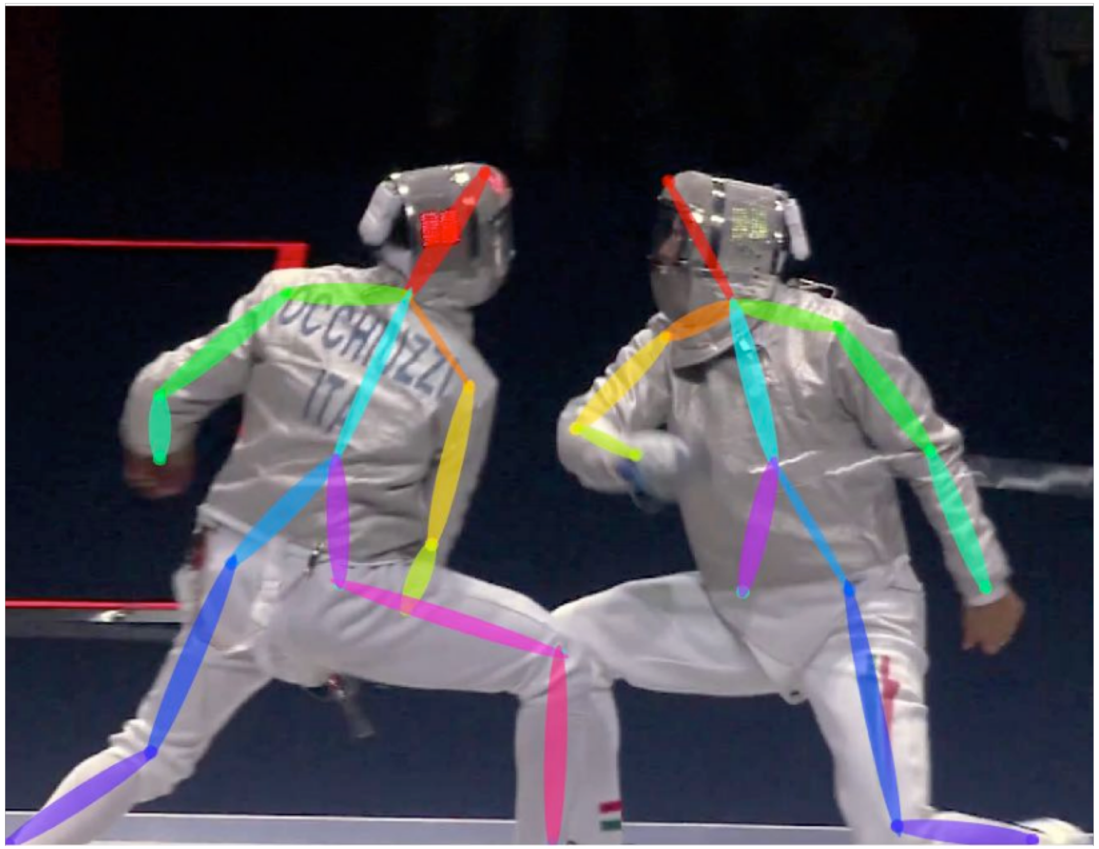
Human pose estimation

The task

- Mark joint locations for person
- Nose
- Right/left shoulder
- Right/left elbow
- Right/left hip
- …



Two versions of task

- Assume people have been detected
- Rough bounding box given
- Key info available:
  - scale
  - only 1 location per joint
- Pros: disentangles detection and pose estimation
- Cons: unrealistic

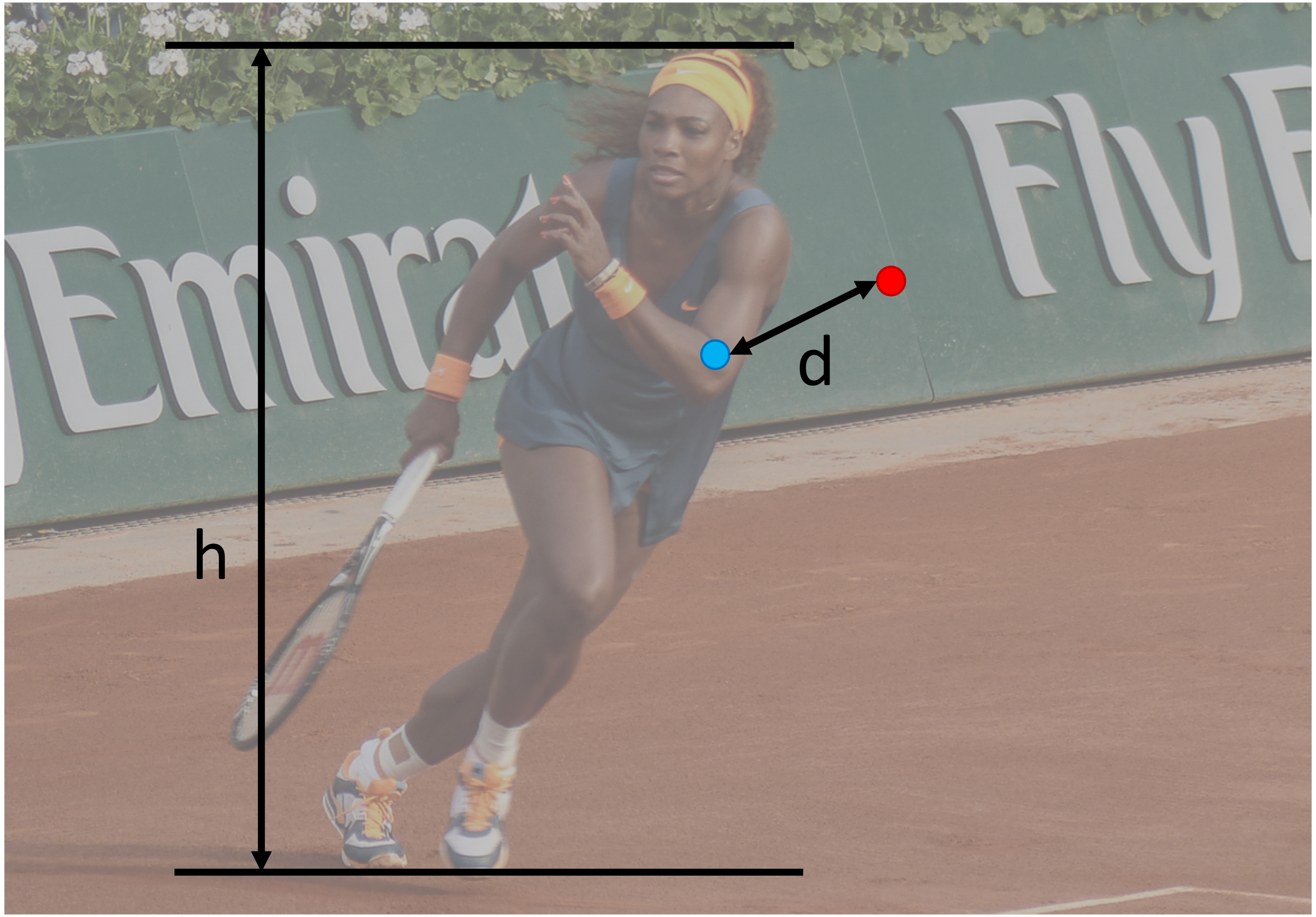
- Tabula rasa without detections
- Challenge: no idea of scale or number
- Possible opportunity: use keypoint estimates to improve detections
- Pros: realistic
- Cons: conflates detection and pose estimation

Pose estimation given detection

Evaluation metric - given detection

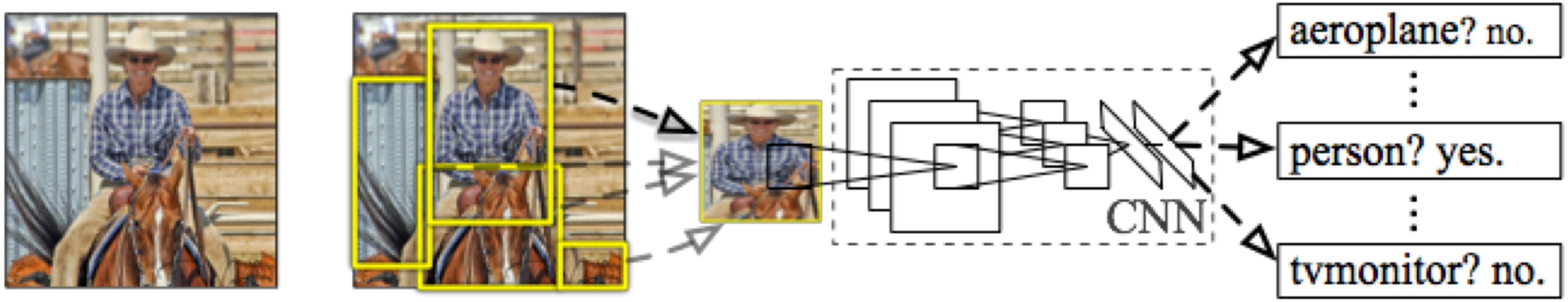
- Evaluate every keypoint separately
- For each person, check if keypoint is correct
- Compure fraction of people for which keypoint is correct: PCK (*Probability of Correct Keypoint*)

Evaluation metric - given detection



d/h < α ?

R-CNN: Regions with CNN features

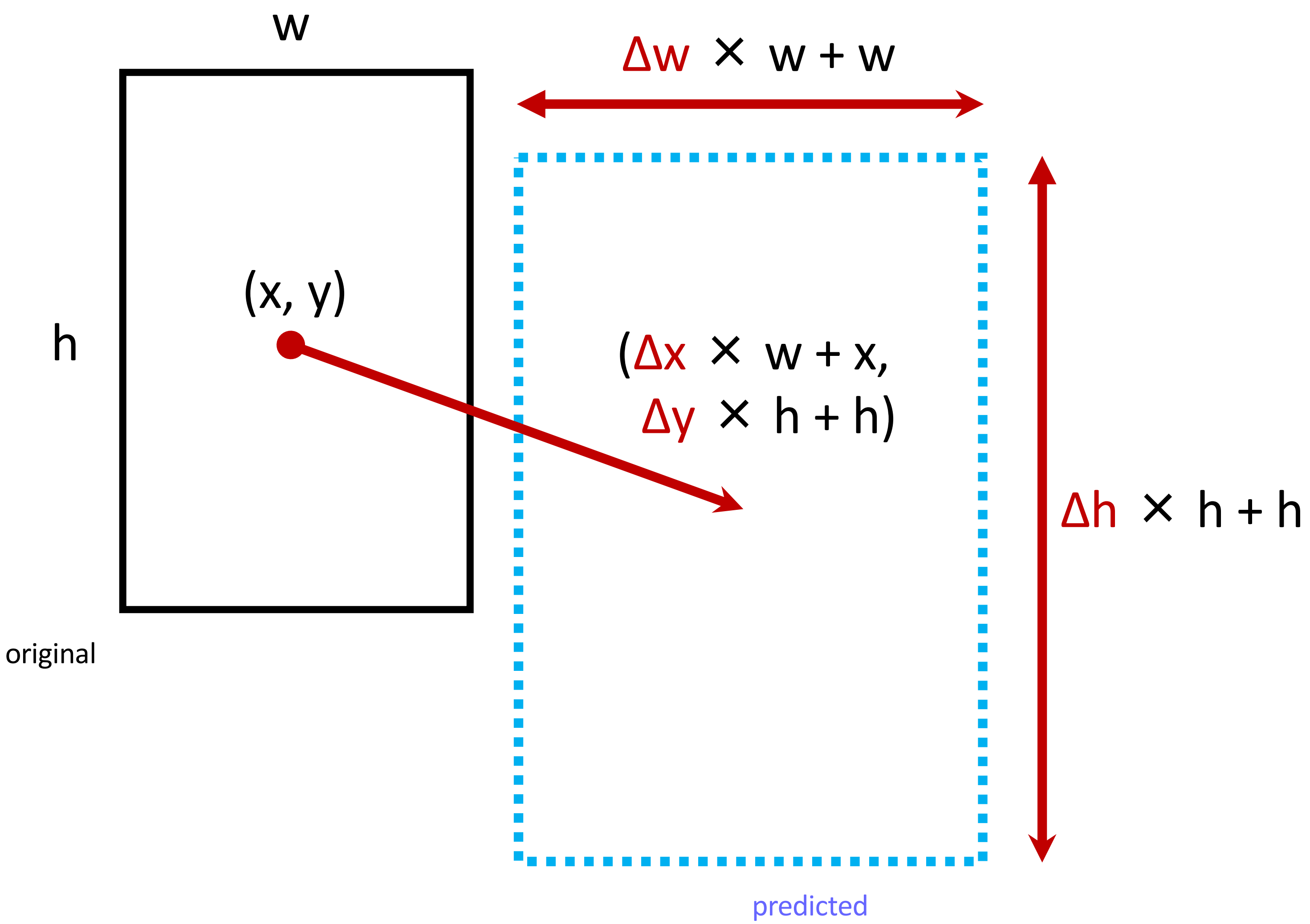


Input image | Extract region proposals (~2k / image) | Compute CNN features | Classify regions (linear SVM)

Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation
R. Girshick, J. Donahue, T. Darrell, J. Malik
IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2014

Slide credit : Ross Girshick

Bounding-box regression



Slide credit : Ross Girshick

Strategy 1: Regression

Right elbow x: 0.45
Right elbow y: 0.12
Left elbow x: 0.98
...

Regression targets relative to bounding box

DeepPose: Human Pose Estimation via Deep Neural Networks. Alexander Toshev and Christian Szegedy. In *CVPR,* 2014.

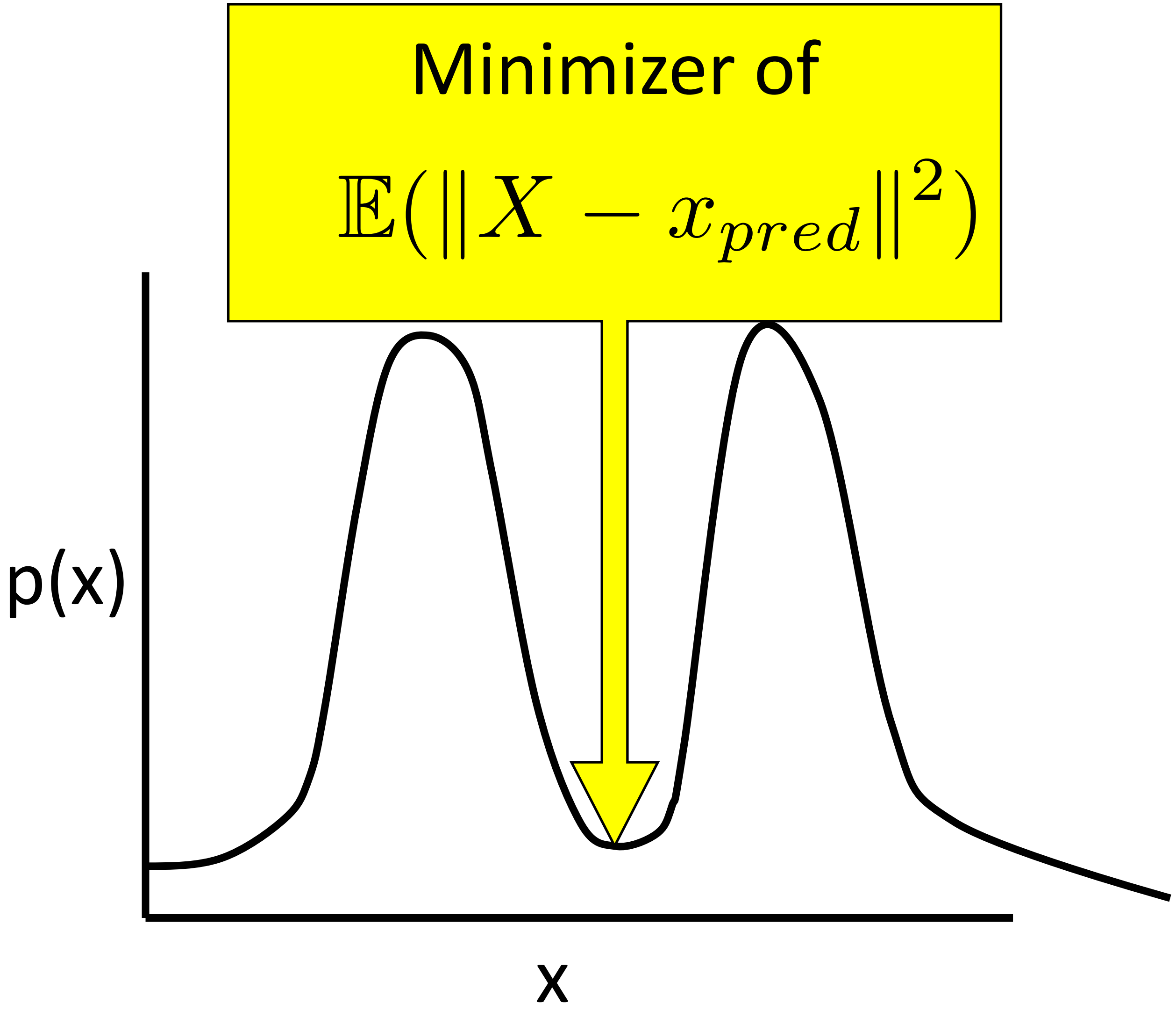
Strategy 1: Regression

- Assumes global object features has enough information for accurate localization
  - Localization info missing due to subsampling?
- Solution: Refinement!

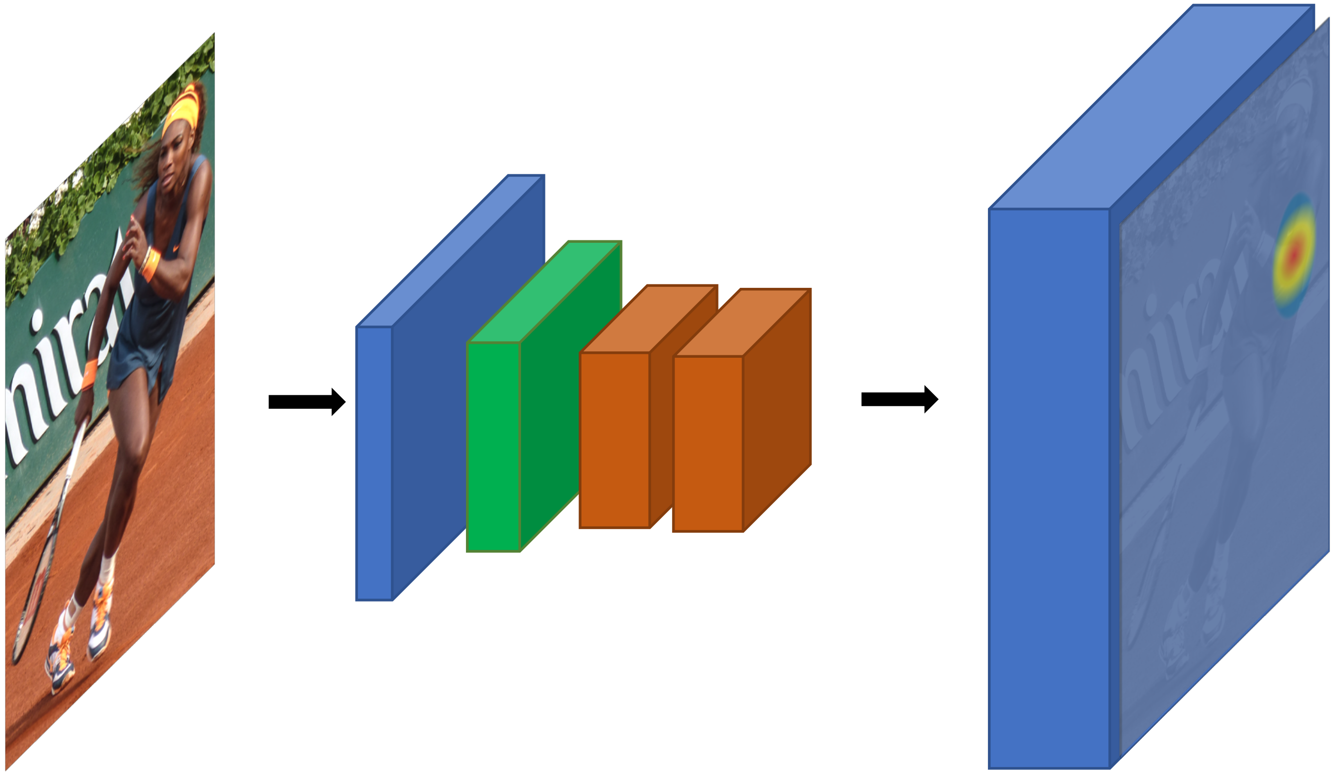
DeepPose: Human Pose Estimation via Deep Neural Networks. Alexander Toshev and Christian Szegedy. In *CVPR,* 2014.

Strategy 1: Regression

- Multimodal distributions?



Strategy 2: Heatmaps



Strategy 2: Heatmaps - Training

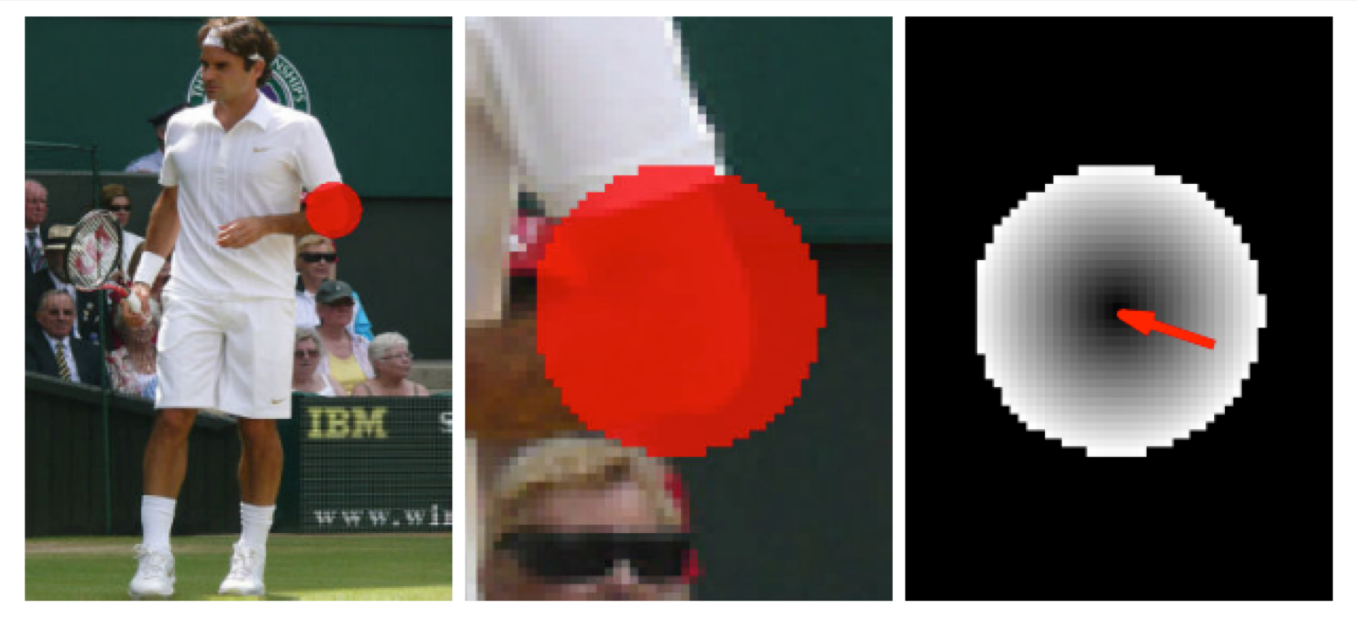
- Each keypoint is a separate binary heatmap
- Keypoint location is positive, all other locations are negative. Options:
  - *Softmax* over all locations in an image
    - $p(x, y) = \frac{e^{s(x,y)}}{\sum_{x',y'} e^{s(x',y')}}$
  - *Sigmoid* at each location
    - $p(x, y) = \frac{1}{1+e^{-s(x,y)}}$

Strategy 2: Heatmaps

- Still have the resolution issue
- Same solutions
  - Dilation?
  - Multiple layers?
  - Multiple image scales?

Heatmaps + Regression

- Use heatmap to predict coarse location
- Also predict at each coarse location an *offset* $(\Delta x, \Delta y)$.



Papandreou, George, et al. "Towards accurate multi-person pose estimation in the wild." *CVPR*. Vol. 3. No. 4. 2017.

Are all keypoints independent given the image?

Equally likely locations for
right elbow

Equally likely locations for
right wrist

Are all keypoints independent given the image?

Capturing keypoint dependence!

- **Structured prediction**
- **l** is a candidate location for each keypoint

Consistency between joints

$$E(\mathbf{l}) = \sum_i s_i(l_i) + \phi(\mathbf{l})$$

Score from heatmap

Are all keypoints independent?

- **l** is a candidate location for each keypoint

Consistency between joints

$$E(\mathbf{l}) = \sum_i s_i(l_i) + \sum_{ij} \phi_{ij}(l_i, l_j)$$

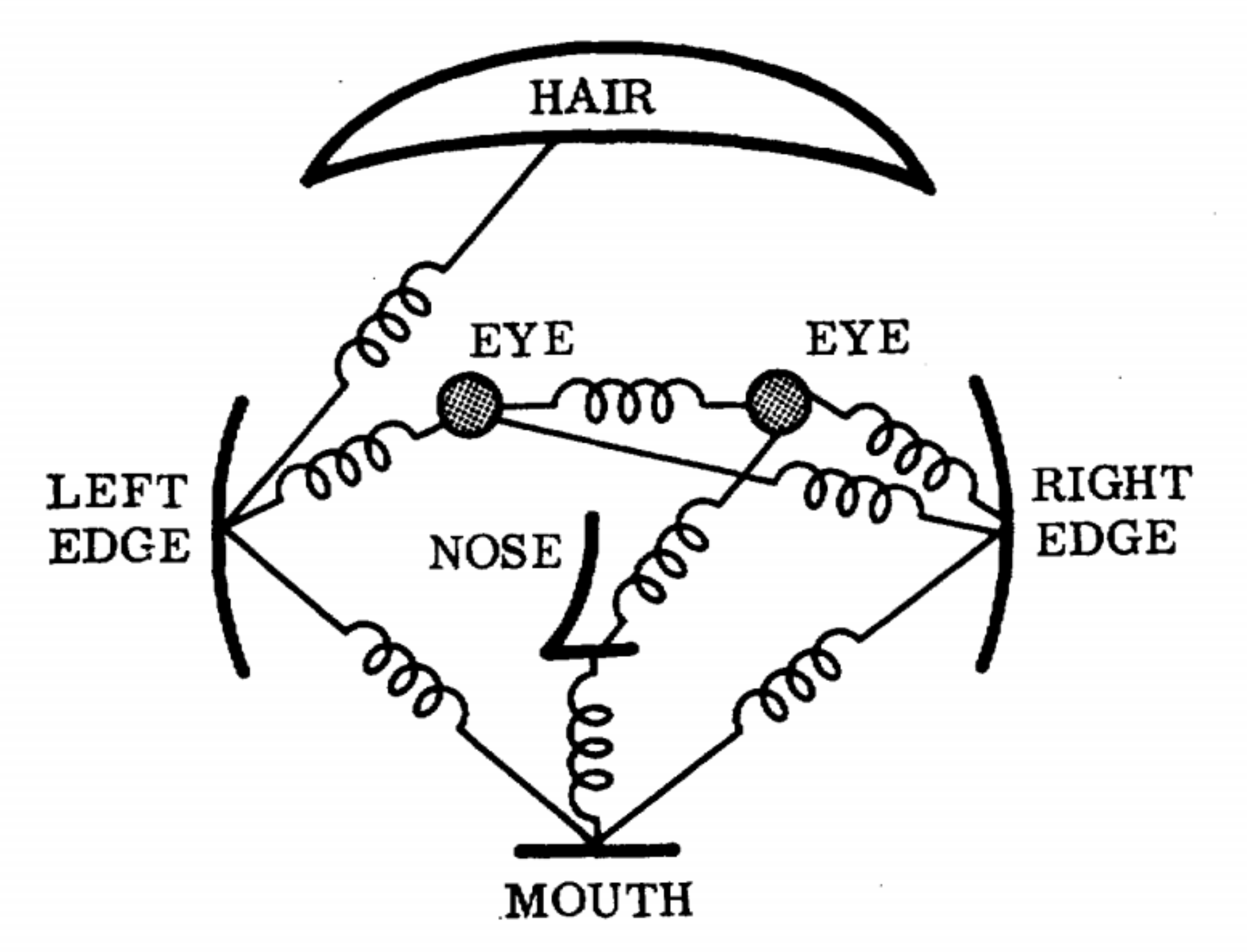
Score from heatmap

Joint prediction of keypoints

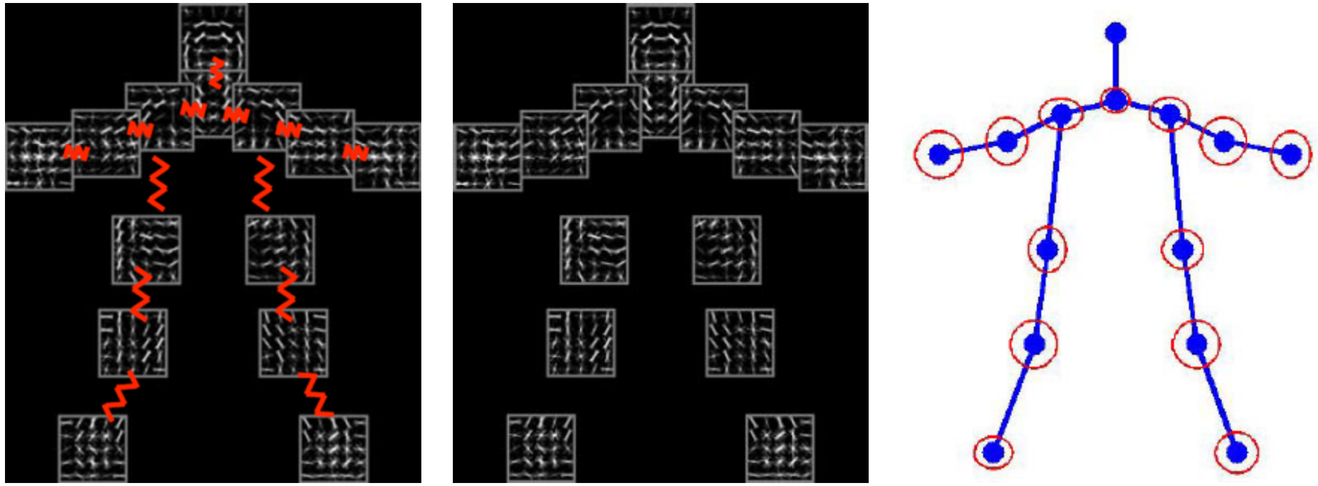
$$\mathbf{l}^* = \arg\min E(\mathbf{l})$$

- Conditional Random Field
- But not just smoothness: ϕ is unknown!
- Needs to be learnt

Pictorial structures



Flexible Mixture of Parts



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

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

Articulated Human Pose Estimation with Flexible Mixtures of Parts. Yi Yang and Deva Ramanan. *TPAMI* 2013.

Slide credit: Yang et al

Flexible Mixture of Parts

- Learning?
- Structured SVMs
  - Very large output spaces
  - A scoring function that scores input-output pairs $h_{\mathbf{w}}(x, \mathbf{y})$
  - Predicted output is arg max of scoring function
  - Loss is margin rescaled loss

Support vector machine learning for interdependent and structured output spaces. Tsochantaridis I, Hofmann T, Joachims T, Altun Y. In *ICML,* 2004

Inference?

$$E(\mathbf{l}) = \sum_i s_i(l_i) + \sum_{ij} \phi_{ij}(l_i, l_j)$$

$$\mathbf{l}^* = \arg\min E(\mathbf{l})$$

$$\min_{\mathbf{l}} \sum_i s_i(l_i) + \sum_{ij} \phi_{ij}(l_i, l_j)$$

$$l_i^* = \arg\min_{l_i} s_i(l_i) + \sum_j \phi_{ij}(l_i, l_j^*)$$

$$l_i^{(t+1)} \leftarrow \arg\min_{l_i} s_i(l_i) + \sum_j \phi_{ij}(l_i, l_j^{(t)})$$

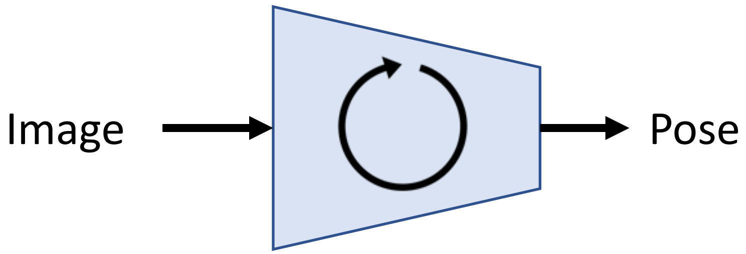
Iterative models

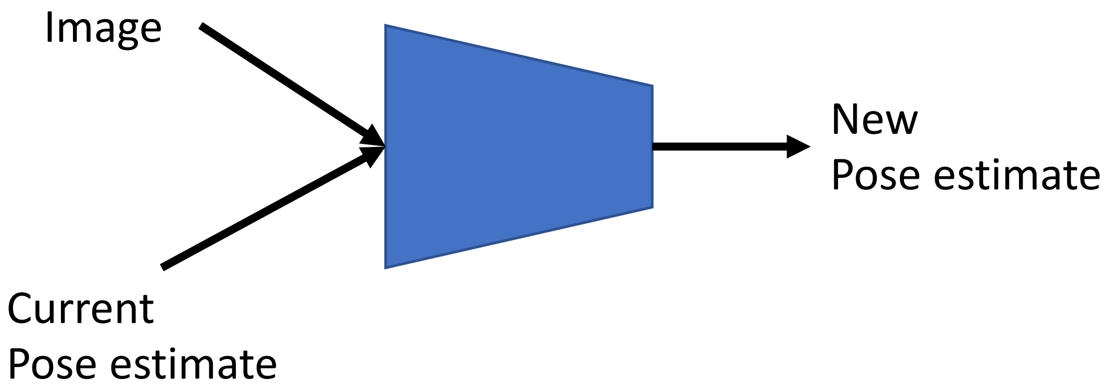
- Inference in MRFs and CRFs usually iterative and approximate

$$l_i^{(t+1)} \leftarrow \arg\min_{l_i} s_i(l_i) + \sum_j \phi_{ij}(l_i, l_j^{(t)})$$

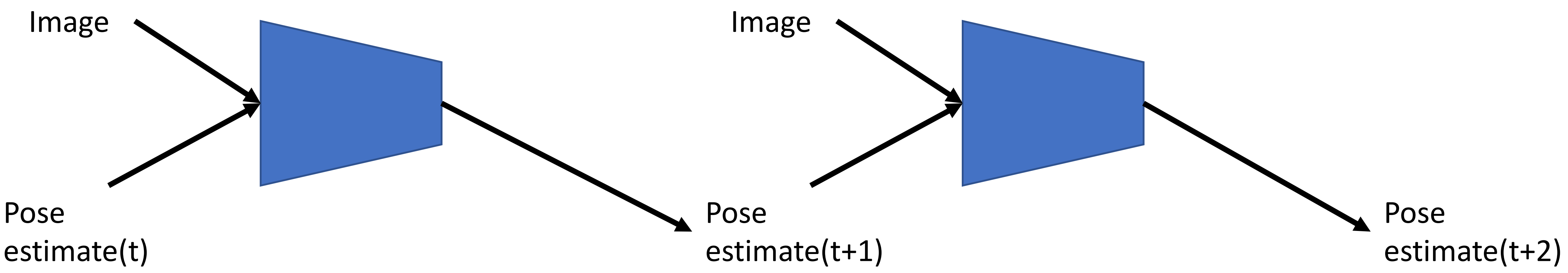
  - Except trees: FMP
- Instead of learning scoring function, then *approximately* minimizing it
- Learn iterative inference procedure?
  - Similar to autocontext/inference machines

Autocontext and Inference Machines





Autocontext and Inference Machines



- Shared parameters: *Inference Machines*
- Unshared parameters: *Autocontext*

Auto-context and Its Application to High-level Vision Tasks. Zhuowen Tu. In *CVPR* 2008.
Learning Message-Passing Inference Machines for Structured Prediction. Stephane Ross, Daniel Munoz, Martial Hebert, J. Andrew Bagnell. In *CVPR* 2011.

Iterative models

- In each iteration, beliefs of one variable are updated using current beliefs of the others

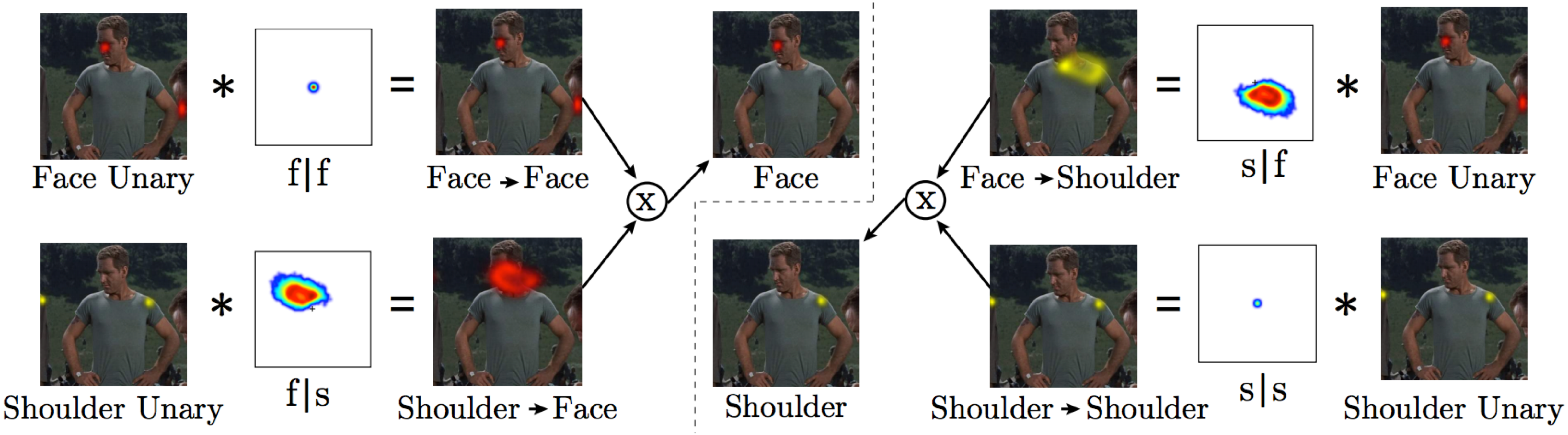
$$l_i^{(t+1)} \leftarrow \arg\min_{l_i} s_i(l_i) + \sum_j \phi_{ij}(l_i, l_j^{(t)})$$

- Frame each iteration of inference as a differentiable function
- Write inference as a convolutional network

Joint Training of a Convolutional Network and a Graphical Model for Human Pose Estimation. Jonathan Tompson, Arjun Jain, Yann LeCun, Christoph Bregler. In *NIPS,* 2014.

Iterative models

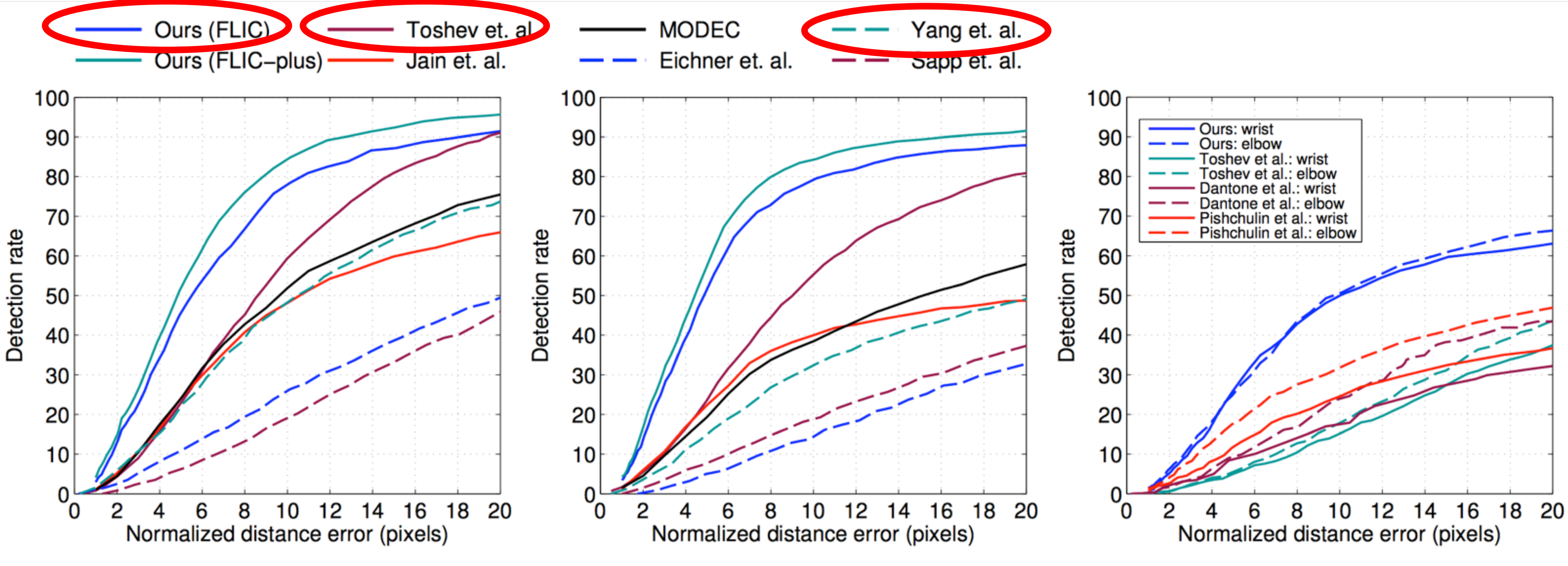
- P(eye at p) = $\sum_q$ P(eye at p | nose at q) P (nose at q)
- P(eye at p | nose at q) only depends on relative location of p and q
- $f(p) = \sum_q w(p - q)\, g(q)$: convolution!
- $f = w * g$



Iterative models

Mixture of parts

Regression

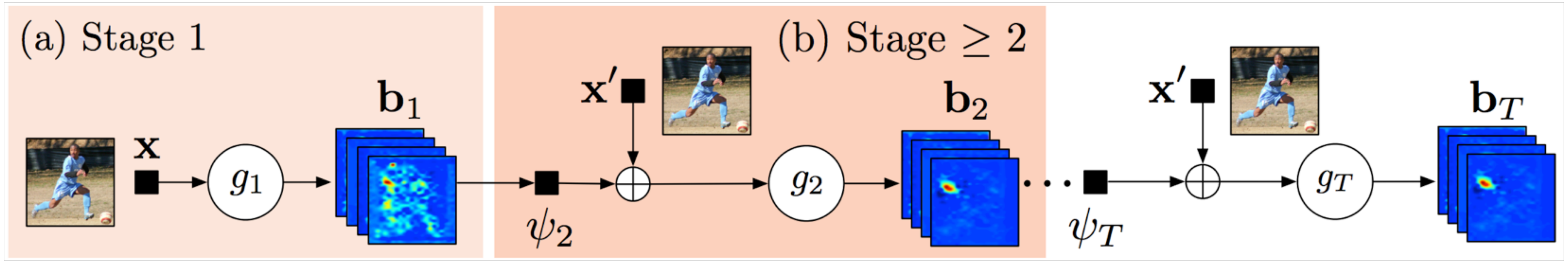


(a) FLIC: Elbow (b) FLIC: Wrist (c) LSP: Wrist and Elbow

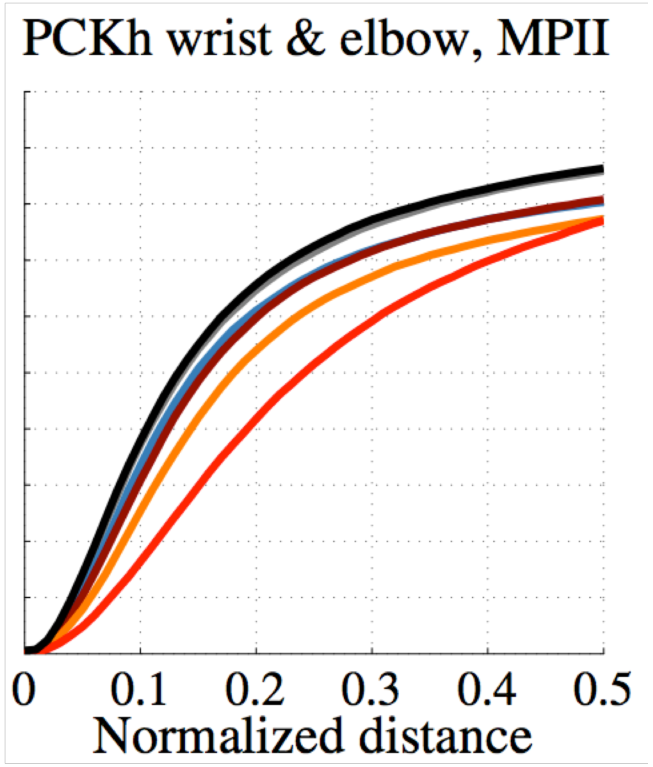
Joint Training of a Convolutional Network and a Graphical Model for Human Pose Estimation. Jonathan Tompson, Arjun Jain, Yann LeCun, Christoph Bregler. In *NIPS,* 2014.

More iterative models

- Why only one convolution?
- Each iteration can involve multiple convolution/subsampling layers over beliefs from previous iteration



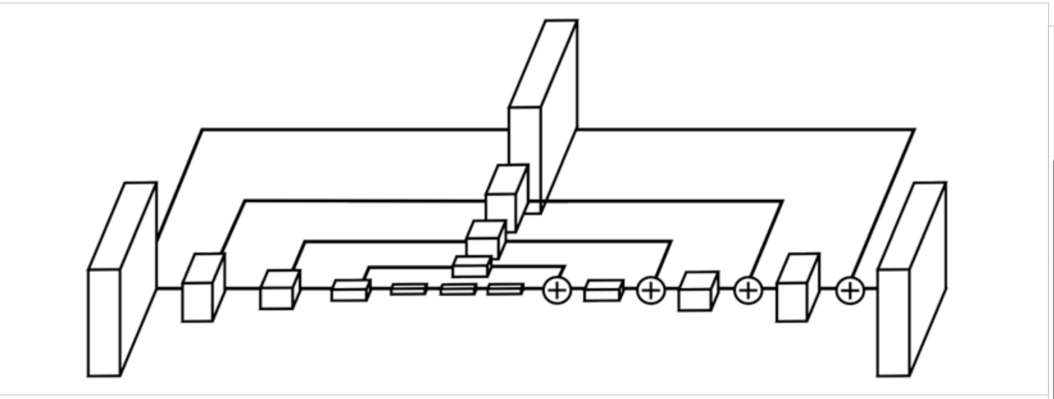
Convolutional Pose Machines. Shih-En Wei, Varun Ramakrishna, Takeo Kanade, Yaser Sheikh. In *CVPR,* 2016

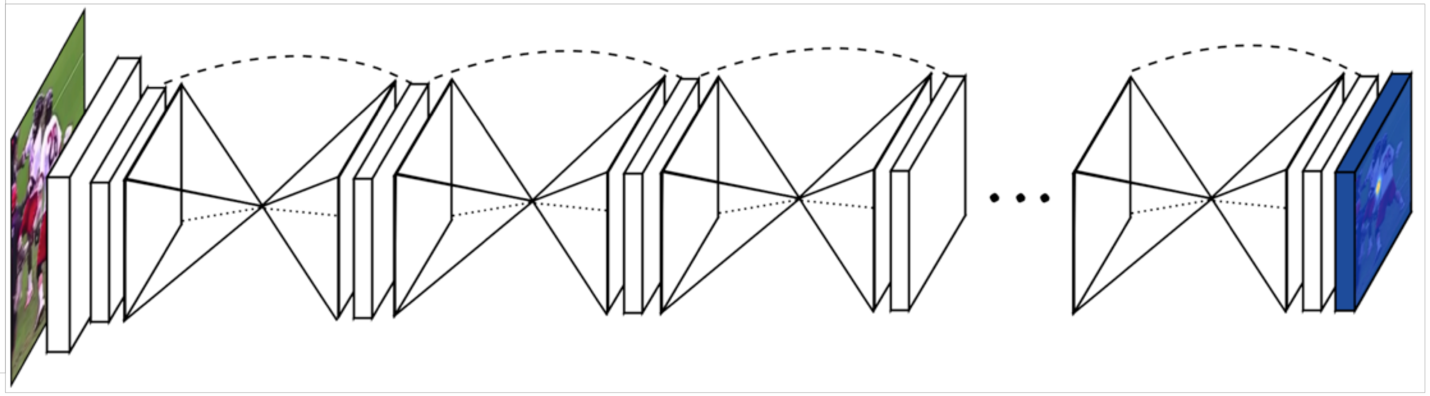


Ours 6–stage + LEEDS Ours 6–stage Pishchulin CVPR'16 Tompson CVPR'15 Tompson NIPS'14 Carreira CVPR'16

Stacked Hourglass Networks

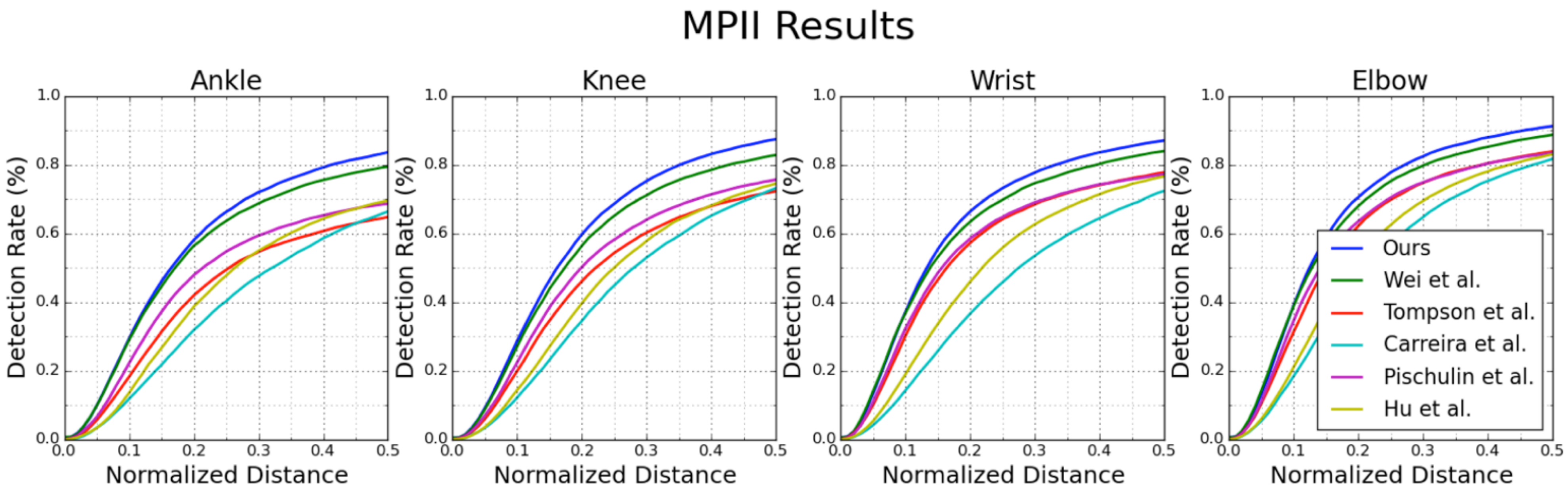
- Each refinement round has to
  - Combine global information about pose
  - Use global pose information to produce new precise pose estimate
- Rounds need not share parameters
- ”Hourglass structure”





Stacked Hourglass Networks for Human Pose Estimation. Alejandro Newell, Kaiyu Yang, and Jia Deng. In *ECCV,* 2016.

Stacked hourglass networks



Pose estimation without detection

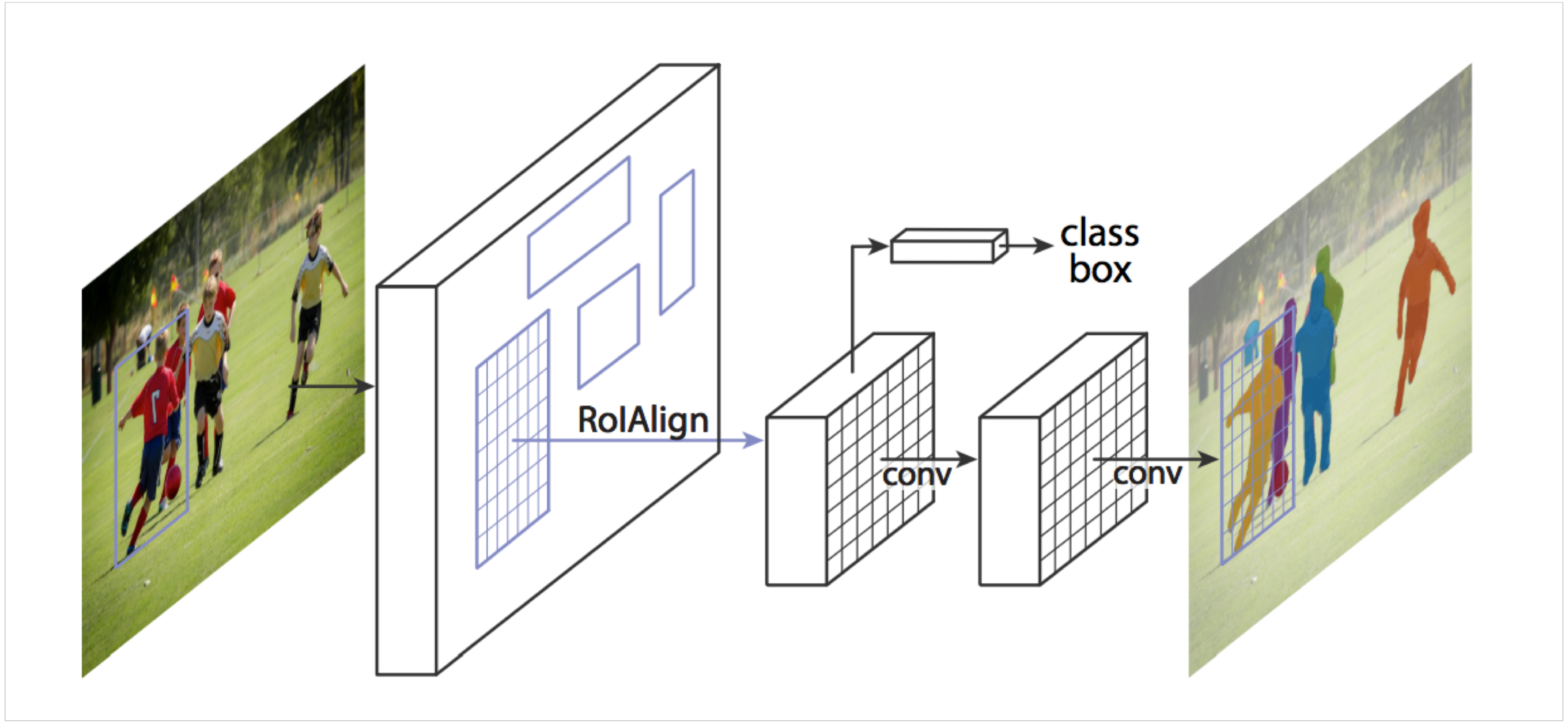
Evaluation metric - tabula rasa

- Algorithm detects keypoints + scores
- Match keypoint to a ground truth keypoint if d/h is less than threshold
- Compute precision-recall curve
- Compute AP (called APK : AP Keypoint)

Two strategies

- First detect, then estimate keypoints
  - Can use any of previous techniques
  - Similar to instance segmentation
  - Easy to get object level information
  - Hard to recover from bad detections
  - e.g. Mask R-CNN
- Detect keypoints, then group into people
  - Need a way to group keypoints: hard problem, requires heuristics
  - No simple way to have object level information

Top-down keypoint detection

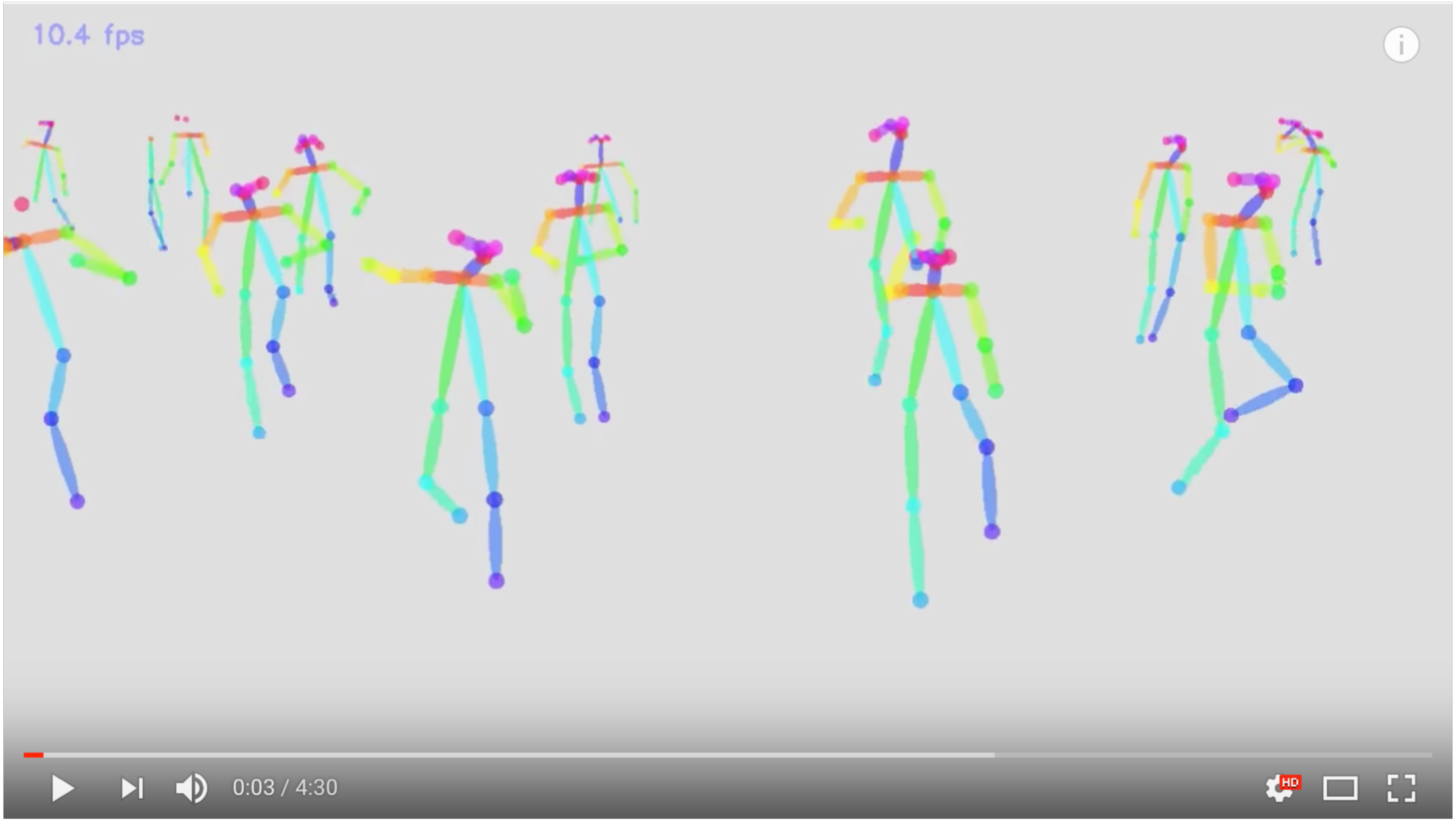


He, Kaiming, et al. "Mask r-cnn." *Computer Vision (ICCV), 2017 IEEE International Conference on*. IEEE, 2017.

Bottom-up keypoint detection

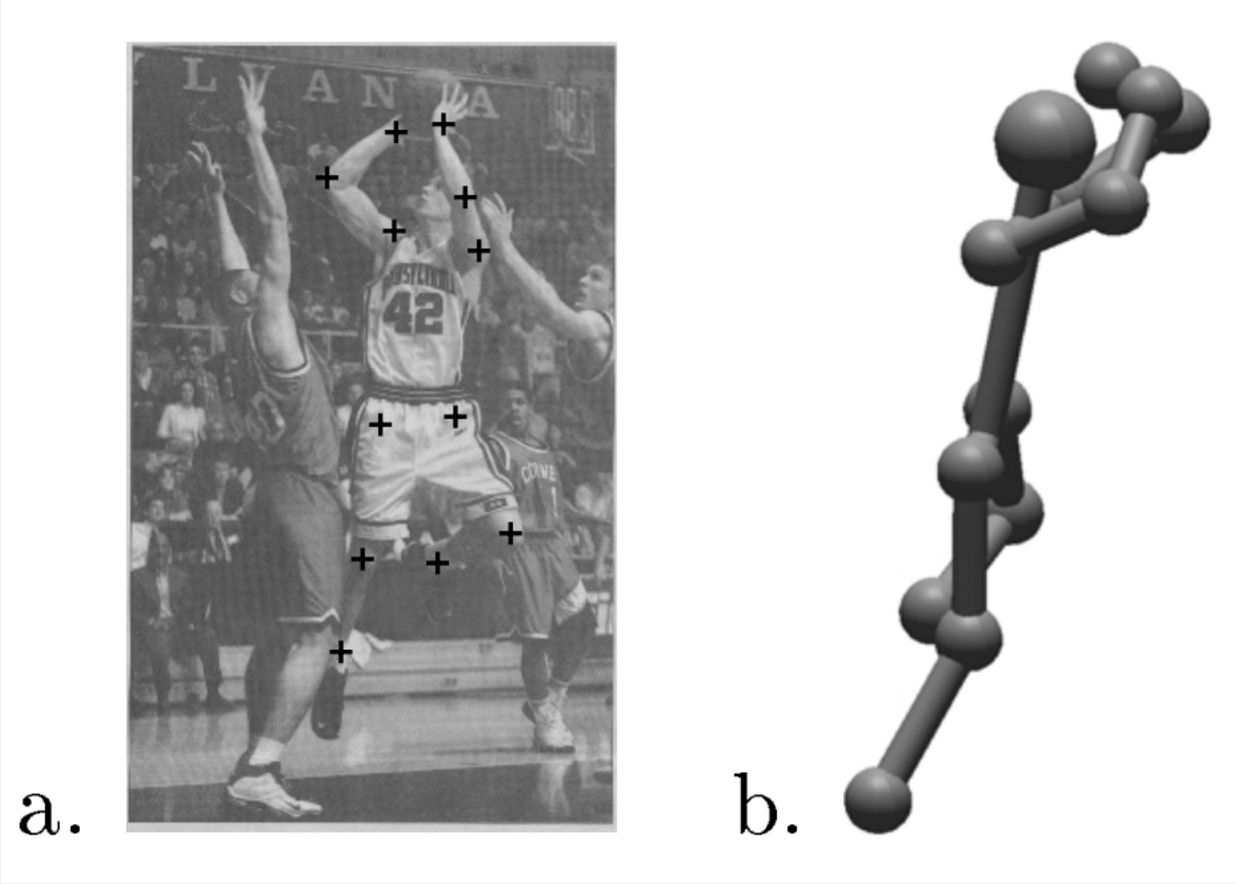
- Need to group keypoints. Can be really ambiguous
- Idea: detect not just keypoints but also limbs + limb orientation

Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields. Zhe Cao, Tomas Simon, Shih-En Wei, Yaser Sheikh. In *CVPR,* 2017.



Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields. Zhe Cao, Tomas Simon, Shih-En Wei, Yaser Sheikh. In *CVPR,* 2017.

Pose estimation in 3D



Reconstruction of Articulated Objects from Point Correspondences in a Single Uncalibrated Image. C. J. Taylor. In *CVPR,* 2000

Pose estimation in 3D

- Key idea: know relative lengths of each limb4
- Assume *scaled orthographic projection*
  - Valid when variation in depth much smaller than depth

$$x = \frac{X}{Z} \approx \frac{X}{Z_0}$$

$$y = \frac{Y}{Z} \approx \frac{Y}{Z_0}$$

constant

Reconstruction of Articulated Objects from Point Correspondences in a Single Uncalibrated Image. C. J. Taylor. In *CVPR,* 2000

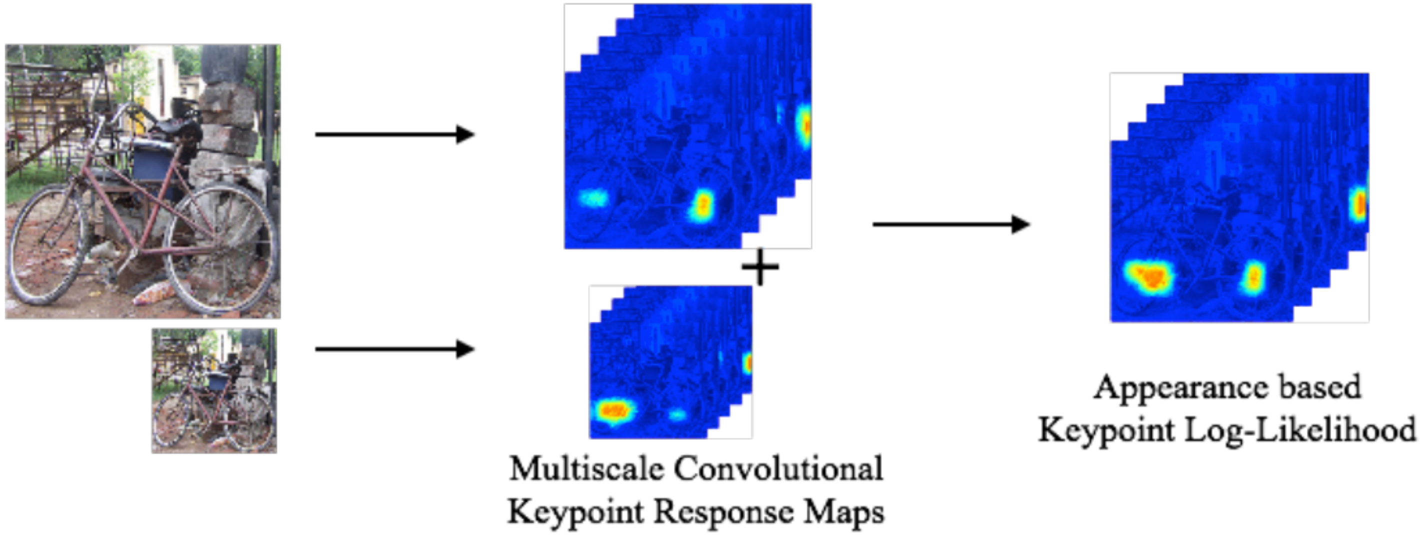
Pose estimation in 3D

$$\begin{aligned}
l^2 &= (X_1 - X_2)^2 + (Y_1 - Y_2)^2 + (Z_1 - Z_2)^2 \\
(u_1 - u_2) &= s(X_1 - X_2) \\
(v_1 - v_2) &= s(Y_1 - Y_2) \\
dZ &= (Z_1 - Z_2) \\
\Rightarrow dZ &= \sqrt{l^2 - ((u_1 - u_2)^2 + (v_1 - v_2)^2)/s^2}
\end{aligned}$$

Reconstruction of Articulated Objects from Point Correspondences in a Single Uncalibrated Image. C. J. Taylor. In *CVPR,* 2000

Pose estimation for rigid objects

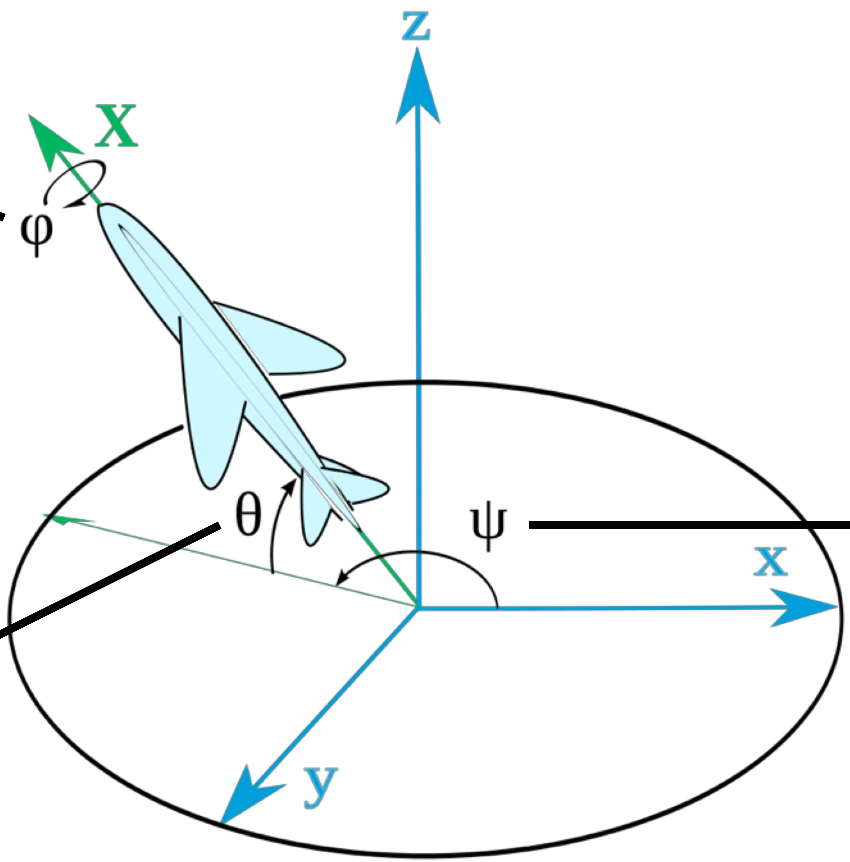
Pose estimation for rigid objects



Viewpoints and keypoints. S. Tulsiani and J. Malik. In *CVPR,* 2015

Pose estimation for rigid objects

Cyclo-rotation / roll

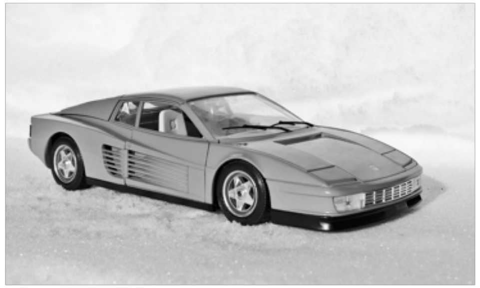


Azimuth / yaw

Elevation / pitch

Viewpoint-conditioned pose

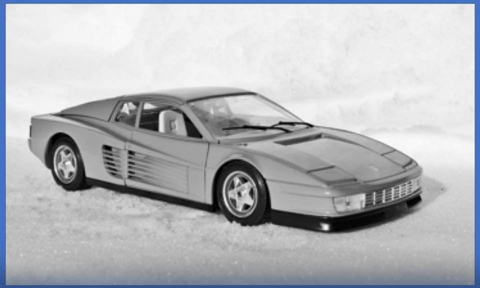
Viewpoint
prediction



Viewpoints and keypoints. S. Tulsiani and J. Malik. In *CVPR,* 2015

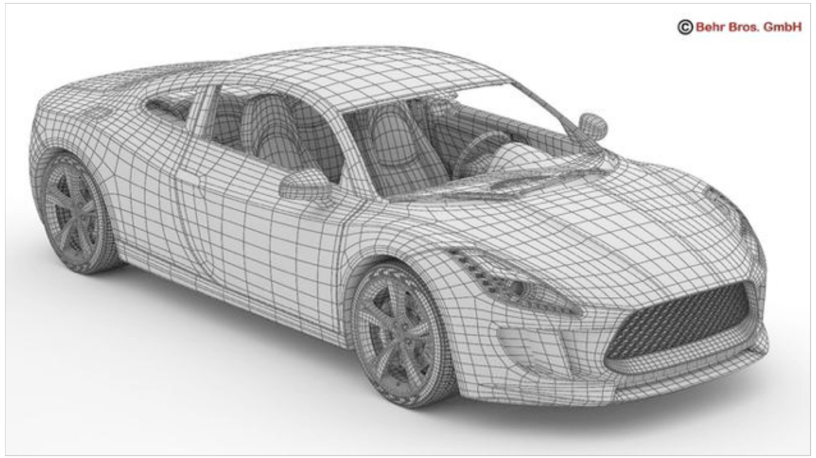
Viewpoint-conditioned pose

Viewpoint
prediction



Viewpoints and keypoints. S. Tulsiani and J. Malik. In *CVPR,* 2015

Fitting viewpoint to keypoints



- Idea: minimize *reprojection error*

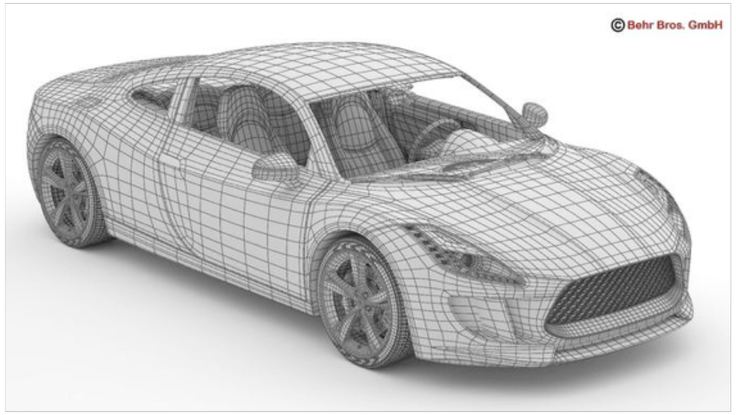
$$\vec{\mathbf{p}}_i = \mathbf{K}[\mathbf{R}|\mathbf{t}]\vec{\mathbf{P}}_i$$

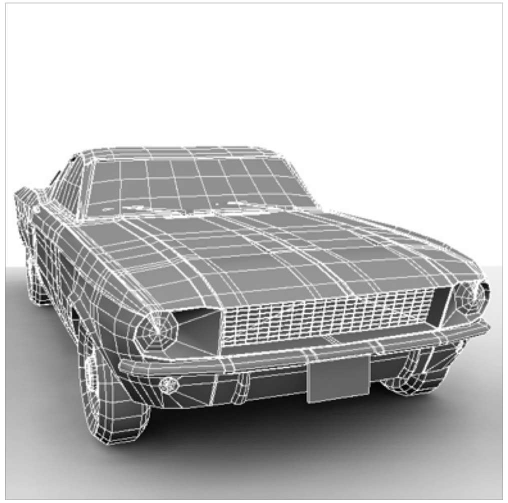
$$x_i = \vec{\mathbf{p}}_i[0]/\vec{\mathbf{p}}_i[2] \qquad y_i = \vec{\mathbf{p}}_i[1]/\vec{\mathbf{p}}_i[2]$$

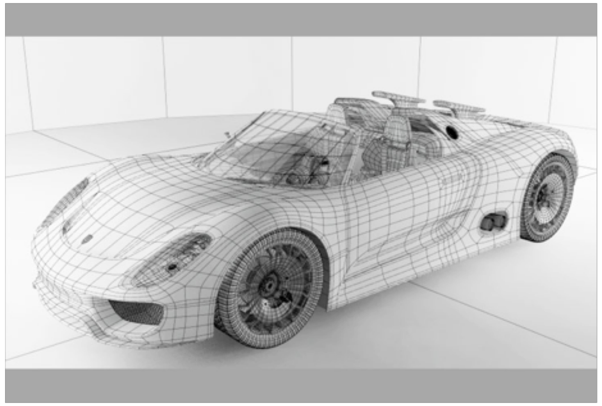
$$\min_{\mathbf{R},\mathbf{t}} \sum_i (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2$$

Shape models

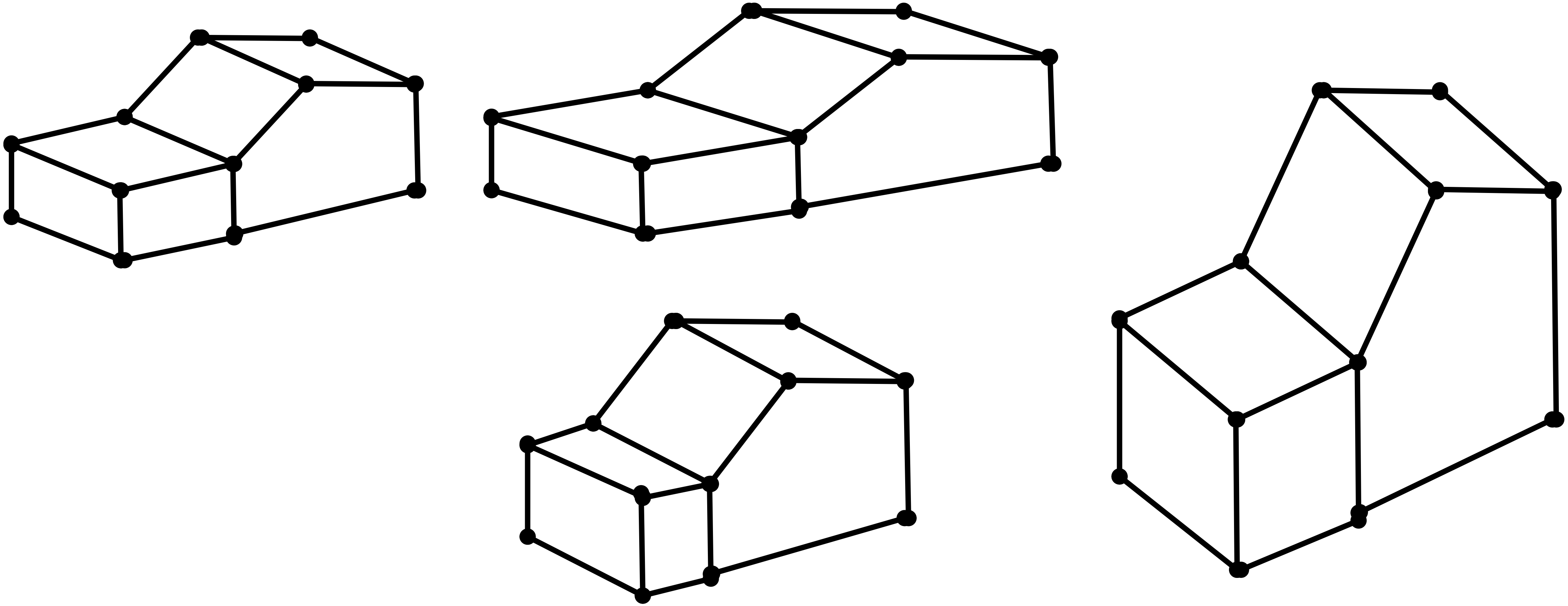
- Problem: we need 3D location of each keypoint in canonical frame
    - E.g., CAD model
- If we have a set of CAD models, then we can try each one



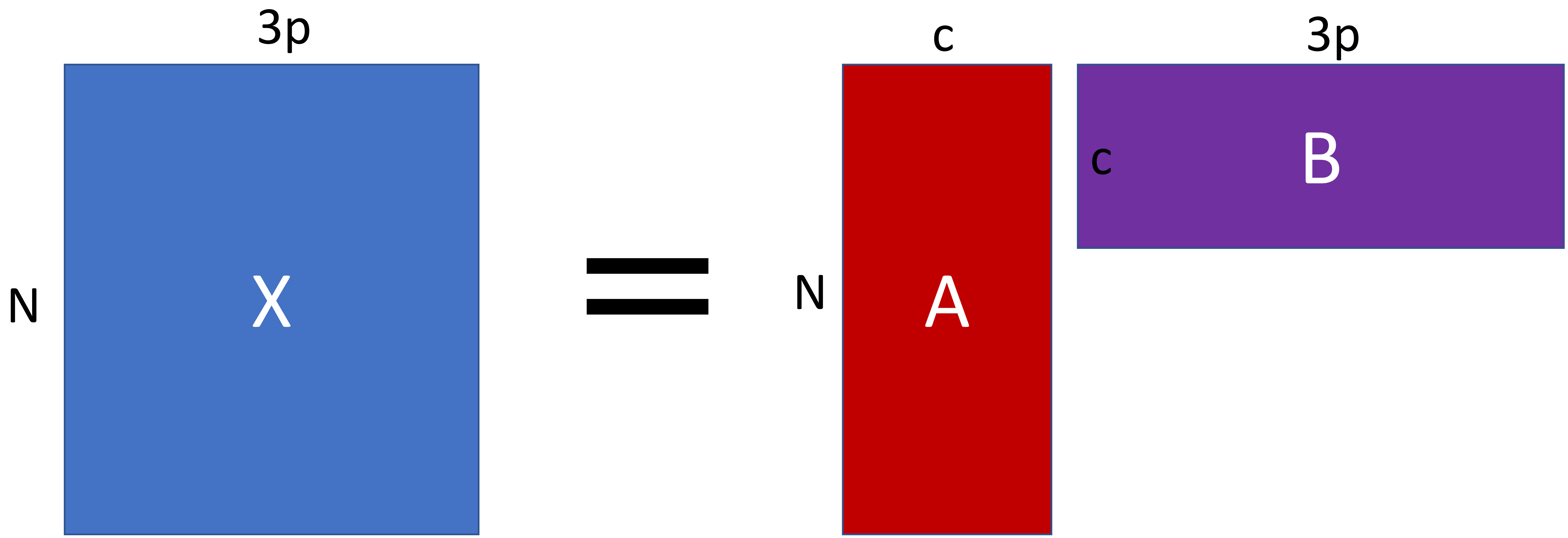




Shape models



Shape models : shape basis



Shape models : shape basis

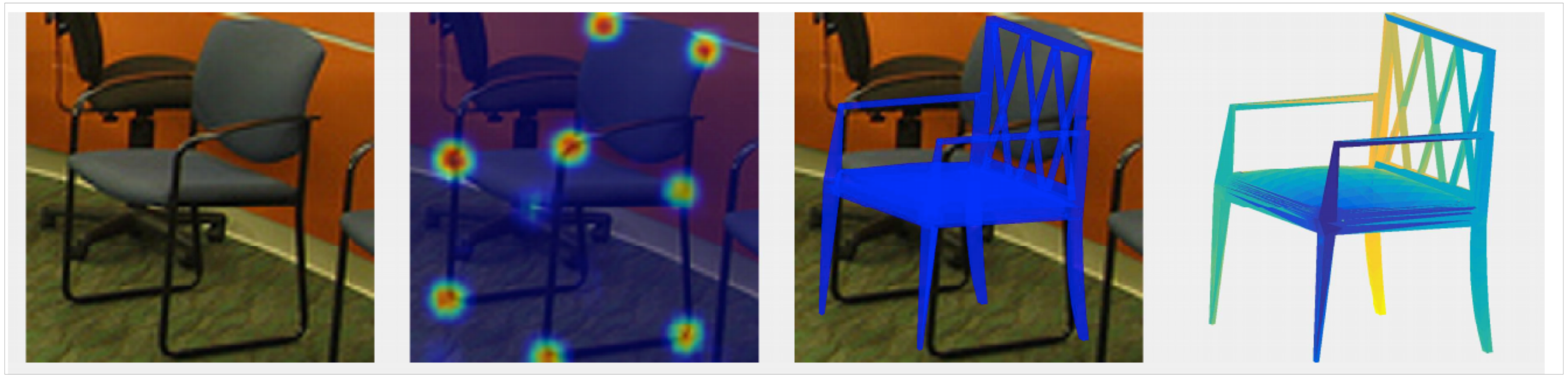
$$\mathbf{P}_i = \sum_j \alpha_j \mathbf{B}_{ij}$$

$$\vec{\mathbf{p}}_i = \mathbf{K}[\mathbf{R}|\mathbf{t}]\vec{\mathbf{P}}_i$$

$$x_i = \vec{\mathbf{p}}_i[0]/\vec{\mathbf{p}}_i[2] \qquad\qquad y_i = \vec{\mathbf{p}}_i[1]/\vec{\mathbf{p}}_i[2]$$

$$\min_{\mathbf{R},\mathbf{t},\boldsymbol{\alpha}} \sum_i (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2$$

Fitting viewpoints to keypoints



6-DoF Object Pose from Semantic Keypoints. Georgios Pavlakos , Xiaowei Zhou , Aaron Chan , Konstantinos G. Derpanis , and Kostas Daniilidis. In *ICRA,* 2017.