

JUNE 18-22, 2023

CVPR



Poster: June 20, 2023 @ TUE-PM-280

Open-Vocabulary Semantic Segmentation with Mask-adapted CLIP

<https://jeff-liangf.github.io/projects/ovseg/>

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TEXAS

The University of Texas at Austin



Traditional segmentation



0: Background/Unknown

1: Person

2: Purse

3: Plants/Grass

4: Sidewalk

5: Building/Structures

[Source: [Jeremy Jordan](#)]

Traditional segmentation model can only segment the classes in the training dataset

Open-vocabulary segmentation



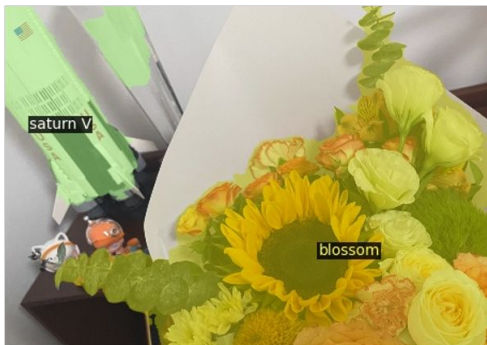
Where is **Saturn V**, **blossom**?



Where is **Oculus**, **Ukulele**?

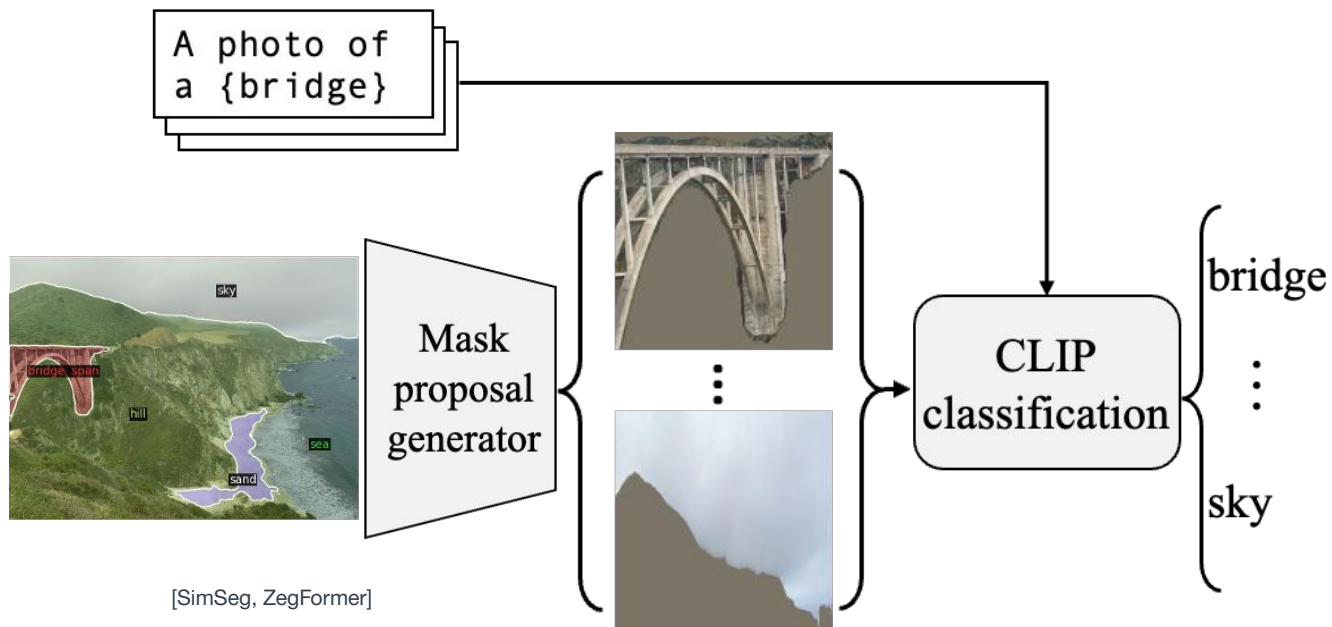


Where is **Golden gate**, **yacht**?



Open-vocab segmentation model can segment any arbitrary class defined by user

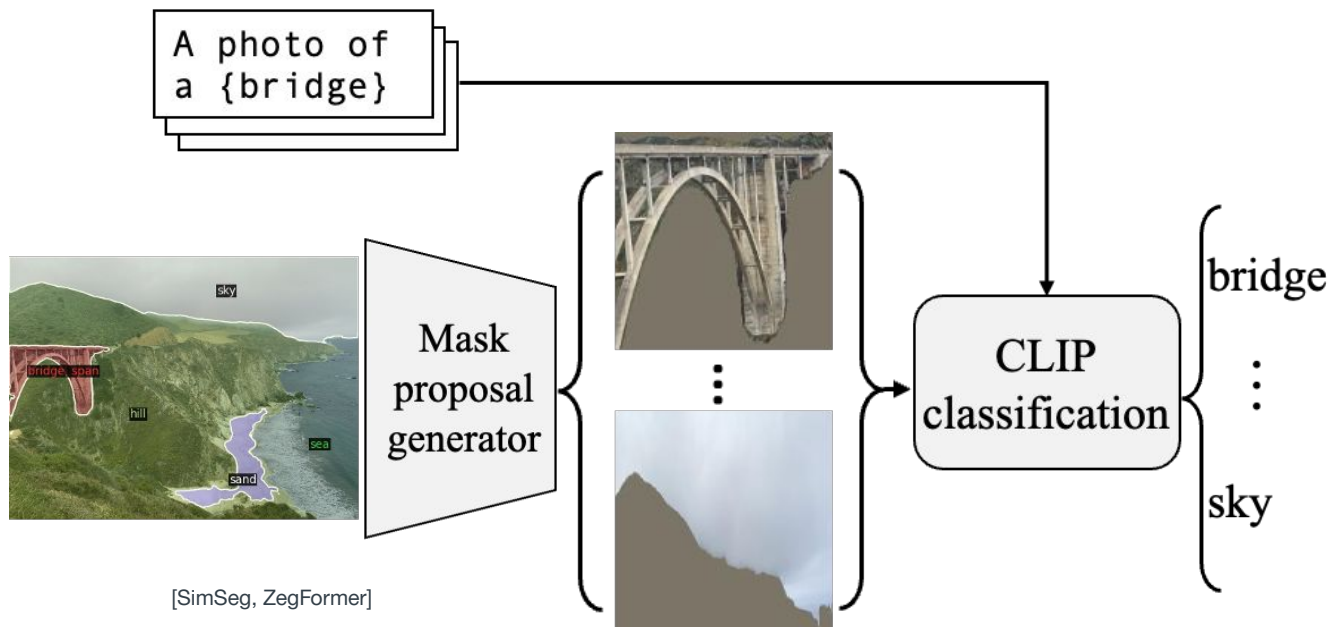
Two-stage open-vocabulary baseline



First generate 'class-agnostic' mask proposals

Then use the pre-trained CLIP to do open-vocabulary classification

Two-stage open-vocabulary baseline



The success of two-stage approaches lies on two assumptions:

- (1) **Mask proposals**: Proposal generator can generalize to unseen categories
- (2) **Classification**: Pre-trained CLIP can perform good classification on mask images

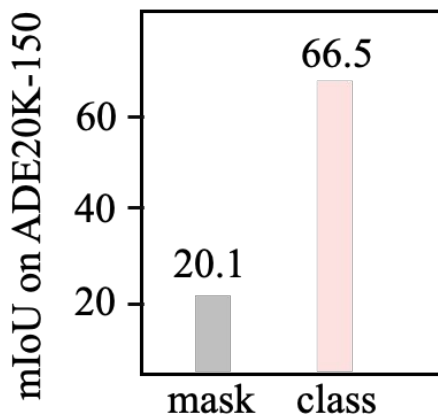
Bottleneck analysis of two-stage baseline

Bottleneck analysis

(1) We use oracle (ground-truth) mask proposals and perform CLIP classification over them

(2) We assume an “oracle” classifier but an ordinary mask proposal generator – a MaskFormer pre-trained on the COCO dataset

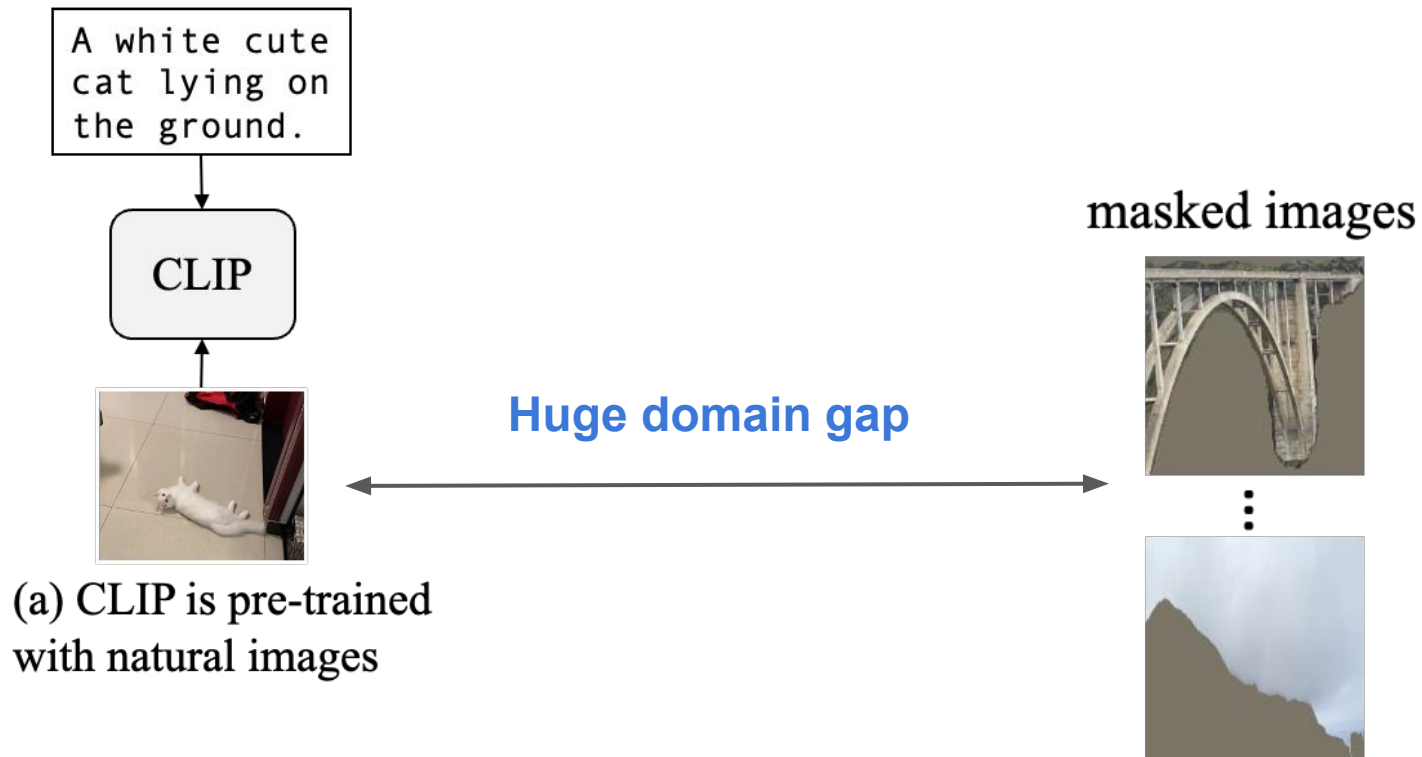
- Oracle mask proposals
- Oracle classification



(c) Bottleneck analysis

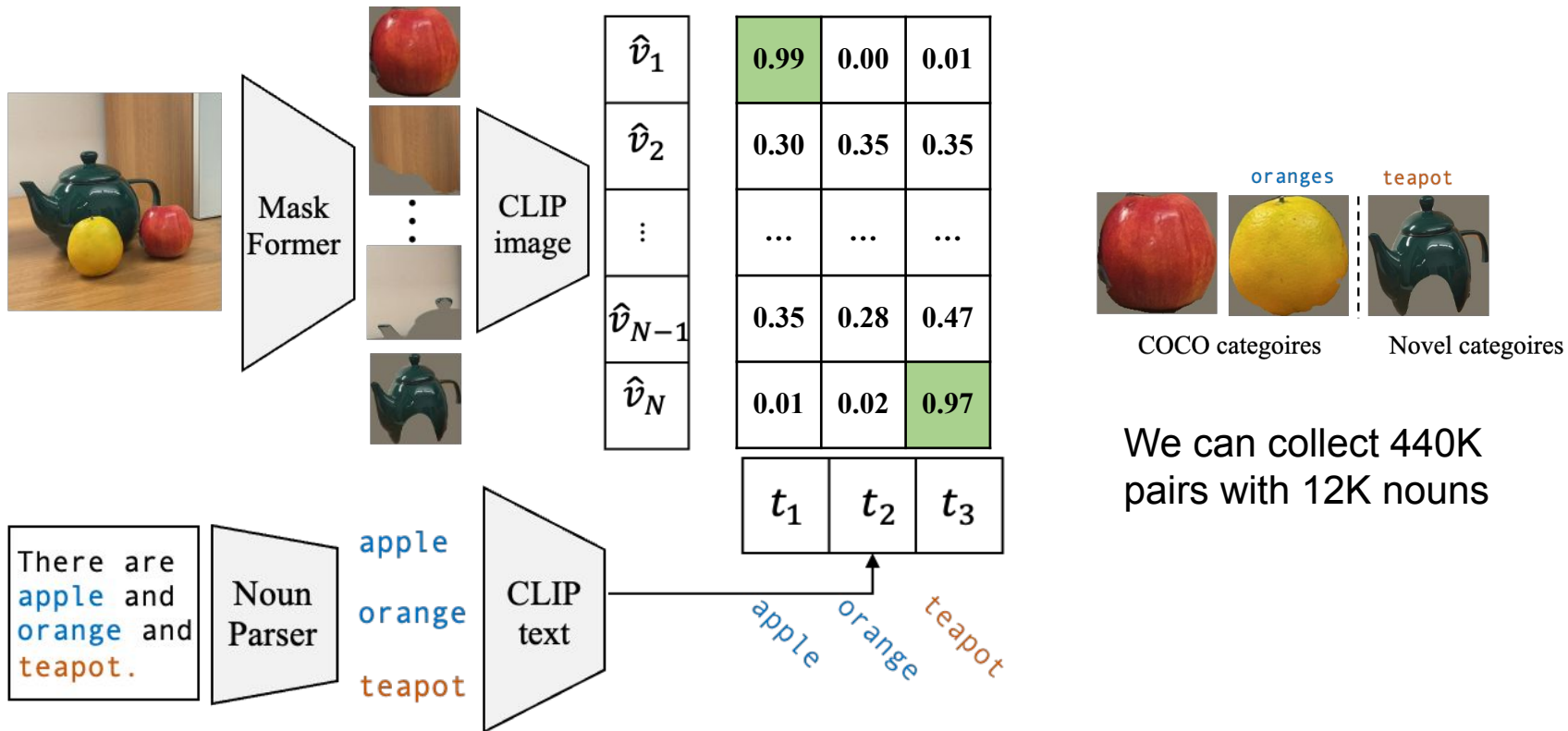
CLIP **can not** perform well on mask proposals, making CLIP the major bottleneck.

CLIP can not perform well on mask proposals



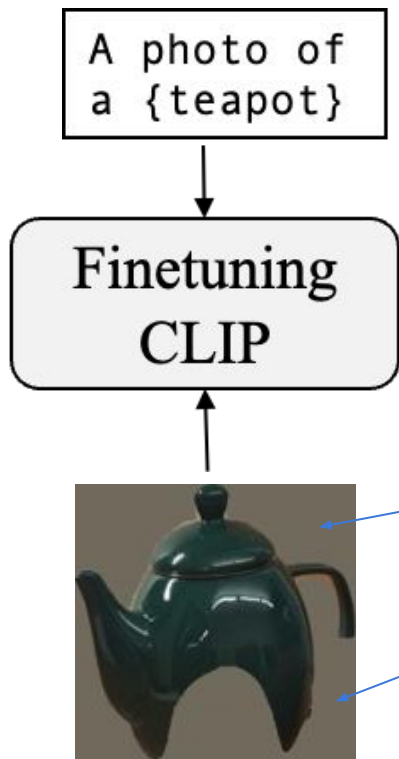
Collecting mask-text pairs to finetune CLIP

We propose adapt CLIP to masked images with collected diverse mask-category pairs from captions



Mask prompt tuning for CLIP

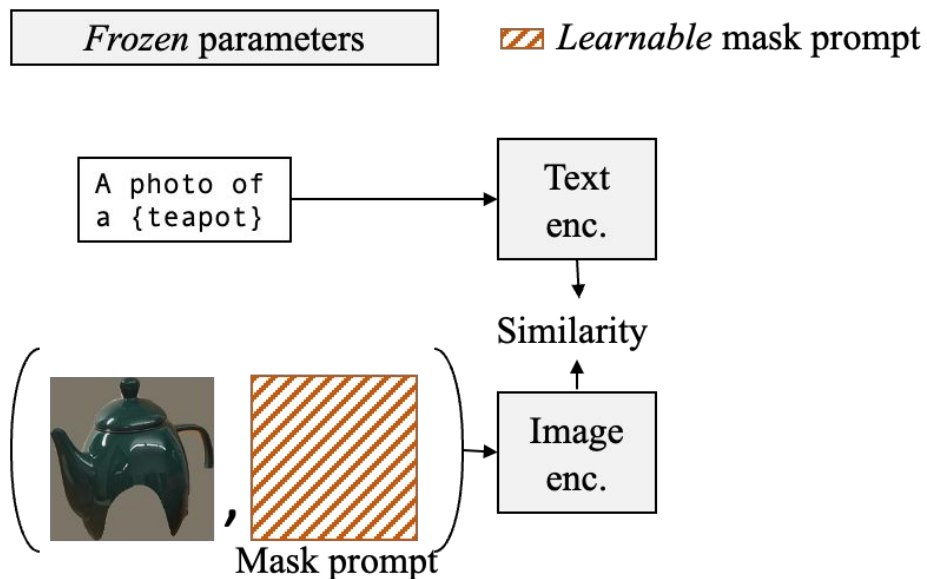
After collecting the data, how can we finetune the CLIP?



The most notable difference between a masked image and a natural image is that background pixels in a masked image are **masked out**.

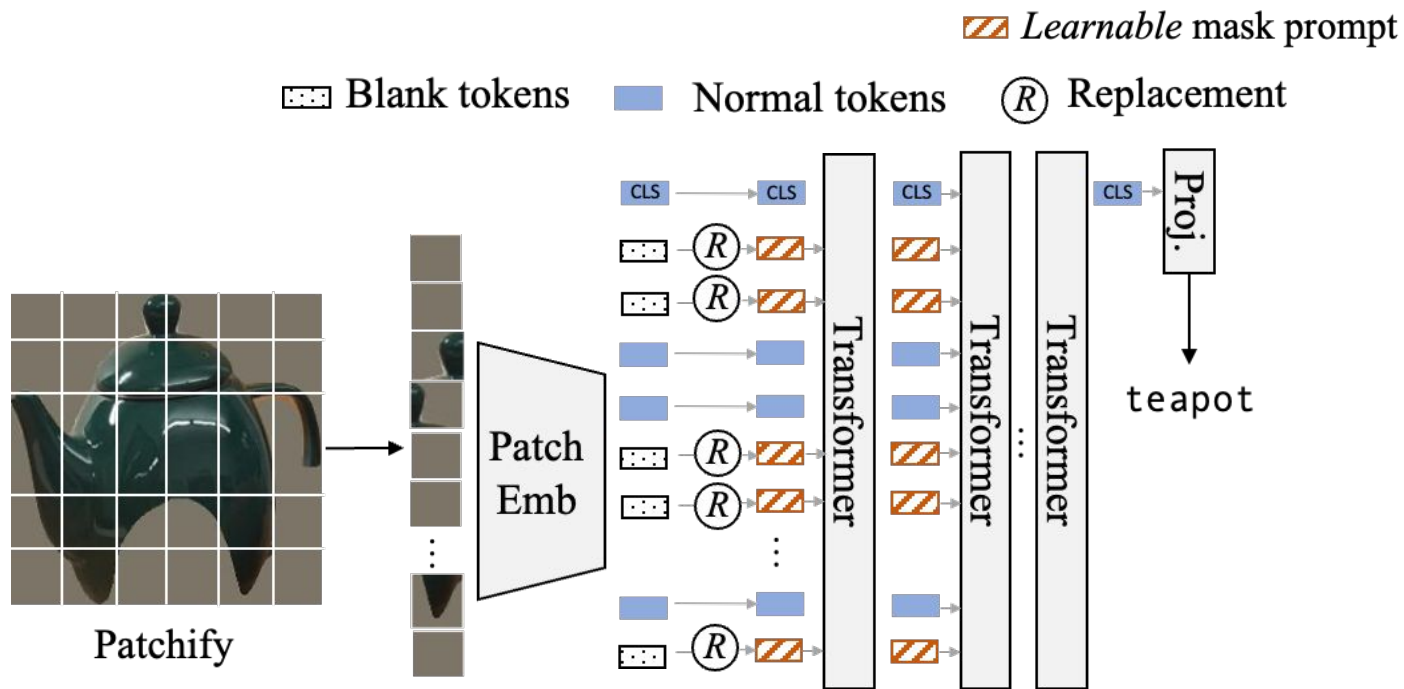
Mask prompt tuning for CLIP

We only need to finetune the 'blank areas' while [keep the entire CLIP model frozen](#).



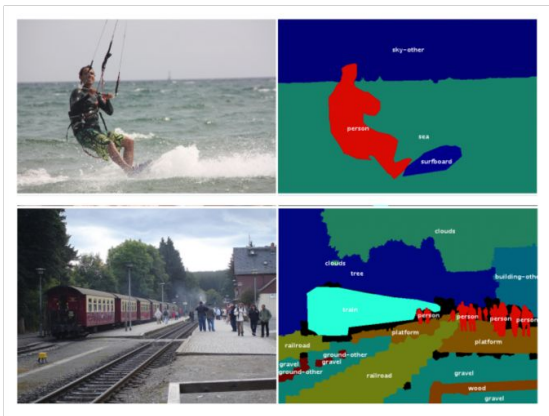
Mask prompt tuning for CLIP

We replace the blank tokens with learnable tokens



Evaluation setting

Training



COCO-stuff
of classes: 171

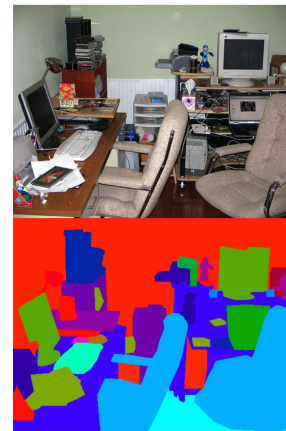
Zero-shot
transfer



Evaluating



ADE-20k
of cls: 150 or 857



Pascal Context
of cls: 59 or 459

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Performance

- A-847/150: ADE with 847/150 classes
- PC-459/59: Pascal Context with 459/59 classes
- PAS-20: VOC 2012 with 20 classes

method	backbone	training dataset	A-847	PC-459	A-150	PC-59	PAS-20
<i>Open-vocabulary generalist models.</i>							
SPNet (Xian et al., 2019)	R-101	PASCAL-15	-	-	-	24.3	18.3
ZS3Net (Bucher et al., 2019)	R-101	PASCAL-15	-	-	-	19.4	38.3
LSeg (Li et al., 2022)	R-101	PASCAL-15	-	-	-	-	47.4
LSeg+ (Ghiasi et al., 2021)	R-101	COCO Panoptic	2.5	5.2	13.0	36.0	59.0
SimBaseline (Xu et al., 2021)	R-101c	COCO-Stuff-156	-	-	15.3	-	74.5
ZegFormer (Ding et al., 2022)	R-50	COCO-Stuff-156	-	-	16.4	-	80.7
OpenSeg (Ghiasi et al., 2021)	R-101	COCO Panoptic	4.0	6.5	15.3	36.9	60.0
OVSeg (Ours)	R-101c	COCO-Stuff-171	7.1	11.0	24.8	53.3	92.6
<hr/>							
LSeg+ (Ghiasi et al., 2021)	Eff-B7	COCO Panoptic	3.8	7.8	18.0	46.5	-
OpenSeg (Ghiasi et al., 2021)	Eff-B7	COCO Panoptic	6.3	9.0	21.1	42.1	-
OVSeg (Ours)	Swin-B	COCO-Stuff-171	9.0	12.4	29.6	55.7	94.5
<hr/>							
<i>Supervised specialist models.</i>							
FCN (Long et al., 2015)	FCN-8s	Same as test	-	-	29.4	37.8	-
DeepLab (Chen et al., 2017)	R-101	Same as test	-	-	-	45.7	77.7
SelfTrain (Zoph et al., 2020)	Eff-L2	Same as test	-	-	-	-	90.0

Our model outperforms the state-of-the-art OpenSeg by a **+8.5%** margin.

For the first-time, we show open-vocabulary generalist models can **match the performance of supervised specialist** model.

OVSeg + Segment_Anything

class names


obama, clinton, bush

Proposal generator

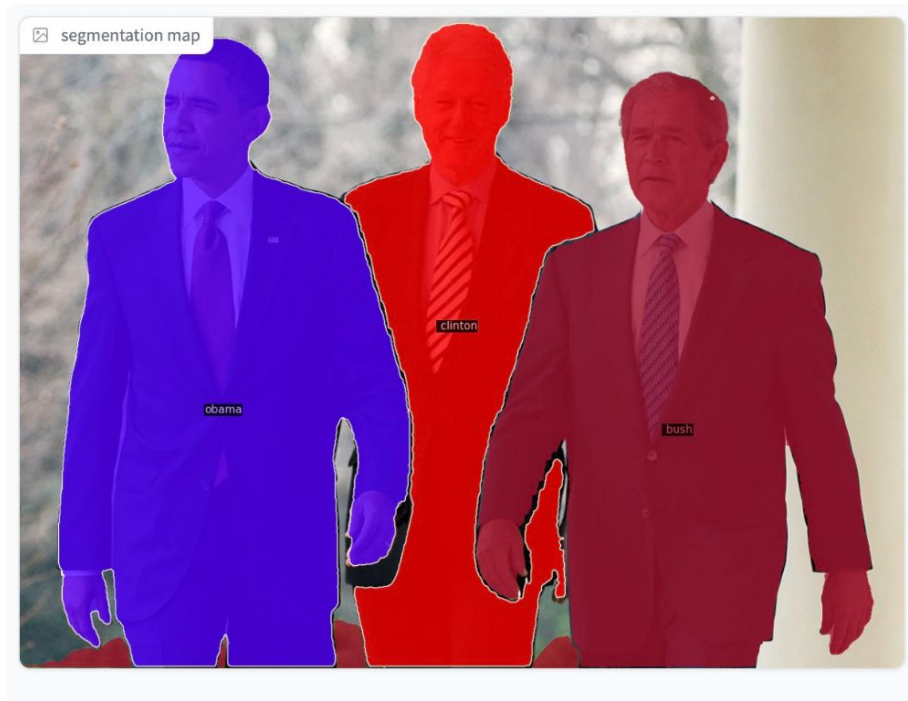
Segment_Anything MaskFormer

For Segment_Anything only, granularity of masks from 0 (most coarse) to 1 (most precise)

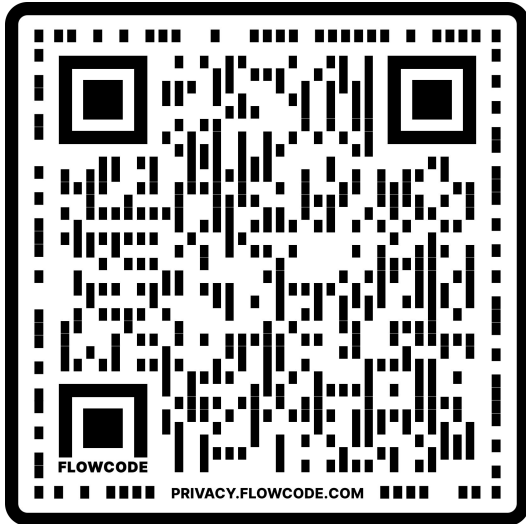
input_img



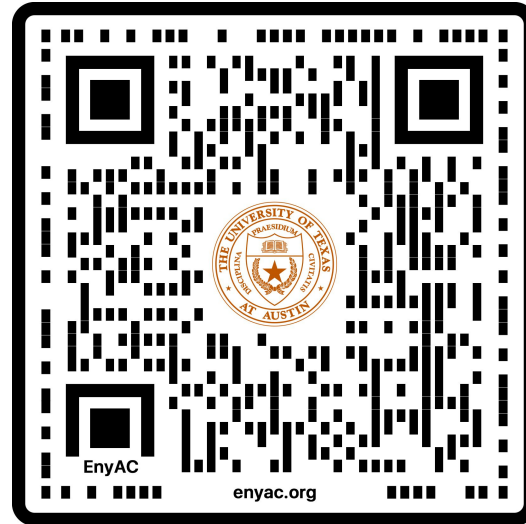
Clear Submit



Feel free to try our model /codes /demo !



OVSeg project



Our EnyAC group