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JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

Bridging the Gap between Model Explanations in Partially Annotated Multi-label Classification

Youngwook Kim, Jae Myung Kim, Jieun Jeong,
Cordelia Schmid, Zeynep Akata, Jungwoo Lee

SEOUL NATIONAL UNIVERSITY

EBERHARD KARLS UNIVERSITÄT TÜBINGEN

MAX-PLANCK-GESELLSCHAFT

Inria

HodooAi

Quick Preview

	[a]	[b]	[c]
person	1	1	1
horse	1		
cat	0	0	
dog	0		
truck	0		

[a] : full annotation
[b] : **partial annotation**
[c] : **single positive label**

Durand et al., Learning a Deep ConvNet for Multi-label Classification with Partial Labels, CVPR 2019.
Cole et al., Multi-Label Learning from Single Positive Labels, CVPR 2021.

Quick Preview

$$
\begin{array}{l}
\textbf{person} \\
\textbf{horse} \\
\text{cat} \\
\text{dog} \\
\text{truck}
\end{array}
\begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}
\begin{pmatrix} 1 \\ \color{red}{0} \\ 0 \\ 0 \\ 0 \end{pmatrix}
\begin{pmatrix} 1 \\ \color{red}{0} \\ 0 \\ 0 \\ 0 \end{pmatrix}
\;\leftarrow \text{False Negative}
$$

[a] [b] [c]

[a] : full annotation
[b] : **partial annotation**
[c] : **single positive label**

Durand et al., Learning a Deep ConvNet for Multi-label Classification with Partial Labels, CVPR 2019.
Cole et al., Multi-Label Learning from Single Positive Labels, CVPR 2021.

Quick Preview

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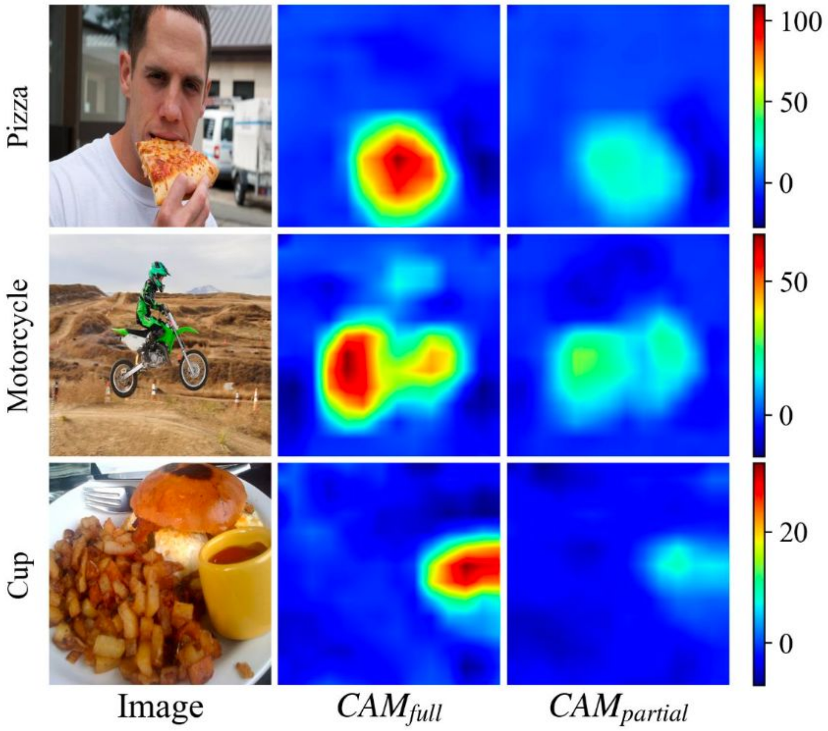

Quick Preview

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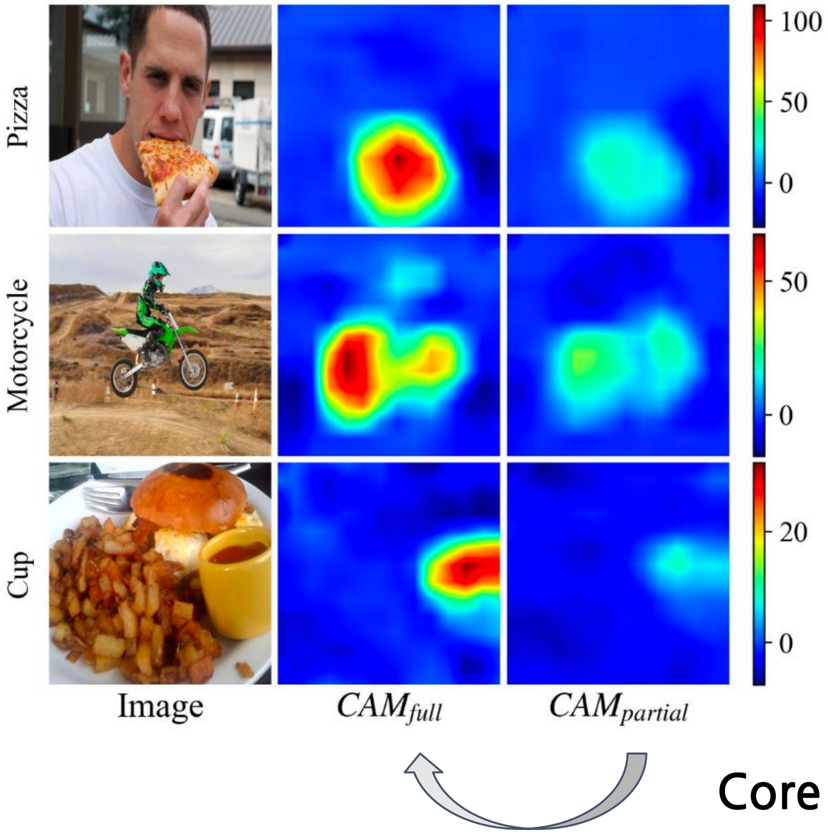


Core Idea : Bridge the gap!

Partially annotated multi-label classification

Baseline approach :

Assuming unannotated labels as **N**egative labels (AN)

$$
\begin{array}{l}
\textbf{person} \\
\textbf{horse} \\
\text{cat} \\
\text{dog} \\
\text{truck}
\end{array}
\begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}
\qquad
\begin{pmatrix} 1 \\ \\ 0 \\ \\ \end{pmatrix}
\Rightarrow
\begin{pmatrix} 1 \\ \mathbf{0} \\ 0 \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix}
\qquad
\begin{pmatrix} 1 \\ \\ \\ \\ \end{pmatrix}
\Rightarrow
\begin{pmatrix} 1 \\ \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix}
$$

[a] [b] [c]

Partially annotated multi-label classification

Baseline approach :

Assuming unannotated labels as **N**egative labels (AN)

Drawback :

Introducing **label noise** (i.e., false negative)

$$
\begin{array}{l}
\textbf{person} \\
\textbf{horse} \\
\text{cat} \\
\text{dog} \\
\text{truck}
\end{array}
\underset{[a]}{\begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}}
\quad
\underset{[b]}{\begin{pmatrix} 1 \\ \\ 0 \\ \\ \end{pmatrix} \Rightarrow \begin{pmatrix} 1 \\ \color{red}{0} \\ 0 \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix}}
\quad
\underset{[c]}{\begin{pmatrix} 1 \\ \\ \\ \\ \end{pmatrix} \Rightarrow \begin{pmatrix} 1 \\ \color{red}{0} \\ \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{pmatrix}}
$$

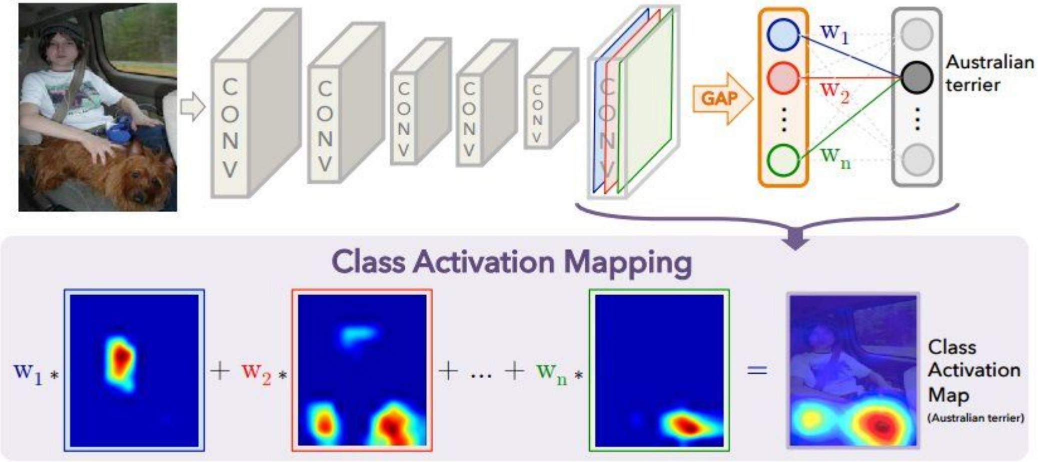
Analysis on model explanation

Q. How false negative labels affect **model explanation**?

Model 1 : Train ResNet-50 with **full annotation**

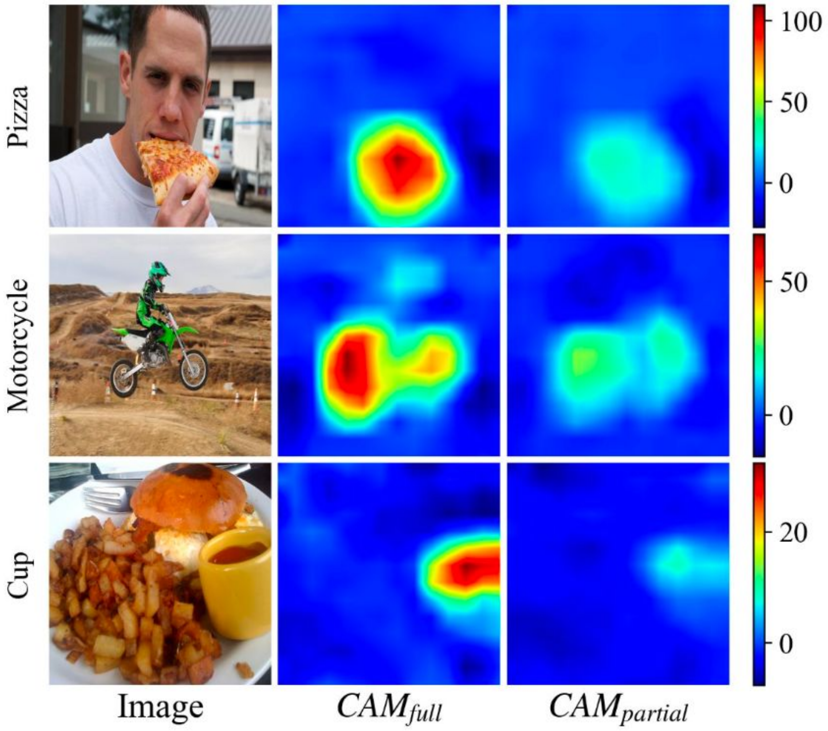
Model 2 : Train ResNet-50 with **partial annotation**

Class Activation Map (CAM)

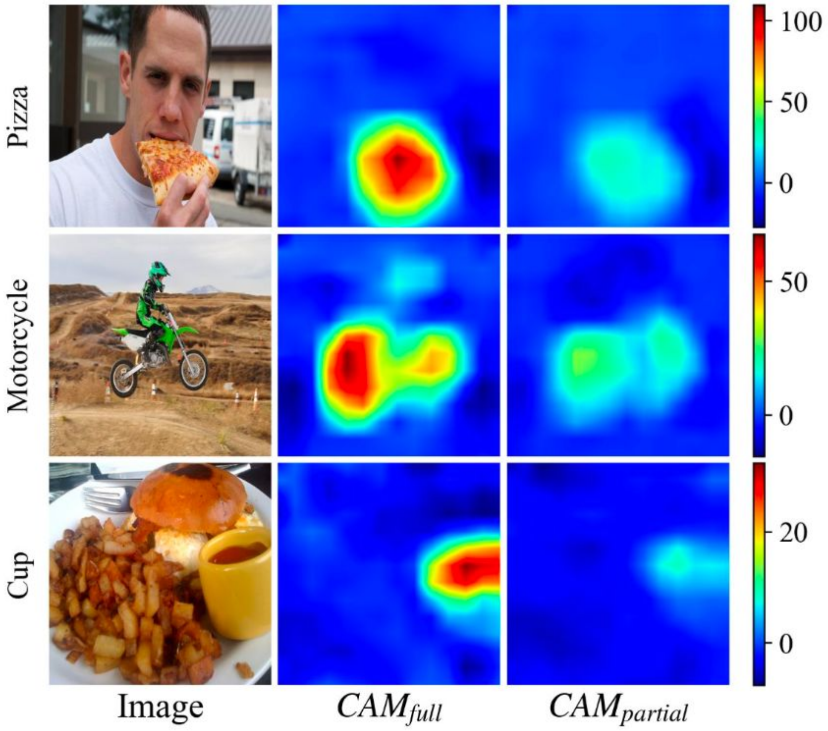


Zhou et al., Learning deep features for discriminative localization, CVPR 2016.

Analysis on model explanation



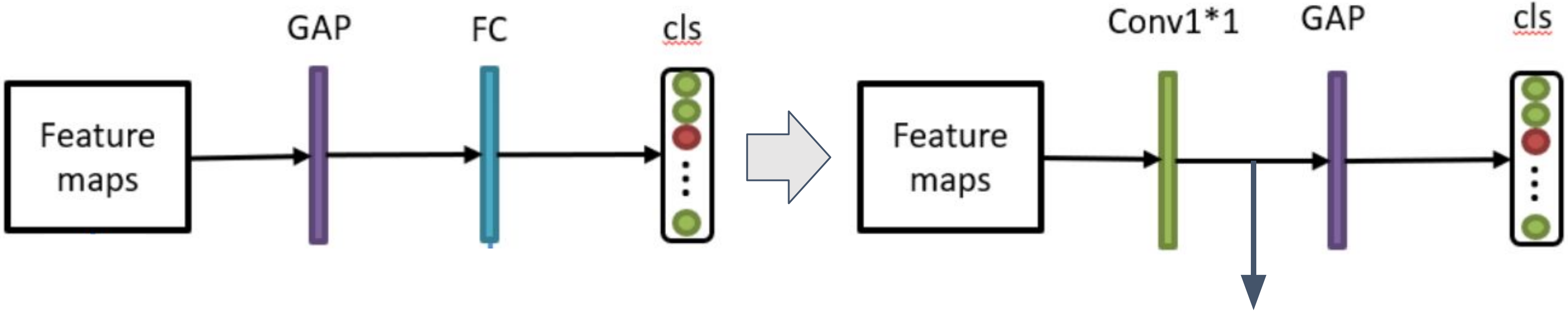
Analysis on model explanation

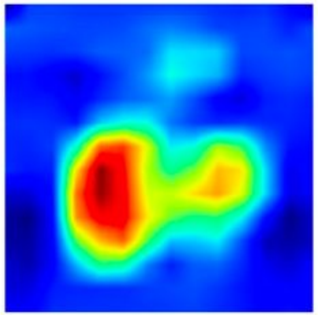


Core Idea : Bridge the gap!

Proposed method : BoostLU

1) Modify CNN classification network architecture





Advantage :

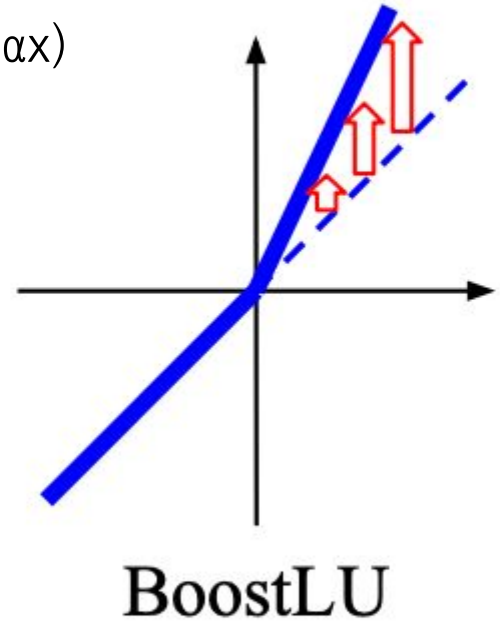
We can obtain CAM **during forward pass**

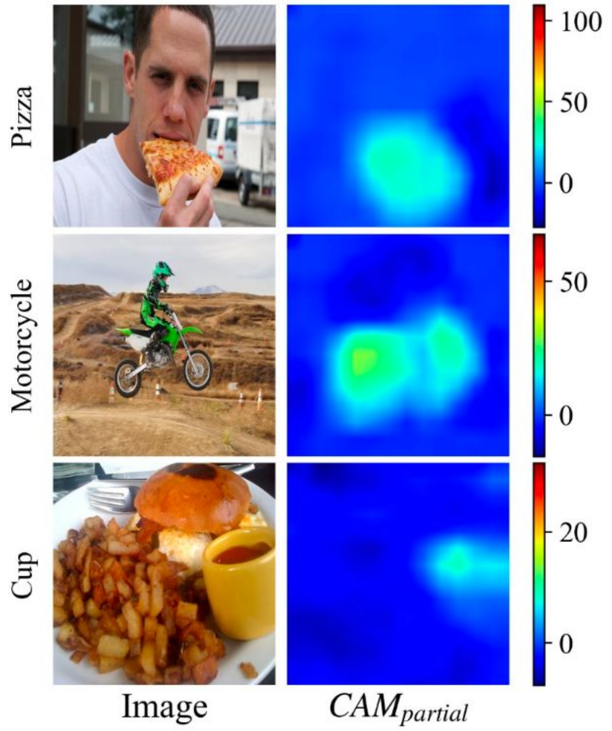
Zhang et al., Adversarial Complementary Learning for Weakly Supervised Object Localization, CVPR 2018.

Proposed method : BoostLU

2) Apply BoostLU on CAM **element-wisely**

$$\text{BoostLU}(x) = \max(x, \alpha x)$$

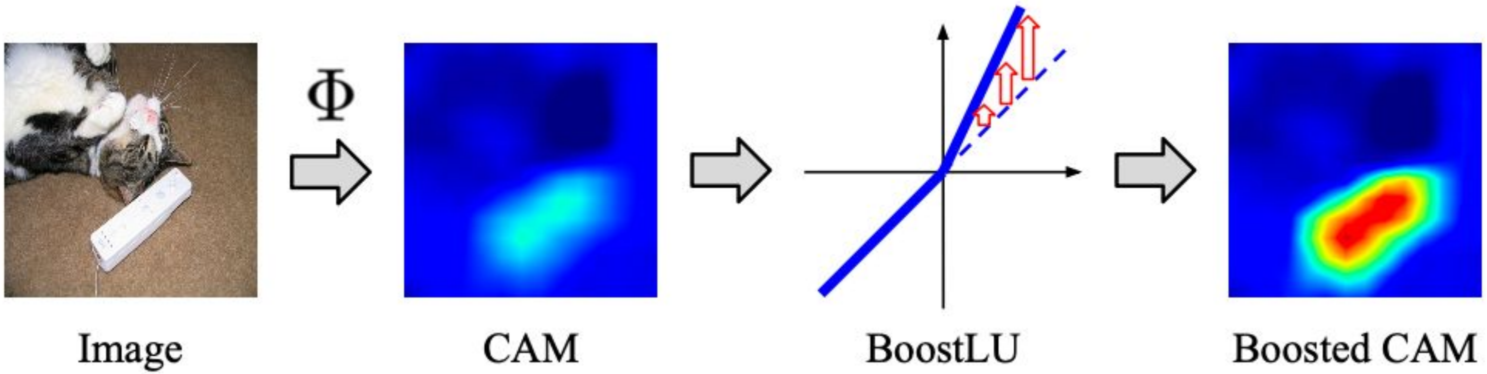




Proposed method : BoostLU

2) Apply BoostLU on CAM **element-wisely**

$$\mathrm{BoostLU}(x) = \max(x, \alpha x),\ \text{set } \alpha=5$$



Proposed method : BoostLU

Several scenarios for BoostLU application

i) Apply only in **inference phase**

=> Performance improves without additional training

BoostLU in inference	Performance VOC	Performance COCO
	86.10	64.58
✓	87.31	66.27

Proposed method : BoostLU

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Several scenarios for BoostLU application

ii) Apply also in **training phase** with **large loss modification scheme**

=> **Performance improves further!**

BoostLU in inference	BoostLU in training	LL-R in training	Performance VOC	Performance COCO
			86.10	64.58
✓			87.31	66.27
✓	✓	✓	**89.27**	**72.82**

Kim et al., Large Loss Matters in Weakly Supervised Multi-Label Classification, CVPR 2022.

Experiment results

1) single positive label setting

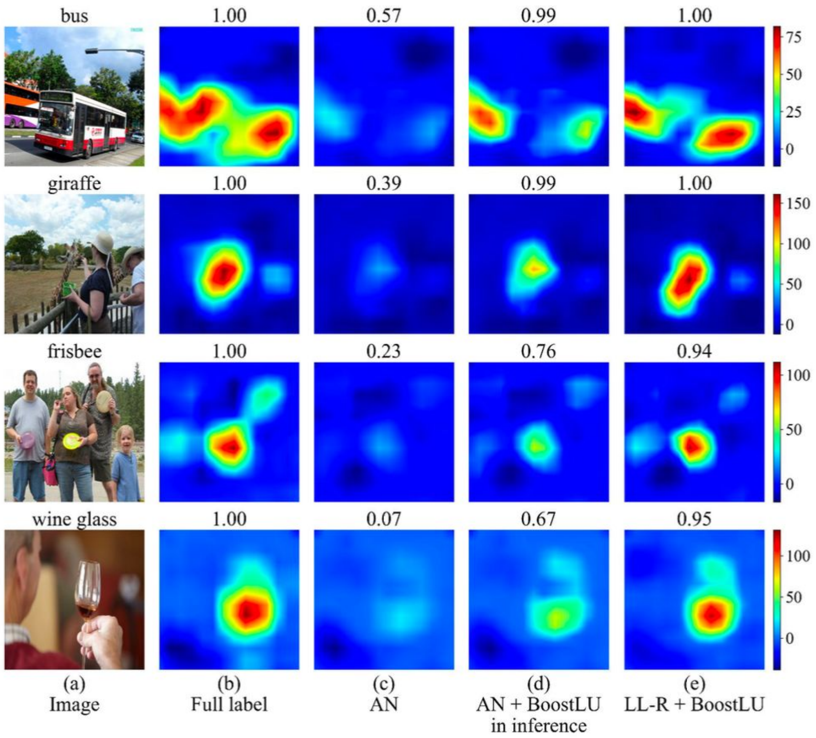
Methods	VOC	COCO	NUS	CUB
Full Label	89.42	76.78	52.08	30.90
AN	85.89	64.92	42.27	18.31
LS [30]	87.90	67.15	43.77	16.26
ASL [33]	87.76	68.78	46.93	18.81
ROLE [11]	87.77	67.04	41.63	13.66
ROLE + LI [11]	88.26	69.12	45.98	14.86
EM [50]	89.09	70.70	47.15	20.85
EM + APL [50]	89.19	70.87	47.59	**21.84**
LL-R [21]	88.27	70.70	48.76	19.56
+ BoostLU (Ours)	**89.29**	**72.89**	**49.59**	19.80
LL-Ct [21]	87.79	70.29	48.08	19.06
+ BoostLU (Ours)	88.61	71.78	48.37	19.25
LL-Cp [21]	87.44	70.27	47.92	19.21
+ BoostLU (Ours)	87.81	71.41	48.61	19.34

2) Openimages v3

Methods	Group 1	Group 2	Group 3	Group 4	Group 5	All Classes
CNN-RNN [39]	68.76	69.70	74.18	78.52	84.61	75.16
Curriculum Labeling [13]	70.37	71.32	76.23	80.54	86.81	77.05
IMCL [17]	70.95	72.59	77.64	81.83	87.34	78.07
P-ASL [2]	73.19	78.61	85.11	87.70	90.61	83.03
LL-R [21]	77.76	79.07	81.94	84.51	89.36	82.53
+ BoostLU (Ours)	79.28	80.81	83.32	85.63	90.27	83.86
LL-Ct [21]	77.76	79.18	81.97	84.46	89.51	82.58
+ BoostLU (Ours)	79.43	80.75	83.41	85.70	90.41	83.94
LL-Cp [21]	77.49	79.22	81.89	84.51	89.18	82.46
+ BoostLU (Ours)	79.53	81.04	83.40	85.85	90.39	**84.04**

Experiment results

3) Qualitative results



Thank you!

Github Link