

In this work package, we investigated and developed different knowledge transfer techniques for several applications. Two of them are highlighted here.

## MultiTask CenterNet

A Multitask network can solve several tasks with a single network architecture. This can make an algorithm robust and versatile while maintaining a low latency even on the limited hardware of automotive chips. We presented the Multitask CenterNet (MCN) [1] for semantic segmentation, human pose estimation and object detection all together (Figure 1).

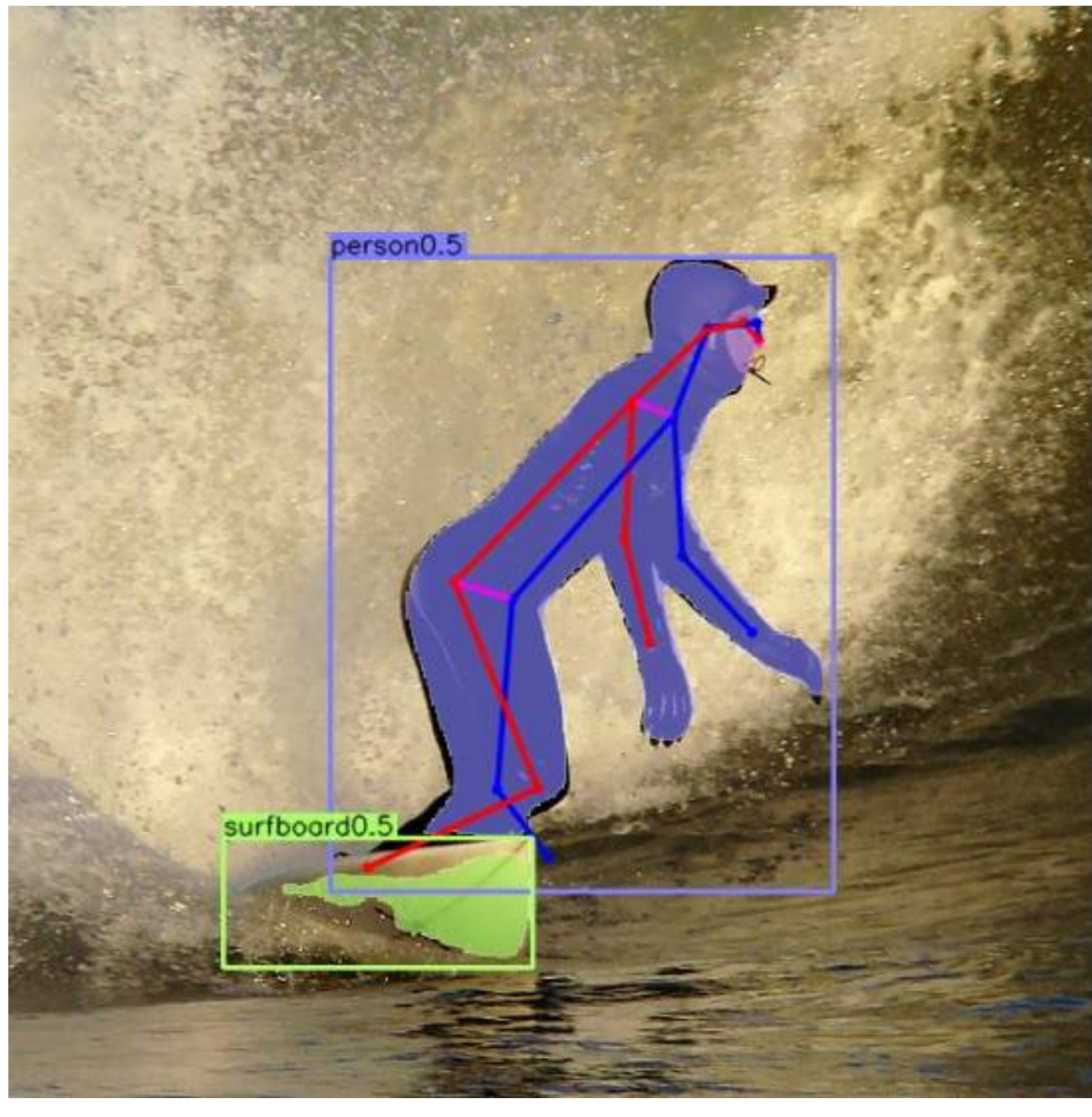


Figure 1: Visualization of a multitask network for object detection, semantic segmentation, and human pose estimation [1]. (©ZF Group)

## Performance Evaluation

The MCN can perform several tasks at once while maintaining, and in some cases even exceeding, the performance values of its corresponding single task networks. Low level processes are learned symbiotically and mutually in the backbone. More importantly, the MCN architecture decreases inference time and reduces network size when compared to a composition of single task networks. Some results are shown in Table 1. For more results, please refer the paper.

Network	Segmentation IoU	Detection AP	Pose mAP
Only Seg	<b>74,4%</b>	NA	NA
Only Det	NA	45,0%	NA
Seg + Det	72,8%	<b>45,2%</b>	NA
Det + Pose	NA	42,8%	53,6%
Seg + Det + Pose	74,3%	42,0%	<b>54,1%</b>

Table 1: Single Task (Seg and Det alone) and Multiple Tasks (Seg + Det, Det + Pose and Seg + Det + Pose) MCNs trained and inferred only for single (human) class of COCO. For the human class, segmentation and detection heads show similar performance values with and without other heads. [1]

## Downstream Task with Masked Autoencoder (MAE)

Masked Autoencoder (MAE) [2] is a technique from the domain of self supervised learning used to train networks without human annotations. MAE use a bottleneck neural network that learns to reconstruct an image from a masked version. It hereby learns the underlying semantics and can later be used to perform downstream tasks (e.g., classification) with the same backbone/network. We are modifying MAE for binary segmentation (foreground, background).

The reconstruction error of an image in MAE can also be used as a measure of relation between patches of an image. We have modified MAE for binary segmentation. The target is to learn a binary segmentation of an image to further augment the abilities of MAE.

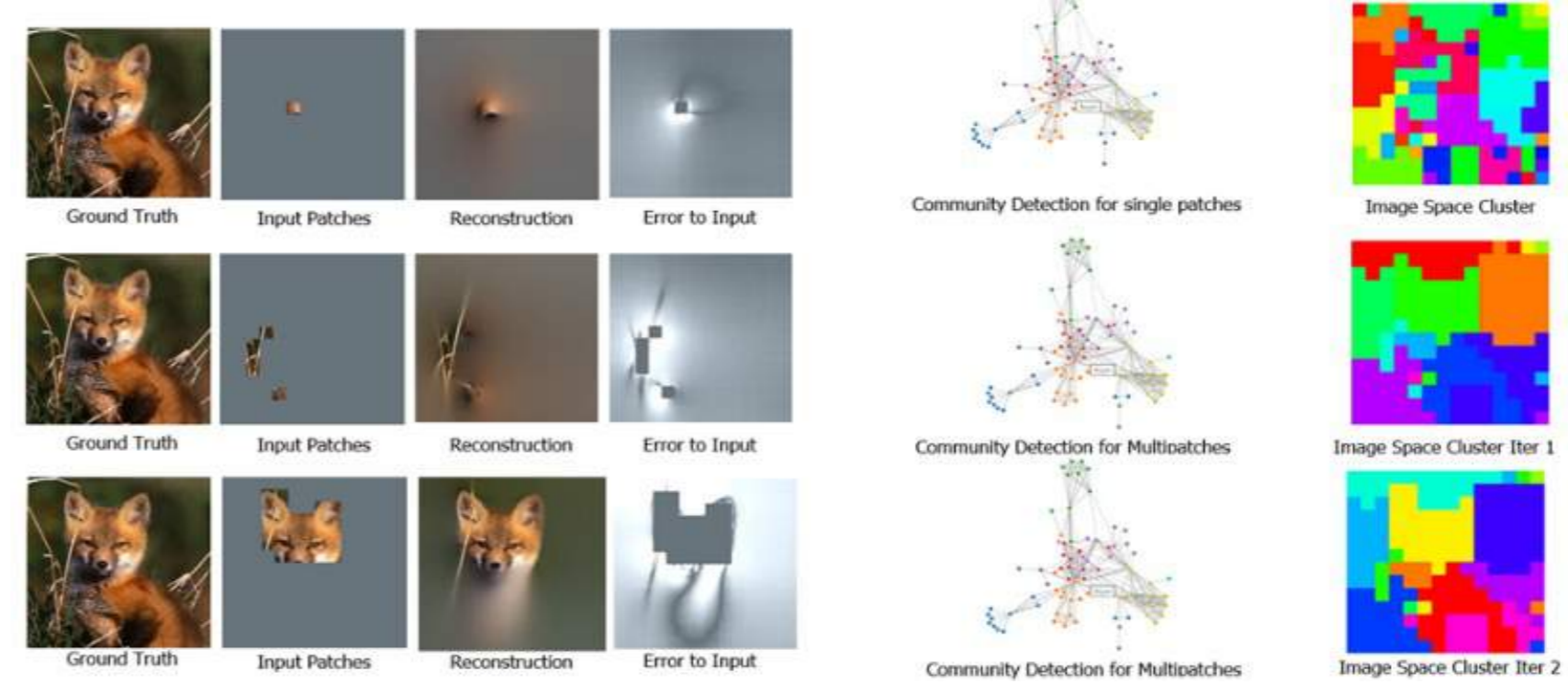


Figure 3: Iterative creation of larger graphs up to complete segmentation. (©ZF Group)

A graph can be built in which patches are considered as its nodes and their relative errors are denoted by edges. To find groups of nodes (objects or object parts), the community detection or the Louvain method [3] is used and thereby creating segmentation. The work is still under progress; however, some preliminary results are shown here in Figure 3.

## References

- 1] F. Heuer, S. Mantowsky, S. S. Bukhari, and G. Schneider. Multitask-CenterNet (MCN): Efficient and diverse multitask learning using an anchor free approach. ICCV - Embedded and Real-World Computer Vision in Autonomous Driving (ICCV-ERCVD, 2021).
- 2] K. He, X. Chen, S. Xie, Y. Li, P. Dollar, and R. Girshick, "Masked Autoencoders Are Scalable Vision Learners," in preprint arXiv:2111.06377, 2021.
- 3] Vincent D Blondel, Jean-Loup Guillaume, Renaud Lambiotte, Renaud Lefebvre, Fast unfolding of communities in large networks, Journal of Statistical Mechanics: Theory and Experiment 2008(10), P10008 (12pp)

## Partners



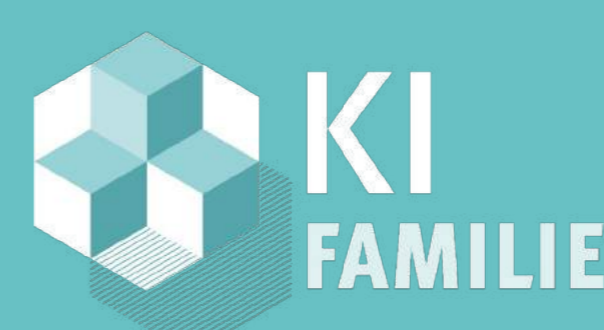
## External partners



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