Abstract—Domain adaptation (DA) aims at improving the performance of a model on target domains by transferring the knowledge contained in different but related source domains. With recent advances in deep learning models which are extremely data hungry, the interest for visual DA has significantly increased in the last decade and the number of related work in the field exploded. The aim of this paper, therefore, is to give a comprehensive overview of deep domain adaptation methods for computer vision applications. First, we detail and compared different possible ways of exploiting deep architectures for domain adaptation. Then, we propose an overview of recent trends in deep visual DA. Finally, we mention a few improvement strategies, orthogonal to these methods, that can be applied to these models. While we mainly focus on image classification, we give pointers to papers that extend these ideas for other applications such as semantic segmentation, object detection, person re-identifications, and others.

Index Terms—visual domain adaptation, deep learning

I. INTRODUCTION

While recent advances in deep learning yielded a significant boost in performance in most computer vision tasks, this success depends a lot on the availability of a large amount of well-annotated training data. As the cost of acquiring data labels remains high, amongst alternative solutions, domain adaptation approaches have been proposed, where the main idea is to exploit the unlabeled data within the same domain together with annotated data from a different yet related domain. Yet, because learning from the new domain might suffer from distribution mismatch between the two domains, it is necessary to adapt the model learned on the labelled source to the actual target domain as pictured in Fig. 1.

With the recent progress on deep learning, a significant performance boost over previous state-of-the-art of visual categorization systems was observed. In parallel, it was shown that features extracted from the activation layers of these deep networks can be re-purposed for novel tasks or domains [1], even when the new task/domain differs from the task/domain originally used to train the model. This is because deep neural networks learn more abstract and more robust representations, they encode category level information and remove, to a certain measure, the domain bias [2], [3]. Hence, these representations are more transferable to new tasks/domains because they disentangle the factors of variations in underlying data samples while grouping them hierarchically according to their relatedness with invariant factors.

These image representations, in general obtained by training the model in a fully supervised manner on large-scale annotated datasets, in particular ImageNet [4], can therefore be directly used to build stronger baselines for domain adaptation methods. Indeed, by simply training a linear classifier with such representations obtained from activation layers [1], and with no further adaptation to the target set, yields in general significantly better results than most shallow DA models trained with previously used handcrafted, generally bag of visual words (BOV) [5], representations. In Fig. 2 we illustrate this using the AlexNet architecture [6], however representations obtained with deeper models [7]–[9] provide even better performance and generalization capacity [10].

While using directly these models trained on the source provides already relatively good results on the target datasets, especially when the domain shift is moderate, for more challenging problems, e.g. adaptation between images and paintings, drawings, clip art or sketches [10]–[12], a classifier trained even with such deep features would have difficulties to handle the domain differences. Therefore, the need for alternative solutions that directly handle the domain shift remains the preferred solution.

Therefore, in which follows we first discuss and compare different strategies about how to exploit deep architectures for domain adaptation. Then, we provide an overview of recent trends in deep visual domain adaptation. Finally, we evoke a few strategies, orthogonal to the deep DA architecture design, that can be applied to improve those models.

II. DEEP LEARNING STRATEGIES

There are several ways to exploit deep models to handle the domain mismatch between the source and the target set, that can be grouped in four main categories: 1) shallow methods
using deep features, 2) using fine-tuned deep architectures, 3) shallow methods using fine-tuned deep features and 4) deep domain adaptation models.

**Shallow DA methods using deep features.** We mentioned above that considering a pre-trained deep model as feature extractor to represent the images and train a classifier on the source provides already a strong baseline. However, we can go a step further by incorporating these representations into traditional DA methods such as [15], [20]. As shown in [1], [10], [21], [22], to cite a few examples, using such DA methods with deep features yields further performance improvement on the target data. Nevertheless, it was observed that the contribution of using deep features is much more significant than the contribution of using various DA methods. Indeed, as Fig. 2 illustrates the gain obtained with any DA on the BOV baseline is low compared to the gain between BOV versus deep features both for the baseline or any DA method.

**Training deep architectures on the source.** The second solution is to train or fine-tune a deep network on the source domain and use directly the model to predict the class labels for the target instances. While, in this case there is no adaptation to the target, as illustrated also in Fig. 3 we observe not only better performance (or equally if ImageNet is the source) compared with the baseline (classifier trained with the features from backbone pretrained on ImageNet), but also with the previous strategy (shallow DA applied with the corresponding image representations). The explanation is that the deep model disregards in certain measure the appearance variation by focusing on high level semantics, and therefore is able to overcome in certain measure the domain gap. However, if the domain difference between the source and target is important, fine-tuning the model on the source can also overfit the model for the source [22], [23] and therefore it is important to correctly select the layers to be fine-tuned [10], [24].

**Shallow methods using fine-tuned deep features.** Note that the above mentioned two strategies are orthogonal and they can be combined to take advantage of both. This is done by first fine-tuning the model on the source set and then the features extracted with this model are used by the shallow DA method to decrease the discrepancy between source and target distributions. In addition to further boosting the performance (see Fig. 3), further advantages of this strategy are the fact that it does not require tailoring the network architecture for DA, and the fine-tuning on the source can be done in advance, even before seeing the target set.

In Fig. 3 we compare these strategies with a corresponding shallow (single layer perceptron on top of the pre-extracted features) and a deep end-to-end architecture where we use the same discrepancy (kernelized MMD [23], [24] and cross-entropy loss. We can see that using a shallow method with deep features extracted from the fine-tuned model indeed combines the advantages of the fine-tuning with domain adaptation and yields results close to the deep Siamese discriminative network designed for the domain adaptation. Similar behaviour was observed in when comparing DeepCORAL [27] with CORAL [22] using features extracted from the pre-trained and fine-tuned network. Note nevertheless that in both cases a relatively simple deep DA method was considered, and as will be discussed in the next sections, these deep models can be further improved in various ways.

**III. Deep DA Models**

Historical shallow DA methods include data re-weighting, metric learning, subspace representations or distribution matching (see for more details the surveys [28], [29]). As discussed above, these methods assume that the image representations are fixed (they are handcrafted or pre-extracted from a deep model) and the adaptation model uses these features as input (see left image in Fig. 4). Amongst the most popular shallow DA approaches, a set of methods focuses on aligning the marginal distributions of the source and the target sets. These methods learn either a linear projection or more complex feature transformations with the aim that in the new space the discrepancy between the domains is significantly
decreased. Then the classifier trained on the labeled source set in the projected space, thanks to the domain alignment, can directly be applied to the target set.

It is therefore not surprising that amongst the first deep DA models we find the generalization of this pipeline, as illustrated in Fig. 4 (right) where the deep representation is jointly learned with the source classifier and domain alignment in an end-to-end manner. These first solutions were followed by a large amount of different deep DA methods and architectures that can be grouped together according to different criterion (see also [30]). In which follows, we recall some of the main trends.

**Discriminative models.** These models, inspired by classical DA methods, have a Siamese architecture [31] with two streams, one for the source set and one for the target set. The two streams can share entirely, partially or not at all the weights, and in general both branches are initialized by the corresponding backbone (e.g. VGG [7], ResNet [8] or GoogleNet [9]), trained on the source set most often using the cross-entropy classification loss. The Siamese network is then trained with the same cross-entropy loss applied only the source stream together with a domain alignment loss defined with both source and target features. This loss uses either the last activation layer before the soft-max prediction [32] or it can be applied to several activation layers [26].

The domain alignment can be achieved by minimizing the feature distribution discrepancy, or by using an adversarial loss to increase domain confusion. To minimize the distribution discrepancy, most often the Kernelized MMD loss is used [26], [32], but amongst the alternative losses proposed, we can mention the Central Moment Discrepancy [33], CORAL loss [27], or Wasserstein distance [34], [35]. Note that the Wasserstein distance is used also to minimize the global transportation cost in optimal transport based DA methods [20], [36], [37], however, these are asymmetric models transporting the source data towards the target samples instead of projecting both sets into a common latent space.

On the other hand, domain confusion can be achieved either with adversarial losses such as GAN loss [38]–[40] and domain confusion loss [41], [42], or by using a domain classifier and gradient reversal layer (GRL) [43], [44]. Note however that the latter can also be formulated as a min-max loss and is achieved by the integration of a simple binary domain classifier and a GRL layer into a standard deep architecture which is unchanged during the forward pass, and reversed for the target during backpropagation. This simple but quite powerful solution became extremely popular when DA is applied for problems beyond image classification, in particular for object detection [45]–[49] (see also Fig. 5), semantic image segmentation [50], [51] or video action recognition [52], [53].

**Class-conditional distribution alignment.** To overcome the drawback that aligning marginal distributions without taking into account explicitly the task might lead to sub-optimal solution, several approaches were proposed. Amongst them we have the ones that tries to align class conditional distributions by minimizing the marginals of features and class predictions jointly [54], or exploit discriminative information conveyed in the classifier predictions to assist adversarial adaptation [55]. Instead, [56] proposes to focus on the Margin Disparity Discrepancy loss defined on the scoring function and use adversarial learning to solve it. [57], [58] proposes to minimize task-specific decision boundaries’ disagreement on target examples while aligning features across domains. [59] explicitly models the intra-class and the inter-class domain discrepancy, where intra-class domain discrepancy is minimized to avoid misalignment and the inter-class domain discrepancy is maximized to enhance the model’s generalization ability. Assuming the access to at least a small set of labeled target samples, [60] proposed to align higher-order scatter statistics between domain-specific and class-specific representations.

**Network parameter adaptation.** The above methods in general keep the same architecture with the same weights for both source and target streams, which essentially aims to learn domain invariant features. In contrast to them, several approaches were proposed, where the goal is to specialize the streams for the respective domains by adapting the parameters of the target stream. As such, [61], [62] explicitly model the domain shift by learning meta parameters that transform the weights and biases of each layer of the network from...
the source stream to the target one. Instead, [63] consider a multi-stream architectures with non shared parameters where learnable gates at multiple levels allows the network to find for each domain a corresponding weighted aggregation of these parallel streams.

**Domain specific batch normalization.** [64]–[66] have shown that domain specific batch normalization is equivalent to projecting the source and target feature distributions to a reference distribution through feature standardization. Hence this yields a simple yet efficient solution for minimizing the gap between domains. [67] proposes batch nuclear-norm maximization to simultaneously enhance the discriminability and diversity of predicted scores. [68] applied domain-specific batch normalization layers in the context of graph-based predictive DA. [69] proposes the DDLSTM architecture for action recognition that performs cross-contaminated recurrent batch normalisation for both single-layer and multi-layer LSTM architectures.

**Encoder–decoder reconstruction.** Early deep auto-encoder frameworks proposed for DA in NLP [70] rely on the feedforward stacked denoising autoencoders [71] where a multi-layer neural network reconstructs the input data from partial random corruptions with backpropagation. [72] has shown that such model can be trained efficiently by marginalizing out the noise that leads to a closed form solution for the transformations between layers. [73] extended this unsupervised network to a supervised one by jointly learning the domain invariance with the cross-domain classifier while keeping the network solvable in a single forward pass.

In contrast to these models that act on the pre-extracted features, more recent reconstruction models trains the encoders/decoders end-to-end. As such, [74] combines the standard CNN for source label prediction with a deconvolutional network [75] for target data reconstruction by alternating between unsupervised and supervised training. [76] integrates both domain-specific encoders and shared encoders, and the model integrates a reconstruction loss for a shared decoder that rely on both domain specific and shared representations.

**Transfer domain style.** In many cases the domain shift between domains is strongly related to the image appearance change such as day to night, seasonal change, synthetic to real. Even stronger domain shift can be observed when the adaptation is aimed to be between images that exhibit different artistic style such as paintings, cartoons and sketches [10]–[12]. To explicitly account for such stylistic domain shifts, a set of papers proposed to use image-to-image (I2I) style transfer methods [77]–[79] to generate a set of target like source images. They have shown that this new set is suitable to train a model for the target set [10], [80]. The main reason why this works is that these synthesized images inherits the semantic content of the source, and hence its label, while their appearances is more similar to the target style (see examples in Figure 6(Left)). Training a model with this set not only outperforms the model trained with the original source set, but it is also easier to further adapt it to the target set [10].

Another set of methods seek to learn how to translate between domains without using paired input-output examples but instead assuming there is some underlying appearance shift between the domains (e.g. day to night, sunny to rainy, synthetic to real). For example, [81]–[83] train the network to synthesize target-like and/or source-like images (see Figure 6(Right)) in general by relying on a Generative Adversarial Networks (GANs) [38], where an adversarial loss force the model to generating fake (target-like) images to be indistinguishable from real (target) photos. A pair of GANs, each corresponding to one of the domains is considered in [84], where the model adapts the input noise vector to paired images that are from the two distributions and share the labels. This work was extended in [85] with Variational Auto-Encoders (VAE), where the image reconstruction, image translation, and the cycle-reconstruction are jointly optimized. [86] proposes to learn a mapping between source and target domains using an adversarial GAN loss while imposing a cycle consistent loss, i.e. the target-like source image mapped back to source style should match the original source image. [87] combined cycle consistency between input and stylized images with task-specific semantic consistency, and extended the method to semantic segmentation (see Figure 7). Transferring the target
image style to generate synthetic source images is at the core of many DA method for semantic segmentation [88]–[92]. GAN-like DA models combined with similarity preserving constraints were often used for adapting cross-domain person re-identification models [93]–[95].

IV. ORTHOGONAL IMPROVEMENT STRATEGIES

In addition to the specifically tailored deep DA architectures, several machine learning strategies can be used with the above models to further improve their performance. While, in some cases such methods were used the main DA solution, we discuss them here separately, as in general these ideas can be easily combined with most of the above mentioned DA models.

Pseudo-labeling the target data. One of the most used such technique is self-supervised learning with pseudo-labeled target data, sometimes referred to as self-labeling or self-training. The underlying assumption here is that at least for a subset of target samples the labeling is correct and hence the model can rely on them to improve the model. In this way the model acts as if it was a semi-supervised DA model, except that instead of having ground-truth target labels, these labels come from a pseudo-labeling process. As not all predictions are correct, often pseudo-labeling confidence scores are computed and used to select which pseudo-labeled samples should be retained for training. Typical approaches to obtain pseudo labels are, using the softmax predictions [96], [97], using distance to class prototypes [98], [99], clustering [59], [100], label propagation on the joint source-target nearest neighbour graph [101], [102], via augmented anchors [103], or even considering a teacher classifier, built as an implicit ensemble of source classifiers [104].

Self-supervising deep DA models with pseudo-labeled target samples is also a popular strategy used to adapt tasks beyond image classification. For example, [100] proposed several strategies to pseudo-label fashion products across datasets and use them to solve the meta-domain gap occurring between consumer and shop fashion images. [105] proposed a DA framework with online relation regularization for person re-identification that uses target pseudo labels to improve the target-domain encoder trained via a joint cross-domain labeling system. [106] used predicted labels with high confidence in a bidirectional learning framework for semantic segmentation, where the image translation model and the segmentation adaptation model are learned alternatively. [107] combines the self-supervised learning strategy with a framework where the model is disentangled into a “things” and a “stuffs” segmentation networks.

Curriculum learning. To minimise the impact of noisy pseudo-labels during alignment, curriculum learning-based [108] approaches have been explored. A simple and most used curriculum learning scenario in DA is to first consider the most confident target samples for the alignment and including the less confident ones at later stages of the training. Pseudo-labeling confidence scores are typically determined using the image classifiers [109], [110], similarity to neighbours [101], [102] or to class prototypes [98], [111]. After each epoch, [110] increases the training set with new target samples that are both highly confident and domain uninformative. To improve the confidence of pseudo-labels, [109] relies on the consensus of image transformations, whereas [96] considers the agreement between multiple classifiers. [112] proposes a weakly-supervised DA framework that alternates between quantifying the transferability of source examples based on their contributions to the target task and progressively integrating from easy to hard examples. [59] considers target clusters initialized by the source cluster centers, and assign target samples to them. At each epoch, first target elements that are
from different domains. and a conditional feature matching loss to align the clusters force the features from the same class to concentrate together pseudo-labels used by a class-conditional clustering loss to training process. [104] builds a teacher classifier, to provide source and target sets and sampling independent batches [124] to domain adaptation considering a separate path for extending the idea of learning with a mean teacher network increasing the variance of the sample based distribution. [123] proposes an adversarial loss for entropy minimization of unlabeled target data with respect to the classifier and an adversarial learning maximizes the conditional entropy minimizes it with respect to the feature encoder. Similarly, [122] proposes an adversarial loss for entropy minimization used to bridge the domain gap between synthetic to real [121] proposes a Minmax Entropy loss for the target samples. In this spirit, [119], proposed a Monte Carlo dropout based ensemble discriminator by gradually increasing the variance of the sample based distribution. [122] extended the idea of learning with a mean teacher network to domain adaptation considering a separate path for source and target sets and sampling independent batches making the batch normalization domain specific during the training process. [109] builds a teacher classifier, to provide pseudo-labels used by a class-conditional clustering loss to force the features from the same class to concentrate together and a conditional feature matching loss to align the clusters from different domains.

Curriculum-learning based DA methods with progressively including harder and harder pseudo-labeled target data was also used for cross-domain person re-identification [113] and image segmentation [116]–[118].

Conditional entropy minimization. Widely used to improve the performance of semi-supervised learning, conditional entropy minimization in the target domain is another way to improve decision boundaries of the model [55], [64], [96], [120]. The Minmax Entropy loss [121] is a variant where an adversarial learning maximizes the conditional entropy of unlabeled target data with respect to the classifier and minimizes it with respect to the feature encoder. Similarly, [122] proposes an adversarial loss for entropy minimization used to bridge the domain gap between synthetic to real semantic segmentation adaptation. [109] proposes the Min-Entropy Consensus that merges both the entropy and the consistency loss into a single unified function.

Self-ensemble learning. The main idea of self-ensemble learning is to train the neural network with small perturbations such as different augmentations, using dropout and various noise while forcing the network to make consistent predictions for the target samples. In this spirit, [119], proposed a Monte Carlo dropout based ensemble discriminator by gradually increasing the variance of the sample based distribution. [122] extended the idea of learning with a mean teacher network to domain adaptation considering a separate path for source and target sets and sampling independent batches making the batch normalization domain specific during the training process. [109] builds a teacher classifier, to provide pseudo-labels used by a class-conditional clustering loss to force the features from the same class to concentrate together and a conditional feature matching loss to align the clusters from different domains.

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