

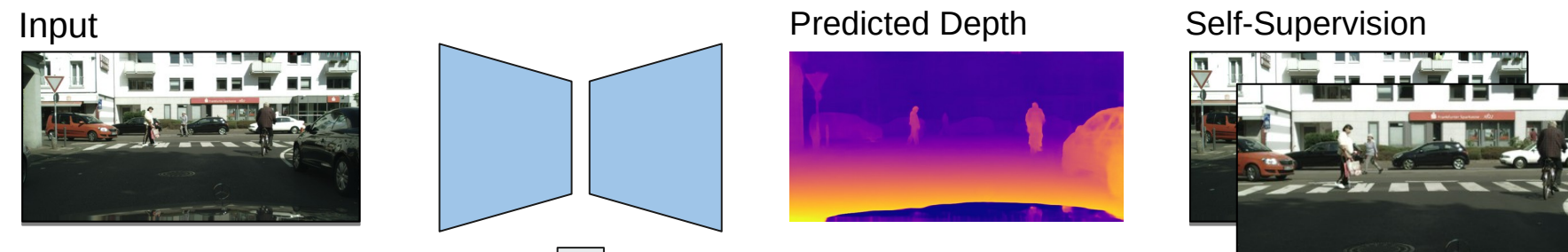
# Three Ways to Improve Semantic Segmentation with Self-Supervised Depth Estimation



## 1 Concept

### Self-Supervised Depth Estimation (SDE)

+ Requires only unlabeled image sequences

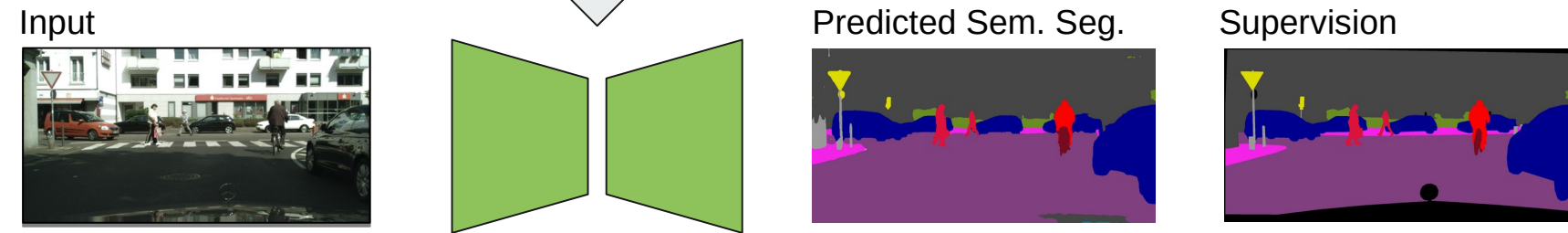


### Semantic Segmentation

- Requires expensive human annotation

### Knowledge Transfer

- Transfer- and Multi-Task Learning
- DepthMix Data Augmentation
- Automatic Data Selection

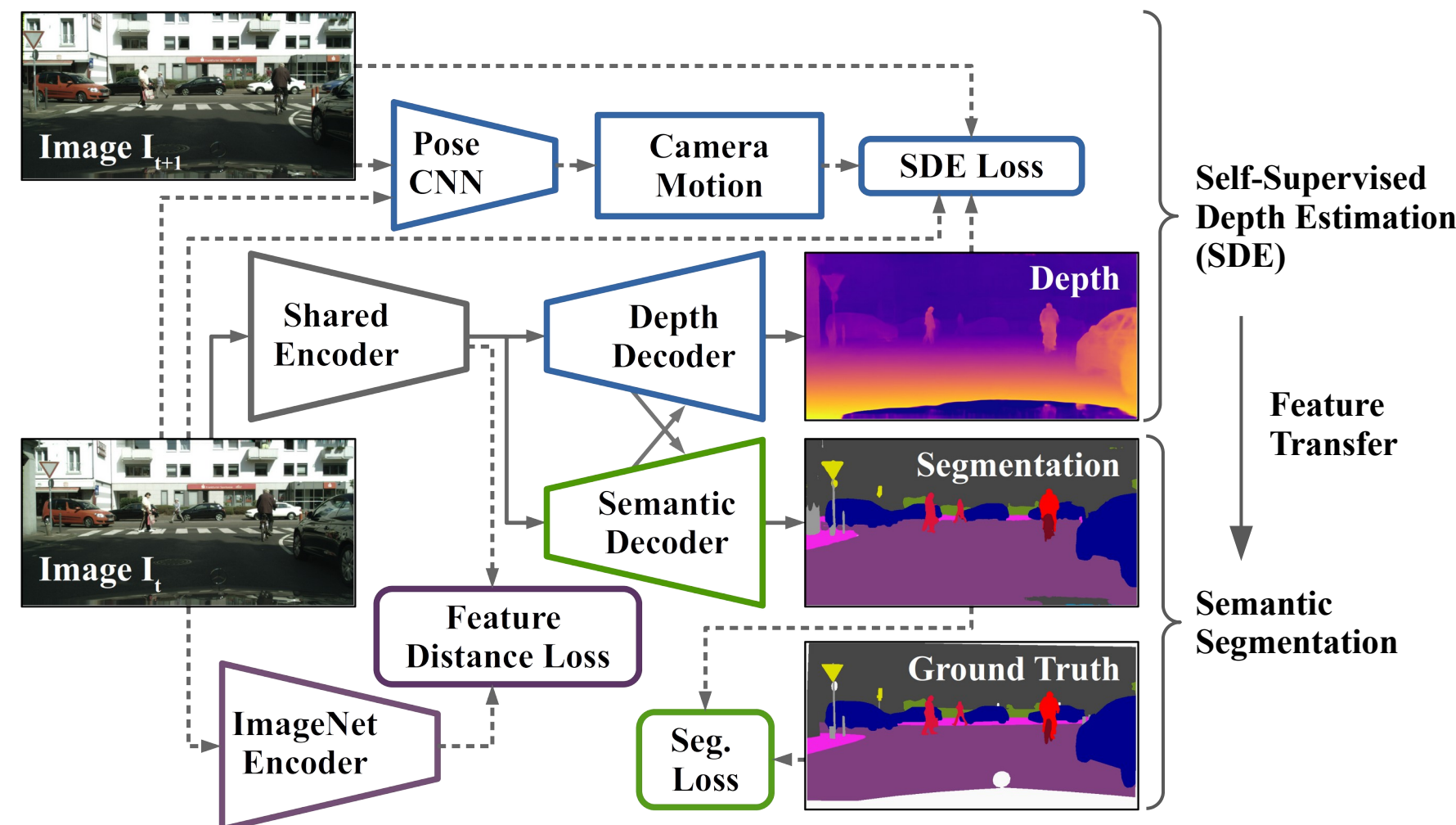


**Advantage:** Knowledge from SDE reduces necessary annotations for semantic segm.  
**Implementation:** [https://github.com/lhoyer/improving\\_segmentation\\_with\\_selfsupervised\\_depth](https://github.com/lhoyer/improving_segmentation_with_selfsupervised_depth)

## 2 Transfer and Multi-Task Learning

**Motivation:** Utilize depth features for semantic segmentation

- Approach:**
- Transfer Learning: Initialize segmentation branch with depth pretraining
  - Multi-Task Learning: Exchange features between depth and segmentation decoder
- Advantage:** SDE learns features from a large set of unlabeled image sequences



## 3 DepthMix

### Concept

**Motivation:** Mitigate occlusion artifacts  
**Approach:** Select pixels closer to camera

Mix Mask:

$$M(a, b) = \begin{cases} 1 & \text{if } \hat{D}_i(a, b) < \hat{D}_j(a, b) + \epsilon \\ 0 & \text{otherwise} \end{cases}$$

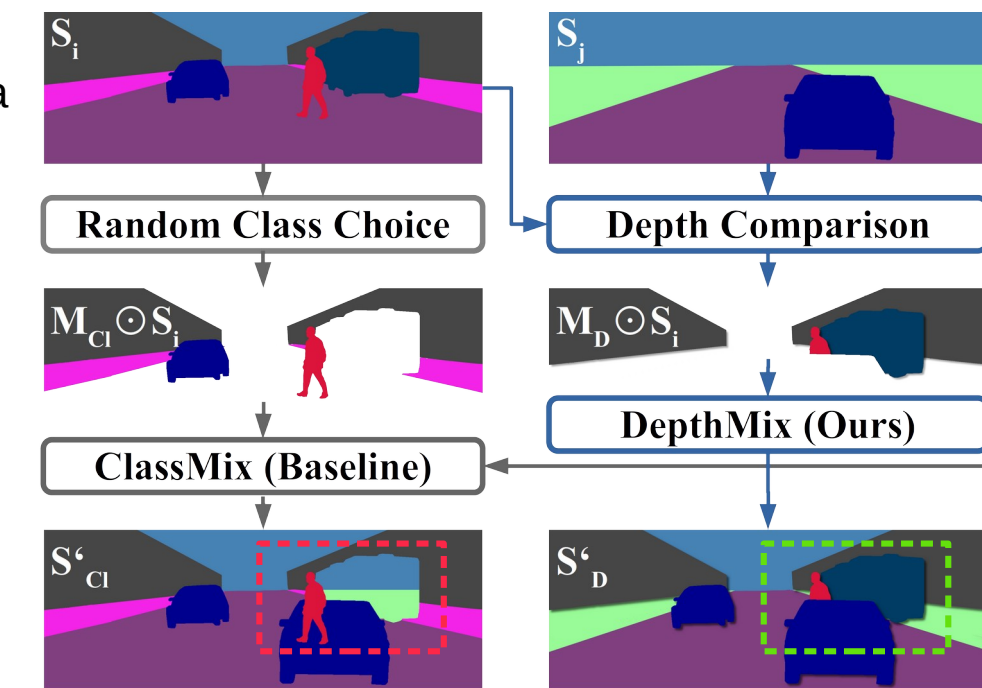
Mixed Image:

$$I' = M \odot I_i + (1 - M) \odot I_j$$

Mixed Segmentation:

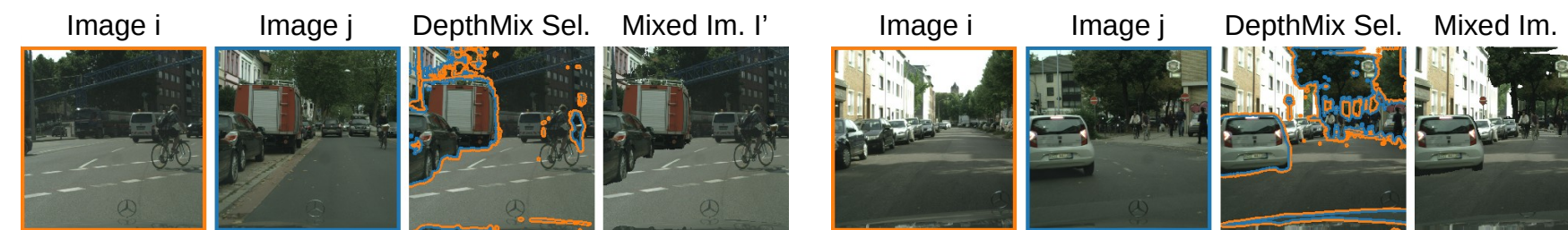
$$S' = M \odot S_i + (1 - M) \odot S_j$$

**Advantage:** Geometrically valid mixing



### Real-World Examples

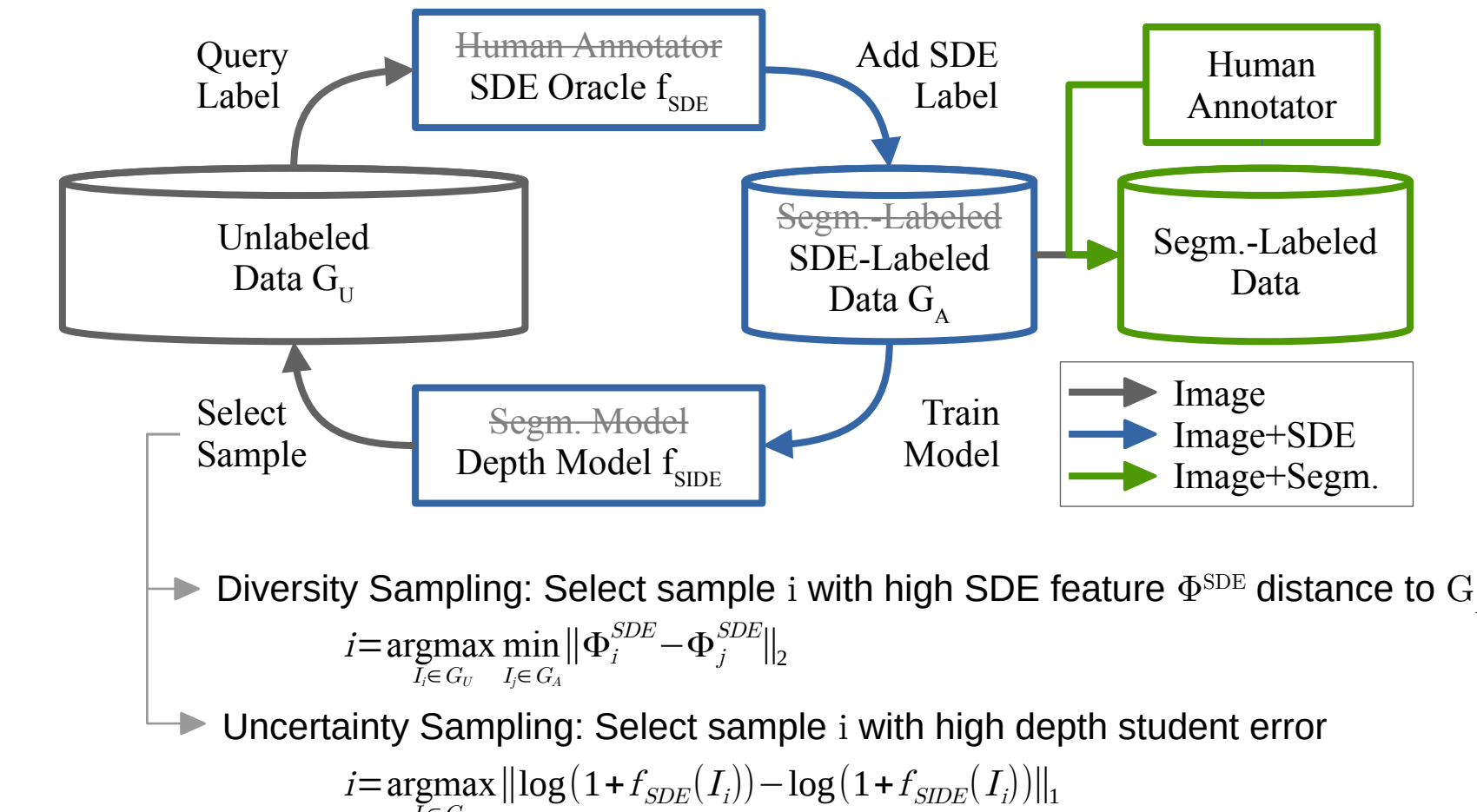
DepthMix produces precise mixing boundaries and effectively handles occlusions



## 4 Automatic Data Selection for Annotation

**Motivation:** Select most beneficial samples to be annotated

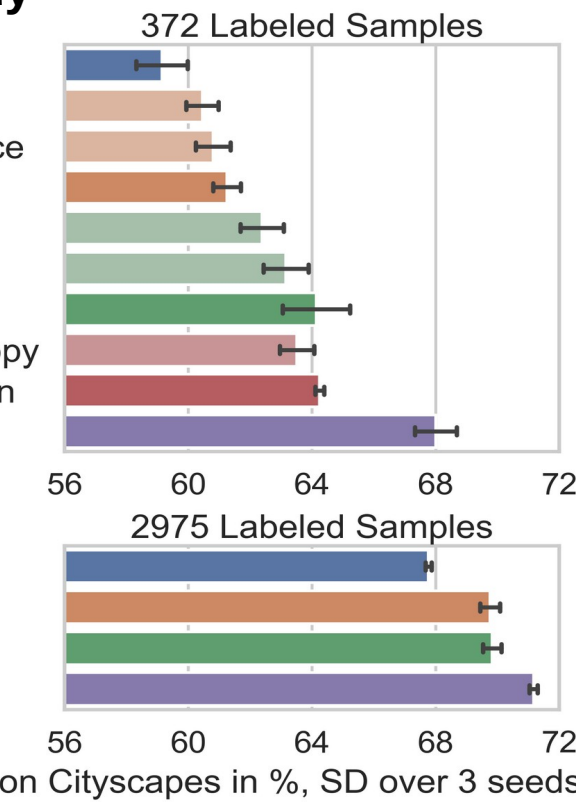
**Approach:** Iterative sample selection with SDE proxy-task oracle  
**Advantage:** No human in the loop → increased flexibility, efficiency, and scalability



## 5 Evaluation on Cityscapes

### Component Study

- Baseline
- Transfer Learning + ImageNet Distance
- Multi-Task Learning
- Pseudo-Labeling
- ClassMix [5]
- DepthMix
- Active Learning Entropy
- Autom. Data Selection
- Combination

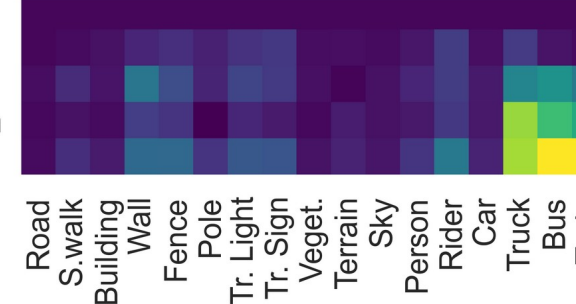


Each contribution significantly outperforms baseline

- Transfer and Multi-Task Learning enable effective feature transfer
- Mixing improves pseudo-labeling
- DepthMix outperforms ClassMix [5]
- Autom. Data Selection outperforms human-in-the-loop active learning with entropy
- Combination further improves performance
- Combination achieves fully-supervised baseline performance with only 1/8 labels
- Our contributions can also improve the fully-supervised performance

### Class-Wise IoU Improvement over Baseline for 372 Labels

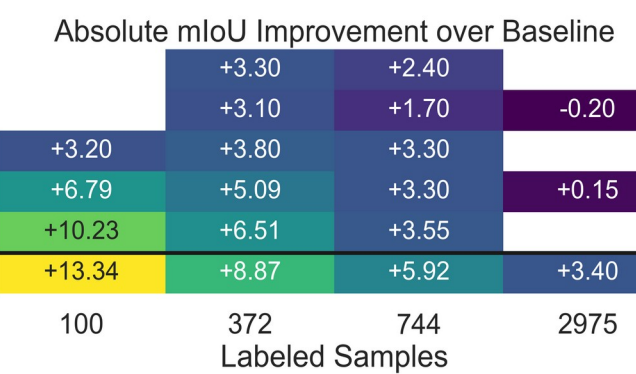
- Baseline
- Multi-Task Learning
- DepthMix
- Autom. Data Selection
- Combination



- Multi-Task Learning improves classes with depth discontinuities
- Autom. Data Selection improves difficult classes
- DepthMix improves both

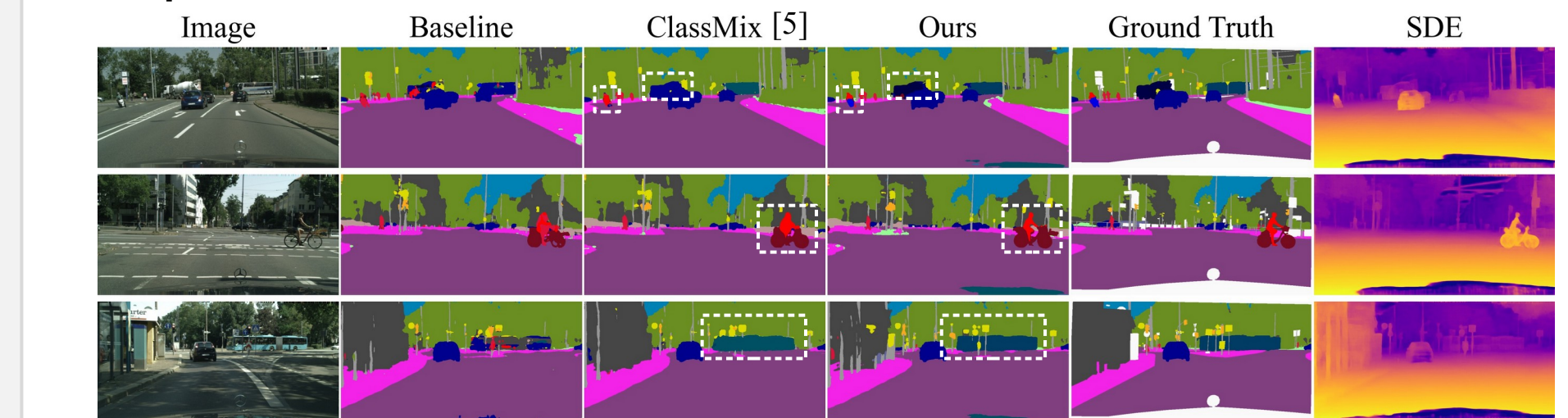
### Comparison with State of the Art

- Adversarial [3]
- s4GAN [4]
- DST-CBC [1]
- CutMix [2]
- ClassMix [5]
- Ours (Combination)



- Our method outperforms previous SoTA methods by a significant margin

### Example Predictions



- Ours better distinguishes difficult classes (e.g. truck, train, and bus)
  - Ours segments finer structures at depth discontinuities (e.g. rider, pole, and tr. sign)
- trained on 100 labeled samples

## 6 References

[1] Feng et al. "Semi-supervised semantic segmentation via dynamic self-training and class-balanced curriculum." arXiv preprint. 2020.  
 [2] French et al. "Semi-supervised semantic segmentation needs strong, varied perturbations." BMVC. 2020.  
 [3] Hung et al. "Adversarial learning for semi-supervised semantic segmentation." BMVC. 2019.  
 [4] Mittal et al. "Semi-supervised semantic segmentation with high- and low-level consistency." PAMI, 2019.  
 [5] Olsson et al. "Classmix: Segmentation-based data augmentation for semi-supervised learning." WACV. 2021.