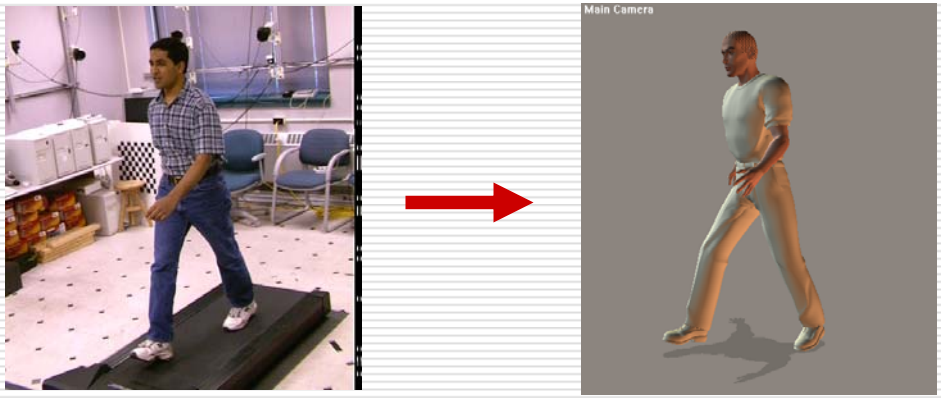
Predicting 3D People from 2D Pictures



Leonid Sigal **Michael J. Black**

Department of Computer Science

Brown University

http://www.cs.brown.edu/people/ls/

Introduction

Articulated pose estimation from single-view monocular image(s)

(2D) Picture **(3D) Person**

Introduction

Articulated pose estimation from single-view monocular image(s)

(2D) Picture **(3D) Person**

- **Entertainment:** Animation, Games
- **Clinical:** Rehabilitation medicine
- **Security:** Surveillance
- **Understanding:** Gesture/Activity recognition

Why is it hard?

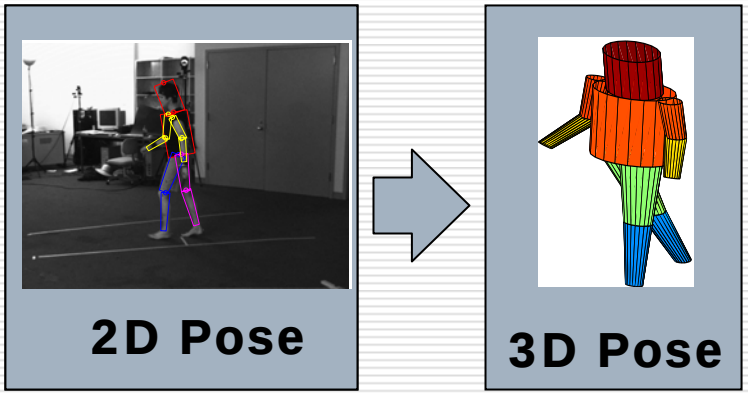
- Appearance/size/shape of people can vary dramatically

- The bones and joints are observable indirectly (obstructed by clothing)

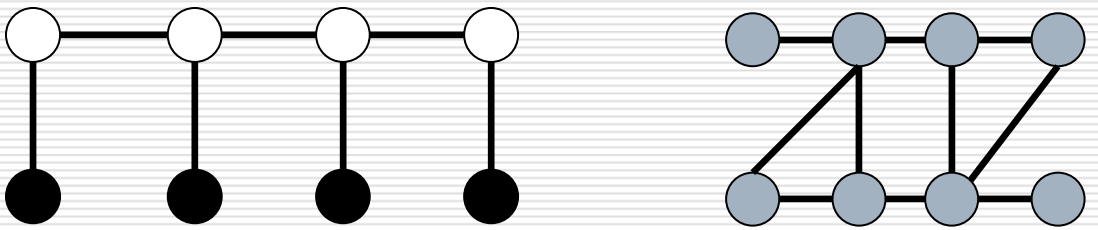
- Occlusions
- High dimensionality of the state space
- Lose of depth information in 2D image projections

Approach

- **Break up a very hard problem into smaller manageable pieces**



- **Tools**
  - Graphical models
  - Belief Propagation



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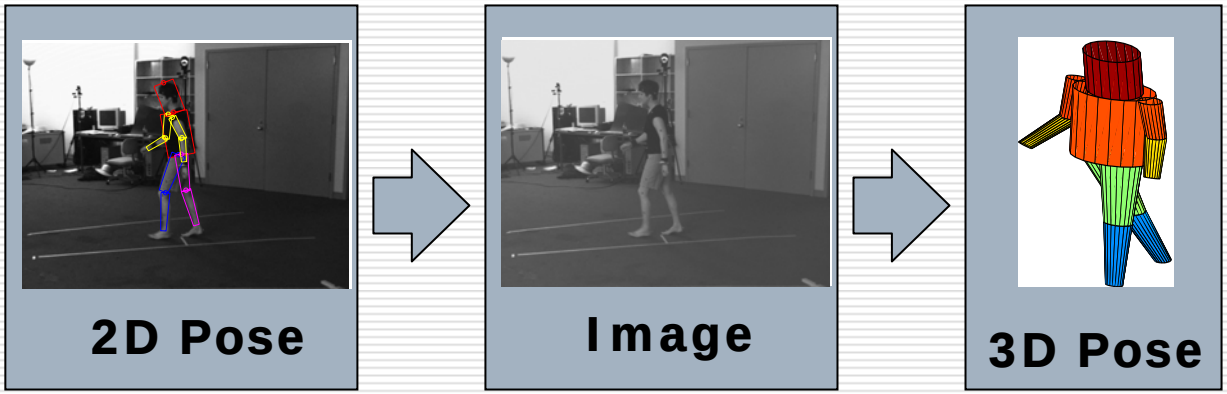

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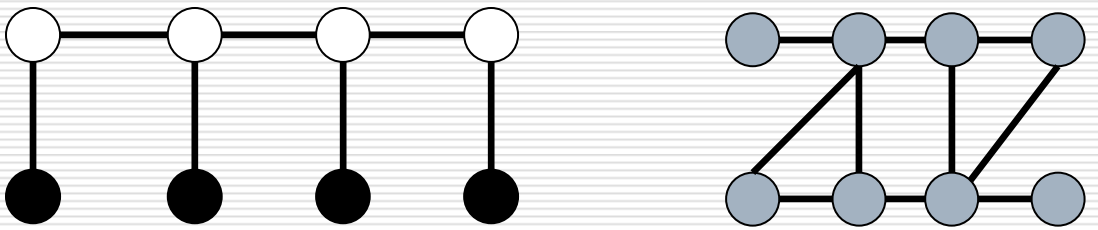

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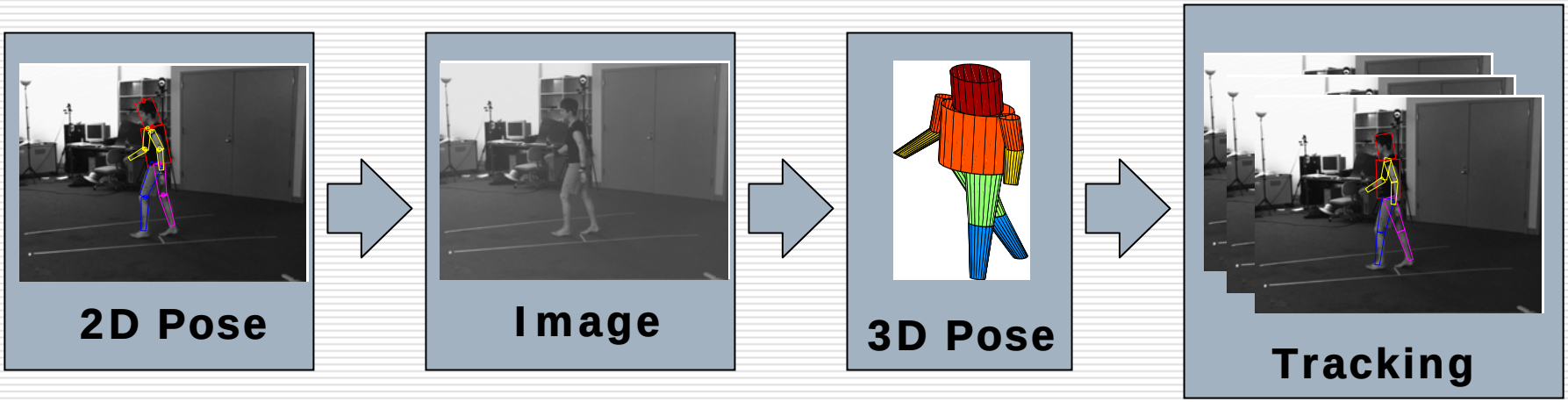

- **Tools**
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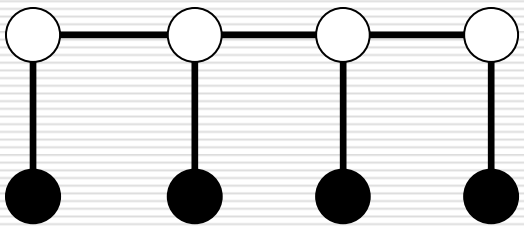
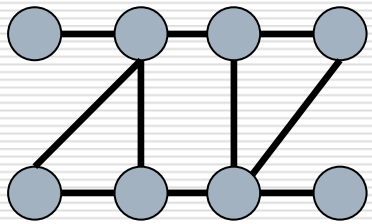
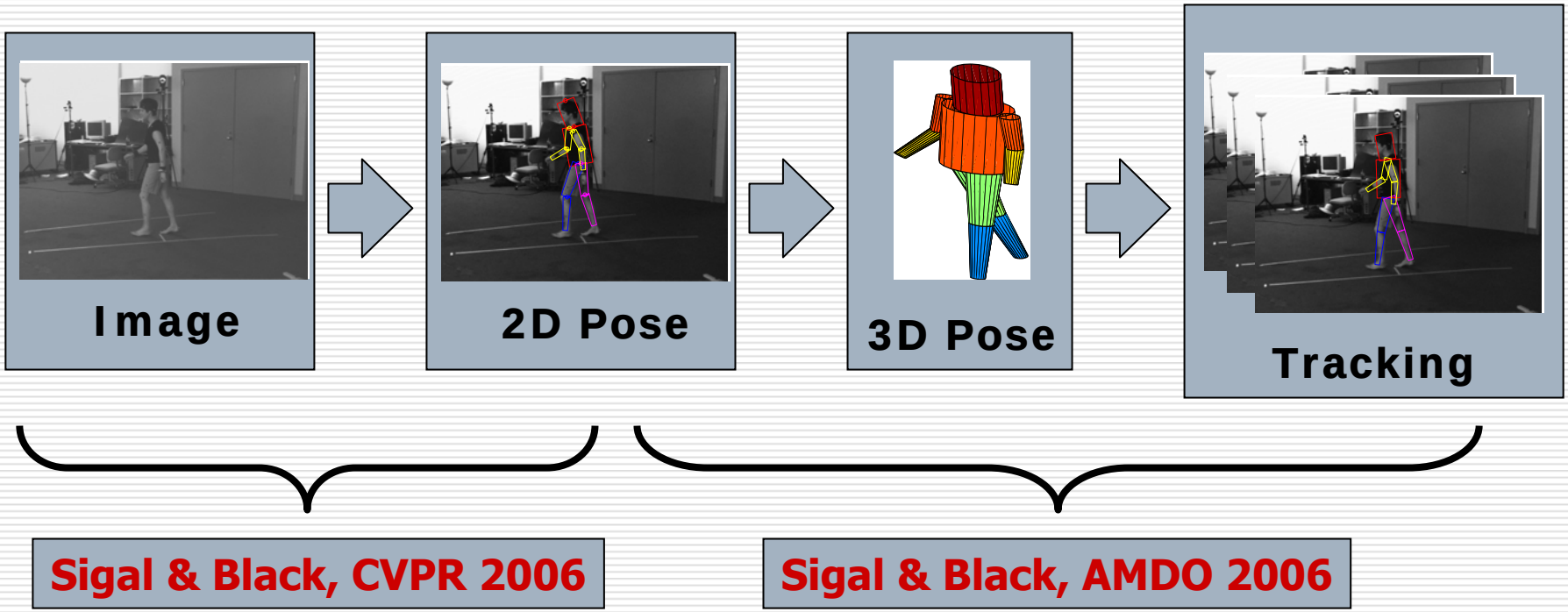
  - Belief Propagation





Hierarchical Inference Framework

- **Break up a very hard problem into smaller manageable pieces**



Hierarchical Inference Framework

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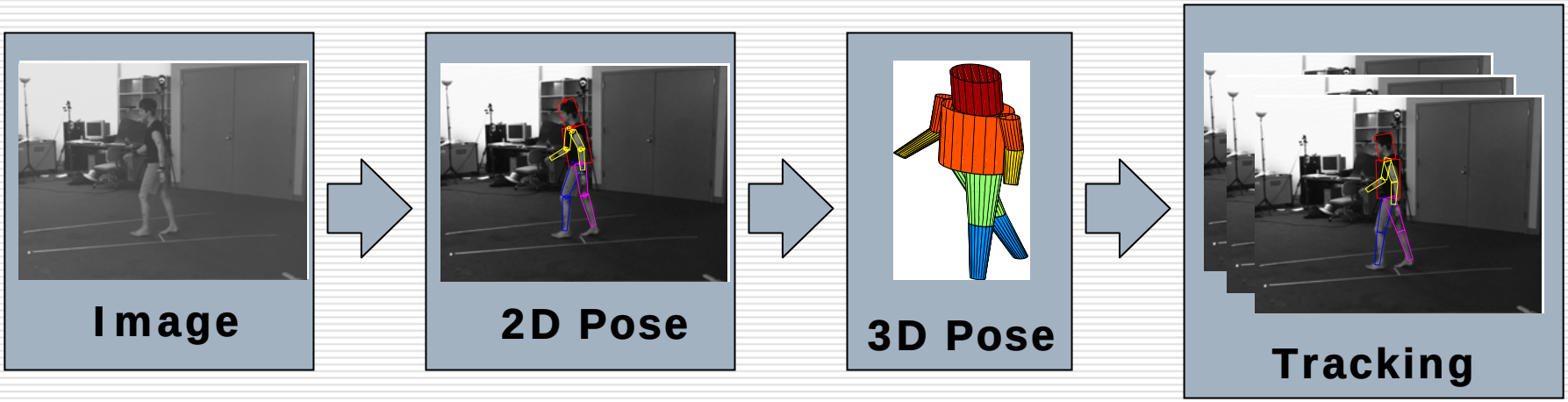
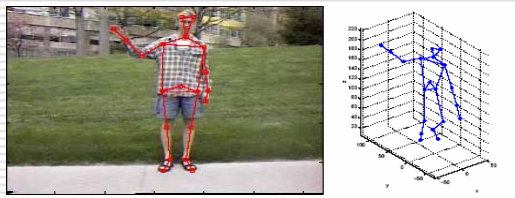


- **We are able to infer the 3D pose from a single image**
- **But, are still able to make use of temporal consistency when it is available**

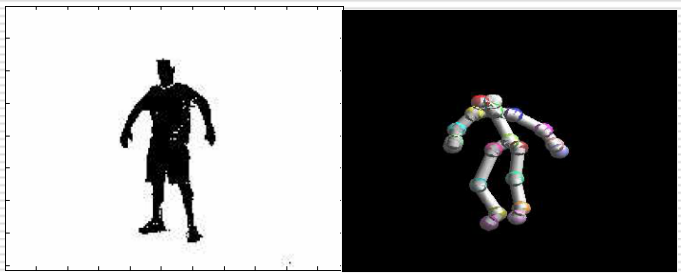


Howe, Leventon, Freeman, '00

Discriminative Approaches

Sminchisescu, Kanaujia, Li, Metaxas, ‘05

Agarwal & Triggs, ‘04

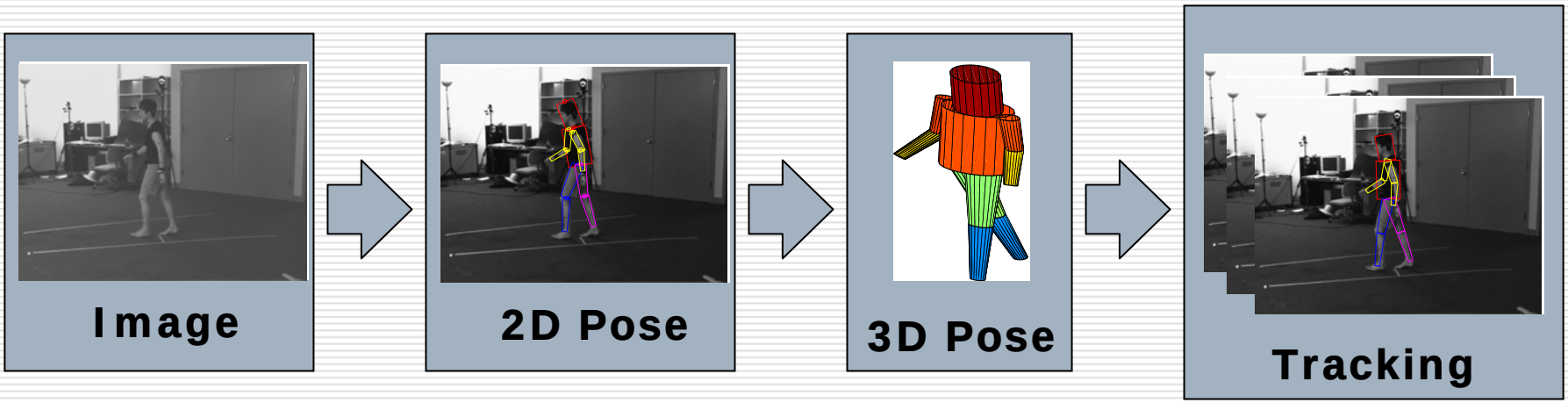


Rosales & Sclaroff, ‘00

Shakhnarovich, Viola, Darrell, ‘03

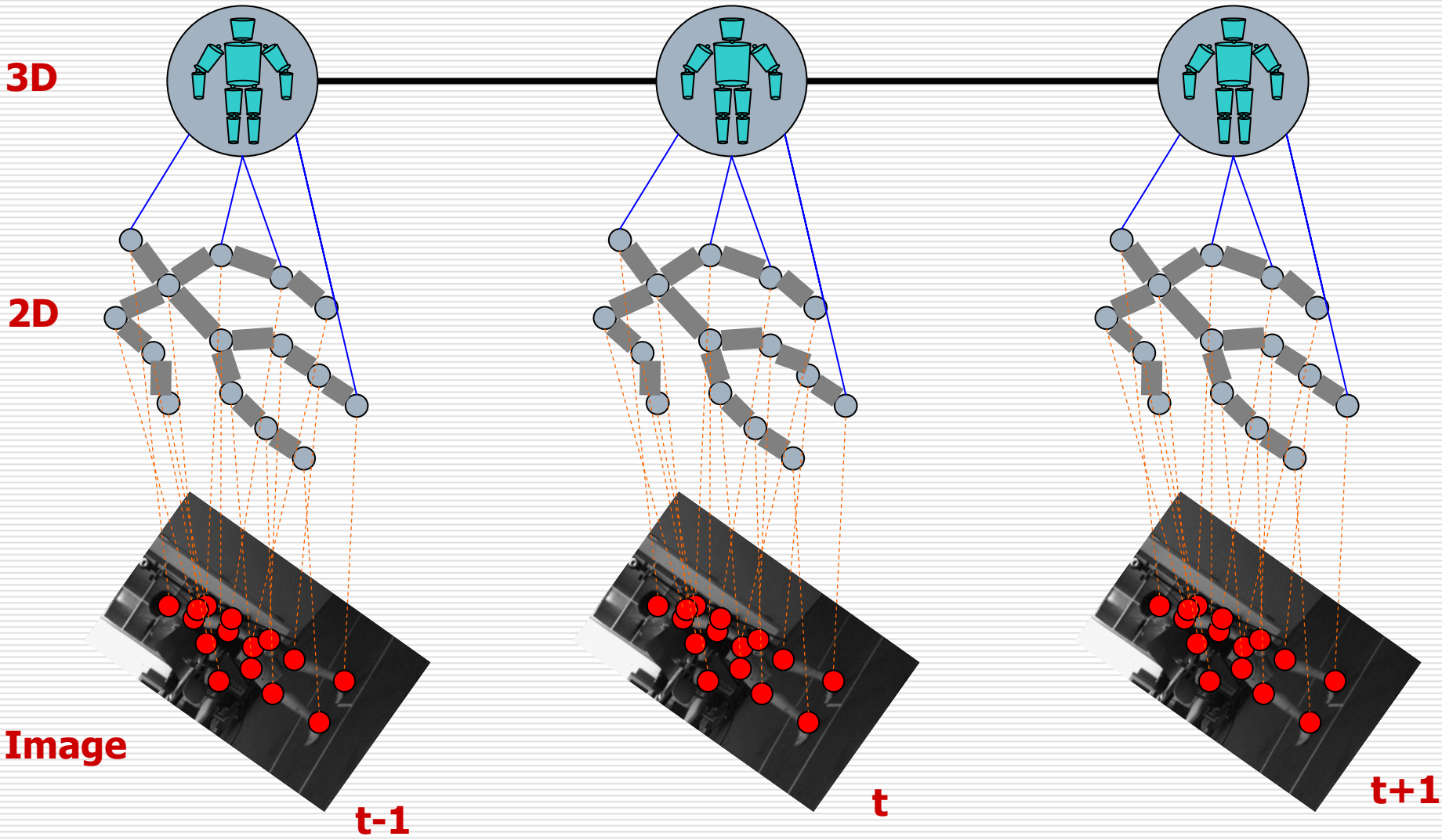
- Tend to be very fast
- Work well on the data they are trained on
- Generalize poorly to data they have never seen

Advantage of Hierarchical Inference

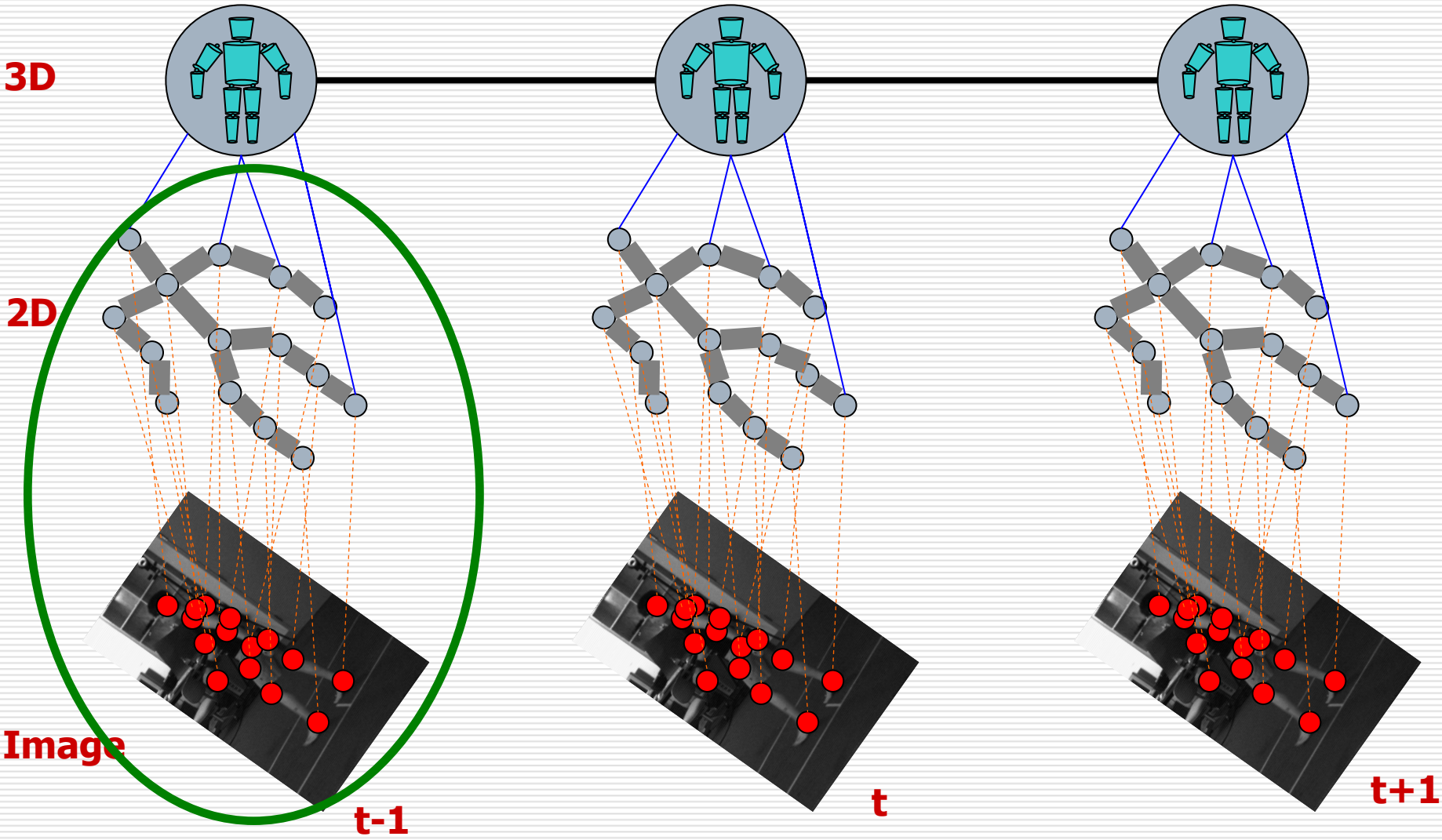


- **Better generalization in situations where good features are unavailable (lack of good silhouettes)**
  - via the use intermediate Generative 2D pose estimation
- **Modularity**
  - Can easily substitute different 2D pose estimation modules
- **Fully probabilistic approach**

Hierarchical Graphical Model Structure



Hierarchical Graphical Model Structure



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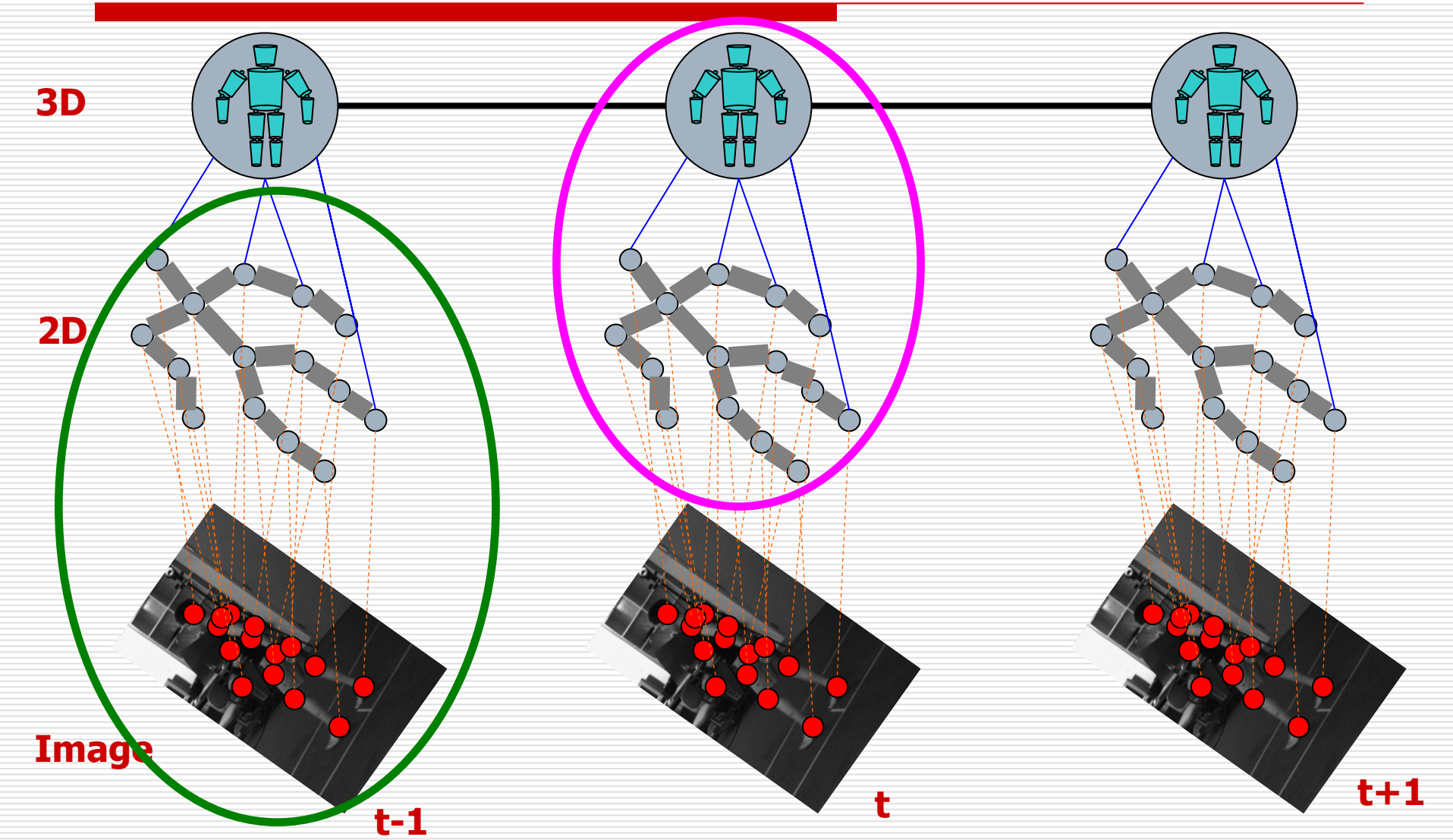
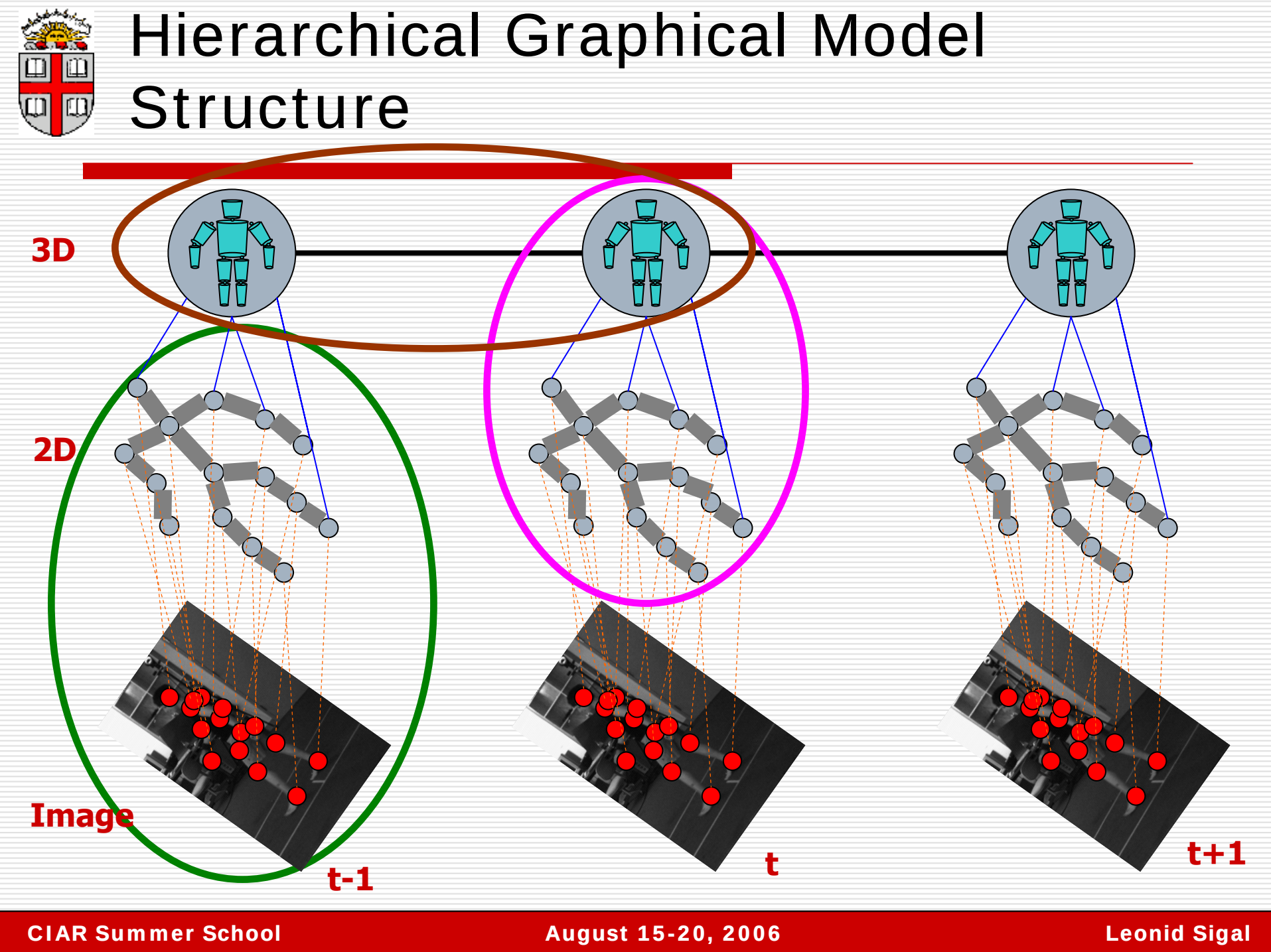
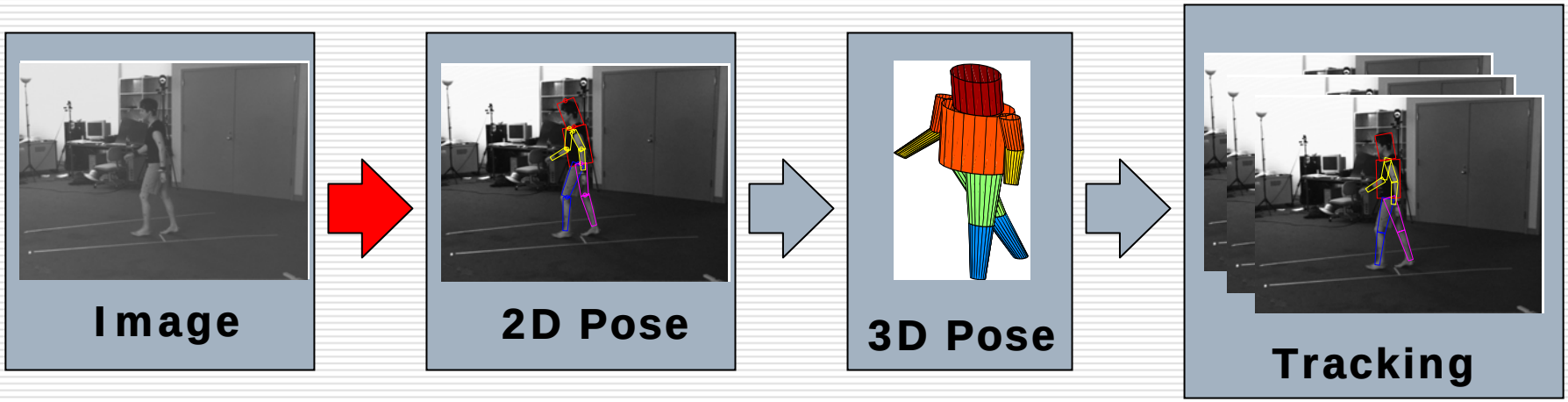


Hierarchical Graphical Model Structure

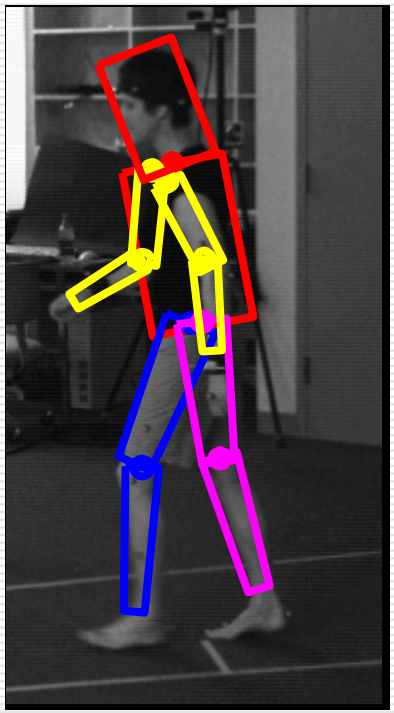


Inferring 2D pose



Occlusion-sensitive "Loose-limbed" body model

2D “Loose-limbed” Body Model



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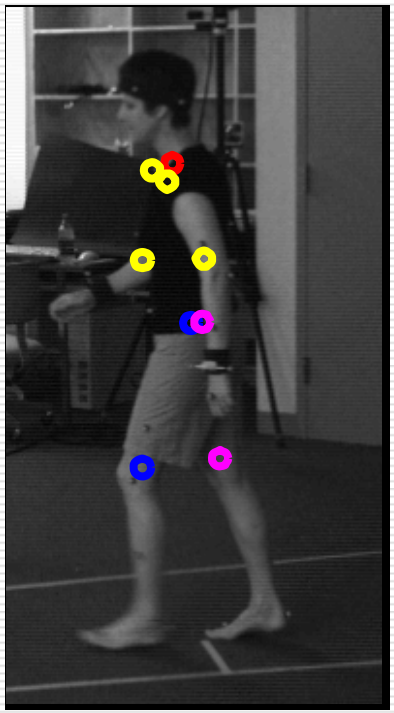

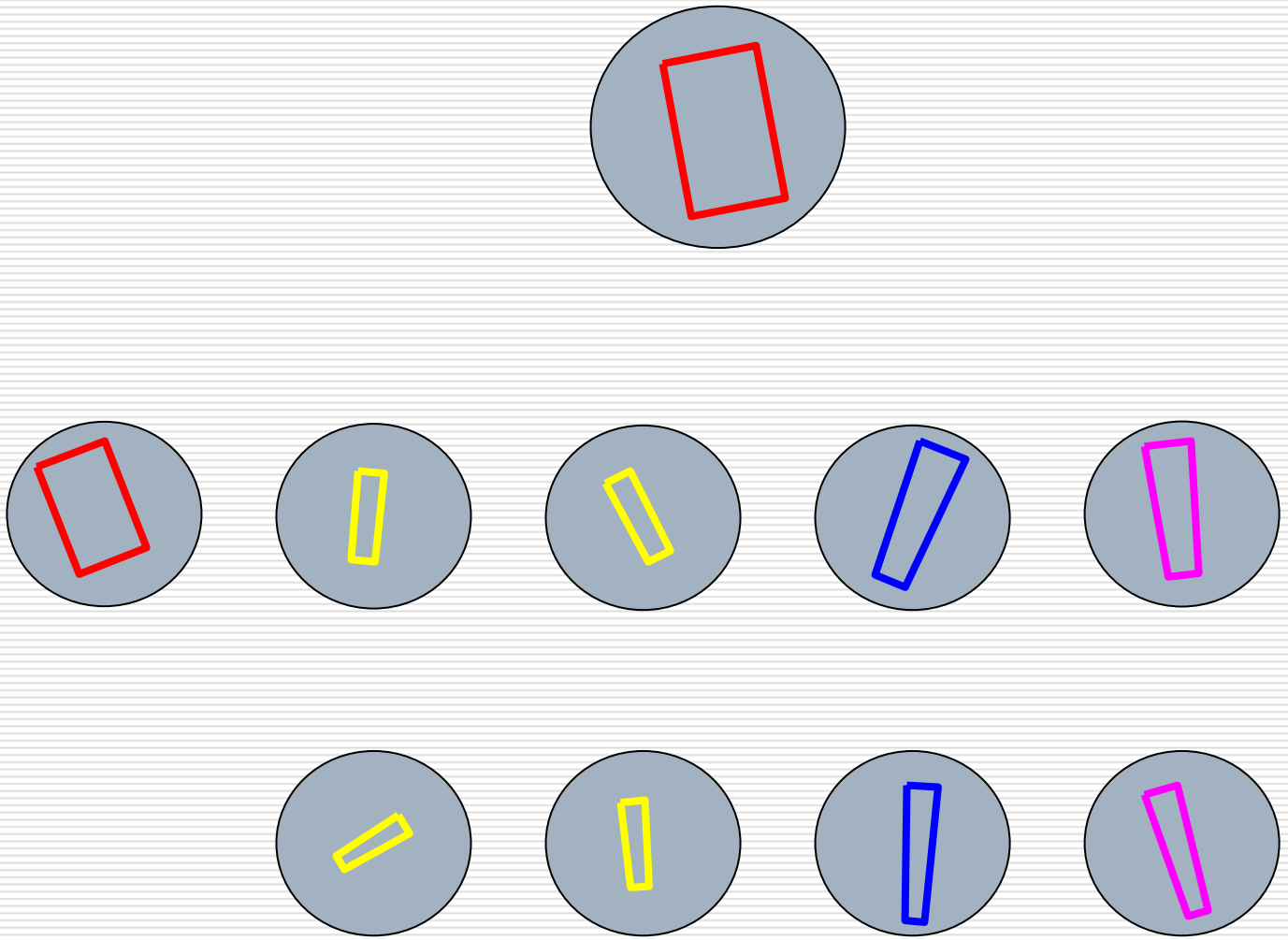

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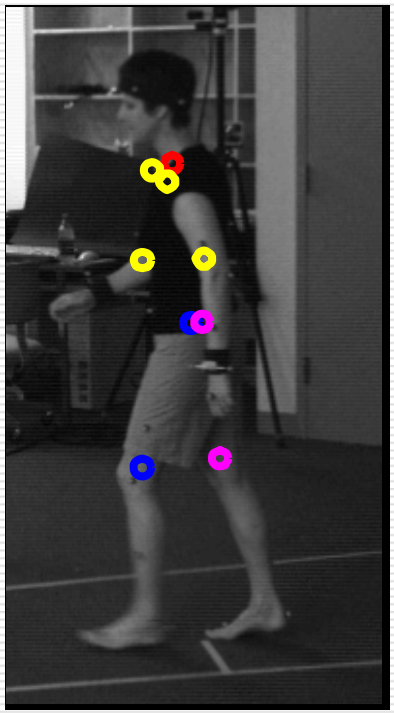

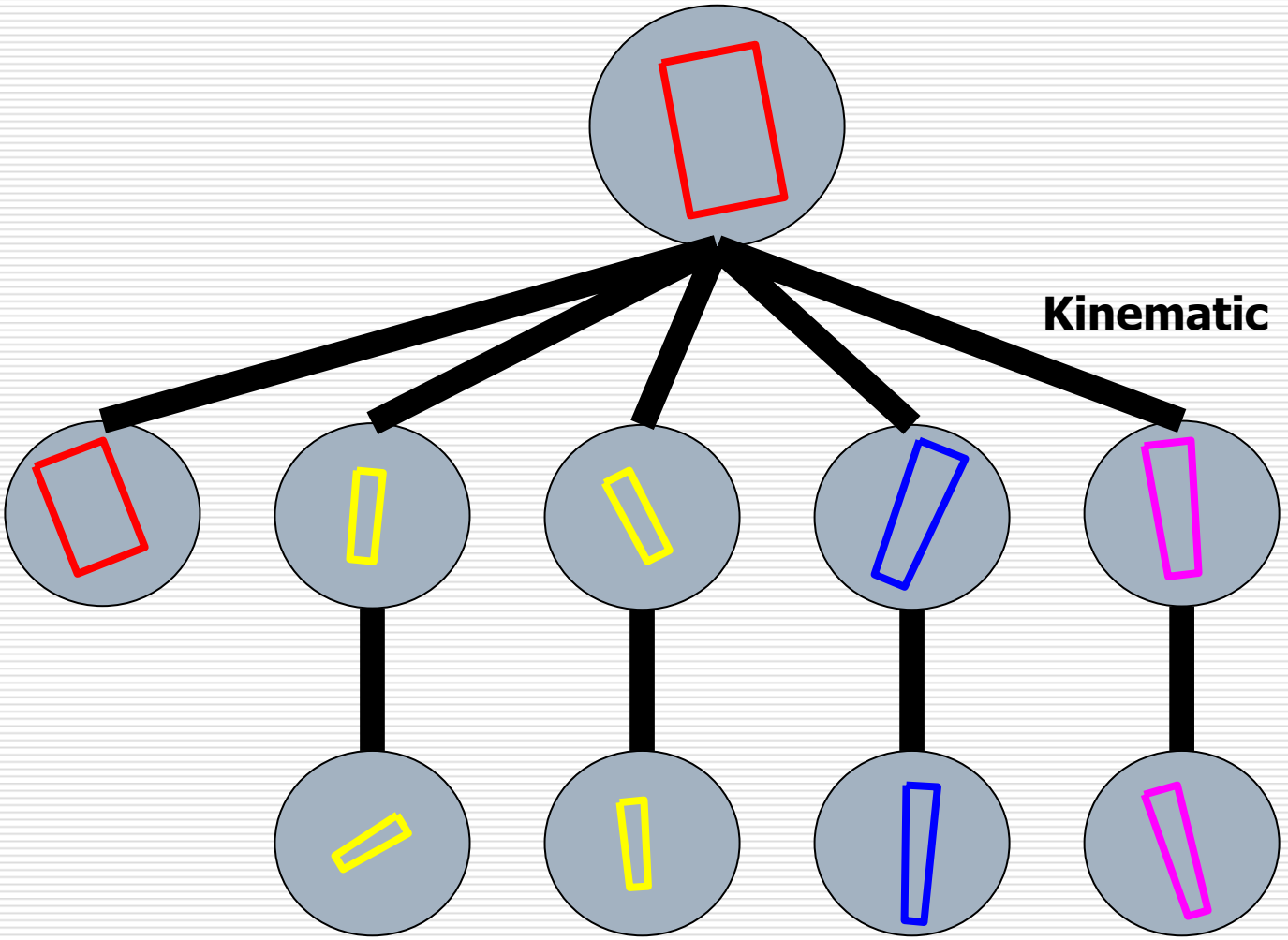

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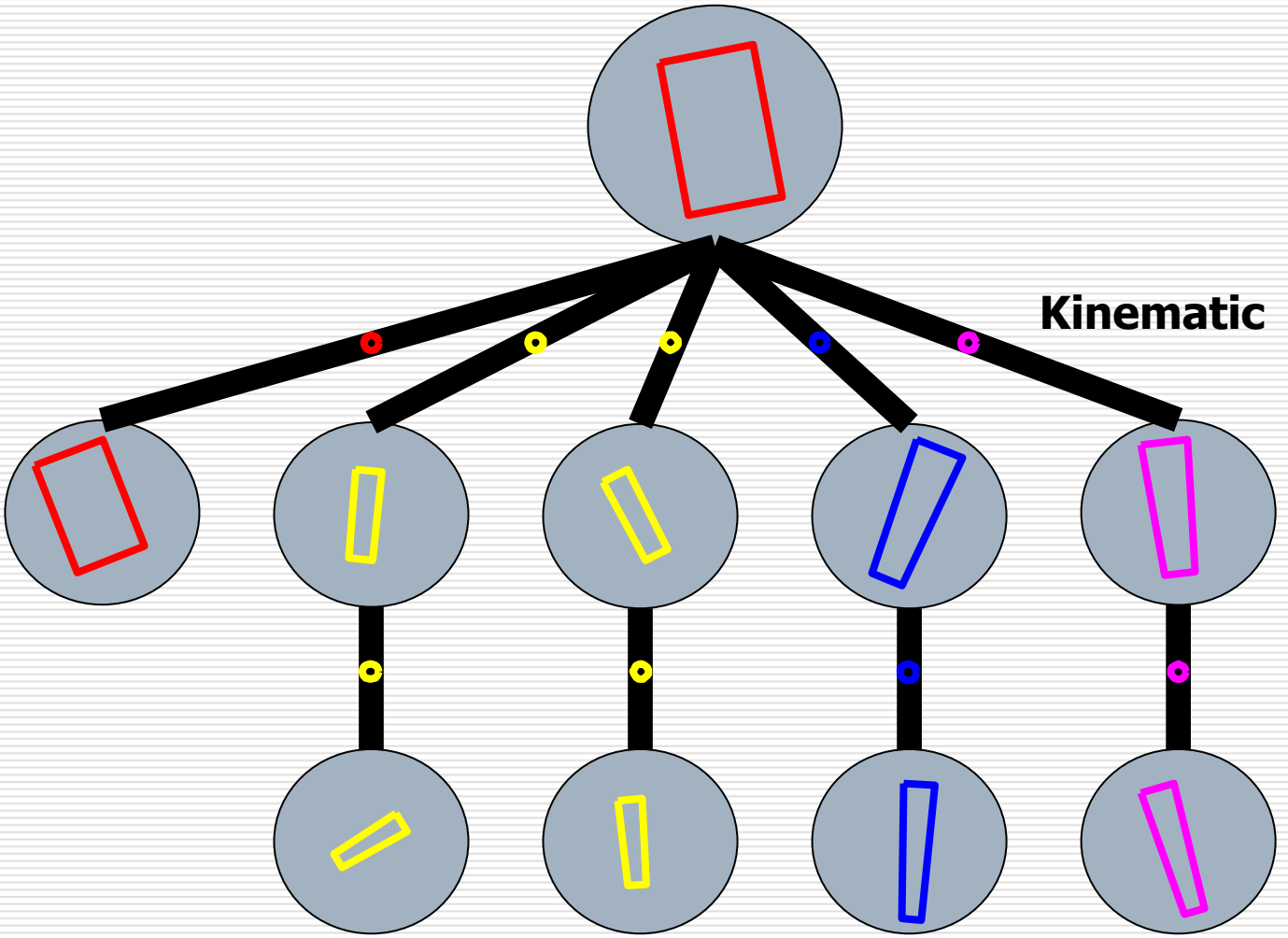

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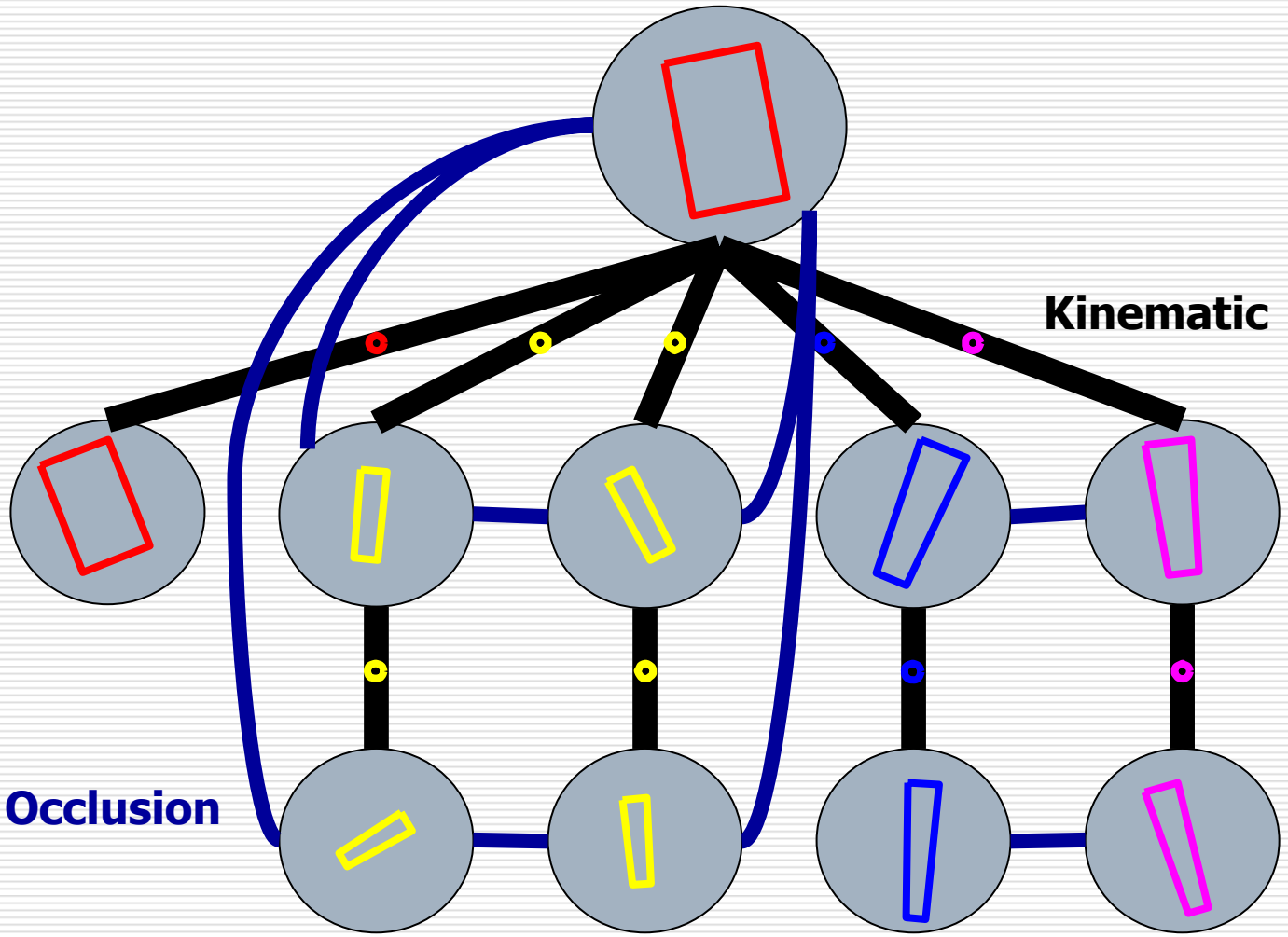

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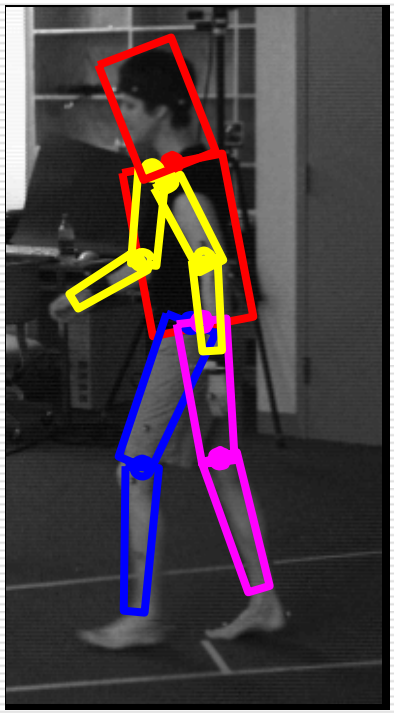
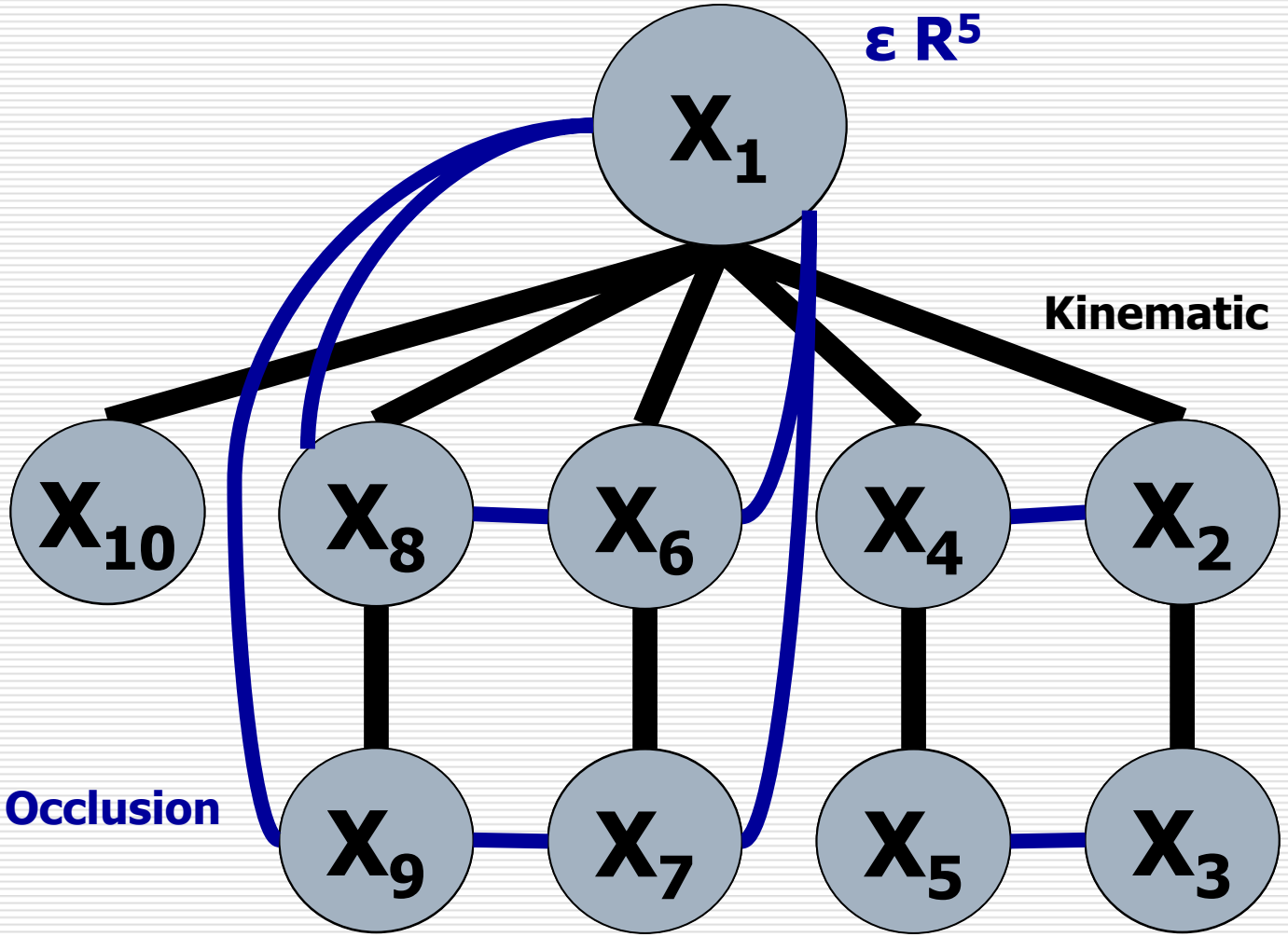
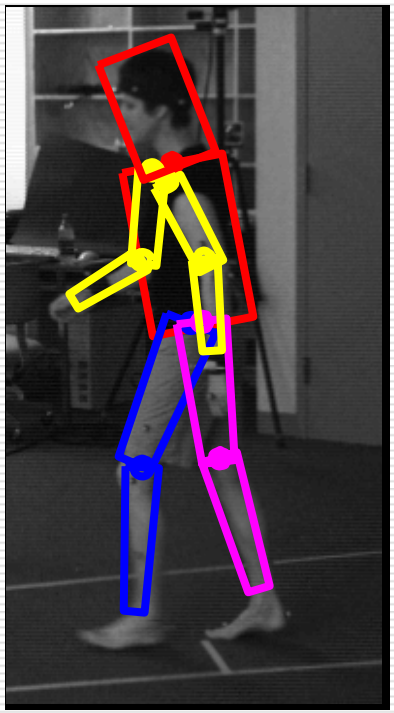
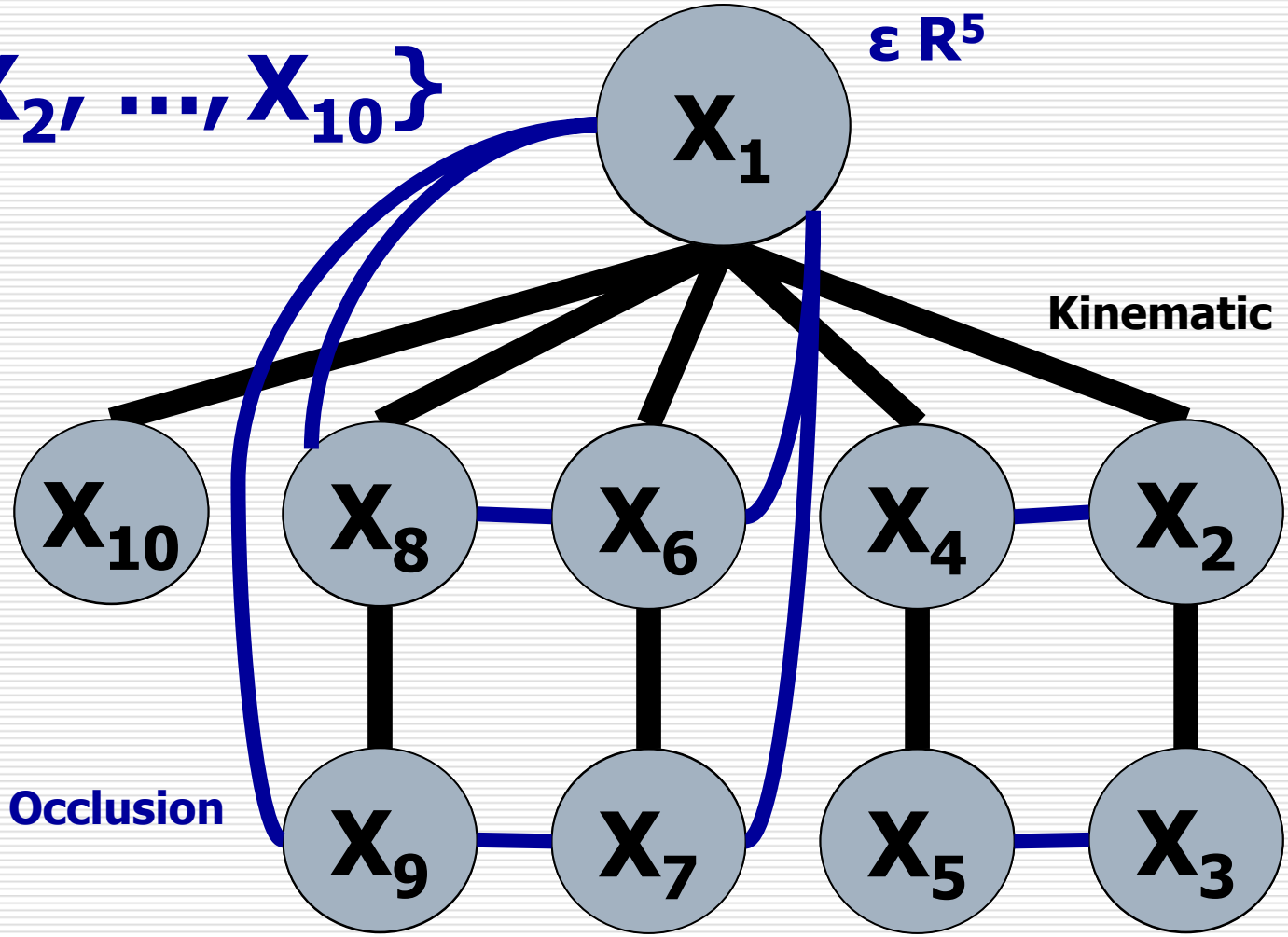




2D "Loose-limbed" Body Model

$X = \{ X_1, X_2, \ldots, X_{10} \}$





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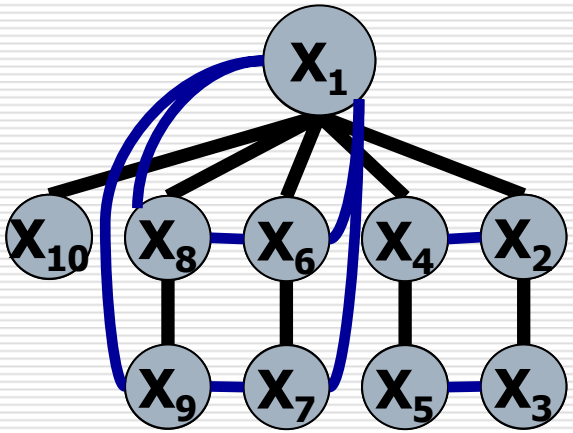
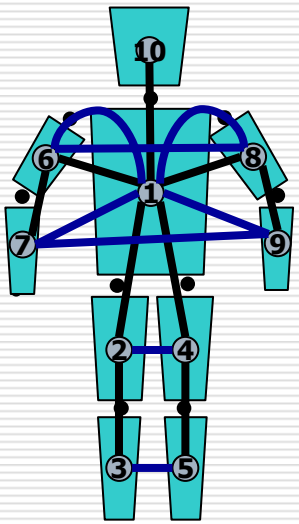
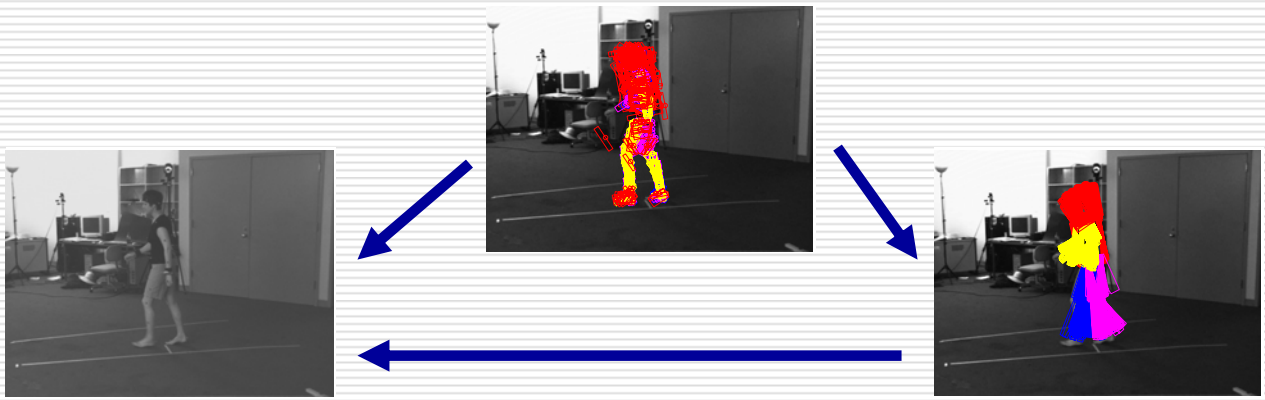




- **Exact inference in tree-structured graphical models can be computed using BP**
- **But, not when**
  - State-space is continuous
  - Likelihoods (or potentials) are not Gaussian
  - Graph contains loops
- **This forces the use of approximate inference algorithms**
  - **PAMPAS:** M. Isard, '03
  - **Non-Parametric BP:** E. Sudderth, A. Ihler, W. Freeman, A. Willsky, '03

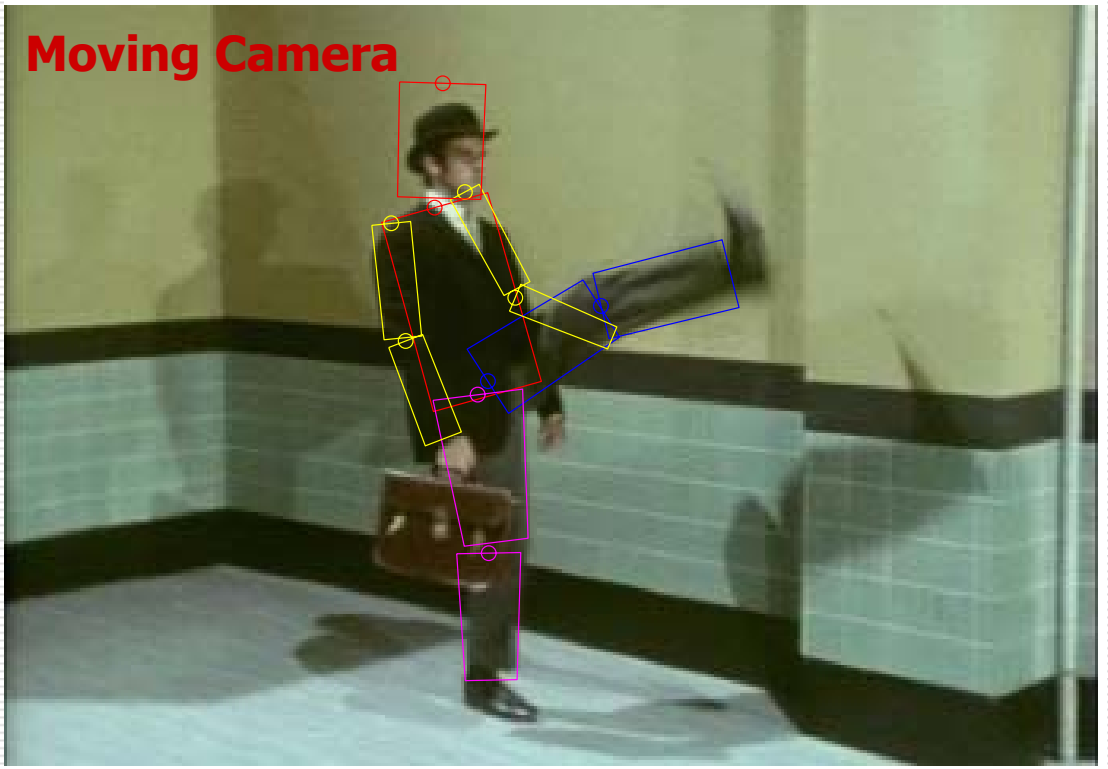
Particle Message Passing

- **Start with some distribution for all or sub-set of parts/limbs**
  - Iterate:
    - Evaluate the likelihood to see which parts/limbs best describe the image
    - Propagate information from parts/limbs to neighboring parts/limbs
    - Postulate (new) consistent poses for limbs based on all available constraints
- **Output the distributions over parts**

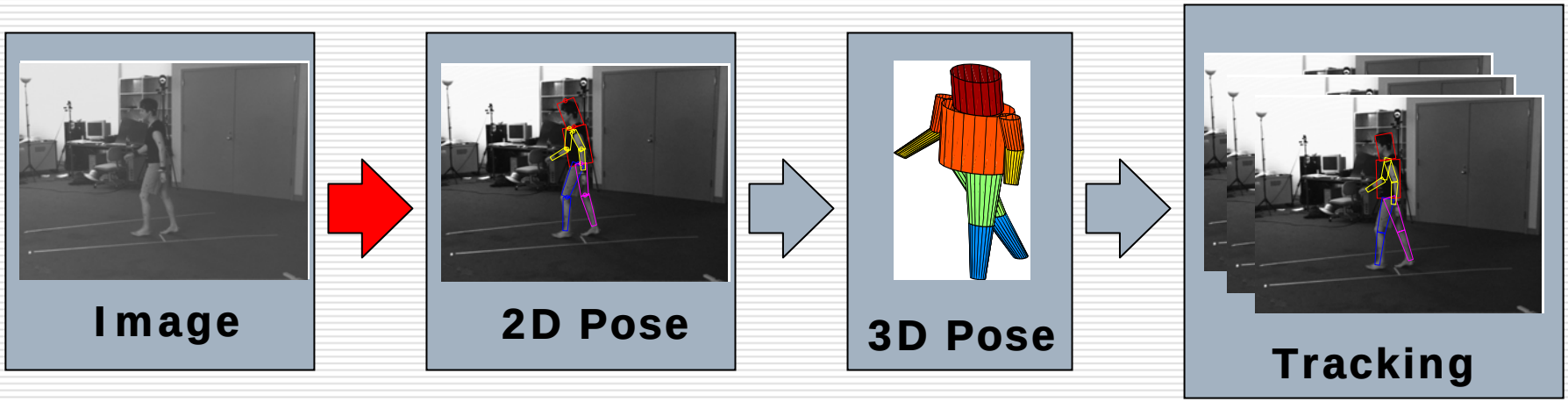


Inferring 2D pose

- **Occlusion-sensitive "Loose-limbed" body model allows us to infer the 2D pose reliably**
- **Even when motions are complex**

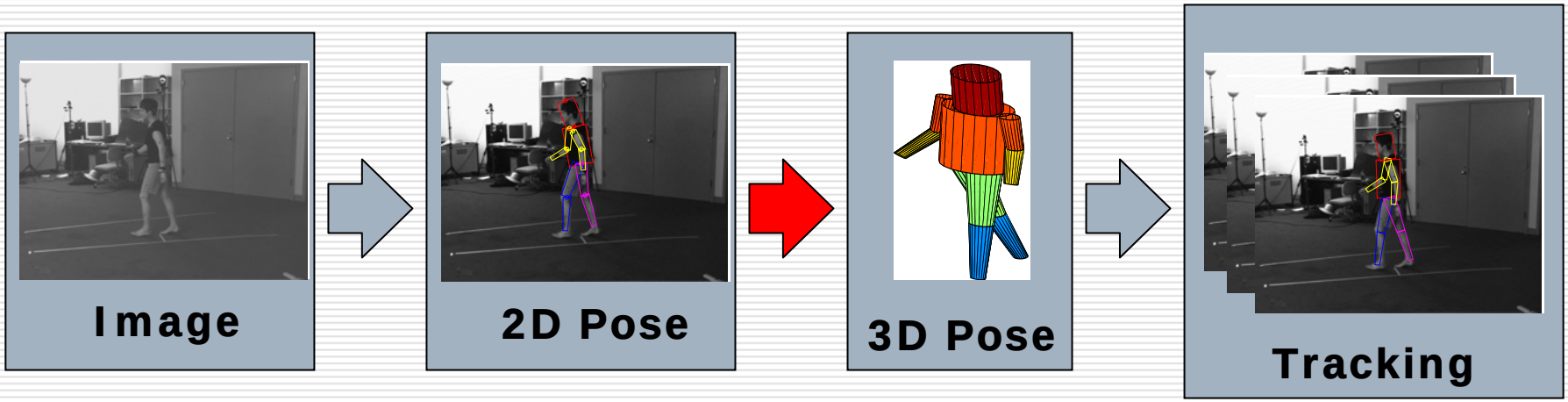


Summary so far …

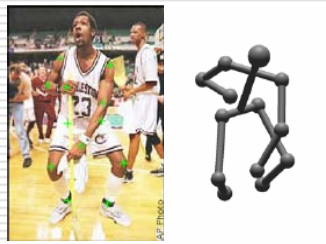


Occlusion-sensitive "Loose-limbed" body model

Inferring 3D pose from 2D pose

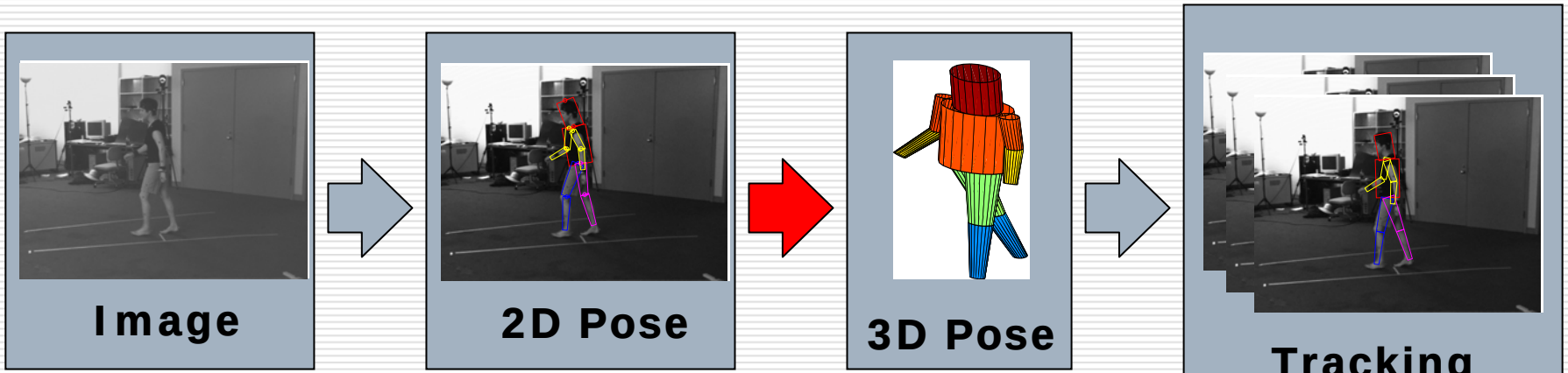


- **We obtain estimates for the joints automatically**
- **We learn direct probabilistic mapping**



Camillo J. Taylor, '00

Inferring 3D pose from 2D pose



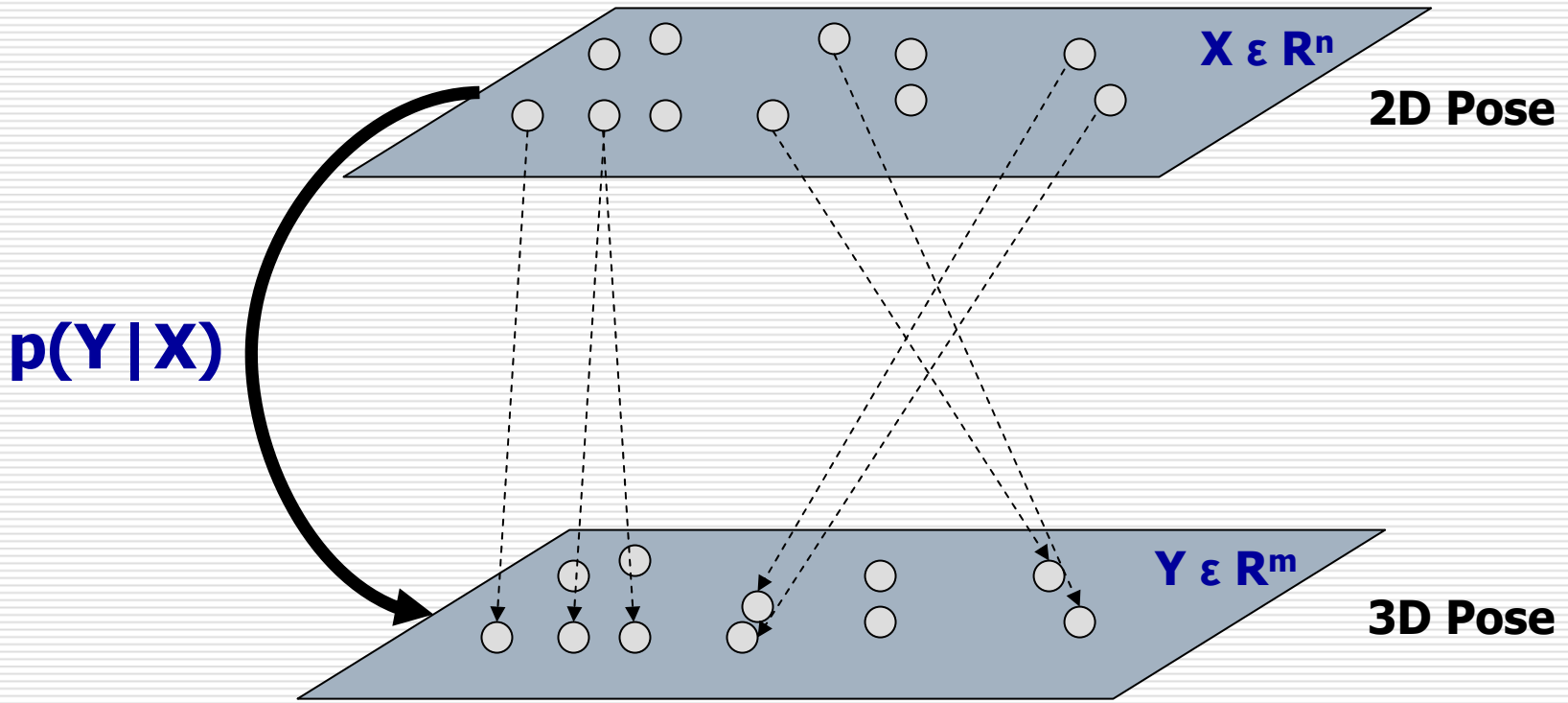
Mixture of Experts (MoE)

Sminchisescu et al, '05

Waterhouse et al, '96

Inferring 3D pose from 2D pose

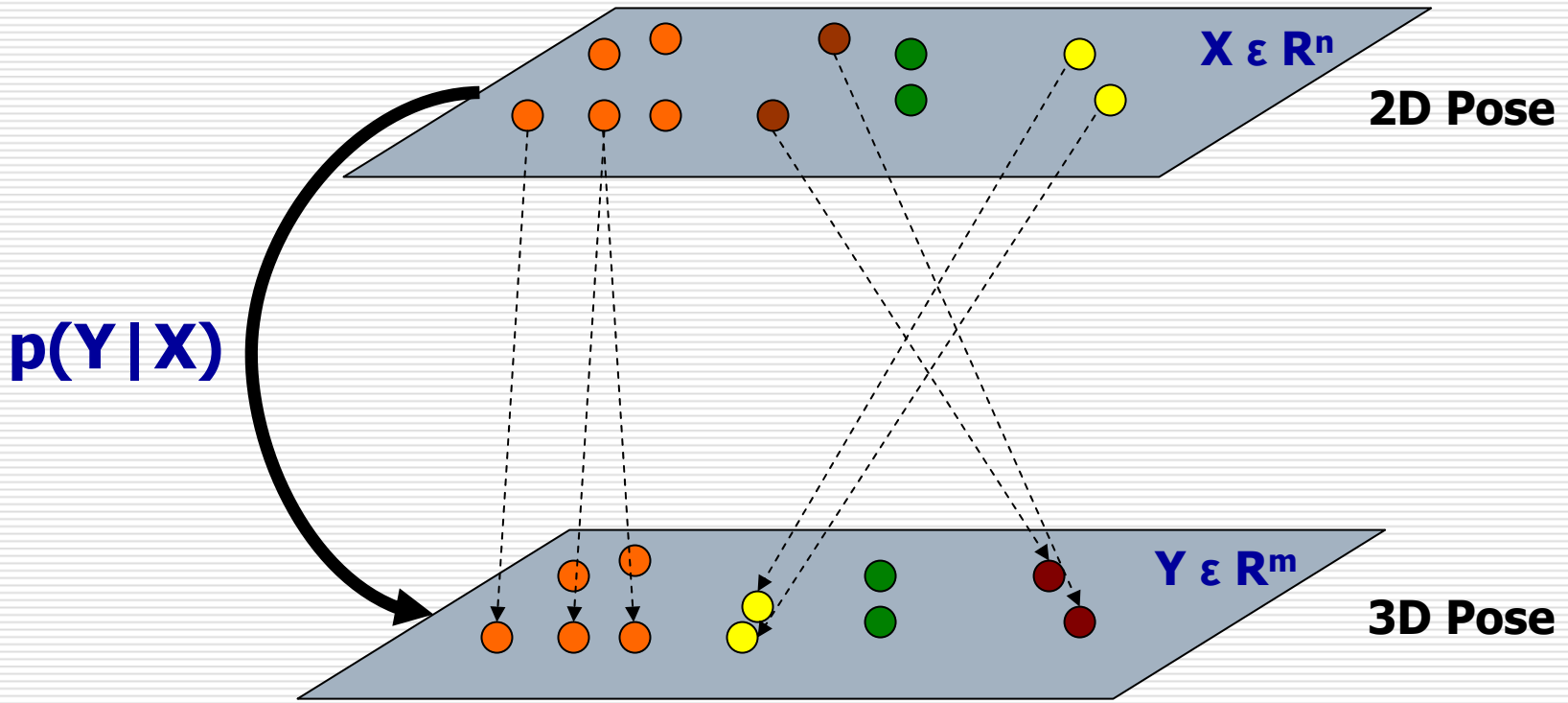
We want to estimate a distribution/mapping p(3D Pose|2D Pose)



Problem: p(Y|X) is non-linear mapping, and not one-to-one

Mixture of Experts (MoE)

We want to estimate a distribution/mapping p(3D Pose|2D Pose)



Solution: p(Y|X) may be approximated by a locally linear mappings (experts)

MoE Formally

Expert: probability of the output 3D pose Y according to the k-th expert

2D Body Pose

$$p(Y \mid X) \propto \sum_{k=1}^{K} p_{e,k}(Y \mid X)\, p_{g,k}(k \mid X)$$

3D Body Pose

Sum over all experts

Gaiting Network: probability that input 2D pose X is assigned to the k-th expert.

- **Training of MoE is done using EM procedure (similar to learning Mixture of Gaussians)**

Illustration of 3D pose inference

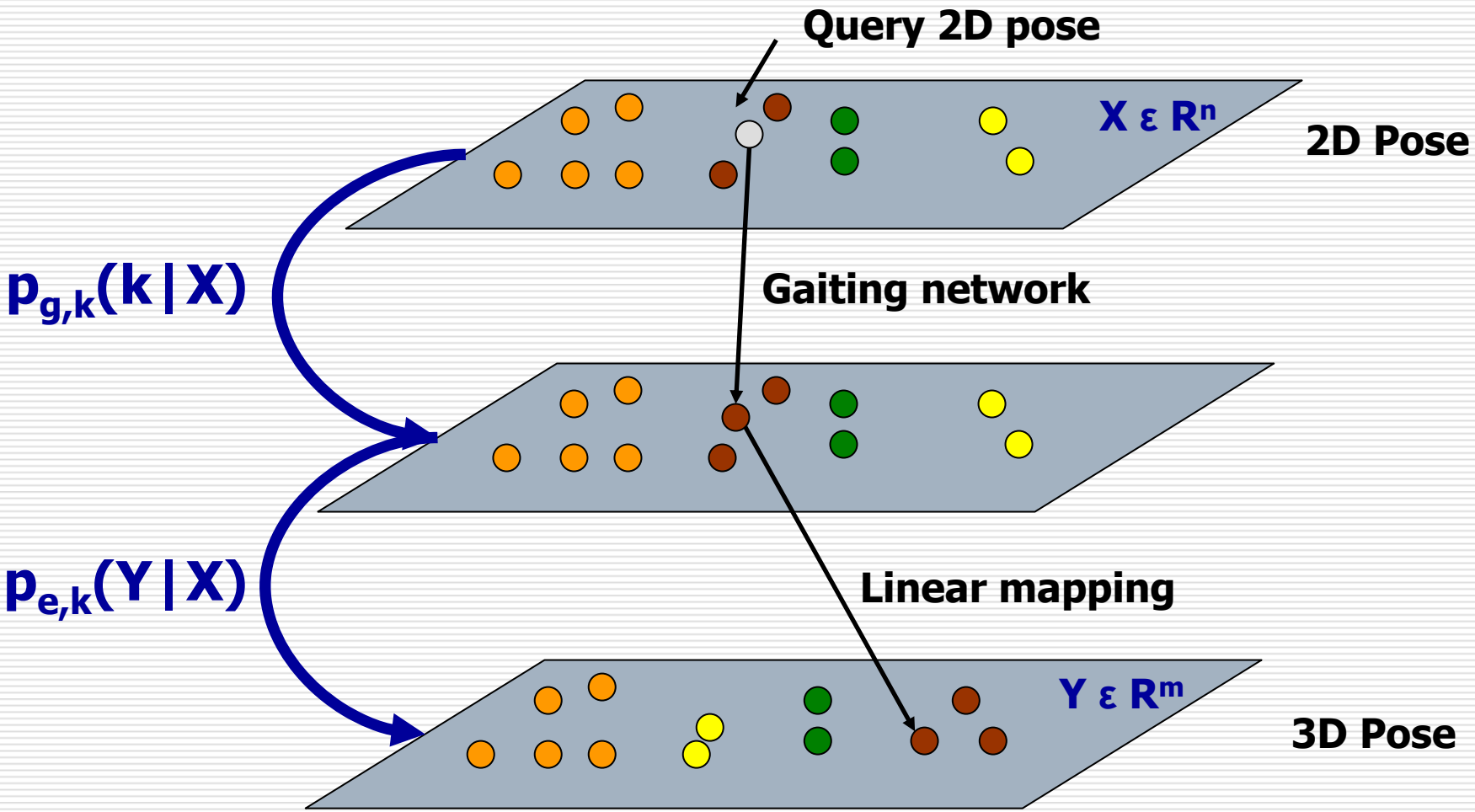
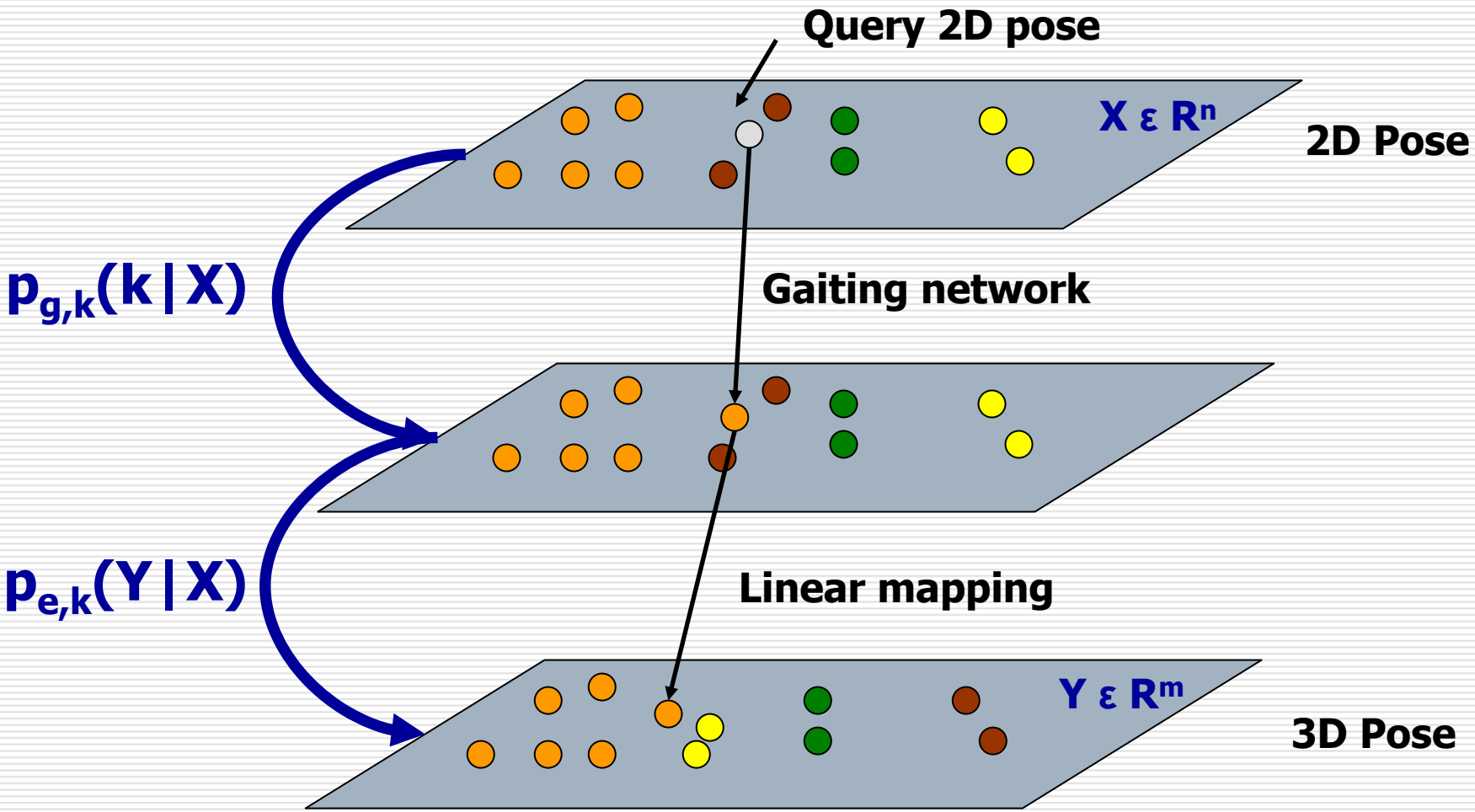


Illustration of 3D pose inference



Performance

- **Two action-specific MoE models are trained**

Walking

- 4587 2D/3D MOCAP pose pairs for training
- 1398 video frames used for testing

Performance

- **View only:** 14 mm
- **Pose only:** 23 mm
- **Overall:** 30 mm

Dancing

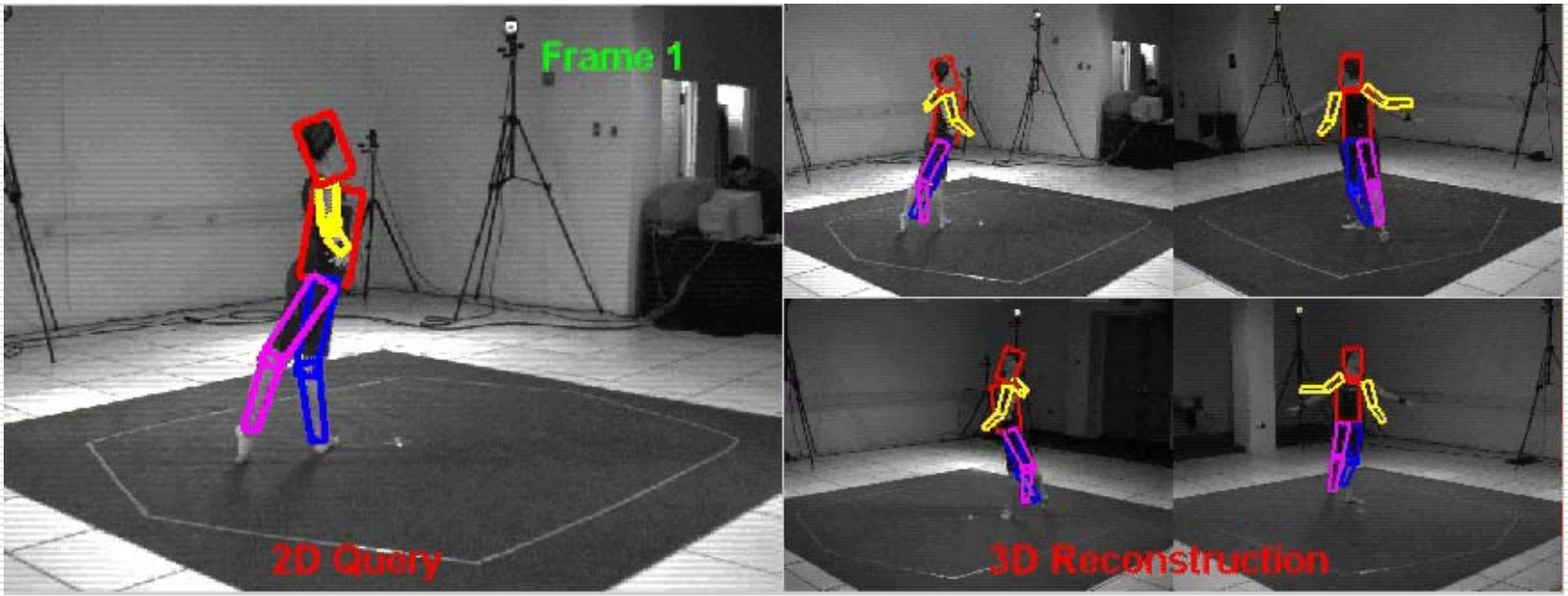
- 4151 2D/3D MOCAP pose pairs for training
- 2074 video frames used for testing

Performance

- **View only:** 22 mm
- **Pose only:** 59 mm
- **Overall:** 64 mm

Structured motion / Performance

How well does MoE model work?



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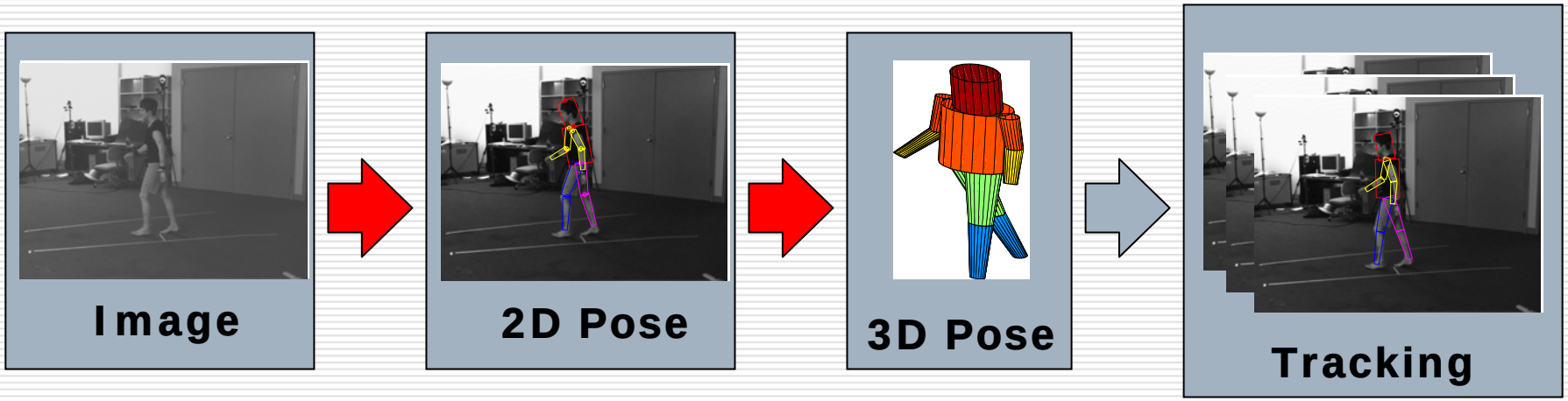
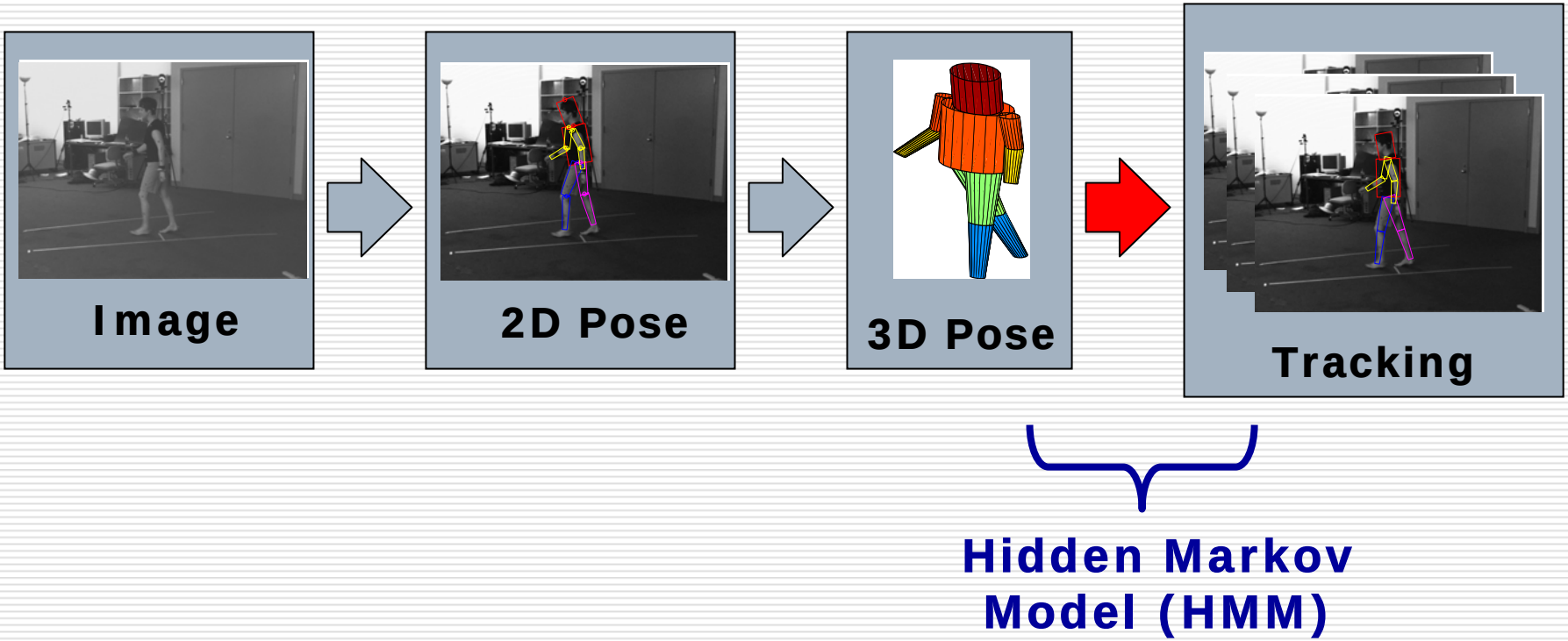


Occlusion-sensitive “Loose-limbed” body model

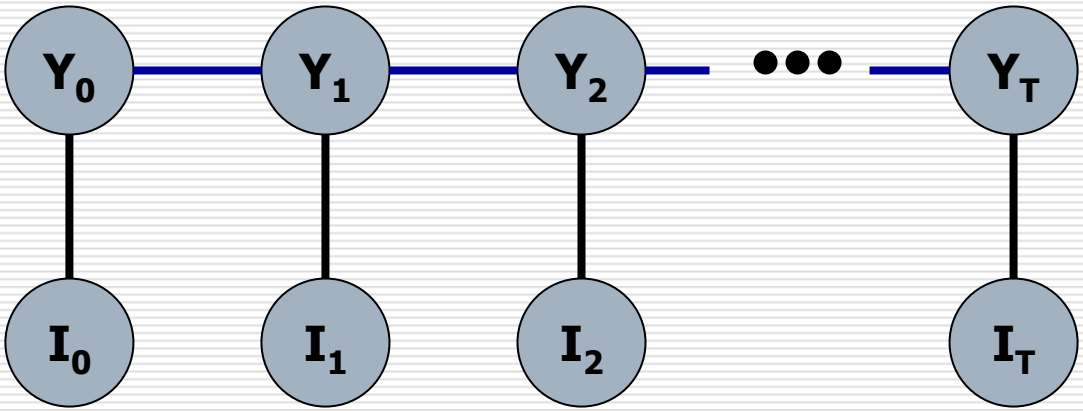
Mixture of Experts (MoE)

Summary so far …



Tracking in 3D

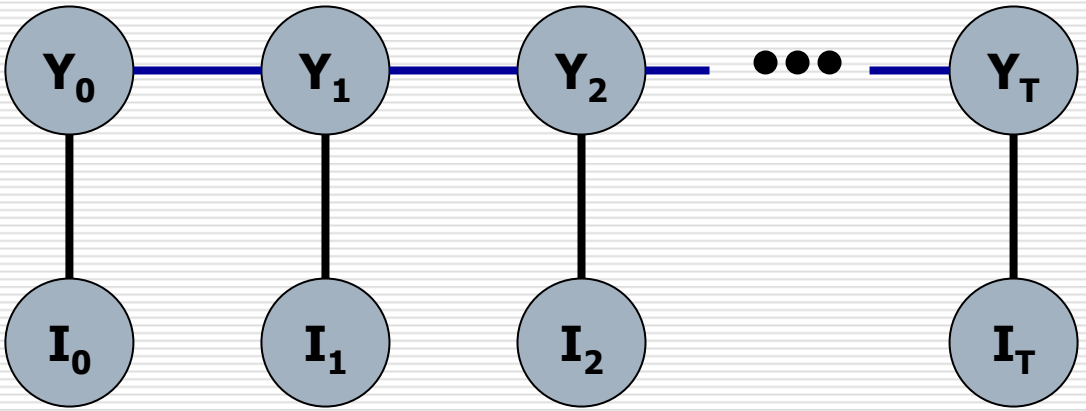
- **We have a distribution over 3D poses at every time instance**



- **Assuming that 3D pose at time t is conditionally independent of the state at time t-2 given state at t-1**

Tracking in 3D (inference)

- **Inference in this graphical model can be done using the tools we already have**
  - PAMPAS/Non-parametric belief propagation



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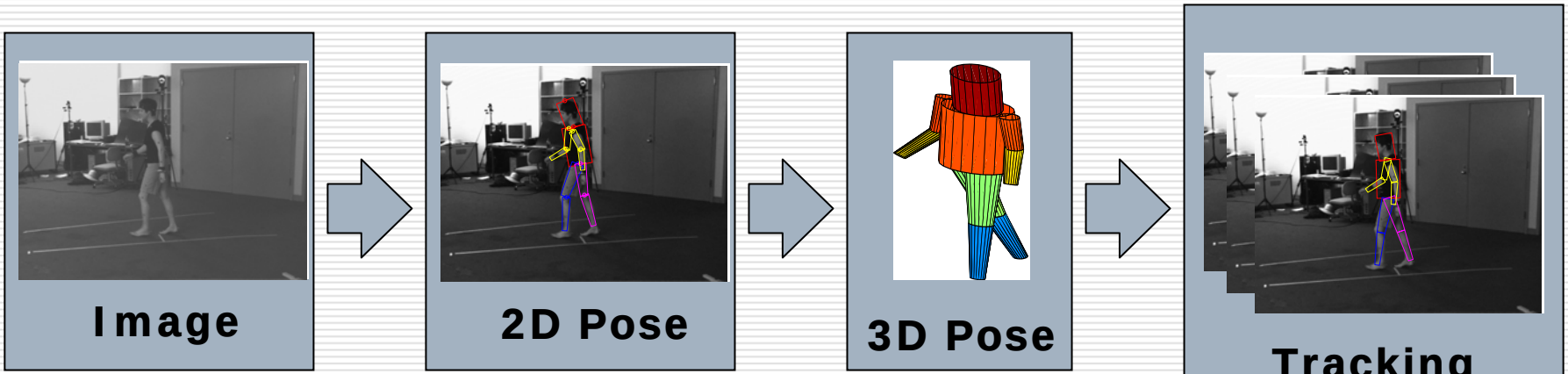
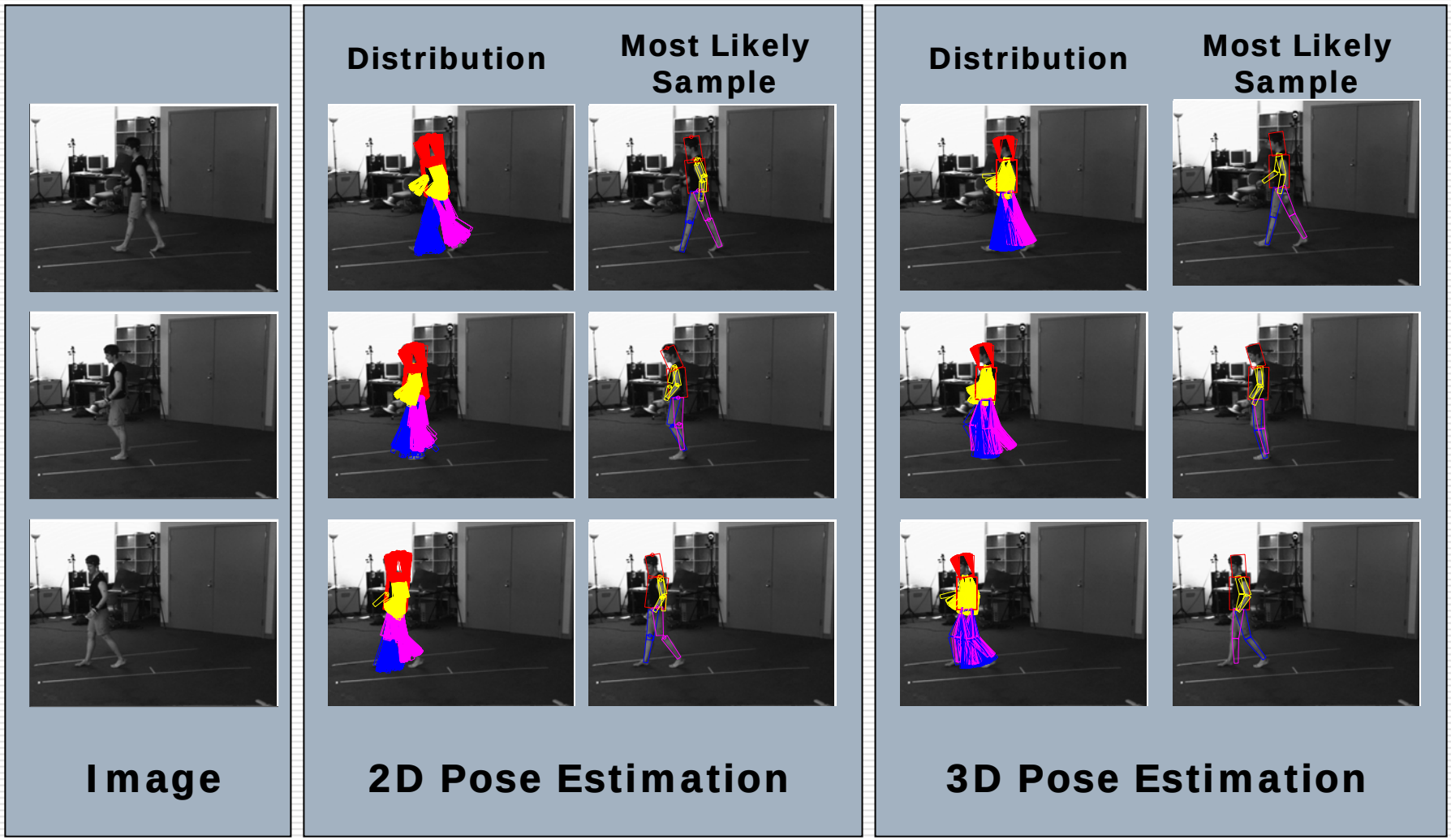


Occlusion-sensitive "Loose-limbed" body model

Mixture of Experts (MoE)

Hidden Markov Model (HMM)

Hierarchical 3D Pose Estimation from Single View Monocular Images



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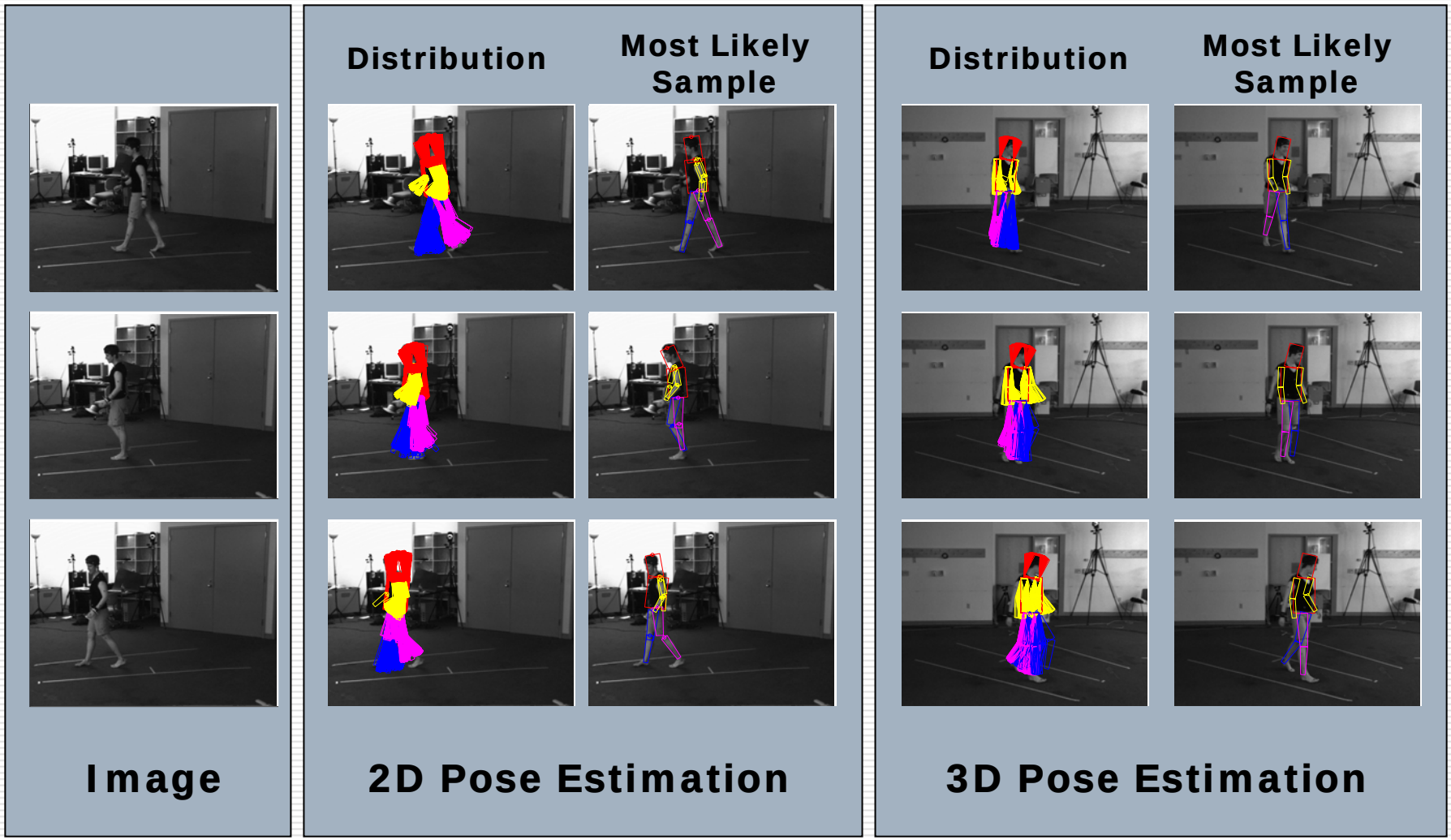
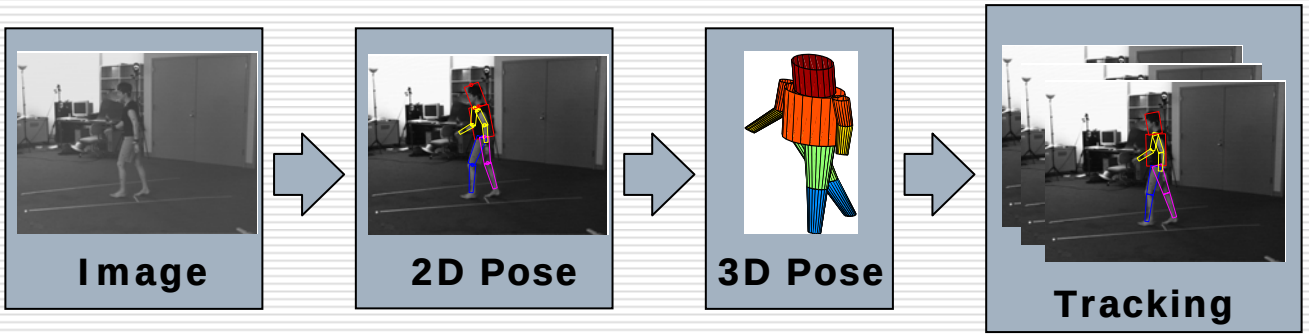


Tracking in 3D

Tracking in 3D

Summary



- **We introduced a novel hierarchical inference framework**
  - Where we mediate the complexity of single-image monocular 3D pose estimation by intermediate 2D pose estimation stage
- **Inference in this framework can be tractably done using a variant of Non-parametric Belief Propagation**
- **Results obtained are very encouraging**

Thank You!

Questions?