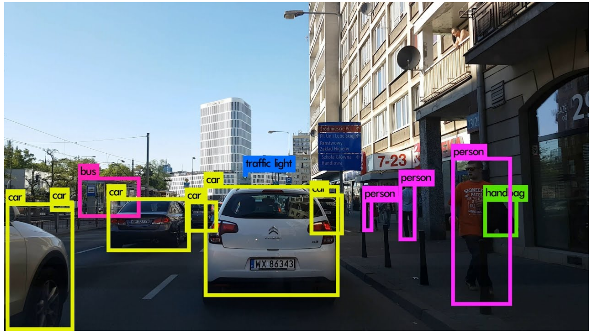
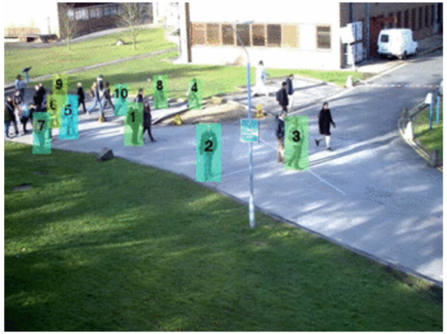
Video Object Segmentation

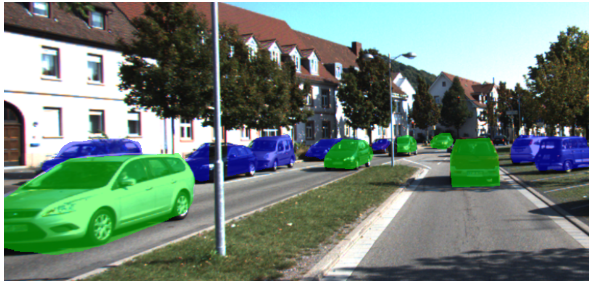
Video Object Segmentation



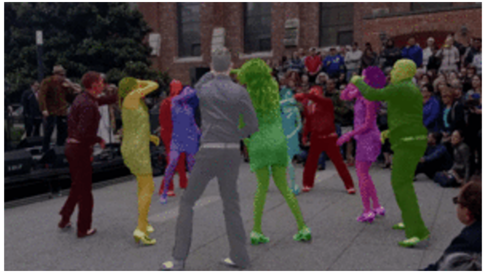
Object Detection



Object Tracking



Object Segmentation

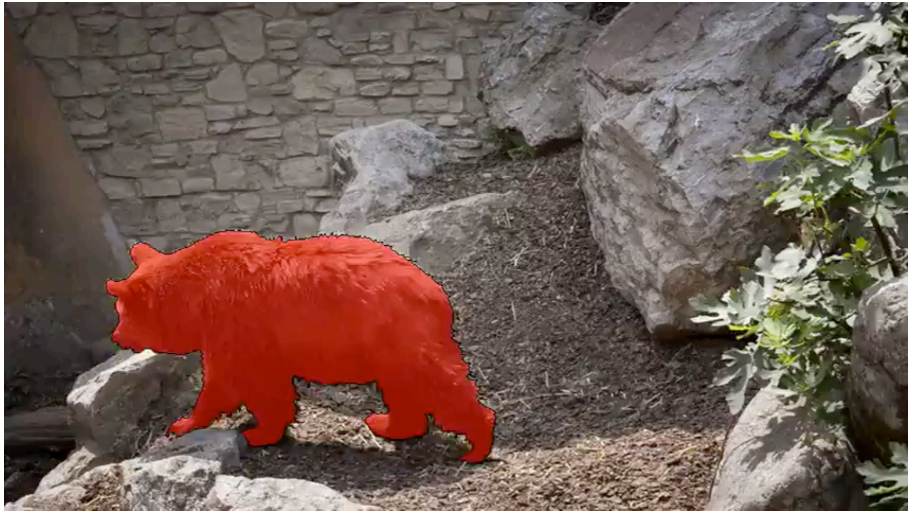


Video Object Segmentation

This lecture

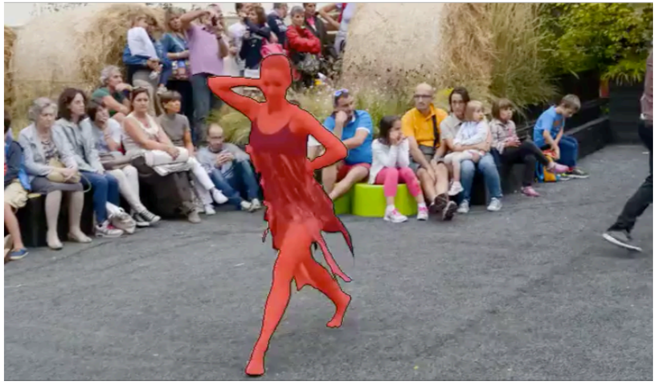
Video Object Segmentation

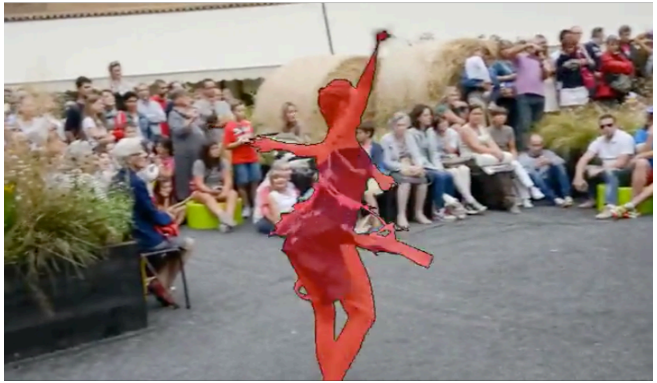
- Goal: Generate accurate and temporally consistent pixel masks for objects in a video sequence.



VOS: some challenges

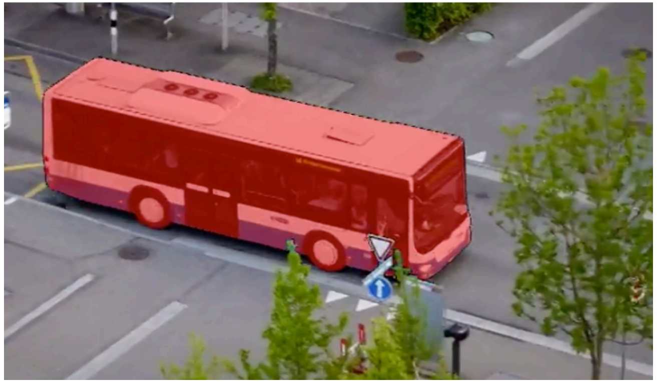
- Strong viewpoint/appearance changes

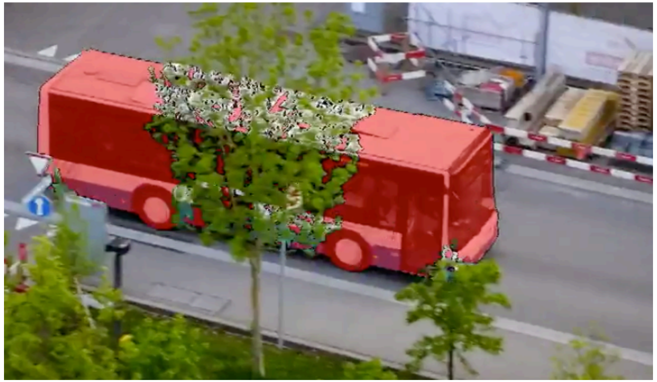




VOS: some challenges

- Strong viewpoint/appearance changes
- Occlusions





VOS: some challenges

- Strong viewpoint/appearance changes
- Occlusions
- Scale changes

VOS: some challenges

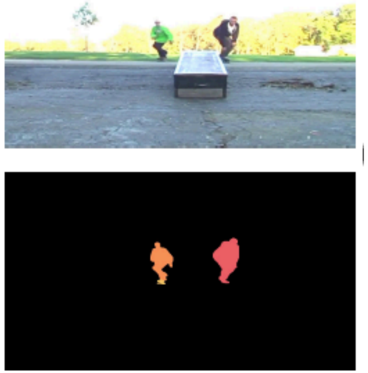
- Strong viewpoint/appearance changes
- Occlusions
- Scale changes
- Illumination
- Shape
- …

Hard to make assumptions about object's appearance

Hard to make assumptions about object's motion

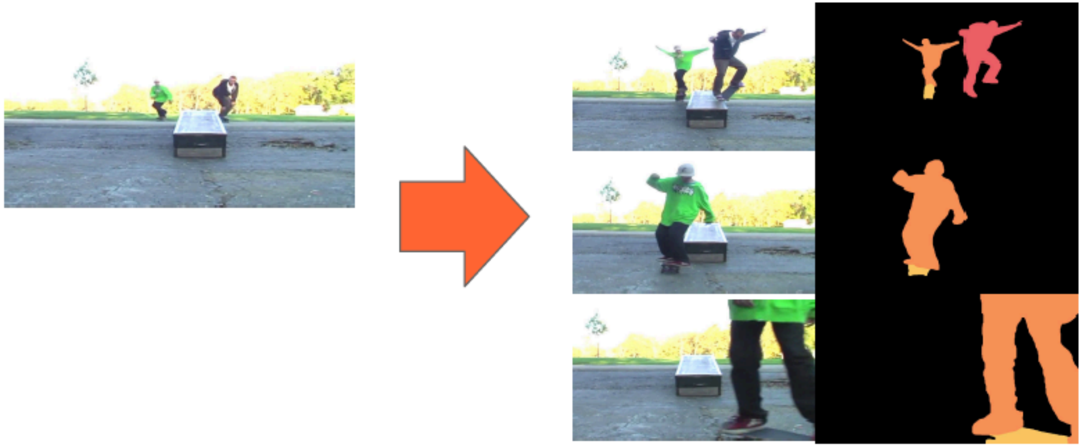
VOS: tasks

Semi-supervised (one-shot) video object segmentation



We get the first frame ground truth mask, we know what object to segment

Unsupervised (zero-shot) video object segmentation

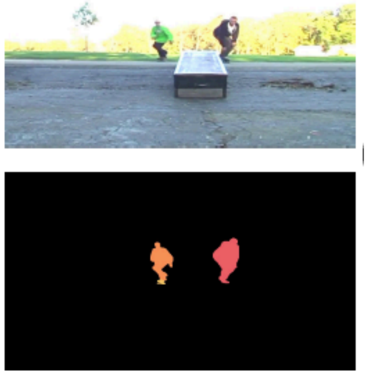


We have to find the objects as well as their masks

VOS: tasks

Motion segmentation, salient object detection..

Semi-supervised (one-shot) video object segmentation



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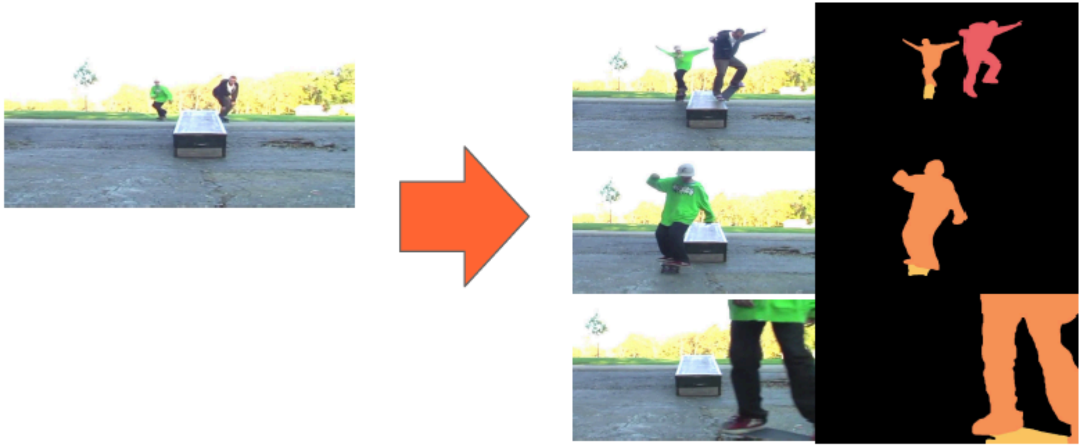
Unsupervised (zero-shot) video object segmentation

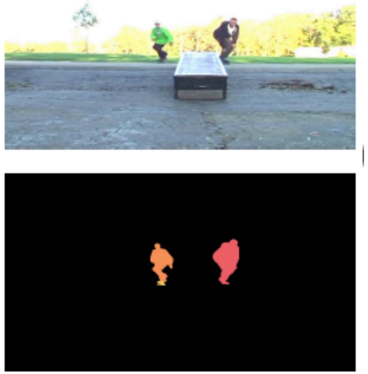


We have to find the objects as well as their masks

VOS: tasks

This lecture

Semi-supervised (one-shot) video object segmentation



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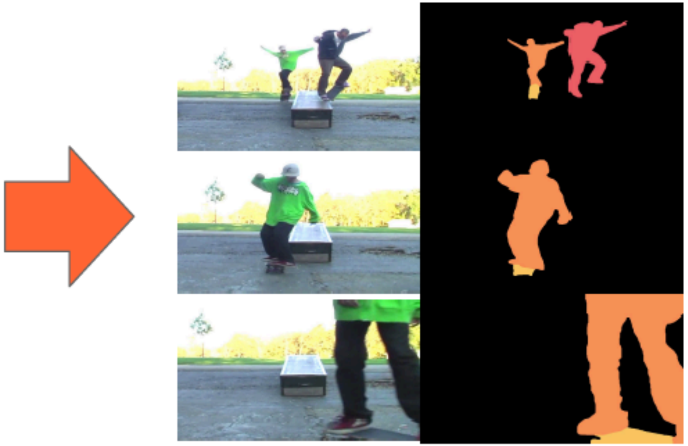
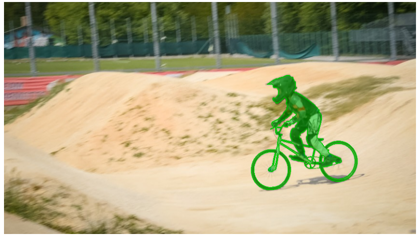
Unsupervised (zero-shot) video object segmentation

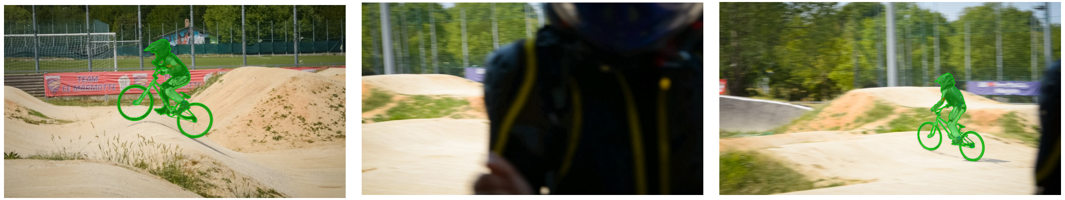


We have to find the objects as well as their masks

Supervised Video Object Segmentation



Given: First-frame ground truth



Goal: Complete video segmentation

- Task formulation
  - Given: segmentation mask of target object(s) in the first frame
  - Goal: pixel-accurate segmentation of the entire video

  - Currently a major testing ground for segmentation-based tracking

VOS Datasets

- Remember that large-scale datasets are needed for learning-based methods

DAVIS 2016
(30/20, single objects, first frames)

DAVIS 2017
(60/90, multiple objects, first frames)

YouTube-VOS 2018
(3471/982, multiple objects, first frame where object appears)

https://davischallenge.org
https://youtube-vos.org

Before we get started…

- Pixel-wise output

- If we talk about pixel-wise outputs and motion, there is a concept in Computer Vision that we need to know first

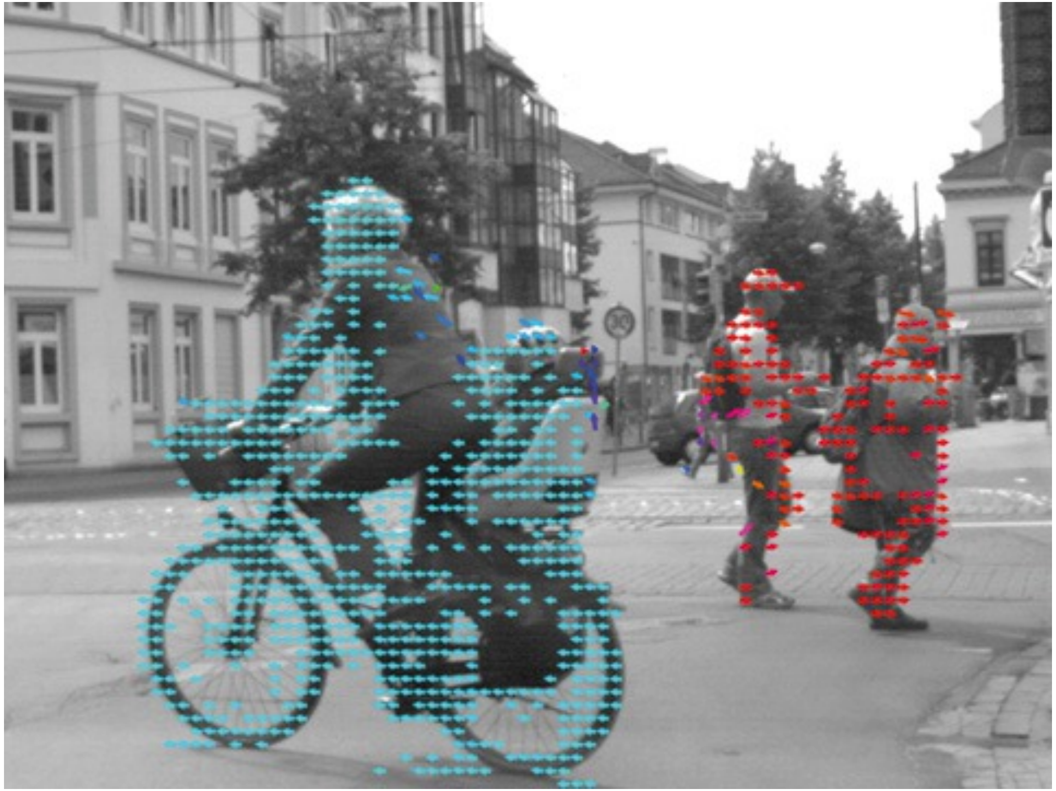
Optical flow

Optical flow

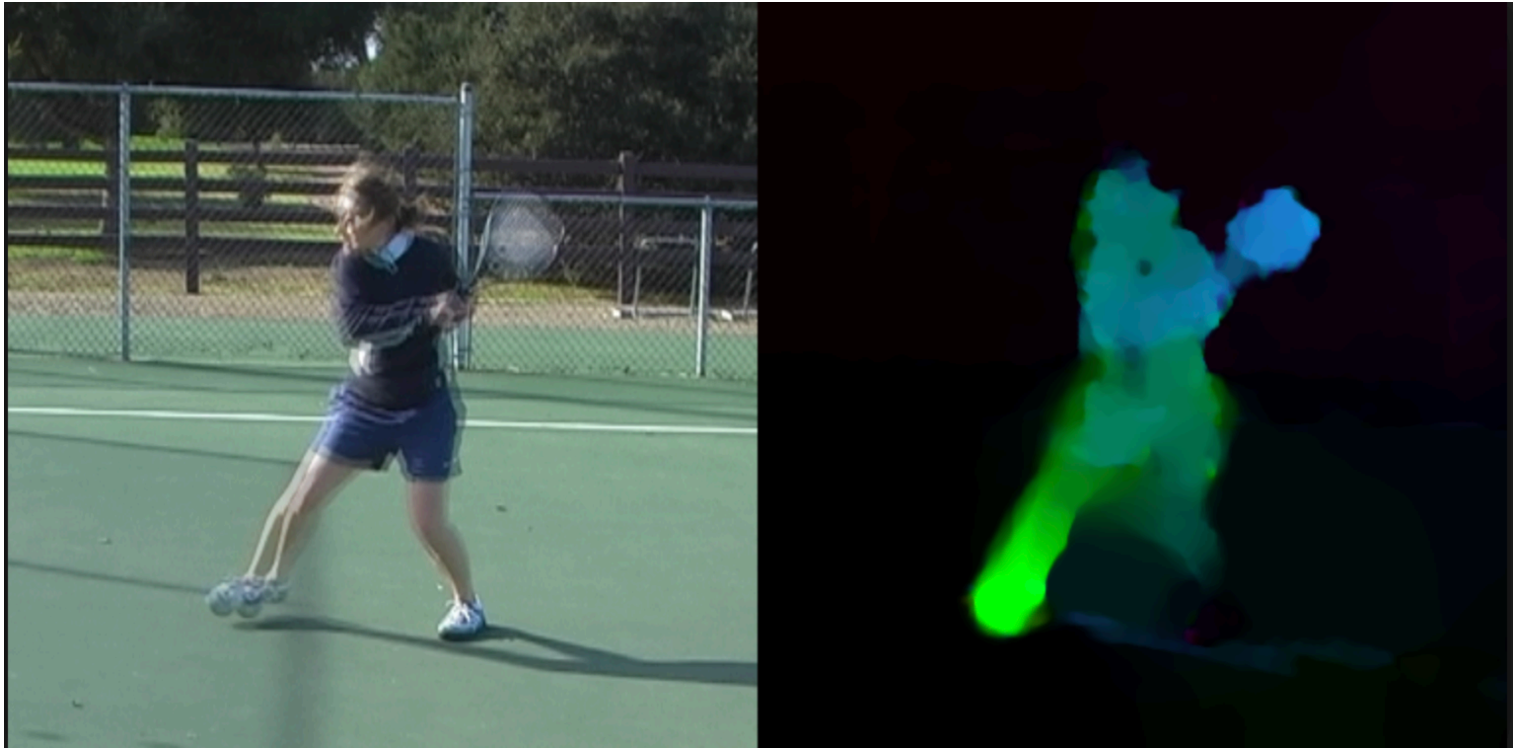
- Input: 2 consecutive images (e.g. from a video)
- Output: displacement of every pixel from image A to image B

- Results in the "perceived" 2D motion, not the real motion of the object

Optical flow

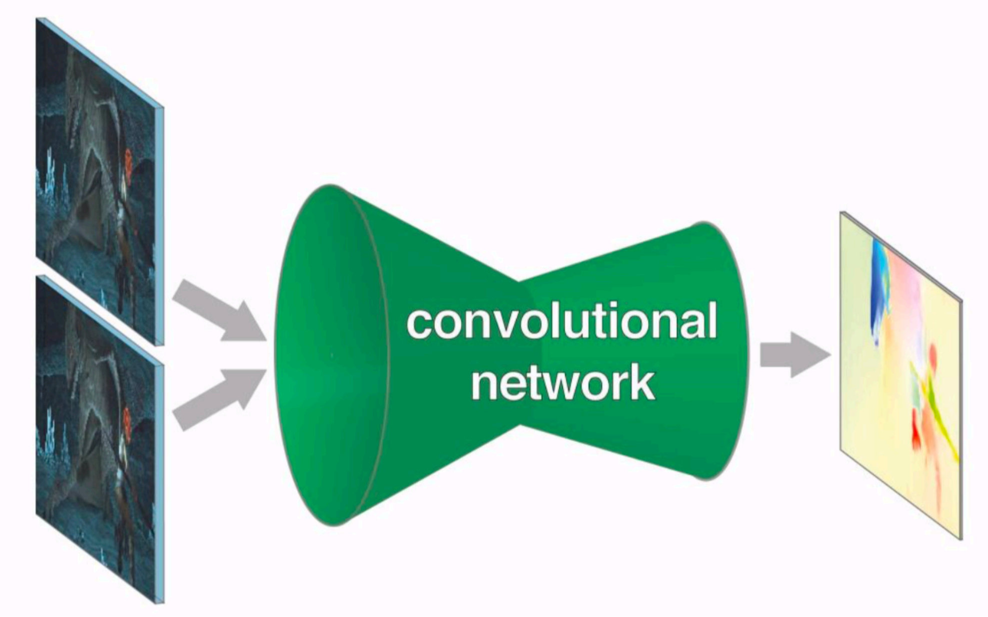


Optical flow



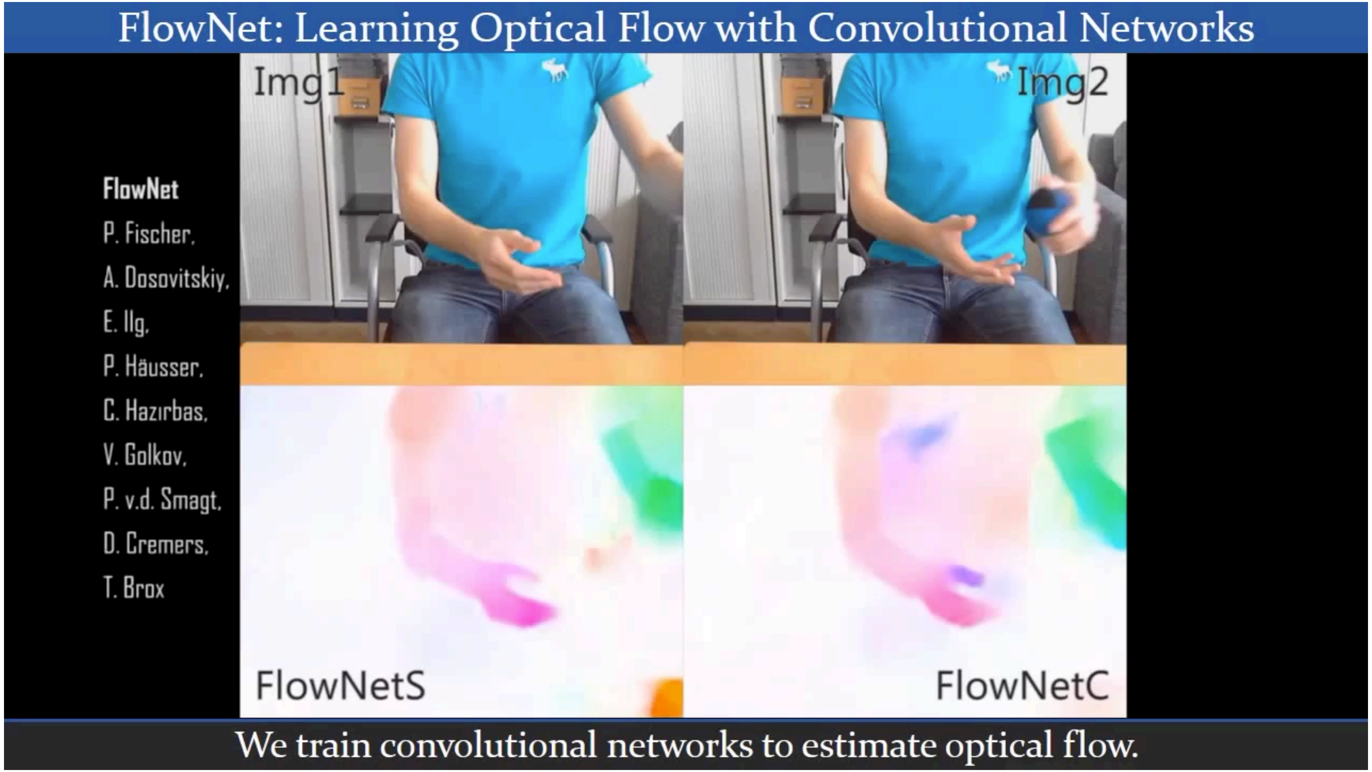
Optical flow with CNNs

- End-to-end supervised learning of optical flow



P. Fischer et al. „FlowNet: Learning Optical Flow With Convolutional Networks". ICCV 2015

Optical flow with CNNs



FlowNet: Learning Optical Flow with Convolutional Networks

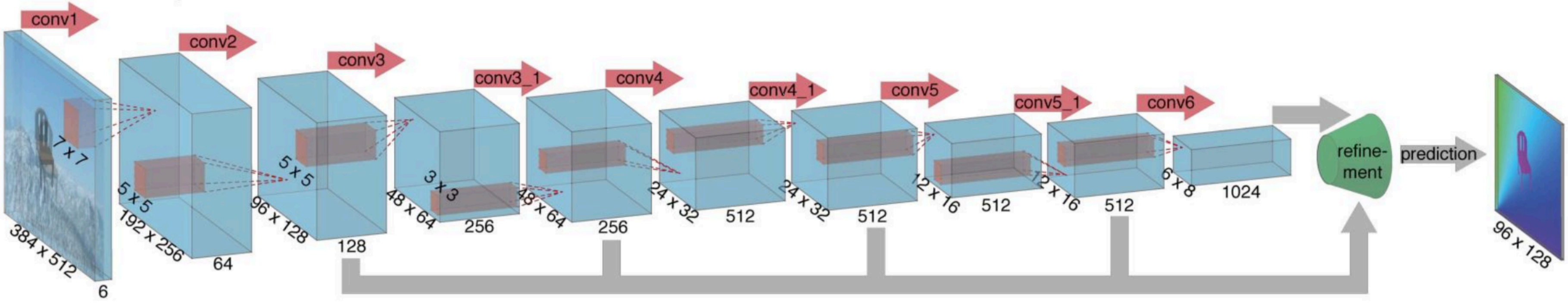
FlowNet
P. Fischer,
A. Dosovitskiy,
E. Ilg,
P. Häusser,
C. Hazırbas,
V. Golkov,
P. v.d. Smagt,
D. Cremers,
T. Brox

We train convolutional networks to estimate optical flow.

P. Fischer et al. „FlowNet: Learning Optical Flow With Convolutional Networks". ICCV 2015

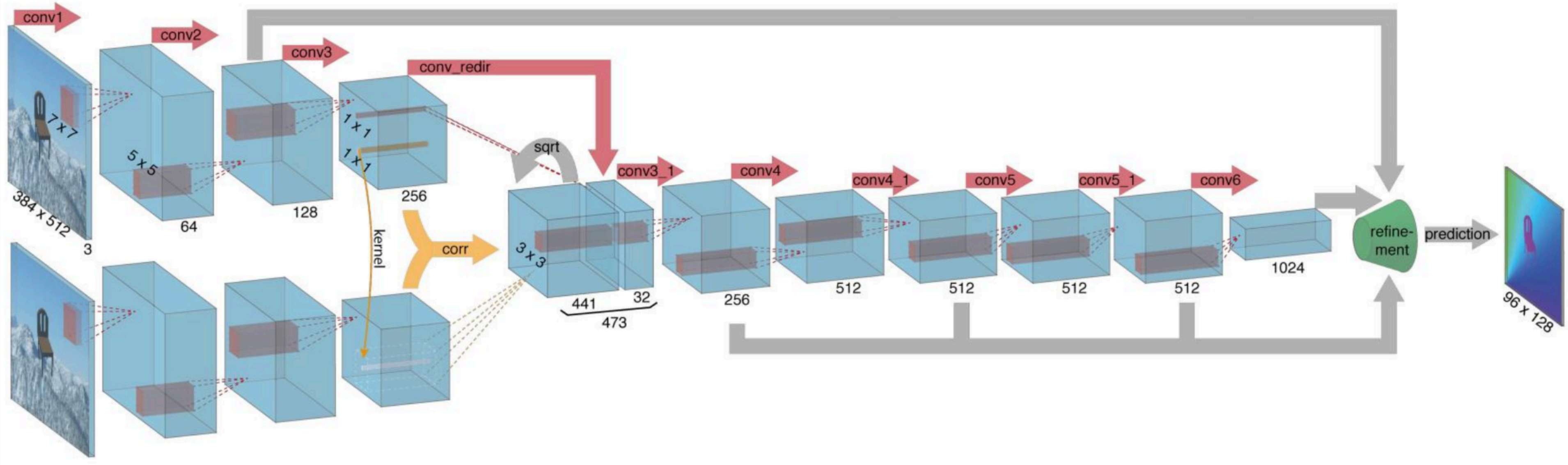
FlowNet: architecture 1

- Stack both images → input is now 2 x RGB = 6 channels



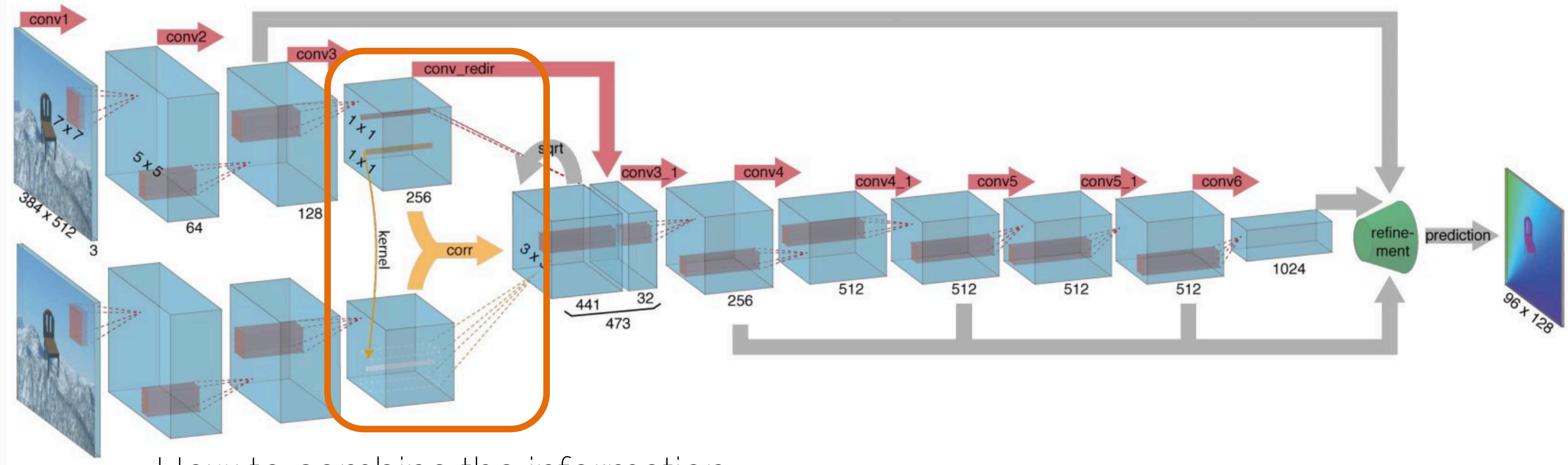
FlowNet: architecture 2

- Siamese architecture



FlowNet: architecture 2

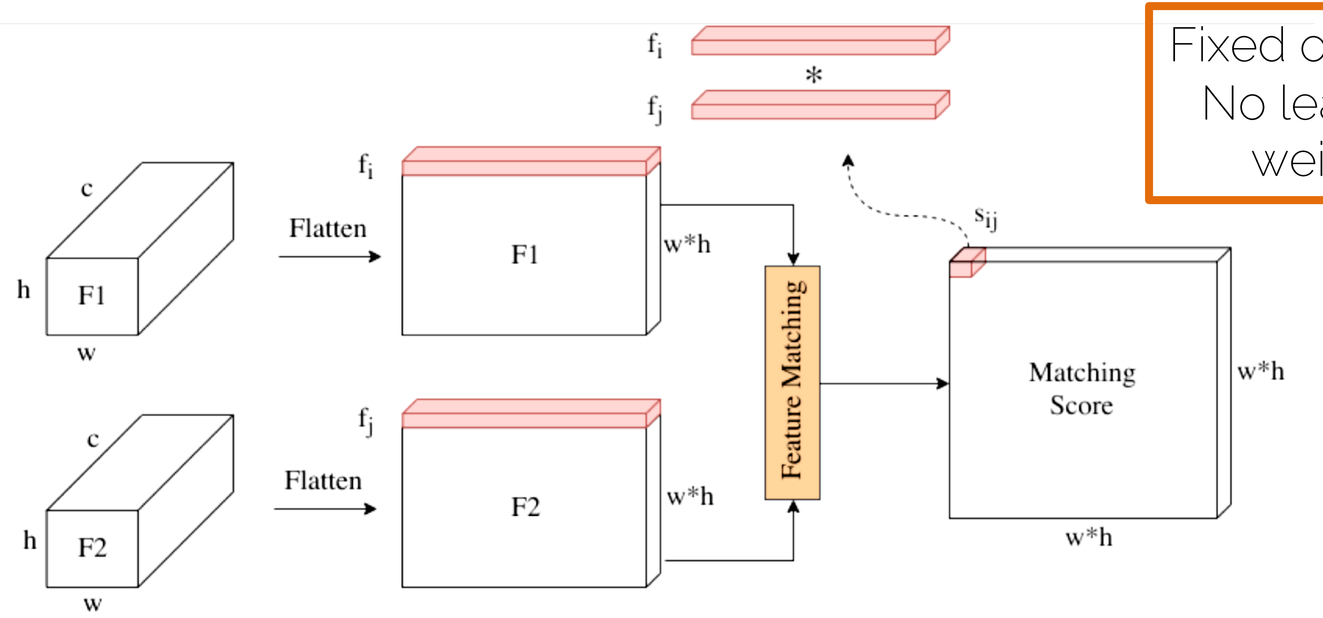
- Two key design choices



How to combine the information from both images?

Correlation layer

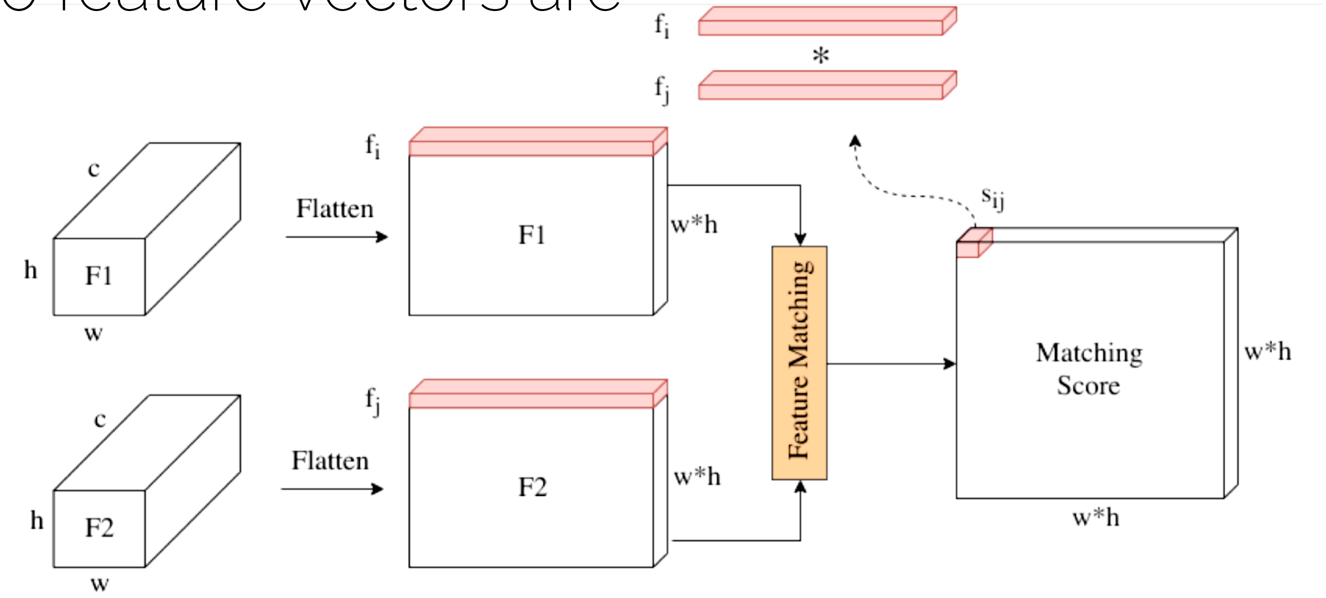
- Multiplies a feature vector with another feature vector



Fixed operation. No learnable weights!

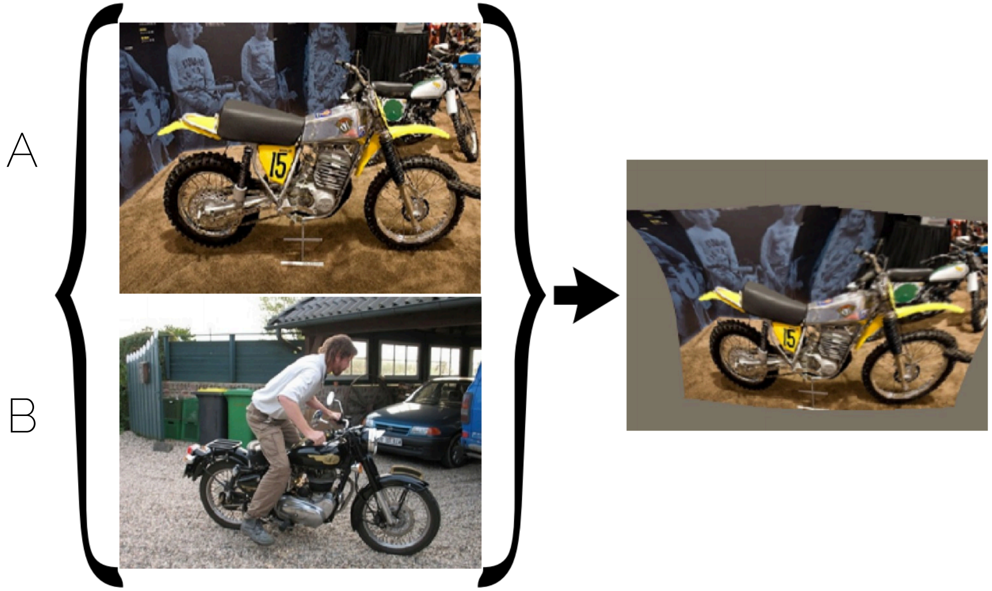
Correlation layer

- The matching score represents how correlated these two feature vectors are



Correlation layer

- Hint for anyone interested in 3D reconstruction: Useful for finding image correspondences

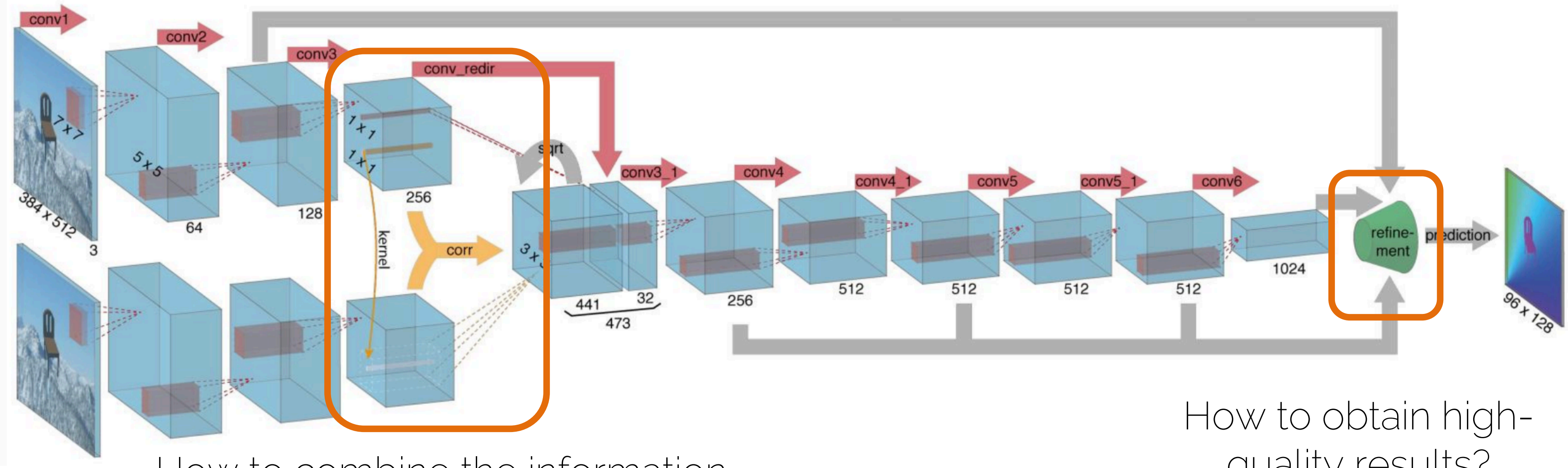


Find a transformation from image A to image B

I. Rocco et al. "Convolutional neural network architecture for geometric matching. CVPR 2017.

FlowNet : architecture 2

- Two key design choices

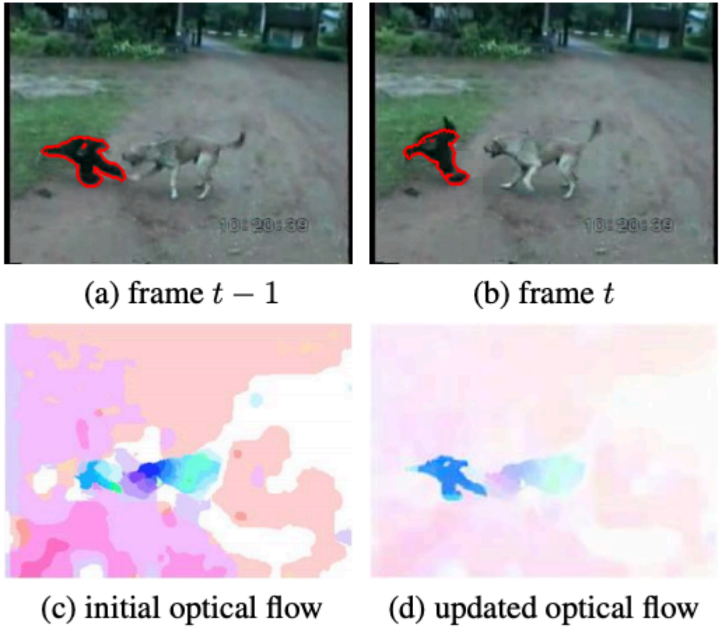


How to combine the information from both images?

How to obtain high-quality results?

Can we do VOS with OF?

- Indeed!
- Better if we focus on the flow of the object
- We can improve segmentation and OF iteratively (no DL yet)



(a) frame $t-1$

(b) frame t

(c) initial optical flow

(d) updated optical flow

Y.H. Tsai et al. "Video Segmentation via Object Flow". CVPR 2016

OSVOS

First-frame fine-tuning

- Goal: Learn the appearance of the object to track

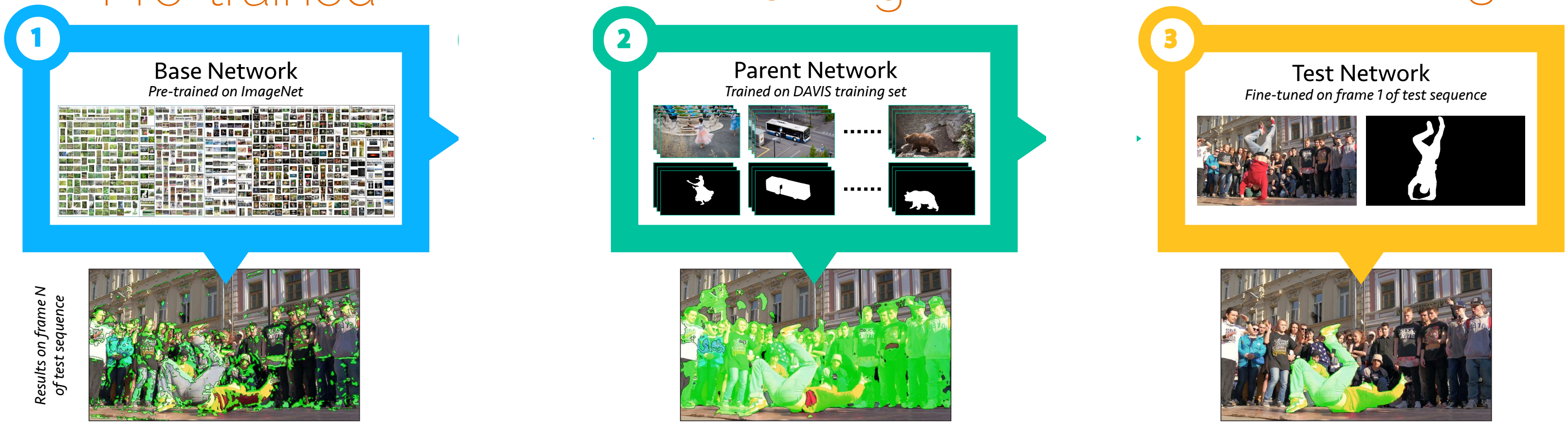
- Main contribution: separate training steps
  - Pre-training for ‘objectness’.
  - First-frame adaptation to specific object-of-interest using fine-tuning.

One-shot VOS

Pre-trained

Training

Finetuning



1 Base Network
Pre-trained on ImageNet

2 Parent Network
Trained on DAVIS training set

3 Test Network
Fine-tuned on frame 1 of test sequence

Results on frame N of test sequence

Edges and basic image features

Learns how to do video segmentation

Learns which object to segment

S. Caelles et al. “One-shot video object segmentation”.CVPR 2017

One-shot VOS

- One-shot: we see the first frame ground truth

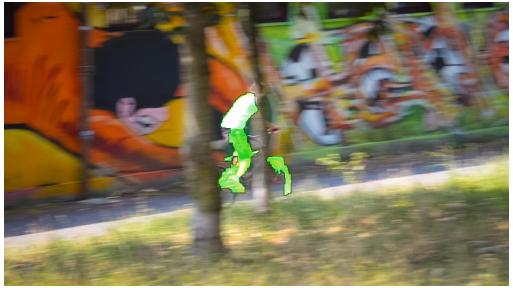
- Finetuning step: this is used to technically *overfit* to the test sequence first frame. Overfitting is therefor used to learn the appearance of the foreground object (and the background!)

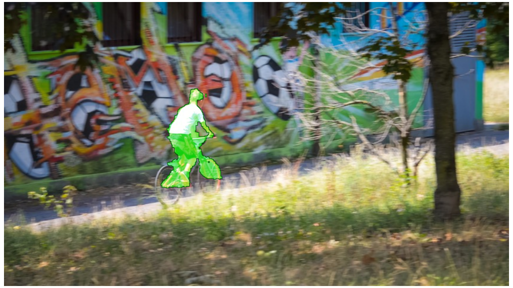
- Test time: each frame is processed independently → no temporal information

S. Caelles et al. "One-shot video object segmentation".CVPR 2017

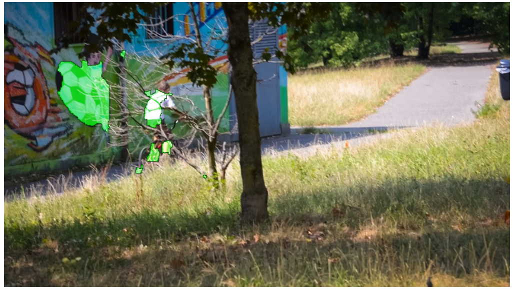
Frame-based segmentation

- PRO: it recovers well from occlusions (unlike mask propagation or optical flow-based methods)

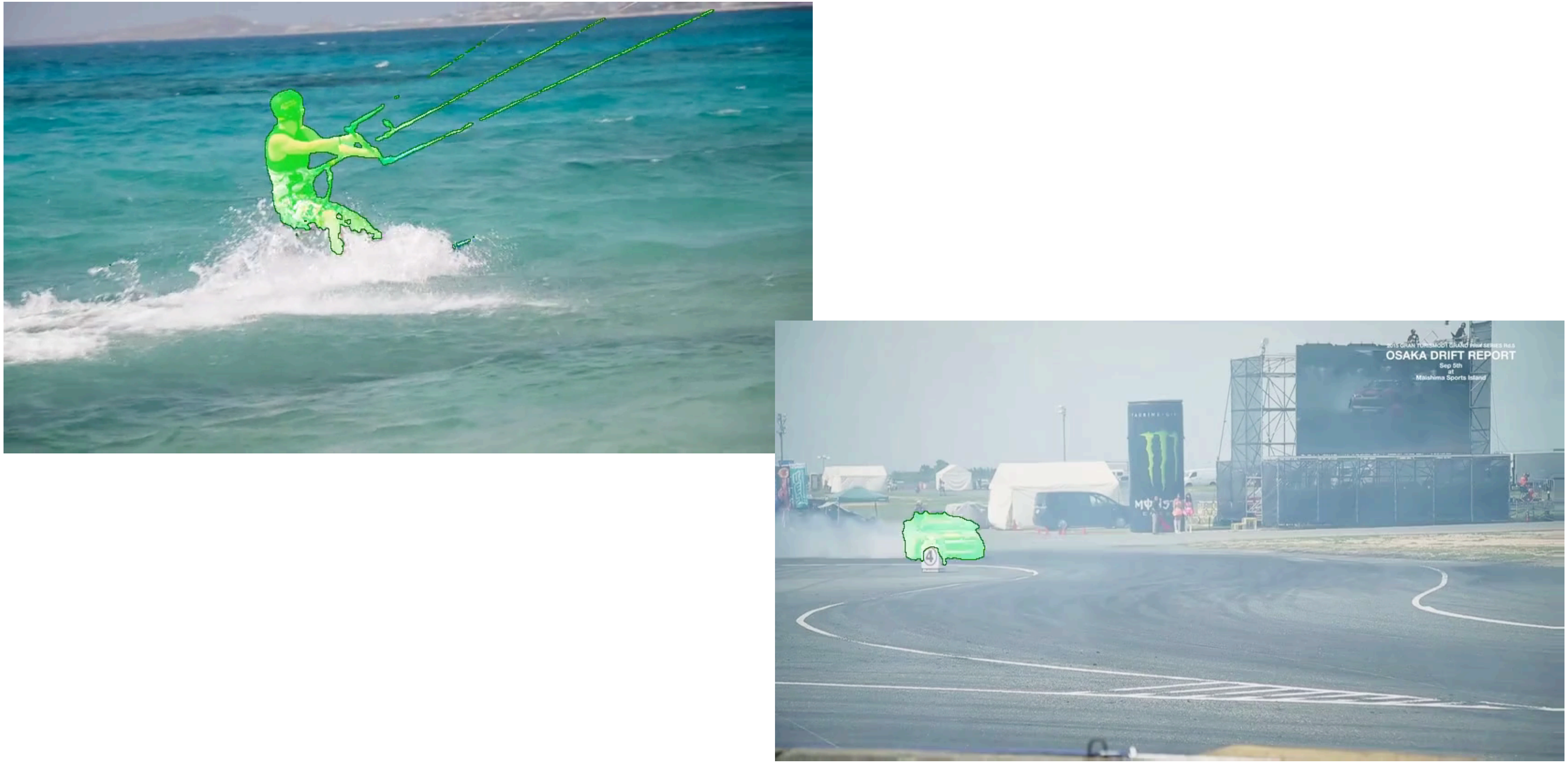




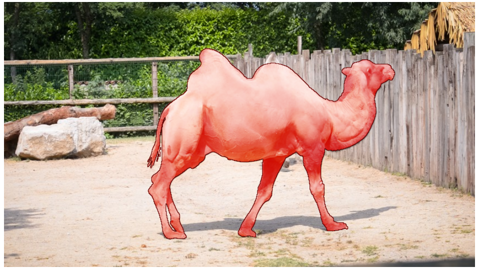
- CON: it is temporally inconsistent

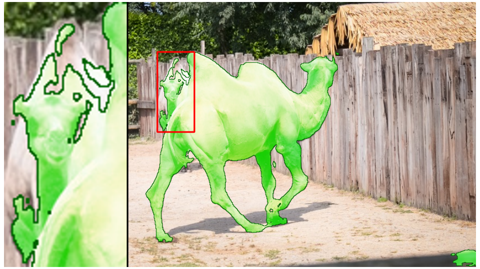


Experiments: highly dynamic scenes



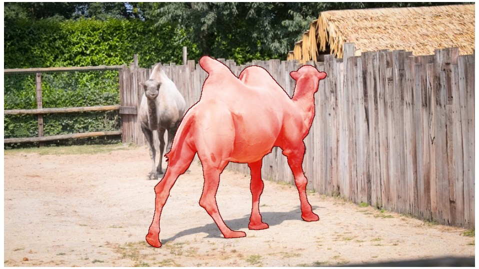
Experiments: accuracy vs annotations

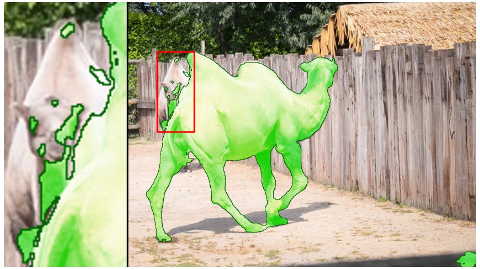




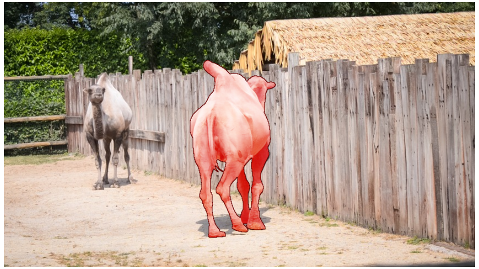
Two camels!

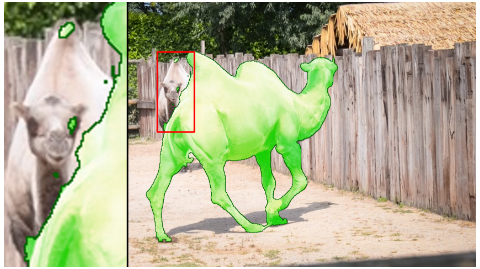
Another annotation where the 2nd camel is background





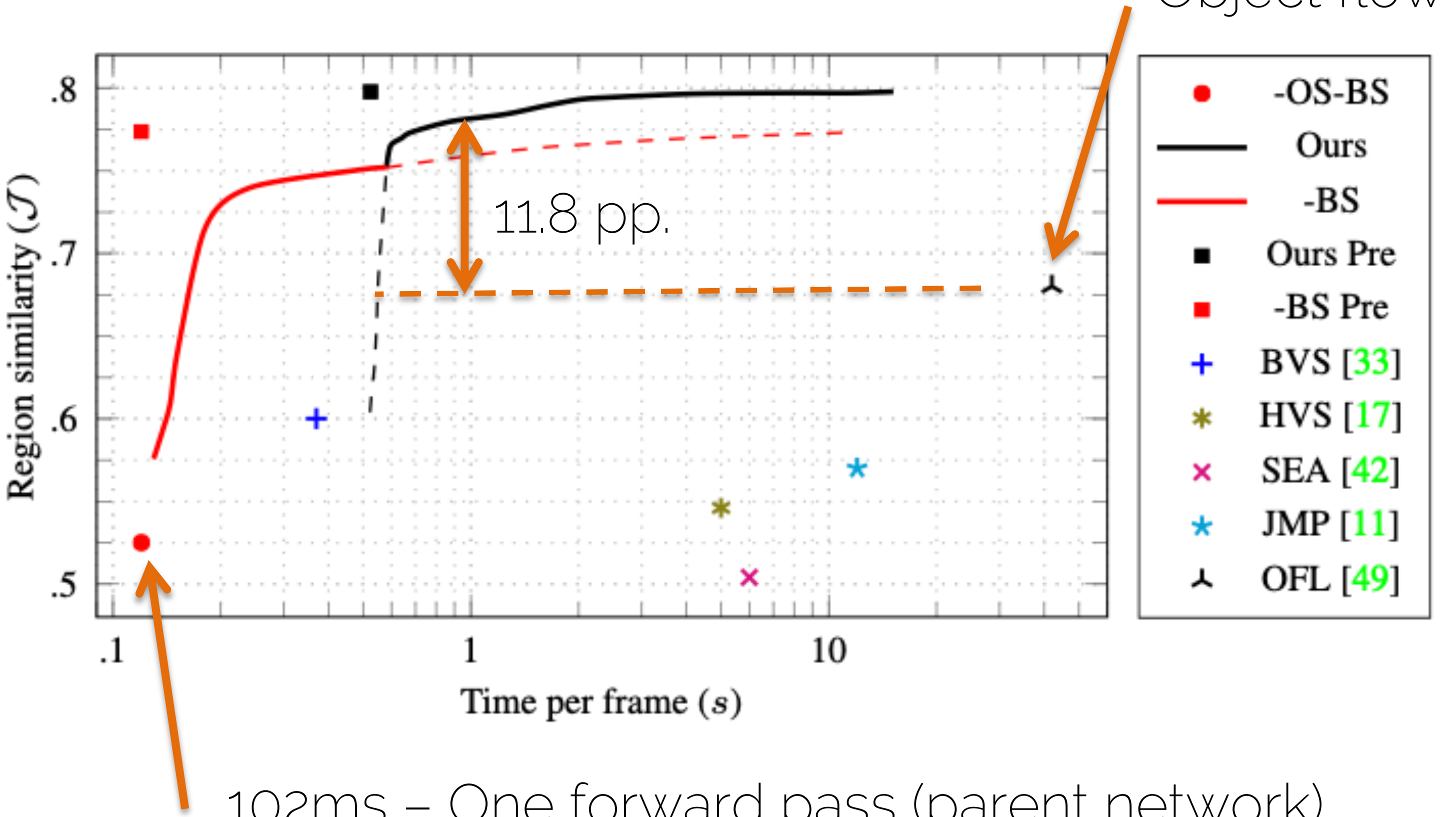
Another annotation





Mask is refined

Finetuning time



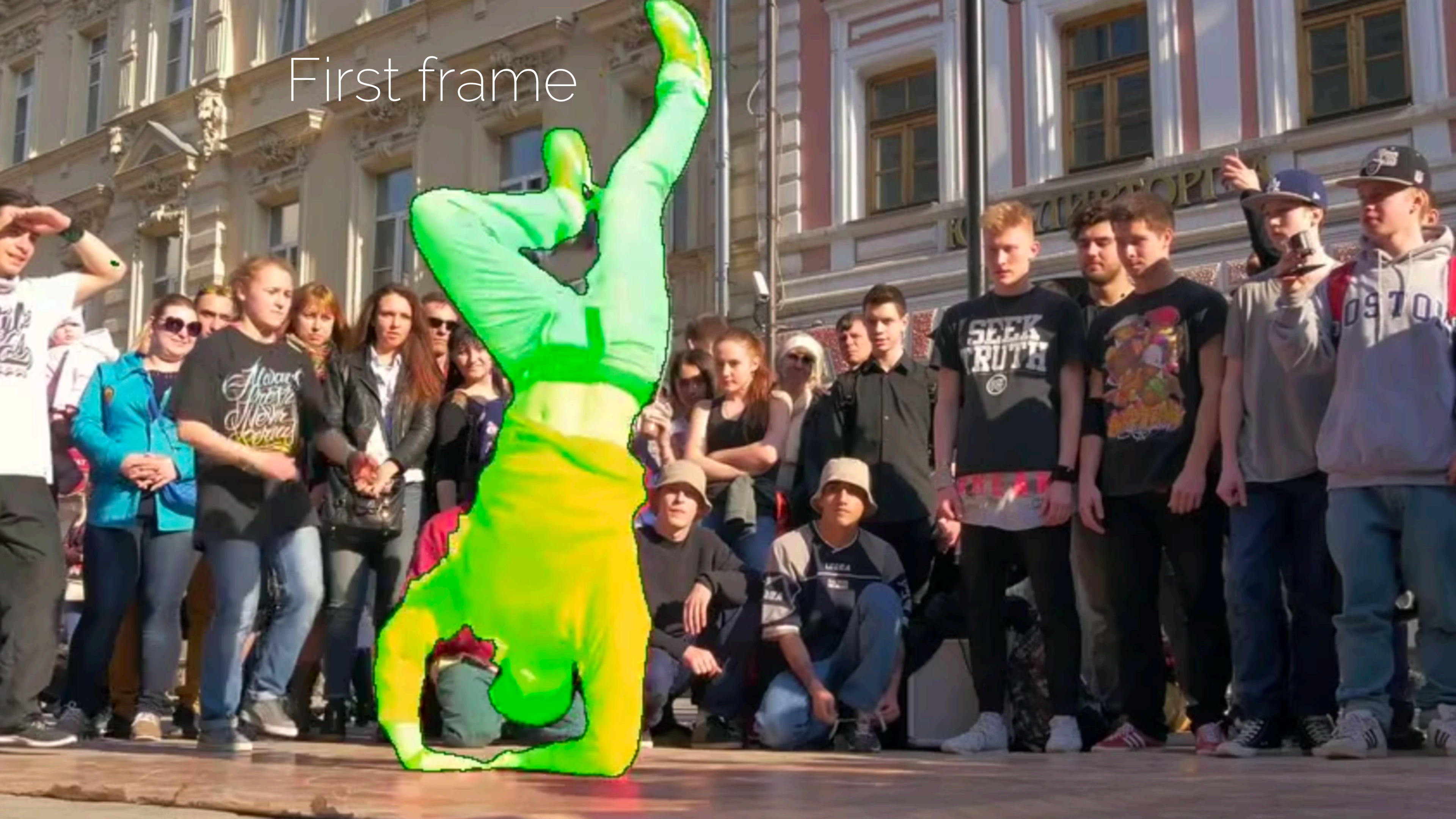
102ms – One forward pass (parent network)

DAVIS dataset

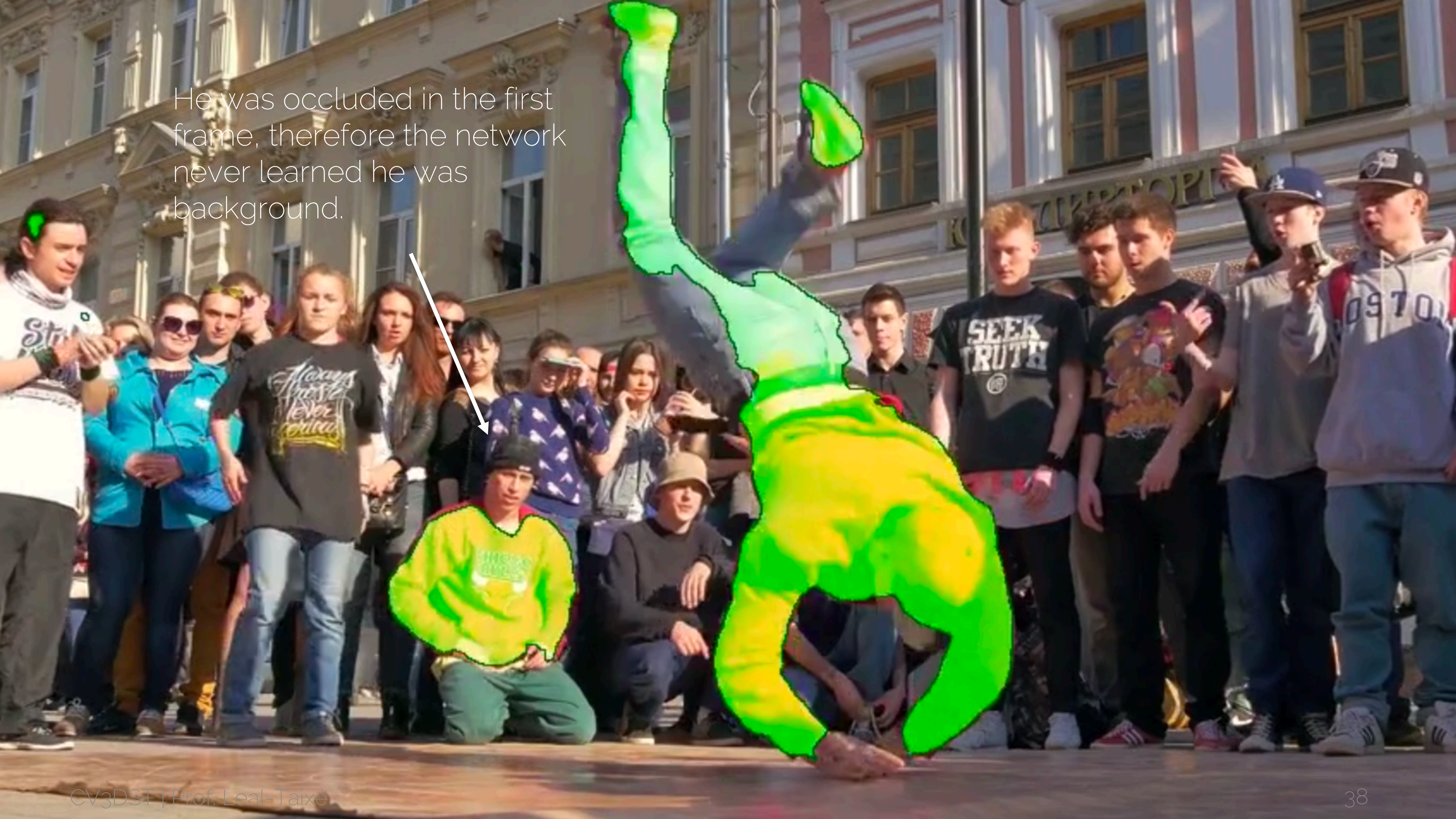
Observations

- OSVOS does not have an object of object shape.

- It is a pure appearance-based method, if the foreground (or the background) appearance changes too much, the method fails



First frame

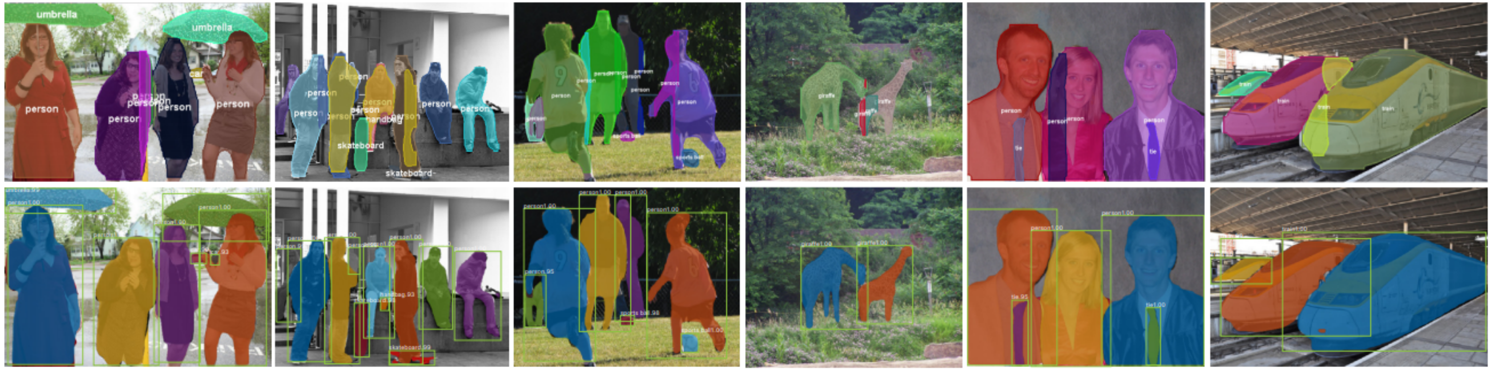


He was occluded in the first frame, therefore the network never learned he was background.

But wait….

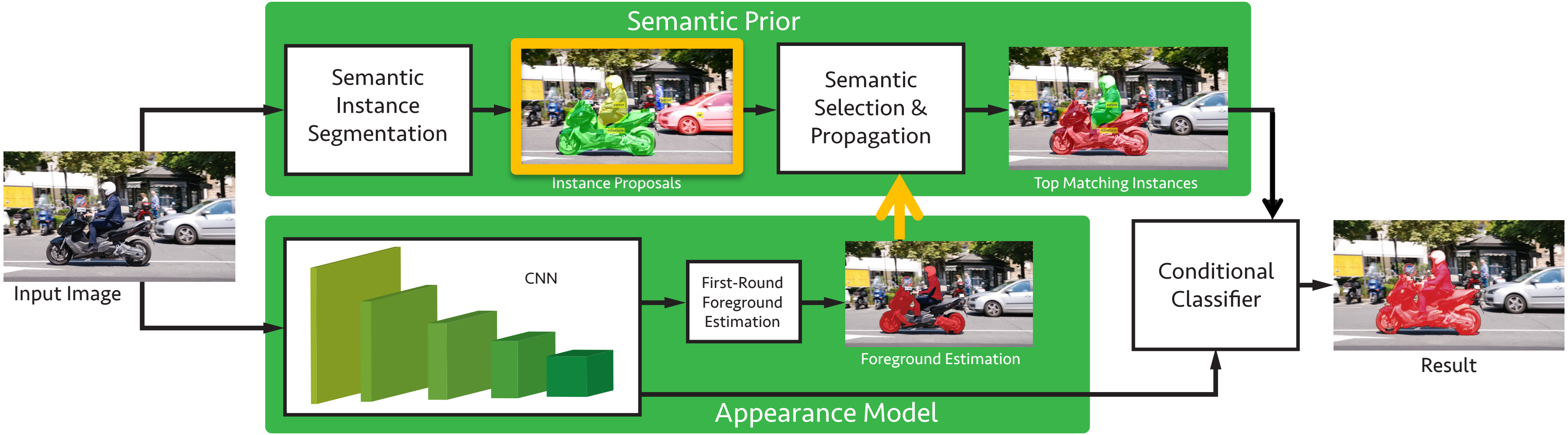
- We have already seen models that have an idea of object shape..

- Instance segmentation methods!



OSVOS-S: Semantic propagation

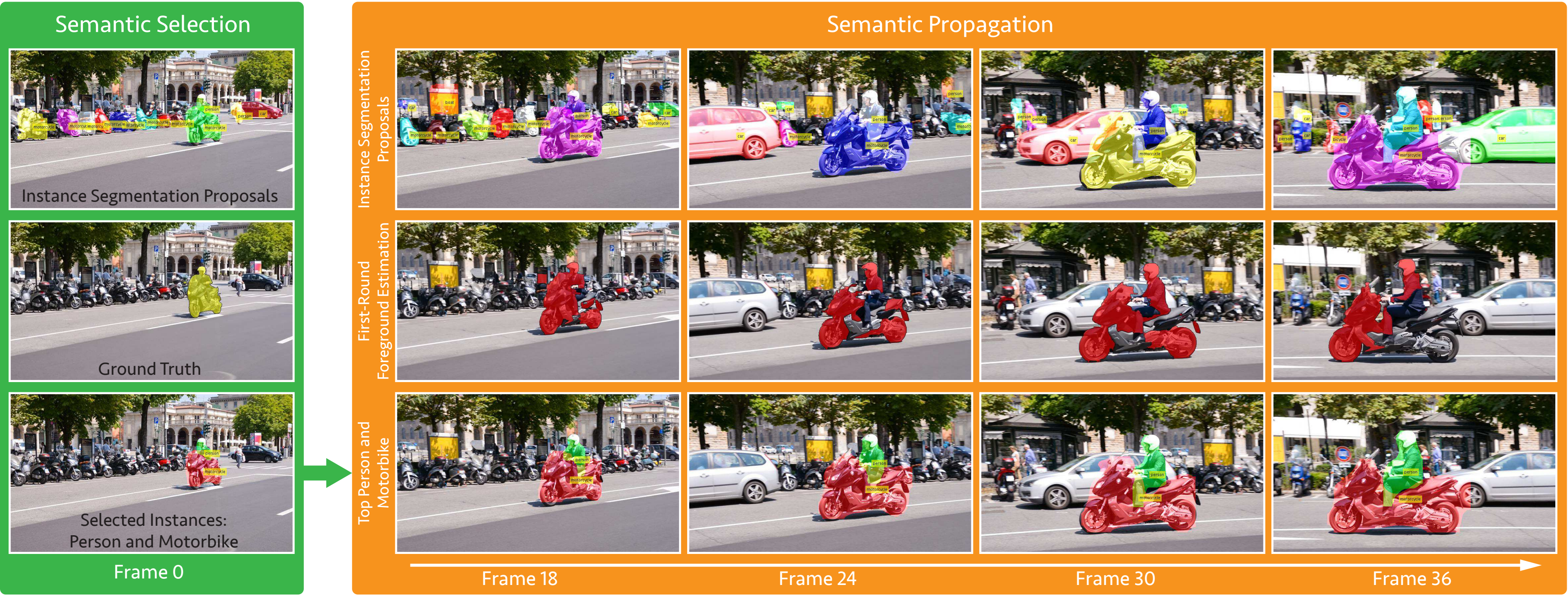
Semantic prior branch that gives us proposals to select from



Prior: semantics stay coherent throughout the sequence

K.-K. Maninis et al. "Video object segmentation without temporal information". TPAMI 2018

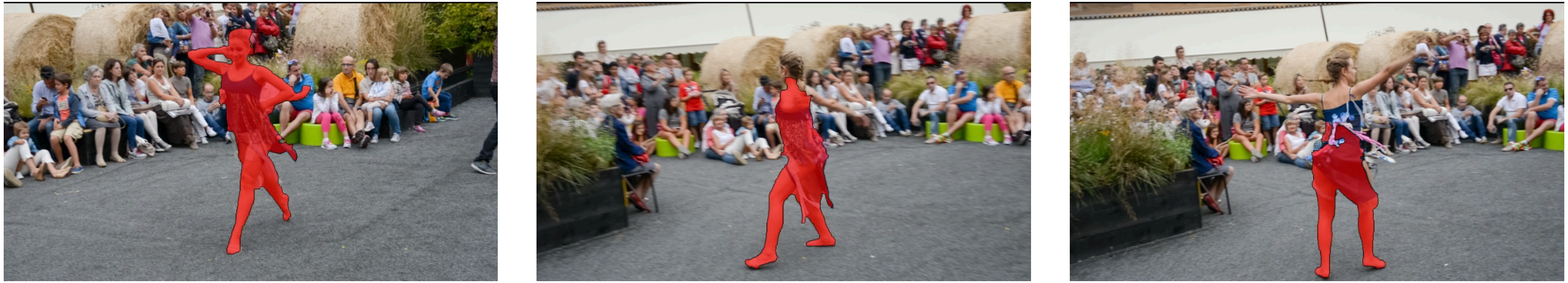
OSVOS-S: Semantic propagation



K.-K. Maninis et al. "Video object segmentation without temporal information". TPAMI 2018

Drifting problem

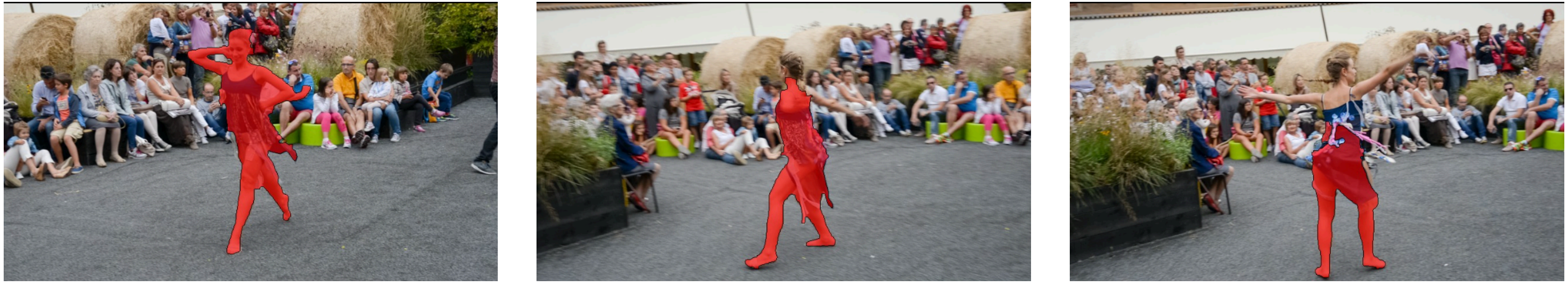
- If the object greatly changes its appearance (e.g., though pose or camera changes), then the model is not powerful anymore



- But this change was gradual….

Drifting problem

- If the object greatly changes its appearance (e.g., though pose or camera changes), then the model is not powerful anymore



Why not gradually update the model?

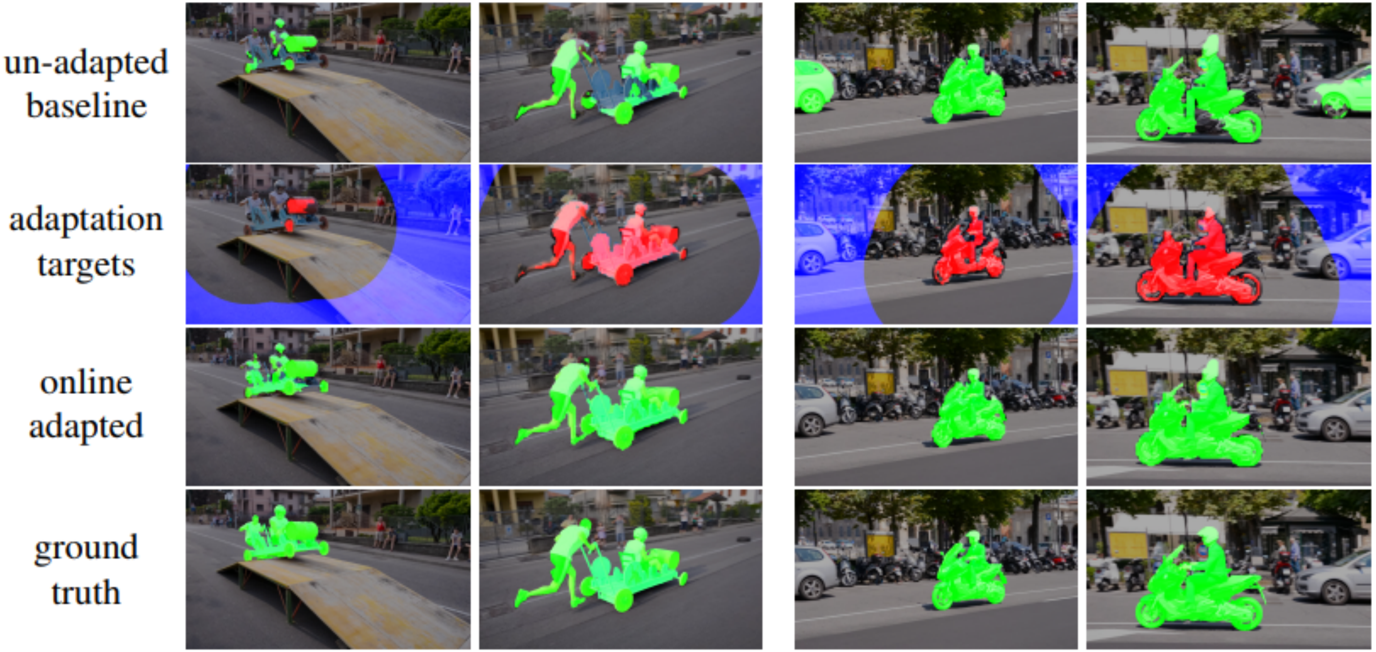
OnAVOS: Online Adaptation

- Online adaptation: adapt model to appearance changes every frame – not just the first frame.
- Iteratively fine-tune the model on previous prediction every frame.

- CON: Extremely slow.

P. Voigtlander and B. Leibe. "Online adaptation of convolutional neural networks for video object segmentation". BMVC 2017

OnAVOS: Online Adaptation



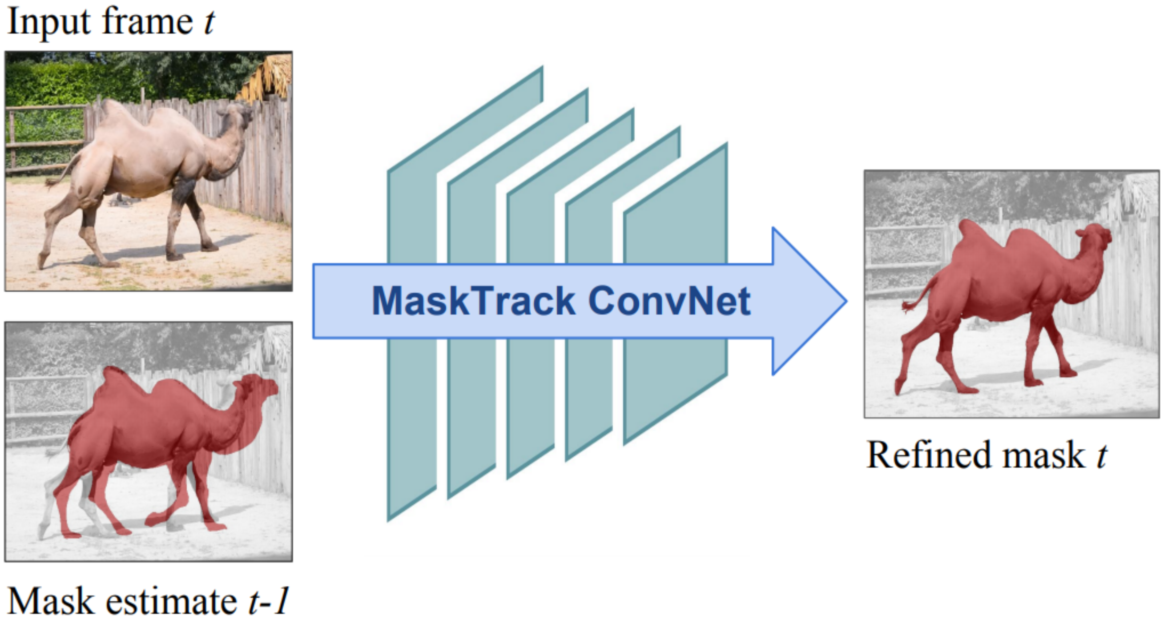
Blue = background samples
Red = foreground samples

P. Voigtlander and B. Leibe. "Online adaptation of convolutional neural networks for video object segmentation". BMVC 2017

Mask Refinement

- Assumption: an object, i.e., a mask, does not move a lot from frame to frame.
- We can often start with an approximate mask (either from previous frame or from coarse estimate).
- We can then use a **refinement** network to accurately refine the mask estimate.
- This can take advantage of crop-and-zoom to do segmentation at a higher resolution.

MaskTrack

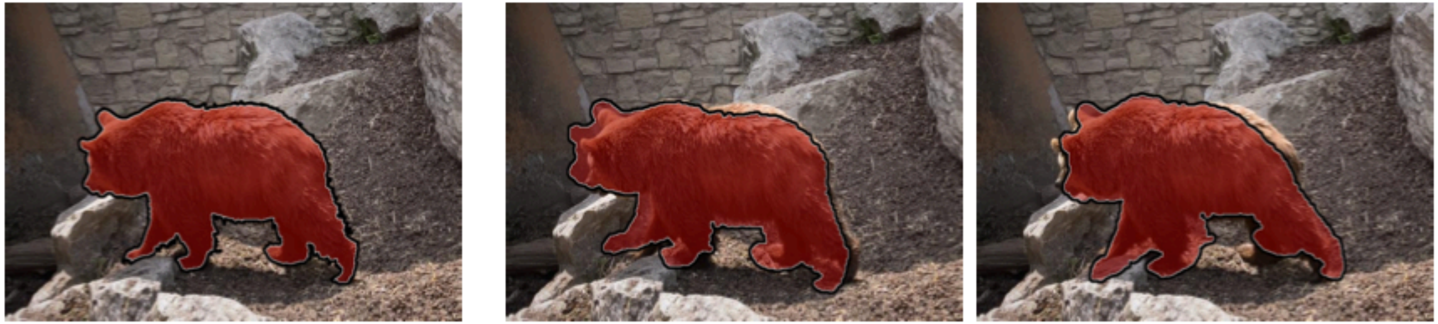


Why the name?

A. Khoreva et al. „Learning Video Object Segmentation from Static Images" CVPR 2017

MaskTrack

- Training inputs can be simulated!
  - Like displacements to train the regressor of Faster-RCNN
  - Very similar in spirit to Tracktor



(a) Annotated image

(b) Example training masks

A. Khoreva et al. „Learning Video Object Segmentation from Static Images“ CVPR 2017

Worth reading

- S. Jain et al. "Fusionseg: Learning to combine motion and appearance for fully automatic segmentation of generic objects in videos." CVPR 2017. → Optical flow propagation
- A. Khoreva et al. "Lucid Data Dreaming for Video Object Segmentation„ IJCV 2019 → clever data augmentation.
- X. Li et al. „Video object segmentation with re-identification" CVPRW 2017. → use reidentification techniques to recover from occlusions

Proposal-based approaches

Proposal Generation

Until now:
- Input is the whole image
- Proposals are put on top just to refine

Now:
Input are proposals
Goal is to “link” them (much like we did in tracking-by-detection)

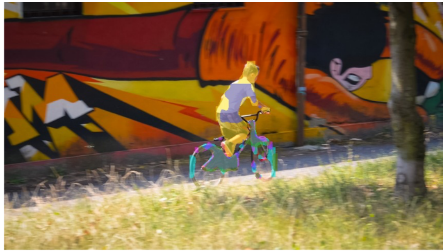
- Instance Segmentation Networks (E.g. Mask-RCNN) give object instance segmentation proposals.
- One can approach video object segmentation as taking these proposals in each frame and then linking them over time using a merging algorithm.

PReMVOS

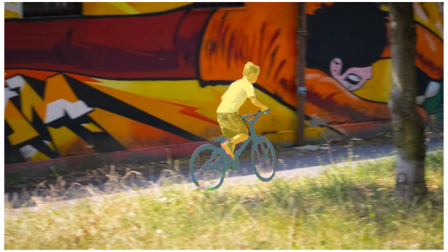
- An approach that combines all of the previous VOS principles and gives state-of-the-art results.
- Combines the following principles:
  - First-frame fine-tuning
  - Mask Refinement
  - Optical Flow Mask Propagation
  - Data Augmentation
  - Object Appearance Re-Identification
  - Proposal Generation

J. Luiten et al. „PReMVOS: Proposal-generation, Refinement and Merging for Video Object Segmentation“. ACCV2018

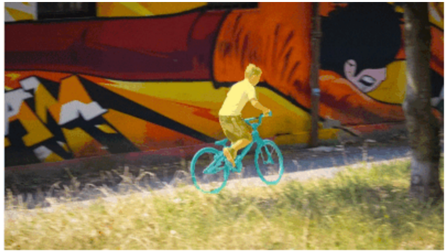
PReMVOS:Overview



Proposal generation



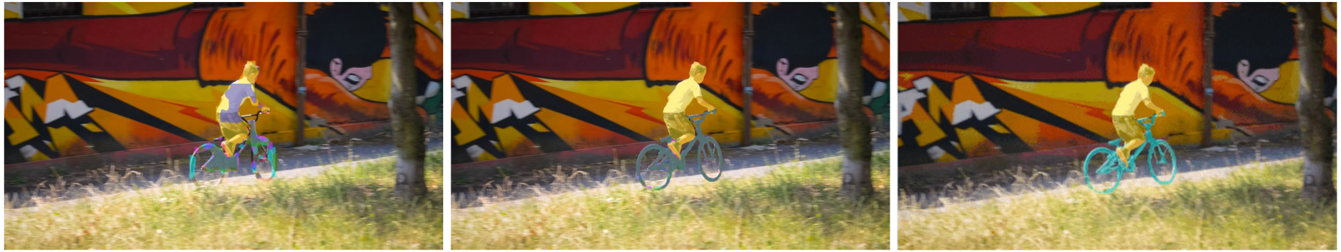
Refinement



Merging

- Proposal generation
  - Category-agnostic Mask R-CNN proposals
- Refinement
  - Fully-convolutional segmentation network trained to refine the segmentation given a proposal bounding box

PReMVOS: Overview



Proposal generation

Refinement

Merging

- Merging
  - Greedy decision process, chooses proposal(s) with best score
  - Optional proposal expansion through Optical Flow propagation
  - Proposal score as combination of
    - Objectness score
    - Mask propagation IoU score (Optical Flow warping)
    - ReID score
    - Object-Object interaction scores

PReMVOS: results

- Very complex but a winner

- DAVIS Challenge 2018 Winner

- Youtube-VOS Challenge 2018 Winner

Lessons Learned

- Challenge 1: How to generate proposals?
  - Deep-learning based region proposal generators are fit for the task
  - Experimented with SharpMask and Mask R-CNN
- Challenge 2: How to track region proposals?
  - Region overlap works as a consistency measure
  - Optical flow based propagation really helps
  - ReID score also helpful
- Open issues
  - PReMVOS has no notion of 3D objects moving through 3D space.
  - Track initialization / termination logic needed for real tracking.
  - How to obtain the initial segmentation?

Slide from: Jonathon Luiten

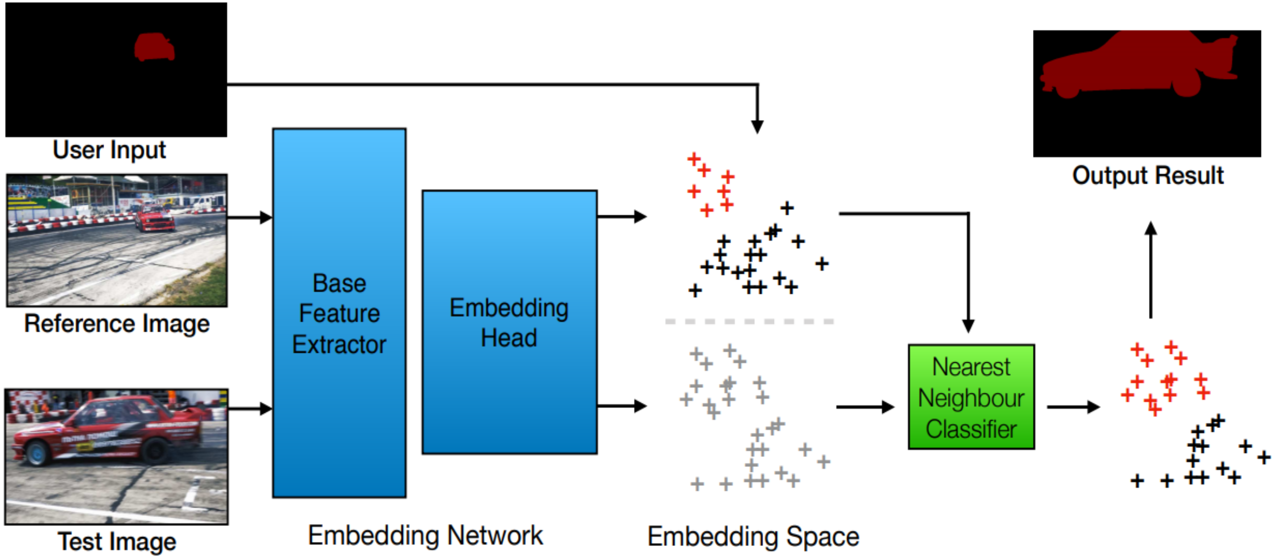
Retrieval approaches

Pixel-wise retrieval

- Re-Identification networks based on bounding-box region proposals work really well.
- This idea can be extended to a Re-Identification embedding for every pixel.

Pixel-wise retrieval

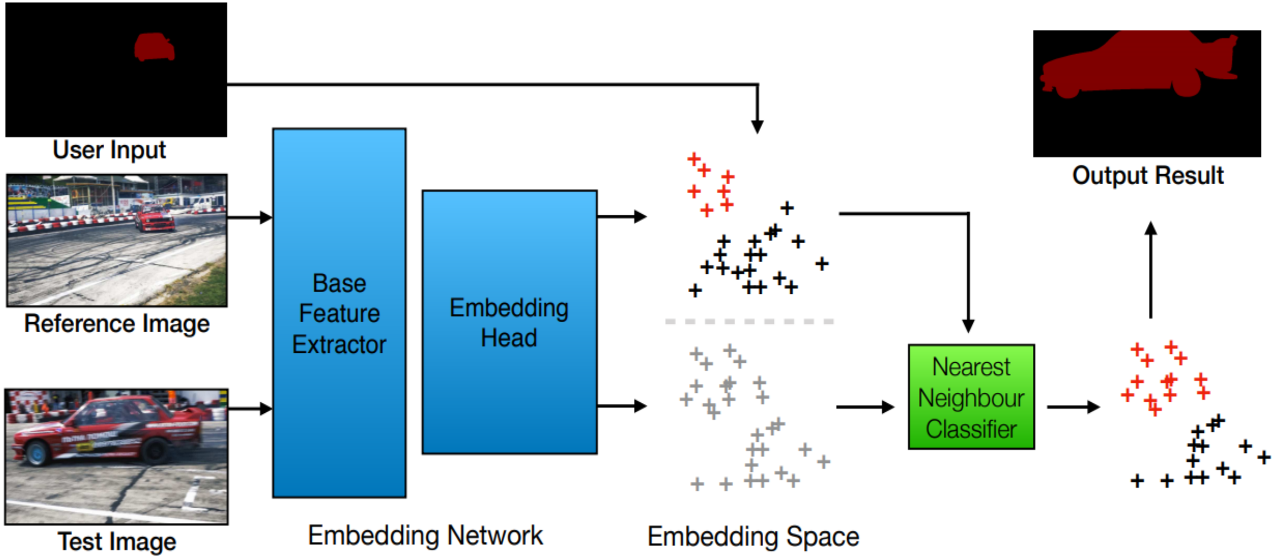
- The user input can be in any form, first-frame groundtruth mask, scribble…



Y. Chen et al. „Blazingly Fast Video Object Segmentation with Pixel-Wise Metric Learning“. CVPR 2018

Pixel-wise retrieval

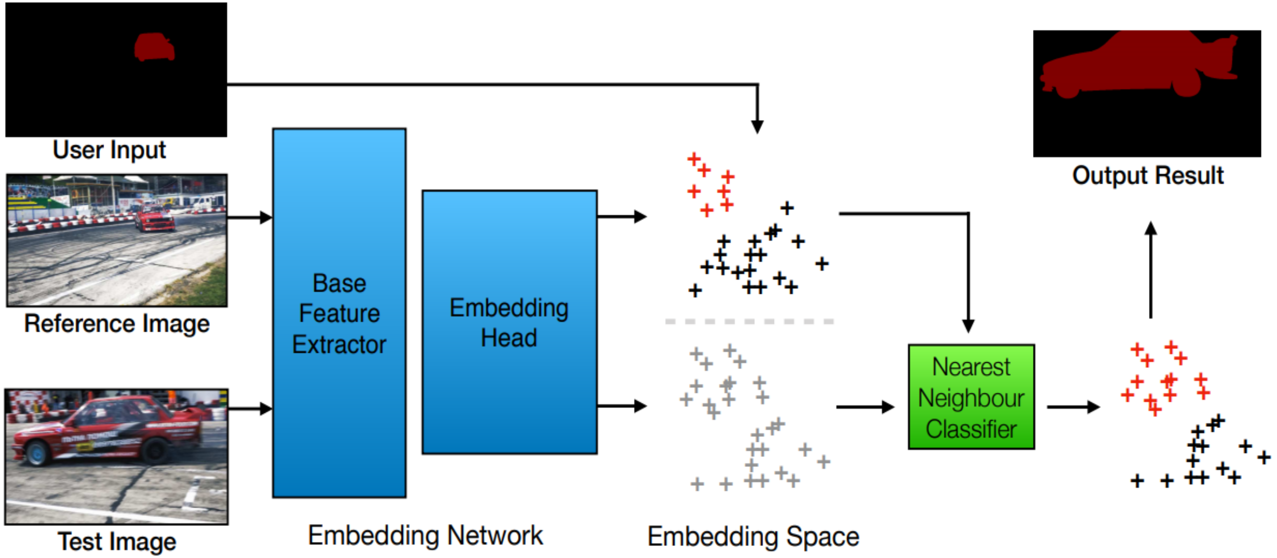
- Training: use the triplet loss to bring foreground pixels together and separate them from background pixels



Y. Chen et al. „Blazingly Fast Video Object Segmentation with Pixel-Wise Metric Learning". CVPR 2018

Pixel-wise retrieval

- Test: embed pixels from both annotated and test frame, and perform a nearest neighbor search for the test pixels.



We do not need to retrain the model for each sequence, nor finetune

Y. Chen et al. „Blazingly Fast Video Object Segmentation with Pixel-Wise Metric Learning". CVPR 2018

We are dealing with video

- Which is a sequence of images….

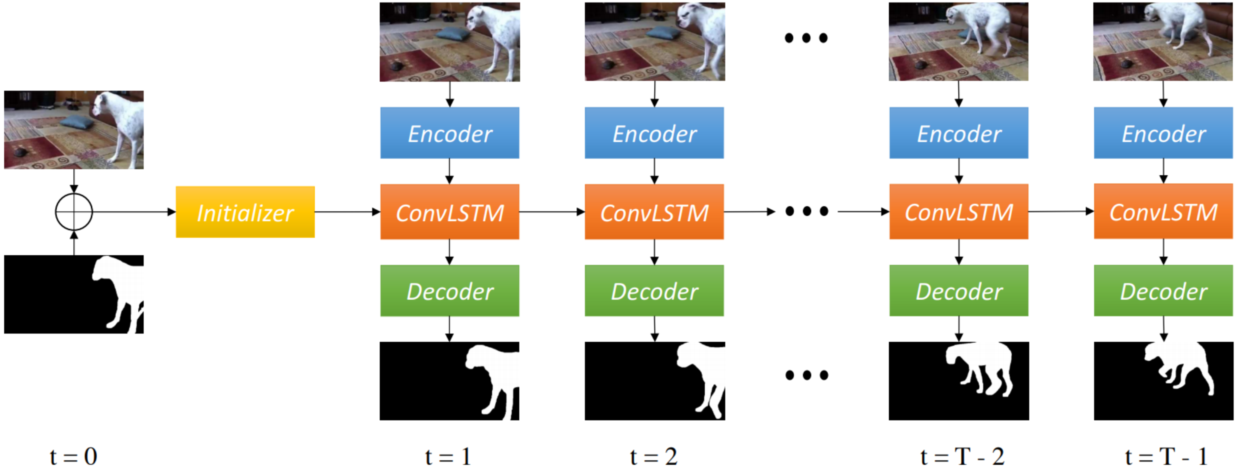
- And we have not talked about….

- Recurrent Neural Networks!

Spatio-temporal approaches

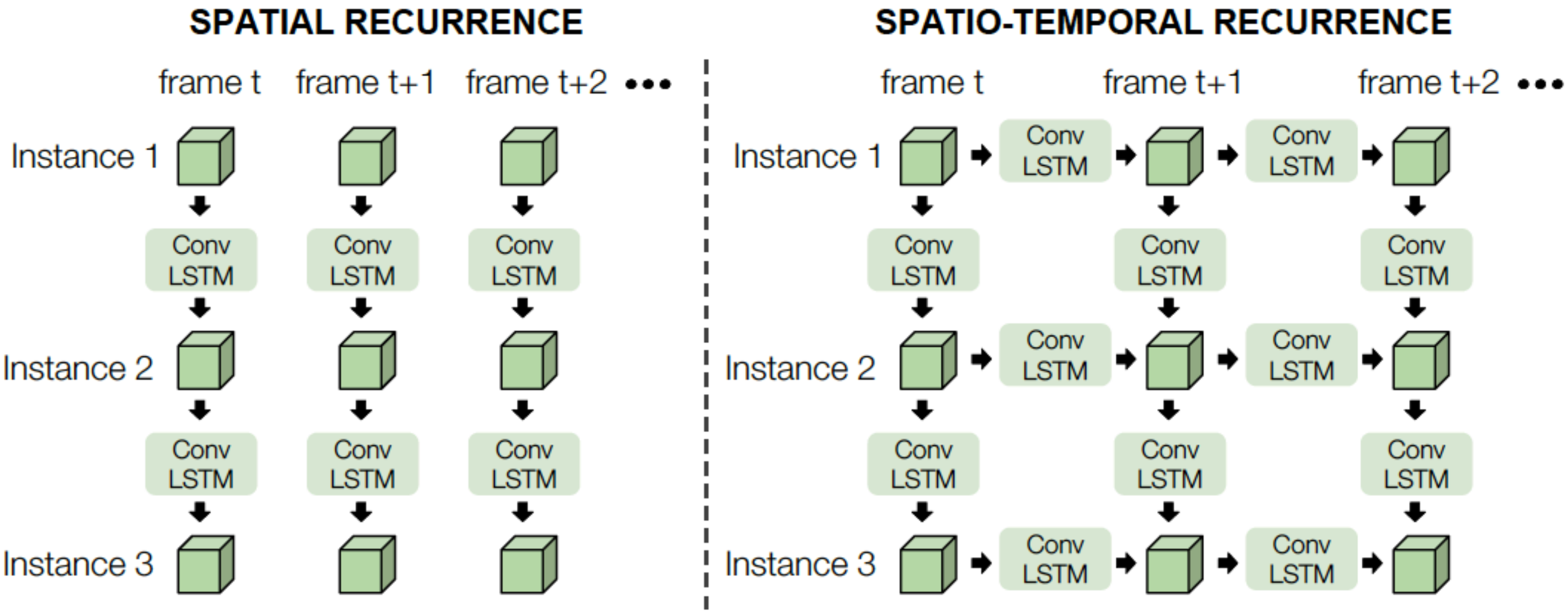
Temporal LSTM

- One-shot video object segmentation
- If we have multiple objects, each of them is predicted independently



N. Xu et al. „Youtube-vos: Sequence-to-sequence video object segmentation." ECCV 2018.

R-VOS: temporal and spatial LSTM

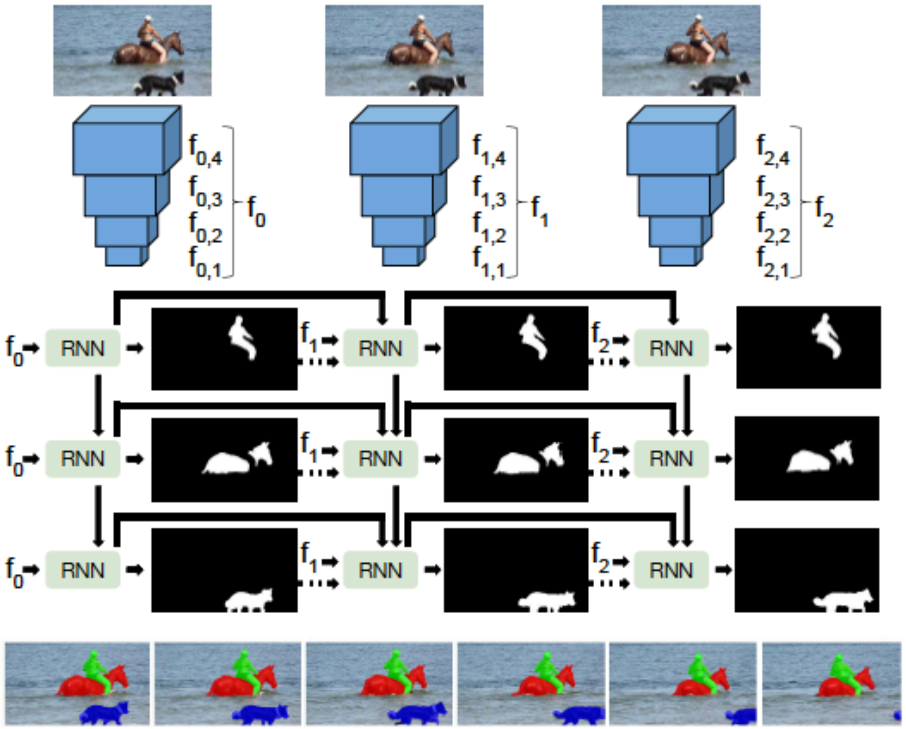


B. Roma-Paredes and P.H.S. Torr. „Recurrent Instance Segmentation" ECCV 2016

C. Ventura et al. „RVOS: end-to-end recurrent network for video object segmentation". CVPR 2019

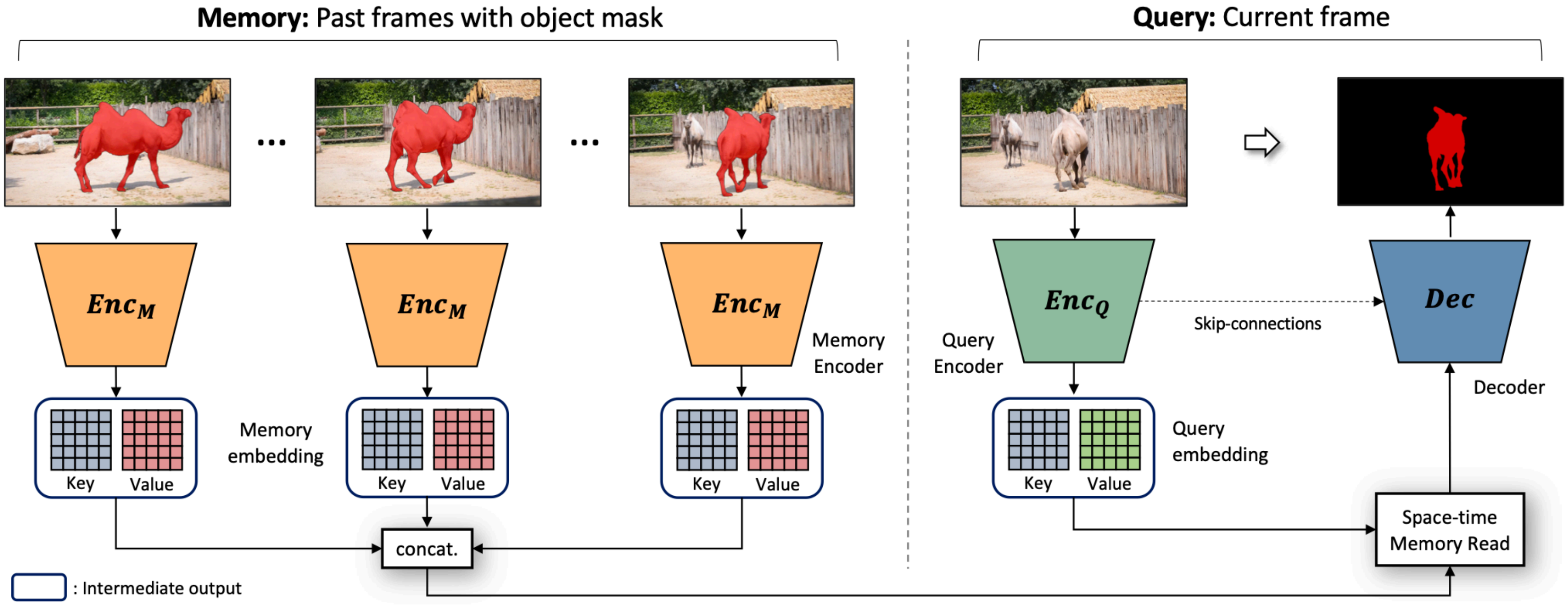
R-VOS: temporal and spatial LSTM

- Instance generation and temporal coherence are both trained end-to-end
- Image just needs to be processed once (unlike ConvLSTM example before)



C. Ventura et al. „RVOS: end-to-end recurrent network for video object segmentation". CVPR 2019

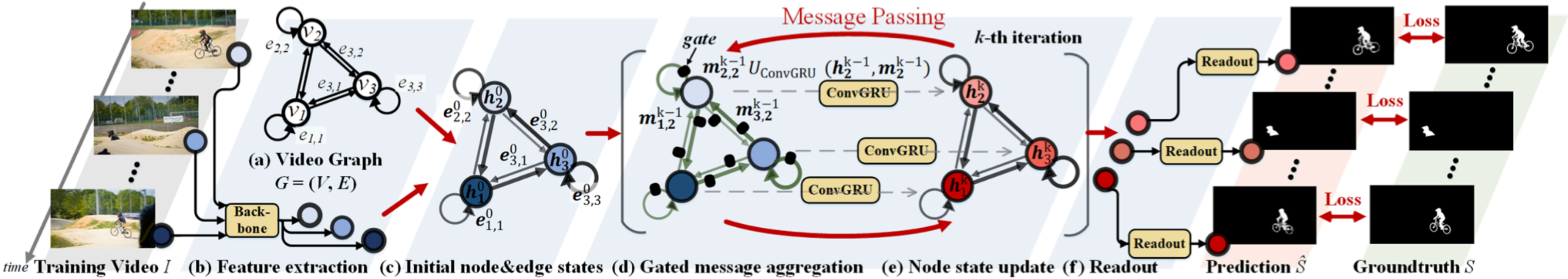
Transformers for VOS



S. Oh "Video Object Segmentation using Space-Time Memory Networks". ICCV 2019

Graph Attention Networks for VOS

- They use it for zero-shot segmentation, but could be similarly used for one-shot VOS.



W. Wang et al. „ Zero-Shot Video Object Segmentation via Attentive Graph Neural Networks ". ICCV 2019

Overview of the methods

- Video Object Segmentation (VOS)
  - OSVOS: First-frame fine-tuning (appearance model)
  - OSVOS-S: + semantic guidance through proposals (shape)
  - OnAVOS: Online Adaptation (stronger appearance model)
  - MaskTrack: Mask Refinement
  - Lucid: clever data augmentation
  - ReID-VOS: Object Appearance Re-Identification
  - PReMVOS: putting it all together
  - Seq2seq and RVOS: recurrent architectures

Shape

Appearance

Motion

Matching

Evaluation and metrics

Metrics for VOS

- **Region similarity**: Jaccard index (IoU) of ground truth mask and predicted mask.
- **Contour Accuracy**: measures the precision and recall of the boundary pixels. This is put together in the F-measure.

$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

$$F = \frac{2 * Prec * Rec}{Prec + Rec}$$

Metrics for VOS

- **Temporal stability**: measures the evolution of object shapes, i.e., how stable the boundaries are in time.
  - Estimate the deformation of the mask from *t* to *t+1*
  - If the transformation is smooth and precise, the result is considered stable.
  - A bad results is a jittery mask evolution
  - Note: this measure has been dropped due to its instability during occlusions.

Metrics for VOS

- You can use error measure statistics
- **Region similarity**: Jaccard index (IoU) of ground truth mask and predicted mask.
  - Mean: average for the dataset
  - Decay: quantifies the performance loss (or gain) over time.
    → This is currently used to judge temporal stability
  - Recall: fraction of sequences scoring higher than a threshold

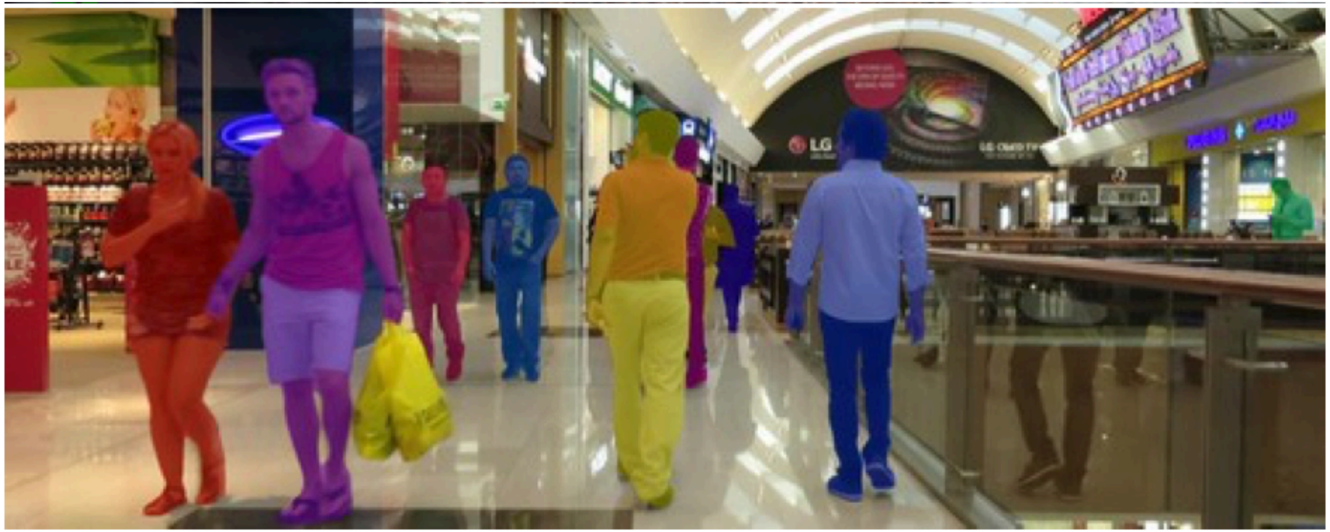
Tracking and Segmentation

VOS -> MOTS

- Video Object Segmentation (VOS) is limited by:
  - First frame mask given (in the supervised case)
  - Short video clips with objects present in almost all frames
  - Objects in a video are (mostly) of different categories
  - Few objects to track (max around 7 per video)
- Multi-Object Tracking and Segmentation (MOTS)
  - Scenarios with a large number of objects (20-40), mostly of the same category (e.g., pedestrians)
  - Long sequences
  - No first frame annotation provided, one has to deal with appearing and disappearing objects.

MOTS dataset

- Segmentations coming to MOTChallenge pedestrian tracking dataset



P. Voigtlaender et al. „MOTS: Multi-Object Tracking and Segmentation". CVPR 2019

Video Object Segmentation

Disclaimer

- This lecture was done borrowing material from:
  - Prof. Xavier Giró, Technical University of Catalonia (UPC)
  - Jonathon Luiten, RWTH Aachen