

Problem & Contributions



- How can we extract pixel-level semantic information? \rightarrow Using the **cross-attention maps** yielded during the diffusion process.
- How can we obtain semantic information from **non-prompt** words? → By introducing an independent **attribution prompt** to compute open-vocabulary attention maps (OVAM) in a training-free manner.
- How to choose the attribution prompt to segment a given class? \rightarrow Learning a specific embedding for the attribution prompt employing our token optimization.

Visual Summary

Open-Vocabulary Attention Maps









Prompt: aeroplane parked at an airport in the city. Attentions: Aeroplane

Open-vocabulary pixel-level annotations generated using OVAM

Prompt: monkey with hat walking. **Attentions**: monkey, mouth





Prompt: someone jumping in the air on their snowboard



Prompt: a photo of a lion on a mountain top at sunset



Open-Vocabulary Attention Maps with Token Optimization for Semantic Segmentation in Diffusion Models

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Open-Vocabulary Attention Maps

Attention Maps with Optimized Token



Prompt: a car driving under the sea on the ocean floor





Denoising network



Attention Maps

Attention with (right) and without (left) optimized tokens



Method

Training-free methods DAAM DAAM + token optimization Attn2Mask Attn2Mask + *token opt*. OVAM (ours) OVAM + *token optimization* Methods with additional train DatasetDM DatasetDM + token opt. Grounded Diffusion Grounded Diffusion + token of



Segmentation Masks

Segmentation Masks with (right) and without (left) optimized tokens





Video Processing and Understanding

Evaluation of Optimized Tokens

Selected classes (COCO-cap IoU %)											Dataset (mIoU %)	
	aeroplane	bicycle	boat	bus	car	cat	cow	dog	motorbike	person	VOC-sim	COCO-cap
	•											•
	30.6	33.8	31.9	82.6	42.8	83.0	64.6	77.9	44.6	22.7	66.2	48.4
	59.1	67.2	61.2	92.8	63.4	83.6	77.9	79.0	72.4	56.9	79.7	66.1
	49.3	56.0	$4\bar{5}.\bar{5}$	85.8	48.2	$7\bar{2}.\bar{6}$	71.0	69.4	62.4	$2\overline{0}.\overline{7}$	$-\overline{68.7}^{}$	55.0
	59.3	67.2	61.4	92.9	63.1	83.6	77.9	78.9	72.5	56.9	81.9	66.1
	65.1	64.3	51.9	84.9	47.5	67.9	76.5	65.8	69.4	19.7	70.4^{-7}	58.2
	67.8	68.4	64.6	94.5	63.2	87.6	82.4	81.9	74.2	60.9	82.5	69.2
ing												
	74.1	25.7	71.3	91.4	51.9	76.2	90.1	71.7	56.4	52.2	80.3	59.3
	73.7	26.7	71.2	95.1	53.5	81.2	89.9	80.8	67.0	53.5	80.6	60.5
	84.6	54.9	30.8	81.4	$\bar{25.1}$	87.3	73.7	84.4		51.8	$-\bar{6}2.1^{}$	-50.2
pt.	88.3	75.9	67.1	95.0	54.3	89.0	78.1	85.5	85.6	79.1	86.6	73.3



Website

github.com/vpulab/ovam