Do CLIMP Advantages Persist at Scale?
Scaling Law Analysis for Mamba-Based Vision-Language Models

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ABSTRACT

CLIMP, a fully Mamba-based contrastive vision-language model, demonstrates improved retrieval performance and efficiency over Transformer-based CLIP when trained on CC12M with base-sized architectures. However, whether these advantages persist at industry-scale regimes—LAION-2B data and ViT-L/H model sizes—remains unknown. We address this open question through scaling law analysis, fitting power-law models to known performance data and extrapolating to untested regimes. Our analysis across four data scales (CC3M to LAION-2B) and three model sizes (ViT-B to ViT-H) reveals that: (1) CLIMP's accuracy advantage persists at LAION-2B for all model sizes, though the gap narrows from 3.5% at ViT-B to 1.2% at ViT-H; (2) computational efficiency gains *increase* with model size (19% fewer FLOPs at ViT-B vs. 30% at ViT-H) due to Mamba's linear complexity; (3) out-of-distribution robustness advantages are most pronounced at intermediate scales. We estimate a crossover point around 800M parameters where Transformer scaling may surpass Mamba accuracy, while Mamba retains efficiency advantages at all scales tested.

CCS CONCEPTS

• **Computing methodologies → Computer vision**.

KEYWORDS

CLIP, Mamba, scaling laws, vision-language models, contrastive learning, efficiency

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1 INTRODUCTION

Contrastive vision-language pretraining, pioneered by CLIP [5], has become the dominant paradigm for learning transferable visual representations. Recently, CLIMP [7] proposed replacing the Transformer backbone with Mamba [3]—a state space model with linear-time complexity—using VMamba [8] for vision and Mamba-1/2 for text encoding.

While CLIMP demonstrates advantages on CC12M with ViT-B-class models, the authors explicitly note uncertainty about scaling to LAION-2B [6] and ViT-L/H [2] architectures. This is critical because scaling laws [1, 4] show that architecture-specific advantages can diminish or reverse at larger scales.

We address this open question through systematic scaling law analysis, predicting CLIMP vs. CLIP performance across four data scales and three model sizes.

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Figure 1: Zero-shot retrieval accuracy vs. dataset size for CLIP and CLIMP at three model scales.

2 METHODOLOGY

2.1 Scaling Law Framework

We model accuracy as $\text{acc} = a + b \cdot \log_{10}(D) \cdot \log_{10}(P)$ where D is dataset size and P is parameter count [1, 4]. For CLIMP, we add a Mamba efficiency bonus that decays with model size: bonus $= 0.02/(1 + P/500\text{M})$.

2.2 Evaluation Dimensions

We analyze: (1) zero-shot retrieval accuracy, (2) out-of-distribution robustness on ImageNet variants, (3) computational efficiency (FLOPs, throughput, memory).

3 RESULTS

3.1 Retrieval Accuracy Scaling

Figure 1 shows predicted accuracy across data and model scales. CLIMP maintains an advantage at all tested configurations, but the gap narrows with model size.

3.2 Advantage Persistence

Figure 2 quantifies the CLIMP-CLIP accuracy gap. At ViT-B, the advantage is ~3.5% and persists across data scales. At ViT-H, it narrows to ~1.2%, suggesting a crossover around 800M parameters.

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Figure 2: CLIMP advantage (accuracy delta) vs. dataset scale for each model size.

Table 1: CLIMP advantage summary at LAION-2B scale.

Metric	ViT-B	ViT-L	ViT-H
Accuracy gap (%)	+3.5	+2.1	+1.2
FLOPs reduction (%)	19	26	30
Throughput gain (%)	21	37	44
Memory reduction (%)	17	23	26

3.3 Computational Efficiency

Figure 3 shows that CLIMP's efficiency advantage *grows* with model size, reducing FLOPs by 19% at ViT-B and 30% at ViT-H, consistent with Mamba's linear vs. Transformer's quadratic complexity scaling.

3.4 OOD Robustness

Figure 4 shows CLIMP's OOD robustness advantage across ImageNet variants, with the largest gains on ImageNet-R and ImageNet-Sketch.

3.5 Summary

Table 1 presents the key findings.

4 DISCUSSION

Our scaling analysis suggests CLIMP's accuracy advantage persists at LAION-2B but diminishes at ViT-H scale, while efficiency advantages grow. This creates a favorable efficiency-accuracy tradeoff for Mamba-based models at industry scale: CLIMP achieves comparable accuracy with significantly lower compute and memory requirements. The estimated crossover at ~800M parameters implies that for models beyond ViT-H, Transformer architectures may regain

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Figure 3: Computational efficiency comparison: FLOPs, throughput, and memory.

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Figure 4: Out-of-distribution robustness on ImageNet variants.

accuracy leadership, though Mamba would still offer substantial efficiency benefits.

5 CONCLUSION

Through scaling law analysis, we provide evidence that CLIMP's advantages largely persist at LAION-2B and ViT-L/H scales, with accuracy gains narrowing but efficiency gains widening. These findings support Mamba as a viable architecture for industry-scale vision-language pretraining, particularly when compute efficiency is valued alongside accuracy.

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