The Emergence of Objectness: Learning Zero-shot Segmentation from Videos




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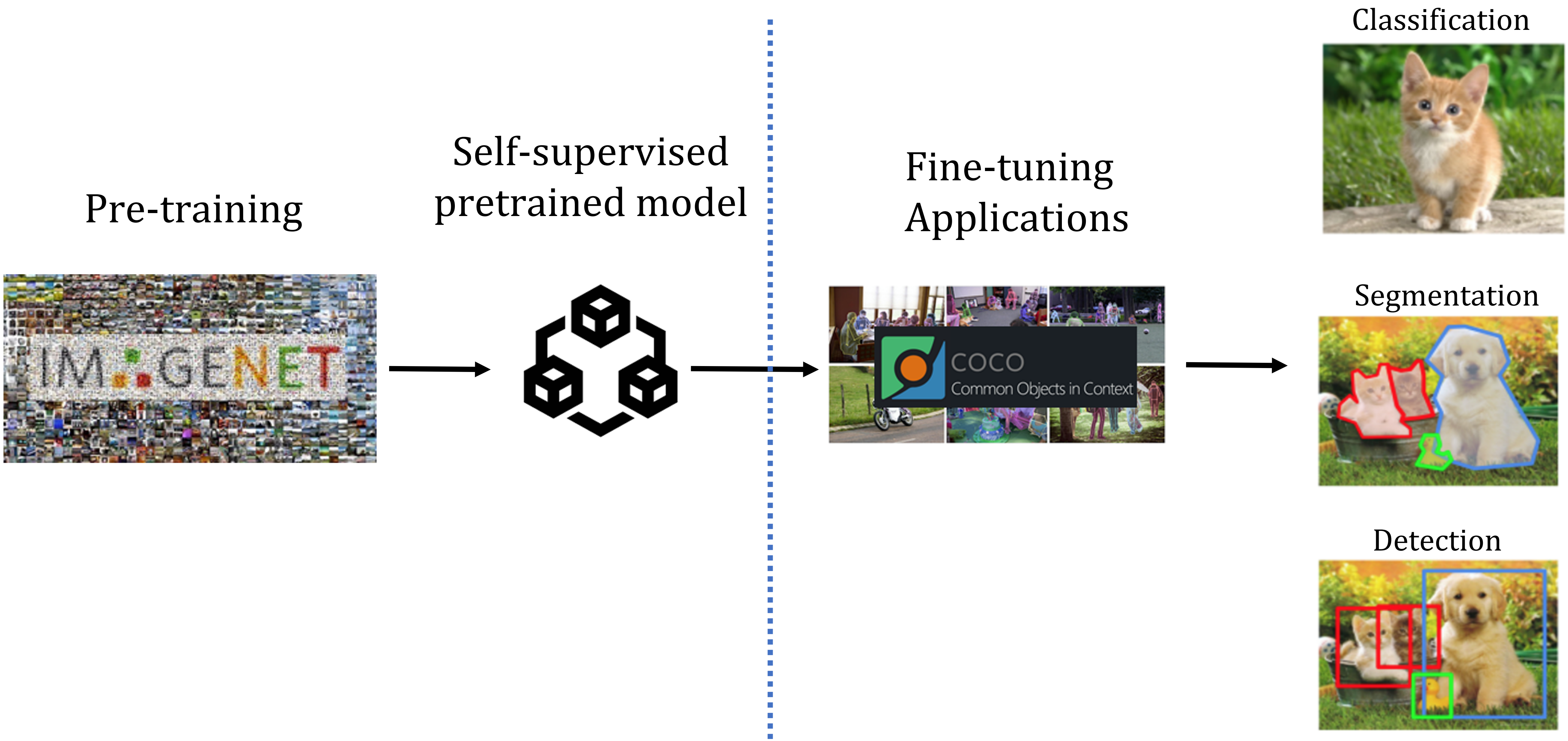
Current Usage of Self-supervised Learning



Current Usage of Self-supervised Learning

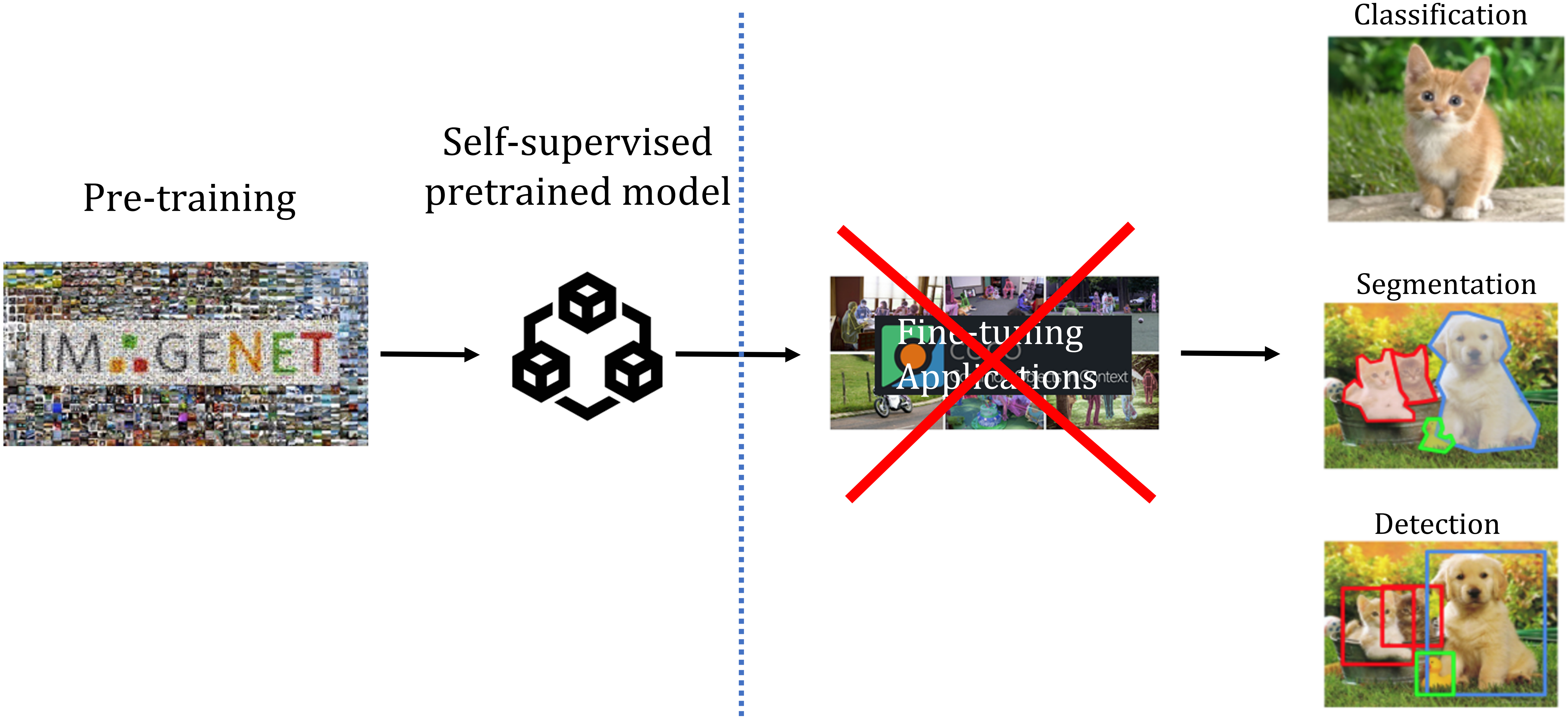
Pre-training

Self-supervised
pretrained model

A representation model

Not directly useful

Our Goal of Self-supervised Learning



Our Goal of Zero-shot Learning

Pre-training

Self-supervised
pretrained model

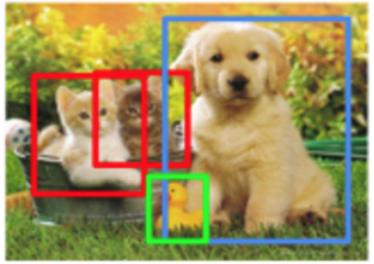
Direct Support
for Applications

No labels
No finetuning

Classification

Segmentation

Detection

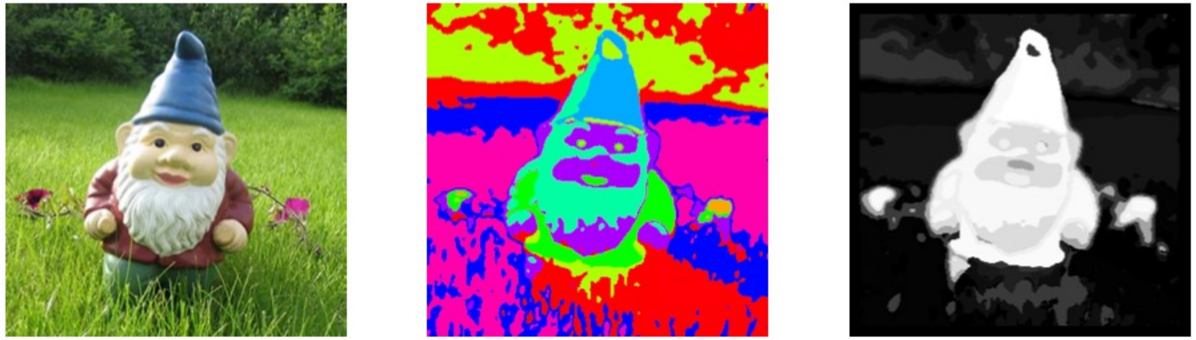


The Problem:
Segment Objects From an Image without Supervision

input

output

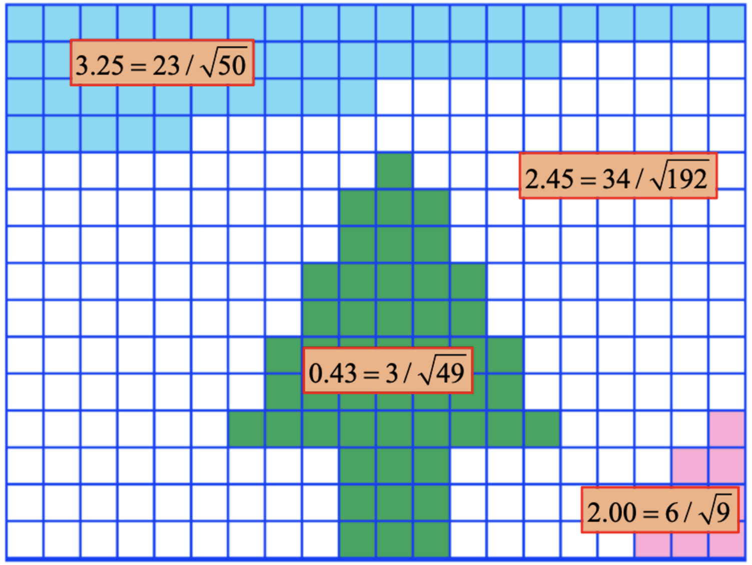
Existing Bottom-up Cues for Objectness Detection



Scharfenberger et al. 2014

the texture prior

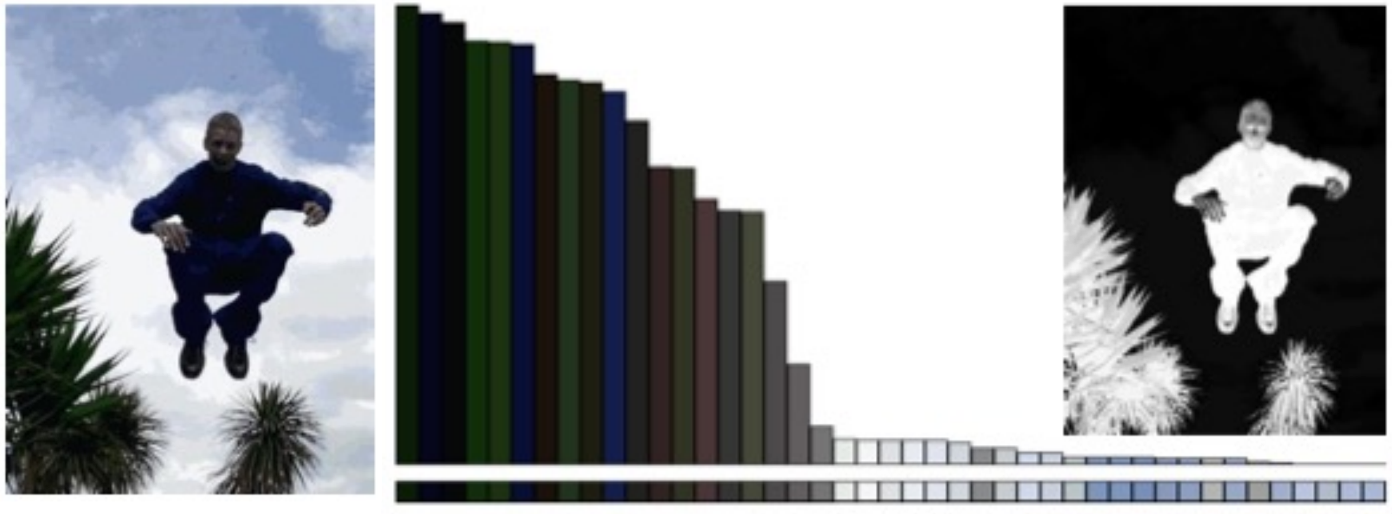
Distinctive region of textures different from the rest of the scene



Zhu et al. 2014

the center prior

regions that has least connectivity to the image bounder tend to be foreground



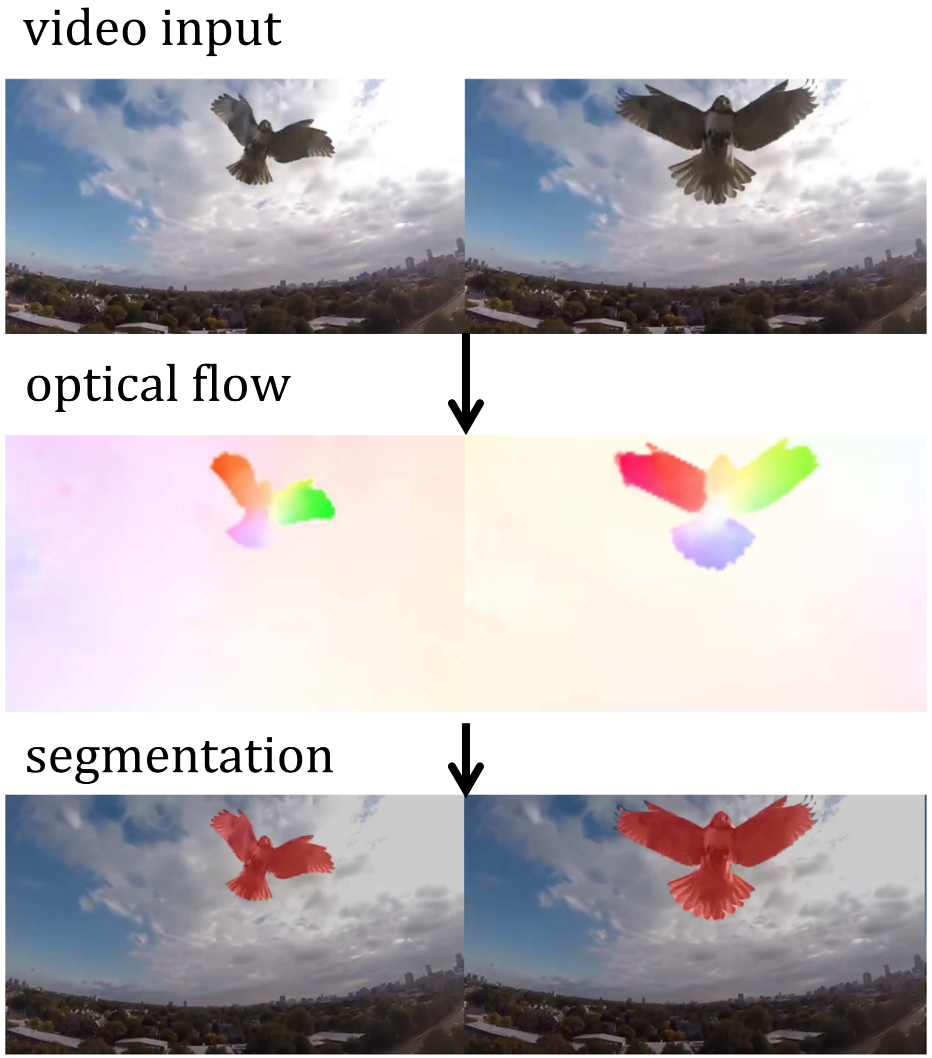
Cheng et al. 2016

the color contrast prior

high color contrast pixels tend to be the foreground

Bottom-up Motion Cues – Motion Segmentation

Group pixels having similar motions into a single region, following the common fate principle.



A series of work differs in:

[Sun 2012, Kumar 2008, Shi 1998, Yang 2019]

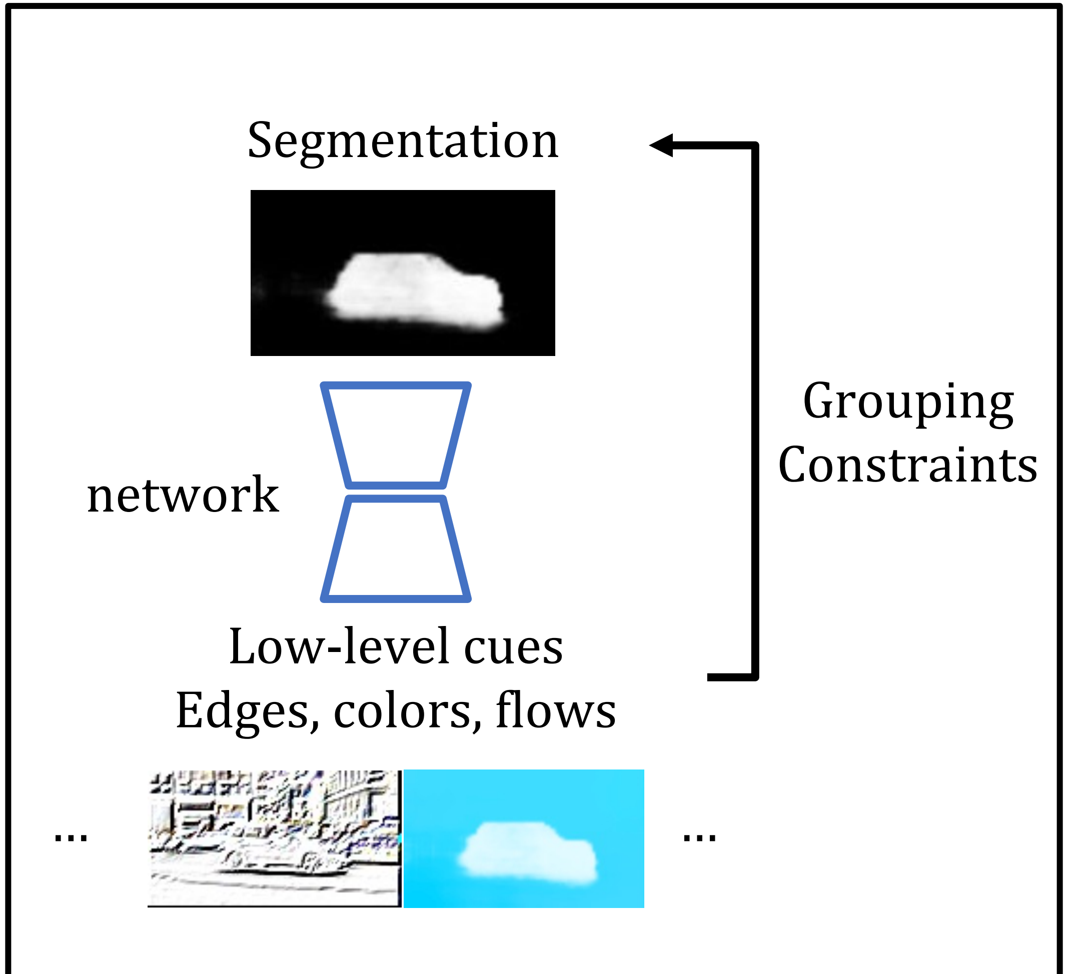
- Short-term or long-term analysis
- Whether to model occlusion
- Energy function to cluster the pixels

All requires a low-level input:

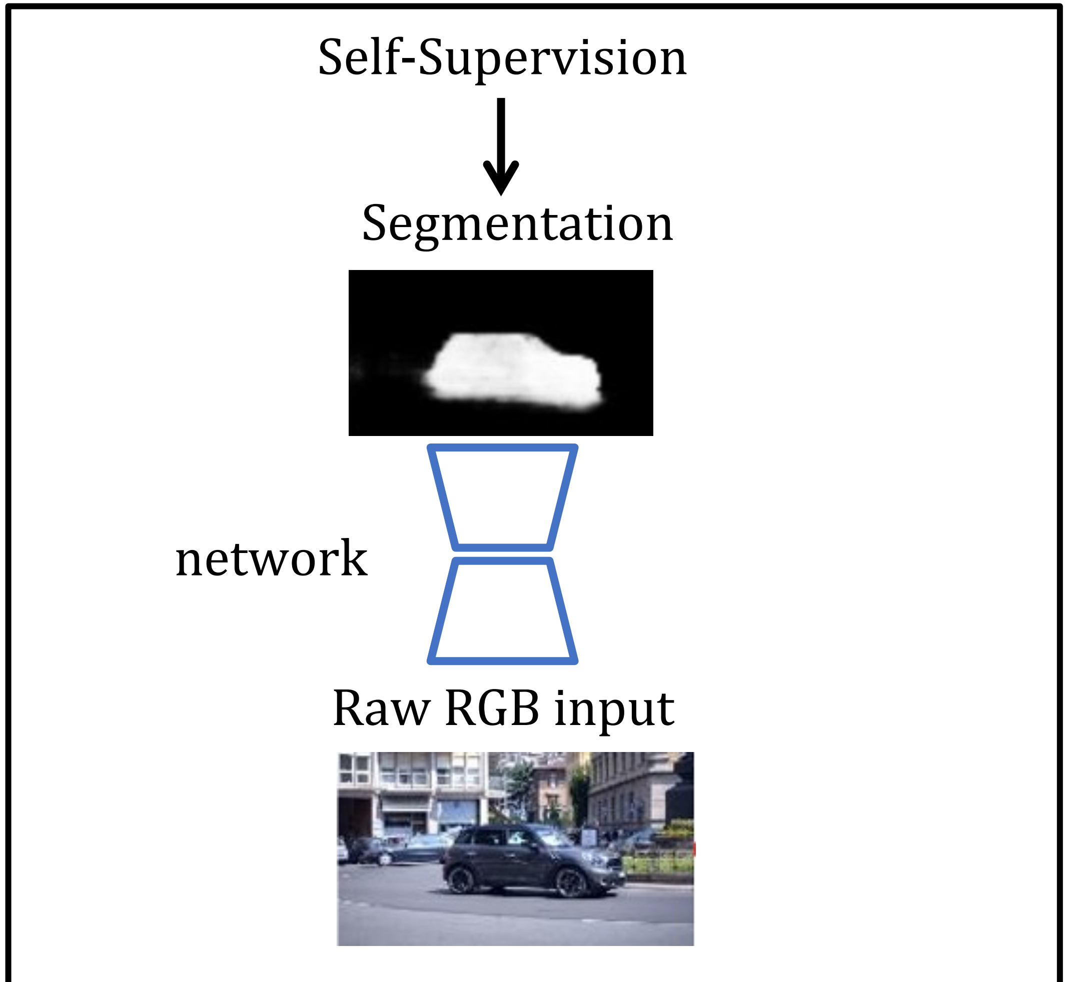
- Dense optical flow

Our Top-down Approach:

Appearance and Motion Decomposition for Videos

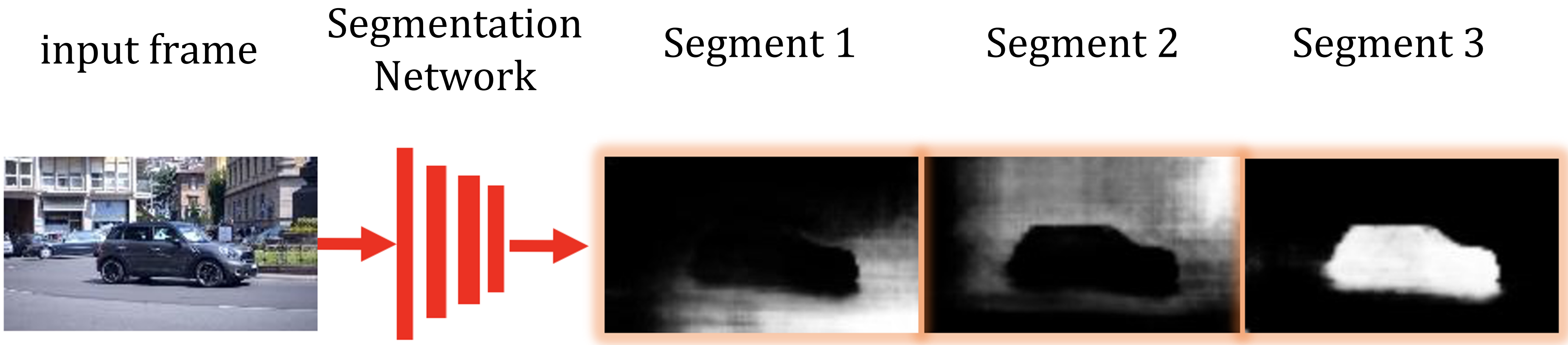


Conventional Bottom-up Analysis

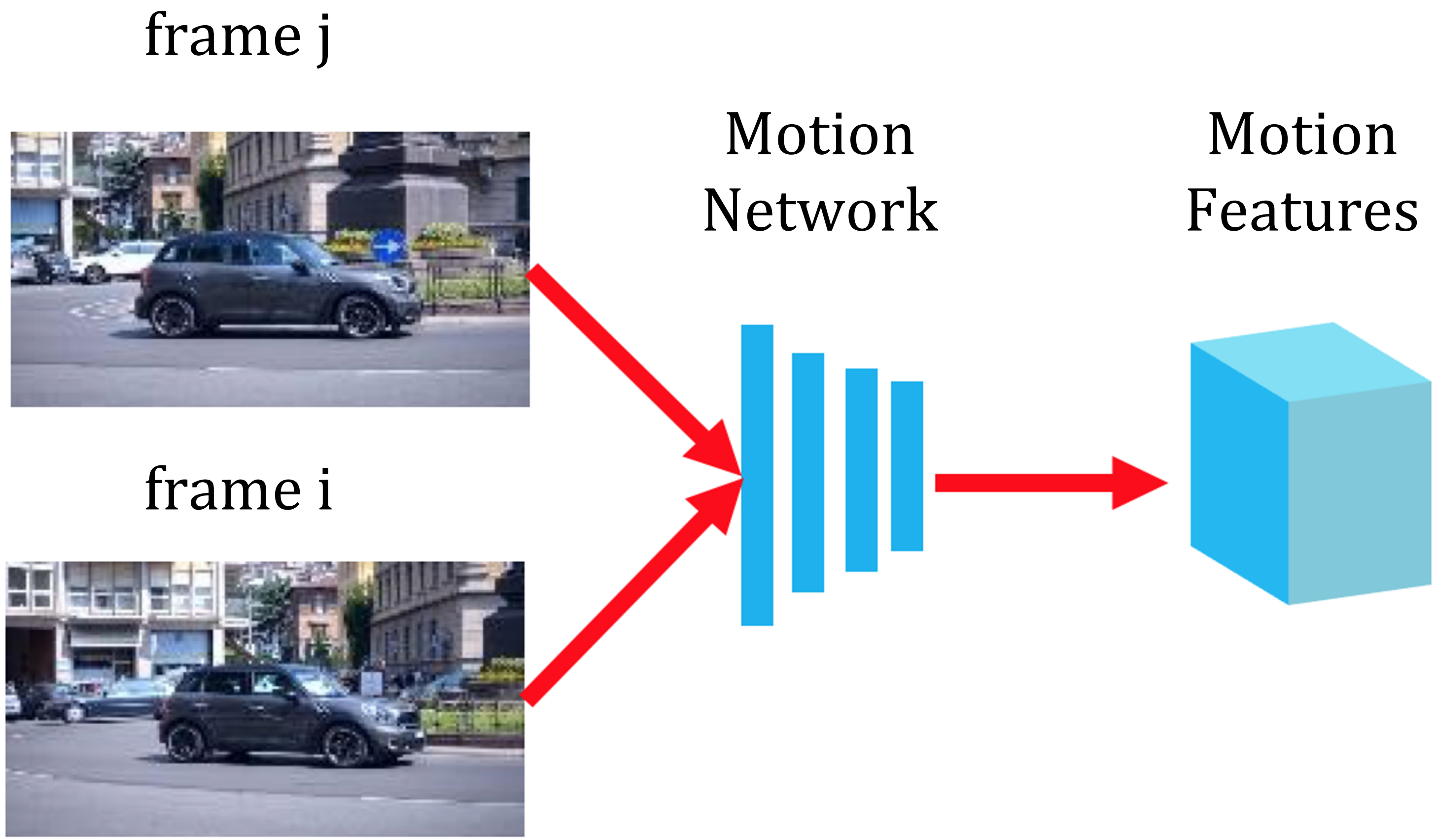


Our Top-down Approach

Appearance Pathway to Segment Object

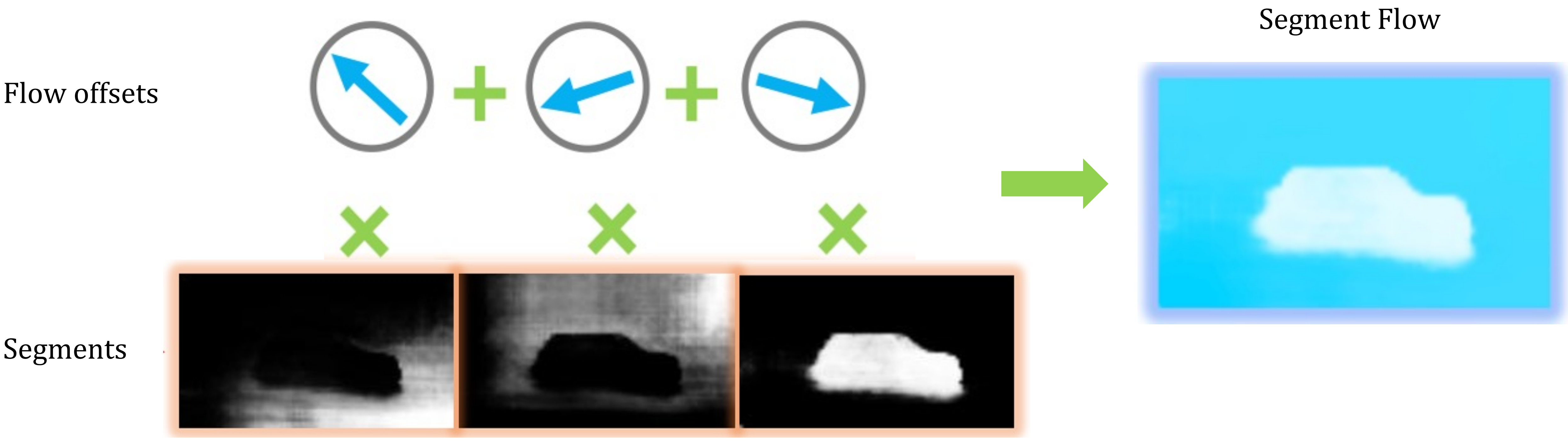


Motion Pathway to Extract Correspondence Features



Segment Flow Representation

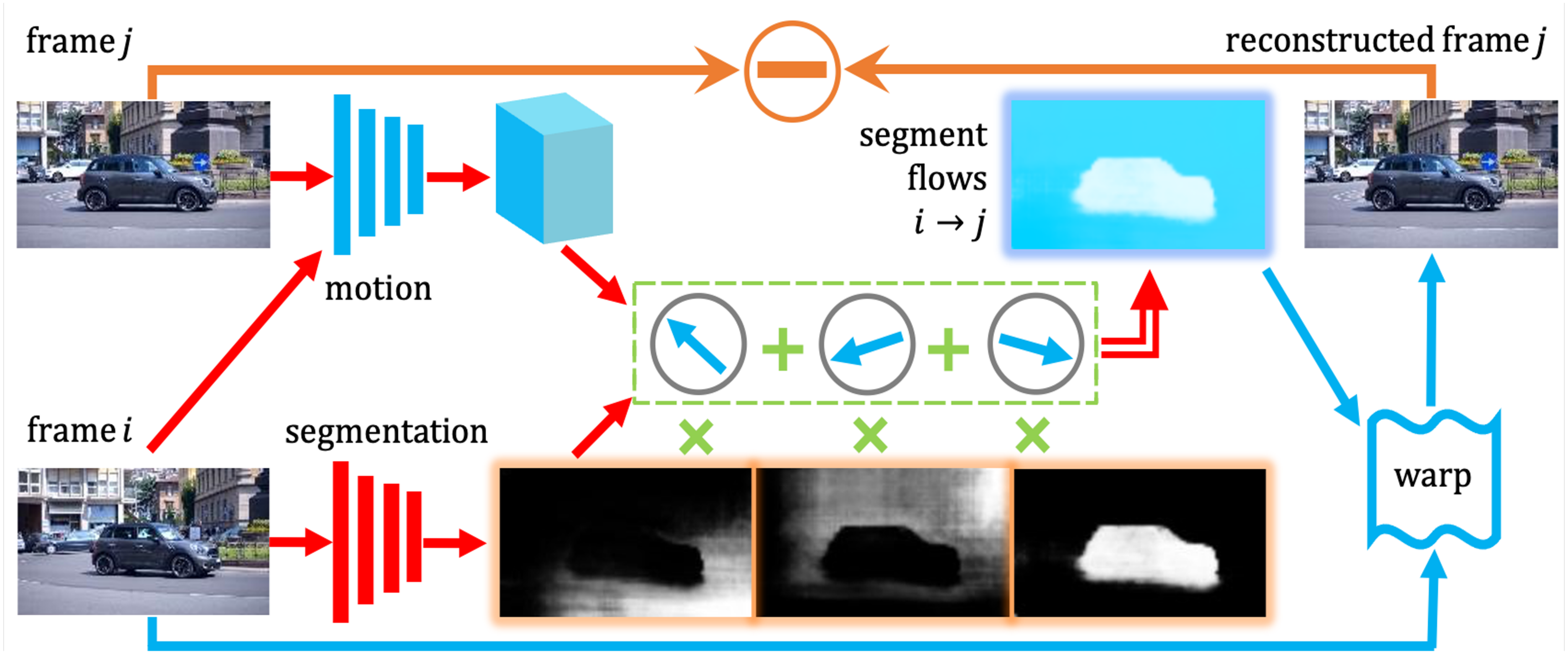
- Predict a flow vector for each segment produced by the appearance pathway.
- Broardcast each flow vector to pixels within each segment.



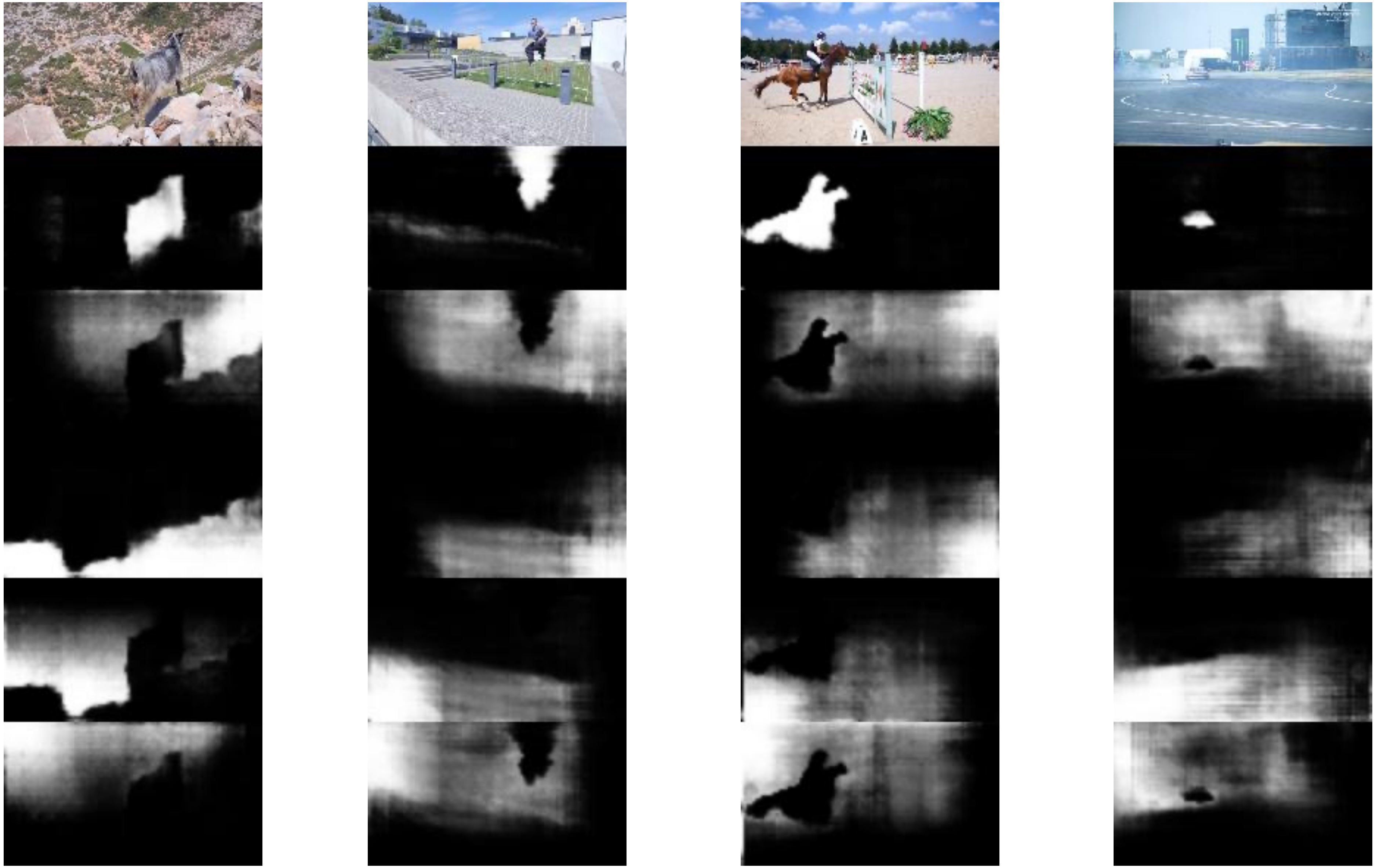
Segment Flow Representation

- Compared with dense flow, segment flow could be inaccurate for per-pixel movement.
- Segment flow captures the motion at the segment level instead of pixel level.

View Synthesis as the Self-supervision Signal



Model Inference Using the Appearance Pathway



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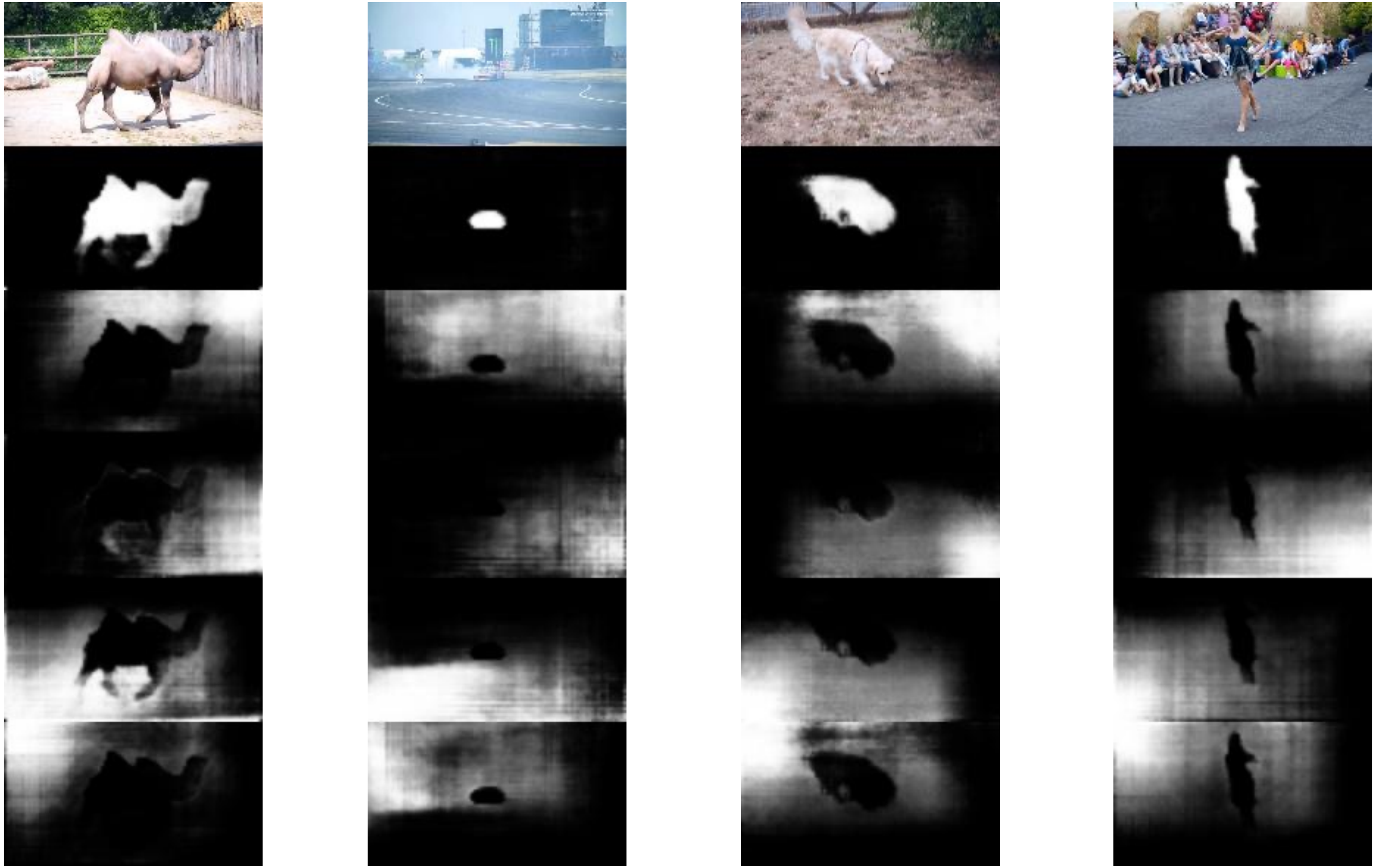


Applications of Our Model

Self-supervised pretraining on the Youtube-VOS dataset with 4000 videos. Then transfer to:

1. Zero-shot object segmentation from images.

2. Zero-shot moving object segmentation from videos.

3. Fine-tuning on labeled data for semantic segmentation.

Zero-shot Object Segmentations from Images

Take the appearance pathway for single image inference.

Evaluation dataset:

the testing split of the DUTS saliency detection benchmark.

	Model	F_β	MAE
Non-learning approaches using priors such as color, edge contrast, and image borders.	RBD[55]	51.0	0.20
	HS[65]	52.1	0.23
	MC[56]	52.9	0.19
	DSR[66]	55.8	0.14
	DRFI[57]	55.2	0.15
Ours	**AMD**	**60.2**	**0.13**

Zero-shot Object Segmentations from Images

Zero-shot Object Segmentations from Videos

Per-img: take the appearance pathway for individual images in a video.

Per-vid: unsupervised test-time adaptation for a video with both pathways.

Test-time adaptation for 100 iterations

Testing Video

Pretrained AMD model

Unsupervised View synthesis Objective

Zero-shot Object Segmentations from Videos

	Model	e2e	Sup.	Flow	DAVIS 2016	SegTrackv2	FBMS59
traditional	SAGE[65]	✗	✗	LDOF[66]	42.6	57.6	61.2
	NLC[14]	✗	edge	SIFTFlow[67]	55.1	67.2	51.5
	CUT[28]	✗	✗	LDOF[66]	55.2	54.3	57.2
	FTS[16]	✗	✗	LDOF[68]	55.8	47.8	47.7
	ARP[15]	✗	saliency	CPMFlow[69]	76.2	57.2	59.8
learning	CIS[18]	✗	✗	PWC[20]	59.2	45.6	36.8
	MG[19]	✗	✗	ARFlow[6]	53.2	37.8*	50.4*
	AMD (per-img)	✓	✗	✗	45.7	28.7	42.9
	AMD (per-vid)	✓	✗	✗	57.8	57.0	47.5

Per-img: take the appearance pathway for individual images in a video.

Per-vid: unsupervised test-time adaptation for a video with both pathways.

Per-image and Per-video Comparisons

Per-image results

Per-video results

Zero-shot Object Segmentations from Videos

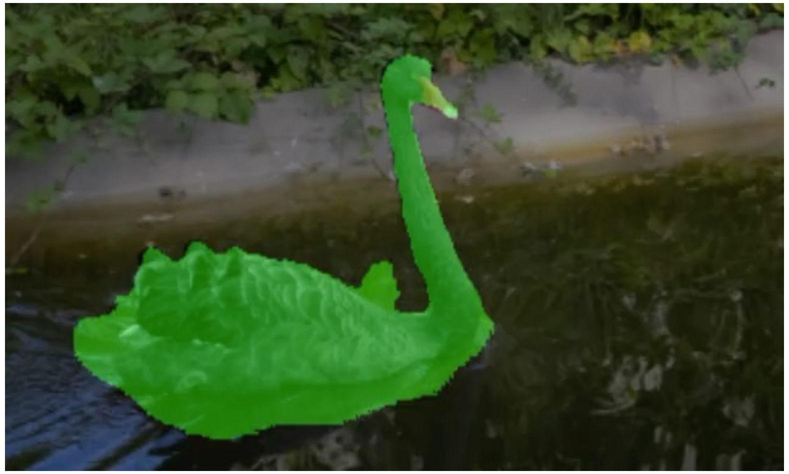
DAVIS 2016

SegTrack

FBMS

Comparison with Prior Approach CIS

Ours



CIS

- CIS is temporally unsmooth due to noise in dense flows

Fine-tuning for Semantic Segmentation:

Evaluation dataset: Pascal VOC 2012

Our model does not rely on heavy augmentations.

Pretraining with light image augmentation
Resize(384), Crop(384)

Model	Data	mIoU
Scratch	–	48.0
TimeCyle[62]	VLOG	52.8
MoCo-v2[2]	YTB	61.5
AMD	YTB	**62.0**

Pretraining with heavy augmentation
ResizedCrop(384), ColorJitter, GrayScaling

Model	Data	mIoU
MoCo-v2[2]	YTB	**62.8**
AMD	YTB	62.1

Summary

The first end-to-end self-supervised approach for zero-shot segmentations.

- Learning from raw videos without built-in visual cues.
- Works with minimal image augmentations.
- Applicable to image/video object segmentation under zero-shot.