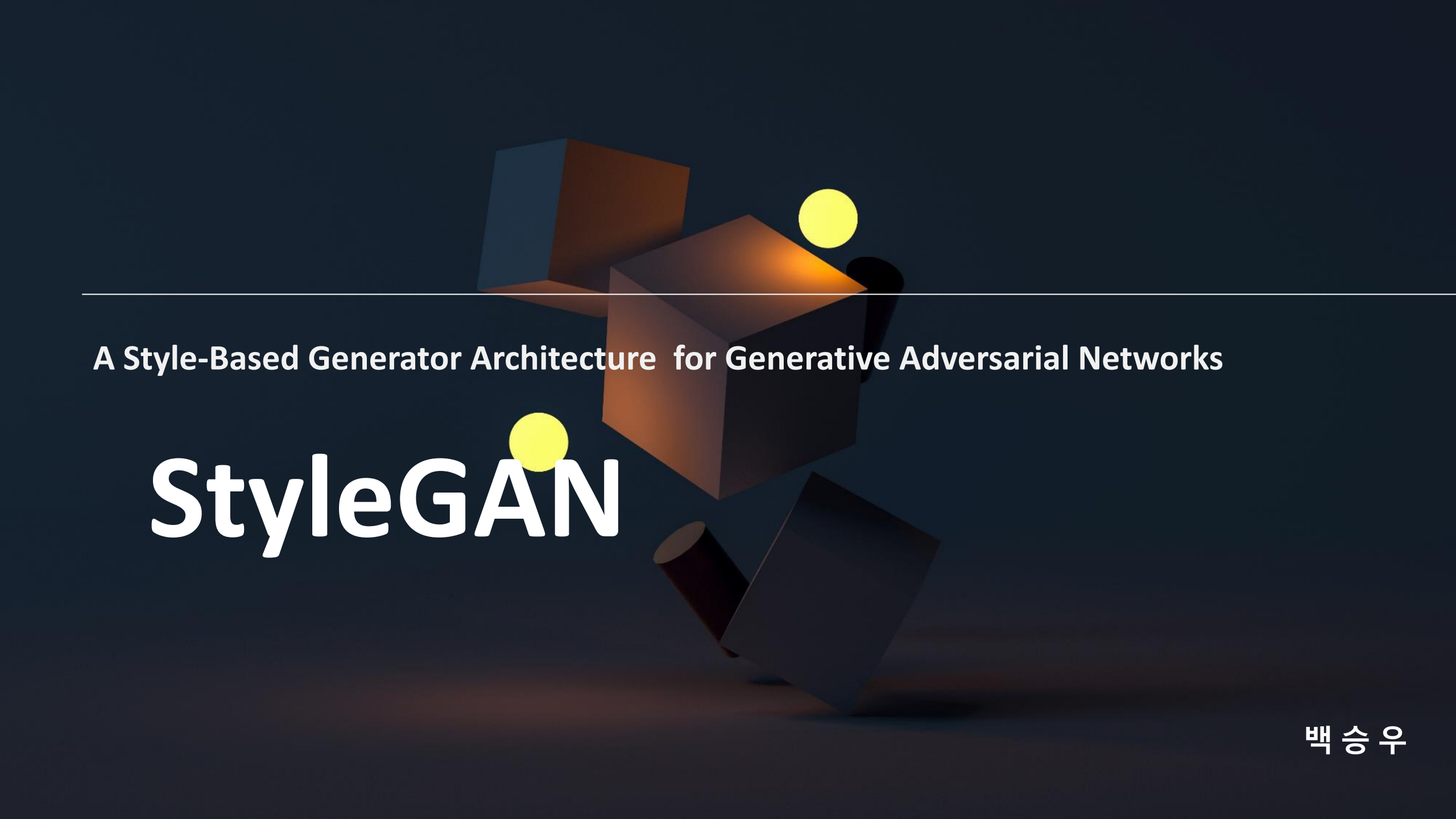
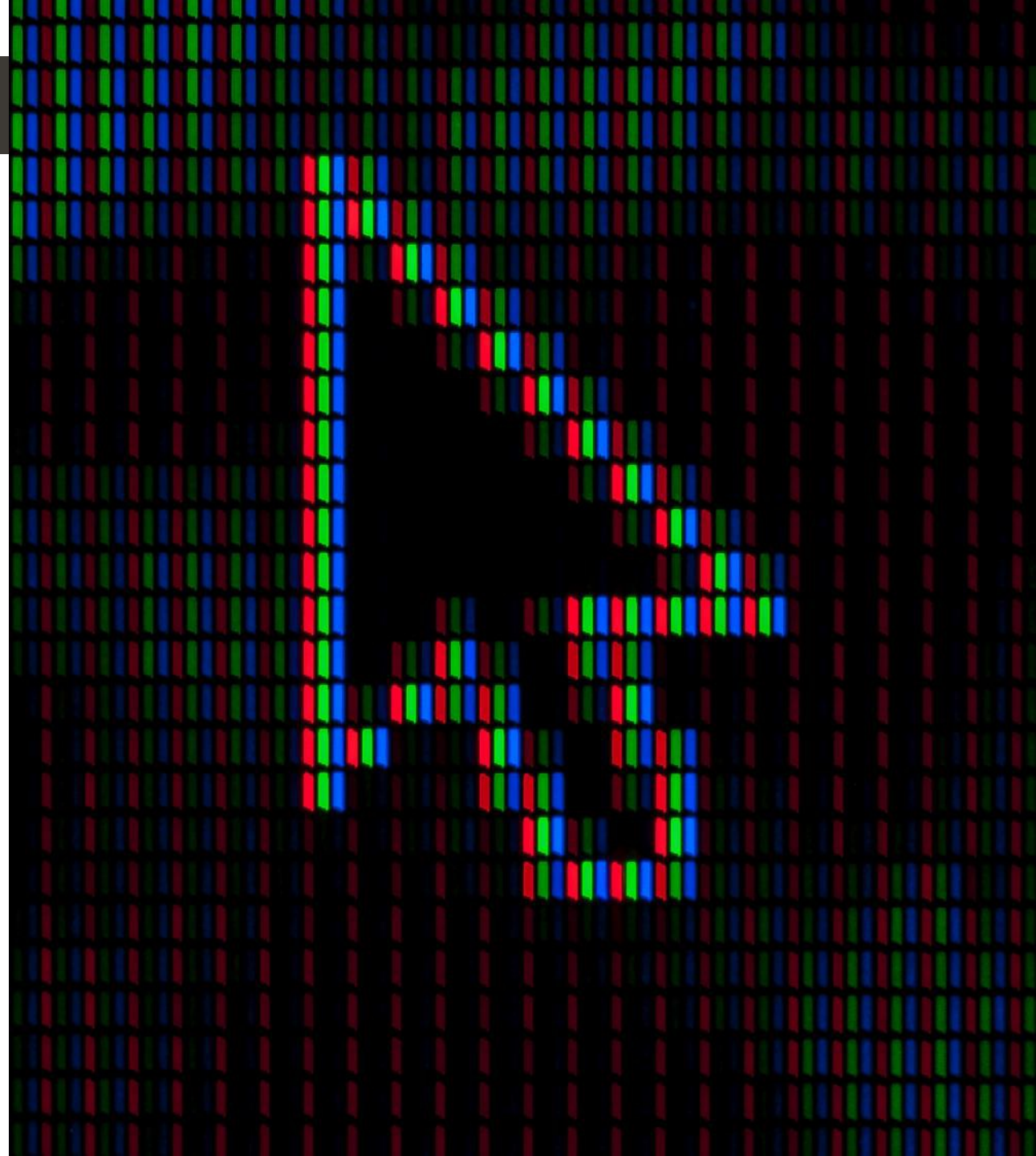


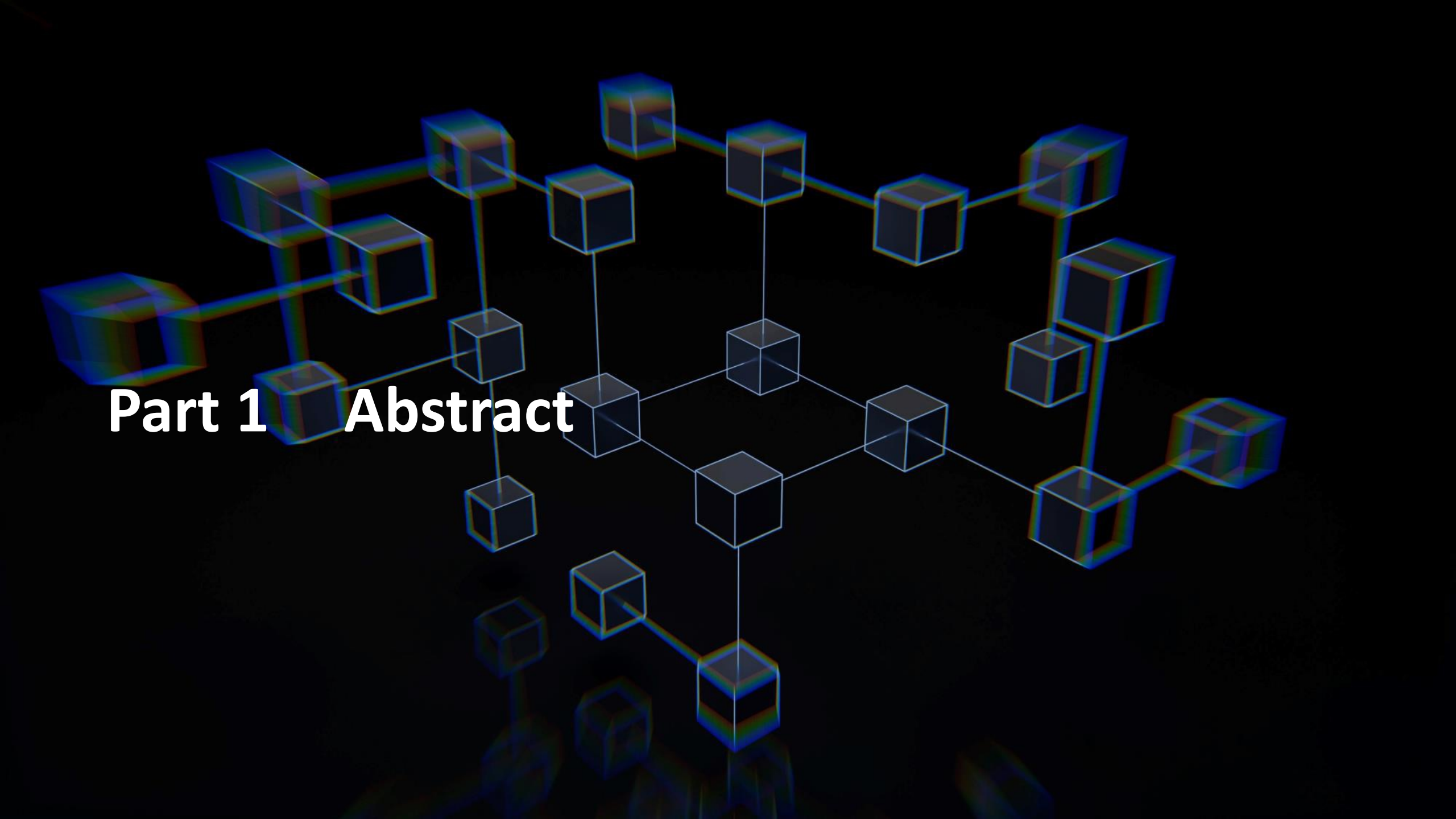
A Style-Based Generator Architecture for Generative Adversarial Networks

StyleGAN

백 승 우

목차 a table of contents



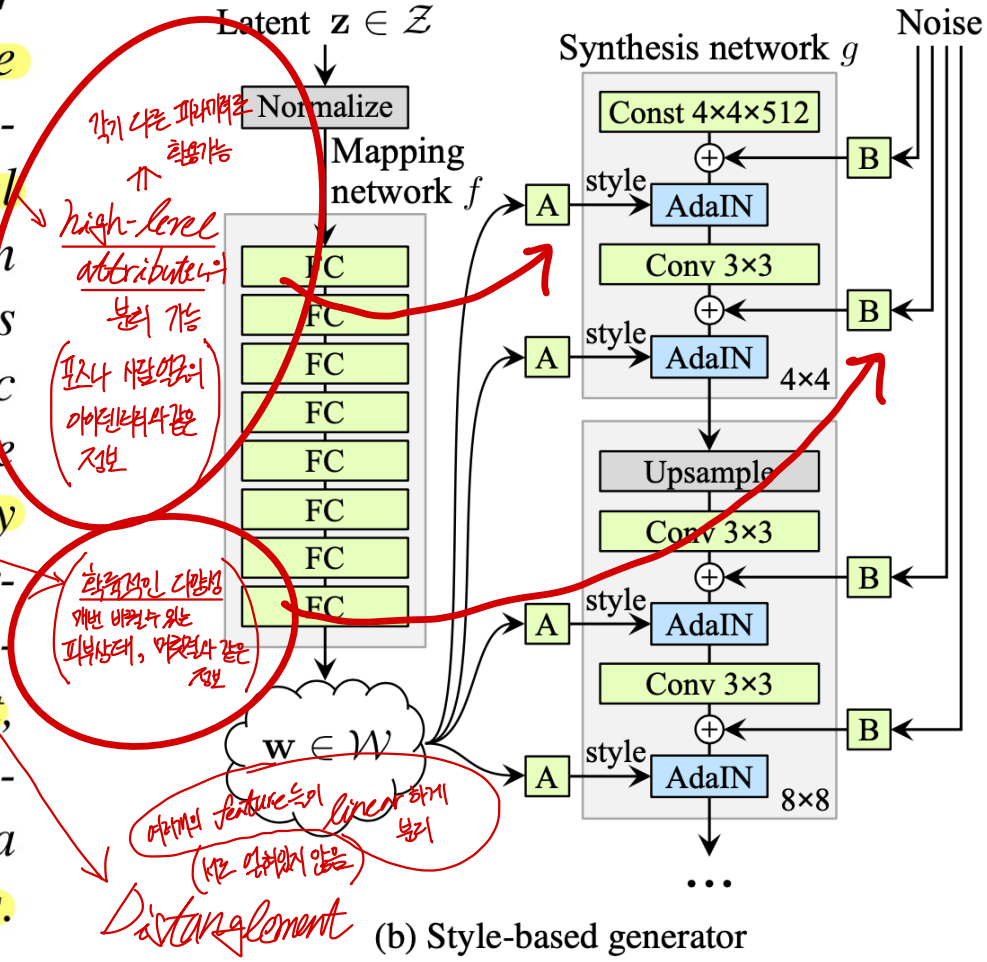


Part 1 Abstract

Part 1

Abstrct

We propose an alternative generator architecture for generative adversarial networks, borrowing from style transfer literature. The new architecture leads to an automatically learned, unsupervised separation of high-level attributes (e.g., pose and identity when trained on human faces) and stochastic variation in the generated images (e.g., freckles, hair), and it enables intuitive, scale-specific control of the synthesis. The new generator improves the state-of-the-art in terms of traditional distribution quality metrics, leads to demonstrably better interpolation properties, and also better disentangles the latent factors of variation. To quantify interpolation quality and disentanglement, we propose two new, automated methods that are applicable to any generator architecture. Finally, we introduce a new, highly varied and high-quality dataset of human faces.



(b) Style-based generator

Generator에 초점을 맞춤

각기 다른 피처맵을 활용함

high-level attribute의 분리 가능

포즈나 시점같은 어트리뷰트같은 정보

확률적인 다양함에 변화를 주는 피처맵들, 머릿결과 같은 정보

여러개의 feature들이 linear하게 분리 (서로 영향받지 않음)

Disentanglement 특성향상

GAN 분야의 성능의 피처레벨에서의 처리

AGGAN 베이스라인 아키텍처 성능향상

고해상도 얼굴 데이터셋(FFHQ) 발표

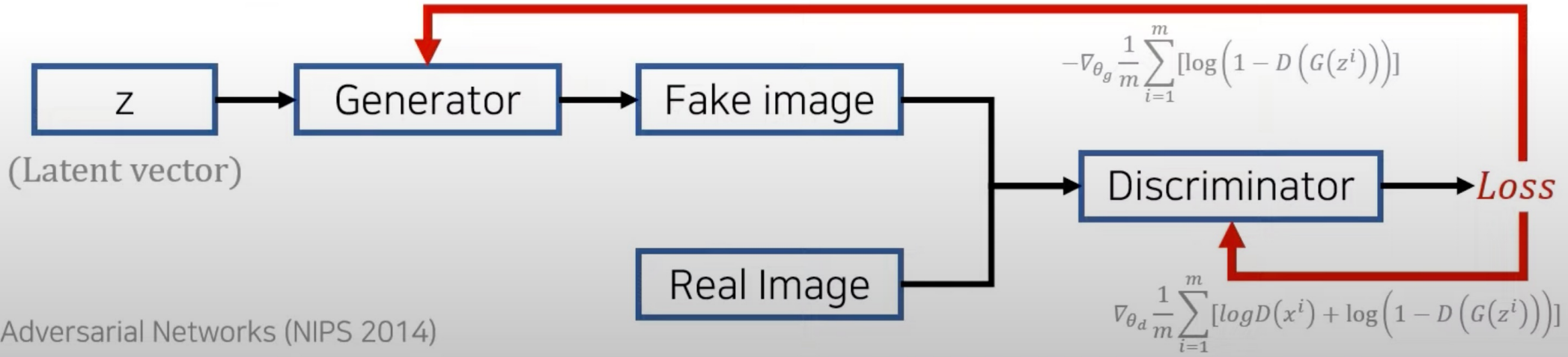
Part 2 Prior Research

GAN

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[logD(x)] + E_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

Generator — G(z): *new data instance*

Discriminator — $D(x) = Probability$: *a sample came from the real distribution* ($Real$: 1 ~ $Fake$: 0)



Generative Adversarial Networks (NIPS 2014)

Part 2 Prior Research

GAN

```
latent_dim = 100


# 생성자(Generator) 클래스 정의
class Generator(nn.Module):
    def __init__(self):
        super(Generator, self).__init__()

        # 하나의 블록(block) 정의
        def block(input_dim, output_dim, normalize=True):
            layers = [nn.Linear(input_dim, output_dim)]
            if normalize:
                # 배치 정규화(batch normalization) 수행(차원 동일)
                layers.append(nn.BatchNorm1d(output_dim, 0.8))
            layers.append(nn.LeakyReLU(0.2, inplace=True))
            return layers

        # 생성자 모델은 연속적인 여러 개의 블록을 가짐
        self.model = nn.Sequential(
            *block(latent_dim, 128, normalize=False),
            *block(128, 256),
            *block(256, 512),
            *block(512, 1024),
            nn.Linear(1024, 1 * 28 * 28),
            nn.Tanh()
        )

    def forward(self, z):
        img = self.model(z)
        img = img.view(img.size(0), 1, 28, 28)
        return img
```

GAN

```python
# 판별자(Discriminator) 클래스 정의
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()

        self.model = nn.Sequential(
            nn.Linear(1 * 28 * 28, 512),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Linear(512, 256),
            nn.LeakyReLU(0.2, inplace=True),
            nn.Linear(256, 1),
            nn.Sigmoid(),
        )

    # 이미지에 대한 판별 결과를 반환
    def forward(self, img):
        flattened = img.view(img.size(0), -1)
        output = self.model(flattened)

        return output
```

Part2 Prior Research

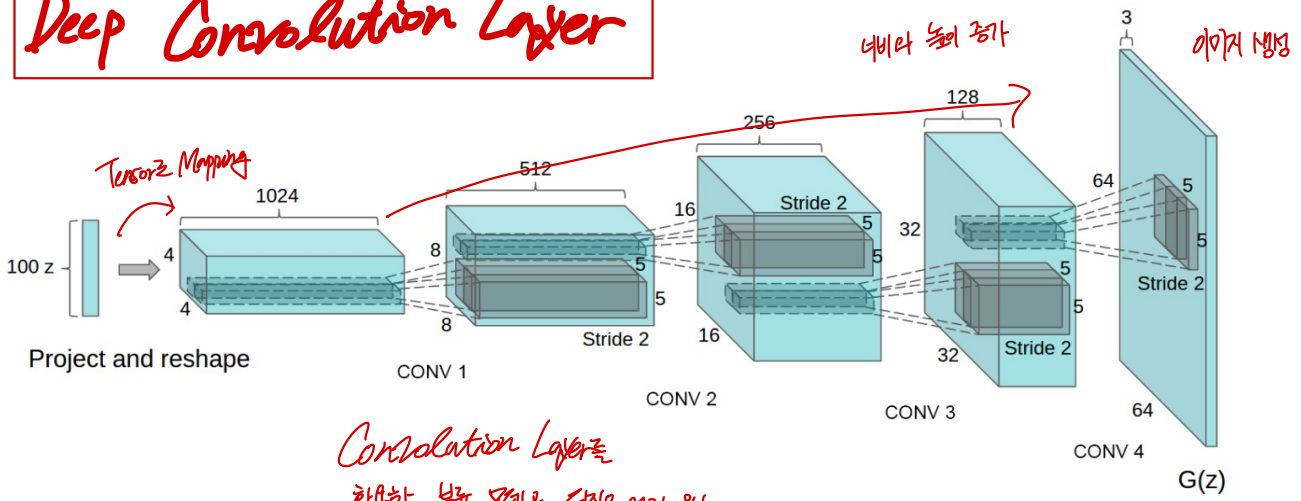
GAN

```python
import time

n_epochs = 200 # 학습의 횟수(epoch) 설정
sample_interval = 2000 # 몇 번의 배치(batch)마다 결과를 출력할 것인지 설정
start_time = time.time()

for epoch in range(n_epochs):
    for i, (imgs, _) in enumerate(dataloader):

        # 진짜(real) 이미지와 가짜(fake) 이미지에 대한 정답 레이블 생성
        real = torch.cuda.FloatTensor(imgs.size(0), 1).fill_(1.0) # 진짜(real): 1
        fake = torch.cuda.FloatTensor(imgs.size(0), 1).fill_(0.0) # 가짜(fake): 0

        real_imgs = imgs.cuda()

        """ 생성자(generator)를 학습합니다. """
        optimizer_G.zero_grad()

        # 랜덤 노이즈(noise) 샘플링
        z = torch.normal(mean=0, std=1, size=(imgs.shape[0], latent_dim)).cuda()

        # 이미지 생성
        generated_imgs = generator(z)

        # 생성자(generator)의 손실(loss) 값 계산
        g_loss = adversarial_loss(discriminator(generated_imgs), real)

        # 생성자(generator) 업데이트
        g_loss.backward()
        optimizer_G.step()

        """ 판별자(discriminator)를 학습합니다. """
        optimizer_D.zero_grad()

        # 판별자(discriminator)의 손실(loss) 값 계산
        real_loss = adversarial_loss(discriminator(real_imgs), real)
        fake_loss = adversarial_loss(discriminator(generated_imgs.detach()), fake)
        d_loss = (real_loss + fake_loss) / 2

        # 판별자(discriminator) 업데이트
        d_loss.backward()
        optimizer_D.step()

        done = epoch * len(dataloader) + i
        if done % sample_interval == 0:
            # 생성된 이미지 중에서 25개만 선택하여 5 X 5 격자 이미지에 출력
            save_image(generated_imgs.data[:25], f"{done}.png", nrow=5, normalize=True)
```

Part 1 **Prior Research**

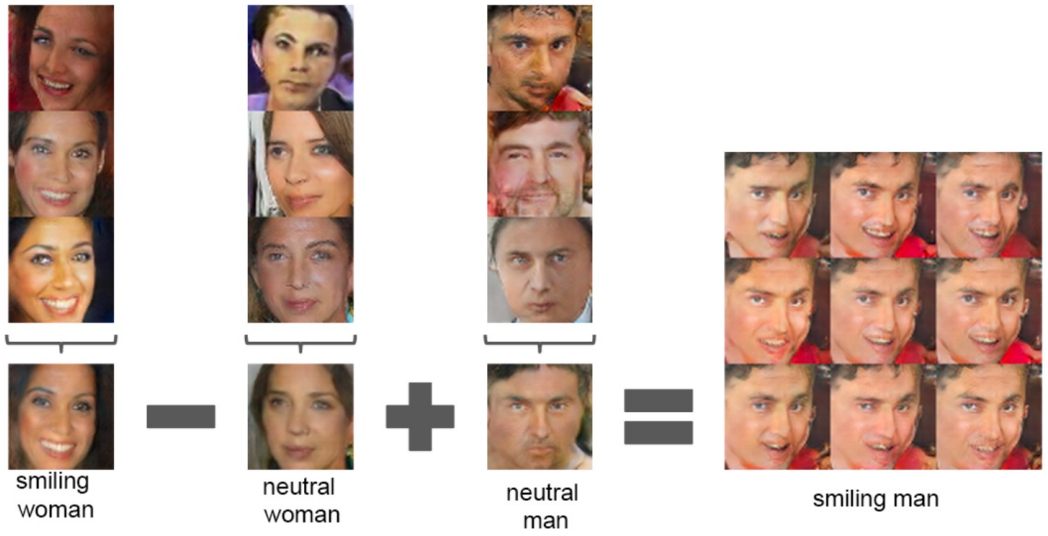
DCGAN

Deep Convolution Layer

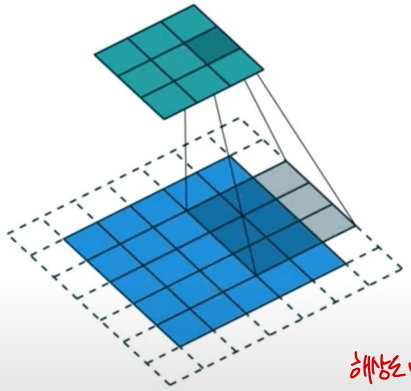


Convolution Layer를
활용한 분류 모델은 다양해짐

DCGAN에서의 벡터 연산



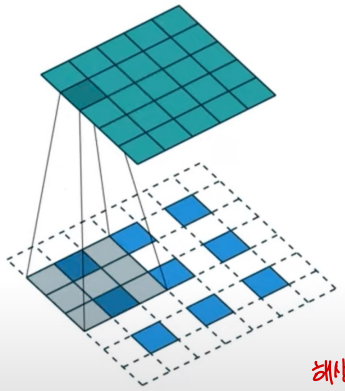
판별자(Discriminator) | Convolution filter | 생성자(Generator)



해상도↓

Strided Convolution: 너비와 높이가 감소

Channel ↑



해상도↑

Transposed Convolution: 너비와 높이가 증가

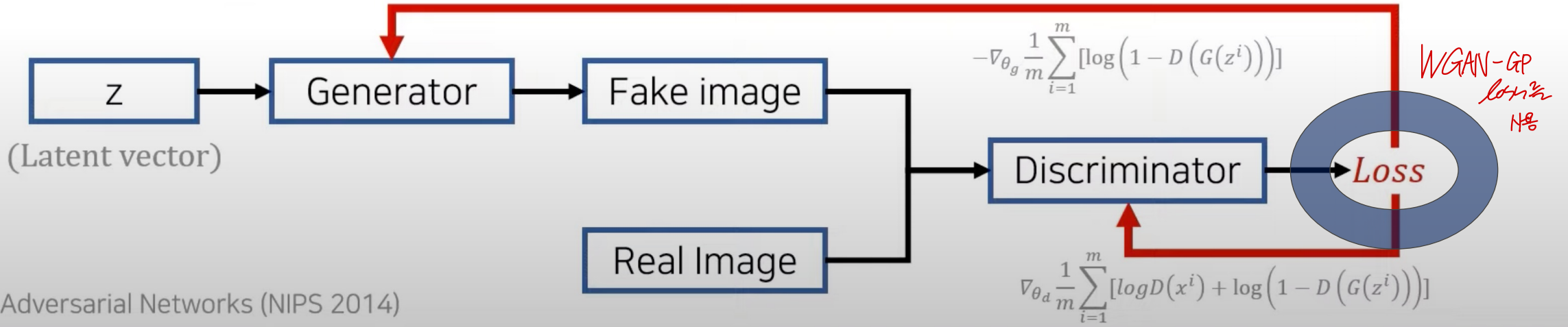
Channel ↓

WGAN

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[logD(x)] + E_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

Generator — G(z): *new data instance*

Discriminator — $D(x) = Probability$: *a sample came from the real distribution* (*Real*: 1 ~ *Fake*: 0)



Generative Adversarial Networks (NIPS 2014)

Part 1 **Prior Research**

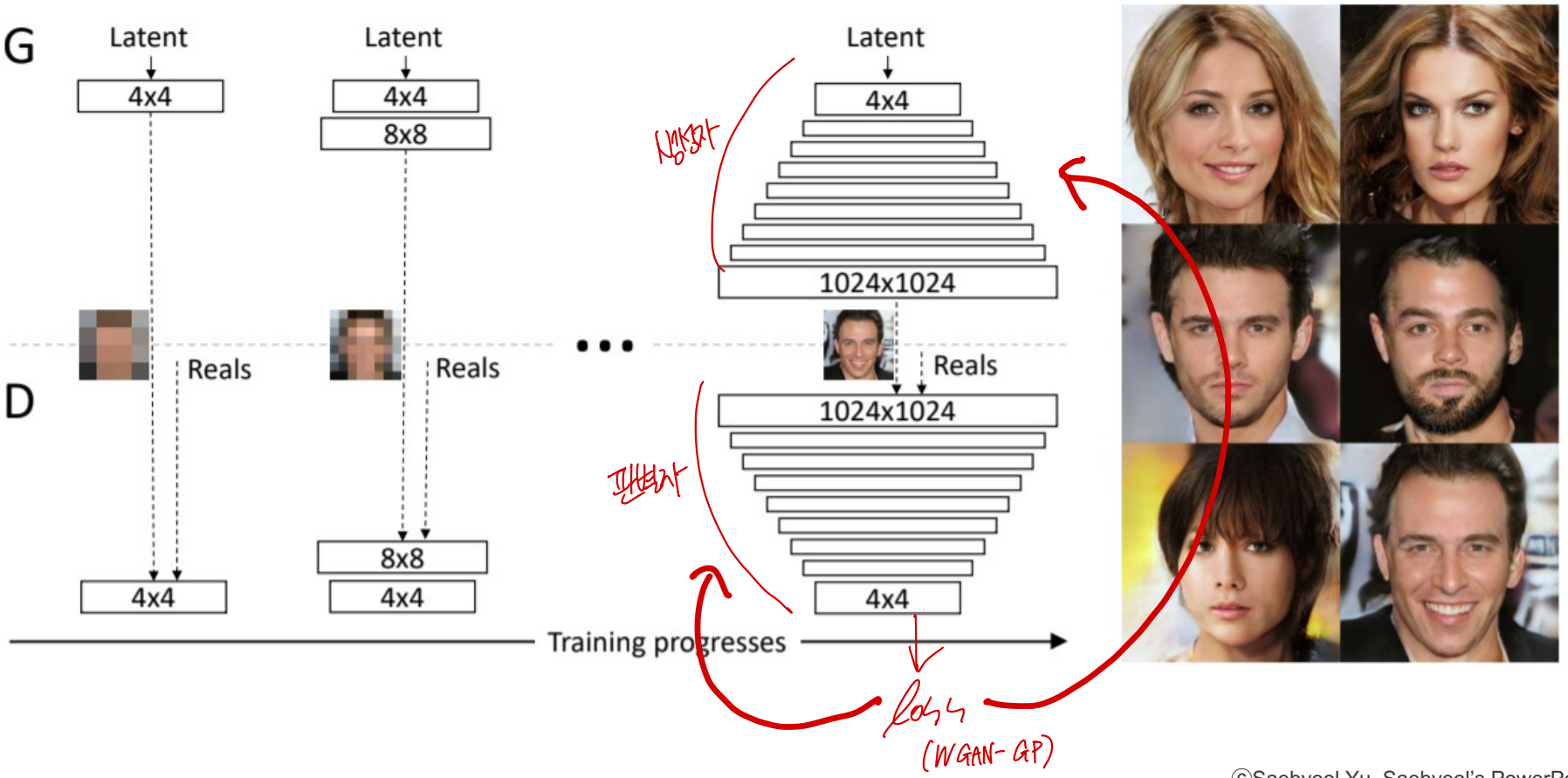
Progressive Growing of GANs

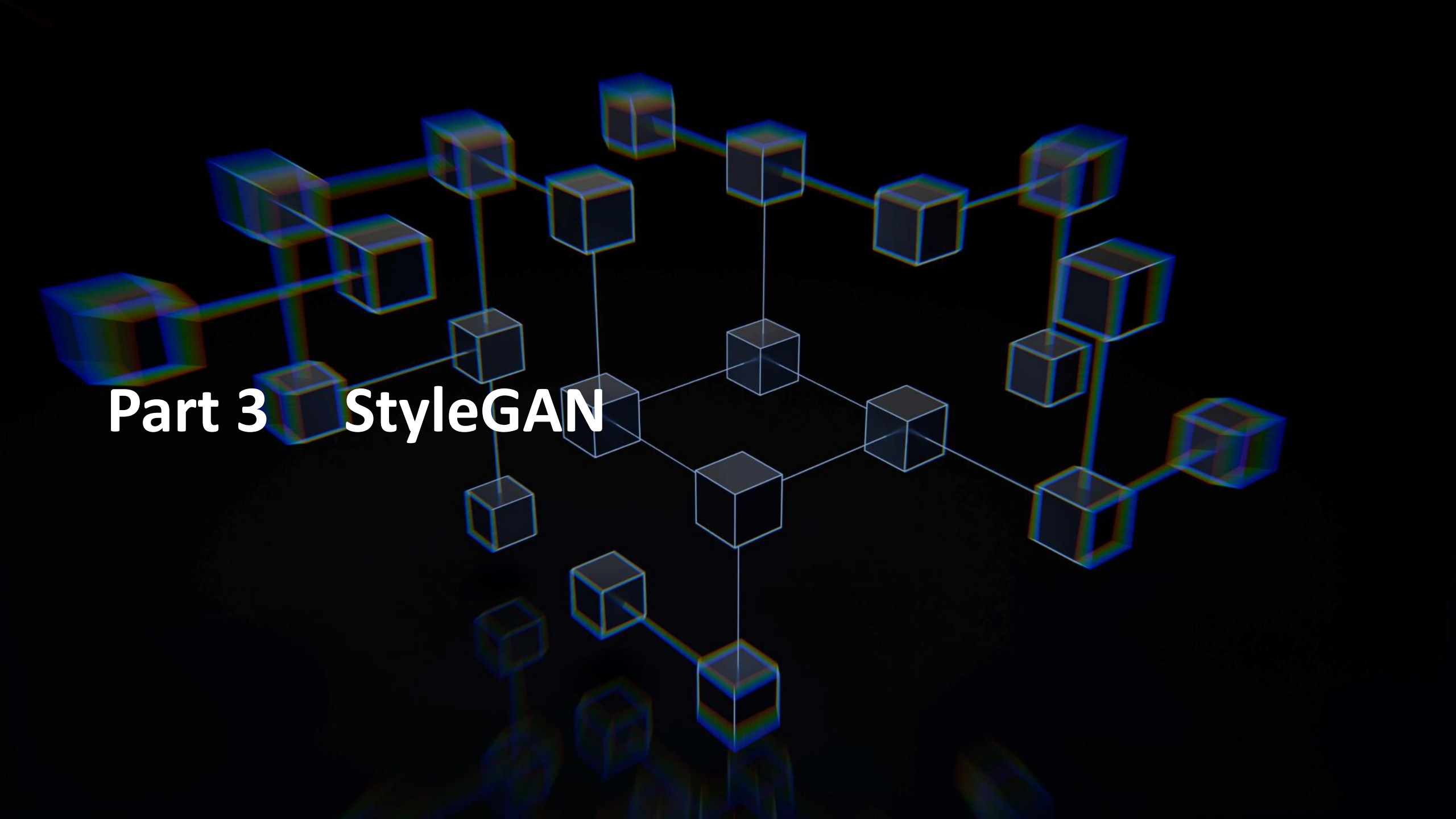
PGGAN

https://sensibilityit.tistory.com/508

- 학습과정에서 레이어를 추가 → 한번에 바로 고해상도 이미지를 만드는것보다 안정적으로 고해상도 이미지를 만들수 있음 & 높은↑
- 고해상도 이미지 학습 성공

But
- 이미지 특징 제어가 어려움
↓
StyleGAN: Disentanglement 향상
↑
PGGAN은 베이스라인으로 삼음.





Part 3 StyleGAN

Mapping Network

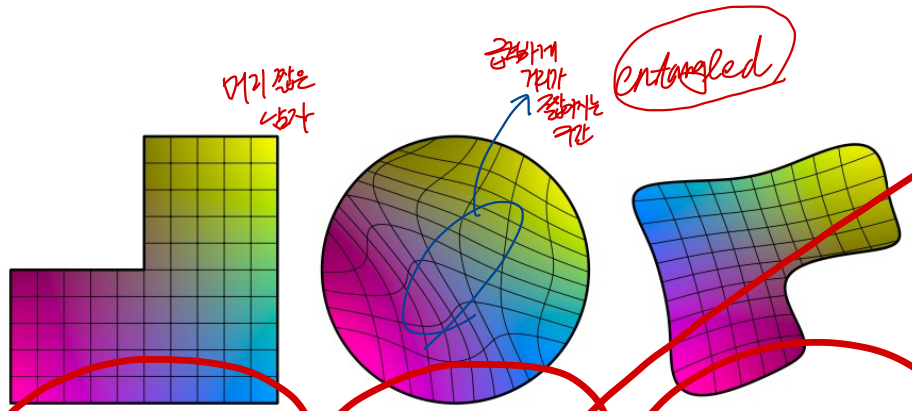
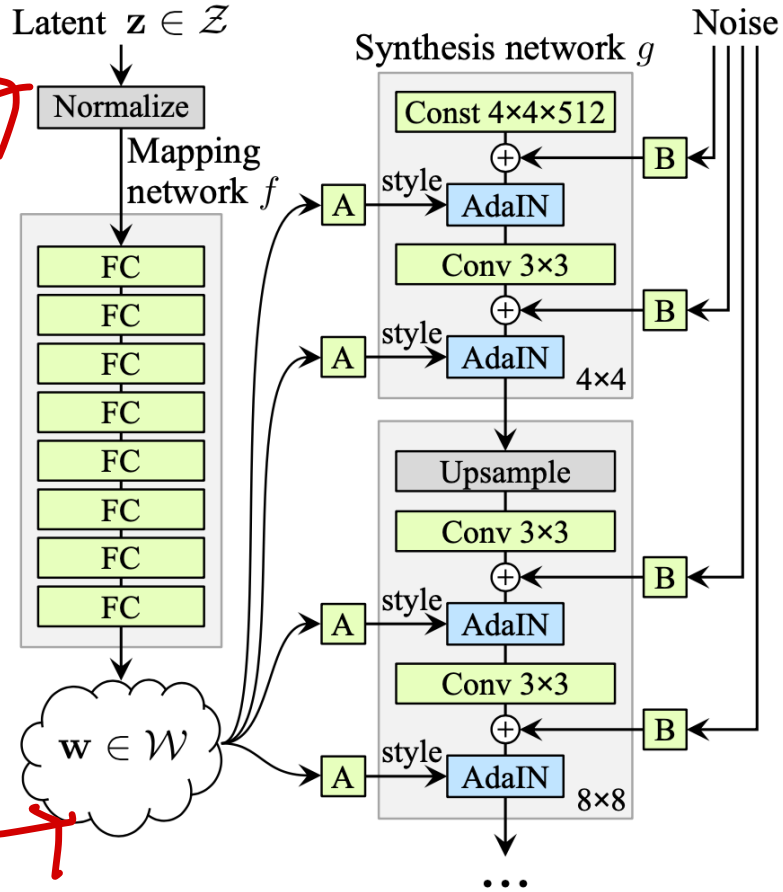
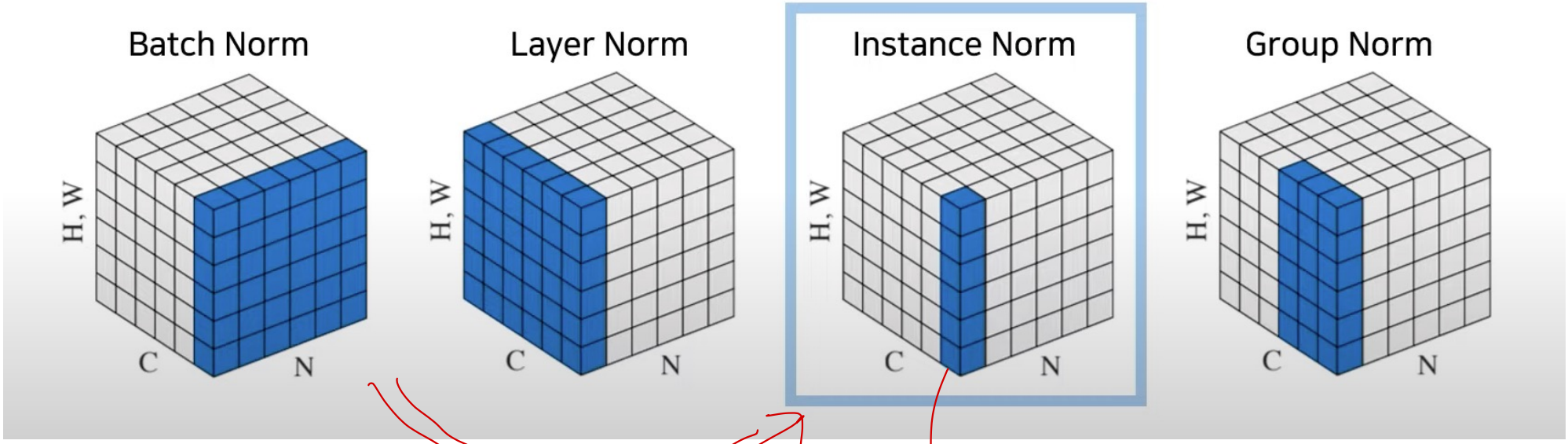


Figure 6. Illustrative example with two factors of variation (image features, e.g., masculinity and hair length). (a) An example training set where some combination (e.g., long haired males) is missing. (b) This forces the mapping from $\mathcal{Z}$ to image features to become curved so that the forbidden combination disappears in $\mathcal{Z}$ to prevent the sampling of invalid combinations. (c) The learned mapping from $\mathcal{Z}$ to $\mathcal{W}$ is able to "undo" much of the warping.

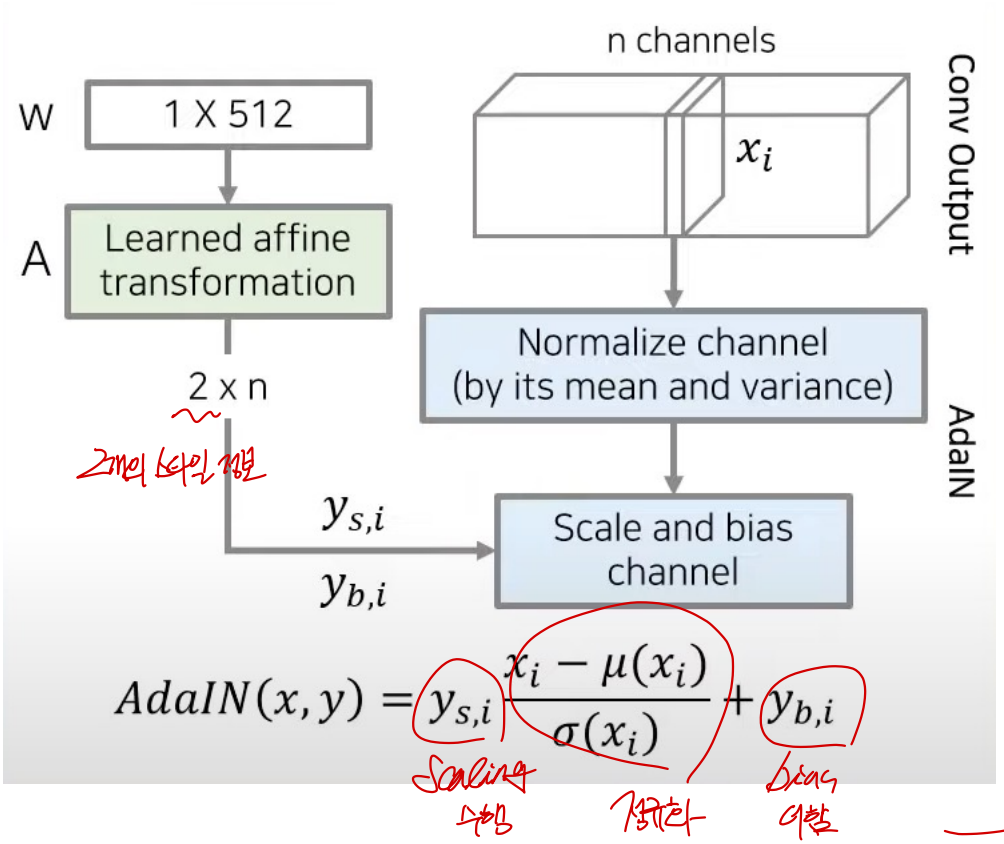


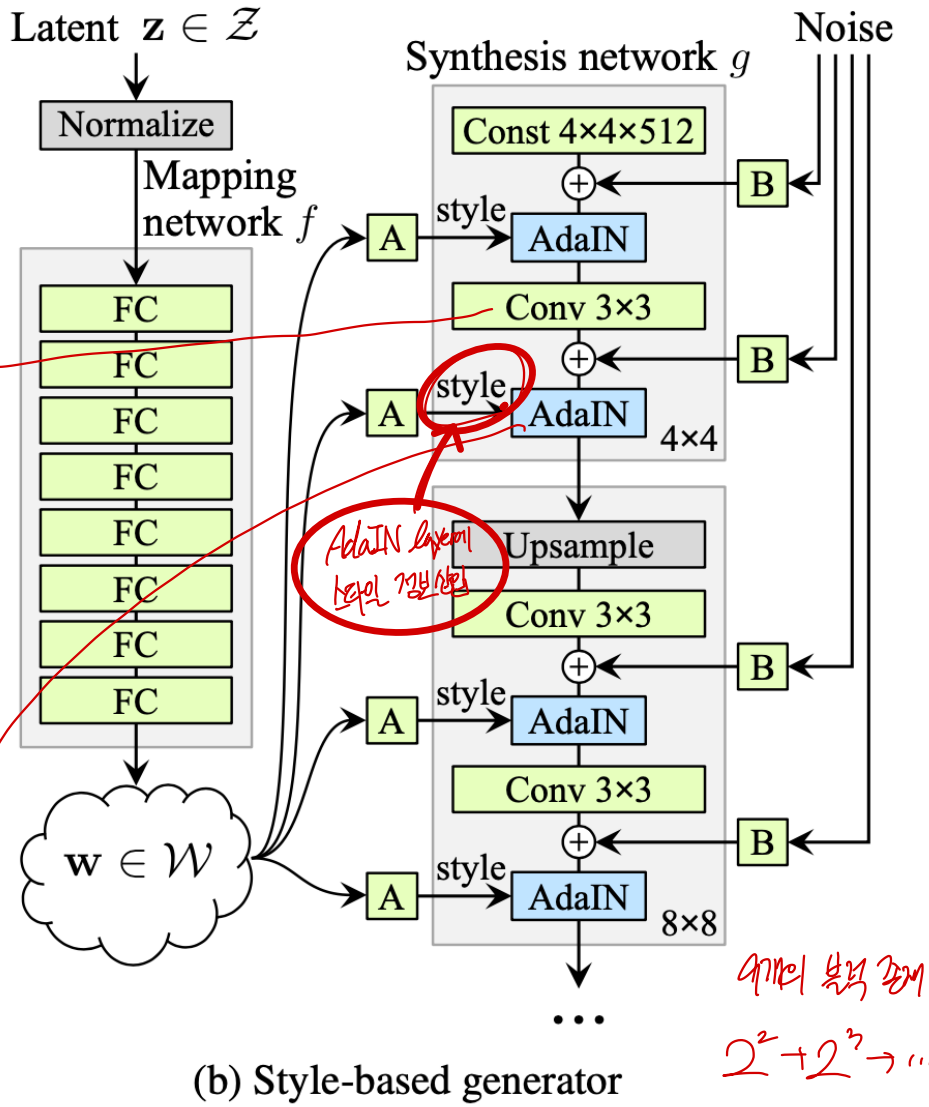
(b) Style-based generator

AdaIN



AdaIN

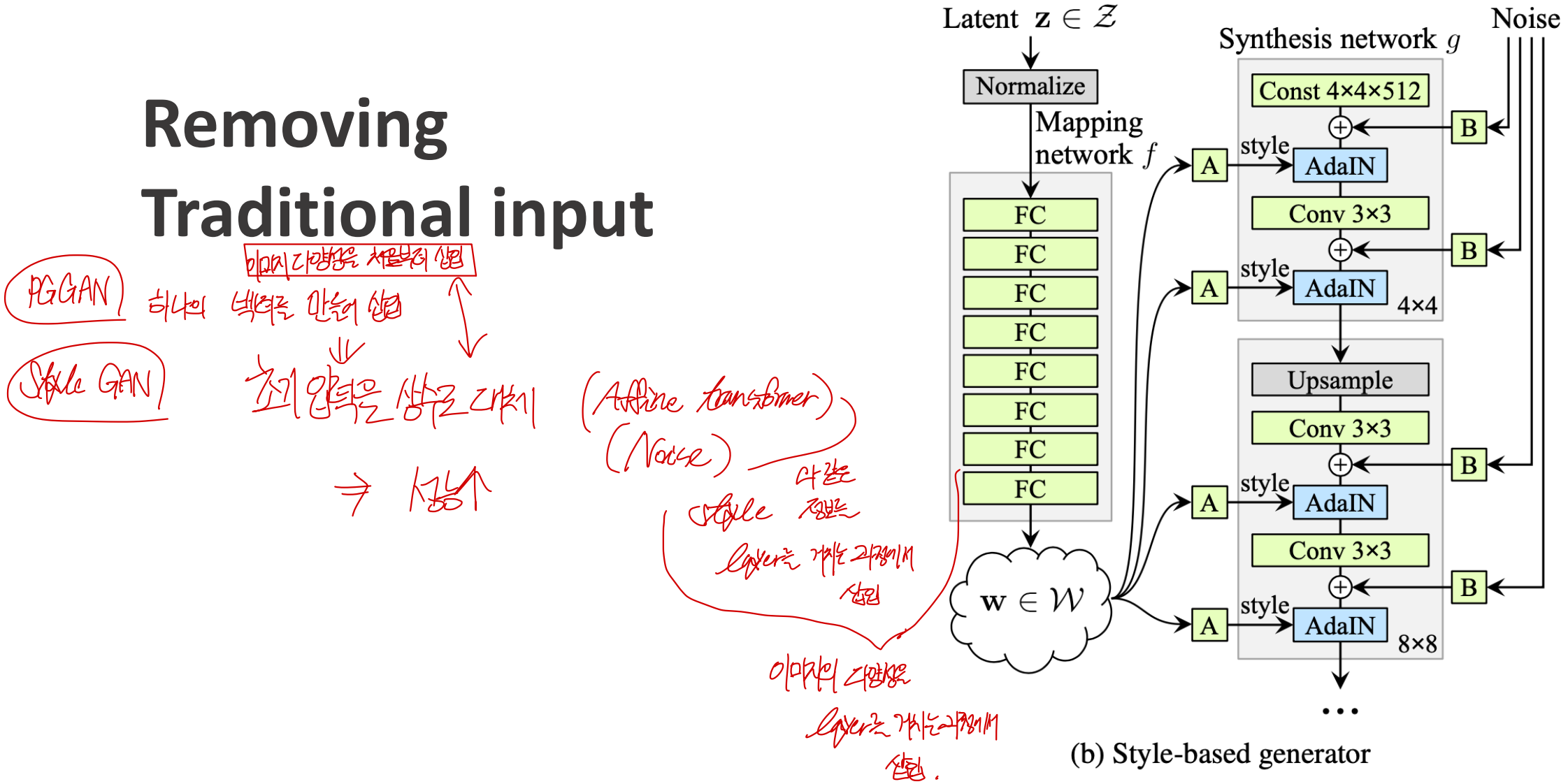




(b) Style-based generator

Part 3 StyleGAN

Removing Traditional input



Part 3 StyleGAN

Stochastic Variation

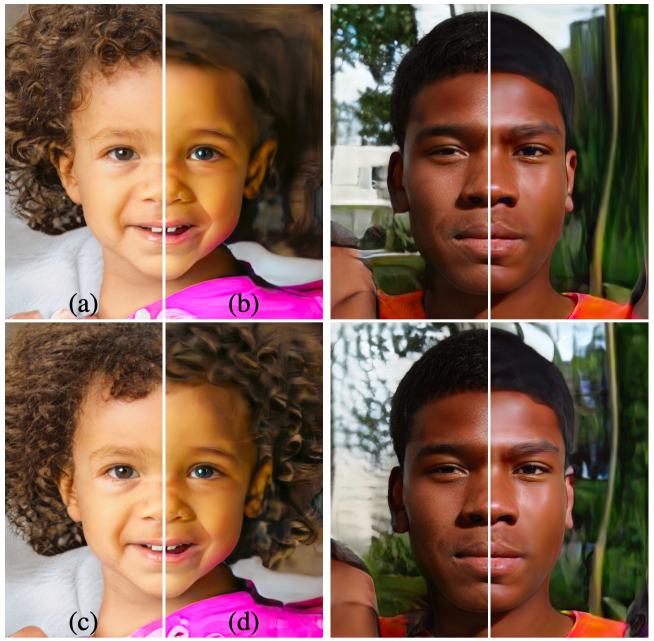
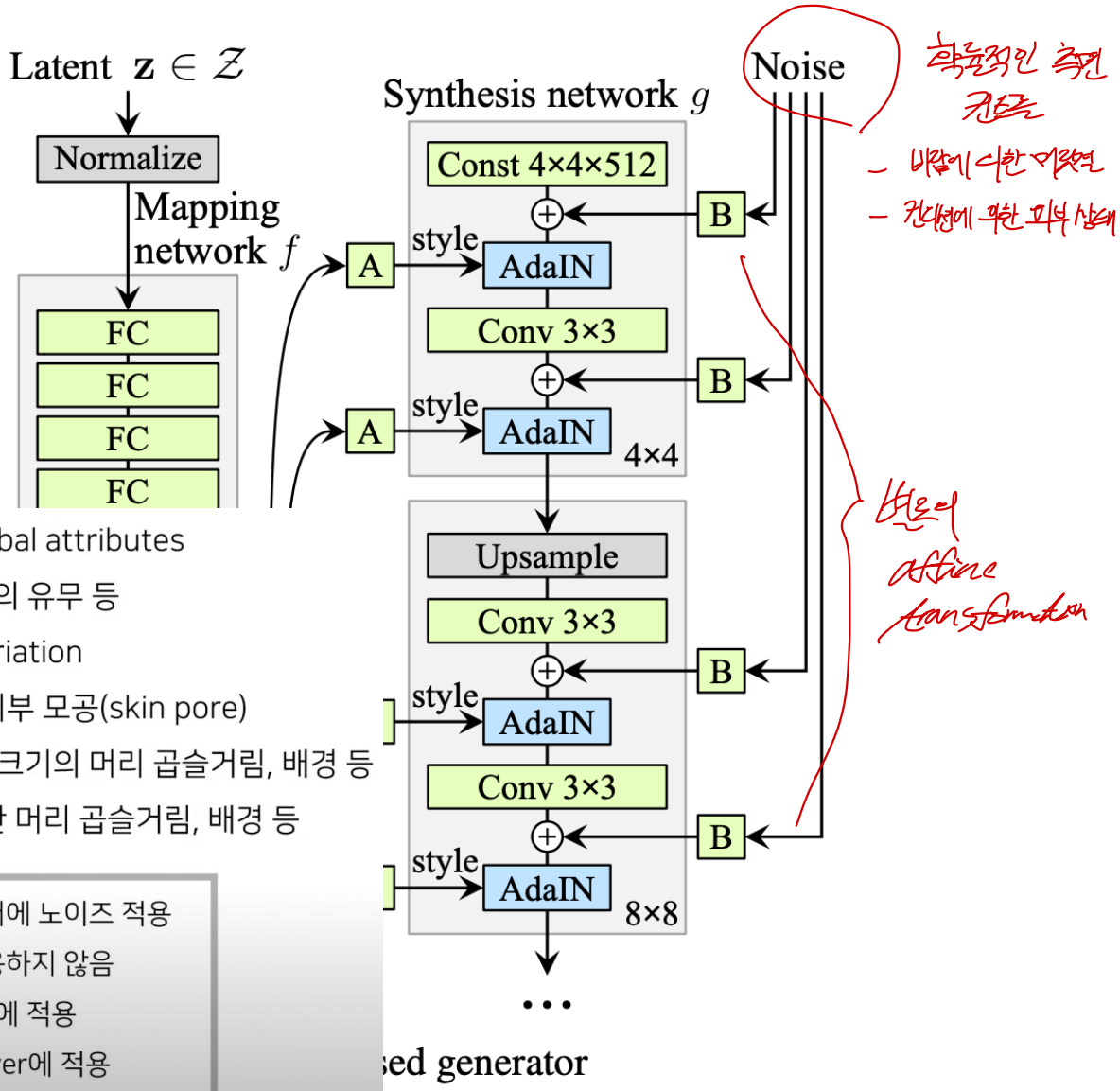


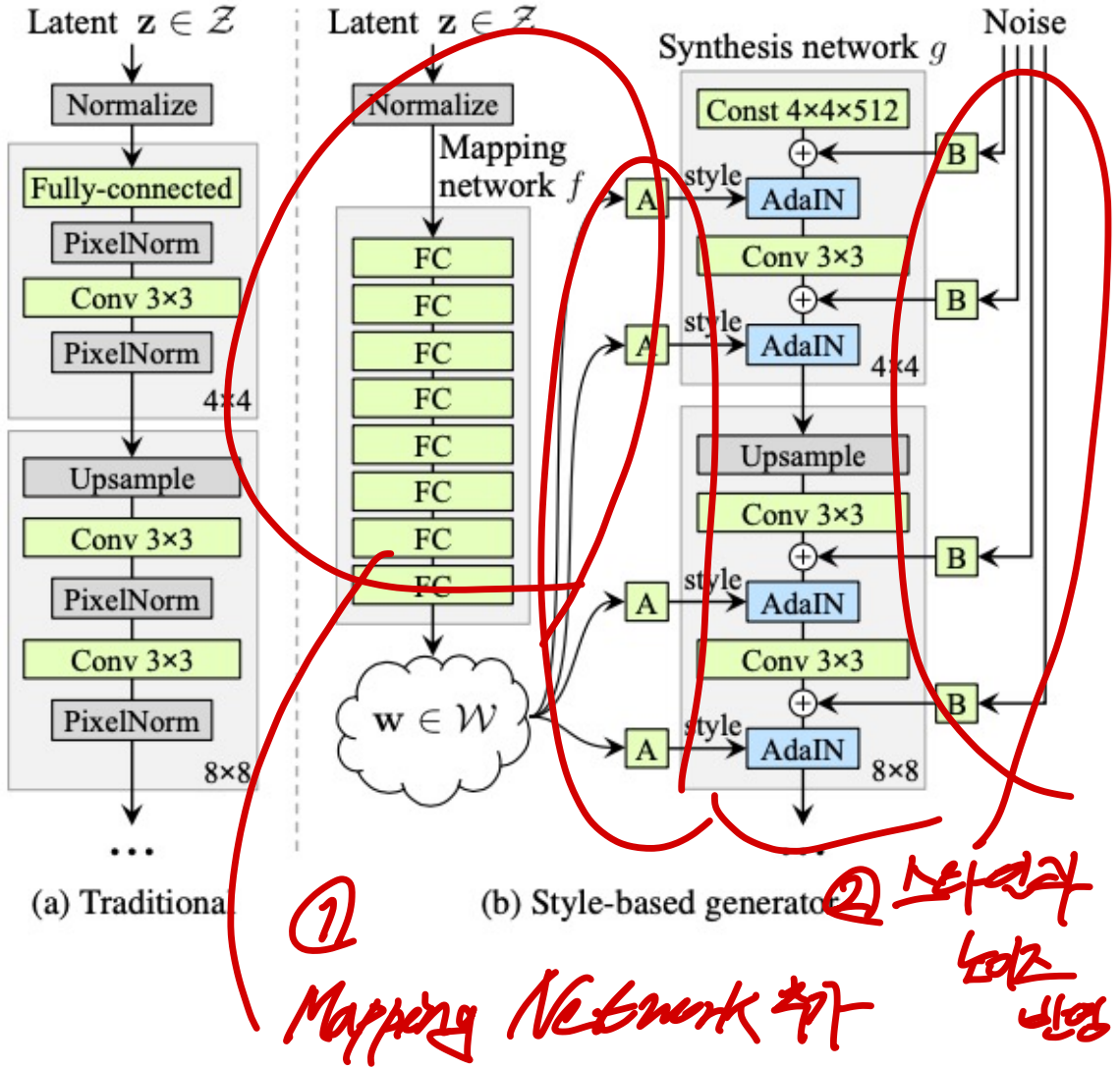
Figure 5. Effect of noise inputs at different layers of our generator. (a) Noise is applied to all layers. (b) No noise. (c) Noise in fine layers only (64^2 – 1024^2). (d) Noise in coarse layers only (4^2 – 32^2). We can see that the artificial omission of noise leads to featureless "painterly" look. Coarse noise causes large-scale curling of hair and appearance of larger background features, while the fine noise brings out the finer curls of hair, finer background detail, and skin pores.



- 스타일: high-level global attributes
  - 얼굴형, 포즈, 안경의 유무 등
- 노이즈: stochastic variation
  - 주근깨(freckle), 피부 모공(skin pore)
  - Coarse noise: 큰 크기의 머리 곱슬거림, 배경 등
  - Fine noise: 세밀한 머리 곱슬거림, 배경 등

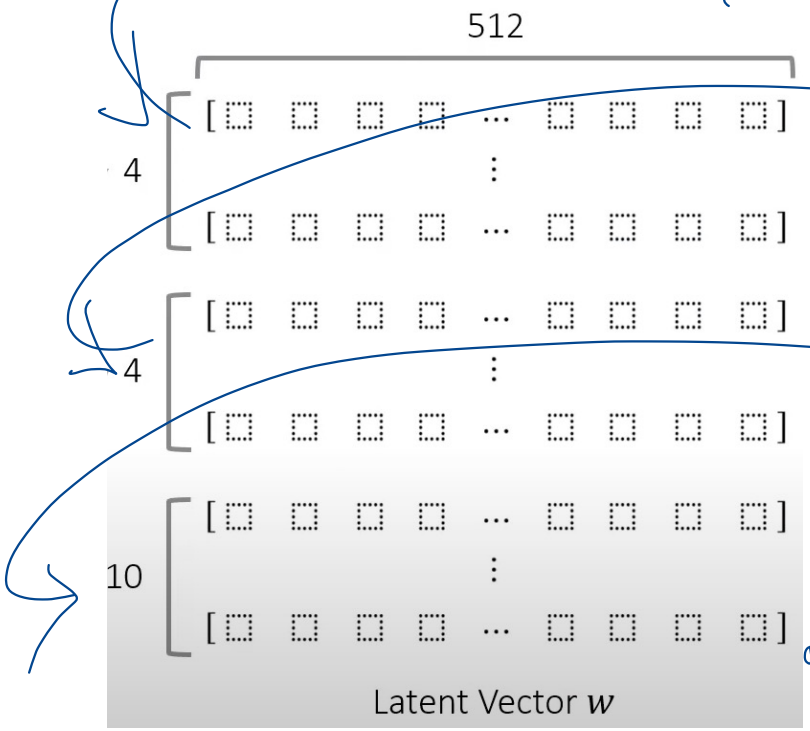
(a) 모든 레이어에 노이즈 적용
(b) 노이즈 적용하지 않음
(c) Fine layer에 적용
(d) Coarse layer에 적용

StyleGAN architecture: Disentanglement



Part 3 StyleGAN

Latent vector Meanings of StyleGAN



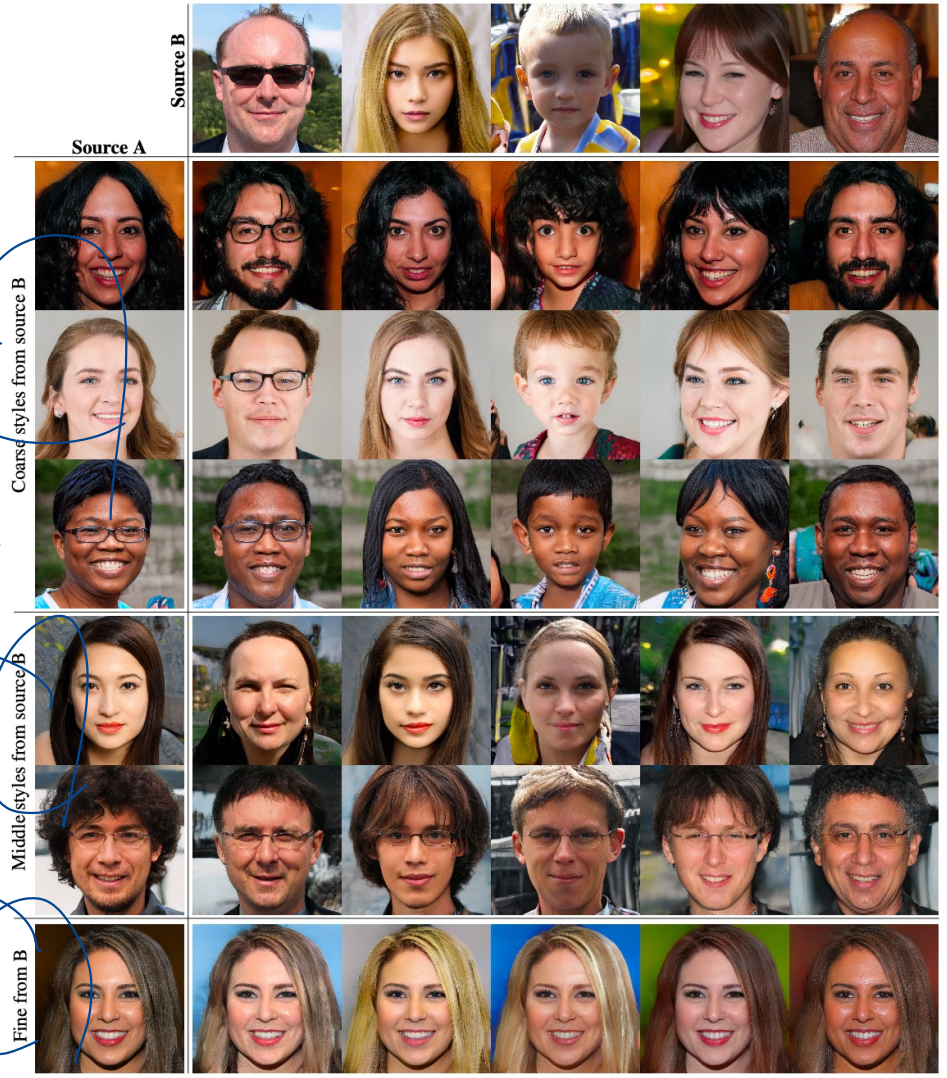
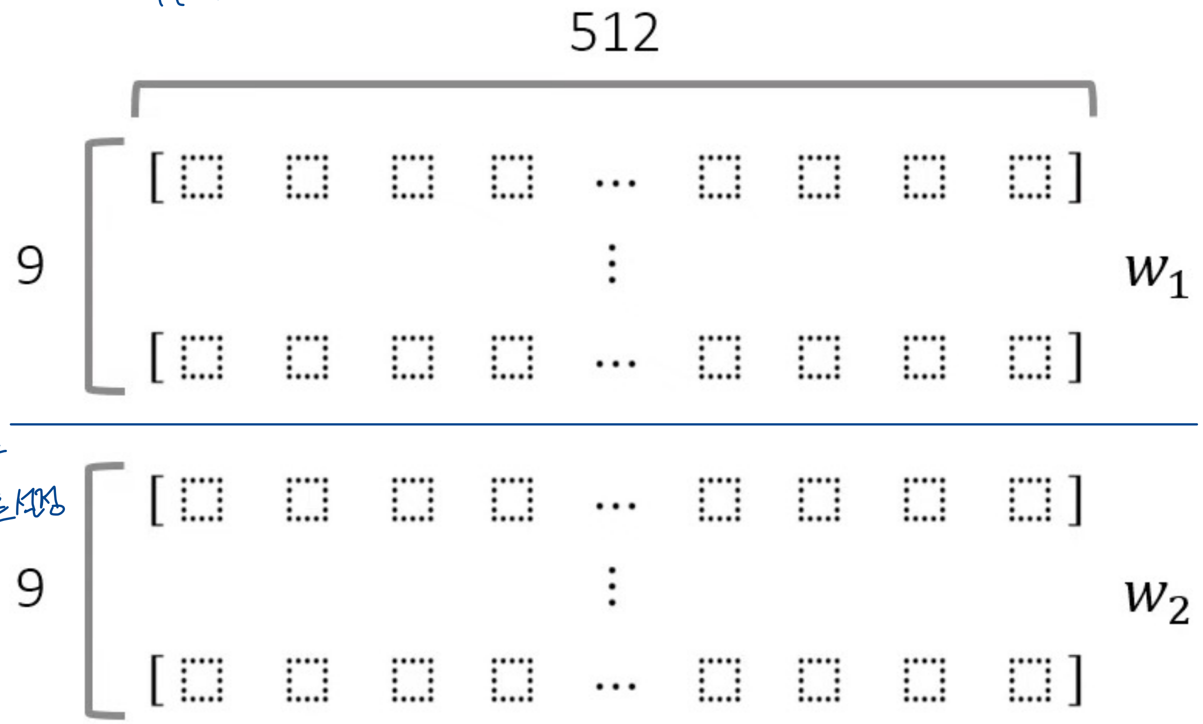


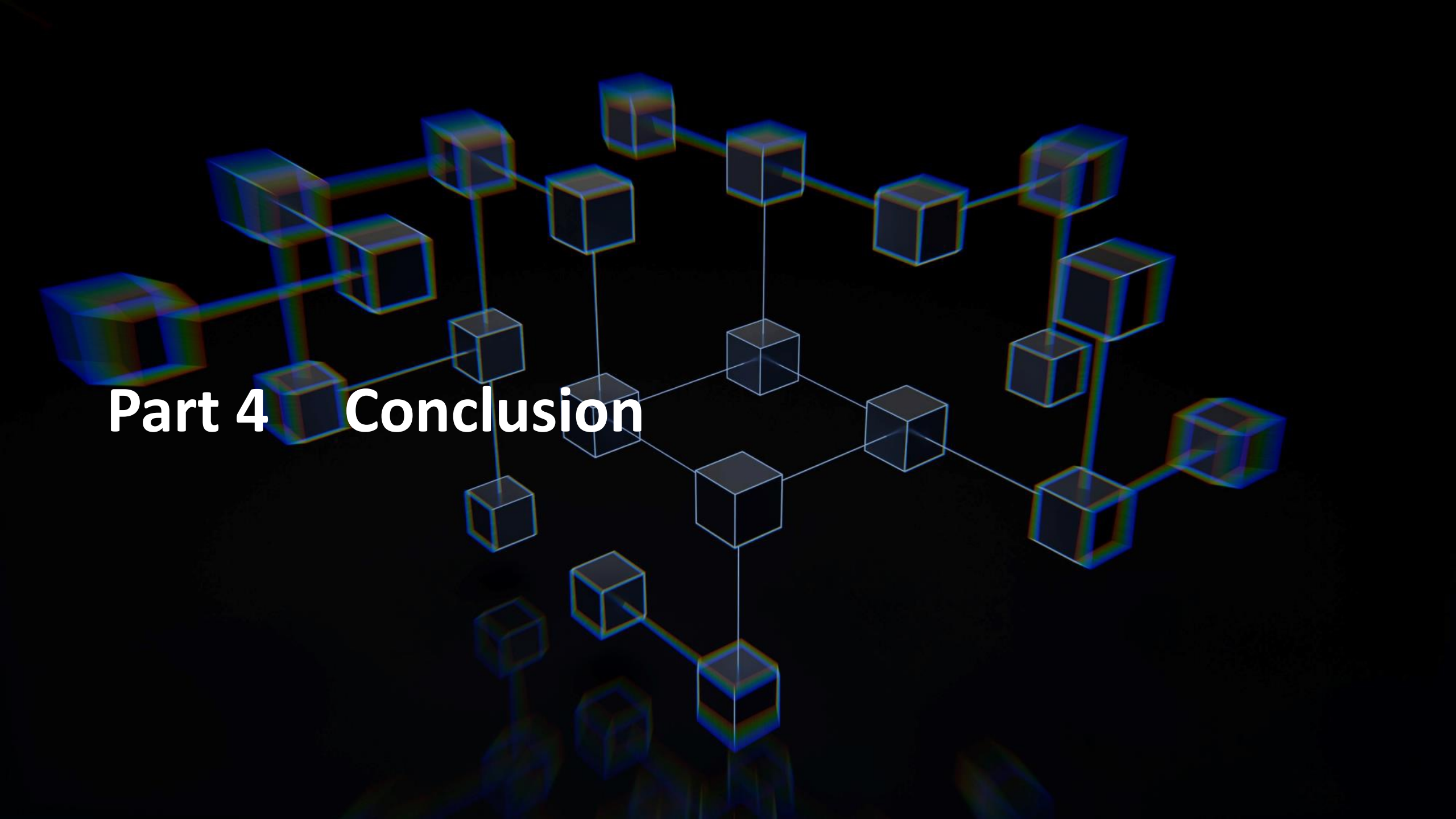
Figure 3. Two sets of images were generated from their respective latent codes (sources A and B); the rest of the images were generated by copying a specified subset of styles from source B and taking the rest from source A. Copying the styles corresponding to coarse spatial resolutions ($4^2 - 8^2$) brings high-level aspects such as pose, general hair style, face shape, and eyeglasses from source B, while all colors (eyes, hair, lighting) and finer facial features resemble A. If we instead copy the styles of middle resolutions ($16^2 - 32^2$) from B, we inherit smaller scale facial features, hair style, eyes open/closed from B, while the pose, general face shape, and eyeglasses from A are preserved. Finally, copying the fine styles ($64^2 - 1024^2$) from B brings mainly the color scheme and microstructure.

Style Mixing

Mixing regularization	Number of latents during testing			
	1	2	3	4
E 0%	4.42	8.22	12.88	17.41
50%	4.41	6.10	8.71	11.61
F 90%	**4.40**	**5.11**	6.88	9.03
100%	4.83	5.17	**6.63**	**8.40**

Table 2. FIDs in FFHQ for networks trained by enabling the mixing regularization for different percentage of training examples. Here we stress test the trained networks by randomizing 1 . . . 4 latents and the crossover points between them. Mixing regularization improves the tolerance to these adverse operations significantly. Labels E and F refer to the configurations in Table 1.





Part 4 Conclusion

Part 4

Conclusion

Based on both our results and parallel work by Chen et al. [6], it is becoming clear that the traditional GAN generator architecture is in every way inferior to a style-based design. This is true in terms of established quality metrics, and we further believe that our investigations to the separation of high-level attributes and stochastic effects, as well as the linearity of the intermediate latent space will prove fruitful in improving the understanding and controllability of GAN synthesis.

We note that our average path length metric could easily be used as a regularizer during training, and perhaps some variant of the linear separability metric could act as one, too. In general, we expect that methods for directly shaping the intermediate latent space during training will provide interesting avenues for future work.

GAN보다 좋은 성능

이 두개가 잘 분리됨.

본문에서 제안한 퍼셉트론 path length는 Metric 자체는 loss 함수로 구성해서 Metric 자체는 최적화를 학습 안됨. 부록참조