Autoencoder and GAN

Hands-On Machine Learning Part2

- Chapter 17 -

TAVE Research DL001

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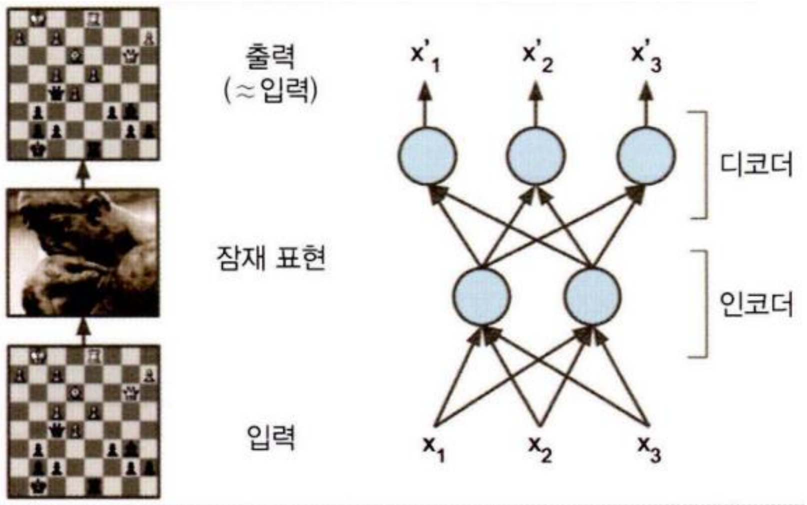
01. Overview

- Autoencoder and GAN are unsupervised learning technique and learn useful representation
- But, they work differently

▶ Autoencoder

- Learns to copy its input to its output
- are restricted in ways that force then to reconstruct the input approximately, preserving only the most relevant aspects of data
- A autoencoder consists of two parts, the encoder and the decoder

⇒ Get to know **how to represent data effectively**



▶ GAN

- Train by two networks (generative network, discriminative network) contesting with each other in a zero-sum game (**adversarial training**)

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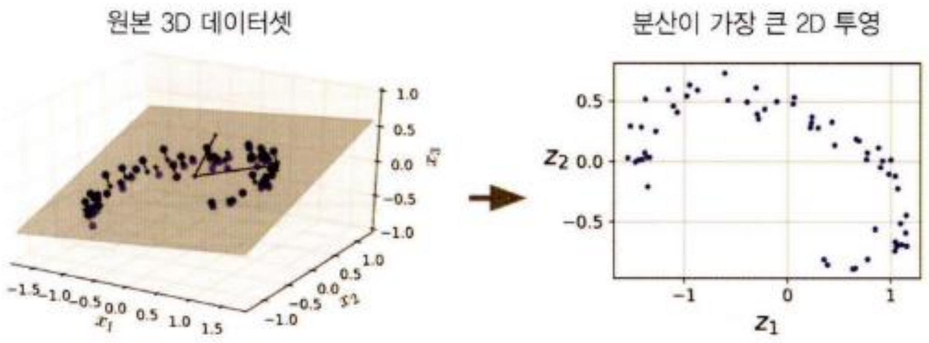
02. Autoencoder

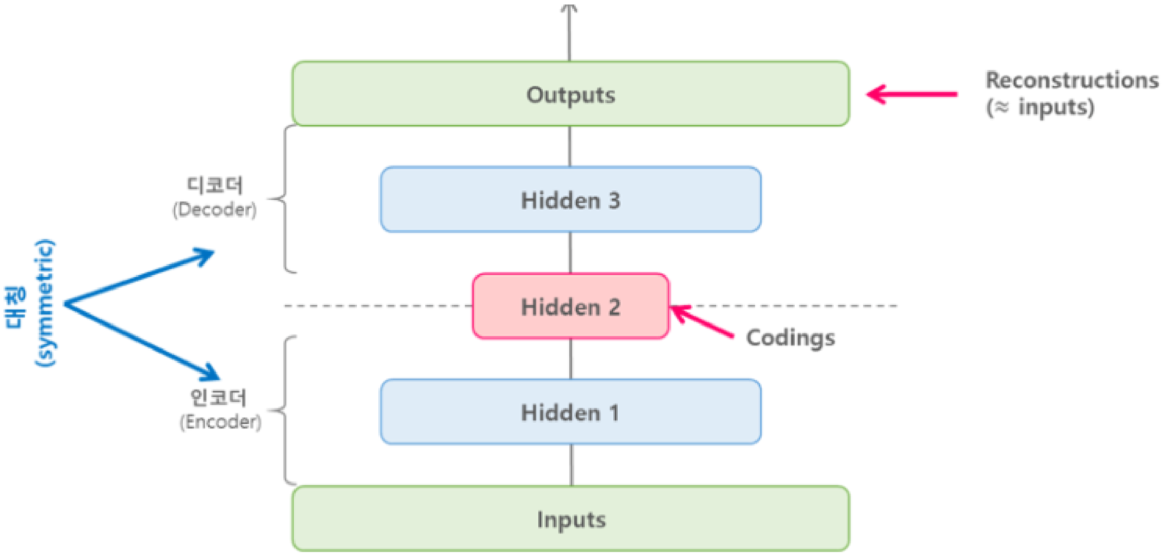
➢ Undercomplete autoencoder

- Undercomplete means **the feature space have lower dimensionality than the input space**
- If autoencoder use only linear activation and MSE as cost function, it is the same as **PCA**




```
history = autoencoder.fit(X_train, X_train, epochs=20)
codings = encoder.predict(X_train)
# 타깃이 X_train
```

- Stacked autoencoder
  - A stacked autoencoder is a neural network consist several hidden layers
  - Can be used for pre-trained model



✓ Be careful not to be **Over-fitting**

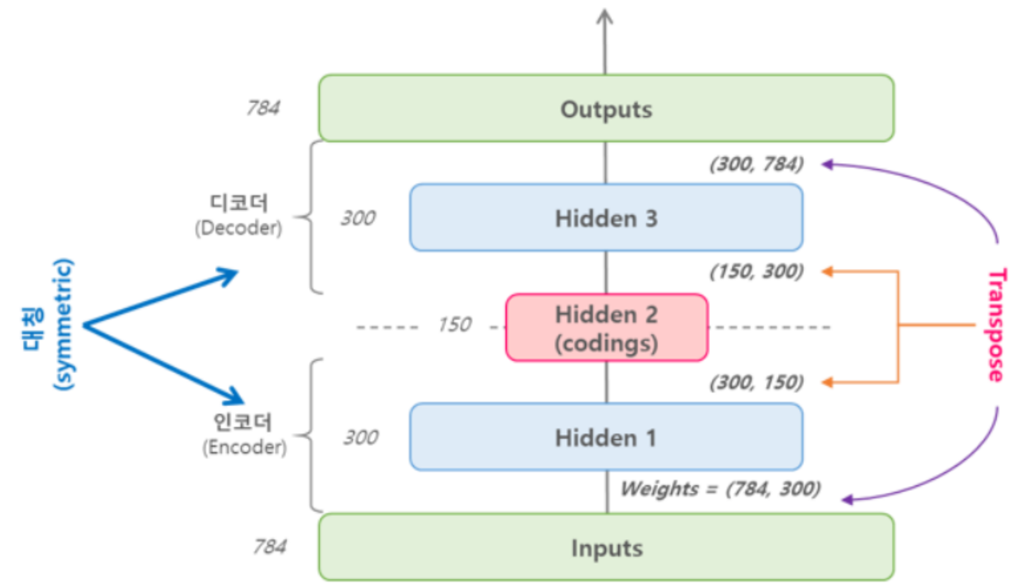
02. Autoencoder

➢ Undercomplete autoencoder

- Weight Tying

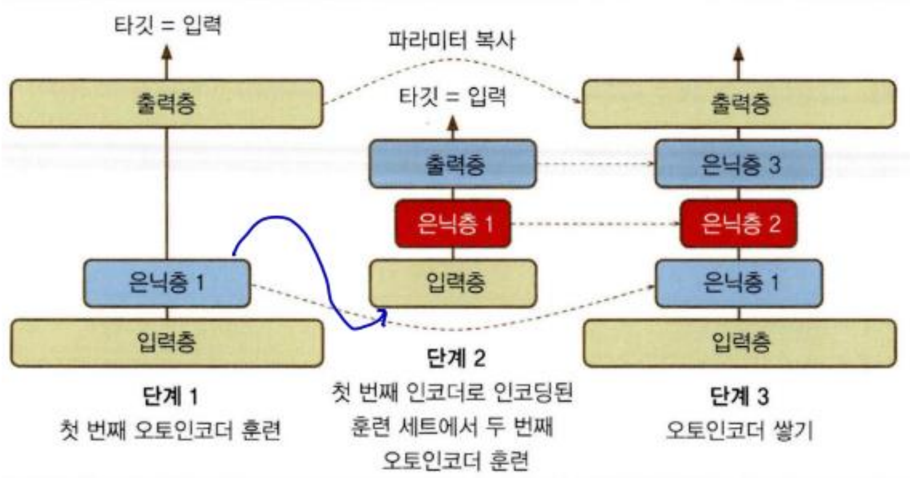
– When the weight matrix in the encoding layer is W, use W^T as the weight matrix in the decoding layer

$$\mathbf{W}_{N-L+1} = \mathbf{W}_L^{T}$$



- Greedy layer-wise training

(not used very well these days)



- Recurrent autoencoder

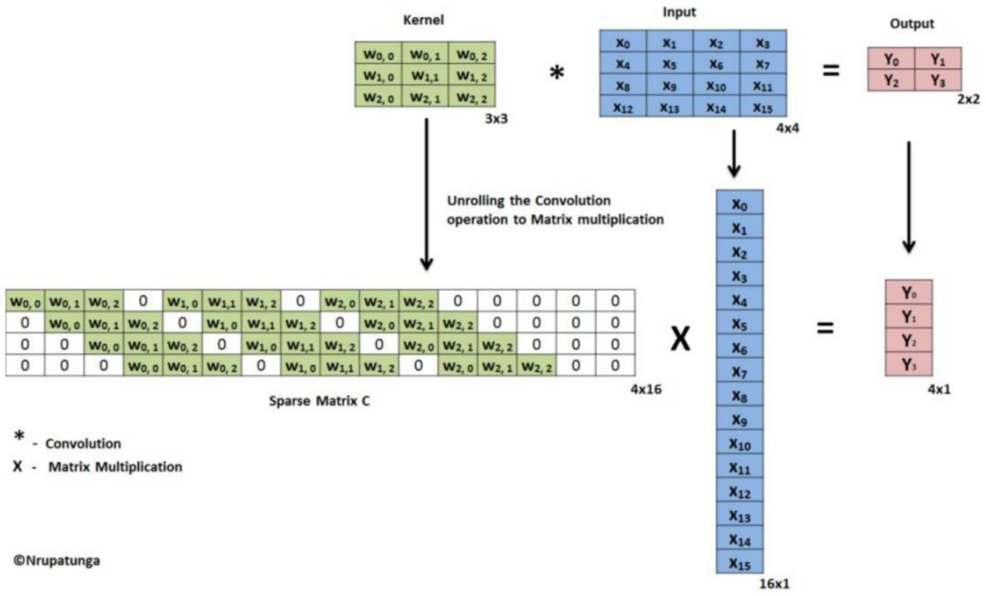
– Regard each row as a sequence

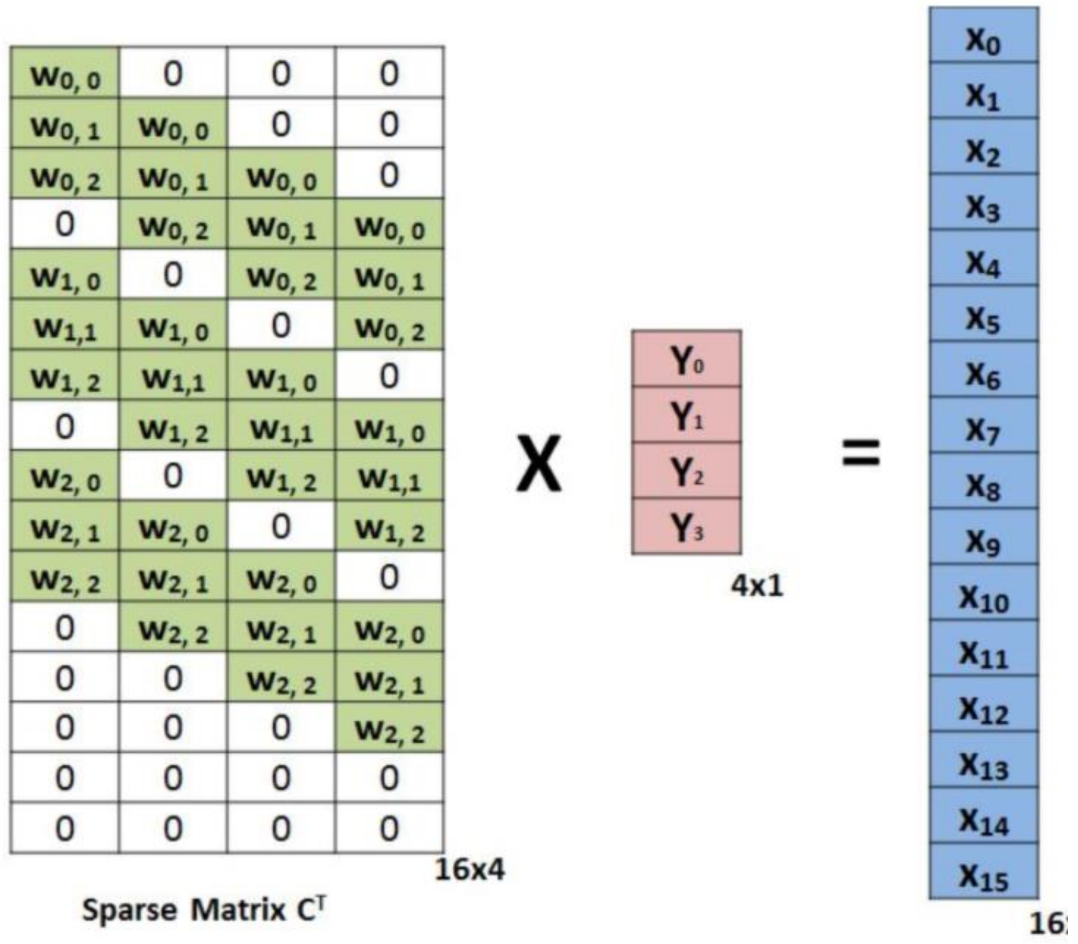
– Encoder is a Sequence-to-Vector RNN and decoder is a Vector-to-Sequence RNN

02. Autoencoder

➢ Undercomplete autoencoder

- Convolutional autoencoder
  - Consists of convolution layers and pooling layers
  - Encoder reduce spatial-wise dimension (i.e. height and width) and increase depth (i.e. the number of feature maps)

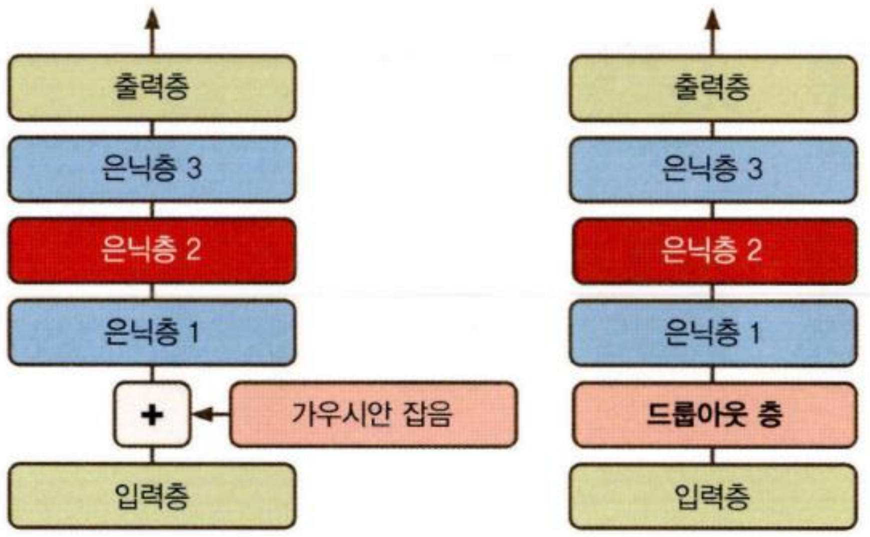




02. Autoencoder

➢ Overcomplete autoencoder

- Stacked denoising autoencoder



✓ For data visualization

✓ For pre-trained model

✓ For eliminating noise

- Sparsity Autoencoder
  - Reduce the number of neurons which activates in coding layer (about 5% of neurons)
  - Use sigmoid function as activation function in coding layer

- ***l*1** regularization $\mathcal{L}(x, \hat{x}) + \lambda \sum_i \left| a_i^{(h)} \right|$

- KL-Divergence $\mathcal{L}(x, \hat{x}) + \sum_j KL\left(\rho || \hat{\rho}_j\right)$

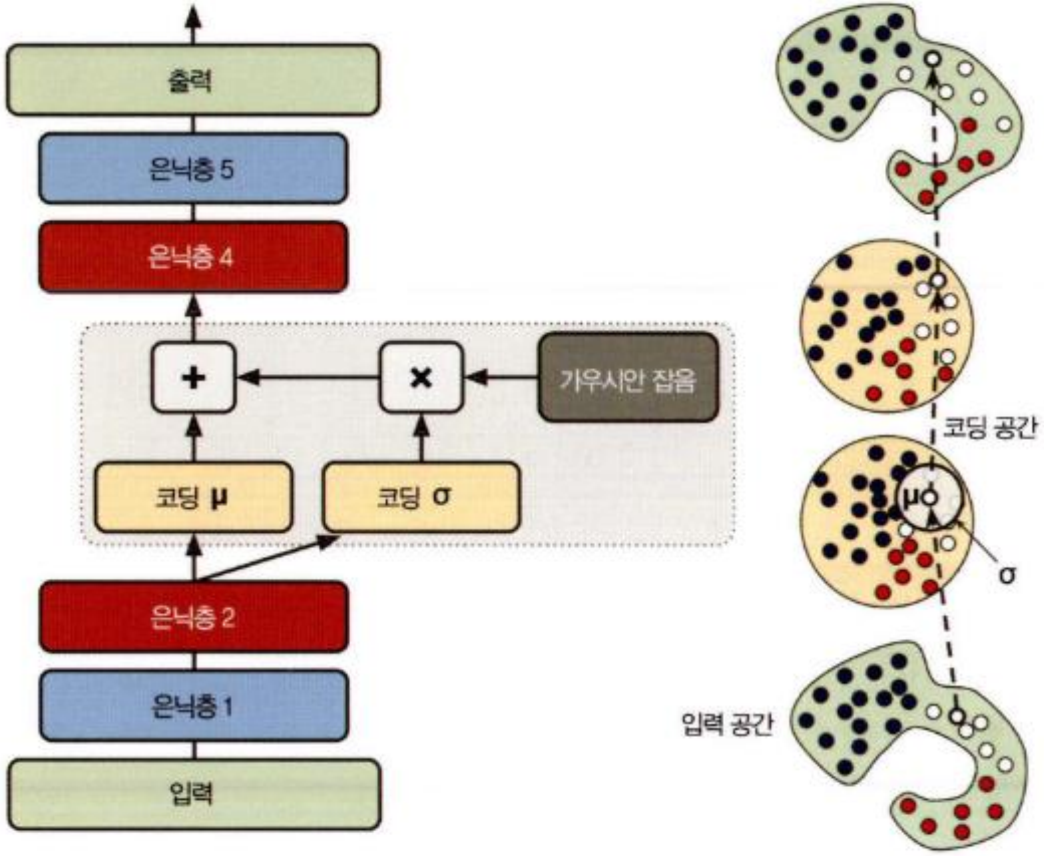
- ρ is a the average activation of a neuron over a collections of samples

$$D_{\mathrm{KL}}(p \parallel q) = p\log\frac{p}{q} + (1-p)\log\frac{1-p}{1-q}$$

02. Autoencoder

➢ Variational autoencoder (VAE)

- **Generative model** (different from AE)
- Encoder calculate mean coding μ and standard deviation coding σ
- And then, select random sample from gaussian distribution with mean μ and variance σ
- Cost function consists of **reconstruction loss** and **latent loss** (distance of distribution before sampling and distribution after sampling)



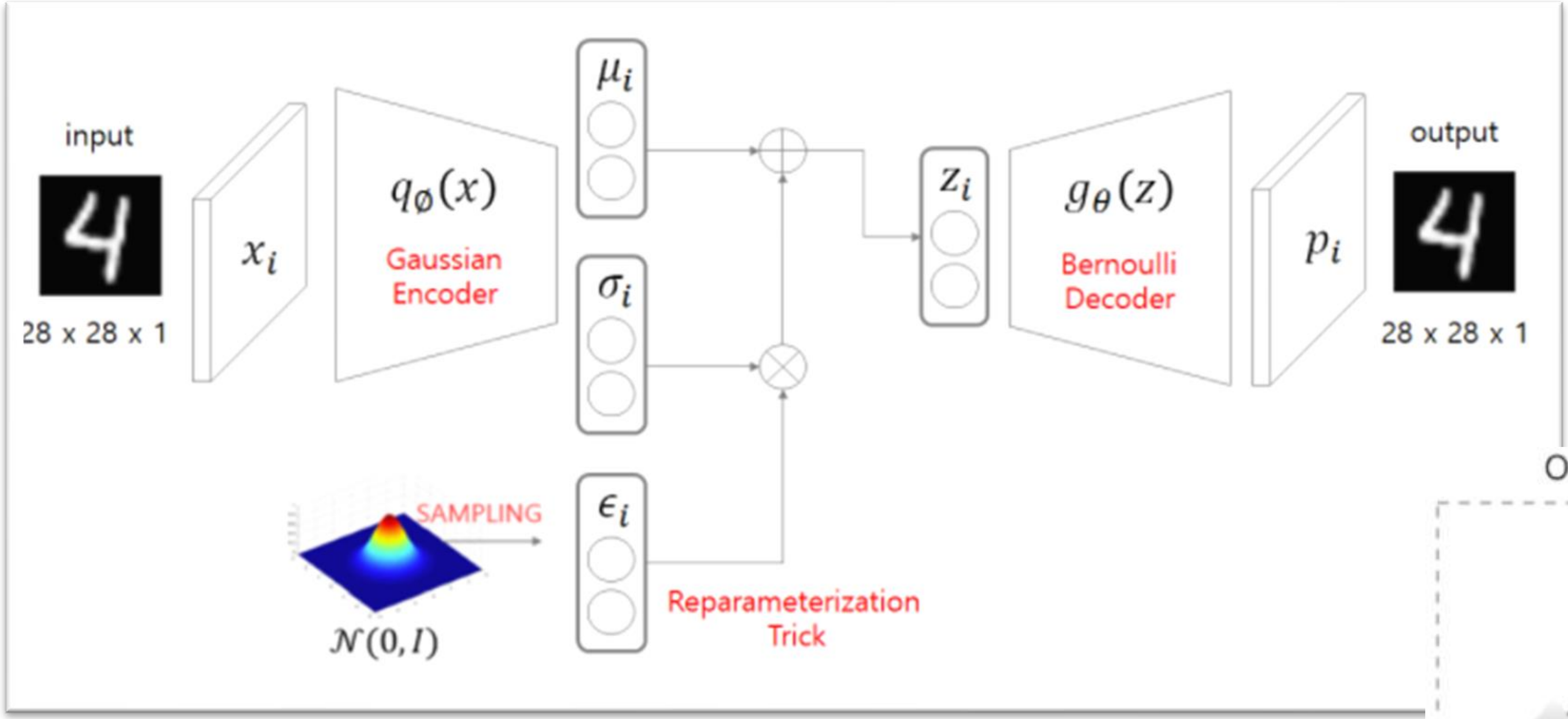
✓ Why don' t we use MLE?

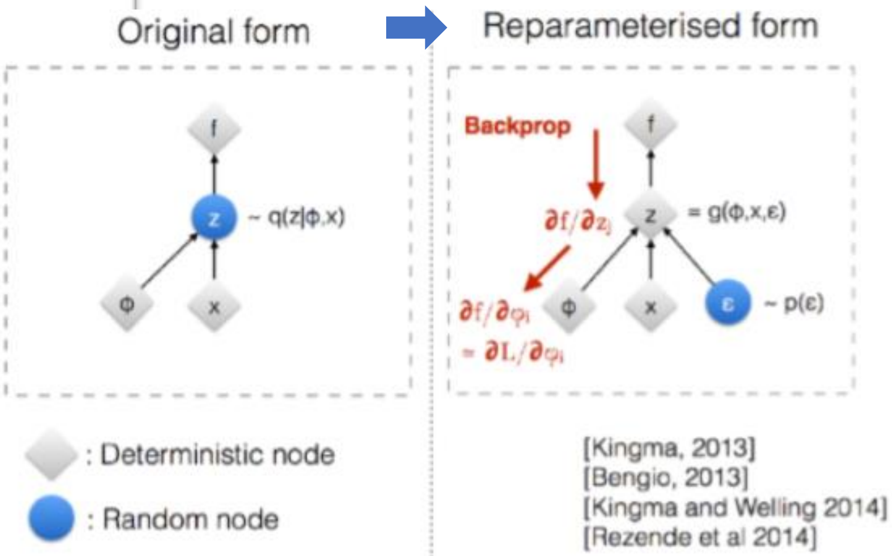
(a) (b) (c)

If $p(x|g_\theta(z)) = \mathcal{N}(x|g_\theta(z), \sigma^2 * I)$, the negative log probability of X is proportional squared Euclidean distance between $g_\theta(z)$ and x.

02. Autoencoder

- Variational autoencoder (VAE)





$$z^{i,l} \sim N(\mu_i, \sigma_i^2 I) \quad \Rightarrow \quad z^{i,l} = \mu_i + \sigma_i^2 \odot \epsilon$$
$$\epsilon \sim N(0, I)$$

Same distribution!
But it makes backpropagation possible!!

02. Autoencoder

➢ Variational autoencoder (VAE)

- ELBO

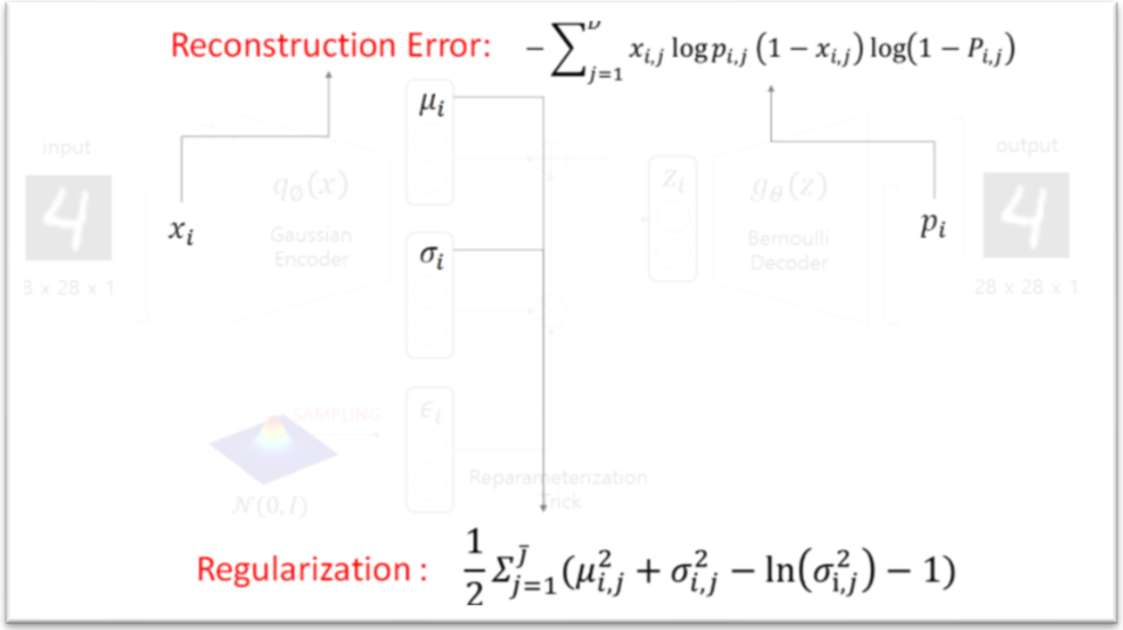
$$\log p\left(x\right) \geq E_{z \sim q(z|x)}\left[\log p(x|z)\right] - D_{KL}\left(q\left(z|x\right)||p\left(z\right)\right) = ELBO$$

Reconstruction term

- 이상적인 샘플링 함수로부터 얼마나 잘 복원을 했는가

Regularlization term

- 이상적인 sampling함수가 최대한 prior과 같도록 만들어준다
- 여러 sample중에서 prior과 유사한 값을 samplin하도록 condition 부여



$$D_{KL}\left(q\left(z|x\right)||p\left(z\right)\right) = D_{KL}\left[N\left(\left(\mu_1,\ldots,\mu_k\right)^T, \mathrm{diag}\left(\sigma_1^2,\ldots,\sigma_k^2\right)\right)||N\left(0,1\right)\right]$$

$$= \frac{1}{2}\sum_{i=1}\left(\sigma_i^2 + \mu_i^2 - \ln\left(\sigma_i^2\right) - 1\right)$$

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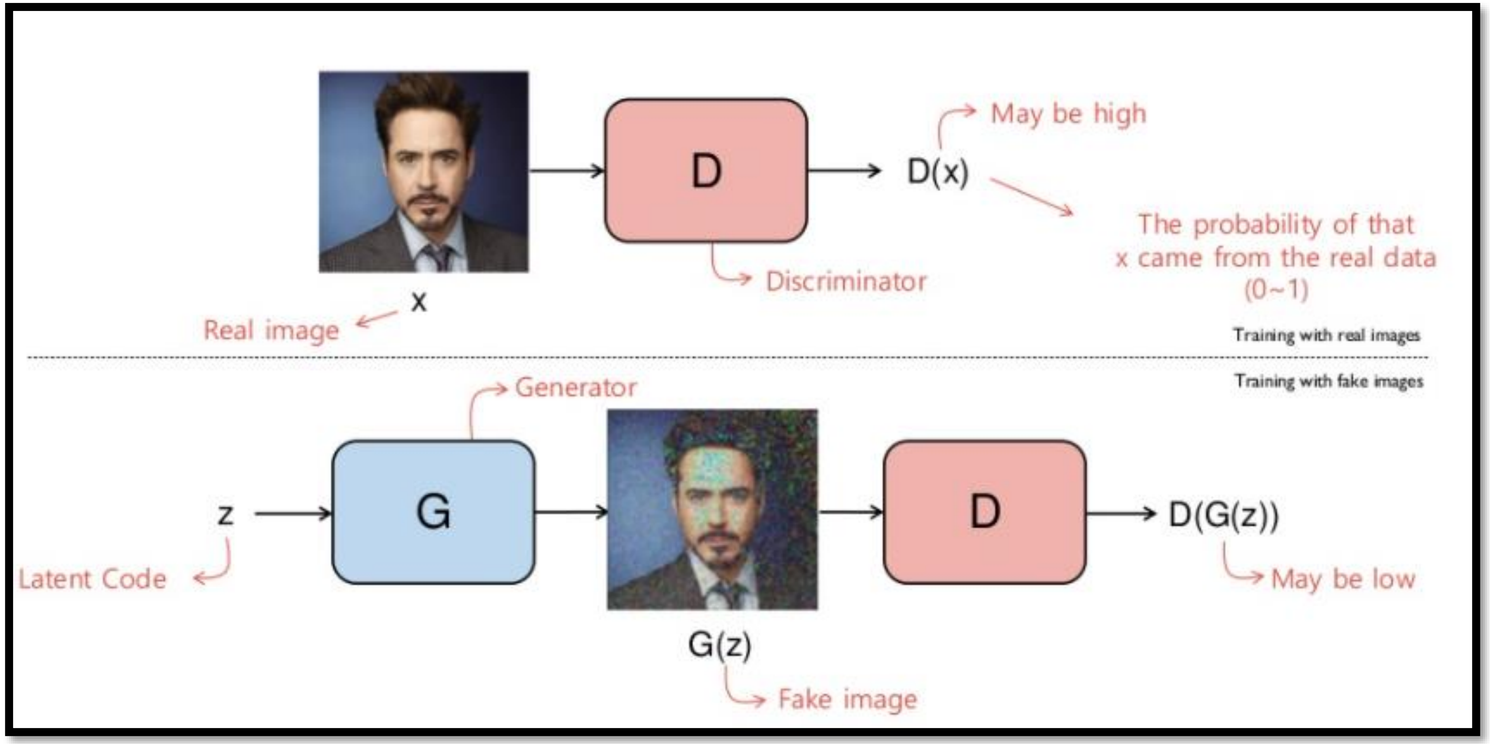
03. GAN

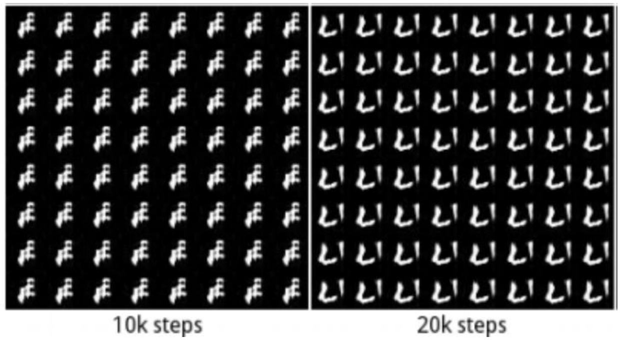
- Training by two networks (generative network, discriminative network) contesting with each other in a zero-sum game (**adversarial training**)
- Process



Toward Nash equilibrium...

Difficulty

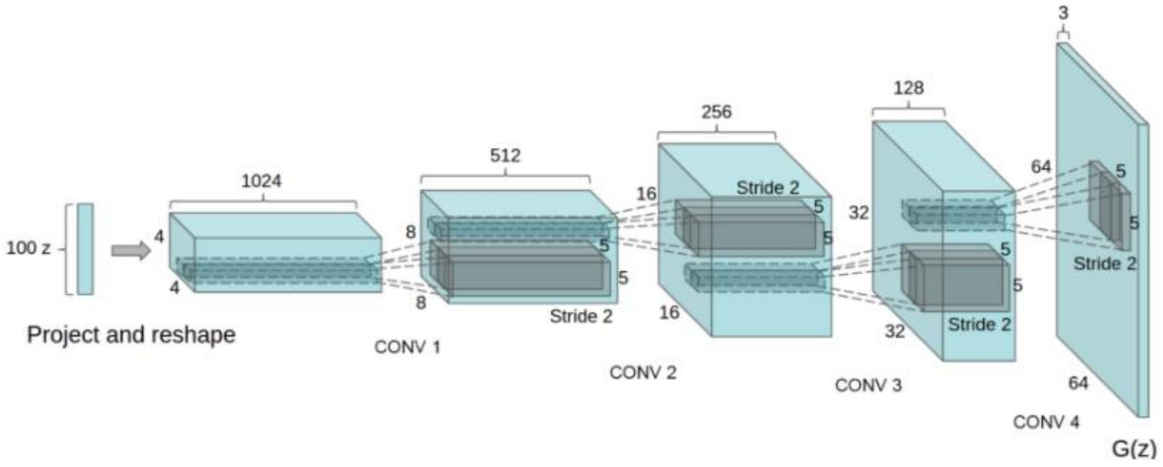
- ✓ Unstable parameters
- ✓ Mode collapse when reduced diversity of the generator' s output

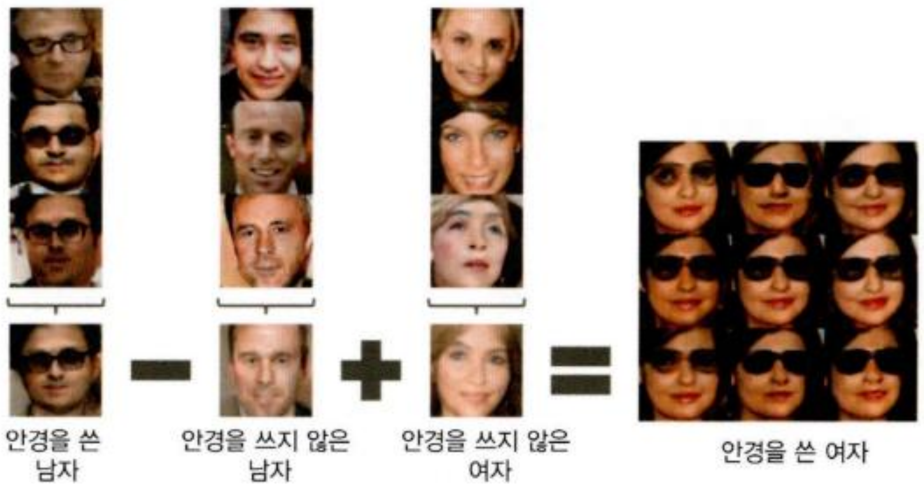


Mode collapse

03. GAN

➢ Deep convolutional GAN (DCGAN)





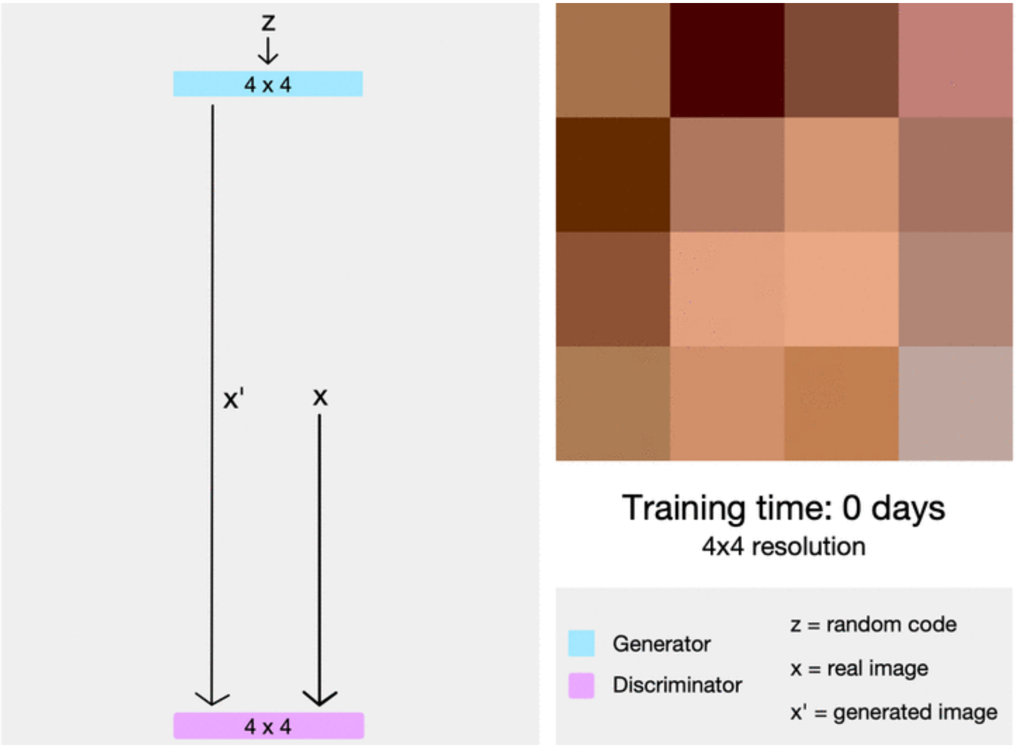
latent vector arithmetic

- Replace all max pooling with convolutional stride
- Use transposed convolution for upsampling.
- Eliminate fully connected layers.
- Use Batch normalization except the output layer for the generator and the input layer of the discriminator.
- Use ReLU in the generator except for the output which uses tanh.
- Use LeakyReLU in the discriminator.

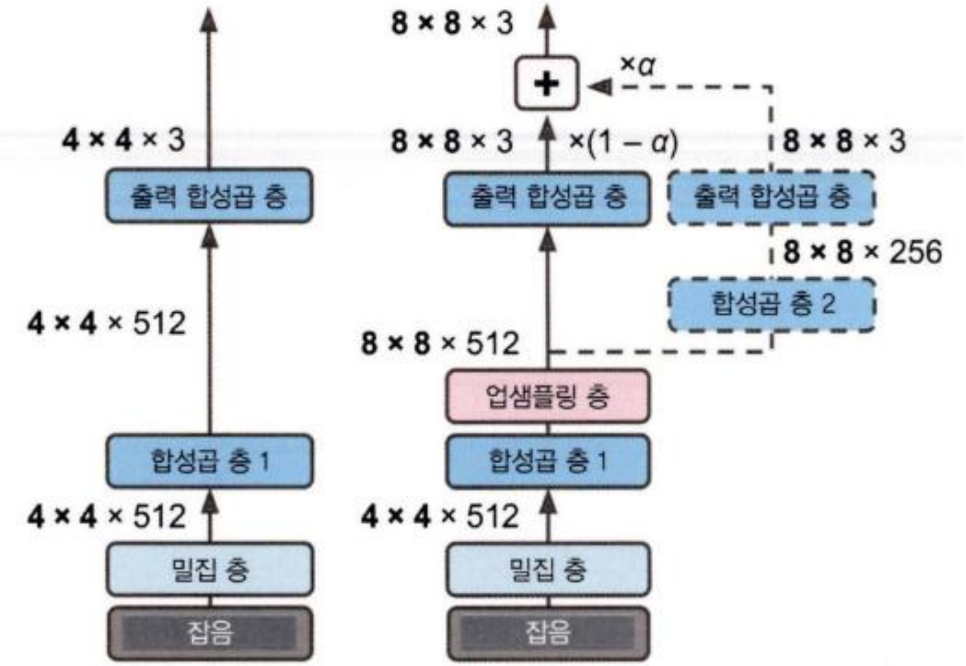
03. GAN

➢ Progressive growing GAN (ProGAN, PGGAN)

- Growing both the generator and discriminator progressively
- This both speeds the training up and greatly stabilizes it.



- **Fade in**
  - fade in the new layers smoothly
  - α is gradually increase from 0 to 1



03. GAN

➢ Progressive growing GAN (ProGAN, PGGAN)

- Increasing Variation using MiniBatch Standard Deviation

– Compute the standard deviation of each feature per spatial location ($N \times C \times H \times W \rightarrow C \times H \times W$)

– And then, average these values to one value per spatial location ($C \times H \times W \rightarrow 1 \times H \times W$)

- Equalized learning rate $\hat{w}_i = \frac{w_i}{c}$

- PixelWise Feature Vector Normalization

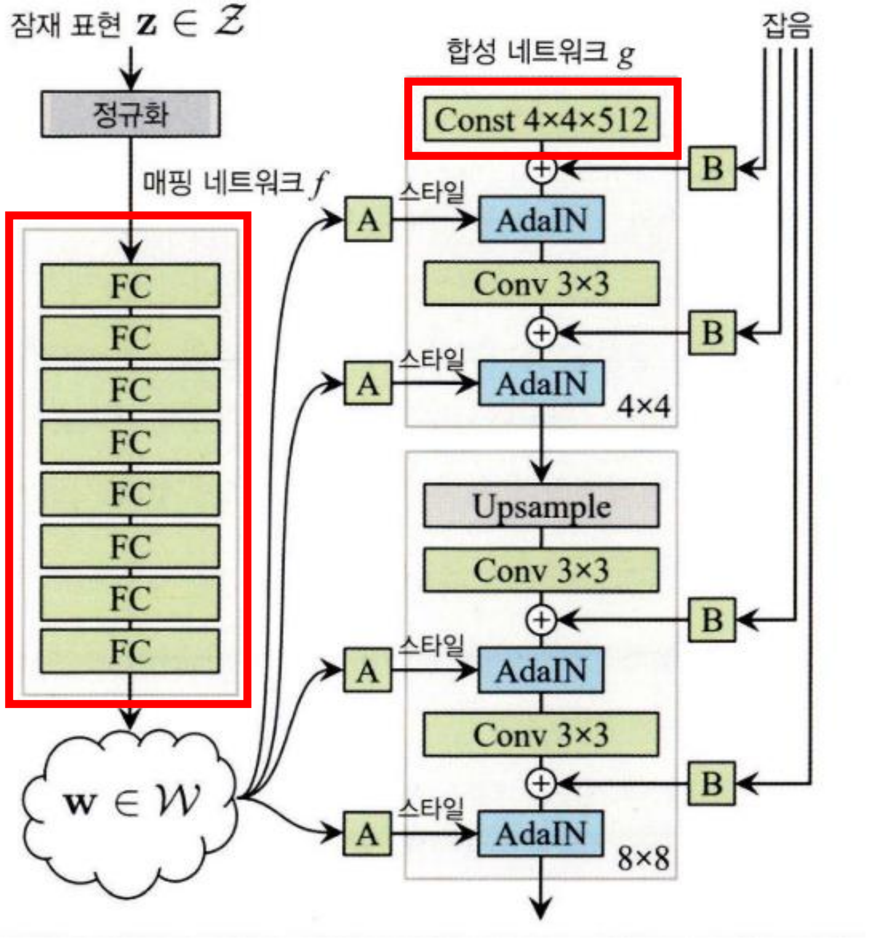
$$b_{x,y} = \frac{a_{x,y}}{\sqrt{\frac{1}{N}\sum_{j=0}^{N-1}(a_{x,y}^j)^2 + \epsilon}}$$

Discriminator	Act.	Output shape	Params
Input image	–	3 × 1024 × 1024	–
Conv 1 × 1	LReLU	16 × 1024 × 1024	64
Conv 3 × 3	LReLU	16 × 1024 × 1024	2.3k
Conv 3 × 3	LReLU	32 × 1024 × 1024	4.6k
Downsample	–	32 × 512 × 512	–
Conv 3 × 3	LReLU	32 × 512 × 512	9.2k
Conv 3 × 3	LReLU	64 × 512 × 512	18k
Downsample	–	64 × 256 × 256	–
Conv 3 × 3	LReLU	64 × 256 × 256	37k
Conv 3 × 3	LReLU	128 × 256 × 256	74k
Downsample	–	128 × 128 × 128	–
Conv 3 × 3	LReLU	128 × 128 × 128	148k
Conv 3 × 3	LReLU	256 × 128 × 128	295k
Downsample	–	256 × 64 × 64	–
Conv 3 × 3	LReLU	256 × 64 × 64	590k
Conv 3 × 3	LReLU	512 × 64 × 64	1.2M
Downsample	–	512 × 32 × 32	–
Conv 3 × 3	LReLU	512 × 32 × 32	2.4M
Conv 3 × 3	LReLU	512 × 32 × 32	2.4M
Downsample	–	512 × 16 × 16	–
Conv 3 × 3	LReLU	512 × 16 × 16	2.4M
Conv 3 × 3	LReLU	512 × 16 × 16	2.4M
Downsample	–	512 × 8 × 8	–
Conv 3 × 3	LReLU	512 × 8 × 8	2.4M
Conv 3 × 3	LReLU	512 × 8 × 8	2.4M
Downsample	–	512 × 4 × 4	–
Minibatch stddev	–	513 × 4 × 4	–
Conv 3 × 3	LReLU	512 × 4 × 4	2.4M
Conv 4 × 4	LReLU	512 × 1 × 1	4.2M
Fully-connected	linear	1 × 1 × 1	513
Total trainable parameters			23.1M

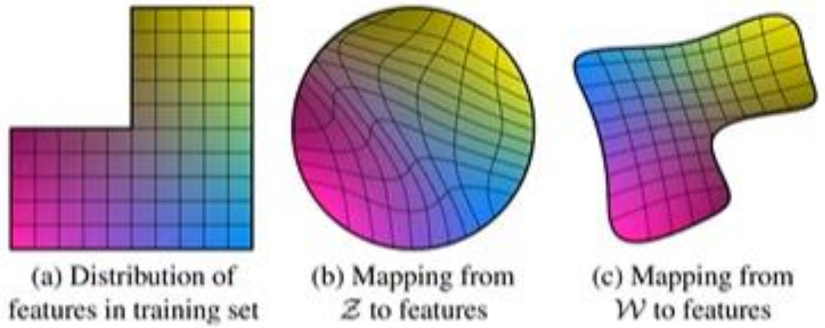
03. GAN

➢ StyleGAN

: A novel GAN using **style transfer method**



- Mapping network



ı W space, the factors of variation become more linear.

Z: Fixed distribution

Learned mapping $f: z \rightarrow w$

- Constant input

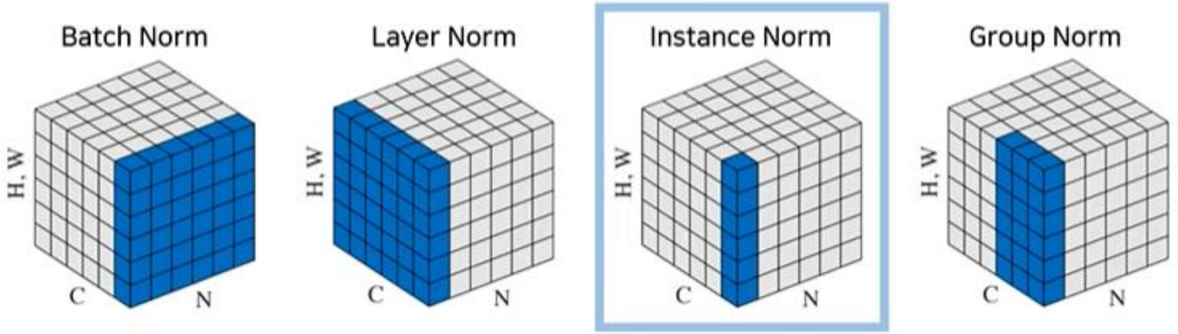
– Use constant as input of synthesis Network

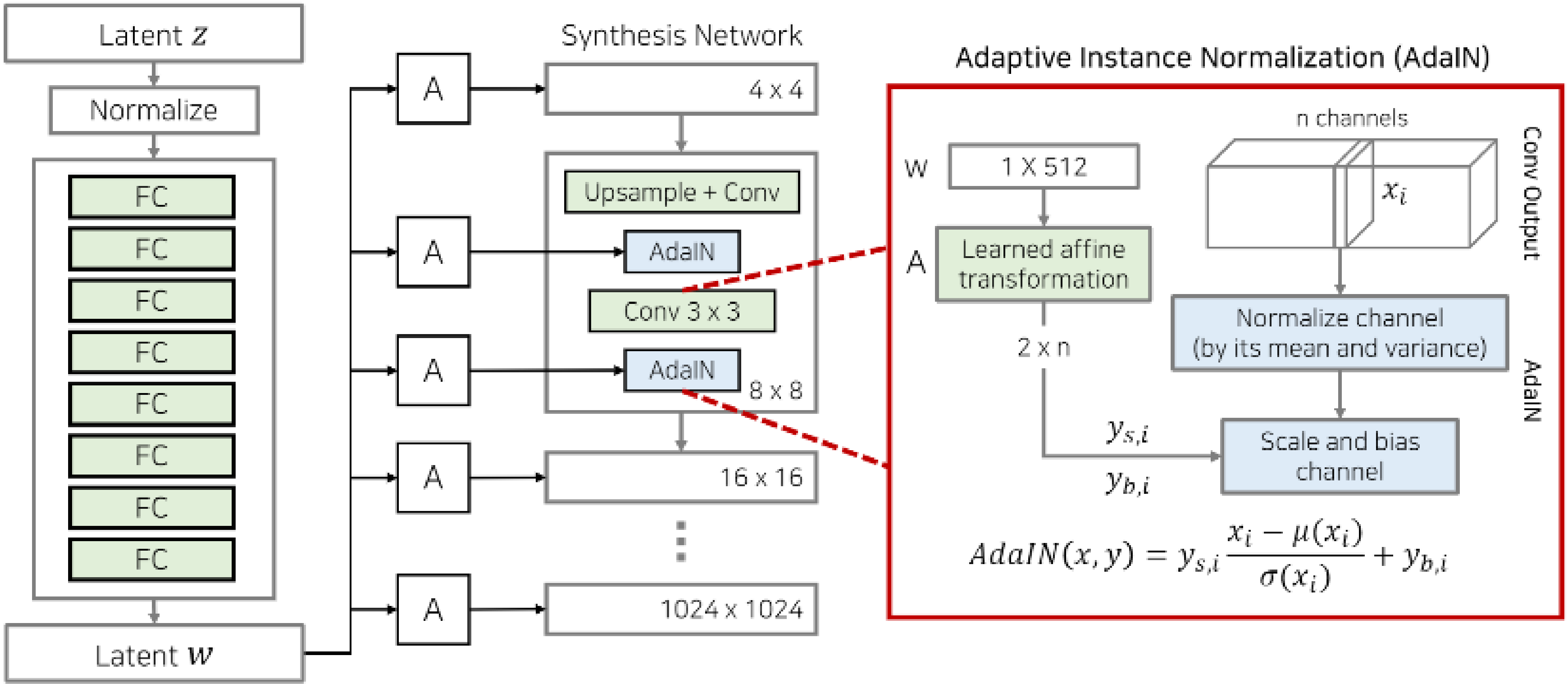
– Increase performance empirically

03. GAN

➢ StyleGAN

- AdaIN – Normalize each feature map



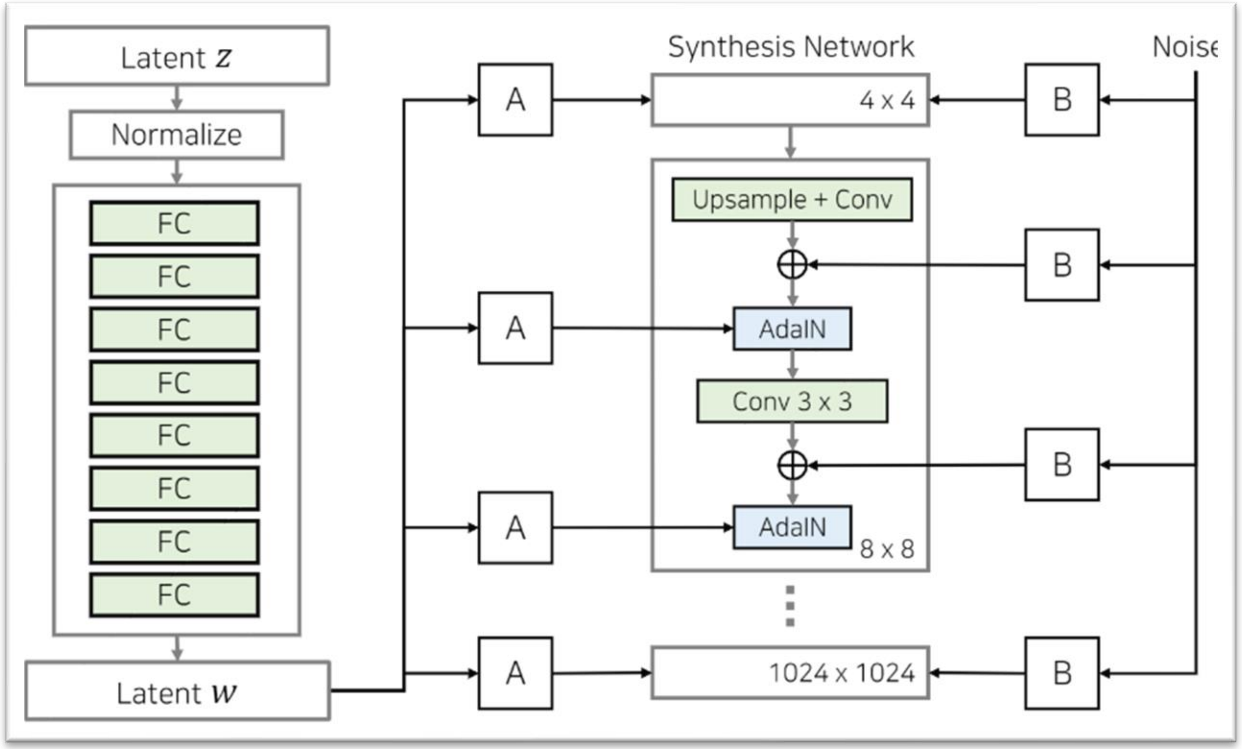


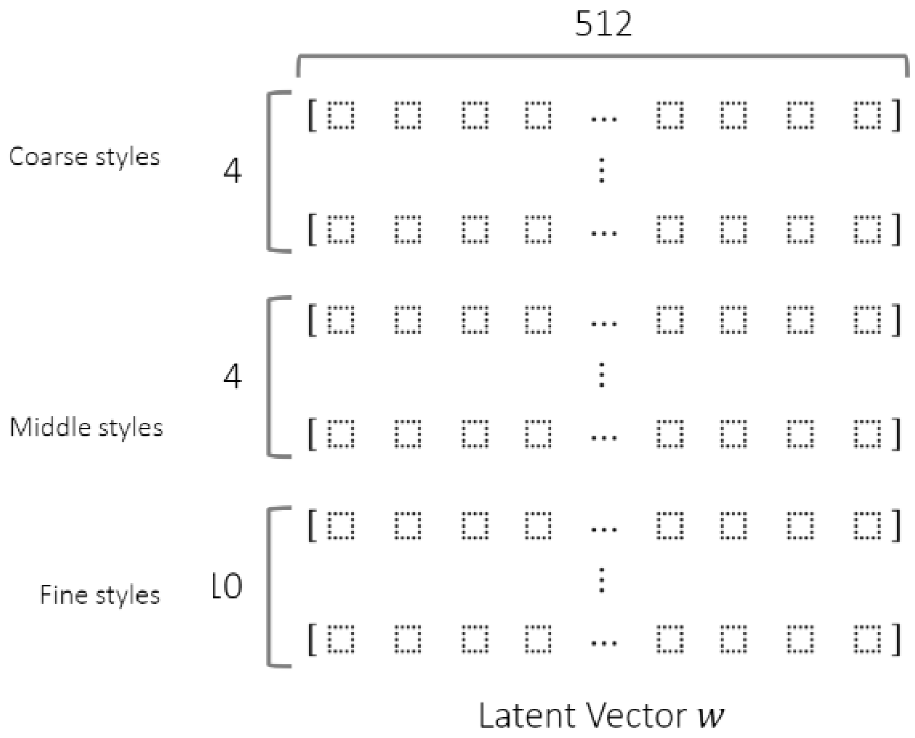
03. GAN

➢ StyleGAN

- Stochastic Variation

– Control stochastic variation like freckles and hair arrangement





03. GAN

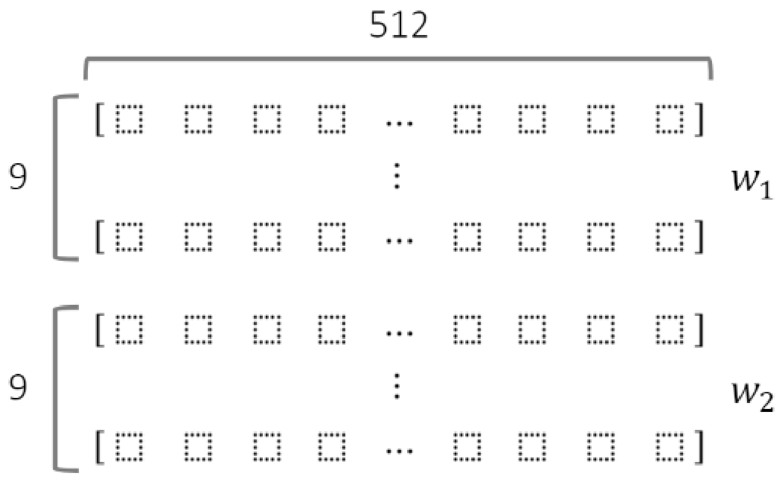
➢ StyleGAN

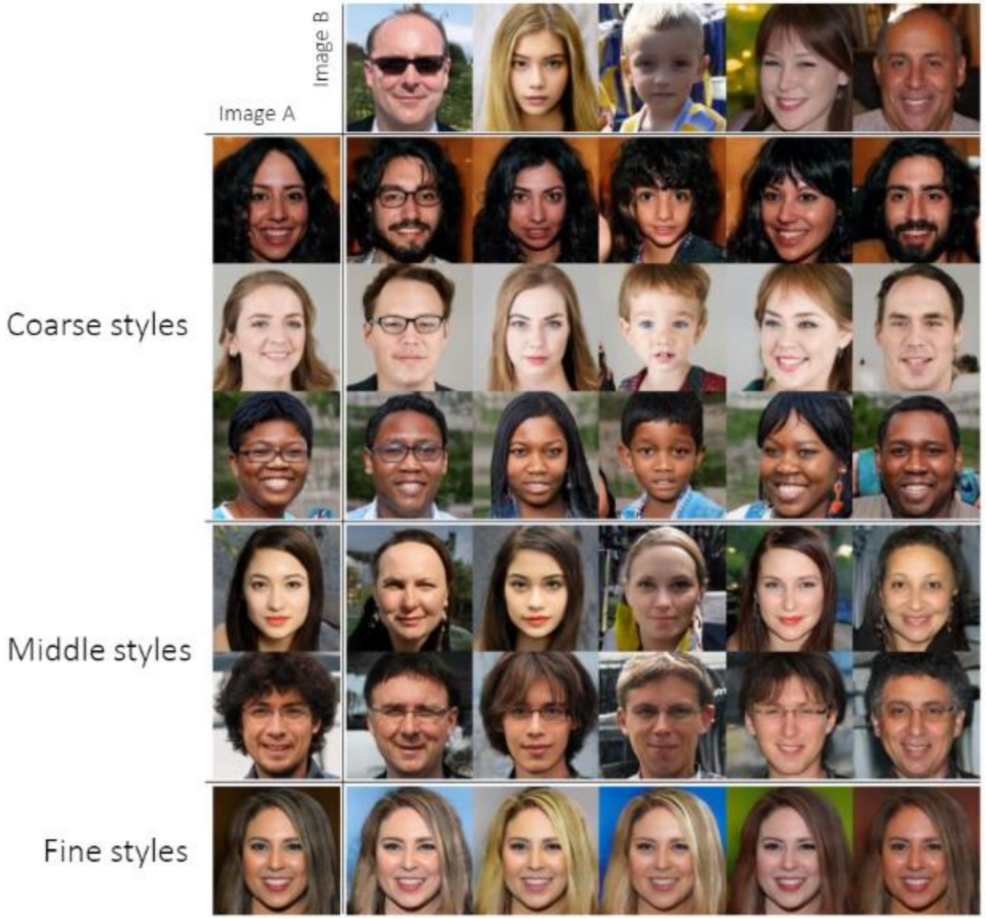
- Style Mixing (Mixing Regularization)

– To reduce the correlation between adjacent layers

– With two input vectors

– Train some of the levels with the first and switches (in a random point) to the other to train the rest of the levels





Thank you