Two Transformers Can Make One Strong GAN

TransGAN

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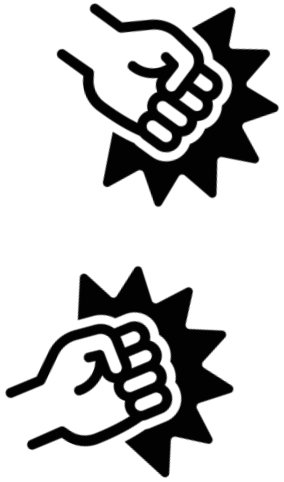
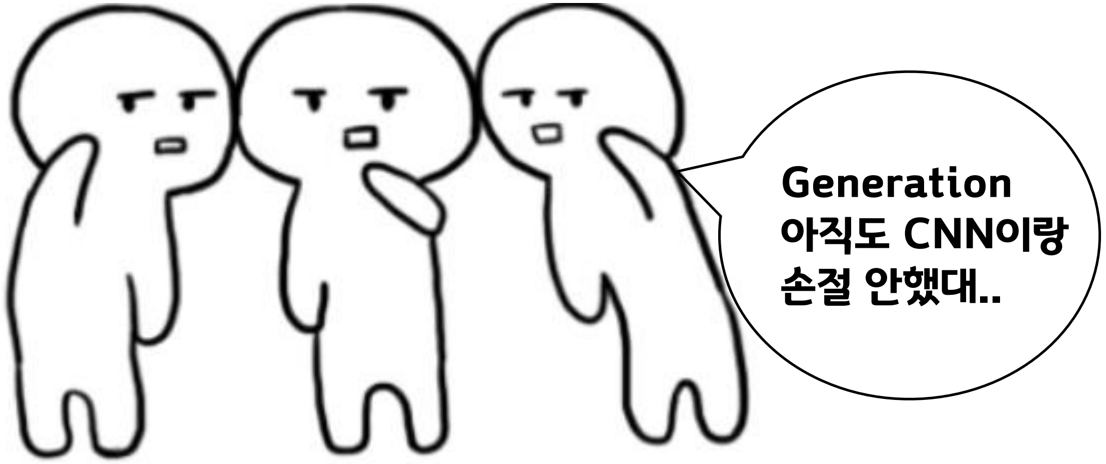
1. 최근 동향

Transformer

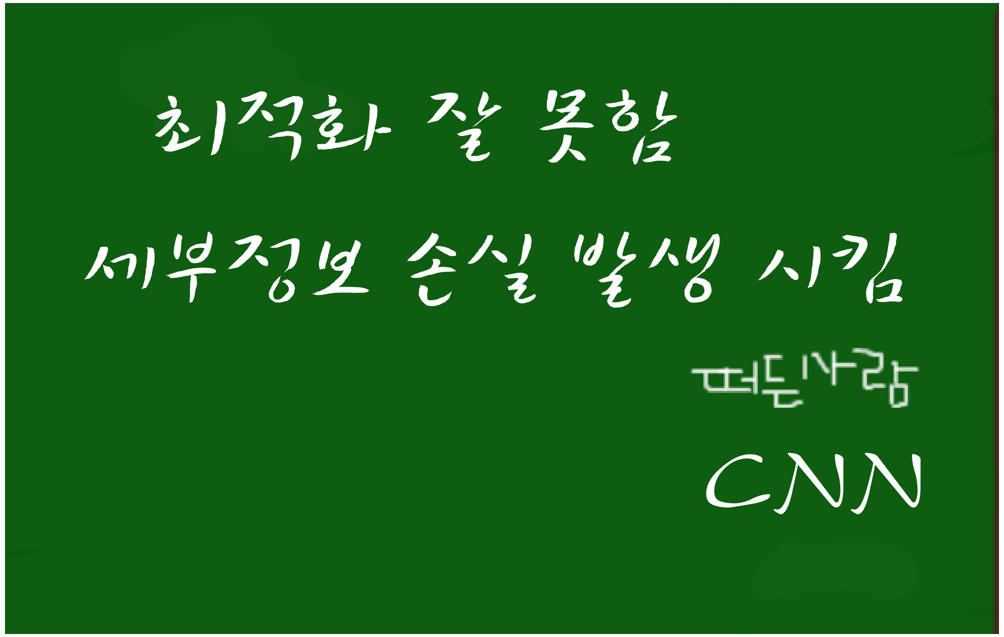


MLP

멸종 위기 CNN



Classification Segmentation Detection



2. Contribution

1. Convolution layer 멈춰!

GAN completely
free of convolution

2. memory-friendly
Transformer

Generator based on
Memory friendly
Transformer

3. SOTA!

STL-10
FID,IS 1st

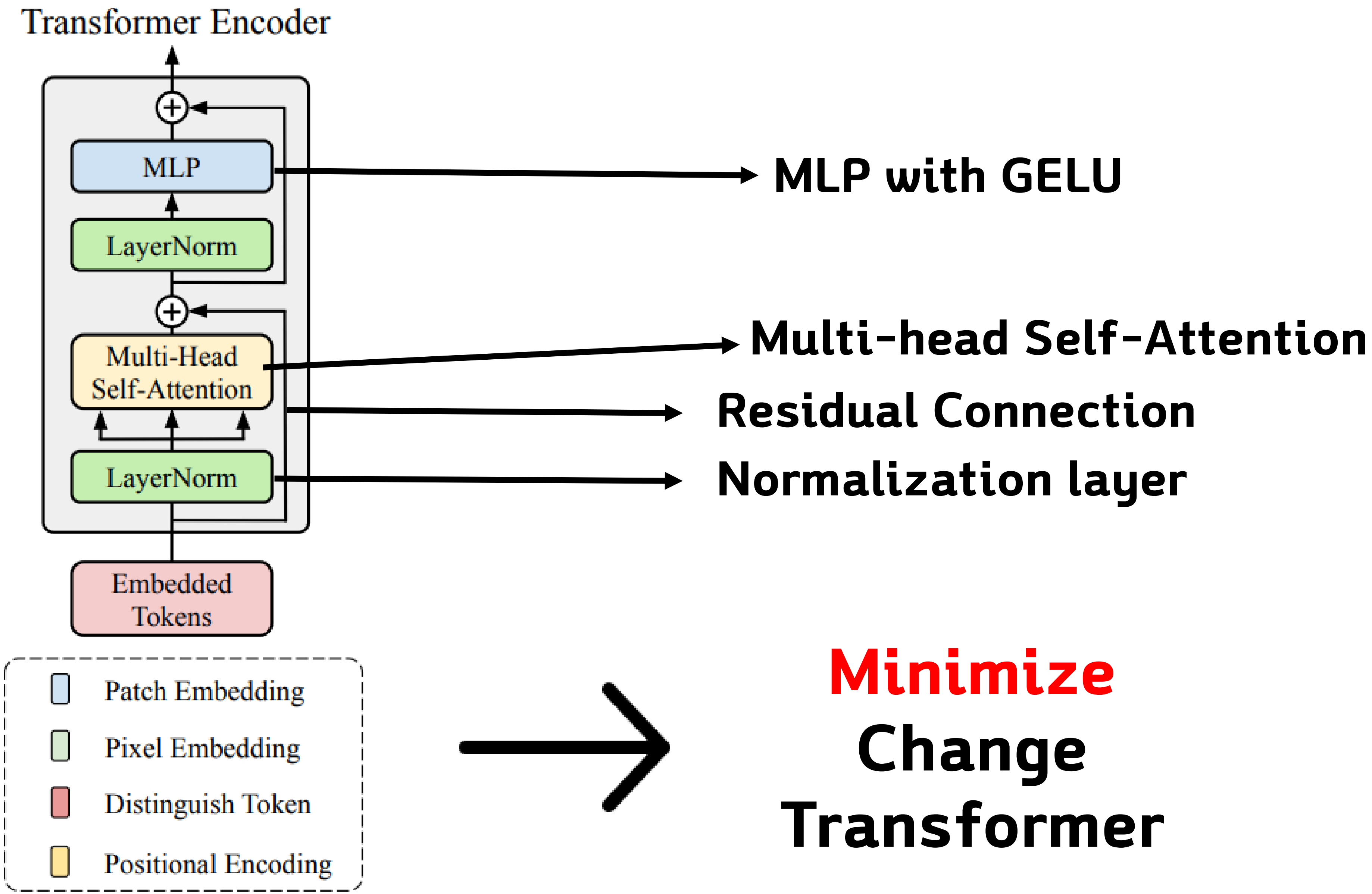
3. Charm of Transformer

1. It has strong representation capability and is free of human-defined inductive bias.

2. the transformer architecture is general, conceptually simple and has the potential to become a powerful "universal" model across tasks and domains

4. A Journey Towards GAN with Pure Transformers

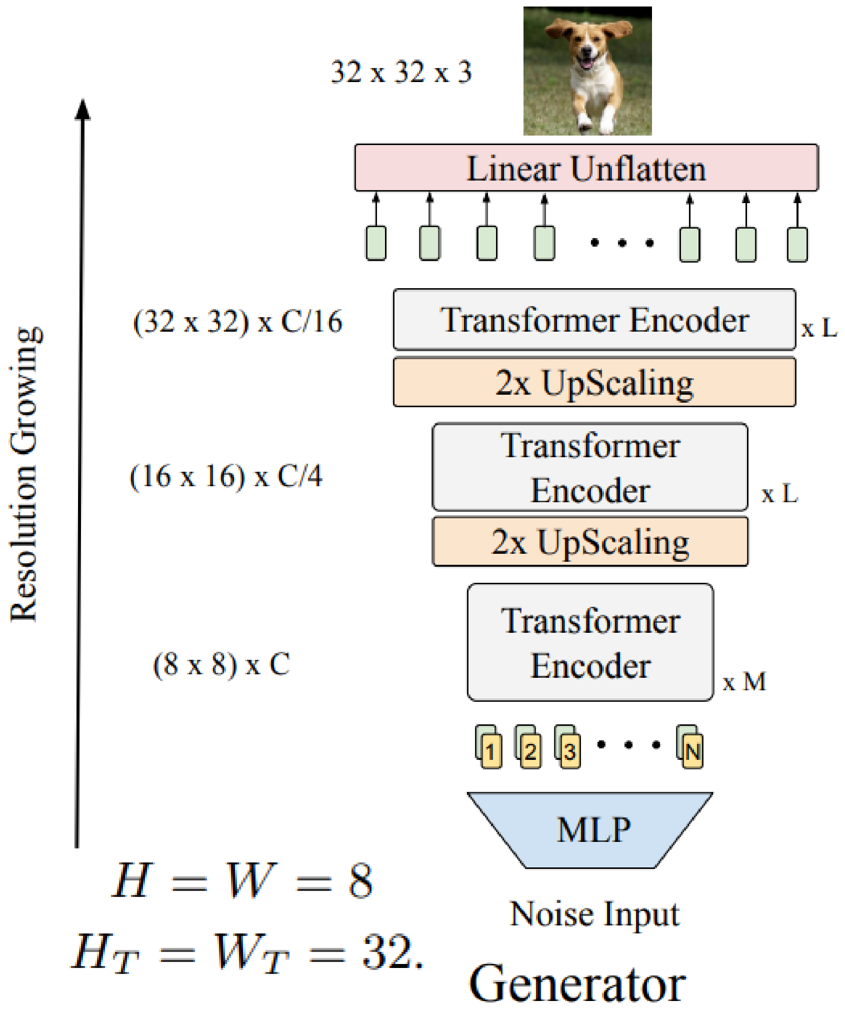
Transformer Encoder As Basic Block



Minimize Change Transformer

4. A Journey Towards GAN with Pure Transformers

Memory-Friendly Generator



$H = W = 8$

$H_T = W_T = 32.$

PixelShuffle method

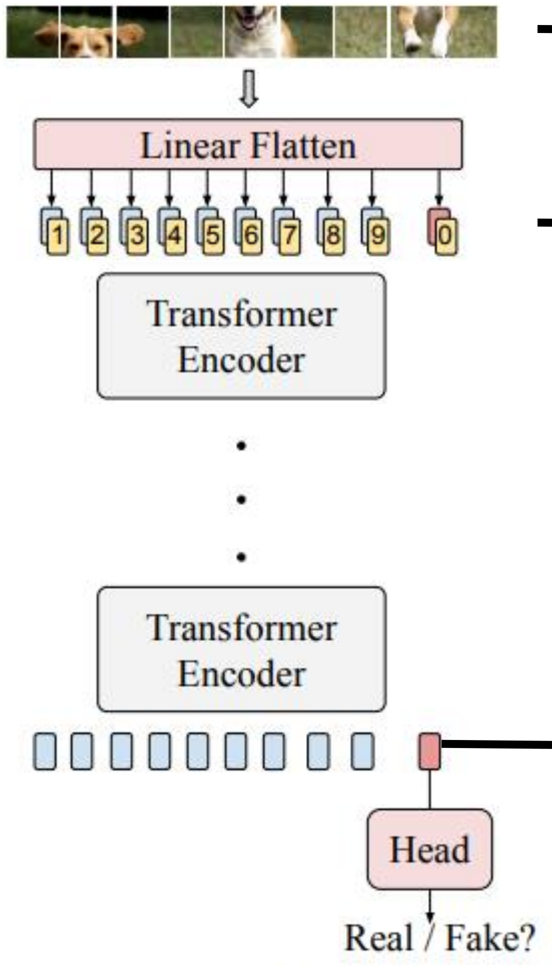
멈춤 조건 $W_T = W, H_T = H$

Pseudo code

```
While W_t == W and H_t == H:
    W *= 2
    H *= 2
    C *= 1/4
    Resolution = W * H * C
Resolution = W_t * H_t * 3
```

4. A Journey Towards GAN with Pure Transformers

Tokenized-Input for Discriminator



Discriminator

Patch-Level Tokenizing

Reshape 1d sequence

[CLS] token → **Predict Real/Fake**

4. A Journey Towards GAN with Pure Transformers

Result

Dataset = CIFAR-10

GENERATOR	DISCRIMINATOR	IS↑	FID↓
AUTOGAN	AUTOGAN	8.55± 0.12	**12.42**
TRANSFORMER	AUTOGAN	**8.59± 0.10**	13.23
AUTOGAN	TRANSFORMER	6.17± 0.12	49.83
TRANSFORMER	TRANSFORMER	6.95 ± 0.13	41.41

→ **Paper method**

Transformer G -> Good Performance

But, Transformer D -> Bad Performance

5. Data Augmentation is Crucial for TransGAN

Few-shot

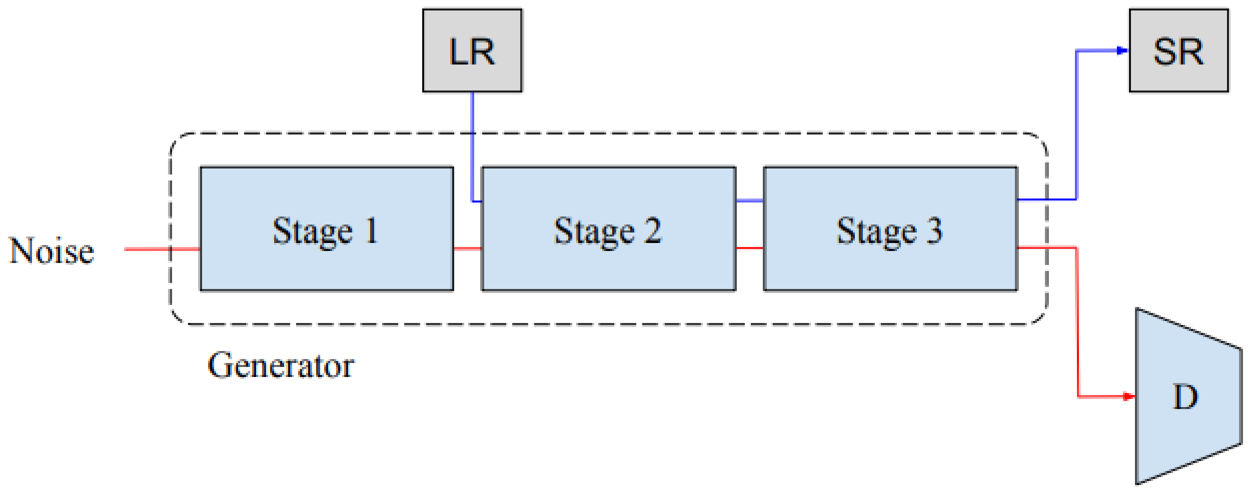
좋은 생성 모델로 만든 가짜 이미지로 데이터 증강을 하는 방법

METHODS	DA	IS ↑	FID ↓
WGAN-GP	×	**6.49** ± 0.09	39.68
(GULRAJANI ET AL., 2017)	√	6.29 ± 0.10	**37.14**
AUTOGAN	×	8.55 ± 0.12	**12.42**
(GONG ET AL., 2019)	√	**8.60 ± 0.10**	12.72
STYLEGAN V2	×	9.18	11.07
(ZHAO ET AL., 2020B)	√	**9.40**	**9.89**
TRANSGAN	×	6.95 ± 0.13	41.41
	√	**8.15 ± 0.14**	**19.85**

Data Augmentation을 통해 눈에 띄는 성능 향상!

6. Co-Training with Self-Supervised Auxiliary Task

MT-CT **Multi-Task Co-Training**



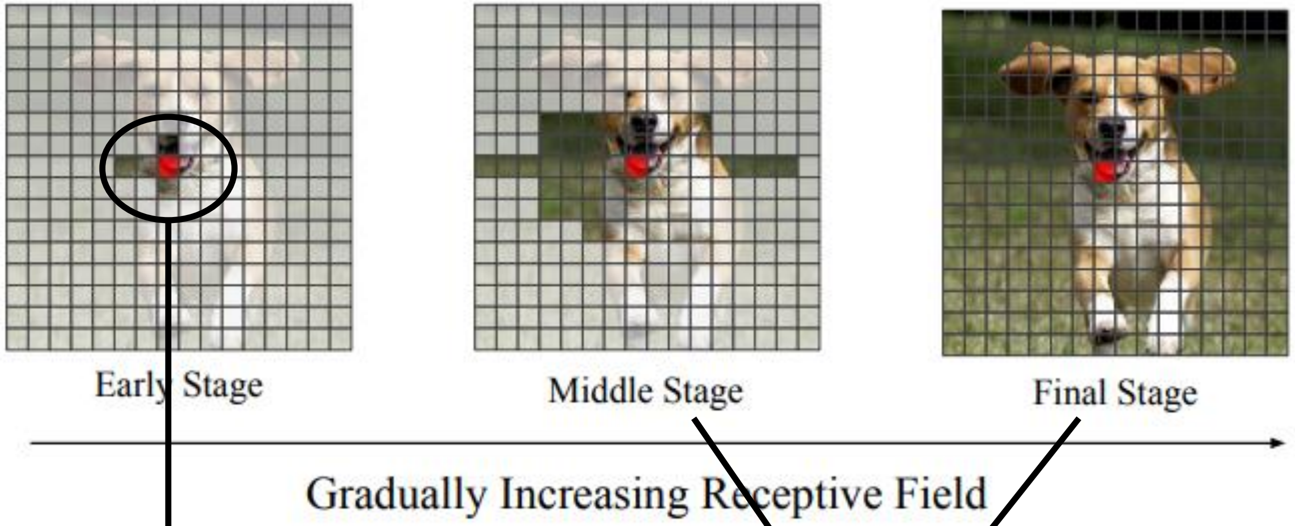
GAN loss + Supper Resolution 보조 task

MODEL	IS↑	FID↓
TRANSGAN + DA (*)	8.15± 0.14	19.85
(*) + MT-CT	8.20± 0.14	19.12

7. Locality-Aware Initialization for Self-Attention

Local Initialization without Convolution

Regularizer 역할



우선순위를 갖게 함

Provides necessary details

Provide More detail & noise

7. Locality-Aware Initialization for Self-Attention

Result

MODEL	IS↑	FID↓
TRANSGAN + DA (*)	8.15± 0.14	19.85
(*) + MT-CT	8.20± 0.14	19.12
(*) + MT-CT + LOCAL INIT.	**8.22± 0.12**	**18.58**

8. Scaling up to Large Model

Model

S : 384x384

M : 512 x 512

L : 768 x 768

XL : 1024x1024

Model	Depth	Dim	IS ↑	FID ↓
TransGAN-S	{5,2,2}	384	8.22 ± 0.14	18.58
TransGAN-M	{5,2,2}	512	8.36 ± 0.12	16.27
TransGAN-L	{5,2,2}	768	8.50 ± 0.14	14.46
TransGAN-XL	{5,4,2}	1024	$\mathbf{8.63 \pm 0.16}$	**11.89**

Number of Encoder Block

9. Comparison with State-of-the-art GANs

CIFAR-10

FID 2등!

METHODS	IS	FID
WGAN-GP (GULRAJANI ET AL., 2017)	6.49 ± 0.09	39.68
LRGAN (YANG ET AL., 2017)	7.17 ± 0.17	-
DFM (WARDE-FARLEY & BENGIO, 2016)	7.72 ± 0.13	-
SPLITTING GAN (GRINBLAT ET AL., 2017)	7.90 ± 0.09	-
IMPROVING MMD-GAN (WANG ET AL., 2018A)	8.29	16.21
MGAN (HOANG ET AL., 2018)	8.33 ± 0.10	26.7
SN-GAN (MIYATO ET AL., 2018)	8.22 ± 0.05	21.7
PROGRESSIVE-GAN (KARRAS ET AL., 2017)	8.80 ± 0.05	15.52
AUTOGAN (GONG ET AL., 2019)	8.55 ± 0.10	12.42
STYLEGAN V2 (ZHAO ET AL., 2020B)	**9.18**	**11.07**
TRANSGAN-XL	8.63 ± 0.16	11.89

STL-10

SOTA!!

IS, FID 1등!

METHODS	IS ↑	FID ↓
DFM (WARDE-FARLEY & BENGIO, 2016)	8.51 ± 0.13	-
D2GAN (NGUYEN ET AL., 2017)	7.98	-
PROBGAN (HE ET AL., 2019)	8.87 ± 0.09	47.74
DIST-GAN (TRAN ET AL., 2018)	-	36.19
SN-GAN (MIYATO ET AL., 2018)	9.16 ± 0.12	40.1
IMPROVING MMD-GAN (WANG ET AL., 2018A)	9.23 ± 0.08	37.64
AUTOGAN (GONG ET AL., 2019)	9.16 ± 0.12	31.01
ADVERSARIALNAS-GAN (GAO ET AL., 2020)	9.63 ± 0.19	26.98
TRANSGAN-XL	$\mathbf{10.10 \pm 0.17}$	**25.32**

감사합니다