Lecture 18: Videos

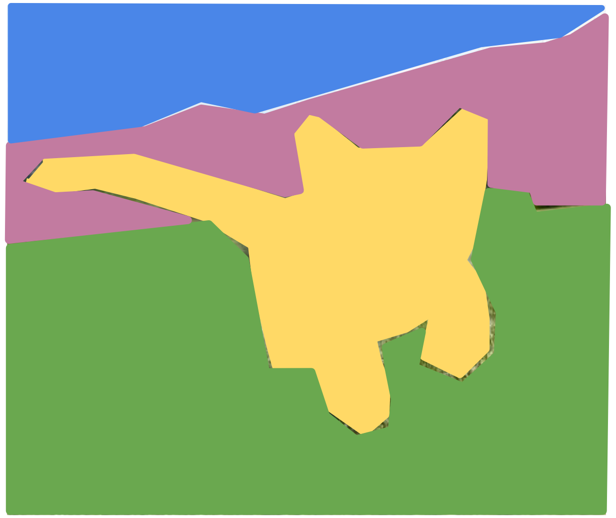
Computer Vision Tasks: 2D Recognition

Classification

CAT

No spatial extent

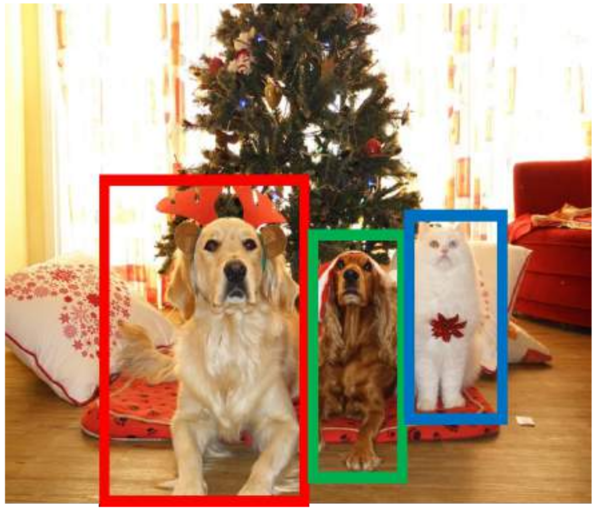
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection



DOG, DOG, CAT

Instance Segmentation

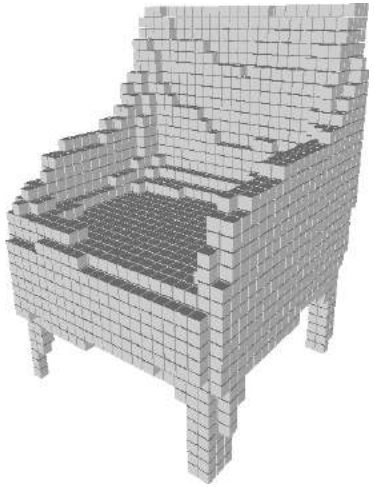
DOG, DOG, CAT

Multiple Objects

Last Time: 3D Shapes

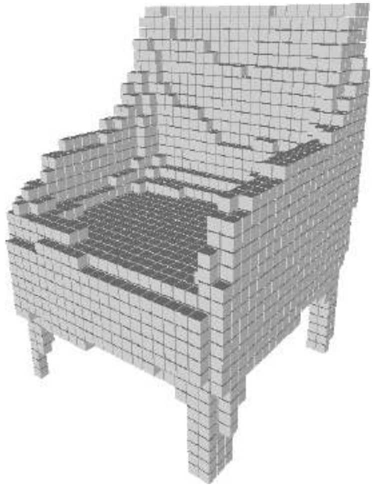
Predicting 3D Shapes from single image

Input Image



3D Shape

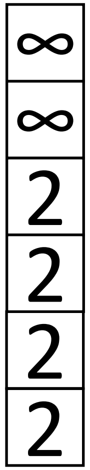
Processing 3D input data



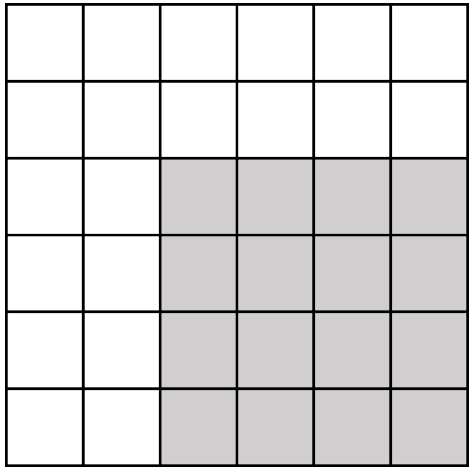
3D Shape

Chair

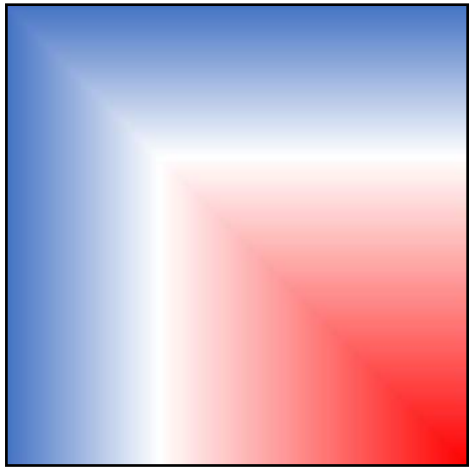
Last Time: 3D Shape Representations



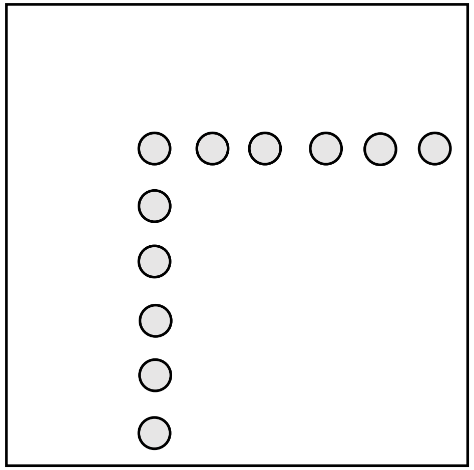
Depth Map



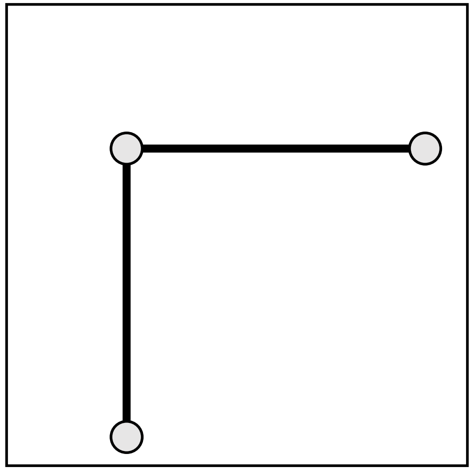
Voxel Grid



Implicit Surface



Pointcloud



Mesh

Today: **Video** = 2D + Time

A video is a **sequence** of images
4D tensor: T x 3 x H x W
(or 3 x T x H x W)

Example task: **Video Classification**

Input video:
T x 3 x H x W

Swimming
Running
Jumping
Eating
Standing

Running video is in the public domain

Example task: Video Classification

Images: Recognize **objects**

Dog
Cat
Fish
Truck

Videos: Recognize **actions**

Swimming
Running
Jumping
Eating
Standing

Running video is in the public domain

Problem: Videos are big!

Input video:
T x 3 x H x W

Videos are ~30 frames per second (fps)

Size of uncompressed video
(3 bytes per pixel):

SD (640 x 480): **~1.5 GB per minute**
HD (1920 x 1080): ~**10 GB per minute**

Problem: Videos are big!

Input video:
T x 3 x H x W

Videos are ~30 frames per second (fps)

Size of uncompressed video (3 bytes per pixel):

SD (640 x 480): **~1.5 GB per minute**
HD (1920 x 1080): ~**10 GB per minute**

Solution: Train on short **clips:** low fps and low spatial resolution
e.g. T = 16, H=W=112
(3.2 seconds at 5 fps, 588 KB)

Training on Clips

Raw video: Long, high FPS

Training on Clips

Raw video: Long, high FPS

Training: Train model to classify short **clips** with low FPS

Training on Clips

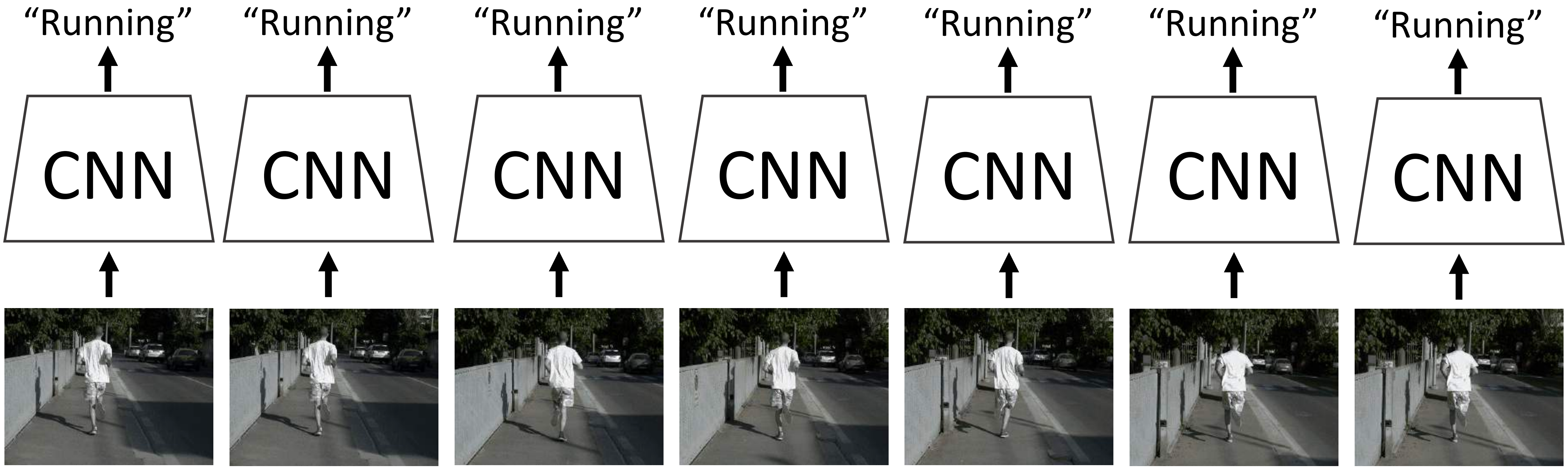
Raw video: Long, high FPS

Training: Train model to classify short **clips** with low FPS

Testing: Run model on different clips, average predictions

Video Classification: Single-Frame CNN

Simple idea: train normal 2D CNN to classify video frames independently!
(Average predicted probs at test-time)
Often a **very** strong baseline for video classification



Video Classification: Late Fusion (with FC layers)

Intuition: Get high-level appearance of each frame, and combine them

Class scores: C

MLP

Clip features: TDH'W'

Flatten

Run 2D CNN on each frame, concatenate features and feed to MLP

Frame features
T x D x H' x W'

CNN CNN CNN CNN CNN CNN

2D CNN on each frame

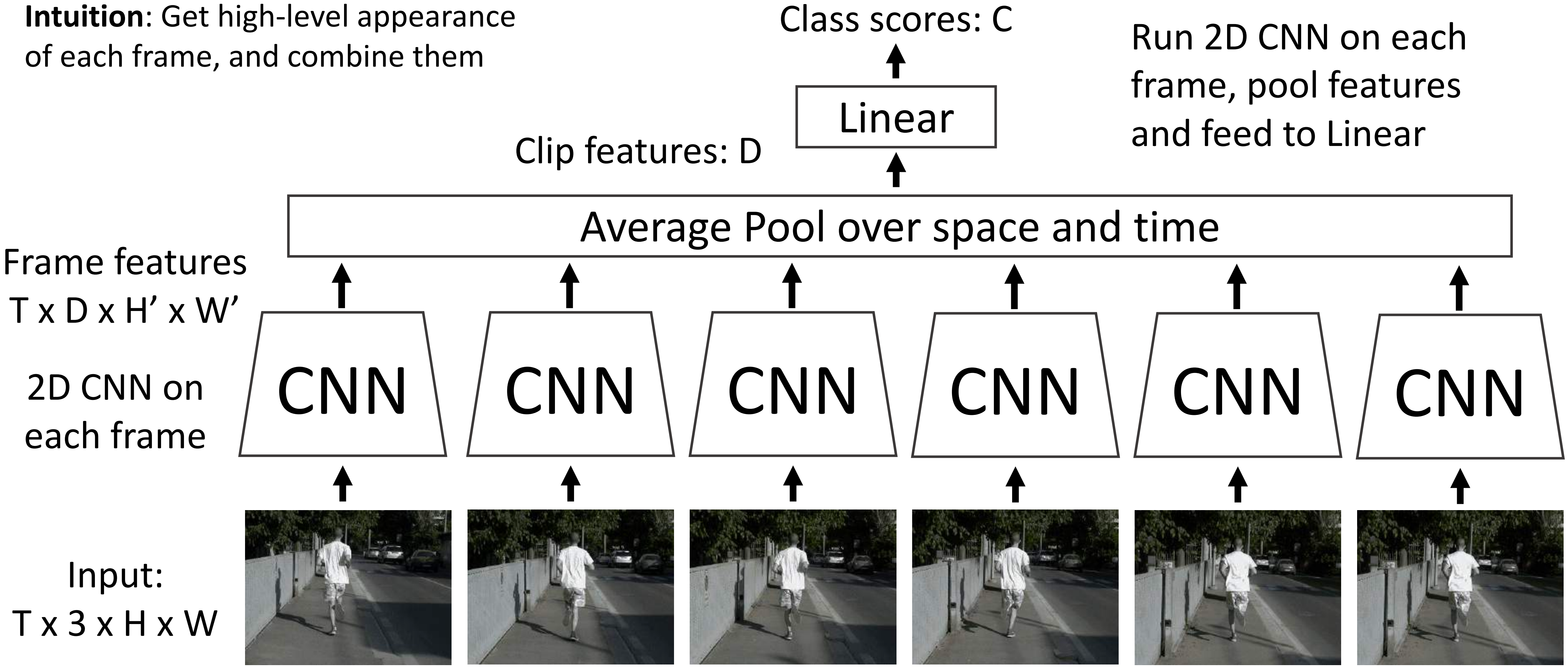
Input:
T x 3 x H x W

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

Video Classification: Late Fusion (with pooling)

Intuition: Get high-level appearance of each frame, and combine them

Run 2D CNN on each frame, pool features and feed to Linear



Video Classification: Late Fusion (with pooling)

Intuition: Get high-level appearance of each frame, and combine them

Problem: Hard to compare low-level motion between frames

Run 2D CNN on each frame, pool features and feed to Linear

Class scores: C

Linear

Clip features: D

Average Pool over space and time

Frame features
T x D x H' x W'

CNN | CNN | CNN | CNN | CNN | CNN

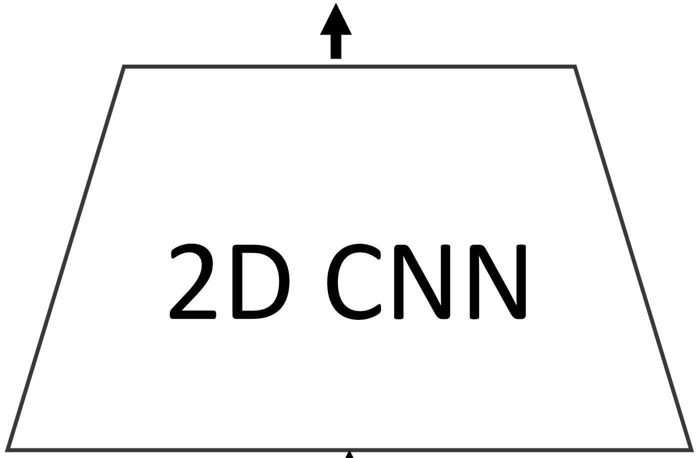
2D CNN on each frame

Input:
T x 3 x H x W

Video Classification: Early Fusion

Intuition: Compare frames with very first conv layer, after that normal 2D CNN

Class scores: C

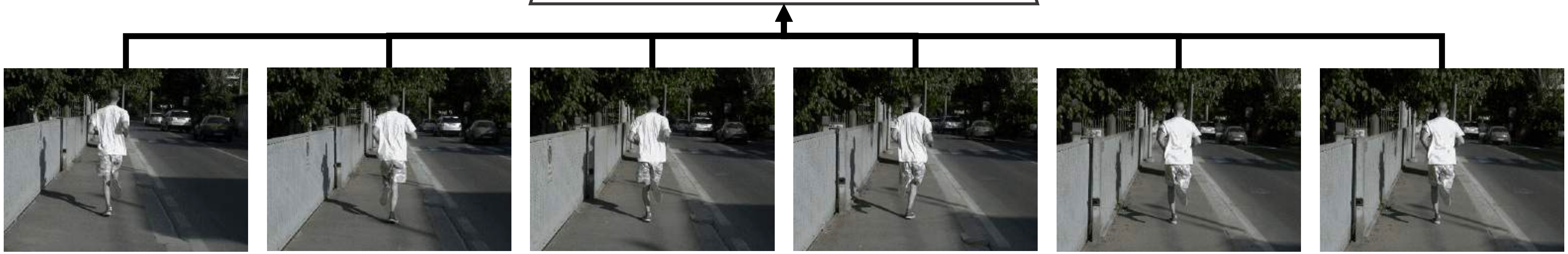


Rest of the network is standard 2D CNN

First 2D convolution collapses all temporal information:
Input: 3T x H x W
Output: D x H x W

Reshape:
3T x H x W

Input:
T x 3 x H x W



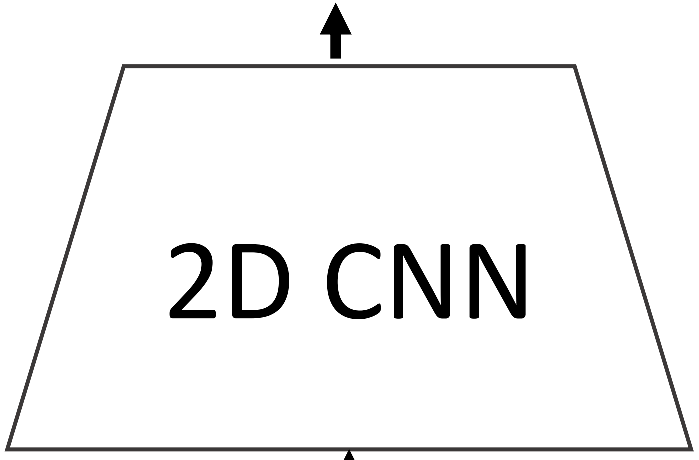
Karpathy et al, “Large-scale Video Classification with Convolutional Neural Networks”, CVPR 2014

Video Classification: Early Fusion

Intuition: Compare frames with very first conv layer, after that normal 2D CNN

Problem: One layer of temporal processing may not be enough!

Class scores: C



Rest of the network is standard 2D CNN

First 2D convolution collapses all temporal information:

Input: 3T x H x W

Output: D x H x W

Reshape:
3T x H x W

Input:
T x 3 x H x W

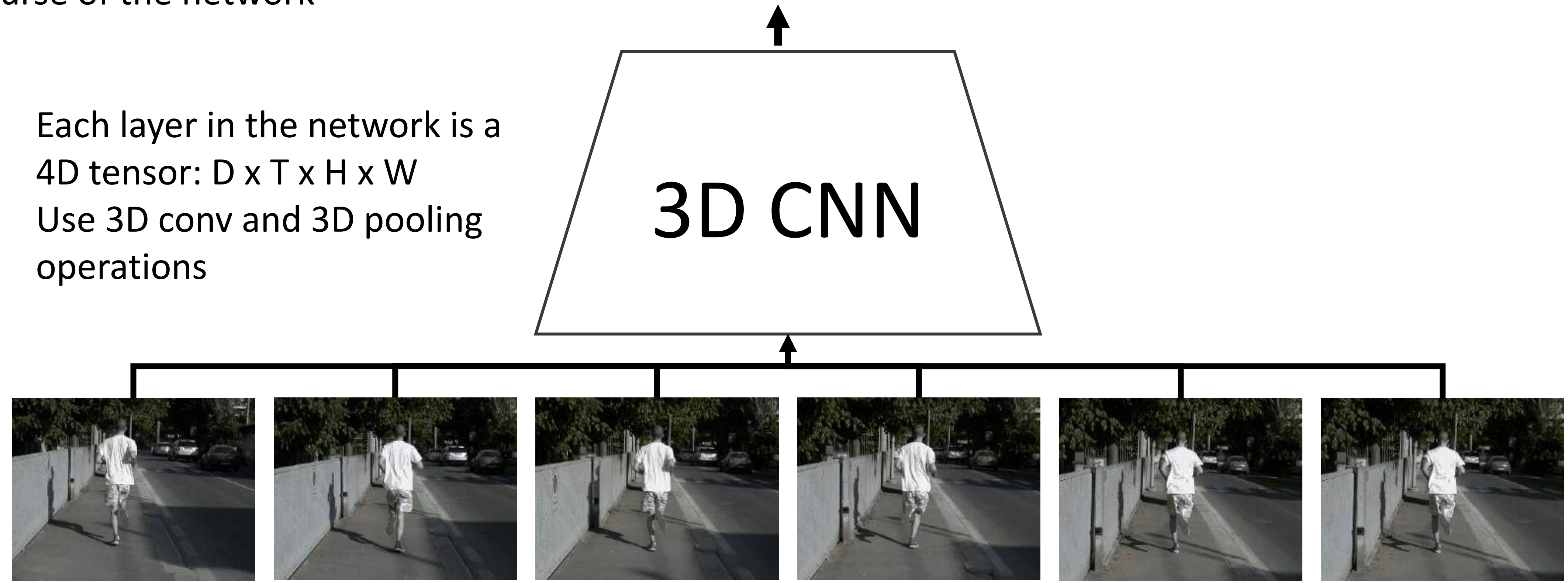
Karpathy et al, "Large-scale Video Classification with Convolutional Neural Networks", CVPR 2014

Video Classification: 3D CNN

Intuition: Use 3D versions of convolution and pooling to slowly fuse temporal information over the course of the network

Each layer in the network is a 4D tensor: D x T x H x W
Use 3D conv and 3D pooling operations

Class scores: C



Input:
3 x T x H x W

Ji et al, "3D Convolutional Neural Networks for Human Action Recognition", TPAMI 2010 ; Karpathy et al, "Large-scale Video Classification with Convolutional Neural Networks", CVPR 2014

Early Fusion vs Late Fusion vs 3D CNN

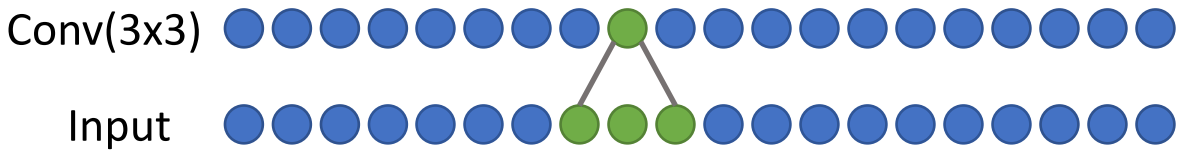
Late Fusion

Layer	**Size (C x T x H x W)**	**Receptive Field (T x H x W)**
Input	3 x 20 x 64 x 64	
Conv2D(3x3, 3->12)	12 x 20 x 64 x 64	1 x 3 x 3

Early Fusion vs Late Fusion vs 3D CNN

Late Fusion

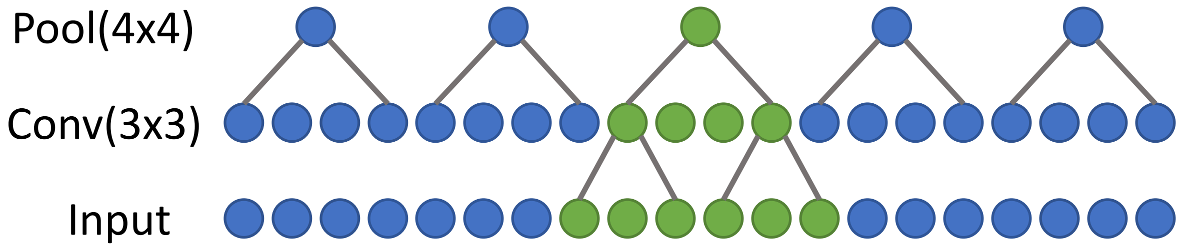
Layer	Size (C x T x H x W)	Receptive Field (T x H x W)
Input	3 x 20 x 64 x 64	
Conv2D(3x3, 3->12)	12 x 20 x 64 x 64	1 x 3 x 3



Early Fusion vs Late Fusion vs 3D CNN

Late Fusion

Layer	Size (C x T x H x W)	Receptive Field (T x H x W)
Input	3 x 20 x 64 x 64	
Conv2D(3x3, 3->12)	12 x 20 x 64 x 64	1 x 3 x 3
Pool2D(4x4)	12 x 20 x 16 x 16	1 x 6 x 6

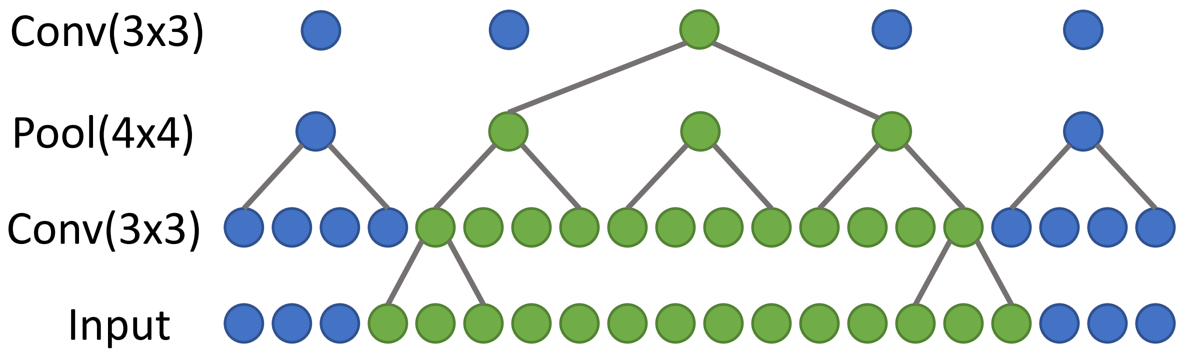


Early Fusion vs Late Fusion vs 3D CNN

Late Fusion

Layer	Size (C x T x H x W)	Receptive Field (T x H x W)
Input	3 x 20 x 64 x 64	
Conv2D(3x3, 3->12)	12 x 20 x 64 x 64	1 x 3 x 3
Pool2D(4x4)	12 x 20 x 16 x 16	1 x 6 x 6
Conv2D(3x3, 12->24)	24 x 20 x 16 x 16	1 x 14 x 14

Build slowly in space

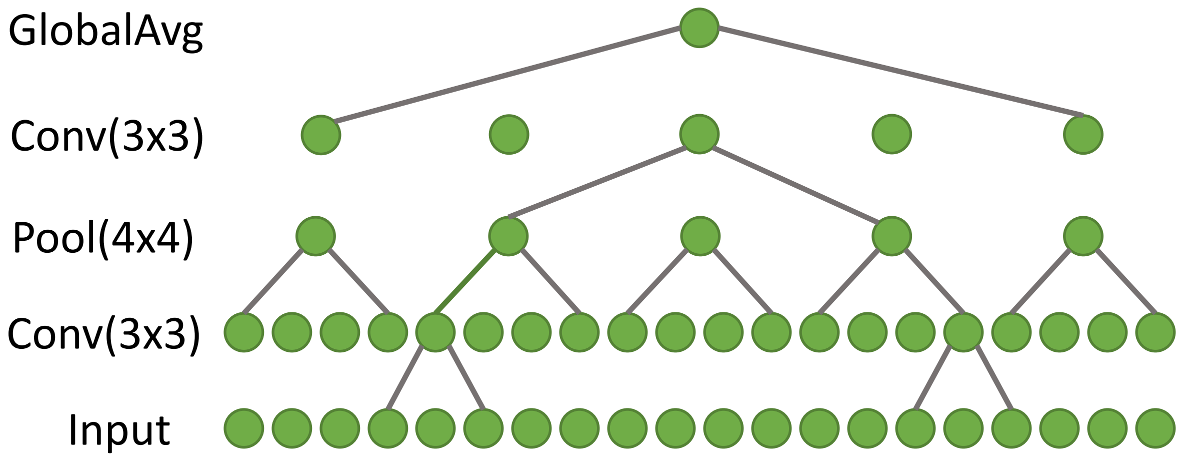


Early Fusion vs Late Fusion vs 3D CNN

Late Fusion

Layer	Size (C x T x H x W)	Receptive Field (T x H x W)
Input	3 x 20 x 64 x 64	
Conv2D(3x3, 3->12)	12 x 20 x 64 x 64	1 x 3 x 3
Pool2D(4x4)	12 x 20 x 16 x 16	1 x 6 x 6
Conv2D(3x3, 12->24)	24 x 20 x 16 x 16	1 x 14 x 14
GlobalAvgPool	24 x 1 x 1 x 1	20 x 64 x 64

Build slowly in space,
All-at-once in time at end



Early Fusion vs Late Fusion vs 3D CNN

	Layer	Size (C x T x H x W)	Receptive Field (T x H x W)
Late Fusion	Input	3 x 20 x 64 x 64	
	Conv2D(3x3, 3->12)	12 x 20 x 64 x 64	1 x 3 x 3
	Pool2D(4x4)	12 x 20 x 16 x 16	1 x 6 x 6
	Conv2D(3x3, 12->24)	24 x 20 x 16 x 16	1 x 14 x 14
	GlobalAvgPool	24 x 1 x 1 x 1	20 x 64 x 64
Early Fusion	Input	3 x 20 x 64 x 64	
	Conv2D(3x3, 3*10->12)	12 x 64 x 64	20 x 3 x 3
	Pool2D(4x4)	12 x 16 x 16	20 x 6 x 6
	Conv2D(3x3, 12->24)	24 x 16 x 16	20 x 14 x 14
	GlobalAvgPool	24 x 1 x 1	20 x 64 x 64

Build slowly in space,
All-at-once in time at end

Build slowly in space,
All-at-once in time at start

Early Fusion vs Late Fusion vs 3D CNN

(Small example architectures, in practice much bigger)

	Layer	Size (C x T x H x W)	Receptive Field (T x H x W)	
Late Fusion	Input	3 x 20 x 64 x 64		Build slowly in space, All-at-once in time at end
	Conv2D(3x3, 3->12)	12 x 20 x 64 x 64	1 x 3 x 3	
	Pool2D(4x4)	12 x 20 x 16 x 16	1 x 6 x 6	
	Conv2D(3x3, 12->24)	24 x 20 x 16 x 16	1 x 14 x 14	
	GlobalAvgPool	24 x 1 x 1 x 1	20 x 64 x 64	
Early Fusion	Input	3 x 20 x 64 x 64		Build slowly in space, All-at-once in time at start
	Conv2D(3x3, 3*10->12)	12 x 64 x 64	20 x 3 x 3	
	Pool2D(4x4)	12 x 16 x 16	20 x 6 x 6	
	Conv2D(3x3, 12->24)	24 x 16 x 16	20 x 14 x 14	
	GlobalAvgPool	24 x 1 x 1	20 x 64 x 64	
3D CNN	Input	3 x 20 x 64 x 64		Build slowly in space, Build slowly in time ”Slow Fusion”
	Conv3D(3x3x3, 3->12)	12 x 20 x 64 x 64	3 x 3 x 3	
	Pool3D(4x4x4)	12 x 5 x 16 x 16	6 x 6 x 6	
	Conv3D(3x3x3, 12->24)	24 x 5 x 16 x 16	14 x 14 x 14	
	GlobalAvgPool	24 x 1 x 1	20 x 64 x 64	

Early Fusion vs Late Fusion vs 3D CNN

What is the difference?

	Layer	Size (C x T x H x W)	Receptive Field (T x H x W)
Late Fusion	Input	3 x 20 x 64 x 64	
	Conv2D(3x3, 3->12)	12 x 20 x 64 x 64	1 x 3 x 3
	Pool2D(4x4)	12 x 20 x 16 x 16	1 x 6 x 6
	Conv2D(3x3, 12->24)	24 x 20 x 16 x 16	1 x 14 x 14
	GlobalAvgPool	24 x 1 x 1 x 1	20 x 64 x 64
Early Fusion	Input	3 x 20 x 64 x 64	
	Conv2D(3x3, 3*10->12)	12 x 64 x 64	20 x 3 x 3
	Pool2D(4x4)	12 x 16 x 16	20 x 6 x 6
	Conv2D(3x3, 12->24)	24 x 16 x 16	20 x 14 x 14
	GlobalAvgPool	24 x 1 x 1	20 x 64 x 64
3D CNN	Input	3 x 20 x 64 x 64	
	Conv3D(3x3x3, 3->12)	12 x 20 x 64 x 64	3 x 3 x 3
	Pool3D(4x4x4)	12 x 5 x 16 x 16	6 x 6 x 6
	Conv3D(3x3x3, 12->24)	24 x 5 x 16 x 16	14 x 14 x 14
	GlobalAvgPool	24 x 1 x 1	20 x 64 x 64

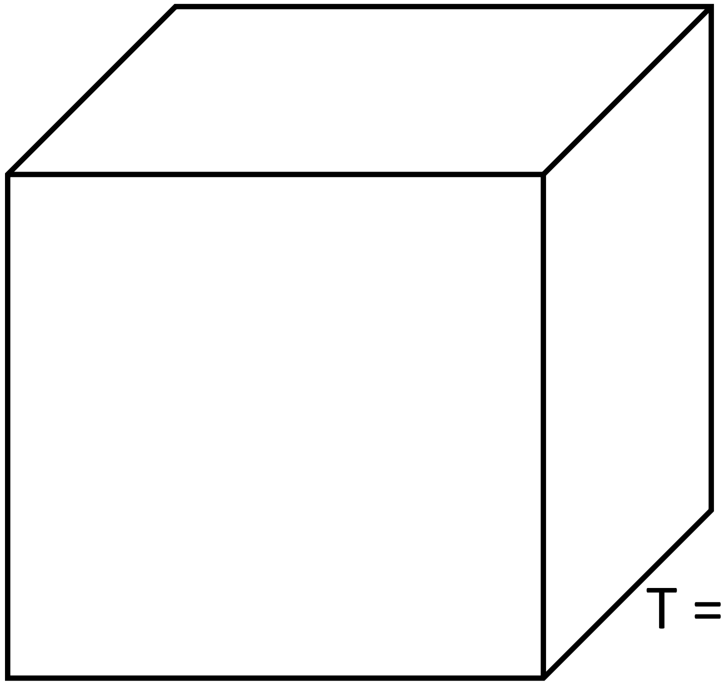
Late Fusion: Build slowly in space,
All-at-once in time at end

Early Fusion: Build slowly in space,
All-at-once in time at start

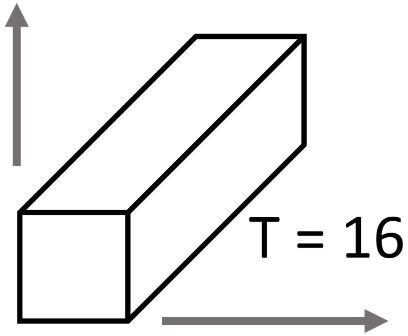
3D CNN: Build slowly in space,
Build slowly in time
"Slow Fusion"

2D Conv (Early Fusion) vs 3D Conv (3D CNN)

Input: C_{in} x T x H x W
(3D grid with C_{in}-dim feat at each point)

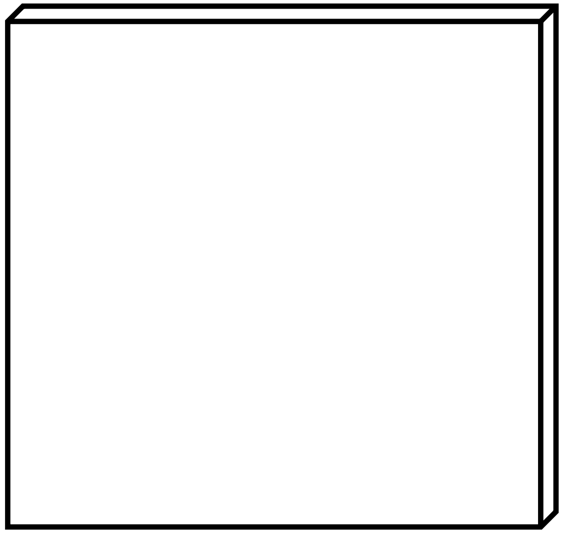


Weight:
C_{out} x C_{in} x T x 3 x 3
Slide over x and y



C_{out} different filters

Output:
C_{out} x H x W
2D grid with C_{out} –dim feat at each point



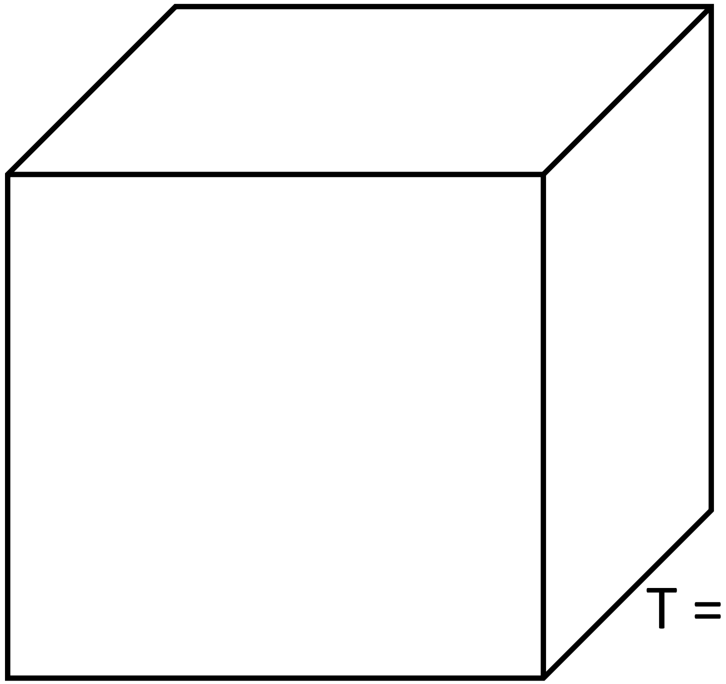
2D Conv (Early Fusion) vs 3D Conv (3D CNN)

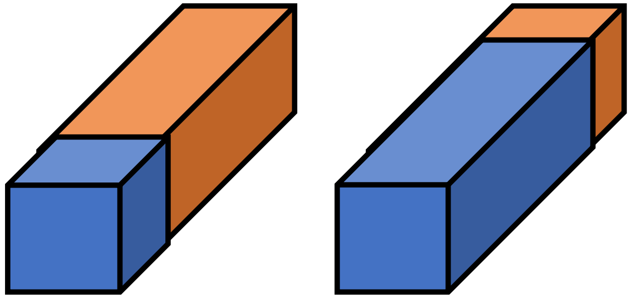
Input: C_{in} x T x H x W
(3D grid with C_{in}-dim feat at each point)

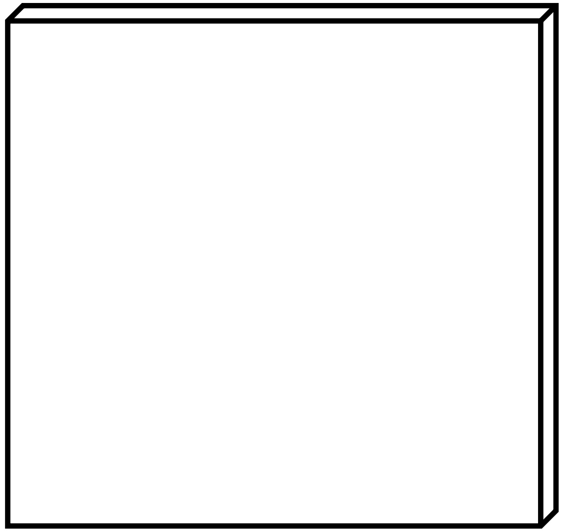
Weight:
C_{out} x C_{in} x T x 3 x 3
Slide over x and y

Output:
C_{out} x H x W
2D grid with C_{out} –dim feat at each point

No temporal shift-invariance! Needs to learn separate filters for the same motion at different times in the clip





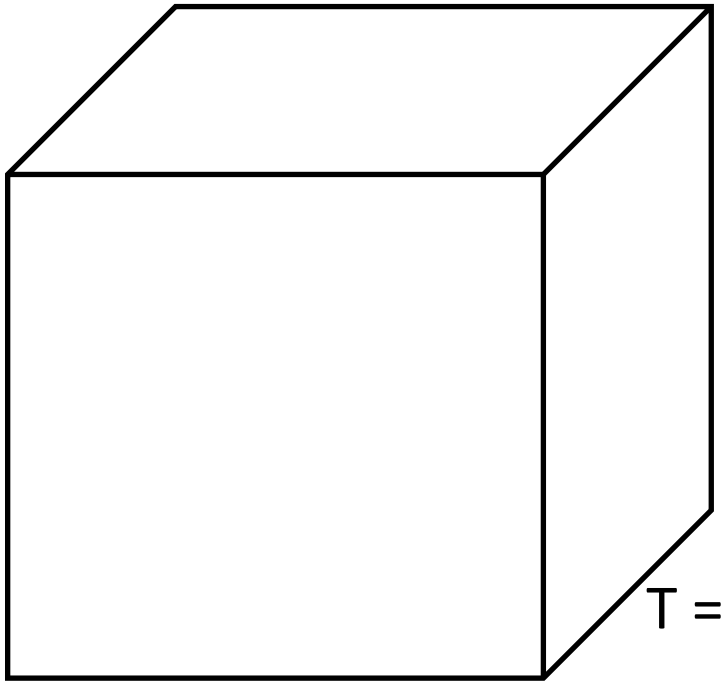


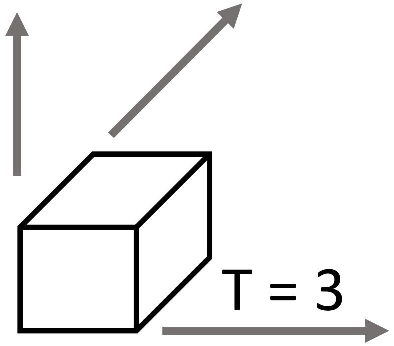
2D Conv (Early Fusion) vs 3D Conv (3D CNN)

Input: C_{in} x T x H x W
(3D grid with C_{in}-dim feat at each point)

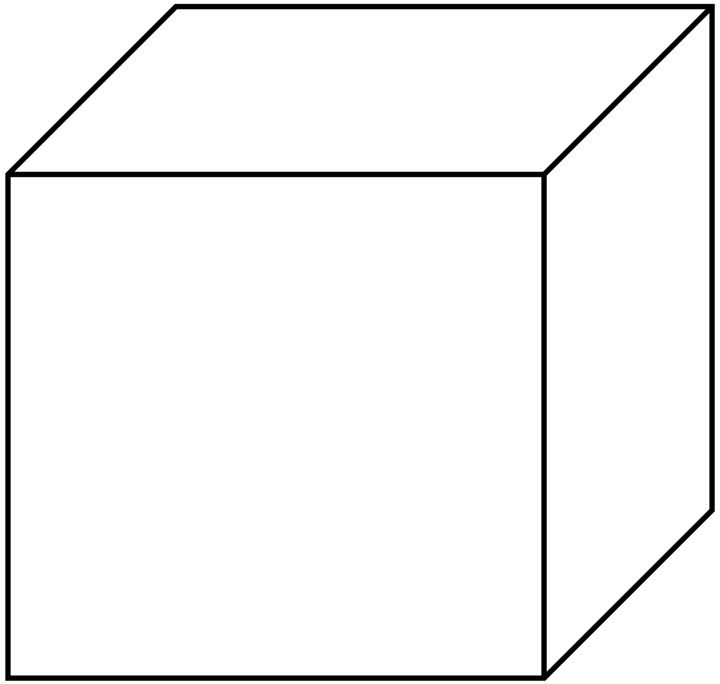
Weight:
C_{out} x C_{in} x 3 x 3 x 3
Slide over x and y

Output:
C_{out} x T x H x W
3D grid with C_{out}–dim feat at each point





C_{out} different filters



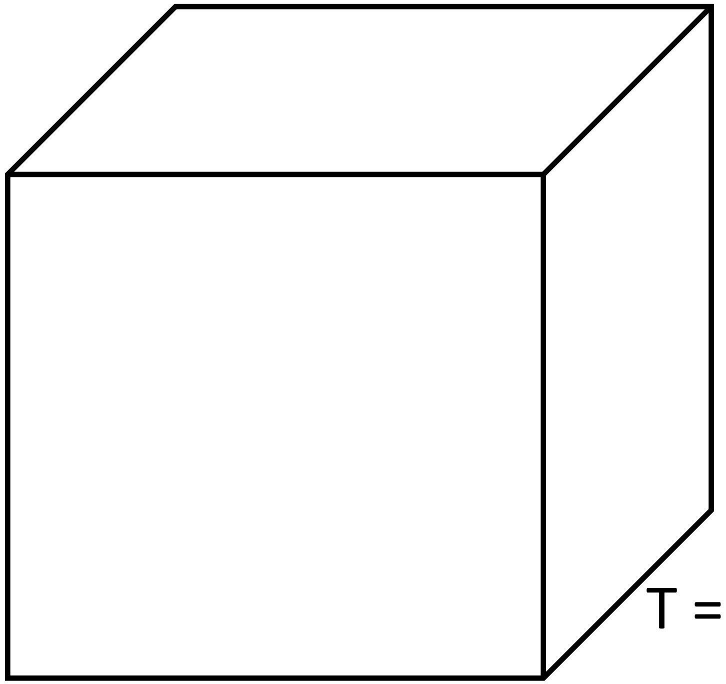
2D Conv (Early Fusion) vs 3D Conv (3D CNN)

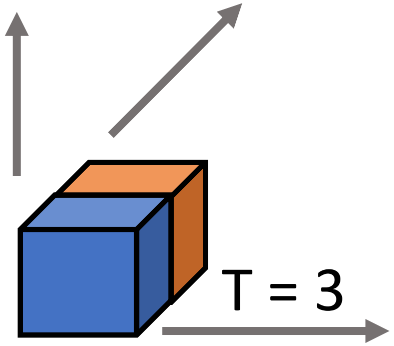
Input: C_{in} x T x H x W
(3D grid with C_{in}-dim feat at each point)

Weight:
C_{out} x C_{in} x 3 x 3 x 3
Slide over x and y

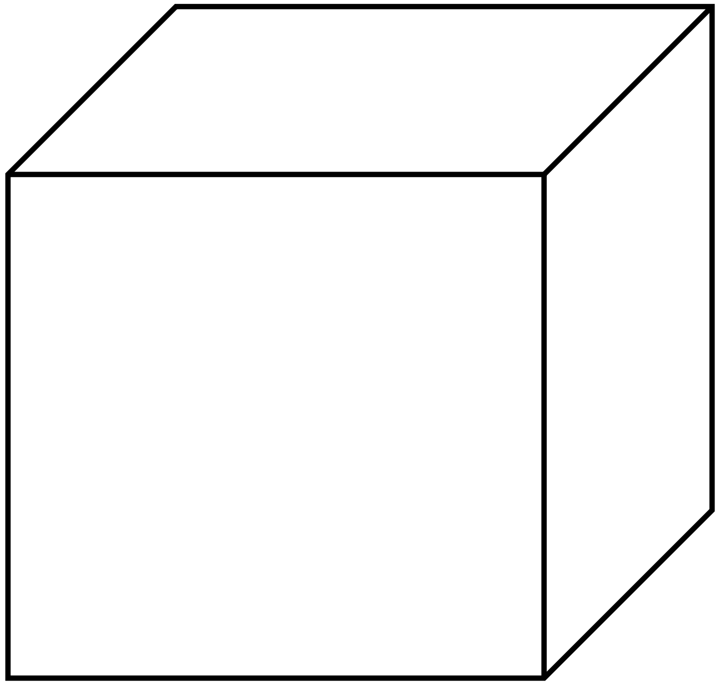
Output:
C_{out} x T x H x W
3D grid with C_{out}–dim feat at each point

Temporal shift-invariant since each filter slides over time!





C_{out} different filters

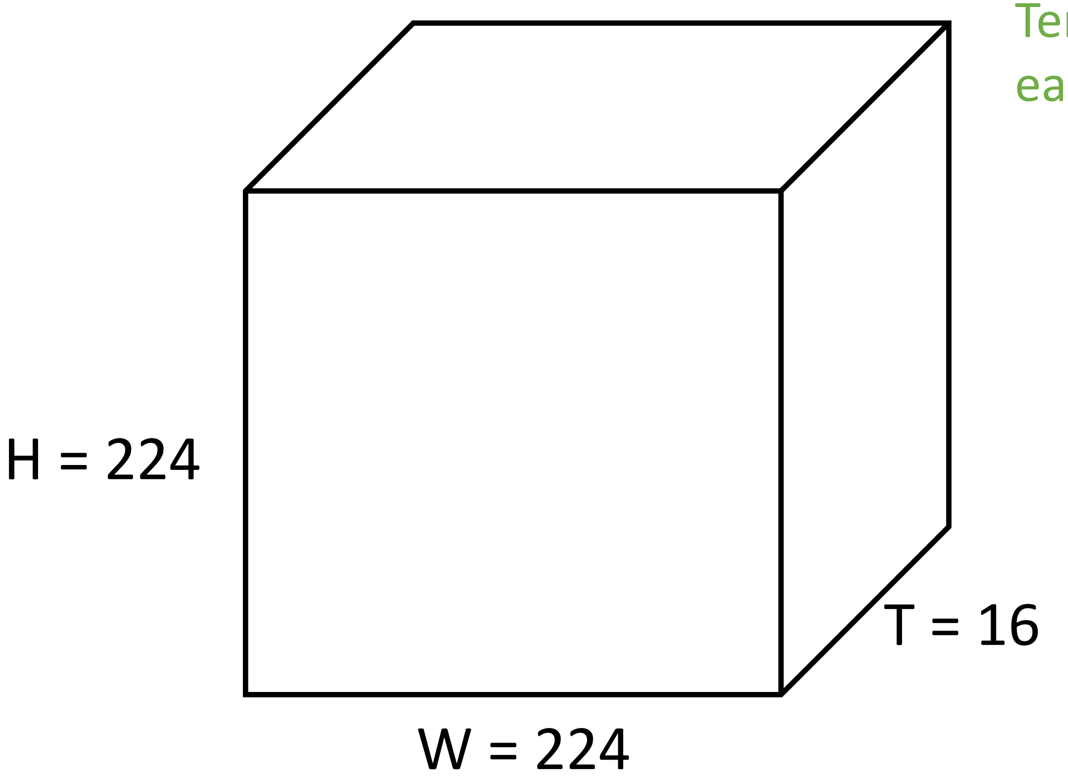


2D Conv (Early Fusion) vs 3D Conv (3D CNN)

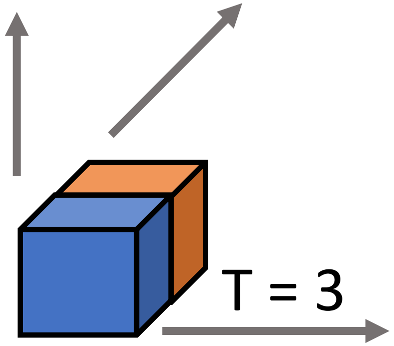
Input: C_{in} x T x H x W
(3D grid with C_{in}-dim feat at each point)

Weight:
C_{out} x C_{in} x 3 x 3 x 3
Slide over x and y

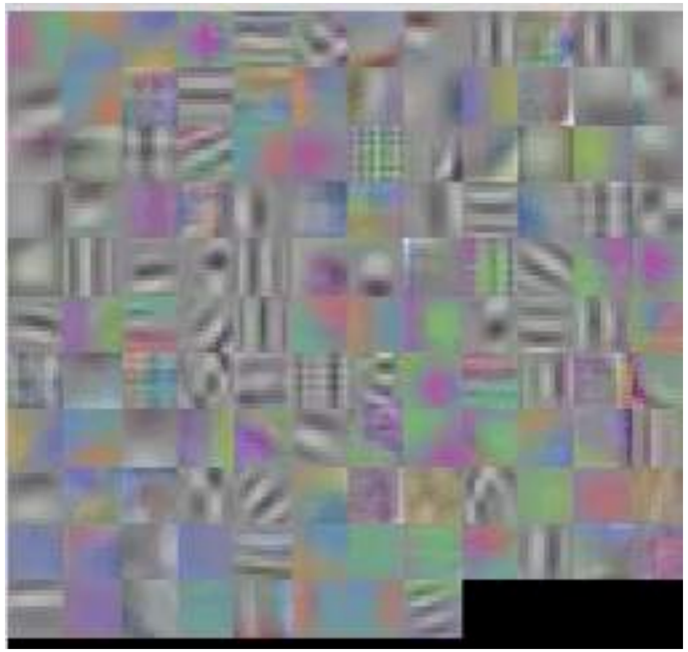
First-layer filters have shape
3 (RGB) x 4 (frames) x 5 x 5 (space)
Can visualize as video clips!



Temporal shift-invariant since each filter slides over time!



C_{out} different filters



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

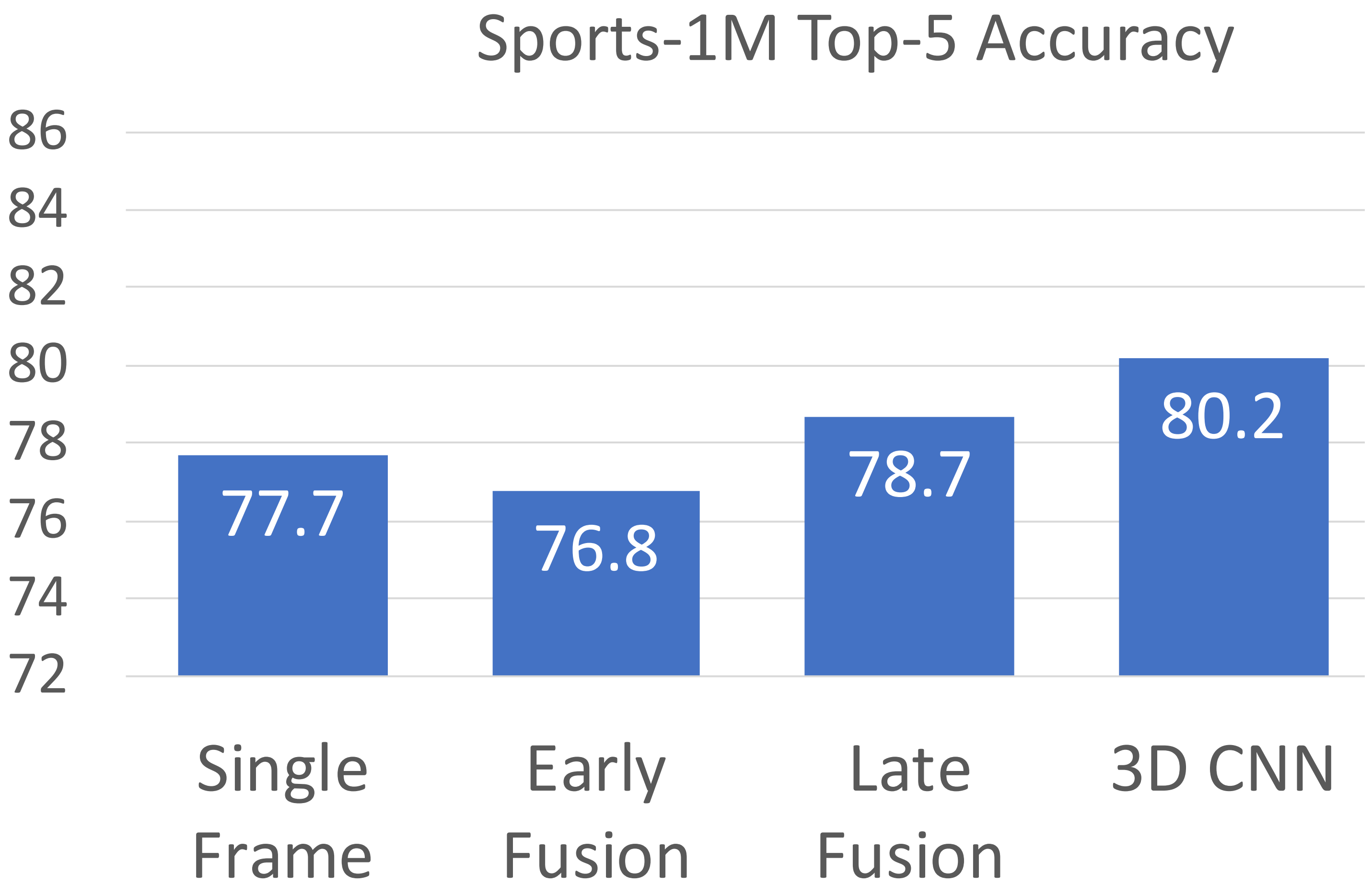
Example Video Dataset: **Sports-1M**

1 million YouTube videos annotated with 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

Early Fusion vs Late Fusion vs 3D CNN



Single Frame model works well – always try this first!

3D CNNs have improved a lot since 2014!

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

C3D: The VGG of 3D CNNs

3D CNN that uses all 3x3x3 conv and 2x2x2 pooling
(except Pool1 which is 1x2x2)

Released model pretrained on Sports-1M: Many people used this as a video feature extractor

Layer	Size
Input	3 x 16 x 112 x 112
Conv1 (3x3x3)	64 x 16 x 112 x 112
Pool1 (1x2x2)	64 x 16 x 56 x 56
Conv2 (3x3x3)	128 x 16 x 56 x 56
Pool2 (2x2x2)	128 x 8 x 28 x 28
Conv3a (3x3x3)	256 x 8 x 28 x 28
Conv3b (3x3x3)	256 x 8 x 28 x 28
Pool3 (2x2x2)	256 x 4 x 14 x 14
Conv4a (3x3x3)	512 x 4 x 14 x 14
Conv4b (3x3x3)	512 x 4 x 14 x 14
Pool4 (2x2x2)	512 x 2 x 7 x 7
Conv5a (3x3x3)	512 x 2 x 7 x 7
Conv5b (3x3x3)	512 x 2 x 7 x 7
Pool5	512 x 1 x 3 x 3
FC6	4096
FC7	4096
FC8	C

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

C3D: The VGG of 3D CNNs

3D CNN that uses all 3x3x3 conv and 2x2x2 pooling
(except Pool1 which is 1x2x2)

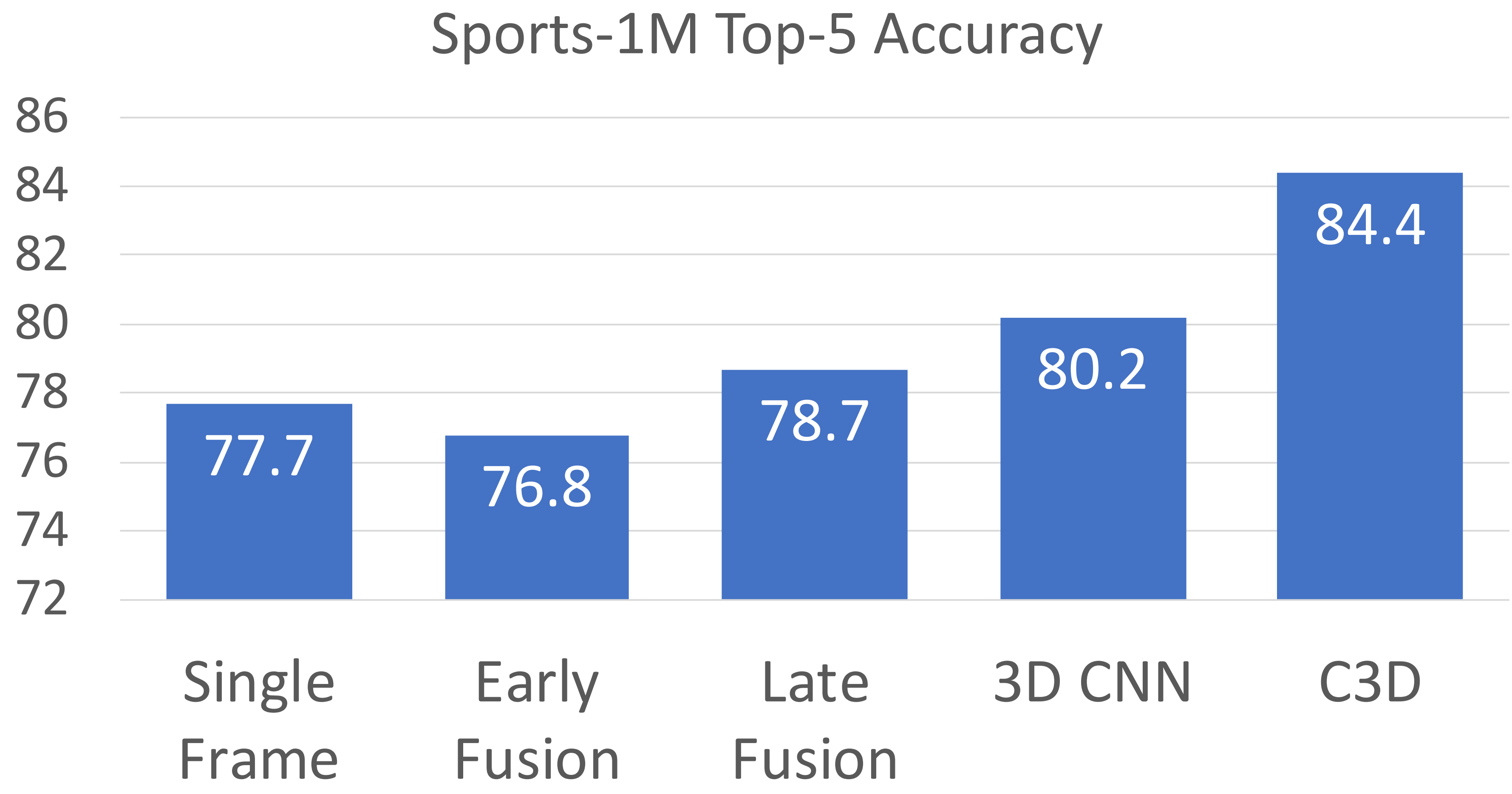
Released model pretrained on Sports-1M: Many people used this as a video feature extractor

Problem: 3x3x3 conv is very expensive!
AlexNet: 0.7 GFLOP
VGG-16: 13.6 GFLOP
C3D: **39.5 GFLOP (2.9x VGG!)**

Layer	Size	MFLOPs
Input	3 x 16 x 112 x 112	
Conv1 (3x3x3)	64 x 16 x 112 x 112	1.04
Pool1 (1x2x2)	64 x 16 x 56 x 56	
Conv2 (3x3x3)	128 x 16 x 56 x 56	11.10
Pool2 (2x2x2)	128 x 8 x 28 x 28	
Conv3a (3x3x3)	256 x 8 x 28 x 28	5.55
Conv3b (3x3x3)	256 x 8 x 28 x 28	11.10
Pool3 (2x2x2)	256 x 4 x 14 x 14	
Conv4a (3x3x3)	512 x 4 x 14 x 14	2.77
Conv4b (3x3x3)	512 x 4 x 14 x 14	5.55
Pool4 (2x2x2)	512 x 2 x 7 x 7	
Conv5a (3x3x3)	512 x 2 x 7 x 7	0.69
Conv5b (3x3x3)	512 x 2 x 7 x 7	0.69
Pool5	512 x 1 x 3 x 3	
FC6	4096	0.51
FC7	4096	0.45
FC8	C	0.05

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

Early Fusion vs Late Fusion vs 3D CNN



Karpathy et al, "Large-scale Video Classification with Convolutional Neural Networks", CVPR 2014
Tran et al, "Learning Spatiotemporal Features with 3D Convolutional Networks", ICCV 2015

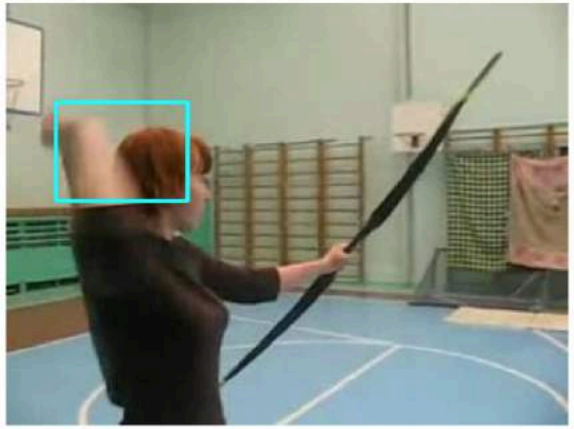
Recognizing Actions from Motion

We can easily recognize actions using only **motion information**

Johansson, "Visual perception of biological motion and a model for its analysis." Perception & Psychophysics. 14(2):201-211. 1973.

Measuring Motion: Optical Flow

Image at frame t



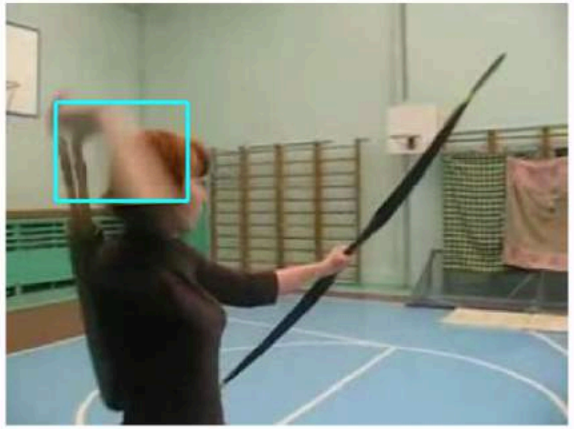
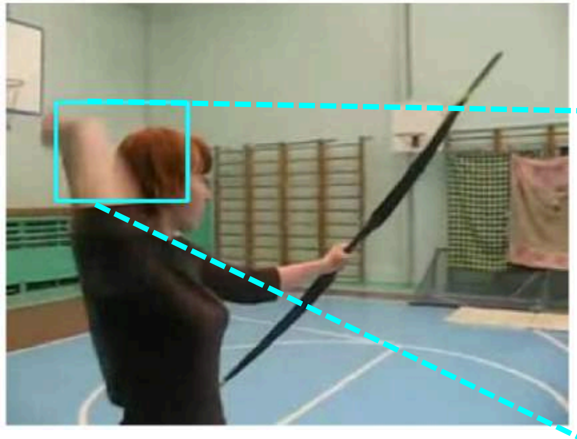


Image at frame t+1

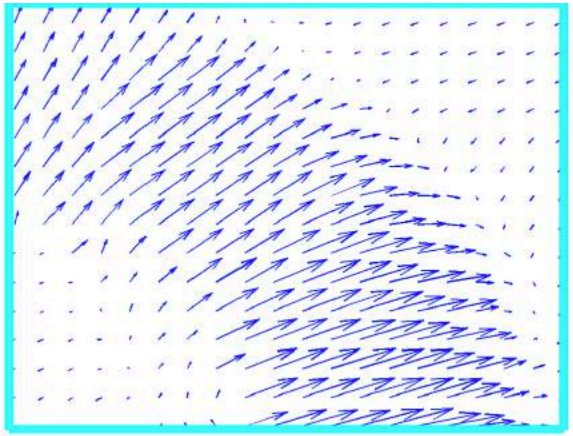
Simonyan and Zisserman, “Two-stream convolutional networks for action recognition in videos”, NeurIPS 2014

Measuring Motion: Optical Flow

Image at frame t



Optical flow gives a displacement field F between images I_t and I_{t+1}



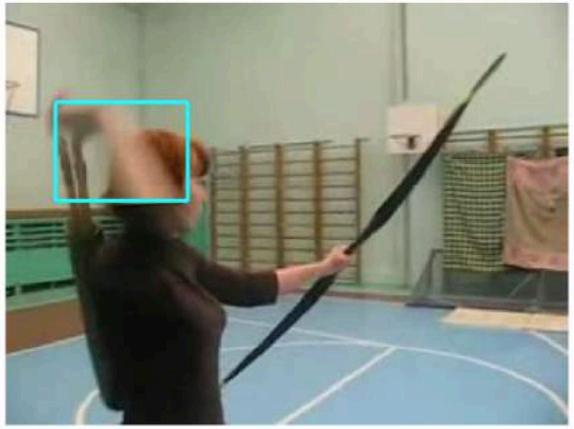


Image at frame t+1

Tells where each pixel will move in the next frame:

$F(x, y) = (dx, dy)$

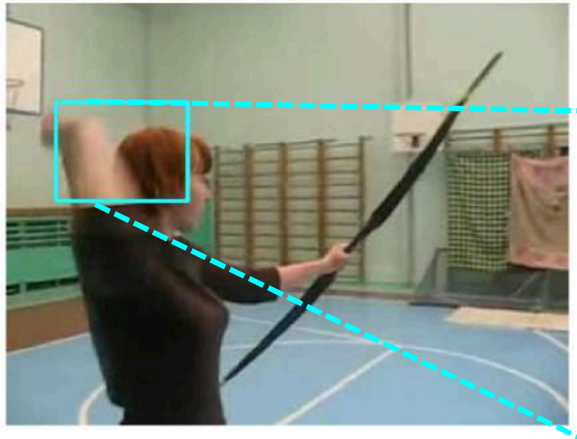
$I_{t+1}(x+dx, y+dy) = I_t(x, y)$

Simonyan and Zisserman, "Two-stream convolutional networks for action recognition in videos", NeurIPS 2014

Measuring Motion: Optical Flow

Optical Flow highlights
local motion

Image at frame t



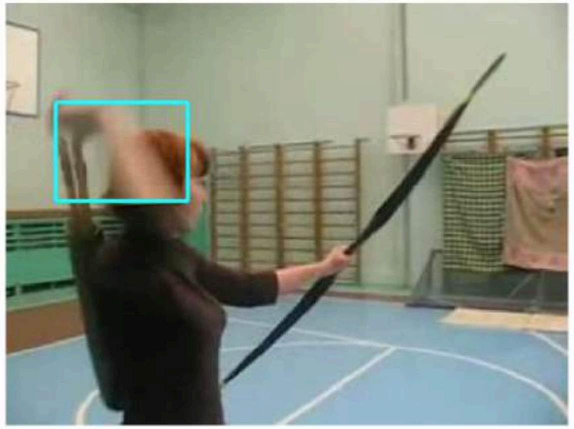


Image at frame t+1

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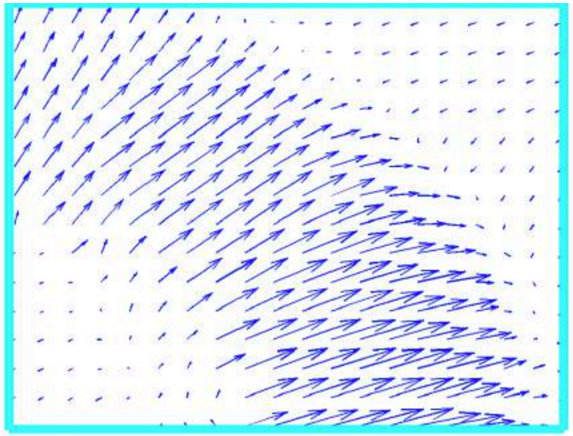
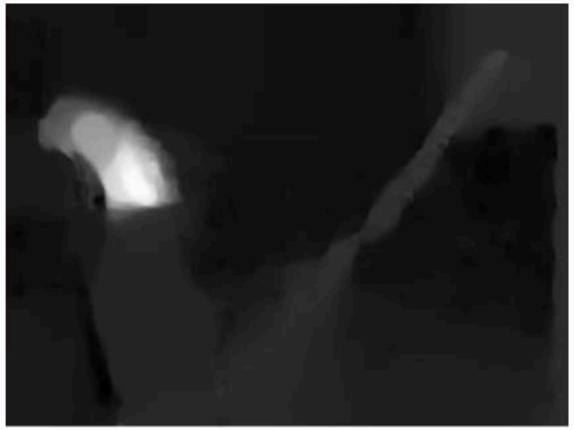


Tells where each pixel will move in the next frame:

$F(x, y) = (dx, dy)$

$I_{t+1}(x+dx, y+dy) = I_t(x, y)$

Horizontal flow dx

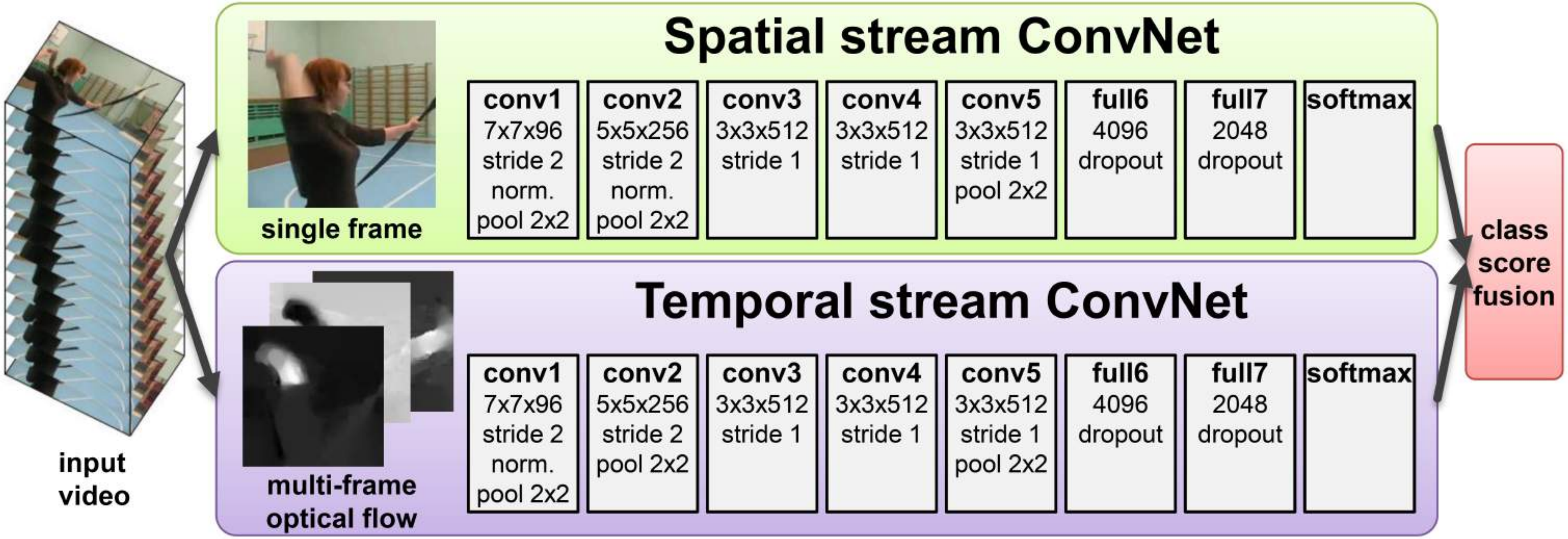


Vertical Flow dy

Simonyan and Zisserman, "Two-stream convolutional networks for action recognition in videos", NeurIPS 2014

Separating Motion and Appearance: Two-Stream Networks

Input: Single Image
3 x H x W

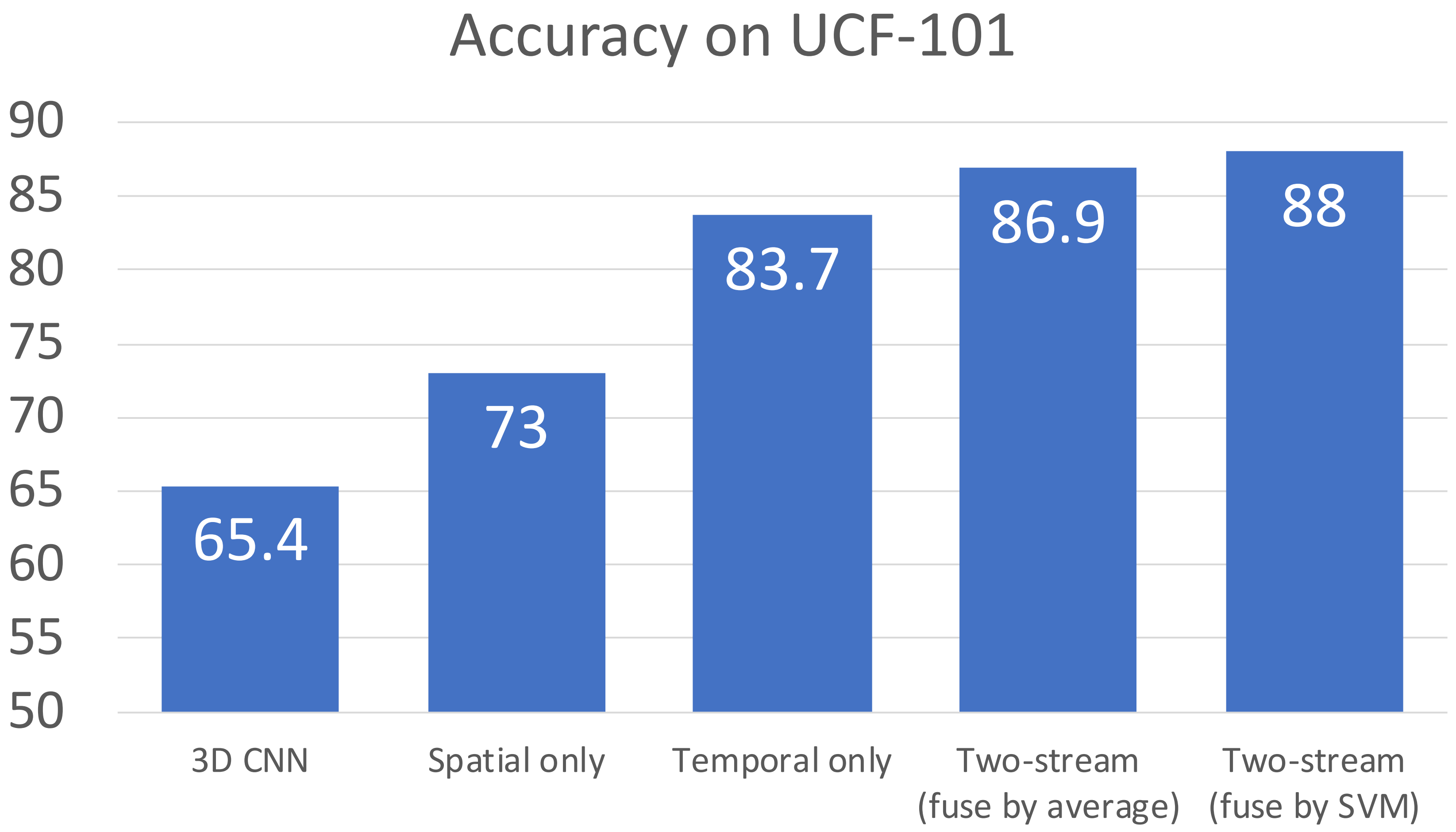


Input: Stack of optical flow:
[2*(T-1)] x H x W

Early fusion: First 2D conv processes all flow images

Simonyan and Zisserman, "Two-stream convolutional networks for action recognition in videos", NeurIPS 2014

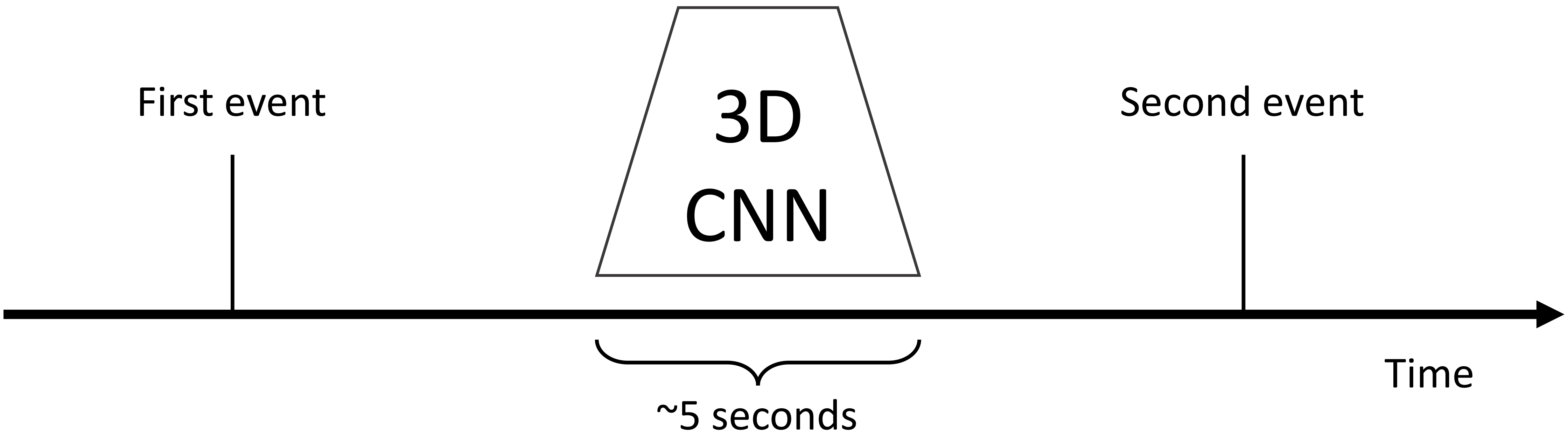
Separating Motion and Appearance: Two-Stream Networks



Simonyan and Zisserman, “Two-stream convolutional networks for action recognition in videos”, NeurIPS 2014

Modeling long-term temporal structure

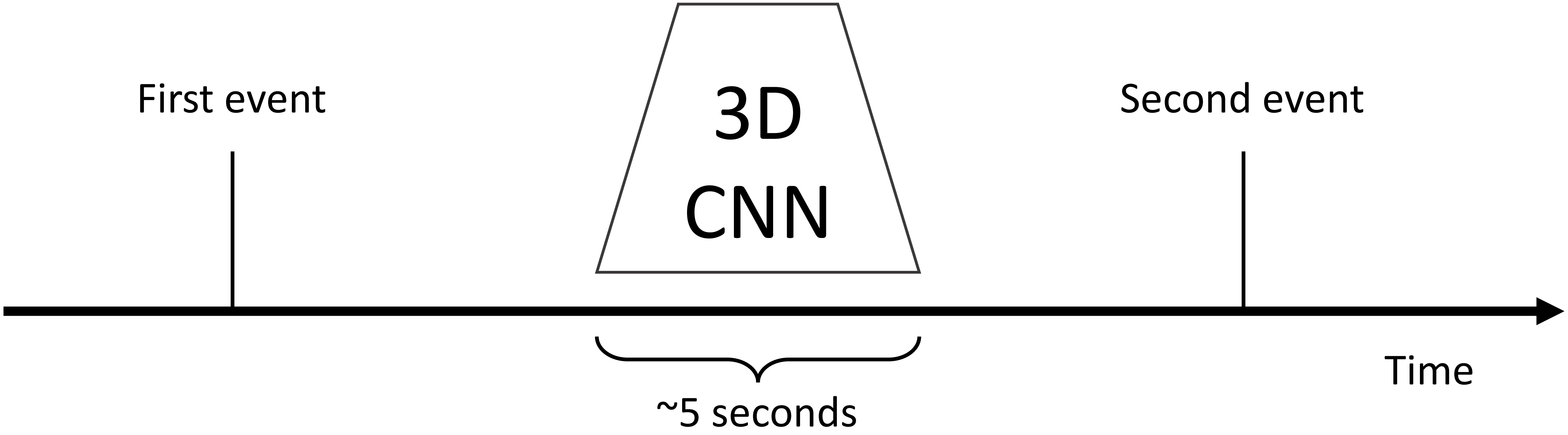
So far all our temporal CNNs only model local motion between frames in very short clips of ~2-5 seconds. What about long-term structure?



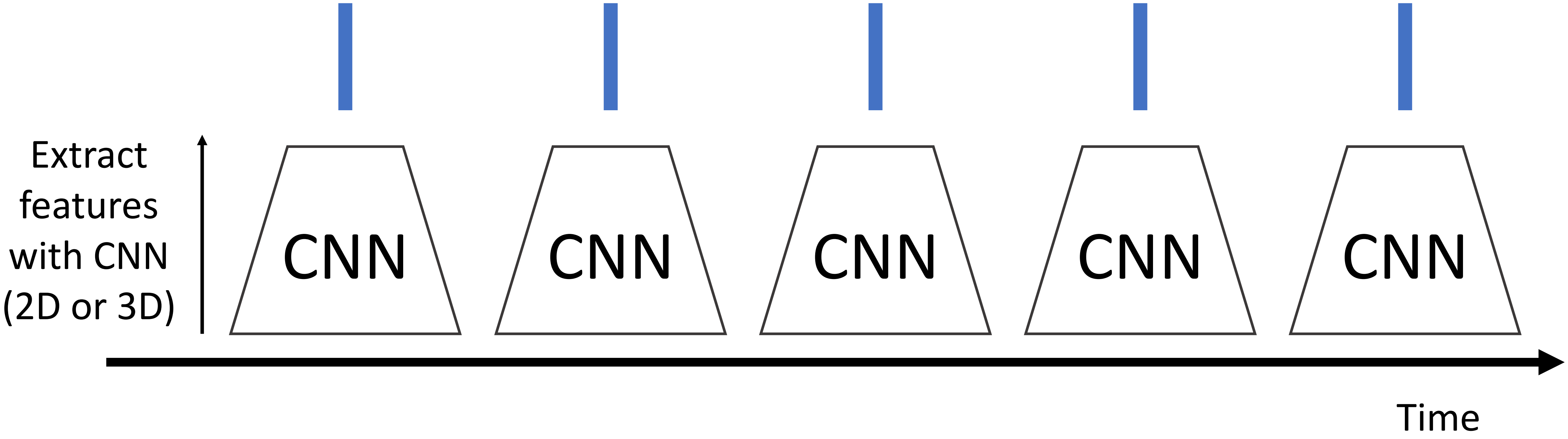
Modeling long-term temporal structure

So far all our temporal CNNs only model local motion between frames in very short clips of ~2-5 seconds. What about long-term structure?

We know how to handle sequences! How about recurrent networks?

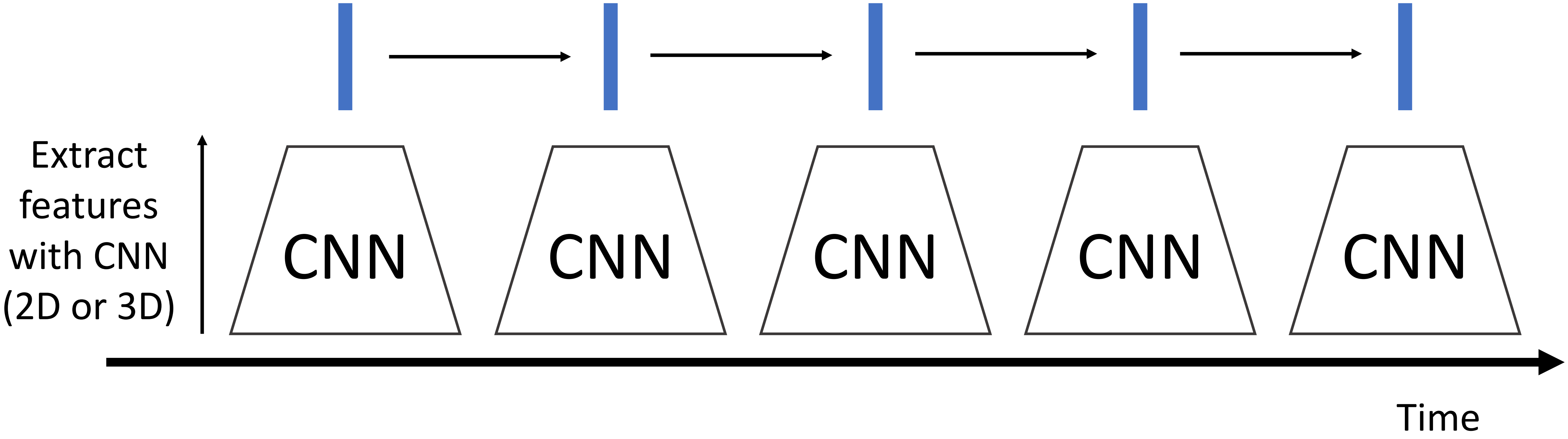


Modeling long-term temporal structure



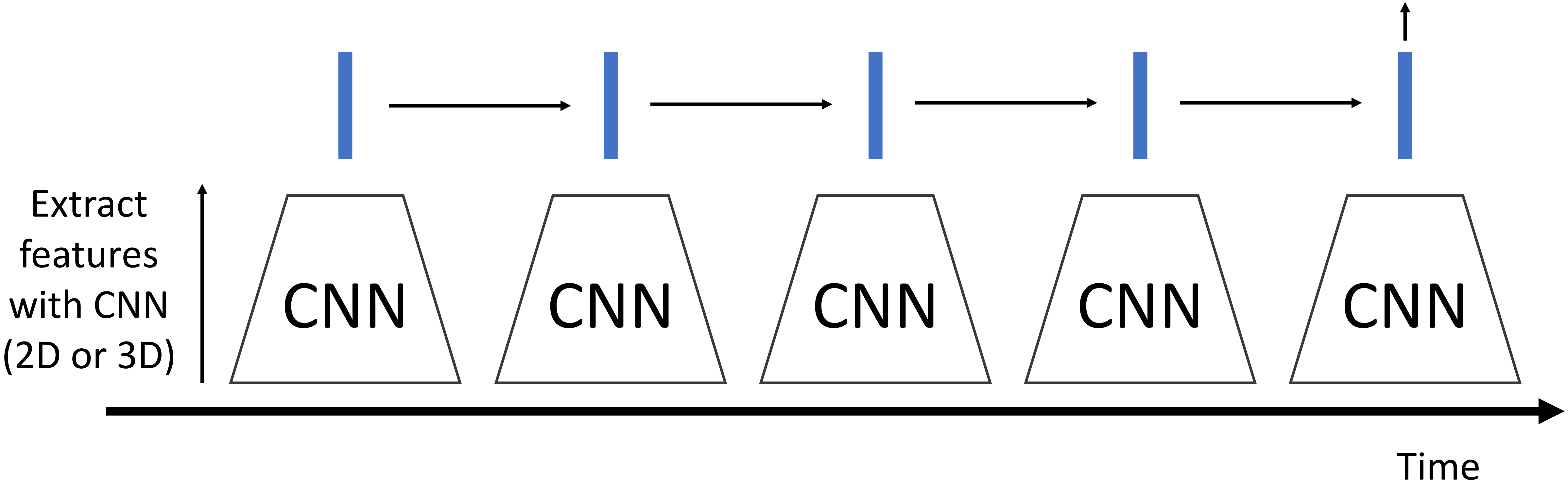
Modeling long-term temporal structure

Process local features using recurrent network (e.g. LSTM)



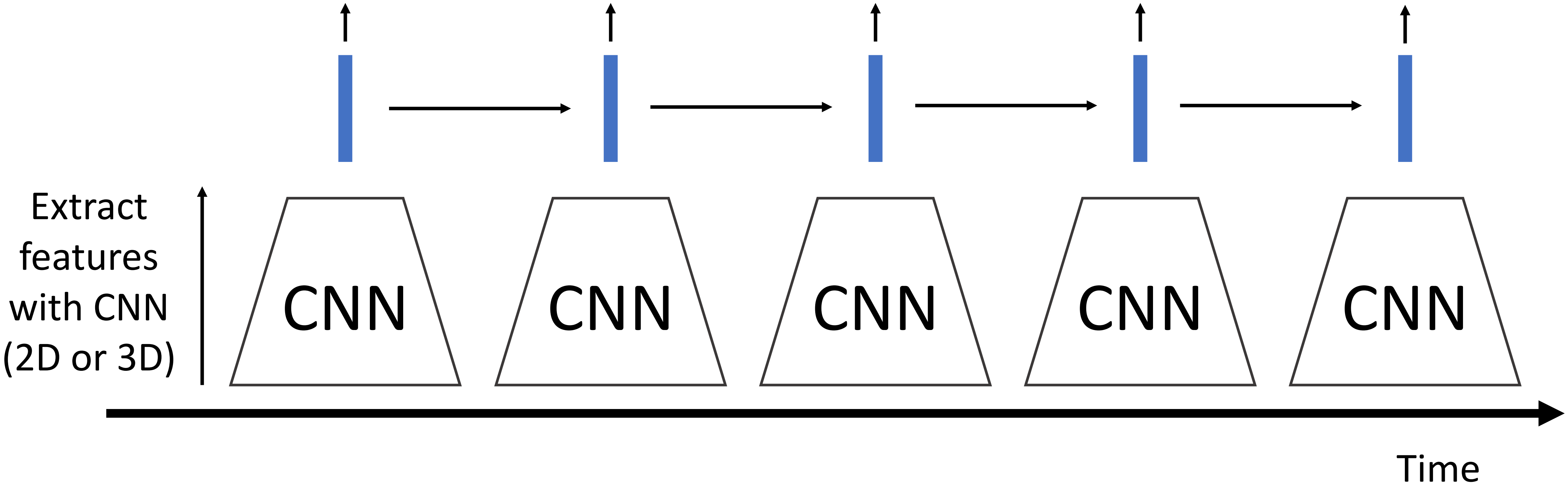
Modeling long-term temporal structure

Process local features using recurrent network (e.g. LSTM)
Many to one: One output at end of video



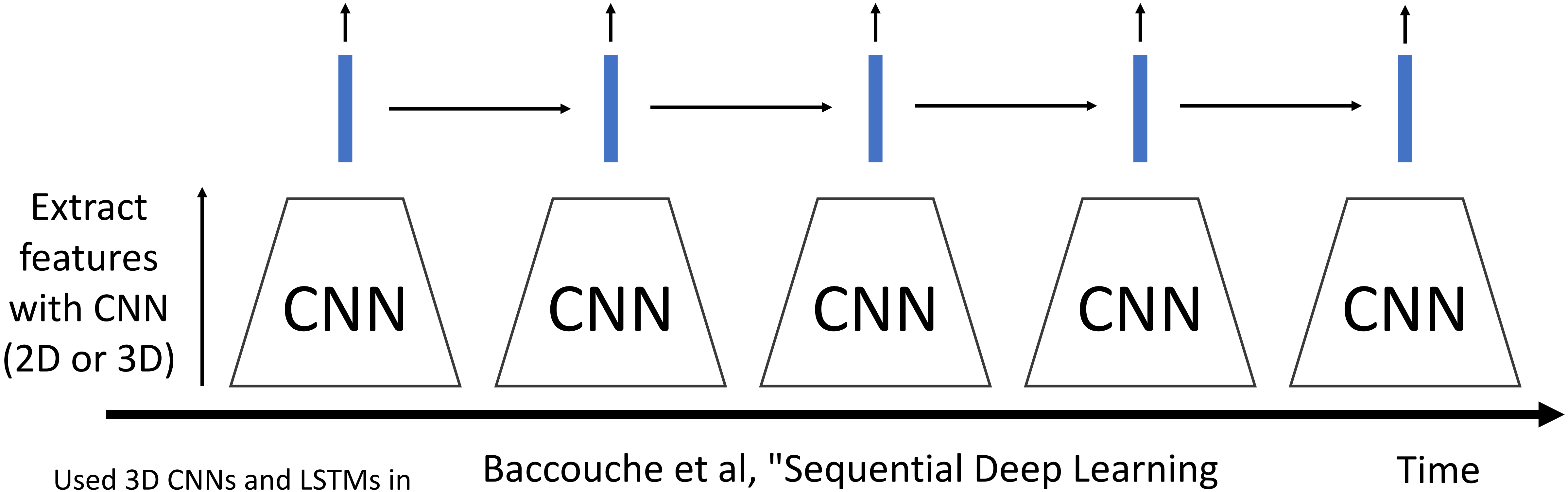
Modeling long-term temporal structure

Process local features using recurrent network (e.g. LSTM)
Many to many: one output per video frame



Modeling long-term temporal structure

Process local features using recurrent network (e.g. LSTM)
Many to many: one output per video frame

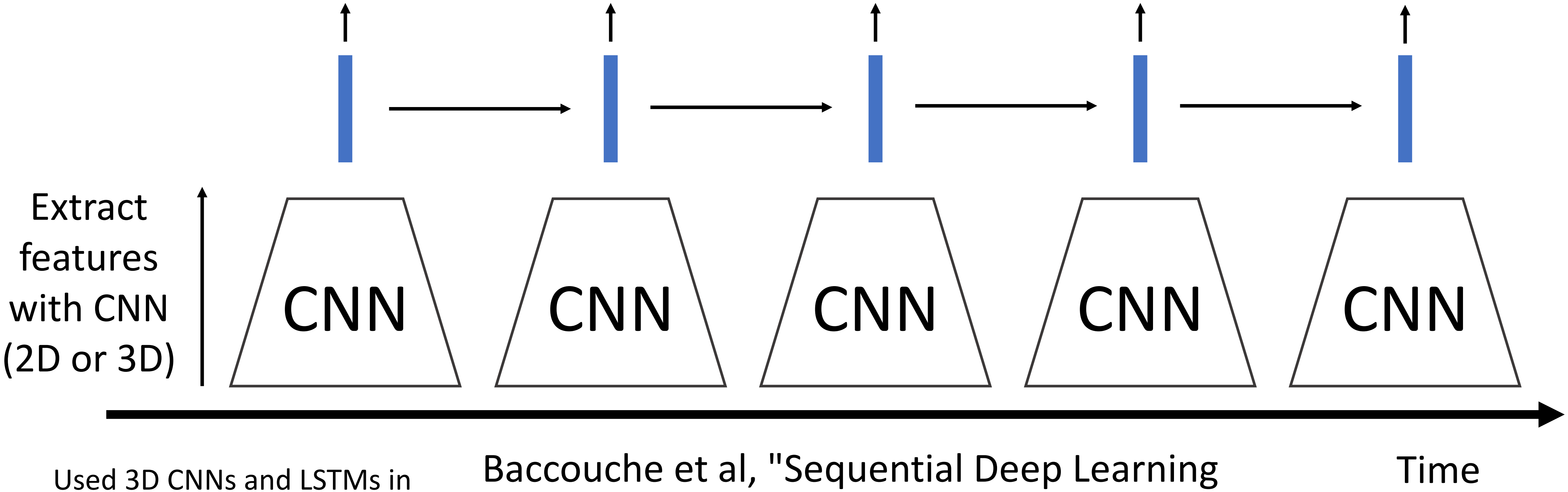


Used 3D CNNs and LSTMs in 2011! Way ahead of its time

Baccouche et al, "Sequential Deep Learning for Human Action Recognition", **2011**

Modeling long-term temporal structure

Process local features using recurrent network (e.g. LSTM)
Many to many: one output per video frame



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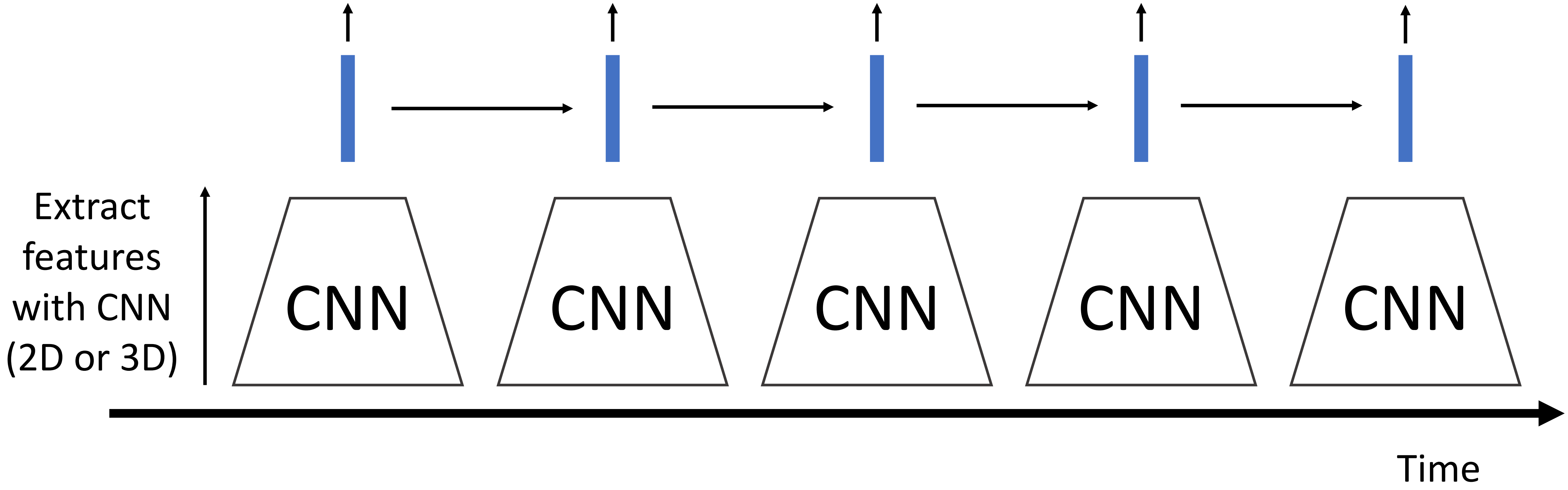
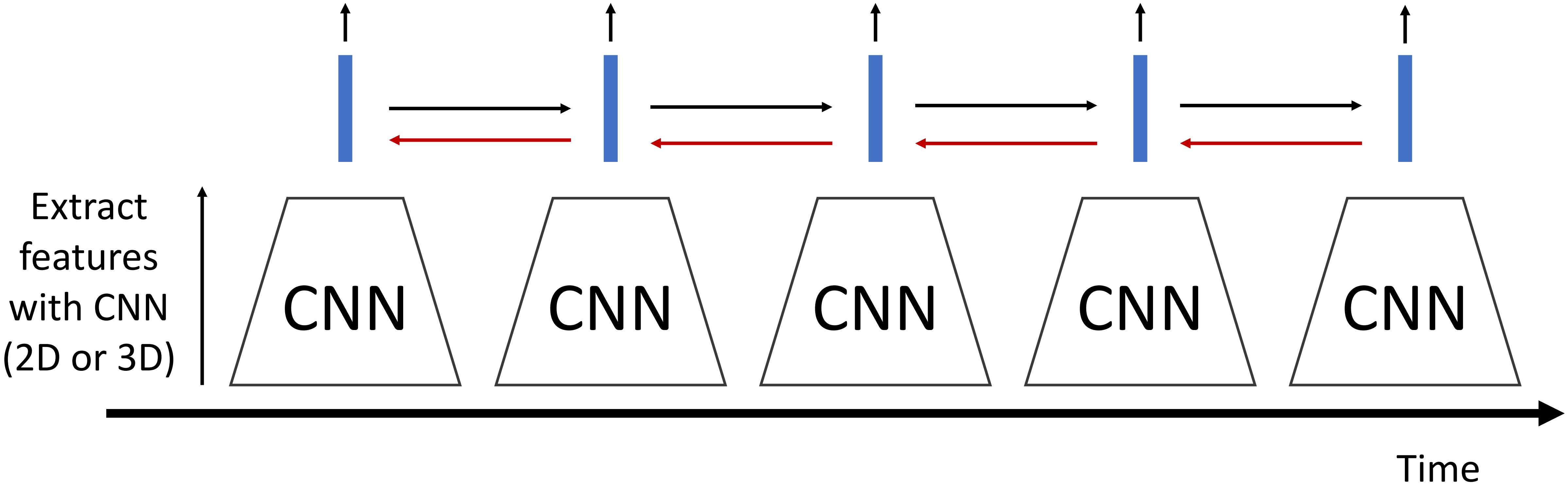


Baccouche et al, "Sequential Deep Learning for Human Action Recognition", 2011
Donahue et al, "Long-term recurrent convolutional networks for visual recognition and description", CVPR 2015

Modeling long-term temporal structure

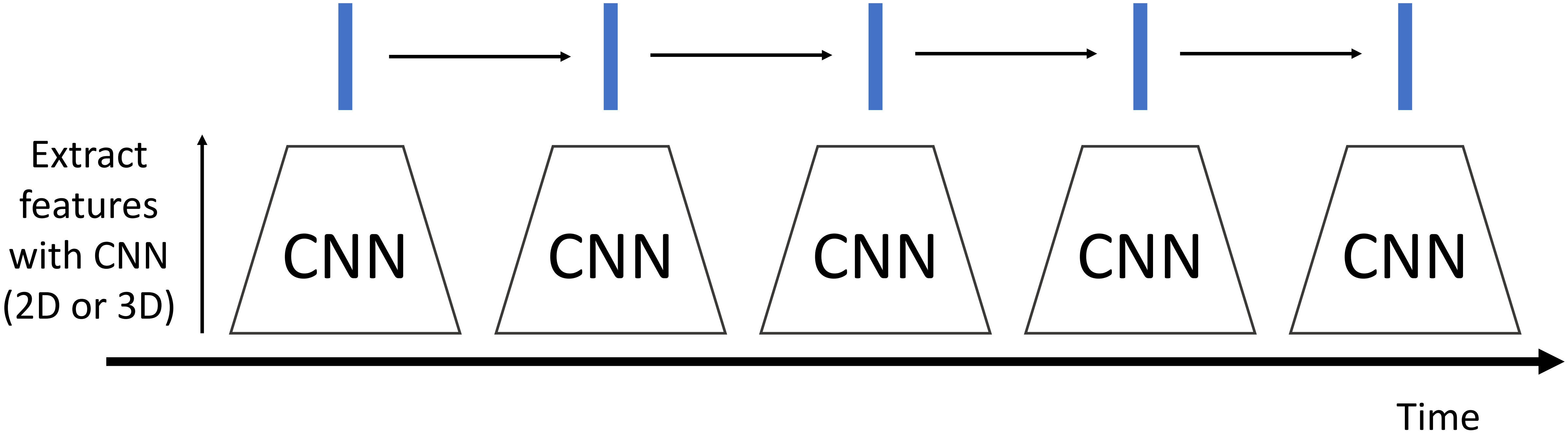
Sometimes don't backprop to CNN to save memory; pretrain and use it as a feature extractor



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

Modeling long-term temporal structure

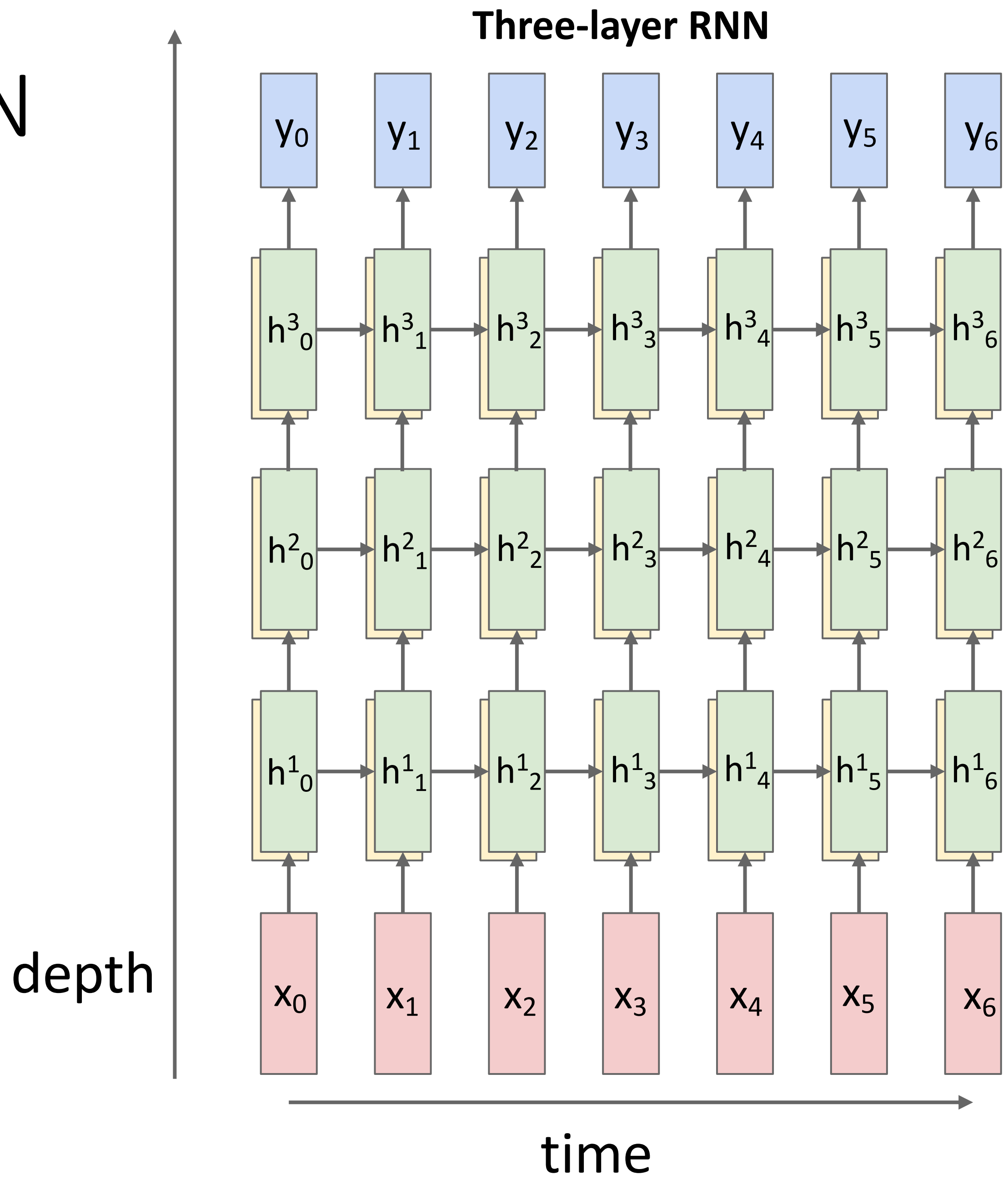
Inside CNN: Each value a function of a fixed temporal window (local temporal structure)
Inside RNN: Each vector is a function of all previous vectors (global temporal structure)
Can we merge both approaches?



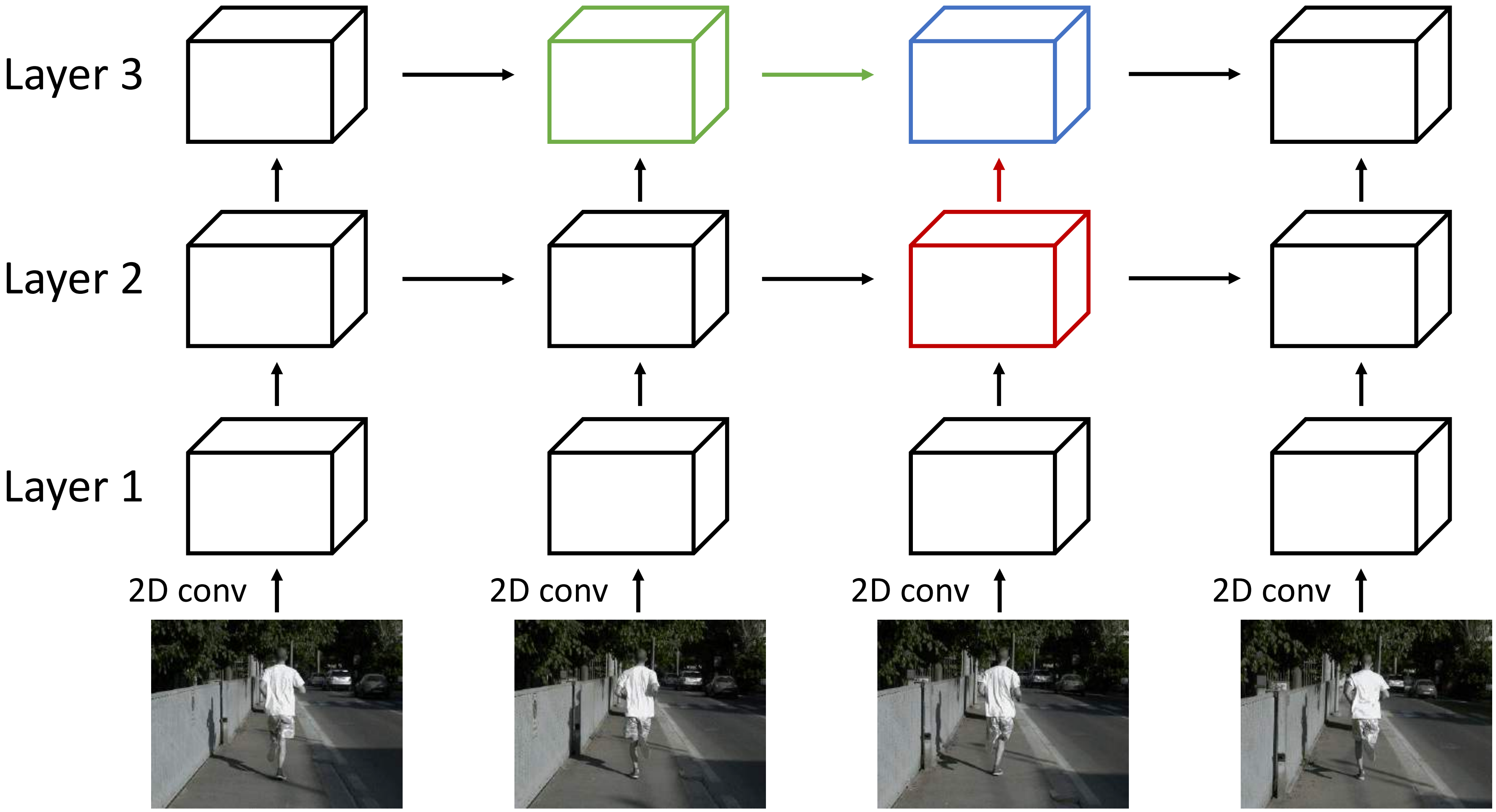
Baccouche et al, "Sequential Deep Learning for Human Action Recognition", 2011
Donahue et al, "Long-term recurrent convolutional networks for visual recognition and description", CVPR 2015

Recall: Multi-layer RNN

We can use a similar structure to process videos!



Recurrent Convolutional Network



Entire network uses 2D feature maps: C x H x W

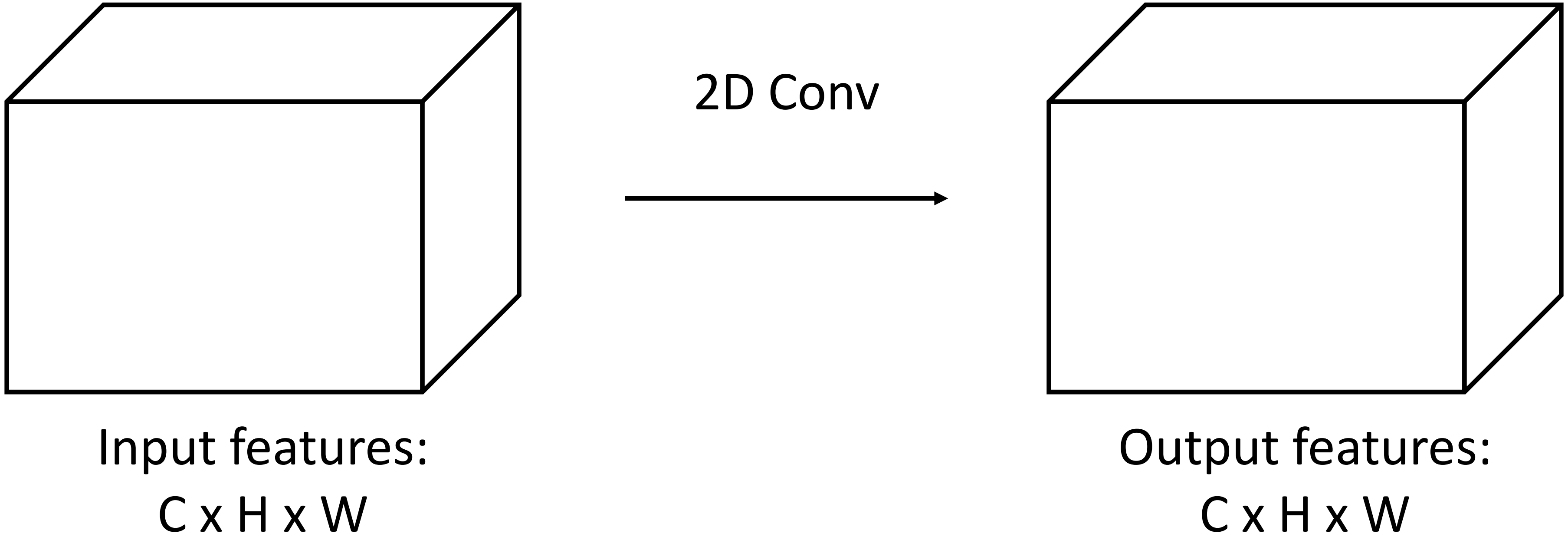
Each depends on two inputs:
1. Same layer, previous timestep
2. Prev layer, same timestep

Use different weights at each layer, share weights across time

Ballas et al, "Delving Deeper into Convolutional Networks for Learning Video Representations", ICLR 2016

Recurrent Convolutional Network

Normal 2D CNN:



Recurrent Convolutional Network

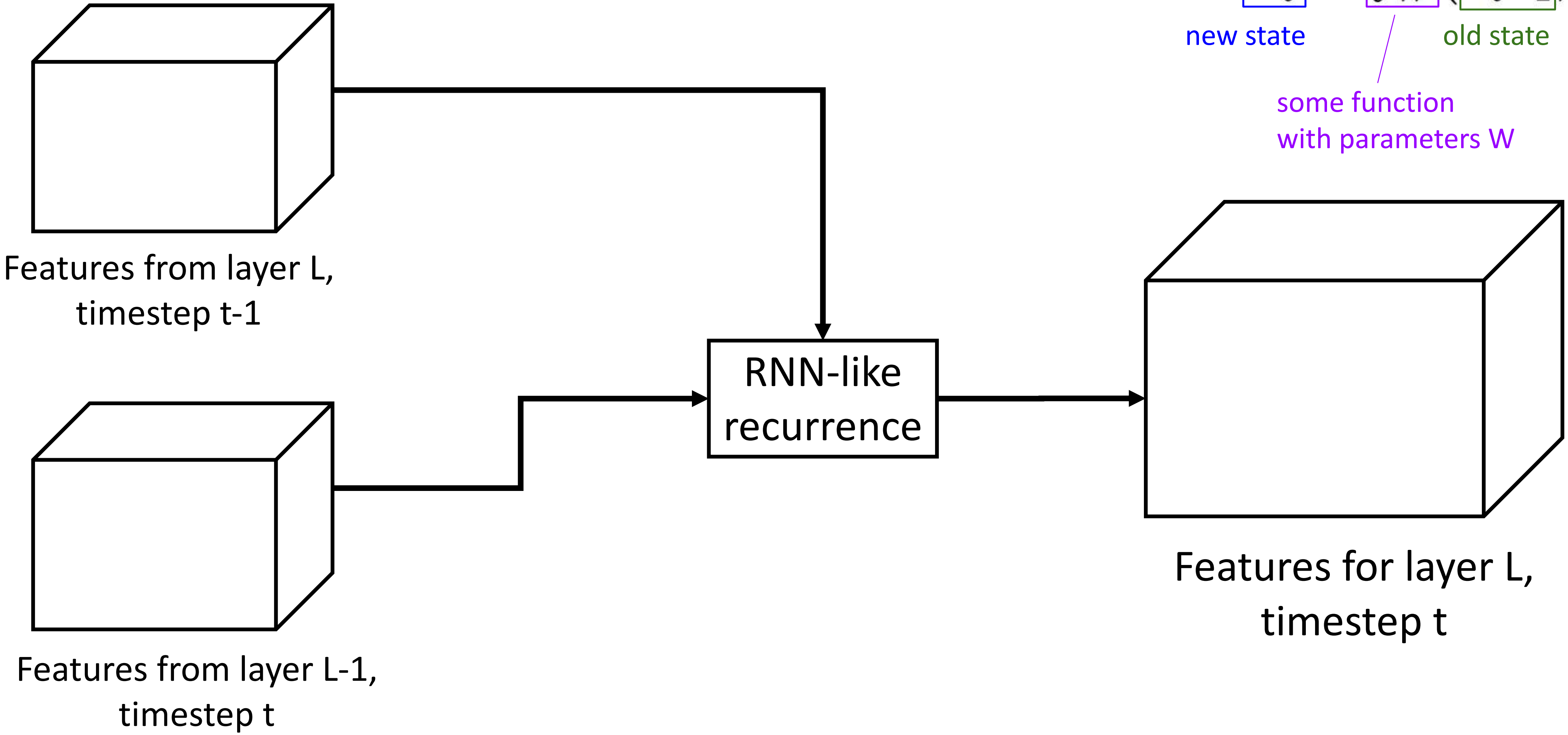
Recall: Recurrent Network

$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

old state

some function
with parameters W



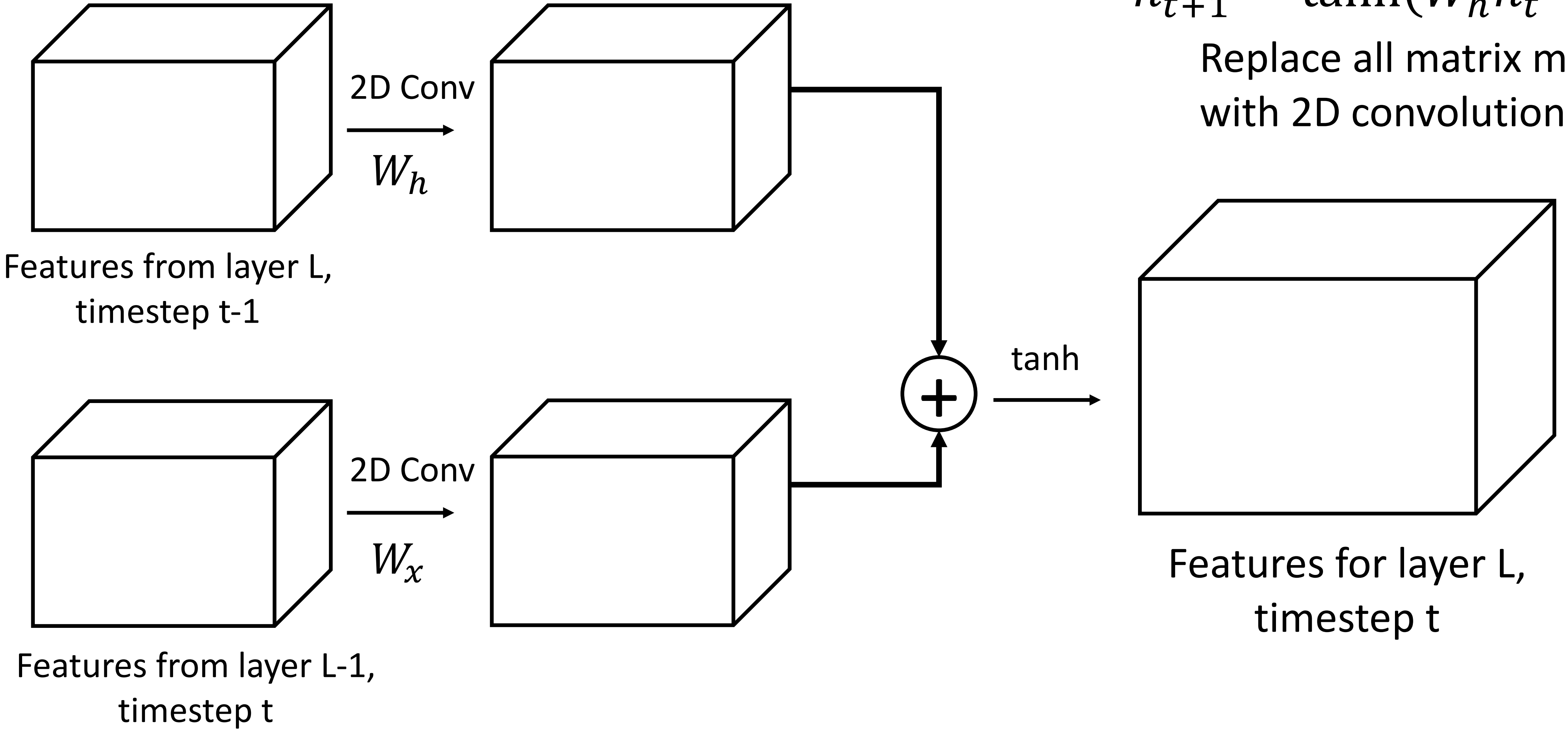
Ballas et al, "Delving Deeper into Convolutional Networks for Learning Video Representations", ICLR 2016

Recurrent Convolutional Network

Recall: Vanilla RNN

$$h_{t+1} = \tanh(W_h h_t + W_x x)$$

Replace all matrix multiply with 2D convolution!



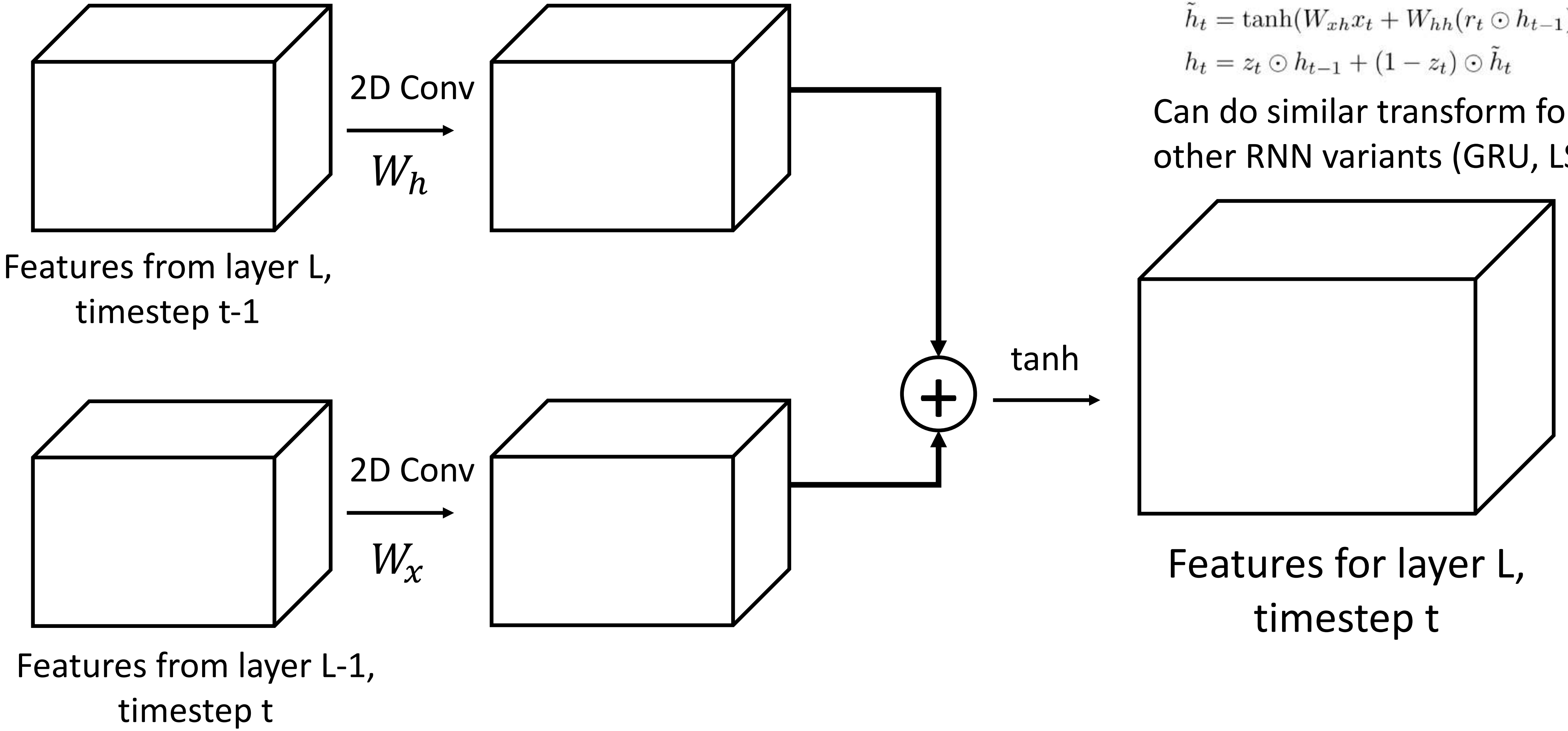
Ballas et al, "Delving Deeper into Convolutional Networks for Learning Video Representations", ICLR 2016

Recurrent Convolutional Network

Recall: GRU

$$
\begin{aligned}
r_t &= \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r) \\
z_t &= \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z) \\
\tilde{h}_t &= \tanh(W_{xh}x_t + W_{hh}(r_t \odot h_{t-1}) + b_h) \\
h_t &= z_t \odot h_{t-1} + (1 - z_t) \odot \tilde{h}_t
\end{aligned}
$$

Can do similar transform for other RNN variants (GRU, LSTM)

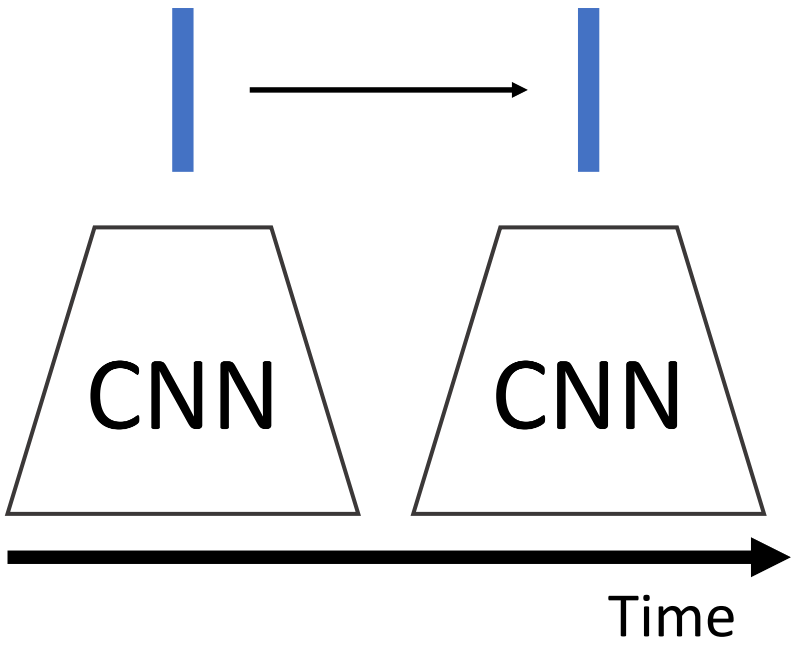


Ballas et al, "Delving Deeper into Convolutional Networks for Learning Video Representations", ICLR 2016

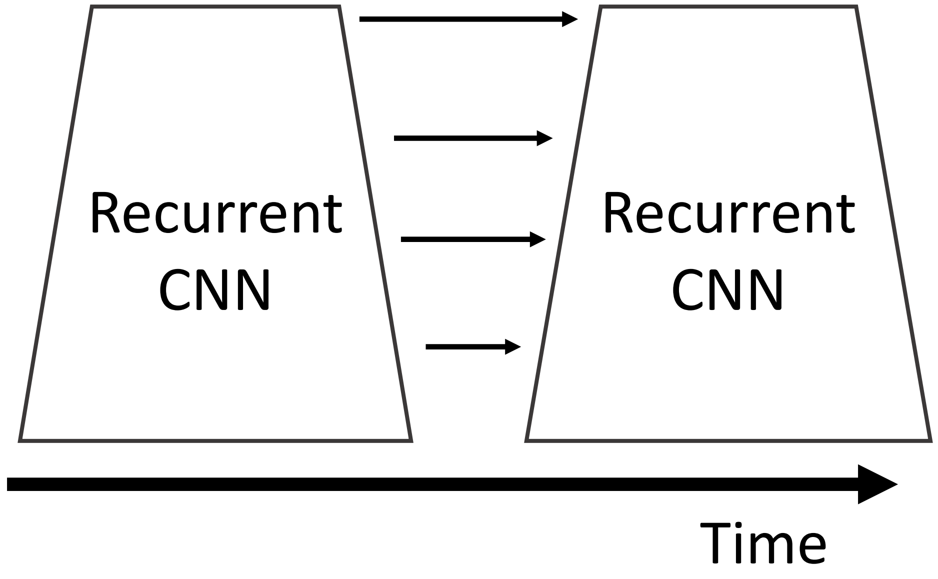
Modeling long-term temporal structure

RNN: Infinite temporal extent (fully-connected)

CNN: finite temporal extent (convolutional)



Recurrent CNN: Infinite temporal extent (convolutional)



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

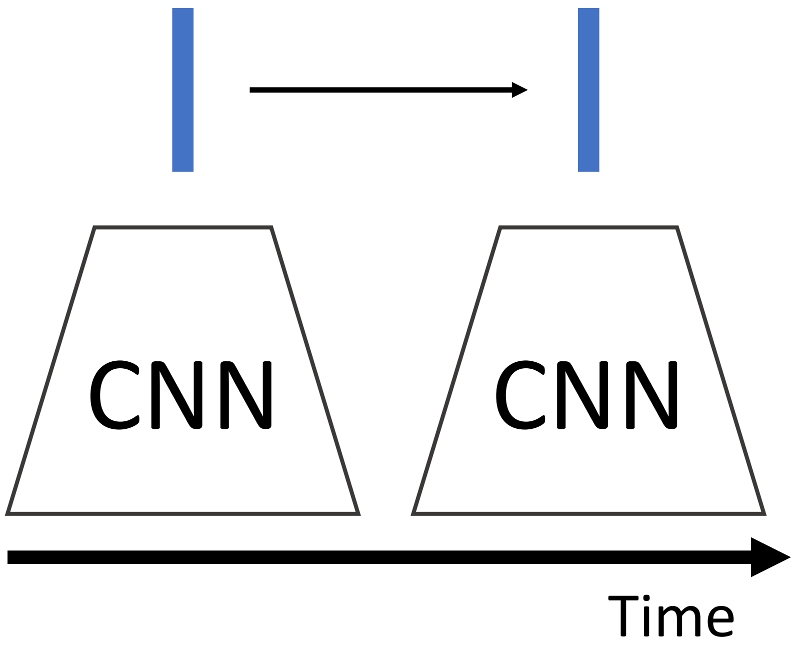
Ballas et al, "Delving Deeper into Convolutional Networks for Learning Video Representations", ICLR 2016

Modeling long-term temporal structure

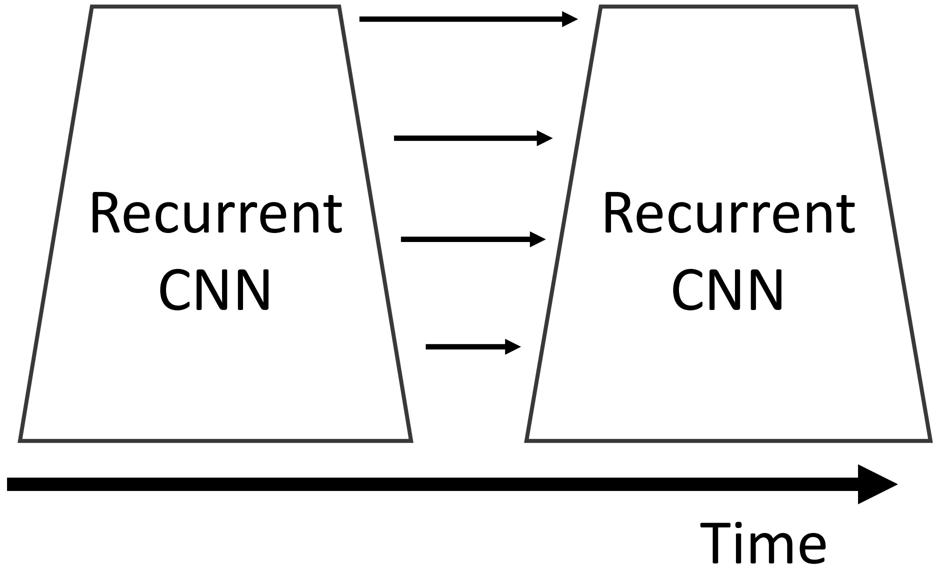
Problem: RNNs are slow for long sequences (can't be parallelized)

RNN: Infinite temporal extent (fully-connected)

CNN: finite temporal extent (convolutional)



Recurrent CNN: Infinite temporal extent (convolutional)



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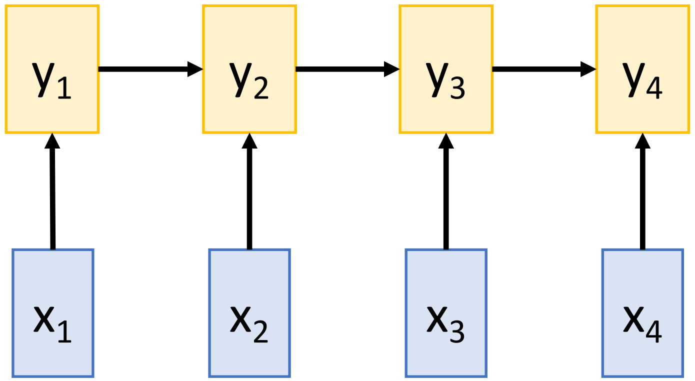
Ballas et al, "Delving Deeper into Convolutional Networks for Learning Video Representations", ICLR 2016

Recall: Different ways of processing sequences

Recurrent Neural Network



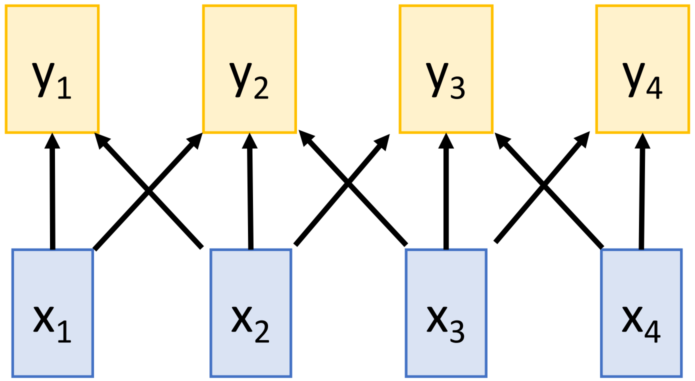
Works on **Ordered Sequences**

(+) Good at long sequences: After one RNN layer, h_T "sees" the whole sequence

(-) Not parallelizable: need to compute hidden states sequentially

In video: CNN+RNN, or recurrent CNN

1D Convolution



Works on **Multidimensional Grids**

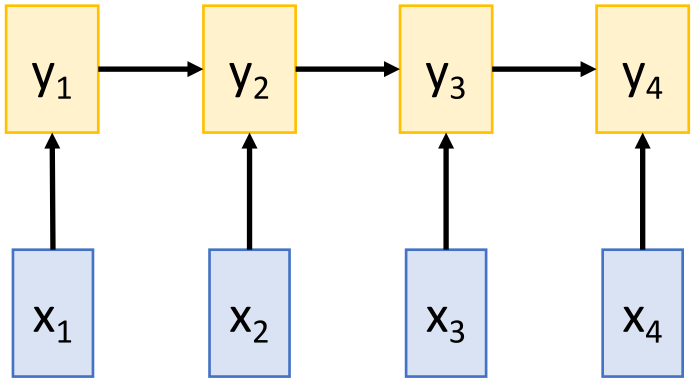
(-) Bad at long sequences: Need to stack many conv layers for outputs to "see" the whole sequence

(+) Highly parallel: Each output can be computed in parallel

In video: 3D convolution

Recall: Different ways of processing sequences

Recurrent Neural Network



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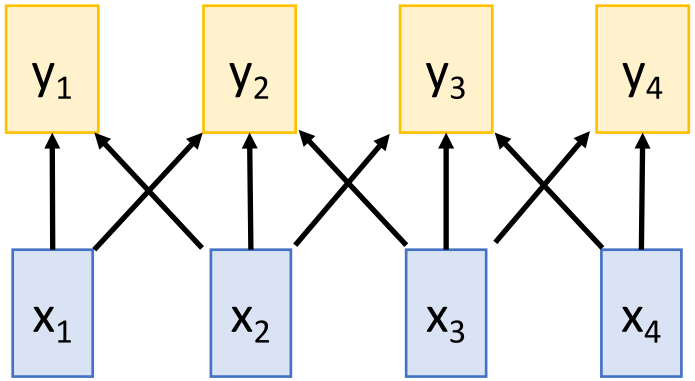

Works on **Multidimensional Grids**

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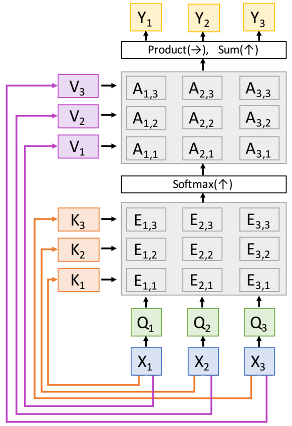
In video: 3D convolution

Self-Attention



Works on **Sets of Vectors**

(-) Good at long sequences: after one self-attention layer, each output "sees" all inputs!

(+) Highly parallel: Each output can be computed in parallel

(-) Very memory intensive

In video: ????

Recall: Self-Attention

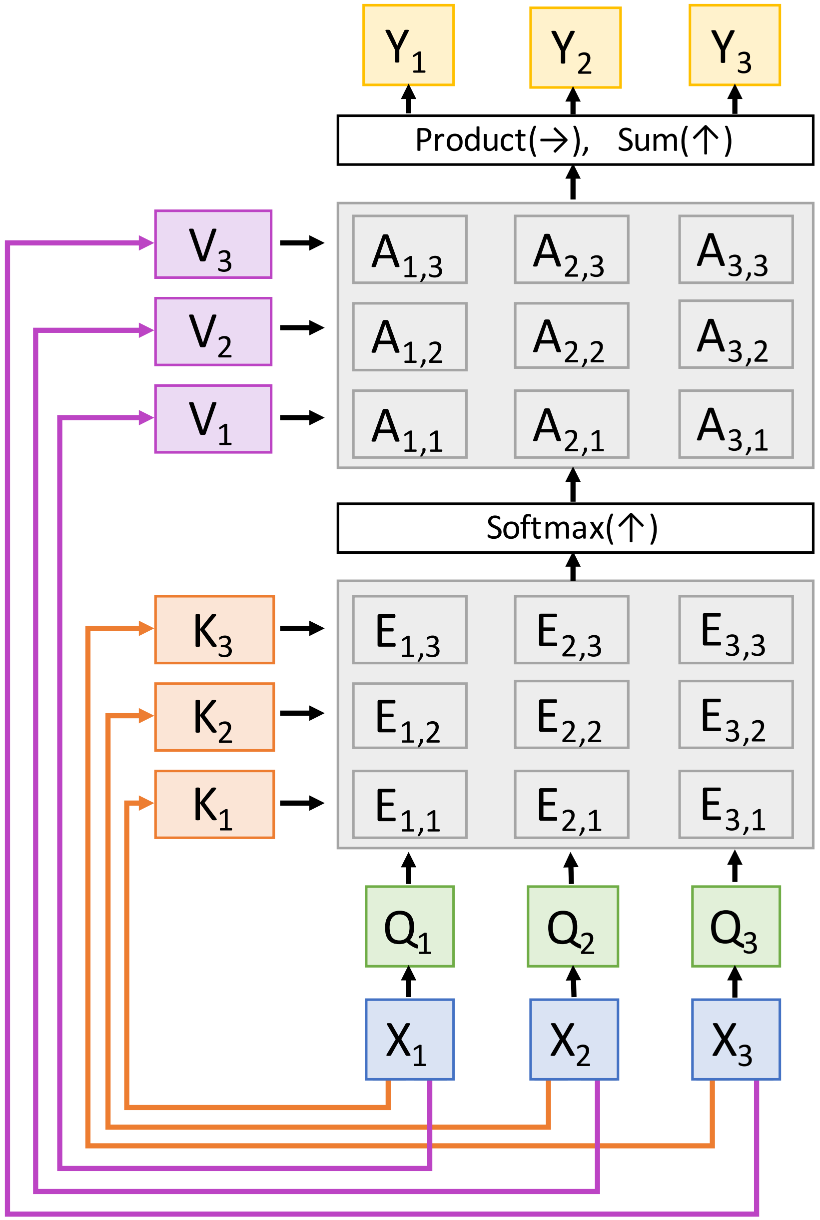
Input: Set of vectors $x_1, \ldots, x_N$

Keys, Queries, Values: Project each x to a key, query, and value using linear layer

Affinity matrix: Compare each pair of x, (using scaled dot-product between keys and values) and normalize using softmax

Output: Weighted sum of values, with weights given by affinity matrix

Features in 3D CNN: C x T x H x W
Interpret as a set of THW vectors of dim C

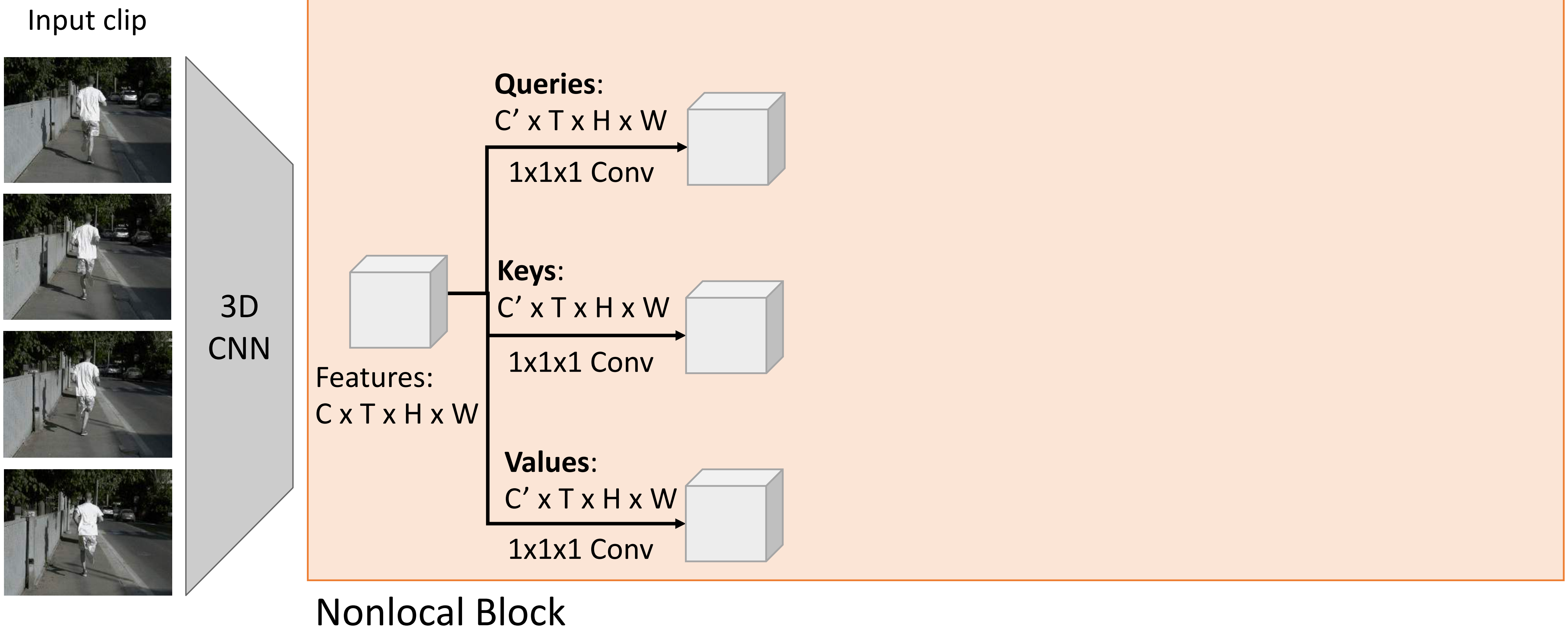


Vaswani et al, “Attention is all you need”, NeurIPS 2017

Spatio-Temporal Self-Attention (Nonlocal Block)

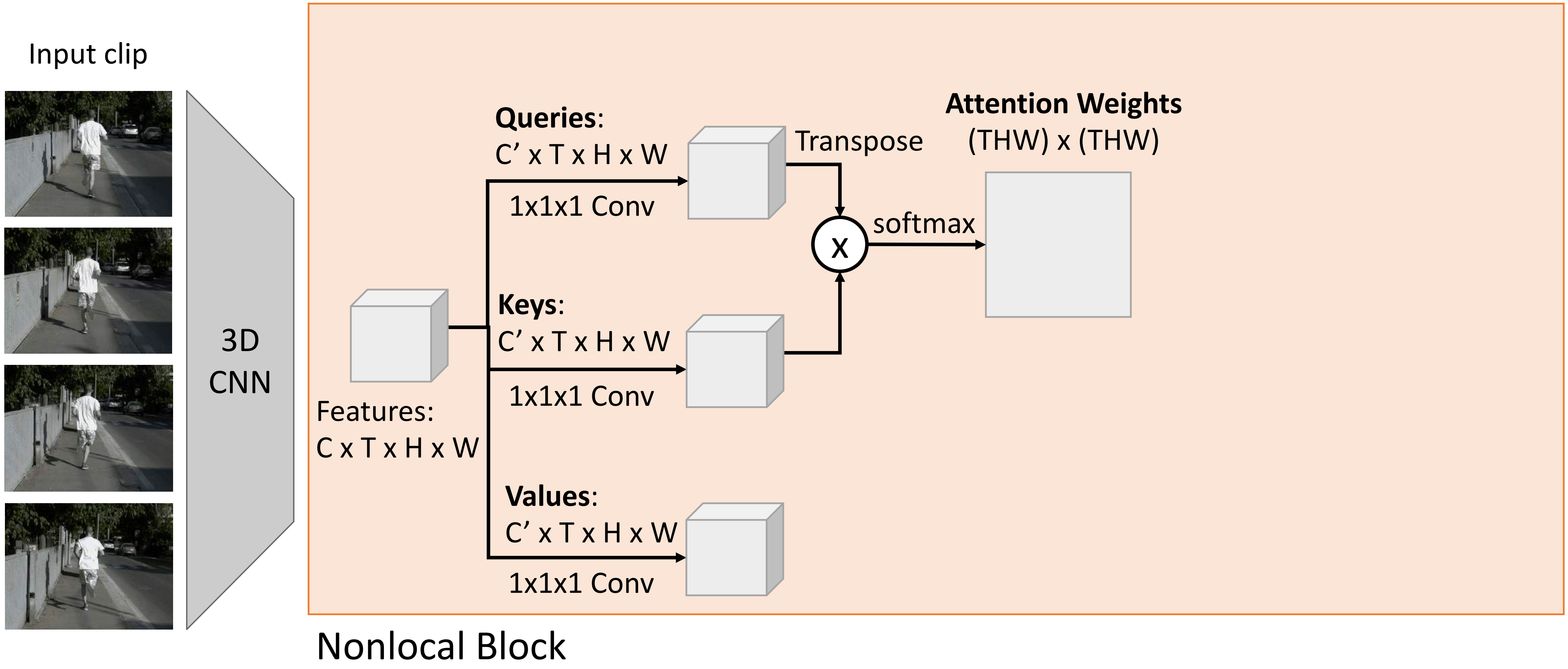
Wang et al, “Non-local neural networks”, CVPR 2018

Spatio-Temporal Self-Attention (Nonlocal Block)



Wang et al, "Non-local neural networks", CVPR 2018

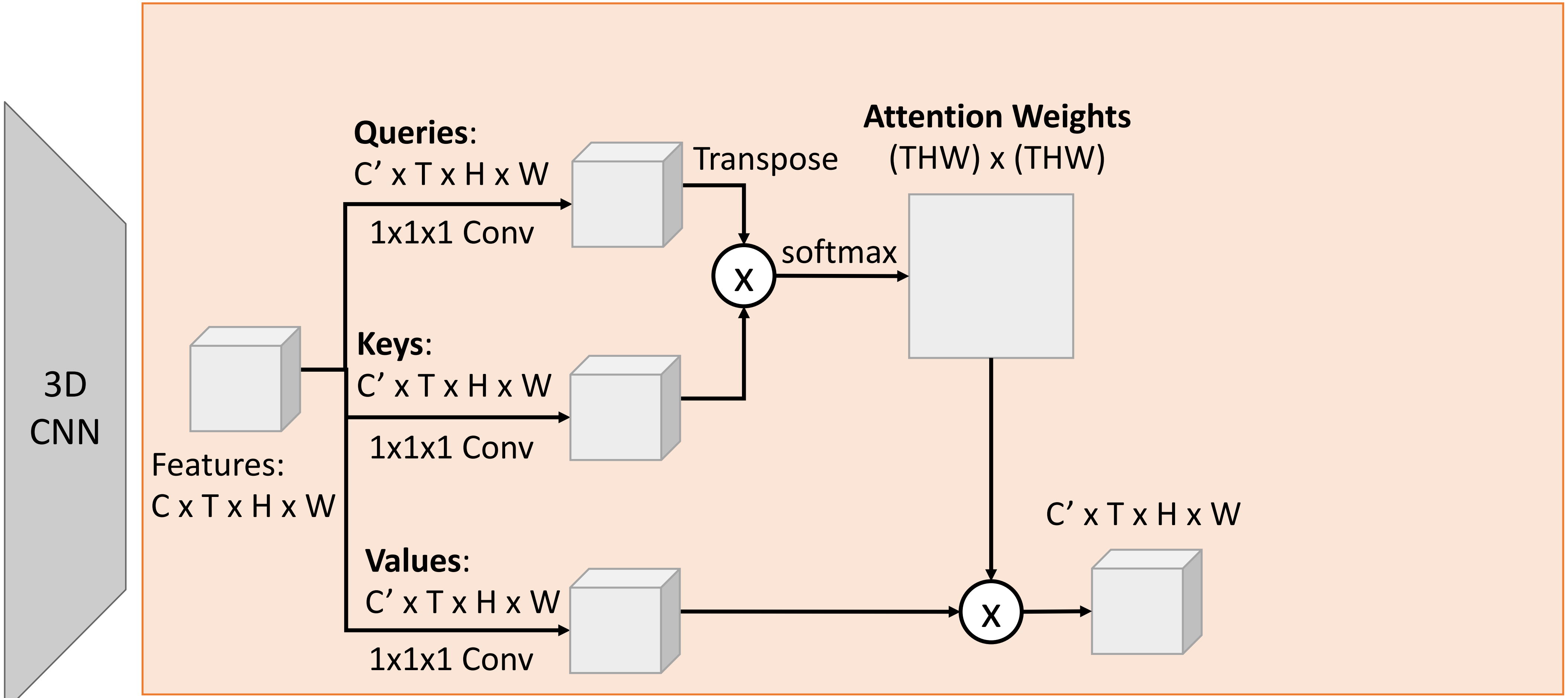
Spatio-Temporal Self-Attention (Nonlocal Block)



Wang et al, "Non-local neural networks", CVPR 2018

Spatio-Temporal Self-Attention (Nonlocal Block)

Input clip

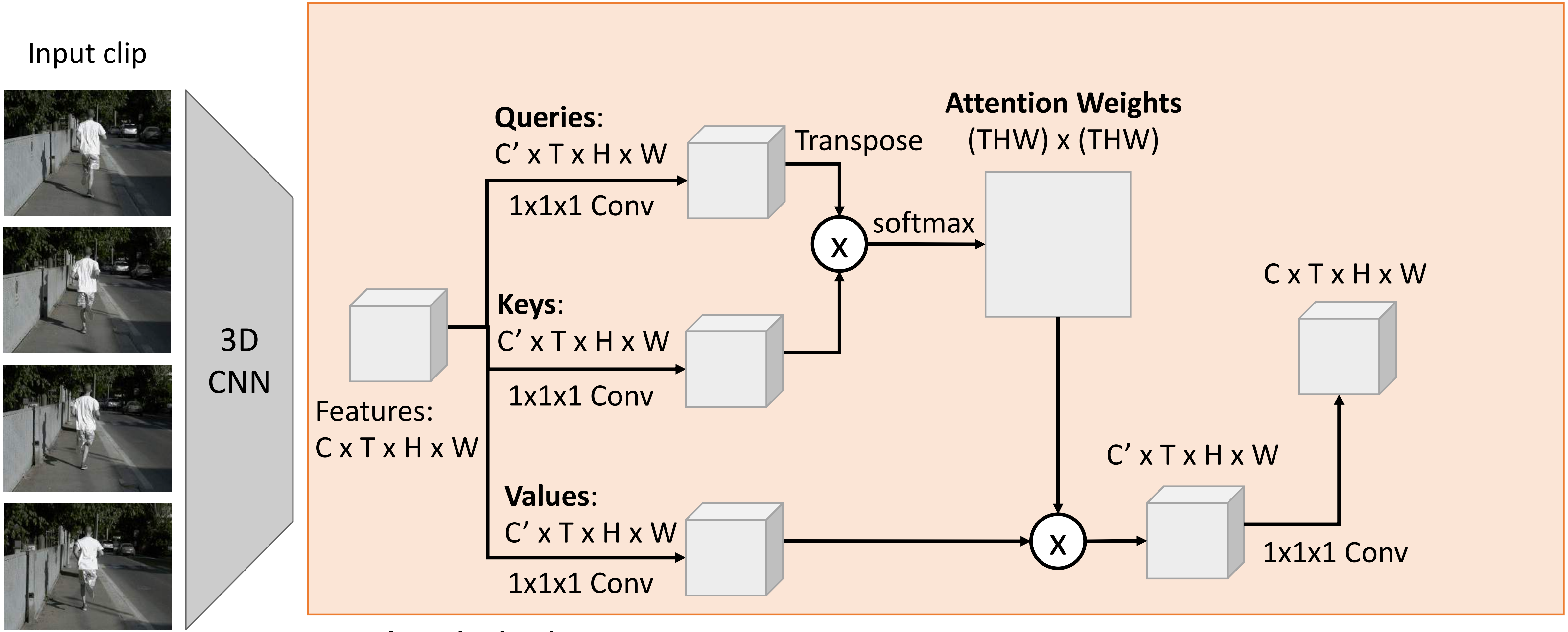


Nonlocal Block

Wang et al, "Non-local neural networks", CVPR 2018

Spatio-Temporal Self-Attention (Nonlocal Block)

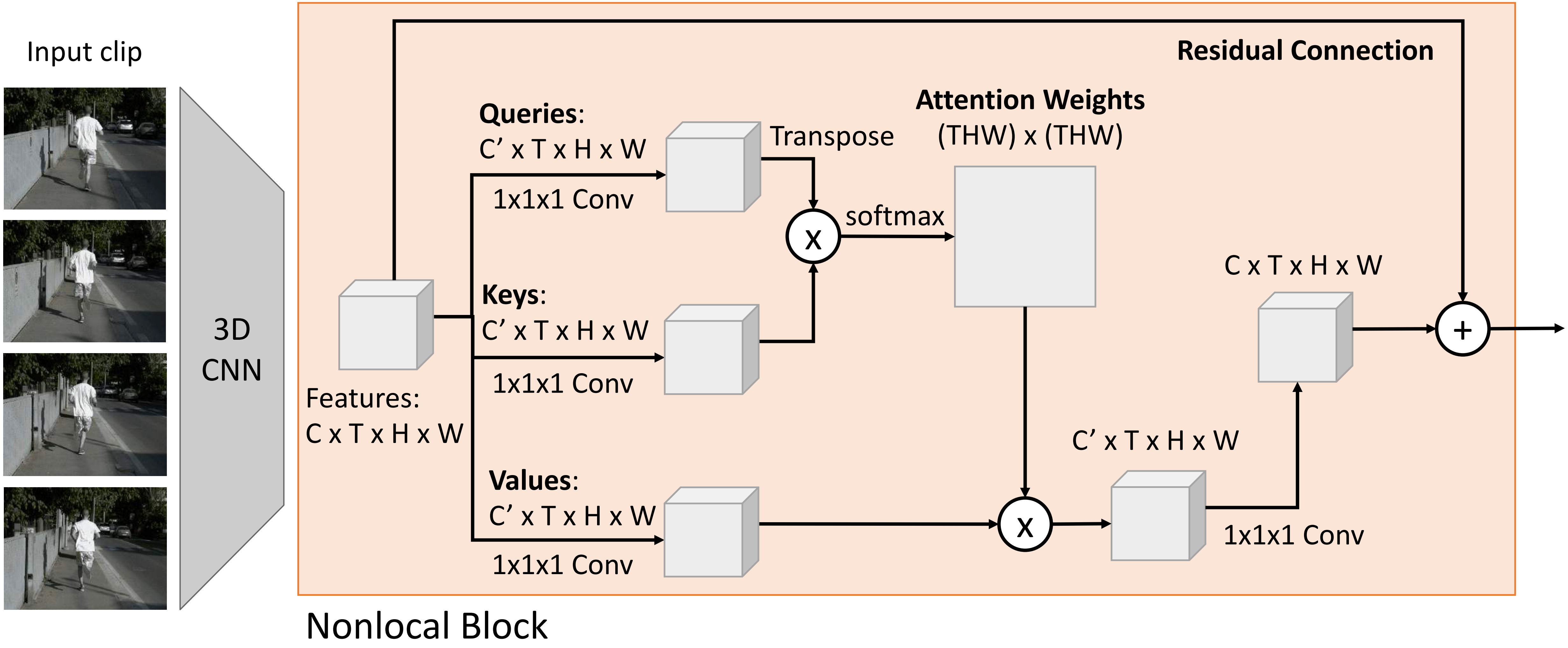
Input clip



Nonlocal Block

Wang et al, "Non-local neural networks", CVPR 2018

Spatio-Temporal Self-Attention (Nonlocal Block)



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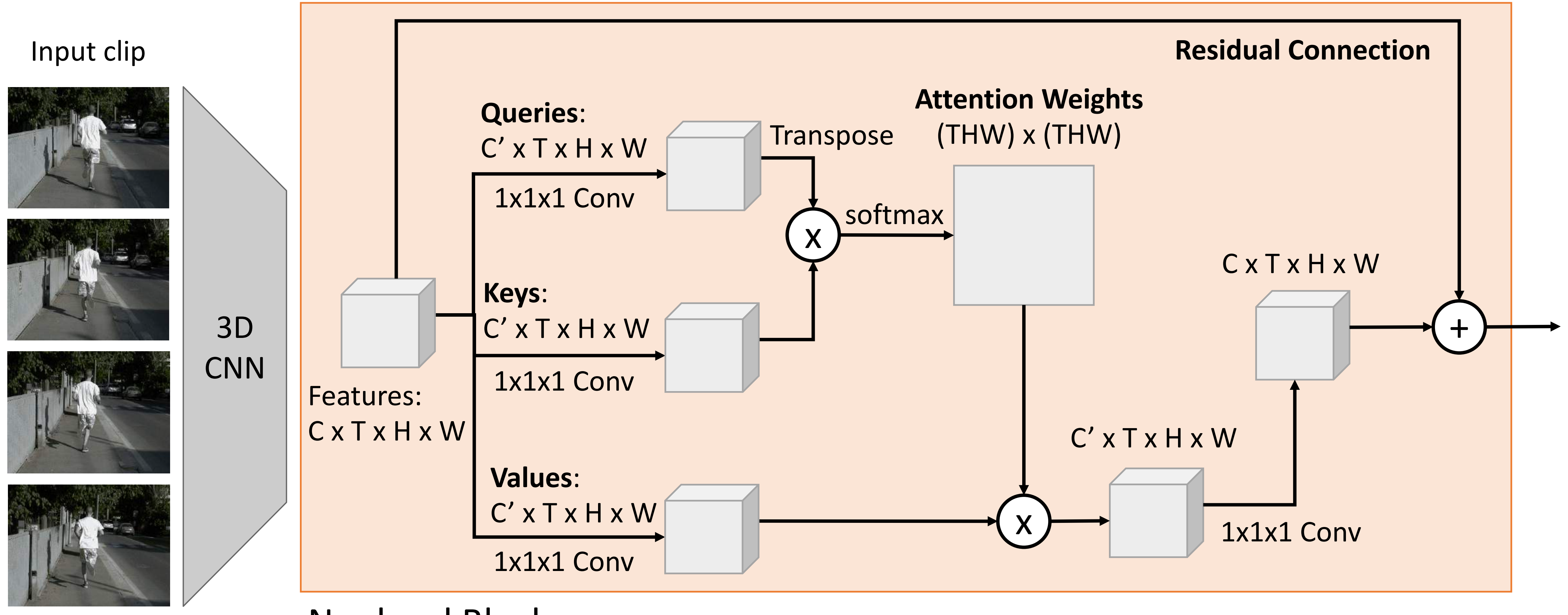
Spatio-Temporal Self-Attention (Nonlocal Block)



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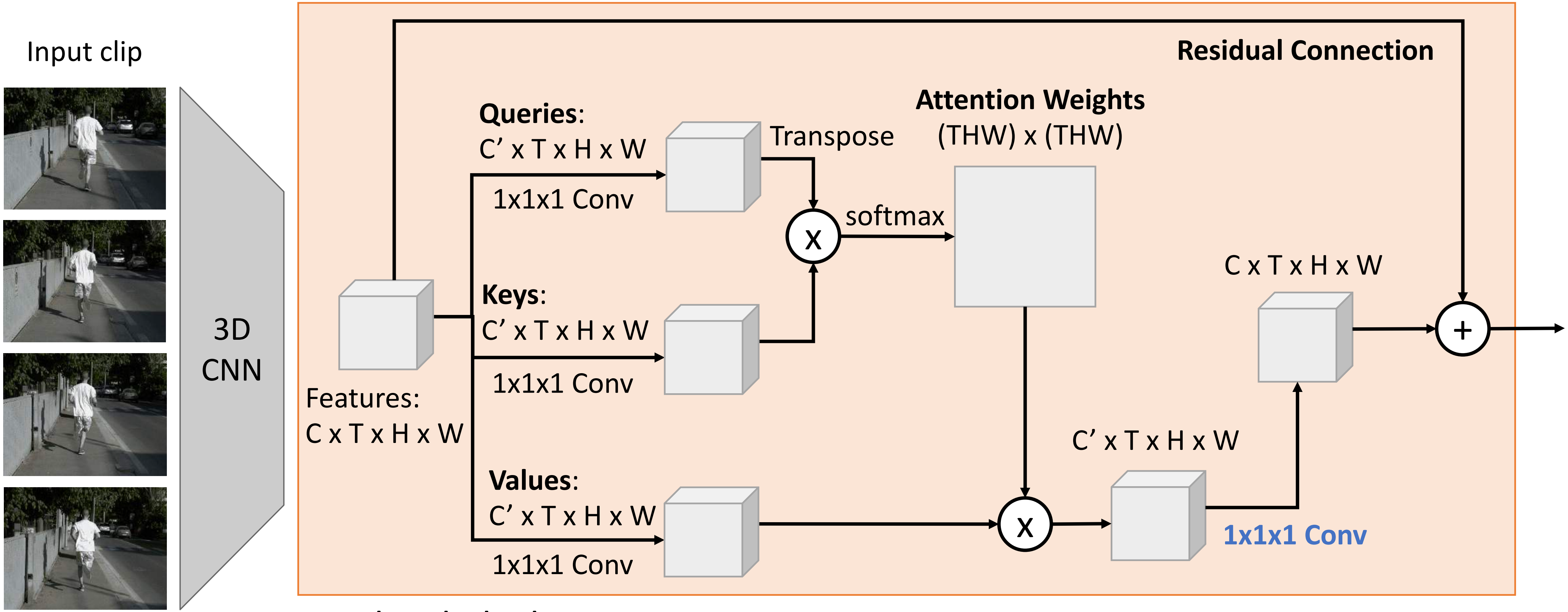
Wang et al, "Non-local neural networks", CVPR 2018

Spatio-Temporal Self-Attention (Nonlocal Block)



Nonlocal Block

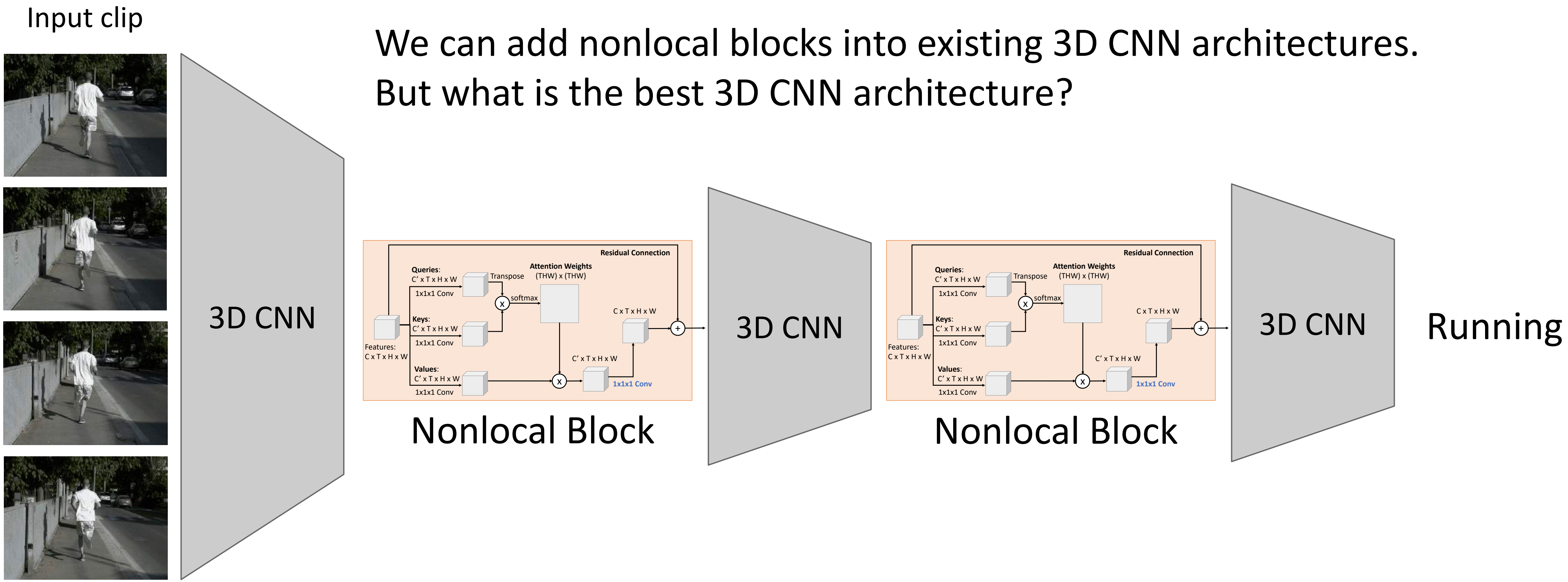
Trick: Initialize last conv to 0, then entire block computes identity. Can insert into existing 3D CNNs

In practice, actually insert BatchNorm layer after final conv, and initialize scale parameter of BN layer to 0 rather than setting conv weight to 0

Wang et al, "Non-local neural networks", CVPR 2018

Spatio-Temporal Self-Attention (Nonlocal Block)

We can add nonlocal blocks into existing 3D CNN architectures.
But what is the best 3D CNN architecture?



Wang et al, "Non-local neural networks", CVPR 2018

Inflating 2D Networks to 3D (I3D)

There has been a lot of work on architectures for images.
Can we reuse image architectures for video?

Idea: take a 2D CNN architecture.

Replace each 2D K_h x K_w conv/pool layer with a 3D K_t x K_h x K_w version

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

Inflating 2D Networks to 3D (I3D)

There has been a lot of work on architectures for images.
Can we reuse image architectures for video?

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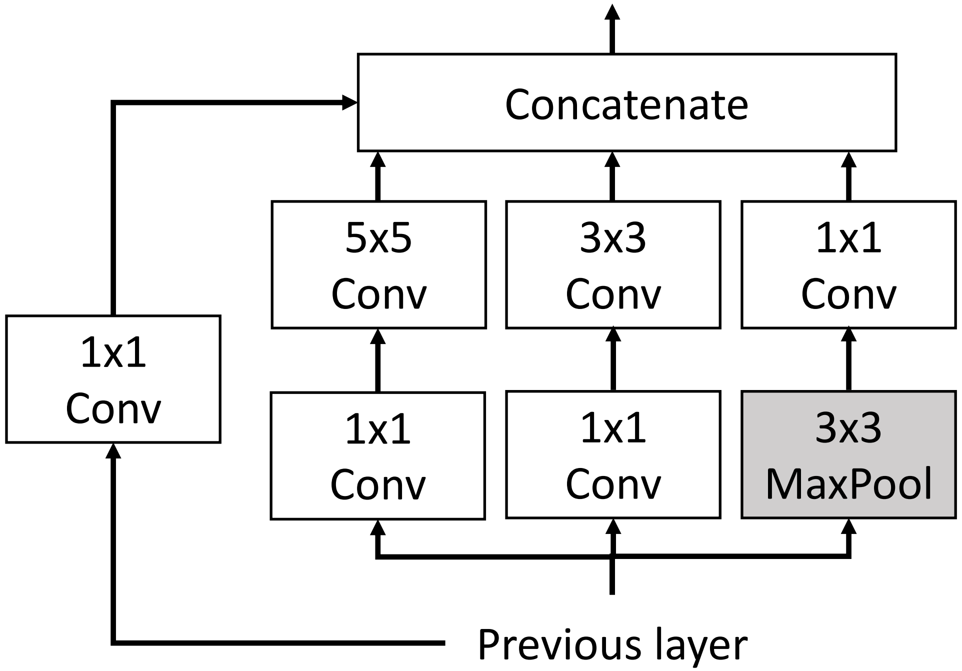
Inception Block: Original



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

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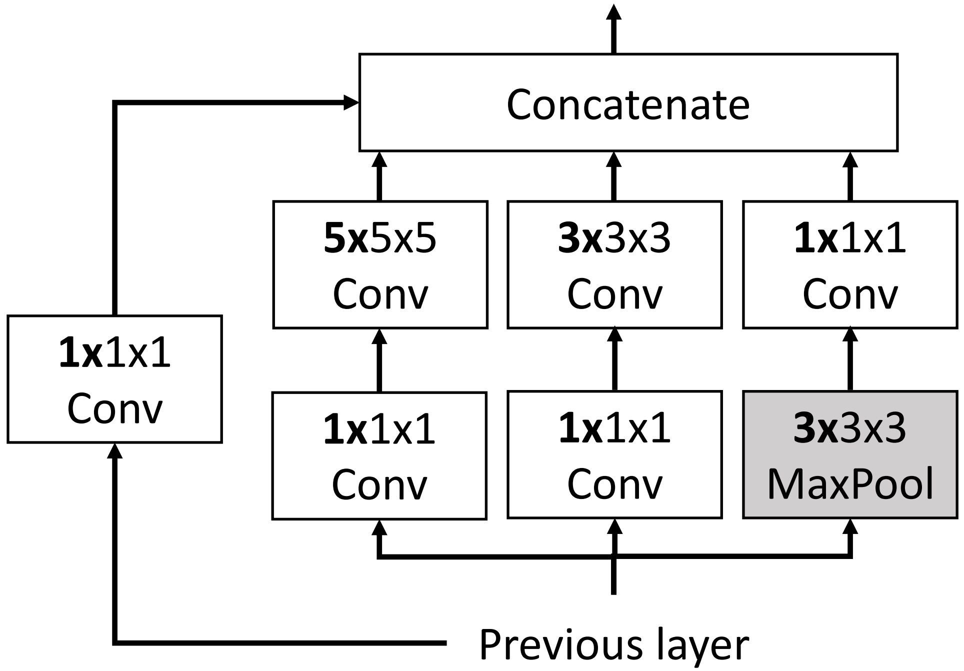
Inception Block: Inflated



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

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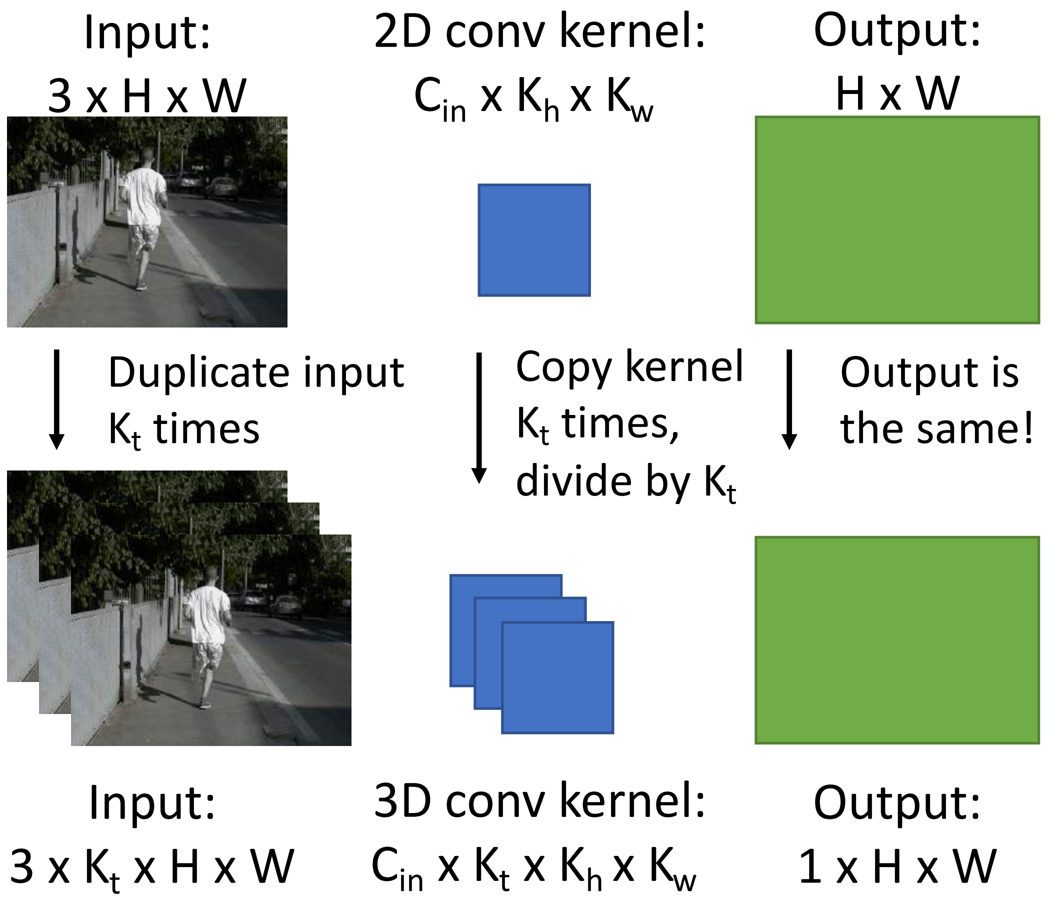
Replace each 2D K_h x K_w conv/pool layer with a 3D K_t x K_h x K_w version

Can use weights of 2D conv to initialize 3D conv: copy K_t times in space and divide by K_t
This gives the same result as 2D conv given "constant" video input



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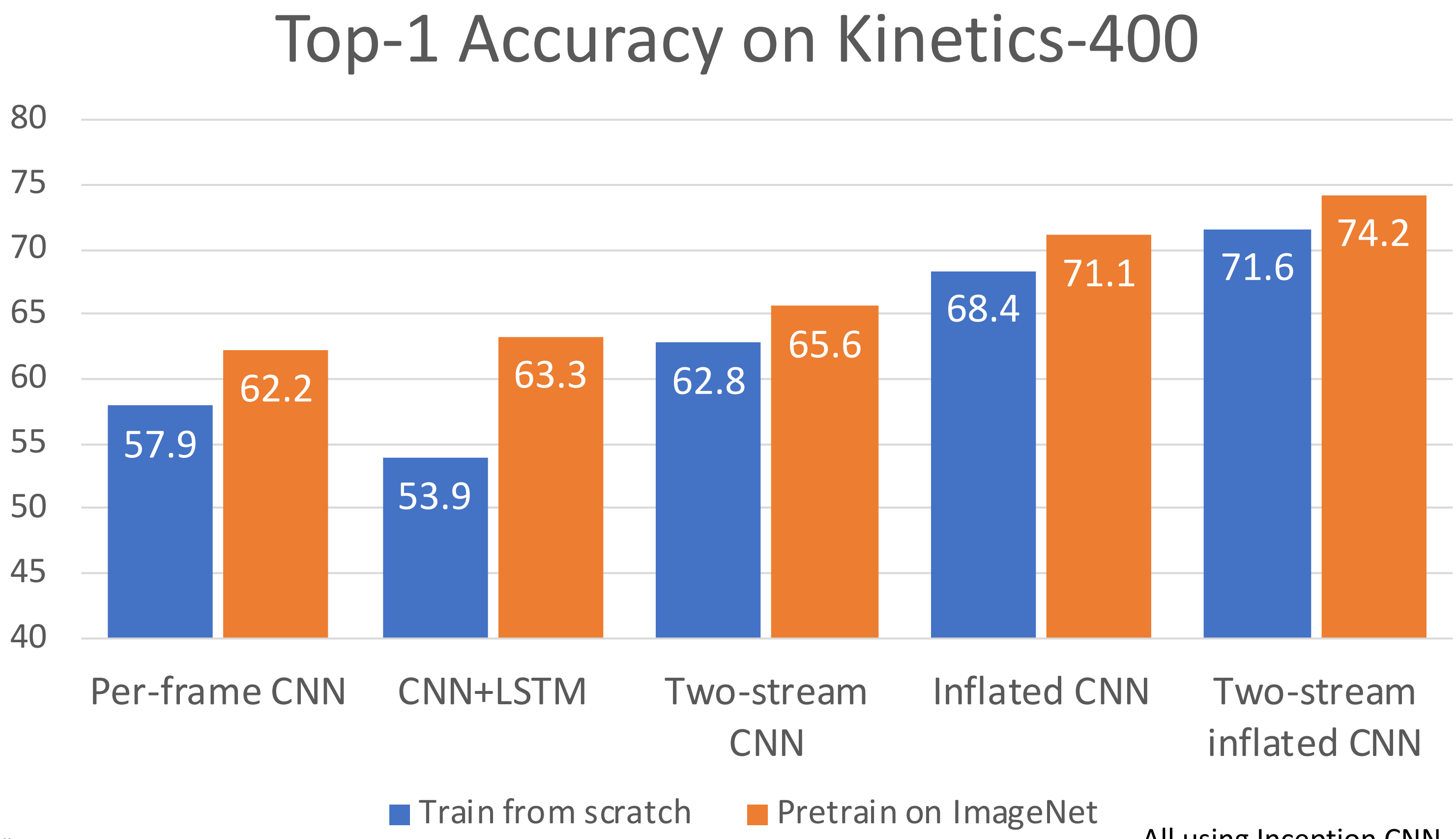


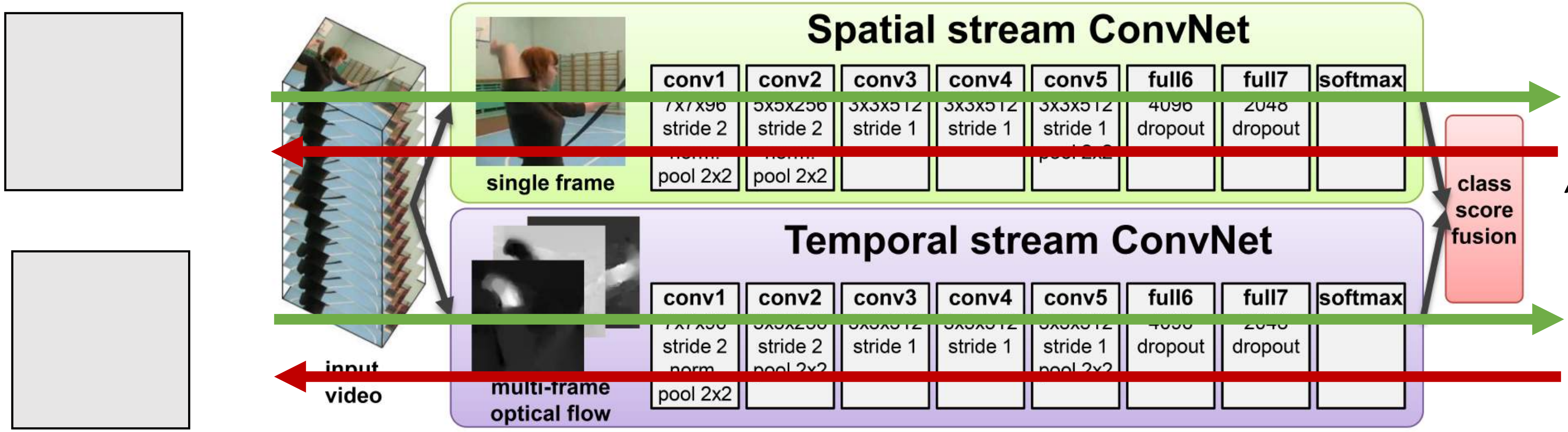
All using Inception CNN

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

Visualizing Video Models

Image

Forward: Compute class score



”weightlifting” score

Flow

Backward: Compute gradient

Add a term to encourage spatially smooth flow; tune penalty to pick out “slow” vs “fast” motion

Figure credit: Simonyan and Zisserman, “Two-stream convolutional networks for action recognition in videos”, NeurIPS 2014
Feichtenhofer et al, “What have we learned from deep representations for action recognition?”, CVPR 2018
Feichtenhofer et al, “Deep insights into convolutional networks for video recognition?”, IJCV 2019.

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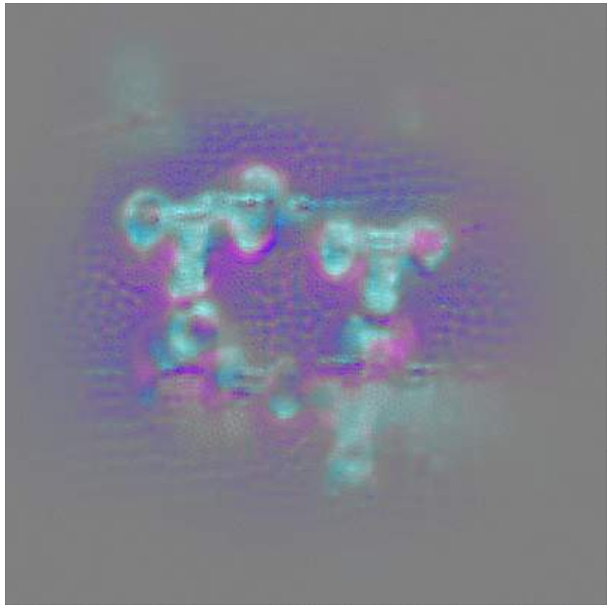
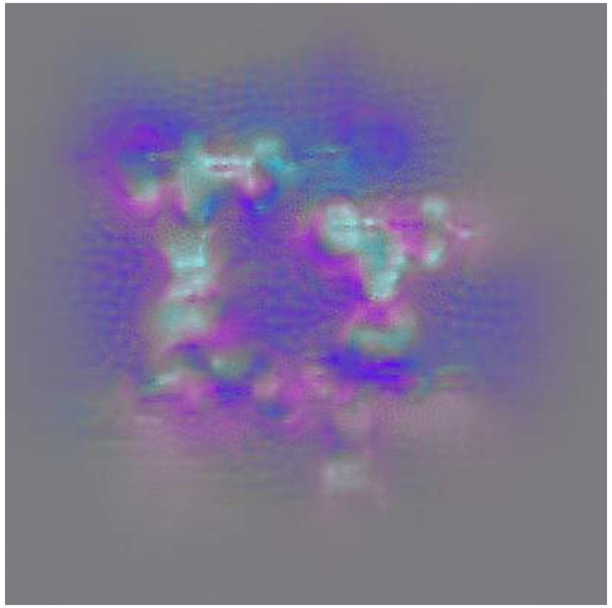
Feichtenhofer et al, "Deep insights into convolutional networks for video recognition?", IJCV 2019.
Slide credit: Christoph Feichtenhofers

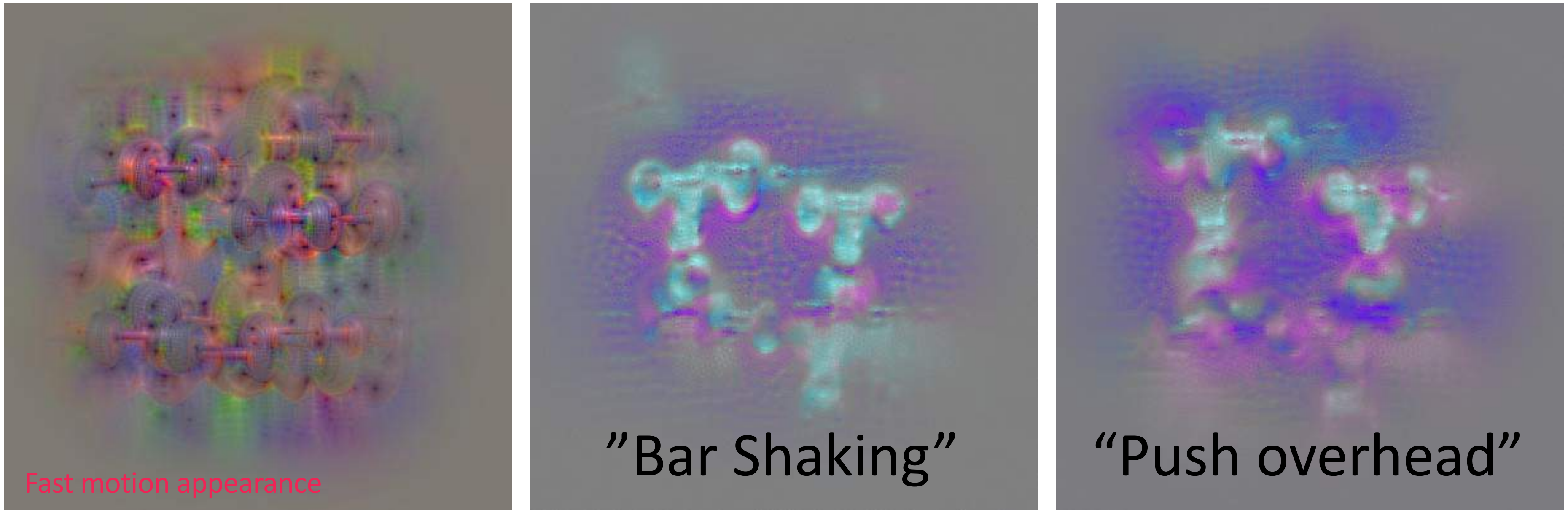
Can you guess the action?

Appearance	"Slow" motion	"Fast" motion
		

Can you guess the action? Weightlifting

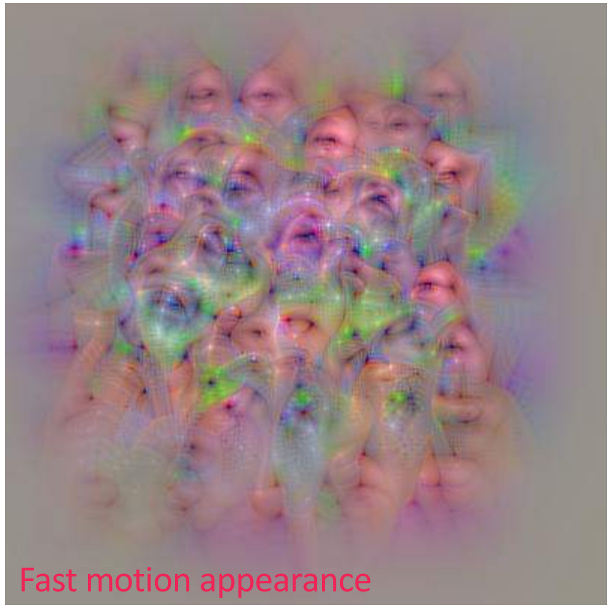
Feichtenhofer et al, “What have we learned from deep representations for action recognition?”, CVPR 2018
Feichtenhofer et al, “Deep insights into convolutional networks for video recognition?”, IJCV 2019.
Slide credit: Christoph Feichtenhofer

Appearance | “Slow” motion | “Fast” motion

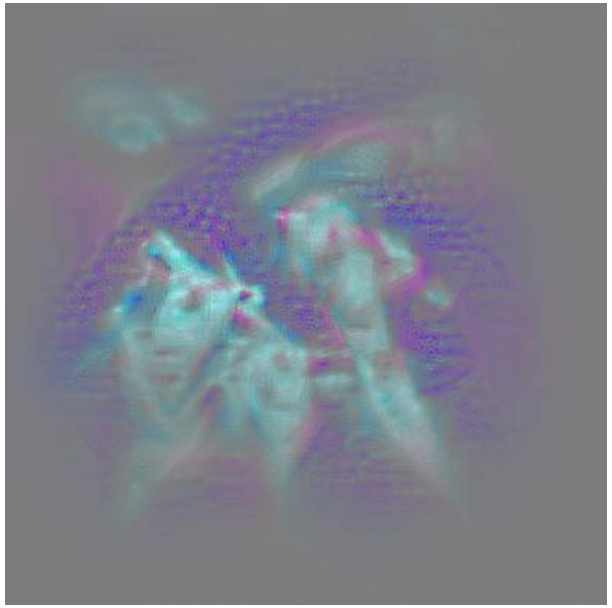


Can you guess the action?

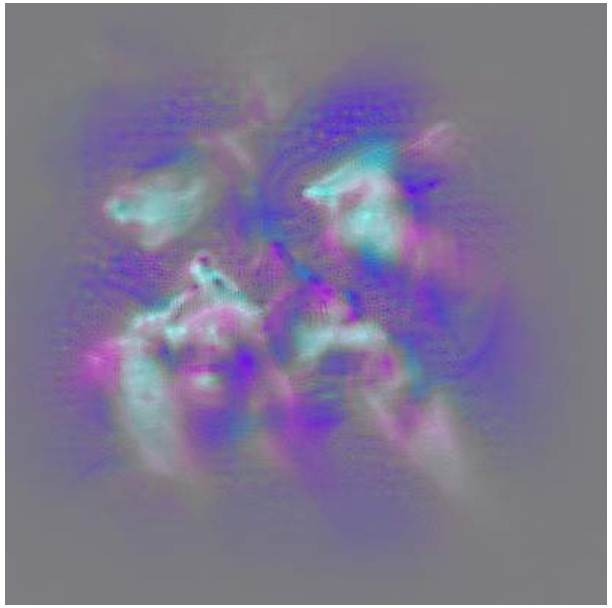
Appearance



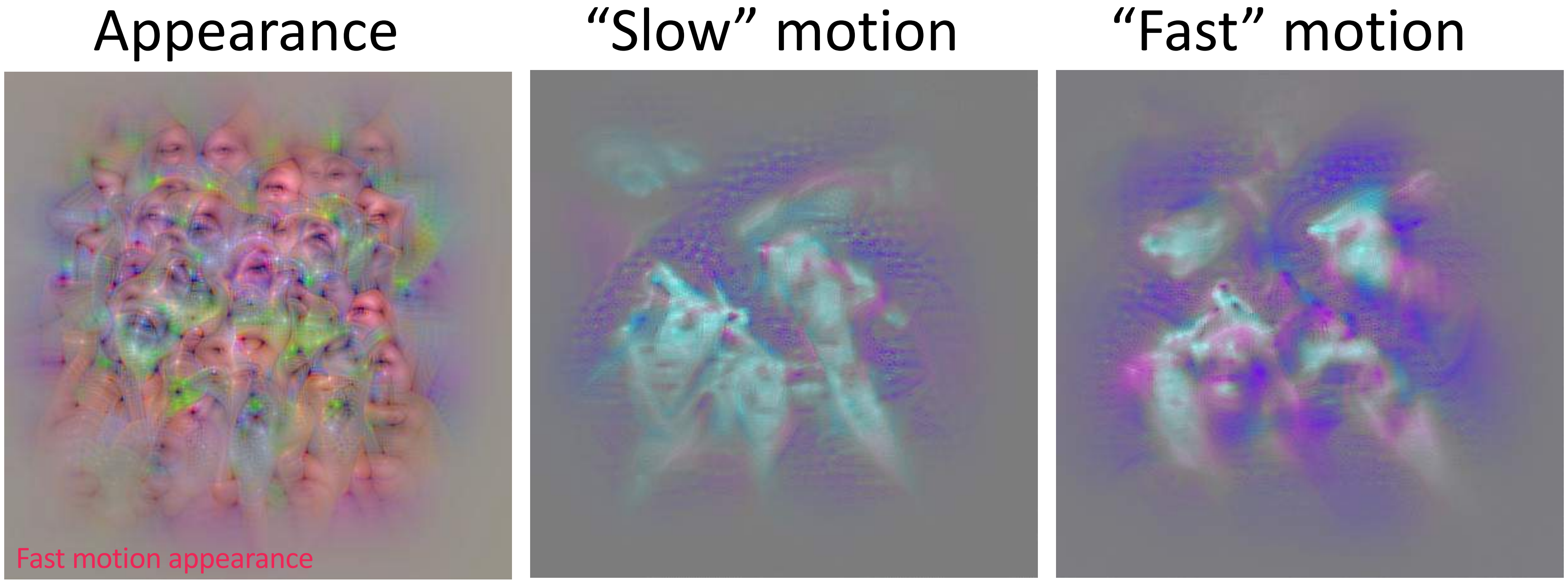
“Slow” motion



“Fast” motion



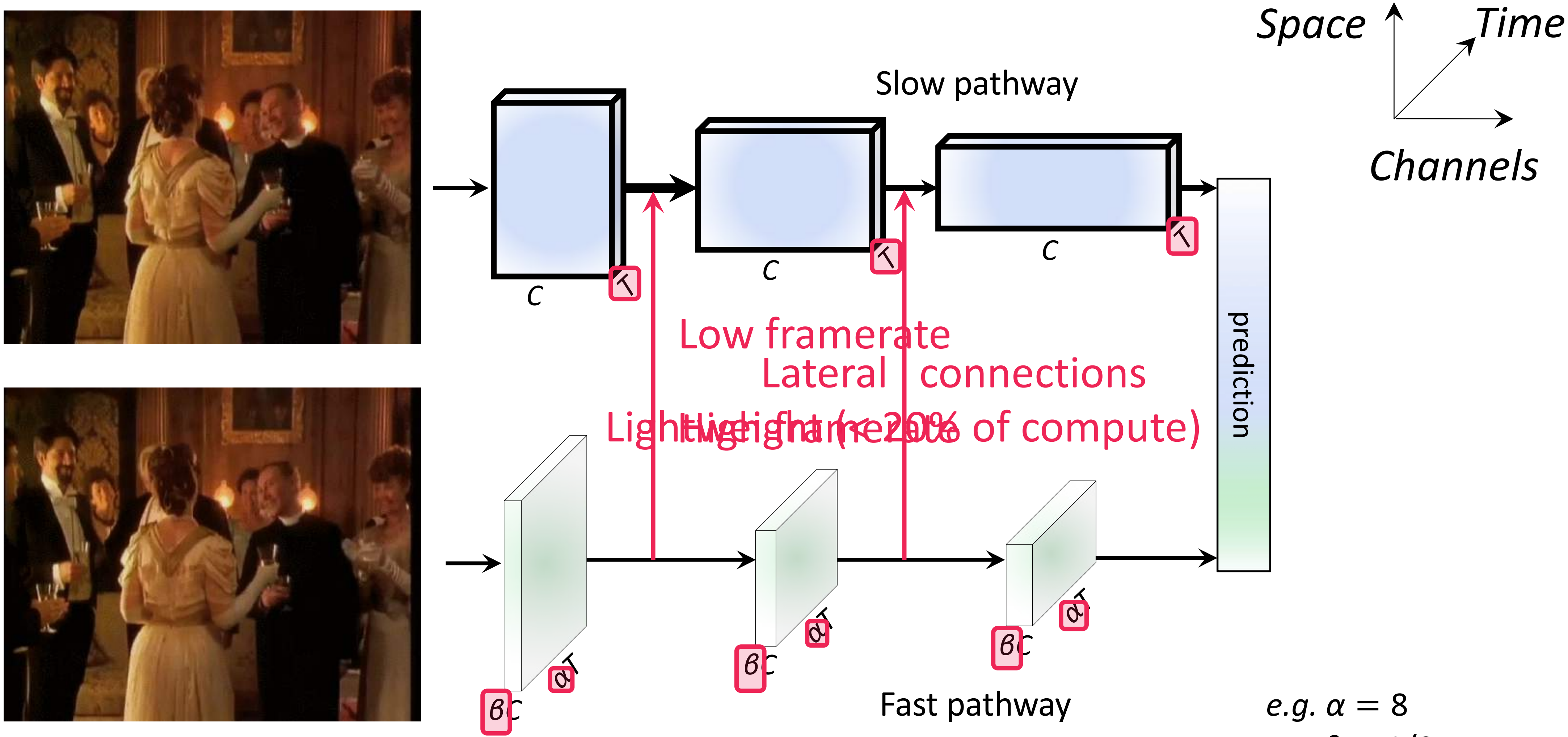
Can you guess the action? Apply Eye Makeup



Treating time and space differently: SlowFast Networks

Slow

Fast



e.g. $\alpha = 8$

$\beta = 1/8$

Feichtenhofer et al, “SlowFast Networks for Video Recognition”, ICCV 2019
Slide credit: Christoph Feichtenhofer

Treating time and space differently: SlowFast Networks

- Dimensions are $\{T \times S^2, C\}$
- Strides are {temporal, spatial^2}
- The backbone is ResNet-50
- Residual blocks are shown by brackets
- Non-degenerate temporal filters are underlined
- Here the speed ratio is $\alpha = 8$ and the channel ratio is $\beta = 1/8$
- Orange numbers mark fewer channels, for the Fast pathway
- Green numbers mark higher temporal resolution of the Fast pathway
- No temporal *pooling* is performed throughout the hierarchy

stage	*Slow* pathway	*Fast* pathway	output sizes $T \times S^2$
raw clip	-	-	64×224^2
data layer	stride 16, 1^2	stride **2**, 1^2	*Slow* : 4×224^2 *Fast* : 32×224^2
conv$_1$	1×7^2, 64 stride 1, 2^2	$\underline{5 \times 7^2}$, 8 stride 1, 2^2	*Slow* : 4×112^2 *Fast* : 32×112^2
pool$_1$	1×3^2 max stride 1, 2^2	1×3^2 max stride 1, 2^2	*Slow* : 4×56^2 *Fast* : 32×56^2
res$_2$	$\begin{bmatrix} 1 \times 1^2, 64 \\ 1 \times 3^2, 64 \\ 1 \times 1^2, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} \underline{3 \times 1^2}, 8 \\ 1 \times 3^2, 8 \\ 1 \times 1^2, 32 \end{bmatrix} \times 3$	*Slow* : 4×56^2 *Fast* : 32×56^2
res$_3$	$\begin{bmatrix} 1 \times 1^2, 128 \\ 1 \times 3^2, 128 \\ 1 \times 1^2, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} \underline{3 \times 1^2}, 16 \\ 1 \times 3^2, 16 \\ 1 \times 1^2, 64 \end{bmatrix} \times 4$	*Slow* : 4×28^2 *Fast* : 32×28^2
res$_4$	$\begin{bmatrix} \underline{3 \times 1^2}, 256 \\ 1 \times 3^2, 256 \\ 1 \times 1^2, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} \underline{3 \times 1^2}, 32 \\ 1 \times 3^2, 32 \\ 1 \times 1^2, 128 \end{bmatrix} \times 6$	*Slow* : 4×14^2 *Fast* : 32×14^2
res$_5$	$\begin{bmatrix} \underline{3 \times 1^2}, 512 \\ 1 \times 3^2, 512 \\ 1 \times 1^2, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} \underline{3 \times 1^2}, 64 \\ 1 \times 3^2, 64 \\ 1 \times 1^2, 256 \end{bmatrix} \times 3$	*Slow* : 4×7^2 *Fast* : 32×7^2
	global average pool, concate, fc		# classes

Feichtenhofer et al, "SlowFast Networks for Video Recognition", ICCV 2019
Slide credit: Christoph Feichtenhofer

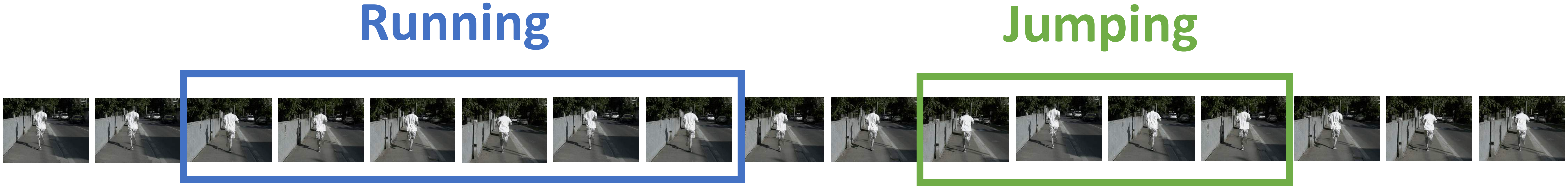
So far: Classify short clips

Videos: Recognize **actions**

Swimming
Running
Jumping
Eating
Standing

Temporal Action Localization

Given a long untrimmed video sequence, identify frames corresponding to different actions



Can use architecture similar to Faster R-CNN: first generate **temporal proposals** then **classify**

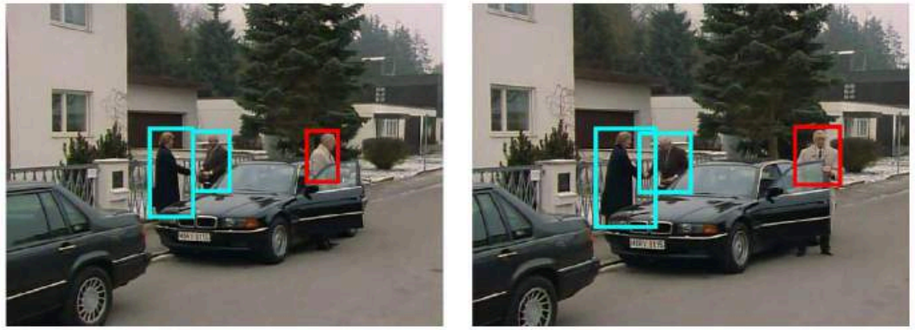
Chao et al, " Rethinking the Faster R-CNN Architecture for Temporal Action Localization", CVPR 2018

Spatio-Temporal Detection

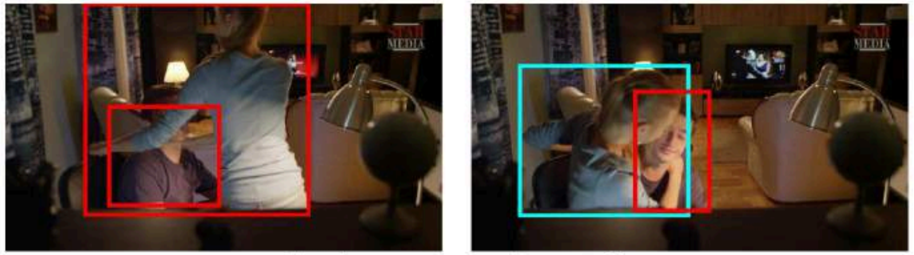
Given a long untrimmed video, detect all the people in space and time and classify the activities they are performing

Some examples from AVA Dataset:

clink glass → drink



open → close



grab (a person) → hug

look at phone → answer phone

Gu et al, "AVA: A Video Dataset of Spatio-temporally Localized Atomic Visual Actions", CVPR 2018

Recap: Video Models

Many video models:
Single-frame CNN (Try this first!)
Late fusion
Early fusion
3D CNN / C3D
Two-stream networks
CNN + RNN
Convolutional RNN
Spatio-temporal self-attention
SlowFast networks (current SoTA)

Next time:
Generative Models, part 1
Generative Adversarial Networks