

Discriminative Latent Variable Models for Human Action Recognition

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SFU

SFU

2012/03/26 PM07:37:04
GardenNVR

What does activity recognition involve?



2012/03/26 PM07:37:04
GardenNVR

Detection: are there people?



2012/03/26 PM07:37:04
GardenNVR

Action recognition

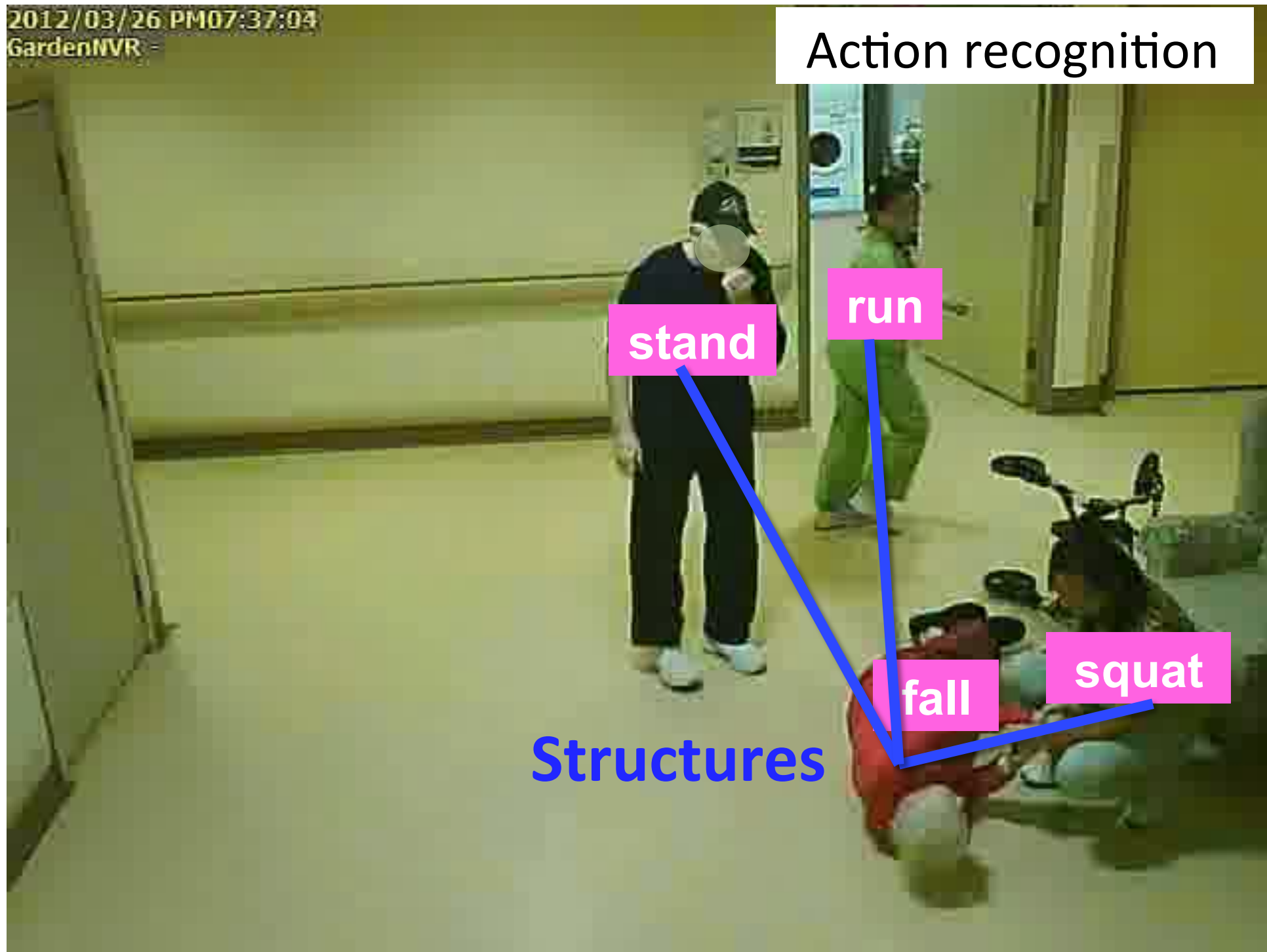
stand

run

fall

squat

Structures



2012/03/26 PM07:37:04
GardenNVR

Group activity recognition

help the fallen
person



2012/03/26 PM07:37:04
GardenNVR

Intention/social role

watch

get help

comfort



Advantages of Modeling Structures

- Analyze levels of detail
 - Body parts vs. whole
 - Actions of individuals
 - Relationships between individuals
 - Overall scene-level understanding
- Provide context for recognition

Activity landscape

Actions



Run

1

Human interactions



Point

2

Group activities



Talk

5-10

Events



Hockey

~10

Number of People

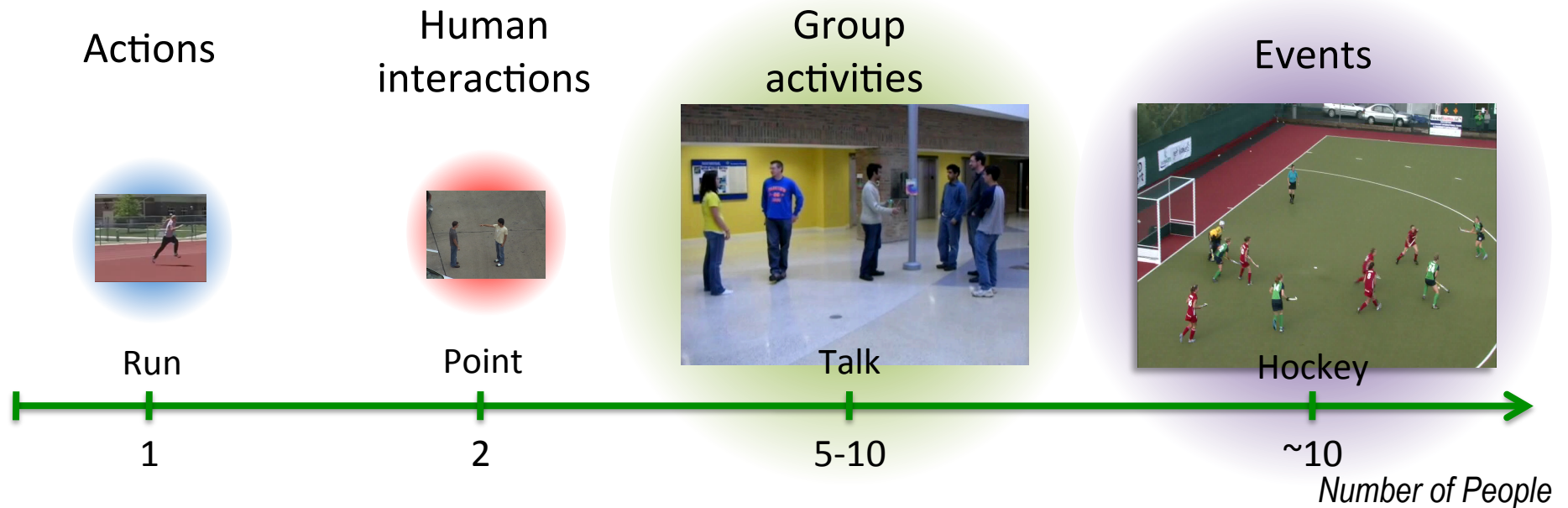
- Bobick & Davis, 2001
- Efros et al, 2003
- Schuldts et al, 2004
- Alper & Shah, 2005
- Dollar et al, 2005
- Blank et al, 2005
- Niebles et al, 2006
- Laptev et al, 2008
- Wang & Mori, 2008
- Rodriguez et al, 2008
- Wang & Mori, 2009
- Liu et al, 2009
- Marszalek et al, 2009
-

- Oliver et al, 1998
- Park & Aggarwal, 2004
- Ryoo & Aggarwal, 2006
- Ryoo & Aggarwal, 2009
- Yuan et al, 2010
- Vahdat et al, 2011
- Patron-Perez et al, 2012

- Cupillard et al, 2002
- Moore & Essa, 2002
- Vaswani et al, 2003
- Khan & Shah, 2003
- Zhang et al, 2006
- Mehran et al, 2009
- Gupta et al, 2009
- Choi & Savarese, 2009
- Lan et al, 2010
- Ryoo & Aggarwal, 2010
- Choi & Savarese, 2011
- Amer & Todorovic, 2011
-

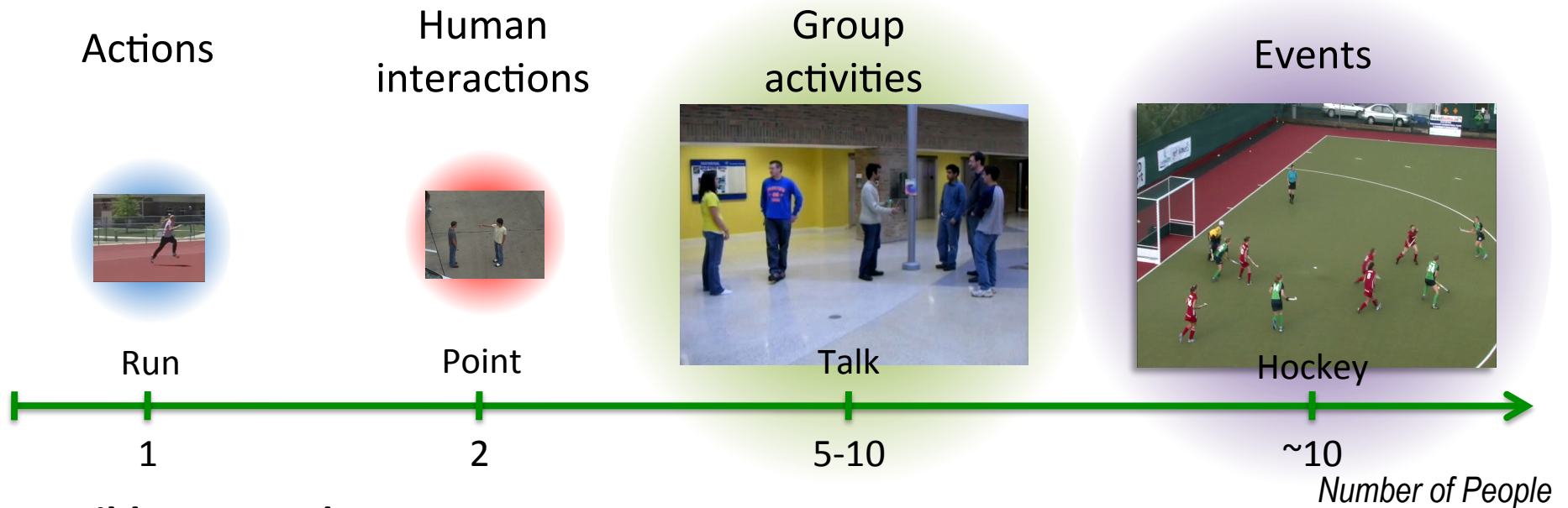
- Intille & Bobick, 2001
- Medioni et al, 2001
- Loy et al, 2010
- Lan et al, 2012
- Amer et al, 2012

Activity landscape



- Performed by multiple people
- Rich human-human interactions
- Events may consist of multiple group activities, and inter-group interactions

Activity landscape



Possible approaches:

Bag of features



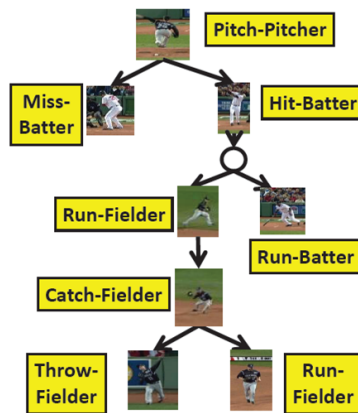
- Statistical methods
- Don't extract semantic descriptions

Laptev et al, 2008

Liu et al, 2009

Tamrakar et al, 2012

DBN, AND-OR Graph, CRF, Latent SVM



- Structural methods
- Complex learning / inference

Xiang & Gong, 2006

Gupta et al, 2009

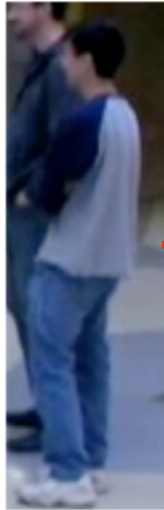
Felzenszwalb et al, 2010

Amer et al, 2012

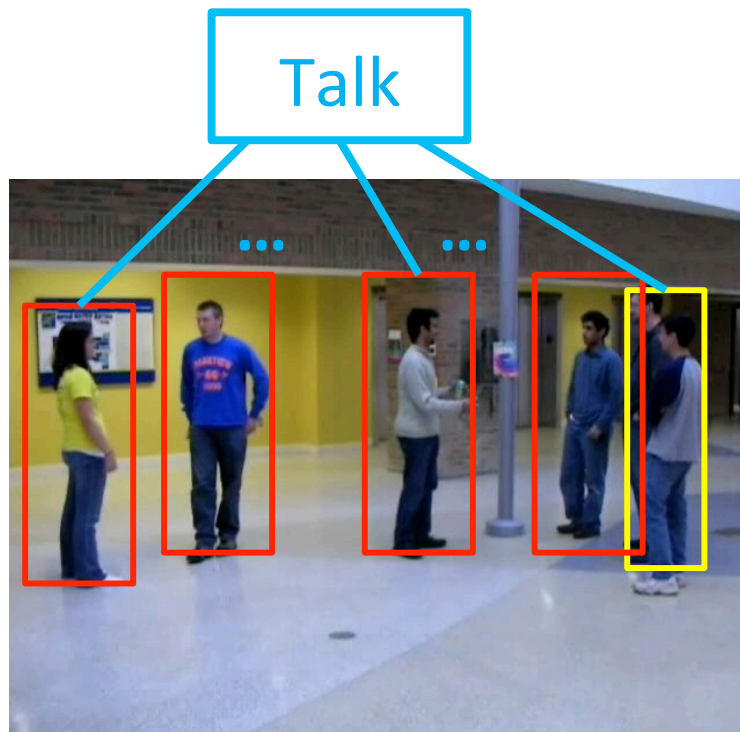
Our Proposal - Structured Models

- Models that account for spatial, temporal, relational, or other structures
 - Flexible
 - Richer representation
- This talk: representation and learning of structured models for activity recognition
- These can be applied across the activity landscape, from individual human actions through to group events

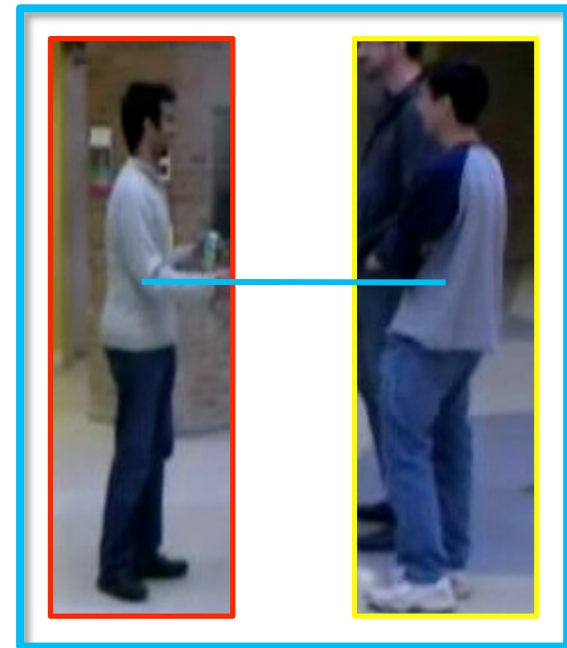
Role of Context in Actions



Group Context

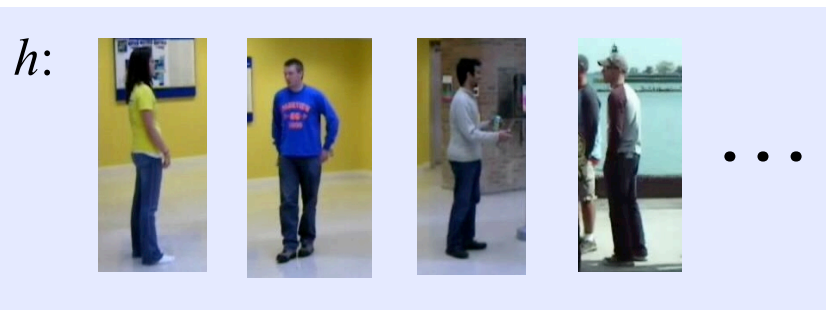


group-person
interaction

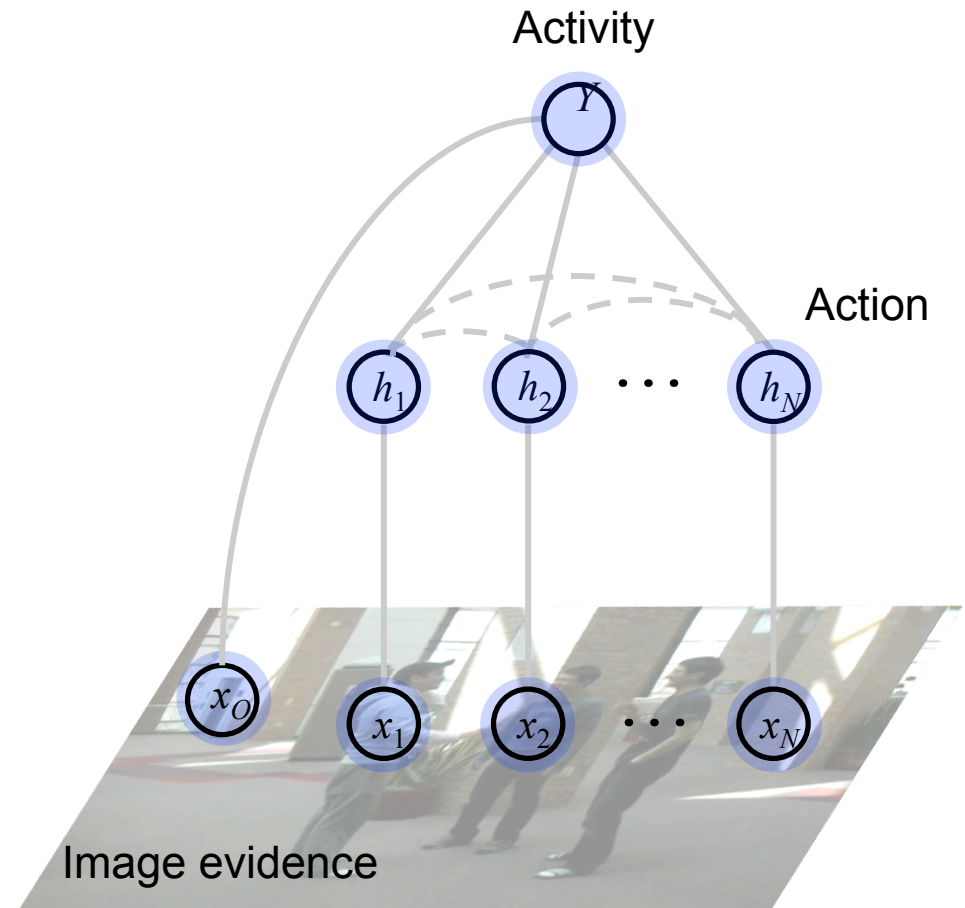


person-person
interaction

Model of Group Activities



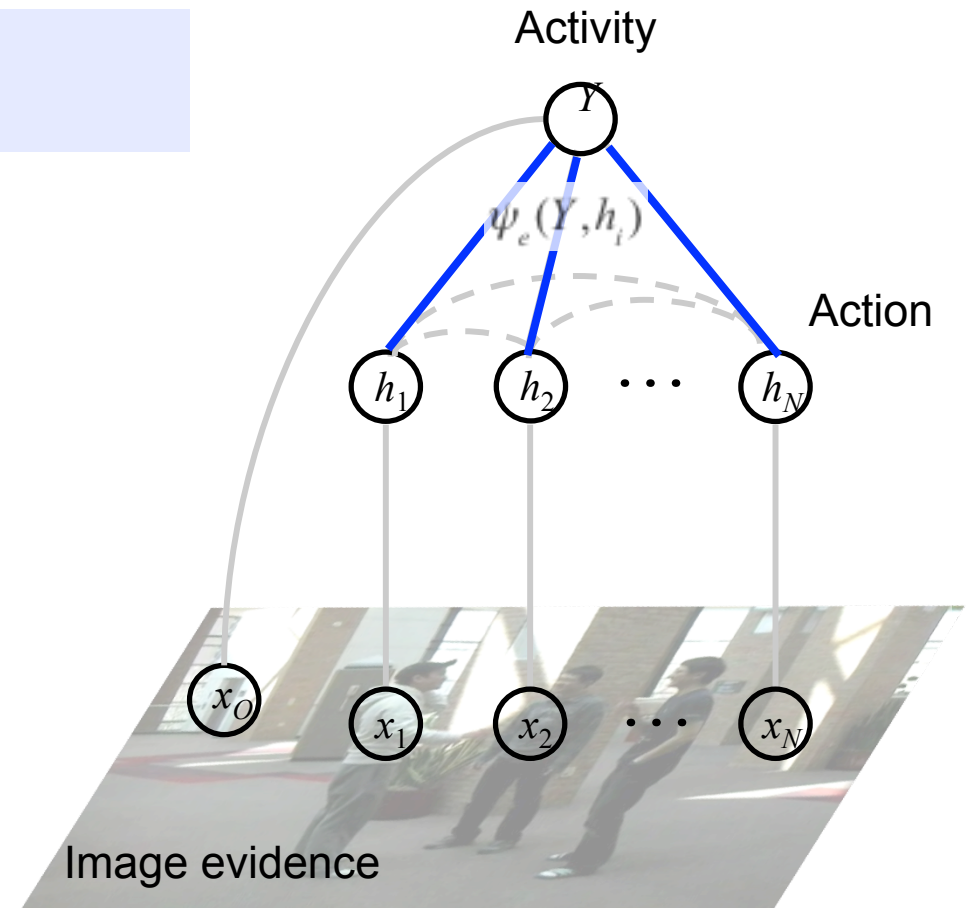
x : HOG [Dalal & Triggs, 2005]



Lan et al. NIPS 2010, TPAMI 2012

Model of Group Activities

- Activity-Action Potential $\psi_e(Y, h_i)$:
Co-occurrence between Y and h_i



Markov Random Field

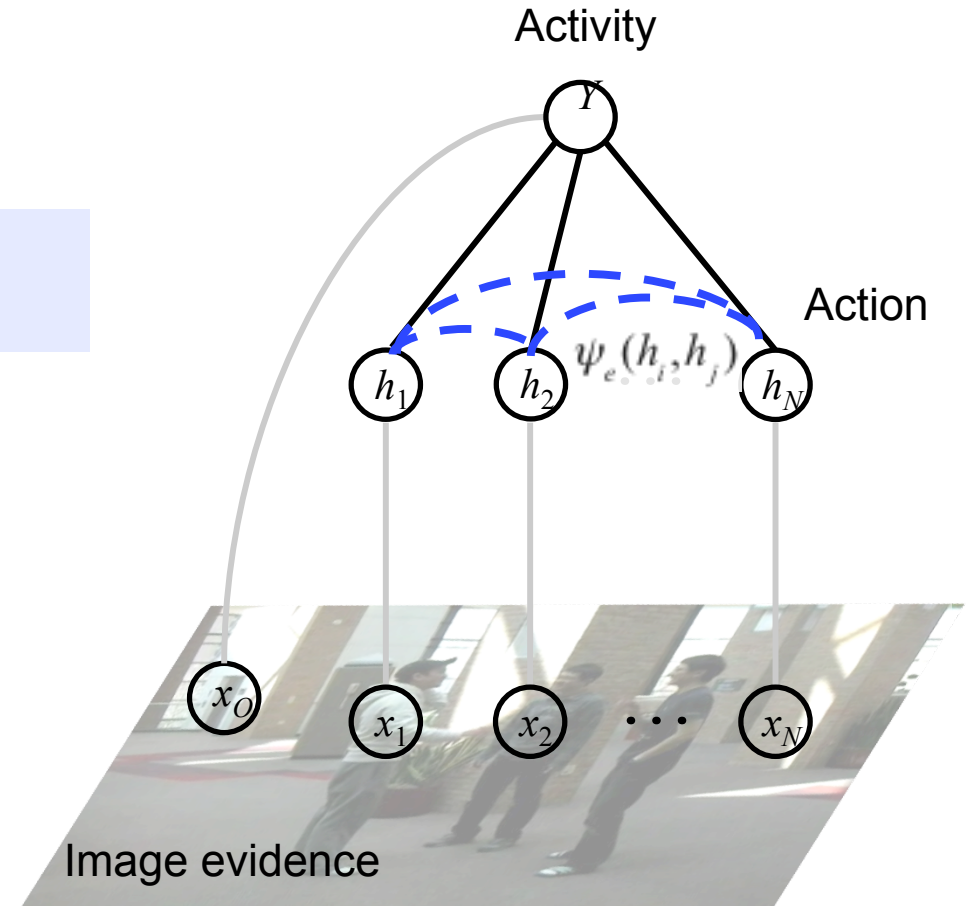
$$\Psi = \sum_{e \in E} w_e \psi_e$$

↑ ↘
Clique weight Clique potential

Model of Group Activities

- Activity-Action Potential $\psi_e(Y, h_i)$:
Co-occurrence between Y and h_i

- Action-Action Potential $\psi_e(h_i, h_j)$:
Co-occurrence between h_i and h_j



Markov Random Field

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

Clique weight Clique potential
 ↑ ↙

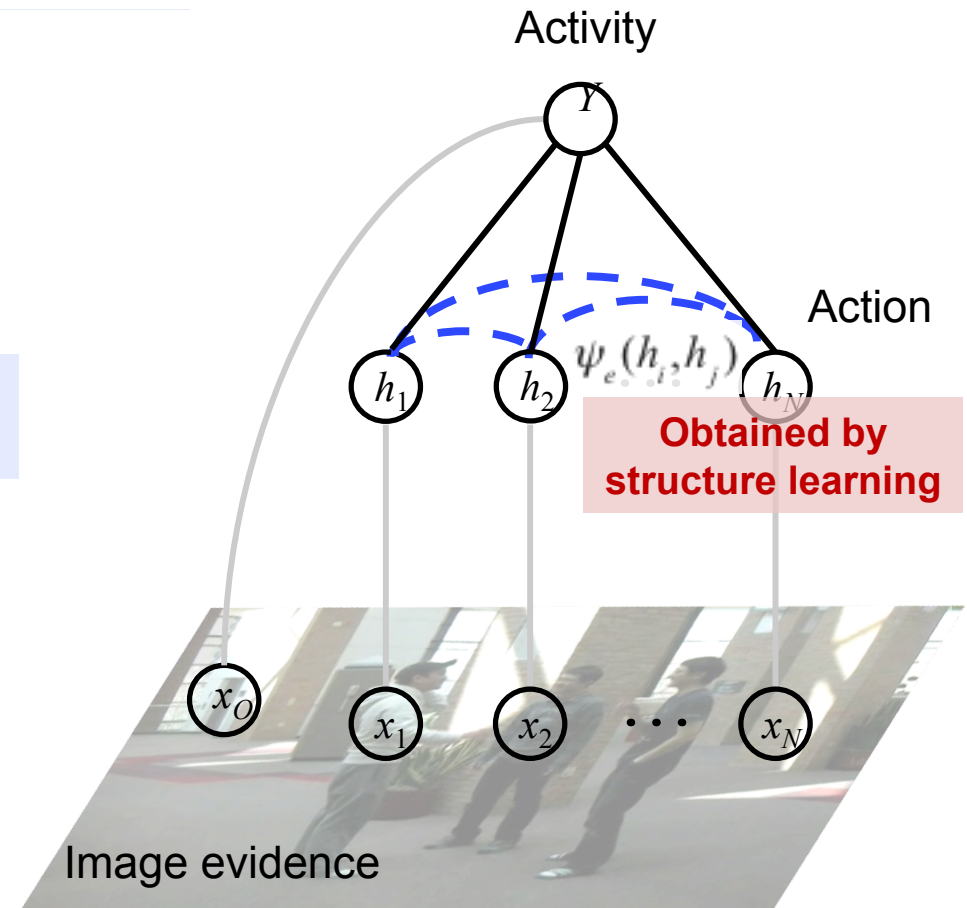
Model of Group Activities

- Activity-Action Potential $\psi_e(Y, h_i)$:
Co-occurrence between Y and h_i
- Action-Action Potential $\psi_e(h_i, h_j)$:
Co-occurrence between h_i and h_j
 - Learn structural connectivity among the actions.

Markov Random Field

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

Clique weight Clique potential



Model of Group Activities

- Activity-Action Potential $\psi_e(Y, h_i)$:
Co-occurrence between Y and h_i

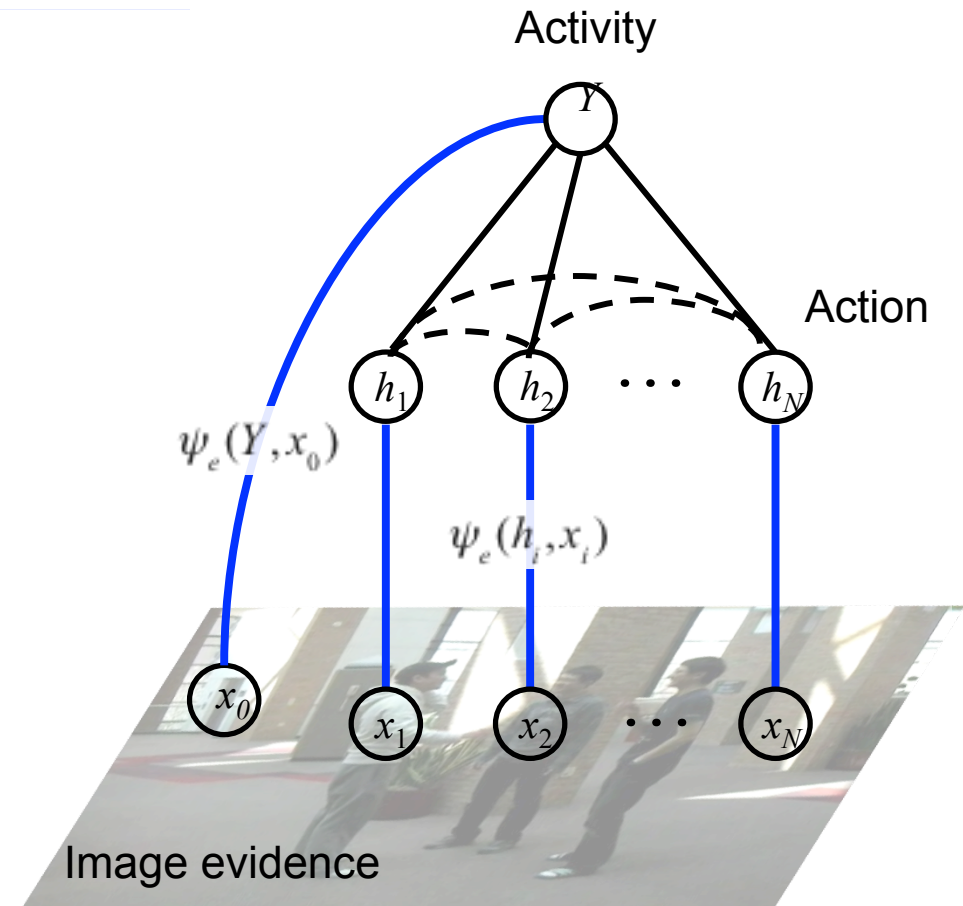
- Action-Action Potential $\psi_e(h_i, h_j)$:
Co-occurrence between h_i and h_j
 - Learn structural connectivity among the actions.

- $\psi_e(Y, x_0)$ and $\psi_e(h_i, x_i)$:
Discriminative action template scores (HOG + SVM).

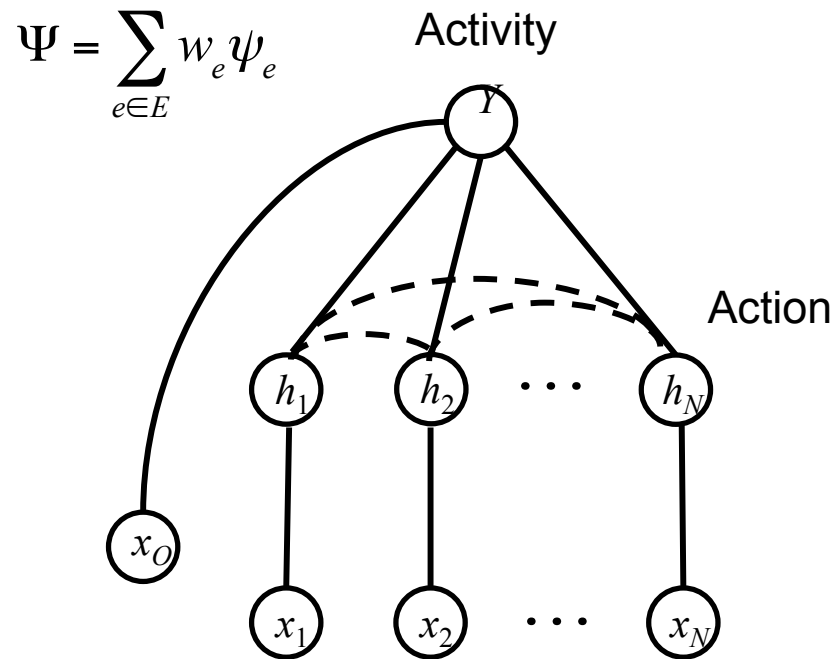
Markov Random Field

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

Clique weight Clique potential
 ↑ ↖



Model Learning

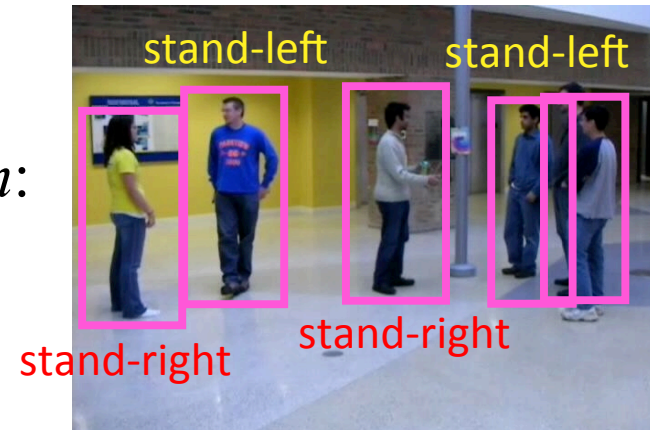


Goals:

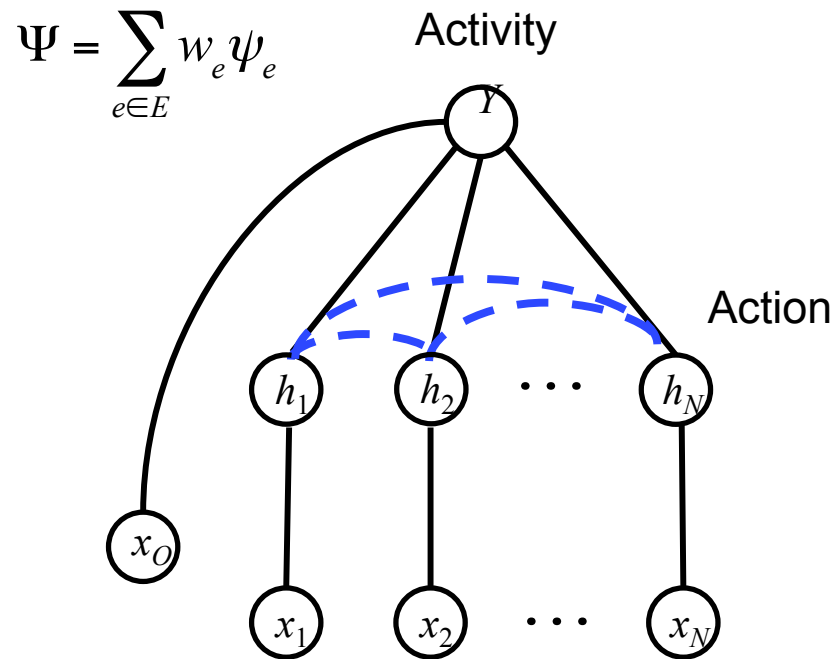
Input:

Y : talk

h :



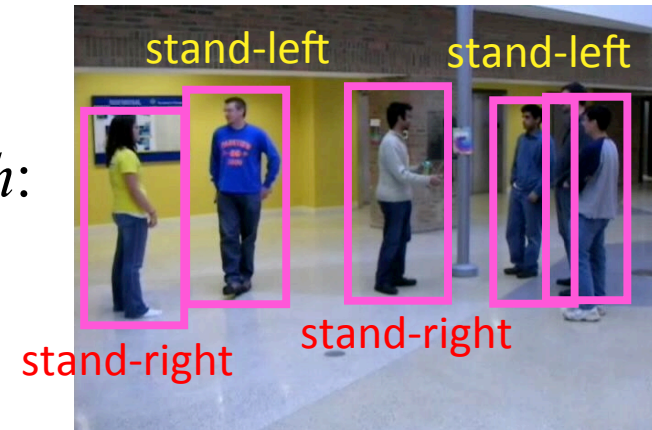
Model Learning



Input:

Y : talk

h :

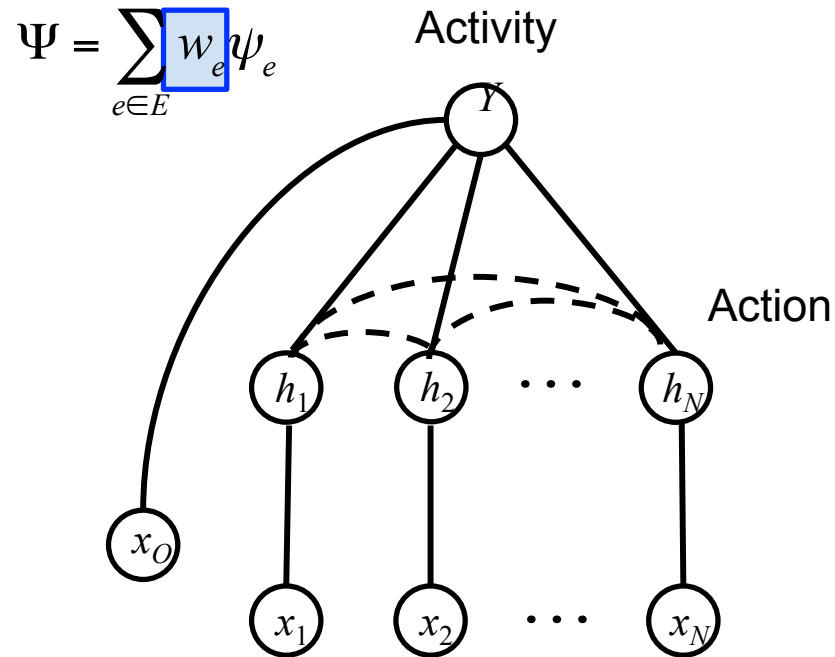


Goals:

Structural connectivity (hidden human-human interactions)

Potential weights

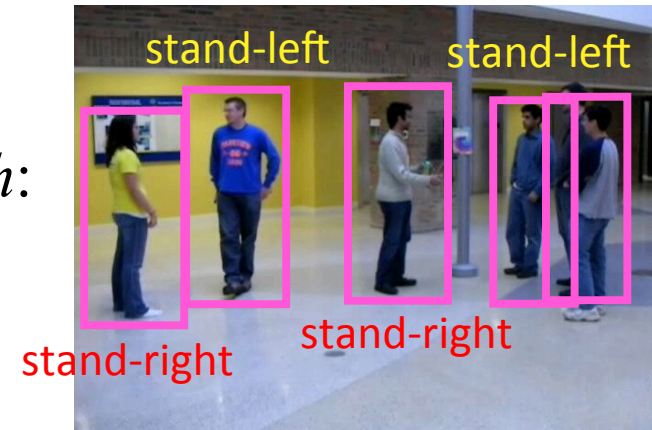
Model Learning



Input:

Y : talk

h :

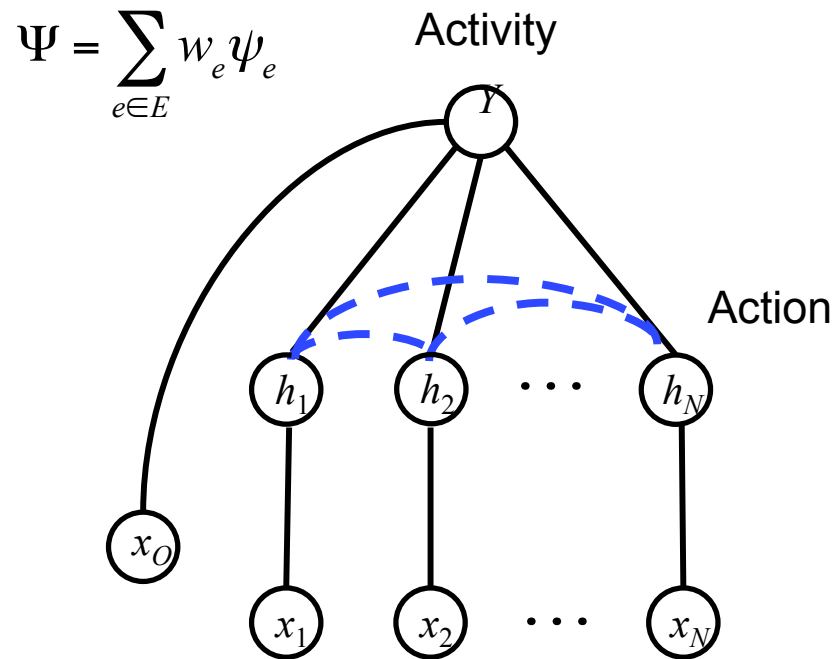


Goals:

Structural connectivity (hidden human-human interactions)

Potential weights

Model Learning

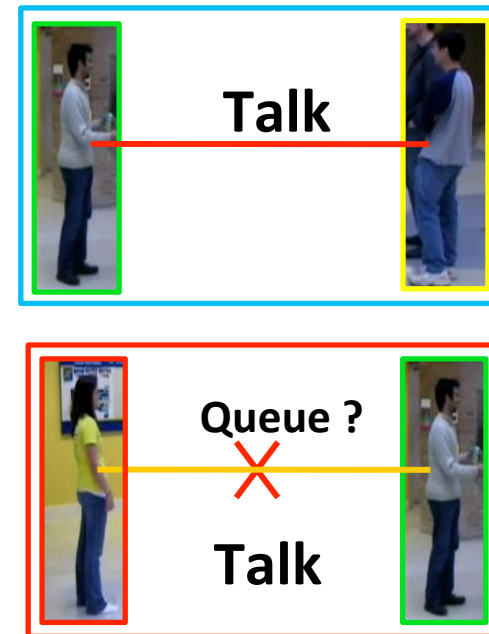


Goals:

Structural connectivity

Potential weights

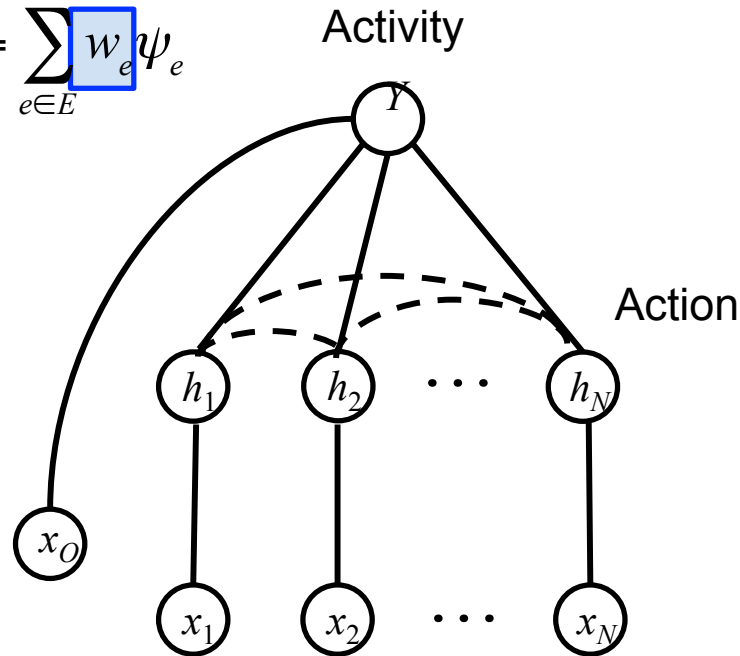
Approach:



$$\text{ILP} \quad \max_{E=\{e\}} \sum_e w_e \psi_e$$

Model Learning

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



Goals:

Structural connectivity

Potential weights

Approach:

Max-margin learning

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

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

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

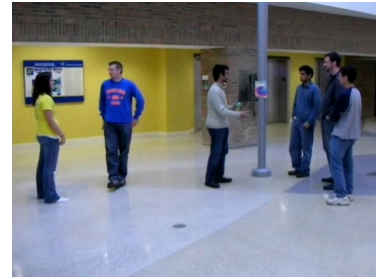
$$\forall i, \xi_i \geq 0$$

Notation

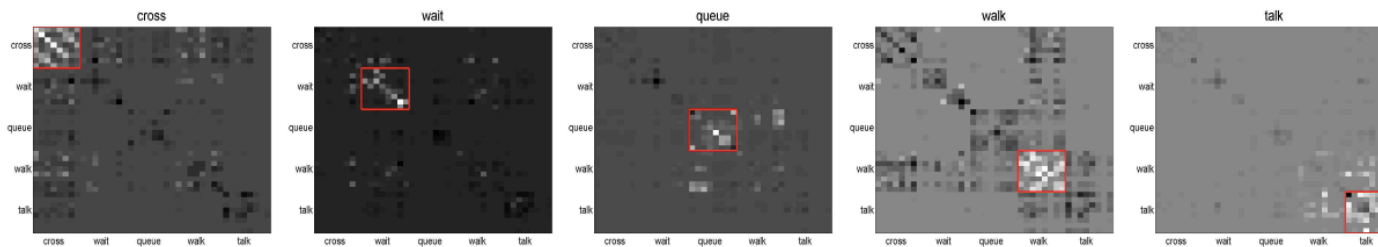
- ψ_i : Potential values of the i -th image.
- \mathbf{w}_r : Potential weights of the r -th activity.
- $y(r)$: r -th activity class.
- ξ_i : A slack variable for the i -th image.

Model Inference

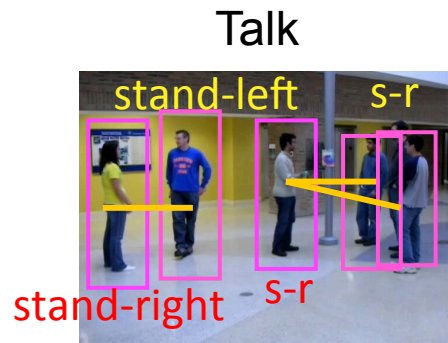
I



The learned models

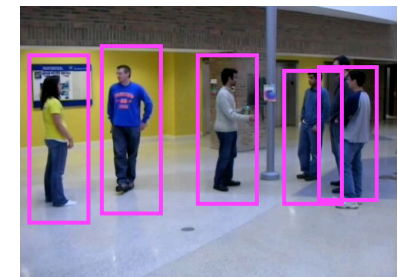


coordinate
ascent
inference



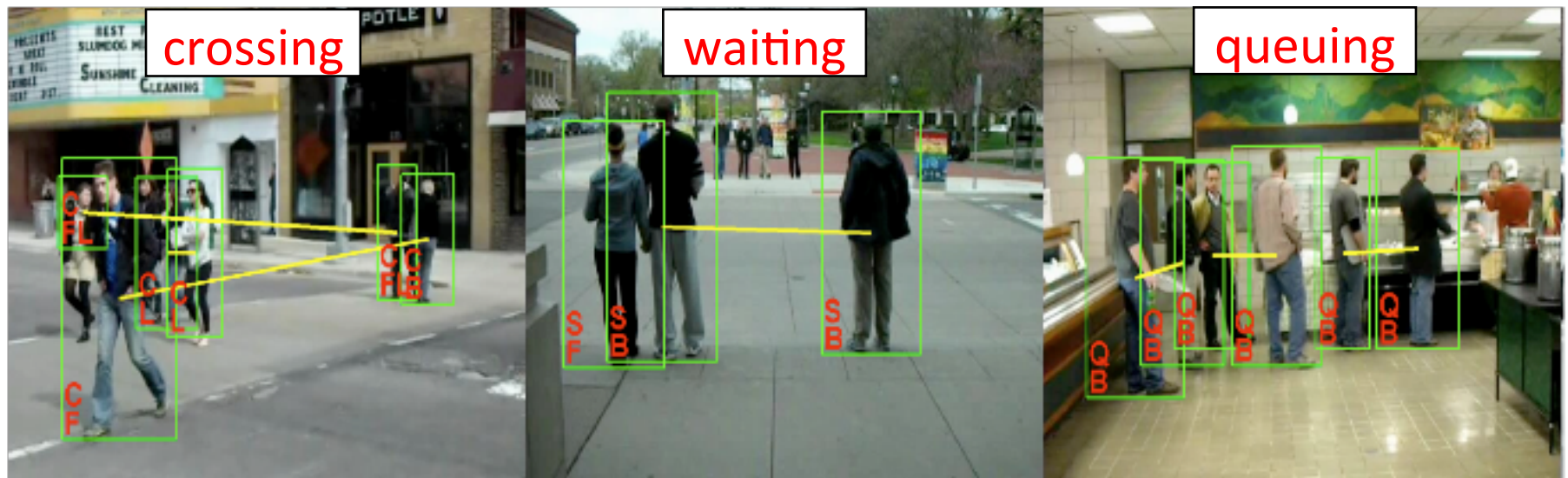
$$\Psi(Y^*, e^*, \{h_{1,n}^*\}_n)$$

Activity, interactions, actions

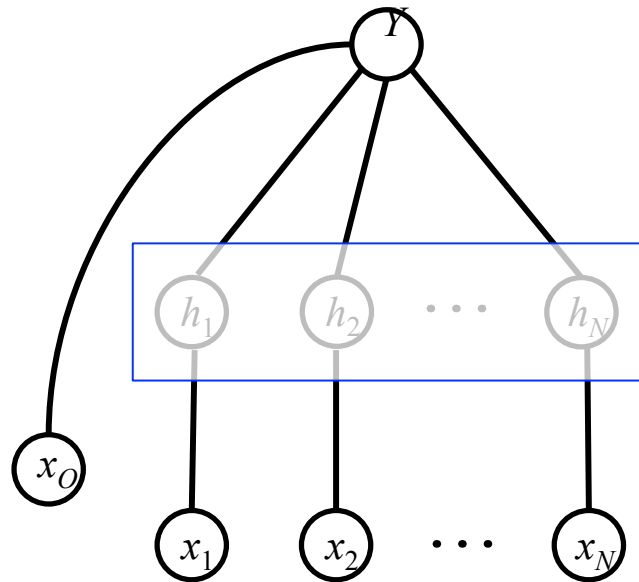


Person detection

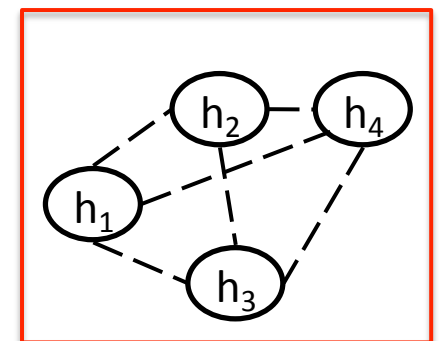
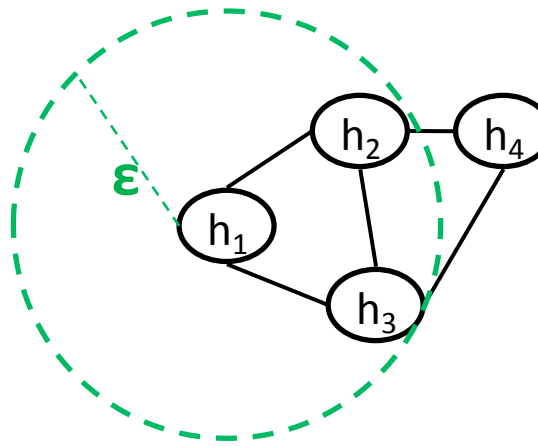
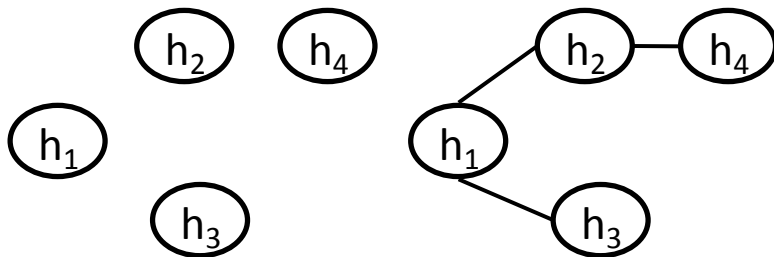
Visualization of the Results



Baselines



- SVM
- No connection
- Min-spanning tree
- ϵ -neighborhood graph



Results – Collective Activity Dataset

Method	Overall	Mean per-class
SVM	70.9	68.6
no connection	75.9	73.7
min-spanning tree	73.6	70.0
ϵ -neighborhood graph, $\epsilon=100$	74.3	72.9
ϵ -neighborhood graph, $\epsilon=200$	70.4	66.2
ϵ -neighborhood graph, $\epsilon=300$	62.2	62.5
complete graph	62.6	58.7
our approach	79.1	77.5

Nursing Home Data

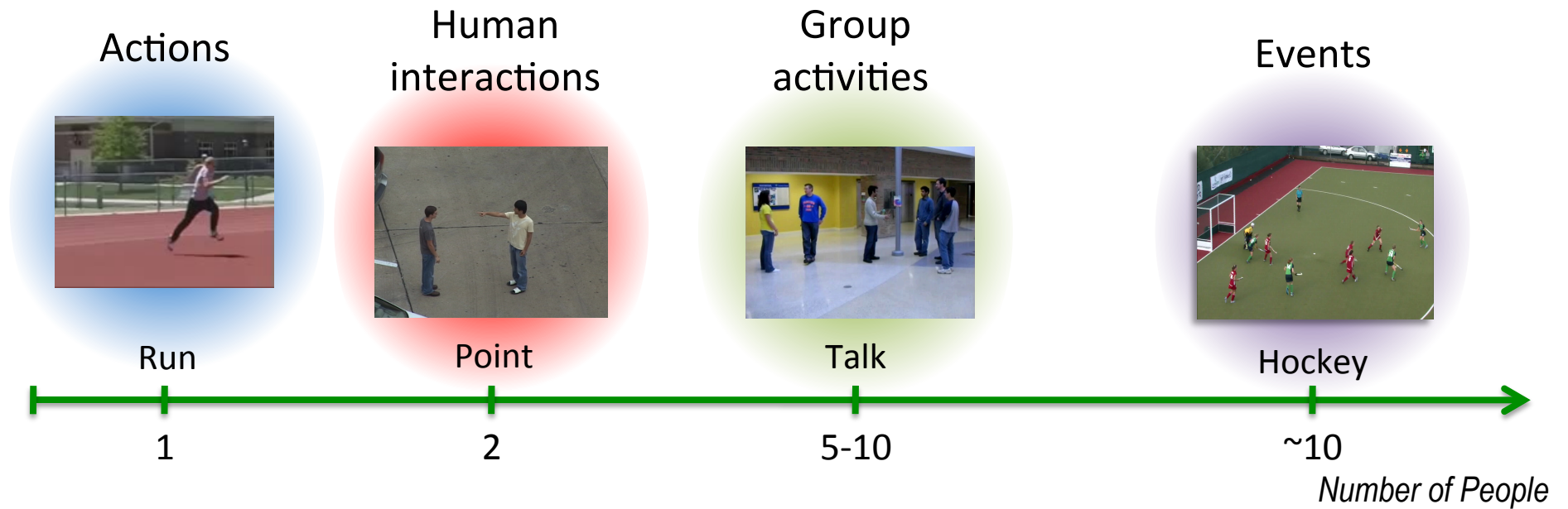


- 22 short clips of fall + a 30-min non-fall clip, 5 actions, 2 group activities

Results – Nursing Home Data

Method	Overall	Mean per-class
SVM	48.0	52.4
no connection	54.4	56.1
min-spanning tree	66.9	62.3
ϵ -neighborhood graph, $\epsilon=100$	72.7	61.3
ϵ -neighborhood graph, $\epsilon=200$	67.6	61.1
ϵ -neighborhood graph, $\epsilon=300$	68.6	64.2
complete graph	70.6	62.2
our approach	71.5	67.4

Roadmap



- Tian Lan, Leonid Sigal, Greg Mori. Social Roles in Hierarchical Models for Human Activity Recognition. CVPR 2012

Semantic Descriptions of Videos



actions

walk
run
jog
bend
shoot
dribble
pass

social roles

attacker
first defenders
man-marking
defend-space
teammate

event

corner hit
free hit
attack play

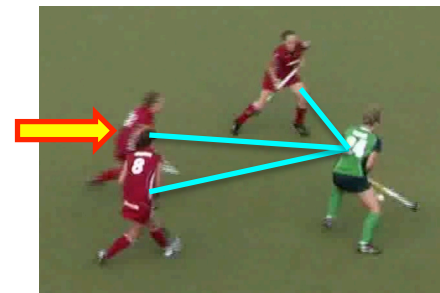
Social Roles

- Mid-level semantics that describe individual/group behaviors in the context of social interactions.

man-marking

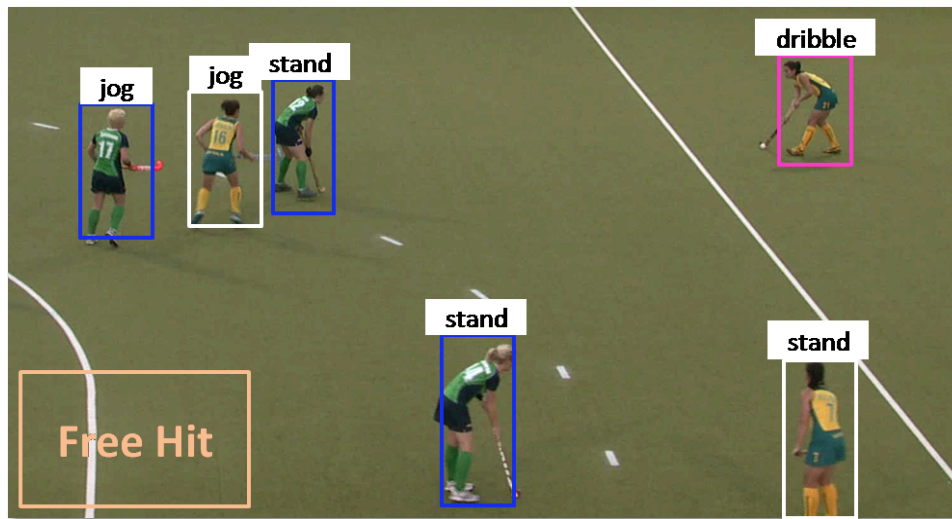


first defenders



Goal

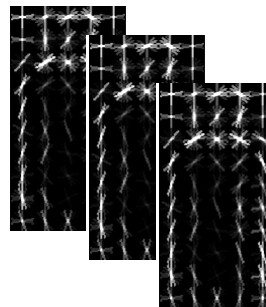
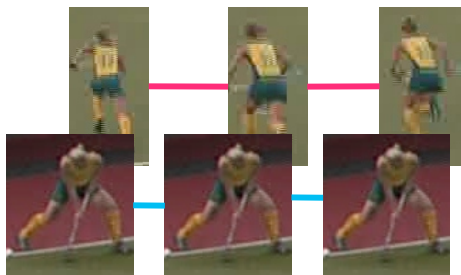
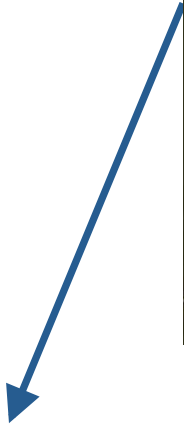
- Label all individuals' actions, social roles and the scene-level events.



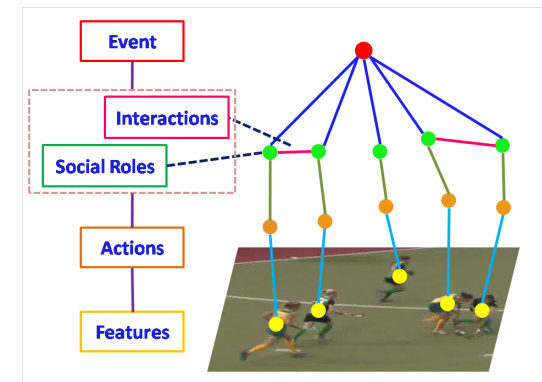
Social Roles	
– attacker	<hr/>
– man-marking	<hr/>
– teammate	<hr/>

- Search for event/social role/action of interest
 - Who is the attacker? What's the overall game situation?

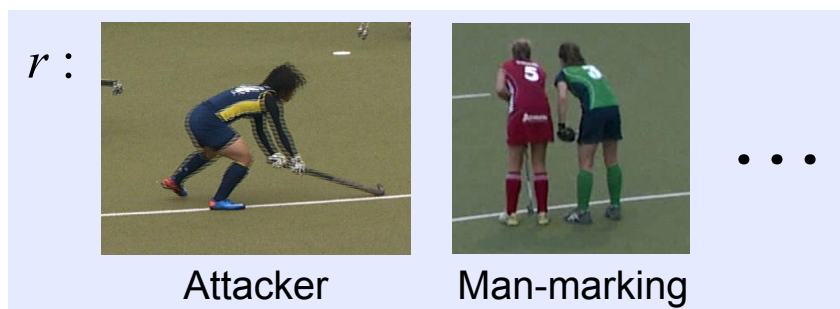
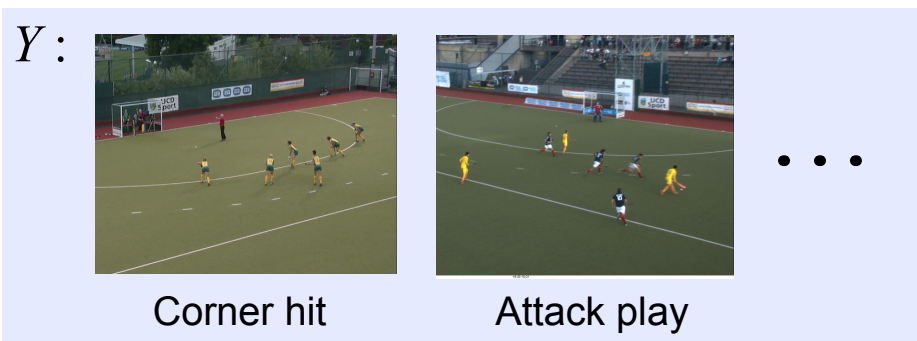
System Overview



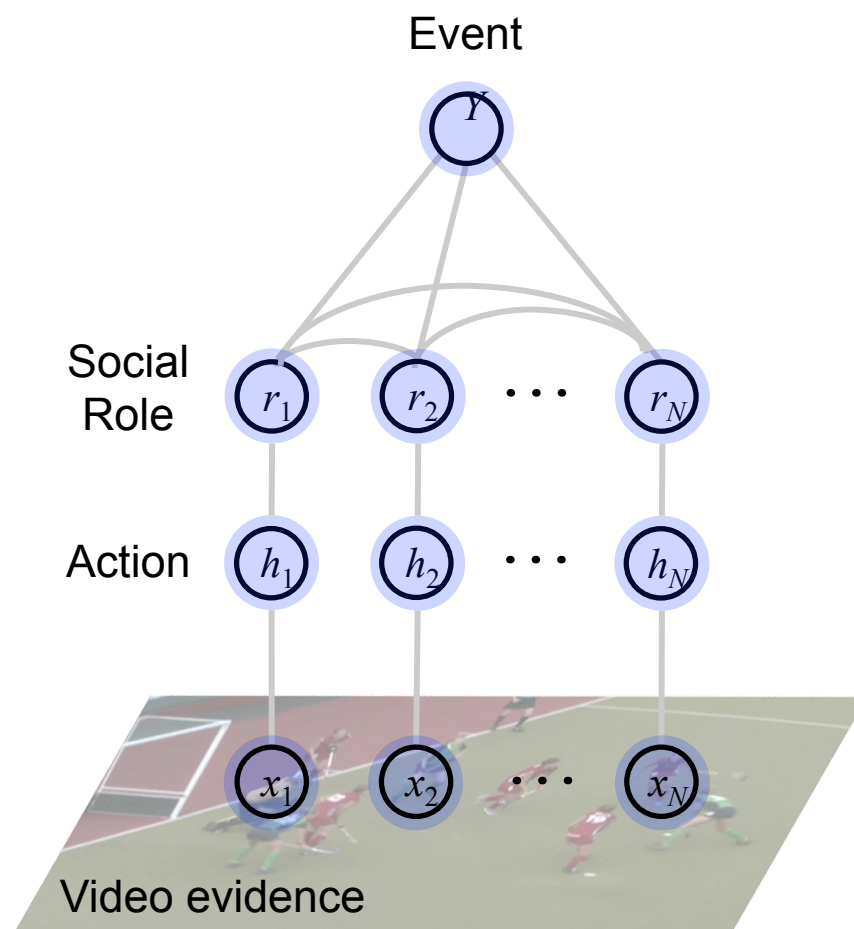
Model



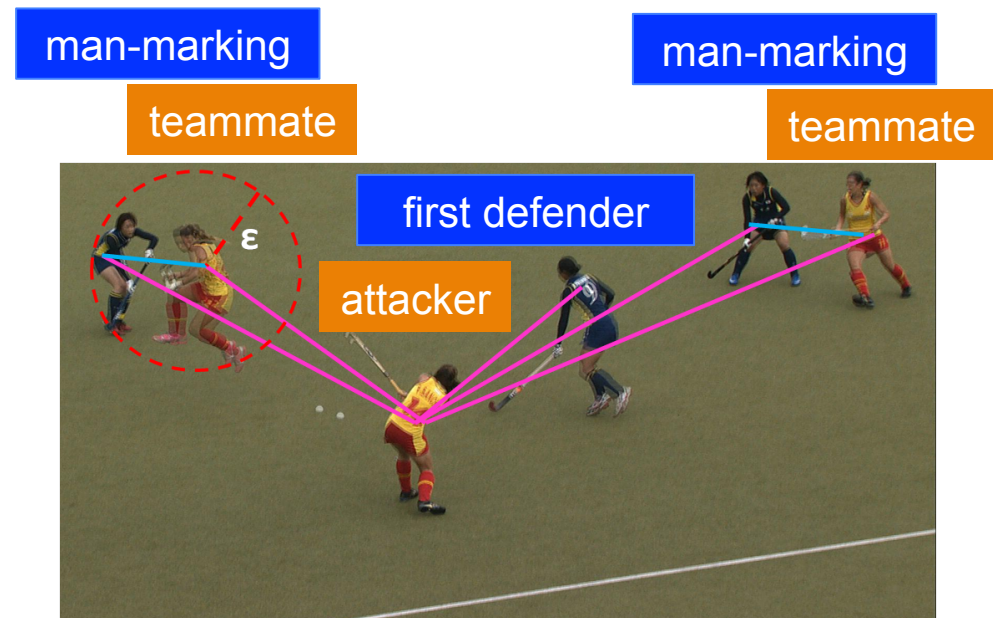
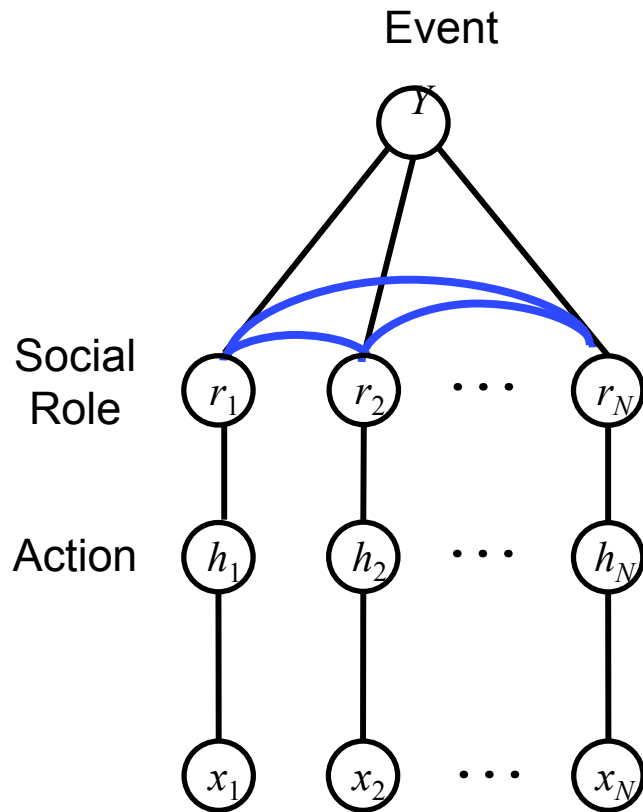
Activity Hierarchy Model Representation



x : Concatenated HOG [Dalal & Triggs, 2005]

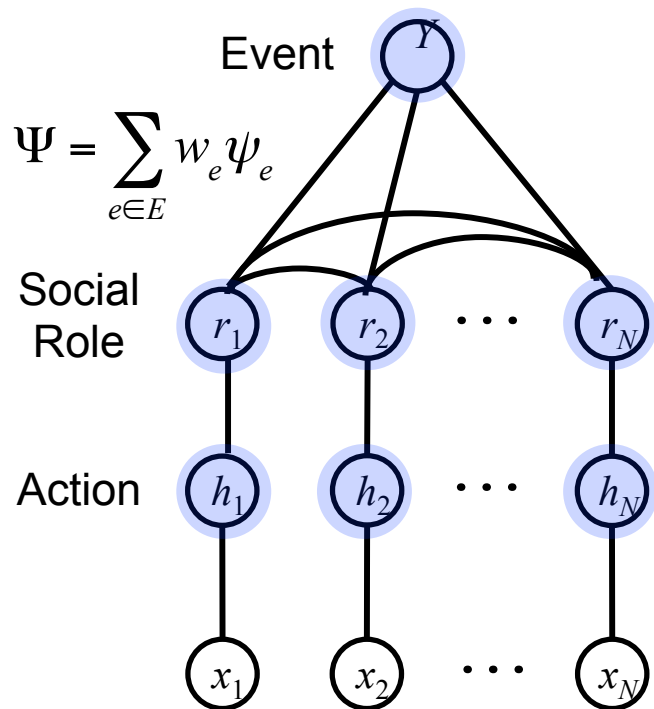


Activity Hierarchy Model Representation



- **Spatial relationships** and **color** among players with different social roles.

Model Learning



Query for event: $loss = \Delta(y, y_i)$

$$\Delta(y, y_i) = \begin{cases} 1 & \text{if } y \neq y_i \\ 0 & \text{otherwise} \end{cases}$$

Query for social roles: $loss = \Delta(r, r_i)$

Query for actions: $loss = \Delta(h, h_i)$

Scene labeling: $loss = \Delta(y, y_i) + \Delta(r, r_i) + \Delta(h, h_i)$

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

s.t. $\forall i, y, r, h$

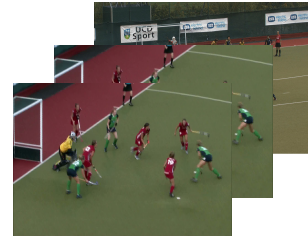
$$\mathbf{w}_{y_i r_i h_i} \cdot \psi_i - \mathbf{w}_{y r h} \cdot \psi_i \geq \boxed{loss} - \xi_i$$

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

Model Inference

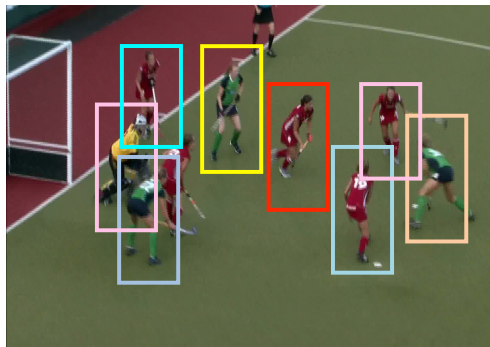
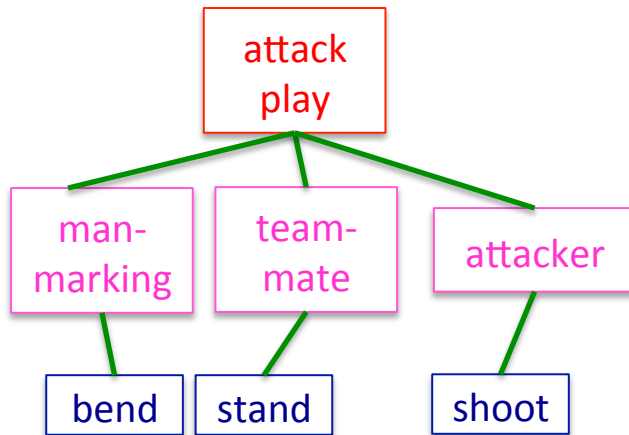
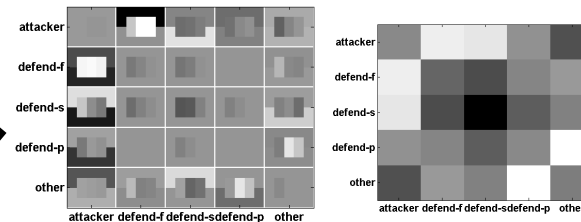
- Query

V



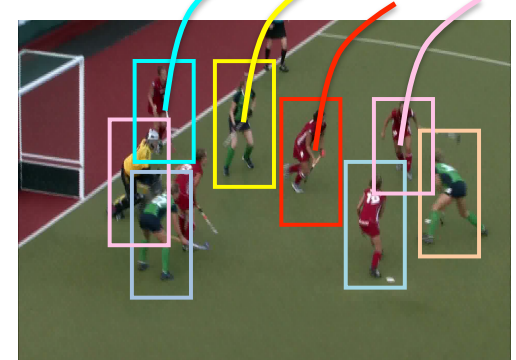
q: User-specified queries
– e.g. find the attack play

The learned models



coordinate
ascent
inference

$$\max_{y,r,h \setminus q} \sum_e w_e \psi_e$$



Person detection and
tracking

Score: $\Psi\left(Y^*, \{r_{1,n}^*\}_n, \{h_{1,n}^*\}_n, q\right)$

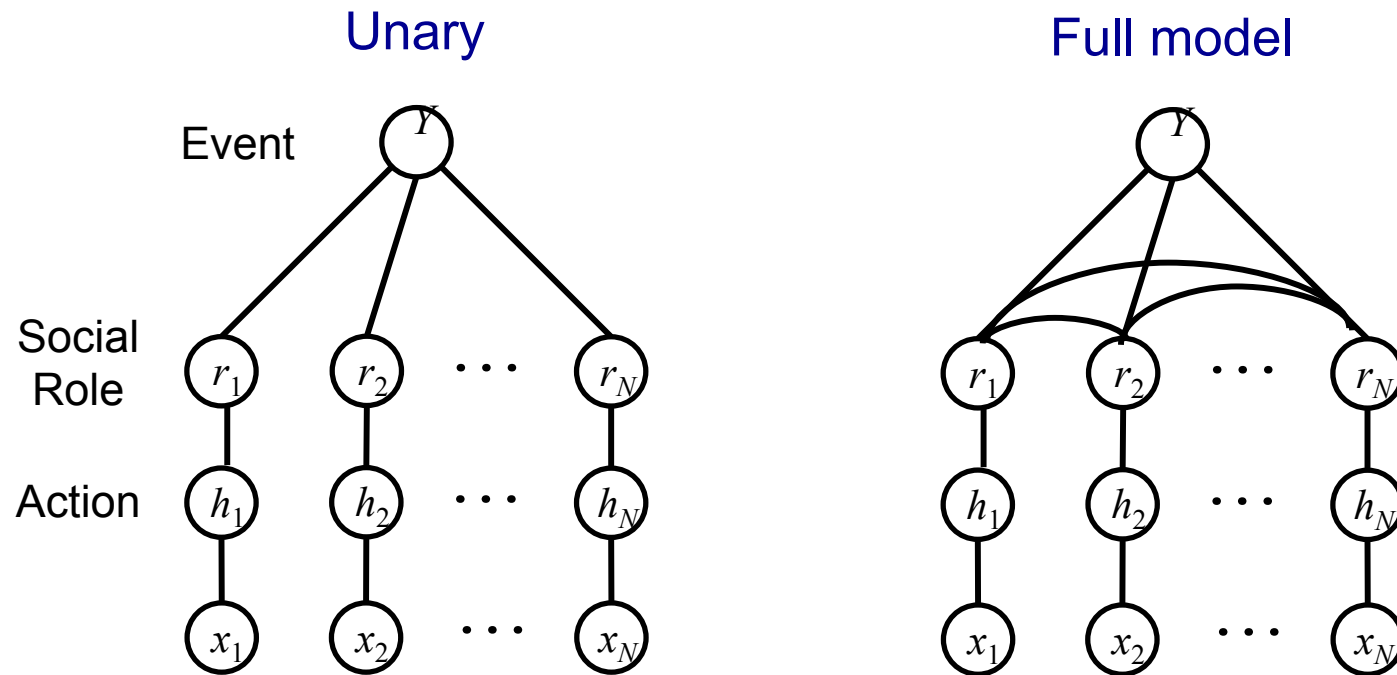
Event, social roles, actions, queries

ESPN Broadcast Field Hockey Data



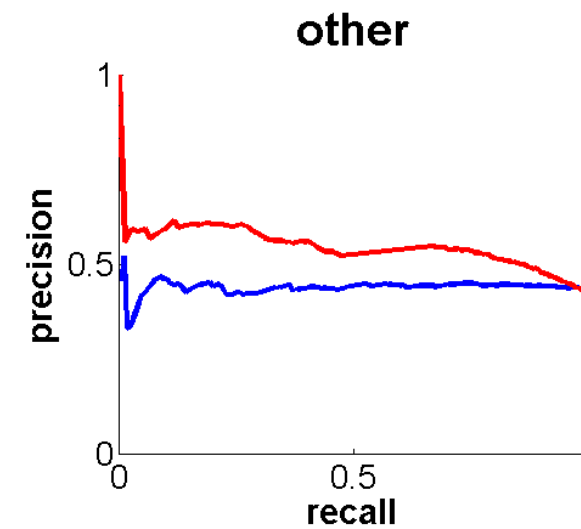
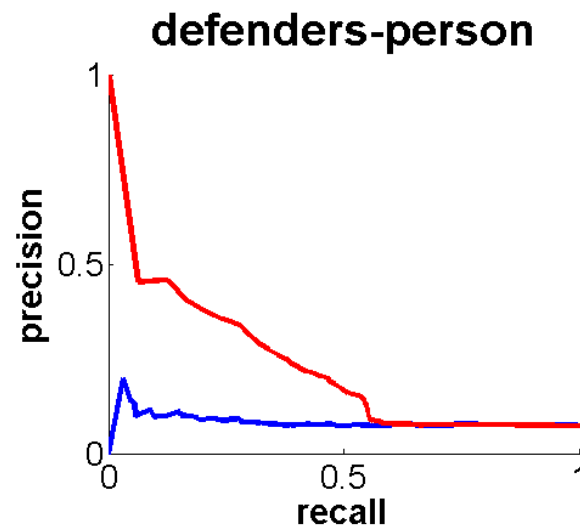
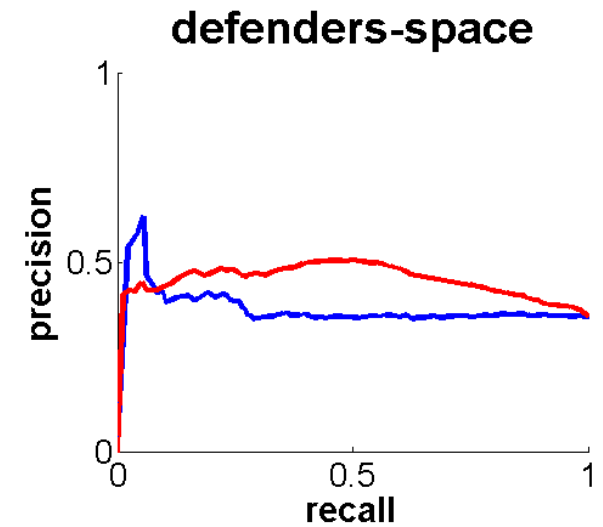
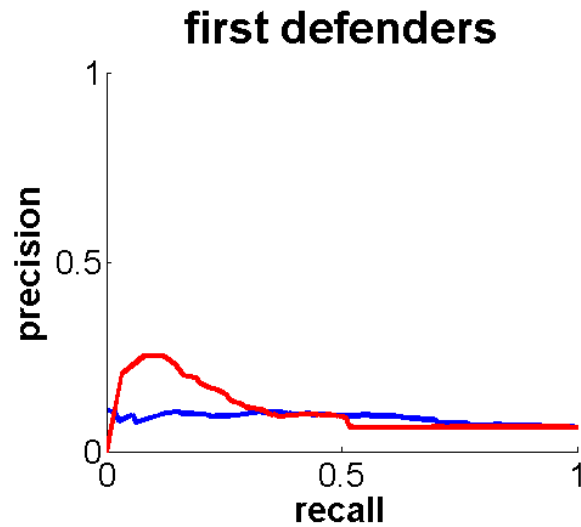
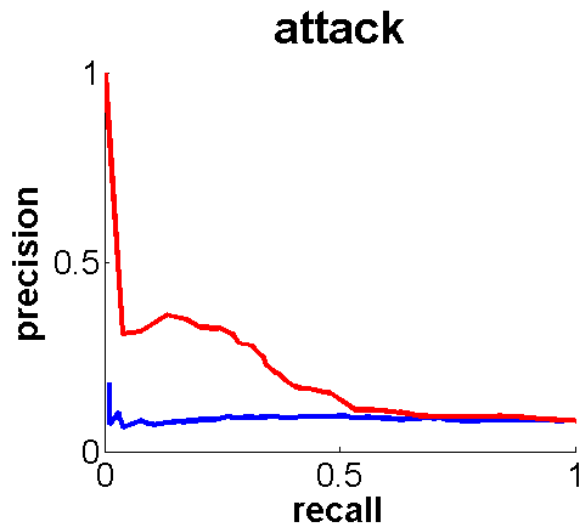
- 58 videos, 11 actions, 5 social roles, 3 scene-level events

Results – Scene Labeling

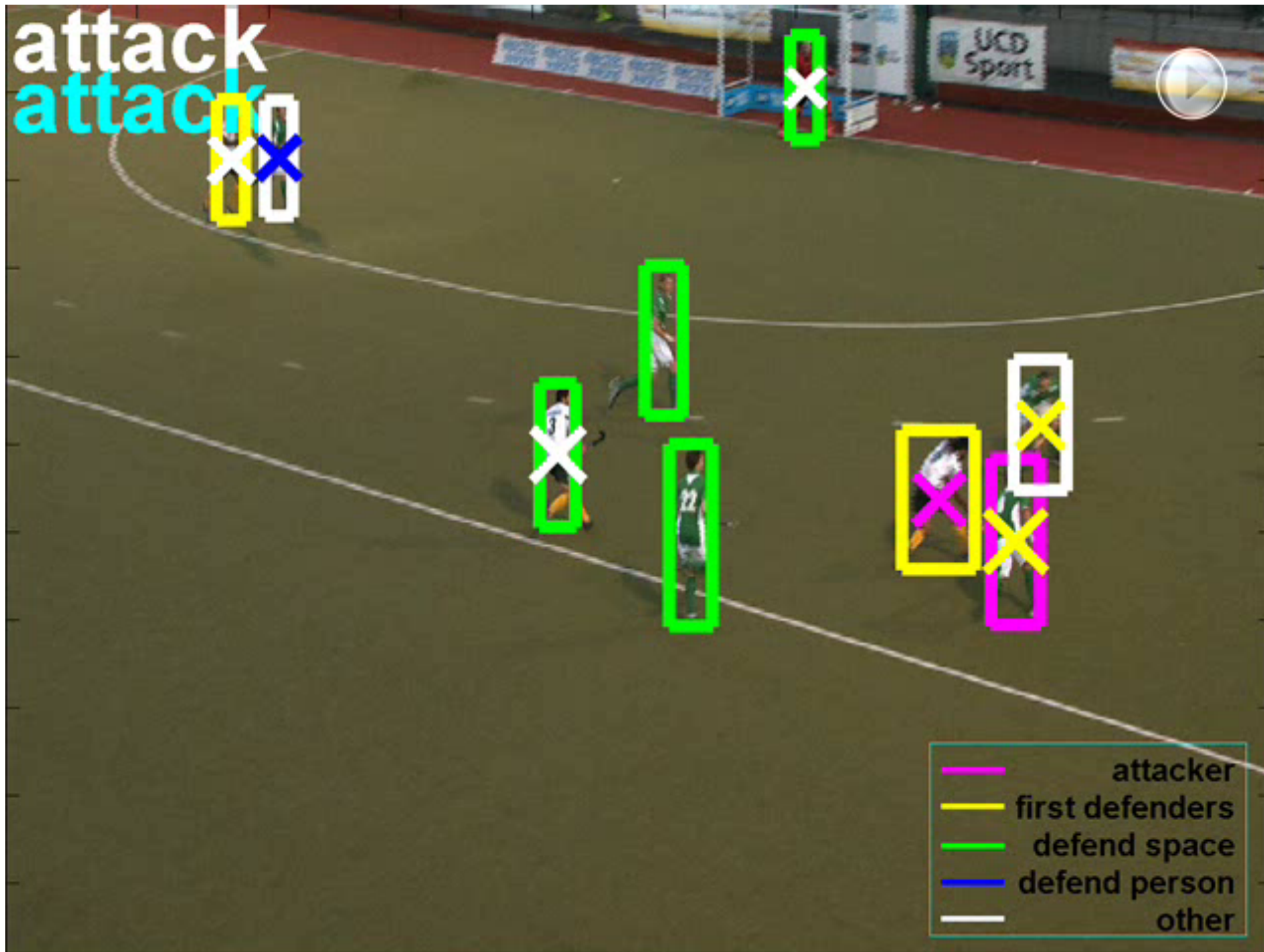


Method	Action	Role	Event
unary	21.5	21.7	56.9
Full model	28.8	44.0	62.8
action model (HOG+SVM)	26.1	N/A	N/A

Results – Query for Social Roles



— Unary
— Full model

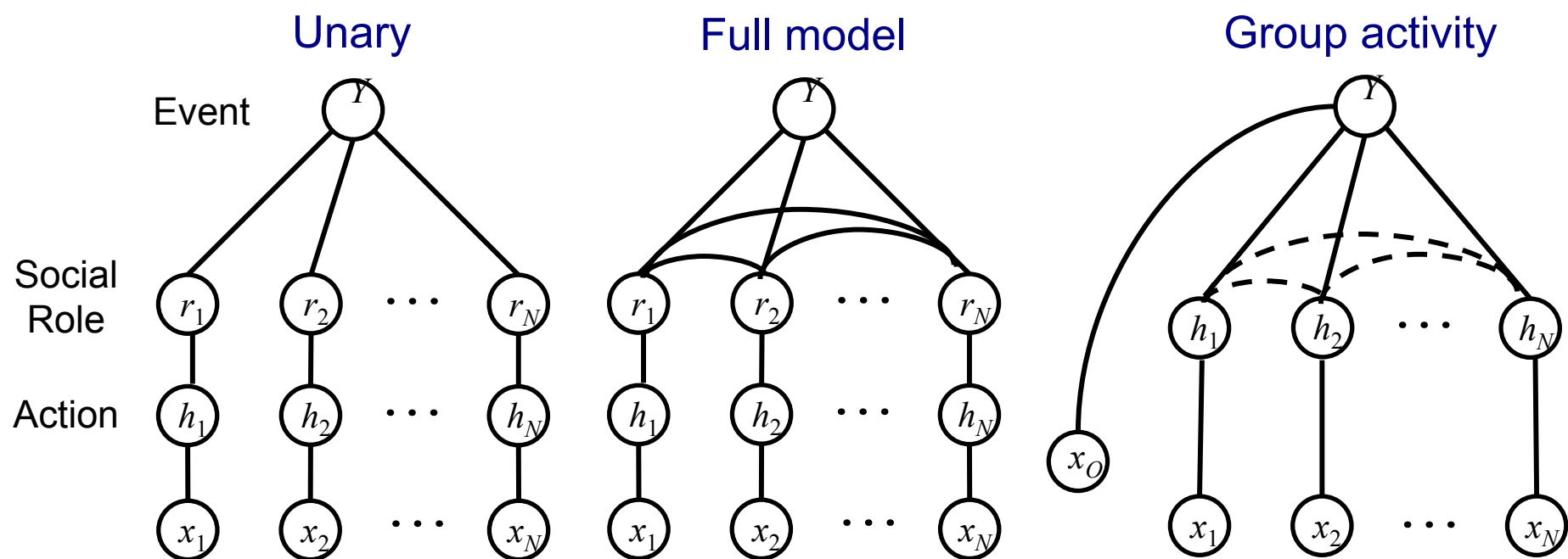


Nursing Home Data



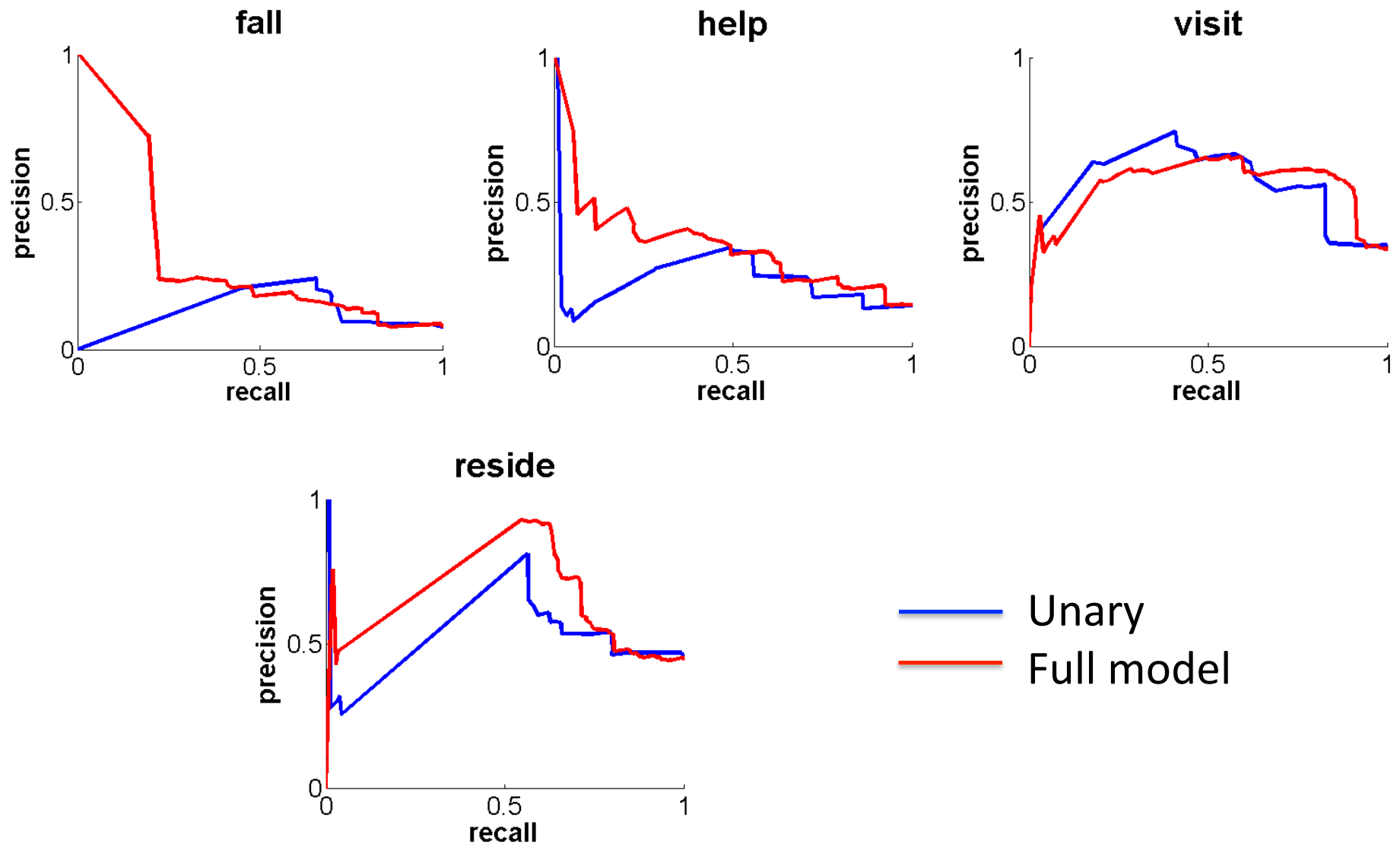
- 22 short clips of fall + a 30-min non-fall video sequence, 5fps, surveillance video
- 5 actions: walk, stand, sit, bend, and fall
- 4 social roles: fall, help, visit and reside
- 2 scene-level events: fall, non-fall

Results – Scene Labeling (Nursing Home)



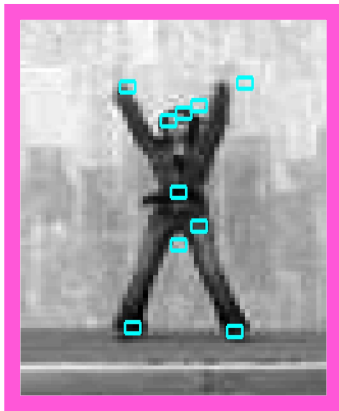
Method	Action	Role	Event
Unary	40.9	35.0	73.2
Full model	42.0	50.1	80.5
Action model (HOG+SVM)	38.7	N/A	N/A
Group activity [Lan et al. PAMI 12]	N/A	N/A	78.5

Results – Query for Social Roles (Nursing Home)



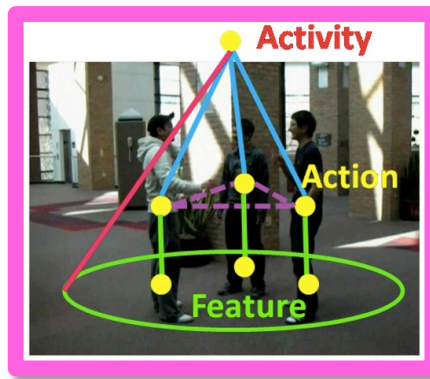
Conclusion

action
recognition



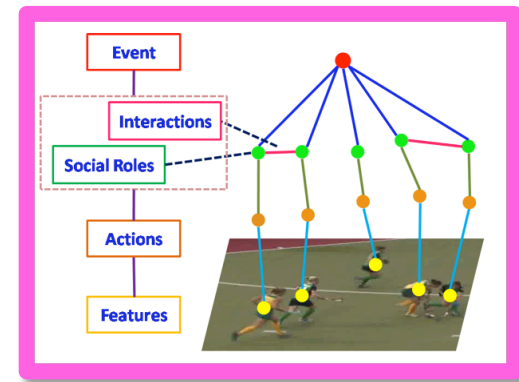
individual

group activity
recognition



group

activity
hierarchies



scene

Structural Recognition
of Human Activities

Acknowledgements



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