Multimodal Autoregressive Pre-training of Large Vision Encoders

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https://github.com/apple/ml-aim

Abstract

We introduce a novel method for pre-training of large-scale vision encoders. Building on recent advancements in autoregressive pre-training of vision models, we extend this framework to a multimodal setting, i.e., images and text. In this paper, we present AIMv2, a family of generalist vision encoders characterized by a straightforward pre-training process, scalability, and remarkable performance across a range of downstream tasks. This is achieved by pairing the vision encoder with a multimodal decoder that autoregressively generates raw image patches and text tokens. Our encoders excel not only in multimodal evaluations but also in vision benchmarks such as localization, grounding, and classification. Notably, our AIMv2-3B encoder achieves 89.5% accuracy on ImageNet-1k with a frozen trunk. Furthermore, AIMv2 consistently outperforms state-of-the-art contrastive models (e.g., CLIP, SigLIP) in multimodal image understanding across diverse settings.

1. Introduction

Research on pre-training of vision models has evolved significantly over time. Initially, specialist models were designed to maximize performance on specific tasks [14, 36, 45, 46, 56, 114]. Gradually, general-purpose models emerged that can be deployed for a number of predefined downstream tasks with minimal adaptation [54, 87, 94, 133]. However, the remarkable success of Large Language Models (LLMs) [1, 5, 96, 116] has introduced new paradigms for utilizing vision models [3, 73, 85, 115]. Unlike the rigid predefined settings where vision models were previously employed, LLMs enable more effective exploration of the pre-trained model capabilities. This shift demands rethinking pre-training methods for vision models.

Generative pre-training is the dominant paradigm for language modeling [23, 92, 93] and has shown remark-

able performance and scalability [50, 55]. Generative pretraining has been extensively explored in computer vision [8, 29, 33, 48, 118], but its performance still lags behind that of discriminative methods [87, 94, 133, 137]. For instance, a formulation highly reminiscent of LLMs pretraining was proposed by El-Nouby et al. [33] and demonstrated encouraging scaling properties. However, it requires much higher capacity models to match the performance of its discriminative counterparts. In contrast, while contrastive techniques are often more parameter efficient, they are notably challenging to train and scale. Although significant progress has been made to mitigate these issues, there remains a gap in developing methods that combine the simplicity and scalability of generative pre-training with the parameter efficiency of discriminative approaches.

In this paper, we introduce AIMv2, a family of open vision models pre-trained to autoregressively generate both image patches and text tokens. During pre-training, AIMv2 uses a causal multimodal decoder that first regresses image patches and then decodes text tokens in an autoregressive manner, as illustrated in Figure 1. Such a simple approach offers several advantages. First, AIMv2 is straightforward to implement and train without requiring excessively large batch sizes [35, 94] or specialized interbatch communication methods [133]. Second, the architecture and pre-training objectives of AIMv2 align well with LLM-powered multimodal applications, enabling seamless integration. Finally, AIMv2 extracts a training signal from every image patch and text token, providing denser supervision compared to discriminative objectives.

Our AIMv2 models are strong generalists that exhibit remarkable performance across various vision and multimodal tasks. In particular, AIMv2 performs favorably on multimodal understanding benchmarks compared to stateof-the-art vision-language pre-trained methods [35, 133]. It outperforms DINOv2 [87] on open-vocabulary object detection and referring expression comprehension, and attains strong recognition performance with a frozen trunk, out-

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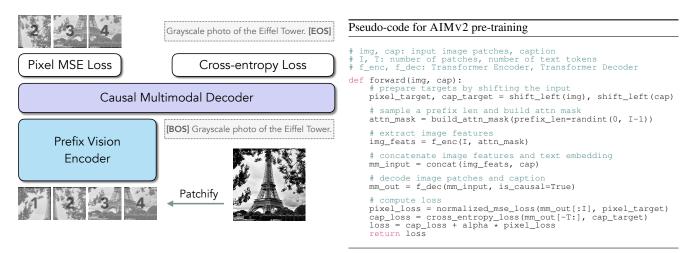


Figure 1. AIMv2 pre-training Overview. (Left) Image patches are processed by a vision encoder trained with prefix attention [33, 95]. The resulting visual representations are concatenated with the text embeddings of their corresponding captions. This combined multimodal sequence is then processed by a joint decoder. The model is pre-trained to autoregressively reconstruct the shifted input. (Right) Pseudocode for the forward pass during AIMv2 pre-training. The pre-training process of AIMv2 is straightforward to implement, resembling that of AIM and LLMs as it relies solely on a simple autoregressive objective.

performing a number of strong baselines. Furthermore, AIMv2 enjoys strong scalability, similar to its languageonly and vision-only counterparts, improving consistently when scaling data or parameters. Moreover, we demonstrate the compatibility of AIMv2 with several modern tools, including support for native image resolution and adaptation to zero-shot recognition [132]. We discuss related works in more detail in Sec. 6.

2. Approach

2.1. Pre-training

Our model extends the standard unimodal autoregressive framework to multimodal settings that integrate both images and text into a unified sequence. Specifically, an image x is partitioned into I non-overlapping patches x_i , $i \in [1, I]$, forming a sequence of tokens. Similarly, a text sequence is broken down into subwords x_t , $t \in [I, I + T]$. These sequences are then concatenated, allowing text tokens to attend to image tokens. While both concatenation directions (image \rightarrow text and text \rightarrow image) are possible, we focus on training a strong vision encoder by always prepending the image first, thereby enabling stronger conditioning on the visual features. This results in a unified multimodal autoregressive modeling process, where the sequence is factorizatized as follows:

$$P(S) = \prod_{j=1}^{I+T} P(S_j | S_{< j}),$$

where S_j represents the *j*-th token in the concatenated sequence of image patches and text tokens, and $S_{<j}$ includes all preceding tokens. This unified factorization allows the model to autoregressively predict the next token in the se-

quence, regardless of what modality it is currently processing. Our pre-training setup consists of a dedicated vision encoder that processes the raw image patches, which are then passed to a multimodal decoder alongside the embedded text tokens, as illustrated in Figure 1. The decoder subsequently performs next-token prediction on the combined sequence, following the factorization above. To support the autoregressive generation process, the vision encoder and multimodal decoder employ prefix and causal self-attention operations, respectively.

Objective function. We define separate loss functions for the image and text domains as follows:

$$L_{\text{img}} = \frac{1}{I} \sum_{i=1}^{I} \|\hat{x}_i(x_{
$$L_{\text{text}} = -\frac{1}{T} \sum_{t=I+1}^{I+T} \log P(x_t|x_{< t};\theta).$$$$

The overall objective is to minimize $L_{\text{text}} + \alpha * L_{\text{img}}$ with respect to model parameters θ . For the text domain, L_{text} is a standard cross-entropy loss that measures the negative log-likelihood of the ground truth token at each step. For the image domain, L_{img} is an ℓ_2 pixel-level regression loss, where the model's predicted patch $\hat{x}_i(\theta)$ is compared to the true patch x_i . We normalize the image patches following He et al. [48]. In practice, we use separate linear layers to map the final hidden state of the multimodal decoder to the appropriate output dimensions for image patches and vocabulary size for vision and language, respectively.

2.2. Architecture

For the vision encoder of AIMv2, we adopt the Vision Transformer (ViT) architecture [30]. We train a series of

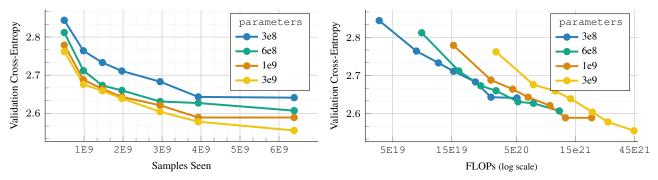


Figure 2. Scaling properties of AIMv2. (Left) Given a fixed pre-training data size, increasing the number of parameters always leads to an improvement in the validation loss. (Right) The optimal model size varies based on the pre-training compute budget. Larger models perform worse than smaller ones when severely undertrained but improves consistently as the compute budget increases. This behavior is consistent with that reported by Hoffmann et al. [50] for text-only autoregressive models.

	model	#params	d_{enc}	L_{enc}	d_{dec}	L_{dec}
1	AIMv2-L	0.3B	1024			
	AIMv2-H	0.6B	1536	24	10	1024
	AIMv2-1B	1.2B	2048	24	12	1024
	AIMv2-3B	2.7B	3072			

Table 1. AIMv2 family of models. We detail the architectural specifications of AIMv2 models including the embedding dimension d, number of layers L for the vision encoder and the mutlimodal decoder, and the total number of encoder parameters.

vision encoders ranging between 300M and 3B parameters. Detailed model specifications are provided in Table 1.

Prefix Attention. Following El-Nouby et al. [33], we constrain the self-attention mechanism within the vision encoder by applying a prefix attention mask [95]. This strategy facilitates the use of bidirectional attention during inference without additional tuning. Specifically, we randomly sample the prefix length as $M \sim \mathcal{U}\{1, 2, \dots, I-1\}$. The pixel loss is computed exclusively for non-prefix patches, defined as $\{x_i \mid i > M\}$.

SwiGLU and RMSNorm. Our vision encoder and multimodal decoder incorporate SwiGLU [102] as the feed-forward network (FFN) and replace all normalization layers with RMSNorm [134]. These modifications leverage the recent successes of SwiGLU and RMSNorm in language modeling [116, 117].

Multimodal Decoder. We adopt a unified multimodal decoder that performs autoregressive generation for both image and text modalities concurrently. Image features and raw text tokens are each linearly projected and embedded into $\mathbb{R}^{d_{dec}}$. The decoder receives concatenated sequences of image and text features as input and employs causal attention in the self-attention operations. The outputs of the decoder are processed through two separate linear heads—one for image tokens and another for text tokens—to predict the next token in each modality respectively. We use the same decoder capacity for all the AIMv2 variants.

The optimization hyperparameters used during pre-training of all AIMv2 models are outlined in Table A1.

dataset	public	caption	#images-text pairs	sampling prob.
DFN [35]	1	alt-text	1,901,228,573	30%
DFN [55]	X	synthetic	3,802,457,146	30%
COYO [13]	1	alt-text	560,171,533	9%
UOITD	X	alt-text	564,623,839	28%
HQITP	X	synthetic	431,506,953	3%

Table 2. Pre-training data mixture. AIMv2 is pre-trained using
a large-scale collection of image and text pairs. For the paired
captions, we utilize alt-text as well as synthetic text generated from
a pre-trained captioner. In this table we list the datasets as well the
sampling probabilities we used for each data source.

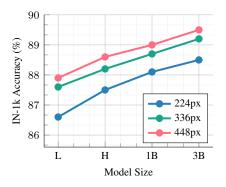
2.3. Data

We pre-train AIMv2 models using a combination of public and private datasets containing paired images and text. We use the publicly available DFN-2B [35] and COYO [13] datasets, along with a proprietary dataset of High Quality Image-Text Pairs (HQITP). In addition to alt-text, we use synthetic captions following the approach of Lai et al. [63]. Details regarding the datasets, including their sizes and the sampling probabilities used for each dataset, are provided in Table 2. Unless mentioned otherwise, all AIMv2 models were pre-trained using 12 billion image-text samples.

2.4. Post-Training

While the initial pre-training stage of AIMv2 yields highly performant models, we explore methods to further enhance the capabilities through various post-training strategies.

High-resolution Adaptation. In the initial pre-training stage, we use image data with a fixed resolution of 224px. However, many downstream task, such as detection, segmentation, and multimodal LLMs, benefit from models adapted to handle higher resolution images. Therefore, we finetune AIMv2 models for 336 and 448 pixel resolutions. The high-resolution adaptation stage utilizes 2 billion image-text pairs sampled from the same pool as the pre-training stage, except that we do not use synthetic captions at this stage. Consistent with the observations of Zhai et al. [133], we find that weight decay of zero is important for maintaining stable optimization.



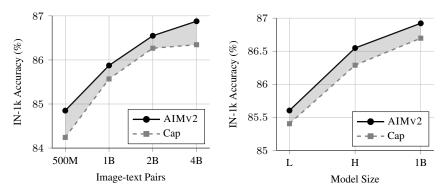


Figure 3. Scaling capacity and resolution. AIMv2 shows strong scalability with respect to model parameters, measured in frozentrunk top-1 accuracy for IN-1k. This behavior is consistent when scaling image resolution.

Figure 4. AIMv2 *vs.* **Captioning.** We investigate the role of the image-level objective in comparison to a captioning-only baseline, particularly as we scale data and model size. Our findings indicate that AIMv2 consistently outperforms the captioning baseline across all dataset and model sizes. Notably, AIMv2 exhibits fewer signs of saturation when scaling data compared to the captioning-only approach.

Native Resolution Fine-tuning. Training models for a dedicated resolution and aspect ratio can be inflexible for many applications that require processing images in their original shapes. Prior works such as FlexiViT [9] and NaViT [26] have tackled these limitation. We adopt a different approach for training with variable aspect ratios and resolutions. Specifically, we define B_i as the number of images in a mini-batch, A_i as the number of patches per image, and C as the total number of image patches in the mini-batch. For a mini-batch i, we randomly sample an area A and resize the images to fit within this area while maintaining their aspect ratios.¹ We then adjust the mini-batch size B_i such that $C = A_i \times B_i$. This strategy is analogous to the approach proposed by Pouransari et al. [91] for training LLMs with variable context lengths. Our implementation does not require heuristics for sequence packing, attention masking, or custom pooling operations. We choose $A = 2^n$, where *n* is sampled from a truncated normal distribution $\mathcal{N}(0,1)$ within the range [-1, 1] and linearly mapped to [7, 12].

3. Analysis

One of the main advantages of AIMv2 is its simplicity; it is easy to implement and scale. Therefore, we investigate the scaling properties of the AIMv2 family of models.

3.1. Scaling AIMv2

First, we investigate the impact of scaling data size and model capacity on the validation performance of AIMv2. We fix the model size and vary the number of samples seen during pre-training. This analysis is similar to "Approach 1" in the study of Hoffmann et al. [50]. The results of this study are illustrated in Figure 2.

Setup. We train four model capacities, ranging from 300 million to 3 billion parameters, and vary the number of

samples seen between 500 million to 6.4 billion image-text pairs. All models are trained to convergence with no early stopping. To achieve this with minimal computational cost, we train a single model for each capacity using 5 billion images with a half-cosine learning rate schedule (*i.e.*, the final learning rate is half the peak learning rate). We select seven intermediate checkpoints from this run and apply a linear cooldown to 1×10^{-6} . The length of the cooldown stage is 20% of the initial pre-training stage.

Results. We observe a consistent improvement in performance with scaling data or parameters. However, diminishing returns appear when scaling data for the lower-capacity models. Additionally, we find that the optimal model size changes as the compute budget varies. At smaller compute budgets, larger-capacity models are undertrained and underperform compared to their lower-capacity counterparts.

3.2. AIMv2 vs. Captioning

We study the role of the image-level autoregressive objective in the pre-training of AIMv2. We compare the performance of models trained with the multimodal autoregressive objective to ones trained only with language supervision. The results are illustrated in Figure 4.

Setup. Unless specified otherwise, this investigation uses a ViT-H backbone and 2 billion image-text pairs for pretraining. All models are trained to convergence with a cosine learning rate schedule. We measure the IN-1k top-1 accuracy after attentive probe with a frozen trunk.

Results. First, the image-level objective of AIMv2 consistently improves performance compared to the captioningonly baseline. This is true even when changing the model capacity and the size of the pre-training data. Moreover, we see both approaches improving consistently when increasing the data size or model capacity; however, we observe signs of plateauing for the captioning baselines with scaling data which we do not observe with AIMv2.

¹We use zero padding if the image cannot be perfectly fitted into the desired area.

model	architecture	IN-1k	iNAT-18	Cifar10	Cifar100	Food101	DTD	Pets	Cars	CAM17	PCAM	RxRx1	EuroSAT	fMoW	Infographic
MAE [48]	ViT-2B/14	82.2	70.8	97.5	87.3	93.4	81.2	95.1	94.9	94.4	90.3	7.3	98.2	60.1	50.2
AIMv1 [33]	ViT-H/14	78.5	64.0	97.2	86.8	90.1	80.1	93.0	93.0	94.3	90.0	7.8	98.4	58.3	45.2
	ViT-7B/14	84.0	75.5	98.9	91.8	94.1	85.6	95.4	95.0	94.2	90.5	8.4	98.5	63.5	57.7
DINOv2 [87]	ViT-g/14	87.2	83.0	99.7	95.6	96.0	86.9	96.8	94.9	95.8	90.1	9.0	98.8	65.5	59.4
OAI CLIP [94]	ViT-L/14	85.7	73.5	98.7	89.7	95.4	83.5	96.2	94.5	94.4	89.2	5.7	98.0	62.0	66.9
DFN-CLIP [35]	VIT-L/14	86.5	75.5	99.2	93.2	96.2	85.8	96.3	96.4	95.0	89.8	5.8	98.3	63.1	66.8
DFN-CLIP [33]	ViT-H/14	86.9	76.4	99.3	93.9	96.3	87.0	96.8	96.7	95.7	90.5	6.1	98.8	63.4	68.1
SigLIP [133]	ViT-L/16	86.5	75.1	98.5	90.4	96.1	86.7	96.7	96.5	93.1	89.5	4.5	98.3	61.7	71.0
Signir [155]	ViT-So400m/14	87.3	77.4	98.8	91.2	96.5	87.7	96.7	96.6	93.3	90.0	4.6	98.6	64.4	72.3
	ViT-L/14	86.6	76.0	99.1	92.2	95.7	87.9	96.3	96.3	93.7	89.3	5.6	98.4	60.7	69.0
	ViT-H/14	87.5	77.9	99.3	93.5	96.3	88.2	96.6	96.4	93.3	89.3	5.8	98.5	62.2	70.4
AIMv2	ViT-1B/14	88.1	79.7	99.4	94.1	96.7	88.4	96.8	96.5	94.2	89.0	6.7	98.8	63.2	71.7
	ViT-3B/14	88.5	81.5	99.5	94.3	96.8	88.9	97.1	96.5	93.5	89.4	7.3	99.0	64.2	72.2
	ViT-3B/14448px	89.5	85.9	99.5	94.5	97.4	89.0	97.4	96.7	93.4	89.9	9.5	98.9	66.1	74.8

Table 3. Frozen trunk evaluation for recognition benchmarks. We report the recognition performance of the AIMv2 family models when compared to a number of self-supervised and weakly-supervised state-of-the-art models. All models are evaluated using attentive probing with a frozen backbone. Unless otherwise specified, all AIMv2 models are trained at 224px resolution on 12B samples.

4. Results

AIMv2 is a generalist vision encoder that can be leveraged off-the-shelf for a wide range of downstream tasks. We evaluate the performance of the AIMv2 family across various tasks, including recognition, detection, captioning, and multiple multimodal benchmarks.

4.1. Image Recognition

Attentive probing. We assess the quality of the AIMv2 models as off-the-shelf backbones for recognition benchmarks which are outlined in Table B1. To this end, we adopt the attentive probing setting proposed by Yu et al. [129], where the vision encoder remains frozen, and only an attentive probe classifier is trained on top of the last layer features. The results are presented in Table 3. Detailed hyperparameters used for the probing experiments are provided in Table A2. First, we observe that AIMv2 significantly outperforms generative unsupervised methods such as MAE [48] and AIM [33], even with much smaller capacity models. Compared to DINOv2 [87], we find that both the similarly sized AIMv2-1B and the smaller AIMv2-H provide competitive performance, outperforming DINOv2 on several benchmarks including IN-1k, Food101, DTD, Cars, and with a particularly large margin on Infographic. However, DINOv2 offers exceptional performance for iNaturalist and fMoW. Furthermore, we find the performance of self-supervised models on medical imaging benchmarks (e.g., RxRx1 and CAM17) noteworthy, as they exhibit stronger performance compared to their weakly supervised counterparts. This affirms the importance of self-supervised learning methods, particularly in low-resource domains.

Second, when compared to other vision-language pretrained baselines, AIMv2 exhibits highly competitive performance. For instance, at the ViT-Large capacity, AIMv2 outperforms OAI CLIP on the majority of benchmarks and achieves stronger performance than DFN-CLIP and SigLIP

	open-voc	abulary	refe	ssion	
model	COCO	LVIS	RefC	RefC+	RefCg
OAI CLIP	59.1	31.0	92.2	86.2	88.3
DFN-CLIP	59.8	30.7	92.5	85.8	88.3
SigLIP	58.8	30.5	92.3	86.1	88.4
DINOv2	60.1	30.8	92.2	85.9	89.1
AIMv2	60.2	31.6	92.6	86.3	88.9

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Table 4. Evaluation after finetuning on grounding dataset mixture. We report the performance on mean average precision (AP) for open-vocabulary detection and Precision @1 for referring expression comprehension tasks.

$model \ \rightarrow$	Cap	AIMv2	CapPa [118]	AIMv2	OAI CLIP	SigLIP
Pre-train/LiT	2B/3B	2B/3B	9B/3B	12B/3B	13B/-	40B/-
IN-1k top-1	75.0	75.3	76.4	77.0	75.5	80.4

Table 5. Zero-shot performance. Comparison of different models with varying amounts of pre-training and LiT pairs, and their performance on IN1k. For CapPa, we compare to the number reported by Tschannen et al. [118].

test resolution \rightarrow	224×224	448×448	native
AIMv2-L _{224px}	86.6	84.8	-
AIMv2-L _{448px}	78.9	87.9	-
AIMv2-L _{native}	86.1	87.1	87.3

Table 6. AIMv2 with native apsect ratio and resolution. We report the IN-1k top-1 performance of the native resolution AIMv2-L model as compared to AIMv2-L models that are pretrained/finetuned for single dedicated resolution.

on several key benchmarks, including IN-1k, iNaturalist, DTD, and Infographic. These results are particularly impressive given that AIMv2 is trained using nearly a quarter of the data required for training DFN-CLIP and SigLIP (12B *vs.* 40B), while also being easier to train and scale. Finally, we find that scaling the capacity of AIMv2 models consistently leads to a stronger performance with AIMv2-3B exhibiting the strongest result, in particular its variant finetuned for 448px images which achieves 89.5% top-1 accuracy on IN-1k with a frozen trunk. Finally, in Figure 3 we observe a clear improvement to the performance of IN-1k when scaling the model capacity and the image resolution

model	architecture	# patches	VQAv2	GQA	OKVQA	TextVQA	DocVQA	InfoVQA	ChartQA	ScienceQA	COCO	TextCaps	NoCaps	SEED	MME_p
OpenAI CLIP	ViT-L/14	576	78.0	72.0	60.0	47.5	25.6	21.8	18.5	73.8	94.9	75.3	93.3	70.1	1481
SigLIP	ViT-L/14	576	76.9	70.3	59.3	44.1	16.9	20.7	14.4	74.7	93.0	69.9	92.7	66.8	1416
SIGLIP	ViT-So400M/14	752	77.7	71.0	60.1	47.5	19.2	21.0	14.7	74.9	94.6	70.8	94.5	67.5	1433
DINOv2	VIT-g/14	3034	76.7	72.7	56.9	15.1	8.2	19.7	12.0	69.5	93.4	42.1	89.1	68.9	1423
	ViT-L/14	576	79.7	72.5	60.8	53.6	26.6	22.8	19.2	74.1	96.9	81.1	99.9	71.8	1472
AIMv2	ViT-H/14	576	80.2	72.8	61.3	55.5	27.8	23.1	19.9	76.8	99.6	80.7	102.7	72.1	1545
AINIV2	ViT-1B/14	576	80.5	73.0	61.5	56.8	28.5	22.1	20.5	76.4	98.4	82.6	101.5	72.7	1508
	ViT-3B/14	576	80.9	73.3	61.7	58.2	30.4	23.0	22.6	77.3	100.3	83.8	102.9	72.9	1545

Table 7. Mutlimodal Evaluations. We compare AIMv2 to state-of-the-art visual backbones for multimodal instruction tuning. Under comparable capacities, AIMv2-L outperforms its counterparts on the majority of benchmarks. Additionally, scaling to the larger AIMv2-3B model results in clear improvements, achieving the highest scores on nearly all benchmarks. All AIMv2 models use 336px resolution.

model	architecture	0-shot	4-shot	8-shot
OAI CLIP [85]	ViT-L/14	39.3	62.2	66.1
DFN-CLIP [85]	ViT-H/14	40.9	62.5	66.4
AIMv2	ViT-L/14	39.6	63.8	67.2

Table 8. ICL few-shot performance. We report the in-context few-shot performance averaged across a wide range of benchmarks as detailed in § 4.3.2. The results for DFN-CLIP and OAI CLIP are as reported by McKinzie et al. [85].

in conjunction. We provide more detailed results for the high-resolution finetuned backbones in Appendix **B**.

Zero-shot via LiT Tuning. We investigate the compatibility of AIMv2 backbones with LiT [132], extending its application to zero-shot settings. We report the IN-1k zero-shot performance in Table 5. First, we observe that AIMv2, with the multimodal autoregressive objective, shows a modest improvement compared to the captioning-only baseline, even in this setting. Furthermore, an AIMv2-L model trained for a longer duration exhibits favorable performance compared to the results reported by Tschannen et al. [118] for CapPa. Overall, our model demonstrates strong zero-shot performance, outperforming OAI CLIP [94], yet still lagging behind dedicated models like SigLIP that are trained for a longer schedule with 40B image-text pairs.

Native resolution. We finetune AIMv2 to process images with a wide range of resolutions and aspect ratios as detailed in § 2.4. In order to assess the quality of this stage of post-training, we compare the performance of an AIMv2 encoder adapted for native resolution to models that are tuned for one specific resolution in Table 6. We observe that AIMv2-L_{native} provides a strong performance across a wide range of resolutions off-the-shelf, experiencing only a minor degradation in performance to the dedicated models. Additionally, evaluating our model using the original native resolutions of the IN-1k validation set images yields a robust accuracy of 87.3%, confirming that AIMv2 maintains exceptional recognition performance while offering high flexibility in both aspect ratio and resolution.

4.2. Object Detection and Grounding

To further demonstrate the capabilities of AIMv2, we evaluate its performance on tasks such as Open-Vocabulary Detection (OVD) and Referring Expression Comprehension (REC). We follow the model architecture introduced by

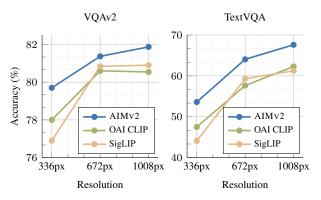


Figure 5. Impact of Scaling Resolution. The performance boost achieved byAIMv2 persists after scaling input resolution via tiling Lin et al. [72], Liu et al. [73] compared to popular vision backbones for VLMs such as OAI CLIP and SigLIP.

MM-Grounding-DINO [74, 136] but adapt ViT-L through the ViTDet [68] formulation as the vision backbone. Our results are presented in Table 4. For OVD capabilities we evaluate on COCO [71] and LVIS [43], while for REC, we evaluate on RefCOCO (RefC) [57], RefCOCO+ (RefC+) [130], and RefCOCOg (RefCg) [79]. All models were trained on the following datasets: Objects365v1 [101], Flickr-30k Entities [90, 127], GQA [52], COCO17 [71], and RefCOCO [57, 79, 130]. During DINOv2 training we fix the window size to 16 [69] to ensure fixed compute cost across backbones. Our results indicate that AIMv2 outperforms DINOv2 as well as other vision-language pre-trained models on all benchmarks but one, showing particularly strong performance on LVIS. We present additional localization and grounding results including closed-vocabulary detection and instance segmentation as well as ablations on varying window sizes in Appendix D.

4.3. Multimodal Understanding

Vision encoders play a crucial role in advancing large multimodal models [6, 73, 85, 115, 138]. To quantify the performance of AIMv2 models in this setting, we perform a multimodal instruction tuning stage similar to Liu et al. [73]. Additionally, we explore the few-shot In-Context Learning (ICL) setting after large-scale multimodal pretraining similar to McKinzie et al. [85].

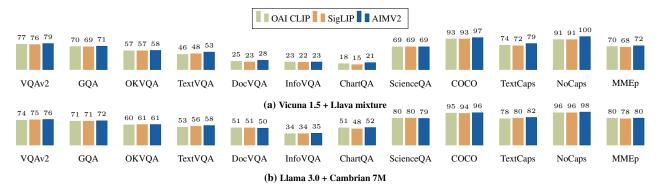


Figure 6. Instruction tuning under different settings. We evaluate instruction-tuned models across combinations of LLM decoders and tuning data mixtures. In all settings, AIMv2 consistently outperforms or matches SigLIP and OAI CLIP on most benchmarks. All models use a ViT-L backbone with 336px images. For better readability, we present normalized MME_p scores by dividing the raw scores by 2000.

4.3.1. Multimodal Instruction Tuning

Setup. We place a 2-layer MLP connector between the vision encoder (*e.g.*, AIMv2-L) and the LLM (*e.g.*, Llama 3.0). The parameters of the vision encoder are frozen during this stage. Contrary to Liu et al. [73], we train the connector and the LLM jointly in a single stage. However, we scale up the learning rate for the connector by a factor of 8. We found this strategy to be simpler while leading to comparable results. We detail the evaluation datasets, task prompts, and hyperparameters used during this stage in Appendix C. Unless mentioned otherwise, we use the Llava SFT mixture [73] and Llama-3.0 8B LLM decoder [32]. We train all models for a single epoch.

Evaluation. We evaluate the instruction-tuned models across various question answering benchmarks covering general knowledge, text-rich images, scientific domains, and captioning. The results for AIMv2 and several baselines are presented in Table 7. Notably, our smallest model, AIMv2-L, outperforms OAI CLIP, SigLIP, and DINOv2 on most benchmarks, even when the baselines use larger capacities or higher input resolutions. Furthermore, performance consistently improves with increasing the AIMv2 backbone capacity, with the AIMv2-3B model achieving the best performance across all benchmarks except one.

Varying the LLM and Data Mixture. In addition to the canonical setting reported in Table 7, we evaluate whether AIMv2 can provide similar gains compared to popular vision encoders across various combinations of LLM decoders and instruction tuning data mixtures. Specifically, we perform the instruction tuning stage under the following settings: (1) Llama 3.0 with the Cambrian data mixture [115] and (2) Vicuna 1.5 [22] with the Llava SFT mixture. We present the results for AIMv2-L alongside similarly sized OAI CLIP and SigLIP backbones in Figure 6. Across all settings, AIMv2 provides a stronger, or at worst on par, performance compared the OAI CLIP and SigLIP. These findings further affirm the robustness and compatibility of AIMv2 within diverse multimodal pipelines.

High-Resolution via Tiling. One of the most popular strategies to enhance the performance of vision-language models is increasing the image resolution. This can be achieved through a tiling strategy [72, 73, 103], where a high-resolution image is divided into a number of equally sized crops that match the pre-training resolution of the available backbones (e.g., 224px or 336px). We investigate the compatibility of AIMv2 with this strategy. Specifically, we use a crop size of 336px and evaluate our pipeline on 672px and 1008px images corresponding to 2×2 and 3×3 grids respectively. The results for AIMv2, SigLIP, and OAI CLIP are presented in Figure 5. We observe that the performance of all methods improves with higher resolutions, with a significant improvement for TextVQA. Notably, AIMv2 maintains its advantage over the baselines in high-resolution tiling settings, demonstrating its versatility.

4.3.2. Multimodal In-Context Learning

We also evaluate AIMv2 in a large-scale multimodal pre-training setting. Following the pre-training recipe as MM1 [85], we simply replace the vision encoder with AIMv2. Given that this model is pre-trained using interleaved image-text documents, it enables in-context evaluations [3]. We report the ICL performance in Table 8. Specifically, we report the average 0-shot, 4-shot, and 8-shot performance across the following benchmarks: COCO [21], NoCaps [2], TextCaps [105], VQAv2 [40], TextVQA [107], VizWiz [44], GQA [53], and OK-VQA [80]. Our results demonstrate that AIMv2 achieves the best performance in the 4-shot and 8-shot settings, surpassing the higher capacity DFN-CLIP adopted by the MM1 series. This highlights the compatibility and effectiveness of AIMv2 in leveraging ICL in a large-scale multimodal setup.

5. Ablation Study

In this section, we investigate various design choices and present the trade-offs associated with each. The results of our study are summarized in Table 9.

model	pre-train attn.	IN-1k	VQAv2	TextVQA		model	bsz	IN-1k	VQAv2	TextVQA		α	IN-1k	VQAv2	TextVQA	
AIMv1	prefix	72.0	65.4	12.7	-	CLIP	8k	84.6	74.1	24.6		0.2	85.6	76.7	37.4	
Cap	bidir	85.1	76.2	34.4		CLII	16k	85.2	74.8	26.3		0.4	85.6	76.9	37.5	
Cap	prefix	85.4	76.8	36.5		CapPa	8k	84.7	75.1	30.6		0.6	85.6	76.7	37.4	
AIMv2	prefix	85.6	76.9	37.5		AIMv2	8k	85.6	76.9	37.5						
(a) Objective.					(b) AIMV2 vs. CLIP.							(c) Criteria Weights.				
	IN-1k	VQAv2	TextVQ	QA	wie	dth IN-	lk	VQAv2	TextVO	QA	dep	th	IN-1k	VQAv2	TextVQA	
separate	e 85.6	77.1	37.2		512	2 85.	3	76.2	35.9) _	8		85.5	76.7	37.0	
joint	85.6	76.9	37.5		102	24 85 .	6	76.9	37.5		12		85.6	76.9	37.5	
0					153	36 85.	1	76.9	36.9)	16		85.6	76.9	36.6	
	(d) Decoder A			(e) Decoder Width.						(f) Decoder Depth.						

Table 9. Ablations. We ablate a number of design choices for AIMv2 and how they impact performance on key recognition and multimodal benchmarks. This includes (a) the contribution of the visual and textual objectives, (b) comparison to other popular objectives, (c) the optimal balancing between the losses, (d-f) the architecture of the multimodal decoder. All models are trained at 224px resolution.

Setup. The default setting for this ablation study utilizes a ViT-Large vision encoder and 2 billion image-text pairs during pre-training. We measure the IN-1k top-1 accuracy after attentive probing, as well as the question-answering accuracy on the validation sets of VQAv2 [40] and TextVQA [106] following instruction tuning, as described in § 2.4. All experiments reported in this ablation study employ images with 224×224 resolution. The metrics selected for this study provide a comprehensive view of the models' capabilities, encompassing recognition, general question answering, and text-rich question answering.

Pre-training Objective. The pre-training objective of AIMv2 comprises a combination of image-level and textlevel autoregressive objectives. We evaluate the performance of each objective independently and assess the impact of combining them, as presented in Table 9a. First, we observe that utilizing only the image-level objective (i.e., AIMv1) results in weaker performance compared to models that incorporate the captioning objective. This is expected, given that AIMv1 operates in an unsupervised manner and demands higher-capacity models to achieve optimal performance, as highlighted by El-Nouby et al. [33]. Second, for the captioning-only model, using prefix attention within the vision encoder yields superior performance compared to fully bidirectional attention. We hypothesize that prefix attention facilitates the encoding of maximally informative contexts even from partial images, as such contexts are utilized by subsequent visual and textual tokens. However, this hypothesis warrants further investigation, which is beyond the scope of this work and is reserved for future research. Finally, we find that combining the image-level and text-level objectives in AIMv2 leads to an improved performance, particularly noticeable for TextVOA.

AIMv2 vs. CLIP vs. CapPa. In Table 9b, we evaluate the performance of models trained with the AIMv2 objective in comparison to other popular vision-language pretraining objectives, specifically CLIP [94] and CapPa [118]. All models are trained using identical architectures, incorporating SwiGLU and RMSNorm, and are pre-trained using the same dataset of image-text pairs. Notably, since CLIP pre-training benefits from larger batch sizes, we report CLIP results using both 8k and 16k batch sizes to ensure a fair comparison. Our findings indicate that, under comparable settings, AIMv2 consistently outperforms both CLIP and CapPA by a significant margin, particularly on the TextVQA benchmark. This performance is especially noteworthy given the simplicity and scalability AIMv2.

Multi-task balancing. We examine whether the pretraining of AIMv2 is sensitive to the balancing between the image-level and text-level objectives in Table 9c. We vary the hyperaparmeter α , as described in § 2.1, and we observe only minor fluctuations in performance around the optimal value of 0.4 across the three benchmarks.

Joint vs. Separate Decoders. In the AIMv2 architecture, we opt for a multimodal joint decoder instead of employing dedicated decoders for each modality. In Table 9d, we examine the performance of an AIMv2 variant that utilizes two dedicated decoders. Using a single joint decoder achieves comparable results to using separate decoders while offering greater simplicity and efficiency during pre-training. This advantage proves valuable when scaling data and model capacity.

Decoder architecture. Finally, we examine the capacity of the multimodal decoder, as detailed in Table 9e and Table 9f. We find that performance is more sensitive to changes in decoder capacity when scaling the width compared to scaling the depth. Additionally, we observe that increasing the decoder capacity beyond a certain threshold, whether by scaling width or depth, leads to a decline in performance. This observation is consistent with the findings of Tschannen et al. [118] for captioning-only models.

6. Related Works

Autoregressive pre-training. Autoregressive modeling has been a foundational idea in machine learning and statistics for decades, long before deep learning [11]. However, it has been popularized and scaled by works such as GPT [12, 92, 93], and LLaMAs [31, 116, 117] which have demonstrated the power of autoregressive pre-training in natural language processing tasks. In vision, autoregressive principles have been applied through models like iGPT [19], which flattens images into a sequence of discretized pixels and then treats them analogously to language tokens. Similarly, Yu et al. [128] also discretize the patches with a VQGAN model [34] and then predicts them autoregressively. AIM [33] brings back the more practical continuous approach and scales to very large vision models. However, AIM still lags behind other state of the art models in sheer performance, as it uses vision-only data and requires large model capacities to perform optimally. This paper addresses these limitations by introducing multimodal pre-training in the AIMv2 family. Concurrent works [77, 104, 113, 122, 124, 125, 131] have also investigated similar multimodal autoregressive approaches that predict text and images. However, they often focus on multimodal generation quality rather than representation quality, and therefore use discrete tokens or leverage diffusion models [98] as decoders [70, 110, 111].

Pre-training in vision. For many years, the computer vision community predominantly focused on supervised pretraining [58, 97, 108], with ImageNet [61] checkpoints serving as the backbone for most visual tasks. This eventually hit a wall in terms of scalability, as labels are expensive to acquire. The community therefore focused on self-supervised methods. Earlier models used pretext tasks such as rotation prediction and patch deshuffling [39, 86, 135]. More sophisticated models like Sim-CLR [20], BYOL [42], SwAV [15] and DINO [16] leverage variations of contrastive learning to train models that are quasi-invariant to a broad range of image augmentations. This turns out to learn strong and general visual representations without supervision. However they require carefully handcrafted data augmentations, which also makes them computationally expensive, especially at scale. On the other hand, MAE and BEiT [8, 48] introduced masking strategies to reconstruct input data, reducing the reliance on augmentations and increasing efficiency but sacrificing performance. In practice, the best performing self-supervised vision-only models use a mixture of augmentations and masking [4, 87, 137]. Unfortunately, they are challenging to scale as they still need multiple forward passes for each training step. AIM [33] departs from these methods by employing a reconstruction-based autoregressive framework that exhibits strong scalability but requires high capacity models to attain optimal performance. Leveraging large-scale, noisy, weakly supervised datasets from the internet [13, 35, 100], an efficient paradigm emerged that aligns vision and text features through contrastive learning [54, 94]. Nevertheless, CLIP-like models require large batch sizes and meticulous dataset filtering [35, 100]. Subsequent works, such as SigLIP [133], EVA CLIP [109], and Fini et al. [37], have addressed these issues by optimizing training processes and improving data filtering [35]. Unlike these approaches, AIMv2 does not perform explicit feature

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space alignment but aligns training objectives through autoregressive modeling for better multimodal synergy.

Captioning. Image captioning has been extensively studied prior to the computer vision literature. Early works [56, 121, 126] focused on aligning visual features with text to generate descriptions using CNNs and RNNs. VirTex [28] and ICMLM [99] utilize captioning for visual pre-training. SimVLM [123] employs a PrefixLM approach, encoding images and partial text tokens with a multimodal encoder and decoding the remaining text. LEMON [51] scales the language model in both parameters and dataset size. Approaches such as [65, 66] combines generative captioning with discriminative contrastive objectives to enhance multimodal learning, which led to scaling to billion-parameter models [62, 67, 129]. Similarly, CapPa [118] trains a captioning model that functions as both a masked and causal decoder, and Caron et al. [17] re-purposes a captioning model for web-scale entity recognition. Different from most previous approaches, AIMv2 does not use cross-attention and treats vision and text tokens symmetrically, similar to large multimodal models (e.g. LLaVA [73] and MM1 [85]). Additionally, AIMv2 incorporates an autoregressive image modeling loss on vision tokens, further enhancing performance beyond captioning-only methods.

7. Conclusion

This paper introduce AIMv2, a family of vision encoders pre-trained with a multimodal autoregressive objective that reconstructs image patches and text tokens. This unified objective enables AIMv2 to excel in diverse tasks, including image recognition, grounding, and multimodal understanding. The superior performance of AIMv2 is attributed to its ability to leverage signals from all input tokens and patches, facilitating efficient training with fewer samples compared to other methods. AIMv2 consistently outperforms or matches existing self-supervised and vision-language pretrained models, demonstrating its strength and versatility as a vision encoder. Additionally, the straightforward pretraining process of AIMv2 ensures easy scalability, paving the way for further advancements in vision model scaling.

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A. Hyperparamters

Pre-training. We outline the optimization hyperaparmeters and data augmentations used during AIMv2 pre-training in Table A1. For the captions, we adopt the tokenizer used by SigLIP [133] and truncate any text longer than 77 tokens.

config	ViT-L ViTs-H ViT-1B ViT-3B						
Optimizer	Fully decoupled AdamW [76]						
Optimizer Momentum	$\beta_1 = 0.9, \beta_2 = 0.95$						
Peak learning rate	1e-3 8e-4 8e-4 4e-4						
Minimum Learning rate	1e-5						
Weight decay	1e-4						
Batch size	8192						
Patch size	(14, 14)						
Gradient clipping	1.0						
Warmup iterations	12,500						
Total iterations	1,500,000						
Learning rate schedule	cosine decay [75]						
Augmentations:							
RandomResizedCrop							
size	224px						
scale	[0.4, 1.0]						
ratio	[0.75, 1.33]						
interpolation	Bicubic						
RandomHorizontalFlip	p = 0.5						

Table A1. Pre-training hyperparameters We detail the hyperaparmeters used for pre-training all AIMV2 variants.

Attentive probing. The optimization and data augmentations hyperaparmeters for the attentive probing stage are detailed in Table A2. We use the same set of hyperaparmeters for all AIMv2 capacities and the baselines. To ensure a fair comparison, we sweep the learning rate and weight decay using the ranges detailed in Table A2 and report the strongest results for each model.

B. Image Recognition

Evaluation benchmarks. In Table 3, we evaluate the recognition performance of AIMv2 and other baselines on a diverse set of benchmarks that encompass fine-grained recognition, medical imaging, satellite imagery, natural environment imagery, and infographic analysis. We detail the datasets, the splits and their sizes in Table B1.

High-resolution adaptation. In Table B2, we show the performance of AIMv2 models with varying image resolutions (224px, 336px, and 448px) across a broad set of recognition benchmarks. These results extend the main paper, which primarily focuses on the 224px resolution and the 3B model at 448px. We observe that scaling both the model capacity and image resolution leads to consistent improvements across most tasks.

config	IN-1k	Others
Optimizer	Pytorch's AdamW	[76]
Optimizer Momentum	$\beta_1 = 0.9, \beta_2 = 0.5$	999
Peak learning rate grid	[5e-5, 1e-4, 2e-4, 3e-4, 5e-4	4, 1e-3, 2e-3]
Minimum Learning rate	1e-5	
Weight decay	[0.05, 0.1]	
Batch size	1024	512
Gradient clipping	3.0	
Warmup epochs	5	0
Epochs	100	
Learning rate schedule	cosine decay	
Augmentations:		
RandomResizedCrop		
size	224px	
scale	[0.08, 1.0]	
ratio	[0.75, 1.33]	
interpolation	Bicubic	
RandomHorizontalFlip	p = 0.5	
Color Jitter	0.3	
AutoAugment	rand-m9-mstd0.5	-incl

Table A2. Attentive probe hyperparameters. We detail the hyperparameters used during attentive probing of AIMv2 and the baselines. For AIMv2 and the baselines we sweep over the learning rates and weight decay and report the best performance for each model.

Dataset	train	test	classes
Imagenet-1k [27]	1,281,167	50,000	1000
iNAT-18 [119]	437,513	24,426	8142
CIFAR-10 [60]	50,000	10,000	10
CIFAR-100 [60]	50,000	10,000	100
Food101 [10]	75,750	25,250	101
DTD [25]	3,760	1,880	47
Pets [88]	3,680	3,669	37
Cars [59]	8,144	8,041	196
Camelyon17 [7]	302,436	34904	2
PCAM [120]	262,144	32768	2
RxRx1 [112]	40,612	9854	1139
EuroSAT [49]	16,200	5400	10
fMoW [24]	76,863	19915	62
Infograph [89]	36,023	15,582	345

Table B1. Recognition benchmarks. We outline the recognition benchmarks, the number of train and test images for each dataset, and the number of categories.

C. Multimodal understanding

C.1. Instruction Tuning Setup

Evaluation benchmarks. We list the multimodal benchmarks we use for assessing the performance of our models and the baselines in Table C2, together with the splits, prompts, and evaluation metric utilized for each dataset.

Hyperparamters. The hyperaparmeters used for the instruction tuning stage are detailed in Table C1. We use the same hyperaparmeters for all language decoders, AIMv2 capacities, and the baselines.

C.2. Additional Results

Instruction tuning with Cambrian. Table C3 evaluates AIMv2, fine-tuned on Cambrian, across different res-

model	architecture	IN-1k	iNAT-18	Cifar10	Cifar100	Food101	DTD	Pets	Cars	CAM17	PCAM	RxRx1	EuroSAT	fMoW	Infographic
	ViT-L/14	86.6	76.0	99.1	92.2	95.7	87.9	96.3	96.3	93.7	89.3	5.6	98.4	60.7	69.0
A IMAZ2	ViT-H/14	87.5	77.9	99.3	93.5	96.3	88.2	96.6	96.4	93.3	89.3	5.8	98.5	62.2	70.4
AIMv2 224px	ViT-1B/14	88.1	79.7	99.4	94.1	96.7	88.4	96.8	96.5	94.2	89.0	6.7	98.8	63.2	71.7
	ViT-3B/14	88.5	81.5	99.5	94.3	96.8	88.9	97.1	96.5	93.5	89.4	7.3	99.0	64.2	72.2
	ViT-L/14	87.6	79.7	99.1	92.5	96.3	88.5	96.4	96.7	93.8	89.4	6.7	98.4	62.1	71.7
AIMv2 336px	ViT-H/14	88.2	81.0	99.3	93.6	96.6	88.8	96.8	96.4	93.3	89.4	7.2	98.7	63.9	73.4
A11v1 v 2 336px	ViT-1B/14	88.7	82.7	99.4	93.9	97.1	88.9	96.9	96.5	94.2	89.5	8.4	98.9	65.1	73.7
	ViT-3B/14	89.2	84.4	99.5	94.4	97.2	89.3	97.2	96.6	93.2	89.3	8.8	99.0	65.7	74.0
	ViT-L/14	87.9	81.3	99.1	92.4	96.6	88.9	96.5	96.6	94.1	89.6	7.4	98.6	62.8	72.7
AIMv2 448px	ViT-H/14	88.6	82.8	99.4	93.6	97.0	88.9	96.8	96.5	93.4	89.6	7.8	98.7	64.8	74.5
A11v1 v 2 448px	ViT-1B/14	89.0	83.8	99.4	94.1	97.2	88.9	97.1	96.6	93.5	89.9	9.2	99.1	65.9	74.4
	ViT-3B/14	89.5	85.9	99.5	94.5	97.4	89.0	97.4	96.7	93.4	89.9	9.5	98.9	66.1	74.8

Table B2. Frozen trunk evaluation for recognition benchmarks, high resolution AIMv2 models. We report the recognition performance of the AIMv2 high resolution family of models when compared to the base 224px models shown in the main paper. All models are evaluated using attentive probing with a frozen backbone.

config	Llava SFT mixture	Cambrian
Optimizer	Pytorch's Adam	nW [76]
Optimizer Momentum	$\beta_1 = 0.9, \beta_2 =$	- 0.999
Decoder peak learning rate	1e-5	2e-5
Connector peak learning rate	8e-5	1.6e-4
Minimum Learning rate	0	
Weight decay	0.01	
Batch size	128	512
Gradient clipping	1.0	
Warmup iterations	250	700
iterations	5000	14,000
Learning rate schedule	cosine dec	ay
Transformations	[PadToSquare,	Resize]

Table C1. Instruction tuning hyperaparmeters. We detail the hyperparameters of the instruction tuning stage, both for the Llava SFT mixture [73] and Cambrian [115].

olutions using a tiling strategy. Unlike the main paper, which uses Llava SFT, Cambrian offers a less in-domain data mix and achieves stronger results on text-rich benchmarks. Starting with a base resolution of 336px (matching the encoder's pretraining resolution), higher resolutions (672px and 1008px) are obtained with tiling; by splitting high-resolution images into 2×2 and 3×3 grids. AIMv2 paired with tiling shows consistent improvements on textrich benchmarks such as InfoVQA, ChartQA, DocVQA, and TextVQA. However, on benchmarks like COCO, No-Caps, TextCaps, and MME_p, no significant gains are observed with increased resolution.

Instruction tuning with DCLM-1B decoder. In Figure C2, we present the same comparison between OAI CLIP, SigLIP, and AIMv2 as in the main paper, but this time using the Llava SFT mixture paired with a DCLM 1B decoder. These results demonstrate that AIMv2 consistently outperforms the baselines, regardless of the decoder's capacity. Notably, in the practical setting of a small decoder, AIMv2 maintains its position as the preferred choice for multimodal understanding tasks.

Benchmark	Split	Prompt	Evaluation Metric
VQAv2 [41]	Val		Accuracy
GQA [52]	Val		Accuracy
OKVQA [81]	Val		Accuracy
TextVQA [106]	Val	Answer the question using a	Accuracy
DocVQA [83]	Test	single word or phrase.	ANLS
InfoVQA [84]	Test		ANLS
ChartQA [82]	Test		Relaxed accuracy
SEED [64]	Test (image split))	Accuracy
ScienceQA [78] MME [38]		Answer with the option's letter from the given choices directly.	Accuracy Accuracy
COCO [71] TextCaps [105] NoCaps [2]	Val Val Val	Provide a one-sentence caption for the provided image.	CIDEr CIDEr CIDEr

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Table C2. Multimodal benchmarks. We provide the list of benchmarks used during the multimodal evaluation including the reference, split, prompt, and the evaluation metric.

C.3. Qualitative Results

The qualitative results in Figure C1 highlight AIMv2's strengths on multimodal evaluations compared to SigLIP [133] and OAI CLIP [94] after instruction tuning on Cambrian. In the first three examples, AIMv2 excels in text-rich tasks by correctly localizing and extracting the relevant textual information. For instance, in the example on the left, AIMv2 is able to identify the correct value for "supreme gasoline" and outputs the correct operation for finding the solution ("Divide 50 by 3.65"). This contrasts with OAI CLIP and SigLIP, which provide generic and incomplete answers that fail to focus on the relevant information. Similarly, AIMv2 successfully identifies the license plate number ("AED-632") in a blurry image, demonstrating robust localization and reading capabilities in challenging settings. In the luggage example, AIMv2 accurately reads the weight ("30.7"), despite the presence of multiple distracting objects in the image, while the other models make mistakes. Finally, in the calorie estimation example, AIMv2 provides a more plausible response ("1000 calories") based on its knowledge, whereas SigLIP and OAI CLIP offer less contextually plausible answers.

Casoline Self Serve Regular 3.49 ♣ Plus 3.55 ♣ Suprem 3.65 ♣ Diesel 3.60 ♣	1830 <u></u>		
L: How many gallons of supreme gasoline can I get with \$50?	L: What is the license plate number?	1 : What might be the weight of this luggage?	L: How many approximate calories is in this meal?
OAI CLIP: To calculate how many gallons of supreme gasoline you can get with \$50, you	OAI CLIP: The license plate number is partially obscured and not fully legible	OAI CLIP: 3.7	OAI CLIP: 500
would divide the total amount of money you	due to the blurriness of the image.	SigLIP: 30 pound	SigLIP: 500
SigLIP: To calculate how many gallons of supreme gasoline you can get with \$50, you would divide \$50 by the price per gallon	SigLIP: The license plate number is not clearly visible in the image provided.	AIMv2: 30.7	AIMv2: 1000
AIMv2: Divide 50 by 3.65.	AIMv2: The license plate number is AED-632		

Figure C1. Qualitative comparison of AIMv2, SigLIP, and OAI CLIP on multimodal tasks after instruction tuning on Cambrian. AIMv2 demonstrates superior performance in both text-rich (e.g. extracting relevant information or reading text in cluttered scenes) and knowledge-based scenarios (e.g., estimating caloric content), showcasing its ability to focus on relevant information, accurately localize text, and provide contextually appropriate answers.

data mix	decoder	resolution	VQAv2	GQA	OKVQA	TextVQA	DocVQA	InfoVQA	ChartQA	ScienceQA	COCO	TextCaps	NoCaps	MME _p
Cambrian	Llama 3.0	336px	75.5	71.5	61.1	58.3	50.2	35.1	51.7	78.7	95.5	82.3	98.1	1594
Cambrian	Llama 3.0	672px	77.5	72.8	62.0	69.1	76.4	48.3	64.7	79.4	92.6	80.6	95.4	1482
Cambrian	Llama 3.0	1008px	77.7	73.2	62.0	72.2	79.2	53.5	65.1	81.6	93.7	81.6	97.6	1507

Table C3. Additional multimodal evaluations. We compare the performance of AIMv2 with different SFT data mixtures (Llava [73] and Cambrian [115]), and resolutions (336px, 672px and 1008px).

	COCO				LVIS Val					
Model	AP_{all}	AP_s	AP_m	AP_l	AP_{all}	AP_r	AP_c	AP_f		
OpenAI CLIP	59.1	43.5	63.5	74.8	<u>31.0</u>	17.6	27.2	41.2		
DFN-CLIP	59.8	<u>44.0</u>	63.8	75.3	30.7	17.2	26.4	<u>41.5</u>		
SigLIP	58.8	41.7	62.8	<u>75.7</u>	30.5	16.5	26.5	41.1		
DINOv2	60.1	43.7	64.2	75.8	30.8	18.5	26.1	41.4		
AIMv2	60.2	44.5	64.3	75.4	31.6	18.0	<u>27.0</u>	42.8		

Table D1. Performance on OVD Benchmarks. We report the performance on mean average precision (AP) for COCO and LVIS. For COCO, we also report AP for the *small, medium*, and *large* subsets, while for LVIS, we report on *rare, medium*, and *frequent* subsets.

D. Detection, Segmentation and Grounding

D.1. Open Vocabulary Detection and Grounding

Performance on Small Objects. In Table D1 we report the breakdowns of COCO between classes that are either *small, medium,* or *large.* We can observe that AIMv2 consistently outperforms on the *small* classes by +0.5 AP, compared to DFN-CLIP, the second best performing model in that breakdown. This is further emphasized by the results reported on LVIS val, as objects in LVIS are more likely to be small. There we observe an improvement of +1.3 AP on the *frequent* subset against DFN-CLIP.

Model	Window Size	COCO AP_{all}	LVIS Val AP_{all}	RefCOCO Val P@1	RefCOCO+ Val P@1	RefCOCOg Val P@1
DINOv2	16	60.1	30.8	92.2	85.9	89.1
AIMv2		60.2	31.6	92.6	86.3	88.9
DINOv2	24	59.6	29.6	92.1	85.0	88.7
AIMv2		59.8	31.2	92.3	85.8	89.1
DINOv2	32	60.2	30.7	92.5	86.1	89.5
AIMv2		60.3	32.9	92.5	86.3	88.9
DINOv2	37	60.2	31.1	92.2	85.9	88.4

Table D2. Ablation across window sizes. We report the performance on mean average precision (AP) for COCO and LVIS. For RefCOCO* we report Precision @1 on the respective validation splits.

Window Size Ablation. Due to varying input resolutions and feature map sizes used during pre-training, we ablate the effect of window size [68] for AIMv2 and DINOv2 in Table D2. For AIMv2 the input image resolution is scaled during pre-training such that the feature map size matches the window size during finetuning, while for DI-NOv2 the window size is fixed to match AIMv2. For comparison we also add DINOv2 trained with a window size of 37, which matches its pre-training feature map size. Across the window sizes, AIMv2 outperforms DINOv2 across all OVD and for two out of three referring comprehension benchmarks. When comparing our best performing AIMv2 with the best performing DINOv2 across all

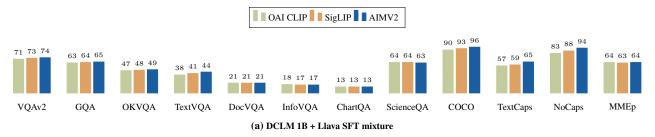


Figure C2. Instruction with a small decoder (DCLM). Performance comparison of OAI CLIP, SigLIP, and AIMv2 across 12 multimodal benchmarks using the Llava SFT mixture paired with a DCLM 1B decoder. AIMv2 exhibits superior performance across most benchmarks, even with the constrained capacity of a small decoder.

	detection mAP50:95				mask mAP50:95				
Model	APall	AP_s	AP_m	AP_l	AP_{all}	AP_s	AP_m	AP_l	
OAI CLIP	53.6	37.2	58.5	69.2	46.7	26.6	50.9	66.2	
DFN-CLIP	53.4	37.1	58.3	69.3	46.2	26.4	50.8	66.4	
SigLIP	53.3	37.2	57.6	69.7	46.6	<u>27.1</u>	50.5	66.3	
DINOv2	55.5	39.5	59.9	70.6	48.3	29.4	52.3	67.4	
AIMv2	54.0	37.4	58.8	70.0	46.7	26.7	51.1	66.5	

Table D3. COCO17 detection and segmentation benchmarks.We report overall detection and segmentation scores along with
the *small, medium,* and *large* subset breakdowns.

benchmarks, we observe that AIMv2 strongly outperforms on LVIS Val while outperforming on all except one benchmark against DINOv2.

D.2. Detection and Segmentation via ViTDet Mask-RCNN

To compare vision only capabilities of the encoders we incorporate them into a Mask-RCNN[47] detection model as backbones by utilizing a ViTDet formulation to accommodate for high resolution (1024) detector training / testing input size. We ensure that ViTDet [68] backbone forward pass outputs match the respective ViT-L implementations before the training. We utilize the same set of hyperparameters for training all compared detectors: consistent windowed attention size (16) ensuring comparable compute, AdamW optimizer, cosine decay learning rate schedule, layer-wise learning rate, and weight decay. All detectors are finetuned on coco17 train split for 100 epochs with a global batch size of 64 following the default recipe from MMDetection [18]. We report results from the coco17-val split in Table D3. AIMv2 consistently outperforms encoders pre-trained on contrastive objectives, falling slightly behind DINOv2 which provides the strongest performance.