Semantic-Aware Dual Contrastive Learning for Multi-label Image Classification

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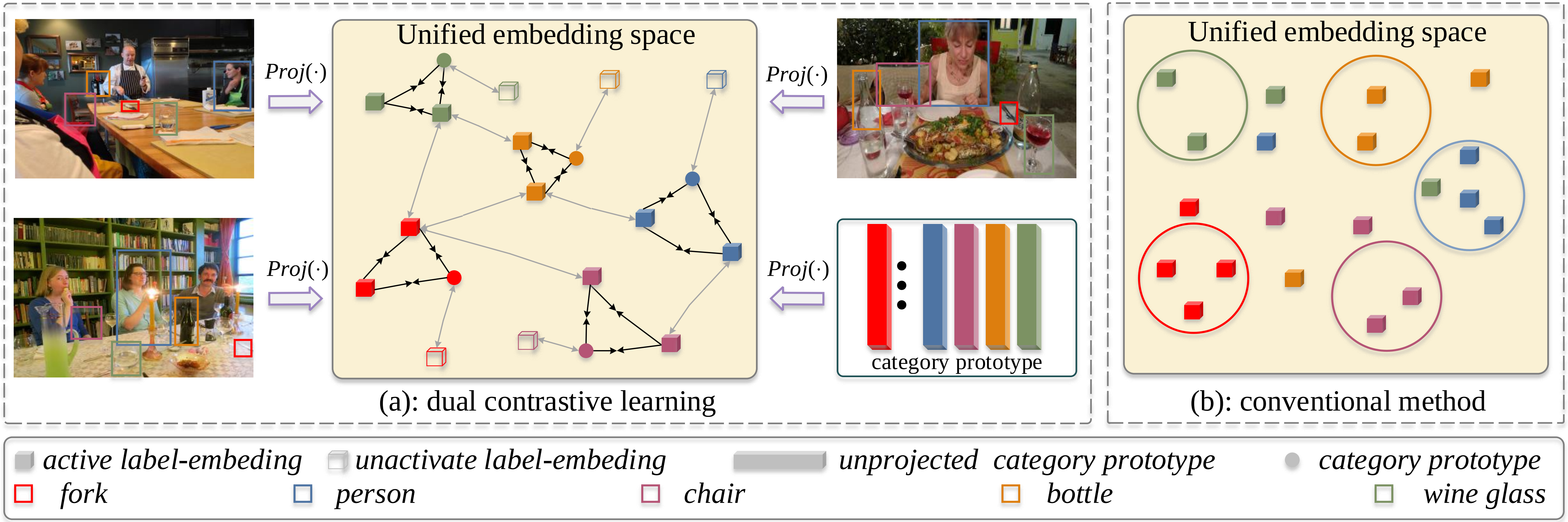
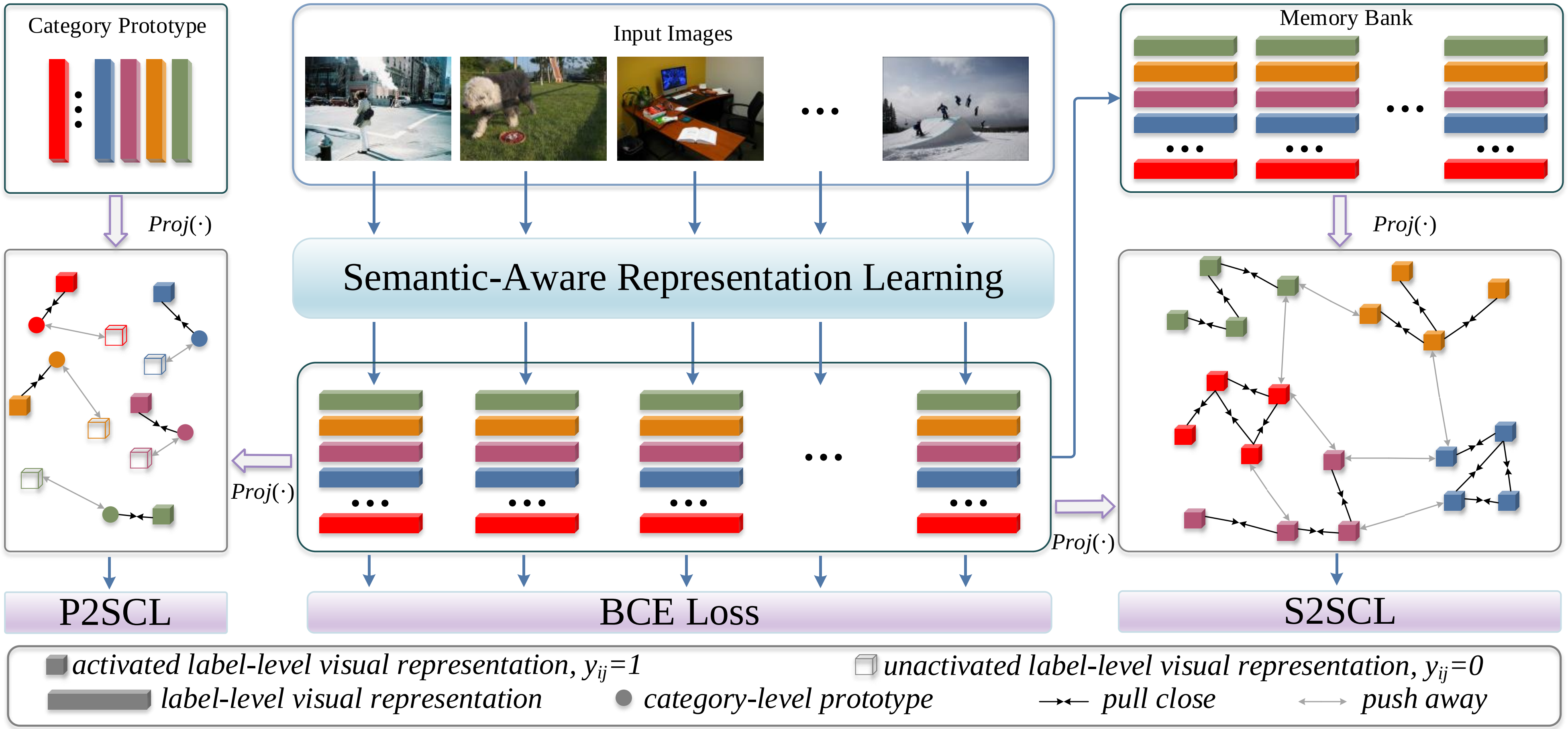
1 Problem



- Common methods fail to localize the semantic region of interest in the image, or the localized object region lacks discrimination and contains potential noise.
- Existing methods consider only inter-category relationships (intra-image), ignoring intra-category relationships (cross-image).

2 Framework and Method



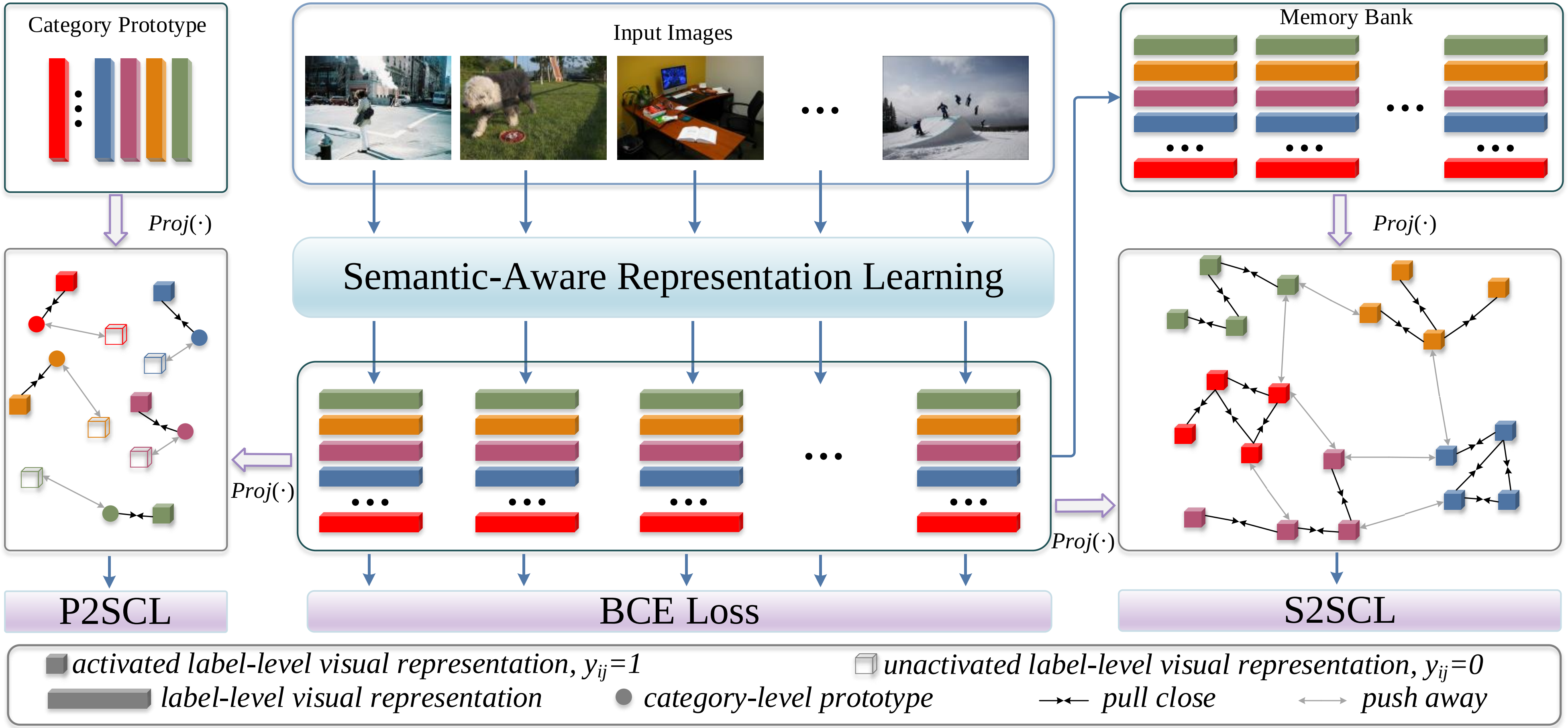
$$\mathcal{L}^{ij}_{S2S} = \sum_{x_{ij(p)} \in \mathcal{P}_{ss}(i,j)} \log \frac{\exp(x_{ij} \cdot x_{ij(p)}/\tau)}{\sum_{x_a \in \mathcal{A}(i,j)} \exp(x_{ij} \cdot x_a/\tau))}, \mathcal{L}_{S2S} = \sum_{x_{ij} \in \mathcal{I}} \frac{-1}{|\mathcal{P}_{ss}(i,j)|} \mathcal{L}^{ij}_{S2S}$$

Sample-to-Sample Contrastive Learning

$$\mathcal{L}_{P2S} = -\sum_{j \in C} \log \frac{\sum_{x_{ij(p)} \in \mathcal{P}_{sp}(i,j)} \exp(c_j \cdot x_{ij(p)}/\tau)}{\sum_{x_{ij} \in \mathcal{P}_{sp}(i,j) \cup \mathcal{N}_{sp}(i,j)} \exp(c_j \cdot x_{ij}/\tau)}$$

Prototype-to-Sample Contrastive Learning

2 Framework and Method



- Our method aims to maximize the inter-class distance and minimize the intra-class distance of visual representations in the unified embedding space.
- Sample-to-sample contrastive learning considers only activated label-level visual representations. We propose a prototype-based contrastive learning loss to fully exploit this unactivated label-level visual representation information.

3 Experiments

Comparisons with SOTA on the MS-COCO dataset

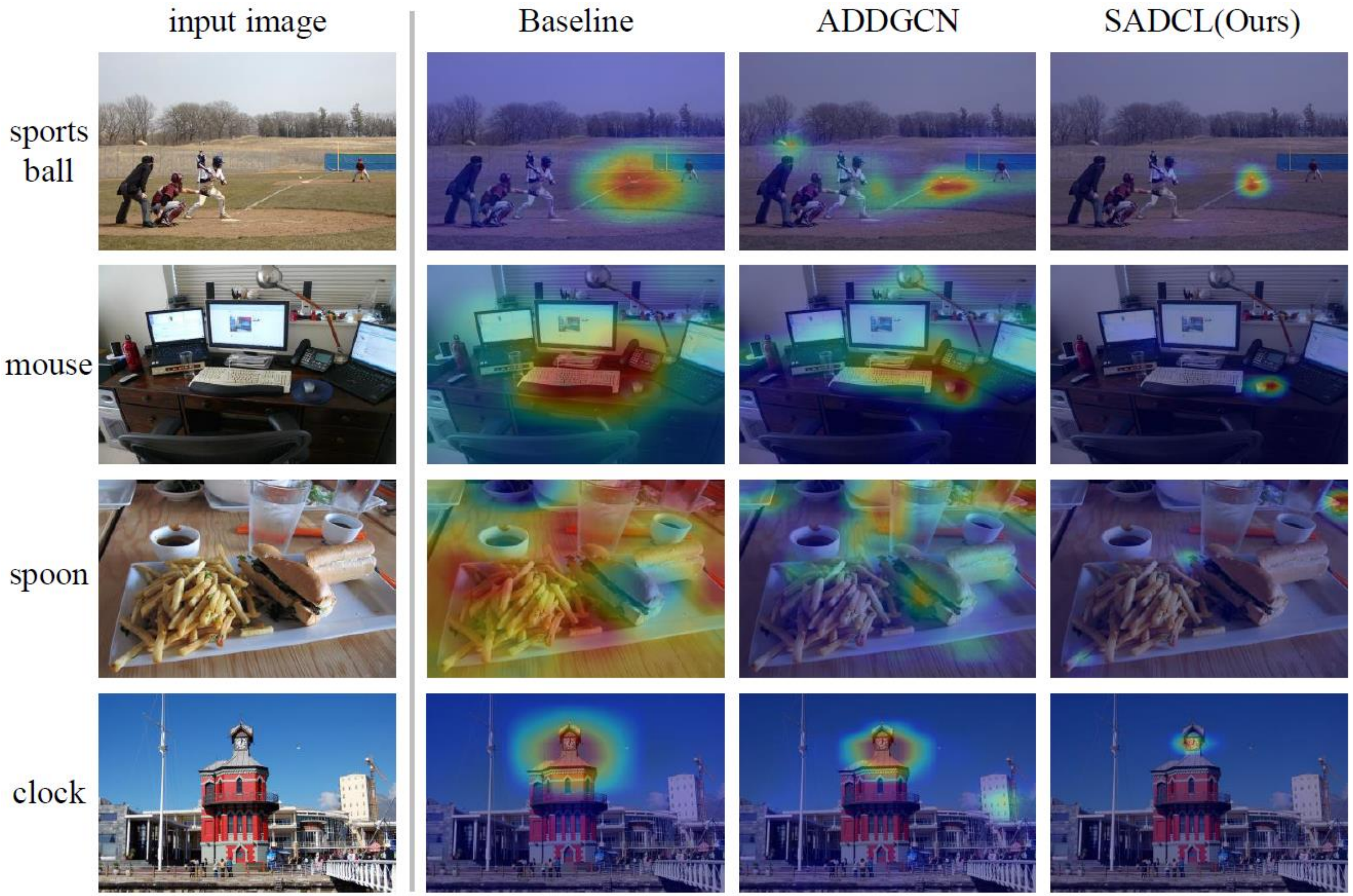
Methods	(R_{train}, R_{test})	mAP	All						Top 3					
			CP	CR	CF1	OP	OR	OF1	CP	CR	CF1	OP	OR	OF1
CNN-RNN [25]	$(-,-)$	61.2	-	-	-	-	-	-	66.0	55.6	60.4	69.2	66.4	67.8
RNN-Att [26]	$(-,-)$	-	-	-	-	-	-	-	79.1	58.7	67.4	84.0	63.0	72.0
ResNet101*[12]	$(448, 448)$	81.5	82.1	71.2	76.0	84.6	75.4	79.7	85.9	62.9	71.6	89.6	66.1	76.1
MLGCN [5]	$(448, 448)$	83.0	85.1	72.0	78.0	85.8	75.4	80.3	89.2	64.1	74.6	90.5	66.5	76.7
MS-CMA [34]	$(448, 448)$	83.8	82.9	74.4	78.4	84.4	77.9	81.0	88.2	65.0	74.9	90.2	67.4	77.1
P-GCN [6]	$(448, 448)$	83.2	84.9	72.7	78.3	85.0	76.4	80.5	89.2	64.3	74.8	90.0	66.8	76.7
GM-MLIC [29]	$(448, 448)$	84.3	87.3	70.8	78.3	88.6	74.8	80.6	90.6	67.3	74.9	94.0	69.8	77.8
MCAR [10]	$(448, 448)$	83.8	85.0	72.1	78.0	88.0	73.9	80.3	88.1	65.5	75.1	91.0	66.3	76.7
TDRG [35]	$(448, 448)$	84.6	86.0	73.1	79.0	86.6	76.4	81.2	89.9	64.4	75.0	91.2	67.0	77.2
CCD-R101 [20]	$(448, 448)$	84.0	87.2	70.9	77.3	88.8	74.6	81.1	89.7	63.9	72.9	92.0	66.5	77.2
MulCon [8]	$(448, 448)$	84.9	84.0	74.8	79.2	85.6	78.0	81.6	87.8	65.9	75.3	90.5	67.9	77.6
Query2Label [21]	$(448, 448)$	84.9	84.8	74.5	79.3	86.6	76.9	81.5	78.0	69.1	73.3	80.7	70.8	75.4
CPSD [30]	$(448, 448)$	84.9	88.4	71.7	79.2	89.3	74.8	81.4	-	-	-	-	-	-
Ours(SADCL)	$(448, 448)$	85.6	84.6	76.0	79.8	86.0	78.5	82.1	88.9	66.6	74.9	91.0	68.3	78.0
ADDGCN [33]	$(448, 576)$	85.2	84.7	75.9	80.1	84.9	79.4	82.0	88.8	66.2	75.8	90.3	68.5	77.9
SSGRL [2]	$(576, 576)$	83.8	89.9	68.5	76.8	91.3	70.8	79.7	91.9	62.5	72.7	93.8	64.1	76.2
AdaHGNN [28]	$(576, 576)$	85.0	-	-	79.9	-	-	81.8	-	-	75.5	-	-	77.6
C-Tran [16]	$(576, 576)$	85.1	86.3	74.3	79.9	87.7	76.5	81.7	90.1	65.7	76.0	92.1	71.4	77.6
TDRG [35]	$(576, 576)$	86.0	87.0	74.7	80.4	87.5	77.9	82.4	90.7	65.6	76.2	91.9	68.0	78.1
CCD-R101 [20]	$(576, 576)$	85.3	88.3	73.1	80.2	88.8	76.3	82.1	91.0	65.2	76.0	92.3	67.3	77.9
Ours(SADCL)	$(448, 576)$	86.8	86.4	77.0	81.1	87.7	79.1	83.2	90.0	67.4	75.7	92.0	68.7	78.7

3 Experiments

Comparisons with SOTA on the VOC 2007 dataset

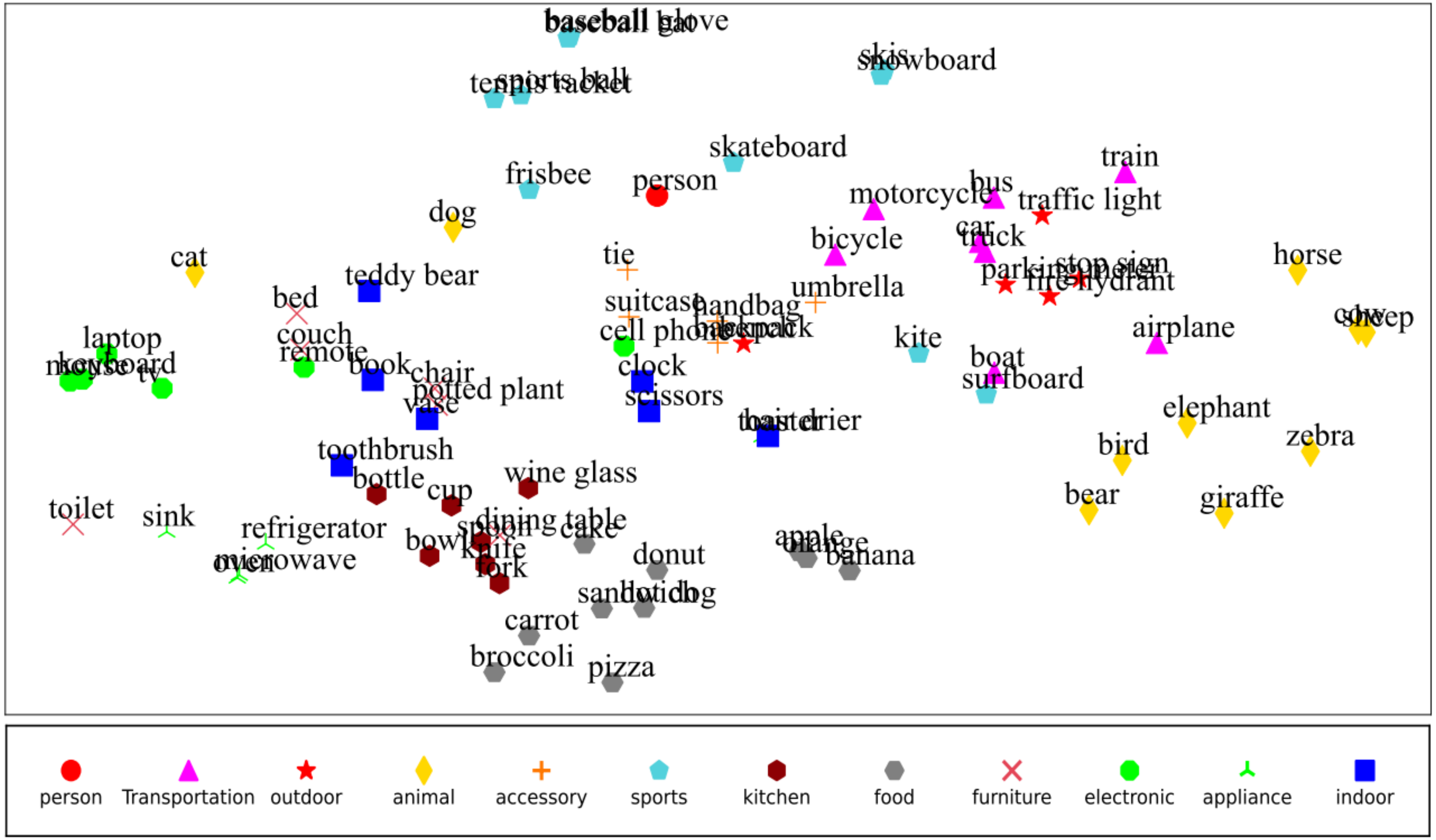
Methods	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	motor	person	plant	sheep	sofa	train	tv	mAP
CNN-RNN [25]	96.7	83.1	94.2	92.8	61.2	82.1	89.1	94.2	64.2	83.6	70.0	92.4	91.7	84.2	93.7	59.8	93.2	75.3	99.7	78.6	84.0
ResNet-101* [12]	99.0	98.4	97.5	96.0	81.4	97.3	97.3	97.1	79.6	96.0	88.1	97.5	98.5	95.8	98.8	85.9	97.2	84.6	98.8	92.0	93.8
RNN-Att [26]	98.6	97.4	96.3	96.2	75.2	92.4	96.5	97.1	76.5	92.0	87.7	96.8	97.5	93.8	98.5	81.6	93.7	82.8	98.6	89.3	91.9
SSGRL* [2]	99.5	97.1	97.6	97.8	82.6	94.8	96.7	98.1	78.0	97.0	85.6	97.8	98.3	96.4	98.1	84.9	96.5	79.8	98.4	92.8	93.4
ML-GCN [5]	99.5	98.5	98.6	98.1	80.8	94.6	97.2	98.2	82.3	95.7	86.4	98.2	98.4	96.7	99.0	84.7	96.7	84.3	98.9	93.7	94.0
P-GCN [6]	99.6	98.6	98.4	98.7	81.5	94.8	97.6	98.2	83.1	96.0	87.1	98.3	98.5	96.3	99.1	87.3	95.5	85.4	98.9	93.6	94.3
ADDGCN* [33]	99.8	99.0	98.4	99.0	86.7	98.1	98.5	98.3	85.8	98.3	88.9	98.8	99.0	97.4	99.2	88.3	98.7	90.7	99.5	97.0	96.0
KGGR* [1]	99.3	98.6	97.9	98.4	86.2	97.0	98.0	99.2	82.6	98.3	87.5	99.0	98.9	97.4	99.1	86.9	98.2	84.1	99.0	95.0	95.0
DSDL [36]	99.8	98.7	98.4	97.9	81.9	95.4	97.6	98.3	83.3	95.0	88.6	98.0	97.9	95.8	99.0	86.6	95.9	86.4	98.6	94.4	94.4
GM-MLIC [29]	99.4	98.7	98.5	97.6	86.3	97.1	98.0	99.4	82.5	98.1	87.7	99.2	98.9	97.5	99.3	87.0	98.3	86.5	99.1	94.9	94.7
TDRG [35]	99.9	98.9	98.4	98.7	81.9	95.8	97.8	98.0	85.2	95.6	89.5	98.8	98.6	97.1	99.1	86.2	97.7	87.2	99.1	95.3	95.0
MulCon* [8]	99.8	98.3	99.3	98.6	83.3	98.4	98.0	98.3	85.8	98.3	90.5	99.3	98.9	96.6	98.8	86.3	99.8	87.3	99.8	96.1	95.6
CPCL [30]	99.6	98.6	98.5	98.8	81.9	95.1	97.8	98.2	83.0	95.5	85.5	98.4	98.5	97.0	99.0	86.6	97.0	84.9	99.1	94.3	94.4
SST [3]	99.8	98.6	98.9	85.5	94.7	97.9	98.6	83.0	96.8	85.7	98.8	98.8	98.9	95.7	99.1	85.4	96.2	84.3	99.1	95.0	94.5
Ours(SADCL)*	100.0	99.0	99.5	99.1	88.9	98.8	98.7	99.6	84.2	98.4	90.1	99.4	99.6	99.0	99.3	90.2	99.6	88.9	99.8	95.3	96.4

3 Experiments



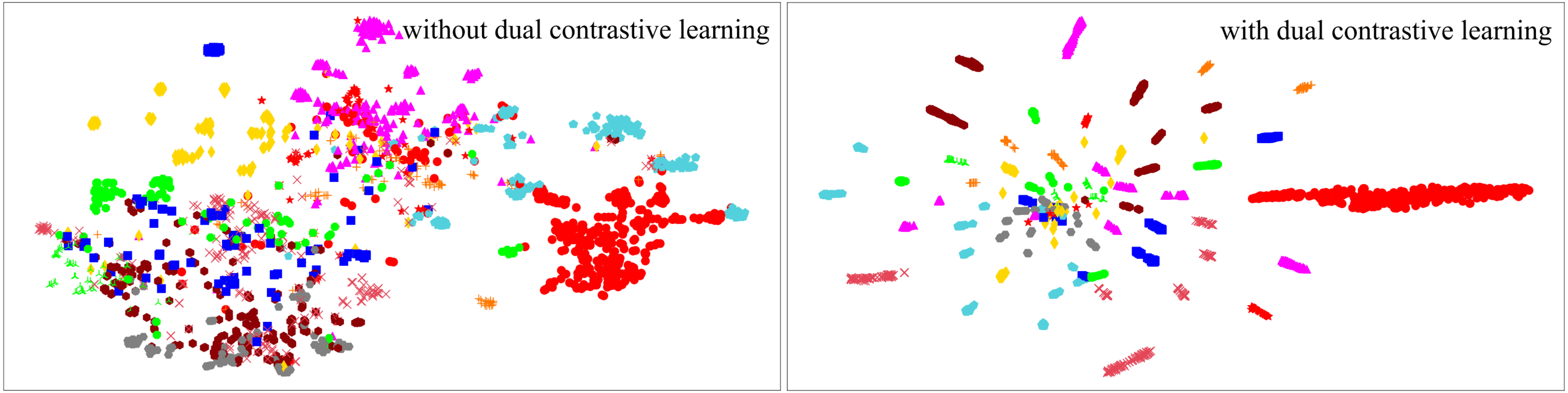
Visualization analysis of baseline, ADDGCN, and our method SADCL.

3 Experiments



Visualization of the learned category prototypes on the MS-COCO dataset.

3 Experiments



Visualization of the 2000 learned label-level visual representations
randomly sampled images of the MS-COCO test datase

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Code and paper