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# Aligning Videos In Space and Time

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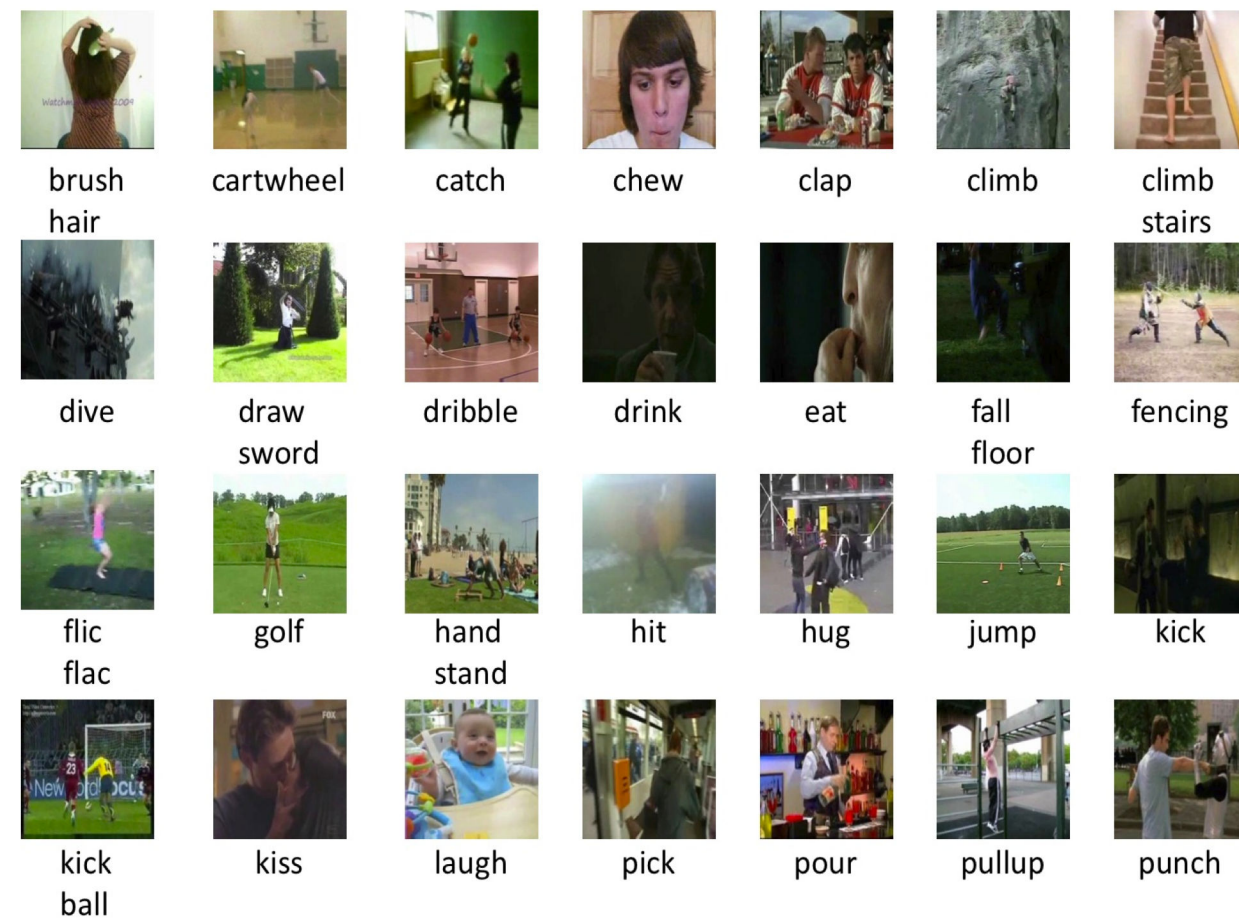
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European Conference on Computer Vision (ECCV), 2020

Long Presentation

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# Video Understanding in Computer Vision



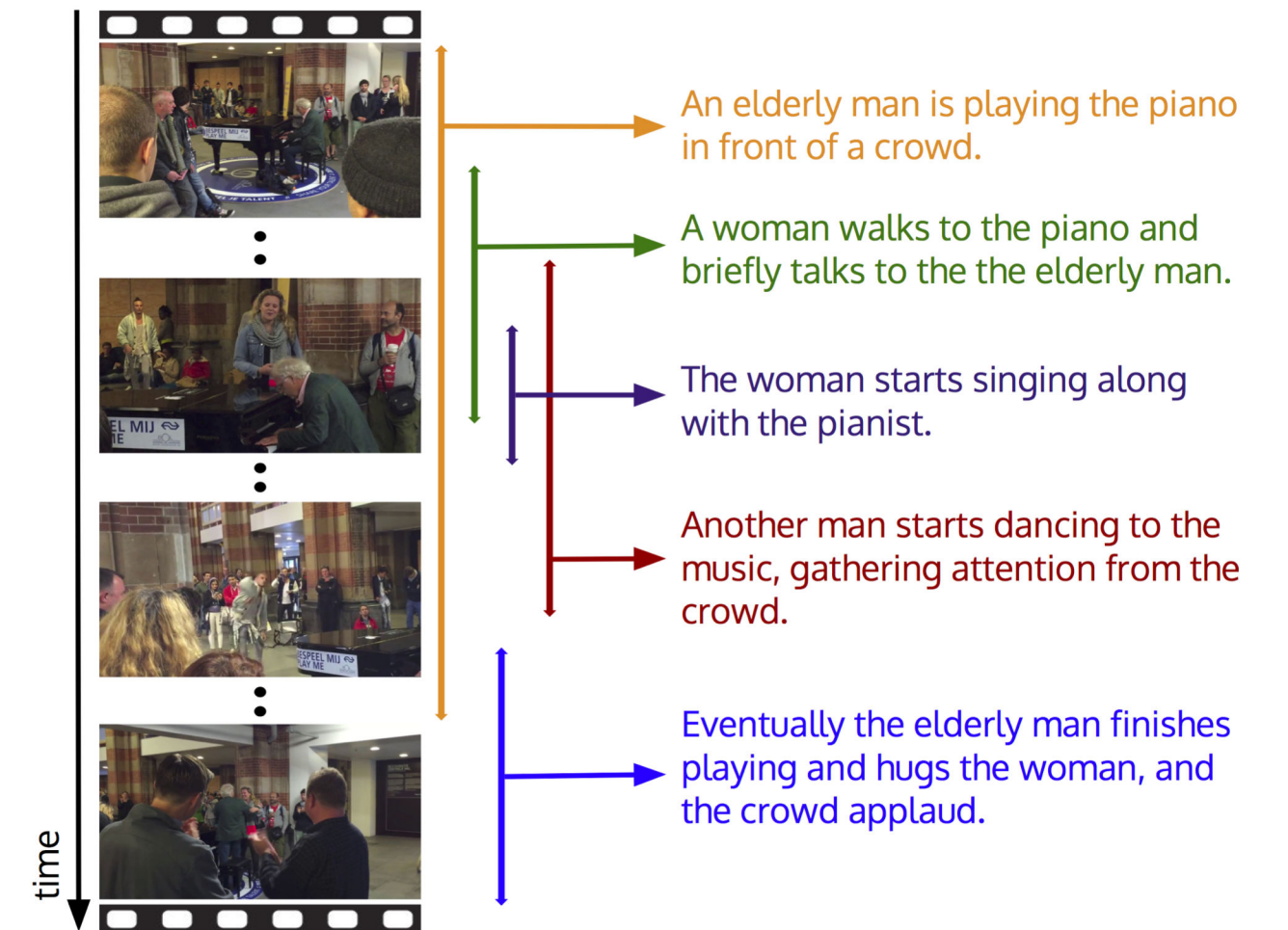
**Action Recognition**

Classification of Videos into Predefined Action Categories



**Action Detection**

Localizing Predefined Actions Temporally in Videos



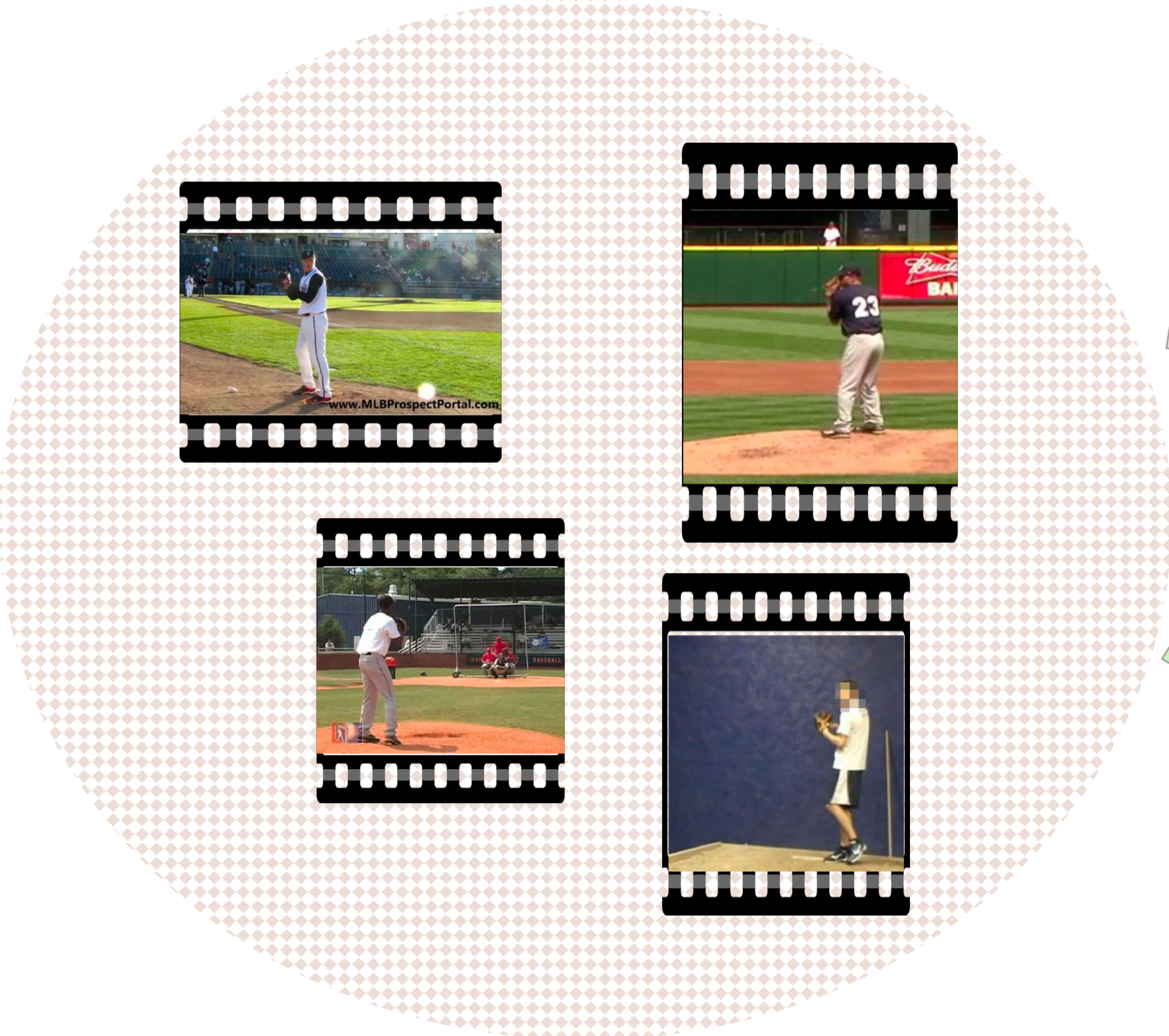
**Video Captioning**

Generating Textual Descriptions for Videos

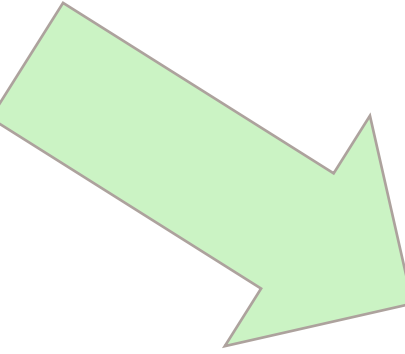
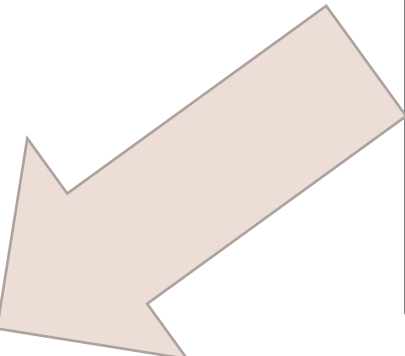
**Coarse Understanding of Videos**  
**Data Collection is Not Scalable**

# Video Understanding via Association

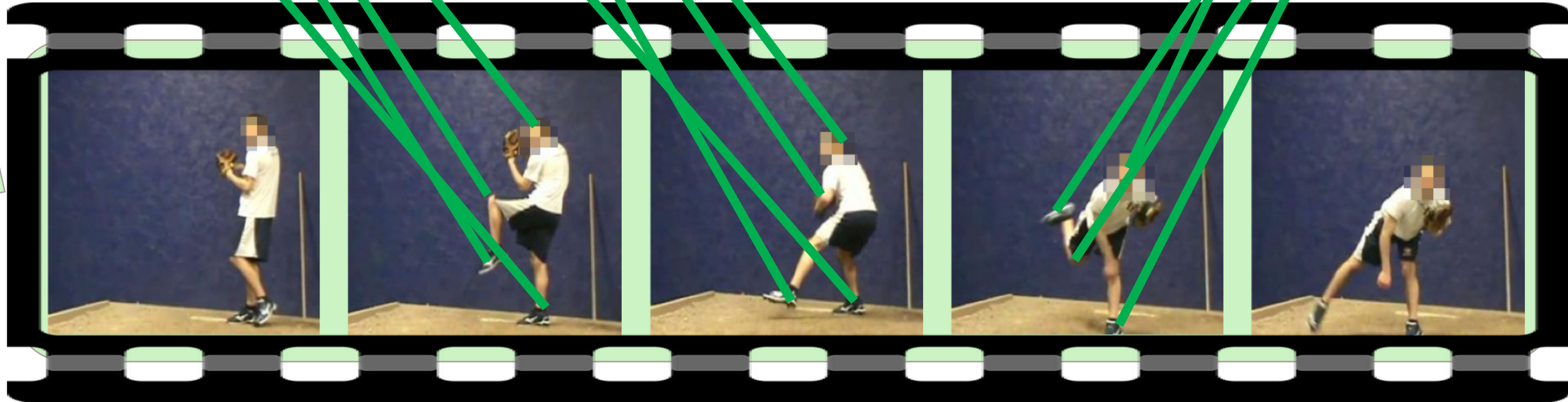
*Ask not "what is this?", ask "what is this like".  
-Moshe Bar*



Baseball Bowling



Query Video



Retrieved Video

# Video Understanding via Association

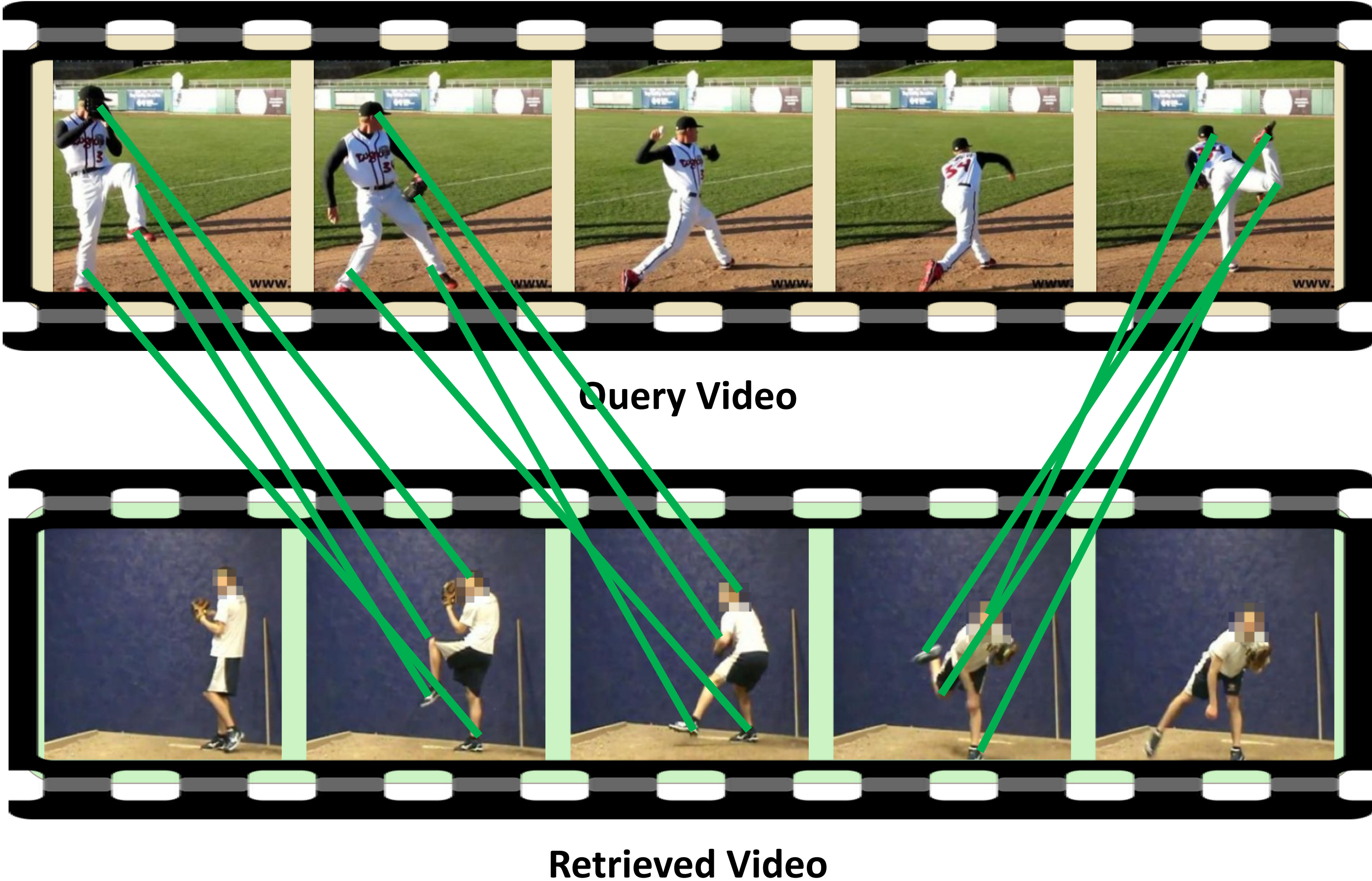
*Ask not “what is this?”, ask “what is this like”.*  
-Moshe Bar

### What does this achieve?

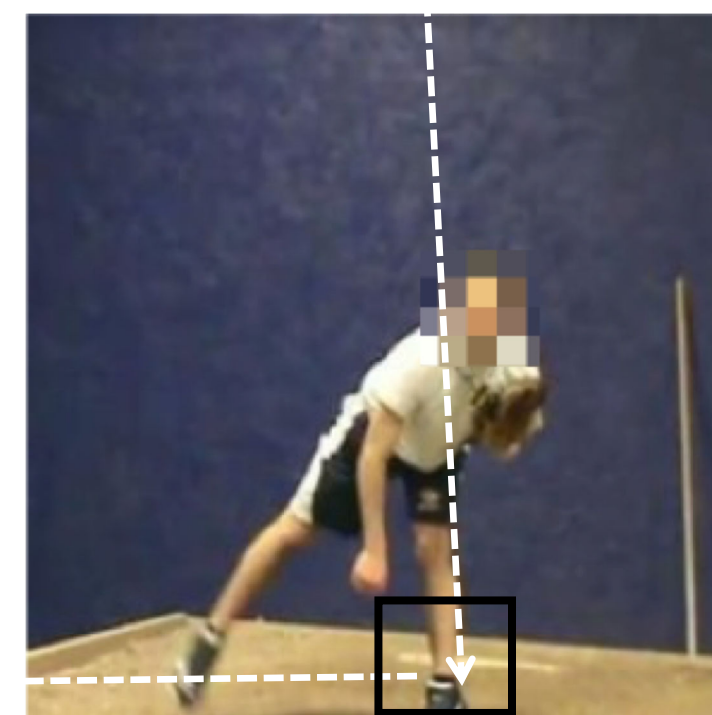
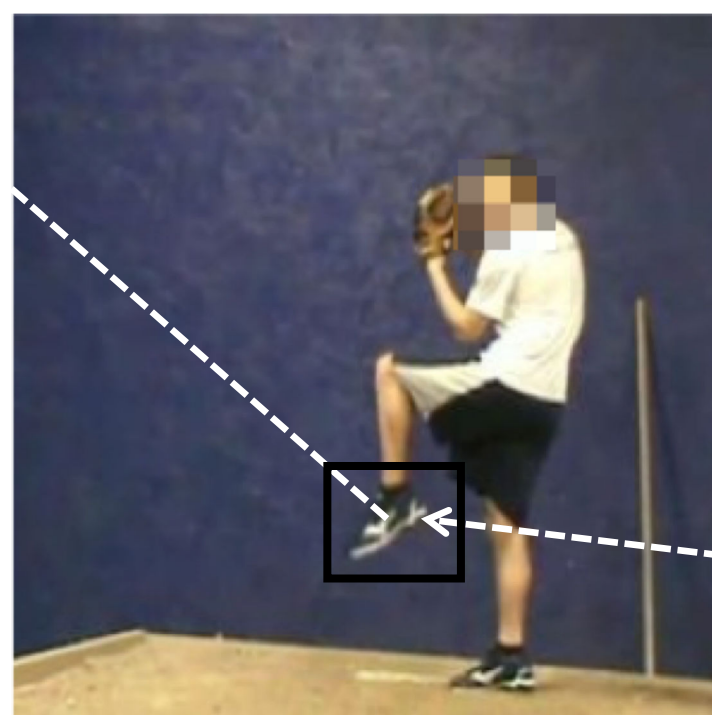
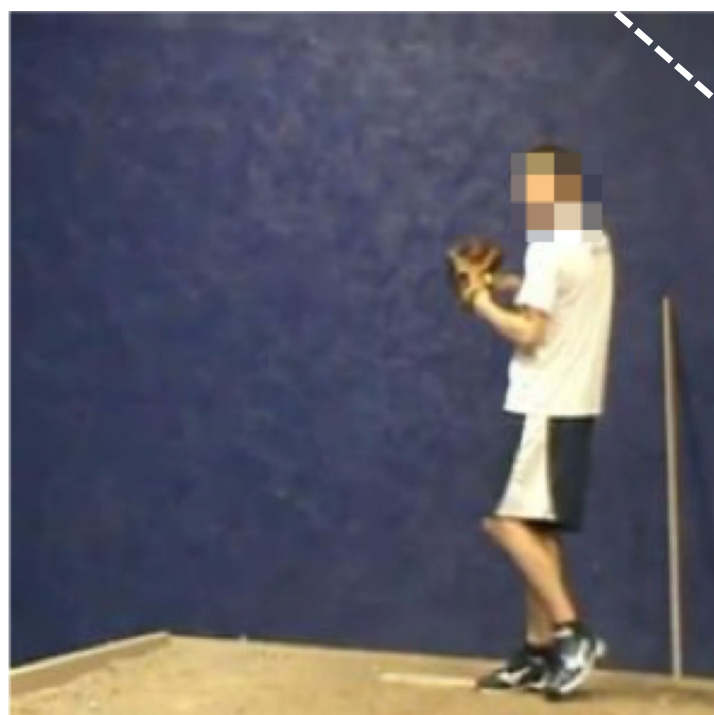
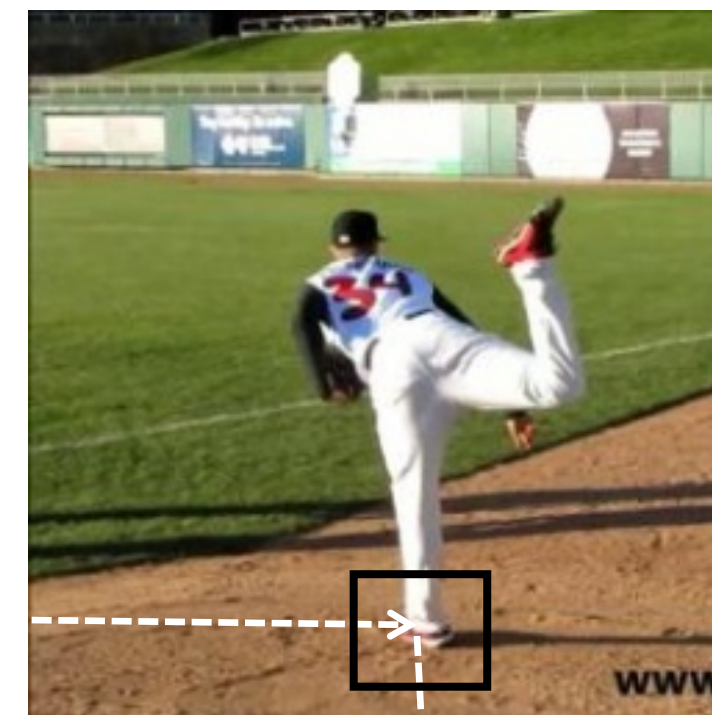
Describing the states object states in one video in terms of known reference videos

Any knowledge about the reference video can be transferred to the query video

**Data collection for this is still infeasible!**



# Spatio-Temporal Associations Through Cycle Consistency



**What is a cycle?**

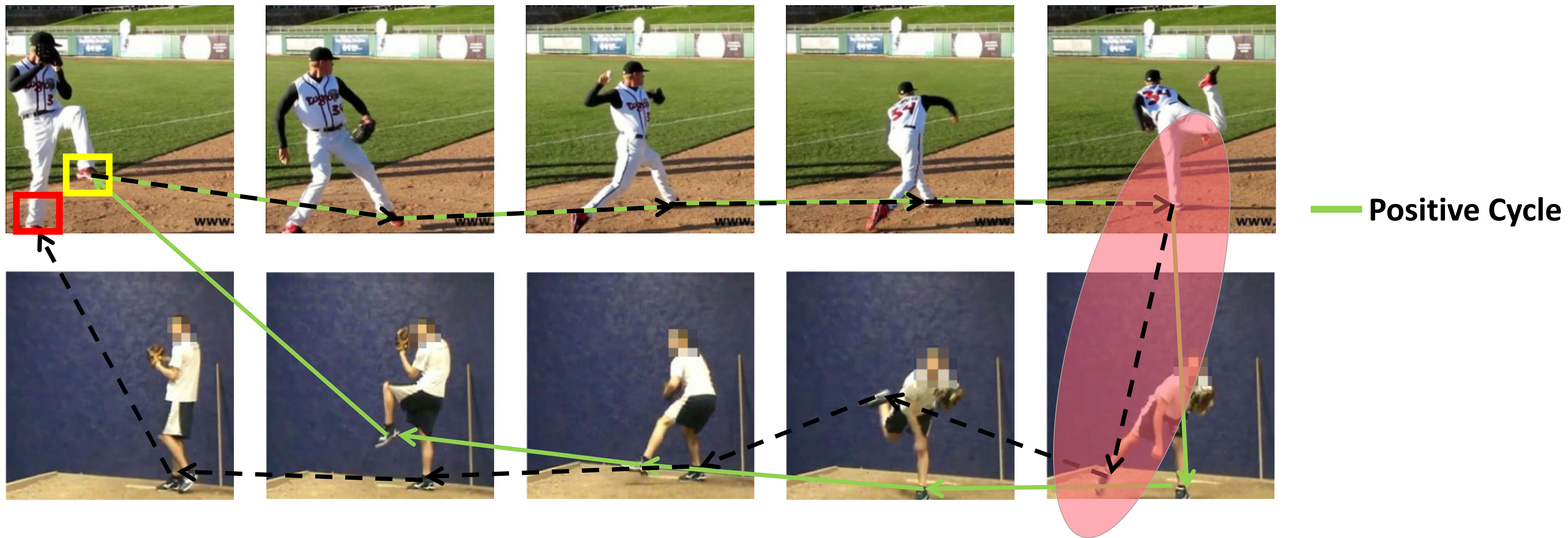
**Match forward in time**

**Match to another video**

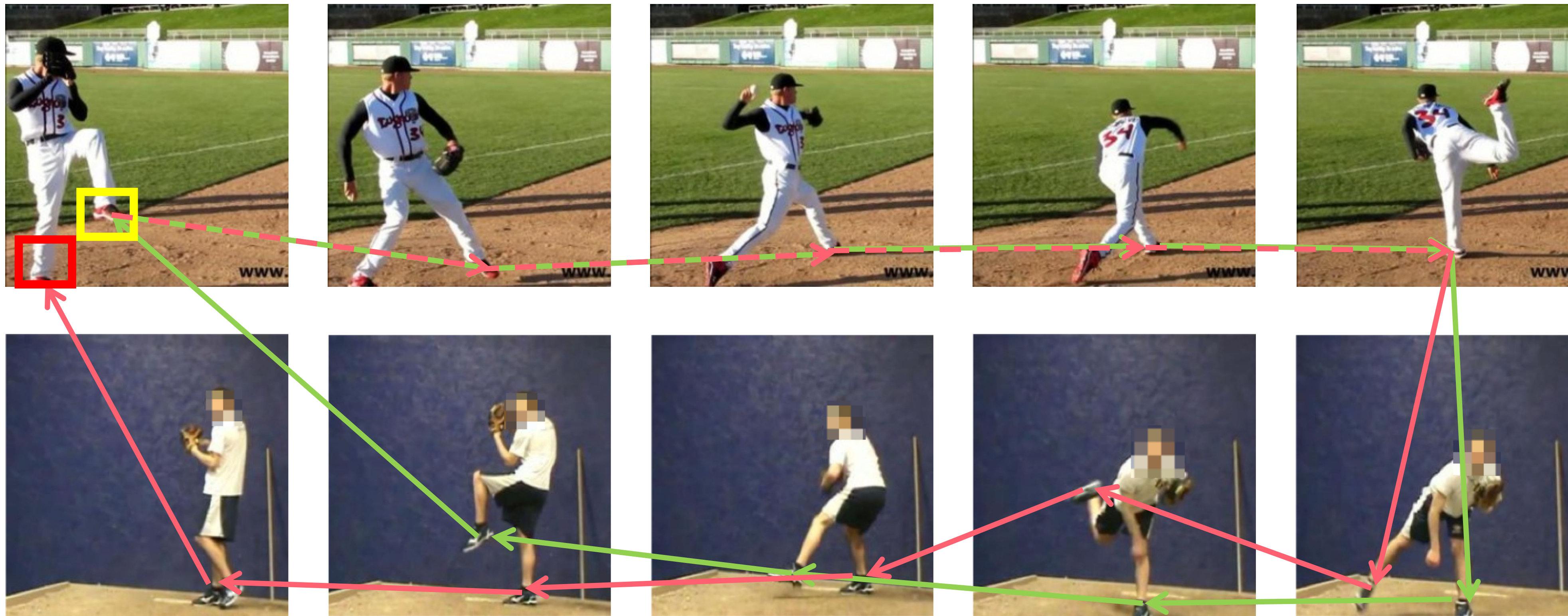
**Match backward in time**

**Match back to first video**

# Spatio-Temporal Associations Through Cycle Consistency



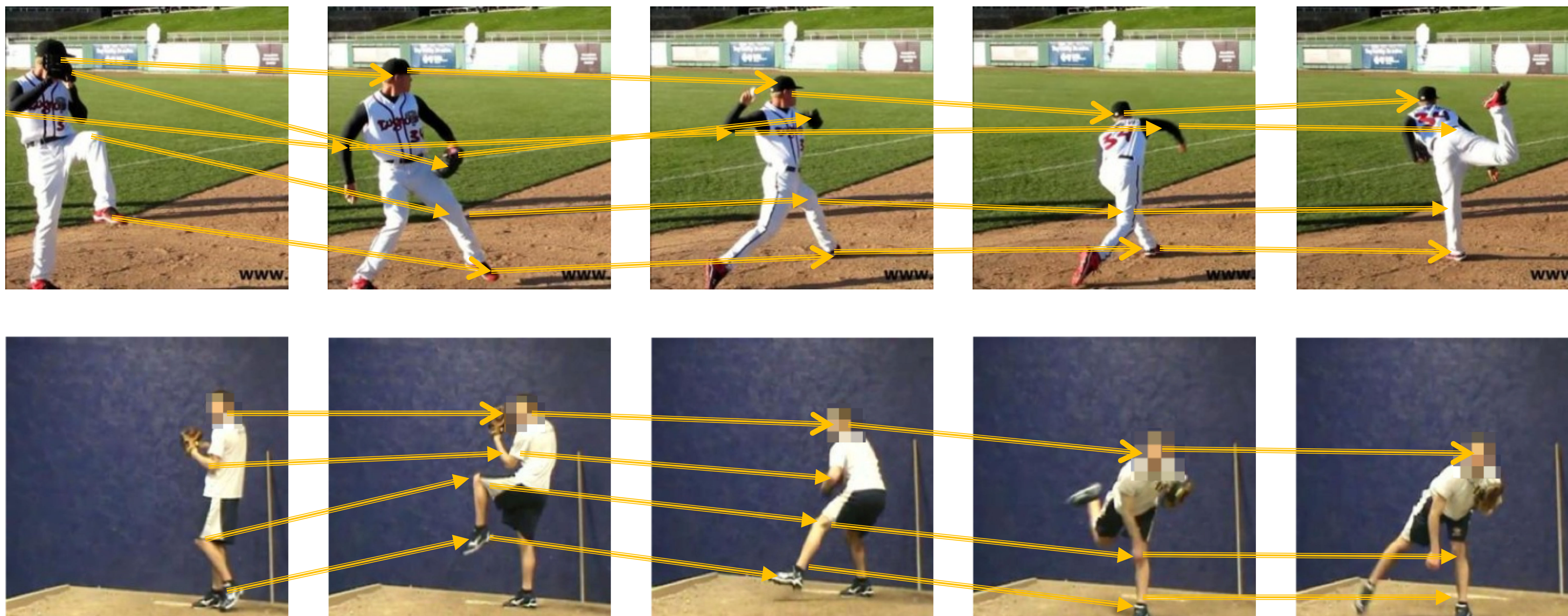
# Spatio-Temporal Associations Through Cycle Consistency



Positive Cycle

Negative Cycle

# Spatio-Temporal Associations Through Cycle Consistency

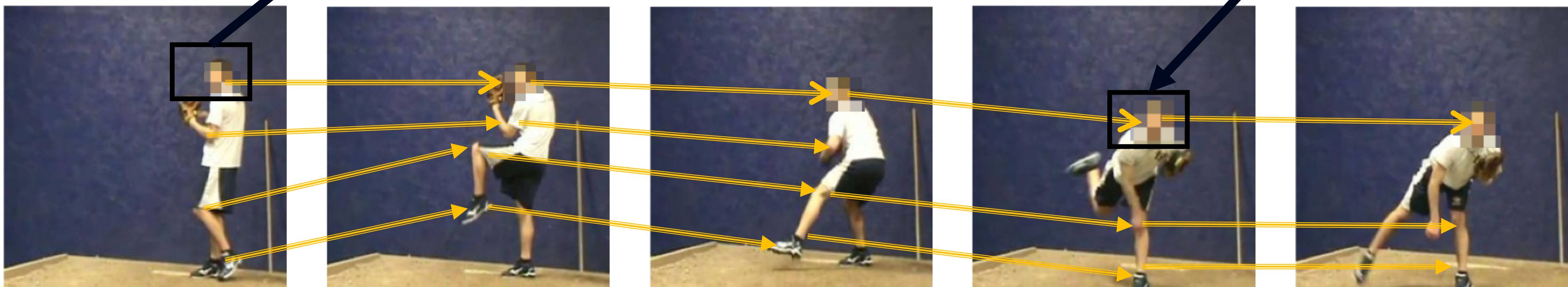


Precompute tracks using an unsupervised tracker



# Spatio-Temporal Associations Through Cycle Consistency

←  $N_1$  →



←  $N_2$  →

**What is a cycle?**

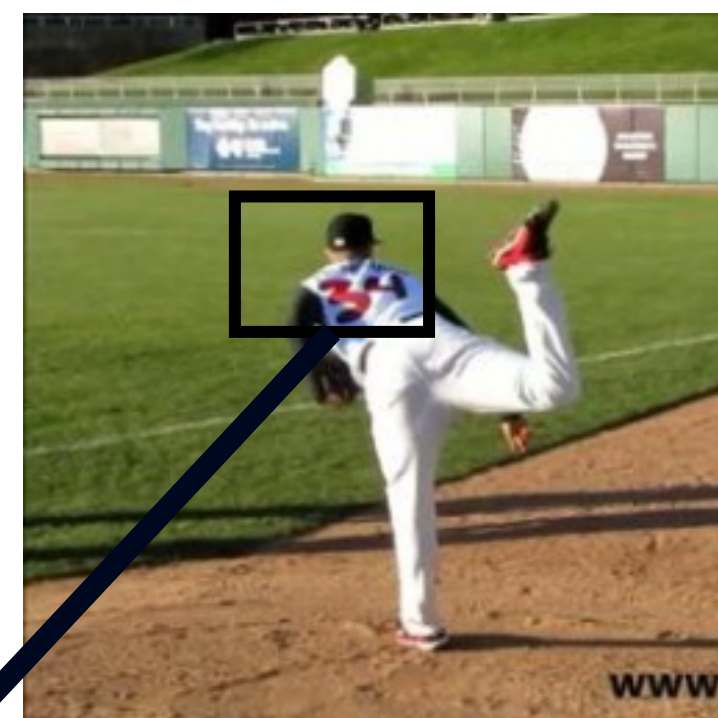
Follow track forward in time

Match to another video

Follow track backward in time

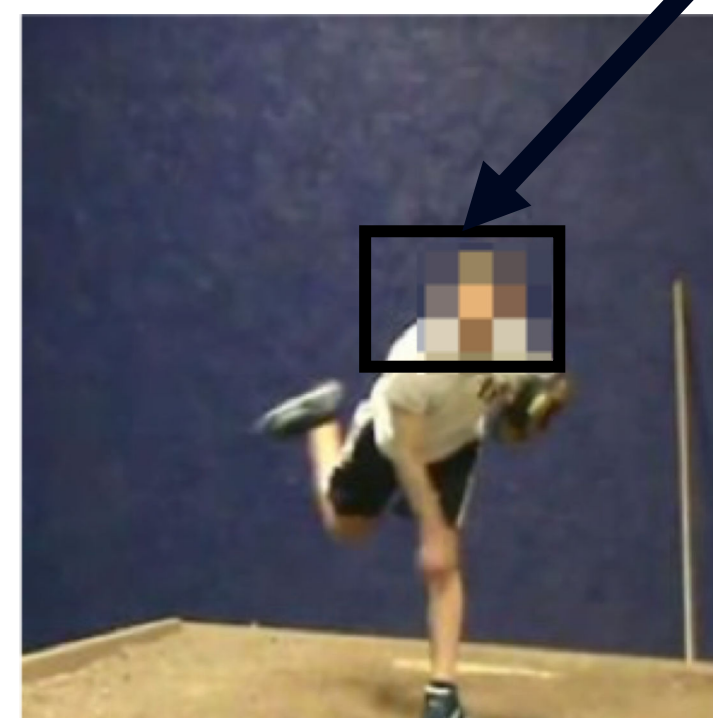
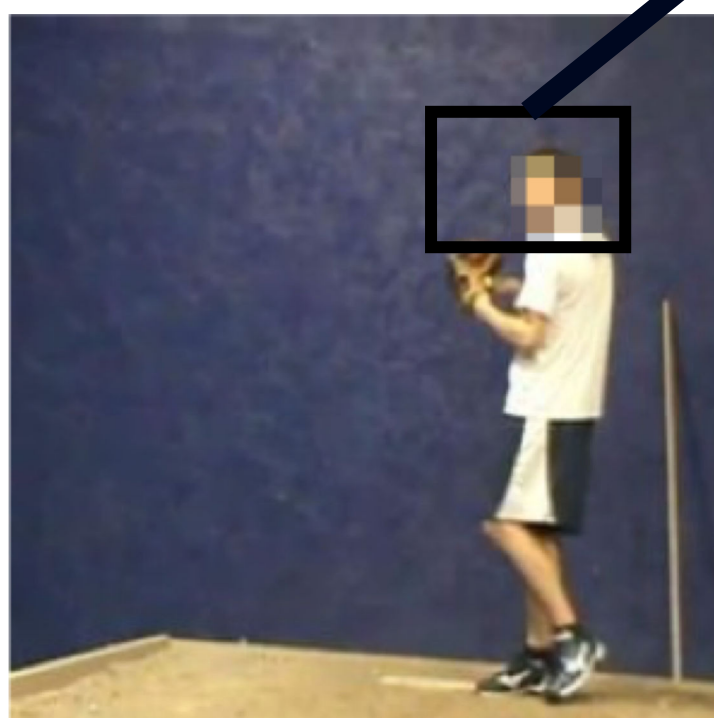
Match back to first video

# Spatio-Temporal Associations Through Cycle Consistency



Depends on the feature extractor

$$f_{\theta}$$



**What is a cycle?**

Follow track forward  $N_1$  frames

**Match to another video**

Follow track backward  $N_2$  frames

**Match back to first video**

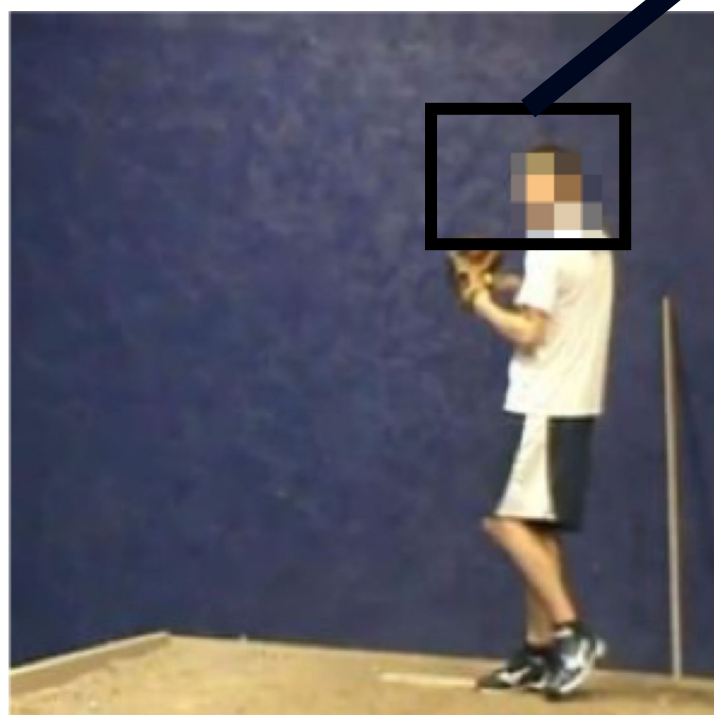
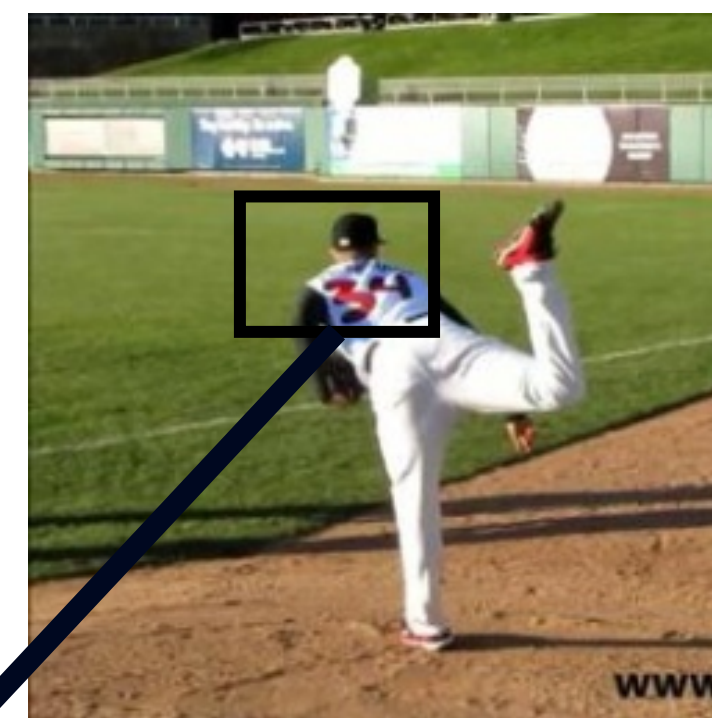
# Spatio-Temporal Associations Through Cycle Consistency

Depends on the feature extractor

$$f_{\theta}$$

Score of a cycle

$$S_{21} + S_{12}$$



What is a cycle?

Follow track forward  $N_1$  frames

Match to another video

Follow track backward  $N_2$  frames

Match back to first video

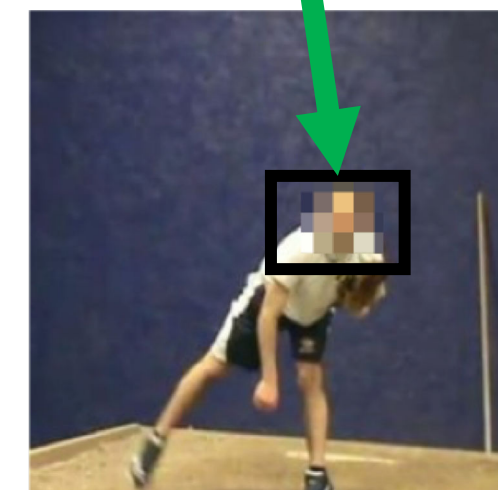
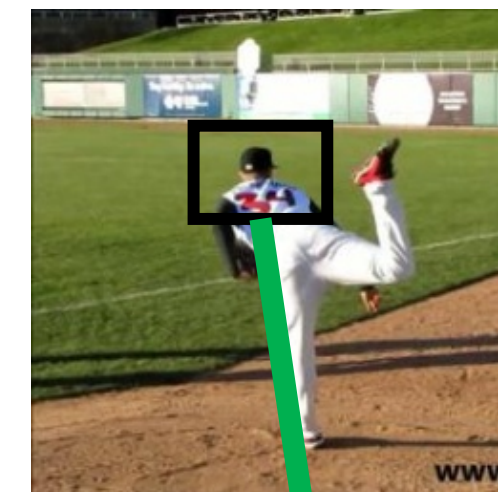
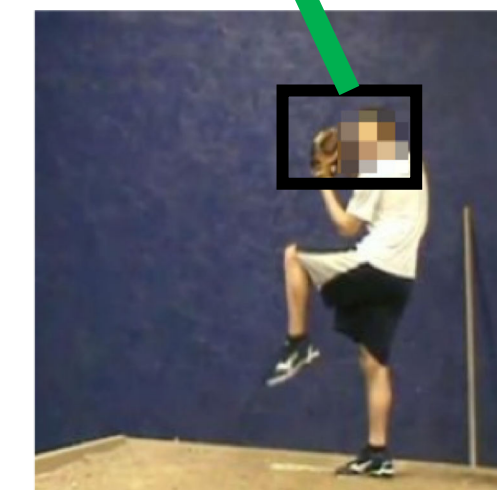
# Spatio-Temporal Associations Through Cycle Consistency

Objective for training  $f_\theta$ :

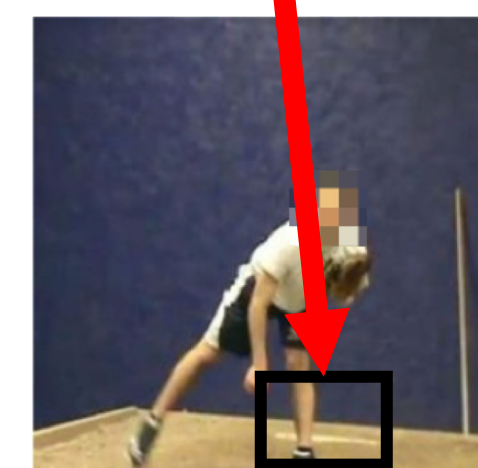
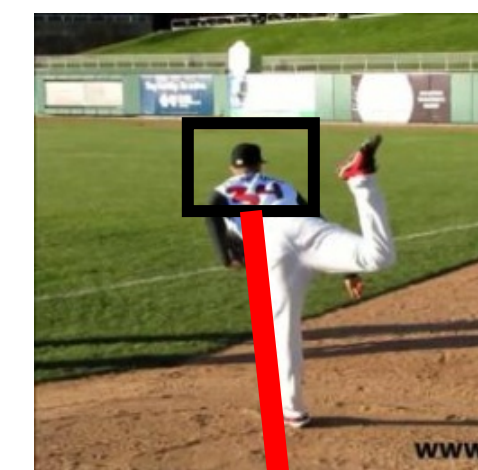
$$L = \max(0, S^- - S^+ + \delta)$$

For a given starting patch

$S^+$  = Score of highest scoring Positive Cycle



$S^-$  = Score of highest scoring Negative Cycle



# Training Datasets



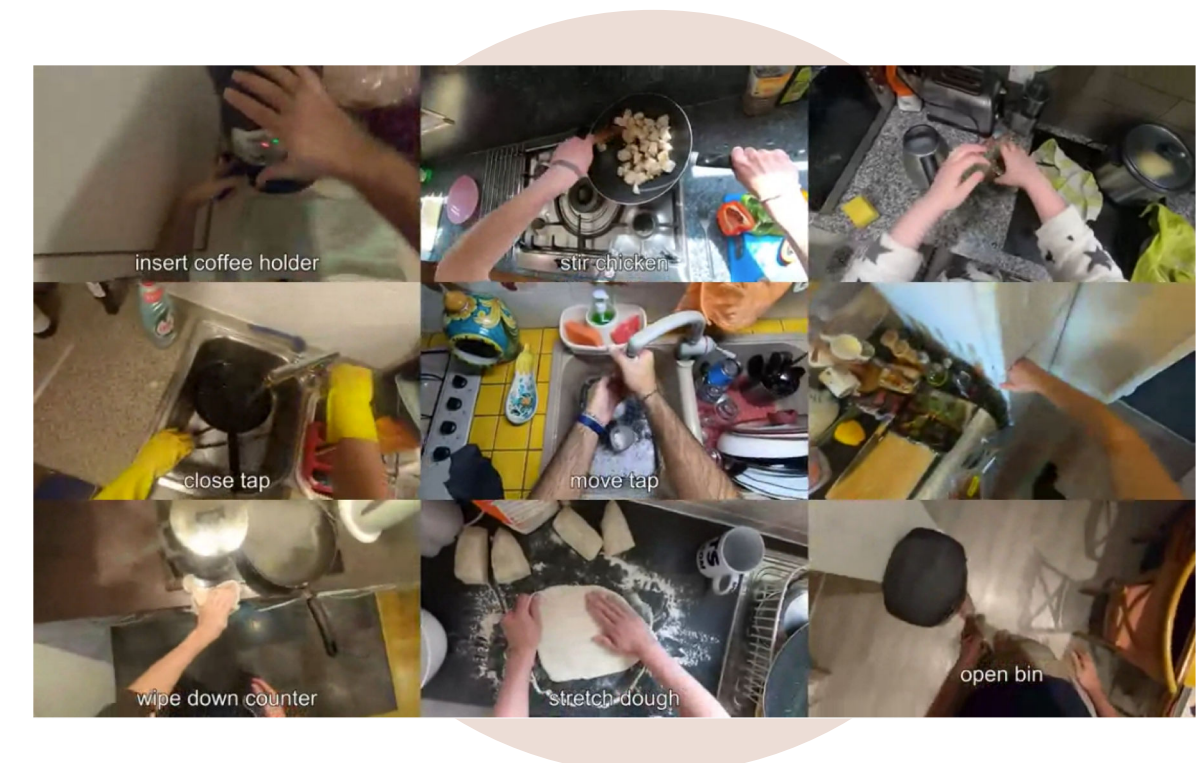
**Penn Action Dataset<sup>1</sup>**

Videos depicting 15 different actions with human joint annotations



**Pouring Dataset<sup>2</sup>**

Videos depicting pouring from one container into another



**Epic Kitchens Dataset<sup>3</sup>**

First-person videos depicting activities in kitchens

1. Weiyu Zhang, Menglong Zhu and Konstantinos Derpanis, "From Actemes to Action: A Strongly-supervised Representation for Detailed Action Understanding" International Conference on Computer Vision (ICCV). Dec 2013.
2. Sermanet, Pierre, Kelvin Xu, and Sergey Levine. "Unsupervised perceptual rewards for imitation learning." *arXiv preprint arXiv:1612.06699* (2016).
3. Damen, Dima, et al. "Scaling egocentric vision: The epic-kitchens dataset." *Proceedings of the European Conference on Computer Vision (ECCV)*. 2018.

# Qualitative Evaluation: Patch Nearest Neighbor

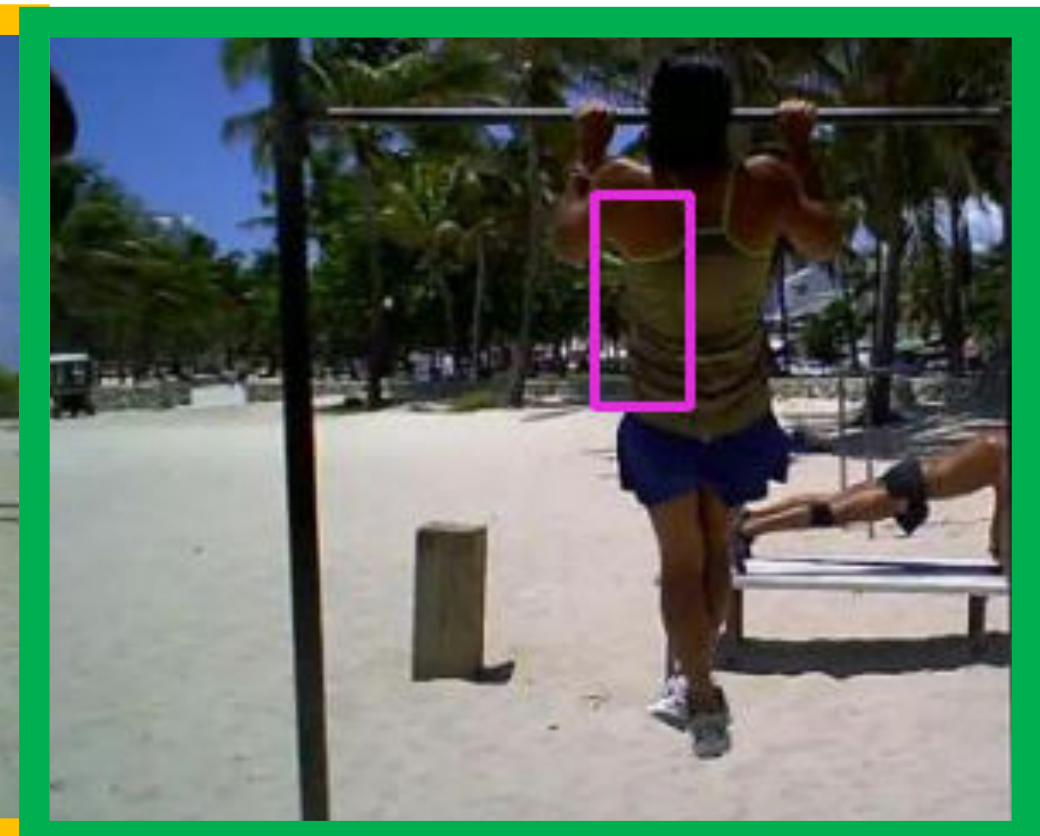
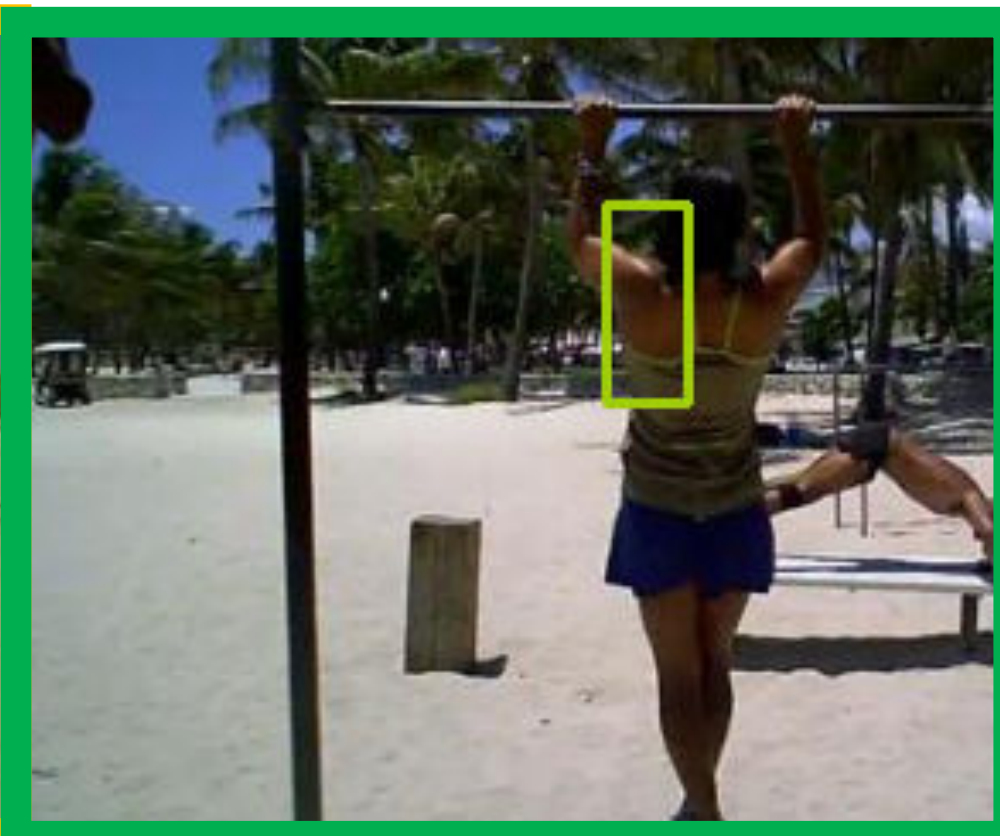
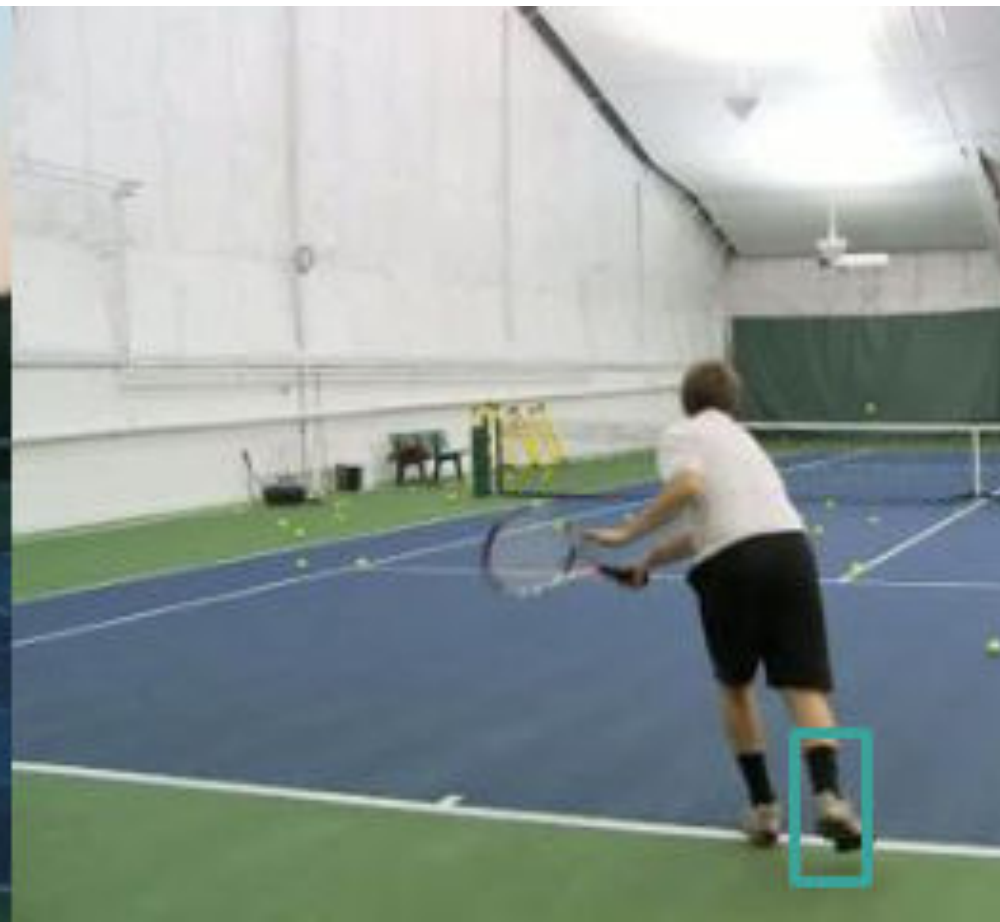
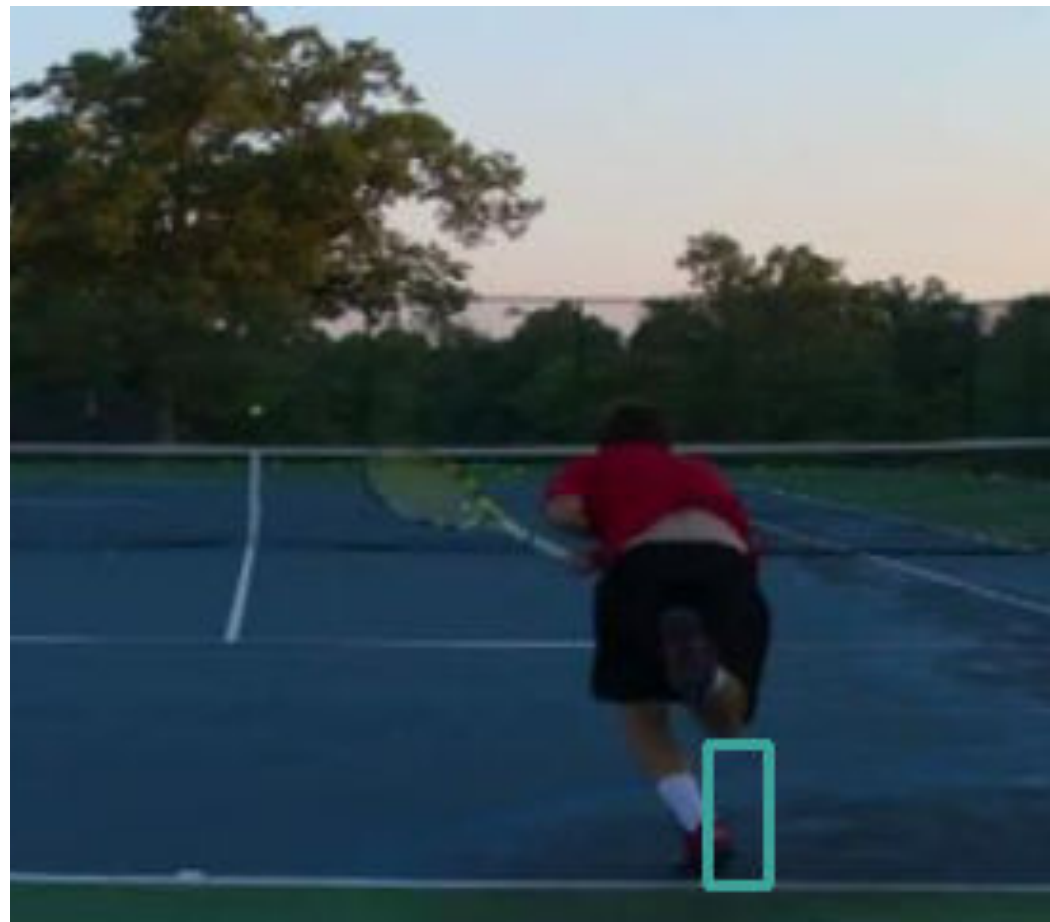
A representation that can **encode patch appearance** while **accounting for object states**

Query

Retrieval

Query

Retrieval



# Qualitative Results: Spatio-Temporal Alignment

Learned representation can effectively *spatio-temporally align videos*



## Aligning Patches

Choose tracks that form high scoring cycles

## Aligning Frames

Frames with high cumulative patch alignment scores



# Quantitative Results: Spatio-Temporal Alignment

Temporal Alignment Error  
Mean difference in joint angles between aligned frames

Spatial Alignment Accuracy  
Accuracy of aligning keypoint patches  
(within some neighborhood)

Initialization Method	Temporal Alignment Err	Spatial Alignment Acc
ImageNet	0.509	0.153
Mask-RCNN [1]	0.504	0.202
Unsupervised Tracker [2]	0.501	0.060
Kinetics Action Classification Model	0.492	0.150
Penn Action Classification Model	0.521	0.157
Our features	<b>0.448</b>	<b>0.284</b>



# Summary

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A spatio-temporal alignment formulation for  
**dense video understanding via association** to known videos

A method to  
**learn representations using cycle-consistency**

Demonstrate that the learned  
**representation encodes object appearance and object states**

Demonstrate that the proposed approach can be  
**effectively used to spatio-temporally align videos**

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Thank you for listening!

Checkout our project paper for relevant links:

<http://www.cs.cmu.edu/~spurushw/publication/alignvideos/>