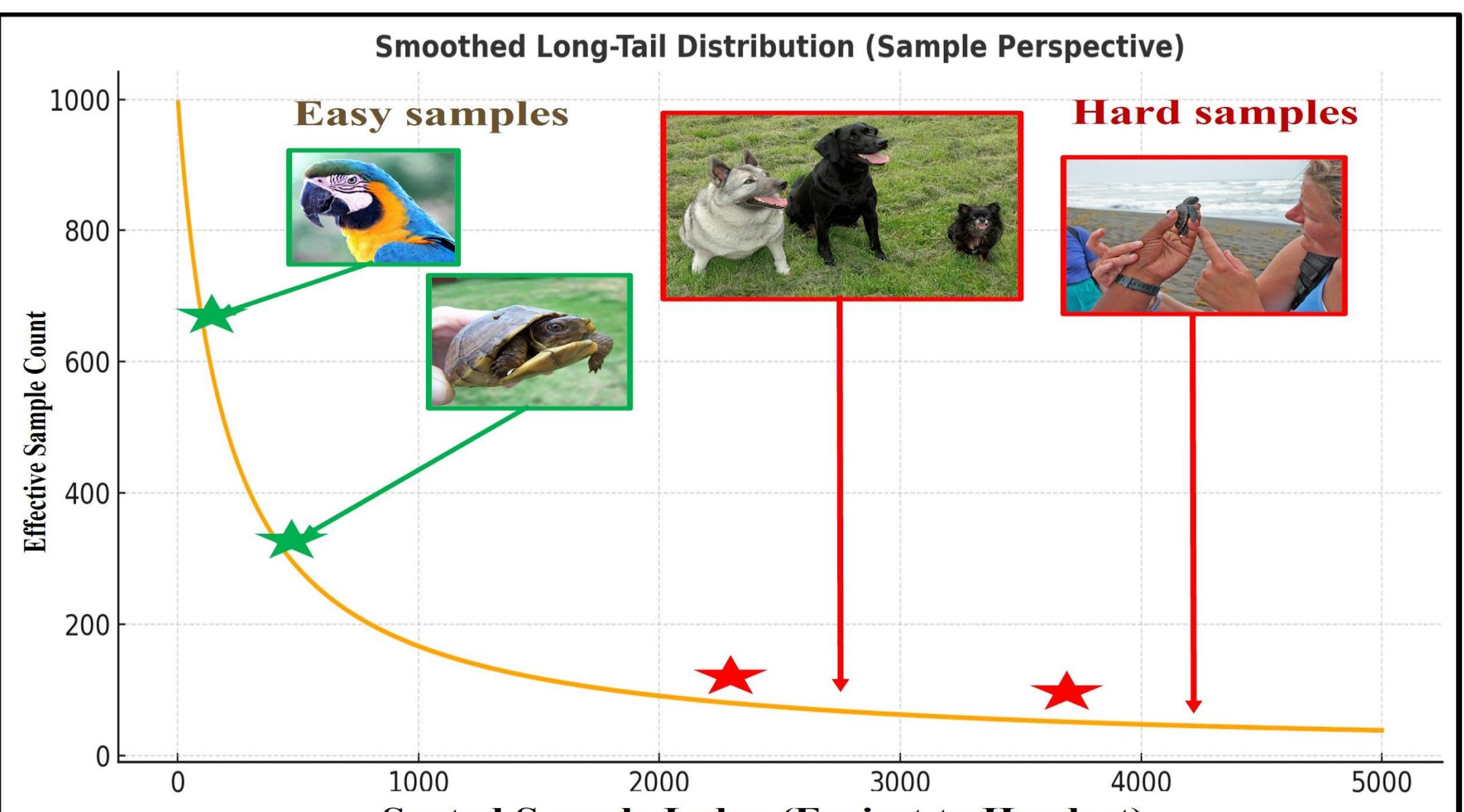


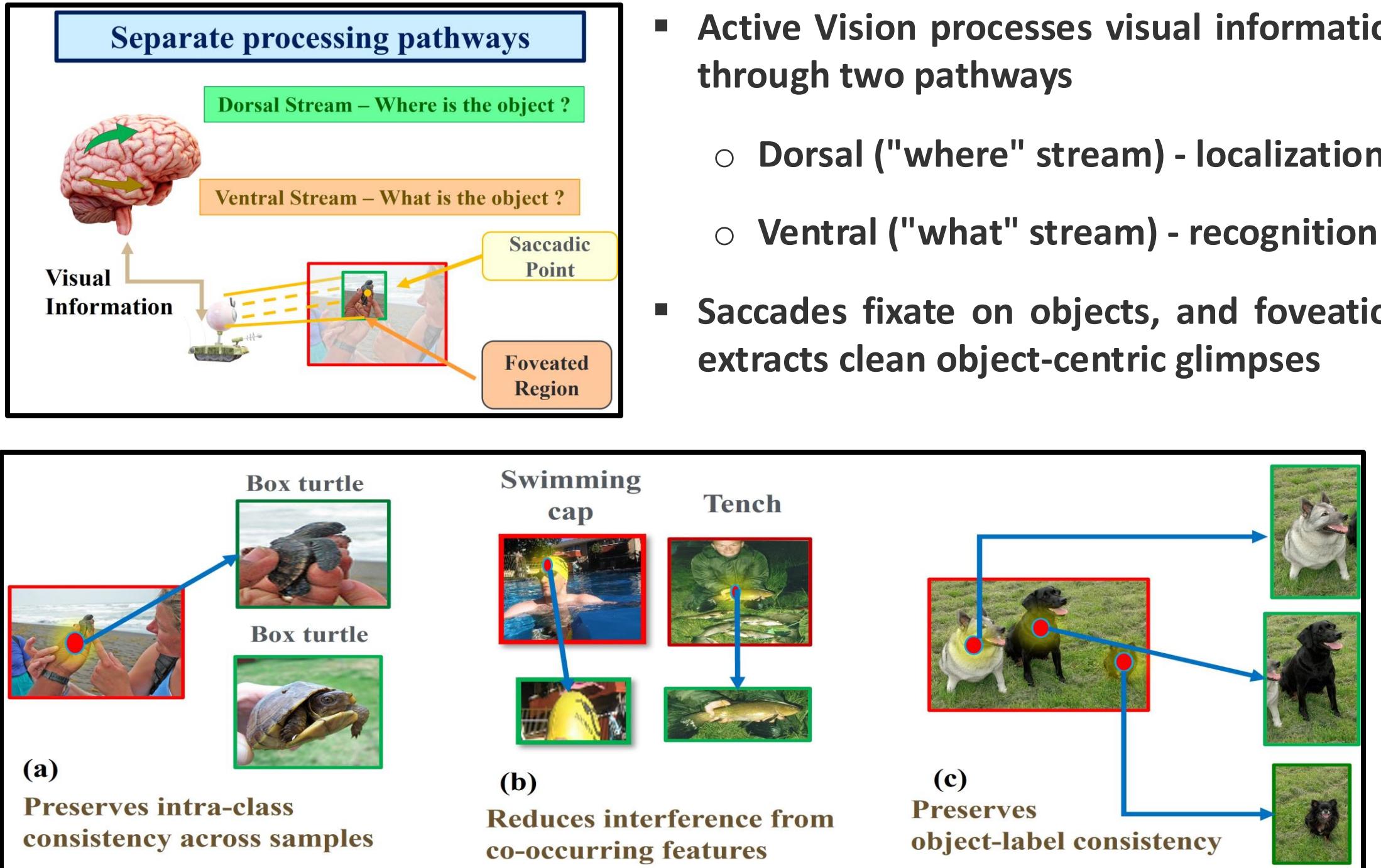


1. Motivation



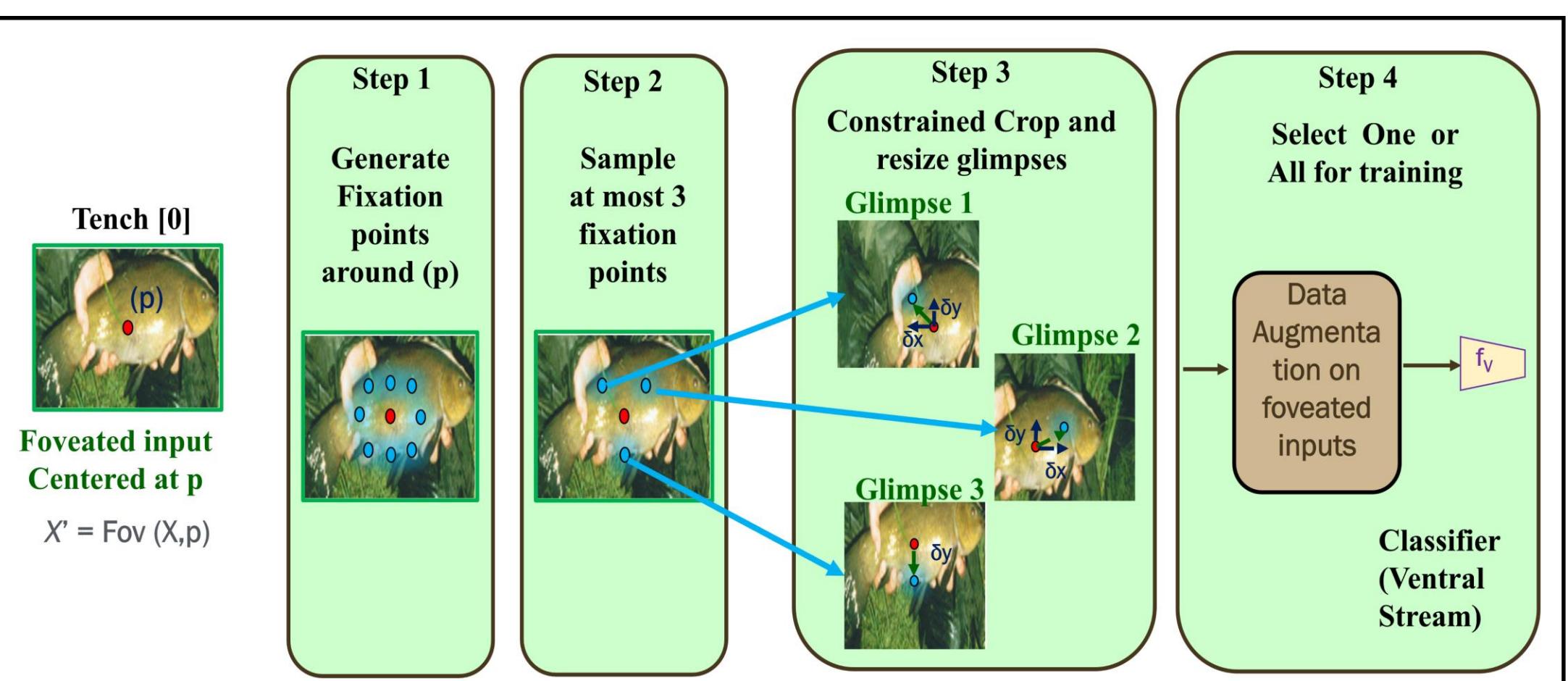
Hard samples cluster in the long tail region

2. Active Vision decouples the “where” from the “what”



Foveated vision reduces variability and improves recognition consistency

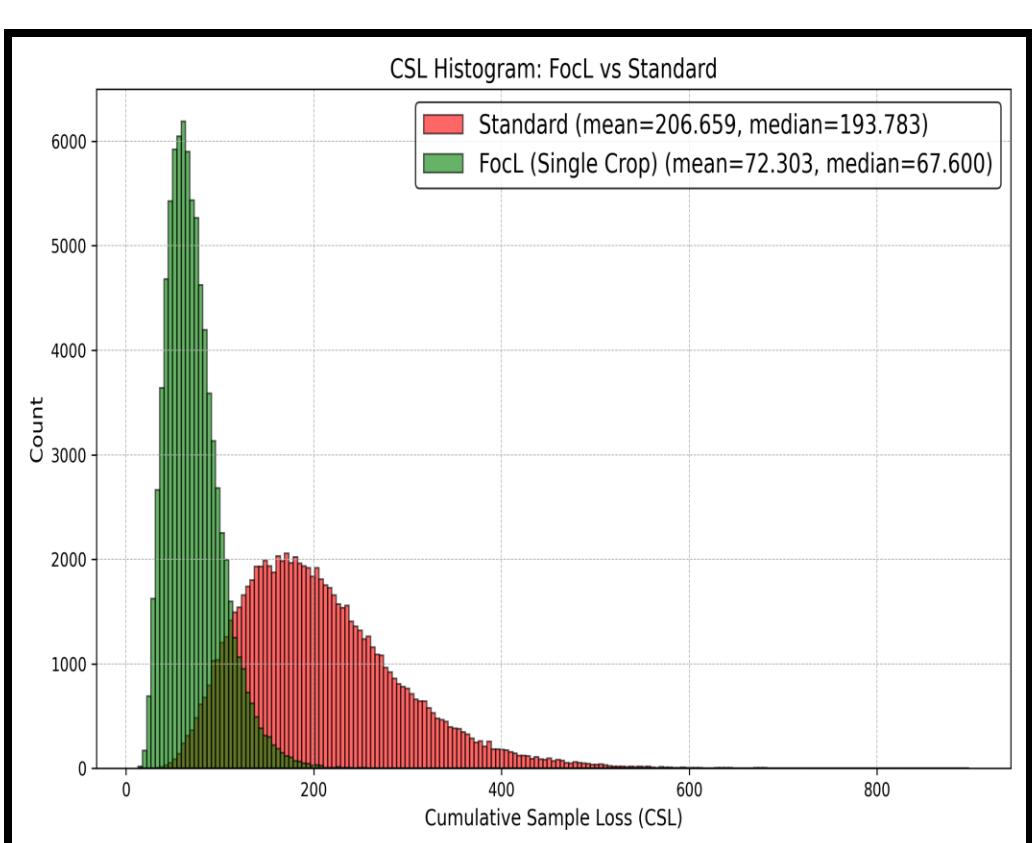
3. Methodology



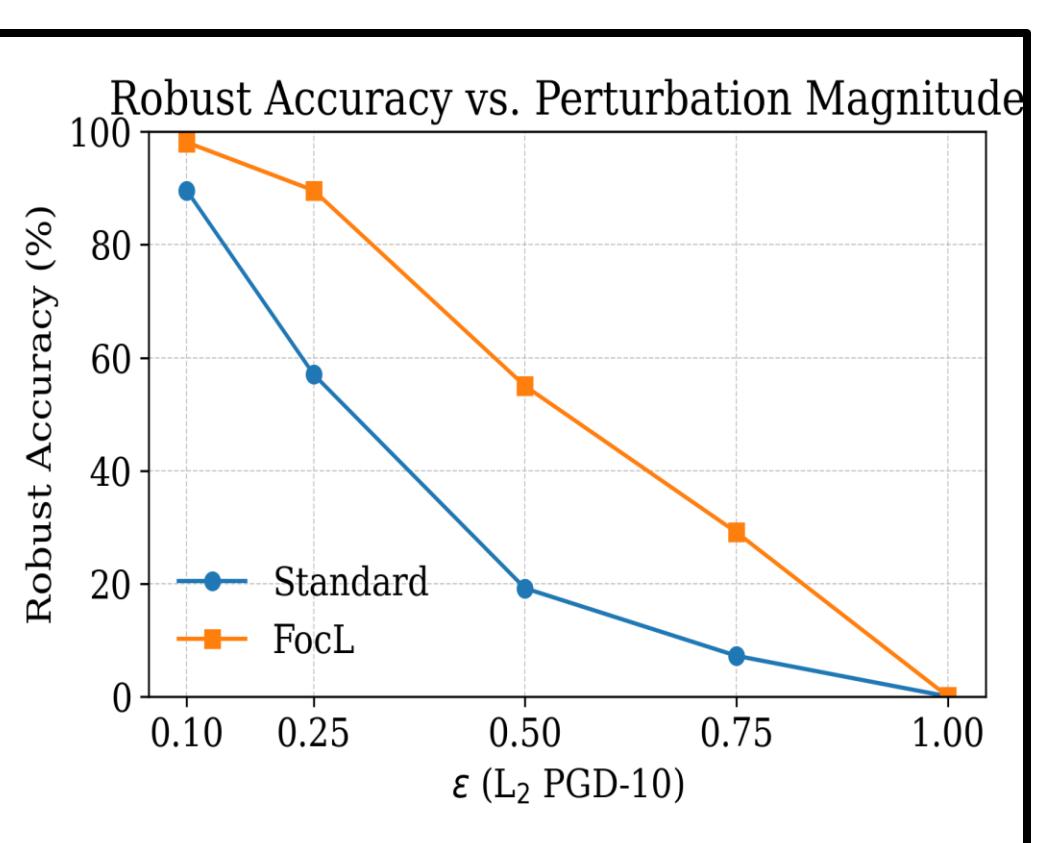
FocL : Multi-glimpse emulating small saccadic shifts

4. Does FocL reduce memorization ?

CSL shift from tail to mode



Higher Adversarial Resistance



FocL reduces sample-level difficulty

5. Does FocL enhance generalization ?

Boosts Any Top-1 by 8% and 10% on 2K samples from ImageNet V1 and V2

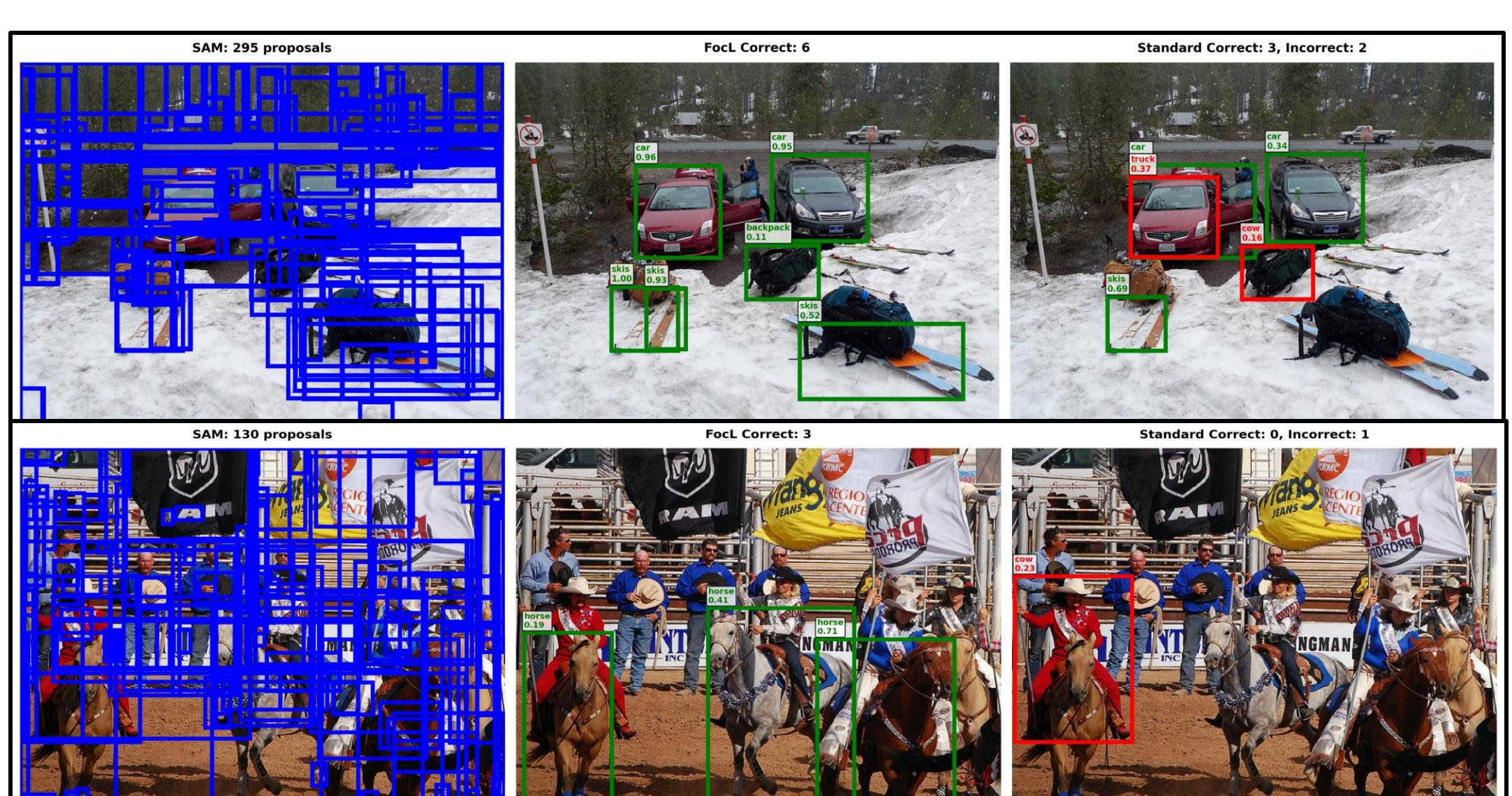
Dataset	Standard only	SAM + Standard	SAM + FocL
ImageNet-V1	60.90 ± 1.10	68.08 ± 0.97	75.82 ± 0.23
ImageNet-V2	49.77 ± 0.94	57.50 ± 1.92	65.80 ± 0.55

Visualization : Background removal hurts generalization for standard classifiers

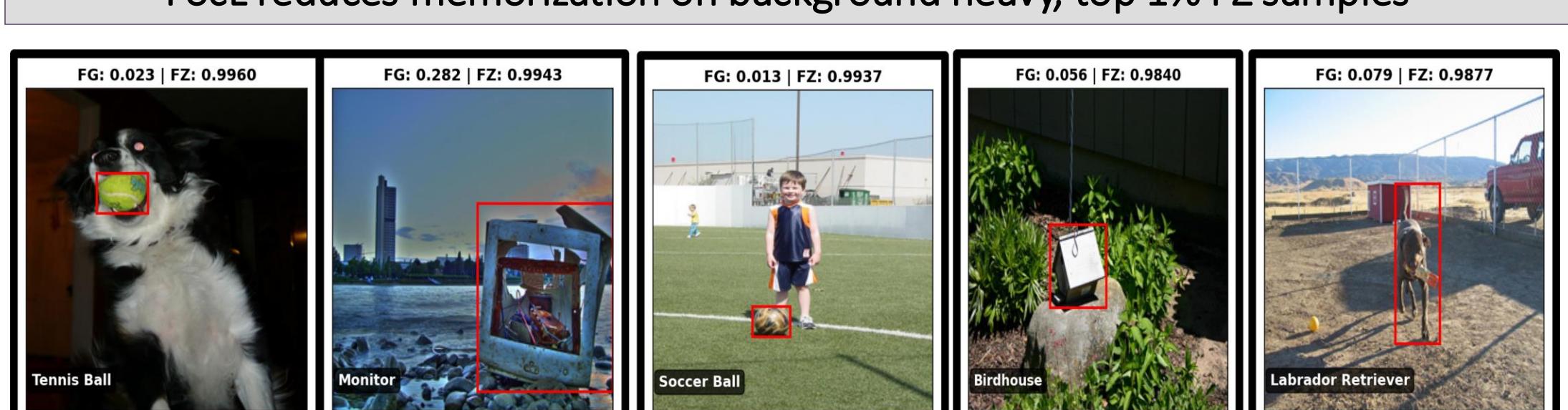


Improves mAP by 3-4 pp on COCO subset showing cross-domain transfer

IoU	(a) Max 20 proposals / image		(b) Max 300 proposals / image	
	SAM + Standard	→ SAM + FocL	SAM + Standard	→ SAM + FocL
0.3	24.39 → 28.22 (+3.83 pp / +16%)		0.3	28.19 → 31.76 (+3.57 pp / +12.7%)
0.5	13.10 → 16.22 (+3.12 pp / +24%)		0.5	14.29 → 17.24 (+2.95 pp / +20.6%)



FocL reduces memorization on background heavy, top 1% FZ samples



6. Key Takeaways

- FocL removes background reliance through object-first viewpoint variations.
- FocL cuts CSL by 62% overall and improves nearly all top FZ samples.
- FocL boosts cross domain generalization (ImageNet V2, COCO) from ImageNet-1K training alone.

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