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Recent Advances in Open Set Recognition: A Survey

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Open Set

- KKC (known known class): 带标记的已知类别样本
- KUC (known unknown class): 已知不关心类别的样本
- UKC (unknown known class): 训练集中没有出现过这些类别的样本，有和类别相关的额外信息
- UUC (unknown unknown class): 类似 UKC 没有额外信息

Open Set

TABLE 1
Differences between Open Set Recognition and its related tasks

SETTING / TASK	TRAINING	TESTING	GOAL
Traditional Classification	Known known classes	Known known classes	Classifying known known classes
Classification with Reject Option	Known known classes	Known known classes	Classifying known known classes & rejecting samples of low confidence
One-class Classification (Anomaly Detection)	Known known classes & few or none outliers from KUCs	Known known classes & few or none outliers	Detecting outliers
One/Few-shot Learning	Known known classes & a limited number of UKCs' samples	Unknown known classes	Identifying unknown known classes
Generalized Few-shot Learning	Known known classes & a limited number of UKCs' samples	Known known classes & unknown known classes	Identifying known known classes & unknown known classes
Zero-shot Learning	Known known classes & side-information[1]	Unknown known classes	Identifying unknown known classes
Generalized Zero-shot Learning	Known known classes & side-information[1]	Known known classes & unknown known classes	Identifying known known classes & unknown known classes
Open Set Recognition	Known known classes	Known known classes & unknown unknown classes	Identifying known known classes & rejecting unknown unknown classes
Generalized Open Set Recognition	Known known classes & side-information[2]	Known known classes & Unknown unknown classes	Identifying known known classes & cognizing unknown unknown classes

Note that the unknown known classes in one-shot learning usually do not have any side-information, such as semantic information, etc. The side-information[1] in ZSL and G-ZSL denotes the semantic information from both KKCs and UKCs, while the side-information[2] here denotes the available semantic information only from KKCs. As part of this information usually spans between KKCs and UUCs, we hope to use it to further 'cognize' UUCs instead of simply rejecting them.

Open Set

The Overlooked Elephant of Object Detection: Open Set

A scenario where a system is tested on instances belonging to classes different from what it was trained on is defined as open-set

因为标注不全，所以有些 UUC 在训练集出现过，这些样本定义为 mixed unknowns

Open World

- 首先进行 Open Set 检测
- 选择有价值的 UUC 样本
- 对样本进行标注
- 使用标注信息持续学习

Open Vocabulary

Open-vocabulary Object Detection via Vision and Language Knowledge Distillation

- 样例 label 由自然语言描述给出
- 与 ZSL 的区别：不含类别相关的额外信息

Extending One-Stage Detection with Open-World Proposals

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IOU Overlap as Objectness

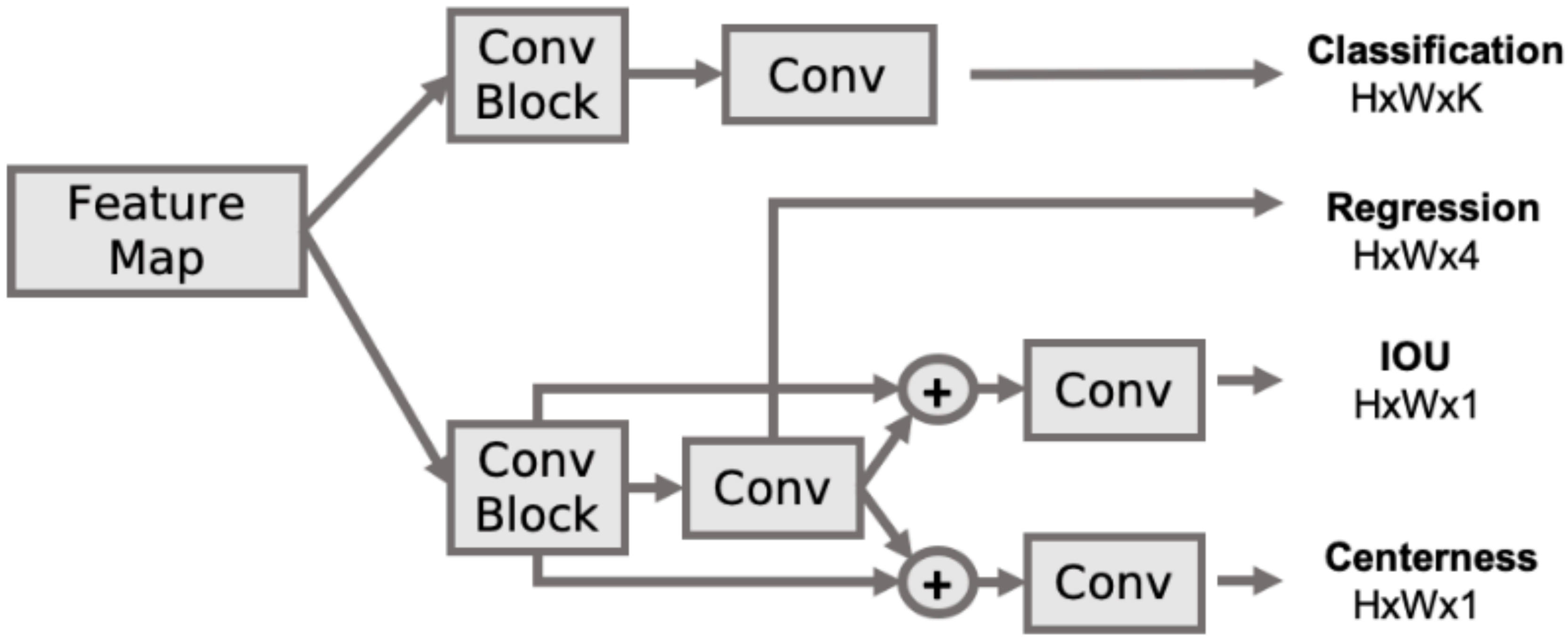

Figure 2. FCOS detection head with Conditional IOU and Centerness. We take the feature maps after Conv Block, concatenate with the regression branch's output and use it as input to the IOU and centerness branches.

Sampling Procedures

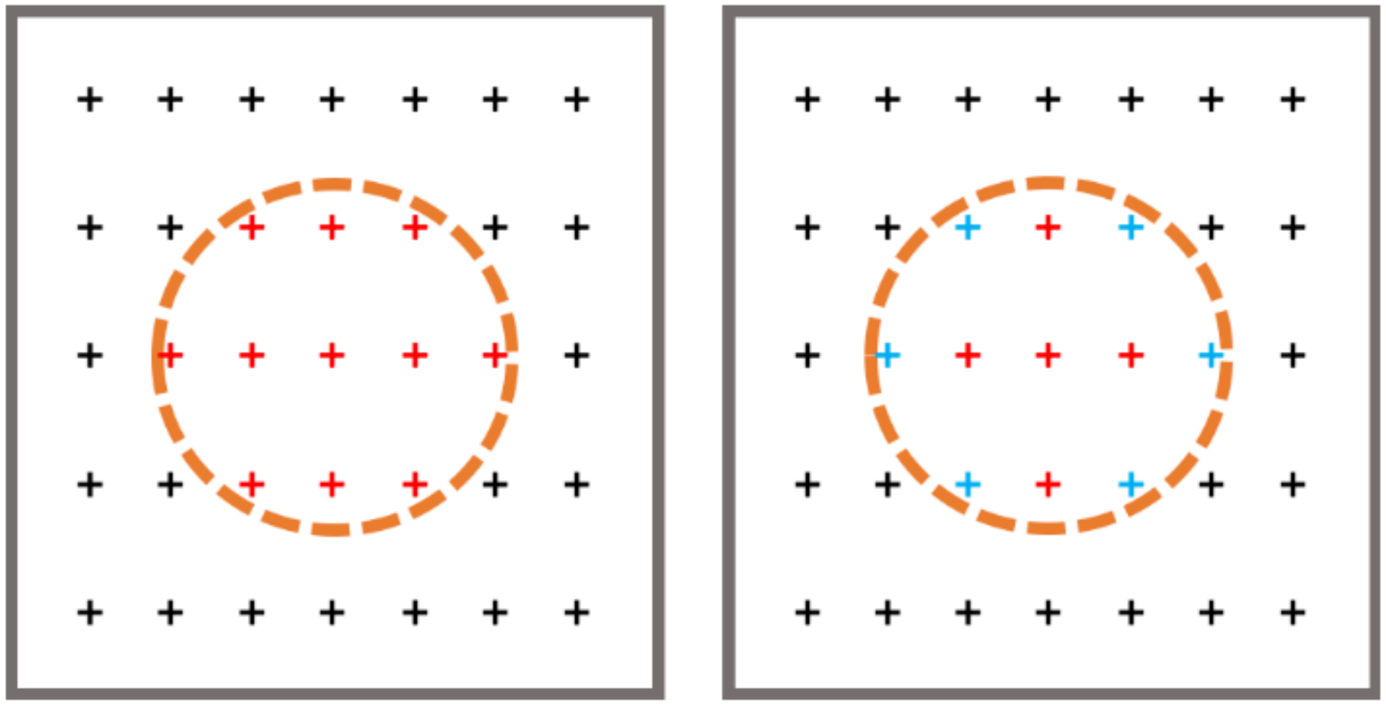

Figure 3. We have two ground-truths boxes, where a black + indicates a foreground sample. The orange circle represents the center-sampling, where the red points are center-sampled. On the right figure, we apply our IOU Sampling technique to create blue +, which are hard-negative samples.

Unknown Object Masking

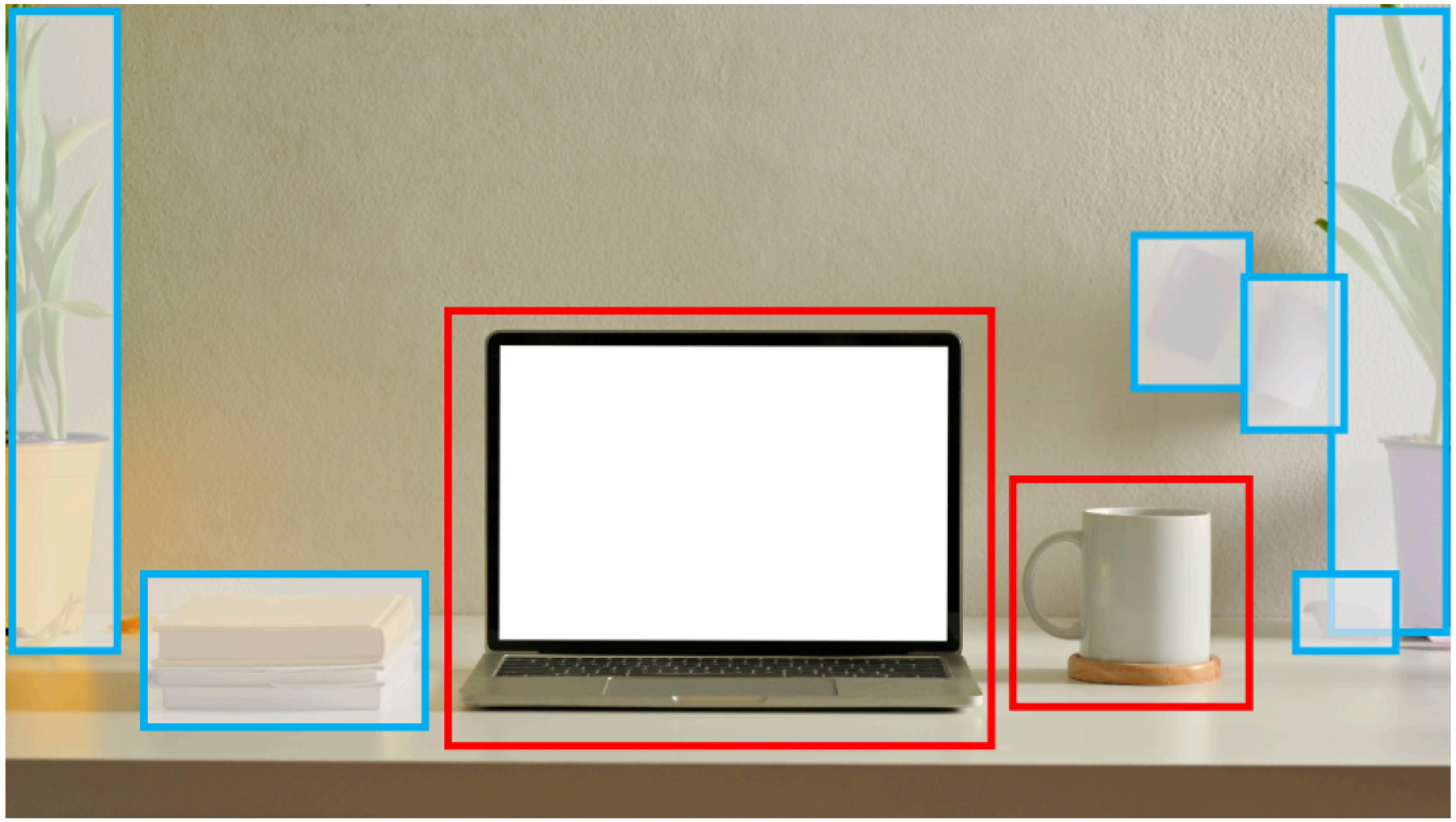

Figure 4. Here the red bounding boxes are the ground-truth annotations; however there are other objects on the table and on the wall that are unannotated. Therefore, we use our objectness branch to mask out the portions of those unknown objects that don't intersect with the ground-truth, represented in blue.

Experiments

Table 1. Here we combine the results of three experiments: Baseline, OWP, OWP-Aware Classification. The Baseline experiment uses the default scoring method from FCOS, which is logits $*$ centerness and evaluates classification AP and proposal AR100 on the base class. OWP are class-agnostic proposal experiments where we seek to only maximize AR100. In OWP-Aware Classification, we seek to maximize AR100 while also maximizing classification AP. For OWP and OWP-Aware Classification, we provide the results for these experiments from OLN [22].

		COCO$^{\text{base}}$			COCO$^{\text{novel}}$	
	Method	AP	AR10	AR100	AR10	AR100
Baseline	logits $*$ centerness [35]	44.21	55.33	59.23	N/A	N/A
OWP	centerness	N/A	22.71	44.09	9.900	25.48
	IOU	N/A	32.67	53.26	13.43	28.31
	$\sqrt{\text{centerness} * \text{IOU}}$	N/A	26.20	48.66	11.60	28.10
	IOU-CS-IS	N/A	32.86	53.59	13.08	**30.19**
	Conditional IOU-CS-IS	N/A	34.52	54.10	14.51	**31.26**
	Class-Agnostic **OLN 1-RPN** [22]	N/A	N/A	N/A	11.70	27.40
	Class-Agnostic **OLN 2-RPN** [22]	N/A	N/A	N/A	17.70	32.70
OWP-Aware Classification	logits $*$ IOU-CS-IS (Finetune)	46.07	59.25	64.12	11.67	**28.39**
	logits $*$ IOU-CS-IS (joint)	46.01	58.24	63.45	11.12	26.89
	joint + unknown	**46.21**	**60.42**	**64.85**	11.32	27.82
	OLN 2-RPN [22]	N/A	N/A	N/A	13.30	26.50