

Divide and Conquer: Object Co-occurrence Helps Mitigate Simplicity Bias in OOD Detection

Boyang Dai, Chaoqi Chen, Yizhou Yu



香港大學

THE UNIVERSITY OF HONG KONG



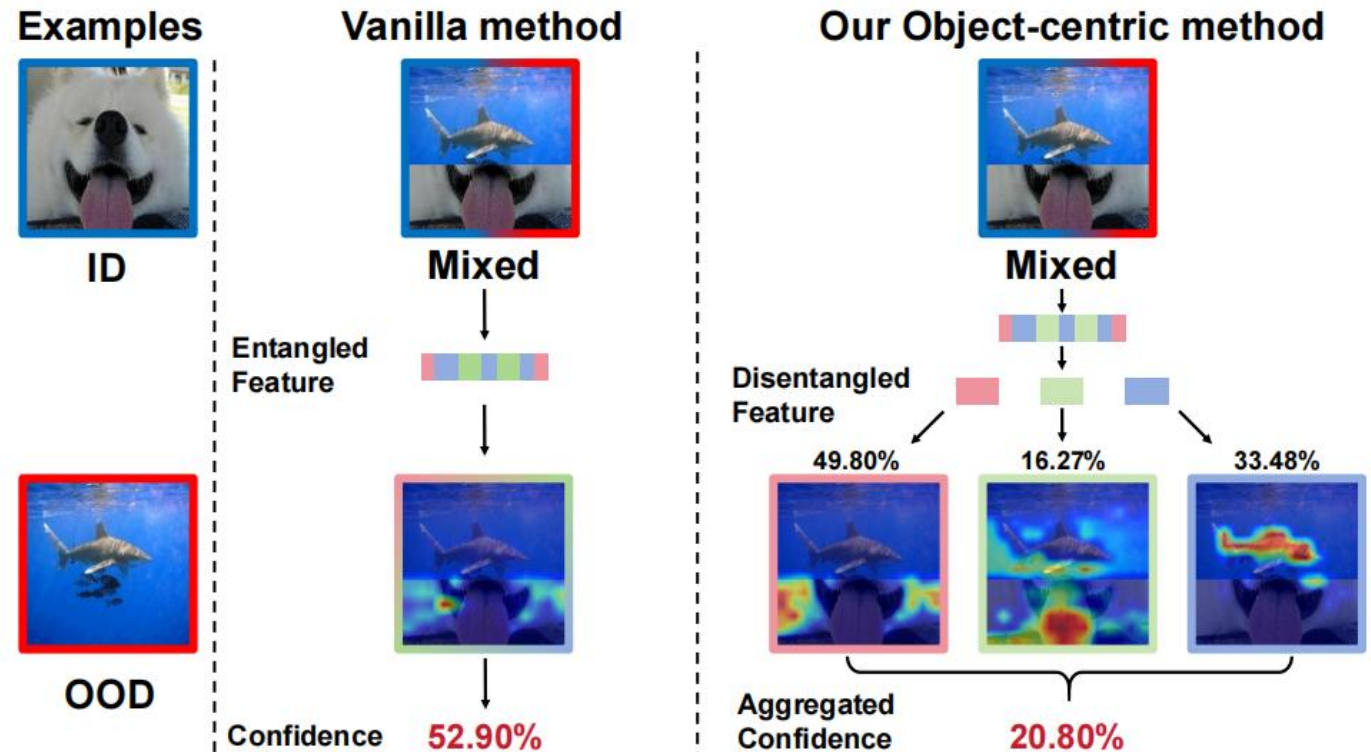
深圳河套學院

Shenzhen Loop Area Institute

Motivation

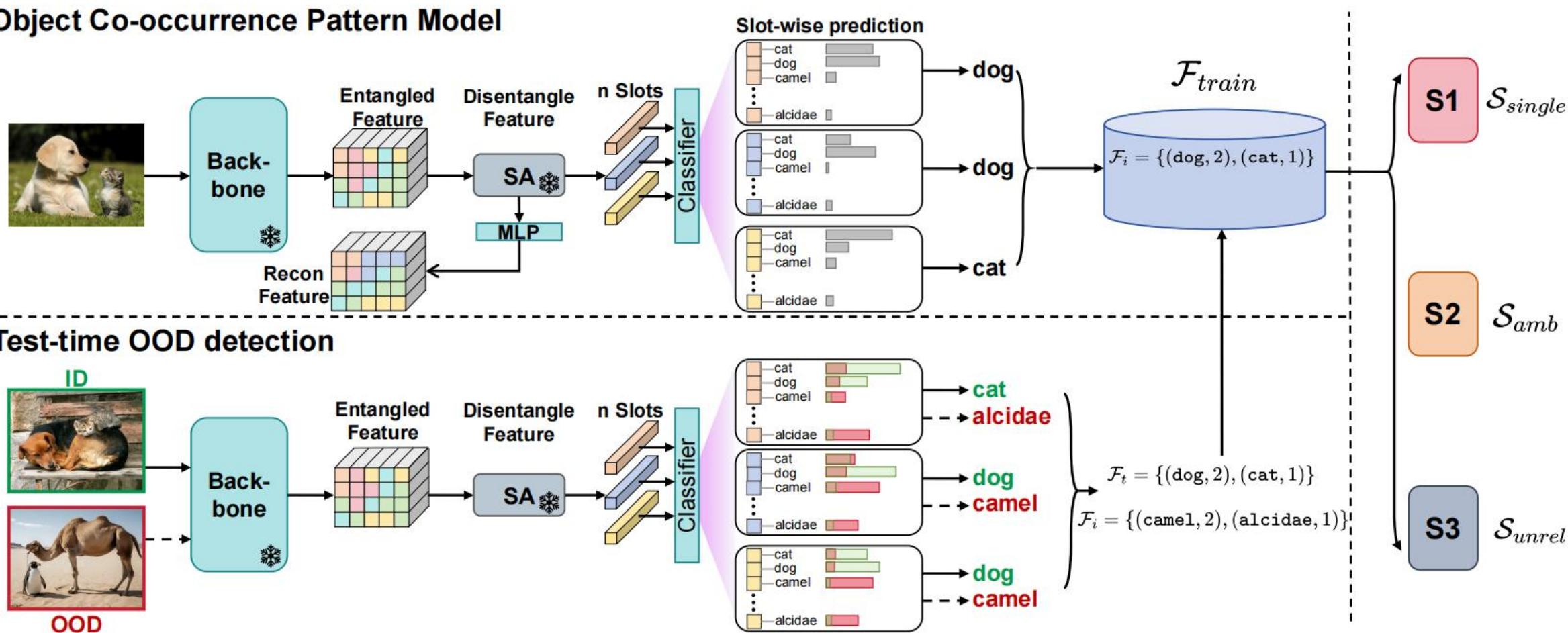
Simplicity Bias in Entangled Representations:

- Vanilla methods may focus on the easiest ID object.
- They can miss contextual incompatibility.
- Object-centric prediction reduces overconfidence.



Overview

Object Co-occurrence Pattern Model



Test-Time Pattern Division

➤ S1: Single Patterns:

$$|F_t| = 1 \quad S_{single} = P_t \cdot p_t^{max}$$

➤ S2: Typical Patterns:

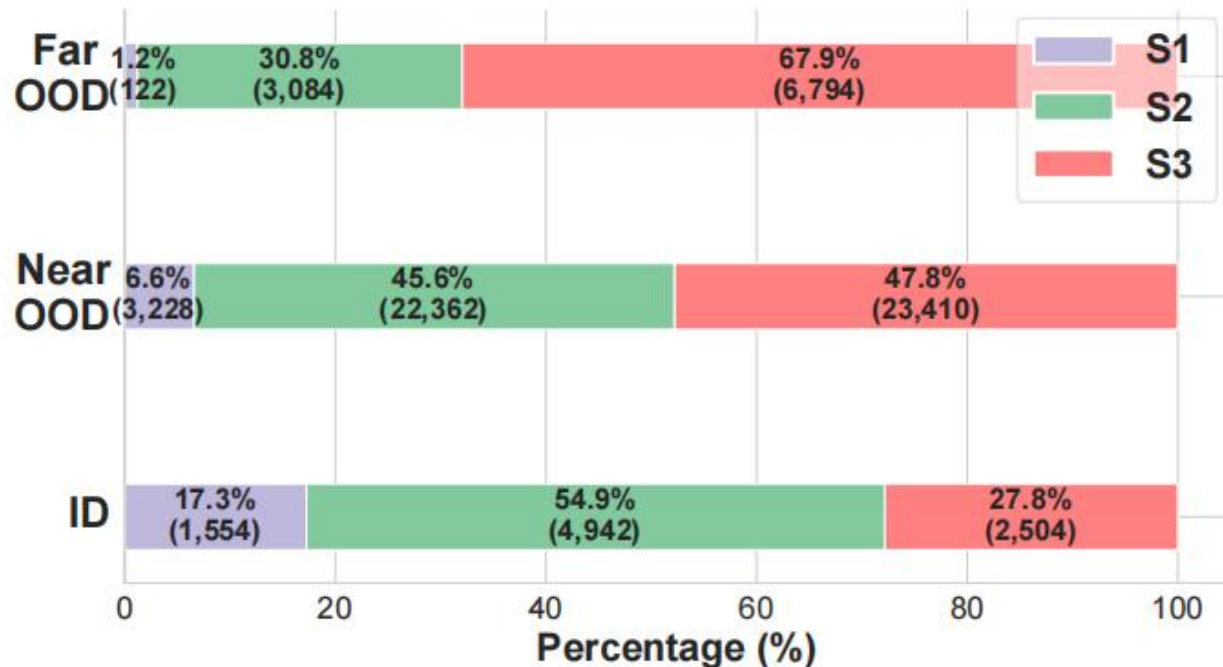
$$|F_t| \geq 2, \quad F_t \in \mathcal{F}_{train}$$

$$S_{amb} = \frac{1}{|F_t| - 1} \sum_{c \neq c'} Bel(c', c)$$

➤ S3: Atypical Patterns

$$|F_t| \geq 2, \quad F_t \notin \mathcal{F}_{train}$$

$$S_{unrel} = p_t^{max} = \max_{k,c} \text{softmax}(l_t^{(k)})$$



Main Result

➤ OOD Detection:

Model	Methods	OOD Datasets					
		SSB-hard	NINCO	iNaturalist	Texture	OpenImage-O	Mean
		FPR95/AUROC	FPR95/AUROC	FPR95/AUROC	FPR95/AUROC	FPR95/AUROC	FPR95/AUROC
ViT	Energy [39]	84.54 / 67.29	67.39 / 79.17	27.52 / 92.61	60.53 / 83.92	47.49 / 86.89	57.49 / 81.98
	MaxLogit [34]	84.13 / 67.78	66.19 / 79.92	26.73 / 93.06	60.26 / 84.13	46.92 / 87.42	56.85 / 82.46
	SHE [69]	89.97 / 59.99	82.23 / 71.16	58.92 / 84.17	84.83 / 74.21	67.34 / 81.42	76.66 / 74.19
	NNguide [45]	85.54 / 62.02	75.05 / 70.65	42.98 / 87.00	69.21 / 79.80	56.43 / 82.04	65.84 / 76.30
	SCALE [64]	84.42 / 67.79	66.54 / 79.75	23.92 / 93.53	55.50 / 84.85	43.81 / 87.90	54.84 / 82.76
	NECO [1]	86.53 / 70.27	83.04 / 79.28	33.23 / 92.66	59.43 / 87.37	67.24 / 86.44	65.89 / 83.20
	FDBD [38]	88.50 / 64.31	68.90 / 79.15	18.22 / 95.33	36.53 / 90.19	36.17 / 90.73	49.66 / <u>83.94</u>
	CoRP [22]	88.73 / 60.07	70.42 / 72.63	28.26 / 93.52	11.28 / 97.12	44.55 / 86.71	<u>48.65</u> / 82.01
	OODD [67]	84.34 / 72.05	67.52 / 77.12	30.41 / 91.51	38.63 / 88.31	52.35 / 90.54	54.65 / 83.91
OCO (Ours)	76.82 / 73.21	60.77 / 81.84	30.31 / 92.41	35.66 / 91.54	32.76 / 91.22	47.26 / 86.04	
DINOv2	Energy [39]	83.58 / 63.62	64.65 / 75.78	14.24 / 95.46	71.71 / 79.61	39.53 / 88.39	54.74 / 80.57
	MaxLogit [34]	83.16 / 64.53	63.75 / 77.08	13.79 / 95.79	71.99 / 80.09	38.74 / 88.96	54.29 / 81.29
	SHE [69]	79.28 / 68.90	62.23 / 79.76	31.10 / 92.75	74.42 / 77.85	49.84 / 86.01	59.37 / 81.05
	NNguide [45]	87.67 / 57.15	75.43 / 67.77	24.83 / 89.96	67.27 / 78.44	51.48 / 83.46	61.34 / 75.36
	SCALE [64]	83.50 / 63.42	63.98 / 75.83	13.40 / 95.73	69.23 / 79.88	37.87 / 88.86	53.60 / 80.74
	NECO [1]	83.63 / 64.17	63.64 / 77.19	12.67 / 96.12	67.45 / 81.65	37.06 / 89.66	52.89 / 81.76
	FDBD [38]	84.21 / 65.45	54.41 / 81.52	11.99 / 96.43	37.25 / 90.61	30.30 / 91.89	43.63 / 85.18
	CoRP [22]	84.99 / 62.44	59.36 / 80.31	16.81 / 95.81	12.64 / 96.54	28.86 / 93.26	<u>40.53</u> / 85.67
	OODD [67]	80.12 / 76.22	58.68 / 81.30	15.49 / 93.78	29.10 / 92.36	31.25 / 91.54	42.93 / <u>87.04</u>
OCO (Ours)	78.43 / 72.13	57.74 / 81.27	10.38 / 97.45	18.36 / 94.36	28.55 / 93.53	38.70 / 87.75	

Main Result

➤ FS-OOD Detection:

Model	Methods	OOD Datasets					
		SSB-hard	NINCO	iNaturalist	Texture	OpenImage-O	Mean
		FPR95/AUROC	FPR95/AUROC	FPR95/AUROC	FPR95/AUROC	FPR95/AUROC	FPR95/AUROC
ViT	Energy [39]	90.28 / 51.83	78.94 / 63.50	48.61 / 80.43	74.23 / 69.31	64.89 / 72.42	71.39 / 67.50
	MaxLogit [34]	90.03 / 52.30	78.15 / 64.50	47.75 / 81.34	74.07 / 69.63	64.50 / 73.30	70.90 / 68.21
	SHE [69]	93.57 / 47.63	88.36 / 58.78	71.73 / 73.09	90.14 / 62.96	77.84 / 69.96	84.33 / 62.48
	NNguide [45]	90.93 / 49.57	83.90 / 58.25	59.54 / 76.90	79.89 / 68.92	70.46 / 70.95	76.94 / 64.92
	SCALE [64]	90.28 / 51.94	78.49 / 63.58	45.76 / 81.22	70.88 / 69.45	62.41 / 72.93	69.56 / 67.82
	NECO [1]	90.95 / 51.41	78.74 / 64.07	47.47 / 81.85	69.57 / 72.08	62.91 / 74.14	69.93 / 68.71
	FDBD [38]	92.73 / 49.80	79.58 / 64.18	39.01 / 85.37	55.53 / 77.10	55.21 / 77.91	64.41 / 70.87
	CoRP [22]	92.73 / 48.71	80.04 / 61.02	40.10 / 84.34	46.28 / 84.64	60.30 / 78.18	<u>63.89 / 71.38</u>
	OODD [67]	84.56 / 73.02	70.35 / 59.13	54.45 / 75.22	58.21 / 69.15	53.12 / 71.98	64.14 / 69.70
OCO (Ours)	84.93 / 57.97	74.19 / 66.99	49.69 / 81.34	54.82 / 80.67	52.37 / 79.09	63.20 / 73.21	
DINOv2	Energy [39]	89.60 / 48.04	77.00 / 59.53	33.84 / 85.60	81.83 / 65.03	58.25 / 74.51	68.10 / 66.54
	MaxLogit [34]	89.35 / 49.05	76.42 / 61.16	32.99 / 86.53	82.01 / 65.91	57.49 / 75.64	67.65 / 67.66
	SHE [69]	94.98 / 40.65	92.94 / 48.23	74.72 / 64.77	91.10 / 56.71	82.59 / 61.58	87.27 / 54.39
	NNguide [45]	92.18 / 43.33	84.14 / 52.53	44.57 / 77.38	78.60 / 64.79	67.31 / 69.88	73.36 / 61.58
	SCALE [64]	89.70 / 47.54	76.75 / 59.17	33.23 / 85.78	80.32 / 64.76	57.15 / 74.66	67.43 / 66.38
	NECO [1]	89.74 / 48.54	76.48 / 60.99	31.96 / 86.90	79.05 / 67.41	56.37 / 76.43	66.72 / 68.05
	FDBD [38]	90.34 / 49.46	70.15 / 65.26	31.54 / 87.59	57.11 / 79.00	51.21 / 79.56	60.07 / 72.17
	CoRP [22]	91.05 / 46.22	74.37 / 64.23	29.70 / 88.34	43.83 / 85.45	49.56 / 82.65	57.70 / 73.38
	OODD [67]	80.50 / 54.88	78.45 / 61.60	41.53 / 79.00	44.10 / 88.32	42.92 / 86.20	<u>57.50 / 74.00</u>
OCO (Ours)	85.07 / 58.25	71.41 / 67.48	28.03 / 90.75	47.44 / 86.58	46.29 / 83.92	55.65 / 77.40	

Analysis

➤ Scenario Scores



Figure 5. OOD detection results under different scenarios.

➤ Hyperparameter Sensitivity

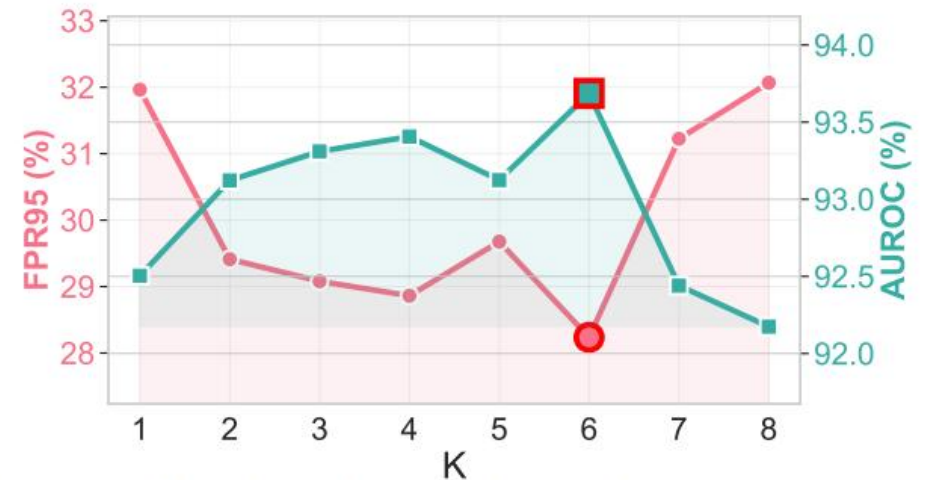


Figure 6. OOD detection results on different slot numbers.

Conclusion

Contribution:

- OCO mitigates simplicity bias by using object-centric representations.
- Learning object co-occurrence patterns from ID training data.
- Applying scenario-specific OOD scores instead of one universal score.
- Improves robustness under both semantic shift and covariate shift.

Thank You !

More details are available in our paper and code.

<https://arxiv.org/abs/2605.07821>

<https://github.com/Michael-McQueen/OCO>