



# Paper Reading

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# Globally and Locally Consistent Image Completion

Satoshi Iizuka, Edgar Simo-Serra, Hiroshi Ishikawa  
Waseda University. In SIGGRAPH ,2017



[https://github.com/satoshiizuka/siggraph2017\\_inpainting](https://github.com/satoshiizuka/siggraph2017_inpainting)

<https://www.slideshare.net/siizuka/siggraph-2017-globally-and-locally-consistent-image-completion>



Input

Image Completion



# Related Work

- Patch-based inpainting
  - Synthesize texture by collecting small image patches
  - **Cannot preserve global structures**
  - **Cannot generate novel objects**



Input

Output



Input

Output

# Related Work

- Learning-based inpainting
  - Learning inpainting with GAN
  - Fixed image resolution( $128 \times 128$  pixels)
  - Fixed mask position and size (center,  $64 \times 64$  pixels)
  - Tends to generate texture that is inconsistent with an input image



Input



Output



Input



Output

# Our Method

- Novel network for globally and locally consistent image completion
  - Completion network that is able to inpaint arbitrary regions
  - Adversarial training with two auxiliary networks
  - **Can generate novel objects**



Input

Output



Input

Output

# Overview of architecture

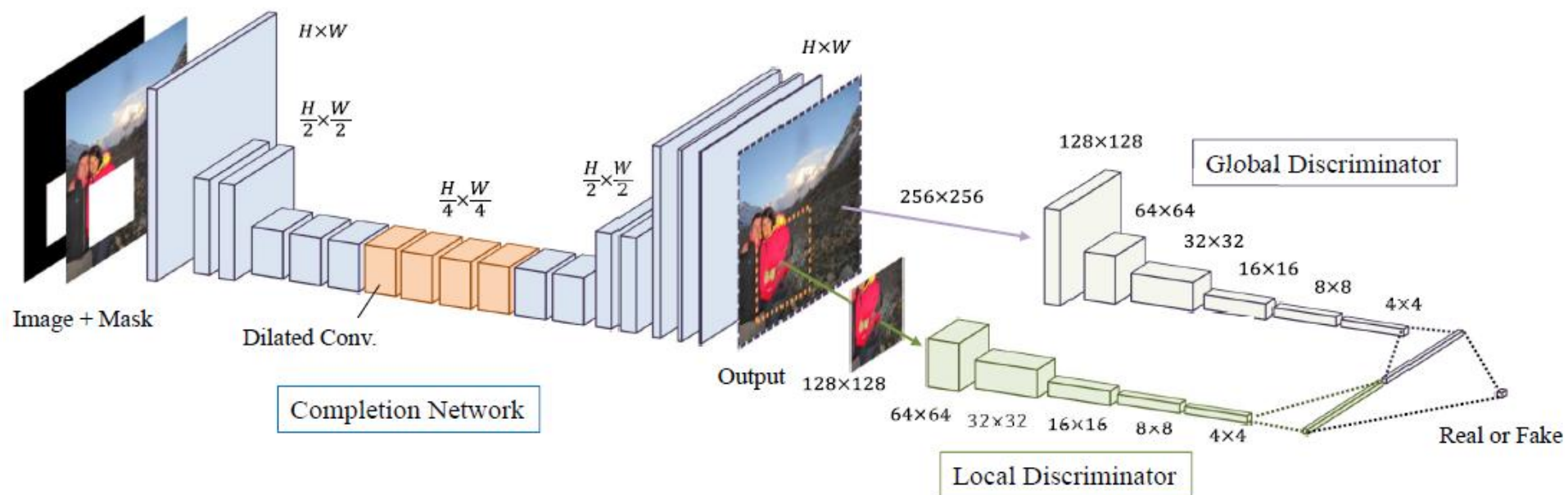
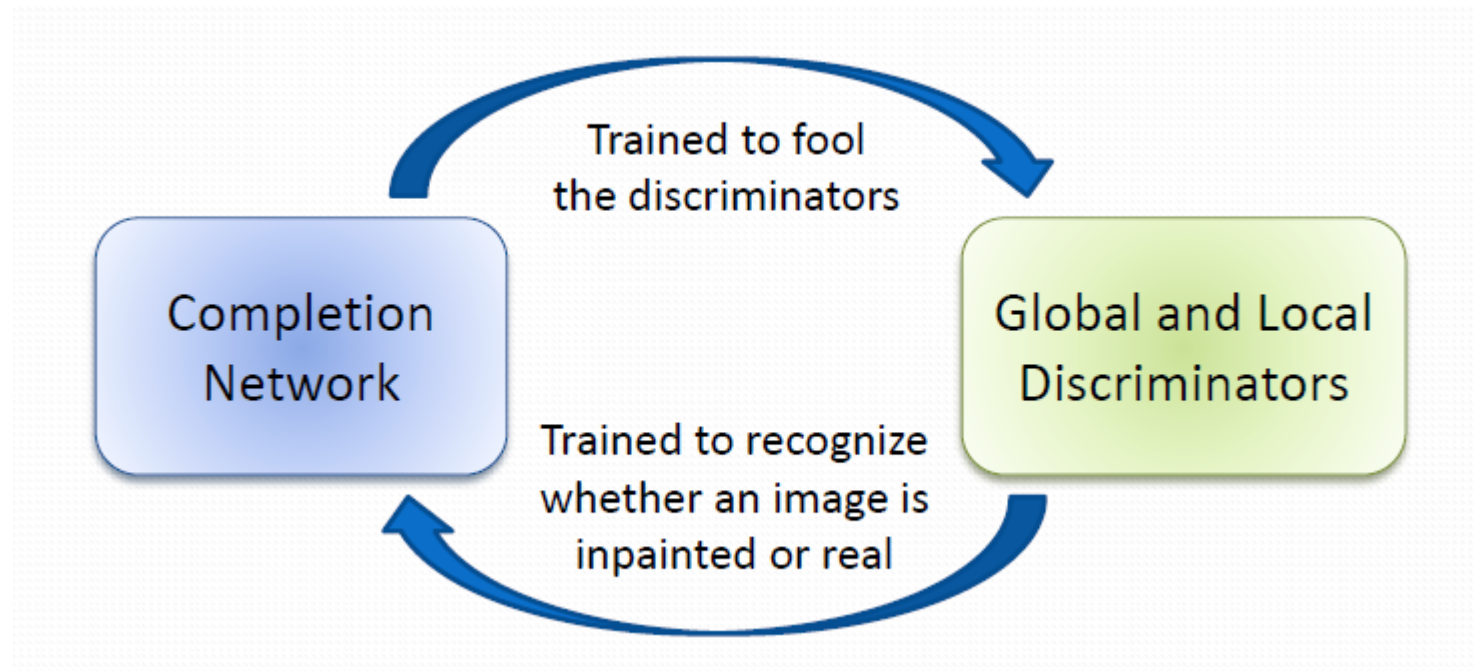


Fig. 2. Overview of our architecture for learning image completion. It consists of a completion network and two auxiliary context discriminator networks that are used only for training the completion network and are not used during the testing. The global discriminator network takes the entire image as input, while the local discriminator network takes only a small region around the completed area as input. Both discriminator networks are trained to determine if an image is real or completed by the completion network, while the completion network is trained to fool both discriminator networks.



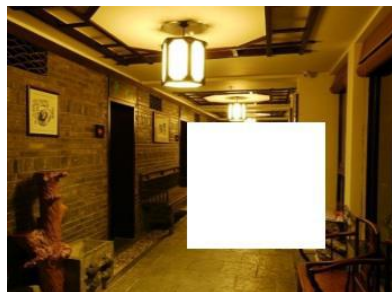
# Training

- Alternately update the completion network and discriminators
  - Based on Generative Adversarial Networks
  - MSE(Mean Squared Error)

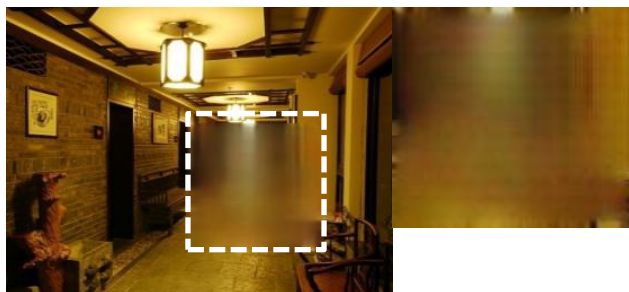




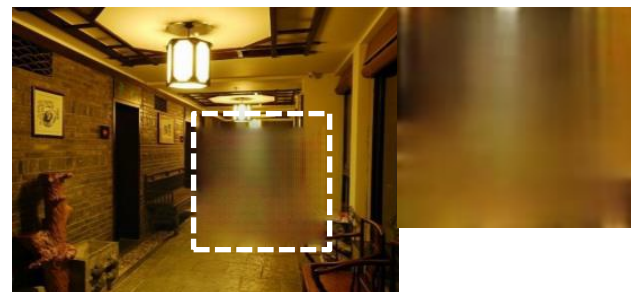
# Training with Different Discriminator Configurations



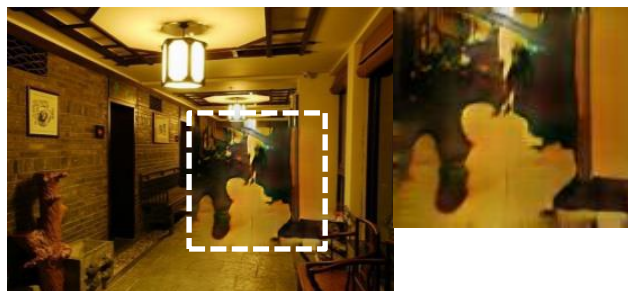
Input



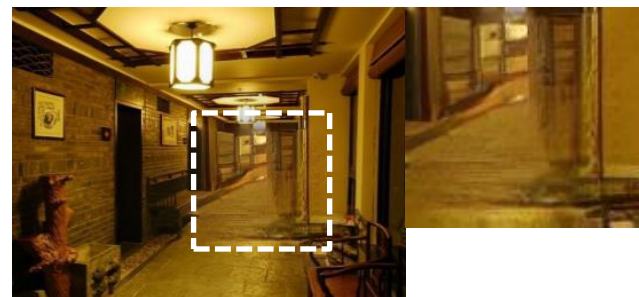
Mean Squared Error(MSE)



MSE + Global discriminator



MSE + Local discriminator



Full method

# Post-processing

## Poisson image blending



(a) Input

(b) Output

(c) Post-processed

Fig. 7. Effect of our simple post-processing.

# Dataset

- Places2 dataset
  - About 8 million images with various scenes
  - Randomly generate a hole for training



Places2 dataset



Input

Ground truth



[https://github.com/satoshiizuka/siggraph2017\\_inpainting](https://github.com/satoshiizuka/siggraph2017_inpainting)



# Result: Image Completion



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# Result: Object Removal



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# Application to Specific Dataset

- Fine-tuning the model using a specific dataset
  - Achieves more complicated inpainting
- Face dataset
  - 200,000 training images
  - 2499 test images



Large-scale Celeb Faces Attributes Dataset(CelebA)



# Result: Face Completion



# Result: Removing Sunglasses



Original

Input

Output

# Failure Case



Input

Ours

Ground truth



***Thank you!***