Computer Vision

Lecture 10 Deep Learning for Video: Action Recognition

References

- Basic reading: Szeliski, Chapter 6.5

Motivation: video classification

track cycling cycling
track cycling
road bicycle racing
marathon
ultramarathon

ultramarathon
ultramarathon
half marathon
running
marathon
inline speed skating

heptathlon
heptathlon
decathlon
hurdles
pentathlon sprint
(running)

bikejoring
mushing
bikejoring
harness racing
skijoring
carting

longboarding
longboarding aggressive
inline skating freestyle
scootering freeboard
(skateboard) sandboarding

ultimate (sport)
ultimate (sport)
hurling flag football
association football
rugby sevens

Activity classification is **the task of identifying a pre-defined set of physical actions (gestures, actions, human-object interactions, interactions, group activities)**

Karpathy, A., Toderici, G., Shetty, S., Leung, T., Sukthankar, R., & Fei-Fei, L. Large-scale video classification with convolutional neural networks. CVPR2014.

What is a video?

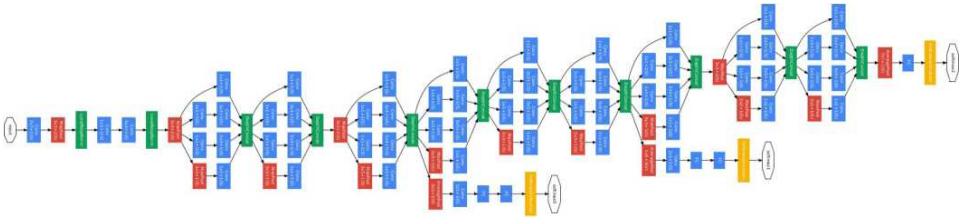
- Formally, a video is a 3D signal

  - Spatial coordinates: x, y
  - Temporal coordinate: t

- If we fix t, we obtain an image. We can understand videos as sequences of images (a.k.a. frames)

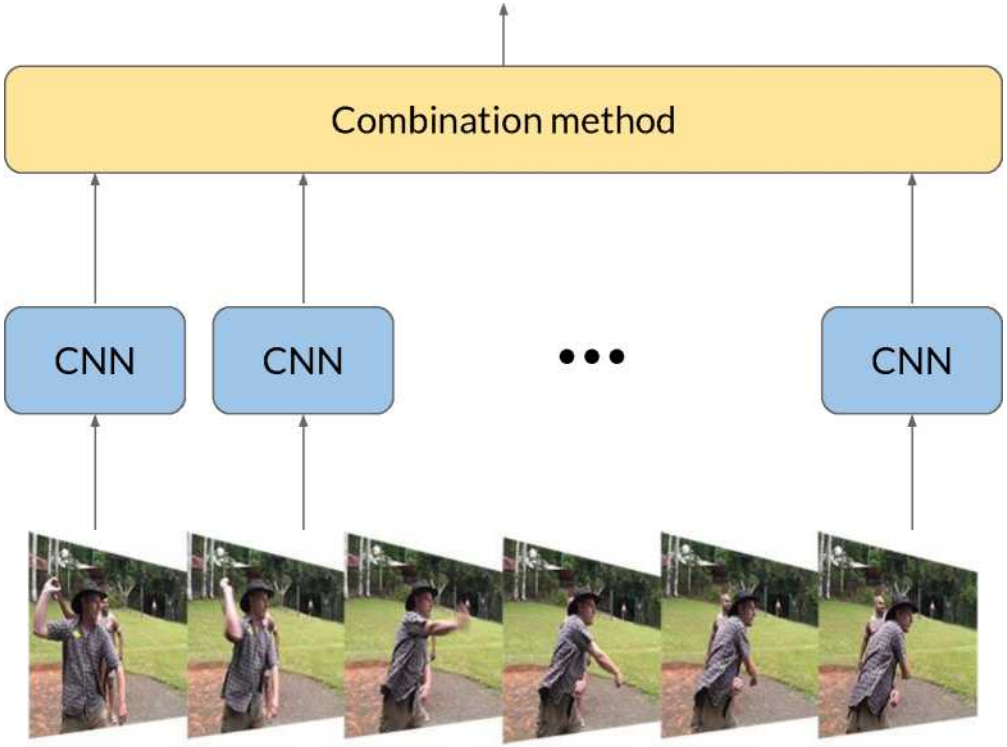
How do we work with images?

Convolutional Neural Networks (CNN) provide state of the art performance on image analysis tasks

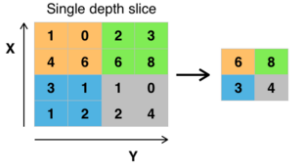


How do we work with videos? How can we extend CNNs to image sequences?

Single frame models



Combination is commonly implemented as a small NN on top of a pooling operation (e.g. max, sum, average).



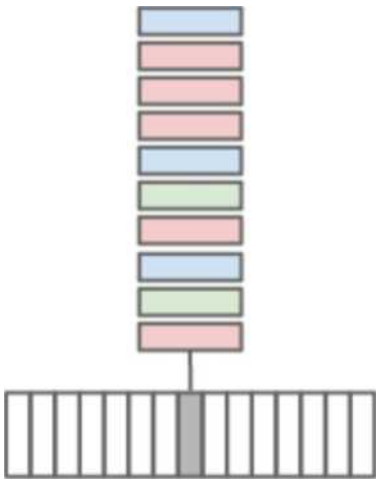
Pro: to reduce the resolution of the feature map retaining features required for classification

Cons: pooling is not aware of the temporal order!

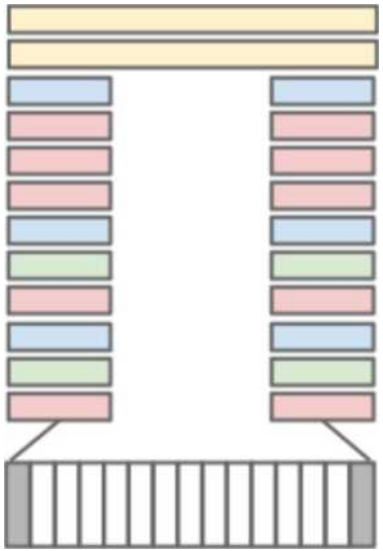
Multiple Frames

Explored approaches for fusing information over temporal dimension through the network

Single Frame

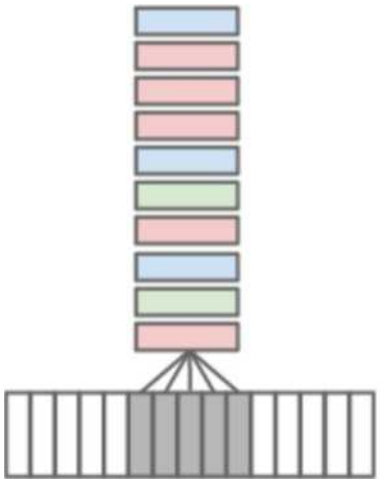


Late Fusion



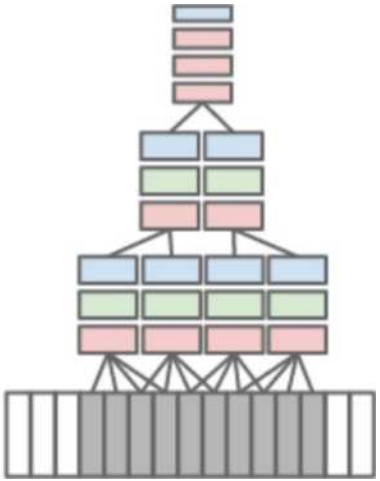
place two separate single-frame networks up to last conv layers with shared parameters a distance of 15 frames apart and then merge the two streams in the first fully connected layers

Early Fusion



11x11x3xT filters on the first convolutional layer
T=10 frames

Slow Fusion



Temporal and spatial convolutions

- Red, green and blue boxes indicate convolutional, normalization and pooling layers respectively.
- In the Slow Fusion model, the depicted columns share parameters

Karpathy, A., Toderici, G., Shetty, S., Leung, T., Sukthankar, R., & Fei-Fei, L. . Large-scale video classification with convolutional neural networks. CVPR 2014

Multiple Frames

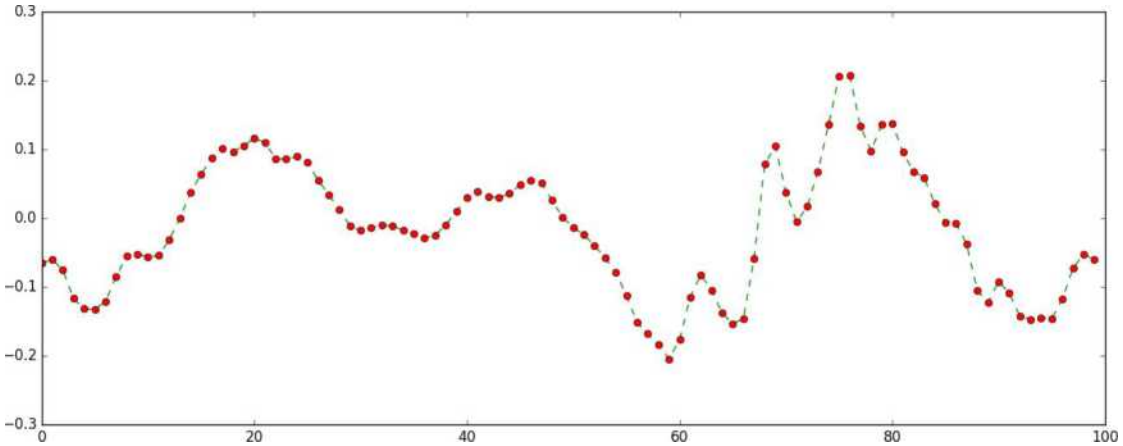
Model	Clip Hit@l	Video Hit@l	Video Hit @5
Feature Histograms + Neural Net	-	55.3	-
Single-Frame	41.1	59.3	77.7
Early Fusion	38.9	57.7	76.8
Late Fusion	40.7	59.3	78.7
Slow Fusion	**41.9**	**60.9**	**80.2**
CNN Average (Single+Early+Late+Slow)	41.4	63.9	82.4

Results on the 200,000 videos of the Sports-1M test set.
Hit@k values indicate the fraction of test samples that contained at least one of the ground truth labels in the top k predictions

Karpathy, A., Toderici, G., Shetty, S., Leung, T., Sukthankar, R., & Fei-Fei, L. . Large-scale video classification with convolutional neural networks. CVPR 2014

Limitation of Feed Forward NN (as CNNs)

If we have a sequence of samples...

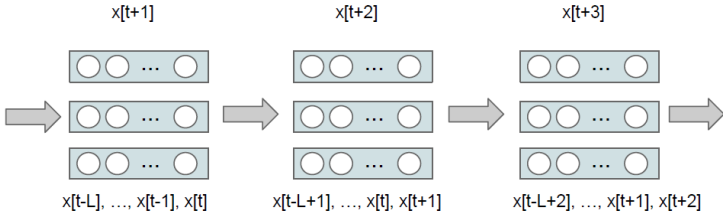


predict sample x[t+1] knowing previous values {x[t], x[t-1], x[t-2], x[t-T]}

Limitation of CNNs

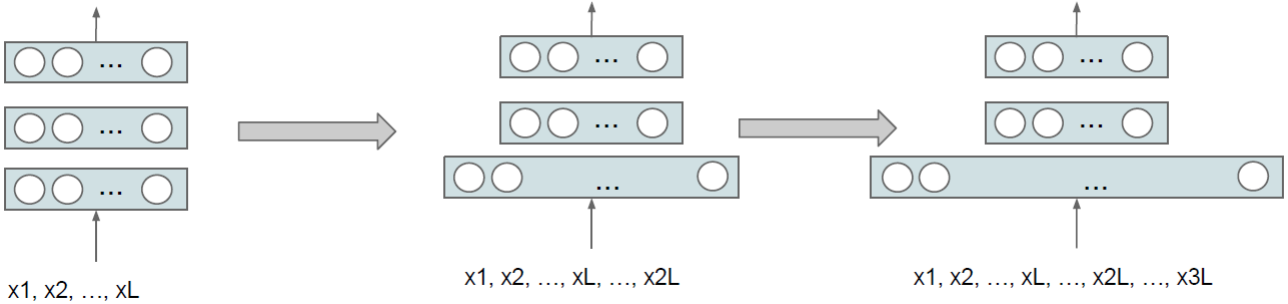
Feed Forward approach:

- static window of size L
- slide the window time-step wise

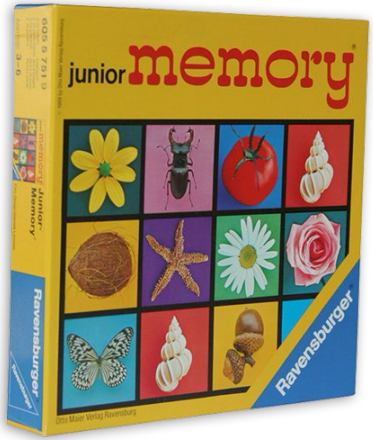


Problems for the feed forward + static window approach:

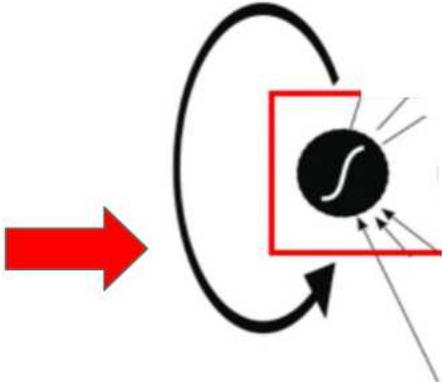
- What's the matter increasing L? —> Fast growth of num of parameters
- Decisions are independent between time-steps
  - The network doesn't care about what happened at previous time-step, only present window matters
- Cumbersome padding when there are not enough samples to fill L size
  - Can't work with variable sequence lengths



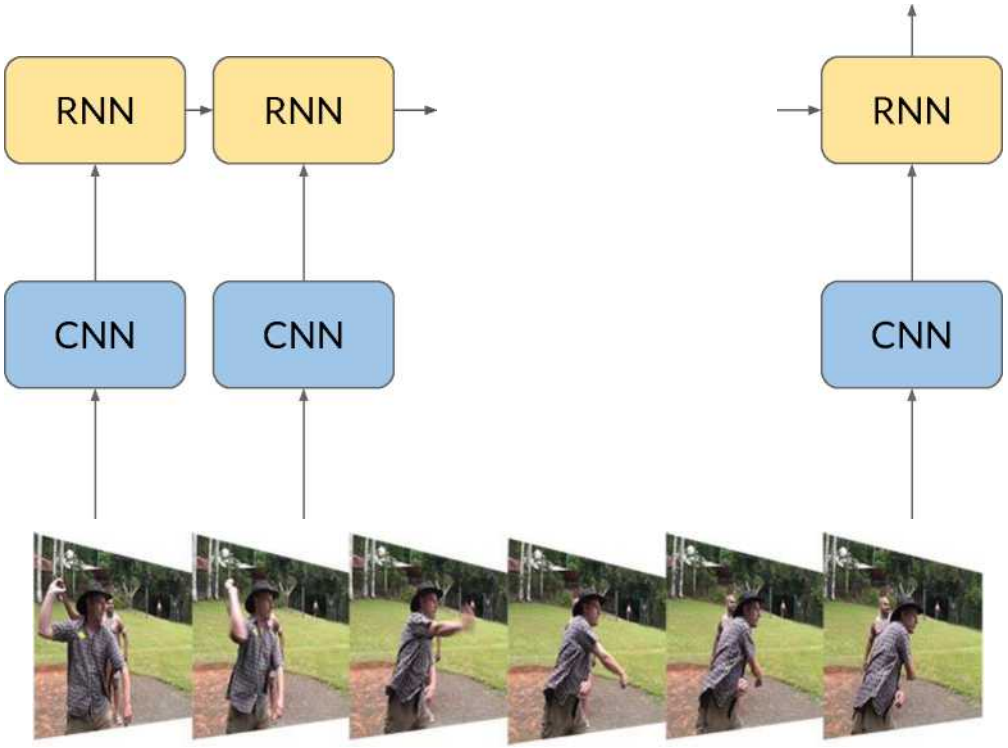
Recurrent Neural Network (RNN)



The hidden layers and the output depend from previous states of the hidden layers



2DCNN + RNN



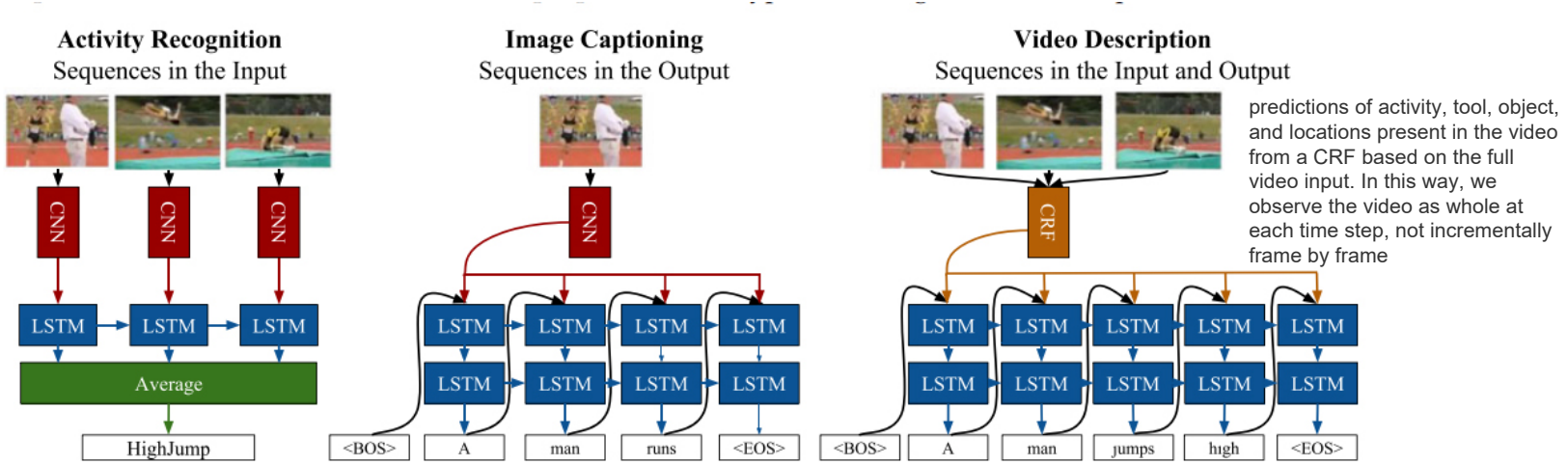
Pro: Recurrent Neural Networks are well suited for processing sequences.

- Used to model sequences of per-frame CNN representations

Cons: RNNs are sequential and cannot be parallelized.

Jeffrey Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Kate Saenko, Trevor Darrel. Long-term Recurrent Convolutional Networks for Visual Recognition and Description, CVPR 2015.

2D CNN + RNN

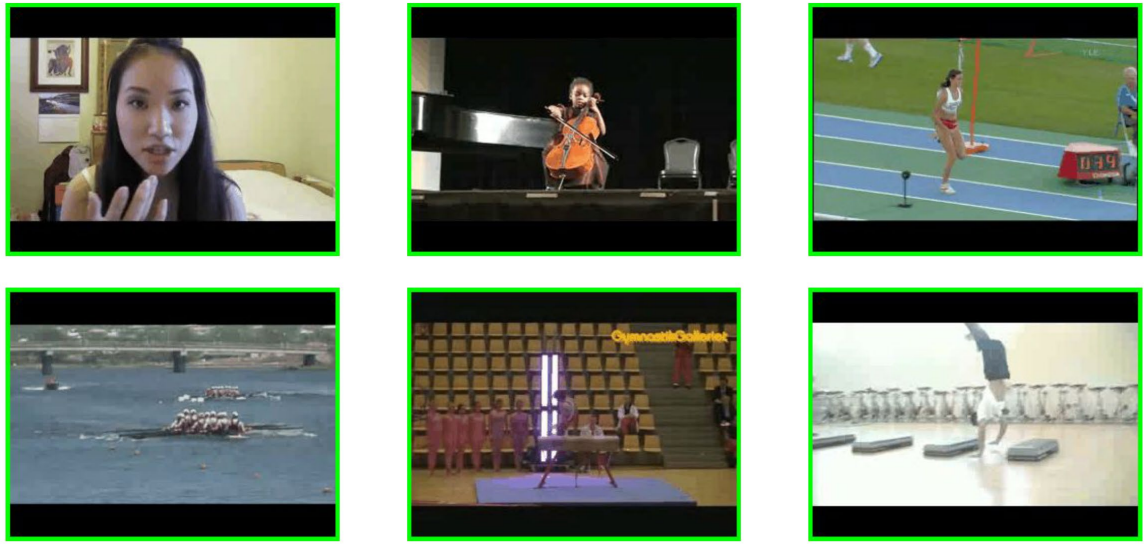


Long-term Recurrent Convolutional Networks (LRCNs)

- LRCN processes the (possibly) variable-length visual input (with a CNN, whose outputs are fed into a stack of recurrent sequence models (LSTMs), which finally produce a variable-length prediction.
- Both the CNN and LSTM weights are shared across time, resulting in a representation that scales to arbitrarily long sequences.

Jeffrey Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Kate Saenko, Trevor Darrel. Long-term Recurrent Convolutional Networks for Visual Recognition and Description, CVPR 2015.

2D CNN + RNN



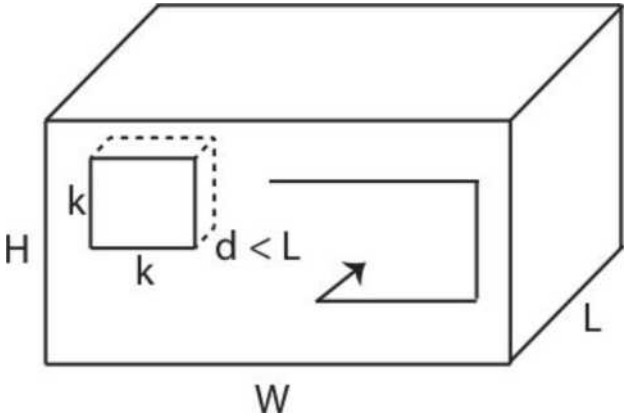
Used Unused

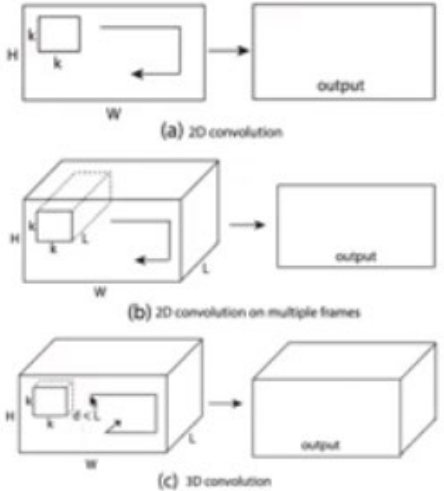
Victor Campos, Brendan Jou, Xavier Giro-i-Nieto, Jordi Torres, and Shih-Fu Chang. "Skip RNN: Learning to Skip State Updates in Recurrent Neural Networks", ICLR 2018.

3D CNN (C3D)

We can add an extra dimension to standard CNNs:

- An image is a HxWxD tensor: MxNxD' conv filters
- A video is a LxHxWxD tensor: KxMxNxD' conv filters

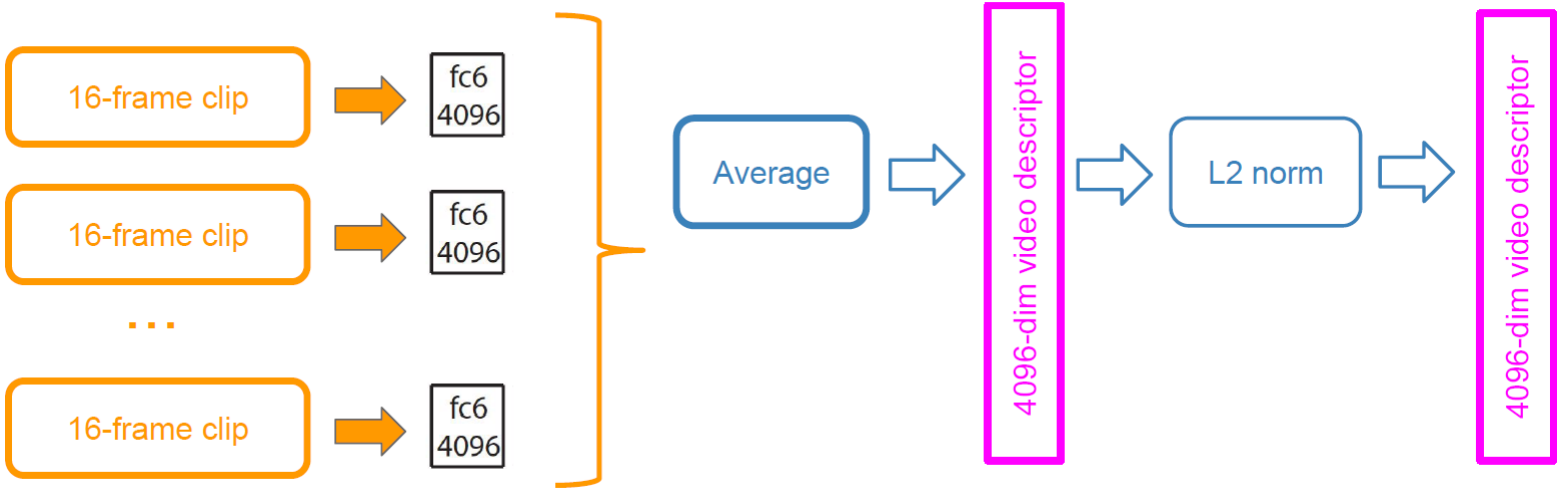




Tran, Du, Lubomir Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. "Learning spatiotemporal features with 3D convolutional networks" ICCV 2015

3D CNN (C3D)

The video needs to be split into chunks (also known as *clips)* with a number of frames that fits the receptive field of the C3D. Usually clips have 16 frames.



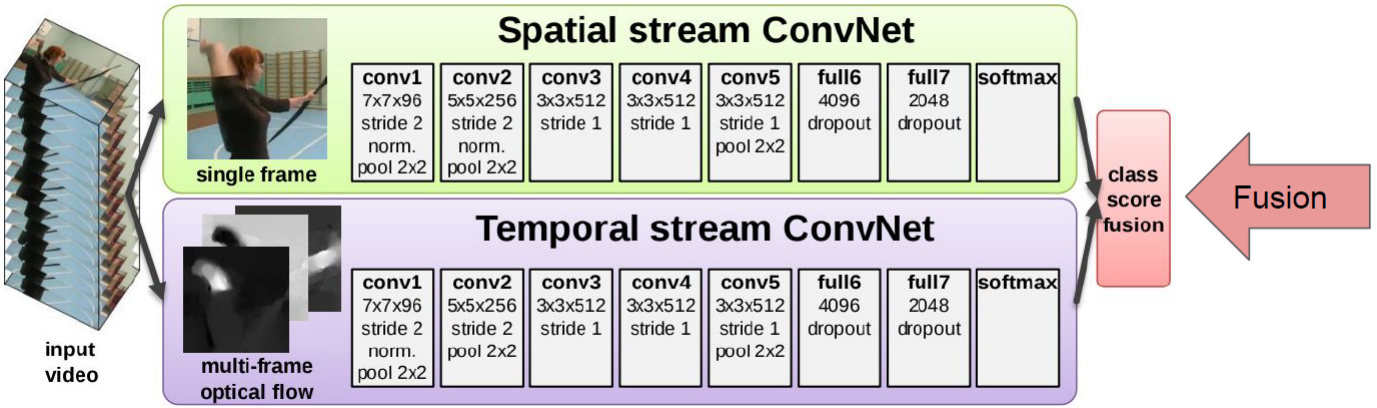
Limitations:

- How can we handle longer videos?
- How can we capture longer temporal dependencies?

Two-streams 2D CNNs

Problem: Single frame models do not take into account motion in videos.

Solution: extract optical flow for a stack of frames and use it as an input to a CNN.



Simonyan, Karen, and Andrew Zisserman. "Two-stream convolutional networks for action recognition in videos." NIPS 2014.

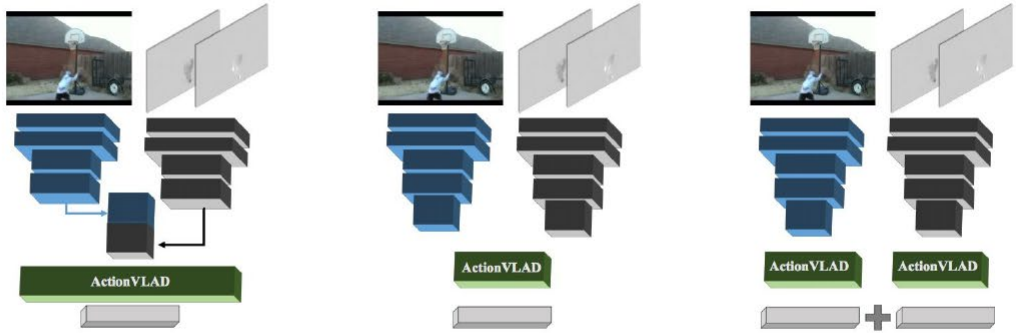
Two-streams 2D CNNs

Vector of Locally Aggragated Descriptor

Effect of training (rgb/flow)

Two-Stream	VLAD	ActionVLAD
47.1/55.2	44.9/55.6	51.2/58.4

How to fuse RGB and Flow?



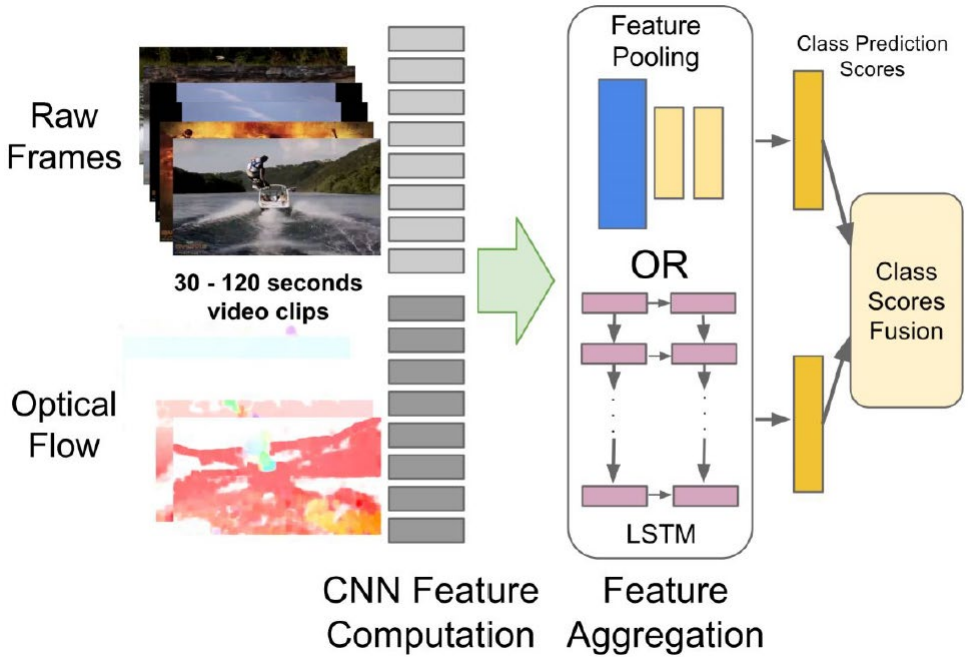
ActionVLAD pooling across space and time

Concat Fuse	Early Fuse	Late Fuse
56.0	64.8	66.9

https://github.com/rohitgirdhar/ActionVLAD

Girdhar, Rohit, Deva Ramanan, Abhinav Gupta, Josef Sivic, and Bryan Russell. "ActionVLAD: Learning spatio-temporal aggregation for action classification." CVPR 2017.

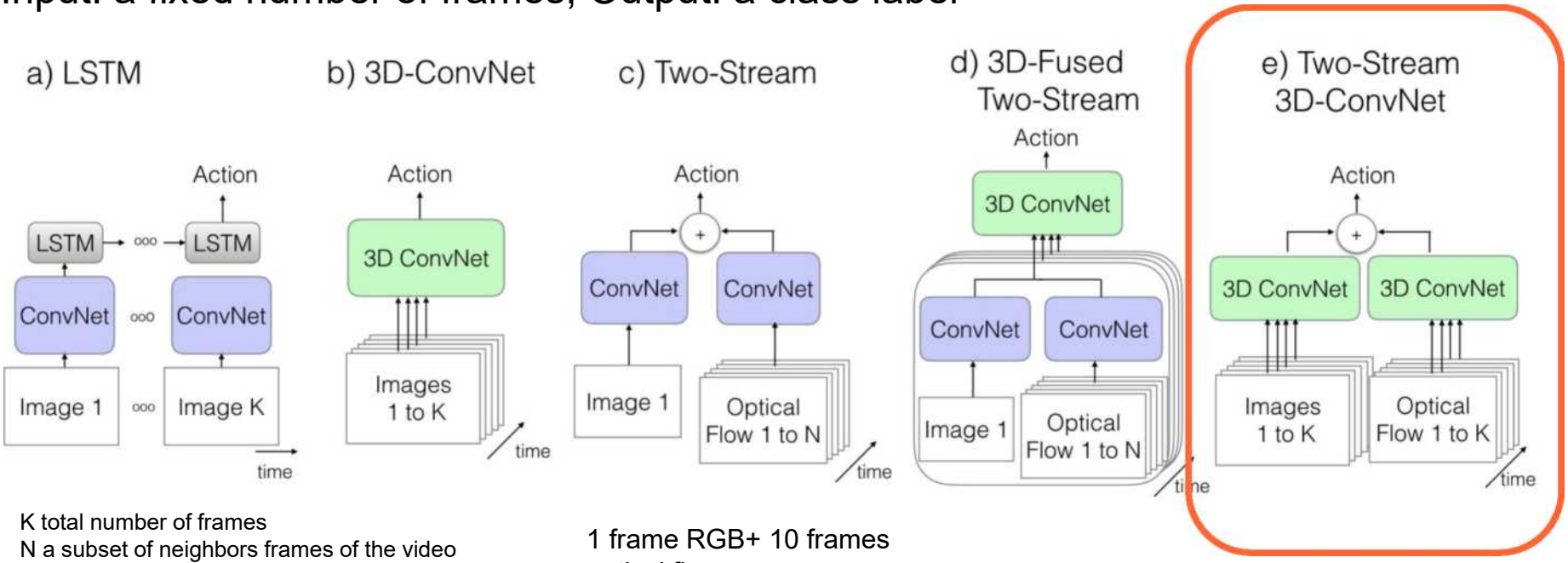
Two-streams 2D CNNs + RNN



Yue-Hei Ng, Joe, Matthew Hausknecht, Sudheendra Vijayanarasimhan, Oriol Vinyals, Rajat Monga, and George Toderici. "Beyond short snippets: Deep networks for video classification." CVPR 2015

Two-streams 3D CNNs

Input: a fixed number of frames, Output: a class label



K total number of frames
N a subset of neighbors frames of the video

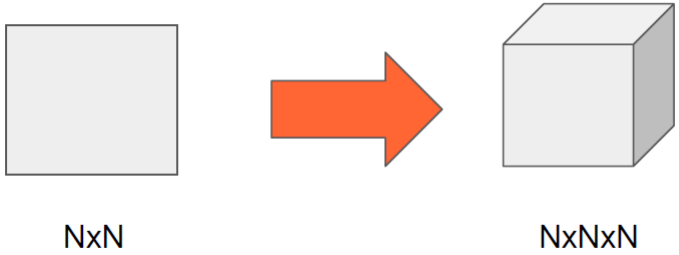
1 frame RGB+ 10 frames optical flows

15-99 frames

Carreira, J., & Zisserman, A. . Quo vadis. action recognition? A new model and the kinetics dataset. CVPR 2017.

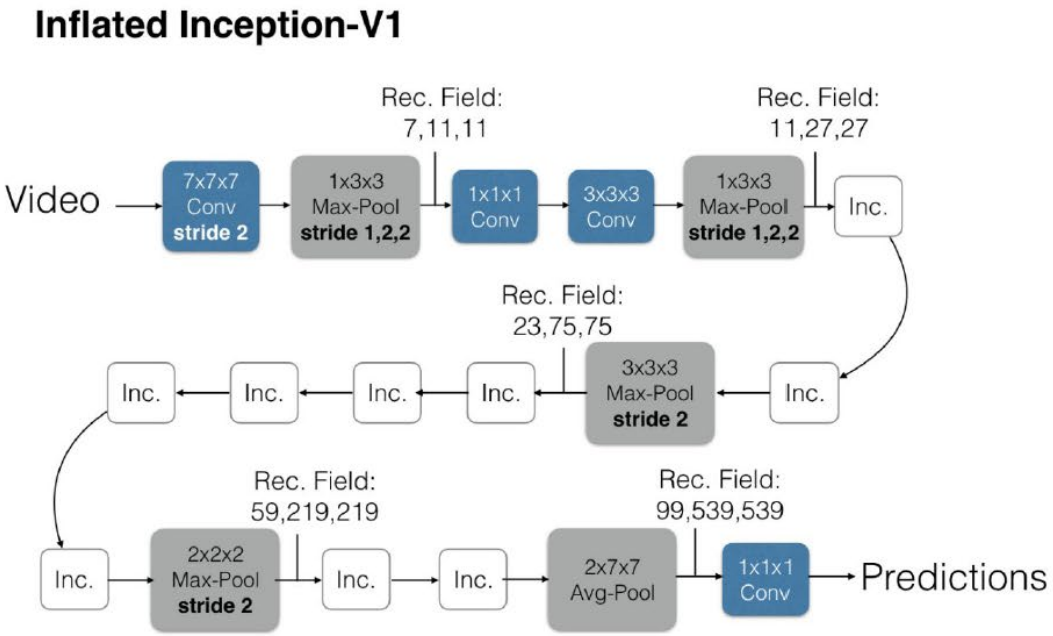
Two-streams Inflated 3D CNNs (I3D)

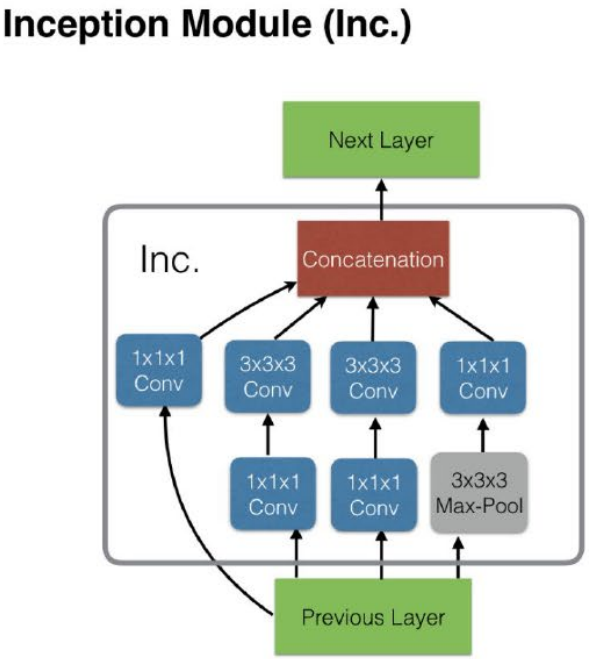
Adapt 2D CNNs found for ImageNet classification to 3D convolutions
Repeating the weights of the 2D filters N times along the time dimension
and rescaling them by dividing by N



- 3D models are initialized with ImageNet images transformed into 'boring' video sequences.
- Train the two networks separately and average their prediction at test time
- Inception architecture

Two-streams 3D CNNs





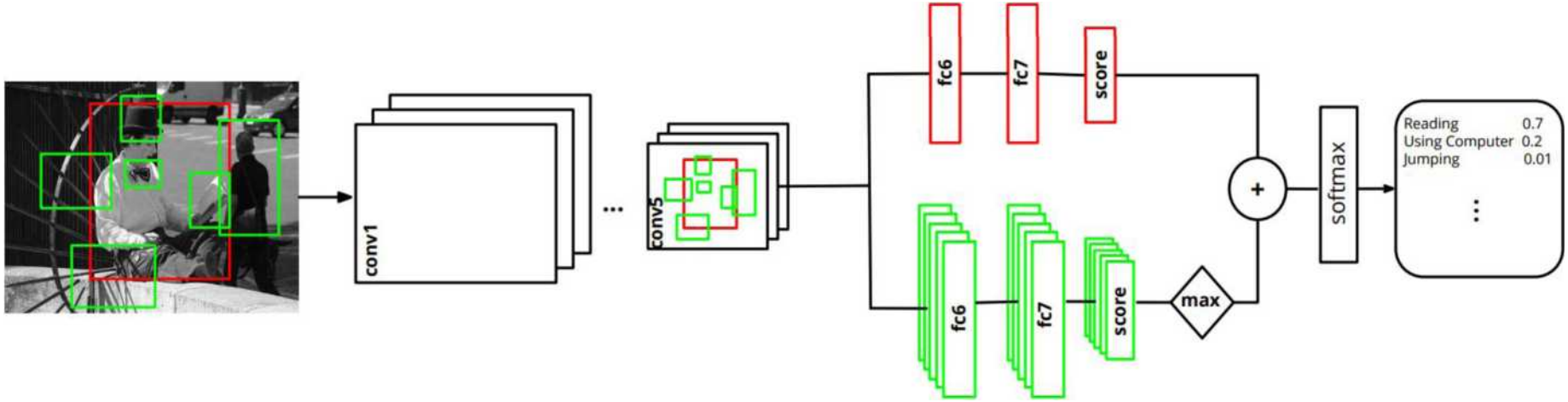
CNNs for sequences of images

CNN Input	RGB	Optical Flow	Fusion
Single frame	2D CNN	-	Pooling + NN
Multiple frames	2D CNN	-	Pooling + NN
Sequence of images	2D CNN	-	RNN
Sequence of clips	3D CNN	-	Pooling
Sequence of clips	3D CNN	-	RNN
Two-stream	2D CNN	2D CNN	Pooling
Two-stream	2D CNN	2D CNN	RNN
Two-stream	Inflated 3D CNN	Inflated 3D CNN	Pooling

Action recognition

Which deep learning techniques at a local scale may help action recognition ?

Action Recognition with object detection



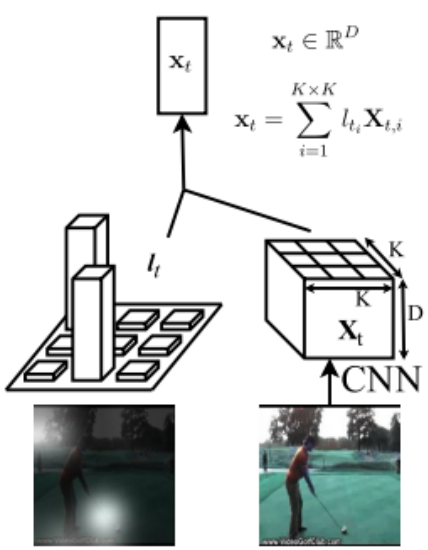
Gkioxari, Georgia, Ross Girshick, and Jitendra Malik. "Contextual action recognition with R*CNN." In ICCV 2015.

Action Recognition with attention

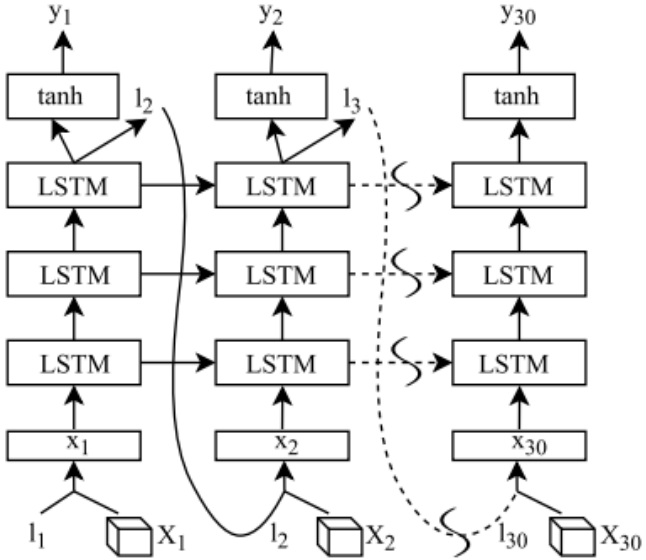
The CNN takes the video frame as its input and produces a feature cube. The model computes the current input xt as an average of the feature slices weighted by the location softmax lt (1b)

At each timestep t, the recurrent network takes a feature slice xt, generated as in (1a), as the input.

It then propagates xt through three layers of LSTMs and predicts the next location probabilities lt+1 and the class label yt.



(a) The soft attention mechanism



(b) Our recurrent model

Sharma, Shikhar et al. “Action Recognition using Visual Attention.” ICLR 2016

Action Recognition with soft attention

Action recognition with soft attention

Class-agnostic bottom-up attention

Class-specific top-down attention

Combined Attention

Action = "playing with animal"

Girdhar, Rohit, and Deva Ramanan. "Attentional pooling for action recognition." NIPS 2017

Soft vs Hard Attention model

Hard attention:

- Attent to a single input location.
- Can’t use gradient descent.
- Need **reinforcement learning.**

Soft attention:

- Compute a weighted combination (attention) over some inputs using an attention network.
- Can use backpropagation to train end-to-end.

Self-attention

- **Self-attention**, a highly **efficient** technique that makes it possible to update the embeddings of every word in the input text in **parallel**.
- **Self-attention**, also known as **intra-attention**, is an attention mechanism relating different positions of a single sequence in order to compute a representation of the same sequence.
    - It has been shown to be very useful in machine reading, abstractive summarization, or image description generation.

Action recognition with trajectory

Action recognition with trajectory pooled convolutional descriptors
[Wang et al. CVPR15]

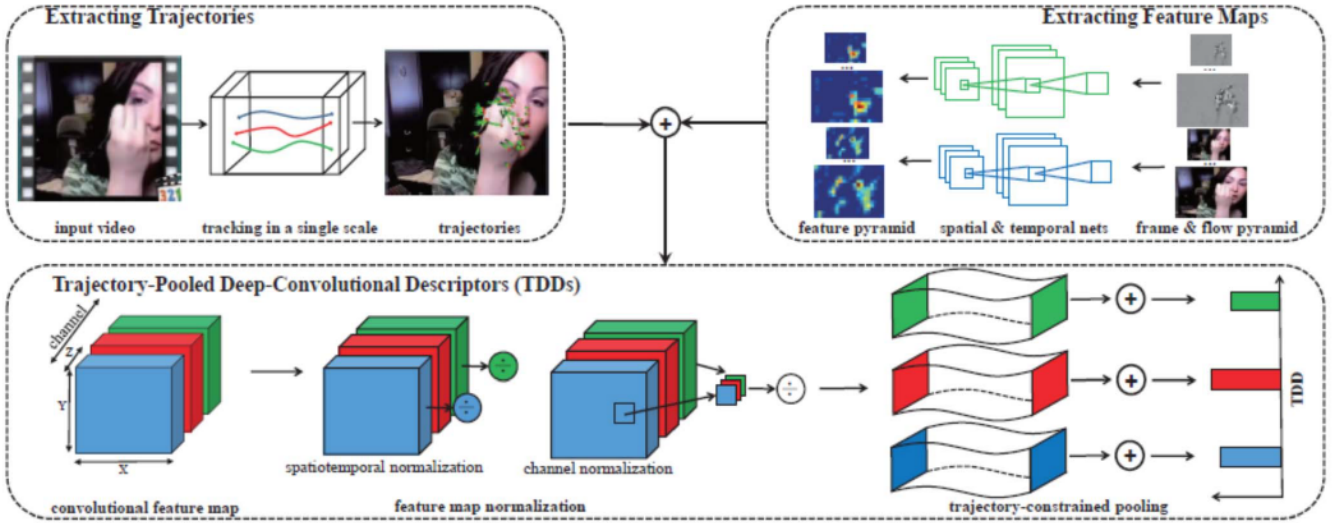
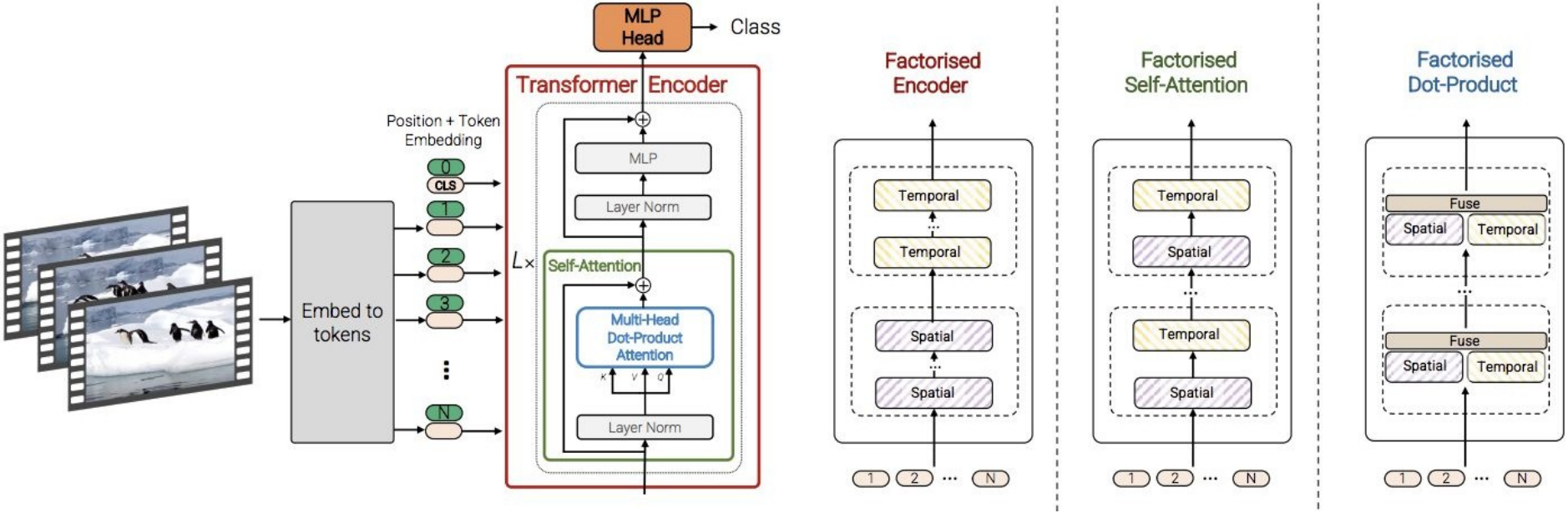


Figure 2. **Pipeline of TDD.** The whole process of extracting TDD is composed of three steps: (i) extracting trajectories, (ii) extracting multi-scale convolutional feature maps, and (iii) calculating TDD. We effectively exploit two available state-of-the-art video representations, namely improved trajectories and two-stream ConvNets. Grounded on them, we conduct trajectory-constrained sampling and pooling over convolutional feature maps to obtain trajectory-pooled deep convolutional descriptors.

Video ViT



[Arnab et al 2021]

Video ViT

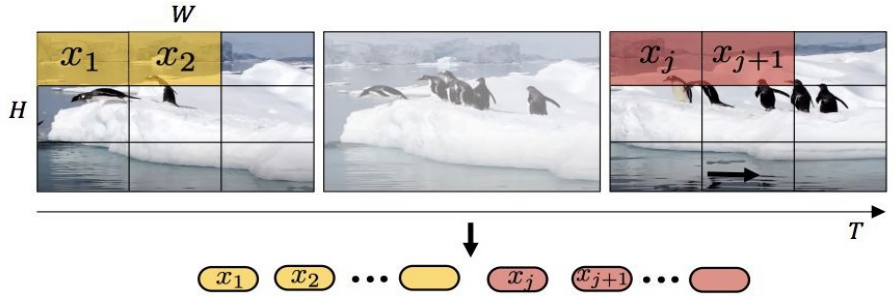


Figure 2: Uniform frame sampling: We simply sample n_t frames, and embed each 2D frame independently following ViT [15].

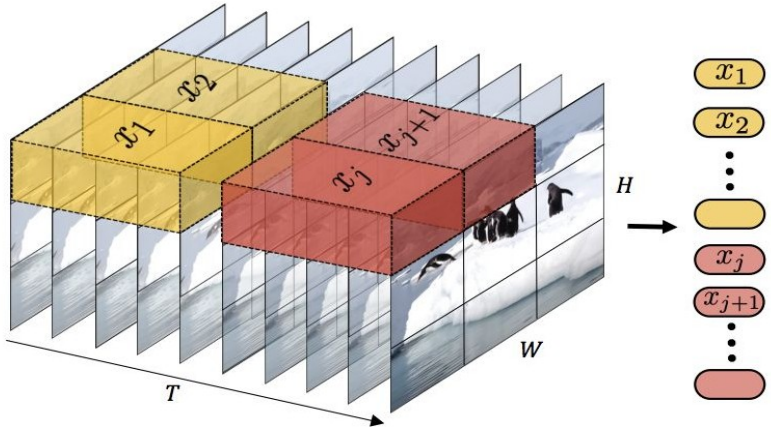
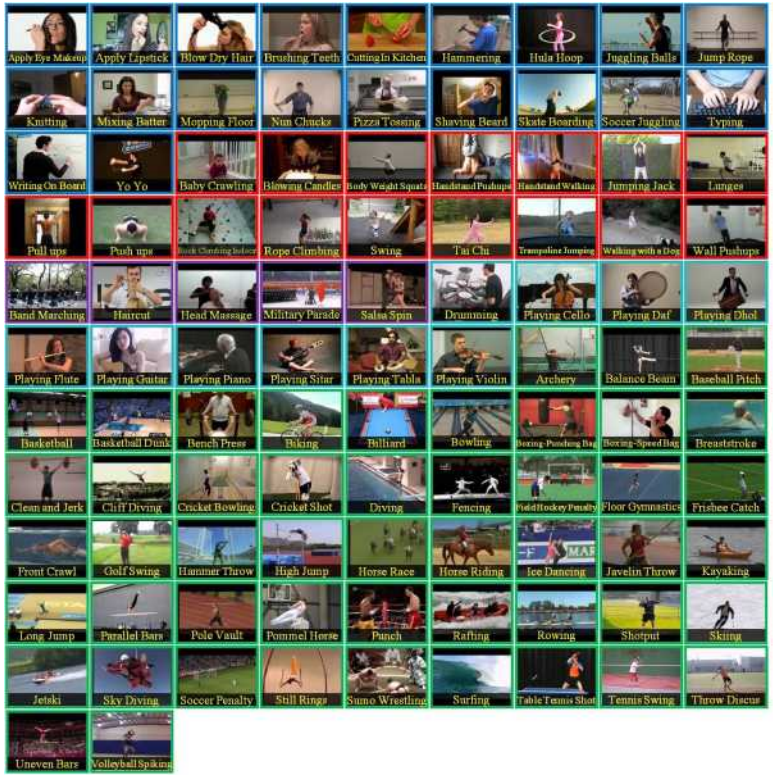
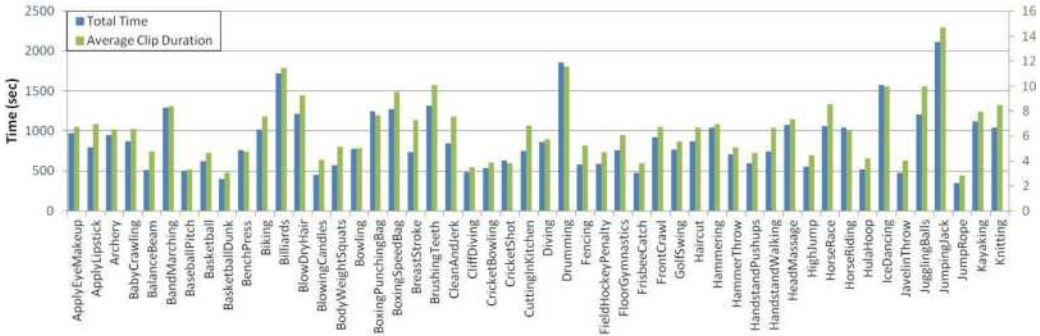


Figure 3: Tubelet embedding. We extract and linearly embed non overlapping tubelets that span the spatio-temporal input volume

Arnab et al 2021

Datasets: UCF-101

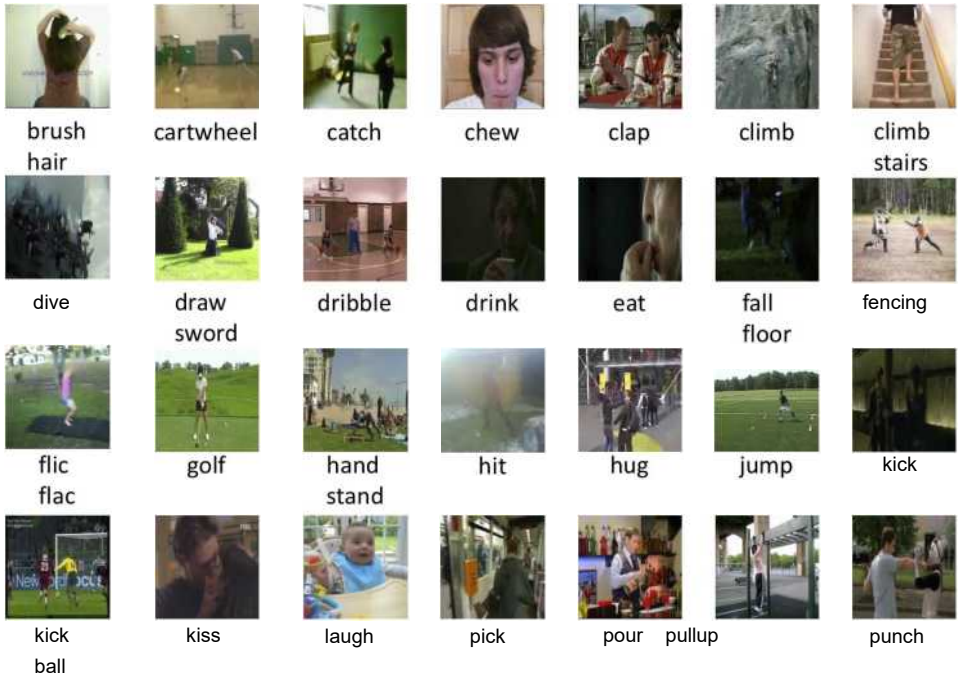




Youtube, 101 categories

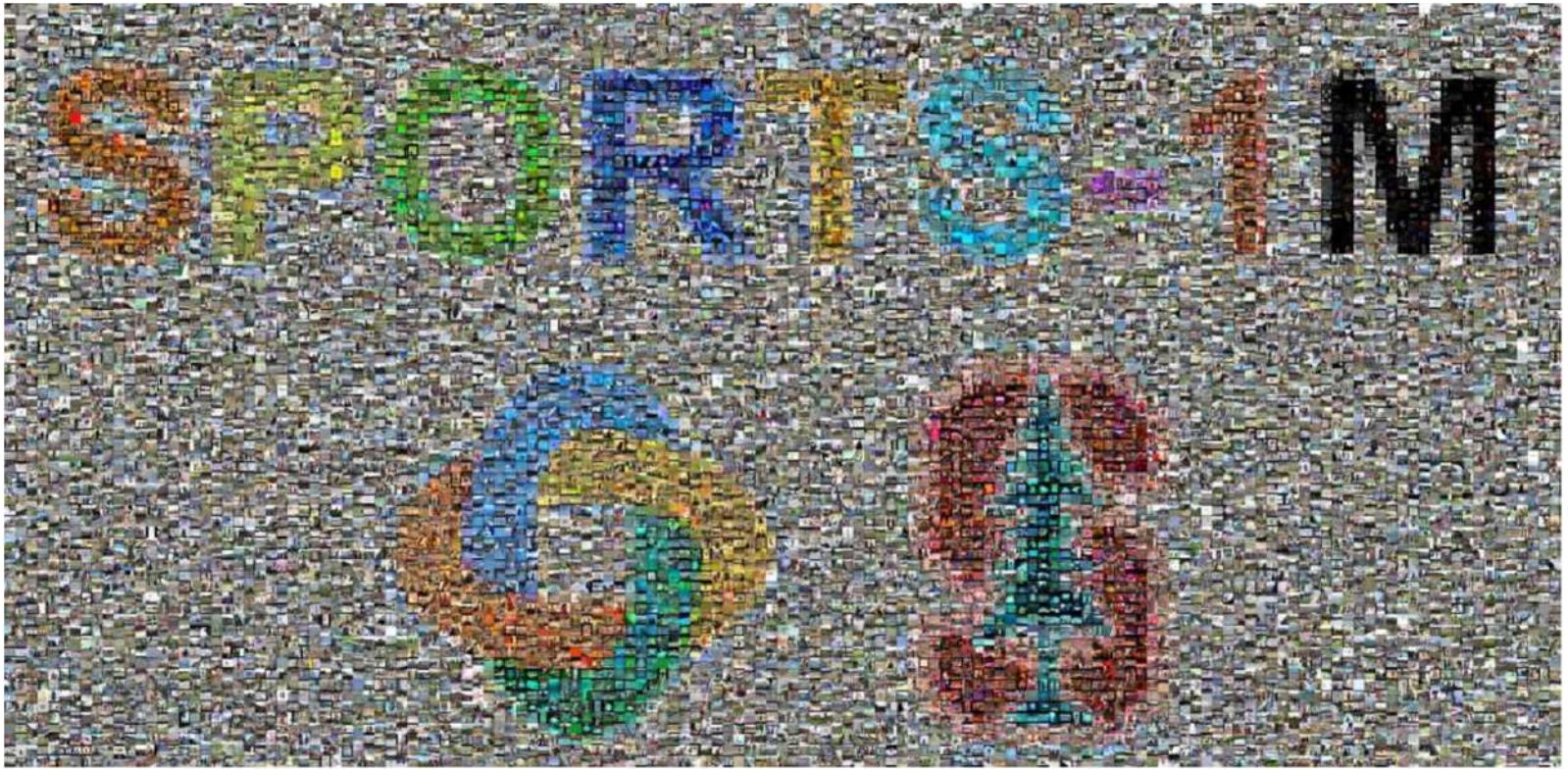
Soomro, K., Zamir, A. R., & Shah, M. (2012). UCF101: A dataset of 101 human actions classes from videos in the wild. arXiv preprint arXiv: 1212.0402.

Datasets: HDMB51 (Brown University)



Kuehne, Hildegard, Hueihan Jhuang, Estfbaliz Garrote, Tomaso Poggio, and Thomas Serre. ”HMDB: a large video database for human motion recognition." ICCV 2011.

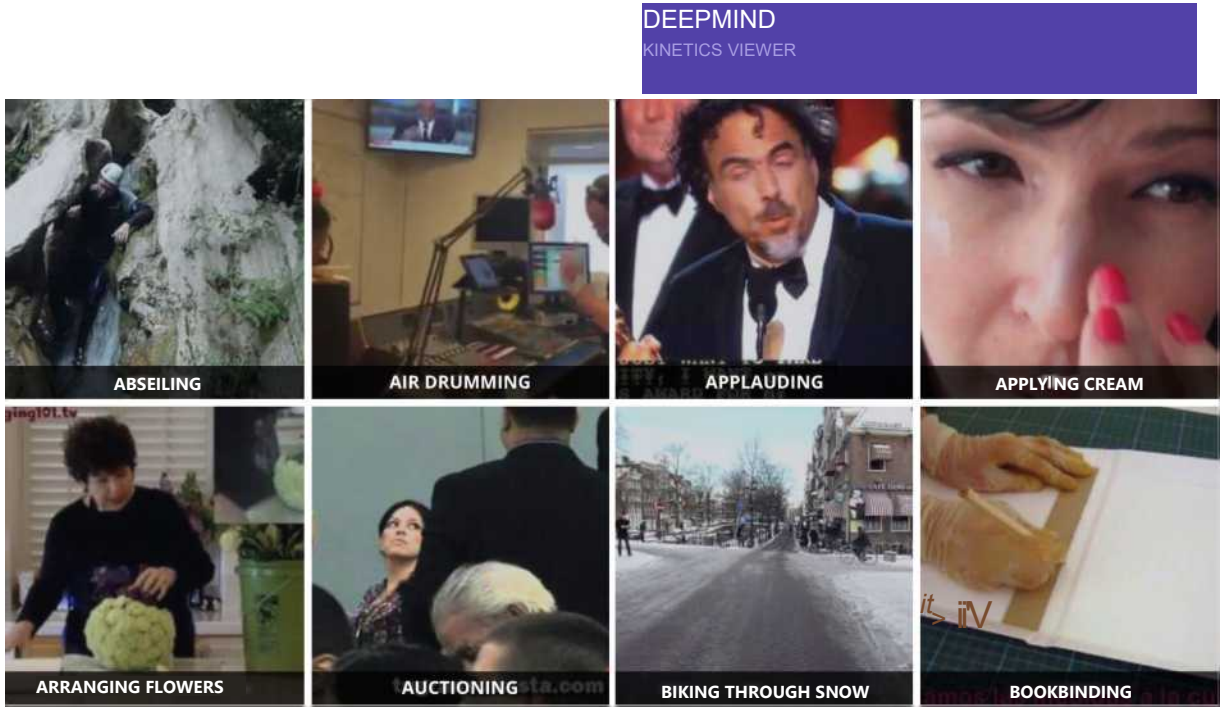
Datasets: Sports 1M (Stanford)



487 classes of sports

Karpathy, A., Toderici, G., Shetty, S., Leung, T., Sukthankar, R., & Fei-Fei, L. Large-scale video classification with convolutional neural networks. CVPR2014.

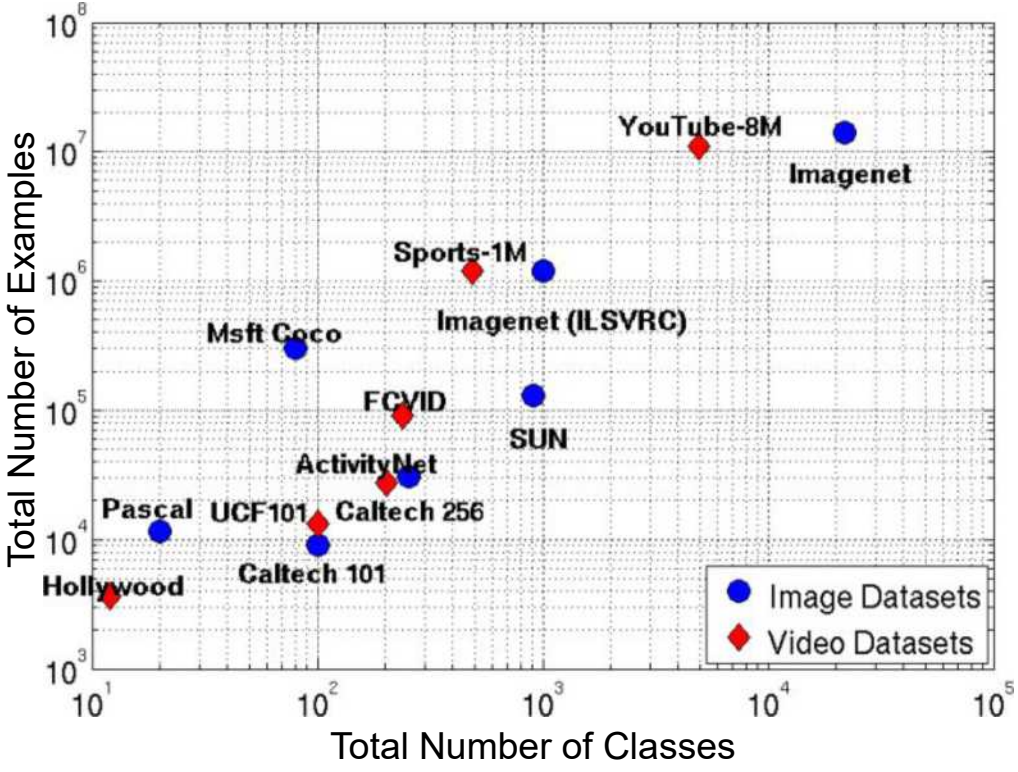
Datasets: Kinectics (DeepMind)



400 human action classes – 400 or more clips per class

Kay, W., Carreira, J., Simonyan, K., Zhang, B., Hillier, C., Vijayanarasimhan, S., ... & Suleyman, M. (2017). The kinetics human action video dataset. arXiv preprint arXiv:1705.06950.

Activity Recognition: Datasets



(Slides by Dfdac Surfs) Abu-El-Haija, Sami, Nisarg Kothari, Joonseok Lee, Paul Natsev, George Toderici, Balakrishnan Varadarajan, and Sudheendra Vijayanarasimhan. "Youtube-8m: A large-scale video classification benchmark." arXiv preprint arXiv:1609.08675 (2016).

Large-scale datasets

- The reference dataset for image classification, ImageNet, has ~1.3M images
  - Training a state of the art CNN can take up to 2 weeks on a single GPU
- Now imagine that we have an 'ImageNet' of 1.3M videos
  - Assuming videos of 30s at 24fps, we have 936M frames
  - This is 720x ImageNet!
- Videos exhibit a large redundancy in time
  - We can reduce the frame rate without losing too much information

- Tips & Tricks bv Victor Campos (2017)

Memory issues

- Current GPUs can fit batches of 32~64 images when training state of the art CNNs
  - This means 32~64 video frames at once
- Memory footprint can be reduced in different ways if a pre-trained CNN model is used
  - Freezing some of the lower layers, reducing the memory impact of backprop
  - Extracting frame-level features and training a model on top of it (e.g. RNN on top of CNN features). This is equivalent to freezing the whole architecture, but the CNN part needs to be computed only once.

I/O bottleneck

- In practice, applying deep learning to video analysis requires for multi-GPU or distributed settings
- In such settings it is very important to avoid *starving* the GPUs or we will not obtain any speedup
  - The next batch needs to be loaded and preprocessed to keep the GPU as busy as possible
  - Using asynchronous data loading pipelines is a key factor
  - Loading individual files is slow due to the introduced overhead, so using other formats such as TFRecord/HDF5/LMDB is highly recommended

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