Continual Coarse-to-Fine Domain Adaptation in Semantic Segmentation

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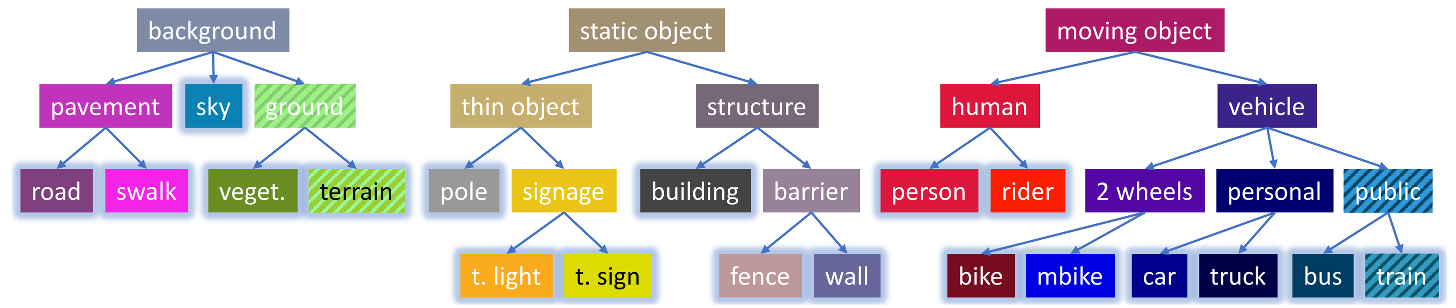
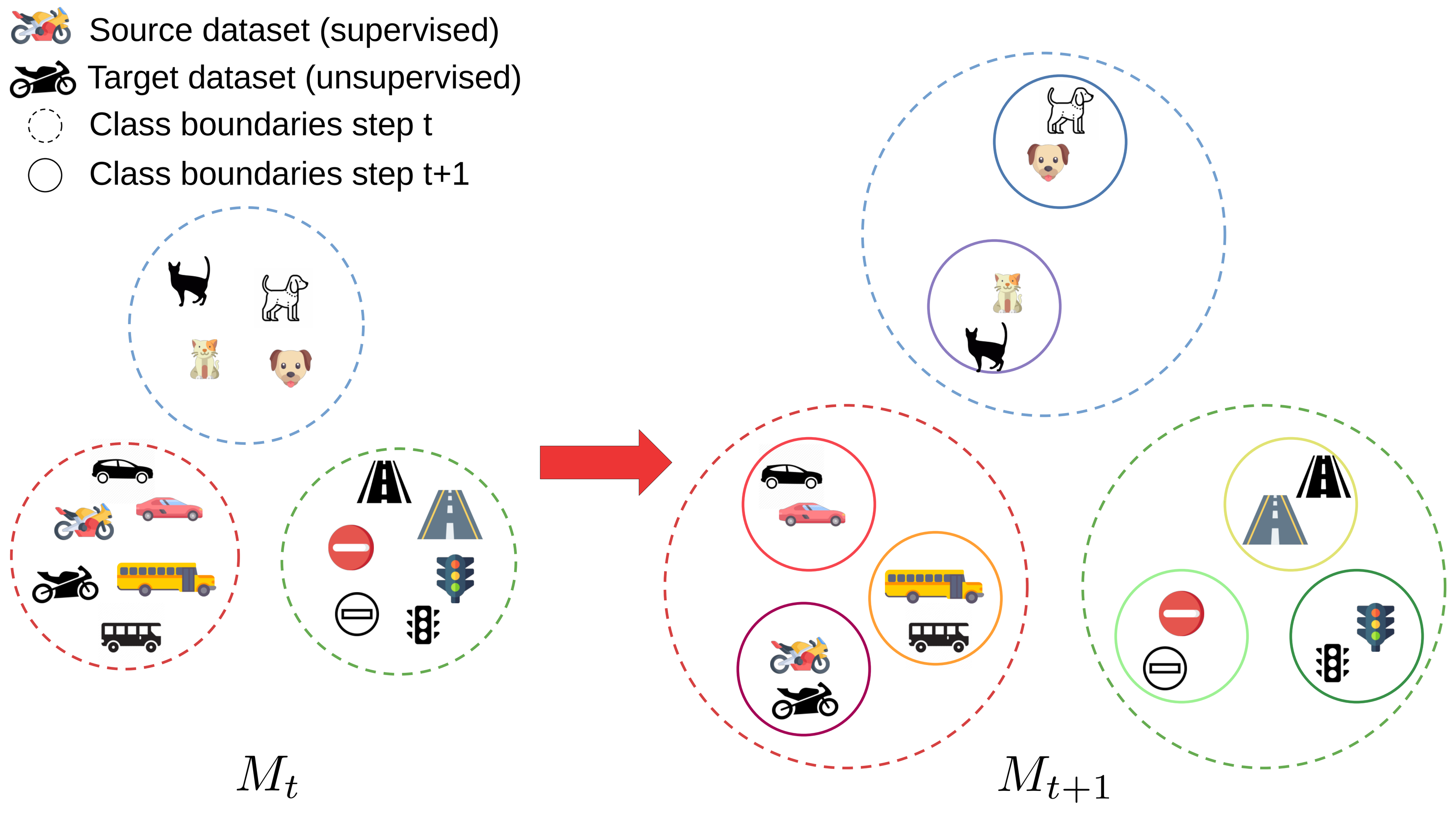
Abstract

We introduce the novel task of coarse-to-fine learning of semantic segmentation architectures in presence of domain shift. We consider subsequent learning stages progressively refining the task at the semantic level. We propose a new approach (CCDA) to tackle this scenario combining a maximums squares loss minimization, a novel Coarse-to-Fine knowledge distillation and weights initialization. To evaluate our approach, we design two benchmarks where source knowledge is extracted from the GTA5 dataset and it is transferred to either the Cityscapes or the IDD datasets, and we show how it outperforms the main competitors.

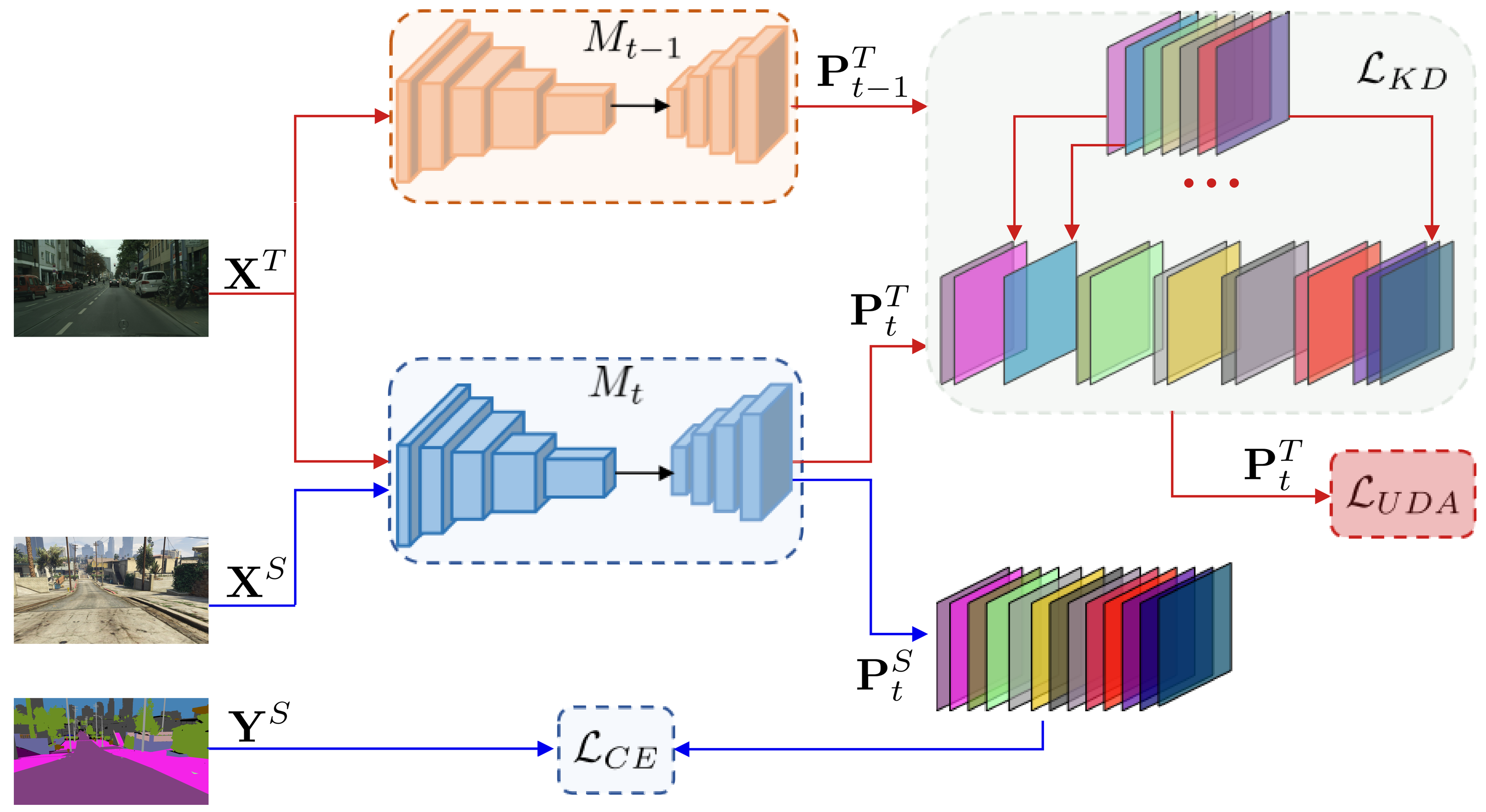
Hierarchical class labeling



C2F-UDA scheme



Proposed Method: CCDA



Unsupervised Domain Adaptation

- Target predictions are more uncertain, higher entropy
- Higher gradient for simpler classes
- More effective adaptation of high level semantics when performing the training in multiple steps
- Reframe max squares loss [1]:

$$\mathcal{L}_{UDA} = -\sum_{\mathbf{X}\in\mathcal{T}_t^T}\sum_{c\in\mathcal{C}_t}\frac{1}{2|\mathcal{C}_t|^{\alpha}(HW)^{1-\alpha}}\left(\mathbf{P}_t^T[c]\right)^2. \qquad (1)$$

Coarse-to-Fine Knowledge Distillation

- Transfer knowledge from coarse to finer classes:

$$\mathcal{L}_{KD}^c = \frac{1}{|\mathcal{T}_t^T|}\sum_{\mathbf{X}\in\mathcal{T}_t^T}\sum_{c\in\mathcal{C}_{t-1}^c}\mathbf{P}_{t-1}^T[c]\sum_{f\in S_t(c)}\log\mathbf{P}_t^T[f]. \qquad (2)$$

- Preserve knowledge of definitive classes:

$$\mathcal{L}_{KD}^f = \frac{1}{|\mathcal{T}_t^T|}\sum_{\mathbf{X}\in\mathcal{T}_t^T}\sum_{c\in\mathcal{C}_{t-1}^f}\mathbf{P}_{t-1}^T[c]\log\mathbf{P}_t^T[c]. \qquad (3)$$

Coarse-to-Fine Weights Initialization

- Initialize fine classes with weights of parent class

$$\{\omega_t^f\} = \{\omega_{t-1}^c\} \quad \forall c\in C_{t-1}^c, \forall f\in S_t(c) \qquad (4)$$
$$\{\omega_t^f\} = \{\omega_{t-1}^f\} \quad \forall f\in C_{t-1}^f. \qquad (5)$$

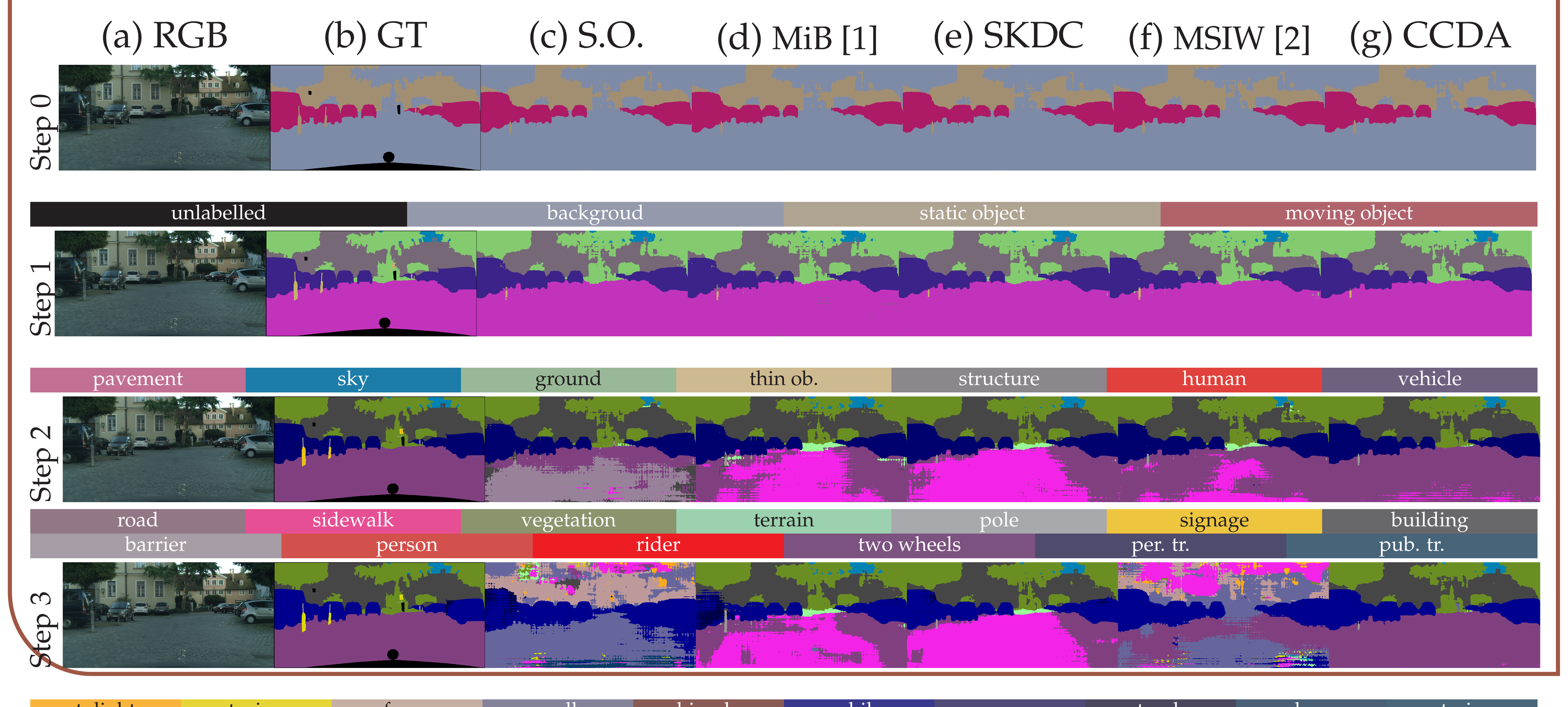
- Spread probability of coarse class towards its set of finer classes

$$\{\beta_t^f\} = \{\beta_t^c - \log(|S_t(c)|)\} \quad \forall c\in C_{t-1}^c, \forall f\in S_t(c) \qquad (6)$$
$$\{\beta_t^f\} = \{\beta_t^f\} \quad \forall f\in C_{t-1}^f. \qquad (7)$$

Quantitative results

	Model	mIoU$_0$	mIoU$_1$	mIoU$_2$	mIoU$_3$
GTA5→CS	JTO	-	-	-	68.6
	TNC	92.1	83.7	72.6	66.5
	Source Only	65.0	56.7	25.1	4.5
	MiB [2]	65.0	56.1	27.8	26.5
	MSIW [1]	**85.4**	62.2	**38.5**	6.9
	SKDC (ours)	65.0	65.4	34.4	30.4
	CCDA (ours)	**85.4**	**67.9**	37.2	**33.1**
GTA5→IDD	JTO	-	-	-	65.9
	TNC	87.0	78.8	73.2	64.2
	Source only	72.9	60.8	30.0	6.1
	MiB [2]	72.9	61.8	**44.7**	26.8
	MSIW [1]	**75.9**	62.7	30.2	8.9
	SKDC (ours)	72.9	60.9	38.7	32.4
	CCDA (ours)	**75.9**	**63.5**	40.3	**33.0**

Qualitative Results



Conclusion

- Introduced a novel framework of continual coarse-to-fine UDA
- Proposed a new approach (CCDA) to address it
- Evaluated CCDA in two synthetic-to-real UDA benchmarks
- Outperforms state-of-the-art UDA and CL techniques

References

[1] M. Chen, H. Xue, D. Cai, Domain adaptation for semantic segmentation with maximum squares loss, in: Proceedings of the International Conference on Computer Vision, 2019.
[2] F. Cermelli, M. Mancini, S. R. Jul'o, E. Ricci, B. Caputo, Modeling the background for incremental learning in semantic segmentation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2020.
[3] D. Shenaj, F. Barbato, U. Michieli and P. Zanuttigh, Continual coarse-to-fine domain adaptation in semantic segmentation, Image and Vision Computing, 2022.