PEEKABOO: Hiding Parts of an Image for Unsupervised Object Localization

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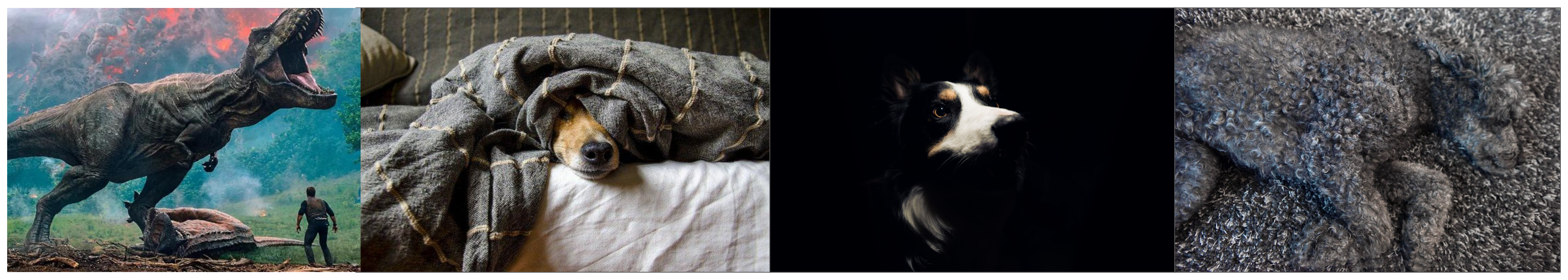
Abstract

Motivation: Localizing salient objects with supervision **requires annotated data** which is time-consuming and **fails in cases of novel objects** due to the finite nature of object classes. Unsupervised learning has challenges due to **absence of visual information** like appearance, type and number of objects and lacks labeled object classes.



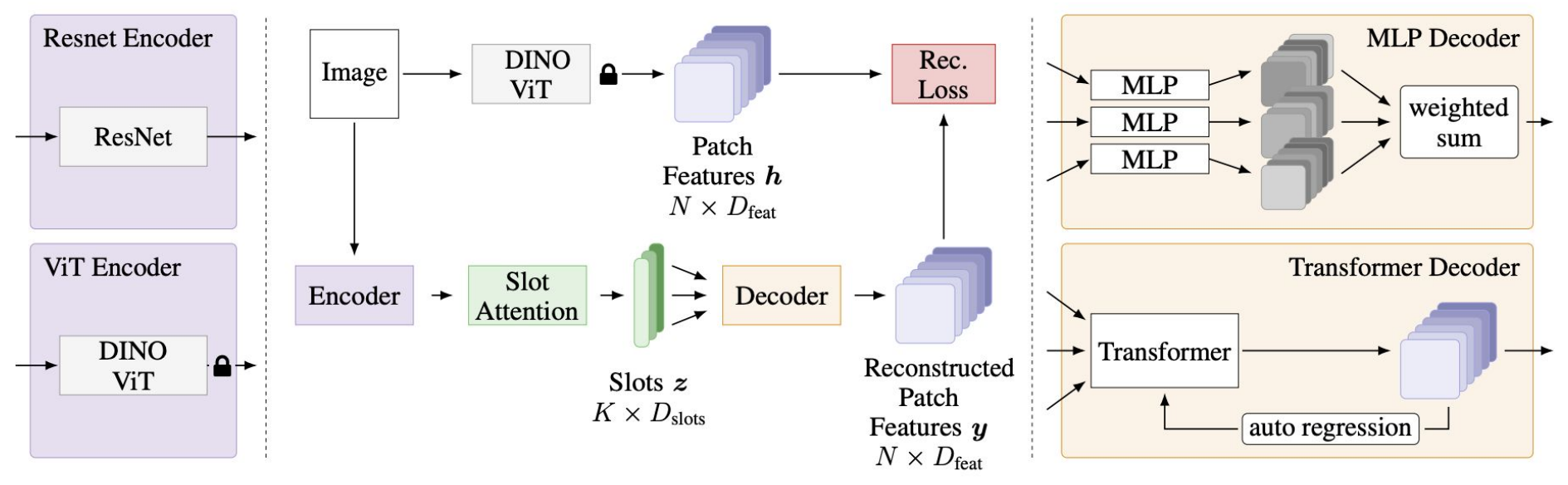
Specific Problem: Existing methods are complex in terms of model and data; they do not explicitly model visual context; fails when objects are small, reflective or under poor illumination.

Model

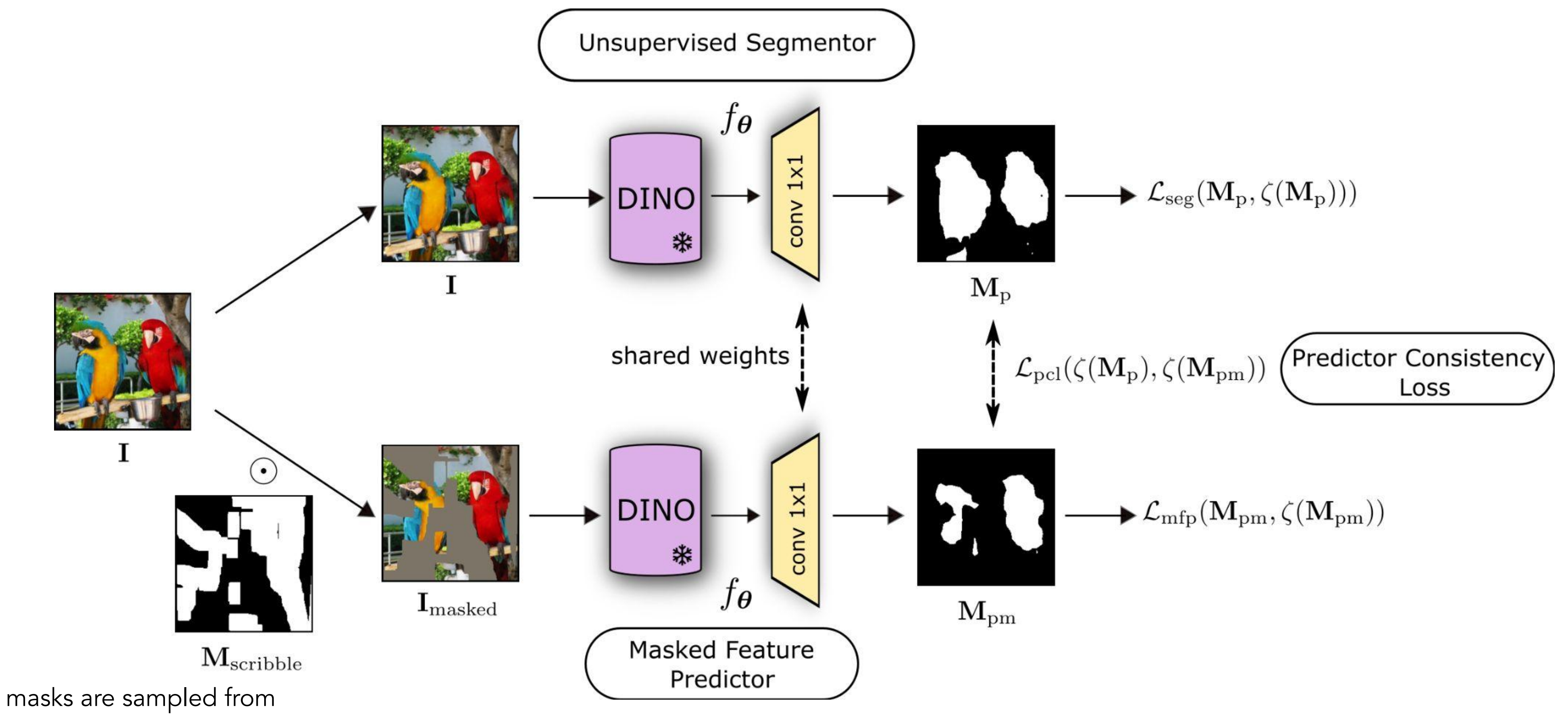
- Multiple stages of training (i.e. test time)
- Millions of learnable parameters
- Combination of multiple networks (i.e. ensembles)

Data:

- Additional real world data
- Generated synthetic data



Peekaboo

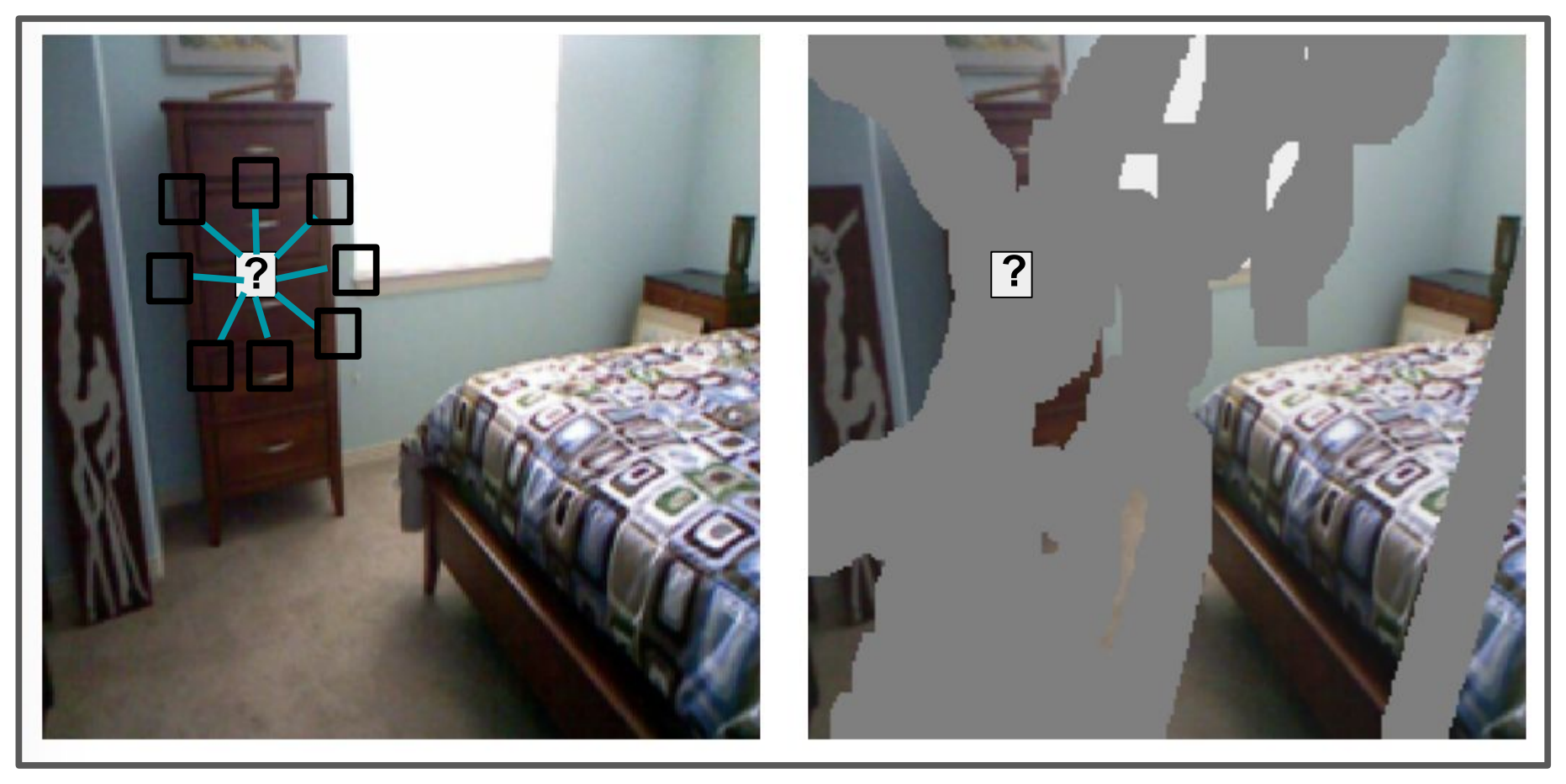

Unsupervised Segmentor
f_θ
DINO
conv 1x1
$\mathcal{L}_{\text{seg}}(\mathbf{M}_{\text{p}}, \zeta(\mathbf{M}_{\text{p}}))$
I
$\mathbf{M}_{\text{p}}$
I
shared weights
$\mathcal{L}_{\text{pcl}}(\zeta(\mathbf{M}_{\text{p}}), \zeta(\mathbf{M}_{\text{pm}}))$
Predictor Consistency Loss
$\odot$
DINO
conv 1x1
$\mathcal{L}_{\text{mfp}}(\mathbf{M}_{\text{pm}}, \zeta(\mathbf{M}_{\text{pm}}))$
$\mathbf{M}_{\text{scribble}}$
$\mathbf{I}_{\text{masked}}$
f_θ
$\mathbf{M}_{\text{pm}}$
Masked Feature Predictor

masks are sampled from Irregular Masks Dataset

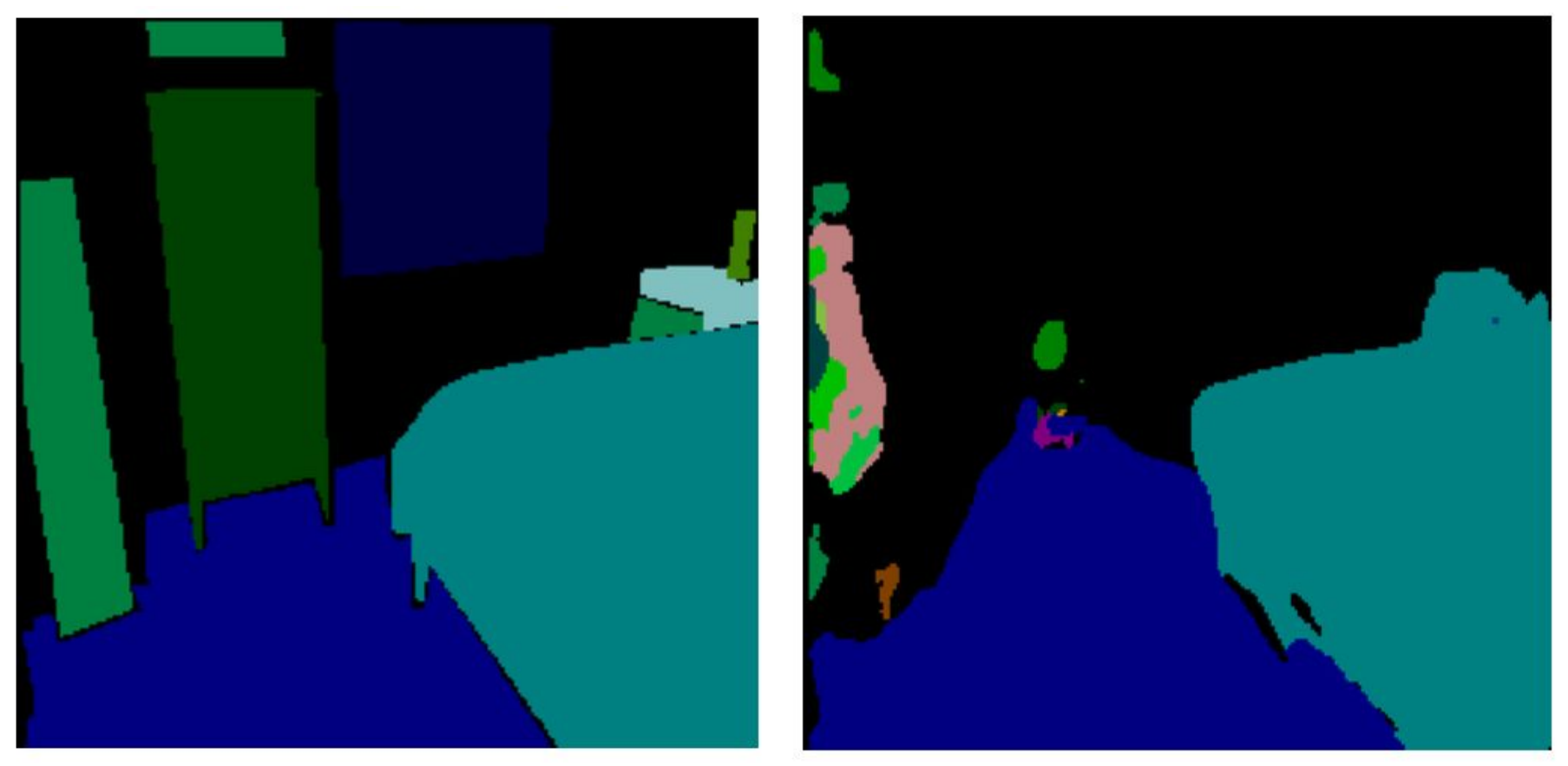
cross-entropy cross-entropy L2 error

$$\mathcal{L}_{\text{total}} = \alpha \mathcal{L}_{\text{seg}}(\mathbf{M}_{\text{p}}, \zeta(\mathbf{M}_{\text{p}})) + \mathcal{L}_{\text{mfp}}(\mathbf{M}_{\text{pm}}, \zeta(\mathbf{M}_{\text{pm}})) + \mathcal{L}_{\text{pcl}}(\zeta(\mathbf{M}_{\text{p}}), \zeta(\mathbf{M}_{\text{pm}})),$$

Masked Feature Predictor (MFP) aims to learn context based representations; Predictor Consistency Loss (PCL) aligns unmasked and masked input predictions.



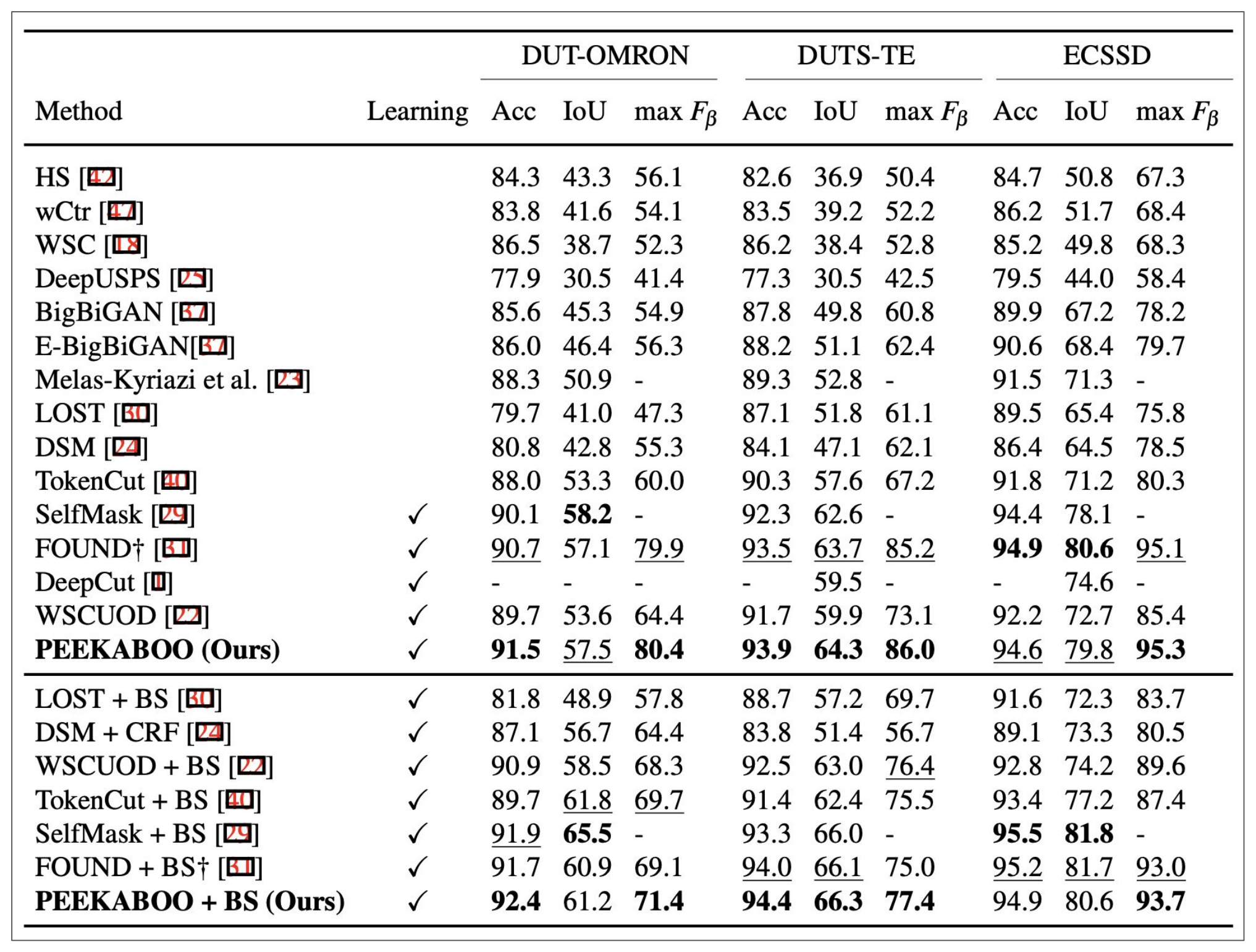
MFP: uses nearby non-masked pixels around objects to make predictions for masked pixels



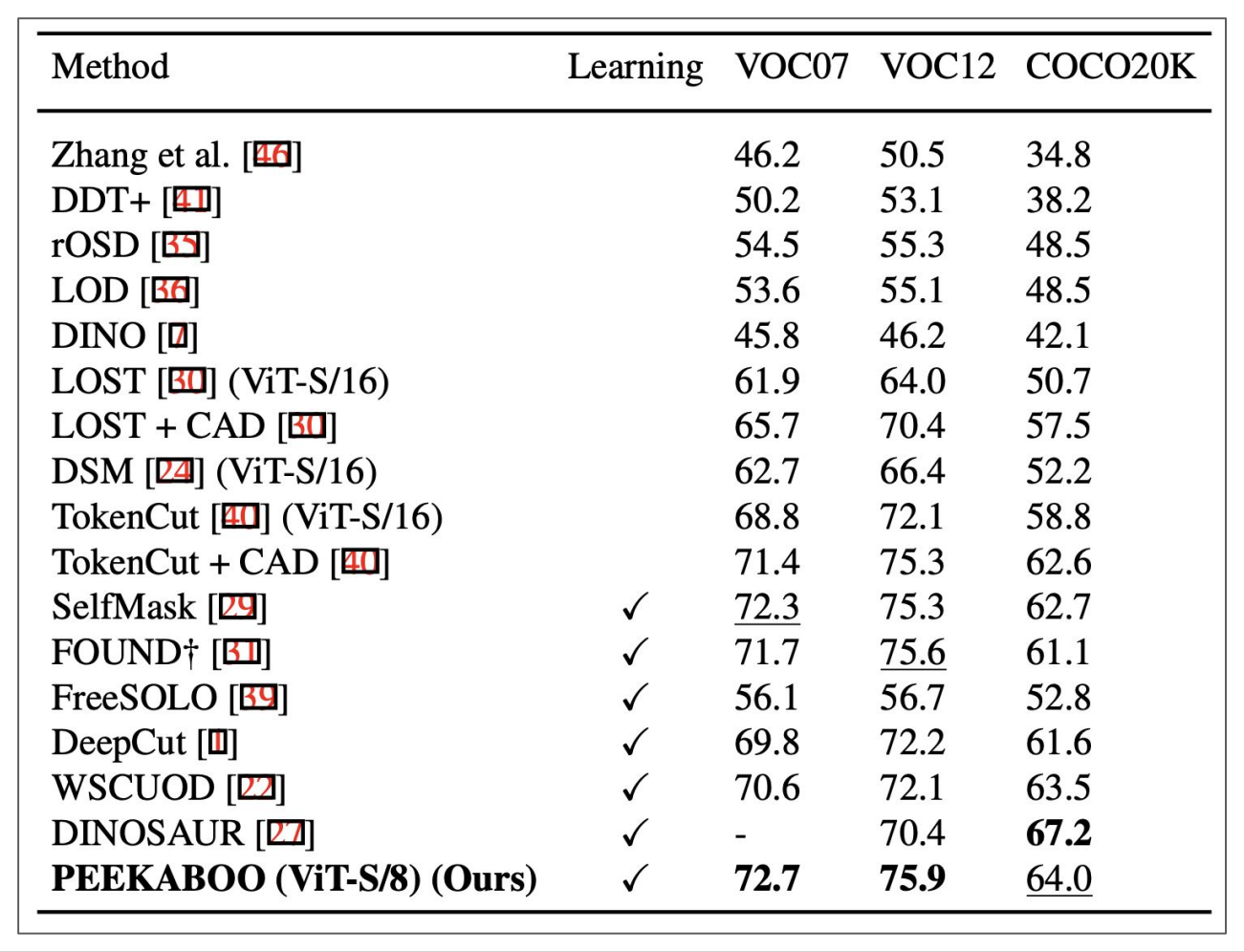
PCL: learns shape level representations by ensuring consistency between predictions of unmasked and masked object

Results

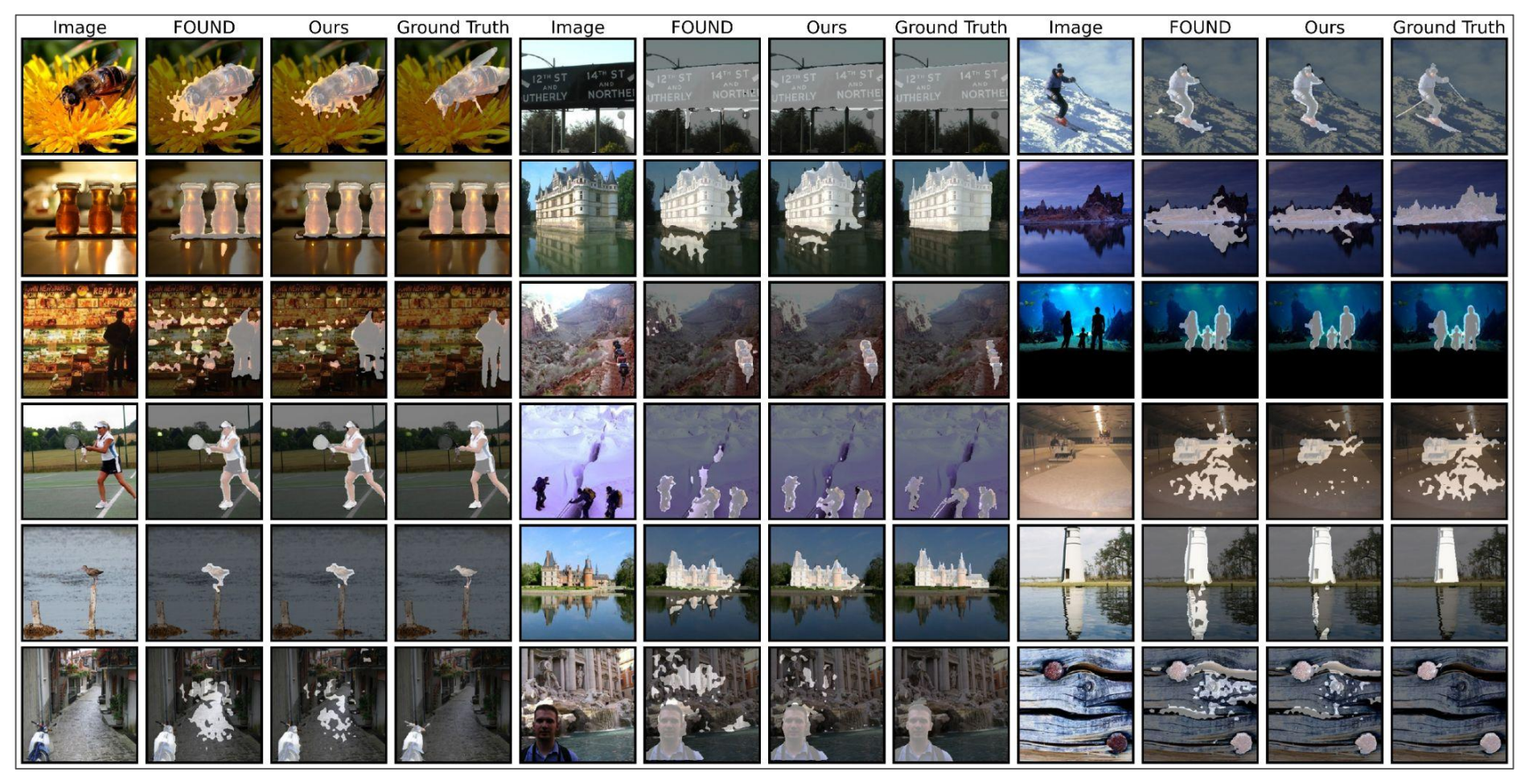
Outperforms SOTA methods on Single Object Discovery and Unsupervised Saliency Detection tasks.



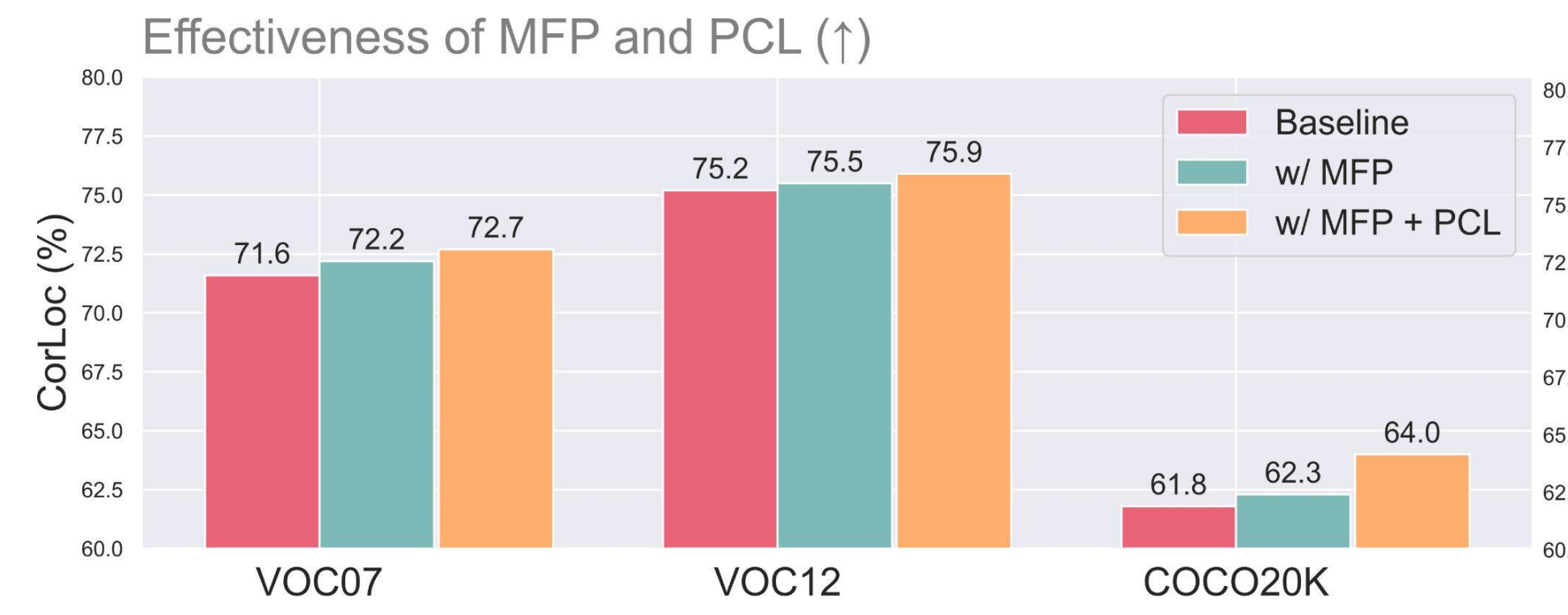
		DUT-OMRON			DUTS-TE			ECSSD		
Method	Learning	Acc	IoU	max F_β	Acc	IoU	max F_β	Acc	IoU	max F_β
HS [42]		84.3	43.3	56.1	82.6	36.9	50.4	84.7	50.8	67.3
wCtr [47]		83.8	41.6	54.1	83.5	39.2	52.2	86.2	51.7	68.4
WSC [18]		86.5	38.7	52.3	86.2	38.4	52.8	85.2	49.8	68.3
DeepUSPS [25]		77.9	30.5	41.4	77.3	30.5	42.5	79.5	44.0	58.4
BigBiGAN [37]		85.6	45.3	54.9	87.8	49.8	60.8	89.9	67.2	78.2
E-BigBiGAN[37]		86.0	46.4	56.3	88.2	51.1	62.4	90.6	68.4	79.7
Melas-Kyriazi et al. [23]		88.3	50.9	-	89.3	52.8	-	91.5	71.3	-
LOST [30]		79.7	41.0	47.3	87.1	51.8	61.1	89.5	65.4	75.8
DSM [24]		80.8	42.8	55.3	84.1	47.1	62.1	86.4	64.5	78.5
TokenCut [40]		88.0	53.3	60.0	90.3	57.6	67.2	91.8	71.2	80.3
SelfMask [29]	✓	90.1	**58.2**	-	92.3	62.6	-	94.4	78.1	-
FOUND† [31]	✓	90.7	57.1	79.9	93.5	63.7	85.2	**94.9**	**80.6**	95.1
DeepCut [1]	✓	-	-	-	-	59.5	-	-	74.6	-
WSCUOD [22]	✓	89.7	53.6	64.4	91.7	59.9	73.1	92.2	72.7	85.4
PEEKABOO (Ours)	✓	**91.5**	57.5	**80.4**	**93.9**	**64.3**	**86.0**	94.6	79.8	**95.3**
LOST + BS [30]	✓	81.8	48.9	57.8	88.7	57.2	69.7	91.6	72.3	83.7
DSM + CRF [24]	✓	87.1	56.7	64.4	83.8	51.4	56.7	89.1	73.3	80.5
WSCUOD + BS [22]	✓	90.9	58.5	68.3	92.5	63.0	76.4	92.8	74.2	89.6
TokenCut + BS [40]	✓	89.7	61.8	69.7	91.4	62.4	75.5	93.4	77.2	87.4
SelfMask + BS [29]	✓	91.9	**65.5**	-	93.3	66.0	-	**95.5**	**81.8**	-
FOUND + BS† [31]	✓	91.7	60.9	69.1	94.0	66.1	75.0	95.2	81.7	93.0
PEEKABOO + BS (Ours)	✓	**92.4**	61.2	**71.4**	**94.4**	**66.3**	**77.4**	94.9	80.6	**93.7**

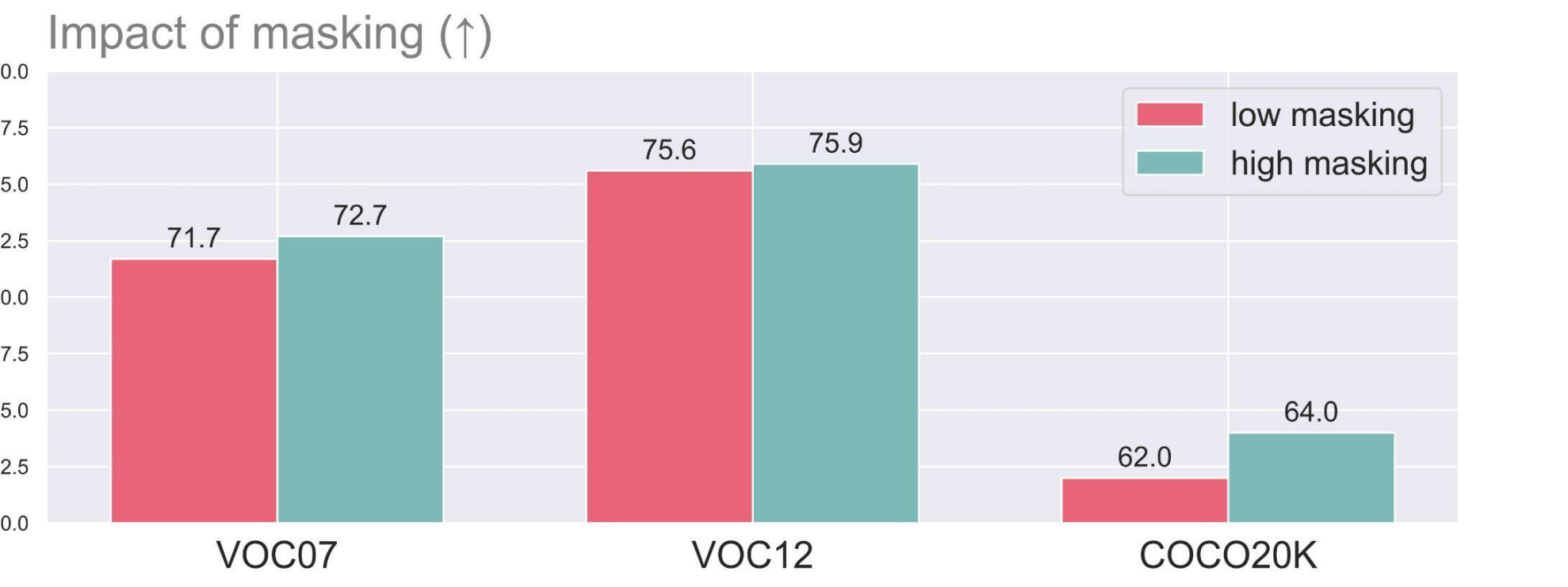


Method	Learning	VOC07	VOC12	COCO20K
Zhang et al. [46]		46.2	50.5	34.8
DDT+ [41]		50.2	53.1	38.2
rOSD [35]		54.5	55.3	48.5
LOD [36]		53.6	55.1	48.5
DINO [7]		45.8	46.2	42.1
LOST [30] (ViT-S/16)		61.9	64.0	50.7
LOST + CAD [30]		65.7	70.4	57.5
DSM [24] (ViT-S/16)		62.7	66.4	52.2
TokenCut [40] (ViT-S/16)		68.8	72.1	58.8
TokenCut + CAD [40]		71.4	75.3	62.6
SelfMask [29]	✓	72.3	75.3	62.7
FOUND† [31]	✓	71.7	75.6	61.1
FreeSOLO [39]	✓	56.1	56.7	52.8
DeepCut [1]	✓	69.8	72.2	61.6
WSCUOD [22]	✓	70.6	72.1	63.5
DINOSAUR [27]	✓	-	70.4	**67.2**
PEEKABOO (ViT-S/8) (Ours)	✓	**72.7**	**75.9**	64.0



Both components complement each other; Peekaboo is better with high masking.





Can discover multiple, diverse and unfamiliar objects of different shapes and scales; basically which are not background.

Conclusion

Peekaboo is a single-stage method that models visual context for unsupervised object localization. It can detect salient objects even when they are small, reflective or under poor illumination and is more efficient than existing methods.

TLDR: A self-supervised segmentation model with zero-shot generalization to unfamiliar images and objects that are small, reflective or under poor illumination without the need for additional training. Do try it!

Project Page: https://hasibzunair.github.io/peekaboo/