Non-Contrastive Learning Meets Language-Image Pre-Training

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Abstract

Contrastive language-image pre-training (CLIP) serves as a de-facto standard to align images and texts. Nonetheless, the loose correlation between images and texts of web-crawled data renders the contrastive objective data inefficient and craving for a large training batch size. In this work, we explore the validity of non-contrastive language-image pre-training (nCLIP), and study whether nice properties exhibited in visual self-supervised models can emerge. We empirically observe that the non-contrastive objective benefits representation learning while sufficiently underperforming under zero-shot recognition. Based on the above study, we further introduce xCLIP, a multi-tasking framework combining CLIP and nCLIP, and show that nCLIP aids CLIP in enhancing feature semantics. The synergy between two objectives lets xCLIP enjoy the best of both worlds: superior performance in both zero-shot transfer and representation learning. Systematic evaluation is conducted spanning a wide variety of downstream tasks including zero-shot classification, out-of-domain classification, retrieval, visual representation learning, and textual representation learning, showcasing a consistent performance gain and validating the effectiveness of xCLIP. The code and pre-trained models will be publicly available at https://github.com/shallowtoil/xclip.

1. Introduction

Language-image pre-training which simultaneously learns textual and visual representation from large-scale image-text pairs has revolutionized the field of representation learning [25, 59], vision-language understanding [22], and text-to-image generation [61]. Compared to traditional visual models, language-instilled ones intrinsically inherit the capability of zero-shot or few-shot learning prominently demonstrated by large language models such as GPT-3 [12]. The precursor system, Contrastive Language-Image Pre-Training [59] (CLIP) that explicitly aligns the projected features of two modalities, has demonstrated surprising capabilities of zero-shot, representation learning, and robustness, being applied to a wide range of fields [32, 52, 60, 70].

To learn from noisy web-crawled image-text pairs, CLIP adopts a formulation of the contrastive objective, where the image and text within a pair are considered as unique instances and are encouraged to be discriminated from all the other negative instances. However, web-crawled image-text pairs [65, 69] are usually loosely correlated in the sense that one caption (image) can match reasonably with multiple images (captions) besides the ground-truth one, as statistically shown in [74]. Hence, it is inaccurate and data-inefficient for representation learning to neglect other sensible matches and overlook the semantics hidden inside the textual description. This is also solidified by the undesirable discriminative ability or transferring performance of the visual encoder pre-trained under the contrastive objective, as suggested in [78]. Mining semantics from plentiful concepts appearing in captions, therefore, solicits further exploration beyond the vanilla contrastive objective.

Previously, some works resort to mining nearest neighbor positive samples via intra-modality similarity [50, 74] but require extra storage for auxiliary modules, i.e., the teacher network [74] or the memory bank [50]. Other works conduct multi-tasking with image-label supervision [57, 78, 80], transforming the captions into tag format or the image tag into the captioning format for unified contrastive

Figure 1. Architecture comparison between CLIP and nCLIP. We take base-size encoders for an instance. CLIP discriminates instances within a batch using 512-dim projected embeddings. nCLIP projects each modality into a 32768-dim probability distribution as the pseudo-label to supervise the prediction from the other modality. Darker blocks of nCLIP depict a higher response for cluster distribution, signifying the clusters to which text or image instances may belong. xCLIP is a multi-tasking framework with both CLIP and nCLIP.
learning. Notwithstanding, such practice is still unable to account for the loose assignment within the image-text captioning pairs. Intuitively, a caption for an image usually identifies existing objects within the image, which can be captured by a probabilistic distribution estimating how the text is assigned to one or multiple object clusters [13, 14]. Such estimation depicts the semantic meanings for its contained visual contents, and thus can be leveraged as a pseudo-label to guide the learning of the visual encoder.

Inspired by the superiority of visual self-supervised learning (SSL) models pre-trained with the non-contrastive objective [14, 15], we explore whether the non-contrastive objective can be used across modalities for pre-training language-image models, and whether nice properties displayed on visual SSL models can be inherited. To this end, we follow the same setup as CLIP except for the objective, and study non-contrastive Language-Image Pre-Training (nCLIP). For an image-text pair, we use the estimation of the textual (visual) distribution as the target to supervise the visual (textual) distribution, measured by cross-entropy. Additional regularizers are applied to avoid trivial solutions.

Schematic comparison between CLIP and nCLIP is shown in Fig. 1. Theoretically, such formulation takes one modality and the cluster centroid that the other modality belongs to as the positive samples to contrast [14], as opposed to direct features of two modalities as in contrastive learning, such that a single image is tolerated to be aligned with multiple captions and concepts. Based on the above formulation, we conduct a systematic study in terms of zero-shot transfer and representation learning. We empirically observe that, while nCLIP demonstrates desirable representation learning capability for both modalities, it underperforms prominently in zero-shot classification and retrieval tasks where models pre-trained with negative samples naturally prevail.

Seeking for unique strengths of both worlds, we further perform multi-tasking of CLIP and nCLIP, short as xCLIP, and seek synergy between two distinct pre-training objectives. With the bearable add-on of computational resources (e.g., ~27% memory-wise and ~30% time-wise), xCLIP achieves consistent performance gain compared to CLIP on a wide range of tasks spanning from zero-shot classification, retrieval, linear probing, and fine-tuning, etc. An extensive study with different pre-training datasets, evaluation metrics, and optimization configurations is conducted to validate xCLIP’s effectiveness in mining semantics and improving data efficiency. Particularly, the base-size model pre-trained using xCLIP under 35-million publicly available image-text pairs achieves a performance gain of 3.3% and 1.5% on an average of 27 classification tasks [59], in terms of zero-shot classification and linear probing accuracy, respectively. Performance gain is also valid in terms of zero-shot retrieval, semi-supervised learning, and fine-tuning, with 3.7 points of R@1 on Flickr30K [58], 1.7% accuracy on 1% subset of ImageNet [24], and 0.3% accuracy on ImageNet, respectively.

2. Related Work

Language-image pre-training. Language-image pre-training, aka vision-language pre-training (VLP), learns to jointly cope with vision and language input using multi-modality models. Early practices [22, 49, 67, 68] separately encode modalities, i.e., texts with linear embedding and images with convolutional neural networks and region proposals [63]. Recent works take direct images instead of pre-fetched region features as input, using e.g., dual-encoder architecture for alignment [42, 57, 59], single-encoder architecture for fusion [43, 73], or their combinatorial practices forming an encoder-decoder architecture [48, 80]. Most recent literature aims to expand as many supported transferable downstream tasks as possible via pre-training large-scale foundation models [6, 80]. Out of previous works, CLIP [59] blazes the trail to learn transferable visual features from text supervision, and demonstrates surprising zero-shot recognition results. Follow-up study includes leveraging dense [79], augmentation [47], and uni-modal self-supervised [50, 55, 74] signals for improved performance. In this work, we base our study on the dual-encoder architecture, and pre-train models either with the contrastive objective as CLIP [59], or the non-contrastive objective. Further, we seek their complementarity and study whether synergy between two objectives exists.

Contrastive learning. The idea of contrastive learning is popularized under visual self-supervised learning (SSL) which aims at learning transferable visual representation from unlabelled images. In common practices [18, 33, 75], each image is considered a single class, attracted to its augmented views while pulled away from views of other images. The contrastive objective is proved robust and effective in a wide range of realms beyond visual understanding, including representation learning for natural language [29], audio [54], structured input [44], robotics [66], and multimodality [21, 59]. However, a caveat of these approaches is the requirement for large batch size [18] or memory bank [33, 75], which lies intrinsic in the formulation of InfoNCE estimator [38] and plagues the pre-training of large-size models due to hardware limitations.

Non-contrastive learning. Beyond the contrastive paradigm, recent state of the arts from visual SSL manage to relieve the dependency on negative samples. With different subtleties to avert collapsing solutions, these works can optimize the affinity of augmented representations alone.
and are categorized as non-contrastive framework. To avoid model collapsing, common practices include asymmetrical architecture [19, 31], dimension de-correlation [11, 27, 81], and clustering [7, 8, 13–15, 71]. Our approach takes inspiration from the last category since it intrinsically frees the absoluteness of assignment of positive samples. Moreover, rich semantics induced by explicit clustering can automatically group visual concepts from noisy image-text pairs, facilitating models’ representation learning.

3. Approach

3.1. Framework

Suppose $g$ and $h \in \mathbb{R}^{D \times 1}$ are projected backbone features of two modalities. $D$ is the feature dimension. We start by formulating the objective of dominant contrastive framework CLIP, followed by the introduced non-contrastive framework nCLIP. The final framework xCLIP takes the multi-tasking of two objectives, the complete computational pipeline of which is shown in Algorithm 1.

**Contrastive pre-training** [59]. Let $u = g/\|g\|$ and $v = h/\|h\|$. $U = [u_1, u_2, ..., u_B] \in \mathbb{R}^{B \times D}$, $V = [v_1, v_2, ..., v_B] \in \mathbb{R}^{B \times D}$ are concatenated embeddings over the batch. $B$ is the batch size. The contrastive objective is formulated as

$$L_{CLIP} = \text{InfoNCE}(U^T V / \sigma)$$

$$= - \frac{1}{B} \sum_{i \in B} \log \frac{\exp(u_i^T v_i / \sigma)}{\sum_{j \in B} \exp(u_i^T v_j / \sigma)},$$

where $\sigma$ is a trainable parameter controlling the temperature. $L_{CLIP}$ is symmetrized by setting $g$ and $h$ as projected features of the images and texts by turns and taking the average of two terms. Vanilla InfoNCE can be decoupled into two terms accounting for affinity and variability separately [81]. While both variability terms in the contrastive and non-contrastive objectives require for batch statistics (e.g., $L_{EH}$ in Sec. (4)), CLIP formulation explicitly maximizes the distance between negative pairs of batch samples. Hence, it degrades the learning performance and data efficiency when models are pre-trained with noisy data where sensible matches occur within negative pairs.

**Non-contrastive pre-training.** Let $p = \text{softmax}(g)$ and $q = \text{softmax}(h)$. We transform the projected feature into probability distributions, which can be seen as an assignment over semantic clusters (i.e., projection weights). We take $p$ as the target distribution and learn to estimate the predicted distribution $q$ by minimizing their cross-entropy:

$$L_{CE} = -p^T \log(q).$$

Note the target and prediction branch are backpropagated at the same time and $L_{CE}$ is symmetrized as $L_{CLIP}$. To avoid collapsing solutions, we incorporate entropy regularizers, i.e., entropy minimization [71] and mean entropy maximization [8, 9], via minimizing:

$$L_{EH} = -p^T \log(p), \quad L_{HE} = \overline{p}^T \log(p),$$

where $\overline{p} = E(p) \approx \frac{1}{B} \sum_{i=1}^{B} p_i$ is the average distribution over batch. $L_{EH}$ and $L_{HE}$ are symmetrized by taking the average with another term where $p$ is replaced by $q$. $L_{EH}$ encourages the model to make deterministic predictions and ensures assignment’s sharpness. $L_{HE}$ encourages the model to utilize a full set of projection weights and ensures the assignment’s smoothness. We illustrate in Sec. 4.4 and Appendix A that $L_{EH}$ and $L_{HE}$ are minimally sufficient to yield non-collapsing solutions. We empirically show in Tab. A1 that the solutions is non-trivial as long as both sharpness and smoothness are guaranteed, e.g., via Sinkhorn algorithm [14] instead of loss regularizers. We opt for Eq. (3) for its simplicity and consistency between pre-training and evaluation. The overall non-contrastive objective is formulated as

$$L_{nCLIP} = L_{CE} + \lambda_1 \cdot L_{EH} - \lambda_2 \cdot L_{HE},$$

where $\lambda_1$ and $\lambda_2$ controls the weight of the regularization. We empirically find that setting $\lambda_1 = \lambda_2 - 1 = 0.5$ yields stable training and favorable transfer performances. We detail our findings in Sec. 4.4 and Appendix B.1. During evaluation, we utilize negative cross-entropy $-L_{CE}$ as the similarity metric for zero-shot transfer experiments. As schematically showcased in Fig. 1, nCLIP does not reply on negative examples but requires a relatively larger projection head and greater output dimension. Comparing nCLIP with CLIP, we empirically find that nCLIP produces more coarse-grained (e.g., zero-shot retrieval in Sec. 4.1) but semantic-rich (e.g., linear probing in Sec. 4.2) projections. Empirical evidence suggests that the model will fail to deliver reasonable zero-shot and retrieval results if pre-trained without negative pairs (e.g., nCLIP’s 25.2 vs. CLIP’s 73.8 points of R@1 under Flickr30K 1→7 retrieval as shown in Tab. 4).

**Contrastive meets non-contrastive.** Given that two objectives each have their own limitations, we further seek the complementarity between $L_{CLIP}$ and $L_{nCLIP}$, and pre-train the models with both objectives, written as

$$L_{xCLIP} = \lambda_{CLIP} \cdot L_{CLIP} + \lambda_{nCLIP} \cdot L_{nCLIP},$$

where $\lambda_{CLIP}$ and $\lambda_{nCLIP}$ control the weight of the objectives. During evaluation, we find using the negative cosine metric with CLIP’s projection head for zero-shot transfer...
experiments generally leads to better results. We note that it is not immediately clear that the two objectives certainly induce stronger models, since they build qualitatively distinct latent spaces. Qualitatively, we show in Sec. 4 that nCLIP helps CLIP to encode semantics which intrinsically lacks in CLIP, while CLIP helps nCLIP to be transferable for zero-shot recognition. The synergy between the two objectives prompts consistent performance gains across a wide range of tasks by xCLIP over CLIP.

3.2. Implementation

Architecture. We train the base-size model with ViT-B/16 [26] as the visual encoder. The model configuration of the base-size text encoder follows CLIP [59] with byte-pair encoding (BPE) and a maximum context length of 77. The projection head generating output for the non-contrastive objective is a 2-layer MLP with 4096-dim hidden layers, GELU [36], and BatchNorm [41]. The last layer is of 32768 output dimension and followed by a BatchNorm without affine transformation. The projection head for the contrastive objective is a single linear layer with no bias and a dimension of 512.

Pre-training data. We train our method with publicly available datasets: COCO [51], Visual Genome [45], SBU Captions [56], Conceptual Caption 3M [65], Conceptual Caption 12M [17], and filtered 14M-size subset of Yahoo Flickr Creative Commons 100M dataset, consisting a total of 35M Image-Text pairs (IT35M). We are also intrigued about the behaviors of models pre-trained on ImageNet-21K [24] (IN21K) dataset taking label names as annotation texts by concatenating them with a sampled prompt, similar to [57, 80]. To notify, ImageNet-21K is a subset of ImageNet-22K with classes of ImageNet-1K excluded for fair downstream evaluation. We detail the models’ data scaling behavior in Tab. 8.

4. Experiments

4.1. Zero-Shot Transfer

Classification. We evaluate 27 classification benchmarks with zero-shot classification protocols following [59]. As shown in Tab. 1, nCLIP achieves an average top-1 accuracy of 32.7%. Though performing 7.6% worse than CLIP, nCLIP demonstrates descent zero-shot recognition capability without explicitly training with negative examples. xCLIP achieves consistent performance gain across a wide range of datasets, with a 43.6% average top-1 accuracy, which is 3.3% higher than CLIP. It indicates that the synergy between contrastive and non-contrastive objectives improves the model’s zero-shot classification ability.

Out-of-domain classification. For out-of-distribution classification, we use 5 datasets following [59]: ImageNet Adversarial [37], ImageNet Rendition [35], ImageNetV2 [62], ImageNet Sketch [72], and ObjectNet [10] with 2 additional datasets: ImageNet-C [76] and Stylized ImageNet [30]. We investigate if the non-contrastive objective inherits the robustness of the contrastive objective to natural distribution shift. As shown in Tab. 2, nCLIP achieves an 18.0% with CLIP an 23.1% average top-1 accuracy, revealing a similar trend to in-domain datasets. xCLIP further improves CLIP’s accuracy by 3.6% and achieves an accuracy of 26.7% across 7 datasets, indicating its effectiveness among out-of-domain datasets.
Table 1. Zero-shot classification. We report on a variety of classification benchmarks with ViT-B/16 pre-trained on IT35M. Detailed protocols for each dataset strictly follow CLIP [59]. xCLIP achieves a consistent performance gain compared to CLIP in a wide range of classification datasets. Best results of each column are bolded.

| Model   | Food-101 | CIFAR-10 | CIFAR-100 | Breakdwn | SUN397 | Cars | Aircraft | VOC2007 | PASCAL | Penn | Caltech101 | Flowers | MSNIST | FER2013 | STL-10 | EuroSAT | RED-45 | GTSRB | KITTI | Cityscapes | PCAM | UCf101 | Kinetics-200 | Kinetics-400 | Imagenet 1M | Average |
|---------|----------|----------|-----------|-----------|---------|------|----------|---------|--------|------|-----------|---------|--------|---------|--------|----------|--------|--------|-------|-------------|--------|--------|--------------|---------------|-----------|--------|
| CLIP    | 61.2     | 79.7     | 50.6      | 23.7      | 56.5    | 15.9 | 5.8      | 46.4    | 27.6   | 54.7 | 71.3       | 48.9    | 10.5   | 37.3    | 91.3    | 24.5     | 39.7    | 13.1   | 31.6    | 9.1      | 50.0    | 45.0     | 32.4    | 12.8    | 53.0       | 49.1       | 45.7     | 40.3   |
| nCLIP   | 28.4     | 79.5     | 49.1      | 11.3      | 57.0    | 5.9  | 4.5      | 51.4    | 22.9   | 14.6 | 65.0       | 23.1    | 9.9    | 13.5    | 94.8    | 15.1     | 21.2    | 2.7    | 35.4    | 5.8      | 51.2    | 42.0     | 28.4    | 12.4    | 50.0       | 37.0       | 32.7     |        |
| xCLIP   | 65.8     | 83.4     | 54.5      | 25.1      | 59.1    | 18.0 | 5.8      | 52.2    | 33.2   | 57.1 | 73.9       | 50.0    | 12.3   | 39.0    | 92.8    | 40.0     | 43.6    | 16.3   | 39.8    | 9.3      | 49.8    | 35.4     | 18.4    | 52.5    | 50.2       | 48.8       | 43.6     |        |

Table 2. Zero-shot out-of-distribution classification. We report on a variety of out-of-distribution classification benchmarks. xCLIP demonstrates stronger robustness on various out-of-domain classification datasets.

| Model   | NUS-WIDE | OpenImages |
|---------|----------|------------|
|         | mAP      | F1@3       | F1@5       | mAP      | F1@10     | F1@20     |
| CLIP    | 15.1     | 33.3       | 16.0       | 81.1     | 13.4       | 7.2        |
| nCLIP   | 16.1     | 35.6       | 16.6       | 81.4     | 11.6       | 6.4        |
| xCLIP   | 15.3     | 35.2       | 16.8       | 81.2     | 13.8       | 7.4        |

Table 3. Zero-shot multi-label classification. We report mAP and F1 scores with ViT-B/16 pre-trained on IT35M. nCLIP showcases the best multi-label classification capability.

Multi-label classification. We evaluate zero-shot multi-label classification on NUS-WIDE [23] and OpenImages [46] following standard protocol [39]. Specifically, we use 81 unseen labels for NUS-WIDE and the most frequent 400 unseen test labels for OpenImages during evaluation, following [40]. As shown in Tab. 3, we observe that nCLIP shows the best mAP compared to CLIP. nCLIP is pre-trained without negative examples, resulting in the model’s intrinsic strengths on recall over overlapped concepts, with 16.1 and 81.4 points of mAP on NUS-WIDE and OpenImages, respectively. Comparatively, xCLIP slightly improves CLIP in this respect while lagging behind nCLIP. The experiments demonstrate that the non-contrastive objective fits well for those downstream tasks in demand of high recall.

Retrieval. We evaluate on 2 retrieval benchmarks: Flickr30K [58] and MSCOCO [51] under zero-shot protocol. We do not use prompt engineering and use the original caption. Compared to zero-shot classification, image-text retrieval requires the model’s recognition capability at a fine-grained level. We empirically observe in Tab. 4 that nCLIP performs drastically worse than CLIP, which is because text captions in retrieval are not mutually exclusive, which is different from label names in classification. Therefore, explicit negative examples during pre-training play an imperative role in zero-shot retrieval. See Appendix E.1 for further discussions. Beyond that, xCLIP achieves a noticeable performance improvement over CLIP, with a gain of 3.7% R@1 on Flickr30K and 3.9% R@1 on MSCOCO, illustrating that the additional non-contrastive objective renders extra semantic signals that can be transferred well to fine-grained recognition.

4.2. Representation Learning

We conduct several evaluation protocols to benchmark representation quality under different objectives for both visual (Sec. 4.2.1) and textual (Sec. 4.2.2) modality.

4.2.1 Visual Representation Learning

Linear probing. We evaluate the quality of visual representation via linear probing protocol, where a linear head is fine-tuned on top of the frozen backbones. We follow the same setup as [20] on the same 27 datasets as standard zero-shot classification. Specifically, we use SGD without momentum as the optimizer, no weight decay, and a total epoch of 100 for all evaluation datasets. We use [CLS] token for classification. Following [82], we sweep a set of different learning rates by adding multiple classification heads over a shared frozen backbone, each with its own optimizer and scheduler. We report the best result across different heads. As shown in Tab. 5, we observe that nCLIP generally leads to comparable linear probing accuracy compared with CLIP, suggesting that non-contrastive objectives are able to derive semantically meaningful embedding spaces. nCLIP achieves 2.5% higher performance compared to CLIP on ImageNet but relatively lower on average. Beyond that, when combining two objectives together, xCLIP achieves 2.7% higher performance on ImageNet and 1.5% higher performance on average across 27 different classification tasks compared to CLIP.

Fine-tuning & semi-supervised learning. We fine-tune the entire network under the full-data regime (100%) and...
To evaluate how well the visual model is capable of deriving explicit scene layout and object boundaries, we conduct mask probing analysis following [31]. As a related evaluation, we also study unsupervised segmentation with GroupViT [77] in Appendix D.2.

4.2.2 Textual Representation Learning

We follow the setup as [29] and evaluate on 7 STS tasks: STS 2012–2016 [1–5], STS Benchmark [16], and SICK-Relatedness [34]. We directly take [EOS] token without any projection as the input for evaluation, which consistently yields better performance compared to the projected feature for all models. We use cosine distance as the similarity metric. The main goal of sentence embeddings is to cluster semantically similar sentences, and hence, we take STS as one yardstick to benchmark textual representation considering the close gap between CLIP and nCLIP in terms of fine-tuning accuracy. xCLIP achieves an 1.7%, 1.0%, and 0.3% performance gain compared with CLIP under three data ratios of 1%, 10%, and 100%, respectively.

Mask probing. To evaluate how well the visual model is capable of deriving explicit scene layout and object boundaries, we conduct mask probing analysis following [15]. For each attention head from the last fully connected layer, we extract the attention map with [CLS] token as the query. We then compute the Jaccard similarity $J$ of each head’s attention mask to the ground truth and retain the attention mask with the highest similarity. We conduct experiments on Pascal VOC 2012 [28] dataset. With IT35M, nCLIP demonstrates better quality in the generated mask with 43.7 points of $J$, while CLIP reaches 41.2 and xCLIP reaches 41.9 points of $J$. Hence, nCLIP learns better representation for object boundaries compared to CLIP, while xCLIP strikes a balance between nCLIP and CLIP. Detailed results are delayed to Appendix D.1. As a related evaluation, we also study unsupervised segmentation with GroupViT [77] in Appendix D.2.
We consider using cyan CLIP’s p 77.2 80 to 15 to demonstrate methods’ com-
We investigate the scaling behavior of pre-training data quality with the non-contrastive objective, while strong representation can always be ensured before the projection.

Pre-training with tagging data. We consider using tagging data, e.g., ImageNet-21K [24], as pre-training to validate method’s generalizability. To do that, we take label names as annotation texts by concatenating them with a sampled prompt, similar to [57, 80]. As shown in Tab. 8, nCLIP shows superiority to CLIP when pre-trained with IN21K by performance gain of 4.9% and 1.9% in terms of zero-shot and linear probing accuracy, respectively. Compared to nCLIP, we instead notice a performance drop of 4.3% for zero-shot accuracy when two objectives multi-tasked, indicating that the contrastive objective stymies the quality of projected probability under tagging data. Note, that an 77.2% linear probing accuracy achieved by xCLIP, 2.1% higher than CLIP, is decently strong compared to 79.0% achieved by the state of the art in SSL, iBOT [82], pre-trained using the same data with 80 epochs.

Pre-training data scaling & domain. Ep. denotes training epochs. Data abbreviations are as follows. ①: CC12M. ②: COCO, VG, SBU, and CC3M. ③: YFCC14M. ④: IN21K. Note ①②③ = IT35M.

| Data | Size | Ep. | ZS / LN Accuracy |
|------|------|-----|------------------|
|      |      |     | CLIP   | nCLIP | xCLIP |
| ①   | 12M  | 25  | 36.8 / 68.5 | 37.5 / 71.0 | **42.4 / 72.2** |
| ④   | 14M  | 32  | 26.5 / 75.1 | 31.4 / 77.0 | 27.1 / 77.2 |
| ①②  | 22M  | 32  | 37.9 / 68.2 | 34.2 / 72.3 | **43.0 / 71.9** |
| ①②③ | 35M  | 32  | 45.7 / 71.4 | 37.0 / 73.9 | **48.8 / 74.1** |

Table 8. Pre-training data scaling & domain. Ep. denotes training epochs. Data abbreviations are as follows. ①: CC12M. ②: COCO, VG, SBU, and CC3M. ③: YFCC14M. ④: IN21K. Note ①②③ = IT35M.

Figure 2. Batch size scaling. xCLIP performs better than CLIP with a small batch size (i.e., 1024).

Figure 3. Training time. xCLIP adds ~1.3x training time cost and performs better with equal seen images.

4.3. Properties

We analyze several crucial properties to demonstrate the generalizability and effectiveness of our method in practical usage. Experiments are conducted with ViT-B/16 on CC12M for 25 epochs by default.

Pre-training data scaling. We study the model’s performance with data scaling in Tab. 8. xCLIP exhibits desirable scaling behaviors similar to CLIP. The performance improves as data increases. However, we do not observe such a tendency in nCLIP in terms of zero-shot accuracy. For example, nCLIP achieves 37.5% with ① but only 34.2% with ①②, the trend of which defies those of CLIP’s (36.8% vs. 37.9%) and xCLIP’s (42.4% vs. 43.0%). On an important note, both nCLIP and xCLIP showcase desirable scaling behaviors under the linear probing protocol. We hypothesize that the performance of zero-shot classification depends on pre-training data quality with the non-contrastive objective.

Computation efficiency. To demonstrate methods’ computation efficiency, we show the FLOPs and GPU memory consumption of xCLIP compared to CLIP. xCLIP enforces bearable additional computation cost on top of CLIP with only 1.4% extra FLOPs and 27% extra GPU memory. As shown in Fig. 3, xCLIP adds ~1.3x extra time cost but with a 6.0% performance gain in terms of zero-shot accuracy.

4.4. Ablation Study

We show in this section the crucial composing factors of nCLIP and xCLIP. The ablations in the first column (Tabs. 9a to 9c) are conducted with $\mathcal{L}_{nCLIP}$ only. The ablations in the second column (Tabs. 9d to 9i) are conducted with full loss $\mathcal{L}_{xCLIP}$. Experiments are conducted with ViT-B/16 on CC12M for 25 epochs. The default settings are highlighted in cyan.
Entropy regularizer. We study the effects of coefficient for entropy regularizers \( \lambda_1 \) and \( \lambda_2 \) in Tab. 9a. The pre-training is unstable without regularizers or with only maximization of the entropy of the mean (\( L_{EH} \)). Specifically, the model will collapse to constant uniform distribution and outputs the same uniform probability distribution despite different inputs. The additional minimization of the mean of the entropy (\( L_{EH} \)) stabilizes training, but incurs dimensional collapse, eroding the performances (26.8% and 23.7% vs. 37.5% in terms of zero-shot accuracy). Simultaneously adjusting \( \lambda_2 \) with constraints \( \lambda_1 + 1 = \lambda_2 \) and \( \lambda_1 = 0.5 \) mitigates the problem and yields the optimal performance, with a 37.5% zero-shot and 71.0% linear-probing accuracy. Details are shown in Appendix B.1.

Projection head. We study the design of two projection heads for \( L_{CLIP} \) and \( L_{nCLIP} \). As shown in Tab. 9b, large projection dimension matters for good performance. We opt for a projection dimension of 32768 balancing the performance and speed. As shown in Tab. 9c, the last BN layer is crucial and leads to more stable optimization in our experiments. We draw on the idea of prototypes [9, 15] by introducing bottleneck and l2-norm layers, while they do not yield a performance gain. We further study whether two projections can share intermediate computation in Tab. 9d. While sharing middle hidden layers with slightly deeper projection heads performs better, we opt for 2-layer MLP without shared layers for its simplicity.

Optimization. We study the effect of hyper-parameters in optimization. In Tab. 9e, we study the optimal loss ratio between \( L_{CLIP} \) and \( L_{nCLIP} \). We further study whether it’s the best route for two objectives to be optimized in separate latent spaces via multi-tasking. Specifically, we consider a bespoke objective Eq. (3) taking account of probability estimation and negative samples simultaneously in a shared latent space. Detailed formulation are shown in Appendix B.2. Optimizing in one latent space yields sub-optimal results with a nearly 13.0% drop in zero-shot accuracy and 3.3% in linear probing accuracy, suggesting two objectives are intrinsically contradictory. We consider debiased sampling, where each batch is sampled from a single data source, since their semantics may be closer and thus more suitable for optimization. This yields similar results. We also add \( L_{nCLIP} \) after warm-up epochs with the linear scheduler to its base scale, which erodes the performance.

5. Conclusion

Aligning images and texts is of overriding significance for vision-language understanding. To conquer the systematic insufficiency of the contrastive objective for acquiring semantics and tackling loose correlations between noisy image-text pairs, we explore the non-contrastive objective for language-image pre-training and unravel its properties. Empirical evidence reveals that the non-contrastive objective induces models to perform favorably in representation learning yet poorly in zero-shot transfer. Observing the distinct mechanisms of the two objectives, we further seek synergy between the two, and introduce a simple multi-tasking framework, xCLIP, that enjoys the best of both worlds: nCLIP aids CLIP mining semantics while CLIP inherits intrinsic strengths for zero-shot recognition. The consistent performance gain of xCLIP over CLIP on a wide variety of downstream tasks consolidates our findings. As potential future work, we may continue to scale up the data size (e.g., LAION400M [64]) as well as the model size (e.g., ViT-L [26]) to verify whether the scaling law applies and the performance improvement endures.
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