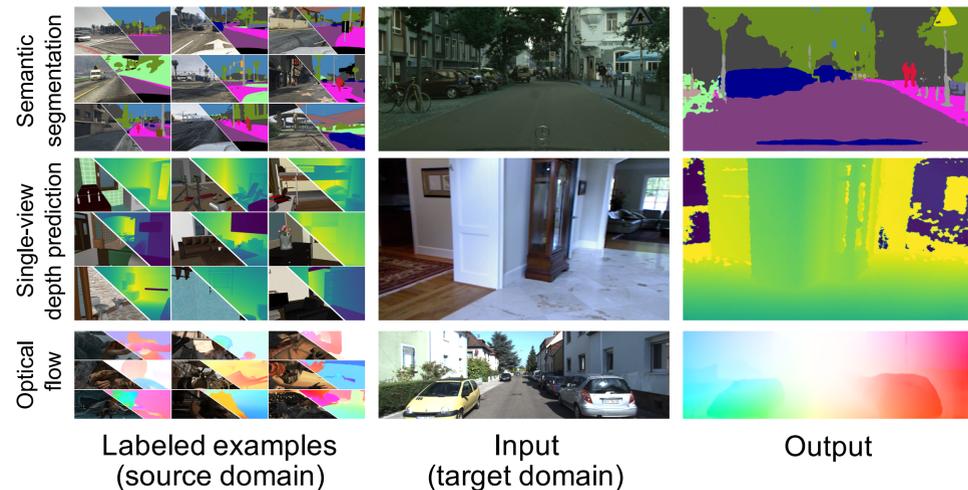




Unsupervised domain adaptation

Input: A source dataset (labeled) and a target dataset (unlabeled)

Goal: Transfer knowledge from source to target domains

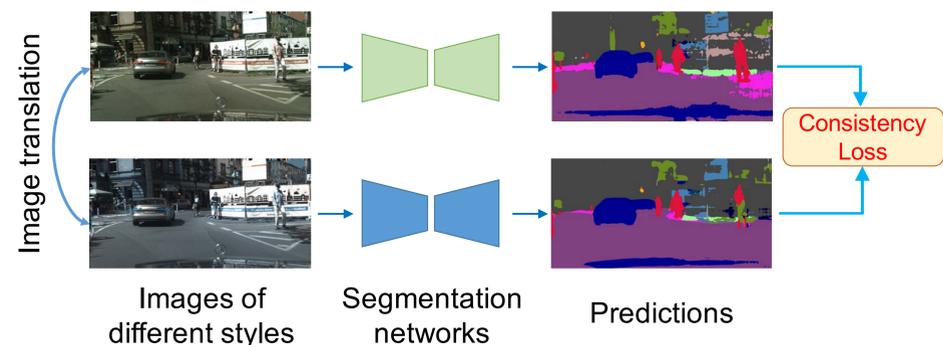


Challenges

- Target domain is unsupervised
- Domain gap between the source and target datasets

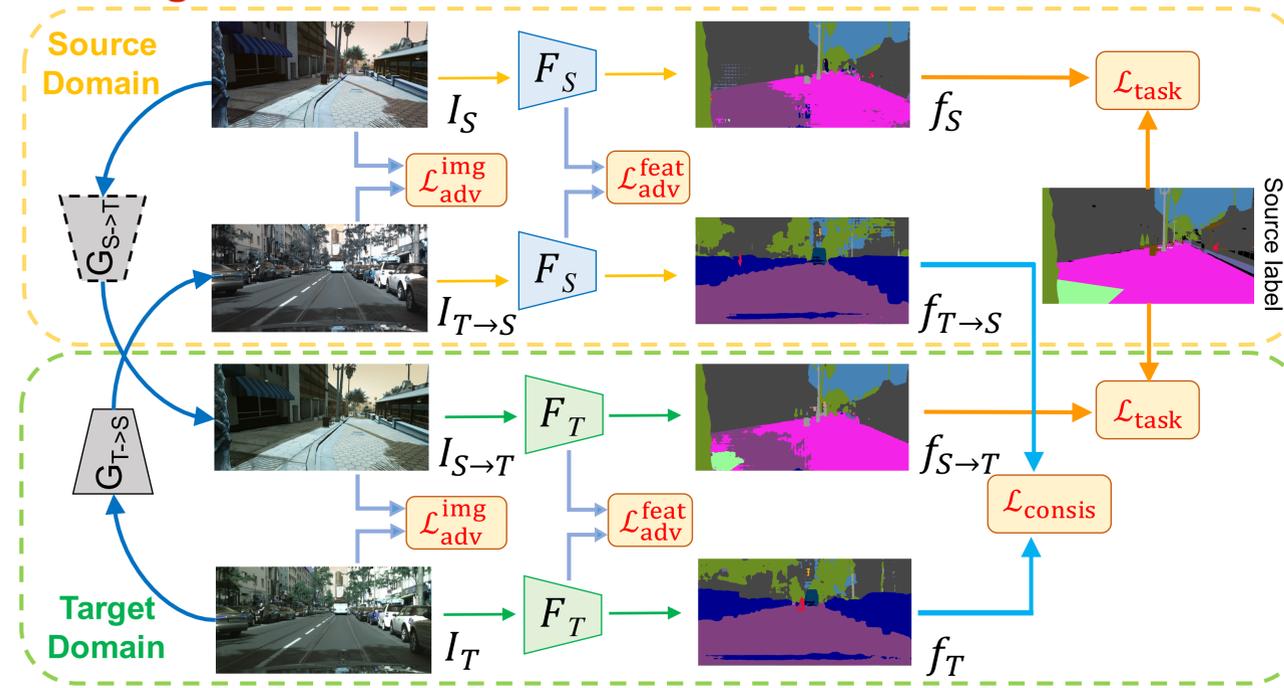
Cross-domain consistency

- Images of different styles should have the same task predictions

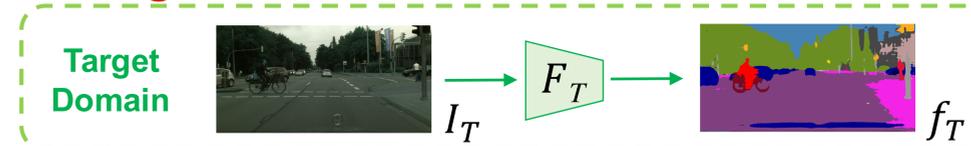


Our approach

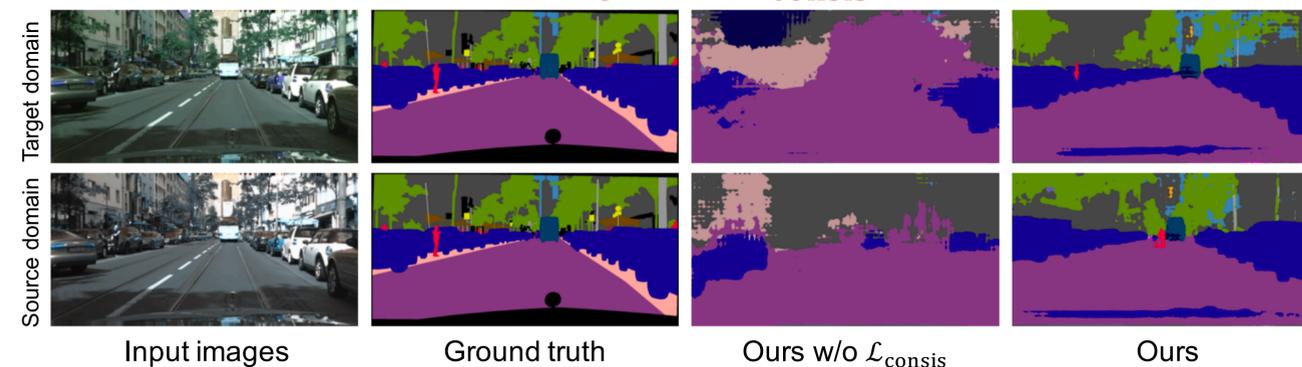
Training



Testing



Cross-domain consistency loss $\mathcal{L}_{consist}$



Experimental results

A) Synthetic-to-real adaptation

Semantic segmentation

Method	GTA5 \rightarrow Cityscapes		SYNTHIA \rightarrow Cityscapes	
	mean IoU	Pixel acc.	mean IoU	Pixel acc.
Synth.	22.9	71.9	18.5	54.6
DS [Dundar arXiv 18]	38.3	87.2	29.5	76.5
UNIT [Liu NeurIPS 17]	39.1	87.1	28.0	70.8
FCNs ITW [Hoffman arXiv 17]	27.1	-	17.0	-
CyCADA [Hoffman ICML 18]	39.5	82.3	-	-
Ours w/o $\mathcal{L}_{consist}$	39.4	85.8	29.8	75.3
Ours	45.1	89.2	33.4	79.5

Optical flow estimation

Method	MPI Sintel \rightarrow KITTI 2012			MPI Sintel \rightarrow KITTI 2015		
	AEPE	AEPE	F1-Noc	AEPE	F1-all	F1-all
FlowNet2 [Ilg CVPR 17]	4.09	-	-	10.06	30.37%	-
PWC-Net [Sun CVPR 18]	4.14	4.22	8.10%	10.35	33.67%	-
Ours w/o $\mathcal{L}_{consist}$	4.16	4.92	13.52%	10.76	34.01%	36.43%
Ours	2.19	3.16	8.57%	8.02	23.14%	25.83%

Single-view depth prediction

Method	SUNCG \rightarrow NYUv2		
	Abs. Rel. \downarrow	Sq. Rel. \downarrow	RMSE \downarrow
Synth.	0.304	0.394	1.024
Baseline (train set mean)	0.439	0.641	1.148
T ² Net [Zheng ECCV 18]	0.257	0.281	0.915
Ours w/o $\mathcal{L}_{consist}$	0.254	0.283	0.911
Ours	0.233	0.272	0.898

B) Cross-city adaptation

Method	Cityscapes \rightarrow Cross-city			
	Rome	Rio	Tokyo	Taipei
Cross-City [Chen ICCV 17]	42.9	42.5	42.8	39.6
CBST [Zou ECCV 18]	53.6	52.2	48.8	50.3
AdaptSegNet [Tsai CVPR 18]	52.2	49.5	46.9	47.5
Ours w/o $\mathcal{L}_{consist}$	51.0	48.9	45.9	46.8
Ours	55.1	50.4	51.2	47.9

C) Visual results

