

Prototypical Contrastive Language Image Pretraining

**Delong Chen^{1,2*}, Zhao Wu¹, Fan Liu², Zaiquan Yang^{1,3}, Yixiang Huang^{1,4},
Yiping Bao¹, and Erjin Zhou¹**

¹MEGVII Technology

²Hohai University

³Beihang University

⁴Beijing University of Posts and Telecommunications

Abstract

Contrastive Language Image Pretraining (CLIP) received widespread attention since its learned representations can be transferred well to various downstream tasks. During CLIP training, the InfoNCE objective aims to align positive image-text pairs and separate negative ones. In this paper, we show a representation grouping effect during this process: the InfoNCE objective indirectly groups semantically similar representations together via randomly emerged within-modal anchors. We introduce **Prototypical Contrastive Language Image Pretraining** (ProtoCLIP) to enhance such grouping by boosting its efficiency and increasing its robustness against modality gap. Specifically, ProtoCLIP sets up prototype-level discrimination between image and text spaces, which efficiently transfers higher-level structural knowledge. We further propose **Prototypical Back Translation** (PBT) to decouple representation grouping from representation alignment, resulting in effective learning of meaningful representations under large modality gap. PBT also enables us to introduce additional external teachers with richer prior knowledge. ProtoCLIP is trained with an online episodic training strategy, which makes it can be scaled up to unlimited amounts of data. Combining the above novel designs, we train our ProtoCLIP on Conceptual Captions and achieved an +5.81% ImageNet linear probing improvement and an +2.01% ImageNet zero-shot classification improvement. Codes are available at <https://github.com/megvii-research/protoclip>.

1 Introduction

Contrastive Language Image Pretraining (CLIP) [1, 2] has achieved impressive performance on learning visual representations from large-scale image-text pairs collected from the Internet. It attracts widespread attention from the deep learning community, since its learned representations can be transferred well to a variety of downstream tasks, including linear probing, zero-shot classification, cross-modal retrieval, etc. The CLIP is trained to optimize the InfoNCE objective [3], which uses the paired image-text representations as positives and unpaired representations within a batch as negatives. Intuitively, optimizing such an objective will directly result in two perfectly aligned representation spaces, where image-text representations of the same sample are embedded together. This can be termed as *representation alignment*. As in Figure 1, optimizing InfoNCE objective converts unaligned representation spaces (a) to aligned spaces (b). But is the representation alignment the *only* prerequisite for strong downstream task performance? We show an extreme case in Figure 1(c), where the representations are perfectly aligned but uniformly distributed. Such representations are class-inseparable (“cat” and “car” are mixed together) and undesired in the downstream tasks [4].

*This work is done when Delong Chen is a research intern at MEGVII Technology.

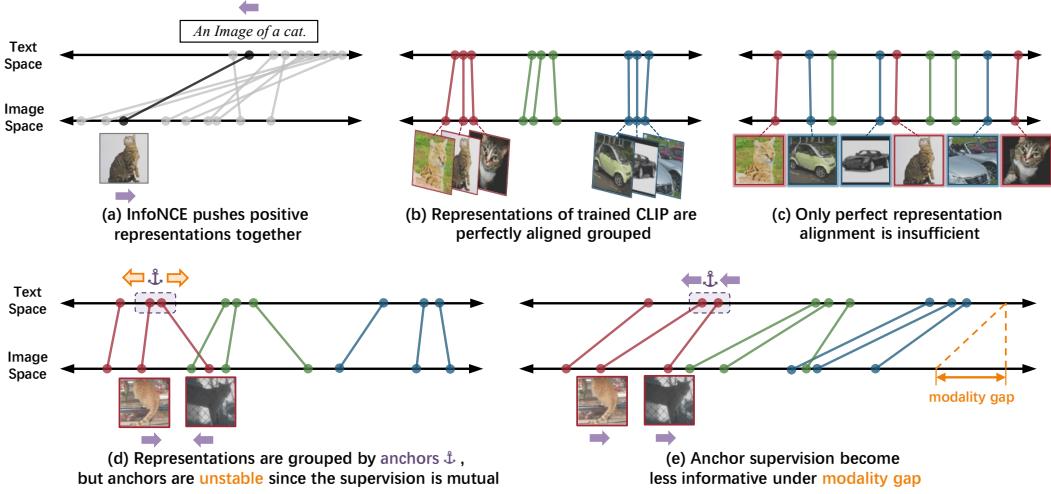


Figure 1: Illustrations of representation alignment and representation grouping in 1-dimensional image-text spaces. Each “●—●” represents a positive image-text pair. Colors indicate ground truth classes.

The pretrained CLIP actually yields well-clustered representations (Figure 1(b)) and excellent downstream performance. We show that, in addition to pursuing alignment, representations are *grouped indirectly* when CLIP pushes positive pairs together. As Figure 1(d), within-modality sample pairs with very close distances will emerge (noted by purple boxes) when the dataset becomes sufficiently large. During aligning positive pairs, these samples serve as anchors that group the corresponding representations in the opposite modality. For example, invariant visual features (e.g., recognizing cats from different angles) can be learned through the co-occurrence of the word “cat” in a pair of captions.

The representation grouping of InfoNCE is effective but has two major weaknesses. **First**, the grouping is done in an *indirect* manner, resulting in unstable anchors and limited grouping efficiency. Specifically, only very close sample pairs that are inseparable by the encoder can push representations in the other modality together. This is due to the fact that the anchoring is mutually done by the InfoNCE objective. Close-but-separable within modality representation pairs are at the risk of being pulled apart by the opposite modality (as noted by the two orange arrows in Figure 1(d)). This leads to a reduced number of effective anchors and yields less grouped representations. **Second**, the anchors become less effective with the existence of a large modality gap. Modality gap [5] is defined as the range between mean representations in image and text spaces. As shown in Figure 1(e), when the two representation spaces are not overall aligned, the InfoNCE objective will focus primarily on aligning them rather than learning meaningful representations. In such cases, representations cannot be pushed together as desired. Instead, they will be moved towards the same direction for alignment at first. Effective representation learning happens only if two spaces are perfectly aligned.



Figure 2: **Left:** Prototypes recognized by ProtoCLIP. **Right:** samples assigned to the corresponding prototype.

We propose **Prototypical Contrastive Language Image Pretraining** (ProtoCLIP), which raises instance-level discrimination to a prototypical-level discrimination by constructing and dynamically updating prototypes on both image-text spaces. As shown in Figure 2, samples assigned to the same prototype have shared semantics, and we use these prototypes to *directly* supervise the opposite modality. This leads to richer supervision signals and more efficient representation grouping. Prototypical supervisions are comparatively more stable since these prototypes are not at the risk of being pulled apart.

For the modality gap issue, we further introduce a simple yet effective **Prototype Back Translation** (PBT) technique to decouple representation grouping from representation alignment. PBT calculates a within-modal centroid for samples that are assigned to a shared prototype, and then groups these representations towards the centroid. With PBT, representation alignment is no longer a prerequisite

for effective learning of representation grouping. Based on the ability of learning representations from unaligned spaces, we can further introduce external teacher (e.g., a pretrained RoBERTa [6]) which has richer prior knowledge.

Furthermore, we present two improvements to previous clustering-based pretraining methods. **First**, DeepCluster [7, 8], SeLa [9], PCL [10], XDC [11] SeLaVi [12], and MCN [13] update the clusters after each training epoch or several consecutive epochs. Such a training strategy can work well on medium-sized ImageNet [14] but is not scalable to larger datasets (e.g., YFCC [15]) due to low cluster updating frequency. To train the ProtoCLIP more efficiently, we design an online episodic training strategy, which makes the training of ProtoCLIP can be scaled up to unlimited amounts of data. We further identify a trade-off between prototype reliability and prototype updating frequency for the episodic training strategy. **Second**, many previous works [7, 9, 11, 12, 10, 16] learn one-hot pseudo labels as hard targets, which ignores the relationship among clusters. For example, though “cat” and “tiger” samples probably belong to different clusters, the distance between them should be much closer than that of “cat” and “car”. To this end, we convert cluster assignment information to probability scores by softmax to enable the effective transfer of such structural relationships.

Overall, our main contributions in this paper are summarized as the following:

- We proposed ProtoCLIP with prototype-level discrimination that enables more efficient representation grouping in large-scale vision-language pretraining. Representations are grouped towards prototypes that have higher semantics compared to individual instances.
- We designed PBT to translate cross-modal prototypes to within-modal centroids. PBT enables ProtoCLIP to learn meaningful representations between unaligned spaces. Based on PBT, we further introduced pretrained RoBERTa as an external teacher for richer supervision.
- We presented two improvements to previous clustering-based pretraining methods: 1) online episodic training strategy that improves cluster updating frequency, and 2) the use of probability-based soft targets which transfer structural relational knowledge.
- Experimental results on Conceptual Captions show that ProtoCLIP outperforms CLIP by +5.81% and +2.01% on ImagNet linear probing and zero-shot classification respectively.

2 Related Works

Vision Language Pretraining. Recent works have exploited learning visual representations from large-scale uncurated web-crawled image-text data and showed promising results. VLP models can be classified into **1)** single-stream and **2)** dual-stream. **1)** Single-stream models [17, 18, 19, 20] fuse image and text based on the advantage of the self-attention mechanism [21] and excel at multimodal fusing and understanding, leading to impressive performance on high-level multimodal tasks such as Visual Question Answering (VQA) and image captioning. Unfortunately, the transferability of single-stream models is weak since they have no independent encoder that can be transferred to single modal tasks. **2)** Dual-stream models set up two separated encoders to align visual and textual representations. Though the methodology is quite simple, pioneer works (CLIP [1] and ALIGN [2]) show prestigious success when combining it with a huge amount of training data. Some follow-up works improved CLIP from the representation alignment perspective. For example, FILIP [22] introduced finer-grained representation alignment to boost multimodal interaction. CLOOB [23] introduced Hopfield Networks for improved learning of feature associations and co-occurrences. More recent efforts focus on improving the learning efficiency, since the training of CLIP is highly expensive. To improve the learning efficiency, EfficientCLIP [24] and SLIP [25] respectively combined BERT [26]-style and SimCLR [27]-style self supervision with CLIP. DeCLIP [28] further integrates multi-view supervision and nearest-neighbor supervision.

Self-supervised Visual Representation Learning. Self-supervised Learning (SSL) [29] aims at learning meaningful representations without human supervision. Early works on SSL focus on exploring pretext tasks [30]. After SimCLR [27] demonstrated the effectiveness of instance discrimination task, contrastive learning become dominant in the field of SSL. SimCLR aligns representations of different data augmentations, which creates augmentation overlaps [4] that groups intra-class samples together. Unfortunately, SimCLR relies on extremely large batch sizes for sufficient negatives. To solve this issue, MoCo [31] introduced momentum contrast, while BYOL [32] and SimSiam [33] showed that representations can be learned without negatives. Though these works effectively

improved SSL learned representations, they share a fundamental weakness that the model is only encouraged to learn augmentation-invariant representations, while higher levels of semantic relations are ignored. Nearest Neighbor-based methods such as NNCLR [34] and MYOL [35] introduced richer supervision signals, but the variance of positive pairs is still limited.

Clustering-based SSL. A promising line of work in SSL is clustering-based approaches. DeepCluster [7] and SeLa [9] assign pseudo labels using K -Means or Sinkhorn Knopp algorithm, then use these labels to supervise model training. SwAv [8] contrasts the cluster assignment between different augmentations of the same image. The clustering of SwAV is done in an online fashion, but it forces the size of each cluster to be equal. PCL [10] and SCCL [16] combined cluster-level contrast with instance-level contrast and demonstrated the effectiveness in image SSL and text SSL respectively. XDC [11] and SeLaVi [12] respectively extend DeepCluster [7] and SeLa to audiovisual pretraining [9]. ProtoCLIP shares some similarities with XDC [11], since both of them utilize the clusters in the opposite modality as supervision. However, ProtoCLIP aims at VLP instead of audio-visual pretraining which only requires representation grouping—in a VLP scenario, representation alignment should be considered as well for zero-shot classification and cross-modal retrieval. Besides, compared to a pure VLP version of XDC, ProtoCLIP contains several novel designs, including PBT, episodic training, learnable temperature, and the use of soft targets.

3 Method

3.1 Prototypical Contrastive Language Image Pretraining

Let’s get started by revisiting the InfoNCE objective used by the original CLIP [1]. CLIP is trained with large-scale image-text dataset $\mathcal{D} = \{(x_i^I, x_i^T)\}_{i=1}^M$ that consists of a total of M training samples. The goal is to learn an image encoder f^I and a text encoder f^T that respectively encode x_i^I and x_i^T to their latent representations, i.e., $f^I(x_i^I) = z_i^I \in \mathbb{R}^{d_z \times 1}$ and $f^T(x_i^T) = z_i^T \in \mathbb{R}^{d_z \times 1}$. The learned representation should fulfill two requirements: representation alignment and representation grouping:

Representation alignment refers to high similarity $z_i^I \cdot z_i^T$ of paired image and text samples x_i^I, x_i^T , and low similarity $z_i^I \cdot z_j^T (i \neq j)$ between the unpaired samples x_i^I, x_j^T . Generally, perfect representation alignment yields strong downstream performance on cross-modal retrieval tasks.

Representation grouping means that representations of semantically similar samples are grouped together, while those of dissimilar samples should be pulled apart. Perfect representation grouping yields strong linear classification performance.

While fulfilling perfect representation alignment and representation grouping at the same time, coupled with a large dataset that contains sufficient open-set concepts, the model can achieve strong zero-shot classification performance. To achieve this objective, CLIP creates an instance discrimination task within each batch, and optimizes the following bi-directional InfoNCE objective [3]:

$$\mathcal{L}_{\text{CLIP}} = -(\underbrace{\frac{1}{N} \sum_{i=1}^N \log \frac{\exp(z_i^I \cdot z_i^T / \tau_{\text{CLIP}})}{\sum_{j=1}^N \exp(z_i^I \cdot z_j^T / \tau_{\text{CLIP}})}}_{\text{image to text}} + \underbrace{\frac{1}{N} \sum_{i=1}^N \log \frac{\exp(z_i^T \cdot z_i^I / \tau_{\text{CLIP}})}{\sum_{j=1}^N \exp(z_i^T \cdot z_j^I / \tau_{\text{CLIP}})}}_{\text{text to image}})/2, \quad (1)$$

where N is the batch size and τ_{CLIP} is a learnable temperature parameter.

As illustrated in Section 1, representation grouping is done indirectly by the InfoNCE objective. Here we want to boost the efficiency by performing representation grouping in a direct manner. We raise the instance-level discrimination to prototype-level discrimination by constructing and updating prototypes. A prototype is a representation for a group of semantically similar instances [10]. Representations will be directly pushed towards the prototype for grouping by a proposed prototypical loss $\mathcal{L}_{\text{Proto}}$.

An illustration of ProtoCLIP architecture is shown in Figure 3. To acquire prototypes, we apply MLP projection heads g^I and g^T on top of z_i^I and z_i^T respectively, then we get projected representations $g^I(z_i^I) = h_i^I \in \mathbb{R}^{d_h \times 1}$ and $g^T(z_i^T) = h_i^T \in \mathbb{R}^{d_h \times 1}$. Prototypes are constructed here in the projected representation spaces (h_i^I and h_i^T) instead of the raw representation spaces (z_i^I and z_i^T). This is done

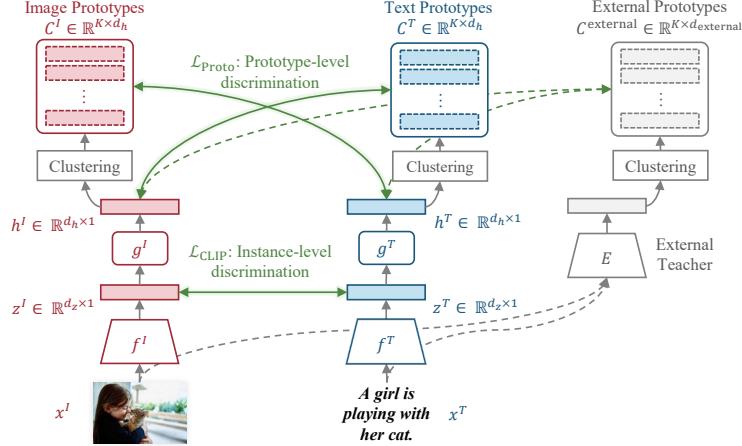


Figure 3: **Model Architecture of ProtoCLIP.** We setup prototype-level discrimination upon the instance-level discrimination. We construct prototypes with representations after projection heads g^I, g^T . The prototypes are used to guide the learning of the opposite modality. An external teacher E is introduced for richer supervision, which will be detailed in Section 3.2.

for two reasons. First, we want ProtoCLIP to hold the instance-level discrimination ability of CLIP by keeping the $\mathcal{L}_{\text{CLIP}}$, so prototypical-level discrimination should be done elsewhere otherwise it will cause conflicts between $\mathcal{L}_{\text{CLIP}}$ and $\mathcal{L}_{\text{Proto}}$. Second, the MLP projection heads g^I and g^T can project representations to lower-dimensional spaces (i.e. $d_h < d_z$), such that the cost of constructing prototypes can be significantly reduced.

We adopt K -Means clustering due to its simplicity and scalability. Other clustering methods can be used here as well. Specifically, we find prototypes $C^I \in \mathbb{R}^{K \times d_h} = [c_1^I, c_2^I, \dots, c_K^I]$ and $C^T \in \mathbb{R}^{K \times d_h} = [c_1^T, c_2^T, \dots, c_K^T]$ that minimize the following K -Means objective:

$$\arg \min_{C^I, C^T} \underbrace{\sum_{k=1}^K \sum_{i=1}^M \|g^T(z_i^T) - c_k^T\|^2}_{\text{clustering text representations}} + \underbrace{\sum_{k=1}^K \sum_{i=1}^M \|g^I(z_i^I) - c_k^I\|^2}_{\text{clustering image representations}} \quad (2)$$

Pseudo labels (or cluster assignment) can be then generated for each sample according to the closeness between its representation and each prototype . Previous clustering-based audiovisual pretraining method XDC [11] have compared different types of supervision and found model learns the best when it is purely supervised by the opposite modality. Inspired by XDC, Here ProtoCLIP also creates cross-modal supervision in a cross-modal manner: we use the prototypes in the opposite modality to guide representation learning². Besides, previous methods such as DeepCluster [7] and XDC [11] generate class indices and train an additional parametric classifier with cross-entropy loss, as usually done in traditional supervised training. However, since there is no mapping between two consecutive cluster assignments, such a method requires frequent re-initialization of the classifier, which interrupts the training procedure. Instead, we use the prototypes as linear classifiers directly [8, 10]. As in Eq. 3, we calculate classification scores $S_i^T \in \mathbb{R}^{k \times 1}$ and $S_i^I \in \mathbb{R}^{k \times 1}$ by applying the prototype classifier to the cross-modal representations, then normalize the scores to possibilities by taking softmax:

$$\begin{aligned} p_i^I &= \text{softmax}(S_i^I / \tau_{\text{Proto}}), & \text{where } S_i^I &= C^T \cdot h_i^I. \\ p_i^T &= \text{softmax}(S_i^T / \tau_{\text{Proto}}), & \text{where } S_i^T &= C^I \cdot h_i^T. \end{aligned} \quad (3)$$

²We empirically found that multi-modal fusion-based supervision (i.e., the CDC [11]) yields significantly degenerated performances for VLP. The density of initial random text representations is much higher than that of image representations, which makes it dominate the pseudo label generation and failed to learn useful knowledge from the image representations.

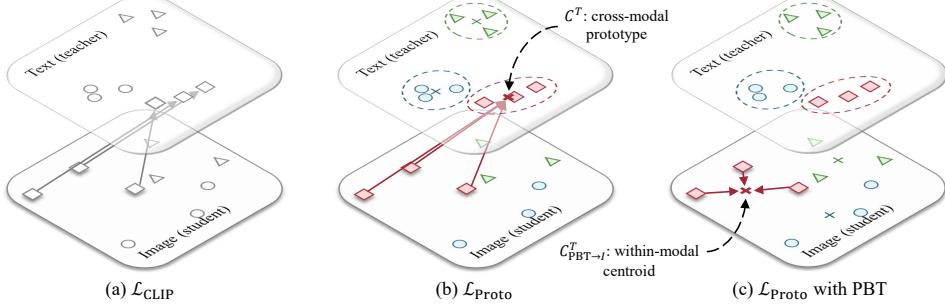


Figure 4: Comparison of $\mathcal{L}_{\text{CLIP}}$, $\mathcal{L}_{\text{Proto}}$, and $\mathcal{L}_{\text{Proto}}$ with PBT. Our PBT translates cross-modal prototypes (C^T) to within-modal centroids ($C_{\text{PBT} \rightarrow I}^T$) according to prototype assignment.

where τ_{Proto} is the temperature hyper-parameter. Instead setting a fixed temperature as in DeepCluster-v2 [8], we set it to a learnable parameter as in $\mathcal{L}_{\text{CLIP}}$ since it yields improved results. Now, we can get $\mathcal{L}_{\text{Proto}}$ by applying the cross entropy loss function:

$$\mathcal{L}_{\text{Proto}} = -(\underbrace{\sum_{i=1}^M \sum_{k=1}^K y_{i,k}^T \log(p_{i,k}^I)}_{\text{image to text}} + \underbrace{\sum_{i=1}^M \sum_{k=1}^K y_{i,k}^I \log(p_{i,k}^T)})/2, \quad (4)$$

Learning from soft targets. In Eq. 4, $y_i^T \in \mathbb{R}^{k \times 1}$ and $y_i^I \in \mathbb{R}^{k \times 1}$ are k-way pseudo target scores. Previous clustering-based methods [7, 9, 10, 11, 12] convert class indices to a one-hot vector as target. Such a one-hot target creates a one-vs-all learning task: representations are pushed towards their assigned prototypes *only* and pushed away from other prototypes *equally*. To learn more structured knowledge, we use probability-based soft target to replace the hard one-hot assignment:

$$\begin{aligned} y_k^T &= \text{softmax}(S_k^T / \tau_y), & \text{where } S_k^T &= C^T \cdot c_k^T. \\ y_k^I &= \text{softmax}(S_k^I / \tau_y), & \text{where } S_k^I &= C^I \cdot c_k^I. \end{aligned} \quad (5)$$

The scores in Eq. 5 are calculated by measuring the dot-product similarity between the “ground truth” prototype c_k^I, c_k^T and all the prototypes C^I, C^T . The “ground truth” prototype will have the highest similarity with itself (e.g., “cat” and “cat”), relatively high similarities with its neighboring prototypes (e.g., “cat” and “tiger”), and low similarities with distant prototypes (e.g., “cat” and “car”). When such relational knowledge is embedded in the targets y_k^I, y_k^T , the ProtoCLIP can learn more structured knowledge. Finally, the ProtoCLIP is trained to minimize $\mathcal{L}_{\text{Proto}}$ and $\mathcal{L}_{\text{CLIP}}$ jointly:

$$\mathcal{L}_{\text{ProtoCLIP}} = \mathcal{L}_{\text{Proto}} + \mathcal{L}_{\text{CLIP}} \quad (6)$$

3.2 Learning Representation Grouping from Unaligned Spaces

We compare the differences between $\mathcal{L}_{\text{CLIP}}$ and $\mathcal{L}_{\text{Proto}}$ in Figure 4(a) and (b)³. Though $\mathcal{L}_{\text{Proto}}$ improves the representation grouping efficiency, it still suffers from the *modality gap* problem. In Figure 4 (b), all the three data points in the student space would be pushed to the right side in order to align them with the prototype in teacher space.

Prototype Back Translation. The core reason of the modality gap problem is that $\mathcal{L}_{\text{Proto}}$ forces the student representations to be strictly anchored to the position of their prototype in the teacher space. We introduce a simple yet effective technique called Prototype Back Translation (PBT) to avoid this problem. As shown in Figure 4(c), for each prototype in teacher space, we retrieve all the samples that are assigned to it, and then calculate a centroid of the corresponding representations in

³Since both of these losses are bi-directional between image and text spaces, here we only visualize the supervision from text (as teacher) to image (as student).

the student space. We denote the obtained image and text centroids as $C_{\text{PBT} \rightarrow I}^T$ and $C_{\text{PBT} \rightarrow T}^I$ and use them to replace the original prototypes C^T and C^I when calculating $\mathcal{L}_{\text{Proto}}$. PBT enables knowledge transfer between unaligned representation spaces since student representations are grouped directly to their within-modal centroid instead of pushed towards their cross-modal prototypes. We note that the advantage of $\mathcal{L}_{\text{Proto}} + \text{PBT}$ over plain $\mathcal{L}_{\text{Proto}}$ are similar to the advantage of Relational Knowledge Distillation (RKD) [36, 37] over traditional Knowledge Distillation (KD) [38]. However, RKD transfers relational knowledge in a per-sample-pair manner, while PBT transfers knowledge via prototypes with a higher level of semantics.

Learning from External Teacher. Since representation grouping is decoupled from representation alignment, we can now ensemble multiple teachers to guide the learning of student representations. For example, in addition to the original mutual knowledge transfer between image and text spaces, we can further introduce an external teacher encoder E to distill richer knowledge to ProtoCLIP. As Figure 3, the encoder E can encode either image x_i^I or text x_i^T , then external prototypes C^{external} can be constructed in the resulting representations space by performing K -Means clustering as before. We use PBT to translate the prototypes C^{external} to within-modal centroids $C_{\text{PBT} \rightarrow I}^{\text{external}}$ and $C_{\text{PBT} \rightarrow T}^{\text{external}}$, then an additional loss term $\mathcal{L}_{\text{Proto}}^{\text{external}}$ can be calculated by applying the obtained prototype classifier, taking softmax, then calculating cross-entropy loss:

$$\mathcal{L}_{\text{Proto}}^{\text{external}} = -(\underbrace{\sum_{i=1}^M \sum_{k=1}^K y_{i,k}^{\text{external}} \log(p_{i,k}^{I,\text{external}})}_{\text{image to external teacher}} + \underbrace{\sum_{i=1}^M \sum_{k=1}^K y_{i,k}^{\text{external}} \log(p_{i,k}^{T,\text{external}})}_{\text{text to external teacher}})/2, \quad (7)$$

where $p_i^{I,\text{external}}$ and $p_i^{T,\text{external}}$ are the scores obtained by applying the prototype classifier to projected image and text representations, while y_i^{external} indicates the “ground truth” of prototype assignment. In practice, we use a pretrained RoBERTa_{large} as the external teacher encoder E . During training, the weights of E are frozen. With external teacher, the loss function of ProtoCLIP becomes:

$$\mathcal{L}_{\text{ProtoCLIP}} = \mathcal{L}_{\text{Proto}} + \mathcal{L}_{\text{CLIP}} + \mathcal{L}_{\text{Proto}}^{\text{external}} \quad (8)$$

3.3 Episodic Training

Previous clustering-based SSL approaches [7, 9, 10, 11, 12, 13] update the clusters after an entire training epoch. Such an approach works well on medium-sized ImageNet [14] dataset since the model can be trained for several hundreds of epochs, which results in several hundreds of cluster updating. However, CLIP is usually trained for much fewer epochs (e.g., 32 epochs in the CLIP-benchmark [39]), which makes the frequency of epoch-wise updating insufficient. To train our ProtoCLIP more efficiently, we propose an *episodic training* strategy. *Episodes* are constructed by randomly choosing $m \ll M$ samples from the entire dataset. Then, three steps including 1) feature extraction, 2) prototype updating, and 3) model training are performed sequentially. After finishing these three steps, a new episode is then constructed. Episodic training makes prototype updating frequency independent of dataset size M , which enables ProtoCLIP to be scaled up to unlimited amounts of training data. To benchmark episodic training-based ProtoCLIP with other models that is trained conventionally, the total number of episode n_{episode} is defined as $n_{\text{episode}} = n_{\text{epoch}} \times \frac{M}{m}$. Episode size m is an important hyper-parameter. Smaller m results in higher prototype updating frequency. However, when m becomes too small, the sparsity of representations within an episode increases. In such situations, samples that are assigned to the same prototypes may have different semantics, which decreases the reliability of prototypes. In practice, m is determined by a hyper-parameter sweep.

4 Experiments

4.1 Ablation Study

This section validates the impact of the hyper-parameters of ProtoCLIP. A one-million subset of the Conceptual Captions (CC) [40] dataset is used for pretraining ProtoCLIP. To avoid testset hyper-parameter tuning, CIFAR10, CIFAR100 and STL10 dataset are adopted here as validation set. Benchmarks on other downstream datasets of model pretrained on full CC data will be reported

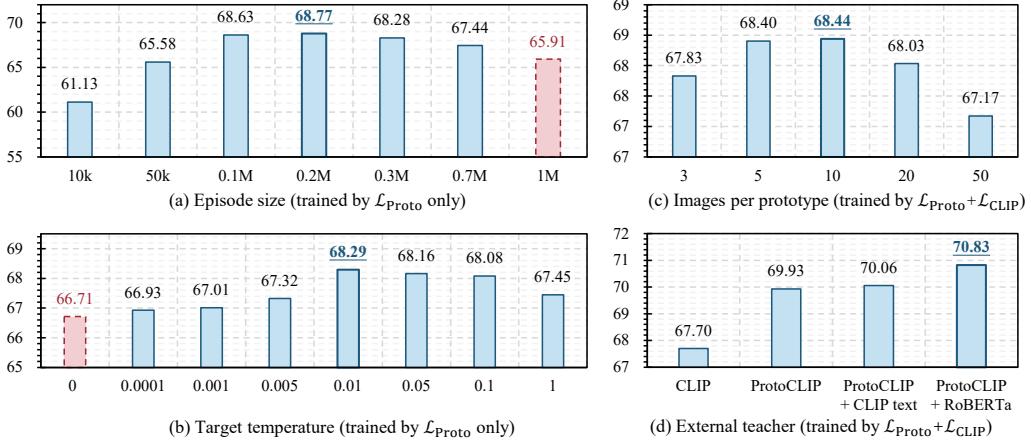


Figure 5: ProtoCLIP ablation experiments on Conceptual Captions 1M data (20 epoch). We report the average linear probing accuracies (%) of CIFAR10, CIFAR100, and STL10. Detailed results are given in Appendix.

in Section 4.2. Total training amount here (episode size $\times n_{\text{episode}}$) is set equivalent to 20 epochs. Following the original setting in CLIP [1], we use the modified ResNet50 [41] and 12-layer transformer as image and text encoders respectively. With a single-node $4\times 2080\text{Ti}$ machine, each training takes roughly 16 hours. The batch size is set to 64 for each GPU, resulting in an effective batch size of 256. The default setting of the ProtoCLIP includes episode size $m = 0.2\text{M}$, no soft target (i.e. using hardmax in Eq. 5), 10 images per prototype, no external teacher, and no data augmentations. K-Means is performed with a max iteration limit of 20 steps, which we found sufficient to converge. More details of experimental settings can be found in the Appendix.

a) Episode size. As illustrated in Section 3.3, there would be a trade-off between prototype reliability and updating frequency. Here we want to find an optimal episode size that can satisfy both sides. We train ProtoCLIP without $\mathcal{L}_{\text{CLIP}}$ with different episode size. Total number of episodes is adjusted accordingly to make sure that total training amounts are equal. As shown in Figure 5(a), an episode size of 0.2M yields the best performance. The rightmost bar in red (episode size=1M) is to update the cluster after one entire training epoch as done in previous methods [7, 9, 10, 11, 12, 13]. With the best value of episode size, our episodic training strategy leads to a +2.86% improvement. **b) Target temperature.** Next, we turn to select the best target temperature τ_y . Though higher value of τ_y transfers structural relation knowledge, too large τ_y makes target scores to be over-smoothed. Figure 5(b) shows that $\tau_y=0.01$ achieves the best performance. Compared to the one-hot label (hardmax, the leftmost bar in red) used in previous clustering-based SSL approaches [7, 9, 11, 12, 10, 16], learning from soft target brings +1.58% improvement. **c) Number of images per prototype.** Clustering-based SSL for ImageNet pretraining often sets the total number of clusters to be several thousands (e.g., $K = 3000$ for SwAV [8]), resulting in about hundreds of images per cluster. We found that with uncurated image-text dataset, this hyper-parameter should be determined more conservatively. The reason is that uncurated image-text dataset contains much more concepts than curated ones [42]. Lower K increases the noise within each cluster. Now we train our model with $\mathcal{L}_{\text{Proto}} + \mathcal{L}_{\text{CLIP}}$. Figure 5(c) shows that 10 images per prototype (i.e. $K = 20\text{k}$ for an episode size of 0.2M) yield the best performance. **d) External teacher.** Finally, we compare the effectiveness of different external teachers. We consider two alternatives, text encoder of pretrained CLIP (ViT/B-32) [1] and pretrained RoBERTa_{large} [6]. Figure 5(d) shows that both of these two external teacher benefit ProtoCLIP, while RoBERTa_{large} brings more improvement.

4.2 Conceptual Captions Pretraining Benchmark

With selected hyper-parameters, now we are ready to train our ProtoCLIP on full CC data. The original CC dataset [40] (collected in 2018) contains over 3.3M samples. Unfortunately, due to broken links, an increasing number of images become inaccessible. To benefit future benchmarking, we use a total of 2,500,000 samples (CC2.5M) from CC to train our model. Such size is much smaller than that of the original CLIP [1]. However, as in Figure 6, we train CLIP with different dataset sizes and found the downstream performance of the CLIP model (blue) scales up steadily (near-logarithmically, as noted by red dotted lines) with dataset size. This is also demonstrated by

Table 1: (a): ProtoCLIP ablation experiment on Conceptual Captions 2.5M data (8 epoch). (b): Conceptual Captions pretraining benchmarks. “▷” indicates results reported by corresponding papers. Note that CyCLIP [50] utilized a subset of ImageNet training set for linear prob instead of using full training set.

| Method | ImageNet linear | ImageNet zero-shot | CIFAR & STL zero-shot Avg. | CIFAR & STL linear Avg. | Batch Size | Data | Epoch | Method | ImageNet linear | ImageNet zero-shot top-1 | ImageNet zero-shot top-5 | 10 dataset zero-shot Avg. | COCO retrieval mean recall |
|-----------------------|--------------------|-----------------------|-------------------------------|----------------------------|---------------|-------|-------|--------|--------------------|-----------------------------|-----------------------------|------------------------------|-------------------------------|
| ProtoCLIP | 46.55 | 11.96 | 42.74 | 70.96 | 512 | 2.5M | 32 | CLIP | 49.41 | 19.46 | 38.42 | 21.87 | 36.48 |
| ProtoCLIP w/o RoBERTa | 44.76 | 11.91 | 42.81 | 69.45 | ProtoCLIP | 55.22 | 21.47 | 40.84 | 22.52 | 35.69 | - | - | - |
| - w/o PBT | 42.93 | 11.23 | 42.32 | 68.89 | ▷ CLIP | 35.47 | 20.03 | 39.35 | - | - | - | - | - |
| - w/o soft target | 44.22 | 11.28 | 42.66 | 69.18 | ▷ CyCLIP [50] | 36.69 | 22.08 | 42.30 | - | - | - | - | - |
| - w/o K-means | 44.27 | 11.62 | 38.67 | 67.22 | ▷ CLIP | - | 20.33 | - | - | - | - | - | - |
| - w/o augmentation | 44.39 | 11.17 | 38.67 | 68.75 | ▷ CLOOB [23] | - | 23.97 | - | - | - | - | - | - |
| | | | | | ▷ CLIP | - | 20.6 | - | - | - | - | - | - |
| | | | | | ▷ DeCLIP [28] | - | 27.2 | - | - | - | - | - | - |

(a)

(b)

Ilharco et al. [43]. Therefore, the dataset size of CC2.5M is already able to reflect the effectiveness of VLP models accurately.

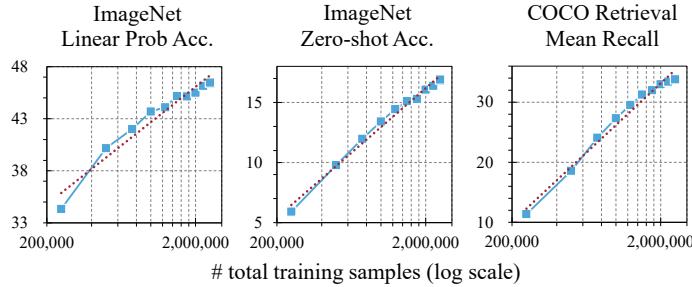


Figure 6: Under same training amount, CLIP performance scales steadily with dataset size. We continue to adopt ResNet-50 [41] and transformer [21] as image and text encoders. We used a $8 \times 2080\text{Ti}$ machine to train ProtoCLIP with a effective batch size of 512. We apply random data augmentations to create implicit contrast within each episode. More details are presented in the Appendix.

Now we validate the effectiveness of each ProtoCLIP component on CC2.5M. We train ProtoCLIP on CC2.5M for 8 epochs, and compare its zero-shot classification and linear probing performance with ProtoCLIP ablations. Classification accuracy on ImageNet and averaged accuracy on CIFAR10, CIFAR100, and STL10 are reported. We first remove the external teacher RoBERTa, then respectively ablates 1) PBT, 2) soft target, 3) K -Means optimizing, and 4) data augmentation. As in Table 1(a), full ProtoCLIP achieve the best performance overall. Every other comparison yields degenerated performance, showing the effectiveness of each component. For ImageNet linear probing accuracy, introducing PBT brings +1.83% improvement, while introducing an external teacher brings +1.76% improvement.

Finally, we benchmark ProtoCLIP by training it on CC2.5M for 32 epochs. We additionally evaluate the zero-shot performance on other nine datasets including Birdsnap [44], Country211 [1], Flowers102 [45], GTSRB [46], UCF101 [47], Stanford Cars [48], CIFAR10, CIFAR100 and STL10. We report averaged zero-shot accuracy of all these ten datasets. Moreover, mean recall of MS-COCO [49] cross-modal retrieval is also reported to evaluate instance discrimination ability. Table 1(b) summarizes main results. Under same setting (2.5M data, 32 epochs), ProtoCLIP outperforms CLIP by +5.81% on ImageNet linear probing and +2.01% on ImageNet zero-shot classification. Meanwhile, ProtoCLIP maintains comparable but slightly degenerated (-0.79%) cross-modal retrieval performances compared to CLIP.

4.3 Visualization and Clustering Evaluation

Figure 7 visualizes the learned representations of CLIP and ProtoCLIP via T-SNE [51]. ProtoCLIP groups “cat”, “dog”, and “monkey” better. It also gives better separation between “airplane” and “ship”, “truck” and “car”. These observations can be proved by comparing clustering performance. We cluster the representations to 10 classes by K -Menras and compare the obtained pseudo labels

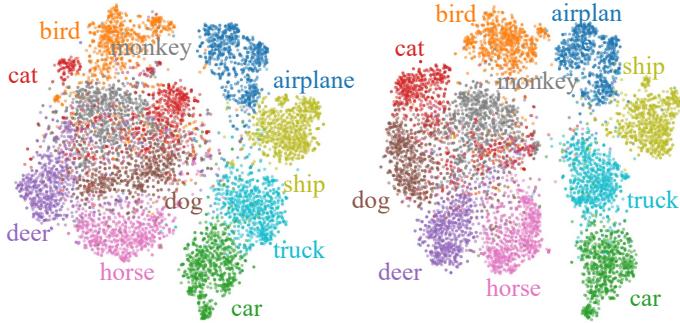


Figure 7: T-SNE visualizations of CLIP (left) and ProtoCLIP (right) representations on STL10. ProtoCLIP yields a more clearly grouped representation space.

with ground truth labels. Representations of ProtoCLIP yields better adjusted rand index ($0.673 \rightarrow 0.732$) and adjusted mutual information ($0.744 \rightarrow 0.788$). More details can be found in Appendix.

5 Conclusion

We have shown that in addition to representation alignment, representation grouping is also an important characteristic of contrastive language image pretraining. The InfoNCE objective groups representations together via randomly emerged anchors, which we found unstable and sensitive to the modality gap. We set up stable and efficient representation grouping via prototypical discrimination (ProtoCLIP) and alleviated the modality gap issue by PBT. PBT also enabled us to introduce an external teacher for additional supervision. Empirical results proved that combining these novel designs brings significant improvement in downstream performance.

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A Implementation of ProtoCLIP

A.1 Implementation Details

Model Architectures. Following CLIP [1], we use the modified ResNet-50 backbone as the image encoder, which has three differences compared to the original ResNet-50 [41]: 1) there are three 3×3 convolutions as “stem” instead of a single 7×7 convolution [52], an average pooling follows the “stem” instead of max pooling; 2) the modified ResNet-50 performs antialiased rect-2 blur pooling [53]; 3) the final global average pooling layer is replaced with a multi-head self attention [21, 1]-based pooling. We unitize Transformer [21, 1] as the text encoder, which consists of 12 layers, 8 attention heads, and a width of 512. The max sequence length is set to 76. For image and text projection heads, we use the same architecture as SwAV [8], which is a 2-layers MLP with ReLU activation, 2048 hidden units and 128 output units. Other hyperparameters are summarized in Table A.2.

Training Configurations. ProtoCLIP is implemented on PyTorch-based OpenCLIP [43] codebase. We employ automatic mixed-precision [54] to reduce the training cost. Same as CLIP [1], we use the Adam optimizer [55] with decoupled weight decay regularization [56]. Gradients are clipped by a maximum norm of 10 to prevent model collapse. Learnable temperatures (τ_{CLIP} , τ_{Proto}) are initialized with 0.07 and clipped by 100 following CLIP [1]. Weight decay is not applied to these temperatures. Warm-up and cosine learning rate scheduler [57] are adopted. Same as PCL [10], we InfoNCE-only warm-up in the first episode. Locked-image tuning [58] is performed for the last epochs. See our open-sourced implementation for more details⁴.

Prototype Construction. We adopt Faiss [59] implemented K -Means for clustering. We cluster the 128-dimensional projected representations (i.e., h^I, h^T) of 200,000 samples in each episode to $K=20,000$ clusters and use the resulting cluster centroids as prototypes. K -Means is optimized for 20 iterations, which we found it sufficient for convergence. For each representation space, we perform K -Means clustering for three times with different initialization. Clustering result that achieve the lowest K -Means objective is selected. We use a pretrained RoBERTa_{large}⁵ as the external teacher. We extract RoBERTa_{large} representations off-line to speed-up ProtoCLIP training, and reduce the representation dimension from 1024 to 64 by PCA to save memory cost.

Table A.2: ProtoCLIP Hyperparameters

| Section | Hyperparameter | Value |
|------------------------|---|--------------------------|
| Episodic Training | Batch size | 512 (8 \times 64) |
| | Episode size | 200,000 |
| | Dataset size | 2,500,000 |
| | Total Episodes | 400 (32 epochs) |
| | Warm-up Episodes | 40 (3.2 epochs) |
| Prototype Construction | Number of clusters in K -Means | 20,000 |
| | K -means Iterations | 20 |
| Optimization | Optimizer | Adam |
| | Adam $\beta_1, \beta_2, \epsilon$ | 0.9, 0.999, 1e-8 |
| | Learning Rate | 5e-4, cosine decay |
| | Weight decay | 0.5 |
| | Maximum gradient norm | 10 |
| Model Architectures | Image Encoder | Modified ResNet-50 |
| | Image Resolution | 224 \times 224 |
| | Text Encoder | Transformer |
| | Text vocabulary size | 49408 |
| | Initial and maximum temperature ($\tau_{\text{CLIP}}, \tau_{\text{Proto}}$) | 0.07, 100 |
| | Representation dimension (d_z) | 1024 |
| | Projected Representation dimension (d_h) | 128 |
| | External Teacher | RoBERTa _{large} |

A.2 Pretraining Dataset

Conceptual Captions [40] is an webly collected high-quality image-text dataset consist of 3,318,333 sample pairs. The dataset was made public⁶ by Google in 2018. Unfortunately, the number of accessible images keeps drooping due to expired image links. This issue is raised by several recent works in the field of VLP [23, 28, 43]. In this work, since we can only collect 2,643,718 images, we randomly sample a 2,500,000 subset (75% of full CC3M) from them to train our ProtoCLIP. Considering the dropping accessibility of image links in Conceptual Captions, we call for the use of this dataset size (2.5M) in future benchmarking for better comparability.

⁴<https://github.com/megvii-research/protoclip>

⁵https://pytorch.org/hub/pytorch_fairseq_roberta

⁶<https://github.com/google-research-datasets/conceptual-captions>

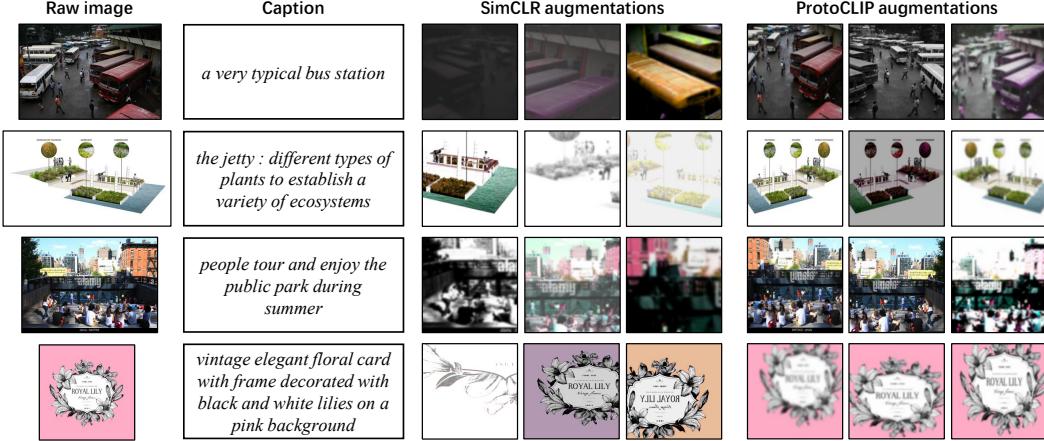


Figure A.8: Visualization of different data augmentations. ProtoCLIP augmentations maintain higher semantic consistency on non-iconic images in Conceptual Captions.

A.3 Data Augmentations

Recent advances in VLP [25, 28, 22] have shown that applying random data augmentations can be beneficial. However, we found that common data augmentation strategies used in image SSL is too aggressive in the VLP scenario. As shown in Figure A.8, standard SimCLR [27] augmentations have a higher chance of changing semantics when it is applied to non-iconic images of Conceptual Captions dataset⁷. Such semantic inconsistency poses extra difficulty to image-text representation alignment. To this end, we design a lighter data augmentation to train ProtoCLIP by making two modifications to the SimCLR augmentations parameters: 1) images are randomly resized and cropped with a scale range of 50% to 100% instead of 8% to 100%; 2) probability of applying color jittering is reduced from 0.8 to 0.2. As Figure A.8, such data augmentation maintains higher semantic consistency than that of SimCLR augmentations.

We note that, with applied random data augmentations, our proposed episodic training strategy and PBT can implicitly create additional contrastive supervision for image representations. Recall that episodic training consists of three steps including 1) feature extraction, 2) prototype construction, and 3) model training. Since the first and the third step is performed independently, different augmentations are drawn and applied to the same image. During the model training step, the representation of an image is pushed to the assigned and translated centroid of its another view built in the feature extraction step, leading to an additional contrastive supervision.

Such implicit contrast shares some similarities with SwAV and DeepCluster-v2 that learn visual representations by “contrasting cluster assignments” [8]. However, they use the cluster assignment to set up within-modal supervision, while the implicit contrast of ProtoCLIP is done through the text representation space. Recent SLIP [25] and DeCLIP [28] also applied data augmentation-based contrast to boost VLP performance. However, they contrasted image representations explicitly by forward additional views of images in each training step, which leads to a significantly expanded memory footprint and decreased maximum allowed batch size.⁸ In our ProtoCLIP, two views for the implicit contrast are built separately during feature extraction and model training. Although it leads to additional time consumption, the maximum allowed batch size is not affected.

A.4 Pseudo Codes

We present PyTorch-style pseudo codes of ProtoCLIP training loop in Algorithm 1 for better understanding of our implementation. For simplicity, here we do not involve the use of external teacher. The external teacher supervisions are implemented in the same way of image-text supervisions.

B Details of ProtoCLIP Evaluation

Zero-shot Classification We use the 1024-dimensional L2-normalized representations (i.e., z^I, z^T) extracted by image and text encoders to perform zero-shot classification. Class names and prompt templates are consistent with CLIP [1] in spite of minor explanations to some classes, e.g., “kite”→“kite (bird of prey)” are added following CLOOB [23]. A total of ten datasets are adopted: Birdsnap [44], Country211 [1], Flowers102 [45],

⁷Several recent works of image SSL have also pointed out that applying SimCLR augmentations on non-iconic scenes images is not optimal. For more details please see ORL [60] and UniVIP [61].

⁸Many recent studies have proved that sufficiently large batch size is crucial for contrastive learning [62].

Table A.3: Dataset used in zero-shot classification evaluation.

| Dataset | Classes | Testset Size | Description |
|---------------|---------|--------------|--|
| ImageNet | 1,000 | 50000 | 1000 categories of objects |
| CIFAR10 | 10 | 10,000 | 10 categories of animals and vehicles |
| CIFAR100 | 100 | 10,000 | 100 categories of animals, vehicles, plants, objects, scenes, people |
| STL10 | 10 | 8,000 | 10 categories of animals and vehicles |
| Birdsnap | 500 | 1,855 | 500 categories of North American bird species |
| Country211 | 211 | 21,100 | 211 countries represented by geo-tagged images |
| Flowers102 | 102 | 6,149 | 102 species of common UK flowers |
| GTSRB | 43 | 12,630 | 43 categories of German traffic signs |
| UCF101 | 101 | 11,213 | 101 categories of human actions using the middle frame of each clip |
| Stanford Cars | 196 | 8,041 | 196 categories of cars (make, model, and year) |

Table A.4: Full zero-shot classification evaluation results. “Random” indicates the chance performance.

| Batch size | Data | Epoch | Method | ImageNet top-1 | ImageNet top-5 | CIFAR10 | CIFAR100 | STL10 | Birdsnap | Country211 | Flowers102 | GTSRB | UCF101 | Stanford Cars | 10 Dataset Avg. |
|------------|------|-------|-------------|-------------------|-------------------|---------|----------|-------|----------|------------|------------|-------|--------|---------------|--------------------|
| 512 | 2.5M | 32 | CLIP | 19.46 | 38.42 | 51.74 | 22.85 | 81.05 | 2.04 | 0.69 | 12.96 | 6.02 | 20.86 | 1.07 | 21.87 |
| | | | ProtoCLIP | 21.47 | 40.84 | 51.93 | 23.43 | 84.66 | 1.88 | 0.62 | 13.97 | 4.57 | 21.68 | 0.98 | 22.52 |
| 512 | 2.9M | 31 | CLIP | 20.33 | - | - | - | - | 2.26 | 0.67 | 12.56 | 7.66 | 20.98 | 0.91 | - |
| | | | CLOOB [23] | 23.97 | - | - | - | - | 3.06 | 0.67 | 13.45 | 6.38 | 22.26 | 1.23 | - |
| 512 | 2.9M | 31 | CLIP | 20.03 | 39.35 | 46.54 | 18.69 | - | - | - | - | - | - | - | - |
| | | | CyCLIP [50] | 22.08 | 42.30 | 51.45 | 23.15 | - | - | - | - | - | - | - | - |
| - | - | - | Random | 0.1 | 0.5 | 10 | 1 | 11.4 | 0.02 | 0.5 | 1.5 | 5.9 | 1.3 | 0.8 | 3.25 |

GTSRB [46], UCF101 [47], Stanford Cars [48], CIFAR10, CIFAR100 and STL10, whose details are summarized in Table A.3. Similar to the Conceptual Captions dataset, the Birdsnap dataset also faces the problem of link expiration. Same as CLIP [1] and CLOOB [23], we use the resources that are available online at the time of writing. Table A.4 presents full results of zero-shot evaluation in Section 4.2. Chance performance is reported in the last row as “Random”.

Linear Probing Frozen 1024-dimensional image representations (z^I) before normalization are used for linear probing. For small-scale CIFAR10, CIFAR100, and STL10, we train a logistic regression classifier using scikit-learn’s L-BFGS implementation, with a maximum of 1,000 iterations following CLIP [1]. For larger ImageNet dataset, we adopt PyTorch-based SGD optimization following MoCo [31], MAE [63] and SLIP [25] to utilize GPU efficiency. Specifically, we train a linear classifier for 100 epochs with a batch size of 1024, a learning rate of 0.1, and a weight decay of 1e-6. SGD optimizer with a momentum of 0.9 and cosine learning rate scheduler are applied. Full results of ProtoCLIP hyper-parameter tuning (Section 4.1) are shown in Table A.5. The best values that adopted in ProtoCLIP benchmarking is marked in blue. Performance drop of using other values compared to the best values are also noted.

Image-text Retrieval Image-text retrieval task consists of image to text retrieval and text to image retrieval. The performance is evaluated on MS-COCO [49] benchmark under the zero-shot setting (i.e., without fine-tuning). The dot-similarity of L2-normalized 1024-dimensional image and text representations (z^I, z^T) are used for ranking. We report recall@1, recall@5 and recall@10 and their average as mean recall. Table A.6 presents full results in Section 4.2. ProtoCLIP generally yields degenerated retrieval performance compared to CLIP since prototypical losses encourage the ProtoCLIP to ignore some instance-specific information.

C Additional Experiment Results

Ablation on ProtoCLIP loss function. Here we study the effectiveness of each loss term in the ProtoCLIP loss function (Eq. 8). Table A.7a summarizes the results of ImageNet linear probing accuracy. Adding $\mathcal{L}_{\text{Proto}}$ to $\mathcal{L}_{\text{CLIP}}$ improves representation grouping and improves linear accuracy by +3.78%, introducing the external teacher further yields +1.79% improvement.

Ablation on ProtoCLIP Augmentation. Table A.7b compares different data augmentation strategies. “No Augmentation” refers to using only the resize and crop with a random scale between 90% and 100%, which achieves the best image-text retrieval performance. Adding SimCLR augmentations degenerates all downstream performance. Our modified augmentations (“ProtoCLIP Augmentation”) improve the retrieval performance compared to “SimCLR Augmentation”, and achieve the best ImageNet linear classification and zero-shot classification performance.

Table A.5: Full ProtoCLIP hyper-parameter ablation results on Conceptual Captions 1M data (20 epoch). The results correspond to the Figure 5 in main text.

| Episode Size | C10 | C100 | STL10 | Avg. | τ_y | C10 | C100 | STL10 | Avg. |
|--------------|--------------|--------------|--------------|----------------------------|----------|--------------|--------------|--------------|----------------------------|
| 10k | 64.95 | 37.58 | 80.85 | 61.13 (\downarrow 7.64) | hardmax | 71.46 | 41.53 | 87.15 | 66.71 (\downarrow 1.58) |
| 50k | 69.19 | 40.82 | 86.73 | 65.58 (\downarrow 3.19) | 0.0001 | 71.98 | 42.14 | 86.66 | 66.93 (\downarrow 1.36) |
| 0.1M | 73.17 | 45.43 | 87.28 | 68.63 (\downarrow 0.14) | 0.001 | 71.87 | 42.52 | 86.65 | 67.01 (\downarrow 1.28) |
| 0.2M | 72.87 | 46.43 | 87.01 | 68.77 | 0.005 | 71.52 | 43.55 | 86.90 | 67.32 (\downarrow 0.97) |
| 0.3M | 71.97 | 45.46 | 87.41 | 68.28 (\downarrow 0.49) | 0.01 | 73.39 | 45.1 | 86.38 | 68.29 |
| 0.7M | 71.69 | 43.18 | 87.44 | 67.44 (\downarrow 1.33) | 0.05 | 73.18 | 44.46 | 86.85 | 68.16 (\downarrow 0.13) |
| 1M | 70.55 | 41.94 | 85.23 | 65.91 (\downarrow 2.86) | 0.1 | 73.11 | 45.58 | 85.54 | 68.08 (\downarrow 0.21) |
| | | | | | 1 | 72.64 | 43.79 | 85.91 | 67.45 (\downarrow 0.84) |

(a) Episode size

| Images per Prototype | C10 | C100 | STL10 | Avg. |
|----------------------|--------------|--------------|--------------|----------------------------|
| 3 | 71.61 | 44.22 | 87.66 | 67.83 (\downarrow 0.61) |
| 5 | 72.09 | 45.31 | 87.81 | 68.40 (\downarrow 0.04) |
| 10 | 72.52 | 45.57 | 87.23 | 68.44 |
| 20 | 71.74 | 45.15 | 87.21 | 68.03 (\downarrow 0.41) |
| 50 | 70.33 | 44.96 | 86.23 | 67.17 (\downarrow 1.27) |

(c) Images per prototype

(b) Target temperature

| Method | C10 | C100 | STL10 | Avg. |
|-----------------------|--------------|--------------|--------------|--------------|
| CLIP | 73.22 | 44.72 | 85.15 | 67.70 |
| ProtoCLIP | 75.24 | 47.33 | 87.21 | 69.93 |
| ProtoCLIP + CLIP Text | 75.93 | 48.84 | 85.40 | 70.06 |
| ProtoCLIP + RoBERTa | 76.29 | 50.14 | 86.05 | 70.83 |

(d) External teacher

Table A.6: **Full retrieval results on MS-COCO dataset.** Prototype-level discrimination leads to degenerated instance-level retrieval performance.

| Method | Image to text | | | Text to image | | | Mean Recall |
|-----------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|----------------------------|
| | Recall@1 | Recall@5 | Recall@10 | Recall@1 | Recall@5 | Recall@10 | |
| CLIP | 20.12 | 43.96 | 56.32 | 15.52 | 36.60 | 47.35 | 36.58 |
| ProtoCLIP | 19.68 (\downarrow 0.44) | 42.84 (\downarrow 1.12) | 54.90 (\downarrow 1.42) | 14.95 (\downarrow 0.57) | 35.28 (\downarrow 1.32) | 46.52 (\downarrow 0.83) | 35.70 (\downarrow 0.88) |

Clustering Evaluation. Here we provide full clustering evaluation results of CLIP and ProtoCLIP trained on CC2.5M for 32 epochs. We extract test set image representations and perform K -Means clustering to derive pseudo labels. The number of clusters (K) is determined by the number of ground truth classes. We perform K -Means clustering for three times with different initialization, each clustering is optimized for 100 iterations. Clustering result that achieve the lowest K -Means objective is selected. We report the Adjusted Rand Index (ARI) and Adjusted Mutual Information (AMI) in Table A.7c. ProtoCLIP outperforms CLIP in 8 out of 10 datasets.

D Understanding ProtoCLIP

What and how does ProtoCLIP actually learn? What happens during the episodic training of ProtoCLIP? In this section, we try to answer these questions by visualizing and analyzing the training procedure of ProtoCLIP.

T-SNE Visualizations. First, we randomly sample an episode with 200,000 samples, construct 20,000 prototypes, and show T-SNE [51] visualizations of untrained and trained ProtoCLIP representations. As in Figure A.9, learned image and text representations are well grouped. Interestingly, we found that random image and text

Table A.7: **Additional experiment results.** (a): ablation study of ProtoCLIP loss function (CC2.5M, 8 epochs); (b): ablation study of data augmentations (CC2.5M, 8 epochs); (c): clustering evaluation (CC2.5M, 32 epochs).

| Loss Terms | ImageNet Linear Probing Accuracy | | | | | | | | | | Data Augmentation | | | | | | | | | | ImageNet | | ImageNet | | Mean | |
|--|----------------------------------|-------|-------|--|--|-----------------------|-------|--|--|--|--|--------------|--|--------------|--|---|--|--|--|--|-------------|-----------|----------|-----|------|--|
| | \mathcal{L}_{CLIP} | | | | | \mathcal{L}_{Proto} | | | | | $\mathcal{L}_{Proto} + \mathcal{L}_{CLIP}$ | | | | | $\mathcal{L}_{Proto} + \mathcal{L}_{CLIP} + \mathcal{L}_{external}$ | | | | | Linear Acc. | Zero-shot | Recall | ARI | AMI | |
| \mathcal{L}_{CLIP} | 40.98 | | | | | 36.89 | | | | | No Augmentation | 44.39 | | 11.17 | | 24.45 | | | | | | | | | | |
| \mathcal{L}_{Proto} | | 44.76 | | | | | 44.76 | | | | SimCLR Augmentation | 43.60 | | 10.05 | | 20.28 | | | | | | | | | | |
| $\mathcal{L}_{Proto} + \mathcal{L}_{CLIP}$ | | | 46.55 | | | | | | | | ProtoCLIP Augmentation | 46.55 | | 11.96 | | 21.65 | | | | | | | | | | |

(a) Ablation study of ProtoCLIP loss function

(b) Ablation study of data augmentation

| | ImageNet | CIFAR 10 | CIFAR100 | STL10 | Bidsnap | Country211 | Flowers102 | GTSRB | UCF101 | Stanford Cars | 10 Dataset | Avg. |
|-----------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|---------------|--------------|--------------|
| | ARI | AMI | ARI | AMI |
| CLIP | 0.128 | 0.343 | 0.270 | 0.401 | 0.130 | 0.340 | 0.673 | 0.744 | 0.033 | 0.060 | 0.016 | 0.091 |
| ProtoCLIP | 0.139 | 0.358 | 0.263 | 0.393 | 0.138 | 0.365 | 0.732 | 0.788 | 0.042 | 0.073 | 0.016 | 0.093 |

(c) Clustering evaluation

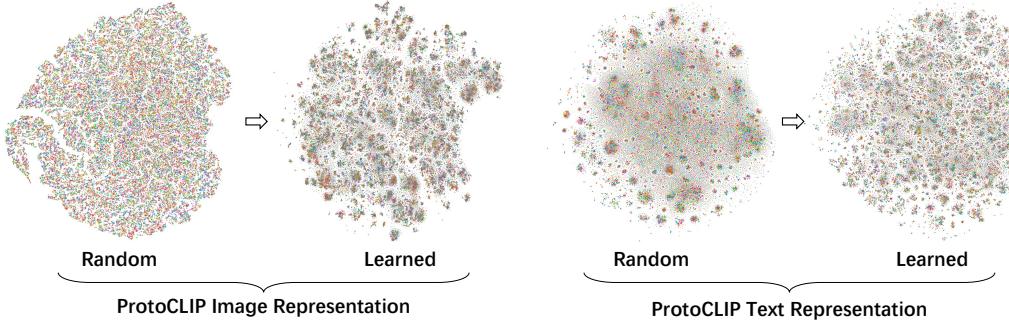


Figure A.9: T-SNE visualizations of ProtoCLIP representations on an episode with 200,000 samples. Colors indicate prototype assignment (Color assignment looks chaotic since there are a total of 20,000 prototypes but only 10 different colors).

representation spaces look quite different: random image representations are distributed almost uniformly, but random text space already contains some weak grouping information. We call such information in random text representations as the “*first pot of gold*” for ProtoCLIP training. It is caused by the fact that texts are human-generated signals, that are highly semantic and information-dense [63]. It has higher level of intrinsic semantics compared to image. Therefore, even based on low-level text features (e.g., word appearance), random text encoders of ProtoCLIP can discover some basic semantic similarities.

Prototype Assignment Visualizations. The “*first pot of gold*” can be observed from the visualizations of the prototype assignment. In Figure A.12, A.13, A.14, and A.15, we visualize the prototype assignment of the four representations spaces of Figure A.9. Samples are sorted by the distance to the prototype (horizontal axis) and the number of samples in the cluster (vertical axis). The first row correspond to the largest cluster, while the leftmost column contains samples that are closest to their prototype. We only show the clusters that have more than ten samples for better visualization. From Figure A.12 we can see that samples in the large random text clusters contain identical or very similar captions. These clusters yield high-quality semantic supervision to the image encoder at the very beginning of ProtoCLIP training as “*first pot of gold*”⁹. However, at the bottom of Figure A.12, random text representations struggle to provide semantic consistent clusters beyond identical captions. Comparatively, learned text representations (Figure A.13) yields much better clusters. For image representations, same as observed in previous image SSL works [7, 34], clusters of random image representations (Figure A.14) prefer to construct clusters according to low-level visual features (especially colors). Comparatively, as shown in Figure A.15, the learned image representations of ProtoCLIP discover various high-level concepts, including statues, markets, graduation ceremony, benches, houses, etc.

Loss Curves. We further visualize the loss curves of $\mathcal{L}_{\text{Proto}}$ and $\mathcal{L}_{\text{external}}$ in Figure. A.10. The curves of the image to text loss (red) and text to image loss (blue) have similar trends, but their losses w.r.t. the external teacher (gray curves) are quite different: text to external loss is much lower than that of image. This can also be reflected by the pseudo label classification accuracy. Initial random text representation achieves a 6% accuracy for the pseudo label of external teacher and reaches 24% by the end of training. Comparatively, random image representation has zero accuracy and reaches only 5% by the end. We argue that the initial 6% accuracy of text to external teacher reflects the “*first pot of gold*” of ProtoCLIP training, while the reason for text achieving lower loss and higher accuracy than that of the image is probably that the RoBERTa external teacher is more “friendly” to the text encoder. In addition, we also zoom in on the loss curve of the first five episodes in Figure. A.10 and confirm that frequent prototype update benefits ProtoCLIP convergence.

Efficiency Analysis of Episodic Training. We analyze the time consumption of each step in the episodic training. On a $8 \times 2080\text{Ti}$ machine with 60 CPUs and 300G RAM, one episode takes an average of 6 minutes. As shown in Figure A.11, episodic training of ProtoCLIP requires an additional feature extraction step compared to CLIP, which takes 32.9% time. The PBT step also takes much time since there are four groups of centroids to translate ($C_{\text{PBT} \rightarrow I}^T, C_{\text{PBT} \rightarrow T}^I, C_{\text{PBT} \rightarrow I}^{\text{external}}, C_{\text{PBT} \rightarrow T}^{\text{external}}$) and each of them requires to iterate over $K=20,000$ prototypes and look up label assignments (lines 62-67 in Algorithm 1). K-Means clustering takes negligible time, since number of samples in an episode is not too large. Smaller episode also save the total K-Means time cost since its time complexity grows superlinearly $O(m^{d_h} \times K+1)$ along the number of samples m to be clustered.

⁹We note that Florence [64] also used samples with identical captions to benefit VLP models. However, Florence requires constructing an additional hash-table to find samples with identical captions, while ProtoCLIP can discover such samples automatically via clustering.

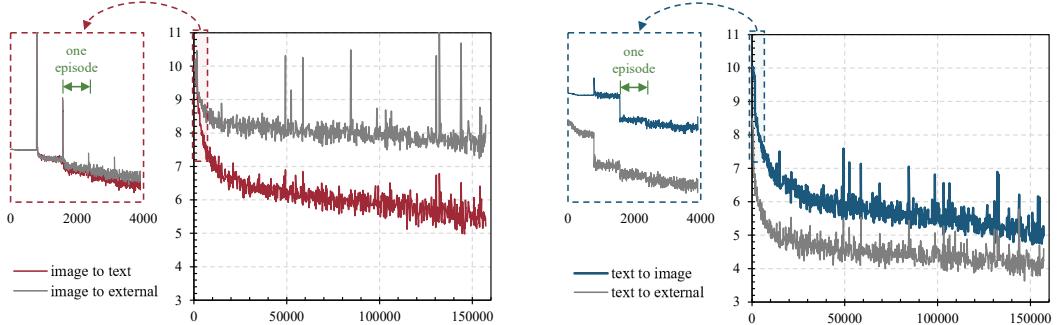


Figure A.10: **Loss curves of $\mathcal{L}_{\text{Proto}}$ and $\mathcal{L}_{\text{External}}$** . Text to external loss is lower and converges faster, probably due to the ‘‘first pot of gold’’ effect and the fact that the RoBERTa external teacher is more ‘‘friendly’’ to the text encoder. Zoom-in of the first five episodes shows that frequent prototype update is beneficial.



Figure A.11: Time profiling of the episodic training strategy.

E Broader Impacts

In this paper, we present a more effective approach for Vision Language Pretraining (VLP). We do not foresee major ethical issues associated with this work. However, like other learning algorithms, VLP models should be applied with caution when deployed in real-world scenarios. It is susceptible to biased learning if the algorithm is given with biased data: the model will learn the inherent properties and structure of the training data, and exhibit biases intrinsically present in the data.

Algorithm 1 Pseudocode of ProtoCLIP Training (w/o external teacher)

```

1   # f_I, f_T: ProtoCLIP image and text encoder
2   # g_I, g_T: ProtoCLIP image and text projection head
3   # dz, dh = 1024, 128: encoder and projection head representation dimension
4   # t_CLIP, t_Proto: learnable temperatures
5   # t_target = 0.01: target_temperature
6
7   # K = 20,000 (number of clusters for K-Means)
8   # episode_size = 200,000
9   # dataset_size = 2,500,000 (CC2.5M)
10  # total_epochs = 32
11
12  # image_features, text_features: feature cache (episode_size, dz)
13
14  dataset = EpisodicDataset()
15  total_episodes = int(dataset_size * total_epochs / episode_size)
16
17  for episode in total_episodes:
18      # Random episode sampling
19      dataset.episode_index_mapping = np.random.choice(dataset_size, episode_size)
20
21  # --- Episodic Training Step 1: Feature Extraction ---
22  for image, text in dataloader: # load a minibatch with N samples
23      with torch.no_grad():
24          # forward propagation
25          h_I, h_T = f_I(image), f_T(text) # (N, dh)
26          z_I, z_T = g_I(h_I), g_T(h_T) # (N, dz)
27          # cache features
28          image_features.update(z_I)
29          text_features.update(z_T)
30
31  # --- Episodic Training Step 2: Prototype Construction ---
32  # K-Means clustering
33  C_I = KMeans(image_features, K) # (K, dh)
34  C_T = KMeans(text_features, K) # (K, dh)
35  # assign pseudo label
36  label_I = C_I @ image_features.T.argmax(dim=0) # (episode_size,)
37  label_T = C_T @ text_features.T.argmax(dim=0) # (episode_size,)
38  # translate cross-modal prototypes to within-modal centorids
39  C_PBT2T = PBT(text_features, C_I, label_I) # (K, dh)
40  C_PBT2I = PBT(image_features, C_T, label_T) # (K, dh)
41
42  # --- Episodic Training Step 3: Model Training ---
43  for image, text in dataloader: # load a minibatch with N samples
44      # forward propagation
45      h_I, h_T = f_I(image), f_T(text) # (N, dh)
46      z_I, z_T = g_I(h_I), g_T(h_T) # (N, dz)
47      # compute losses
48      loss_CLIP = 0.5 * (InfoNCE(h_I, h_T, t_CLIP) + InfoNCE(h_T, h_I, t_CLIP)) # Eq. 1
49      loss_Proto = 0.5 * (loss_Proto(h_I, C_PBT2I, label_T, t_Proto) + loss_Proto(h_T, C_PBT2T,
           label_I, t_Proto)) # Eq. 4
50      loss = loss_CLIP + loss_Proto # Eq. 6
51      # backward propagation
52      loss.backward()
53      update(f_I, f_T, g_I, g_T, t_CLIP, t_Proto) # update model parameters
54
55
56  def loss_Proto(features, target_centroids, label, t_Proto):
57      student_scores = features @ target_centroids.T / t_Proto # Eq.3
58      target_scores = target_centroids[label] @ target_centroids.T / t_target # Eq.5
59      return cross_entropy(student_scores, target_scores.softmax(dim=1))
60
61
62  def PBT(features, C, label):
63      translated_centroids = torch.zeros(K, dz)
64      for k in range(K):
65          assigned_samples = torch.where(teacher_labels==k)
66          translated_centroids[k] = torch.mean(features[assigned_samples], dim=0)
67      return translated_centroids
68
69
70  class EpisodicDataset():
71      def __getitem__(episode_index):
72          dataset_index = self.episode_index_mapping[episode_index]
73          image, text = self.images[dataset_index], self.texts[dataset_index]
74          image = random_augmentation(image)
75          return image, text
76      def __len__():
77          return episode_size

```

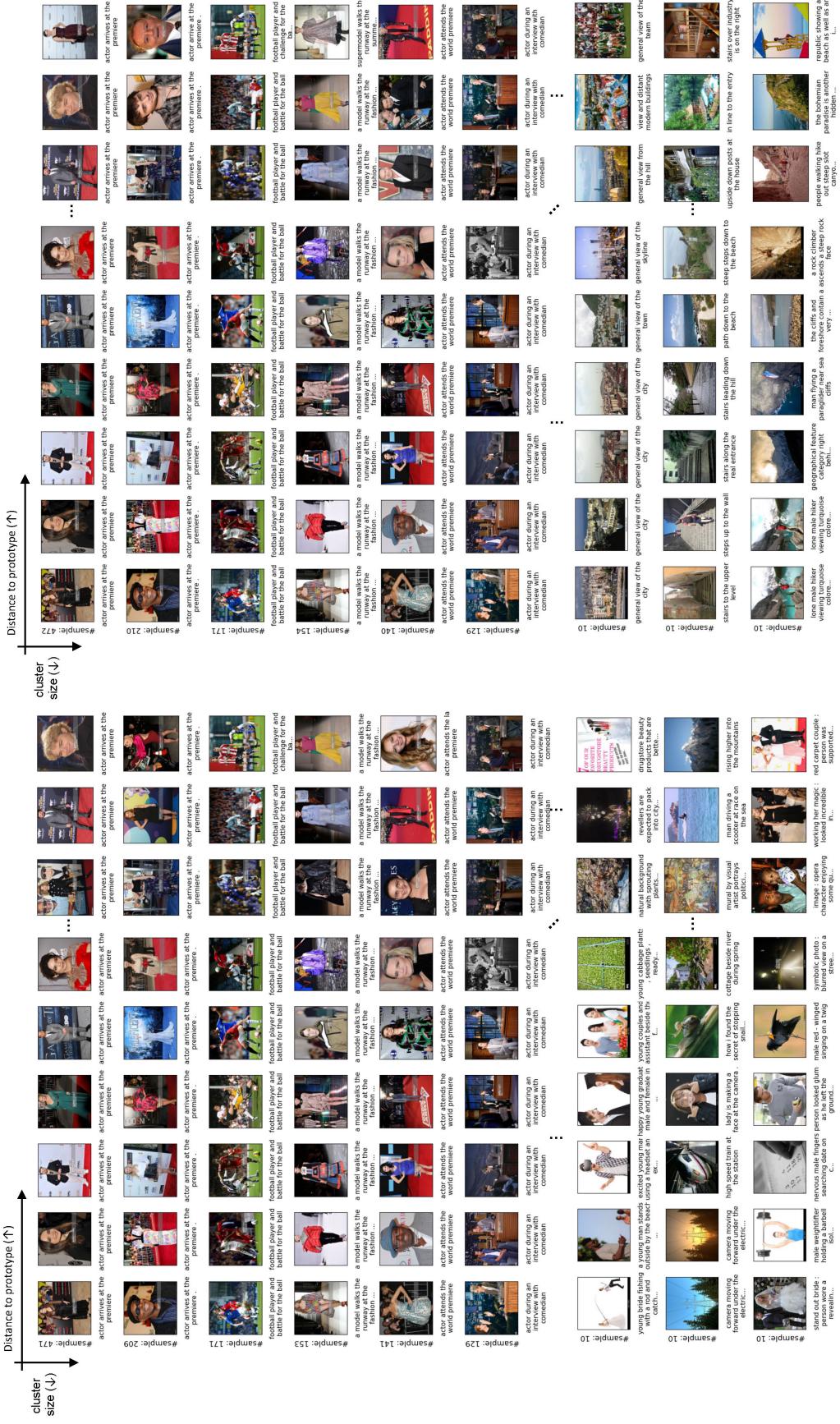


Figure A.12: Prototype assignment of randomly initialized text representations.

Figure A.13: Prototype assignment of trained ProtoCLIP text representations.

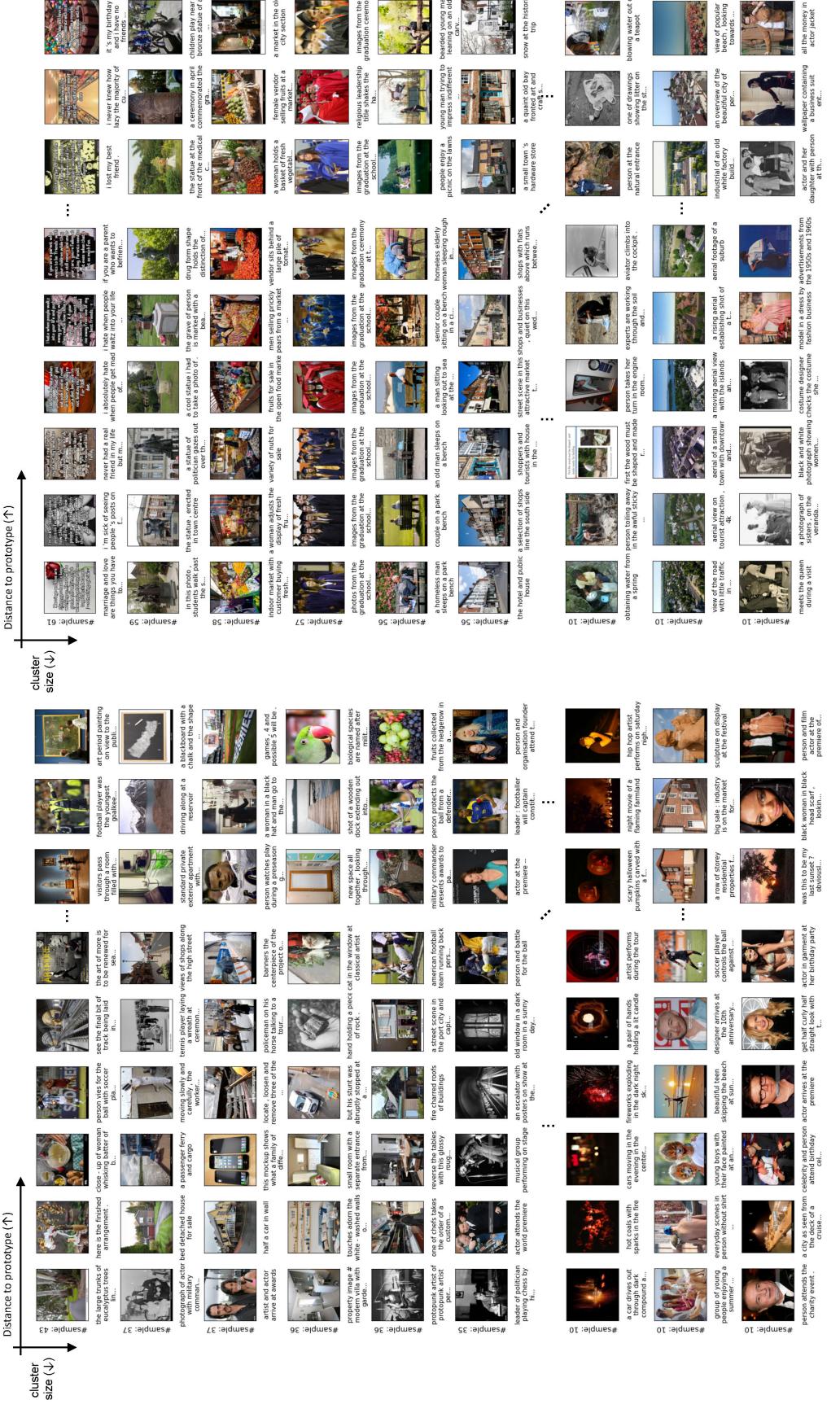


Figure A.14: Prototype assignment of randomly initialized image representations.

Figure A.15: Prototype assignment of trained ProtoCLIP image representations.