Unsupervised Transfer Learning with Self-Supervised Remedy

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Abstract—Generalising deep networks to novel domains without manual labels is challenging to deep learning. This problem is intrinsically difficult due to unpredictable changing nature of imagery data distributions in novel domains. Pre-learned knowledge does not transfer well without making strong assumptions about the learned and the novel domains. Different methods have been studied to address the underlying problem based on different assumptions, e.g. from domain adaptation to zero-shot and few-shot learning. In this work, we address this problem by transfer clustering that aims to learn a discriminative latent space of the unlabelled target data in a novel domain by knowledge transfer from labelled related domains. Specifically, we want to leverage relative (pairwise) imagery information, which is freely available and intrinsic to a target domain, to model the target domain image distribution characteristics as well as the prior-knowledge learned from related labelled domains to enable more discriminative clustering of unlabelled target data. Our method mitigates nontransferrable prior-knowledge by self-supervision, benefiting from both transfer and self-supervised learning. Extensive experiments on four datasets for image clustering tasks reveal the superiority of our model over the state-of-the-art transfer clustering techniques. We further demonstrate its competitive transferability on four zero-shot learning benchmarks.

Index Terms—Transfer Learning, Self-supervised Learning, Clustering

1 INTRODUCTION

Despite the remarkable progress advanced by deep convolutional neural networks (CNNs) on computer vision in recent years [1], [2], the i.i.d (independent and identically distributed) assumption widely held by most of the deep learning models restricts their transferability and usability in novel domains without additional labelled training data. In general, realistic data of interest usually have different and unknown distributions in novel domains (domain shift). It is both labour-intensive to manually annotate sufficient data and computationally expensive to retrain a model in every new target domain. To overcome this fundamental problem, transfer learning (TL) [3] has been widely studied, which aims to leverage the knowledge gained from one domain to help acquire a better understanding of other related domains. Moreover, only unlabelled data are mostly available at scale, therefore, unsupervised transfer learning [4] serves as a more natural solution in the deep learning context and has attained increasing attention [5], [6], [7].

Recent efforts on unsupervised transfer learning mainly start from three different assumptions. To deal with target data sampled from arbitrary distributions, Unsupervised Domain Adaptation (UDA) [8] assumes that they are drawn from the same label space as the source data (Fig 1 (c)). In this case, the trained model can be adapted to the target domain by refining decision boundaries that are optimal for both distributions. However, the largest imagery database [9] available today contains samples from only 1,000 classes, which is far less than the number of object categories known by human (e.g. in language), let alone the countless unknown ones. Therefore, assuming all the newly collected data are from the known classes is sometimes impractical. To relax such assumptions, Zero-Shot Learning (ZSL) [10] and Few-Shot Learning (FSL) [11] are introduced, in which the target data are from novel classes that are either unseen or weakly-seen during model training. Importantly, additional information on the relationships between seen and unseen or weakly-seen classes are required. That is, in ZSL novel classes (unseen) must be known semantically in a word vector space in a sense that they are in proximity to the seen classes semantically, i.e. interpretable in a text space (Fig 1 (d)). In FSL, novel classes are weakly-seen by having a few labelled samples (usually 1~5 samples per class) as the anchors (Fig 1 (e)). Moreover, novel classes are also implicitly assumed to be known and in proximity to the seen classes in a visual feature space, i.e. interpretable visually. As it is hopeless to define all the categories even in relatively restricted settings [6], it remains an open question as how to generalise a trained CNN model to the data from real novel classes, that is, both unseen and unknown.

Whilst existing unsupervised transfer learning methods make different assumptions that limit their usability to different scenarios, they do share the same objective of mapping images with no/limited labelled training data (target data) into a discriminative latent space, in which samples from the same classes are closer than those from different classes (Fig 1 (b)). We observe this objective being identical to that of cluster analysis, and we consider that the key challenge of unsupervised transfer learning is to leverage knowledge from human supervision on related source data for more discriminative clustering of unlabelled samples.

1. Due to the efforts made by FSL on cross-domain knowledge transfer with insufficient labelled data supervision, we discuss it in the wider context of unsupervised transfer learning although it is not strictly unsupervised.
target data, i.e. Transfer Clustering (TC) [6]. Transfer Clustering is fundamentally more challenging than the above-mentioned settings due to the fewer assumptions it makes on target domains. We empirically show that our proposed TC method can attain competitive knowledge transferring ability on ZSL tasks, whilst it provides a more generic solution to unsupervised transfer learning than contemporary ZSL models.

In this work, we introduce a novel transfer clustering method called self-SUPervised REMEdy (SUPREME). The motivation of the SUPREME model is that, the supervision constructed according to the prior-knowledge acquired from related domains, called transferred supervision, is not always sufficient for all the target samples due to distribution shift and class non-proximity (discrepancy). Therefore, additional complementary supervision is necessary for learning a model to better describe the target distribution. Specifically, by exploring the auxiliary learning principle [12], SUPREME jointly learns by transferred supervision and self-supervision, which are individually adjusted on each (unlabelled) target image sample according to the estimated confidence of the prior-knowledge on it. The transferred supervision is only considered reliable for the samples that falling within the overlapping areas of both source and target distributions whilst self-supervision is introduced to enhance the weak or ambiguous transferred supervision for the remaining samples. Both types of supervision are formulated in a single objective function harmoniously to enable end-to-end model learning.

The contributions of this work are three-folded: (1) We propose the idea of exploiting self-supervision as the remedy for unreliable unsupervised transfer learning so to yield more discriminative modelling of the target distributions. To our best knowledge, this is the first attempt at jointly using related domain prior-knowledge and novel target domain self-supervision for clustering by deep neural networks. (2) We formulate a self-SUPervised REMEdy (SUPREME) method for transfer clustering that enables an effective implementation of leveraging related source domain prior-knowledge whilst simultaneously mitigating the negative impact of ambiguous transferred supervision by self-supervised learning in a target domain. (3) We empirically show that transfer clustering by SUPREME is a more generic solution to unsupervised transfer learning than ZSL.

The superiority of the proposed method over a wide range of existing unsupervised transfer learning techniques is shown by extensive experiments on both transfer clustering and ZSL tasks using 8 benchmarks: CIFAR10/100 [13], SVHN [14], ImageNet [9], CUB [15], SUN [16], FLO [17] and AWA2 [18].

2 Related Work

Instead of focusing narrowly on transfer clustering, we consider the bigger picture of unsupervised transfer learning. This is partly because our method of exploring self-supervised learning is closely related to unsupervised transfer learning by training deep networks with insufficient labelled data supervision.

Unsupervised Transfer Learning. Unsupervised Domain Adaptation (UDA) has been widely studied to transfer knowledge across different data distributions. Critically, by assuming all the domains are sharing the same label space, UDA learns to either align feature distributions [19], [20] or map the relationships between the decision boundaries and feature representations so that the boundaries are valid for both domains [5], [21]. However, UDA is not always practical as it cannot enumerate all the categories for model training let alone exhaustively collecting and annotating the data. Alternatively, Zero-shot Learning (ZSL) and Few-shot Learning (FSL) have drawn increasing attention, in which target data of novel classes are unseen or insufficiently-seen during model training. It is intrinsically challenging to generalise CNN models to unseen categories. To overcome this problem, both learning tasks hold an assumption that the novel classes are known according to their pre-defined relationships with the seen classes. In ZSL [10], [22], [23], all the seen (source) and unseen (target) classes are described by a common representational space, e.g. attribute space, so that data from unseen classes can be classified by novel combinations of attributes which are building blocks shared with the seen classes. Different from ZSL, FSL [7], [11] assumes that a few anchor samples with labels are available for each novel class as its prototype (so strictly not unseen), and the novel classes and seen classes are in proximity in their distributions. In this case, the target data can be classified according to their distances to different anchor samples with the assistance of the distributions of seen classes. Whilst standard ZSL and FSL assume that the target label space is completely disjoint to the seen label space in test, Generalised ZSL/FSL (GZSL/GFSL) [7], [23] consider that target samples possibly consist of both seen and novel
Transfer clustering. Han et al. [6] first introduced the task of transfer clustering formally, which aims to jointly learn both the representations and the decision boundaries of unlabelled target data with the help of the labelled data from related domains. They construct the initial clustering solution by applying K-means upon the feature representation produced by a pretrained model and learn to sharpen the initial assignment distribution of each sample. There are other attempts at transferring knowledge across domains for achieving learning tasks that are similar to transfer clustering. KCL [25] and MCL [26] are based on a Constrained Clustering Network (CCN), which learns to transfer pairwise similarities from a source to a target domain so that the cross-domain and cross-task transfer learning are decoupled. This aims to reduce the model learning complexity. Another method called Centroid Networks [27] is proposed to jointly learn data embeddings and clustering using the Sinkhorn K-means algorithm. Due to distribution shift and discrepancy in label space proximity, the clustering of some target samples during model training will not yield sufficient supervision from the prior-knowledge of the source domain, therefore, poorly modelled. We aim to solve this problem by self-supervision so that the model can better explain the target distribution.

Self-supervised Learning. Self-supervised learning is a general concept that explores inherent information in visual data without labelling in order to construct pseudo-supervision in model training. The formulation of self-supervision has many manifestations. One popular approach is to explore pixel information that trains a model to reconstruct the data distributions, known as a generative model, e.g. the Restricted Bolzmann Machines (RBMs) [28], [29], Autoencoder [30], [31], and Generative Adversarial Networks (GANs) [32], [33]. Data perturbation is another approach to construct supervision by introducing positive sample pairs [34], [35], [36], [37]. Self-supervision can also be formulated according to spatial context [38], [39], [40], and colour distributions [41], [42]. Although many self-supervised learning techniques show the potential to learn and colour distributions [41], [42]. Self-supervision can also explain the target distribution. This is intrinsically challenging as the arbitrarily complex appearance patterns and variations exhibited in the imagery data usually lead to intricate relationships between source domain and target domain distributions.

To address this problem, we formulate a self-SUPervised REMEdy (SUPREME) method. It shares the spirit of auxiliary learning that trains a model jointly by transferred knowledge and self-supervision. Our key idea is that, it can be error-prone and rather arbitrary to truncate the ambiguous supervision and convert them mandatorily to be determined (Fig 2 (a)), e.g. converting the assignment probabilities (soft-labels) to pseudo (hard) labels according to the nearest cluster. We consider it is more consistent to replace those supervisions by the intrinsic information encoded in data. i.e. self-supervision (Fig 2 (c)). Although self-supervision does not rely on prior-knowledge unlike the truncated transferred supervision [25], [26], it can minimise the misleading effect of applying nontransferrable knowledge to the target domain. Moreover, SUPREME method differs significantly from the selection strategy [6]. [43]. The latter neglects samples having ambiguous transferred supervision, therefore, introducing bias in model training that can lead to less discriminative feature space (Fig 2(b)). The effectiveness of the proposed SUPREME model on a wide range of benchmarks demonstrates its ability to utilise target samples with insufficient prior-knowledge supervision, rather than ignore them. An overview of SUPREME is depicted in Fig 3.

3 TRANSFER CLUSTERING

Given $N^s$ image-label pairs $\{I^s, y^s\}_{i=1}^{N^s}$ drawn from a source label space $S = \{1, 2, \cdots, K^s\}$ and $N^t$ target images $\{I^t\}_{i=1}^{N^t}$ from $T = \{1, 2, \cdots, K^t\}$ where $S \neq T$. In transfer clustering, no class label is annotated on target images. The objective is to jointly learn a feature representation of target samples $f_0 : I^t \rightarrow x^t$ and the probabilities that they belong to each of $K^t$ clusters $f_s : x^t \rightarrow p$ so that the target samples of the same class labels are more likely to be allocated into the same partitions. Due to the absence of labelling in the target domain, the target distribution is agnostic, so as the discrepancy between it and the source distribution. It is therefore necessary to consider not only an effective way for source domain knowledge transfer in target sample clustering, but also how to identify and deal with those target samples having insufficient (weak or ambiguous) support from the source domain prior-knowledge. This is intrinsically challenging as the arbitrarily complex appearance patterns and variations exhibited in the imagery data usually lead to intricate relationships between source domain and target domain distributions.

3.1 Self-supervised Knowledge Transfer

We start from how to construct the initial clustering solution with the help of a model pretrained on a source domain to transfer prior-knowledge. Given a model $f_0$ which is pretrained by supervised learning on source data $\{I^s, y^s\}_{i=1}^{N^s}$, transfer learning assumes that there is some transferrable common knowledge shared by the source and target domains. As such, we yield an initial representation of target images $I^t$ by feeding them into $f_0 : x^t = f_0(I^t)$. An initial clustering of $x^t$ is computed by any standard
Fig. 3. Overview of the proposed self-SUPervised REMEdy (SUPREME) method for transfer clustering. (a) We first acquire the prior-knowledge from source domain by training with manual labels. (b) K-means is then applied upon the resulting feature representations to construct the soft constraints between each pair of target samples, whose confidence is measured by a novel joint-entropy based metric. (c) Self-supervision is then introduced to make up for the ambiguous constraints. (d) By jointly trained with the prior-knowledge and self-supervision, our model finally learns a discriminative latent space as well as the decision boundaries for the target data.

technique (e.g. K-means). By separating \( \tilde{x}^t \) into \( K^t \) groups, we are assuming that all the prior-knowledge of the source domain are applicable to the target domain by this initial clustering solution. However, this assumption is not always true due to the distribution shift and discrepancy in label space proximity. To address this problem, we formulate the transfer clustering as a constrained clustering task in which the constraints are formed by pairwise similarities between target samples determined by their initial assignment and weighted by the estimated confidence.

Soft constraints construction. Given the representations \( \tilde{x}^t \) and the \( K^t \) clusters centroid \( \{ c \} \), we measure the probability \( \tilde{p}(c_j | I^t_i) \) that sample \( I^t_i \) belongs to cluster \( c_j \) by computing a student’s \( t \)-distribution following [6, 13]:

\[
\tilde{p}(c_j | I^t_i) = \frac{(1 + \| \tilde{x}^t_i - c_j \|^2/\alpha)^-(\alpha+1)/2}{\sum_{j'=1}^{K^t} (1 + \| \tilde{x}^t_i - c_{j'} \|^2/\alpha)^-(\alpha+1)/2}
\]

(1)

Parameter \( \alpha \) in Eq (1) is the freedom of student’s \( t \)-distribution and is set to 0 in our implementation. We denote \( \tilde{p}(c_j | I^t_i) \) by \( \tilde{p}_{i,j} \) for brevity. With the initial assignment probabilities, we then estimate how likely two samples are from the same class by the inner product between their initial assignment distributions:

\[
\tilde{r}_{i,j} = \tilde{p}_{i,i}^T \cdot \tilde{p}_{j,j} = \sum_{k=1}^{K^t} \tilde{p}_{i,k} \cdot \tilde{p}_{j,k}
\]

(2)

By taking the joint probabilities of sample pairs as the measure of positive relation, we explore both the global and local structures of the pretrained feature space. The value of \( \tilde{r}_{i,j} \) reaches its maximum \( \tilde{r} \rightarrow 1 \) only when two samples are both close to each other (local structure) and close to the same cluster’s centroid (global structure). In which case, they are considered “confidently positive”. Otherwise, the pairwise relation is either ambiguous (neither samples is close to any cluster centroid) or “confidently negative” (two samples are close to different cluster centroids), resulting in the positive probability between them becomes the minimum \( \tilde{r} \rightarrow 0 \). We then train a CNN model with the following soft constraints to encourage target pairs with large \( \tilde{r}_{i,j} \) to be assigned into the same groups:

\[
\mathcal{L}_{\text{clus}} = -\frac{1}{n^t} \sum_{i=1}^{n^t} \sum_{j=1}^{n^t} \tilde{r}_{i,j} \log r_{i,j}, \quad r_{i,j} = \sum_{k=1}^{K^t} \tilde{p}_{i,k} \cdot \tilde{p}_{j,k}
\]

(3)

where \( n \) is the mini-batch size and \( r_{i,j} \) is the up-to-date positive probability of the sample pair consisting of \( I^t_i \) and \( I^t_j \). To optimise \( \mathcal{L}_{\text{clus}} \), the assignment distribution \( p \) is encouraged to be “sharp” (one-hot in extreme case). Hence, even the samples initially are ambiguous will gradually shift together with other samples of high visual similarity to the most plausible clusters.

In the formulation of \( \mathcal{L}_{\text{clus}} \), ambiguous and confidently negative sample pairs hold similar low probabilities to be assigned into the same clusters. However, comparing with confidently negative pairs, samples of ambiguous pairs are likely positive. It means that the prior-knowledge transferred to the confidently negative pairs are more reliable than that to the ambiguous pairs. Instead of learning from all the prior in equal importance, the model should be encouraged to focus on the transferrable parts. To that end, we assume that target samples near the initial clusters’ centroids are able to form confident pairwise relations while those close to the decision boundaries cannot. We quantify the confidence of the pairwise relations according to the joint entropy of initial assignment distributions:

\[
H(I^t_i, I^t_j) = -\sum_{k=1}^{K^t} \tilde{p}_{i,k} \tilde{p}_{j,k} \log \tilde{p}_{i,k} \tilde{p}_{j,k}, \quad H_{\text{max}} = \log(K^t)^2
\]

\[
w_{i,j} = \frac{\exp((H_{\text{max}} - H(I^t_i, I^t_j))/(H_{\text{max}} \cdot \tau))}{\sum_{i',j'}^{n} \exp((H_{\text{max}} - H(I^t_{i'}, I^t_{j'}))/(H_{\text{max}} \cdot \tau))}
\]

(4)

where \( \tau \) is the temperature that controls the concentration of the confidence distribution; \( H(I^t_i, I^t_j) \) is the joint entropy of \( \tilde{p}_i \) and \( \tilde{p}_j \); \( w_{i,j} \) is the normalised confidence of constraint \( \tilde{r}_{i,j} \). The overall penalty of a mini-batch will then be determined by the weighted sum instead of the average in Eq (3):

\[
\mathcal{L}_{\text{clus}} = -\sum_{i=1}^{n^t} \sum_{j=1}^{n^t} w_{i,j} \tilde{r}_{i,j} \log r_{i,j}
\]

(5)

The confidence strategy measures the reliability of prior-knowledge from the source domain in terms of different tar-
get samples, which mitigates the misleading effects caused by applying nontransferrable prior to target domain.

**Self-supervised Remedy.** As determined by the cost function $L_{\text{clu}}$, samples falling into an ambiguous area of the initial feature space make necessarily less contribution to model learning as they are given smaller weights. However, those samples actually play a significant role to learn a more discriminative feature space. Due to the absence of ground-truth labels and the ineffectiveness of source domain prior-knowledge on these “hard” samples, the information we can leverage instead for additional supervision on model learning are intrinsic characteristics of the target images. Inspired by recent unsupervised learning ideas [34], [35], we formulate the self-supervision to augment transfer learning by being invariant to data perturbations. By applying random image transformations $g(\cdot)$ on the original data, the positive probability $r_{i,j}$ in Eq. [5] is computed according to the assignment distribution of sample $I_i^t$ and that of $g(I_j^t)$:

$$r_{i,j} = \sum_{k=1}^{K^t} p_{r,k} \cdot g(p_{j,k}) \text{ where } g(p_{j,k}) = f_s(f_a(g(x_j^t))))$$

Moreover, we set $\tilde{r}_{i,i} = w_{i,i} = I_\forall i \in [1,n]$ because the perturbed copies of images are certainly with the same class labels as the originals. In this case, the two supervisions are integrated harmoniously by our soft-constrained formulation (Eq. [5]).

### 3.2 Model Training

Beyond the self-supervised transfer objective $L_{\text{clu}}$, our model is also trained with several regularisations to refrain from degenerated solutions. The training objective of cluster analysis encourages the maximisation of intra-cluster compactness and inter-cluster diversity, hence, the model can possibly collapse by assigning all the samples into one single cluster. Therefore, we introduce a balance regularisation on cluster size:

$$L_{\text{balance}} = \log K^t + \frac{1}{n} \sum_{k=1}^{K^t} s_k \log s_k, \quad s_k = \frac{1}{n} \sum_{i=1}^{n} p_{r,k}$$

where $s_k$ is the approximated size of the $k$-th cluster and the maximal entropy $\log K^t$ is added to ensure positive regularisation values. We train the model to minimise the negative entropy of the approximated cluster size distribution so as to avoid extremely imbalanced distributions. Moreover, to avoid learning trivial data representations, we map the visual features to a common factor space shared by both the source and target domains with the motivation to map the visual features to a common factor space shared so as to avoid extremely imbalanced distributions.

### 4 Experiments

**Datasets.** Evaluations of the proposed SUPREME method are conducted on 8 benchmarks. CIFAR10/100 [13]. An imagery dataset containing 50,000/10,000 training and testing data drawn from 10(100) classes uniformly.

**SVHN [14]:** The Street View House Numbers dataset includes 73,257/26,032 train/test images lying in 10 digit classes 0 ∼ 9. ImageNet [9]: A large scale imagery dataset with over 1.2 million images from 1,000 classes. CUB [15]: Caltech-UCSD-Birds contains 11,788 images from 200 breeds of birds with 312 binary attributes annotations. FLO [17]: Oxford Flower dataset gathers images from 102 flower categories with each class consisting of between 40 and 258 instances. SUN [16]: SUN Attribute is another common fine-grained datasets used in ZSL with 14,303 images included. AWA2 [18]: Animals with Attributes2 consists of 37,322 images of 50 animals classes with 85 numeric attributes for each class.

**Experimental setup.** To transfer knowledge across domains in an unsupervised manner, we assume that human annotations are only available on source domains and take the number of target classes as the only prior. We aim to provide a generic solution to unsupervised transfer learning with fewer assumptions than most of the existing settings. To that end, in addition to comparing with transfer clustering techniques following the same setups as [6] on four benchmarks, we further evaluated the effectiveness of SUPREME on four ZSL benchmark datasets. Note, SUPREME does not utilise any word-vector embedding space knowledge on either the source or the target class labels as compared to the ZSL methods. We use the same data splits as [50] for fair comparisons.

**Performance metrics.** We adopt two standard metrics in cluster analysis for evaluation: (a) Accuracy (ACC) is determined by the percentage of test samples that are assigned into the cluster which is matched with the correct ground-truth class with minimum weight. (b) Normalised Mutual Information (NMI) quantifies the normalised mutual dependence between the predicted assignments and the ground-truth memberships. Both of these metrics are falling within the range of [0, 1] and higher values indicate better performances. ZSL usually takes Top-1 accuracy as the performance metric, nevertheless, this is not applicable
in our case due to the deprecation of classes description. In this case, we instead report our clustering accuracy. Although they are not strictly comparable, they both reveal the model’s discrimination ability and are within the same scale. Therefore, we put them in the same tables to provide an intuitive comparison.

**Implementation details.** We used the same network architectures as the ones adopted by [6] as well as the corresponding model weights pretrained on source domains provided by them on the transfer clustering evaluation and the ImageNet pretrained ResNet101 [23] on ZSL to be consistent with [50]. The Adam algorithm [51] is adopted for model training with a fixed learning rate (1e−3). All the models are randomly initialised and trained with 100 epochs without L2 regularisation. The image transformations we used for data perturbation include random rescale and random horizontal flip, which are also adopted by [6]. All the main results are averaged over 10 runs while the ones from ImageNet are averaged over 3 runs with different data splits following [6, 25, 26].

### 4.1 Unsupervised Transfer Learning

**Transfer Clustering.** We first evaluated our method’s effectiveness on clustering unlabelled data with the help of prior-knowledge from source domains by comparing with the state-of-the-art transfer clustering models on four benchmarks. Results in Table 1 show that: (1) Most of the unsupervised transfer clustering methods yield superior performances than K-means. As a cross-domain deployment solution, K-means generally applies the knowledge acquired from one domain to another without any selection or adaptation. Its disadvantages demonstrate the necessity of dealing with distribution shift/discrepancy. (2) The proposed SUPREME method surpasses all the competitors on the first three datasets mostly with significant margins. This suggests the effectiveness of our auxiliary learning design, which leverages the self-supervision to fill in the gap where prior-knowledge is not transferable. (3) The advantages of SUPREME on ImageNet is weaker than that on others. One possible reason is that, the more complex and diverse image variations exhibited in such a larger scale dataset lead to more severe intra-class variance and stronger inter-class similarity. Our self-supervision was constructed by relatively limited variations from image transformation, which may have not provided sufficient inter-sample variations on a larger scale. Nevertheless, this doesn’t degrade the contribution of our key idea of complementing source domain transferred knowledge with target domain self-supervision. It encourages to exploit more fully on larger scale data.

To provide a more intuitive interpretation of the effects of SUPREME, we visualise the representations of target samples in both the pretrained and transferred feature spaces. Fig 4 shows that, even though the target samples can roughly form some groups in the pretrained feature space, the internal structure of them are loose and they are closely adjacent to each other. As our objective function encourages determined assignments, which means no samples should hold similar probabilities to be assigned into multiple clusters, our models can yield clusters in higher compactness and discriminativeness. Moreover, according to the highlighted part in Fig 4(b), thanking to the auxiliary supervision constructed by intrinsic information on target data, our method is able to correctly cluster samples of the same classes but are initially far away from each other.

**Zero-shot Learning.** In addition to unsupervised image clustering, we also compared the proposed SUPREME method with ZSL approaches. The experimental results indicate that our approach to unsupervised transfer learning provides a plausible generic solution to other related learning tasks. Table 2 shows that transductive learning methods for ZSL are likely to produce higher accuracy by leveraging additional unlabelled target data in model learning, which is consistent with our training strategy. The competitive results yielded by SUPREME on all the datasets except SUN demonstrate its discrimination ability on target domains even without any word vector prototype mapping in the text space or human labelled attribute learning on class description. However, the rather poor performance on SUN, in which the number of target samples is limited to around 1,000 but the target classes are larger than other benchmarks, implies that sufficient training data is still required by our model even without labels.

### 4.2 Component Analysis and Discussions

We conducted detailed ablation studies to investigate the effectiveness of different design choices in our model for in-depth analysis.

**Transferred supervision vs. Self-supervision.** As our key idea holds the assumption that self-supervision can provide complementary constrains to the target samples
to which the prior-knowledge is not applicable, we evaluated the effectiveness of both the transferred supervision and self-supervision to better understand their individual contributions to the model. According to Fig 5 (a), both the prior-knowledge and the self-supervision are able to provide useful constraints independently in model training. Our SUPREME model achieves better performance in most cases, which indicates these two supervisions can benefit each other. It is also interesting to see that the self-supervised model marginally surpasses SUPREME on CIFAR10. This suggests that the prior-knowledge from the source domain sometimes contains misleading and inaccurate (nontransferrable) information of high confidence to the target domain.

Confidence Distribution Concentration. The temperature $\tau$ used to compute the confidence of constraints in Eq 4 decides the concentration degree of the normalised confidence distribution, hence, it can be interpreted as the reliability of prior-knowledge in terms of self-supervision. As shown in Fig 5 (b), our model is able to attain promising performance with a wide range of $\tau$ but the best result is sometimes achieved at different values on different datasets. This is actually within expectation because measuring the transferability of prior-knowledge is intrinsically challenging and the setting of $\tau$ is intricately related to various factors, e.g. capacity of pretrained models. Due to the existence of human annotations on source domains, a reasonable setting of $\tau$ can be determined by cross-validation, which is a conventional solution in transfer learning [18].

Regularisations. The SUPREME model is trained with several regularisations and we investigated their necessity as well as our model’s robustness to them by varying their weights within different ranges. As shown in Fig 6, the significant performance drop in most cases caused by removing either of these regularisations (setting the weight to 0) demonstrate that none of them is redundant for effective knowledge transfer. Furthermore, the stability and the similar trends in parameter values on different datasets indicate the scalability and robustness of our model which requires no exhaustive parameter tuning.

5 CONCLUSION

In this work, we addressed a common underlying problem among several unsupervised transfer learning approaches that aim to model a discriminative latent space in an unsupervised manner with the help of the prior-knowledge...
acquired from related domains. To that end, we propose a more scalable solution to unsupervised transfer learning by formulating a self-SUPervised REMEdy (SUPREME) method to augment transfer clustering with self-supervised learning. It is inevitable that some of the target samples will fail to yield reliable transferred supervision from prior knowledge due to distribution shift/discrepancy, the proposed SUPREME method is designed to identify those target samples and provide them with self-supervision based on intrinsic pairwise similarities among the target images in relation to the source domain pre-knowledge. Extensive experiments on four transfer clustering benchmarks demonstrate the superiority of the proposed method over a wide range of the state-of-the-art models. Moreover, SUPREME also shows competitive discrimination ability on ZSL benchmarks without utilising any additional semantic knowledge representation either in the word to vector text space or attribute learning. Ablation studies and in-depth analysis are conducted to give insights on SUPREME design considerations.

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