UNICOM: UNIVERSAL AND COMPACT REPRESENTATION LEARNING FOR IMAGE RETRIEVAL

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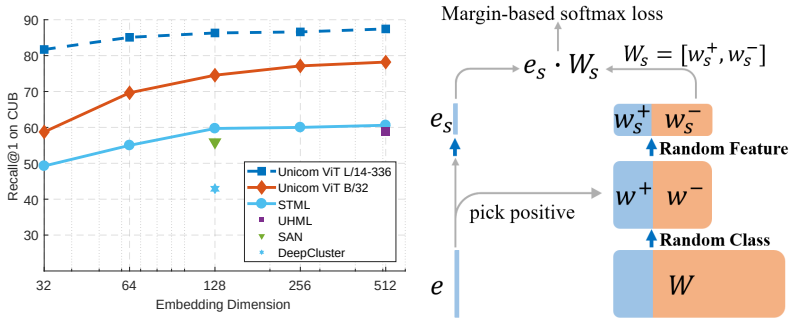
ABSTRACT

Modern image retrieval methods typically rely on fine-tuning pre-trained encoders to extract image-level descriptors. However, the most widely used models are pre-trained on ImageNet-1K with limited classes. The pre-trained feature representation is therefore not universal enough to generalize well to the diverse open-world classes. In this paper, we first cluster the large-scale LAION 400M dataset into one million pseudo classes based on the joint textual and visual features extracted by the CLIP model. Due to the confusion of label granularity, the automatically clustered dataset inevitably contains heavy inter-class conflicts. To alleviate such conflicts, we randomly select partial inter-class prototypes to construct the margin-based softmax loss. To further enhance the low-dimensional feature representation, we randomly select partial feature dimensions when calculating the similarities between embeddings and class-wise prototypes. The dual random partial selections are with respect to the class dimension and the feature dimension of the prototype matrix, respectively, making the classification conflict-robust and the feature embedding compact. Our method outperforms state-of-the-art unsupervised and supervised image retrieval approaches on multiple benchmarks with substantial improvement under different dimension constraints. Pre-processed data, training code, and pre-trained models will be released to reproduce our results.

1 INTRODUCTION

Modern image retrieval methods (Lim et al., 2022; Roth et al., 2022; Kim et al., 2022; Ermolov et al., 2022; Patel et al., 2022) can be roughly decomposed into two major components: (1) the encoder (e.g., Convolutional Neural Networks (Szegedy et al., 2015; He et al., 2016) or Vision Transformer (Touvron et al., 2021; Dosovitskiy et al., 2021)) mapping the image to its compact representation and (2) the loss function (Musgrave et al., 2020) grouping the representations of similar objects while pushing away representations of dissimilar objects in the embedding space. To train the encoder, networks pre-trained on crowd-labeled datasets (e.g., ImageNet (Deng et al., 2009)) are widely used for fine-tuning (Wang et al., 2019; Kim et al., 2021). However, ImageNet only contains 1,000 pre-defined object classes. The feature representation learned from ImageNet is not universal enough to generalize to diverse open-world objects.

Even though fully supervised pre-training can benefit from a strong semantic learning signal for each training example, supervised learning is not scalable because manual annotation of large-scale training data is time-consuming, costly, and even infeasible. By contrast, self-supervised pre-training methods (He et al., 2020; 2022; Radford et al., 2021; Jia et al., 2021) can be easily scaled to billions of unlabeled examples by designing an appropriate pretext task, such as solving jigsaw puzzles (Noroozi & Favaro, 2016), invariant mapping (Chen & He, 2021), and image-text matching (Radford et al., 2021; Jia et al., 2021). Among them, instance discrimination that identifies each instance as an individual class is the most popular due to its straightforward objective. Nevertheless, instance discrimination methods can hardly encode the semantic structure of training data, because instance-wise contrastive learning always treats two samples as a negative pair if they are from different instances, regardless of their semantic similarity. When thousands of instances are selected into the training batch to form the contrastive loss, negative pairs that share similar semantics will be undesirably pushed apart in the embedding space. In addition, intra-class variation captured by instance discrimination methods is limited to the specific image transformations used during training.



(a) Performance comparison on CUB (b) The proposed Unicom

Figure 1: (a) Accuracy in Recall@1 versus embedding dimension on the CUB dataset. The proposed Unicom is only trained on the LAION 400M dataset dataset in an unsupervised way. (b) The proposed Unicom employs two random selections along the class dimension and the feature dimension to alleviate inter-class conflict and achieve compact representation, respectively.

To handle the limitations of instance discrimination, cluster discrimination has been proposed for deep unsupervised learning through jointly learning image embeddings and cluster assignments. Learning representations with clusters will pull similar instances together, which is beneficial for capturing semantic structures in data. DeepCluster (Caron et al., 2018) performs iterative clustering by k-means and classification by cross-entropy loss, while SeLa (Asano et al., 2020) proposes to solve an optimal transport problem for balanced assignment. However, both DeepCluster and SeLa need labels to be assigned offline in a batch mode with representations of all instances. To reduce the cost of batch mode clustering, ODC (Zhan et al., 2020), SwAV (Caron et al., 2020), and CoKe (Qian et al., 2022) apply online clustering to avoid the multiple iterations over the entire dataset. Despite improved efficiency, the online clustering method still suffers from the collapsing problem (i.e., a dominant cluster includes instances from multiple classes or most of the instances).

In this paper, we only conduct one step of off-line clustering by using the image and text features from a pre-trained CLIP model (Radford et al., 2021). Due to the limited discrimination power of the CLIP model, the pseudo clusters contain heavy inter-class conflict and the image numbers of clusters are also not balanced. Instead of optimizing the cluster assignment, we focus on how to robustly train a classifier on the automatically clustered large-scale data. More specifically, we explore two random selections on the prototype matrix $W \in R^{d \times k}$ when preparing the classification loss (as illustrated in Fig. 1(b)). The first one is with respect to the class dimension (k), and only part of negative prototypes are selected for inter-class comparisons, which helps alleviate inter-class conflict. The second one is with respect to the feature dimension (d), and only part of features are randomly selected to construct the classification loss, making feature representation compact for the efficient image retrieval task. Concurrent with our work, partial selection mechanisms along class and feature are separately proposed in (An et al., 2021) and (Xu et al., 2022) to accelerate model training and enhance locally distinguishable features. Both of their experiments are conducted on cleaned face recognition datasets. By contrast, we target at universal and compact representation learning from automatically clustered large-scale data. The main contributions of our paper are the following:

- We propose a cluster discrimination method for universal representation learning. In the clustering step, we employ both image and text features from the pre-trained CLIP model. In the discrimination step, we explore two random selections along class and feature, which can potentially alleviate inter-class conflict and improve the feature compactness, respectively.
- For universal feature representation, the proposed cluster discrimination method can significantly boost the representation power of the instance discrimination based model (e.g., CLIP).
- For dimension constrained image retrieval, the proposed method achieves state-of-the-art performance across multiple benchmarks under both unsupervised and supervised settings.

2 Related Work

Visual Model Pre-training. Model pre-training for visual recognition can be categorized into three main groups: (1) supervised pre-training on datasets with class labels (e.g., ImageNet-1K/-21K (Deng et al., 2009) and JFT-300M/-3B (Dosovitskiy et al., 2021; Zhai et al., 2022)), (2) weakly-supervised

pre-training by using hashtag (Mahajan et al., 2018; Singh et al., 2022), and (3) unsupervised pre-training by employing instance discrimination (Chen et al., 2020; Misra & Maaten, 2020; He et al., 2020; Radford et al., 2021; Jia et al., 2021) or cluster discrimination (Caron et al., 2018; Zhan et al., 2020; Li et al., 2020a). In this paper, we focus on unsupervised pre-training which has the advantages of being easily scaled to billions of training images and being able to learn universal feature representations for downstream tasks. Instance discrimination is realized with a contrastive loss which targets at pulling closer samples from the same instance while pushing away samples from different instances. Despite the impressive performance, instance-wise contrastive learning can not capture the semantic information from the training data because it is trained to ignore the similarity between different instances. Cluster discrimination is processed with iterative steps: the clustering step to assign pseudo class labels for each sample, and then the classification step to map each sample to its assigned label. Since one cluster has more than one instance, learning representations with clusters will gather similar instances together, which can explore potential semantic structures in data. As a representative work, DeepCluster (Caron et al., 2018) adopts a standard k-means for clustering, but it contains degenerate solutions. To this end, recent research work (Asano et al., 2020; Caron et al., 2020; Qian et al., 2022) focuses on improving the label assignment during clustering but employs a standard cross-entropy loss during discrimination. By contrast, we only employ one step of off-line cluttering but design a robust classifier to achieve good feature representation when training on the automatically clustered large-scale data.

Image Retrieval. Image retrieval task typically relies on fine-tuning pre-trained visual models (Szegedy et al., 2015; He et al., 2016; Dosovitskiy et al., 2021) and can be divided into two learning categories: supervised and unsupervised metric learning. For supervised metric learning, pair-wise loss (Hadsell et al., 2006; Schroff et al., 2015; Sohn, 2016) and cross-entropy loss (Zhai & Wu, 2019; Wang et al., 2018; Deng et al., 2019; Sun et al., 2020; Qian et al., 2019) are extensively studied and recent bench-marking results (Musgrave et al., 2020) indicate that the margin-based softmax loss (e.g., CosFace (Wang et al., 2018) and ArcFace (Deng et al., 2019)) can achieve state-of-the-art performance. For unsupervised metric learning, pseudo labeling methods are employed to discover pseudo classes by applying k-means clustering (Kan et al., 2021; Li et al., 2020b), hierarchical clustering (Yan et al., 2021), random walk (Iscen et al., 2018), and class-equivalence relations (Kim et al., 2022) to unlabeled training data. In this paper, we focus on universal and compact feature representation learning for both unsupervised and supervised image retrieval tasks by training on automatically clustered large-scale data.

3 METHODOLOGY

3.1 PRELIMINARIES OF INSTANCE AND CLUSTER DISCRIMINATION

Given a training set $X = \{x_1, x_2, ..., x_n\}$ including n images, representation learning aims to learn a function f_θ that maps images $X = \{x_1, x_2, ..., x_n\}$ to embeddings $E = \{e_1, e_2, ..., e_n\}$ with $e_i = f_\theta(x_i)$, such that embeddings can describe the similarities between different images. The objective is to optimize the network parameter θ by maximizing the log-likelihood function over n samples:

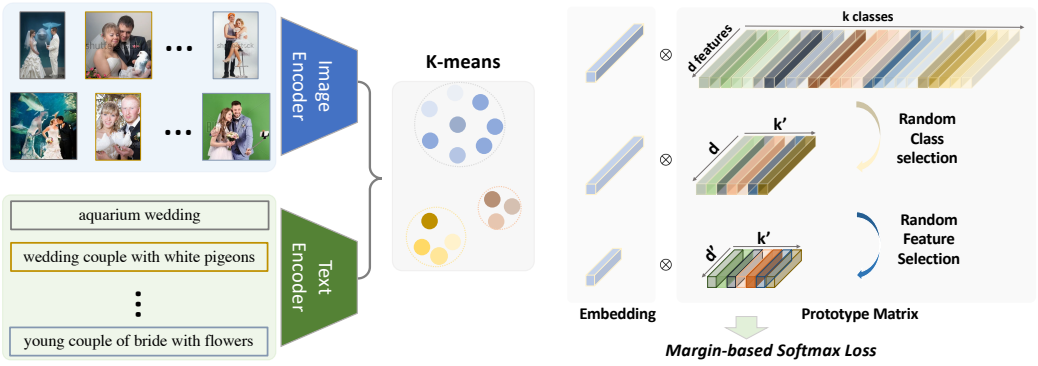
$$\theta^* = \arg\max_\theta \sum_{i=1}^{n} \log p(x_i; \theta). \tag{1}$$

Instance discrimination achieves this objective by optimizing a contrastive loss function defined as:

$$\mathcal{L}_{\text{instance}} = -\sum_{i=1}^{n} \log \frac{\exp(e_i'^T e_i)}{\sum_{j=0}^{m} \exp(e_j'^T e_i)}, \tag{2}$$

where e_i and e_i' are positive embeddings of the instance i, and e_j' consists of one positive embedding of i and its m negative embeddings from other instances.

By contrast, cluster discrimination for representation learning consists of two main phases: clustering and discrimination. The clustering step assigns each instance a pseudo class label that will be subsequently used as supervision to train a classifier in the discrimination step. Following this, we first perform k-means on the features $e_i = f_\theta(x_i)$ to obtain k clusters and take the centroid w_i as the prototype of i-th cluster. Then, we partition the training data $\{x_i\}_{i=1}^n$ to k classes represented by prototypes $W = \{w_i\}_{i=1}^k$. Based on the pseudo class label, we can re-write the log-likelihood function as:



(a) Multi-modal Clustering (b) Discrimination

Figure 2: Illustration of the proposed method. (a) The multi-modal clustering includes one off-line step of k-means on features from image and text produced by a pre-trained CLIP model (Radford et al., 2021). (b) Using the assigned clusters as pseudo-labels, we propose a conflict-robust and representation-compact classification method through random class and feature selection along the two dimensions of the prototype matrix.

$$\theta^* = \arg\max_{\theta} \sum_{i=1}^{n} \sum_{w_i \in W} \mathbb{1}(x_i \in w_i) \log p(x_i, w_i; \theta), \tag{3}$$

where $\mathbb{1}(x_i \in w_i) = 1$ if x_i belongs to the cluster represented by w_i; otherwise $\mathbb{1}(x_i \in w_i) = 0$. With pseudo labels and centers obtained from the clustering step, cluster discrimination can be implemented by optimizing a standard softmax classification loss as:

$$\mathcal{L}_{\text{cluster}} = -\sum_{i=1}^{n} \log \frac{\exp(w_i^T e_i)}{\sum_{j=1}^{k} \exp(w_j^T e_i)}, \tag{4}$$

where $e_i = f_\theta(x_i)$ and $x_i \in w_i$. By comparing Eq. 2 and Eq. 4, we can observe the difference that instance discrimination employs an augmented feature e'_i to calculate the similarities while cluster discrimination uses a prototype w_i.

3.2 Multimodal Clustering

In this paper, we focus on the standard clustering algorithm, k-means, which takes a set of vectors as input and clusters them into k distinct groups based on the nearest neighbor criterion. To seek a better representation, we combined the image and text features produced by the pre-trained CLIP model (Radford et al., 2021) due to their mutual complementary nature. The clustering step jointly learns a $d \times k$ centroid matrix W and the cluster assignments y_i of each image x_i by solving the following problem:

$$\min_{W \in \mathbb{R}^{d \times k}} \frac{1}{n} \sum_{i=1}^{n} \min_{y_i \in \{0,1\}^k} \|\Phi(f_\theta(x_i), f'_{\theta'}(x'_i)) - W y_i\|_2^2 \quad \text{s.t.} \quad y_i^\top \mathbf{1_k} = \mathbf{1}, \tag{5}$$

where $f_\theta(x_i)$ is the image feature embedding by the image encoder f_θ and $f'_{\theta'}(x'_i)$ is the text feature embedding by the text encoder $f'_{\theta'}$, Φ is a feature ensemble function, $W \in R^{d \times k}$ is the centroid matrix, y_i in $\{0,1\}^k$ is a single label assignment constrained by $y_i^\top \mathbf{1_k} = \mathbf{1}$, and $\mathbf{1_k}$ is 1-vector of size k. In this paper, we employ the simplest feature ensemble function, that is, averaging the image and text features, as the CLIP model provides an aligned visual-textual representation.

Considering that iterative clustering and discrimination are time-consuming, we only employ one step of off-line clustering in this work. Aided by the efficient feature quantization (Johnson et al., 2019), the large-scale LAION 400M dataset can be clustered within 10 minutes using the embedded image and text features. The only hyper-parameter we consider here is the cluster number k. Even though the clustering step is straightforward, the automatically clustered large-scale dataset inevitably confronts two problems: (1) imbalanced distribution among different classes (as illustrated in Fig. 3(a)), and (2) inter-class conflict due to multi-label signals in one image and specific definition of class granularity

(a) k = 1000,000 (b) Wedding+Flower (c) Wedding+Pair (d) Wedding+Place

Figure 3: (a) Data distribution of pseudo 1M classes clustered by the image encoder and text encoder of the pre-trained CLIP model. (b) (c) and (d) are three exemplar pseudo classes. The class name is given based on the observation of images and texts. Inter-class conflict exists due to specific granularity definitions and multi-label signals in one image.

(as illustrated in Fig. 3). For instance, the bird pair in Fig. 3(c) is clustered into wedding pair, which will be conflicted with another specific category of bird. In addition, the close-up capture of wedding flowers in Fig. 3(b) also exists in the class of wedding place, where flowers are the most popular decoration.

3.3 CONFLICT-ROBUST AND REPRESENTATION-COMPACT DISCRIMINATION

Based on the clustering step, we can employ a vanilla classification loss (e.g., softmax) to learn the feature representation. For the softmax loss given in Eq. 4, the derivatives to a sample embedding feature $e_i \in \mathbb{R}^d$ and a class-wise prototype $w_j \in \mathbb{R}^d$ are:

$$\frac{\partial \mathcal{L}}{\partial e_i} = \sum_{j=1}^{k} (p_{ij} - \mathbb{1}\{y_i == j\}) w_j, \qquad \frac{\partial \mathcal{L}}{\partial w_j} = \sum_{i=1}^{b} (p_{ij} - \mathbb{1}\{y_i == j\}) e_i, \tag{6}$$

where k is the class number, b is the batch size, and $p_{ij} = e^{w_j^T e_i} / \sum_{l=1}^{k} e^{w_l^T e_i}$ is the normalized probability of the sample embedding e_i belonging to the prototype w_j, $\mathbb{1}(\cdot)$ is the indicator function which is 1 when the statement is true and 0 otherwise. In Eq. 6, the derivative of the sample feature is a "weighted sum" over the prototypes of all classes, and the derivative of the prototype is a "weighted sum" over sample features from the mini-batch. If conflicted classes exist, wrong gradient signals from these conflicted negative prototypes will affect the update of model parameters.

To this end, we propose a random negative prototype selection to efficiently construct a negative prototype subset from the entire negative prototypes. Here, the only hyper-parameter is the sampling ratio $r \in [0, 1]$. In practice, only positive prototypes and a subset of negative prototypes are selected and updated in each iteration. By doing so, the inter-class conflict will be reduced because the possibility of sampling a conflict negative prototype is directly decreased by r, and unbalanced data distribution will be alleviated because the prototypes of tail classes will receive less passive updates from the training samples from other classes.

To achieve a compact representation for efficient image retrieval, previous methods (Babenko & Lempitsky, 2015; Tolias et al., 2016) adopt Principal Component Analysis (PCA) on an independent set for dimension reduction. To reduce the descriptor dimension to d', only eigenvectors corresponding to d' largest eigenvalues are retained. However, the representation produced by PCA is sub-optimal because it is a post-processing step detached from the target task. To this end, we propose a feature approximation strategy by randomly selecting d' subspace features to construct the classification loss:

$$\mathcal{L}_{\text{unicom}} = -\sum_{i=1}^{n} \log \frac{\exp((\Gamma_t \odot w_i)^T (\Gamma_t \odot e_i))}{\sum_{j \in \mathbb{S}} \exp((\Gamma_t \odot w_j)^T (\Gamma_t \odot e_i))}, \tag{7}$$

where $\Gamma_t \in \{0, 1\}^d$ is a random binary vector with d' elements equal to 1 at the iteration step of t, $\odot$ denotes element-wise product, and $\mathbb{S}$ is a subset of all negative classes and one positive class, $|\mathbb{S}| = k', k' = k * r$. Since the binary vector varies at different iterations, different features are trained to optimize the same objective. This leads to a solution that each feature contains the similarity representation power.

The schematic of the proposed method is in Fig. 2(b). As shown, the prototype matrix W is maintained in the dimension of $d \times k$, but only part of the classes and features are randomly selected to construct

Table 1: Top-1 accuracy(%) of linear probe on 13 image classification datasets. The proposed cluster discrimination significantly outperforms OPEN-CLIP (Ilharco et al., 2021) on average by using the same training data (i.e., LAION 400M). "CLIP-R" denotes testing the public CLIP-ViT models in our code base. "-336" refers to one additional epoch of pre-training at a higher 336×336 resolution to boost performance.

		CIFAR10	CIFAR100	Caltech101	Cars	Flowers	Food101	Birdsnap	SUN397	DTD	Aircraft	Pets	EuroSAT	ImageNet	Average
CLIP	ViT B/32	95.1	80.5	93.0	81.8	96.9	88.8	58.5	76.6	76.5	52.0	90.0	97.0	76.1	81.8
	ViT B/16	96.2	83.1	94.7	86.7	98.1	92.8	67.8	78.4	79.2	59.5	93.1	97.1	80.2	85.1
	ViT L/14	98.0	87.5	96.5	90.9	99.2	95.2	77.0	81.8	82.1	69.4	95.1	98.2	83.9	88.8
	ViT L/14-336	97.9	87.4	96.0	91.5	99.2	95.9	79.9	82.2	83.0	71.6	95.1	98.1	85.4	89.5
CLIP-R	ViT B/32	96.0	82.5	94.1	86.0	97.8	92.7	61.1	79.1	78.4	58.9	93.0	95.3	75.3	83.9
	ViT B/16	96.0	82.5	94.1	86.0	97.8	92.7	69.5	79.1	78.4	58.9	93.0	95.3	79.6	84.8
	ViT L/14	98.1	87.2	96.0	90.7	99.2	95.3	77.8	81.5	80.9	68.0	94.9	96.7	84.1	88.5
	ViT L/14-336	97.8	87.1	96.3	91.4	99.2	95.9	80.9	82.2	82.4	71.2	95.1	96.8	84.9	89.3
OPEN	ViT B/32	95.3	82.2	93.3	87.5	96.5	86.2	61.4	75.3	78.8	52.4	88.0	96.5	73.8	82.1
	ViT B/16	96.4	84.0	94.1	91.8	98.1	90.7	71.2	78.7	81.6	59.3	90.0	96.2	78.5	85.4
	ViT L/14	97.9	87.9	95.5	93.6	98.8	93.3	78.0	81.0	83.0	64.4	93.3	97.1	81.5	88.1
Ours	ViT B/32	96.8	86.6	94.6	93.3	98.5	85.8	70.2	74.6	78.0	70.7	93.1	96.8	75.0	85.7
	ViT B/16	97.3	87.7	95.1	94.3	98.9	91.2	79.3	77.1	81.2	73.4	93.9	97.0	79.1	88.1
	ViT L/14	98.5	90.8	95.7	94.6	99.3	93.4	82.4	80.0	82.2	74.5	94.2	96.7	81.8	89.5
	ViT L/14-336	98.5	90.7	95.7	95.1	99.4	94.3	85.1	79.7	82.0	78.1	94.5	97.2	82.7	90.2

the softmax loss. The first random selection along the class dimension is for conflict-robust learning to achieve universal representation and the second random selection along the feature dimension is for feature compression required by efficient retrieval. Therefore, we name our method UNIversal and COMpact (UNICOM) representation learning.

4 Experiments

4.1 Implementation Details

Unless otherwise specified, all ViT models in our experiments follow architecture design in CLIP, and are pre-trained for 32 epochs on the automatically clustered LAION 400M dataset (Section 3.2) with cluster number $k = 1M$. During training, we randomly crop and horizontally flip each image to get the input image with 224×224 resolution. We set the random class sampling ratio r as 0.1 without random feature selection in the pre-training step. The training is conducted on 128 NVIDIA V100 GPUs across 16 nodes. To save memory and scale up the batch size, mixed-precision and gradient checkpoint are used. We use AdamW (Loshchilov & Hutter, 2018) as the optimizer with an initial learning rate of 0.001, a batch size of $16,384$, and a weight decay of 0.05. We employ margin-based softmax loss (Deng et al., 2019; Wang et al., 2018) for both pre-training and image retrieval tasks. The margin value is set to 0.3 and the feature scale is set to 64. To achieve compact representation for unsupervised retrieval, we fine-tune models on LAION 400M dataset for one epoch with the proposed random feature selection ($d' = 256$). For supervised retrieval, we follow the data-split settings of the baseline methods (Patel et al., 2022; Ermolov et al., 2022) to fine-tune models.

4.2 Comparisons on Feature Representation Learning

Linear Probe. Following the same evaluation setting as CLIP (Radford et al., 2021), we freeze the pre-trained models on LAION 400M dataset and only fine-tune the last linear classification layer. We report the linear probing performance over 13 datasets in Tab. 1. The proposed conflict-robust cluster discrimination method significantly outperforms the CLIP and OPEN-CLIP (Ilharco et al., 2021) models. Notably, our ViT B/32, ViT B/16, and ViT L/14 models surpass counterparts of OPEN-CLIP by 3.6%, 2.7% and 1.4% on average with the same training data, indicating that the proposed cluster discrimination can enhance the representation power over instance discrimination.

Fine-tune for ImageNet-1K Classification. In Tab. 2, we compare our method with state-of-the-art supervised and weakly supervised pre-training (Dosovitskiy et al., 2021; Zhai et al., 2022; Singh et al.,

Table 2: Transfer-learning accuracy of models pre-trained on the specified dataset followed by fine-tuning and testing on ImageNet.

Model	Pre-training Dataset	Resolution Pretrain	Resolution Finetune	IN-1K Top-1 Accuracy	FLOPs (B)
Supervised pre-training					
ViT L/32 (Dosovitskiy et al., 2021)	IN-21k	224	384	81.3	54.4
ViT B/16 (Dosovitskiy et al., 2021)	IN-21k	224	384	84.0	55.6
ViT L/16 (Dosovitskiy et al., 2021)	IN-21k	224	384	85.2	191.5
ViT L/16 (Dosovitskiy et al., 2021)	JFT 300M	224	512	87.8	362.9
ViT L/16 (Zhai et al., 2022)	JFT 3B	224	384	88.5	191.5
Weakly supervised pre-training					
ViT B/16 (Singh et al., 2022)	IG 3.6B	224	384	85.3	55.6
ViT L/16 (Singh et al., 2022)	IG 3.6B	224	512	88.1	362.9
Unsupervised pre-training					
ViT B/32 OPEN-CLIP	LAION 400M	224	384	83.0	15.5
ViT B/16 OPEN-CLIP	LAION 400M	224	384	85.4	55.6
ViT L/14 OPEN-CLIP	LAION 400M	224	518	87.7	507.8
ViT B/32 Ours	LAION 400M	224	384	83.6	15.5
ViT B/16 Ours	LAION 400M	224	384	85.9	55.6
ViT L/14 Ours	LAION 400M	224	518	88.3	507.8

Table 3: Object detection and instance segmentation on COCO. We evaluate bounding-box AP (AP^{bb}) and mask AP (AP^{mk}) on val2017.

Method	Pre-training Data	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}	AP^{mk}	AP^{mk}_{50}	AP^{mk}_{75}
ViT B/16 (Li et al., 2022)	IN-1K	47.6	-	-	42.4	-	-
ViT B/16 (Li et al., 2022)	IN-21K	47.8	-	-	42.6	-	-
ViT B/16 OPEN-CLIP	LAION 400M	48.1	69.1	51.7	42.6	66.4	44.3
ViT B/16 Ours	LAION 400M	48.5	69.8	52.4	42.9	66.9	45.9

2022) in transfer-learning experiments on ImageNet-1k. Our models consistently outperform OPEN-CLIP models in the Top-1 accuracy, showing superiority of the proposed cluster discrimination. For ViT B/16, our unsupervised pre-training achieves 85.9%, surpassing both the supervised pre-training on IN-21K (84.0%) and the weakly supervised pre-training on IG 3.6B (85.3%). In addition, our ViT L/14 obtains 88.3%, outperforming ViT L/16 pre-trained on JFT 300M (87.8%) and ViT L/16 pre-trained on IG 3.6B (88.1%). The overall results in ImageNet-1K classification task show that our models are very competitive as they can achieve better or comparable accuracy even though the training data used by the competitors are much larger (e.g., JFT 3B and IG 3.6B).

Fine-tune for COCO Detection and Segmentation. Following the experiment setting in (Li et al., 2022), we use Mask R-CNN (He et al., 2017) for bounding-box object detection and instance segmentation. We fine-tune models on the COCO (Lin et al., 2014) train2017 split and evaluate on the val2017 split. In Tab. 3, our method outperforms both OPEN-CLIP and supervised pre-training in all metrics, demonstrating the effectiveness of the proposed cluster discrimination.

4.3 Comparisons on Image Retrieval

Unsupervised Image Retrieval. In Tab. 4, we compare the performance of unsupervised image retrieval by directly using the pre-trained models for feature embedding. The GLDv2 (Weyand et al., 2020) employs mean Average Precision@100 (mAP@100) as the evaluation metric, while other datasets use Recall@1. Our ViT L/14 model achieves 69.6% average result across 7 image retrieval datasets, surpassing the OPEN-CLIP counterpart by 7.3% and even outperforming the larger OPEN-CLIP model ViT H/14 by 5.4%. The reason behind this significant improvement is that the proposed cluster discrimination can capture the semantic structure in data, which is crucial for the image retrieval task. At the bottom of Tab. 4, we further explore unsupervised image retrieval under dimension constraints (e.g., 128-D and 64-D). We set the random feature selection dimension as 256 for one additional epoch of training. Then, we select the first 128-D and 64-D features for testing across different datasets. Our ViT L/14 model constrained to 128-D and 64-D still surpasses the

Table 4: Performance of unsupervised image retrieval.

		CUB	Cars	SOP	In-Shop	INaturalist	VehicleID			GLDv2		Average
							Small	Medium	Large	Private	Public	
CLIP	B/32	53.5	79.0	60.5	45.4	53.0	54.8	52.2	44.6	7.5	7.5	45.8
	B/16	63.6	85.2	63.2	56.1	63.1	55.1	50.9	43.8	8.4	10.6	50.0
	L/14	73.7	90.3	65.6	62.9	72.9	62.4	58.9	51.8	12.1	13.6	56.4
	L/14-336	75.4	90.9	67.8	66.3	76.8	64.1	60.3	53.8	17.0	15.6	58.8
OPEN	B/32	59.9	89.2	65.9	64.6	54.9	71.0	67.1	59.9	9.17	8.4	55.0
	B/16	70.1	92.9	68.7	74.2	64.1	73.3	70.1	63.7	12.1	11.0	60.0
	L/14	78.3	94.9	70.6	77.1	71.0	72.0	69.1	62.0	14.5	13.8	62.3
	H/14	80.9	95.7	72.7	78.8	77.0	72.7	69.7	61.9	17.7	15.3	64.2
Ours	B/32	78.2	95.9	70.0	72.8	64.6	74.9	72.0	65.4	15.1	13.3	62.2
	B/16	84.7	96.8	70.4	74.6	73.6	74.5	70.6	58.7	18.7	17.2	63.9
	L/14	86.8	96.9	72.7	83.6	77.1	83.7	80.2	74.6	21.1	20.1	69.6
	L/14-336	87.4	97.3	74.5	86.7	81.0	84.1	81.4	75.6	23.2	22.0	71.3
Unicom	B/32^{128}	74.5	94.4	66.8	69.2	58.6	73.6	70.4	63.6	9.1	10.9	59.1
	B/32^{64}	69.6	91.2	64.6	63.8	50.8	70.9	67.1	60.3	5.5	6.7	55.1
	B/16^{128}	82.4	96.3	69.4	69.9	69.4	72.2	67.9	61.4	14.3	15.8	61.9
	B/16^{64}	78.8	95.1	65.6	65.7	63.9	69.6	65.4	58.4	9.9	11.3	58.4
	L/14^{128}	85.0	97.2	69.7	82.4	74.0	82.9	79.3	72.7	17.6	18.7	68.0
	L/14^{64}	83.7	96.6	66.5	78.3	70.1	81.6	77.4	70.9	14.1	15.4	65.5
	L/14-336^{128}	86.3	97.2	71.7	84.5	78.3	83.2	80.1	73.9	19.7	20.3	69.5
	L/14-336^{64}	85.1	96.7	67.9	81.2	74.9	82.5	78.7	72.2	16.5	16.8	67.3

Table 5: Comparison with Recall@k Surrogate Loss (Patel et al., 2022) for supervised image retrieval on iNaturalist, SOP, VehicleID and Cars datasets.

Method	Arch.^{dim}	iNaturalist				SOP				VehicleID						Cars			
		Recall@k								Small		Medium		Large					
		1	4	16	32	10^0	10^1	10^2	10^3	1	5	1	5	1	5	1	2	4	8
RS@k	$RN50^{128}$	69.3	82.9	90.6	93.1	80.6	91.6	96.4	98.8	**95.6**	**97.8**	**94.4**	**96.8**	**93.5**	**96.6**	78.1	85.8	91.1	94.5
RS@k+SiMix	$RN50^{128}$	69.6	83.3	91.2	93.8	80.9	91.7	96.5	98.8	95.4	97.5	93.8	96.6	93.0	96.2	84.7	90.9	94.7	96.9
Unicom	ViT B/32^{128}	**71.0**	**84.0**	**91.6**	**94.2**	**85.1**	**94.5**	**97.9**	**99.2**	95.2	97.4	93.9	96.7	92.9	96.0	**95.7**	**97.5**	**98.4**	**98.9**
SAP	ViT B/32^{512}	72.2	84.6	91.6	93.9	83.7	94.0	97.8	99.3	94.8	97.7	93.5	**96.8**	92.1	96.3	78.1	85.7	91.0	94.8
RS@k	ViT B/32^{512}	**75.9**	**87.1**	**93.1**	**95.1**	85.1	94.6	98.0	99.3	95.1	97.7	**94.1**	96.7	93.2	**96.5**	78.1	86.4	92.3	95.6
Unicom	ViT B/32^{512}	75.8	86.9	93.0	95.0	**87.5**	**95.9**	**98.3**	**99.4**	**95.4**	**97.8**	**94.1**	96.6	**93.1**	96.4	**96.2**	**98.0**	**98.7**	**99.2**
SAP	ViT B/16^{512}	79.1	89.0	94.2	95.8	86.6	95.4	98.4	99.5	95.5	97.7	94.2	96.9	93.1	96.6	86.2	92.1	95.1	97.2
RS@k	ViT B/16^{512}	83.9	92.1	95.9	97.2	88.0	96.1	98.6	99.6	96.2	98.0	**95.2**	**97.2**	94.7	97.1	89.5	94.2	96.6	98.3
Unicom	ViT B/16^{512}	**84.1**	**92.0**	**96.2**	**97.5**	**88.7**	**96.2**	**98.7**	**9.7**	**96.4**	**98.0**	95.1	97.0	**95.0**	**97.3**	**97.3**	**98.6**	**98.9**	**99.3**

OPEN-CLIP ViT L/14 (768-D) model by 5.7% and 3.2%, indicating the superiority of the proposed random feature selection for compact feature representation learning. Here, we have not included the results from STML (Kim et al., 2022) for comparison as STML employs an ImageNet-1K pre-trained GoogleNet (Szegedy et al., 2015) and then explores unsupervised training on each retrieval dataset. By contrast, our ViT based model is only pre-trained on the LAION 400M dataset in an unsupervised way without any further training on each image retrieval dataset. In Fig. 1(a), we show that Unicom can outperform STML by a large margin on the CUB dataset.

Supervised Image Retrieval. In Tab. 5 and 6, we compare the proposed Unicom ($d' = 256$) with the latest methods (Brown et al., 2020; Patel et al., 2022; Ermolov et al., 2022) trained with vision transformer. Under different dimension constraints, Unicom consistently surpasses the RA@K on iNaturalist, SOP, and Cars datasets, and outperforms Hyp-ViT on CUB, Cars and In-shop datasets. On VehicleID and SOP, Unicom also achieves comparable performance compared to RA@K and Hyp-ViT if it does not rank first in specific tracks.

Table 6: Comparison with Hyperbolic ViT (Ermolov et al., 2022) for supervised image retrieval on CUB, Cars, SOP and In-shop datasets.

Method	Dim	CUB				Cars				SOP				In-Shop			
		1	2	4	8	1	2	4	8	10^0	10^1	10^2	10^3	1	10	20	30
Hyp-DeiT	384	77.8	86.6	91.9	95.1	86.4	92.2	95.5	97.5	83.3	93.5	97.4	99.1	90.5	97.8	98.5	98.9
Hyp-DINO	384	80.9	87.6	92.4	95.6	89.2	94.1	96.7	98.1	85.1	94.4	97.8	99.3	92.4	98.4	98.9	99.1
Hyp-ViT	384	85.6	91.4	94.8	96.7	86.5	92.1	95.3	97.3	85.9	94.9	**98.1**	**99.5**	92.5	98.3	98.8	99.1
Unicom ViT B/32	384	**85.7**	**91.6**	**95.0**	**96.9**	**96.2**	**98.0**	**98.7**	**99.2**	**87.4**	**95.6**	**98.1**	99.2	**94.9**	**99.2**	**99.4**	**99.5**
Hyp-DeiT	128	74.7	84.5	90.1	94.1	82.1	89.1	93.4	96.3	83.0	93.4	97.5	99.2	90.9	97.9	98.6	98.9
Hyp-DINO	128	78.3	86.0	91.2	94.7	86.0	91.9	95.2	97.2	84.6	94.1	97.7	99.3	92.6	98.4	99.0	99.2
Hyp-ViT	128	84.0	90.0	94.2	96.4	82.7	89.7	93.9	96.2	**85.5**	**94.9**	**98.1**	**99.4**	92.7	98.4	98.9	99.1
Unicom ViT B/32	128	**85.3**	**90.9**	**94.5**	**96.5**	**95.7**	**97.5**	**98.4**	**98.9**	85.1	94.5	97.9	99.2	**94.7**	**99.1**	**99.3**	**99.5**

Table 7: Ablation study on multi-modal clustering and random negative class selection during discrimination. ViT-B/16 is used here and we report the average accuracy of linear probe over 13 datasets and the average performance of unsupervised image retrieval over 7 datasets.

Tasks	Encoder			Cluster Number			Random Class Ratio (r)			
	Image	Text	Joint	100K	1M	10M	0.05	0.1	0.3	1
Linear Probe	85.5	86.8	88.1	77.1	88.1	84.7	87.2	88.1	86.4	80.4
Unsupervised Retrieval	61.4	62.2	63.9	54.1	63.9	60.3	63.1	63.9	62.8	55.7

Table 8: Ablation study of random feature selection on the CUB dataset. ViT-B/32 is used here and the embedding size is 512. For Unicom, we use the first 512-D, 128-D, 64-D and 32-D features for dimension-constrained testing.

Test Dimension	Adaptive Pooling	PCA	FC	Unicom (d')					
				512	384	256	128	64	32
512	85.8	85.8	85.8	85.8	85.7	85.9	85.5	84.7	81.7
128	84.8	84.9	85.1	84.9	85.3	85.3	84.9	83.8	81.6
64	84.0	83.8	84.0	83.6	83.8	84.2	83.5	83.0	80.2
32	80.9	81.3	81.7	81.0	81.5	82.1	82.0	80.4	78.1
average	83.9	84.0	84.2	83.8	84.1	84.4	84.0	83.0	80.4

4.4 Ablation Study

Encoder for Clustering and Cluster Number. In Tab. 7, we compare the results of linear probe and unsupervised retrieval under image-based clustering and text-based clustering. As we can see, the text encoder is more powerful than the image encoder, and image and text signals are complementary as the joint clustering significantly outperforms each individual. Regarding the cluster number, too small cluster number will incur heavy intra-class noise, which dramatically decreases the performance of the pre-trained classification model. Besides, too many clusters will increase the computation and storage burden on the FC layer and the over decomposition will also undermine the discriminative power of the pre-trained model. Therefore, we select the pseudo class number as 1 million, with the average image number per class being around 400.

Random Class and Feature Selection. In Tab. 7, the basic margin-based softmax loss ($r = 1$) only help achieve 80.4% on the linear probe task as it can hardly adapt to the heavy inter-class conflict in the automatically clustered dataset. By contrast, the proposed random negative class selection ($r = 0.1$) can significantly boost the robustness of margin-based softmax loss, obtaining 88.1% on the linear probe task. In Tab. 8, we compare the proposed random feature selection with Adaptive Pooling, PCA and FC. As we can see, PCA slightly outperforms Adaptive Pooling by 0.1%, and additionally trained FC surpasses PCA by 0.2%. When the feature dimension decreasing from 512 to 32 during the training of the proposed Unicom, the test accuracy under low dimension constraint (e.g., 64-D and 32-D) first increases and then decreases, indicating appropriate random feature selection during training is able to enhance compact feature representation.

5 Conclusions

This paper introduces Unicom, a simple yet effective framework for universal and compact feature embedding. Given the automatically clustered large-scale data, we employ one random negative class selection to improve the robustness under the heavy inter-class conflict and another random feature selection to improve the compactness of the feature representation. For both unsupervised and supervised image retrieval on different datasets, the proposed Unicom achieves state-of-the-art performance under different dimension constraints, confirming that cluster discrimination is beneficial to explore the semantic structure within the large-scale training data.

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A Appendix

A.1 Model Architectures

We follow the same architecture design as CLIP. Tab. 9 describes the details of architectures.

A.2 Visualization of Pseudo Clusters and Data Distribution

In Fig. 4, we show some exemplar classes from the proposed automatic clustering. As we can see, there are some fine-grained classes, such as the top with love icons and the top with cartoons. Even though such clustering is reasonable and explainable, there is class confusion if we classify these samples from other views, such as color and targeting customer age. In Fig. 5, we show the unbalanced data distribution under different settings of class number k.

A.3 Linear Probe Datasets

We use 13 image classification datasets to prove the effectiveness of our method. These datasets include CIFAR10(Krizhevsky et al., 2009), CIFAR100(Krizhevsky et al., 2009), Caltech101(Fei-Fei et al., 2004), Stanford Cars(Krause et al., 2013a), Oxford Flowers(Nilsback & Zisserman, 2008), Food-101(Bossard et al., 2014), Birdsnap(Berg et al., 2014), SUN397(Xiao et al., 2010), Describable Textures(Cimpoi et al., 2014), FGVC Aircraft(Maji et al., 2013), Oxford-IIIT Pets(Parkhi et al., 2012), EuroSAT(Helber et al., 2019), ImageNet-1k(Russakovsky et al., 2015). Details on each dataset and the corresponding evaluation metrics are provided in Tab. 10.

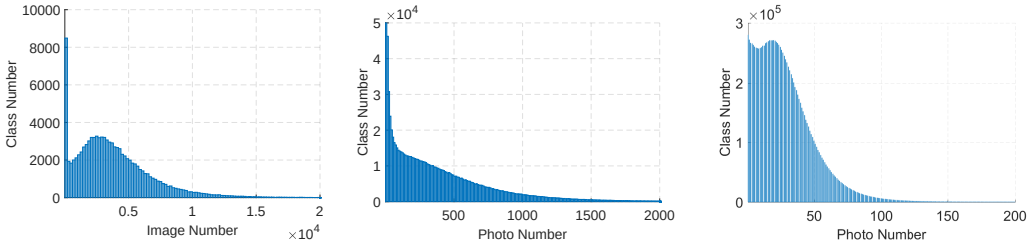
Table 9: The architecture parameters for ViT models.

Model	FLOPs	Embedding dimension	Input resolution	Vision Transformer layers	width	heads
ViT-B/32	4.3	512	224	12	768	12
ViT-B/16	17.6	512	224	12	768	12
ViT-L/14	80.9	768	224	24	1024	16
ViT-L/14-336	191.3	768	336	24	1024	16

(a) Bag+Monkey (b) Bag+Wing (c) Bag+Fantasy

(d) Top+Love (e) Grey Top+Pink Sleeve (f) Top+Cartoon

Figure 4: Pseudo classes clustered by the image encoder and text encoder of the pre-trained CLIP model. The class name is given based on the manual observation of images and texts.



(a) k = 100,000 (b) k = 1000,000 (c) k = 10,000,000

Figure 5: Unbalanced data distribution under different settings of class number k.

Table 10: List of linear probe datasets with the data distribution and evaluation metrics.

Dataset	**Classes**	**Train size**	**Test size**	**Evaluation metric**
CIFAR-10	10	50,000	10,000	accuracy
CIFAR-100	100	50,000	10,000	accuracy
Caltech-101	102	3,060	6,085	mean-per-class
Stanford Cars	196	8,144	8,041	accuracy
Oxford Flowers	102	2,040	6,149	mean per class
Food-101	102	75,750	25,250	accuracy
Birdsnap	500	42,283	2,149	accuracy
SUN397	397	19,850	19,850	accuracy
Describable Textures	47	3,760	1,880	accuracy
FGVC Aircraft	100	6,667	3,333	mean per class
Oxford-IIIT Pets	37	3,680	3,669	mean per class
EuroSAT	10	10,000	5,000	accuracy
ImageNet	1000	1,281,167	50,000	accuracy

Table 11: Dataset composition for training and evaluation in the image retrieval task.

Dataset	**Images**	**Classes**
CUB Train (Welinder et al., 2010)	5,864	100
CUB Test (Welinder et al., 2010)	5,924	100
Cars196 Train (Krause et al., 2013b)	8,054	98
Cars196 Test (Krause et al., 2013b)	8,131	98
SOP Train (Oh Song et al., 2016)	59,551	11,318
SOP Test (Oh Song et al., 2016)	60,502	11,316
In-Shop (Liu et al., 2016b)	25,882	3,997
In-Shop (Liu et al., 2016b)	26,830	3,985
iNaturalist Train (Van Horn et al., 2018)	325,846	5,690
iNaturalist Test (Van Horn et al., 2018)	136,093	2,452
VehicleID Train (Liu et al., 2016a)	110,178	13,134
VehicleID Test (Liu et al., 2016a)	40,365	4,800
GLDv2 Train (Weyand et al., 2020)	1,580,470	81,314
GLDv2 Test (Weyand et al., 2020)	762,884	1,129

Table 12: Comparison on the GLDv2 retrieval task. The mAP@100 scores on the public and private test sets are reported.

Method	Arch.	GLDv2 Private	GLDv2 Public
ArcFace (Weyand et al., 2020)	ResNet101	25.6	23.3
RRT (Tan et al., 2021)	ResNet50	27.0	24.6
CVNet-Global (Lee et al., 2022)	ResNet101^{2048}	32.5	-
Ours	ViT B/32^{512}	32.6	29.7
Ours	ViT B/16^{512}	35.7	32.4

A.4 Image Retrieval Datasets

The training and evaluation of image retrieval experiments on seven widely used datasets, namely CUB-200-2011(CUB) (Welinder et al., 2010), Stanford Cars(Cars196) (Krause et al., 2013b), Stanford Online Products(SOP) (Oh Song et al., 2016), In-shop Clothes Retrieval(In-Shop) (Liu et al., 2016b), iNaturalist (Van Horn et al., 2018), VehicleID (Liu et al., 2016a), and Google Landmarks dataset (GLDv2) (Weyand et al., 2020). The number of examples and classes can be found in Tab. 11.

A.5 Comparison on Google Landmarks Dataset v2

We also compare our model with state-of-the-art methods on the instance-level large-scale image retrieval task of the Google Landmarks dataset v2 (Weyand et al., 2020) (referred to as GLDv2). We evaluate on the standard test set, which contains 1,129 query images and 761,757 gallery images. The performance is evaluated using a mean Average Precision@100 (mAP@100) metric.

For the training of the proposed Unicom, the input image is augmented with random cropping/aspect ratio distortion and resized to 512×512 following (Lee et al., 2022). We fine-tune our pre-trained models (e.g., ViT B/32 and ViT B/16) on the training set of GLDv2. Random class selection and random feature selection are not used here as the training set is clean and there is no dimension limitation. Tab. 12 shows a comparison between the results of the proposed models and state-of-the-art image retrieval methods on GLDv2. The proposed Unicom ViT B/32 outperforms CVNet-Global (Lee et al., 2022) by 0.1% on the private test set with less computation cost and more compact feature representation. The proposed Unicom ViT B/16 achieves 35.7%, surpassing CVNet-Global by 3.2%.

Table 13: Results on the Google Universal Image Embedding competition. The embedding dimensionality is constrained to 64. UNICOM selects first 64-D features as the embedding.

		Adaptive Pooling	UNICOM ($d' = 256$)
CLIP	RN50	28.6	-
	RN101	32.7	-
	RN50x4	33.0	-
	RN50x16	37.4	-
	RN50x64	40.9	-
	B/32	30.6	-
	B/16	35.5	-
	L/14	40.8	-
	L/14-336	44.4	-
OPEN-CLIP	B/32	38.5	-
	B/16	45.9	-
	L/14	49.9	-
	H/14	51.1	-
	g/14	52.4	-
Our	B/32	40.9	44.3
	B/16	49.7	53.1
	L/14	53.4	56.1
	L/14-336	56.2	58.9

A.6 GOOGLE UNIVERSAL IMAGE EMBEDDING COMPETITION

Google Universal Image Embedding competition is part of the Instance-Level Recognition workshop at ECCV 2022, which aims to create universal image representations that work across many visual domains. The evaluation dataset of this competition is kept private, containing images of apparel & accessories, packaged goods, landmarks, furniture & home decor, storefronts, dishes, artwork, toys, memes, illustrations and cars. Labels are defined generally at the instance level, for example, the same T-shirt, the same building, the same painting, and the same dish. In this competition, participants need to submit models to be evaluated by the test server. The submitted models take an image as an input and return a float vector (i.e., the image embedding) as the output. The embedding dimensionality is constrained to 64, and the submissions are evaluated according to the mean Precision@5 metric.

To prove the proposed Unicom can provide universal embeddings, we compared it with CLIP and OPEN-CLIP models in this competition. As shown in Tab. 13, our models significantly improve the score. Our ViT L/14-336 model achieves 56.2%, surpassing the CLIP counterpart by 11.8% and even outperforming the larger OPEN-CLIP model ViT g/14 by 3.8%. This improvement confirms that cluster discrimination can explore the semantic structure within the data, showing superiority over instance discrimination on the image retrieval task. We further explore the proposed random feature selection for unsupervised image retrieval under dimension constraints. We set the random feature selection dimension as 256 for one additional epoch of training on the automatically clustered LAION-400M dataset, and we further improve score of ViT L/14-336 by 2.7%.