Pose2Instance: Harnessing Keypoints for Person Instance Segmentation

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Abstract

Human keypoints are a well-studied representation of people. We explore how to use keypoint models to improve instance-level person segmentation. The main idea is to harness the notion of a distance transform of oracle provided keypoints or estimated keypoint heatmaps as a prior for person instance segmentation task within a deep neural network. For training and evaluation, we consider all those images from COCO where both instance segmentation and human keypoints annotations are available. We first show how oracle keypoints can boost the performance of existing human segmentation model during inference without any training. Next, we propose a framework to directly learn a deep instance segmentation model conditioned on human pose. Experimental results show that at various Intersection Over Union (IOU) thresholds, in a constrained environment with oracle keypoints, the instance segmentation accuracy achieves 10% to 12% relative improvements over a strong baseline of oracle bounding boxes. In a more realistic environment, without the oracle keypoints, the proposed deep person instance segmentation model conditioned on human pose achieves 3.8% to 10.5% relative improvements comparing with its strongest baseline of a deep network trained only for segmentation.

1. Introduction

The instance segmentation problem deals with the pixelwise delineation of multiple objects, combining segment-level localization and per-pixel object category classification. This task is more challenging than semantic segmentation, for example the number of object instances is not fixed, unlike the number of object categories. Additionally, separating instances that share similar local appearances is highly challenging. Instance segmentation, in particular person instance segmentation is a promising research frontier for a range of applications such as human-robot interaction, sports performance analysis, and action recognition.

Deep convolutional neural networks are the current state-of-the-art methods for the task of instance level segmentation. For example, the entrants to the 2016 COCO segmentation challenge [34] achieve excellent performance on instance segmentation for the 80 object categories considered on the COCO dataset. Although these methods work extremely well for *any* category of objects, there is a potential for human-specific domain knowledge to boost the person segmentation performance.

In this paper, we investigate the importance of human keypoints as a prior for the task of instance-level person segmentation. With the availability of image datasets that include both segmentation masks and keypoints annotations, we consider a methodical approach to quantify the importance of keypoints for people instance segmentation. We explore what happens if an oracle provides all the keypoints, or only bounding boxes, and how people instance segmentation can be improved respectively.

Our motivation is two-fold. First and foremost, we wish to develop a thorough understanding of whether person-specific domain knowledge is useful for person instance segmentation. Second, we wish to quantify the importance of human keypoints as a useful domain knowledge for improving segmentation over the baseline of best performing deep learning models trained only for segmentation.

In order to evaluate the segmentation conditioned on human pose, we consider all instances of people[1] from the COCO segmentation dataset [22] where the instances also have keypoints ground truth. By comparing the image and instance identifiers from the COCO segmentation and COCO keypoints dataset, we see there exists $45,174$ images in the training dataset and $21,634$ images in the validation dataset. This amounts to $185,316$ and $88,153$ ground truth person instances with both segmentation and keypoints annotations in the training and validation split respectively. We call this intersection between COCO instance segmentation dataset and COCO person keypoints dataset as the

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[1]We do not include COCO person instances that are marked as "crowd".
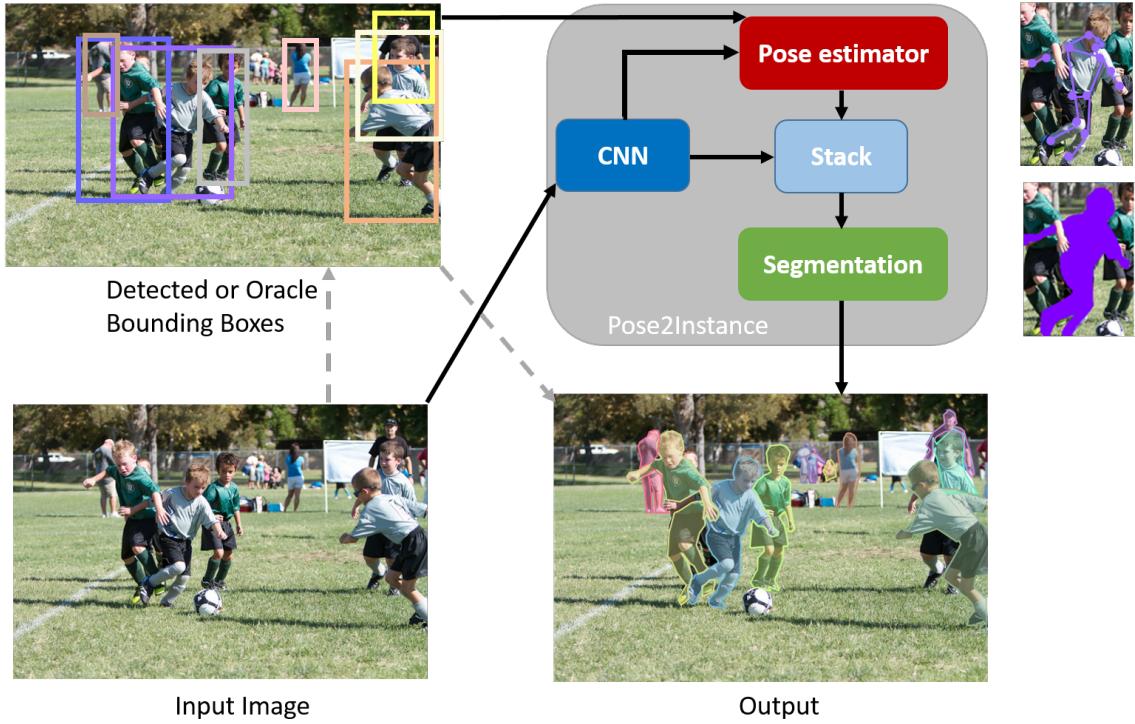
Figure 1.1. Pose2Instance model for People Instance Segmentation. This model incorporates a *learnable* component conditioned on the human "pose". The model generates keypoint heatmaps and segmentations at instance level by sharing CNN parameters up to the penultimate layer and uses the keypoints heatmaps output as an additional input to the segmentation. (best viewed in color)

COCO dataset throughout this paper.

We first explore a human pose prior represented as the distance transform of a skeleton and show how this prior can directly yield instance-level human segmentation when combined with existing semantic segmentation model such as DeepLab [7] trained for human segmentation. This analysis also validates the idea of combining even two existing different models, one for pixel-level person segmentation (non-instance) and another for detecting keypoints, for improving instance segmentation.

Next, we propose an approach to directly generate the per-pixel probability of people instances conditioned on human poses using a deep convolutional neural network (CNN). We call this pose-conditioned segmentation model *Pose2Instance*. Figure 1.1 outlines the approach. Person instance bounding boxes are either provided by an oracle or they come from a person detector. The model is trained for generating keypoints heatmaps and segmentation at instance level by sharing *cnn* parameters up to the penultimate layer and using the keypoints heatmap as an additional input channel for the segmentation output.

In summary, we contribute the following.

- We show that human pose prior represented as the distance transform of the human skeleton yields significant performance gain for the deep people instance

segmentation during inference without any training.

- We show how the *learned* segmentation can be conditioned on the keypoints by learning additional parameters specifically for mapping shape to segmentation while training a DCNN *jointly* for keypoints and segmentation.

- We perform extensive empirical investigation of the proposed Pose2Instance method on the intersection of COCO instance segmentation and COCO keypoints dataset. We show the effectiveness of the pose conditioned deep instance segmentation model by qualitative and quantitative analysis.

2. Related Work

Our work builds upon a rich literature in both semantic segmentation using convolutional neural networks and joint pose-segmentation modeling.

Semantic and Instance Segmentation
DeepLab [7] and FCN [25] achieved significant breakthroughs for the challenging task of semantic segmentation using deep convolutional neural networks. Subsequently, a set of instance segmentation methods [18, 37, 16, 19, 8,

30, 27, 3] were proposed, which begin with pixel-wise semantic segmentation and generate instance-level segmentation from them. Recently, [17] achieved the state-of-the-art performance on the 80-category instance segmentation using a fully convolutional end-to-end solution. Except [16], none of these methods look into learning implicit or explicit shapes of different object categories.

Human Pose Estimation
Human pose estimation from static images [31, 15, 9, 24] or videos [11] with hand-crafted features and explicit modeling gained considerable interest in the last decade. Human pose estimation using an articulated grammar model is proposed in [31]. Hernández-Vela *et al.* [11] proposed Spatio-Temporal GrabCut-based human segmentation that combines tracking and segmentation with hand-crafted initialization. In [9], Eichner and Ferrari proposed a multi-person pose estimator framework that extends pictorial structures for explicitly modeling interaction between people. A detailed review on pose estimation literature survey is available in [24].

Recently, convolutional neural networks have been successfully applied for pose estimation from videos [23], human body parts segmentation [26], and multi-person pose estimation [28, 13, 5, 14]. Additionally, among the most accurate results are those shown by *chained prediction* [10].

Joint Pose Estimation and Segmentation
The most closely related works to this one are those that also seek to jointly estimate human pose and segmentation in static images or videos [15, 20, 2, 32]. Kohli *et al.* [15] proposed *PoseCut*, a conditional random field (CRF) framework to tackle segmentation and pose estimation together for a *one* person. The CRF model explicitly combines hand crafted image features and a prior on shape and pose in a Bayesian framework. The prior is represented by the distance transform of a human *skeleton*. The *inference* in PoseCut finds the MAP solution of the energy of the pose-specific CRF. The test time prediction finds MAP by doing optimization over different configurations of the latent shape prior. With a *good* initialization the inference step requires 50 seconds per frame. Similar inference strategies for deep models are computationally prohibitive.

Among other significant efforts towards joint pixel-wise segmentation and pose estimation of multiple people, Alahari and Seguin *et. al.* [2, 32] use additional motion and disparity cues from stereo videos. The appearance and disparity cues are generated using HOG features. The pose estimation model [2] is represented as a set of parts, where a part refers to a patch centered on a body-joint or on an interpolated point on a line connecting two joints. They learn up to eight mixture components for each part and an articulated pose mask for the mixture components.

We propose a different and effective framework for incorporating pose prior into deep segmentation models. The proposed DCNN model consists of additional parameters that are trained/optimized specifically for the mapping of shape to segmentation. The Pose2Instance *inference* does not require optimization such as finding the MAP solution. The prediction task involves only *one* forward pass through the trained network.

3. Methods

Our Pose2Instance approach looks at the problem of incorporating a pose prior into segmentation in two ways. We begin with a constrained environment study where the keypoints are provided by an oracle, and we investigate a way for improving the instance segmentation inference given a state-of-the-art pixel-level person classifier [7]. Next, we move to a more realistic case where oracle keypoints are not available and propose a framework to train segmentation model directly while benefiting from a pose estimator.

3.1. Pose2Instance Inference Only

We first present Pose2Instance within a constrained environment that assumes that the keypoints are provided by an oracle. This allows us to investigate the contribution of the pose prior independent of the other components of the whole system. In the COCO dataset, 17 person keypoints along with their corresponding visibility flags are annotated. We will handle these as part of a *skeleton* that links joint keypoints by the corresponding body parts.

In the investigation of the prior alone, with oracle keypoints, we address the inference stage of instance segmentation without any training. The sole task-specific training is done on the already existing DeepLab [7] network. In the section 3.1.1 below, we first fine-tuned this network for person-specific segmentation on COCO, with other labels discarded. This model directly predicts per-pixel probability of the *person* class label for the whole image. We call this model *DeepLab-people* in this paper.

3.1.1 Person Instances from Oracle Keypoints

We use the notion of a distance transform of the person skeleton [15], generated from the oracle keypoints, as a prior for the instance segmentation task. For this proof of concept, we follow the below steps.

We create a Region Adjacency Graph (RAG), $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ where the nodes $\mathbf{V}$ are superpixels and the weights of the edges $\mathbf{E}$ between the nodes depend on the strength of image edges. We obtain superpixels using SLIC [1], and the image edge responses using Sobel operator. We can define the pose prior as a distribution over the labels of this graph. Given a superpixel $p \in \mathbf{V}$, we can compute a conditional probability it belongs to a given instance. For each instance, we color those nodes where the corresponding superpixel contains a part of the human skeleton line that is generated
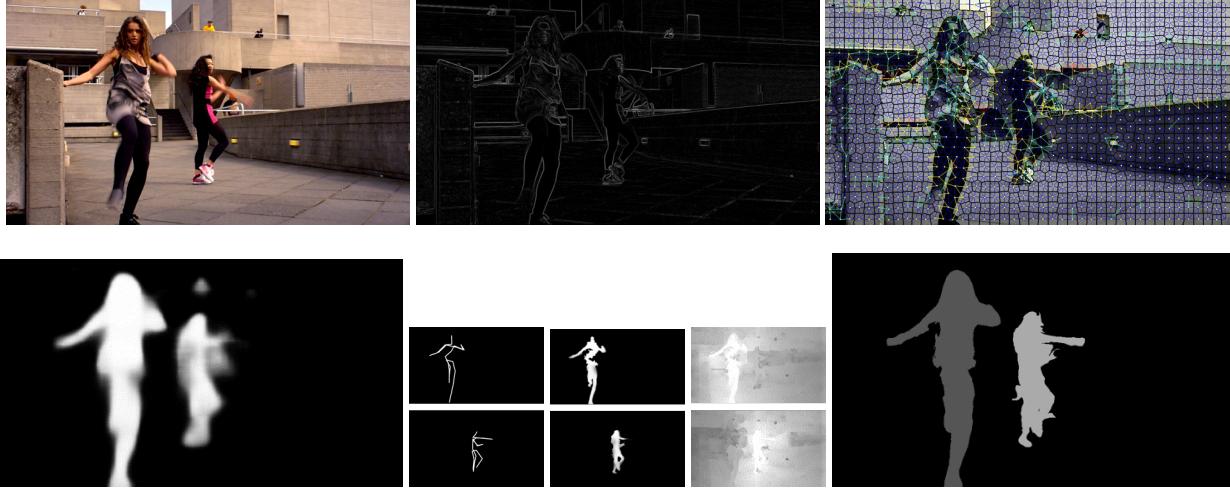
Figure 3.1. Instance Segmentation with oracle skeleton. Top row: An image from Inria stereo people segmentation dataset; Sobel edge responses on the image; RAG with edge strength from sobel responses where warmer color means higher weights. Bottom row: DeepLab *person* segmentation; oracle skeleton, masks for distance transform in RAG space, *pose-instance-maps* and the final instance segmentation which is an argmax on point-wise multiplication of pose-instance map and the DeepLab-people score.

from the oracle keypoints with valid visibility flags. The colored nodes in the RAG represent a foreground binary mask, and are assigned the highest probability of belonging to this instance. For each such binary mask corresponding to each person, we apply distance transform in the RAG using Floyd-Warshall [12] shortest paths algorithm. A point-wise softmax of this distance transform then represents the likelihood of each person's gross shape. We call this shape-likelihood the *pose-instance map*. For an image of height h and width w, with n oracle instances, the shape of pose-instance map is $h \times w \times n$. Figure 3.1 shows these intermediate steps of generating the RAG, its nodes and the weights of its edges, the oracle skeletons and the instance segmentations.

Instance-level to Image-level inference: Element-wise multiplication of this pose-instance map and the DeepLab-people score generates instance heatmap of size $h \times w \times n$. Here, h, w and n denote the height and width of the image, and the oracle-provided number of person instances respectively. An argmax on instance heatmap produces the final instance segmentation on the image.

Figure 3.2 shows intermediate results for the inference step in this constrained setup. There are 9 persons in this image. Combining DeepLab-people score with pose-instance map improves the instance segmentation quality over the pose-instance map. Quantitative results in section 4.1 show that person keypoints represented as the distance transform can be an excellent source of additional domain knowledge for improving people instance segmentation.
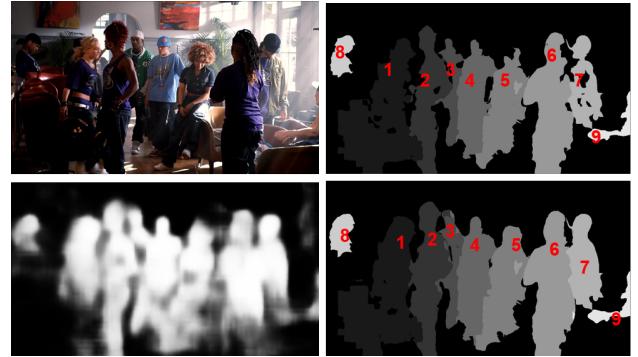
Figure 3.2. Pose2Instance inference with oracle skeleton. Top row: An image from Inria stereo person segmentation containing 9 persons; Instance classification by argmax on pose-instance map; Bottom row: DeepLab-people score, and the *Pose2Instance* inference output which is an argmax on *instance heatmap* generated by fusing DeepLab-people and *pose-instance map*.

3.1.2 Person Instances from Oracle Bounding Boxes

As a baseline, we take the approach of snapping the pixel-level DeepLab-people score at oracle bounding boxes for the COCO validation images. Though this bounding box approach does not comply with the relative depth ordering or visibility of one instance over another, the method still can be used as a reasonable baseline to compare the performance of Pose2Instance inference.

We performed similar experiments with fast-sweeping [35] based distance transform on pixel grid for reducing complexity using single-pixel width skeleton as the binary

mask. However, the distance transform produces worse result comparing with the specified non-grid RAG approach.

3.2. Learning Pose2Instance

After this proof of concept in the inference stage in a controlled setup with oracle keypoints, we move to a more realistic scenario where ground truth keypoints annotations are unavailable and we strive for learning a segmentation model by jointly optimizing for the segmentation and pose.

Our proposed network has a DeepLab-style architecture [7]. This is a modified VGG network [33] that uses atrous convolution with hole filling [7] and replaces fully-connected layers by fully-convolutional layers. The baseline model is a 2-class *DeepLab-people* model. To construct this model, we start with the publicly available Deeplab model trained on the PASCAL VOC dataset, and fine-tune it for predicting only people on the COCO training instances. The second and third exploratory architectures involve two output layers each, a segmentation output and a 17-channel heatmap for pose estimation output. The first among them *Pose and Seg* is a multitask model, where the two parallel output layers share the parameters up to previous convolutional layers. The 2-class segmentation layer and the 17-class pose estimation output layers use cross-entropy loss after softmax and sigmoid activations respectively. The later one, *Pose2Seg*, is a cascaded model, where the 17-channel keypoints heatmap is followed by an 1×1 convolution to generate the shape likelihood. Segmentation feature maps from the last layer is combined with the above shape likelihood, and the softmax segmentation is trained. Comparing with the segmentation only model, the cascaded model has only 18 extra parameters for learning the 1×1 convolutional kernels. 17 parameters are for the key-points heatmaps, and 1 for shape likelihood.

Figure 3.3 shows the two above mentioned architectures. The *stack* operation is a 1×1 convolution on the estimated 17-channel pose heatmap. Its output can be used as the gross shape-likelihood of a person based on the estimated keypoints. In the cascaded model, the segmentation output is directly conditioned on the pose heatmap. As we also see in Fig 4.5, the 1×1 convolution on the pose heatmap preserves the general notion of shape of a person from its keypoints, the segmentation model thus can be thought of conditioned on the latent shape of a person.

In the Pose2Instance framework, we try to improve the segmentation accuracy from both keypoints and segmentation supervision. In particular, a model learned with one supervisory signal *pose-estimation* acts as a prior to the model learned with another supervisory signal *segmentation*. Different sources of supervision have proven to be useful for learning segmentation. For example, ScribbleSup [21] performs semantic segmentation from additional scribble based supervision broadly in grabcut [6] like frame-

work. In [4], Bearman *et al.* discussed various levels of supervisions such as pixel-level strong supervision, and sparse point-level supervision for semantic segmentation. Our method is substantially different from these since none of the above specifically addresses (instance) segmentation problem with one as a prior to the other.

4. Results

We implement the Pose2Instance model using TensorFlow-Slim. We train the model on specified COCO training instances. We initialize the model from DeepLab-people and continue training for $20,0000$ iterations using stochastic gradient descent with mini-batch size of 16 and momentum 0.9.

4.1. Pose2Instance in a Constrained Setup

In order to analyze the Pose2Instance inference with oracle keypoints, we use COCO validation images. While table 4.1 shows the performance of Pose2Instance inference with oracle keypoints, figure 4.2 shows some qualitative results comparing with the oracle bounding box baselines. The figures show that for overlapping person instances, the proposed pose prior significantly outperforms a baseline using the bounding box as an ad-hoc prior.

Instance Segmentations on COCO validation Images

Methods	$AP^r 0.5$ IoU=0.5	AP^r IoU=[0.5 to 0.9]
DeepLab+Oracle BB	0.437	0.252
DeepLab+Oracle keypoints	**0.533**	**0.283**
FAIRCNN[36]	0.504	0.206
CUHK[29]	0.478	0.214

Table 4.1. Oracle keypoints provides 10% to 12% relative improvement over oracle bounding box case at various IOU thresholds when applied on DeepLab-people segmentation model. Results are shown from COCO Leaderboard for FAIRCNN[36] and CUHK[29] that also use VGG as the base network.

The inference stage which consists of combining the existing semantic segmentation model and the oracle keypoints outperforms the oracle bounding box case by 10% relative improvement. FAIRCNN[36] and CUHK[29] are the instance segmentation models that also use VGG as the base network. We include their instance segmentation results only on *'person'* category from COCO detection challenge Leaderboard as references. Newer models from the Leaderboard use more powerful ResNet in their backend, so are not directly comparable.

Figure 4.3 shows qualitative results of instance segmentation on COCO validation dataset in such constrained environments. We note that this method only applies during
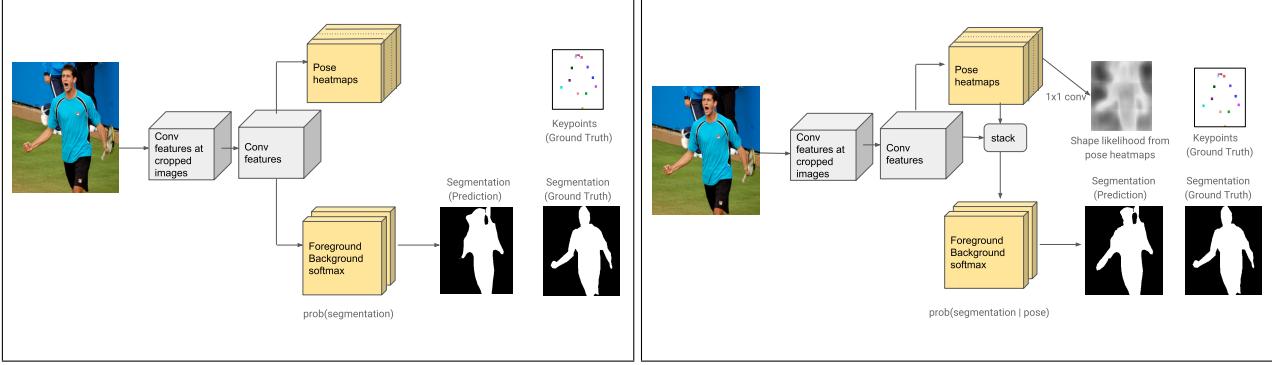
Figure 3.3. Pose2Instance: architecture variation for joint pose and segmentation learning. Left: Multitask model where pose estimation and segmentation are two parallel output paths. Right: Cascaded Model where pose dedicated parameters are *learned* for mapping pose to segmentation.
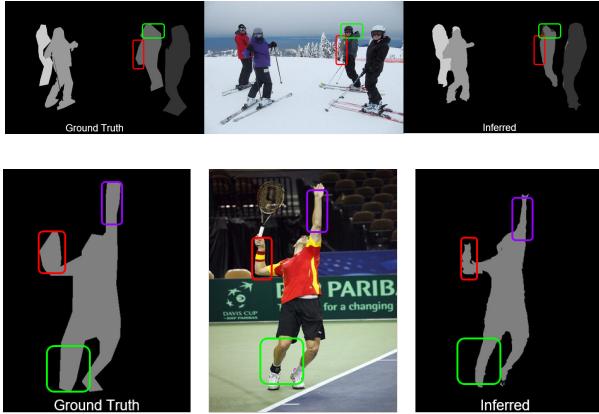

Figure 4.1. From left to right: Ground truth instance segmentations; Corresponding image from COCO keypoints dataset; Pose2Instance inference with oracle keypoints. Colored boxes show errors in segmentation ground truth that are corrected using our keypoint conditioned model.

Instance Segmentations without Oracle Keypoints

Methods	AP^r IoU=0.5	AP^r IoU=[0.5 to 0.95]
DeepLab Seg only	0.79	0.38
Multitask: Pose and Seg	0.80	0.40
Cascaded: Pose2Seg	**0.82**	**0.42**

Table 4.2. Evaluation of segmentation accuracy on instances from COCO validation dataset. Joint pose estimation and segmentation outperforms the *segmentation only* model. Pose2Instance *cascaded* model achieves improved accuracy over the *multitask* model. Overall, relative improvement from *segmentation only* model is 3.8% to 10.5% at various IOU thresholds.

the inference step with oracle keypoints and does not involve any training. Human keypoints ground truth is easier to collect than precise segmentation ground truth. Figure 4.1 shows how the errors in the segmentation ground truth can be corrected with our pose-conditioned segmentation model.

4.2. Pose2Instance in Realistic Environments

After validating the effectiveness of the inference with keypoint-specific distance transform, we evaluate the proposed Pose2Instance model on COCO validation instances in a more realistic environment where oracle keypoints are unavailable. We assume the availability of oracle bounding boxes. The model estimates the keypoints and segmentations at all instances.

In Table 4.2, we show the comparative segmentation performance evaluation for the proposed Pose2Instance method without oracle keypoints. Average Precision at 0.5 IOU improves by 3% over the *segmentation only* model and 2% over the multitask model. The corresponding improvements for the [0.5, 0.9] IOU are 4% and 2% respectively.

In terms of relative improvements, at 0.5 IoU and [0.5, 0.9] IoU, the pose-conditioned segmentation model improves the AP^r by 3.8% and 10.5% over the *segmentation only* model [Table 4.2] respectively. This demonstrates the proof-of-concept of how to incorporate pose prior effectively into deep segmentation model.

Figure 4.5 shows qualitative results on some challenging examples. These rectangular regions contain one or more partial person instances in addition to the primary person instance. We see that the Pose2Instance model learns to produce instance segmentation only for the intended one. The last two figures are examples of most difficult cases with many people in close proximity, and the Pose2Instance predictions are far from being ideal due to the current limitation of the VGG-based pose-estimator output.

In this work, we assess the effectiveness of pose conditioned segmentation performance, and did not evaluate the parallel key-points estimation output. We performed some
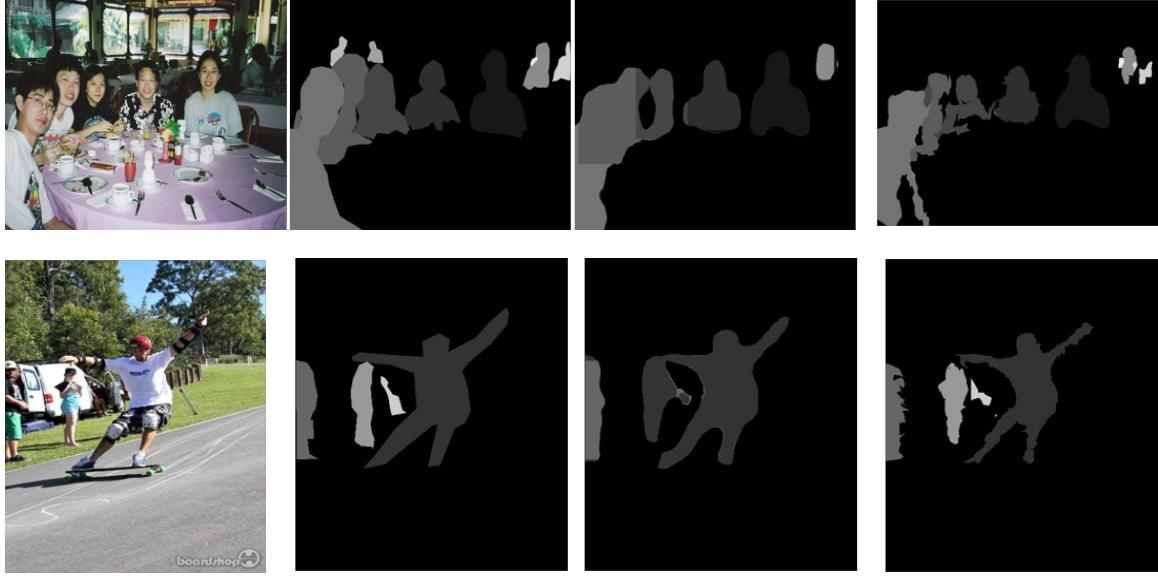
Figure 4.2. Pose2Instance with oracle bounding boxes vs oracle keypoints. From left to right: A frame from COCO keypoints dataset; Ground truth instance segmentations; Baseline instance segmentation from oracle bounding boxes and Pose2Instance inference from oracle keypoints.
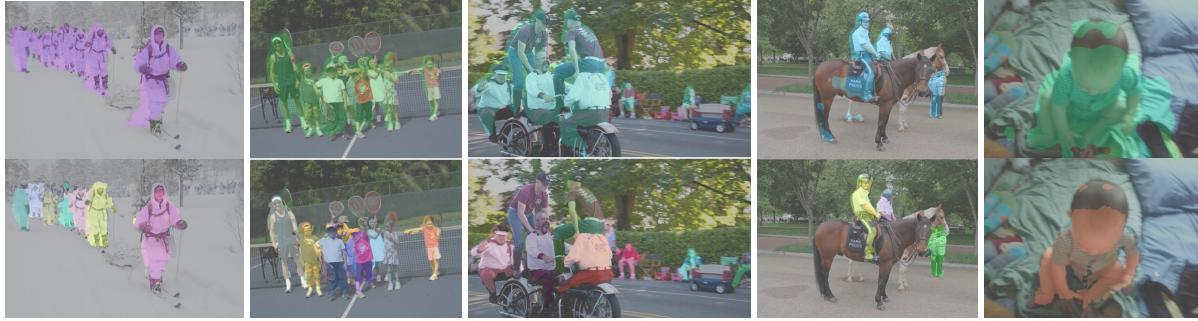
Figure 4.3. Pose2Instance in a constrained setup. Top: DeepLab person segmentation. Bottom:Pose2Instance inference from oracle keypoints on COCO evaluation dataset. (best viewed in color)

qualitative analysis for the pose estimation output from the described multitask and cascaded models. Additionally, we implemented another vanilla pose estimator model with the same network except the segmentation output. We call this model a *PoseOnly* model which is optimized only for 17-class pose-estimation problem. Our subjective analysis of the latent shape likelihood of person include *PoseOnly*, *multitask* and *cascaded* models. Figure 4.4 shows some visualizations of the latent shape likelihood (section 3.2) on some COCO validation images.

5. Discussions

Our experiments suggest that human pose is a useful domain knowledge even atop state-of-the-art deep person segmentation models. We show that in a constrained en-

vironment with oracle keypoints, at various IOU thresholds, the instance segmentation accuracy achieves 10% to 12% relative improvement over a strong baseline with oracle bounding boxes without any training. In a more realistic environment, without the oracle keypoints, the proposed Pose2Instance deep model achieves relatively 3.8% to 10.5% higher segmentation accuracy than the strongest baseline of a deep network trained only for segmentation.

Our proposed method is applicable to *any* such architecture that shares the necessary properties of the Deeplab model. Models optimized for the segmentation task, including the one covered in our experiments and future better-performing segmentation models, could potentially incorporate the same methodology to utilize pose information.

While at present we show results on images, likely similar dynamics are embedded in videos. Human keypoints
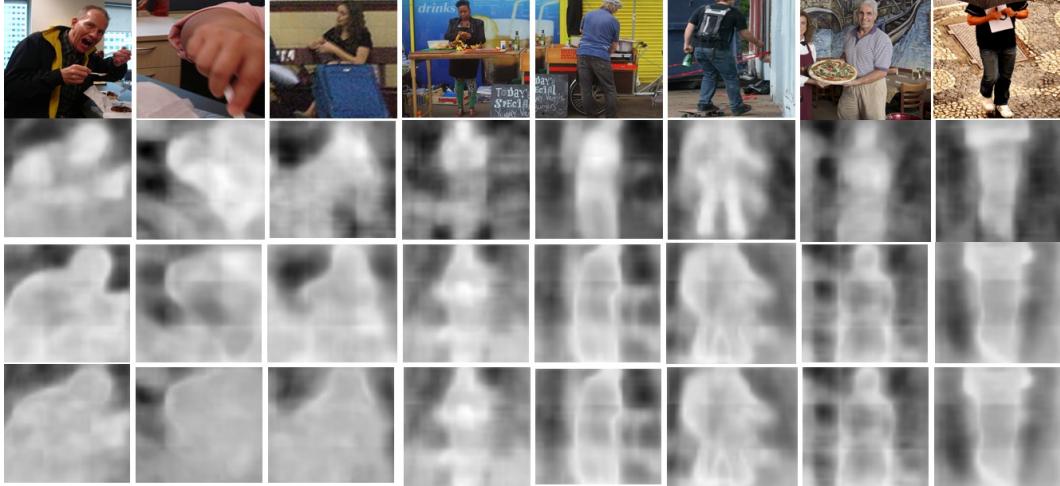
Figure 4.4. Qualitative results for shape likelihood from pose estimation. Top to Bottom: Instances from COCO validation dataset; visualization of intermediate latent shape likelihood for (i) *Pose Only model*; (ii) *Multitask model* and (iii) *Cascaded model* respectively. *Pose Only* model produces high likelihood around the keypoints; whereas other two joint models learns to capture the overall person contour shape.

Figure 4.5. Pose2Instance without oracle keypoints. Top row: Instance bounding boxes of COCO validation images. Middle row: Ground truth segmentation at instance level. Bottom row: predicted segmentation masks for the instance bounding boxes. Bounding boxes contain multiple full or partial person instances. While the first three columns show successful instance segmentation results, the last two examples show *yet to improve* segmentation results due to failure of the pose-estimator output in the VGG based Pose2Instance model. Improving the pose-estimator can improve the accuracy of the pose-conditioned segmentation model.

ground truth is easier to collect than precise segmentation masks. Thus, a pose conditioned segmentation model can be more powerful for person instance segmentation for nat-ural scenes where people tend to appear in groups, have dynamic interactions, and partial occlusions. This work represents a first step towards embedding pose into segmen-

tation in complex scenes. An exploratory follow-up work can include investigation on incorporating keypoints based dynamic person model into video segmentation.

Acknowledgments

References

[1] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Susstrunk. Slic superpixels compared to state-of-the-art superpixel methods. *IEEE Trans. Pattern Anal. Mach. Intell.*, 34(11):2274–2282, Nov. 2012. 3

[2] K. Alahari, G. Seguin, J. Sivic, and I. Laptev. Pose estimation and segmentation of people in 3d movies. In *Proc. IEEE International Conference on Computer Vision*, 2013. 3

[3] A. Arnab and P. H. Torr. Bottom-up instance segmentation using deep higher-order crfs. *British Machine Vision Conference (BMVC) 2016*, 2016. 2

[4] A. Bearman, O. Russakovsky, V. Ferrari, and L. Fei-Fei. What's the Point: Semantic Segmentation with Point Supervision. *ECCV*, 2016. 5

[5] Z. Cao, S.-E. Wei, T. Simon, and Y. Sheikh. Multiperson pose estimation using part affinity fields. http://image-net.org/challenges/talks/2016/Multi-person%20pose%20estimation-CMU.pdf. 3

[6] A. B. Carsten Rother, Vladimir Kolmogorov. Grabcut - interactive foreground extraction using iterated graph cuts. In *ACM Transactions on Graphics (SIGGRAPH)*, August 2004. 5

[7] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille. Semantic image segmentation with deep convolutional nets and fully connected crfs. In *ICLR*, 2015. 2, 3, 5

[8] J. Dai, K. He, Y. Li, S. Ren, and J. Sun. Instance-sensitive fully convolutional networks. *ECCV*, 2016. 2

[9] M. Eichner and V. Ferrari. We are family: Joint pose estimation of multiple persons. In K. Daniilidis, P. Maragos, and N. Paragios, editors, *ECCV*, volume 6311 of *Lecture Notes in Computer Science*, pages 228–242. Springer, 2010. 3

[10] G. Gkioxari, A. Toshev, and N. Jaitly. Chained predictions using convolutional neural networks. In *ECCV*, volume abs/1605.02346, 2016. 3

[11] A. Hernández-Vela, M. Reyes, V. Ponce, and S. Escalera. Grabcut-based human segmentation in video sequences. *Sensors*, (11), 2012. 3

[12] S. Hougardy. The floyd–warshall algorithm on graphs with negative cycles. *Inf. Process. Lett.*, 110(8-9):279–281, Apr. 2010. 4

[13] E. Insafutdinov, L. Pishchulin, B. Andres, M. Andriluka, and B. Schiele. Deepercut: A deeper, stronger, and faster multi-person pose estimation model. In *ECCV*, 2016. 3

[14] N. Kanazawa, G. Papandreou, A. Toshev, T. Zhu, H. Adam, C. Bregler, K. Murphy, and J. Tompson. G-RMI pose estimation. http://mscoco.org/dataset/#keypoints-leaderboard. 3

[15] P. Kohli, J. Rihan, M. Bray, and P. H. S. Torr. Simultaneous segmentation and pose estimation of humans using dynamic graph cuts. *International Journal of Computer Vision*, 79(3):285–298, 2008. 3

[16] K. Li, B. Hariharan, and J. Malik. Iterative instance segmentation. *CVPR*, 2016. 2, 3

[17] Y. Li, H. Qi, J. Dai, X. Ji, and Y. Wei. Translation-aware Fully Convolutional Instance Segmentation. https://github.com/daijifeng001/TA-FCN. 3

[18] X. Liang, Y. Wei, X. Shen, Z. Jie, J. Feng, L. Lin, and S. Yan. Reversible recursive instance-level object segmentation. In *CVPR*, 2016. 2

[19] X. Liang, Y. Wei, X. Shen, J. Yang, L. Lin, and S. Yan. Proposal-free network for instance-level object segmentation. *CoRR*, abs/1509.02636, 2015. 2

[20] T. Lim, S. Hong, B. Han, and J. Hee Han. Joint segmentation and pose tracking of human in natural videos. In *The IEEE International Conference on Computer Vision (ICCV)*, December 2013. 3

[21] D. Lin, J. Dai, J. Jia, K. He, and J. Sun. Scribblesup: Scribble-supervised convolutional networks for semantic segmentation. In *CVPR*, 2016. 5

[22] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollr, and C. L. Zitnick. Microsoft coco: Common objects in context. In *European Conference on Computer Vision (ECCV)*, Zrich, 2014. 1

[23] M. Linna, J. Kannala, and E. Rahtu. Real-time human pose estimation from video with convolutional neural networks. *CoRR*, abs/1609.07420, 2016. 3

[24] Z. Liu, J. Zhu, J. Bu, and C. Chen. A survey of human pose estimation. *J. Vis. Comun. Image Represent.*, 32(C):10–19, Oct. 2015. 3

[25] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In *CVPR*, 2015. 2

[26] G. Oliveira, A. Valada, C. Bollen, W. Burgard, and T. Brox. Deep learning for human part discovery in images. In *IEEE International Conference on Robotics and Automation (ICRA)*, 2016. 3

[27] E. Park and A. C. Berg. Learning to decompose for object detection and instance segmentation. *ICLR*, 2016. 2

[28] L. Pishchulin, E. Insafutdinov, S. Tang, B. Andres, M. Andriluka, P. V. Gehler, and B. Schiele. Deepcut: Joint subset partition and labeling for multi person pose estimation. In *CVPR*, 2016. 3

[29] X. Qi, J. Shi, S. Liu, R. Liao, J. Jia, undefined, undefined, undefined, and undefined. Semantic segmentation with object clique potential. *2015 IEEE International Conference on Computer Vision (ICCV)*, 00:2587–2595, 2015. 5

[30] B. Romera-Paredes and P. H. S. Torr. Recurrent instance segmentation. In *ECCV*, pages 312–329, 2016. 2

[31] B. Rothrock, S. Park, and S. Zhu. Integrating grammar and segmentation for human pose estimation. In *2013 IEEE Conference on Computer Vision and Pattern Recognition, Port-*

land, OR, USA, June 23-28, 2013, pages 3214–3221, 2013. 3

[32] G. Seguin, K. Alahari, J. Sivic, and I. Laptev. Pose estimation and segmentation of people in 3d movies, 2015. 3

[33] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014. 5

[34] P. Wang, S. Guadarrama, and K. Murphy. G-RMI Instance Segmentation. http://mscoco.org/dataset/#detections-leaderboard. 1

[35] O. Weber, Y. S. Devir, A. M. Bronstein, M. M. Bronstein, and R. Kimmel. Parallel algorithms for approximation of distance maps on parametric surfaces. *ACM Trans. Graph.*, 27(4):104:1–104:16, Nov. 2008. 4

[36] S. Zagoruyko, A. Lerer, T. Lin, P. H. O. Pinheiro, S. Gross, S. Chintala, and P. Dollár. A multipath network for object detection. *CoRR*, abs/1604.02135, 2016. 5

[37] Z. Zhang, S. Fidler, and R. Urtasun. Instance-level segmentation with deep densely connected mrfs. In *CVPR*, 2016. 2