

Stacked Hourglass Networks for Human Pose Estimation

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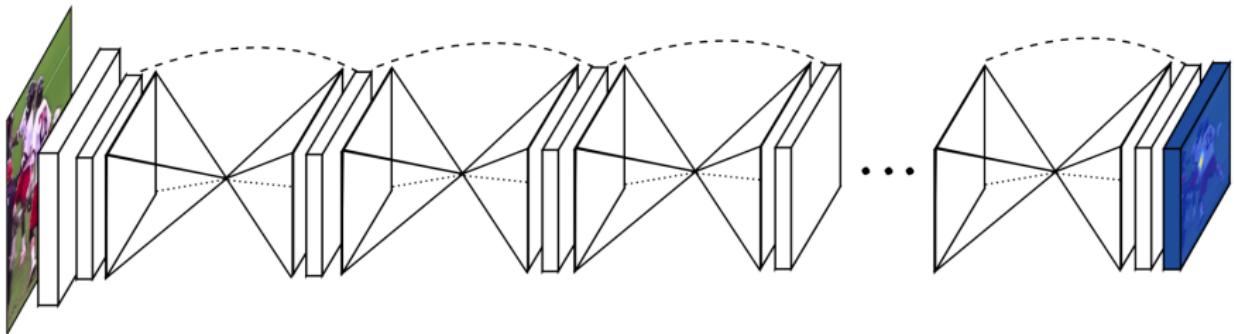
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Overview

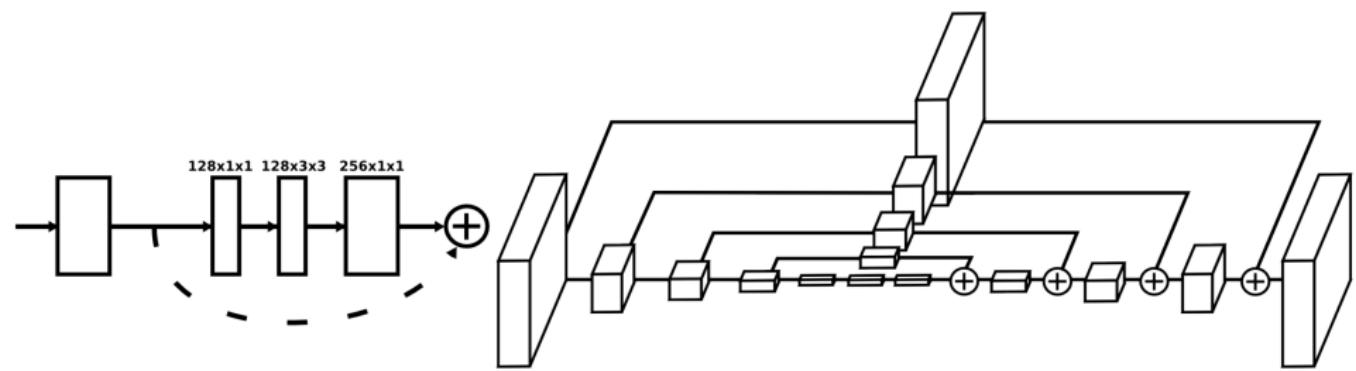
- ▶ Problem:
 - ▶ Detect position of human body joints in an image
- ▶ Proposed a novel architecture called Stacked Hourglass





Hourglass Design

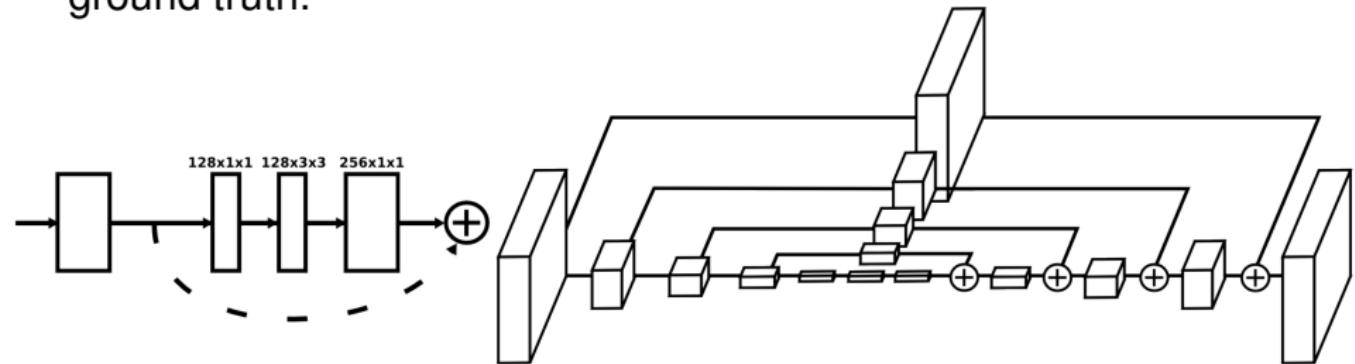
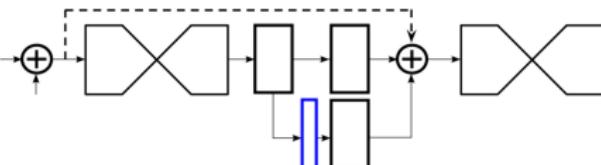
- ▶ Motivations: need to capture information at every scale
- ▶ Set up HG modules
 - ▶ Convolutional and max pooling layers are used to process features down to a very low resolution
 - ▶ After reaching the lowest resolution, the network begins the sequence of upsampling and combination of features across scales
 - ▶ No Conv layers have filter greater than 3×3





Stacked Hourglass with Intermediate Supervision

- ▶ Stacking multiple hourglasses
- ▶ Feeding the output of one as input into the next
- ▶ Loss is applied to the predictions of all hourglasses using the same ground truth.





Configurations (1/4)

▶ Running Information

- ▶ NVIDIA TitanX GPU with 12 GB
- ▶ Network has 8 HG modules
- ▶ Input images are resized to 256×256 pixels
- ▶ Do data augmentation with
 - ▶ Rotation (+/- 30 degrees)
 - ▶ Scaling (.75 – 1.25)
- ▶ Using Torch7 framework
- ▶ Training takes 3 days
- ▶ A single forward pass takes 75 ms
- ▶ Result of an image is the average of the heatmaps of origin input and the flipped version (1% improvement)

Configurations (2/4)

▶ Datasets

- ▶ Frames Labeled In Cinema (FLIC)
(<https://bensapp.github.io/flic-dataset.html>)
 - ▶ 5003 images (3987 training, 1016 testing)
 - ▶ Taken from films.



- ▶ MPII Human Pose
 - ▶ 25k images
 - ▶ 40k annotated samples (28k training, 11k testing)

Configurations (3/4)

- ▶ MPII Human Pose examples





Configurations (4/4)

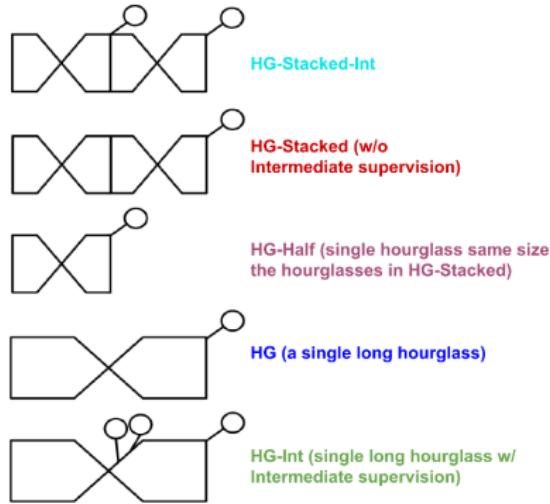
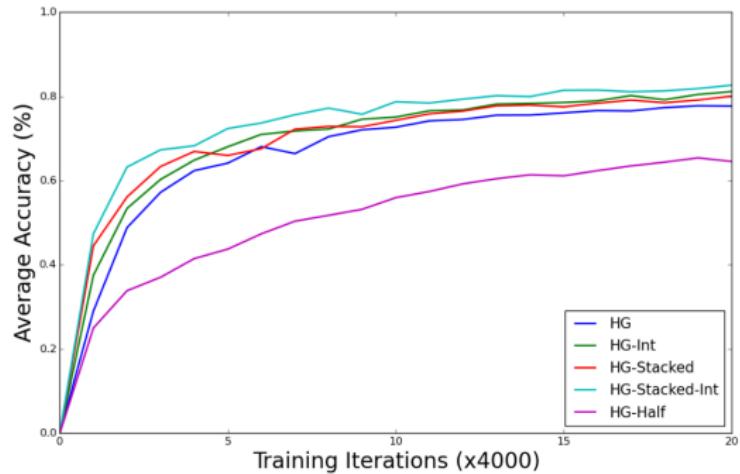
- ▶ Using Percentage of Correct Keypoints (PCK) metric
- ▶ A candidate keypoint to be correct if it falls within $\alpha \cdot \max(h, w)$ pixels of the groundtruth keypoint, where h and w are the height and width of the bounding box of human (usually use torso)
- ▶ PCKh: using head size instead of bounding box size



Evaluation (1/4)

- ▶ Comparison of training with different types of HG network

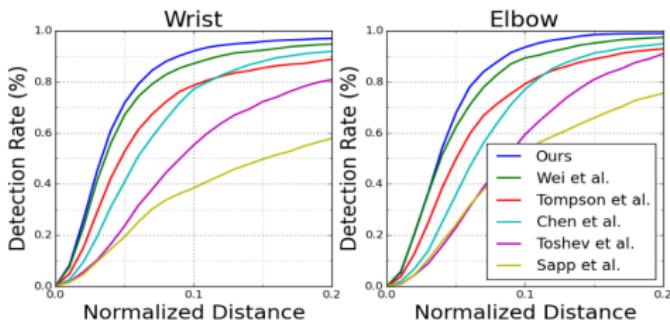
Validation Accuracy Across Training



Evaluation (2/4)

► Experiments on FLIC (PCK@0.2)

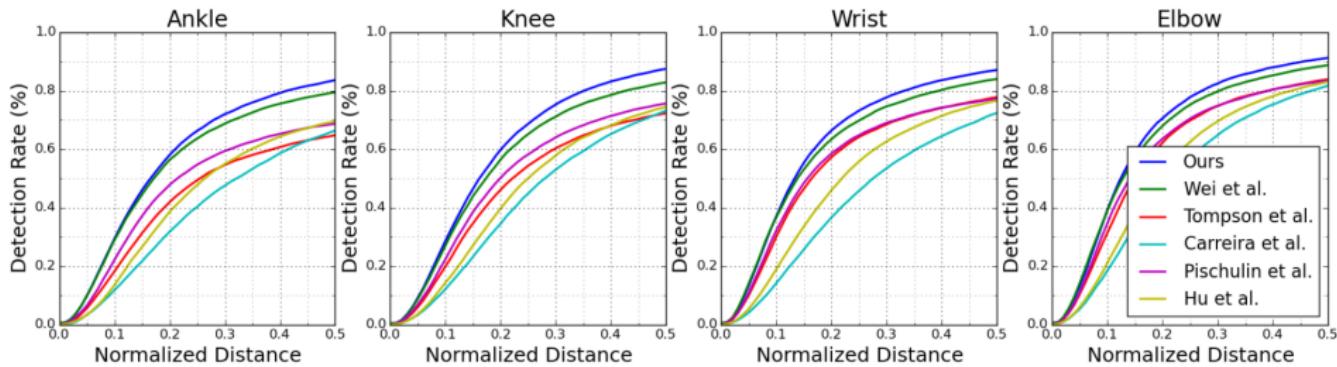
FLIC Results



	Elbow	Wrist
Sapp et al. [1]	76.5	59.1
Toshev et al. [24]	92.3	82.0
Tompson et al. [16]	93.1	89.0
Chen et al. [25]	95.3	92.4
Wei et al. [18]	97.6	95.0
Our model	99.0	97.0

Evaluation (3/4)

► Experiments on MPII (PCKh@0.5)



	Head	Shoulder	Elbow	Wrist	Hip	Knee	Ankle	Total
Tompson et al. [16], CVPR'15	96.1	91.9	83.9	77.8	80.9	72.3	64.8	82.0
Carreira et al. [19], CVPR'16	95.7	91.7	81.7	72.4	82.8	73.2	66.4	81.3
Pishchulin et al. [17], CVPR'16	94.1	90.2	83.4	77.3	82.6	75.7	68.6	82.4
Hu et al. [27], CVPR'16	95.0	91.6	83.0	76.6	81.9	74.5	69.5	82.4
Wei et al. [18], CVPR'16	97.8	95.0	88.7	84.0	88.4	82.8	79.4	88.5
Our model	98.2	96.3	91.2	87.1	90.1	87.4	83.6	90.9

Evaluation (4/4)

- ▶ Failure in case of multiple people
- ▶ Can fail if there is a slight translation and/or change of scale of the input image
- ▶ Reasons:
 - ▶ Network is trained for estimate pose of single person
 - ▶ Person is in the center of training images





Conclusion

- ▶ Proposed a new convolutional network architecture called Stacked Hourglass Network for human pose estimation task
 - ▶ Achieve state-of-the-art results
 - ▶ Can capture information in many scales
- ▶ Comments
 - ▶ Weakness:
 - ▶ Detect single person
 - ▶ Result depends on how good of people detector
 - ▶ Good idea for capture information in every scales





Thank you for your attention!

