CLIP-Lite: Information Efficient Visual Representation Learning from Textual Annotations

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Abstract

We propose CLIP-Lite, an information efficient method for visual representation learning by feature alignment with textual annotations. Compared to the previously proposed CLIP model, CLIP-Lite requires only one negative image-text sample pair for every positive image-text sample during the optimization of its contrastive learning objective. We accomplish this by taking advantage of an information efficient lower-bound to maximize the mutual information between the two input modalities. This allows CLIP-Lite to be trained with significantly reduced amounts of data and batch sizes while obtaining better performance than CLIP. We evaluate CLIP-Lite by pretraining on the COCO-Captions dataset and testing transfer learning to other datasets. CLIP-Lite obtains a +15.4% mAP absolute gain in performance on Pascal VOC classification, and a +22.1% top-1 accuracy gain on ImageNet, while being comparable or superior to other, more complex, text-supervised models. CLIP-Lite is also superior to CLIP on image and text retrieval, zero-shot classification, and visual grounding. Finally, by performing explicit image-text alignment during representation learning, we show that CLIP-Lite can leverage language semantics to encourage bias-free visual representations that can be used in downstream tasks.

1. Introduction

Pretraining image classification networks on the ImageNet dataset has led to visual representations that transfer to other tasks \cite{1,14,32,53,60}. However, such classification based pretraining requires a large amount of human-annotated data which is hard to obtain at scale. In contrast, captioned image data is an information-dense source of supervision that is relatively cheap to collect and plentiful on the internet. Therefore, recent methods have used joint vision-language pretraining to learn representations from image-caption pairs \cite{10,42}. Recently, CLIP \cite{40}, a vision-language pretraining model, was developed using contrastive learning between the two modalities on an Internet-sized dataset of 400 million image-caption pairs. Contrastive learning methods work by pulling closer the representations of independent views of the same datum \textit{i.e.} a positive or matching image-caption pair and pushing apart the representations of independent views of different data \textit{i.e.} negative or non-matching image-caption pairs. However, contrastive learning in vision-language pretraining still has some limitations as it seems to be most effective only with large scale data, and it requires a large number of negative image-caption pairs during training.

Our work aims to address and explore these two limitations by proposing CLIP-Lite, an information efficient variation of CLIP that is useful even in smaller data regimes, does not rely in as many negative sample pairs during training, and provides comparable or superior performance on standard benchmarks against other methods trained at the same scale. Our work is motivated by the observation that multiple contrastive objectives maximize a lower-bound on
the mutual information between two or more views of the same datum [55]. CLIP particularly maximizes the mutual information between the image and its caption by using a mutual information lower bound based on InfoNCE [37]. The InfoNCE bound has seen wide adoption due to its favorable properties such as stability and low variance. However, the bound is theoretically loose in cases when the true mutual information is larger than \( \log K \) where \( (K - 1) \) is the number of negative samples used for training. The negative pairs can be randomly sampled but usually a large amount of negative pairs are required to have a good estimate of the mutual information between the two input streams, and hence the need for rather large batch sizes [2, 9] or memory-banks [8, 18, 47]. We instead adopt a lower bound based on Jensen Shannon Divergence to maximize the mutual information [20, 36], thus requiring no more than one negative example pair for each positive example pair. This reduces the number of negative examples in a training batch to \( O(n) \), where \( n \) is the batch size. In contrast, CLIP uses \( O(n^2) \) negative example pairs per batch. Figure 5 illustrates this difference.

We implement this strategy and demonstrate thoroughly the efficacy of CLIP-Lite through experiments on several tasks and datasets at various scales. Our method demonstrates impressive data efficiency and is able to outperform CLIP trained on the entire COCO-Captions dataset while only training on 25% of the same dataset. We also demonstrate that CLIP-Lite can be used as a good source of pre-trained features by showing good generalization on Pascal VOC and Imagenet classification. We also show that the visual feature backbone of CLIP-Lite can be finetuned in the iNaturalist dataset to match top performances on this benchmark with caption supervision pretraining. Furthermore, we show that CLIP-Lite leads to good visual features for image retrieval compared to regular CLIP trained on COCO Captions. CLIP-Lite can also be used for removing concepts from visual representations. Our work extends and complements the work using contrastive learning, especially addressing the computational requirements of the original CLIP model in terms of memory overhead through minimizing the number of negative sample image-text pairs required during training and shows its effectiveness in smaller data regimes including for zero-shot learning on CIFAR-10, image-text retrieval and object localization.

2. Related Work

Our work is related to several strands of research on visual pretraining without full-supervision.

Vision-Language Pretraining. Research on learning visual representations by using textual labels or annotations has a long history. In [39], the authors learn data-efficient image representation using manifold learning in the weight space of classifiers trained to predict token in image captions. Following this work, [23] used convolutional neural networks to predict words in image captions to learn image representations. This approach was later extended in [28] to learning by predicting phrase n-grams, which demonstrates impressive zero-shot performance on downstream classification tasks. Recently, VirTex [10] used proxy language modeling tasks, such as image-captioning to train a visual encoder and a transformer based language decoder which generates captions. Concurrently, ICMLM [42] demonstrated a similar masked language modeling approach but relied on pretrained textual encoders for generating textual features. In [45], video representations are learned using paired textual metadata, however the method does not extend to visual pretraining for images.

In general, these methods distill the rich semantic information from a caption into the visual representation by learning to predict each token in the caption given the corresponding image. More recent work, such as CLIP [40], has shown that a simpler contrastive objective for aligning image and caption pairs is also able to learn a powerful visual representation. Our work extends CLIP using a more information-efficient approach.

Contrastive Representation Learning and Mutual Information Estimation. We observe that, as demonstrated in [55], all such contrastive frameworks essentially learn by maximizing the mutual information (MI) between different views of a given data point. For images, this is achieved by maximizing the MI between different augmentations of the data in SimCLR [2, 7]. While for sequential data such as conversational text, consecutive utterances can be considered as different views [44]. Similarly, several other contrastive frameworks have been proposed that learn representations in domains such as images [6, 16], text [35, 44], graphs [52], and videos [22].

We note that the value of mutual information is extremely challenging to estimate, especially for high-dimensional continuous representation used in deep learning. To this end, various tractable lower-bounds on mutual information are used for optimization. Recently, MINE [3] proposed a general-purpose parameterized neural estimator of mutual information. It uses a Donsker-Varadhan [12] representation of KL-divergence as the lower-bound on mutual information. MINE [3] used a neural network critic to distinguish positive and negative pairs of samples. Another popular bound on mutual information that has seen wide adoption due to its low variance is the InfoNCE [37] bound. In [20], the infoNCE bound on the mutual information is used for unsupervised representation learning. While it is used by several other methods for self-supervised [7] representation learning for images. The capacity of the bound is limited by the number of contrastive samples used [34]. Additionally, InfoNCE can underestimate large amounts of
true MI which is generally the case with high-dimensional representations of natural images. To this end, DeepInfoMax [20] proposed using a lower-bound on mutual information that is based on the Jensen-Shannon Divergence (JSD) instead of the traditional KL-divergence (KLD). The authors show that the JSD based lower bound is stable, differentiable, and can be optimized with just one negative sample. Inspired by this, we extend the use of this bound for vision-language pretraining setup.

3. CLIP-Lite

In this section, we describe our pretraining framework (Figure 2) for visual representation learning. Given a dataset of image-caption pairs, our goal is to train an image encoder and a text encoder such that representations learned from the visual and the textual streams share maximum information. Consider an image encoder network, \( f_i \) with parameters \( \theta_i \) and a textual encoder, \( f_t \) with parameters \( \theta_t \). Let \( (x_i, t_i) \) be a sampled image-caption pair from the dataset and \( f_i(x_i) \) and \( f_t(x_i) \) denote the representations extracted from the networks. Based on the information bottleneck principle [49], the maximum mutual information (MI) predictive coding framework [20, 34, 37] aims to learn representations that maximize the MI between inputs and representations. In recent years, several methods [2, 7, 18] have used this principle to maximize MI between representations extracted from multiple views of a shared context. In the case of visual self-supervised learning, this is achieved by creating two independently-augmented copies of the same input and maximizing the MI between the respective features produced by an encoder. This framework can be extended further by considering an image \( x_i \) and its caption \( t_i \) as distinct views of the same input. This setup is motivated by the observation that image captions contain rich semantic information about images, for instance, presence of objects, location of objects, their relative spatial configurations, etc. Distilling this information into our visual representation is useful for robust representation learning [40]. To this end, we formulate our objective as follows:

\[
\arg \max_{\theta_i, \theta_t} I(f_i(x_i), f_t(x_i)) \leq I(x_i; x_i),
\]

where the upper-bound is due to the data processing inequality between visual and textual streams.

3.1. Mutual Information Maximization

For given random variables \( y \) and \( z \), their mutual information is defined as a Kullback-Leibler (KL) divergence between their joint distribution \( p(y, z) \) and the product of their marginal distributions, \( p(y)p(z) \) as,

\[
I(y; z) = D_{KL}(p(y, z) \| p(y)p(z)).
\]  

However, mutual information is notoriously hard to estimate for high-dimensional continuous variables, especially when the distributions \( p(y, z) \), \( p(x) \), or \( p(z) \) are not explicitly known. As a result, recent approaches use various tractable lower bounds on the mutual information which are differentiable and hence can be maximized with gradient-descent based optimization. For contrastive learning, the infoNCE [37] loss based on a Noise-Contrastive Estimation bound is commonly used [17]. This bound is relatively more stable and has been shown to work in a wide variety of tasks [2, 7, 8] including CLIP [40] which, similar to our method, aims to learn visual representations from textual annotations. The infoNCE bound has seen wider adoption as it demonstrates lower variance compared to the Donsker-Varadhan [12] bound. However, both of these bounds require a large number of negative samples and as a result, recent methods either train with extremely large batch-sizes [7, 40] or an additional memory-bank of negative samples [8, 48].

Unlike these works, we estimate mutual information using a Jensen-Shannon Divergence (JSD) bound, similar to formulations used for generative modeling [36] and source separation [5]. This bound on mutual information is derived by replacing the KL-divergence in equation 2 with the Jensen-Shannon divergence. Interestingly, this lower bound derived as such is stable, differentiable, monotonically related to the mutual information \( I(y; z) \), and most importantly, not dependent on the number of negative samples.

\[
I(Y; Z) \geq \hat{I}_{\omega}^{JSD}(Y; Z) := E_{P(Y, Z)}[-\log(1 + e^{-T \omega})] - E_{P(Y)}P(Z)\log(1 + e^{T \omega}),
\]
where $T_{\omega} : \mathcal{Y} \times \mathcal{Z} \rightarrow \mathbb{R}$ is the discriminator neural network with trainable parameters $\omega$ which are jointly optimized to distinguish between a paired-sample from a joint distribution (positive image-caption pair) and one pair from the product of marginals (negative image-caption pair). Therefore we are able to optimize our overall objective with just one negative sample as follows:

$$\left(\hat{\omega}, \hat{\theta}_i, \hat{\theta}_t\right) = \arg\max_{\omega, \theta_i, \theta_t} \hat{I}_{\omega}^{\text{JS-D}}(f_i(x_i), f_t(x_t))$$

where the visual encoder is a convolution neural network, and features are extracted from the pre-classification layer of the network. The textual encoder is parameterized by a neural network that takes the caption as a string of textual-tokens and generates a one-dimensional representation.

### 3.2. Mutual Information Discriminator

As described in section 3.1, our JSD-based lower-bound on mutual information relies on a discriminator function, $T_{\omega} : \mathcal{Y} \times \mathcal{Z} \rightarrow \mathbb{R}$, which distinguishes between samples extracted from the joint distribution, $P(Y, Z)$ i.e. a positive image-caption pair and the product of marginals, $P(Y)P(Z)$ i.e. a negative image-caption pair. This discriminator function can be modelled as an arbitrary neural network with parameters $\omega$ that can be jointly optimized with the encoders during training [3]. In this work, we use a projection and alignment based architecture similar to the one presented in Deep InfoMax [20].

Given a pair of input one-dimensional representations, both vectors are first projected using a projection module with two linear layers separated by a ReLU and a linear shortcut. A dot-product of these projections is then computed to get alignment scores. The projection function maps these representations to an aligned cross-modal latent space. Separate projection functions are used for image and text representations. Positive and negative pairs of image-text representations are passed through the discriminator to get respective scores which are then used to estimate and maximize mutual information using the objective in Eq. 3. This architecture, in addition to being simple and computationally inexpensive, also offers alignment of the representations into a common cross-modal latent space which uses cosine similarity as the distance metric.

### 4. Experiments

In this section, we describe the experiments that demonstrate the value of using textual captions for learning visual representations using CLIP-Lite. In our experiments, the CLIP-Lite architecture consists of ResNet-50 image encoder and the BERT-base textual encoder and is trained on the COCO Captions [9] dataset. We evaluate the robustness of our visual encoder through the following downstream tasks which use the visual encoder as (1) frozen feature extractor, or (2) weight initialization for finetuning.

#### 4.1. Architecture and Training Details

In all experiments, we use a standard ResNet-50 [19] that takes in a $224 \times 224$ image and generates 2048-dimensional features at the pre-logit layer. For textual encoding, we use a transformer [51] model initialized using the BERT-base [11] and use the output $[CLS]$ token as the text representation.

We use the COCO Captions dataset [9] which has 118K images with five captions each image. During training time we apply (1) random crop b/w 0.2 and 1.0, (2) color jitter, (3) random horizontal flip while interchanging the words ‘left’ and ‘right’ in the caption, (4) normalize using the ImageNet mean. We use SGD with momentum 0.9 [38, 46] and weight decay $10^{-4}$ wrapped in Lookahead [58] with $\alpha = 0.5$, and 5 steps. We perform distributed training across 8 GPUs with batch normalization [21] per GPU with an overall batch size of 1024 images for 250K iterations. We use linear learning rate warmup [15] for the first 10K iterations followed by cosine decay [33] to zero. Code implementation will be made public upon publication. Additionally, we train CLIP [40] on the COCO-dataset using an open-source implementation\(^1\) with the originally recommended [40] or implementation recommended training schedule that suit smaller datasets, reasonable batch-sizes, and compute resources. Specifically, we train using the Adam Optimizer [24] with decoupled weight decay regularization [33] for all weights except gains or biases. We train with a batch-size of 1024 and warm-up to an initial learning rate of $10^{-4}$ in 10K steps and decay to zero with the cosine schedule. We found that the performance slightly improves on elongated training therefore we train for 250K iterations, similar to ours. All other training details and hyper-parameters were kept the same as the original work [40].

#### 4.2. Transfer Learning with Frozen Backbone

In these experiments, we train linear models on frozen visual backbones pretrained using CLIP-Lite and compare with other pretraining methods on PASCAL VOC [13] and ImageNet-1k [41] classification problems.

**PASCAL VOC linear classification:** For this experiment, our setup is identical to VirTex [10]. We train on VOC07 trainval split (9K images, 20 classes) and report mAP on the test split. For classification, we train per-class SVMs on 2048-dimensional global average pooled features extracted from the last layer of our trained visual encoder. For each class, we train SVMs for cost values $C \in \{0.01, 0.1, 1, 10\}$ and select best $C$ by 3-fold cross-validation.

\(^1\)https://github.com/mlfoundations/open_clip
CLIP-Lite also performs better than supervised and self-performance is competitive with more complex vision-language backbone networks pretrained on the COCO Dataset. CLIP-Lite’s performance is comparable or better than supervised and self-supervised models trained on COCO images, without captions.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Method & \# images & Annotations & VOC07 & IN-1k \\
\hline
COCO-Sup. & 118K & labels & 86.2 & 46.4 \\
MoCo-COCO & 118K & self-sup. & 67.5 & 46.5 \\
ICMLM [42] & 118K & captions & 87.5 & 47.9 \\
VirTex [10] & 118K & captions & 88.7 & 53.8 \\
CLIP-COCO & 118K & captions & 72.8 & 33.2 \\
CLIP-Lite & 118K & captions & 88.2 & \textbf{55.3} \\
\hline
\end{tabular}
\caption{Frozen Backbone Results: On Pascal VOC07 and Imagenet-1k classification, CLIP-Lite outperforms baseline CLIP when evaluated using linear classifiers trained on top of frozen backbone networks pretrained on the COCO Dataset. CLIP-Lite’s performance is competitive with more complex vision-language models. CLIP-Lite also performs better than supervised and self-supervised models trained on COCO images, without captions.}
\end{table}

CLIP-Lite is comparable or better to image-only SSL learning models trained with images alone, even those trained with 5-10x more images. (IN-Sup. = ImageNet-supervised.)

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Method & \# images & Annotations & iNat 18 \\
\hline
Random Init & - & - & 61.4 \\
IN-sup & 1.28M & labels & 65.2 \\
IN-sup-50% & 640K & labels & 63.2 \\
IN-sup-10% & 128K & labels & 60.2 \\
MoCo-COCO & 118K & self-sup. & 60.5 \\
MoCo-IN & 1.28M & self-sup. & 63.2 \\
VirTex [10] & 118K & captions & 63.4 \\
CLIP-COCO & 118K & captions & 61.8 \\
CLIP-Lite & 118K & captions & 63.1 \\
\hline
\end{tabular}
\caption{Backbone Finetuning Results: When performing transfer learning using visual backbone finetuning, CLIP-Lite outperforms CLIP-COCO on the iNaturalist fine-grained visual classification problem, and performs comparably to VirTex. CLIP-Lite’s performance is comparable or superior to self-supervised and supervised learning models trained with images alone, even those trained with 5-10x more images. (IN-Sup. = ImageNet-supervised.)}
\end{table}

Data Efficiency: For this experiment, our setup is identical to VirTex [10]. We train on the ILSVRC 2012 train split and report top-1 accuracy on val split. We train a linear classifier (fully connected layer + softmax) on 2048-dimensional global average pooled features extracted from the last layer of the visual backbone. For training, we use a batch-size of 256 for 100 epochs. We use SGD with momentum 0.9 and weight decay 0. The learning rate schedule is decayed by 0.1 after 60 & 80 epochs with an initial LR of 30.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
# images & VOC07 & IN-1k \\
\hline
CLIP COCO-100% & 118K & 74.2 & 33.2 \\
CLIP-Lite COCO-25% & 29.5K & 77.7 & 45.1 \pm 11.9 \\
CLIP-Lite COCO-50% & 59K & 84.4 & 51.3 \pm 18.1 \\
CLIP-Lite COCO-75% & 88.5K & 86.8 & 53.2 \pm 20.0 \\
CLIP-Lite COCO-100% & 118K & 88.2 & 55.3 \pm 22.1 \\
\hline
\end{tabular}
\caption{Data Efficiency: CLIP-Lite is more data efficient than CLIP, as shown in this experiment where we pretrain on \{25, 50, 75, 100\}% of the COCO Captions dataset and evaluate the models on VOC and ImageNet classification tasks with a frozen backbone. CLIP-Lite trained with just 25% of COCO already surpasses CLIP trained on the whole dataset.}
\end{table}

Results: We compare CLIP-Lite to supervised, self-supervised and textually-supervised models in Table 7. CLIP-Lite significantly outperforms baseline CLIP when trained with the same amount of data on both tasks. When compared to other image-caption pretraining methods, CLIP-Lite performs competitively with VirTex [10] and outperforms ICMLM [42] which are both trained on a relatively complex language modeling tasks. In addition, different from them, our method also provides cross-modal alignment between textual and visual representations, which enables additional downstream tasks such as zero-shot retrieval. CLIP-Lite also outperforms a fully-supervised model trained with COCO image labels, showing that it learns a better visual representation from information-dense captions as compared to training with labels alone. Additional results in the supplement show that CLIP-Lite is comparable or better to image-only SSL learning models trained on ImageNet, even though it is trained on much fewer images, albeit with textual supervision.

\section*{4.3. Transfer Learning with Backbone Finetuning}

Next, we evaluate the performance of our visual backbone when the entire network is finetuned for the downstream task. For this purpose, we perform fine-grained classification on the iNaturalist 2018 [50] dataset, which contains images from 8,142 fine-grained categories, with a long-tailed distribution. We train with the ‘train2018’ split and evaluate in the ‘val2018’ split. We finetune pretrained ResNet-50 models with a linear layer, using SGD with momentum 0.9 and weight decay $10^{-4}$ for 100 epochs. Initial
| Method               | Flickr30k | COCO     | Flickr30k | COCO     |
|---------------------|-----------|----------|-----------|----------|
|                     | R@1      | R@5      | R@10     | R@1      | R@5      | R@10     | R@1      | R@5      | R@10     |
| Visual N-Grams [29] | 15.4      | 35.7     | 45.1      | 8.7      | 23.1     | 33.3     | 8.8      | 21.2     | 29.9     |
| CLIP-COCO           | 19.9      | 41.9     | 54.9      | 18.9     | 42.9     | 54.6     | 13.9     | 33.0     | 43.8     |
| CLIP-Lite           | **28.8**  | **55.8**  | **67.4**  | **26.0** | **54.6** | **68.0** | **23.1** | **51.1** | **62.9** |

Table 4. Retrieval Results: When performing image and text retrieval, CLIP-Lite substantially outperforms CLIP-COCO and the baseline Visual N-grams [29] approach. CLIP-Lite is superior when evaluated on the COCO test split, which is similar to the CLIP-Lite training set and on Flickr30K, generalizing to unseen images and text in a zero-shot manner.

**Results:** We summarize our results in Table 3. CLIP-Lite is competitive with supervised and self-supervised learning models trained with images alone. Its performance matches closely with a model trained with full-supervision on 50% of the ImageNet [26] dataset, equal to $5.4 \times$ the number of images as our pretraining dataset. Finally, CLIP-Lite obtains a 1.3% improvement over CLIP-COCO, while being competitive with VirTex.

4.4. Image-Text and Text-Image Retrieval

Our method is expected to produce optimal representations for the task of image-text retrieval as it train by aligning text and image representations. We evaluate the image-text retrieval capabilities of CLIP-Lite on the validation set of COCO and the test split of Flickr30k [56] datasets, following CLIP. We perform image-text and text-image retrieval by ranking image-text pairs by their alignment score, which is the dot product of the normalized representations in the shared latent space.

**Results:** Table 4 shows that CLIP-Lite substantially outperforms CLIP-COCO on all metrics for both text and image retrieval. The performance improvement is large both when evaluated on the COCO validation set, which is similar to the the COCO-Captions training split used for CLIP-Lite training; and when testing zero-shot on unseen text vocabulary and object categories of Flickr30K. Taken together, these results show that CLIP-Lite learns a superior representation for retrieval tasks as compared to CLIP, when trained on same amounts of data.

4.5. Zero-Shot Transfer

We use the cross-modal alignment capability of CLIP-Lite to perform zero-shot classification on an out-of-domain CIFAR10 [25] dataset. Our model generates a shared latent space where we can readily compute the alignment between given (image, text) pairs as the cosine similarity of their representations. Therefore, we use the names of the classes in the CIFAR10 dataset to generate a a textual description of each class label (class prompt). In this experiment, we use templates such as, “a photo of a {class name}” to generate such class prompts, following CLIP [40]. For a given image, we compute its alignment with each of the class prompts which are then normalized into a probability distribution via a softmax. The class with the highest probability is then chosen as the prediction.

**Results:** Our results for zero-shot transfer task on the CIFAR-10 dataset are compiled in Table 5. We test three different class prompt templates and compare our performance against the equivalently trained CLIP model on the COCO dataset. Given the zero-shot nature of the task, CLIP-Lite obtains satisfactory performance on CIFAR-10, outperforming CLIP trained with the same amount of data.

4.6. Evaluating Visual Grounding

Next, we evaluate the capability of CLIP-Lite to localize a region in the image that corresponds to a given textual description. We extend Grad-CAM [43] to image-text matching to obtain attention heatmaps. Specifically, we compute the dot-product of the visual and textual embedding and compute its gradients with respect to the last convolutional layer of the ResNet. We global average pool these gradients and perform a weighted sum with the last convolutional activations and clip the negative values to obtain Grad-CAM. We then use the areas highlighted by Grad-CAM to approximate a predicted bounding box. We evaluate this experiment on the RefCOCO+ [57] dataset.
Figure 3. Visual Grounding on RefCOCO+: CLIP-Lite is able to localize textual descriptions to relevant areas in the image, shown here through Grad-CAM visualization using the alignment score with the mentioned textual description. Top left: CLIP-Lite is able to localize the action phrases such as “bending over”. This demonstrates the value of learning from semantically rich textual captions.

We note that the images in the RefCOCO+ dataset are extracted from the training set of the COCO [9] dataset which our model is pretrained on. Therefore, we view this evaluation as an explorative study to establish that our model is focusing on the relevant areas of the image while computing the alignment score with the caption. RefCOCO+ results can be seen in the table to the right. CLIP-Lite significantly outperforms CLIP on all settings. Qualitative results in Figure 3 demonstrates that even though the network hasn’t been trained with any localization supervision, it is surprising good at localizing any given phrase in the image. For e.g., in Figure 3 bottom left, for the phrase “blue”, the network looks at all the blue regions in the player’s outfit. Interestingly, it is also able to localize abstract concepts such as “blurry player”.

4.7. Editing Concepts from Image Representations

One salient feature of CLIP-Lite, which other methods like VirTex [10] and ICMLM [42] lack, is that CLIP-Lite is able to generate a shared latent space that encodes both image and text modalities. In addition, it is able to cheaply compute cross-modal alignment. This enables us to find representations and subspaces associated with abstract concepts that are better expressed with language than with visual examples. Using this, we demonstrate a methodology to remove concepts from visual representations. For instance, it is hard to collect visual examples that demonstrate the concept of gender well. While it is relatively straightforward, if not exhaustive, to express this concept using language tokens. This allows us to identify the gender subspace in our shared embedding space and use the identified gender direction to remove variance along this direction to mute the concept of gender from image representations without changing the weights of the model. Please note that we use gender as an accessible example to demonstrate our concept deletion methodology. Removing gender from visual representations however, may or may not be ideal for practical scenarios.

Identifying the Concept Subspace: The first step of our approach is to isolate the direction in the embedding space that captures the maximum gender variance. For this purpose, we follow a strategy similar to Kusner et al. [27] that deals with debiasing word representations. For characterizing features across male and female genders, we use word pairs (man, woman), (son, daughter) that indicate opposite genders. Following this, consider a dataset \( \mathcal{D} = \{(w_m, w_f)\}_{i=1}^n \) where each entry \((w_m, w_f)\) is a tuple of opposite gendered words. Intuitively, every such tuple should contain words that have the same meaning if not for the target attribute. As we are dealing with sentence representations, to make the set \( \mathcal{D} \) more robust, we used the contextualization strategy presented in Liang et al. [31]. In this step, the predefined sets of gendered tokens in the set, \( \mathcal{D} \), are used to generate paired sentences which have the same meaning except for the gender attribute. We perform this contextualization by using simple sentence templates such as “I am a [word]” where [word] can be replaced with the word pairs in our dataset \( \mathcal{D} \) to give, for instance, (“I am a boy.”, “I am a girl.”). Hence, we obtain a contextualized bias attribute dataset \( \mathcal{S} = \{(s_m, s_f)\}_{i=1}^n \) where each entry is a tuple of semantically similar sentences with opposite genders. Now we extract the sentence representations for
Figure 4. Demonstrating Neutral Representations: Qualitative demonstration of our concept editing methodology. For each text prompt, top 10 images are retrieved from male and female buckets of the gendered COCO subset before (top row) and after (bottom row) gender deletion. We show that once the representations are gender-neutralized the gendered tokens become inconsequential and the image is only retrieved based on its remaining contents. Alignment score decreases from left to right for each set of queried images. Note that gender deletion is only performed on the image representations and the query text’s representation is used as it is.

Table 6. Removing Gender Subspace: We compute the mean alignment scores for the top 10 images queried using prompts that either contain male or female gendered tokens. The images are queried using gendered and neutralized representations. We observe that after gender-deletion the alignment score for images with men and women converge to similar values.

| Images with Men | Images with Women |
|-----------------|------------------|
| Male queries    | Female queries   |
| ---             | ---              |
| gendered        | gendered         |
| neutral         | neutral          |
| delta           | delta            |
| 0.085           | 0.042            |
| 0.069           | 0.068            |
| +0.016          | -0.026           |
| 0.057           | 0.089            |
| 0.067           | 0.062            |
| -0.010          | +0.027           |

Analysis: To evaluate concept editing, we use the gendered subset of COCO-Captions [54, 59] for studying bias. The gender labels for images in the COCO dataset are derived from the captions. We obtain a subset from the COCO dataset with 16225 images with men and 6601 images with women. We use 10 male and 10 female held-out sentences from the set S and use them as prompts for this study. For each gendered prompt, we query the top 10 images independently from the male and the female image sets using both biased and debiased representations to compute alignment with the prompt. The mean alignment scores are then computed for each of these sets given the prompt. Results summarized in Table 6 show that the alignment scores roughly equalize for members of the two groups after removing the variance along the gender direction from the visual representations which indicates the invariance of the visual representations to gendered tokens.

5. Conclusion

We introduced CLIP-Lite an image-text pretrained model using contrastive learning that leverages a different objective than the CLIP model that allows for it to be more data efficient. CLIP-Lite relies on less negative image-caption pairs and shows superior results on lower data regimes while still demonstrating some of the most remarkable capabilities of the original CLIP model such as transferrable features and some of its zero-shot capabilities. Finally, we consider that our method due to its efficiency will also enable the training of higher quality image-text models at a larger scale than currently possible. Please refer to the supplement for a detailed discussion on limitations and potential impact of our approach.
References

[1] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In Proceedings of the IEEE international conference on computer vision, pages 2425–2433, 2015. 1

[2] Philip Bachman, R Devon Hjelm, and William Buchwalter. Learning representations by maximizing mutual information across views. arXiv preprint arXiv:1906.00910, 2019. 2, 3

[3] Mohamed Ishmael Belghazi, Aristide Baratin, Sai Rajeshwar, Sherjil Ozair, Yoshua Bengio, Aaron Courville, and DeVon Hjelm. Mutual information neural estimation. In International Conference on Machine Learning, pages 531–540. PMLR, 2018. 2, 4

[4] Tolga Bolukbasi, Kai-Wei Chang, James Y Zou, Venkatesh Saligrama, and Adam T Kalai. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. Advances in neural information processing systems, 29:4349–4357, 2016. 8

[5] Philemon Brakel and Yoshua Bengio. Learning independent features with adversarial nets for non-linear icl. arXiv preprint arXiv:1710.05050, 2017. 3

[6] Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, and Armand Joulin. Unsupervised learning of visual features by contrasting cluster assignments. arXiv preprint arXiv:2006.09882, 2020. 2, 12

[7] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In International conference on machine learning, pages 1597–1607. PMLR, 2020. 2, 3

[8] Xinlei Chen, Haoqi Fan, Ross Girshick, and Kaiming He. Improved baselines with momentum contrastive learning. arXiv preprint arXiv:2003.04297, 2020. 2, 3

[9] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco captions: Data collection and evaluation server. arXiv preprint arXiv:1504.00325, 2015. 2, 4, 7, 12

[10] Karan Desai and Justin Johnson. Virtex: Learning visual representations from textual annotations. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 11162–11173, 2021. 1, 2, 4, 5, 7, 12

[11] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018. 4, 13

[12] Monroe D Donsker and SR Srinivasa Varadhan. Asymptotic evaluation of certain markov process expectations for large time. iv. Communications on Pure and Applied Mathematics, 36(2):183–212, 1983. 2, 3

[13] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. International journal of computer vision, 88(2):303–338, 2010. 4, 13

[14] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 580–587, 2014. 1

[15] Priya Goyal, Dhruv Mahajan, Abhinav Gupta, and Ishan Misra. Scaling and benchmarking self-supervised visual representation learning. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 6391–6400, 2019. 4

[16] Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre H Richemond, Elena Buchatskaya, Carl Dörsch, Bernardo Avila Pires, Zhaohan Daniel Guo, Mohammad Gheshlaghi Azar, et al. Bootstrap your own latent: A new approach to self-supervised learning. arXiv preprint arXiv:2006.07733, 2020. 2

[17] Michael Gutmann and Aapo Hyvärinen. Noise-contrastive estimation: A new estimation principle for unnormalized statistical models. In Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics, pages 297–304. JMLR Workshop and Conference Proceedings, 2010. 3

[18] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 9729–9738, 2020. 2, 3, 12

[19] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016. 4

[20] R Devon Hjelm, Alex Fedorov, Samuel Lavoie-Marchildon, Karan Grewal, Phil Bachman, Adam Trischler, and Yoshua Bengio. Learning deep representations by mutual information estimation and maximization. arXiv preprint arXiv:1808.06670, 2018. 2, 3, 4

[21] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In International conference on machine learning, pages 448–456. PMLR, 2015. 4

[22] Allan Jabri, Andrew Owens, and Alexei A Efros. Space-time correspondence as a contrastive random walk. arXiv preprint arXiv:2006.14613, 2020. 2

[23] Armand Joulin, Laurens Van Der Maaten, Allan Jabri, and Nicolas Vasilache. Learning visual features from large weakly supervised data. In European Conference on Computer Vision, pages 67–84. Springer, 2016. 2

[24] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980, 2014. 4

[25] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009. 6

[26] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25:1097–1105, 2012. 6

[27] Matt J Kusner, Joshua R Loftus, Chris Russell, and Ricardo Silva. Counterfactual fairness. arXiv preprint arXiv:1703.06856, 2017. 7

[28] Jimmy Lei Ba, Kevin Swersky, Sanja Fidler, et al. Predicting deep zero-shot convolutional neural networks using textual.
descriptions. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 4247–4255, 2015.

[29] Ang Li, Allan Jabri, Armand Joulin, and Laurens van der Maaten. Learning visual n-grams from web data. *Proceedings of the IEEE International Conference on Computer Vision*, pages 4183–4192, 2017.

[30] Junnan Li, Pan Zhou, Caiming Xiong, and Steven CH Hoi. Prototypical contrastive learning of unsupervised representations. *arXiv preprint arXiv:2005.04966*, 2020.

[31] Paul Pu Liang, Irene Mengze Li, Emily Zheng, Yao Chong Lim, Ruslan Salakhutdinov, and Louis-Philippe Morency. Towards debiasing sentence representations. *arXiv preprint arXiv:2007.08100*, 2020.

[32] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3431–3440, 2015.

[33] Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. *arXiv preprint arXiv:1608.03983*, 2016.

[34] David McAllester and Karl Stratos. Formal limitations on the measurement of mutual information. In *International Conference on Artificial Intelligence and Statistics*, pages 875–884. PMLR, 2020.

[35] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.

[36] Sebastian Nowozin, Botond Cseke, and Ryota Tomioka. f-gan: Training generative neural samplers using variational divergence minimization. In *Proceedings of the 30th International Conference on Neural Information Processing Systems*, pages 271–279, 2016.

[37] Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*, 2018.

[38] Boris T Polyak. Some methods of speeding up the convergence of iteration methods. *Ussr computational mathematics and mathematical physics*, 4(5):1–17, 1964.

[39] Ariadna Quattoni, Michael Collins, and Trevor Darrell. Learning visual representations using images with captions. In *2007 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–8. IEEE, 2007.

[40] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. *arXiv preprint arXiv:2103.00020*, 2021.

[41] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. *International journal of computer vision*, 115(3):211–252, 2015.

[42] Mert Bulent Sariyildiz, Julien Perez, and Diane Larlus. Learning visual representations with caption annotations. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part VIII*, pages 153–170. Springer, 2020.

[43] Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE international conference on computer vision*, pages 618–626, 2017.

[44] Karl Stratos. Mutual information maximization for simple and accurate part-of-speech induction. *arXiv preprint arXiv:1804.07849*, 2018.

[45] Jonathan C Stroud, Zhihao Lu, Chen Sun, Jia Deng, Rahul Sukthankar, Cordelia Schmid, and David A Ross. Learning video representations from textual web supervision. *arXiv preprint arXiv:2007.14937*, 2020.

[46] Ilya Sutskever, James Martens, George Dahl, and Geoffrey Hinton. On the importance of initialization and momentum in deep learning. In *International conference on machine learning*, pages 1139–1147. PMLR, 2013.

[47] Yonglong Tian, Dilip Krishnan, and Phillip Isola. Contrastive representation distillation. *arXiv preprint arXiv:1910.10699*, 2019.

[48] Yonglong Tian, Chen Sun, Ben Poole, Dilip Krishnan, Cordelia Schmid, and Phillip Isola. What makes for good views for contrastive learning? *arXiv preprint arXiv:2005.10243*, 2020.

[49] Naftuli Tishby and Noga Zaslavsky. Deep learning and the information bottleneck principle. In *2015 IEEE Information Theory Workshop (ITW)*, pages 1–5. IEEE, 2015.

[50] Grant Van Horn, Oisin Mac Aodha, Yang Song, Yin Cui, Chen Sun, Alex Shepard, Hartwig Adam, Pietro Perona, and Serge Belongie. The inaturalist species classification and detection task. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 8769–8778, 2018.

[51] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008, 2017.

[52] Petar Veličković, William Fedus, William L Hamilton, Pietro Liò, Yoshua Bengio, and R Devon Hjelm. Deep graph infomax. *arXiv preprint arXiv:1809.10341*, 2018.

[53] Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. Show and tell: A neural image caption generator. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3156–3164, 2015.

[54] Tianlu Wang, Jieyu Zhao, Mark Yatskar, Kai-Wei Chang, and Vicente Ordonez. Balanced datasets are not enough: Estimating and mitigating gender bias in deep image representations. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5310–5319, 2019.

[55] Mike Wu, Chengxu Zhuang, Milan Mosse, Daniel Yamins, and Noah Goodman. On mutual information in contrastive learning for visual representations. *arXiv preprint arXiv:2005.13149*, 2020.

[56] Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. *Transactions of the Association for Computational Linguistics*, 2:67–78, 2014.
[57] Licheng Yu, Patrick Poirson, Shan Yang, Alexander C Berg, and Tamara L Berg. Modeling context in referring expressions. In European Conference on Computer Vision, pages 69–85. Springer, 2016.

[58] Michael R Zhang, James Lucas, Geoffrey Hinton, and Jimmy Ba. Lookahead optimizer: k steps forward, 1 step back. arXiv preprint arXiv:1907.08610, 2019.

[59] Jieyu Zhao, Tianlu Wang, Mark Yatskar, Vicente Ordonez, and Kai-Wei Chang. Men also like shopping: Reducing gender bias amplification using corpus-level constraints. arXiv preprint arXiv:1707.09457, 2017.

[60] Yuke Zhu, Oliver Groth, Michael Bernstein, and Li Fei-Fei. Visual7w: Grounded question answering in images. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4995–5004, 2016.
A. Appendix

This appendix is organized as follows:

- **A.1.** Discussion on Limitations and Broader Impacts
- **A.2.** Comparison with Self-Supervised and other pre-training methods
- **A.3.** Ablations on (1) batch sizes, (2) visual encoders, (3) textual encoders

### A.1. Limitations and Broader Impacts

CLIP-Lite pretrains the visual encoder by maximizing the mutual information between images and their captions. We observe that language supervision provides rich semantic density which can be distilled into visual representations. The visual encoder is encouraged to learn visual representations that encode maximum information from captions. As such, the visual encoder is only aware of concepts and objects that human-annotators have mentioned in the captions. Therefore the visual encoder lags behind task-specific models that are trained specifically for a given fine-grained task. For instance, visual encoders trained with CLIP-Lite struggle with relatively contextual downstream tasks that involve reading text or counting number of objects in an image.

In this work, we train CLIP-Lite on the COCO-Captions [9] dataset which has high-quality curated captions for images. However, when trained on larger datasets with text paired with images from the internet, the textual captions can be significantly unfiltered and noisy. Our method essentially learns by aligning the caption and text representations. Therefore, the model is susceptible learning harmful biases that are represented in the captions. Our method demonstrates impressive zero-shot retrieval or search performance. For instance, it can query relevant images or text in a database given the other. Hence, deployment of visual backbones trained with CLIP-Lite and other pretraining methods which use natural language supervision need to be analyzed specifically for such biases. In this work, we present in the main text an approach to edit concepts from visual representations using the shared vision-language latent space learnt by our method. For instance, we demonstrate this capability by editing visual representations such that they are invariant to gendered tokens in language. However, further explorations are required to develop this concept editing mechanism further.

### A.2. Comparison with SSL Pretraining Methods

In this section, we evaluate the performance of our method against other pre-training frameworks and image-only SSL methods. We observe that CLIP-Lite is comparable or better to image-only SSL learning models trained on downstream ImageNet classification with a frozen ResNet-50 backbone, even though our method is trained on much fewer images, albeit with textual supervision.

![Figure 5. CLIP-Lite: Pseudo code for our pretraining framework.](image)

| Method          | # images | Annotations | VOC07 | IN-1k |
|-----------------|----------|-------------|-------|-------|
| COCO-Sup.       | 118K     | labels      | 86.2  | 46.4  |
| IN-Sup.         | 1.28M    | labels      | 87.6  | 75.6  |
| MoCo-COCO       | 118K     | self-sup.   | 67.5  | 46.5  |
| MoCo-IN v1 [18] | 1.28M    | self-sup.   | 79.4  | 60.8  |
| PCL v1 [30]     | 1.28M    | self-sup.   | 83.1  | 61.5  |
| SwAV (200 ep.)  | 1.28M    | self-sup.   | 87.9  | 72.7  |
| ICMLM [42]      | 118K     | captions    | 87.5  | 47.9  |
| VirTex [10]     | 118K     | captions    | 88.7  | 53.8  |
| CLIP-COCO       | 118K     | captions    | 72.8  | 33.2  |
| CLIP-Lite       | 118K     | captions    | 88.2  | 55.3  |

Table 7. CLIP-Lite outperforms CLIP-COCO on both VOC and ImageNet classification tasks, and performs comparably to VirTex. CLIP-Lite’s performance is comparable or superior to both supervised and self-supervised learning models trained with images alone, even those trained with 10x more images. (IN-Sup. = ImageNet-supervised.)

| Batch Size | VOC07 |
|------------|-------|
| 64         | 74.7  |
| 128        | 81.3  |
| 256        | 84.9  |
| 512        | 87.5  |
| 1024       | 87.9  |

Table 8. Batch size Ablations: We show the performance of a ResNet-50 trained with CLIP-Lite using varying batch-sizes. We observe that the performance drops marginally with the batch size 512. Additionally, we can see that the model is able to converge fairly well with the significantly lower batch size of 64.
A.3. Ablations

**Batch-size Ablations:** A salient feature of our pre-training framework is that we use a lower-bound on the mutual information that can be optimized with only one negative sample. This allows us to use much smaller batch-sizes compared to the original CLIP [40] model. In this section, we evaluate the PASCAL VOC classification performance of the visual backbones trained with batch sizes 64, 128, 256, 512 and 1024. These ablations are performed with a 2-layered BERT model as the text-encoder and a ResNet-50 as the image encoder for 200K iterations.

**Visual Encoder Ablations:** In this section, we compare the performance of our pretraining method using a ResNet-18, ResNet-50, and ResNet-101 backbones using the downstream PASCAL VOC classification task. These ablations are performed with a 2-layered BERT model as the text-encoder with a batch-size of 512 for 200K iterations.

| Visual Backbone | VOC'07 |
|-----------------|--------|
| ResNet-18       | 83.8   |
| ResNet-50       | 87.5   |
| ResNet-101      | 87.8   |

Table 9. **Visual Encoder Ablations:** We show the performance of CLIP-Lite using 3 visual backbones of varying sizes.

**Text Encoder Ablations:** In this section, we compare the downstream PASCAL VOC [13] classification performance of a ResNet-50 visual backbone pretrained using a text encoder transformer with varying capacities. We train 4 transformer variants, (1) pre-trained BERT\textsubscript{base} [11], (2) 2-layered, (3) 4-layered, (4) 6-layered, and a (5) 12-layered BERT-like transformer. These ablations are performed with a ResNet-50 as the image encoder with a batch-size of 512 for 200K iterations.

| Text Encoder  | VOC'07 |
|---------------|--------|
| BERT\textsubscript{base} init. | 88.1   |
| 2-layers      | 87.5   |
| 4-layers      | 87.6   |
| 6-layers      | 87.6   |
| 12-layers     | 87.9   |

Table 10. **Text Encoder Ablations:** We show the performance of a ResNet-50 trained with CLIP-Lite using different text encoders. We observe that the performance drops marginally when training from scratch. Additionally, we also see that using a transformer with 2-layers works almost as well as a 12-layered transformer when trained from scratch.