-layer adaptation with multi-kernel MMD.

4.1. Setup

Office-31 (Saenko et al., 2010) This dataset is a standard benchmark for domain adaptation, which consists of 4,652 images within 31 categories collected from three distinct domains: Amazon (A), which contains images downloaded from amazon.com, Webcam (W) and DSLR (D), which
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are images taken by web camera and digital SLR camera in an office with different environment variation, respectively. We evaluate our method across the 3 transfer tasks, $A \rightarrow W$, $D \rightarrow W$ and $W \rightarrow D$, which are commonly adopted in deep learning methods (Donahue et al., 2014; Tzeng et al., 2014). For completeness, we further include the evaluation on the other 3 transfer tasks, $A \rightarrow D$, $D \rightarrow A$ and $W \rightarrow A$.

**Office-10 + Caltech-10** (Gong et al., 2012) This dataset consists of the 10 common categories shared by the Office-31 and Caltech-256 (C) (Griffin et al., 2007) datasets and is widely adopted in transfer learning methods (Long et al., 2013; Baktashmotlagh et al., 2013). We can build another 6 transfer tasks: $A \rightarrow C$, $W \rightarrow C$, $D \rightarrow C$, $C \rightarrow A$, $C \rightarrow W$, and $C \rightarrow D$. With more transfer tasks, we are targeting an unbiased look at the dataset bias (Torralba & Efros, 2011).

In performance comparison study, we take TCA (Pan et al., 2011), GFK (Gong et al., 2012), CNN (Krizhevsky et al., 2012), LapCNN (Weston et al., 2008), DDC (Tzeng et al., 2014) as baselines. TCA is the pioneering transfer learning method based on MMD regularized PCA. GFK is a widely-adopted method on our datasets, which interpolates infinite number of intermediate subspaces to bridge the source and target. CNN is the champion method in the ImageNet 2012 competition, and turns out to be a strong model for learning transferable features (Yosinski et al., 2014). LapCNN is a semi-supervised variant of CNN based on Laplacian graph regularization. Finally, DDC is a domain adaptation variant of CNN that adds an adaptation layer between the fc7 and fc8 layers, and is regularized by single-kernel MMD. We implement the CNN-based methods, i.e. CNN, LapCNN, DDC, and DAN by Caffe (Jia et al., 2014) implementation of AlexNet (Krizhevsky et al., 2012) trained on ImageNet dataset, hence our results are comparable to the community.

In order to study the effectiveness of multi-layer adaptation and multi-kernel MMD, we evaluate the following variants of DAN: 1) DAN using only one hidden layer, either fc7 or fc8 for adaptation, termed DANfc7 and DANfc8 respectively; 2) DAN using single-kernel MMD for adaptation, termed DANSK. We note that DDC (Tzeng et al., 2014) is closely related to DANfc7, but DDC only adopts single-kernel MMD for the adaptation layer fc7, hence its adaptation capability may be limited by suboptimal kernel (Gretton et al., 2012).

In our experiments, we follow standard protocol for unsupervised adaptation and use all source examples with labels and all target examples without labels (Gong et al., 2013). In semi-supervised adaptation, we follow standard protocol (Saenko et al., 2010) in that we further require 3 labeled target examples per category. We report the averages and standard errors of classification accuracy for each task. For baseline methods, we follow the standard procedures for model selection as explained in their respective papers. For MMD-based methods, i.e. TCA, DDC, and DAN, we adopt Gaussian kernel $k(x_i, x_j) = e^{-∥x_i − x_j∥^2/γ^2}$ with bandwidth $γ$ set to the median pairwise distances on the training data, i.e. the median heuristic (Gretton et al., 2012). For DAN we use multi-kernel MMD, and choose the family of $m$ Gaussian kernels $\{k_m\}_{m=1}$ by varying bandwidth $γ$ between $2^{-8γ}$ and $2^8γ$ with a multiplicative step-size of 2 (Gretton et al., 2012). All the MMD-based methods have a MMD-regularization parameter $λ$, whose value can neither be too small to have no effect on learned representation, nor be too large to produce degenerate representation. We fix $λ = 1.0$ empirically like DDC (Tzeng et al., 2014) for the 12 unsupervised transfer tasks, while in semi-supervised adaptation, the small amount of labeled target examples can jointly serve as a validation set for selecting this parameter. We use the fine-tuning architecture (Yosinski et al., 2014), however, due to limited training samples in our datasets, we fix convolutional layers conv1–conv3 that were copied from pre-trained model, fine-tune conv4–conv5 and fully connected layers fc6–fc7 with learning rate 0.1, and train layer fc8 with learning rate 1.0, both via back propagation.

### Table 3. Multi-class classification accuracy on the 31-category Office dataset with standard semi-supervised adaptation setting.

| Method | $A \rightarrow W$ | $D \rightarrow W$ | $W \rightarrow D$ | Average |
|--------|-----------------|-----------------|-----------------|---------|
| DDC    | 84.1 ± 0.6      | 95.4 ± 0.4      | 96.3 ± 0.3      | 91.9    |
| DAN    | 85.6 ± 0.3      | 95.8 ± 0.2      | 96.7 ± 0.2      | 92.7    |

### 4.2. Results and Discussion

The unsupervised adaptation results on the first six Office-31 transfer tasks are shown in Table 1, and the results on the other six Office-10 + Caltech-10 transfer tasks are shown in Table 2, respectively. To compare with DDC, we also report semi-supervised results of the same tasks used by DDC in Table 3. We can observe that the proposed DAN algorithm significantly outperforms all the competing methods on most transfer tasks, and achieves comparable performance on easy transfer tasks, e.g. $D \rightarrow W$ and $D \rightarrow W$ where source and target are similar. This is reasonable as the adaptability may vary across different transfer tasks. The performance gain demonstrates that our architecture of multi-layer adaptation via multi-kernel MMD is able to transfer pre-trained deep models across different domains. Note that the 31-category tasks are more difficult than the 10-category tasks, which is explained by the accuracy gap.

From the experimental results, we can make the following observations. 1) Deep learning based methods significantly outperform conventional shallow transfer learning methods by a large margin, which is consistent with current practice of deep learning in extracting highly abstract and invariant features under domain discrepancy (Yosinski et al., 2014). 2) Among the deep learning methods, the semi-supervised
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Table 1. Multi-class accuracy on the 31-category Office dataset with standard unsupervised adaptation configuration.

| Method   | $A \rightarrow W$ | $D \rightarrow W$ | $W \rightarrow D$ | $A \rightarrow D$ | $D \rightarrow A$ | $W \rightarrow A$ | Average |
|----------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|---------|
| GFK      | 21.4±0.2           | 69.1±0.3           | 65.0±0.2           | 30.2±0.1           | 13.8±0.4           | 15.0±0.2           | 35.8    |
| TCA      | 38.3±0.3           | 60.0±0.2           | 61.1±0.4           | 38.2±0.3           | 29.3±0.2           | 34.8±0.2           | 42.7    |
| CNN      | 59.4±0.5           | 94.4±0.3           | 98.8±0.2           | 63.0±0.5           | 49.3±0.6           | 48.4±0.4           | 68.9    |
| LapCNN   | 60.4±0.3           | 94.7±0.5           | 99.1±0.2           | 63.1±0.6           | 51.6±0.4           | 48.2±0.9           | 69.5    |
| DDC      | 60.5±0.7           | 94.8±0.5           | 98.5±0.4           | 63.7±0.3           | 52.1±0.8           | 49.2±0.4           | 69.8    |
| DAN$_T$  | 61.2±0.2           | 94.6±0.4           | 98.5±0.3           | 63.6±0.4           | 52.6±0.6           | 50.6±0.4           | 70.5    |
| DAN$_S$  | 61.6±0.4           | 94.8±0.5           | 98.6±0.6           | 62.9±0.4           | 51.8±0.6           | 51.4±0.7           | 70.2    |
| DAN$_{SK}$ | 62.0±0.3         | 94.8±0.2           | 98.9±0.4           | 64.1±0.7           | 53.6±0.5           | 50.8±0.6           | 70.7    |
| DAN      | 64.5±0.4           | 95.2±0.3           | 98.6±0.2           | 66.5±0.4           | 54.0±0.5           | 51.5±0.7           | 71.7    |

Table 2. Multi-class accuracy on the 10-category Office + Caltech dataset with standard unsupervised adaptation setting.

| Method   | $A \rightarrow C$ | $W \rightarrow C$ | $D \rightarrow C$ | $C \rightarrow A$ | $C \rightarrow W$ | $C \rightarrow D$ | Average |
|----------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|---------|
| GFK      | 39.0±1.7           | 36.1±0.9           | 34.5±0.8           | 47.2±2.3           | 38.8±3.2           | 38.5±2.7           | 39.0    |
| TCA      | 39.4±1.3           | 38.1±1.1           | 35.5±1.1           | 50.9±1.1           | 49.8±1.0           | 47.1±1.2           | 43.5    |
| CNN      | 84.5±0.3           | 77.6±0.5           | 81.1±0.4           | 92.3±0.2           | 82.1±0.3           | 82.5±0.5           | 83.4    |
| LapCNN   | 83.6±0.8           | 77.8±0.5           | 80.6±0.4           | 92.1±0.3           | 81.6±0.4           | 87.8±0.6           | 83.9    |
| DDC      | 84.8±0.5           | 75.6±0.6           | 82.1±0.2           | 91.1±0.3           | 86.8±0.3           | 87.6±0.5           | 84.6    |
| DAN$_T$  | 85.7±0.3           | 75.5±0.5           | 80.5±0.3           | 91.9±0.4           | 87.1±0.3           | 88.5±0.5           | 84.8    |
| DAN$_S$  | 85.7±0.3           | 76.1±0.4           | 82.8±0.2           | 92.1±0.3           | 87.5±0.4           | 84.3±0.4           | 84.7    |
| DAN$_{SK}$ | 84.9±0.4         | 75.6±0.6           | 81.1±0.5           | 91.3±0.3           | 88.9±0.5           | 88.5±0.7           | 85.1    |
| DAN      | 86.2±0.5           | 76.1±0.6           | 82.8±0.4           | 92.3±0.3           | 90.6±0.4           | 90.7±0.6           | 86.4    |

LapCNN only achieves marginal improvement from CNN, which manifests the challenge that the domain discrepancy cannot be properly bridged by semi-supervised learning. 3) DDC, a cross-domain variant of CNN with single-layer adaptation via single-kernel MMD, generally outperforms CNN, confirming the effectiveness in learning transferable features using MMD-regularized deep models. We have to note that, while DDC based on Caffe AlexNet was shown to significantly outperform DeCAF (Donahue et al., 2014) in which fine-tuning was not carried out, it cannot attain that significant gain over the Caffe AlexNet using fine-tuning. This manifests the limitation of single-layer adaptation via single-kernel MMD, which cannot explore the strengths of deep networks and multiple kernels for domain adaptation.

To attain a deeper insight into the efficacy of DAN, we also present the experimental results of three variants of DAN. 1) DAN$_T$ achieves better performance than DDC, and this highlights that multi-kernel MMD can bridge the domain discrepancy more effectively than single-kernel MMD. The reason is that multiple kernels with different bandwidths can match both the low-order moments and high-order moments and lead to lower Type II error (Gretton et al., 2012). 2) DAN$_{SK}$ also attains higher accuracy than DDC, and this confirms the capability of deep architecture for distribution adaptation. The rational is similar to that of deep networks: each layer of deep network is intended to extract features at a different abstraction level, and hence we need to match the distributions at each layer to consolidate the adaptation quality at all levels. The multi-layer architecture is one of the crucial contributors to the efficacy of deep learning, and we believe it is also important for MMD-based adaptation. It is reasonable that the multi-layer variant DAN$_{SK}$ further outperforms the multi-kernel variants DAN$_T$ and DAN$_S$.

As expected, DAN obtains the best performance by jointly exploring multi-layer adaptation with multi-kernel MMD. An off-the-shelf benefit of multi-layer adaptation is that by jointly adapting layers $fc_6$–$fc_7$ (representation layer) and layer $fc_8$ (classifier layer), we can essentially match the domain discrepancy underlying both marginal distribution (i.e. features) and conditional distribution (i.e. classifiers), which is crucial for transfer learning (Zhang et al., 2013). We do not fine-tune DAN on convolutional layers $conv$–$conv3$, because in deep CNN the features must eventually transition from general to specific by the last layer of the network, and the transferability gap grows with the domain discrepancy and becomes unacceptably large when transferring task-specific layers $fc_6$–$fc_8$ (Yosinski et al., 2014).

4.3. Empirical Analysis

Feature Visualization To demonstrate the transferability of the DAN learned features, we follow (Donahue et al., 2014; Tzeng et al., 2014) and plot in Figures 2(a)–2(b) and 2(c)–2(d) the t-SNE embeddings of the images in task $C \rightarrow W$ with DDC features and DAN features, respectively. We
can make the following interesting observations. 1) With DDC features, the target points are not discriminated very well as some categories overlap with each other; With DAN features, the target points are discriminated much better. 2) With DDC features, the categories between the source and target are not aligned very well; With DAN features, the target points are discriminated much better. Both these two observations can explain the superior performance of DAN over DDC: 1) implies that the target points are more easily discriminated with DAN features, and 2) implies that the target points can be better discriminated with the source classifier. In a word, DAN can learn more transferable features for robust domain adaptation.

\textbf{A-Distance} Theoretical results in (Ben-David et al., 2010) suggested \(A\)-distance as a measure of domain discrepancy, which is a crucial part of a generalization bound for domain adaptation. As computing exact \(A\)-distance is intractable, an approximate one is defined as \(\hat{d}_A = 2(1 - 2\epsilon)\), where \(\epsilon\) is the generalization error of a classifier (Logistic Regression in our case) trained on the binary problem to distinguish input samples between the source and target domains. Figure 3(a) shows \(\hat{d}_A\) on raw features, CNN features, and DAN features, respectively, where each point corresponds to one transfer task, with 2-dimensional coordinate defined as \((\hat{d}_A(\text{raw}), \hat{d}_A(\text{deep}))\). It reveals a surprising observation that \(\hat{d}_A\) on CNN features is larger than \(\hat{d}_A\) on raw features, which implies worse generalization bound (Glorot et al., 2011). On the contrary, we see that \(d_A\) on DAN features is smaller than \(d_A\) on raw features, which confirms that DAN can learn more transferable features for domain adaptation.

\textbf{Parameter Sensitivity} Finally, we investigate the effects of the only parameter \(\lambda\), which is introduced to equip DAN with the capability of learning transferable features through distribution adaptation. Figure 3(b) gives an illustration of the variance of transfer classification performance as \(\lambda \in \{0.1, 0.4, 0.7, 1, 1.4, 1.7, 2\}\) on tasks \(A \rightarrow W\) and \(C \rightarrow W\). We can observe that the DAN accuracy firstly increases and then deceases as \(\lambda\) varies and demonstrates a bell-shaped curve. This confirms the motivation of jointly learning deep features and adapting distribution discrepancy, since a good trade-off between them can enhance feature transferability.

\section{5. Conclusion}

In this paper, we have proposed a novel Deep Adaptation Network (DAN) architecture to enhance the transferability of features from task-specific layers of the neural network. We confirm that while general features can generalize well to a novel task, specific features tailored to an original task cannot bridge the domain discrepancy effectively. We show that feature transferability can be enhanced substantially by mean embedding matching of the multi-layer representations across domains in a reproducing kernel Hilbert space. An optimal multi-kernel selection strategy further improves the embedding matching effectiveness, while an unbiased estimate of the mean embedding naturally leads to a linear-time algorithm that is very desirable for deep learning from large-scale datasets. An extensive empirical evaluation on standard domain adaptation benchmarks demonstrates the efficacy of the proposed model against the existing results.

In the future, we plan to explore the effects of distribution adaptation over the convolutional layers (\textit{conv1}–\textit{conv5}) of CNN for learning more transferable and unbiased features.
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