What have we learned from deep representations for action recognition?

work with

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Outline

- Two-Stream Architectures for Action Recognition

What have we learned in:

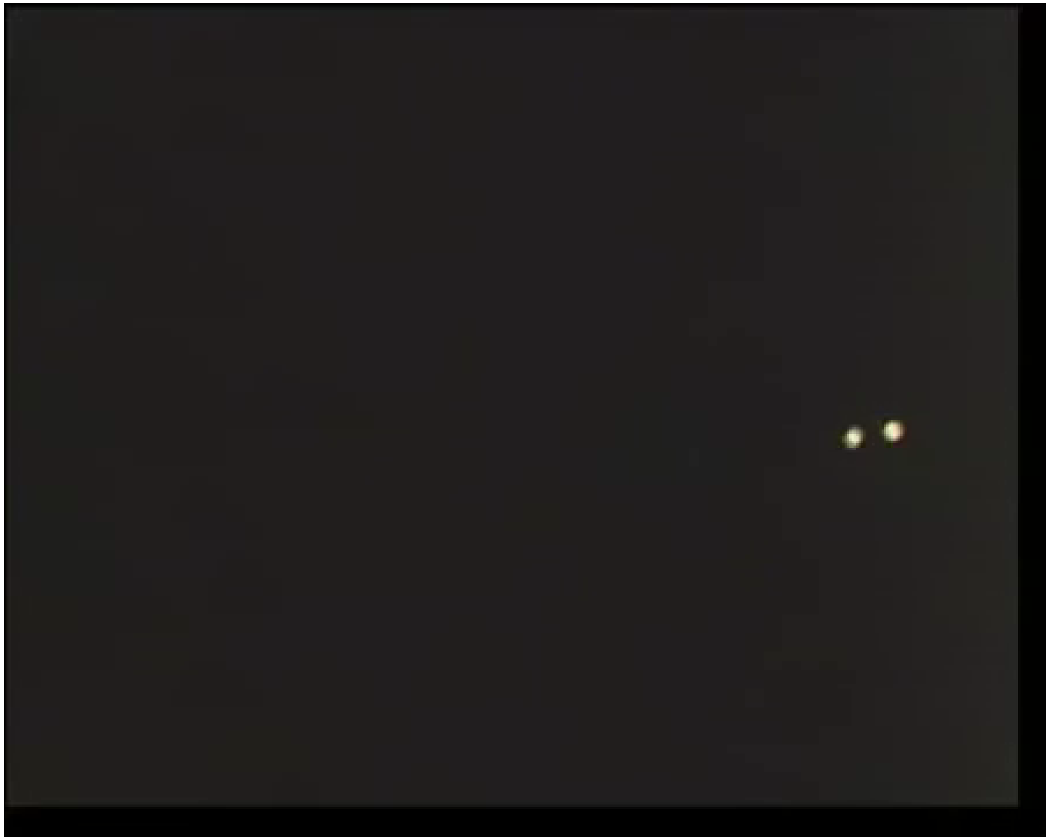
  - Fusion of appearance and motion streams
  - Long-term feature aggregation

- Visualization of Two-Stream representations

Intuitions for why:

  - Explicit motion models perform better
  - Fusion leads to good feature abstractions

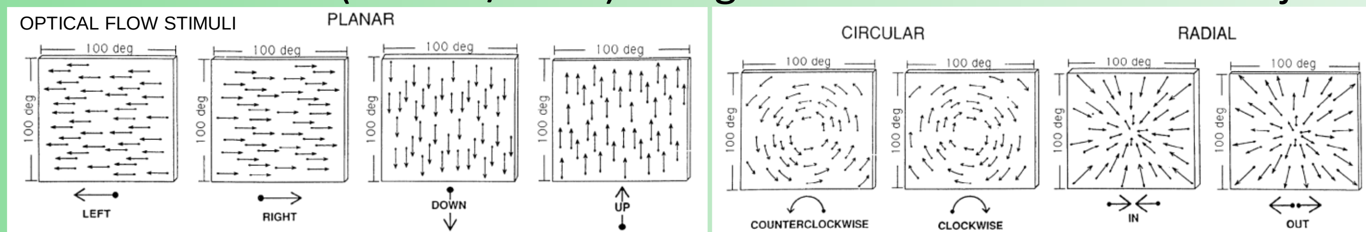
➔ Amazing what the brain can do without appearance information

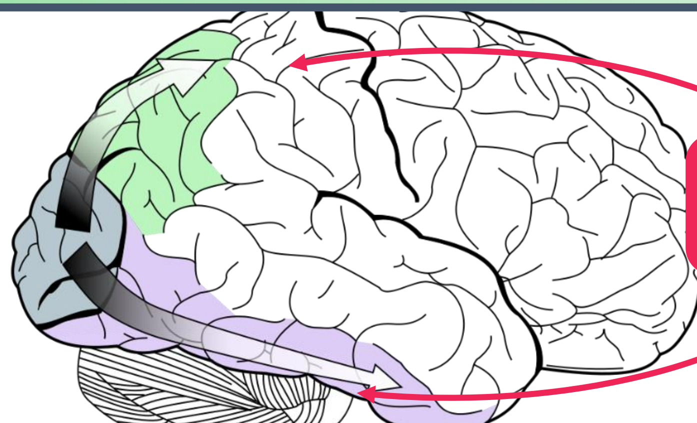


Sources: Johansson, G. “Visual perception of biological motion and a model for its analysis.” Perception & Psychophysics. 14(2):201-211. 1973.

Motivation: Separate visual pathways in nature

➔ Dorsal stream ('where/how') recognizes motion and locates objects





➔ "Interconnection" e.g. in STS area

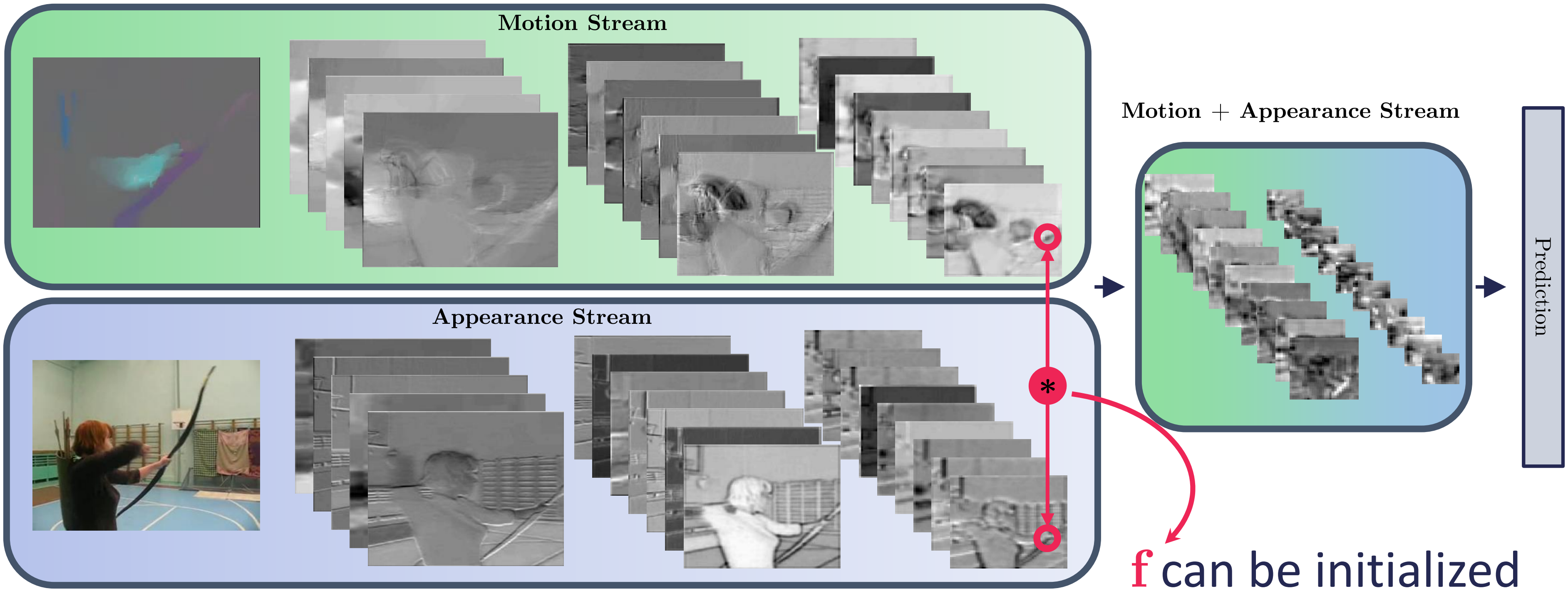
➔ Ventral ('what') stream performs object recognition

Sources: *"Sensitivity of MST neurons to optic flow stimuli. I. A continuum of response selectivity to large-field stimuli." Journal of neurophysiology 65.6 (1991).*
"A cortical representation of the local visual environment", Nature. 392 (6676): 598–601, 2009
https://en.wikipedia.org/wiki/Two-streams_hypothesis

Convolutional Two-Stream Network Fusion

- We study a number of ways of fusing two-stream ConvNets

[Simonyan & Zisserman, NIPS'14]

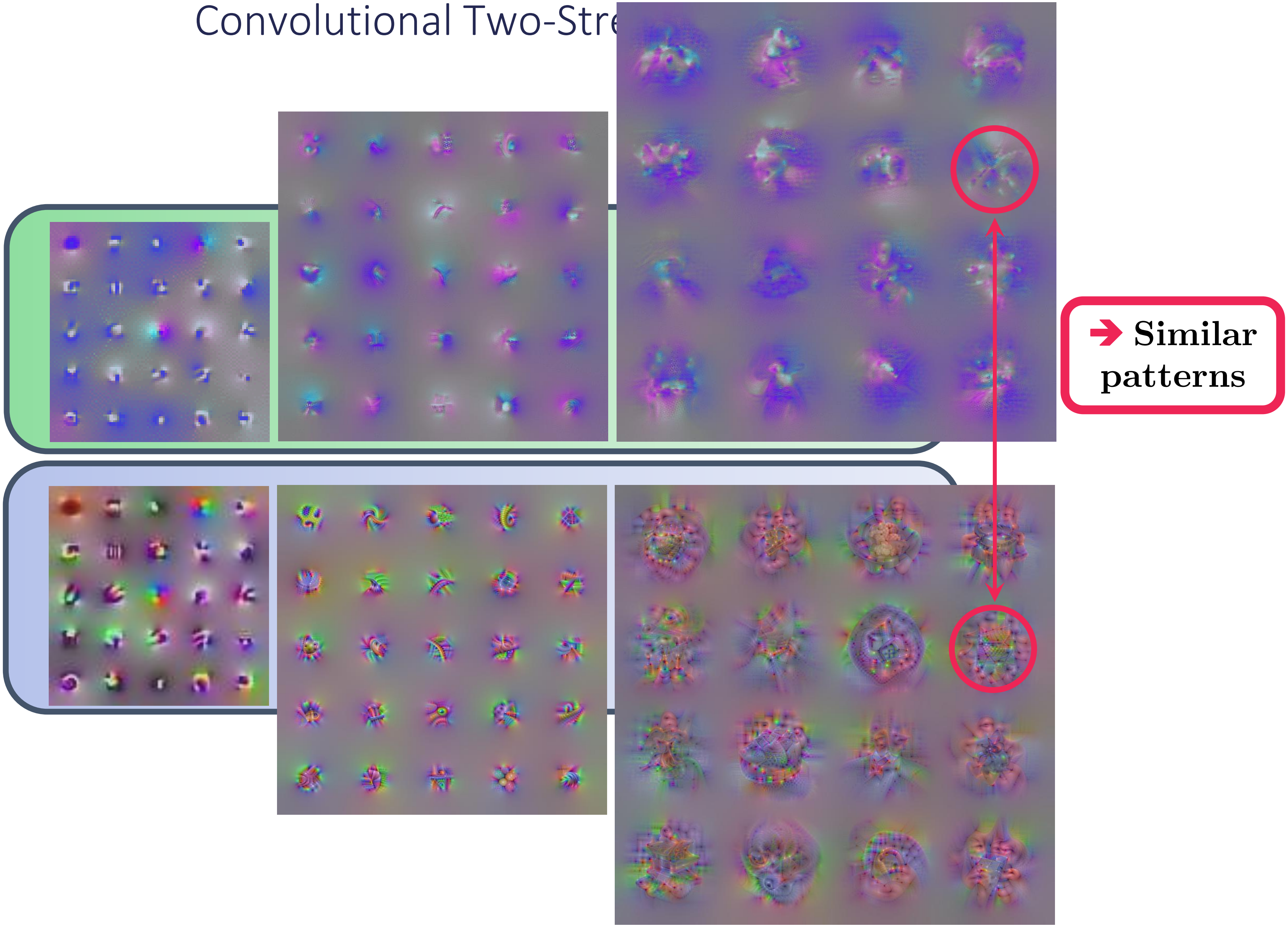


f can be initialized as a sum kernel + feature identity mapping

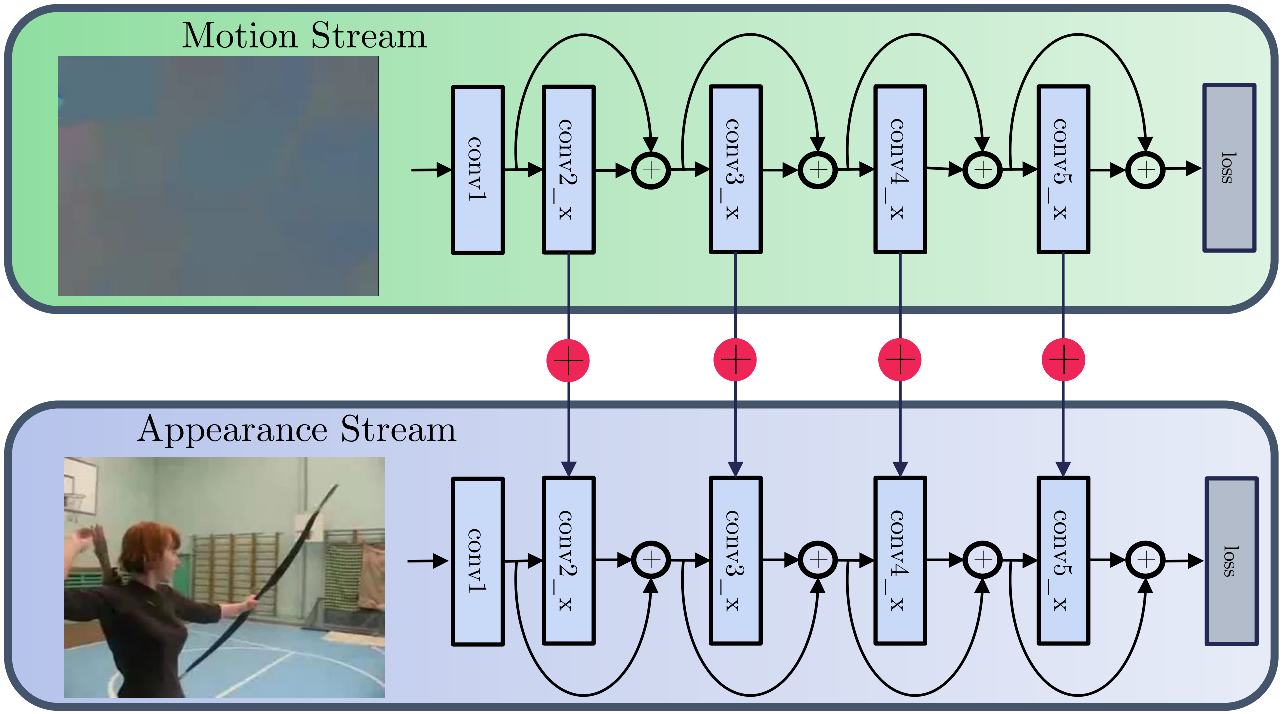
- Sum fusion works surprisingly well

Feichtenhofer, Pinz, Zisserman, CVPR 2016

Convolutional Two-Stre



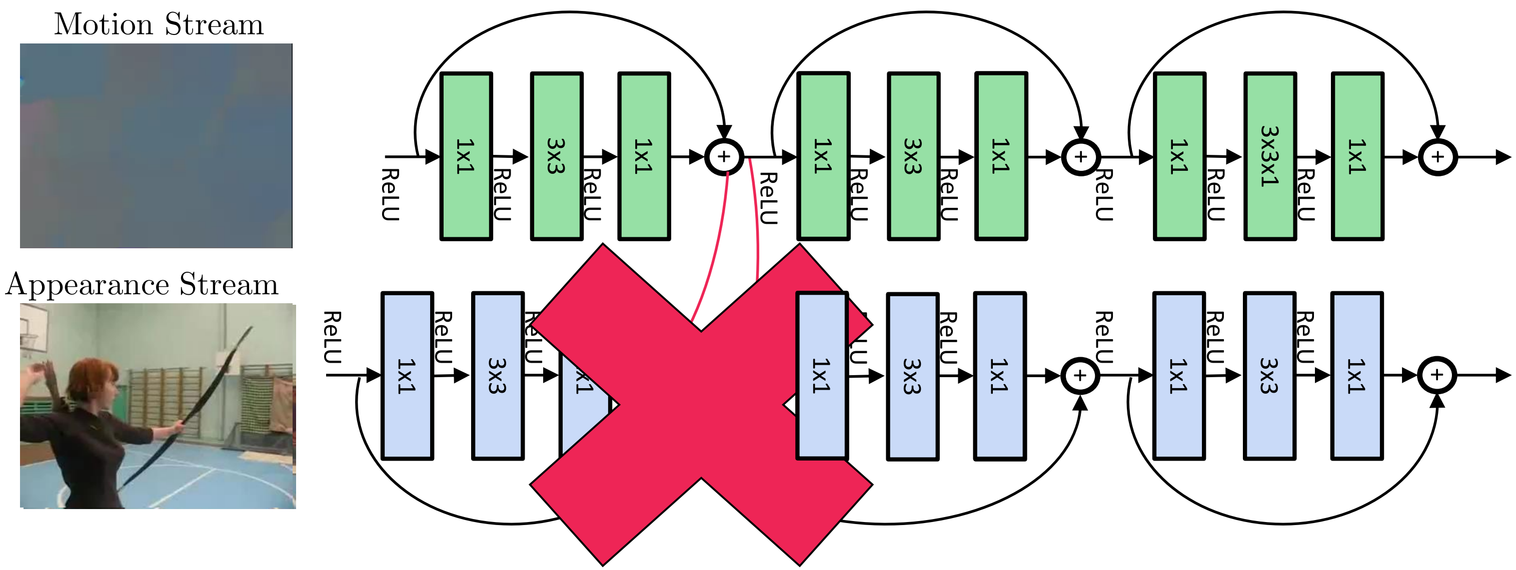
Spatiotemporal Residual Networks



- ST-ResNet allows the hierarchical learning of spacetime features by connecting the appearance and motion channels of a two-stream architecture.
- Though, naive fusion does not work.

Feichtenhofer, Pinz, Wildes, NIPS'16 & CVPR'17

Fusing Two-Stream ResNets & Injecting Temporal Filters

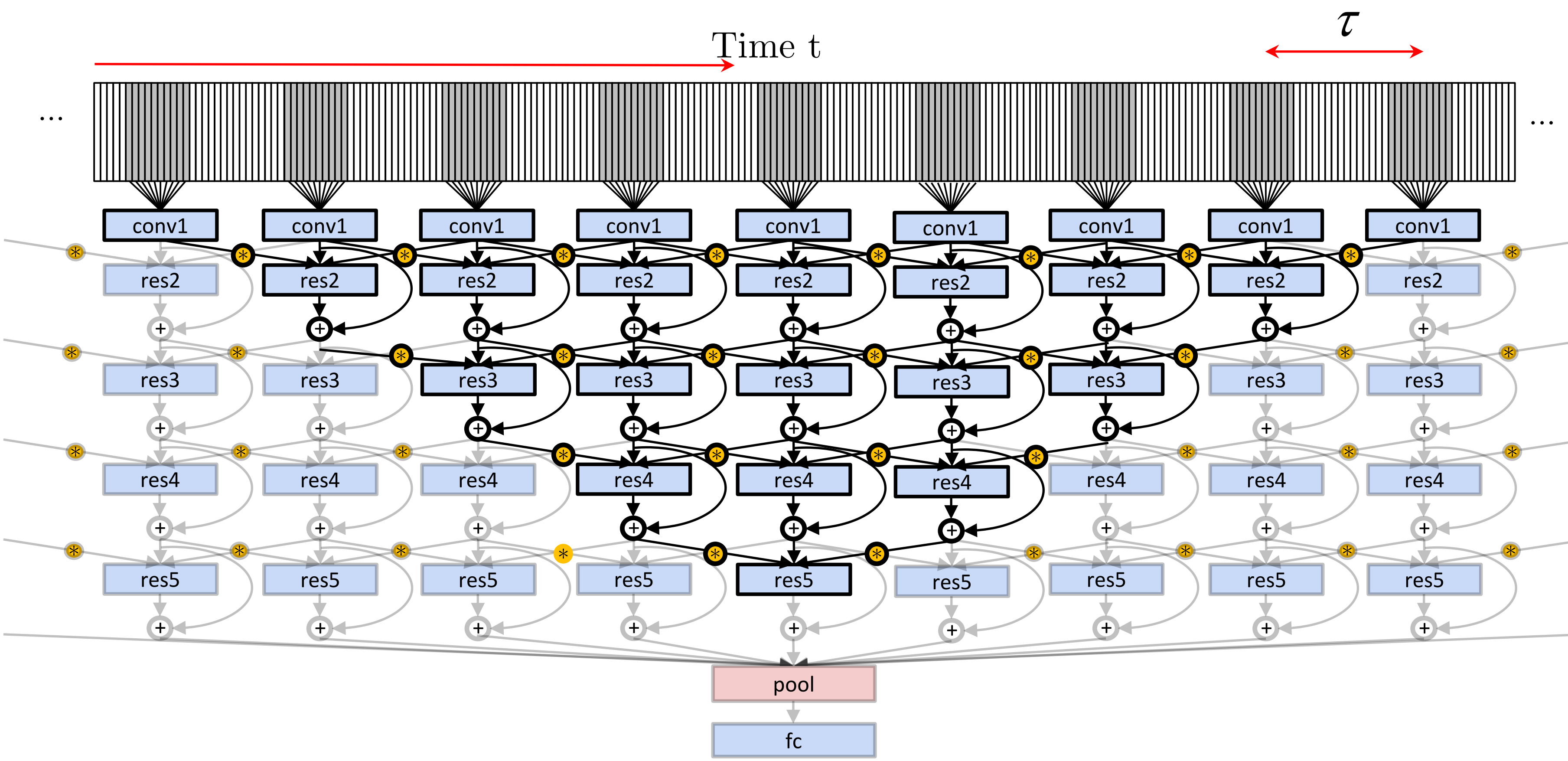


- ResNets for the spatiotemporal domain by introducing residual connections in two ways
  1. Residuals between the motion and appearance pathways to allow spatiotemporal interaction between the streams
  2. Transformation * of pretrained image ConvNets by filters initialized as residuals in time

- Our most recent work (@CVPR'17) reconsiders the combination these approaches more thoroughly to increase our understanding of how these techniques interact.

Feichtenhofer, Pinz, Wildes, NIPS'16 & CVPR'17

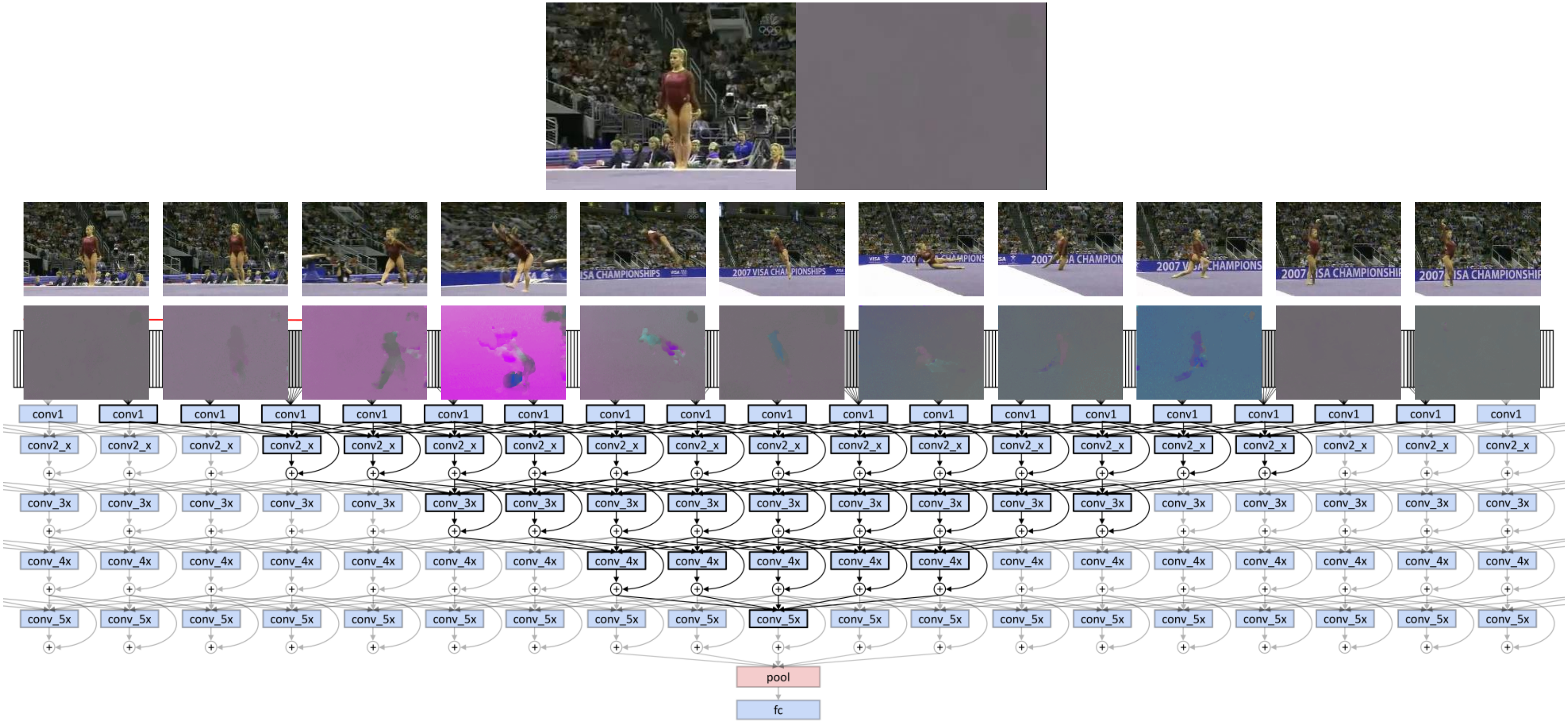
Increasing the temporal receptive field of ResNets



○ The temporal receptive field is modulated by the temporal filters * and input stride τ

Feichtenhofer, Pinz, Wildes, NIPS'16

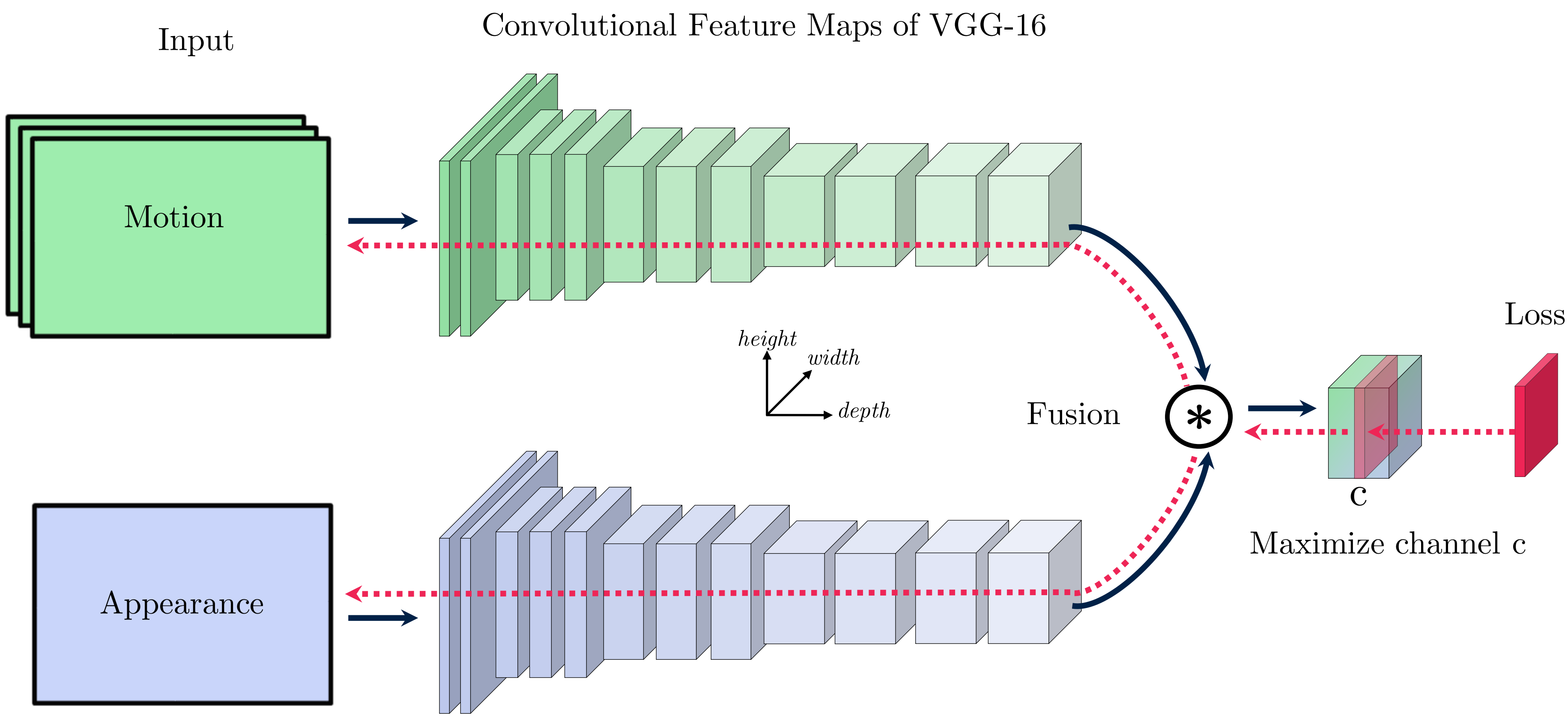
Transforming spatial filters to spatiotemporal ones



- Chaining temporal filters supports *hierarchical* learning of long-term correspondences between features of the appearance and motion stream.
- For example, if the stride is set to $\tau = 15$ frames and we transform 8 filters, a unit at conv5_3 sees a window of $17 \times 15 = 255$ frames.

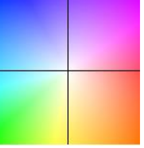
Feichtenhofer, Pinz, Wildes, NIPS'16

Visualizing the learned representation



[Erhan et al. 2009]
[Simonyan et al. 2013]
[Mahendran & Vedaldi 2014]
[Yosinski et al. 2014]

Feichtenhofer, PhD Thesis 2017

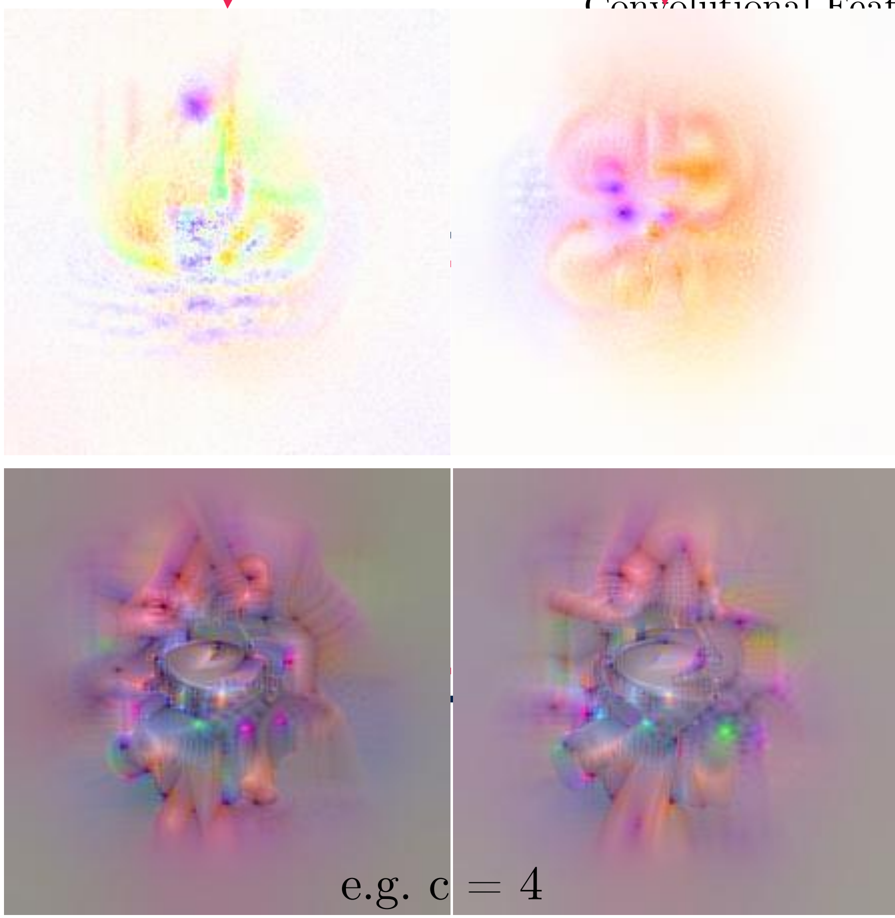


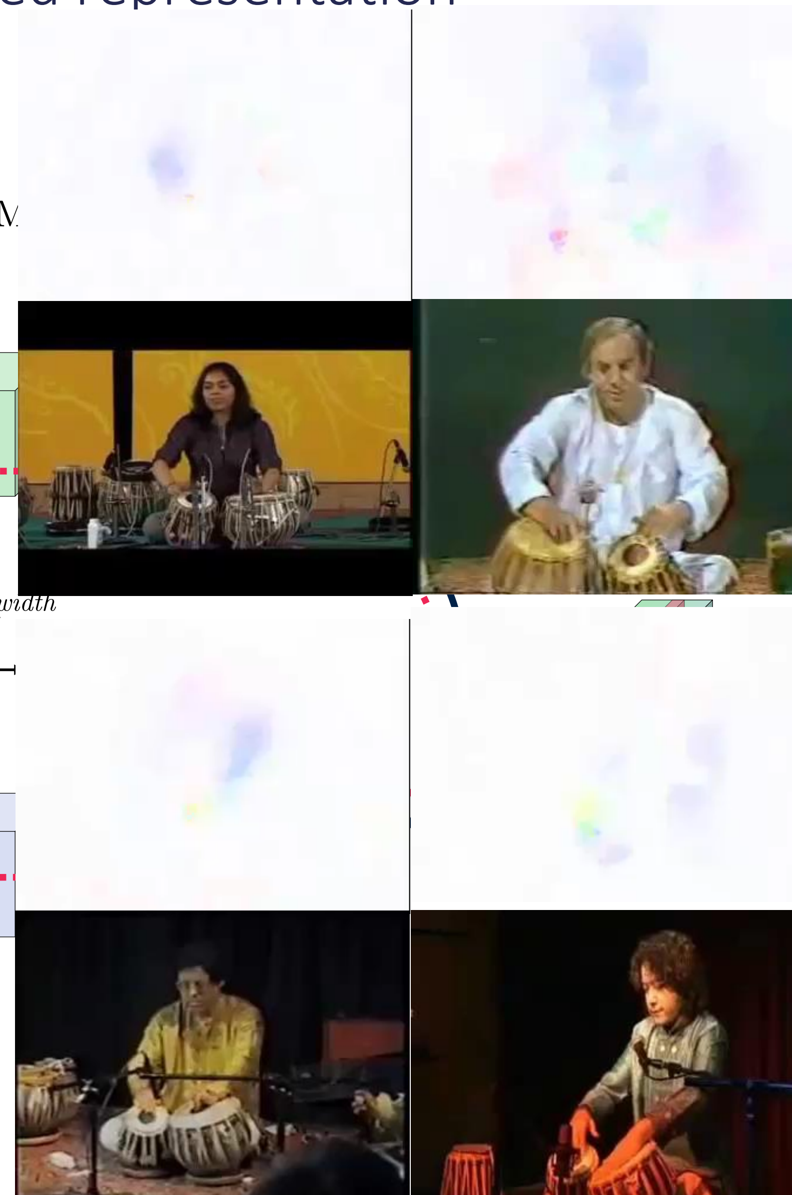
Visualizing the learned representation

Slow motion

Fast motion

Convolutional Feature M





eight

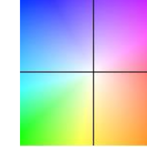
width

Loss

c

2014]

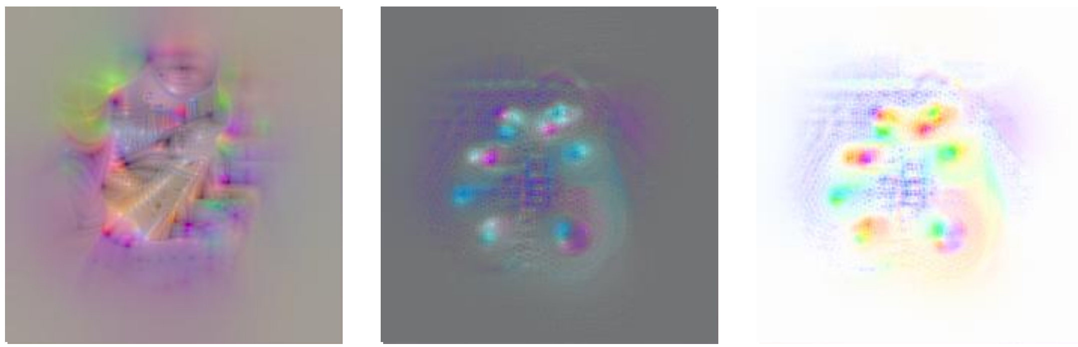
Feichtenhofer, PhD Thesis 2017



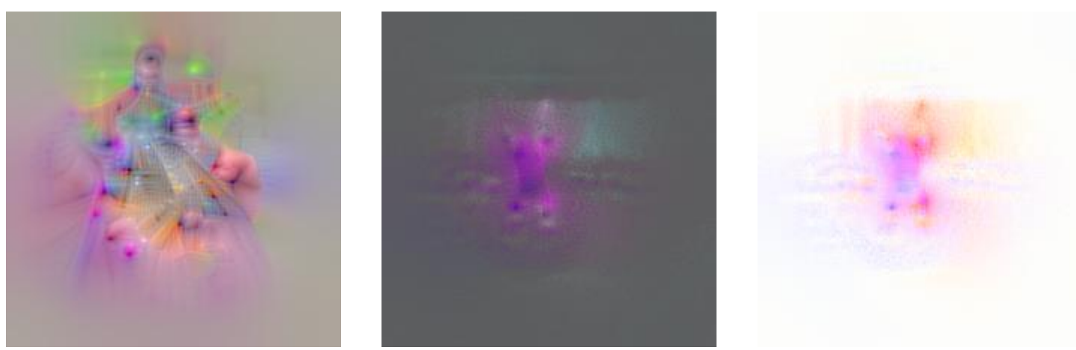
Filter #21 at conv5 fusion – a local Billiard neuron ?

➔ (mostly) linear motion

Slow motion



Fast motion

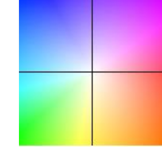


slower

w (direction)

➔ accelerating motion in all directions

Feichtenhofer, PhD Thesis 2017



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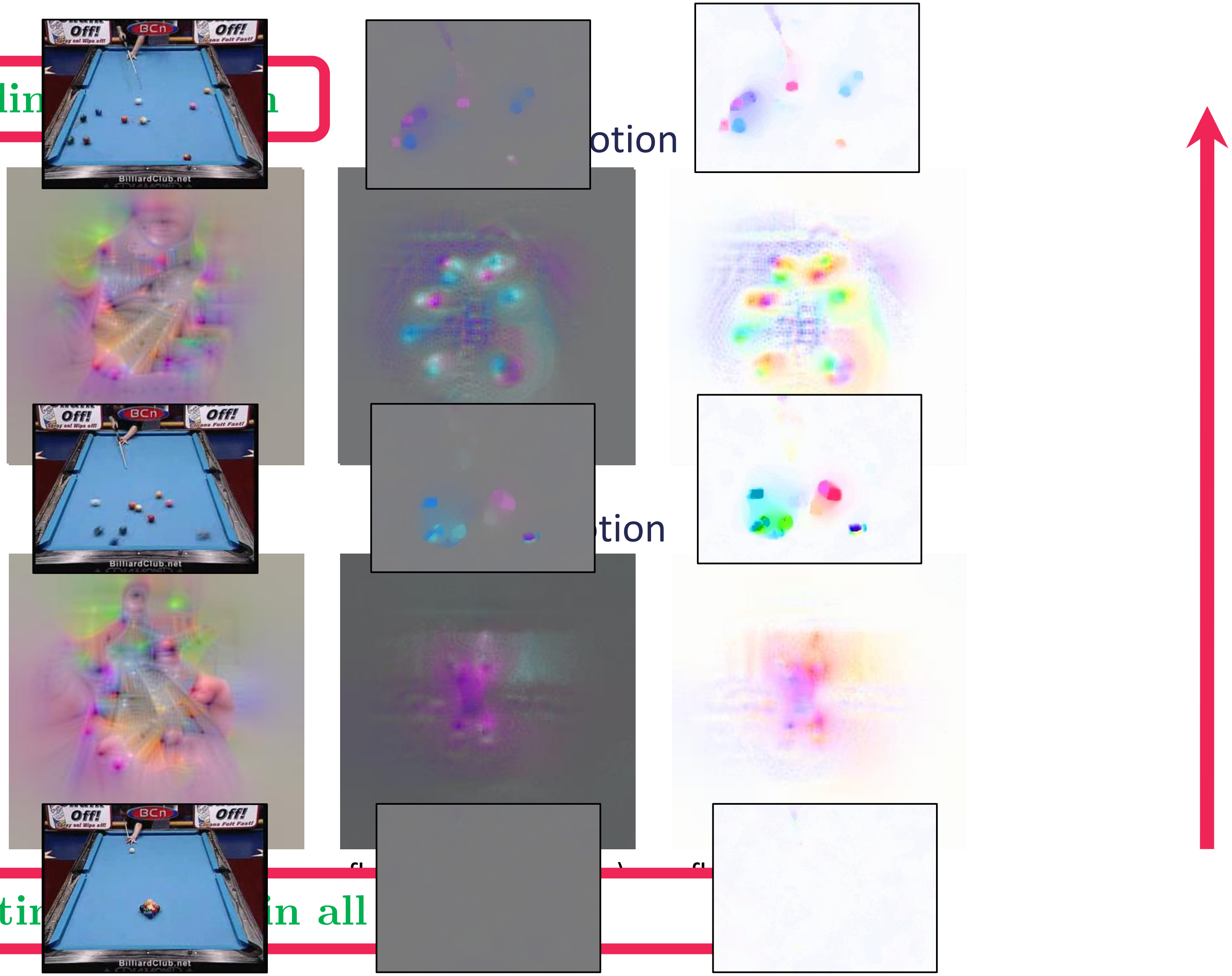

→ Test set example snippets

→ accelerati in all

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Last layer

→ “Billiards”

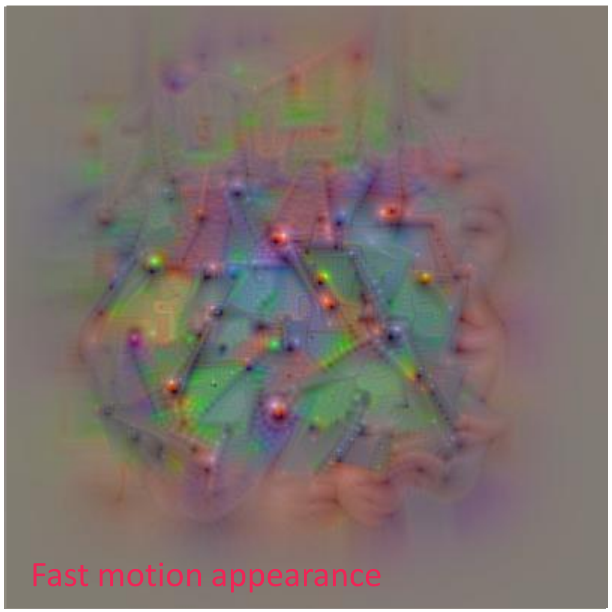
Appearance

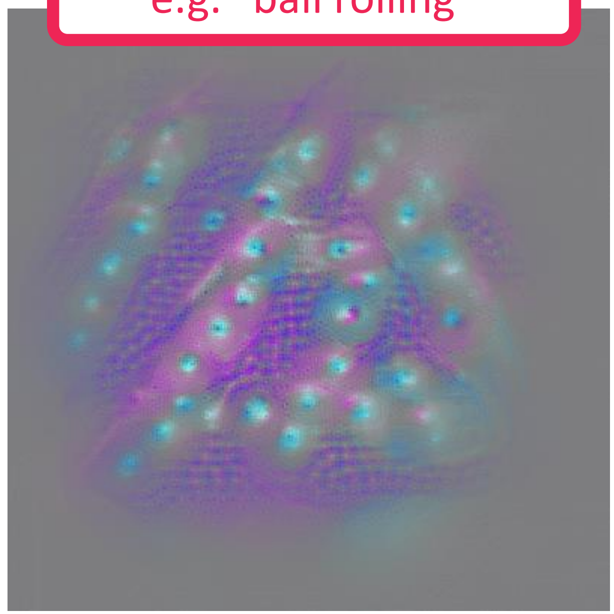
Slow motion

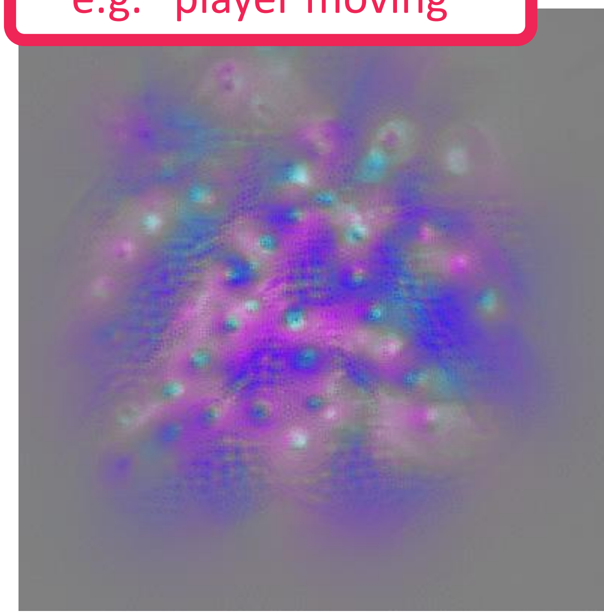
Fast motion

e.g. “ball rolling”

e.g. “player moving”







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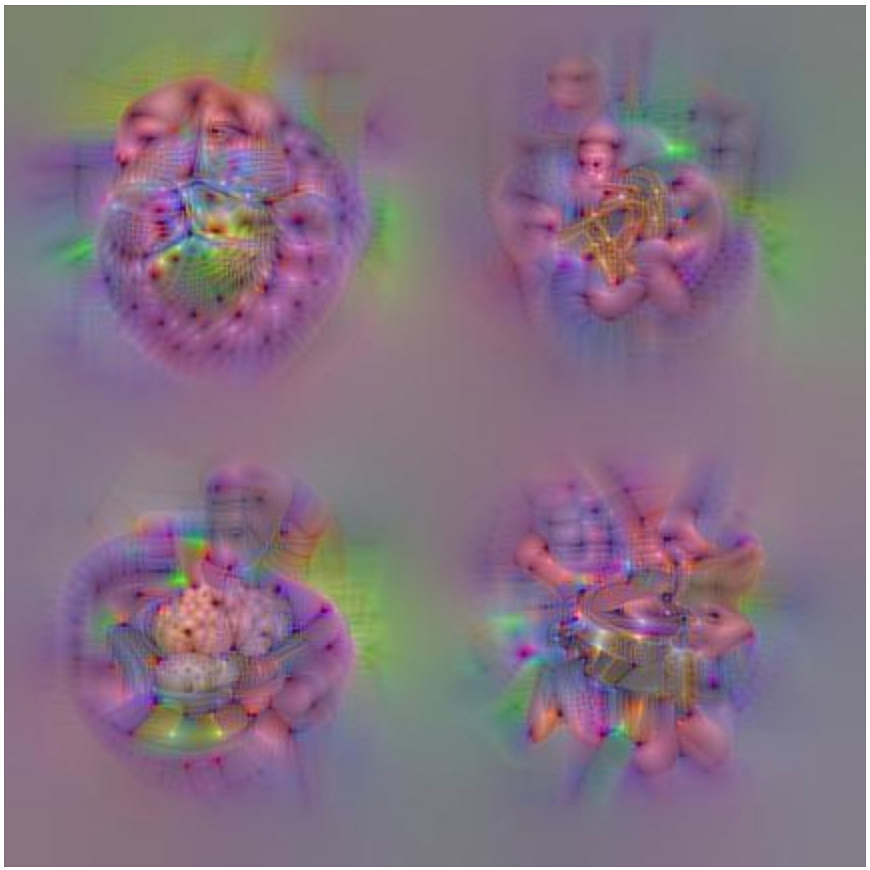
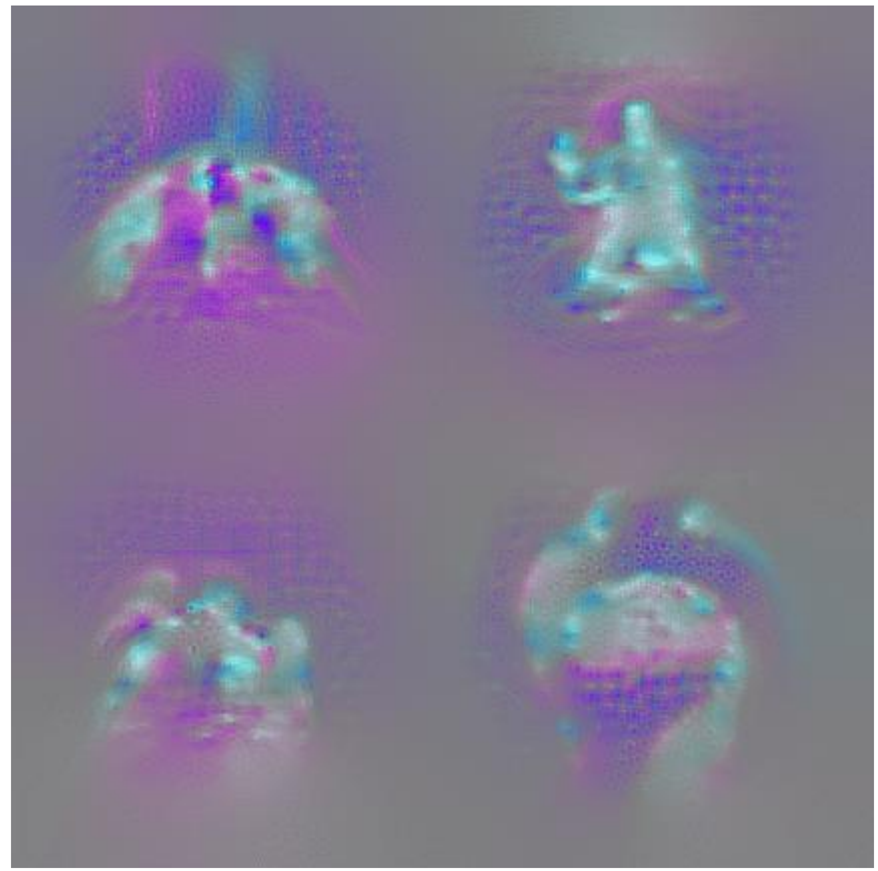
Going through the conv layers of VGG-16
(first four filters of each layer are shown)

Appearance

conv5_3 f1-4

Slow motion





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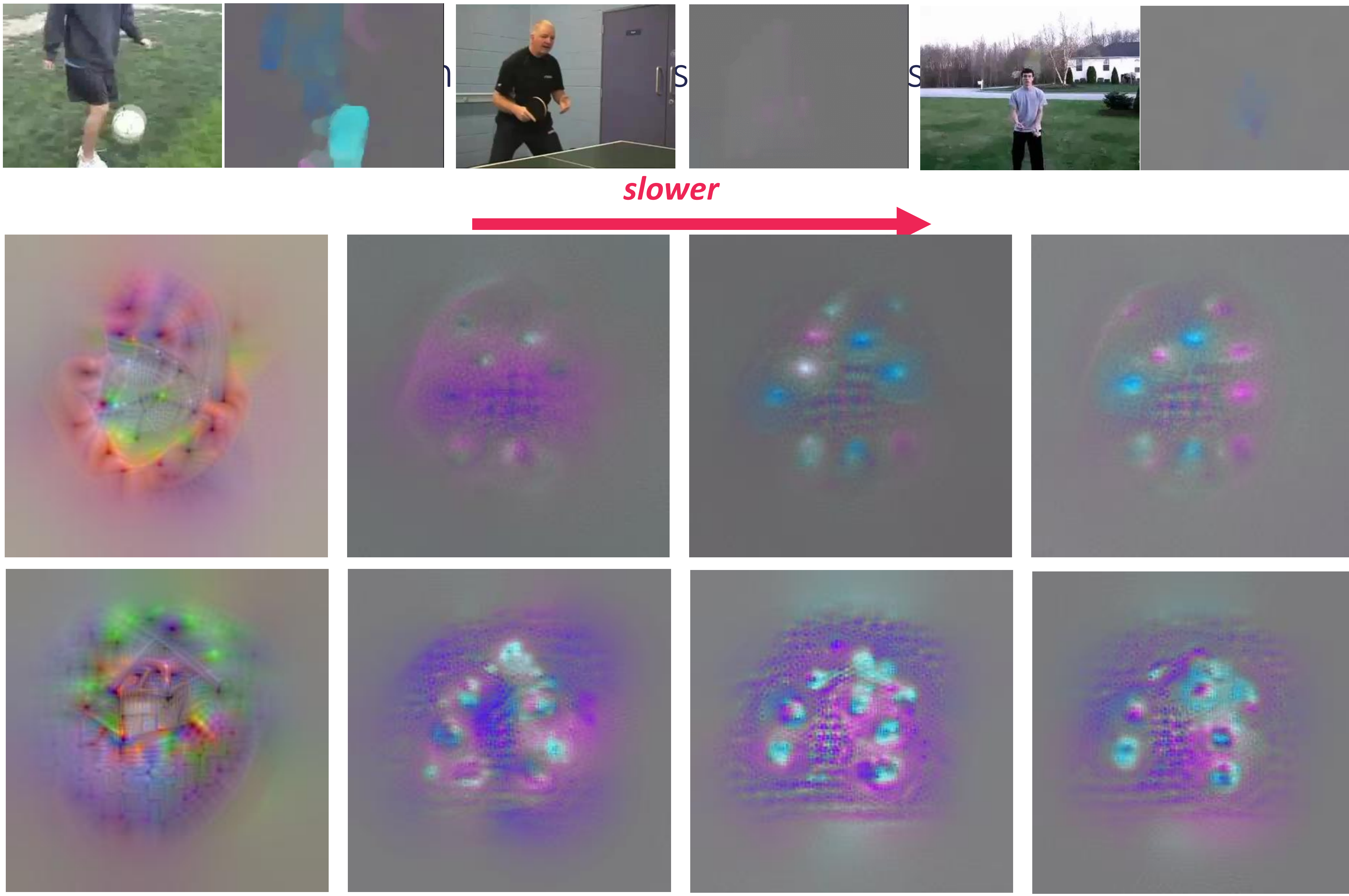

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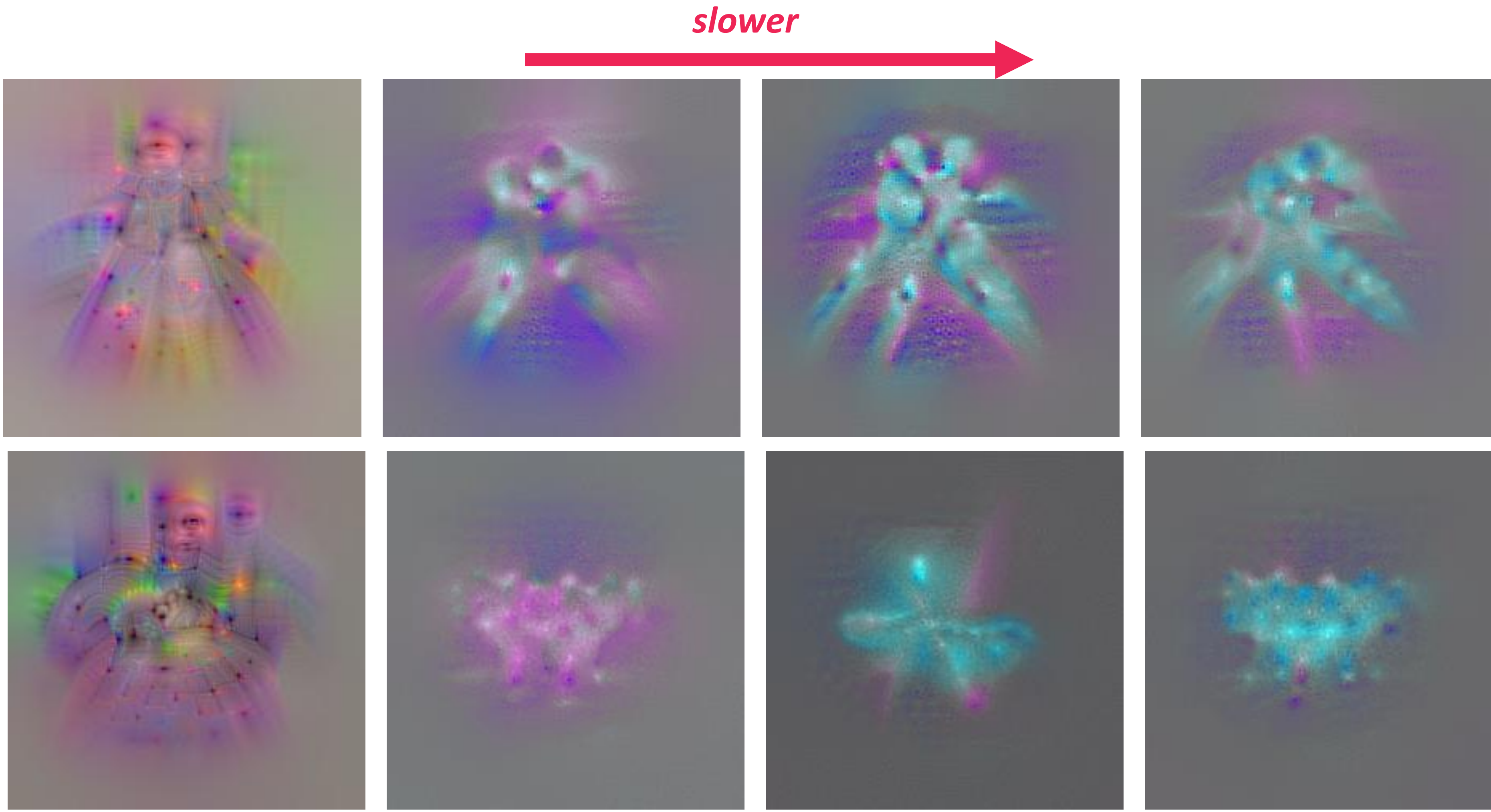

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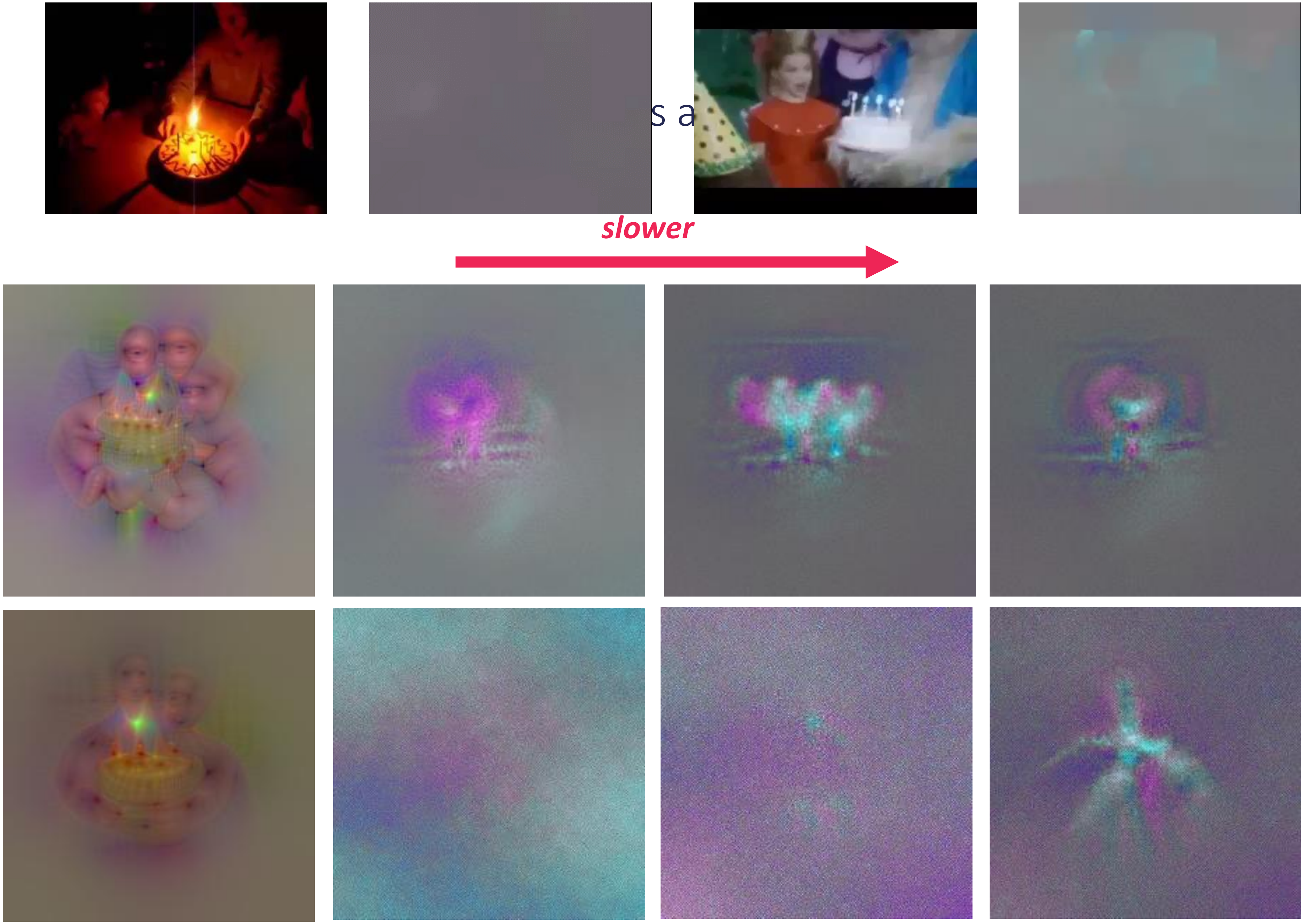

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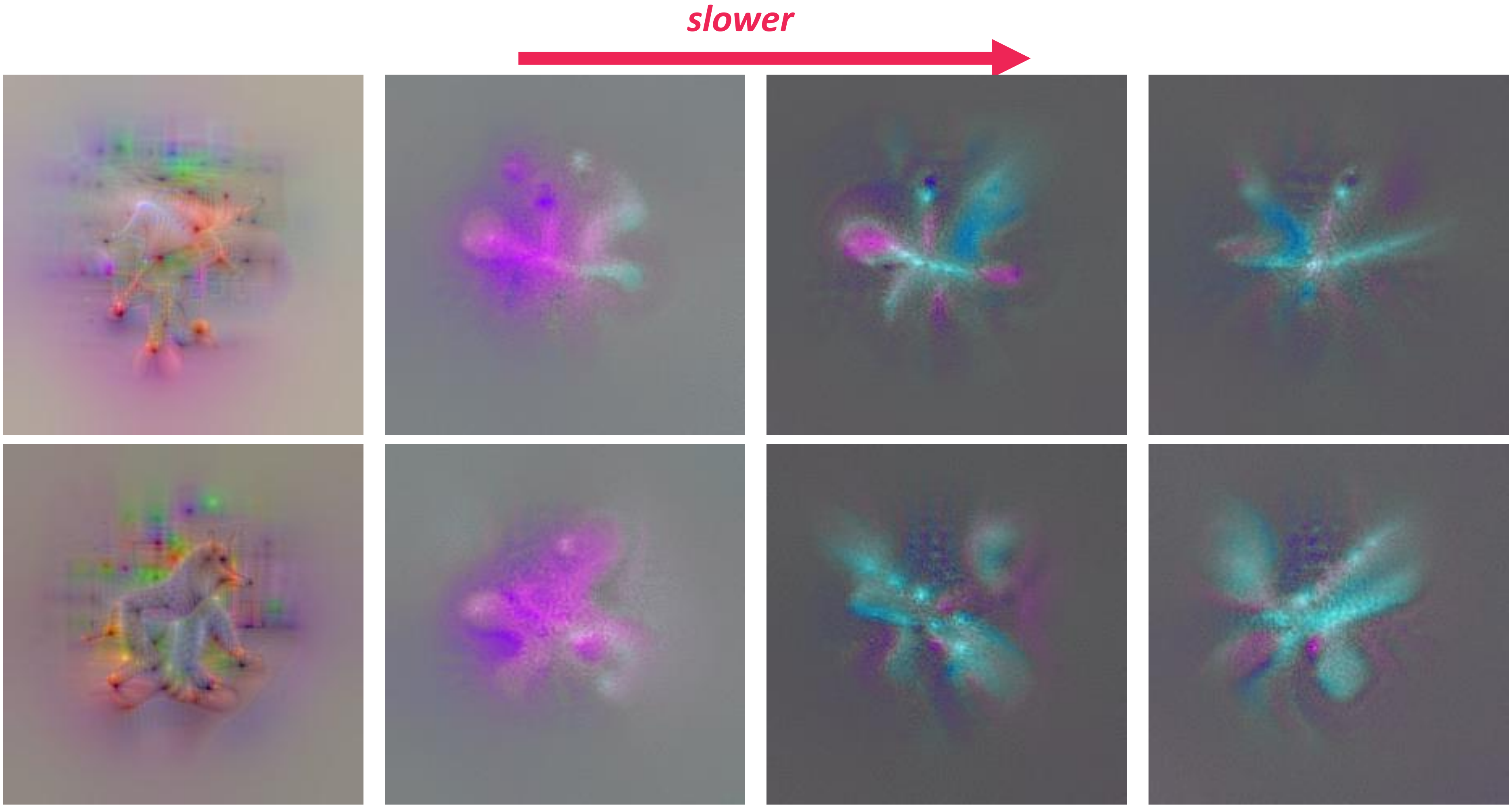

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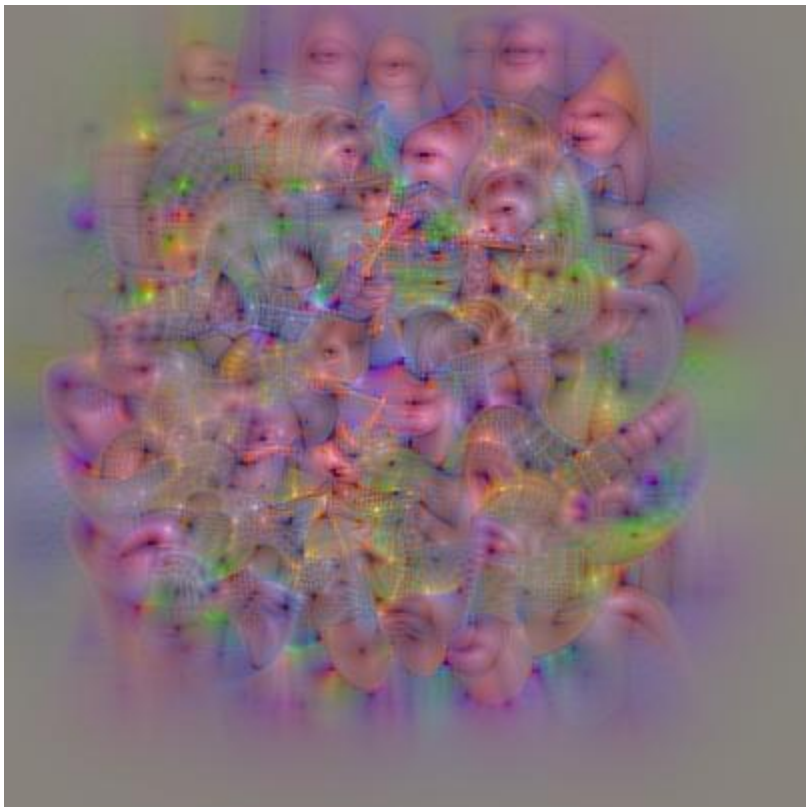
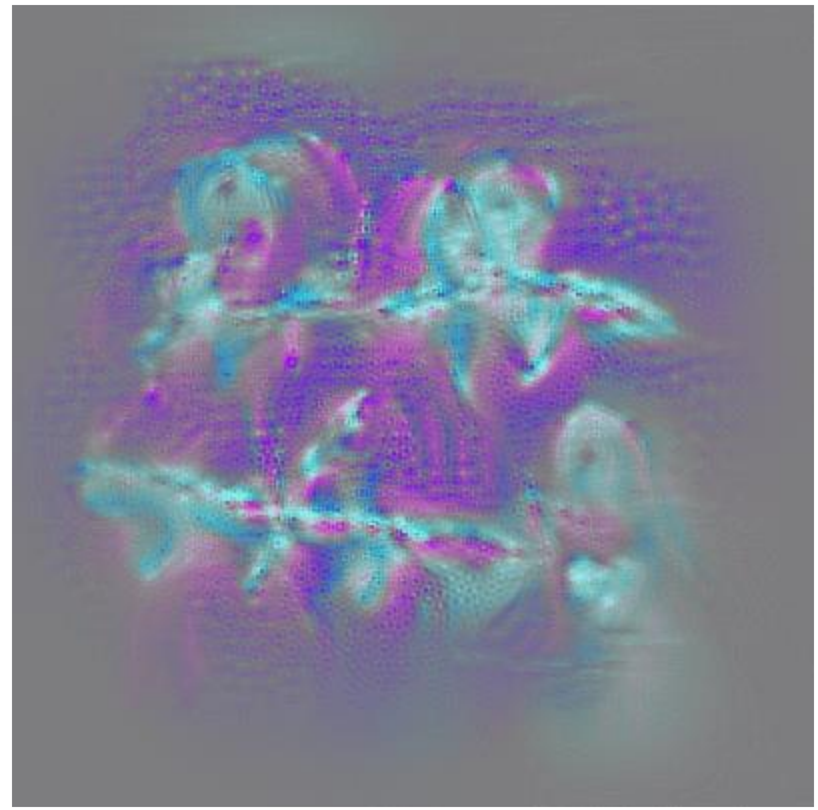
FC 6 (4096 features; RF 404x404)

Appearance



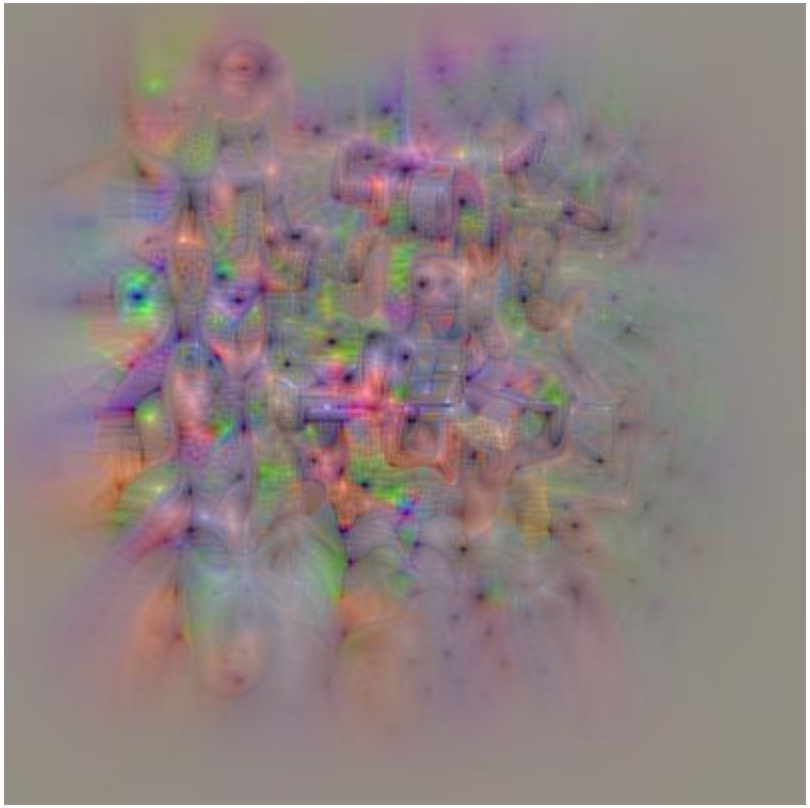
Slow motion



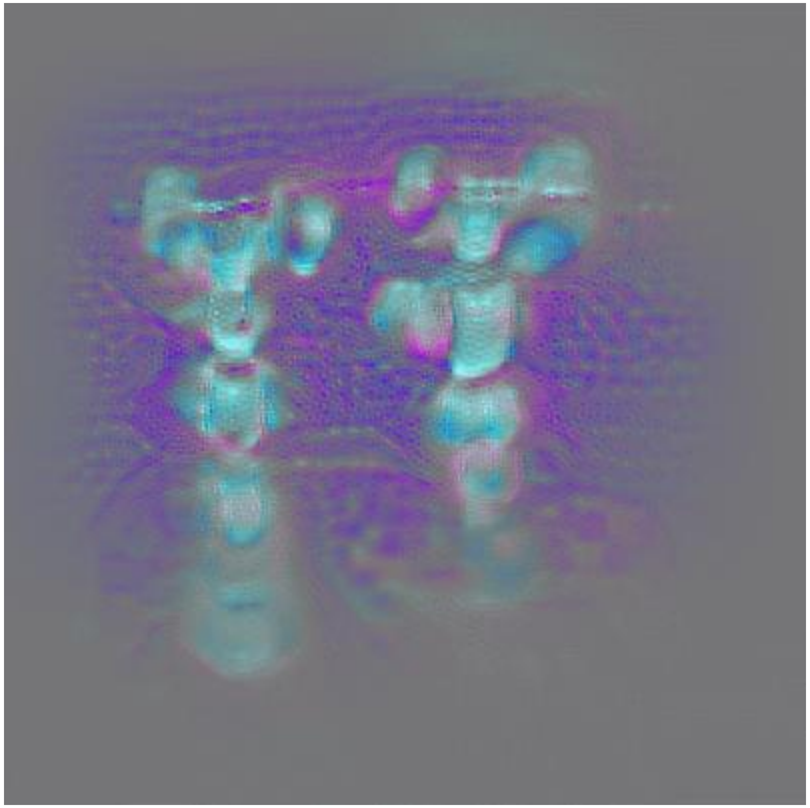
Feichtenhofer, PhD Thesis 2017

FC 7 (4096 features; RF 404x404)

Appearance



Slow motion



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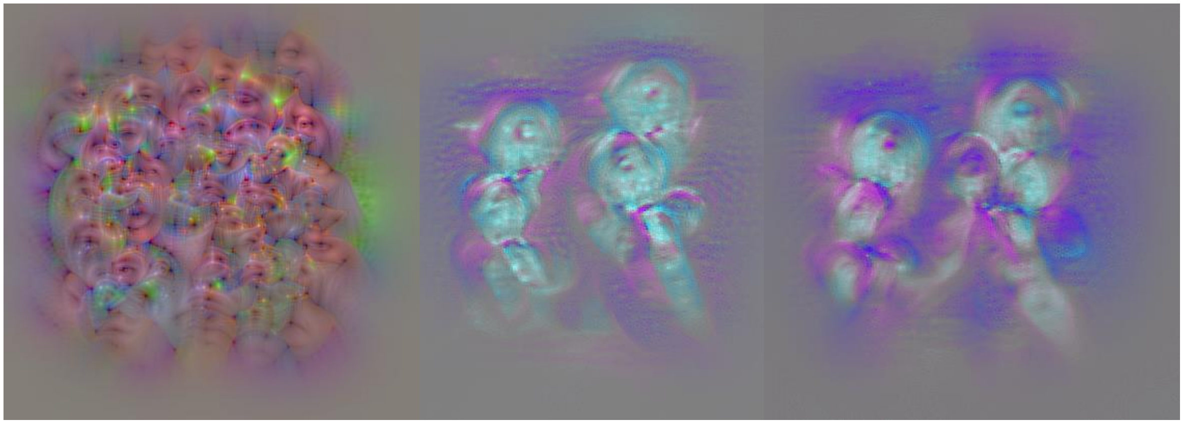
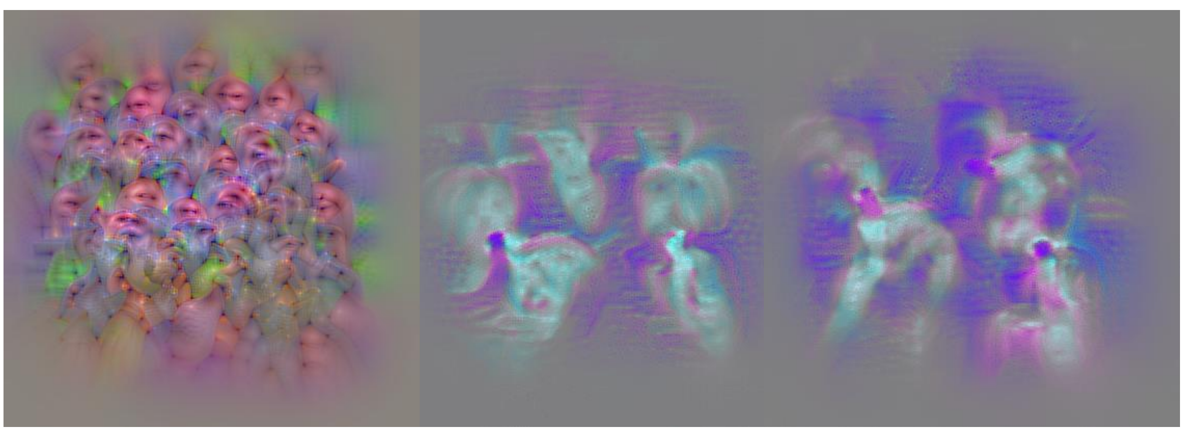
Explaining failure cases:

Appearance | Slow motion | Fast motion



BrushingTeeth 52% accuracy

(33% confused with ShavingBeard)



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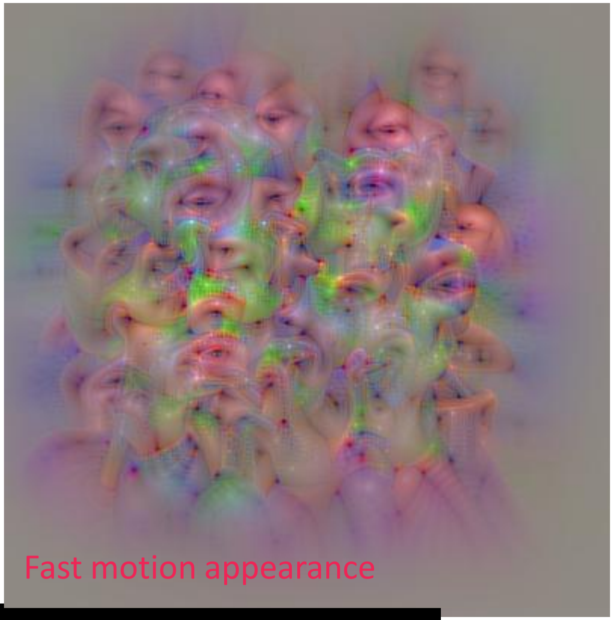
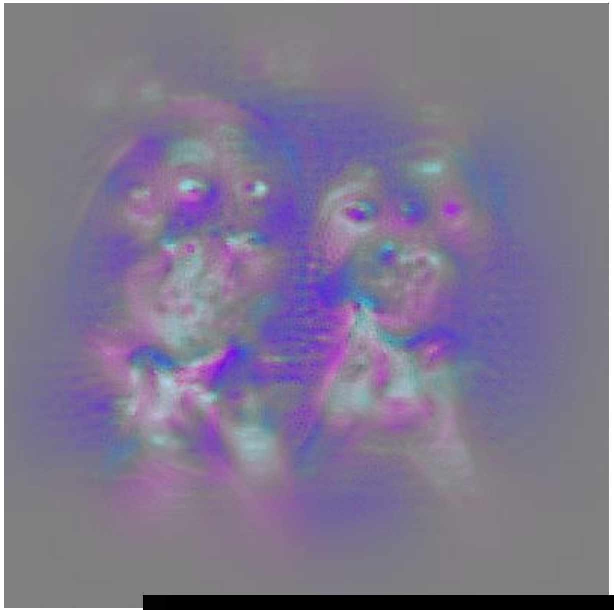
Revealing idiosyncracies in data

➔ "ApplyLipstick"

Appearance | Slow motion | Fast motion





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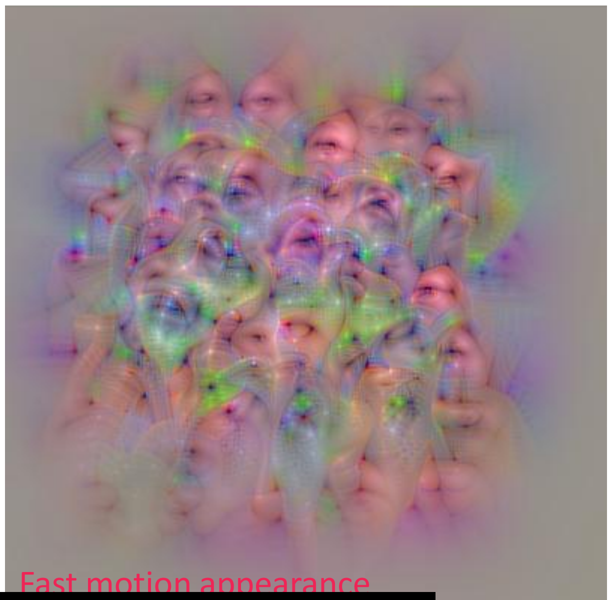
Revealing idiosyncracies in data

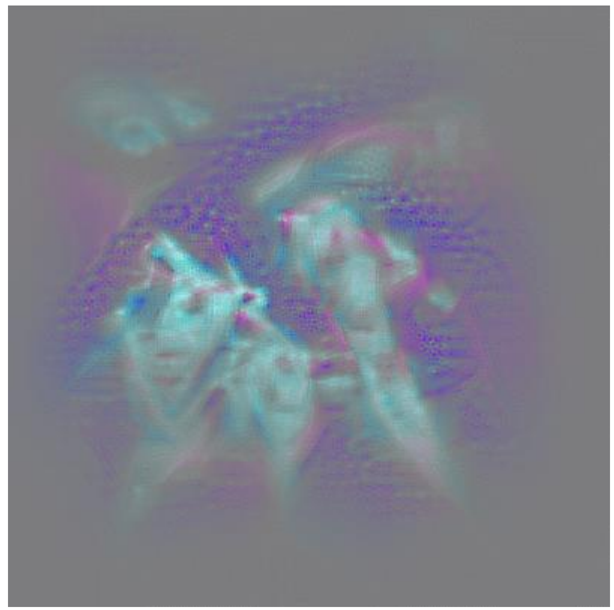
➔ "ApplyEyeMakeup"

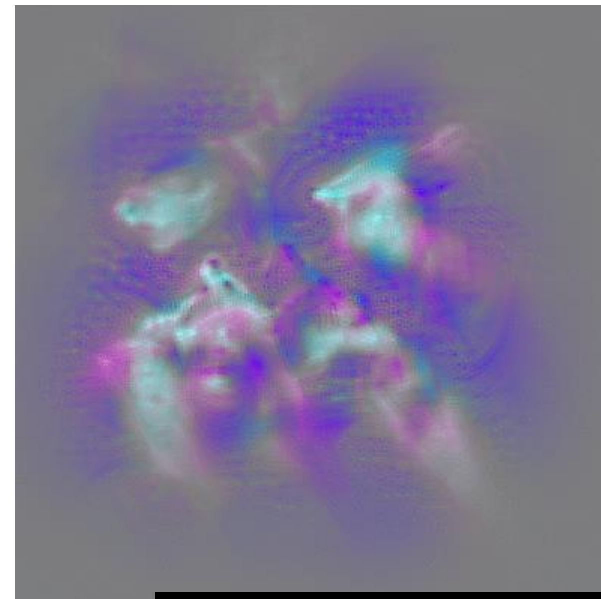
Appearance

Slow motion

Fast motion







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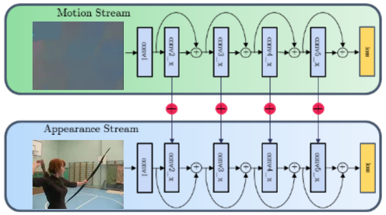
Summary of our insights

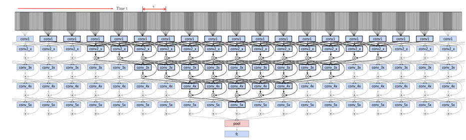
We study ways of connecting appearance and motion ConvNets

spatially



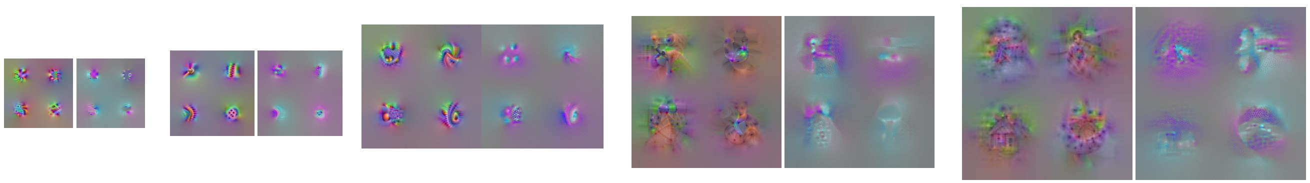
and

temporally

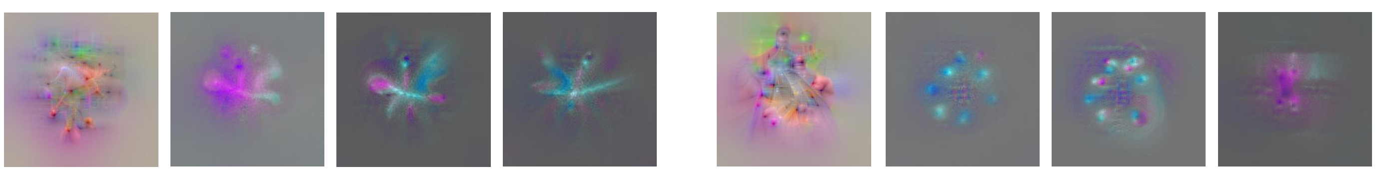


By visualizing the learned representation we find that:

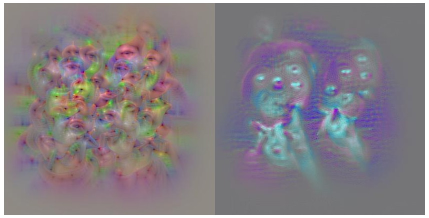
- Early layers show similar spatial structures for appearance and flow



- Higher layer conv-fusion-filters are broadly tuned to multiple speeds and can be specific but also generic across classes



- Class visualizations aid in analyzing system strengths and weaknesses



vs.