Unsupervised Representation Learning With Deep Convolutional Generative Adversarial Networks

Ha-larm

Supervised Learning(labeling)의 강세..

Unsupervised Learning(clusterling)은??

Candidate

=>DCGANS(deep convolutional generative adversarial networks)

Past: CNN+GAN(scale up) -> Fail!

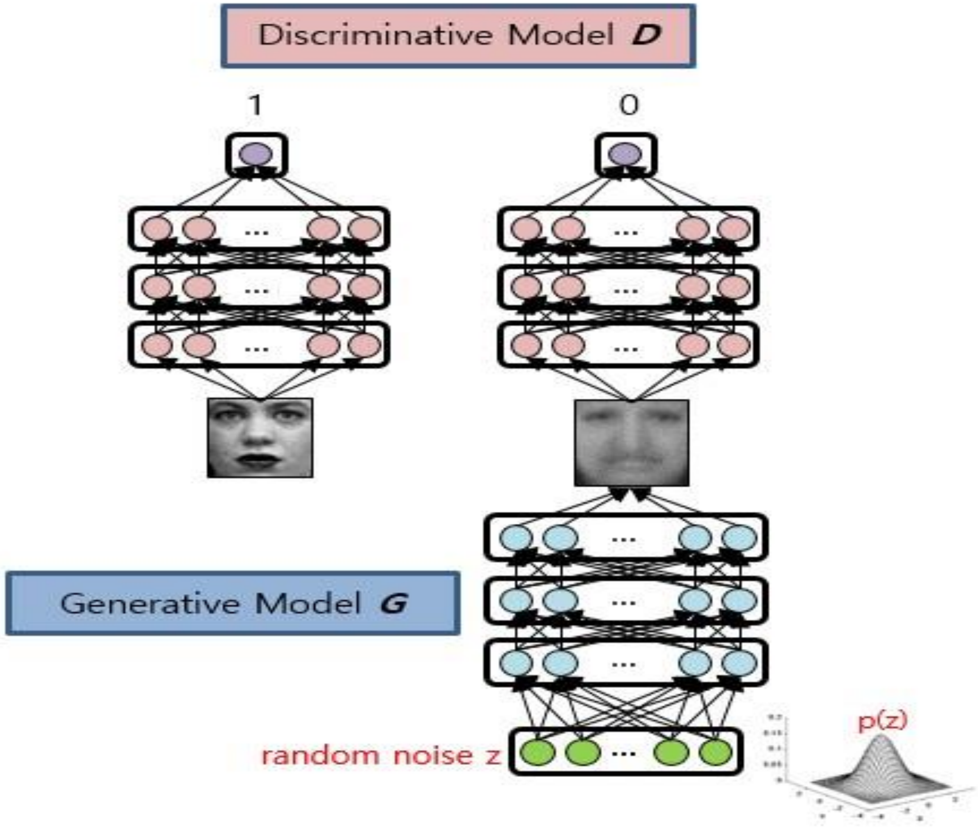
So,,,

1.Upscale and low resolution

2.Allowed higher resolution set
And deeper generative model

DCGAN

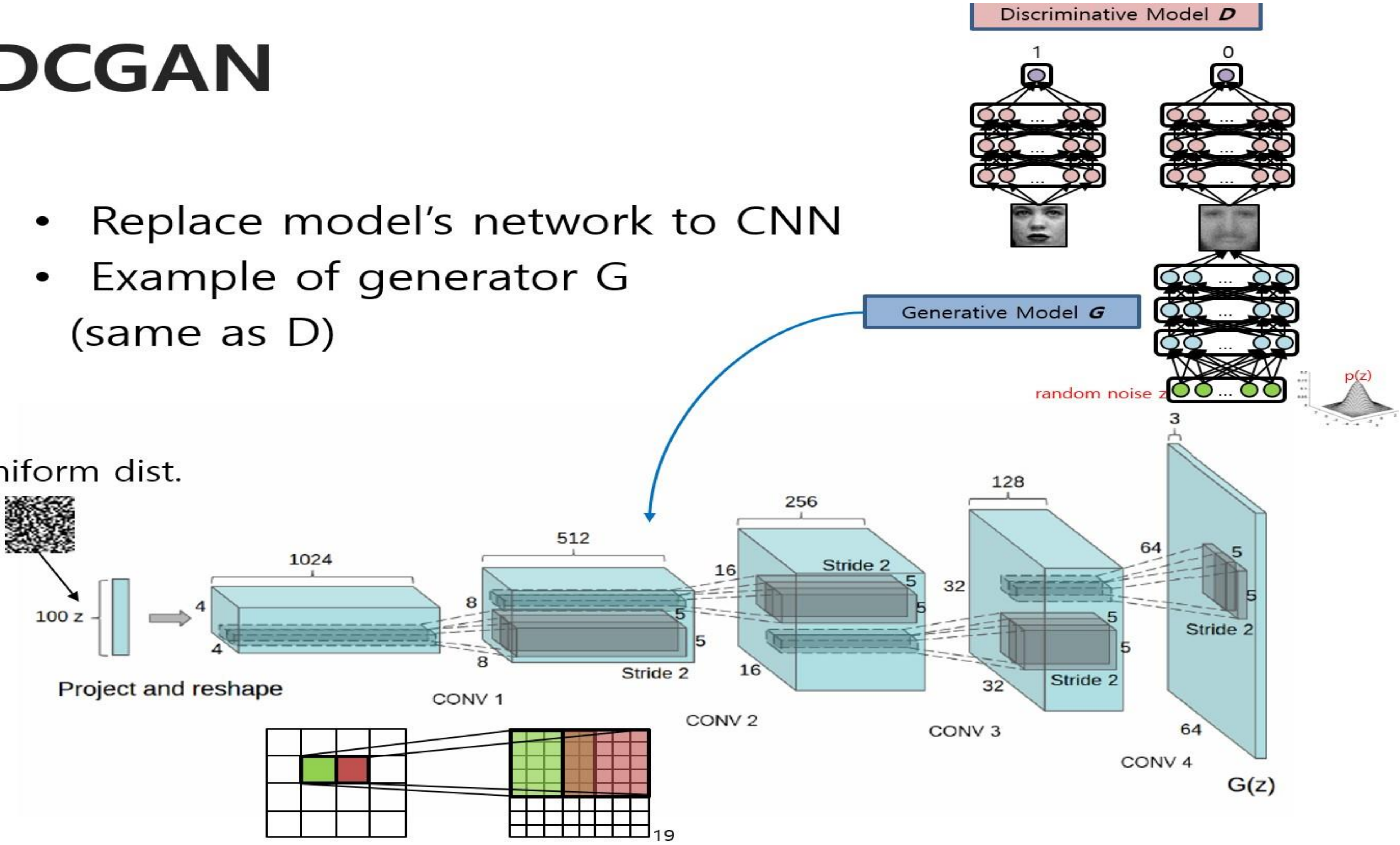
- Deep Convolutional Network + GAN
- Tricks for stable training
- Experimental Analysis



DCGAN

- Replace model's network to CNN
- Example of generator G
  (same as D)

z: uniform dist.



Experiments

- Which activations(feature map) in CNN has representation of 'window'?
- At feature activations, assign neuron in the window region is 1, otherwise 0.
- Logistic regression to find window-representative feature map.

Window feature map removal

1. REPRESENTATION LEARNING FROM UNLABELED DATA

=>hierarchical clustering of image patches

2. GENERATING NATURAL IMAGES

3. VISUALIZING THE INTERNALS OF CNNS

=>using a gradient descent on the inputs lets us inspect the ideal image that activates certain subsets of filters

Model Structure

1.Convolutional net

=>network to learn its own spatial downsampling

(Using at generator)

2.Eliminating fully connected layers on top

3. Batch Normalization

=>stabilizes learning by normalizing the

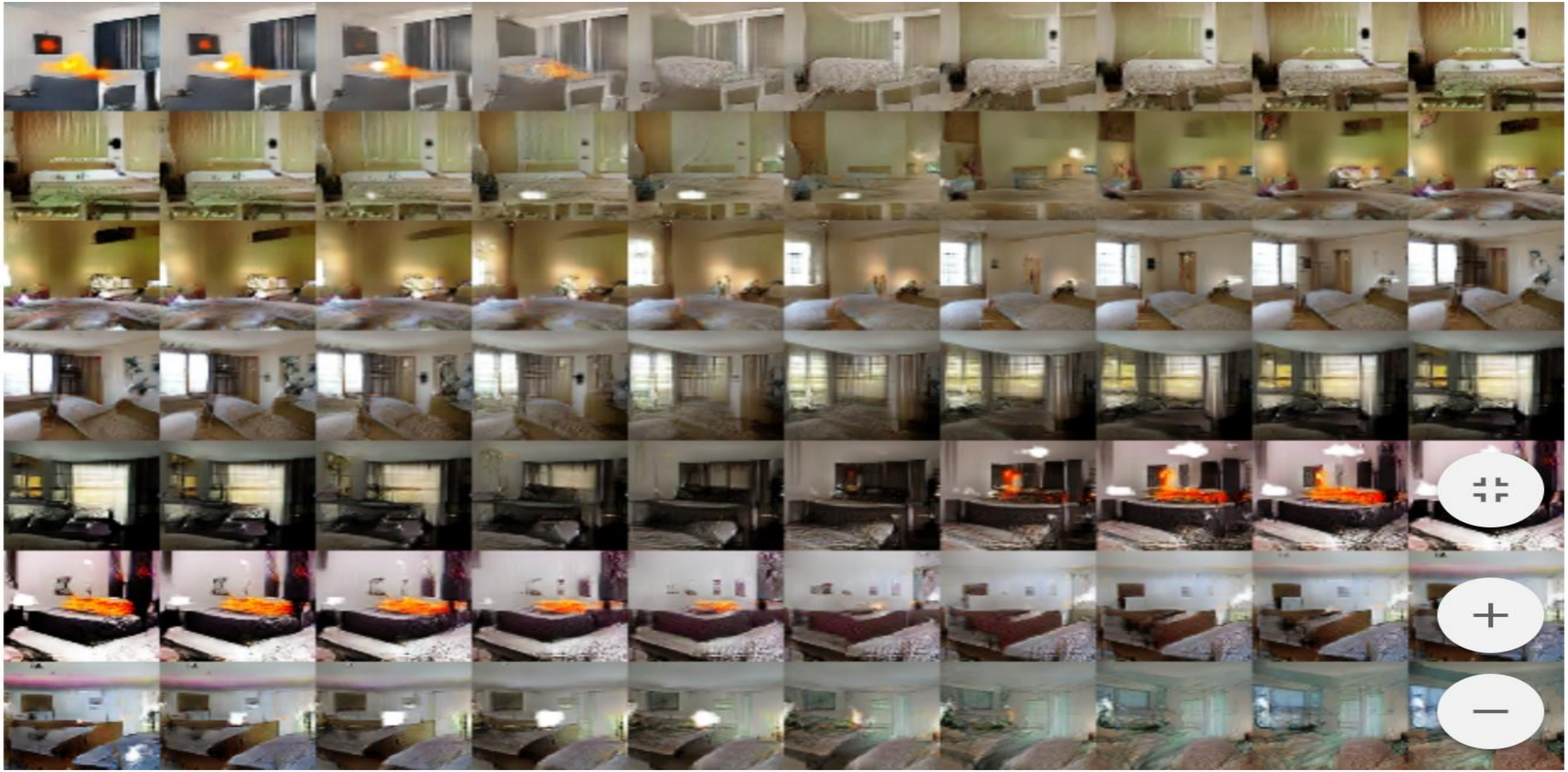
input to each unit

해상도의 향상

=>overfitting concern(LSUN data-set,high resolution)

중복제거

To further decrease the likelihood of the generator memorizing input examples



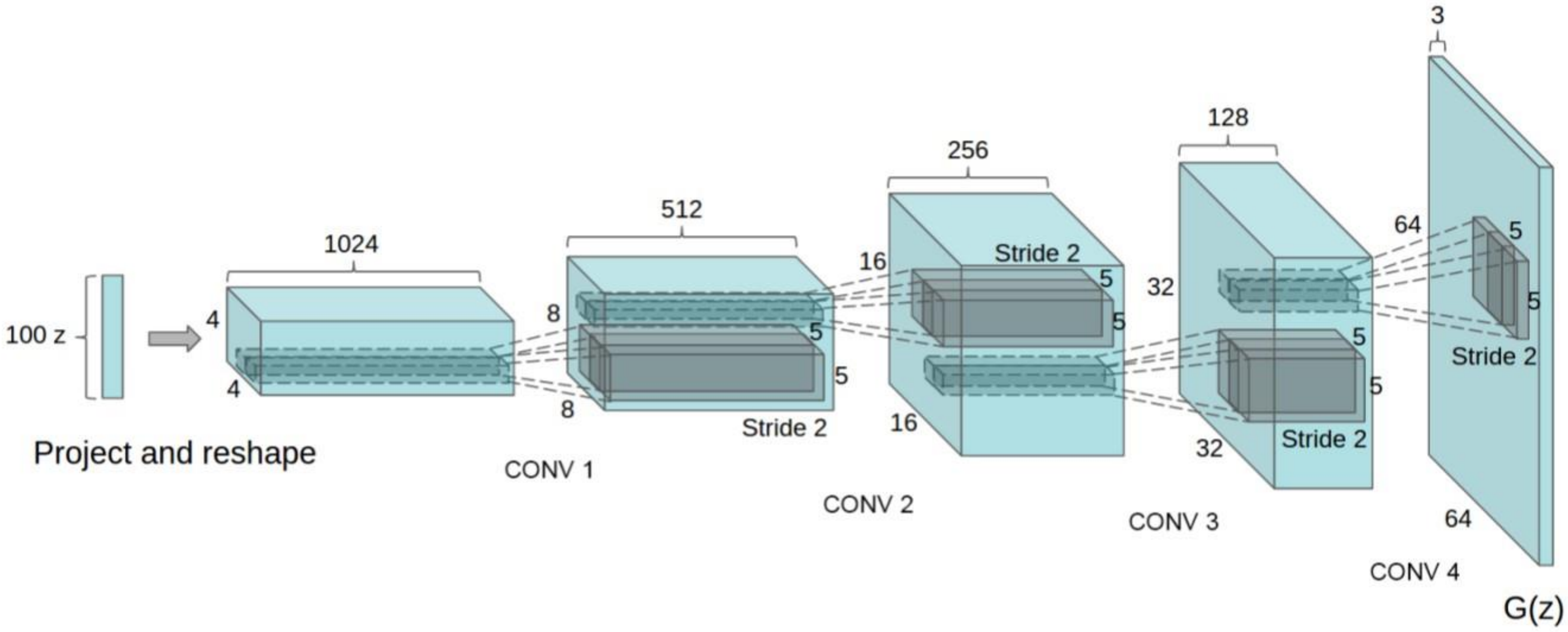


Figure 1: DCGAN generator used for LSUN scene modeling. A 100 dimensional uniform distribution Z is projected to a small spatial extent convolutional representation with many feature maps. A series of four fractionally-strided convolutions (in some recent papers, these are wrongly called deconvolutions) then convert this high level representation into a 64×64 pixel image. Notably, no fully connected or pooling layers are used.

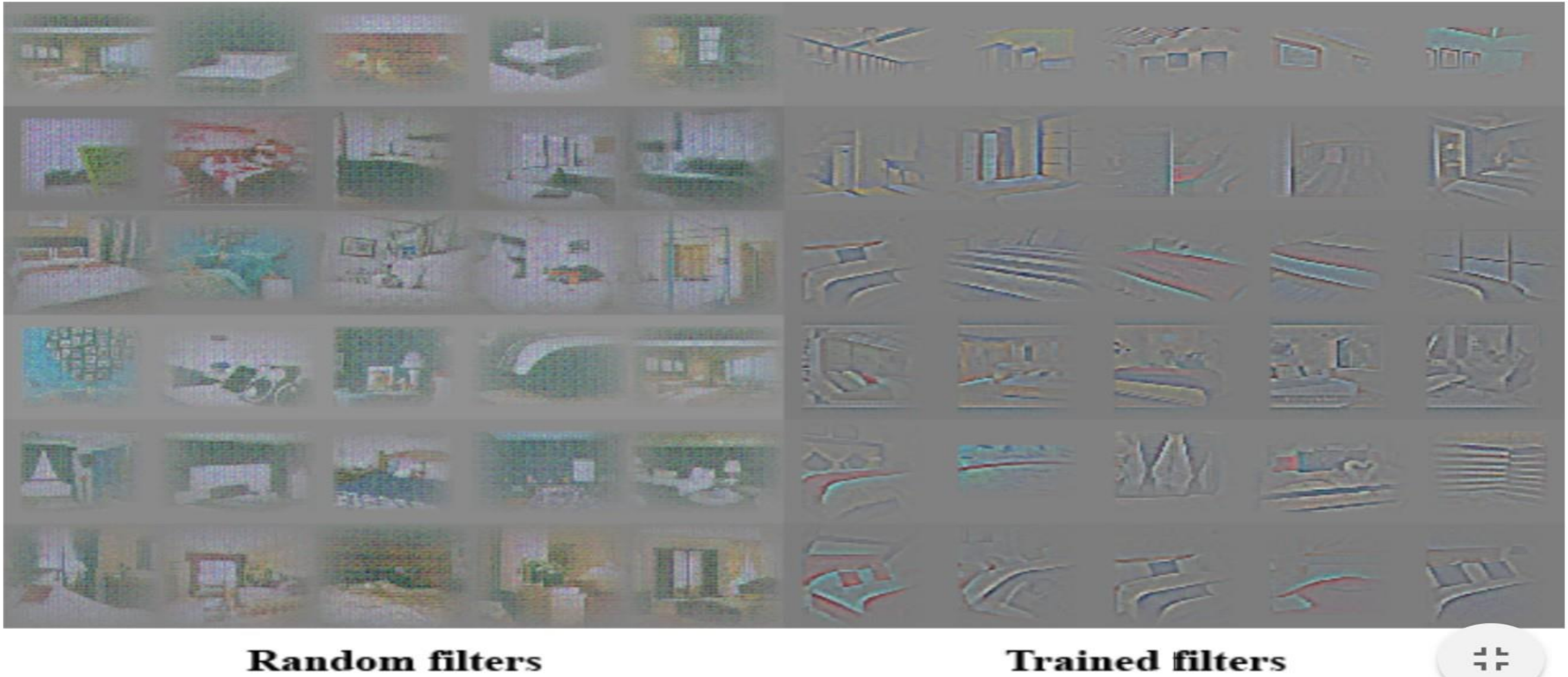
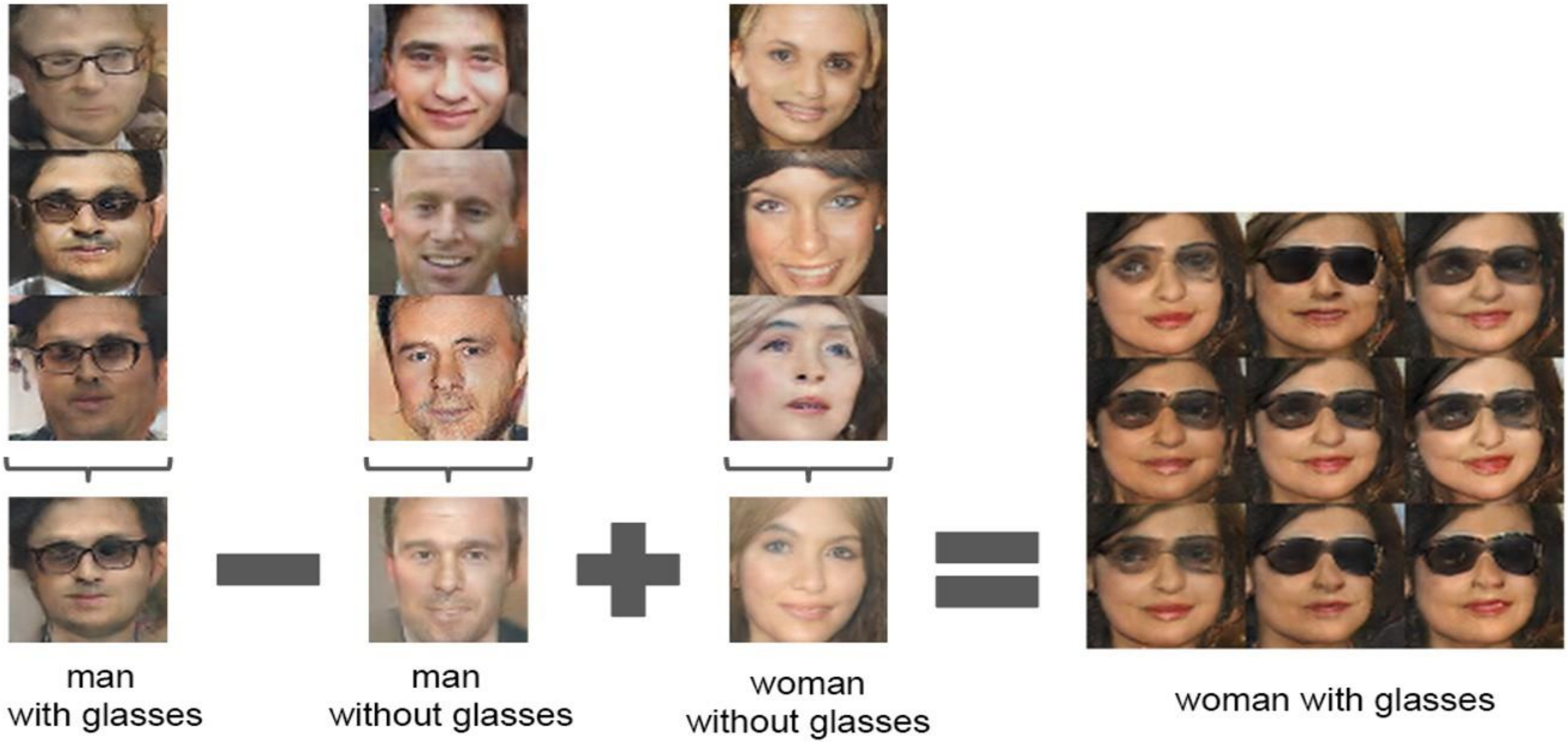


Figure 5: On the right, guided backpropagation visualizations of maximal axis-aligned responses for the first 6 learned convolutional features from the last convolution layer in the discriminator. Notice a significant minority of features respond to beds - the central object in the LSUN bedrooms dataset. On the left is a random filter baseline. Comparing to the previous responses there is little to no discrimination and random structure.

Figure 6: Top row: un-modified samples from model. Bottom row: the same samples generated with dropping out "window" filters. Some windows are removed, others are transformed into objects with similar visual appearance such as doors and mirrors. Although visual quality decreased, overall scene composition stayed similar, suggesting the generator has done a good job disentangling scene representation from object representation. Extended experiments could be done to remove other objects from the image and modify the objects the generator draws.

Dropout을 통한 "학습"증명



Vector algorithm could dramatically reduce the amount of data needed for conditional generative modeling of complex image distributions.

Conclusin

1.Propose more stable set of architectures for training generative adversarial networks

2.give evidence that adversarial networks learn good representations of images for supervised learning and generative modeling

Q & A

Thank you!

Reference: UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS

Ref:https://github.com/sjchoi86