GAN을 이용한 이미지 변환

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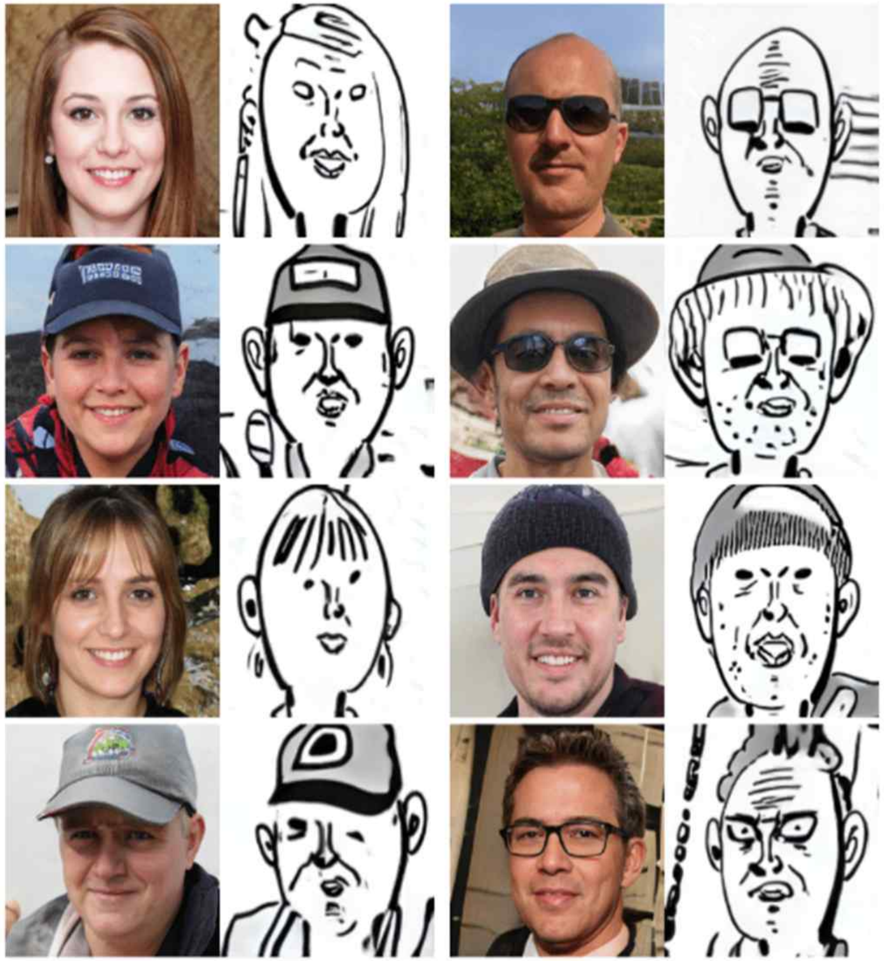
1. Motive

1. Motive



웹툰 작가 이말년 그림체로 변환한 결과

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1. Motive

SNOW 사진

1 *Motive*

2 *GAN*

3 *Network Architecture*

4 *Result & Compliment*

1. Motive

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1. Motive

[리얼 실리콘밸리] 넷플릭스가 지브리에 2조 원 베팅한 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

가 가

" TechM "

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2. GAN

1 *Motive*
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2. GAN

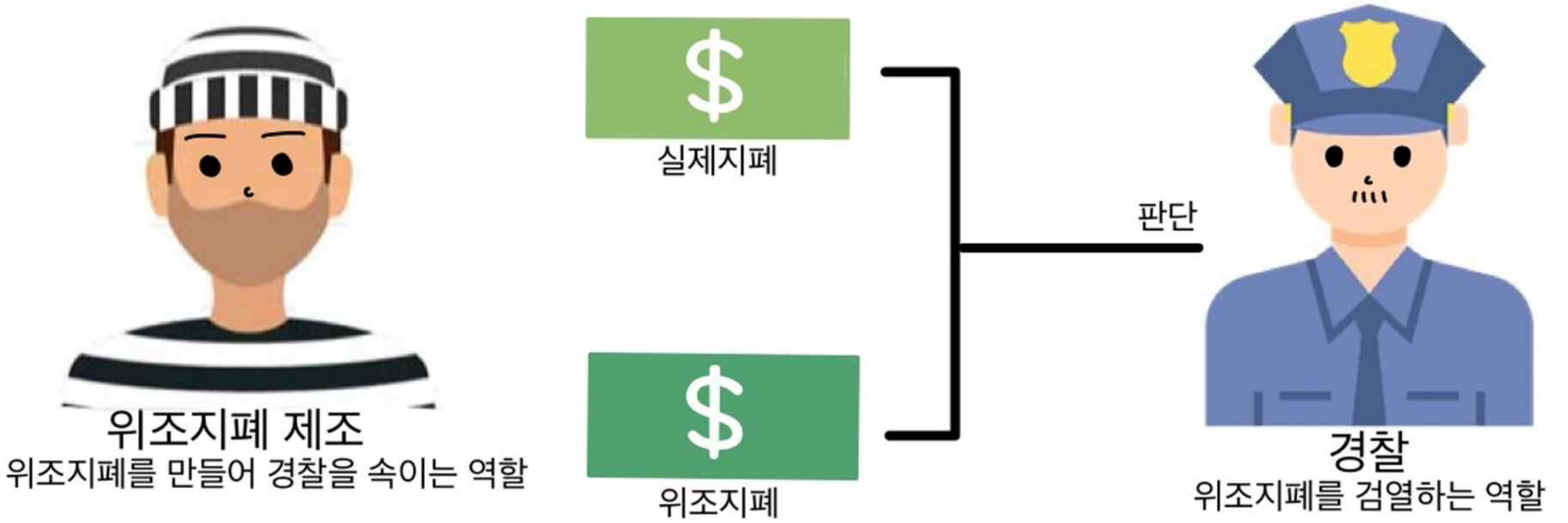
What is GAN?

- Generative Adversarial Network : 생성적 적대 신경망

  Generator : 가짜 이미지를 생성

  Discriminator : 이미지가 진짜인지 판별

2. GAN



Generator

Discriminator

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2. GAN

Generative Adversarial Network

X : 실제이미지

Discriminator(D) → D(x)

Z → Generator(G) →

→ D → D(G(z))

G(z) : 만들어진 가짜 이미지

3. Network Architecture

1 Motive

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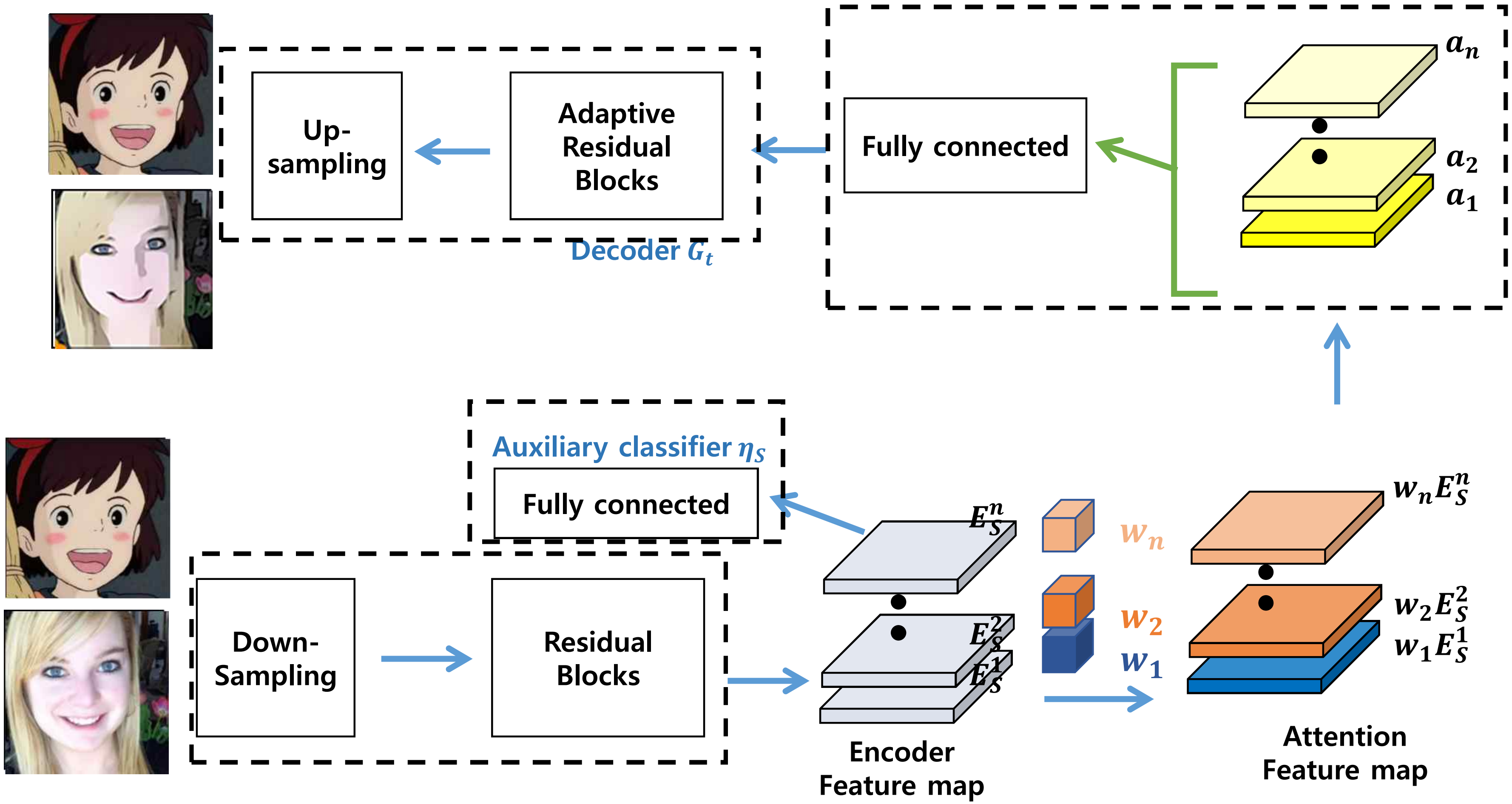
3. Network Architecture - Generator



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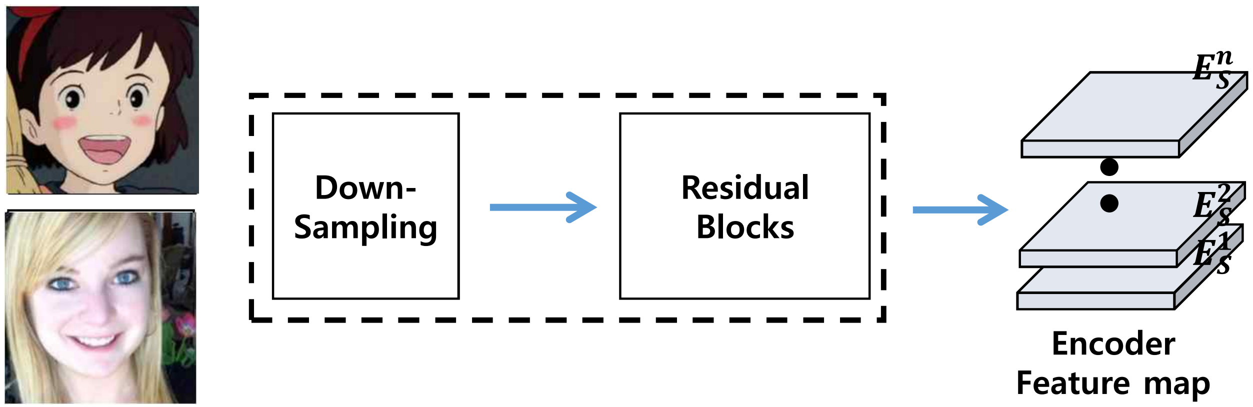
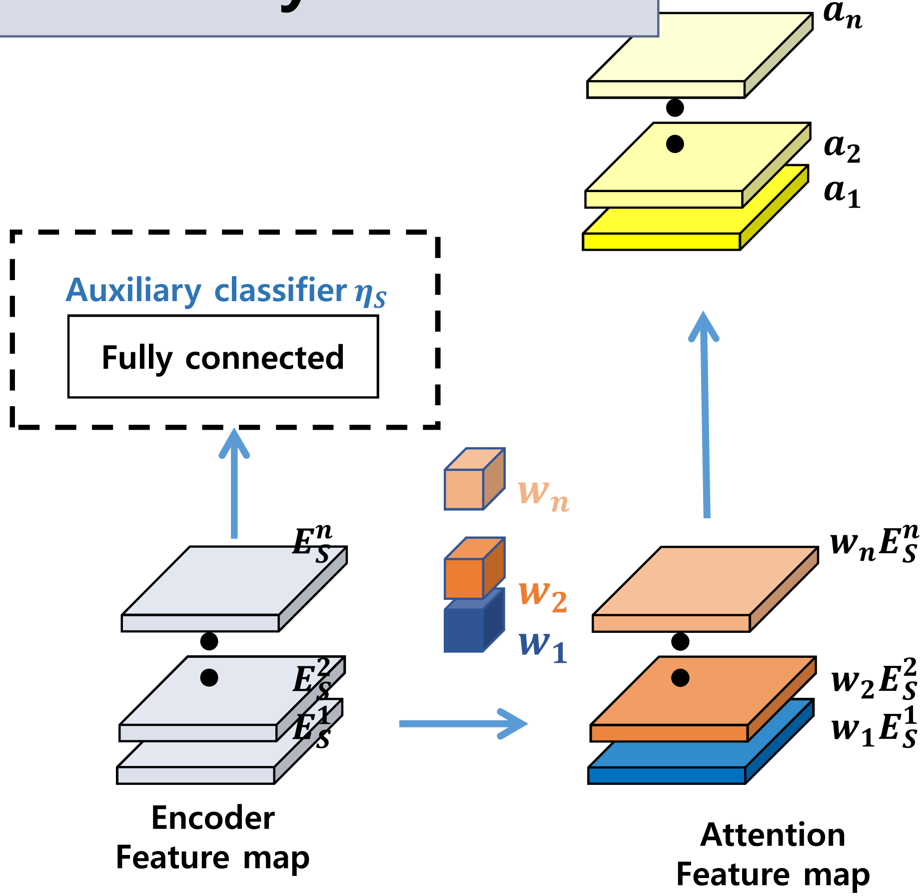
3. Network Architecture - Generator

Generator - Encoder



Generator - Auxiliary Classifier



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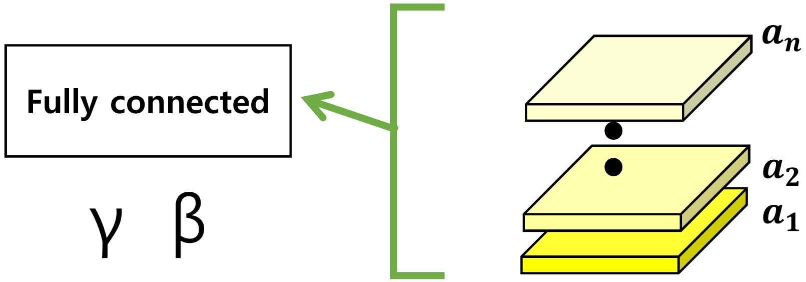
Generator - Fully connected



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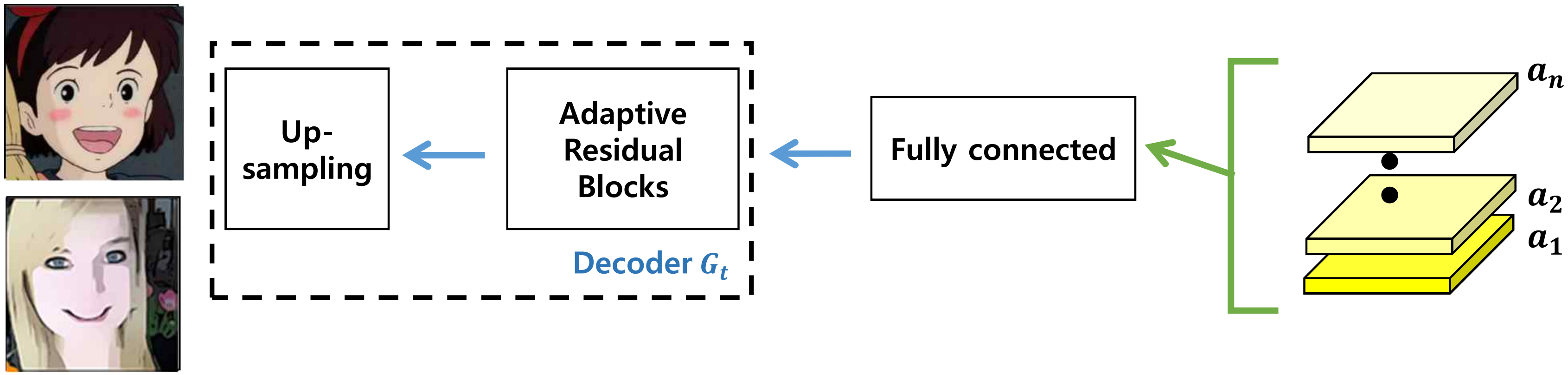
Generator - Decoder



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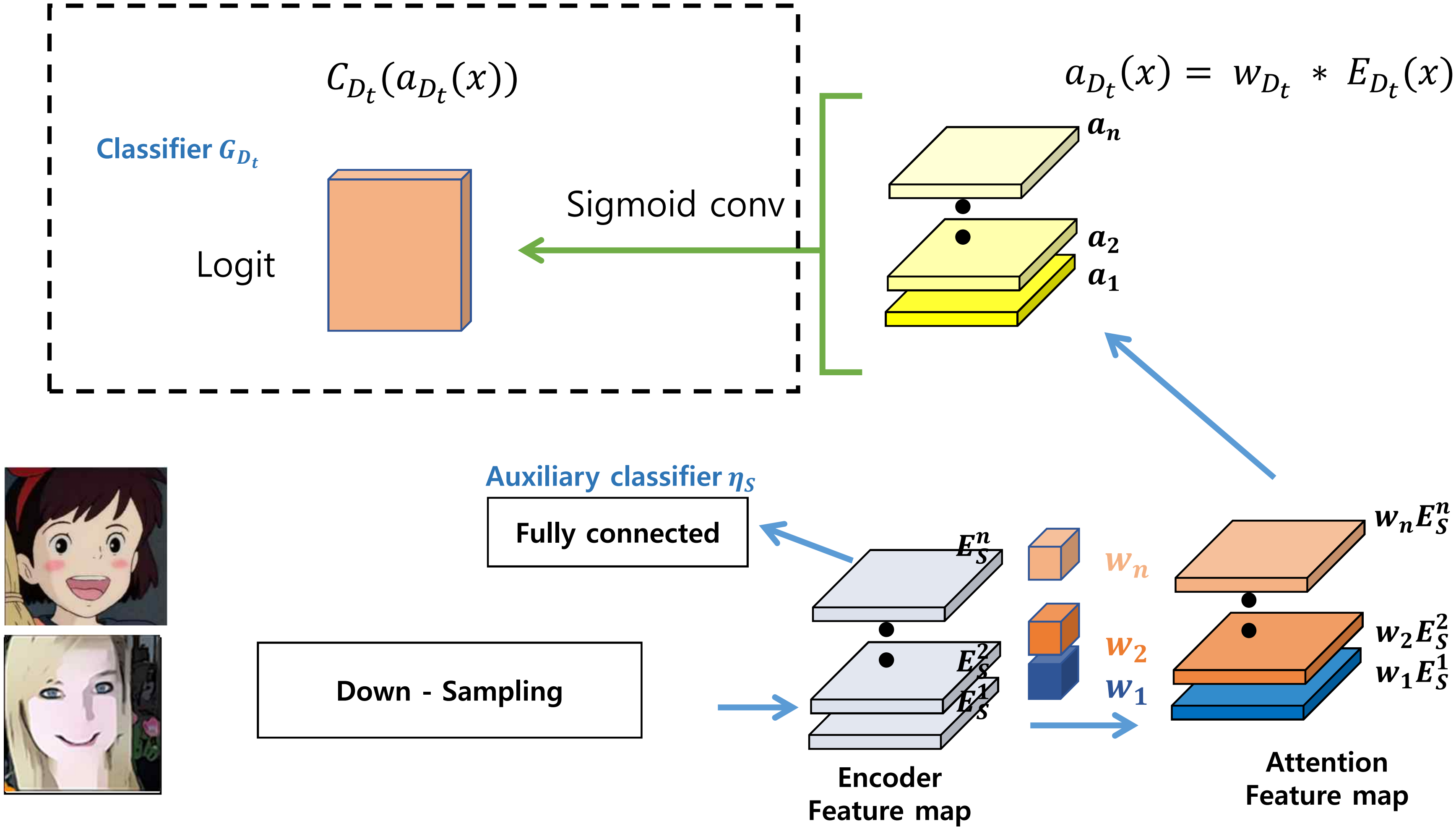
3. Network Architecture - Discriminator



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3. Network Architecture – Loss Function

Adversarial Loss

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

Cycle Loss

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

Identity Loss

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

CAM Loss

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

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

3. Network Architecture – Loss Function

Adversarial Loss 변환된 이미지가 캐릭터 이미지의 형태와 비슷하도록 규제

S- 사람이미지
T- 캐릭터이미지

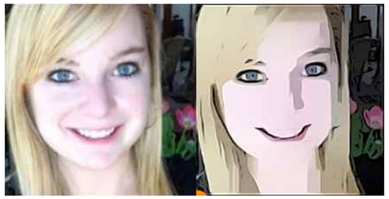
G입장

$$L_{lsgan}^{s\to t} = \left(\mathbb{E}_{x\sim X_t}\left[\overbrace{\underbrace{(D_t(x))^2}_{1}}^{0}\right] + \mathbb{E}_{x\sim X_s}\left[\overbrace{\underbrace{\left(1 - D_t(G_{s\to t}(x))\right)^2}_{0}}^{1}\right]\right).$$

=G ↓

=D ↑

D입장



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Cycle Loss

모델의 형태를 보존하기 위해 CycleGAN 컨셉 적용

G입장

$$L_{cycle}^{s\to t} = \mathbb{E}_{x\sim X_s}\left[\left|\underset{1}{\underline{\overset{0}{\overline{x - G_{t\to s}(G_{s\to t}(x))}}}}\right|\right].$$

=G ↓

=D ↑

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

원본 이미지와 비슷하게

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

원본 이미지와 다르게

=G ↓

=D ↑

D입장

3. Network Architecture – Loss Function

CAM Loss

보조분류기에서 $G_{s\to t}$와 D_t에 대해 현재 상태에서
큰 차이를 파악해 규제

η_s : 이미지가 s일 확률
η_t : 이미지가 t일 확률

G입장

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

=G ↓

=D ↑

D입장

CAM Loss

보조분류기에서 $G_{s\to t}$와 D_t에 대해 현재 상태에서
큰 차이를 파악해 규제

η_s : 이미지가 s일 확률
η_t : 이미지가 t일 확률

G입장

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

=G ↓

=D ↑

D입장

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3. Network Architecture – Loss Function

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

$$\min_{G_{s \to t}, G_{t \to s}, \eta_s, \eta_t} \max_{D_s, D_t, \eta D_s, \eta D_t} = = \lambda_1 L_{lsgan} + \lambda_2 L_{cycle} + \lambda_3 L_{identity} + \lambda_4 L_{cam}$$

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

모델을 train하는데 최적화하는 loss 함수를 찾음.

4. Result & Compliment

4. Result & Compliment

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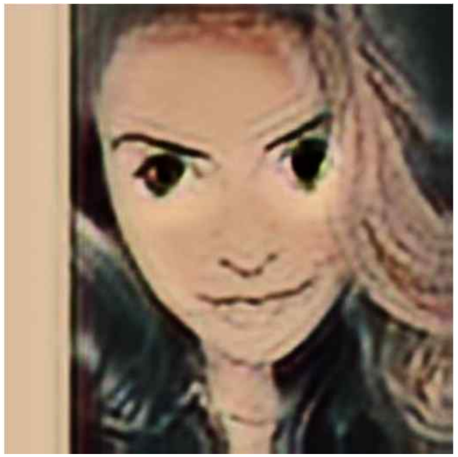
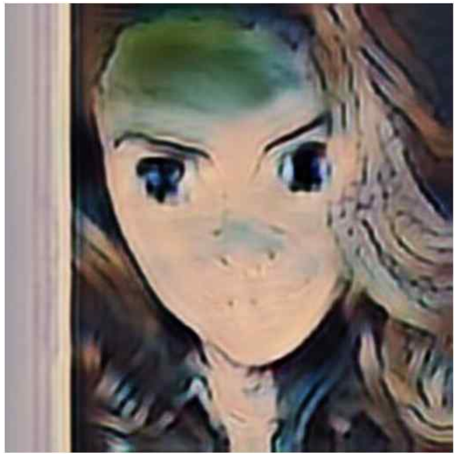
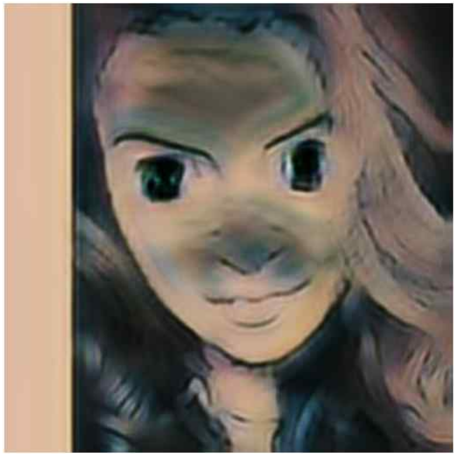
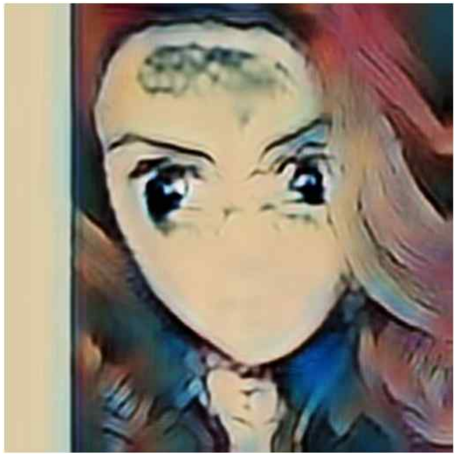
4. Result & Compliment









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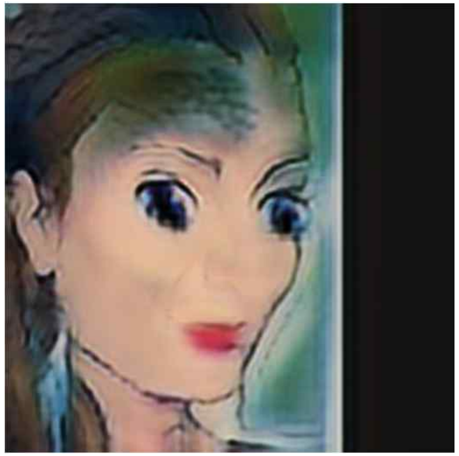

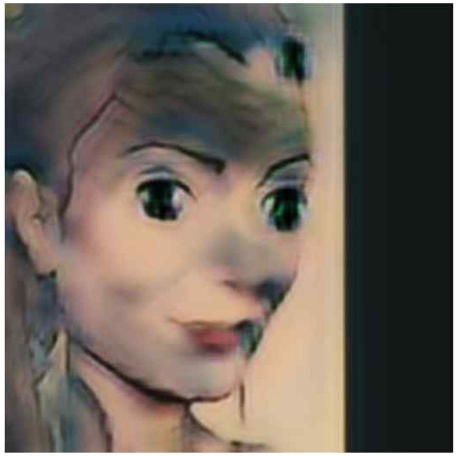

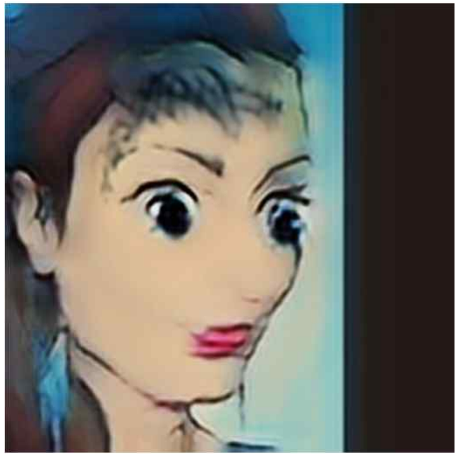

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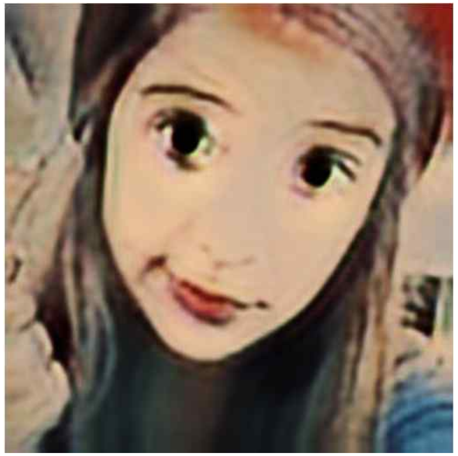

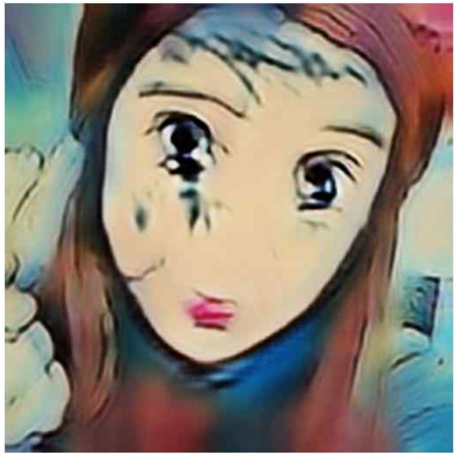

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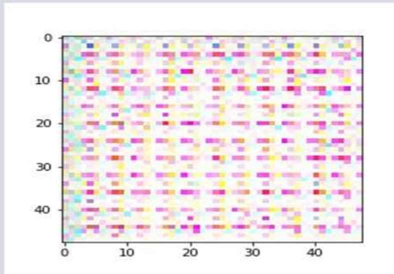

Dataset의 일관성

Data양

코드 최적화

4. Result & Compliment

전체 파일 : 763개 파일

Dataset의 일관성

Data양

코드 최적화

4. Result & Compliment

```
Epoch: [70] [    3/   100] time: 72807.7642 d_loss: 3.05394506
, g_loss: 1188.32092285
Epoch: [70] [    4/   100] time: 72929.2178 d_loss: 2.92211246
, g_loss: 1270.15832520
Epoch: [70] [    5/   100] time: 73057.1874 d_loss: 3.24292827
, g_loss: 1300.79760742
Epoch: [70] [    6/   100] time: 73185.5358 d_loss: 2.75377941
, g_loss: 1119.76660156
Epoch: [70] [    7/   100] time: 73313.3165 d_loss: 3.40126085
, g_loss: 1584.58984375
```

Dataset의 일관성

Data양

코드 최적화

4. Result & Compliment

<출처>
U-GAT-IT 논문 : Junho Kim Hyeonwoo Kang, Kwanghee
https://github.com/taki0112/UGATIT

참고 논문 자료 : 인공지능연구원(AIRI) 정정민
https://www.slideshare.net/jungminchung/ugatit-unsupervised-generative-attentional-networks-with-adaptive-layerinstance-normalization-for-imagetoimage-translation-173206999 ,

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Q & A