

# *GAN을 이용한 이미지 변환*

학교	경상대학교	학과	수학과
소속	수DA쟁이		
이름	조한별, 최우철, 허지혜, 이수빈		

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# 1. Motivation

## 1. Motivation

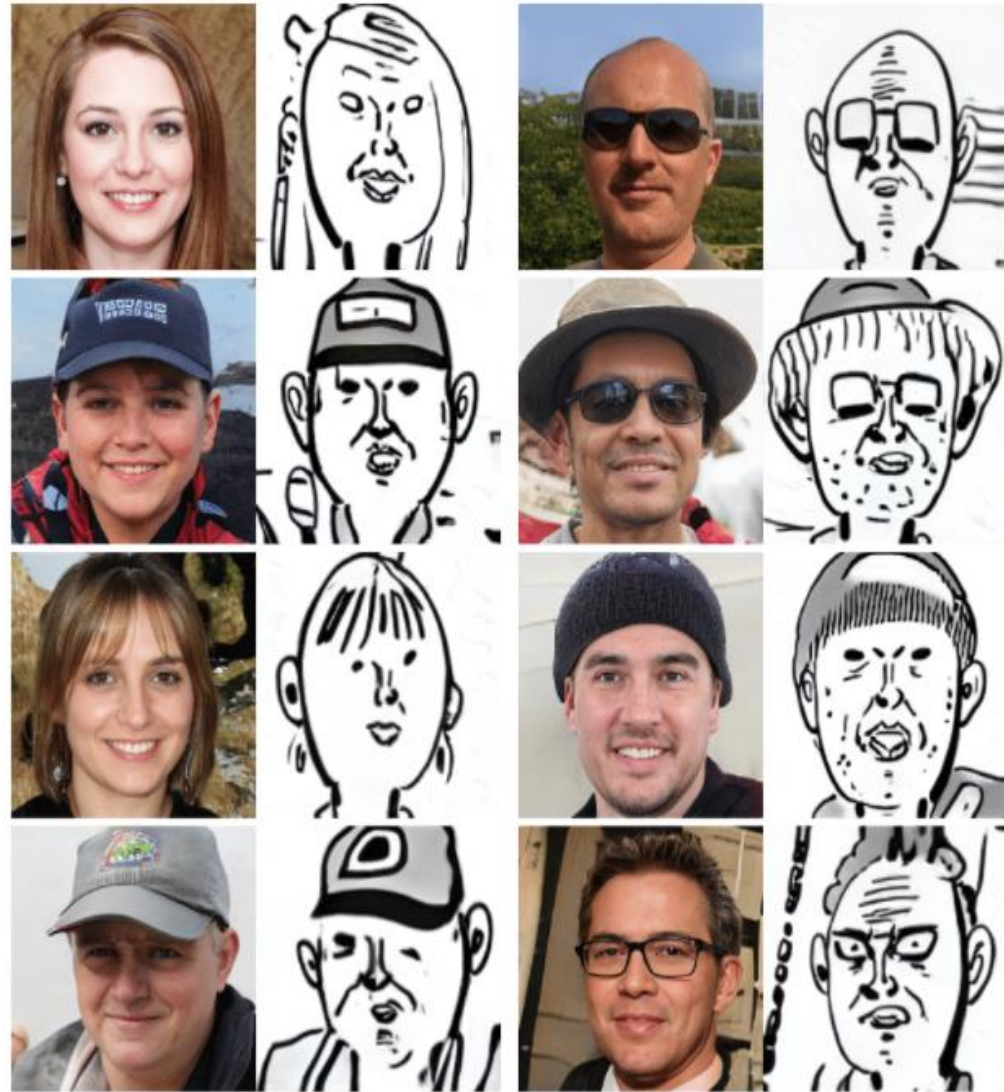
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# 1. Motivation



웹툰 작가 이말년 그림체로 변환한 결과

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# 1. Motivation



어플 SNOW 사진

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# 1. Motivation



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# 1. Motivation

## [리얼 실리콘밸리] 넷플릭스가 지브리에 2조 원 베틀한 이유

작품당 1130억 원으로 알려져...'디즈니 플러스'의 대항마 기대

" 비즈한국 "

## 넷플릭스가 지브리에 2조 썼다고?... '억 소리' 나는 콘텐츠 투자 동향

✎ 김임수 기자 | ⓒ 승인 2020.03.12 16:27



" TechM "

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## 2. GAN

## 2. GAN

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### What is GAN?

- Generative Adversarial Network : 생성적 적대 신경망

Generator : 가짜 이미지를 생성

Discriminator : 이미지가 진짜인지 판별

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## 2. GAN

### Generative Adversarial Network



$x$  : 실제 이미지



$G(z)$  : 만들어진 가짜 이미지

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## 3. Network Architecture

### 3. Network Architecture

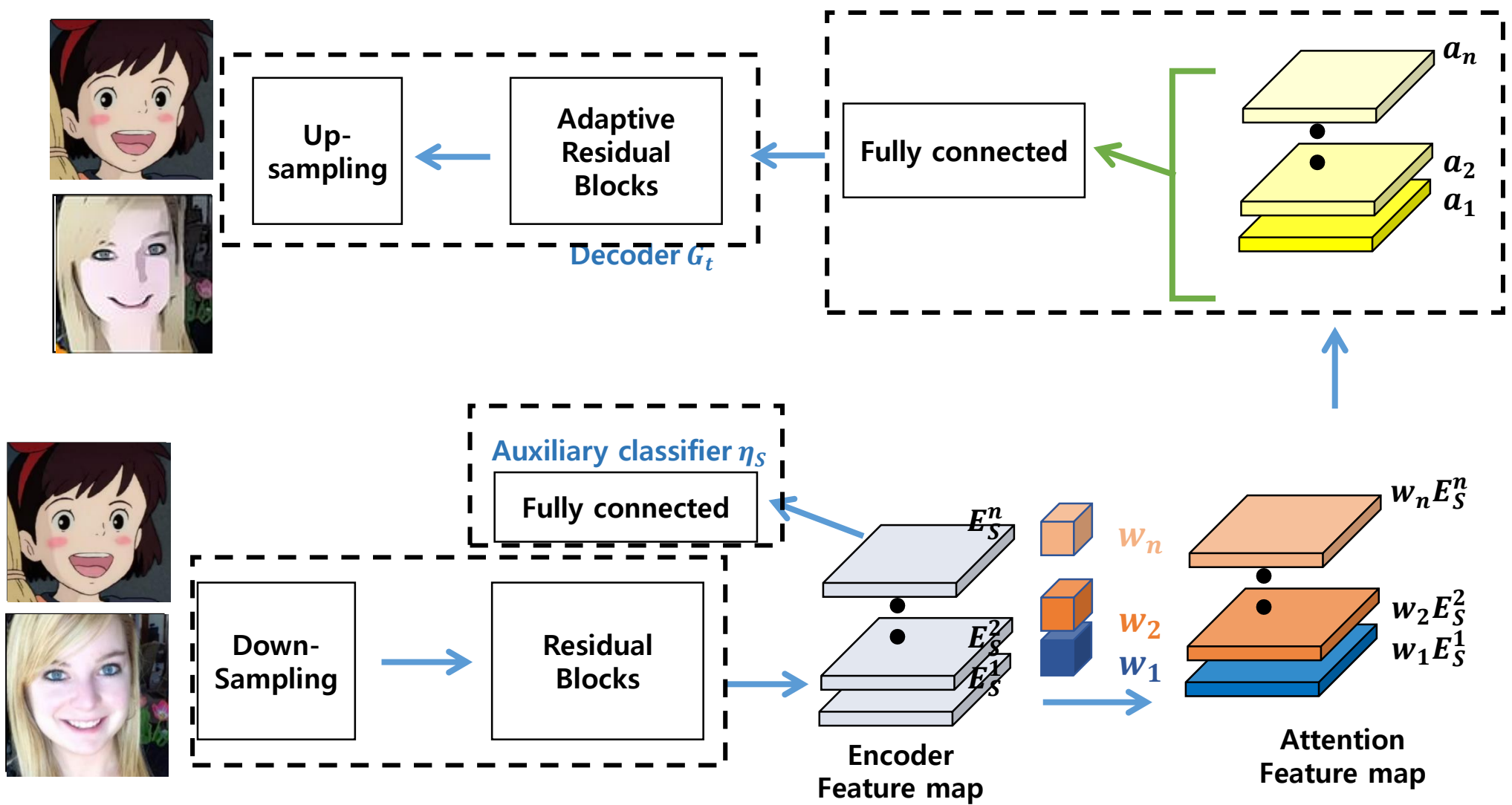
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### 3. Network Architecture - Generator



1 Motive

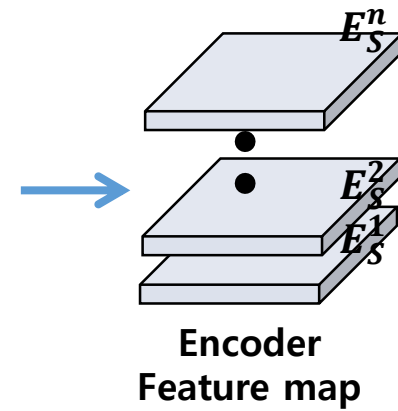
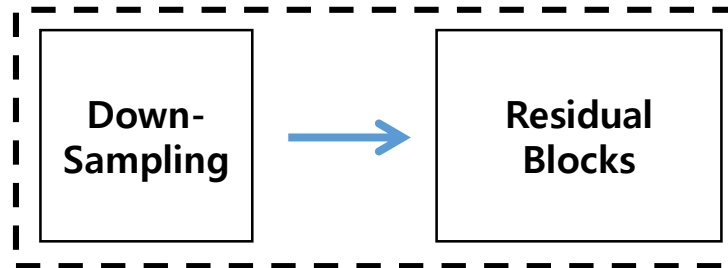
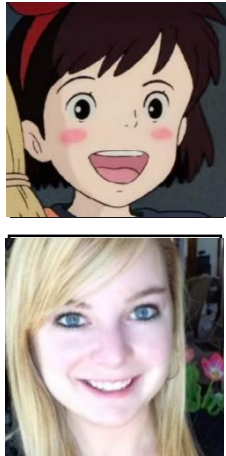
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### 3. Network Architecture - Generator

#### Generator - Encoder



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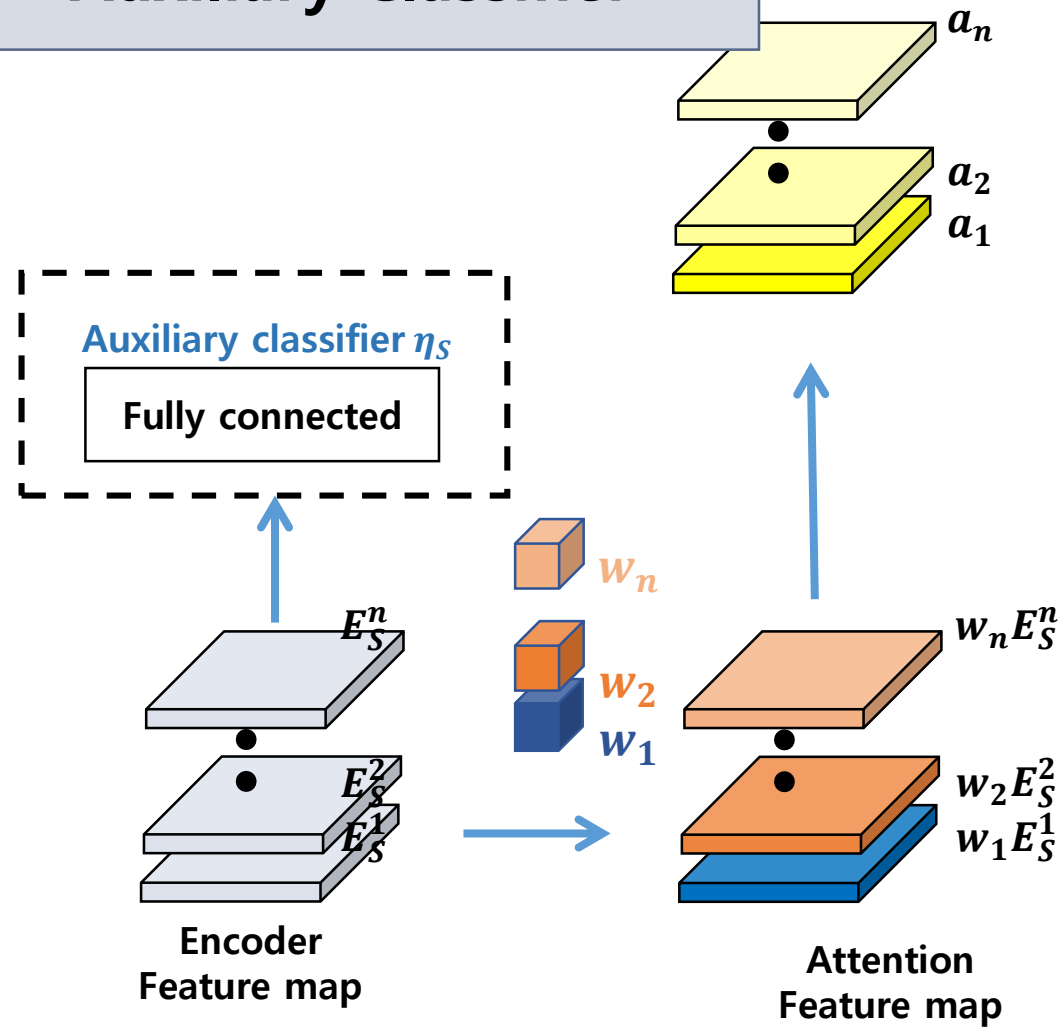
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### 3. Network Architecture - Generator

#### Generator - Auxiliary Classifier



1 Motive

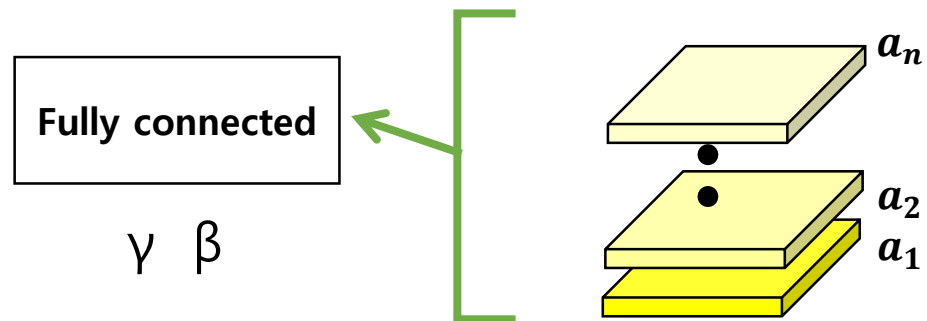
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### 3. Network Architecture - Generator

#### Generator - Fully connected



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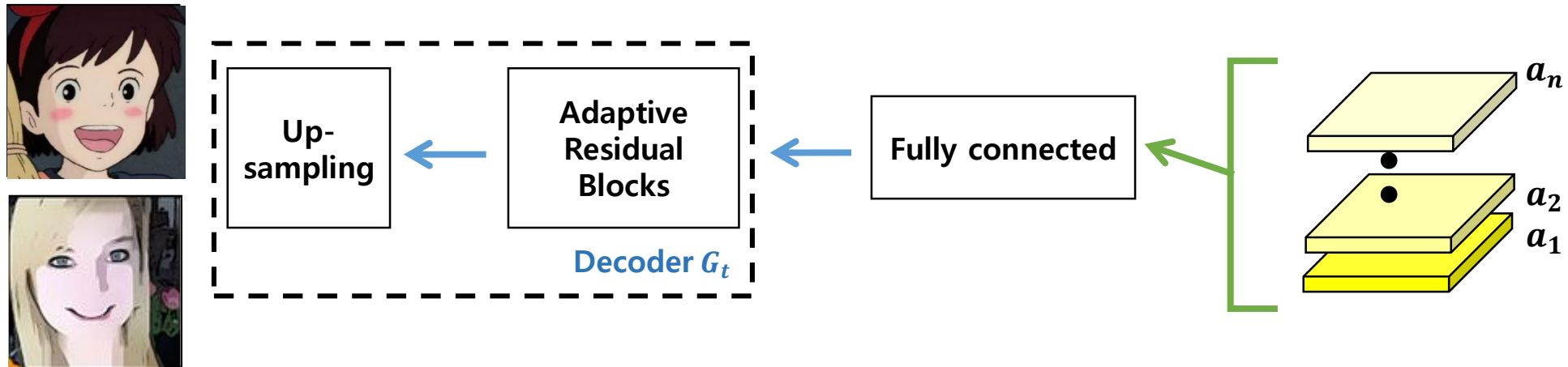
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### 3. Network Architecture - Generator

#### Generator - Decoder



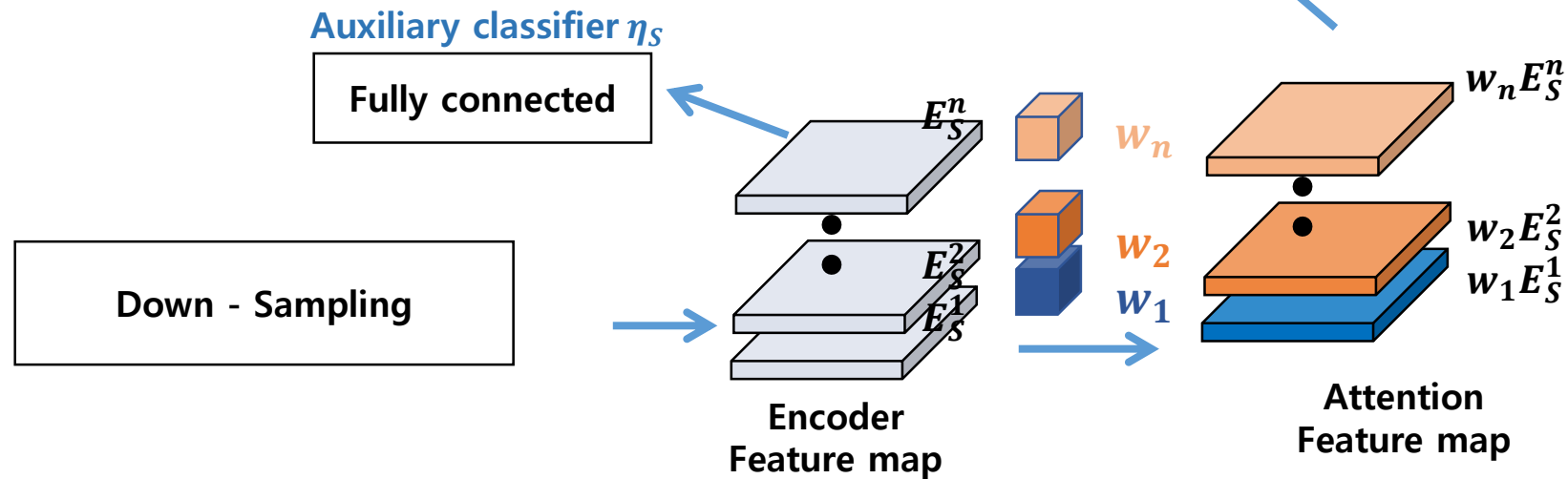
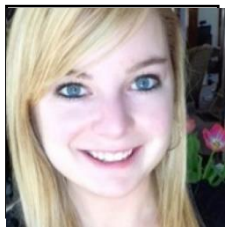
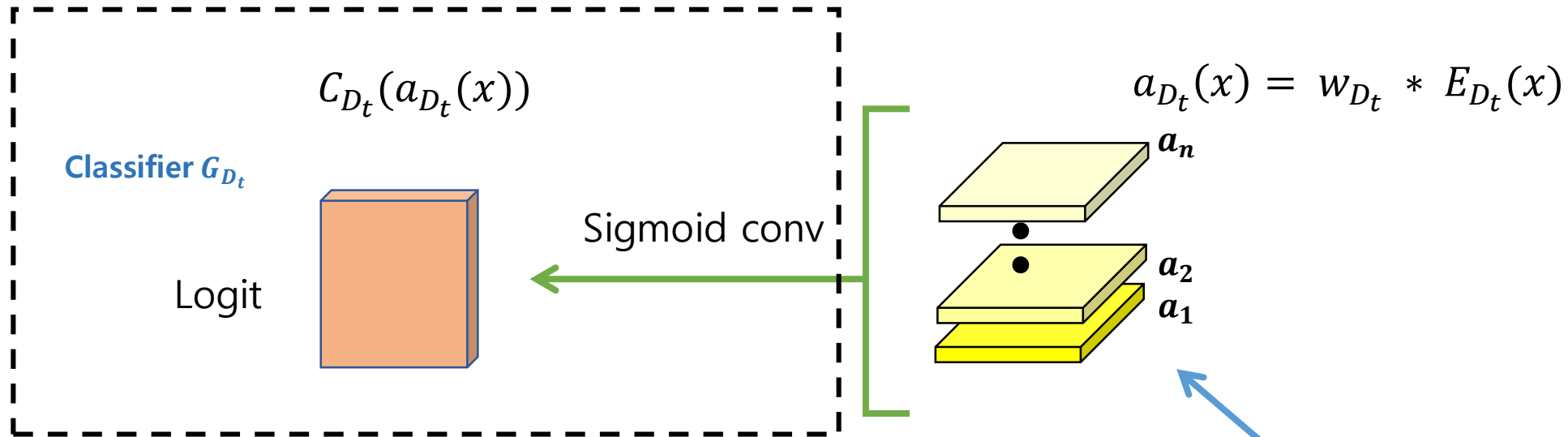
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### 3. Network Architecture - Discriminator



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### 3. Network Architecture – Loss Function

#### Adversarial Loss

$$L_{lsGAN}^{s \rightarrow t} = \left( \mathbb{E}_{x \sim X_t} \left[ (D_t(x))^2 \right] + \mathbb{E}_{x \sim X_s} \left[ \left( 1 - D_t(G_{s \rightarrow t}(x)) \right)^2 \right] \right).$$

#### Cycle Loss

$$L_{cycle}^{s \rightarrow t} = \mathbb{E}_{x \sim X_s} [|x - G_{t \rightarrow s}(G_{s \rightarrow t}(x))|_1].$$

#### Identity Loss

$$L_{identity}^{s \rightarrow t} = \mathbb{E}_{x \sim X_t} [|x - G_{s \rightarrow t}(x)|_1].$$

#### CAM Loss

$$L_{cam}^{s \rightarrow t} = -(\mathbb{E}_{x \sim X_s} [\log(\eta_s(x))] + \mathbb{E}_{x \sim X_t} [\log(1 - \eta_s(x))]),$$

$$L_{cam}^{D_t} = \mathbb{E}_{x \sim X_t} [(\eta_{D_t}(x))^2] + \mathbb{E}_{x \sim X_s} \left[ \left( 1 - \eta_{D_t}(G_{s \rightarrow t}(x)) \right)^2 \right].$$

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### 3. Network Architecture – Loss Function

#### Adversarial Loss

변환된 이미지가 캐릭터 이미지의 형태와 비슷하도록 규제

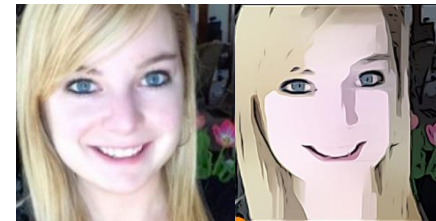
S- 사람이미지  
T- 캐릭터이미지

G입장

$$L_{ls\text{gan}}^{s \rightarrow t} = \left( \mathbb{E}_{x \sim X_t} \left[ \frac{0}{1} \left( D_t(x) \right)^2 \right] + \mathbb{E}_{x \sim X_s} \left[ \frac{1}{0} \left( 1 - D_t(G_{s \rightarrow t}(x)) \right)^2 \right] \right).$$

= G ↓  
= D ↑

D입장



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### 3. Network Architecture – Loss Function

#### Cycle Loss

모델의 형태를 보존하기 위해 CycleGAN 컨셉 적용

G입장

$$L_{cycle}^{s \rightarrow t} = \mathbb{E}_{x \sim X_s} \left[ \frac{\overbrace{|x - G_{t \rightarrow s}(G_{s \rightarrow t}(x))|}^0}{\underbrace{1}} \right]. \quad \begin{matrix} = G \downarrow \\ = D \uparrow \end{matrix}$$

D입장

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### 3. Network Architecture – Loss Function

#### Identity Loss

Input image와 output image의 색상 분포가 비슷하도록  
G에 Identity consistency 제약을 적용

G입장

$$L_{identity}^{s \rightarrow t} = \mathbb{E}_{x \sim X_t} [ |x - \underbrace{G_{s \rightarrow t}(x)}_{\text{원본 이미지와 비슷하게}}| ].$$

= G ↓  
= D ↑

원본 이미지와 다르게

D입장

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### 3. Network Architecture – Loss Function

#### CAM Loss

보조분류기에서  $G_{s \rightarrow t}$ 와  $D_t$ 에 대해 현재 상태에서 큰 차이를 파악해 규제

$\eta_s$  : 이미지가 s일 확률  
 $\eta_t$  : 이미지가 t일 확률

G입장

$$L_{cam}^{s \rightarrow t} = -(\mathbb{E}_{x \sim X_s} [\log(\frac{0}{1}(\eta_s(x))) ] + \mathbb{E}_{x \sim X_t} [\log(\frac{1}{0}(1 - \eta_s(x)))])$$

**= G ↓**  
**= D ↑**

D입장

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### 3. Network Architecture – Loss Function

#### CAM Loss

보조분류기에서  $G_{s \rightarrow t}$ 와  $D_t$ 에 대해 현재 상태에서 큰 차이를 파악해 규제

$\eta_s$  : 이미지가 s일 확률  
 $\eta_t$  : 이미지가 t일 확률

G입장

$$L_{cam}^{D_t} = \mathbb{E}_{x \sim X_t} \left[ \frac{0}{1} (\eta_{D_t}(x))^2 \right] + \mathbb{E}_{x \sim X_s} \left[ \left( 1 - \frac{1}{0} \eta_{D_t}(G_{s \rightarrow t}(x)) \right)^2 \right]$$

= G ↓  
= D ↑

D입장

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### 3. Network Architecture – Loss Function

$$L_{lsgan} = L_{lsgan}^{s \rightarrow t} + L_{lsgan}^{t \rightarrow s}$$

$$\text{Loss Fuction} = \lambda_1 L_{lsgan} + \lambda_2 L_{cycle} + \lambda_3 L_{identity} + \lambda_4 L_{cam}$$

$$(\lambda_1 = 1, \lambda_2 = 10, \lambda_3 = 10, \lambda_4 = 1000)$$

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## 4. Result & Compliment

### 4. Result & Compliment

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*GAN*

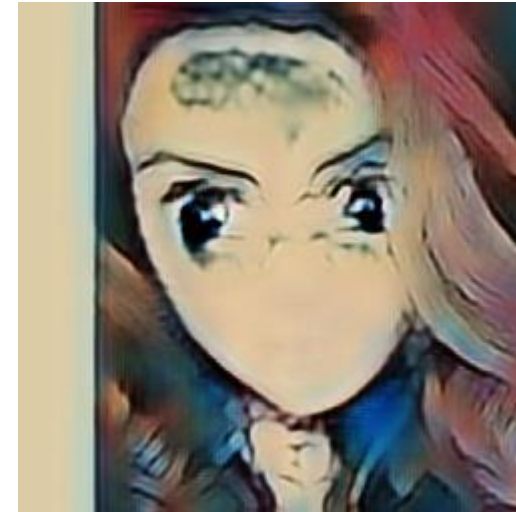
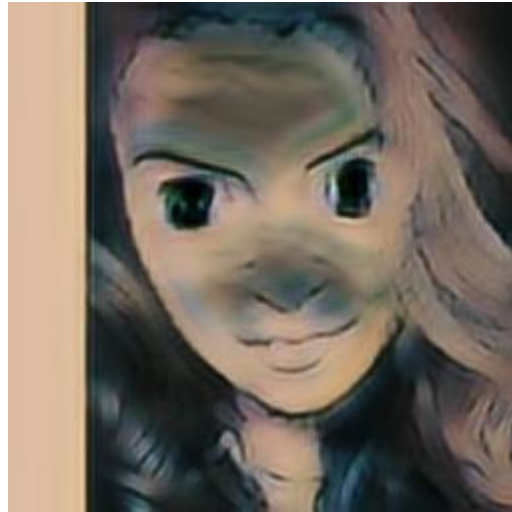
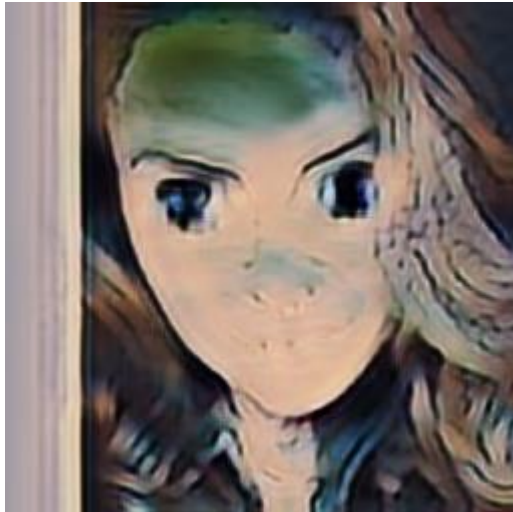
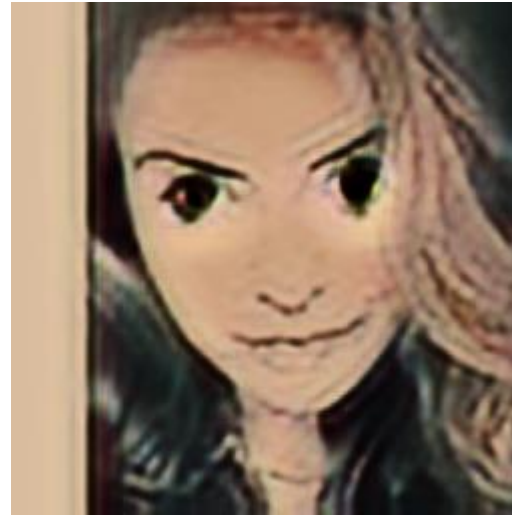
3

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## 4. Result & Compliment



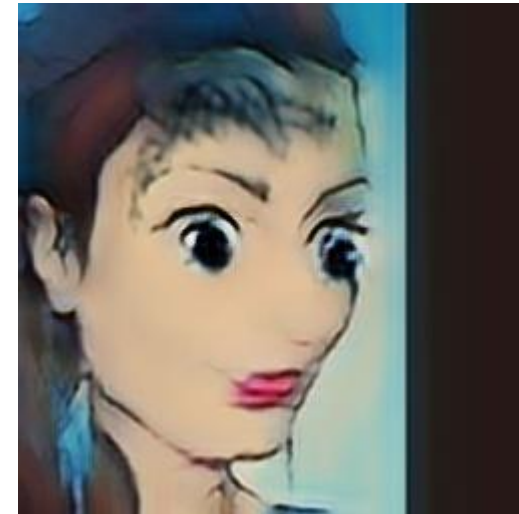
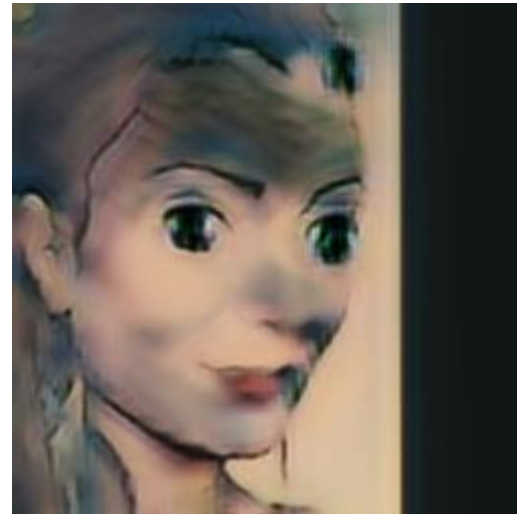
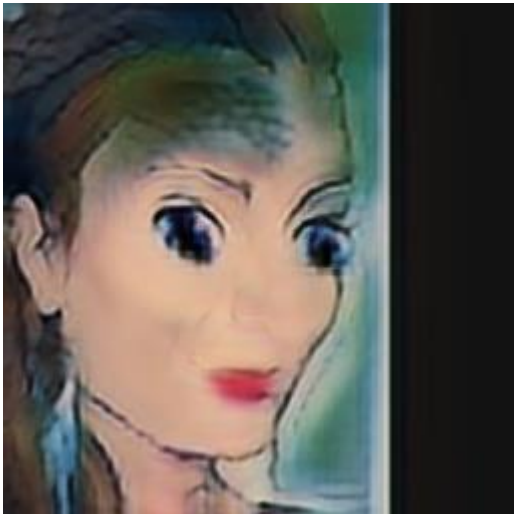
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## 4. Result & Compliment



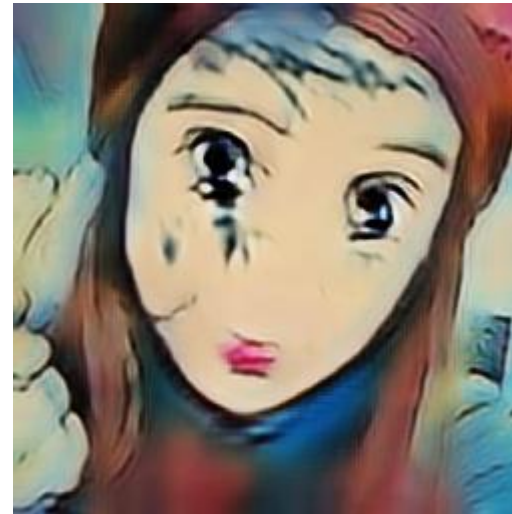
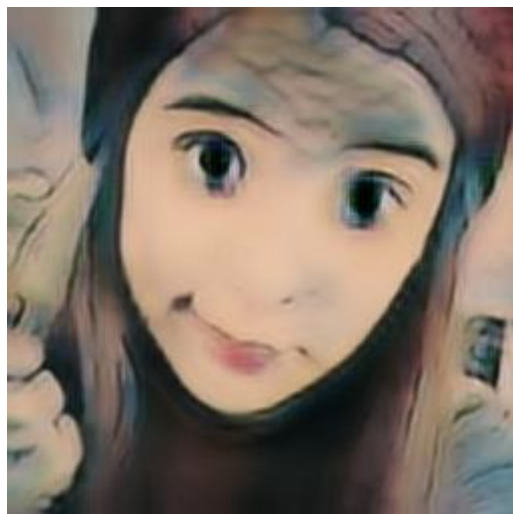
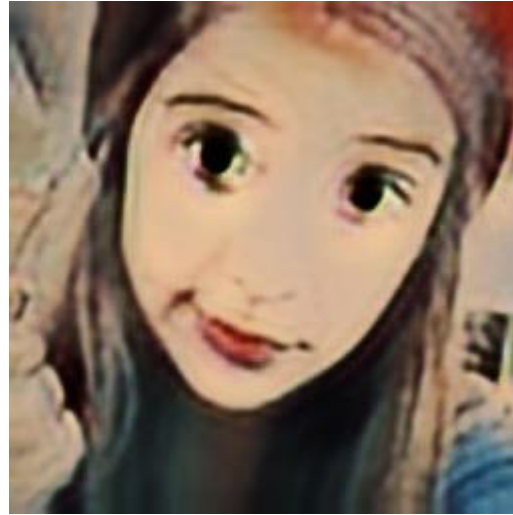
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## 4. Result & Compliment



1 *Motive*

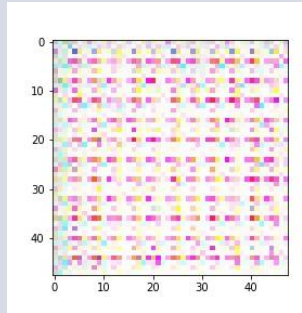
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## 4. Result & Compliment



```
807.7642 d_loss: 3.05394506  
929.2178 d_loss: 2.92211246  
057.1874 d_loss: 3.24292827  
185.5358 d_loss: 2.75377941  
313.3165 d_loss: 3.40126085
```

Dataset의 일관성

Data양

코드 최적화

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## 5. References

- [1] [리얼 실리콘밸리] 넷플릭스가 지브리에 2조 원 베팅한 이유,  
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- [2] 넷플릭스가 지브리에 2조 썼다고?... '억 소리' 나는 콘텐츠 투자 동향,  
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- [4] Kim, Junho, et al. "U-gat-it: unsupervised generative attentional networks with adaptive layer-instance normalization for image-to-image translation." arXiv preprint arXiv:1907.10830 (2019).

Q & A