

Poselet Conditioned Pictorial Structures

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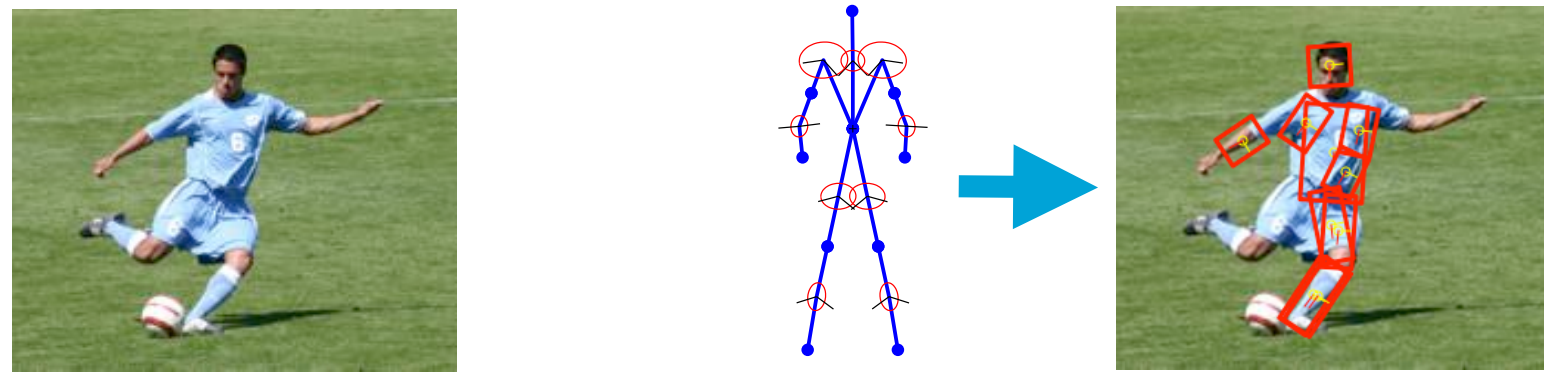


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State of the Art

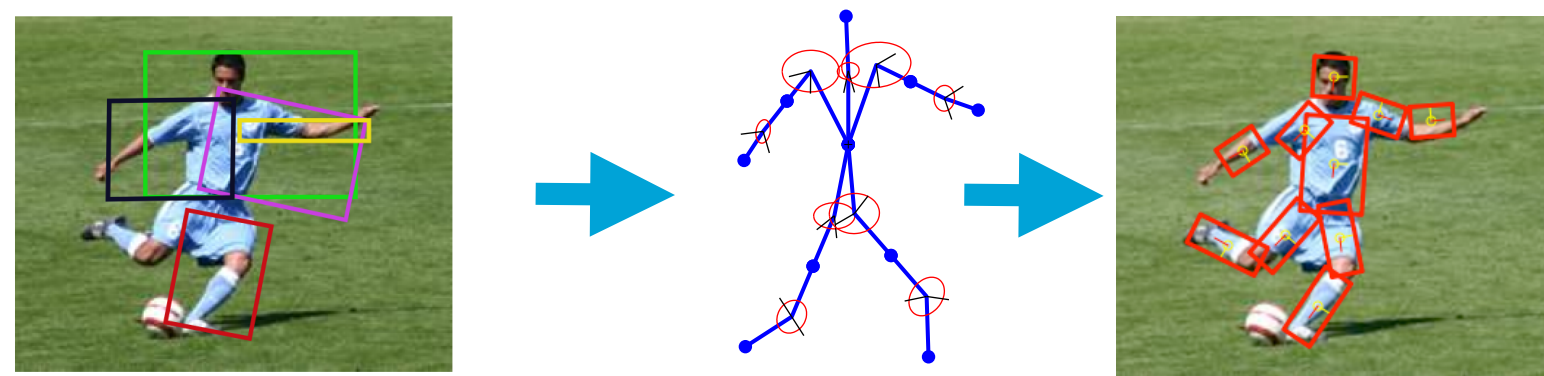
- Tree-structured pictorial structures models



- generic kinematic tree
- capture **adjacent** part dependencies **only**
- + exact and efficient

Contributions

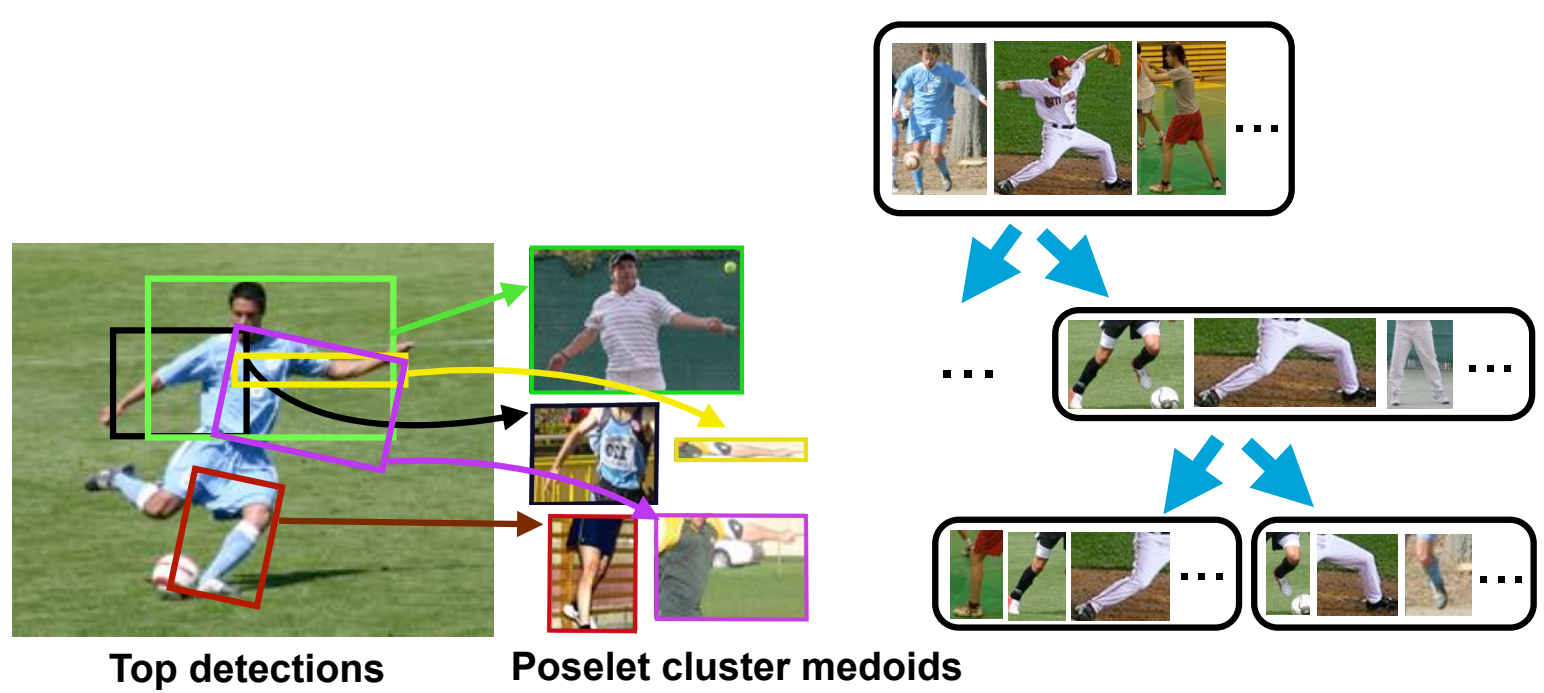
- Novel image conditioned pictorial structures model



- + **poselet conditioned** kinematic tree
- + **poselets** capture **non-adjacent** part dependencies
- + exact and efficient

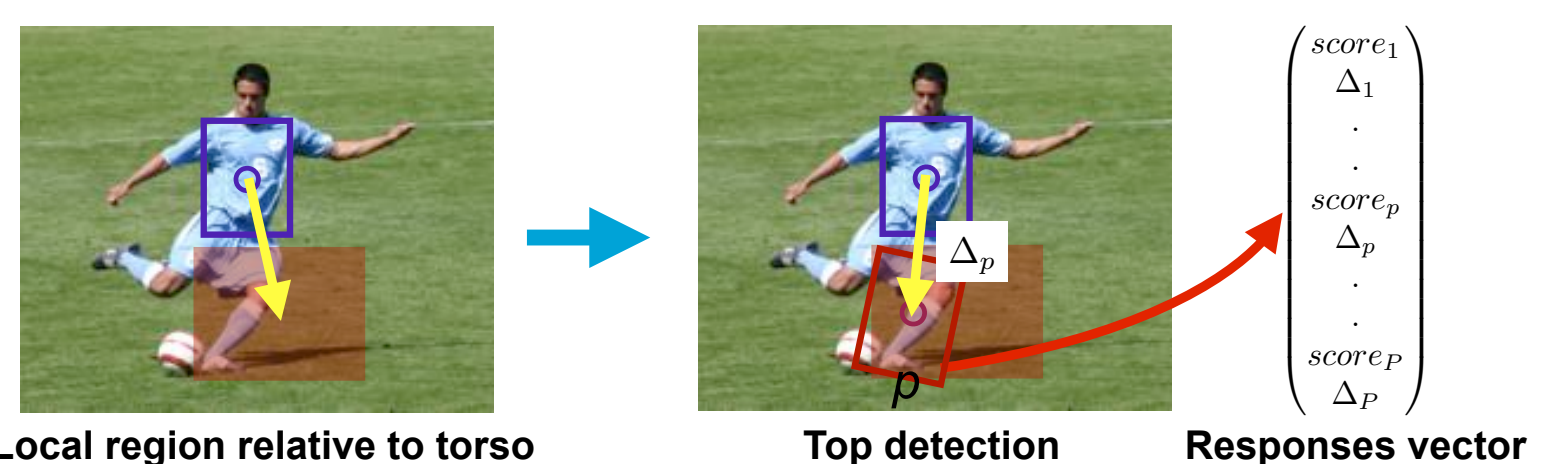
Poselets

- Detect joint part configurations [2]
⇒ capture **non-adjacent** part dependencies
- Trained for different levels of abstraction

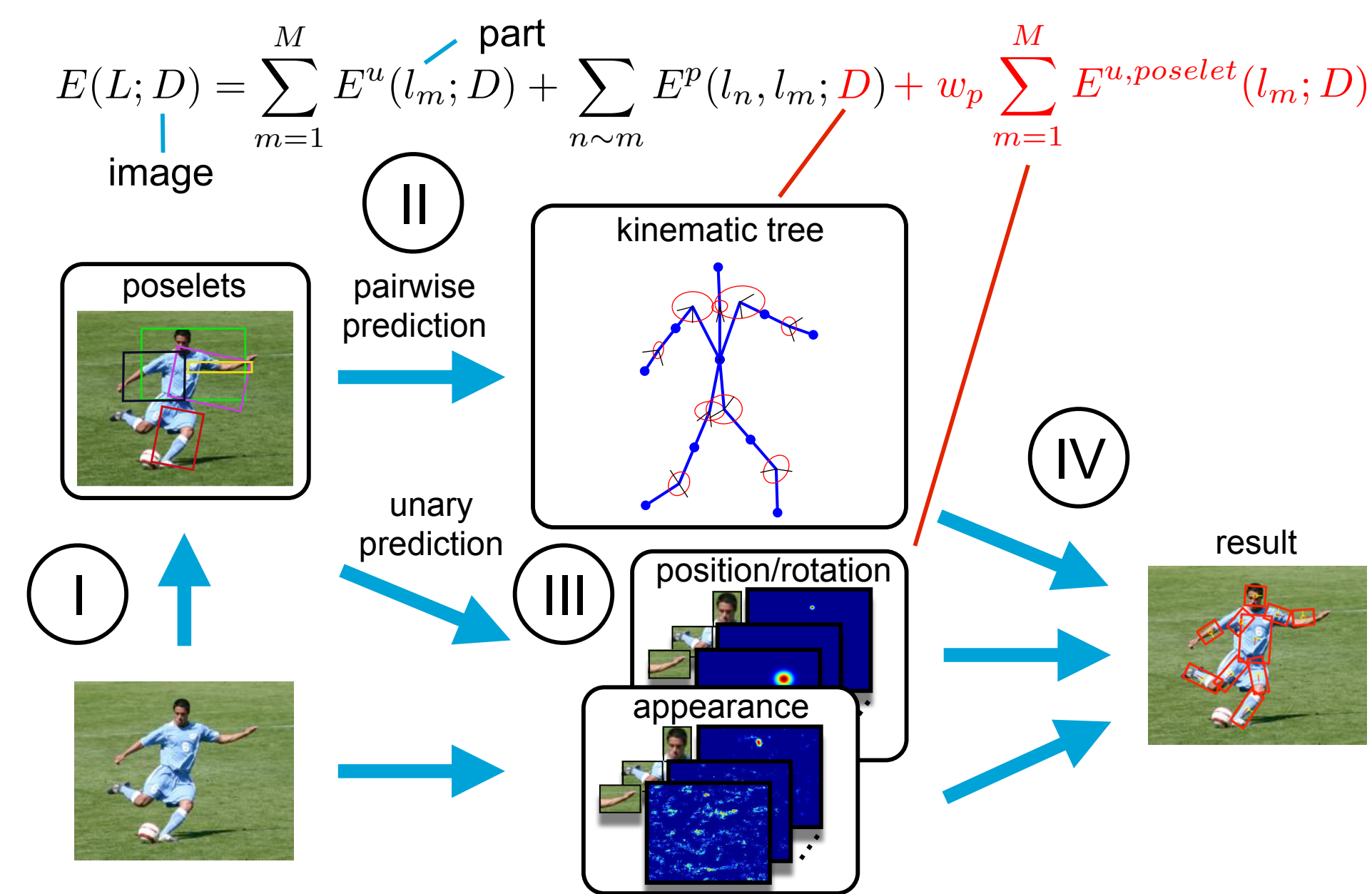


Poselets responses vector as **mid-level representation**:

- detect torso using strong detector [7]
- poselet offset w.r.t torso defines center of pooling region
- top response and offset contribute to vector



Poselet Conditioned Pictorial Structures

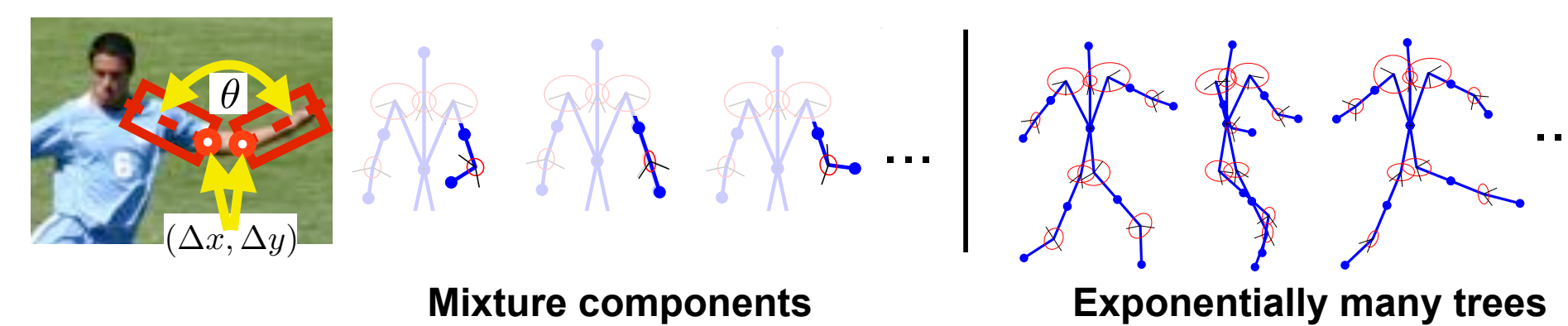


I. Mid-level representation based on poselets

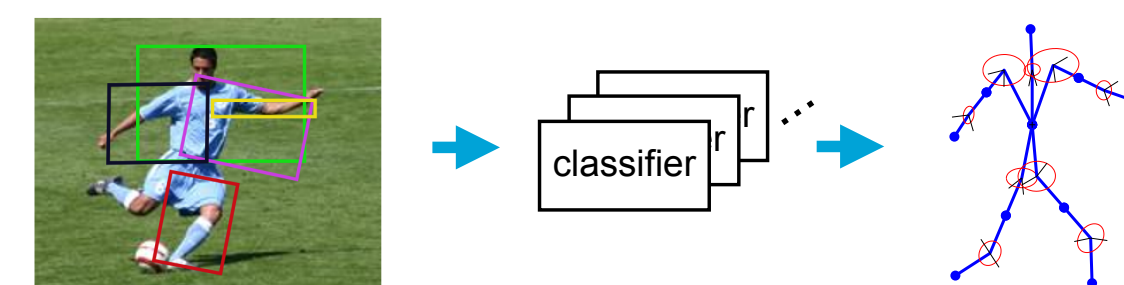
- compute poselets responses vector

II. Predicting pairwise parameters

- pairwise: relative offset $(\Delta x, \Delta y)$ and rotation θ
- learn mixtures *per pairwise* from clustering θ
⇒ allows to model exponentially many trees



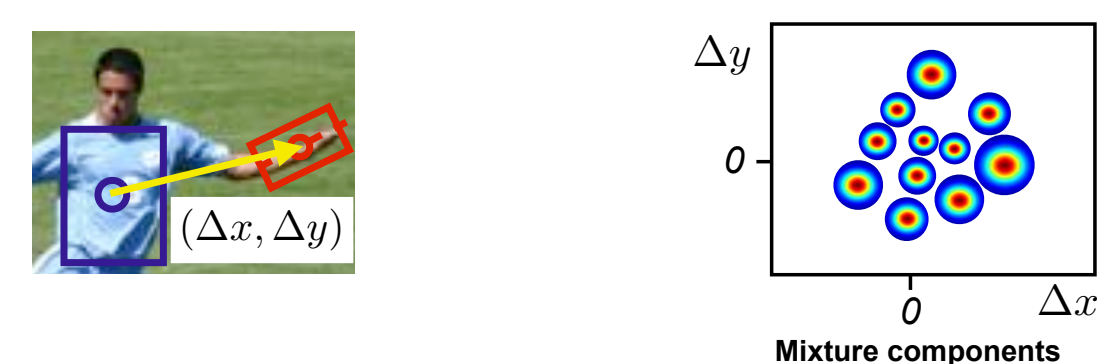
- Prediction**: multi-class classifier on poselets responses



⇒ prediction **before** pose inference: exact and efficient inference

III. Predicting part position and rotation

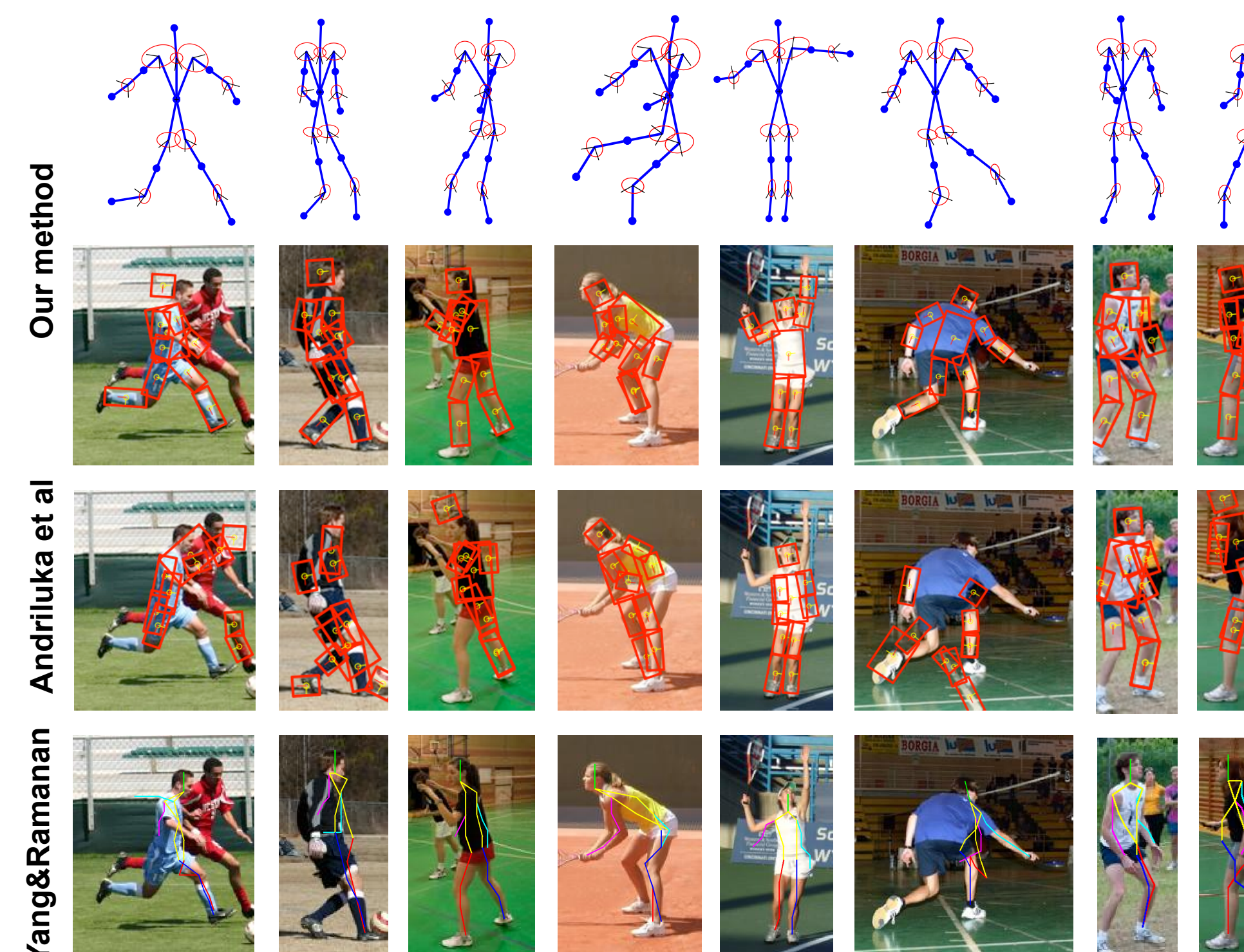
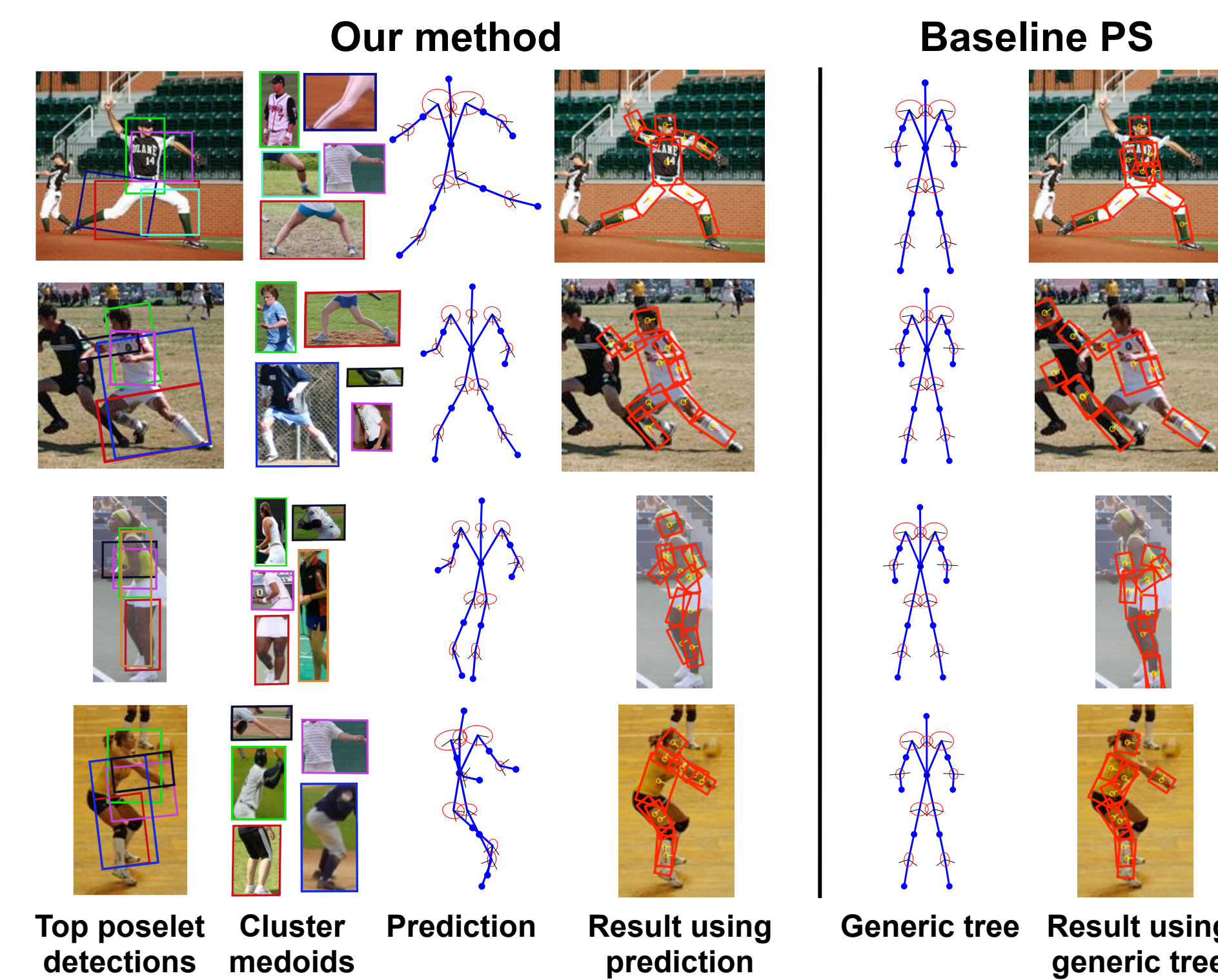
- Part position relative to torso
–learning: cluster offsets into mixture components



–prediction: multi-class classifier

- Absolute part rotation:
–learning: bin rotation to get mixture components
–prediction: similar to predicting part position

Qualitative Results



Quantitative Results

Leeds Sports Poses (LSP) [5]

- 1,000 train, 1,000 test images
- set parameters using validation set
- observer-centric annotations for testing [4]
- Percentage Correct Parts (PCP)* criterion



| Method | Torso | Upper leg | Lower leg | Upper arm | Fore arm | Head | Total |
|------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Andriluka et al., [1] | 80.9 | 67.1 | 60.7 | 46.5 | 26.4 | 74.9 | 55.7 |
| predict pairwise | 85.8 | 74.0 | 66.1 | 51.7 | 30.9 | 78.0 | 60.9 |
| predict unary | 86.1 | 73.3 | 65.8 | 52.8 | 31.0 | 76.0 | 60.8 |
| predict pairwise+unary | 87.5 | 75.7 | 68.0 | 54.2 | 33.9 | 78.1 | 62.9 |
| Yang&Ramanan [9] | 84.1 | 69.5 | 65.6 | 52.5 | 35.9 | 77.1 | 60.8 |
| Eichner&Ferrari [4] | 84.9 | 73.1 | 68.3 | 55.8 | 38.6 | 80.1 | 63.7 |

Image Parse (IP) [8]

- 100 train, 205 test images

| Method | Torso | Upper leg | Lower leg | Upper arm | Fore arm | Head | Total |
|-------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| ours | 92.2 | 74.6 | 63.7 | 54.9 | 39.8 | 70.7 | 62.9 |
| ours + [7] | 90.7 | 80.0 | 70.0 | 59.3 | 37.1 | 77.6 | 66.1 |
| Andriluka et al. [1] | 86.3 | 66.3 | 60.0 | 54.6 | 35.6 | 72.7 | 59.2 |
| Yang&Ramanan, [9] | 82.9 | 69.0 | 63.9 | 55.1 | 35.4 | 77.6 | 60.7 |
| Duan et al., [3] | 85.6 | 71.7 | 65.6 | 57.1 | 36.6 | 80.4 | 62.8 |
| Pishchulin et al., [7] | 88.8 | 77.3 | 67.1 | 53.7 | 36.1 | 73.7 | 63.1 |
| Johnson&Everingham, [6] | 87.6 | 74.7 | 67.1 | 67.3 | 45.8 | 76.8 | 67.4 |

Limitations

- prediction
–prediction: 62.9% PCP; oracle: 88.1% PCP (on LSP)
- typical failure cases



References

- [1] M. Andriluka, S. Roth, and B. Schiele. Pictorial structures revisited: People detection and articulated pose estimation. In *CVPR*, 2009.
- [2] L. Bourdev and J. Malik. Poselets: Body part detectors trained using 3D human pose annotations. In *ICCV'09*.
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- [5] S. Johnson and M. Everingham. Clustered pose and nonlinear appearance models for human pose estimation. In *BMVC'10*.
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- [7] L. Pishchulin, A. Jain, M. Andriluka, T. Thormählen, and B. Schiele. Articulated people detection and pose estimation: Reshaping the future. In *CVPR*, 2012.
- [8] D. Ramanan. Learning to parse images of articulated objects. In *NIPS'06*.
- [9] Y. Yang and D. Ramanan. Articulated pose estimation with flexible mixtures-of-parts. In *CVPR'11*.