Structured Out Prediction (Pose)

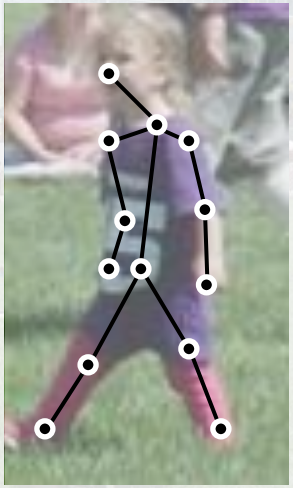
Hyun Soo Park

Challenges of Visual Recognition

- Appearance
  - DOF: texture, illumniation, material, shading, …
- Shape
  - DOF: object category, geometric pose, viewpoint, …

Human

$$f(I) = l_{human}$$



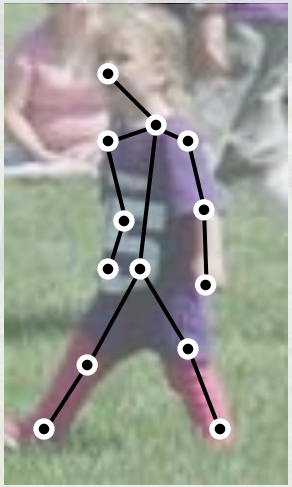
Human pose

$$f(I) = \begin{bmatrix} x_1 \\ y_1 \\ \vdots \\ x_n \\ y_n \end{bmatrix}$$

Structured output

Challenges of Visual Recognition

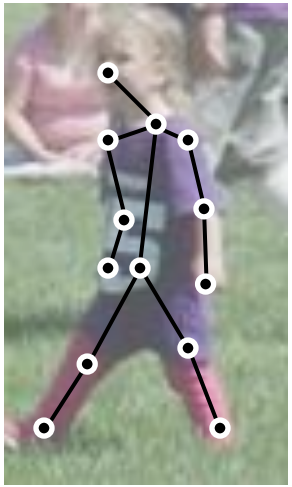
- Appearance
  - DOF: texture, illumniation, material, shading, …
- Shape
  - DOF: object category, geometric pose, viewpoint, …

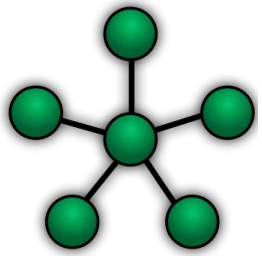


Landmark localization (**structured prediction**)

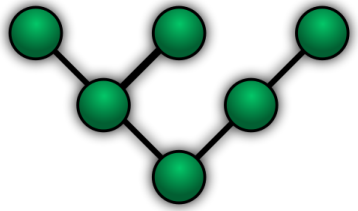
Learning appearance and spatial relation together

Topological Model

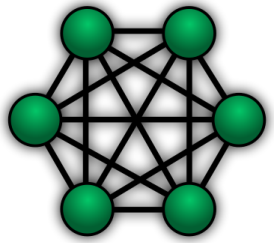




Star topology

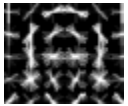


Tree topology



Fully connected topology

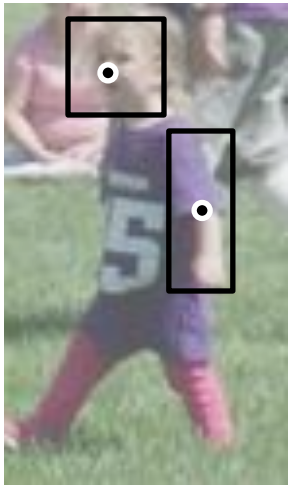
Problem Definition

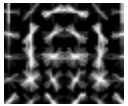


Head detector

$$w_{head} \cdot \underbrace{\phi(I, x_{head})}_{\text{Feature extractor}} > 0$$

Problem Definition





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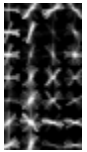
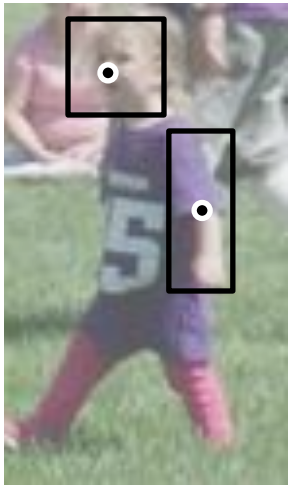
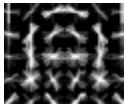


Arm detector

$$w_{arm} \cdot \phi(I, x_{arm}) > 0$$

Problem Definition





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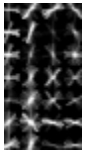


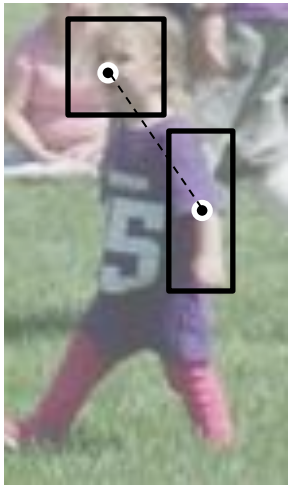
Arm detector

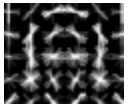
$$w_{arm} \cdot \phi(I, x_{arm}) > 0$$

Objective:

$$L = w_h \cdot \phi(I, x_h) + w_a \cdot \phi(I, x_a)$$

Problem Definition





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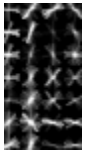


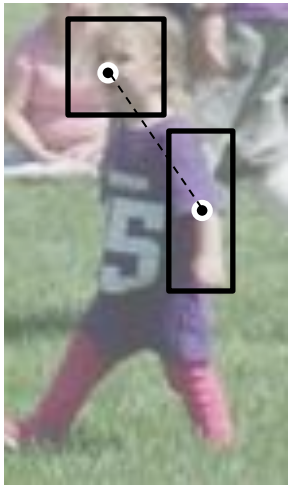
Arm detector

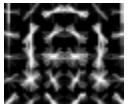
$$w_{arm} \cdot \phi(I, x_{arm}) > 0$$

Objective:

$$L = w_h \cdot \phi(I, x_h) + w_a \cdot \phi(I, x_a) + \underbrace{\varphi(x_h, x_a)}_{\text{Spatial relationship}}$$

Problem Complexity





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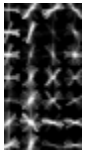


Arm detector

$$w_{head} \cdot \underline{\phi(I, x_{head})} > 0$$

Feature extractor

$$w_{arm} \cdot \phi(I, x_{arm}) > 0$$

# of configurations

$O(h^2)$

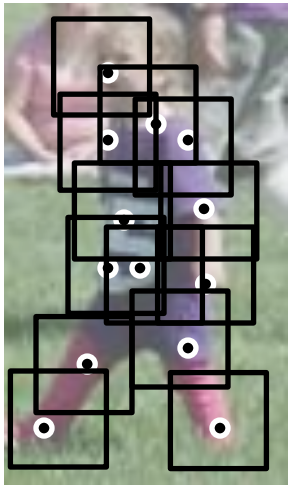
h : # of pixels

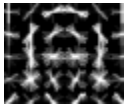
Objective:

$$L = w_h \cdot \phi(I, x_h) + w_a \cdot \phi(I, x_a) + \underline{\varphi(x_h, x_a)}$$

Spatial relationship

Problem Complexity





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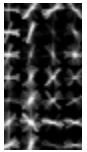


Arm detector

$$w_{arm} \cdot \phi(I, x_{arm}) > 0$$

# of configurations

$O(h^n)$

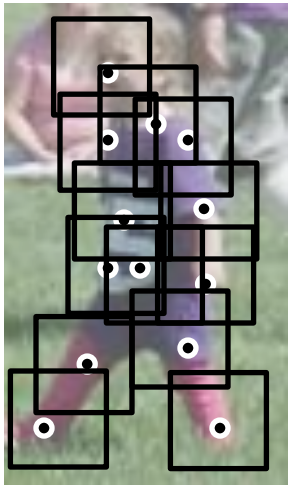
h : # of pixels

n : # of landmarks

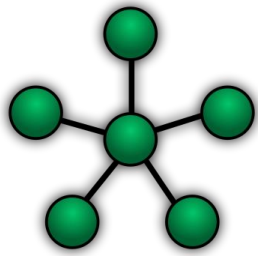
Objective:

$$L = \sum_i w_i \cdot \phi(I, x_i) + \sum_{i,j} \varphi(x_i, x_j)$$

Model Topology

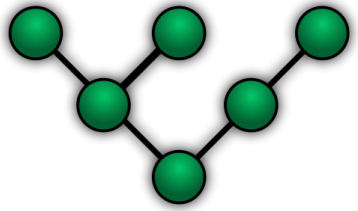


$O(nh^2)$



Star topology

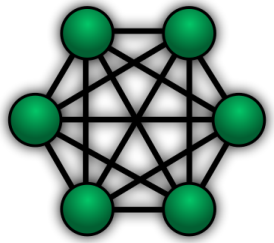
$O(nh^2)$



Tree topology

Can be solved by dynamic programming

$O(h^n)$



Fully connected topology

NP-hard

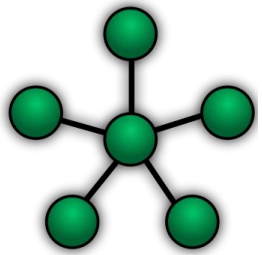
CVPR 2008
2018 Longuet-Higgins Prize for fundamental contributions in computer vision

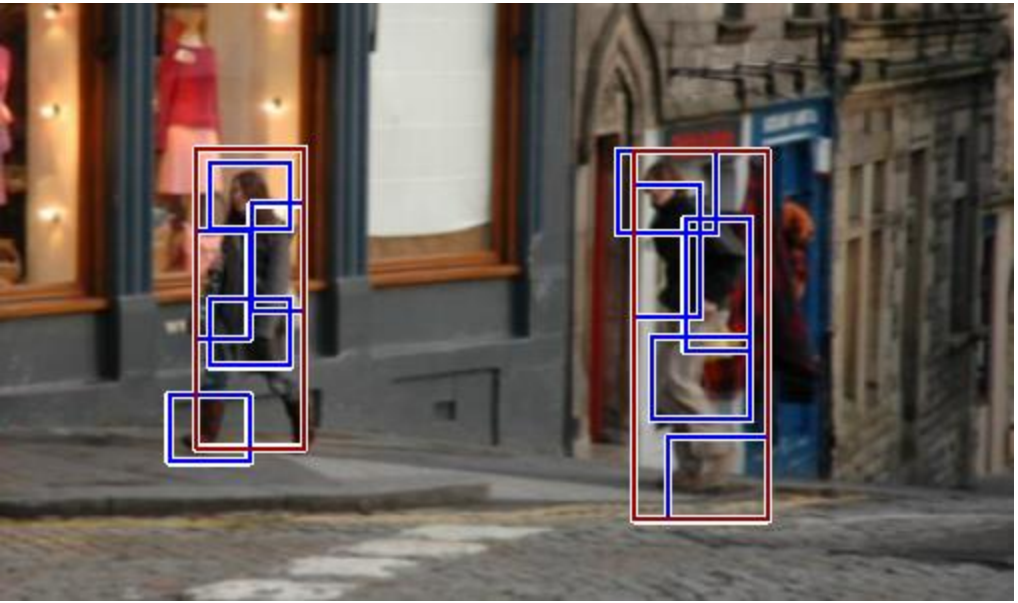
Object Detection with Discriminatively Trained Part Based Models

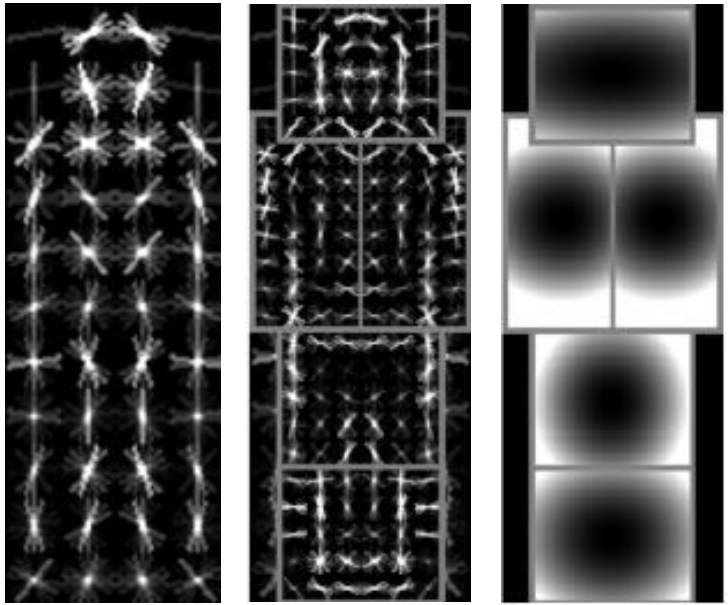
Pedro F. Felzenszwalb, Ross B. Girshick, David McAllester and Deva Ramanan

Slide inpired by Felzenszwalb and Girshick

Deformable Part Model (DPM)

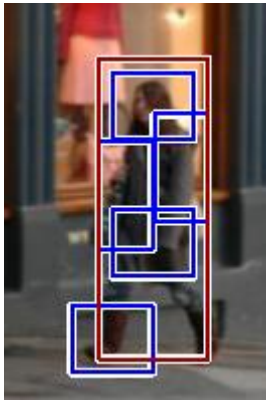


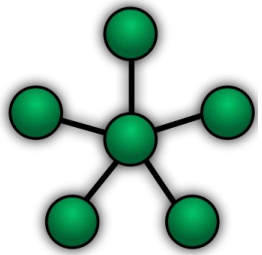




Root filter Part desc. Deformation

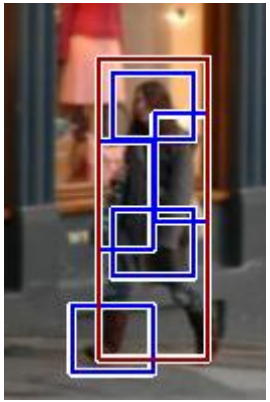
DPM

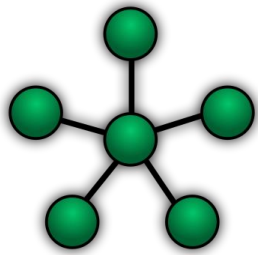




$$L = \sum_i w_i \cdot \phi(I, x_i) + \sum_{i,j} \varphi(x_i, x_j)$$

DPM

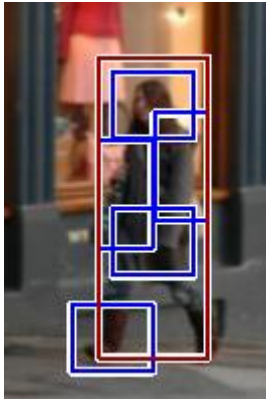


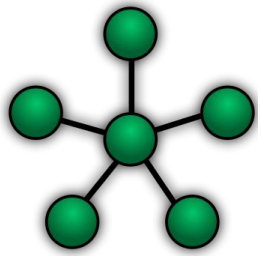


$$L = \sum_i w_i \cdot \phi(I, x_i) + \sum_{i,j} \varphi(x_i, x_j)$$

$$score(x_0, x_1, \cdots, x_n) = \underbrace{\sum_{i=0} w_i \cdot \phi(I, x_i)}_{\text{Appearance (filter response)}} - \sum_{i=1} d_i \cdot (dx_i^2)$$

DPM

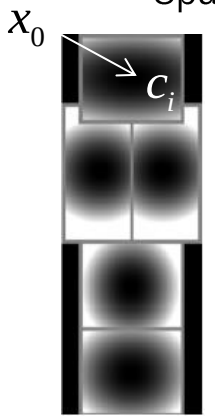




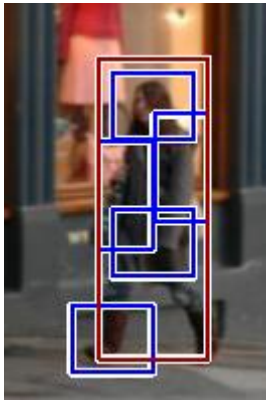
$$L = \sum_i w_i \cdot \phi(I, x_i) + \sum_{i,j} \varphi(x_i, x_j)$$

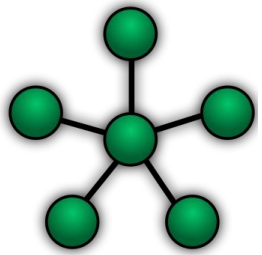
$$score(x_0, x_1, \cdots, x_n) = \sum_{i=0} w_i \cdot \phi(I, x_i) - \underbrace{\sum_{i=1} d_i \cdot (dx_i^2)}_{\text{Spatial rel. (spring force)}}$$

where $dx_i = x_0 + \underbrace{c_i}_{\text{Offset}} - x_i$



DPM





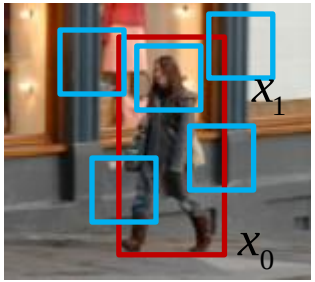
Score for root location based on part location

$$score(x_0) = \max_{x_1,\cdots,x_n} score(x_0, x_1, \cdots, x_n)$$

$$= w_0 \cdot \phi(I, x_0) + \sum_{i=1} \max_{x_i} score(x_0, x_i)$$

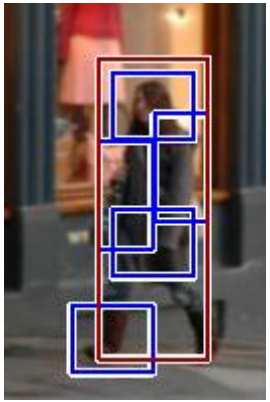
$$= w_0 \cdot \phi(I, x_0) + \sum_{i=1} \max_{x_i} \underbrace{\left(w_i \cdot \phi(I, x_i) - d_i \cdot dx^2 \right)}$$

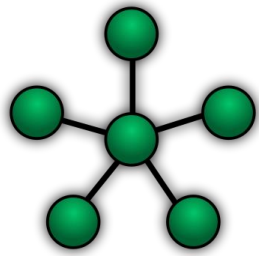
Part evidence to predict the root



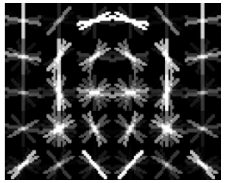
How does the head location tell us about the root location?

DPM

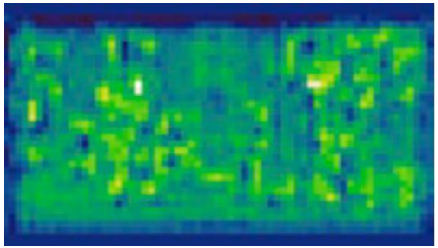




Input image

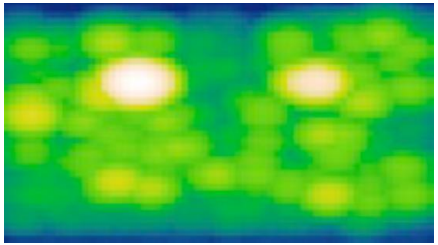


Head filter



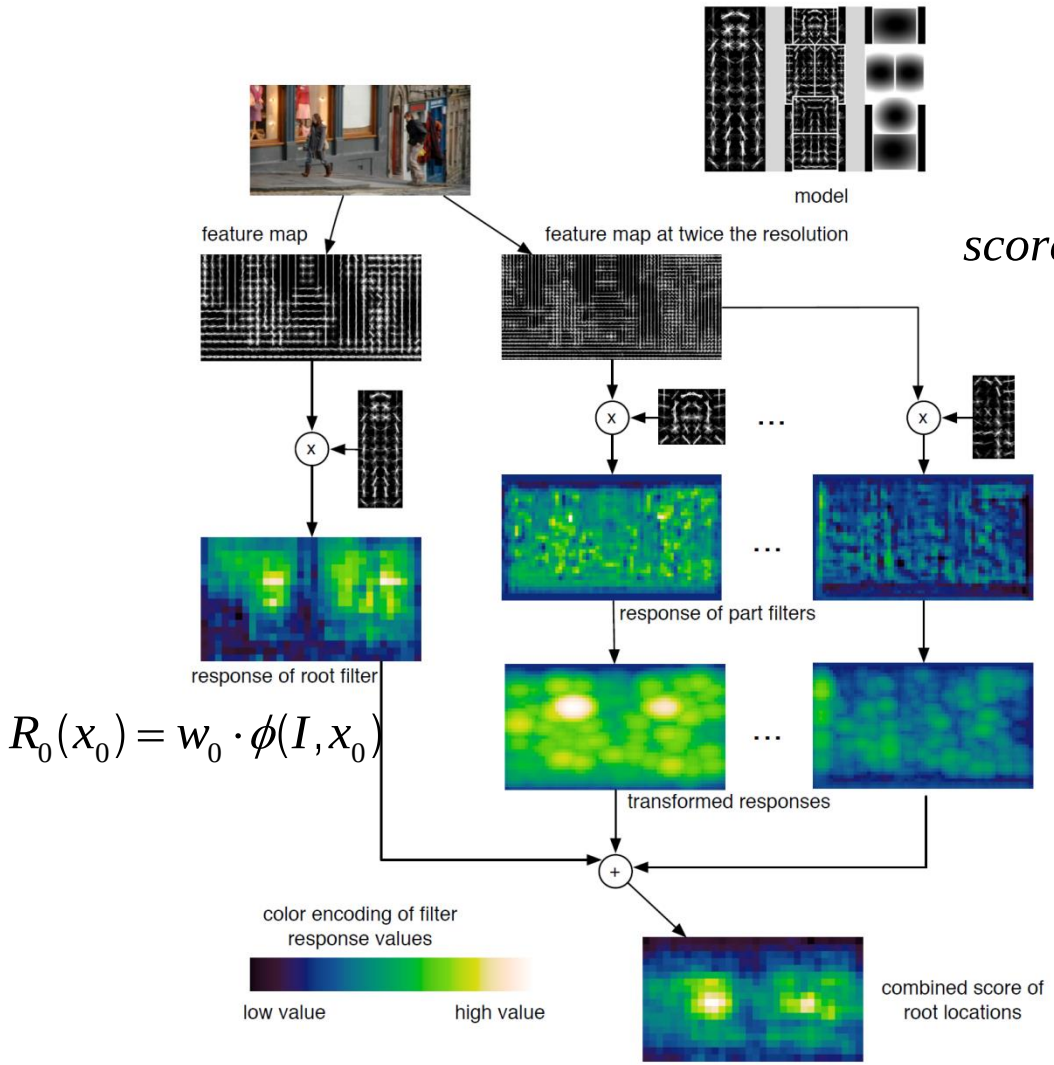
Filter response

$$R_h(x_h) = w_h \cdot \phi(I, x_h)$$



Transformed response

$$D_h(x_0) = \max_{dx,dy} \left(R_h(x_0 + dx) - d_h \cdot dx^2 \right)$$



$$score(x_0) = R_0(x_0) + \sum_{i=1} \max_{x_i} \left(R_i(x_0 + dx) - d_i \cdot dx^2 \right)$$

$$R_h(x_h) = w_h \cdot \phi(I, x_h)$$

$$R_0(x_0) = w_0 \cdot \phi(I, x_0)$$

$$D_h(x_0) = \max_{dx,dy} \left(R_h(x_0 + dx) - d_h \cdot dx^2 \right)$$

CVPR 2011
2018 Longuet-Higgins Prize for fundamental contributions in computer vision

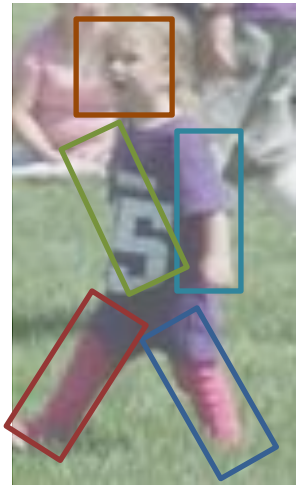
Articulated pose estimation with flexible mixtures-of-parts

Yi Yang Deva Ramanan
Dept. of Computer Science, University of California, Irvine
{yyang8,dramanan}@ics.uci.edu

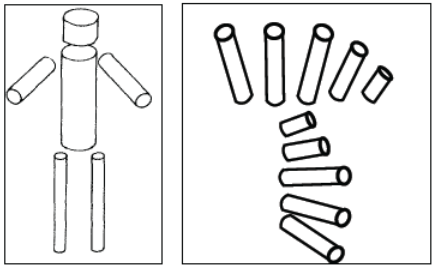
Slide inpired by Yang

LIMITATION OF DPM

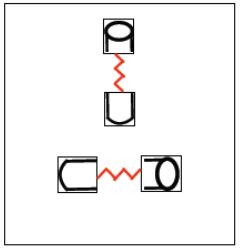
In-plane rotation 	Foreshortening 
Scaling 	Out-of-plane rotation 
Intra-category variation 	Aspect ratio 



Part based model



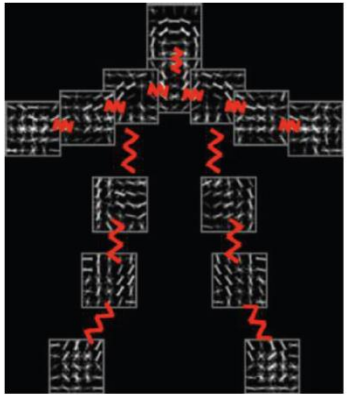
Marr, Nishihara (1978)



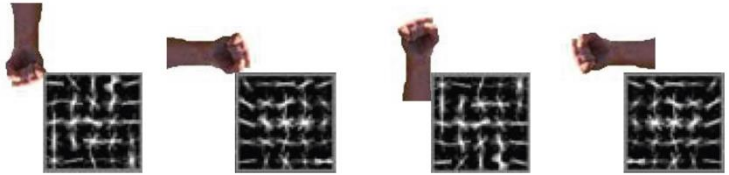
3D deformation ~
Mixture of mini-parts

(a) Original (b) Foreshortening (c) Out-of-plane

MIXTURE PART MODEL

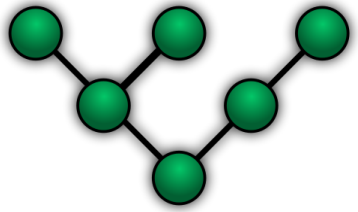


$$L(I,x) = \sum_{i \in V} \alpha_i \cdot \phi(I, x_i) + \sum_{i,j \in E} \beta_{ij} \cdot \varphi(x_i, x_j)$$



m^1_{hand} m^2_{hand} m^3_{hand} m^4_{hand}

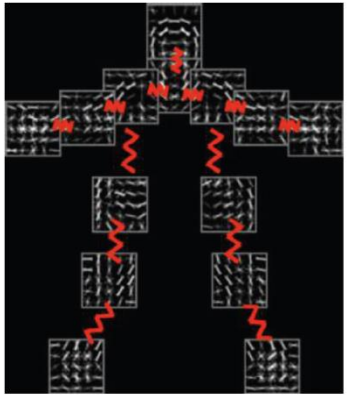
Mixture part model



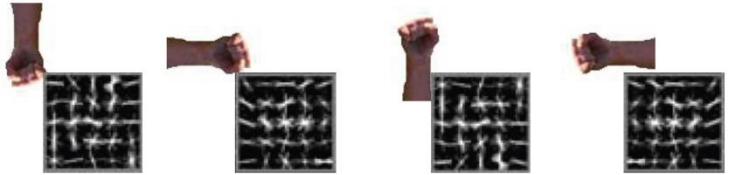
$$L(I,x,m) = \sum_{i \in V} \alpha_i^{m_i} \cdot \phi(I, x_i) + \sum_{i,j \in E} \beta_{ij}^{m_i m_j} \cdot \varphi(x_i, x_j)$$

Appearance

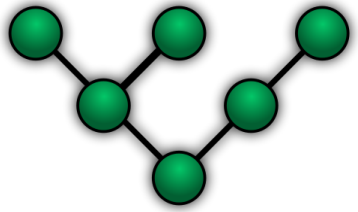
MIXTURE PART MODEL



$$L(I,x) = \sum_{i \in V} \alpha_i \cdot \phi(I, x_i) + \sum_{i,j \in E} \beta_{ij} \cdot \varphi(x_i, x_j)$$



m^1_{hand} m^2_{hand} m^3_{hand} m^4_{hand}

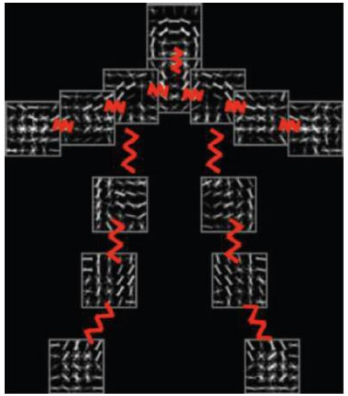


Mixture part model

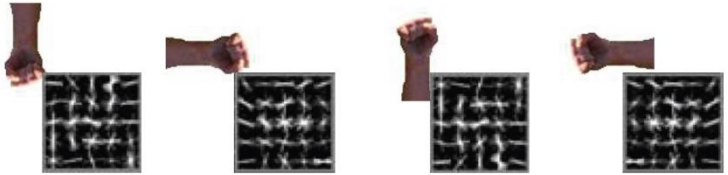
$$L(I,x,m) = \sum_{i \in V} \alpha_i^{m_i} \cdot \phi(I, x_i) + \sum_{i,j \in E} \beta_{ij}^{m_i m_j} \cdot \varphi(x_i, x_j)$$

Appearance Spatial rel.

MIXTURE PART MODEL

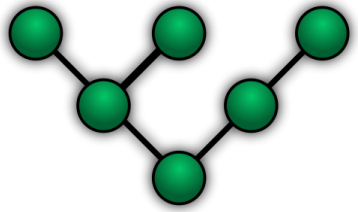


$$L(I,x) = \sum_{i \in V} \alpha_i \cdot \phi(I, x_i) + \sum_{i,j \in E} \beta_{ij} \cdot \varphi(x_i, x_j)$$



m^1_{hand} m^2_{hand} m^3_{hand} m^4_{hand}

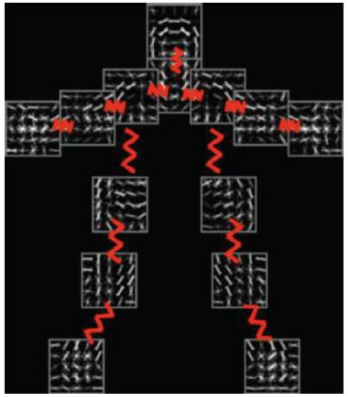
Mixture part model

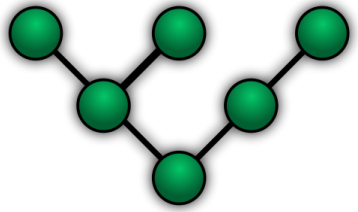


$$L(I,x,m) = \sum_{i \in V} \alpha_i^{m_i} \cdot \phi(I, x_i) + \sum_{i,j \in E} \beta_{ij}^{m_i m_j} \cdot \varphi(x_i, x_j) + S(m)$$

Appearance | Spatial rel. | Mixture prior

Mixture Part Model



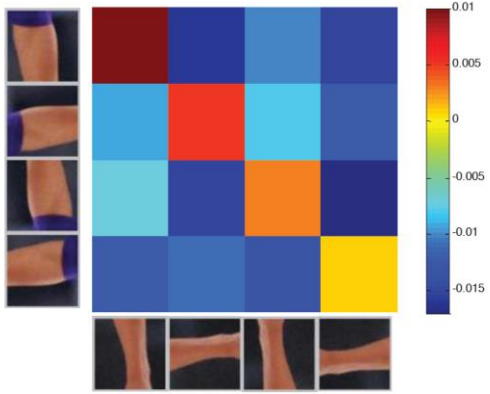


Mixture prior

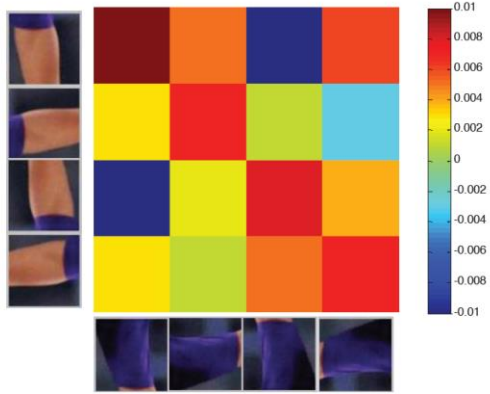
$$S(m) = \sum_{i \in V} b_i^{m_i} + \sum_{i,j \in E} b_{ij}^{m_i m_j}$$

$b_i^{m_i}$ Prior on mixture m_i

$b_{ij}^{m_i m_j}$ Co-occurance prior between m_i and m_j

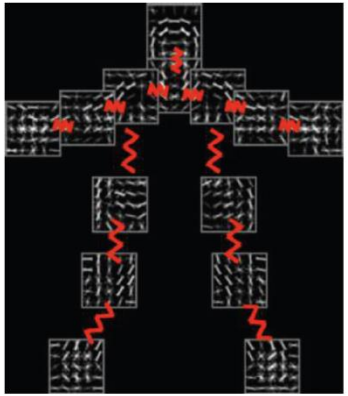


Same part



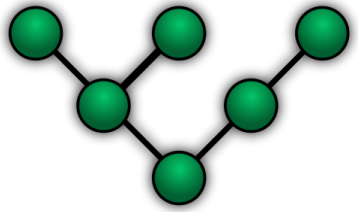
Different part

MIXTURE PART MODEL



$$score_i(x_i, m_i) = \alpha_i^{m_i} \cdot \phi(I, x_i) + b_i^{m_i} + \sum_{k \in kids(i)} u_k(x_i, m_i)$$

$$u_k(x_i, m_i) = \max_{x_j, m_j} \left(score_k(x_j, m_j) + \beta_{ij}^{m_i m_j} \cdot \varphi(x_i, x_j) + b_{ij}^{m_i m_j} \right)$$



Cf) $$score(x_0) = R_0(x_0) + \sum_{i=1} \max_{x_i} \left(R_i(x_0 + dx) - d_i \cdot dx^2 \right)$$

MIXTURE PART MODEL

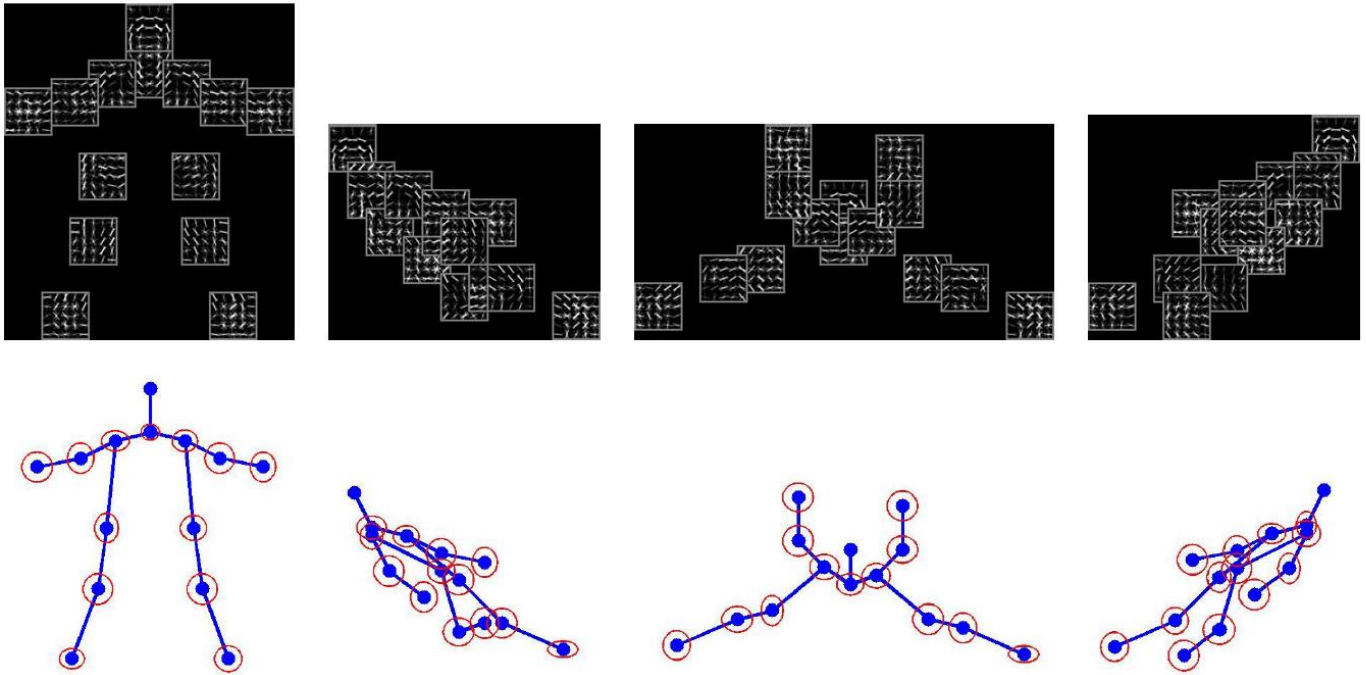
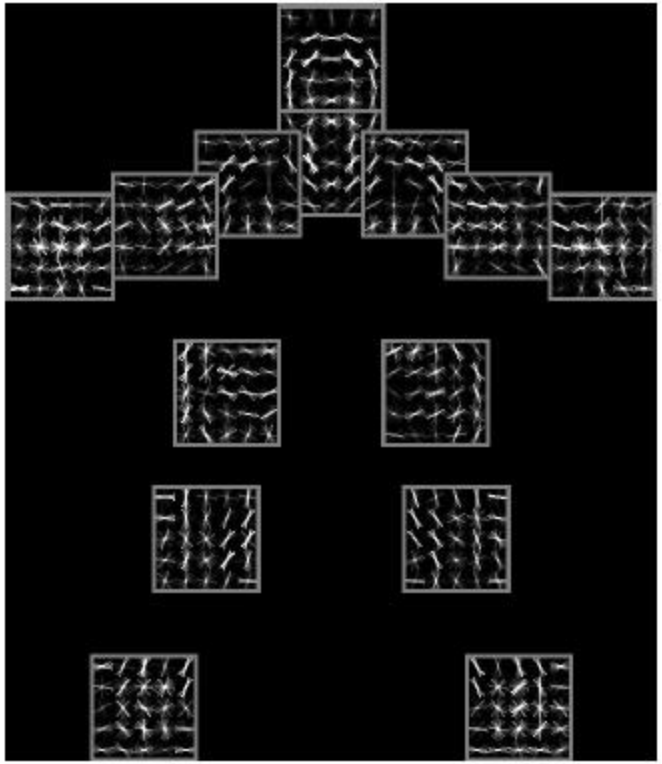
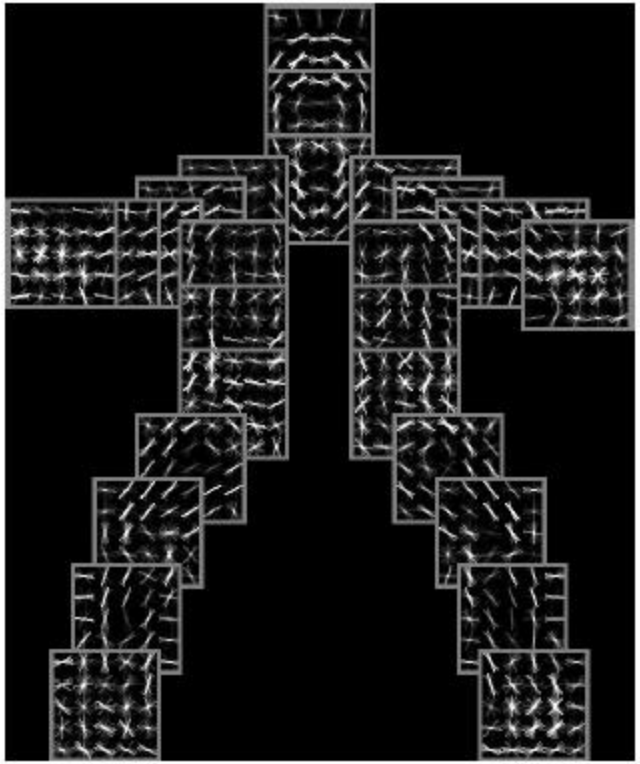


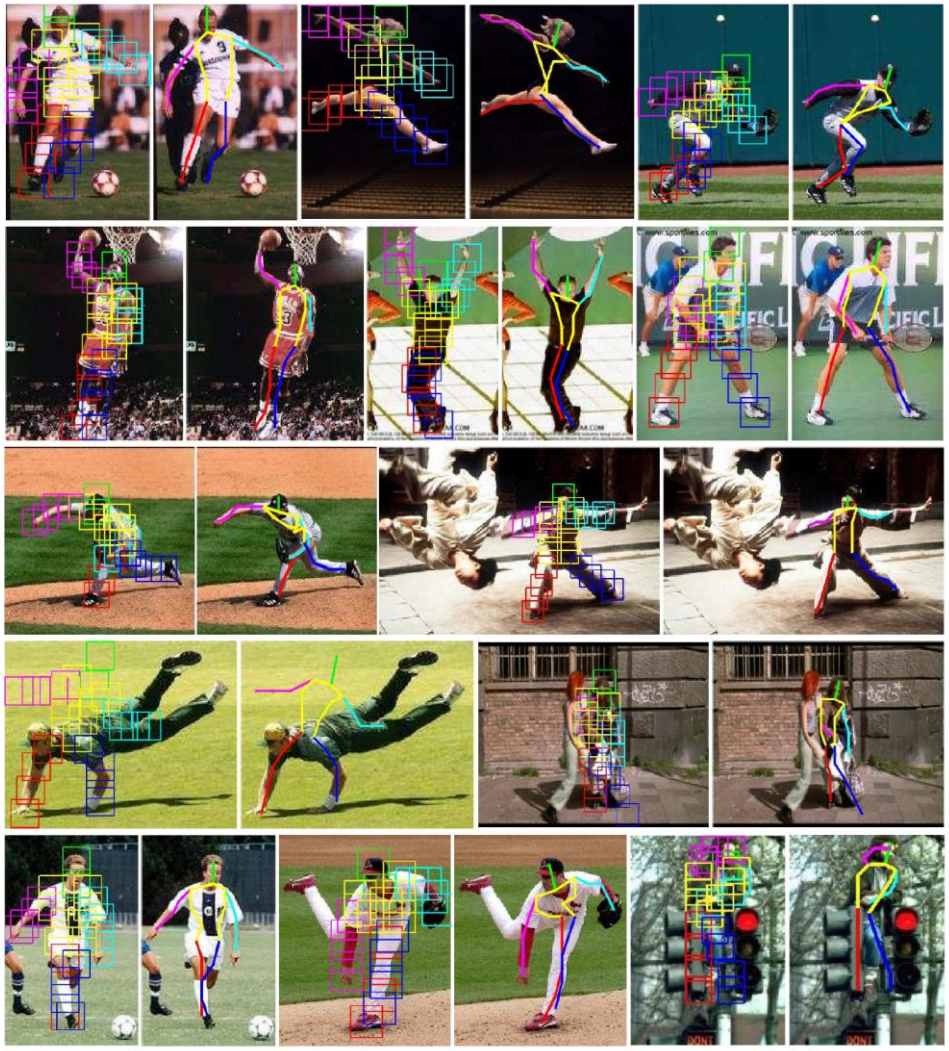
Fig. 6: A visualization of our model for $K = 14$ parts and $T = 4$ local mixtures, trained on the Parse dataset. We show the local templates **above**, and the tree structure **below**, placing parts at their best-scoring location relative to their parent. Though we visualize 4 trees, there exists $T^K \approx 2e7$ global combinations, obtained by composing different part types together with different springs. The score associated with each combination decomposes into a tree, and so is efficient to search over using dynamic programming (1).



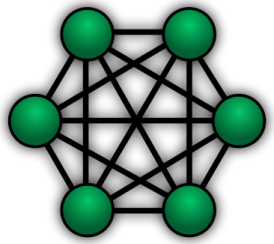
$K = 14$ parts



$K = 26$ parts



ECCV 2014



Pose Machines: Articulated Pose Estimation via Inference Machines

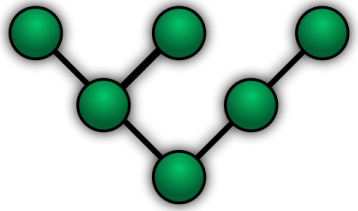
Varun Ramakrishna, Daniel Munoz, Martial Hebert,
J. Andrew Bagnell, and Yaser Sheikh

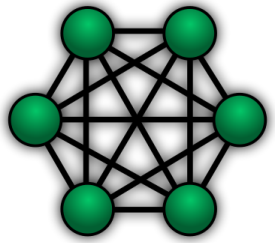
The Robotics Institute, Carnegie Mellon University

Slide inpired by Ramakrishna

POSE INFERENCE MACHINE

Elbow estimation

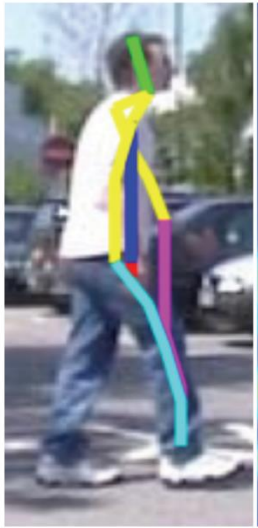




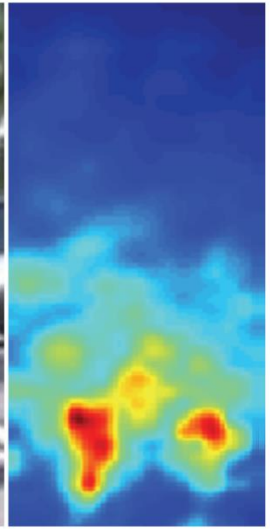
$$\sum_{ij} \beta_{ij}^{m_i m_j} \cdot \varphi(x_i, x_j)$$

All possible pairs of joints

Input Image

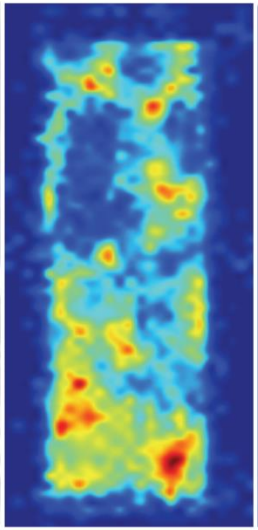


Estimated Pose

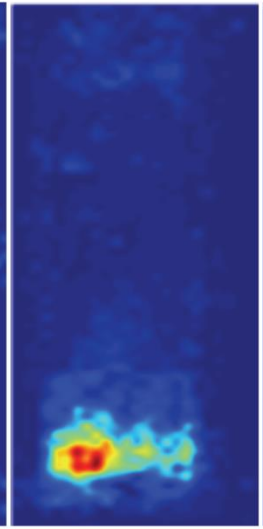


Max Marginal
(left ankle)

Estimated Pose

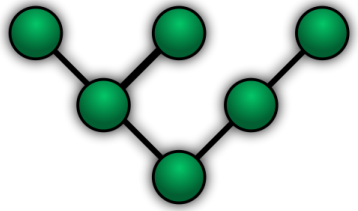


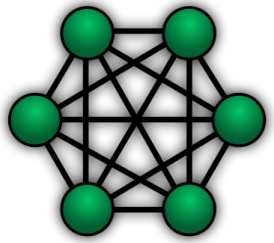
Stage I
Confidence



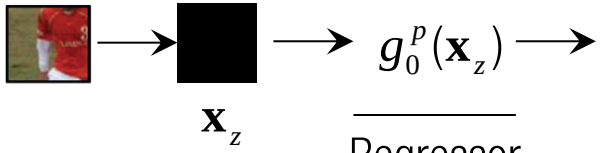
Stage II
Confidence

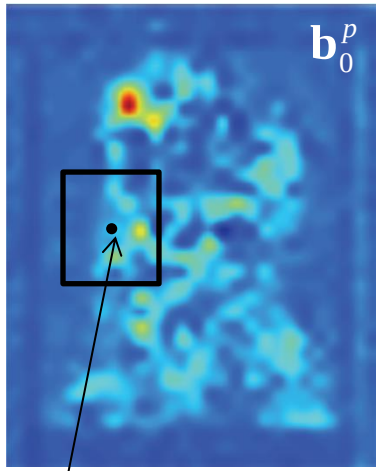
Stage III
Confidence





POSE INFERENCE MACHINE

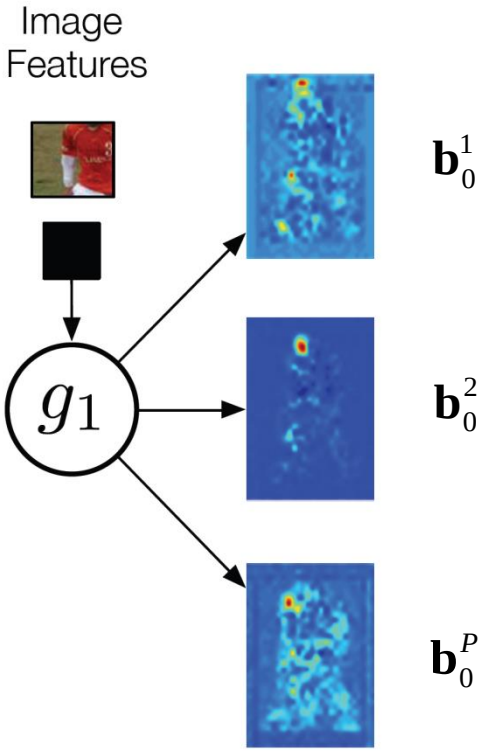


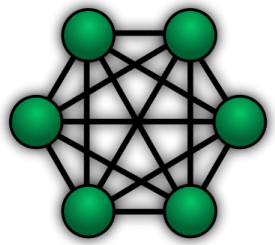


$b_0(Y_p = z) = g_0^p(\mathbf{x}_z)$

Y_p : location of p joint

POSE INFERENCE MACHINE





$$b_0(Y_p = z) = g_0^p(\mathbf{x}_z)$$

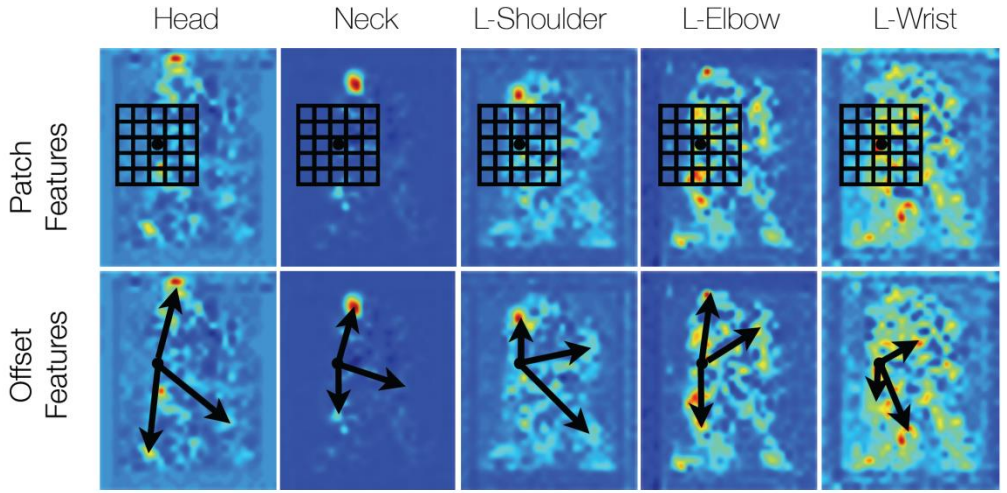
$$b_1(Y_p = z) = g_1^p(\mathbf{x}_z; \oplus\varphi(z; \mathbf{b}_0^p))$$

Context from previous prediction

Cf)

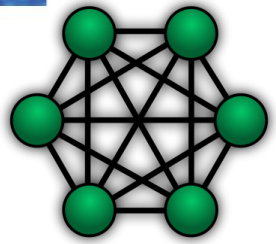
$$L(I,x) = \sum_{i \in V} \alpha_i \cdot \phi(I, x_i) + \sum_{i,j \in E} \beta_{ij} \cdot \varphi(x_i, x_j)$$

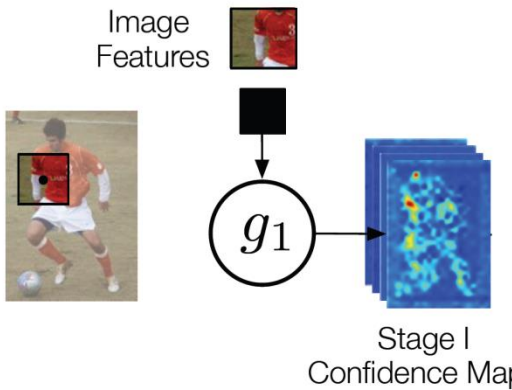
CONTEXT FEATURES



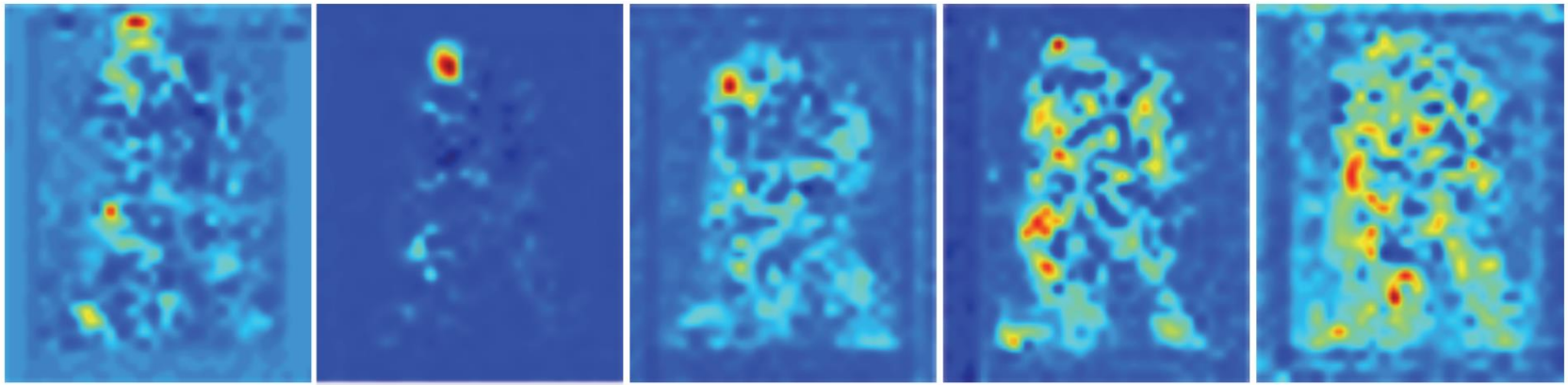
$$b_1(Y_p = z) = g_1^p(\mathbf{x}_z; \oplus\varphi(z; \mathbf{b}_0^p))$$

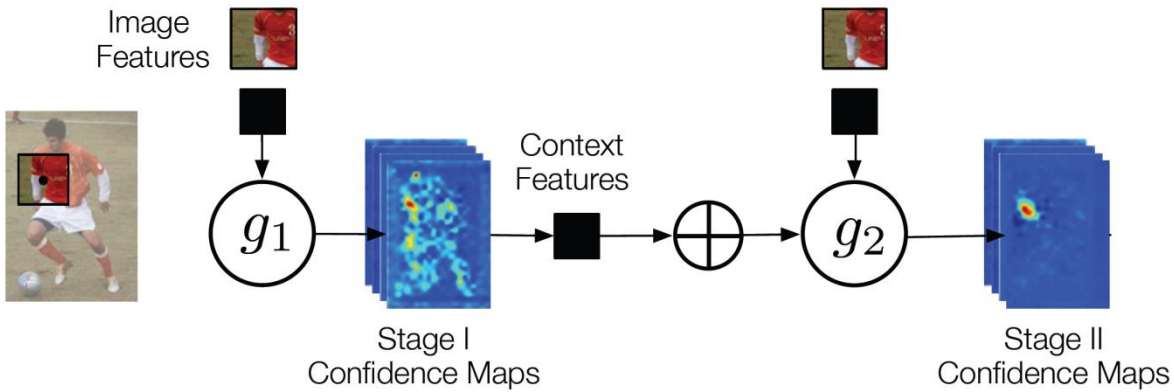
Context from previous prediction



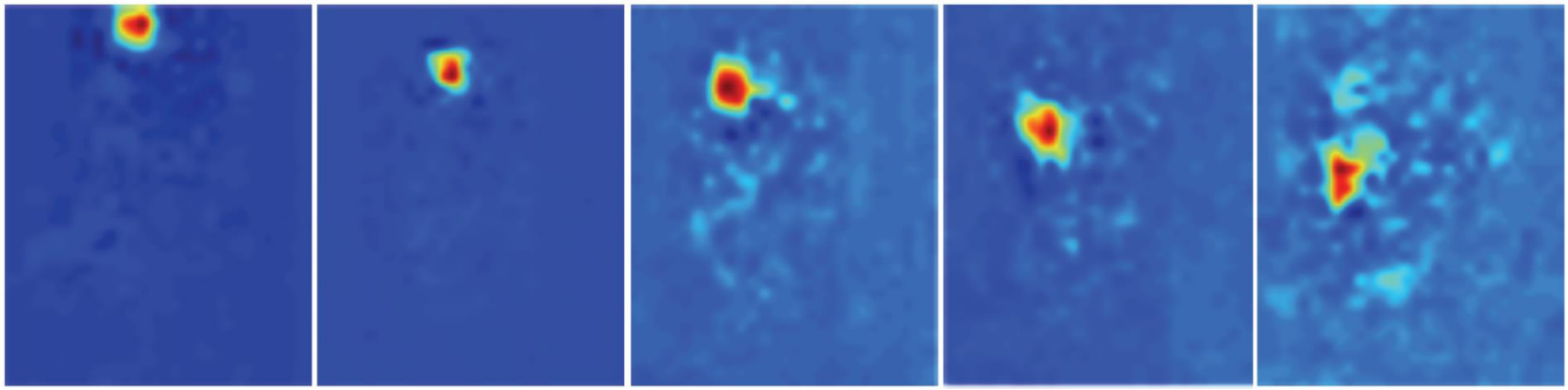


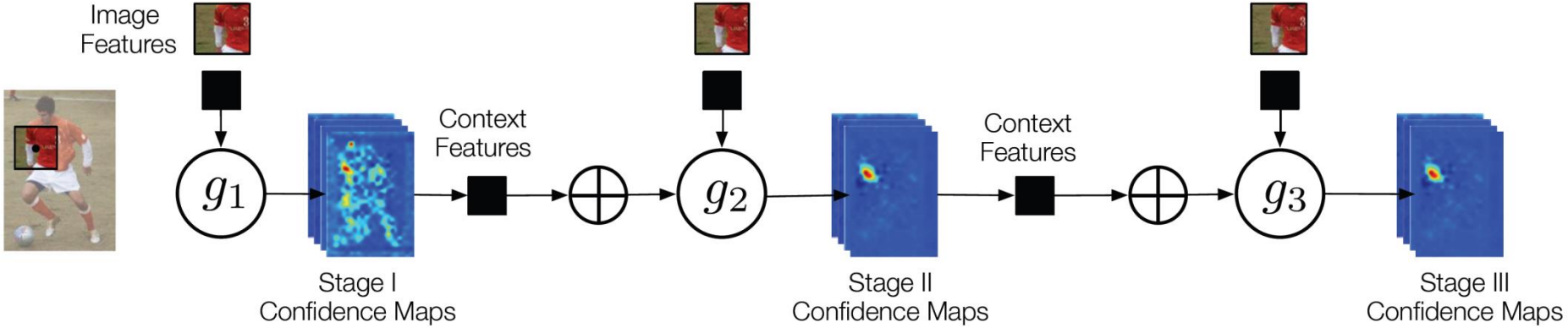
Stage I Confidence



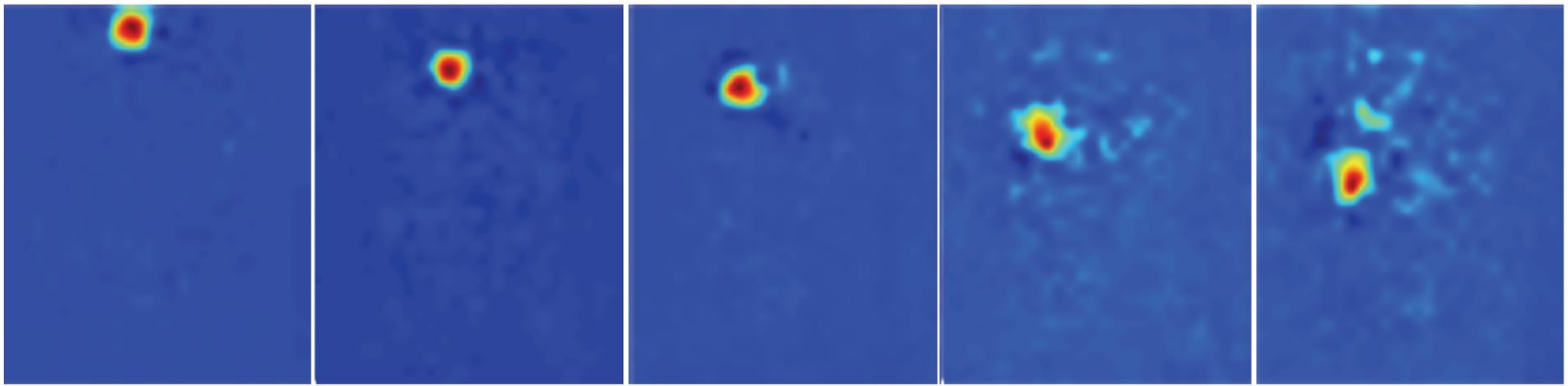


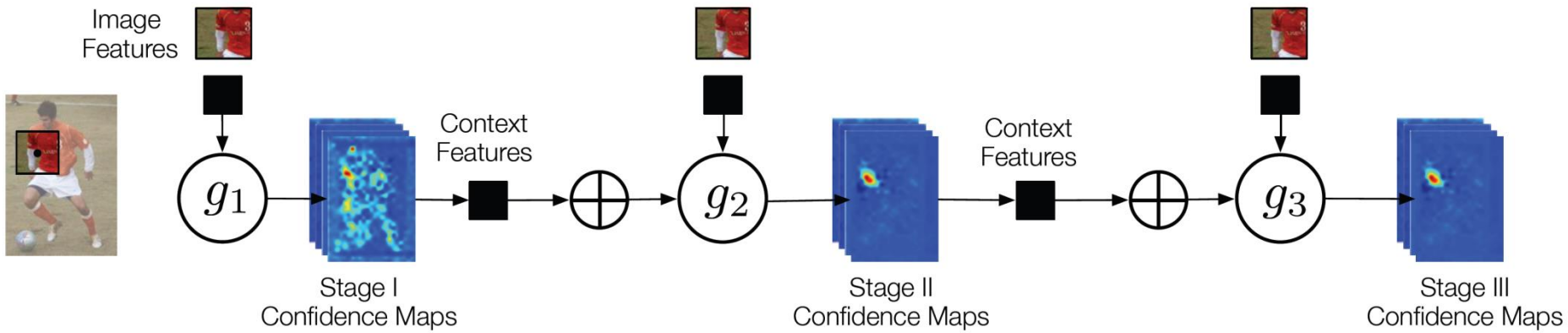
Stage II Confidence





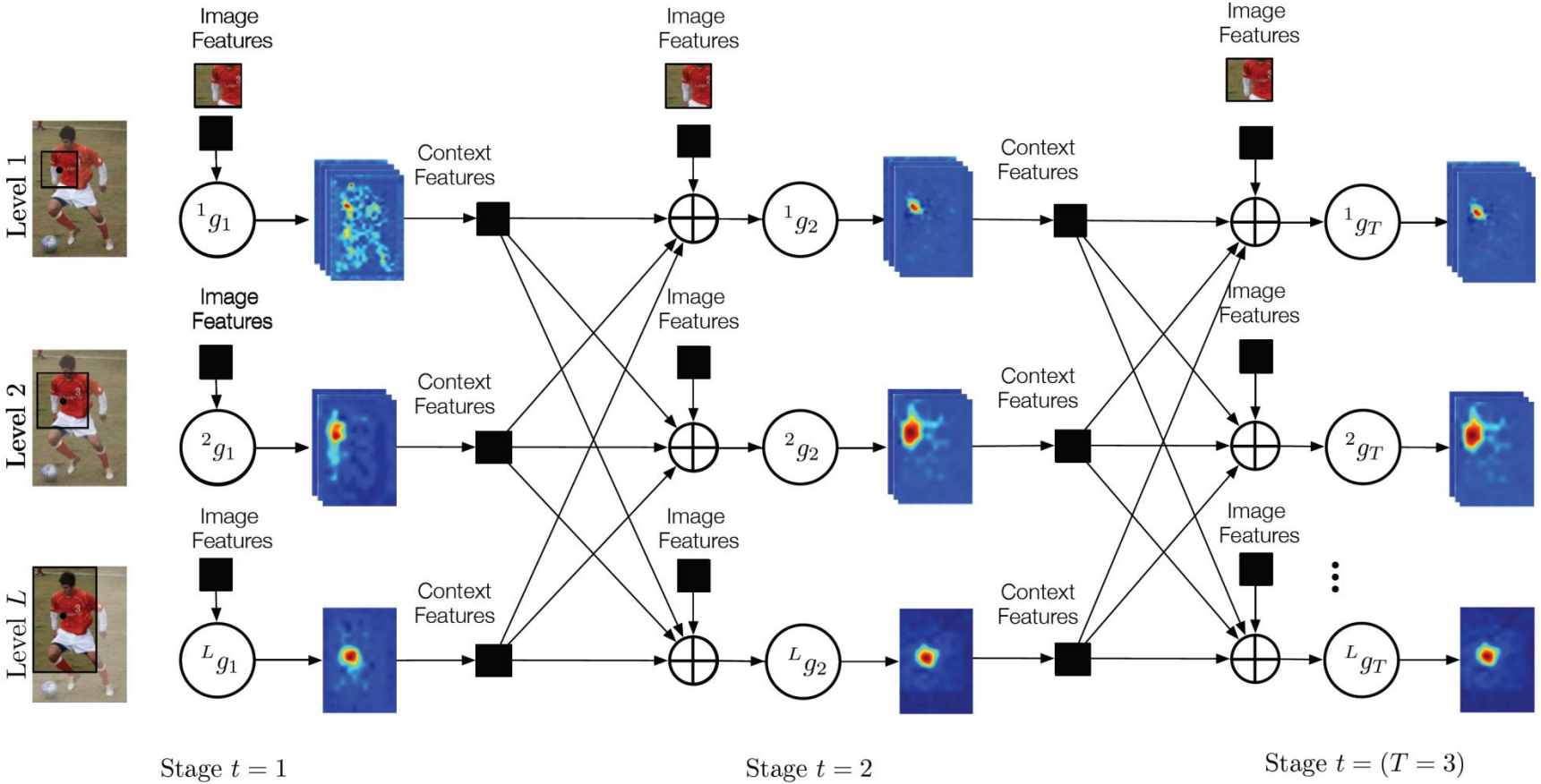
Stage III Confidence

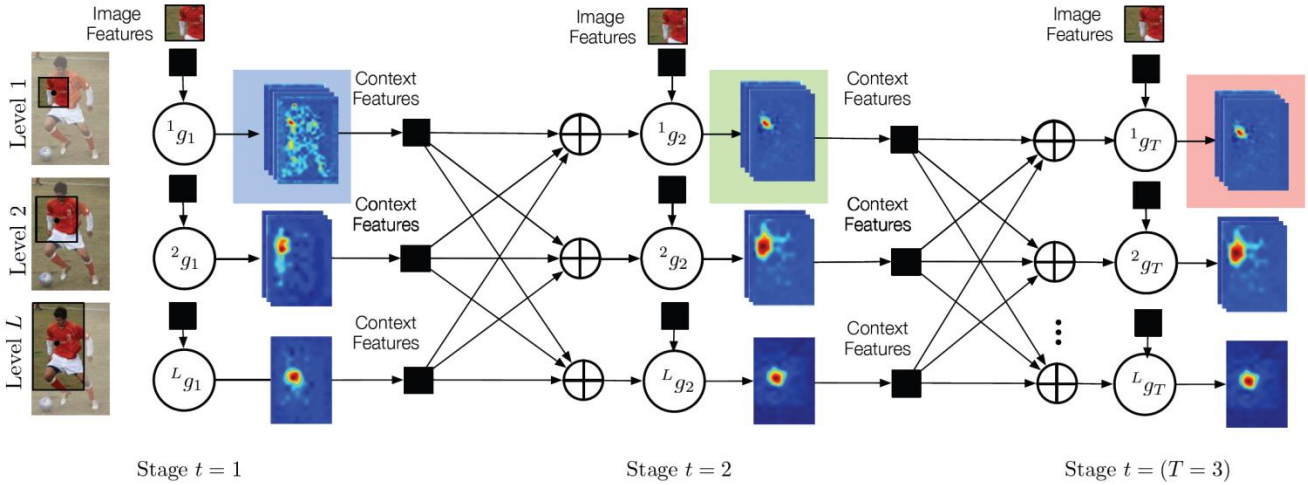




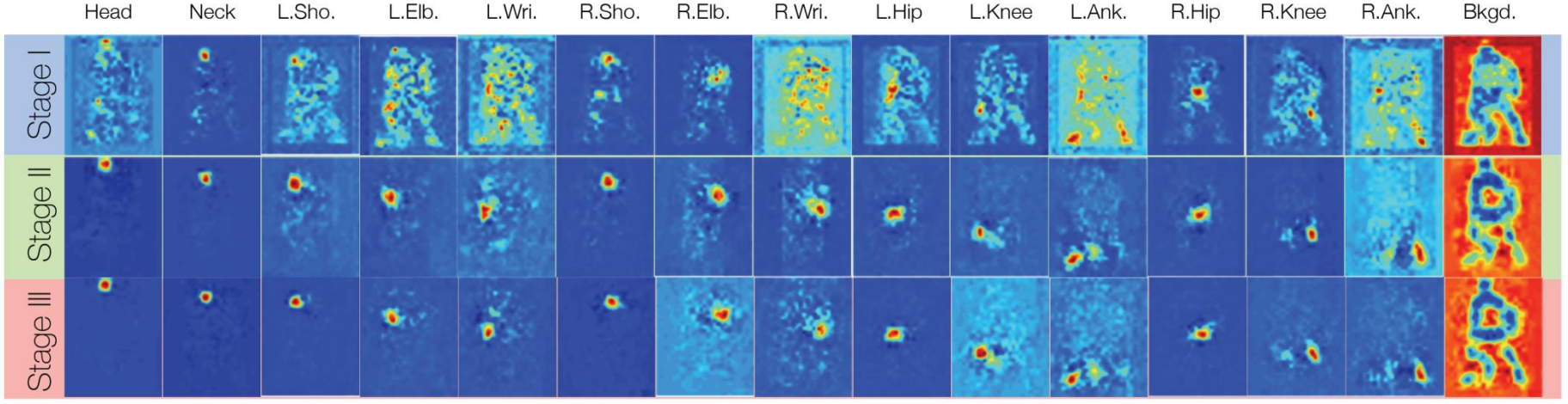
Stage III Confidence

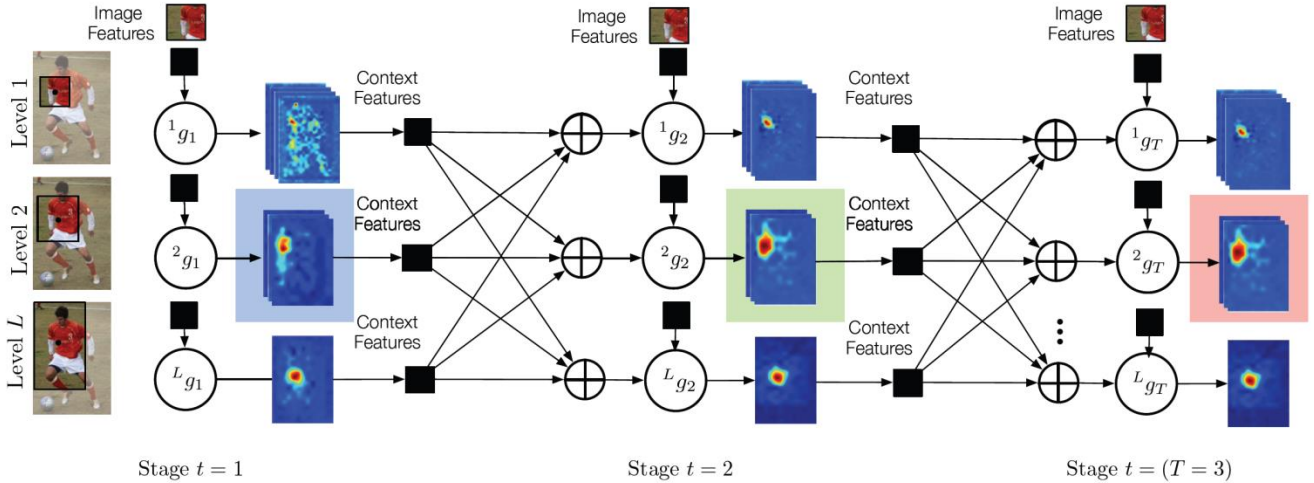
HIERACHICAL REPRESENTATION



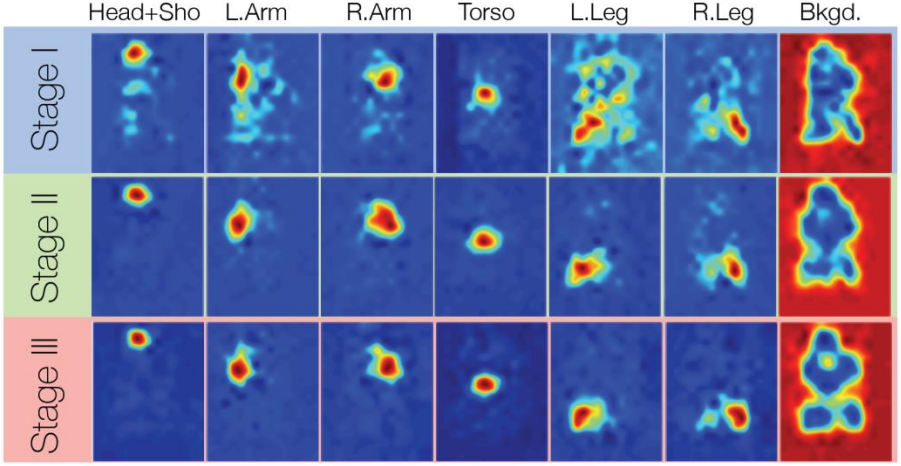


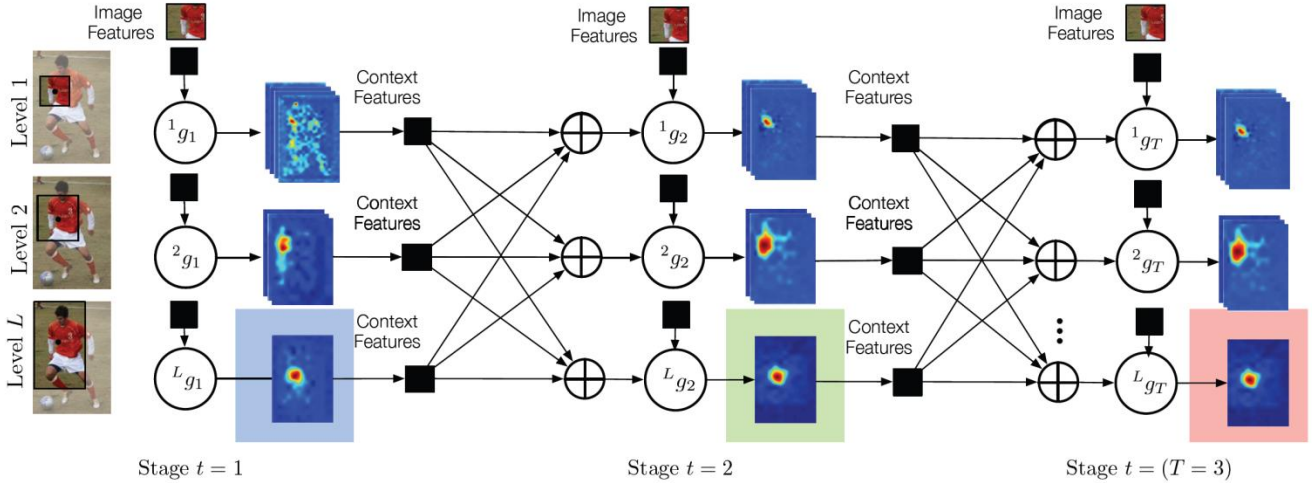
Level I Confidence Maps



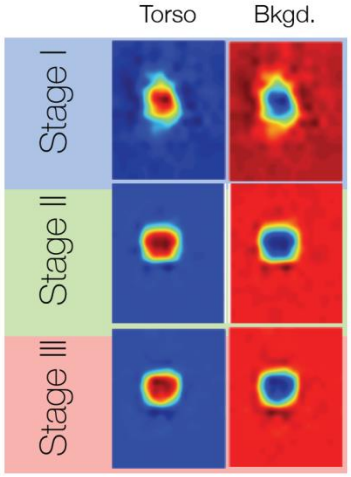


Level 2 Confidence Maps





Level 3 Confidence Maps



DATASETS

FLIC (Frame Labeled In Cinema) dataset (CVPR 2013)

- Human detection on Hollywood movies
- Mechanical Turker for annotation
- Upper body
- 20928 labeled images

DATASETS

MPII dataset (CVPR 2014)

- YouTube videos
- 25k images
- 40k humans
- Full body

DATASETS

MSCOCO dataset (ECCV 2014)

- Internet images
- 200k images
- 250k humans
- Full body

CVPR 2014

DeepPose: Human Pose Estimation via Deep Neural Networks

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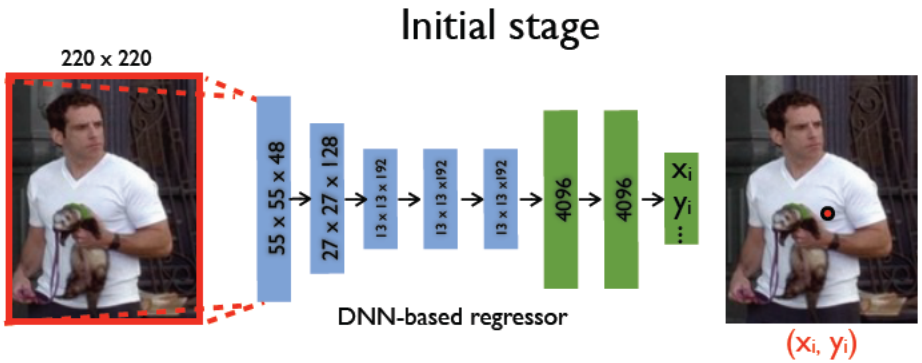
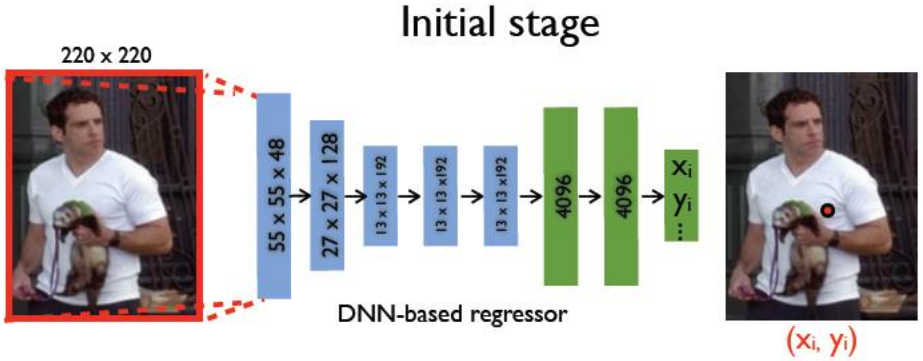
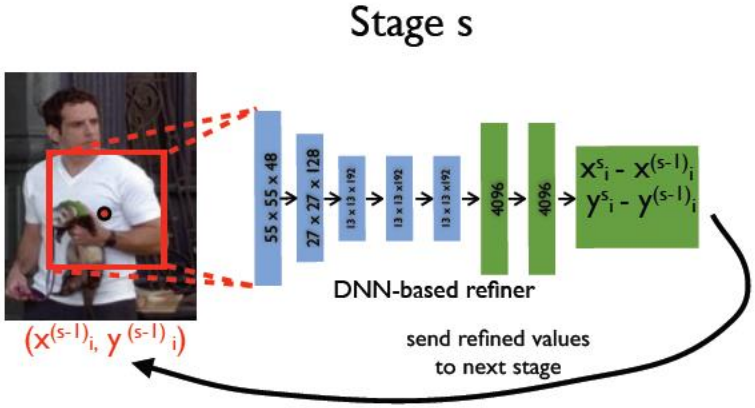
COORDINATE REGRESSION



$$\begin{bmatrix} x_1 \\ y_1 \\ \vdots \\ x_n \\ y_n \end{bmatrix} = z = f(I;\theta) \qquad \underset{\theta}{\operatorname{argmin}} \sum_i \left\| z_i - f(I_i;\theta) \right\|^2$$

COORDINATE REGRESSION



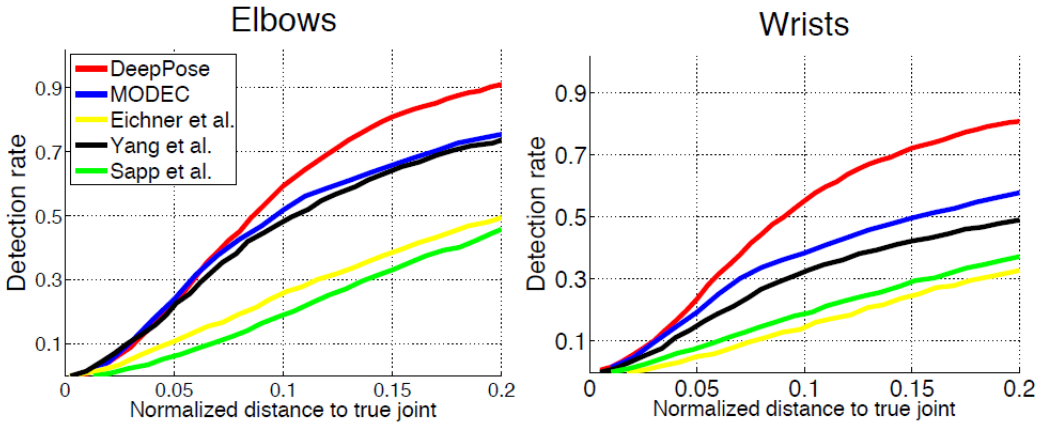


$$\begin{bmatrix} x_1 \\ y_1 \\ \vdots \\ x_n \\ y_n \end{bmatrix} = z = f(I;\theta)$$

$$\arg\min_{\theta} \sum_i \left\| z_i - f(I_i;\theta) \right\|^2$$

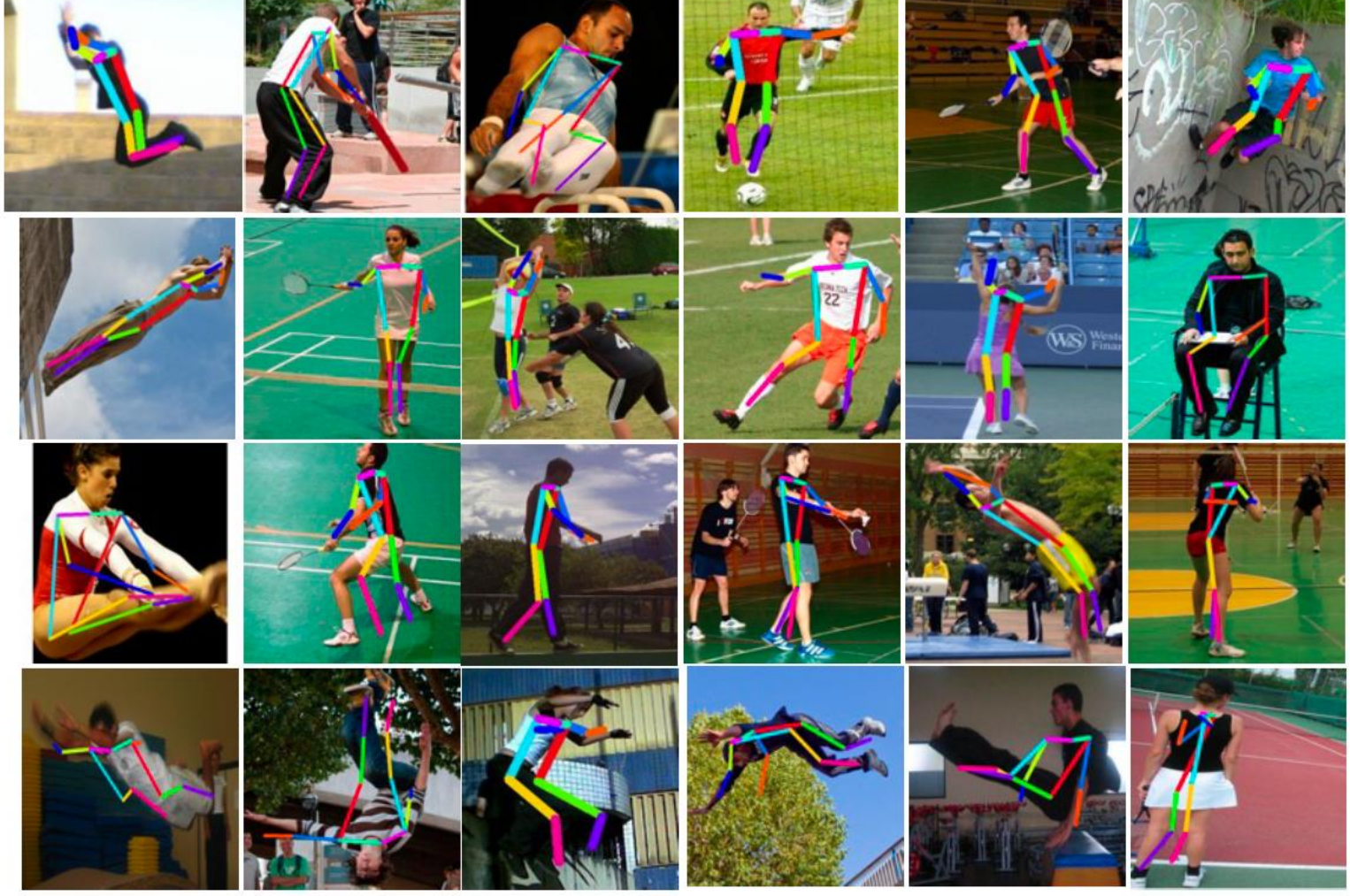
$$\arg\min_{\theta} \sum_i \left\| z_i - f(b(I_i);\theta) \right\|^2$$

Pose refinement in the bounding box



Method	Arm		Leg		Ave.
	Upper	Lower	Upper	Lower	
DeepPose-st1	0.5	0.27	0.74	0.65	0.54
DeepPose-st2	**0.56**	0.36	**0.78**	0.70	0.60
DeepPose-st3	**0.56**	**0.38**	0.77	**0.71**	**0.61**
Dantone et al. [2]	0.45	0.25	0.65	0.61	0.49
Tian et al. [25]*	0.52	0.33	0.70	0.60	0.56
Johnson et al. [13]	0.54	**0.38**	0.75	0.66	0.58
Wang et al. [26]*	**0.565**	0.37	0.76	0.68	0.59
Pishchulin [18]°	0.49	0.32	0.74	0.70	0.56

Figure 6. Predicted poses in red and ground truth poses in green for the first three stages of a cascade for three examples.



CVPR 2016

Convolutional Pose Machines

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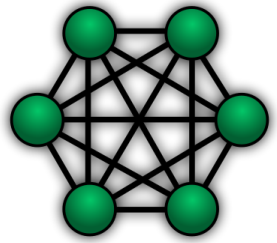
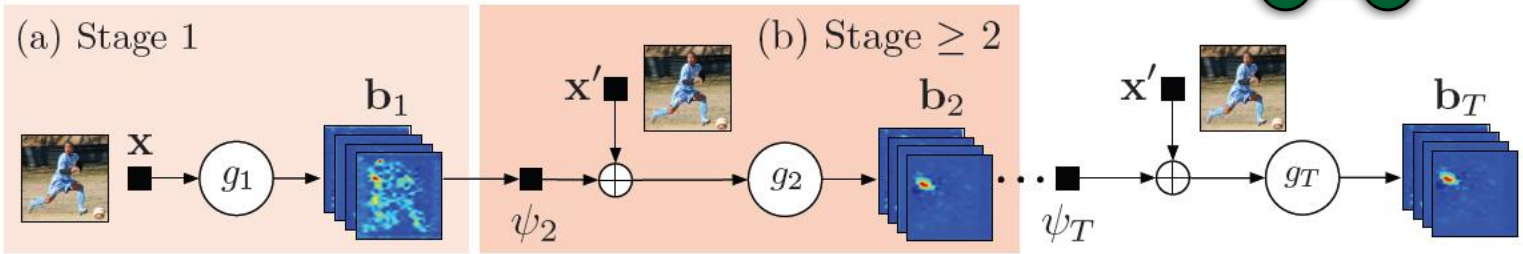
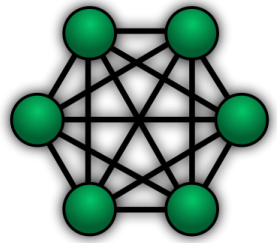
CONVOLUTIONAL POSE MACHINE (CPM)

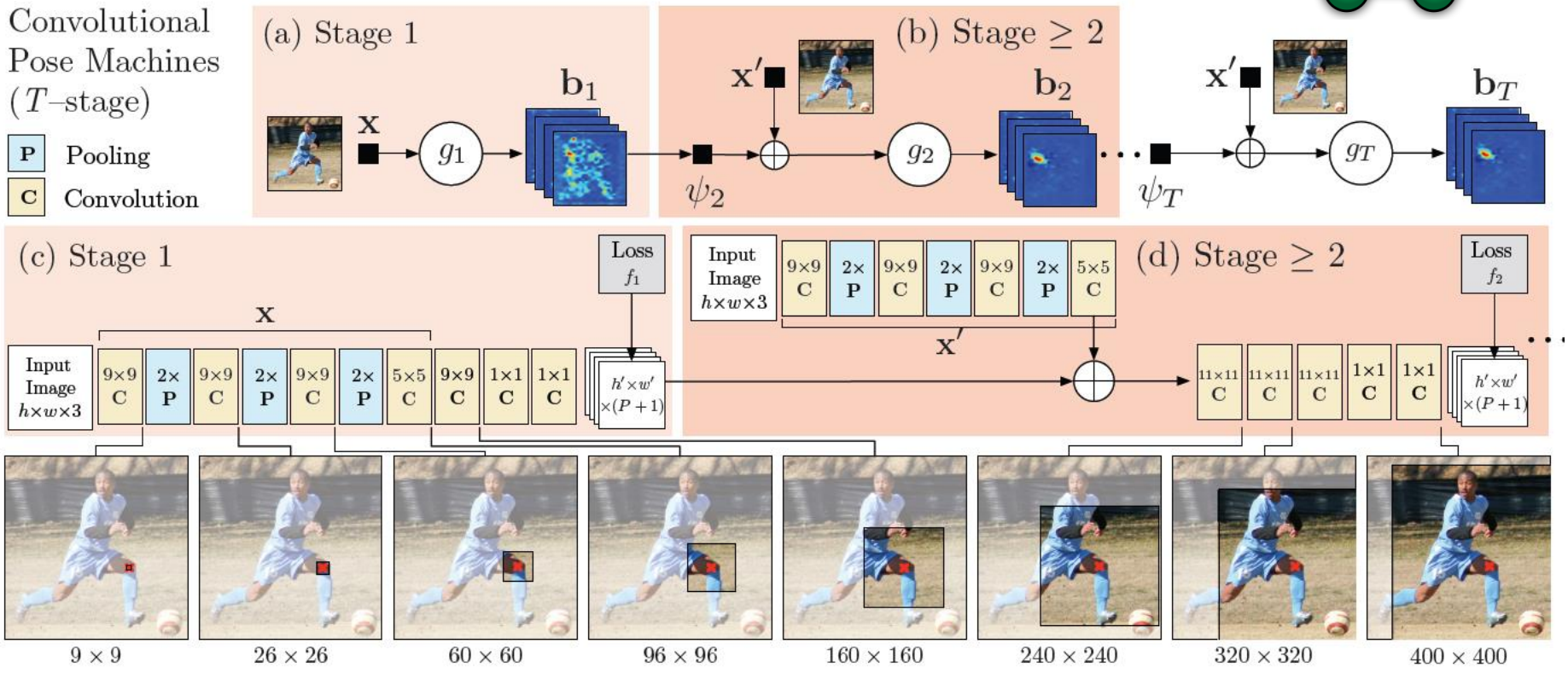


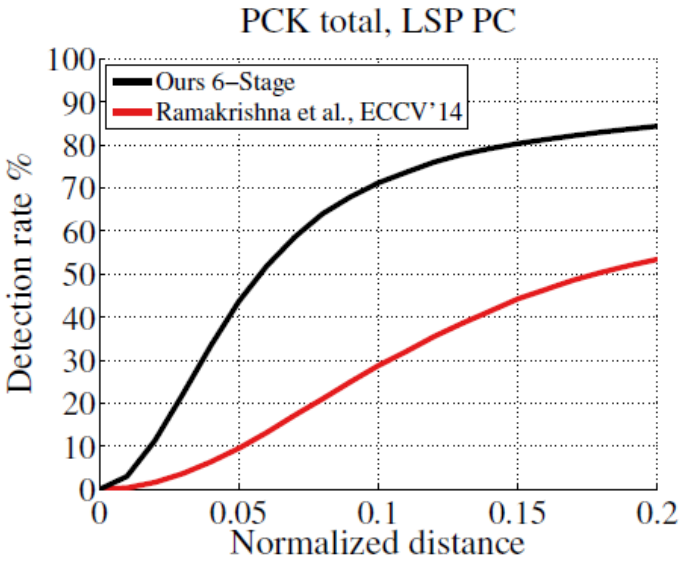
Pose machine

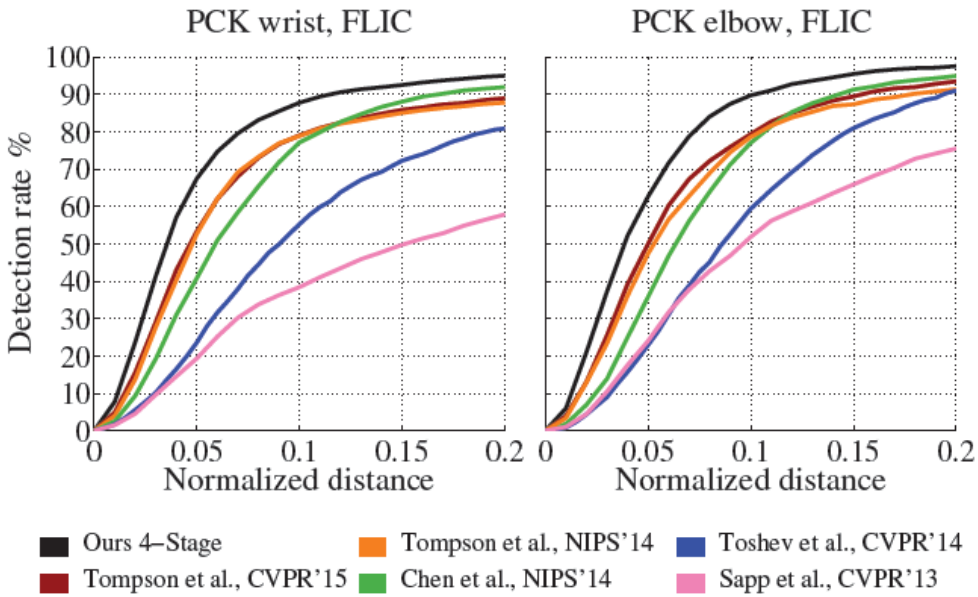


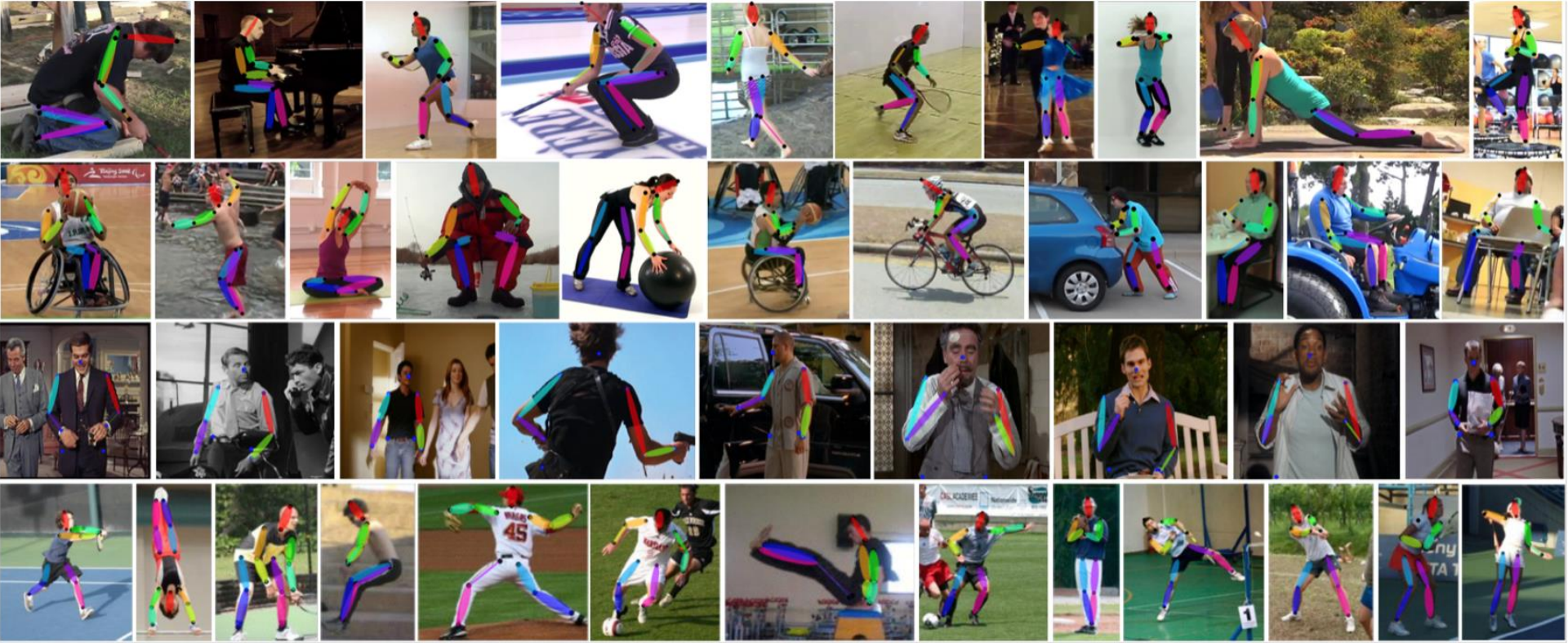
CONVOLUTIONAL POSE MACHINE (CPM)






PCK total, LSP PC
Ours 6–Stage
Ramakrishna et al., ECCV'14
Detection rate %
Normalized distance
0
10
20
30
40
50
60
70
80
90
100
0
0.05
0.1
0.15
0.2


PCK wrist, FLIC
PCK elbow, FLIC
Detection rate %
Normalized distance
Normalized distance
Ours 4–Stage
Tompson et al., CVPR'15
Tompson et al., NIPS'14
Chen et al., NIPS'14
Toshev et al., CVPR'14
Sapp et al., CVPR'13



CVPR 2017

Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields *

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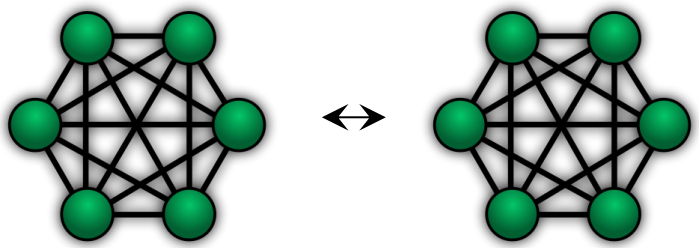
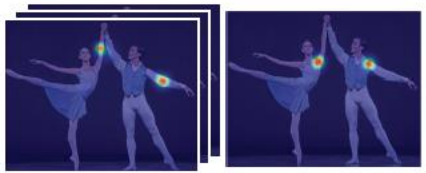


PART AFFINITY FIELDS

(a) Input Image

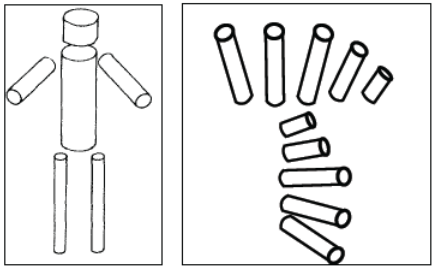


(b) Part Confidence Maps

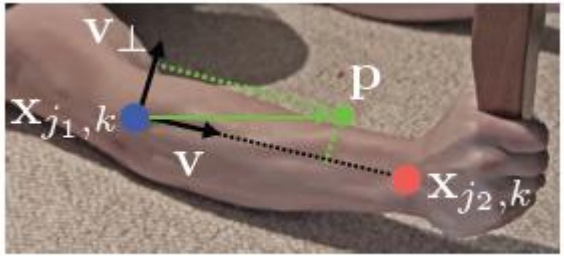
(c) Part Affinity Fields

(d) Bipartite Matching

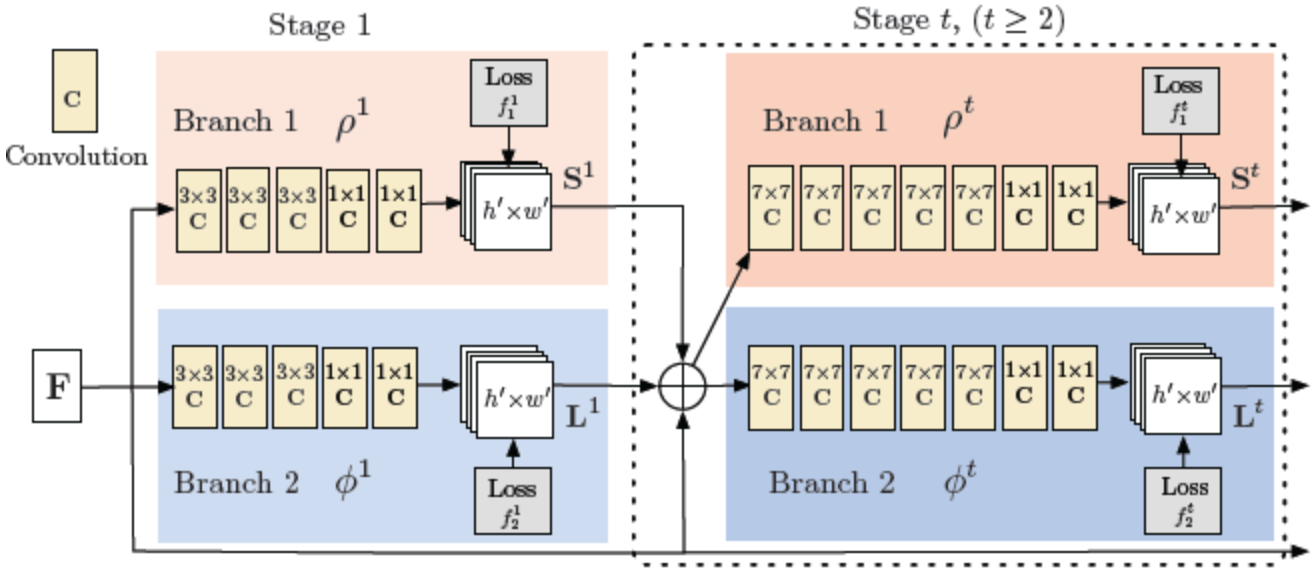
(e) Parsing Results



Marr, Nishihara (1978)



PART AFFINITY FIELDS



PAF inference

Joint inference

Part Affinity Fields Based Connection

Method	Hea	Sho	Elb	Wri	Hip	Kne	Ank	**mAP**	s/image
Subset of 288 images as in [22]									
Deepcut [22]	73.4	71.8	57.9	39.9	56.7	44.0	32.0	54.1	57995
Iqbal et al. [12]	70.0	65.2	56.4	46.1	52.7	47.9	44.5	54.7	10
DeeperCut [11]	87.9	84.0	71.9	63.9	68.8	63.8	58.1	71.2	230
Ours	**93.7**	**91.4**	**81.4**	**72.5**	**77.7**	**73.0**	**68.1**	**79.7**	**0.005**
Full testing set									
DeeperCut [11]	78.4	72.5	60.2	51.0	57.2	52.0	45.4	59.5	485
Iqbal et al. [12]	58.4	53.9	44.5	35.0	42.2	36.7	31.1	43.1	10
Ours (one scale)	89.0	84.9	74.9	64.2	71.0	65.6	58.1	72.5	0.005
Ours	**91.2**	**87.6**	**77.7**	**66.8**	**75.4**	**68.9**	**61.7**	**75.6**	**0.005**

- https://www.youtube.com/watch?v=pW6nZXeWIGM