

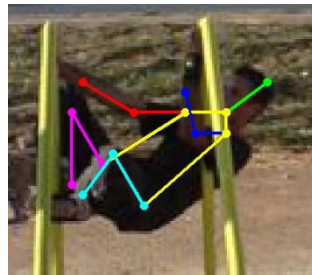
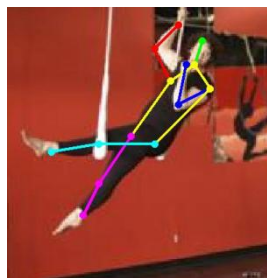
# 人体姿态识别年度总结

欧阳万里



香港中文大学

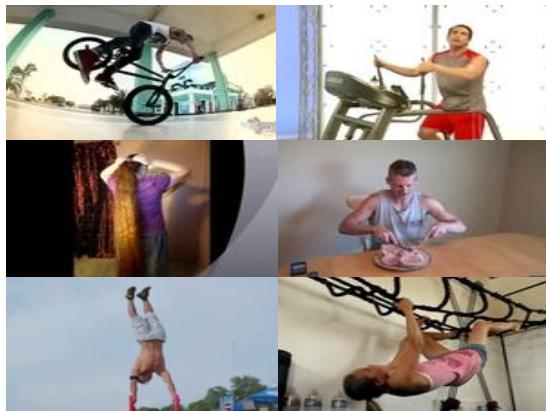
# What is Human Pose Estimation?



Results are generated by our proposed methods (without temporal constraints).

*Video Credit:* [Peter Jasko solo - M-idzomer 2013](#)

# Applications



Action Recognition



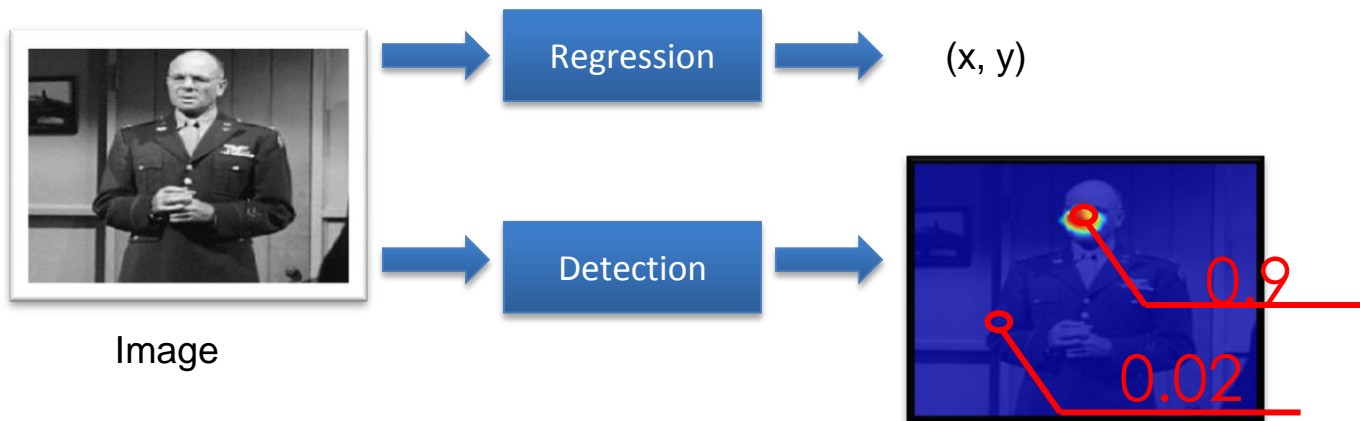
HCI, Game and Animation



Clothing Parsing  
[Yamaguchi et al. CVPR'14]

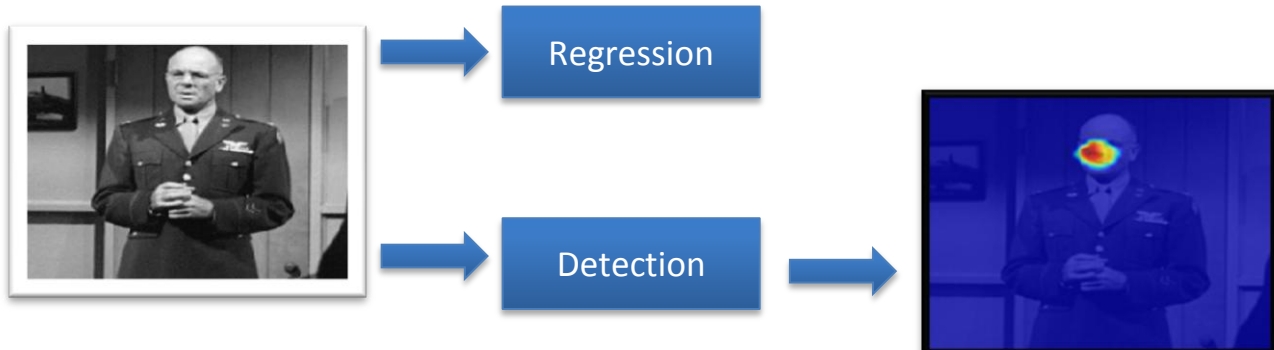
# Regression or detection?

- ❖ Output coordinates
  - ❖ To regress the body locations
- ❖ Output heatmaps
  - ❖ To detect the body locations



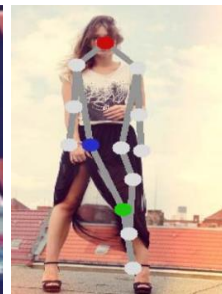
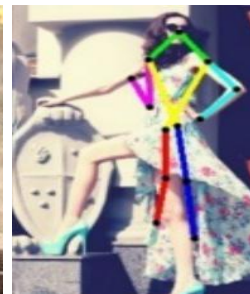
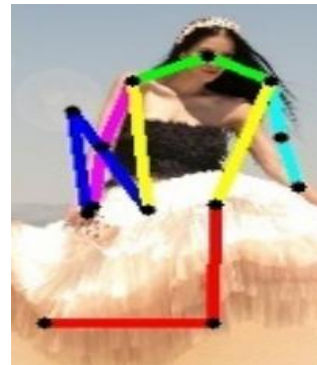
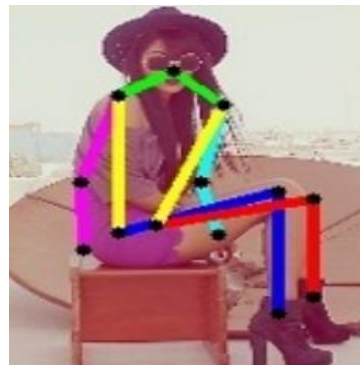
# Limitations

- ❖ Regression
  - ❖ Low accuracy in high precision region caused by flexible body movement
  - ❖ Hard to extend when pose estimation is used for unknown number of persons
- ❖ Detection



# Challenge

- Body movement
- Foreshortening
- Clothing

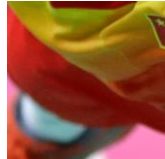


Dantone et al. CVPR 2013

Can you tell which part is from an image patch?



# What about this patch?





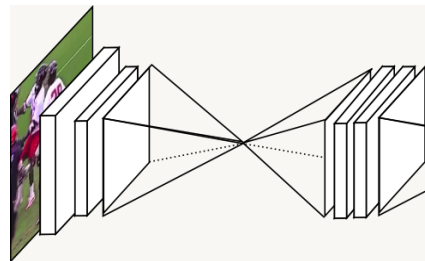
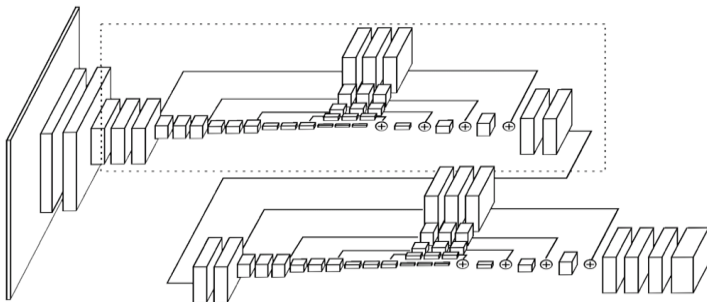


- ❖ Local appearance is insufficient
- ❖ Global appearance is helpful

# Stacked hourglass network

## ❖ Hourglass

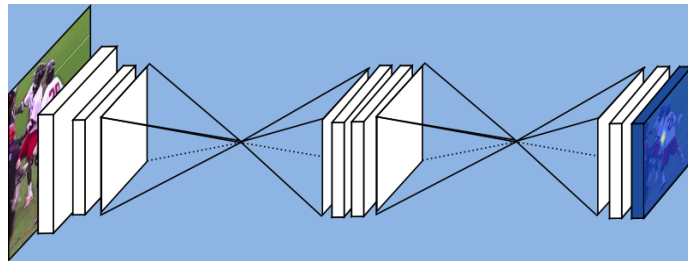
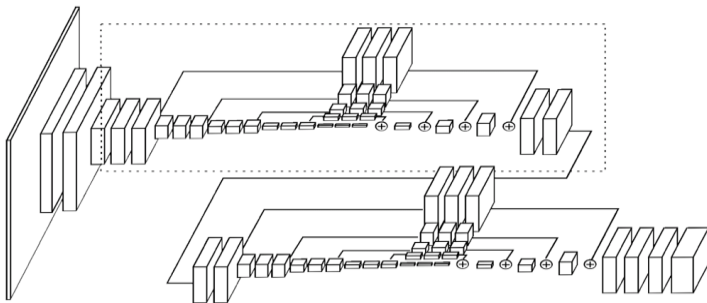
- ❖ Subsampling: lower resolution for less computation and larger receptive field
- ❖ => upsampling: higher resolution for more accurate localization



Newell, Alejandro, Kaiyu Yang, and Jia Deng. "Stacked hourglass networks for human pose estimation." *ECCV*, 2016. @ [University of Michigan](#)

# Stacked hourglass network

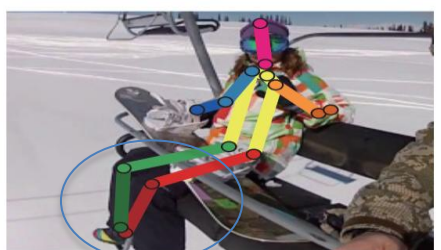
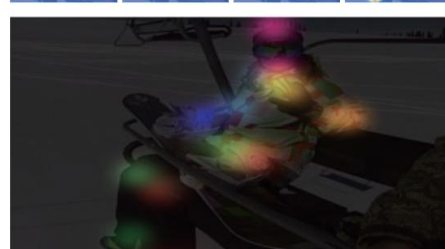
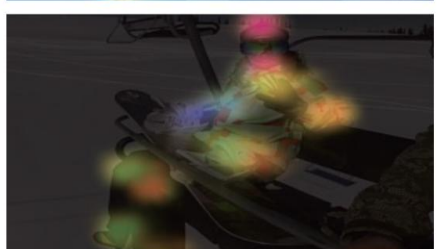
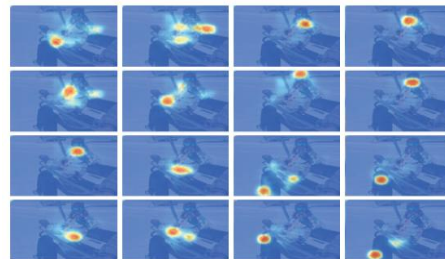
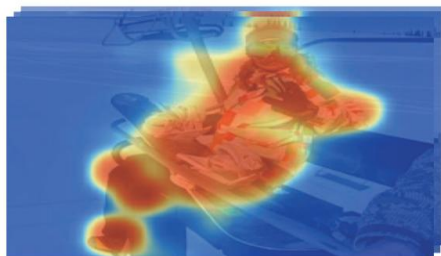
- ❖ Hourglass, subsampling => upsampling
- ❖ Stack multiple hourglass structures



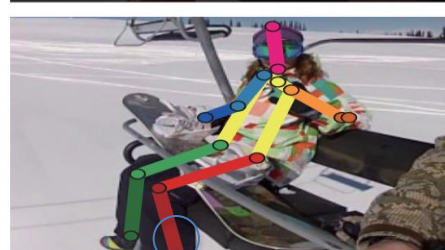
Newell, Alejandro, Kaiyu Yang, and Jia Deng. "Stacked hourglass networks for human pose estimation." *ECCV*, 2016. [@ University of Michigan](#)

# How attention helps human pose estimation?

Pose

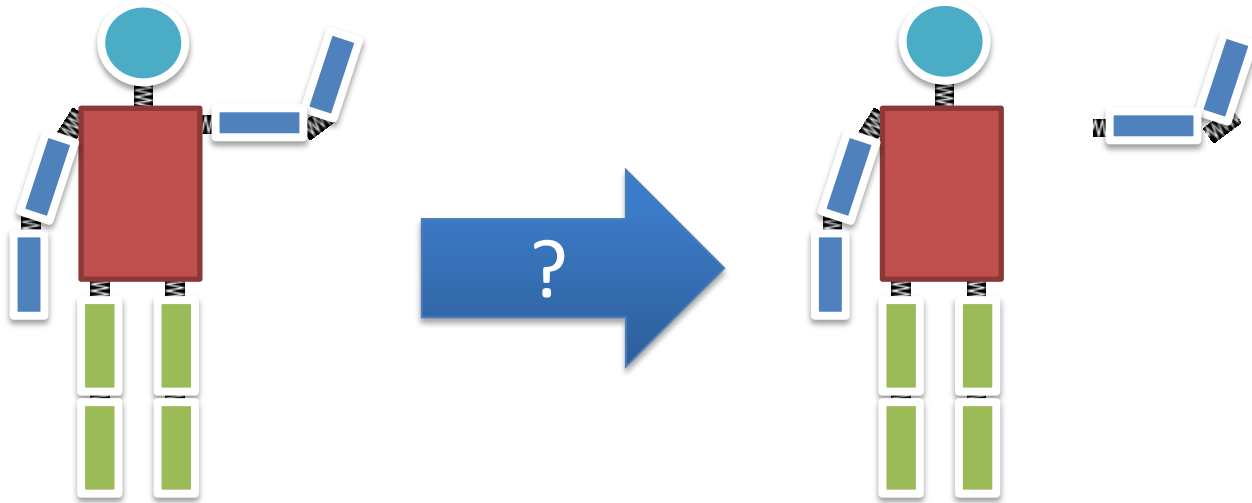


Global Attention

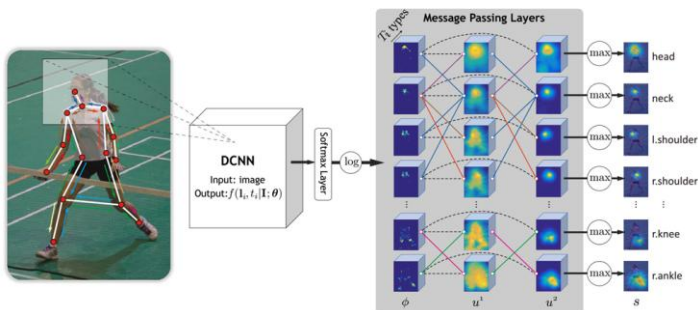


Part Attention

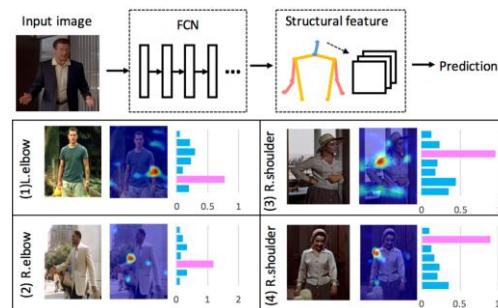
# Structure also matters...



# Structure also matters...



Deep Mixture of Parts

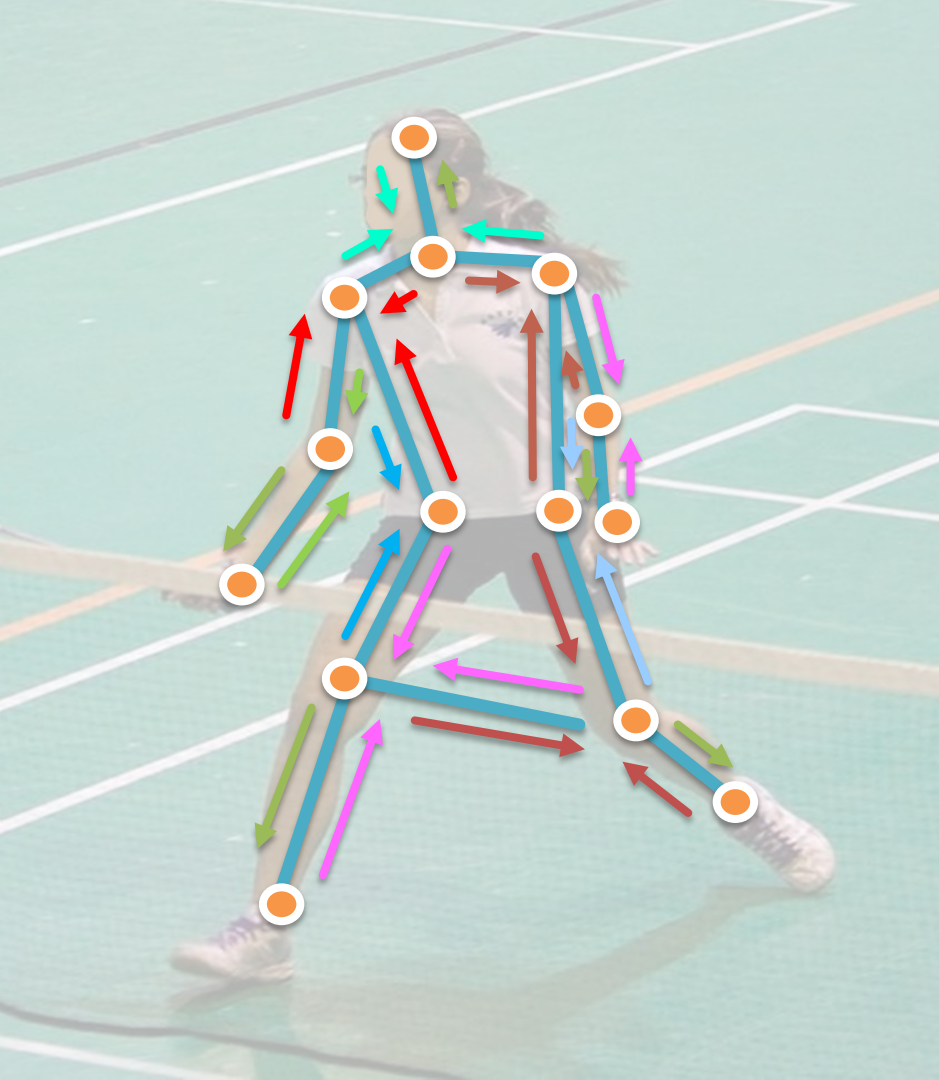


Structured Feature Learning  
(source code provided)

Wei Yang, Wanli Ouyang, Hongsheng Li and Xiaogang Wang "End-to-End Learning of Deformable Mixture of Parts and Deep Convolutional Neural Networks for Human Pose Estimation", In *Proc. CVPR 2016* (Oral).

X. Chu, Wanli Ouyang , H. Li, and X. Wang. "Structured feature learning for pose estimation", In *Proc. CVPR 2016*.





## Graph model

$$G = (V, E)$$

- **Vertices**

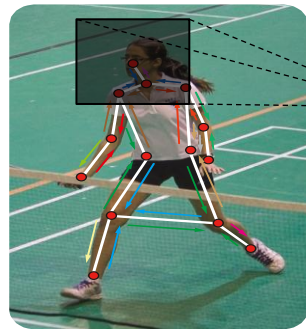
- Locations and mixture types of body parts
- Modeled by a front-end CNN

- **Edges**

message passing

- Pairwise spatial relationships between body parts
- Modeled by message passing layers

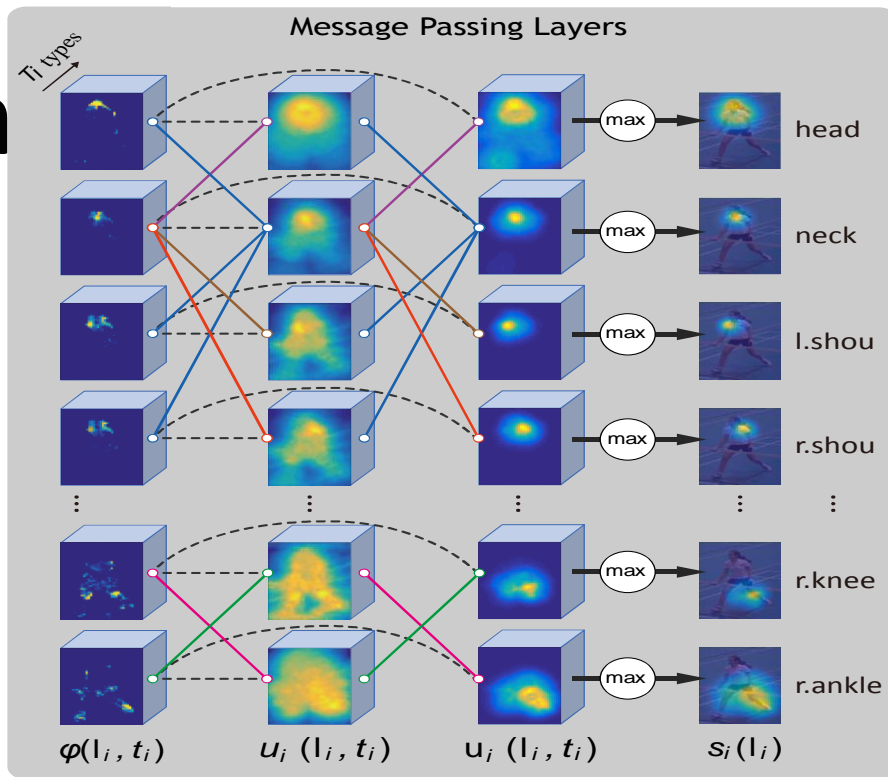
# Frame



Front-end  
CNN

Softmax

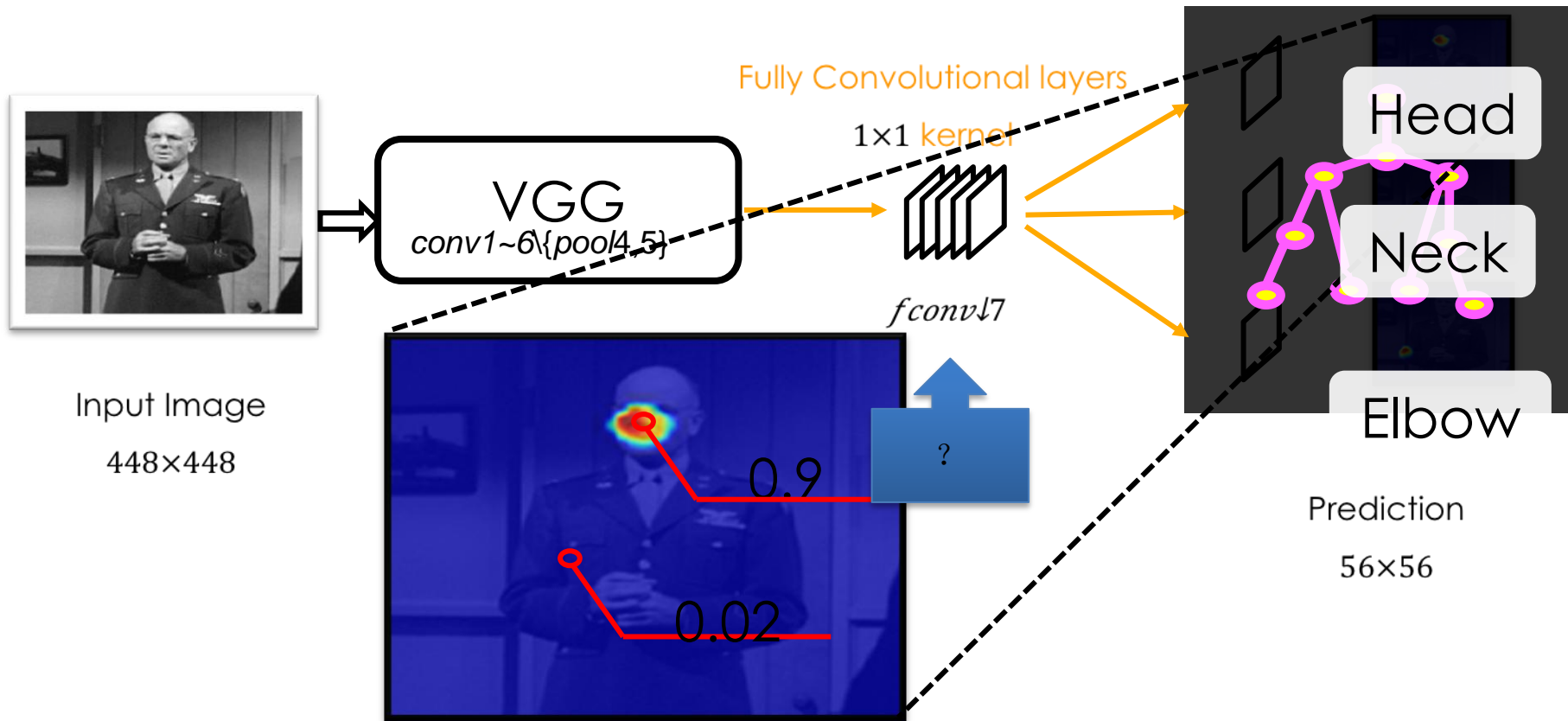
Logarithm



$$F(l, t|I; \theta, \omega) = \sum_{i \in V} \phi(l_i, t_i|I; \theta) + \sum_{(i,j) \in E} \psi(l_i, l_j, t_i, t_j|I; \omega_{i,j}^{t_i, t_j})$$

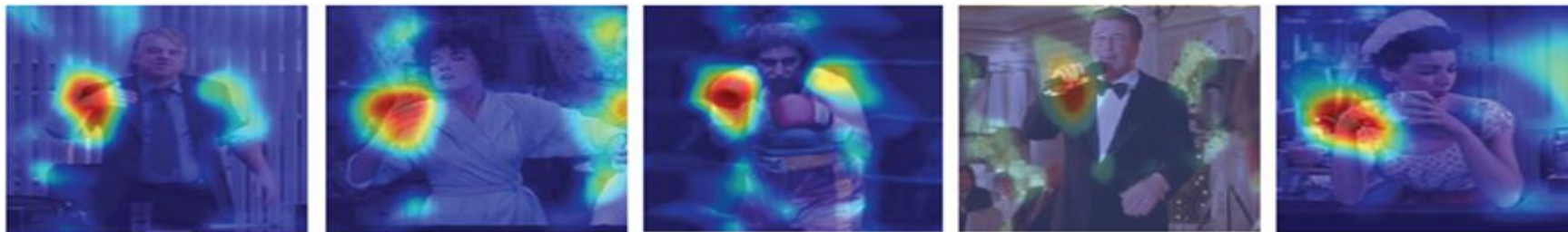


# Fully convolutional net for Human pose estimation



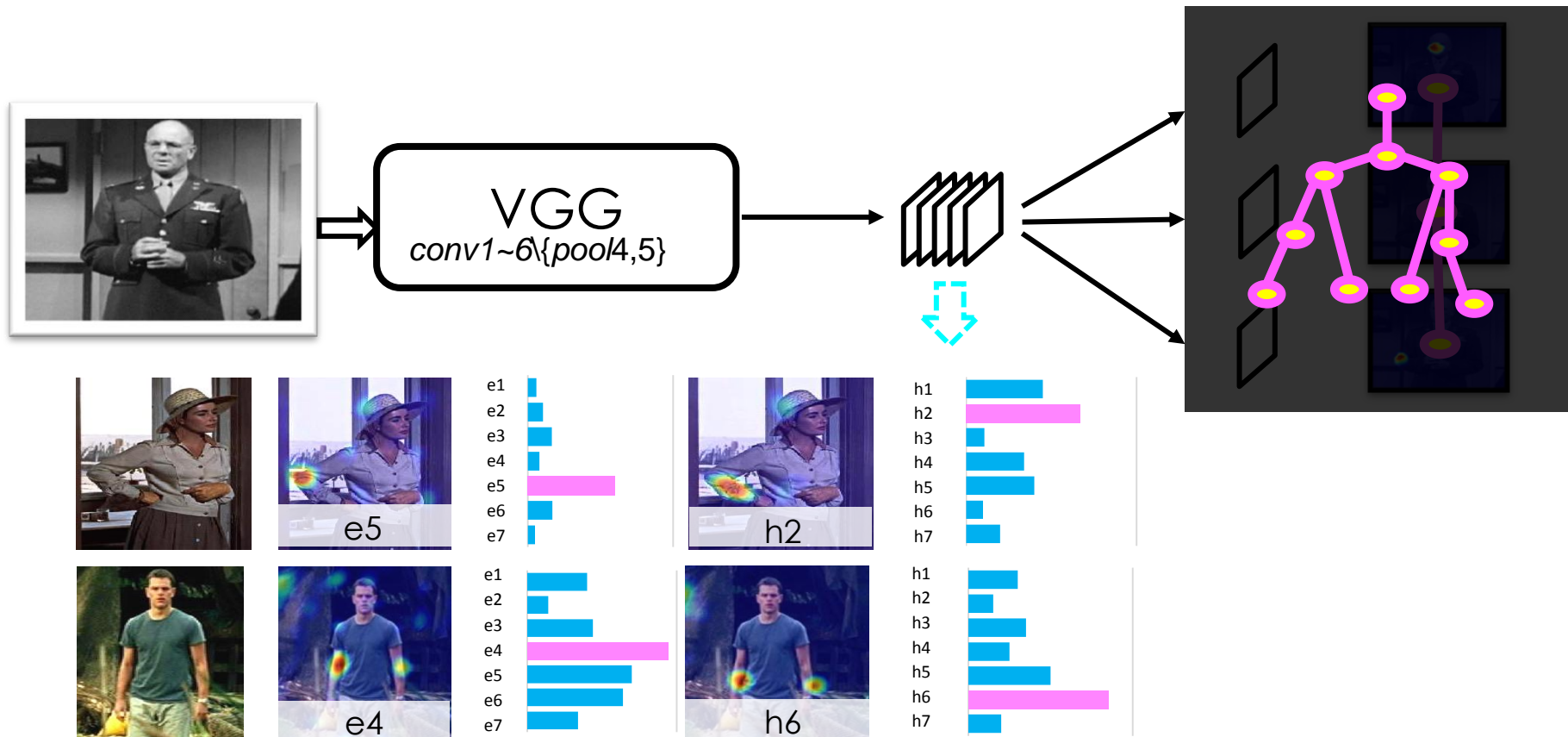


High responding images for channel 1 for neck

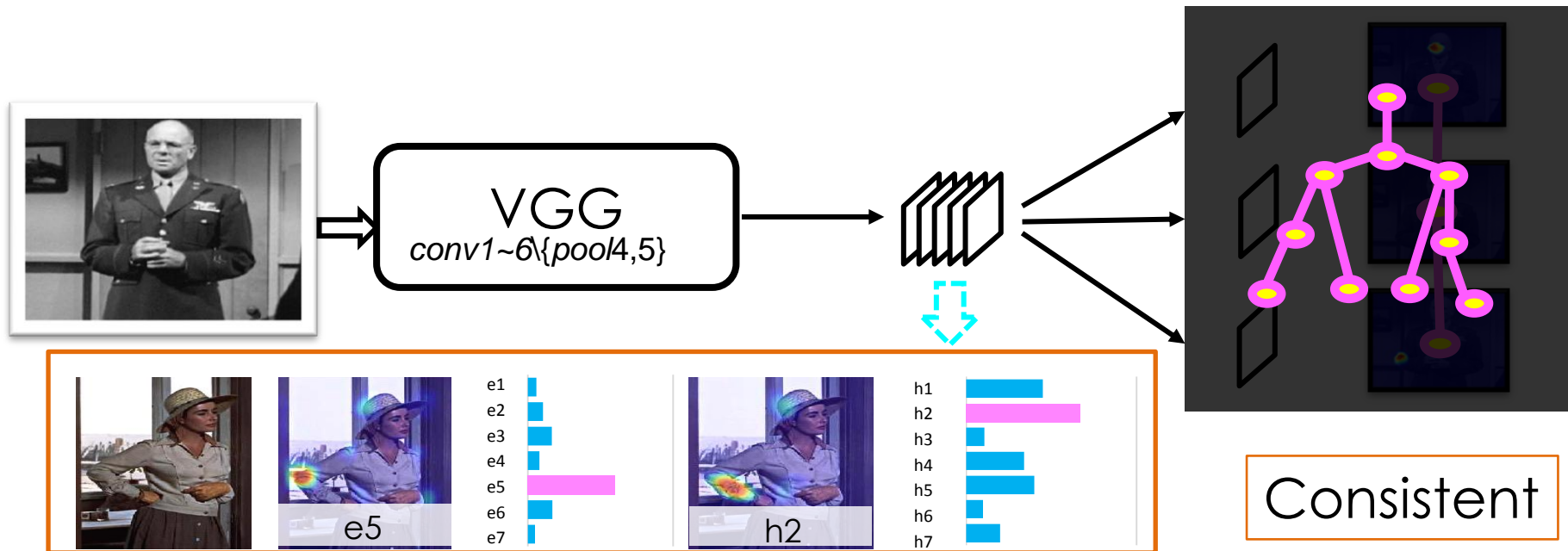


High responding images for channel 2 for left shoulder

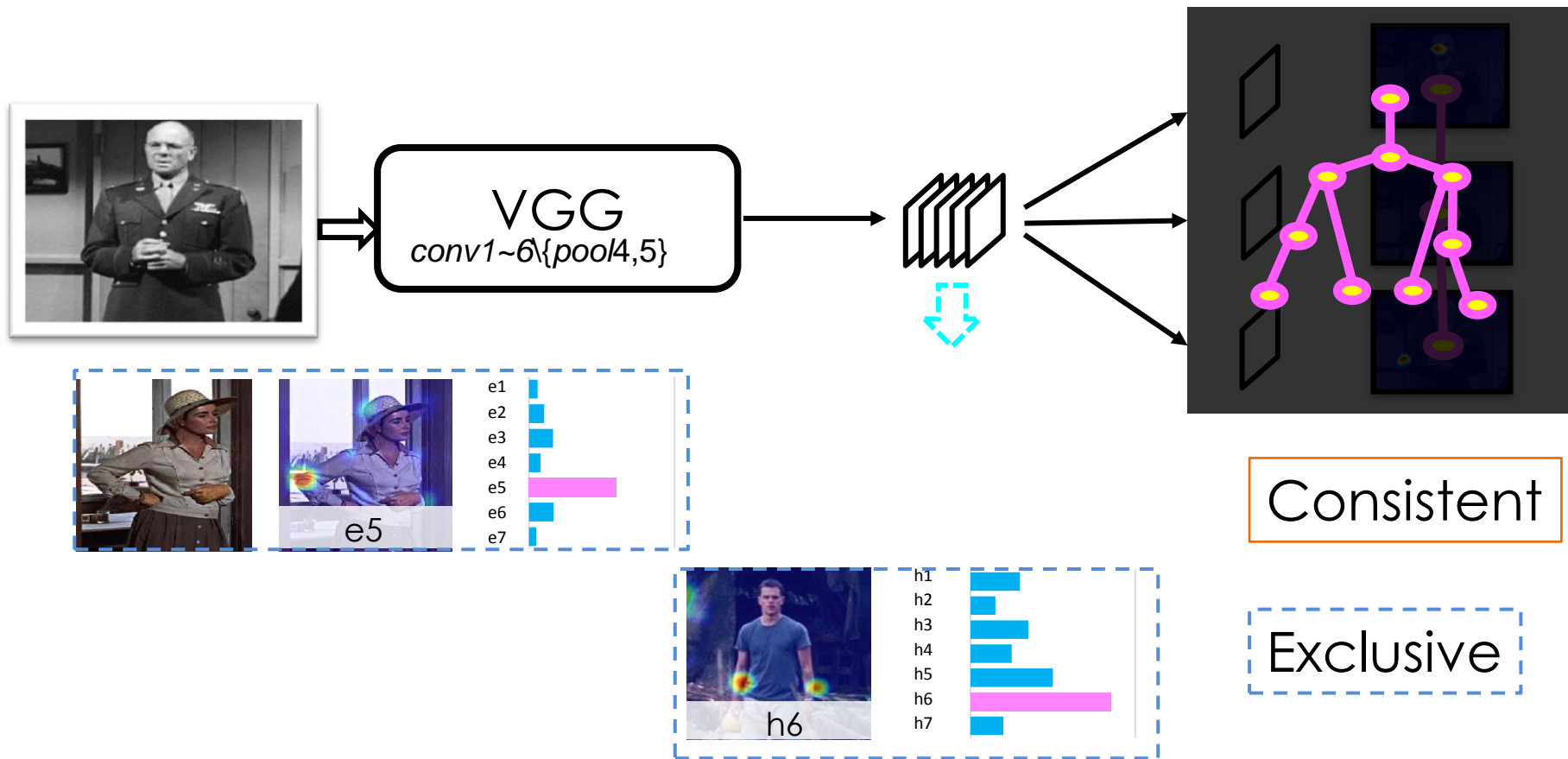
# Fully convolutional net for Human pose estimation

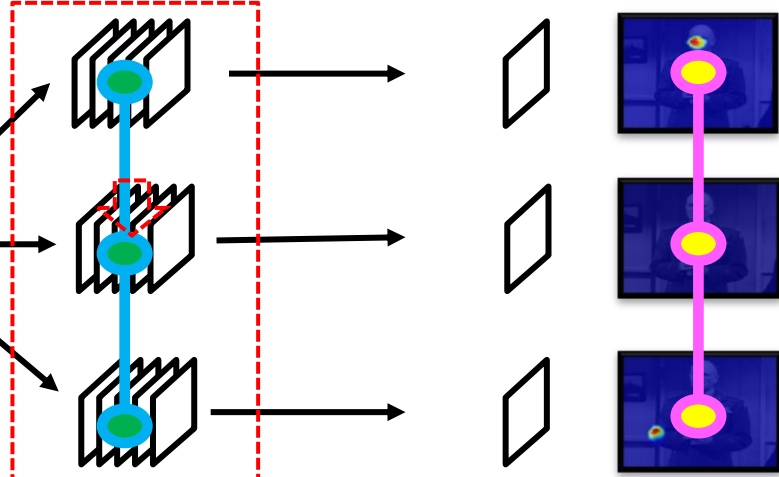


# Fully convolutional net for Human pose estimation



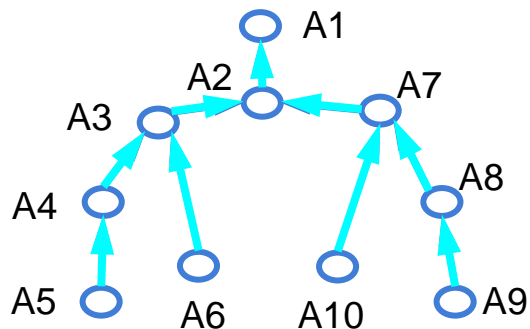
# Fully convolutional net for Human pose estimation



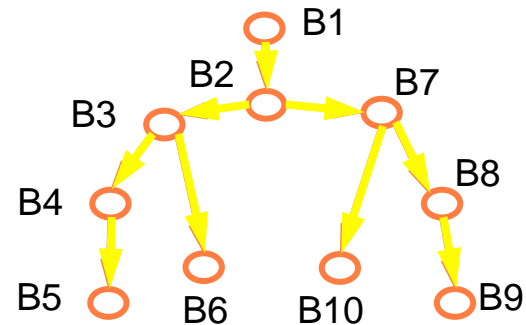


## Structured Feature Learning

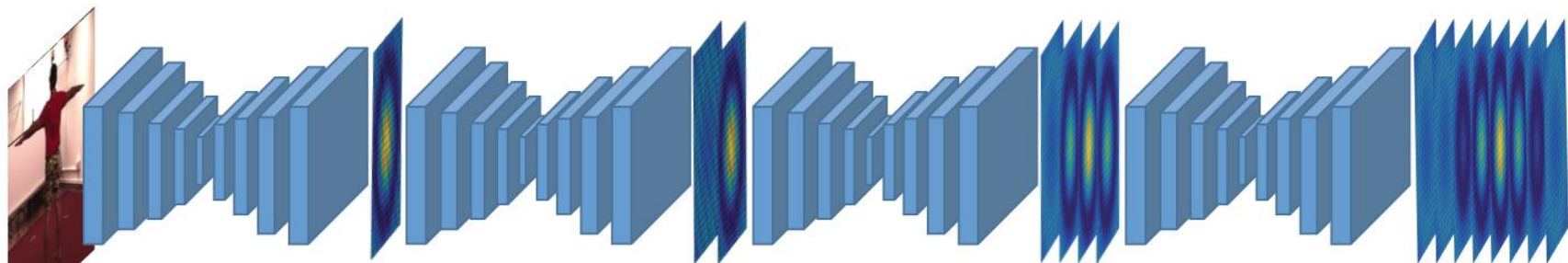
Positive Direction



Revert Direction



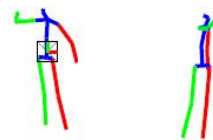
# 2D pose to 3D pose (from image)



2D pose

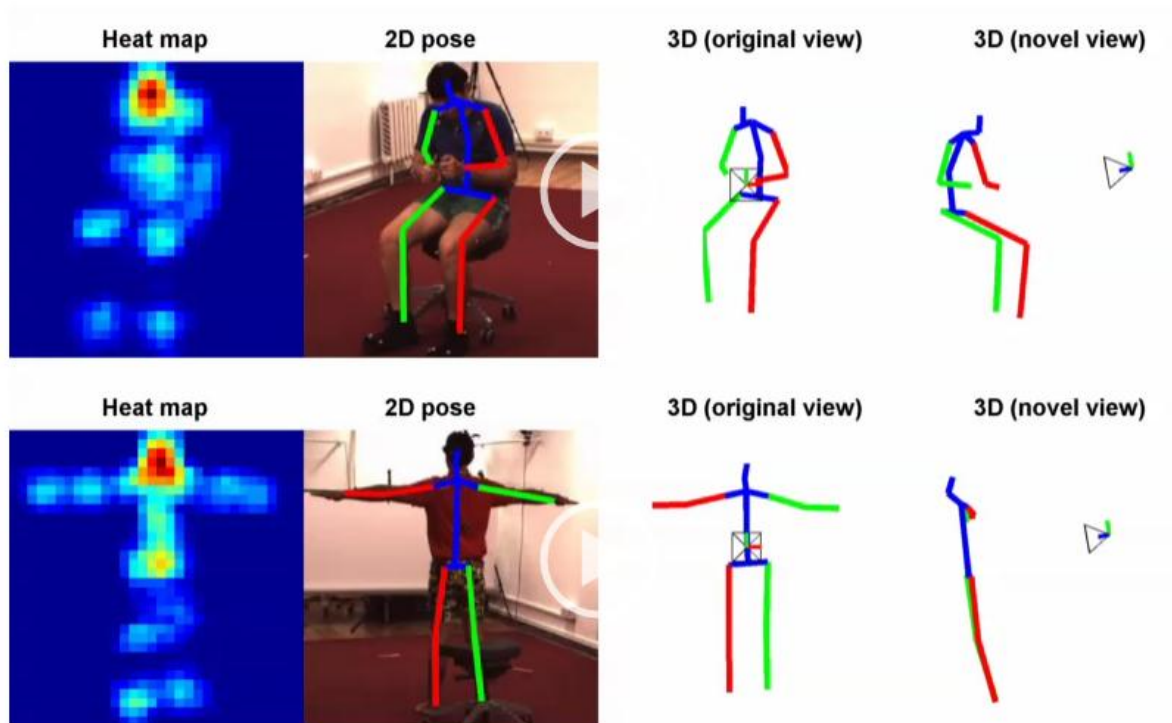
Coarse 3D pose

Fine 3D pose



# 2D pose to 3D pose (from video)

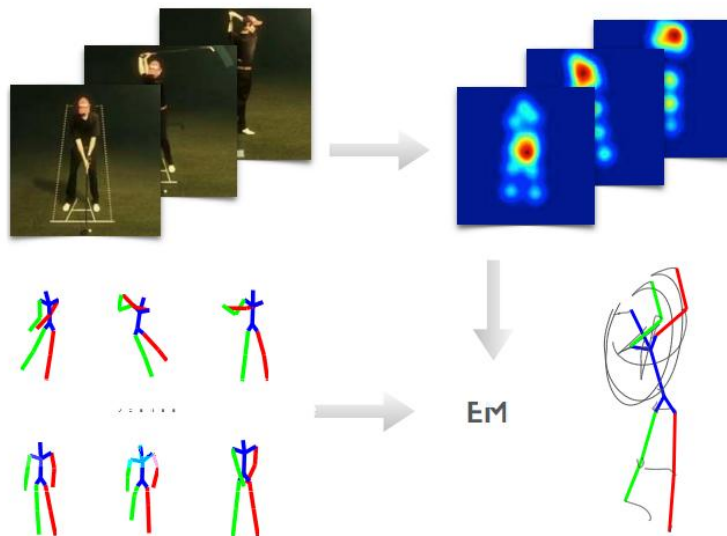
## Example results





# 2D pose to 3D pose (from video)

- Sparsity-driven 3D geometric prior
  - 3D pose can be represented as a linear combination of predefined basis poses
- Temporal smoothness
  - Poses are similar in adjacent frames



# Other interesting papers

- ❖ Toshev, Alexander, and Christian Szegedy. "DeepPose: Human pose estimation via deep neural networks." CVPR 2014.
- ❖ Tompson, Jonathan J., et al. "Joint training of a convolutional network and a graphical model for human pose estimation." NIPS, 2014.
- ❖ Chen, Xianjie, and Alan L. Yuille. "Articulated pose estimation by a graphical model with image dependent pairwise relations." NIPS, 2014.
- ❖ Jain, Arjun, et al. "Learning human pose estimation features with convolutional networks." ICLR, 2014.
- ❖ Jain, Arjun, et al. "Modeep: A deep learning framework using motion features for human pose estimation." ACCV, 2014.
- ❖ Tompson, Jonathan, et al. "Efficient object localization using convolutional networks." CVPR. 2015.
- ❖ Fan, Xiaochuan, et al. "Combining local appearance and holistic view: Dual-source deep neural networks for human pose estimation." CVPR, 2015.
- ❖ Pfister, Tomas, James Charles, and Andrew Zisserman. "Flowing convnets for human pose estimation in videos." ICCV, 2015.
- ❖ Chu, Xiao, et al. "Structured feature learning for pose estimation." CVPR, 2016.
- ❖ Yang, Wei, et al. "End-to-end learning of deformable mixture of parts and deep convolutional neural networks for human pose estimation." CVPR, 2016.
- ❖ Xiao Chu, Wei Yang, W. Ouyang, Xiaogang Wang, Alan Yuille. "Multi-Context Attention for Human Pose Estimation", *Proc. CVPR*, 2017.
- ❖ Gkioxari, Georgia, Alexander Toshev, and Navdeep Jaitly. "Chained Predictions Using Convolutional Neural Networks." ECCV, 2016.
- ❖ J. Charles, et al, Personalizing Human Video Pose Estimation, CVPR16
- ❖ Carreira, Joao, et al. "Human pose estimation with iterative error feedback." CVPR 2016.
- ❖ Insafutdinov E, Pishchulin L, Andres B, et al. DeeperCut: A Deeper, Stronger, and Faster Multi-person Pose Estimation Model. ECCV 2016.
- ❖ Pishchulin, L., Insafutdinov, E., Tang, S., Andres, B., Andriluka, M., Gehler, P., & Schiele, B. DeepCut: Joint Subset Partition and Labeling for Multi Person Pose Estimation, CVPR 2016

[illegible]