Domain Adaptation for Visual Applications: A Comprehensive Survey

Gabriela Csurka

Abstract The aim of this paper is to give an overview of domain adaptation and transfer learning with a specific view on visual applications. After a general motivation, we first position domain adaptation in the larger transfer learning problem. Second, we try to address and analyze briefly the state-of-the-art methods for different types of scenarios, first describing the historical shallow methods, addressing both the homogeneous and the heterogeneous domain adaptation methods. Third, we discuss the effect of the success of deep convolutional architectures which led to new type of domain adaptation methods that integrate the adaptation within the deep architecture. Fourth, we overview the methods that go beyond image categorization, such as object detection or image segmentation, video analyses or learning visual attributes. Finally, we conclude the paper with a section where we relate domain adaptation to other machine learning solutions.

1 Introduction

While huge volumes of unlabeled data are generated and made available in many domains, the cost of acquiring data labels remains high. To overcome the burden of annotation, alternative solutions have been proposed in the literature in order to exploit available unlabeled data from the domain (referred to as semi-supervised learning), or labeled data or models available in similar domains (referred to as transfer learning). Domain Adaptation (DA) is a particular case of transfer learning (TL) that leverages labeled data in one or more related source domains, to learn a classifier for unseen or unlabeled data in a target domain, where in general it is assumed that the task is the same, i.e. class labels shared with the source domains. The domains are assumed to be related, but not identical in which case it becomes a standard machine learning (ML) problem that assumes the test data is drawn from the same distribution as the training data. When this assumption is not verified, i.e. the distributions on training and test set do not match, the performance at test time can be significantly degraded.

In visual applications, such distribution difference, called domain shift can be a consequence of changing conditions, such as background, location, pose, but the domain mismatch might be more severe when the source
and target domains contain images of different types, such as RGB photos, NIR, paintings, sketches [127, 47, 28, 188]. Domain shifts are common in real-life applications. Service provider companies are especially concerned since for the same service (task), the distribution of the data may vary a lot from one customer to another. In general, machine learning components of service solutions that are re-deployed from a given customer or location to a new customer or location require specific customization to accommodate the new conditions. Examples include brand sentiment management, where it is critical to tune the models to the way users talk about their experience given the different products; or surveillance and urban traffic understanding, where models pretrained on previous locations might need adjustment to the new environment. All these entail either acquisition of annotated data in the new field or the calibration of the pretrained models to achieve the contractual performance in the new situation. However, the former solution, i.e., data labeling, is expensive and time consuming due to the significant amount of human effort involved. Therefore, the second option is preferred when possible. This can be achieved either by adapting the pretrained models taking advantage of the unlabeled (and if available small labeled) target set or, by exploiting both previously acquired labeled source data and the new unlabeled target data together to build the target model.

Numerous approaches have been proposed in the last years to address adaptation needs that arise in different application scenarios (see a few examples in Figure 1). Examples include DA and TL solutions for named entity recognition and opinion extraction across different text corpora [59, 161, 15, 276], multilanguage text classification [16, 273], sentiment analysis [35, 100], WiFi-based localization [159], speech recognition across different speakers [132, 175], object recognition in images acquired in different conditions [185, 103, 83, 140, 216], video concept detection [259], video event recognition [69], activity recognition [78, 277], facial action unit detection [44], 3D pose estimation [255], face recognition [261, 200, 195].
facial landmark localization [209], human motion parsing from videos [201], document categorization across different customer datasets [40, 50, 53], etc.

In this paper, we mainly focus on domain adaptation methods applied to visual tasks. For a broader review of the transfer learning literature as well as for approaches specifically designed to solve non-visual tasks, e.g., text or speech, please refer for example to the recent survey [245].

The rest of the paper is organized as follows. In Section 2, we define more formally transfer learning and domain adaptation. In Section 3, we review shallow DA methods that can be applied on visual features extracted from the images, both in the homogeneous case when the feature space is the same for the source and target domains, and heterogeneous case, where the source and target data have different representations. In Section 4, we address more recent deep domain adaptation methods. Section 5 describes domain adaptation solutions proposed for computer vision applications beyond image classification, such as detection, segmentation, object tracking, etc. Section 6 relates DA to other transfer learning and standard machine learning approaches and Section 7 concludes the paper.

Fig. 2 An overview of different transfer learning approaches. (Image: Courtesy to S.J. Pan [160].)
2 Transfer learning and domain adaptation

In this section, we follow the definitions and notation of [160, 245]. Accordingly, a domain $D$ is composed of a $d$-dimensional feature space $X \subset \mathbb{R}^d$ with a marginal probability distribution $P(X)$ and a task $T$ defined by a label space $Y$ and the conditional probability distribution $P(Y|X)$, where $X$ and $Y$ are random variables. Given a particular sample set $X = \{x_1, \ldots, x_n\}$ of $X$, with corresponding labels $Y = \{y_1, \ldots, y_n\}$ from $Y$, $P(Y|X)$ can in general be learned in a supervised manner from these feature-label pairs $\{x_i, y_i\}$. Let us assume that we have two domains with their related tasks: a source domain $D^s = \{X^s, P(X^s)\}$ with $T^s = \{Y^s, P(Y^s|X^s)\}$ and a target domain $D^t = \{X^t, P(X^t)\}$ with $T^t = \{Y^t, P(Y^t|X^t)\}$.

If the two domains corresponds, i.e. $D^s = D^t$ and $T^s = T^t$, traditional ML methods can be used to solve the problem, where $D^s$ becomes the training set and $D^t$ the test set. When this assumption does not hold, i.e. $D^t \neq D^s$ or $T^t \neq T^s$, the models trained on $D^s$ might perform poorly on $D^t$, or not applicable directly if $T^t \neq T^s$. When the source domain is somewhat related to the target, it is possible to exploit the related information from $\{D^s, T^s\}$ to learn $P(Y^t|X^t)$. This process is known as transfer learning (TL).

We distinguish between homogeneous TL, where the source and target are represented in the same the feature space, $X^t = X^s$, with $P(X^t) \neq P(X^s)$ due to domain shift, and heterogeneous TL where the source and target data can have different representations or they can be even of different modalities, $X^t \neq X^s$.

Based on these definitions, Pan and Yang in [160] categorize TL approaches into three main groups depending on the different situations concerning source and target domains and the corresponding tasks. These are the inductive TL, transductive TL and unsupervised TL (see also Figure 2 and Section 6.1). The inductive TL is the case where the target task is different but related to the source task, no matter whether the source and target domains are the same or not. It requires at least some labeled target instances to induce a predictive model for the target data. In the case of transductive TL, the source and target tasks are the same, and either the source and target domains are different (domain adaptation) or there is a selection bias between the training and the test set (sample selection bias). Finally, the unsupervised TL refers to the case where both the domains and the tasks are different but somewhat related. In general, labels are not available neither for the source nor for the target and the focus is on exploiting the (unlabeled) information in the source domain to solve unsupervised learning tasks in the target domain. These tasks include clustering, dimensionality reduction and density estimation [55, 247].

According to this classification, DA methods are transductive TL solutions, where it is assumed that the tasks are the same, i.e. $T^t = T^s$. In general they refer to a categorization task, where both the set of labels and the conditional distributions are assumed to be shared between the two domains, i.e. $Y^s = Y^t$ and $P(Y|X^s) = P(Y|X^t)$. However, the second assumption is rather strong and does not always hold in real-life applications. Therefore, the definition of domain adaptation is extended to the case where only the first assumption is required, i.e. $Y^s = Y^t = Y$.

In the DA community, we further distinguish between the unsupervised (US) case where the labels are available only for the source domain and the semi-supervised (SS) case where a small set of target examples might have labels.

Note also that the unsupervised DA is not related to unsupervised TL, where in general the task to be solved is unsupervised and no source labels are available.
3 Shallow domain adaptation methods

In this section, we review shallow DA methods that can be applied on visual features extracted from the images. First, in Section 3.1 we survey homogeneous domain adaptation methods, where the feature representation for the source and target domains is the same, i.e. $X^s = X^t$ with $P(X^s) \neq P(X^t)$ and the tasks shared, i.e. $Y^s = Y^t$. Then, in Section 3.2 we discuss methods that can exploit efficiently several source domain. Finally, in 3.3 the heterogeneous case, where the source and target data have different representations is discussed.

3.1 Homogeneous domain adaptation methods

Instance re-weighting methods. When we assume that the conditional distribution $P(Y|X^s) = P(Y|X^t)$ is shared between the two domains, the DA problem is often referred to as dataset bias or covariate shift [204]. Then, in order to learn $P(Y|X^t)$, one could simply apply the model learned on the source to estimate $P(Y|X^t)$. However, as $P(X^s) \neq P(X^t)$, the source model might yield a poor performance when applied on the target set despite of the underlying $P(Y|X^s) = P(Y|X^t)$ assumption. The most popular early solutions proposed to overcome this to happen are based on instance re-weighting. The main idea of these methods is to weight each instance by the ratio between the likelihoods of being a source or target example (see Figure 3). This is done either by estimating these probabilities independently with a domain classifier [267] or by approximating directly the ratio between the densities with a Kullback-Leibler Importance Estimation Procedure [215, 125].

Another popular measure used in [118, 108, 159] to weight data instances is the Maximum Mean Discrepancy (MMD) [17] computed between the data distributions in the two domains. The method proposed by Dudík et al. [73] infers re-sampling weights through maximum entropy density estimation, while Shimodaira [204] improves predictive inference under covariate shift by weighting the log-likelihood function. The Importance Weighted Twin Gaussian Processes (IWTGP) [255] directly learns the importance weight function, without going through density estimation by using the relative unconstrained least-squares importance fitting. The Selective Transfer Machine (STM) [44] jointly optimizes the weights as well as the classifier parameters to preserve the discriminative power of the new decision boundary.
Dai et al. proposed the Transfer Adaptive Boosting (TrAdaBoost) [54], which is an extension to AdaBoost [86]. The method iteratively re-weights the source examples in order to automatically select and adapt part of the source data during the learning of a target classifier. This is done by increasing the weights of misclassified target instances as in the traditional AdaBoost, but decreasing the weights of misclassified source samples in order to diminish their importance during the training process (see Figure 4). The TrAdaBoost was further extended by integrating dynamic updates in [4, 41].

Parameter adaptation methods. Another set of early DA methods, but which does not necessarily assume $P(Y|X^s) = P(Y|X^t)$, investigates different options to adapt the classifier trained on the source domain, e.g. an SVM, in order to perform better on the target domain. Note that these methods in general require at least a small set of labeled target examples per class, hence they can only be applied in the semi-supervised DA scenario. As such, the Transductive SVM [123] that aims at decreasing the generalization error of the classification, by incorporating knowledge about the target data into the SVM optimization process. The Adaptive SVM (A-SVM) [258] progressively adjusts the decision boundaries of the source classifiers with the help of a set of so called perturbation functions built by exploiting predictions on the available labeled target examples (see Figure 5). The Domain Transfer SVM [68] simultaneously reduces the mismatch in the distributions (MMD) between two domains and learns a target decision function.

Fig. 4 Illustration of the TrAdaBoost method [54] where the idea is to decrease the importance of the misclassified source examples while focusing, as in AdaBoost [86], on the misclassified target examples. (Image: Courtesy to S.J. Pan)

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3 Code at https://github.com/BoChen90/machine-learning-matlab/blob/master/TrAdaBoost.m
4 The code for several methods, such as A-SVM, A-MKL, DT-MKL can be downloaded from http://www.codeforge.com/article/248440
The Adaptive Multiple Kernel Learning (A-MKL) \cite{69} generalizes this by learning an adapted classifier based on multiple base kernels and the pre-trained average classifier. The model minimizes jointly the structural risk functional and the mismatch between the data distributions (MMD) of the two domains.

The domain adaptation SVM (DASVM) \cite{23} exploits within the semi-supervised DA scenario both the transductive SVM \cite{123} and its extension, the progressive transductive SVM \cite{38}. The cross-domain SVM, proposed by Jiang \textit{et al.} in \cite{122}, constrains the impact of source data to the k-nearest neighbors (similarly to the spirit of the Localized SVM \cite{39}). This is done by down-weighting support vectors from the source data that are far from the target samples.

**Feature augmentation.** One of the simplest method for DA was proposed by Daume in \cite{58}, where the original representation is augmented with itself and zeros as follows: the source features become $[x^s x^s 0]$ and target features $[x^t 0 x^t]$. Then an SVM is trained on these augmented features to figure out which features are shared between domains and which ones are domain specific.

The idea of feature augmentation is also behind the Geodesic Flow Sampling (GFS) \cite{106, 107} where representations of intermediate domains are sampled gradually following the geodesic path between the source and target domains and concatenated (see illustration in Figure 6). Instead of sampling on the Grassman manifold, Gong \textit{et al.} proposed the Geodesic Flow Kernel (GFK) \cite{103, 101} that extends GFS to the infinite case. Indeed, the proposed kernel makes the solution equivalent to integrating over all common subspaces lying on the geodesic flow that connects the source and target subspaces. A more generic framework, proposed by Gopalan \textit{et al.} in \cite{107}, accommodates domain representations in high-dimensional Reproducing Kernel Hilbert Space (RKHS) using kernel methods and low-dimensional manifold representations corresponding to Laplacian Eigenmaps.

Motivated by the manifold-based incremental learning framework in \cite{106}, Ni \textit{et al.} \cite{154} generates a set of intermediate dictionaries which smoothly connect the source and target domains. This is done by decomposing the target data with the current intermediate domain dictionary to get a reconstruction residue used to update domain dictionary.

\footnote{Code available at \url{http://www-scf.usc.edu/~boqinggo/domain_adaptation/GFK_v1.zip}}
the current dictionary. In this way the reconstruction residue on the target is incrementally reduced, while the transition is ensured to be smooth. Concatenating these intermediate representations allows to build better cross domain classifiers.

These methods exploit intermediate cross-domain representations that are built without the use of class labels. Hence, they can be applied in both, the US and SS, scenarios. Exploiting the available labeled set and using the new cross-domain representation, either a discriminative classifier is trained [107] or the target labels are deduced by nearest neighbor search in the kernel space [103, 101].

**Feature space alignment.** Instead of augmenting the features, other methods tries to align the source features with the target ones. As such, the Subspace Alignment (SA) [83] learns an alignment between the source subspace obtained by PCA and the target PCA subspace, where the PCA dimensions are selected by minimizing the Bregman divergence between the subspaces. It advantage is its simplicity, as shown in Algorithm 1. Similarly, the linear Correlation Alignment (CORAL) [216] can be written in few lines of MATLAB code as illustrated in Algorithm 2. The method minimizes the domain shift by using the second-order statistics of the source and target distributions. The main idea is a whitening of the source data using its covariance followed by a "re-coloring" using the target covariance matrix.

Alternatively to feature alignment, a large set of feature transformation methods were proposed with the objective to find a projection of both the source and target into a latent common space where the discrepancy between the source and target distributions is decreased after projection. The projections can be shared between the domains, or they can be domain specific projections. Feature Transformation methods that learn a common feature projection $\psi$ for both the source and target, can be grouped into methods where the learning procedure of $\psi$ is unsupervised using no class labels or supervised, when the transformation is learned by also exploiting class labels (only from the source or also from the target when available).
Algorithm 1: Subspace Alignment (SA) \[83\]

Input: Source data $X^s$, target data $X^t$, subspace dimension $d$

1: $P^s \leftarrow \text{PCA}(X^s, d)$, $P^t \leftarrow \text{PCA}(X^t, d)$;
2: $X^s_a = X^s P^s (P^s)^\top$, $X^t_a = X^t P^t$;

Output: Aligned source, $X^s_a$ and target, $X^t_a$ data.

Algorithm 2: Correlation Alignment (CORAL) \[216\]

Input: Source data $X^s$, target data $X^t$

1: $C_s = \text{cov}(X^s) + \text{eye}(\text{size}(X^s, 2))$, $C_t = \text{cov}(X^t) + \text{eye}(\text{size}(X^t, 2))$
2: $X^s_w = X^s * C_s^{-1/2}$ (whitening), $X^t_w = X^t * C_t^{-1/2}$ (re-coloring)

Output: Source data $X^s_w$ adjusted to the target.

Unsupervised feature transformation. One of the first unsupervised feature learning approach proposed for DA is the Transfer Component Analysis (TCA) \[159\]. Its main idea is to discover common latent features that have the same marginal distribution across the source and target domains, while maintaining the intrinsic structure of the original domain. The latter is achieved by a smoothness term enforcing the preservation of the local geometry (data manifold).

Instead of restricting the discrepancy to a simple distance between the sample means in the lower-dimensional space, Baktashmotlagh et al. \[10\] propose the Domain Invariant Projection (DIP) approach that compares directly the distributions in the RKHS while constraining the transformation to be orthogonal. They go a step further in \[11\] and based on the fact that probability distributions lie on a Riemannian manifold, propose the Statistically Invariant Embedding (SIE) that uses the Hellinger distance on this manifold to compare kernel density estimates between the source and target data. Both the DIP and SIE, involve non-linear optimizations and are solved with the conjugate gradient algorithm \[74\].

The Transfer Sparse Coding (TSC) \[138\] learns robust sparse representations for classifying cross-domain data accurately. To bring the domains closer, the distances between the sample means for each dimensions of the source and the target is incorporated into the objective function to be minimized. The Transfer Joint Matching (TJM) \[141\] aims at learning a new space in which the distance between the empirical expectations of source and target data is minimized using a kernel mapping that yields a non-linear transformation between the two domains. To put less emphasis on the source instances that are irrelevant to classify the target data, they additionally use instance re-weighing.

The feature transformation proposed by Chen et al. in \[35\] exploits the correlation between the source and target set to learn a robust feature representation by reconstructing the original features from their noised counterparts. The method called Marginalized Denoising Autoencoder (MDA) is based on a quadratic loss and a noise that factorizes over all feature dimensions. This allows the method to avoid explicit data corruption by marginalizing out the noise and to have a closed-form solution for the feature transformation. Note that it is straightforward to stack together several layers with optional non-linearities between layers to obtain a deep

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6 Code at https://drive.google.com/uc?export=download&id=0B9_PW9TCpxT0c292bW1RaWtXRHc
7 Code at https://drive.google.com/uc?export=download&id=0B9_PW9TCpxT0SEdMQ1pCNzdZeKU
8 Code at http://ise.thss.tsinghua.edu.cn/~mlong/doc/transfer-sparse-coding-cvpr13.zip
9 Code at http://ise.thss.tsinghua.edu.cn/~mlong/doc/transfer-joint-matching-cvpr14.zip
Algorithm 3: Stacked Marginalized Denoising Autoencoder (sMDA) \cite{35}.

**Input:** Source data $X^s$, target data $X^t$.

**Input:** Parameters: $p$ (noise level), $\omega$ (regularizer) and $k$ (number of stacked layers).

1. $X = [X^s, X^t]$, $S = X^\top X^s$ and $X_0 = X$.
2. $P = (1 - p)S$ and $Q = (1 - p)^2S + p(1 - p)\text{diag}(S)$.
3. $W = (Q + \omega I_D)^{-1}P$.
4. (Optionally), stack $K$ layers with $X_{(k)} = \tanh(X_{(k-1)} W^{(k)})$.

**Output:** Denoised features $X_k$.

In general, the above mentioned methods learn the transformations without using any class label. After projecting the data in the new space, any classifier can be used to learn a model that aims to perform well on both the source and target data. The model often works even better if in addition a small set of the target examples are hand-labeled (SS adaptation). However, the labels can also help to learn a better transformation. When only the source class labels are exploited, they can still be applied to US scenarios, however if target labels are also used, the method is only applicable in the SS case.

**Supervised feature transformation.** These methods exploit class labels, either only from the source or also from the target (when available), to learn the transformation. Several unsupervised feature transformation methods, cited above, have supervised extensions that capitalize on class labels to learn a better transformation. Among the extensions we can mention the Semi-Supervised TCA (SSTCA) \cite{159, 146} where the objective function that is minimized contains a label dependency term in addition to the distance between the domains and the manifold regularization term enforcing the smoothness of the projections. The label dependency term has the role of maximizing the alignment of the projections with the source labels and when available target labels.

Similarly, Csurka et al. in \cite{51} add into the MDA framework \cite{35} a quadratic regularization term \cite{10} which depends on the pre-trained source classifier, that encourages the model to keep the denoised source data well classified. Moreover, the domain denoising and cross-domain classifier can be learned jointly by iteratively solving a Sylvester linear system to estimate the transformation and a linear system to get the classifier in closed form.

To take advantage of class labels, the distance between the source samples in each class and the corresponding class means is added as regularizer into the DIP \cite{10} respectively SIE model \cite{11}. This term encourages clusters in the latent space of the source samples with the same class labels.

The Adaptation Regularization based Transfer Learning \cite{139} (ARTL) \cite{139} performs a domain adaptation process while learning the final classifier by optimizing simultaneously the structural risk functional, the joint distribution matching between domains, and the manifold consistency underlying marginal distribution. The Max-Margin Domain Transform \cite{117} (MMDT) \cite{117} optimizes both the transformation and classifier parameters jointly, by introducing an efficient cost function based on the misclassification loss.

\footnote{Code at https://github.com/sclincha/xrce_mada_da_regularization}

\footnote{Code at http://ise.thss.tsinghua.edu.cn/~mlong/doc/adaptation-regularization-tkde14.zip}

\footnote{Code at https://cs.stanford.edu/~jhoffman/code/Hoffman_ICLR13_MMDT_v3.zip}
Another set of methods extends the idea of minimizing the distance between the data distributions to the distance between the conditional distributions [273, 140] involving data labels (both from source and from target). Thus, Zong et al. in [273] propose an adaptive kernel approach that maps the marginal distribution of target-domain and source-domain data into a common kernel space, and utilize a sample selection strategy to draw conditional probabilities between the two domains closer. The Joint Distribution Adaptation (JDA) [140] jointly adapts both the marginal distribution through a principled dimensionality reduction procedure (integrating PCA) and the conditional distribution between the domains, where only source labels are required and instead of the target labels, the pseudo (predicted) labels are used.

**Metric learning based feature transformation.** These methods are supervised feature transformation methods that involves that at least a limited set of target labels are available, and use metric learning techniques to bridge the relatedness between the source and target domains. Thus, Zha et al. [270] proposes the Log-determinant regularized Distance Metric Learning (L-DML) and the Manifold regularized Distance Metric Learning (M-DML) for adapting face recognition systems. The Information-Theoretic Metric Learning (ITML) [60] was used by Saenko et al. in [185] to directly learn a distance metric across different domains. This method was further extended by incorporating non-linear kernels in [129] allowing the model to be also applicable in the heterogeneous case, where the representation space for the source and target are not the same.

The metric learning for the Domain Specific Class Means (DSCM) [52] learns a transformation of the feature space that minimizes the weighted soft-max distances to the corresponding domain specific class means. This allows decreasing the intraclass and increasing the interclass distances in the projected space (see Figure 10). Furthermore, exploiting unlabeled target instances, the Self-adaptive Metric Learning Domain Adaptation (SaMLDA) [52] framework iteratively refines the metric using increasing target set and labels predicted with DSCM. This method was inspired by the Naive Bayes Nearest Neighbor based Domain adaptation [14].

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13 Code at [http://ise.thss.tsinghua.edu.cn/~mlong/doc/joint-distribution-adaptation-iccv13.zip](http://ise.thss.tsinghua.edu.cn/~mlong/doc/joint-distribution-adaptation-iccv13.zip)

14 Code at [http://www.tatianatommasi.com/2013/DANBNNdemo.tar.gz](http://www.tatianatommasi.com/2013/DANBNNdemo.tar.gz)
The OTDA [46] consider a local transportation plan for each sample in the source domain to transport the training samples close to the target examples. (Image: Courtesy to N. Courty.)

(NBNN-DA) [228] framework, which iteratively combines metric learning and Naive Bayes Nearest Neighbor classifier based sample selection to adjust the instance-to-class distances by tuning the per class metrics and to progressively make the metric more suitable for the target domain (see Figure 7). In both cases, at each iteration the most ambiguous source example of each class is replaced by the target example for which the classifier (DSCM respectively NNBA) is the most confident for that class.

Local feature transformation. The previous methods learn a global transformation to be applied to each source and target example. In contrast, the Adaptive Transductive Transfer Machines (ATTM) [77] applies sample-based transformation to refine the probability density function of source domain samples assuming that the transformation from the source to the target domain is locally linear. This is done by finding an optimal translation parameter that maximizes the likelihood of the translated source as a posterior given a target Gaussian Mixture Model (GMM).

Similarly, the Optimal Transport for Domain Adaptation (OTDA) [46], considers a local transportation plan for each source. The model can be seen as a graph matching problem, where the final coordinates of each sample are found by mapping the source samples to target samples while respecting the marginal distribution of the target domain (see Figure 8). To exploit class labels, a regularization term with group-lasso is added inducing on one hand group sparsity and on the other hand constraining source samples of the same class to remain close during the transport.

Landmark selection. In order to improve the feature learning process, several methods have been proposed to sample the most relevant instances or instance sets from the source and use only those so-called landmark examples to learn the adaptation model. While strongly related to instance re-weighting with binary weights, the landmark selection process can be rather seen as data preprocessing and hence complementary to the adaptation process. Gong et al. [101] proposed to minimize a variant of the MMD to identify good landmarks by creating a set of auxiliary tasks that offer multiple views of the original problem, while the Statistically Invariant Sample Selection (SISS) [11], uses the Hellinger distance on the statistical manifold instead of MMD (see examples in Figure 9). The selection is forced to keep the proportions of the source samples per class the

[15] Code at http://www-scf.usc.edu/~boqinggo/domain_adaptation/landmark_v1.zip
same as in the original data. In contrast to these approaches, the Multi-scale Landmark Selection [5] does not require any class labels. It takes each instance independently and considers it as being a good candidate if the Gaussian distributions of the source examples and of the target points centered on the instance are similar over a set of different scales (variances of the Gaussian).

3.2 Multi-source domain adaptation

Most of the above mentioned methods were designed for a single source versus target case. When multiple sources are available, they can be concatenated to form a “single” source but this might not be always a good option. Alternatively, the models built for each source-target pair and their results can be combined to make a final decision. However, a better option might be to take advantage of them as distinct domains exploiting the specificity of each domain simultaneously. As such, the Feature Augmentation (FA) [58] and Adaptive SVM [258] methods, described in Section 3.1, exploit naturally the multi-source aspect of the dataset. Indeed in FA an extra feature set is concatenated to the features for each source domain. In the case of the Adaptive SVM [258] an ensemble of source specific auxiliary classifiers is used to adjust the parameters of the target classifier. Similarly, both the domain regularization and classifier based regularization of the extended MDA proposed in [51] have source specific components. The method proposed in [52] relies on domain specific class means both to learn the metric and to predict the target class labels (see illustration in Figure 10).

The Domain Adaptation Machine (DAM) [70] for multiple source domains learns the target classifier by leveraging a set of source classifiers. This is done by the integration of a domain-dependent regularizer term based on a smoothness assumption. It forces the target classifier to share similar decision values with the relevant source classifiers on the unlabeled target instances. The Conditional Probability based Multi-source

16 Code at [http://home.seeere.com/data/cvpr-2015/LSSA.zip](http://home.seeere.com/data/cvpr-2015/LSSA.zip)
Metric learning for the DSCM classifier, where $\mu^s_i$ and $\mu^t_i$ represent source specific class means and $\mu^t_i$ class means in the target domain. The feature transformation $W$ is learned by minimizing for each sample the weighted soft-max distances to the corresponding domain specific class means in the projected space.

Domain Adaptation (CP-MDA) approach [31] extends the above idea by adding weight values for each source classifier based on conditional distributions.

The Robust Domain Adaptation via Low-Rank Reconstruction (RDALRR) [120] transforms each source domain into an intermediate representation such that the transformed samples can be linearly reconstructed from the target samples (see Figure 11). Within each source domain, the intrinsic relatedness of the reconstructed samples is imposed by using a low-rank structure where the outliers are identified using sparsity constraints. By enforcing different source domains to have jointly low ranks, a compact source sample set is formed with a distribution close to the target domain. The whole transformation procedure is unsupervised (requires no label information).

To better take advantage of the presence of multiple source domains, extensions to methods previously designed for a single source versus target case were proposed in [107, 27, 116, 265]. As such, [107] describes a multi-source version of the Geodesic Flow Sampling [106] that was further extended by Caseiro et al. in [27] to the Subspaces by Sampling Spline Flow (SSF) approach. It uses smooth polynomial functions described by splines on the manifold to interpolate between all the sources and the target domain. Hoffmann et al. propose in [116] a constrained clustering algorithm[17] to identify automatically "source" domains in a large data set, on which they apply a multi-source extension of the Asymmetric Kernel Transforms (AST) [129]. Yao and Doretto in [265] efficiently extends the TrAdaBoost [54] to multiple source domains.

Source domain weighting. When multiple sources are available, it is desired to select those domains that provide the best information transfer and to remove the ones that have more likely negatively impact on the final model. Hence, in order to reduce negative transfer effect from unrelated source domains, Ge et al. in [96] assign to each source a weight called the Supervised Local Weight (SLW). This is done by using a spectral clustering algorithm on each domain and propagating the available labels to the corresponding clusters.

[17] Code at https://cs.stanford.edu/~jhoffman/code/hoffman_latent_domains_release_v2.zip
Fig. 11 The RDALRR [120] transforms each source domain into an intermediate representation such that the transformed samples can be linearly reconstructed from the target samples. (Image: Courtesy to I.H. Jhuo.)

SLW of each source cluster is computed by comparing the source and target clusters and is used by the final target learner to attenuate the effects of negative transfer.

Similarly, Gao et al. propose in [96] a Locally Weighted Ensemble (LWE) framework to combine multiple source models. They approximate the optimal model weights using a graph-based approach where they measure the similarity between the local structures centered on source and target instances by comparing neighborhood graphs. The CP-MDA [31], mentioned above, uses a weighted combination of source learners, where the weights are estimated as a function of conditional probability differences between the source and target domains. Gong et al. define in [103] a Rank of Domain (ROD) value that measures the relatedness between each source and target domain. The ROD metric integrates the alignment between subspaces measured by the overlap between the source and target subspaces and the KL divergences between data distributions, once they are projected into the subspaces. The Multi-Model Knowledge Transfer (MMKT) [227] minimizes the negative transfer by giving higher weights to the most related linear SVM source classifiers. These weights are determined through a leave one out learning process.

3.3 Heterogeneous domain adaptation

Heterogeneous transfer learning (HTL) refers to the setting when the representation spaces are different for the source and target domains ($X^t \neq X^s$ as defined in Section 2). As a particular case, when the tasks are assumed to be the same, i.e. $Y^s = Y^t$, we refer to it as heterogeneous domain adaptation (HDA).

Both HDA and HTL are strongly related to multi-view learning [250, 239], where the presence of multiple information sources presents an opportunity to learn better representations (features) by analyzing the views simultaneously and hence be able to solve the task on test data for which not all the views are available. Such situations appears when simultaneously recording audio and video [32], data contains both image and text (e.g.
Fig. 12 Heterogeneous DA through an intermediate domain allowing to bridge the gap between the features representing the two domains. For example, when the source domain contains only text, and the target only images, the intermediate domain can be composed by a set of crawled Web pages containing both text and images. (Image courtesy B. Tan [222]).

We can also have multi-view situations even when the views have the same data modalities (textual, visual, audio), such as in the case of parallel texts in different languages [236, 79], photos of the same person taken across different poses, illuminations and expressions [261, 195, 196, 170].

In classical multi-view learning it is assumed that during training there are multi-view examples, i.e. for the same data instance different types of information is available (e.g., a person can be identified by photograph, fingerprint, signature or iris). On the contrary, in the case of HTL and HDA, this assumption rarely holds. Therefore, a first set of methods proposed to solve HDA relies on some multi-view auxiliary data to bridge the gap between the domains (see Figure 12).

Methods relying on auxiliary domains. HDA/HTL methods relying on auxiliary domains principally exploit feature co-occurrences (e.g. between words and visual features) in the multi-view domain. As such, we can mention the Transitive Transfer Learning (TTL) [222] that first selects an appropriate domain from a large data set guided by domain complexity and distribution differences between the original domains (source and target) and the selected one (auxiliary). Then, using Non-negative Matrix Tri-factorization [61] it performs feature clustering and label propagation simultaneously through the intermediate domain.

The Mixed-Transfer approach [223] builds a joint transition probability graph of mixed instances and features, considering the data in the source, target and intermediate domains. The label propagation on the graph is done by a random walk process to overcome the data sparsity. Zhu et al. [279] enrich the representations of the target images with semantic concepts extracted from the intermediate data through a Collective Matrix Factorization [208]. They show that these generated latent semantic features allow to build a better image classifier.

Qi et al. [168] propose to learn a translator function between the source and target domain by learning directly the product of the two transformation matrices that map each domain into a common (hypothetical)

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18 Most often when the bridge is to be done between visual and textual representations, a common practice is to crawl the Web for pages containing both text and images to build such intermediate multi-view data.

19 Code available at [http://www.cse.ust.hk/~yzin/htl4ic.zip](http://www.cse.ust.hk/~yzin/htl4ic.zip)

20 Code available at [http://www.ifp.illinois.edu/~eqi4/TTI_release_v1.zip](http://www.ifp.illinois.edu/~eqi4/TTI_release_v1.zip)
latent topic built on the co-occurrence data. Following the principle of parsimony, they encode as few topics as possible in order to be able to match text and images. Using the translator, the semantic labels are propagated from the labeled text corpus to unlabeled new images by a cross-domain label propagation mechanism.

Yang et al. in [260] proposed to describe the relatedness of the domains by so called transfer weights computed on the co-occurrence data. To do this, they compute the principal components in each feature space such that co-occurrence data is represented by these principal components. Then, a Markov Chain Monte Carlo [7] can be employed to construct a directed cyclic network where each node is a domain and each edge weight represent the conditional dependence between the corresponding domains.

Yan et al. in [257] studied online HDA, where offline labeled data from a source domain is transferred to enhance the online classification performance for the target domain. The main idea is to build an offline classifier based on heterogeneous similarity using labeled data from a source domain and unlabeled co-occurrence data collected from Web pages and social networks (see Figure 13). The online target classifier is combined with the offline source classifier using Hedge weighting strategy used in Adaboost [86] to update their weights for ensemble prediction.

Alternatively, instead of relying on external data, several HDA methods exploit directly the data distribution in the source and target domains willing to remove simultaneously the gap between the feature representations and the data distribution shift. This is done by learning either a projection for each domain into a domain-invariant common latent space, referred to as symmetric transformation based HDA [21] or a transformation from the source space towards the target space, called asymmetric transformation based HDA. These approaches require at least a limited amount of labeled target examples (semi-supervised DA).

**Symmetric feature transformation.** The aim of symmetric transformation based HDA approaches is to learn projections for both the source and the target space into a common latent (embedding) feature space that is better suited to learn the task for the target. These methods are related, on one hand, to the feature transformation based homogeneous DA methods described in Section 3.1 seeking a latent space in which the domain shift

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21 Note that these methods can be used even if the source and target data are represented in the same feature space, i.e. $X^S = X^T$. Therefore, it is not surprising that several methods are direct extensions of homogeneous DA methods described in Section 3.1.
Fig. 14 The SDDL proposes to learn a dictionary in a latent common subspace while maintaining the manifold structure of the data. (Image: Courtesy to S. Shekhar [200])

is minimized and, on another hand, to multi-view embedding [110, 153, 196, 104, 25, 238], where different views are embedded in a common latent space. Inspired by the latter, several methods originally designed for the homogeneous case, were extended to heterogeneous data. As such, the Heterogeneous Feature Augmentation (HFA) [71], prior to data augmentation, embeds the source and target into a common latent space (see Figure 15). In order to avoid the explicit projections, the transformation metrics are computed by the minimization of the structural risk functional of SVM as a function of these projection matrices. The final target prediction function is computed by an alternating optimization algorithm that simultaneously solves the dual SVM and finds the optimal transformations. This model was further extended by Li et al. in [134], where each projection matrix is decomposed into a linear combination of a set of rank-one positive semi-definite matrices allowing the usage of Multiple Kernel Learning to find the solution.

To deal with both domain shift and heterogeneous data, Shekhar et al. in [200] proposed the Shared Domain-adapted Dictionary Learning (SDDL) [200] that learns a class-wise discriminative dictionary in the latent projected space (see Figure 14). This is done by jointly learning the dictionary and the projections of the data from both domains onto a common low-dimensional space, while maintaining the manifold structure of data represented by sparse linear combinations of dictionary atoms.

The Heterogeneous Spectral Mapping [203] unifies different feature spaces using spectral embedding where the similarity between the domains in the latent space is maximized with the constraint to preserve the original structure of the data. Combined with a source sample selection strategy, a Bayesian-based approach is applied to model the relationship between the different output spaces.

22 Code available at https://sites.google.com/site/xyzliwen/publications/HFA_release_0315.rar
23 Code available at http://www.umiacs.umd.edu/~pvishalm/Codes/DomainAdaptDict.zip
Xiao and Guo propose in [249] a semi-supervised subspace co-projection method to address heterogeneous multi-class DA based on discriminative subspace learning while exploiting unlabeled data to enforce a MMD criterion across domains in the projected subspace. They use Error Correcting Output Codes (ECOC) to address the multi-class classification aspect and to enhance the discriminative informativeness of the projected subspace. The Semi-supervised Domain Adaptation with Subspace Learning [264] jointly explores invariant low-dimensional structures across domains to correct data distribution mismatch and leverages available unlabeled target examples to exploit the underlying intrinsic information in the target domain.

The Domain Adaptation Manifold Alignment (DAMA) [237] models each domain as a manifold and creates a separate mapping function to transform the heterogeneous input space to a common latent input space while preserving the underlying structure of each domain. This is done by representing each domains with a Laplacian matrix that captures the closeness of the instances sharing the same label. The RDALRR [120] mentioned in Section 3.2 (see also Figure 11) transforms each source domain into an intermediate representation such that the source samples linearly reconstructed from the target samples are enforced to be related to each other under a low-rank structure. Note that both DAMA and RDALRR are multi-source HDA approaches.

**Asymmetric feature transformation.** In contrast to symmetric transformation based HDA, these methods aim to learn a projection of the source features into the target space such that the distribution mismatch within each classes is minimized. Amongst methods proposed to solve heterogeneous DA with asymmetric transformation we can mention the followings. The Asymmetric Regularized Cross-domain Transformation (ARC-t) [129] builds an objective function responsible for domain invariant transformation that is learned in a non-linear Gaussian RBF kernel space. The Multiple Outlook MAPping algorithm (MOMAP) [111] finds the transformation matrix using the singular value decomposition process allowing for the marginal distributions within the class groupings to be aligned while maintaining the structure of the data. It requires a limited amount of labeled target data to be able to group the instances by classes both in source and target domains. For each class group, the features are mean adjusted to zero and each individual source class group is paired with the corresponding target class group. Zhou et al. [275] propose to learn a sparse and class-invariant feature mapping by leveraging the weight vectors of the binary classifiers learned in the source and target domains. They show that this learning task can be casted as a Compressed Sensing [66] problem and they use the ECOC scheme to generate a sufficient number of binary classifiers given the set of classes.

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24 Code available at [http://vision.cs.uml.edu/code/DomainTransformsECCV10_v1.tar.gz](http://vision.cs.uml.edu/code/DomainTransformsECCV10_v1.tar.gz)
4 Deep domain adaptation methods

With the recent progress in image categorization due to deep convolutional architectures - trained in a fully supervised fashion on large scale annotated datasets\(^{25}\) - allowed a significant improvement of the categorization accuracy over previous state-of-the-art solutions. Furthermore, it was shown that features extracted from the activation layers of these deep convolutional networks can be re-purposed to novel tasks\(^{26}\) even when the new tasks differ significantly from the task originally used to train the model.

Concerning domain adaptation, the results obtained on the two most popular benchmark datasets, Office31 (OFF31)\(^{185}\) and Office+Caltech10 (OC10)\(^{103}\) using features extracted from any popular CNN model\(^{26}\) outperforms by a large margin the results obtained with the SURF BOV features originally provided with these datasets. The results obtained with these Deep Convolutional Activation Features\(^{27}\) (DeCAF)\(^{65}\) even without any adaptation to the target are significantly better that the results obtained with any DA method using the SURF BOV features\(^ {42, 65, 216, 51}\). As shown also in\(^ {13, 266}\), this suggests that deep neural networks learn more abstract and robust representations, encode category level information and remove, to a certain measure, the domain bias\(^ {65, 216, 51, 188}\). Note, however that in OFF31 and OC10 both the images and

\(^{25}\) In particular on part of ImageNet\(^ {184}\).

\(^{26}\) Such as AlexNet\(^ {128}\), VGGNET\(^ {207}\), ResNet\(^ {113}\) or GoogleNet\(^ {221}\).

\(^{27}\) Code to extract features available at\(^ {https://github.com/UCBAIR/decaf-releas}\)
the classification task (object recognition) remain relatively similar to the images and the task used to train these models (usually ILSVRC12 \[184\]). In contrast, considering adaptation of category models between for example images and paintings, drawings, clip art or sketches (see examples from the CMPlaces dataset\[28\] in Figure 16), the models or DeCAF features without adaptation are not sufficient to handle the domain differences \[127, 48, 47, 28\] and alternative solutions are necessary. Solutions proposed in the literature to adapt deep models or features can be grouped into three main categories.

**Shallow methods with deep features.** The first, obvious solution is to use the deep network as feature extractor yielding Deep Convolutional Activation Features (DeCAF) \[65\]. These DeCAF features extracted from both source and target examples can then be used within any shallow DA method described in Section 3. As such, Feature Augmentation \[57\], Max-Margin Domain Transforms \[117\] and Geodesic Flow Kernel \[103\] were applied to DECAF features in \[65\], and Subspace Alignement \[83\] and Correlation Alignment (CORAL) in \[216\]. Csurka *et al.* in \[51\] experimented with extended MDA framework \[35\] while Saxena and Verbeek in \[188\] explored various metric learning approaches to align deep features extracted from RGB face images (source) and NIR or sketches (target).

In general, these DA methods allow to further improve the classification accuracy of the source classifiers trained with these DeCAF features \[65, 216, 51, 188\]. Note however that the gain is often relatively small and significantly lower that the gain obtained with these same methods when used with the SURF BOV features.

**Fine-tuning deep CNN architectures.** The second and most used solution is to fine-tune the deep network model on the new type of data and for the new task \[268, 157, 9, 43\]. But, fine-tuning requires in general a relatively large amount of annotated data which is not available for the target domain, or it is very limited. Therefore, the model is in general fine-tuned on the source (and the small labeled target set when available) which allows in a first place to adjust the deep model to the new task (output class labels) common between the source and target in the case of DA. This is fundamental if these class labels are not among the 1000 ILSVRC12 \[184\] classes used to pre-train in general the deep models. However, if the domain difference between the source and target is important, fine-tuning the model on the source might over-fit the model for the source. In this case the performance can be worse than just fine-tuning the last layer while freezing or using a much smaller learning rate for all the others\[29\] (see examples in \[42, 216\]). When at least a small set of target

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\[28\] Dataset available at [http://projects.csail.mit.edu/cmplaces/](http://projects.csail.mit.edu/cmplaces/).

\[29\] Equivalent with training a source classifier without adaptation on DeCAF features corresponding to the last feature layer (e.g. DECAF7 of AlexNet \[128\] or fc7 of VGGNET \[207\]).
Fig. 18 Adversarial adaptation methods can be viewed as instantiations of the same framework with different choices regarding their properties \cite{232} (Image courtesy E. Tzeng).

Label instances is available (SS scenario) adding them to the training set allow the adjustment of the model to the target.

4.1 DeepDA architectures

Finally, the most promising are the deep domain adaptation (deepDA) methods that build new deep learning architectures to address domain adaptation. One of the first deepDA method is the Stacked Denoising Autoencoders \cite{235} proposed to adapt sentiment classification between reviews of different products \cite{100}. This model aims at finding common features between the source and target collection relying on denoising autoencoders, where a multi-layer neural network is trained to reconstruct input data from partial random corruptions with backpropagation. The Stacked Marginalized Denoising Autoencoders \cite{35} is a variant of the SDA where the random corruption is marginalized out yielding a unique optimal solution computed in closed form and hence eliminates the need of backpropagation. It is a stacked version of the MDA \cite{35}, a feature transformation based DA method described in Section ??.

The Deep Learning for Domain Adaptation \cite{42} was inspired by the intermediate representations on the geodesic path \cite{103,107}, proposes a deep model based interpolation between domains (see Figure ??). This is done by a deep nonlinear feature extractor trained in an unsupervised manner using the Predictive Sparse Decomposition \cite{126} on intermediate datasets, where the amount of source data is gradually replaced by target samples.
Most popular DeedDA methods are the ones inspired by the Siamese deep architecture \cite{22} considering two streams, one for the source and one for the target, where the classification loss (applied on the source data) is combined with an adversarial loss. According to the unified framework for adversarial adaptation methods by Tzeng \textit{et al}. \cite{232}, these methods can be grouped based on the loss used, on whether they are generative or discriminative, and on whether the parameters are shared or not in the Siamese architecture (see illustration in Figure 18).

**Discriminative models.** These methods use in general discrepancy (in general MMD) based loss defined in general between activation layers corresponding to the source and target network and are strongly related with the shallow feature space transformation methods described in Section ?? One of the first such method is the Deep Domain Confusion \cite{30} (DDC) \cite{231}, that proposes to simultaneously transfer the learned source semantic structure to the target domain by optimizing the network to produce activation distributions that match those learned for source data in the source only CNN. The layer to be considered for matching and its dimension is automatically selected amongst a set of fine-tuned networks based on the MMD between the source and the target. The main drawbacks of this model is, that it requires fine-tuning of several models and that only a single layer of the network is adapted with a linear MMD, limiting its performance. Therefore, to make the model more suitable for the target, Long \textit{et al}. proposed the Deep Adaptation Network \cite{31} (DAN) \cite{137} that consider the sum of MMDs corresponding to several layers including the soft prediction layer. Furthermore, DAN explore multiple kernels for adapting these deep representations, which substantially enhances adaptation effectiveness compared to a single kernel method used in \cite{97} and \cite{231}. DAN \cite{137} was further improved by the Joint Adaptation Networks (JAN) proposed in \cite{142}. JAN, instead of considering the sum of marginal distributions (MMD) of features corresponding to different layers (several intermediate ones and the soft prediction layer) of the deep model, aims to minimize jointly these distribution discrepancies.

Ghifary \textit{et al}. \cite{97} uses such denoising auto-encoder as a pre-training stage for the Domain Adaptive Neural Network that is trained on the labeled source data \cite{32}. To ensure that the model continue to adapt to the target, the MMD is embedded as a regularization in the supervised backpropagation process (added to the cross-entropy based classification loss of the labels source examples).

\footnote{Code available at \url{https://github.com/erictzeng/caffe/tree/confusion}}

\footnote{Code available at \url{https://github.com/thuml/transfer-caffe}}

\footnote{Code available at \url{https://github.com/ghif/mtae}}
The Deep CORAL \cite{218} extends the shallow CORAL \cite{216} method described in Section ?? to deep architectures\footnote{Code available at \url{https://github.com/VisionLearningGroup/CORAL}}. The main idea is to learn a nonlinear transformation that aligns correlations of activation layers in the deep model. This idea is similarly to DDC and DAN except that instead of MMD the CORAL loss\footnote{Note that this can be seen as minimizing the MMD with a polynomial kernel.} (expressed by the distance between the covariances) is used to minimize discrepancy between the domains.

In contrast to the above methods, Rozantsev \textit{et al.} \cite{183} consider the MMD between the weights of the source respectively target models of different layers, where an extra regularizer term ensures that the weights in the two models remains linearly related. Aljundi and Tuytelaars in \cite{6} propose a light-weight domain adaptation method, which using only a few target samples analyze and reconstruct the output of the filters that were found affected by the domain shift. The aim of the reconstruction is to make the filter responses given a target image resemble to the response map of a source image. This is done by simultaneously selecting and reconstructing the response maps of the bad filters using a Lasso based optimization with a KL-divergence measure that guides the filter selection process.

The Domain-Adversarial Neural Networks (DANN) \cite{95}, integrates a gradient reversal layer into the standard architecture to promote the emergence of features that are discriminative for the main learning task on the source domain and indiscriminate with respect to the shift between the domains (see Figure ??). This layer is left unchanged during the forward propagation and reverses the gradient during backpropagation.

The Adversarial Discriminative Domain Adaptation \cite{232}, in contrast to the above mentioned methods consider an inverted label GAN loss used by Generative Adversarial Networks \cite{105}. The model furthermore consider independent source and target mappings allowing domain specific feature extraction to be learned, where the target weights are initialized by the network pre-trained on the source.

\footnote{35 Code available at \url{https://github.com/ddtm/caffe/tree/grl}}
Generative models. These methods are in general based on Generative Adversarial Network (GAN) [105] that became extremely popular nowadays. As such, the Coupled Generative Adversarial Networks [136] consists of a tuple of GANs (Generative Adversarial Networks [105]) each corresponding to one of the domains. It learns a joint distribution of multi-domain images without any tuple of corresponding images. This is achieved by enforcing a weight-sharing constraint that limits the network capacity and favors a joint distribution solution over a product of marginal distributions one.

The model proposed by Bousmalis et al. in [19] also exploit GANs with the aim to generate source-domain images such that they appear as if drawn from the target domain. Prior knowledge regarding the low-level image adaptation process, such as foreground-background segmentation mask, can be integrated in the model through content-similarity loss defined by a masked Pairwise Mean Squared Error [75] between the unmasked pixels of the source and generated images. As the model decouples the process of domain adaptation from the task-specific architecture, it is able to generalize also to object classes unseen during the training phase.

Data reconstruction (encoder-decoder) based methods. In contrast to the above methods, the Deep Reconstruction Classification Network [36] proposed in [98] combines the standard convolutional network for source label prediction with a deconvolutional network [269] for target data reconstruction (see Figure ??). To jointly learn source label predictions and unsupervised target data reconstruction, the model alternates between unsupervised and supervised training. The encoding parameters of the DRCN are shared across both tasks, while the decoding parameters are separated. The data reconstruction can be viewed as an auxiliary task to support the adaptation of the label prediction.

The Domain Separation Networks (DSN) [20] introduces the notion of a private subspace for each domain, which captures domain specific properties, such as background and low level image statistics. A shared subspace, enforced through the use of autoencoders and explicit loss functions, captures common features between

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36 Code available at [https://github.com/ghif/drcn](https://github.com/ghif/drcn)
the domains. The model integrates a reconstruction loss using a shared decoder that learns to reconstruct the input sample by using both the private (domain specific) and source representations (see Figure 21).

**Heterogeneous deepDA.** Concerning heterogeneous or multi-modal deep domain adaptation, we can mention the Transfer Neural Trees (TNT) [36] that aims at relating and recognizing heterogeneous cross-domain data. The model consists of a feature mapping layer and a prediction layer. The former layer, without observing correspondence information across domains, is able to derive a domain-invariant intermediate representation. The latter layer is a Transfer Neural Decision Forest (Transfer-NDF) used for joint adaptation and classification. The weakly-shared Deep Transfer Networks for Heterogeneous-Domain Knowledge Propagation [206] learns a domain translator function from a multi-modal source data that can be used to predict class labels in the target even if only one of the modality is present. This proposed structure has the advantage to be flexible enough to represent both domain-specific features and the shared features across domains (see Figure 22).

5 Beyond image classification

In the previous sections, we attempted to provide an overview of visual domain adaptation methods with emphasis on image categorization. Compared to this vast literature focused on object recognition, relatively few papers go beyond image classification and address DA related to other computer vision problems such as object detection, semantic segmentation, pose estimation, tracking, video concept, event or action detection and localization. One of the main reason is probably due to the fact that these problems are more complex and have often additional challenges and requirements such as precision related to the localization in case of detection, pixel level accuracy in image segmentation, increased amount of annotation burden in case of videos, etc. On the other hand, adapting visual representations such as shapes, contours, deformable and articulated 2-D or 3-D models, graphs, random fields, or visual dynamics, is less obvious with classical ”vectorial” DA techniques.
Nevertheless, most often when some of these tasks are addressed in the context of domain adaptation, a first attempt is to rewrite the problem, as a classification problem with a vectorial feature space \( X \) and a set of labels \( Y \), where the main emphasis is in finding the best feature representation for the given the task. When this is possible, shallow DA methods described in the Section 3 can be applied to the problem. Hence, DA solutions such as Adaptive SVM [258], DT-SVM [68], Adaptive MKL [69] or Selective Transfer Machine [44], were applied to video concept detection [259], video event recognition [69], activity recognition [78, 277], facial action unit detection [44], and 3D Pose Estimation [255].

When such problem rewriting is less obvious, as the case of image segmentation, object part detection or action localization where the output is not a single label but a structured output or a graph, most often the target training set is simply enriched [62, 37, 49] with available source or data crawled from the Web (webly supervised) to train traditional detection, segmentation, action localization algorithm with the augmented data set. Alternatively to Web crawling for source data, to overcome the lack of labels in the target domain, a popular solution is to enrich the training set with synthetically generated data (that can be seen as source domain) to train the model for the real (target) set. The usage of the synthetic data became even more popular since the massive adoption of deep CNNs to perform computer vision tasks requiring large amount of annotated data.
Using synthetic data. Early methods used 3D CAD models to improve solutions for pose and viewpoint estimation [2,205,162,214], object and object part detection [213,166,217,182,165,112,145,16], segmentation and scene understanding [187,33,163]. The recent progress in computer graphics and modern high-level generic graphics platforms such as game engines allowed for generating photo-realistic virtual worlds with diverse, realistic, and physically plausible events and actions. Popular virtual worlds are SYNTHIA [37], Virtual KITTI [91] and GTA-V [176] (see also Figure 23). Such virtually generated and controlled environments come with different levels of labeling for free and therefore have great promise for deep learning across a breadth of computer vision problems, including optical flow [148,24,156,147], object trackers [225,91], depth estimation from RGB [192], object detection [144,234,253], semantic segmentation [109,179,176] or human actions recognition [211]. In most cases, the synthetic data is used to enrich the real training data for building the models as in [179].

However, DA techniques can further help to adjust the model to the target real data especially when no or few labeled examples are available in the real domain [230,252,211]. As such, Tzeng et al. in [230] propose a deep spatial feature point architecture for visuomotor representation using synthetic examples to pre-train and then to transfer to real imagery using a few supervised examples. This is done by combining a pose estimation loss, a domain confusion loss to align the synthetic and real domains, and a contrastive loss to align specific pairs in feature space. Together, these three losses ensure that the representation is conducive to the pose estimation task while remaining robust to the synthetic-real domain shift.

Gaidon et al. [211] propose to learn an end-to-end action recognition model called Cool Temporal Segment Networks (Cool-TSN) for real-world target categories by combining a few examples of labeled real-world videos with a large number of procedurally generated videos for different surrogate categories. The model is a deep multi-task representation learning architecture able to mix synthetic and real videos, even if the action categories differ (see Figure 24).

37 Available at http://synthia-dataset.net
38 At http://www.xrce.xerox.com/Research-Development/Computer-Vision/Proxy-Virtual-Worlds

Fig. 24 Illustration of the Cool-TSN deep multi-task learning architecture [211] for end-to-end action recognition in videos. (Image courtesy C. De Souza).
5.1 Object detection

After image level categorization, object detection received the most attention from the domain adaptation community. Object detection models until recently were composed of a window selection mechanism and window classifiers trained on the features extracted from labeled bounding boxes. At test time the classifiers decide if a region of interest obtained by sliding windows or generic window selection models contains the object or not. Hence, DA methods can help the adjustment of the classifiers trained on a source domain to the target domain, especially when a set of labeled bounding boxes is also available for the target (SS scenario).

Such semi-supervised DA methods proposed for object detection are the Projective Model Transfer SVM (PMT-SVM) and the Deformable Adaptive SVM (DA-SVM) proposed by Aytar et al. in [8]. These approaches adapt the HOG deformable source template to the target examples and the new model is used to detect the presence or absence of an object class in the sliding windows of a test image. The PMT-SVM was further combined by Donhahue et al. in [64] with the Max-Margin Domain Transforms to handle complex domain shifts. They also show that by imposing smoothness constraints on the classifier scores over the unlabeled data using instance correspondences (e.g. the same object observed simultaneously from multiple views or tracked between video frames) the detector can further be improved.

Mirrashed et al. in [150] use the Transfer Component Analysis (TCA) to adapt the image level HOG representation between source and target domains. Zhang et al. in [271] proposed a Taylor Expansion Based Classifier Adaptation for either boosting or logistic regression to adapt person detection between videos of different meeting rooms. The latter model can be viewed as using the Hessian matrix on the old data-set to regularize the logistic regression optimization on the new data-set.

**Online adaptation of the detector.** Most early works related to object detector adaptation concern online adaptation of a generic detector trained on strongly labeled images (bounding boxes) to detect objects (in general cars or pedestrians) in videos. These methods exploit the redundancy in videos allowing to obtain potential positive target examples (windows) either by background modeling/subtraction [181, 212], or by combination of tracking with regions proposed by the generic detector [224, 198, 92, 90] (see the main idea in Figure 25). Using these new samples the model can be updated by using semi-supervised techniques such as self-training [180, 248], or co-training [119, 133].
Wang et al. [240] propose a non-parametric detector adaptation algorithm, which can adapt an offline frame-based object detector to the visual characteristic of a new specific video clip. Xu et al. [251] propose the Structure-Aware Adaptive Structural SVM (SA-SSVM) to adapt online the deformable part-based model (DPM) [63] for pedestrian detection. For the case when no target label is available, a strategy inspired by self-paced learning and supported by a Gaussian Process Regression is used to automatically label samples in the target domains (see Figure 26). The temporal structure of the video is exploited through a similarity constraints imposed on the adapted detector.

Multi-object tracking. Multi-task and multi-instance learning was mainly exploited to perform category-to-instance adaptation in the case of multi-object tracking which aims at automatic detection and tracking of individual object (e.g., car or pedestrian) instances [197, 92, 90]. As such, [197] introduces a Multiple Instance Learning (MIL) loss function for Real Adaboost and presents a tracking based effective unsupervised online sample collection mechanism to collect samples for incrementally adapting pre-trained detector. Gaidon et al. in [92] propose an unsupervised, online, and self-tuning learning algorithm to optimize a multi-task learning convex objective using a high-precision but low-recall off-the-shelf generic detector. It exploits the structure of the problem to jointly learn online an ensemble of instance-level trackers, from which adapted category-level object detectors are derived. The main idea in [90] is to jointly learn all detectors (the target instance models and the generic one) using an online adaptation via Bayesian filtering coupled with multi-task learning to efficiently share parameters and reduce drift, while gradually improving recall.

The transductive approach of Tang et al. [224] re-trains the detector with automatically discovered target domain examples starting with the easiest first, and iteratively re-weighting labeled source samples by scoring trajectory tracks. Sharma et al. in [198] introduce a multi-class random fern adaptive classifier where different categories of the positive samples (corresponding to different video tracks) are considered as different target classes, and all negative online samples are considered as a single negative target class. Breitenstein et al. [21] propose a particle filtering framework for multi-person tracking-by-detection to predict the target locations.
The method is based on the combination of the generic pedestrian detector with the class-specific person detector.

**Deep neural architectures.** More recently, end-to-end deep learning object detection models were proposed that integrate and learn simultaneously the region proposals and the object appearance. In general, these models are initialized or take advantage from deep models pre-trained on ILSVRC12 [184] with image level annotations. Indeed, the pre-trained deep model combined with class-agnostic region of interest proposals, can be used to predict the presence or absence of the object of interest in the proposed local regions of interest [190, 99, 157, 114]. When strongly labeled target data is available the model can be further fine-tuned using the labeled bounding boxes to improve the object localization. As such, the Large Scale Detection through Adaptation (LSDA) [114] learns to transform an image classifier into an object detector by fine-tuning the CNN model on a small subset of categories for which bounding box information is available. The advantage of this model is that it generalizes well even for localization of classes for which there were no bounding box annotations during the training phase.

Alternatively, Raj et al. [173] proposed to use Subspace Alignment [83] (SA) between class specific source subspaces obtained from strongly annotated source images and the target bounding boxes obtained with the RCNN-detector [99] trained on the source. The detector is re-trained with the target aligned source features and used to classify the target data projected on the target subspace.

### 6 Beyond domain adaptation: unifying perspectives

In this section first we briefly discuss how domain adaptation is related to other transfer learning (TL) techniques. Then, more generally, we relate DA to several classical machine learning (ML) approaches illustrating how they are exploited in various DA solutions. Finally, we briefly discuss methods concerning heterogeneous data.

**6.1 DA within transfer learning**

We have seen in Section 2 that DA is a particular case of the Transductive TL (see also Figure 2). As such, DA is in contrast to unsupervised TL, where both the domains and the tasks are different with no labels available. Indeed, the aim of DA is to solve in general a classification task common to the source and target by simultaneously exploiting labeled source and unlabeled target examples.

DA is rather different also from self-taught learning [172], which exploits a limited labeled target data for a classification task together with a large amount of unlabeled source data mildly related to the task. The main idea behind self-taught learning is to explore the large set of unlabeled source data to discover repetitive patterns that could be used for the supervised learning task of interest.

On the other hand, the relation between DA and domain generalization [151, 254, 97, 94, 155], multi-task learning [26, 76, 178] or few-shot learning [149, 80] is much stronger.

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39 Code available at [https://github.com/jhoffman/lsda/zipball/master](https://github.com/jhoffman/lsda/zipball/master)
Domain generalization. Domain generalization \([151, 254, 97, 94, 155]\), similarly to multi-source DA \([31, 70, 120]\), aims to extract and average knowledge from several related source domains, in order to learn a model for data in a new target domains. However, in contrast to DA where unlabeled target instances are used to adapt the model, in the case of domain generalization, the target domain is in general unseen at the training stage.

Multi-task learning. In multi-task learning \([26, 76, 178]\) different tasks (sets of the labels) are learned at the same time using a shared representation such that what is learned for each task can help the other tasks be learned better. Considering in DA the tasks in both domains (source and target) as domain specific tasks, a semi-supervised domain adaptation method can be seen as a sort of two-task learning problem where learning the source specific task helps learning the target specific task. Furthermore, in the case of multi-source domain adaptation \([143, 67, 227, 265, 220, 116, 200, 102, 107, 52]\) different source specific tasks are jointly exploited in the interest of the target task.

On another hand, as we have seen in Section 5.1 multi-task learning techniques were exploited for online DA, and in particular for multi-object tracking and detection \([92, 90]\), where a generic object detector (trained on source data) is adapted for each individual object instances.

Few-shot learning. Few-shot learning \([149, 80, 227, 226]\) aims to learn information about object categories from only a few training images making use of prior knowledge of related categories for which large amount of annotated data is available. In general, it is solved by knowledge transfer through the reuse of model parameters \([85]\), by sharing parts or features \([12]\), or by contextual information \([152]\). An extreme case of few-shot learning is the zero-shot learning \([84, 130]\), where the new task is deduced from previous tasks without the need of any training data available for this task. Usually, to address zero shot learning, the methods rely on a set of machine-detectable attributes. These attributes can be a set of nameable image characteristics and semantic concepts \([84, 130, 158, 88]\), or latent topics discovered by the system from the data \([199, 131, 89]\). In both cases, detecting these attributes can be seen as the common tasks between the training classes (that can be seen as source domains) and the new classes (target domains).

Unified DA and TL models. We have seen that the particularity of DA is the shared label space, in contrast to other TL approaches where the focus is often on the task transfer (transfer between classes). However, as Patricia and Caputo claim in \([164]\), task transfer and domain shift can be seen as different declinations of learning to learn paradigm, i.e. the ability to leverage prior knowledge when attempting to solve a new task. Based on this observation, \([164]\) propose a framework to leverage source data regardless of the origin of the distribution mismatch. Considering prior models as experts, the original features are augmented with the output confidence values of the source models and target classifiers are learned with these features. Similarly, the Transductive Prediction Adaptation (TPA) in \([45]\) augments the target features with class predictions from source experts, but it applies the MDA framework \([35]\) to these augmented features, showing that the denoised predictions yield improved classification accuracy. In contrast to the method in \([164]\), TPA works also in the case when no label is available for the target (US scenario).

Saenko et al. propose in \([185]\) to learn a regularized non-linear transformation, called Cross-Domain Transformations, that uses supervised data from both domains to map source examples closer to the target ones. They show that the models built in this new space, generalize well not only to new samples from categories used to train the transformation (DA) but also to new categories that were not present at training time (task transfer).

The Unifying Multi-Domain Multi-Task Learning (MDMT) \([263]\) proposed by Yang et al. is a Neural Network framework that can be flexibly applied to multi-task, multi-domain and zero-shot learning or even to
zero-shot domain adaptation.

6.2 DA related to traditional ML methods

**Semi-supervised learning.** DA can be seen as a particular case of the semi-supervised learning [30, 278], where, similarly to most DA approaches, unlabeled data is exploited to remedy the lack of labeled data. Hence, ignoring the domain difference, traditional semi-supervised learning can be used as a solution for DA, where the source instances form the supervised part, and the target domain provides the unlabeled data exploited to improve the model. For this reason, DA methods often exploit or extend semi-supervised learning techniques such as transductive SVM [23], self-training [180, 248, 228, 52], or co-training [119, 133]. When the domain shift is small, traditional semi-supervised methods can already bring significant improvement over the results of the pre-trained source model [23].

**Active learning.** Instance selection based DA methods exploit ideas from active learning [191] to select a set of instances to be used to help the training process. Thus, Liao et al. [135] proposed the Migratory-Logit algorithm that explores data from both target and source domain to actively select unlabeled target samples to be added to the training set. Combining TrAdaBoost [54] and standard SVM, Shi et al. [202] developed an active learning method to select and label target samples. Novotny et al. [155] use active learning and domain adaptation techniques to generalize semantic object parts (e.g., eyes or legs) learned from a limited number of classes (animals) and example images to unseen classes (unseen animals). Similarly, the methods described in [29, 171, 186, 228, 52, 243] combine transfer learning or domain adaptation with target sample selection and labeling to iteratively update the target models.

**Online learning.** Online or sequential learning [193, 18, 194] is related to active learning in the sense that in both cases the model is iteratively and continuously updated using new data. However, while in active learning the data to be used for the update is actively selected, in online learning generally the new data is acquired sequentially. Domain adaptation combined with online learning yields online domain adaptation. As examples, we have seen the online adaptation for incoming video frames of a generic object detector trained offline on labeled image sets [21, 251]. Yan et al. in [257] proposed an online adaptation of image classifier to user generated content in social computing applications.

Furthermore, as we have discussed in Section 4, fine-tuning a deep model [268, 42, 157, 9, 43, 216] trained in general on a part of ImageNet [184] (source) for a new dataset (target) can be seen as sort of semi-supervised domain adaptation. Both, fine-tuning as well as training deepDA models [95, 137, 98], are learned sequentially using batch of examples and stochastic gradient updates. If we assume that these batches contain target data acquired sequentially, this learning process can be used for online DA adaptation of the original model.

**Metric learning.** We have seen in Section 3 that metric learning [60, 244] was often used by DA to learn how to bridge the relatedness between the source and target while exploiting class labels. Such supervised feature transformation methods were proposed for example in [270, 185, 272, 129, 169, 52]. Indeed, [270] proposes a new distance metric for the target domain by using the existing distance metrics learned on the source domain. [185] uses information-theoretic metric learning as a distance metric across different domains, which was extended to non-linear kernels in [129]. [169] uses metric learning to effectively mine the information shared
Fig. 27 Illustrating through an example the difference between TL to ML in the case of homogeneous data and between multi-view and HTL/HDA when working with heterogeneous data. Image courtesy Q. Yang [262].

between the training data from two image categories, and these metrics are used to build a cross-category ensemble to learn the target classifier. [52] proposes a metric learning adapted to the Domain Specific Class Means (DSCM) classifier, while [272] define a multi-task metric learning framework to learn relationships between source and target tasks.

**Classifier ensembles.** Classifier ensembles have also been considered for DA and TL. As such, Kamishima et al. [124] applied a bagging approach for transferring the learning capabilities of a model to different domains where a high number of trees was learned on data from both source and target to build a pruned version of the final ensemble to avoid negative transfer. Rodner et al. [177] used random decision forests for transferring feature relevance. The optimization framework in [1] takes as input several classifiers learned on the source domain as well as the results of a cluster ensemble operating solely on the target domain, yielding a consensus labeling of the data in the target domain. Boosting was extended to DA and TL in [54] [4] [271] [265] [41].

### 6.3 HDA related to multi-view/multi-modal learning

In many scientific data analytics problems such as video surveillance, social computing, medical health records or environmental sciences, data are collected from diverse domains or obtained from various feature extractors and exhibit heterogeneous properties. For example, a person can be identified by face, fingerprint, signature or iris with information obtained from multiple sources or in video surveillance an action or event can be
recognized using multiple cameras. Obviously, when working with such heterogeneous or multi-view data most methods try to exploit simultaneously different modalities to build better final models.

As such, multi-view learning methods are related to HDA/HTL as discussed also in Section 3.3, however the main difference being that while multi-view learning assumes that during training multi-view examples are available, in the case of HDA [203, 237, 120, 200, 264], this assumption rarely holds (see illustration in 27). On contrary, the aim is in general to transfer information between source domain represented with one type of information (e.g., text) to target domain represented with another type of information (e.g., images). While, this assumption essentially differentiates cross-view learning from HDA/HTL, nevertheless, we have also seen in Section 3.3 that several HDA methods [279, 168, 223, 222, 260, 257] rely on an auxiliary intermediate multi-view domain (e.g., by crawling Web pages containing both images and text). Therefore, HDA and HTL can strongly benefit from multi-view learning techniques such as canonical correlation analyses [110], co-training [34], spectral embedding [203], multiple kernel learning [71].

Multi-view intermediate domains are also often exploited to define for example cross-modal similarities [3, 121], semantic [246, 174, 87, 256] or multi-view embedding [110, 153, 196, 104, 25, 238] especially used to perform cross-modal image retrieval.

In the same spirit, webly supervised approaches [82, 242, 189, 14, 62, 37, 93] are also related to DA and HDA as is these approaches rely on collected Web data (source) data used to refine the target model. Duan et al. [72] used multiple kernel learning to adapt visual events learned from the Web data for video clips. [219] and [93] propose domain transfer approaches from weakly-labeled Web images for action localization and event recognition tasks.

7 Conclusion

This paper attempted to provide an overview of different visual domain adaptation solutions, including shallow methods and more recent deep models. We grouped the methods both by their similarity concerning the problem (homogeneous versus heterogeneous data, unsupervised versus semi-supervised scenario) and the solution proposed (feature transformation, instance reweighing, deep models, online learning). We also reviewed methods that solve domain adaptation in the case of heterogeneous data as well as approaches that addresses computer vision problems beyond image classification, such as object detection or multi-object tracking. Finally, we ended the paper situating domain adaptation within a larger context relating it to other transfer learning techniques as well as to traditional machine learning approaches.

Because the lack of the space and the large amount of methods mentioned, we could only briefly describe each method with only one or two sentences, but the interested reader can follow the reference for deeper reading. We also decided did not provide any comparative experimental results between these methods for the following reasons. Even if many DA methods were tested on OFF31 [185] and OC10 [103] datasets, papers use often different experimental protocols (sampling the source versus using the whole data, unsupervised versus supervised) and also different parameter tuning (fix parameter sets, tuning on the source, cross validation or unknown). Also, results reported in different papers given some of the methods (e.g., GFK [103], TCA [159], SA [83]) vary a lot between different re-implementations. For all these reasons, making a fair comparison between all the methods is rather difficult. Furthermore, these datasets are rather small, results with SURFBOV rather old and therefore relying only on these published results is not sufficient to derive general conclusions concerning which methods provides best solutions. For a fair comparison, deep methods should be compared to shallow methods using deep features, however as DECAF features extracted from the latest deep models
performs extremely well on OFF31 and OC10 even without adaptation, there is a real need to compare the performance of different methods on larger and more difficult datasets, such as the Testbed Cross-Dataset [40][229], or even more challenging ones such as adaptation between photos and paintings or sketches [127][47][28][188].

Finally, most DA solutions in the literature are tested on these relatively small datasets (both in terms of number of classes and number of images). However, with the recent proliferation of sensors, larger and more diverse information is being collected, increasing the need for solutions able to address large datasets as well as heterogeneous data. We have also seen that only relatively few papers addresses adaptation beyond recognition and detection. Image and video understanding semantic and instance level segmentation, human pose, event and action recognition, motion and 3D scene understanding, where trying to simply describe the problem with a feature vector and classical domain adaptation, even when it is possible, has serious limitations. In the last few years, when data is available these challenging problems are addressed more and more often with deep methods requiring large amount of data. How to adapt these new models between domains with no or very limited amount of data is probably one of the main challenge that should be addressed by the visual domain adaptation and transfer learning community in the next few years.

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