

# OW-VISCapTor: Abstractors for Open-World Video Instance Segmentation and Captioning

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Wed, Dec 11, Poster Session 2 (4:30 - 7:30 p.m. PST)



#### Overview



# New task: Open-World Video Instance Segmentation and Captioning (OW-VISCap)



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### Open-World Video Instance Segmentation and Captioning (OW-VISCap)





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### Open-World Video Instance Segmentation and Captioning (OW-VISCap)

Detect, segment and track objects across frames



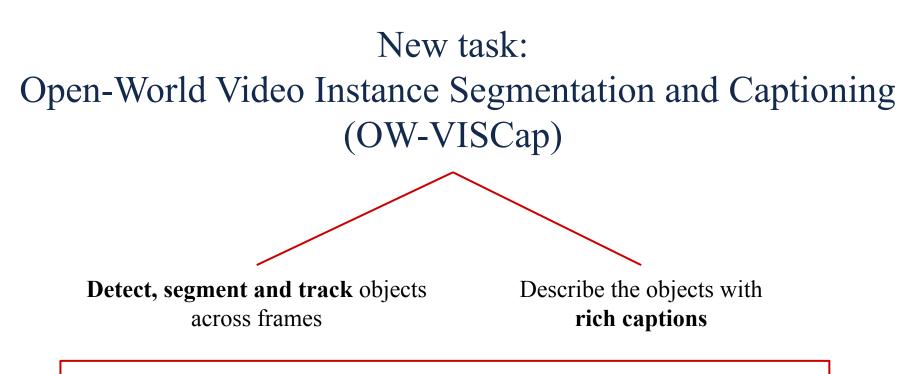
#### New task:

Open-World Video Instance Segmentation and Captioning (OW-VISCap)

**Detect, segment and track** objects across frames

Describe the objects with rich captions





For both seen (closed-world) or never before seen (open-world) objects

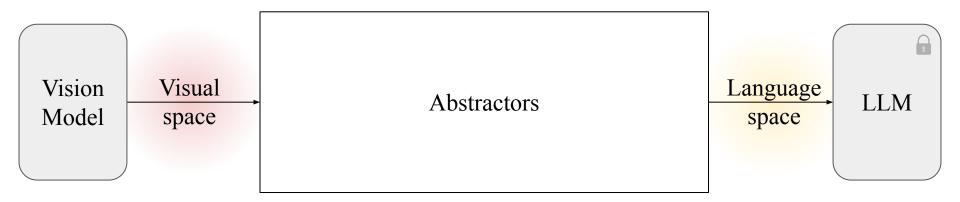


#### OW-VISCap: Addressed by Abstractors

Abstractors

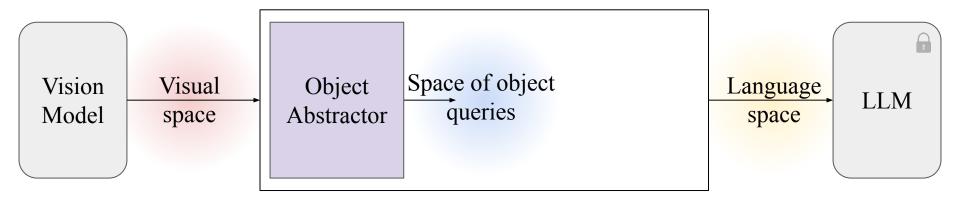


#### OW-VISCap: Addressed by Abstractors



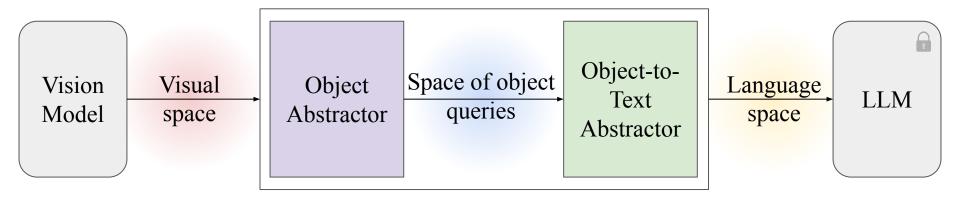


### Addressed by Developing Abstractors





### Addressed by Developing Abstractors





#### **OW-VISCapTor:** Evaluation

Open-World Video Instance Segmentation **OWTA improved by 5.6 points**  Dense Video Object Captioning CapA improved by 7.1 points



### Motivation



Choudhuri et al., CVPR 2023
 Huang et al., NeurIPS 2022
 Wang et al., CVPR 2021

#### Prior Work on VIS

#### Assigns one word label to segmented objects [1, 2, 3] in the closed world

# car, car, pedestrian, pedestrian, pedestrian, pedestrian, pedestrian, pedestrian, pedestrian, pedestrian





Choudhuri et al., CVPR 2023
 Huang et al., NeurIPS 2022
 Wang et al., CVPR 2021

### Prior Work on VIS

Assigns one word label to segmented objects [1, 2, 3] in the closed world

One word labels convey a limited information

car, car, pedestrian, pedestrian, pedestrian, pedestrian, pedestrian, pedestrian, pedestrian, pedestrian, pedestrian





[1] Jin et al., NeurIPS 2022[2] Li et al., arXiv 2023

## Prior Work on Captioning

Video-level or image-level captioning [1, 2]

#### A street with people walking and cars driving





[1] Jin et al., NeurIPS 2022[2] Li et al., arXiv 2023

### Prior Work on Captioning

Video-level or image-level captioning [1, 2]

Doesn't capture object-centric details

A street with people walking and cars driving





#### New Task: OW-VISCap

a car is driving down the street a car driving down the street a woman walking down the street a man with a crutch crossing the street a woman is standing at a red table by the side of a street a trash can by the side of a street





#### New Task: OW-VISCap

a man with a crutch crossing the street





#### OW-VISCapTor to Address OW-VISCap

AbstracTors for Open-World Video Instance Segmentation and Captioning



#### OW-VISCapTor to Address OW-VISCap

AbstracTors for Open-World Video Instance Segmentation and Captioning

Networks that project information from one space to another



### Abstractors for OW-VISCap: Challenges

• Haven't been explored to connect object and language spaces



### Abstractors for OW-VISCap: Challenges

- Haven't been explored to connect object and language spaces
- How to extend them to the open-world without prompts?



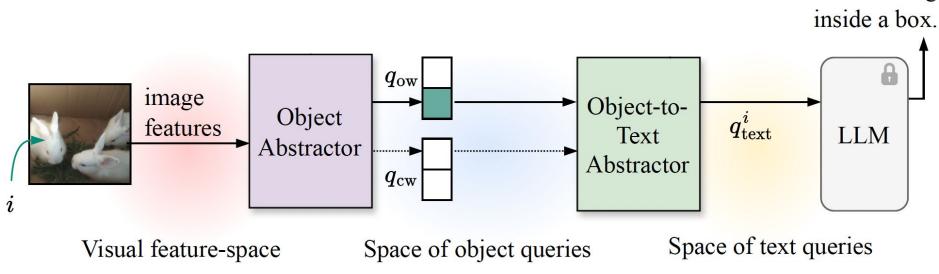


# OW-VISCapTor

 $q_{ow}$ : open-world object queries  $q_{cw}$ : closed-word object queries  $q_{text}^i$ : text query for *i*-th object

A rabbit sitting

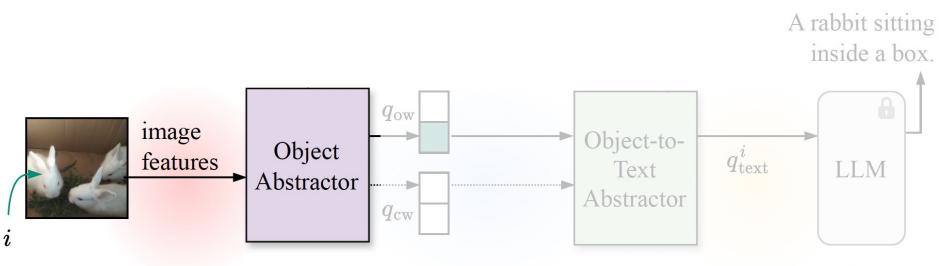
#### OW-VISCapTor





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### **Open-World Object Discovery**



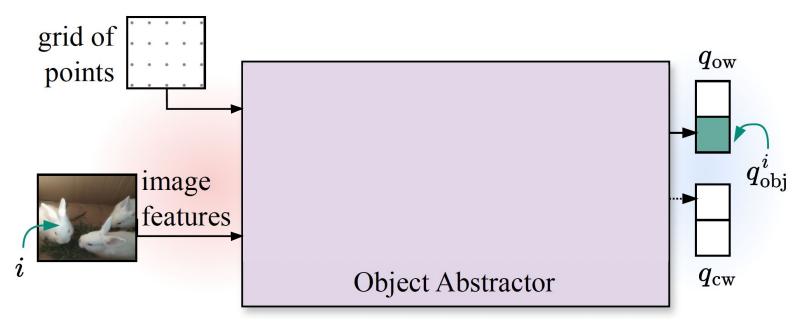
Visual feature-space

Space of object queries

Space of text queries

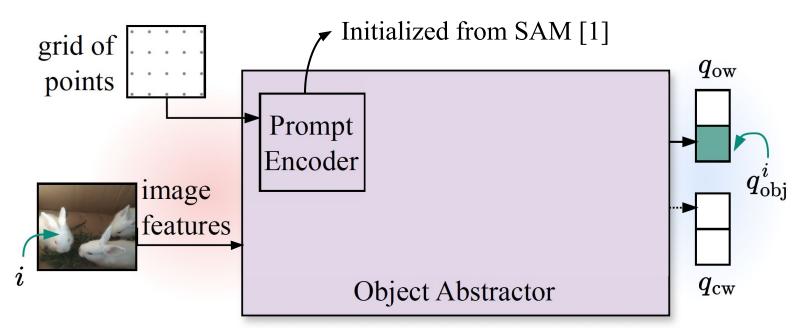


 $q_{ow}$ : open-world object queries  $q_{cw}$ : closed-word object queries  $q_{obj}^i$ : *i*-th object query





#### $q_{ow}$ : open-world object queries $q_{cw}$ : closed-word object queries $q_{obj}^i$ : *i*-th object query





 $e_{ow}$ : open-world embeddings  $q_{ow}$ : open-world object queries  $q_{cw}$ : closed-word object queries  $q_{obj}^{i}$ : *i*-th object query

#### grid of $q_{ m ow}$ points $e_{\rm ow}$ Prompt Encoder $q^{*}_{ m obj}$ image features i $q_{ m cw}$ **Object Abstractor**



#### grid of $q_{\mathrm{ow}}$ points $e_{\rm ow}$ Prompt Encoder $q_{ m obj}^{\,\prime}$ image features $e_{\rm cw}$ i $q_{\rm cw}$ **Object Abstractor**



#### grid of $q_{ m ow}$ points $e_{\rm ow}$ Prompt Transformer Encoder $q_{ m obj}^{\iota}$ Decoder image features $e_{\rm cw}$ i $q_{\rm cw}$ **Object Abstractor**



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 $q_{ow}$ : open-world object queries  $q_{cw}$ : closed-word object queries  $q_{text}^i$ : text query for *i*-th object DH: Detection Head

#### mask of igrid of A rabbit sitting DH inside a box. points $q_{\rm ow}$ image Object-to-Object $q^i_{ m text}$ features Text Abstractor Abstractor $q_{ m cw}$

Visual feature-space

**Object-Centric Captioning** 

Space of object queries

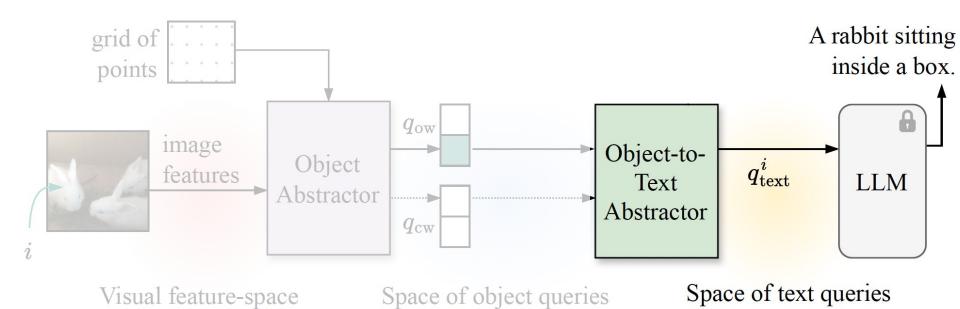
Space of text queries



i

 $q_{ow}$ : open-world object queries  $q_{cw}$ : closed-word object queries  $q_{text}^i$ : text query for *i*-th object

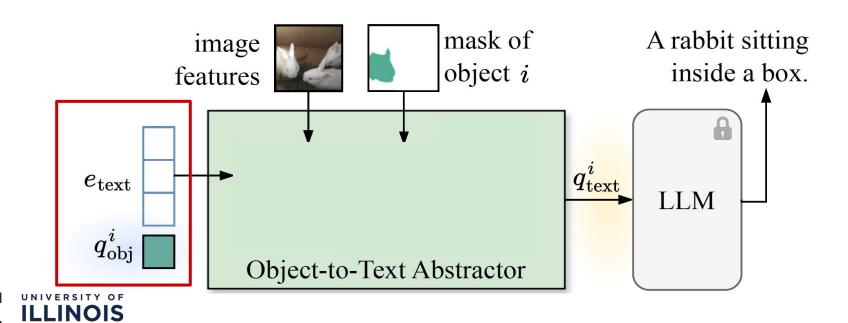
## **Object-Centric Captioning**



UNIVERSITY OF

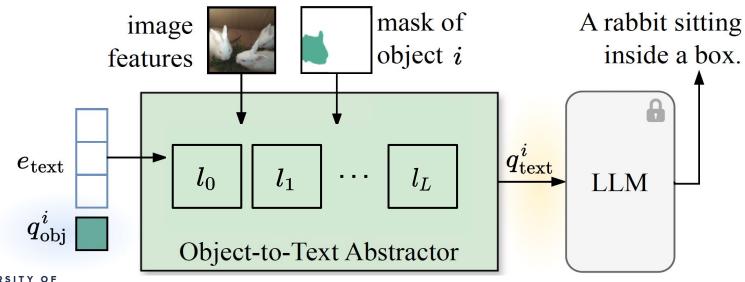
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## **Object-Centric Captioning**



 $e_{\text{text}}$ : text embeddings  $q_{\text{obj}}^{i}$ : *i*-th object query  $q_{\text{text}}^{i}$ : text query for *i*-th object

## **Object-Centric Captioning**





#### Results



#### Results on BURST [1] Dataset

Segmentation of open-world and closed-world objects

[1] Athar et al., WACV 2023
 [2] Liu et al.' CVPR 2022
 [3] Cheng et al., CVPR 2022
 [4] Cheng et al., Neurips 2021
 [5] Cheng et al., ICCV 2023
 [6] Qi et al., PAMI 2022

Method	Accuracy		
	Unseen	Overall	Seen
OWTB [2]	38.8	55.8	59.8
Mask2Former [3] + STCN [4]	25.0	64.6	71.0
Mask2Former [3] + DEVA [5]	42.3	69.5	74.6
EntitySeg [6] + DEVA [5]	<u>49.6</u>	68.8	72.7
Ours + DEVA [5]	55.2	<u>69.0</u>	<u>73.5</u>



Zhang et al., CVPR 2020
 Zhou arXiv 2023
 Choudhuri et al., CVPR 2023

#### Results on VidSTG [1] Dataset

Bounding box detections and captioning on closed-world objects

		Captioning	Overall
Method	Mode	accuracy	accuracy
DenseVOC-DS (joint training) [2]	offline	36.8	51.6
DenseVOC-DS (disjoint training) [2]	offline	10.0	28.0
Ours + CAROQ [3]	online	43.9	53.1





<u>a large construction</u> <u>truck with a trailer on it.</u>

a car is driving in the rain on a street.

...





#### <u>a large construction</u> <u>truck with a trailer on it.</u>

# a car is driving in the rain on a street.

<u>a tractor with black and</u> <u>orange front and rear.</u>

a woman is riding an orange lawn mower.

a white dog near a tractor.





#### To Summarize

• We propose a new task: Open-World Video Instance Segmentation and Captioning (OW-VISCap).



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- We propose a new task: Open-World Video Instance Segmentation and Captioning (OW-VISCap).
- OW-VISCapTor:
  - **Object abstractor**: spatially rich open-world object queries
  - **Object-to-text abstractor**: rich object-centric captions



#### To Summarize

- We propose a new task: Open-World Video Instance Segmentation and Captioning (OW-VISCap).
- OW-VISCapTor:
  - **Object abstractor**: spatially rich open-world object queries
  - **Object-to-text abstractor**: rich object-centric captions
- Our generalized approach surpasses individual SOTA on open-world object discovery and video object captioning



#### Thank You!

Please visit our poster on

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Website:

https://anwesachoudhuri.github.io/OpenWorldVISCap/

