



Learning Hierarchical Image Segmentation For Recognition and By Recognition

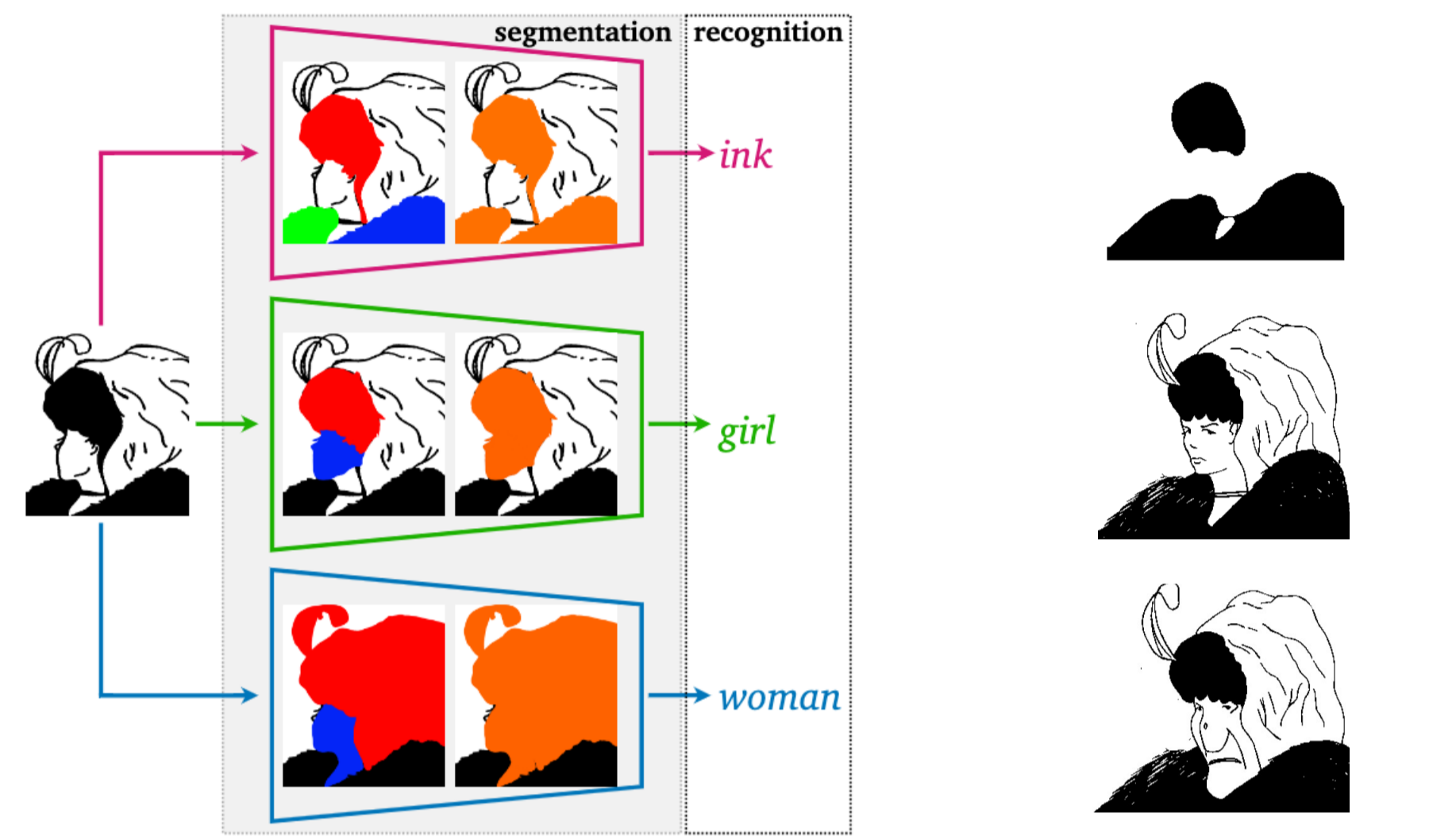


Tsung-Wei Ke *

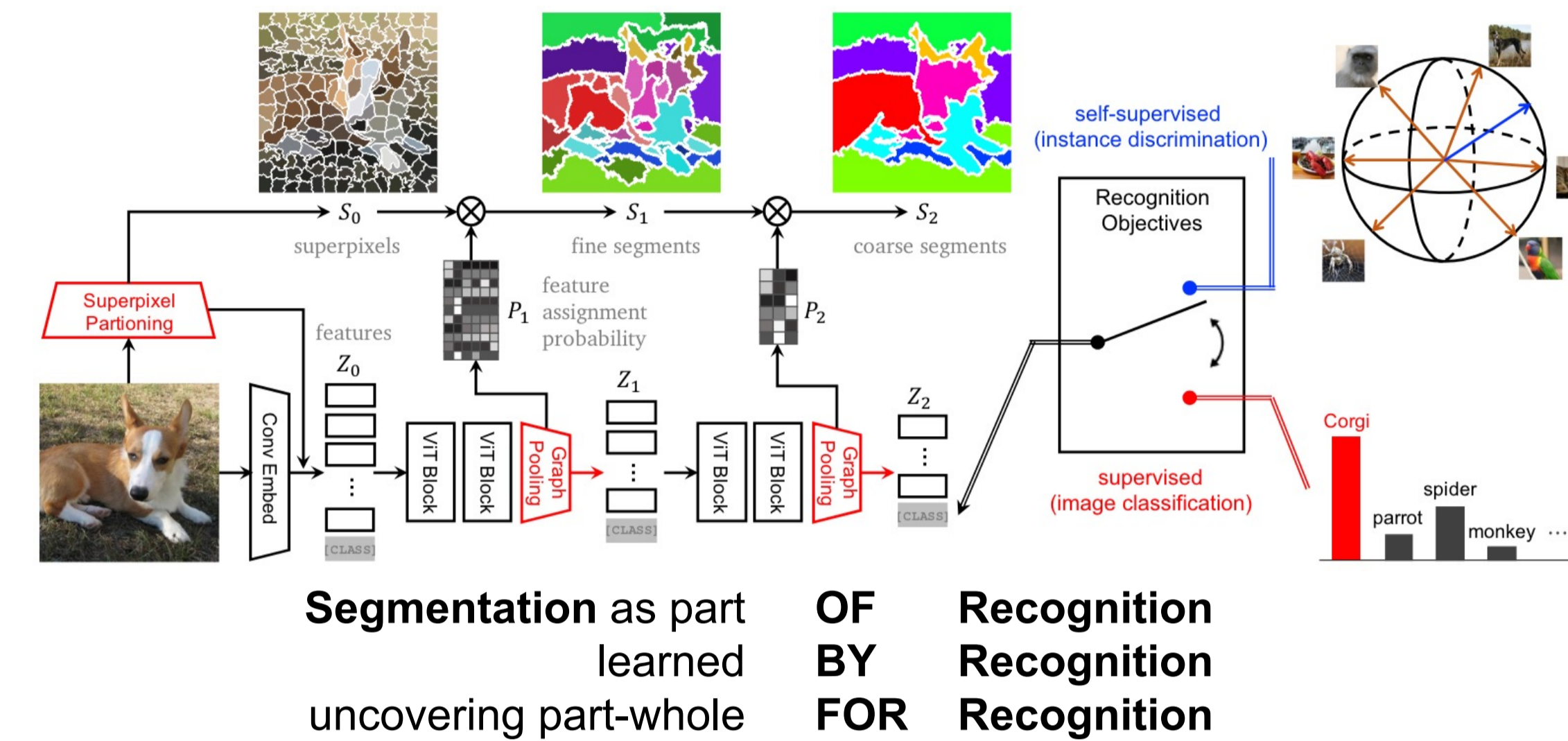
Sangwoo Mo *

Stella X. Yu

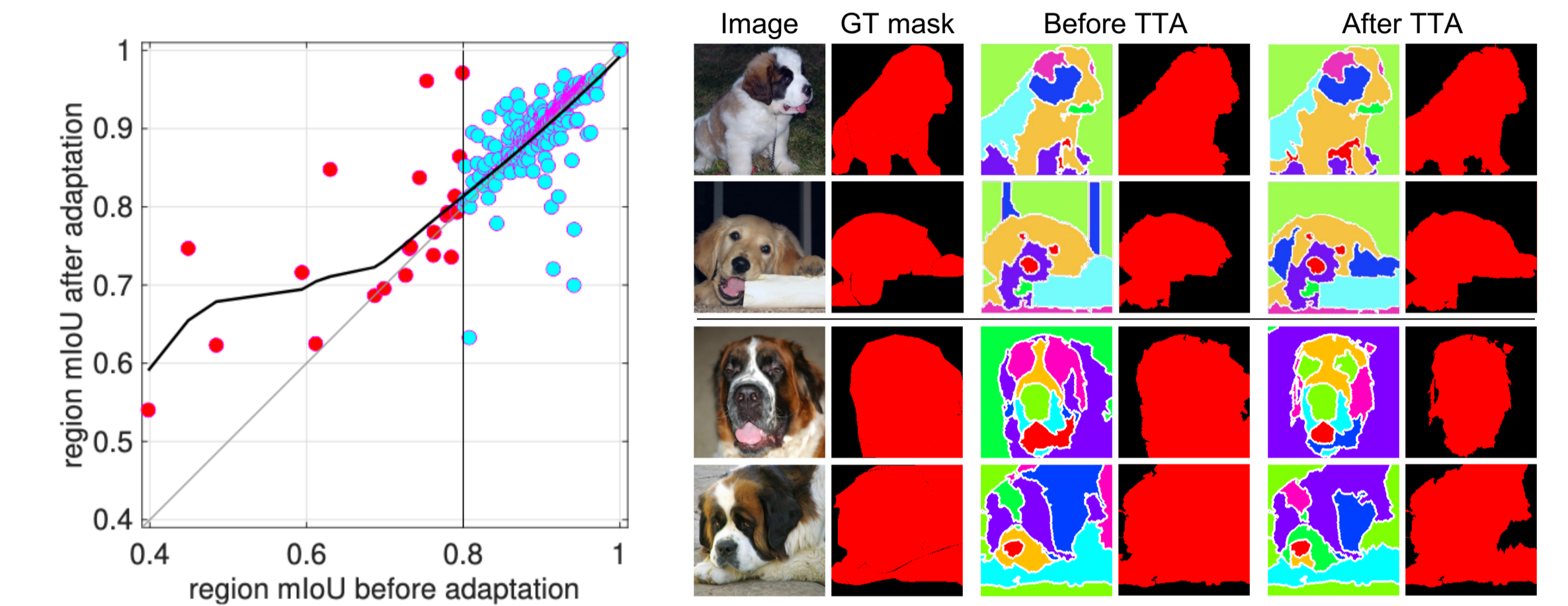
Consistency of Visual Parsing instead of Text Labels



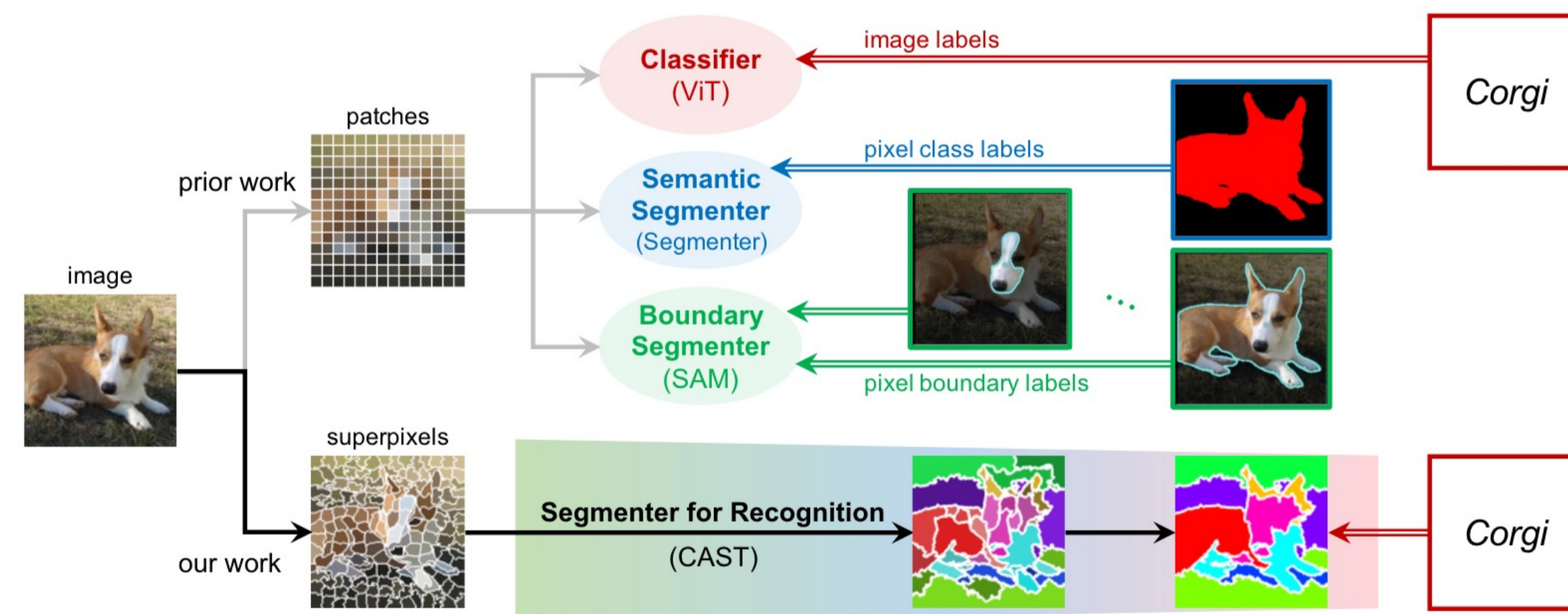
Our CAST = ViT w/ Superpixels + Graph Pooling



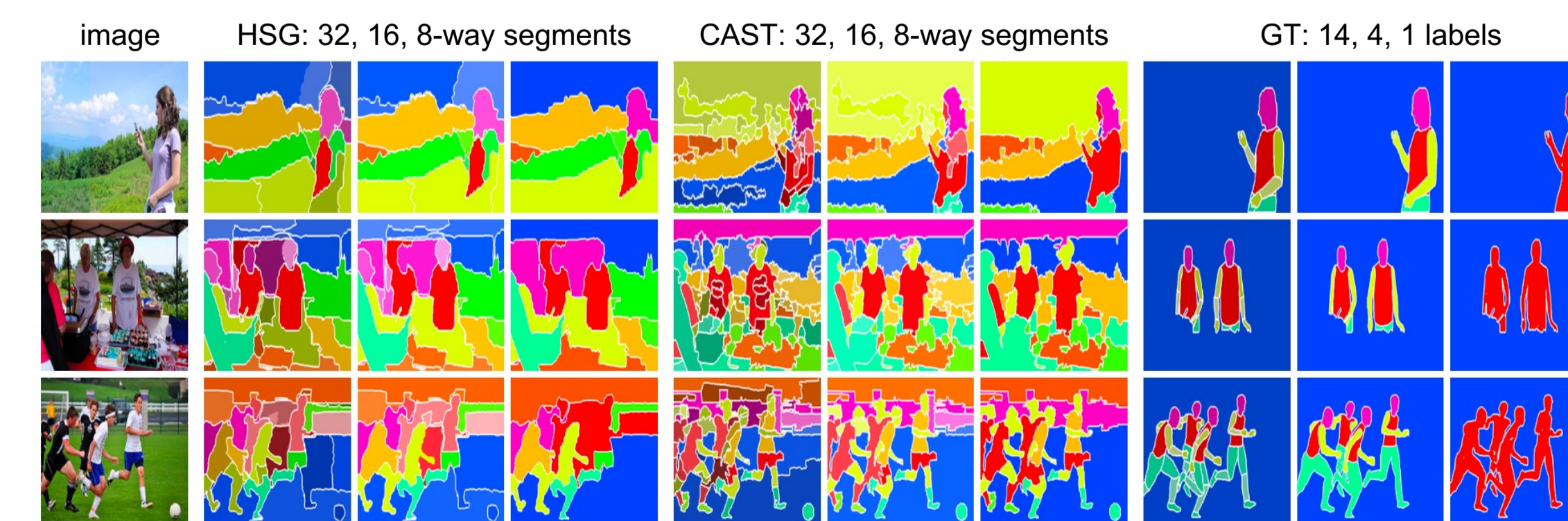
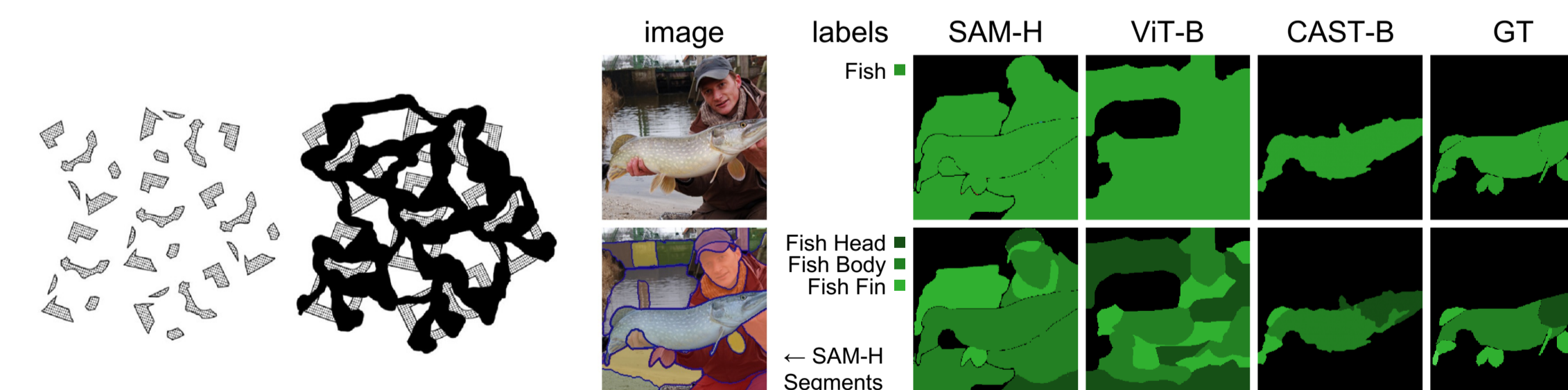
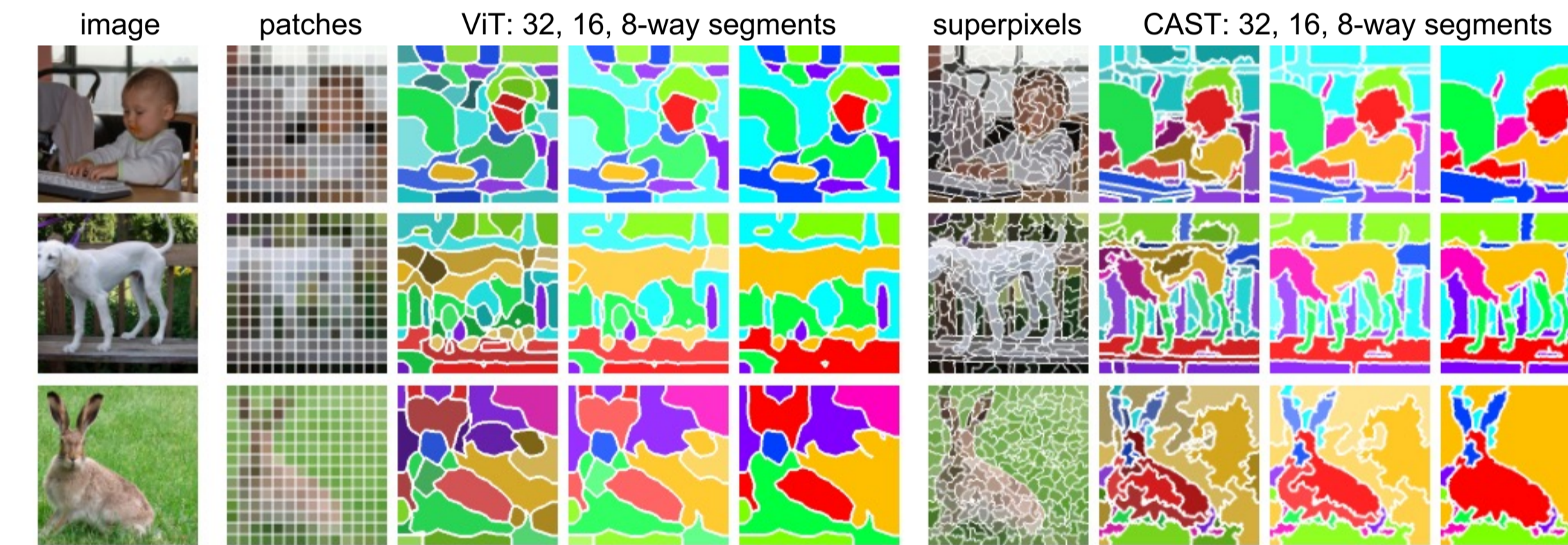
2. Solidify Recognition by Adapting Segmentation



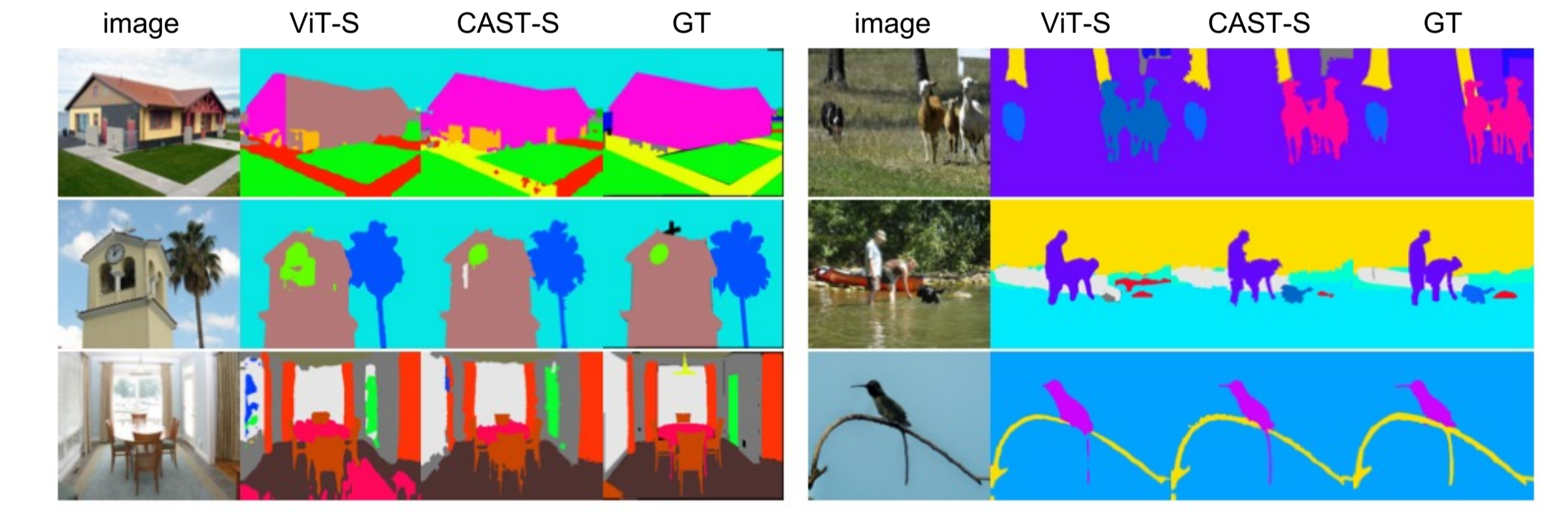
Continuum of Internal Segmentation onto Recognition



1. Unsupervised Part-Whole Discovery



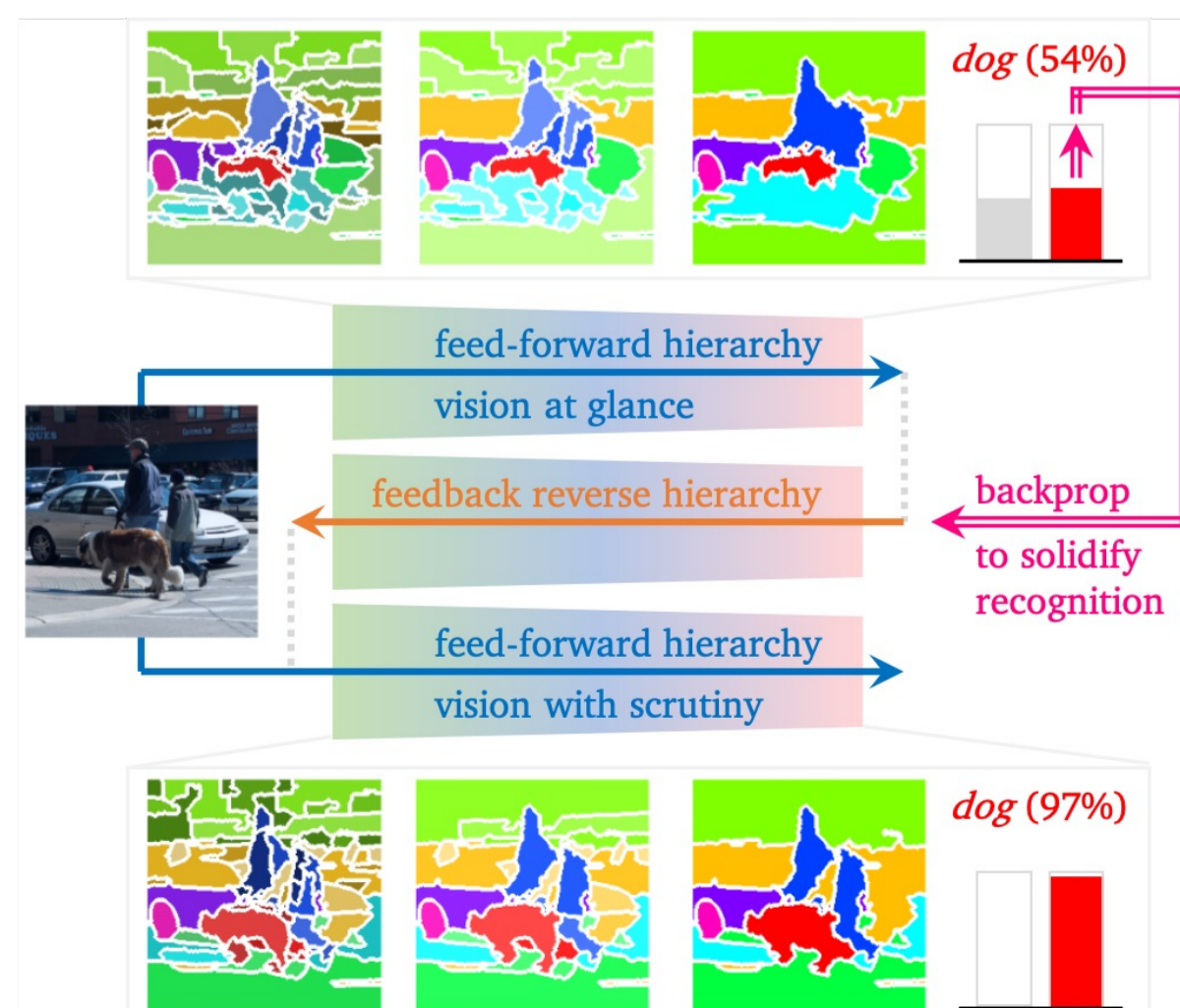
3. Generalization and Efficiency



model	GFLOPS	region mIoU	boundary F-score	P	R	F	14 labels	4 labels	1 label
SAM-B	677	18.03	10.15	20.71	7.25		20.7	18.6	19.6
SAM-H	3166	21.97	12.07	32.66	11.82		24.1	30.6	26.9
ViT-B	18	25.34	11.74	10.92	4.64		26.3	44.9	33.2
CAST-B	13	29.66	13.20	22.32	6.52		24.8	33.2	28.4
gain		0.4	5.5	2.9	0.7	2.6	1.5	5.8	8.8

test on PASCAL-VOC	before tuning	after tuning	Model	GFLOPS	IN-100	IN-1K		
ViT-S	30.9	16.1	65.8	40.7	ViT-S	4.7	78.1	67.9
ViT-S but with token pooling	34.5	19.8	67.2	41.9	Swin-T	4.5	78.3	63.0
ViT-S but with superpixels	32.2	21.2	66.5	46.7	CAST-S	3.4	79.9	68.1
CAST-S	38.4	27.0	67.6	48.1				

Concurrency of Segmentation and Recognition



1. Always trained, tested, and adapted together
2. Segmentation substantiates recognition
3. Recognition leads segmentation

1. Beats ViT on unsupervised hierarchical segmentation on ImageNet
2. Beats SAM on unsupervised object segmentation on PartImageNet
3. Beats HSG on unsupervised human-body parsing on DensePose
4. Better downstream semantic segmentation
5. Better recognition and efficiency
6. Both superpixels and token pooling contribute to performance gains

