Deep learning advances on human pose and shape estimation

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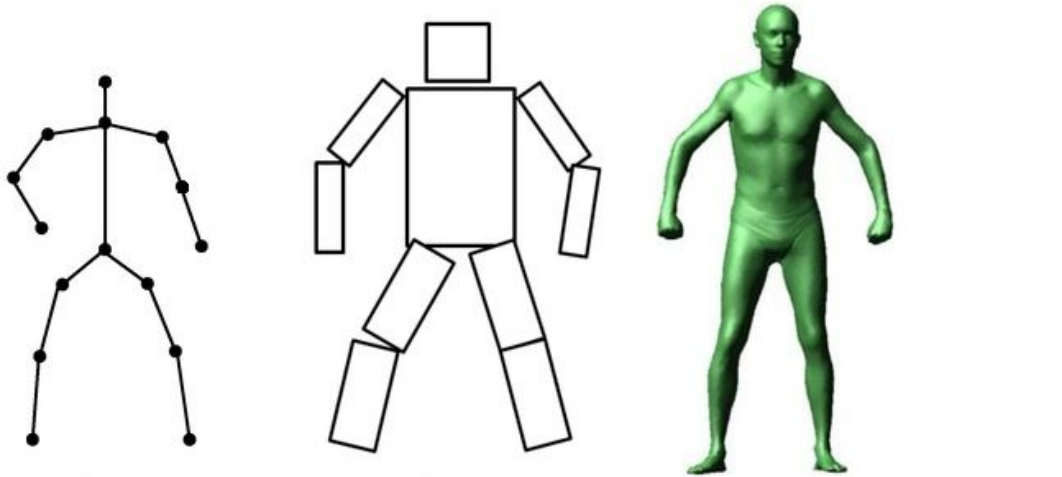
What is articulated human pose?

- Given body kinematic tree, human pose is defined as the vector of joints locations either in 2D (image coordinate in pixels) or 3D (world coordinate in meters).
- Human body pose estimation is a way of representing humans in the images,
- It can be represented and estimated from coarse to fine models.

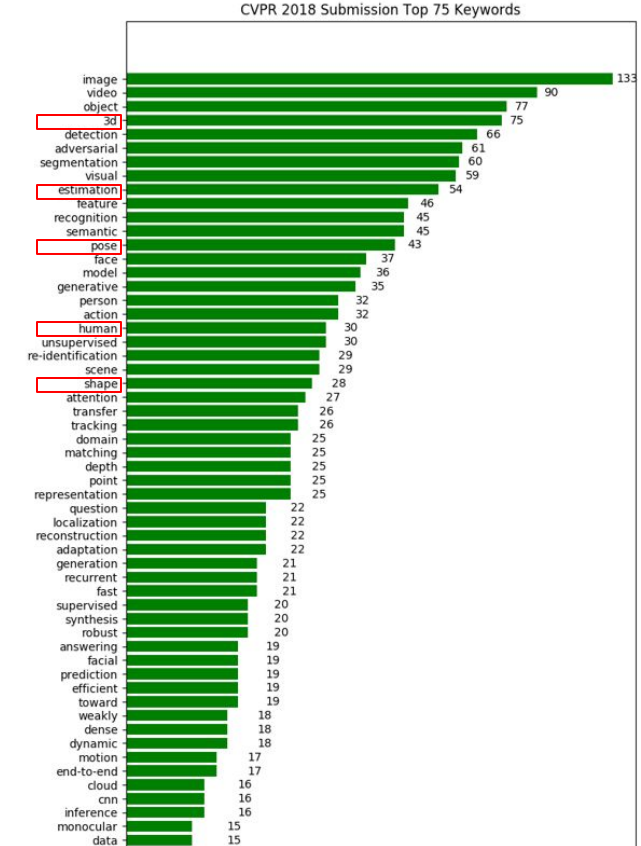


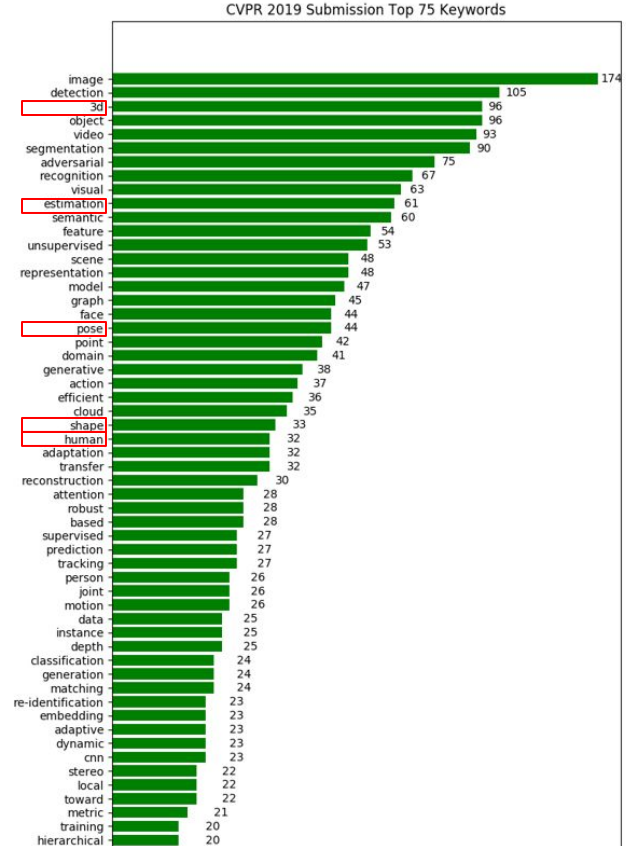
Kinematic model | Cardboard model | Volumetric/parametric model

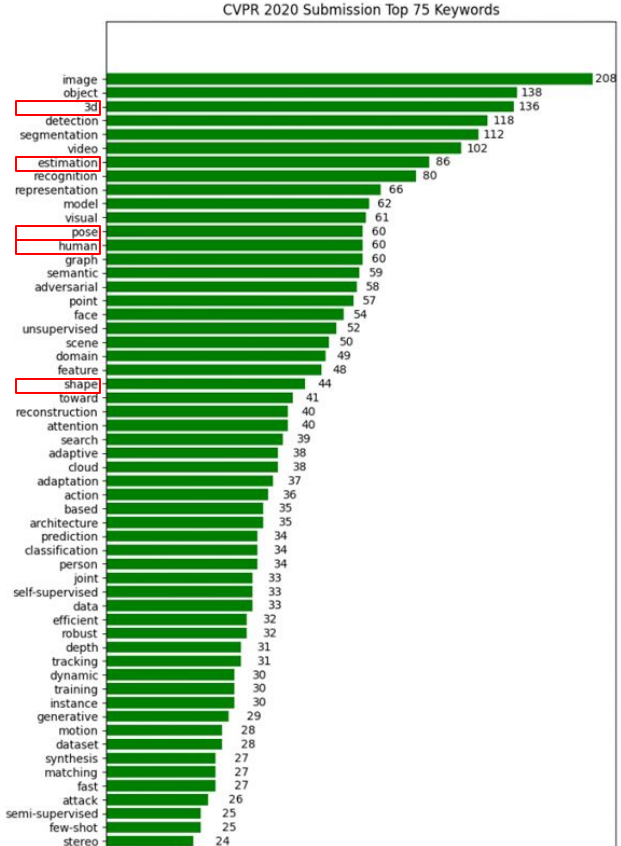
Image credit: https://www.mdpi.com/1424-8220/16/12/1966/htm

Importance of the pose estimation

Image credit: https://github.com/hoya012/







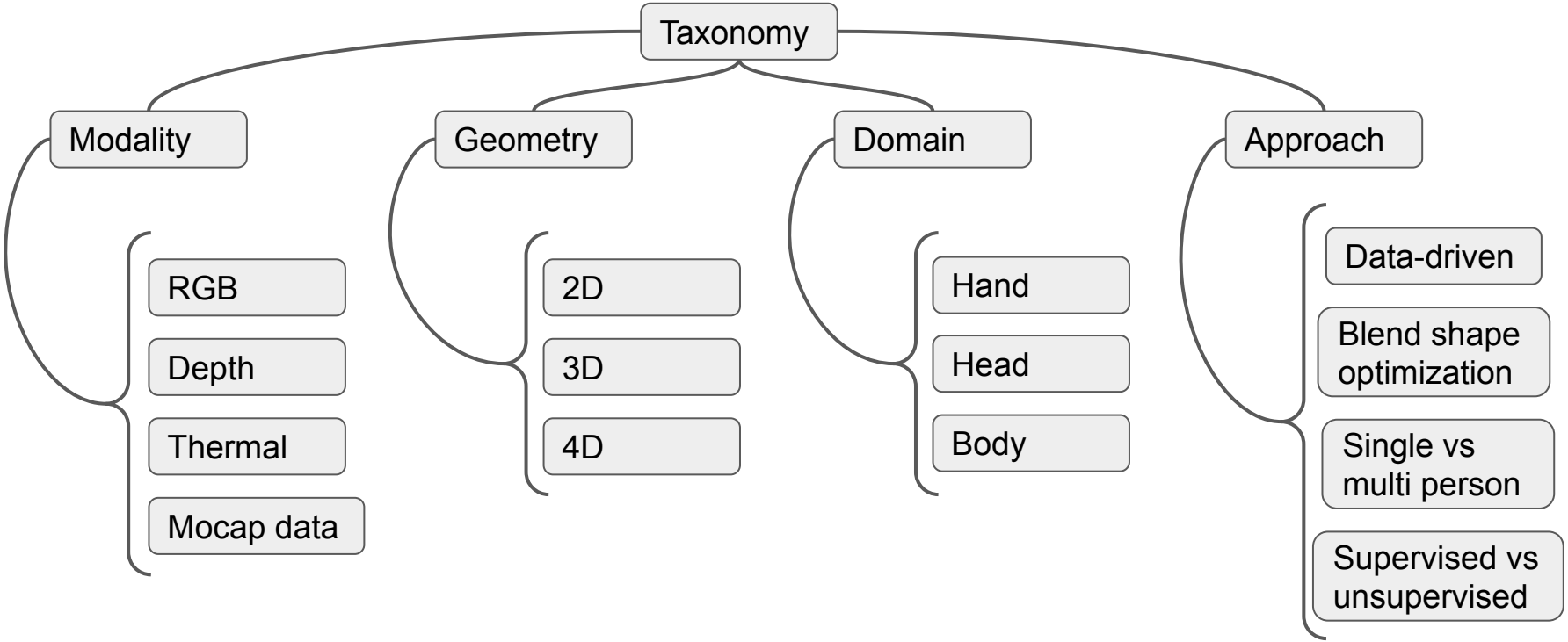
Applications

Image credit: https://www.sciencedirect.com/science/article/pii/S1047320315001121

Challenges

Image credit: https://www.slideshare.net/plutoyang/human-pose-estimation-by-deep-learning

Taxonomy of pose estimation

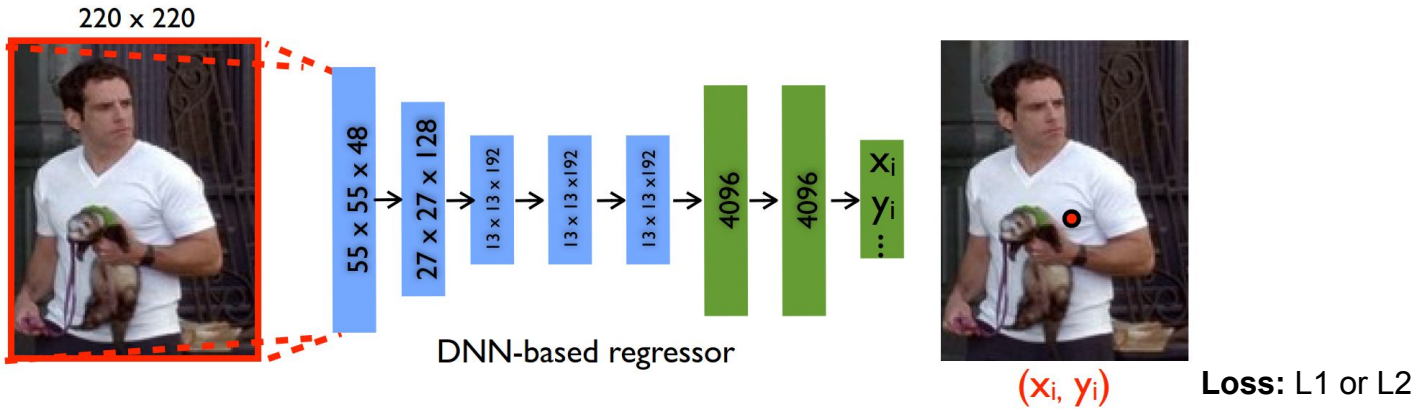


Outlines

- 2D human body pose estimation,
  - Pose regression,
  - Heatmap-based solutions and cascading,
  - Bottom-up and top-down inference.
- 3D human body pose estimation,
  - Lifting 2D to 3D,
  - Volumetric heatmaps and soft-argmax.
- 3D human body pose and shape estimation,
  - Unsupervised estimation,
  - Pose and shape estimation from intermediate representations.
- 3D hand pose estimation,
  - Voxel to voxel prediction.

Human pose regression

- The output of the network is directly a vector of (x,y) joints locations,
- This is a difficult task for the network because
  - Pose vector is a highly nonlinear variable,
  - Network must deal with scale and translation as well.



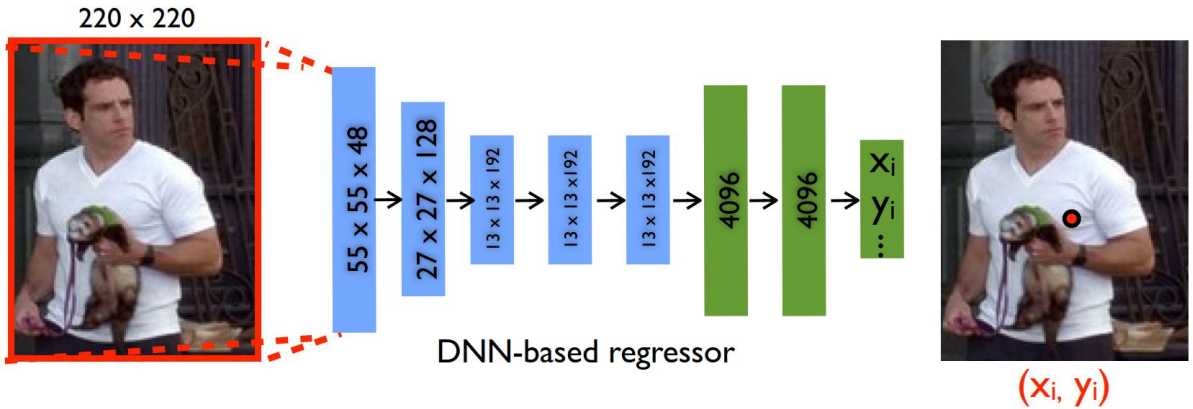
Loss: L1 or L2

Image credit: https://arxiv.org/pdf/1312.4659.pdf

Human pose regression

- The output of the network is directly a vector of (x,y) joints locations,
- This is a difficult task for the network because ⟸ **A better alternative:** a dense probability map for each joint.
  - Pose vector is a highly nonlinear variable, ⟸ **Solution:** cascade of pose regressors.
  - Network must deal with scale and translation as well.

⟹ **Solution:** crop person bounding box as pre-processing.



Loss: L1 or L2

Image credit: https://arxiv.org/pdf/1312.4659.pdf

Cascade of pose regressors

- Given an initial estimation of the joints (in holistic view), iteratively refines the error (in local view).

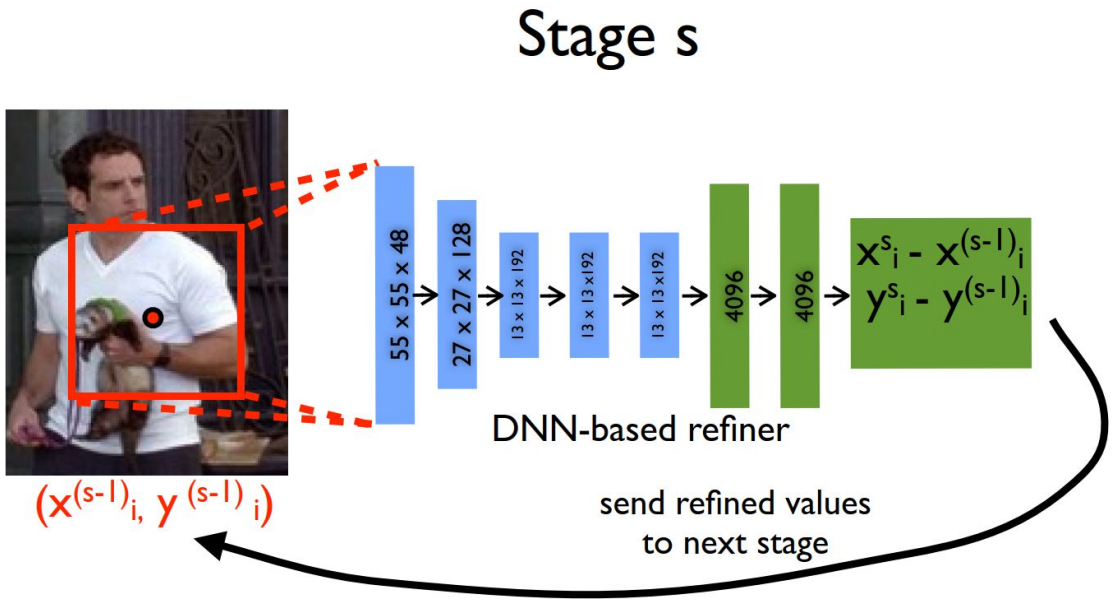


Image credit: https://arxiv.org/pdf/1312.4659.pdf

Cascade of pose regressors

Limitations:

- Sensitive to initial estimation,
- Local solution, easily can stick to local minima,
- Lack of structured predictions.

Image credit: https://arxiv.org/pdf/1312.4659.pdf

Results on LSP dataset

Image credit: https://arxiv.org/pdf/1312.4659.pdf

Results on LSP dataset

Image credit: https://arxiv.org/pdf/1312.4659.pdf

Joints heatmaps instead of pose vector

- It is an easier problem for the network,
- Still can be combined with pose regressors,
- The map can be fed into graphical models to learn higher order joint relationships.

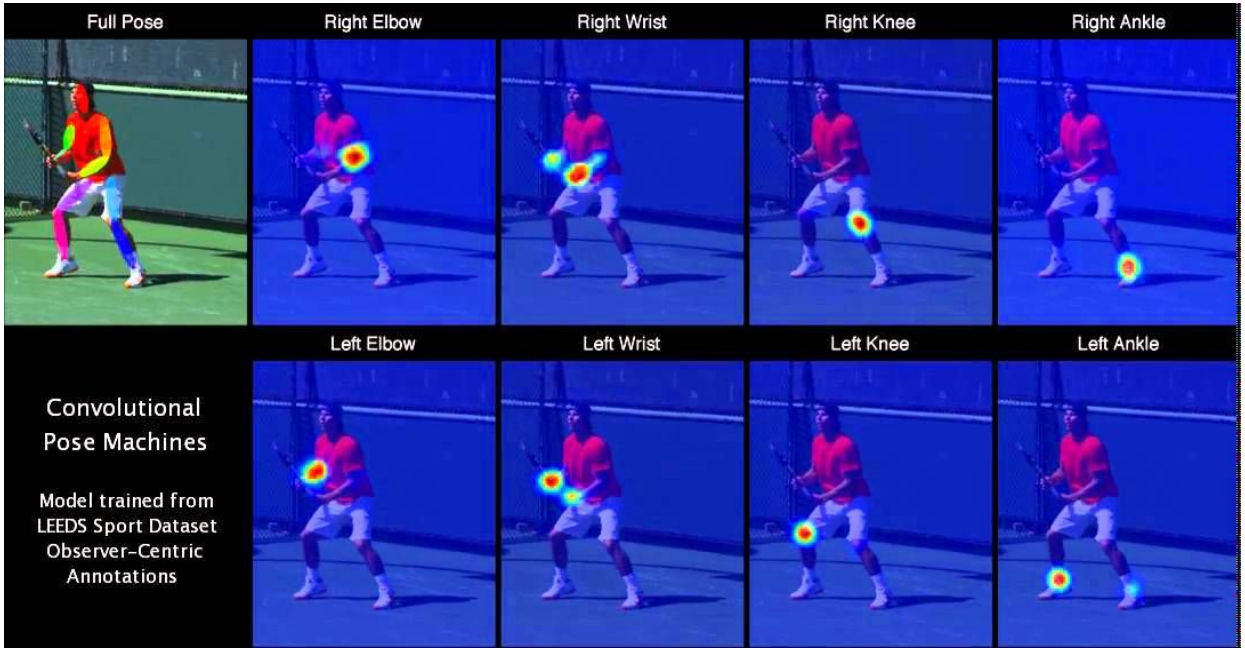


Image credit: https://www.youtube.com/watch?v=hcnBHWo2RGw

Context is important

Which part belongs to a human body?

Context is important

Which part belongs to a human body?

- Local evidence is weak,
- Larger receptive field = more context,
- Recover from failures by cascading.

Stacked Hourglass Network (SHN)

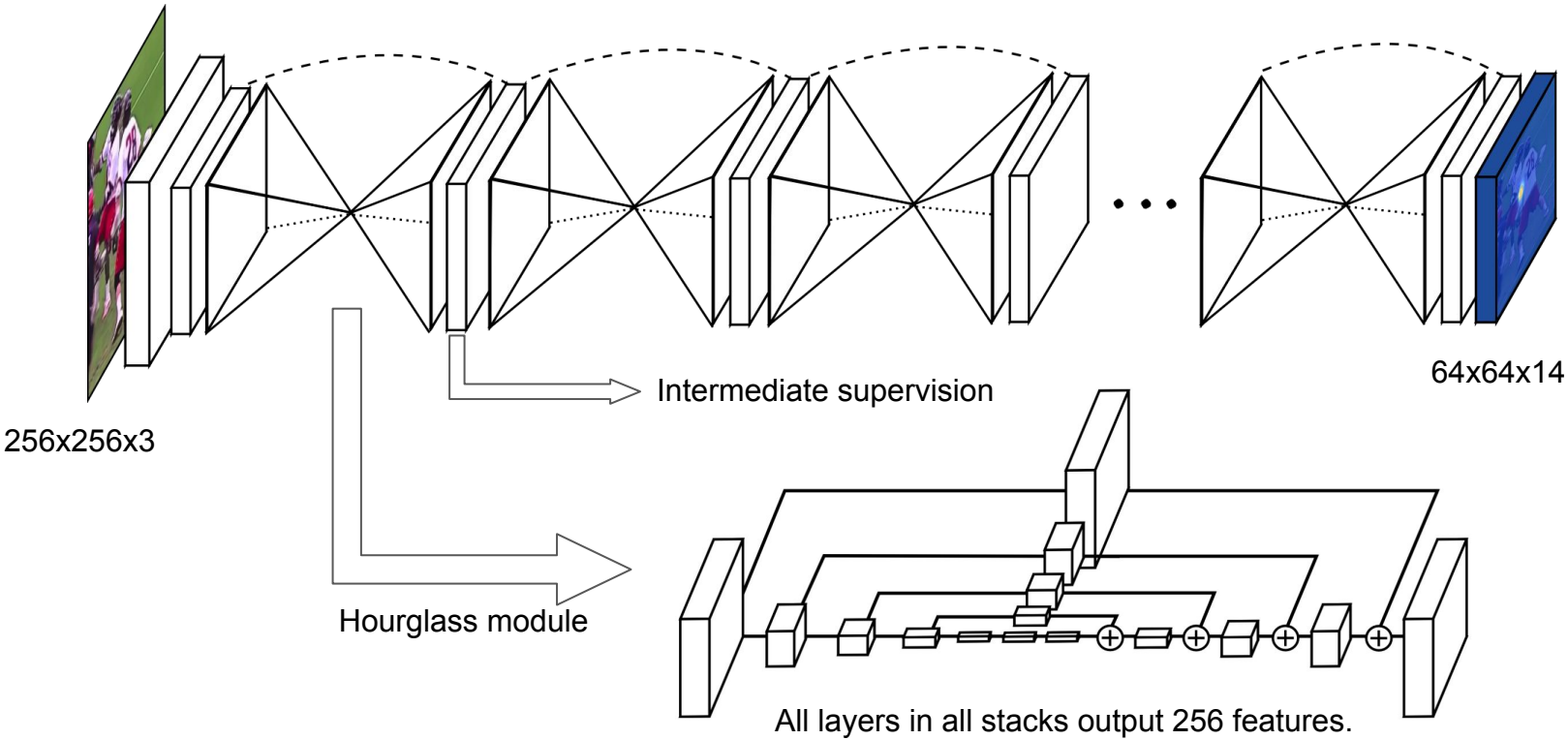


Image credit: https://arxiv.org/pdf/1603.06937.pdf

Stacked Hourglass Network: intermediate supervision

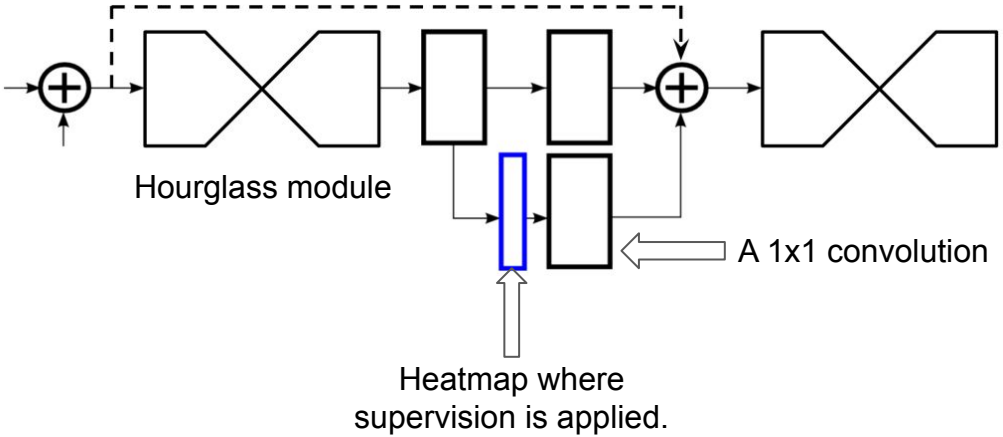


Image credit: https://arxiv.org/pdf/1603.06937.pdf

Stacked Hourglass Network

Cons:

- Quite heavy in GPU,
- Joints may be confused with background,
- Still does not explicitly deal with structure.

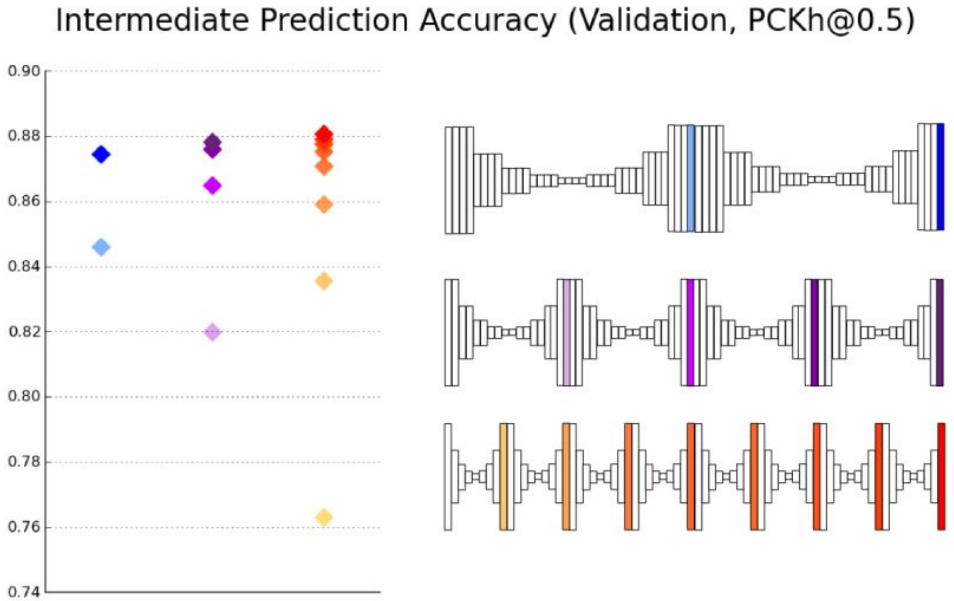


Image credit: https://arxiv.org/pdf/1603.06937.pdf

Some results on MPII dataset

Image credit: https://arxiv.org/pdf/1603.06937.pdf

AND-OR graph as body part representation

- The goal is to optimize a model to find the best possible combination of leaf nodes,
- Body representation as a hierarchy satisfies some articulation constraints.

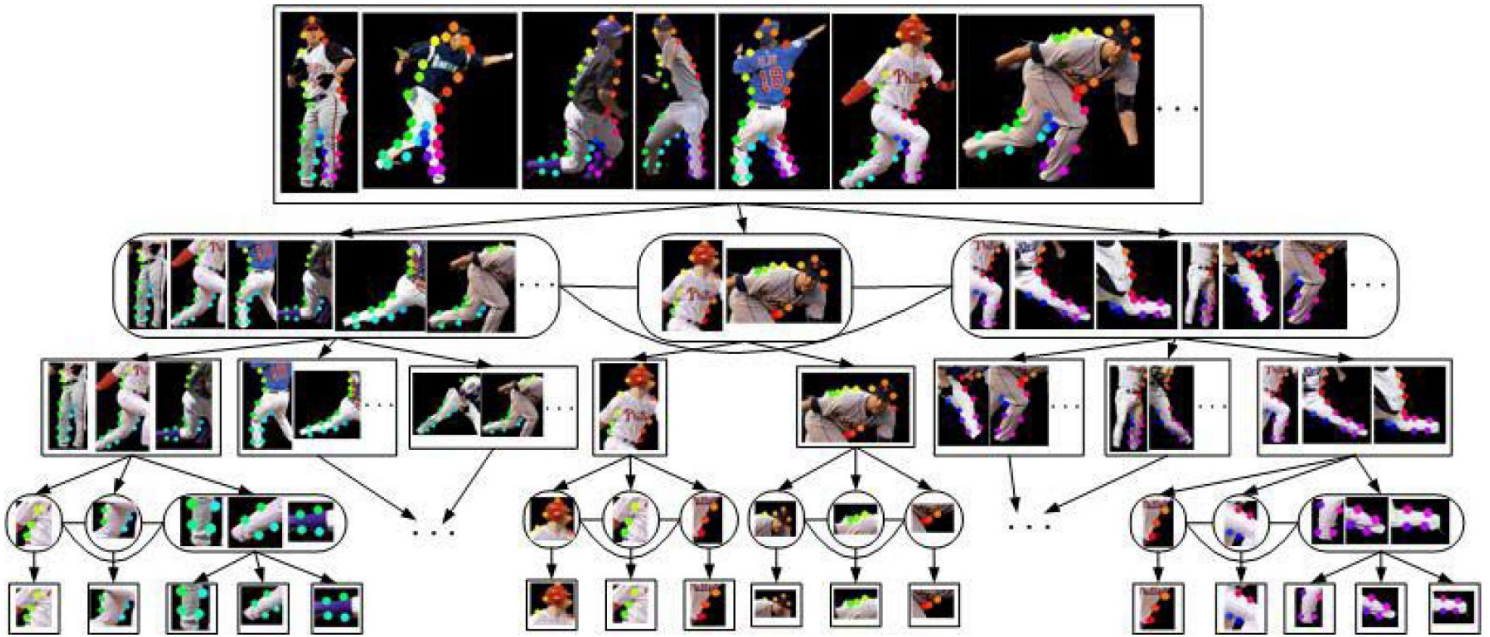
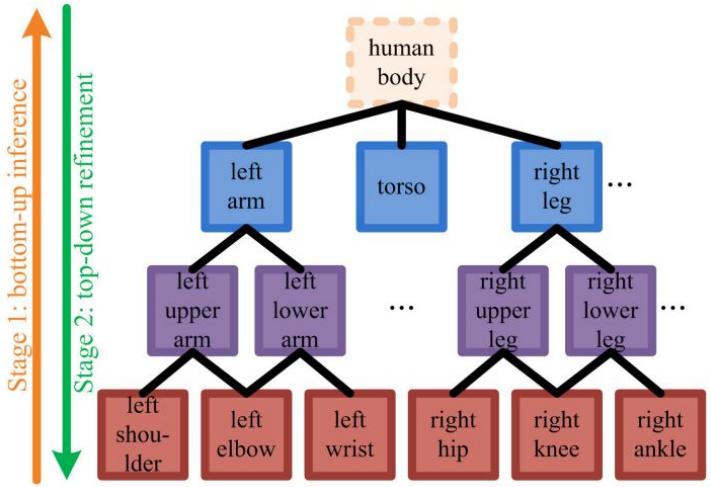


Image credit: Zhu, Long, et al. "Max margin and/or graph learning for parsing the human body.", *CVPR 2008.*

Deeply learned compositional models

1. We have a compositional model of part-subpart relationships,
2. Traditional solutions by modelling the graph (or tree) with Gibbs formulation,
3. We want a bottom-up and top-down inference,

Question: How to model it with CNN models?



$$p(\Omega|\mathbf{I}) = \frac{1}{Z}\exp\{-E(\Omega,\mathbf{I})\}$$

$$S(\Omega) \equiv -E(\Omega,\mathbf{I}) = \sum_{u\in\mathcal{V}^{leaf}} \phi_u^{leaf}(w_u,\mathbf{I}) + \sum_{u\in\mathcal{V}^{and}}\sum_{v\in ch(u)} \phi_{u,v}^{and}(w_u,w_v)$$

Minimizing the energy *E* is equal to maximizing the score *S*

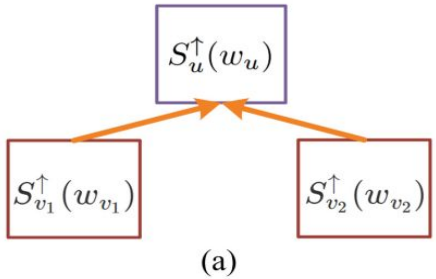
Unary term

Pairwise term

Image credit: Tang et al., "Deeply learned compositional models for human pose estimation." *ECCV*. 2018.

First define updating rule

Bottom-up inference:

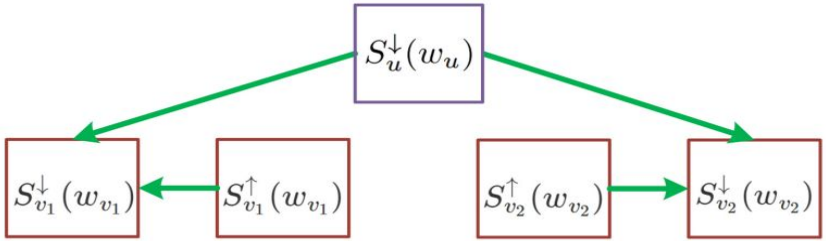


(a)

$$\text{(Leaf)}\ S_u^{\uparrow}(w_u) = \phi_u^{leaf}(w_u, \mathbf{I})$$

$$\text{(And)}\ S_u^{\uparrow}(w_u) = \sum_{v \in ch(u)} \max_{w_v} [\phi_{u,v}^{and}(w_u, w_v) + S_v^{\uparrow}(w_v)]$$

Top-down refinement:



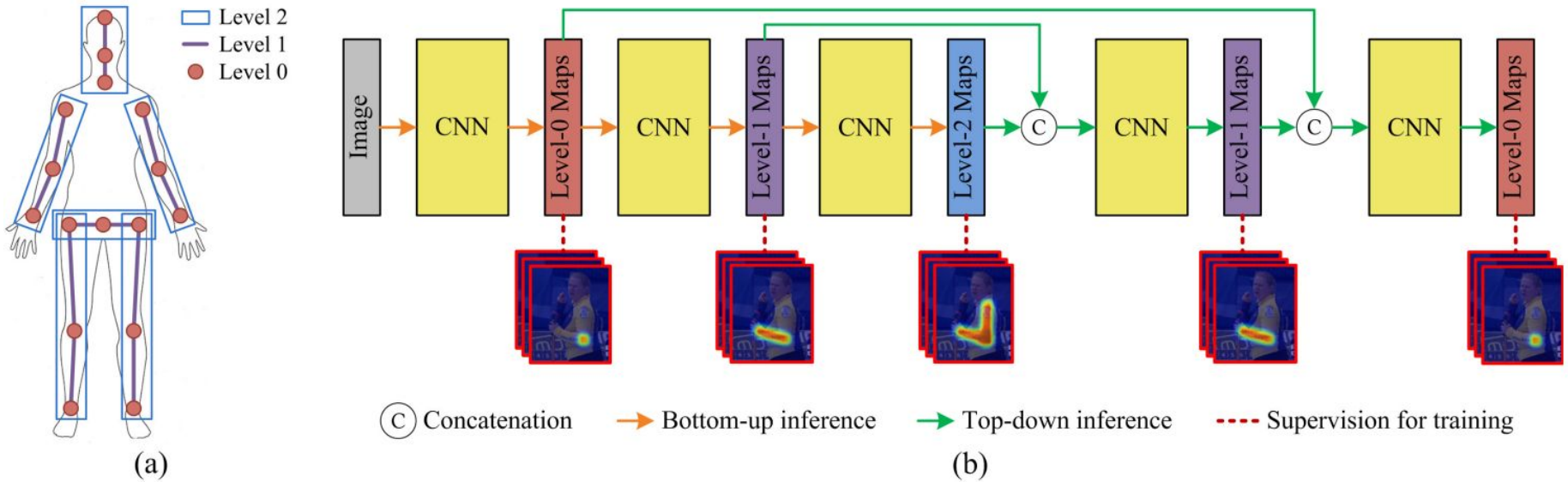
(b)

$$\text{(Root)}\quad w_u^* = \text{argmax}_{w_u}\, S_u^{\downarrow}(w_u) \equiv \text{argmax}_{w_u}\, S_u^{\uparrow}(w_u)$$

$$\text{(Non-root)}\ w_v^* = \text{argmax}_{w_v}\, S_v^{\downarrow}(w_v) \equiv \text{argmax}_{w_v} [\phi_{u,v}^{and}(w_u^*, w_v) + S_v^{\uparrow}(w_v)]$$

Image credit: Tang et al., "Deeply learned compositional models for human pose estimation." *ECCV*. 2018.

Revisit stacked hourglass network



Heatmaps of level *i* (*i*>0) are composed of heatmaps of level 0 and level *i*.

Image credit: Tang et al., "Deeply learned compositional models for human pose estimation." *ECCV*. 2018.

Some results comparing to the 8-stack hourglass

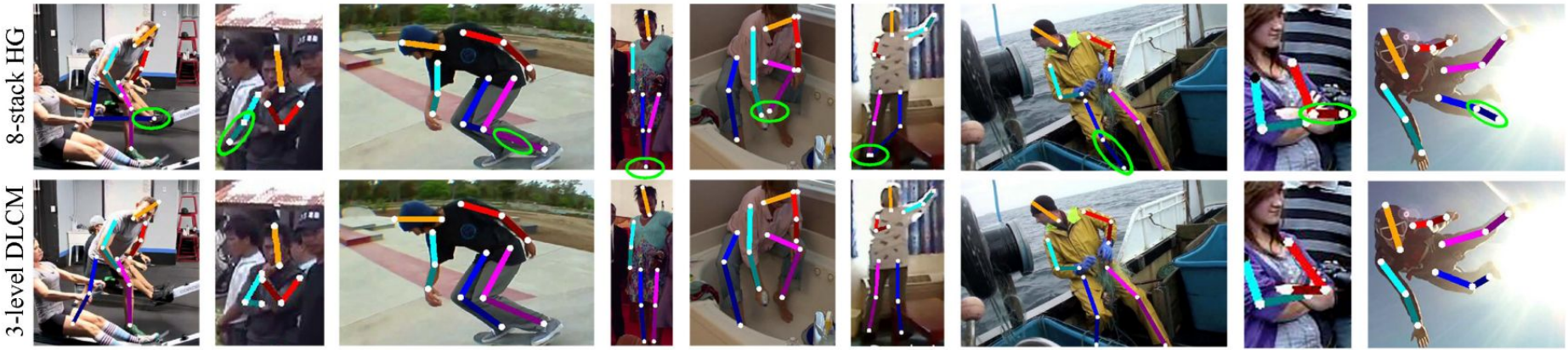


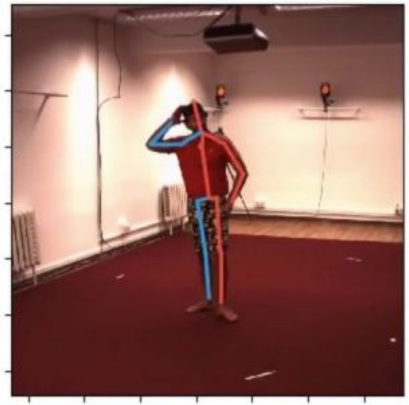
Image credit: Tang et al., "Deeply learned compositional models for human pose estimation." *ECCV*. 2018.

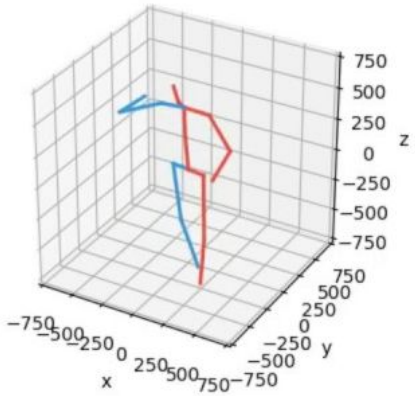
Further reading

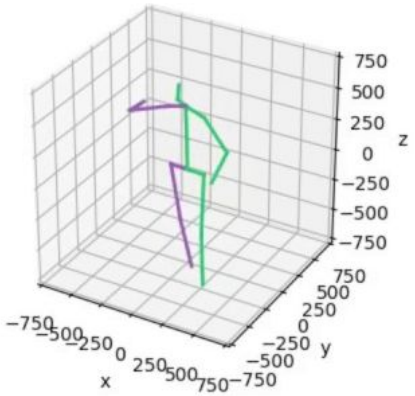
- Multi-context attention maps: http://openaccess.thecvf.com/content_cvpr_2017/papers/Chu_Multi-Context_Attention_for_CVPR_2017_paper.pdf
- End-to-end training of graphical models and CNN: www.ee.cuhk.edu.hk/~xgwang/papers/yangOLWcvpr16.pdf
- Pose estimation by the help of generative adversarial training: http://lamda.nju.edu.cn/weixs/publication/iccv17.pdf

3D human body pose

- 3D pose is the vector of body joints in 3D space,
- 2D pose is the projection of 3D pose to image plane,
- 3D pose is defined with the same models as 2D pose,
- 3D pose estimation is a challenging task since depth dimension is lost during projection to RGB image.







2d observation **3d ground truth** **3d prediction**

Image credit: https://www.youtube.com/watch?v=Hmi3Pd9x1BE

3D human body pose estimation

Solutions:

- Directly regress 3D pose from RGB image,
- Estimate 2D pose and then regress 3D pose from 2D,
- Apply volumetric heatmaps and estimate 3D pose,
- Apply multi-task learning by the use of different modalities.

3D human body pose estimation

Solutions:

- Directly regress 3D pose from RGB image, ⟸ A difficult problem to the network similar to 2D pose.
- Estimate 2D pose and then regress 3D pose from 2D,
- Apply volumetric heatmaps and estimate 3D pose,
- Apply multi-task learning by the use of different modalities. ⟸ Annotating data for all modalities is not a trivial task for many datasets.

3D human body pose estimation

Solutions:

- Directly regress 3D pose from RGB image,
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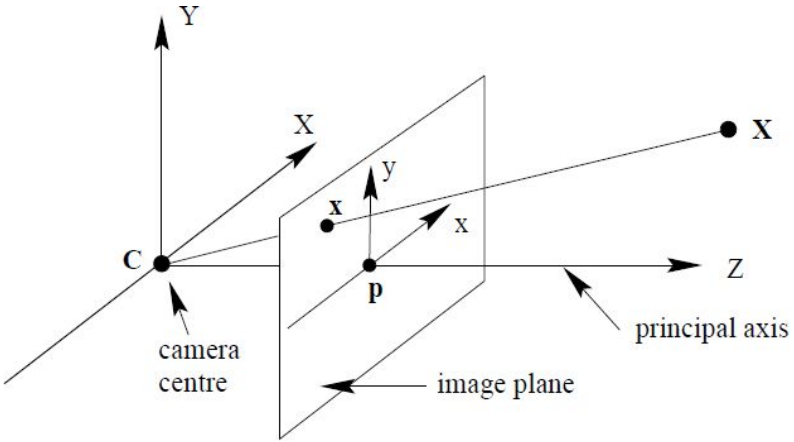
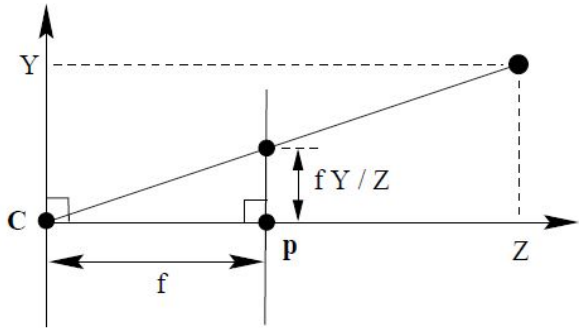
Perspective projection





f: focal length
p: image center

$$K = \begin{bmatrix} f_x & 0 & p_x \\ 0 & f_y & p_y \\ 0 & 0 & 1 \end{bmatrix}$$

Projection matrix

3D to 2D >>>> $[u\ v\ 1]^T = K\ [X/Z\ Y/Z\ 1]^T$

2D to 3D >>>> $[X\ Y\ Z]^T = K^{-1}\ [uZ\ vZ\ Z]^T$

$u = f_x X/Z + p_x$

$v = f_y Y/Z + p_y$

Lifting 2D joints to 3D: A simple solution

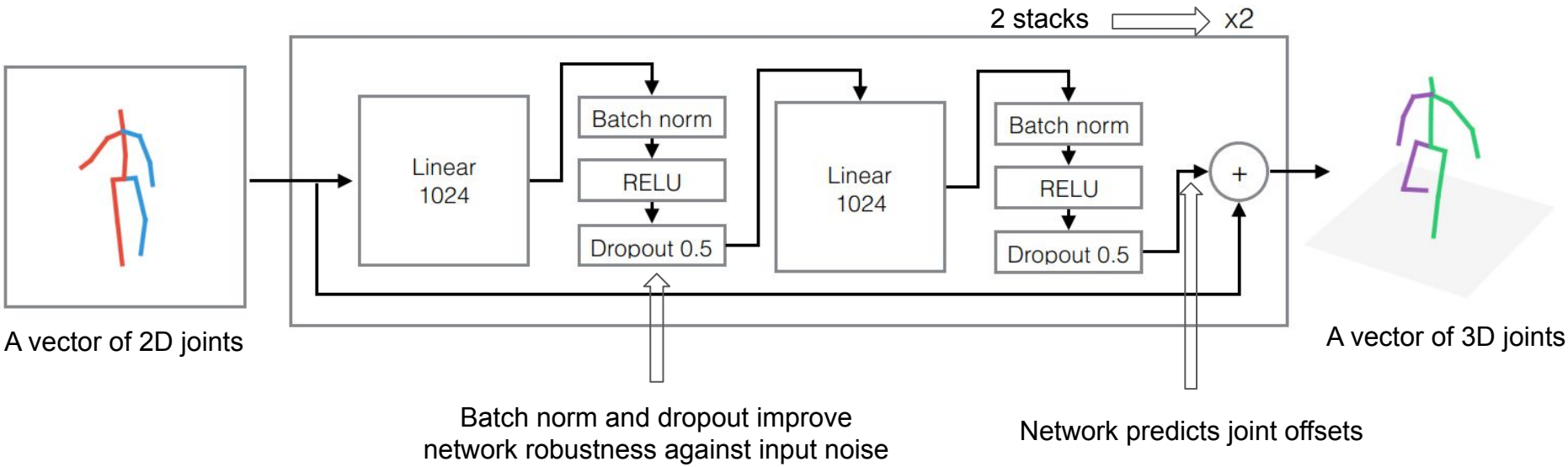
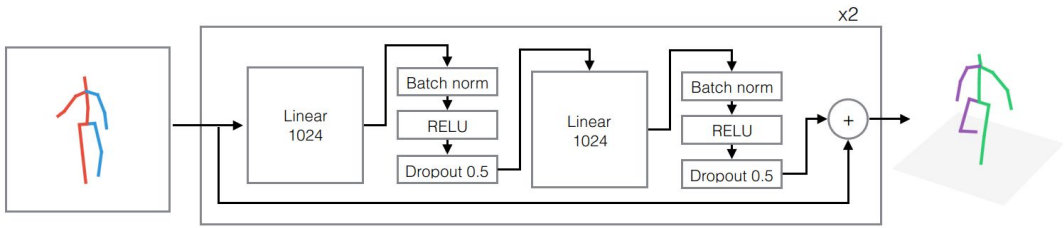


Image credit: https://arxiv.org/pdf/1705.03098.pdf

Lifting 2D joints to 3D: A simple solution

Limitations:

- This is an ill-posed problem, because many 3D poses can be projected to the same 2D pose,
- If 2D pose and 3D pose are not trained jointly, then solution is suboptimal. Because 2D errors are propagated to 3D.

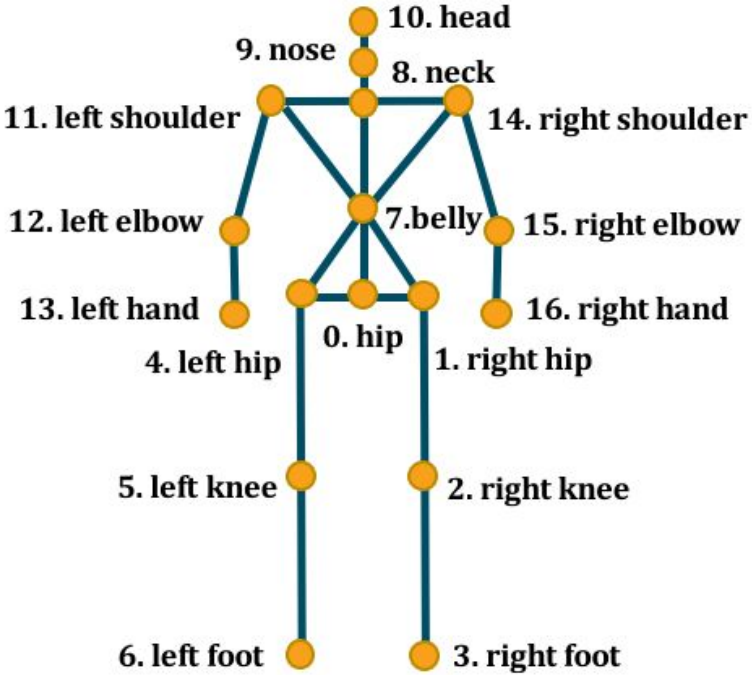


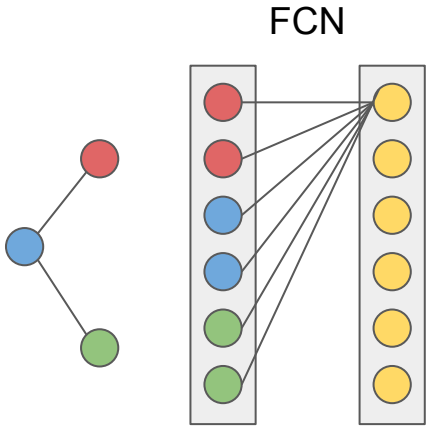
	error (mm)	Δ
Ours	67.5	–
w/o batch norm	88.5	21.0
w/o dropout	71.4	3.9
w/o batch norm w/o dropout	76.0	8.5
w/o residual connections	75.8	8.3
w/o camera coordinates	101.1	33.6
1 block	74.2	6.7
2 blocks (Ours)	67.5	–
4 blocks	69.3	1.8
8 blocks	69.7	2.4

Table 5. Ablative and hyperparameter sensitivity analysis.

Image credit: https://arxiv.org/pdf/1705.03098.pdf

Lifting 2D joints to 3D: Grouping correlated joints





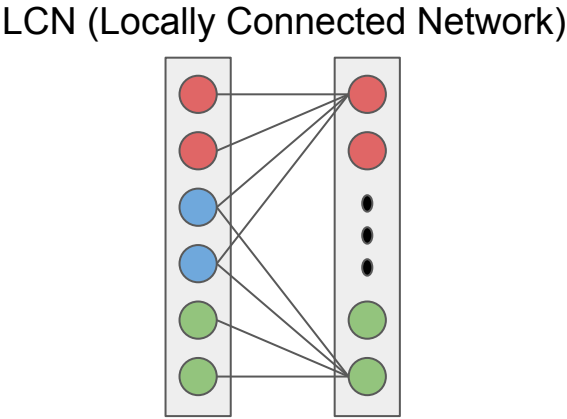
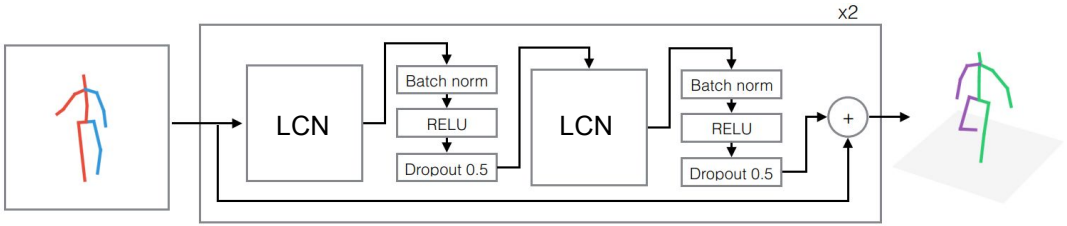


Image credit:
https://openaccess.thecvf.com/content_ICCV_2019/papers/Ci_Optimizing_Network_Structure_for_3D_Human_Pose_Estimation_ICCV_2019_paper.pdf

Lifting 2D joints to 3D: Grouping correlated joints



Model	Coordinate System	Error
Martinez *et al.* [18]	camera CS	67.50
Martinez *et al.* [18]	pixel CS	63.21
LCN (3-NN)	camera CS	62.95
LCN (3-NN)	pixel CS	57.56

Image credit:
https://openaccess.thecvf.com/content_ICCV_2019/papers/Ci_Optimizing_Network_Structure_for_3D_Human_Pose_Estimation_ICCV_2019_paper.pdf

Volumetric heatmaps for 3D pose estimation

- A volumetric heatmap is defined as a tensor in the form of (*#Width x #Height x #Depth x #Joints),*
- A joint's depth is a continuous value which is discretized into several bins, i.e. *#Depth,*
- Ground truth heatmap can be defined by a Gaussian.

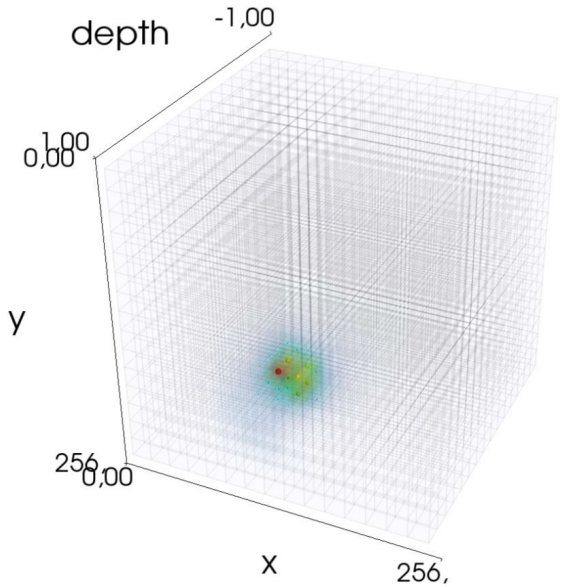
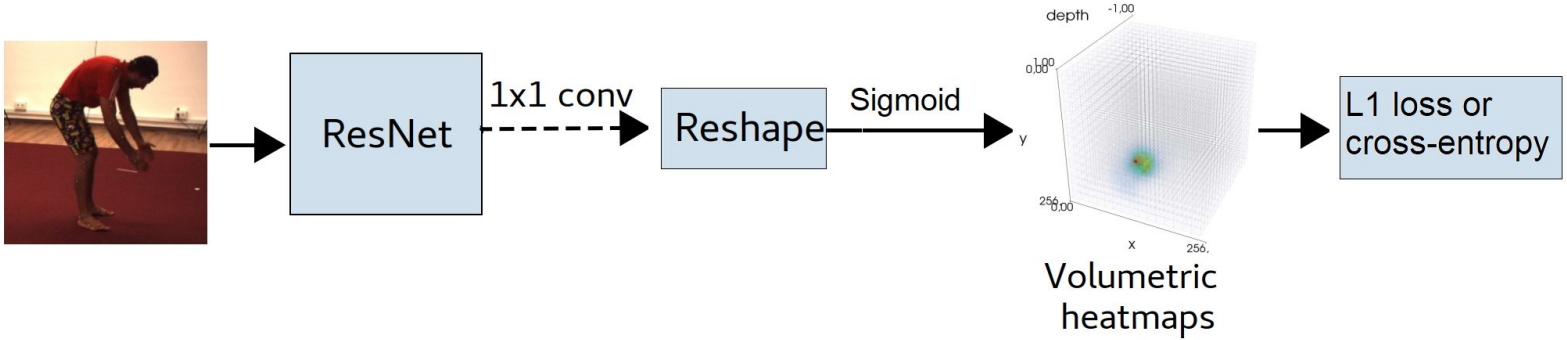


Image credit: https://www.vision.rwth-aachen.de/media/papers/synthetic_occl_augm/posetrack3d-sarandi-poster.pdf

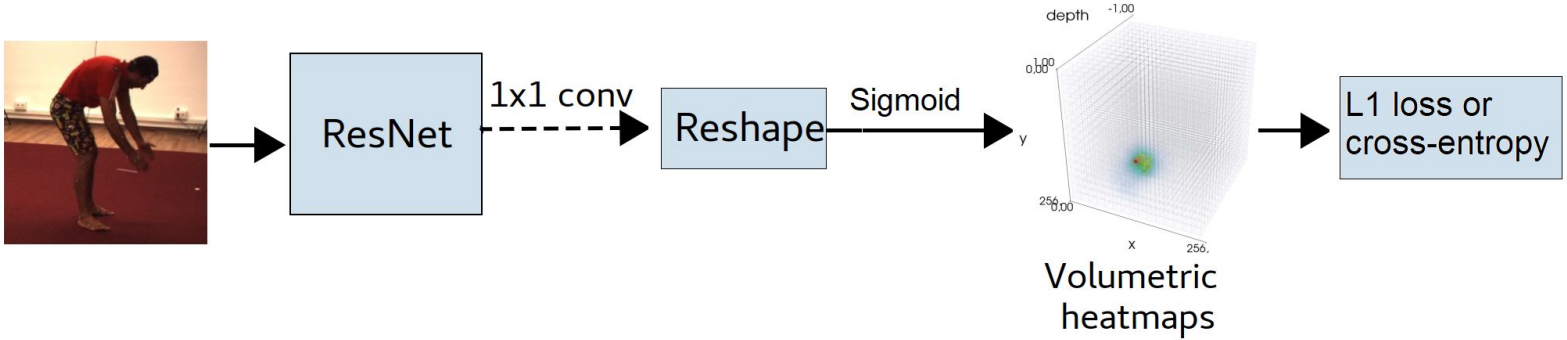
A simple solution



Downside: Depth discretization causes an offset error in joint's depth when *argmax* is applied.

Image credit with modification: https://www.vision.rwth-aachen.de/media/papers/synthetic_occl_augm/posetrack3d-sarandi-poster.pdf

A simple solution



Downside: Depth discretization causes an offset error in joint's depth when *argmax* is applied.

Solution: Using *Soft-argmax* instead of *argmax*.

$$\text{Softmax}(v_{i,j,k}) = \frac{e^{v_{i,j,k}}}{\sum e^{v}}, v \in \mathbb{R}^{H \times W \times D}$$

$$\text{Soft-argmax}(v) = \sum_i \sum_j \sum_k W_{i,j,k} \ \text{Softmax}(v_{i,j,k})$$

$$W_{i,j,k} = [\frac{i}{H}, \frac{j}{W}, \frac{k}{D}]^T$$

Image credit with modification: https://www.vision.rwth-aachen.de/media/papers/synthetic_occl_augm/posetrack3d-sarandi-poster.pdf

A simple solution - data augmentation

2638 occluder objects from Pascal VOC

Filter out ‘person’, ‘truncated’, ‘difficult’ and small object segments

Augmented inputs with pasted occluders

Applied with 50% probability, 1–8 objects, at random scale, at random position

Image credit: https://www.vision.rwth-aachen.de/media/papers/synthetic_occl_augm/posetrack3d-sarandi-poster.pdf

A simple solution - results on H3.6M dataset

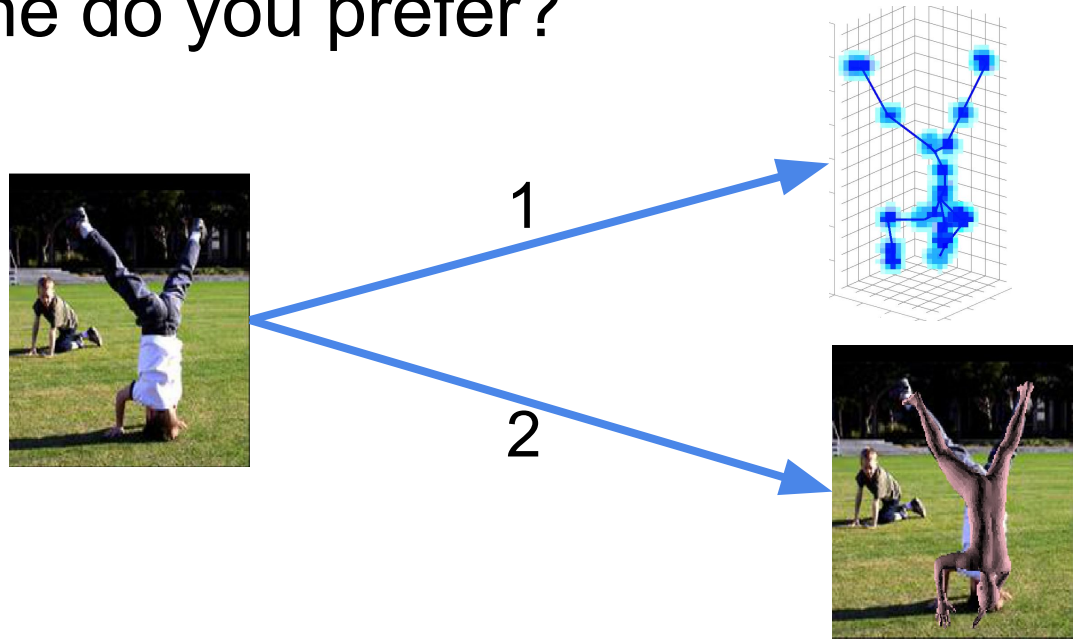
Method	Extra pose data in training?	
	no	yes
Sun (ICCV'17) [3]	92.4	59.1
Martinez (ICCV'17) [4]	–	62.9
Zhou (ICCV'17) [5]	–	55.9
Pavlakos (CVPR'18) [6]	71.9	56.2
Sun (ArXiv) [7]	64.1	**49.6**
Ours (no occlusion augm.)	65.7	–
Ours (full)	**55.4**	–

Image credit: https://www.vision.rwth-aachen.de/media/papers/synthetic_occl_augm/posetrack3d-sarandi-poster.pdf

Further reading

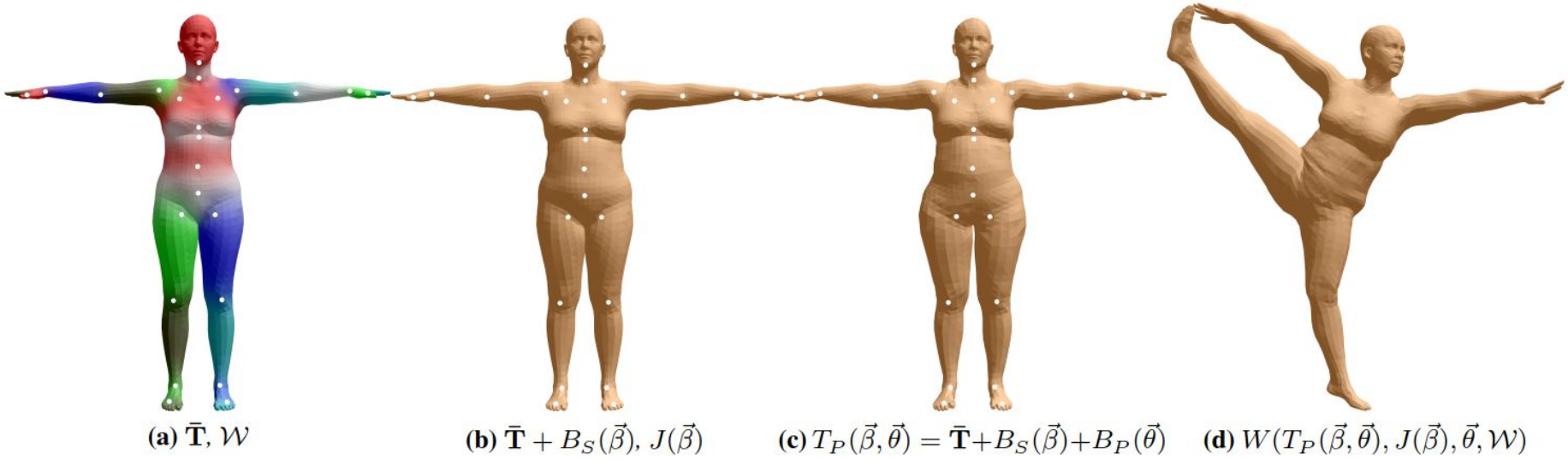
- Compositional pose regression: https://arxiv.org/abs/1704.00159
- Ordinal depth supervision: https://arxiv.org/abs/1805.04095
- Single shot multi person: https://arxiv.org/abs/1712.03453
- Temporal estimation: https://arxiv.org/abs/1811.11742
- Multi-view: https://arxiv.org/abs/1803.04775

Which one do you prefer?



- 3D joints does not represent body anatomy and surface topology,
- We want to estimate a richer representation of body given an RGB image,
- SMPL model has been used for estimation of 3D body joints and mesh.

3D pose and shape by SMPL



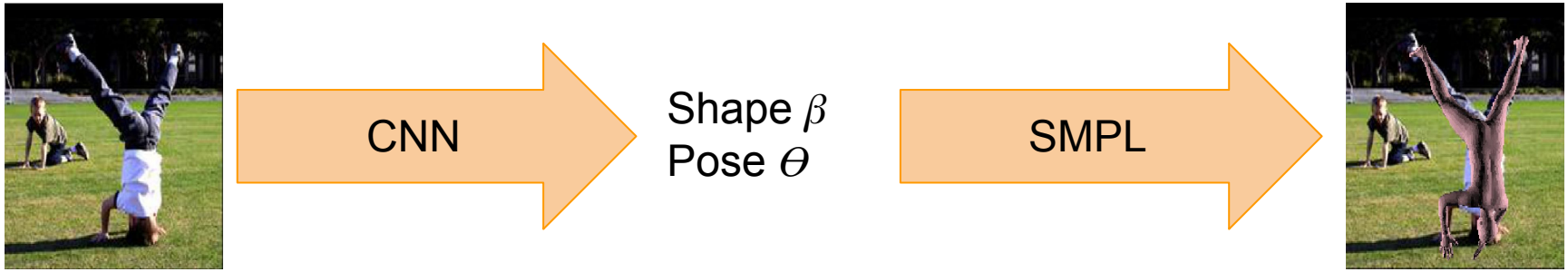
(a) $\bar{\mathbf{T}}, \mathcal{W}$ (b) $\bar{\mathbf{T}} + B_S(\vec{\beta}), J(\vec{\beta})$ (c) $T_P(\vec{\beta}, \vec{\theta}) = \bar{\mathbf{T}} + B_S(\vec{\beta}) + B_P(\vec{\theta})$ (d) $W(T_P(\vec{\beta}, \vec{\theta}), J(\vec{\beta}), \vec{\theta}, \mathcal{W})$

Shape β
Pose Θ

SMPL

3D mesh

A naive solution



Cons
this is a challenging task for the network, plus the noise sensitivity of the model. Besides, direct regression of SMPL parameters may generate artifacts.

Unsupervised pose and shape estimation

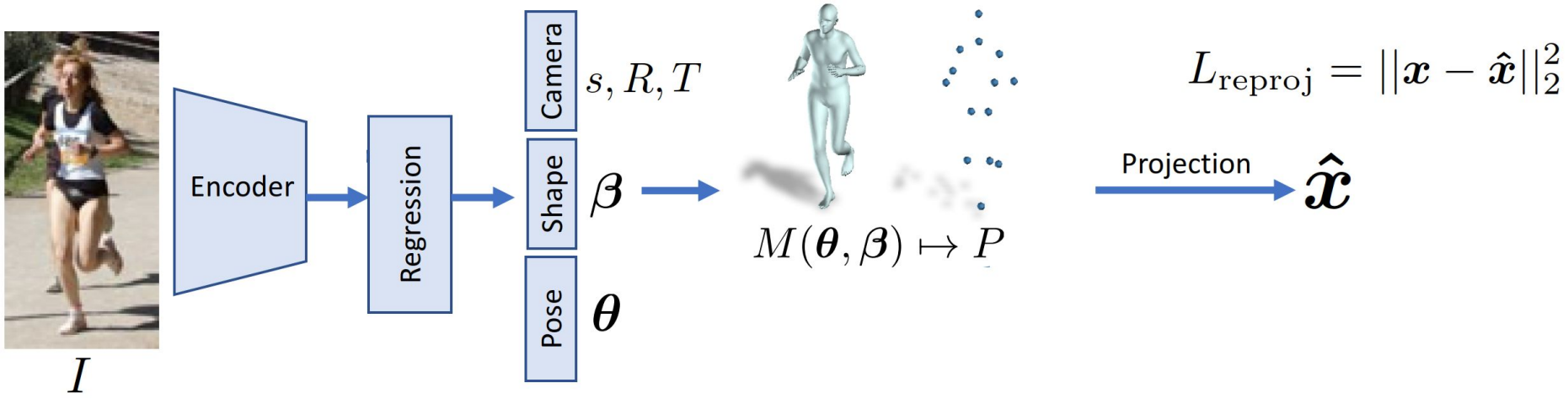


Image credit: https://arxiv.org/abs/1712.06584

Unsupervised pose and shape estimation

I

Encoder

Regression

Camera

Shape

Pose

s, R, T

β

θ

$M(\theta, \beta) \mapsto P$

Projection

$\hat{x}$

$$L_{\text{reproj}} = ||x - \hat{x}||_2^2$$

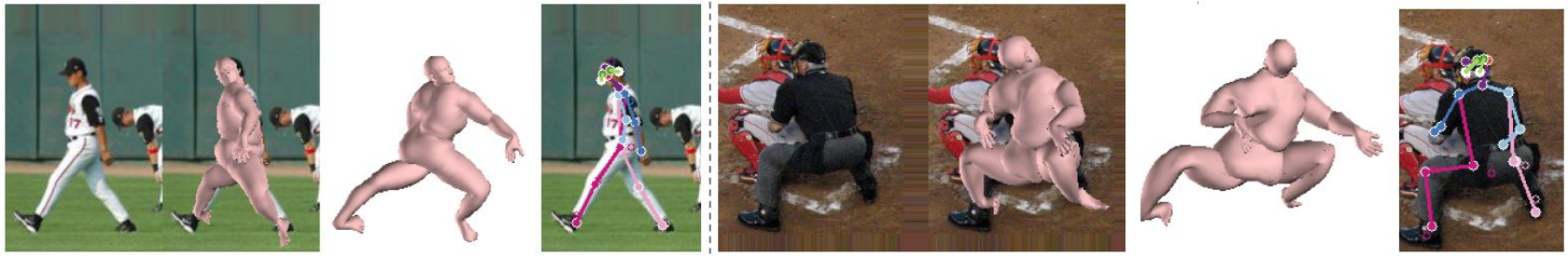


Image credit: https://arxiv.org/abs/1712.06584

Unsupervised pose and shape estimation

Factorized adversarial prior

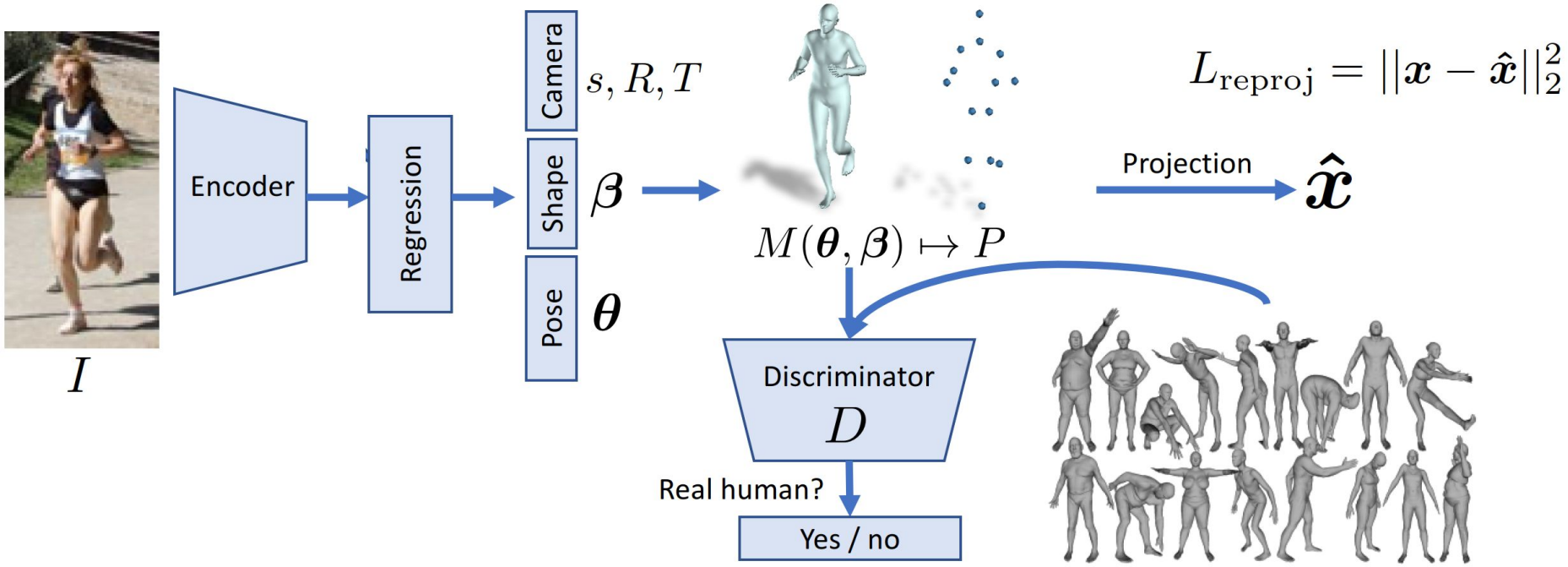


Image credit: https://arxiv.org/abs/1712.06584

Pose and shape estimation with 3D supervision

Iterative 3D supervision with feedback

$$\Theta_{t+1} = \Theta_t + \Delta\Theta_t$$

I

Encoder

Regression

Camera

Shape

Pose

s, R, T

$\boldsymbol{\beta}$

$\boldsymbol{\theta}$

$M(\boldsymbol{\theta}, \boldsymbol{\beta}) \mapsto P$

Projection

$\hat{\boldsymbol{x}}$

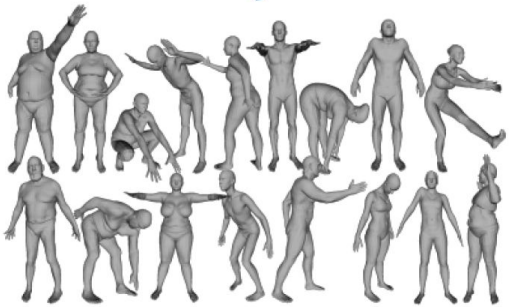
$$L_{\text{reproj}} = ||\boldsymbol{x} - \hat{\boldsymbol{x}}||_2^2$$

Discriminator

D

Real human?

Yes / no



$$L_{\text{3D}} = L_{\text{3D joints}} + L_{\text{3D smpl}}$$

$$L_{\text{joints}} = ||(\mathbf{X_i} - \hat{\mathbf{X}}_\mathbf{i})||_2^2$$

$$L_{\text{smpl}} = ||[\boldsymbol{\beta}_i, \boldsymbol{\theta}_i] - [\hat{\boldsymbol{\beta}}_i, \hat{\boldsymbol{\theta}}_i]||_2^2$$

Unsupervised pose and shape estimation

Method	MPJPE	Reconst. Error
Tome *et al.* [44]	88.39	
Rogez *et al.* [36]	87.7	71.6
VNect *et al.* [28]	80.5	
Pavlakos *et al.* [33]	71.9	**51.23**
Mehta *et al.* [27]	68.6	
Sun *et al.* [40]	**59.1**	
*Deep Kinematic Pose [52]	107.26	
*HMR	**87.97**	58.1
*HMR unpaired	106.84	67.45

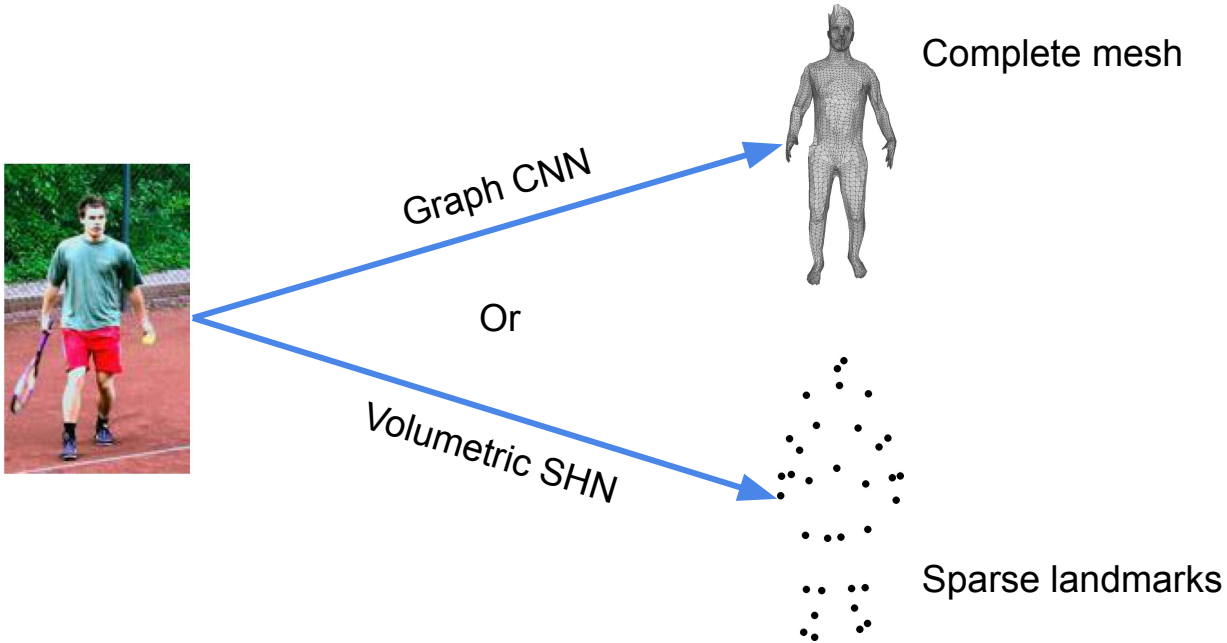
Table 2: **Human3.6M, Protocol 1.** MPJPE and reconstruction loss in mm. * indicates methods that output more than 3D joints.

- MPJPE: mean per joint position error,
- Reconstruction error: MPJPE after rigid alignment of the prediction with ground truth via Procrustes Analysis.

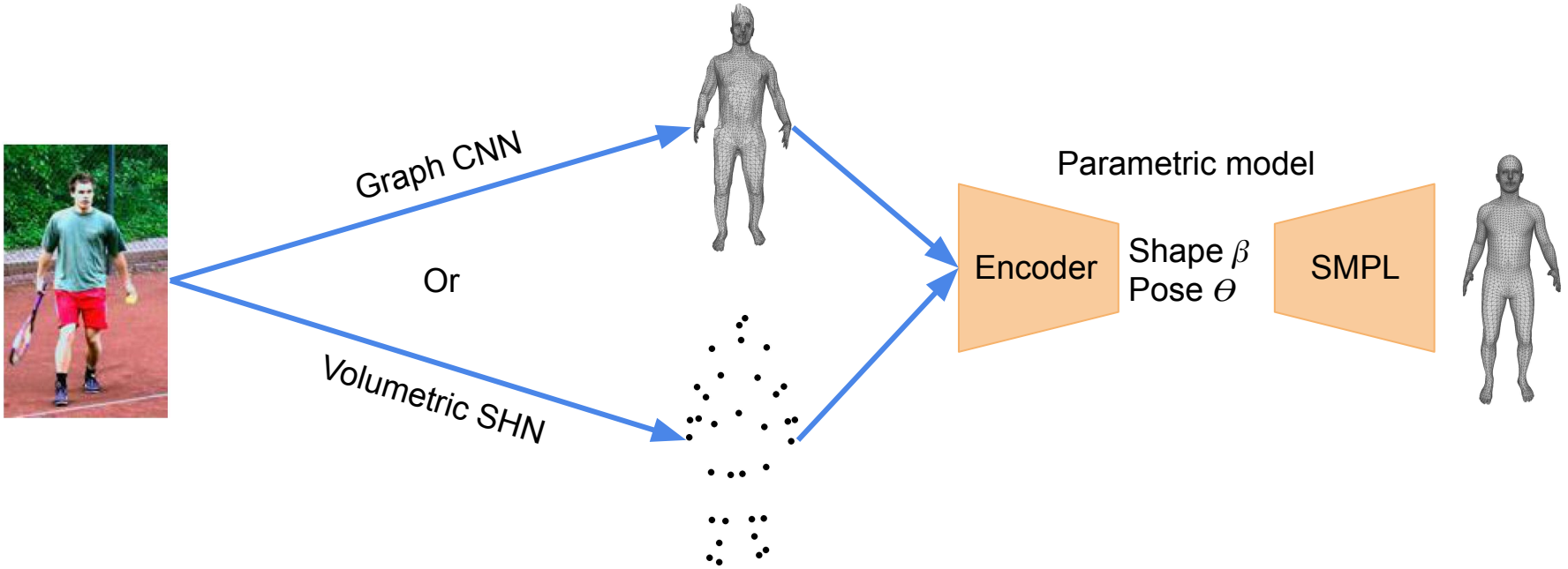
Pros: Unsupervised approach is useful for in-the-wild applications.
Cons: As expected, direct regression of SMPL parameters is challenging, even with 3D supervision.

Image credit: https://arxiv.org/abs/1712.06584

Regressing body vertices rather than SMPL param.



Regressing SMPL parameters on top of the 3D mesh/landmarks



A review on graph convolutional network

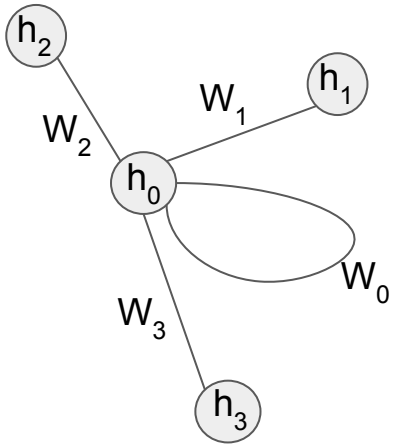
$$f(H^{(l)}, A) = \sigma\left(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(l)}W^{(l)}\right)$$

Activation function

Symmetrically normalized adjacency matrix

Features

Weights



A review on graph convolutional network

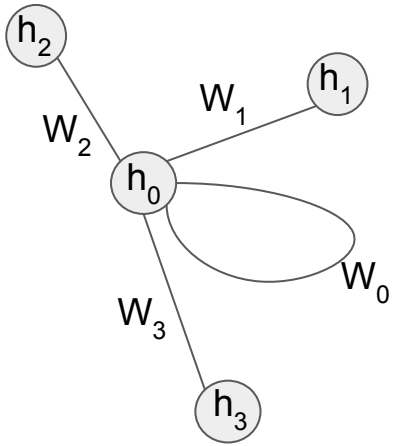
$$f(H^{(l)}, A) = \sigma\left(D^{-\frac{1}{2}}AD^{-\frac{1}{2}}H^{(l)}W^{(l)}\right)$$

Activation function

Symmetrically normalized adjacency matrix

Features

Weights



- Each node has a different topology, therefore weights are shared among adjacent nodes, i.e. $\{W_0, W_n=W_1 | n>0\}$,
- Arbitrary levels of adjacency can be applied,
- Batch normalization, dropout, pooling, etc are applicable,
- For simplicity, graph topology is fixed among all the samples,
- Due to weight sharing, GCN requires more filters in each layer than CNN.

Mesh regression through graph CNN

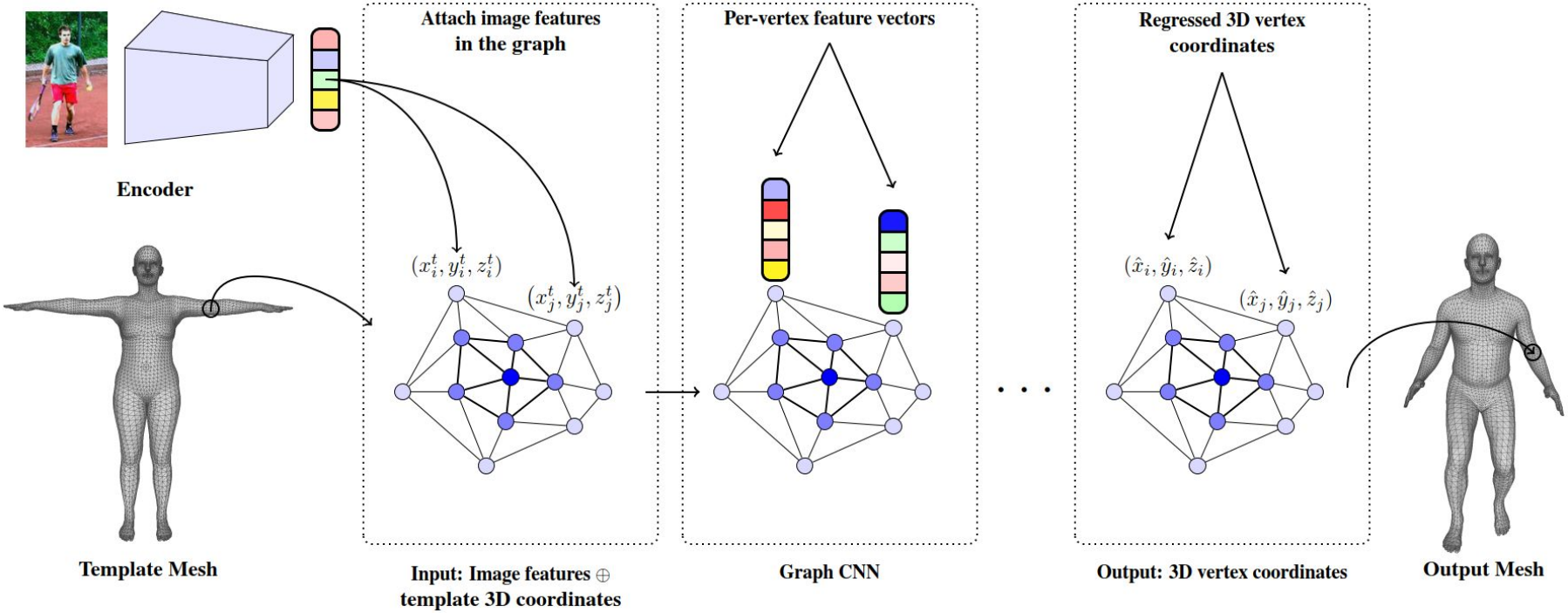


Image credit: https://arxiv.org/abs/1905.03244

Mesh regression through graph CNN

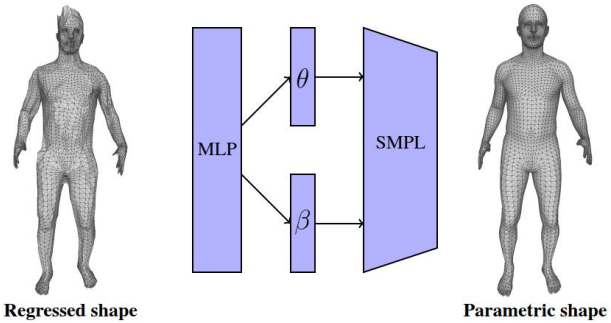
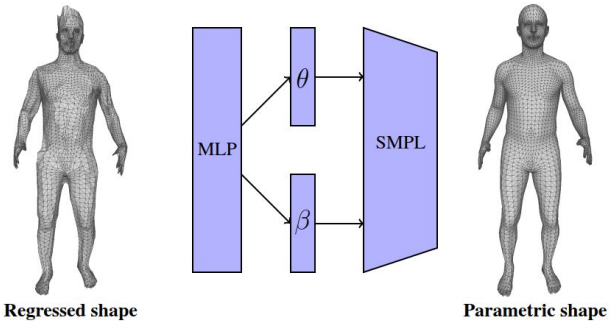
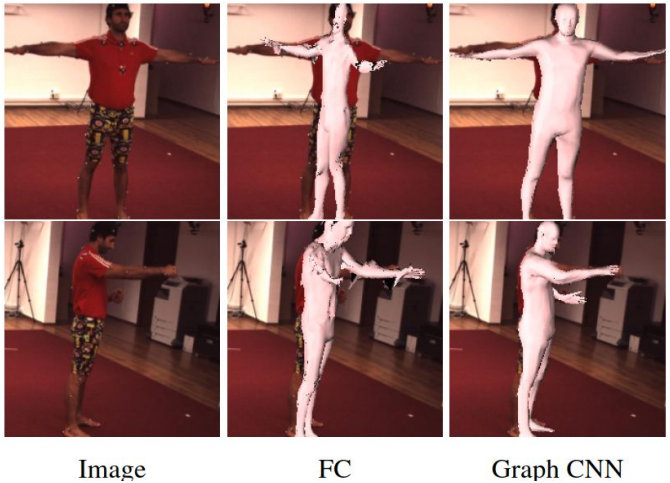


Image credit: https://arxiv.org/abs/1905.03244

Mesh regression through graph CNN



Method	MPJPE	Reconst. Error
SMPL Parameter Regression [15]	-	77.6
Mesh Regression (FC)	200.8	105.8
Mesh Regression (Graph)	**102.1**	69.0
Mesh Regression (Graph + SMPL)	113.2	**61.3**



Pros:

- Local convolutions over the mesh better deals with local minima than FC layers,
- Mesh regression is an easier problem than SMPL parameters regression.

Cons:

- It easily overfits on the training set,
- It requires 3D ground truth hard to annotate in the real world applications.

Image credit: https://arxiv.org/abs/1905.03244

Sparse landmarks regression

- Landmarks can represent body surface geometry,
- They can be annotated easier than the whole mesh,
- They must be sparse but optimized in terms of the amount and location.

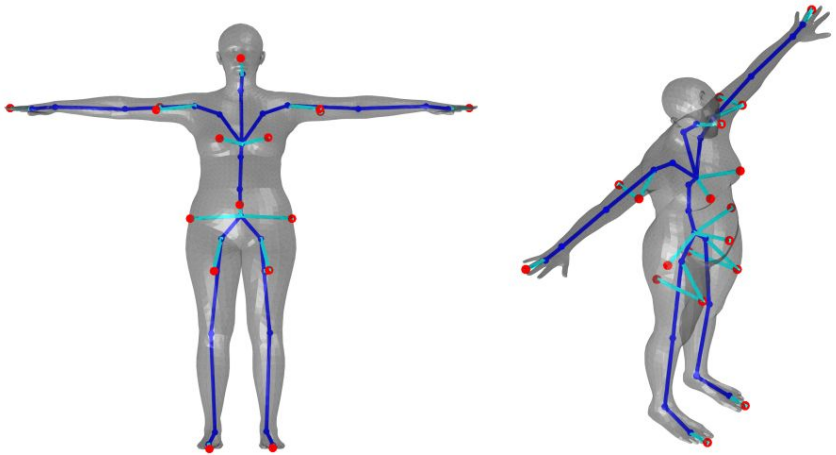


Image credit: https://arxiv.org/pdf/1812.10766.pdf

Joints + sparse landmarks regression through SHN

- The output layer of SHN is updated to be a volumetric tensor (width, height, depth, #joints + #landmarks),
- Volumetric SHN is a heavy model consuming a lot of memory in training,

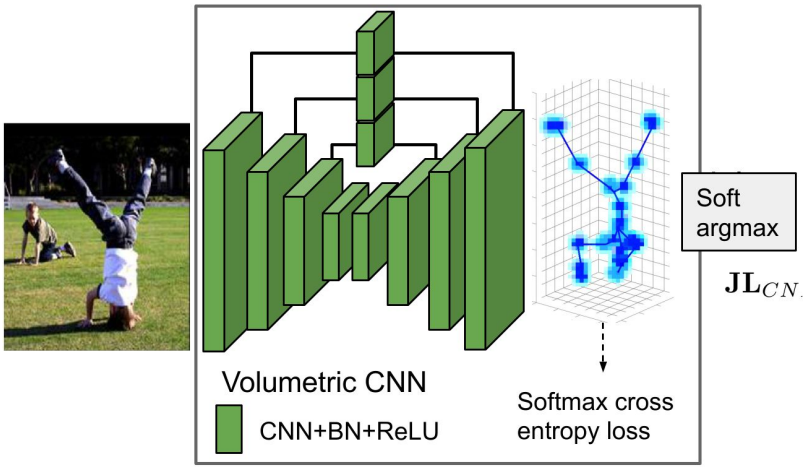
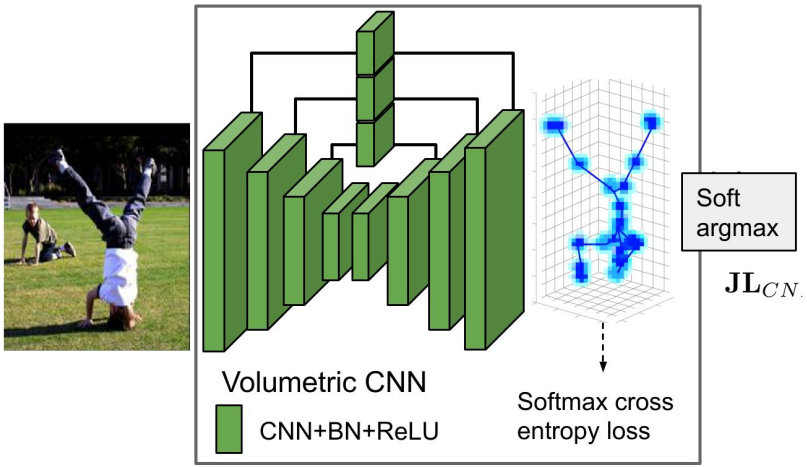


Image credit: https://arxiv.org/pdf/1812.10766.pdf

Joints + sparse landmarks regression through SHN

- The output layer of SHN is updated to be a volumetric tensor (width, height, depth, #joints + #landmarks),
- Volumetric SHN is a heavy model consuming a lot of memory in training,
- Inspired from compositional SHN, volumetric SHN can be updated with limb heatmaps, i.e. (width, height, depth, #joints + #landmarks + #limbs)



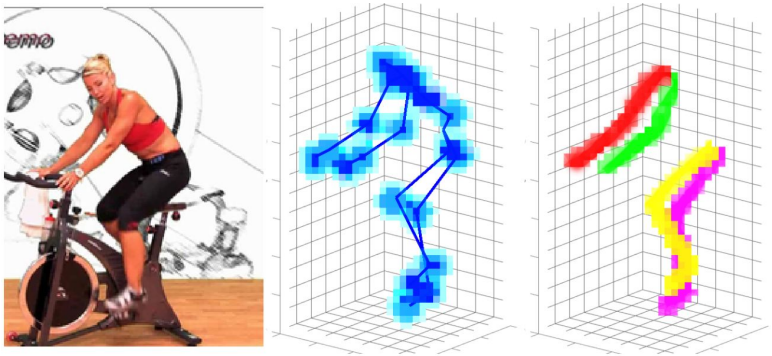
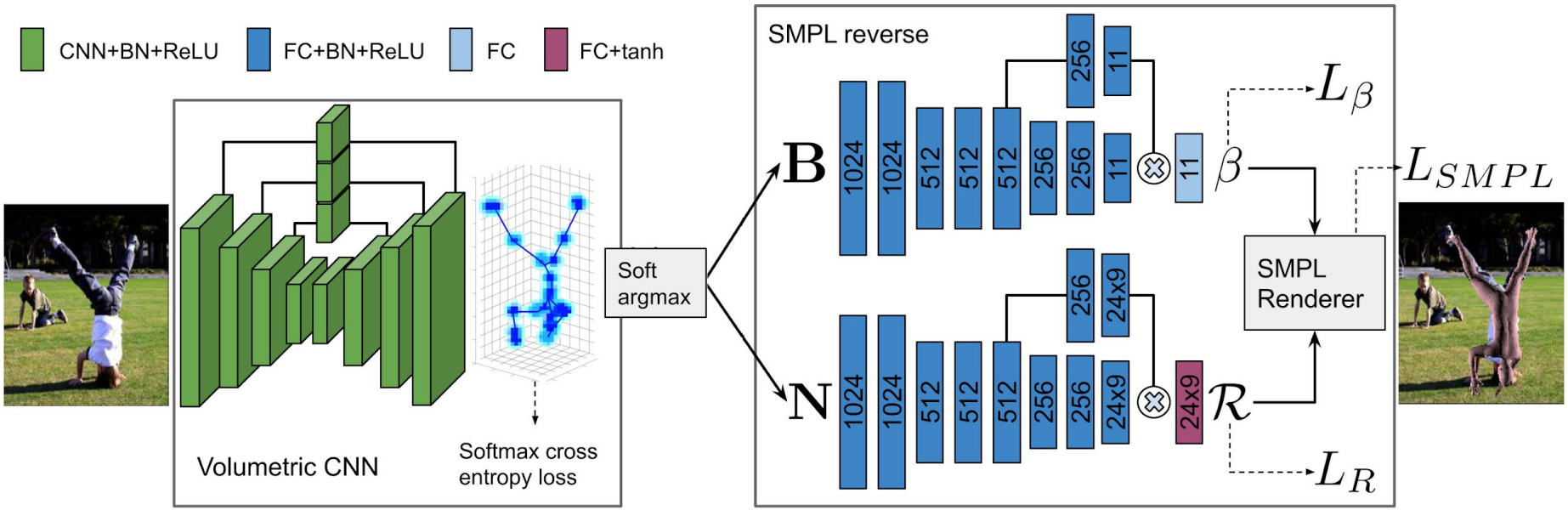


Image credit: https://arxiv.org/pdf/1812.10766.pdf

Regressing SMPL param. from joints and landmarks

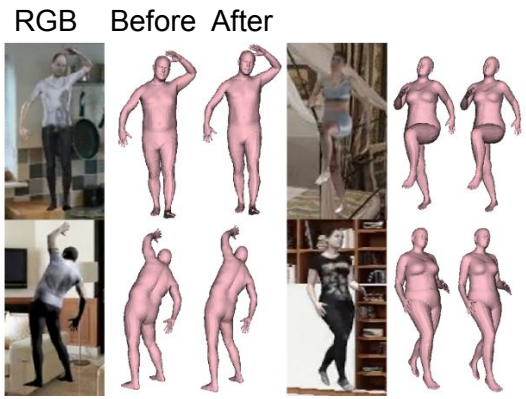


Joint and landmark locations are decomposed into B and N features:

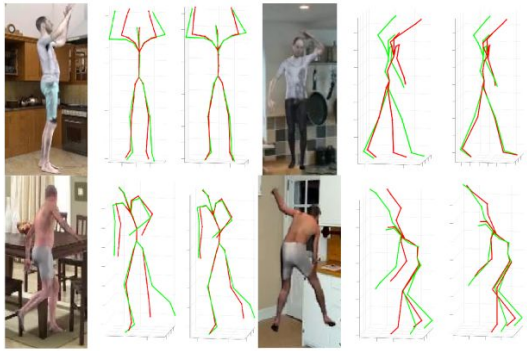
- B: relative length w.r.t. the kinematic tree,
- N: relative norm w.r.t. the kinematic tree.

Image credit: https://arxiv.org/pdf/1812.10766.pdf

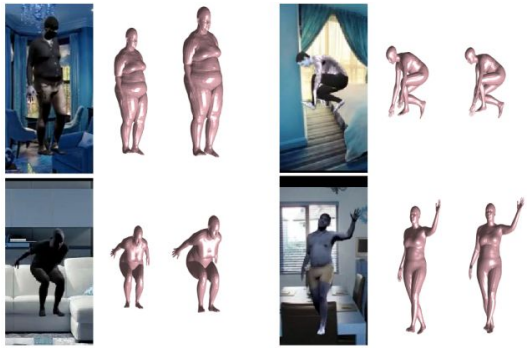
Regressing SMPL param. from joints and landmarks



Training SMPL regression with landmarks improves the estimated shape.



Training SHN end-to-end with SMPL regression improves SHN predictions.



Procrustes alignment of SMPL output with SHN output improves gender failures and global orientation.

Image credit: https://arxiv.org/pdf/1812.10766.pdf

Regressing SMPL param. from joints and landmarks

	Prot. 1	Prot. 2
Bogo [7]	-	82.3
Lassner [12]	-	80.7
Tung [31]*	98.4	-
Pavlakos [8]	-	75.9
Omran [13]	-	59.9
Kanazawa [9]	87.9	56.8
Kolotouros [35]	74.7	**51.9**
ALL	67.9	52.2
ALL_{Proc}	**62.6**	52.2

Methods in which the output is SMPL dense mesh

	Prot. 1	Prot. 2
Tome [25]	88.4	70.7
Pavlakos [27]	71.9	51.9
Zhou [36]	64.9	-
Martinez [20]	62.9	47.7
Sun [24]	59.1	48.3
Sun [37]**	64.1	-
Fang [38]	60.4	**45.7**
SHN^{final}	61.3	50.1
SHN^{final}_{e2e}	**56.5**	46.3

Methods in which the output is just 3D joints

Prot. 1: MPJPE
Prot. 2: reconstruction error

Kanazawa [9]: direct pose and shape regression

Kolotouros [35]: dense mesh regression by graph CNN

ALL: the whole pipeline

ALL_{Proc}: the results after procrustes alignment

SHN^{final}: SHN training with data augmentation

SHN_{e2e}: SHN results after end to end training

Image credit: https://arxiv.org/pdf/1812.10766.pdf

3D hand pose estimation based on depth images

Image credit: http://daariga.github.io/

Applications

- Human-computer interaction,
- Virtual reality,
- Training robot hands,
- Sign language and gesture recognition.

Voxel to voxel predictions

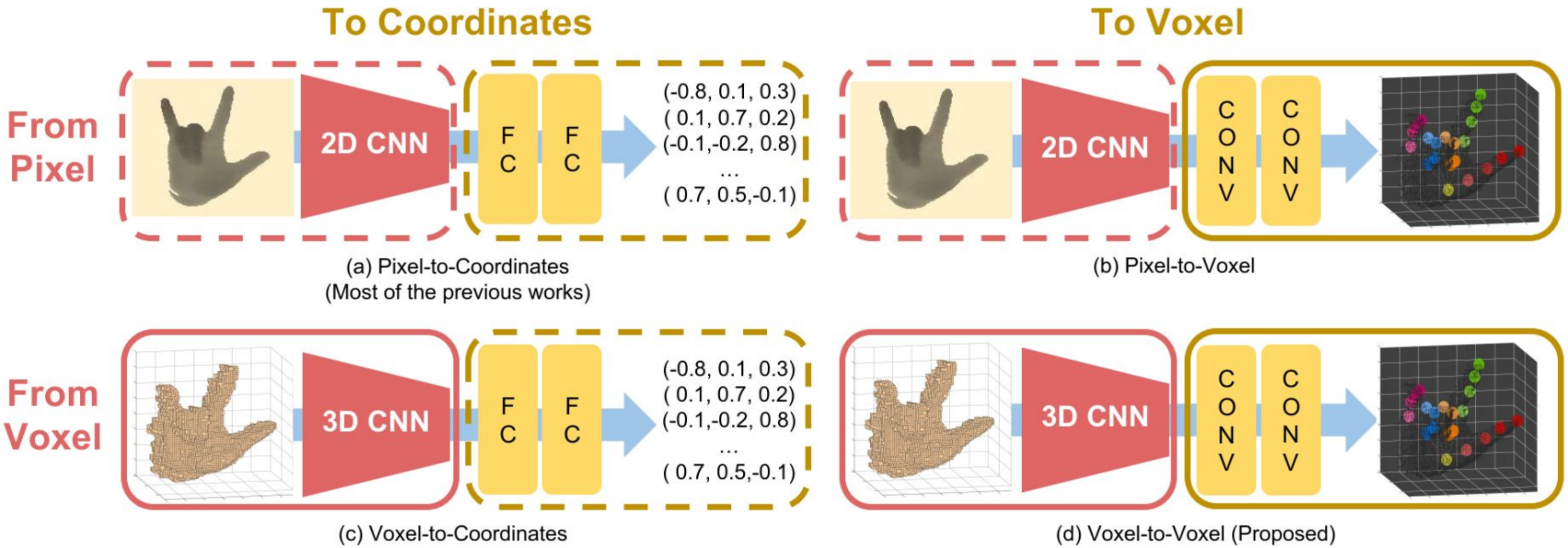


Image credit: https://arxiv.org/pdf/1711.07399

Voxel to voxel predictions

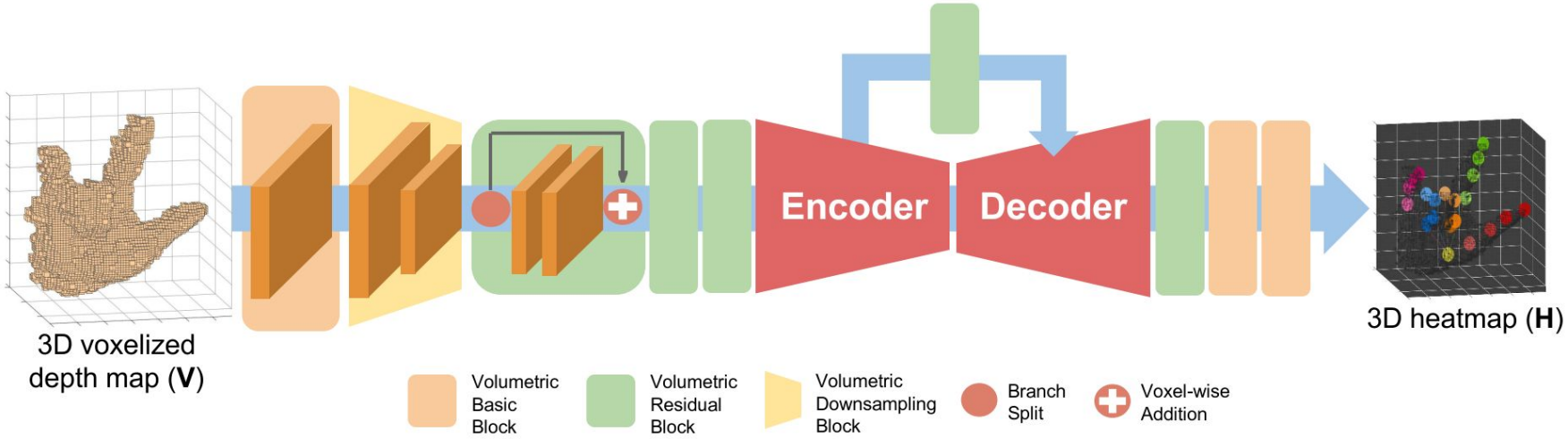


Image credit: https://arxiv.org/pdf/1711.07399

Voxel to voxel predictions - results on NYU dataset

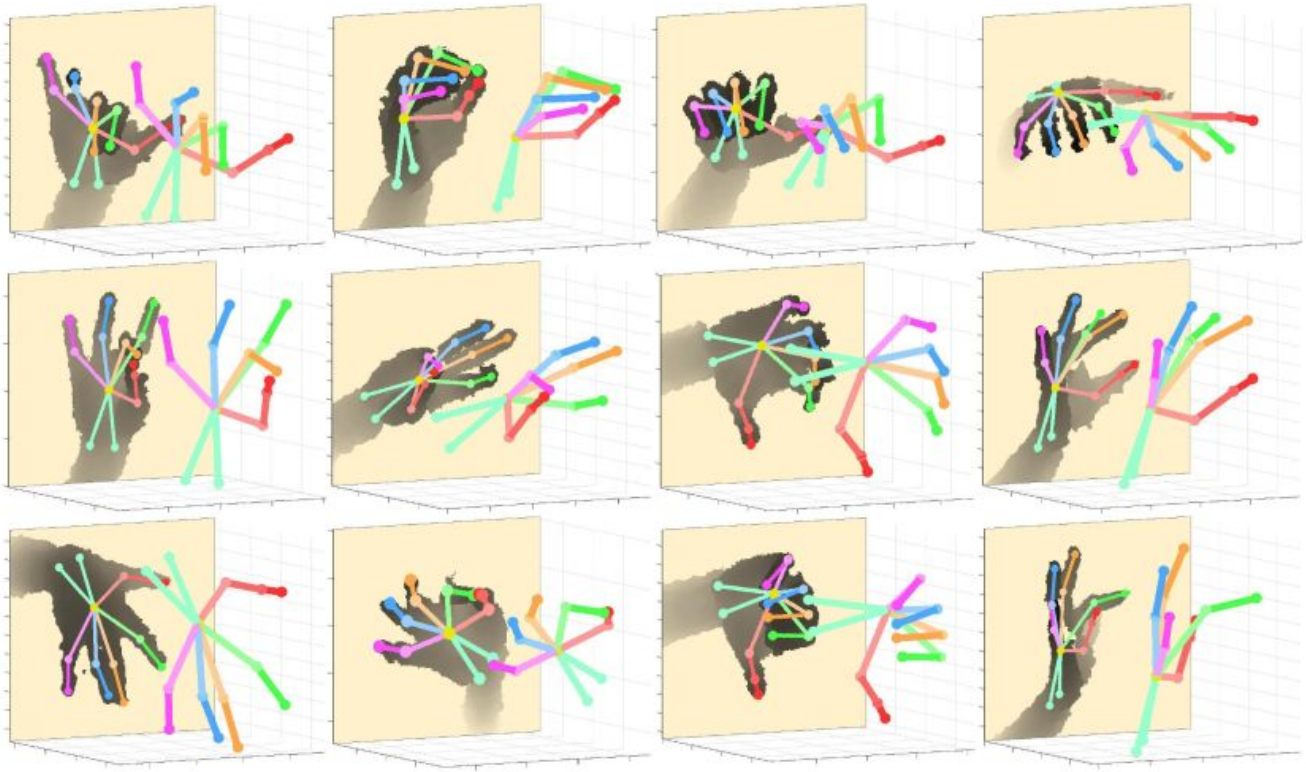


Image credit: https://arxiv.org/pdf/1711.07399

Further reading

- Pose guided region ensemble: image.ee.tsinghua.edu.cn/pdf/2018_chenxh_neucom.pdf
- Global-local pose: https://arxiv.org/abs/1705.09606
- Feature mapping: https://arxiv.org/abs/1712.03904
- Pose from RGB image: https://arxiv.org/pdf/1705.01389.pdf