Action Recognition

Computer Vision

Jia-Bin Huang, Virginia Tech

Many slides from D. Hoiem

This section: advanced topics

- Convolutional neural networks in vision
- Action recognition
- 3D Scenes and Context

What is an action?

Action: a transition from one state to another

- Who is the actor?
- How is the state of the actor changing?
- What (if anything) is being acted on?
- How is that thing changing?
- What is the purpose of the action (if any)?

How do we represent actions?

Categories

Walking, hammering, dancing, skiing, sitting down, standing up, jumping

Poses

Nouns and Predicates

<man, swings, hammer>
<man, hits, nail, w/ hammer>

What is the purpose of action recognition?

- To describe

  https://www.youtube.com/watch?v=bcgXAQcvxdc

- To predict

  http://www.youtube.com/watch?v=LQm25nW6aZw

How can we identify actions?

Motion

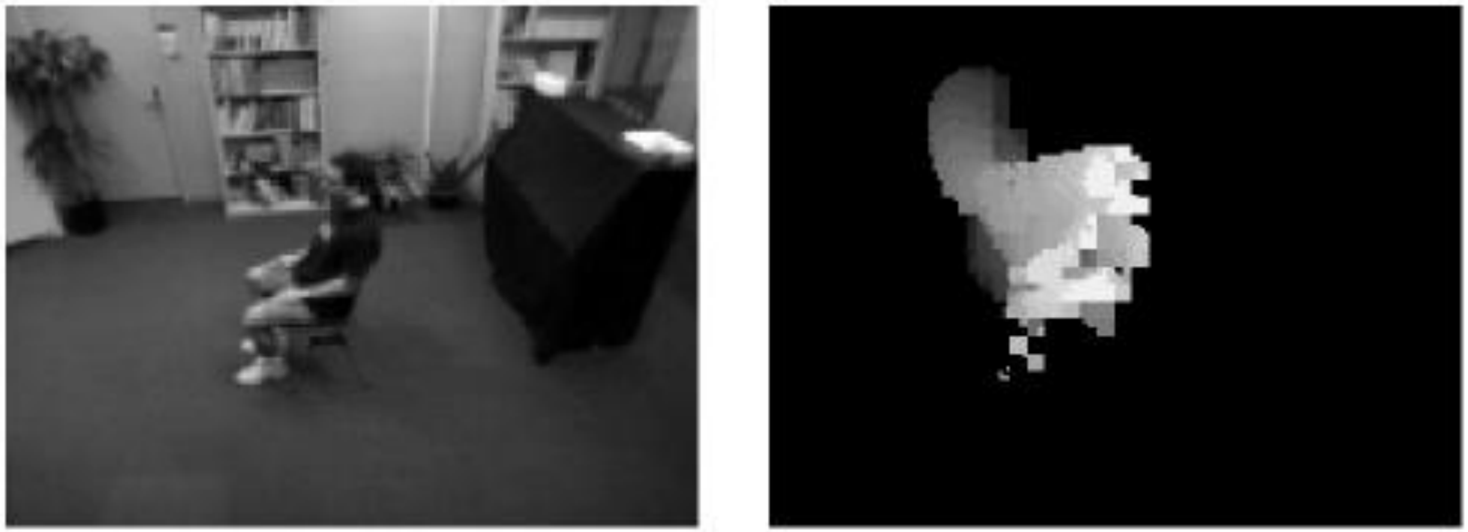
Pose

Held Objects

Nearby Objects

Representing Motion

Optical Flow with Motion History



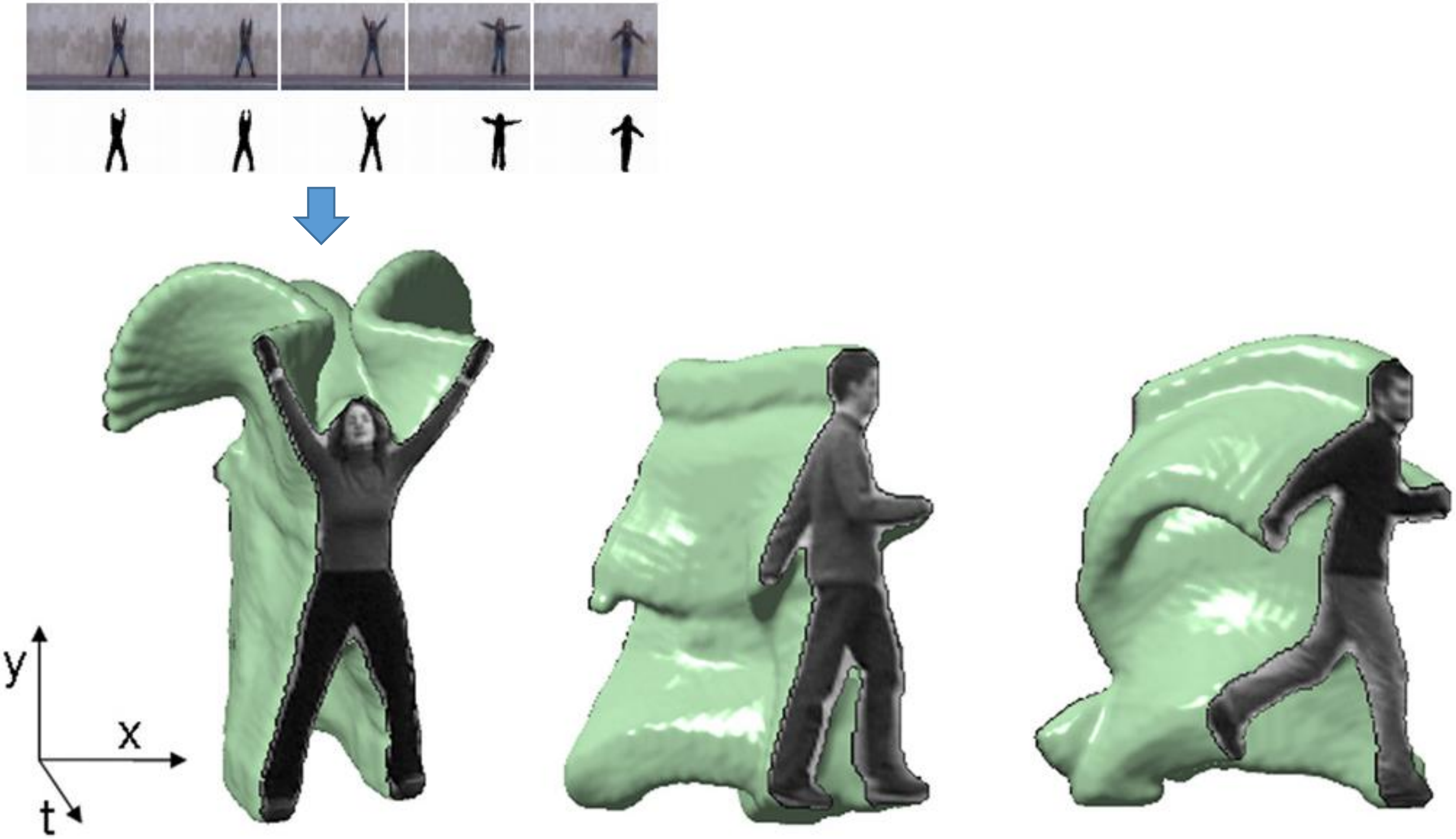
sit-down

sit-down MHI

Bobick Davis 2001

Representing Motion

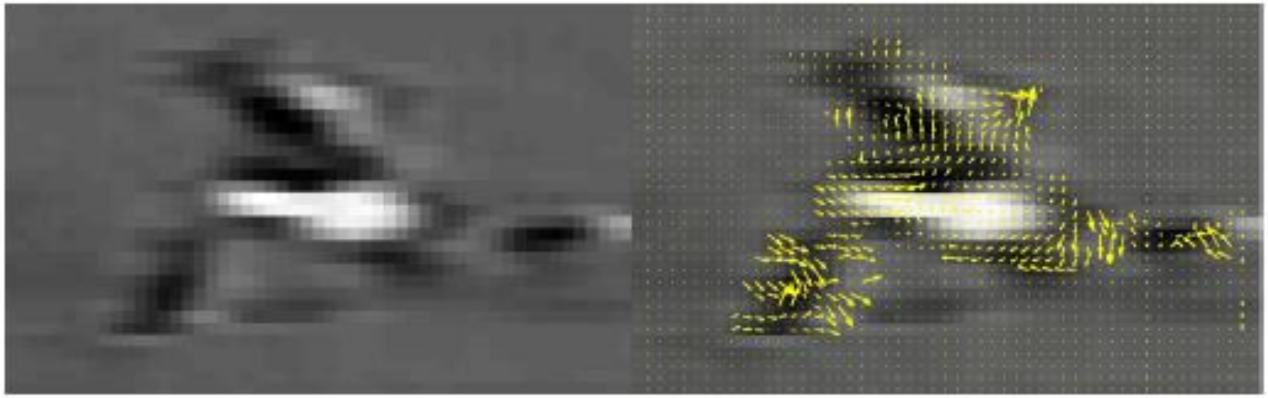
Space-Time Volumes



Blank et al. 2005

Representing Motion

Optical Flow with Split Channels



(a) original image

(b) optical flow $F_{x,y}$

(c) F_x, F_y

optical flow

(d) $F_x^+, F_x^-, F_y^+, F_y^-$

split into pos/neg channels

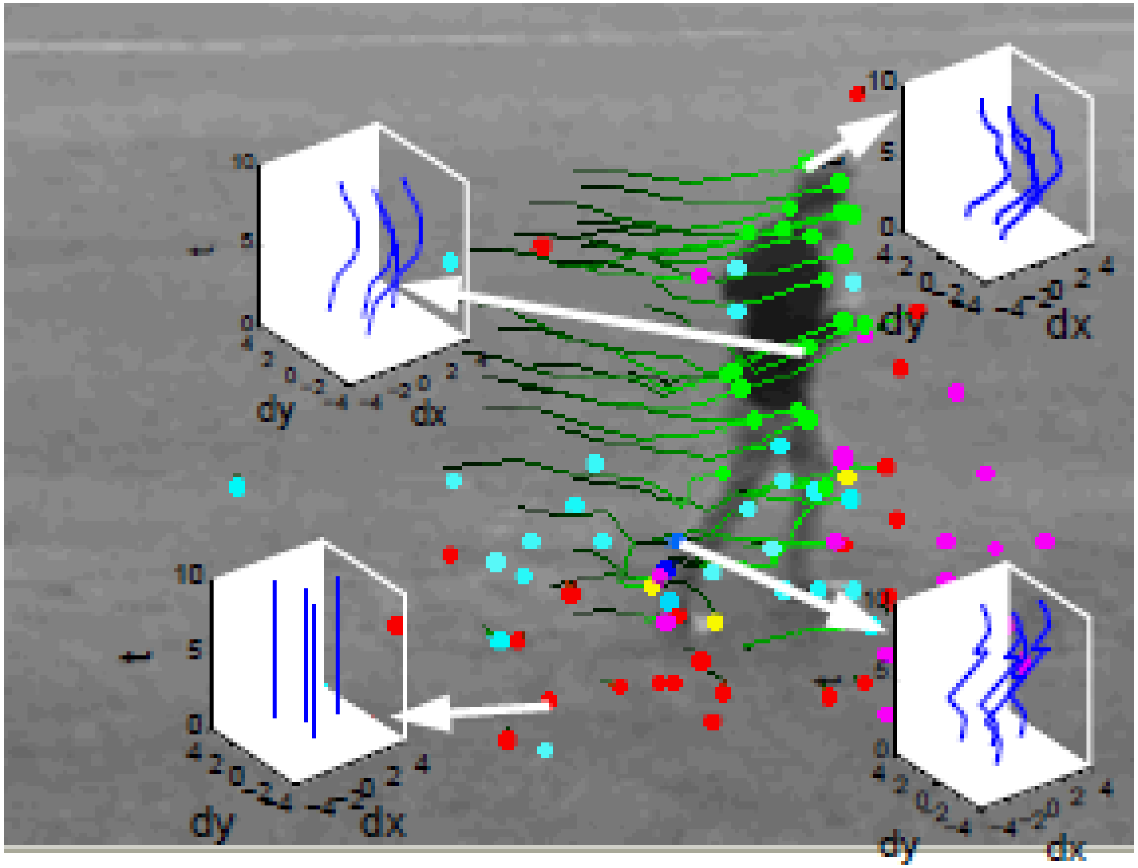
(e) $Fb_x^+, Fb_x^-, Fb_y^+, Fb_y^-$

blurred pos/neg flow

Efros et al. 2003

Representing Motion

Tracked Points



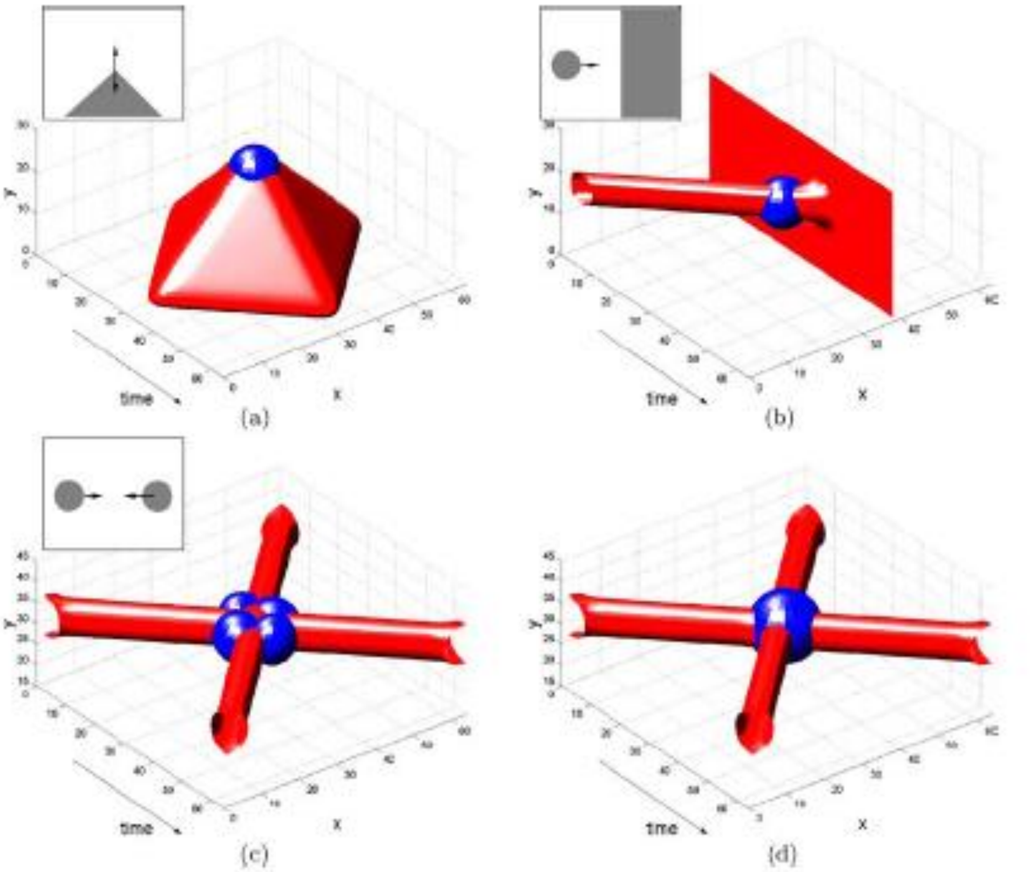
Matikainen et al. 2009

Representing Motion

Space-Time Interest Points

Moving corner

Ball hits wall



Balls collide

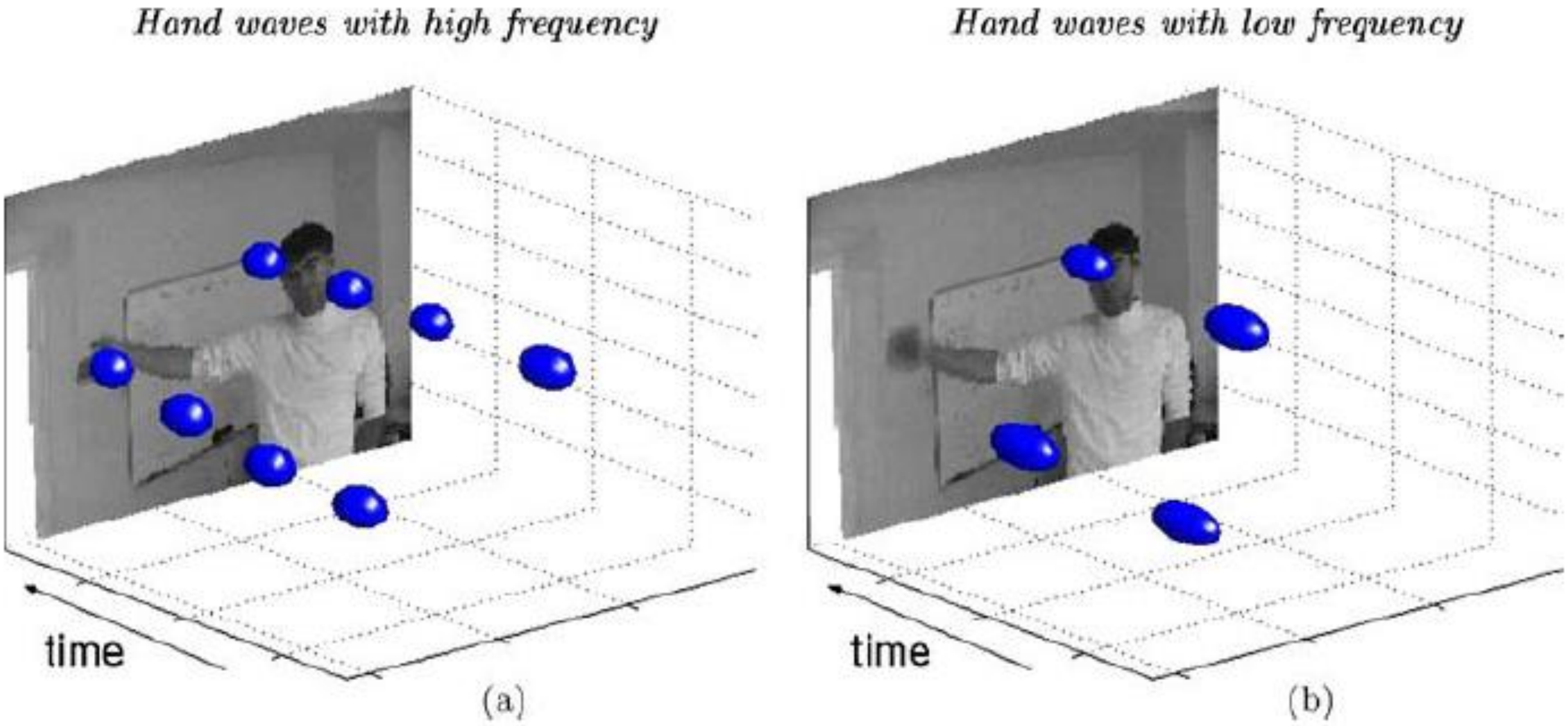
Balls collide (different scale)

Corner detectors in space-time

[Laptev 2005](#)

Representing Motion

Space-Time Interest Points



Laptev 2005

Examples of Action Recognition Systems

- Feature-based classification

- Recognition using pose and objects

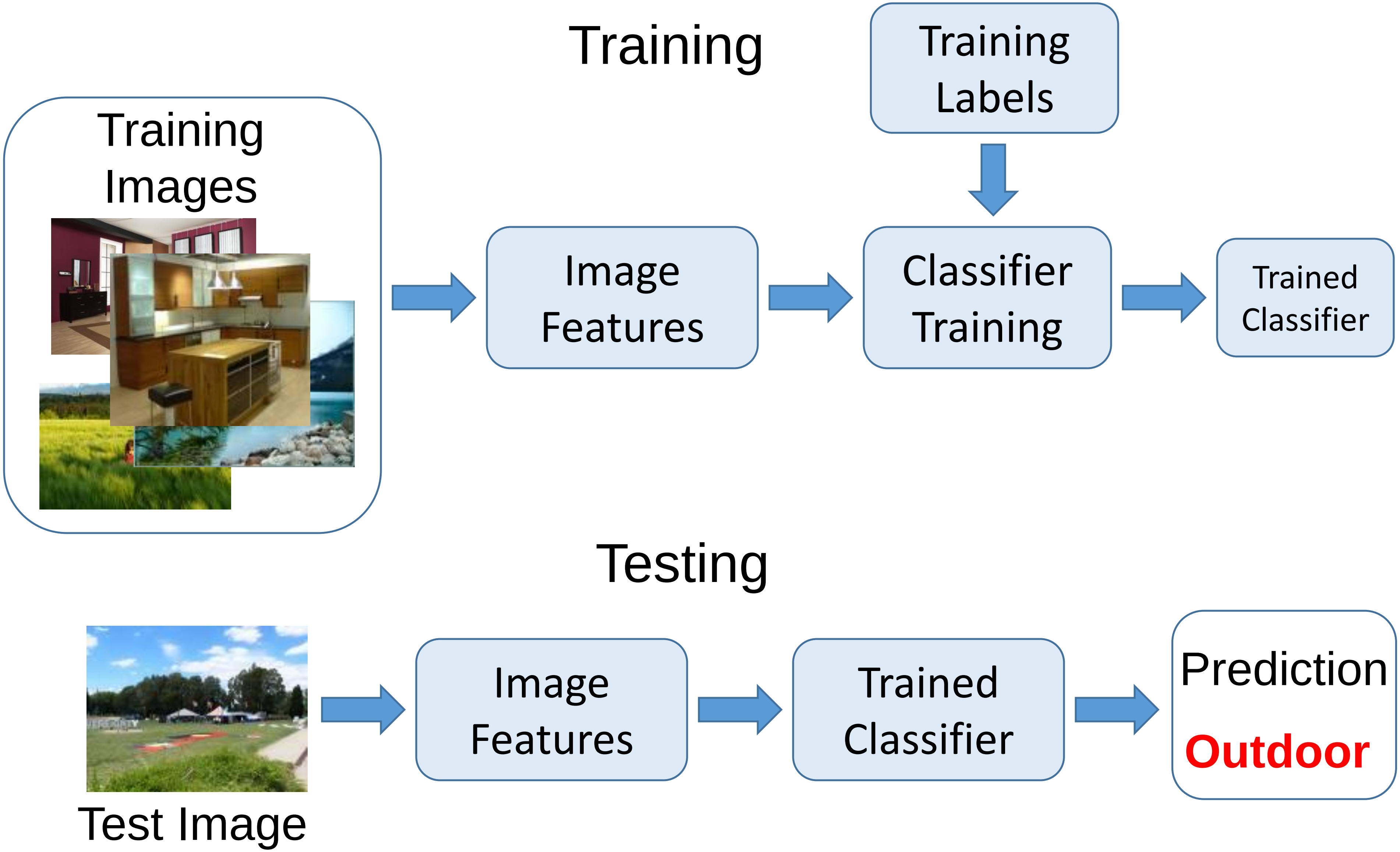
Action recognition as classification


training samples

test samples

Retrieving actions in movies, Laptev and Perez, 2007

Remember image categorization…



Training

Training Labels

Training Images

Image Features

Classifier Training

Trained Classifier

Testing

Test Image

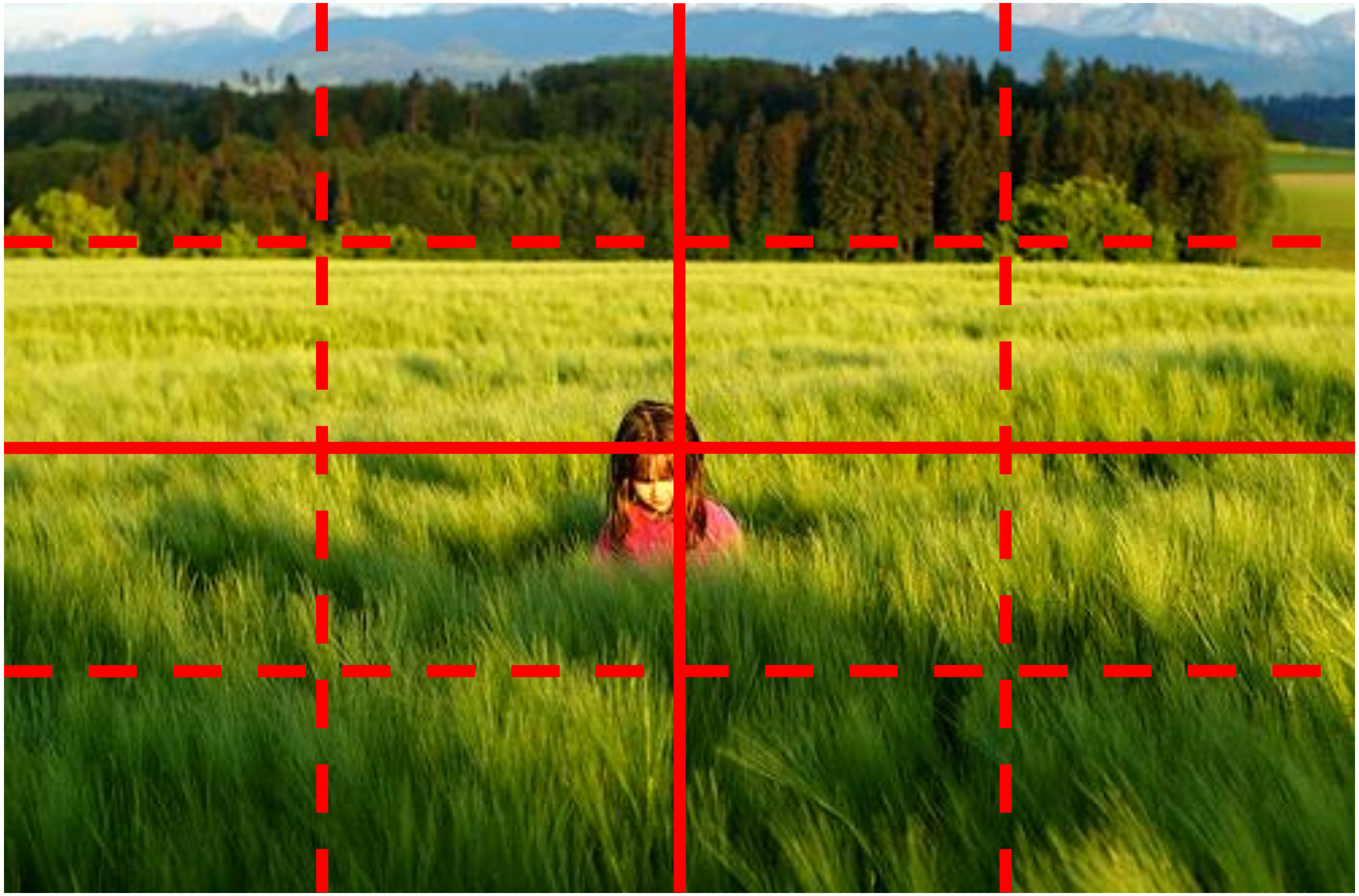
Image Features

Trained Classifier

Prediction

Outdoor

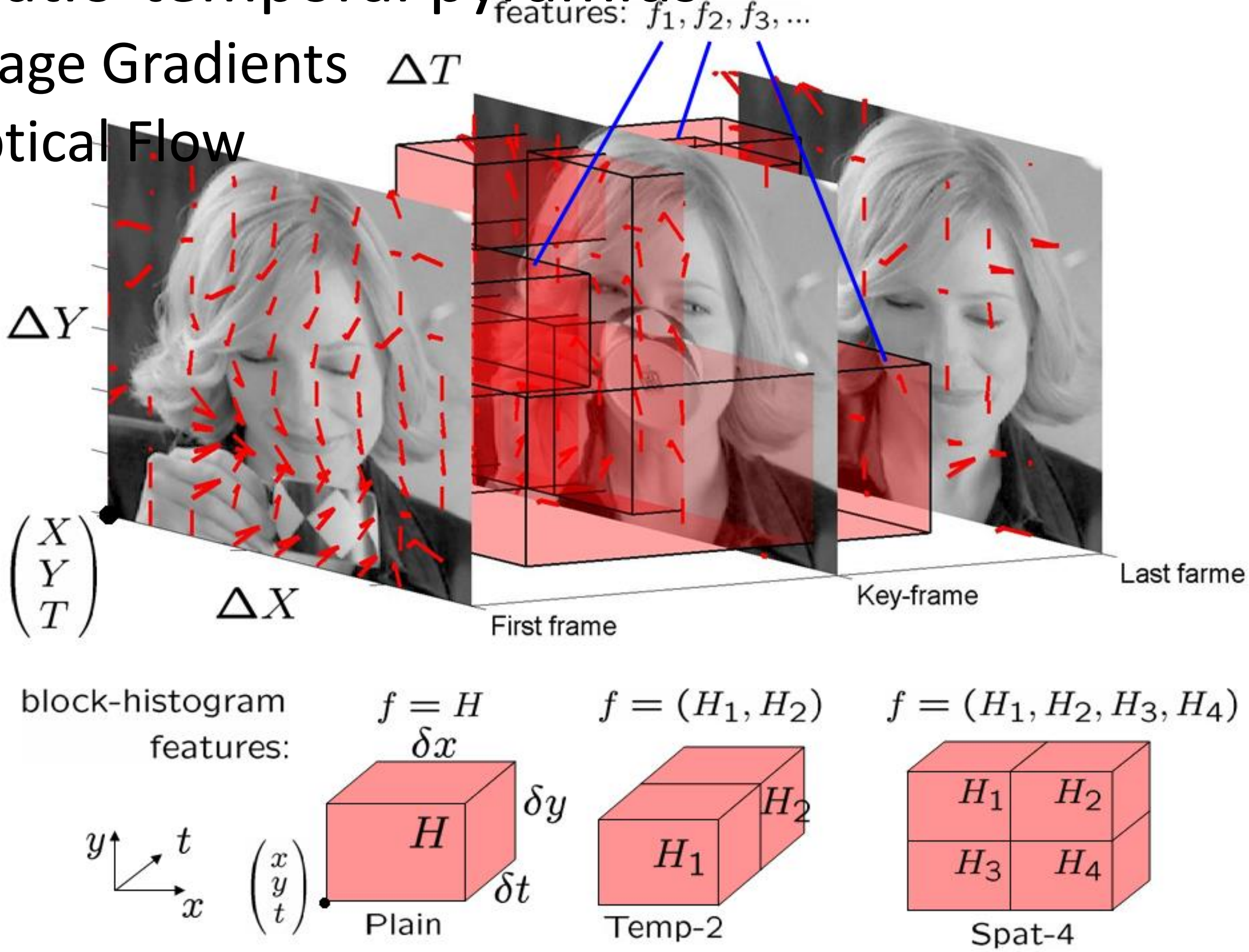
Remember spatial pyramids….



Compute histogram in each spatial bin

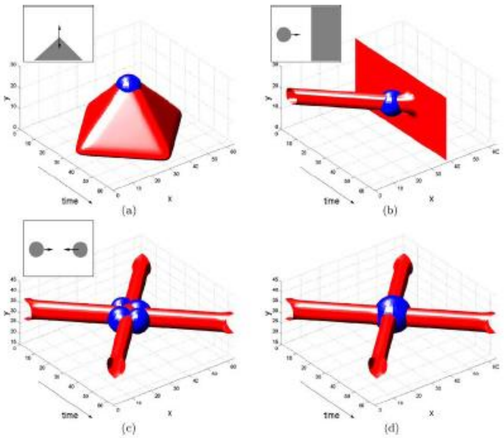
Features for Classifying Actions

1. Spatio-temporal pyramids
    - Image Gradients
    - Optical Flow

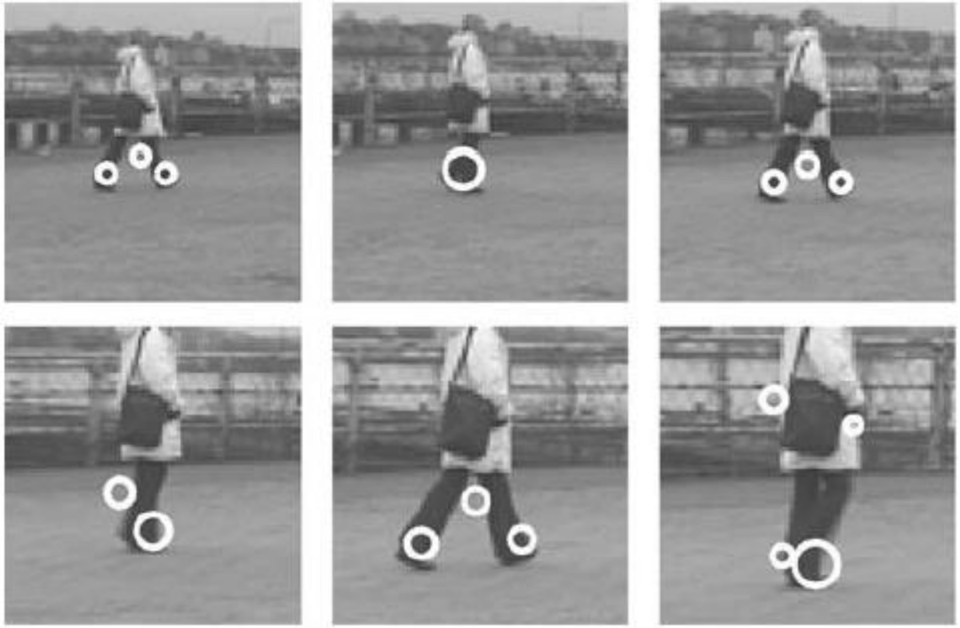


Features for Classifying Actions

l in



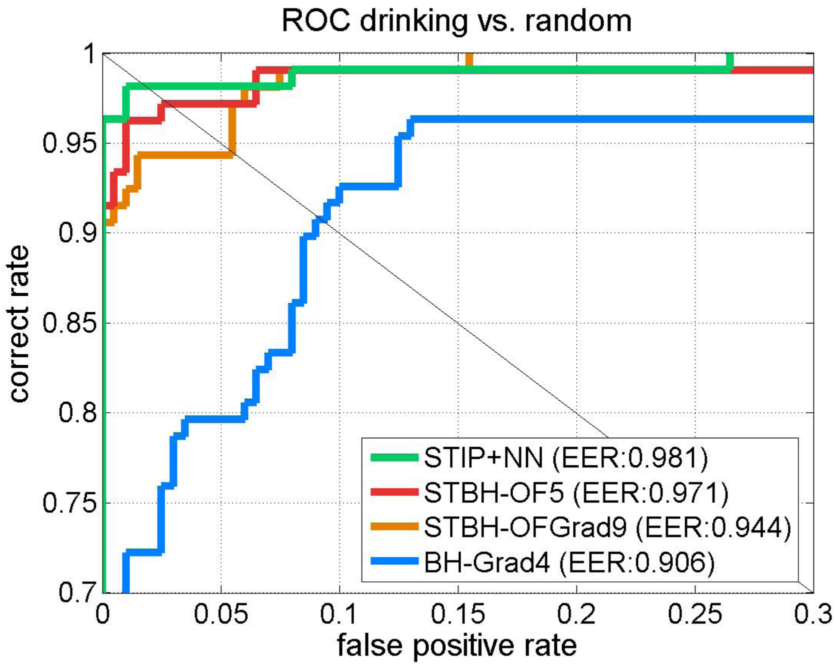
Corner detectors in space-time

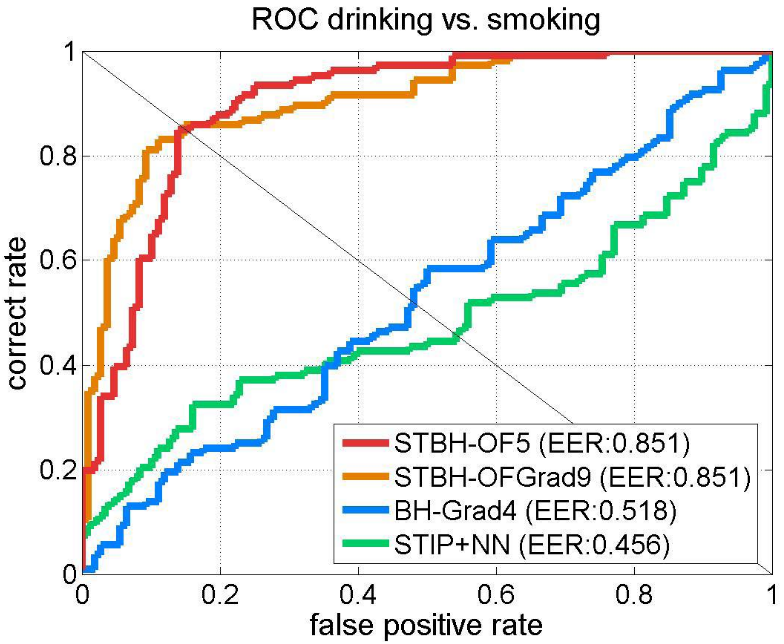


Descriptors based on Gaussian derivative filters over x, y, time

Classification

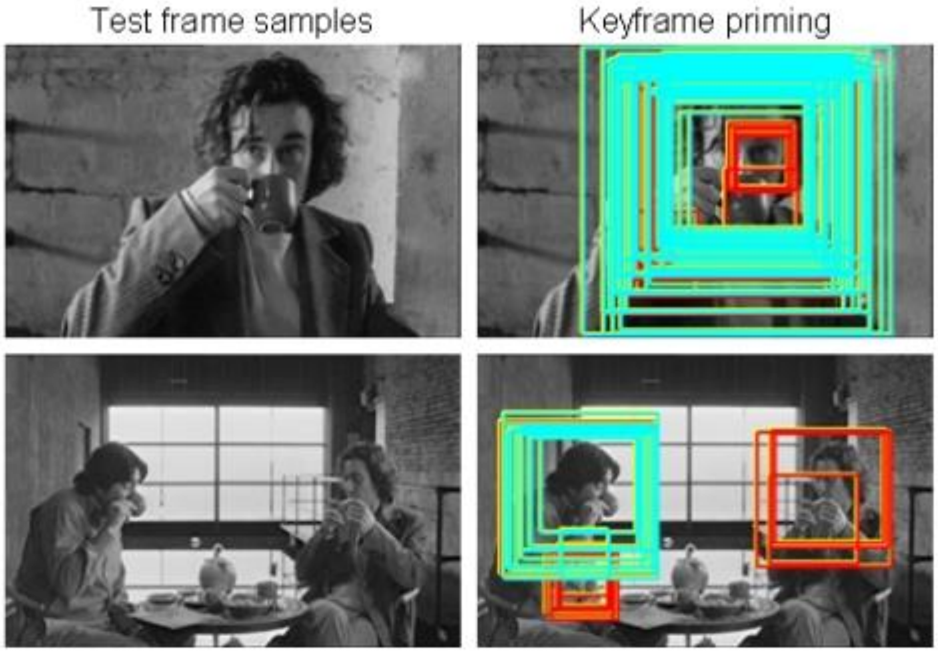
- Boosted stubs for pyramids of optical flow, gradient
- Nearest neighbor for STIP

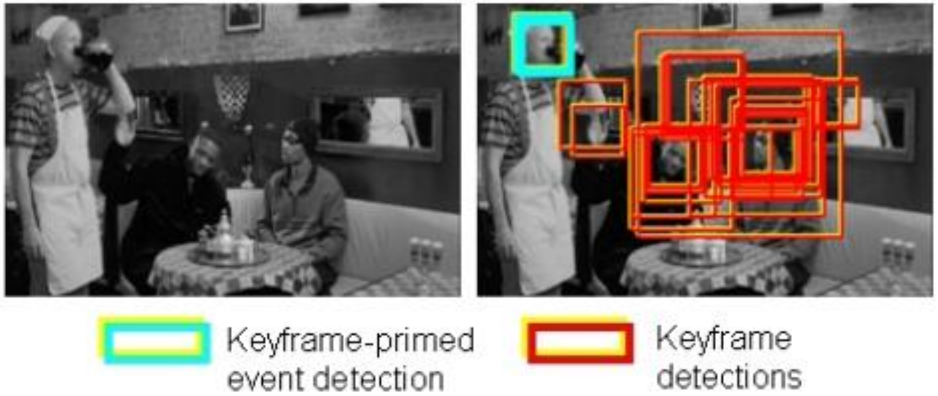




Searching the video for an action

1. Detect keyframes using a trained HOG detector in each frame
2. Classify detected keyframes as positive (e.g., “drinking”) or negative (“other”)

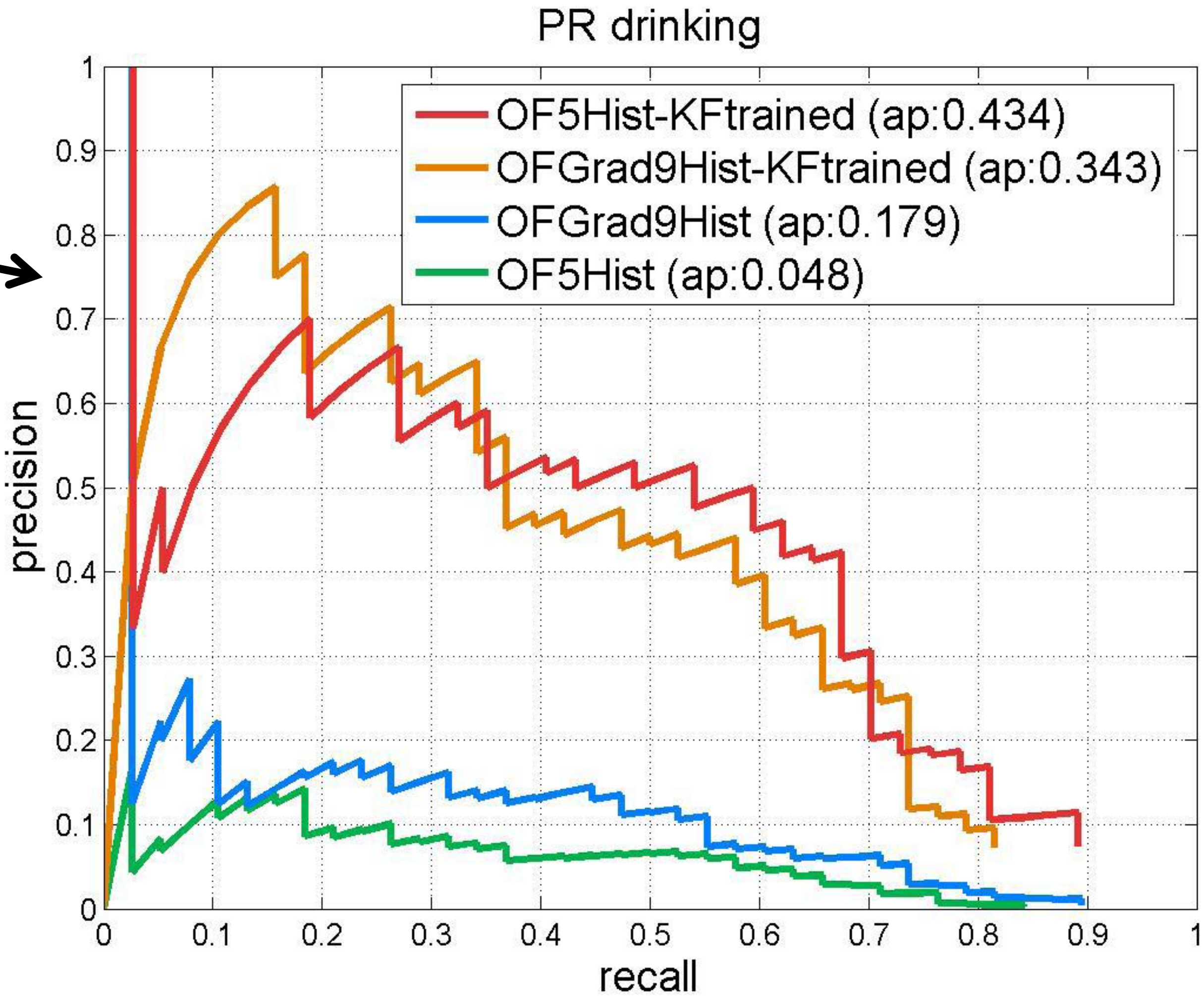




Accuracy in searching video

With keyframe detection

Without keyframe detection



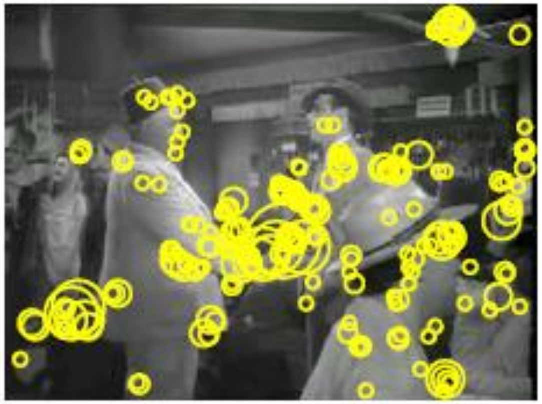
“Talk on phone”

“Get out of car”

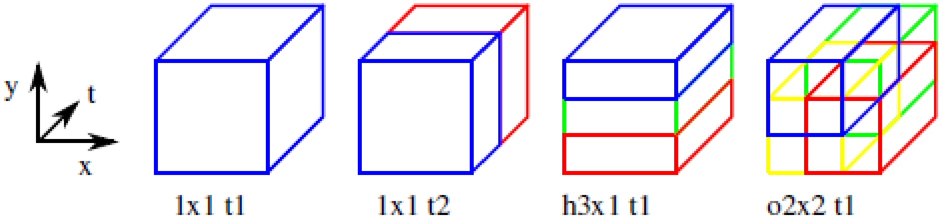
[Learning realistic human actions from movies, Laptev et al. 2008]

Approach

- Space-time interest point detectors
- Descriptors
  - HOG, HOF
- Pyramid histograms (3x3x2)
- SVMs with Chi-Squared Kernel

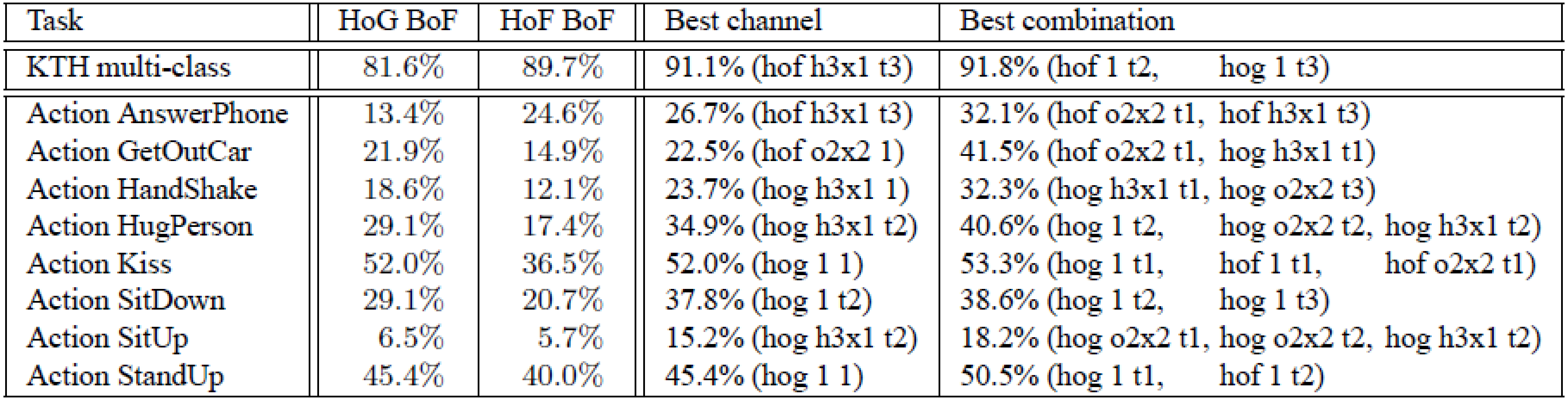


Interest Points



Spatio-Temporal Binning

Results



Task	HoG BoF	HoF BoF	Best channel	Best combination
KTH multi-class	81.6%	89.7%	91.1% (hof h3x1 t3)	91.8% (hof 1 t2, hog 1 t3)
Action AnswerPhone	13.4%	24.6%	26.7% (hof h3x1 t3)	32.1% (hof o2x2 t1, hof h3x1 t3)
Action GetOutCar	21.9%	14.9%	22.5% (hof o2x2 1)	41.5% (hof o2x2 t1, hog h3x1 t1)
Action HandShake	18.6%	12.1%	23.7% (hog h3x1 1)	32.3% (hog h3x1 t1, hog o2x2 t3)
Action HugPerson	29.1%	17.4%	34.9% (hog h3x1 t2)	40.6% (hog 1 t2, hog o2x2 t2, hog h3x1 t2)
Action Kiss	52.0%	36.5%	52.0% (hog 1 1)	53.3% (hog 1 t1, hof 1 t1, hof o2x2 t1)
Action SitDown	29.1%	20.7%	37.8% (hog 1 t2)	38.6% (hog 1 t2, hog 1 t3)
Action SitUp	6.5%	5.7%	15.2% (hog h3x1 t2)	18.2% (hog o2x2 t1, hog o2x2 t2, hog h3x1 t2)
Action StandUp	45.4%	40.0%	45.4% (hog 1 1)	50.5% (hog 1 t1, hof 1 t2)

Action Recognition using Pose and Objects

Modeling Mutual Context of Object and Human Pose in Human-Object Interaction Activities, B. Yao and Li Fei-Fei, 2010

Slide Credit: Yao/Fei-Fei

Human-Object Interaction

Holistic image based classification

Integrated reasoning

- **Human pose estimation**

Slide Credit: Yao/Fei-Fei

Human-Object Interaction

Holistic image based classification

Integrated reasoning

- Human pose estimation
- **Object detection**

Slide Credit: Yao/Fei-Fei

Human-Object Interaction

Holistic image based classification

Integrated reasoning

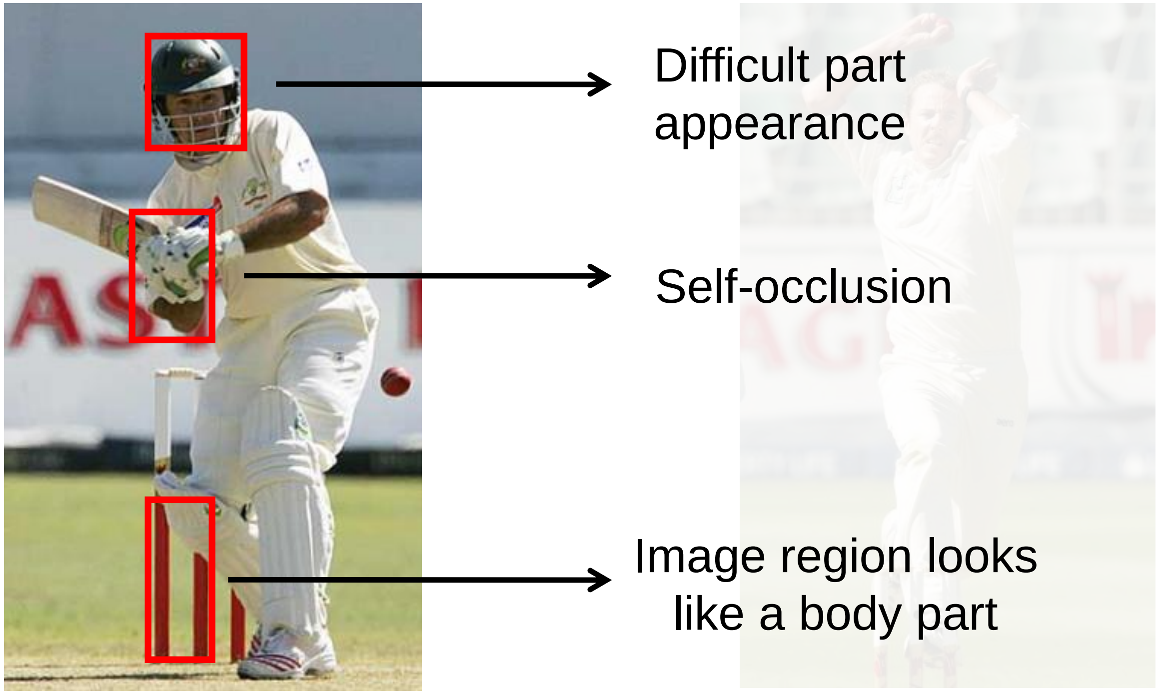
- **Human pose estimation**
- **Object detection**
- **Action categorization**

Activity: Tennis Forehand

Slide Credit: Yao/Fei-Fei

Human pose estimation & Object detection

Human pose estimation is challenging.



Difficult part appearance

Self-occlusion

Image region looks like a body part

- Felzenszwalb & Huttenlocher, 2005
- Ren et al, 2005
- Ramanan, 2006
- Ferrari et al, 2008
- Yang & Mori, 2008
- Andriluka et al, 2009
- Eichner & Ferrari, 2009

Slide Credit: Yao/Fei-Fei

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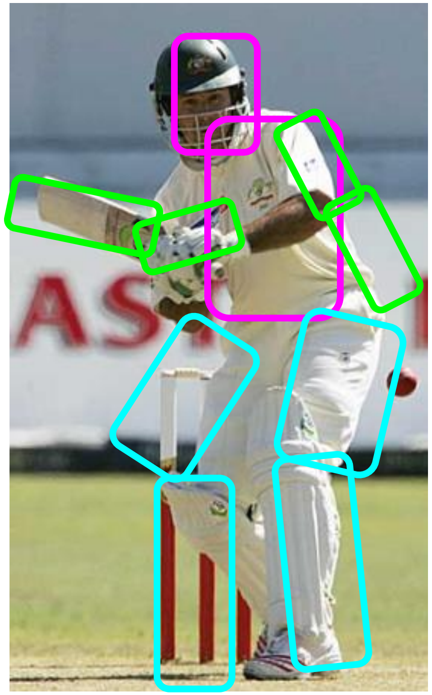

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Slide Credit: Yao/Fei-Fei

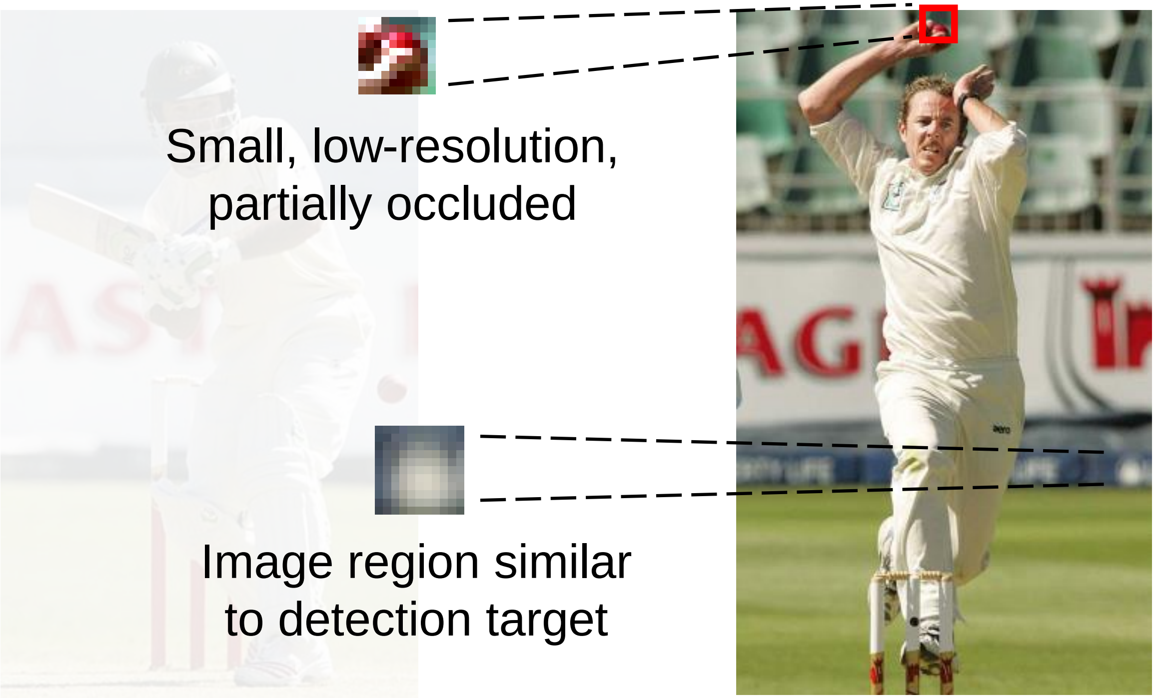
Human pose estimation & Object detection

Facilitate

Given the object is detected.

Slide Credit: Yao/Fei-Fei

Human pose estimation & Object detection



Small, low-resolution, partially occluded

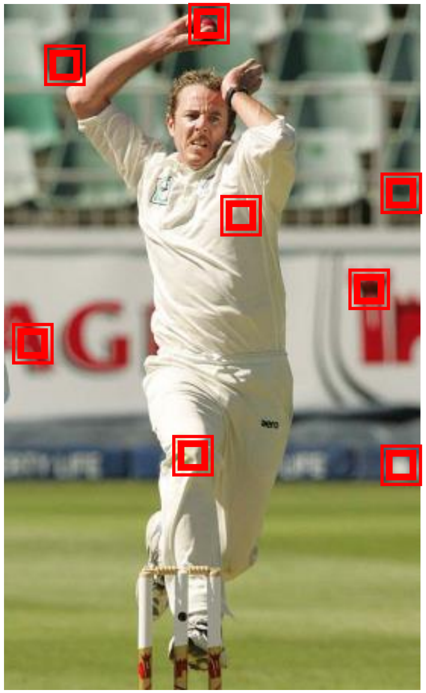
Image region similar to detection target

Object detection is challenging

- Viola & Jones, 2001
- Lampert et al, 2008
- Divvala et al, 2009
- Vedaldi et al, 2009

Slide Credit: Yao/Fei-Fei

Human pose estimation & Object detection



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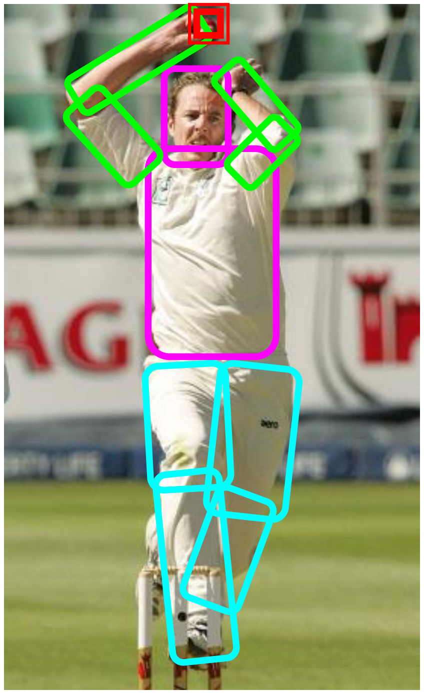
Human pose estimation & Object detection

Facilitate



Given the pose is estimated.

Slide Credit: Yao/Fei-Fei

Human pose estimation & Object detection

Mutual Context

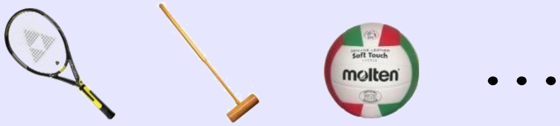
Slide Credit: Yao/Fei-Fei

Mutual Context Model Representation

A:

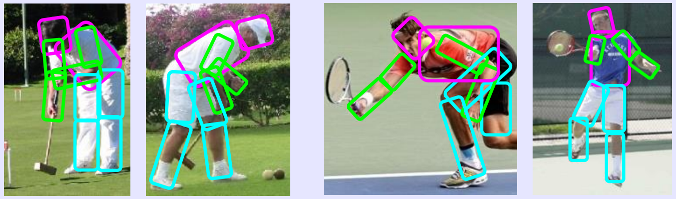
Tennis forehand | Croquet shot | Volleyball smash | . . .

O:



Tennis racket | Croquet mallet | Volleyball | . . .

H:

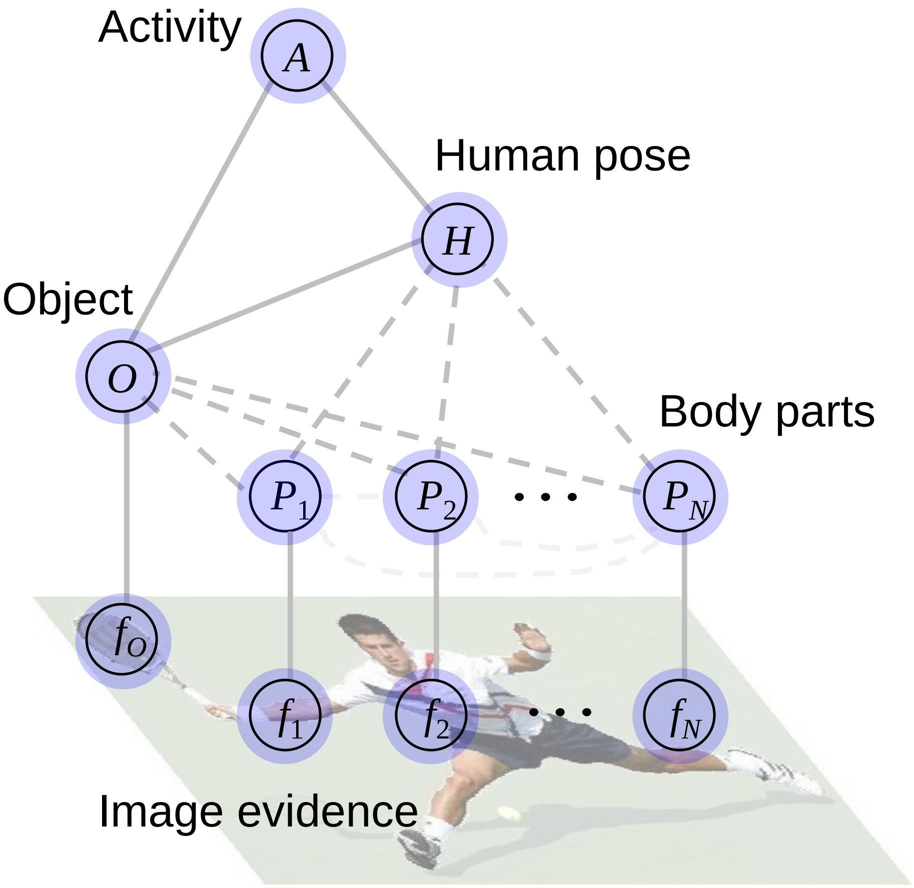


Intra-class variations

- More than one H for each A;
- **Unobserved** during training.

P: l_P: location; θ_P: orientation; s_P: scale.

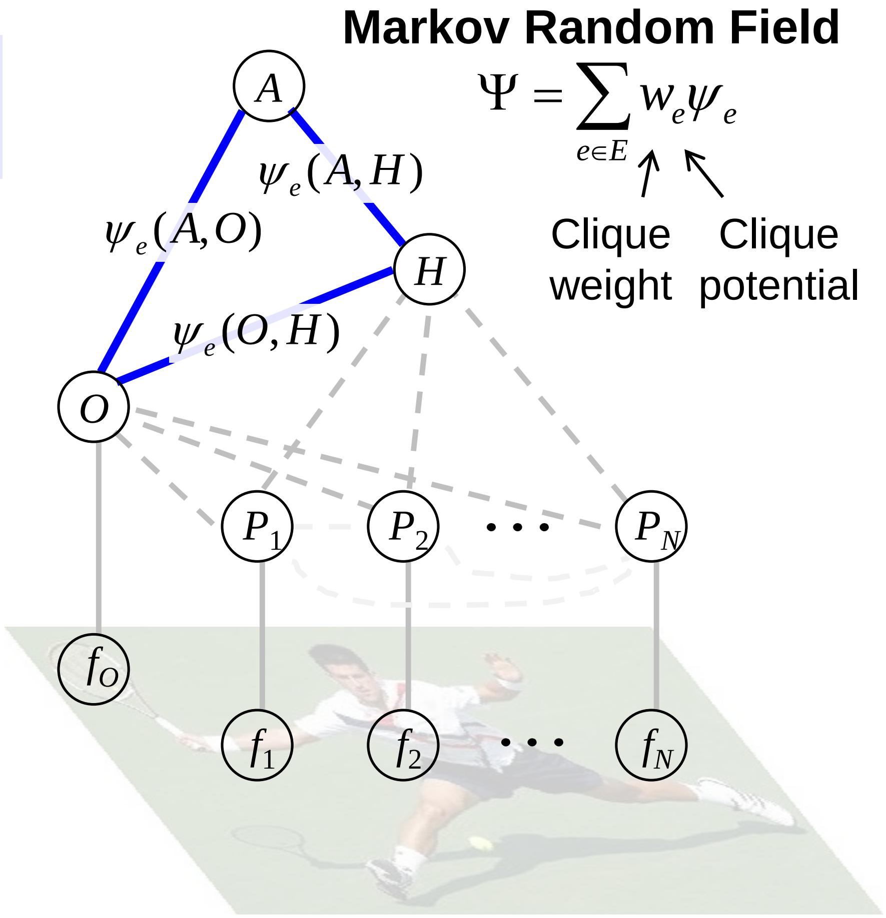
f: Shape context. [Belongie et al, 2002]



Slide Credit: Yao/Fei-Fei

Mutual Context Model Representation

- $\psi_e(A,O)$, $\psi_e(A,H)$, $\psi_e(O,H)$: Frequency of co-occurrence between A, O, and H.



Markov Random Field

$$\Psi = \sum_{e \in E} w_e \psi_e$$

Clique weight

Clique potential

Slide Credit: Yao/Fei-Fei

Mutual Context Model Representation

- $\psi_e(A,O)$, $\psi_e(A,H)$, $\psi_e(O,H)$: Frequency of co-occurrence between A, O, and H.

- $\psi_e(O,P_n)$, $\psi_e(H,P_n)$, $\psi_e(P_m,P_n)$: Spatial relationship among object and body parts.

$$\underbrace{\text{bin}\left(l_O - l_{P_n}\right)}_{\textbf{location}} \cdot \underbrace{\text{bin}\left(\theta_O - \theta_{P_n}\right)}_{\textbf{orientation}} \cdot \underbrace{\text{N}\left(s_O / s_{P_n}\right)}_{\textbf{size}}$$

Markov Random Field

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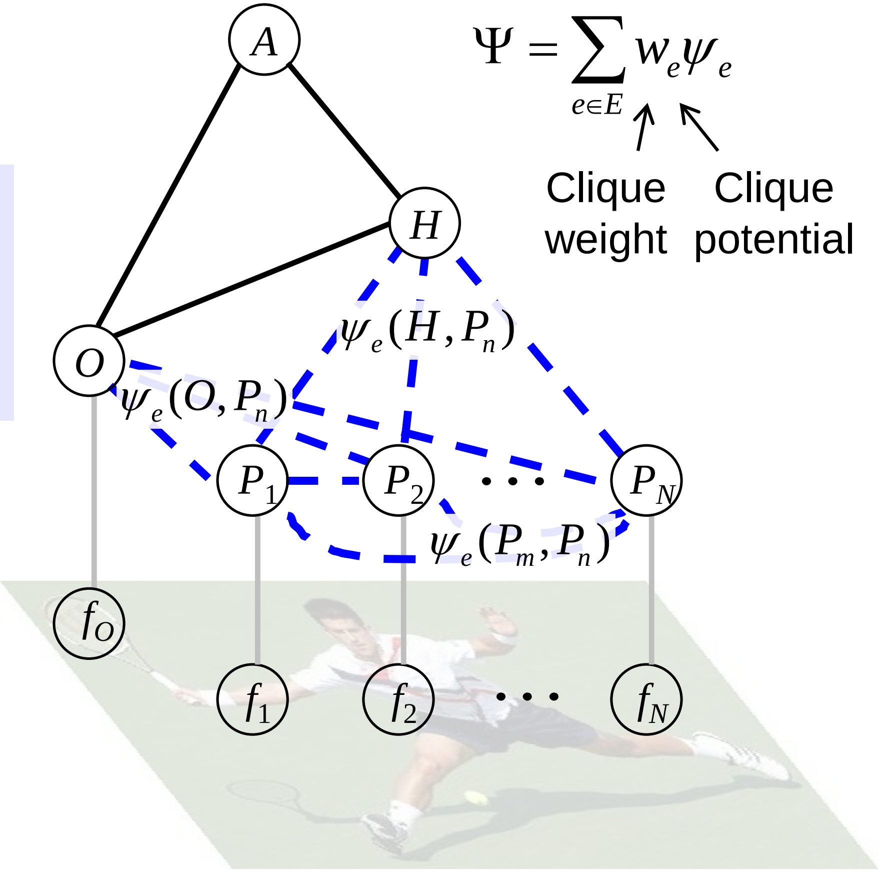
Clique weight

Clique potential



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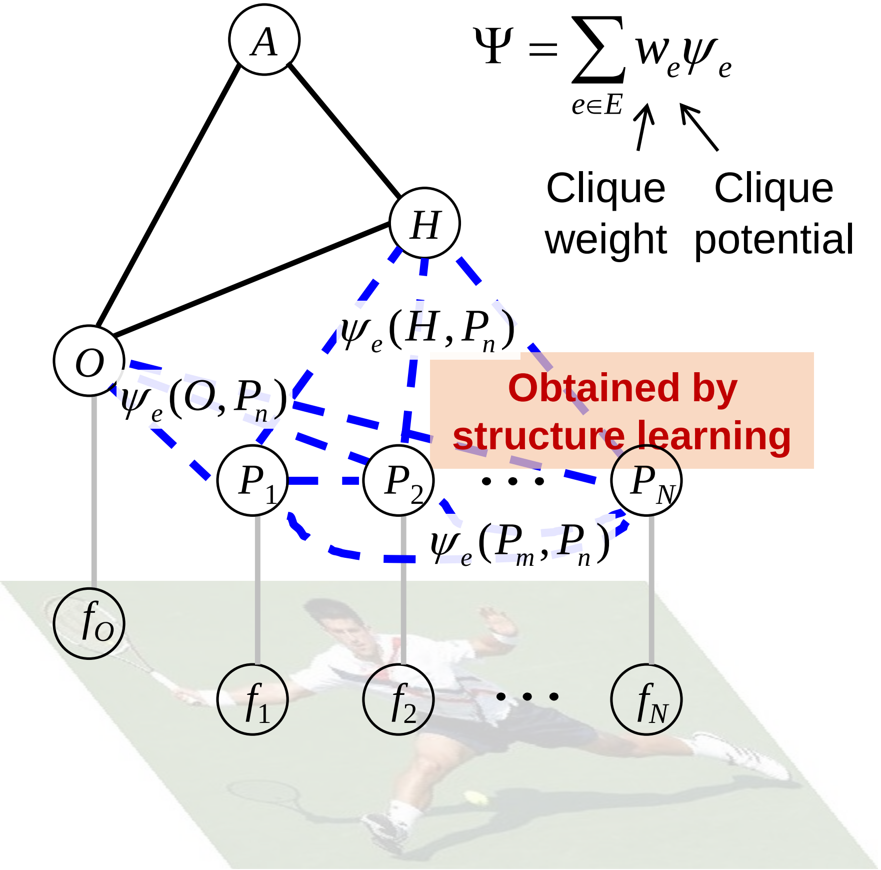
- Learn structural connectivity among the body parts and the object.



Markov Random Field

$$\Psi = \sum_{e \in E} w_e \psi_e$$

Clique weight

Clique potential

Obtained by structure learning

Slide Credit: Yao/Fei-Fei

Mutual Context Model Representation

- $\psi_e(A,O)$, $\psi_e(A,H)$, $\psi_e(O,H)$: Frequency of co-occurrence between A, O, and H.

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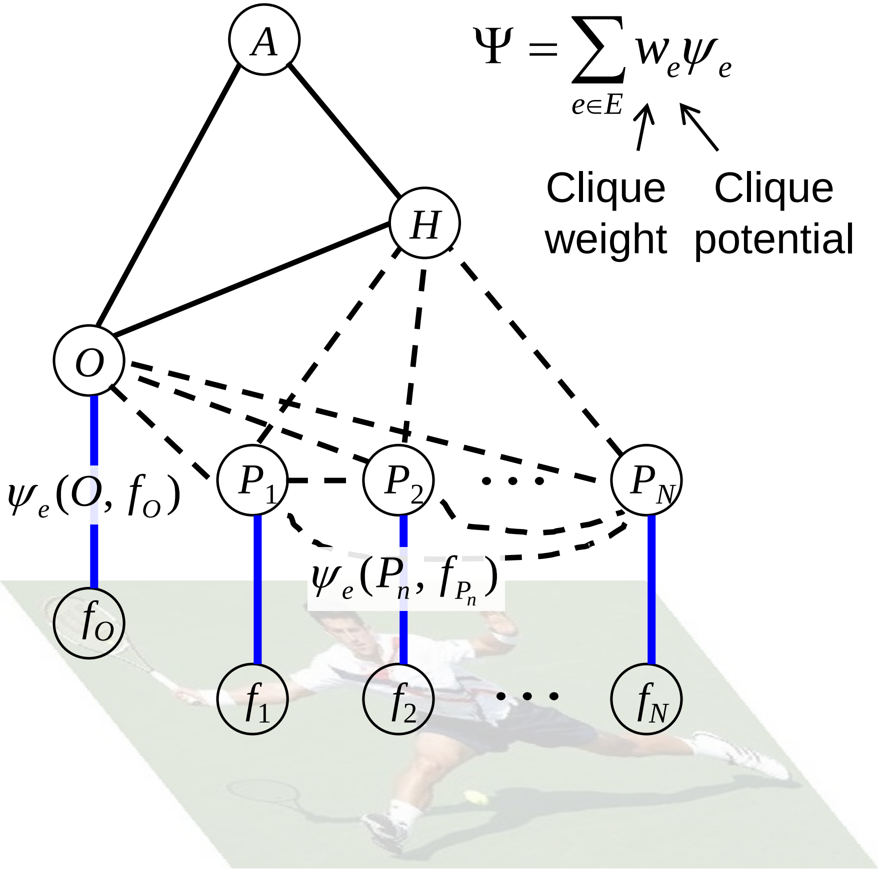
- Learn structural connectivity among the body parts and the object.

- $\psi_e(O,f_O)$ and $\psi_e(P_n,f_{P_n})$: Discriminative part detection scores.

  Shape context + AdaBoost

  [Andriluka et al, 2009]
  [Belongie et al, 2002]
  [Viola & Jones, 2001]



Markov Random Field

$$\Psi = \sum_{e \in E} w_e \psi_e$$

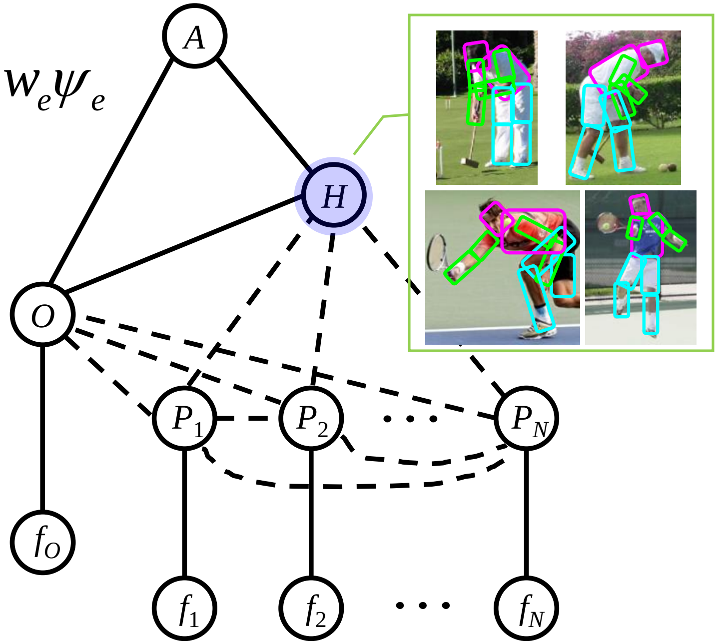
Clique weight

Clique potential

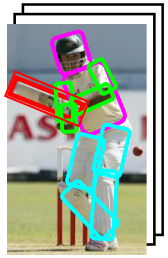
Slide Credit: Yao/Fei-Fei

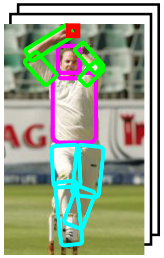
Model Learning

$$\Psi = \sum_{e \in E} w_e \psi_e$$



Input:


cricket shot


cricket bowling

. . .

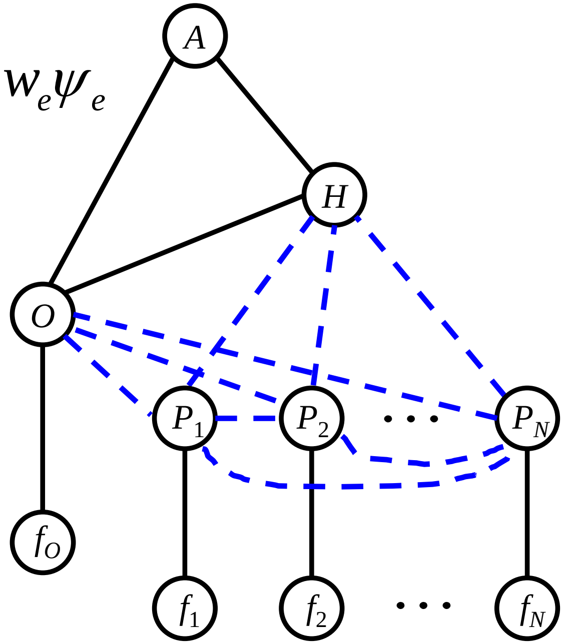
Goals:

Hidden human poses

Slide Credit: Yao/Fei-Fei

Model Learning

$$\Psi = \sum_{e \in E} w_e \psi_e$$



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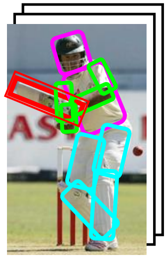
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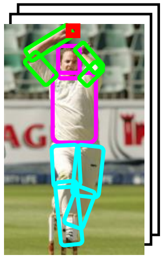

cricket bowling

…

Goals:

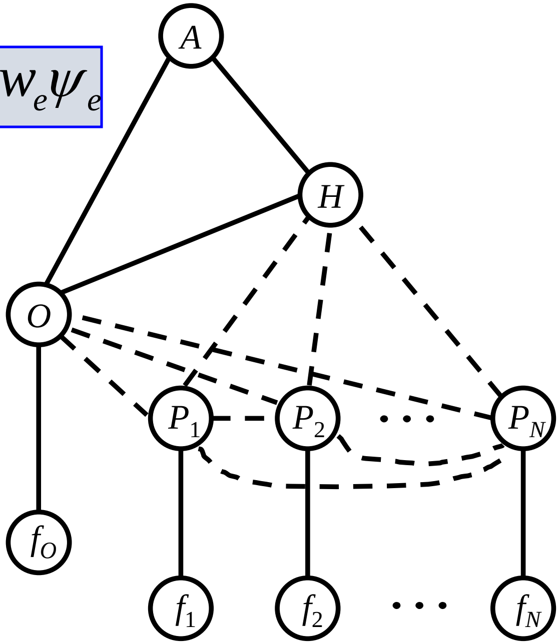
Hidden human poses

Structural connectivity

Slide Credit: Yao/Fei-Fei

Model Learning

$$\Psi = \sum_{e \in E} \boxed{w_e \psi_e}$$



Input:

cricket shot

cricket bowling

Goals:

Hidden human poses

Structural connectivity

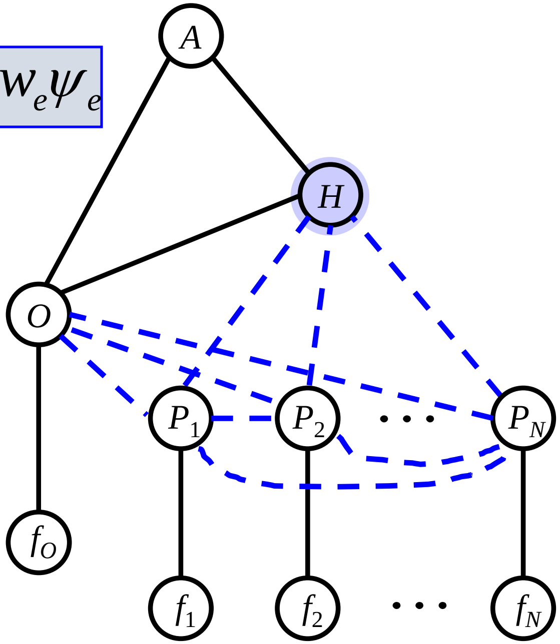
Potential parameters

Potential weights

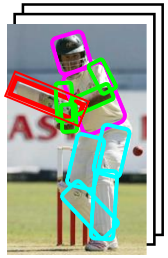
Slide Credit: Yao/Fei-Fei

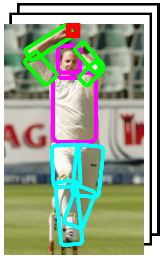
Model Learning

$$\Psi = \sum_{e\in E} \boxed{w_e \psi_e}$$



Input:


cricket
shot


cricket
bowling

. . .

Goals:

Hidden human poses → **Hidden variables**

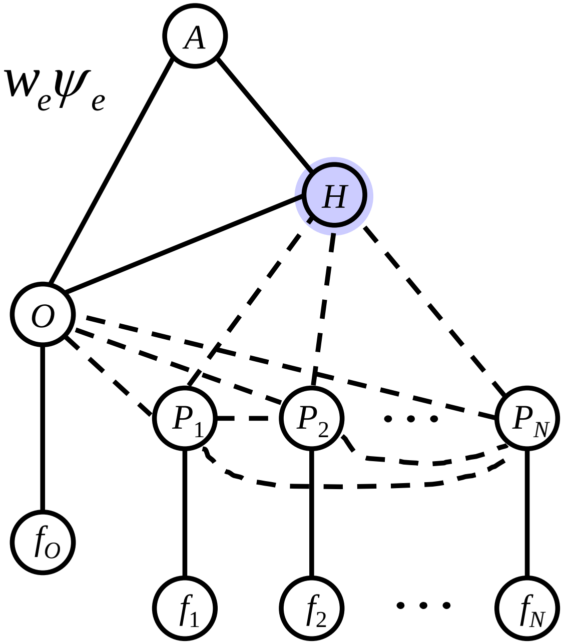
Structural connectivity → **Structure learning**

Potential parameters
Potential weights } **Parameter estimation**

Slide Credit: Yao/Fei-Fei

Model Learning

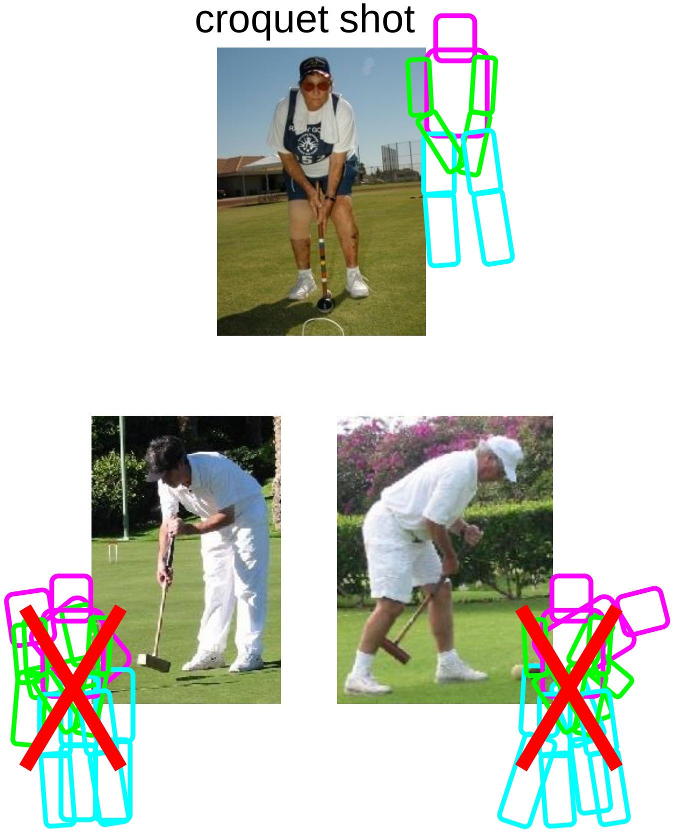
$$\Psi = \sum_{e \in E} w_e \psi_e$$



Goals:

- **Hidden human poses**
- Structural connectivity
- Potential parameters
- Potential weights

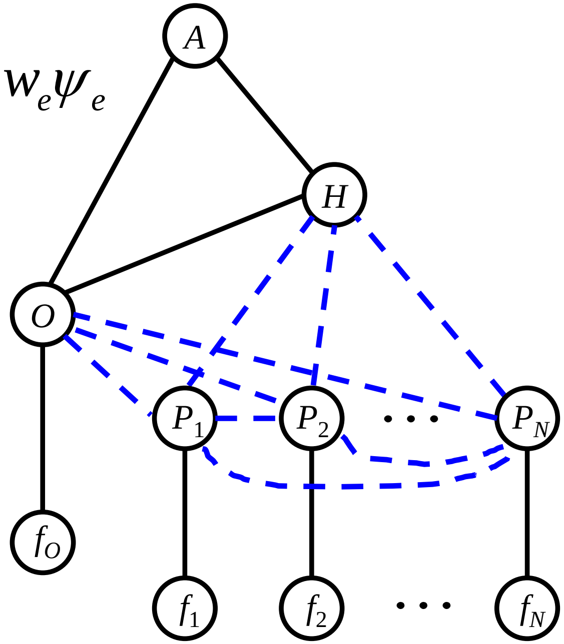
Approach:



Slide Credit: Yao/Fei-Fei

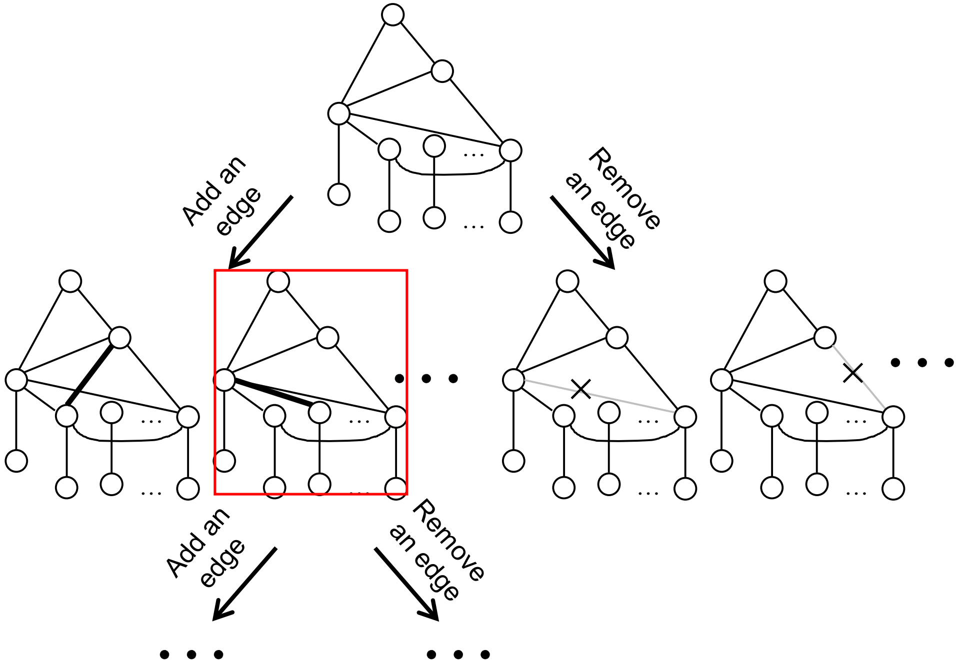
Model Learning

$$\Psi = \sum_{e\in E} w_e \psi_e$$



Approach:

Hill-climbing $$\max_{E=\{e\}} \left\{ \underbrace{\sum_e w_e \psi_e}_{\text{Joint density of the model}} - \underbrace{\frac{\left(|E|-\mu\right)^2}{2\sigma^2}}_{\text{Gaussian priori of the edge number}} \right\}$$



Goals:

Hidden human poses

Structural connectivity

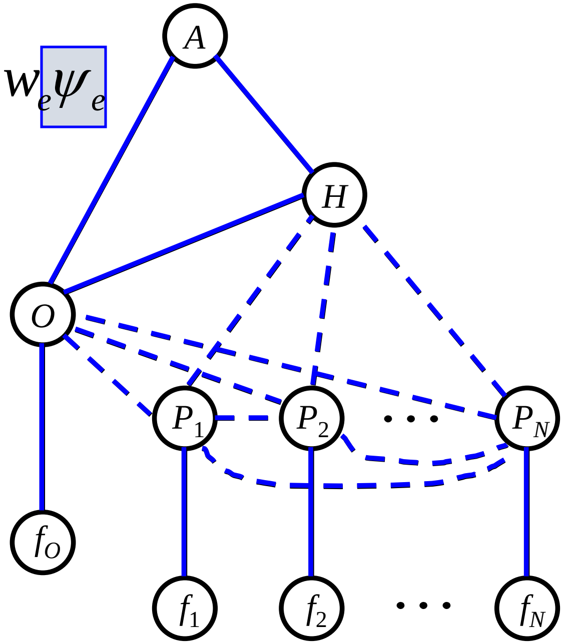
Potential parameters

Potential weights

Slide Credit: Yao/Fei-Fei

Model Learning

$$\Psi = \sum_{e \in E} w_e \boxed{\psi_e}$$



Goals:

Hidden human poses

Structural connectivity

Potential parameters

Potential weights

Approach:

- Maximum likelihood

$\psi_e(A, O)$ $\psi_e(A, H)$ $\psi_e(O, H)$

$\psi_e(H, P_n)$ $\psi_e(O, P_n)$ $\psi_e(P_m, P_n)$

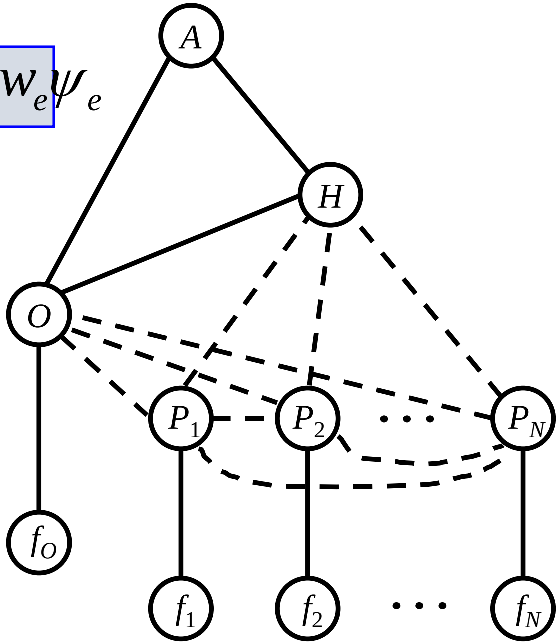
- Standard AdaBoost

$\psi_e(O, f_O)$ $\psi_e(P_n, f_{P_n})$

Slide Credit: Yao/Fei-Fei

Model Learning

$$\Psi = \sum_{e \in E} \boxed{w_e} \psi_e$$



Goals:

Hidden human poses

Structural connectivity

Potential parameters

Potential weights

Approach:

Max-margin learning

$$\min_{\mathbf{w},\xi} \frac{1}{2} \sum_r \left\| \mathbf{w}_r \right\|_2^2 + \beta \sum_i \xi_i$$

$$\text{s.t.} \ \forall i, r \ \text{where} \ y(r) \neq y(c_i),$$

$$\mathbf{w}_{c_i} \cdot \mathbf{x}_i - \mathbf{w}_r \cdot \mathbf{x}_i \geq 1 - \xi_i$$

$$\forall i, \xi_i \geq 0$$

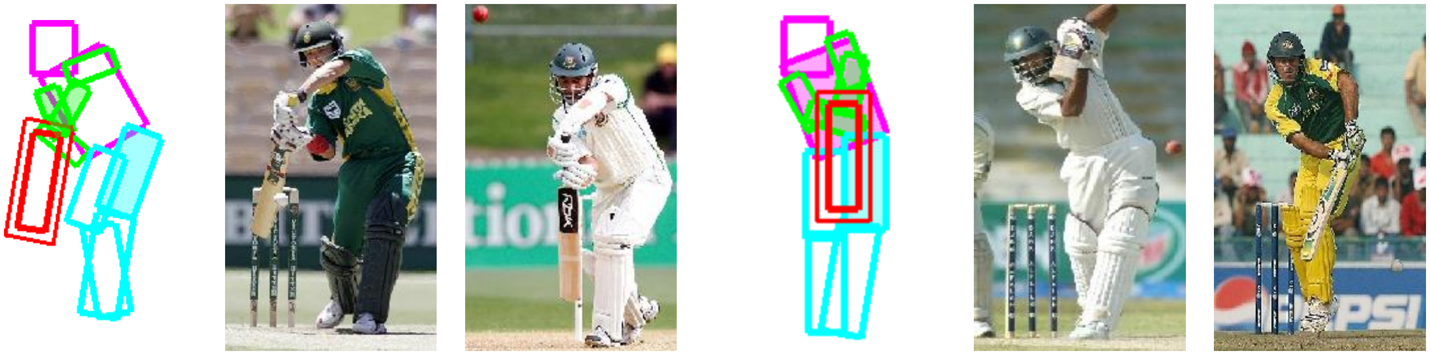
Notations

- $\mathbf{x}_i$: Potential values of the i-th image.
- $\mathbf{w}_r$: Potential weights of the r-th pose.
- $y(r)$: Activity of the r-th pose.
- ξ_i: A slack variable for the i-th image.

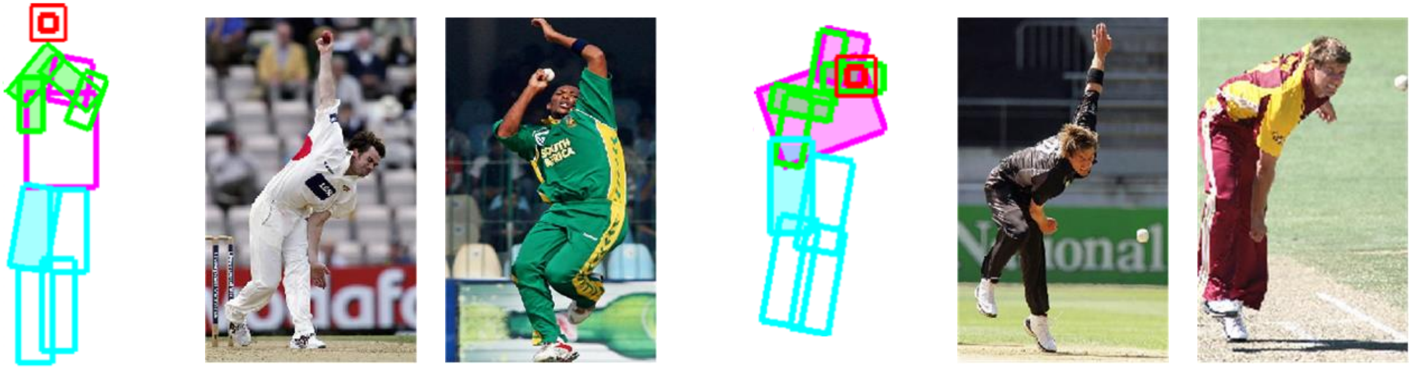
Slide Credit: Yao/Fei-Fei

Learning Results

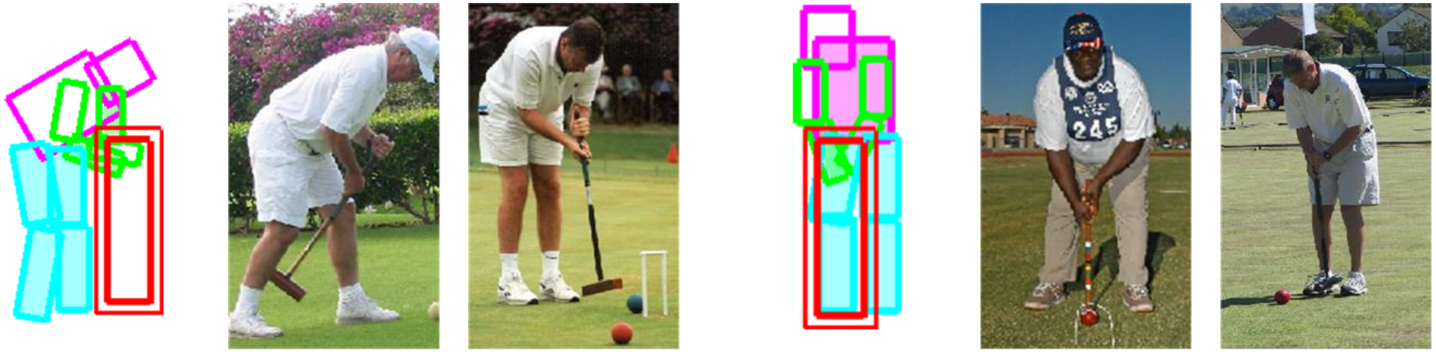
Cricket defensive shot



Cricket bowling

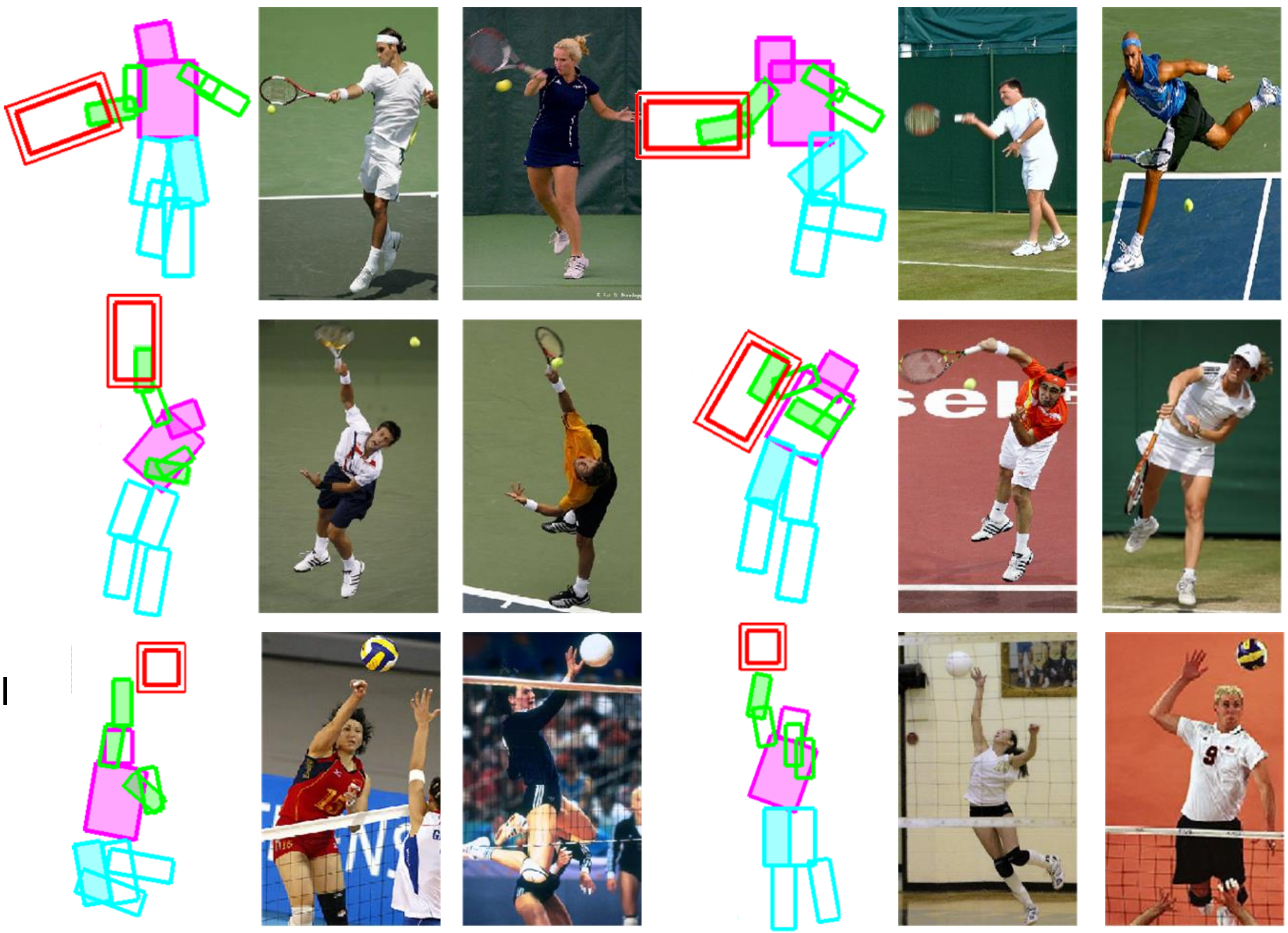


Croquet shot



Slide Credit: Yao/Fei-Fei

Learning Results

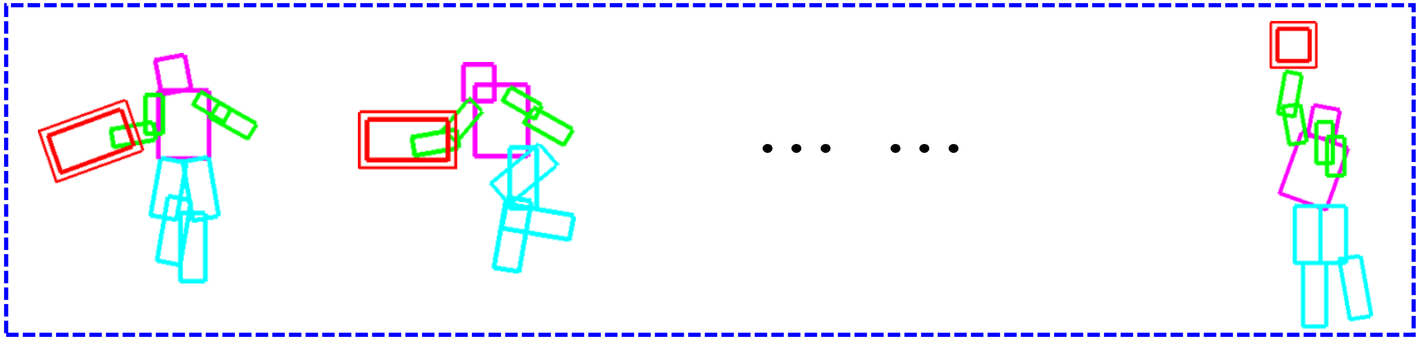


Slide Credit: Yao/Fei-Fei

Model Inference

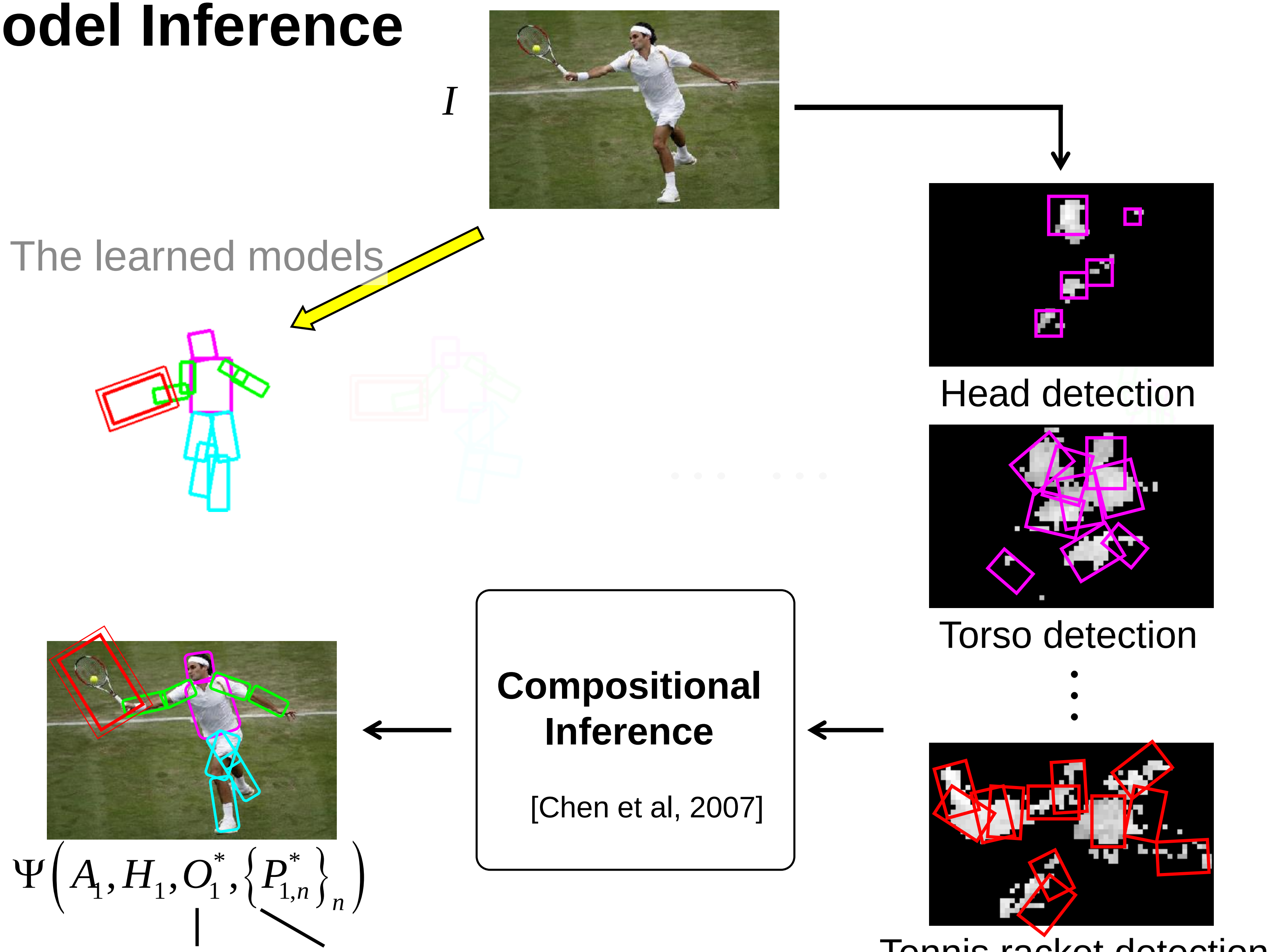
I

The learned models



Slide Credit: Yao/Fei-Fei

Model Inference



I

The learned models

Head detection

Torso detection

⋮

Tennis racket detection

Compositional Inference

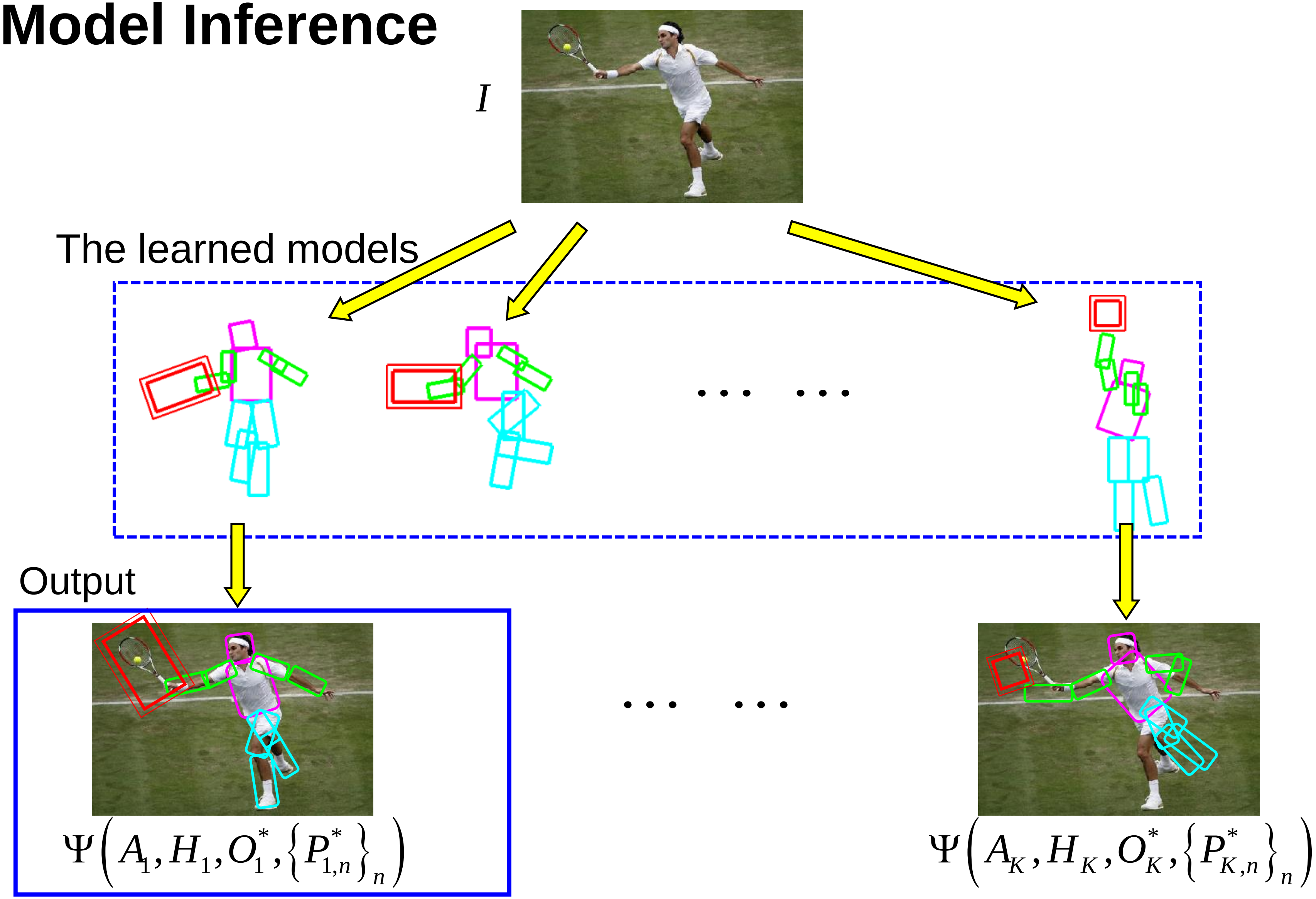
[Chen et al, 2007]

$$\Psi\left(A_1, H_1, O_1^*, \left\{P_{1,n}^*\right\}_n\right)$$

Layout of the **object** and **body parts**.

Slide Credit: Yao/Fei-Fei

Model Inference



I

The learned models

… …

Output

… …

$\Psi\left(A_1, H_1, O_1^*, \left\{P_{1,n}^*\right\}_n\right)$

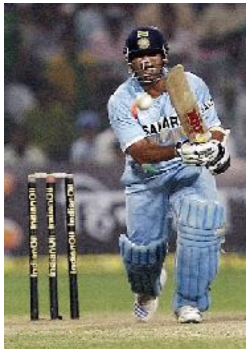
$\Psi\left(A_K, H_K, O_K^*, \left\{P_{K,n}^*\right\}_n\right)$

Slide Credit: Yao/Fei-Fei

Dataset and Experiment Setup

Sport data set: 6 classes

180 training (supervised with object and part locations) & 120 testing images



Cricket defensive shot

Cricket bowling

Croquet shot

Tennis forehand

Tennis serve

Volleyball smash

[Gupta et al, 2009]

Tasks:

- Object detection;
- Pose estimation;
- Activity classification.

Slide Credit: Yao/Fei-Fei

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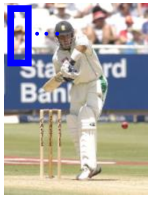
[Gupta et al, 2009]

Tasks:

- **Object detection;**
- Pose estimation;
- Activity classification.

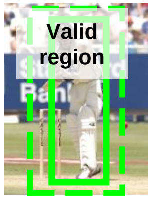
Slide Credit: Yao/Fei-Fei

Object Detection Results



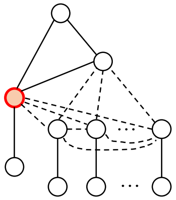
Sliding window

[Andriluka et al, 2009]



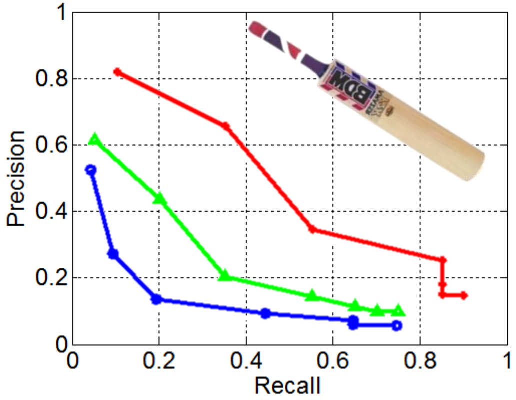
Pedestrian context

[Dalal & Triggs, 2006]

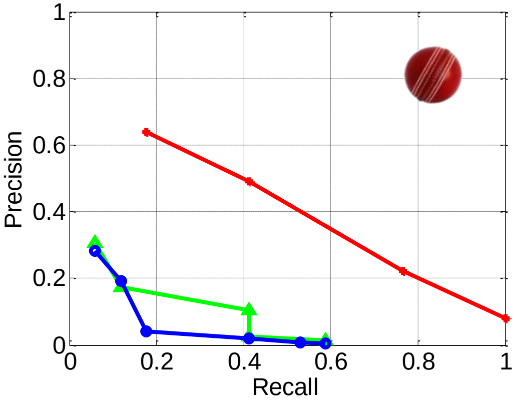


Our Method

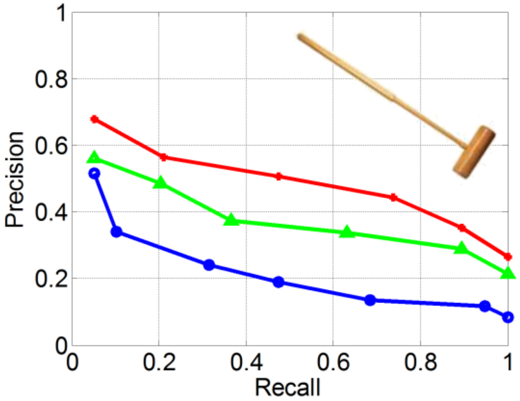
Cricket bat



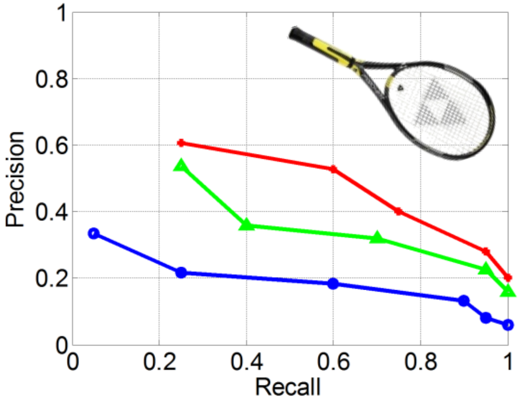
Cricket ball



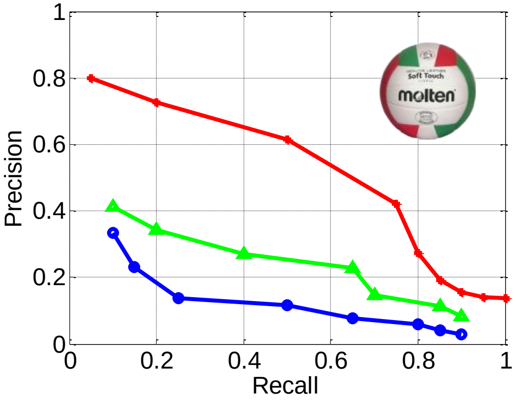
Croquet mallet



Tennis racket

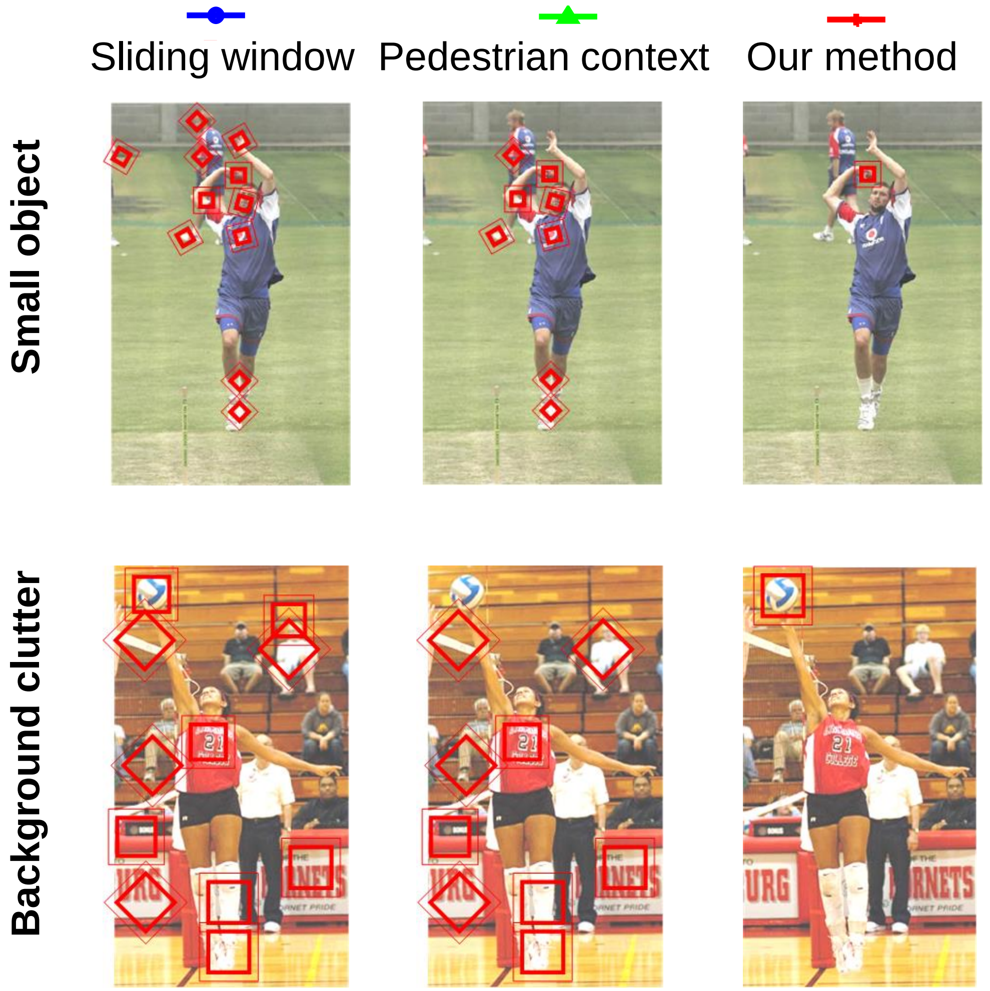


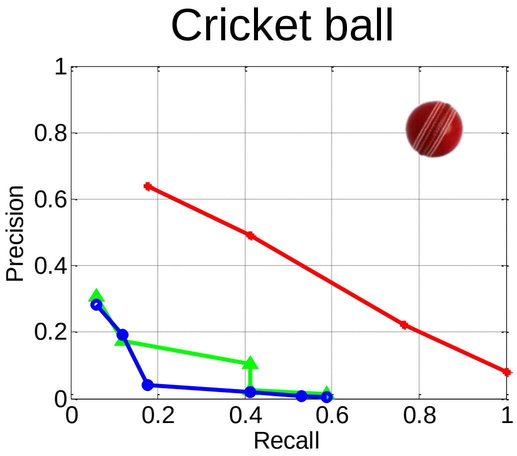
Volleyball

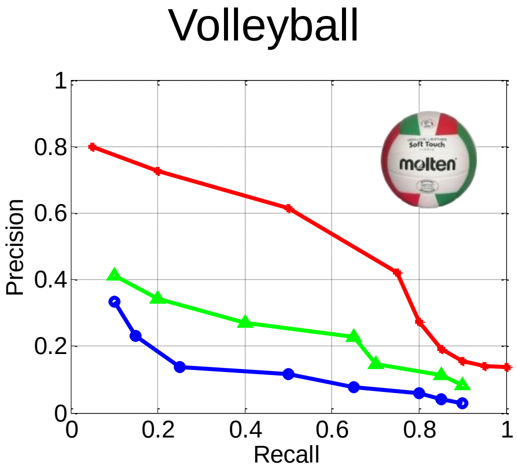


Slide Credit: Yao/Fei-Fei

Object Detection Results







Slide Credit: Yao/Fei-Fei

Dataset and Experiment Setup

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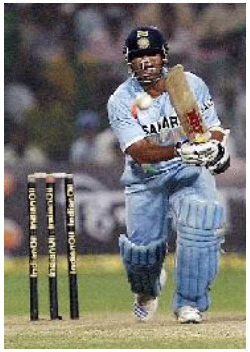
180 training & 120 testing images



Cricket
defensive shot

Cricket
bowling

Croquet
shot

Tennis
forehand

Tennis
serve

Volleyball
smash

[Gupta et al, 2009]

Tasks:

- Object detection;
- **Pose estimation;**
- Activity classification.

Slide Credit: Yao/Fei-Fei

Human Pose Estimation Results

Method	Torso	Upper Leg		Lower Leg		Upper Arm		Lower Arm		Head
Ramanan, 2006	.52	.22	.22	.21	.28	.24	.28	.17	.14	.42
Andriluka et al, 2009	.50	.31	.30	.31	.27	.18	.19	.11	.11	.45
Our full model	**.66**	**.43**	**.39**	**.44**	**.34**	**.44**	**.40**	**.27**	**.29**	**.58**

Slide Credit: Yao/Fei-Fei

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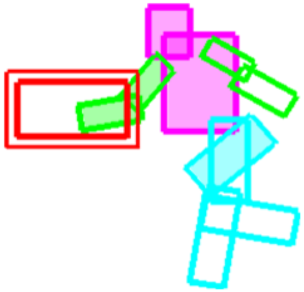
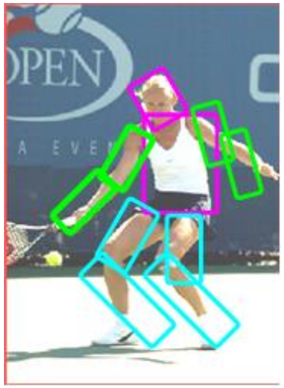


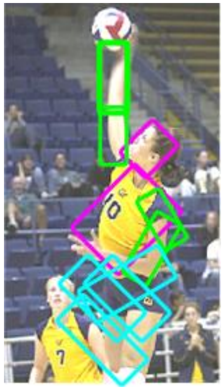
Tennis serve model



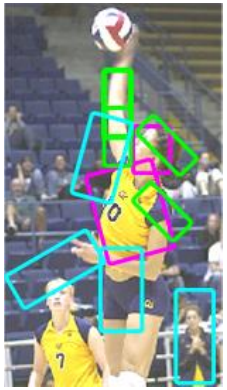
Our estimation result

Andriluka et al, 2009

Volleyball smash model



Our estimation result



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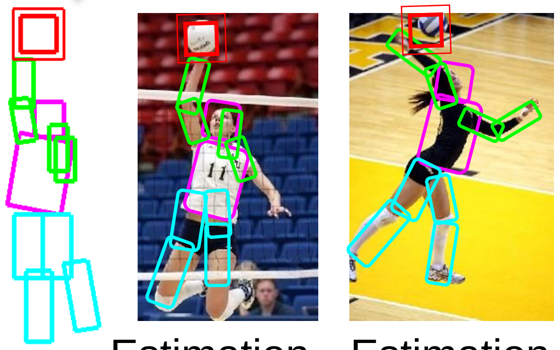
One pose per class	.63	.40	.36	.41	.31	.38	.35	.21	.23	.52



Estimation result

Estimation result

Estimation result

Estimation result

Slide Credit: Yao/Fei-Fei

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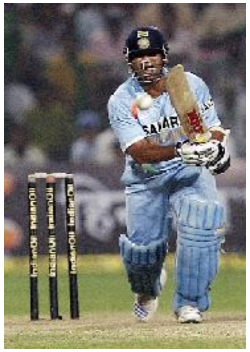


Cricket defensive shot

Cricket bowling

Croquet shot

Tennis forehand

Tennis serve

Volleyball smash

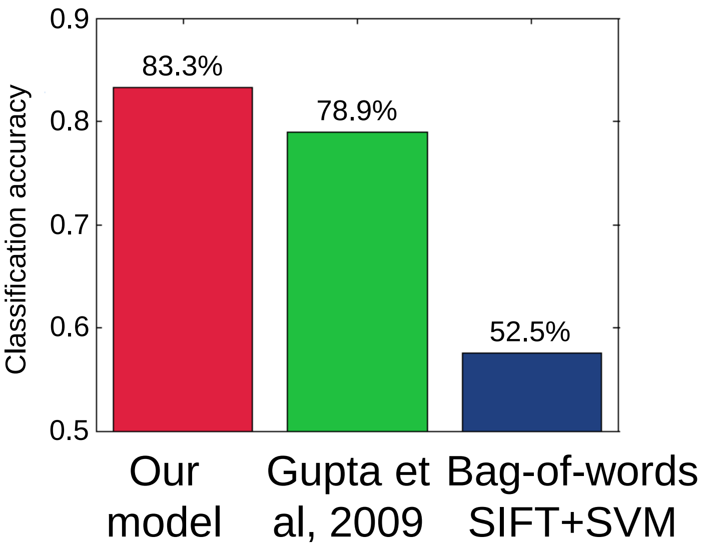
[Gupta et al, 2009]

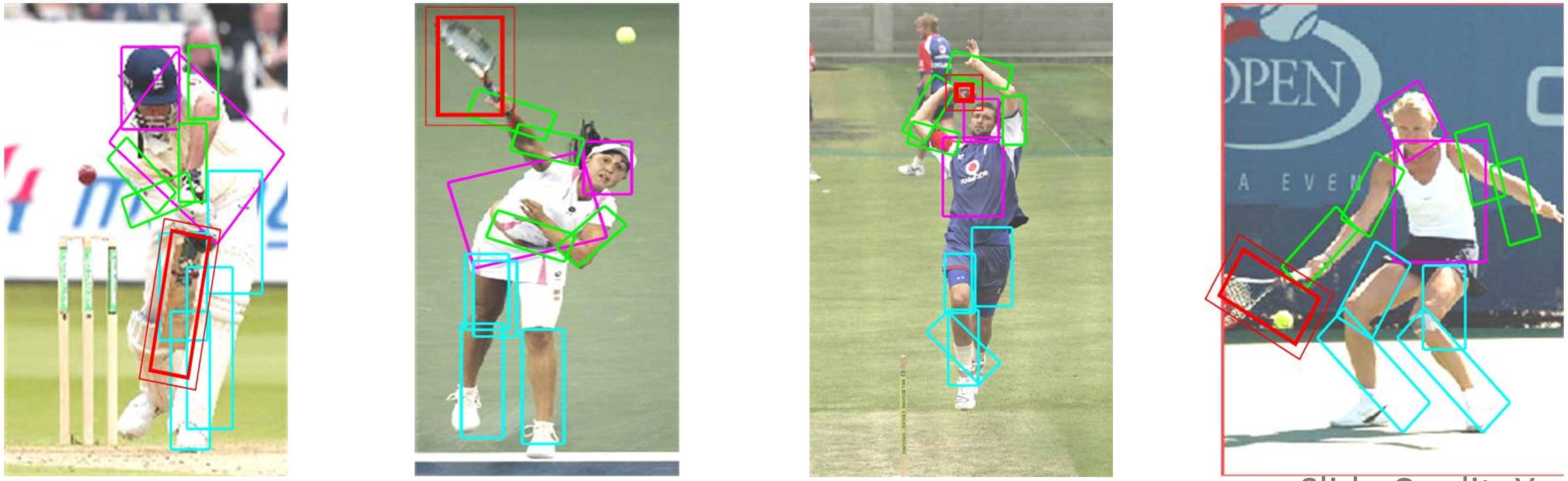
Tasks:

- Object detection;
- Pose estimation;
- **Activity classification.**

Slide Credit: Yao/Fei-Fei

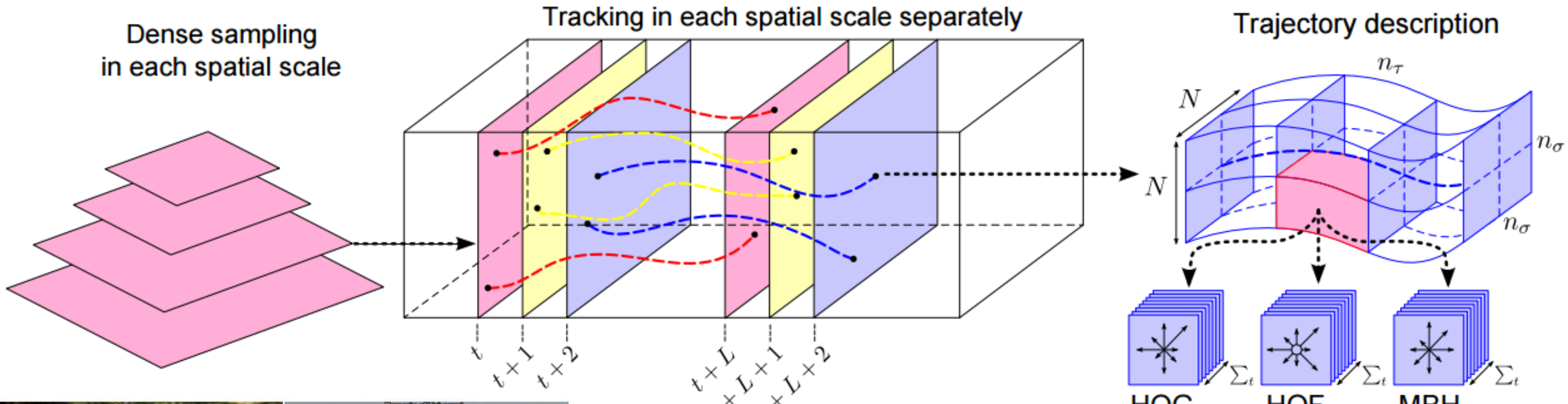
Activity Classification Results

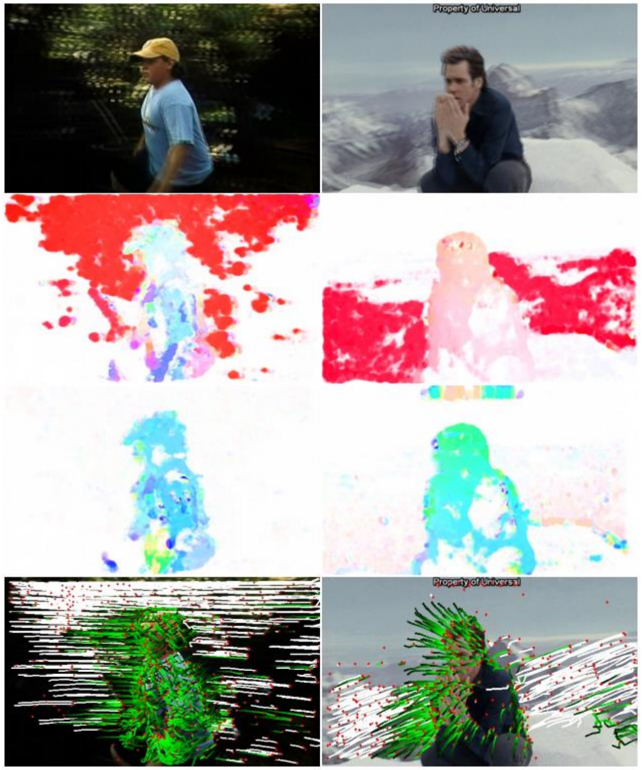




Slide Credit: Yao/Fei-Fei

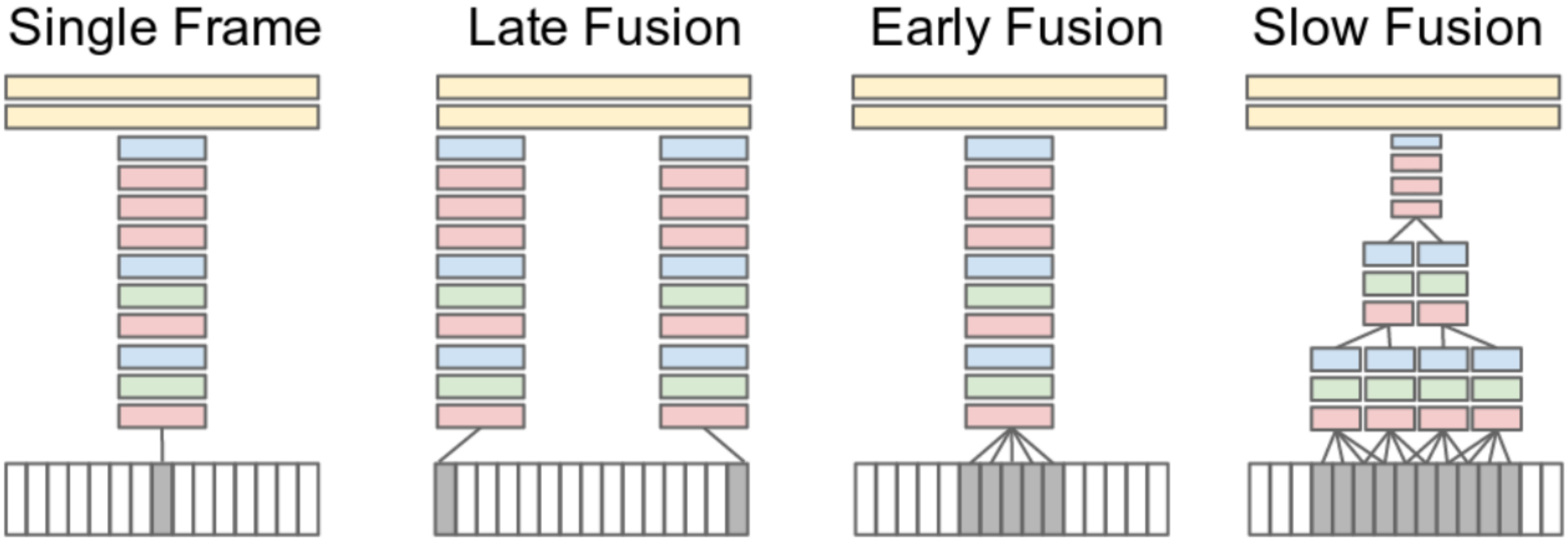
Motion features – Dense Trajectory

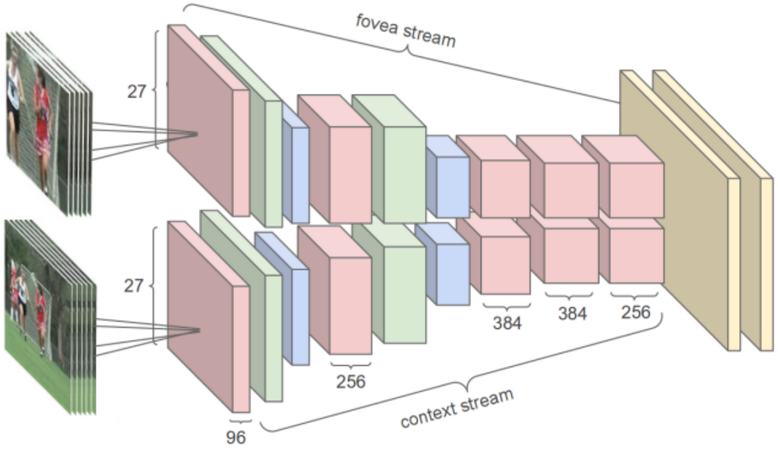




Action Recognition by Dense Trajectories, CVPR 2011
Action Recognition with Improved Trajectories, ICCV 2013

Video classification with CNNs



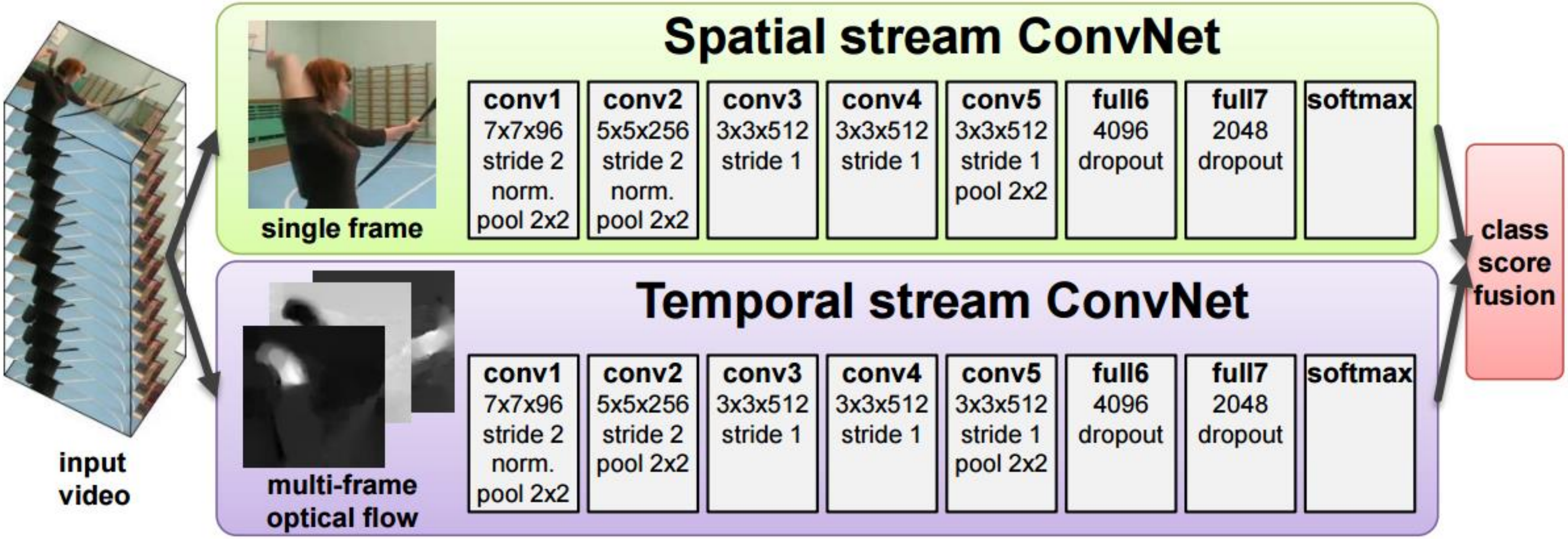


Large-scale Video Classification with Convolutional Neural Networks, CVPR 2014

Video classification with CNNs

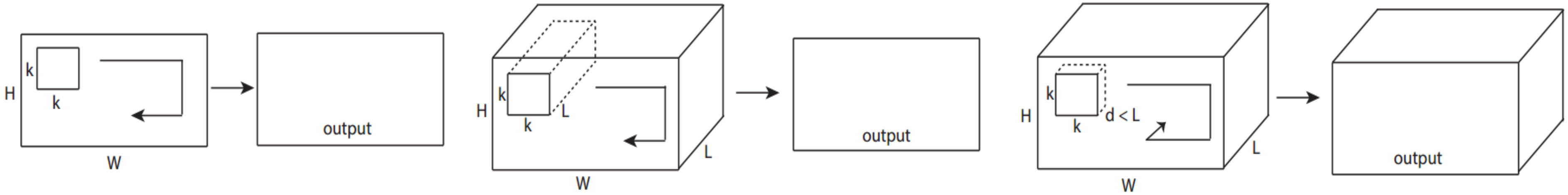
Large-scale Video Classification with Convolutional Neural Networks, CVPR 2014

Two-stream CNN



Two-Stream Convolutional Networks for Action Recognition in Videos, NIPS 2014

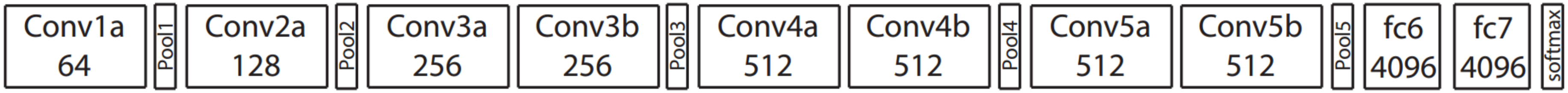
3D Convolutional Networks

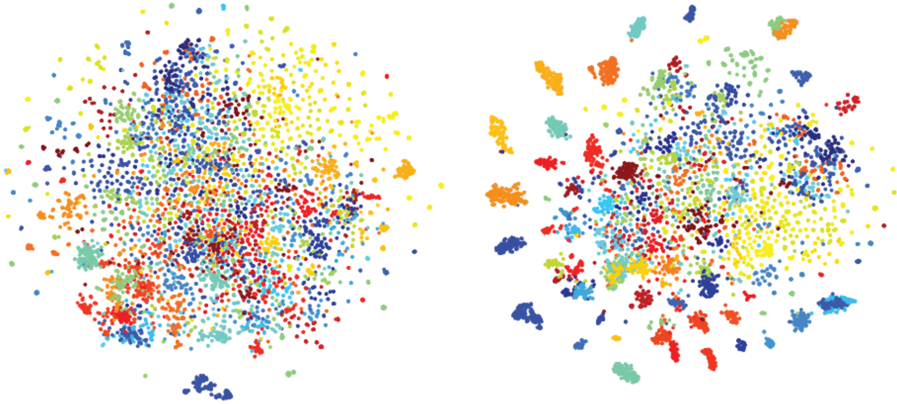


(a) 2D convolution

(b) 2D convolution on multiple frames

(c) 3D convolution





Imagenet

C3D

Learning Spatiotemporal Features with 3D Convolutional Networks, ICCV 2015

Take-home messages

- Action recognition is an open problem.
  - How to define actions?
  - How to infer them?
  - What are good visual cues?
  - How do we incorporate higher level reasoning?

Take-home messages

- Some work done, but it is just the beginning of exploring the problem. So far…
    - Actions are mainly categorical
      (could be framed in terms of effect or intent)
    - Most approaches are classification using simple features (spatial-temporal histograms of gradients or flow, s-t interest points, SIFT in images)
    - Just a couple works on how to incorporate pose and objects
    - Not much idea of how to reason about long-term activities or to describe video sequences

Next class: 3D Scenes and Context