

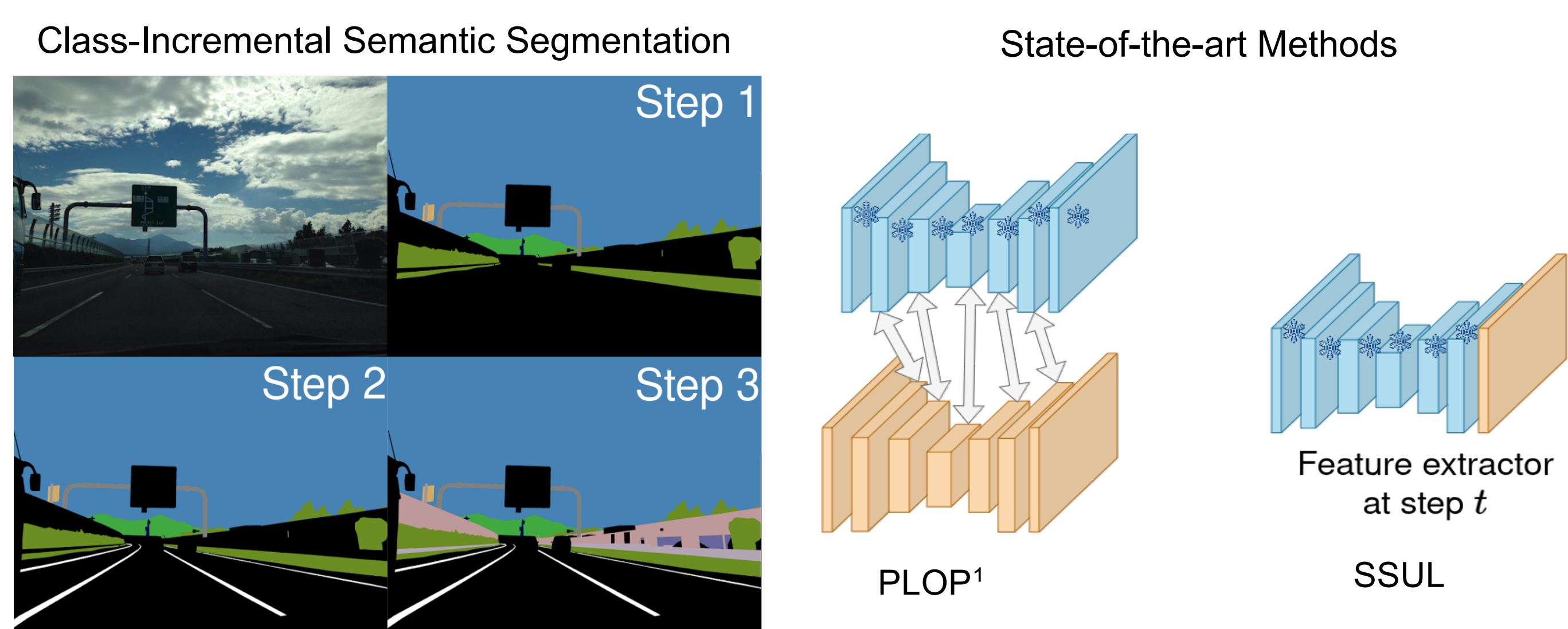
Taxonomy-Aware Class-Incremental Semantic Segmentation for Open-World Perception

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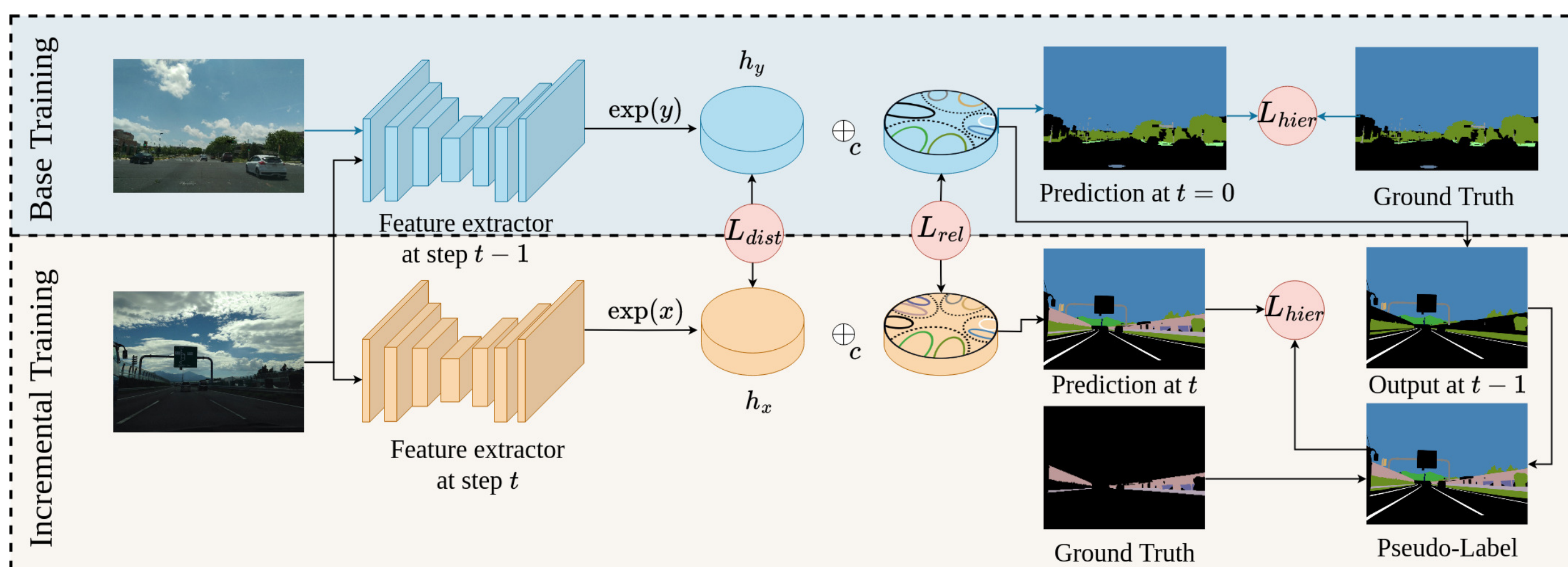
Motivation

- Autonomous vehicles operate in an open-world scenario where training data with **new object** classes appear over time.
- Class-Incremental Semantic Segmentation (CISS)** aims to update the model with new classes at periodic timesteps.
- State-of-the-art methods constrain features of the new model to imitate those of the prior model with direct feature distillation or freeze entire backbones.



Method

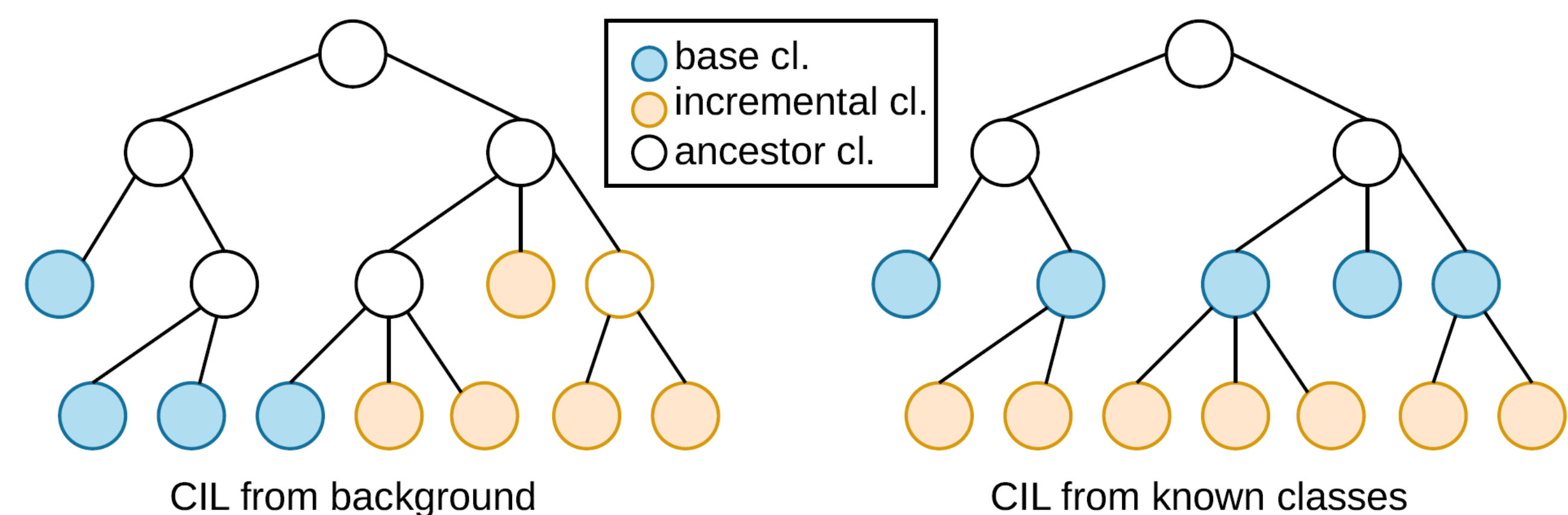
- Our proposed **Taxonomy-Oriented Poincaré-regularized Incremental Class Segmentation (TOPICS)** approach enforces features conform to **taxonomy-tree structures**.
- We model the class hierarchy in **hyperbolic space** due to its property of **equidistant node connections** on all levels.
- Consequently, distances are inversely proportional to the semantic similarity of classes.



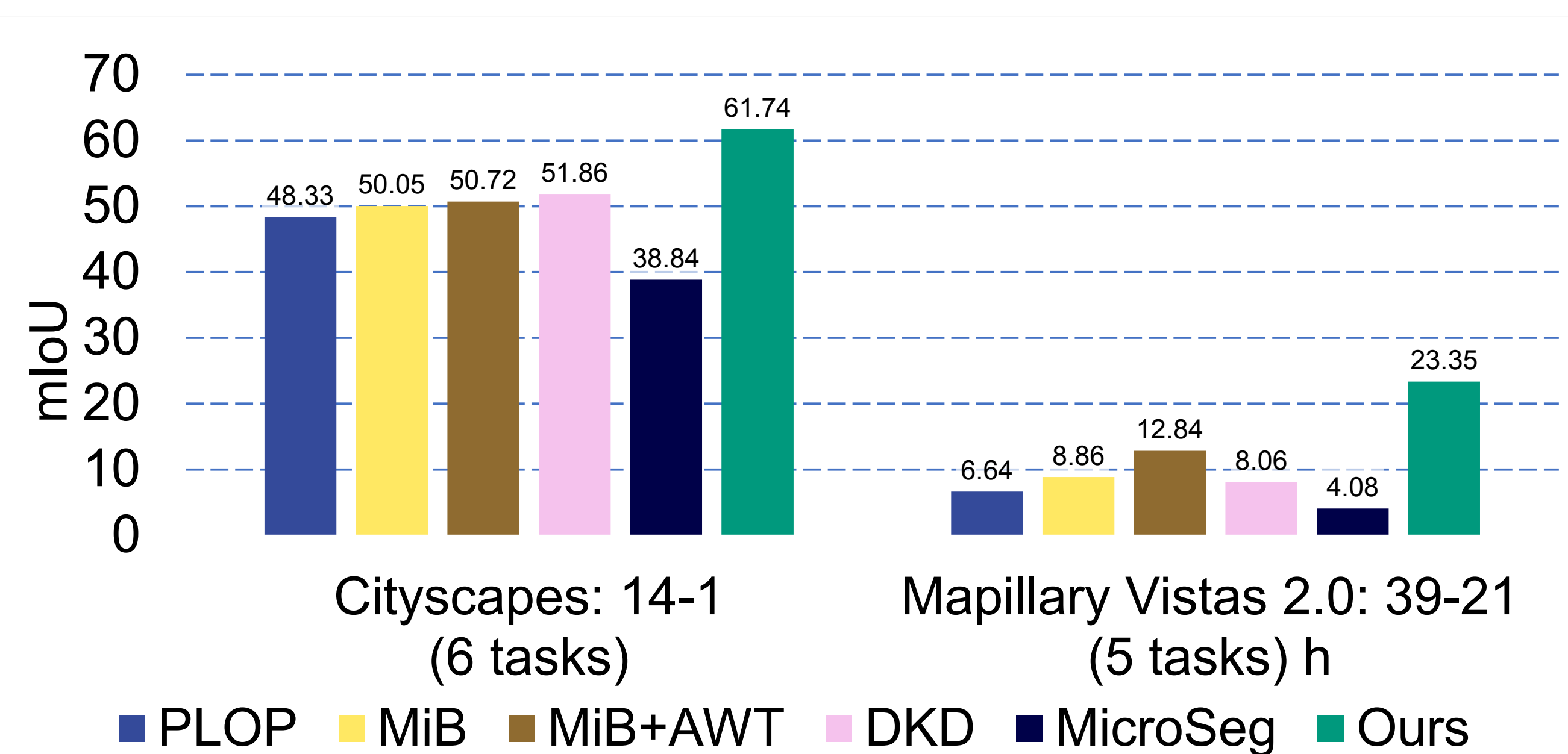
- We first train the model on the **base dataset**. The class hierarchy is explicitly enforced (L_{hier}) in the final network layer which is mapped in hyperbolic space.
- During the **incremental steps**, we leverage the old model's weights to create **pseudo-labels** for the background.
- We employ an **hyperbolic InfoNCE loss** to maintain classes in a similar constellation in the updated model (L_{rel}).
- We enforce features of the new and old model to be **equidistant** from the center of the Poincaré ball (L_{dist}).

Results

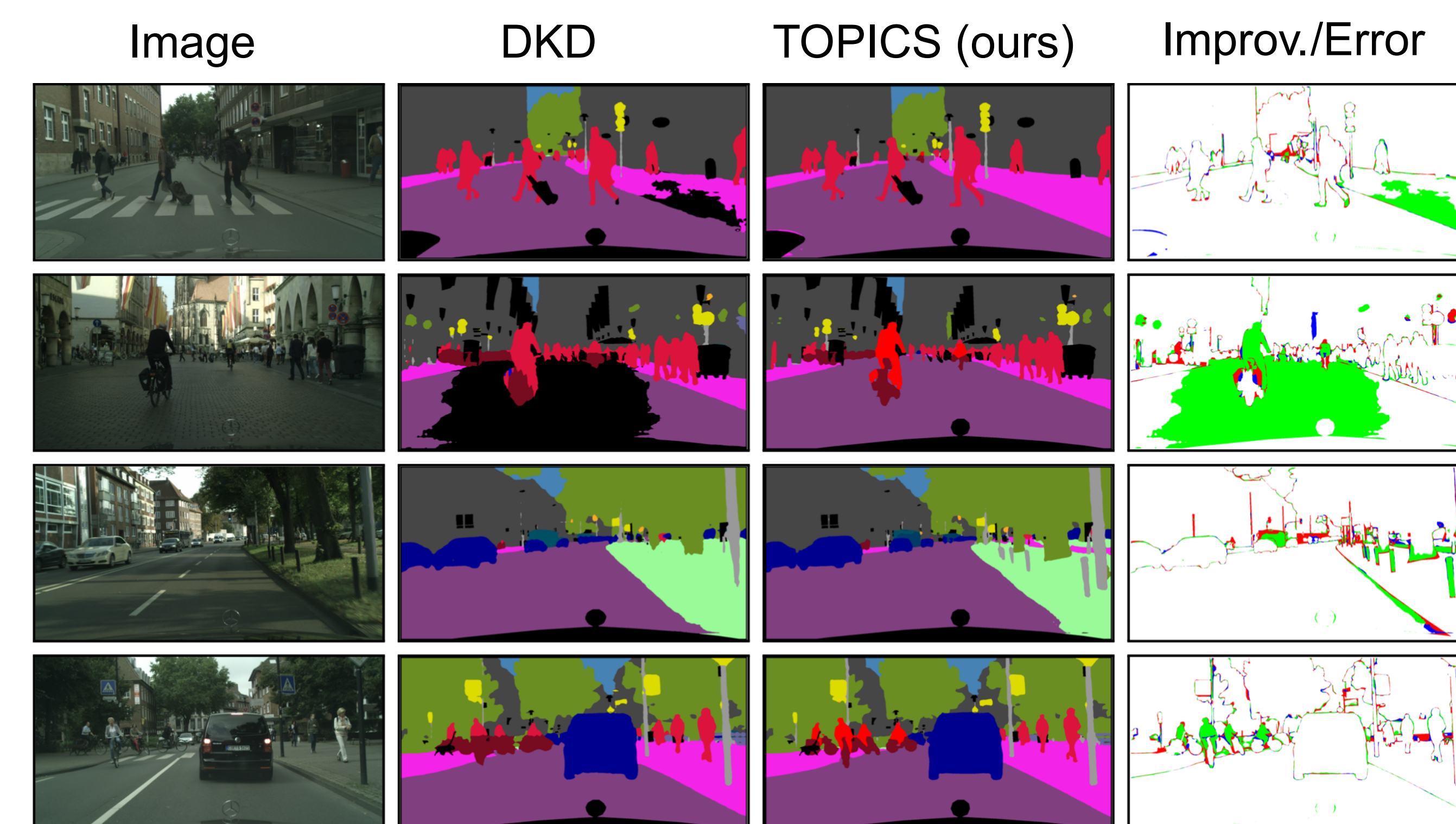
- We define CISS protocols where increments primarily originate from the background or known classes.



- We evaluate TOPICS on the **Cityscapes** and **Mapillary Vistas 2.0** datasets.



- TOPICS outperforms all baselines on both datasets.
- Qualitative results show that our method remembers old classes, such as road and sidewalk, and continuous to accurately predict them after having learned new classes.



Conclusion

- In this work, we proposed TOPICS, a novel CISS approach that models features conforming to taxonomy-tree structures.
- We model the class hierarchy in hyperbolic space to balance rigidity and plasticity in incremental learning.
- Our method is one of the early works that uniformly addresses the bifurcation of previously observed classes and incremental classes from the background.
- We emphasize the benefit of hierarchical modeling in hyperbolic space and motivate future work to explore its potential for various open-world challenges