

# Instance-Level Generation for Representation Learning

**Yankun Wu**

*The University of Osaka*

*yankun@is.ids.osaka-u.ac.jp*

**Zakaria Laskar**

*School of Data Science*

*IISER Thiruvananthapuram*

*zakaria.laskar@iisertvm.ac.in*

**Giorgos Kordopatis-Zilos**

*VRG, FEE*

*Czech Technical University in Prague*

*kordogeo@fel.cvut.cz*

**Noa Garcia**

*The University of Osaka*

*noagarcia@ids.osaka-u.ac.jp*

**Giorgos Tolias**

*VRG, FEE*

*Czech Technical University in Prague*

*toliageo@fel.cvut.cz*

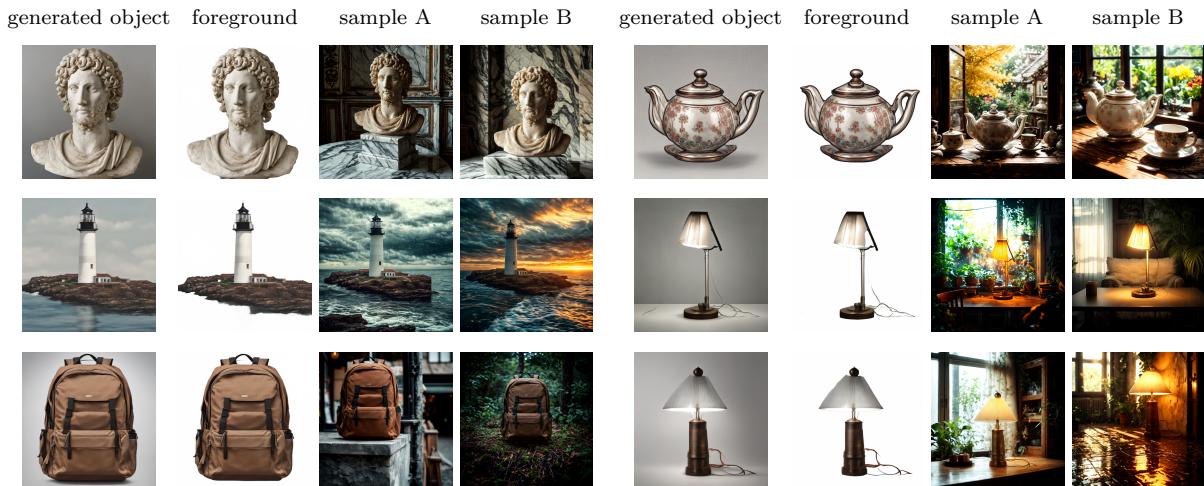


Figure 1: Examples of images generated for learning instance-level representations. Given an object generated by a generative diffusion model (column 1), the foreground is segmented (column 2) and different background variations are added (columns 3 & 4), producing images of the same instance under diverse conditions.

## Abstract

Instance-level recognition (ILR) focuses on identifying individual objects rather than broad categories, offering the highest granularity in image classification. However, this fine-grained nature makes creating large-scale annotated datasets challenging, limiting ILR’s real-world applicability across domains. To overcome this, we introduce a novel approach that synthetically generates diverse object instances from multiple domains under varied conditions and backgrounds, forming a large-scale training set. Unlike prior work on automatic data synthesis, our method is the first to address ILR-specific challenges without relying on any real images. Fine-tuning foundation vision models on the generated data significantly im-

---

proves retrieval performance across seven ILR benchmarks spanning multiple domains. Our approach offers a new, efficient, and effective alternative to extensive data collection and curation, introducing a new ILR paradigm where the only input is the names of the target domains, unlocking a wide range of real-world applications.

## 1 Introduction

Object recognition and retrieval span multiple levels of granularity, from semantic-level labels (Russakovsky et al., 2015) to fine-grained categories (Gosselin et al., 2014; Krause et al., 2015), and the most detailed form, i.e. instance-level recognition (ILR) (Ypsilantis et al., 2021). Unlike semantic recognition, which groups objects into broad classes, ILR identifies unique object instances, treating each real-world entity as its own category. This extreme granularity makes ILR particularly challenging.

ILR has applications in domains such as landmarks (Weyand et al., 2020; Philbin et al., 2007; 2008), artwork (Ypsilantis et al., 2021), products (Oh Song et al., 2016; Peng et al., 2020), fashion (Liu et al., 2016), and everyday objects (Wang & Jiang, 2015; Kordopatis-Zilos et al., 2025). However, large-scale training data remains a major bottleneck. Unlike semantic or fine-grained recognition, where class names help structure data and reduce false negatives, ILR requires exhaustive, instance-specific annotations, an expensive and labor-intensive process. Single-domain datasets rely on manually curated ground truth, while multi-domain datasets often lack dedicated training sets (Wang & Jiang, 2015; Kordopatis-Zilos et al., 2025). Collecting images of the same instance under different conditions further compounds the challenge, slowing progress.

To address this, we propose a novel pipeline that automatically generates images of unique objects under diverse conditions, enabling instance-level representation learning without manual data collection. The pipeline requires only the name of one or more domains, e.g. “everyday objects” or “artworks”, as input and outputs a representation model fine-tuned for those domains. A large language model (LLM) (Hurst et al., 2024) generates a list of relevant object categories, and a generative diffusion model (GDM) (Sauer et al., 2024; Rombach et al., 2022) synthesizes images for those categories. We assume that generations from a given seed define an instance-level class, while different seeds correspond to distinct classes. To ensure diversity, we introduce background and lighting variations using ICLight (Zhang et al., 2025).

The generated instances (see Figure 1) are used to fine-tune a foundational vision encoder such as SigLIP (Zhai et al., 2023). We adopt a metric learning approach (Patel et al., 2022), treating images of the same instance as positives and others as negatives, and optimize an information retrieval metric across large batches. The resulting representation improves over the base model across multiple ILR benchmarks, including artwork, landmark, and product datasets.

This is the first work to learn a single representation model that generalizes across diverse ILR domains while providing an effective alternative to large-scale real data. While prior research explored synthetic training data (Peng et al., 2015; Fan et al., 2024; Tian et al., 2024), our method is the first tailored specifically for ILR. The pipeline synergistically integrates LLMs and GDMs, leveraging rapid advances in both fields and remaining adaptable to future improvements.

## 2 Related work

**Instance-level representations** Instance-level recognition requires image representations that capture fine-grained object details while distinguishing them from numerous semantically similar classes. Generic models like ResNet (He et al., 2016) and CLIP (Radford et al., 2021) struggle in this setting, as they prioritize high-level semantics over instance-specific features. A common solution is fine-tuning pre-trained backbones on domain-specific datasets—such as artwork (Ypsilantis et al., 2021), landmarks (Lee et al., 2022; Shao et al., 2023; Cao et al., 2020; Suma et al., 2024), or products (Patel et al., 2022; Ramzi et al., 2022)—to enhance their ability to differentiate individual instances. Recent efforts focus on universal embeddings (Ypsilantis et al., 2023) that cover jointly a whole range of domains and tasks. However, models still require fine-tuning with class-supervised learning to acquire the necessary discriminative properties, making the scarcity of high-quality labeled datasets a major challenge. Data augmentation techniques (Ypsilantis

---

et al., 2021) help mitigate this issue by generating diverse variations of an instance from limited samples. The only prior work that also leverages generative models for instance-level tasks (Sundaram et al., 2025) fine-tunes a separate model for each instance, requiring a few real images as input. In contrast, our approach trains a single model that generalizes well across objects and domains without relying on any real images.

**Training with synthetic images** Synthetic data has been used in a variety of computer vision problems, such as object detection (Peng et al., 2015; Rozantsev et al., 2015; Georgakis et al., 2017), segmentation (Chen et al., 2019; Ros et al., 2016), autonomous driving (Abu Alhaija et al., 2018), object pose estimation (Cai et al., 2022; Labb   et al., 2020), 3D-tasks (Chang et al., 2015), and recently for representation learning (Tian et al., 2024; Wu et al., 2023). An early practice is to cut the real objects and paste them onto backgrounds to generate synthetic images for instance or object detection (Dwibedi et al., 2017; Georgakis et al., 2017). However, challenges remain in reducing the boundary artifacts and achieving consistent lighting conditions between the object and background, as these problems often result in unrealistic composite images. More recently, the main sources of synthetic images are computer graphics pipeline or rendering engines (Mahmood et al., 2019), generative adversarial networks (GAN) (Besnier et al., 2020; Brock, 2018), and text-to-image GDM (Fan et al., 2024; Saraydiz et al., 2023). Images generated through rendering engines often suffer from domain gap when compared to real-world test images, requiring domain adaptation techniques to mitigate the gap during training. In contrast, GAN and GDM produce more realistic images that do not typically require post-generation domain adaptation (Wang et al., 2020). Text-to-image GDM, in particular, offers a higher degree of control in the image generation process, for example, changing the background of the target object using text prompts (Mokady et al., 2023; Raj et al., 2023; Geng et al., 2024; Zhang et al., 2023). This ability to control image features through text makes GDM particularly valuable for generating diverse images, which is crucial for representation learning (Tian et al., 2024; Wu et al., 2023). However, synthesizing images for instance-level task is not trivial, as it requires generating a synthetic object under various conditions while preserving its structure and texture.

**Metric learning for image retrieval** Given a training dataset, the most common approach for training deep representation networks for image retrieval is supervised learning using categorical labels. As a result, a large number of methods have proposed classification-based losses (Zhai & Wu, 2018; Deng et al., 2019; Teh et al., 2020; Qian et al., 2019; Kim et al., 2020). Despite not directly optimizing the pairwise distance metric that is used at test time, such approaches achieve very good performance, especially when combined with propagating the representation across examples (Elezi et al., 2020; Seidenschwarz et al., 2021; Kotovenko et al., 2023). Other methods directly optimize the distance metric with pairwise losses. These most often rely on hand-crafted loss functions, such as the most popular contrastive (Hadsell et al., 2006), and triplet loss (Schroff et al., 2015), by postulating a correlation between such a training objective and the test time objective which is typically an information retrieval metric. Finding informative pairs and triplets (Musgrave et al., 2020; Roth et al., 2020; Oh Song et al., 2016; Sohn, 2016) appears to be very important. As a natural follow-up, a few recent methods directly optimized differentiable approximations of retrieval metrics, such as average precision (R  l  nek et al., 2020; He et al., 2018; Revaud et al., 2019; Ramzi et al., 2021; 2022) and recall (Patel et al., 2022). In this work, we rely on recall@k (Patel et al., 2022) as a loss function which is demonstrating top results on a variety of benchmarks in the literature and does not require hard negative mining. Self-supervised (Kim et al., 2022) methods exist as well and are shown effective, but are tested only on training data from the target distributions, which is not a realistic setup. A recent alternative to CLIP (Radford et al., 2021), called Unicom (An et al., 2023), trains on LAION 400M (Schuhmann et al., 2021), treats captions as weak annotations to perform text-based clustering, and reformulates the learning as a classification task. Their results show improvements in a set of different retrieval datasets, including instance-level ones. Alternatively, we propose leveraging synthetic data to introduce an extensive collection of objects with diverse variations into the training dataset.

### 3 Method

Next, we formulate the target task and describe the training data generation and representation learning. An overview of the proposed generation process is shown in Figure 2.

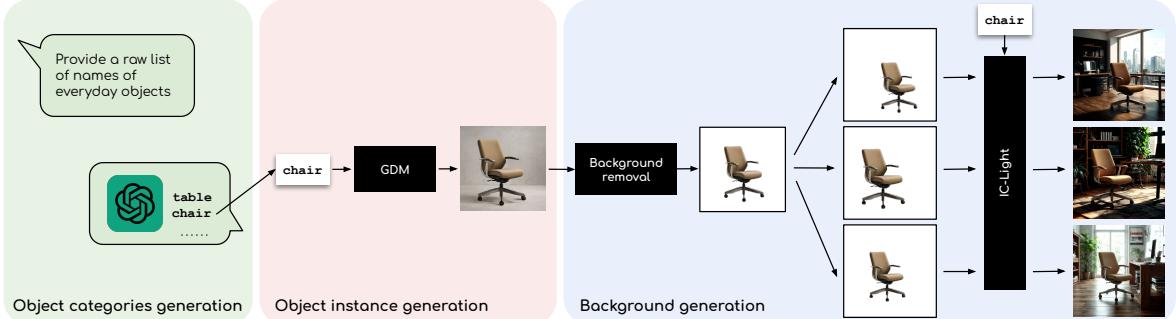


Figure 2: Overview of instance-level training data generation. A domain name or description is the only input, which is used to prompt an LLM to provide a list of object category names. Then, we generate examples of those categories using a GDM, remove the background, and synthesize lighting and background multiple times per generated example to create a diverse set of positive images for each instance.

### 3.1 Task formulation

The target task is instance-level image retrieval. Given a query image, the goal is to retrieve all positive images from a database (db), i.e. those that depict the same object instance as the query. Images depicting different object instances, even if they belong to the same semantic category, are negatives and should not be retrieved. This is an open-world task, testing on unseen objects from a variety of domains which may be seen or unseen during training.

We consider the efficient retrieval variant using global descriptors. Formally, an image  $x$  is mapped to a  $d$ -dimensional global descriptor  $\mathbf{z} = f_\theta(x) \in \mathbb{R}^d$ . Retrieval is performed via nearest neighbor search in Euclidean space, ranking database descriptors based on their cosine similarity to the query. The encoder, parameterized by  $\theta$ , is optimized during training. We focus on fine-tuning foundational models (Zhai et al., 2023) that already perform well by pretraining.

### 3.2 Instance-level training data generation

We propose a pipeline that requires only the name, or a textual description, of a target domain as input, and automatically generates an image training set with instance-level labels. The process consists of four stages: (i) *Objects categories generation* by prompting an LLM to provide a list of object category names; (ii) *Object instance generation* by prompting a GDM to generate object instances from each category; (iii) *Background generation* by synthesizing diverse backgrounds per instance; (iv) *Viewpoint variations* by augmenting the generated images with geometric transformations. Each stage of the process is detailed below.

**Object categories generation** Object categories (e.g. *table*, *chair*, *clock*) are needed to prompt the GDM for image generation. We automatically obtain a list of object categories by prompting an LLM with minimal information about the domain of interest. In the general case in which we do not target a specific domain, the prompt we use is “Provide a raw list of names of everyday objects.” For specific domains, such as artwork, landmark, or product, we enrich the prompt with relevant information and hint with a few examples of object categories. Full details of the designed prompts are provided in the supplementary material. This approach yields a rich and diverse list of  $C$  object categories. Examples of category names generated for the general case are *sofa*, *desk*, while for the specific domains are *bust*, *castle*, and *polaroid film*, for artwork, landmark, and product, respectively.

**Object instance generation** We prompt a GDM, in particular Stable Diffusion Turbo (Sauer et al., 2024), with an object category to generate  $K$  images per category. We assume that generating images with different random seeds produces variations that are distinct and recognizable as separate instances within the same category. Therefore, following an instance-level class definition, each of the  $M$  generated images, where  $M = CK$ , is treated as a separate class in our training set. To facilitate the follow-up step of background

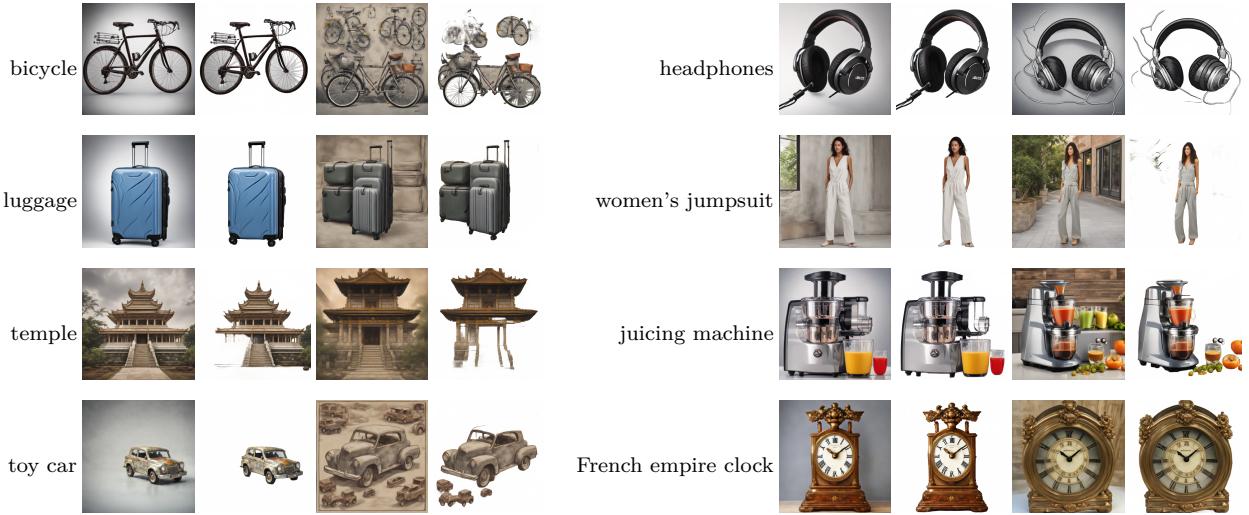


Figure 3: Examples of object instances generated by GDM for specific categories. We show the category name, the generated image and the background removal process with using “in a clean background” (columns 1 & 2) and without it (columns 3 & 4).

generation, we target a simple or uniform background. To achieve this, we add “in a clean background” to the prompt after the object category as in, “*a table in a clean background.*” Examples in Figure 3 show that, even though the background removal process may fail in both cases, it is less likely to happen with the extended prompt, while the original prompt provides outputs with richer background.

**Background generation** We create variations of an object instance by generating images with multiple, distinct backgrounds and lighting conditions. Given a generated instance in the previous step, we rely on ICLight (Zhang et al., 2025) to perform the relighting and add different backgrounds. Firstly, background removal is conducted to ensure that the input image only depicts the object of interest. Our generated images are typically quite easy to have their background removed. We additionally perform padding with a random amount and resize to the original resolution so that the object appears at different sizes and positions. Then, the object category is used as a prompt, which guides ICLight to generate an environment that is commonly appropriate for the specific object. We repeat this process  $N$  times per generated object instance with different seeds to generate multiple backgrounds. The  $N$  images are all elements of the same class in our training set and the only members of this class. Figure 4 shows examples of generated lighting and background for a variety of object categories.

**Viewpoint variations** All images of a class depict the object under different background and similar viewpoint which only varies because of the padding of the previous step. We additionally rely on simple random geometric augmentations during training to further modify the object’s geometry. This process resembles self-supervised learning with instance-discrimination (Oquab et al., 2023; Chen et al., 2020), where two positive examples are just two different random augmentations of the same input image. Nevertheless, there is an essential difference in our case, that the background and lighting significantly vary. Such a factor makes our training setting a unique of its kind.

### 3.3 Representation learning

In total, our generated dataset contains  $CKN$  training images, forming  $CK$  classes coming from  $C$  object categories. We construct training batches by sampling  $B$  classes and all their corresponding images, resulting in  $NB$  images per batch. During training, we adopt a query v. s. database scheme: one image from each of the  $N$  images per class is randomly chosen as the query, while the remaining  $NB - 1$  images of the batch form the database, as shown in Figure 5.

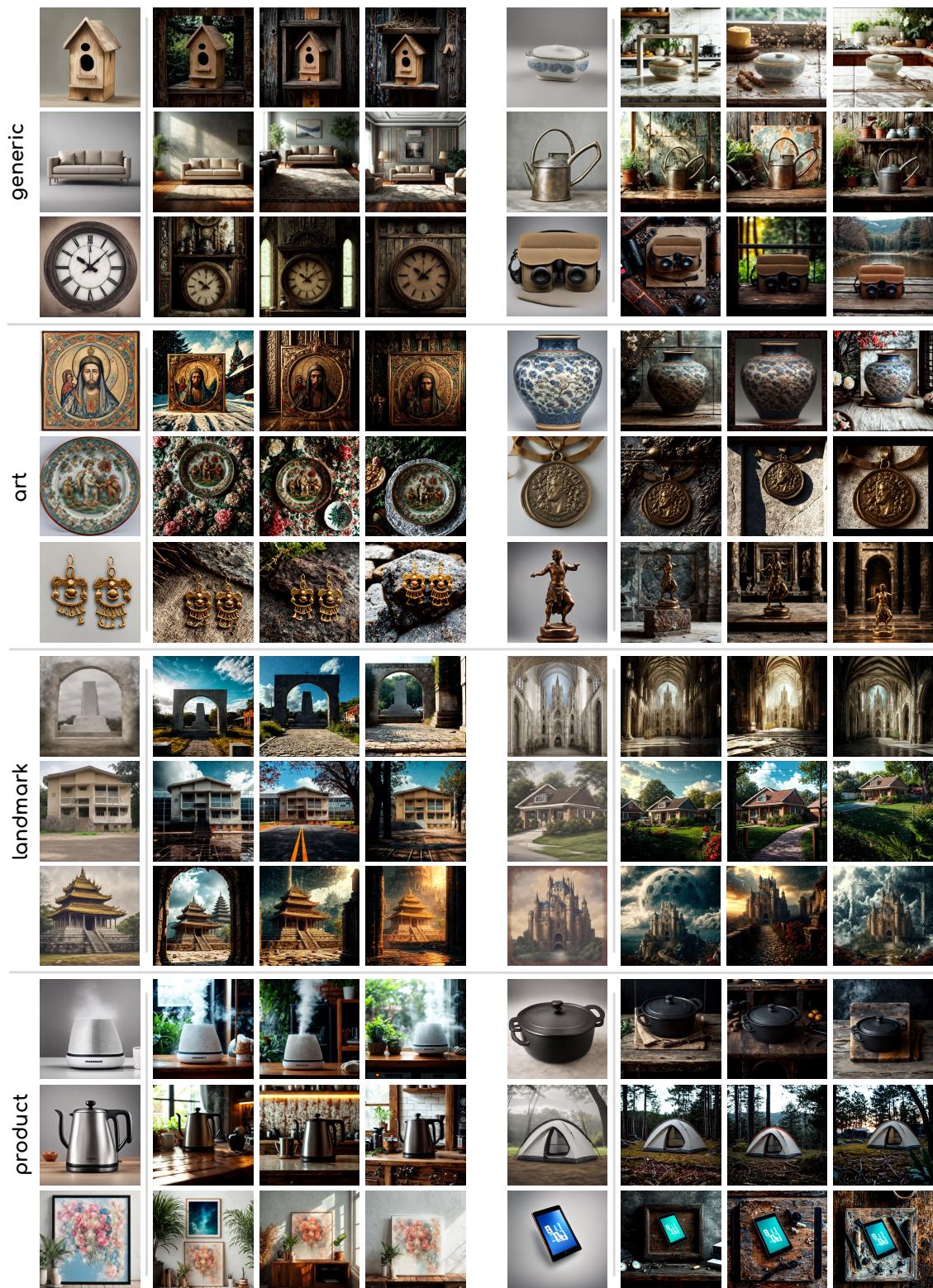


Figure 4: Examples of object instances generated by GDM (column 1), and the generated images that leave the object intact and add lighting and background that is well suited to the object (columns 2 ~ 4).

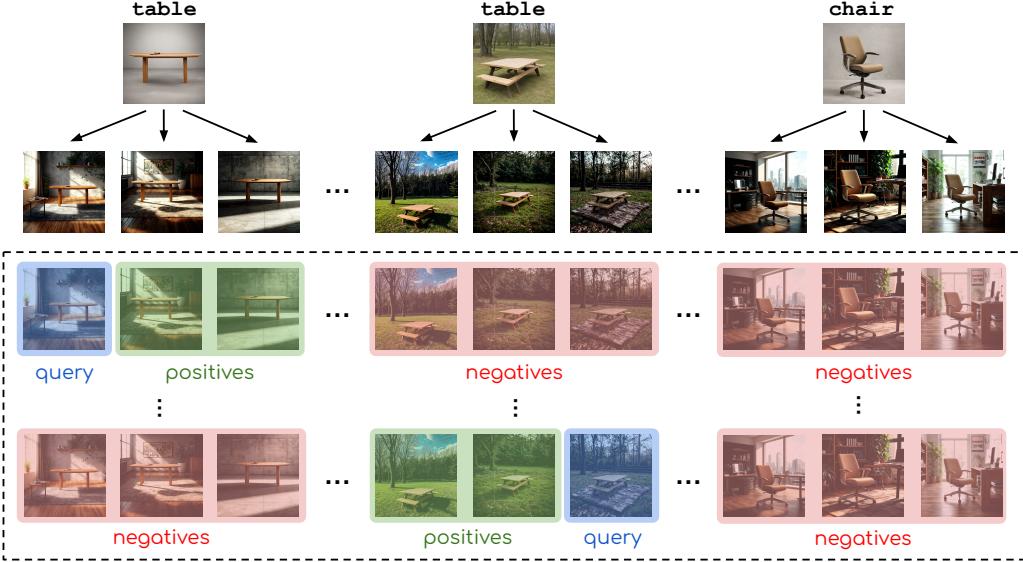


Figure 5: Training batch construction for instance-level representation learning. A batch simulates a retrieval task with a query (blue) and database of positive (green) and negative (red) images. Images are considered positive if they belong to the same class, otherwise they are negatives. An image encoder is trained with metric learning on this batch.

Table 1: Statistics of the generated training dataset. ILGen-G and ILGen-S comprise only objects from the generic domain and one of the specific domains, respectively. ILGen-ALL comprises 50% of objects from the generic domain (10K) and all objects from the three specific domains (10K), i.e. 20K objects in total.

domain of objects	$C$	$K$	instances
generic	2,000	10	20,000
art	200	15	3,000
landmark	50	80	4,000
product	200	15	3,000

The similarity between the query and db images is computed in  $\hat{\mathbf{y}} \in \mathbb{R}^{NB-1}$ , while  $\mathbf{y} \in \{0, 1\}^{NB-1}$  denotes the labels of all db images with respect to the query, i.e. positive or negatives based on their classes. We optimize an information retrieval metric as the loss function, in particular an approximation of recall at the top- $k$  ranks, based on  $\hat{\mathbf{y}}$ , and  $\mathbf{y}$ . We train with the average of recall@ $k$  loss estimated for different values of  $k$ . The approximation of recall is possible by formulating its estimation with the use of step functions, which, during training, are replaced with a sigmoid function. The technical and implementation details can be found in the original paper (Patel et al., 2022).

## 4 Experiments

### 4.1 Experimental details

**Data generation details** We use GPT-4o (Hurst et al., 2024) as an LLM for the object categories generation. The LLM is prompted to generate two types of objects: generic and domain-specific. Generic objects consist of daily-life objects, while domain-specific objects are objects represented in the particular domains of our evaluation benchmarks. Details about the number of generated object categories are in Table 1. We set the number of inference steps to 1 when generating instances from each object category using Stable Diffusion Turbo. Before applying ICLight to synthesize four distinct backgrounds, i.e.  $N = 4$ ,

Table 2: Details of evaluation datasets.

dataset	queries	database	domain	metric
MET ( <a href="#">Ypsilantis et al., 2021</a> )	19K	397K	artwork	mAP@100
R-Oxford ( <a href="#">Radenović et al., 2018</a> )	70	4.9K	landmark	mAP
R-Paris ( <a href="#">Radenović et al., 2018</a> )	70	6K	landmark	mAP
GLDV2 ( <a href="#">Weyand et al., 2020</a> )	1K	761K	landmark	mAP@100
SOP ( <a href="#">Oh Song et al., 2016</a> )	60.5K	60.5K	product	mAP@100
INSTRE ( <a href="#">Wang &amp; Jiang, 2015</a> )	1.2K	27K	multi	mAP
mini-ILIAS ( <a href="#">Kordopatis-Zilos et al., 2025</a> )	1.2K	5M	multi	mAP@1K

we add random padding (up to 50% of the image resolution) to the foreground-segmented instance, keeping the same aspect ratio.

**Training set variants** To evaluate the quality of our generated data, we compare the performance of the backbone models trained on our generated dataset, some of its variants and alternatives with real objects and/or images.

- **Pretrained:** The original datasets which the backbones are pretrained on. SigLIP and CLIP are pretrained on web-based text-image datasets, WebLI ([Chen et al., 2023](#)) and WIT ([Radford et al., 2021](#)), respectively. ViT is pretrained on ImageNet ([Dong et al., 2009](#)). The frozen backbones are evaluated.
- **ILGen-ALL - all domains:** Our generated dataset with 10K objects from the generic domain and 10K objects from the specific domains. This dataset is used by default, unless otherwise stated. See Table 1 for details.
- **ILGen-G - generic domain:** Our generated dataset with up to 20K objects from the generic domain only.
- **ILGen-S - specific domain:** Our generated dataset with images from only one of the three specific domains.
- **ILGen-ALL without background:** Our generated dataset without background generation.
- **Objaverse-background:** Objaverse 1.0 ([Deitke et al., 2023](#)) is a large-scale 3D object dataset with 818K 3D objects across various categories. We randomly select 20K objects, render each 3D object into 16 views ([Liu et al., 2024](#)), and choose the four views around the main one, resulting in a total of 80K images to match the statistics of our generated dataset. For each view, we add a background with the same generation process as in our method. This dataset allows us to compare with training on real objects rather than synthetic ones, but on synthesized images via rendering.
- **Real-S - specific domain:** To compare with training on real images that are manually annotated, we use the MET, GLDV2, and SOP training sets to obtain domain-specific models for artwork, landmark, and product, respectively. We follow the same dataset split as in [Ypsilantis et al. \(2023\)](#). To provide a direct comparison, we use the same number of instances as the corresponding domain-specific parts of our dataset, i. e. 3K, 4K, and 3K, respectively, and 4 images per instance.
- **Real-ALL - all domains:** The above is extended to compose a dataset by merging the training sets of SOP, InShop, RP2k, GLDV2 and MET. We use all classes with at least 4 images from the first three datasets that are small, and complement with enough classes equally from the other two datasets to reach 20K instances. We sample 4 images per class.

**Training details** During training, we use random cropping, resizing, flipping, color jitter, and mapping to grayscale as image augmentations ([He et al., 2020](#)). We use a batch size of 1,600 images ( $B = 400, N = 4$ ) and optimize over 400 queries, one per class. We use the vanilla version of the recall@k loss with its default hyper-parameters, and train until all classes have been loaded in a batch. We use learning rate  $10^{-5}$  and

Table 3: Evaluation results using SigLIP with different training datasets, number of instances, and use of synthetic background (bg). ILGen-G uses generic domain object categories, while ILGen-ALL includes domain-specific objects.

ID	data	instance	avg	artwork		landmark		product		multi	
				MET	ROP	GLD	SOP	INS	mIL		
1	pretrained	-	47.5	67.3	45.0	15.7	55.4	80.6	21.0		
2	Objaverse-background	20K	51.4	74.0	43.5	16.4	57.7	87.3	29.8		
3	ILGen-G	5K	51.5	72.3	46.8	17.4	55.6	86.1	31.2		
4	ILGen-G	10K	51.8	72.7	46.1	17.9	55.4	87.2	<b>31.4</b>		
5	ILGen-G	20K	51.0	72.2	46.4	17.7	55.8	85.3	28.7		
6	ILGen-ALL w/o bg	20K	49.4	72.4	45.7	17.2	<b>60.5</b>	77.9	22.7		
7	ILGen-ALL	20K	<b>52.6</b>	<b>75.0</b>	<b>48.7</b>	<b>18.3</b>	55.3	<b>87.4</b>	30.8		

Adam optimizer (Kingma & Ba, 2015) with a weight decay  $10^{-6}$ . Experiments are run on a single A100 or V100 GPU.

**Backbones** We use SigLIP ViT-L/16 (Zhai et al., 2023), CLIP ViT-L/14 (Radford et al., 2021), and ViT-B/16 (Dosovitskiy et al., 2021), briefly referred to as SigLIP, CLIP, and ViT-B. Images are resized to  $336 \times 336$ ,  $384 \times 384$ , and  $224 \times 224$  pixels, respectively, according to their pretraining setup. We load the pre-trained models from timm<sup>1</sup> and treat the [CLS] token as the global descriptor.

**Evaluation benchmarks** We use a set of standard and diverse ILR retrieval and classification datasets for evaluation. ILR datasets are comprised of queries, a database in which the same instances as queries exist as positives, and occasionally, a distractor set of irrelevant images. Details are provided in Table 2 and the dataset list is as follows:

- **Artwork domain:** The MET dataset (Ypsilantis et al., 2021) comprises a database of catalog photos from the Metropolitan Museum of Art and query images taken by visitors inside the museum. To adapt the benchmark for retrieval, we retain only queries with at least one positive match in the database, i.e. we discard the distractor queries, and keep only the first positive per query in the database asserting visual overlap between the two images.
- **Landmark domain:** R-Oxford (Radenović et al., 2018), R-Paris (Radenović et al., 2018), and GLDV2 (Weyand et al., 2020) are the most widely used datasets in this domain. For R-Oxford and R-Paris, we report results on the Medium and Hard evaluation split with distractors, and following standard practice, we report average performance across the two datasets, denoted as ROP.
- **Product domain:** SOP (Oh Song et al., 2016) whose images are crawled from e-commerce websites.
- **Multi-domain:** We use INSTRE (Wang & Jiang, 2015) and ILIAS (Kordopatis-Zilos et al., 2025) which include a variety of objects from multiple domains such as daily objects, landmarks, etc. We use the mini version of ILIAS with 5M distractor images.

## 4.2 Results for different training sets

Table 3 shows the main results for SigLIP after training on a variety of datasets.

**Impact of synthetic data** ILGen-ALL (ID7) provides consistent improvement compared to the pretrained (ID1) model on all datasets except SOP where performance does not change, with an average improvement equal to 5.1. Compared to Objaverse, which uses images rendered from 3D objects rather than automatically generated, ILGen-ALL performs better on most datasets, especially on ROP. This suggests that our method, which relies solely on synthesized objects, learns representations that are at least as effective as those learned on rendered objects.

<sup>1</sup><https://timm.fast.ai/>

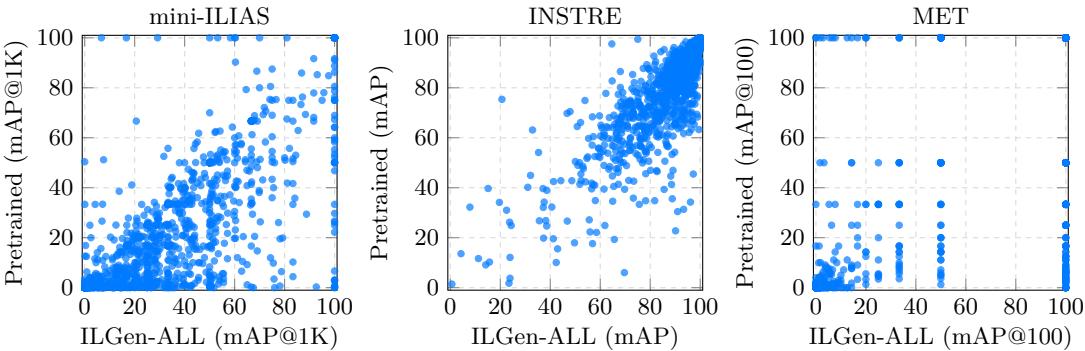


Figure 6: Average Precision (AP) per query for the pretrained backbone (y-axis) and the backbone fine-tuned on ILGen-ALL (x-axis). Each point represents a query in the evaluation dataset. Points below the diagonal indicate a query with improved performance when fine-tuned on ILGen-ALL. Results using SigLIP.

Table 4: Comparison between training on real-labeled images and training our synthetic images on four different domains using SigLIP .

dataset	avg	artwork		landmark		product		multi	
		MET	ROP	GLD	SOP	INS	mIL		
pretrained	47.5	67.3	45.0	15.7	55.4	80.6	21.0		
Real-S (artwork)	49.9	<b>75.2</b>	46.8	17.18	<b>57.0</b>	80.9	22.4		
ILGen-S (artwork)	<b>51.2</b>	73.7	<b>47.0</b>	<b>17.24</b>	55.6	<b>85.4</b>	<b>28.3</b>		
Real-S (landmark)	50.0	69.6	<b>55.0</b>	<b>19.8</b>	<b>56.7</b>	78.6	20.2		
ILGen-S (landmark)	<b>51.0</b>	<b>72.5</b>	50.7	19.7	54.6	<b>84.4</b>	<b>24.2</b>		
Real-S (product)	48.3	63.8	46.1	16.9	<b>60.3</b>	80.7	21.8		
ILGen-S (product)	<b>50.5</b>	<b>71.6</b>	<b>46.4</b>	<b>17.0</b>	55.9	<b>85.0</b>	<b>27.1</b>		
Real-ALL	51.4	69.3	<b>55.3</b>	<b>19.7</b>	<b>71.8</b>	72.7	19.3		
ILGen-ALL	<b>52.6</b>	<b>75.0</b>	48.7	18.3	55.3	<b>87.4</b>	<b>30.8</b>		

**Number of instances** We evaluate SigLIP backbone trained on the generic-domain version of the dataset, ILGen-G, with different numbers of instances: 5K, 10K, and 20K (corresponding to ID3, ID4, and ID5 in Table 3). Even with the smallest set of 5K generic instances (ID3), performance on all the benchmarks is better than the pre-trained backbone (ID1). When the number of instances increases to 10K (ID4), the average performance increases further, but saturates for the largest set (ID5).

**Diverse v.s. clean background** Training on ILGen-ALL with clean background (ID6) improves the performance on most datasets compared to the pretrained backbone. However, performance drops on INSTRE and the improvement is small on mini-ILIAS, which are two datasets with high background clutter. Synthesizing realistic and diverse backgrounds (ID7) leads to a substantial improvement on most datasets compared to clean background (ID6). SOP forms an exception, where having clean background is the variant that brings a noticeable improvement, which is related to the commonly clean background in this test set.

**Domain of the instances** Complementing ILGen-G-10K (ID4) with 10K images from domain-specific objects (ID7) is much better on average than complementing it with 10K generic objects (ID5). Such a choice strengthens performance on the tests sets related to those specific domains, i. e. MET, ROP, and GLDv2, but has smaller or no improvement on datasets with a large variety of objects, i. e. INSTRE and mini-ILIAS. Therefore, leveraging synthetic images in a diverse set of targeted domains, our method has the potential to effectively address data scarcity and obtain universal representation models.

**Improvement per query** In Figure 6, we compare the performance of the pretrained and the ILGen-ALL fine-tuned backbone on a query basis. Training on the dataset of the proposed method improves the

Table 5: Evaluation results on different backbones. Representations learned on synthetic data using ILGen-ALL outperform the pretrained representations on all datasets, except SigLIP and ViT on SOP.

model	data	avg	artwork		landmark		product		multi	
			MET	ROP	GLD	SOP	INS	mIL		
SigLIP	pretrained	47.5	67.3	45.0	15.7	<b>55.4</b>	80.6	21.0		
	ILGen-ALL	<b>52.6</b>	<b>75.0</b>	<b>48.7</b>	<b>18.3</b>	55.3	<b>87.4</b>	<b>30.8</b>		
CLIP	pretrained	37.5	47.1	40.0	10.5	41.8	75.1	10.4		
	ILGen-ALL	<b>46.8</b>	<b>69.6</b>	<b>43.7</b>	<b>16.8</b>	<b>45.5</b>	<b>81.7</b>	<b>23.8</b>		
ViT-B	pretrained	25.7	34.2	24.6	5.7	<b>43.7</b>	41.9	4.0		
	ILGen-ALL	<b>34.3</b>	<b>50.8</b>	<b>29.8</b>	<b>9.1</b>	40.8	<b>65.1</b>	<b>10.1</b>		

Table 6: Evaluation results by training SigLIP on ILGen-ALL using different loss function.

loss	avg	artwork		landmark		product		multi	
		MET	ROP	GLD	SOP	INS	mIL		
pretrained	47.5	67.3	45.0	15.7	55.4	80.6	21.0		
recall@k (Patel et al., 2022)	<b>52.6</b>	75.0	<b>48.7</b>	18.3	55.3	87.4	30.8		
infoNCE (Chen et al., 2020)	52.2	<b>75.1</b>	48.6	<b>18.8</b>	54.2	86.0	30.7		
contrastive (Chopra et al., 2005)	50.6	62.8	46.0	16.1	53.8	86.4	<b>38.4</b>		
softmax margin (Wang et al., 2018)	51.5	70.1	47.3	18.4	<b>55.4</b>	<b>88.0</b>	29.8		

performance on the majority of queries and over the whole range of performance values with the pretrained model, even for many highly performing queries of INSTRE.

**Comparison to real manually labeled images** We train SigLIP on both real-labeled and our synthetic images with recall@k loss under the same setting and present results in Table 4. We make the following observations. Training with our synthetic images yields better overall performance compared to real-labeled images. Although training with real images from a single domain achieves better performance within the specific domain, our synthetic images have better performance across other domains except for product. Notably, results on multi-domain (INSTRE and mini-ILIAS) reveal that our synthetic images are the best in all cases, indicating the strength of our approach to cover a large range of domains. Performance when testing on ROP is always better when training on real images, possibly indicating shortcomings of the generative models for large objects with many details.

### 4.3 Ablations and more results

**Backbones** In Table 5 we present results for fine-tuning two additional backbones. Performance improvements are similar to those of SigLIP, demonstrating the general applicability of our method.

**Different loss function** We train SigLIP using infoNCE loss (Chen et al., 2020), contrastive loss (Chopra et al., 2005), and softmax margin loss (Wang et al., 2018), which are widely used in representation learning, and present results in Table 6. The generated training set is shown to be effective with a diverse set of losses, while the recall@k loss remains the best overall choice.

**Training images per class** Table 7 shows the performance with different numbers of images per instance-level class during training (ID-S1 and ID-S2). We decrease the number of images per class  $N$  in the training set to 3 and 2. The trained models achieve an average performance of 51.5 and 50.3, respectively, which is a considerable drop compared to the main variant that achieves 52.6.

**LLM models and prompts** To examine the effect of the prompts and LLMs, we evaluate variants from ID-S3 to ID-S5 in Table 7. In ID-S3, we use a fixed prompt template across all the generic and specific domains with GPT-4o (see the supplementary material). In ID-S4 and ID-S5, we use our designed prompts with two other LLMs, DeepSeek-V3 and Claude 3.7 Sonnet, respectively. The similar results suggest that our method is robust regardless of the LLM or prompt type.

Table 7: Ablation study on training data (S1-S2), LLM (S3-S5), GDM (S6-S7), and background generation (S8-S9). ID1 (pretrained) and ID7 (ILGen-ALL) were presented in Table 3. Each ablation modifies only one component compared to ID7. *Pos* refers to the number of training images per instance class. *Steps* are the inference steps during image generation. SD Turbo uses 1 step by default. SD refers to Stable Diffusion.

ID	data		LLM		GDM		background		results						
	dataset	pos	prompt	model	model	steps	model	padding	avg	MET	ROP	GLD	SOP	INS	mIL
1	pretrained	-	-	-	-	-	-	-	47.5	67.3	45.0	15.7	55.4	80.6	21.0
S1	generated	3	designed	GPT-4o	SD Turbo	1	ICLight	✓	51.5	73.7	47.8	18.3	56.2	85.6	27.7
S2	generated	2	designed	GPT-4o	SD Turbo	1	ICLight	✓	50.3	71.3	46.6	17.8	55.3	85.5	25.2
S3	generated	4	template	GPT-4o	SD Turbo	1	ICLight	✓	52.6	74.9	48.0	18.6	56.5	86.2	31.6
S4	generated	4	designed	DeepSeek	SD Turbo	1	ICLight	✓	52.6	75.3	47.0	18.2	55.0	88.0	32.1
S5	generated	4	designed	Claude	SD Turbo	1	ICLight	✓	52.5	74.6	48.8	18.3	55.5	87.5	30.6
S6	generated	4	designed	GPT-4o	SD v2.0	50	ICLight	✓	51.8	74.1	47.6	18.2	56.6	86.9	27.6
S7	generated	4	designed	GPT-4o	SD Turbo	5	ICLight	✓	53.0	74.7	49.1	18.2	56.6	88.3	31.0
S8	generated	4	designed	GPT-4o	SD Turbo	1	SD v2.0	✓	47.1	70.8	48.8	17.8	54.6	75.4	15.2
S9	generated	4	designed	GPT-4o	SD Turbo	1	ICLight	✗	51.5	75.1	49.9	19.1	57.4	82.9	24.7
7	generated	4	designed	GPT-4o	SD Turbo	1	ICLight	✓	52.6	75.0	48.7	18.3	55.3	87.4	30.8

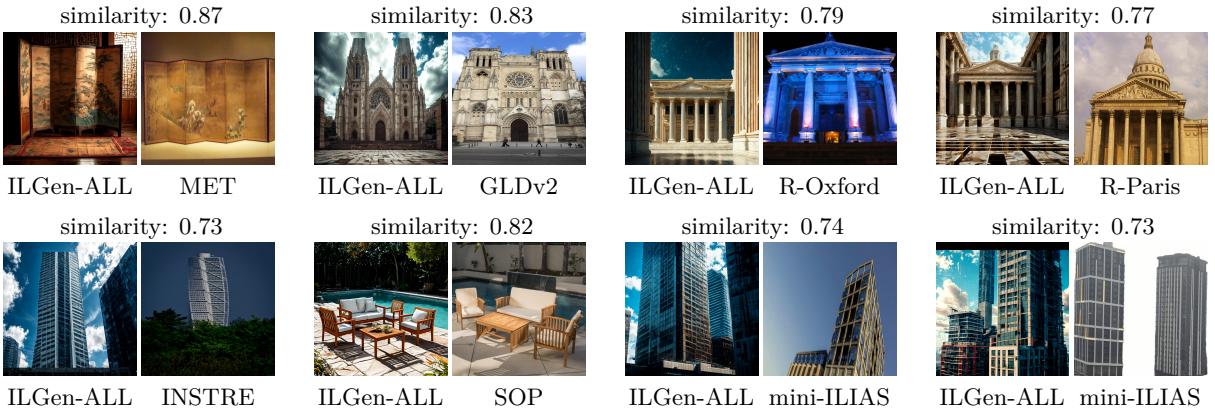


Figure 7: Pairs of ILGen-ALL and test sets with the highest similarity score. While these pairs share some common appearance, they do not indicate data leakage from an ILR point of view.

**GDM** We apply different GDMs and higher-quality images to study how instance generation quality affects performance, as shown in ID-S6 and ID-S7 in Table 7. In ID-S6, we change SD Turbo to SD v2.0, resulting in worse performance, likely due to more intricate backgrounds that hinder accurate foreground segmentation. We use 50 inference steps following the default setting. In ID-S7, we increase the inference steps of SD Turbo from the default 1 to 5, aiming to generate higher-quality images. Although the visual quality is better, there was no overall significant performance improvement. Additional details are in the supplementary material.

**Background generation** As shown in Table 7, changing ICLight to SD v2.0 for background generation (ID-S8) leads to worse performance even than the pretrained model (ID1). This is due to poor identity preservation, while ICLight is tailored to this task. When we switch off padding (ID-S9), which is our way of varying object size and position, the average performance drops by 1.1%, demonstrating that even such a simple viewpoint variation has a positive impact.

**Train and test set overlap** To investigate whether objects from the test sets have leaked into the generated training set, we perform the following mining process. We use the trained model as a descriptor extractor and perform retrieval using the test queries as queries and the generated training set as the database. We visually inspect the results with the highest similarity scores and do not identify any cases of such leakage as shown in Figure 7. The pairs showcase similar characteristics (a strength of our approach), but are not positive from an instance-level point of view.

---

## 5 Conclusion

This work introduces a novel approach to training ILR models using generative diffusion models to automatically create diverse, instance-specific training images. By eliminating the need for extensive data collection and curation, our method opens up new opportunities to easily train ILR models across various domains. Although foundational representation models are generally considered universal and capable of performing well across a wide range of domains, we show that fine-tuning these models exclusively on synthetic instance-level data results in notable performance improvements.

## References

- Hassan Abu Alhaija, Siva Karthik Mustikovela, Lars Mescheder, Andreas Geiger, and Carsten Rother. Augmented reality meets computer vision: Efficient data generation for urban driving scenes. [IJCV](#), 2018. 3
- Xiang An, Jiankang Deng, Kaicheng Yang, Jaiwei Li, Ziyong Feng, Jia Guo, Jing Yang, and Tongliang Liu. Unicom: Universal and compact representation learning for image retrieval. In [ICLR](#), 2023. 3
- Victor Besnier, Himalaya Jain, Andrei Bursuc, Matthieu Cord, and Patrick Pérez. This dataset does not exist: training models from generated images. In [ICASSP](#), 2020. 3
- Andrew Brock. Large scale gan training for high fidelity natural image synthesis. In [ICLR](#), 2018. 3
- Dingding Cai, Janne Heikkilä, and Esa Rahtu. Ove6d: Object viewpoint encoding for depth-based 6d object pose estimation. In [CVPR](#), 2022. 3
- Bingyi Cao, André Araujo, and Jack Sim. Unifying deep local and global features for image search. In [ECCV](#), 2020. 2
- Angel X Chang, Thomas Funkhouser, Leonidas Guibas, Pat Hanrahan, Qixing Huang, Zimo Li, Silvio Savarese, Manolis Savva, Shuran Song, Hao Su, et al. Shapenet: An information-rich 3d model repository. arXiv preprint arXiv:1512.03012, 2015. 3
- Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In [ICML](#), 2020. 5, 11
- Xi Chen, Xiao Wang, Soravit Changpinyo, AJ Piergiovanni, Piotr Padlewski, Daniel Salz, Sebastian Goodman, Adam Grycner, Basil Mustafa, Lucas Beyer, et al. Pali: A jointly-scaled multilingual language-image model. In [ICLR](#), 2023. 8
- Yuhua Chen, Wen Li, Xiaoran Chen, and Luc Van Gool. Learning semantic segmentation from synthetic data: A geometrically guided input-output adaptation approach. In [CVPR](#), 2019. 3
- Sumit Chopra, Raia Hadsell, and Yann LeCun. Learning a similarity metric discriminatively, with application to face verification. In [CVPR](#), 2005. 11
- Matt Deitke, Dustin Schwenk, Jordi Salvador, Luca Weihs, Oscar Michel, Eli VanderBilt, Ludwig Schmidt, Kiana Ehsani, Aniruddha Kembhavi, and Ali Farhadi. Objaverse: A universe of annotated 3d objects. In [CVPR](#), 2023. 8
- Jiankang Deng, Jia Guo, Niannan Xue, and Stefanos Zafeiriou. Arcface: Additive angular margin loss for deep face recognition. In [CVPR](#), 2019. 3
- Wei Dong, Richard Socher, Li Li-Jia, Kai Li, and Li Fei-Fei. ImageNet: A large-scale hierarchical image database. In [CVPR](#), 2009. 8
- Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In [ICLR](#), 2021. 9

- 
- Debidatta Dwibedi, Ishan Misra, and Martial Hebert. Cut, paste and learn: Surprisingly easy synthesis for instance detection. In ICCV, 2017. 3
- Ismail Elezi, Sebastiano Vascon, Alessandro Torcinovich, Marcello Pelillo, and Laura Leal-Taixé. The group loss for deep metric learning. In ECCV, 2020. 3
- Lijie Fan, Kaifeng Chen, Dilip Krishnan, Dina Katabi, Phillip Isola, and Yonglong Tian. Scaling laws of synthetic images for model training... for now. In CVPR, 2024. 2, 3
- Zigang Geng, Binxin Yang, Tianshui Hang, Chen Li, Shuyang Gu, Ting Zhang, Jianmin Bao, Zheng Zhang, Houqiang Li, Han Hu, et al. Instructdiffusion: A generalist modeling interface for vision tasks. In CVPR, 2024. 3
- Georgios Georgakis, Arsalan Mousavian, Alexander C Berg, and Jana Kosecka. Synthesizing training data for object detection in indoor scenes. arXiv preprint arXiv:1702.07836, 2017. 3
- Philippe-Henri Gosselin, Naila Murray, Hervé Jégou, and Florent Perronnin. Revisiting the fisher vector for fine-grained classification. Pattern Recognition Letters, 2014. 2
- Raia Hadsell, Sumit Chopra, and Yann LeCun. Dimensionality reduction by learning an invariant mapping. In CVPR, 2006. 3
- Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR, 2016. 2
- Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In CVPR, 2020. 8
- Kun He, Yan Lu, and Stan Sclaroff. Local descriptors optimized for average precision. In CVPR, 2018. 3
- Aaron Hurst, Adam Lerer, Adam P Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, et al. Gpt-4o system card. arXiv preprint arXiv:2410.21276, 2024. 2, 7
- Sungyeon Kim, Dongwon Kim, Minsu Cho, and Suha Kwak. Proxy anchor loss for deep metric learning. In CVPR, 2020. 3
- Sungyeon Kim, Dongwon Kim, Minsu Cho, and Suha Kwak. Self-taught metric learning without labels. In CVPR, 2022. 3
- Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In ICLR, 2015. 9
- Giorgos Kordopatis-Zilos, Vladan Stojnić, Anna Manko, Pavel Šuma, Nikolaos-Antonios Ypsilantis, Nikos Eftymiadis, Zakaria Laskar, Jiří Matas, Ondřej Chum, and Giorgos Tolias. ILIAS: Instance-level image retrieval at scale. In CVPR, 2025. 2, 8, 9
- Dmytro Kotovenko, Pingchuan Ma, Timo Milbich, and Björn Ommer. Cross-image-attention for conditional embeddings in deep metric learning. In CVPR, 2023. 3
- Jonathan Krause, Hailin Jin, Jianchao Yang, and Li Fei-Fei. Fine-grained recognition without part annotations. In CVPR, 2015. 2
- Yann Labb  , Justin Carpentier, Mathieu Aubry, and Josef Sivic. Cosypose: Consistent multi-view multi-object 6d pose estimation. In ECCV, 2020. 3
- Seongwon Lee, Hongje Seong, Suhyeon Lee, and Euntai Kim. Correlation verification for image retrieval. In CVPR, 2022. 2
- Yuan Liu, Cheng Lin, Zijiao Zeng, Xiaoxiao Long, Lingjie Liu, Taku Komura, and Wenping Wang. Sync-dreamer: Generating multiview-consistent images from a single-view image. In ICLR, 2024. 8

- 
- Ziwei Liu, Ping Luo, Shi Qiu, Xiaogang Wang, and Xiaoou Tang. Deepfashion: Powering robust clothes recognition and retrieval with rich annotations. In CVPR, 2016. 2
- Naureen Mahmood, Nima Ghorbani, Nikolaus F Troje, Gerard Pons-Moll, and Michael J Black. Amass: Archive of motion capture as surface shapes. In ICCV, 2019. 3
- Ron Mokady, Amir Hertz, Kfir Aberman, Yael Pritch, and Daniel Cohen-Or. Null-text inversion for editing real images using guided diffusion models. In CVPR, 2023. 3
- Kevin Musgrave, Serge Belongie, and Ser-Nam Lim. A metric learning reality check. In ECCV, 2020. 3
- Hyun Oh Song, Yu Xiang, Stefanie Jegelka, and Silvio Savarese. Deep metric learning via lifted structured feature embedding. In CVPR, 2016. 2, 3, 8, 9
- Maxime Oquab, Timothée Darcet, Théo Moutakanni, Huy Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel Haziza, Francisco Massa, Alaaeldin El-Nouby, et al. Dinov2: Learning robust visual features without supervision. arXiv preprint arXiv:2304.07193, 2023. 5
- Yash Patel, Giorgos Tolias, and Jiří Matas. Recall@ k surrogate loss with large batches and similarity mixup. In CVPR, 2022. 2, 3, 7, 11
- Jingtian Peng, Chang Xiao, and Yifan Li. RP2K: A large-scale retail product dataset for fine-grained image classification. arXiv preprint arXiv:2006.12634, 2020. 2
- Xingchao Peng, Baochen Sun, Karim Ali, and Kate Saenko. Learning deep object detectors from 3d models. In ICCV, 2015. 2, 3
- J. Philbin, O. Chum, M. Isard, J. Sivic, and A. Zisserman. Object retrieval with large vocabularies and fast spatial matching. In CVPR, 2007. 2
- J. Philbin, O. Chum, M. Isard, J. Sivic, and A. Zisserman. Lost in quantization: Improving particular object retrieval in large scale image databases. In CVPR, 2008. 2
- Qi Qian, Lei Shang, Baigui Sun, Juhua Hu, Hao Li, and Rong Jin. Softtriple loss: Deep metric learning without triplet sampling. In ICCV, 2019. 3
- Filip Radenović, Ahmet Iscen, Giorgos Tolias, Yannis Avrithis, and Ondřej Chum. Revisiting oxford and paris: Large-scale image retrieval benchmarking. In CVPR, 2018. 8, 9
- Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In ICML, 2021. 2, 3, 8, 9
- Amit Raj, Srinivas Kaza, Ben Poole, Michael Niemeyer, Nataniel Ruiz, Ben Mildenhall, Shiran Zada, Kfir Aberman, Michael Rubinstein, Jonathan Barron, et al. Dreambooth3d: Subject-driven text-to-3d generation. In ICCV, 2023. 3
- Elias Ramzi, Nicolas Thome, Clément Rambour, Nicolas Audebert, and Xavier Bitot. Robust and decomposable average precision for image retrieval. In NeurIPS, 2021. 3
- Elias Ramzi, Nicolas Audebert, Nicolas Thome, Clément Rambour, and Xavier Bitot. Hierarchical average precision training for pertinent image retrieval. In ECCV, 2022. 2, 3
- Jerome Revaud, Jon Almazán, Rafael S Rezende, and Cesar Roberto de Souza. Learning with average precision: Training image retrieval with a listwise loss. In ICCV, 2019. 3
- Michal Rolínek, Vít Musil, Anselm Paulus, Marin Vlastelica, Claudio Michaelis, and Georg Martius. Optimizing rank-based metrics with blackbox differentiation. In CVPR, 2020. 3
- Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In CVPR, 2022. 2

- 
- German Ros, Laura Sellart, Joanna Materzynska, David Vazquez, and Antonio M Lopez. The synthia dataset: A large collection of synthetic images for semantic segmentation of urban scenes. In CVPR, 2016. 3
- Karsten Roth, Timo Milbich, Samarth Sinha, Prateek Gupta, Bjorn Ommer, and Joseph Paul Cohen. Revisiting training strategies and generalization performance in deep metric learning. In ICML, 2020. 3
- Artem Rozantsev, Vincent Lepetit, and Pascal Fua. On rendering synthetic images for training an object detector. CVIU, 2015. 3
- Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. IJCV, 2015. 2
- Mert Bülent Sariyıldız, Karteek Alahari, Diane Larlus, and Yannis Kalantidis. Fake it till you make it: Learning transferable representations from synthetic imagenet clones. In CVPR, 2023. 3
- Axel Sauer, Dominik Lorenz, Andreas Blattmann, and Robin Rombach. Adversarial diffusion distillation. In ECCV, 2024. 2, 4
- Florian Schroff, Dmitry Kalenichenko, and James Philbin. Facenet: A unified embedding for face recognition and clustering. In CVPR, 2015. 3
- Christoph Schuhmann, Robert Kaczmarczyk, Aran Komatsuzaki, Aarush Katta, Richard Vencu, Romain Beaumont, Jenia Jitsev, Theo Coombes, and Clayton Mullis. LAION-400M: Open dataset of clip-filtered 400 million image-text pairs. In NeurIPS Workshop Datacentric AI, 2021. 3
- Jenny Seidenschwarz, Ismail Elezi, and Laura Leal-Taixé. Learning intra-batch connections for deep metric learning. In ICML, 2021. 3
- Shihao Shao, Kaifeng Chen, Arjun Karpur, Qinghua Cui, André Araujo, and Bingyi Cao. Global features are all you need for image retrieval and reranking. In ICCV, 2023. 2
- Kihyuk Sohn. Improved deep metric learning with multi-class n-pair loss objective. In NeurIPS, 2016. 3
- Pavel Suma, Giorgos Kordopatis-Zilos, Ahmet Iscen, and Giorgos Tolias. Ames: Asymmetric and memory-efficient similarity estimation for instance-level retrieval. In ECCV, 2024. 2
- Shobhita Sundaram, Julia Chae, Yonglong Tian, Sara Beery, and Phillip Isola. Personalized representation from personalized generation. In ICLR, 2025. 3
- Eu Wern Teh, Terrance DeVries, and Graham W Taylor. Proxynca++: Revisiting and revitalizing proxy neighborhood component analysis. In ECCV, 2020. 3
- Yonglong Tian, Lijie Fan, Phillip Isola, Huiwen Chang, and Dilip Krishnan. Stablerep: Synthetic images from text-to-image models make strong visual representation learners. In NeurIPS, 2024. 2, 3
- Gu Wang, Fabian Manhardt, Jianzhun Shao, Xiangyang Ji, Nassir Navab, and Federico Tombari. Self6d: Self-supervised monocular 6d object pose estimation. In ECCV, 2020. 3
- Hao Wang, Yitong Wang, Zheng Zhou, Xing Ji, Dihong Gong, Jingchao Zhou, Zhifeng Li, and Wei Liu. Cosface: Large margin cosine loss for deep face recognition. In CVPR, 2018. 11
- Shuang Wang and Shuqiang Jiang. Instre: a new benchmark for instance-level object retrieval and recognition. ACM TOMM, 2015. 2, 8, 9
- Tobias Weyand, André Araujo, Bingyi Cao, and Jack Sim. Google landmarks dataset v2 - A large-scale benchmark for instance-level recognition and retrieval. In CVPR, 2020. 2, 8, 9
- Yankun Wu, Yuta Nakashima, and Noa Garcia. Not only generative art: Stable diffusion for content-style disentanglement in art analysis. In ICMR, 2023. 3

---

Nikolaos-Antonios Ypsilantis, Noa Garcia, Guangxing Han, Sarah Ibrahimi, Nanne Van Noord, and Giorgos Tolias. The met dataset: Instance-level recognition for artworks. In NeurIPS, 2021. [2](#), [8](#), [9](#), [3](#)

Nikolaos-Antonios Ypsilantis, Kaifeng Chen, Bingyi Cao, Mário Lipovský, Pelin Dogan-Schönberger, Grzegorz Makosa, Boris Bluntschli, Mojtaba Seyedhosseini, Ondřej Chum, and André Araujo. Towards universal image embeddings: A large-scale dataset and challenge for generic image representations. In ICCV, 2023. [2](#), [8](#)

Andrew Zhai and Hao-Yu Wu. Classification is a strong baseline for deep metric learning. arXiv preprint arXiv:1811.12649, 2018. [3](#)

Xiaohua Zhai, Basil Mustafa, Alexander Kolesnikov, and Lucas Beyer. Sigmoid loss for language image pre-training. In ICCV, 2023. [2](#), [4](#), [9](#)

Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. In ICCV, 2023. [3](#)

Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. Scaling in-the-wild training for diffusion-based illumination harmonization and editing by imposing consistent light transport. In ICLR, 2025. [2](#), [5](#)

---

## Supplementary material

This supplementary material reports further experiment details discussed in the main paper. The document is organized into the following sections:

- Section A: Data generation.
- Section B: Training details.
- Section C: Additional study.
- Section D: Evaluation dataset examples.

### A Data generation

**Prompts on object categories generation** Table S1 provides the designed and template prompts used to generate object categories for each domain. Designed prompts are used in all cases except for ID-3 in Table 7, where we use template prompts for ablation study. The template is “*Provide a raw list of 2000 object names from the domain of <domain> objects. Here are some examples, which you can include in your list too but also get inspired by <examples>*.” For each domain, we substitute the <domain> and <examples> accordingly. We randomly sample images to match the number of instances per domain in Table 1.

**Examples with difference inference steps** Examples generated by Stable Diffusion Turbo with different inference steps are shown in Figure S1. Increasing the number of steps enhances the quality of the objects, but also results in more detailed backgrounds. To balance the higher quality of the object and a less detailed background, we choose images with 5 inference steps for the ablation study.



Figure S1: Images generated by GDM with inference steps ranging from 1 to 9. To minimize artifacts in the object while preventing a detailed background, we select 5 steps for the ablation study.

**Background generation details** The background removal tool used in background generation is RMBG v1.4<sup>2</sup>. We use ICLight with its default parameters and condition the generation on the object category name.

### B Training Details

**Backbone details** Table S2 includes further details of the three backbones.

**Recall@k loss** We use  $k = \{1, 2, 4, 8\}$  for the recall@k loss, with the two temperatures set to 0.01 and 1.0 as in the original work.

**InfoNCE loss** For infoNCE loss, we follow the same strategy for batch construction and training parameters as for the recall@k loss. Each image acts as one query, and its positive and negative pairs depend on the instance-level class label. We use a 0.05 temperature during training.

<sup>2</sup><https://huggingface.co/briaai/RMBG-1.4>

---

Table S1: Designed and template prompts for object categories generation.

domains	Designed prompts	Template prompts
generic	Provide a raw list of 2000 objects names from the domain of everyday objects, such as household items, retail products, electronics, collectibles, vehicles, buildings, outdoor objects, etc. Here are some examples, which you can include in your list too but also get inspired by sandal, mug, laptop, chair, bottle, temple, house, dress, teapot, dog, toy, rabbit, teddybear, car, toy, car, bowl, church, skyscraper hotel.	Provide a raw list of 2000 objects names from the domain of <i>everyday</i> objects. Here are some examples, which you can include in your list too but also get inspired by <i>sandal, mug, laptop, chair, house, dress, teddybear, car, toy, church</i> .
art	Provide a raw list of 200 object names from the domain of museum items. Consider a encyclopedic art museum that is home to collections classic art such as paintings, graphic work, jewelry, vases, sculptures, but also of musical instruments, costumes, and decorative arts and textiles, as well as antique weapons and armor from around the world.	Provide a raw list of 2000 objects names from the domain of <i>museum</i> objects. Here are some examples, which you can include in your list too but also get inspired by <i>Renaissance oil painting, Baroque tapestry, Egyptian faience amulet, Medieval longsword, Japanese samurai armor, Greek krater vase, Rococo gilded mirror, Ancient Roman cameo ring, Venetian glass chandelier, 19th-century concert grand piano</i> .
landmark	Provide a raw list of 50 object names from the domain of buildings, landmarks, urban structures, outdoor constructions, such as church, neoclassical building, train station, temple, cathedral, tower building, square. It can be fine-grained too, e.g., catholic church. Please name the most common things, such as house in standard modern European architecture.	Provide a raw list of 2000 objects names from the domain of <i>landmarks</i> objects. Here are some examples, which you can include in your list too but also get inspired by <i>catholic church, neoclassical building, train station, temple, cathedral, tower building, square, Mosque, Skyscraper, Castle</i> .
product	Provide a raw list of 200 object names from the domain of retail products, supermarket products, e-shop electronics, clothes, fashion items, shoes, anything that someone would sell in a second hand online market.	Provide a raw list of 2000 objects names from the domain of <i>retail products</i> objects. Here are some examples, which you can include in your list too but also get inspired by <i>Leather jacket, Smartphone, Gaming console, Bluetooth headphones, Smartwatch, Designer handbag, Running shoes, Vintage dress, DSLR camera</i> .

Table S2: Details of backbones.

backbone	params	dim
SigLIP	316M	1,024
CLIP	304M	1,024
ViT-B	86M	768

**Contrastive loss** Regarding the contrastive loss, we treat each image as a query and randomly sample one positive among images with the same instance-level class label. For the negatives, we mine the hardest one in the dataset based on the cosine similarity of the image descriptors. We use a margin of 1. The learning rate is  $10^{-7}$ . The batch size is 8. Other settings are following recall@k loss.

**Softmax margin loss** Softmax margin loss is a classification loss. Following the training process proposed in UnED (Ypsilantis et al., 2021), the backbone remains frozen for the first two epochs, and only the classifier is trained with a learning rate of  $10^{-3}$ . In the following epochs, the network is trained end-to-end with a  $10^{-6}$  learning rate. Since this is a classification loss, no specific curation of the batches is necessary. We use a batch size of 16. The scale and margin parameters are set at 16 and 0, respectively, as in UnED.

**Training time** The training process of ILGen-ALL with SigLIP takes approximately 2.5 hours on a single A100 GPU.

## C Additional study

**Additional study on Objaverse** When training on Objavese, we match the same dataset sizes (20K) as ILGen-ALL to ensure a fair comparison (ID2). As shown in Table S3, increasing the number of Objaverse images to 40K performs a bit worse (ID-S10). Therefore, we did not increase further. We additionally tested the impact of real viewpoint variations from Objaverse by switching from 4 views of our main experiment to one view, where only the background differs (ID2 vs ID-S11). There is a small impact. Richer viewpoint variations are for sure worth further investigation.

Table S3: Additional study on training on Objaverse. Views refer to viewpoints before background generation.

ID	dataset	instances	views	avg	artwork		landmark		product		multi	
					MET	ROP	GLD	SOP	INS	mIL		
1	pretrained	-	-	47.5	67.3	<b>45.0</b>	15.7	55.4	80.6	21.0		
2	Objaverse-background	20K	4	<b>51.4</b>	<b>74.0</b>	43.5	<b>16.4</b>	57.7	<b>87.3</b>	<b>29.8</b>		
S10	Objaverse-background	40K	4	50.1	72.6	40.6	14.6	<b>58.3</b>	86.4	27.9		
S11	Objaverse-background	20K	1	50.3	73.4	42.5	15.9	57.4	85.8	27.1		

**Training real-labeled images with softmax margin loss** Table S4 presents the results of training real-labeled images with softmax margin loss on four domains using SigLIP. We observe a consistent improvement over the pre-trained model on average. Real-ALL achieves the best overall performance, particularly on ROP and SOP. Similar to the trend observed with recall@k loss, training on the artwork domain yields the most improvement on MET and mini-ILIAs.

Table S4: Training on real-labeled images using SigLIP with softmax margin loss.

dataset	avg	artwork		landmark		product		multi	
		MET	ROP	GLD	SOP	INS	mIL		
pretrained	47.5	67.3	45.0	15.7	55.4	80.6	21.0		
Real-S (artwork)	51.5	<b>77.4</b>	47.8	17.6	58.7	82.2	<b>25.1</b>		
Real-S (landmark)	51.8	73.3	56.8	21.4	57.8	80.3	21.2		
Real-S (product)	52.0	72.1	47.1	17.5	68.7	83.1	23.2		
Real-ALL	<b>56.1</b>	76.8	<b>58.3</b>	<b>21.9</b>	<b>71.0</b>	<b>83.5</b>	25.0		

## D Evaluation dataset examples

Figure S2 shows some examples of the queries and positives from the seven test sets. The examples illustrate the diversity within the image domains and highlight the challenges posed by variations in viewpoint and background between queries and positive matches. In detail, in the MET dataset, queries consist of photos taken by visitors inside the museum, often have complex backgrounds, whereas the database images, collecting from the museum’s website, typically have clean backgrounds. R-Oxford, R-Paris, and GLDv2

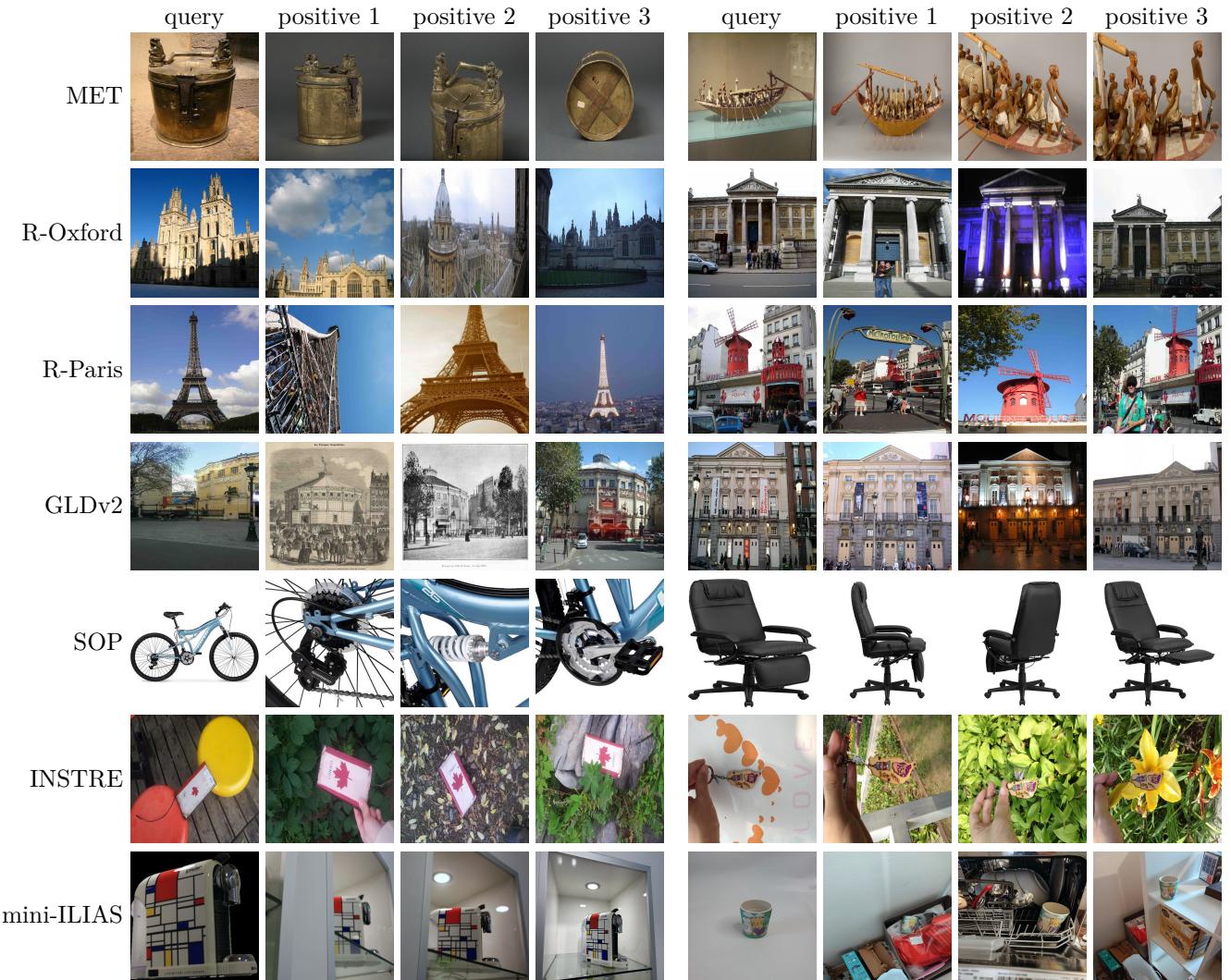


Figure S2: Examples of queries (column 1) and positives (columns 2 ~ 4) from all the test sets.

are landmark datasets where both the query and database images have complex backgrounds. In the SOP dataset, retailed product images are collected from e-commerce websites, with both query and database having clean backgrounds. Lastly, INSTRE and mini-ILIAS include multi-domain objects. In INSTRE, both query and database have diverse backgrounds, while in mini-ILIAS, queries have clean backgrounds.