Conditional Prototype Learning for Few-Shot Object Detection

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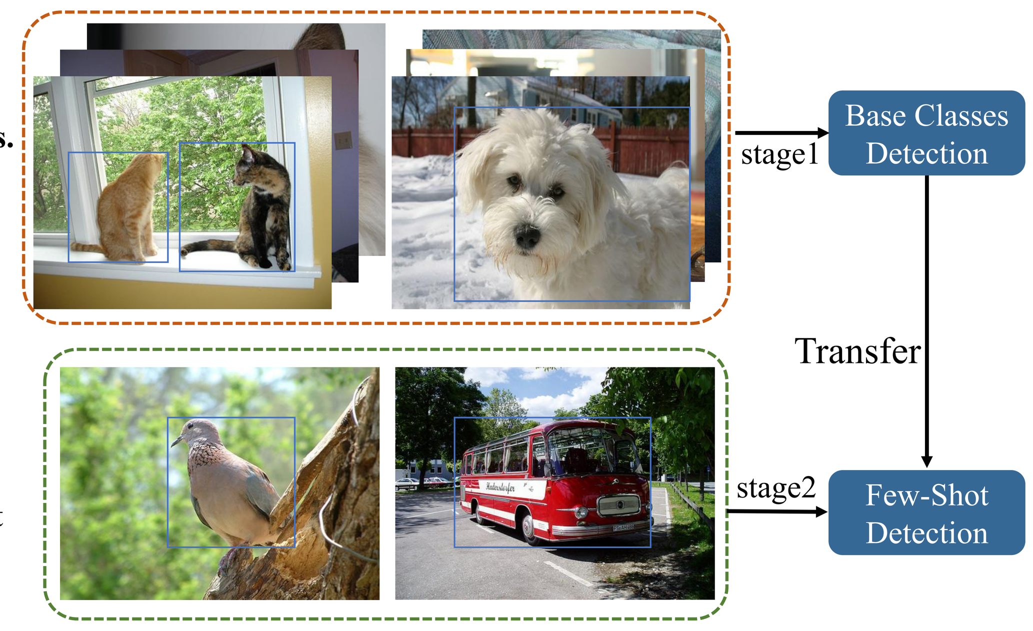
github

1.Background

What is Few-Shot Object Detection?

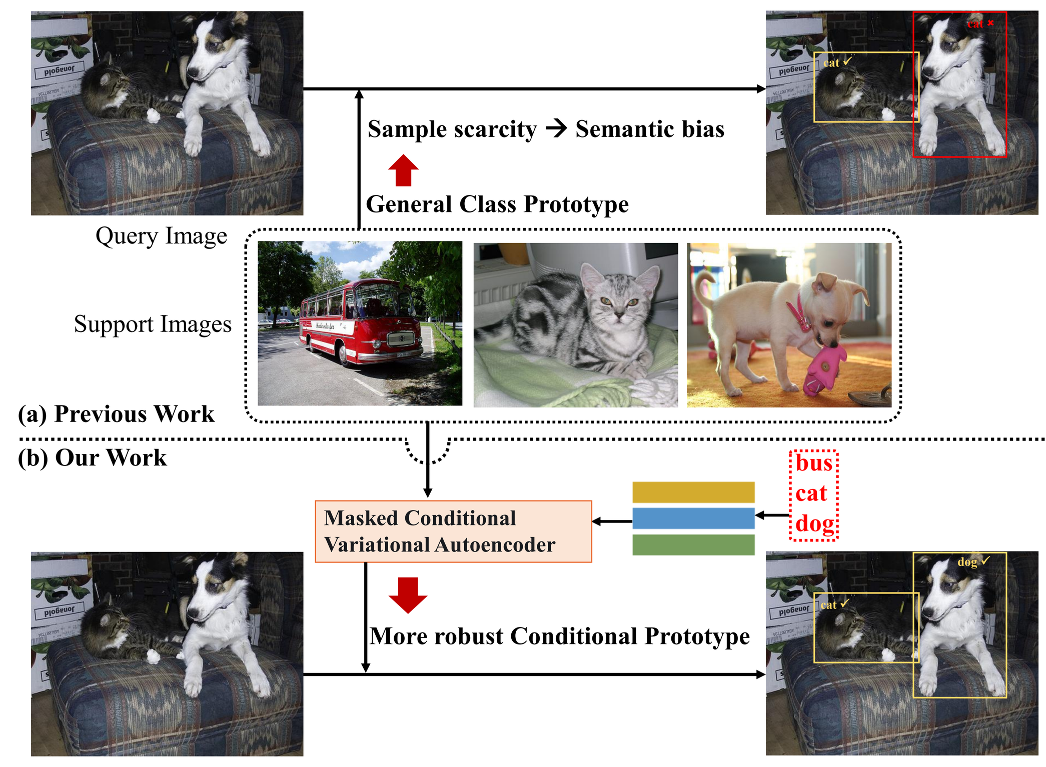
- **Detect with Few Examples**
  Few-Shot Object Detection aims to detect objects from **novel classes** using **only a handful of annotated samples.**
- **Handle Data Scarcity**
  In real-world scenarios, **collecting and labeling data is expensive**. FSOD tackles this by enabling detection for **rare or underrepresented categories** with limited supervision.
- **Learn to Generalize**
  FSOD uses **meta-learning** or **transfer learning** to extract knowledge from base classes and **generalize to novel classes quickly** with minimal data.



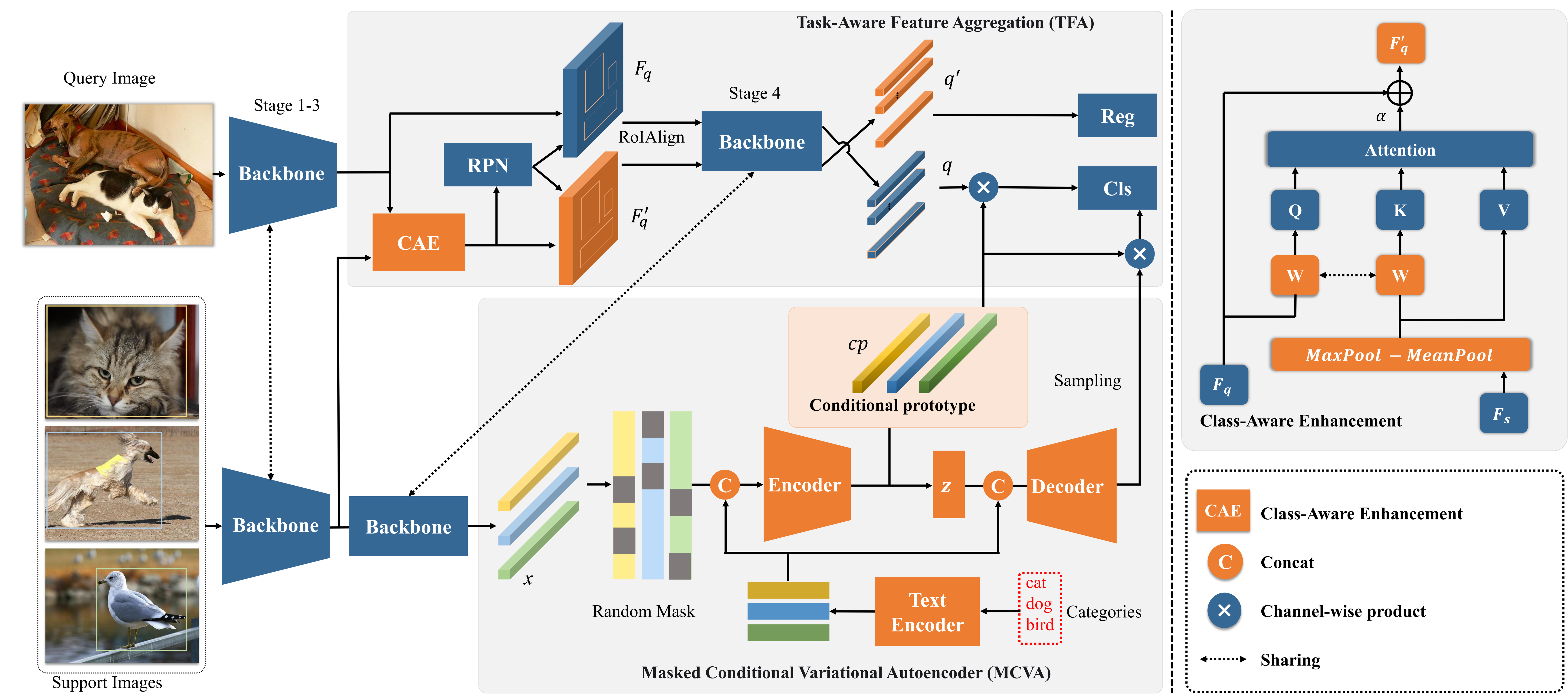
2.Motivation

In few-shot object detection (FSOD), prototypes guide learning. But with few samples, prototypes often overfit to sample-specific details rather than true class semantics → **semantic bias.**

To reduce semantic bias, we guide learning using category-specific semantics, enabling the model to generate **more robust prototypes** that better adapt to novel classes.



3.Overall Framework



4.Experimental Results

Few-shot object detection performance (nAP50) on PASCAL VOC dataset. We evaluate the performance on three different splits.

Methods		split 1					split 2					split 3				
		1	2	3	5	10	1	2	3	5	10	1	2	3	5	10
FSRW [19]	ICCV19	14.8	15.5	26.7	33.9	47.2	15.7	15.3	22.7	30.1	40.5	21.3	25.6	28.4	42.8	45.9
Meta RCNN [42]	ICCV19	19.9	25.5	35.0	45.7	51.5	10.4	19.4	29.6	34.8	45.4	14.3	18.2	27.5	41.2	48.1
TFA w/ cos [35]	ICML20	39.8	36.1	44.7	55.7	56.0	23.5	26.9	34.1	35.1	39.1	30.8	34.8	42.8	49.5	49.8
MPSR [38]	ECCV20	41.7	-	51.4	55.2	61.8	24.4	-	39.2	39.9	47.8	35.6	-	42.3	48.0	49.7
DCNet [18]	CVPR21	33.9	37.4	43.7	51.1	59.6	23.2	24.8	30.6	36.7	46.6	32.3	34.9	39.7	42.6	50.7
QA-FewDet [12]	ICCV21	42.4	51.9	55.7	62.6	63.4	25.9	37.8	46.6	48.9	51.1	35.2	42.9	47.8	54.8	53.5
FSCE [34]	CVPR21	44.2	43.8	51.4	61.9	63.4	27.3	29.5	43.5	44.2	50.2	37.2	41.9	47.5	54.6	58.5
DeFRCN [27]	ICCV21	53.6	57.5	61.5	64.1	60.8	30.1	38.1	47.0	53.3	47.9	48.4	50.9	52.3	54.9	57.4
KFSOD [47]	CVPR22	44.6	45.2	54.4	60.9	65.8	37.8	38.4	43.1	48.1	50.4	34.8	42.7	44.1	52.7	53.9
MRSN [25]	ECCV22	47.6	48.6	57.8	61.9	62.6	31.2	38.3	46.7	47.1	50.6	35.5	30.9	45.6	54.4	57.4
Meta FR-CNN [13]	AAAI22	43.0	54.6	60.6	66.1	65.4	27.7	35.5	46.1	47.8	51.4	40.6	46.4	53.4	59.9	58.6
σ-ADP [6]	ICCV23	52.3	55.5	63.1	65.9	66.7	42.7	45.8	48.7	54.8	56.3	47.8	51.8	56.8	60.3	62.4
ICPE [24]	AAAI23	54.3	59.5	62.4	65.7	66.2	33.5	40.1	48.7	51.7	52.5	50.9	53.1	55.3	60.6	60.1
VFA [14]	AAAI23	57.7	64.6	64.7	67.2	67.4	41.4	46.2	51.1	51.8	51.6	48.9	54.8	56.6	59.0	58.9
FPD [37]	AAAI24	48.1	62.2	64.0	67.6	68.4	29.8	43.2	47.7	52.0	53.9	44.9	53.8	58.1	61.6	62.9
FM-FSOD [11]	CVPR24	40.1	53.5	57.0	68.6	72.0	33.1	36.3	48.8	54.8	64.7	39.2	50.2	55.7	63.4	68.1
CPL	Ours work	60.6	68.2	69.5	70.9	70.2	43.0	51.5	55.5	55.9	56.9	54.0	58.5	60.9	64.1	63.0

Visualization of the detection results on novel classes.

5.Ablation Study

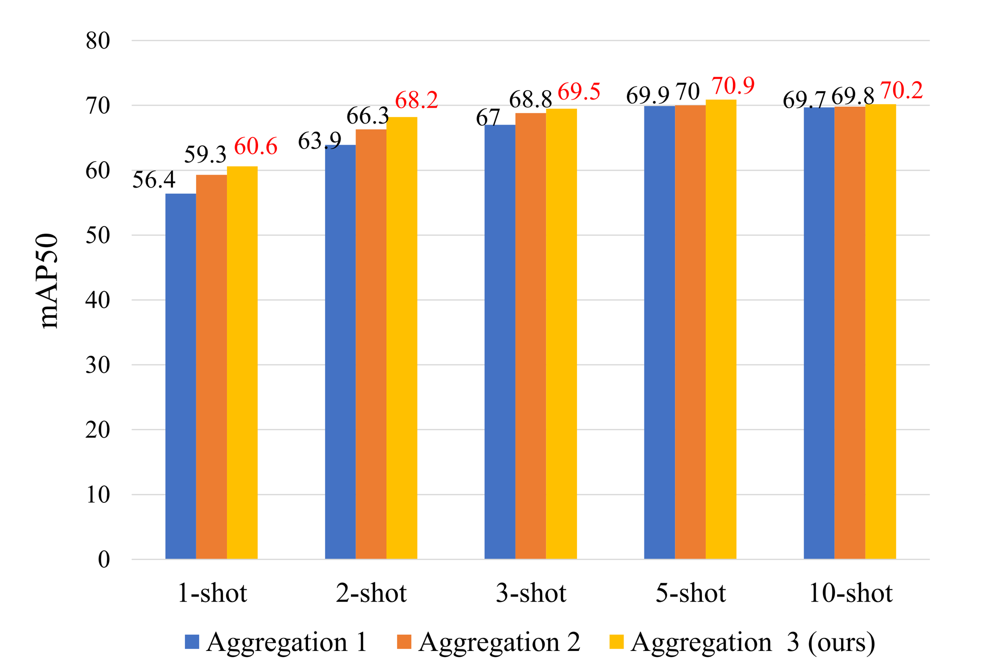
Ablation study of different components.

Method	MCVA	TFA	shot 1	shot 3	shot 5
Baseline			40.2	54.0	55.0
Ours	✓		53.0	67.5	69.9
		✓	53.2	65.2	68.3
	✓	✓	**60.6**	**69.5**	**70.9**

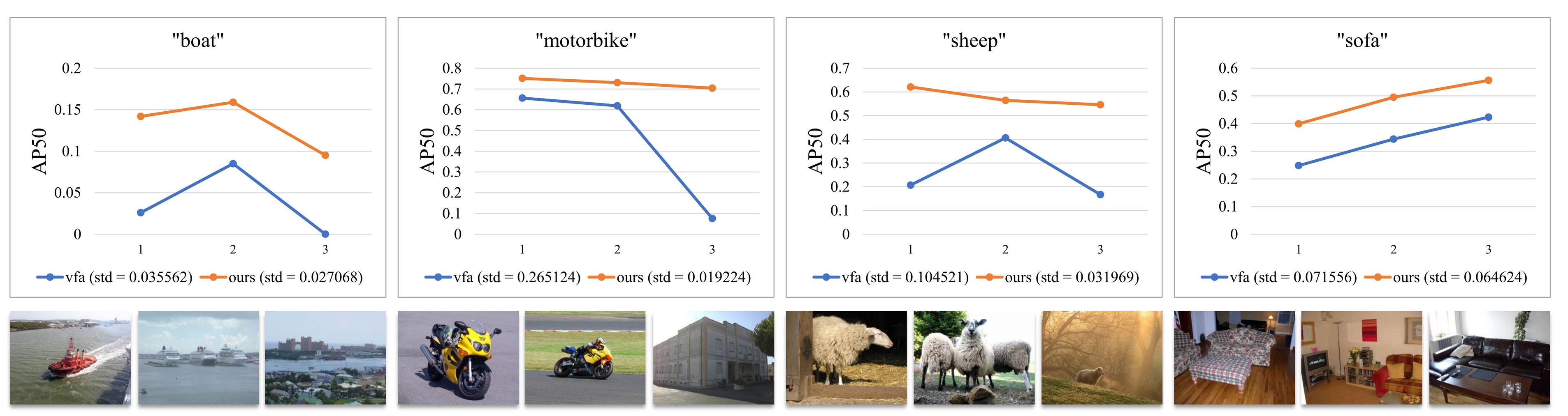
Analysis of different text encoders. Both the word embedding methods help the model achieve better performance, while CILP performs better.

Method	Text Encoder	shot				
		1	2	3	5	10
Ours	w/o reference	54.9	64.3	67.4	69.1	68.9
	CLIP [28]	**60.6**	**68.2**	**69.5**	**70.9**	**70.2**
	Word2Vec [26]	56.4	66.2	67.5	69.6	69.0

Analysis of different aggregation methods.



Detection performance varies with different training samples. We selected three different samples for "boat", "motorbike", "sheep", and "sofa". And conducted training under the 1-shot setting, using the Standard Deviation (std) to measure stability.



6. Conclusion

- We explore the issue of **semantic bias in class prototypes** for few-shot object detection (FSOD) under the meta-learning paradigm
- We introduce the **Masked Conditional Variational Autoencoder (MCVA)** to refine the semantic bias in class prototypes, generating more robust conditional prototypes.
- Considering that the classification and regression tasks need different kinds of features, we propose the **Task-Aware Feature Aggregation (TFA)** module, which separately enhances features for the two tasks.
- Extensive experiments on PASCAL VOC and MS COCO demonstrate that our approach achieves state-of-the-art performance.

7. Acknowledgement

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