Self-Supervised Learning Across Domains

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Abstract—Human adaptability relies crucially on learning and merging knowledge from both supervised and unsupervised tasks: the parents point out a few important concepts, but then the children fill in the gaps on their own. This is particularly effective, because supervised learning can never be exhaustive and thus learning autonomously allows to discover invariances and regularities that help to generalize. In this paper we propose to apply a similar approach to the problem of object recognition across domains: our model learns the semantic labels in a supervised fashion, and broadens its understanding of the data by learning from self-supervised signals on the same images. This secondary task helps the network to learn the concepts like spatial orientation and part correlation, while acting as a regularizer for the classification task. Extensive experiments confirm our intuition and show that our multi-task method combining supervised and self-supervised knowledge shows competitive results with respect to more complex domain generalization and adaptation solutions. It also proves its potential in the novel and challenging predictive and partial domain adaptation scenarios.

Index Terms—Self-Supervision, Domain Generalization, Domain Adaptation, Multi-Task Learning.

1 INTRODUCTION

Many definitions of intelligence have been formulated by psychologists and learning researches along the years. Despite the differences, they all indicate the ability to adapt and achieve goals under a wide range of conditions as a key component [1]. Artificial intelligence inherits these definitions, with the most recent research demonstrating the importance of knowledge transfer and domain generalization [13]. Indeed, in many practical applications the underlying distributions of training (i.e. source) and test (i.e. target) data are inevitably different, asking for robust and adaptable solutions. When dealing with visual domains, most of the current strategies are based on supervised learning. These processes search for semantic spaces able to capture basic data knowledge regardless of the specific appearance of input images: some decouple image style from the shared object content [7], others generate new samples [72] or impose adversarial conditions to reduce feature discrepancy [43], [45]. With the analogous aim of getting general purpose feature embeddings, an alternative research direction is pursued by self-supervised learning that captures visual invariances and regularities solving tasks that do not need data annotation like image orientation recognition [30] or image coloring [82]. Unlabeled data are largely available and by their very nature are less prone to bias (no labeling bias issue [69]), thus they seem the perfect candidate to provide visual information independent from specific domain styles. However their potential has not been yet fully exploited: the existing self-supervised approaches often come with tailored architectures that need dedicated fine-tuning strategies to re-engineer the acquired knowledge [57]. Moreover, they are mainly applied on real-world photos without considering cross-domains scenarios with images of paintings or sketches.

This clear separation between learning intrinsic regularities from images (self-supervised knowledge) and robust classification across domains (supervised knowledge) is in contrast with the visual learning strategies of biological systems, and in particular of the human visual system. Indeed, numerous studies highlight that infants and toddlers learn both to categorize objects and about regularities at the same time [6]. For instance, popular toys for infants teach to recognize different categories by fitting them into shape sorters; jigsaw puzzles of animals or vehicles to encourage learning of object parts’ spatial relations are equally widespread among 12-18 months old. This joint learning is certainly a key ingredient in the ability of humans to reach sophisticated visual generalization abilities at an early age [26].

Inspired by this, our original paper [12] was the first to introduce a multi-task approach that learns simultaneously how to recognize objects by exploiting supervised data and how to generalize to new domains by leveraging intrinsic self-supervised information about spatial co-location of image parts (Figure 1) and [3]. Specifically we proposed to recover an original image from its shuffled parts, re-purposing the popular game of solving jigsaw puzzles. Differently from previous approaches that deal with fea-
Fig. 2. Illustration of the proposed multi-task approach when using jigsaw puzzle as self-supervised task. We start from images of multiple domains and use a $3 \times 3$ grid to decompose them in 9 patches which are then randomly shuffled and used to form images of the same dimension of the original ones. By using the maximal Hamming distance algorithm in [55] we define a set of $P$ patch permutations and assign an index to each of them. Both the original ordered and the shuffled images are fed to a convolutional network that is optimized to satisfy two objectives: object classification on the ordered images and jigsaw classification (meaning permutation index recognition) on the shuffled images. An analogous scheme holds using rotation recognition as self-supervision. The names assigned to each network part refer to the terminology adopted in Sec. 3.

2 RELATED WORK

2.1 Self-Supervised Learning

Self-Supervised Learning is a paradigm developed to learn visual features from large-scale unlabeled data [37]. Its first step is a pretext task that exploits inherent data attributes to automatically generate surrogate labels: part of the existing knowledge about the images is manually removed (e.g. the color, the orientation, the patch order) and the task consists in recovering it. It has been shown that the first layers of a network trained in this way capture useful semantic knowledge [3]. The second step of the learning process consists in transferring the self-supervised learned model of those initial layers to a supervised downstream task (e.g. classification, detection), while the ending part of the network is newly trained. As the number of annotated samples of the downstream task gets lower, the advantage provided by the transferred model generally gets more evident [3, 80].

The possible pretext tasks can be organized in three main groups. One group relies only on original visual cues and involves either the whole image with geometric transformations (e.g. translation, scaling, rotation [24, 50]), clustering [13], inpainting [59] and colorization [82], or considers image patches focusing on their equivariance (learning to count [56]) and relative position (solving jigsaw puzzles [55], [57]). A second group uses external sensory information either real or synthetic: this solution is often applied for multi-cue (visual-to-audio [58], RGB-to-depth [60]) and robotic data [55, 59]. Finally, the third group relies on video and on the regularities introduced by the temporal dimension [67, 74]. The most recent SSL research trends are mainly two. On one side there is the proposal of novel pretext tasks, compared on the basis of their ability to initialize a downstream task with respect to using supervised models as in standard transfer learning [29, 36]. On the other side there are new approaches to combine several pretext tasks together in multi-task settings [23, 60]. Our work investigates a new research direction: the combination of supervised and self-supervised knowledge in a multi-task framework, studying its effect on domain generalization and adaptation.

2.2 Domain Generalization and Adaptation

Several algorithms have been developed to cope with domain shift, mainly in two different settings: domain generalization (DG) and domain adaptation (DA). In DG the target is unknown at training time: the learning process can usually leverage multiple labeled sources to define a model robust to any new, previously unseen domain [53]. In DA the learning process has access to the labeled source data and to the unlabeled target data, so the aim is to generalize to the given specific target set [18]. In multi-source DA the domain label of the sources may be unknown [13, 53, 49], while for most of the DG methods it remains a crucial information that has to be provided since the beginning.

There are three main families of solutions for both DG and DA. Feature-level strategies focus on learning domain invariant data representations mainly by minimizing different domain shift measures [5, 46, 47, 68]. The domain shift can also be reduced by training a domain classifier and inverting the optimization to guide the features towards maximal domain confusion [27, 70]. This adversarial approach has several variants, some of which also exploit class-specific domain recognition modules [45, 64]. Metric learning [52] and deep autoencoders [7, 28, 43] have also been used to search for domain-shared embedding spaces. In DG, these approaches leverage on the availability of multiple
sources and on the access to the domain label for each sample, meaning that the identity of the source distribution from which every sample is drawn is strictly needed. Model-level strategies either change how the data are loaded with ad-hoc episodes or modify conventional learning algorithms to search for more robust minima of the objective function. Besides these main approaches, other solutions consist in introducing domain alignment layers, aggregation layers, or using low-rank network parameter decomposition with the goal of identifying and neglecting domain-specific signatures. Finally, data-level techniques exploit variants of the Generative Adversarial Networks (GANs) to synthesize new images. Indeed, producing source-like target images or/and target-like source images help to reduce the domain gap.

Some recent works have started investigating intermediate settings between DA and DG. In predictive DA a labeled source and several auxiliary unlabeled domains are available at training time together with meta-data that describe their relation and can be used to compose an adapted model when target meta-data is provided at test time.

In both DA and DG, the main assumption is that source and target share the same label set, with few works studying exceptions to this basic condition. In particular, the Partial Domain Adaptation (PDA) setting allows the target to cover only a subset of the source class set. In this case it is important to adjust the adaptation process so that the samples with not-shared labels would not influence the learned model. The more commonly used techniques consist in adding a re-weight source sample strategy to a standard DA approach. Alternative solutions leverage on two separate deep classifiers and their prediction inconsistency on the target or on feature norm matching.

As indicated by this brief overview, previous literature did not investigate self-supervision for DA or DG. In this work we present a thorough study of self-supervised learning across domains.

3 Method

We introduce here the technical notation for our multi-task approach across domains and specify the objectives in each of the considered settings. Let us assume to observe data from one or more source distributions. We consider all the samples together as belonging to the domain \( S \) with \( \mathcal{D}_S = \{ (x^n_i, y^n_i) \}_{n=1}^{N} \). Here \( x^n_i \) represent the \( i \)-th image while \( y^n_i \) the corresponding label. Starting from these images we can always apply different procedures to generate self-supervised variants. One simple choice is that of applying rotation to produce 4 copies of each sample with \( 0^\circ, 90^\circ, 180^\circ, 270^\circ \) orientation. The related self-supervised task consists in choosing the correct image rotation. A more structured alternative is that of decomposing the original images according to a \( 3 \times 3 \) grid: this produces 9 squared patches from every sample, which are then moved from their original locations and repositioned to form a set of \( 9! \) shuffled images. This task reminds the jigsaw puzzle game, where the tiles have to be rearranged to get back the original image. For both the described cases, \( \{(z^n_k, p^n_k)\}_{k=1}^{K^s} \) refer to the newly obtained images. The label \( p = 1, \ldots, P \) for patch shuffling, while use \( p = 1, \ldots, P \) for patch shuffling, where we choose \( P \) as a subset of the \( 9! \) possible permutations selected by following the Hamming distance based algorithm in [55]. The total number of images changes depending on the self-supervised task: \( K^s = 4 \times n^s \) for rotation and \( K^p = P \times n^s \) for patch shuffling. Regardless of the specific chosen self-supervised objective we can combine it with supervised learning through a multi-task model realized with a multi-branch ending network [16]. One output branch will be dedicated to the supervised task exploiting the labels of the source data, while the other will solve the self-supervised problem: rotation or jigsaw puzzle permutation recognition (see Figure 3). By reciprocally leveraging the inductive bias of the related objectives, we expect that the two tasks regularize each other producing features with a higher generalization potential.

3.1 Domain Generalization

For our network we indicate the convolutional feature extraction backbone with \( G_f \), parametrized by \( \theta_f \). The parameters of the object classifier \( G_c \) and of the self-supervised task \( G_p \) are respectively \( \theta_c \) and \( \theta_p \). Overall we train the network to obtain the optimal model through

\[
\arg \min_{\theta_f, \theta_c, \theta_p} \frac{1}{n} \sum_{i=1}^{n} \mathcal{L}_c(G_c(G_f(x^n_i)), y^n_i) +
\alpha_s \frac{1}{K^s} \sum_{k=1}^{K^s} \mathcal{L}_p(G_p(G_f(z^n_k)), p^n_k)
\]

(1)

where \( \mathcal{L}_c \) and \( \mathcal{L}_p \) are cross entropy losses for both the object and self-supervised classifiers. We underline that the self-supervised loss is also calculated on the original images. Indeed, the \( 0^\circ \) orientation as well as the correct patch sorting correspond also to one of the possible self-supervised variants. Differently, the supervised classification loss is not influenced by the shuffled or rotated images, as this would make object recognition tougher. At test time we use the object classifier \( G_c \) to predict on the new target images.

3.2 Domain Adaptation

By its nature self-supervised learning does not need data annotation, which allows an immediate extension of its objective to the unlabeled target data \( \{ x^n_j \}_{j=1}^{n^t} \) when available in the DA setting. We indicate with \( \{(z^n_k, p^n_k)\}_{k=1}^{K^t} \) the transformed (rotated, puzzled) versions of the target data. Moreover, we use the prediction of the source model on the original target samples \( \hat{y} = G_c(G_f(x^n_j)) \) to estimate the related uncertainty through the entropy \( H = -\sum_{j=1}^{n^t} \hat{y}_j \log \hat{y}_j \) which is minimized enforcing the decision boundary to pass through low-density areas. The overall learning objective is formalized as

\[
\arg \min_{\theta_f, \theta_c, \theta_p} \frac{1}{n^t} \sum_{k=1}^{n^t} \mathcal{L}_c(G_c(G_f(x^n_j)), y^n_j) +
\alpha_s \frac{1}{K^s} \sum_{k=1}^{K^s} \mathcal{L}_p(G_p(G_f(z^n_k)), p^n_k) +
\eta \frac{1}{n^t} \sum_{j=1}^{n^t} H(G_c(G_f(x^n_j))) +
\alpha_t \frac{1}{K^t} \sum_{k=1}^{K^t} \mathcal{L}_p(G_p(G_f(z^n_k)), p^n_k).
\]

(2)

3.3 Partial Domain Adaptation

In PDA the label space of the target domain is contained in that of the source domain \( \mathcal{Y}_t \subseteq \mathcal{Y}_s \). Thus, besides dealing with the standard marginal shift \( S \neq T \), it is necessary to take care
of the difference in the label space which makes the problem even more challenging. If this information is neglected and the matching between the whole source and target data is forced, any adaptive method may incur in a degenerate case producing worse performance than its plain non-adaptive version due to negative transfer [61]. Still the objective remains that of learning both class discriminative and domain invariant feature models.

The two \( L_n \) terms in (3) help domain shift reduction, however their co-presence may be redundant: the features are already chosen to minimize the source classification loss and the self-supervised task on the target back-propagates inducing a cross-domain adjustment on the learned features. Thus, for PDA we can drop the source self-supervised term, which corresponds to setting \( \alpha_s = 0 \). This choice has a double positive effect: on one side it reduces the number of hyper-parameters in the learning process, leaving space for the introduction of other complementary learning conditions, on the other we let the self-supervised module focus only on the target without involving the extra classes of the source.

To further enforce the focus on the shared classes, our approach can be extended to integrate a weighting mechanism analogous to that presented in [10]. The source classification output on the target data are accumulated as follow: 
\[
\gamma = \frac{1}{n^s} \sum_{i=1}^{n^s} y^t_i
\]
and normalized \( \gamma \leftarrow \gamma / \max(\gamma) \), obtaining a \(|Y|\)-dimensional vector that quantifies the contribution of each source class. Moreover, we can easily integrate a source vs target domain discriminator \( G_d \) as in [27] and adversarially maximize the related binary cross-entropy to increase the domain confusion, taking also into consideration the defined class weighting procedure for the source samples. In more formal terms, the final objective of our multi-task problem in the PDA setting is
\[
\begin{align*}
\arg\min_{\theta_f, \theta_c, \theta_d} \max_{\eta} \quad & \frac{1}{n^s} \sum_{i=1}^{n^s} \gamma_y \left( L_c(G_c(G_f(x_i^s)), y_i^t) + \lambda \log(G_d(G_f(x_i^s))) \right) + \\
& \frac{1}{n^t} \sum_{j=1}^{n^t} \gamma_y \left( \eta \cdot H(G_c(G_f(x_j^t))) + \lambda \log(1 - G_d(G_f(x_j^t))) \right) + \\
& \alpha_t \frac{1}{K_t} \sum_{k=1}^{K_t} \left( L_s(G_p(G_f(y_k^t)), p_k^t) \right)
\end{align*}
\]
where \( \lambda \) is a hyper-parameter that adjusts the importance of the introduced domain discriminator. We adopted the same scheduling of [27] to update the value of \( \lambda \), so that the importance of the domain discriminator increases with the training epochs. When \( \lambda = 0 \) and \( \gamma_y = 1/|Y| \) we fall back to the standard DA case. A schematic illustration of the method is presented in Fig. 3.

### 3.4 Implementation details

We designed our multi-task network to leverage over different convolutional deep architectures: it is sufficient to remove the last fully connected layer of an existing backbone and substitute it with the new object and self-supervised classification layers. Thus, the initial standard part of the network has the role of feature extractor defined as \( G_f \), while the specific object and self-supervised classifiers \( G_c, G_p \) are implemented each by an ending fully connected layer. In the PDA setting we introduced the domain classifier \( G_d \) by adding three fully connected layers after the last pooling layer of the main backbone, and using a sigmoid function for the last activation as in [27]. For all our experiments we trained the network end-to-end by fine-tuning all the feature layers from Imagenet pre-trained models [19], while \( G_c, G_p \) and \( G_d \) are learned from scratch.

Overall the network for DG has two main hyper-parameters: \( \alpha \) that weights the self-supervised loss, and the data bias parameter \( \beta \) which regulates the data input process. The self-supervised variants of the images enter the network together with the original ones, hence each image batch contains both of them with \( \beta \) specifying their relative ratio. For instance \( \beta = 0.6 \) means that for each batch, 60% of the images are standard, while the remaining 40% are rotated or composed of shuffled patches. Other parameters appear in the DA setting: \( \alpha \) decouples in \( \alpha_s \) and \( \alpha_t \) respectively for source and target data, while \( \eta \) is the weight assigned to the entropy loss. Finally, \( \lambda \) balances the importance of the gradient reversal layer when included in PDA. For the jigsaw puzzle task we also need to include two extra parameters: the grid size \( n \times n \) used to define the image patches and the cardinality of the patch permutation subset \( P \). As we will detail in the following section, our multi-task approach is robust to these values and for all our experiments we kept them fixed, using \( 3 \times 3 \) patch grids and \( P = 30 \). We used a simple data augmentation protocol by randomly cropping the images to retain between \( 80 - 100\% \) and randomly applied horizontal flipping. Following [57] we randomly (10% probability) convert an image tile to grayscale.

For all our DG and DA experiments we show and discuss the effect of tuning the \( \alpha \) and \( \beta \) parameters. We also use the entropy loss for DA, setting \( \eta = 0.1 \). Our DG/DA model is trained with an SGD solver, 30 epochs, batch size 128, learning rate set to 0.001 and stepped down to 0.0001 after 80% of the training epochs. For PDA we set \( \alpha_s = 0 \), \( \alpha_t = 1 \), \( \eta = 0.2 \). Our model is trained with SGD with momentum set at 0.9, weight decay 0.0005 and 24 epochs. We used batch size of 64 and initial learning rate 0.0005. Different training details are used in the predictive-DA setting as described in Sec. 4.1. We implemented our deep methods in PyTorch and the code is available at https://github.com/silvia1993/Self-Supervised_Learning_Across Domains.

### 4 Experiments

In this section we present an extensive evaluation of using self-supervised knowledge across visual domains. First of all we focus on DG (Sec. 4.1). We test both the rotation and jigsaw puzzle self-supervised pretexts before using them extensively as auxiliary tasks together with supervised learning in our multi-task model. The second part of our analysis is dedicated to the DA scenario (Sec. 4.2) and its more challenging partial-DA setting.
we name it C-CFN. Regardless of the specific architecture used, we indicate with DeepAll the single-task model trained on all the original source images (i.e., \( \alpha = 0 \)), while we use Jigsaw (Puzzle) or Rotation to specify the multi-task case where each of those self-supervised tasks was trained jointly with the object classification. Results: From the results in the bottom part of Table 1 we can draw two conclusions. First, combining supervised and self-supervised learning provides better results than a single-task supervised model across domains. This is true regardless of the chosen architecture, as indicated by the comparison between the DeepAll and Jigsaw/Rotation variants. Second, a plain single branch architecture is better suited for the multi-task problem at hand. In this case, moving the jigsaw puzzle task from feature to image level allows to simplify the self-supervised task and to easily combine it with the supervised objective. The whole-image Rotation auxiliary task supports generalization even slightly better than Jigsaw.

4.1.3 Multi-Source Domain Generalization

Here we provide an extensive evaluation of our multi-task approach against state-of-the-art multi-source DG methods.

Baselines: We consider different families of DG approaches. The first is based on low-rank constraints applied on network parameters: TF [41], SLRC [20]. The second exploits domain-specific component aggregation: Epi-FCR [42], D-SAM [22]. The third builds on meta-learning strategies: MLDG [40], MetaReg [4]. MASF [25]. Finally, the fourth family leverages adversarial classifiers in different ways: DDAIG [85], PAR [73], MMLD [59].

Datasets: Besides PACS, we also consider other two data collections. The VLCS [69] aggregates images of 5 object categories shared by the PASCAL VOC 2007, LabelMe, Caltech and Sun datasets. We followed the standard protocol of [29] dividing each domain into a training set (70%) and a test set (30%) by random selection from the overall dataset. The Office-Home dataset [71] contains 65 categories of daily objects from 4 domains: Art, Clipart, Product and Real-World. For this dataset we used the same experimental protocol of [22]. Note that Office-Home and PACS are related in terms of domain types and it is useful to consider both as test-beds to check if our multi-task self-supervised approach scales when the number of categories changes from 7 to 65. Instead VLCS offers different challenges by combining object categories from Caltech with scene images of the other domains. Results: Table 2 shows the results of our multi-task approach on the dataset PACS. We tested Jigsaw, Rotation and their combination considering two auxiliary network tasks together with the main classification objective. On average our approach produces results equal or better than all the competitors with the only exception of DDAIG which got the top results on Resnet-18. We highlight that DDAIG for its transformation network needs domain annotation for each source sample. In many practical conditions this information might not be available [49], and our multi-task method does not rely on it. Moreover, DDAIG benefits from a tailored per-domain model parameter selection, different from our approach for which the parameters are fixed and shared by all the domain pairs of each dataset. Analogous observations hold for the results on VLCS (Table 3) and Office-Home (Table 4). In the last one, Rotation appears more suitable than Jigsaw.

#### Table 1

Test on different tasks and architectures: DG classification accuracy (% averaged over three repetitions of each run. The column title indicates the domain used as target. Top: results showing the effect of self-supervised pretraining on Imagenet, followed by fine-tuning on the source. (p) indicates the methods that use patch-based networks, while (w) the ones that use whole-images networks. Bottom: effect of the supervised pretraining on Imagenet followed by the multi-task combination of self-supervised objective and supervised fine-tuning.

| PACS             | art_paint. cartoon sketches photo | Avg.                     |
|------------------|----------------------------------|--------------------------|
| CFN              | self-supervised pretraining      |                          |
| J-CFN (p)        | 47.23                            | 62.18                    | 58.03 | 70.18 | 59.41 |
| J-CFN+ (p)       | 51.14                            | 58.83                    | 54.85 | 73.44 | 59.57 |
| J-AlexNet (w)    | 38.93                            | 53.75                    | 49.00 | 64.23 | 51.48 |
| R-AlexNet (w)    | 52.08                            | 59.24                    | 56.54 | 72.91 | 60.19 |

Top

| Supervised Pretraining and MultiTask | PACS | Avg. |
|--------------------------------------|------|------|
| C-CFN-DeepAll (p)                    | 59.69| 59.88| 45.66| 85.42| 62.66|
| C-CFN-Jigsaw (p)                     | 60.68| 60.55| 55.66| 82.68| 64.89|
| AlexNet-DeepAll (w)                  | 66.50| 69.65| 61.42| 89.68| 71.81|
| AlexNet-Jigsaw (w)                   | 67.79| 70.79| 64.01| 89.64| 73.05|
| AlexNet-Rotation (w)                 | 69.43| 69.40| 65.20| 89.17| 73.30|

4.1 Self-Supervision for Domain Generalization

4.1.1 Self-Supervised Pretraining

We test here the robustness of image orientation and patch co-location knowledge across domains by using both rotation and jigsaw puzzle as pretext tasks for domain generalization.

Baselines. As first step we considered three jigsaw puzzles and one rotation model trained on Imagenet (ILSVRC12, [19]) data without original labels. For the jigsaw puzzle, we used the two Context-Free-Network (CFN) models provided by the authors of [55], [57]. The CFN has 9 AlexNet-based siamese branches that extract features separately from each image patch and then recompose them before entering the final classification layer. We indicate these models respectively as J-CFN [55] and J-CFN+ [57]. The third puzzle-based model is obtained by training an AlexNet on whole images recomposed from disordered patches, which we call J-AlexNet. Inspired by [30], we also trained an AlexNet model for rotation recognition that we dub R-AlexNet.

Dataset. We used the PACS dataset [41] that covers 65 categories of daily objects from 4 domains: Art, Clipart, Product and Real-World. For this dataset we used the same experimental protocol of [22]. Note that Office-Home and PACS are related in terms of domain types and it is useful to consider both as test-beds to check if our multi-task self-supervised approach scales when the number of categories changes from 7 to 65. Instead VLCS offers different challenges by combining object categories from Caltech with scene images of the other domains.

Results: The obtained results are collected in the top part of Table 1 and show that using a patch-based (p) jigsaw method provides on average a more reliable pretext model than dealing with the whole (w) recomposed image. The rotation pretext model shows the best results with a small advantage over the patch based jigsaw approaches. In summary, we find that moving the jigsaw puzzle task from the feature to the image level when training a pretext model does not appear as a good choice and that the rotation task is the simplest and more effective solution.

4.1.2 Supervised Pretraining and Multi-task Learning

In designing our multi-task approach which combines supervised and self-supervised learning we have several options, both in terms of the architecture to use and of the best self-supervised task.

Baselines and Dataset. We compare the CFN multi-branch architecture with a plain AlexNet backbone. In both cases we rely on models originally trained on Imagenet for object classification. To differentiate the classification-aware CFN model with respect to the self-supervised pretraining discussed in the previous Section

We are aware of recent DG solutions based on data augmentation. In [83], MSCOCO (http://cocodataset.org) and WikiArt (https://www.kaggle.com/c/painter-by-number) are used for style transfer. None of the other considered references exploit those extra data collections so do not include this method.
as auxiliary task with a gain larger than three percentage points over the DeepAll baseline and with even higher advantage in the Jigsaw+Rotation case. DDAIG, although producing apparently the same backbone (conv-pool-conv-pool-fc-fc-softmax), we repro-

The generalization ability of a model depends both on the learning process and on the used training data. To better evaluate the regularization effect provided by the self-supervised tasks, we investigate the case of training data from a single source domain. **Baseline and Datasets:** For these experiments we compare against **Office-Home** Art Clipart Product Real-World

**Results:** In Figure 4 we show the performance of Jigsaw and Rotation when varying the data bias \( \beta \) and the self-supervised task weight \( \alpha \). With the red background shadow we indicate the overall range covered by Adv.DA results when changing its parameters, while the horizontal line is the reference Adv.DA results around which the authors of [72] ran their ablation analysis. The figure indicates that, although Adv.DA can reach high peak values, it is also very sensitive to the chosen hyperparameters. On the other hand, our multi-task approach is much more stable and usually performs better than Adv.DA. One exception arises on SVHN, with Jigsaw when the data bias is 0.5, and with Rotation when the self-supervised task weight is 0.9: both correspond to limit cases for the proper combination of object classification and self-supervised learning as will be discussed in the next Section. Moreover, Jigsaw and Rotation have similar performance to Adv.DA on MNIST-M and significantly outperform it on SVHN.

### 4.1.4 Single-Source Domain Generalization

The generalization ability of a model depends both on the learning process and on the used training data. To better evaluate the regularization effect provided by the self-supervised tasks, we investigate the case of training data from a single source domain. **Baseline and Datasets:** For these experiments we compare against **Office-Home** Art Clipart Product Real-World

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### 4.1.5 Ablation and hyper-parameter tuning

As mentioned in Sec. [3.4] the parameters \( \alpha \) and \( \beta \) of our multi-task approach regulates respectively the importance of the self-supervised auxiliary loss, and the amount of samples out of each input data batch that reaches the self-supervised branch. By considering extreme cases for those parameters we obtain an ablation study on the respective roles of the self-supervised and of the supervised task of the learning model. In the particular case of using Jigsaw, two further parameters are involved: the number of
patch permutations, meaning the number of Jigsaw classes $P$, and the dimension of the patch grid $n \times n$. We test the robustness of our method to their exact value by observing how the performance changes when tuning them.

**Baseline and Dataset:** For these experiments we focus on the Alexnet-PACS DG setting. We keep the jigsaw hyperparameters fixed with a $3 \times 3$ patch grid and $P = 30$ jigsaw classes when studying ablation. Setting $\{\alpha = 0, \beta = 1\}$ means that the self-supervised task is off, and the data batches contain only original ordered images, which corresponds to our DeepAll baseline.

**Results - Jigsaw ablation:** The value assigned to the data bias $\beta$ drives the overall training: it moves the focus from the self-supervised task when using low values ($\beta < 0.5$), to object classification when using high values ($\beta \geq 0.5$). We set the data bias to $\beta = 0.6$ which means that we fed the network with more ordered than shuffled images, thus keeping the classification as the primary goal of the network. In this case, when changing the loss weight $\alpha$ in $\{0.1, 1\}$, we observe results which are always either statistically equal or better than the DeepAll baseline as shown in the first plot on the left of Figure 5. The second plot indicates that, for high values of $\alpha$, tuning $\beta$ has a significant effect on the overall performance. Indeed $\{\alpha \sim 1, \beta = 1\}$ means that jigsaw task is on and highly relevant in the learning process, but we are feeding the network only with ordered images: in this case the jigsaw task is trivial and forces the network to recognize always the same permutation class which, instead of regularizing the learning process, may increase the risk of data memorization and overfitting. Further experiments confirm that, for $\beta = 1$ but lower $\alpha$ values, our multi-task method based on jigsaw puzzle and DeepAll perform equally well. Setting $\beta = 0$ means feeding the network only with shuffled images. For each image we have $P$ variants, only one of which has the patches in the correct order and is allowed to enter the object classifier, resulting in a drastic reduction of the real batch size. In this condition the object classifier is unable to converge, regardless of whether the Jigsaw classifier is active ($\alpha > 0$) or not ($\alpha = 0$). In those cases the accuracy is very low ($< 20\%$), so we do not show it in the plots to ease the visualization.

**Results - Jigsaw hyperparameter tuning:** By using the same experimental setting of the previous paragraph, the third plot in Figure 5 shows the change in performance when the number of Jigsaw classes $P$ varies between 5 and 1000. We started from a low number, with the same order of magnitude of the number of object classes in PACS, and we grew till 1000 which is the value used for the experiments in [55]. We observe an overall variation of 1.5 percentage points in the accuracy which still remains almost always higher than the DeepAll baseline. Finally, we ran a test to check the accuracy when changing the grid size and consequently the patch number. Even in this case, the range of variation is limited when passing from a $2 \times 2$ to a $4 \times 4$ grid, confirming the conclusions of robustness already obtained for this parameter in [55] and [17]. Moreover all the results are better than the DeepAll.

**Results - Rotation ablation:** Changing the orientation has a milder effect on the global appearance of the image with respect to patch decomposition and reordering of jigsaw puzzles. One significant further difference between the Rotation and Jigsaw tasks is in the number of self-supervised classes which is $P \sim 10–50$ for Jigsaw and just 4 for Rotation, which actually reduces to 3 if we consider that one of the classes matches with the original image orientation. In this conditions, even using a low $\beta = 0.4$ does not distract the network focus from the main object classification task and, combined with $\alpha = 0.4$ produces the best results reported in Table 2. For the ablation analysis we keep each of the two parameters fixed while varying the other: the results are always above the DeepAll baseline and on average the performance variation is limited (around 1 percentage point) indicating low sensitivity to the specific parameter settings.

**Results - self-supervised performance:** We have seen how the self-supervised tasks support the main supervised classifier for domain generalization, but it is also interesting to check their own internal functioning and whether those tasks get meaningful results. We show their performance when testing on the same target images used to evaluate the object classifier but with shuffled patches for Jigsaw and randomly changed orientation for the Rotation task. In Figure 7 the first plot shows the accuracy over the learning epochs for the object, Rotation and Jigsaw permutation classifier indicating that all grow simultaneously (on different scales). The second plot shows the Jigsaw recognition accuracy when changing the number of permutation classes $P$: of course the performance decreases when the task becomes more difficult, but overall the
obtained results indicate that the Jigsaw model is always effective in reordering the shuffled patches.

4.1.6 Visual Explanation and Failure Cases
By solving jigsaw puzzles we encourage the network to localize and re-join relevant object sub-parts regardless of the visual domain. Also the rotation self-supervised task has a similar effect: to recognize the image orientation is helpful to focus on its object content. To analyse these behaviour we used the Class Activation Mapping (CAM, [84]) method on ResNet-18 DG experiments, with which we produced the activation maps in Figure 8 for the PACS dataset. The first two rows show that our multi-task approach with Jigsaw or Rotation self-supervision is better at localizing the object class with respect to DeepAll. Rotation seems slightly less precise than Jigsaw in capturing the object shapes especially when dealing with sketches (see the dog on the second and sixth row), cartoon and paintings (fourth and fifth row), while works reasonably well with photos. The last two rows indicate that for Jigsaw the recognition mistakes are related to some flaw in data interpretation, while the localization remains meaningful.

4.1.7 Predictive-DA
Recent works have started investigating intermediate settings between DG and DA. In Predictive-DA [48], [79] one labeled and several auxiliary unlabeled source domains are available at training time together with descriptive meta-data. In a first stage of the testing procedure, only the meta-data of the target are available: they can be used to relate the target domain to the known sources and compose a target model which is finally evaluated on the target data. Considering that the target model is defined without having access to the target samples, we are still in the DG scenario. However, this setting is clearly simplified by the possibility of leveraging on the domain auxiliary information.

Our multi-task approach can exploit the extra unlabeled source samples without requiring any auxiliary meta-data neither from sources, nor from the target. This means that we have a much cheaper solution with respect to any method developed ad-hoc for Predictive-DA, but we do not benefit from the side information that can guide the learning process. Still we decided to evaluate our method in this setting to understand its effectiveness.

Baseline and Dataset: We consider as baseline the source-only case and AdaGraph [48]. The latter is a very recent approach that exploits domain-specific batch-normalization layers to learn models for each source domain in a graph, where the graph is provided on the basis of the source auxiliary meta-data. We follow the experimental protocol described in [48] on the Comprehensive Cars (CompCars) dataset [78]. We used a subset of 24,151 images with 4 categories (MPV, SUV, sedan and hatchback) which are type of cars produced between 2009 and 2014 and taken under 5 different view points (front, front-side, side, rear, rear-side). Each view point and each manufacturing year define a separate domain, leading to a total of 30 domains. We selected a pair of domains as source and target and use the remaining 28 as auxiliary unlabeled source data. Considering all possible domain pairs, we got 870 experiments and observe the average accuracy results over all of them. More in details, we started from an ImageNet pretrained model and trained for 6 epochs on source domain using Adam as optimizer with weight decay of $10^5$. The batch size used is 16 and the learning rate is $10^{-3}$ for the classifier and $10^{-4}$ for the rest of the network; the learning rate is decayed by a factor of 10 after 4 epochs. We tried both Jigsaw and Rotation with loss weight parameter set to $\alpha = 0.5$.

Results: Table 8 collects the obtained results and show that our multi-task approach significantly improves over the baseline which learns only from the single labeled source and cannot exploit unlabeled data. On the other hand, AdaGraph, which leverages on both the meta-information and the unlabeled data, shows the top result. Considering the limited gap between AdaGraph and our Jigsaw based result, we claim that when the meta-data information is noisy or missing, our approach can be used as reliable and inexpensive fallback.

TABLE 5
Predictive DA results.

|                | Resnet-18 |
|----------------|-----------|
| Baseline       | 56.80     |
| AdaGraph       | 65.10     |
| Jigsaw         | 63.00     |
| Rotation       | 61.77     |

![Fig. 5. Ablation results and hyperparameter analysis on the Alexnet-PACS DG setting when using Jigsaw. The reported accuracy is the global average over all the target domains with three repetitions for each run. The red line represents our DeepAll average from Table 2.](image1)

![Fig. 6. Ablation results on the Alexnet-PACS DG setting when using Rotation. We report the average accuracy over all target domains with three repetitions for each run. The red line is our DeepAll from Table 2.](image2)

![Fig. 7. Analysis of the Jigsaw classifier on Alexnet-PACS DG setting. In the left plot each axes refers to the color matching curve in the graph.](image3)
4.2 Self-Supervised Domain Adaptation

4.2.1 Single- and Multi-Source Domain Adaptation

When unlabeled target samples are available at training time we can use any self-supervised task on them. Indeed we can run patch reordering and orientation recognition on both source and target data to support adaptation of the source classification model.

**Baselines and Datasets:** To verify this intuition we compare our multi-task approach against several DA methods. In particular we consider four families of DA approaches. The first is based on measuring the Maximum Mean Discrepancy (MMD, [66]) across domains and minimizing it to reduce the domain shift: DAN [46], JAN [47]. The second family is that of the adversarial approaches as DANN [27] which is based on reverse gradient backpropagation from the auxiliary domain classification network branch. A third family is that based on batch normalization: Dial [14] introduced adaptive layers to match source and target distribution to a standard gaussian. In DDiscovery [49] the same idea is revisited to first discover the existence of multiple latent domains in the source and then differently adapt their knowledge to the target. Finally the fourth family focuses on increasing the feature norms of the two domains with the Hard Adaptive Feature Norm (HAFN, [77]) method and its step-wise variant SAFN.

Several domain adaptation approaches minimize the entropy loss as an extra domain alignment condition (e.g. SAFN+ENT):
in this way the source model is encouraged to assign maximum prediction probability to a single label rather than distributing it over multiple class options. For a fair comparison we also turned on the entropy loss for our self-supervised method with weight $\eta = 0.1$. Moreover we solve the self-supervised task either involving both the source and the target or considering only the latter. In the former case we can weight the source and target self-supervised loss equally or we can treat them separately with dedicated source ($\alpha_s$) and target ($\alpha_t$) weights.

As datasets we considered Office-Home for the single-source experiments and PACS for the multi-source setting.

**Results:** Tables 6 shows the single source results on Office-Home. Our multi-task approach improves over its baseline and over DAN, JAN, DANN but has worse performance than HAFN, SAFN and SAFN+ENT. Although not usually presented, we show the specific baseline (ResNet-50) results of the HAFN/SAFN methods to better evaluate their relative gain. Indeed their basic architecture has an extra fully connected layer with respect to a standard ResNet which appears particularly helpful in this cross-domain setting.

We included in the table also an analysis on the results stability when varying $\alpha_s$ and $\alpha_t$; the obtained accuracy values show that most of the adaptive effect originates from running the self-supervised task on the target data ($\alpha_t \neq 0$), so we can set $\alpha_s = 0$ without any loss in performance.

The multi-source experiments in Table 7 shed further light on the adaptive abilities of the auxiliary self-supervised objective included in our multi-task approach. When the source domain is rich and covers large style variability, our method is able to outperform not only the batch-normalization based techniques Dial and DDiscovery, but also the state-of-the-art DA approaches HAFN and SAFN which have more difficulties in aligning the norms between the multiple sources and a single target domain. Among Jigsaw and Rotation, the second appears more suitable for domain adaptation, with higher performance and better stability to hyperparameter tuning. When the two self-supervised tasks are combined we get on average a small accuracy improvement.

### 4.2.2 Partial Domain Adaptation

The setting with source and target domains sharing exactly the same classes may be too restrictive. Here we discuss experimental results on the more realistic PDA setting where the target domain contains only a subset of the source classes.

**Baselines:** We consider as reference five PDA methods all based on down-weighting the importance of source classes which are absent in the target. The methods SAN [9], PADA [10], and DRCN [44], exploit the source model prediction to evaluate the target class distribution. A different solution is proposed by IWAN [61], where each domain has its own feature extractor and the source sample weight is obtained from the domain recognition model rather than from the source classifier. The most recent ETN [11] uses only the relevant source examples to train both the label classifier and the domain discriminator. The relevance (weight) of each source example is computed through an auxiliary domain discriminator, not directly involved in the adaptation phase, which quantifies the source example transferability.

The methods HAFN and SAFN already presented in the previous Section, leverage only the same norm samples rather than the whole domain distributions and are quite robust to negative transfer also in the PDA setting, without the need of any weighting mechanism. Thus, we also considered them as reference. Finally, we report the results of DAN and DANN as basic adaptive baselines, to show the effect of methods not originally designed to deal with PDA.

**Datasets:** We follow previous literature in choosing two datasets and their related setting for the PDA experiments. We use Office-31 [63] which contains 4652 images of 31 object categories common in office environments. Samples are drawn from three annotated distributions: Amazon (A), Webcam (W) and DSLR (D) which correspond respectively to online vendor website, digital SLR camera and web camera images. Similarly to [9, 10], 10 classes are used as target for this dataset (the same classes shared by this dataset with Caltech-256 [32]). The second test-bed is VisDA2017, originally used in the 2017 Visual Domain
Adaptation challenge (classification task): with respect to the other datasets, it allows us to investigate the proposed multi-task approach on a very large-scale sample size scenario. It has two domains, synthetic 2D object renderings and real images with a total of 208k images organized in 12 categories. We focus on the synthetic-to-real shift, the same considered in the challenge, but keeping only the first 6 categories of the target in alphabetic order. For all the experiments we use ResNet-50 as backbone.

Results: Tables 8 and 9 show the obtained results respectively on Office-31 and VisDA2017 datasets. Each table is organized in four horizontal blocks: the first one shows the results obtained without adaptation or with standard DA methods, the second block illustrates the performance with algorithms designed to deal with PDA, the third one includes the performance of the norm-based adaptation approaches HAFN/SAFN together with their corresponding ResNet-50 baseline. Finally, the fourth part contains the results of our method. We remind that, as described in Sec. 3.3, our approach in the PDA setting does not involve the source data in the auxiliary self-supervised task: indeed the results obtained in the DA setting for single source already showed that it is possible to set $\alpha_t = 0$ without any performance drop. Moreover, we set $\alpha_t = 1.0$ for all the experiments.

All the tables show that both the Jigsaw and Rotation outperform the first group of adaptive references. With respect of the PDA techniques in the second group, our method shows better results on VisDA2017 even if many of these competitors take advantage by a ten-crop image evaluation procedure (indicated by the star*). The top result on Office-31 is obtained by ETN which however, has a dedicated parameter selection procedure for each domain pair, different from our approach for which the parameters are fixed and shared by all the domain pairs of a dataset. Finally the HAFN/SAFN variants in the third group confirm the effectiveness of the norm-based methods also for PDA. Their results are comparable or worse than ours.

Despite not being tailored for the PDA setting, the obtained performance show that the auxiliary self-supervised task supports adaptation also in this scenario. Given that our solution is orthogonal to the sample selection strategies, we further tried to combine them together to evaluate if they complement each other. Specifically, we focused on Office-31 and the Jigsaw: we estimated the target class statistics through the weight $\gamma$ and included also a domain discriminator weighted by the parameter $\lambda$, following [10] as discussed in Sec. 3.3. To allow a fair comparison we also adopted the ten-crop evaluation. The results in the last two rows of Table 8 indicate that estimating the target statistics helps the network to focus only on the shared categories, with an average accuracy improvement of two percentage points over the plain Jigsaw method, getting up to a result comparable with that of ETN considering the standard deviation. Moreover, we can state that the advantage comes from a better alignment of the domain features: by comparing the $\gamma$ values on the A$\rightarrow$W domain shift we observe that Jigsaw-$\gamma$ is more precise in identifying the missing classes of the target (see Figure 9). We indicate with Jigsaw-$\gamma$, $\lambda$ the case that includes the domain classifier: since the produced features are already well aligned across domains, we fixed $\lambda$-max to 0.1 and observed a further small average improvement. From the last bar plot on the right of Figure 9 we also observe a better identification of the target classes.

## 5 Conclusion

This work provides an extensive study on the use of self-supervised learning across domains. In particular we focused on solving jigsaw puzzles and recognizing image orientation, showing that they can be easily integrated in a multi-task approach with supervised learning. The results show an improvement in cross-domain robustness and an advantage on generalization performance: the obtained results are competitive with that of more elaborate domain adaptation and domain generalization methods. Our work paves the way for many other adaptive methods exploiting the invariances captured by the most recent self-supervised solutions [29], [36], also beyond object classification towards other challenging tasks like semantic segmentation [75], detection [21] or 3D visual learning [2] where the domain shift effect strongly impacts the deployment of methods in the wild.

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