You Only Need Adversarial Supervision for Semantic Image Synthesis

ICLR 2021

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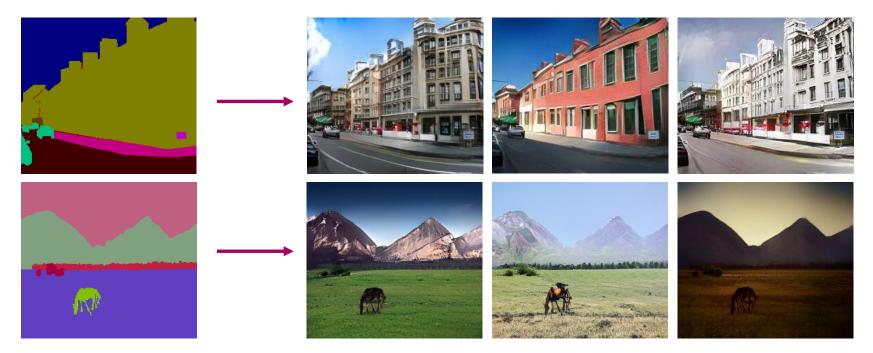
*Equal contribution

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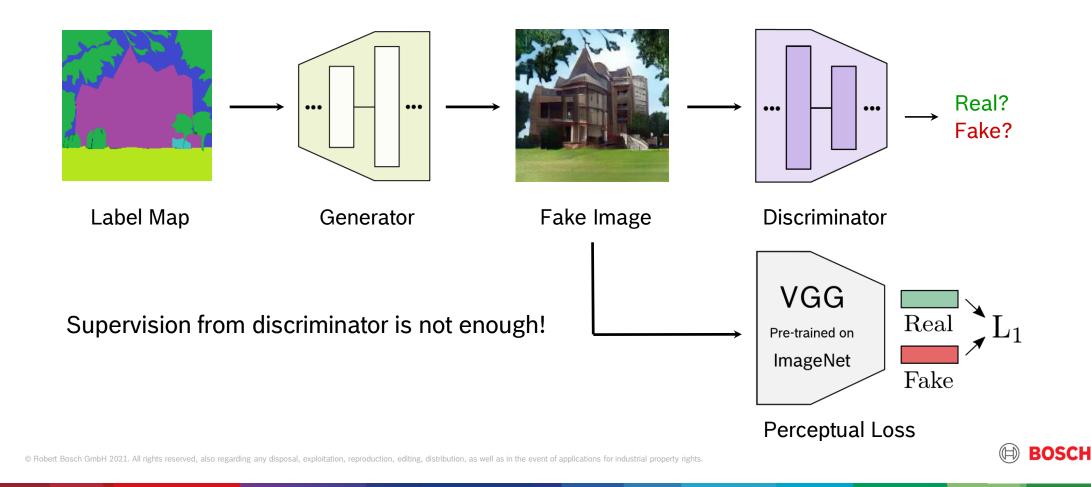
Semantic image synthesis Problem statement

Our goal: multi-modal photorealistic image generation in alignment with a given semantic label map

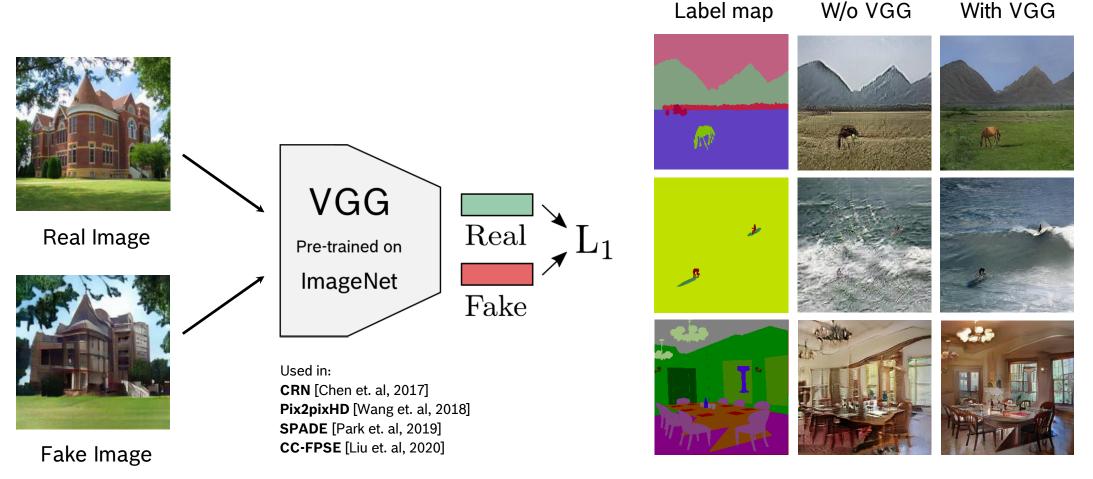




Limitations of previous GAN methods Perceptual loss

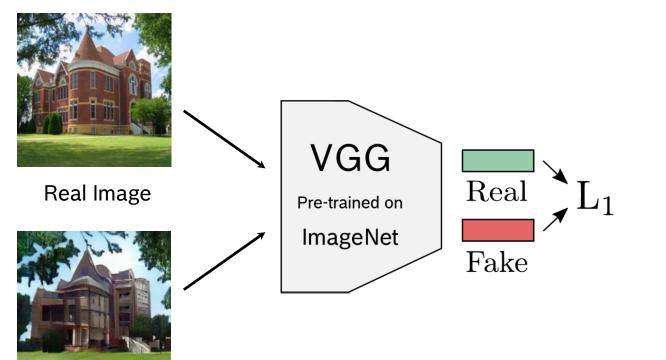


Limitations of previous GAN methods Perceptual loss





Limitations of previous GAN methods Perceptual loss



Effect of the perceptual loss:

- Stabilized training
- Improved quality of images

Drawbacks:

Computational overhead

BOSCH

- Texture and color bias
- Constrained diversity

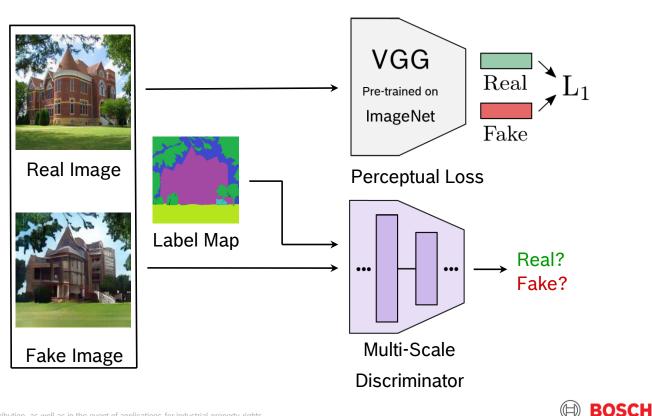
Fake Image

How to achieve high quality without the perceptual loss?

Baseline: SPADE [Park et al., 2019]

Our solution:

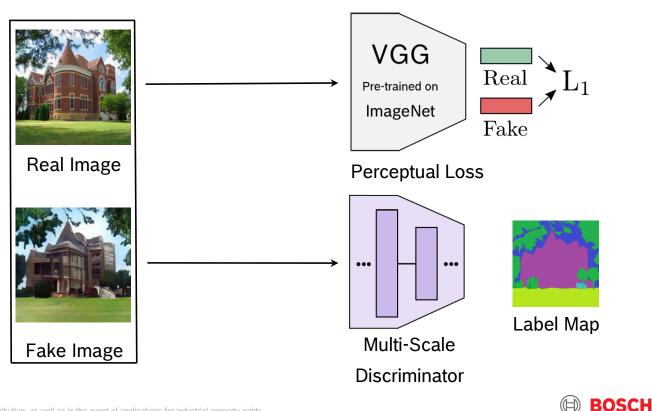
Label map is a target, not input



Baseline: SPADE [Park et al., 2019]

Our solution:

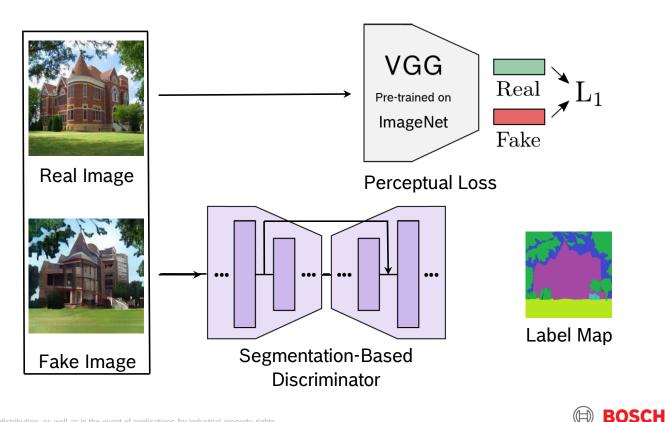
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Baseline: SPADE [Park et al., 2019]

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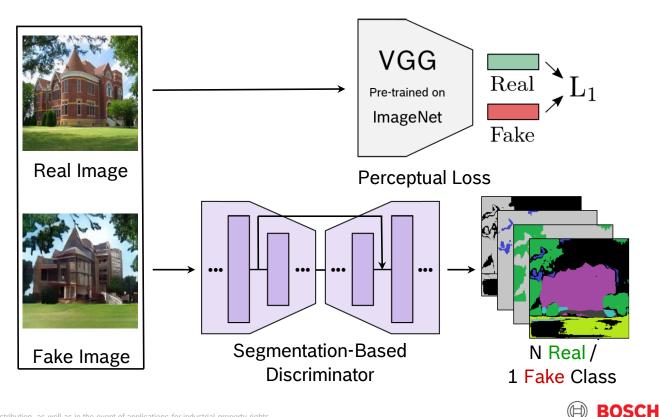
- Label map is a target, not input
- Discriminator's task = segmentation



Baseline: SPADE [Park et al., 2019]

Our solution:

- Label map is a target, not input
- Discriminator's task = segmentation
- N+1 loss = adversarial loss

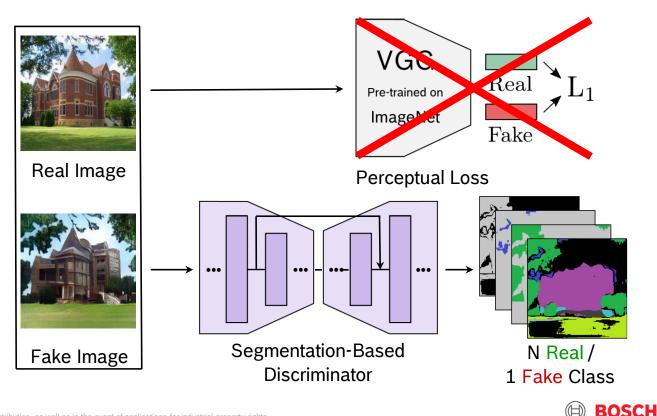


Baseline: SPADE [Park et al., 2019]

Our solution:

- Label map is a target, not input
- Discriminator's task = segmentation
- N+1 loss = adversarial loss

VGG loss becomes unnecessary!



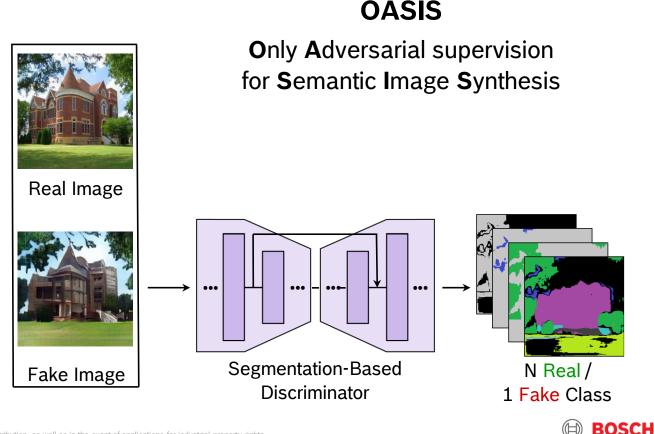
Baseline: SPADE [Park et al., 2019]

Our solution:

- ► Label map is a target, not input
- Discriminator's task = segmentation
- N+1 loss = adversarial loss

VGG loss becomes unnecessary!

D architecture	w/o	VGG	with	i VGG
	FID↓	mIoU↑	FID↓	mIoU↑
SPADE	60.7	21.0	32.9	42.5
OASIS	29.3	51.6	29.2	51.1



Results Comparison to prior art





Semantic image synthesis Multi-modality









Images from [Park et. al, 2019]

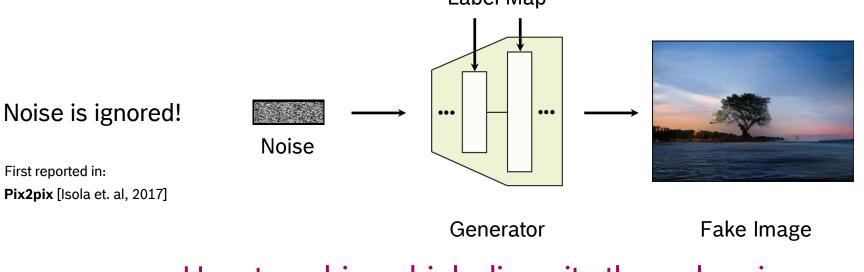




Problems of previous GAN methods Limited diversity



Label Map



How to achieve high diversity through noise sampling?

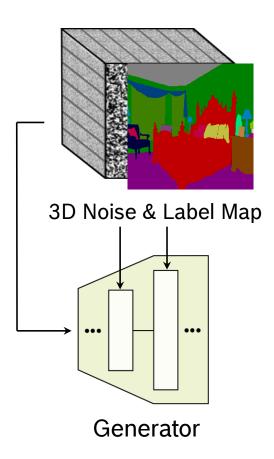
BOSCH

Step 1: Create a composite tensor

- 1. Sample a 3D noise tensor
- 2. Concatenate 3D noise with the (3D) label map

Step 2: Inject the 3D composite tensor

- 1. Input to 1^{st} generator layer
- 2. Input at *every* generator layer via the *spatially-adaptive* norm ("SPADE" layer)



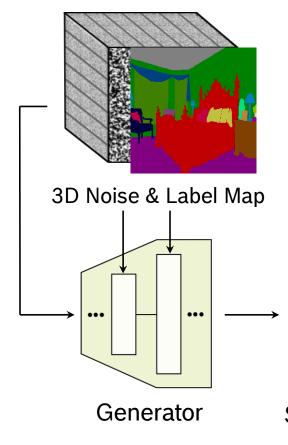


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Test time Global resampling:



Synthesized Image



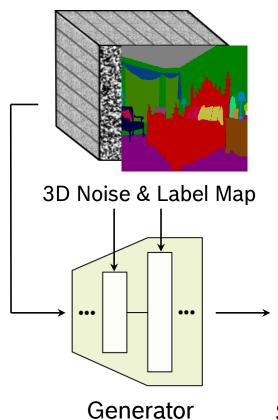


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Test time Global resampling:



BOSCH

Synthesized Image

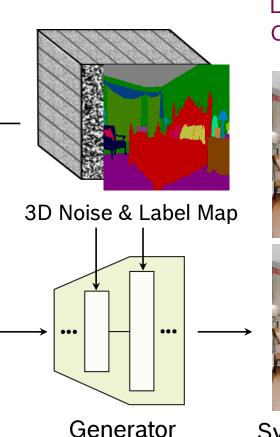


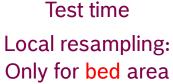
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Synthesized Image





Results Multi-modal generation

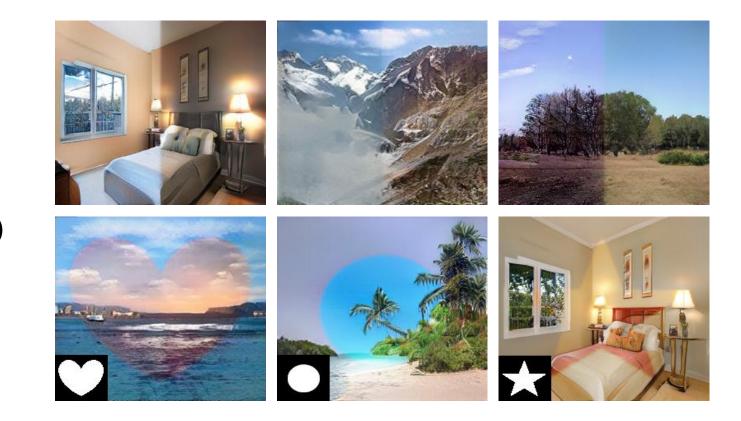
Global

Local

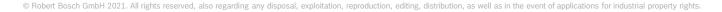




Results Multi-modal generation



Local (shape)





Summary Our contributions

- 1. New state of the art model
- 2. Segmentation-based discriminator with an N+1 adversarial loss
- 3. 3D noise injection scheme



SPADE [Park et al., 2019]

OASIS (our model)

BOSCH

Thank you!

Paper: https://arxiv.org/abs/2012.04781 **Code:** https://github.com/boschresearch/OASIS



