Semi-Supervision with Adversarial Learning

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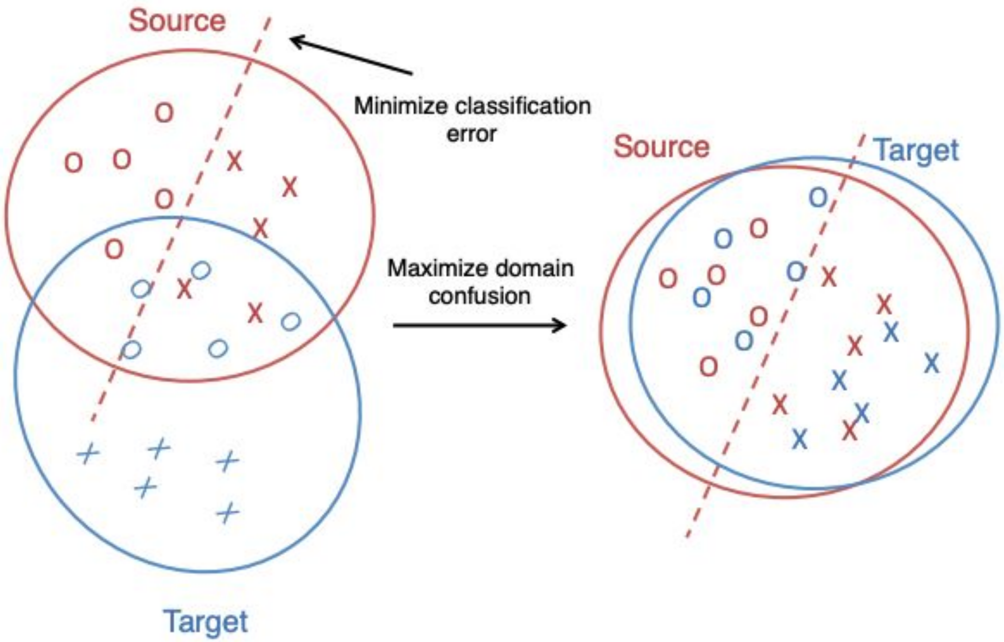
Domain Adaptation

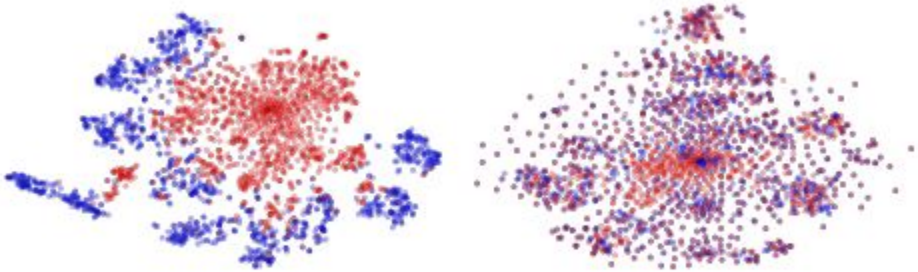
- Overcoming the domain gap, i.e. the differences between the source and target distributions, without any supervision from the target domain.
- Domain adaptation: Csurka (2017)
- Also known as
  - Domain-invariant learning: Hoffman et al., 2013; Herath et al., 2017; Yan et al., 2017; Ganin & Lempitsky, 2015
  - Statistical Alignment: Tzeng et al., 2014; Long et al., 2015
- Used when lacking ground truth in the target domain.

Domain Adaptation



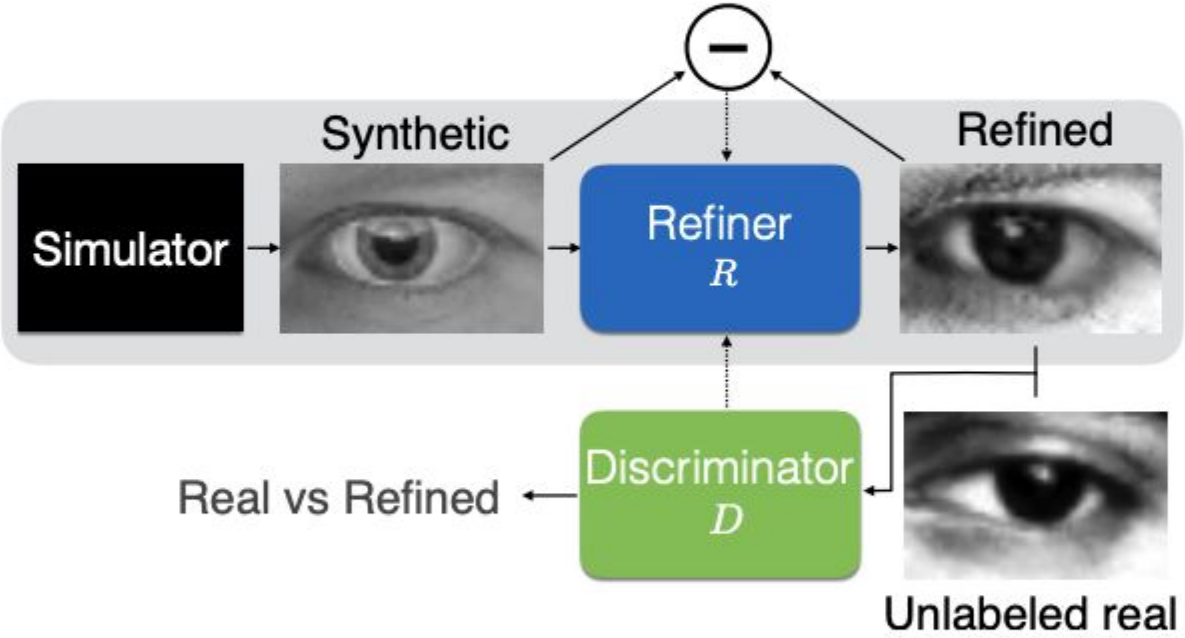
Domain Adaptation

MNIST → MNIST-M: top feature extractor layer



(a) Non-adapted (b) Adapted

SimGAN



Synthetic
Refined
Simulator
Refiner
R
Discriminator
D
Real vs Refined
Unlabeled real

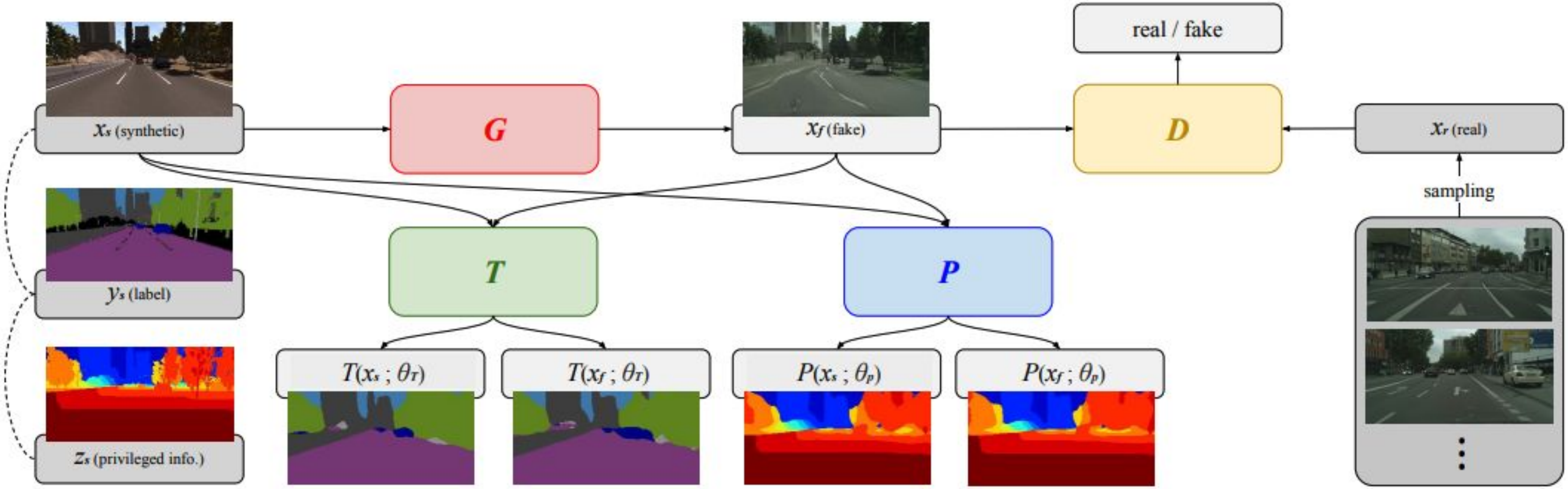
SimGAN

Adapt synthetic images (eye gaze direction, hand pose estimation) to the domain of real images.

What they do:

- Refiner: Generator that accepts synthetic image as input
- Self-regularizing loss for the refiner network
    - Penalize large changes between synthetic image and generated (refined) image
- GAN training stabilization via replay buffer
- Local Adversarial loss. “Patch Discriminator”

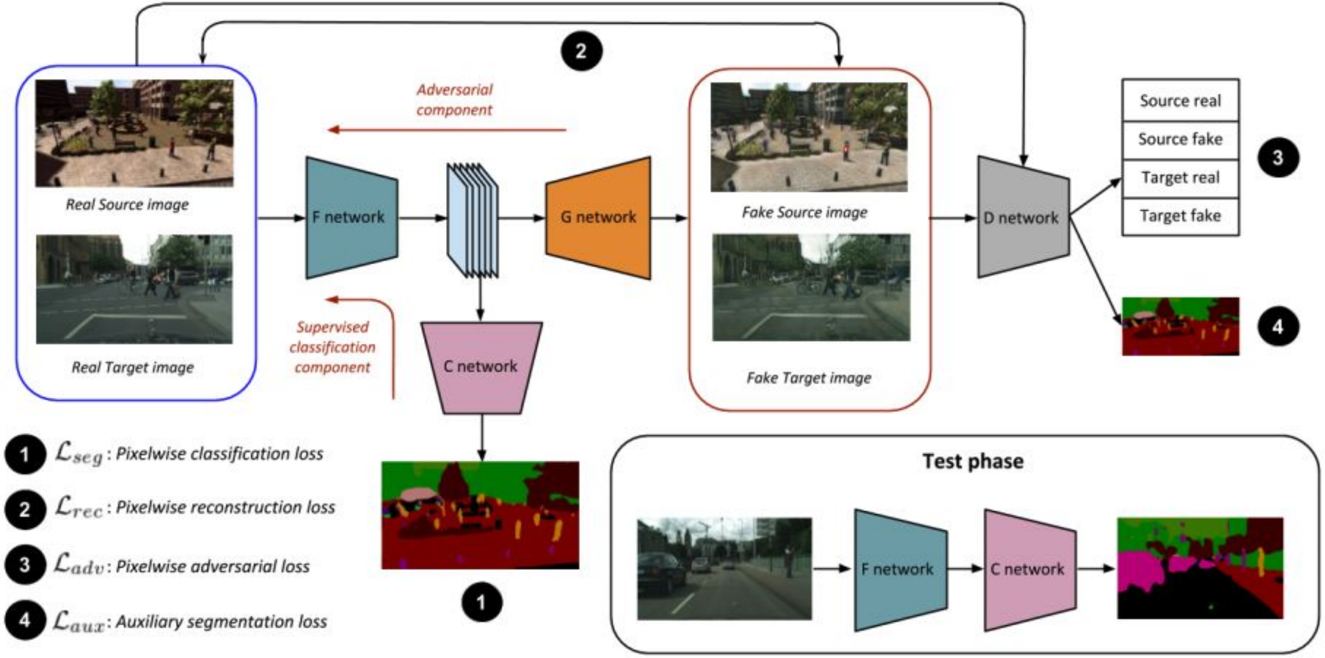
SPIGAN - Use of privileged information



SPIGAN

- Here a simulator is used for the source of unsupervised data that includes a wealth of extra information not available to even the supervised domain.
- PI: Depth map information from the simulator

Learning From Synthetic Data: Addressing Domain Shift for Semantic Segmentation



Learning From Synthetic Data: Addressing Domain Shift for Semantic Segmentation

- Patch discriminator, i.e. local adversarial loss as described in the SimGAN work, with 4 outputs for: source-real, source-fake, target-real, target-fake
- ACGAN / Auxiliary Classifier architecture
  - Use of labels to help improve the generator only for the source domain.

Unsupervised Pixel–Level Domain Adaptation with Generative Adversarial Networks