VideoLSTM

Convolves, attends and flows for action recognition

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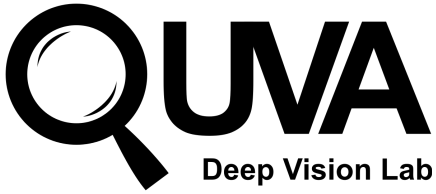
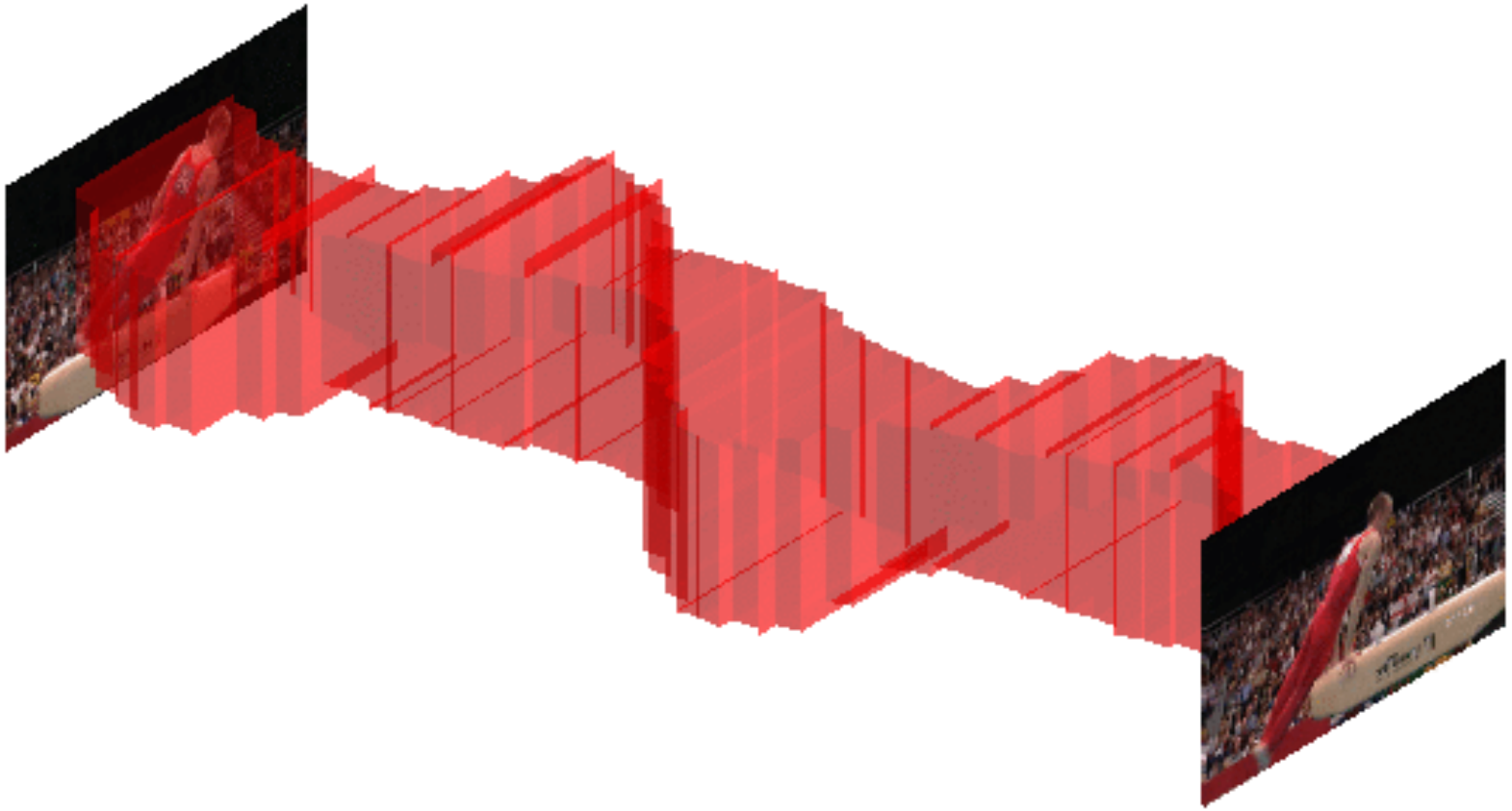


Motivation: Internet of things that video

Goal: Action Recognition

Understand **what** is happening **where** and **when**



Related work

DEEP LEARNING FOR ACTIONS

ConvNet

Ji et al. ICML10

Karpathy et al., CVPR14

Simonyan & Zisserman, NIPS14

Tran et al., ICCV15

3D convolutions

Need large amounts of data to learn filters

Two-stream

Learn spatial and temporal filters separately

We propose a more principled approach for learning frame-to-frame appearance and motion transitions.

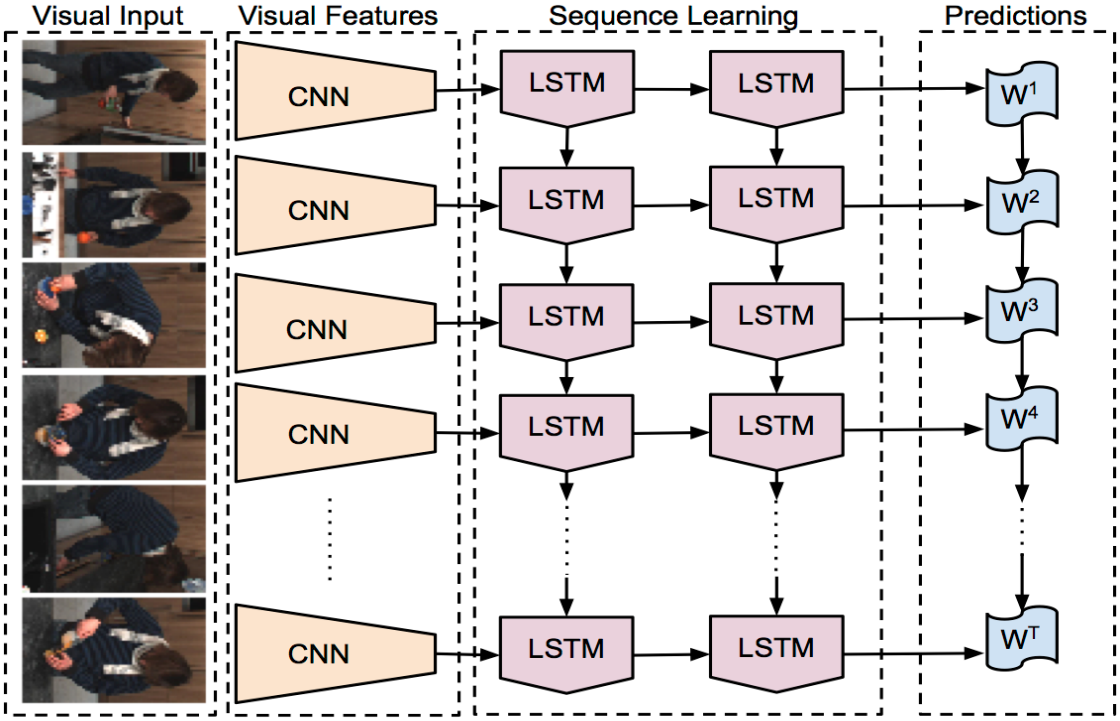
We localize the action as well.

Baccouche et al. ICANN10
Donahue et al. / Ng et al. CVPR15
Srivastava et al. ICML15

LSTM

LSTM models sequential memories in the long and short term

Use ConvNet fc **vectors** as input, no spatial information encoded



Rather than vectorizing a video frame, we rely on **convolutions**

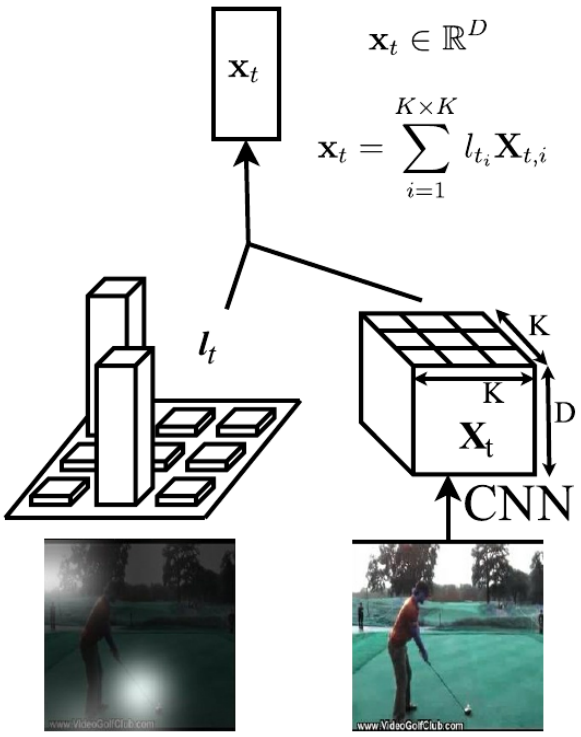
Sharma et al. NIPS15 / ICLR16

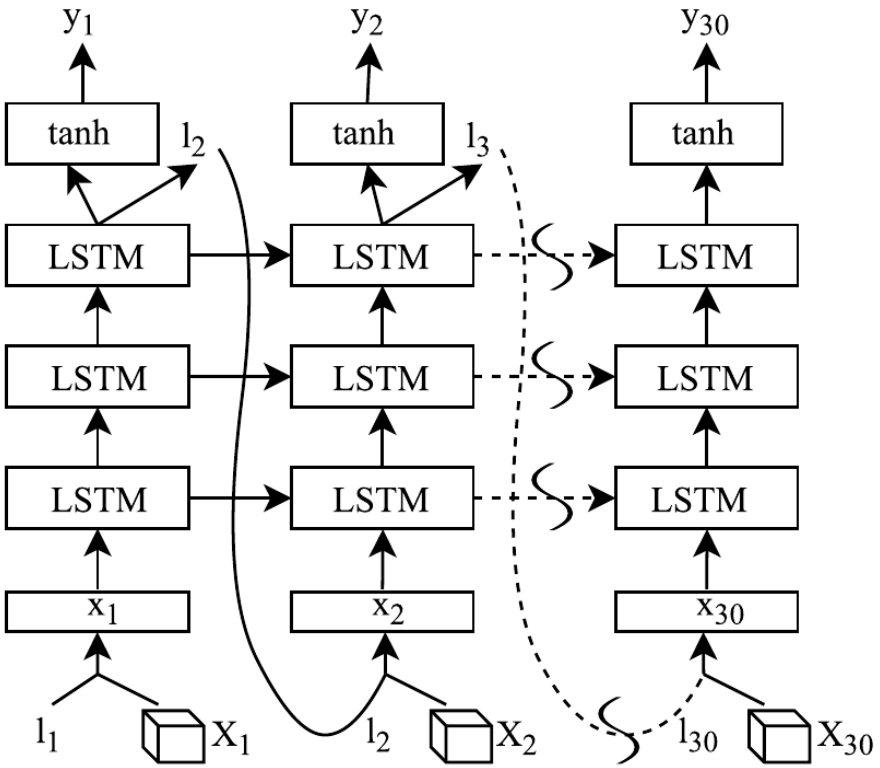
A(ttention)LSTM

Look for best locations leading to correct action classification

Stays close to soft-Attention architecture for image captioning [Xu et al. ICML15],

Vectorizes attention and appearance, and ignores the motion inside a video.





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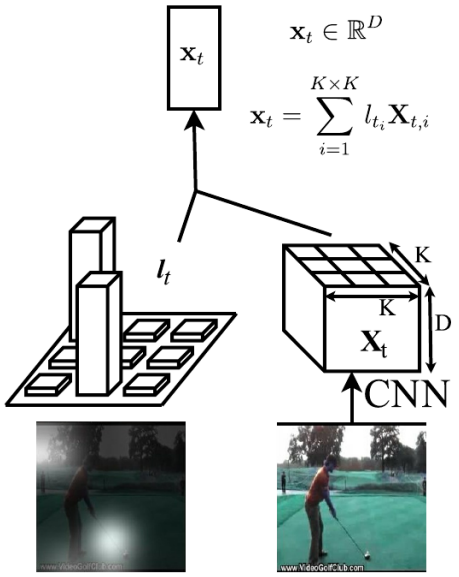
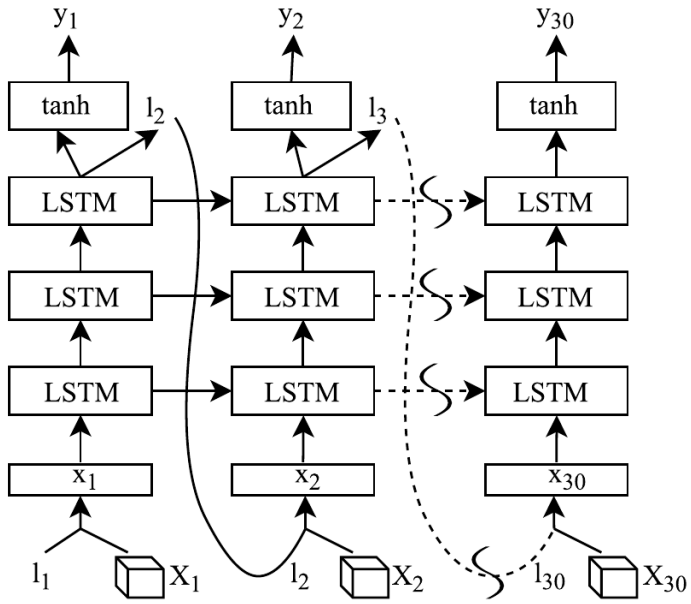




We add **convolutions** and **motion** for better action classification

We localize the action as well.

Our proposal: VideoLSTM

Model spatiotemporal dynamics of videos by

- preserving spatial structure of the frames over time
- adding motion-based attention
- enabling action localization from action class labels only

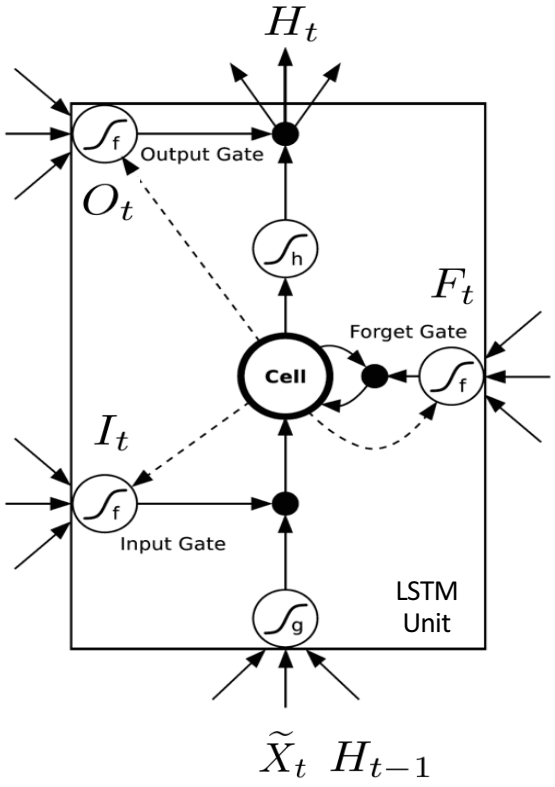
VIDEOLSTM

VideoLSTM convolves, attends and flows for action recognition.
Zhenyang Li, Efstratios Gavves, Mihir Jain, and Cees Snoek. Arxive16.
http://arxiv.org/abs/1607.01794

Convolutional (A)LSTM

Replace the fully connected multiplicative operations in an LSTM unit with convolutional operations

$$
\begin{aligned}
I_t &= \sigma(W_{xi} * \widetilde{X}_t + W_{hi} * H_{t-1} + b_i) \\
F_t &= \sigma(W_{xf} * \widetilde{X}_t + W_{hf} * H_{t-1} + b_f) \\
O_t &= \sigma(W_{xo} * \widetilde{X}_t + W_{ho} * H_{t-1} + b_o) \\
G_t &= \tanh(W_{xc} * \widetilde{X}_t + W_{hc} * H_{t-1} + b_c) \\
C_t &= F_t \odot C_{t-1} + I_t \odot G_t \\
H_t &= O_t \odot \tanh(C_t),
\end{aligned}
$$



Generate attention by shallow ConvNet instead of MLP

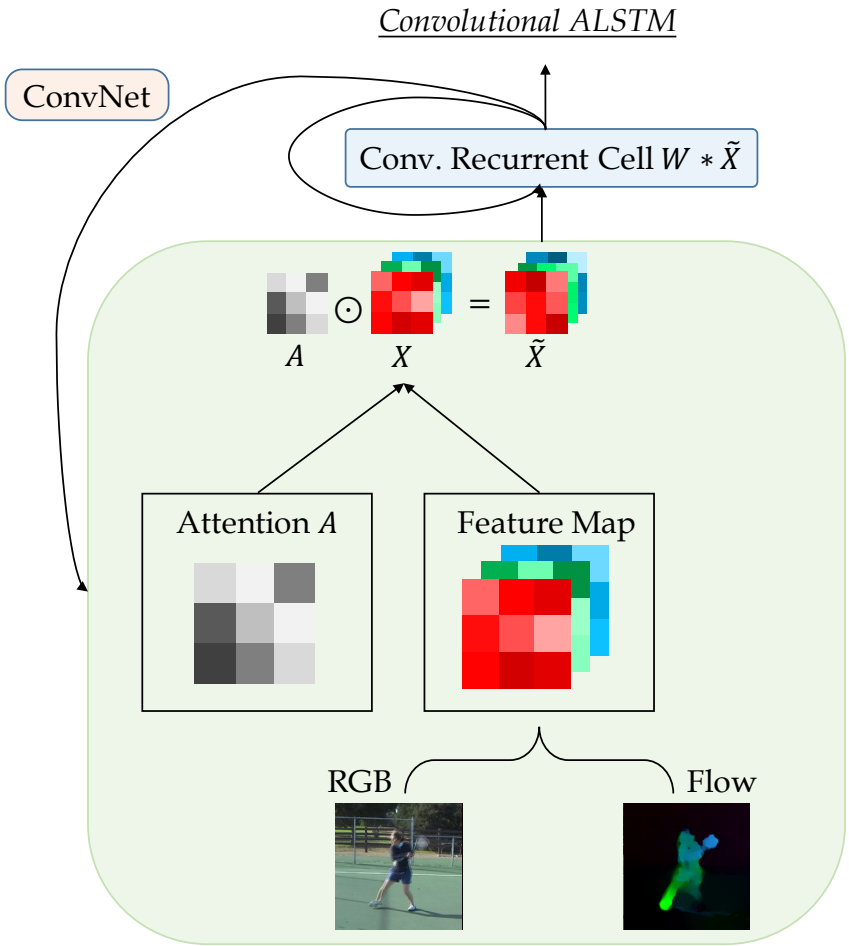
Convolutional ALSTM

Attention map is generated by a two-layer ConvNet

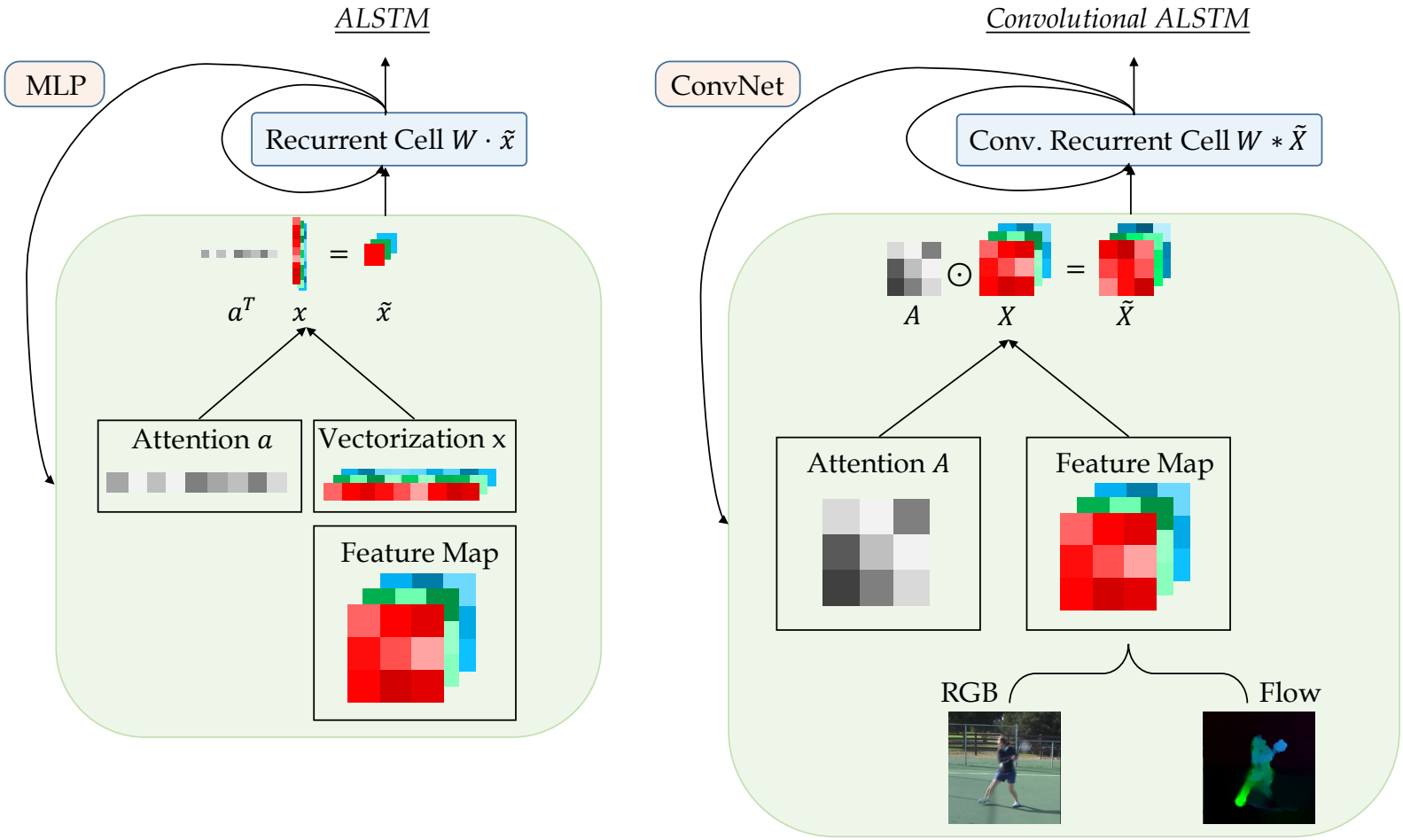
$$Z_t = W_z * \tanh(W_{xa} * X_t + W_{ha} * H_{t-1} + b_a)$$

$$A_t^{ij} = p(att_{ij}|X_t, H_{t-1}) = \frac{\exp(Z_t^{ij})}{\sum_i \sum_j \exp(Z_t^{ij})}$$

$$\widetilde{X}_t = A_t \odot X_t$$



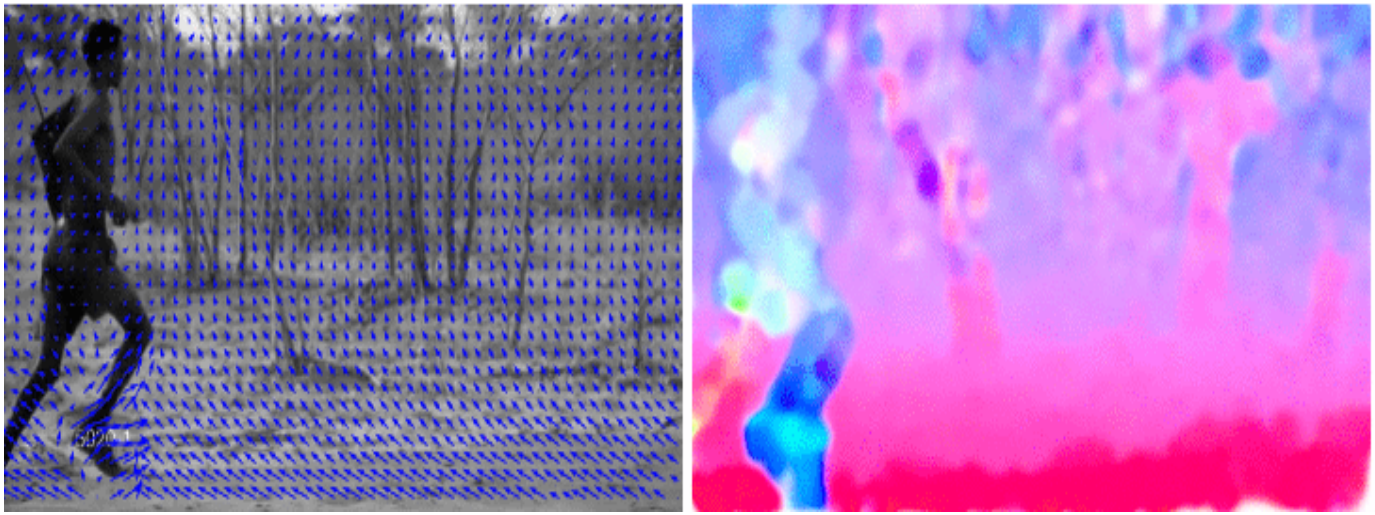
ALSTM vs Convolutional ALSTM



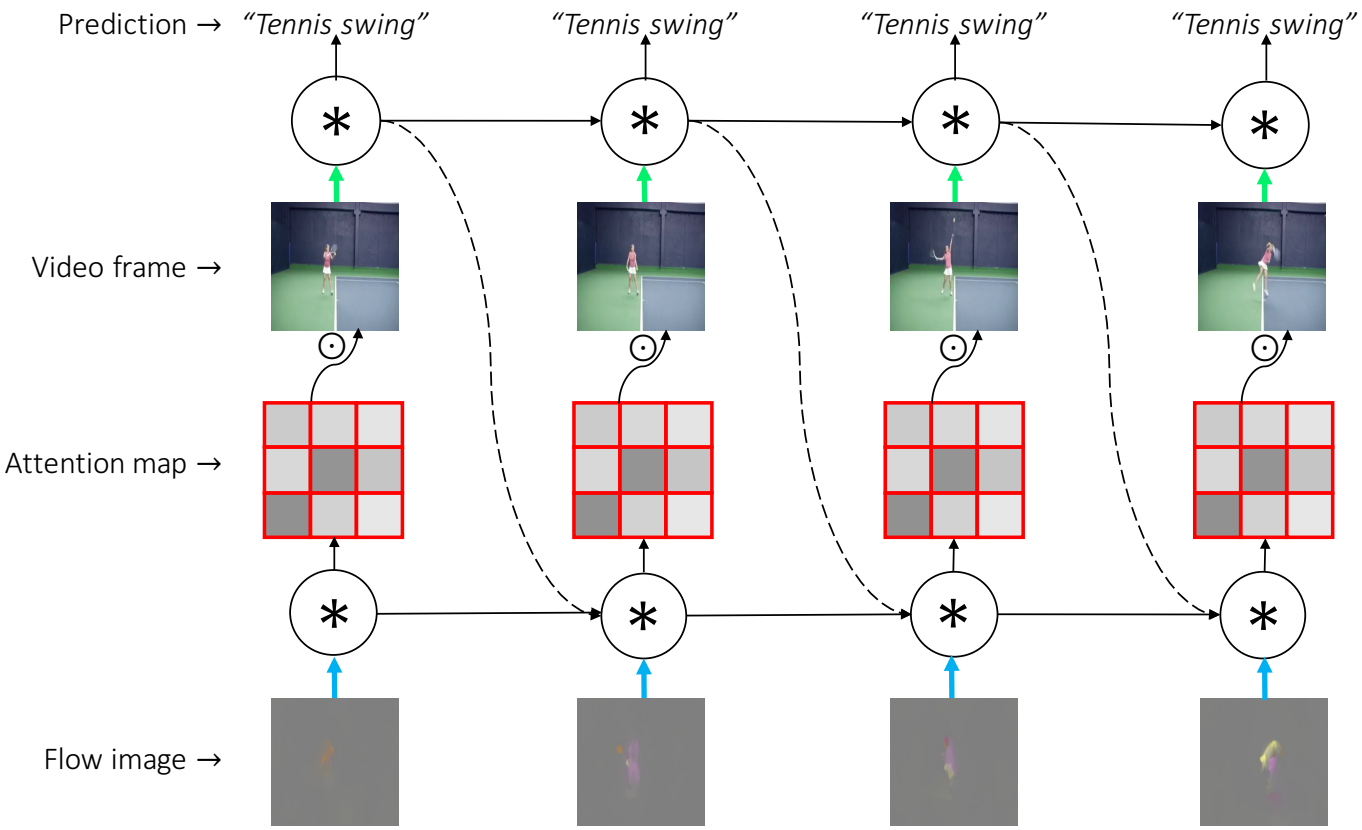
Convolutional ALSTM preserves spatial dimensions over time

Motion-based attention

Motion offers crucial clue where to attend in video



Motion-based attention



Motion information to infer the attention in each frame

Experimental setup

Datasets:

UCF101, **HMDB51** for action classification

Comparison using similar designs and training regime:

ConvNet: VGG-16 trained for both RGB frame and optical flow.

LSTM: Use subsequences of every 30 frames, extract fc7 or pool5 features at each frame as input.

Convolutions: 3x3 kernels for input-to-state and state-to-state transitions in LSTM, and 1x1 kernels to generate the attention map

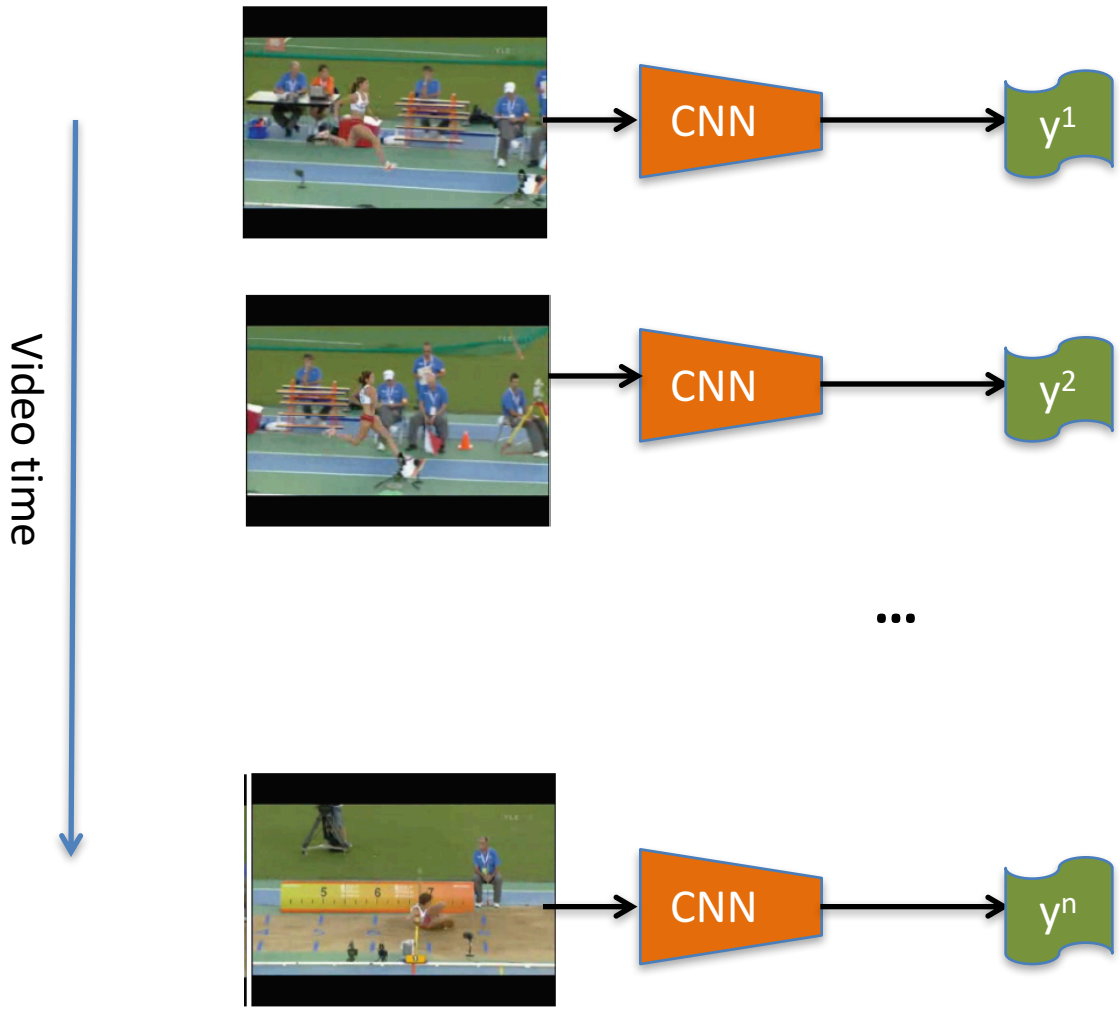
Experiments

1. What deep learning architecture?

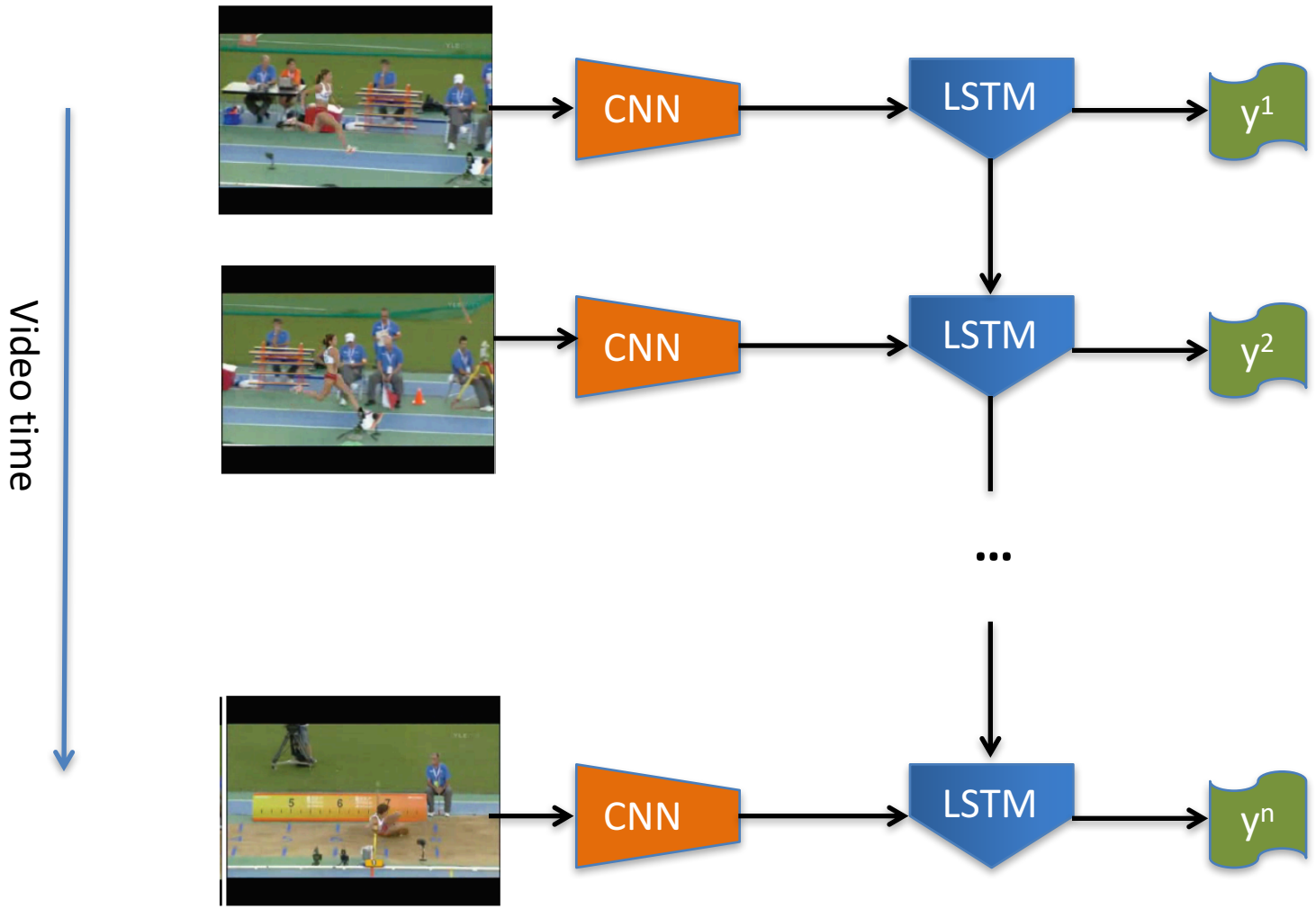
2. Influence of motion-based attention

3. Quality of action localization

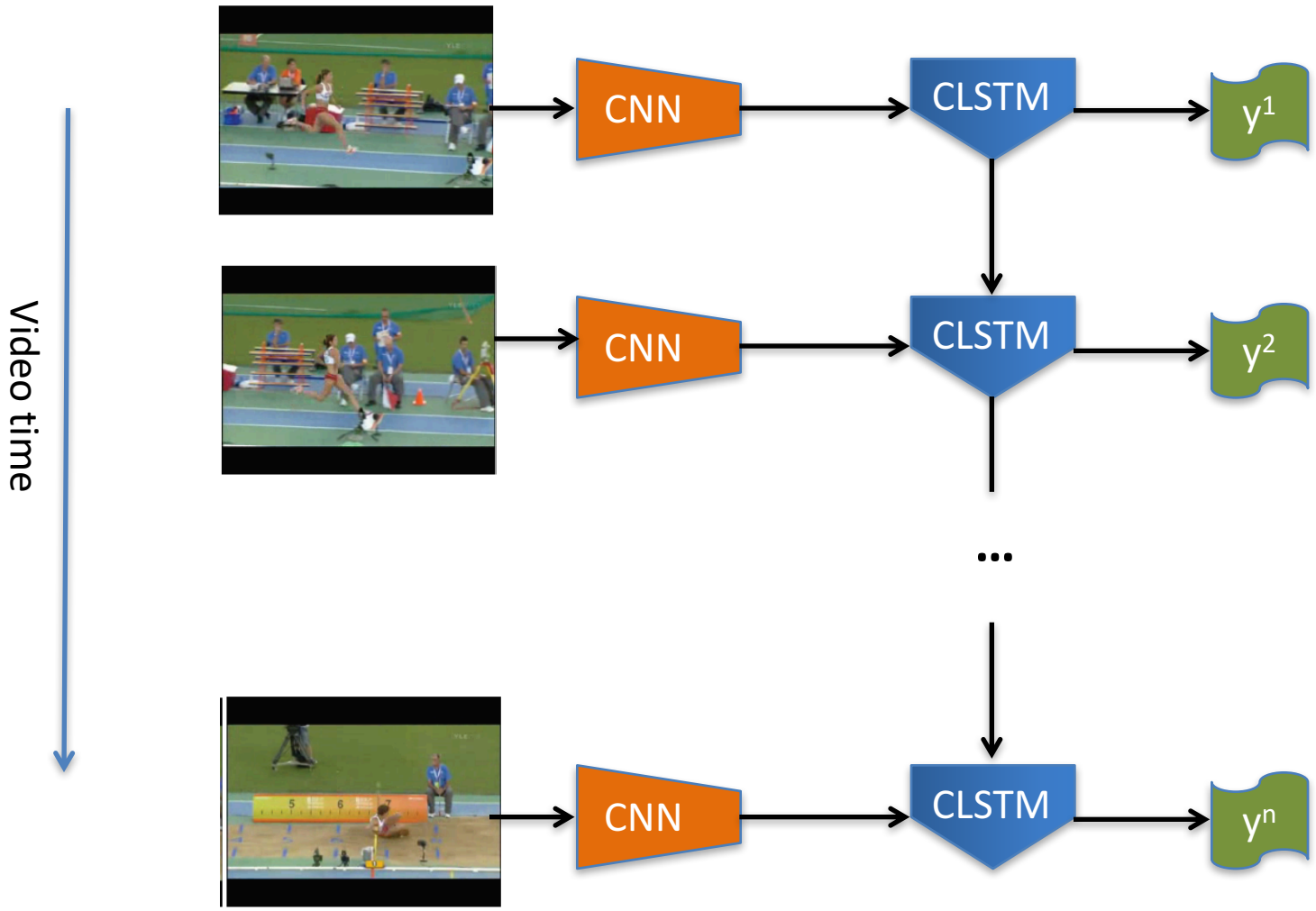
ConvNet



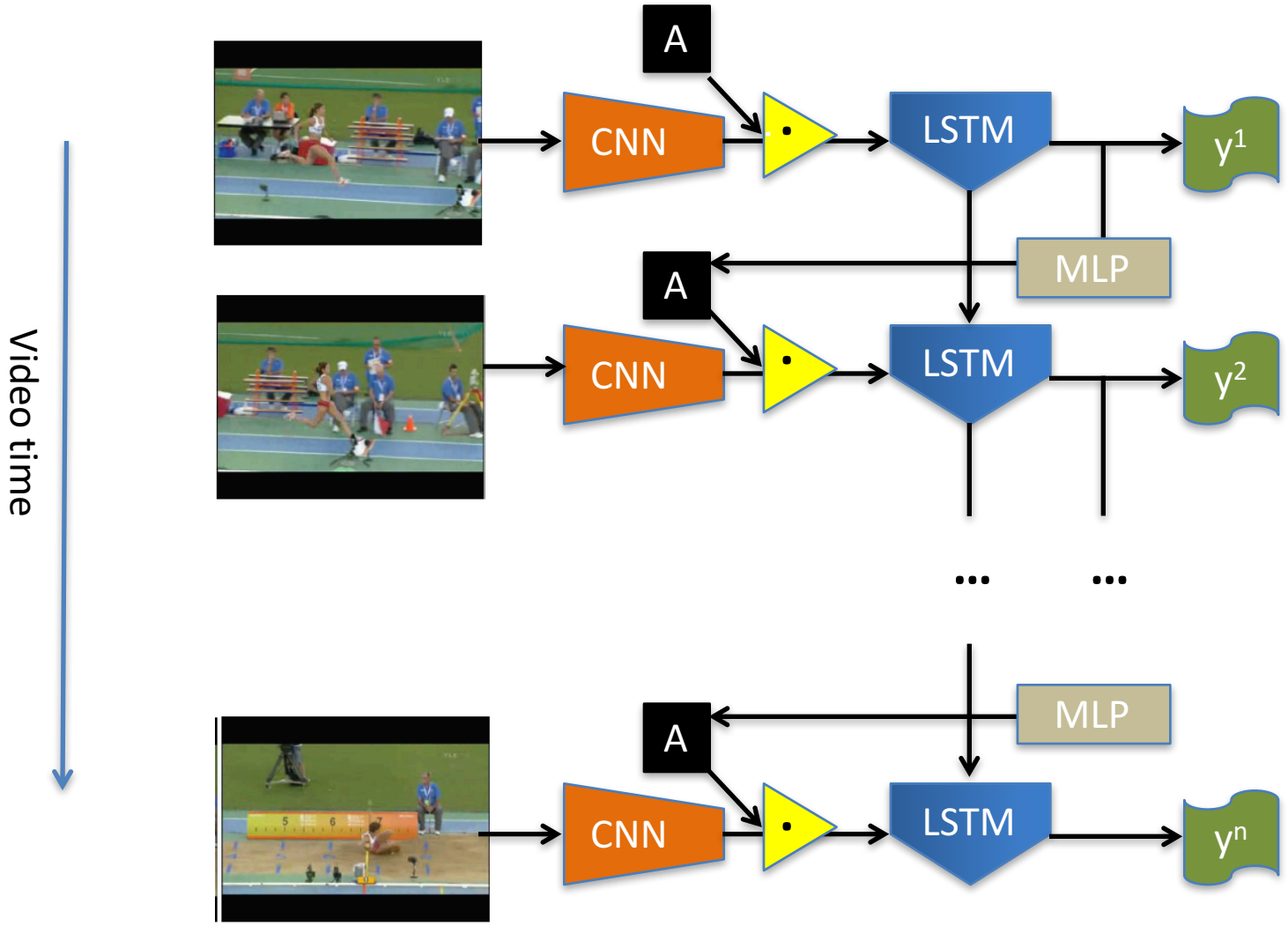
LSTM



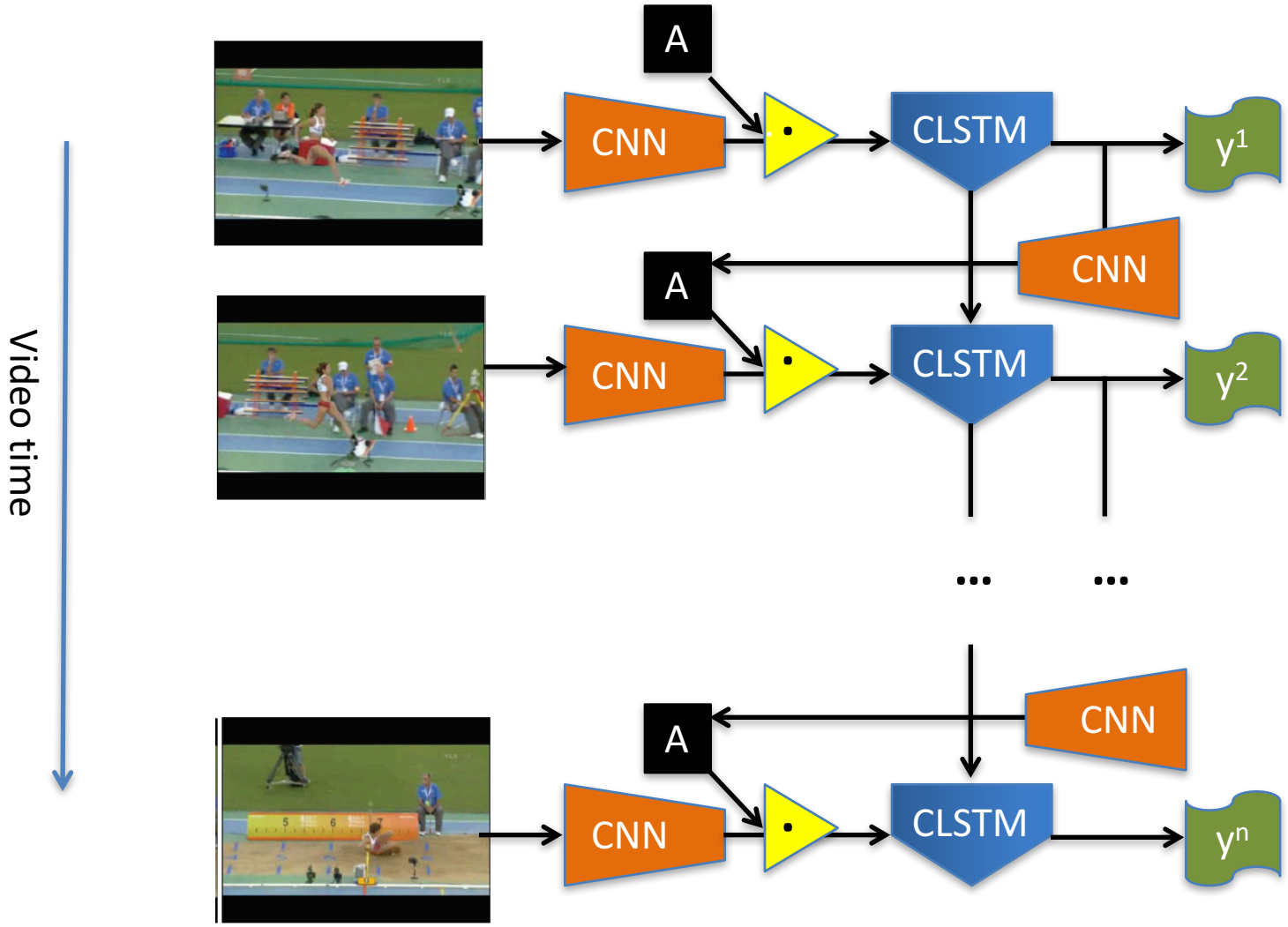
Convolutional LSTM



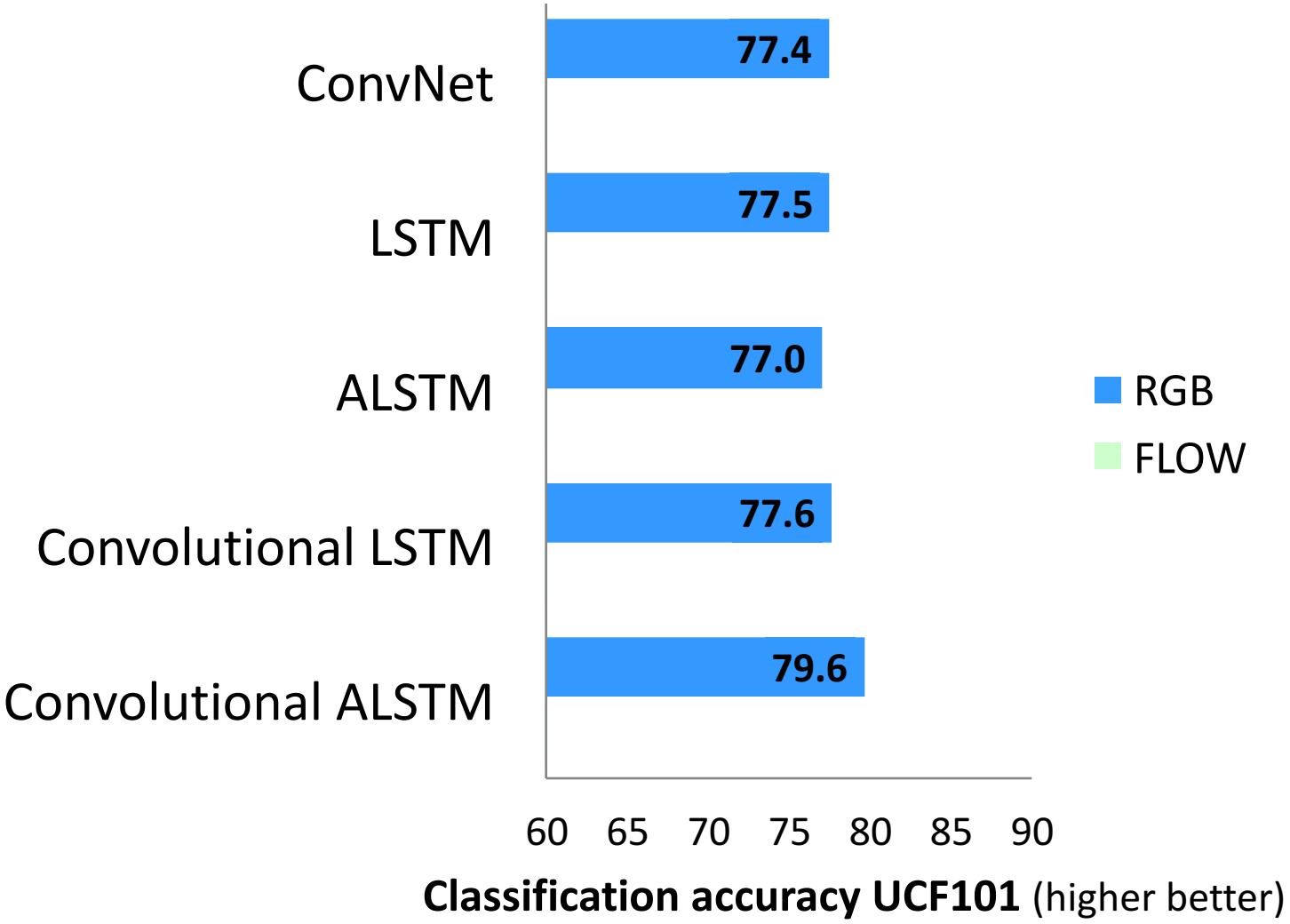
ALSTM



Convolutional ALSTM



Convolution, attention and flow



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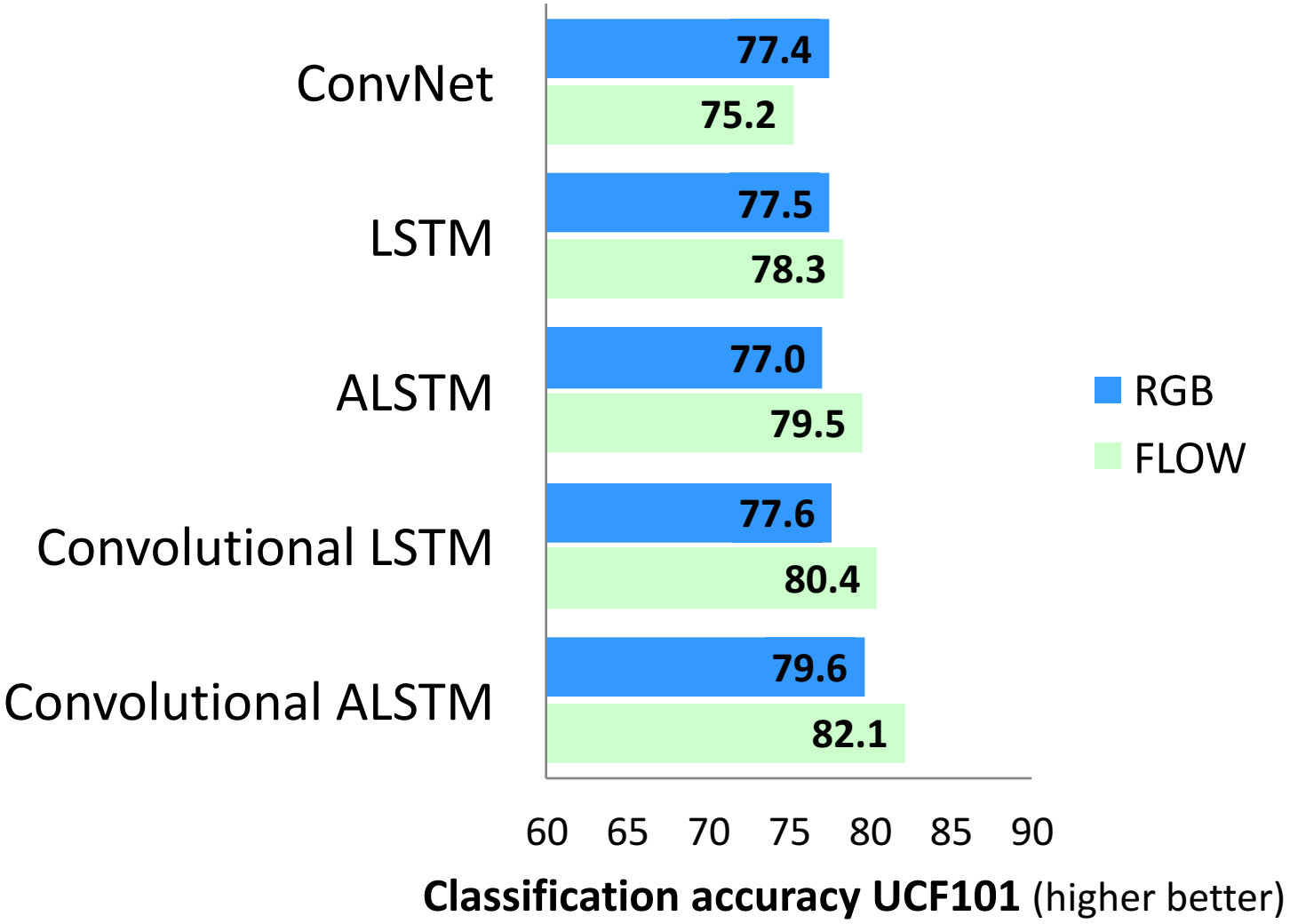

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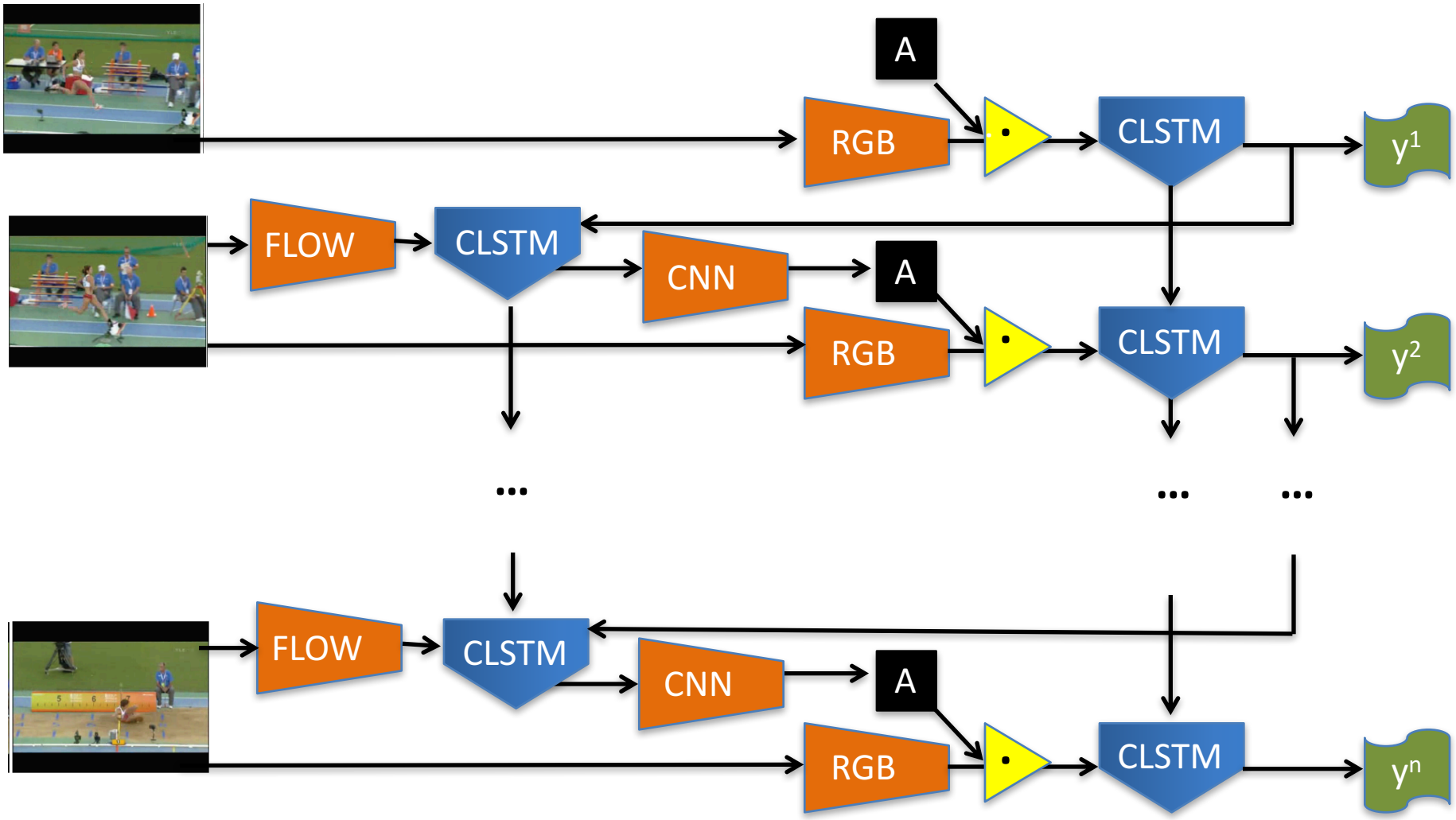
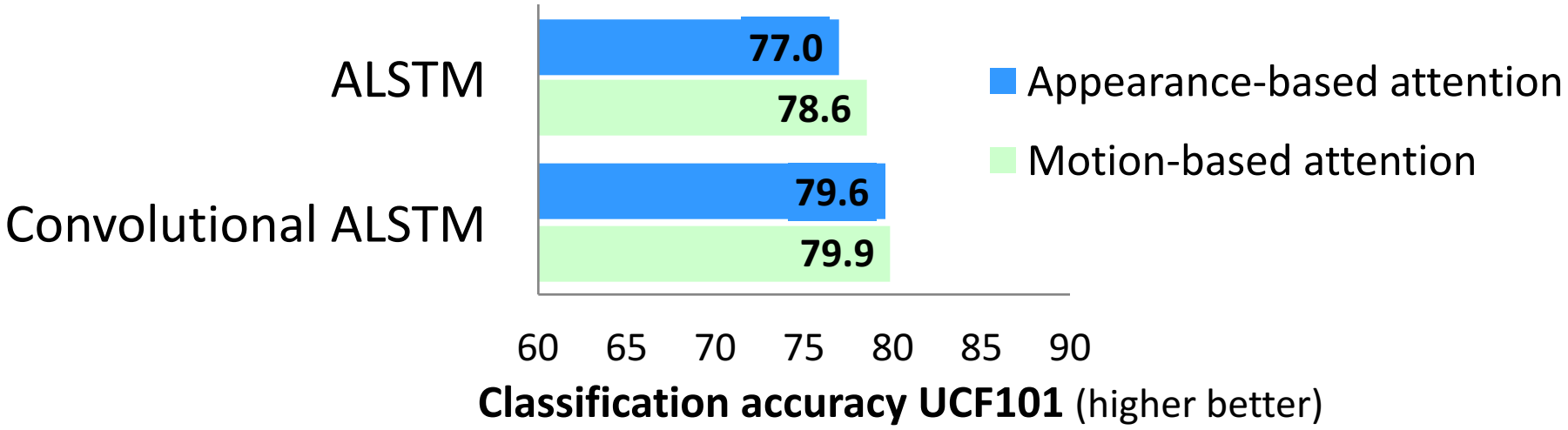
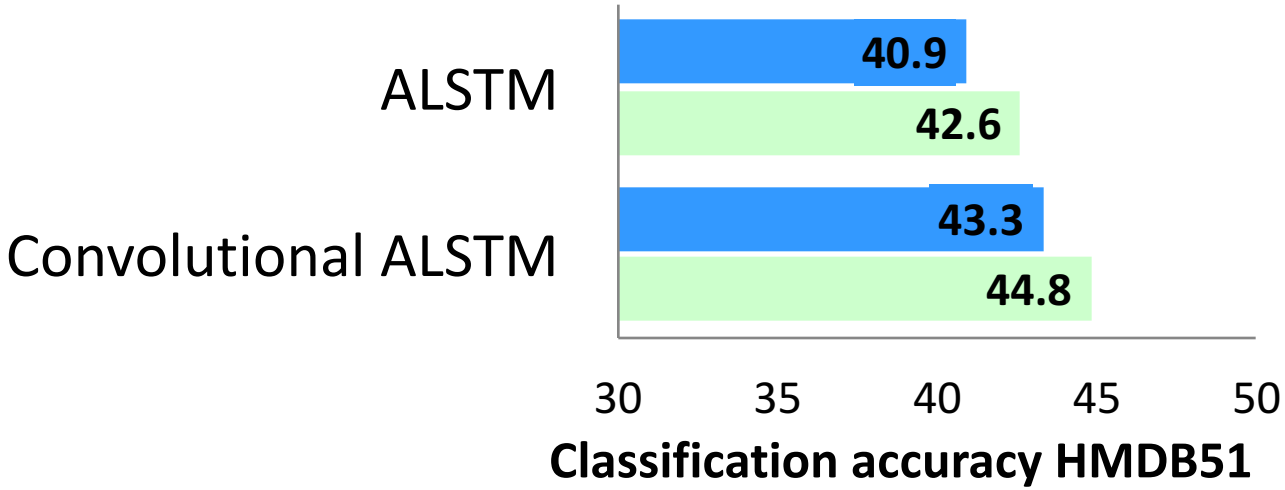
Recap: Motion-based attention



Motion attention makes more sense





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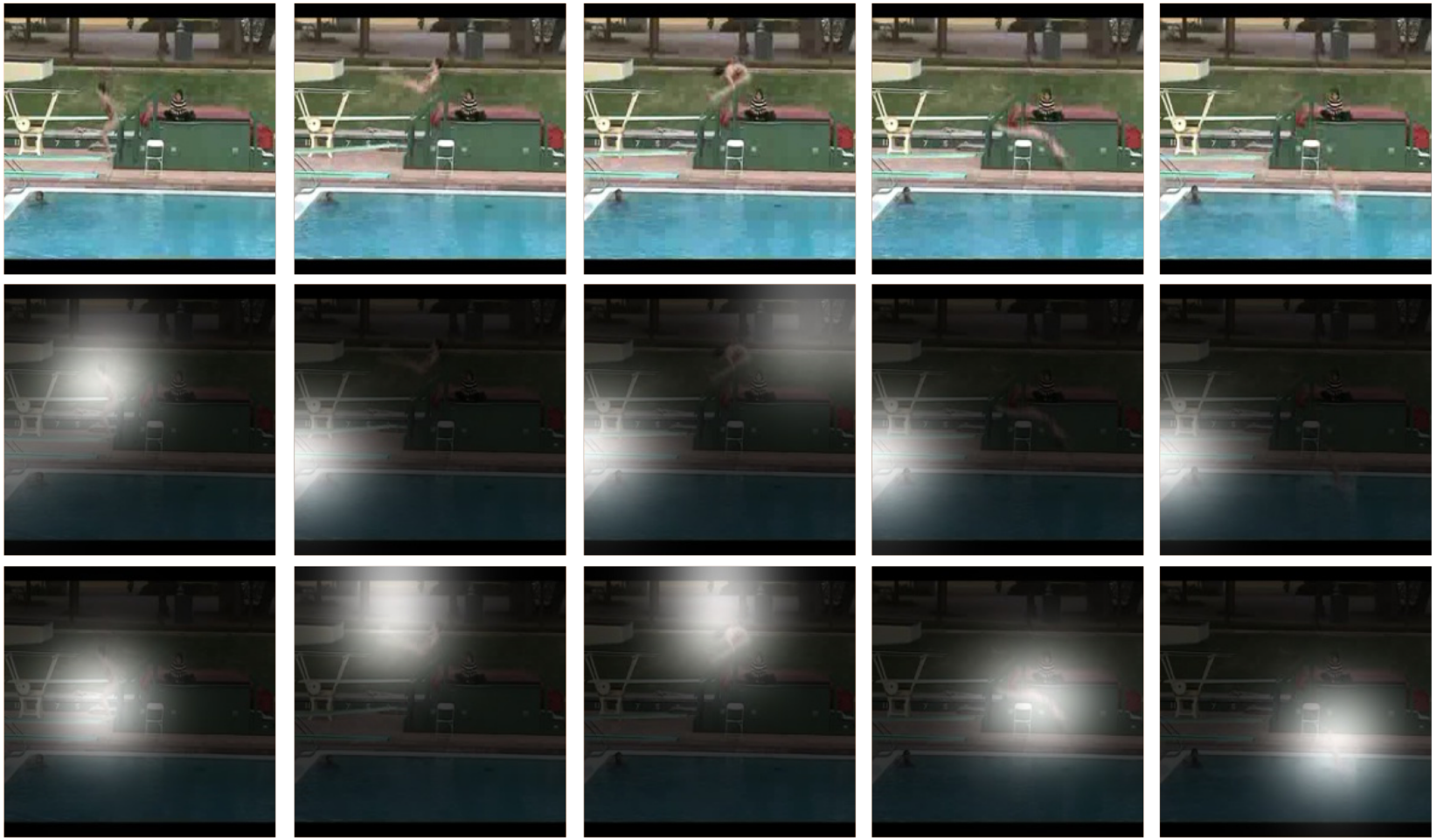


Experiments

1. What deep learning architecture?

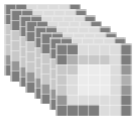
2. Influence of motion-based attention

3. Quality of action localization

Temporal smoothing

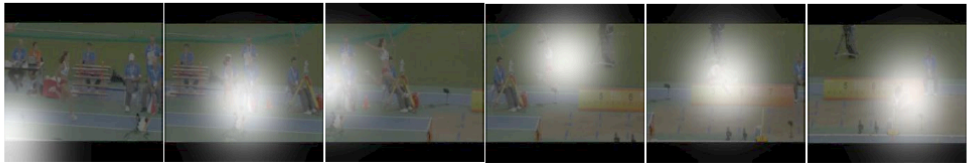
Input frame sequence

VideoLSTM



Attention feature maps

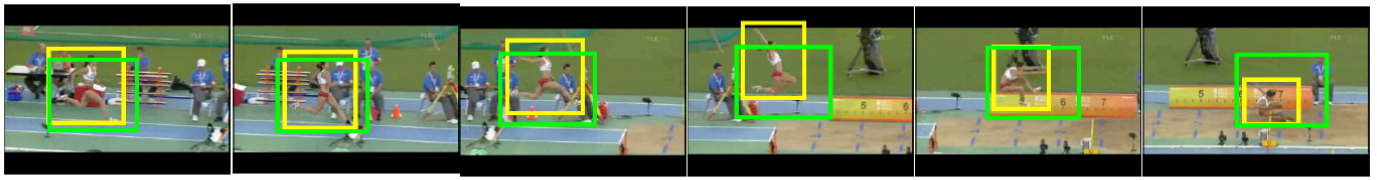
Up-sampling



Attention saliency over frames

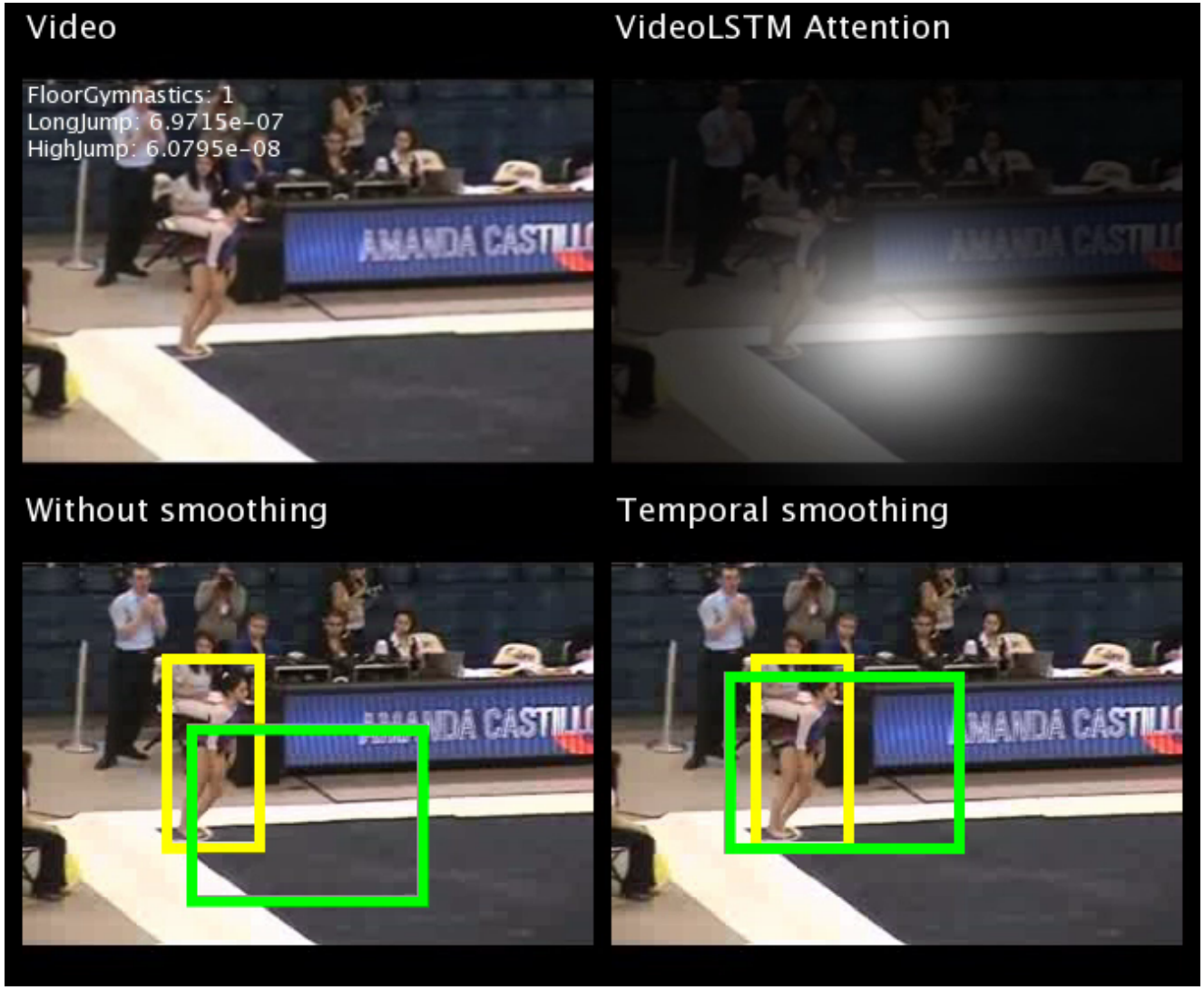
Thresholding + Connected components

Temporal smoothing



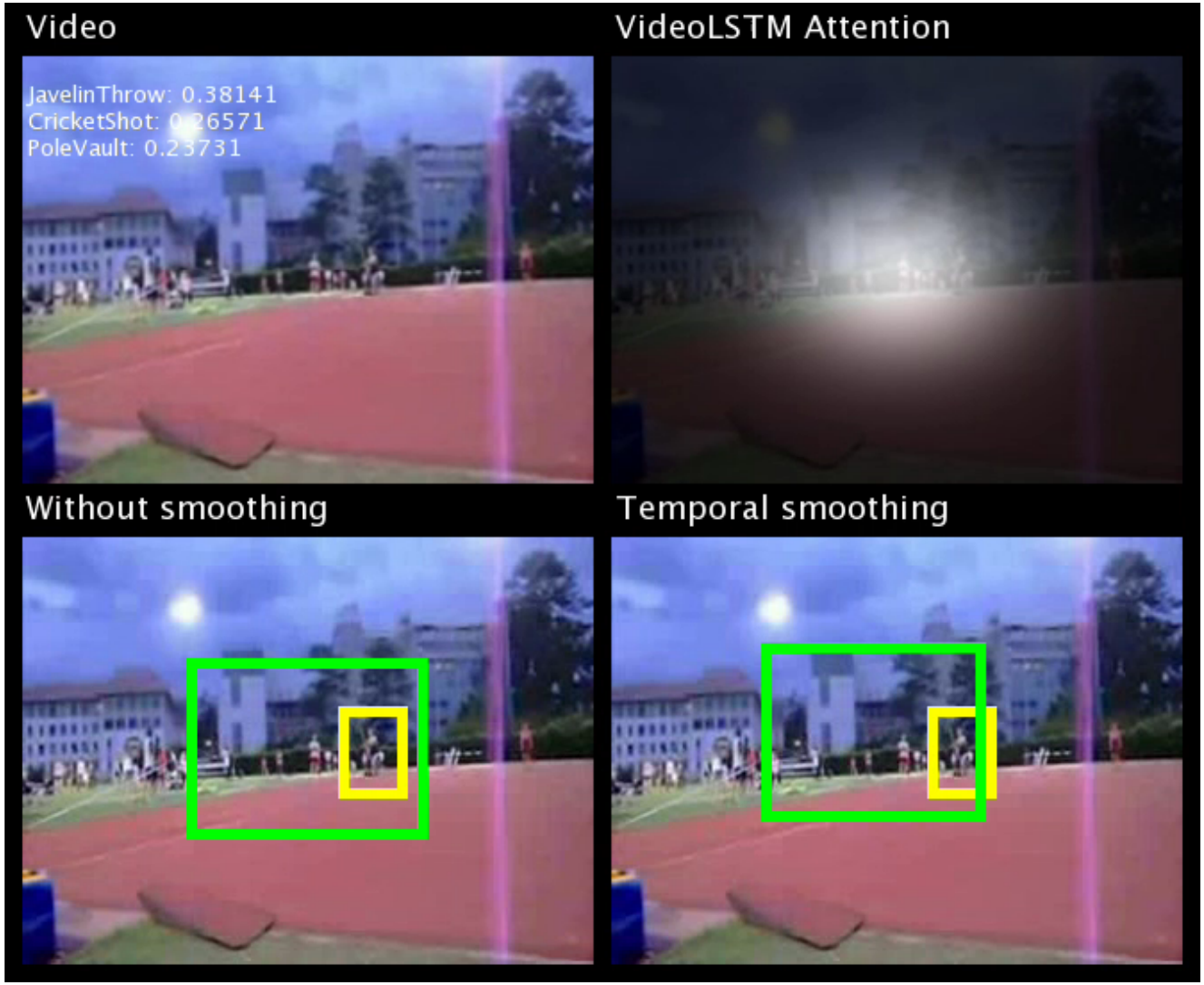
Action localization

Qualitative results



http://isis-data.science.uva.nl/zhenyang/videolstm/localization_examples/

Qualitative results



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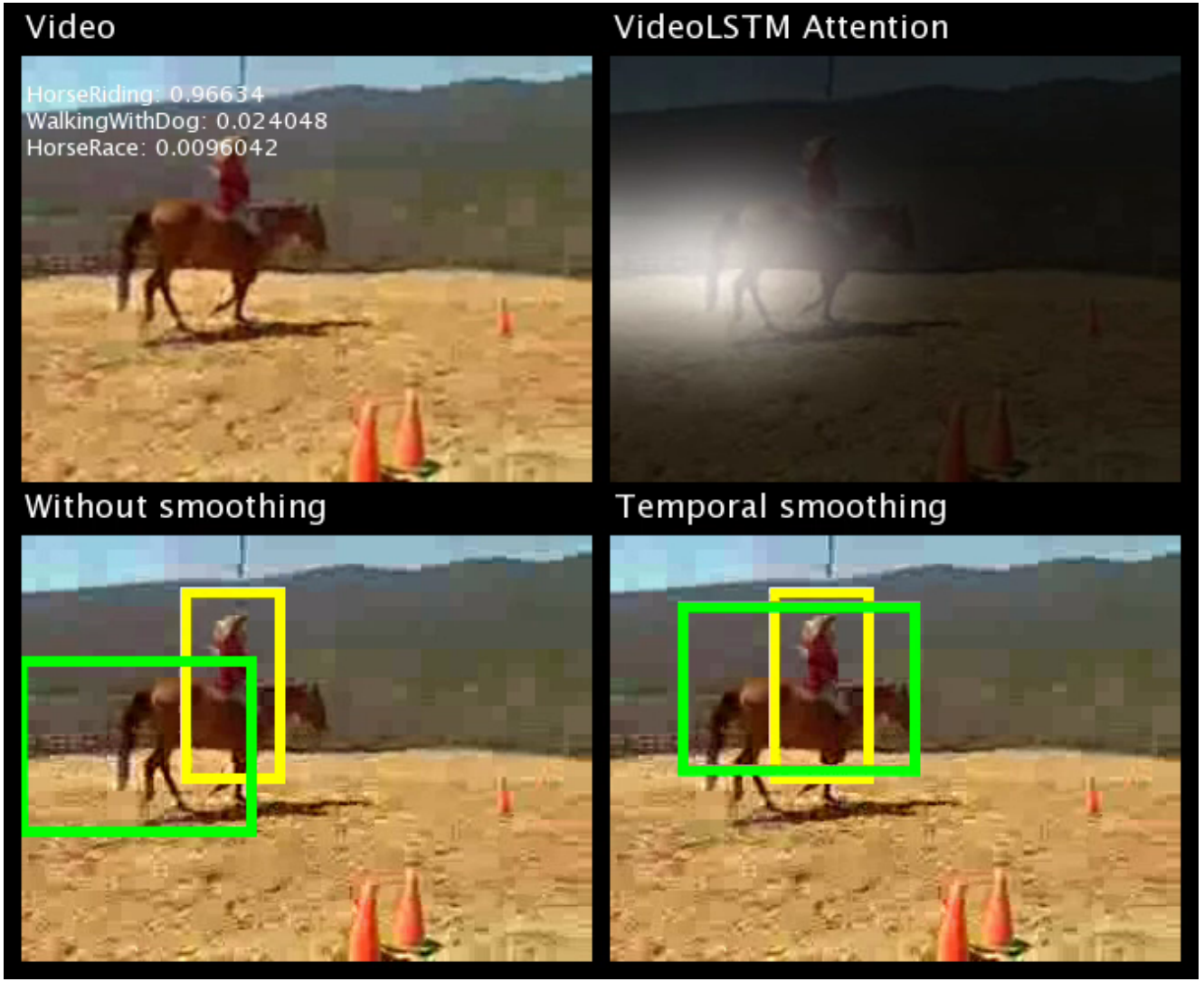

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Conclusions on VideoLSTM

Promising deep vision architecture for action localization

- Hardwires convolutions in attention LSTM
- Derives attention from what moves in video

Localization from a video-level action class label only

http://arxiv.org/abs/1607.01794