Teaching Structured Vision & Language Concepts to Vision & Language Models

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Abstract

Vision and Language (VL) models have demonstrated remarkable zero-shot performance in a variety of tasks. However, some aspects of complex language understanding still remain a challenge. We introduce the collective notion of Structured Vision & Language Concepts (SVLC) which includes object attributes, relations, and states which are present in the text and visible in the image. Recent studies have shown that even the best VL models struggle with SVLC. A possible way of fixing this issue is by collecting dedicated datasets for teaching each SVLC type, yet this might be expensive and time-consuming. Instead, we propose a more elegant data-driven approach for enhancing VL models’ understanding of SVLCs that makes more effective use of existing VL pre-training datasets and does not require any additional data. While automatic understanding of image structure still remains largely unsolved, language structure is much better modeled and understood, allowing for its effective utilization in teaching VL models. In this paper, we propose various techniques based on language structure understanding that can be used to manipulate the textual part of off-the-shelf paired VL datasets. VL models trained with the updated data exhibit a significant improvement of up to 15% in their SVLC understanding with only a mild degradation in their zero-shot capabilities both when training from scratch or fine-tuning a pre-trained model. Our code and pretrained models are available at: https://github.com/SivanDoveh/TSVLC

1. Introduction

Recent Vision & Language (VL) models [19, 31, 43, 44, 47, 57] achieve excellent zero-shot performance with respect to various computer-vision tasks such as detection, classification, segmentation, etc. However, recent studies [68, 82] have demonstrated that even the strongest VL models struggle with the compositional understanding of some basic Structured VL Concepts (SVLC) such as object attributes, inter-object relations, transitive actions, object states and more. Collecting specialized large scale data to teach VL models these missing ‘skills’ is impractical, as finding specialized text-image pairs for each kind and possible value of the different attributes, relations, or states, is both difficult and expensive.

Another important challenge in training VL models with new concepts is catastrophic forgetting, which is a common property to all neural models [7, 34, 37, 49, 58] and has been explored for VL models in a recent concurrent work [14]. Large VL models such as CLIP [57] and CycCLIP [19] have exhibited excellent zero-shot learning abilities in many tasks. Therefore, even given a large dataset with new concepts, it is important not to lose these abilities when performing the adaptation to the new data.

Figure 1. Teaching language structure to VL models. (a) Standard contrastive text-to-image loss (e.g. CLIP) is solvable by "bag of objects". (b) Our additional language structure augmented losses force language structure topology on the image embedding.
In this paper, we propose a way to leverage existing (off-the-shelf) VL pre-training data sources in order to improve the SVLC understanding skills of a given model, while at the same time maintaining its zero-shot object recognition accuracy. Naturally, succeeding in this goal would lead to potential improvement w.r.t. SVLC understanding in a wide variety of downstream tasks building upon pre-trained VL models, such as zeros-shot detection, segmentation, image generation, and many more.

Recent research [68, 82] has shown that VL models exhibit an ‘object bias’ partially due to the contrastive text-to-image loss used in their pre-training. For example, the popular CLIP-loss [57] is computed over a random batch of text-image pairs sampled from a large-scale and diverse VL dataset with the chance of two images in the same batch containing the same set of objects being very low. For such a loss, representing just a ‘bag of objects’ in each image or text is sufficient for matching the corresponding pairs. Intuitively, this leads to the ‘object bias’ where SVLCs like attributes, states, and relations are being underrepresented (e.g. having a much smaller amplitude in the resulting feature superposition), consequently causing the aforementioned issues with SVLC understanding.

Based on this intuition, we propose a simple data-driven technique that harnesses existing language parsing and modeling capabilities to enhance the importance of SVLCs in the VL model training losses. For each text in the training batch, we automatically generate alternative negative or positive text by manipulating its content to be opposite or equivalent to the original text. Using the newly generated texts, we explicitly teach SVLC to the model via additional losses (see Fig. 1) that enforce differentiating between different (original and generated) SVLC texts and are no longer satisfiable by the ‘bag of objects’ representation.

Towards this end, we propose several techniques for implementing this approach, including (i) rule-based priors based on classical NLP parsing and word substitution vocabulary according to attribute/relation type; (ii) prompting a Large Language Model (LLM) (e.g. [53]) for analogous text; (iii) generating different meaning (negative) alternatives by LLM-based unmasking of parsed text entities of different kinds; (iv) combinations of these methods.

We demonstrate that all these techniques can lead to significant improvements of up to 15% percent when measuring the VL models’ SVLC understanding. We verify this on 5 datasets: VG [39], HAKE [48], VAW [54], SWIG [55], and all combined, using the protocol recently proposed in VL-Checklist [82]. In addition, we show that the resulting VL models largely preserve their zero-shot object recognition performance. For the latter, we also propose a variant of efficient LLM fine-tuning using low-rank residual adapters (LoRA) [27] adjusted to VL models. Finally, we show that our framework allows better harnessing of the standard available VL data, e.g. CC3M [62] and LAION [61]. This is exhibited by the aforementioned gains, both in new VL models trained from scratch, as well as in models fine-tuned using strong available VL models such as CLIP [57] and CyCLIP [19].

To summarize, we offer the following contributions: (i) We propose a data-driven approach for better harnessing the standard available VL data to improve VL models’ SVLC understanding skills, such as understanding object attributes, inter-object relations, transitive actions, object states, and more, without sacrificing zero-shot object recog-
Table 1. **VL-Checklist and Zero-Shot classification evaluation (ImageNet + 20 datasets).** Finetuned models (for 5 epochs as detailed in Sec. 3.3, starting from officially released CLIP [57] and CyCLIP [19] weights) are marked with ✓ in the Pre-trained (Pre) column, while models trained from scratch (for 10 epochs) are marked with x. The gains and losses of our approach (+Ours) are in color and are computed w.r.t. to corresponding baselines in each section. CLIP/CyCLIP + LoRA indicate finetuning in the same way and on the same data, but without our approach. Finetuning without LoRA on the same data yields significantly worse performance in all metrics. Sections are separated by bold horizontal lines. (a) *CC3M fine-tuning - CLIP - Vit-B/32:* we significantly improve the SVLC understanding, observing only small ZS performance drops, 0.77%; (b) *CC3M fine-tuning - CLIP - Vit-B/16:* we can observe similar improvements as in (a), with an even smaller impact on ZS performance; (c) *CC3M from scratch - CLIP - Vit-B/32:* we significantly improve SVLC understanding with only a small (1%) decrease in ZS performance; (d) *CC3M from scratch - CLIP - Vit-B/16:* compared to (c), even greater SVLC understanding improvement is observed (up to 30.36%), at no cost in ZS performance, and even improvement of over 5%; (e) *CC3M fine-tuning - CyCLIP:* we use CyCLIP original code (with LoRA integration) and losses, as can be seen - adding our techniques improves CyCLIP SVLC performance considerably without sacrificing ZS performance; (f) *CC3M from scratch - CyCLIP:* observing even larger gains in SVLC understanding compared to (e) (up to 16.5%), with small reduction in ZS performance of 0.42%; (g) *LAION fine-tuning - CLIP - Vit-B/32:* we improve SVLC understanding without any decrease in ZS performance.

| Dataset | Model | Pre | Arch | Object | VL-Checklist | Relation | 21 Zero-Shot Tasks Average |
|---------|-------|-----|------|--------|--------------|----------|---------------------------|
| CLIP [57] | ✓ Vit-B/32 | 81.58% | 67.60% | 63.05% | 56.37% |          |
| CLIP + LoRA | ✓ Vit-B/32 | 80.93% | 66.28% | 55.52% | 56.41% | 56.41% (+0.84%) |
| CLIP + Ours RB Neg | ✓ Vit-B/32 | 83.89% | 73.35% | 75.33% | 54.32% | 54.32% (+2.85%) |
| CLIP + Ours LLM Neg | ✓ Vit-B/32 | 84.44% | 71.63% | 74.82% | 55.60% | 55.60% (+7.77%) |
| CLIP + Ours RB+LLM Negs | ✓ Vit-B/32 | 85.09% | 73.90% | 78.72% | 54.66% | 54.66% (+7.51%) |
| CLIP + Ours Combined | ✓ Vit-B/32 | 85.00% | 71.97% | 68.95% | 54.77% | 54.77% (+1.68%) |
| CLIP [57] | ✓ Vit-B/16 | 82.91% | 67.32% | 61.80% | 60.00% |          |
| CLIP + Ours RB+LLM Negs | ✓ Vit-B/16 | 85.82% | 73.92% | 77.40% | 59.37% | 59.37% (+6.83%) |
| CLIP + Ours Combined | ✓ Vit-B/16 | 84.75% | 71.18% | 69.68% | 59.87% | 59.87% (+1.33%) |
| CLIP | X Vit-B/32 | 71.17% | 57.86% | 45.20% | 21.96% |          |
| CLIP + Ours Combined | X Vit-B/32 | 71.79% | 63.29% | 58.13% | 20.96% | 20.96% (+0.88%) |
| CLIP [57] | X Vit-B/16 | 64.01% | 54.27% | 41.57% | 15.49% |          |
| CLIP + Ours RB+LLM Negs | X Vit-B/16 | 73.11% | 65.32% | 71.93% | 20.78% | 20.78% (+5.29%) |
| CLIP + Ours Combined | X Vit-B/16 | 72.99% | 63.01% | 62.95% | 20.61% | 20.61% (+5.12%) |
| CyCLIP [19] | ✓ R50 | 73.49% | 59.33% | 53.83% | 26.00% |          |
| CyCLIP + LoRA | ✓ R50 | 73.30% | 58.89% | 53.03% | 26.30% | 26.30% (+0.30%) |
| CyCLIP + Ours Combined | ✓ R50 | 74.20% | 63.52% | 59.47% | 26.31% | 26.31% (+0.31%) |
| CyCLIP | X R50 | 69.41% | 57.59% | 53.70% | 21.02% |          |
| CyCLIP + Ours Combined | X R50 | 71.50% | 65.69% | 70.20% | 20.44% | 20.44% (+0.42%) |
| LAION | CLIP [57] | ✓ Vit-B/32 | 81.58% | 67.60% | 63.05% | 56.37% |          |
| CLIP + LoRA | ✓ Vit-B/32 | 82.18% | 68.48% | 62.72% | 57.15% | 57.15% (+0.78%) |
| CLIP + Ours Combined | ✓ Vit-B/32 | 82.54% | 69.64% | 66.05% | 56.71% | 56.71% (+0.24%) |

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2. Related Work

**Vision-language (VL) Models.** (e.g., CLIP [57] and ALIGN [31]) show significant advances in diverse zero-shot downstream tasks. They are pre-trained using contrastive image-text alignment on a large-scale noisy dataset of text-image pairs collected from the web. Several methods [9, 46,
in diverse NLP applications. In VL tasks, previous work explores machine translation between different languages [6, 35], generating synthetic captions [43], adversarial/synthetic data augmentation for VQA [59, 67] or mixup for VL [20]. We focus on leveraging the well-understood and modeled language structure for manipulating text in a way that explicitly targets teaching SVLC semantics to VL models. To the best of our knowledge, this has not been attempted before.

3. Method

In this section, we discuss the proposed framework for improving SVLC performance of VL models using already available VL data. Sec. 3.1 and Sec. 3.2 present our main techniques for teaching SVLC to VL models. These approaches can be effectively applied both for fine-tuning existing strong VL pre-trained models, as well as for training VL models from scratch. In both cases, they exhibit significantly improved SVLC performance as demonstrated in our experiments in Sec. 4. Sec. 3.3 presents our strategy for fine-tuning VL models on VL-enhanced VL data, while at the same time being parameter efficient and significantly reducing forgetting, thus, maintaining the VL model Zero-Shot (ZS) performance. Qualitative examples showing improvements attained by our proposed approach, as well as some examples of failure cases, are provided in the supplementary material.

3.1. Teaching SVLC Using NLP and LLMs

In this section, we present several ways in which the data of existing VL pre-training paired datasets can be enhanced to emphasize SVLC in the texts, and teaching them to the VL model. We propose two kinds of data enhancements - generating negative and positive text alternatives. When generating negative examples, only one word of the sentence is changed such that the semantic meaning of the sentence changes. We propose two methods for the generation of the negatives: (i) rule-based (Sec. 3.1.1); and (ii) LLM-based (Sec. 3.1.2). Positive alternatives are generated as sentences with semantically similar meanings, but different wording (Sec. 3.1.3). We then present the losses which properly take these two types of generated textual data into account during training in Sec. 3.2.

3.1.1 Generating Rule-Based (RB) Negatives

One simple yet effective method for negative text generation is using a collection of pre-defined language rules which match and replace words of a specific entity type or a pattern, such as color, material, size, etc. This method is especially useful when one has prior knowledge of a specific aspect of the language that needs to be taught. For example, if we know that our model lacks the ability to understand the colors of objects, we can easily create a rule for detecting

Data Augmentation. Augmentation plays a key role in many computer vision applications [8, 63]. Several advanced image augmentation methods (CutMix [78], mixup [79], AutoAugment [11], RandAugment [12], etc) have been proposed and greatly improved computer vision task performance. Text augmentation has been tackled through back-translation [73], word and frame-semantic embedding augmentations [69], word replacement [81], random word insertion/deletion/swap [71], or using a text generative model [41] in diverse NLP applications. In VL tasks, previous work explores machine translation between different languages [6, 35], generating synthetic captions [43], adversarial/synthetic data augmentation for VQA [59, 67] or mixup for VL [20]. We focus on leveraging the well-understood and modeled language structure for manipulating text in a way that explicitly targets teaching SVLC semantics to VL models. To the best of our knowledge, this has not been attempted before.

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and replacing color words in the text, for generating negative text that does not correspond to its paired image. To employ the generation of the rule-based negative, for each taught SVLC we define a list of words belonging to its characteristic. We then scan the VL data texts searching for the words within these lists. If a word is located, we simply replace it with a randomly selected word from the same list to generate a negative pair. For example, applying the color rule to a sentence: “A big brown dog” can lead to “A big yellow dog”. If a text has multiple candidates of words to be replaced, one of them is chosen randomly. We perform this process multiple times for the full list of SVLC characteristics of interest such as color, size, material, spatial relations, etc. These generated negative texts are SVLC specific and differ from the original text in only one word. For a detailed description and more examples of the RB negative generation, please refer to the supplementary material.

3.1.2 LLM-based Negative Generation via Unmasking

A natural extension of rule-based negatives technique is the generation of negatives using Large Language Models (LLMs) unmasking. Recent LLMs are explicitly trained in a self-supervised manner with the objective of “unmasking” parts of the text. Given a sentence with one missing word, models such as BERT [13], can suggest multiple words that fit the context of the sentence. Using this useful property of LLMs, we can therefore automatically create plausible negative examples without the need for prior knowledge of the SVLC characteristics of interest. In order to focus the randomly selected masked words to be likely to belong to SVLCs of interest, we use common NLP parsing techniques (such as spacy [26]) to parse the sentence into its components such as nouns, verbs, adjectives, adverbs, etc. We then randomly choose a type of sentence part and a word belonging to this part type, mask out the selected word and replace it with one of the options suggested by the LLM’s unmasking. These negative examples, when used properly in the loss function (Eq. (3)) focus the network on the important details that affect the SVLC understanding. As we show in Sec. 4, this method is extremely useful and can significantly improve the VL model’s understanding of different SVLCs. Further details and examples of the LLM negative generation are provided in the supplementary material.

3.1.3 Generating Text Analogies via LLM Prompting

While the goal of the negative text generation (Sec. 3.1.1 and Sec. 3.1.2) was to make minor perturbations to a given text such that the meaning changes, the goal here is exactly the opposite. We would like to make major changes to the text, while still keeping the same semantic meaning. For example “A woman standing left to a sitting cat” and “A cat sitting to the right of a standing woman” are two very different texts describing the exact same scene. One effective way to generate such semantically similar texts is by prompting the foundational LLMs. Specifically, we use the open access BLOOM [53] model. In the spirit of recently popular in-context learning [18], we present the model with a textual prompt with examples of semantically similar texts (see Fig. 2). We then append the current image caption and retrieve the BLOOMs prediction of a semantically similar text. For a detailed description, we refer the reader to the supplementary material.

3.2. Losses

All of our evaluated models (CLIP [57] and CyCLIP [19]) admit a text & image pair $(T, I)$ and are comprised of two parts: (i) image encoder $e_I = E_I (I)$; (ii) text encoder $e_T = E_T (T)$. In this notation, the text-to-image similarity score is therefore computed as:

$$S(T, I) = \exp \left( \frac{\tau e_T^T e_I}{\|e_T\| \|e_I\|} \right),$$  

(1)

where $\tau$ is a learned temperature parameter.

Contrastive Loss. As most contemporary VL models, we employ the contrastive CLIP-loss [57] as one of our losses for each batch $B$.

$$L_{cont} = \sum_i \log \left( \frac{S(T_i, I_i)}{\sum_j S(T_i, I_j)} \right) + \log \left( \frac{S(T_i, I_i)}{\sum_k S(T_k, I_i)} \right).$$  

(2)

Negatives Loss. In our ablation study in Sec. 5, we show that for a given text $T_i$ simply adding the corresponding generated negative text $T_i^{neg}$ to the contrastive loss $L_{cont}$ is much less effective than having a separate loss individually attending to the similarity difference of $T_i$ and $T_i^{neg}$ w.r.t. the image $I_i$ corresponding to $T_i$. We, therefore, employ the following negatives loss:

$$L_{neg} = \sum_i - \log \left( \frac{S(T_i, I_i)}{S(T_i, I_i) + S(T_i^{neg}, I_i)} \right).$$  

(3)

Analogy Loss. For the generated analogy texts $T_i^{sim}$ produced from the text $T_i$ which corresponds to image $I_i$, we employ the combination of the two following losses:

$$L_{sim}^{text} = \sum_i - \log \left( \frac{S(T_i^{sim}, T_i)}{\sum_j S(T_i^{sim}, T_j)} \right),$$  

(4)

where with some abuse of notation, $S(T_1, T_2)$ denotes the exponent cosine similarity between text $T_1$ and text $T_2$ text-embeddings, and:

$$L_{sim}^{img} = \sum_i - \log \left( \frac{S(T_i^{sim}, I_i)}{\sum_j S(T_i^{sim}, I_j)} \right),$$  

(5)
which simply corresponds to the second summand of $L_{cont}$ in Eq. (2), with replacing $T_i$ by $T_{k\text{sim}}$.

Our final loss is, therefore:

$$L = L_{cont} + \alpha \cdot L_{neg} + \beta \cdot (L^{\text{text}}_{\text{sim}} + L^{\text{img}}_{\text{sim}}).$$

3.3. Fine-tuning Pre-trained VL Models

Each of the $E_T$ and $E_I$ networks is comprised of a mix of non-parametric functions and two types of parametric functions: linear layers and embedding layers. Roughly, each of those functions, $F_k^{\text{lin}}(x)$ and $F_k^{\text{emb}}(x)$ where $k$ is layer index, is parameterized by a weight matrix $W_k$ so that:

$$F_k^{\text{lin}}(x) = W_k \cdot x$$

$$F_k^{\text{emb}}(x) = EMB(x; W_k)$$

where $EMB$ is the embedding operator assuming $x$ is a stream of integers and picking the respective columns of $W_k$. Following the idea proposed in LoRA [27] for efficient LLM fine-tuning using low-rank residual adapters, when adapting a pre-trained VL model $M = (E_T, E_I)$ we parameterize the adapted weights $W_k^*$ of the model $M^*$ fine-tuned from $M$ as:

$$W_k^* = W_k + A_k \cdot B_k$$

where for $W_k$ of size $m \times l$, $A_k$ and $B_k$ are rank-$r$ matrices of sizes $m \times r$ and $r \times l$ respectively. These low-rank residual adapters can be applied efficiently as:

$$F_k^{\text{lin}}(x) = F_k^{\text{lin}}(x) + A_k \cdot (B_k \cdot x)$$

$$F_k^{\text{emb}}(x) = F_k^{\text{emb}}(x) + A_k \cdot EMB(x; B_k)$$

During the fine-tuning of $M^*$, we freeze all the base model $M$ parameters $\forall k, \{W_k\}$ and only the LoRA adapters $\forall k, \{(A_k, B_k)\}$ are being learned. In the above notation we disregard possible bias terms of the linear functions, if they are present, since we keep them frozen too.

There are several interesting things to note about the proposed architecture: (i) as opposed to [64], who evaluated the use of efficient LLM fine-tuning techniques for VL models adaptation, we add our LoRA adapters everywhere, i.e to all layers of both the text and image encoders, and not only to the text encoder/decoder as done in [64]; (ii) as opposed to [80] who attach a small side network only to the output of the adapted model, our LoRA adapters are added to all the parametric functions inside the model and affect all the intermediate computations; (iii) same as noted in the original [27] paper, at inference all the LoRA adapters can be folded back into the original weight matrices by simple summation, thus returning the number of total parameters to be the same as in the original model and hence have the same inference speed; (iv) with rank $r$ kept low, the number of extra parameters added by all the LoRA adapters can be very low making adaptation fast and efficient; finally, (v) such form of fine low-rank adaptation allows for significantly mitigating the zero-shot performance forgetting effects as demonstrated in our results and explored in the corresponding ablation (Sec. 5).

4. Experiments

4.1. Datasets

We train the model using common Image-Text pair datasets, namely Conceptual Captions 3M [62] and LAION 400M [61] and test using the VL-Checklist [82] datasets, which will be described below.

**Conceptual Captions 3M (CC3M)** [62] is a dataset of three million image-text pairs automatically crawled from the internet where image descriptions are harvested from Alt-text attributes and then processed and filtered to create relatively clean descriptions.

**LAION 400M** [61] is a very large scale image-text pair dataset which, similarly to CC3M has been automatically harvested from the internet. One major difference between the two, apart from the size, is that LAION examples have been filtered using the pretrained CLIP model, such that the CLIP image-text similarity is high by design. Recent re-implementations of the original CLIP paper have successly used LAION 400M to reproduce similar capabilities as the original CLIP model.

**VL-Checklist** [82] combines images and annotations from the Visual Genome [39], SWiG [55], VAW [54], and HAKE [48] datasets. It is processed such that each image is annotated with two captions, one positive and one negative. The positive caption originates in its source dataset and corresponds to the image. The negative caption is constructed from the positive caption so that only one word, corresponding to the tested SVLC of interest, is changed to negate the SVLC (e.g., color, size, material, etc.). VL-Checklist evaluates three main types of VL concepts further subdivided into 7 types of SVLCs total: (1) Object: its spatial location and size, (2) Attribute: color, material, size, state, and action, and (3) Relation: spatial or action relation between two objects. In the following sections we report results on a combined VL-Checklist dataset. The results on individual comprising datasets (Visual Genome [39], SWiG [55], VAW [54], and HAKE [48]) are provided in the supplementary material.

**Zero-Shot Classification** We evaluated our method on 21 classification dataset using the Zero-Shot classification protocol described in the ELEVATER Image Classification Toolkit [42]. The evaluation included 21 different datasets, including common classification datasets such as ImageNet [60], CIFAR100 [40], EuroSat [21], and others, in Tables 1-3 we report the average results over the 21 tasks.
Table 2. Ablation study - separate Negative Losses (Sec. 3.2) vs adding negatives to contrastive loss.

| Method                        | Object | VL-Checklist Attribute | Relation | 21 Zero-Shot Tasks Average |
|-------------------------------|--------|------------------------|----------|----------------------------|
| CLIP [57]                    | 81.58% | 67.60%                 | 63.05%   | 56.37%                     |
| CLIP +LoRA                   | 80.93% (-0.66%) | 66.28% (-1.32%) | 55.52% (-7.53%) | 55.37% (-1.00%) |
| w/o Neg Loss                 | 82.27% (+0.69%) | 67.58% (-0.02%) | 55.17% (-7.88%) | 55.37% (-1.00%) |
| Ours RB+LLM Negs             | 85.09% (+3.50%) | 73.90% (+6.30%) | 78.72% (+15.67%) | 54.66% (-1.71%) |

4.2. Implementation Details

For CLIP we use the ML-Foundation Open-CLIP repository [28] and for CyCLIP [19] we use its original code repository, which is also based on Open-CLIP. In most experiments, unless stated otherwise, we train our model for five epochs on 4 V100 NVIDIA GPUs, with a total batch size of 512. When starting from a pre-trained model, we use rank 4 LoRA adapters (Sec. 3.3) and the learning rate is set to $5 \times 10^{-6}$. When training from scratch, for CLIP we use the default parameters set in the open-CLIP library, and for CyCLIP the defaults of its original implementation. For all CLIP experiments, we use ViT/32-B as the model architecture and ResNet-50 when training CyCLIP (following [19]). When fine-tuning we initialize with the original model weights released by the respective authors. In all experiments involving a combination of CyCLIP [19] and our method (in Sec. 4.4-4.5), in addition to Eq. (6) loss we also employ all the extra losses proposed in CyCLIP [19].

4.3. Baselines

We compare our method to two strong baselines under several configurations. The first is the CLIP [57] OpenAI pretrained model trained on 400M image-text pairs which achieves high ZS performance. The second is the very recent CyCLIP [19] method which, similarly to us, improves over the original CLIP loss. For a fair comparison all methods use the same network architecture and the same initialization from the OpenAI pretrained model. For the CyCLIP baseline we continue training from the pretrained initialization using LoRA and the CyCLIP losses. As CyCLIP losses are orthogonal to ours, we also show a unified version of the two methods (CyCLIP + Ours Combined).

4.4. Fine-tuning VL Models

In the following experiments we show the effects of finetuning a pre-trained VL model using our additional data enhancement methods and losses. All experiments are initialized from the official OpenAI CLIP. We compare our method to two baselines on the VL-Checklist tasks, and on the Zero-Shot image classification task. The first baseline is the original pretrained model without any further training. The second, is the same model with the additional LoRA parameters, trained on CC3M (Table 1a) and LAION (Table 1g) using the original CLIP loss function. Table 1a shows several configurations of our method compared to the baselines. We see that our method shows significant improvements on all VL-Checklist tasks reaching up to 15% improvement. Figure 3 displays the relative gains on all tasks of the “Attribute” and “Relation” tests. It is clear that our gains are across all tests. These improvements come at a price of some minor degradation to the Zero-Shot performance compared to CLIP. Moreover, when fine-tuning CLIP on the LAION dataset (Table 1g) we do not see these degradations. In Tab. 1b we show consistent gains to ones in Tab. 1a when finetuning with a stronger (higher ZS) ViT-B/16 CLIP [57] pre-trained image encoder, observing an even lower drop in ZS performance. In Tab. 1e we show significant gains in fine-tuning CyCLIP on CC3M, comparing fine-tuning before and after integrating our proposed approach, this also comes at no ZS performance cost.

4.5. Training from scratch

In these experiments, we show the advantage of integrating our approach throughout the whole training procedure. To this end, we train from scratch on CC3M - both CLIP and CyCLIP, either on their own, or together with our proposed method integrated. Tables - Tab. 1c, Tab. 1d, and Tab. 1f show that, similar to finetuning, our method significantly improves both CLIP and CyCLIP SVLC capabili-
ties, while still keeping similar ZS performance. Figure 4 shows the detailed parsing of the “Attribute” and “Relation” tests with consistent gains across the specific tasks. These findings suggest that had we trained our method for many epochs on a large dataset, such as the full LAION-9B, we would reach similar ZS performance while greatly enhancing the SVLC performance of the model.

5. Ablations

In this section we will examine several aspects and components of our proposed methods.

5.1. Negative Losses

Section 3.2 details our additional loss functions which utilize our generated texts. Specifically, Eq. (3) describes the loss which contrasts a given example only with its generated negatives. Table 2 clearly shows the importance of this loss as opposed to simply adding the negative examples to the original contrastive loss (Eq. (2)). Without explicitly forcing the network to attend to the small changes in the text (Eq. (3)), the generated negative examples, when inserted only to the contrastive loss (Eq. (2)) do not provide the desired gains over the baseline.

5.2. Component analysis

In Section 3 we describe several components of our proposed method. Specifically we present our RB negative generation (Sec. 3.1.1), our LLM-based negative generation (Sec. 3.1.2), and our LLM-based analogy generation, referred to here as “Pos” (Sec. 3.1.3). Tab. 3 provides a detailed analysis and comparison of the contribution of each component to the final result. Through this analysis we see two contradicting forces between the SVLC capabilities and the original Zero-Shot performance. We can see that each negative generation method plays a crucial role in some of the tasks while the use of both is usually the best performing option. On the other hand, the LLM-based analogy generation stabilizes the Zero-Shot performance and mitigates the drop with respect to the baseline. The joint version of all components (“Ours Combined”) exhibits a good trade-off between the two contradicting forces.

6. Conclusions

We have presented a data-driven technique for enhancing the performance of VL models in the important task of SVLC understanding without sacrificing their impressive ZS object recognition capabilities. Our proposed method attains significant gains in multiple experiments on a variety of base VL models and datasets. It builds upon the modeling strength and knowledge of language structure to teach this structure to VL models in an orthogonal way, suggesting wide applicability to existing or future VL models.

While attaining impressive gains in SVLC understanding, we believe the small drop observed in ZS performance could be further reduced. An additional possible extension of our work is using more sophisticated sequence generation techniques for improving our batch data. One may combine annotation efforts with a language model to get improved data for training and evaluation [51]. Another possibility is adding a corrector [72] in the training that validates whether the VL model learns the correct concepts or not. We leave all of these exciting directions to future work.

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