Comprendre les données visuelles à grande échelle

ENSIMAG
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https://project.inria.fr/bigvisdata/

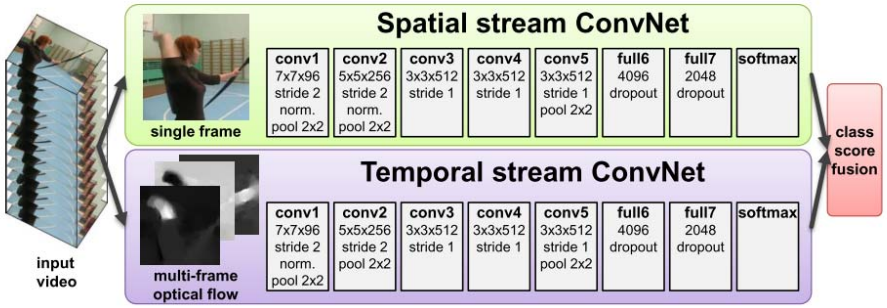
Au programme

- Organisation du cours
- Introduction
  - Contexte et applications
  - Aperçus des taches
  - Evaluation
- Représentation des données visuelles
  - Descripteurs locaux et globaux, réseaux de neurones
  - Application à la fouille de donnée
- Problème de la reconnaissance
  - Classification d'images et de vidéo
  - Séparateurs à Vaste marge (SVM)
  - Pour aller plus loin

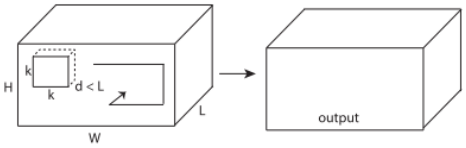
Crédits pour les transparents: C. Schmid, D. Wynen

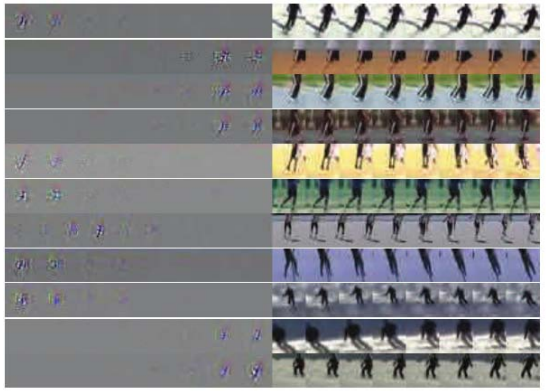
Recent CNN methods

Two-Stream Convolutional Networks for Action Recognition in Videos [Simonyan and Zisserman NIPS14]

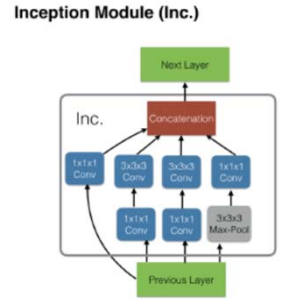


Learning Spatiotemporal Features with 3D Convolutional Networks [Tran et al. ICCV15]





Quo vadis action recognition? A new model and the Kinetics dataset [Carreira et al. CVPR17]



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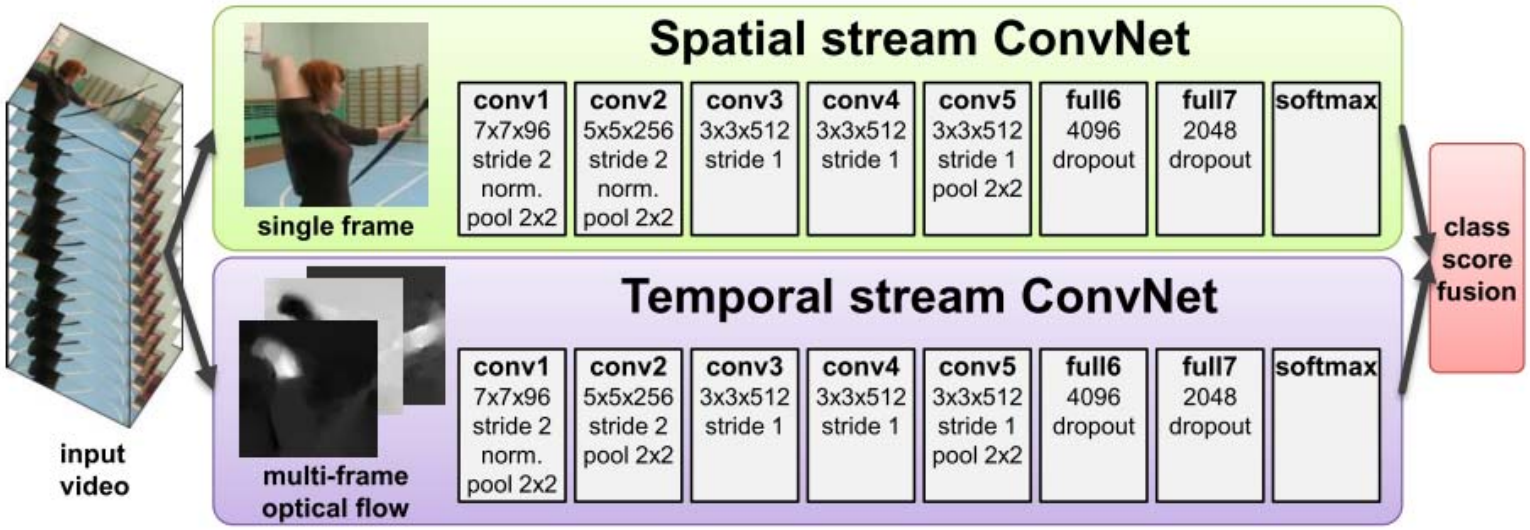


Method

50,000 ft

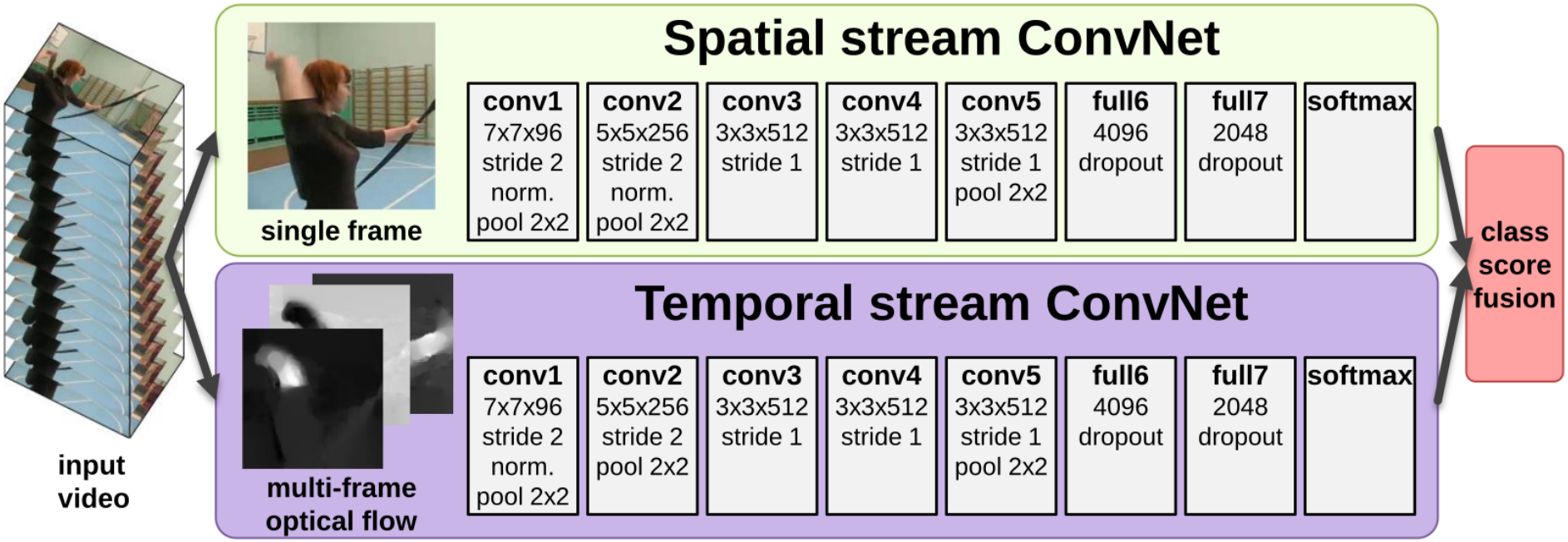
Hyposthesis

The human brain uses separate pathways to recognize objects and motions.

Idea

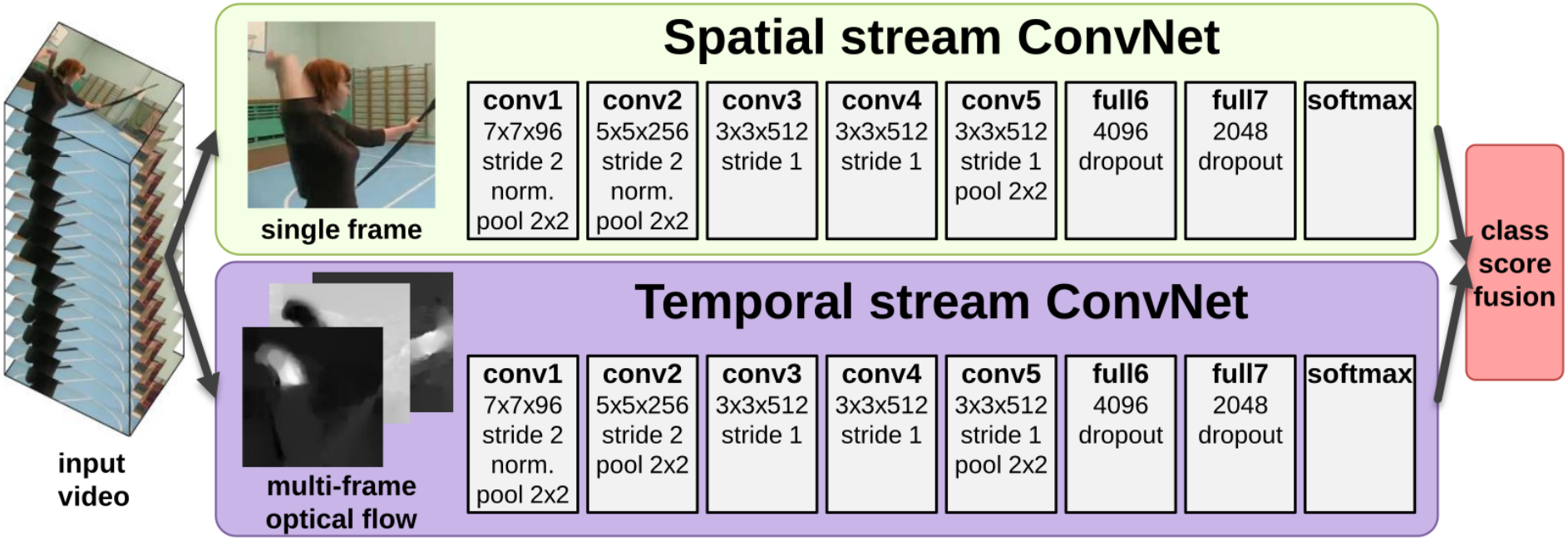
Make a network that mimics this strategy.

Network Architecture I



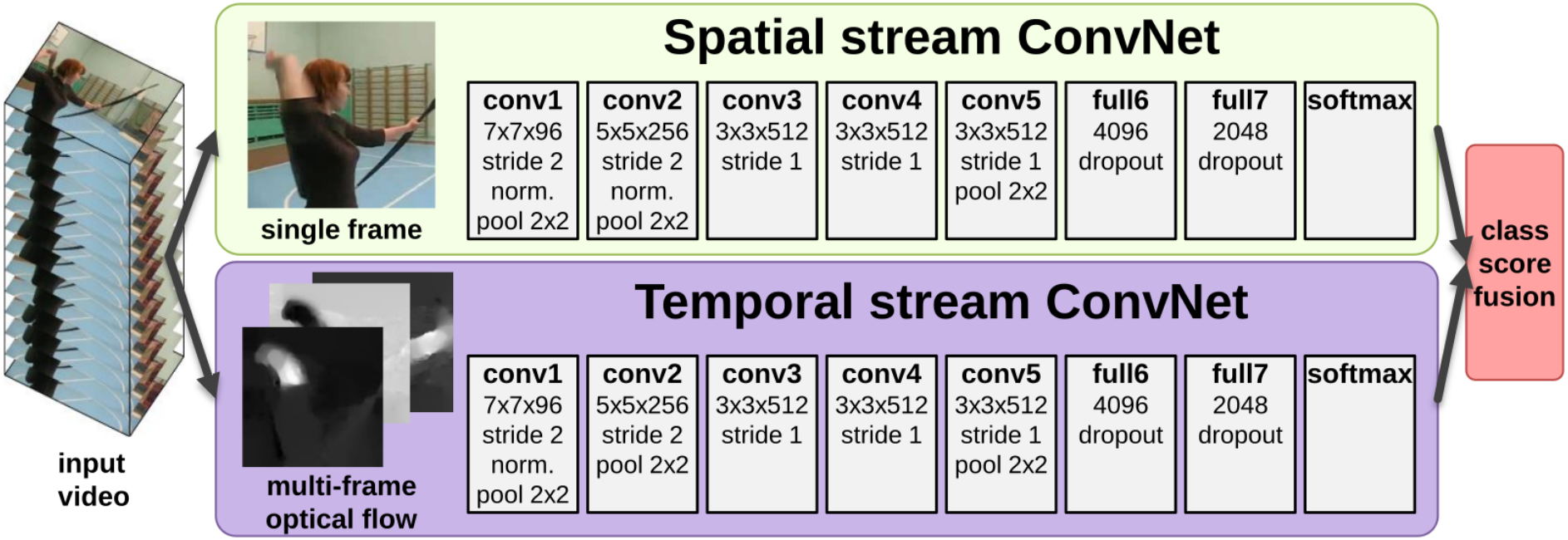
- Still images go into **Spatial Network**
  - Input is a single frame
  - CNP-C**N**P-C-C-C-CP-FD-FD-S

Network Architecture II



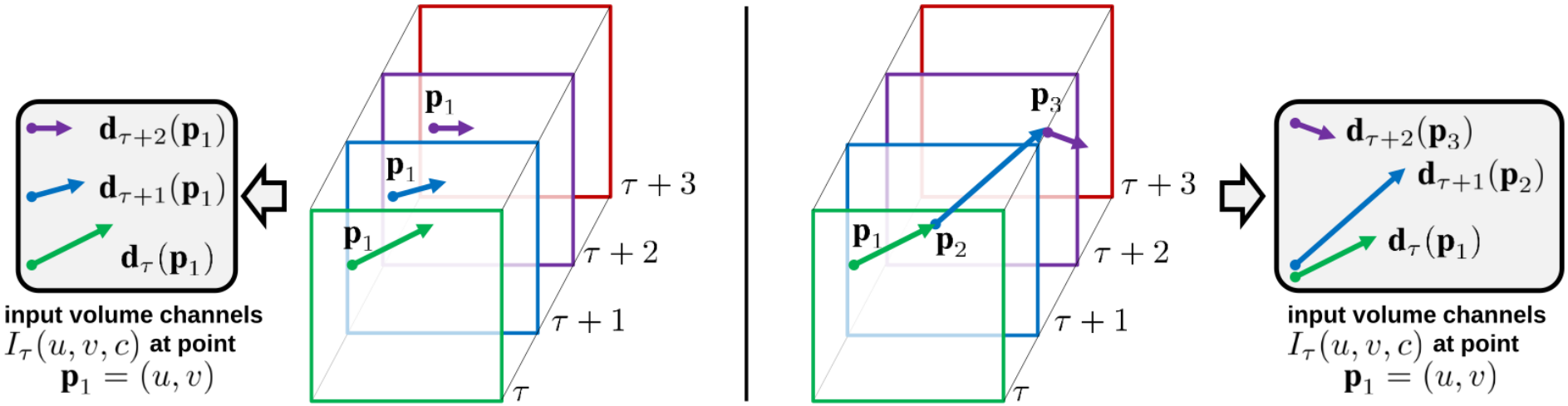
- Flow description goes into **Temporal Network**
  - CNP-CP-C-C-C-CP-FD-FD-S
  - Input is a stack of flow for L frames

Network Architecture III



- No combination of layer outputs up until output layer
  - Outputs of both networks are class scores
  - Combination by averaging or linear SVM
    - Combination via F-Layer had problems with overfitting

Flow Stacking I



Two methods to build input for flow network:

- [u, v, τ:$\tau + L$] describes flow at point [u, v] over time
  - i.e. use flow directly as input
- [u, v, τ:$\tau + L$] describes trajectory starting at [u, v, τ]

Flow Stacking II

Also use Backward Flow

- Also calculate backward flow
- Use $\frac{L}{2}$ frames forward and backward each

Camera Movement

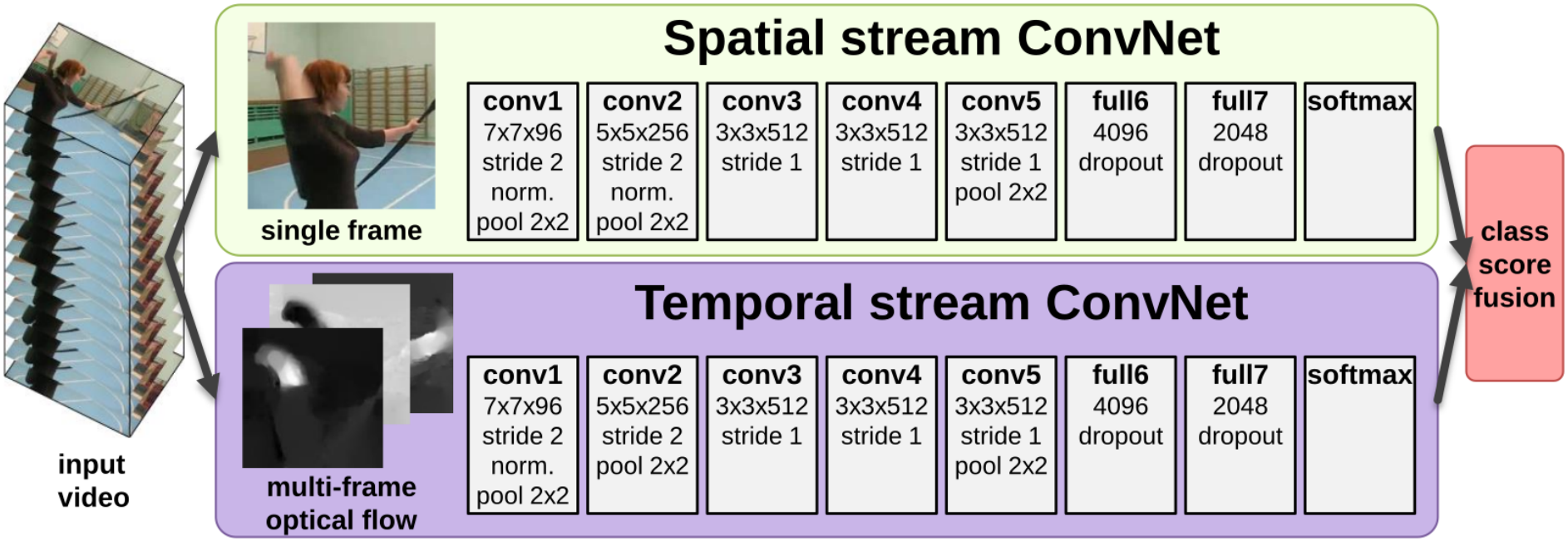
- Subtract mean flow for simple camera movement correction

Multitask Learning

- Use more than one dataset for training
- One softmax output layer per dataset
- Combine loss functions
  - Loss for videos of "other" datasets is zero
  - Sum up loss/gradient across batch/training set

Implementation Details

Implementation Details: Networks



- ReLUs
- Max-pooling on 3×3, stride 2
- Local Response Normalization [1]
  - Normalize activation by sum of activations of "neighbouring" filters

[1] Krizhevsky, Sutskever, Hinton: ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012

Mini-batch SGD

- Momentum 0.9
- Batch size 256
- Learning rate
  - Full Training:
    - 10^{-2} for 50K $\rightarrow$ 10^{-3} for 20K $\rightarrow$ 10^{-4} for 10K
    - $\Rightarrow$ 80K iterations
  - Fine tuning:
    - 10^{-2} for 14K $\rightarrow$ 10^{-3} for 6K

Input Processing

- Select 256 random videos for each mini-batch
- Select random anchor frame for each videos
- Scale so that smaller spatial dimension is 256
- **Spatial net input:** Crop random 224×224 patch, flip, jitter
- **Temporal net input:**
  - anchor "stack of flow" with length $2L$ at chosen frame
  - crop random 224×224 tube
  - random flipping

Testing

- Sample 25 anchor frames at equally spaced times
  - For temporal net, extract stack of flow around
- Crop to corners & to center $\rightarrow 224 \times 224$
- Flip each image/tube horizontally
- $\Rightarrow 25 \cdot 2 \cdot 5 = 250$ inputs for each network
- Average over resulting class scores

The Rest

- Optical flow straight from OpenCV
  - Precomputed and stored in 8-bit resolution $\rightarrow$ only 27GB
- Patched Caffe to run on multiple graphics cards

Experiments & Results

Spatial Net

Evalutation on UCF101

- Training from scratch
  - Overfits

Training setting	Dropout ratio	
	0.5	0.9
From scratch	42.5%	52.3%
Pre-trained + fine-tuning	70.8%	**72.8%**
Pre-trained + last layer	**72.7%**	59.9%

Spatial Net

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- Pretrain on ILSVRC-2012, fine-tune on UCF101
  - Works, but careful about over regularizing!

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Spatial Net

Evalutation on UCF101

- Training from scratch
  - Overfits
- Pretrain on ILSVRC-2012, fine-tune on UCF101
  - Works, but careful about over regularizing!
- Pretrain on ILSVRC-2012, re-train softmax layer
  - Works, use this from now on

Training setting	Dropout ratio	
	0.5	0.9
From scratch	42.5%	52.3%
Pre-trained + fine-tuning	70.8%	**72.8%**
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Temporal Net

Evalutation on UCF101

- $L = 5$ much better than $L = 1$
- $L = 10$ a bit better yet
- Stacking largely irrelevant

Input configuration	Mean subtraction	
	off	on
Single-frame optical flow (L = 1)	-	73.9%
Optical flow stacking (1) (L = 5)	-	80.4%
Optical flow stacking (1) (L = 10)	79.9%	**81.0%**
Trajectory stacking (2) (L = 10)	79.6%	80.2%
Optical flow stacking (1) (L = 10) ,bi-dir.	-	**81.2%**

Implemented Slow Fusion[2]

- Yields 56% accuracy (in line with that paper)
- Conclusion: motion needs to be presented appropriately

[2] Large-scale Video Classification with Convolutional Neural Networks

Multi-task Learning of Temporal Net

Evalutation on HMDB-51

Training setting	Accuracy
Training on HMDB-51 without additional data	46.6%
Fine-tuning a ConvNet, pre-trained on UCF-101	49.0%
Training on HMDB-51 with classes added from UCF-101	52.8%
Multi-task learning on HMDB-51 and UCF-101	**55.4%**

- Using more data helps!
- At least in this direction
  - UCF101 alone: 81%
  - UCF101+HMDB-51: 81.**5**%

Combined Networks

Spatial ConvNet	Temporal ConvNet	Fusion Method	Accuracy
Pre-trained + last layer	bi-directional	averaging	85.6%
Pre-trained + last layer	uni-directional	averaging	85.9%
Pre-trained + last layer	uni-directional, multi-task	averaging	86.2%
Pre-trained + last layer	uni-directional, multi-task	SVM	**87.0%**

Figure: Fused Results on UCF101 Split 1

Observations

- Fusion improves on each individual network
- SVM is better than averaging
- Multi-task learning helps
- Bi-directional flow does *not* help

Comparison to State of the Art (Mean over Splits)

Method	UCF-101	HMDB-51
Improved dense trajectories (IDT) [26, 27]	85.9%	57.2%
IDT with higher-dimensional encodings [20]	**87.9%**	61.1%
IDT with stacked Fisher encoding [21] (based on Deep Fisher Net [23])	-	**66.8%**
Spatio-temporal HMAX network [11, 16]	-	22.8%
"Slow fusion" spatio-temporal ConvNet [14]	65.4%	-
Spatial stream ConvNet	73.0%	40.5%
Temporal stream ConvNet	83.7%	54.6%
Two-stream model (fusion by averaging)	86.9%	58.0%
Two-stream model (fusion by SVM)	**88.0%**	**59.4%**

- Spacial net: pretrained + last layer
- Temporal net: unidirectional stacked flow, centered, multi-task

- Each net individually better than "The Other Paper" \o/
- Combination even better
- But not quite state of the art on HMDB

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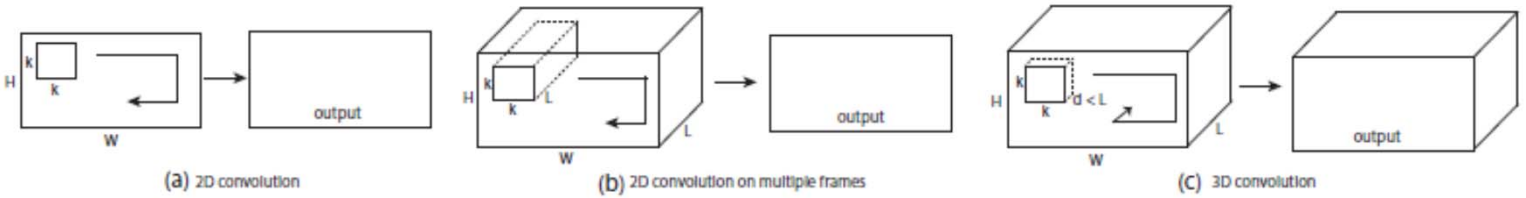
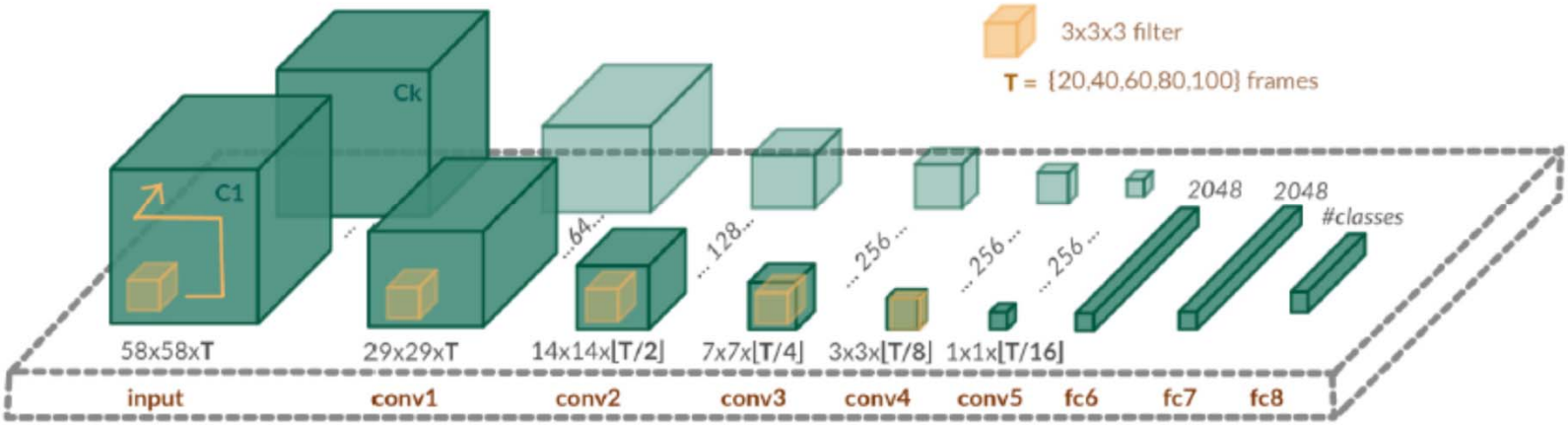


Figure 1. **2D and 3D convolution operations**. a) Applying 2D convolution on an image results in an image. b) Applying 2D convolution on a video volume (multiple frames as multiple channels) also results in an image. c) Applying 3D convolution on a video volume results in another volume, preserving temporal information of the input signal.



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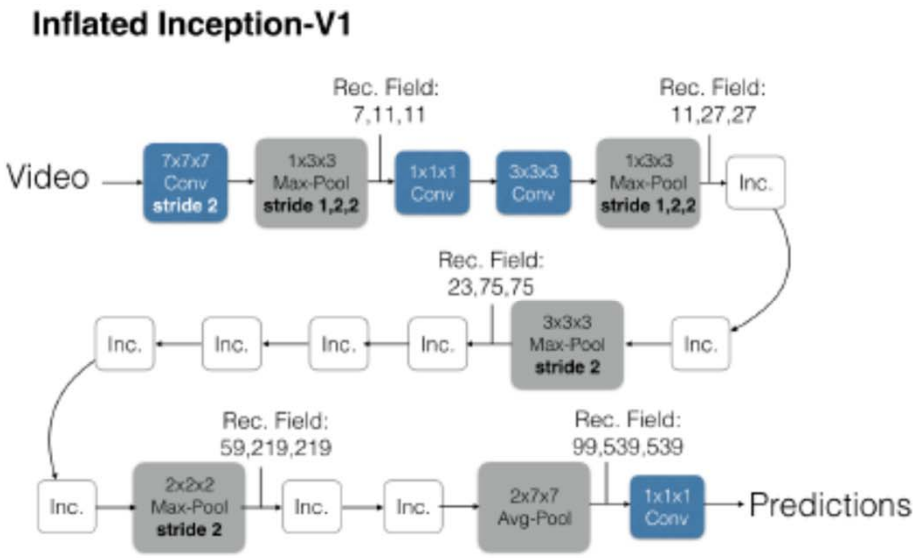
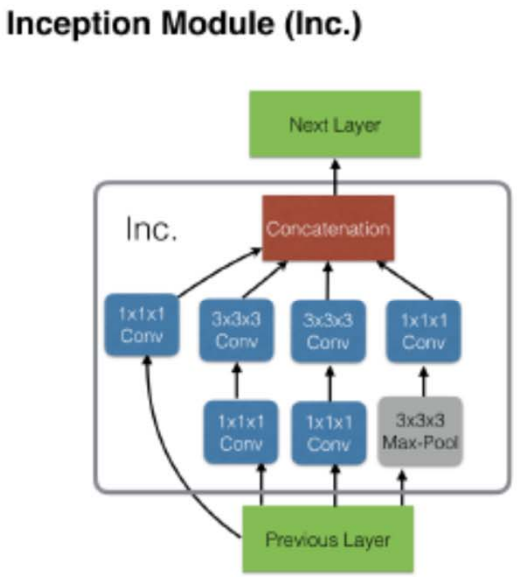




Pre-training on the large-scale Kinetics dataset 240k training videos
→ significant performance grain

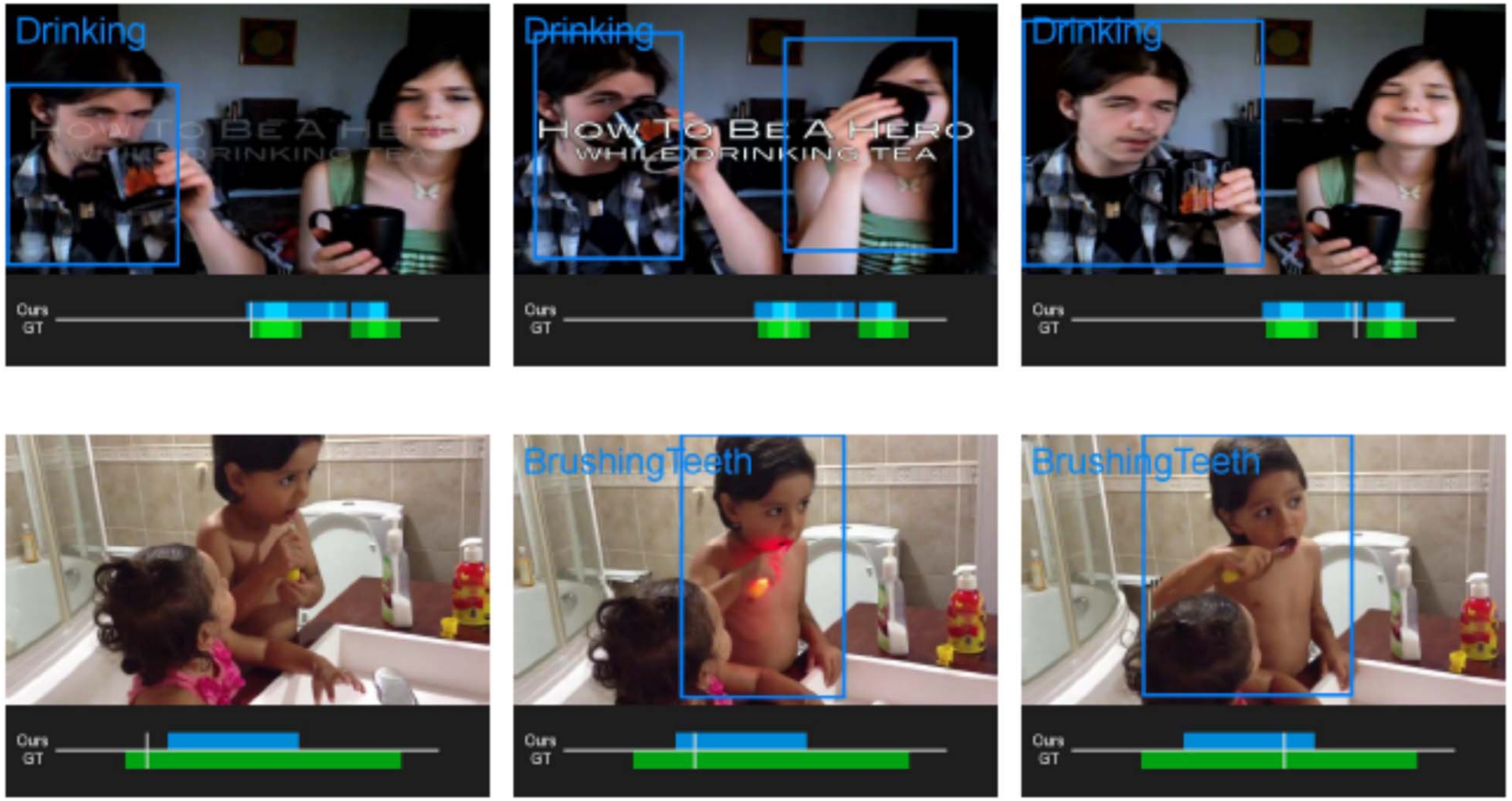
Summary

- 3D convolution capture spatio-temporal dynamics well
- Importance of sufficient training data

Overview

- Optical flow
- Video classification
  - Bag of spatio-temporal features
- *Action localization*
  - *Spatio-temporal human localization*

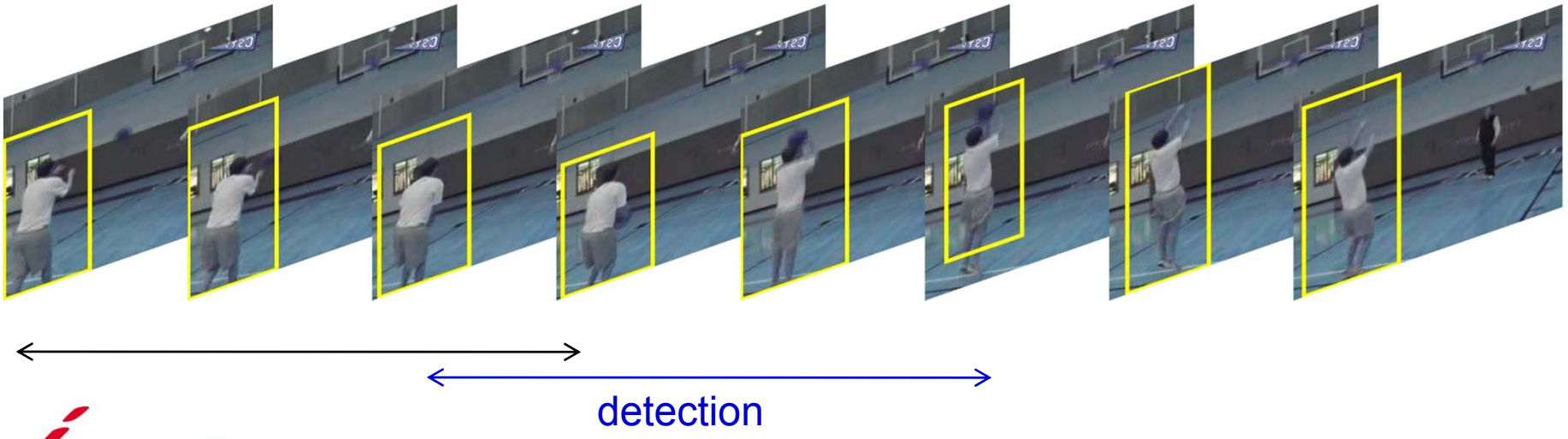
Spatio-temporal action localization



informatics mathematics

Temporal action localization

- Temporal sliding window
  - Robust video repres. for action recognition, Oneata et al., IJCV'15
  - Automatic annotation of actions in video, Duchenne et al., ICCV'09
  - Temporal localization of actions with actoms, Gaidon et al., PAMI'13
- Shot detection
  - ADSC Submission at Thumos Challenge 2015



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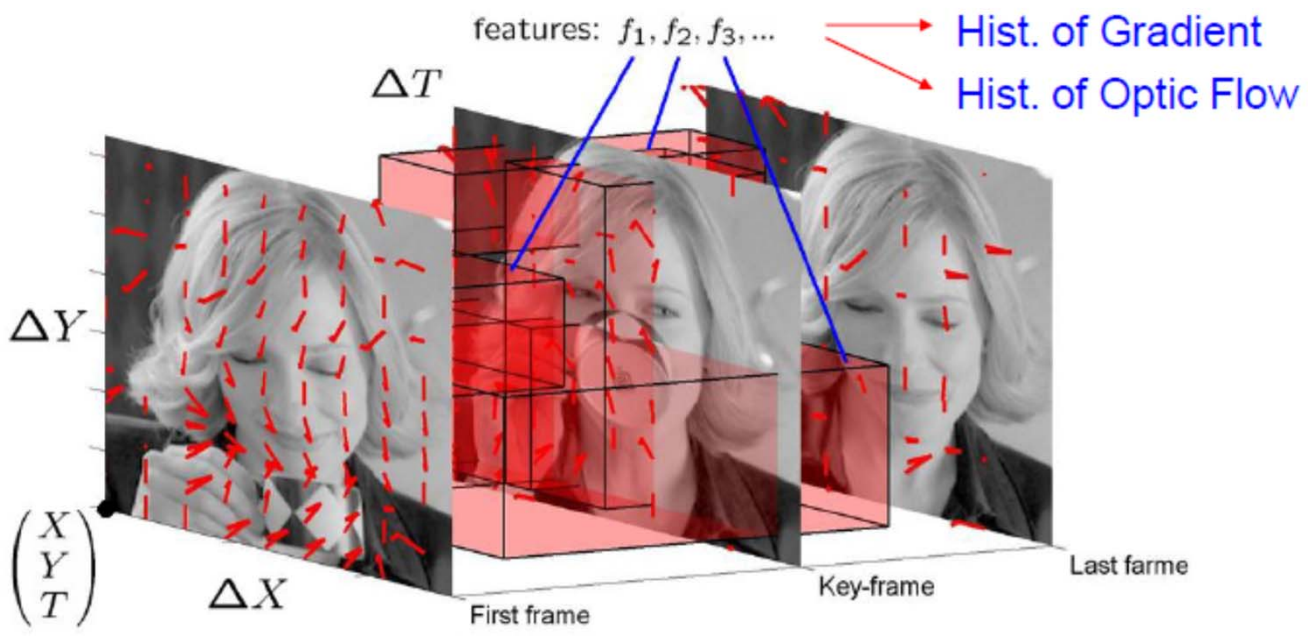
State of the art

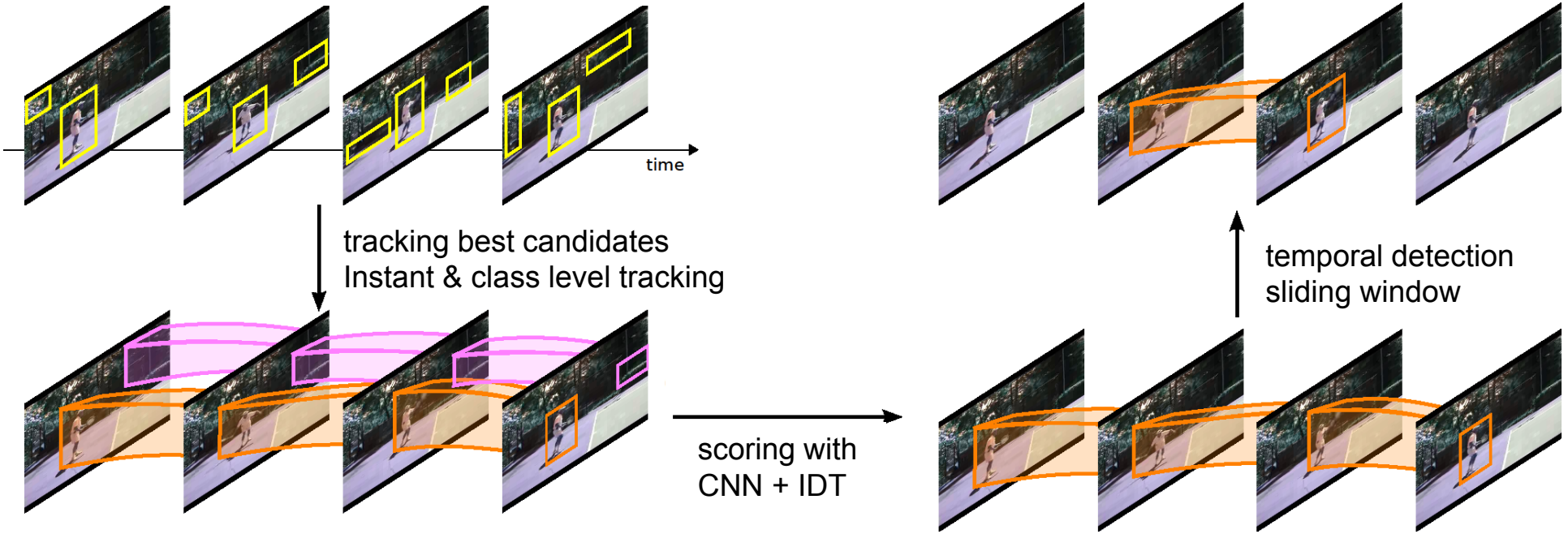
- Spatio-temporal action localization
  - Space-time sliding window
    - Spatio-temporal features selection with a cascade, Laptev & Perez, ICCV'07



informatics mathematics

Learning to track for spatio-temporal action localization

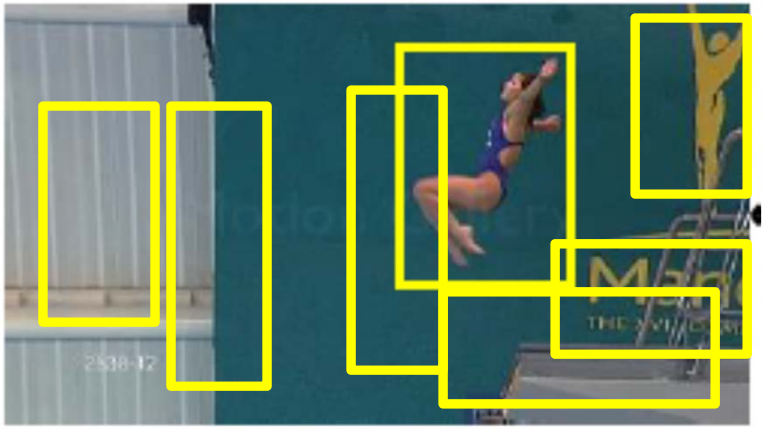
frame-level object proposals and CNN action classifier
[Gkioxari and Malik, CVPR 2015]



[Learning to track for spatio-temporal action localization,
P. Weinzaepfel, Z. Harchaoui, C. Schmid, ICCV 2015]

Frame-level candidates

- For each frame
  - Compute object proposals: EdgeBoxes [Zitnick et al. 2014]

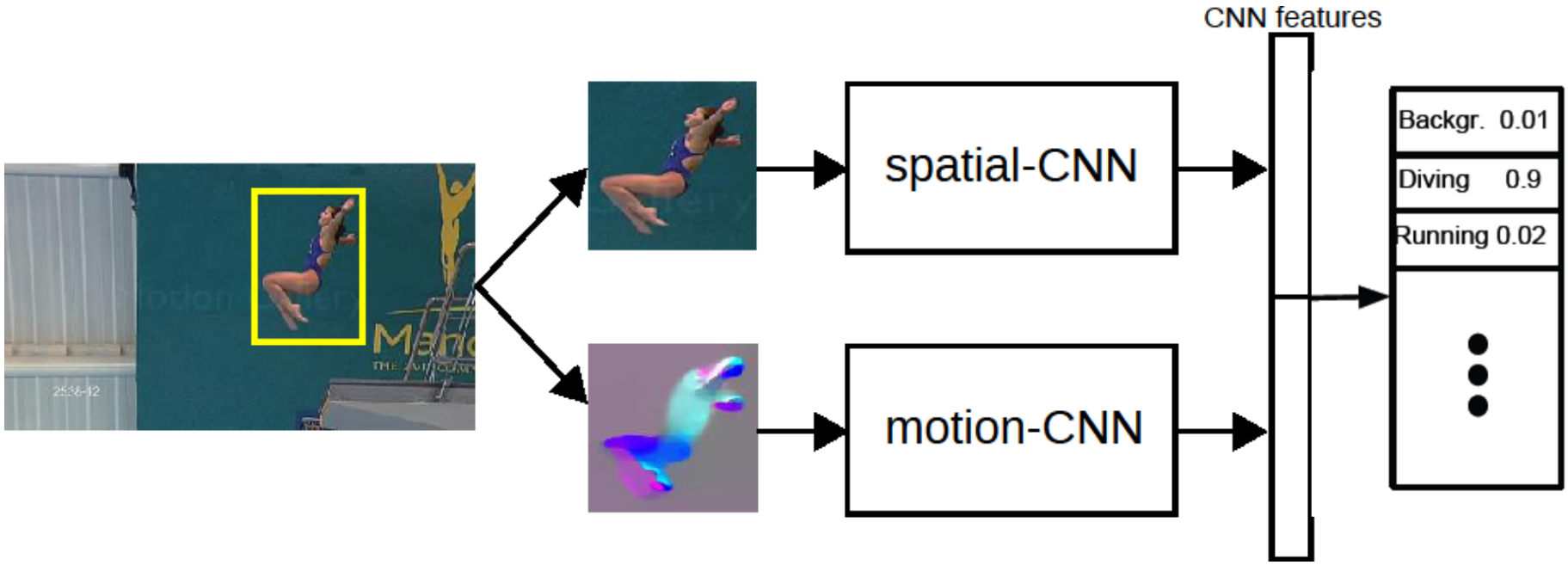


Frame-level candidates

- For each frame
  - Compute object proposals: EdgeBoxes [Zitnick et al. 2014]
  - Extraction of salient boxes based on edgeness

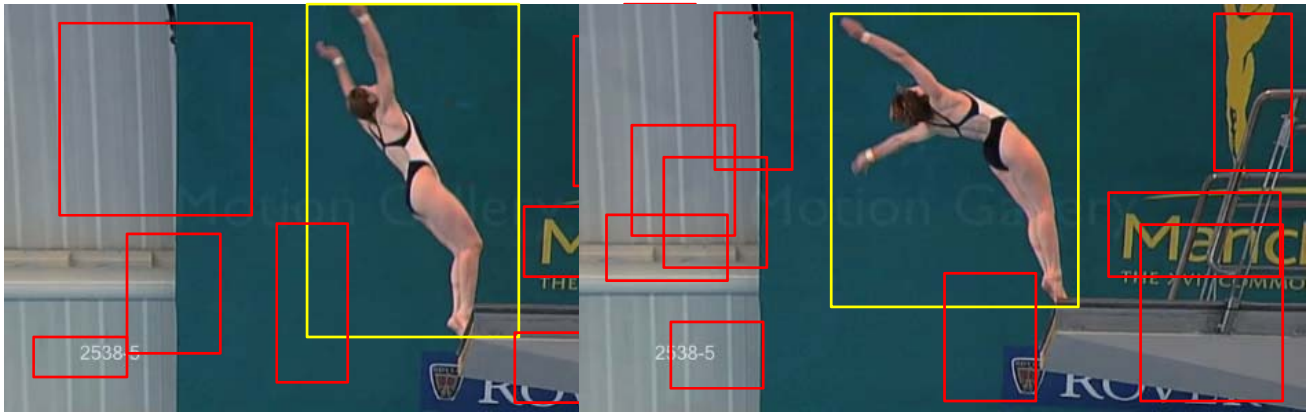
Frame-level candidates

- For each frame
  - Compute object proposals (EdgeBoxes [Zitnick et al. 2014])
  - Extract CNN features (training similar to R-CNN [Girshicket al. 2014])
  - Score each object proposal



[Gkioxari and Malik'15, Simonyan and Zisserman'14]

Extracting action tubes - tracking



- Tracking an action detection (select highest scoring proposal)
  - Learn an instance-level detector

    mining negatives in the same frame
  - For each frame:
    - Perform a sliding-window and select the best box according to the class-level detector and the instance-level detector
    - Update instance-level detector

Extracting action tubes

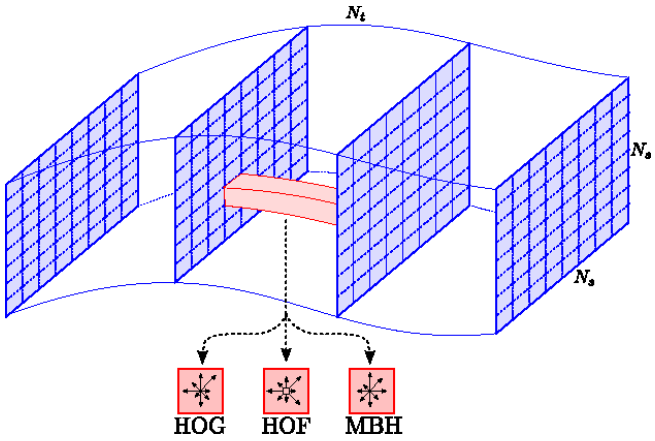
- Start with the highest scored action detection in the video
- Track forward and the backward
- Once tracking is done, delete detections with high overlap
- Restart from the highest scored remaining action detection

- Class-level → robustness to drastic change in poses (Diving, Swinging)

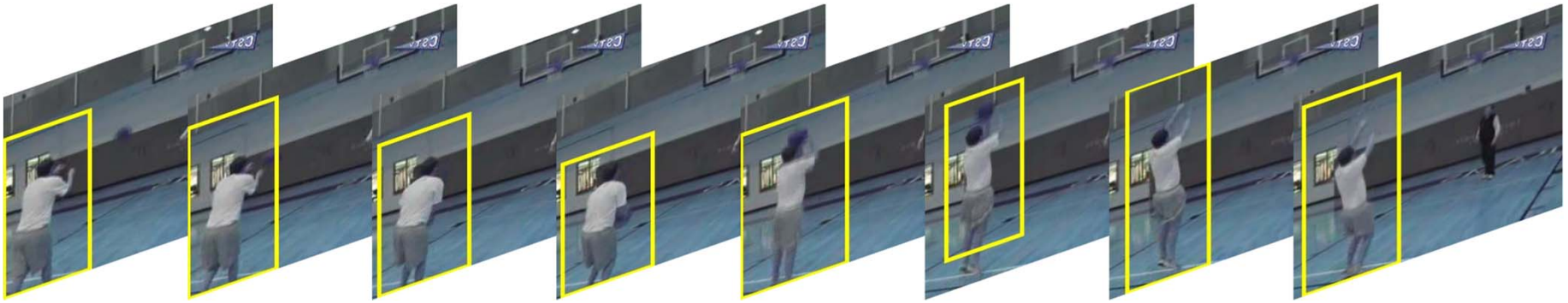
- Instance-level → models specific appearance

Rescoring and temporal sliding window

- To capture the dynamics
  - ► Dense trajectories [Wang et Schmid, ICCV'13]



- Temporal sliding window



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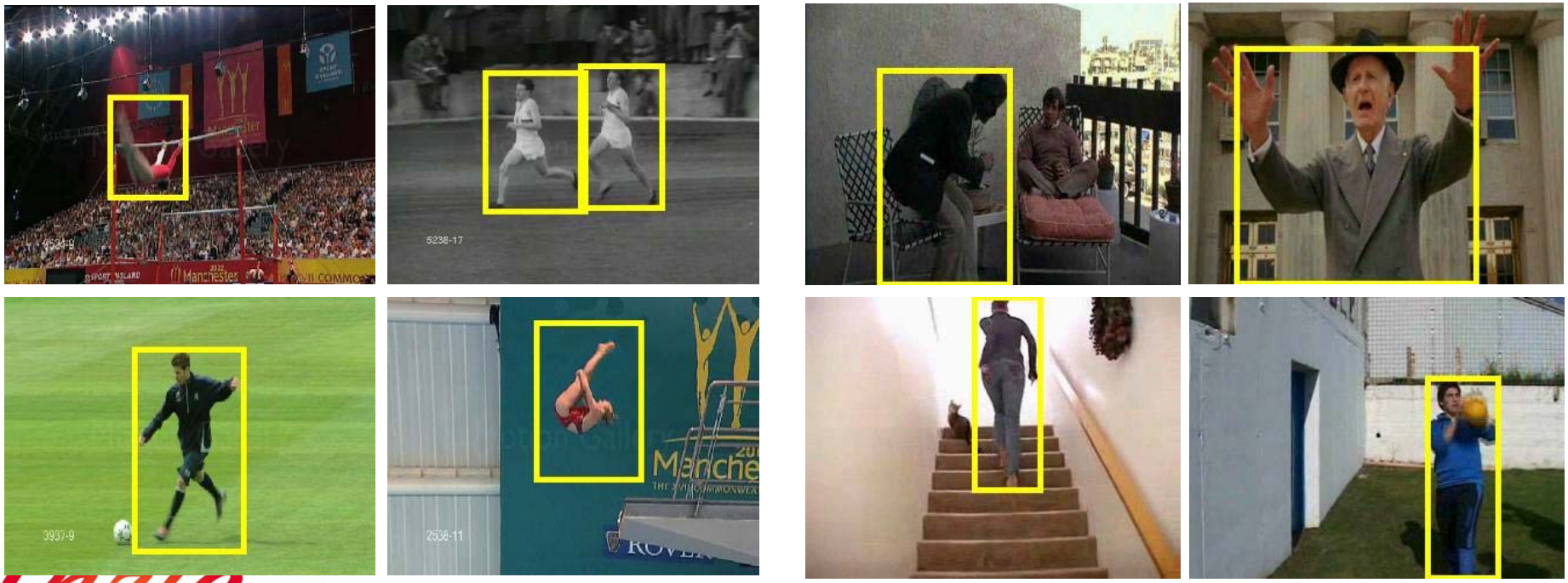
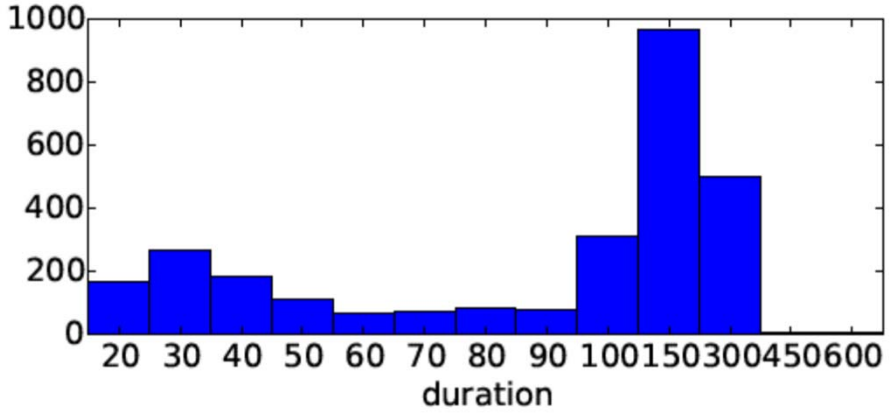
Datasets (spatial localization)

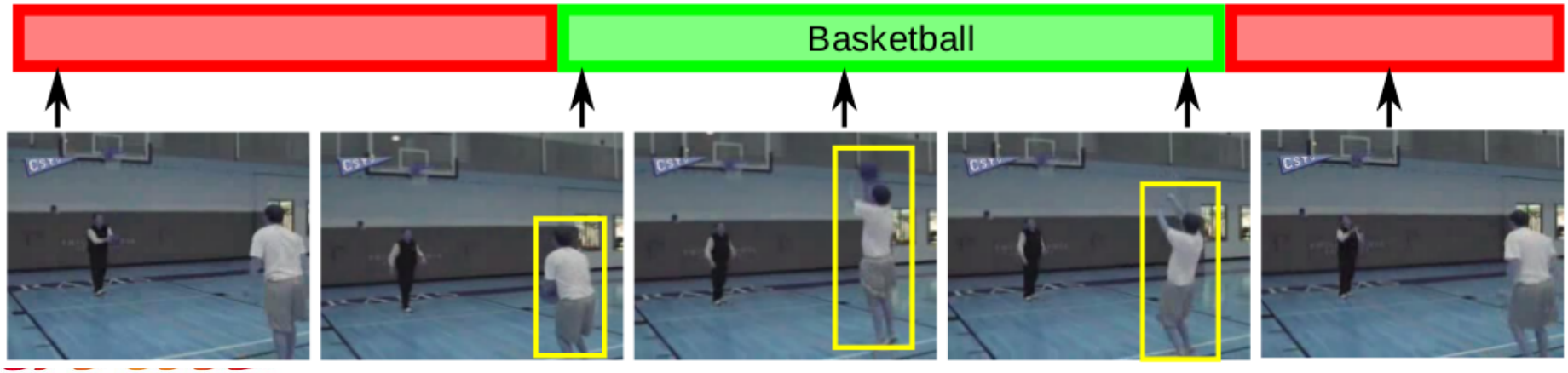
	UCF-Sports [Rodriguez et al. 2008]	J-HMDB [Jhuang et al. 2013]
Number of videos	150	928
Number of classes	10	21
Average length	63 frames	34 frames



Datasets

- UCF-101 [Soomro et al. 2012]
  - ► Spatio-temporal localization for a subset of the dataset
  - ► 3207 videos, 24 classes
  - ► Average length: 176 frames





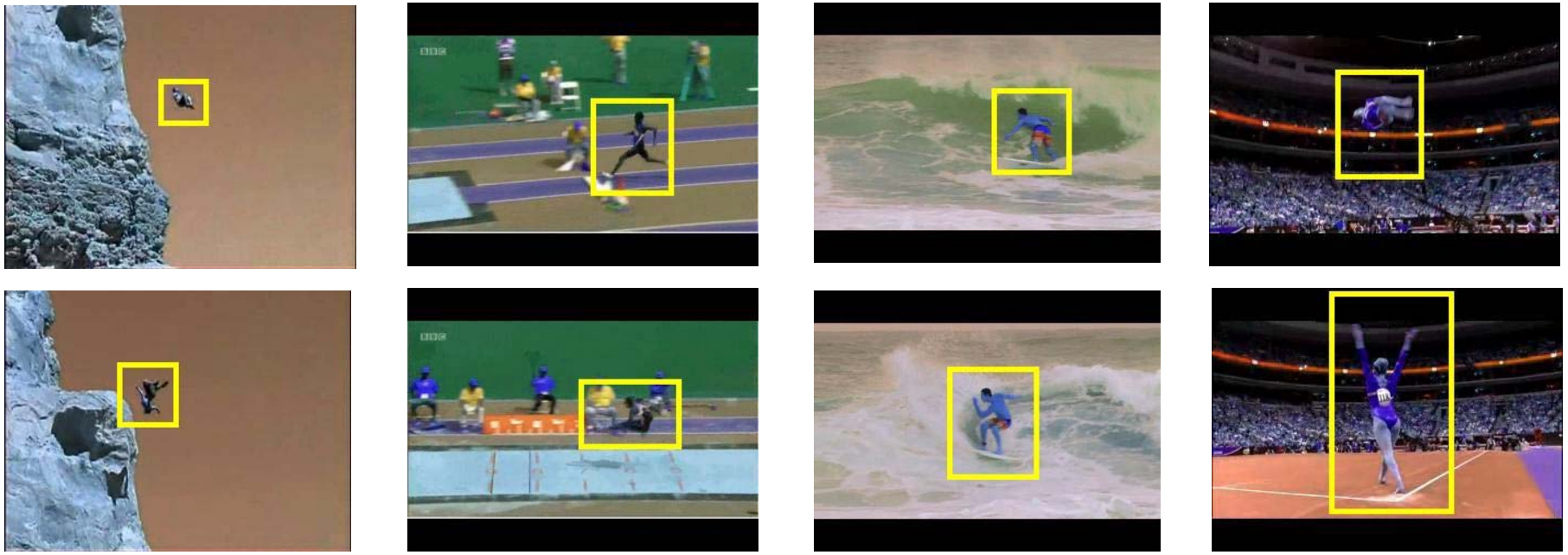
Experimental results

Impact of the tracker

Detectors in the tracker	mAP	
	UCF-Sports	J-HMDB (split 1)
instance-level + class-level	**95.1%**	**65.0%**
instance-level	77.5%	61.1%
class-level	91.0%	60.6%
Comparison to the state of the art		
Gkioxari & Malik, 15	75.8%	53.3%

Quantitative evaluation on UCF-101

mAP	0.2	0.3
Ours	46.7	37.8



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