Training Generative Adversarial Networks from Incomplete Observations using Factorised Discriminators

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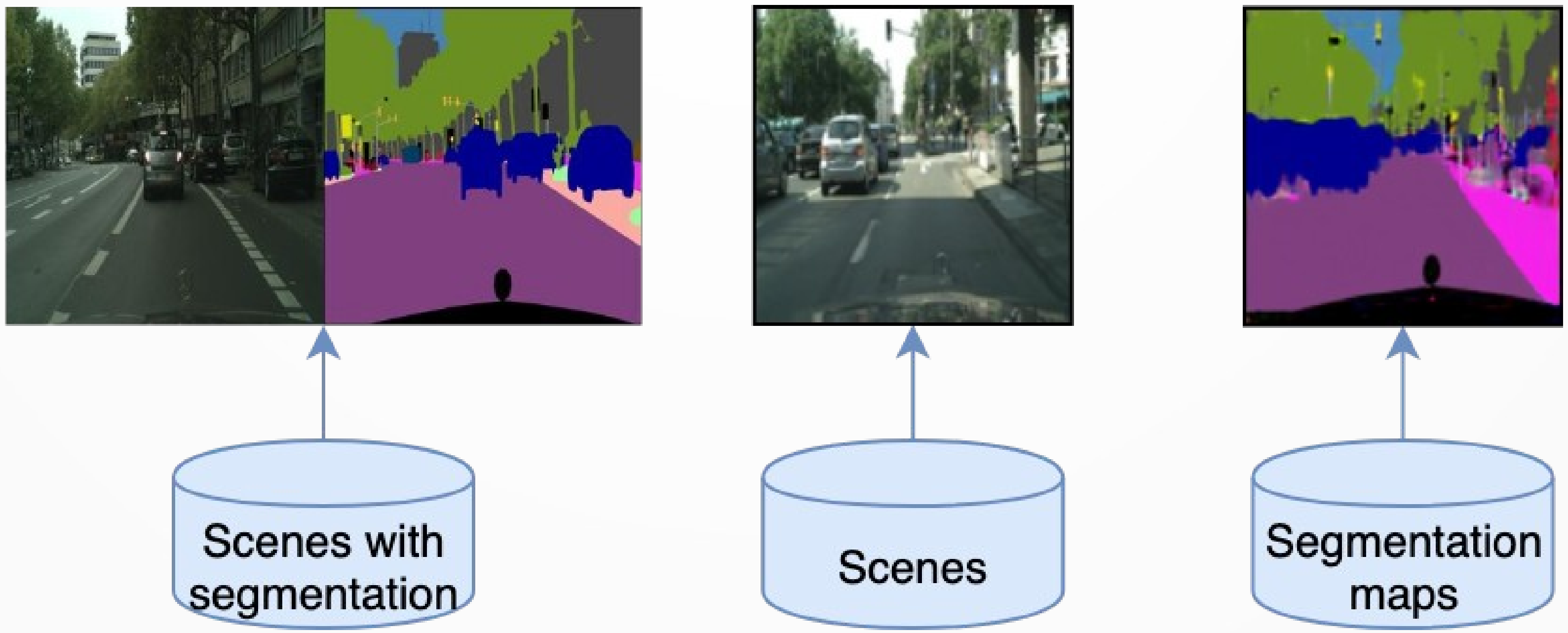
Motivation

- GANs for generation and prediction tasks
- Assumption: Sample can be naturally divided into multiple parts
- Example: Image segmentation:

Sample x $= (x^1 , x^2)$

Motivation

- How to exploit additional data?



- (Conditional) GANs need full samples for training

Theory

$$\frac{p(\mathbf{x}^2|\mathbf{x}^1)}{q(\mathbf{x}^2|\mathbf{x}^1)}$$

Theory

- Factorisation of density ratio:

$$\frac{p(\mathbf{x}^2|\mathbf{x}^1)}{q(\mathbf{x}^2|\mathbf{x}^1)} = \frac{c_P(\mathbf{x}^1, \mathbf{x}^2)}{c_Q(\mathbf{x}^1, \mathbf{x}^2)} \frac{p(\mathbf{x}^2)}{q(\mathbf{x}^2)}$$

- Marginal discriminator

Theory

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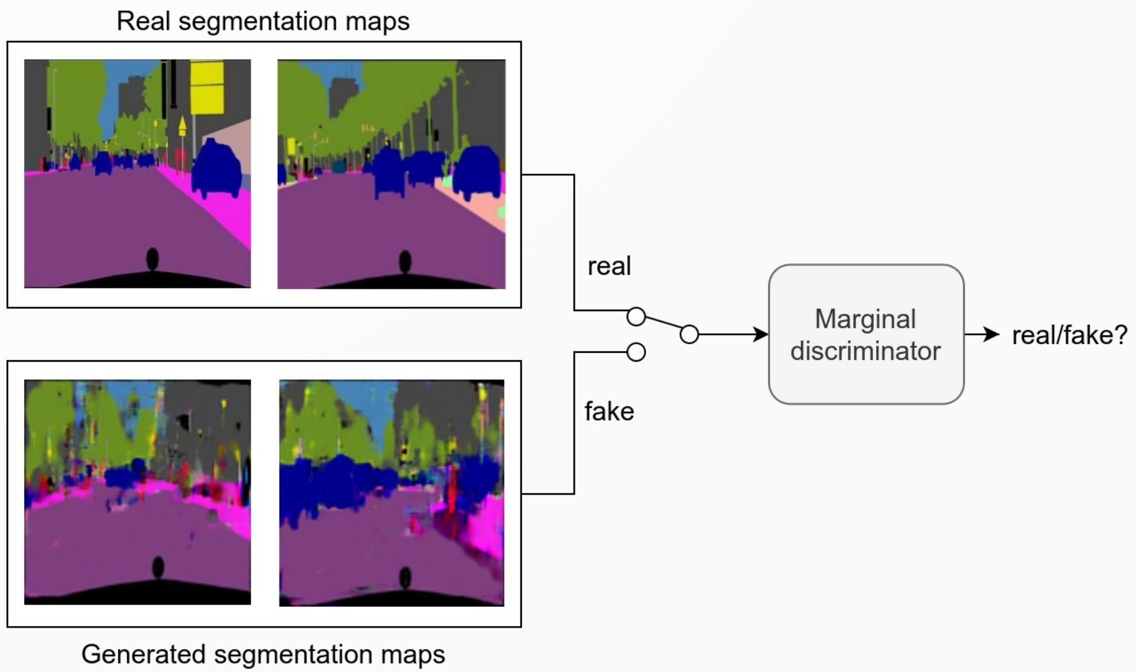
- Marginal discriminator



Theory

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$$c_P(\mathbf{x}^1, \mathbf{x}^2) = \frac{p(\mathbf{x}^1, \mathbf{x}^2)}{p(\mathbf{x}^1)p(\mathbf{x}^2)}$$

- Marginal discriminator
- Dependency discriminators

Theory

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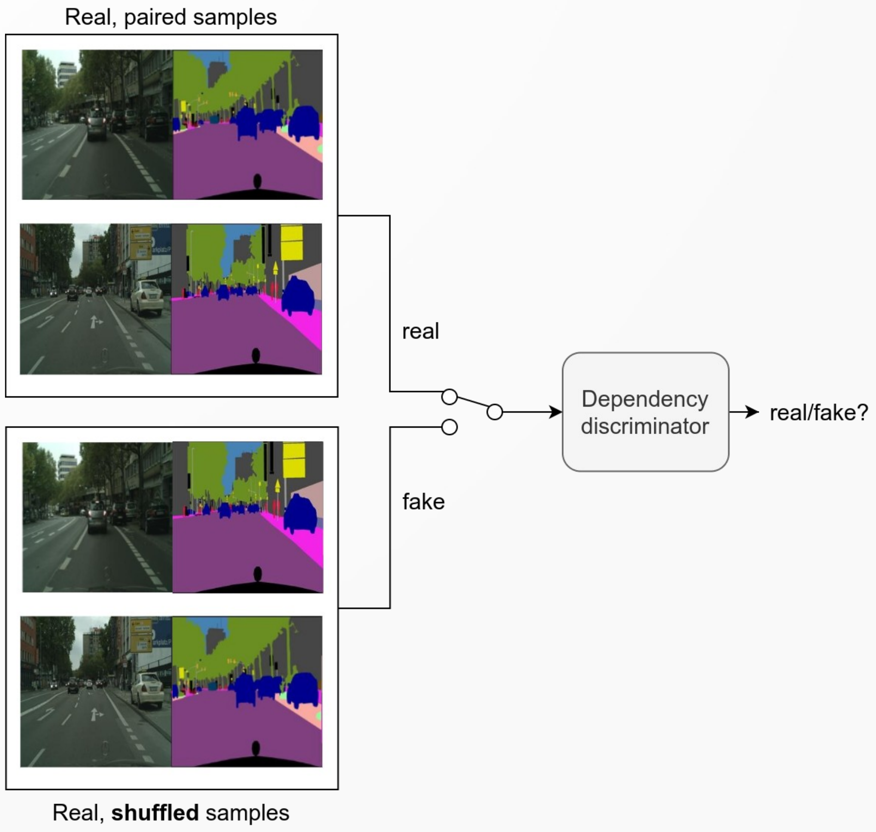


Theory

- Factorisation of density ratio:

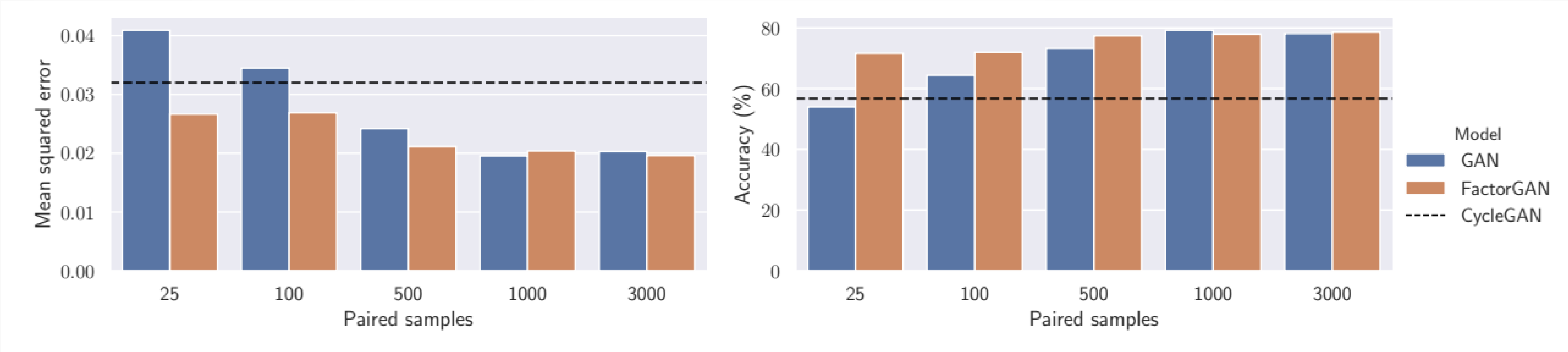
$$\frac{p(\mathbf{x}^2|\mathbf{x}^1)}{q(\mathbf{x}^2|\mathbf{x}^1)} = \frac{c_P(\mathbf{x}^1,\mathbf{x}^2)}{c_Q(\mathbf{x}^1,\mathbf{x}^2)}\frac{p(\mathbf{x}^2)}{q(\mathbf{x}^2)} \text{ with}$$

$$c_P(\mathbf{x}^1,\mathbf{x}^2) = \frac{p(\mathbf{x}^1,\mathbf{x}^2)}{p(\mathbf{x}^1)p(\mathbf{x}^2)} \text{ and } c_Q(\mathbf{x}^1,\mathbf{x}^2) = \frac{q(\mathbf{x}^1,\mathbf{x}^2)}{q(\mathbf{x}^1)q(\mathbf{x}^2)}.$$

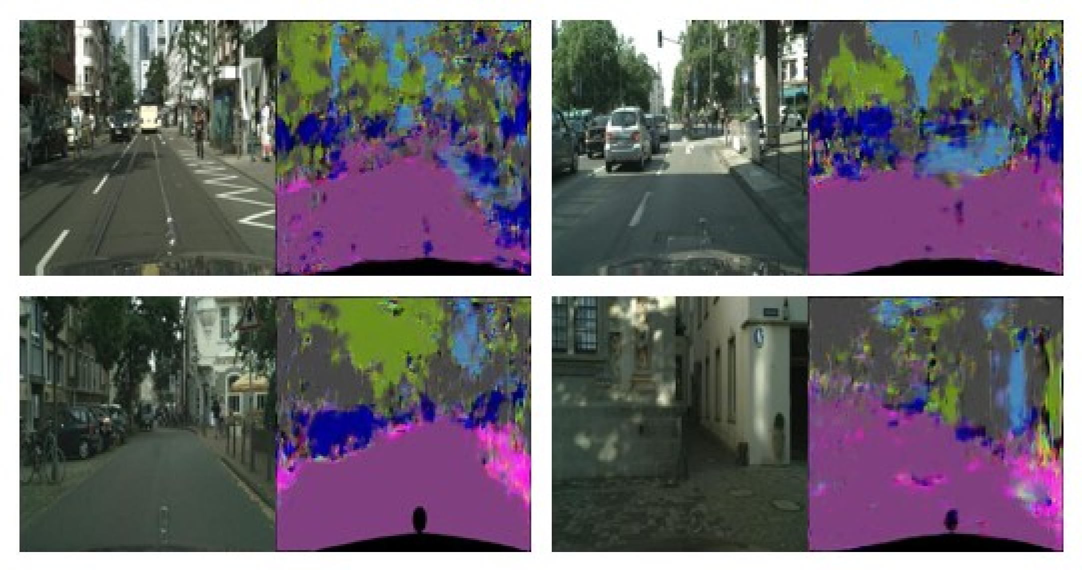
- Marginal discriminator
- Dependency discriminators

Results

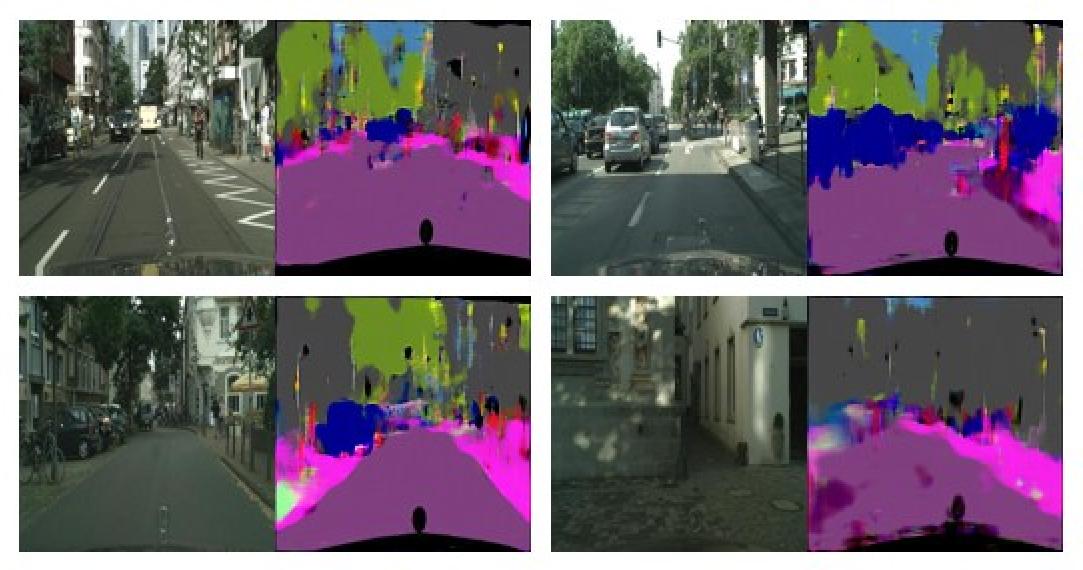
Performance comparison on Cityscapes



Results



Normal GAN



FactorGAN

More experiments in the full paper

Code available at

https://github.com/f90/FactorGAN