

Video Instance Segmentation (VIS)

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Presented by Amit, Michael, and Jun

VIS takes inspiration from the image domain

Motivation

- Detects boundaries of objects
- Classifies objects
- Demarcates separate instances of each class
- Each pixel is assigned a specific object instance (or to the background)

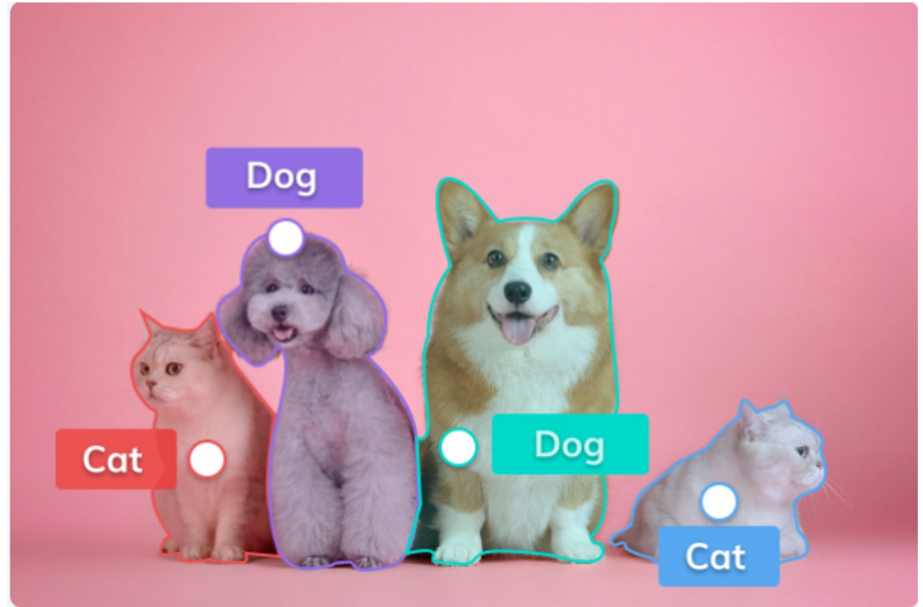


Image Instance Segmentation

Motivation

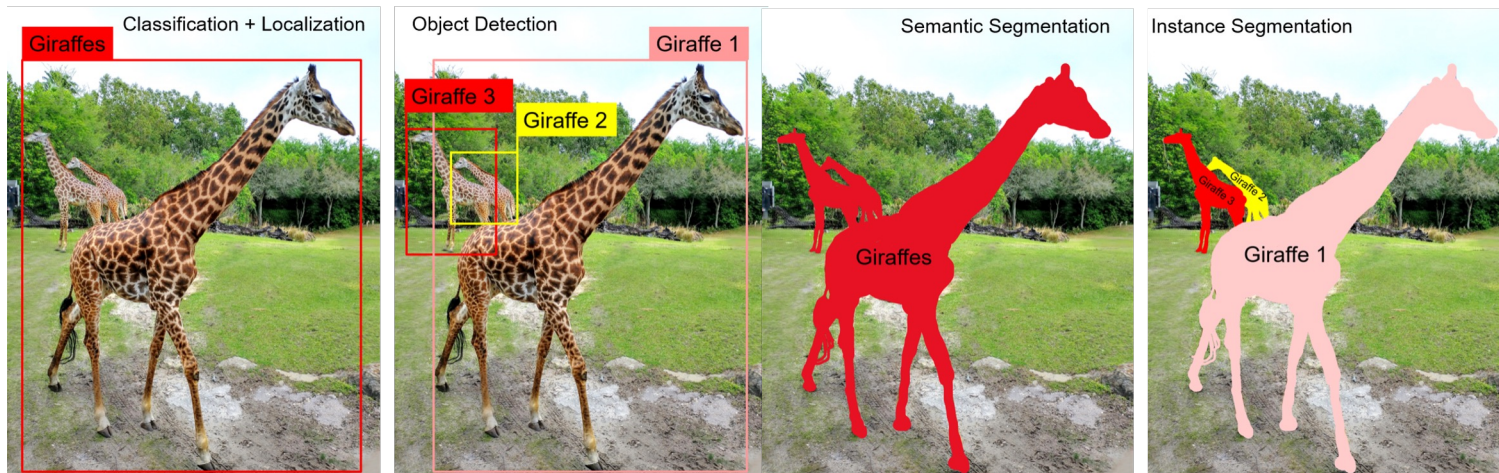


Image Instance Segmentation **combines** ideas of other image-based tasks

VIS brings this idea to the video domain

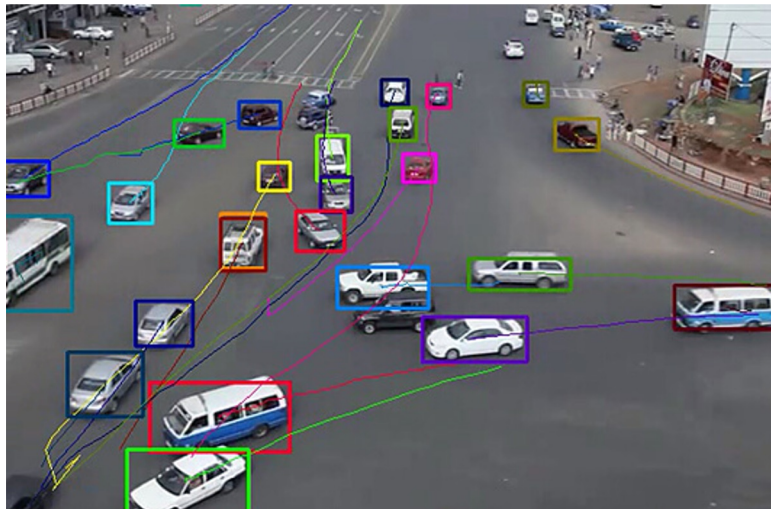
Past Work

Video Object Tracking

Video Object
Detection

Video Semantic
Segmentation

Video Object
Segmentation



Track objects in a video given their initial bounding box

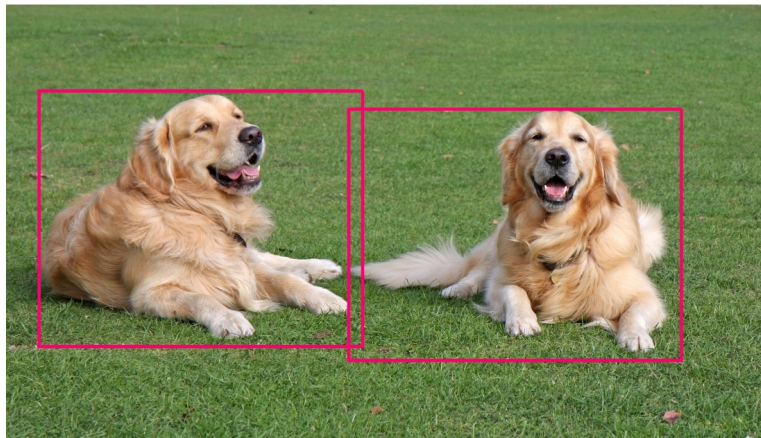
Past Work

Video Object Tracking

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Video Object
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Detect objects within a video without any initialization

Past Work

Video Object Tracking

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Video Semantic
Segmentation

Video Object
Segmentation



Image pixels are predicted as different semantic classes to understand objects and regions in a video

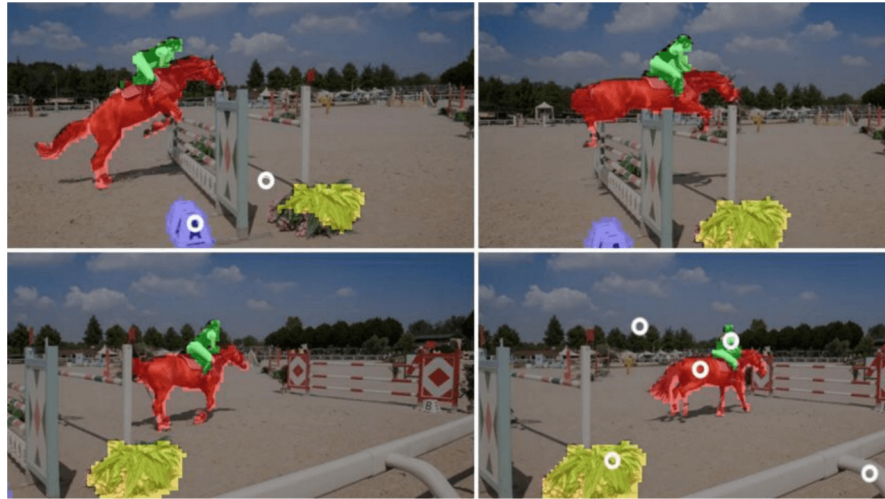
Past Work

Video Object Tracking

Video Object
Detection

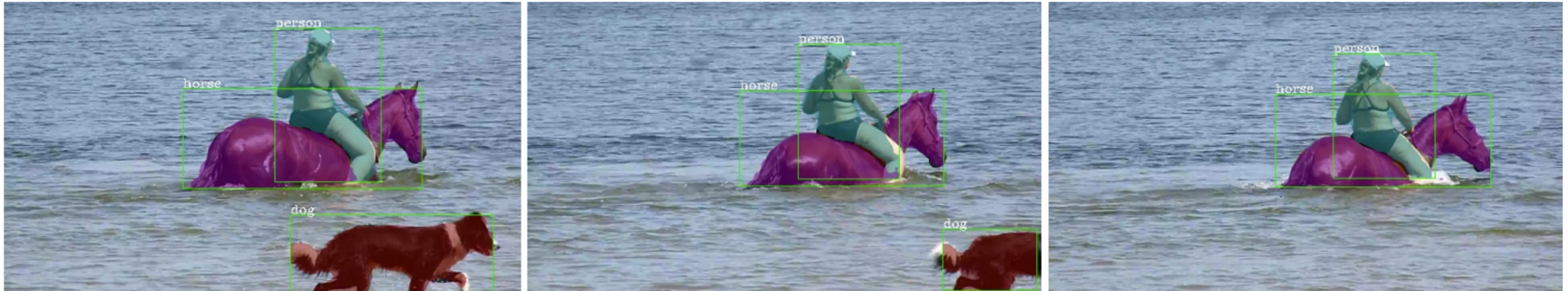
Video Semantic
Segmentation

Video Object
Segmentation



Segment the object from the background and follow changes in movement

Video Instance Segmentation



Simultaneous detection, segmentation, and tracking of object instances in videos across frames

To embark on a new research field, you need

1. A newly annotated benchmark that provides temporal instance labels.
 - a. No existing large-scale dataset can serve the purpose of VIS.

1. A newly designed model that can do
 - a. Object detection
 - b. Instance segmentation (object classification + segmentation)
 - c. Instance tracking

The dataset: Youtube-VIS

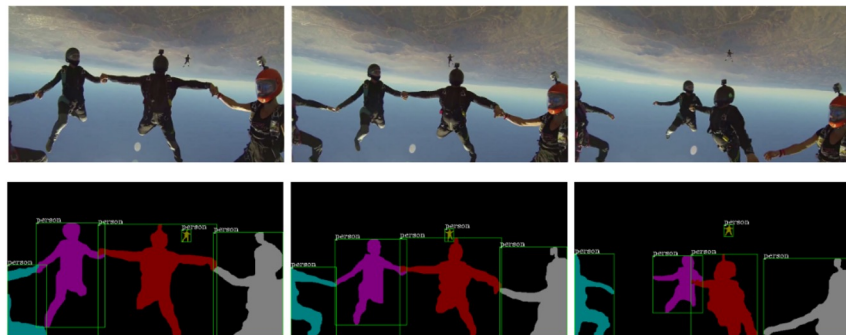
Youtube-VOS



- 4,453 youtube videos
- 94 categories
- 6,048 objects
- Object masks are not exhaustive



Youtube-VIS

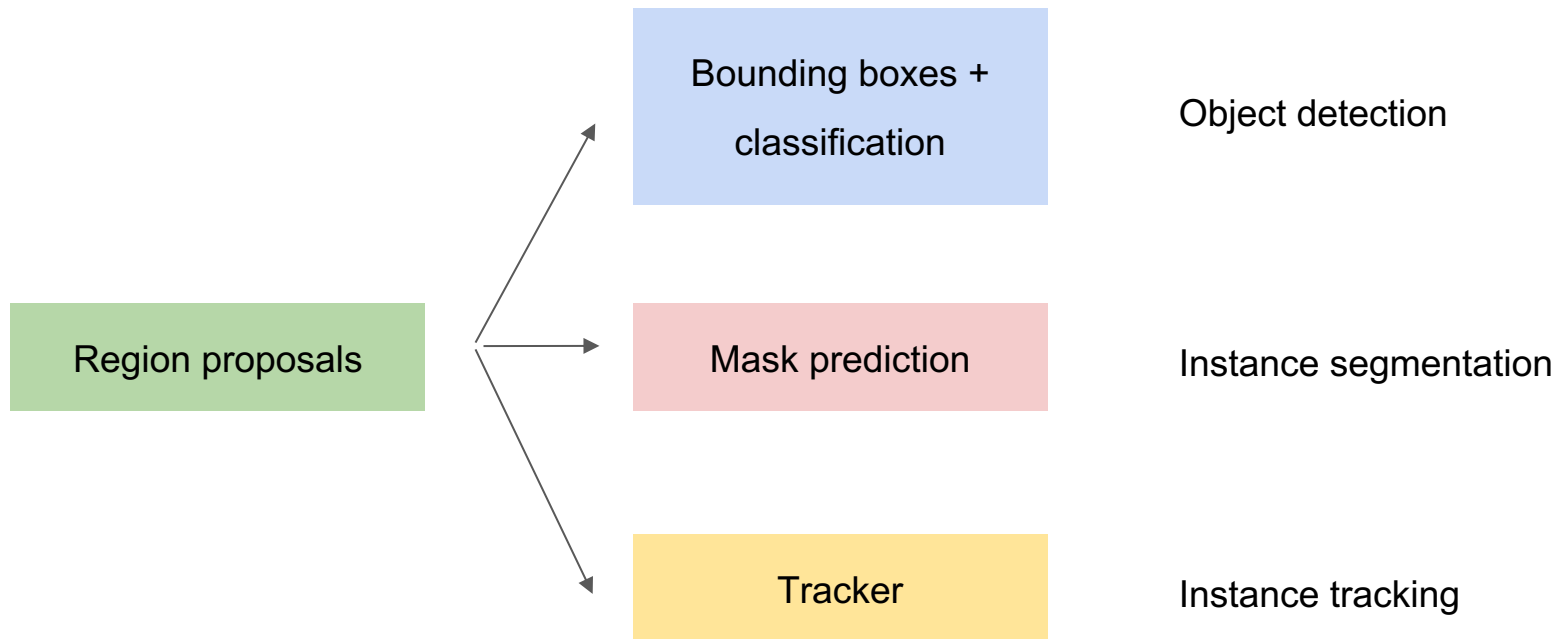


Selected:

- ~ 2,900 videos
- 40 categories
- 4,883 **unique** objects
- Exhaustively annotated

The model: Mask-Track R-CNN

Model breakdown

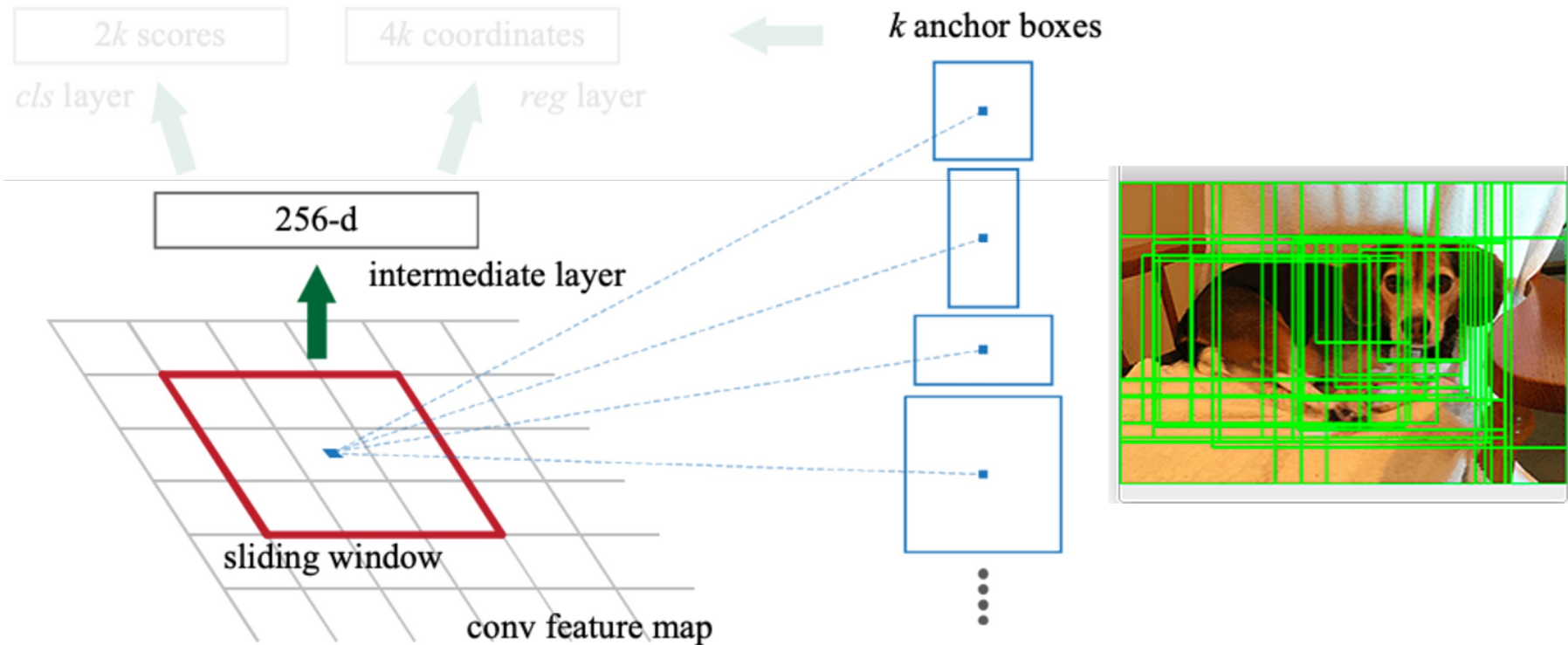


Region proposals

Bounding boxes +
classification

Mask prediction

Tracker

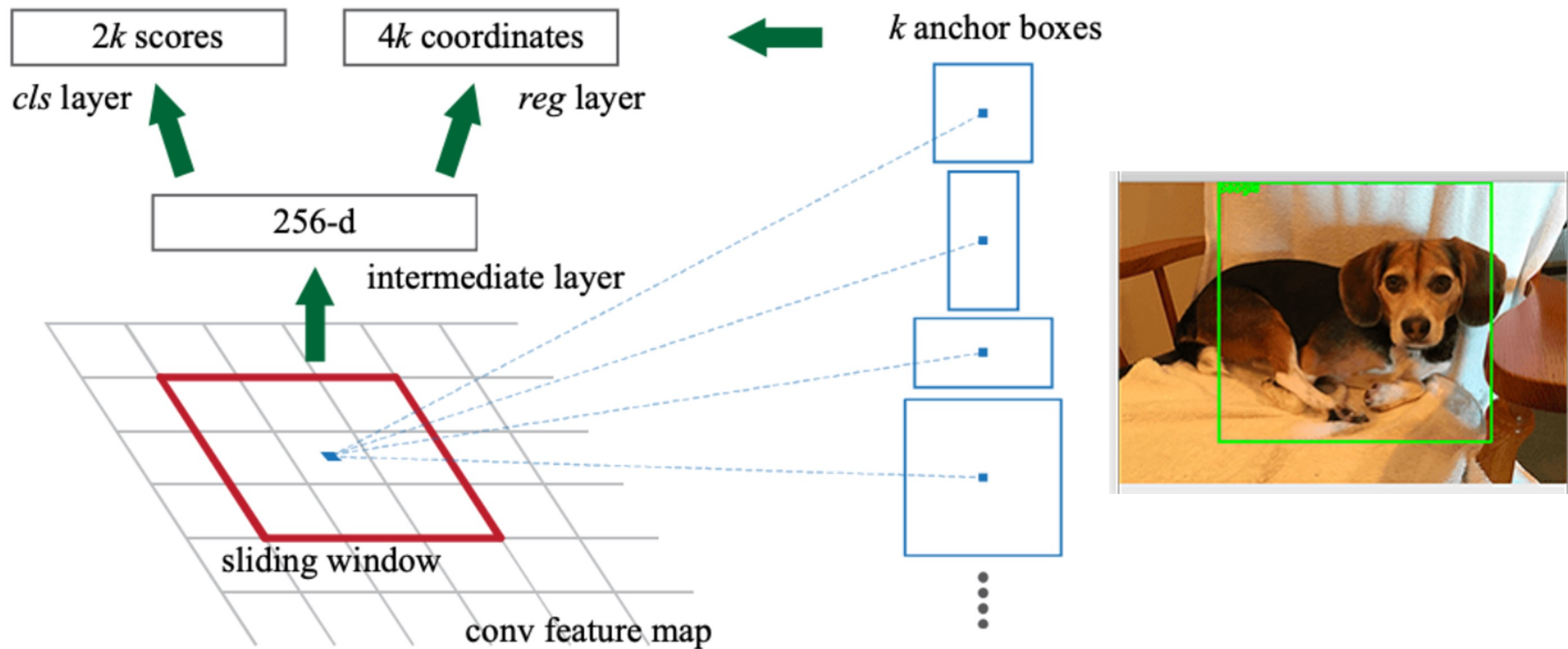


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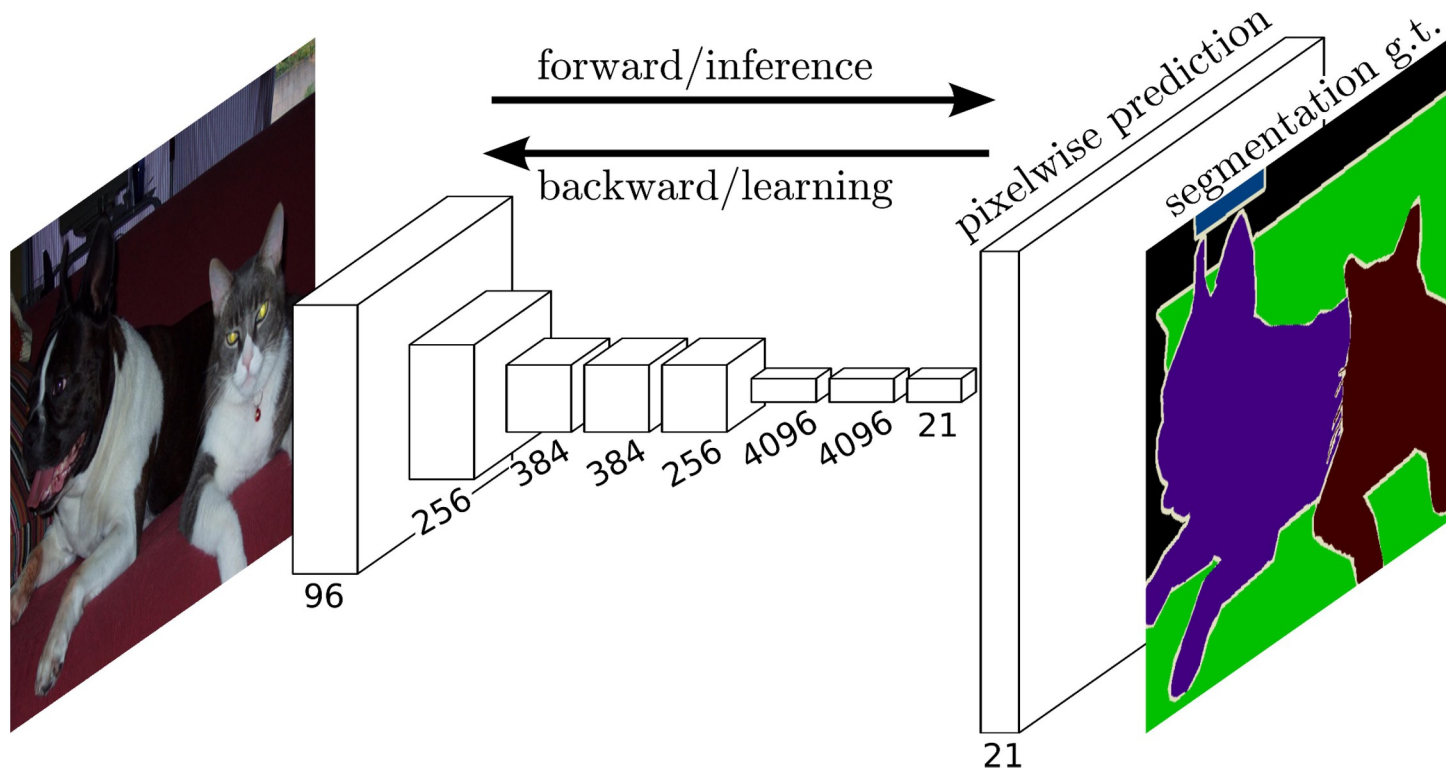


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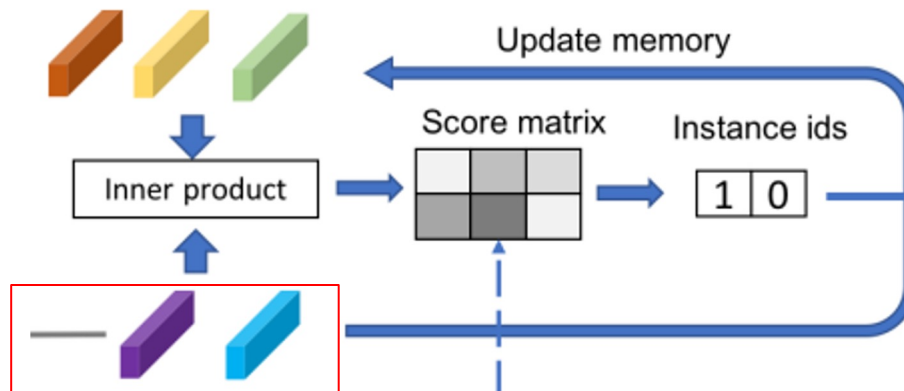
Region proposals

Bounding boxes +
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Mask prediction

Tracker

1. Extract feature vectors from the current frame



Region proposals

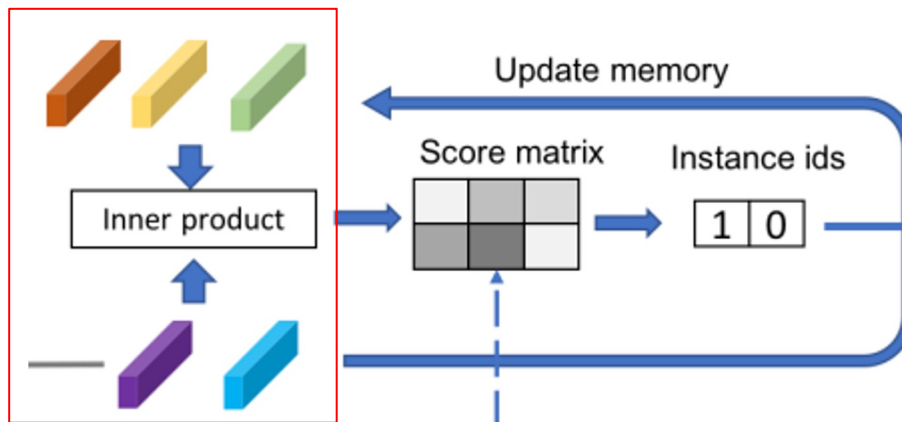
Bounding boxes +
classification

Mask prediction

Tracker

2. Similarity comparison (dot product)

Feature vectors from previous frames



Feature vectors from the current frame

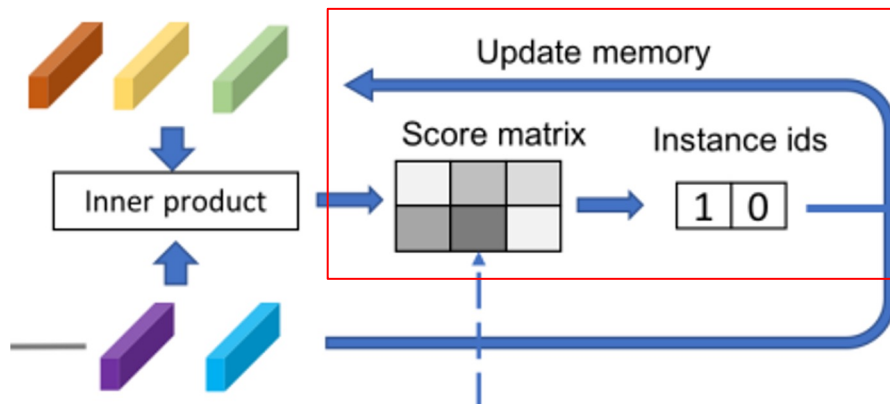
Region proposals

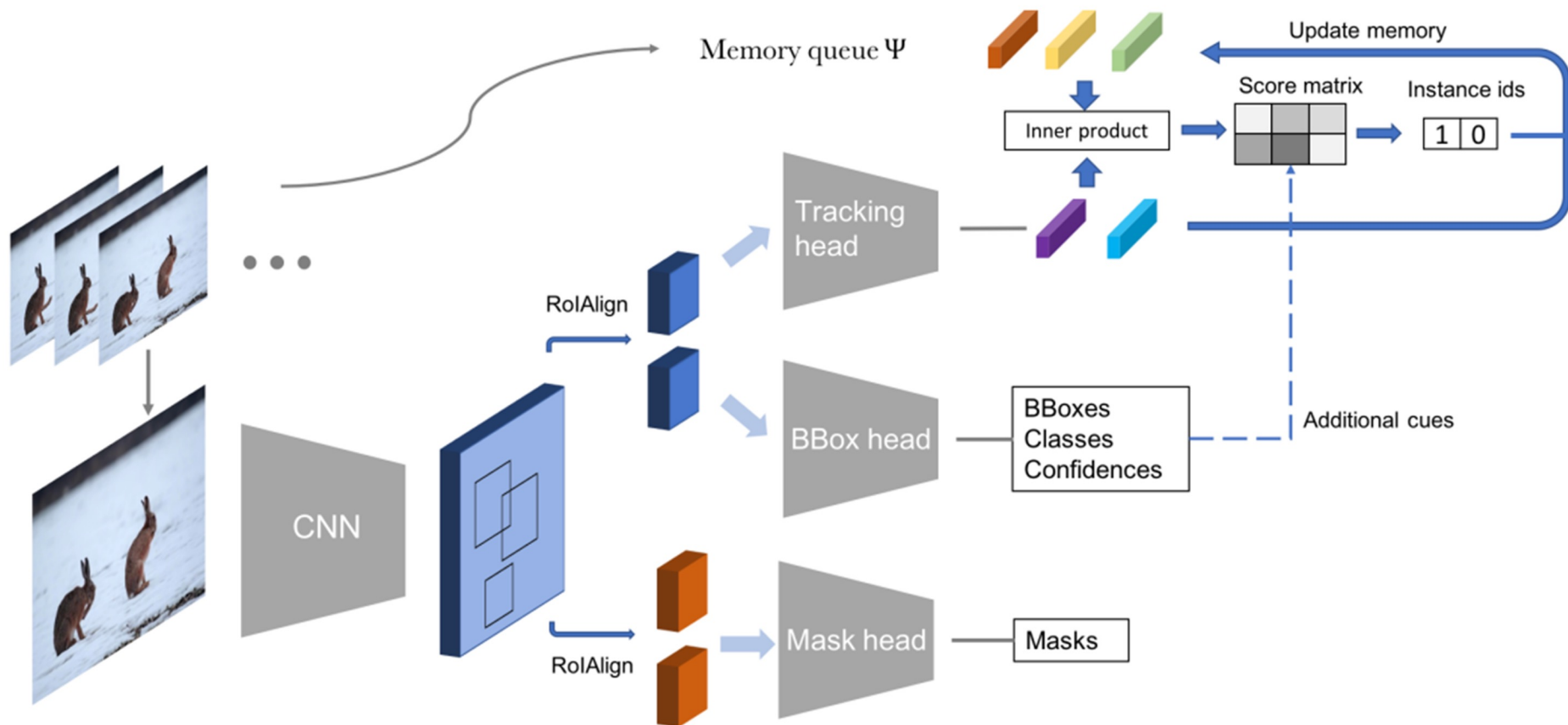
Bounding boxes +
classification

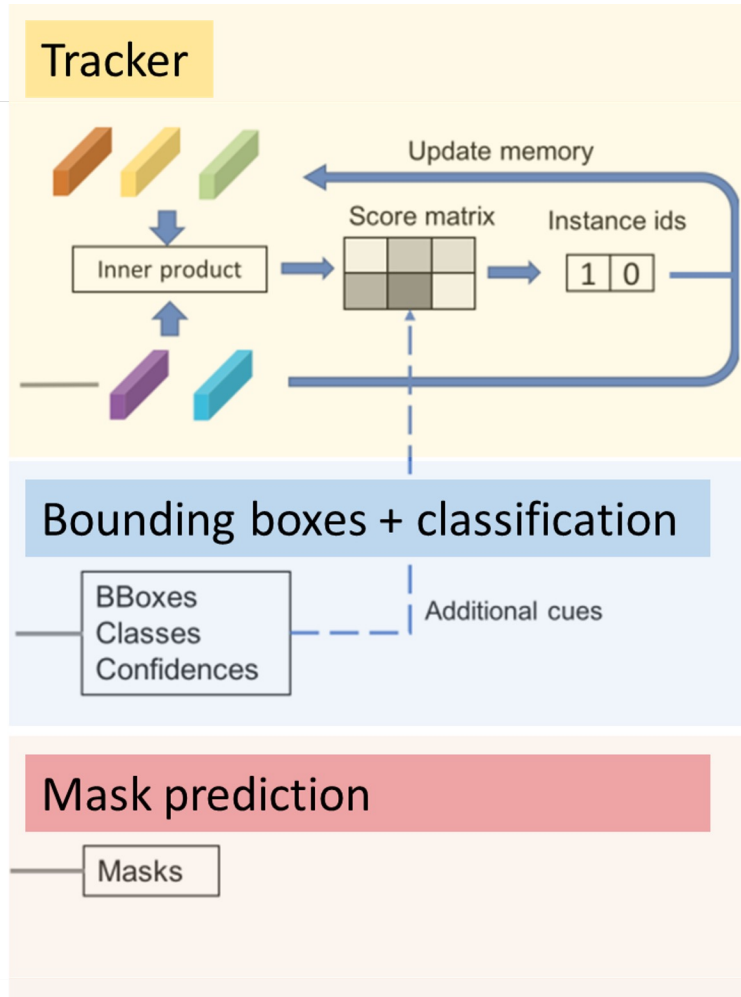
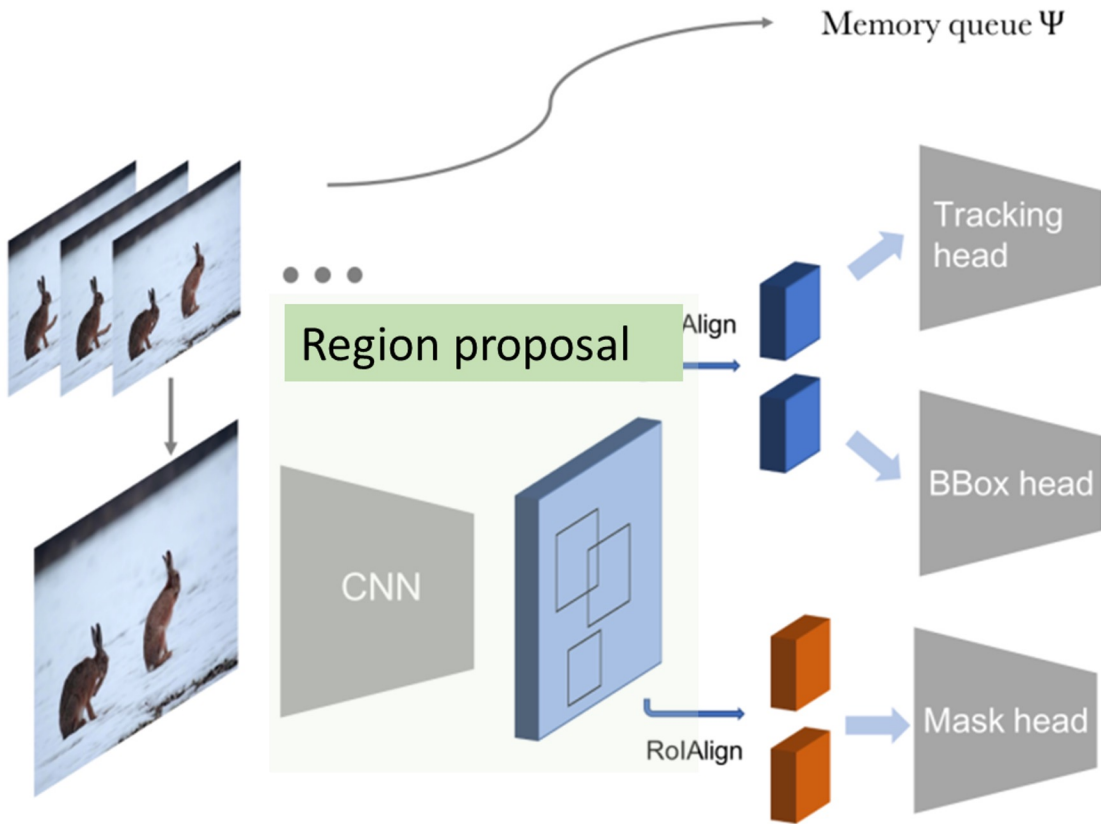
Mask prediction

Tracker

3. Assign instance labels and update the memory bank







Metrics

1. Average Precision (AP) : the area under the precision-recall curve
 - a. Precision : $TP / (TP + FP)$
 - b. Recall : $TP / (TP + FN)$
 - c. Intersection-over-union (IOU)
 - d. Precision-recall curve

1. Average Recall (AR)

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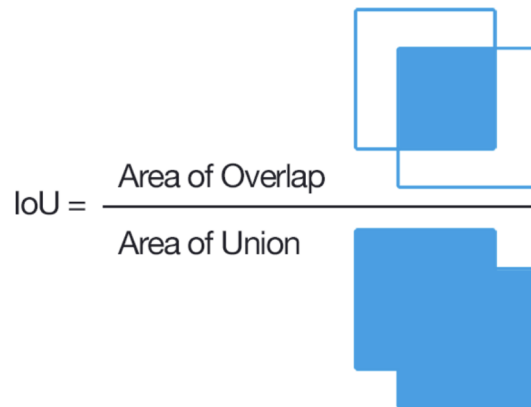
		Actual	
		Positive	Negative
Predicted	Positive	True Positive	False Positive
	Negative	False Negative	True Negative

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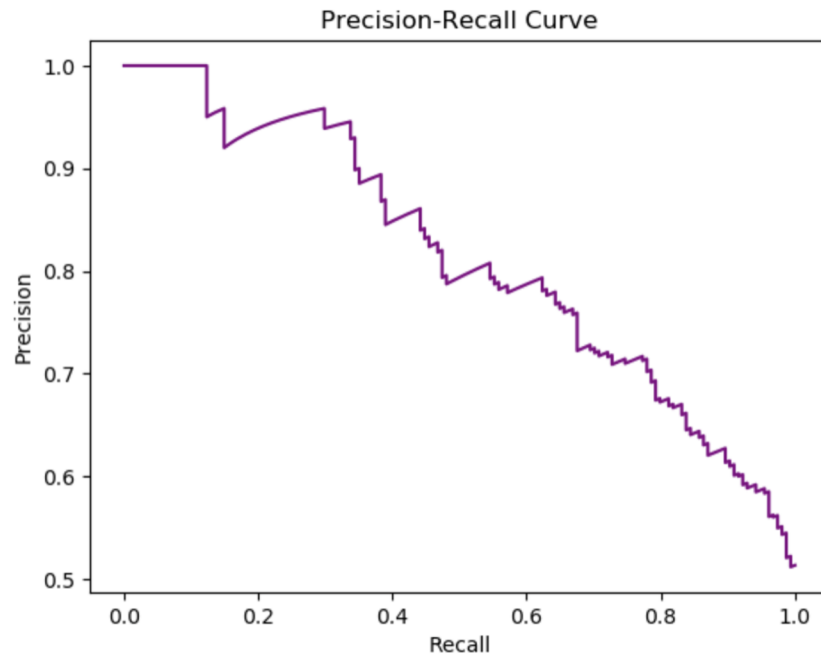
$$IoU(i, j) = \frac{\sum_{t=1}^T |\mathbf{m}_t^i \cap \tilde{\mathbf{m}}_t^j|}{\sum_{t=1}^T |\mathbf{m}_t^i \cup \tilde{\mathbf{m}}_t^j|}$$

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2. Average Recall (AR) : the maximum recall given some fixed number of segmented instance per video

- a. Recall : $TP / (TP + FN)$

		Actual	
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Predicted	Positive	True Positive	False Positive
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Evaluated per category -> averaged over the category set

Higher is better

Result & Experiments

The video-level prediction corrects these mistakes by majority voting of all frames.

1. Video-level prediction corrects mistakes by majority voting of all frames



1. Track the object after it disappears and reoccurs



Result & Experiments

Quantitative comparison to others

Methods		validation set					test set				
		AP	AP ₅₀	AP ₇₅	AR ₁	AR ₁₀	AP	AP ₅₀	AP ₇₅	AR ₁	AR ₁₀
Mask propagation	OSMN [36]	23.4	36.5	25.7	28.9	31.1	27.3	44.4	28.0	28.8	34.0
	FEELVOS [31]	26.9	42.0	29.7	29.9	33.4	29.6	45.4	30.7	33.4	36.8
Track-by-detect	IoUTracker+	23.6	39.2	25.5	26.2	30.9	25.2	41.9	26.2	28.7	33.7
	OSMN [36]	27.5	45.1	29.1	28.6	33.1	27.3	44.4	28.0	28.8	34.0
	DeepSORT [33]	26.1	42.9	26.1	27.8	31.3	27.2	44.0	29.2	29.1	33.3
	SeqTracker	27.5	45.7	28.7	29.7	32.5	29.5	48.1	31.2	32.0	34.5
	MaskTrack R-CNN	30.3	51.1	32.6	31.0	35.5	32.3	53.6	34.2	33.6	37.3

Thank you