Building Vision Foundation Models with Very Limited Resources

Hirokatsu Kataoka

National Institute of Advanced Industrial Science and Technology (AIST)

Visual Geometry Group, University of Oxford (Oxford VGG)

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Hirokatsu Kataoka

Ph.D. in Engineering (Keio University; Mar 2014)

Profile：

- Chief Senior Researcher, AIST（Apr 2023 - Present）
- Academic Visitor, Visual Geometry Group, University of Oxford (Sep 2024 - Present)
- PI, LIMIT.Lab (Jun 2025 – Present; Research initiative w/ VGG community)
- Visiting Associate Professor, Keio University (Sep 2024 - Present)
- Adjunct Researcher, SB Intuitions (May 2024 - Present)
- Adjunct Associate Professor, Tokyo Denki University（Apr 2024 - Present）
- PI, cvpaper.challenge (May 2015 – Present; Community with 1,500+ collaborators)

片岡裕雄（かたおかひろかつ）

Recently Selected Projects (within 3 years)：

"Scaling Backwards: Minimal Synthetic Pre-training? (ECCV24)"
"Rethinking Image Super-Resolution from Training Data Perspectives (ECCV24)"
"Pre-training Vision Transformers with Very Limited Synthesized Images (ICCV23)"
"Primitive Geometry Segment Pre-training (BMVC23 Best Industry Paper Finalist)"
"SegRCDB: Semantic Segmentation via Formula-Driven Supervised Learning (ICCV23)"
"Visual Atoms: Pre-training Vision Transformers with Sinusoidal Waves (CVPR23)"
"Replacing Labeled Real-Image Datasets with Auto-Generated Contours (CVPR22)"
"Point Cloud Pre-training with Natural 3D Structures (CVPR22)"
"Pre-training without Natural Images (IJCV22; ACCV Best Paper Honorable Mention)"

http:// hirokatsukataoka.net/

1 Visual Pre-training with Minimal Data & Supervision

Can a natural law train a visual model?

- ACCV 2020 Best Paper Honorable Mention Award
- Featured in MIT Technology Review (Feb. 4th, 2021)
- One single synthetic image enables to pre-train ViT (ECCV24)

2 Visual Foundation Models without Real Data

Can synthetic pre-training make a vision foundation model?

- Industry-focused vision foundation models (arXiv 2025 / on-going work)
- Primitive Geometry Segmentation for medical 3D data (BMVC 2023 Best Industry Paper Finalist)

3 Multimodal AI Models with Generative Models

Can generative models make next foundation models?

- Zero-shot 3D understanding (CVPRW25 / on-going work)
- Leading research initiative (LIMIT.Lab with VGG community)

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Starting from the [Kataoka+, ACCV20/IJCV22], our team have proven...

- Visual pre-training can be done with mathematically generated images / without any real data
- Representations in video/3D/audio | Tasks in cls/det/seg are also learnable (Any Modality, Any Task)

Where did that idea come from?

<u>How could we learn huge #parameters with only 1M images?</u>

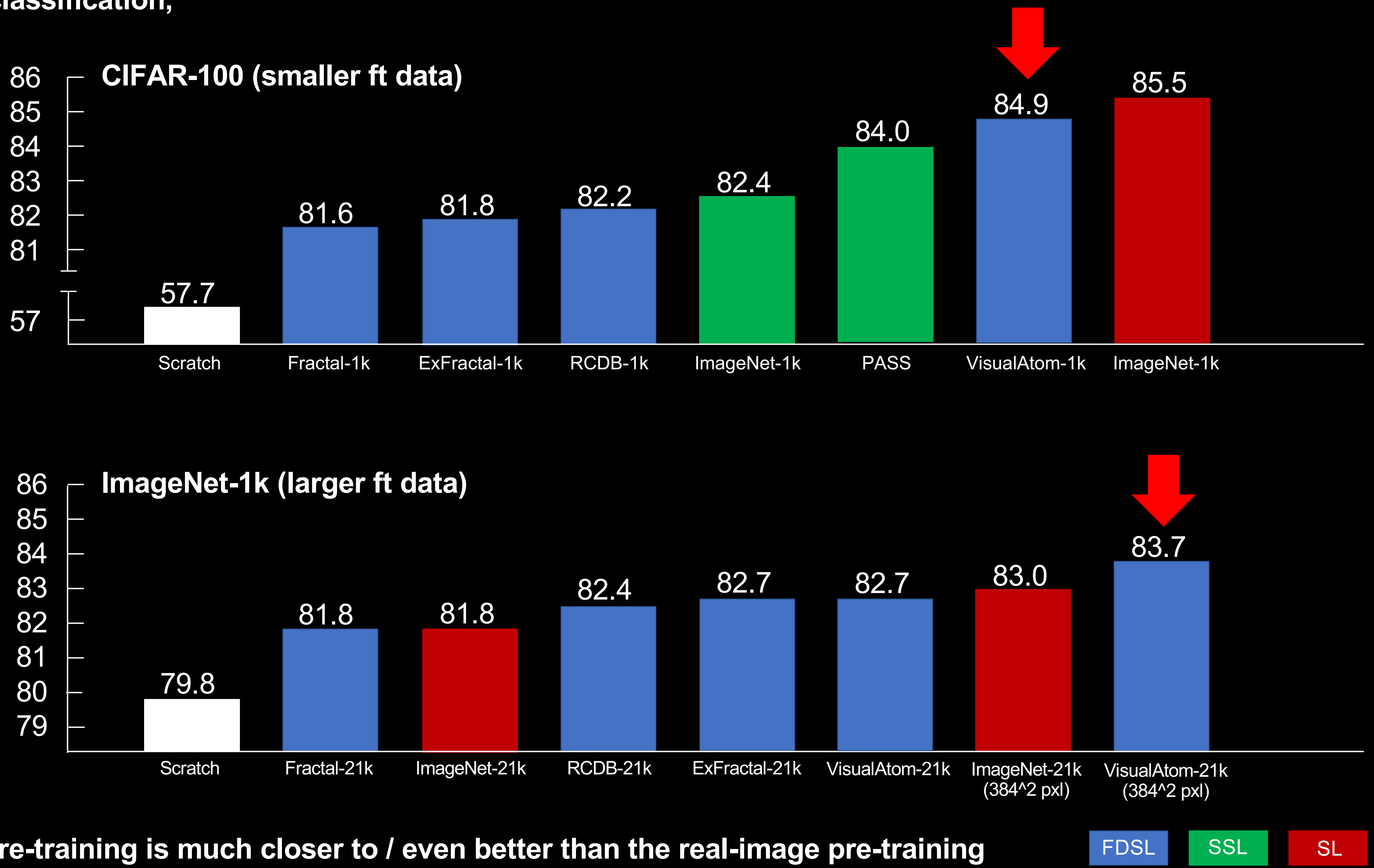
- Something like ‘Natural Law’ inside of the image dataset

Observed fractal geometry on ImageNet dataset

We hypothesize DNN could learn ‘Natural Law’ inside of the dataset

Directly render and train primitives

In image classification,



Synth pre-training is much closer to / even better than the real-image pre-training

Scaling Backwards:
Minimal Synthetic Pre-training?

ECCV 2024
(Collaborating with Oxford VGG & UTN FunAI Lab)

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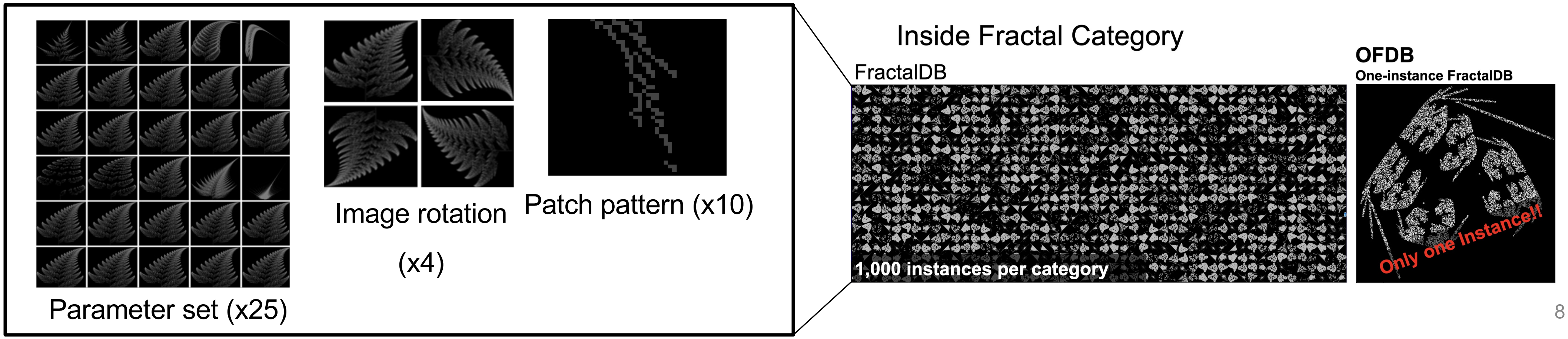
Think backwards

How can we minimize the visual pre-training in the framework?

FractalDB:	1,000 categories	x 1,000 instances	| 1M images
OFDB:	1,000 categories	x 1 instance	| 1k images
The idea:	1 category	x 1 instance	| 1 image



Think backwards

Ultimately, is it possible to learn from just a single image?

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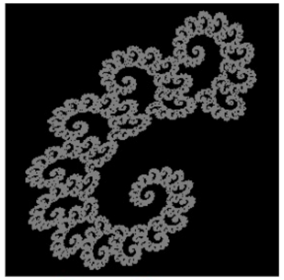


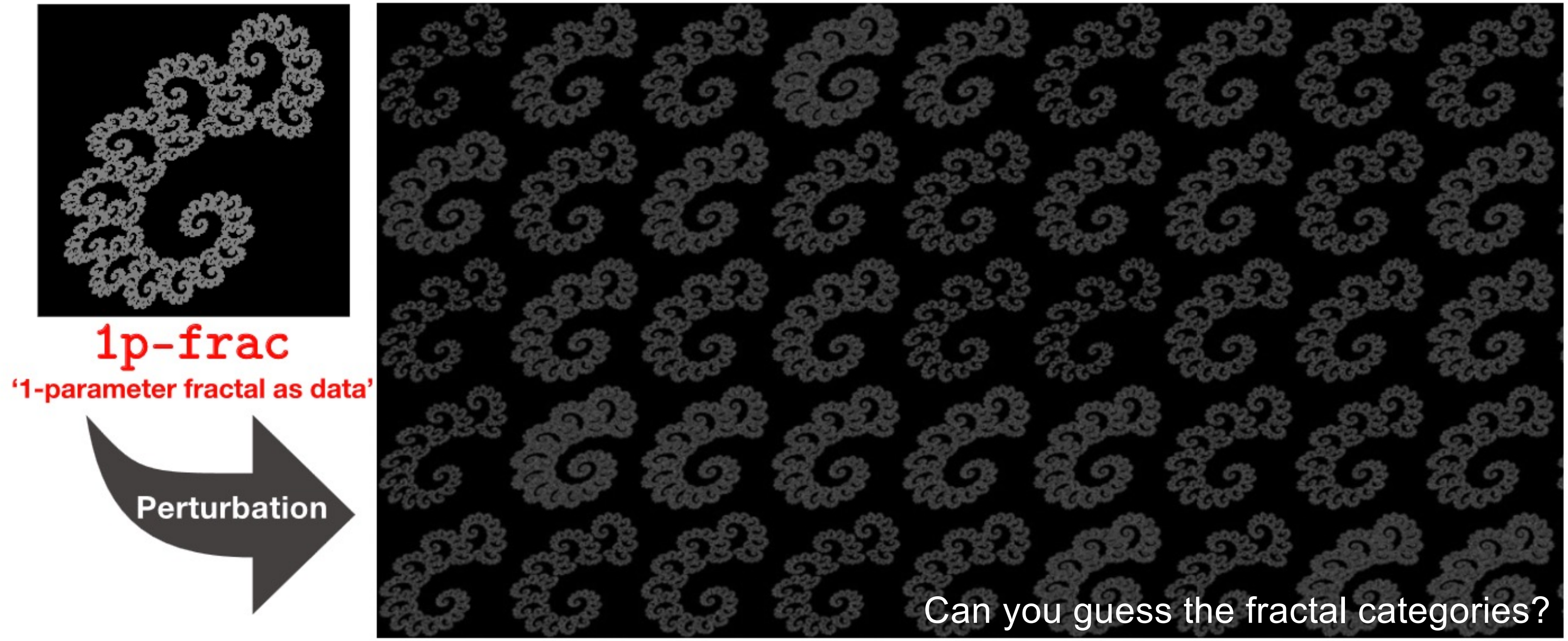
"Can a single synthetic image match a million real images?"

Sounds like a crazy idea, but my intuition is 'possible'

What is the minimum requirement in visual pre-training?

Essence is about classifying minute differences?

Only a single fractal image, treating minute variations as pseudo-categories



Perturbations makes image categories / this enables to conduct a visual pre-training

Scaling backwards?

The comparisons between real and synthetic images

- Real images: ImageNet-1k
- Synth images: FractalDB, OFDB, and 1p-frac

Table 1: Scaling backwards in synthetic pre-training (Accuracies on CIFAR-100, Real: ImageNet, Synth: Fractal images).

Type\#Img	1	1k	1M
Real	N/A	76.9	85.5
Synth	84.2	84.0	81.6

Pre-training effectiveness

- Real img: #Images is important
- Synth img: Better performance for the task setting

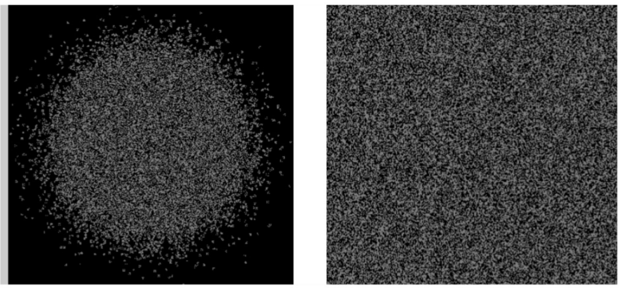
Any random-image training possible?

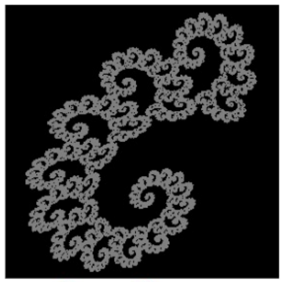
No pre-training effects in random / Gaussian images

- The result shows it is important to use a good formulation like fractal geometry

Table 4: Comparison with pre-training with a single noise image.

Method	C100	IN100
Gaussian$^{\diamond}$	1.1	5.7
Uniform$^{\diamond}$	2.0	71.1
`1p-frac`$^{\diamond}$	**84.2**	**89.0**





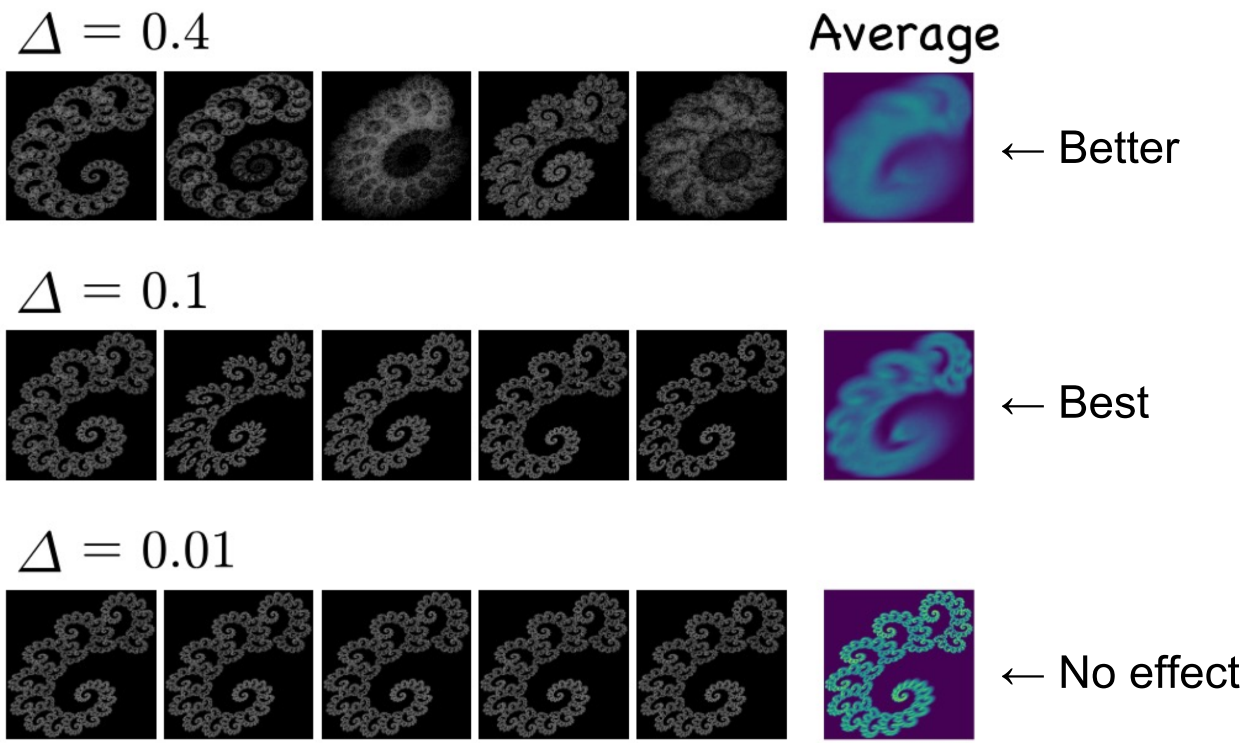
How fine does the shapes need to be?

Perturbation should be adjusted

➢ The perturbation values are shown in the following figure

Table 5: Effects of perturbation degree Δ ($\sigma = 3.5$).

Δ	C100	IN100
0.001	1.2	1.9
0.01	19.9	61.8
0.1	**84.2**	**89.0**
0.2	83.4	88.5
1.0	82.6	88.1



Vision transformer can classify even the case of ‘Δ=0.1’

How about the scaling ViT?

Its plausible 21k categories from a single fractal parameter

Even better than that of the ImageNet-21k pre-training (see 82.1 vs 81.8)

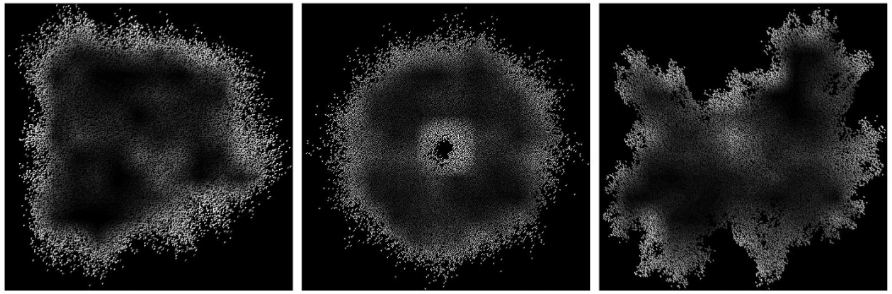
Pre-training	#Img	Type	ViT-B	
Scratch	–	–	79.8	
ImageNet-21k	14M	SL	81.8	← IN-21k
FractalDB-21k	21M	FDSL	81.8	
ExFractalDB-21k	21M	FDSL	82.7	
RCDB-21k	21M	FDSL	82.4	
VA-21k	21M	FDSL	82.7	
OFDB-21k	21k	FDSL	82.2	
3D-OFDB-21k	21k	FDSL	82.7	
`1p-frac` (ours)	**1**	FDSL	82.1	← The proposal

Lessons from the synthetic training project

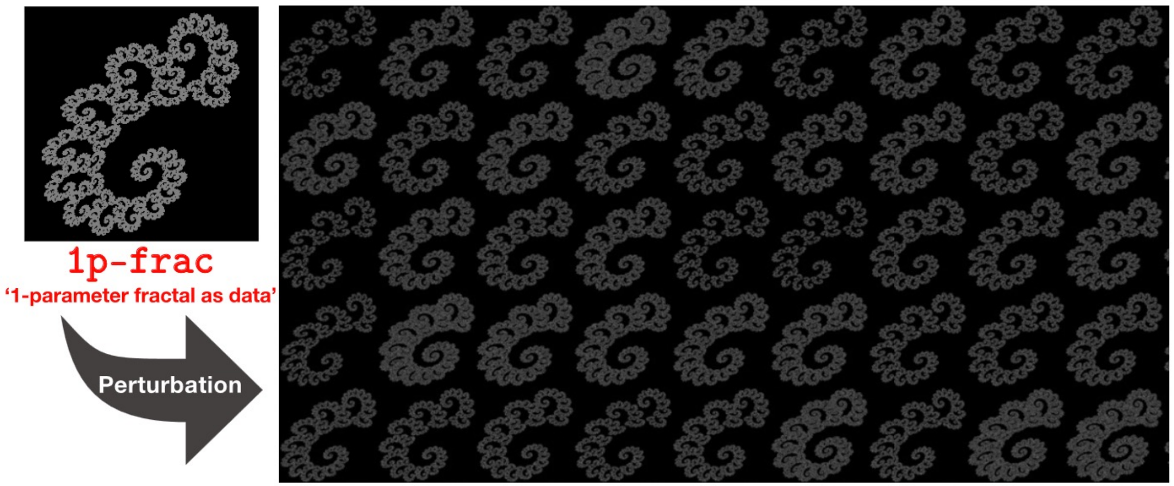
What is the essence of visual pre-training?

- Previous: ViT tends to activate shape contours in visual tasks
- This work: ViT can classify pixel-level minute changes in categories

In synthetic data, a model indefinitely trains better performance,
but learning efficiently with selected data yields better results



(d) Attention maps in fractal images with FractalDB-1k pre-trained DeiT. The brighter areas show more attentive areas.



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Industrial Synthetic Segment Pre-training

arXiv: 2505.13099

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Towards the vision foundation models with synth train / limited resources

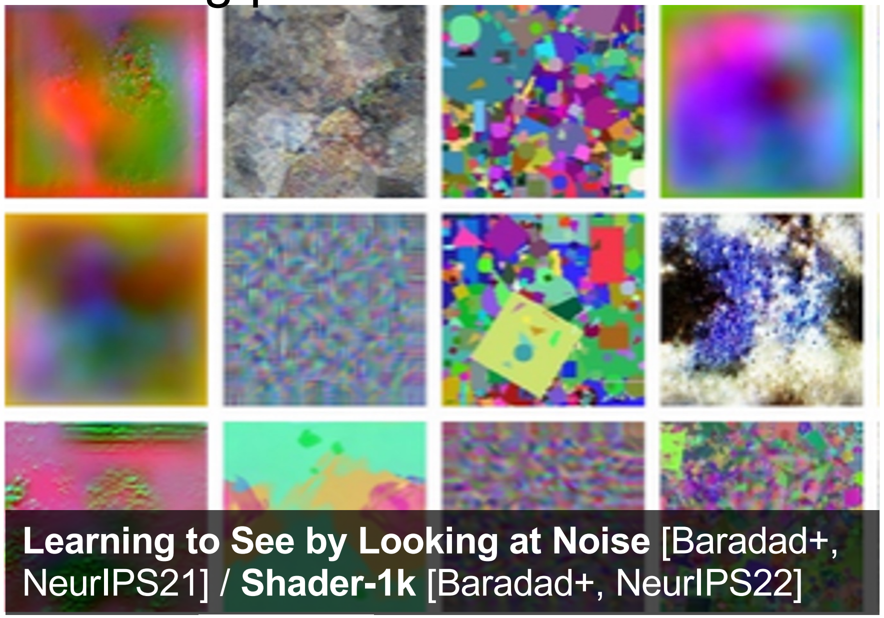
Research questions:

How can we beat SAM…

- with only synthetic data in pre-training phase?
- without any human supervision and real images?

Insights from the prior art & industrial data

Learning primitives



Learning to See by Looking at Noise [Baradad+, NeurIPS21] / **Shader-1k** [Baradad+, NeurIPS22]

AT

PI

Industrial data looks like…

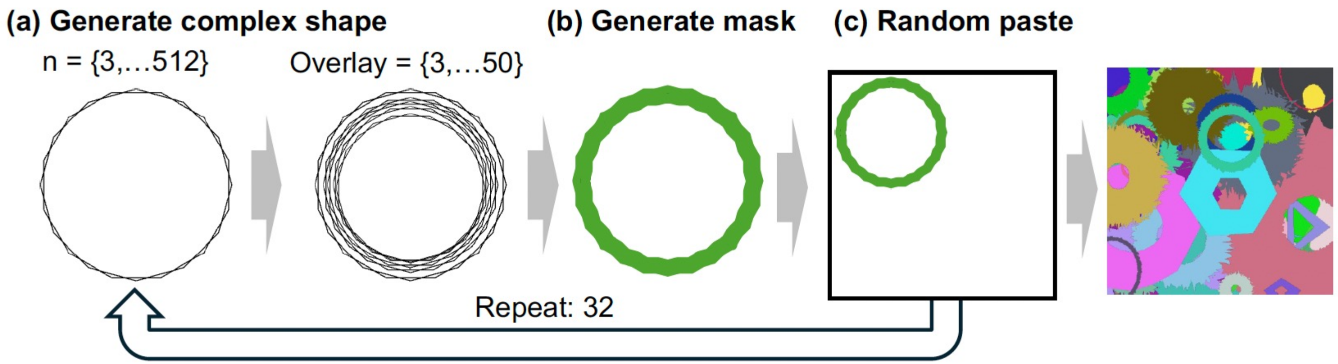
https://robot-mujinka.com/wp-content/uploads/2019/09/bara.jpg

Complex, dense and hierarchical occlusion are the key in industrial & visual foundation models

Visual pre-training for complex, dense and hierarchical occlusion handling

Instance Core – Combination of many mathematically generated images

That is all, but much more difficult to separate each other comparing to the real world

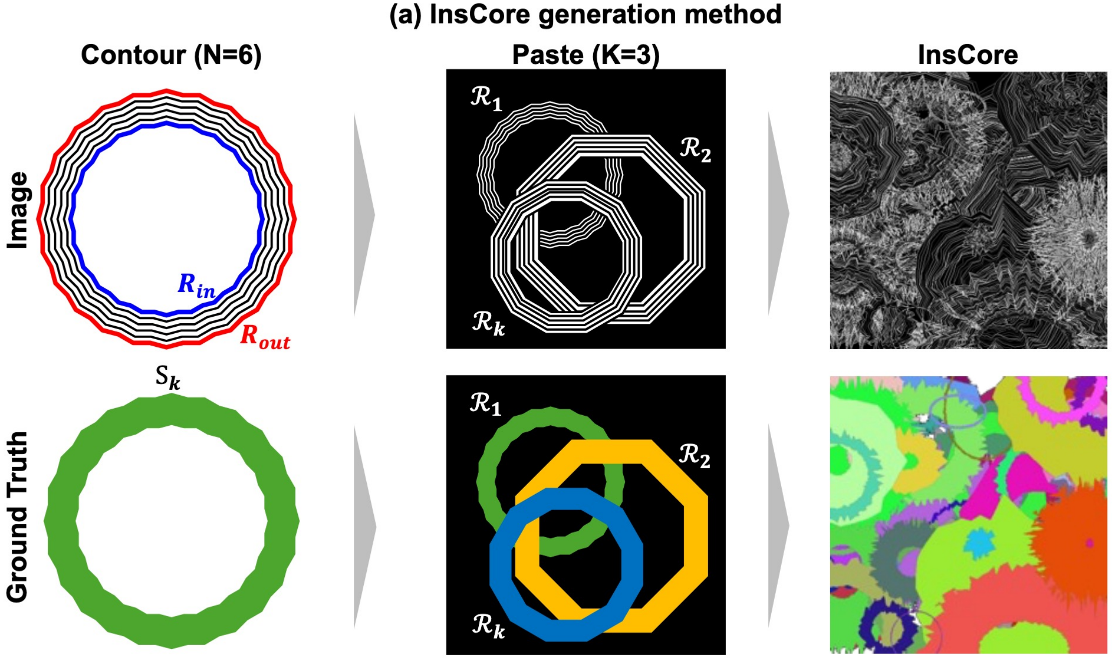


- ➢ Generate shape-oriented images
- ➢ Iterate putting pattern in 32 times

Visual pre-training for complex, dense and hierarchical occlusion handling

Instance Core – Combination of many mathematically generated images

That is all, but much more difficult to separate each other comparing to the real world



- A pair for image and semantic label
- Complex occlusions, dense and hierarchical masks

Industrial image dataset

Industrial data has different scenarios aren't covered by web data

- #Images and domain?
- We focused 'occlusion handling' visual pre-training

Evaluation dataset	Industrial domain	#Train Image	#Train MaskW	#Test Image	#Test Mask	#Classes
NuInsSeg [23]	Medical	532	23,127	133	7,571	6
LIVECell [10]	Biomedical	3,253	1,018,576	1,564	462,261	1
SpaceNet2 [32]	Remote sensing	3,080	8,7301	771	21,641	1
Industrial-iSeg [19]	Manufacturing	1,109	25,308	89	523	6
LogiSeg [22]	Logistics	1,384	10,018	300	2,093	7

The impact of learning from the image primitives

The InsCore pre-trained model is better effects on MS COCO segmentation

- Better than the ImageNet pre-trained model
- Only using x140 smaller pre-training dataset

    ImageNet 14M imgs vs. InsCore 0.1M synth imgs

Dataset	#Data	mAP	mAP_{50}	mAP_{75}
From scratch	–	42.3	65.7	45.5
ImageNet-21k	14M	43.7	67.4	47.3
SegRCDB	0.1M	43.8	67.4	47.4
InsCore (Ours)	0.1M	**44.4**	**68.2**	**47.5**

The impact of learning from the image primitives

Analysis of #synth-images in visual pre-training

- Enough with 100k synthetic images

#Data	Fine-tuning (mAP)				
	ES	LC	SN2	IiSeg	LS
20k	36.3	15.3	60.8	21.6	94.9
100k	37.1	**18.3**	**61.6**	**25.5**	**95.1**
200k	**37.2**	15.5	61.5	24.4	94.5
400k	37.1	16.6	61.4	25.3	95.0

The impact of learning from the image primitives

The InsCore pre-trained model surpassed the fine-tuned SAM!

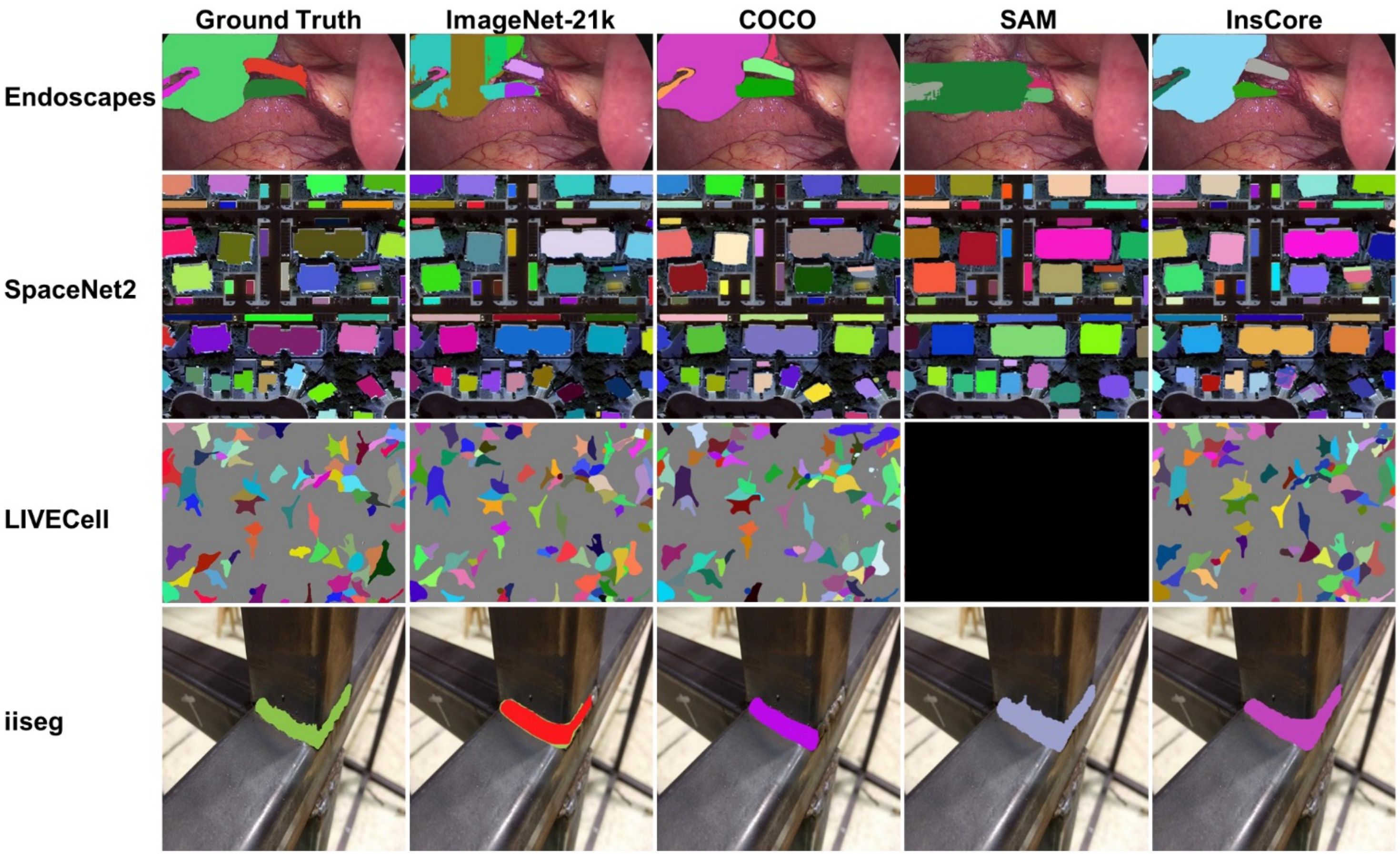
- Without real images nor human supervision in pre-training phase
- Only using x110 smaller pre-training dataset
  - SA-1B 11M imgs, 1B segments vs. InsCore 0.1M synth imgs

Model	Backbone	Prompt	Pre-training		Fine-tuning (mIoU)			
			Dataset	Size	NuInsSeg	SpaceNet2	iiseg	LogiSeg
SAM (Zero-shot)	ViT-B	GT bbox	SA-1B	11M	40.1	56.0	46.4	91.1
SAM (Fine-tuning)					51.5	73.1	60.6	95.6
Mask R-CNN (Ours)	Swin-B	–	InsCore	0.1M	**66.0**	**76.9**	**60.8**	**96.4**

We can further improve the visual pre-training without real data, human supervision

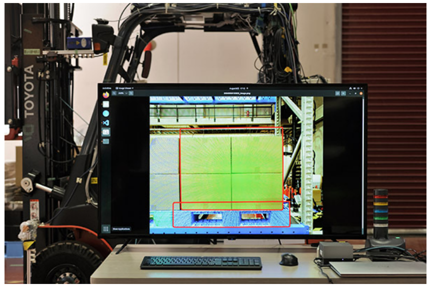
Visual results

Qualitative results at each industrial dataset



The InsCore pre-trained segmentation surpassed SAM!

Tech transfer with Toyota Industry Company (TICO)



https://www.aist.go.jp/aist_j/magazine/20250205.html

I led the successful tech transfer from academic research to industry

Primitive Geometry Segment Pre-training for 3D Medical Image Segmentation

BMVC 2023

Best Industry Paper Finalist

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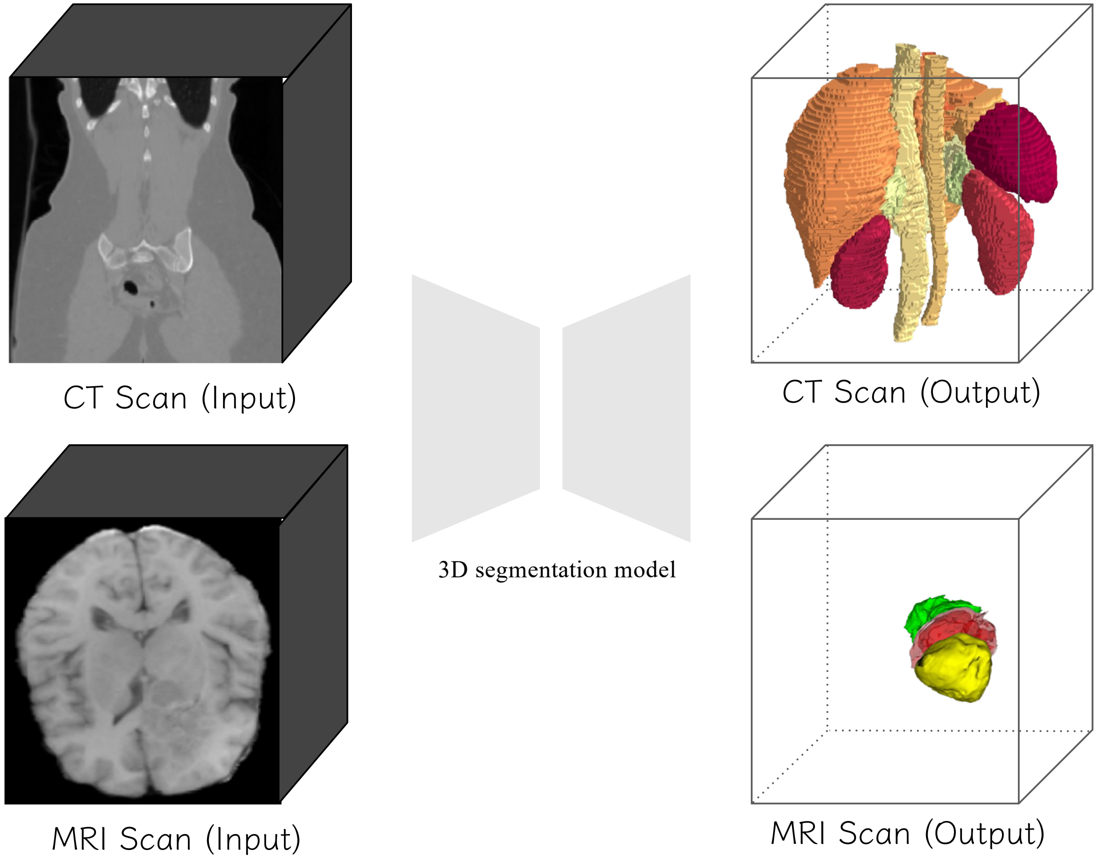
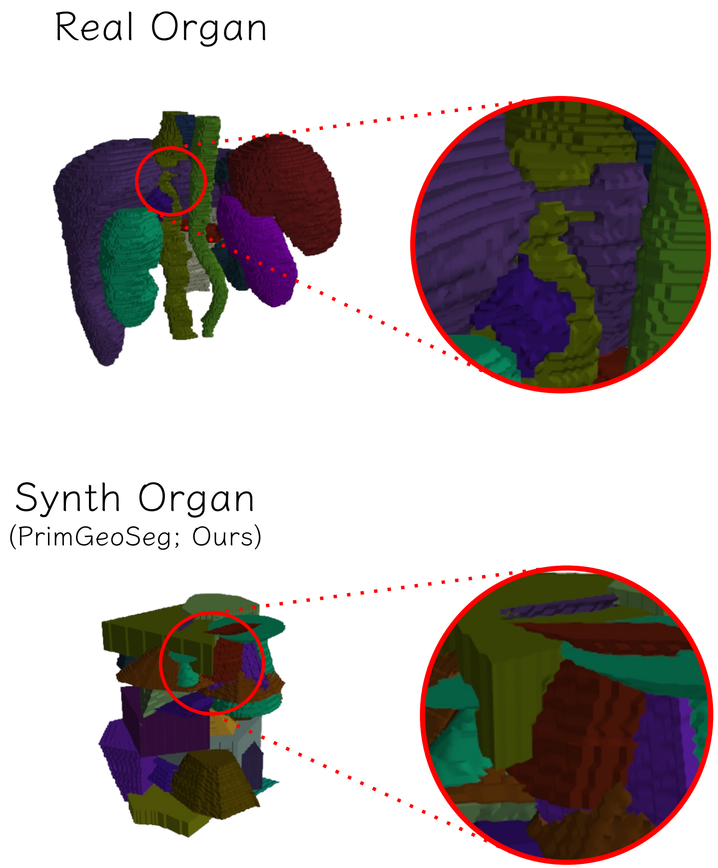
3D medical image segmentation

From the perspective, InsCore can be applied in the 3D x medical domain!

Tumor/Organ Segmentation



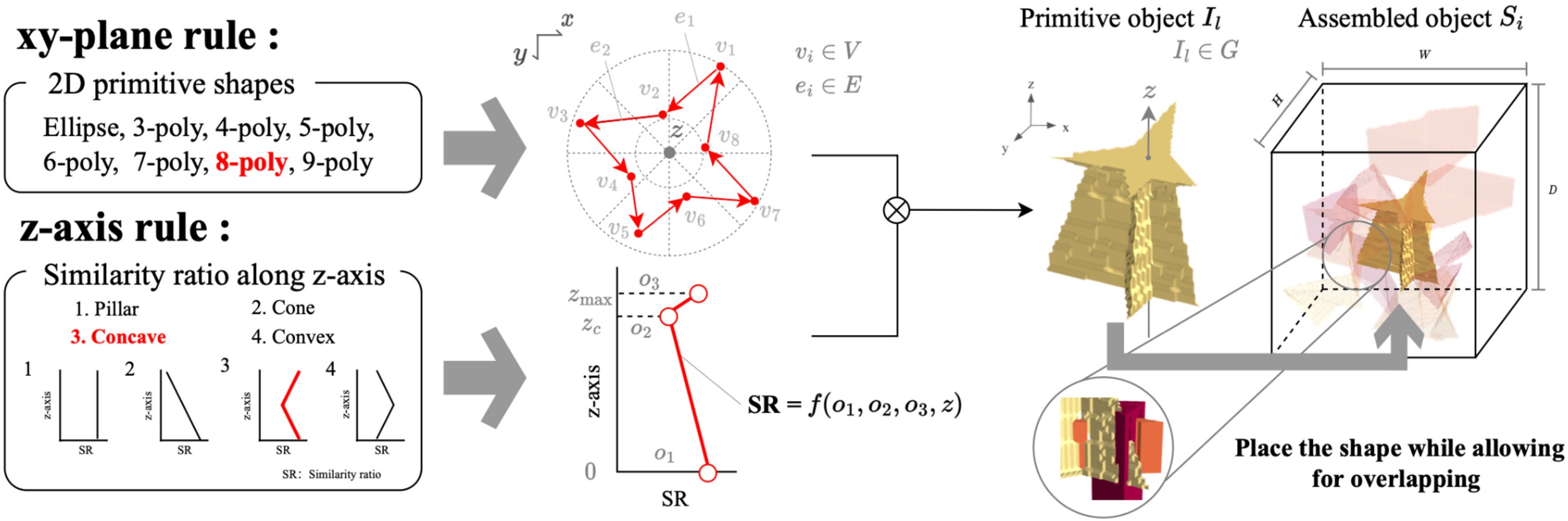
Deep analysis and their synthetic data



Construction of PrimGeoSeg dataset

1. **Primitive object generation** : Combining simple **xy-plane** and **z-axis** rule

2. **Assembled object generation** : Randomly arranging primitive objects in 3D voxel



Primitive object generation **Assembled object generation**

Experimental results: comparison with prior arts

☞ BTCV：13 organs in abdomen

Pre-training	PT Num	Type	Avg.	Spl	RKid	LKid	Gall	Eso	Liv	Sto	Aor	IVC	Veins	Pan	rad	lad
UNETR																
Scratch	0	–	73.0	90.2	91.1	90.7	47.0	63.8	95.3	76.5	85.1	82.1	67.9	72.3	46.1	40.8
Chen *et al.* [6]	0.8K	SSL	75.8	95.2	**95.5**	93.8	51.9	52.3	**98.8**	80.0	87.8	82.7	66.1	68.9	60.8	51.3
PrimGeoSeg	0.8K	FDSL	77.4	88.9	94.0	93.8	59.8	65.7	95.4	79.3	88.3	82.6	69.9	76.8	58.5	53.3
PrimGeoSeg	50K	FDSL	**80.9**	**95.7**	94.2	**94.1**	**61.9**	**69.6**	96.7	**85.5**	**89.5**	**84.4**	**74.7**	**81.9**	**64.3**	**58.7**
SwinUNETR																
Scratch	0	–	78.3	92.3	93.2	93.8	55.9	61.3	94.0	77.0	87.5	80.4	74.2	76.1	68.8	63.6
Tang *et al.* [25]	5K	SSL	81.6	95.3	93.2	93.0	**63.6**	74.0	96.2	79.3	**90.0**	83.3	**76.1**	82.3	**69.0**	**65.1**
PrimGeoSeg	5K	FDSL	**82.0**	**95.7**	**94.4**	**94.4**	61.0	**75.5**	**96.7**	**83.3**	89.1	**85.6**	75.2	**84.3**	67.9	62.4

☞ MSD：Lung tumor / spleen

Pre-training	Type	UNETR Lung	UNETR Spleen	SwinUNETR Lung	SwinUNETR Spleen
Scratch	–	52.5	95.0	63.5	96.3
Tang *et al.* [25]	SSL	–	–	65.2	96.5
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☞ BraTS：Brain tumor

Pre-training	Type	UNETR Avg.	UNETR ET	UNETR WT	UNETR TC	SwinUNETR Avg.	SwinUNETR ET	SwinUNETR WT	SwinUNETR TC
Scratch	–	88.1	84.8	91.3	88.1	90.0	86.8	**92.9**	90.3
PrimGeoSeg	FDSL	**88.7**	**85.6**	**91.8**	**88.9**	**90.3**	**87.0**	**92.9**	**91.0**

For further comparison, please see supplementary materials

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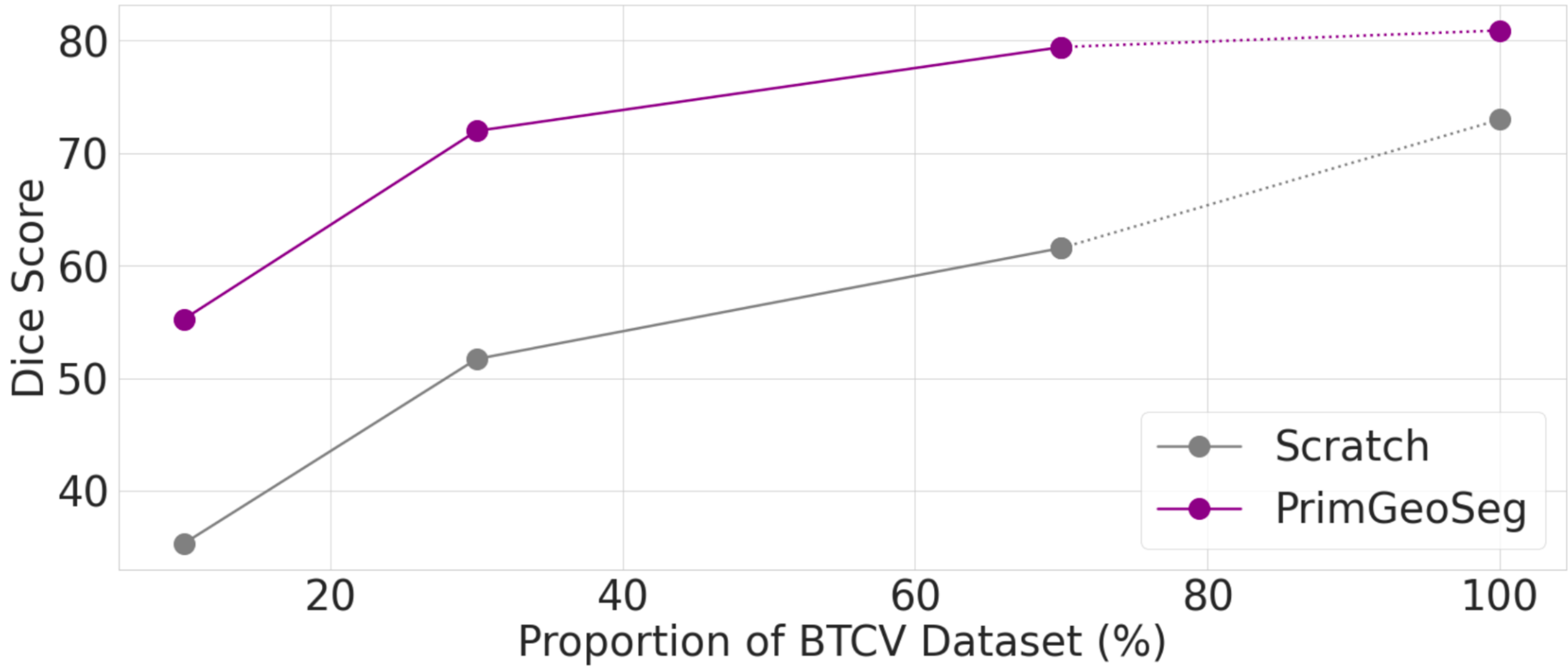
☞ **On BTCV dataset：13 organs in abdomen**

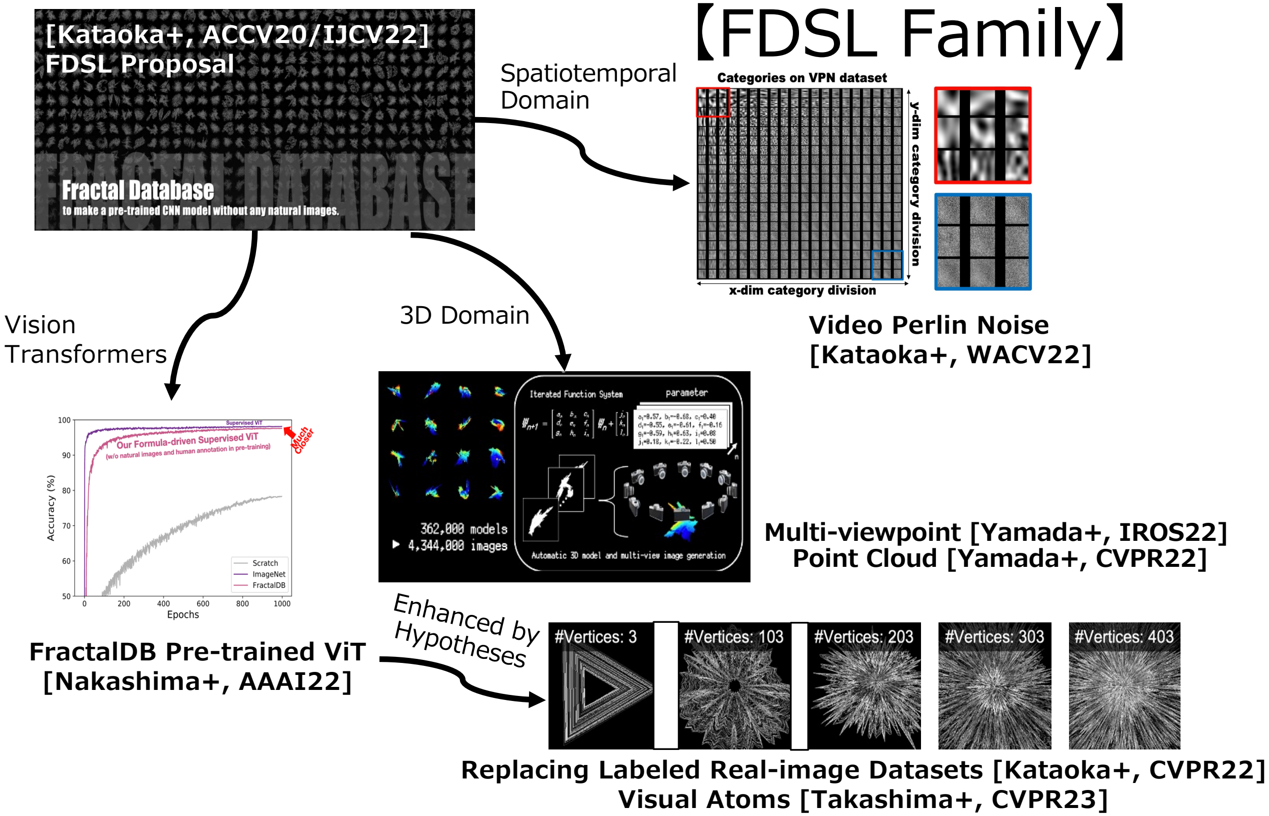


✔ PrimGeoSeg is more effective under limited data settings

Lessons from the synthetic training projects

Any task, any modality in limited synthetic data?

- ➢ Flexibly define the modality and its labels with generative models / mathematical formula
- ➢ Its possible to construct foundation models with very limited data



<u>Now added:</u>

- ➢ Audio training [Shibata+, ICASSP25]
- ➢ Text-to-Image (On-going)
- ➢ Super resolution [Kodama+, CVPRW25]
- ➢ Multimodal - 2D image + 3D point cloud [Yamada+, ECCV24]
- ➢ Multimodal – 2D, 3D, and text (next slides)
- ➢ and other modalities / tasks

1

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Multimodal AI Models with Generative Models

Can generative models make next foundation models?

- Zero-shot 3D understanding (CVPRW25 / on-going work)
- Leading research initiative (LIMIT.Lab with VGG community)

Text-guided Synthetic Geometric Augmentation for Zero-shot 3D Understanding

CVPRW 2025 / On-going work

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http://www.hirokatsukataoka.net/

Towards multimodal AI models

We've proved that "primitive patterns" can make a vision foundation model

- Can generative models flexibly make next foundation models?
- How about a multimodal AI model? Zero-shot recognition in the wild?

Generated 3D dataset for zero-shot understanding

"Wine bottle"
text

2D image

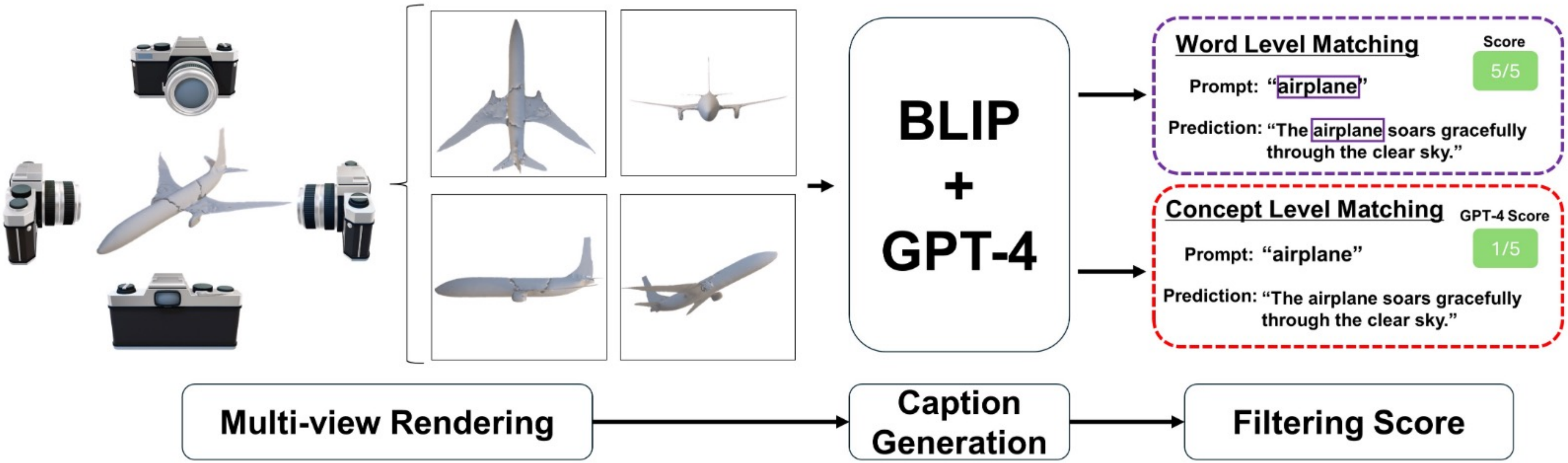
3D point cloud

Its not a positive way in the limited-resource concept, but this is the first step…

Detailed pipeline

Text-to-3D-to-Image

- Text-to-3D model: Point-E
- 3D dataset: ShapeNet
- 2D images: multi-view rendering
- Text: BLIP + GPT-4

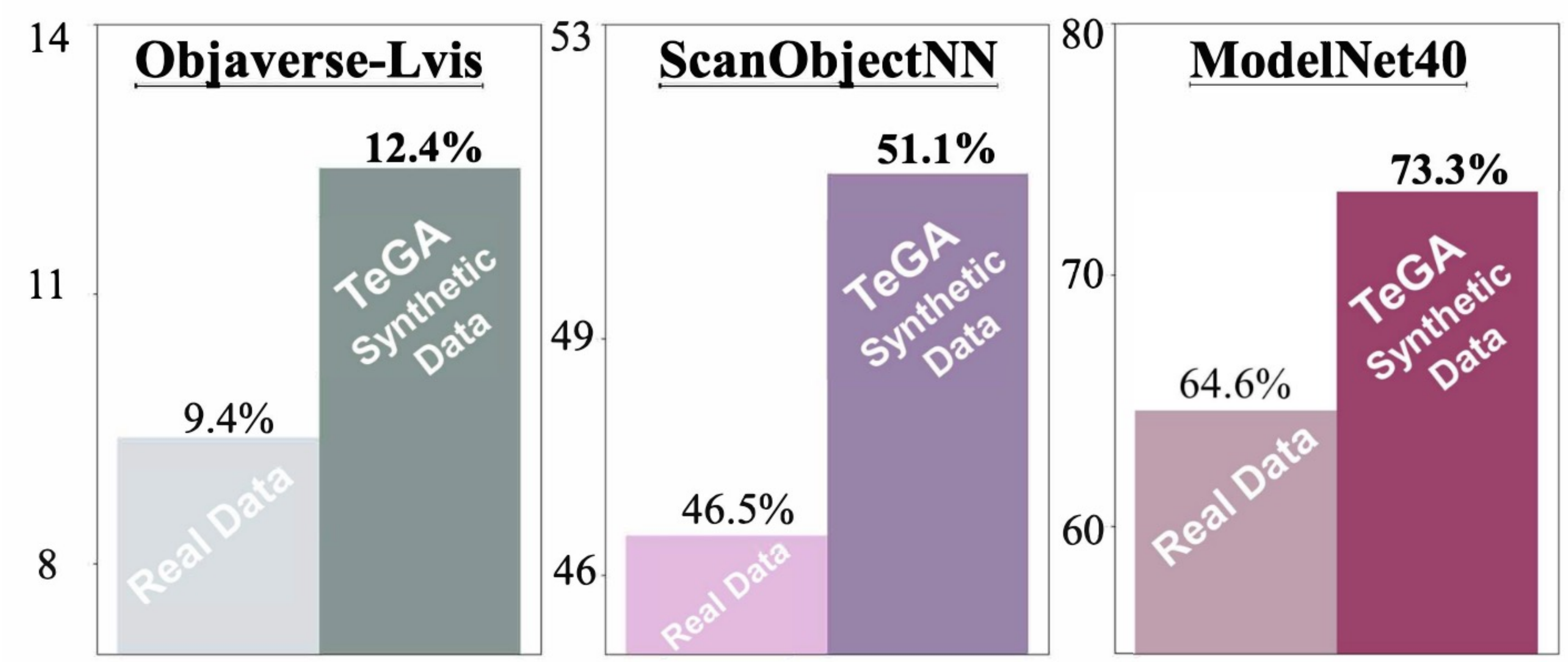


[Torimi et al. CVPRW25]

Main results

With and without synthetic 3D data (TeGA)

- Models: 2D-3D-Text models (MixCon3D)
- Zero-shot 3D understanding on three datasets (Objaverse, ScanObjectNN, ModelNet)

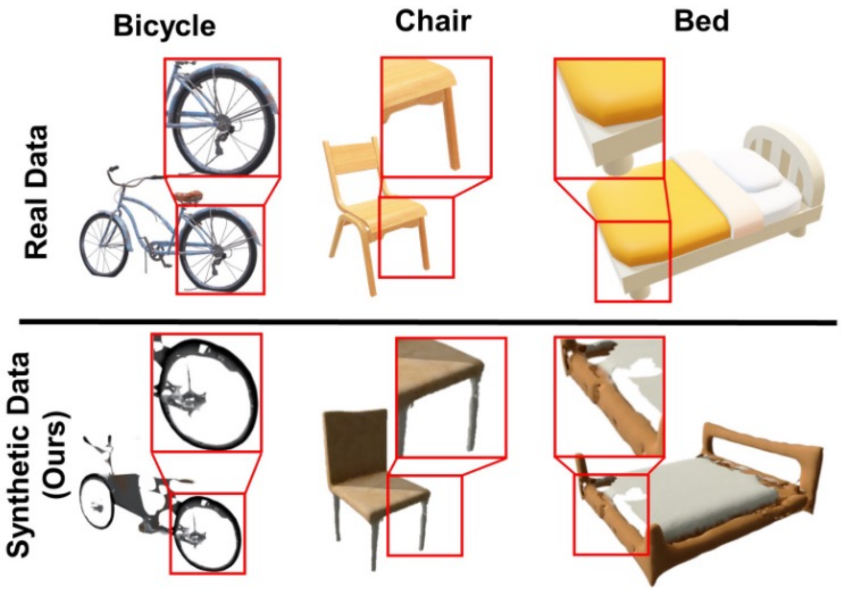


Not a perfect method for now, but its reaching latest levels in zero-shot 3D understanding

Dataset analysis

Generated dataset by Point-E

- ShapeNet vs. Generated data (left fig)
- Data filtering: IN & OUT (right fig)



LIMIT.Lab

-Research initiative-
Multimodal AI Foundation Models with Very Limited Resources

Hirokatsu Kataoka

National Institute of Advanced Industrial Science and Technology (AIST)
Visual Geometry Group, University of Oxford (Oxford VGG)

http://www.hirokatsukataoka.net/

LIMIT.Lab

Research initiative w/ VGG community

【LIMIT.Community / LIMIT.Lab】

LIMIT.LAB

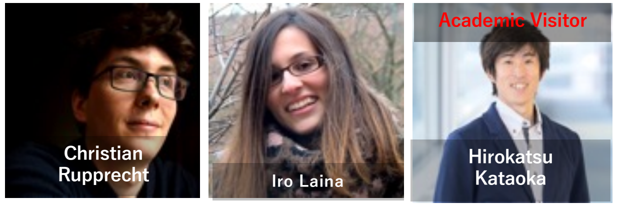
Community => LIMIT.Community
- 100+ researchers / students
- LIMIT Workshops @ ICCV25&CVPR24

Research Lab => LIMIT.Lab
- 🇯🇵 AIST
- 🇬🇧 Oxford VGG, Cambridge VSL
- 🇩🇪 UTN FunAI Lab
- 🇳🇱 UvA VISLab

I'm leading this community-driven research!

- 10-year experience in Japanese community-driven research
- We enhance the CV researches w/ world-wide talent starting from VGG community?

【Oxford VGG🇬🇧】



＋Postdocs, Ph.D. students at VGG

【UTN FunAILab🇩🇪 / former UvA VISLab🇳🇱】

＋Postdocs, Ph.D. students at FunAILab

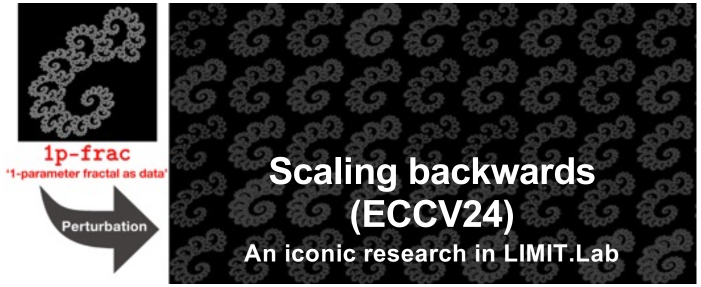
【Cambridge VSL🇬🇧】

＋Upcoming Ph.D. students at VSL

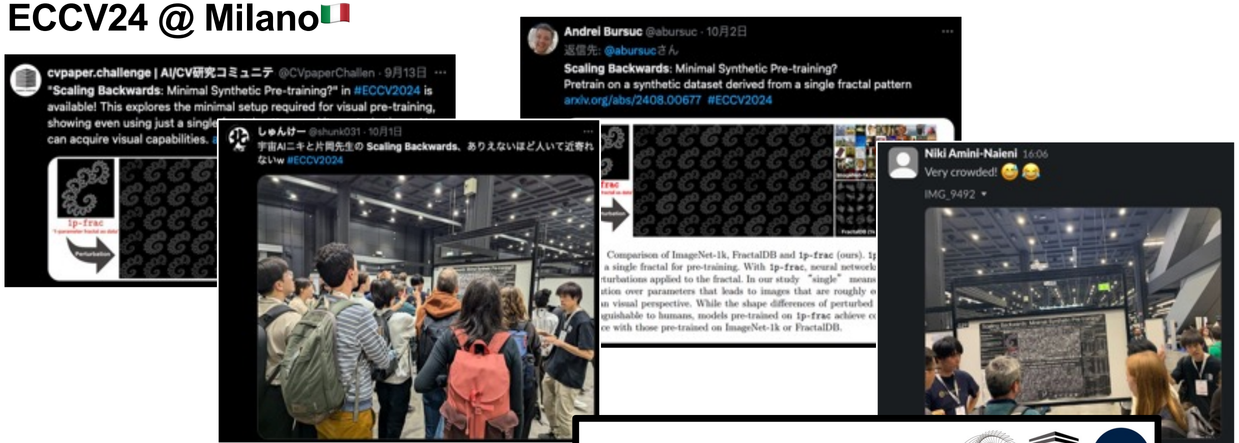
LIMIT.Lab, so far

As a stealth mode,

- Organizing several workshops / networking
- Conceptual researches in limited resources
- CVPR 2025 report



ECCV24 @ Milano



LIMIT Workshop Organizers

CVPR 2025 Report

Hirokatsu Kataoka, Yoshihiro Fukuhara,

Ryousuke Yamada, Daichi Otsuka, Rintaro Yanagi, Kazuya Nishimura,
Moeri Okuda, Yuto Matsuo, Ren Ohkubo, Yue Qiu, Noritake Kodama,
Gido Kato, Kenzo Yamabuki, Joe Hasei, Ryuichi Nakahara,
Yukinori Yamamoto, Sho Okazaki, Kohsuke Ide, Yuiga Wada,
Daichi Yashima, Shinichi Mae, Hinako Mitsuoka, Maika Takada,
Oishi Deb, Orest Kupyn, Jianyuan Wang

LIMIT.Lab / cvpaper.challenge / Visual Geometry Group (VGG)

LIMIT.Lab, from now!

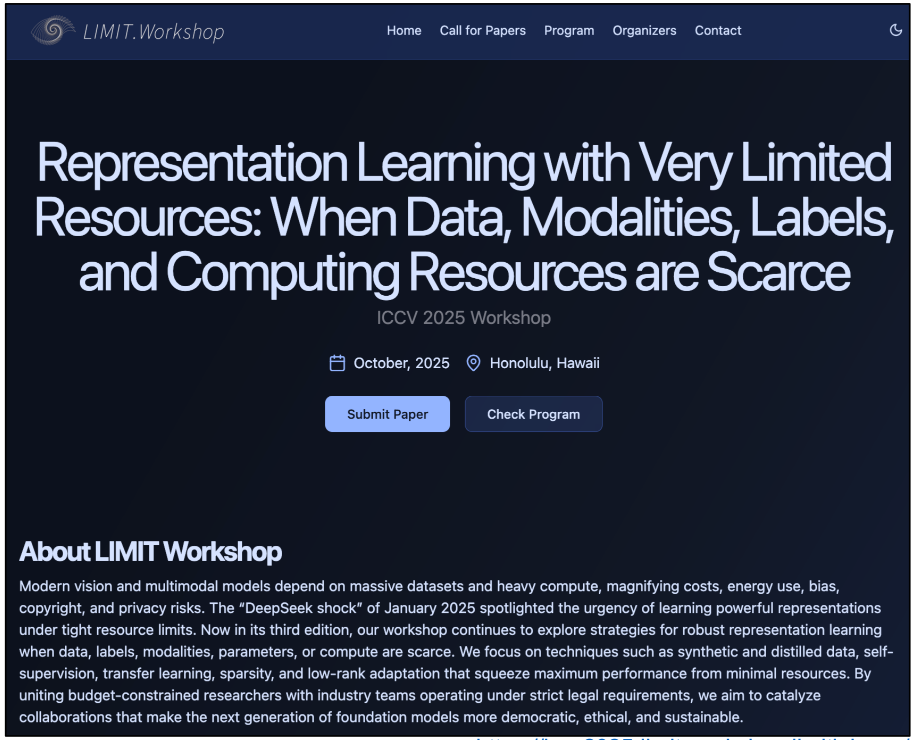
LIMIT researches in multiple aspects

- 1. Minimalist 3D foundation models (like VGGT) for minimal representation?
- 2. Synthetic data for zero-shot understanding in the wild?
- 3. Multipurpose Transformer pre-training?

Concept switching, from “LIMIT” to “FOUND” FOUNdation Data

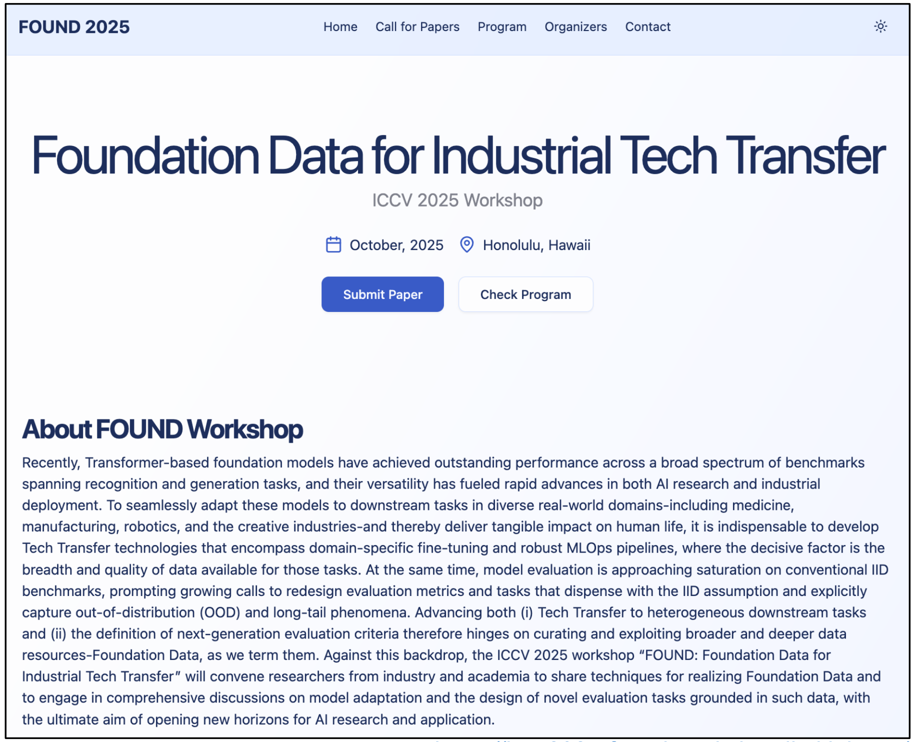
Two accepted organizing workshops at ICCV 2025

LIMIT: Representation Learning with Very Limited Resources



https://iccv2025-limit-workshop.limitlab.xyz/

FOUND: Foundation Data for Industrial Tech Transfer



https://iccv2025-found-workshop.limitlab.xyz/

- Good connection from LIMIT to FOUND in terms of academic/industry, research community, & tech transfer with AI models
- LIMIT: Building multimodal AI foundation models with very limited resources
- FOUND: Foundation data for the last-mile industrial tech transfer

A better academic research, a better tech transfer in the concept of LIMIT