Exploiting Deep Generative Prior for Versatile Image Restoration and Manipulation

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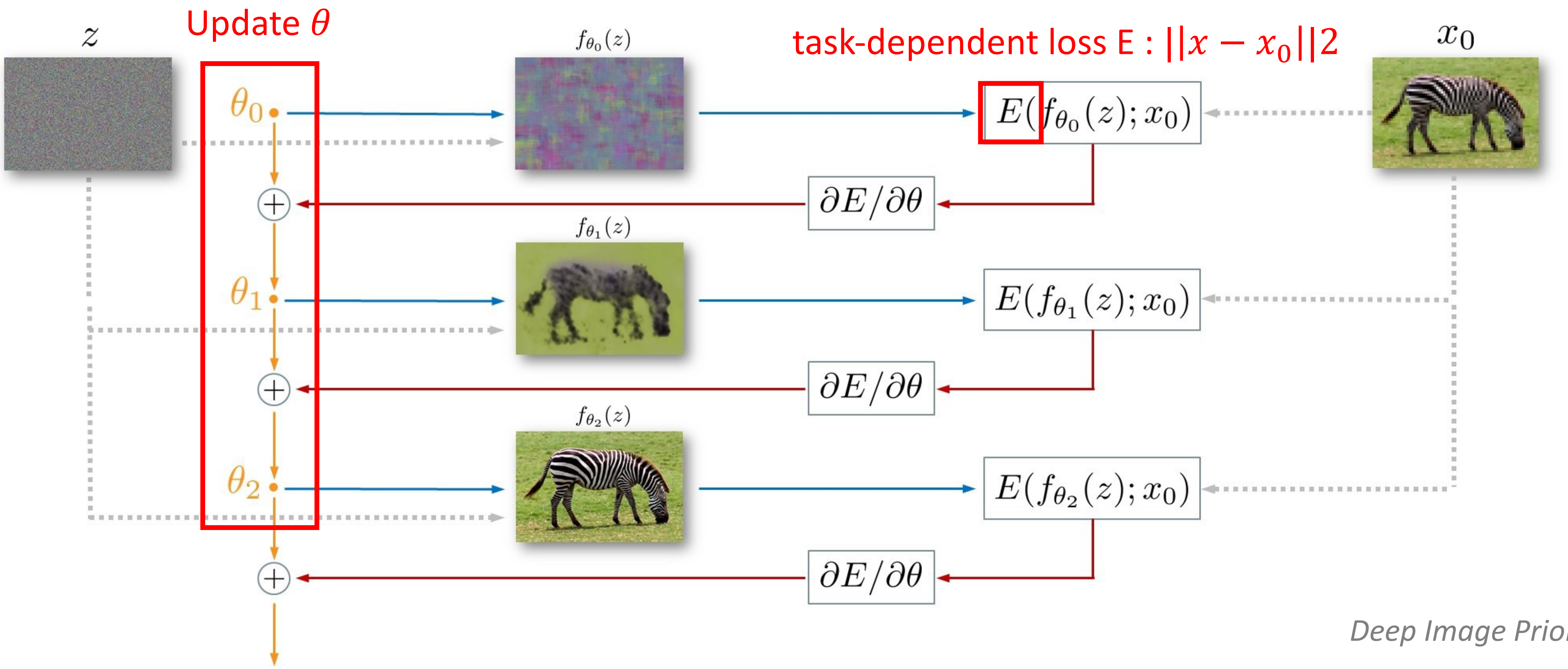
CONTENTS

Background

Previous work : Deep Image Prior



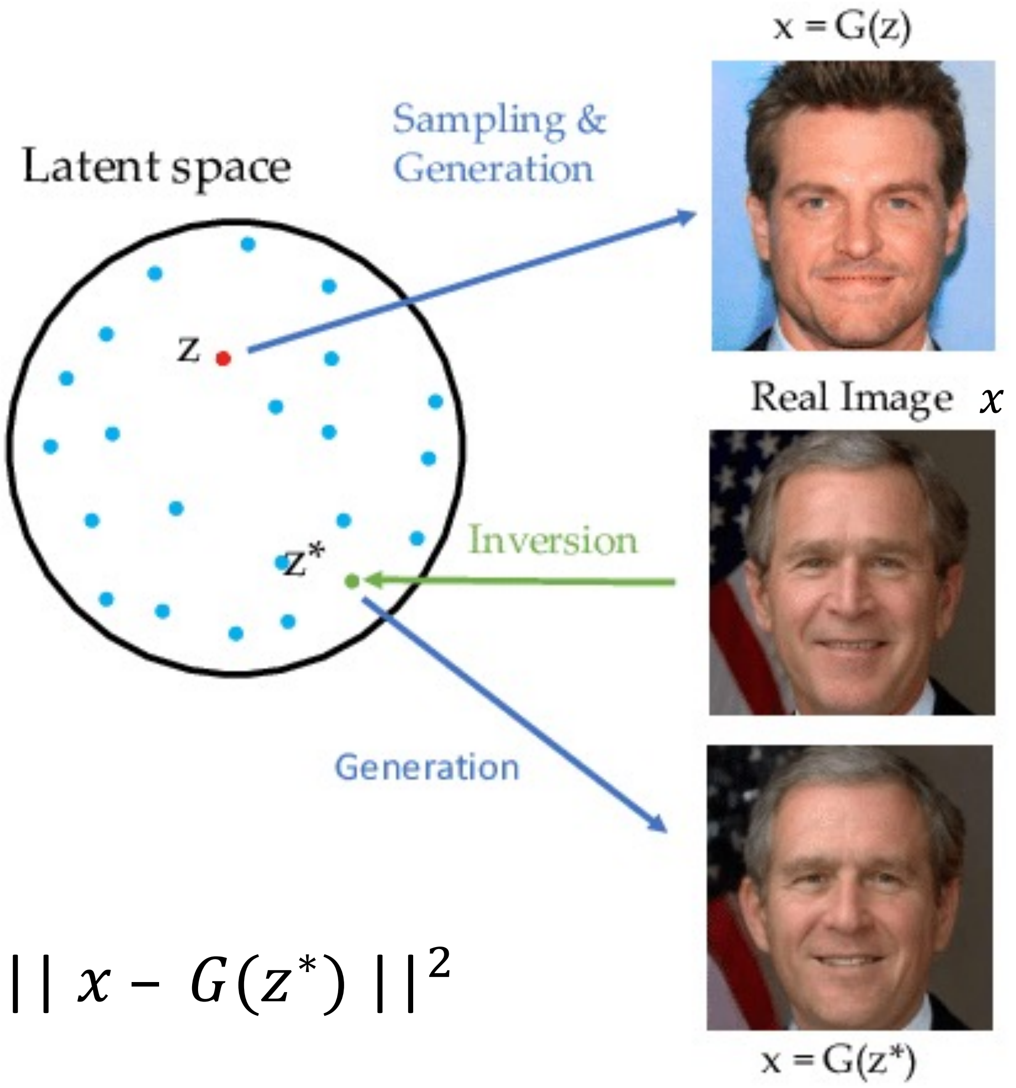
Deep Image Prior, CVPR 2018

Limitation : Still exist gaps toward image prior that captures rich image semantics. (e.g. color, textures, high-level concepts)

01. Background

GAN-Inversion

Latent random vector Z
~ N (0, I)



➡ GAN

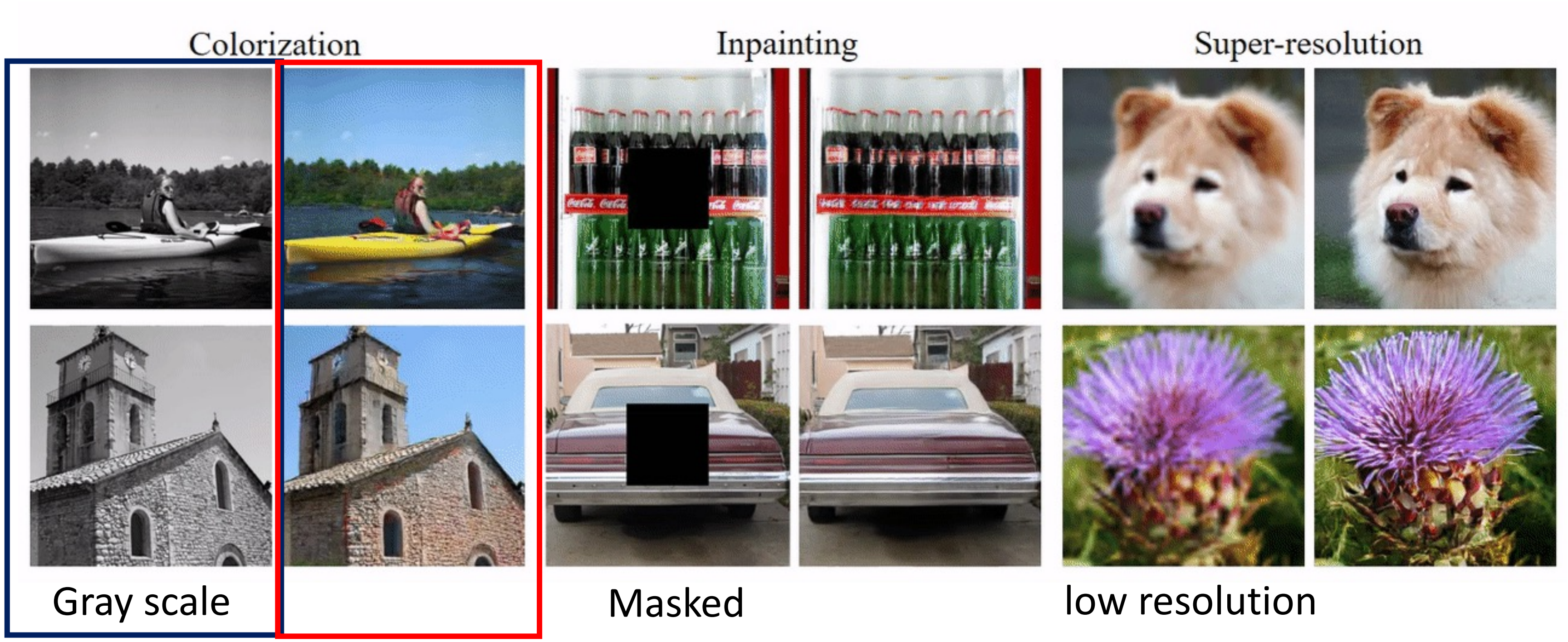
➡ GAN-Inversion

$$z^* = argmin \; || \; x - G(z^*) \; ||^2$$

Methodology of Deep Generative Prior

02. Methodology of DGP

Goal : exploiting generic image prior of GAN



Gray scale

Masked

low resolution

Degraded image (left side) → GAN → Restored image (right side)

02. Methodology of DGP

Main Contribution

1. **Training Generator** through **relaxed GAN-Inversion** **methods**.

2. Allow **the generator to be fine-tuned on-the-fly in a** **progressive manner** regularized by **feature distance** **obtained by the discriminator** in GAN.

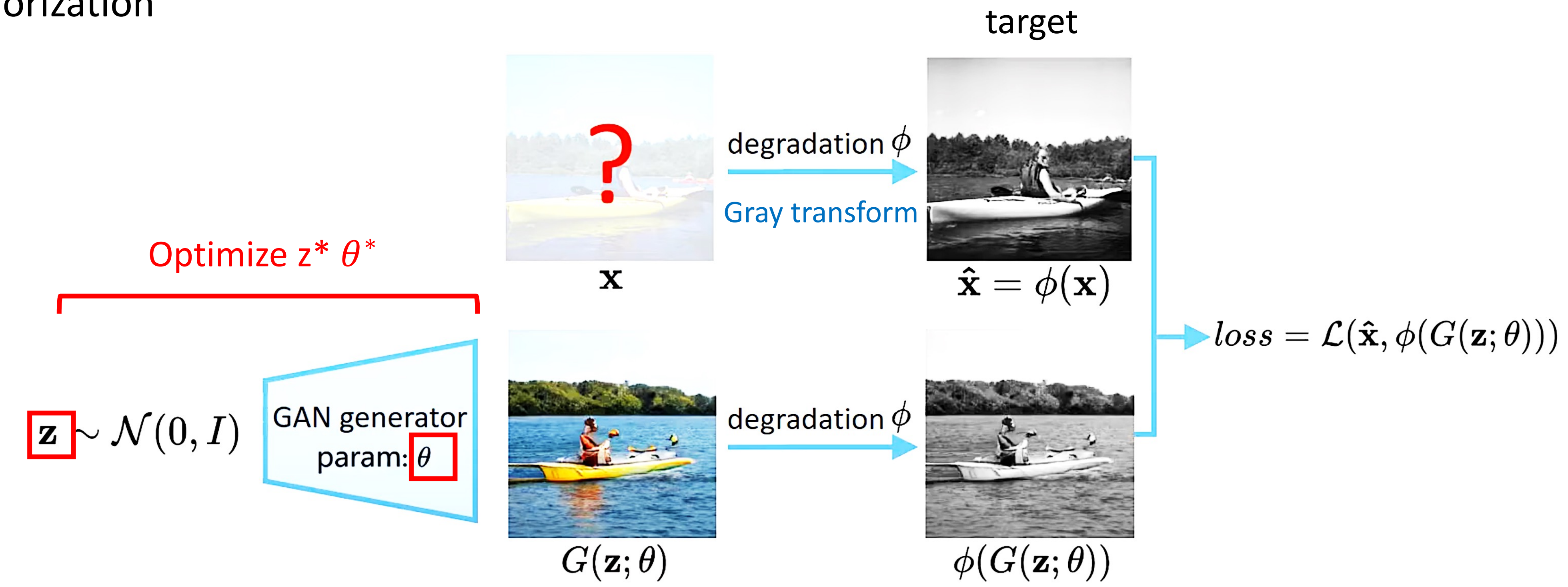
↓

“ **Restore** missing semantics and enable diverse **image manipulation** ”

02. Methodology of DGP

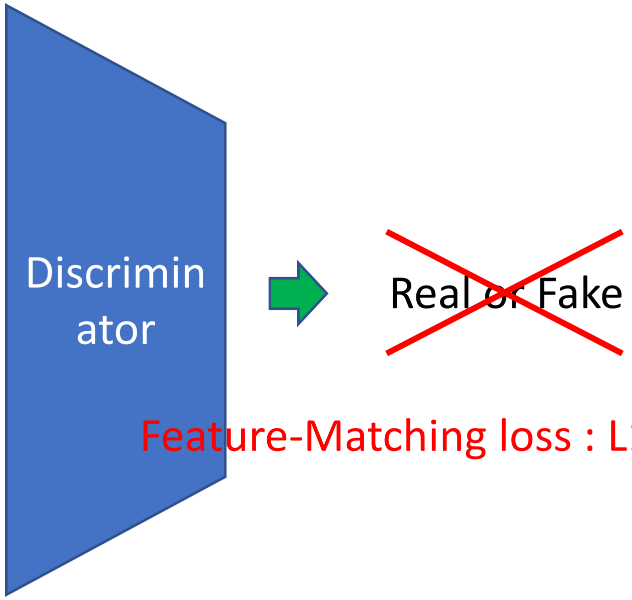
1) Relax the Generator for GAN-Inversion

e.g. colorization

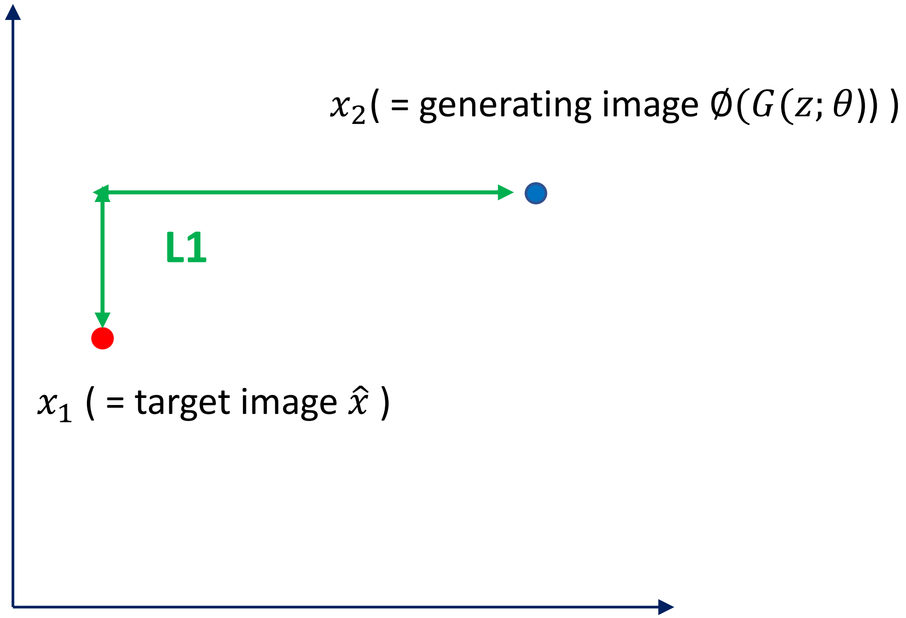


Updated objective : $$\boldsymbol{\theta}^*, \mathbf{z}^* = \arg\min_{\boldsymbol{\theta},\mathbf{z}} \mathcal{L}(\hat{\mathbf{x}}, \phi(G(\mathbf{z};\boldsymbol{\theta}))), \quad \mathbf{x}^* = G(\mathbf{z}^*;\boldsymbol{\theta}^*).$$

2) Discriminator Guided Progressive Reconstruction – Feature Matching loss



Feature-Matching loss : L1 distance



Discriminator feature space

$$\mathcal{L}(\mathbf{x}_1, \mathbf{x}_2) = \sum_{i \in \mathcal{I}} \| D(\mathbf{x}_1, i), D(\mathbf{x}_2, i) \|_1$$

- $D(x_1, i)$ 는 $discriminator$의 i 번째 $block$에서의 x의 $feature$
- I 는 사용한 $block$의 $index\ set$

02. Methodology of DGP

2) Discriminator Guided Progressive Reconstruction

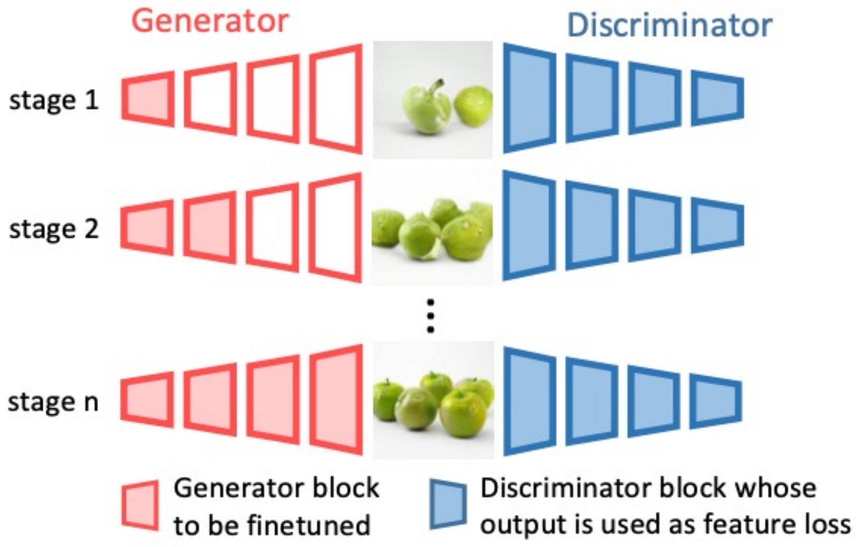


Fig. 4. Progressive reconstruction of the generator can better preserves the consistency between missing and existing semantics in comparison to simultaneous fine-tuning on all the parameters at once. Here the list of images shown in the middle are the outputs of the generator in different fine-tuning stages.

➡ The generator can better **preserve the consistency** between missing and existing semantics.

02. Methodology of DGP

2) Discriminator Guided Progressive Reconstruction

proposed strategy

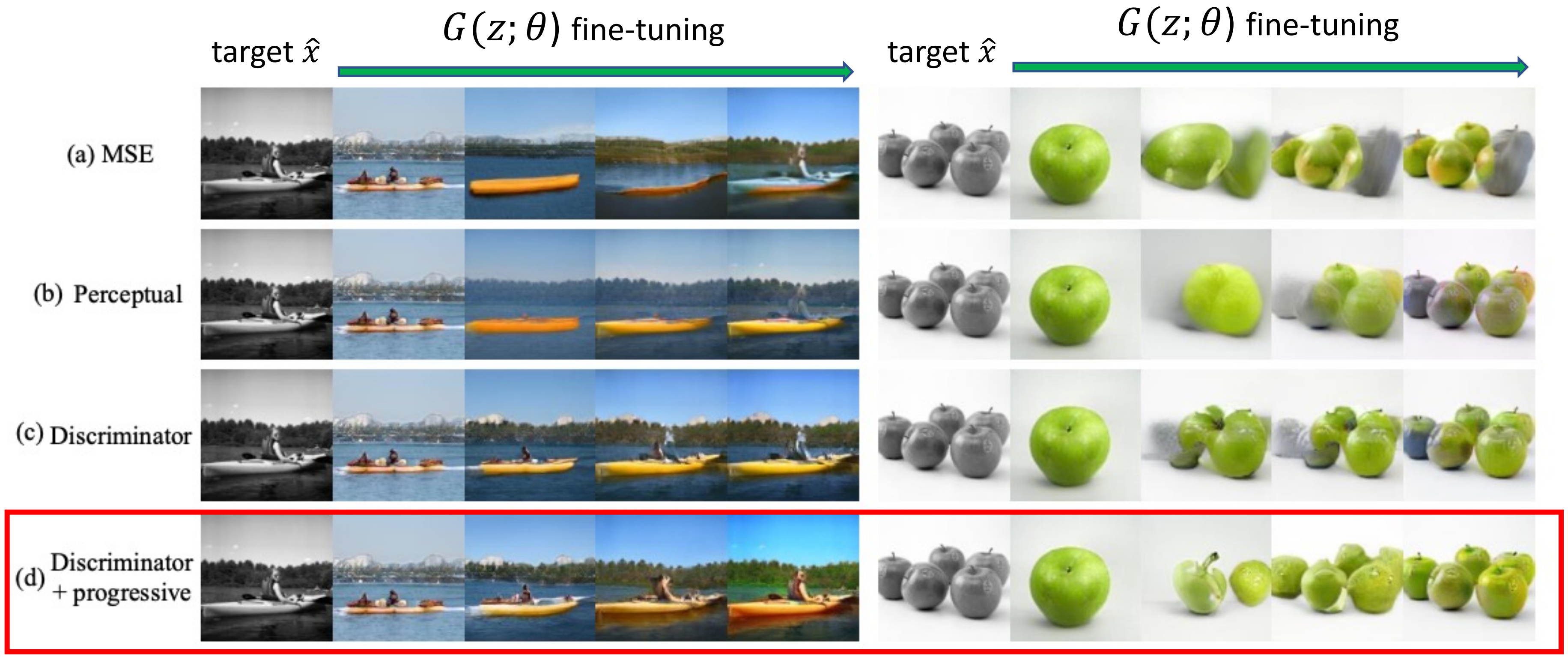


Fig. 3. Comparison of different loss types when fine-tuning the generator to reconstruct the image

Experiment / Result

03. Experiment

1) Task

Image Restoration

- Inpainting
- SR
- Colorization
- Adversarial defense

Image Manipulation

- Random jittering
- Image morphing
- Category transfer

2) Architecture : BigGAN (Pretrained on **ImageNet /** Test on 1K images from ImageNet Validation set**)**

3) Initialization of Z : randomly sample 500 images using the GAN, select the neighbor of the target image under the discriminator feature metric as the starting point.

4) Fine-tuning : a little differences for each tasks

03. Quantitative Result

1) Image Restoration

Colorization

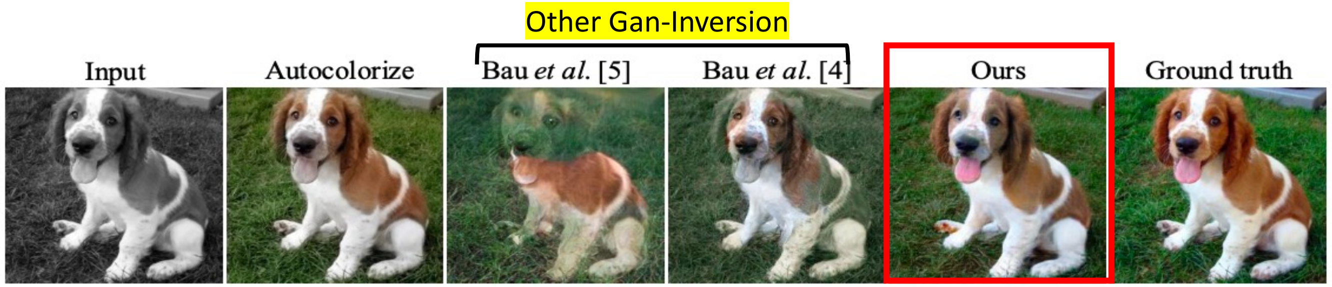


Fig. 5. Colorization. Qualitative comparison of Autocolorize [25], other GAN-inversion methods [5] [4], and our DGP

Inpainting

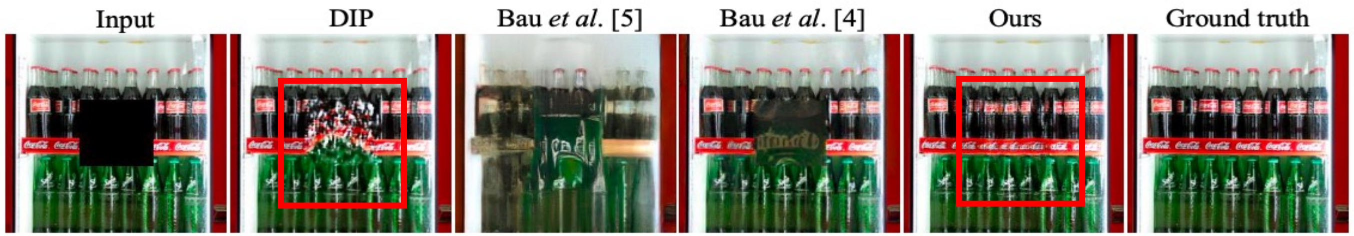


Fig. 6. Inpainting. Compared with DIP and [5] [4], the proposed DGP could preserve the spatial coherence in image inpainting with large missing regions

SR

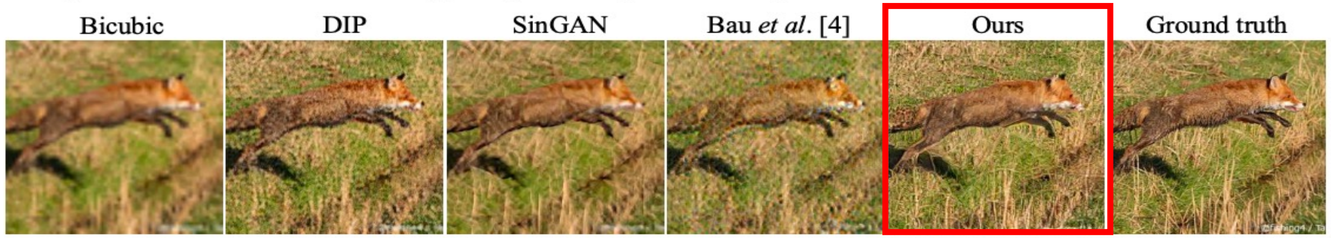


Fig. 7. Super-resolution ($\times 4$) on 64×64 size images. The comparisons of our method with DIP, SinGAN, and [4] are shown, where DGP produces sharper super-resolution results

03. Quantitative Result

1) Image Restoration : Adversarial defense

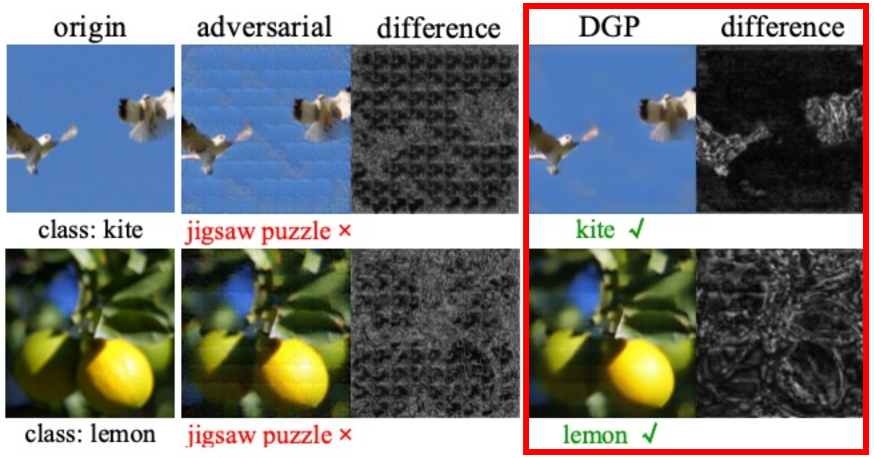


Fig. 10. Adversarial defense. DGP is capable of filtering out unnatural perturbations in the adversarial samples by reconstructing them

Table 5. Adversarial defense evaluation. We reported the classification accuracy of a ResNet50. The results are evaluated on the 1k ImageNet validation set

method	clean image	adversarial	DefenceGAN	DIP	Ours
top1 acc. (%)	74.9	1.4	0.2	37.5	41.3
top5 acc. (%)	92.7	12.0	1.4	61.2	65.9

Pros 1: Flexibility of DGP

(a) conditional colorization (b) hybrid restoration

Fig. 8. (a) Colorizing an image under different class conditions. (b) Simultaneously conduct colorization, inpainting, and super-resolution ($\times 2$)

(b) Hybrid degradation : $\beta(x) = \beta a(\beta b(\beta c(x))$

Pros 2: Generalization of DGP

Colorization

Inpainting

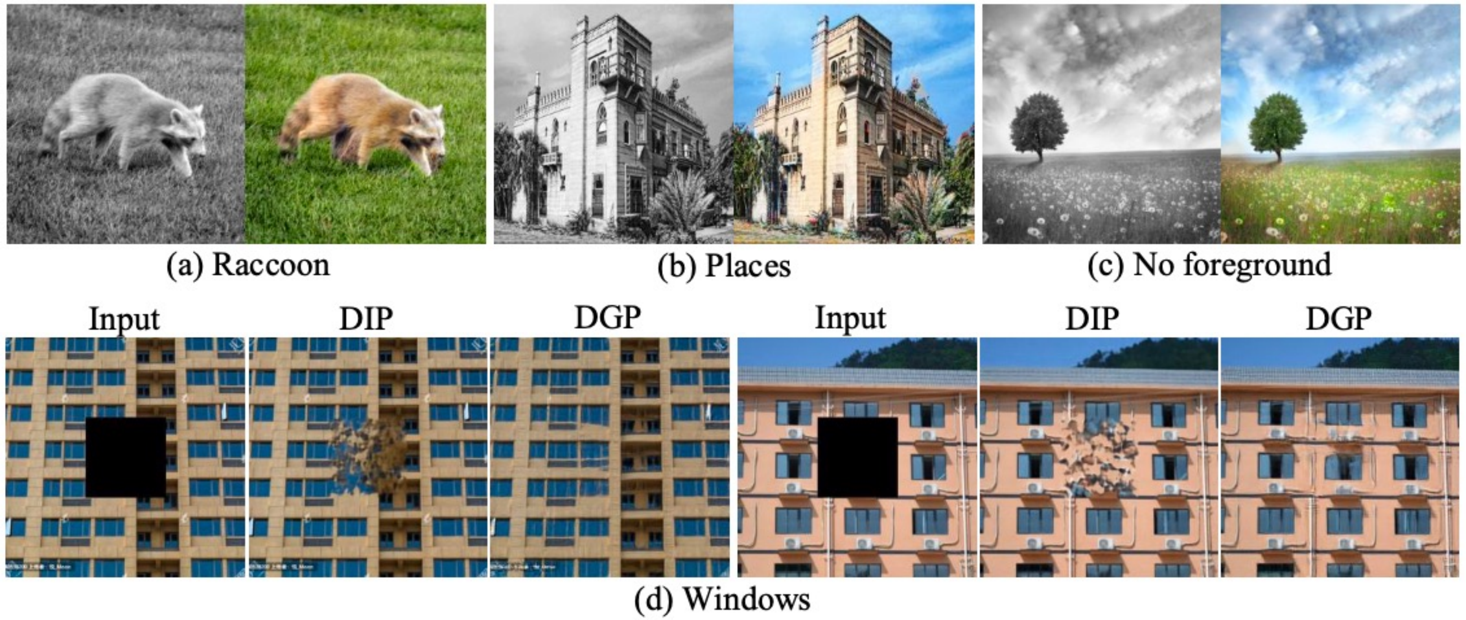
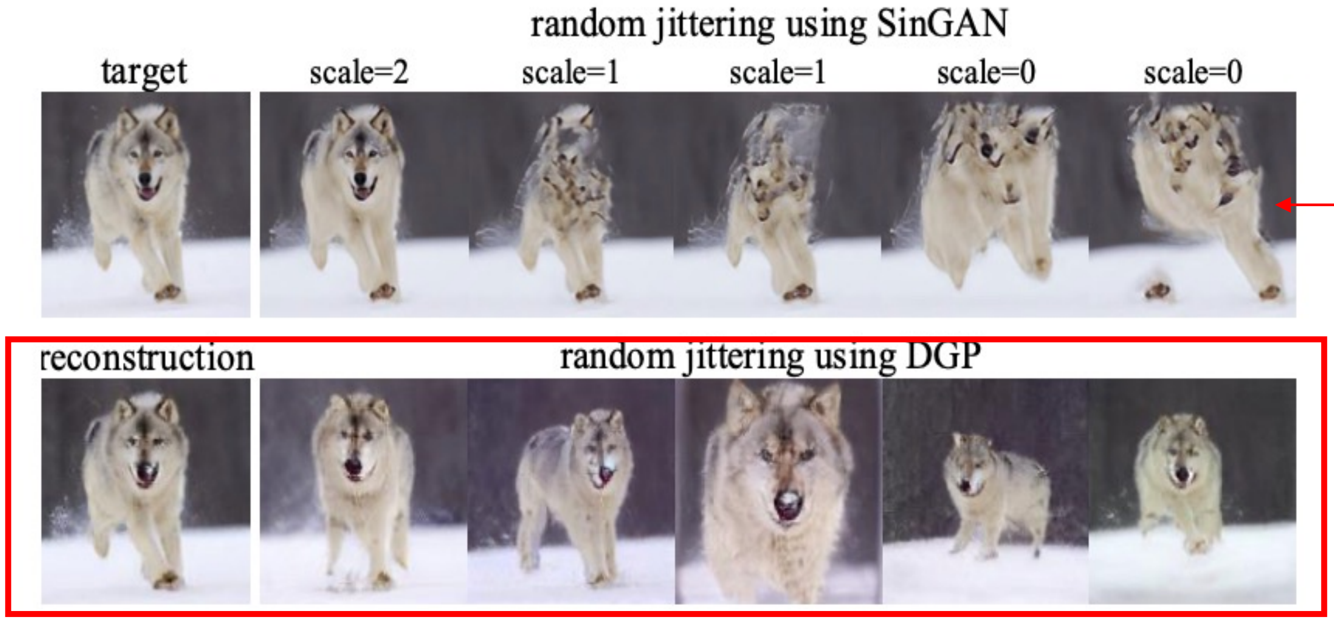


Fig. 9. Evaluation of DGP on non-ImageNet images, including (a) 'Raccoon', a category not belonging to ImageNet categories, (b) image from Places dataset [44], (c) image without foreground object, and (d) windows. (a)(c)(d) are scratched from Internet

03. Quantitative Result

2) Image Manipulation : random jittering



Losing concept of ‘dog’

Fig. 11. Comparison of **random jittering** using SinGAN (above) and DGP (below)

* Random jittering ? add Gaussian noise to the latent vector z*

03. Quantitative Result

2) Image Manipulation : image morphing, category transfer

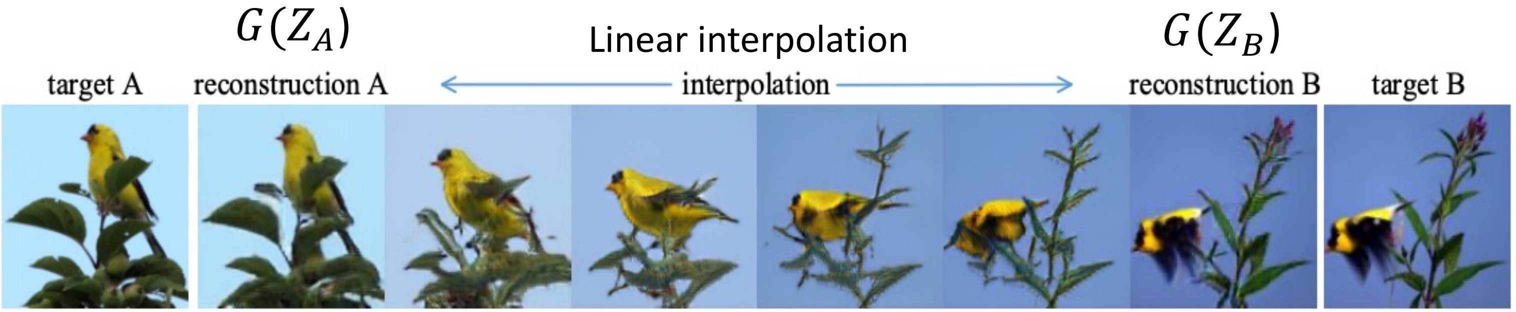
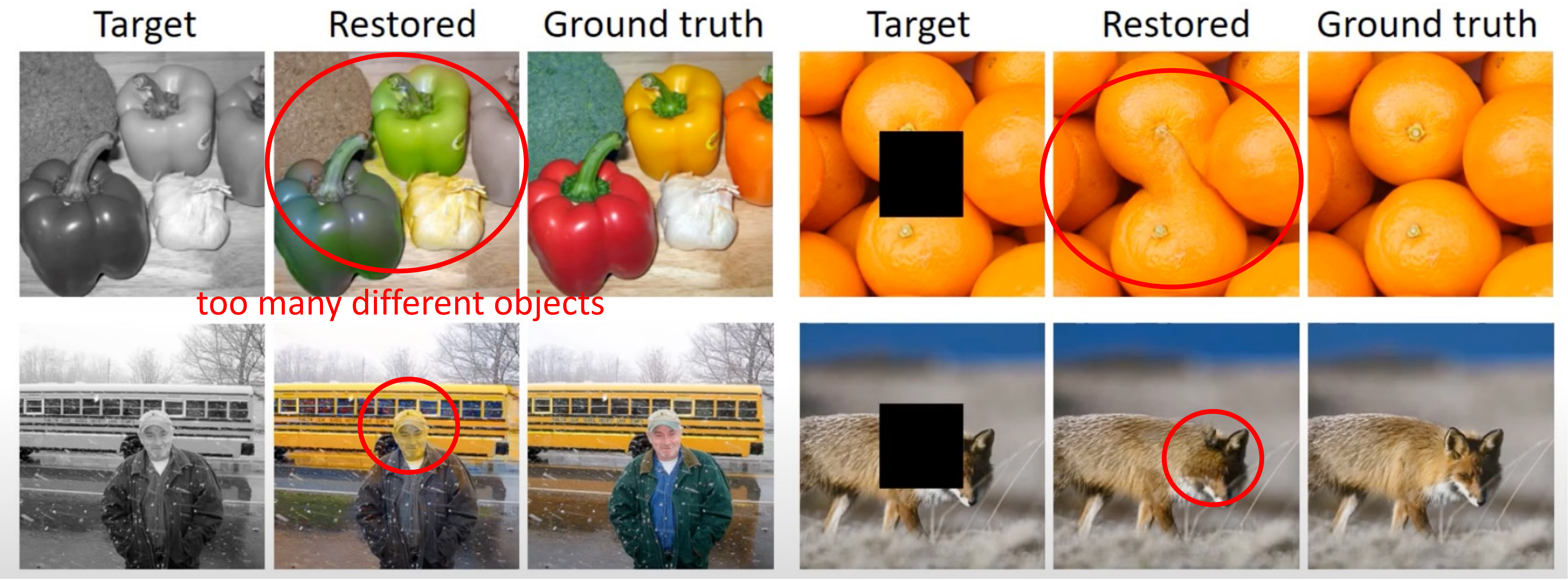


Fig. 12. Image morphing. Our method achieves visually realistic image morphing effects

Fig. 13. Category transfer. DGP enables the editing of semantics of objects in images

03. Quantitative Result

Cons : Failure Case



small face object

Conclusion

04. Conclusion

Conclusion

- GAN generator trained on massive natural images could be used as a generic image prior (DGP).
- DGP could be used to restore the missing information of a degraded image by progressively reconstructing it under the discriminator metric.
- Show the potential of a universal image prior captured by a GAN in image restoration and manipulation.

Future work ?

References

[Research Papers]

- *Deep Image Prior, CVPR 2018*
  https://openaccess.thecvf.com/content_cvpr_2018/papers/Ulyanov_Deep_Image_Prior_CVPR_2018_paper.pdf

- *GAN-Inversion in domain, ECCV 2020* *https://arxiv.org/pdf/2004.00049.pdf*

- *Exploiting Deep Generative Prior for Versatile Image Restoration and Manipulation, ECCV 2020*
  https://arxiv.org/pdf/2003.13659.pdf

[참고 자료]

- *Pytorch code : https://github.com/XingangPan/deep-generative-prior*

- *2020 ECCV Presentation video : https://www.youtube.com/watch?v=p7ToqtwfVko*

Q & A

Q&A

감사합니다.

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