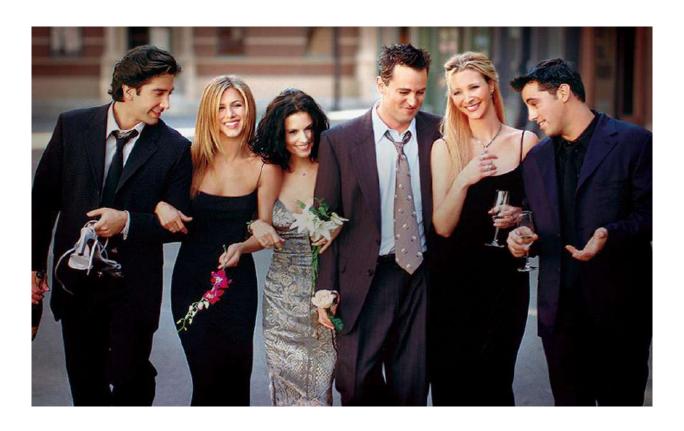
Proxemics Recognition



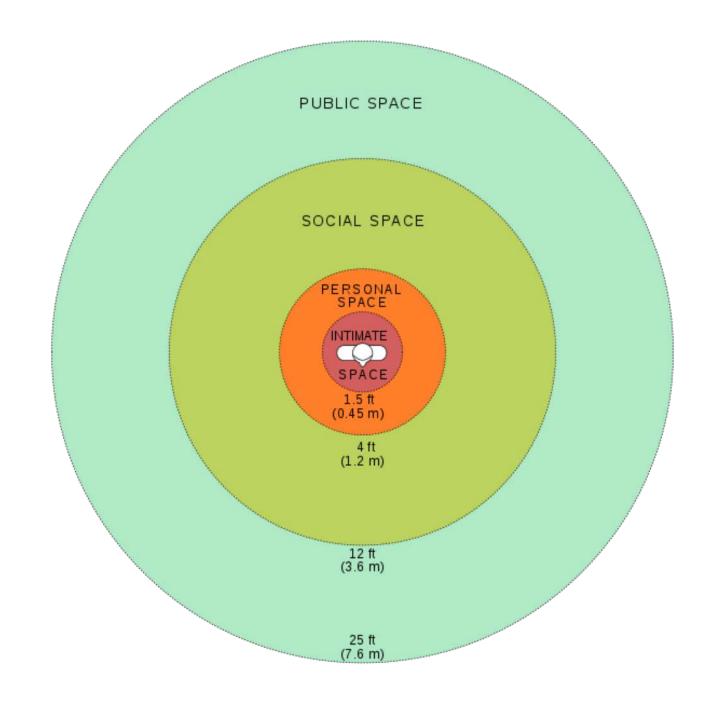
Yi Yang¹, Simon Baker, Anitha Kannan, Deva Ramanan¹

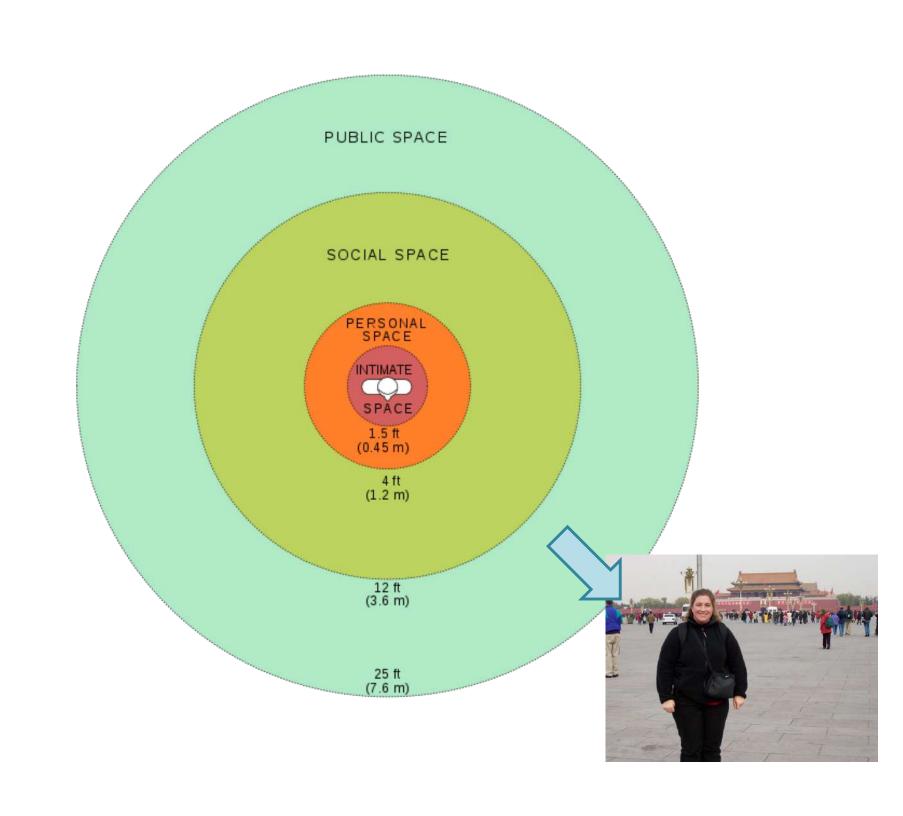
¹Department of Computer Science, UC Irvine

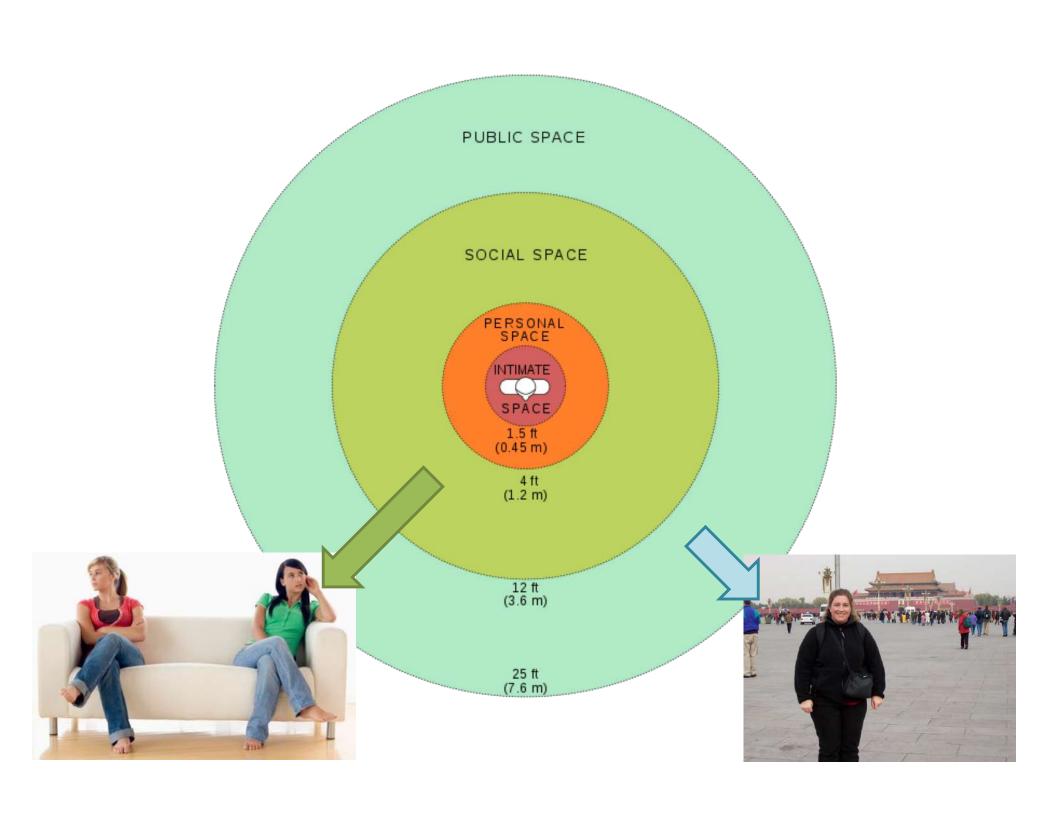
Proxemics

Proxemics: the study of spatial arrangement of people as they interact

- anthropologist **Edward T. Hall** in 1963









PUBLIC SPACE

SOCIAL SPACE

PERSONAL SPACE

INTIMATE

SPACE

1.5 ft (0.45 m)

4 ft (1.2 m)

12 ft (3.6 m)

25 ft (7.6 m)







PUBLIC SPACE



SOCIAL SPACE

PERSONAL SPACE

INTIMATE

SPACE

1.5 ft (0.45 m)

> 4 ft (1.2 m)

12 ft (3.6 m)

25 ft (7.6 m)



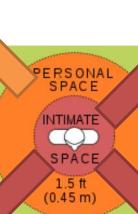




Brother and Sister Holding Hands

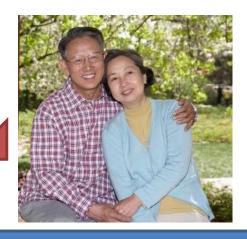


Mom Holding Baby





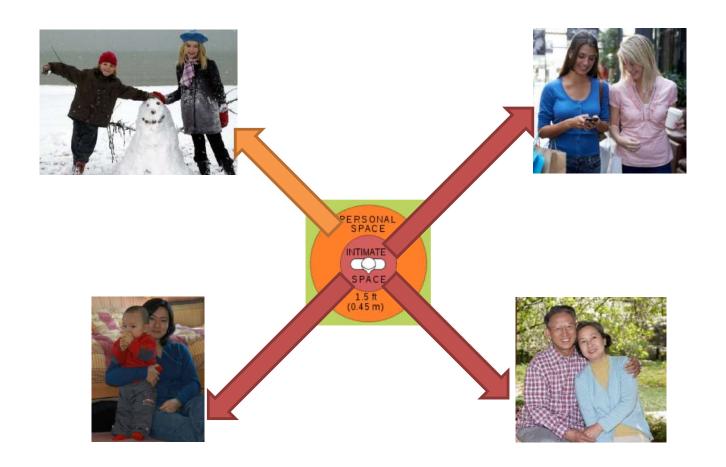
Friends Walking Side by Side



Husband Hugging and Holding Wife's Hand

Touch Code

- Hand Touch Hand
- Hand Touch Shoulder
 Arm Touch Torso
- Shoulder Touch Shoulder



Applications

- Personal Photo Search:
 - Find a specific interesting photo
- Analysis of TV shows and movies
- Kinect
- Web Search
- Auto-Movie/Auto-Slideshow
- Locate interesting scenes

Proxemics DataSet

- 200 training images
- 150 testing images
- Collected From
 - Simon, Bing, Google, Gettyimage, Flickr
- No video data
- No Kinect 3d depth data

Proxemics DataSet



Input Image

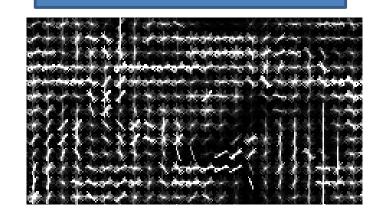


Input Image





Image Feature

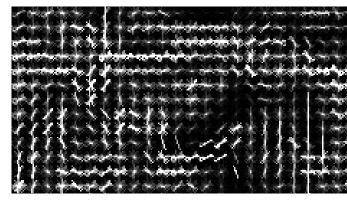


Input Image

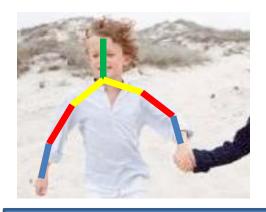




Image Feature









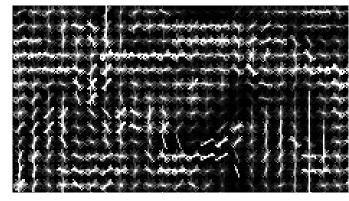
Pose Estimation i.e. Find skeletons

Input Image



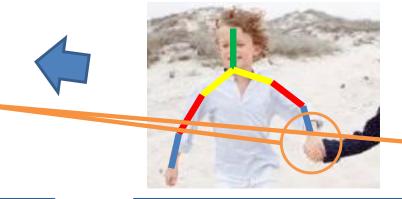


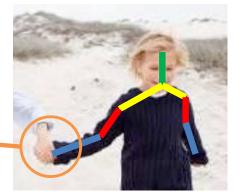
Image Feature





Hand touch Hand





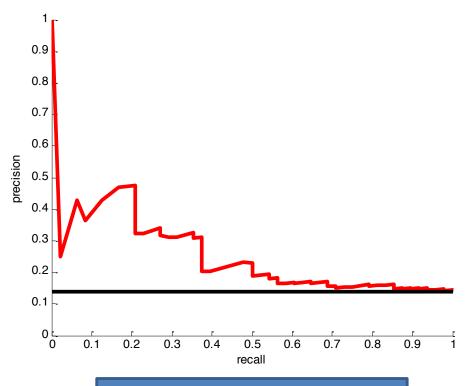
Interaction Recognition

Pose Estimation i.e. Find skeletons

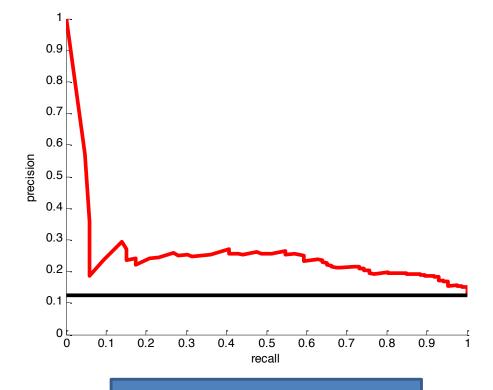
Naïve Approach Results

From pose estimation

Random guess



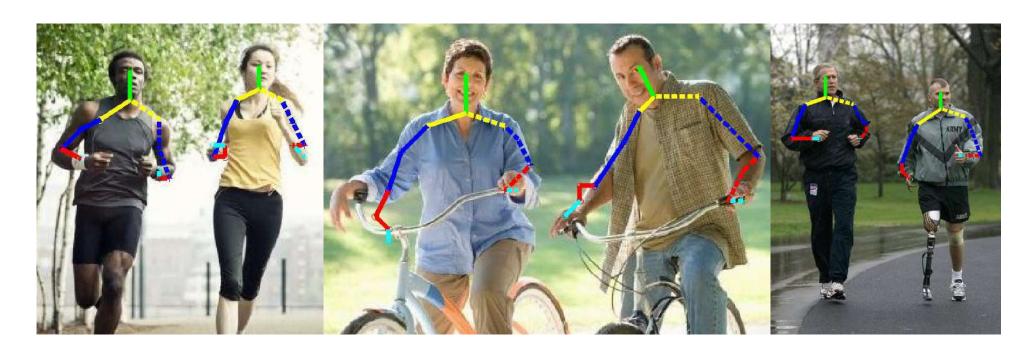
Hand touch Hand



Hand touch Shoulder

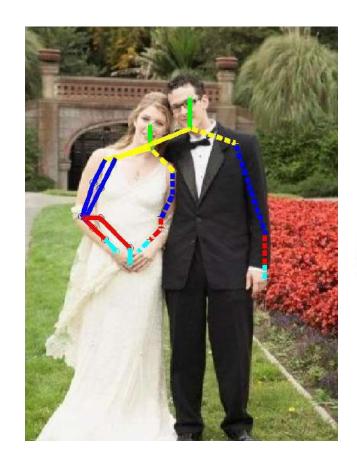
Human Pose Estimation

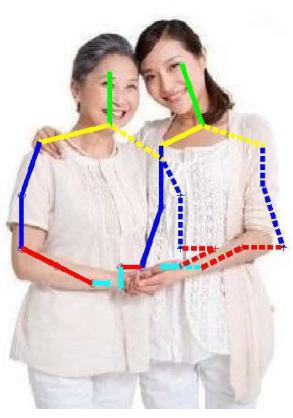
Not bad when no real interaction between people



Interactions Hurt Pose Estimation

Occlusion + Ambiguous Parts







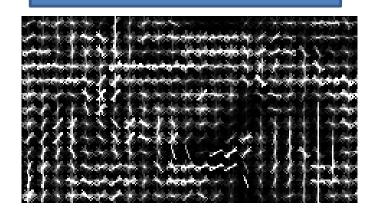
Our Approach Direct Proxemics Recognition

Input Image





Image Feature



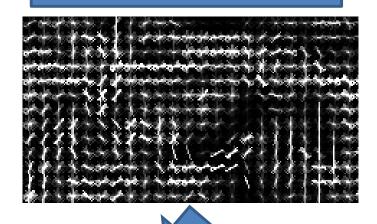
Our Approach Direct Proxemics Recognition

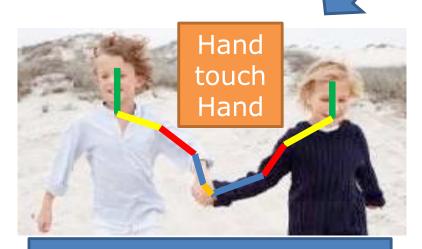
Input Image





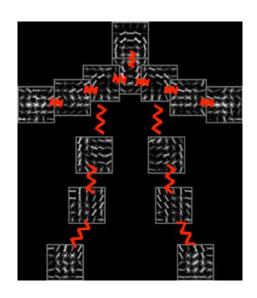
Image Feature





Interaction Recognition

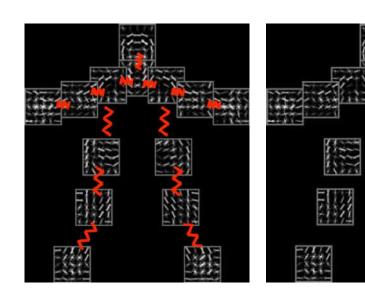
Pictorial Structure Model



S(I,L)

- *I*: Image
- l_i : Location of part i

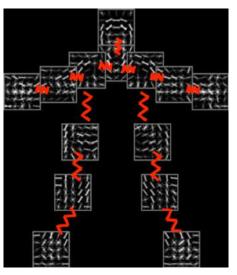
Pictorial Structure Model

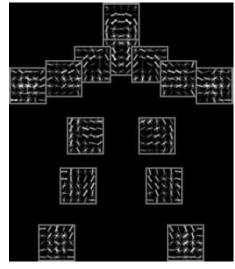


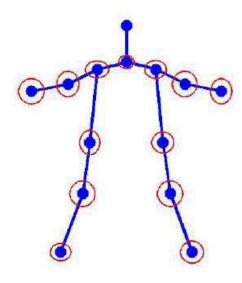
$$S(I,L) = \sum_{i \in V} \alpha_i \cdot \phi(I, l_i)$$

- α_i : Unary template for part i
- $\phi(l, l_i)$: Local image features at location l_i

Pictorial Structure Model





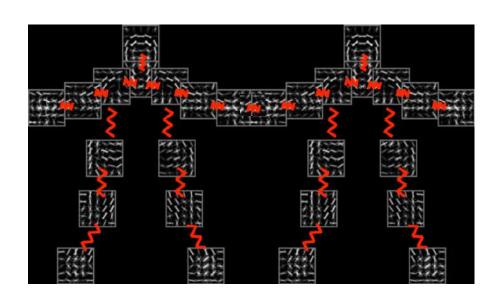


$$S(I,L) = \sum_{i \in V} \alpha_i \cdot \phi(I,l_i) + \sum_{ij \in E} \beta_{ij} \cdot \psi(l_i,l_j)$$

- $\psi(l_i, l_j)$: Spatial features between l_i and l_j
- β_{ij} : Pairwise springs between part i and part j

"Two Head Monster" Model

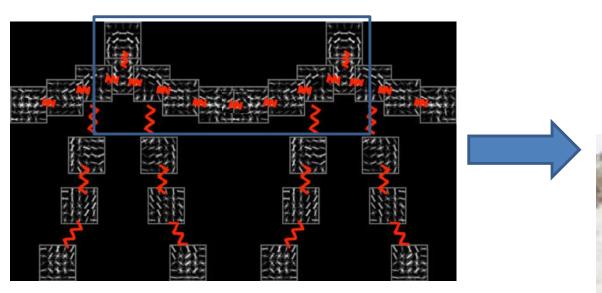
i.e. "Hand-Touching-Hand"

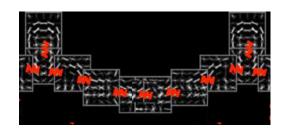


$$S(I,L) = \sum_{i \in V} \alpha_i \cdot \phi(I,l_i) + \sum_{ij \in E} \beta_{ij} \cdot \psi(l_i,l_j)$$

"Two Head Monster" Model

i.e. "Hand-Touching-Hand"



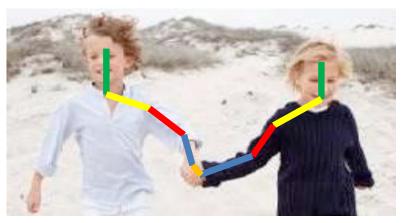




$$S(I,L) = \sum_{i \in V} \alpha_i \cdot \phi(I,l_i) + \sum_{ij \in E} \beta_{ij} \cdot \psi(l_i,l_j)$$

The models

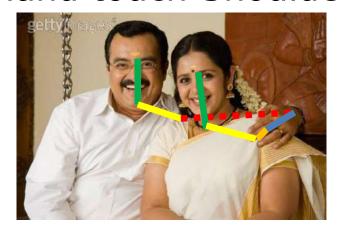
Hand touch Hand



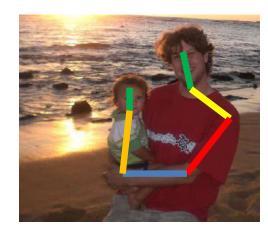
Shoulder touch Shoulder



Hand touch Shoulder



Arm touch Torso



Match Model to Image

Inference:

$$\max_{L} S(I, L)$$

- Efficient algorithm:
- Dynamic programming
- Learning:
 - Structural SVM Solver

Refinements + Extensions

Sub-categories

Because of symmetry, 4 models for hand-hand etc



Refinements + Extensions

Sub-categories

Because of symmetry, 4 models for hand-hand etc



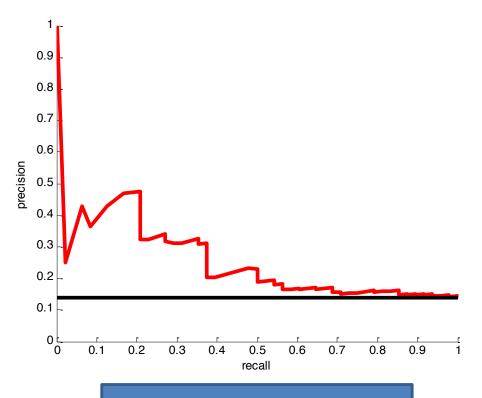
Co-occurrence of proxemics:

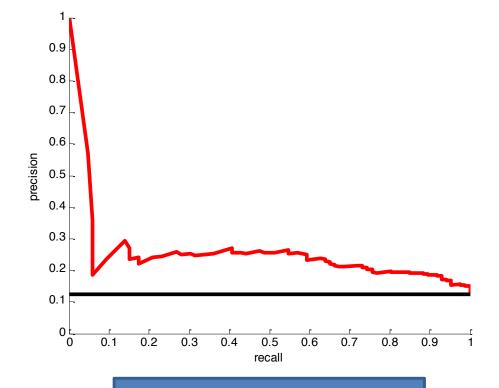
Reduce redundancy, map Multi-Label -> Multi-Class

Naïve Approach Results

From pose estimation

Random guess

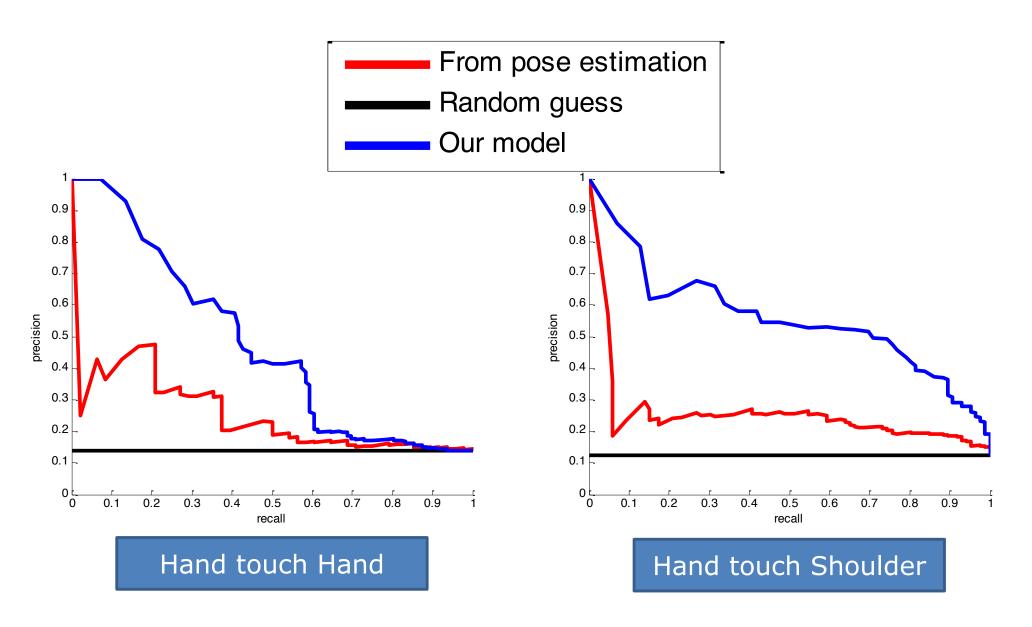




Hand touch Hand

Hand touch Shoulder

Direct Approach Results



Quantitative Results

Proxemic Recognition Average Precision

Proxemics	Hand Hand	Hand Shoulder	Shoulder Shoulder	Hand Torso	Average
Random guess	14.0	12.6	24.6	9.9	15.3
From pose estimation [1]	26.5	25.6	71.7	18.7	35.6
Our direct model	46.9	-55.2	72.0	87.3	65.4

Improves Pose Estimation

Y & D CVPR 2011

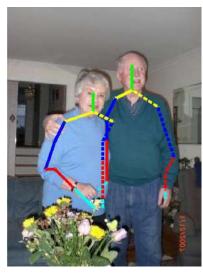


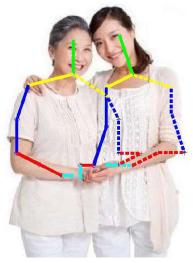
Our Model

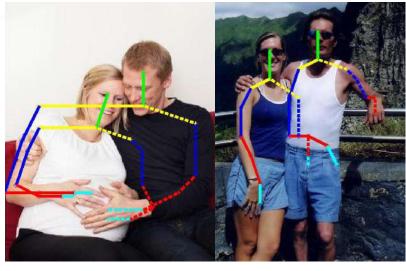


Improves Pose Estimation

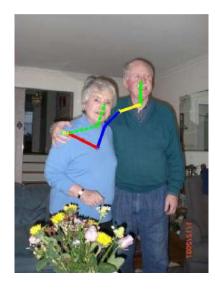
Y & D CVPR 2011



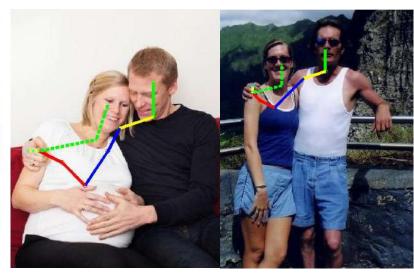




Our Model

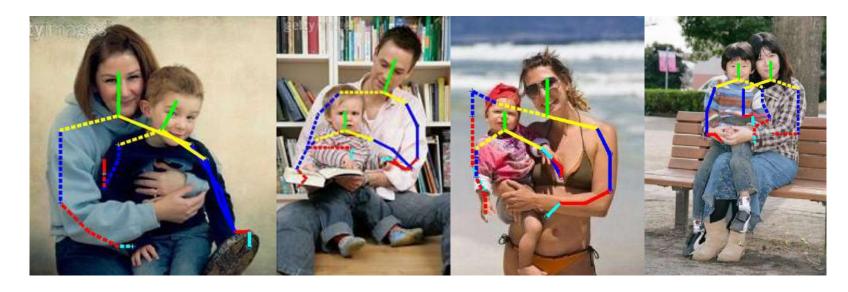




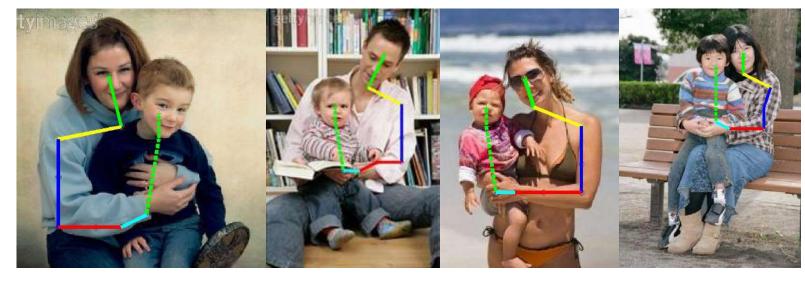


Improves Pose Estimation

Y & D CVPR 2011



Our Model



Conclusion

 Proxemics and touch codes for human interaction

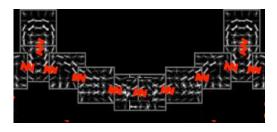


Conclusion

 Proxemics and touch codes for human interaction

 Directly recognizing proxemics significantly outperforms





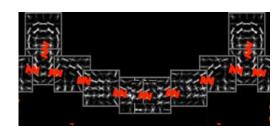
Conclusion

 Proxemics and touch codes for human interaction FUBLIC SPACE

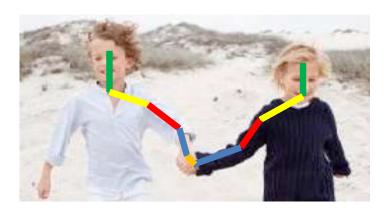
SOCIAL SPACE

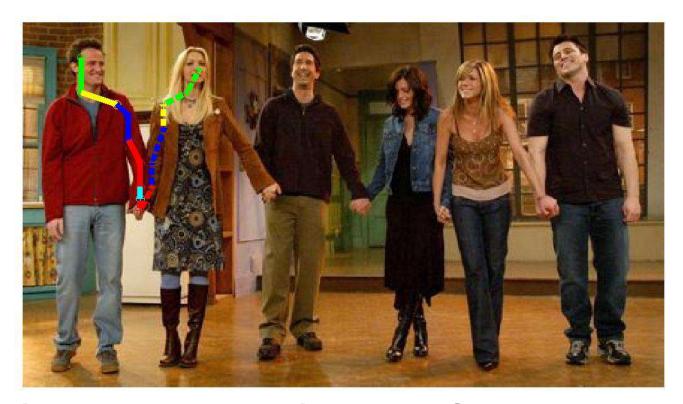
SO

 Directly recognizing proxemics significantly outperforms

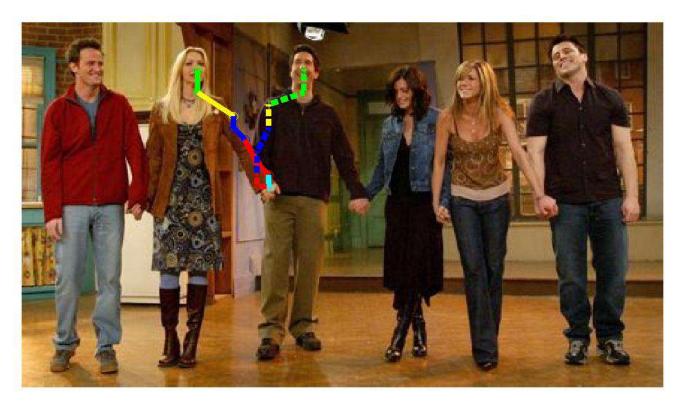


 Recognizing proxemics helps pose estimation

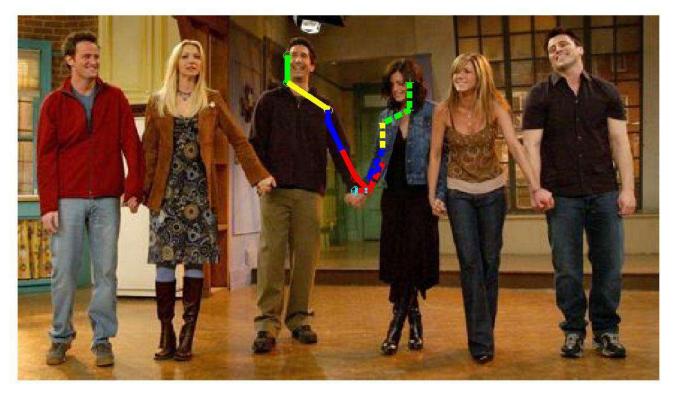




Thank Simon and MSR for internship



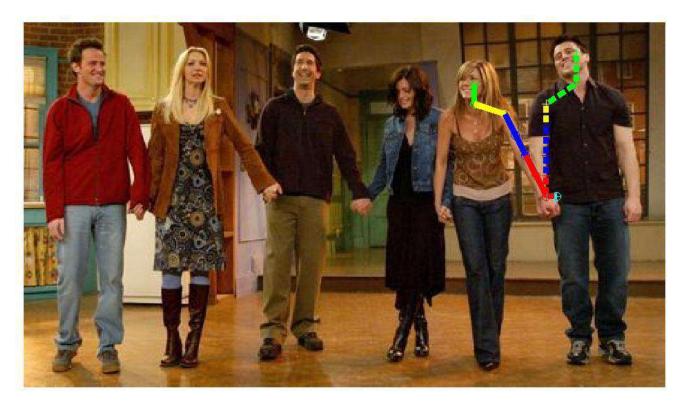
Thank Anitha for a lot of suggestions



Thank Anarb for gettyimages



Thank Eletee for her beautiful smiling



Thank everybody for not falling asleep

Thank you



Articulated Pose Estimation

Percentage of Correctly Localized Parts on Proxemic Dataset

DataSet	Shoulders	Elbows	Wrists	Hands	
Single Person	93.0	61.7	38.7	34.6	
Interacting People	86.6	46.2	22.0	17.4	
Difference	6.4	15.5	16.7	17.2	

Inference & Learning

Inference

 $\max_{L,M} S(I,L,M)$

For a tree graph (V,E): dynamic programming

Learning

$$\min_{w} \frac{1}{2} \|w\|$$
s. t. $\forall n \in \text{pos } w \cdot \phi(I_n, z_n) \ge 1$
 $\forall n \in \text{neg, } \forall z \ w \cdot \phi(I_n, z) \le -1$

Given labeled positive $\{I_n, L_n, M_n\}$ and negative $\{I_n\}$, write $z_n = (L_n, M_n)$, and $S(I, z) = w \cdot \phi(I, z)$