

Augmenting CLIP with Improved Visio-Linguistic Reasoning

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Abstract

Image-text contrastive models such as CLIP are useful for a variety of downstream applications including zero-shot classification, image-text retrieval and transfer learning. However, these contrastively trained vision-language models often fail on compositional visio-linguistic tasks such as Winoground with performance equivalent to random chance. In our paper, we address this issue and propose a sample-efficient light-weight method called SDS-CLIP to improve the compositional visio-linguistic reasoning capabilities of CLIP. The core idea of our method is to use differentiable image parameterizations to fine-tune CLIP with a distillation objective from large text-to-image generative models such as Stable-Diffusion which are relatively good at visio-linguistic reasoning tasks. On the challenging Winoground compositional reasoning benchmark, our method improves the absolute visio-linguistic performance of different CLIP models by up to 7%, while on the ARO dataset, our method improves the visio-linguistic performance by upto 3%. As a byproduct of inducing visio-linguistic reasoning into CLIP, we also find that the zero-shot performance improves marginally on a variety of downstream datasets. Our method reinforces that carefully designed distillation objectives from generative models can be leveraged to extend existing contrastive image-text models with improved visio-linguistic reasoning capabilities.

1 Introduction

In the past few years, image-text contrastively pre-trained multimodal models such as CLIP (Radford et al. 2021a) have shown tremendous ability to perform zero-shot classification (Mu et al. 2021; Minderer et al. 2022), image-text retrieval (Diwan et al. 2022; Thrush et al. 2022) and image-captioning (Yu et al. 2022; Li et al. 2022; Mokady, Hertz, and Bermano 2021). These contrastive models are also used as a part of various state-of-the-art pipelines for downstream tasks such as segmentation (Wang et al. 2021; Lüddecke and Ecker 2021), object-detection (Minderer et al. 2022; Zhong et al. 2021) and model interpretability (Moayeri et al. 2023). However, recent works have shown that these models fail on visio-linguistic reasoning tasks, for example identifying the relative position between objects in an image. In fact, the performance of CLIP on Winoground (Thrush et al. 2022; Diwan et al. 2022), a challenging benchmark for

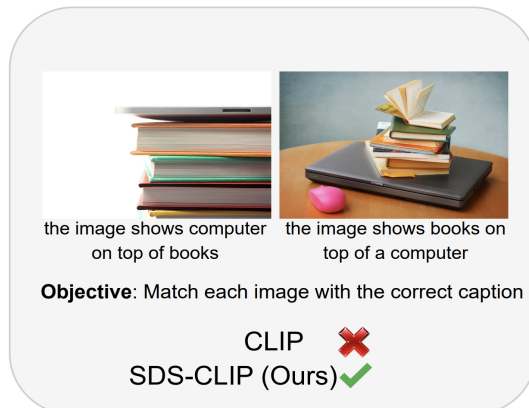


Figure 1: **Our simple fine-tuning method SDS-CLIP improves over CLIP on challenging vision-language tasks which require compositional reasoning.**

visio-linguistic reasoning, is very close to random chance. The failure of CLIP on this benchmark has been shown to be an artifact of its contrastive training objective which learns shortcuts as it optimizes for the task of retrieval (Yuksekgonul et al. 2023). These shortcuts enable CLIP to perform well for image-text retrieval and zero-shot classification, but lead to failures in visio-linguistic tasks which require more fine-grained understanding of the objects in an image and their spatial positions (Tejankar et al. 2021; Yuksekgonul et al. 2023; Huang et al. 2023). In contrast, text-to-image generative models like Stable Diffusion (Rombach et al. 2021; Saharia et al. 2022; Ramesh et al. 2022; Zhang et al. 2023; Balaji et al. 2023) have been shown to have reasonable visio-linguistic reasoning abilities (Li et al. 2023a; Clark and Jaini 2023). Recent works have shown that this might be attributed to their text conditioning mechanism which leads to more semantically consistent cross-attention maps and hence better learned correspondences between objects in an image and words in the text that have a visual grounding (Hertz et al. 2022; Tang et al. 2022; Orgad, Kavar, and Belinkov 2023; Li et al. 2023b). Perhaps because of this, text-to-image also perform well in zero-shot classification (Krojer et al. 2023; Clark and Jaini 2023; Chen et al. 2023; Li et al. 2023a).

To perform image-text matching, the denoising diffusion score can be computed – which is essentially the expectation of the gap between the predicted noise (conditioned on

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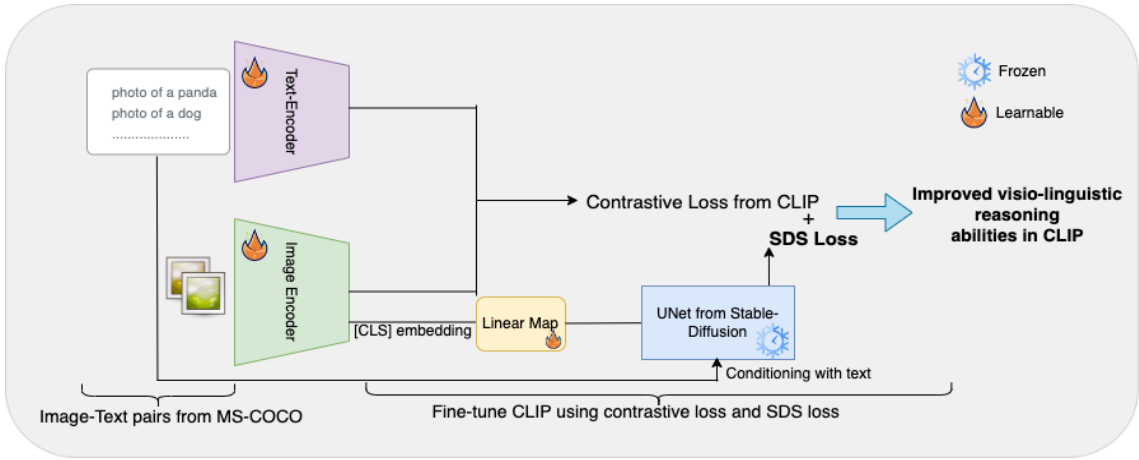


Figure 2: **We introduce a fine-tuning method for CLIP using a distillation loss from any text-to-image generative model (e.g., Stable-Diffusion) which improves the visio-linguistic reasoning abilities of CLIP.** Our method fine-tunes the Layer-Norm parameters in CLIP using a combination of contrastive loss and SDS loss with *only* 118k image-text pairs from MS-COCO. This makes our method extremely sample-efficient as well as parameter-efficient during fine-tuning.

the text) and the noise added to the original image across multiple time-steps. For e.g., (Li et al. 2023a) show that the denoising diffusion score from Stable-Diffusion outperforms CLIP variants on Winoground, whereas (Clark and Jaini 2023) show that text-to-image generative models such as Imagen outperform CLIP on similar visio-linguistic reasoning tasks.

The strong vision-linguistic reasoning capabilities of these generative text-to-image models make them attractive for many vision-language tasks, however, their computationally expensive inference makes them infeasible to use in all cases. For example, for an image-text matching task, multiple forward passes through the large text-to-image model are required with different levels of noise across many time-steps. In contrast, CLIP models can classify an image with just a single forward pass through an image and text-encoders. In Fig 3 and Fig 4, we show that this can lead to CLIP being up to 40x faster than the denoising diffusion score from Stable-Diffusion in solving the Winoground tasks.

Can we augment CLIP with improved visio-linguistic capabilities by distilling knowledge from text-to-image generative models such as Stable-Diffusion? To this end, we design an extremely light-weight sample-efficient and parameter-efficient fine-tuning method for CLIP which improves its visio-linguistic reasoning abilities while also marginally improving its zero-shot abilities on a wide range of downstream datasets. In particular, we use score-distillation sampling (SDS) (Poole et al. 2022) with Stable-Diffusion (Rombach et al. 2021) to regularize the contrastive loss during fine-tuning (see Fig 2) with a small paired image-text dataset. To implement this regularizer, we use differentiable image parameterizations (Mordvintsev et al. 2018) which optimizes the embeddings from CLIP such that they are also aligned with respect to the denoising diffusion loss. Using only $\sim 118k$ image-text pairs from MS-COCO and tuning only the LayerNorm parameters of CLIP during fine-tuning,

we find that our method boosts the visio-linguistic reasoning scores of a variety of CLIP models by a 1.5-7 % margin on the Winoground dataset. Notably, we find that augmenting CLIP with visio-linguistic reasoning also marginally boosts its zero-shot classification capabilities. Our work highlights that existing internet-scale image-text contrastive models can be improved in a post-hoc light-weight fine-tuning step. In summary, the contributions in our paper are as follows:

- We highlight the importance of the denoising diffusion loss from large-scale text-to-image models in visio-linguistic reasoning.
- We introduce a novel sample-efficient and parameter-efficient fine-tuning method to equip CLIP with better visio-linguistic reasoning capabilities, empirically validated on challenging visio-linguistic benchmarks.
- We show that improving the visio-linguistic reasoning capabilities of CLIP improves its downstream zero-shot performance on a variety of downstream datasets.

2 Related Works

Image-text contrastive models. Image-text models that have been contrastively trained on internet-scale data, such as CLIP (Radford et al. 2021a), have been shown to have strong zero-shot classification capabilities. However, recent works (Thrush et al. 2022; Diwan et al. 2022) have highlighted their limitations in visio-linguistic reasoning, as shown in the challenging Winoground benchmark. Yuksekgonul et al. (2023) also observe this issue and introduce a new benchmark ARO for image-text models which require a significant amount of visio-linguistic reasoning to solve. We note that (Yuksekgonul et al. 2023) use a fine-tuning strategy to improve on their benchmark, but the strategy is akin to adversarial training where one already knows the downstream failure mode.

Emerging Abilities of Text-to-image diffusion models. One of the emerging abilities of these image-to-text mod-

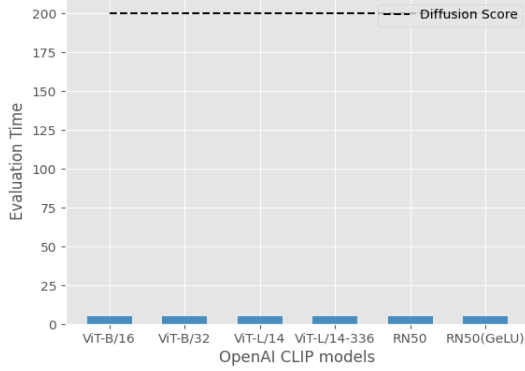


Figure 3: **Denoising Diffusion Score computation takes $\sim 40\times$ more time than the image-text alignment score in CLIP.** The higher inference time incurred by diffusion score computation from text-to-image generative models such as Stable-Diffusion make it infeasible to be usable in practice.

els is the strong semantic correspondences between image and text in the cross-attention layers. This has been highlighted in a string of recent works (Tang et al. 2022; Hertz et al. 2022; Xu et al. 2023; Mokady et al. 2022; Liao et al. 2023; Chen, Laina, and Vedaldi 2023). These strong correspondences have also shown emerging abilities in solving zero-shot classification and vision-language tasks which require some form of visual reasoning (Clark and Jaini 2023; Li et al. 2023a; Krojer et al. 2023; Chen et al. 2023). We highlight that works such as (Li et al. 2023a; Krojer et al. 2023) use Stable-Diffusion which itself consists of CLIP’s text-encoder for the conditional text-embedding. This shows that the diffusion objective potentially has a strong contribution in the improved visio-linguistic reasoning abilities of text-to-image generative models.

3 Preliminaries

CLIP

CLIP (Radford et al. 2021b) is a image-text model which is pre-trained using a contrastive objective, typically on internet-scale data. The core intuition of the training objective is to align the text and image embeddings of image-text pairs in a shared embedding space. To do this, CLIP consists of two components: (i) an image encoder f_ϕ which transforms a raw image x_i into an image embedding $e_{img}(x_i) = f_\phi(x_i) \in \mathbb{R}^d$, also denoted by the $\langle \text{CLS} \rangle$ token; and (ii) a text encoder g_γ which transforms a raw text caption c_i into a text embedding $e_{text}(c_i) = g_\gamma(c_i) \in \mathbb{R}^d$ also denoted by $\langle \text{EOS} \rangle$ token, both of which map to an embedding dimensionality d . Given a dataset $\mathcal{D} = \{(x_i, c_i)\}_{i=1}^N$ of image-text pairs, where (x_i, y_i) is the i^{th} image-text pair, CLIP uses a contrastive objective to pull the image and text embeddings of matched pairs together, while pushing those of unmatched pairs apart. Formally, the contrastive objective can be defined as:

$$L_{CLIP} = L_{image-text} + L_{text-image} \quad (1)$$

where:

$$L_{image-text} = -\frac{1}{2N} \sum_{j=1}^N \log \left\{ \frac{\exp(e_{img}(x_j)^T e_{text}(c_j)/\tau)}{\sum_{k=1}^N \exp((e_{img}(x_j)^T e_{text}(c_k)/\tau))} \right\} \quad (2)$$

$$L_{text-image} = -\frac{1}{2N} \sum_{j=1}^N \log \left\{ \frac{\exp(e_{img}(x_j)^T e_{text}(c_j)/\tau)}{\sum_{k=1}^N \exp((e_{img}(x_k)^T e_{text}(c_j)/\tau))} \right\} \quad (3)$$

where τ is a trainable temperature parameter. Usually \mathcal{D} is an internet-scale dataset consisting of millions of image-text pairs. Furthermore, during pre-training, the embeddings $e_{img}(x_i)$ and $e_{text}(c_i)$ are normalized to have a unit-norm.

Benchmark datasets

Winoground (Thrush et al. 2022; Diwan et al. 2022) is a challenging vision-language dataset for evaluating the visio-linguistic characteristics of contrastively trained image-text models. The dataset consists of 400 tasks, where each task consists of two image-text pairs. The objective is to independently assign the correct text caption to each image (see Fig 1). Each task is also annotated with meta-data corresponding to whether the task requires object-understanding, relational-understanding or both. The tasks in Winoground are challenging as the images differ in fine-grained ways and assigning the correct text captions requires inherent compositional visual reasoning.

ARO (Yuksekgonul et al. 2023) similarly tests visio-linguistic reasoning and consists of three types of tasks: (i) Visual Genome Attribution to test the understanding of object properties; (ii) Visual Genome Attribution to test for relational understanding between objects; and (iii) COCO-Order and Flickr30k-Order to test for order sensitivity of the words in a text, when performing image-text matching. We highlight that Winoground though slightly smaller in size than ARO is more challenging as it requires reasoning beyond visio-linguistic compositional knowledge (Diwan et al. 2022).

Denoising Diffusion Score

Concurrent works (Clark and Jaini 2023; Li et al. 2023a; Krojer et al. 2023) to this paper show that it is possible to use the denoising diffusion score from text-to-image generative models to perform image-matching tasks. These works find that this approach performs comparably to CLIP at zero-shot classification, but performs much better than CLIP on relational and attribute-binding tasks which require compositional generalization. Given an image x and a caption c , the denoising diffusion score denoted by $d(x, c)$ is defined as:

$$d(x, c) = \mathbb{E}_{t \sim T, \epsilon \sim \mathcal{N}(0, I)} [\|\epsilon_\theta(v_\alpha(x), t, c) - \epsilon\|^2] \quad (4)$$

In the case of Winoground image-text matching tasks where an image x needs to be matched with the correct caption from a set of captions denoted as $C = \{c_i\}_{i=1}^n$, the denoising diffusion score is used in the following way to select a caption c^* from the set C :

$$c^* = \arg \min_{c \in C} \mathbb{E}_{t \sim T, \epsilon \sim \mathcal{N}(0, I)} [\|\epsilon_\theta(v_\alpha(x), t, c) - \epsilon\|^2] \quad (5)$$

where t is the sampled time-step, ϵ_θ is the noise prediction UNet (Ronneberger, Fischer, and Brox 2015), v_α is an encoder (e.g., VQ-VAE) which maps the image x to a latent code and ϵ is the sampled Gaussian noise.

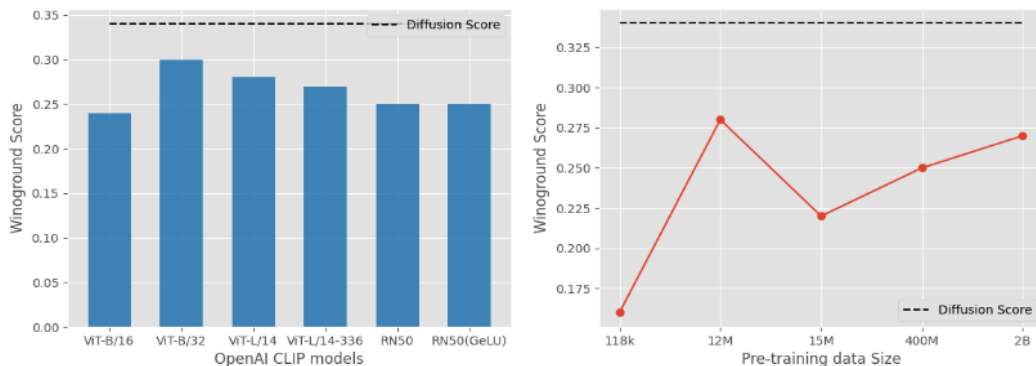


Figure 4: **Various CLIP variants underperform on the Winoground visio-linguistic reasoning benchmark when compared to the diffusion score from Stable-Diffusion.** (Left): Different CLIP architectures pre-trained on OpenAI’s private data lag behind denoising diffusion score. (Right). Pre-training CLIP on a larger pre-training corpus (e.g. LAION-2B) **does not** improve its performance on Winoground.

4 Generative Text-to-Image Models are Strong Visio-Linguistic Reasoners

In this section, we use the diffusion denoising score eq. (4) to compute the performance of Stable-Diffusion on the Winoground tasks. In particular, for every possible caption $c \in C$, we perform 50 samplings of time-steps and noise for the denoising diffusion score eq. (4). In Fig 4-(Left), we find that the denoising diffusion score for the Winoground image-text matching task is better than all the CLIP varieties pre-trained on distinct architectures using OpenAI’s private dataset of image-text pairs. For e.g., the denoising diffusion score from Stable-Diffusion leads with an accuracy of 34% on Winoground, whereas various CLIP variants have accuracies between 24% – 30%.

Does the scale of pre-training data impact CLIP’s visio-linguistic reasoning abilities? We measure the performance of different CLIP varieties pre-trained on various scales of data upto to 2B image-text pairs (see Fig 4 - Right). We find that increasing the amount of pre-training data does not uniformly improve CLIP’s performance on the Winoground tasks, with it still falling short of Diffusion Score performance. Even with 2B image-text pairs (at a similar scale to which Stable-Diffusion is trained) CLIP lags behind Stable-Diffusion by 6.5%, thus highlighting that the scale of pre-training data in Stable-Diffusion is not the main contributor for its Winoground performance.

Does the lack of cross-attention impact CLIP’s visio-linguistic reasoning abilities? One argument for CLIP’s lower performance in visio-linguistic reasoning tasks is the lack of cross-attention layers, or the late-fusion between the image and text embeddings. As an alternative, we compare its performance to CoCa (Yu et al. 2022). CoCa is similarly trained with a contrastive objective but it has an additional image-captioning objective and also fuses the image and text embeddings with a cross-attention layer in the early layers of the multimodal text-encoder (i.e. early-fusion). We find that CoCa pre-trained on 2B image-text pairs achieves 30% on Winoground which is similar to CLIP’s performance with ViT-B/32. When fine-tuned on MS-COCO, however, the performance of CoCa drops down to 16.5%. In both

cases, the performance is still below the denoising diffusion score.

These observations reinforce that the contrastive objective in CLIP may be ill-suited to handling vision-language tasks beyond retrieval which require more fine-grained forms of compositional reasoning and understanding.

5 Distilling Visio-linguistic Reasoning to CLIP

In the earlier section, we showed that the denoising diffusion score is a strong metric for solving tasks which require visio-linguistic reasoning. In this section, we present a post-hoc fine-tuning method for CLIP which distills knowledge from Stable-Diffusion to improve its visio-linguistic reasoning capabilities.

SDS-CLIP: Our Method

The core idea of our approach is to regularise the contrastive objective in CLIP with the denoising diffusion score from Stable Diffusion (see Eq.(4)). Our method builds on recent works such as Dreamfusion (Poole et al. 2022) where they learn the parameters of a 3D NeRF model by mapping the output of the NeRF into the input space of the UNet and optimizing it with the denoising diffusion loss, also known as the score-distillation sampling (SDS). In a similar vein, we fine-tune the parameters of CLIP using SDS. Our set-up can be thought of as a special case of knowledge distillation where the teacher is the text-to-image model and the CLIP is the student model. In inference, this allows CLIP to leverage the visio-linguistic reasoning capabilities of text-to-image diffusion models.

Formally, we map the output of the image encoder f_ϕ in CLIP to the input space of the UNet ϵ_θ . Specifically, given the image encoder f_ϕ from CLIP, we map the $\langle \text{CLS} \rangle$ embedding for a given image x through a linear map $h_w \in \mathcal{R}^{d \times 4 \times 64 \times 64}$ into the input space of Stable Diffusion’s UNet, ϵ_θ . This can be formalized as $\epsilon_\theta(h_w(f_\phi(x)), t, c)$ where t is the time step and c is the corresponding text caption for the given image. We then use this term in place of $\epsilon_\theta(v_\alpha(x), t, c)$ in Eq. (5) to arrive as a denoising diffusion

Model	Overall	Object	Relation	Both	1 Main Pred	2 Main Preds
ViT-B/16(CLIP)	0.24	0.28	0.18	0.57	0.29	0.11
Only COCO FT	0.23	0.27	0.19	0.56	0.30	0.11
Ours	0.31	0.35	0.25	0.69	0.36	0.16
ViT-B/32(CLIP)	0.30	0.35	0.22	0.80	0.34	0.18
Only COCO FT	0.28	0.31	0.20	0.76	0.31	0.16
Ours	0.32	0.38	0.23	0.69	0.36	0.20
ViT-L/14(CLIP)	0.28	0.27	0.25	0.57	0.29	0.24
Only COCO FT	0.26	0.27	0.25	0.56	0.30	0.23
Ours	0.295	0.32	0.25	0.53	0.32	0.18
ViT-L/14-336(CLIP)	0.27	0.32	0.21	0.57	0.30	0.19
Only COCO FT	0.23	0.28	0.19	0.53	0.26	0.17
Ours	0.285	0.34	0.23	0.56	0.31	0.21
ResNet-50(CLIP)	0.25	0.29	0.19	0.5	0.27	0.18
Only COCO FT	0.24	0.27	0.20	0.49	0.27	0.16
Ours	0.265	0.30	0.21	0.42	0.29	0.19

Table 1: **Our fine-tuning method SDS-CLIP improves CLIP performance on the Winoground benchmark by 1.5% to 7% across various CLIP variants.** Specifically, we find that our method improves on the sub-categories involving *object-swap* and *relational* understanding which comprise of the majority of the tasks in Winoground. Note that *only* fine-tuning with image-text pairs from MS-COCO without the distillation loss often leads to a drop in performance for Winoground.

Algorithm 1: Algorithm to fine-tune CLIP with distillation from Stable-Diffusion for improved visio-linguistic reasoning

Require: \mathcal{D} : image-text pairs, f_ϕ : CLIP’s image-encoder, g_γ : CLIP’s text-encoder, ϵ_θ : UNet; N : Number of Epochs; λ : Hyper-parameter for the regularizer; $|B|$: Batch-size.

while $i \neq N$ **do**

$\{x_j, y_j\}_{j=1}^{|B|} \leftarrow$ Sample a batch from \mathcal{D}

$t \leftarrow$ Sample time-steps using DDPM

$\epsilon \leftarrow$ Sample Gaussian noise $\epsilon \sim \mathcal{N}(0, I)$

$L_{clip} \leftarrow$ Compute contrastive loss as in eq. (4)

$L_{SDS} \leftarrow$ Compute SDS loss as in eq. (6)

$L_{total} \leftarrow L_{clip} + \lambda L_{SDS}$

$L_{total}.backward()$ ▷ Backprop

$\phi, \gamma, w \leftarrow$ Update the relevant parameters

$i \leftarrow i + 1$

end while

loss L_{SDS} which encourages image-text binding with feedback from the diffusion loss:

$$L_{SDS} = \mathbb{E}_{t \sim T, \epsilon \sim \mathcal{N}(0, I)} [\|\epsilon_\theta(h_w(f_\phi(x)), t, c) - \epsilon\|^2] \quad (6)$$

We practically implement this by adding the denoising diffusion loss to the original contrastive objective of CLIP such that it acts as a regularizer:

$$L_{total} = L_{CLIP} + \lambda L_{SDS} \quad (7)$$

where λ is a hyper-parameter that can be set with a grid-search. We note that there are multiple ways to incorporate a diffusion loss into CLIP’s objective. We found that as an additional loss term led to the best results, however, we include the full set of design choices we considered in the Appendix.

Similar to differentiable image parameterizations (Mordvintsev et al. 2018) where a given function is optimized by

backpropagation through the image generation process, the UNet parameters θ are kept frozen during the optimization process. Specifically, given $L_{total}(\phi, \gamma, w, \theta)$:

$$\phi^*, \gamma^*, w^* = \min_{\phi, \gamma, w} L_{total}(\phi, \gamma, w, \theta) \quad (8)$$

where ϕ, γ, w are the learnable parameters of CLIP’s image, text-encoder and the linear map between CLIP and the UNet in Stable-Diffusion.

6 Experiments

In this section, we empirically validate our proposed method SDS-CLIP on visio-linguistic reasoning using two challenging benchmarks (Winoground, ARO) and zero-shot image classification using a suite of downstream datasets (ImageNet, CIFAR-100, and others). Overall, we show that our method improves CLIP’s performance significantly on Winoground and some key tasks in ARO, while also marginally improving the downstream zero-shot performance.

Experimental Setup

CLIP Models. We consider the following CLIP variants in our experiments: (i) CLIP ViT-B/16; (ii) CLIP ViT-B/32; (iii) CLIP-ViT-L-14; (iv) CLIP-ViT-L-14 336px; (v) CLIP-ResNet-50. For each variant, we use our proposed method SDS-CLIP to fine-tune its parameters from the official OpenAI pre-trained checkpoint. We provide further results with a CLIP variant pre-trained on public data in the Appendix (C).

Implementation Details. Due to computational limit, we fine-tune CLIP from a publicly available checkpoint instead of training from scratch. Notably, we only fine-tune the LayerNorm parameters (Basu et al. 2023) of CLIP using image-text pairs from MSCOCO (Lin et al. 2014). In particular, we choose MSCOCO as it is relatively small and less

Model	VG-Relation	VG-Attribution	COCO-Order	Flickr-Order
ViT-B/16(CLIP)	0.52	0.62	0.38	0.46
<i>Only COCO FT</i>	0.51	0.62	0.37	0.45
Ours	0.535	0.63	0.38	0.46
ViT-B/32(CLIP)	0.50	0.61	0.37	0.48
<i>Only COCO FT</i>	0.50	0.60	0.37	0.48
Ours	0.53	0.62	0.36	0.48
ViT-L/14(CLIP)	0.53	0.61	0.35	0.44
<i>Only COCO FT</i>	0.53	0.61	0.36	0.44
Ours	0.55	0.64	0.36	0.44
ViT-L/14-336(CLIP)	0.53	0.61	0.38	0.43
<i>Only COCO FT</i>	0.53	0.61	0.37	0.42
Ours	0.54	0.63	0.38	0.42
ResNet-50(CLIP)	0.53	0.63	0.44	0.51
<i>Only COCO FT</i>	0.52	0.63	0.44	0.50
Ours	0.55	0.66	0.43	0.51

Table 2: **Distillation from Stable-Diffusion primarily helps on the *relational-understanding* and *attribute-binding* tasks from ARO dataset.** Performance of fine-tuned CLIP with our distillation loss on the ARO Benchmark.

noisy than other image-text datasets such as CC-3M or CC-12M (Sharma et al. 2018). In total, we fine-tune CLIP using our proposed method with only 118k image-text pairs (see Algo.(1) for the fine-tuning steps). Both these factors make our fine-tuning method extremely sample-efficient as well as parameter-efficient. With the linear transformation and the LayerNorm parameters, our fine-tuning method optimizes only $\sim 8M$ parameters of CLIP’s total parameters. We tune the regularization hyper-parameter λ for ViT-B/16 and use it for the other CLIP variants (see Appendix for more details). We fine-tune each CLIP model for 5 epochs, though find that after 1 epoch, performance is already very strong.

Baselines. We compare our method with two different baselines: (i) Pre-trained CLIP checkpoints; and (ii) Fine-tuned CLIP with MS-COCO using *only* the contrastive loss without the additional distillation loss. (ii) is particularly crucial to eliminate the effect of the image-text pairs from MS-COCO in the fine-tuning step.

Results on Winoground

We first evaluate our proposed method SDS-CLIP on Winoground (Thrush et al. 2022), a highly challenging visio-linguistic reasoning benchmark. In Table.(1), we show that our proposed method leads to an absolute improvement of between 1.5 – 7% across all sub-categories in the benchmark and across all CLIP variants. For ViT-B/16 (CLIP), we find that the overall improvement is the largest with a gain of 7%. For other CLIP variants, we find the gain to be consistently between 1.5% – 2%. In the Appendix, we report results on CLIP variants pre-trained on public data, where we see similar improvements. Next, we dissect the performance of SDS-CLIP on the sub-categories of Winoground: *object-swap*, *relation* and *both* sub-categories. We also dissect performance by the number of predicates present in the captions. We find that SDS-CLIP consistently improves on the *object-swap* and *relational* understanding sub-categories. On the tasks containing only one predicate, SDS-CLIP consistently improves across all the variants of CLIP, while on tasks containing two predicates, SDS-CLIP improves on all

CLIP variants except ViT-L/14. Interestingly, while we observed a performance gain in each sub-category separately, we found that tasks containing *both* sub-categories incurred a drop. We note, however, that the tasks containing both *object-swap* and *relation* tags make up only $\sim 5\%$ of all Winoground tasks which might not be entirely representative of tasks reasoning about object swaps as well as their relational understanding together. Overall, we find that our fine-tuning method consistently improves the performance on a wide set of CLIP variants on the Winoground tasks especially on the *object-swap* and *relational* sub-categories, as well as on tasks with captions containing different number of predicates. These results highlight the potential in distilling knowledge encoded in text-to-image models to contrastive models.

Results on ARO dataset

We also evaluate the effectiveness of SDS-CLIP on the ARO dataset (Yuksekgonul et al. 2023). This dataset consists of three types of tasks constructed which focus on (i) *attribute-understanding*, (ii) *relational-understanding* and (iii) order-understanding. In Table. (2), we show that SDS-CLIP improves on the *attribute-binding* and *relational understanding* tasks by 1% – 3% across a variety of CLIP models. However, we do not observe any improvement in the order-understanding tasks as the denoising diffusion score from the teacher Stable-Diffusion is itself erroneous, which we describe in details in the next section.

When does distillation not help CLIP?

While we find that distilling knowledge from Stable-Diffusion to CLIP helps in *object-swap*, *relational-understanding* and *attribution-binding* visio-linguistic tasks, it does not help on tasks where the order of the text is perturbed (e.g. the COCO-Order and Flickr-Order tasks in the ARO dataset). This is shown in the final two columns of Table (2). In fact, we find that the denoising diffusion score in eq. (4) leads to accuracies of 0.24 for COCO-Order and

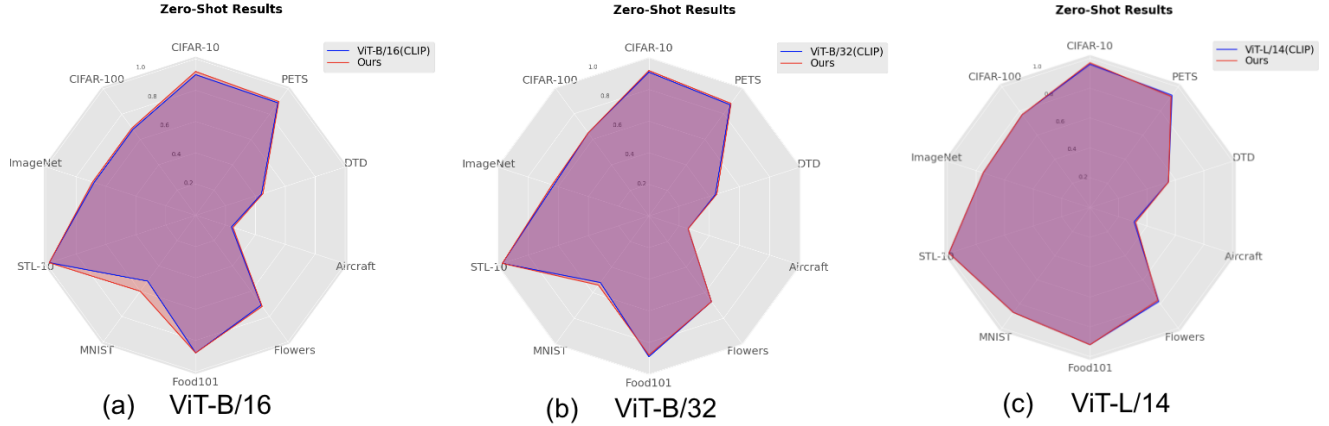


Figure 5: **Our fine-tuning method does not harm the zero-shot abilities of CLIP.** In fact for certain downstream datasets (e.g., ImageNet, CIFAR-10, MNIST, Aircraft, Flowers) – we observe an improvement in the zero-shot performance between 1% – 8% for ViT-B/16. For other CLIP models (ViT-B/32 and ViT-L/14), we find no drop in zero-shot performance.

0.34 for Flickr-Order which is in fact lower than CLIP models. Concurrent works (Krojer et al. 2023) has shown similarly low performance for text-ordering tasks. A potential reason could be that ordering tasks only test for grammatical understanding which current text encoders cannot effectively model. Another reason could be that the denoising diffusion score is not affected by word ordering as the image semantics are not changed as a result.

Does the zero-shot performance get affected?

One of the drawbacks of fine-tuning CLIP using an additional distillation objective along with contrastive loss can be a potential decrease in the downstream zero-shot performance. The contrastive losses used to train CLIP are known to be a proxy for a retrieval task (Radford et al. 2021b). Thus, downweighting this loss via an additional objective could harm CLIP’s zero-shot performance, which in itself is a retrieval task. In practice, we find this *not* to be the case (see Fig 5). In fact, we find that the zero-shot performance of ViT-B/16 increases across a variety of downstream datasets (ImageNet, MNIST, Aircraft, Flowers, DTD, PETS). The zero-shot improvement ranges from 1% up to 8% across the downstream datasets. For other ViT-based CLIP architectures such as ViT-B/32 and ViT-L/14, we find marginal improvements in the range of 1%-1.5% (see Fig 5) and find no drop in zero-shot performances across various downstream datasets. These results suggest that improving the visio-linguistic reasoning abilities of contrastive models such as CLIP in a post-hoc fine-tuning step does not harm its inherent zero-shot abilities, but instead can lead to marginal zero-shot improvements in certain cases. Given that our current results are obtained with small batch-sizes, we hypothesize that increasing the batch-sizes may even further boost zero-shot results.

Does distilling features directly from UNet help?

Previous works such as (Xu et al. 2023) find that the frozen features of the UNet contain structural information about the image. Motivated by this, we also investigate if distilling

knowledge directly from the frozen UNet features is beneficial. Given an image x and its caption c , the frozen features f from the UNet (where $I(x, c) = \epsilon_{\theta}(v_{\alpha}(x), t, c)$, similar to (Xu et al. 2023)) can be extracted. We then use these frozen internal representations from the UNet to regularize features of the image encoder in CLIP. In particular:

$$L_{total} = L_{CLIP} + \lambda \|h_w(f_{\phi}(x) - I(x, c))\|_2^2 \quad (9)$$

However, we find that distillation in this way does not lead to improved performances for visio-linguistic reasoning. In fact, for ViT-B/16 (CLIP) we find the Winoground score to decrease from 0.24 to 0.23. This result shows that using score-distillation sampling which involves backpropagation through the UNet is critical to distill knowledge from diffusion models to other discriminative models and subsequently achieve strong visio-linguistic performance.

7 Conclusion

In our paper, we show that knowledge distillation from text-to-image generative models (e.g., Stable-Diffusion) to contrastive vision-language models such as CLIP can improve CLIP’s visio-linguistic reasoning abilities on *object-swap*, *relational-understanding* and *attribute-binding* tasks. Our method for distillation – SDS-CLIP is extremely lightweight and parameter-efficient, requiring only $\sim 118k$ training image-text pairs from MS-COCO and fine-tuning only the LayerNorm parameters in CLIP. Our empirical results also show that this improvement does not come at the cost of downstream zero-shot performance. In summary, our work provides evidence that distilling knowledge from strong text-to-image models can indeed be helpful in improving contrastive vision-language models, especially for visio-linguistic reasoning.

Future Directions. (i) Understanding the deficiencies of text-to-image models on the ordering tasks and mitigating them. (ii) Designing distillation methods without backpropagation through the UNet which will enable the use of larger batch-sizes.

References

- Balaji, Y.; Nah, S.; Huang, X.; Vahdat, A.; Song, J.; Zhang, Q.; Kreis, K.; Aittala, M.; Aila, T.; Laine, S.; Catanzaro, B.; Karras, T.; and Liu, M.-Y. 2023. eDiff-I: Text-to-Image Diffusion Models with an Ensemble of Expert Denoisers. *arXiv:2211.01324*.
- Basu, S.; Massiceti, D.; Hu, S. X.; and Feizi, S. 2023. Strong Baselines for Parameter Efficient Few-Shot Fine-tuning. *arXiv:2304.01917*.
- Chen, H.; Dong, Y.; Wang, Z.; Yang, X.; Duan, C.-D.; Su, H.; and Zhu, J. 2023. Robust Classification via a Single Diffusion Model. *ArXiv*, abs/2305.15241.
- Chen, M.; Laina, I.; and Vedaldi, A. 2023. Training-Free Layout Control with Cross-Attention Guidance. *arXiv:2304.03373*.
- Clark, K.; and Jaini, P. 2023. Text-to-Image Diffusion Models are Zero-Shot Classifiers. *arXiv:2303.15233*.
- Diwan, A.; Berry, L.; Choi, E.; Harwath, D.; and Mahowald, K. 2022. Why is Winoground Hard? Investigating Failures in Visuolinguistic Compositionality. *arXiv:2211.00768*.
- Hertz, A.; Mokady, R.; Tenenbaum, J.; Aberman, K.; Pritch, Y.; and Cohen-Or, D. 2022. Prompt-to-Prompt Image Editing with Cross Attention Control. *arXiv:2208.01626*.
- Huang, Y.; Tang, J.; Chen, Z.; Zhang, R.; Zhang, X.; Chen, W.; Zhao, Z.; Lv, T.; Hu, Z.; and Zhang, W. 2023. Structure-CLIP: Enhance Multi-modal Language Representations with Structure Knowledge. *arXiv:2305.06152*.
- Krojer, B.; Poole-Dayana, E.; Voleti, V.; Pal, C.; and Reddy, S. 2023. Are Diffusion Models Vision-And-Language Reasoners? *arXiv:2305.16397*.
- Li, A. C.; Prabhudesai, M.; Duggal, S.; Brown, E.; and Pathak, D. 2023a. Your Diffusion Model is Secretly a Zero-Shot Classifier. *arXiv:2303.16203*.
- Li, J.; Li, D.; Xiong, C.; and Hoi, S. C. H. 2022. BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation. *CoRR*, abs/2201.12086.
- Li, Z.; Zhou, Q.; Zhang, X.; Zhang, Y.; Wang, Y.; and Xie, W. 2023b. Guiding Text-to-Image Diffusion Model Towards Grounded Generation. *arXiv:2301.05221*.
- Liao, T.-H.; Ge, S.; Xu, Y.; Lee, Y.-C.; AlBahar, B.; and Huang, J.-B. 2023. Text-driven Visual Synthesis with Latent Diffusion Prior. *arXiv:2302.08510*.
- Lin, T.; Maire, M.; Belongie, S. J.; Bourdev, L. D.; Girshick, R. B.; Hays, J.; Perona, P.; Ramanan, D.; Dollár, P.; and Zitnick, C. L. 2014. Microsoft COCO: Common Objects in Context. *CoRR*, abs/1405.0312.
- Lüddecke, T.; and Ecker, A. S. 2021. Prompt-Based Multi-Modal Image Segmentation. *CoRR*, abs/2112.10003.
- Minderer, M.; Gritsenko, A.; Stone, A.; Neumann, M.; Weissenborn, D.; Dosovitskiy, A.; Mahendran, A.; Arnab, A.; Dehghani, M.; Shen, Z.; Wang, X.; Zhai, X.; Kipf, T.; and Hounsby, N. 2022. Simple Open-Vocabulary Object Detection with Vision Transformers. *arXiv:2205.06230*.
- Moayeri, M.; Rezaei, K.; Sanjabi, M.; and Feizi, S. 2023. Text-To-Concept (and Back) via Cross-Model Alignment. *arXiv:2305.06386*.
- Mokady, R.; Hertz, A.; Aberman, K.; Pritch, Y.; and Cohen-Or, D. 2022. Null-text Inversion for Editing Real Images using Guided Diffusion Models. *arXiv:2211.09794*.
- Mokady, R.; Hertz, A.; and Bermano, A. H. 2021. ClipCap: CLIP Prefix for Image Captioning. *arXiv:2111.09734*.
- Mordvintsev, A.; Pezzotti, N.; Schubert, L.; and Olah, C. 2018. Differentiable Image Parameterizations. *Distill*. <https://distill.pub/2018/differentiable-parameterizations>.
- Mu, N.; Kirillov, A.; Wagner, D. A.; and Xie, S. 2021. SLIP: Self-supervision meets Language-Image Pre-training. *CoRR*, abs/2112.12750.
- Orgad, H.; Kavar, B.; and Belinkov, Y. 2023. Editing Implicit Assumptions in Text-to-Image Diffusion Models. *arXiv:2303.08084*.
- Poole, B.; Jain, A.; Barron, J. T.; and Mildenhall, B. 2022. DreamFusion: Text-to-3D using 2D Diffusion. *arXiv:2209.14988*.
- Radford, A.; Kim, J. W.; Hallacy, C.; Ramesh, A.; Goh, G.; Agarwal, S.; Sastry, G.; Askell, A.; Mishkin, P.; Clark, J.; Krueger, G.; and Sutskever, I. 2021a. Learning Transferable Visual Models From Natural Language Supervision. *arXiv:2103.00020*.
- Radford, A.; Kim, J. W.; Hallacy, C.; Ramesh, A.; Goh, G.; Agarwal, S.; Sastry, G.; Askell, A.; Mishkin, P.; Clark, J.; Krueger, G.; and Sutskever, I. 2021b. Learning Transferable Visual Models From Natural Language Supervision. *CoRR*, abs/2103.00020.
- Ramesh, A.; Dhariwal, P.; Nichol, A.; Chu, C.; and Chen, M. 2022. Hierarchical Text-Conditional Image Generation with CLIP Latents. *arXiv:2204.06125*.
- Rombach, R.; Blattmann, A.; Lorenz, D.; Esser, P.; and Ommer, B. 2021. High-Resolution Image Synthesis with Latent Diffusion Models. *CoRR*, abs/2112.10752.
- Ronneberger, O.; Fischer, P.; and Brox, T. 2015. U-Net: Convolutional Networks for Biomedical Image Segmentation. *CoRR*, abs/1505.04597.
- Saharia, C.; Chan, W.; Saxena, S.; Li, L.; Whang, J.; Denton, E.; Ghasemipour, S. K. S.; Ayan, B. K.; Mahdavi, S. S.; Lopes, R. G.; Salimans, T.; Ho, J.; Fleet, D. J.; and Norouzi, M. 2022. Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding. *arXiv:2205.11487*.
- Sharma, P.; Ding, N.; Goodman, S.; and Soricut, R. 2018. Conceptual Captions: A Cleaned, Hypernymed, Image Alt-text Dataset For Automatic Image Captioning. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2556–2565. Melbourne, Australia: Association for Computational Linguistics.
- Tang, R.; Liu, L.; Pandey, A.; Jiang, Z.; Yang, G.; Kumar, K.; Stenatorp, P.; Lin, J.; and Ture, F. 2022. What the DAAM: Interpreting Stable Diffusion Using Cross Attention. *arXiv:2210.04885*.

Tejankar, A.; Sanjabi, M.; Wu, B.; Xie, S.; Khabsa, M.; Pirsiavash, H.; and Firooz, H. 2021. A Fistful of Words: Learning Transferable Visual Models from Bag-of-Words Supervision. *CoRR*, abs/2112.13884.

Thrush, T.; Jiang, R.; Bartolo, M.; Singh, A.; Williams, A.; Kiela, D.; and Ross, C. 2022. Winoground: Probing Vision and Language Models for Visio-Linguistic Compositionality. arXiv:2204.03162.

Wang, Z.; Lu, Y.; Li, Q.; Tao, X.; Guo, Y.; Gong, M.; and Liu, T. 2021. CRIS: CLIP-Driven Referring Image Segmentation. *CoRR*, abs/2111.15174.

Xu, J.; Liu, S.; Vahdat, A.; Byeon, W.; Wang, X.; and Mello, S. D. 2023. Open-Vocabulary Panoptic Segmentation with Text-to-Image Diffusion Models. arXiv:2303.04803.

Yu, J.; Wang, Z.; Vasudevan, V.; Yeung, L.; Seyedhosseini, M.; and Wu, Y. 2022. CoCa: Contrastive Captioners are Image-Text Foundation Models. arXiv:2205.01917.

Yuksekgonul, M.; Bianchi, F.; Kalluri, P.; Jurafsky, D.; and Zou, J. 2023. When and Why Vision-Language Models Behave like Bags-Of-Words, and What to Do About It? In *The Eleventh International Conference on Learning Representations*.

Zhang, C.; Zhang, C.; Zhang, M.; and Kweon, I. S. 2023. Text-to-image Diffusion Models in Generative AI: A Survey. arXiv:2303.07909.

Zhong, Y.; Yang, J.; Zhang, P.; Li, C.; Codella, N.; Li, L. H.; Zhou, L.; Dai, X.; Yuan, L.; Li, Y.; and Gao, J. 2021. Region-CLIP: Region-based Language-Image Pretraining. *CoRR*, abs/2112.09106.

Model	Overall	Object	Relation	Both	1 Main Pred	2 Main Preds
ViT-B/16(LAION 400M)	0.24	0.29	0.17	0.59	0.28	0.11
Only COCO FT	0.24	0.26	0.21	0.54	0.31	0.10
Ours	0.30	0.34	0.23	0.55	0.33	0.14

Table 3: **Additional results on Winoground with ViT-B/16 CLIP pre-trained on public data (LAION-400M).**

8 Appendix

Experimental Details

We perform a hyperparameter sweep for the learning rate and the regularization hyperparameter λ for ViT-B/16. We use these same hyperparameters for different CLIP variants including ViT-B/32, ViT-B/14, ViT-L/14-336px and ResNet-50. In particular, we set $\lambda = 0.001$ and set the learning rate as 5×10^{-5} . We use a batch-size of 32 for all the different CLIP models.

Note on Full Fine-tuning. All our experiments were primarily done by fine-tuning only the LayerNorm parameters. In the initial phase of the project, we also fine-tune all the parameters of the text and image encoder in CLIP, however it results in worse performances than those reported in Table. (1). Potentially, this can be due to overfitting issues when used in conjunction with the new regularizer. We therefore run all the experiments with LayerNorm tuning as it leads to the best results.

Additional Visio-Linguistic Reasoning Results

In Table(3) – we provide additional results and show that our fine-tuning method improves on CLIP pre-trained on public data (LAION-400M), thus highlighting the efficacy of our method.

Note on Additional Design Choices for Distillation

We also perform additional experiments by fine-tuning the text-encoder g_γ in CLIP using our SDS loss from eq. (4). In particular, we learn a linear map h_w between g_γ and the text conditioning in the UNet. However, we observe worse results than fine-tuning the image-encoder and the baselines used in our paper – therefore primarily focus on using our method for tuning CLIP’s image encoder. For e.g., with ViT-B/16, on Winoground we observe a performance of 0.22 and with ViT-B/32, we observe a performance of 0.27 – both of which are worse than fine-tuning the image encoder and the baseline pre-trained CLIP checkpoints.

Limitations of using SDS loss in CLIP

One of the practical limitations of using the SDS loss for fine-tuning CLIP is that it requires back-propagation through the entire UNet, even though the parameters of the UNet are frozen. Since our method uses UNet from Stable-Diffusion, which contains ~ 890 M parameters, we had to decrease the batch-size during fine-tuning even on a 48GB A6000 GPU. Despite this, we still observed improved visio-linguistic reasoning results, thus we hypothesize that our results can be further improved by using larger batch-sizes.