Scaling (Down) CLIP: A Comprehensive Analysis of Data, Architecture, and Training Strategies

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Abstract

This paper investigates the performance of the Contrastive Language-Image Pre-training (CLIP) method when scaled down to limited computation budgets. We explore CLIP from three perspectives: data, architecture, and training strategies. With regards to data, we demonstrate the significance of high-quality training data and show that a smaller dataset of high-quality data can outperform a larger dataset with lower quality. We also examine how model performance varies with different dataset sizes, suggesting that smaller ViT models are better suited for smaller numbers of sample data, while larger models perform better on larger datasets with fixed compute. Additionally, we provide guidance on when to choose a CNN-based architecture or a ViT-based architecture for CLIP training. Moreover, we compare four CLIP training strategies - SLIP, FLIP, CLIP, and CLIP+Data Augmentation - and show that the choice of training strategy depends on the available compute resources. Our analysis reveals that CLIP+Data Augmentation can achieve comparable performance to CLIP using only half of the training data. This work provides practical insights into how to effectively train and deploy CLIP models, making them more accessible and affordable for practical use in various applications.

1 Introduction

In recent years, there has been a surge of interest in image-and-language representation learning (Radford et al., 2021; Jia et al., 2021; Pham et al., 2021; Ramesh et al., 2022), which aims to capture the rich and complex interplay between visual and textual information. One of the most promising approaches in this area is the Contrastive Language-Image Pre-Training (CLIP) framework (Radford et al., 2021; Jia et al., 2021), which leverages large-scale text and image data to learn a unified representation space for both modalities. CLIP has achieved state-of-the-art performance on a range of downstream tasks and has been shown to generalize well to out-of-distribution data (Chen et al., 2019; Jia et al., 2021; Miller et al., 2021; Taori et al., 2020; Nguyen et al., 2022; Gontijo-Lopes et al., 2021).

While previous studies on scaling Contrastive Language-Image Pre-Training (CLIP), such as Li et al. (2022); Cherti et al. (2022); Radford et al. (2021), have primarily focused on large-computation scenarios, our work aims to explore the performance of CLIP under resource constraints. We present a comprehensive study of scaling down CLIP from three perspectives: data, architecture, and training strategies. Specifically, we investigate the effect of using different training data sizes, compare the performance of various architectures at different computation budgets, and evaluate the effectiveness of different pre-training strategies. Our experiments are conducted on a large image-and-language dataset, WebLI (Chen et al., 2022), which contains over 3.4 billion image-text pairs in English. Particularly, we set a computation limit for most of our experiments, and the total number of sampled data for most experiments is **at most 3.4B**.

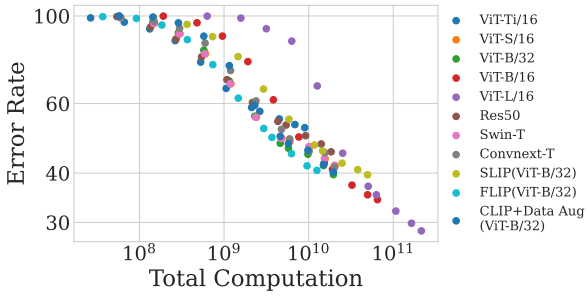
Our work makes contributions to the understanding and optimization of CLIP models by bridging gaps in previous research and providing new insights into scaling down CLIP. Regarding data, we train datasets with various sizes for multiple epochs to explore if the trends in performance on ImageNet variants always align with performances on ImageNet. We also emphasize the importance of data quality and demonstrate that a smaller set of high-quality data can outperform larger datasets. We find that using only the top 40%

filtered data can achieve better performance than using the entire dataset, and we investigate how model performance changes with increasing dataset sizes. Our results provide guidance on how to select training data for CLIP models, a critical issue for practical applications.

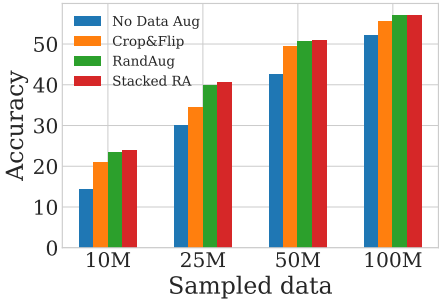
Concerning architecture, we compare multiple architectures under various dataset sizes. We investigate how to choose size of the vision encoder depending on the dataset size and compute budget. We show that the a larger ViT (Dosovitskiy et al., 2020) is not always better. We also demonstrate the importance of selecting between CNN (He et al., 2016) and ViT architectures for CLIP training. Although previous studies have shown that ViT-based CLIP has better performance than CNN-based CLIP models, we find that when the number of sampled data is small, CNNs perform better.

Finally, we compare four training strategies: SLIP (Mu et al., 2021), FLIP (Li et al., 2022), CLIP, and CLIP+Data Augmentation. We show that SLIP Mu et al. (2021) is not always the best choice compared to CLIP and FLIP. When the size of the training set is small, SLIP performs better than CLIP. However, as the training data size increases, SLIP has similar performance to CLIP but incurs twice the computational cost. Our results provide insights into the trade-offs between computational cost and performance in CLIP training, a critical issue for practical applications.

Overall, our work provides insights into the design and optimization of CLIP models, with practical implications for a wide range of downstream tasks. We hope that our findings will inspire further research and development of CLIP models, contributing to the growing field of multimodal AI.



(a) Total computation V.S. Zero-Shot ImageNet Error Rate



(b) Comparison between various data augmentation for CLIP

Figure 1: **Training a High-Quality CLIP Model:** This figure highlights the main contributions of our work. In Figure 1(a), we demonstrate the relationship between different models, strategies, and error rates on the ImageNet dataset. The total computation is computed by GFLOPs per sample times the number sampled data. Additionally, in Figure 1(b), we illustrate how data augmentation methods improve the zero-shot performance of various datasets.

2 Related Work

Contrastive Language-Image Pre-Training: In recent years, the field of natural language processing (NLP) has made significant strides in pre-training language models on large amounts of text data (Peters et al., 2018; Devlin et al., 2019; Radford et al., 2018). Concurrently, computer vision has witnessed a surge in pre-training convolutional neural networks (CNNs) on large-scale image datasets (He et al., 2016; Huang et al., 2017; Simonyan & Zisserman, 2014). The CLIP model (Radford et al., 2021) is introduced as a joint pre-training framework for image and text representations. It utilizes a contrastive loss function to learn a shared embedding space between images and their corresponding textual descriptions. CLIP has demonstrated remarkable zero-shot performance on various visual classification tasks, achieving accuracy levels comparable to those obtained by supervised learning methods.

Recently, LiT (Zhai et al., 2021) has been proposed as an extension to CLIP. LiT introduces locked-image tuning, which adopts a pre-trained visual encoder and updates only the text model. As a result, LiT can

attain better zero-shot performances more efficiently. The success of CLIP has also inspired the work of SLIP (Mu et al., 2021), which combines self-supervised learning with CLIP to enhance the visual encoder.

Scaling Language-Image Pre-training: In recent years, considerable effort has been devoted to enhancing the efficiency and scalability of the Contrastive Language-Image Pre-training (CLIP) method. To improve scalability, Li et al. (2022) have proposed a method called FLIP, which masks half or more patches of the training images to reduce computation by 2x and allow for the use of larger batch sizes, while maintaining the performance of the original CLIP models. In a similar vein, Cherti et al. (2022) have provided further insights into the scaling laws of CLIP models, revealing that the training distribution plays a pivotal role in scaling laws, as evidenced by the different scaling behaviors exhibited by OpenAI and OpenCLIP (Ilharco et al., 2021) models, despite having identical model architectures and similar training procedures. Kumar et al. (2022) reported that while the ViT models improve in most metrics when being scaled up, their perceptual similarity metrics tend to detoriate with scale.

However, previous research on scaling CLIP models has predominantly focused on training with significant computational resources, often starting from a ViT large model and training on massive datasets over multiple epochs. For example, the largest number of sampled data in Cherti et al. (2022) is 34 billion. Less attention has been paid to the performance of CLIP models with smaller training datasets. Therefore, in this study, we investigate the effects of training dataset size on CLIP model scalability, ranging from smaller to larger datasets. Our work contributes to a deeper understanding of the factors that influence the performance of CLIP models and has practical implications for the design of large-scale visual-semantic models.

3 Methods

Training Pipeline We adopt the same training pipeline as CLIP (Radford et al., 2021), which employs a contrastive loss to train both the vision encoder and text encoder from scratch. The contrastive loss encourages the vision and text encoders to map corresponding image-text pairs to similar feature representations in a shared embedding space. Specifically, the contrastive loss minimizes the distance between the representations of positive pairs (i.e., image-text pairs that belong together) while maximizing the distance between the representations of negative pairs (i.e., image-text pairs that do not belong together).

Dataset and Data Pre-processing We conduct our experiments on WebLI (Chen et al., 2022), a large image-and-language dataset built from the public web, containing over 10 billion image-text pairs from more than 100 languages. We specifically focus on pairs in the English language, resulting in a dataset of approximately 3.4 billion pairs. In our experiments, we do not apply any data augmentation to images, except for resizing it to 224x224 and normalizing pixel values to the range of -1 to 1.

For text processing, we use a SentencePiece tokenizer with a vocabulary size of 32k. We set the token length to 16 and pad or truncate sentences to that length.

Hyper-parameters In our study, we ensure consistency with prior works and provide a fair comparison with other models by adopting the hyper-parameter settings used in a previous work by Zhai et al. (2021). We use Adafactor (Shazeer & Stern, 2018) as the optimizer with β_1 and β_2 set to 0.9 and 0.999, respectively, and set the batch size of all our models to 16k. To adjust the learning rate, we use a cosine learning scheduler with an initial rate of 0.001, and we set the weight decay to 0.0001. These hyper-parameters are carefully selected to ensure optimal performance of the CLIP model in our experiments.

Evaluation Metrics In the zero-shot transfer evaluation, our objective is to evaluate the model's capacity to generalize to new tasks without requiring any fine-tuning. To ensure a fair comparison with previous studies (Radford et al., 2021; Zhai et al., 2021), we adhere to identical evaluation settings. We employ the same prompts as those collected in these studies and preprocess the test images by resizing them and subsequently applying a central crop with a 0.875 aspect ratio to achieve the desired resolution.

In the linear probing evaluation, we freeze the vision encoder and initialize the fully connected layer with zeros to prevent overfitting. Subsequently, we perform a sweep of the learning rate to identify the optimal rate for different architectures. This evaluation offers valuable insights into the effective utilization of learned visual and textual representations for downstream tasks.

For the evaluation of retrieval performance on MSCOCO captions, we report the results based on the test set. For image-to-text retrieval metrics, we rank all text captions in descending order based on the cosine similarity of their embeddings with the image embedding. Subsequently, we report the proportion of images that achieved the Recall@1 performance. For text-to-image retrieval, we follow a similar approach but rank the images instead and calculate the average results across all texts.

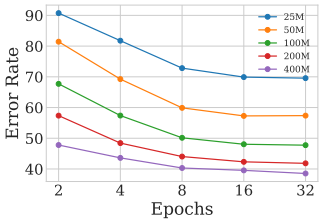
4 Data

Data Quantity To assess the influence of data quantity on performance, we conduct experiments using five datasets of varying sizes: 10M, 25M, 100M, 200M, and 400M. The 400M dataset is selected as the largest dataset in this section, aligning with the common practice in CLIP training and previous studies (Radford et al., 2021; Li et al., 2022). In this section, all CLIP models employ ViT-B/32 as the vision encoder and undergo training for epochs ranging from 2 to 32.

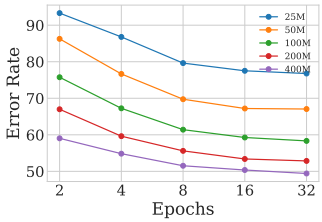
The findings regarding the zero-shot performance of CLIP models on ImageNet are depicted in Figure 2(a). The experiments reveal that the impact of training data quantity on model performance is contingent upon both the dataset size and the number of training epochs. In particular, we note that for smaller datasets such as the 25M dataset, increasing the training epochs does not yield significant performance improvements on ImageNet. However, for larger datasets like the 400M dataset, longer training epochs do result in enhanced performance on ImageNet.

Additionally, we evaluate the average zero-shot performance of our models on ImageNet variants, as illustrated in Figure 2(b). The average zero-shot performance across six ImageNet variants follows a similar trend to that observed on ImageNet: larger datasets and longer training result in improved performances. However, we observe that the performance trends on ImageNet variants do not consistently correspond to those on ImageNet for each specific variant, as shown in Figure 20 in Appendix. For instance, while increasing the number of epochs from 16 to 32 does not improve performance on ImageNet for the 25M dataset, it does lead to improved performance on ImageNet-A. Similarly, our models trained for 32 epochs exhibit significantly better performance on ImageNet-R and -Sketch compared to those trained for 16 epochs, despite no improvement on ImageNet.

Additionally, we conduct experiments on few-shot and retrieval scenarios, and the results pertaining to few-shot and retrieval performances across different dataset sizes are depicted in Figures 3 and 4. We observe that the few-shot performances demonstrate a similar trend to the zero-shot performances on ImageNet. However, we notice a slightly distinct trend in retrieval performances. Specifically, we note that when the number of epochs surpasses eight, there is minimal improvement in both image retrieval and text retrieval performances.



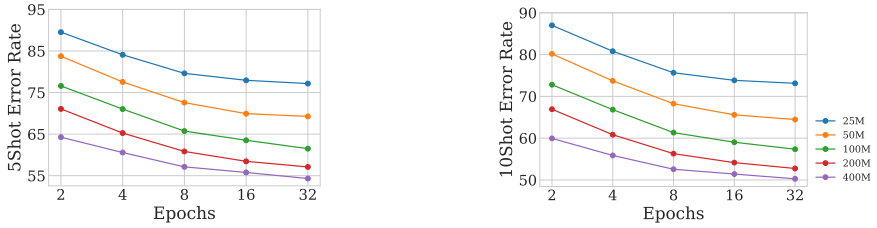
(a) Training Epochs V.S. ImageNet Accuracy



(b) Training Epochs V.S. Average ImageNet Variants Error Rate

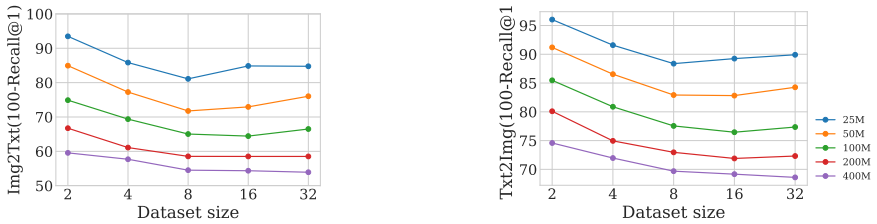
Figure 2: **Data Quantity:** Zero-Shot performances with the same dataset size across varied training epochs

Data Quality Previous studies on scaling CLIP (Cherti et al., 2022; Li et al., 2022) typically employ the entire dataset to train CLIP models. In our study, we compute the similarity between images and texts to create subsets from the 3.4B dataset, containing the top 20



(a) 5 Shot (b) 10 Shot

Figure 3: **Data Quantity:** Few-Shot Performances on ImageNet.

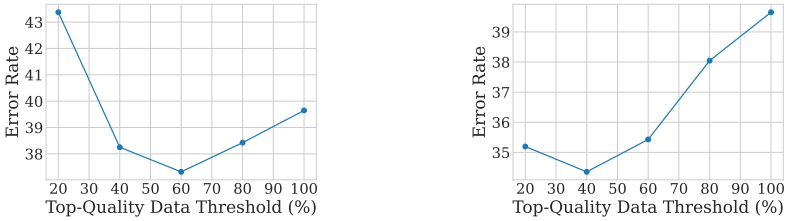


(a) Text Retrieval (b) Image Retrieval

Figure 4: **Data Quantity:** Retrieval Performances on MSCOCO (Chen et al., 2015).

To ensure a fair comparison among datasets of varying quality, we also train datasets with an equal number of sampled data points, and the results are presented in Figure 5(b). Our findings suggest that, on ImageNet, the Top40

We display the few-shot and retrieval performances on datasets with different qualities in Figure 6 and Figure 7, respectively. The results indicate that datasets with higher quality yield superior few-shot and retrieval performances, even with a relatively small number of sampled data points. Moreover, when the number of sampled data points is consistent, datasets of higher quality demonstrate superior 5-shot and 10-shot performances. Particularly, the top 80% dataset exhibits the most impressive retrieval performances.

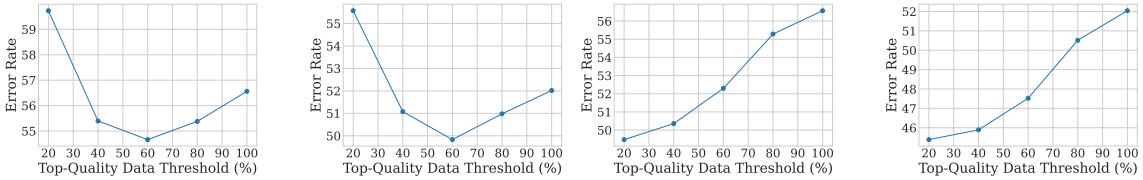


(a) (b)

Figure 5: **Data Quality:** Zero-Shot Performances on ImageNet. Figure 5(a) shows results trained for **one epoch**. Figure 5(b) shows results trained for **the same number of sampled data**. We use ViT-B/32 as the vision encoder and ViT-B as the text encoder.

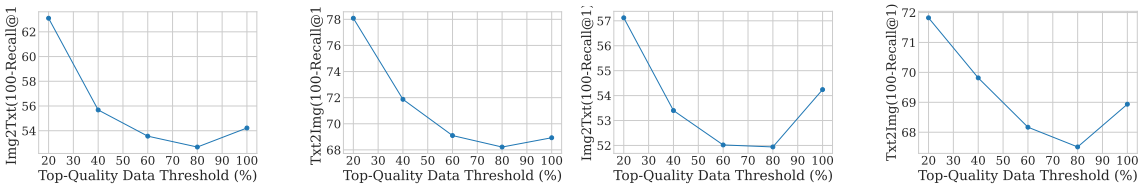
5 Variants of Vision Transformers

In this section, our aim is to investigate how the performance of different CLIP models, which vary in the size of their vision encoders, is affected by dataset size and the number of sampled data. To achieve this goal, we present the zero-shot performance(Jia et al., 2021; Radford et al., 2021) and linear probing results of



(a) 5 Shot-**one epoch** (b) 10 Shot-**one epoch** (c) 5 shot-**same iterations** (d) 10 shot-**same iterations**

Figure 6: **Data Quality:** Few-Shot Performances on ImageNet. We train dataset for various quality thresholds for **one epoch** in (a) and (b). We train dataset for various quality thresholds for **the same number of sampled data** in (c) and (d).



(a) Text Retrieval-**one epoch** (b) Image Retrieval-**one epoch** (c) Text Retrieval-**same iterations** (d) Image Retrieval-**same iterations**

Figure 7: **Data Quality:** Retrieval Performances on MSCOCO. We train dataset for various quality thresholds for **one epoch** in (a) and (b). We train dataset for various quality thresholds for **the same number of sampled data** in (c) and (d)

these models, providing a more comprehensive understanding of the impact of dataset size and the number of data samples on CLIP's performance.

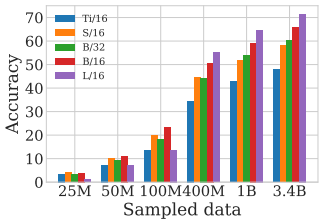
To investigate the effect of vision encoders on CLIP's performance, we fixed the size of text transformers as vit-base and experimented with various vision encoders, including ViT-Ti/16, S/16, B/32, B/16, and L/16(Dosovitskiy et al., 2020).

The literature on scaling up CLIP (Radford et al., 2021; Li et al., 2022) typically demonstrates a power law starting with a large computation cost. To evaluate CLIP's performance as we scale up the dataset size, we sampled ten subsets from the entire dataset, with sizes ranging from 10M to 3.4B. These subsets have the same data distribution and quality and are used in this section and subsequent sections. To assess the effect of the number of sampled data, we provide results for all subsets trained for one epoch. To ensure a fair comparison, we also provide results for all subsets trained for the same number of iterations, resulting in the same number of sampled data.

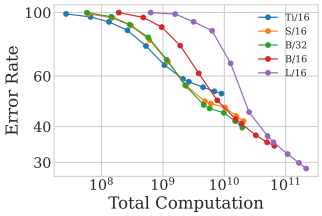
Zero-Shot Figure 8(a) showcases the zero-shot performances on ImageNet after training for one epoch using various sizes of training sets with different ViT models. As we train one epoch on each subset, the diversity of dataset will not affect the result. The results indicate that ViT-L/16 does not consistently outperform other ViT models. In fact, when the number of samples fed to CLIP is less than 100 million, ViT-L performs the worst among the ViT family. However, as the number of sample data increases, larger vision encoders exhibit better performances.

As the sizes and FLOPs of various ViT models differ, we present power law of the total computation cost versus ImageNet error rate in Figure 8(b). We observe that when the computation budget is low, smaller ViT models perform better. This could be because smaller ViT models require less computation and can extract useful features from smaller datasets more efficiently. On the other hand, when the computation budget is high, larger ViT models such as L/16 and B/32 can achieve better zero-shot performance. In summary, a large model is not always the best choice. Therefore, choosing the appropriate ViT model size based on the available computational resources is important.

Furthermore, our investigation also delves into the correlation between ViT size and data size. We conduct experiments on different datasets for an equal number of iterations, keeping the number of sampled data constant. Our results reveal that a larger dataset yields better performance, even when the number of iterations is held constant. Notably, we observe that augmenting the dataset to 400M does not yield any significant improvement in zero-shot performance due to our computation limits. Moreover, we discover that the performance gap between larger ViTs and their smaller counterparts widens as the dataset size increases.

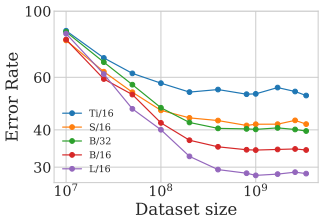


(a) Sampled data V.S. ImageNet Accuracy

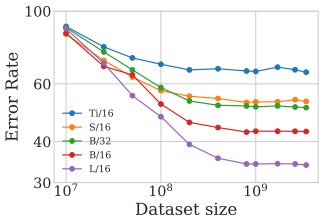


(b) Total Computation V.S. ImageNet Error Rate

Figure 8: **Various ViTs:** Zero-Shot performances with **various numbers of sample data**. We use various vision encoders and the same text encoder ViT-B. The total computation is computed by GFLOPs per sample times the number sampled data. The total computation is computed by GFLOPs per sample times the number sampled data.



(a) Data size V.S. ImageNet Error Rate



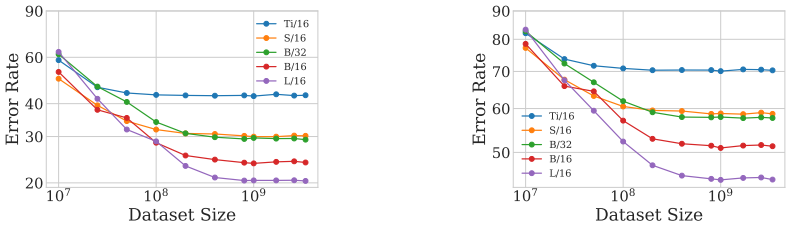
(b) Data size V.S. Average ImageNet Variants Error Rate

Figure 9: **Various ViTs:** Zero-Shot performances with **the same number of sampled data: 3.4B**. We use various vision encoders and the same text encoder ViT-B.

Our experiments also investigate the relationship between zero-shot performance on ImageNet and other distributional datasets. We find that the accuracy curves for ImageNet-R (Hendrycks et al., 2020), ImageNet-Sketch (Wang et al., 2019), ImageNet-V2 (Recht et al., 2019), and ObjectNet (Barbu et al., 2019) are nearly linear as shown in Figure 21 in Appendix, indicating that the image classification ability of CLIP models improves consistently across these datasets. However, the accuracy of ImageNet-A (Hendrycks et al., 2019) does not exhibit a linear relationship with that of ImageNet (Deng et al., 2009) as shown in Figure 21(a) in Appendix. Specifically, when ImageNet accuracy is below 50%, the accuracy of ImageNet-A increases only slightly, while it grows more rapidly for higher ImageNet accuracies. We attribute this behavior to the presence of more challenging test examples in ImageNet-A, which is not present in the other four datasets that only contain variants of ImageNet images. We also find that for most of OOD datasets, when the standard accuracy is same, a larger ViT will have better robustness performances.

Linear Probing As shown in Figure 10, we present the linear-probing results and observe that for smaller datasets, the performance of ViT-L/16 is inferior to that of the other three models. However, for larger numbers of sampled data, the larger ViT models deliver significantly better results.

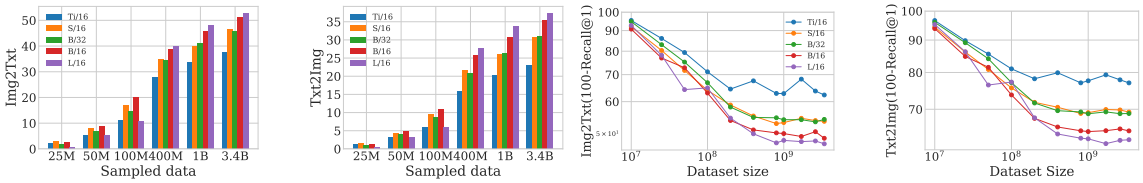
Furthermore, in Figure 22 in Appendix, we compare ImageNet with other out-of-distribution (OOD) variants and find that the performance of vision encoders significantly declines for most OOD variants, except for ImageNet-V2.



(a) Data size V.S. ImageNet

(b) Data size V.S. Average on OOD datasets

Figure 10: **Various ViTs:** Linear probing performances with various sizes of vision encoders. We train all subsets with **the same number of sampled data: 3.4B**.



(a) Text Retrieval-**one epoch**

(b) Image Retrieval-**one epoch**

(c) Text Retrieval

(d) Image Retrieval

Figure 11: **Various ViTs:** Retrieval Performances on MSCOCO.

Our results also show that for smaller ViTs, the effect of data diversity is smaller. For Ti/16, when the dataset size is larger than 25M, the increase of dataset size will not benefit the linear probing performance. However, for L/16, the increase of data diversity will benefit the linear probing performance until the training dataset size is larger than 400M. These findings demonstrate the importance of using large datasets for larger CLIP models.

Retrieval The results shown in Figure 11 demonstrate that ViT-L/16 exhibits poor performance for retrieval tasks when the number of sampled data points is less than 100M. However, with an increase in the number of sampled data points, larger ViT models demonstrate improved performance.

Furthermore, when the number of sampled data points is held constant, the trend in retrieval performances aligns with that of zero-shot performance. Moreover, as the dataset size increases, the performance of smaller ViT models plateaus earlier than that of larger models, suggesting that larger models derive greater benefits from additional data.

6 A Comparison of Network Architectures

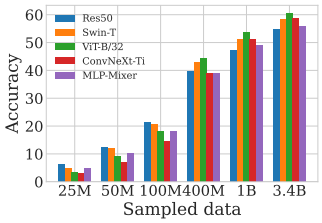
Previous studies (Zhai et al., 2021; Radford et al., 2021) have investigated different vision encoders for CLIP, including ResNet (He et al., 2016), MLP-Mixer (Tolstikhin et al., 2021), and ViT (Dosovitskiy et al., 2020). However, architectures such as Swin-Transformer (Liu et al., 2021)) and ConvNext (Liu et al., 2022) have not been explored. Moreover, previous works have only compared network performance for only one data point. In this section, we compare several CNN and vision transformer architectures with similar FLOPs, namely ViT-B/32, ResNet-50, ConvNext-T, Swin-T, and Mixer-B/32.

Zero-Shot We begin our investigation by examining the selection of networks for different numbers of sampled data. As illustrated in Figure 12(a), we observe that ResNet-50 outperforms ViT-B/32 when the number of sampled data is limited. However, as the number of samples increases, ViT-B/32 achieves better performance. This suggests that CNNs possess more inductive bias and can capture more local information even with a small number of samples. Moreover, we find that the performance of advanced vision transformers does not show notable improvements with a limited number of samples, and in most

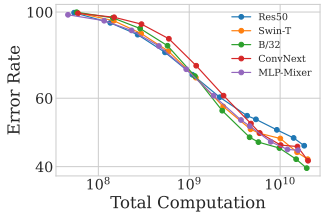
cases, Swin-T's performance is inferior to that of ViT-B/32. In order to facilitate a fairer comparison between various architectures, we plot the total computation cost versus error rate in Figure 12(b). When the total computation cost is low, ResNet-50 outperforms other architectures.

Next, we evaluate the effect of dataset size on the zero-shot performance of different architectures, while keeping the number of iterations constant. As demonstrated in Figure 13, ViT-B/32 consistently delivers the best performance. We observe that the impact of data diversity is similar across different networks, and increasing the dataset size beyond 400M does not offer any significant benefit to the zero-shot performance of any network. Therefore, the improvement in zero-shot performance due to data diversity is mainly related to model size rather than model architecture.

We also present the zero-shot performances of ImageNet and its variants in Figure 23 in Appendix. When the ImageNet accuracy is comparable, Swin-T and ViT-B/32 exhibit better performances on ImageNet variants, particularly on ImageNet-A. Our findings suggest that when the training dataset is sufficiently large, ViT is a better choice as the vision encoder of CLIP.

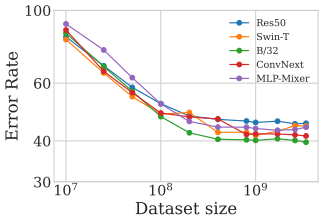


(a) Sampled data V.S. ImageNet Accuracy

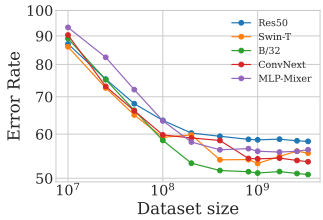


(b) Total Computation V.S.ImageNet Error Rate

Figure 12: **Various architectures:** Zero-Shot performances with **various numbers of sampled data**. We train them for **one epoch**.



(a) Data size V.S. ImageNet Error Rate



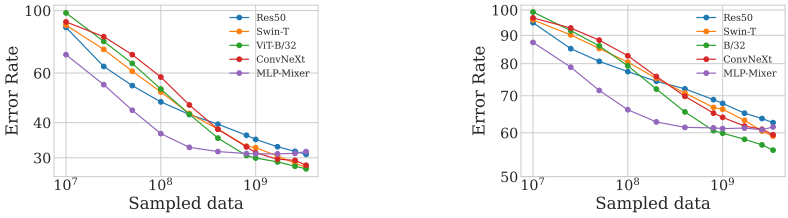
(b) Data size V.S. Average ImageNet Variants Error Rate

Figure 13: **Various architectures:** Zero-Shot performances with **various dataset sizes** and **the same number of steps**.

Linear Probing To validate the performance of various encoders in CLIP models, we evaluate them using linear probing and present the results in Figure 14. It can be observed that when the number of sampled data is below 100 million, ResNet-50 outperforms the other four architectures on both ImageNet and other OOD variants. However, as the number of sampled data increases, ViT-B/32 exhibits better results, particularly on OOD variants. These results provide insights for selecting appropriate feature extractors for datasets with different sizes. Specifically, ResNet is a better choice when the number of sampled data is small, while ViT can achieve better robustness and standard accuracy when the number of sampled data is sufficiently large.

In Figure 24 in Appendix, we present the results of linear probing on ImageNet and various OOD datasets. Notably, we observed a significant drop in performance on ImageNet-A, -R, and ObjectNet after linear probing, whereas the performances on ImageNet-V2 and -Real improved. When the standard accuracy is close, we noticed that ViT and MLP-Mixer demonstrate better robustness. We hypothesize that this

might be due to the relatively lower inductive bias of these two architectures, meaning they are less prone to overfitting to the specific dataset they were trained on. This can lead to better generalization and performance on out-of-distribution datasets.



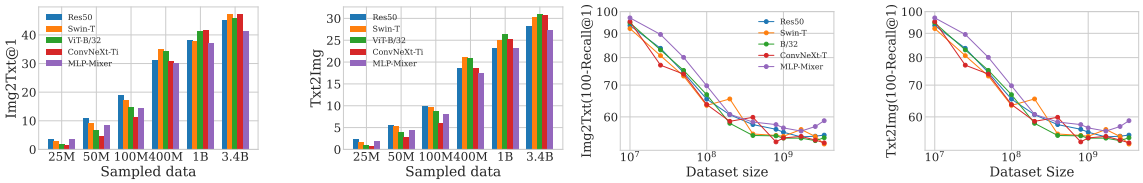
(a) Data size V.S. ImageNet

(b) Data size V.S. Average on OOD datasets

Figure 14: **Various architectures:** Linear Probing with **the same number of sampled data**.

Retrieval When considering different numbers of sampled data points, ResNet-50 demonstrates superior performance for smaller sample sizes, as depicted in Figures 15(a) and 15(b). However, as the number of sampled data points exceeds 400M, ViT-B/32 surpasses ResNet-50 in performance for both few-shot and retrieval tasks.

Moreover, when the number of sampled data points is consistent, Mixer-B/32 exhibits the poorest performance for retrieval tasks, as shown in Figures 15(c) and 15(d). These results indicate that ViT is the preferred choice for the vision encoder not only in zero-shot and linear probing tasks but also in few-shot and retrieval tasks.



(a) Text Retrieval-**one epoch**

(b) Image Retrieval-**one epoch**

(c) Text Retrieval-**same iter.**

(d) Image Retrieval-**same iter.**

Figure 15: **Various Architectures:** Retrieval Performances on MSCOCO.

7 Training Strategies

In this section, we compare the training strategies of SLIP (Mu et al., 2021) and FLIP (Li et al., 2022) with the original CLIP. We use ViT-B/32 as the vision encoder and ViT-B as the text encoder for all three strategies. We follow the implementation of SLIP as described in Mu et al. (2021). For FLIP (Li et al., 2022), we apply a 50% patch masking and double the batch size. We also propose our own training strategy, *CLIP+Data Augmentation*.

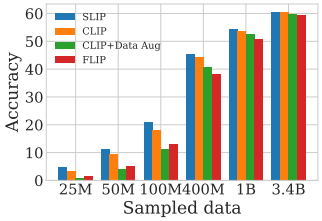
CLIP + Data Augmentation While Mu et al. (2021) proposed enhancing the vision encoder of CLIP models through self-supervised learning, this comes at a significant computation cost compared to the original CLIP. To achieve similar enhancements to the vision encoder while saving on computation, we propose applying data augmentation to input images of CLIP. We validate the effectiveness of this approach on four subsets, training them for 30 epochs to ensure model convergence. We apply three data augmentation methods: crop&flip, RandAugment (Cubuk et al., 2019), and Stacked RandAugment (Khosla et al., 2020). The results, shown in Figure 1(b), demonstrate that all three methods improve performance compared to raw CLIP, highlighting the effectiveness of data augmentation in CLIP. Moreover, data augmentation on input images does not bring any extra computation cost compared to CLIP. Even when trained on a dataset

of 25 million samples, the Stacked RA model can achieve comparable performance to that obtained with a dataset of 50 million samples.

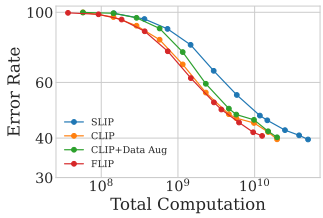
Zero-Shot Our experimental results on the ImageNet dataset, as depicted in Figure 16(a), demonstrate that SLIP outperforms the other two strategies when the number of training samples seen by models is less than one billion. This suggests that self-supervised learning for the vision encoder can be beneficial when the number of training samples is limited. However, as the number of training samples increases, both CLIP and FLIP achieve similar results and outperform SLIP. These results indicate that enhancing the vision encoders may not be necessary when the training dataset is large. Notably, when the model architecture is the same, SLIP is two times more computationally expensive than CLIP. As illustrated in Figure 16(b), when the total computation cost is the same, SLIP has the worst zero-shot performance on ImageNet. We also observed that data augmentation hurts the zero-shot performance when we only train these subsets for one epoch.

Moreover, we investigated how the four training strategies perform with various dataset sizes, with a fixed number of sampled data. As shown in Figure 17, SLIP outperforms CLIP and FLIP when the dataset size is small on ImageNet. However, as the dataset size increases, SLIP does not show better performance on ImageNet variants. On the other hand, CLIP + Data Aug performs better than the other three training methods, especially on ImageNet variants. Our results suggest that data augmentation on input images can bring better generalization performance with almost no extra cost.

In Figure 25 in Appendix, we present the results of our study on ImageNet compared to various OOD variants. SLIP also does not show better performance on these variants when the ImageNet accuracy is the same. However, CLIP + Data Aug brings better performance on ImageNet-Sketch and -R. In conclusion, we can say that CLIP + Data Aug can bring better zero-shot performance on both ImageNet and its variants when we train multiple epochs for the dataset.

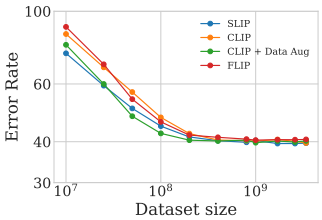


(a) Sampled data V.S. ImageNet Accuracy

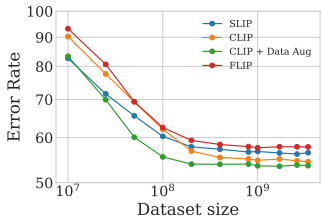


(b) Total Computation V.S. ImageNet Error Rate

Figure 16: **Various Training Stategies:** Zero-Shot performances with **various numbers of sampled data**. We all subsets for **one epoch**. We use ViT-B/32 as the vision encoder and ViT-B as the text encoder for all strategies.



(a) Data size V.S. ImageNet

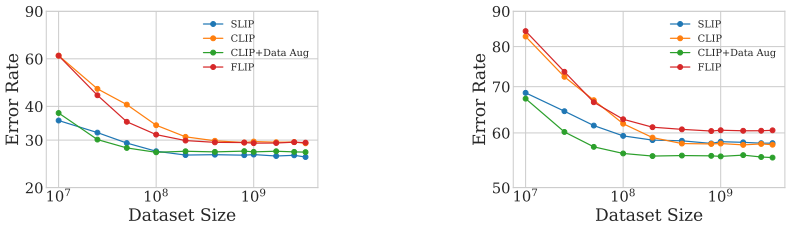


(b) Data size V.S. Average on ImageNet Variants

Figure 17: **Training Stategies:** Zero-Shot performances with various subsets while **the same number of sampled data**. We use ViT-B/32 as the vision encoder and ViT-B as the text encoder for all strategies.

Linear Probing We evaluated vision encoders trained with various strategies using linear probing and found that those trained with CLIP + Data Aug consistently outperform the other three strategies across

all data points, particularly on OOD datasets as shown in Figure 18. The performances of ImageNet and OOD variants are compared in Figure 26 in Appendix, where CLIP and CLIP + Data Aug show better robustness than SLIP when ImageNet accuracy is the same. Considering the linear probing performances and computation cost, we believe that combining CLIP and data augmentation can result in a better feature extractor.



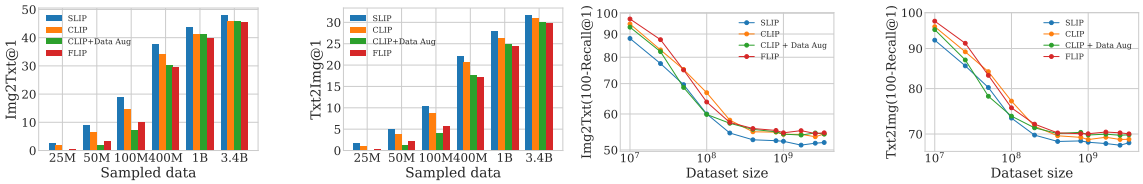
(a) Data size V.S. ImageNet

(b) Data size V.S. Average on OOD datasets

Figure 18: **Various Training Stategies:** Linear probing performances with various subsets while **the same number of sampled data**.

Retrieval The performance of SLIP, CLIP+Data Aug, CLIP, and FLIP is evaluated for few-shot and retrieval tasks on ImageNet with varying numbers of sampled data. Moreover, SLIP consistently outperforms the other methods on both image and text retrieval tasks as shown in Figures 19(a) and 19(b).

When the number of sampled data is fixed, the performance of each method for few-shot and retrieval tasks shows a different trend compared to the zero-shot performance. For retrieval tasks, SLIP consistently performs best across all dataset sizes as shown in Figures 19(c) and 19(d). These results suggest that SLIP is a better strategy for retrieval tasks, although it may not be the best one for classification tasks.



(a) Text Retrieval-**one epoch**

(b) Image Retrieval-**one epoch**

(c) Text Retrieval-**same iterations**

(d) Image Retrieval-**same iterations**

Figure 19: **Training Strategies:** Retrieval Performances on MSCOCO.

8 Conclusion

In this paper, we investigate the impact of data size, network architecture, and training strategies on the performance of CLIP. Our experiments demonstrate the importance of data quantity and data quality. We also show that data augmentation techniques can enhance the performance of CLIP without significantly increasing the computational cost. Additionally, we explore the impact of different network architectures and training strategies on the performance of CLIP. Our results suggest that some architectures and training strategies perform better than others, highlighting the importance of careful selection of these factors. Overall, our study provides practical tips into how to optimize the performance of CLIP for a given (small) compute budget.

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