TTT-UCDR: Test-time Training for Universal Cross-Domain Retrieval

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Abstract

Image retrieval under generalized test scenarios has gained significant momentum in literature, and the recently proposed protocol of Universal Cross-domain Retrieval is a pioneer in this direction. A common practice in any such generalized classification or retrieval algorithm is to exploit samples from multiple domains during training to learn a domain-invariant representation of data. Such criterion is often restrictive, and thus in this work, for the first time, we explore the challenges associated with generalized retrieval problems under a low-data regime, which is quite relevant in many real-world scenarios. We attempt to make any retrieval model trained on a small cross-domain dataset (containing just two training domains) more generalizable towards any unknown query domain or category by quickly adapting it to the test data during inference. This form of test-time training or adaptation of the retrieval model is explored by means of a number of self-supervision-based loss functions, for example, Rotnet, Jigsaw-puzzle, Barlow twins, etc., in this work. Extensive experiments on multiple large-scale datasets demonstrate the effectiveness of the proposed approach.

1 Introduction

Cross-domain information retrieval has emerged as an important and quite relevant research topic in today’s world because of the availability of large amounts of data across multiple domains and categories. A number of research has been going on to address this problem in a specific form or specific domain of retrieval, such as text-based image retrieval [Cao et al., 2022], sketch-based image retrieval [Liu et al., 2017], audio-based object retrieval [Arandjelovic and Zisserman, 2018] etc. Even though all of these retrieval scenarios have important individual applications in real life, in recent times, we have observed these domain boundaries to be blurrier than ever. For example, Google has a search platform, which can process user input or queries in the forms of keywords (text-based retrieval), voice commands (audio-based retrieval), and image, all simultaneously. Maintaining different networks to process each of these input domains for such a multi-domain information retrieval system is a solution, which can result in high costs and a huge volume of training data requirement to maintain the quality of retrieval. This indicates the need for a generalized model which can seamlessly handle such user queries from multiple domains or even from unknown domains.

There are many notable research papers to address such domain generalization (DG) problem for object classification, but very few paper explore this problem in terms of retrieval. Traditionally, retrieval problems have explored the generalization of object categories in depth, especially in zero-shot sketch-based image retrieval (ZS-SBIR) [Shen et al., 2018][Yelamarthi et al., 2018]. ZS-SBIR addresses the problem of image retrieval from a gallery or search-set when the query sketch is unseen or unknown to the trained model. Universal Cross-domain Retrieval (UCDR) [Paul et al., 2021] combined the problem of ZS-SBIR and domain-generalization for cross-domain retrieval, where the users’ query may belong to an unknown category, as well as an unknown domain. A common practice followed in all such DG-work is that the training data consists of samples from multiple domains (eg. sketch, info-graph, clip-art, cartoon etc.) and the trained model is tested for queries from an unknown domain (eg. Quickdraw), which was not encountered by the model during training. Needless to say that such a requirement of training data spanning across multiple training domains and categories is very restrictive in nature. Thus the generalization achieved in such scenarios may not directly translate to a low-data regime.

In this work, we aim to explore the generalization challenges in retrieval context under a low-data scenario. By “low-data,” we refer to the training data from only two domains followed in traditional cross-domain or cross-modal retrieval problems [Liu et al., 2017][Dutta and Akata, 2019a]. We attempt to explore the possibilities of making such traditional models more generalizable towards any unknown (domain or category-wise) test data. Thus, the UCDR [Paul et al., 2021] protocol has been chosen as the test condition since it already combines the category-wise and domain-wise generalization challenges and thus very closely represents a real-world retrieval scenario. We refer to this challenging problem as low-data UCDR, and use Semantic-neighbourhood and Mixture-prediction Network (SnMpNet [Paul et al., 2021], originally proposed to address UCDR) as our base model for
all analysis throughout this paper. We first observe the effect of a reduced training set (smaller number of domains and categories than [Paul et al., 2021]) on the performance of SnMpNet to justify further research in this direction. Next, we explore possible directions to address the drop in performance of SnMpNet in a data-scarce situation. We propose to obtain this by adapting the model to the test data during inference. Such adaptation is performed by minimizing variations of self-supervised losses because of their ability to learn from unlabeled or unstructured data. RotNet [Gidaris et al., 2018], jigsaw puzzles [Noroozi and Favaro, 2016], and Barlow Twins [Zbontar et al., 2021] are some of these losses studied in this paper. This approach is based on our hypothesis that any information extracted from a query sample of an unknown domain and/or category may help an already trained model adapt to the underlying distribution shift quickly and thus result in a better retrieval list. Such test-time training methodologies have shown promise previously in ZS-SBIR [Sain et al., 2022]. It should be mentioned that even though our experiments are reported using only SnMpNet as the base model, the proposed approach can be seamlessly extended to any cross-domain retrieval models to generalize under UCDR.

Thus, we summarize the contribution of this paper here:

1. In this work, we attempt to explore the UCDR problem in low or restricted data regime. Towards that goal, SnMpNet [Paul et al., 2021] is treated as the base model.
2. We explore a number of self-supervision based learning techniques to bridge the domain-gap during inference.
3. Extensive experiments and analysis across multiple-datasets are performed to demonstrate the effectiveness of the proposed training and adaptation strategy.

Next, we briefly discuss the relevant recent work in this direction in Section 2. The rest of the paper is organized in the following fashion: we discuss the proposed test-time training approach using self-supervised losses in Section 3, followed by our findings and analysis in Section 4. Finally, we conclude this paper with a summary in Section 5.

2 Related Work

Here, we discuss some of the seminal works in image retrieval, test-time training, and self-supervised representation learning to elaborate on the background of this paper.

Zero-shot Sketch-based Image Retrieval (ZS-SBIR): It addresses the problem of sketch-based image retrieval when the query sketch belongs to a category that was not seen by the model during training. The problem was first introduced by [Shen et al., 2018][Yelamarthi et al., 2018], as a category-wise generalization extension of traditional sketch-based image retrieval (SBIR) [Liu et al., 2017][Zhang et al., 2018]. Later, [Dey et al., 2019][Dutta and Akata, 2019b][Dutta et al., 2020a][Dutta et al., 2020b] have reported significant improvements in this direction. The general approach for this problem followed in these papers is to learn a latent-space or shared-space representation of sketch and images, by means of a semantic supervision (generally the word2vec or GloVe-representation of the training category names), so that the sketch and images from same categories can be placed close to each other in this learned latent-space. In contrast to this popular approach, [Liu et al., 2019] proposed a single-branch architecture for both domains with a domain-indicator function to reduce the number of trainable parameters. This architecture has been adopted very closely in our base model SnMpNet [Paul et al., 2021] for UCDR.

Universal Cross-Domain Retrieval (UCDR): UCDR-protocol [Paul et al., 2021] further extends ZS-SBIR towards domain-wise generalization during retrieval. Thus, it proposed to move beyond sketch-query, successfully modeling any real-life retrieval scenario. The proposed model SnMpNet for UCDR learns a domain-invariant and semantically meaningful representation of data for retrieval using a single-branch architecture as in [Liu et al., 2019]. The details of this model have been discussed in Section 3.1.

Test-Time Training (TTT): This was first introduced by [Sun et al., 2020], where the test data is treated as an unlabelled dataset, and the model weights are updated via a self-supervised learning approach. It aims at improving model generalization by increasing robustness against distribution shifts, owing to the real-life situation where the train and test data often belong to different distributions. The rotation prediction task proposed by [Gidaris et al., 2018] is used as the learning objective for this self-supervision task. Recently, [Liu et al., 2021] performed a detailed analysis of such test-time training strategies under significant distribution shift, and proposed a test-time feature-alignment and moment-matching strategy to address the same. Tent [Wang et al., 2020a] adapts the model parameters to distribution shifts in test-time by minimizing the entropy of model predictions. However, the entropy minimization loss can only be used in the classification setting since it belongs to a class of probabilistic losses, which is not present in the retrieval setting of SnMpNet. [Bartler et al., 2022] combines meta-learning, self-supervision, and test-time adaptation to address corrupted image classification benchmark on the CIFAR-10 dataset. A contrastive self-supervision learning technique is combined with pseudo-labeling in [Chen et al., 2022]. [Wang et al., 2022] proposes a continual learning technique for test-time adaptation. Sketch3T [Sain et al., 2022] utilizes a self-supervised task of sketch-raster to sketch vector translations. This helps in adapting the model to the unique style of new sketches in test-time, as well as new categories. This is the first work to apply test-time training to the ZS-SBIR task. However, it deals solely with the sketch domain. In the UCDR setting, the query sample can belong to any unseen domain, and hence we cannot use such a specialized self-supervised loss.

Self-Supervised Learning: Recent self-supervised algorithms share a common methodology of learning semantic information about data, and are independent of variations in style, orientation, and distortions. Few notable works in this direction are RotNet [Gidaris et al., 2018], Jigsaw Puzzles [Noroozi and Favaro, 2016], Barlow Twins [Zbontar et al., 2021], [Grill et al., 2020], [Chen et al., 2020] etc. RotNet [Gidaris et al., 2018] argues that a model capable of predicting the rotational angles applied to an image necessarily has contextual and class awareness, and therefore the rotation
3 Proposed Method

We begin the discussion of the proposed method with a short description of the base model SnMpNet [Paul et al., 2021].

3.1 Base Model - SnMpNet:
The Semantic Neighbourhood and Mixture Prediction Network (SnMpNet) has a deep neural architecture, with SE-ResNet50 as its backbone feature extractor. SnMpNet aims to learn a domain-invariant, as well as a semantically meaningful representation of data so that domain-generalization and category-wise generalization can be achieved simultaneously. Following CuMix [Mancini et al., 2020], SnMpNet also treats the input data in a mixed format, where the mixing may be performed inter or intra-domain. To obtain the domain-invariance, the mixture-prediction loss $L_{Mp}$ is introduced. The objective of this loss is to predict the correct ratio of the component categories present in the input mixed sample. By predicting only the component categories in this mixed sample, essentially, the model tries to forget the domain-specific information present in it, thus producing a domain-invariant representation of data. Additionally, SnMpNet also minimizes a semantic neighbourhood loss $L_{Sn}$, which is essentially a cross-entropy loss computed between the latent-space representation of those mixed samples and their corresponding semantic ground-truth data (e.g., word2vec representations of their category-name). This is a generic approach followed by many ZS-SBIR algorithms to obtain a semantically meaningful representation of unseen category data, which can bring the relevant sketch and images close to each other in the representation space. Final retrieval is performed in this semantic-space on the basis of the Euclidean distance between the query sample and search-set instances. In our work, we retain the architecture and training methodology of SnMpNet as it is, which provisions for this base model to be replaced by any cross-domain retrieval algorithm with a shared-space representation learning technique.

Next, we discuss the test-time training proposed on top of
such a black-box retrieval algorithm to enhance its performance for UCDR. We begin this discussion by providing a brief insight into the self-supervision techniques explored for the same.

3.2 Self-supervision Techniques for Unknown Data

Self-supervised learning (SSL) has become a popular choice when learning from unlabeled or unstructured data. In this work, we specifically explore the following three SSL-loss components in this regard. We choose RotNet [Gidaris et al., 2018] and Jigsaw [Noroozi and Favaro, 2016] because of their simplicity, as well as Barlow twins [Zbontar et al., 2021] for their effectiveness in the low-data condition. Here, we first describe the losses.

RotNet Loss: RotNet [Gidaris et al., 2018] has been a very popular choice for introducing self-supervision in a feature learning network, due to its simplicity and effectiveness. It uses four rotations of an input image, such as in angles \( \{0^\circ, 90^\circ, 180^\circ, 270^\circ\} \), and learns to predict the rotation-index of any such sample from its corresponding feature representations. Thus, the RotNet-loss is computed as,

\[
L_{rotNet} = \frac{1}{n} \sum_{i=1}^{n} L_{CE}(r_i, h_i)
\]

where \( L_{CE} \) is the cross-entropy loss computed between the true rotation-index \( r_i \) and the predicted index \( h_i \). The loss is averaged over the total \( n \)-number of samples present in the training set. This loss is minimized without the direct class supervision of the samples, but indirectly learns the semantic content of the data through the rotation prediction.

Jigsaw Puzzles Loss: Similar to RotNet, jigsaw puzzle [Noroozi and Favaro, 2016] is another very effective self-supervision component, which has been used in any downstream tasks, such as domain-generalization [Wang et al., 2020b]. Here, any input image is broken down into a number of patches, based on the fixed grid size. For example, following the authors’ approach in [Noroozi and Favaro, 2016], we resize and then break down an image into 9-patches using a 3 \times 3 grid. These 9-patches are then shuffled and total possible 31-combinations of jigsaw images are created through permutations. Now, the network is trained to predict the possible permutation index of such jigsaw images, forming the following jigsaw-puzzle loss,

\[
L_{jigsaw} = \frac{1}{n} \sum_{i=1}^{n} L_{CE}(p_i, h_i)
\]

where this cross-entropy loss is computed between the true permutation-index \( p_i \) and the predicted index \( h_i \), and averaged over the total number of samples present in the test set.

Barlow Twins Loss: We follow a similar formulation of this loss, as proposed in [Zbontar et al., 2021]. For each image in the test set, \( X_i \), we create two differently augmented version of the same as \( X_i^{(1)} \) and \( X_i^{(2)} \). Augmented versions are created through various image operations, such as Gaussian blur, grayscale transformation, solarization, etc. A cross-correlation matrix \( C \in \mathbb{R}^{d \times d} \) is computed between the feature representations of these augmented versions as \( x_i^{(1)} \in \mathbb{R}^d \) and \( x_i^{(2)} \in \mathbb{R}^d \) and the following loss function is minimized,

\[
L_{SSSL}^{BT} = \frac{1}{n} \sum_{i=1}^{n} \left( \sum_{a=1}^{d} (1 - C_{aa})^2 + \gamma \sum_{a=1}^{d} \sum_{b \neq a} C_{ab}^2 \right)
\]

where,

\[
C_{ab} = \frac{\sum_{i=1}^{n} x_i^{(1)} x_i^{(2)}}{\sqrt{\sum_{i=1}^{n} (x_i^{(1)})^2} \sqrt{\sum_{i=1}^{n} (x_i^{(2)})^2}}
\]

Here, the main idea is to make the diagonal term of the cross-correlation matrix 1, so that the embedding becomes invariant to any distortion. Additionally, the off-diagonal terms are pushed towards zero to de-correlate the different vector components of the embedding [Zbontar et al., 2021]. It has been reported to be particularly successful in image classification problems in the low-data regime.

In our formulation, the base model stays as a black-box and is trained in the usual manner. These above-mentioned self-supervised losses only become active to adapt the already trained base model on the test sets during retrieval. Next, we discuss such adaptation or test-time training in detail.

3.3 Test-time Training (TTT) for UCDR

Here, we discuss the proposed test-time training or adaptation framework to address the UCDR under low-data regime. In our setup, since the training data does not have samples from many numbers of domains or categories, the generalization ability of the base model SnMpNet would be low. In other words, the network may be biased towards the job of sketch-based image retrieval, in case sketch and image are the domains present during training. But its performance degrades (details in the experiments section, Table 1) when a cartoon or painting is presented as query. We hypothesize that under such a condition, any information or clue extracted from test query may help the network to adapt and retrieve better for that query domain.

Towards that goal, we propose to perform a single-step parameter update of the network using the gradient computed through any of the SSL-loss components. Thus, for any test sample \( X_{te} \), we perform a forward-propagation, compute the \( L_{SSSL}^v \in \{ \text{rotnet, jigsaw, BT} \} \), and then compute the corresponding gradients and back-propagate through the end-to-end network components just once to tune the already trained SnMpNet on the basis of the test sample itself. We make the final inference on the retrieval list for the test sample using this updated model instead of the previously-trained SnMpNet. Such adaptation towards the unknown test samples provides a better generalization in the low-data regime, which we can observe from the experimental data presented in Section 4.

3.4 Proposed SnMpNet-variants

Thus, depending on the SSL-loss component used for test-time adaptation of the model, we propose three variants of SnMpNet as described below:
1. rotation-SnMpNet: During test-time, the test samples are rotated as stated previously, to create an augmented test-set. A linear projection layer on top of the 2048-dimensional feature embedding of SnMpNet predicts probabilities of the 4 rotation angles. The network parameters are updated only once on the basis of $\mathcal{L}_{\text{SSL}}$ computed over this newly generated test set.

2. jigsaw-SnMpNet: Here, during test-time training, only $\mathcal{L}_{\text{SSL}}$ will be active. The test samples are resized, and jigsaw images are created for the same. Similar to rotation-SnMpNet, a linear projection layer predicts the permutation index of the jigsaw image.

3. BT-SnMpNet: Finally, for this variant, noisy or distorted test samples are generated to compute the cross-correlation matrix $C$. $C$ between the 2 augmentations is computed using the 300-dimensional semantic embedding output of SnMpNet. We compute $\mathcal{L}_{\text{SSL}}$ based $C$ and accordingly update the model.

Thus, the proposed test-time training methodology is very easy and can be seamlessly used with any trained cross-domain retrieval model without any modification in its architecture or training process. Now, with this discussion, we’ll move on to the experimental validation in the next section. Our overall approach is illustrated in Figure 1.

4 Experiments

We discuss the experimental validation of our proposed test-time training strategy for low-data UCDR. As we mentioned before, SnMpNet [Paul et al., 2021] stays as our base model throughout all the experiments and we also analyse the performance of each of the variants discussed in the previous section. Here we report our results for three different test-cases: (1) Low-data UCDR: where the training set for the SnMpNet is small (only two training domains) as presented in [Dey et al., 2019][Dutta et al., 2020a] etc.; (2) UCDR: where the training set contains huge multi-domain data, as in [Paul et al., 2021]; (3) Cross-dataset UCDR: where the training data is large [Paul et al., 2021], but the test domains belong to a different dataset, thus bringing larger domain-gap in the picture. First, we briefly introduce the datasets used for this analysis.

4.1 Datasets

We experimented with two large-scale datasets for analysis.

Sketchy extended [Sangkloy et al., 2016] contains 75,471 sketches and 73,002 images across 125 categories. Out of these total 125-categories, 93, 1, 11, and 21-classes are used for training, validation, and testing, respectively (following the ZS-SBIR setup popularly used in [Dey et al., 2019]). Since this dataset contains data from only two domains, thus it provides a real-time training scenario, where collecting multi-domain data as part of the training is challenging. While evaluating our approach for Low-data UCDR, we utilize samples (which belong to a domain other than sketch and image, as well as from an unknown category) from another dataset DomainNet(details in the next paragraph) to face a significant domain-wise and category-wise difference between the query, and the training data - which is the true objective of a generalized retrieval.

DomainNet [Peng et al., 2019] has approximately 6,00,000 samples from 345 categories, collected in six domains, namely, Clip-art, Sketch, Real, Quickdraw, Infograph, and Painting. Following [Mancini et al., 2020], 245 and 55 classes are used for training and validation [Mancini et al., 2020], respectively. To simulate the unknown domain, generally one domain is held out and rests are used for training any model. For UCDR and Cross-dataset UCDR, we use training samples from DomainNet, but for Cross-dataset UCDR, the test samples belong to Sketchy-dataset.

For fair comparison, we reported results of SnMpNet and proposed variants on the same data-split.

4.2 Implementation details

We use PyTorch 1.1.0 (following [Paul et al., 2021]) and a single Nvidia Tesla v100 GPU for implementation. SGD optimizer with weight decay (momentum set to 0) is used to be on par with [Sun et al., 2020]. A batch size of 64 is maintained for all experiments. We apply standard data augmentations like random resized-crop, horizontal-flip, and color-jitter during the single epoch of training.

During inference, we just update the trained model for a single epoch (as we find this is usually sufficient for parameter adaptation) based on the available test sets. From our experiments, we don’t observe any major improvement by training for more epochs. To prevent parameter divergence from the learned distribution on the training samples, we use a lower learning rate (1e-6 to 1e-4) than what was used for training. Also, we employ different learning rates for the final projection layers compared to the rest of the network. Particularly, the backbone is learned at $1/10$ of the learning rate for the projection layer.

4.3 Test-time Training for low-data UCDR

First, we analyze the effect of limited training data for UCDR. Towards that goal, we train the original SnMpNet model [Paul et al., 2021] with the training-split of Sketchy-extended dataset, and test on the additional domain query data from DomainNet. We compare this performance with the results reported in [Paul et al., 2021], where the same model is trained with multi-domain data of DomainNet. Following [Paul et al., 2021], these results are reported in the form of mAP@200 and Prec@200 in Table 1. Also, we perform experiments for two different configurations of the search set: (1) when the search set contains samples from unseen categories only; and (2) when both seen and unseen categories are present in the search set. We exclude the Sketch domain of DomainNet from testing as it is already present in the training set of Sketchy-extended and hence isn’t unseen.

As we can observe from Table 1, the performance of SnMpNet drops significantly when the number of training domains becomes restricted. This has been observed for all unseen query domains, except for Quickdraw. This may be because the contents of Quickdraw is basically Sketch (but very abstract in nature); thus, SnMpNet performs retrieval for this case easily, compared to other drastically different query do-
| Query Domain | Training Domains | Method | Unseen-class Search Set | Seen+Unseen-class Search Set |
|--------------|------------------|--------|-------------------------|-----------------------------|
|              |                  |        | mAP@200 | Prec@200 | mAP@200 | Prec@200 |
| Painting     | Real, Sketch, Infograph, QuickDraw, Clipart | SnMpNet | 0.4031 | 0.3332 | 0.3635 | 0.3019 |
|              | Sketch, Image | SnMpNet | 0.3827 | 0.3167 | 0.3480 | 0.2842 |
|              | rotation-SnMpNet | jigsaw-SnMpNet | 0.3899 | 0.3239 | 0.3508 | 0.2892 |
|              | jigsaw-SnMpNet | BT-SnMpNet | 0.3807 | 0.3154 | 0.3441 | 0.2829 |
|              |                  | SnMpNet | 0.3932 | 0.3337 | 0.3481 | 0.2905 |
| Clipart      | Real, Sketch, Infograph, QuickDraw, Painting | SnMpNet | 0.4198 | 0.3323 | 0.3765 | 0.2959 |
|              | Sketch, Image | SnMpNet | 0.3318 | 0.2539 | 0.2923 | 0.2172 |
|              | rotation-SnMpNet | jigsaw-SnMpNet | 0.3568 | 0.2796 | 0.3150 | 0.2414 |
|              | jigsaw-SnMpNet | BT-SnMpNet | 0.3579 | 0.2803 | 0.3158 | 0.2425 |
|              |                  | SnMpNet | 0.3465 | 0.2744 | 0.2987 | 0.2271 |
| QuickDraw     | Real, Sketch, Infograph, Clipart, Painting | SnMpNet | 0.1736 | 0.1284 | 0.1512 | 0.1111 |
|              | Sketch, Image | SnMpNet | 0.1845 | 0.1471 | 0.1551 | 0.1241 |
|              | rotation-SnMpNet | jigsaw-SnMpNet | 0.1913 | 0.1489 | 0.1581 | 0.1222 |
|              | jigsaw-SnMpNet | BT-SnMpNet | 0.1905 | 0.1498 | 0.1577 | 0.1227 |
|              |                  | SnMpNet | 0.1515 | 0.1231 | 0.1082 | 0.0819 |
| Infograph    | Real, Sketch, Clipart, QuickDraw, Painting | SnMpNet | 0.2079 | 0.1717 | 0.1800 | 0.1496 |
|              | Sketch, Image | SnMpNet | 0.1660 | 0.1322 | 0.1358 | 0.1071 |
|              | rotation-SnMpNet | jigsaw-SnMpNet | 0.1950 | 0.1587 | 0.1634 | 0.1325 |
|              | jigsaw-SnMpNet | BT-SnMpNet | 0.1904 | 0.1539 | 0.1592 | 0.1281 |
|              |                  | SnMpNet | 0.1634 | 0.1326 | 0.1322 | 0.1034 |
| Average      | 5/6 DomainNet domains | SnMpNet | 0.3011 | 0.2414 | 0.2678 | 0.2146 |
|              | Sketch, Image | SnMpNet | 0.2663 | 0.2125 | 0.2328 | 0.1852 |
|              | rotation-SnMpNet | jigsaw-SnMpNet | 0.2832 | 0.2278 | 0.2468 | 0.1963 |
|              | jigsaw-SnMpNet | BT-SnMpNet | 0.2799 | 0.2248 | 0.2442 | 0.1940 |
|              |                  | SnMpNet | 0.2636 | 0.2160 | 0.2218 | 0.1757 |

Table 1: UCDR Evaluation of SnMpNet and proposed variants when training data is limited to only two domains.

mains. Thus, this observation justifies the need for further effort in this direction.

Next, we explore the effectiveness of test-time training in this context. We observe the performance of all 3 SnMpNet variants under limited training domain conditions in Table 1. We can observe that for all 4 query domains (sketch excluded), test-time training has improved the performance of SnMpNet [Paul et al., 2021], trained on Sketchy-extended data. Particularly, rotation-SnMpNet significantly outperforms the base model on all 4 query domains and almost matches the original SnMpNet trained on the 5 DomainNet domains. These results are encouraging and support our previous hypothesis that any information/hint extracted from the unknown test sample could help improve the model’s performance under such a challenging condition of UCDR.

### 4.4 Effectiveness of Test-time Training for UCDR

Next, we study the effectiveness of TTT when low-data constraint is removed. We assume that multi-domain data in sufficient quantity is available to the model for training, and aim to explore if TTT can further improve the performance of the model for UCDR. Here, the pretrained SnMpNet uses training data from DomainNet. To simulate the “unknown domain and unknown class” query-data notion, one domain is left out during training, and we use samples from unused category of this held-out domain for testing. We summarize the observations in Table 2. We see that at least one of the proposed variants outperforms SnMpNet on Sketch, Painting, and Clipart domains for both configurations of the search set. However, performance drops for Infograph and Quickdraw by small amounts. This also impacts the overall Average performance. Only BT-SnMpNet outperforms SnMpNet on Prec@200 for unseen-class search set. We observe this to be a limitation of test-time adaptation in UCDR. In case sufficient training data is available during training, the proposed self-supervision-based TTT cannot make improvement on the trained model’s retrieval performance. Similar failure analysis for TTT has been performed by TTT++ [Liu et al., 2021] in the context of image-classification.

### 4.5 Cross-dataset UCDR

We also perform experiment where the training data is not low, but the test set has lower number of categories than the training set. For this, we trained the model using five domains, except Sketch, from DomainNet and then tested it on the unseen-class query sketches from the Sketchy-extended dataset. The results are reported in Table 3. We observe that we get improved performance over SnMpNet with BT-SnMpNet, and it’s quite close to the original ZS-SBIR numbers (mAP@200: 0.5781 and Prec@200: 0.5155) reported in [Paul et al., 2021]. However, rotation-SnMpNet and jigsaw-SnMpNet depict a significant drop. Similar to 4.4, we conclude this as a failure case for TTT, where the adaptation leads to more harm than improvement. This may be because of the...
Table 2: Comparison of SnMpNet and its TTT-variants for UCDR protocol on DomainNet.

| Training Domains | Query Domain | Method           | Unseen-class Search Set | Seen+Unseen-class Search Set |
|------------------|--------------|------------------|-------------------------|-----------------------------|
| Training Domains |              |                 | mAP@200 | Prec@200 | mAP@200 | Prec@200 |
| Real, Painting,  | Sketch       | SnMpNet          | 0.3007  | 0.2432   | 0.2624  | 0.2134  |
| Clipart, QuickDraw, |              | rotation-SnMpNet | 0.3033  | 0.2448   | 0.2658  | 0.2090  |
| Infograph        |              | jigsaw-SnMpNet   | 0.3082  | 0.2501   | 0.2724  | 0.2148  |
| Clipart          |              | SnMpNet          | 0.1736  | 0.1284   | 0.1512  | 0.1111  |
|                 |              | rotation-SnMpNet | 0.1595  | 0.1129   | 0.1199  | 0.0925  |
|                 |              | jigsaw-SnMpNet   | 0.1588  | 0.1115   | 0.1210  | 0.0854  |
|                 |              | BT-SnMpNet       | 0.2993  | 0.2479   | 0.2440  | 0.1987  |
| Average          |              | SnMpNet          | 0.2079  | 0.1713   | 0.1800  | 0.1496  |
|                 |              | rotation-SnMpNet | 0.1993  | 0.1734   | 0.1659  | 0.1365  |
|                 |              | jigsaw-SnMpNet   | 0.1944  | 0.1573   | 0.1609  | 0.1317  |
|                 |              | BT-SnMpNet       | 0.1903  | 0.1597   | 0.1502  | 0.1229  |
| Average          |              | SnMpNet          | 0.2079  | 0.1713   | 0.1800  | 0.1496  |
|                 |              | rotation-SnMpNet | 0.1993  | 0.1734   | 0.1659  | 0.1365  |
|                 |              | jigsaw-SnMpNet   | 0.1944  | 0.1573   | 0.1609  | 0.1317  |
|                 |              | BT-SnMpNet       | 0.1903  | 0.1597   | 0.1502  | 0.1229  |

Table 3: UCDR evaluation of proposed SnMpNet-variants for relatively easier test-sets.

relatively high and diverse data during training, hence TTT induces parameter divergence in a generalized model.

Thus, this study clearly shows how test-time training can alleviate the domain gap across a wide range of test domains with just a single epoch of self-supervised training with the test data available at hand. Hence, test-time training can be a potential solution for retrieval in a data-constrained setting where the training data is limited, and the test data can come from a radically different distribution and any unseen domain or class.

5 Conclusion & Future Work

In this work, we proposed test-time training heuristics for the UCDR task in a low-data regime using 3 different self-supervision techniques. To the best of our knowledge, this is the first such work in this direction. Previously, test-time training has been mainly explored in the classification and ZS-SBIR settings. In addition, we also study cross-dataset generalization in the UCDR setting and show how test-time training can massively bridge the domain gap across datasets. Extensive experiments and comparisons on two large-scale datasets show the effectiveness of our proposed techniques.

To build on our work further, we plan to introduce the self-supervised loss components, especially, RotNet-loss, during the training stage of SnMpNet. We specifically choose RotNet because of its relative simplicity of implementation and also its superior performance in the low-data regime among the 3 self-supervised losses. We hypothesize that this would help the network to learn the RotNet loss dynamics better before being exposed to it at test-time.

Ethical Statement

There are no ethical issues.

References

[Arandjelovic and Zisserman, 2018] Relja Arandjelovic and Andrew Zisserman. Objects that sound. In Proceedings of the European conference on computer vision (ECCV), pages 435–451, 2018.

[Bartler et al., 2022] Alexander Bartler, Andre Bühler, Felix Wiewel, Mario Döbler, and Bin Yang. Mt3: Meta test-time training for self-supervised test-time adaption. In International Conference on Artificial Intelligence and Statistics, pages 3080–3090. PMLR, 2022.

[Cao et al., 2022] Min Cao, Shiping Li, Juntao Li, Liqiang Nie, and Min Zhang. Image-text retrieval: A survey on recent research and development. In International Joint Conference on Artificial Intelligence, 2022.

[Chen et al., 2020] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework
for contrastive learning of visual representations. In *International conference on machine learning*, pages 1597–1607. PMLR, 2020.

[Chen et al., 2022] Dian Chen, Dequan Wang, Trevor Darrell, and Sayna Ebrahimi. Contrastive test-time adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 295–305, 2022.

[Dey et al., 2019] Sounek Dey, Pau Riba, Anjan Dutta, Josep Lladós, and Yi-Zhe Song. Doodle to search: Practical zero-shot sketch-based image retrieval. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2179–2188, 2019.

[Dutta and Akata, 2019a] A. Dutta and Z. Akata. Semantically tied paired cycle consistency for zero-shot sketch-based image retrieval, 2019. CVPR.

[Dutta and Akata, 2019b] Anjan Dutta and Zeynep Akata. Semantically tied paired cycle consistency for zero-shot sketch-based image retrieval. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 5089–5098, 2019.

[Dutta et al., 2020a] Titir Dutta, Anurag Singh, and Soma Biswas. Adaptive margin diversity regularizer for handling data imbalance in zero-shot sbir. In *European Conference on Computer Vision*, pages 349–364. Springer, 2020.

[Dutta et al., 2020b] Titir Dutta, Anurag Singh, and Soma Biswas. Styleguide: zero-shot sketch-based image retrieval using style-guided image generation. *IEEE Transactions on Multimedia*, 23:2833–2842, 2020.

[Gidaris et al., 2018] Spyros Gidaris, Praveer Singh, and Nikos Komodakis. Unsupervised representation learning by predicting image rotations. *arXiv preprint arXiv:1803.07728*, 2018.

[Grill et al., 2020] Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires, Zhaohan Guo, Mohammad Gheshlaghi Azar, et al. Bootstrap your own latent-a new approach to self-supervised learning. *Advances in neural information processing systems*, 33:21271–21284, 2020.

[Liu et al., 2017] Li Liu, Fumin Shen, Yuming Shen, Xianglong Liu, and Ling Shao. Deep sketch hashing: Fast freehand sketch-based image retrieval. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2862–2871, 2017.

[Liu et al., 2019] Qing Liu, Lingxi Xie, Huiyu Wang, and Alan L Yuille. Semantic-aware knowledge preservation for zero-shot sketch-based image retrieval. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 3662–3671, 2019.

[Liu et al., 2021] Yuejiang Liu, Parth Kothari, Bastien van Delft, Baptiste Bellot-Gurlet, Taylor Mordan, and Alexandre Alahi. Ttt+++: when does self-supervised test-time training fail or thrive? In *Proceedings of Neural Information Processing Systems*, 2021.

[Mancini et al., 2020] M. Mancini, Z. Akata, E. Ricci, and B. Caputo. Towards recognizing unseen categories in unseen domains, 2020. ECCV.

[Noroosi and Favaro, 2016] Mehdi Noroosi and Paolo Favaro. Unsupervised learning of visual representations by solving jigsaw puzzles. In *European conference on computer vision*, pages 69–84. Springer, 2016.

[Paul et al., 2021] Soumava Paul, Titir Dutta, and Soma Biswas. Universal cross-domain retrieval: Generalizing across classes and domains. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 12056–12064, 2021.

[Peng et al., 2019] X. Peng, Q. Bai, X. Xia, Z. Huang, K. Saenko, and B. Wang. Moment matching for multi-source domain adaptation, 2019. ICCV.

[Sain et al., 2022] Aneeshan Sain, Ayan Kumar Bhunia, Vaishnav Potlapalli, Pinaki Nath Chowdhury, Tao Xiang, and Yi-Zhe Song. Sketch3t: Test-time training for zero-shot sbir. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7462–7471, 2022.

[Sangkloy et al., 2016] P. Sangkloy, N. Burnell, C. Ham, and J. Hays. The sketchy database: learning to retrieve badly drawn bunnies. *ACM TOG*, 35(4):1–12, 2016.

[Shen et al., 2018] Yuming Shen, Li Liu, Fumin Shen, and Ling Shao. Zero-shot sketch-image hashing. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3598–3607, 2018.

[Sun et al., 2020] Yu Sun, Xiaolong Wang, Zhuang Liu, John Miller, Alexei Efros, and Moritz Hardt. Test-time training with self-supervision for generalization under distribution shifts. In *International conference on machine learning*, pages 9229–9248. PMLR, 2020.

[Wang et al., 2020a] Dequan Wang, Evan Shelhamer, Shaoqiong Liu, Bruno Olshausen, and Trevor Darrell. Tent: Fully test-time adaptation by entropy minimization. *arXiv preprint arXiv:2006.10726*, 2020.

[Wang et al., 2020b] S. Wang, L. Yu, C. Li, C. W. Fu, and P. A. Heng. Learning from extrinsic and intrinsic supervision for domain generalization, 2020. ECCV.

[Wang et al., 2022] Qin Wang, Olga Fink, Luc Van Gool, and Dengxin Dai. Continual test-time domain adaptation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7201–7211, 2022.

[Yelamarthi et al., 2018] Sasi Kiran Yelamarthi, Shiva Krishna Reddy, Ashish Mishra, and Anurag Mittal. A zero-shot framework for sketch based image retrieval. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 300–317, 2018.

[Zbontar et al., 2021] Jure Zbontar, Li Jing, Ishan Misra, Yann LeCun, and Stéphane Deny. Barlow twins: Self-supervised learning via redundancy reduction. In *International Conference on Machine Learning*, pages 12310–12320. PMLR, 2021.
[Zhang et al., 2018] Jingyi Zhang, Fumin Shen, Li Liu, Fan Zhu, Mengyang Yu, Ling Shao, Heng Tao Shen, and Luc Van Gool. Generative domain-migration hashing for sketch-to-image retrieval. In Proceedings of the European conference on computer vision (ECCV), pages 297–314, 2018.