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Latent Domains Modeling for Visual Domain Adaptation

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Abstract

To improve robustness to significant mismatches between source domain and target domain - arising from changes such as illumination, pose and image quality - domain adaptation is increasingly popular in computer vision. But most of methods assume that the source data is from single domain, or that multi-domain datasets provide the domain label for training instances. In practice, most datasets are mixtures of multiple latent domains, and difficult to manually provide the domain label of each data point. In this paper, we propose a model that automatically discovers latent domains in visual datasets. We first assume the visual images are sampled from multiple manifolds, each of which represents different domain, and which are represented by different subspaces. Using the neighborhood structure estimated from images belonging to the same category, we approximate the local linear invariant subspace for each image based on its local structure, eliminating the category-specific elements of the feature. Based on the effectiveness of this representation, we then propose a squared-loss mutual information based clustering model with category distribution prior in each domain to infer the domain assignment for images. In experiment, we test our approach on two common image datasets, the results show that our method outperforms the existing state-of-the-art methods, and also show the superiority of multiple latent domain discovery.

Introduction

Despite significant improvements in machine learning models, and the development of visual features invariant to a wider range of nuisance variation (in pose, etc.), learning-based vision systems still have limited generalizability. When trained using labeled data from a *source domain*, which is not sufficiently representative of the test data, differences in computed features arising from changing image quality, photo realism, or background content (Liu et al. 2011; Alessandro Bergamo 2010) will drive down the performance of learned models.

In order to address this issue, various domain adaptation methods (Shimodaira 2000; Sun et al. 2011; Pan et al. 2011; Kulis, Saenko, and Darrell 2011; Glorot, Bordes, and Bengio 2011) have been advanced in recent years. These methods improve generalization by learning how features from the source domain relate to features in the *target domain*, in which we hope to apply a learned model. Certain datasets have also been shown to generalize better to an unlabeled target domain, providing a mean for unsupervised domain adaptation. In other cases, a small amount of labeled data in the target domain may be used for semi-supervised domain adaptation (Xiao and Guo 2012).

While successes in improving the generalization performance between different source and target domains, these methods don't quite solve the "in the wild" recognition problem. In order to provide better performance on unconstrained test sets, e.g. web images, it is natural to train object recognition models using labeled data from the web. In this case, though, the training data no longer resides in a single domain; web images may be drawings or real camera images of varying quality and pose. Most domain adaptation methods fail to account for this, and implicitly assume that the training data is self-consistent or that domain labels are provided (Duan et al. 2009; Chattopadhyay et al. 2012). Gong et al. (Gong et al. 2012), for instance, improve generalization performance between self-consistent domains containing high-quality commercial images or low-quality webcam images, but assume that it is known in advance the domain to which a given training and test image belongs. This will be useful when images come from the same generative process, e.g. a network of similar surveillance cameras, but will not perform as well on random images drawn from the web.

In order to address this, we propose a novel model to explicitly estimate the domain associated with each training image from the web. First, we design a new representation for latent domain modeling, which is based on the same intuition as used by Gong et al. (Gong et al. 2012), namely that the visual features reside in a low-dimensional subspace within the larger feature space. As such, we estimate the manifold structure of the different domains, as outlined in the following sections. First, using its neighboring points within the same semantic category, we infer a novel descriptor for each image that represents the local invariant subspace of the domain-related feature at the original feature point. This subspace could be low-rank. Then, we propose a regularized square-loss mutual information based clustering method that incorporate the prior of category distribution of images within each domain.

In our experiments, we demonstrate both improved do-

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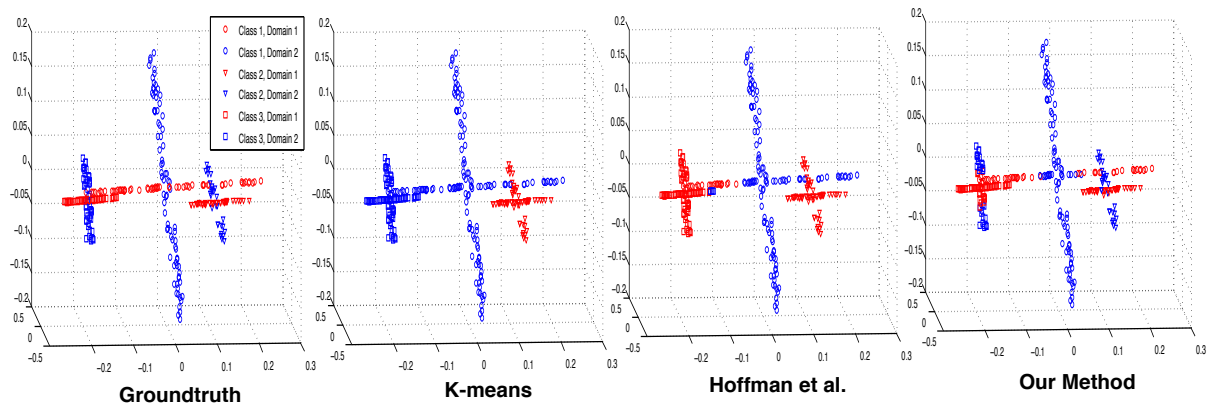

Figure 1: A toy example comparing different methods for latent domain discovery. The example data are 3-dimensional features that represent 3 categories (different shapes) and 2 domains (different color). Consistent with our intuition that features from the same domain reside on a manifold, each of our toy domains is 2-dimensional subspaces. Our method performs better than other methods like k-means and Hoffman et al. (Hoffman et al. 2012) because we do not assume a specific distribution shape of the domain within the feature space. *Best viewed in color.*

main discovery relative to (Hoffman et al. 2012) (using the office dataset from (Saenko et al. 2010)) and the necessity of domain discovery for domain adaptation in the wild (using the Bing-Caltech 256 dataset (Alessandro Bergamo 2010)).

Related Works

The closest work to ours is the method of Hoffman et al. (Hoffman et al. 2012), which estimate the membership of training data in multiple latent domains using an iterative approach. Initial clusters in the feature space are assumed to arrange the data by both domains and object category, and domains are estimated by further grouping these clusters subject to the constraint that no two clusters for the same object category are combined. These steps are iterated until convergence, but performance may be adversely impacted by a poor initial clustering based on our experience with their code. Algorithmically, the key difference is that, whereas Hoffman et al. model domains as a Gaussian distribution in the feature space, our method models the domain as a manifold embedded in the feature space without any assumptions about its distribution. Figure 1 demonstrates the benefit of this generality on a toy example of 3 categories (marker shapes) from 2 domains (colors), where our method provides a better domain assignment than either k-means or Hoffman et al.'s method (Hoffman et al. 2012).

The modeling of domains as manifolds within a larger feature space has been demonstrated in previous work where domain adaptation is applied to a monolithic test domain, or to a test set with given domain labels (Gong et al. 2012; Gopalan, Li, and Chellappa 2011; Jhuo et al. 2012). While not manifold-based, Kulis et al. (Kulis, Saenko, and Darrell 2011) proposed to use category constraints to learn an asymmetric non-linear transform for adaptation between monolithic domains, which Hoffman et al. (Hoffman et al. 2012) extended to multi-domain settings.

Several papers have addressed the related problem of training classifier models from training data spanning multiple domains (Mansour, Mohri, and Rostamizadeh 2009; Duan et al. 2009; Sun et al. 2011; Chattopadhyay et al. 2012). Several of these (Alessandro Bergamo 2010; Chattopadhyay et al. 2012; Duan et al. 2009) are classifier adaptation methods, which require the provision of labeled training data for each domain. Since 'in the wild' test datasets may include domains not represented in the training data, this limits their applicability. More importantly, these methods assume that the domain label is known in advance. For example, the method of Chattopadhyay et al. (Chattopadhyay et al. 2012) detects fatigue from samples which are directly associated with an individual. Since no corresponding label is provided with web images, our approach is to perform domain discovery in order to effectively adapt categoryification to multiple, unlabeled domains.

Problem Statement

Motivation

Unlike existing domain adaptation methods that must be provided the domain label for each point, our objective is to improve classification accuracy for 'in the wild' datasets by automatically estimating domain labels. The key challenge of domain assignment, in most cases, is that existing robust visual features are naturally designed to separate the underlying semantic categories. Using these kind of features directly with standard clustering method, for example, may not obtain desirable domain estimation results. To handle this challenge, we first propose a simple novel local subspace representation of each image based on a different understanding of feature distributions in the latent domains modeling problem.

We consider each domain as a different low-rank manifold embedded in the feature space. For each data image, its original feature representation is considered as containing two

parts: one part depends on the semantic label and the other is dependent on its latent domain; though inferred from the same visual feature, we refer to these parts as the category-feature and the domain-feature. Within the same semantic category, due to the domain-feature, the intra-category images are variedly distributed on multiple manifolds in the feature space.

Drawing inspiration from multiple manifold learning methods (that assume the whole data set consists of multiple low-rank manifolds in the high-dimensional space) (Elhamifar and Vidal 2011; Gong, Zhao, and Medioni 2012), we assume multiple latent domains in same class are distributed as multiple manifolds, and in the same manifold the local subspace should be similar to each other. Thus we attempt to obtain category-specific local subspace embedding for each image to identify the multiple manifolds within same category. We assume the local structure of each point is smooth and can be derived from its ϵ-nearest neighbor points within the same category, then we infer a local subspace representation that presents the change tendency around the image such as illumination, pose and so on.

Based on new subspace representation, we also propose a novel regularized square-loss mutual information (Suzuki et al. 2009) based domain labeling method, in which we formulate two key properties: the first one is to ensure the mutual information between domain assignment and new subspace representation to be maximized; the second one is a regularized prior that encourages the underlying category distribution in each domain is close to the category distribution in the whole training dataset, for which we adopt the squared difference of two probability distributions. Within this prior, we assume the frequent image category in the whole dataset should also be frequent in each domain respectively, which is common in visual data collections (Alessandro Bergamo 2010). More technique details in next section.

Problem Description

Let $(X, Y) = \{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\}$ denote data pertaining to k semantic categories and m unknown latent domains, $x_i \in \mathcal{R}^D$ and $y_i \in \{1, \cdots, k\}$ is the semantic category label of data point x_i. Our goal is to infer the domain assignment matrix for all data points $Z \in \{0, 1\}^{n \times m}$ that: $Z_{ij} = 1$ if data point x_i belongs to domain j, and $Z_{ij} = 0$ otherwise. The formulation of problem is:

$$Z = \underset{Z \in \{0,1\}^{n \times m}}{\operatorname{argmin}} \Delta(Z, Y) - \lambda SMI(Z|\{\gamma(x_i, y_i)\}_{i=1}^n)$$
$$s.t. \forall i, \sum_j z_{ij} = 1, \forall j, \forall y, \sum_i 1_{y_i = y} Z_{ij} \geq 1 \quad (1)$$

where $SMI(\cdot|\cdot)$ is the objective function representing the compactness of domains which is based on square-loss mutual information between new image representation and domain assignment; $\gamma(x_i, y_i)$ is our category-specific local subspace representation for training image (x_i, y_i) learning the its neighbors within same category y_i; and $\Delta(\cdot, \cdot)$ is a prior term that measures the difference of the category distribution between each domain and global training dataset. In the constraint part, the first constraint ensures each image to be assigned to unique domain, and the second one requires that there is at least one image for each category in each domain.

Though we use the semantic labels of training data for domain assignment, this is still an unsupervised clustering problem for domain assignment. In the problem, our goal is to learn compact domain clusters, each of which will contain data points from different semantic categories.

Latent Domains Discovery

As described above, our method has two novel elements: a new subspace-based domain representation $\gamma(x_i, y_i)$ for each training pair $(x_i y_i)$, and the information-maximization based domain labeling model that consists of $SMI(Z|\{\gamma(x_i, y_i)\}_{i=1}^n)$ and $\Delta(Z, Y)$. These key elements are described in the following subsections.

Class-Specific Local Subspace Learning for Domain Representation $\gamma(x_i, y_i)$

The original feature presentation of image consists of category-feature, domain-feature and noise. Within same category, domain-feature is a key property that causes the intra-category images distributed onto different manifolds, such as multi-view classification. And it also causes the difficulty to distinguish the images between categories. Thus, we need to find a new representation $\gamma(x_i, y_i)$ that only includes domain information and unmixes with other informations.

Given image datasets $(x_i, y_i)_{i=1}^n$, we assume that the feature vectors $\{x_i\}_{i=1}^n$ are sampled from multiple domain-related manifolds based on their category labels $\{y_i\}_{i=1}^n$ as follows:

$$x_i = f(\tau_i) + g_{y_i}(\tau_i) + n_i \quad (2)$$

where $f(\cdot)$ is the smooth mapping function that embeds a latent variable τ_i to original feature space for domain-feature; $g_{y_i}(\cdot)$ maps τ_i to feature space for category-feature; and n_i represents noise. Then within the same category, for two data points x_i and its neighbor point x_j that $y_i = y_j$, the Taylor expansion is

$$x_i - x_j = f(\tau_i) - f(\tau_j) + g_{y_i}(\tau_i) - g_{y_i}(\tau_j) + n_i - n_j$$
$$= J(f; \tau_i)(\tau_j - \tau_i) + e_{ij} + (g_{y_i}(\tau_i) - g_{y_j}(\tau_j) + n_i - n_j) \quad (3)$$

where x_j is ϵ-nearest neighbor of x_i in same category y_i, e_{ij} is Taylor approximation error and $J(f; \tau_i)$ is Jacobian matrix (which we abbreviate J_i). Obviously, J_i represents the change tendency of category y_i at position x_i in the original feature space. And this change tendency always reflects the domain that image belongs to. For example, same category object images collected from dark and light situation, the change tendency J_i expects the illumination change.

Obtaining local subspace J_i for Domain Representation $\gamma(x_i, y_i)$ Since x_j is nearest neighbor of x_i in same category y_i, the category-feature difference between the points will be small, i.e. the distribution of this difference is Gaussian with small variance. We then treat $n_{ij}^{'} = (g_{y_i}(\tau_i) -$

$g_{y_j}(\tau_j) + n_i - n_j)$ as an i.i.d. noise term with a homogeneous Gaussian distribution. Thus we can have

$$X_i - x_i 1_{m_i}^T = J_i(T_i - \tau_i 1_{m_i}^T) + E_i + N_i \quad (4)$$

where $X_i = [x_{i_1}, x_{i_2}, \cdots, x_{i_{m_i}}]$ are m_i points in the ϵ-neighborhood of x_i within category y_i, $T_i = [\tau_{i_1}, \tau_{i_2}, \cdots, \tau_{i_{m_i}}]$ is corresponding latent coordinate matrix and $E_i = [e_{i_1}, e_{i_2}, \cdots, e_{i_{m_i}}]$ is the local Taylor approximation error matrix. To estimate J_i, which minimizes $|E_i - N_i|_F^2$, the objective function can be:

$$\begin{aligned} J_i &= \underset{J_i}{\operatorname{argmin}} |(X_i - x_i 1_{m_i}^T) - J_i(T_i - \tau_i 1_{m_i}^T)|_F^2 \\ &= \underset{J_i}{\operatorname{argmax}} Tr|J_i^T (X_i - x_i 1_{m_i}^T)(X_i - x_i 1_{m_i}^T)^T J_i| \quad (5) \\ & \qquad s.t. J_i^T J_i = I_{d_i} \end{aligned}$$

where $Tr(\cdot)$ is trace of matrix. To ensure the uniqueness of J_i, we enforce the local isometry assumption making J_i an orthonormal matrix, i.e. $J_i^T J_i = I_{d_i}$. Essentially, the solution of above equation is the largest d_i eigenvectors of matrix $(X_i - x_i 1_{m_i}^T)(X_i - x_i 1_{m_i}^T)^T$. We choose the number d_i of eigenvectors based on the change of the corresponding eigenvalues. Thus, our local subspace representation for each image could be linear subspaces with different number of dimensions which is common that different domains are represented by different subspaces.

It is also interesting that when x_i equals to the mean vector of X_i, then Eq. 5 is same as PCA in local feature space with same category.

Similarity Measurement for $\gamma(x_i, y_i)$ With local subspace representation $\gamma(x_i, y_i) = J_i$, it's not suitable to use the Euclidean distance to measure their similarity, we define a new similarity function with Gaussian kernel $K(\gamma(x_i, y_i), \gamma(x_j, y_j))$:

$$K(\gamma(x_i, y_i), \gamma(x_j, y_j)) = exp(-\frac{\theta(\gamma(x_i, y_i), \gamma(x_j, y_j))^2}{\sigma^2}) \quad (6)$$

where $\theta(\gamma(x_i, y_i), \gamma(x_j, y_j))$ is the principal angles (Wang, Li, and Tao 2011) between the subspace space $\gamma(x_i, y_i)$, and $\gamma(x_j, y_j)$.

Regularized Square-loss Mutual Information for Domain Discovery

Based on the new feature representation $\gamma(x_i, y_i)$, we propose a novel approach for domain assignment in this section. As introduced in Sec., the formulation of our approach includes two parts: $SMI(Z|\{\gamma(x_i, y_i)\}_{i=1}^n)$ and $\Delta(Z, Y)$.

Modeling $SMI(Z|\{\gamma(x_i, y_i)\}_{i=1}^n)$ As an information measurement, squared-loss mutual information (SMI) (Suzuki et al. 2009) is used to measure the statistical correlation between random variables which is based on Pearson divergence. Although mutual information (MI) (Shannon 2001) is also a common measurement, but in this paper, we adopt SMI because MI is nonconvex and thus not straightforward to find a good local optimal solution.

Similar to (Sugiyama et al. 2011), with the new representation $\gamma(x_i, y_i)$, our $SMI(Z|\{\gamma(X, Y)\})$ (we use SMI as abbreviate) is defined by

$$\begin{aligned} SMI = & \frac{1}{2} \int_{(X,Y)} \sum_z p(\gamma(x, y)) p(z) \\ & (\frac{p(\gamma(x, y), z)}{p(\gamma(x, y)) p(z)} - 1)^2 d(x, y) \quad (7) \end{aligned}$$

By adopting the uniform domain-prior probability $p(z) = 1/m$, we can obtain our SMI:

$$SMI = \frac{m}{2} \int_{(X,Y)} \sum_z p(z|\gamma(x, y))^2 p(\gamma(x, y)) d(x, y) - \frac{1}{2} \quad (8)$$

Then we approximate domain-posterior probability $p(z|\gamma(x, y))$ as following kernel model:

$$p(z|\gamma(x, y)) \approx \sum_{i=1}^n \alpha_{z,i} K(\gamma(x, y), \gamma(x_i, y_i)) \quad (9)$$

where $\alpha_{i,z} = \frac{Z_{iz}}{\sum_{i=1}^n Z_{iz}}$, and $K(\cdot, \cdot)$ is the kernel similarity defined in Eq.6. Furthurmore, empirically approximation expectation, our SMI is derived as:

$$SMI = \frac{m}{2n} tr(\alpha^T K^2 \alpha) - \frac{1}{2} \quad (10)$$

where $\alpha = (\alpha_1, \cdots, \alpha_m)$ is matrix representation of domain assignment and $\alpha_z = (\alpha_{z,1}, \cdots, \alpha_{z,n})^T$.

Modeling $\Delta(Z, Y)$ Since we assume the category occures frequently in whole dataset, it also should be frequent in each domain, therefore we propose a category distribution prior for each domain. We choose the total sume of the squared difference of category probability $p(y|z)$ in each domain and the category probability $q(y)$ in whole dataset as our loss function:

$$\Delta(Z, Y) = \frac{1}{2} \sum_{z=1}^m \sum_{y=1}^k (p(y|z) - q(y))^2 \quad (11)$$

Since $p(y|z) = \sum_i 1_{y_i=y} \alpha_{i,z}$ and $q(y) = \sum_i 1_{y_i=y}/n$ is constant as the category probability in whole dataset, we can derive $\Delta(Z, Y)$ as:

$$\begin{aligned} \Delta(Z, Y) = & const. + \sum_{z=1}^m \frac{1}{2} \alpha_z^T \sum_{y=1}^k (\mathcal{Y}_y \mathcal{Y}_y^T) \alpha_z \\ & - \alpha_z^T \sum_{y=1}^k (\mathcal{Y}_y \cdot q(y)) \quad (12) \end{aligned}$$

where $\mathcal{Y} = [\mathcal{Y}_1, \cdots, \mathcal{Y}_k] \in \{0, 1\}^{n \times k}$ is the category indicator matrix that $\mathcal{Y}_{iy} = 1$ if $y_i = y$.

Subsequently, we combine Eq.10 and Eq.12, reformulate

the optimization of domain assignment as

$$\min_{\alpha_1,\cdots,\alpha_m \in R^n} \sum_{z=1}^{m} \frac{1}{2}\alpha_z^T (\sum_{y=1}^{k} (\mathcal{Y}_y \mathcal{Y}_y^T) - \frac{m}{n}\lambda K^2)\alpha_z \qquad (13)$$

$$- \alpha_z^T (\sum_{y=1}^{k} \mathcal{Y}_y \cdot q(y)) + \beta \cdot \mathcal{R}(\alpha)$$

$$s.t. \forall z, \forall i, \alpha_{i,z} \geq 0, \sum_{i=1}^{n} \alpha_{i,z} = 1$$

$$\forall i, 1/k \geq \sum_{z=1}^{m} \alpha_{i,z} \geq 1/(n-(m-1)k)$$

$$\mathcal{R}(\alpha) = -\sum_{j=1}^{m}\sum_{l=1}^{m} (\alpha_j - \alpha_l)^T (\alpha_j - \alpha_l) \ .$$

In new formulation, we first relax the discrete assignment to the real value $\alpha_z \in R^n$, and to avoid all the solution $\{\alpha_z\}_{z=1}^m$ to be reduced to same vector, we add a regularization term for α which maximize the difference of solutions of domains: $(\alpha_j - \alpha_l)^T(\alpha_j - \alpha_l)$ if $j \neq l$. Then rewrite the second constraint which ensure that every domain has at least one image per category, thus the number of images per domain is between k and $n-(m-1)k$. Since this relaxed problem is quadratic function with linear constraints, but the quadratic function could be nonconvex, so we adopt CCCP (Yuille and Rangarajan 2002) method to achieve satisfactory result and assign the x_i into domain z that $z = \text{argmax}_z\, p(z|\gamma(x_i, y_i))$. In the experiment, we set $\lambda = 5$ and $\beta = 10$.

Experiment

In this section, we evaluate our approach in terms of its performance for both domain assignment and visual on domain adaptation using obtained assignment. We first compare our domain assignment with a baseline method and state-of-the-art methods from the literature. Then, using our domain assignment result, we demonstrate improved classification performance using a domain adaptation method that is applicable to 'in the wild' problems.

Dataset

Our experiments use two different datasets: office dataset (Saenko et al. 2010) and bing-caltech dataset (Alessandro Bergamo 2010). The office dataset is commonly used to test domain adaptation, and provides the domain label of each data point. It contains 31 object categories over three domains: Amazon(a), Webcam(w) and Digital SLR(d).

In order to demonstrate improvement for domain adaptation, we also use a subset of bing-caltech dataset which are collected by searching Bing for an object keyword. Since it contains real web data, this data set is more representative of the 'in the wild' recognition problem, as it contains multiple latent domains for each object category.

Given the visual image dataset, we use SURF (Bay et al. 2008) to extract features, which are quantized to words in an 800-bin histogram, based on k-means clustering within the feature space. The histograms are normalized and then z-score to have zero means and unit standard deviation in each dimension.

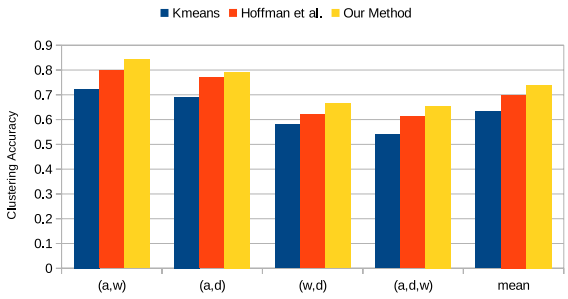

Figure 2: domain clustering results in office dataset.

Comparison Result in Domain Assignment

Since latent domain discovery is a new problem, to our best knowledge, Hoffman et al. (Hoffman et al. 2012) is the only paper to try to address the problem to date and provide source code. Using their reference code, we compare their performance to our method. As in their paper, we also test k-means as a baseline method for domain assignment.

We use the office dataset for domain assignment experiment, since it provides the domain label for each image. To make use of this dataset effectively, we test the various combinations of the three domains in the office dataset. Finally, we obtain four different domain assignment experiments: three instances of two-domain problem (Amazon(a),Webcam(w)), (Amazon(a),DSLR(d)), (DSLR(d),Webcam(w)) and one instance of three-domain problem (Amazon(a),Webcam(w),DSLR(d)). The results are shown in Figure 2. Comparing the three methods, ours always gets a better result than both Hoffman et al. and k-means. This is because both assume a Gaussian shaped domain distribution in the original feature space. More generally, the figure shows better performance for all methods in separating the Amazon domain from the DSLR domain, as compared to separating the DLSR and Webcam domains. Intuitively, this may be due to the lack of background texture in the Amazon domain, while both the DSLR and Webcam domains have confounding background textures.

Multiple Domain Adaptation with Identified Domain from Source Image Datasets

With the domain membership matrix S for source dataset, we introduce a straightforward way of applying our domain assignments for domain adaptation. First, we train a domain classifier $P(z|x_t)$ by Random Forest (Breiman 2001) and compute the probability of domain assignment for any given test data point x_t. Then, given the testing set from target domain, we choose one of discovered domains for super-

vised/unsupervised domain adaptation as follow:

$$z^* = \underset{j}{\operatorname{argmax}} P(z|X_T) = \prod_{t=1}^{N} P(z|x_t) \qquad (14)$$

The goal is to choose the 'similar' source domain for domain adaptation. This is also a suitable way to demonstrate the purity of our discovered domains, since the mixing of true domains within an estimated domain will degrade the performance of classification.

Comparison in Supervised Domain Adaptation Having demonstrated the improved performance of our domain assignment, it is natural to wonder how this improves the performance of domain adaptation. In this section, we adopt multiple source domain transformation based on discovered latent domains as Hoffman et al. (Hoffman et al. 2012).

We use a subset of bing-caltech 256 dataset (Alessandro Bergamo 2010). First we choose bing dataset as source domain, since bing data set includes multi-latent domains. Then from the Bing dataset we choose 50 images from each of the first 20 categories as source data. Set caltech-256 as our target domain. we change the number of labeled data points sampled from target domain (caltech data set) that try to show the robustness of domain label obtained by our method. Besides Hoffman et al.'s multi-domain adaptation framework, we add two other baseline methods for supervised domain adaptation:

- SVM-t: A support vector machine using target training data.
- arct: A category general feature transform method proposed by (Saenko et al. 2010) which is single source domain adaptation. We implement the transform learning and then apply a SVM classifier.

Domain adaptation performance is shown in Figure 3. The most obvious conclusion which can be drawn from this is that multiple domain transformation methods out-perform those that ignore latent domains while training with 'wild' data. Also, as we increase the number of samples from target domain, only using the target data for training, SVM-t can get better results than arct (Saenko et al. 2010) that single domain transformation method, and multiple domain transformation methods work better than SVM-t. It means the mixing of multiple domains could lead to bad transformation based on arct (Saenko et al. 2010), and demonstrates the necessity of domain discovery in complex data. Comparing our domain adaptation performance with the state of art method of Hoffman et al., we believe that our improved performance is derived from the improved domain assignment performance shown in the previous section.

Comparison in Unsupervised Domain Adaptation In addition to the previous section's demonstration of improved performance for supervised domain adaptation, this section shows its improvement in *un*supervised domain adaptation. Whereas the supervised domain adaptation performance could be attributed to the multiple domain transformation, the discovered domain may not work if we use it to do domain adaptation alone.

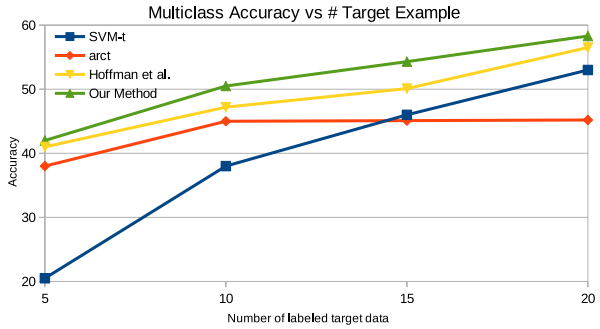

Figure 3: Supervised domain adaptation performance based on domain discovery results in bing-caltech dataset.

	(a,d)->w	(a,w)->d	(d,w)->a	Mean
Single Domain	23.15	43.48	11.35	25.99
Hoffman et al. 2012	24.75	42.69	12.82	26.75
Our Method	29.31	43.62	13.25	28.73

Figure 4: The result of unsupervised domain adaptation with discovered domain in office dataset.

Here, we adopt the office data set for this experiment, training with mixed data from two of the three domains and testing on a target domain of the held out data. Since in the unsupervised domain adaptation problem, there is no labeled target data, we do not compare to SVM-t in this experiment.

In this experiment, we adopt the two-step way for domain adaptation. After discovering domains in the training data, we learn domain-specific classifiers and test the classifier on all data from target set. Then, based on Eq. 14, we choose the domain with the maximum total weight and run the unsupervised domain adaptation (Gong et al. 2012) between the chosen domain and the target domain. In figure 4, our results demonstrate that domain selection performs better than treating the source data as single domain, and that our method outperforms Hoffman et al's method. It strongly demonstrates the superiority of our method.

Conclusions

In this paper, we propose a novel model for latent domains discovery for visual domain adaptation. First, we provide a new local subspace representation for each data based on its neighbors within the same semantic category that reflects local variations of the intrinsic intra-category change tendency. Second, we propose a novel objective model based on mutual information between new subspace representation and domain assignment, and the prior of class distribution in each domain. In future, we are planning to adopt our method on other different area, such as sentimental classification.

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