

# On the Language Encoder of Contrastive Cross-modal Models

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## Abstract

Contrastive cross-modal models such as CLIP and CLAP aid various vision-language (VL) and audio-language (AL) tasks. However, there has been limited investigation of and improvement in their language encoder, which is the central component of encoding natural language descriptions of image/audio into vector representations. We extensively evaluate how unsupervised and supervised sentence embedding training affect language encoder quality and cross-modal task performance. In VL pre-training, we found that sentence embedding training language encoder quality and aids in cross-modal tasks, improving contrastive VL models such as CyCLIP. In contrast, AL pre-training benefits less from sentence embedding training, which may result from the limited amount of pretraining data. We analyze the representation spaces to understand the strengths of sentence embedding training, and find that it improves text-space uniformity, at the cost of decreased cross-modal alignment.

## 1 Introduction

Significant progress have been made in pretraining large-scale cross-modal models, such as CLIP (Radford et al., 2021) and ALIGN (Jia et al., 2021), for various vision-language (VL) applications such as retrieval and zero-shot image classification. These models are often pretrained with large amounts of data, e.g., OpenAI leverages  $\approx 400\text{M}$  caption-image pairs to train CLIP. The amount of data has been scaled up to 5B with LAION-5B (Schuhmann et al., 2022; Cherti et al., 2023). Such a large amount of multimodal pretraining data contains text captions at the same scale as the pretraining corpora of large language models (LLMs) such as BERT, which is pretrained on 3.3B words (Devlin et al., 2019).

The success of VL pretraining encourages research on contrastive learning models for other modalities like audio. Pretrained audio-language

(AL) models such as AudioCLIP (Guzhov et al., 2022) and CLAP (Wu et al., 2023; Elizalde et al., 2023) show promising results on AL retrieval and zero-shot audio classification tasks.

It is clear that the language encoder in cross-modal contrastive models plays a central role when scaling-up pretraining of a specific modality and/or the amount of modalities. Therefore, analyzing and improving the language encoder become increasingly crucial. CLIP’s language encoder (CLIP LM) – a decoder-only language model similar to GPT-2 (Radford et al., 2019) – has been investigated. Yan et al. (2022) showed that the CLIP LM outperforms BERT (Devlin et al., 2019) in clustering entities with prompting. Wolfe and Caliskan (2022) probed the CLIP LM, showing that word representations from it are less anisotropic (Ethayarajh, 2019), i.e., more uniformly distributed with respect to direction, than the similar-sized GPT-2. Complementary to research on CLIP LM, we focus on pretraining. CLIP-like models are often pretrained with cross-modal contrastive learning. *We measure – during pretraining – the effectiveness of systematically modeling the image captions with sentence embedding training* (Reimers and Gurevych, 2019; Gao et al., 2021), which is a natural fit to the captions.

We pretrain CLIP and one of its new variants CyCLIP (Goel et al., 2022) with sentence embedding training, as well as the conventional cross-modal contrastive learning. In addition to CLIP’s cross-modal contrastive learning objective, CyCLIP explicitly optimizes for geometry consistency between the text and image representation spaces, making it a suitable model for validating the effectiveness of NLP methods. We evaluate pretrained models on an array of tasks involving one or two modalities such as SentEval, zero-shot VL retrieval, and image classification. We find that unsupervised sentence embedding training improves the language encoder quality and VL tasks. Supervised

sentence embedding training improves language encoder quality, but the benefit does not necessarily transfer to VL tasks. We analyze the learned representation spaces and find that sentence embedding training improves text-space uniformity (Wang and Isola, 2020) and reduces anisotropy (Ethayarajh, 2019; Wolfe and Caliskan, 2022).

We also investigate AL contrastive models such as CLAP (Wu et al., 2023). In contrast to VL pretraining, AL pretraining suffers from data scarcity and often leverages pretrained LLMs and audio encoders. We determine the effectiveness of sentence embedding training in both scenarios: continued pretraining with LLMs and audio encoders, and pretraining from scratch. We find that the benefits of sentence embedding training are less noticeable and noisy. To the best of our knowledge, this is the first study on investigating and trying to improve the language encoder of AL contrastive learning, and we expect our results will encourage more research in this direction.

In summary, our **contributions** are as follows: (i) We extensively evaluate how unsupervised and supervised sentence embedding trainings affect VL and AL contrastive pretraining. Experimental results indicate improved VL performance, however, the results on AL tasks are noisy and the improvements are less noticeable. (ii) We show that unsupervised sentence embedding training improves the language encoder of CyCLIP (Goel et al., 2022), hence improves performance of cross-modal tasks. (iii) We conduct a comprehensive analysis on the alignment and uniformity of learned representation spaces following Wang and Isola (2020), and show that sentence embedding training improves uniformity of the text representation space, but at the cost of decreased cross-modal alignment.

## 2 Related work

**CLIP LM.** Research has focused on the language encoder of OpenAI CLIP (Radford et al., 2021). The model consists of a language encoder (CLIP LM) and an image encoder that are jointly trained on Web-scale caption-image pairs. Yan et al. (2022) stressed the importance of CLIP LM, showing that it outperforms BERT (Devlin et al., 2019) in tasks, such as entity clustering, through prompting. Bielawski et al. (2022) showed that CLIP LM outperforms BERT in “human-centric” tasks such as genre classification on books or movies. Santurkar et al. (2023) highlighted the importance of text cap-

tions for representation learning of CLIP by comparing it with SimCLR (Chen et al., 2020) in which no language supervisions is present. Training signals from language are shown to be detrimental, worthing any number of images in a sufficiently large dataset. Our work follows this direction, with a focus on determining how supervised or unsupervised sentence embedding trainings affect CLIP LM and VL contrastive learning.

Goel et al. (2022) introduced CyCLIP, incorporating extra training objectives than cross-modal contrastive learning such that the geometry consistency between the text and image spaces is improved. One of CyCLIP’s training objectives is computing similarities between captions; this motivates us to determine how systematically modeling the captions through supervised or unsupervised sentence embedding training affects CyCLIP/CLIP.

**Contrastive audio-language pretraining** models have also been proposed. Guzhov et al. (2022) extended CLIP to audio tasks by adding an extra module and continued training on audio datasets. Similar distillation methods such as Wav2CLIP (Wu et al., 2022), have also been proposed. Elizalde et al. (2023) and Wu et al. (2023) independently proposed CLAP, in which a language encoder and an audio encoder are jointly trained on AL datasets, which resembles CLIP. We focused on the language encoder in pretraining AL models, and demonstrated the impact of sentence embedding training. To the best of our knowledge, this is the first step in this direction.

**Sentence embedding** is an extensively investigated NLP topic. Methods ranging from bag-of-word averaging non-contextualized embeddings (Mikolov et al., 2013; Pennington et al., 2014) to training LSTMs (Hochreiter and Schmidhuber, 1997), e.g., SkipThought (Kiros et al., 2015) and InferSent (Conneau et al., 2017), have been proposed to effectively compose individual tokens to meaningful sentence representations. Methods that leverage post-hoc transforming (Li et al., 2020; Su et al., 2021) or finetuning the pretrained BERT in supervised (Reimers and Gurevych, 2019) or unsupervised scenarios (Gao et al., 2021) are also introduced. Zhang et al. (2022) show that grounding sentence embedding learning to images improves semantic textual similarity tasks. We present a focused investigation on the LM in CLIP/CyCLIP. We pretrained from scratch an LM and ResNet-50 (He et al., 2016) with cross-modal contrastive learn-

ing, as well as unsupervised or supervised sentence embedding training with image captions. Verifying the effectiveness of sentence embeddings – a critical component for retrieval and clustering (Reimers and Gurevych, 2019; Gao et al., 2021; Wang et al., 2021; Thakur et al., 2021; Geigle et al., 2022) – is of great importance because retrieval has been one of the main applications of CLIP-like models.

### 3 Method

Cross-modal contrastive learning plays a key role in training models such as CLIP/CLAP. We take image modality as an example for introducing this method. Consider a caption-image dataset  $\{(I_i, T_i)\}_{i=1}^N$  that includes  $N$  caption-image pairs, and denote  $I^e$  and  $T^e$  as the output representations from an image and language encoder, respectively.

The cross-modal contrastive loss (Radford et al., 2021) is defined as

$$\mathcal{L}_{\text{contra.}}(\tau) = - \sum_{j=1}^N \log \frac{\exp(\langle I_j^e, T_j^e \rangle / \tau)}{\sum_k \exp(\langle I_j^e, T_k^e \rangle / \tau)} - \sum_{k=1}^N \log \frac{\exp(\langle I_k^e, T_k^e \rangle / \tau)}{\sum_j \exp(\langle I_j^e, T_k^e \rangle / \tau)},$$

where  $\tau$  is a trainable temperature parameter initialized to 0.07 and  $\langle \cdot, \cdot \rangle$  computes cosine similarity.

CLIP’s training objective solely stresses the alignment between the two modalities. CyCLIP (Goel et al., 2022) has improved CLIP (Radford et al., 2021) by additionally optimizing for improved representation space geometry, such that the image and text spaces are more consistent with each other. Concretely, CyCLIP explicitly optimizes two additional objectives for cross-modal and in-modal consistency as well as  $\mathcal{L}_{\text{contra.}}$ :

$$\mathcal{L}_{\text{C-cyclic}} = \sum_j \sum_k (\langle I_j^e, T_k^e \rangle - \langle I_k^e, T_j^e \rangle)^2, \\ \mathcal{L}_{\text{I-cyclic}} = \sum_j \sum_k (\langle I_j^e, I_k^e \rangle - \langle T_k^e, T_j^e \rangle)^2.$$

Intuitively, decreasing the cross-modal consistency loss  $\mathcal{L}_{\text{C-cyclic}}$  makes the cross-modal similarity matrix more symmetric, as shown in Figure 1. Note that solely optimizing  $\mathcal{L}_{\text{contra.}}$  is expected to symmetrize the cross-modal similarity matrix because the similarity of non-diagonal pairs are trained to be zero. Goel et al. (2022) showed that this scenario does not occur in practice and explicitly optimizing  $\mathcal{L}_{\text{C-cyclic}}$  is beneficial.

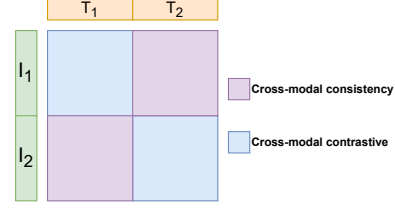


Figure 1: Cross-modal similarity matrix. Diagonal elements refer to cosine similarity between aligned caption-image pairs while non-diagonal elements refer to mismatched caption-image pairs.

Optimizing  $\mathcal{L}_{\text{I-cyclic}}$ , however, reduces the inconsistency between the overall geometry of the text and image spaces. Computing  $\mathcal{L}_{\text{I-cyclic}}$  requires calculating the similarity between two text captions, i.e.,  $\langle T_k^e, T_j^e \rangle$ . It is thus reasonable to hypothesize that *accurately computing caption similarities is beneficial for optimizing  $\mathcal{L}_{\text{I-cyclic}}$* . We use unsupervised and supervised sentence embedding training methods and test the hypothesis (§4).

We use the widely used SimCSE (Gao et al., 2021) method for learning caption representations. SimCSE also uses contrastive learning: a caption is input to a language encoder twice to obtain two vectors  $T^e$  and  $T_+^e$ . With dropout enabled,  $T^e$  and  $T_+^e$  are generally different. These paired vectors serve as the positive training pairs for contrastive learning, while mismatched captions form negative pairs. We denote the unsupervised SimCSE loss as

$$\mathcal{L}_s(\tau) = - \sum_j \log \frac{\exp(\langle T_j^e, T_{j,+}^e \rangle / \tau)}{\sum_k \exp(\langle T_j^e, T_{k,+}^e \rangle / \tau)},$$

where  $\tau$  is fixed to 0.05 following (Gao et al., 2021).

Another direction of sentence embedding training is supervised training (Reimers and Gurevych, 2019) on natural language inference (NLI) datasets, e.g., SNLI and MNLI (Bowman et al., 2015; Williams et al., 2018). We denote the objective as  $\mathcal{L}_n$  and follow Gao et al. (2021) in using entailment pairs as  $T^e$  and  $T_+^e$  and the contradiction sentence as a hard negative.

Table 1 lists various models we use in our experiments as well as their training objectives. During the experiments, we sum up the objectives but weight them with different hyperparameters ( $\lambda$ ) depending on the combinations, which are shown in §4. We add a suffix “s” to the name of models trained with  $\mathcal{L}_s$  and “n” to models trained with  $\mathcal{L}_n$ .

	$\mathcal{L}_{\text{contra.}}$	$\mathcal{L}_{\text{C-cyclic}}$	$\mathcal{L}_{\text{I-cyclic}}$	$\mathcal{L}_s$	$\mathcal{L}_n$
CLI (A) P	✓	-	-	-	-
CLI (A) Ps	✓	-	-	✓	-
CLI (A) Pn	✓	-	-	-	✓
CyCLI (A) P	✓	✓	✓	-	-
CyCLI (A) Ps	✓	✓	✓	✓	-
CyCLI (A) Pn	✓	✓	✓	-	(✓)

Table 1: List of training objectives. We follow Radford et al. (2021) for CLIP, Wu et al. (2023) for CLAP, and Goel et al. (2022) for CyCLIP.

## 4 Experiments

### 4.1 Datasets

To *pretrain VL models* such as CLIP and CyCLIP, we follow Bugliarello et al. (2021); Goel et al. (2022) and use the Conceptual Captions dataset, which consists of approximately<sup>1</sup> 3M caption-image pairs (CC3M; Sharma et al. (2018)). CC3M has a reasonable size for pretraining and contains a broad coverage of Web content, making it a good option for learning generic VL representations (Bugliarello et al., 2021).

To *evaluate the trained VL models*, we follow (Radford et al., 2021) and conduct evaluations with zero-shot image-text retrieval on the Karpathy (Karpathy and Fei-Fei, 2015) test splits of Flickr30K (Plummer et al., 2015) and MSCOCO (Chen et al., 2015). We skip the evaluation on Flickr30K when supervised sentence embedding training is used, i.e., when  $\mathcal{L}_n$  is considered in training. This is because Flickr30K captions are the premises in the SNLI dataset (Bowman et al., 2015), overlapping with the supervised sentence embedding training data. For zero-shot image classification, we use the standard benchmarks CIFAR10, CIFAR100 (Krizhevsky et al., 2009), and ImageNet1K (Russakovsky et al., 2015). Zero-shot image classification with domain shift, out-of-domain, and adversarial examples are also considered: ImageNetV2 (Recht et al., 2019), ImageNet-Sketch (Wang et al., 2019), ImageNet-O, ImageNet-A, and ImageNet-R (Hendrycks et al., 2021b,a).

To *pretrain AL models*, e.g., CLAP and CyCLAP, we conduct experiments with Clotho (Drossos et al., 2020) consisting of  $\approx 6\text{K}$  caption-audio pairs and AudioCaps consisting of  $\approx 50\text{K}^2$  caption-audio

<sup>1</sup>CC3M images need to be downloaded by users. Due to broken URLs, the exact amount of data varies from time to time; Table 2 shows the exact number of images.

<sup>2</sup>Similar to CC3M, AudioCaps only provides audio captions while users need to download corresponding YouTube videos and convert their audio to waveforms; Table 2 shows

	Dataset	Pretraining	Retrieval	ZS	Size
VL	CC3M	✓	-	-	2,806,641
	MSCOCO	-	✓	-	5,000
	Flickr30K	-	✓	-	1,000
	CIFAR10	-	-	✓	10,000
	CIFAR100	-	-	✓	10,000
	ImageNet1K	-	-	✓	50,000
	ImageNetV2	-	-	✓	10,000
	ImageNetSketch	-	-	✓	5,0889
	ImageNet-O	-	-	✓	2,000
	ImageNet-A	-	-	✓	7,500
	ImageNet-R	-	-	✓	30,000
AL	Clotho	✓	✓	-	5,929
	AudioCaps	✓	✓	-	50,725
	ESC50	-	-	✓	400
	US8K	-	-	✓	8,732

Table 2: Datasets and their amount of examples. We report amount of images for VL datasets and of waveform files for AL datasets. “ZS”: zero-shot classification.

pairs (Kim et al., 2019), similar to LAION-CLAP (Wu et al., 2023). In contrast to the VL scenario, AL pretraining is known to be challenging due to data scarcity (Wu et al., 2023). We use Clotho and AudioCaps because they contain natural language descriptions of the audio instead of simple tags; thus, there is no need to generate pseudo-natural language captions from tags using services such as ChatGPT/GPT3 (Mei et al., 2023).

To *evaluate pretrained AL models*, we conduct cross-modal retrieval and zero-shot audio classification tasks. For Clotho, we train the models on the training split and report retrieval results on the validation split. For AudioCaps, we select the best-performing checkpoint on the validation split and report test split results. We conduct zero-shot classification on the Environmental Sound Classification dataset (ESC50; Piczak (2015)) and Urban-Sound8K (US8K; Salamon et al. (2014)), which have been widely used (Wu et al., 2023; Elizalde et al., 2023). ESC50 contains short audio clips containing the sound of different common events such as cats meowing and dogs barking; the clips are categorized into 50 classes, and US8K contains audio clips of urban event sounds such as drilling and street music; the clips are categorized into ten classes.

Table 2 lists all the cross-modal datasets and their usage. We follow Goel et al. (2022) in processing the VL datasets and Wu et al. (2023) in processing the AL datasets; the detailed steps of these processes are shown in Appendix §A.1.

the exact amount of waveforms we used.



## 4.2 Experiment settings

To *pretrain the VL models*, we use the same model architecture as CyCLIP (Goel et al., 2022), i.e., a ResNet-50 as the image encoder and Transformer (Vaswani et al., 2017) as the language encoder. We pretrain the model from scratch and largely reuse CyCLIP’s hyperparameters. To weight different training objectives (Table 1) in CyCLIP, we set  $\lambda_{\text{I-cyclic}}$  and  $\lambda_{\text{C-cyclic}}$  to 0.25,  $\lambda_{\text{contra.}}$  is set to 1.0, and we empirically set  $\lambda_s$  and  $\lambda_n$  to 0.1. We use a batch size of 80, and each pretraining trial is run for 64 epochs, taking four days with four A100 GPUs. We enable dropout in the language encoder and use dropout rate of 0.1. Appendix §A.1 lists the details of the hyperparameters.

The VL pretraining dataset CC3M has a validation split consisting of  $\approx 15\text{K}$  text-image pairs. We select the best-performing checkpoint on this validation split for downstream task evaluations.

Due to data scarcity, *AL pretraining* often leverages pretrained language and audio encoders. We use the same model architecture as LAION-CLAP (Wu et al., 2023): pretrained RoBERTa-base (Liu et al., 2020) as the language encoder and pretrained Hierarchical Token-Semantic Audio Transformer (HTSAT; Chen et al. (2022)) as the audio encoder. HTSAT has shown to outperform CNNs in various audio tasks (Chen et al., 2022). We use the HTSAT-tiny variant with 31M parameters. Due to small dataset size, each pretraining experiment takes less than one day on a single A100 GPU. We use the default dropout rate of 0.1 of RoBERTa-base in our experiments. In pilot experiments on Clotho, we found that the default hyperparameters<sup>3</sup> lead to underfitting<sup>4</sup>. We find that longer training and a smaller learning rate improve performance, as shown in Table 4. Table 10 lists our hyperparameters, which are kept the same when we pretrain the AL models on Clotho or AudioCaps.

For weighting the training objectives, due to the small model size and dataset size, we grid search the optimal  $\lambda_{\text{I-cyclic}}$ ,  $\lambda_{\text{C-cyclic}}$ , and  $\lambda_s$  from [0.1, 0.25, 0.5];  $\lambda_{\text{contra.}}$  is set to 1.0. Supervised sentence embedding training ( $\lambda_n$ ) is not considered due to the small size of the AL datasets.

Clotho and AudioCaps both contain validation splits; thus, we select the best-performing check-

<sup>3</sup>[https://github.com/LAION-AI/CLAP/blob/main/experiment\\_scripts/train-only-clotho.sh](https://github.com/LAION-AI/CLAP/blob/main/experiment_scripts/train-only-clotho.sh)

<sup>4</sup>This is reflected by the increasing validation performance in learning curves publicly shared by the LAION-CLAP project on WnB.

	Text Retrieval			Image Retrieval		
	R@1	R@5	R@10	R@1	R@5	R@10
CLIP	15.70	37.22	49.06	12.48	31.10	42.23
CLIPs	<b>17.78</b>	<b>38.92</b>	<b>50.10</b>	<b>13.46</b>	<b>32.93</b>	<b>44.09</b>
CLIPn	15.74	35.66	47.38	13.12	31.46	42.55
CyCLIP	18.92	41.46	54.00	15.40	35.61	46.95
CyCLIPs	<b>21.30</b>	<b>44.34</b>	<b>56.54</b>	<b>16.69</b>	<b>37.75</b>	<b>49.24</b>
CyCLIPn	16.32	36.76	48.16	14.53	34.07	45.52

	Text Retrieval			Image Retrieval		
	R@1	R@5	R@10	R@1	R@5	R@10
CLIP	31.80	62.10	72.90	25.50	52.28	<b>64.34</b>
CLIPs	<b>35.20</b>	<b>63.20</b>	<b>75.30</b>	<b>26.70</b>	<b>52.34</b>	64.32
CyCLIP	37.30	66.10	76.40	30.22	56.70	67.40
CyCLIPs	<b>40.00</b>	<b>69.30</b>	<b>79.70</b>	<b>31.74</b>	<b>58.02</b>	<b>69.46</b>

Table 3: Zero-shot **VL retrieval results (%)** on MSCOCO (top) and Flickr30K (bottom). Integrating unsupervised sentence embedding learning (CLIPs and CyCLIPs) noticeably improves zero-shot retrieval; supervised embedding training (CLIPn and CyCLIPn) has neutral to negative impacts.

mAP@10	Text Retrieval	Audio Retrieval
CLAP	12.24	<b>21.21</b>
CLAP (Wu et al., 2023)	<b>13.80</b>	20.40
CLAP	<b>51.34</b>	<b>55.60</b>
CLAP (Wu et al., 2023)	45.70	51.30

Table 4: AL training validation performance (%). We report mean average precision at ten (mAP@10) on validation split of Clotho (top) and AudioCaps (bottom).

point on the validation splits then conduct evaluation on downstream tasks.

## 5 Results and analyses

### 5.1 Results

Table 3 lists the **zero-shot VL retrieval** results on MSCOCO and Flickr30K, following the settings in Radford et al. (2021). We first utilize the pretrained image and language encoders in a VL model to encode images and captions into vectors. In text retrieval, we then input the image vector to retrieve the aligned captions and vice-versa for image retrieval. We report Recall@N for N in [1, 5, 10].

**Comparing CyCLIP and CLIP variants.** We see that CyCLIP clearly outperforms CLIP across the board for both datasets, highlighting the significant value of incorporating  $\mathcal{L}_{\text{C-cyclic}}$  and  $\mathcal{L}_{\text{I-cyclic}}$  in optimizing for consistent geometry of the text and image representation spaces (Goel et al., 2022).

When **comparing CyCLIPs/CLIPs to CyCLIP/CLIP**, we observe the effectiveness of im-

	Text Retrieval			Audio Retrieval		
	R@1	R@5	R@10	R@1	R@5	R@10
CLAP	<b>13.88</b>	34.16	48.90	11.67	<b>33.80</b>	<b>47.10</b>
CLAPs	13.49	<b>35.60</b>	<b>49.00</b>	<b>11.92</b>	32.54	45.47
CyCLAP	14.74	35.50	48.52	11.90	<b>34.95</b>	<b>48.61</b>
CyCLAPs	<b>14.93</b>	<b>36.84</b>	<b>51.00</b>	<b>12.08</b>	34.09	46.76

	Text Retrieval			Audio Retrieval		
	R@1	R@5	R@10	R@1	R@5	R@10
CLAP	<b>44.10</b>	<b>76.80</b>	<b>87.67</b>	<b>34.82</b>	<b>70.62</b>	82.93
CLAPs	42.73	75.44	87.57	34.69	69.80	<b>82.99</b>
CyCLAP	<b>40.65</b>	74.19	<b>86.52</b>	34.13	69.24	82.30
CyCLAPs	39.81	<b>74.40</b>	85.79	<b>34.23</b>	<b>70.24</b>	<b>82.74</b>

Table 5: **Text-audio retrieval results (%)** on Clotho (top) and AudioCaps (bottom). Adding unsupervised sentence embedding training improves performance of CLAP/CyCLAP in general, but improvements are noisy and less noticeable than in VL scenario.

proving the language encoder with unsupervised sentence embedding training  $\mathcal{L}_s$ . CyCLIPs/CLIPs clearly surpass CyCLIP/CLIP in all configurations except Flickr30K-CLIPs-ImageRetrieval-R@10. This suggests that, *we improve CyCLIP on zero-shot vision-language retrieval tasks through learning better representations of the captions*. We also observe more gains in text retrieval than in image retrieval. For example, on Flickr30K@1, CyCLIPs outperforms CyCLIP by 2.70% (absolute) in text retrieval and by 1.52% (absolute) in image retrieval. This observation reflects the effectiveness of improved caption representations.

In contrast to the unsupervised embedding training scenario ( $\mathcal{L}_s$  and CyCLIPs/CLIPs), supervised sentence embedding training ( $\mathcal{L}_n$  and CyCLIPn/CLIPn) results in a neutral to negative impact on the overall retrieval results. Investigating the text and image representation spaces, we find that  $\mathcal{L}_n$  extensively enforces a uniform text representation space such that the alignment between the text and image spaces is negatively affected; we provide more in-depth analyses in §5.2.

**AL retrieval results** on Clotho and AudioCaps are listed in Table 5. Supervised sentence embedding training objective  $\mathcal{L}_n$  is not considered because NLI datasets are much larger than AL datasets (MNLI: 433K; Clotho: 6K; AudioCaps: 53K); subsampling introduces extra random factors that are difficult to control.

**On Clotho**, we observe overall improvements when comparing CyCLAP to CLAP. We see one

exception on text-retrieval-R@10 (i.e., 48.90 for CLAP and 48.52 for CyCLAP); however, the overall improvement outweighs performance drops, demonstrating that explicitly optimizing for the consistency between the audio and text spaces (Goel et al., 2022) is also promising for improving AL retrieval on Clotho. When comparing CyCLAPs/CLAPs with CyCLAP/CLAP, we see clear improvements on text retrieval. However, this comes with a decreased performance on audio retrieval results.

**On AudioCaps**, CyCLAP falls behind CLAP. This is somewhat surprising because AudioCaps is considered an easier dataset than Clotho (Koeperke et al., 2022). The HTSAT audio encoder has already been pretrained with audio classification tasks on AudioSet (Gemmeke et al., 2017), from which AudioCaps is derived. This may contribute to the noisy results. For example, LAION-CLAP (Wu et al., 2023) reported that adding additional 630K AL pairs largely boosts AL retrieval performance on Clotho, but hurts on AudioCaps. We observe similar results when comparing CyCLAPs/CLAPs with CyCLAP/CLAP.

**Comparing VL and AL retrieval results** in Table 3 and Table 5, we observe that (1) CyCLIP noticeably improves over CLIP than CyCLAP over CLAP, and CLAP even outperforms CyCLAP on AudioCaps; and (2) improving the language encoder with sentence embedding training is more beneficial to VL than AL. We hypothesize that this is because AL pretraining starts with pretrained encoders, which have geometry that is difficult to alter due to the small AL dataset size. We further conduct AL pretraining from scratch (Appendix §A.4), where the language and audio encoders are re-initialized. Sentence embedding training brings more noticeable results, however, the overall results are still noisy due to the particularly small dataset sizes. We believe resolving the data scarcity issue is a critical step towards clearer regularities in AL pretraining. Researchers have started to exploit directions like using ChatGPT (Mei et al., 2023).

For **zero-shot image classification**, Table 6 lists the Top1 accuracy on standard image classification datasets (top) and datasets with distribution shifts or adversarial examples (bottom). We follow Radford et al. (2021) and use their prompts for zero-shot classification. For an image to be classified, we compute the cosine similarity between its vector and the encoded vector of all classes. Each

	CLIP	CLIPn	CLIPs	CyCLIP	CyCLIPn	CyCLIPs
CIFAR10	28.31	<b>44.06</b>	36.80	38.67	41.16	<b>44.97</b>
CIFAR100	13.23	<b>17.93</b>	10.72	17.44	19.82	<b>22.05</b>
ImageNet1K	14.94	15.97	<b>16.01</b>	20.99	18.13	<b>22.13</b>
ImageNetV2	12.85	13.41	<b>14.09</b>	17.77	15.65	<b>18.68</b>
ImageNet-Sk.	7.72	7.75	<b>8.14</b>	11.67	9.93	<b>12.85</b>
ImageNet-O	20.75	<b>21.95</b>	21.30	27.05	24.45	<b>29.55</b>
ImageNet-A	3.59	3.41	<b>3.95</b>	5.03	4.45	<b>5.19</b>
ImageNet-R	18.39	<b>18.51</b>	18.24	24.37	23.07	<b>26.72</b>

Table 6: Zero-shot image classification (R@1 in %) on standard datasets (top) and datasets with distribution shift or adversarial examples (bottom).

of the classes is reformulated with various prompts. E.g., the ImageNet class “plane” is reformulated with 80 templates<sup>5</sup> such as “a photo of a” and “a blurry photo of a”, resulting in prompts “a photo of a plane” and “a blurry photo of a plane” (Radford et al., 2021). The vectors of encoded prompts of a class are averaged; we select the class with the maximum cosine similarity with the image vector.

Similar trends as in the retrieval tasks are observed. CyCLIP variants outperform their CLIP counterparts; unsupervised sentence embedding training benefits both CyCLIP/CLIP while supervised sentence embedding training does not result in consistent improvement or deterioration.

For **zero-shot audio classification**, Table 7 list the Top1 accuracy on ESC50 and US8K of models pretrained on Clotho and AudioCaps respectively. We follow LAION-CLAP (Wu et al., 2023) and use their template “This is a sound of”. In contrast to the image scenario, only one template is provided. CyCLAP generally outperforms CLAP, except for AudioCaps-US8K. We observe no improvements of sentence embedding training when comparing CyCLAPs/CLAPs with CyCLAP/CLAP. We leave the extensive “prompt engineering” of designing more prompts for future work<sup>6</sup>.

## 5.2 Analyses

**Alignment and uniformity of representation spaces.** In this section, we take a closer look at the learned representation spaces. Following Wang and Isola (2020), we inspect the alignment and uniformity on the hypersphere of learned spaces. Considering a caption-image dataset  $\{(I_i, T_i)\}_{i=1}^N$ , we can compute the alignment and uniformity scores

<sup>5</sup>OpenAI templates are public on [GitHub link](#).

<sup>6</sup>Following the VL scenario, we write prompts and conduct more experiments on zero-shot audio classification. Appendix §A.3 shows results and discussions. We see improved performance, however, the generalization ability of this prompt engineering needs to be tested, and we leave it for future work.

		CLAP	CLAPs	CyCLAP	CyCLAPs
Clotho	ESC50	<b>72.25</b>	71.75	<b>78.00</b>	75.75
	US8K	<b>67.76</b>	67.42	<b>70.46</b>	65.98
AudioCaps	ESC50	<b>74.50</b>	72.75	<b>77.50</b>	75.50
	US8K	<b>69.78</b>	64.14	<b>67.90</b>	66.94

Table 7: Zero-shot audio classification (R@1 in %) on ESC50 and US8K of models pretrained on Clotho or AudioCaps.

defined as:

$$\begin{aligned}\mathcal{L}_{\text{align}} &\triangleq \mathbb{E}_{(I,T) \sim p_{\text{pos}}} \|I^e - T^e\|_2^2 \\ \mathcal{L}_{\text{T,uniform}} &\triangleq \log \mathbb{E}_{T_i, T_j \stackrel{\text{i.i.d.}}{\sim} p_{\text{data}}} e^{-2\|T_i^e - T_j^e\|_2^2} \\ \mathcal{L}_{\text{I,uniform}} &\triangleq \log \mathbb{E}_{I_i, I_j \stackrel{\text{i.i.d.}}{\sim} p_{\text{data}}} e^{-2\|I_i^e - I_j^e\|_2^2}\end{aligned}$$

where  $(I, T) \sim p_{\text{pos}}$  refers to aligned text-images pairs,  $(T_i, T_j) \sim p_{\text{data}}$  refers to independent and identically distributed (IID) sampled text pairs,  $(I_i, I_j) \sim p_{\text{data}}$  refers to IID sampled image pairs, and  $I^e, T^e$  respectively refer to the encoded image and text vectors.

Recall that the trained models output L2 normalized vectors residing on the unit ball. Intuitively, we want vectors of aligned pairs of two modalities to be well aligned in the representation space, such that  $\mathcal{L}_{\text{align}}$  is close to zero. However, we want the space of a single modality to be more uniform than anisotropic (Ethayarajh, 2019; Wolfe and Caliskan, 2022), such that the overall representation space capacity is well used. This results in a near minus infinite  $\mathcal{L}_{\text{uniform}}$ .

Figure 2 illustrates the results. We only show  $\mathcal{L}_{\text{align}}$  w.r.t.  $\mathcal{L}_{\text{T,uniform}}$  since our main focus is the language encoder. We see that unsupervised sentence embedding training trades cross-modal alignment for improving the text space uniformity. For VL pretraining, supervised sentence embedding training overly focuses on text space uniformity while the VL space alignment deteriorates. This observation is further evidenced when visualizing with CyCLIP and CyCLIPn using the Flickr30K (\*) dataset in which the captions largely overlap with the dataset for supervised sentence embedding training (§4.1).

Another interesting observation is that the text encoder of CyCLIP/CyCLAP outputs representation space less uniform than that of CLIP/CLAP, as shown in Figure 2 (x-axis). Liang et al. (2022)

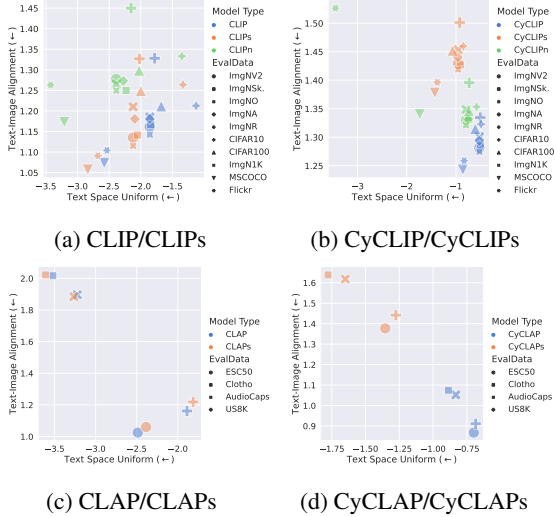


Figure 2: Visualizing cross-modal alignment w.r.t. text space uniformity of trained VL and AL models. To visualize AL results, we use models pretrained on AudioCaps due to it being larger than Clotho. We observe that sentence embedding training trades cross-modal alignment for text space uniformity.

show that randomly initialized encoders output vectors residing in different cones. The in-modal cyclic loss  $\mathcal{L}_{I-cyclic}$  (§3) stresses consistency between cones; it is thus expected to be challenging to learn a uniform space while simultaneously preserving consistency between two spaces<sup>7</sup>. Sentence embedding training provides extra training signals.

**LM quality.** We evaluate the language encoder quality of pretrained VL models. Our motivation is two-fold. First, as a sanity check, we want to verify that incorporating sentence embedding training in VL contrastive learning still improves the language encoder’s ability of representing general sentences. Second, the evaluation results help us measure the compatibility and possible interferences among the various training objectives (Pfeiffer et al., 2023).

To this goal, we leverage the sentence embedding benchmark SentEval (Conneau and Kiela, 2018). Default SentEval configurations are used in all experiments. Our intrinsic evaluation tasks are the semantic textual similarity tasks: STS12-ST16, STS-B, SICKR (Marelli et al., 2014; Cer et al., 2017; Agirre et al., 2012, 2013, 2014, 2015, 2016). Extrinsic evaluation tasks are movie review (MR; Pang and Lee (2005)) product review (CR; Hu and Liu (2004)) subjectivity status (SUBJ; Pang and Lee (2004)), opinion polarity (MPQA; Wiebe

<sup>7</sup>We find that improving text space uniformity also benefits the image space for CyCLIP. More discussions are presented in Appendix §A.2.

	CLIP	CLIPn	CLIPs	CyCLIP	CyCLIPn	CyCLIPs
STS12	46.14	54.25	50.31	37.84	45.60	40.42
STS13	50.24	59.67	48.44	52.35	37.82	54.90
STS14	48.70	59.26	51.73	46.58	40.55	49.46
STS15	64.90	73.81	66.09	63.25	59.62	67.01
STS16	51.94	63.08	55.62	50.96	46.80	52.87
STS-B	61.54	68.36	65.04	60.30	54.88	60.72
SICKR	64.70	73.09	65.82	64.78	62.62	64.34
Avg	55.45	<b>64.50</b>	57.58	53.72	49.70	<b>55.67</b>
MR	61.07	63.66	61.11	59.51	62.78	60.65
CR	67.63	71.07	68.03	67.02	73.67	66.12
SUBJ	76.39	78.09	77.52	74.24	78.90	77.36
MPQA	74.60	77.25	74.80	74.69	80.13	76.16
SST2	61.67	66.89	63.65	61.50	68.42	64.25
TREC	60.80	56.00	60.60	55.80	53.80	62.80
MRPC	67.07	67.77	67.77	68.00	68.75	68.29
Avg	67.03	<b>68.68</b>	67.64	65.82	<b>69.49</b>	67.95

Table 8: Intrinsic (top) and extrinsic (bottom) SentEval task performance of the language encoder in VL models.

et al. (2005)), sentiment analysis on SST2 (Socher et al., 2013), question-type classification (TREC; Voorhees and Tice (2000)), and paraphrase detection (MRPC; Dolan et al. (2004)). Table 8 lists the results. We observe that unsupervised sentence embedding training is beneficial generally for CyCLIP/CLIP on both intrinsic and extrinsic tasks. Supervised sentence embedding training results in more significant improvements<sup>8</sup>, however, it negatively affects CyCLIPn on the sensitive intrinsic tasks.

In this section, we have shown that (1) Sentence embedding training improves text-space uniformity with decreased cross-modal alignment. Better balancing the two goals helps improve retrieval performance. (2) Sentence embedding training improves language encoder quality on SentEval, resonating the improved text-space uniformity.

## 6 Conclusion

We extensively evaluate the effectiveness of sentence embedding training for pretraining contrastive vision-language and audio-language models. We show that it improves vision-language pretraining, resulting in a better CyCLIP. However, the benefits to audio-language pretraining are noisy and less noticeable. We conduct comprehensive analyses and show that sentence embedding training increases text space uniformity, but with a cost of reduced cross-modal alignment.

<sup>8</sup>Improvements of supervised sentence embedding training may due to the observation that NLI datasets have similar domains and language use as SentEval tasks. In Appendix §A.5, we show that the improvements are indeed from supervised training, rather than domain similarity.



## 7 Limitations

We acknowledge a few limitations that should be considered.

We restrict our scope to cross-modal contrastive models involving three specific modalities: language, image, and audio. While contrastive learning has been successfully extended to other modalities such as music, incorporating music poses additional challenges, particularly regarding licensing and the heterogeneity of music sources. Downloading music from the internet and mining reliable music-language pairs are time-consuming tasks, which we did not consider in detail in this study. Nevertheless, we conducted initial experiments on the music modality using MusicCaps (Agostinelli et al., 2023). The results are shown in §A.6.

In our audio-language pretraining experiments, we explored both pretraining from scratch and pretraining from publicly available language and audio encoders. However, we believe that a more promising direction would involve adapting the pretrained language encoder to the audio domain by performing additional pretraining on audio descriptions before engaging in cross-modal contrastive learning. Nevertheless, we chose to follow the current methods in the literature to ensure consistent evaluations and facilitate meaningful comparisons.

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## A Appendix

### A.1 Datasets and hyperparameters

For VL pretraining, our experiments largely follow those for CyCLIP (Goel et al., 2022) and for CLIP (Radford et al., 2021). We also directly reuse CyCLIP training hyperparameters but with a smaller batch size, as listed in Table 9.

For AL pretraining, our experiments largely follow that of for LAION-CLAP (Wu et al., 2023). To process the audio data, we sample the wavefiles at a rate of 48kHz and then convert them to FLAC format using FFmpeg<sup>9</sup>. We then use a hop size of 480, window size of 1024, and 64 mel-bins for computing Short-time Fourier transform (STFT) and mel-spectrograms. The audio encoder input thus has a dimension of 1024 for time steps and 64 for frequency bins. We list the hyperparameters in Table 10.

### A.2 Text and image space consistency

CyCLIP variants ensure cross-modal consistency, such that improving the uniformity of the text space with sentence embedding training also benefits image space uniformity as shown in Figure 3. As expected, this observation does not hold for CLIP.

<sup>9</sup><https://ffmpeg.org/>

Hyperparameter	Value
Logit scale range	0 to 4.6052
Epochs	64
Batch size	80
Learning rate	0.0005
Optimizer	Adam
Scheduler	Cosine
Learning rate warmup steps	10000
Language encoder dropout	0.1

Table 9: Hyperparameters used for training VL models

Hyperparameter	Value
Logit scale range	0 to 4.6052
Epochs	90
Batch size	80
Learning rate	0.00009
Optimizer	AdamW
Scheduler	Cosine
Learning rate warmup steps	9600
Language encoder dropout	0.1

Table 10: Hyperparameters used for training AL models

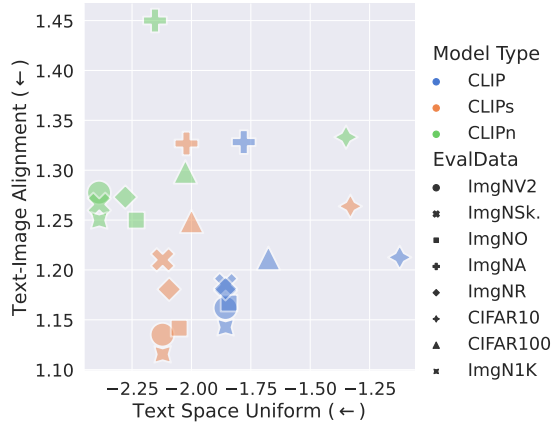
### A.3 Zero-shot audio classification with more prompts

To resemble zero-shot image classification in VL experiments, we write more prompts for zero-shot audio classification, as listed in Table 12. Table 11 shows zero-shot audio classification with these prompts.

It can be observed that (1) results in Table 11 clearly outperform Table 7 results, illustrating the importance of using many prompts; (2) sentence embedding training improves the models trained on Clotho.

### A.4 Training audio-language models from scratch

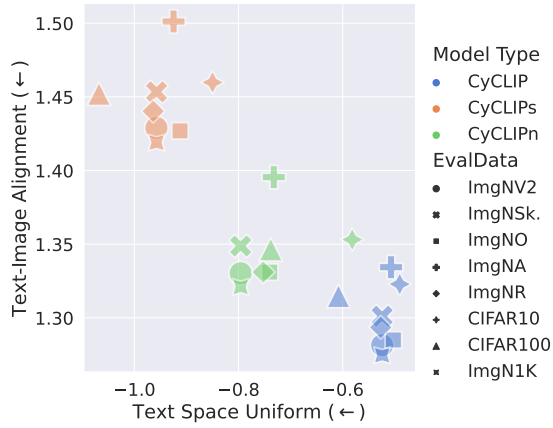
In §5.1 we show that sentence embedding training brings more noticeable impacts in learning VL models than in AL models; we conjecture that this is resulted from the fact that AL pretraining often leverages pretrained language and audio encoders (Elizalde et al., 2023; Wu et al., 2023). As a result, we conduct the experiments of pretraining the AL model from scratch, i.e., the language and audio encoders re-initialized. Table 13 lists the retrieval results on Clotho and AudioCaps.



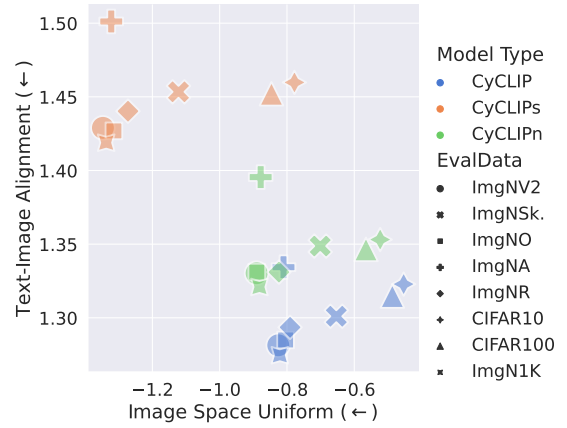
(a) CLIP: alignment vs. text space uniformity



(b) CLIP: alignment vs. image space uniformity



(c) CyCLIP: alignment vs. text space uniformity



(d) CyCLIP: alignment vs. image space uniformity

Figure 3: Comparing the text and image space consistency between CLIP and CyCLIP variants. Improving uniformity of the text space also benefits image space in CyCLIP.

		CLAP	CLAPs	CyCLAP	CyCLAPs
Clotho	ESC50	73.00	<b>73.25</b>	77.00	<b>77.75</b>
	US8K	69.64	<b>70.27</b>	<b>71.82</b>	68.75
AudioCaps	ESC50	<b>79.25</b>	75.00	<b>80.50</b>	78.50
	US8K	<b>72.00</b>	66.49	<b>69.46</b>	69.38

Table 11: Zero-shot audio classification (R@1 in %) on ESC50 and US8K. Prompts in Table 12 are used.

Compared with Table 5, we observe a significant performance drop since the encoders are pretrained from scratch. The results are still noisy. We consider that larger scale AL datasets are necessary to highlight the effectiveness of learning consistent representation spaces and sentence embedding training.

### A.5 Unsupervised sentence embedding training with NLI datasets

When evaluating the language encoder on SentEval tasks (§5.2), it is possible that the improvements brought by supervised sentence embedding training is due to the fact that NLI datasets have similar domain and language use as the SentEval tasks. We thus conduct a new type of training, where we use sentences in the NLI datasets for unsupervised sentence embedding training with SimCSE, in addition to VL contrastive learning. We name this new training scheme as CLIPe and CyCLIPe.

Table 16 shows that the new training schemes, CLIPe and CyCLIPe fall behind the supervised sentence embedding training counterparts CLIPn and CyCLIPn on SentEval. This confirms that the gains of supervised sentence embedding trainings is from the NLI task supervision, e.g., premise and hypothesis relations, instead of other factors such as domain. For completeness, we also report CLIPe/CyCLIPe performance on VL retrieval tasks in Table 14 and zero-shot image classification in Table 17.

### A.6 Preliminary experiments on the music modality

We further conducted a new experiment with the music modality: music-text retrieval on the MusicCaps dataset introduced by MusicLM (Agostinelli et al., 2023). MusicCaps consists of 5521 music-caption pairs, of which 2858 pairs are for training and 2663 are for validation. Each music clip is associated with hand-curated English descriptions (including genre, mood, tempo, singer voices etc.)

A sound of label
a sound of label.
A constant sound of label
a constant sound of label
A constant sound of label.
a constant sound of label.
A big sound of label
a big sound of label
A big sound of label.
A small sound of label
a small sound of label
A small sound of label.
A label is making a sound.
a label is making a sound
An label is making a sound.
an label is making a sound
A sound of label followed by a sound of label
A sound of label followed by label
A label@
A label
An label
an label
label@
label
label and label
A label is running.
A label is running
A label is happening.
A label is happening

Table 12: We prepare additional prompts for zero-shot audio classification resembling the VL prompts. “label” refers to the audio class label. When a prompt contains whitespace, we display it with “@” for better visualization.

from expert musicians. We use MusicCaps because it is open-sourced and publicly available. Following tables show the retrieval results (the same experiment configurations as the audio modality are used; cf. §A.1).

It can be observed from Table 15 that improving the text encoder with unsupervised sentence embedding training also helps music-text retrieval in the music modality, especially in the text retrieval scenario (CLAPs generally outperforms CLAP; CyCLAPs generally outperforms CyCLAP). These music modality results are consistent with our previous findings on the image and audio modalities, and plan to explore more in this direction in future work.

	Text Retrieval			Audio Retrieval		
	R@1	R@5	R@10	R@1	R@5	R@10
CLAP	<b>2.30</b>	7.85	13.88	2.28	7.94	13.47
CLAPs	2.11	<b>8.32</b>	<b>15.98</b>	<b>2.81</b>	<b>8.84</b>	<b>14.91</b>
CyCLAP	2.97	9.09	14.07	2.07	7.67	13.11
CyCLAPs	<b>3.54</b>	<b>10.05</b>	<b>15.41</b>	<b>2.64</b>	<b>8.88</b>	<b>14.87</b>

	Text Retrieval			Audio Retrieval		
	R@1	R@5	R@10	R@1	R@5	R@10
CLAP	16.30	43.78	<b>58.41</b>	<b>14.19</b>	<b>40.02</b>	<b>53.98</b>
CLAPs	<b>17.76</b>	<b>44.10</b>	57.99	13.81	38.60	52.02
CyCLAP	<b>18.81</b>	44.83	<b>61.23</b>	<b>14.96</b>	39.94	54.67
CyCLAPs	18.18	<b>47.23</b>	61.02	13.96	<b>40.56</b>	<b>54.84</b>

Table 13: Text and audio retrieval results (%) on Clotho (top) and AudioCaps (bottom) when pretraining AL models from scratch.

	Text Retrieval			Image Retrieval		
	R@1	R@5	R@10	R@1	R@5	R@10
CLIP	15.70	37.22	49.06	12.48	31.10	42.23
CLIPs	<b>17.78</b>	<b>38.92</b>	<b>50.10</b>	<b>13.46</b>	<b>32.93</b>	<b>44.09</b>
CLIPn	15.74	35.66	47.38	13.12	31.46	42.55
<b>CLIPe</b>	16.90	38.40	49.92	13.21	31.21	42.26
CyCLIP	18.92	41.46	54.00	15.40	35.61	46.95
CyCLIPs	<b>21.30</b>	<b>44.34</b>	<b>56.54</b>	<b>16.69</b>	<b>37.75</b>	<b>49.24</b>
CyCLIPn	16.32	36.76	48.16	14.53	34.07	45.52
<b>CLIPe</b>	16.22	37.52	49.22	14.05	32.56	43.15

Table 14: Zero-shot **VL retrieval results** (%) on MSCOCO (top) and Flickr30K (bottom).

	Text Retrieval			Music Retrieval		
	R@1	R@5	R@10	R@1	R@5	R@10
CLAP	<b>6.05</b>	18.42	28.33	5.46	18.45	<b>28.50</b>
CLAPs	5.99	<b>18.66</b>	<b>28.85</b>	<b>6.05</b>	<b>19.01</b>	28.43
CyCLAP	<b>6.37</b>	18.98	29.45	<b>6.69</b>	18.87	<b>29.45</b>
CyCLAPs	6.34	<b>20.06</b>	<b>30.08</b>	6.62	<b>19.36</b>	29.13

Table 15: Text and music retrieval results (%) on MusicCaps.



	CLIP	CLIPn	CLIPe	CLIPs	CyCLIP	CyCLIPn	CyCLIPe	CyCLIPs
STS12	46.14	54.25	46.54	50.31	37.84	45.60	42.03	40.42
STS13	50.24	59.67	46.29	48.44	52.35	37.82	35.56	54.90
STS14	48.70	59.26	47.66	51.73	46.58	40.55	27.57	49.46
STS15	64.90	73.81	65.48	66.09	63.25	59.62	46.65	67.01
STS16	51.94	63.08	52.39	55.62	50.96	46.80	33.83	52.87
STS-B	61.54	68.36	60.99	65.04	60.30	54.88	44.63	60.72
SICKR	64.70	73.09	62.86	65.82	64.78	62.62	47.53	64.34
Avg	55.45	<b>64.50</b>	54.60	57.58	53.72	49.70	39.69	<b>55.67</b>
MR	61.07	63.66	59.91	61.11	59.51	62.78	59.60	60.65
CR	67.63	71.07	68.74	68.03	67.02	73.67	64.61	66.12
SUBJ	76.39	78.09	75.86	77.52	74.24	78.90	74.16	77.36
MPQA	74.60	77.25	73.54	74.80	74.69	80.13	73.95	76.16
SST2	61.67	66.89	60.19	63.65	61.50	68.42	60.46	64.25
TREC	60.80	56.00	56.60	60.60	55.80	53.80	57.60	62.80
MRPC	67.07	67.77	67.83	67.77	68.00	68.75	67.48	68.29
Avg	67.03	<b>68.68</b>	66.10	67.64	65.82	<b>69.49</b>	65.41	67.95

Table 16: Evaluating the language encoder of different VL models with intrinsic (top) and extrinsic (bottom) SentEval tasks.

	CLIP	CLIPn	CLIPe	CLIPs	CyCLIP	CyCLIPn	CLIPe	CyCLIPs
CIFAR10	28.31	<b>44.06</b>	33.97	36.80	38.67	41.16	<b>50.48</b>	44.97
CIFAR100	13.23	<b>17.93</b>	12.30	10.72	17.44	19.82	21.76	<b>22.05</b>
ImageNet1K	14.94	15.97	15.74	<b>16.01</b>	20.99	18.13	20.07	<b>22.13</b>
ImageNetV2	12.85	13.41	13.51	<b>14.09</b>	17.77	15.65	17.34	<b>18.68</b>
ImageNet-Sk.	7.72	7.75	6.36	<b>8.14</b>	11.67	9.93	11.54	<b>12.85</b>
ImageNet-O	20.75	<b>21.95</b>	20.45	21.30	27.05	24.45	27.20	<b>29.55</b>
ImageNet-A	3.59	3.41	3.59	<b>3.95</b>	5.03	4.45	4.93	<b>5.19</b>
ImageNet-R	18.39	<b>18.51</b>	18.25	18.24	24.37	23.07	24.36	<b>26.72</b>

Table 17: Zero-shot image classification (R@1 in %) on standard datasets (top) and datasets with distribution shift or adversarial examples (bottom).