

Unsupervised Panoptic Segmentation

Annotating large 3D outdoor environments is a costly and laborious task. Thus, we propose to learn 3D panoptic segmentation in an unsupervised way, without relying on ground-truth annotations. Due to its scalability, our approach is most applicable for generating semantic virtual worlds, minimizing the need for human annotators. Additionally, it excels at extracting object properties from unlabeled data, leading to increased driving safety. We construct a learning framework consisting of two components:

- 1) a pseudo-annotation generation algorithm
- 2) a chunk-based self-training algorithm

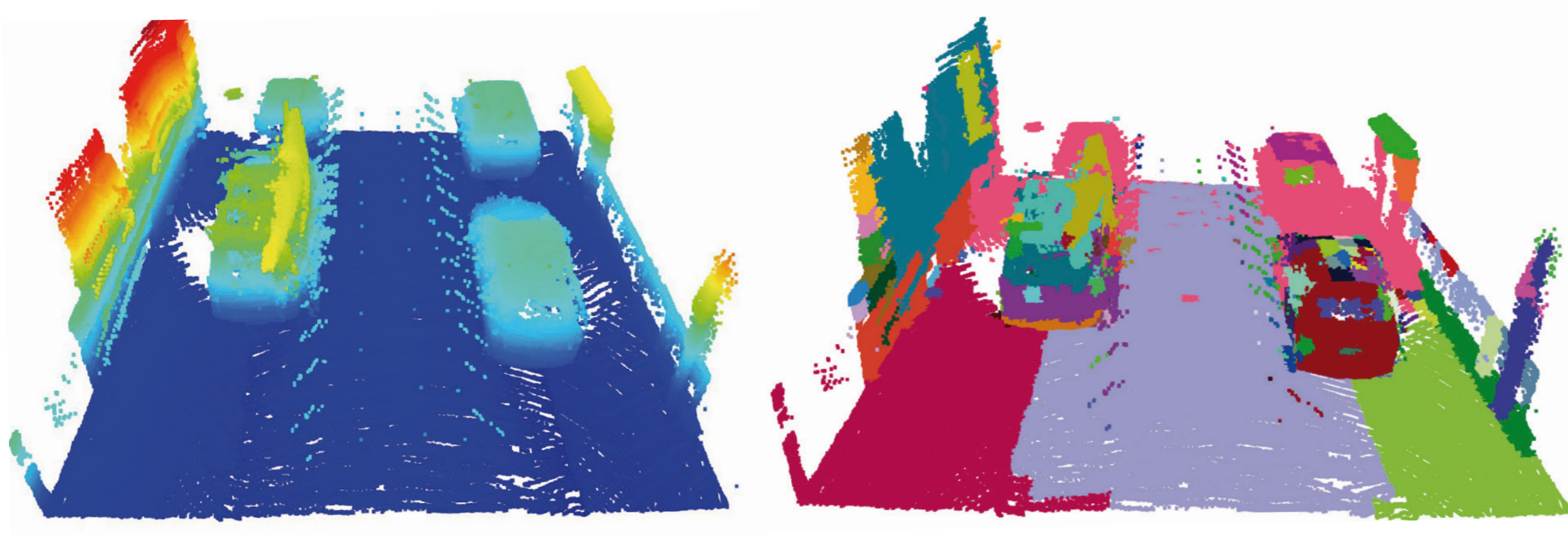


Figure 1: raw chunk-based point cloud (left) and pseudo-annotation of our graph-cuts algorithm (right)

Pseudo Annotations

To enable pseudo-annotation, we extract chunk-based self-supervised features at each timestep individually and aggregate them into a fused representation. We aim to create strong initial pseudo-masks and therefore leverage multi-modal image and point-based features. To enable pseudo-annotation, we construct a weighted proxy-graph by connecting 3D points with edges integrating 2D self-supervised features from SAM [1] and Dinov2 [2], as well as 3D features from TARL [3].

Combining these self-supervised features with spatial distances, we perform graph-cuts to generate individual pseudo-instances.

Self-Training

Based on our initially noisy pseudo-labels, we learn to perform self-trained [4,5] chunk-based instance segmentation. During the self-training process, the most confident predictions are reintegrated in the training loop, resulting in significant refinement of our initial proposals. Consequently, we construct a method to generate scene-level instance segmentation. We leverage a state-of-the-art 3D backbone [6] for our chunk-based self-training. As driving safety is crucial for autonomous driving applications, we employ an uncertainty-aware panoptic segmentation head based on evidential deep learning [7] for our 3D backbone. We compare our method against existing approaches [8] on several challenging outdoor LiDAR point cloud datasets.

References:

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- [7] K. Sirohi et al., "Uncertainty-aware LiDAR Panoptic Segmentation", arXiv [cs.CV], 10-Oct-2022.
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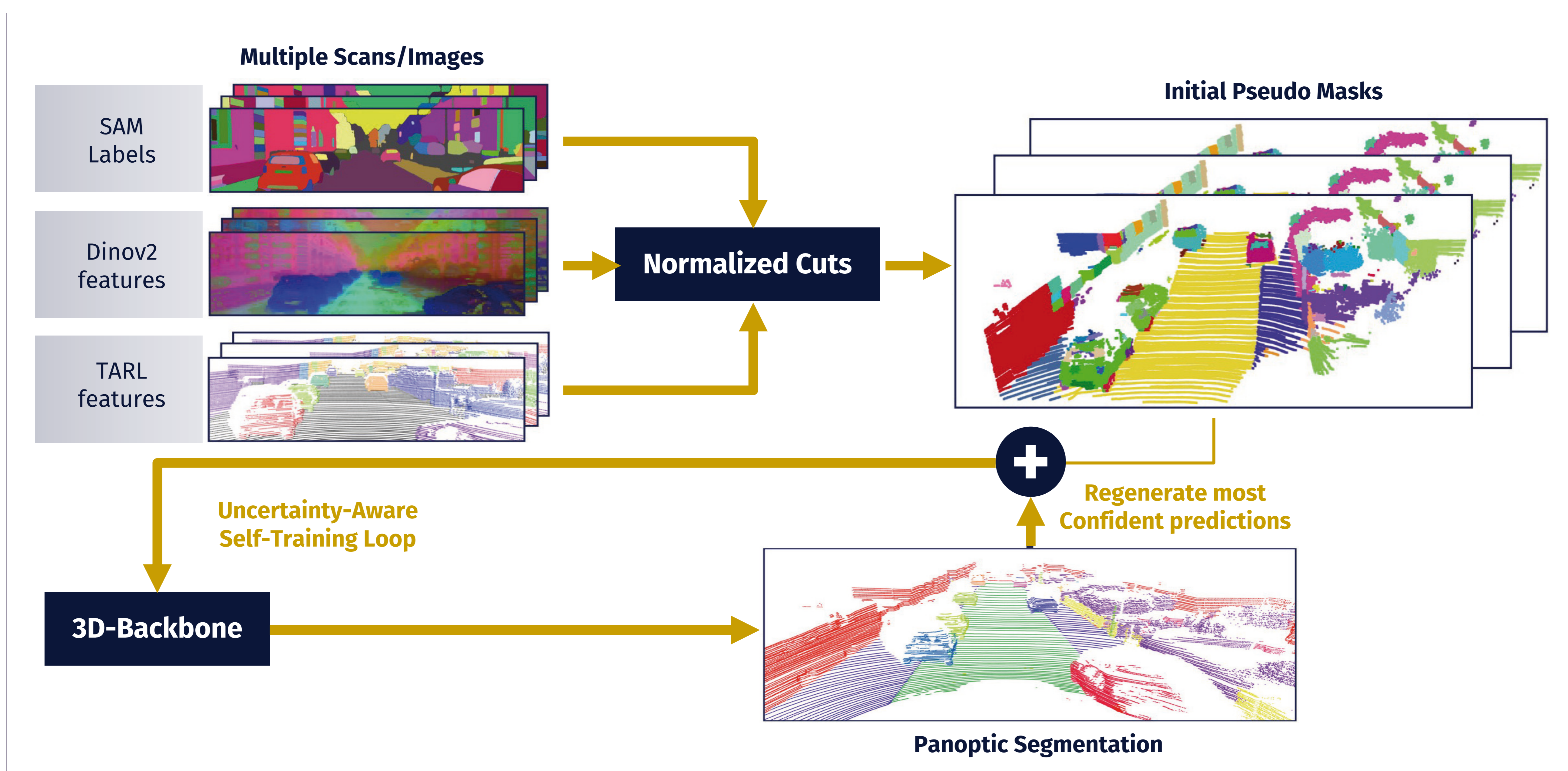


Figure 2: Overview of the pseudo mask generation and the uncertainty aware self-training pipeline

Partners



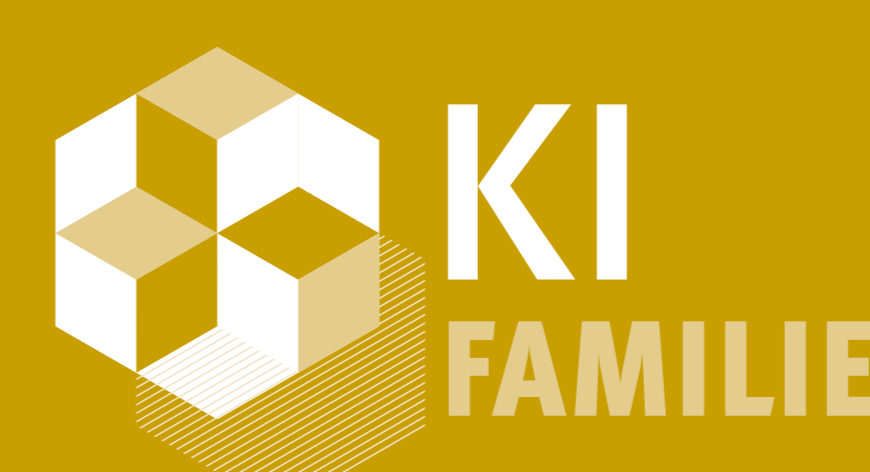
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