Learning from Videos

Feb 6st, 2023

Tali Dekel

Videos

Videos are all around us

Span an enormous space of spatial and temporal signals

Challenges in Videos: size of video

Image

video

Size of video >> size of image

Computational constrains → short, low-res clips

3 x H x W

4D tensor:
T x 3 x H x W

time

~30 frames per second (fps)

Uncompressed size (3 bytes per pixel):
SD (640 x 480): **~1.5 GB per minute**
HD (1920 x 1080): **~10 GB per minute**

Reduce spatial and temporal resolution

5fps, half the spatial resolution

Slide inspiration: Justin Johnson, EECS 498-007

Challenges in Videos: size of video

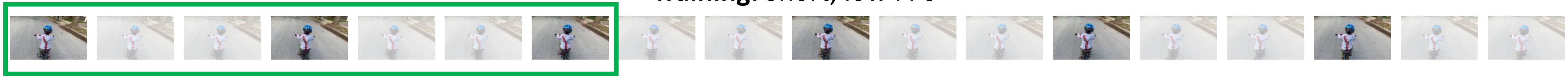
Computational constrains → short, low-res clips

Input video

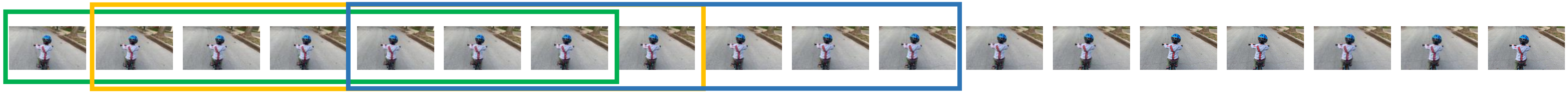
Walking
Running
Cycling
Jumping
.
.

Original video(long, high FPS)

Training: Short, low FPS



Test time: inference on different short clips, average predictions



Challenges in Videos: Videos Datasets

space of video >> space of image → lots of training data

"ImageNet"-equivalent dataset for videos?

Massive human labelling efforts

UCF101

YouTube videos

13320 videos, 101 action categories

Kinetics

Kinetics

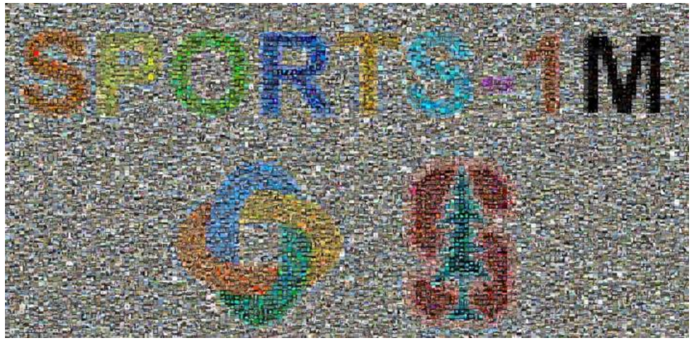
YouTube videos

650,000 video clips, 600 human action classes

YouTube 8M

YouTube-8M

8M video clips, Machine-generated annotations from 3,862 classes



Sports-1M

YouTube videos

1,133,157 videos, 487 sports labels

Today

Deep Learning-based Models for Videos

- How to reduce computation cost without sacrificing accuracy?
- What architecture to best capture temporal patterns?

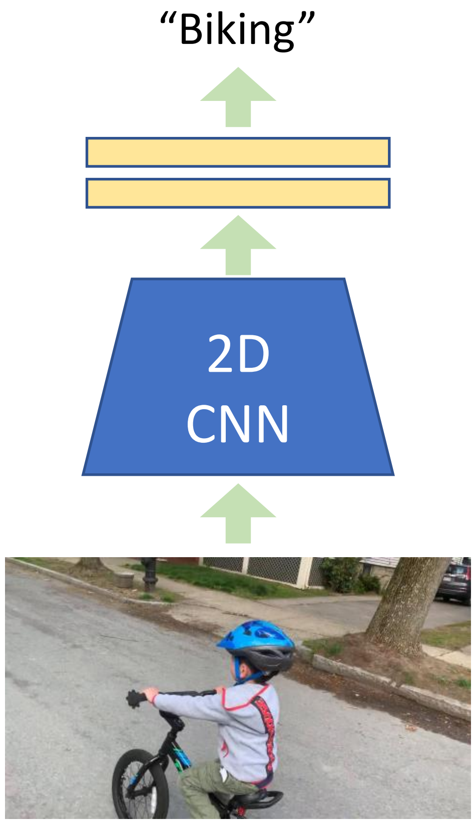
Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Self-Supervision in Videos

- Which types of pretext tasks can we define to capture temporal information?
- Learning from a single video and neural video represenation

Models for Videos: Single-Frame Baseline

- Train 2D CNN to classify video frames independently



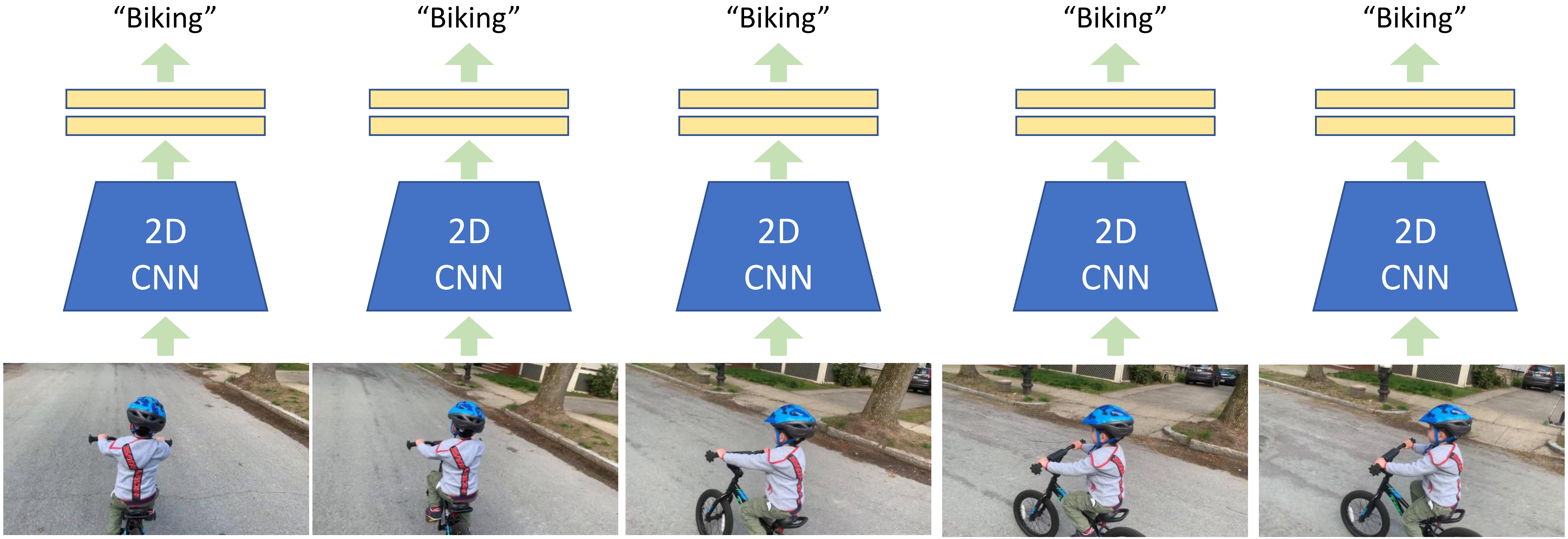
Input video frame

Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Single-Frame Baseline

- Train 2D CNN to classify video frames independently
- Average predicted probs at test-time

Often a surprisingly strong baseline!

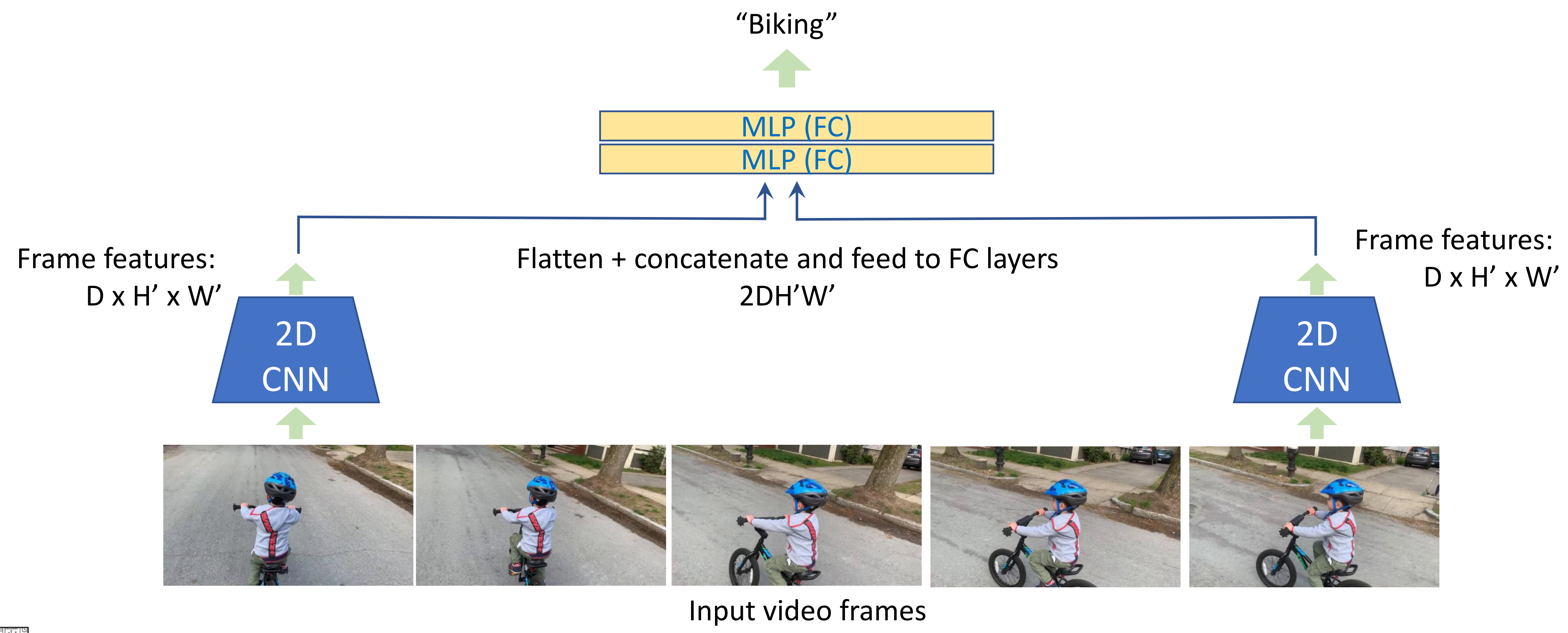


Input video frames

Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Late Fusion

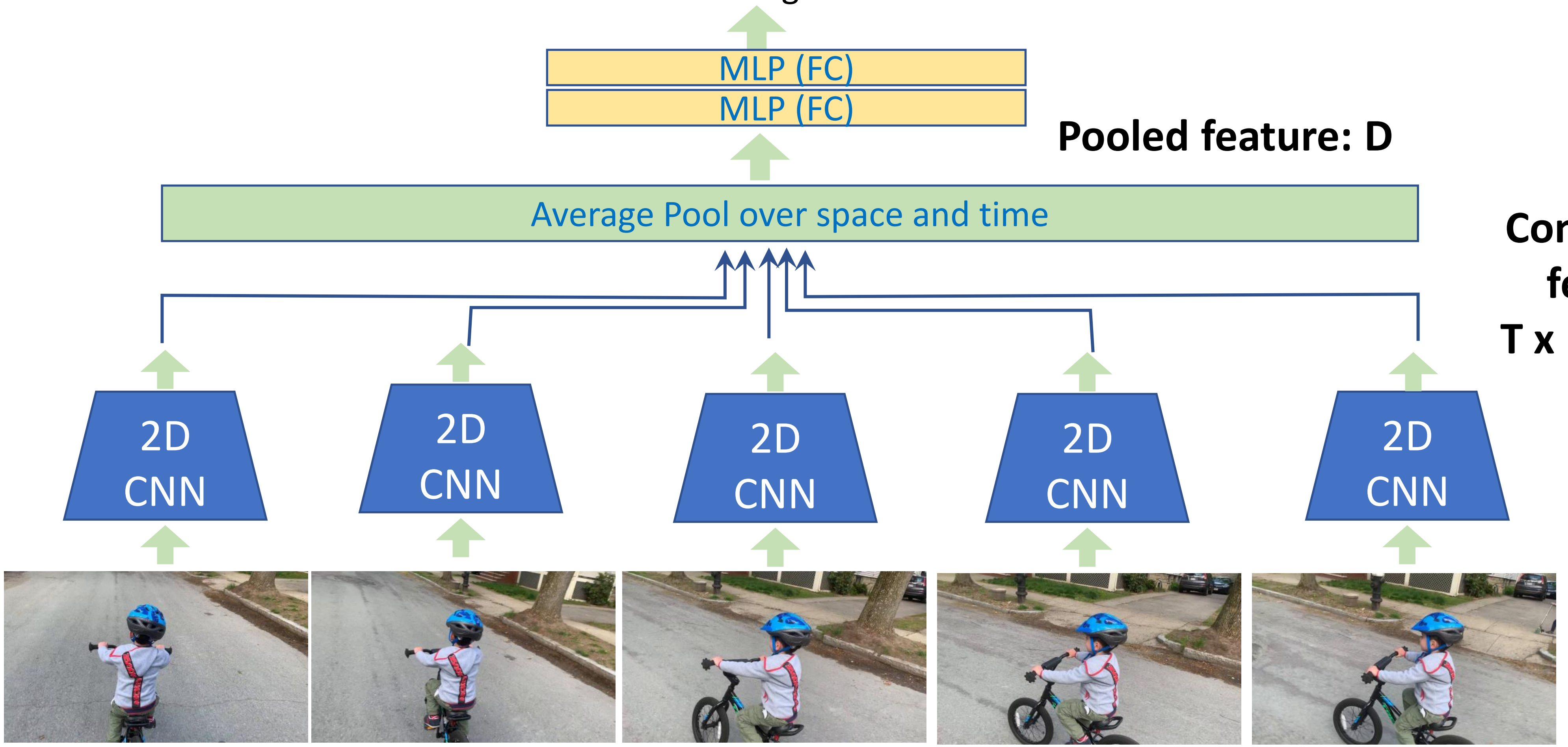
- Learn features for each frame using a 2D CNN, concatenate feature, and fuse



Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Late Fusion w/ pooling

Learn features for each frame, apply spatial-temporal average pool, and then fuse



Input video frames

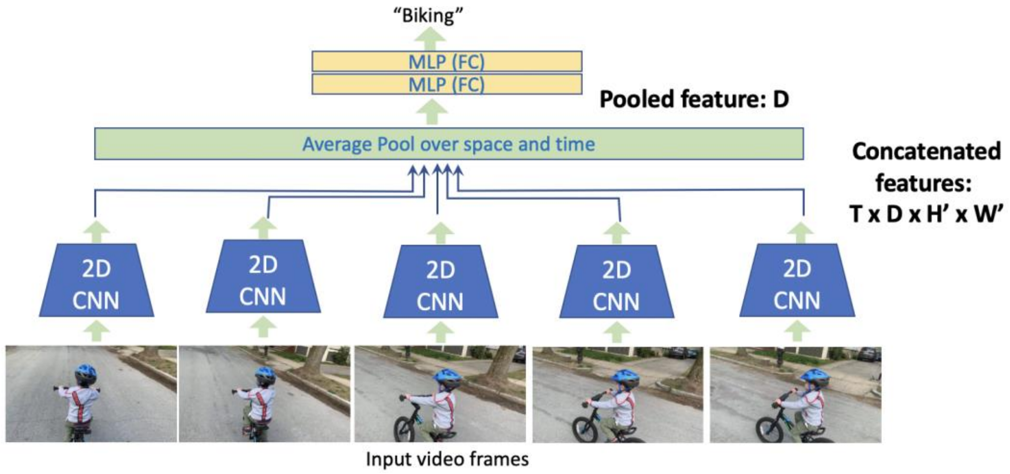
Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Late Fusion w/ pooling

Learn features for each frame, apply spatial-temporal average pool, and then fuse

Pros: allow the network to learn global motion characteristics by comparing outputs of both towers

Cons: late fusion is late…
hard to represent low level motion between frames

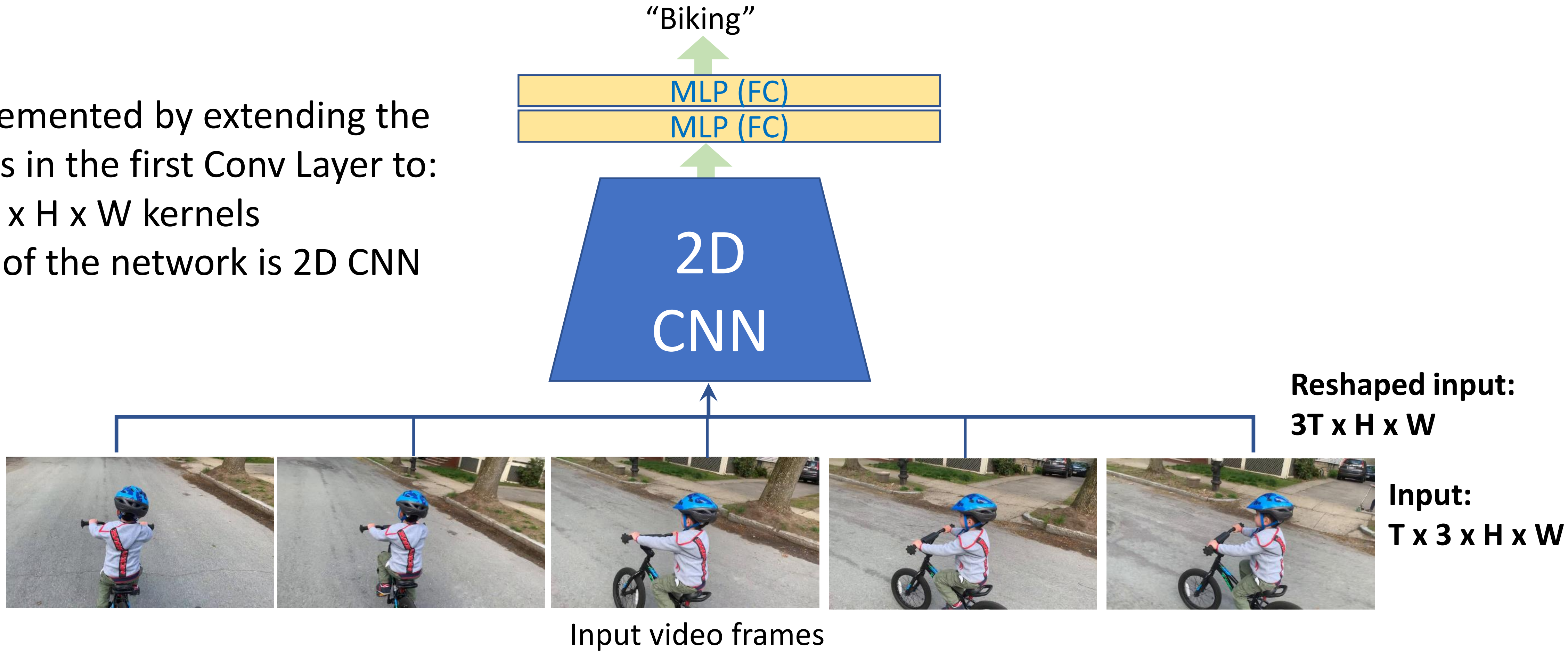


Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Early Fusion

- Combines temporal information immediately on the pixel level
- Treat time as another “channel” dimension

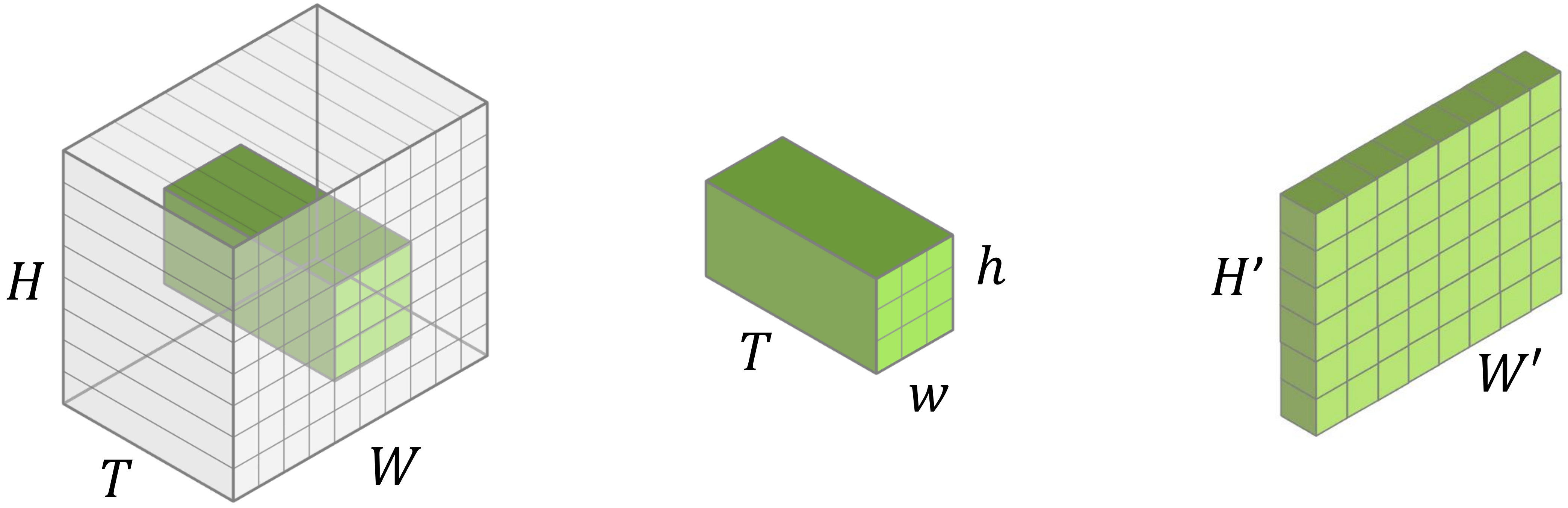
Implemented by extending the filters in the first Conv Layer to:
T x 3 x H x W kernels
Rest of the network is 2D CNN



Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Early Fusion

Extending the filters in the first Conv Layer to: T x 3 x H x W kernel



Input: T x 3 x H x W

Weights: C x T x 3 x h x w

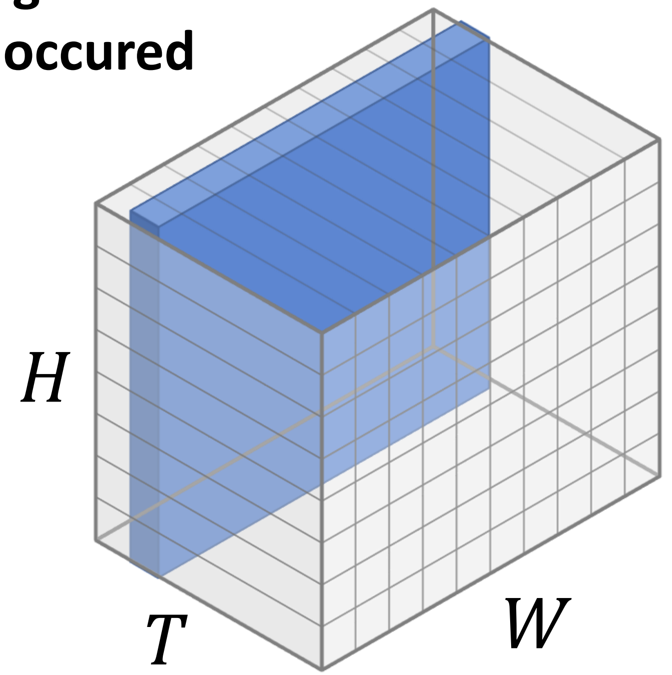
Output: C x H’ x W’

Models for Videos: Early Fusion

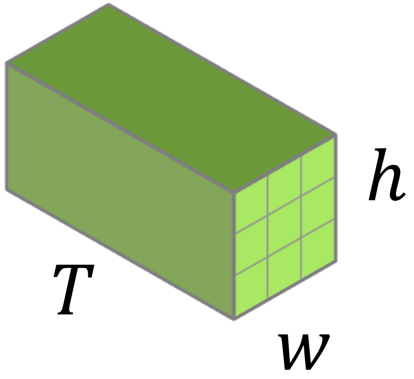
Extending the filters in the first Conv Layer to: T x 3 x H x W kernel

- Not temporal shift invariance; specific filter is learned to each time step

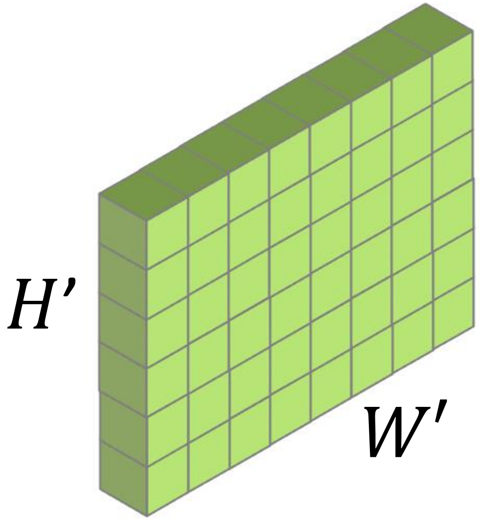
Large motion occured



Input: T x 3 x H x W



Weights: C x T x 3 x h x w



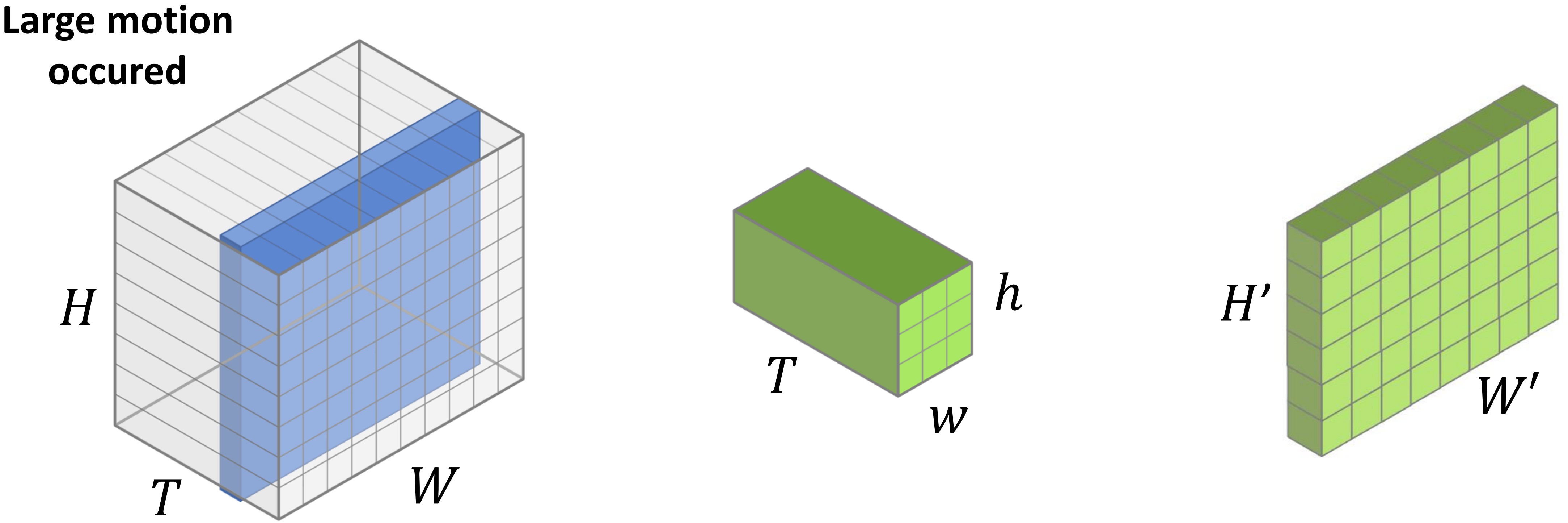
Output: C x H’ x W’

Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Early Fusion

Extending the filters in the first Conv Layer to: T x 3 x H x W kernel

- Not temporal shift invariance; specific filter is learned to each time step



Input: T x 3 x H x W

Weights: C x T x 3 x h x w

Output: C x H’ x W’

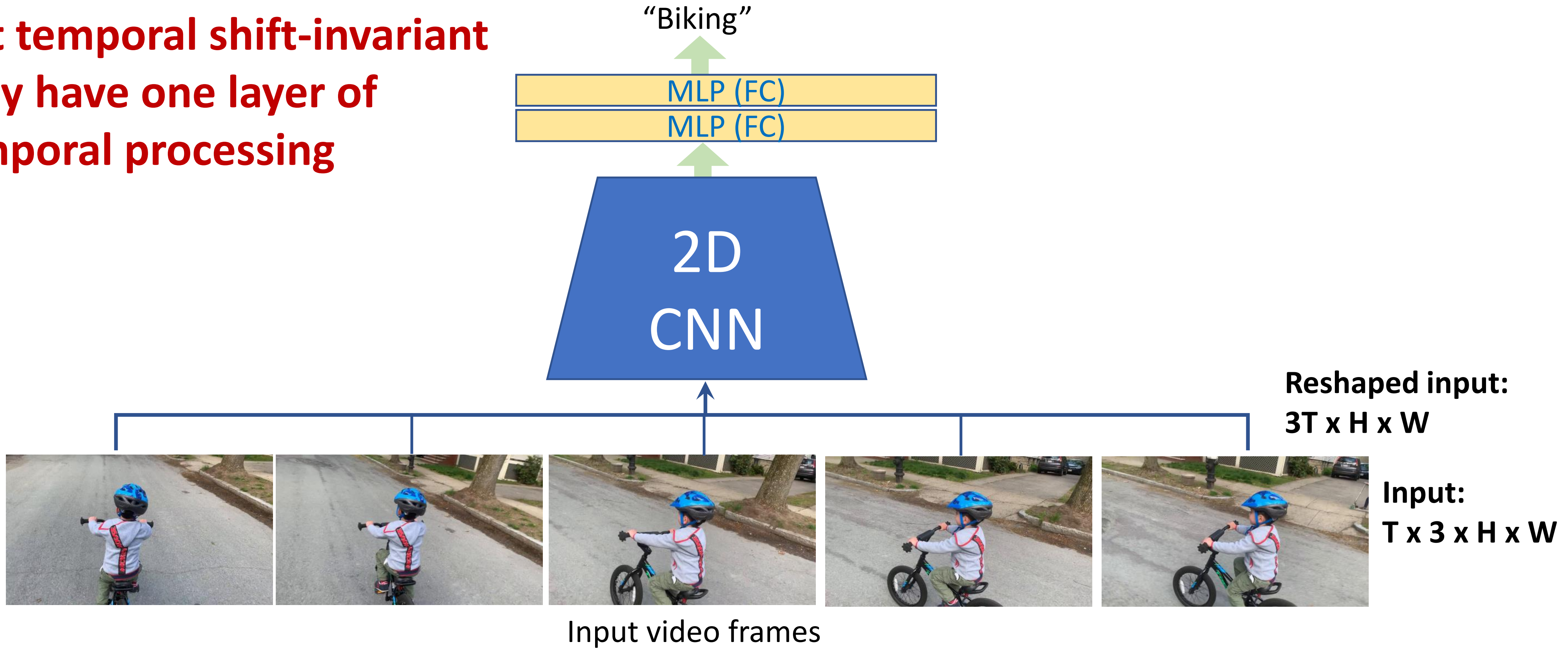
Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Early Fusion

Pros: Allow the network to learn local motion characteristics

Cons:

- Not temporal shift-invariant
- Only have one layer of temporal processing

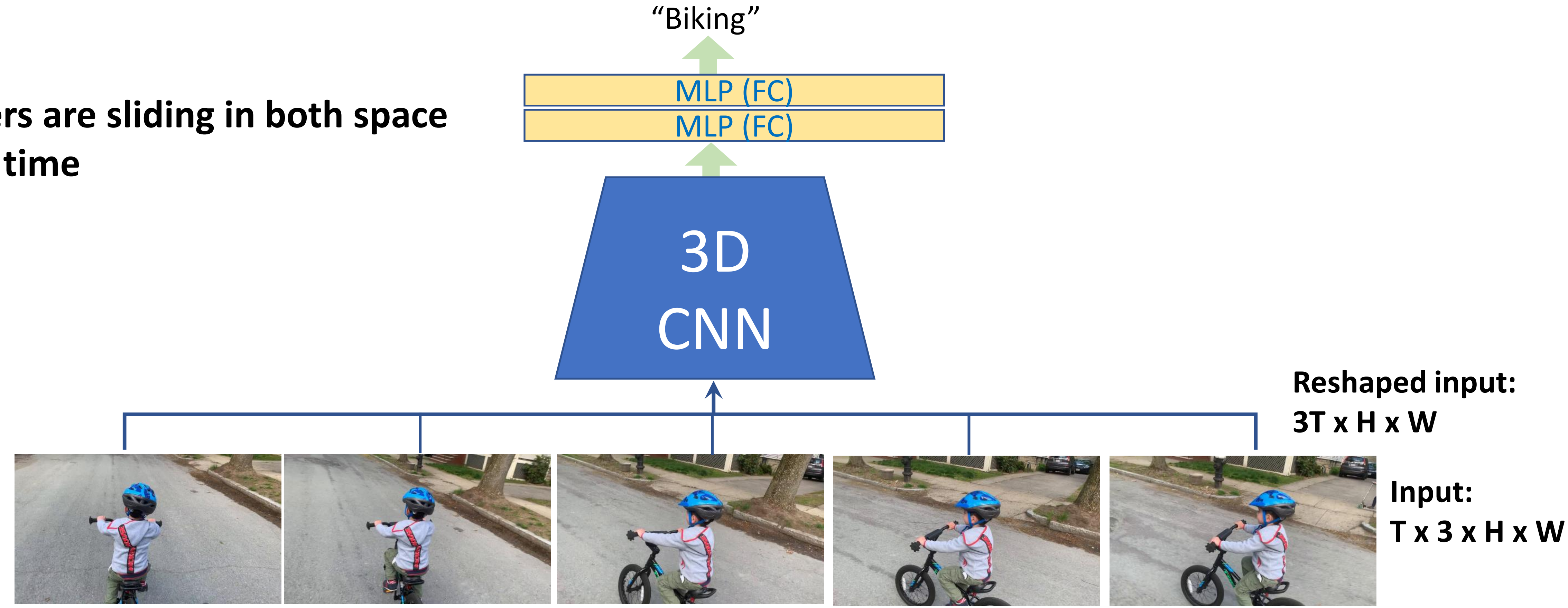


Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Slow Fusion a.k.a 3D Convs

- Extend 2D Convs and pooling to 3D to slowly fuse temporal information throughout the model

Filters are sliding in both space and time

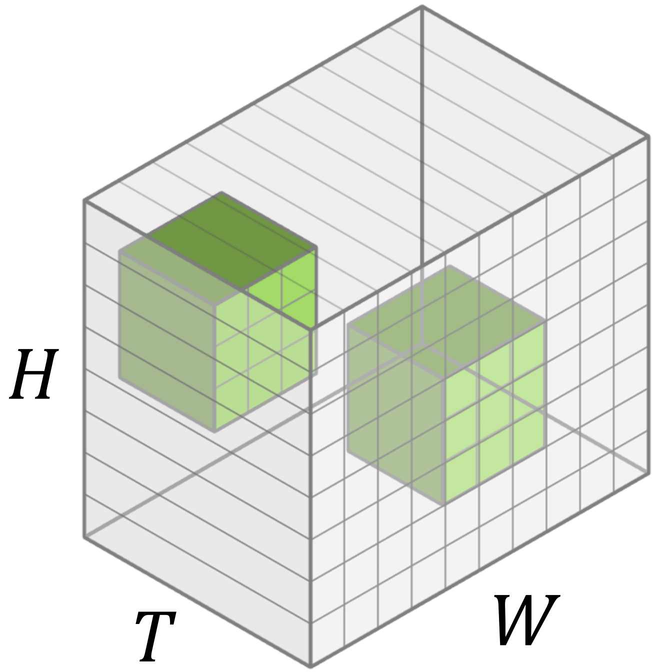


Input video frames

Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

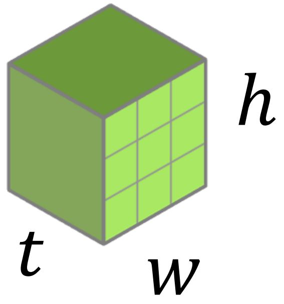
Models for Videos: Slow Fusion a.k.a 3D Convs

- Extend 2D Convs and pooling to 3D to slowly fuse temporal information throughout the model
- **Slide the kernels in both space and time**

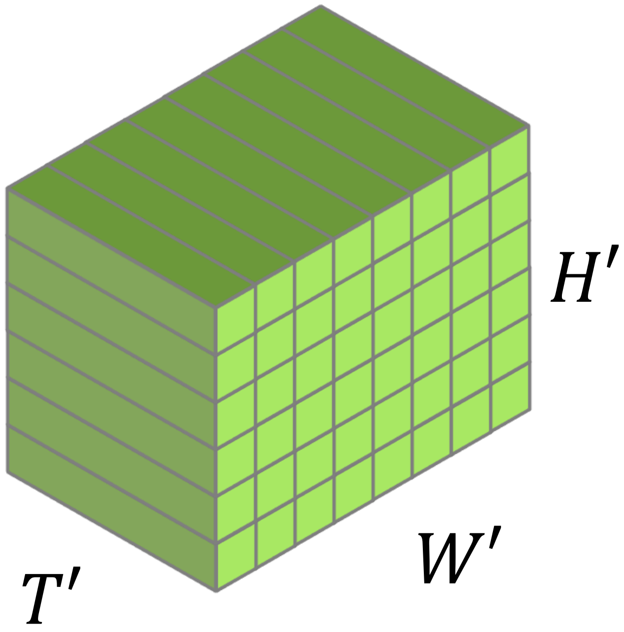


Input: T x 3 x H x W

- **Temporal shift-invariant!**



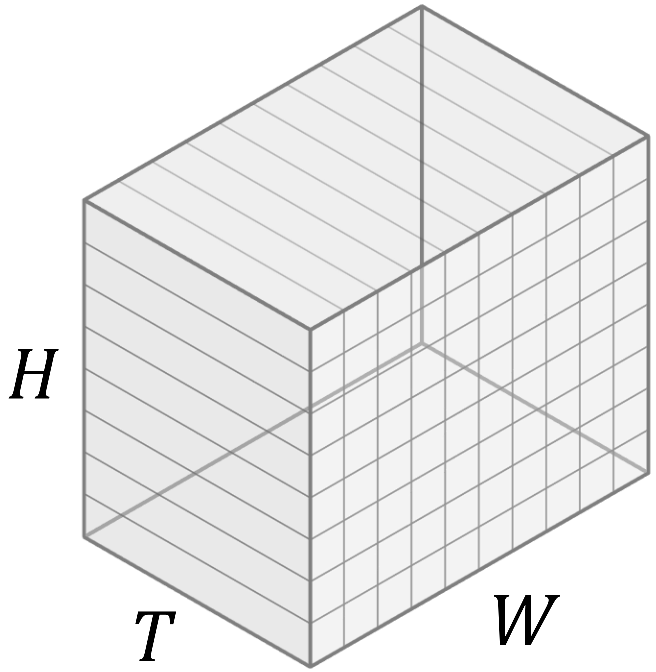
Weights: C x t x 3 x h x w



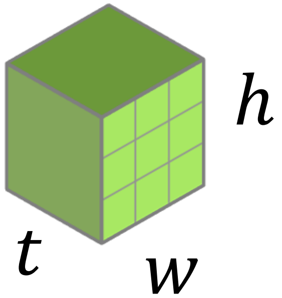
Output: C x T' x H' x W'

Models for Videos: Slow Fusion a.k.a 3D Convs

- Extend 2D Convs and pooling to 3D to slowly fuse temporal information throughout the model
- **Slide the kernels in both space and time**



Input: T x 3 x H x W



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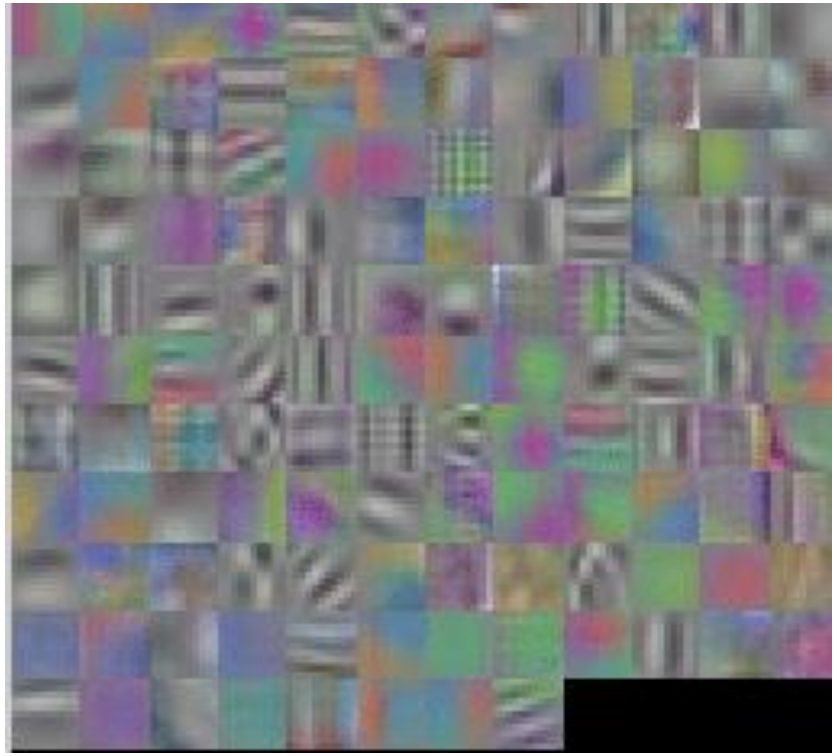


First layer filters
3(rgb) x 4 (t) x 5 (h) x 5 (w)

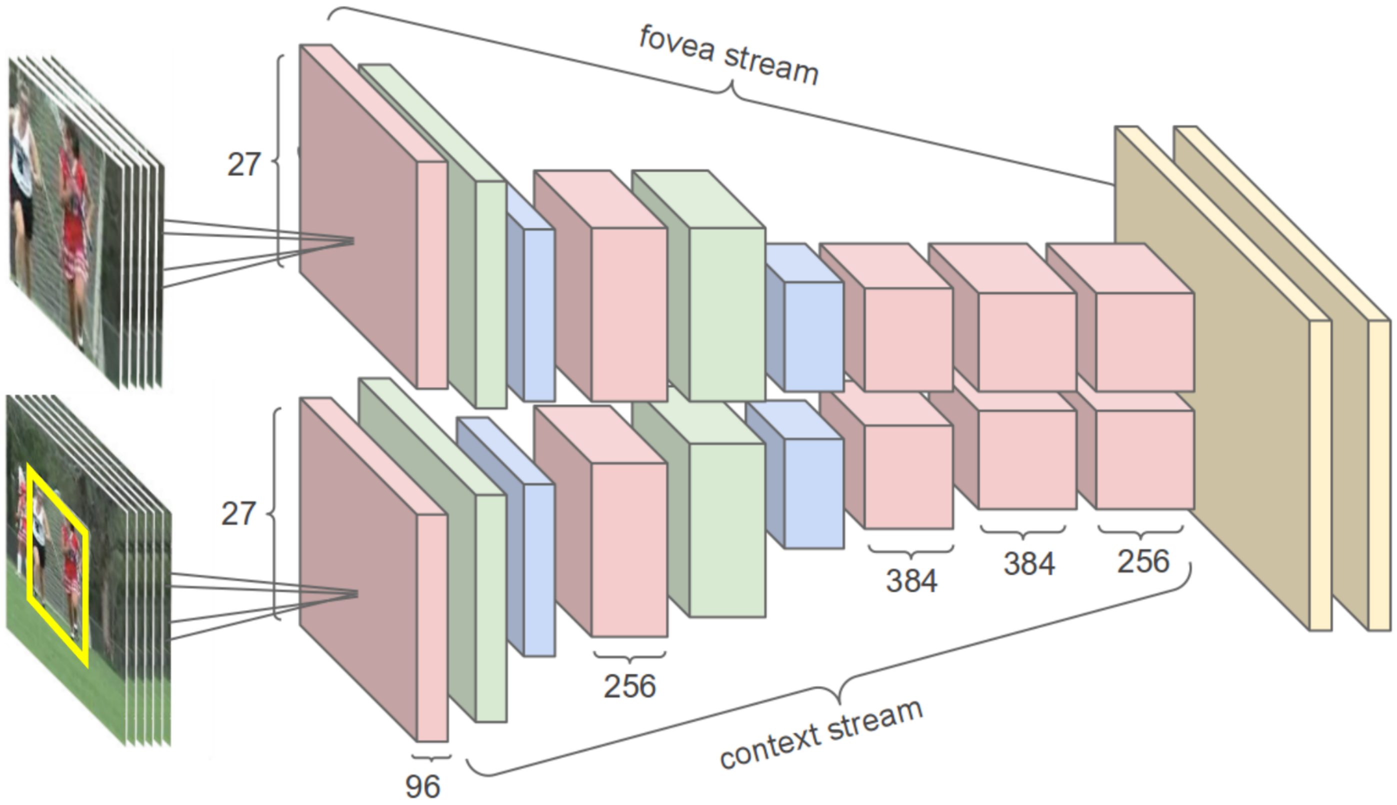
Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Models for Videos: Multi-scale

How can we reduce computational cost while maintaining accuracy?

Reduce video resolution → lower performance

Reduce network's capacity → lower performance



- Context stream ***(low res)***:
  process low res video frames (H/2, W/2)

- Fovea sterm ***(high res)***:
  process a (H/2, W/2) crop from the original resolution

Reduce the input dimentionalty by half

Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

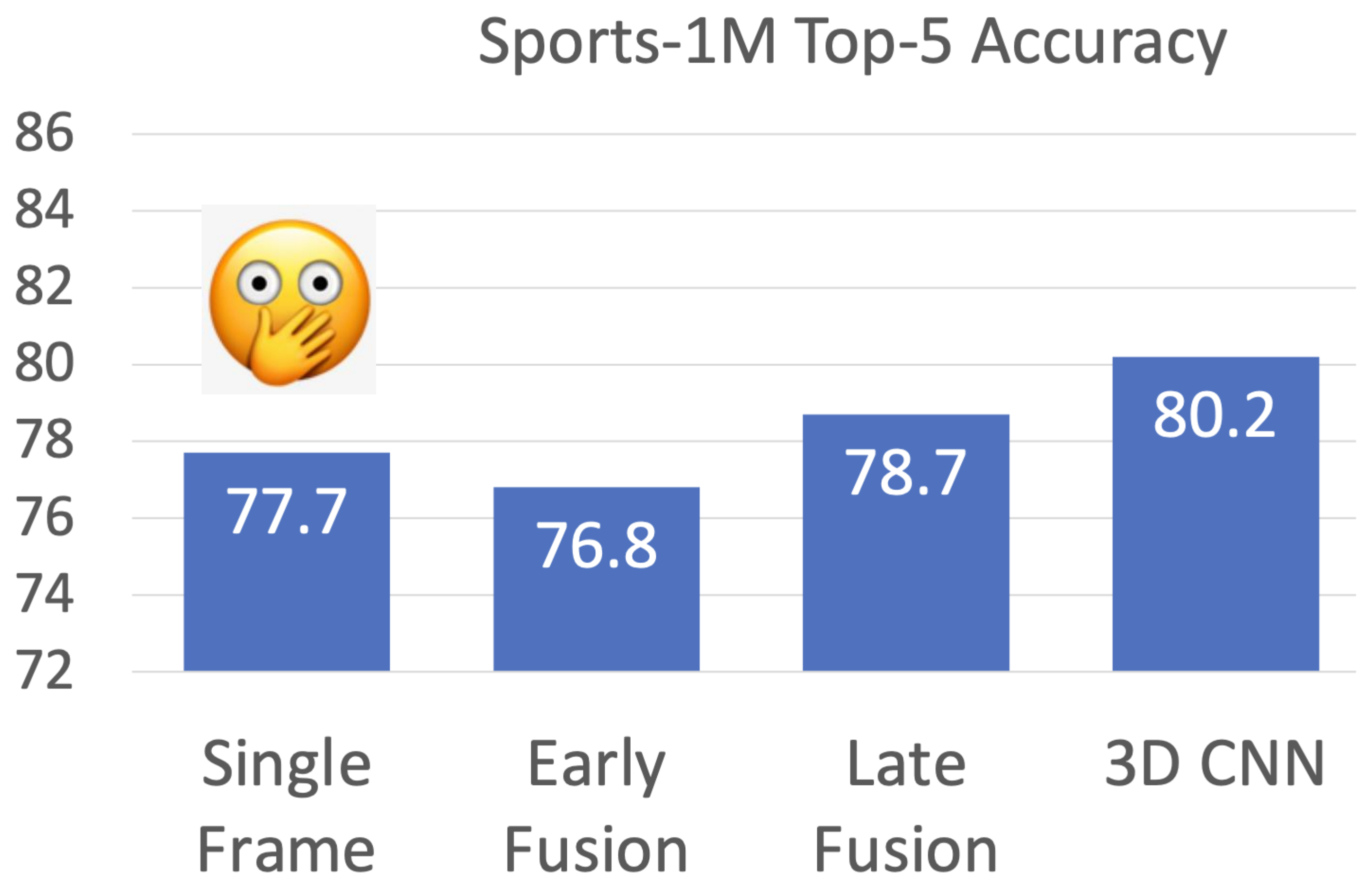
Action classification -- Sports-1M

- **1 million YouTube videos**
- **Fine grained labels for 487 different types of sports**

- **Ground truth**
- **Correct prediction**
- **Incorrect prediction**

Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014

Action classification -- Sports-1M



Single frame: a shockly powerful baseline

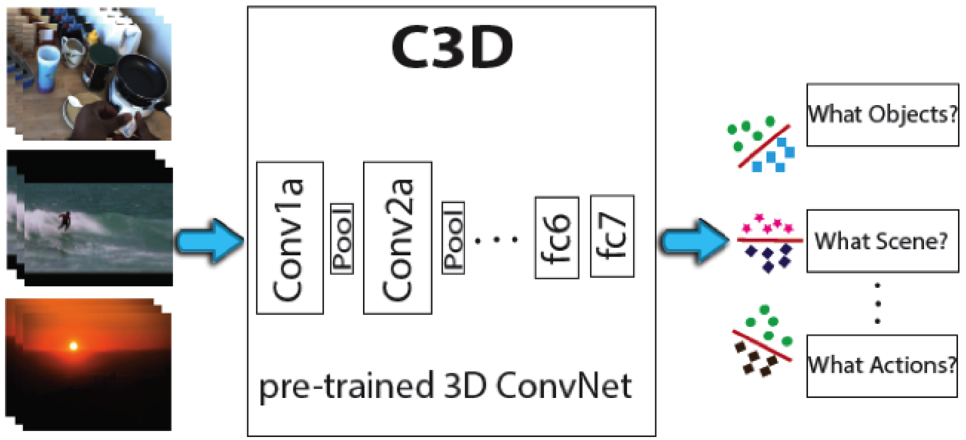
This is from 2014…

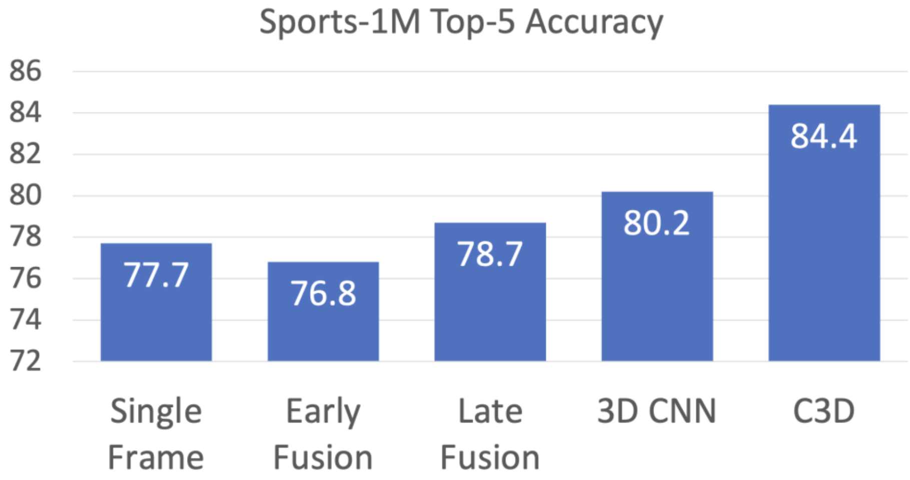
Karpathy et. al., Large-scale Video Classification with Convolutional Neural Networks, CVPR, 2014   Slide credit: Justin Johnson, EECS 498-007

Models for Videos: C3D (Convolutional 3D)

- 3D CNN that uses all 3x3x3 Convs and 2x2x2 poolings
- The "VGG" of 3D CNNs

- Transfer learning: extract learned video features, train a simple linear classifier for various tasks



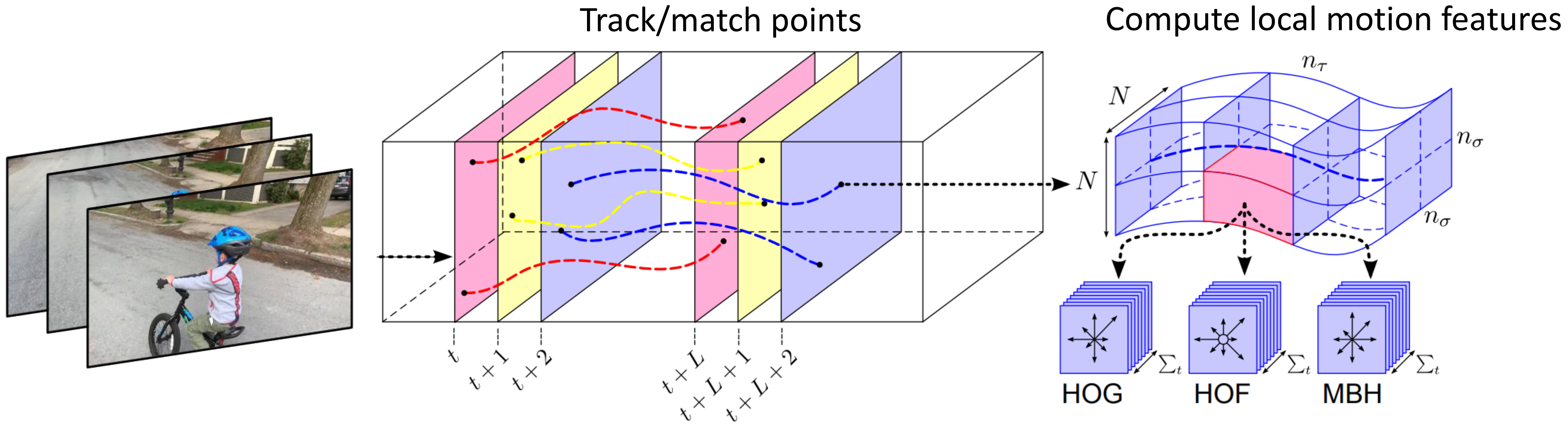


- Problem: 3D convs are VERY expensive!
  C3D on small inputs takes 3x VGG and 56x AlexNet FLOPs

Tran et al, "Learning Spatiotemporal Features with 3D Convolutional Networks", ICCV 2015

Non-deep learning video classification

Motion is the most informative cue for action recognition → design hand crafted motion features:



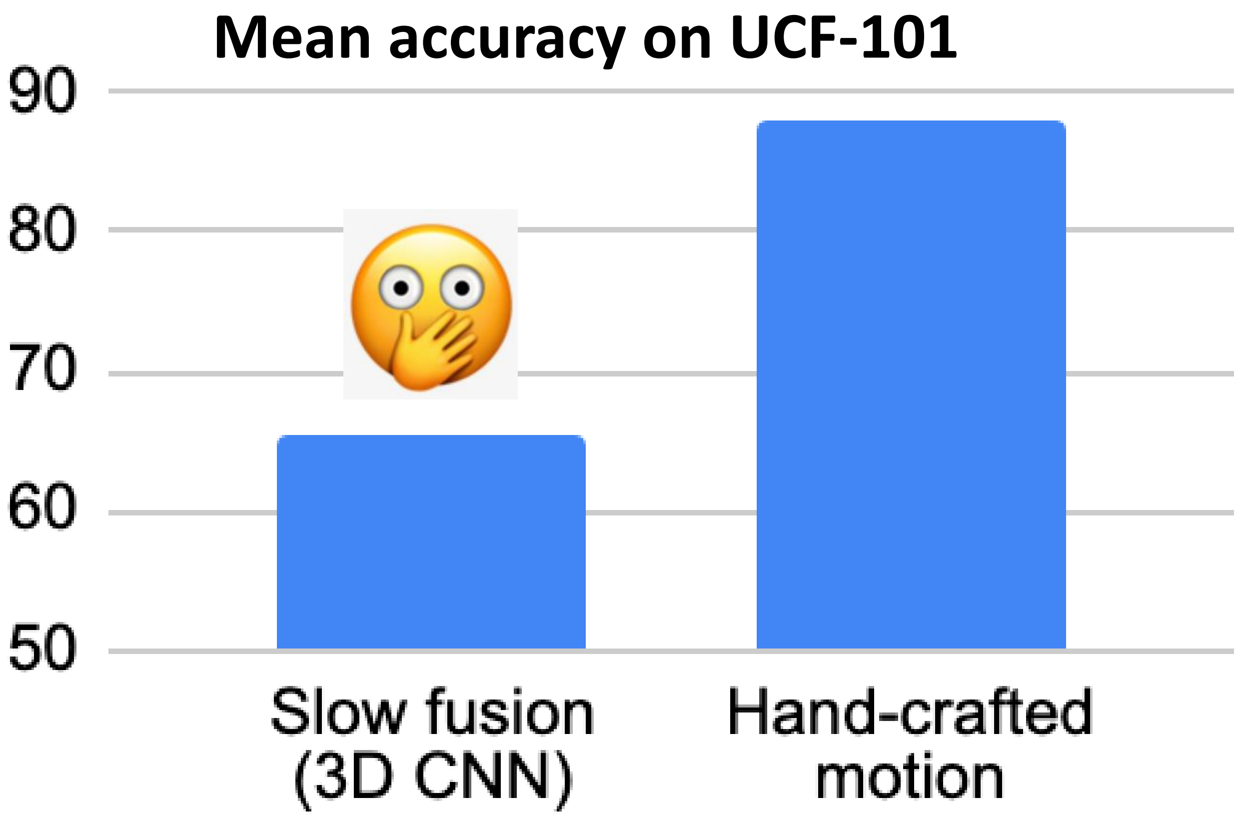
Aggregate local motion features to compute a global representation of the video → linear SVM for action recognition

MODEL MOTION EXPLICITLY

Wang et. al., Dense trajectories and motion boundary descriptors for action recognition, 2013
Peng et. al., Bag of Visual Words and Fusion Methods for Action Recognition: Comprehensive Study and Good Practice, 2014

Non-deep learning video classification

Motion is the most informative cue for action recognition → hand crafted motion features:

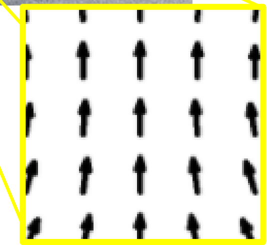


Explicitly modeling motion in deep-based models

Optical flow: For each pixel in frame t, determines its corresponding pixel in frame t+1

Frame t+1

Frame t



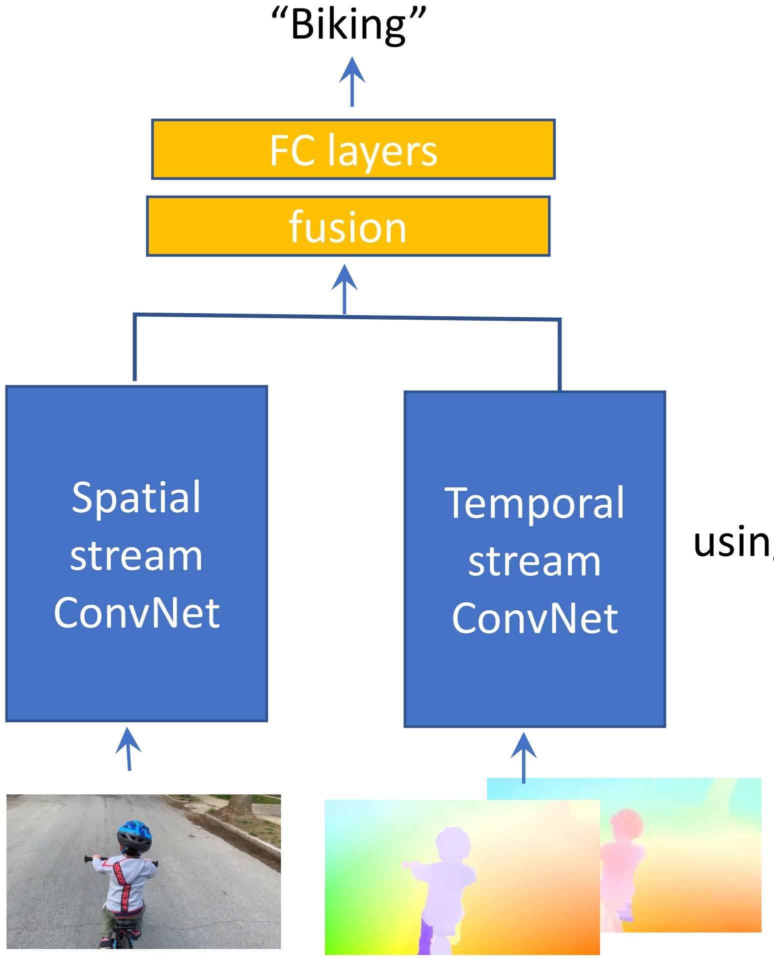
Optical flow provides **local motion cues**

Optical flow between two frames

Color wheel
Saturation = mag.
Color = angle

Two Stream Networks: modeling motion explicitly

Idea: separate motion (multi-frame) from static appearance (single frame)



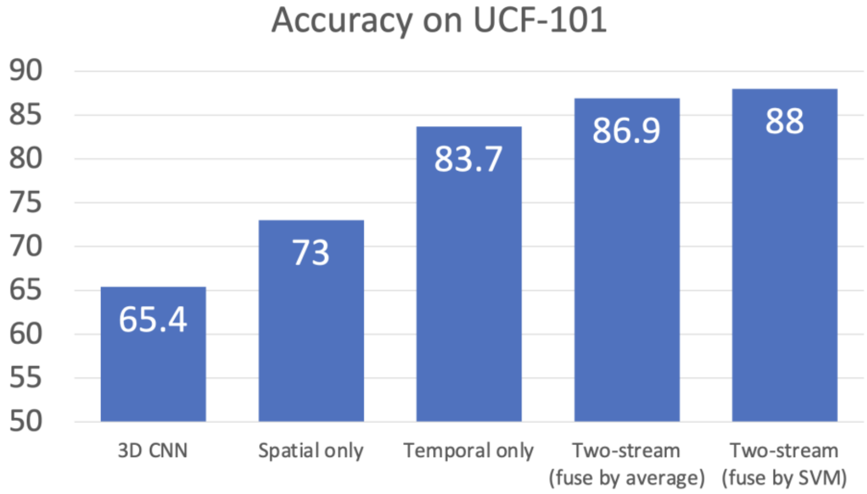
”Single Frame” baseline

using “Early Fusion” baseline

Frame t

Multi-frame optical flow

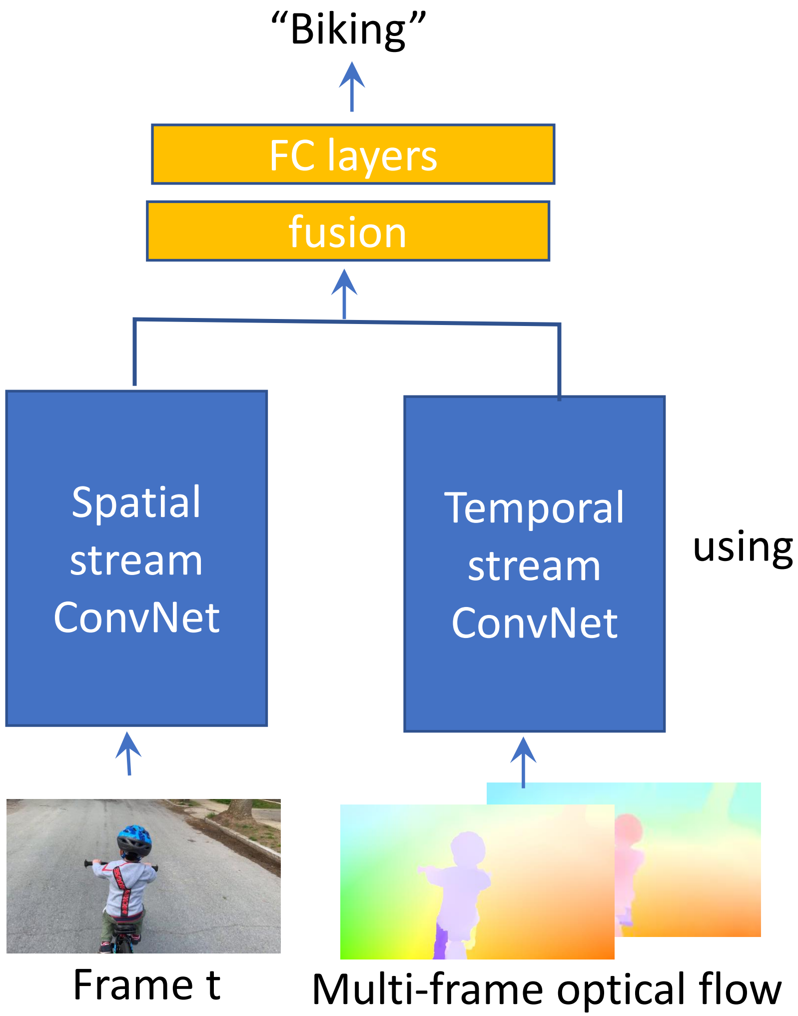
Precomputed flow fields between concuective frames



Simonyan and Zisserman, Two-Stream Convolutional Networks for Action Recognition in Videos, NIPS 2014

Two Stream Networks: modeling motion explicitly

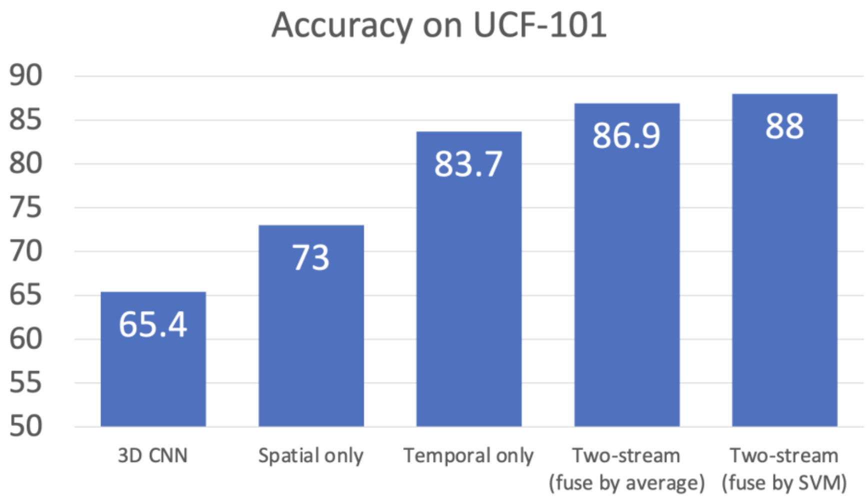
Idea: separate motion (multi-frame) from static appearance (single frame)



"Single Frame" baseline

using "Early Fusion" baseline

Precomputed flow fields between concuective frames



Simonyan and Zisserman, Two-Stream Convolutional Networks for Action Recognition in Videos, NIPS 2014

Additional models

Inflating 2D networks to 3D (I3D)

Take an existing 2D CNN model → convert it to a 3D CNN model

Transfer the weights from 2D and 3D

Carreira and Zisserman, “Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset”, CVPR 2017

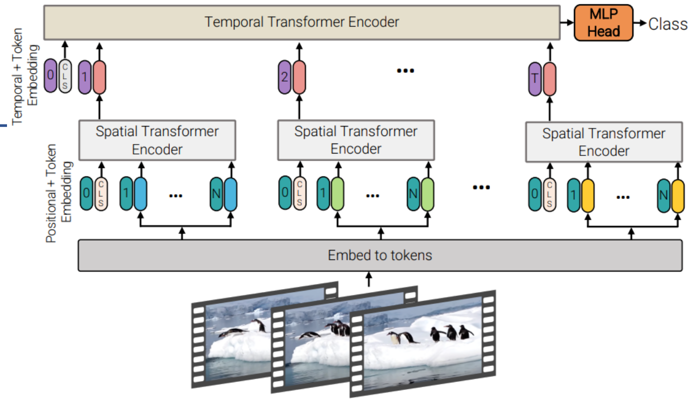
Long range temporal processing

Use LSTMs and RNNs to model long range temporal information

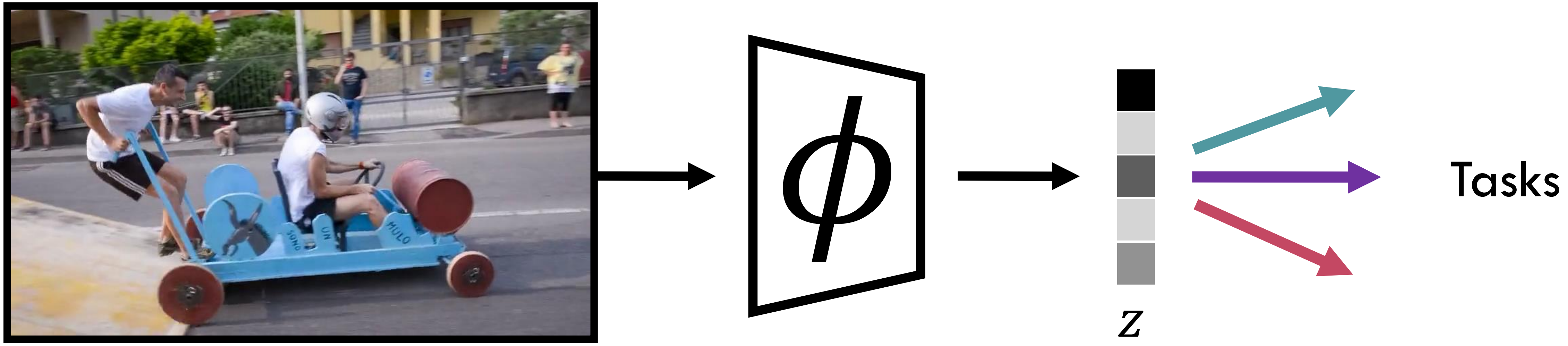
Baccouche et al, "Sequential Deep Learning for Human Action Recognition”, 2011 Donahue et al, “Long-term recurrent convolutional networks for visual recognition and description”, CVPR 2015

Long range temporal processing

Self attention, non-local networks, Transformers



Self-Supervision in Videos

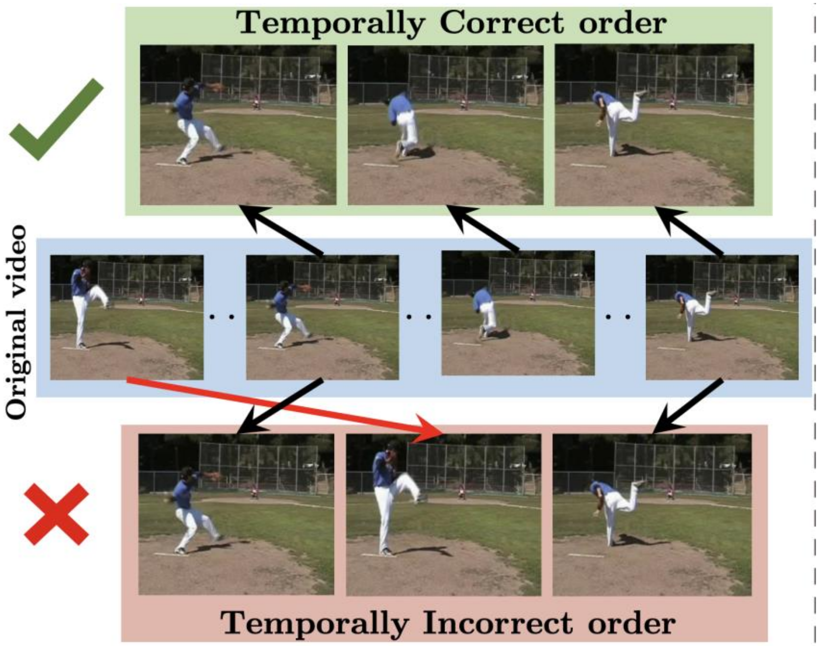


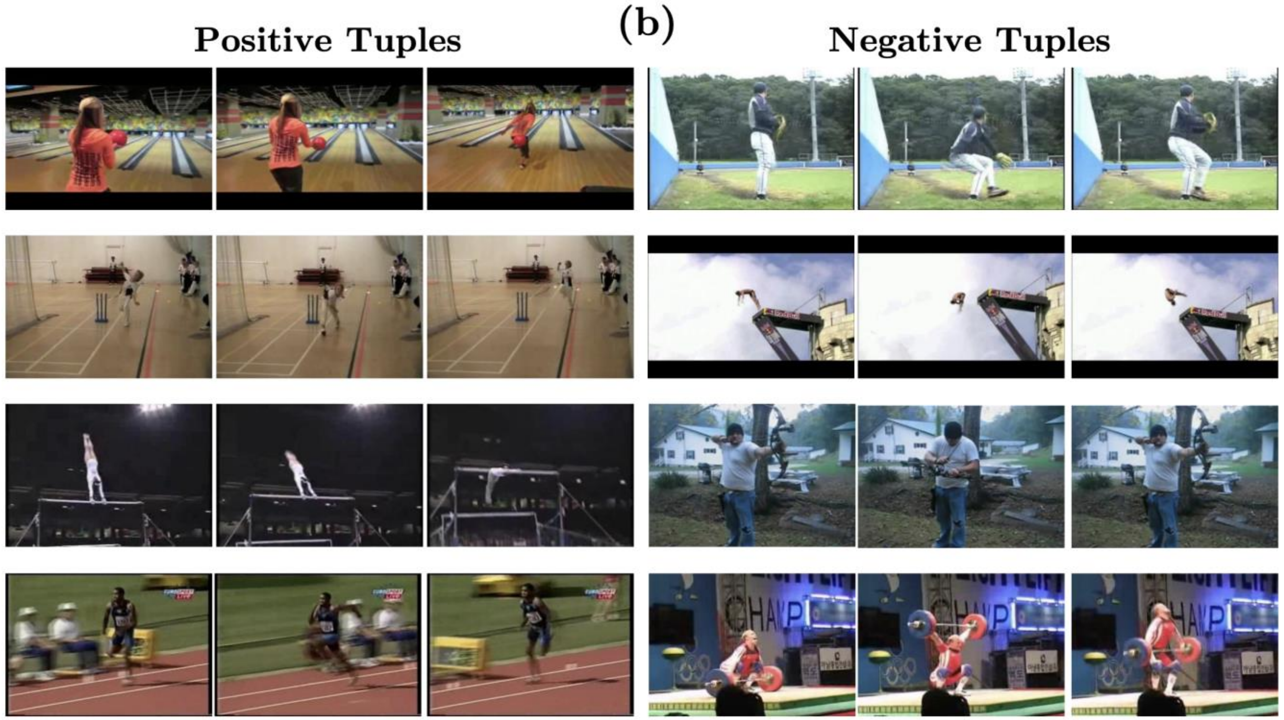
- Temporal order
- Cycle consistency
- Video Speedup
- Video colorization

Video: https://ajabri.github.io/timecycle/

Self-Supervision in Videos: frame ordering

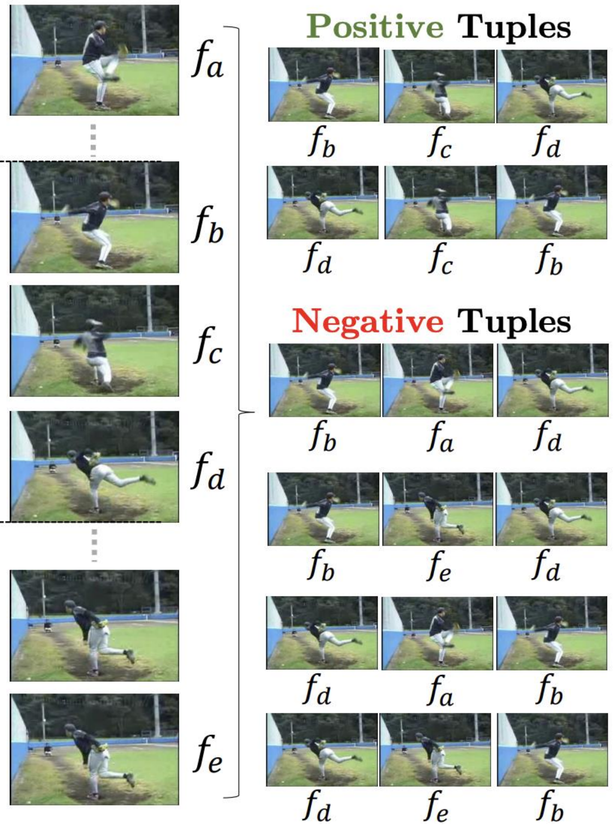
Training data: shuffled video frames, original video frames
Pretext task: predict if the frames are in the correct temporal order (binary classification task)



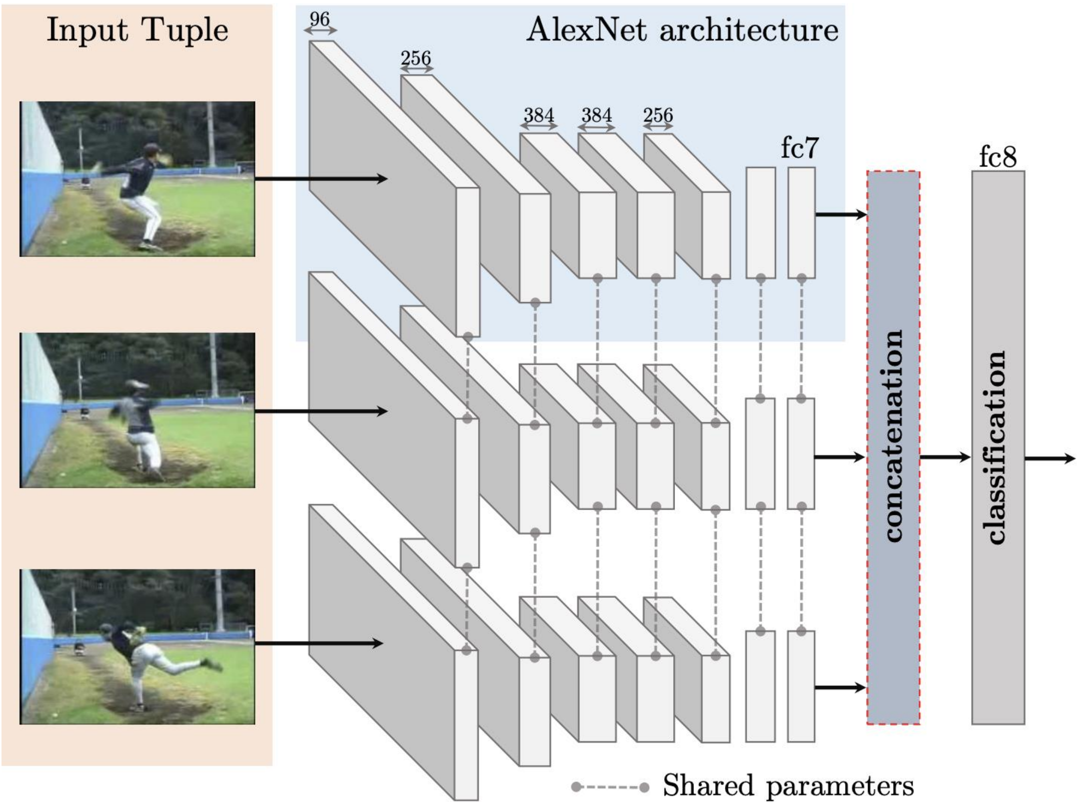


Misra et. al., Shuffle and Learn: Unsupervised Learning using Temporal Order Verification, ECCV 2016

Self-Supervision in Videos: frame ordering



Generating positive and negative examples

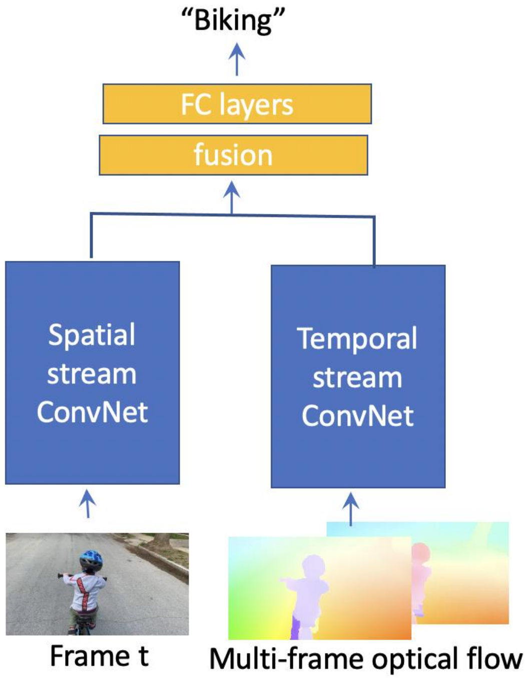


Triplet Siamese network for sequence verification

Misra et. al., Shuffle and Learn: Unsupervised Learning using Temporal Order Verification, ECCV 2016

Self-Supervision in Videos: frame ordering

Transfer learning: fine-tune spatial stream for video classification

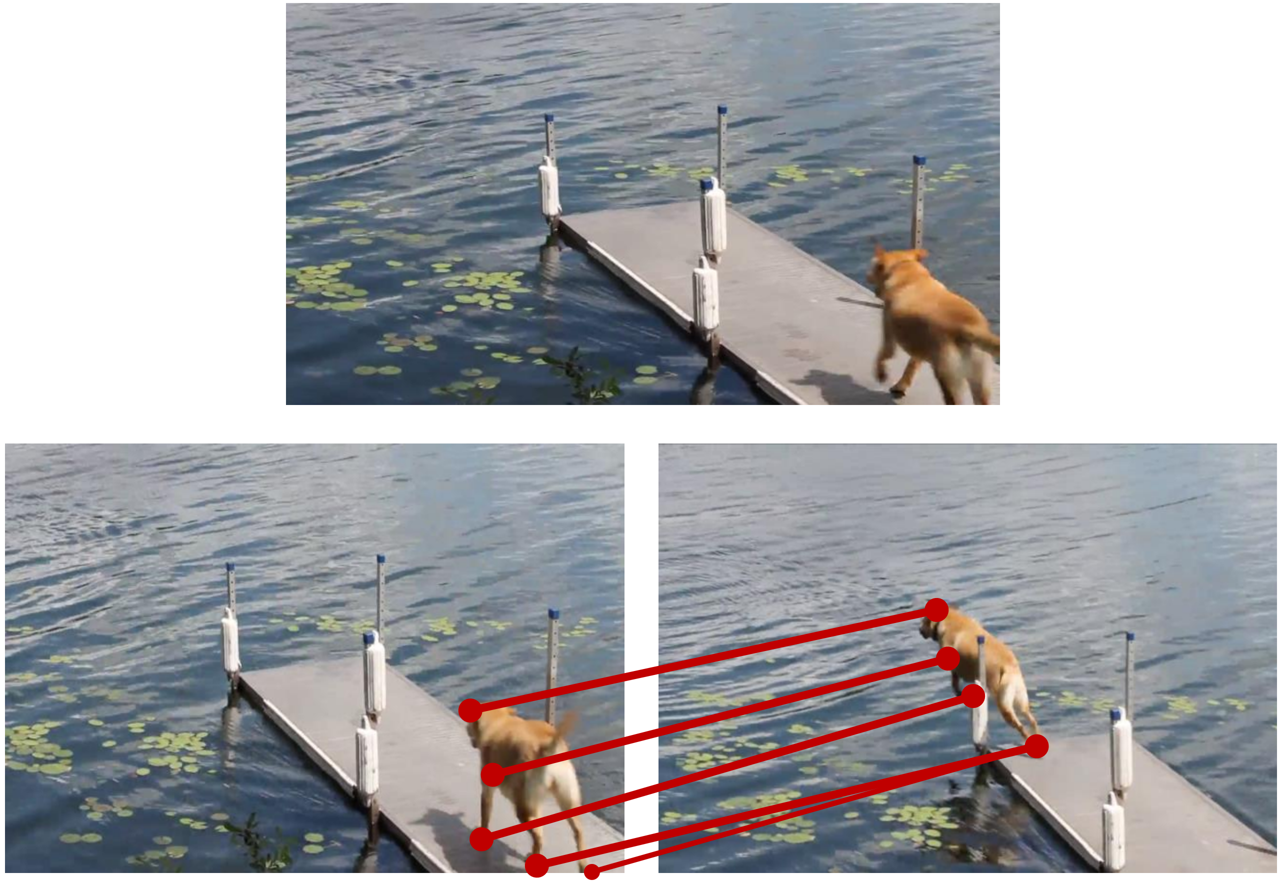


Dataset	Initialization	Mean Accuracy
UCF101	Random	38.6
	(Ours) Tuple verification	**50.2**
HMDB51	Random	13.3
	UCF Supervised	15.2
	(Ours) Tuple verification	**18.1**

Misra et. al., Shuffle and Learn: Unsupervised Learning using Temporal Order Verification, ECCV 2016

Self-Supervision in Videos: Learning correspondence

Ultimate goal: Correspondence



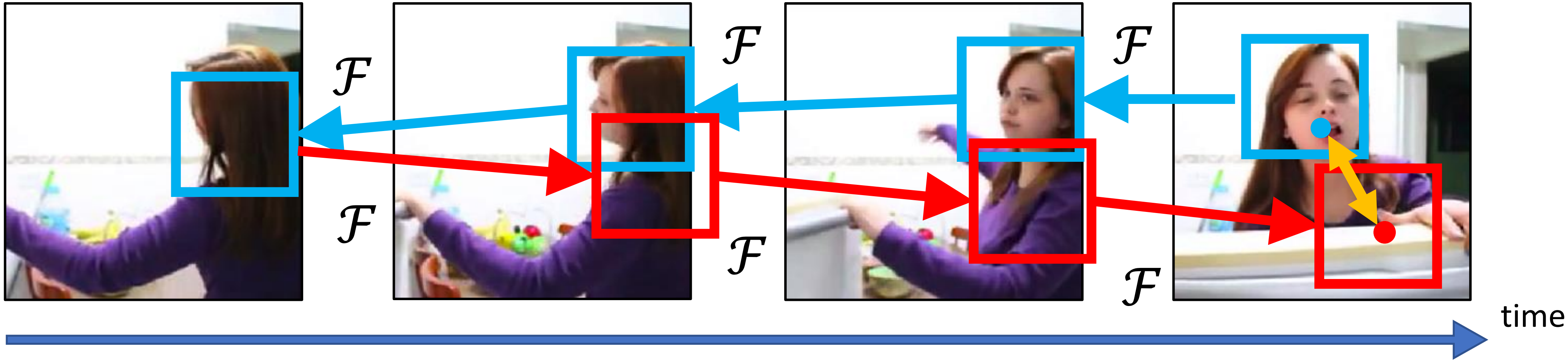
Wang and Efros, Learning Correspondence from the Cycle-consistency of Time, CVPR 2019

Self-Supervision in Videos: Learning correspondence

Ultimate goal: Correspondence, without using off-the-shelf tracking methods

How to obtain supervision?

Supervision: Cycle-Consistency in Time



Track backwards in time

Track forwards, back to the future

Wang and Efros, Learning Correspondence from the Cycle-consistency of Time, CVPR 2019

Self-Supervision in Videos: Learning correspondence

Supervision: Cycle-Consistency in Time
Challenge: Occlusions

Skip-cycles: skipping occlusions

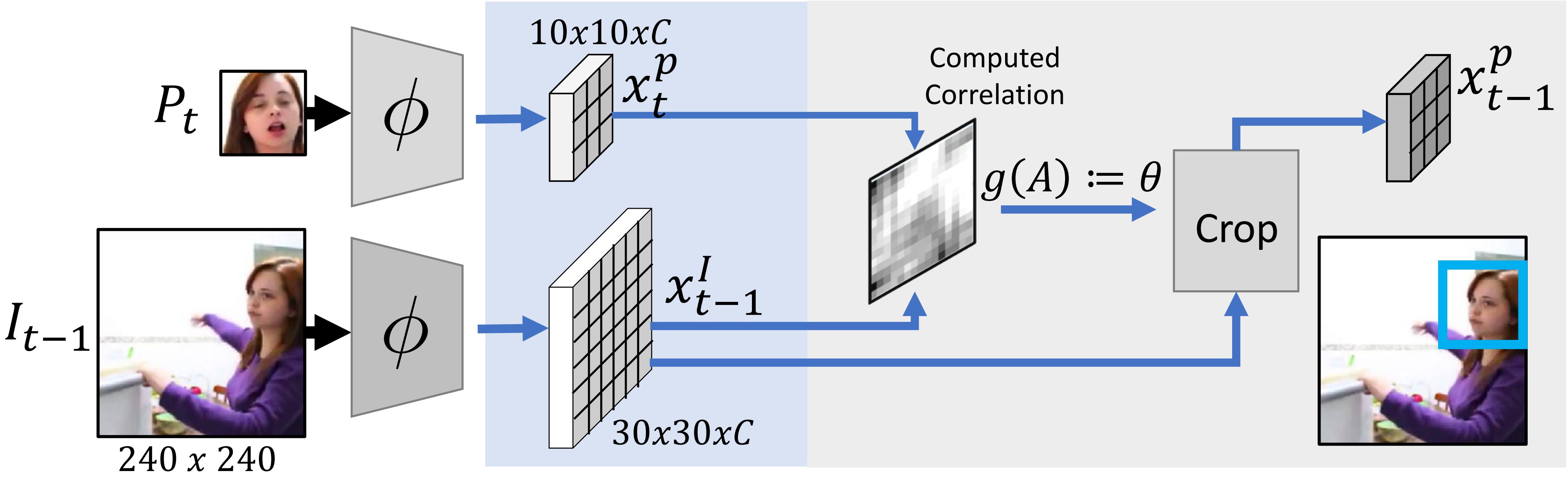
Wang and Efros, Learning Correspondence from the Cycle-consistency of Time, CVPR 2019

Self-Supervision in Videos: Learning correspondence

Differentiable tracker: densely match features in learned feature space

$$A(j,i) = \frac{\exp\left(x^I(j)^\intercal x^p(i)\right)}{\sum_j \exp\left(x^I(j)^\intercal x^p(i)\right)}$$

$A \in R^{900x100}$



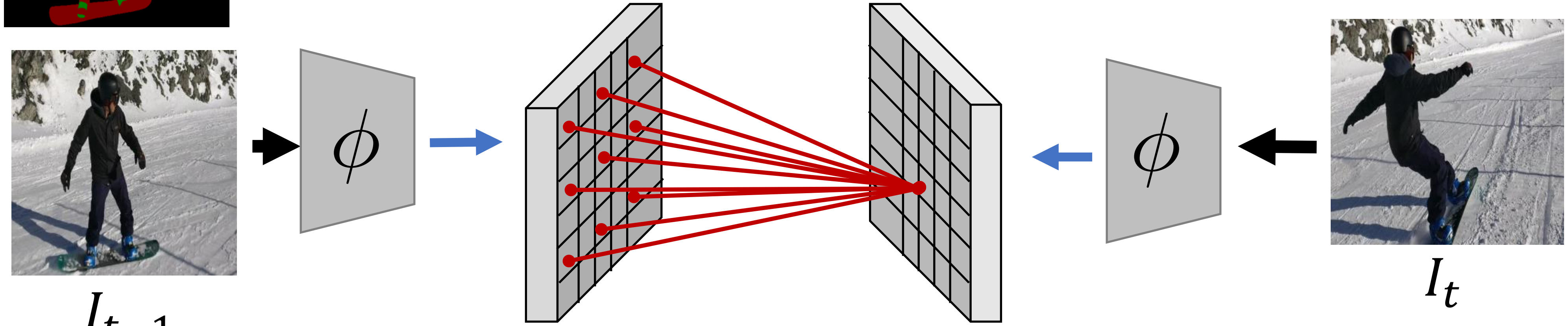
Wang and Efros, Learning Correspondence from the Cycle-consistency of Time, CVPR 2019

Self-Supervision in Videos: Learning correspondence

Test time: compute features to each frame, compute features affinity, propagate information using the affinities

y_{t-1}

$$y_t(i) = \sum_j A_{t-1,t}(j,i) y_{t-1}(j)$$

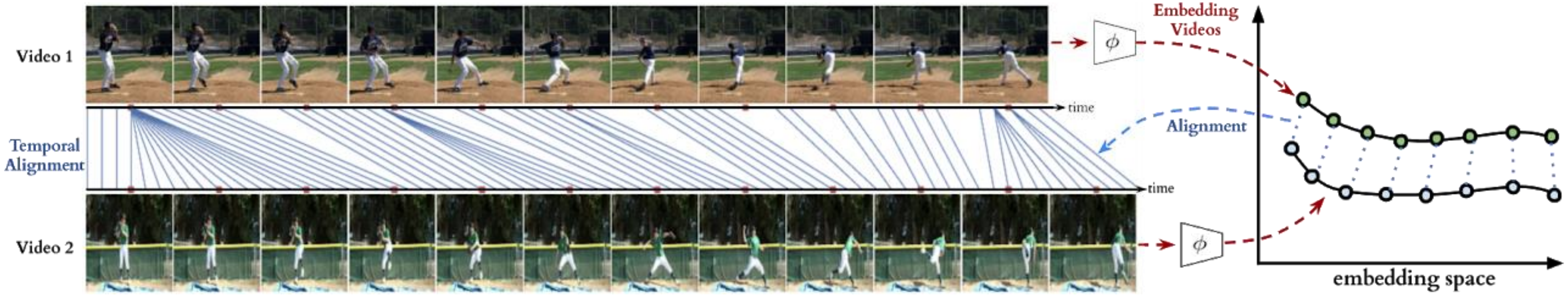


Wang and Efros, Learning Correspondence from the Cycle-consistency of Time, CVPR 2019

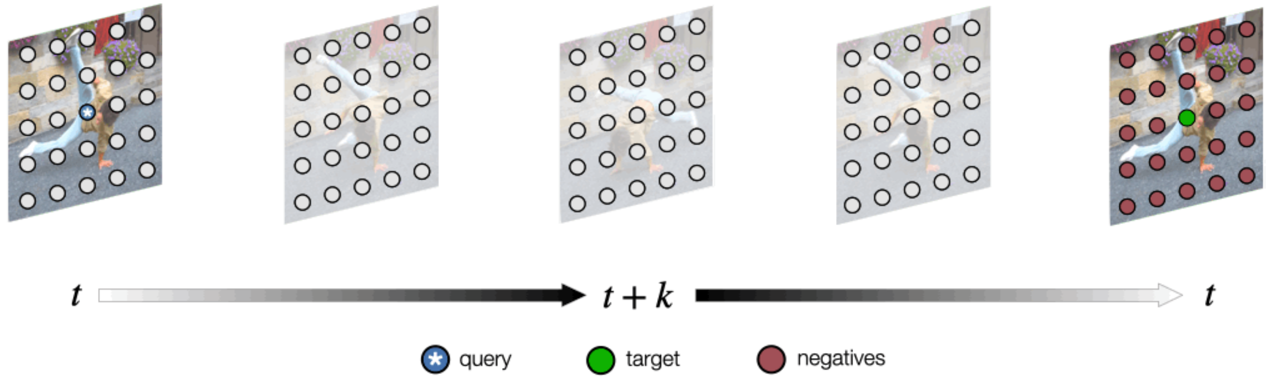
Self-Supervision in Videos: Learning correspondence

Wang and Efros, Learning Correspondence from the Cycle-consistency of Time, CVPR 2019

Self-Supervision in Videos: Temporal cycle consistency



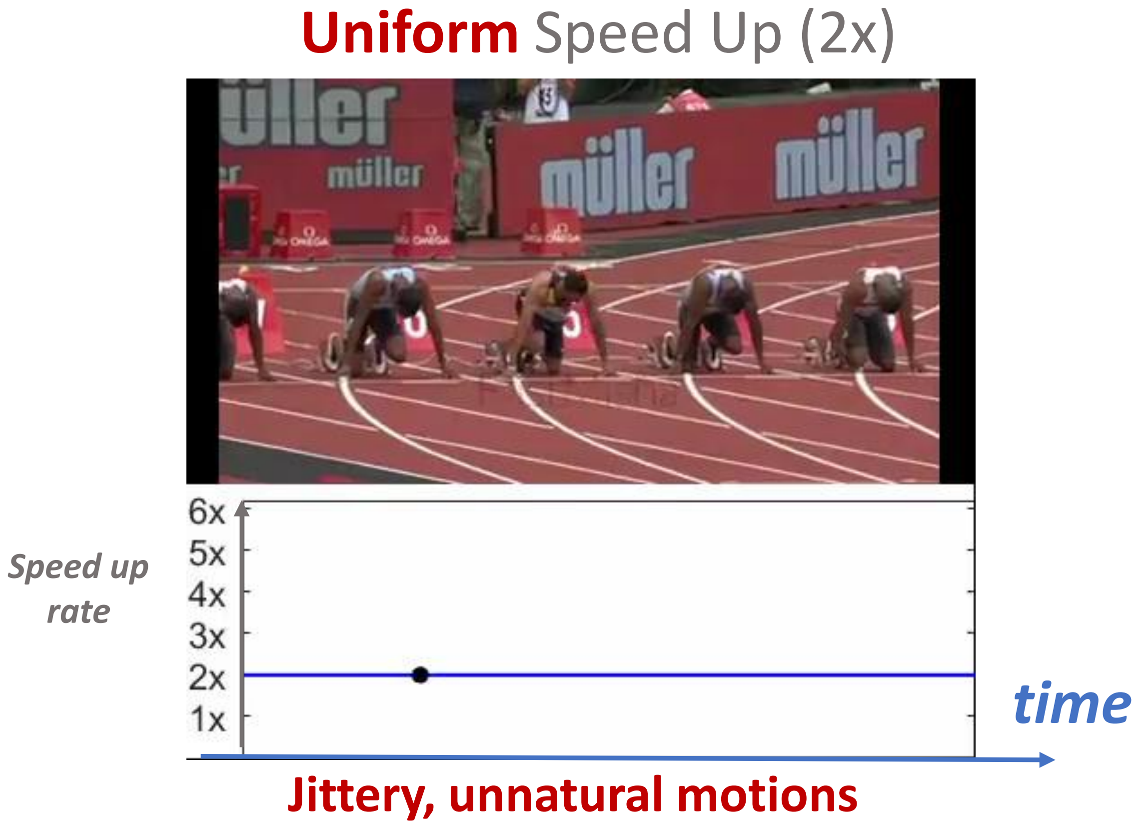
Dwibed et. al. Temporal Cycle-Consistency Learning, CVPR'19

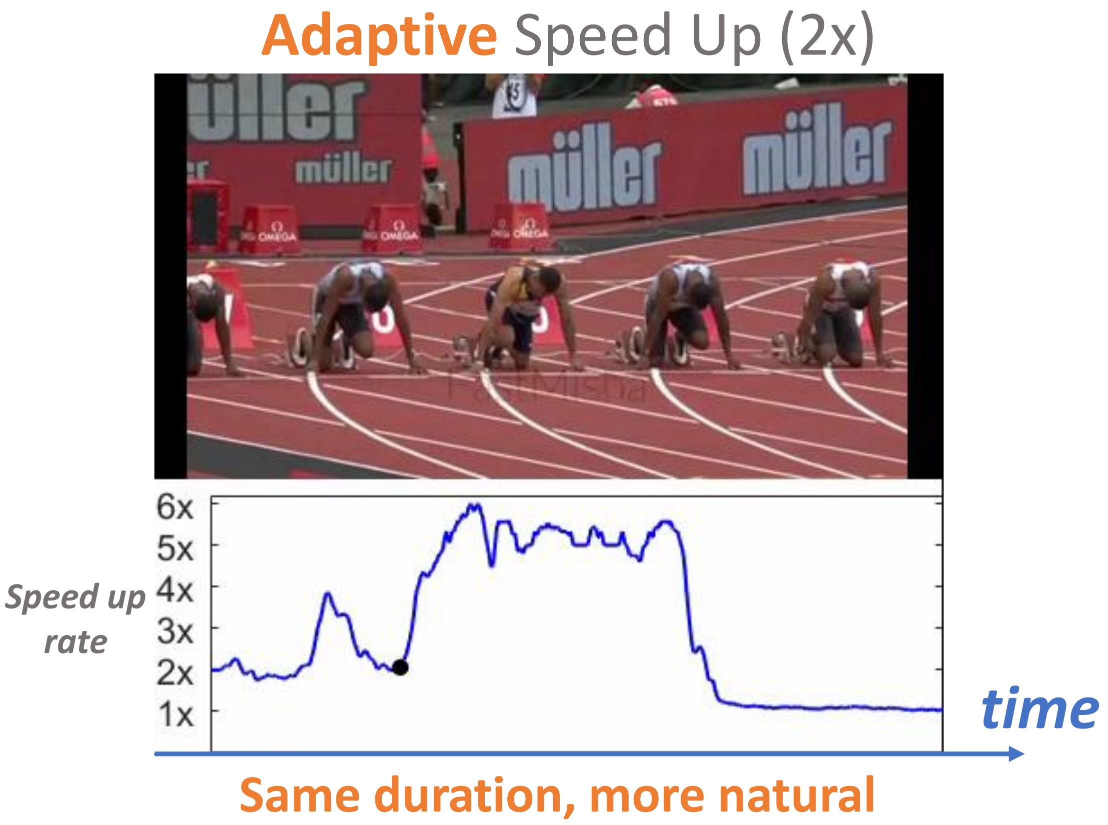


Jabri et. al, Space time correspondence as Contrastive Random Walk, NeurIPS 2020

Self-Supervision in Videos: Learning the Speediness in Videos

Ultimate goal: Watch video content faster by adaptively speeding up the video





Joint work with: Sagie Benaim, Ariel Ephrat, Oran Lang, Inbar Mosseri, Bill Freeman, Miki Rubinstein and Michal Irani, CVPR 2020

“Speediness” in Videos

Slower

Normal speed

Faster

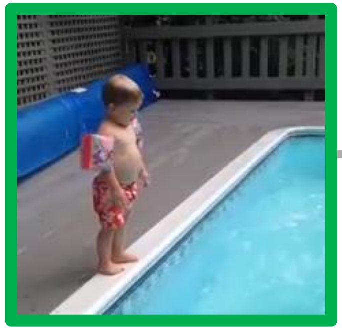
WAIC

Joint work with: Sagie Benaim, Ariel Ephrat, Oran Lang, Inbar Mosseri, Bill Freeman, Miki Rubinstein and Michal Irani, CVPR 2020

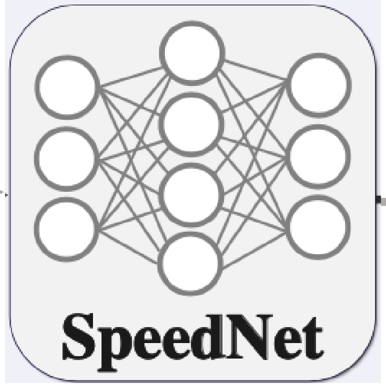
Self-Supervision in Videos: Learning the Speediness in Videos

Pretext task: Predict if a given video segment is sped up or not
Training data: sped up video segments + original video segments

Self supervised training on Kinetics



Input segment (30 frames)



Normal speed
or
Sped Up

"Learning and Using the Arrow of Time", Wei at. al, CVPR 2018

Self-Supervision in Videos: Learning the Speediness in Videos

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Self supervised
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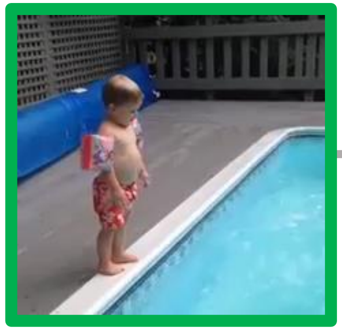
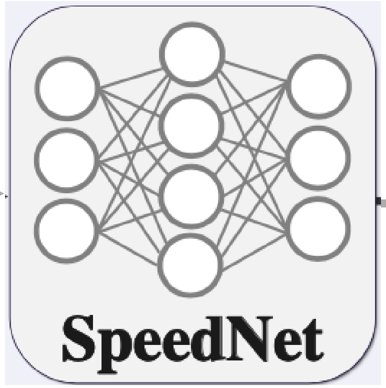


Input segment
(30 frames)



Normal speed
or
Sped Up

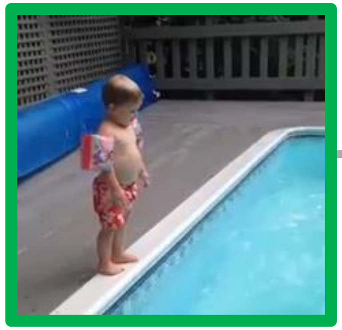
Networks are lazy!

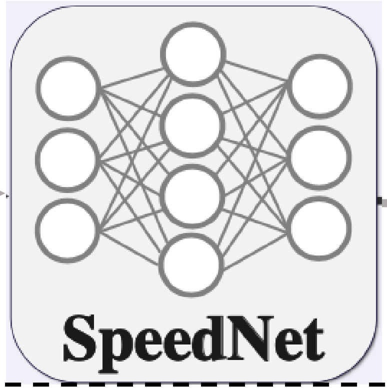
Learning properties of natural motion, avoid "easy cheats" → **very challenging!**

Self-Supervision in Videos: Learning the Speediness in Videos

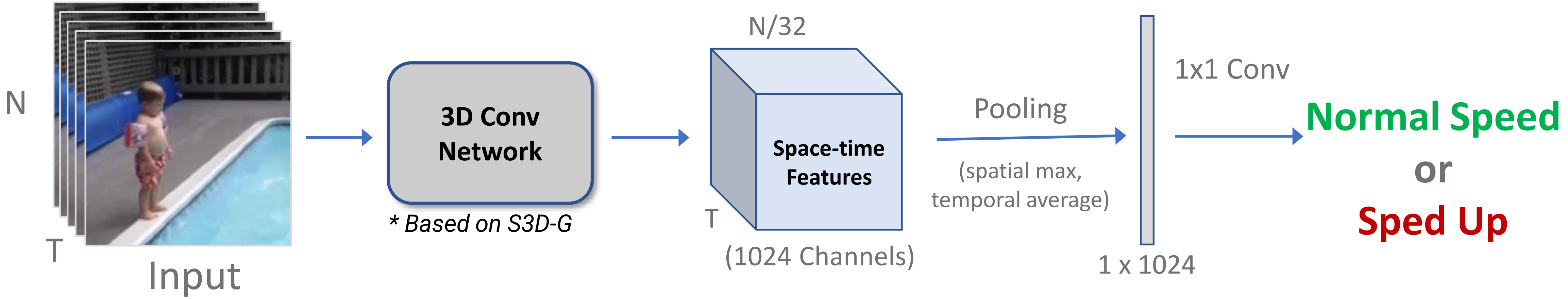
Pretext task: Predict if a given video segment is sped up or not
Training data: sped up video segments + original video segments

Self supervised training on Kinetics





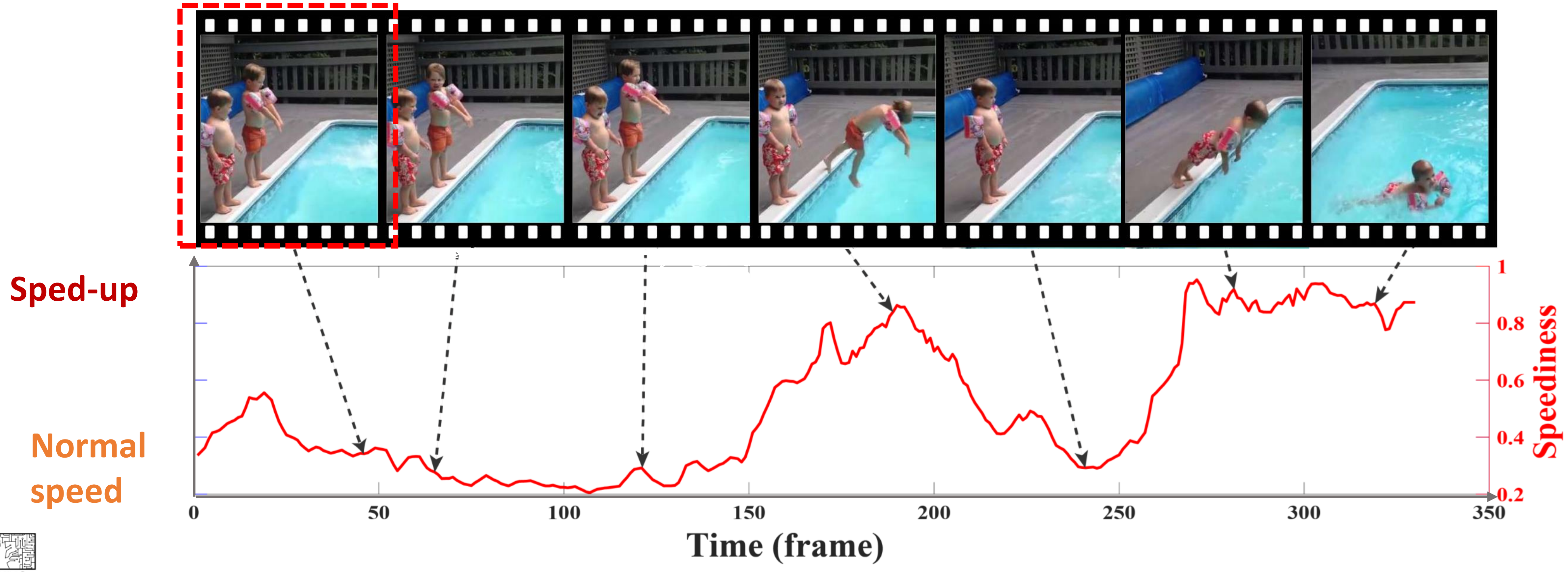
Normal speed
or
Sped Up



* *"Rethinking spatiotemporal feature learning: Speed-accuracy trade-offs in video classification"*, Saining Xie, Chen Sun, Jonathan Huang, Zhuowen Tu, and Kevin Murphy, ECCV'18.

Self-Supervision in Videos: Learning the Speediness in Videos

Inference: sliding window → prediction for every frame

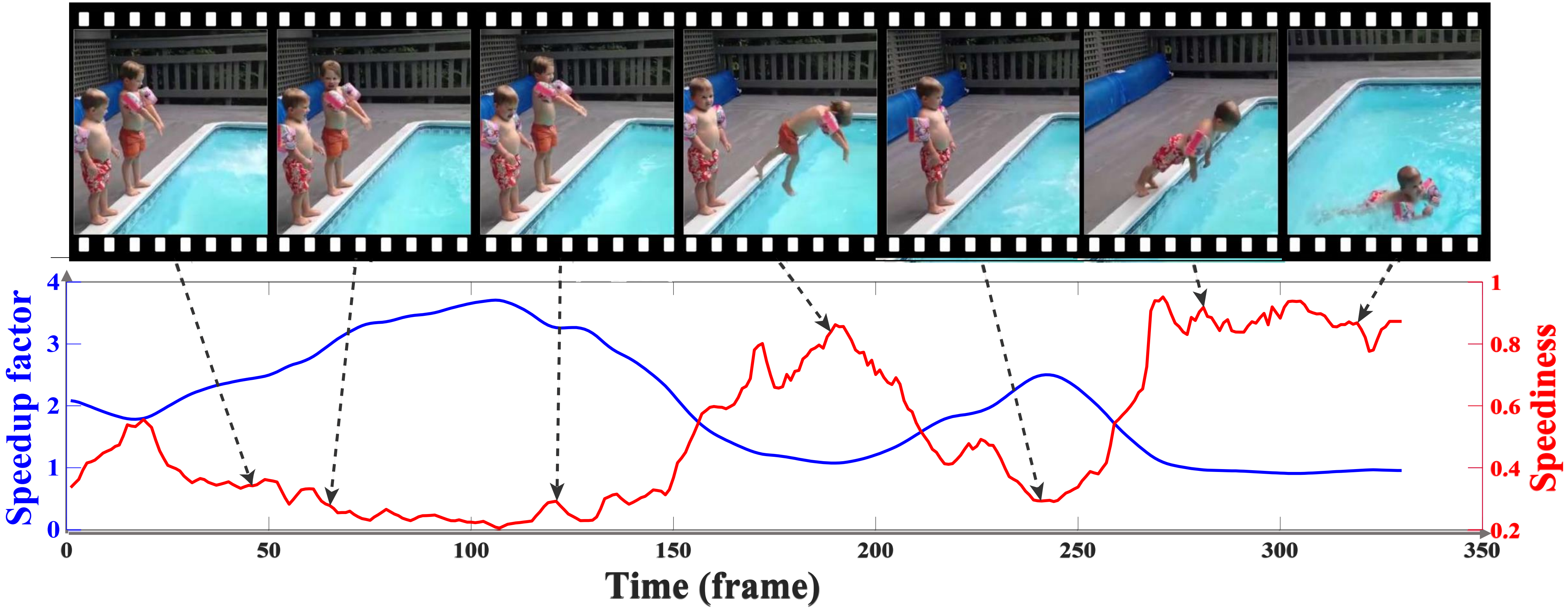


Self-Supervision in Videos: Learning the Speediness in Videos

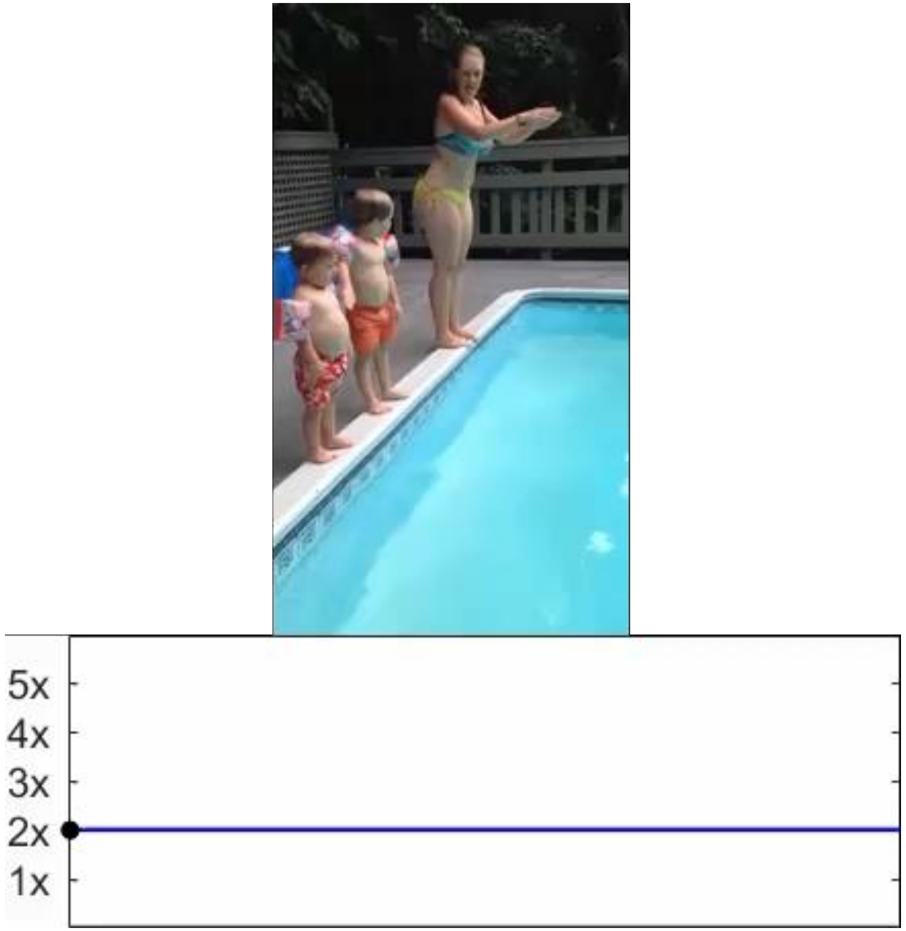
From “Speediness” to Speedup factor:

Low speediness → speedup more

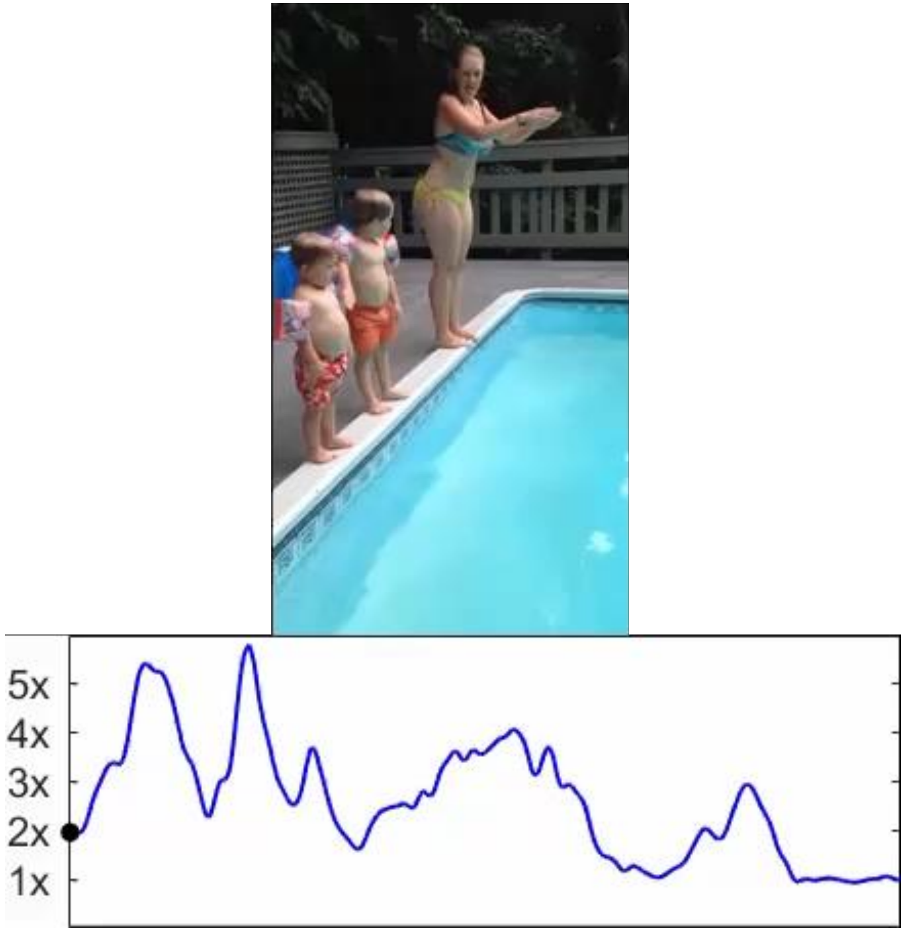
High speediness→ speedup less



Learning the Speediness in Videos: Adaptive Video Speedup



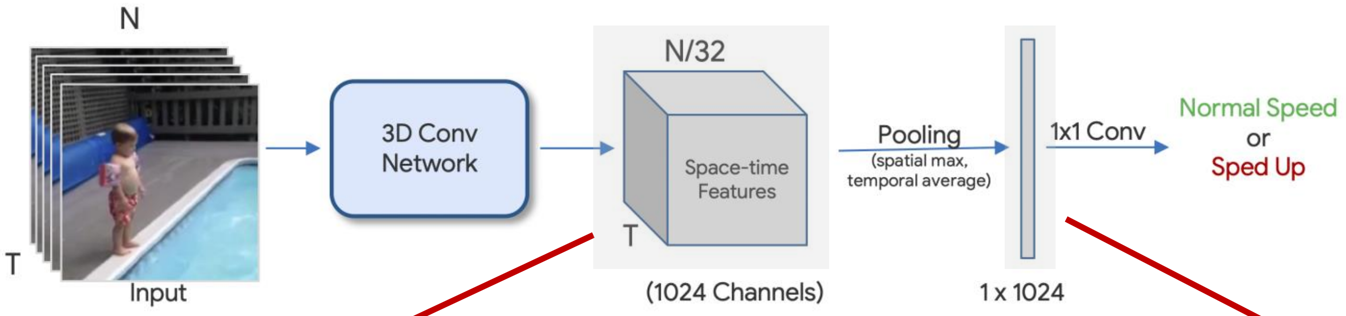
Uniform Speedup 2x



Adaptive Speedup 2x (ours)

Learning the Speediness in Videos: Transfer Learning

Pre-trained SpeedNet

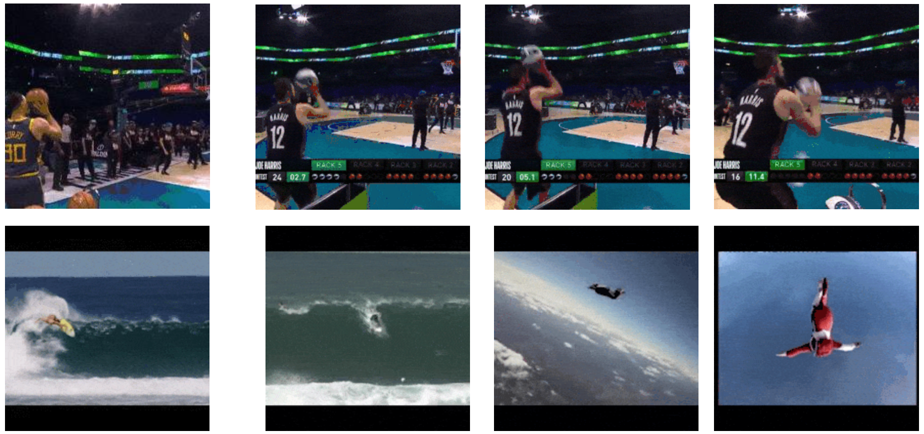


Self Supervised Action Recognition

Method	Initialization Architecture	Supervised accuracy UCF101	HMDB51
Random init	S3D-G	73.8	46.4
ImageNet inflated	S3D-G	86.6	57.7
Kinetics supervised	S3D-G	96.8	74.5
CubicPuzzle [19]	3D-ResNet18	65.8	33.7
Order [40]	R(2+1)D	72.4	30.9
DPC [13]	3D-ResNet34	75.7	35.7
AoT [38]	T-CAM	79.4	-
SpeedNet (Ours)	S3D-G	**81.1**	**48.8**

Video Retrieval

Query — Retrieved top-3 results



Learning the Speediness in Videos: CAM visualizations

“Memory Eleven”
artistic video by Bill Newsinge

Our space-time
speediness visualization

blue/green =
normal speed

yellow/orange =
slowed down

https://www.youtube.com/watch?v=djylS0Wi_Io

Re-rendering Everyday Videos

Enhance the way we perceive our dynamic world








Re-rendering Everyday Videos

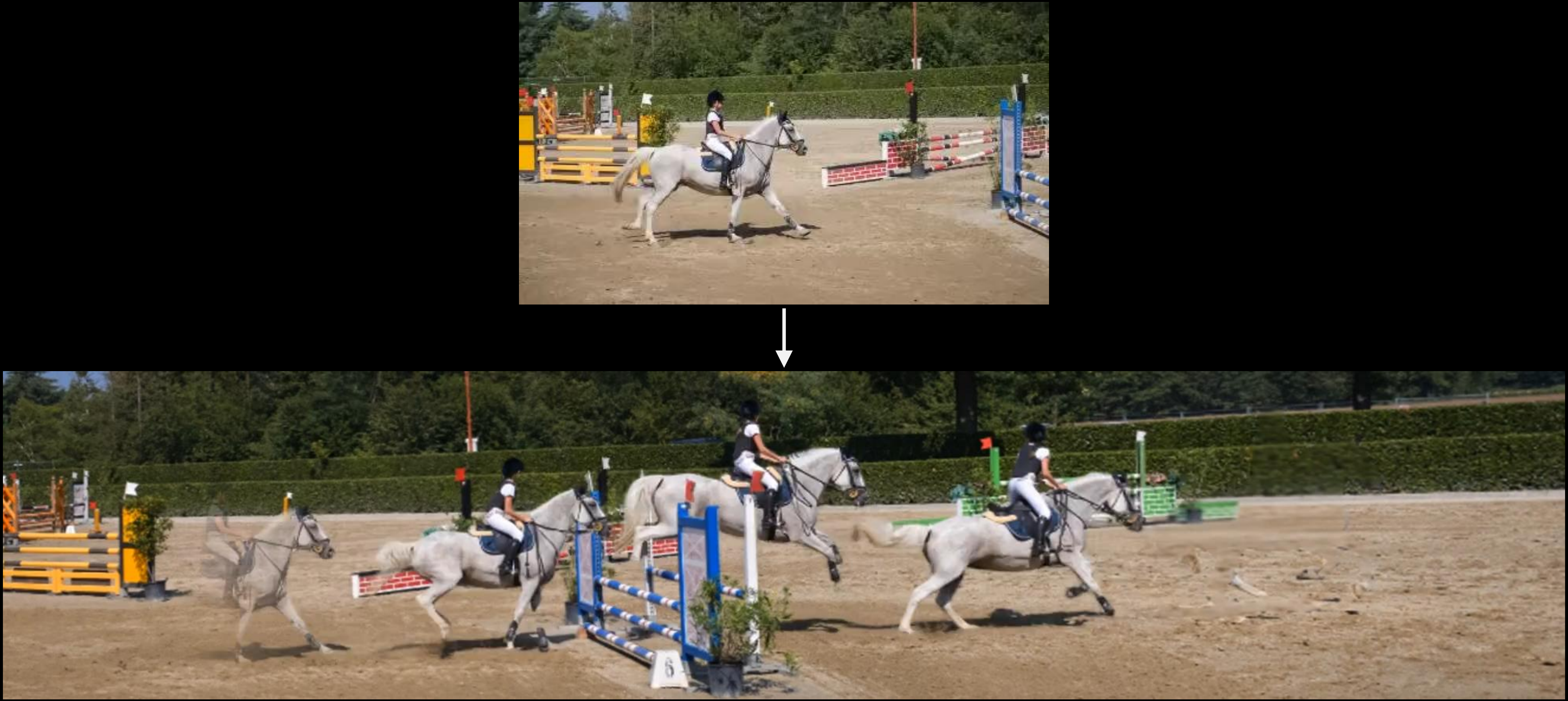
Retime the motions of **individual people** within frames

along with their **scene effects!**

“Layered Neural Rendering for Retiming People in Video”

SIGGRAPH Asia’20

Re-rendering Everyday Videos



nnimatte: Associating Objects and Their Effects in Video”, **CVPR’21 (Oral)**

Re-rendering Everyday Videos

Input video

Re-rendering Everyday Videos

nnimatte: Associating Objects and Their Effects in Video”, **CVPR’21 (Oral)**

Re-rendering Everyday Videos

Editing everyday videos – key challenge

Associating objects and their scene effects !

Input segments [Mask-RCNN]

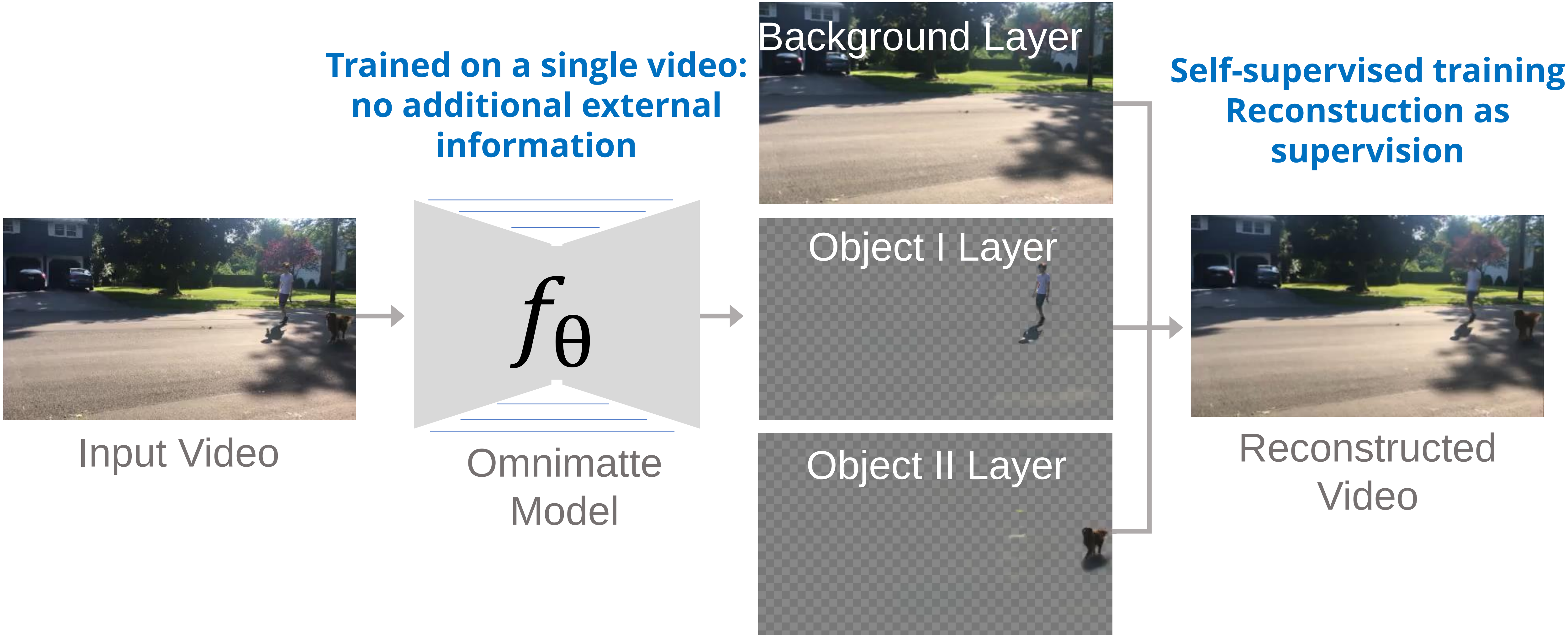
Omnimatte: Associating objects and their scene effects

Input Video

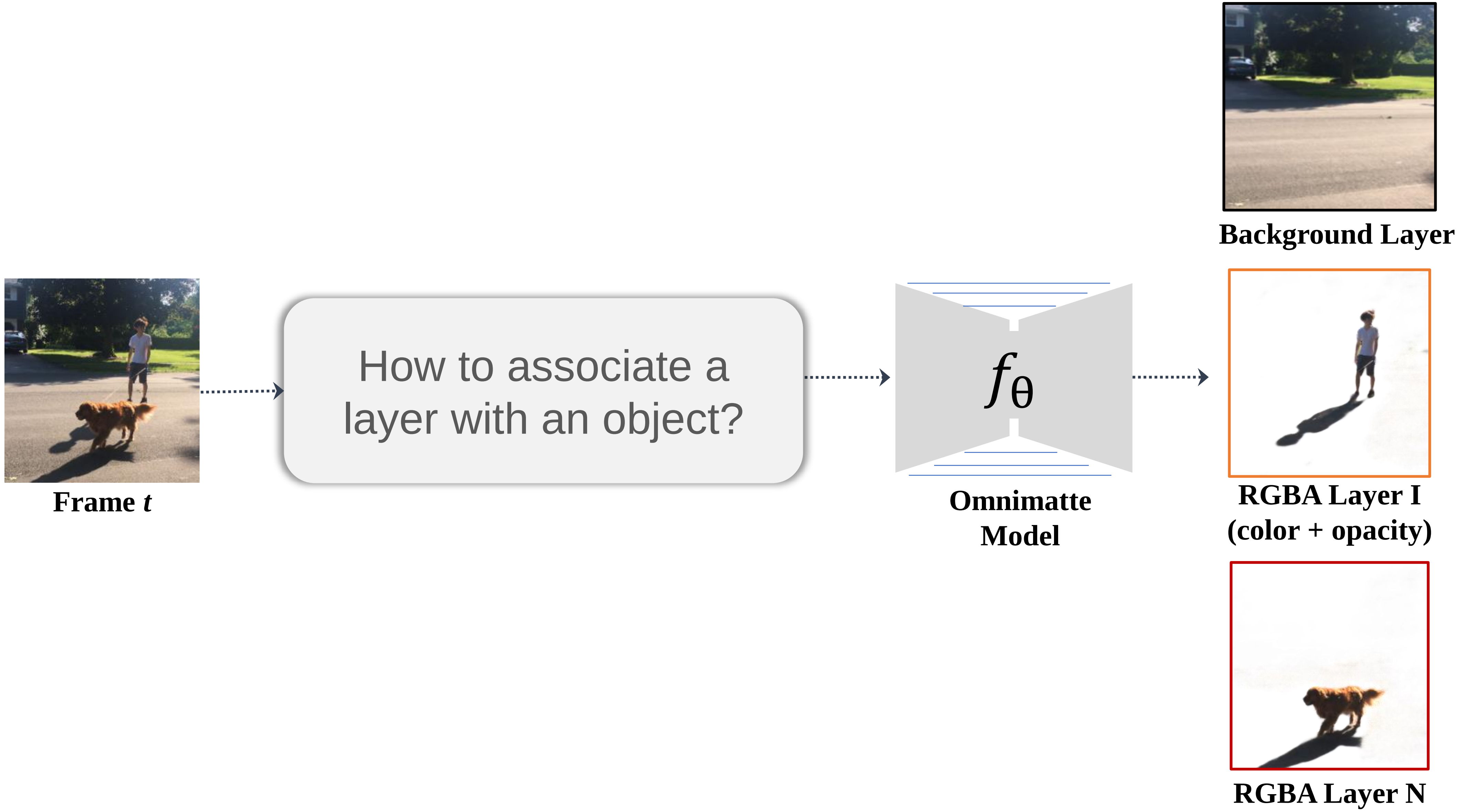
Input Mask 1*

Input Mask 2*

Omnimatte Method

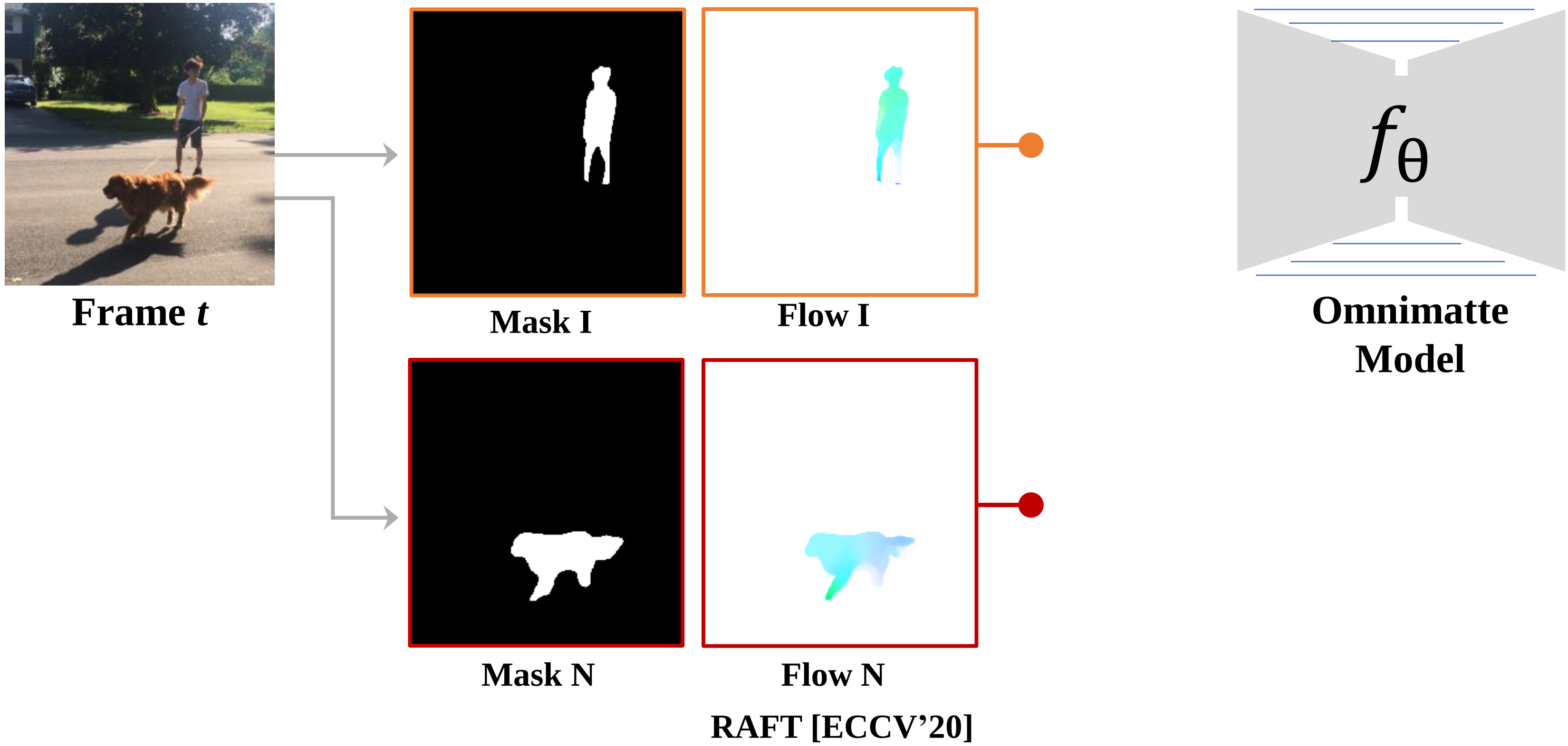


Omnimatte Method



Omnimatte Method

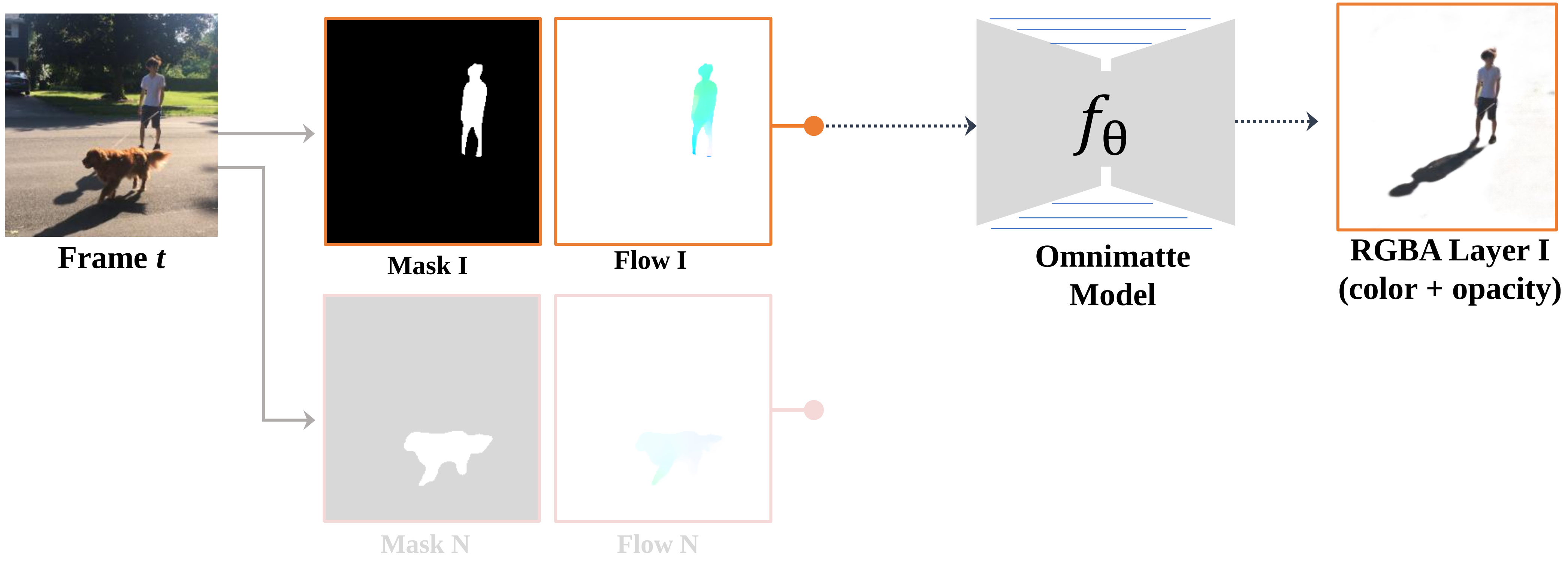
Model **objects** + **static background** explicitly!



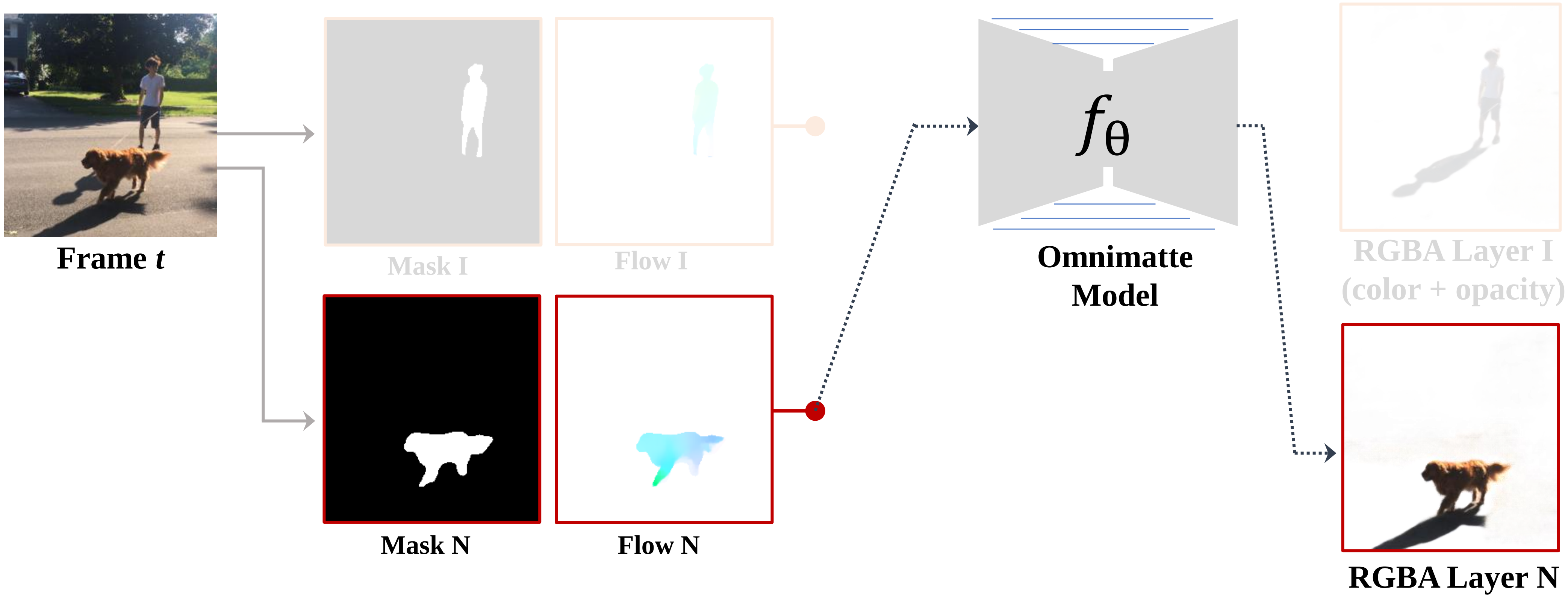
WAIC

Omnimatte Method

Model **objects** + **static background** explicitly!

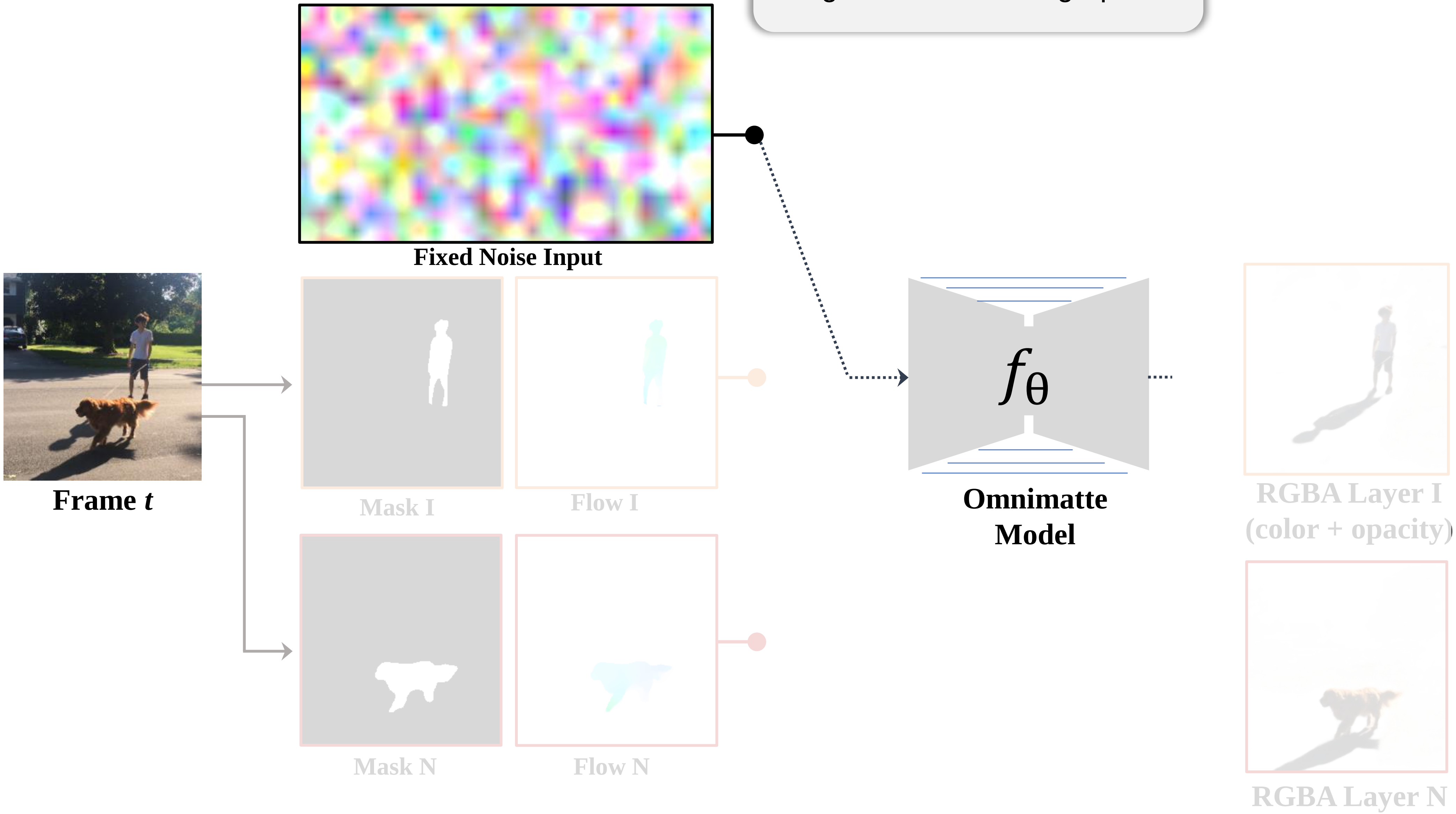


Omnimatte Method



Omnimatte Method

- **Static background**
- Bg. motion ≅ homographies



Omnimatte Method

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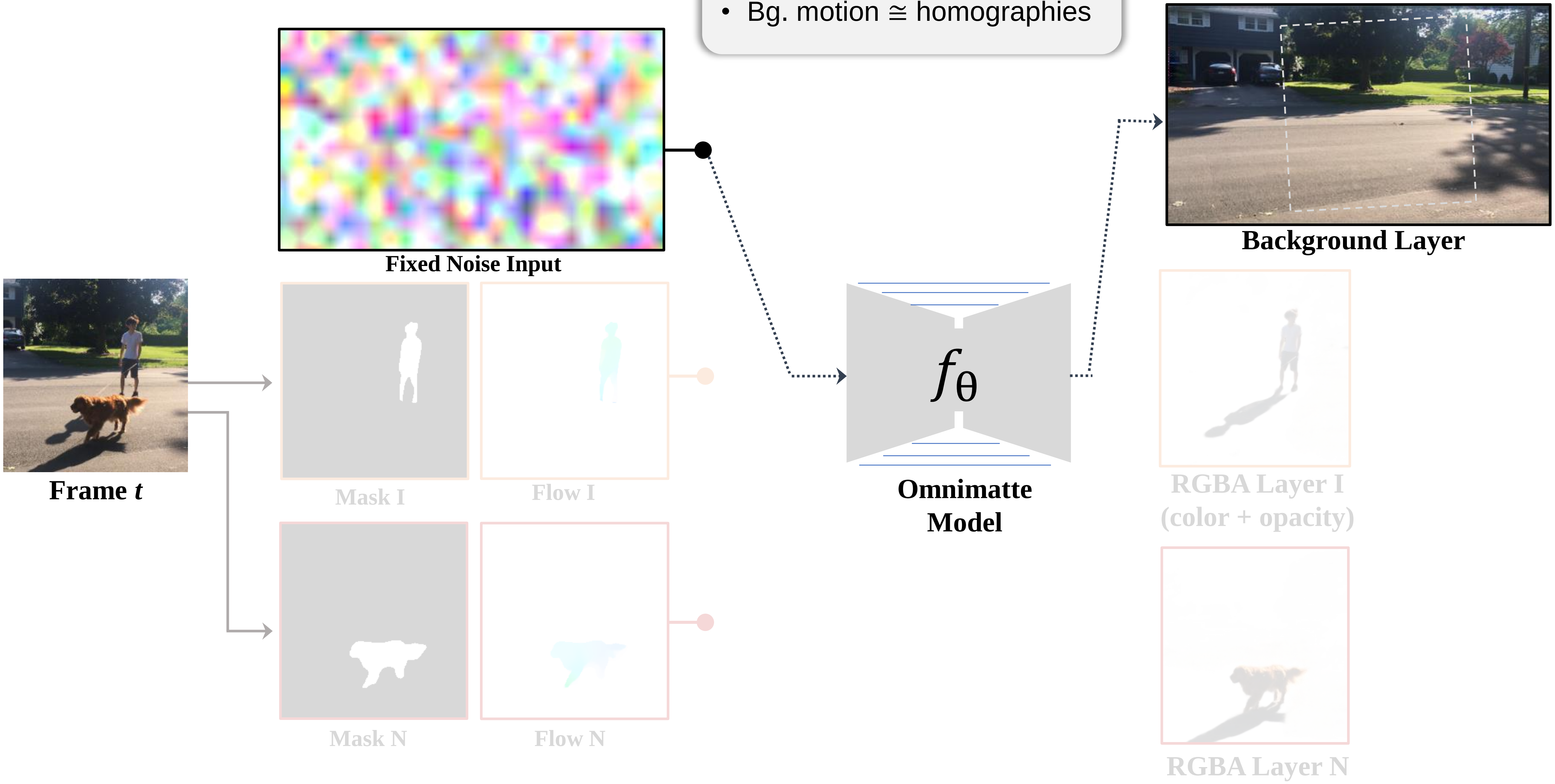
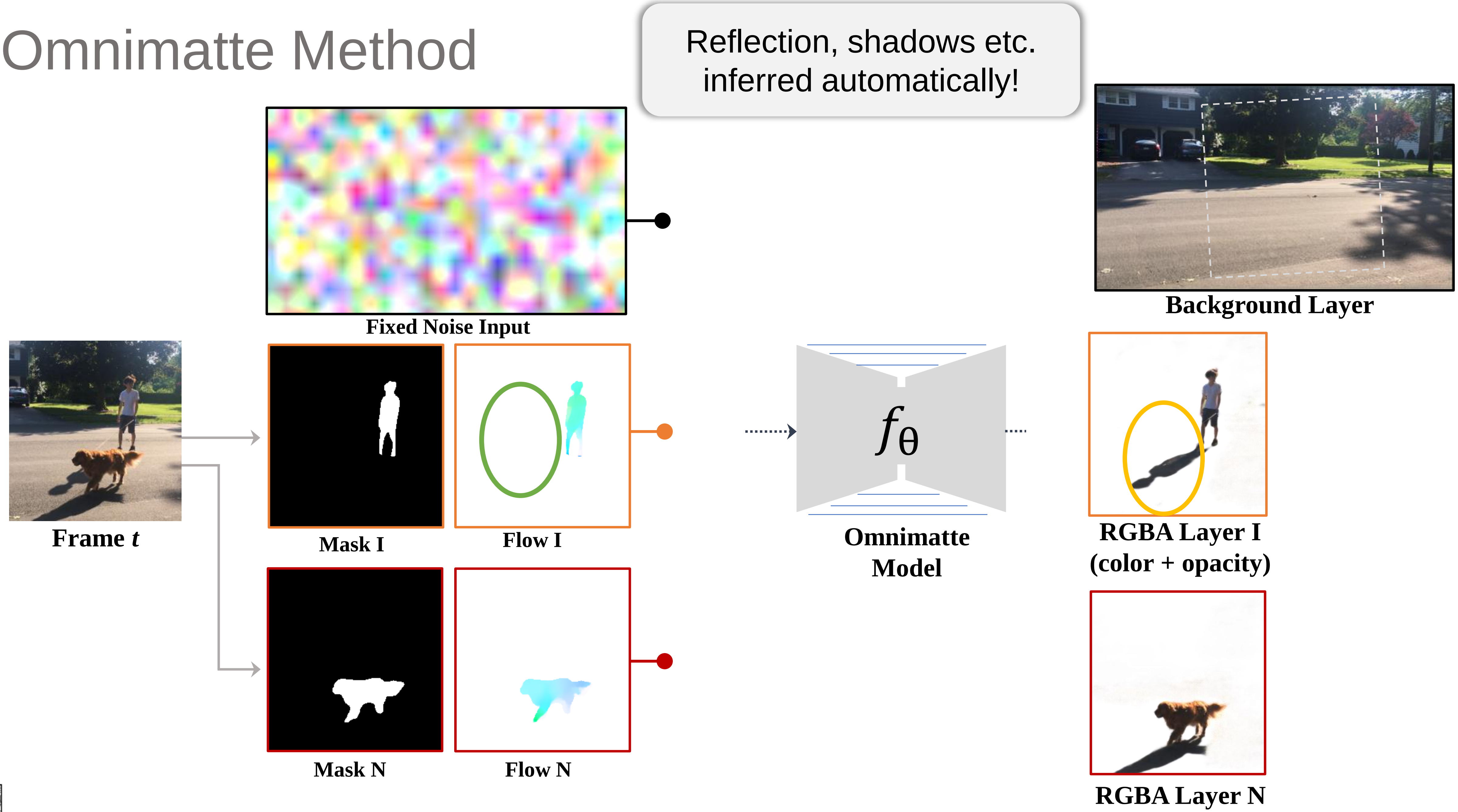


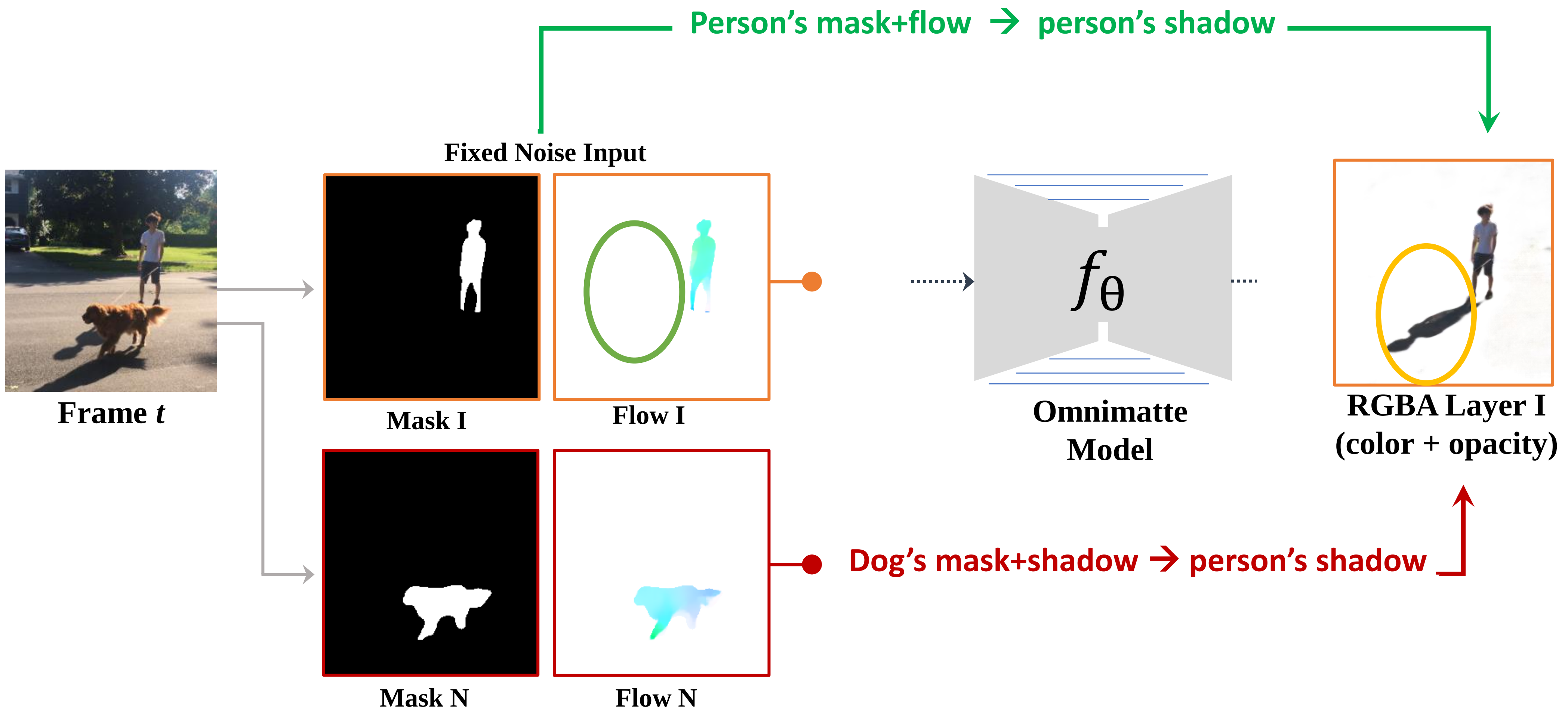
Omnimatte Method



Omnimatte Method

High correlation → Easy to predict (fewer iterations)!

Low correlation → Difficult to predict (more iterations)



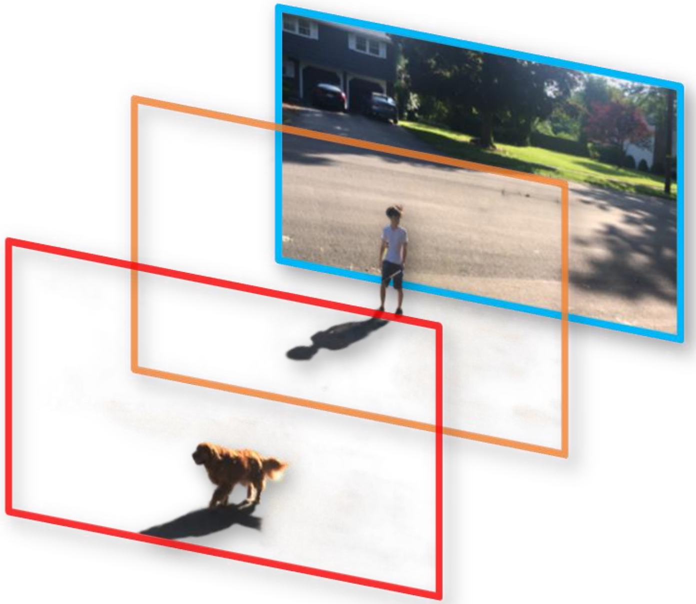
Losses

$$\underbrace{E_{\text{recon}}(\mathcal{L}_t, I_t)}_{\text{Reconstruction}} + \underbrace{E_{\text{reg}}(\boldsymbol{\alpha_t})}_{\text{Opacity regularization}} + \underbrace{E_{\text{mask}}(\boldsymbol{\alpha_t})}_{\text{initialization}}$$

Original Frame

Input Mask 1

Input Mask 2



Back-to-front compositing

Reconstruction (Frame t)

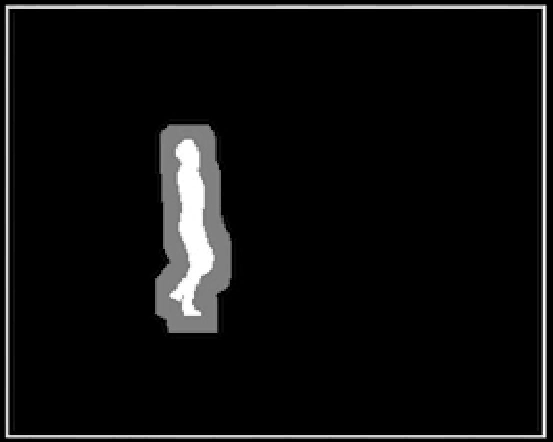
Why It Works?

Synthetic test case I (single person)

Why It Works?

Initialization

Original



Foreground Trimap

Synthetic test case I (single person)

Why It Works?

Details (cloths, hair) are learned as training progresses

Original Frame

Training Progression

Synthetic test case I (single person)

Why It Works?

Synthetic test case II
(correlated vs. uncorrelated motion)

Why It Works?

Correlated motion is learned earlier than uncorrelated motion

Input

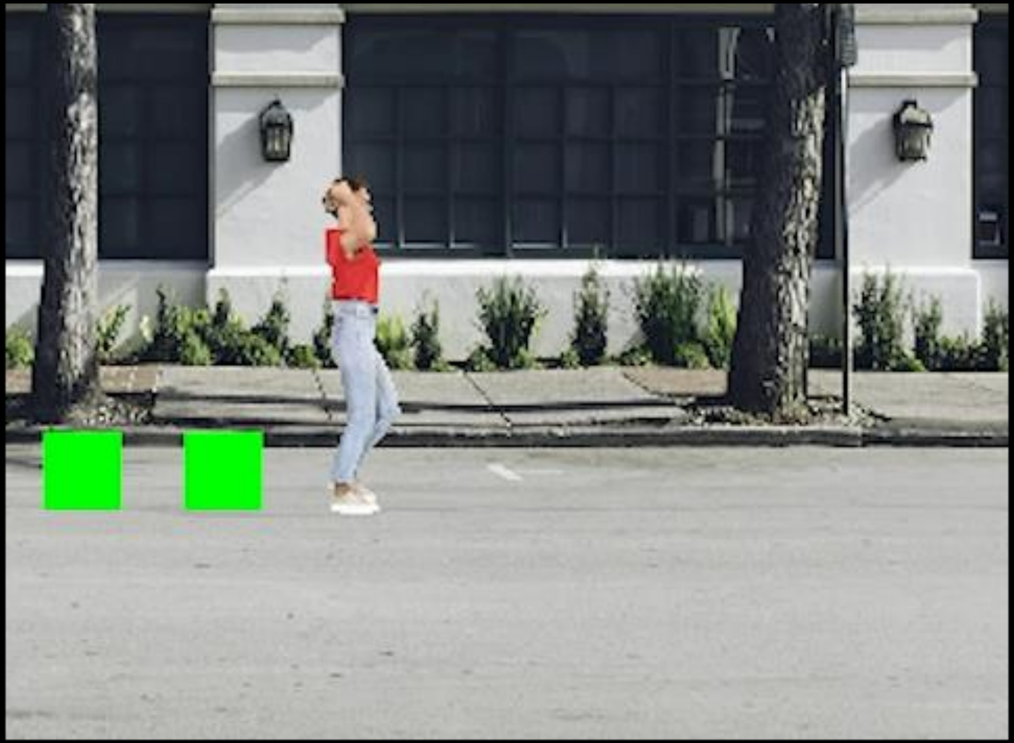
Foreground

Background

Synthetic test case II
(correlated vs. uncorrelated motion)

Why It Works?

Nearby effects are learned earlier than distant effects



Synthetic test case III
(nearby vs. distant effects)

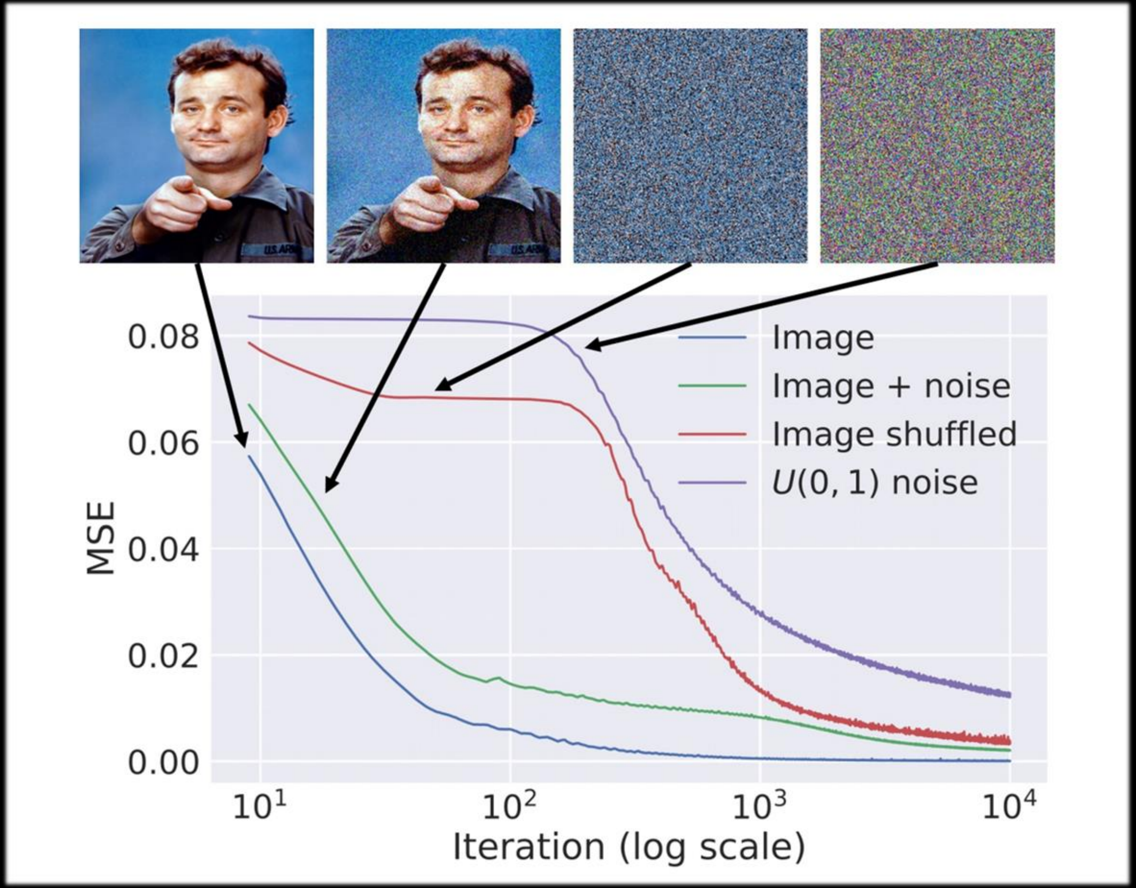
Why It Works?

Each person "grabs" its most correlated elements early

Synthetic test case IV (multiple people)

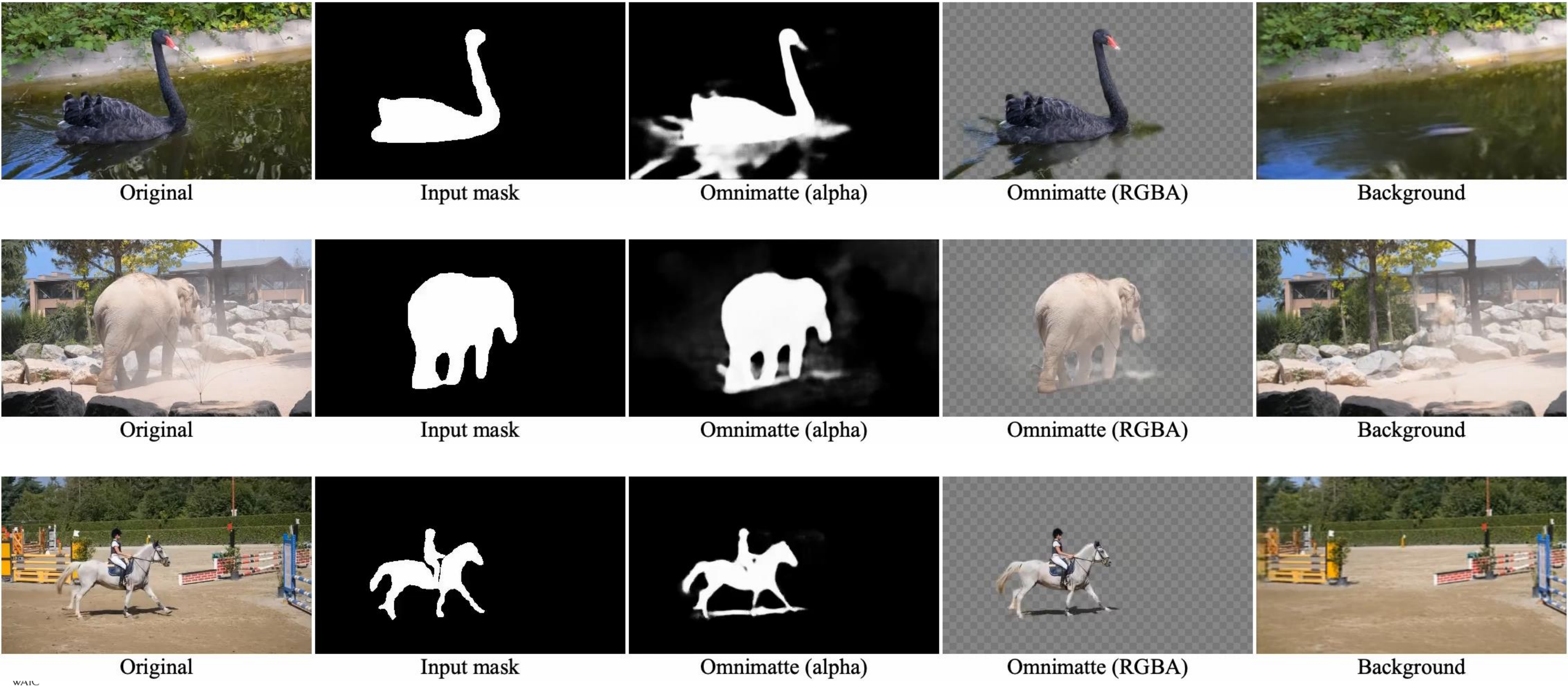
Why does this work?

Deep Image Prior, Ulyanov, et al., CVPR 2018



Omnimatte Results

DAVIS 2017 dataset.
Masks generated using
STM [ICCV'19]



Editing Effects Using Omnimatte – Logo Insertion

Input video

Editing Effects Using Omnimatte – Logo Insertion

Logo inserted

Editing Effects Using Omnimatte – Logo Insertion

Foreground RGBA layer

Layered Neural Representations for Video

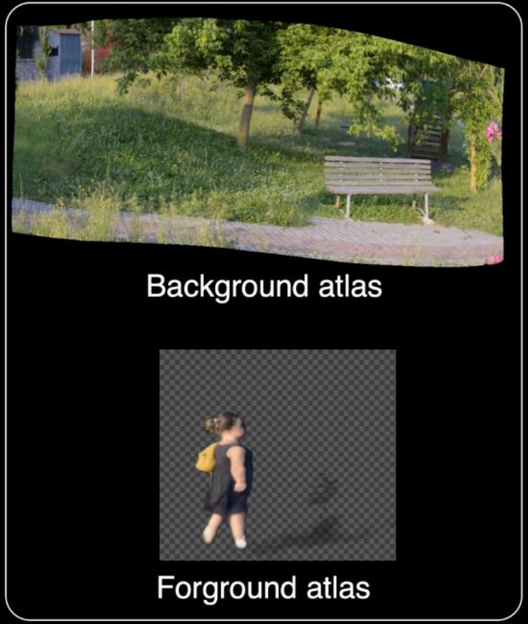
Omnimatte: Per-frame RGBA layers

Per-frame RGBA Layers

- **Per-frame representation**
- **Editing is restricted to per-frame manipulation**

Neural Atlases: Per-video Atlas layers

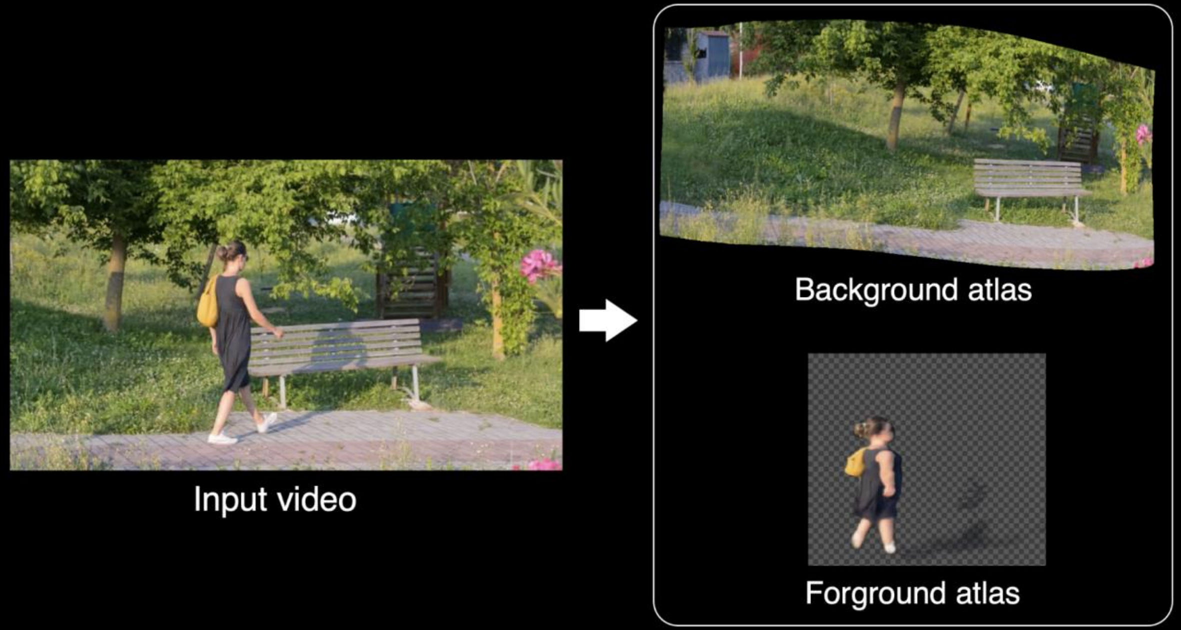
Input video



Estimated per-video atlases

- **A unified representation**
- **Easy and intuitive editing across time**

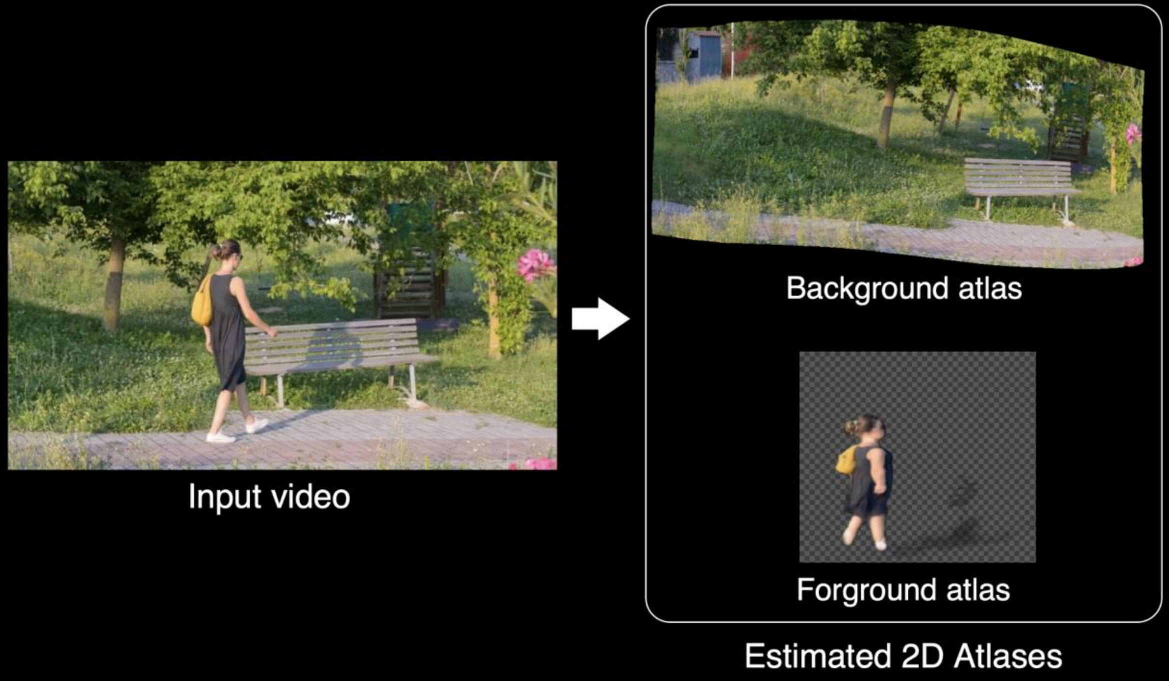
Layered Atlases for Video



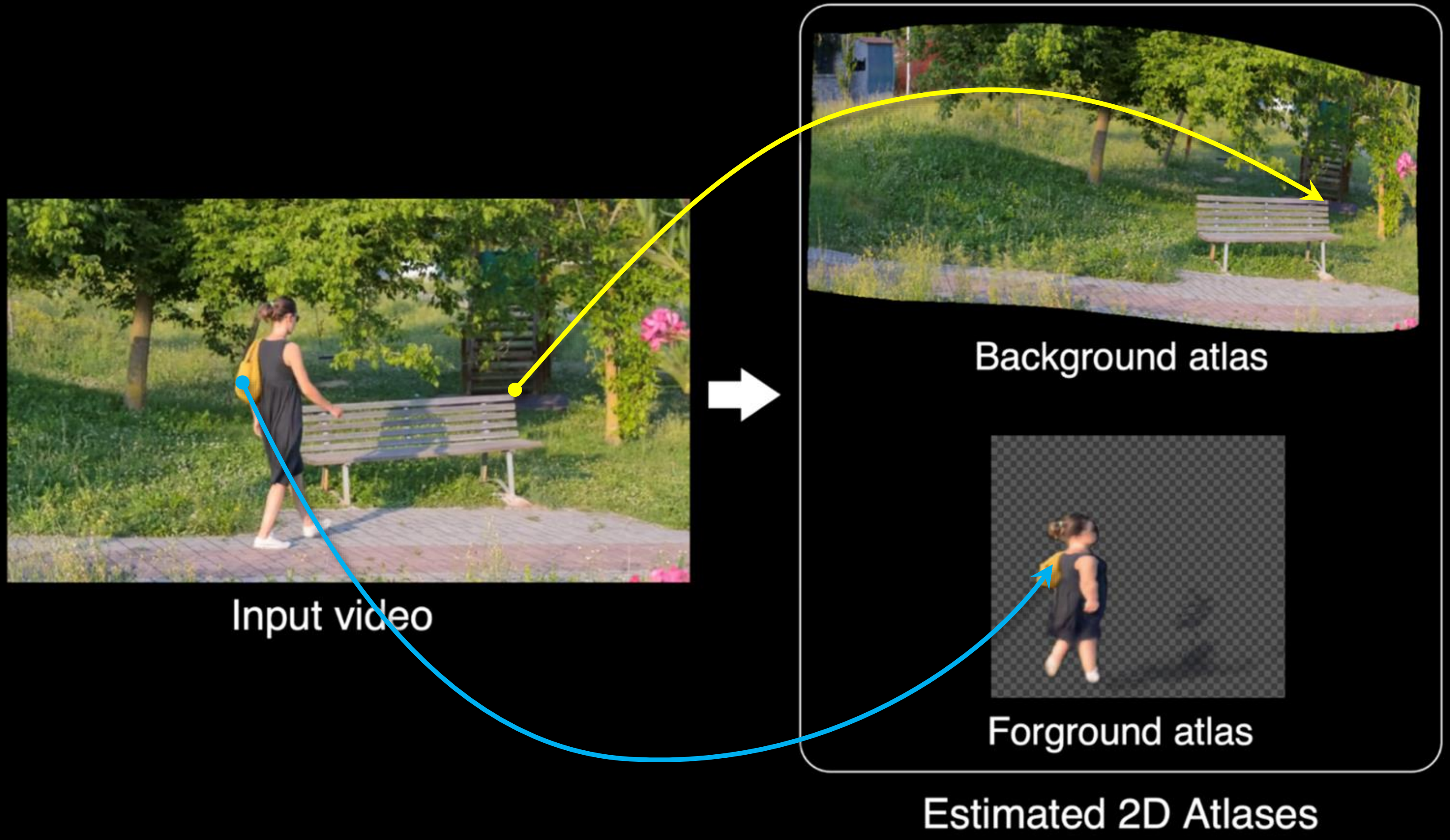
Estimated **per-video** atlases

"Layered Neural Atlases for Consistent Video Editing"
SIGGRAPH Asia'21

Layered Atlases for Video



Layered Atlases for Video



WAIC

Layered Atlases for Video

Input video

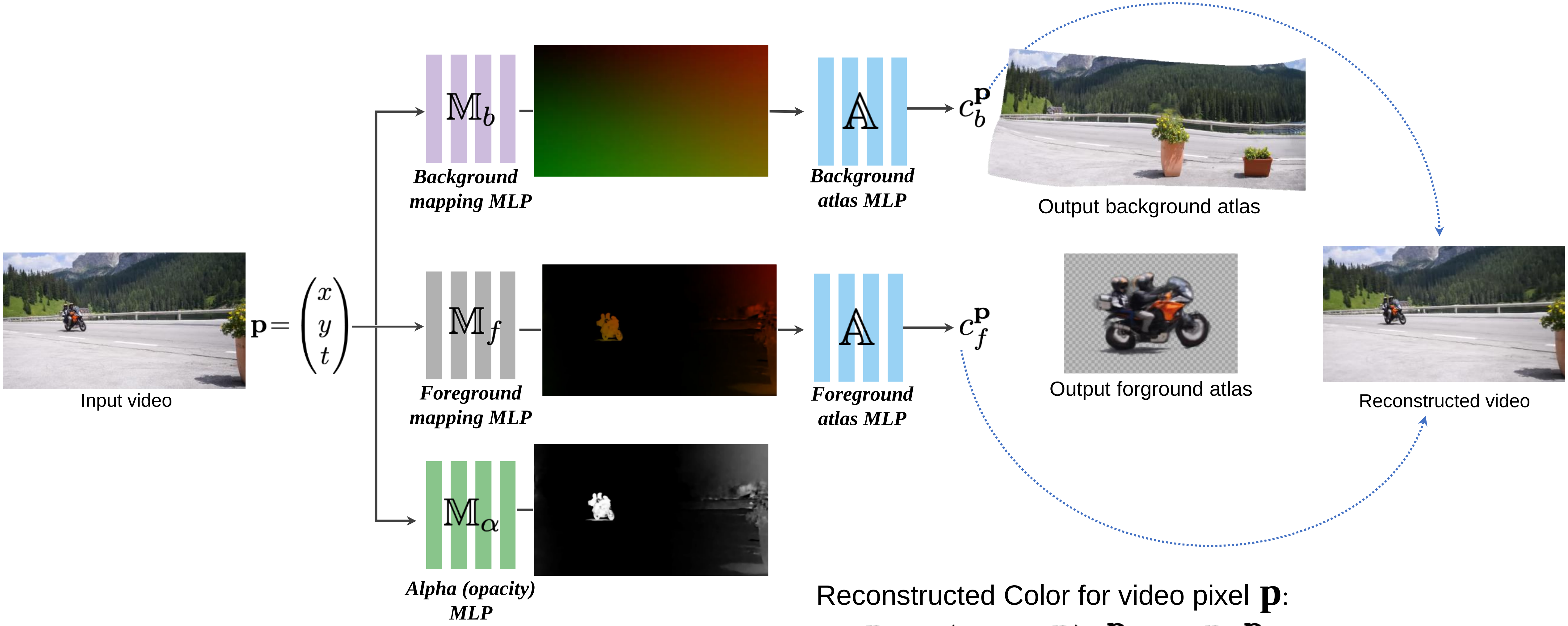
Background atlas

Forground atlas

Estimated 2D Atlases

Edited video

Layered Neural Atlases



Reconstructed Color for video pixel $\mathbf{p}$:

$$c^{\mathbf{p}} = (1 - \alpha^{\mathbf{p}})c_b^{\mathbf{p}} + \alpha^{\mathbf{p}} c_f^{\mathbf{p}}$$

WAIC

Losses

$$\mathcal{L} = \mathcal{L}_{color} + \mathcal{L}_{flow} + \mathcal{L}_{rigid} + \mathcal{L}_{sparsity}$$

Losses

$$\mathcal{L} = \boldsymbol{\mathcal{L}_{color}} + \mathcal{L}_{flow} + \mathcal{L}_{rigid} + \mathcal{L}_{sparsity}$$

- **Reconstruction of the original video**

$\|$

Input
Frame $\boldsymbol{t}$

$-$

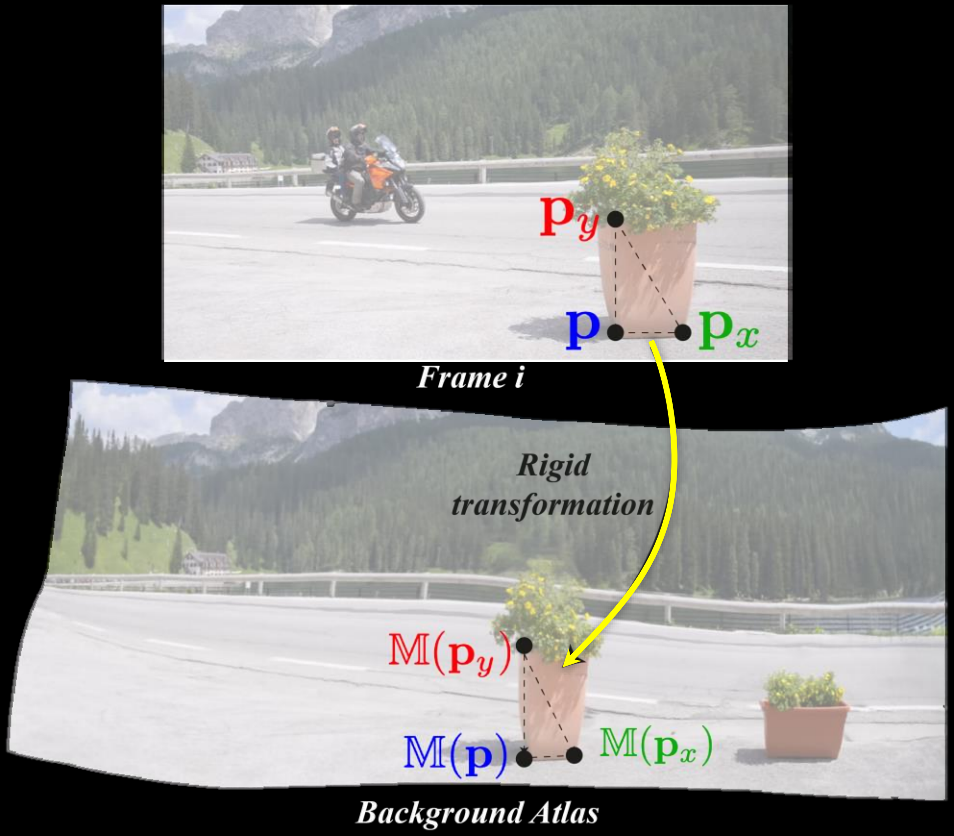
Reconstruction
Frame $\boldsymbol{t}$

$\|$

Losses

$$\mathcal{L} = \mathcal{L}_{color} + \boldsymbol{\mathcal{L}_{rigid}} + \mathcal{L}_{flow} + \mathcal{L}_{sparsity}$$

- Preserve the original structures in the atlases



Losses

$$\mathcal{L} = \mathcal{L}_{color} + \cancel{\mathcal{L}_{rigid}} + \mathcal{L}_{flow} + \mathcal{L}_{sparsity}$$

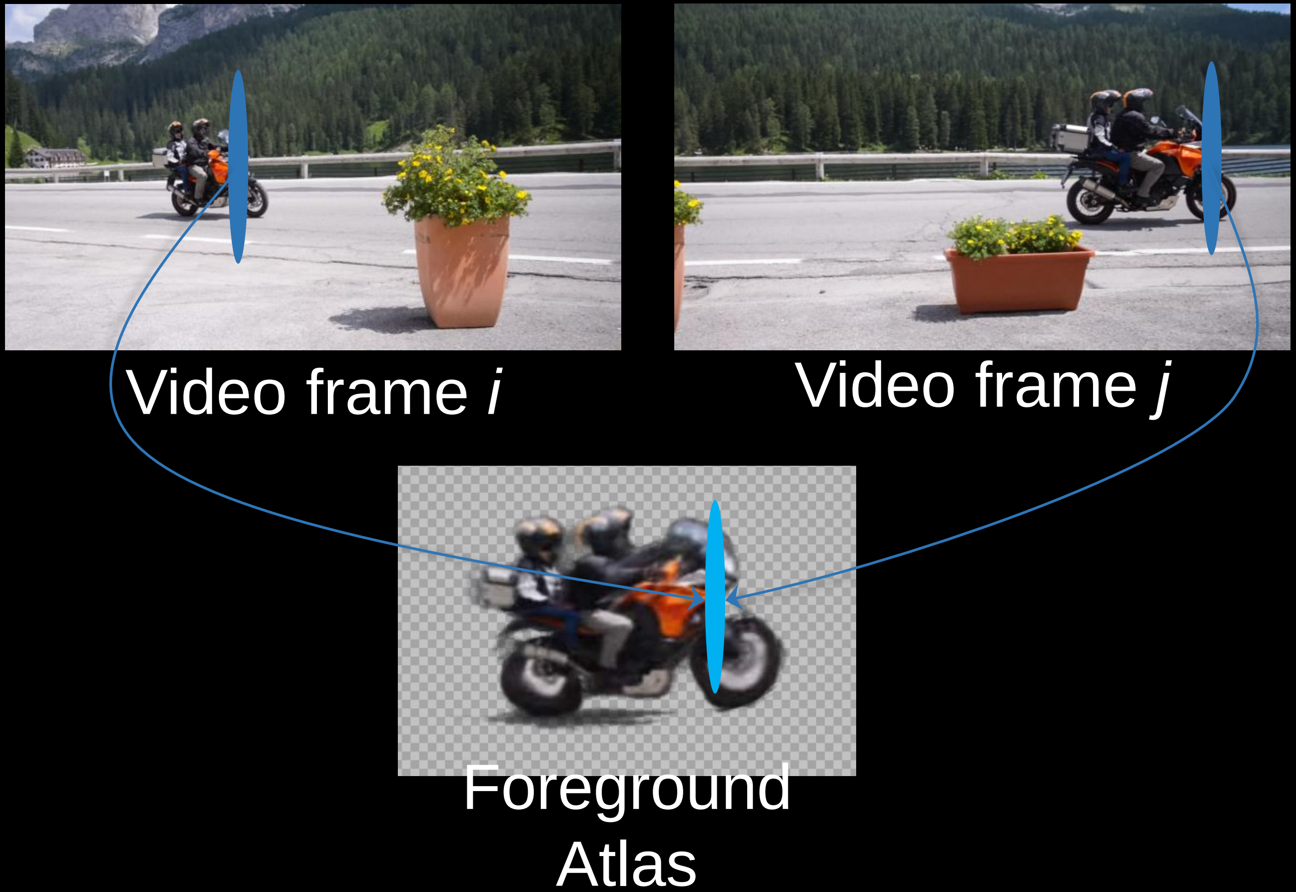
No Rigidity Loss (29.63dB)

Foreground atlas

Background atlas

Losses

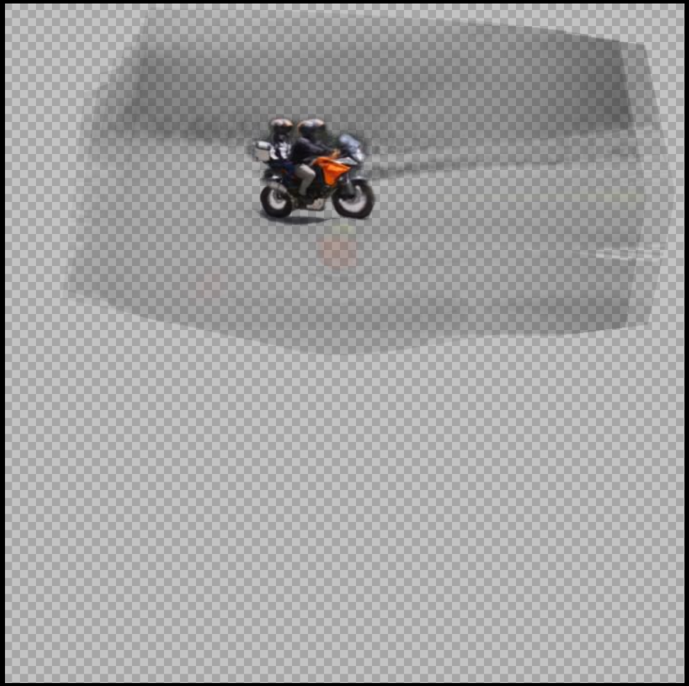
$$\mathcal{L} = \mathcal{L}_{color} + \mathcal{L}_{rigid} + \mathcal{L}_{flow} + \mathcal{L}_{sparsity}$$



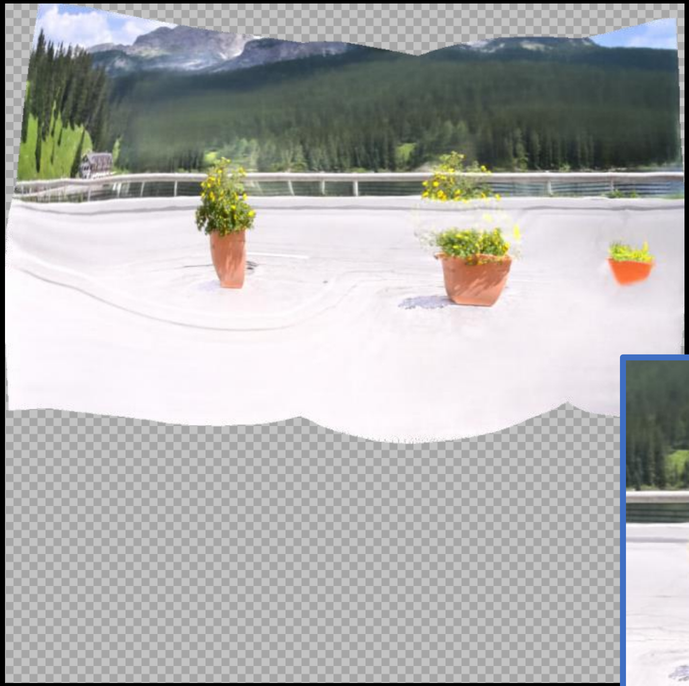
Losses

$$\mathcal{L} = \mathcal{L}_{color} + \mathcal{L}_{rigid} + \cancel{\mathcal{L}_{flow}} + \mathcal{L}_{sparsity}$$

No Optical Flow Loss (27.74dB)



Foreground atlas



Background atlas

Losses

$$\mathcal{L} = \mathcal{L}_{color} + \mathcal{L}_{rigid} + \mathcal{L}_{flow} + \boldsymbol{\mathcal{L}_{sparsity}}$$

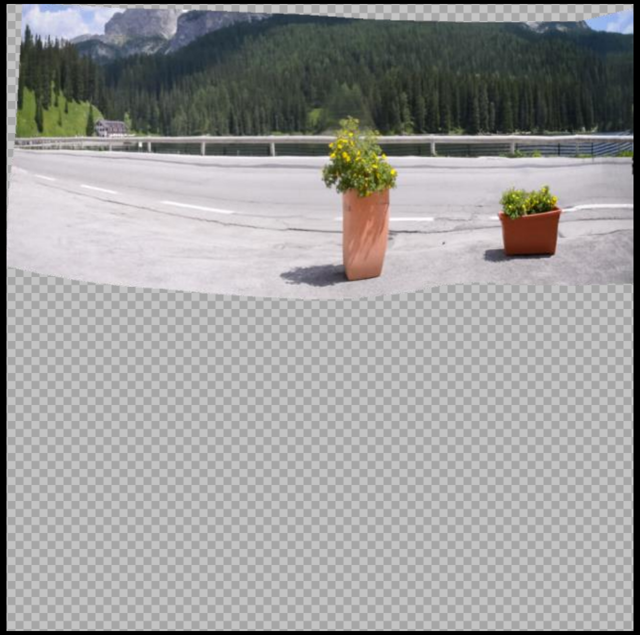
- Encourage a “minimal atlas”

Losses

$$\mathcal{L} = \mathcal{L}_{color} + \mathcal{L}_{rigid} + \mathcal{L}_{flow} + \mathcal{L}_{\cancel{sparsity}}$$

No Sparsity Loss (28.80dB)

Foreground atlas



Background atlas

Losses

$$\mathcal{L} = \mathcal{L}_{color} + \mathcal{L}_{rigid} + \mathcal{L}_{flow} + \mathcal{L}_{sparsity}$$

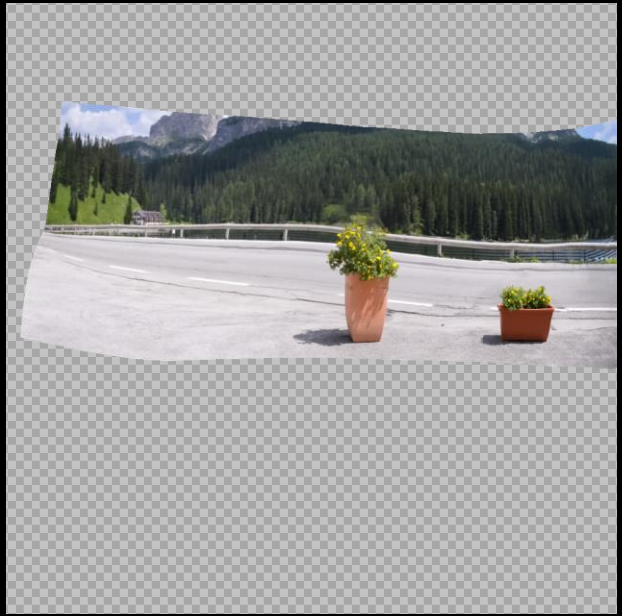
- Reconstruction of the original video
- Preserve the original structures in the atlases
- Corresponding points mapped to the same atlas point
- Encourage a “minimal atlas”

Losses

$$\mathcal{L} = \mathcal{L}_{color} + \mathcal{L}_{rigid} + \mathcal{L}_{flow} + \mathcal{L}_{sparsity}$$

Complete Model (29.85dB)

Foreground atlas



Background atlas

Alpha initialization

Masks are refined during training

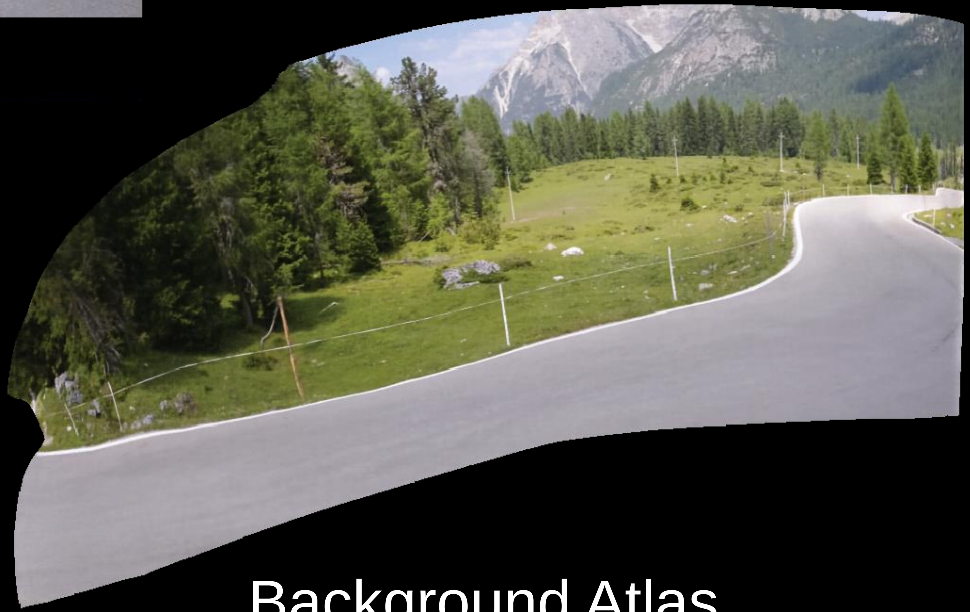
Original Video

User Input Masks

Atlas decomposition results

Original

Foreground Atlas



Background Atlas

Atlas decomposition results

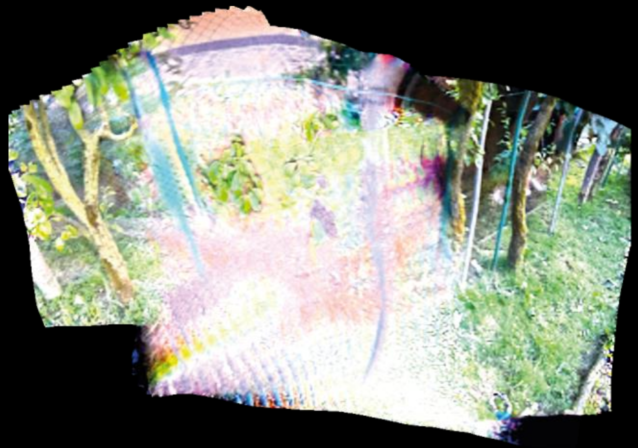
Original

Foreground Atlas

Background Atlas

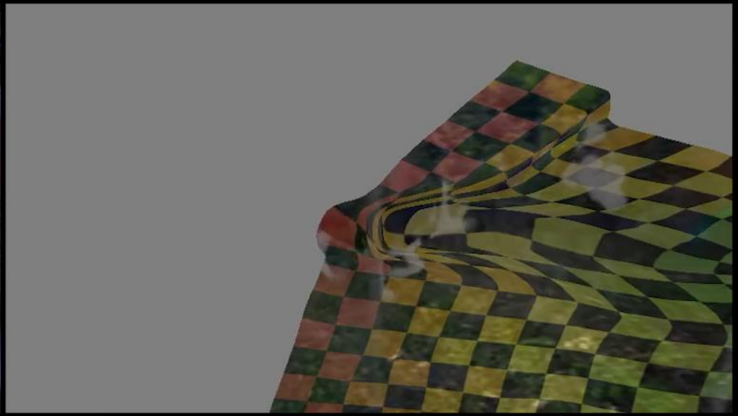
Grid Atlas Ablation

Replacing the continuous Atlas with a discrete Atlas, and fine-tuning

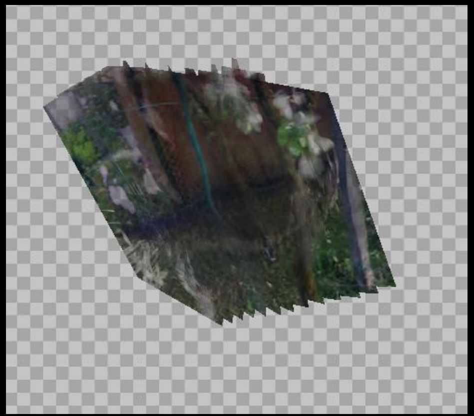


Background atlas

Original



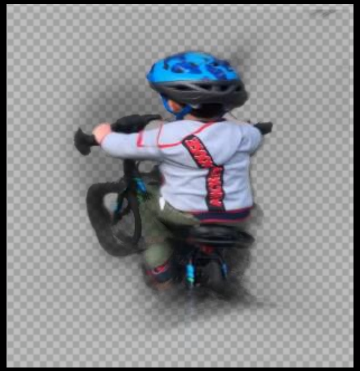
Texture mapped (overlay)



Foreground atlas

Reconstruction

RGBA foreground layer



Foreground atlas

Background atlas

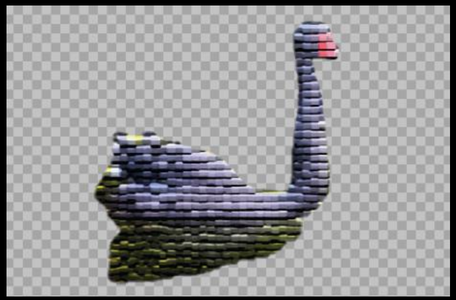
Off-the-shelf
Image style transfer

Stylized background atlas

Background atlas

Foreground atlas

Photoshop Filter



Stylized background atlas

Foreground atlas

Background atlas

Add texture

Edited background atlas

Limitations

- Complex geometry, self-occlusions and extreme deformations → multiple foreground layers
- Limited capacity: quality ↓ video length ↑

Original

Foreground atlas

Background atlas

Predicted Alpha

Edited Result

Next tutorial:
“Text and Image”