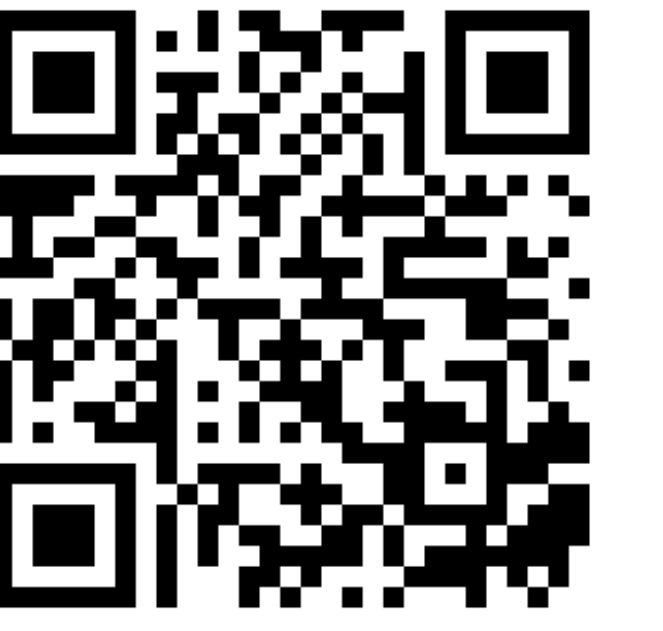


# End-to-End (Instance)-Image Goal Navigation through Correspondence as an Emergent Phenomenon

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## Motivation

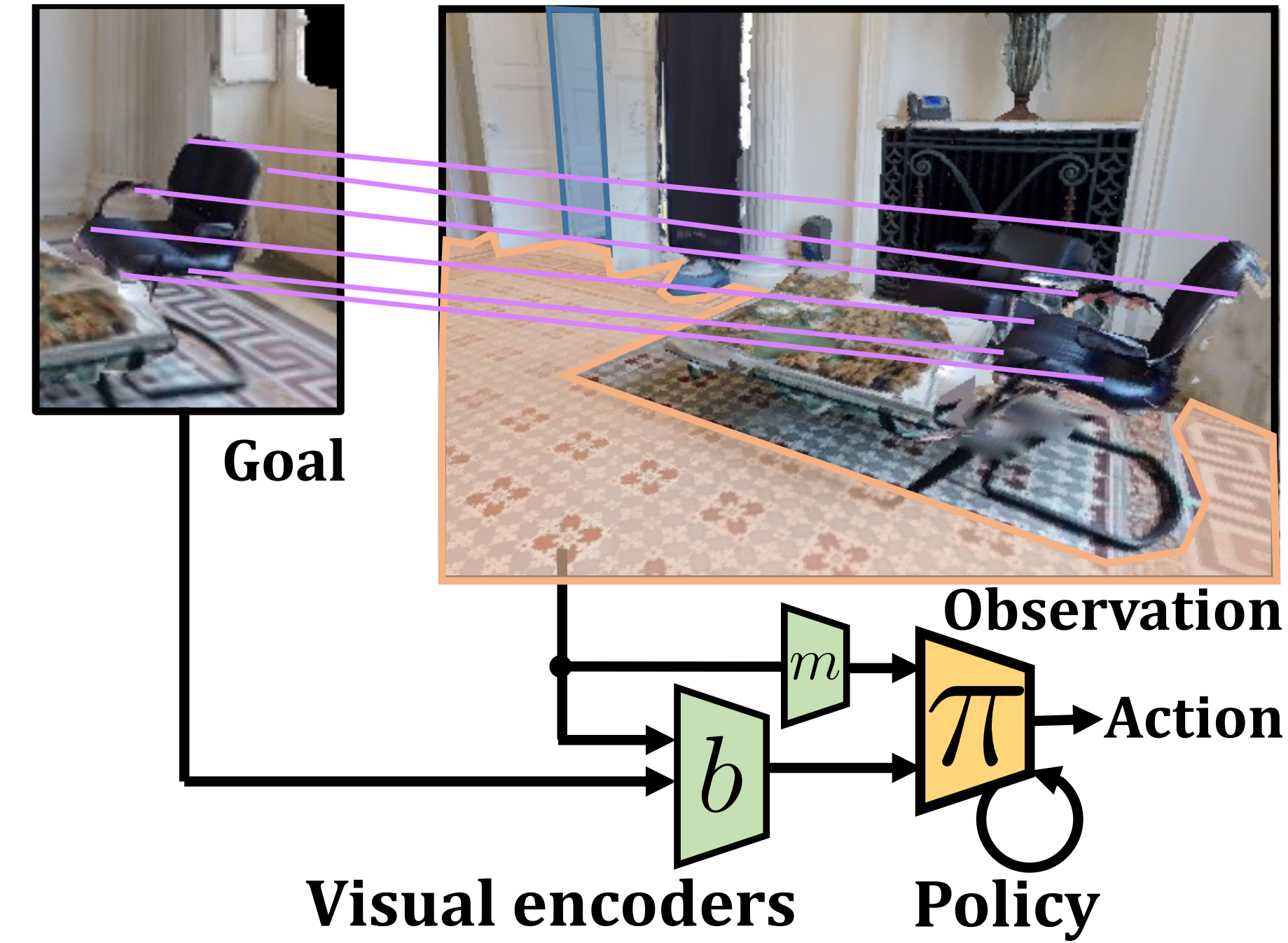
**Task:** ImageNav: navigation to a goal specified by an image.

**Requires:** (1) Nav skills: **detection of navigable space, exits etc.**  
(2) Detection of **relative pose wrt the goal**

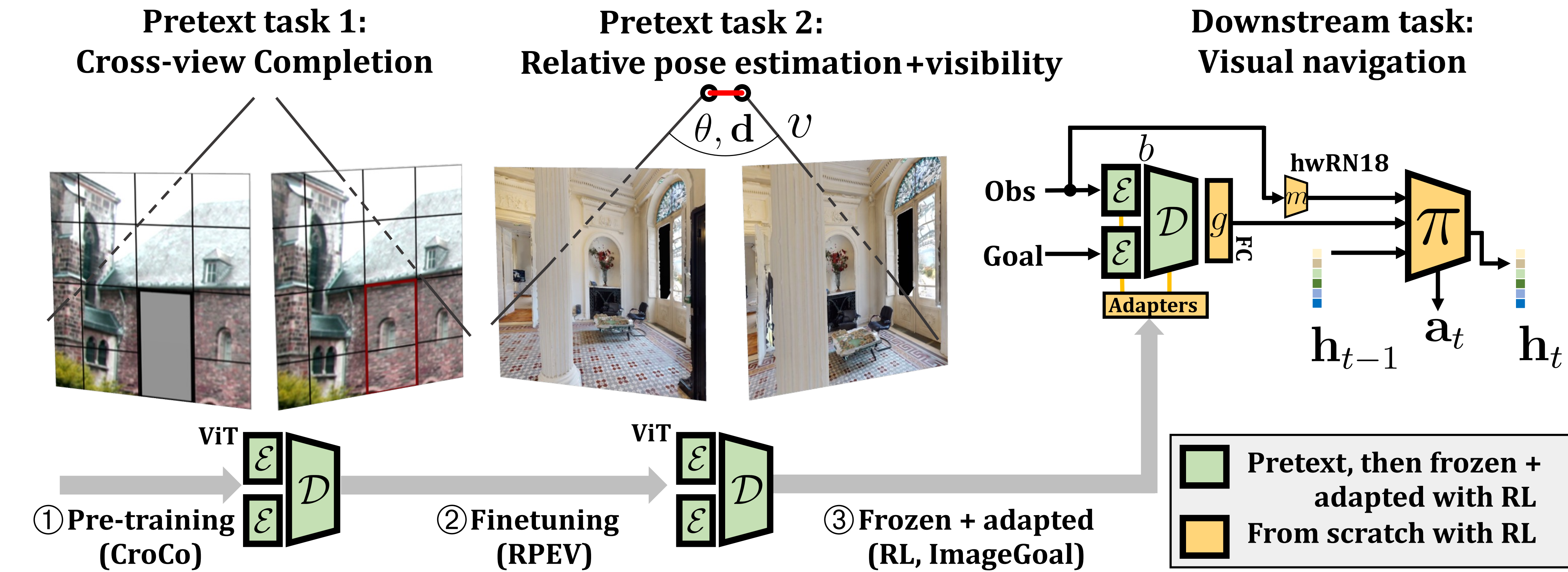
**Cur SOTA:** Train visual encoder + policy end-to-end, or outsource goal detection to local feature based methods.

**Idea:** Pre-train a **binocular ViT** with cross-attention on different losses:

- Cross-view competition as in Weinzaepfel et al., NeurIPS 2022
  - Extremely-wide baseline relative pose + visibility est.
- Use as visual encoder in an end-to-end policy trained with RL. Encoder is frozen + adaptors.



## Training pipeline



## Correspondence solutions emerge after pre-training (CroCo + RPEV)

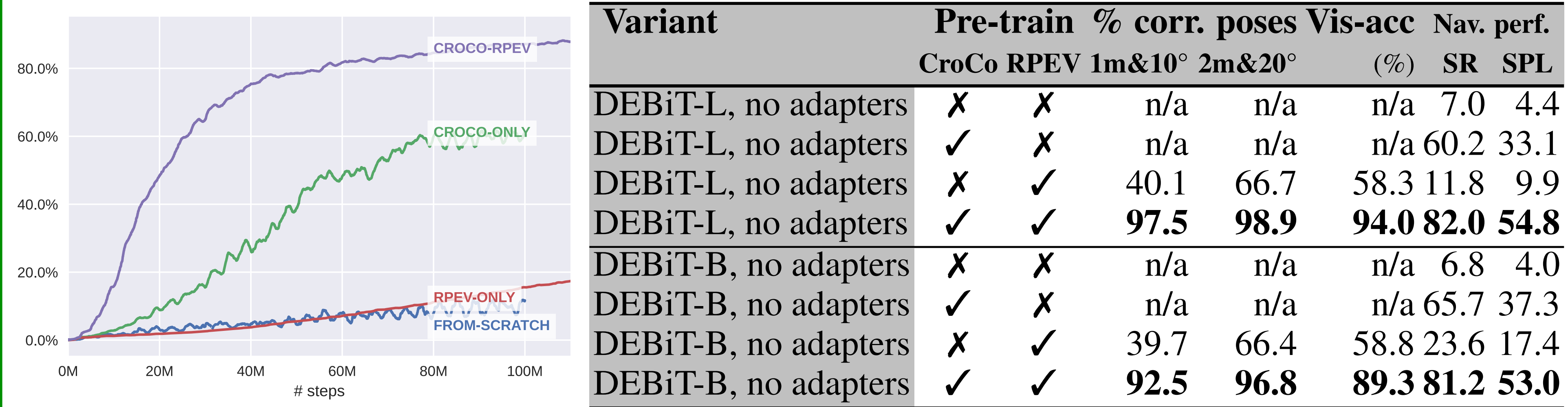


Shown: cross-attention of the last head average over all heads. Patches selected based on total attention.

## Impact of architecture variants and sizes

Variant	Encoder			Decoder			#params (binoc)	Monoc	% correct poses		Vis-acc (%)	Nav. perf.	
	L	H	d	L	H	d			1m&10°	2m&20°		SR (%)	SPL (%)
DEBiT-L (“Large”), no adapters	12	12	768	8	16	512	120M	hwRN18	97.5	98.9	94.0	82.0	59.6
DEBiT-B (“Base”), no adapters	12	6	384	8	16	512	55M	hwRN18	92.5	96.8	89.3	83.0	55.6
DEBiT-S (“Small”), no adapters	12	6	384	2	8	256	24M	hwRN18	82.7	93.5	81.6	79.6	52.1
DEBiT-T (“Tiny”), no adapters	8	6	384	2	8	256	17M	hwRN18	80.3	92.4	80.6	79.3	50.0

## Impact of pre-training strategies



## Comparison w. SOTA: ImageNav

Method	#steps	SR (%)	SPL (%)	Pretrained weights
Siam. hwRN18	180M	10.1	9.6	None, from scratch
Siam. hwRN18 <sup>2</sup>	500M	-	8.0 <sup>1</sup>	None, from scratch
Mem. Aug. (Mezghani et al., 2022) <sup>3</sup>	500M	-	9.0 <sup>1</sup>	Finetuned
ZSEL (Al-Halah et al., 2022)	500M	29.2 <sup>1</sup>	21.6 <sup>1</sup>	Obs.&policy frozen, goal from scratch
ZSON (Majumdar et al., 2022a)	500M	36.9 <sup>1</sup>	28.0 <sup>1</sup>	Obs. finetuned, goal frozen (CLIP)
VC1-ViT-L (Majumdar et al., 2023)	500M	81.6 <sup>1</sup>	-	Finetuned
OVRL (Yadav et al., 2022)	500M	54.2 <sup>1</sup>	27.0 <sup>1</sup>	Finetuned
OVRL-v2 (Yadav et al., 2023)	500M	82.0 <sup>1</sup>	58.7 <sup>1</sup>	Finetuned
ANS (Chaplot et al., 2020b) + DEBiT-L		32.0	15.0	Modular architecture + our frozen encoder
Ours (DEBiT-B), no adapters	200M	83.0	55.6	Frozen
Ours (DEBiT-L), no adapters	200M	82.0	59.6	Frozen
Ours (DEBiT-L) + adapters	200M	94.0	71.7	Frozen + adapted

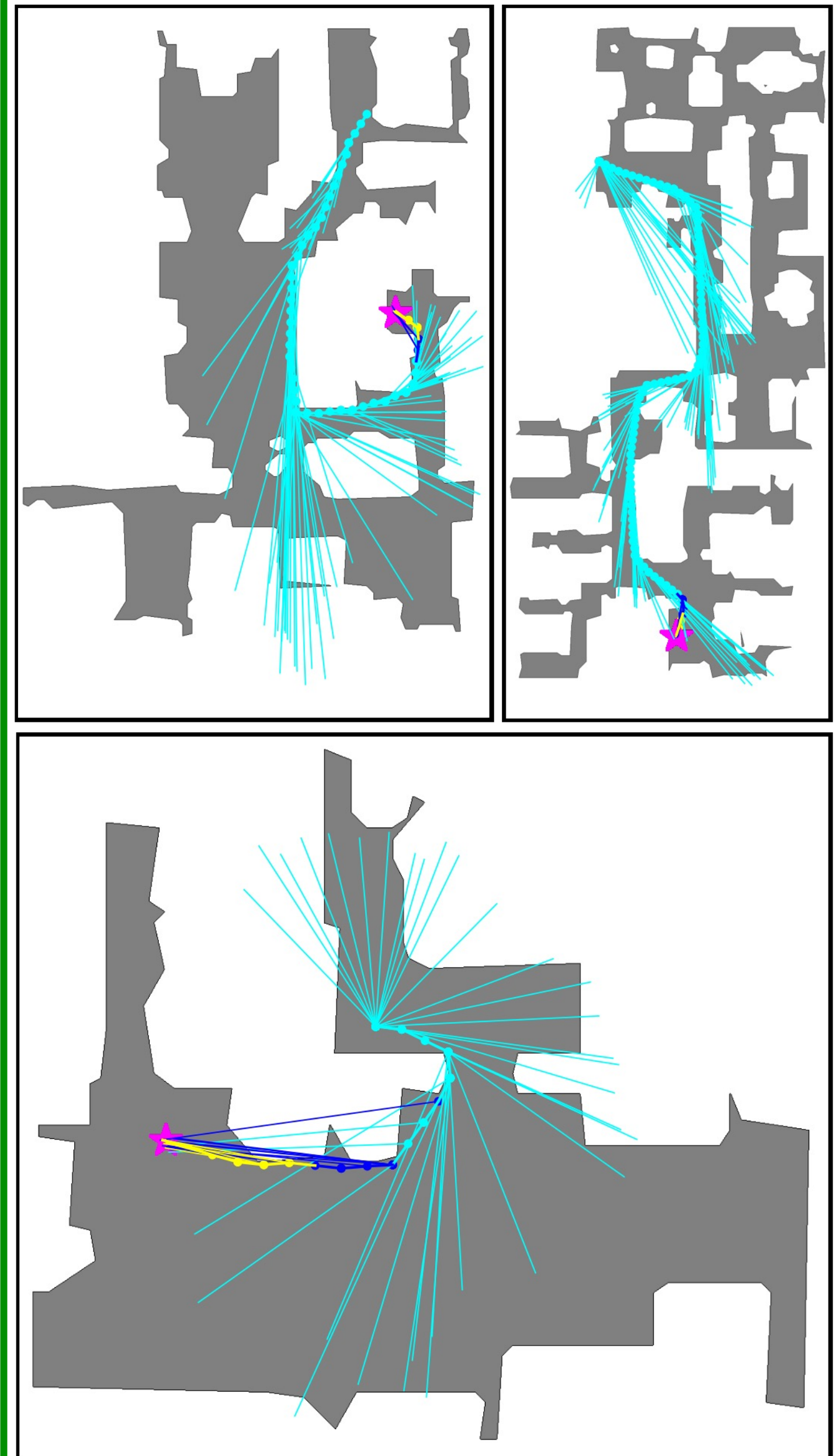
<sup>1</sup> Perf. from orig. papers; <sup>2</sup> Mono-view ablation of baseline in Table III of (Mezghani et al., 2022);

<sup>3</sup> Retrained in mono-view settings, see Table 1 of (Al-Halah et al., 2022)

## Comparison w. SOTA: Instance ImageNav

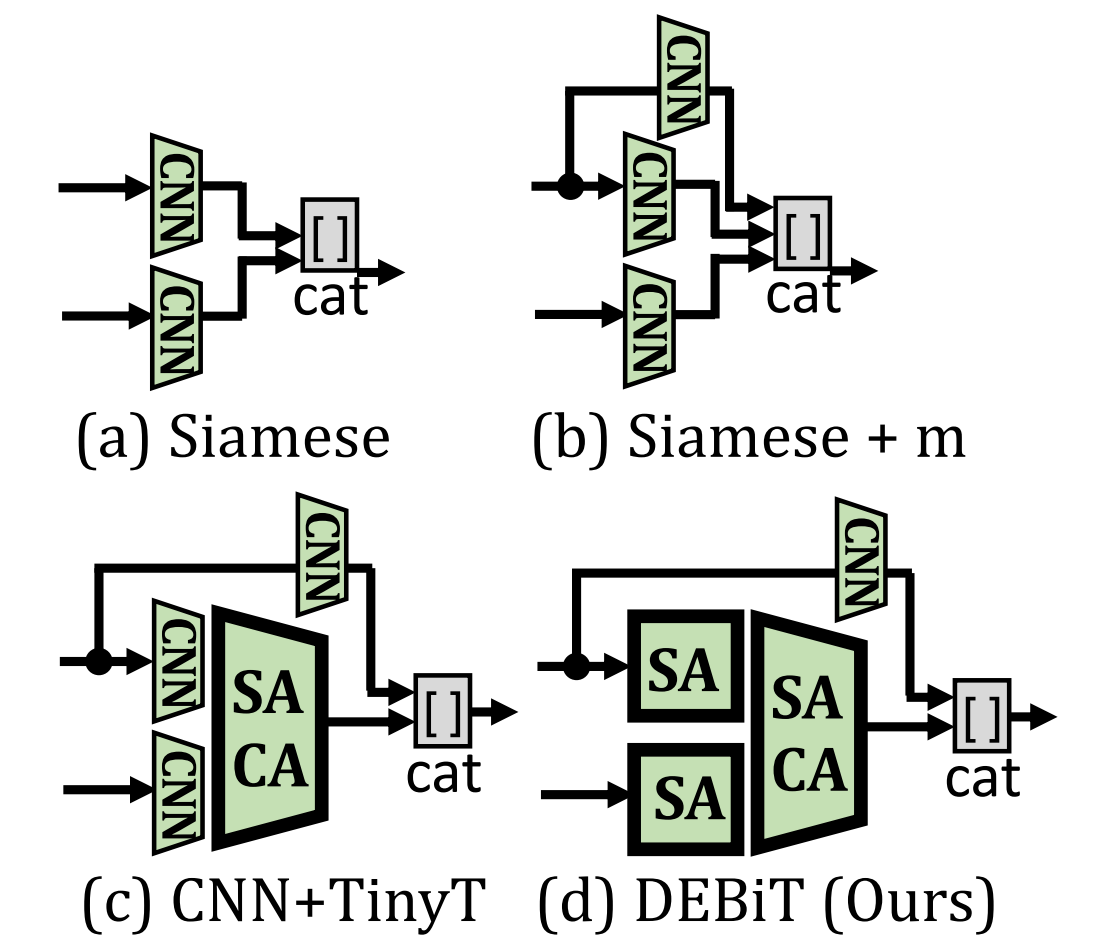
Method	#steps	SR (%)		SPL (%)		Task: camera intrinsics and height may differ btw obs and goal.
		max	avg	max	avg	
(Krantz et al., 2022)	3500M	5.5	n/a	2.3	n/a	<b>Method:</b> pre-train on ImageNav, finetune policy and adaptors w. RL on Instance-ImageNav
(Krantz et al., 2023)	n/a	56.1	n/a	23.3	n/a	
Ours(DEBiT-L)+adapters	200M	61.1	59.3	33.5	32.4	

## RPEV Results during Nav



TN ( $v^* < \tau, v < \tau$ ), TP ( $v^* > \tau, v > \tau$ )  
FP ( $v^* < \tau, v > \tau$ ), FN ( $v^* > \tau, v < \tau$ )

## Alignment architecture / loss



Visual encoder	Pre-train	#parms	SR	SPL
(a) Siamese hwRN18*	No	4.1M	10.1	9.6
(b) Siamese hwRN18* + m	RPEV	8.3M	8.0	7.7
(c) hwRN18+Cross-Att+m	No	10M	7.4	4.7
(d) hwRN18+Cross-Att+m	RPEV	10M	7.4	7.2
(d) DEBiT-B (Ours), no adapters	No	60M	6.8	4.0
(d) DEBiT-B (Ours), no adapters	CroCo+RPEV	60M	83.0	55.6

\* Baseline in (Mezghani et al., 2022), inspired by (Zhu et al., 2017)