

Learning Low-Shot Generative Networks for Cross-Domain Data

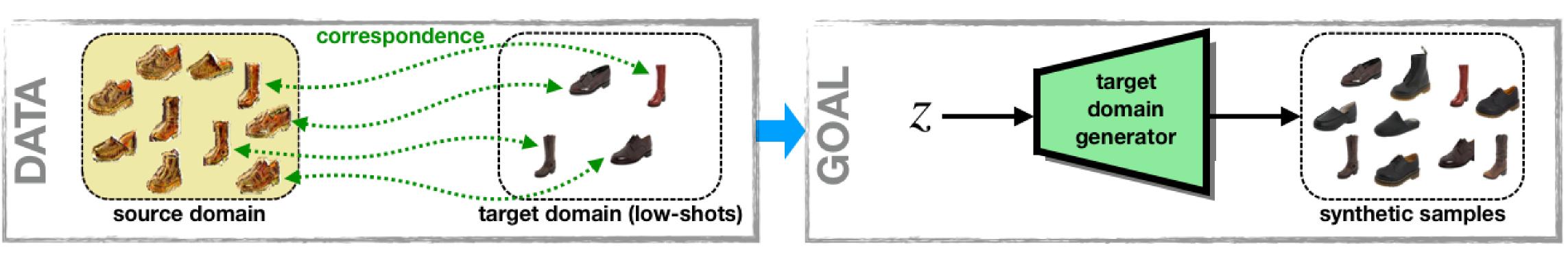
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Overview

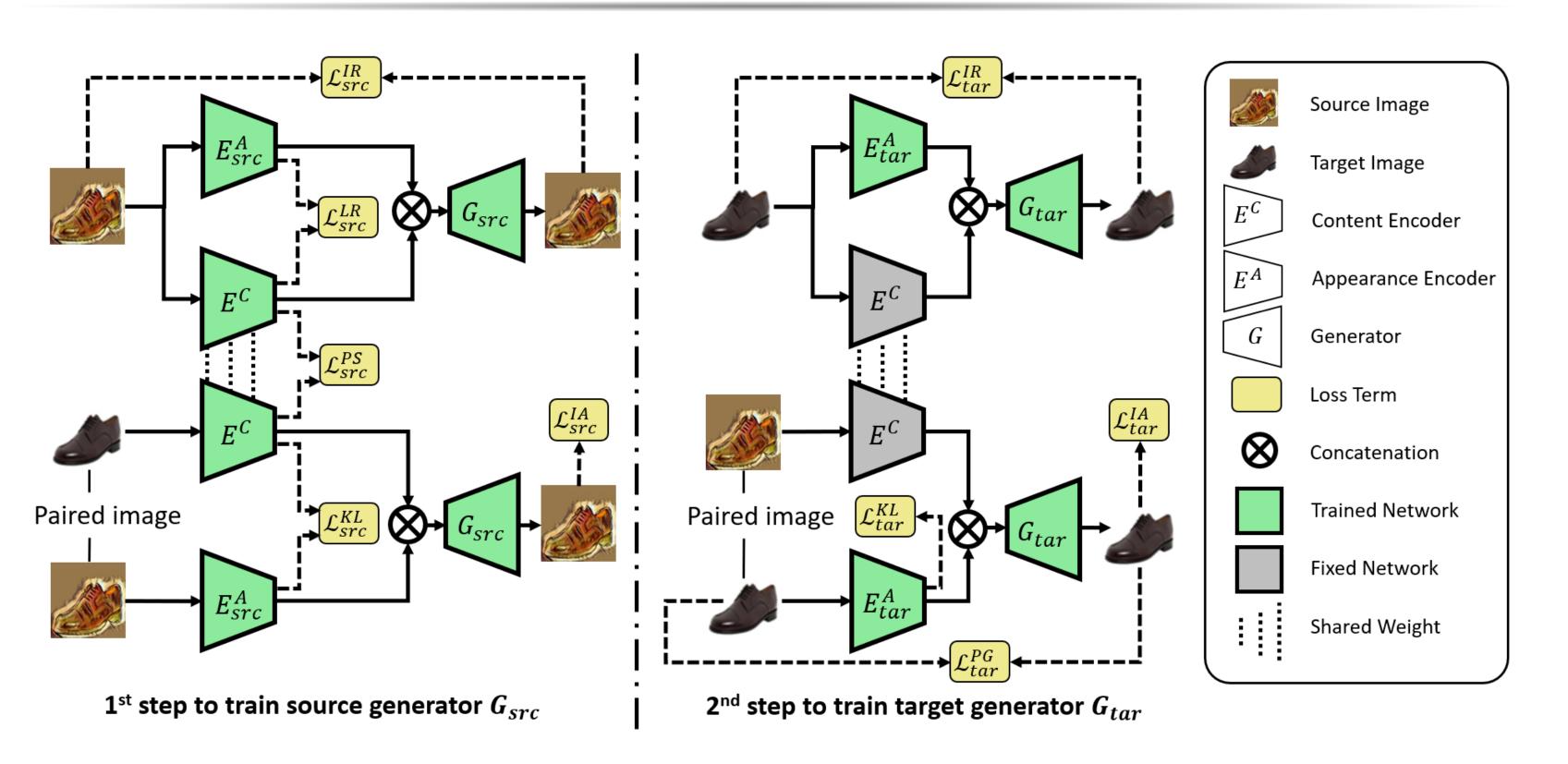
We tackle a novel problem of learning generators for cross-domain data under a specific scenario of low-shot learning. Basically, given a source domain with sufficient amount of training data, we aim to transfer the knowledge of its generative process to another target domain, which not only has few data samples but also contains the domain shift with respect to the source domain. This problem has great potential in practical use and is different from the well-known image translation task, as the target-domain data can be generated without requiring any source-domain ones and the large data consumption for learning target-domain generator can be alleviated. Built upon a cross-domain dataset where (1) each of the low shots in the target domain has its correspondence in the source and (2) these two domains share the similar content information but different appearance, two approaches are proposed: a Latent-Disentanglement-Orientated model (LaDo) and a Generative-Hierarchy-Oriented (GenHo) model.



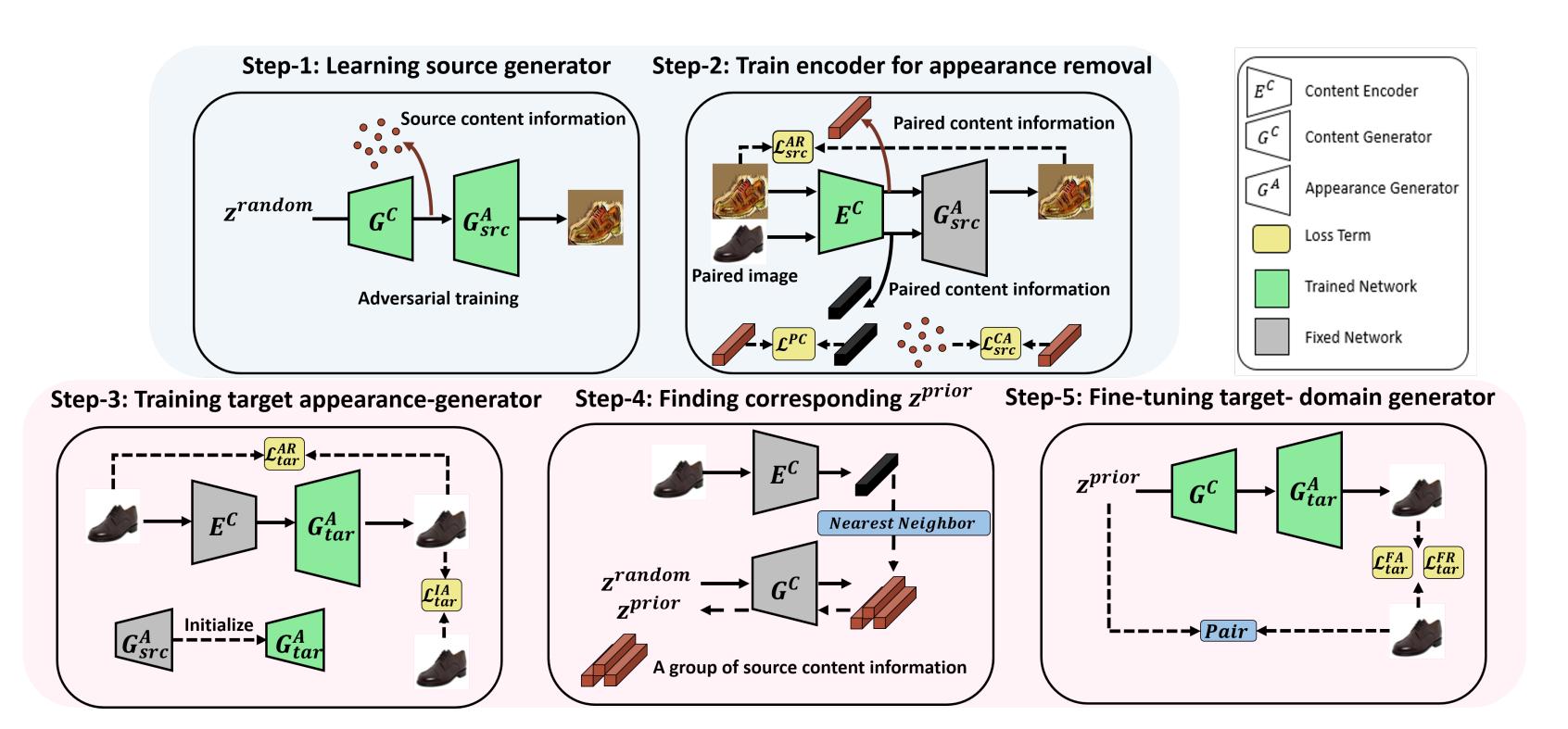
Contributions

- We define and explore a new challenging problem of learning a standalone target-domain generator with a few target-domain samples.
- We propose two approaches to address the problem from different perspectives, which are Latent-Disentanglement-Oriented (LaDo) and Generative- Hierarchy-Oriented (GenHo) models.
- Our experiments reveal the insights on latent distribution of generative networks under low-shot setting.
- We apply our methods on CelebA dataset to alleviate the constraint for more realistic scenario.

Proposed Method



Latent-Disentanglement-Oriented (LaDo)



Generative-Hierarchy-Oriented (GenHo)

Qualitative Results



Generated samples by various methods trained with 50 target-domain samples.

Quantitative Results

	$N_{tar} = 50$				$N_{tar} = 100$				$N_{tar} = 500$			
Target	Shoes		Faces		Shoes		Faces		Shoes		Faces	
Source	Edge	Style	Sketch	Style	Edge	Style	Sketch	Style	Edge	Style	Sketch	Style
Baseline	199.46		233.15		169.45		237.73		125.74		150.94	
Baseline++	114.72	166.87	54.83	28.78	79.13	89.24	30.81	24.6	55.04	45.66	20.57	15.65
CoGAN [1]	187.40	166.50	186.14	179.53	50.42	46.85	184.39	57.64	62.78	44.19	211.48	188.83
LaDo	66.16	84.89	51.44	57.03	42.73	49.95	28.63	30.42	35.05	44.36	18.21	17.74
GenHo	76.67	100.78	32.78	24.34	43.77	43.19	19.68	17.07	28.4	23.06	16.25	17.51

The FID comparison between different approaches with 50, 100, and 500 target-domain samples under various experimental settings.

References

[1] M.-Y. Liu and O. Tuzel, "Coupled generative adversarial networks," in *Advances in Neural Information Processing Systems (NIPS)*, 2016.