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Scaling Language-Free Visual Representation Learning

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ICCV HONOLULU HAWAII OCT 19-23, 2025

ICCV 2025 Highlight

Meta NYU

Current State of Visual Representation Learning

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Self-Supervision:

Language-Supervision:

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Self-Supervision:

- E.g. MoCo, MAE, DINO

Language-Supervision:

- E.g. CLIP, SigLIP, MetaCLIP

Current State of Visual Representation Learning

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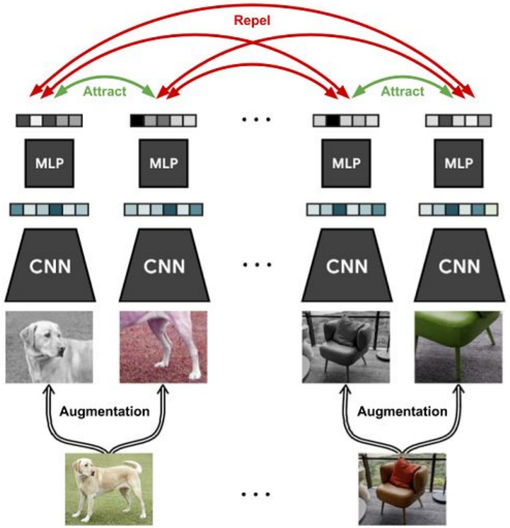
- Learning from images directly (e.g. augmentation, masking)



Language-Supervision:

- E.g. CLIP, SigLIP, MetaCLIP
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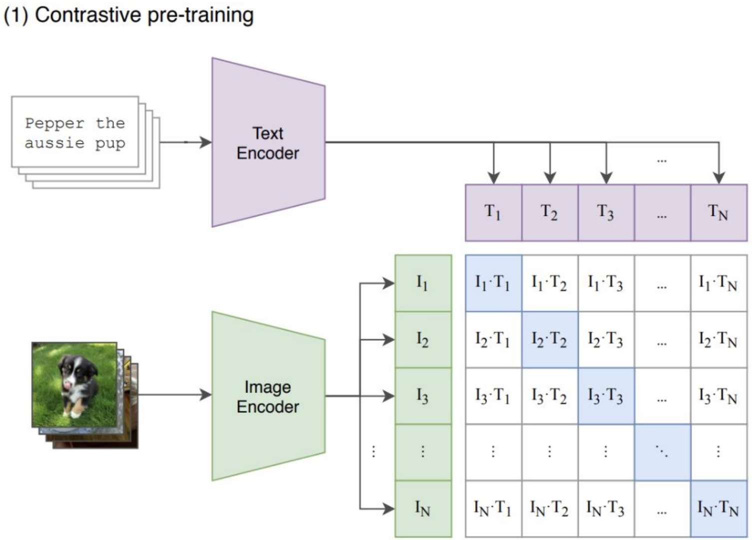

Current State of Visual Representation Learning

Self-Supervision:

- E.g. MoCo, MAE, DINO
- Learning from images directly (e.g. augmentation, masking)
- Training on ImageNet-like data (1M to >100M scale)

Language-Supervision:

- E.g. CLIP, SigLIP, MetaCLIP
- Learning from language captions that describe the image
- Training on image-text pairs from the Internet (400M to 100B scale)

Current State of Visual Representation Learning

Self-Supervision:

- E.g. MoCo, MAE, DINO
- Learning from images directly (e.g. augmentation, masking)
- Training on ImageNet-like data (1M to >100M scale)
- Good at classification, segmentation, depth estimation, etc

Language-Supervision:

- E.g. CLIP, SigLIP, MetaCLIP
- Learning from language captions that describe the image
- Training on image-text pairs from the Internet (400M to 100B scale)
- Good at classification, and widely used as backbone for **multimodal** models

The Success of CLIP as an Encoder in Multimodal Models

- CLIP has become the dominant visual representation learning method in multimodal models.

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  - VLM: LLaVA, Cambrian, PaliGemma, SEED-VL …
  - VLA: Pi, Otter, …
  - …

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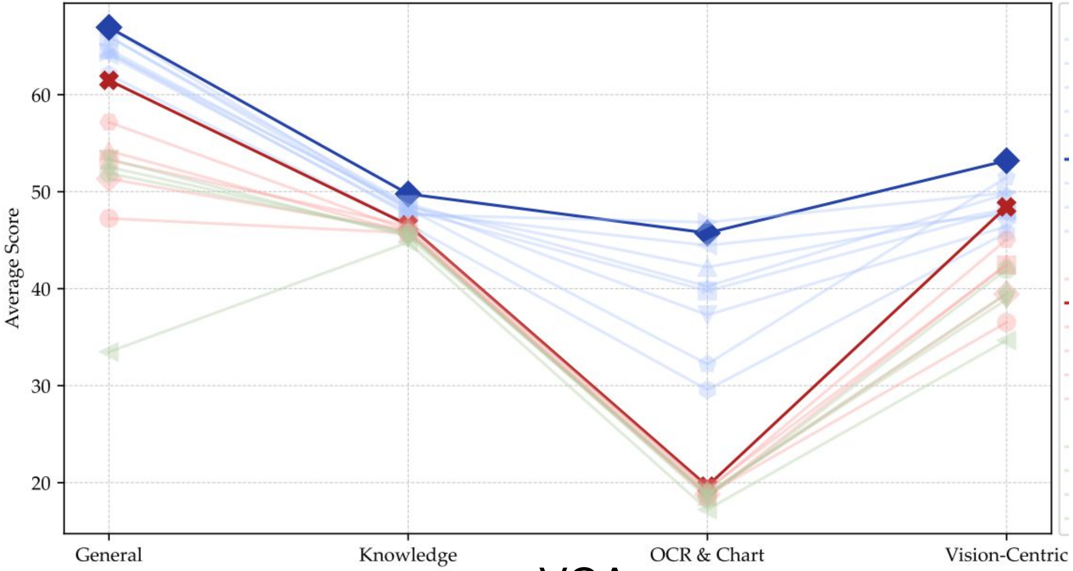

VQA

Tong, S., et al. (2024). Cambrian-1: A Fully Open, Vision-Centric Exploration of Multimodal LLMs.

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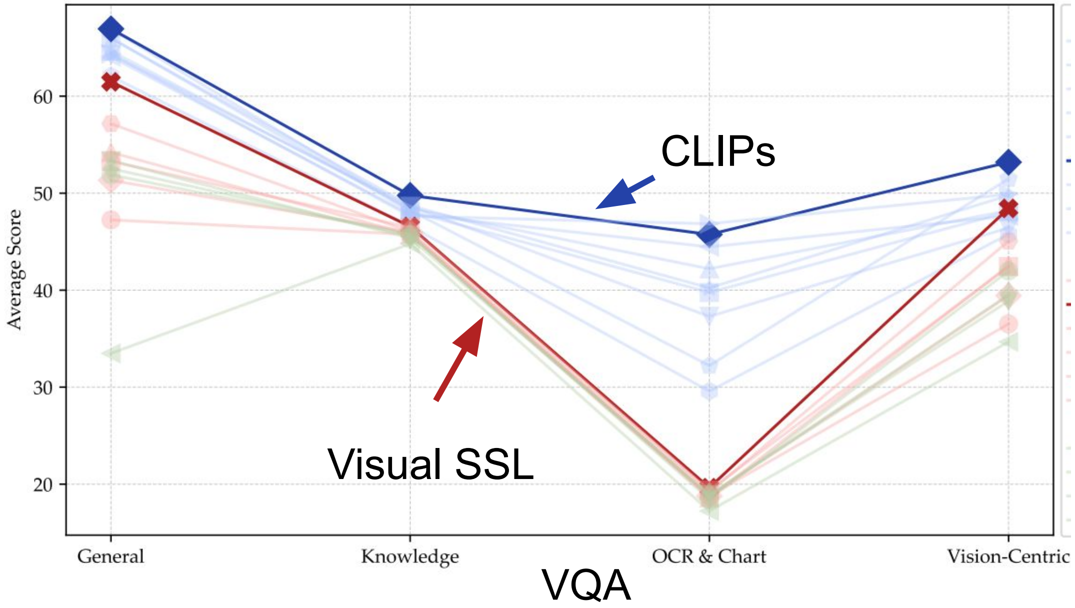

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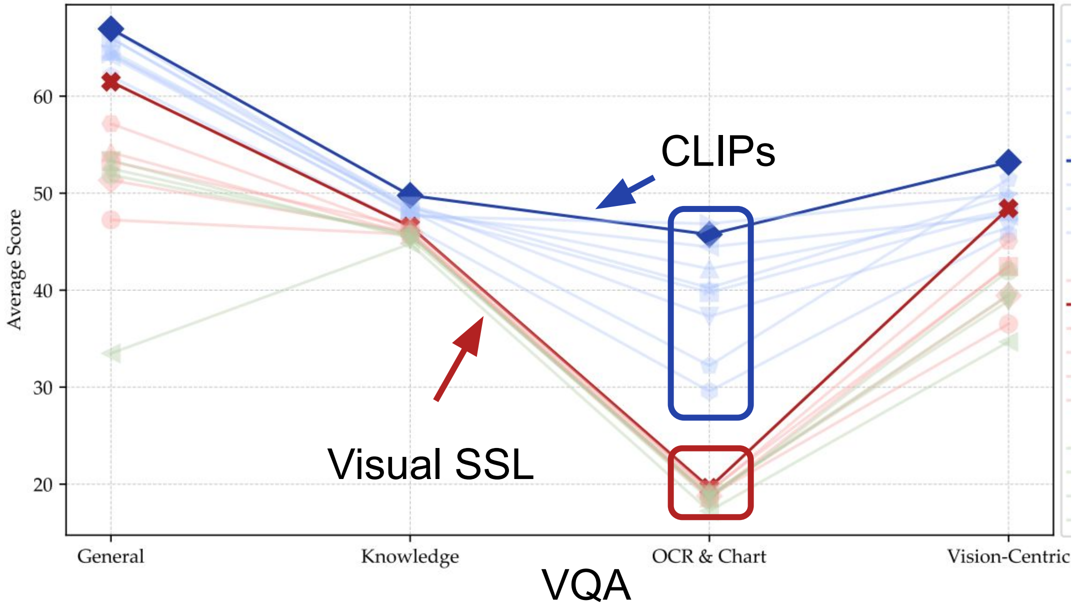

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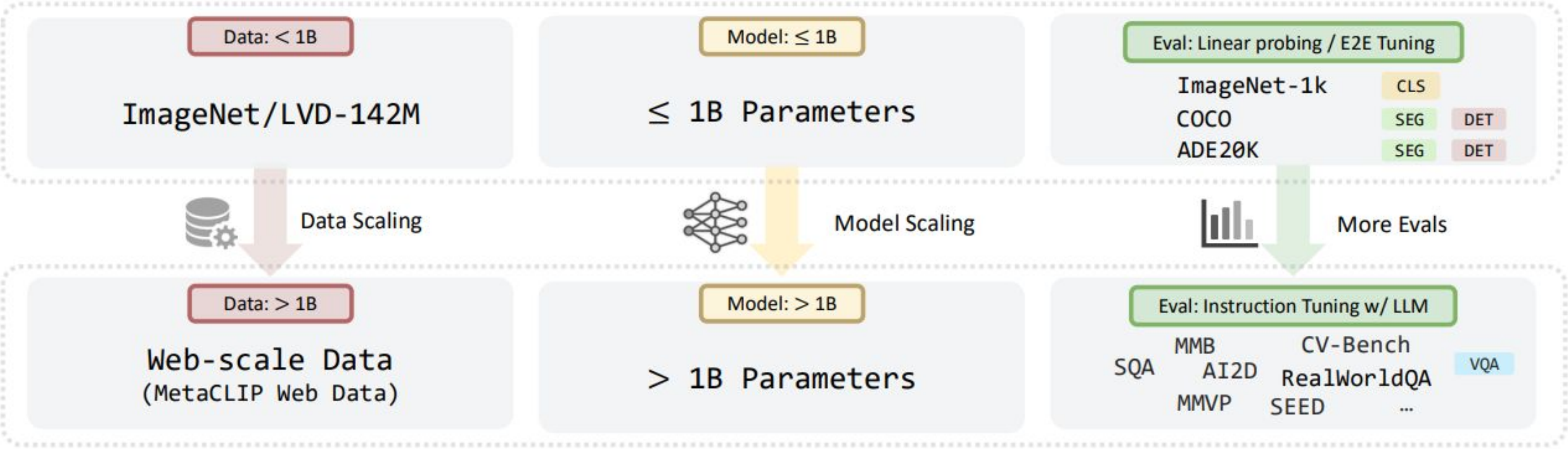
- CLIP has become the dominant visual representation learning method in multimodal models.
- Is CLIP better because of **language supervision** or **data distribution**?
- To really understand this, we need controlled comparisons on the data.

WebSSL: Towards Modernizing Visual SSL



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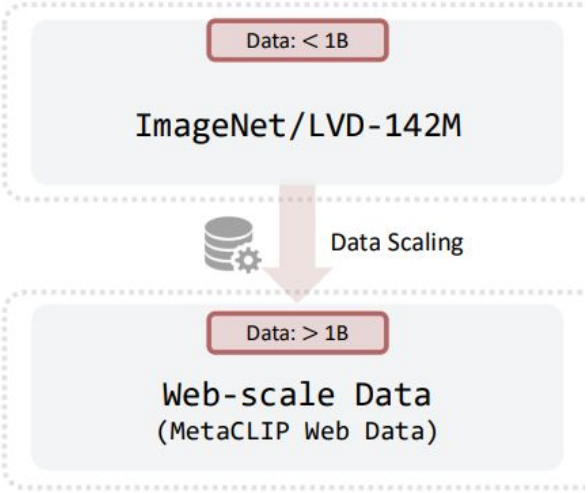

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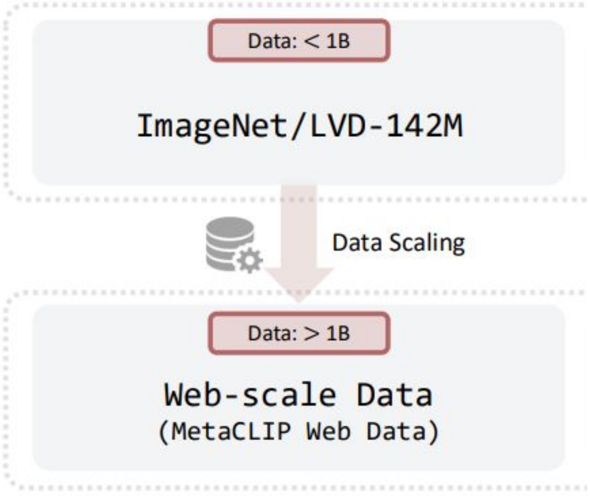

ImageNet / LVD-142M[1]:

Million scale ImageNet
or
ImageNet-like distribution
of mostly natural images

→

Web-Scale Images:

Billion scale diverse "random" images from the Internet

E.g. MetaCLIP[2] ("*MC-2B*")

We only use the images for SSL

[1] Oquab, M., et al. (2023). DINOv2: Learning Robust Visual Features without Supervision

[2] Xu, H., et al. (2023). Demystifying CLIP Data.

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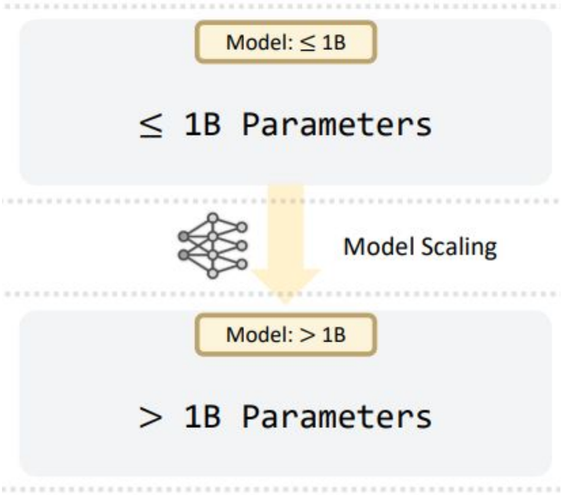

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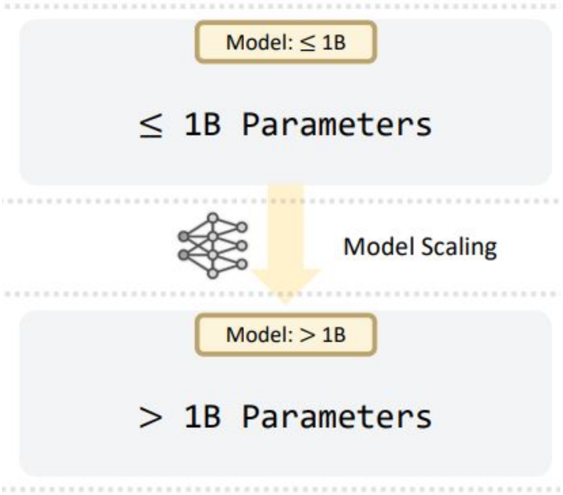

Less than 1B params:

ViT-B, ViT-L, ViT-H, ViT-g

→

More than 1B params:

ViT-1B, …, VIT-7B and beyond

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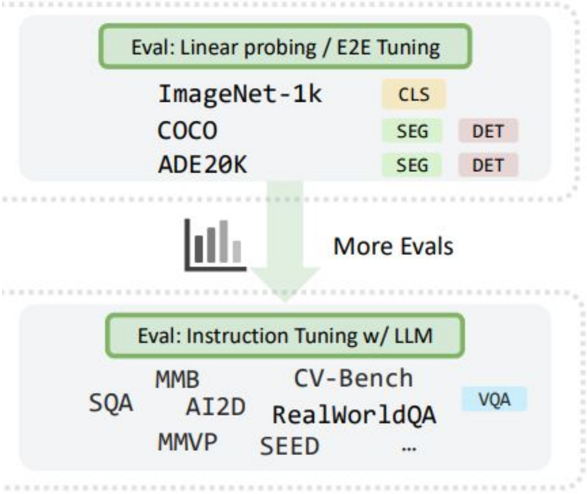

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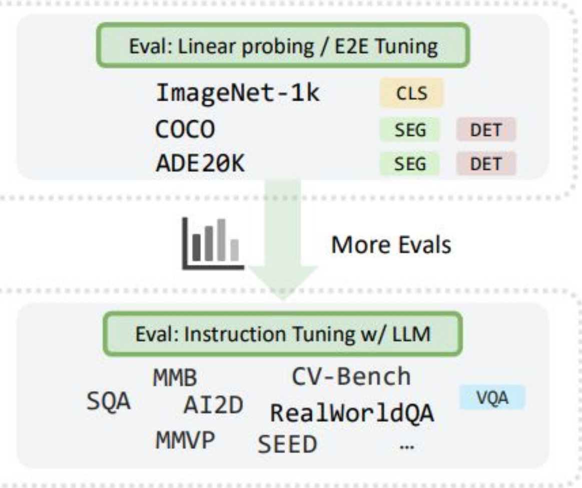
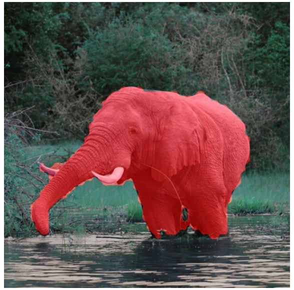


Classic Vision Eval:

Classification, segmentation, depth estimation, etc.



Elephant

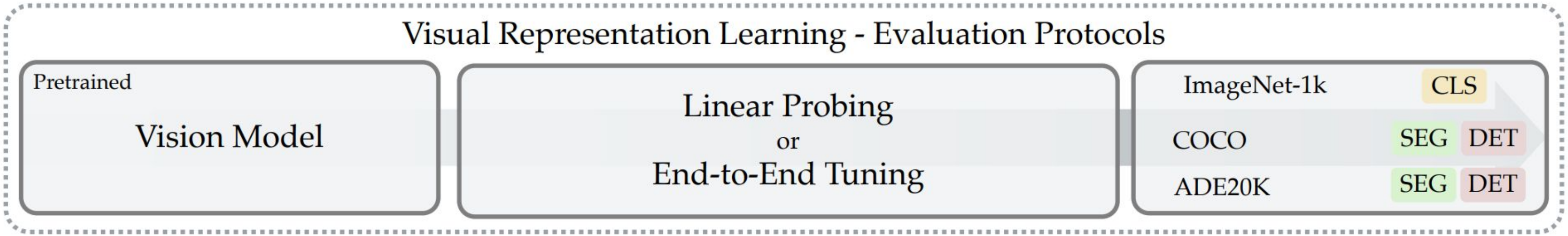
→

VQA as a Vision Eval:

Assesses wider range of capabilities and more diverse questions

How many cars are in the image?

Evaluation Setup



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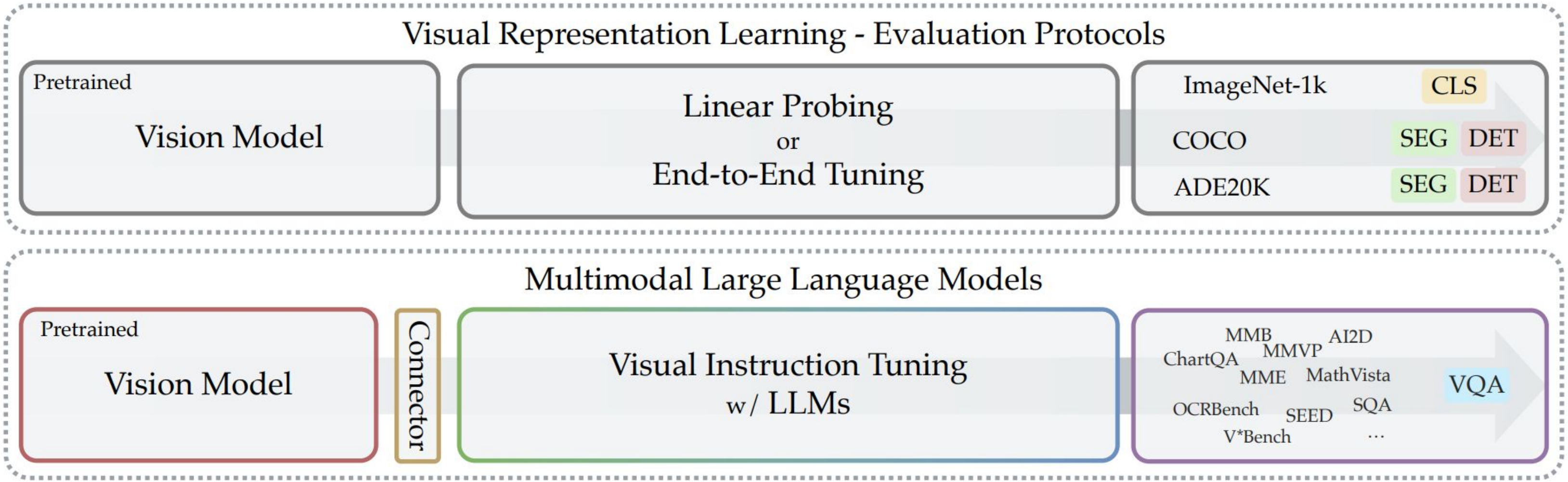

We use Cambrian with a *frozen* vision encoder (but finetuned adapter + LLM) to evaluate on VQA tasks: **General, Knowledge, OCR&Chart, Vision-Centric**

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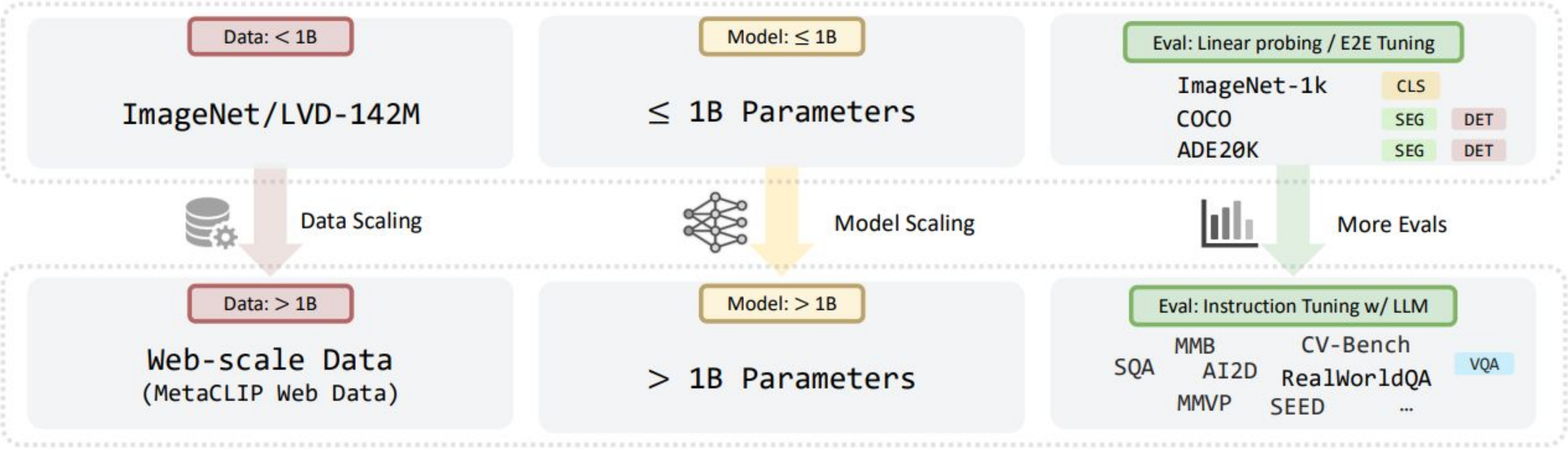
"Is language supervision or the data more important?"

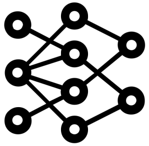
“Is language supervision or the data more important?”



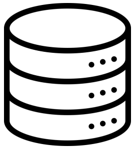
Let’s train WebSSL and find out via controlled experiments!

WebSSL

1. Scaling up model



2. Scaling up data



WebSSL: Scaling Up Model

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- **Data**: *MC-2B*, 2 billion samples seen
- **Model**: ViT-1B, ViT-2B, ViT-3B, ViT-5B, ViT-7B
- **Method**: DINOv2 (SSL) vs. CLIP (Language-Supervised)
- **Eval**: Use VQA as evaluation and categorize Cambrian eval benchmarks:

General	Knowledge	OCR & Chart	Vision-Centric
MMBench-En	AI2D	ChartQA	CV-Bench 2D
MME	MathVista	DocVQA	CV-Bench 3D
GQA	MMMU	OCRBench	MMVP
SEED	ScienceQA	TextVQA	RealWorldQA

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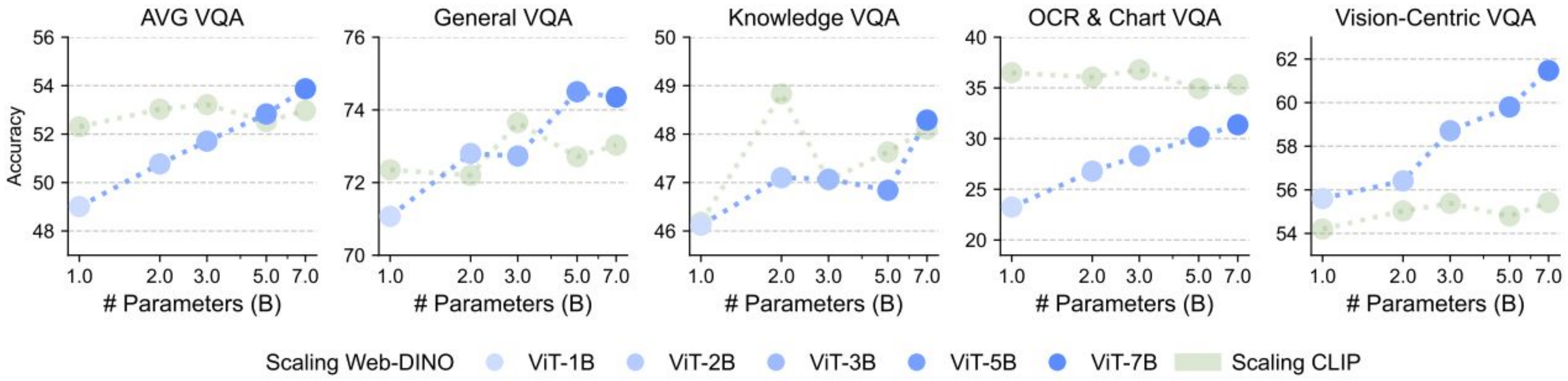

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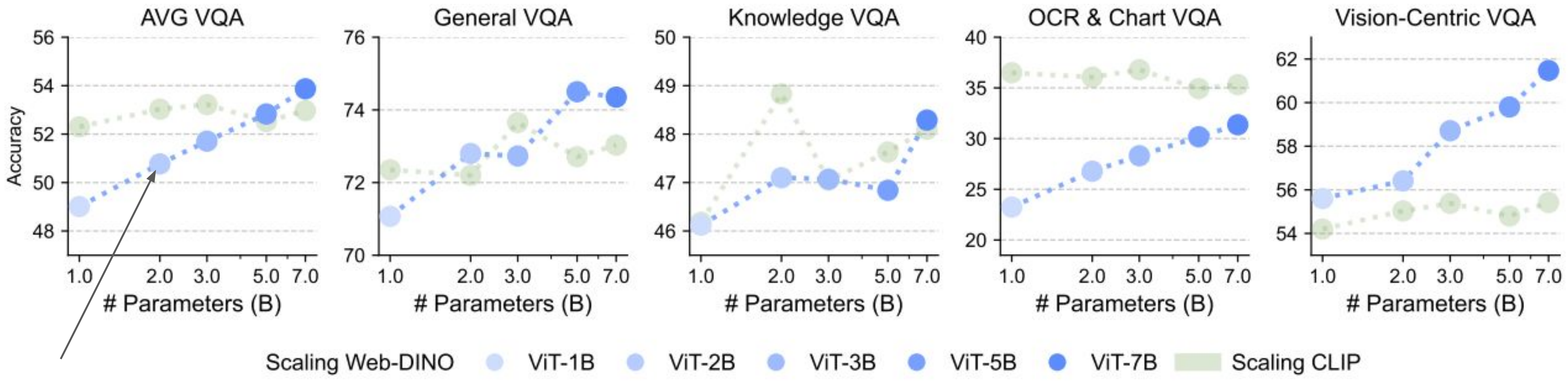

DINO

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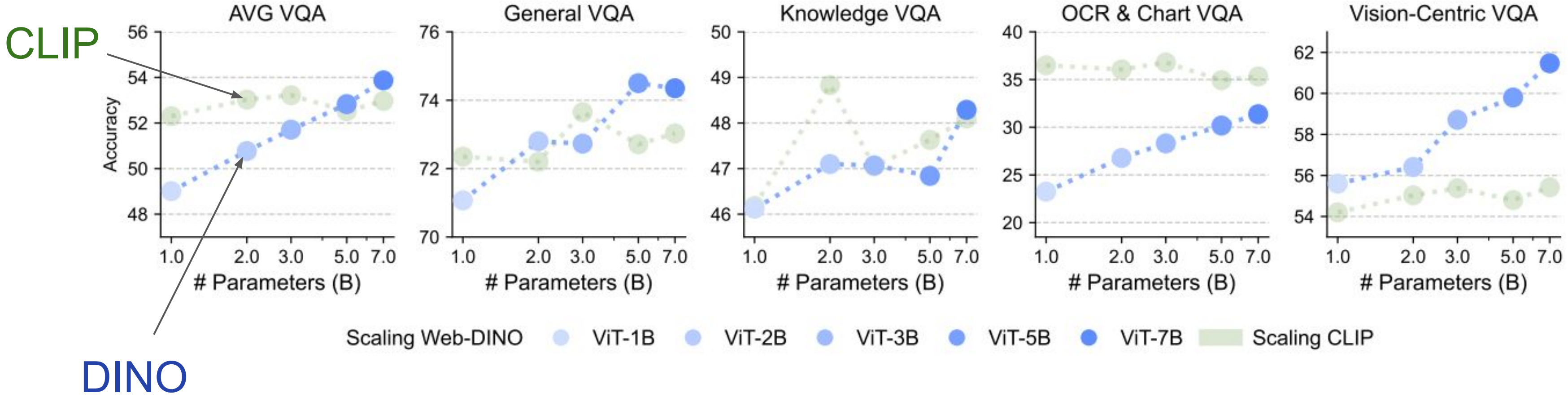

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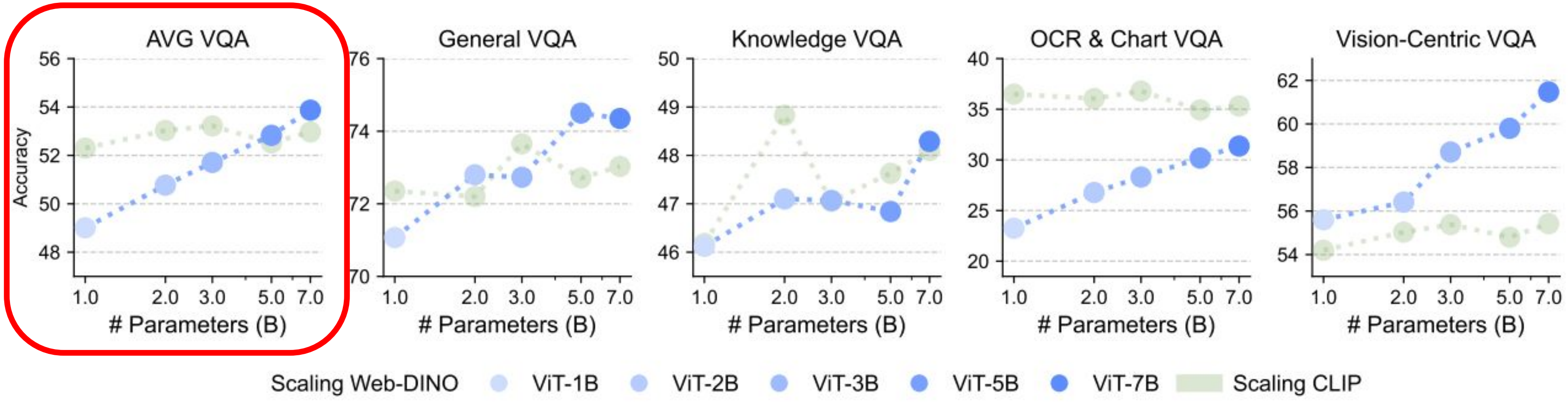
1. Web-DINO scales log-linearly *w.r.t* to model sizes



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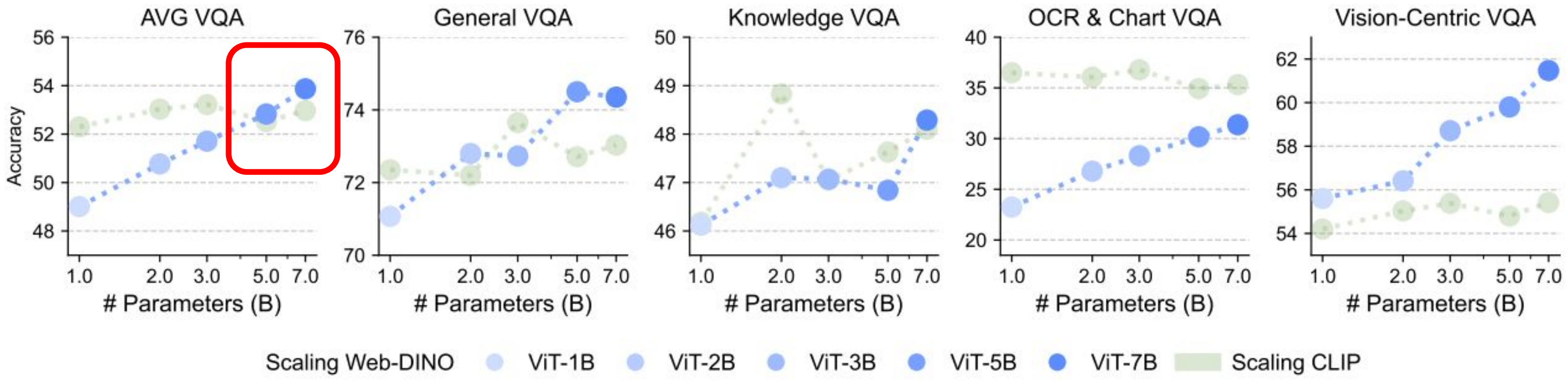

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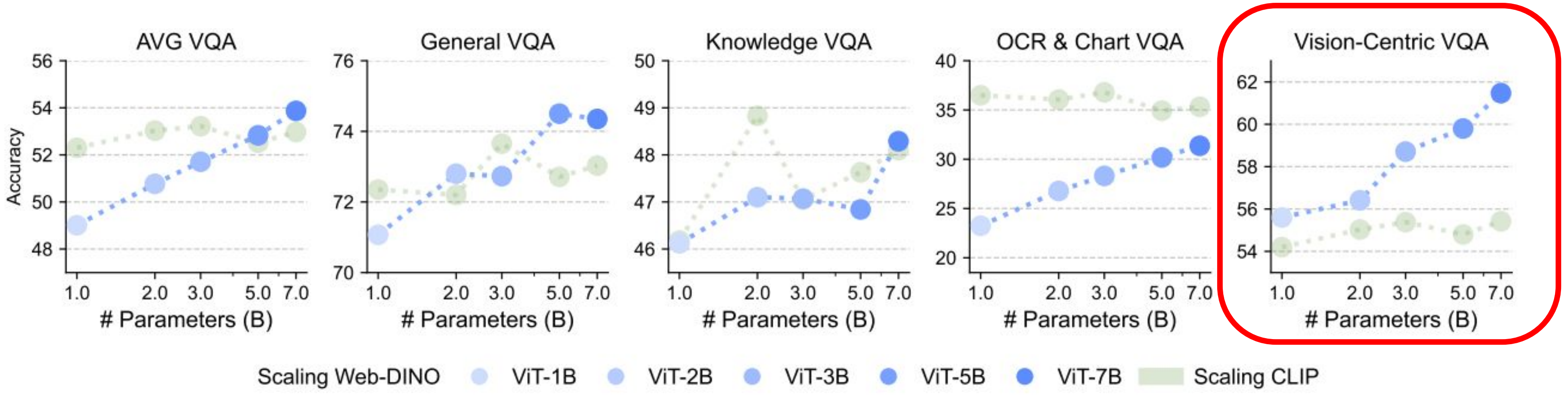

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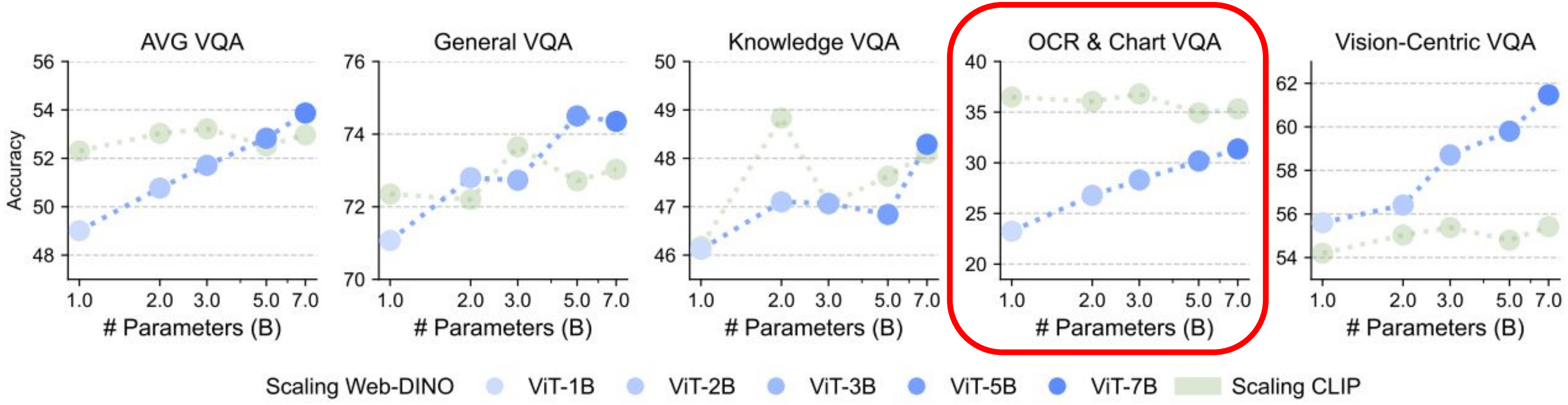
4. The gap on OCR & Chart is closing!



WebSSL: Scaling Up Data

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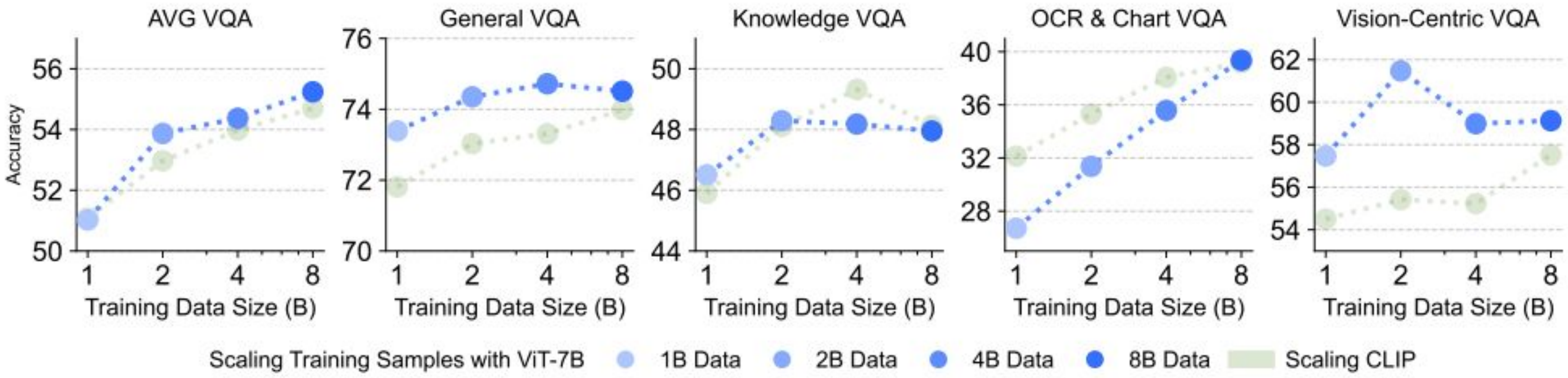
- **Data**: *MC-2B*:
  - 1 billion samples seen
  - 2 billion samples seen
  - 4 billion samples seen
  - 8 billion samples seen
- **Model**: ViT-7B
- **Method**: DINOv2 (SSL) vs. CLIP (Language-Supervised)
- **Eval**: Use VQA as evaluation.

WebSSL: Scaling Up Data



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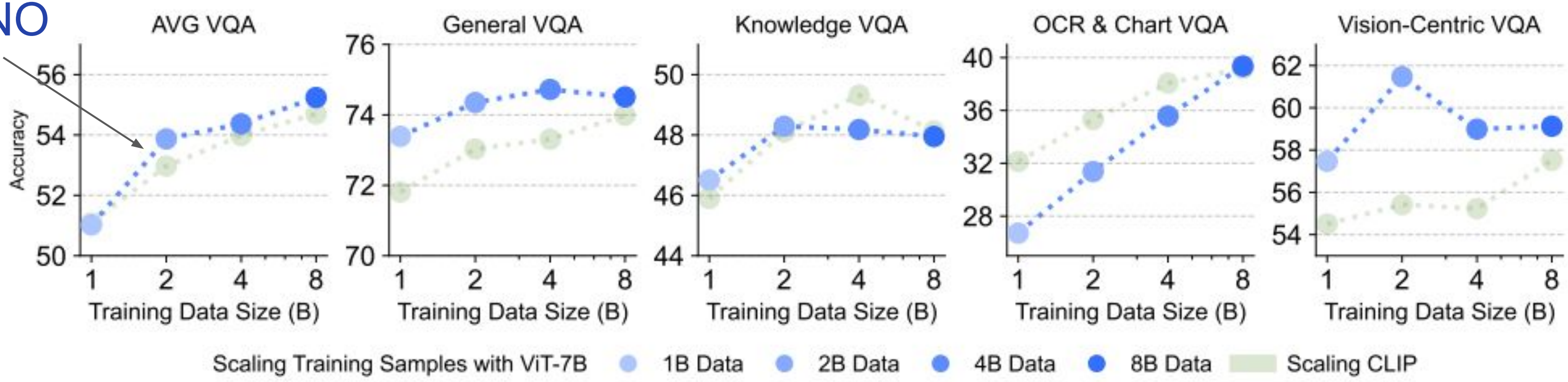

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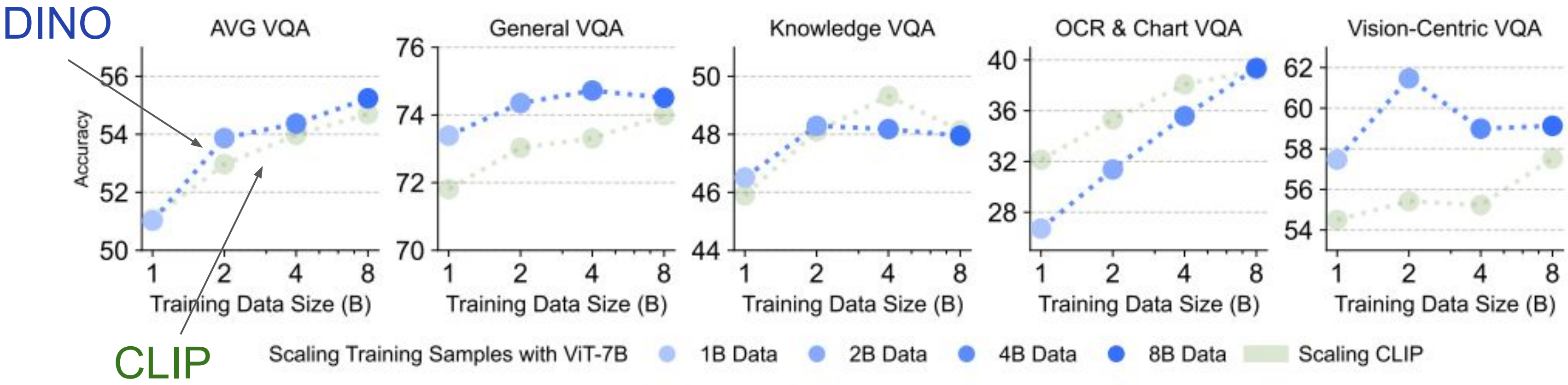

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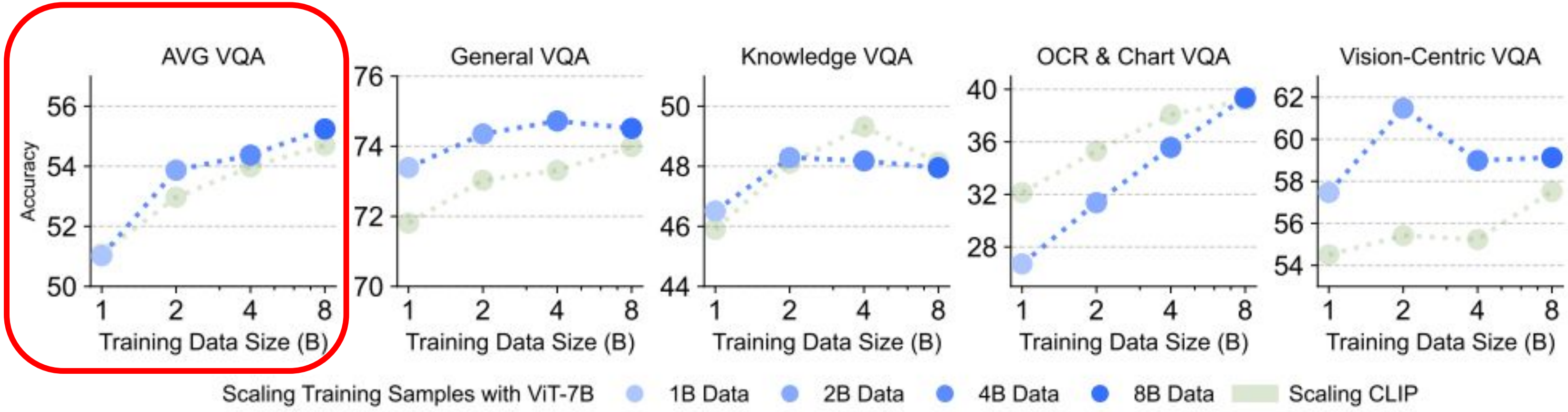

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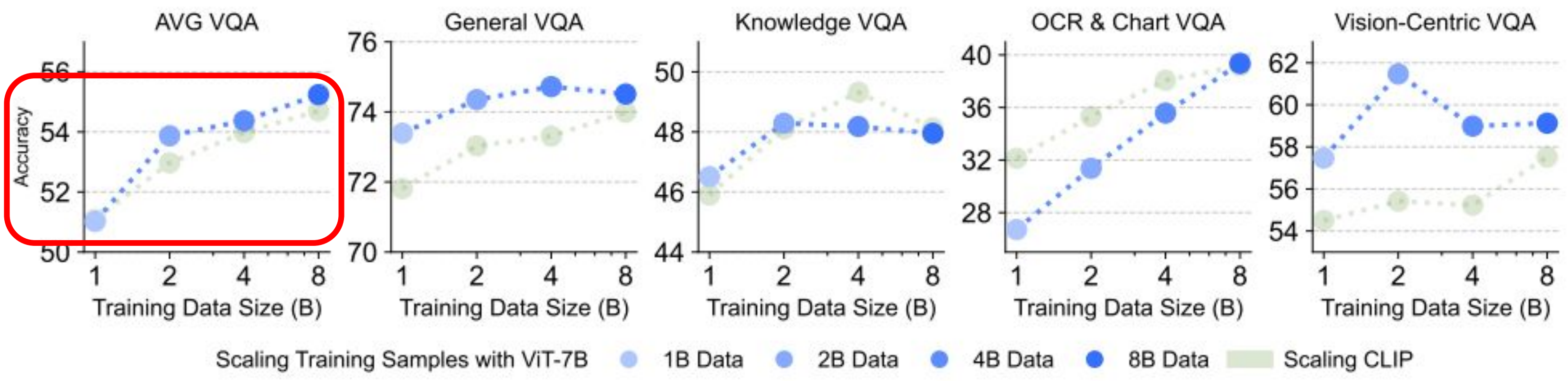
2. SSL models consistently outperform CLIP models at all data sizes



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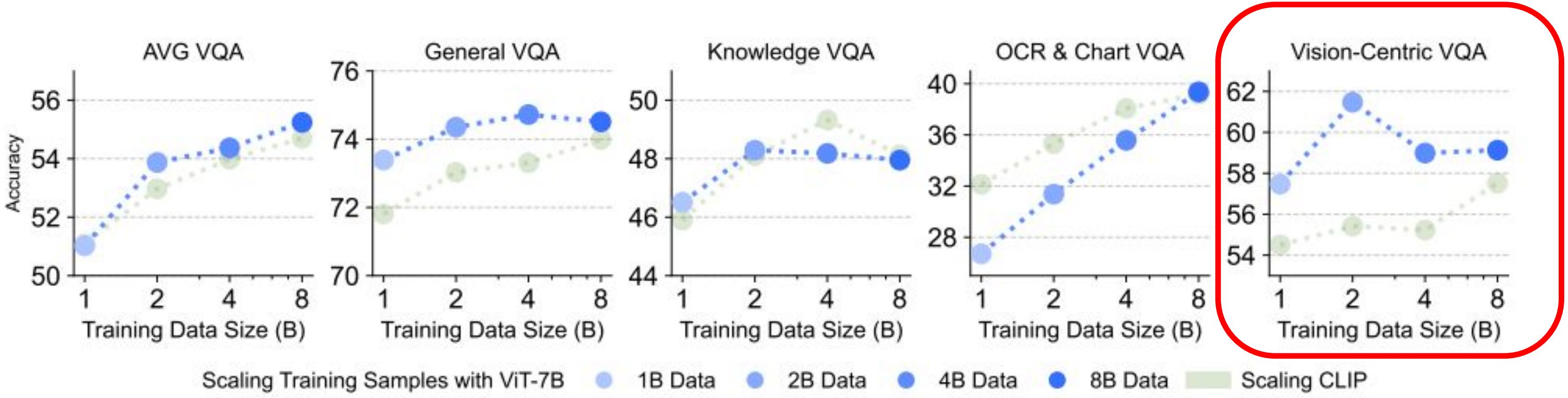

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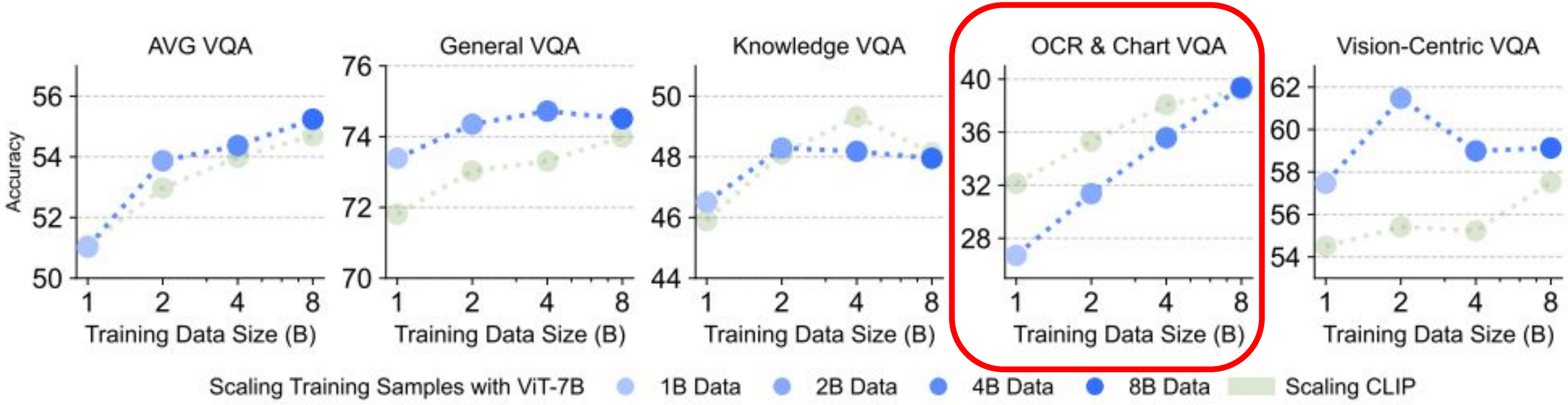

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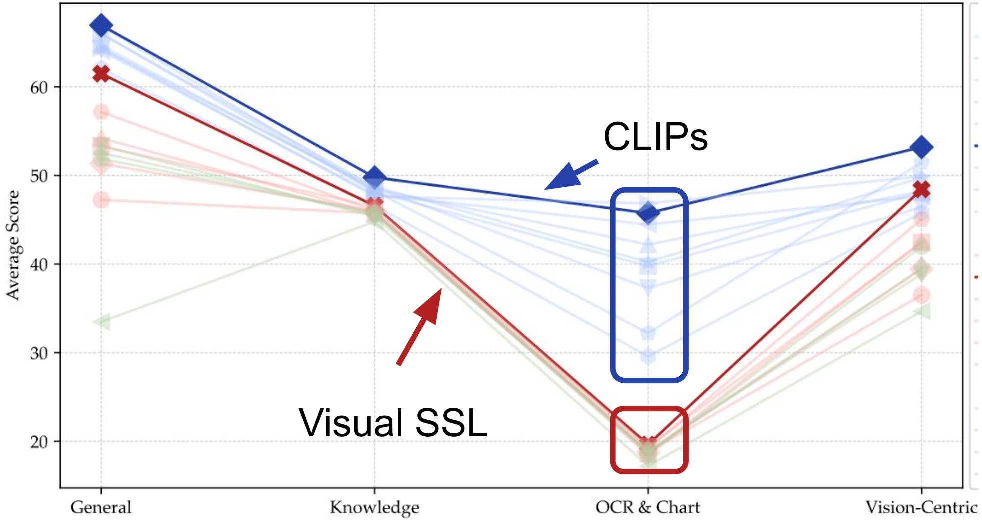

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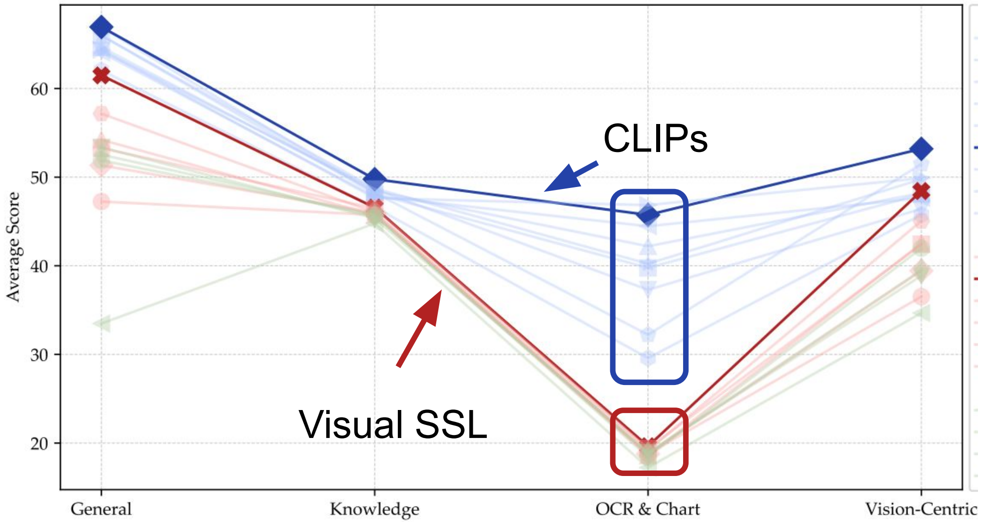
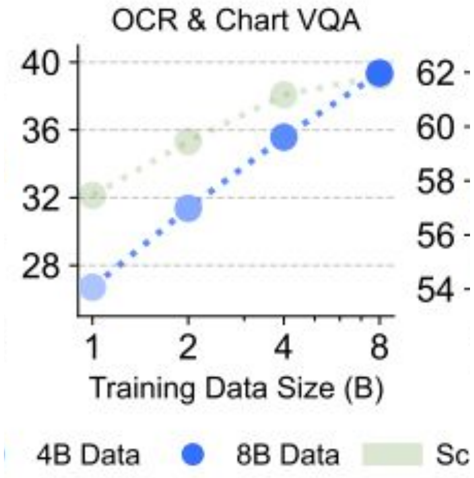


Now



WebSSL: Scaling Up Data

VQA capability is **not unique** to language-supervised vision encoders!
SSL vision encoders can do just as well at scale :)

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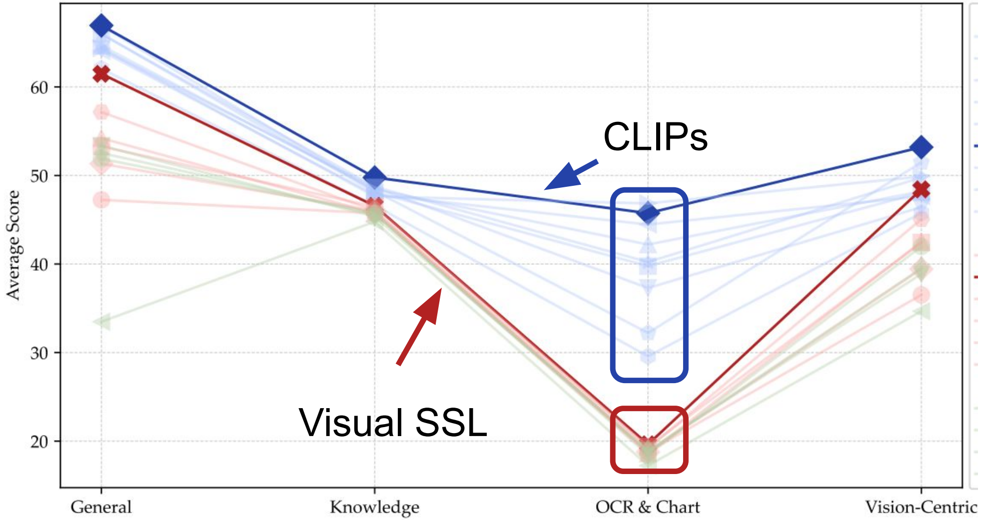

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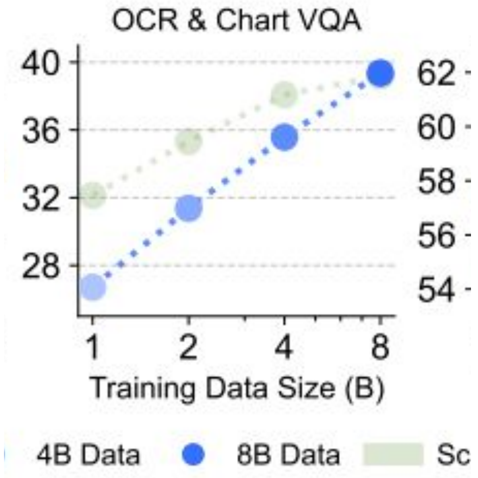

Takeaways from Scaling Up WebSSL

SSL performance improves with …

1. Larger model size
2. More data seen

SSL scales better than CLIP and is competitive with CLIP when controlling for the data.

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SSL scales better than CLIP and is competitive with CLIP when controlling for the data.

So it’s more about the **data**, not language supervision!

Deep Dive and Analysis

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1. Does the observed scaling behavior generalize to other visual SSL methods?

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Answer: we conduct similar experiments on MAE (another SSL method) to see if the behavior is unique to DINO or not

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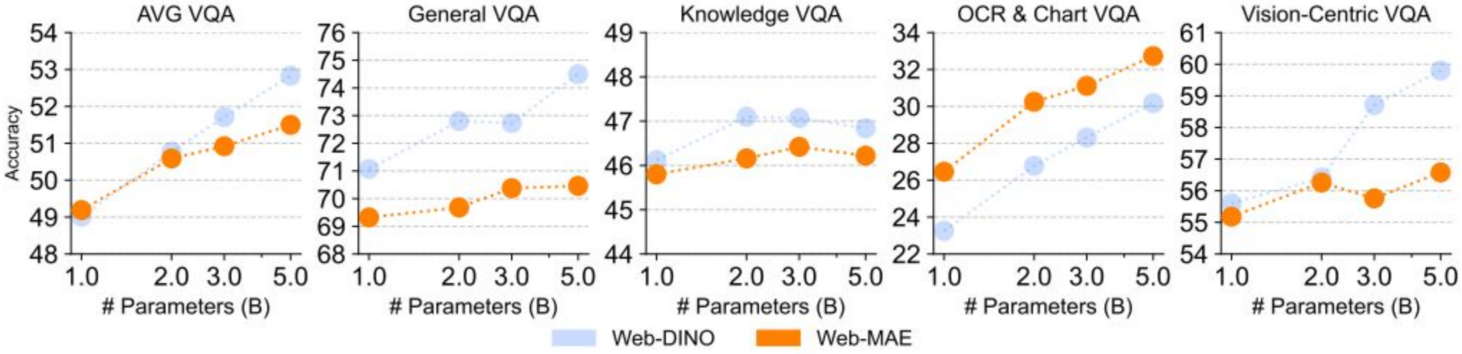

He, K., et al. (2021). Masked Autoencoders Are Scalable Vision Learners.

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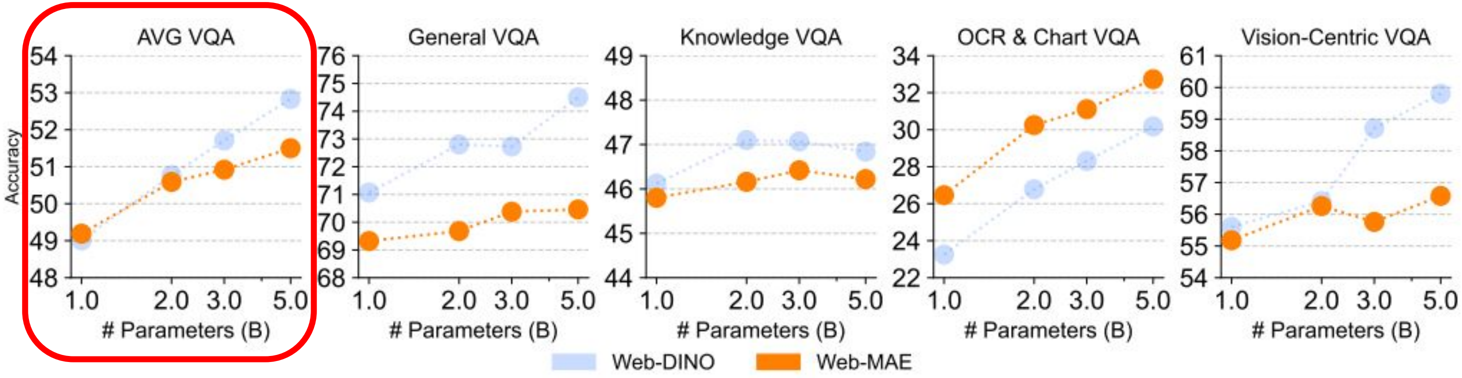

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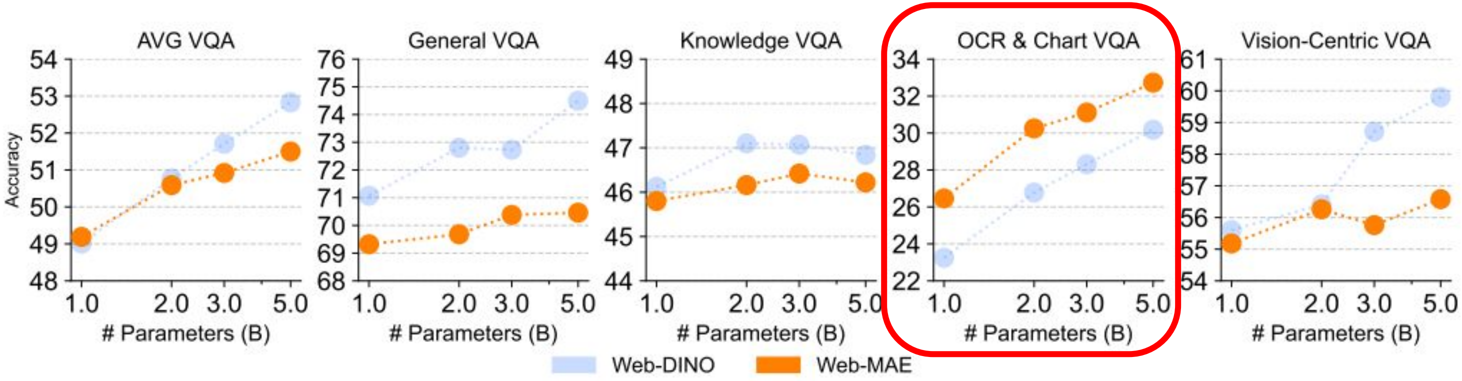
2. Yet different SSL methods still learn different features
    a. MAE is consistently better than DINO at OCR & Chart



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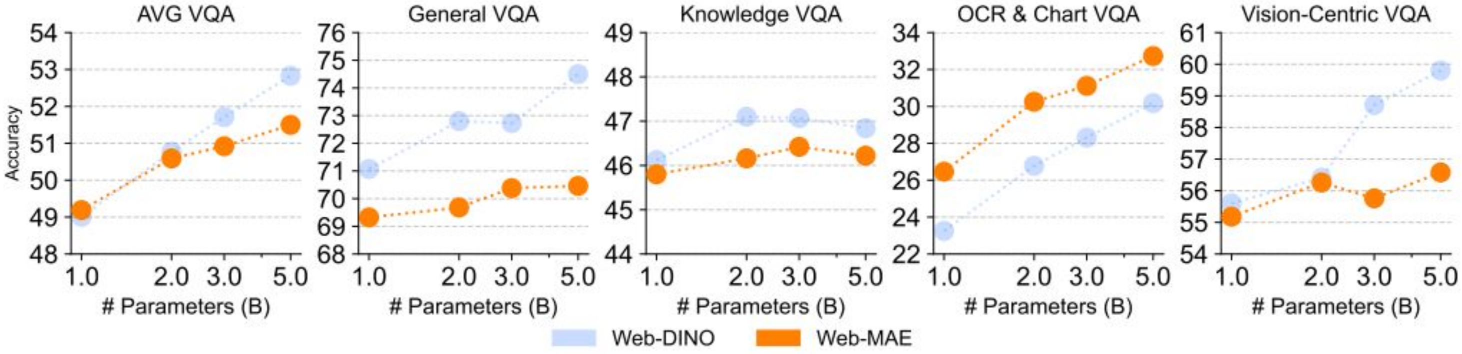
Yes, the observed behavior generalizes to other SSL methods!



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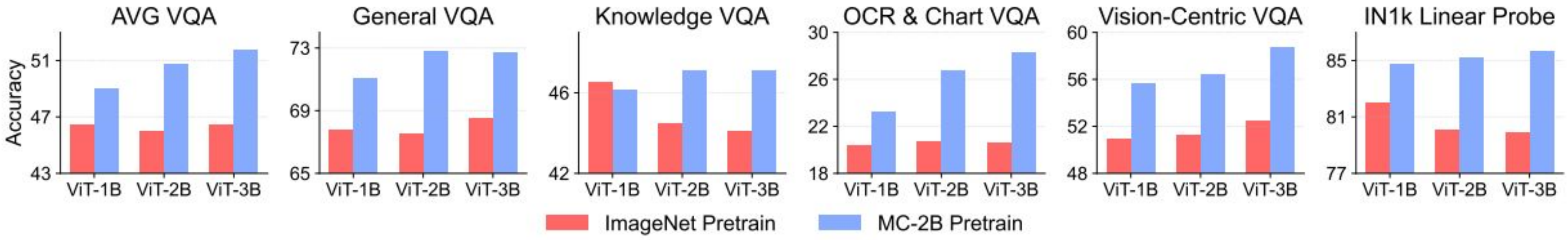
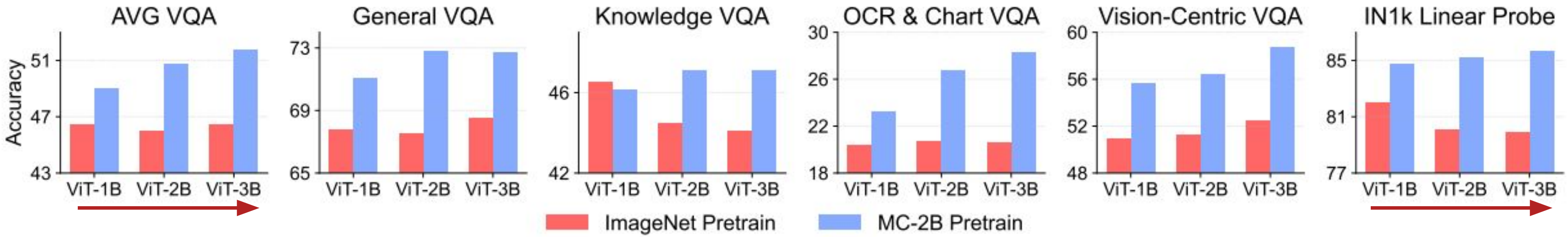


Q2.Does visual SSL exhibit similar scaling behavior on smaller scale conventional data such as ImageNet?

Answer: we conduct similar experiments training on ImageNet-1k

No obvious scaling on both VQA and ImageNet-1k evaluation.

We need large and diverse data in order to scale SSL.



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3. How do WebSSL models perform on classic vision tasks?

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Answer: Evaluate our trained Web-DINO on classic vision benchmarks with linear probes.

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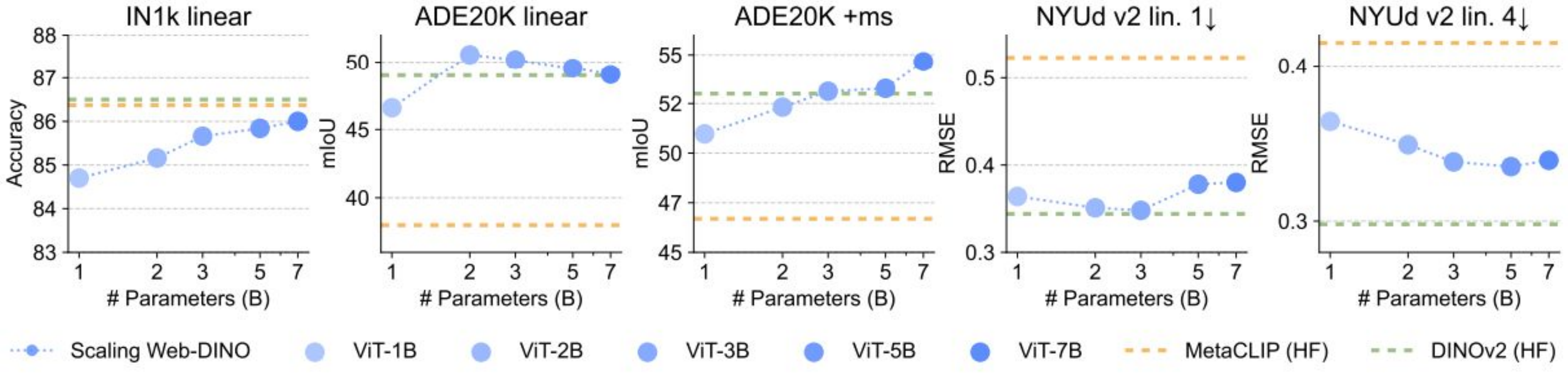
- Classification:
  - ImageNet-1k
- Segmentation:
  - ADE20k (last layer)
  - ADE20k (multi-scale)
- Depth Estimation:
  - NYUd v2 (last layer)
  - NYUd v2 (four layers)

Q3. How do WebSSL models perform on classic vision tasks?

Answer: Evaluate our trained Web-DINO on classic vision benchmarks with linear probes.



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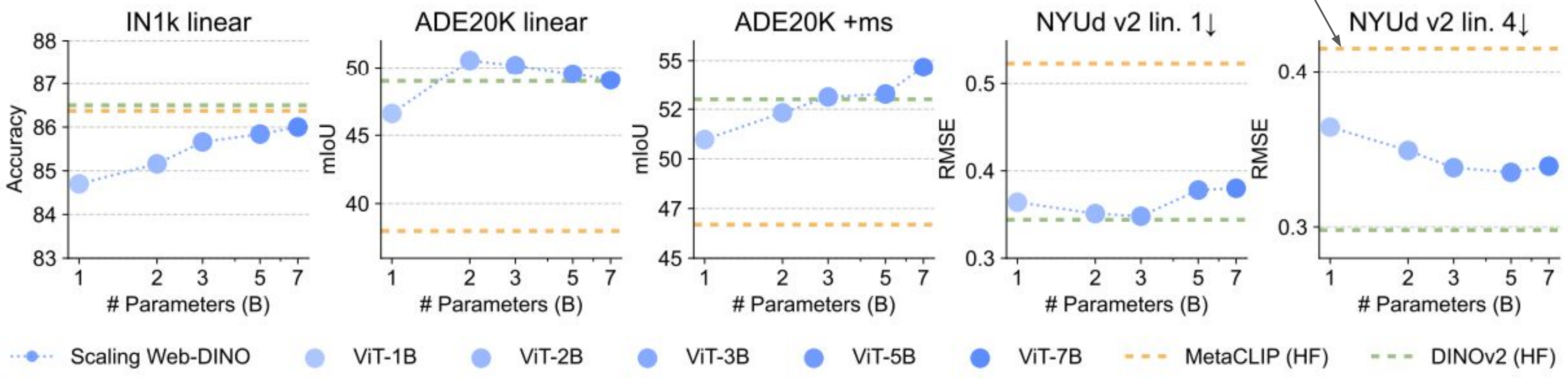
Best off-shelf MetaCLIP



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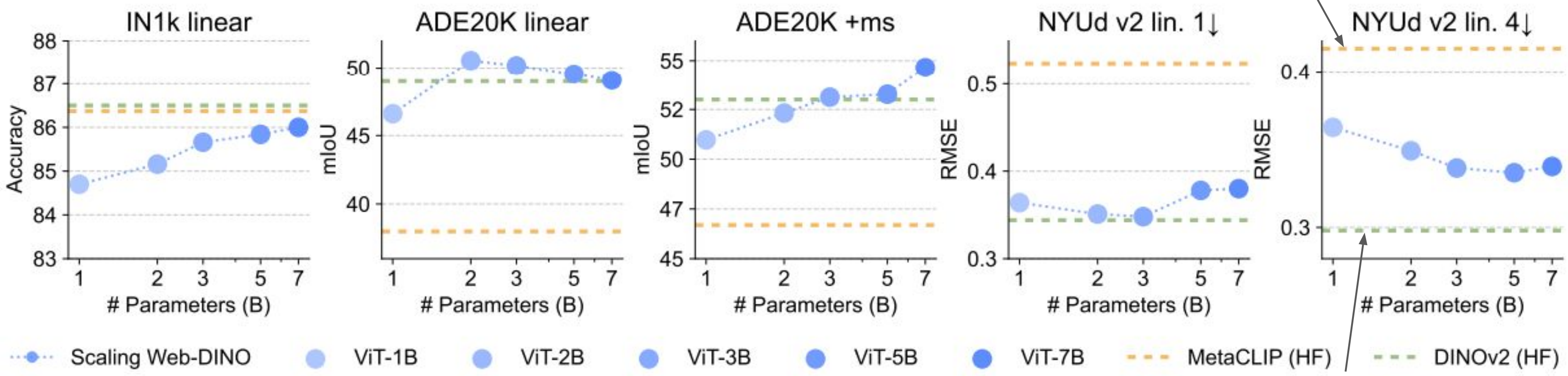

Best off-shelf
DINOv2

Q3. How do WebSSL models perform on classic vision tasks?

Answer: Evaluate our trained Web-DINO on classic vision benchmarks

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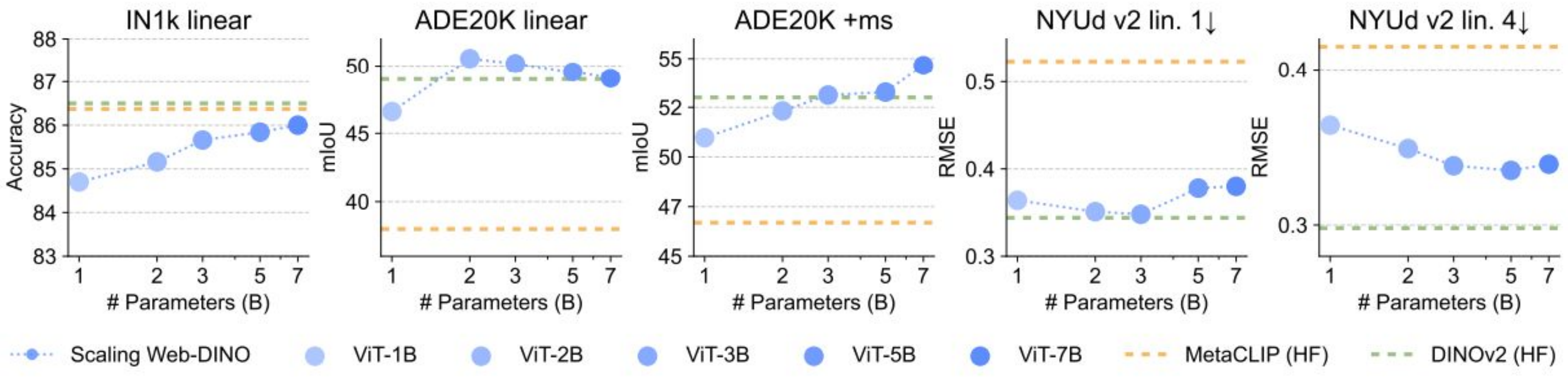

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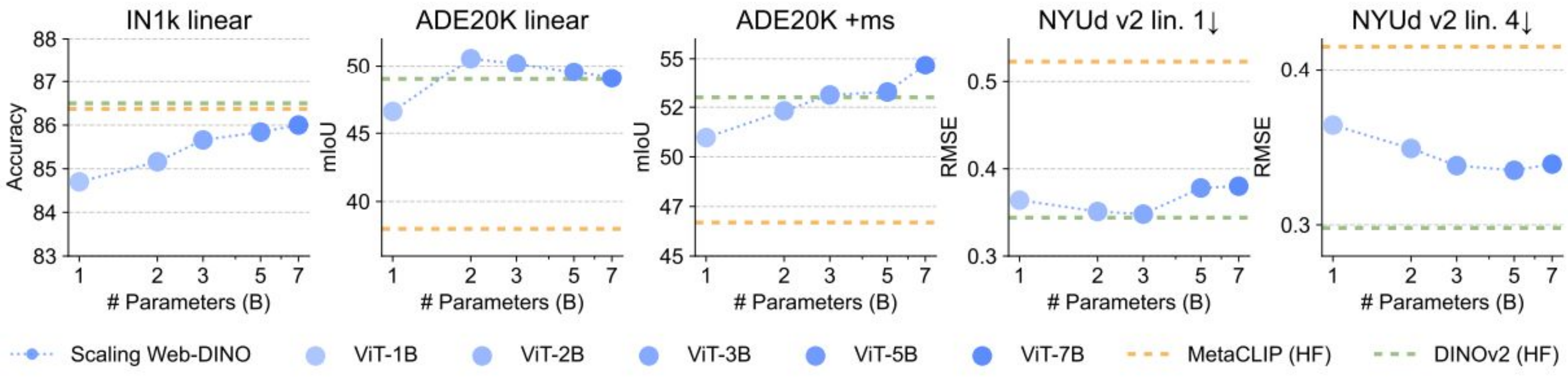

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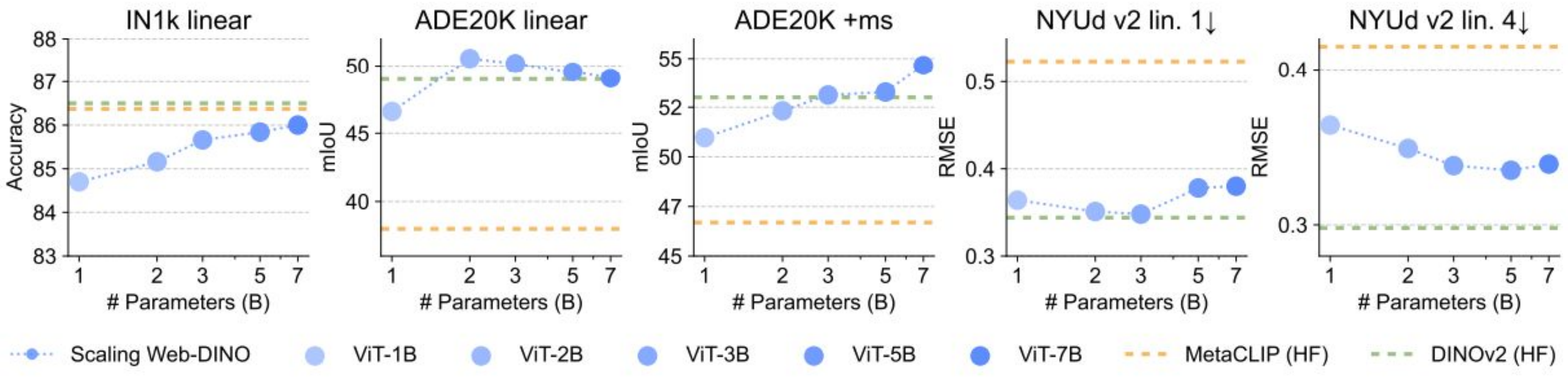
    a. Challenging! Since LVD142M (DINOv2 train data) is retrieved from classic vision tasks.



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CLIP 2B	100%	53.0	72.2	48.8	55.0	36.1	32.8	32.9	52.6	26.0
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Web-DINO 2B	1.3%	53.7 (+2.9)	70.7 (-2.1)	47.3 (+0.2)	56.2 (-0.2)	40.4 (+13.6)	47.5 (+24.2)	29.4 (+13.8)	52.8 (+3.6)	32.0 (+13.0)

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Trained on images **containing *any* text**

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Trained on images **containing charts, documents, *heavy* text …**

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The "text" in images contributes to improved OCR & Chart ability, and SSL methods can implicitly learn this from the data.

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Measure its alignment with LLM via “Platonic Hypothesis”

Huh, M., et al. (2024). The Platonic Representation Hypothesis.

Platonic Representation Measurements

- Frozen visual encoder + off-shelf LLM (no post-training / alignment)
- Uses 1024 Samples from WiT-1024 (A image-text dataset based on Wikipedia)
- Compute the representation from Vision Model ([cls]) and Language Model ([avg])
- For each [Image, Text], compute k=10 nearest neighbors each, measure how many overlap.
  - If 2 neighbors overlap, alignment score = 2/10 = 0.2
- Alignment Score is the average alignment score across all samples

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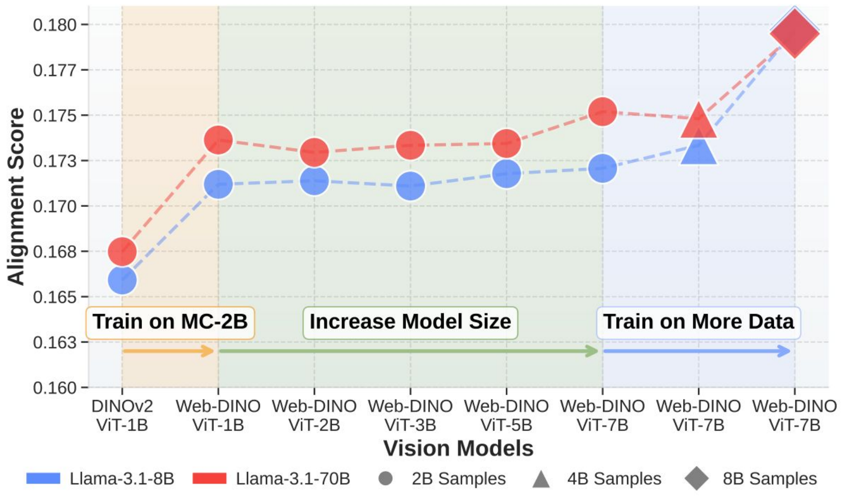
Q5. Why can SSL learn strong visual representations for multimodal modeling, without language supervision?



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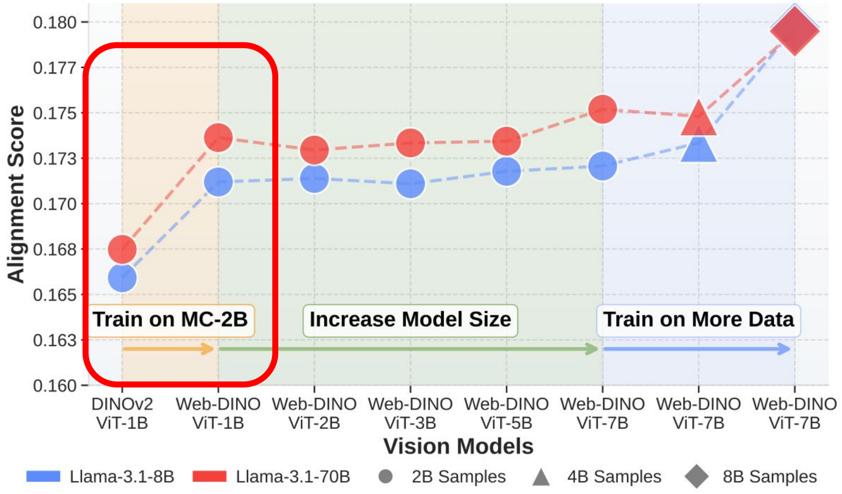

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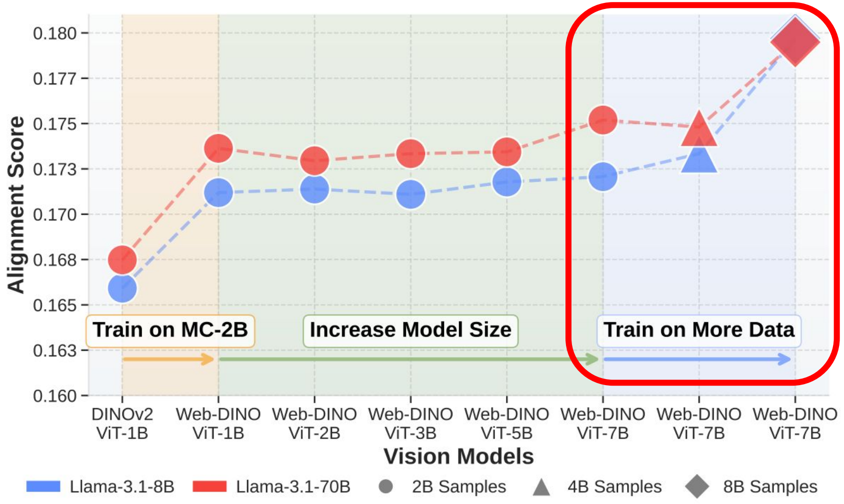

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As SSL scales to larger models or more data, its representation naturally aligns more with off-shelf LLMs

… without any explicit alignment!

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5. Why can SSL learn strong visual representations for multimodal modeling, without language supervision?

   A: As SSL scales larger or train longer, the representation intrinsically aligns more with off-shelf LLMs, without any explicit alignment.

How Does WebSSL Compare with *SOTA*?

(Now the system-level comparisons are no longer apples-to-apples)

How Does WebSSL Compare with *SOTA*?

Model				MLLM Evaluator					Classic Vision Tasks				
Method	Pretrain Data	Pretrain Samples Seen	Res	AVG	General	Knowledge	OCR & Chart	Vision-Centric	IN1k lin.	ADE20K lin.	ADE20K ms.	NYUd lin. 1 (↓)	NYUd lin. 4 (↓)
Language-Supervised Models													
SigLIP ViT-SO400M	WebLI	45.0B	224	55.4	74.4	48.7	39.5	58.9	86.5	36.5	38.0	0.607	0.525
			384	60.0	76.3	50.4	53.5	59.7	87.3	39.5	47.2	0.582	0.438
SigLIP2 ViT-SO400M	WebLI	45.0B	224	56.3	74.4	50.7	42.1	58.1	87.5	41.1	44.2	0.562	0.539
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MetaCLIP ViT-G	MetaCLIP	12.8B	224	54.8	75.5	48.2	37.3	58.4	86.4	38.0	46.7	0.524	0.415
Visual Self-Supervised Models													
MAE ViT-H	ImageNet-1k	2.0B	224	45.2	64.6	43.9	20.6	51.7	76.6	33.3	30.7	0.517	0.483
I-JEPA ViT-H	ImageNet-22k	0.9B	224	44.7	65.4	43.9	21.2	48.4	68.8	31.6	34.6	0.548	0.520
DINOv2 ViT-g	LVD-142M	1.9B	518	47.9	70.2	45.0	21.2	55.3	86.0	49.0	53.0	0.344	0.298
Web-DINO ViT-7B	MC-2B	8.0B	224	55.2	74.5	48.0	39.4	59.1	86.5	42.1	52.6	0.491	0.376
			378	57.4	73.9	47.7	50.4	57.7	86.3	42.3	53.1	0.498	0.366
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2. And better than CLIP models on classic vision.

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WebSSL also improves with higher resolution (more room for improvement!)

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SigLIP2 ViT-SO400M	WebLI	45.0B	224	56.3	74.4	50.7	42.1	58.1	87.5	41.1	44.2	0.562	0.539
			384	62.0	76.6	51.9	58.4	61.0	88.1	43.5	50.2	0.524	0.469
MetaCLIP ViT-G	MetaCLIP	12.8B	224	54.8	75.5	48.2	37.3	58.4	86.4	38.0	46.7	0.524	0.415
Visual Self-Supervised Models													
MAE ViT-H	ImageNet-1k	2.0B	224	45.2	64.6	43.9	20.6	51.7	76.6	33.3	30.7	0.517	0.483
I-JEPA ViT-H	ImageNet-22k	0.9B	224	44.7	65.4	43.9	21.2	48.4	68.8	31.6	34.6	0.548	0.520
DINOv2 ViT-g	LVD-142M	1.9B	518	47.9	70.2	45.0	21.2	55.3	86.0	49.0	53.0	0.344	0.298
Web-DINO ViT-7B	MC-2B	8.0B	224	55.2	74.5	48.0	39.4	59.1	86.5	42.1	52.6	0.491	0.376
			378	57.4	73.9	47.7	50.4	57.7	86.3	42.3	53.1	0.498	0.366
			518	59.9	75.5	48.2	55.1	60.8	86.4	42.6	52.8	0.490	0.362

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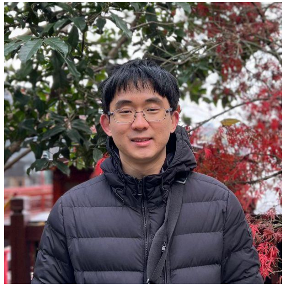
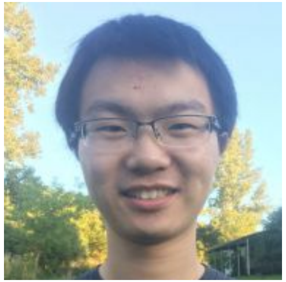
- We can continue to train better SSL models! (Better / More Data, Larger Model, …)

Thanks to Our Amazing Team!!!





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