Introduction of Generative Adversarial Networks

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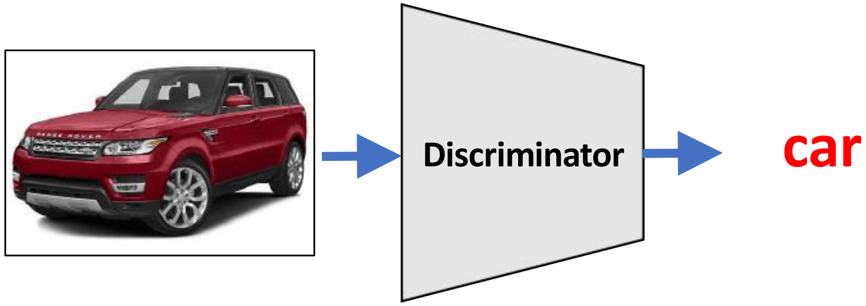
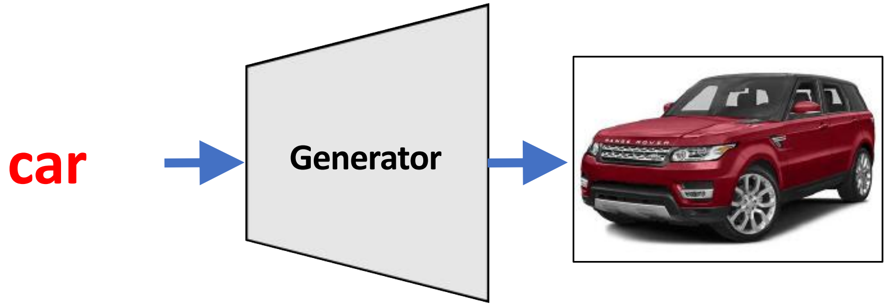
Peking University

Computer Vision

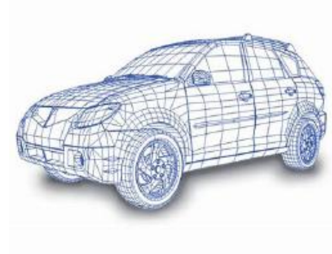
Discriminative Task:



Generative Task:



Computer Graphic:



Introduction of Generative Adversarial Networks (GAN)

- Vanilla GAN
- GAN with Encoder
- Summary

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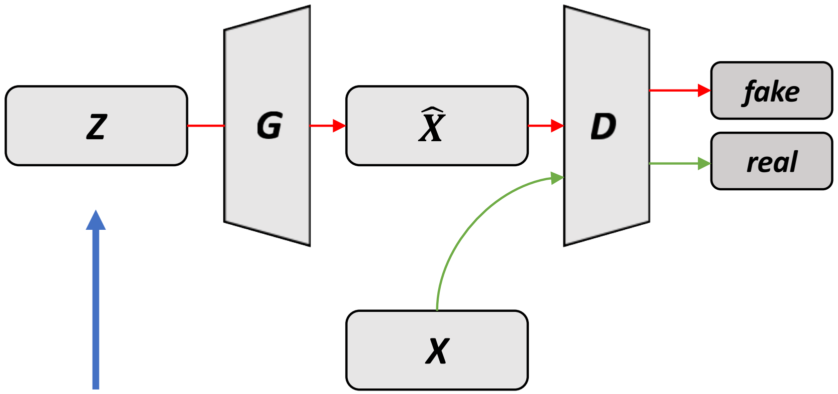
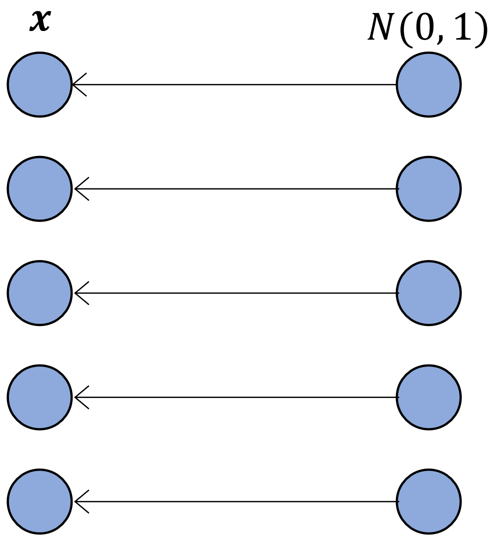
Vanilla GAN

Vanilla GAN



Normal/~~uniform~~
distribution



Unidirectional Mapping

GAN: map a distribution to another distribution

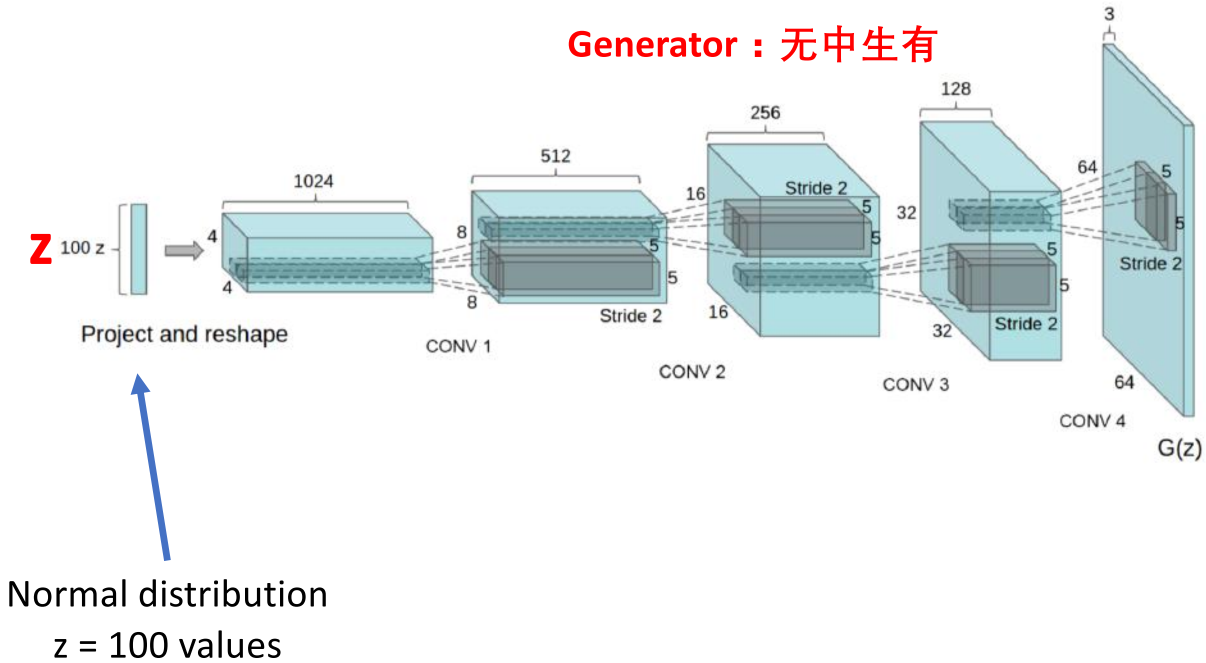
$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{data}}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_z}[\log(1-D(G(\boldsymbol{z}))]$$

$$\mathcal{L}_D = -\boxed{\mathbb{E}_{\boldsymbol{x}\sim p_{data}}[\log D(\boldsymbol{x})]} - \boxed{\mathbb{E}_{\boldsymbol{z}\sim p_z}[\log(1-D(G(\boldsymbol{z}))]}$$

$$\mathcal{L}_G = -\boxed{\mathbb{E}_{\boldsymbol{z}\sim p_z}[\log D(G(\boldsymbol{z}))]}$$

Vanilla GAN – Deep Convolutional GAN (DCGAN)

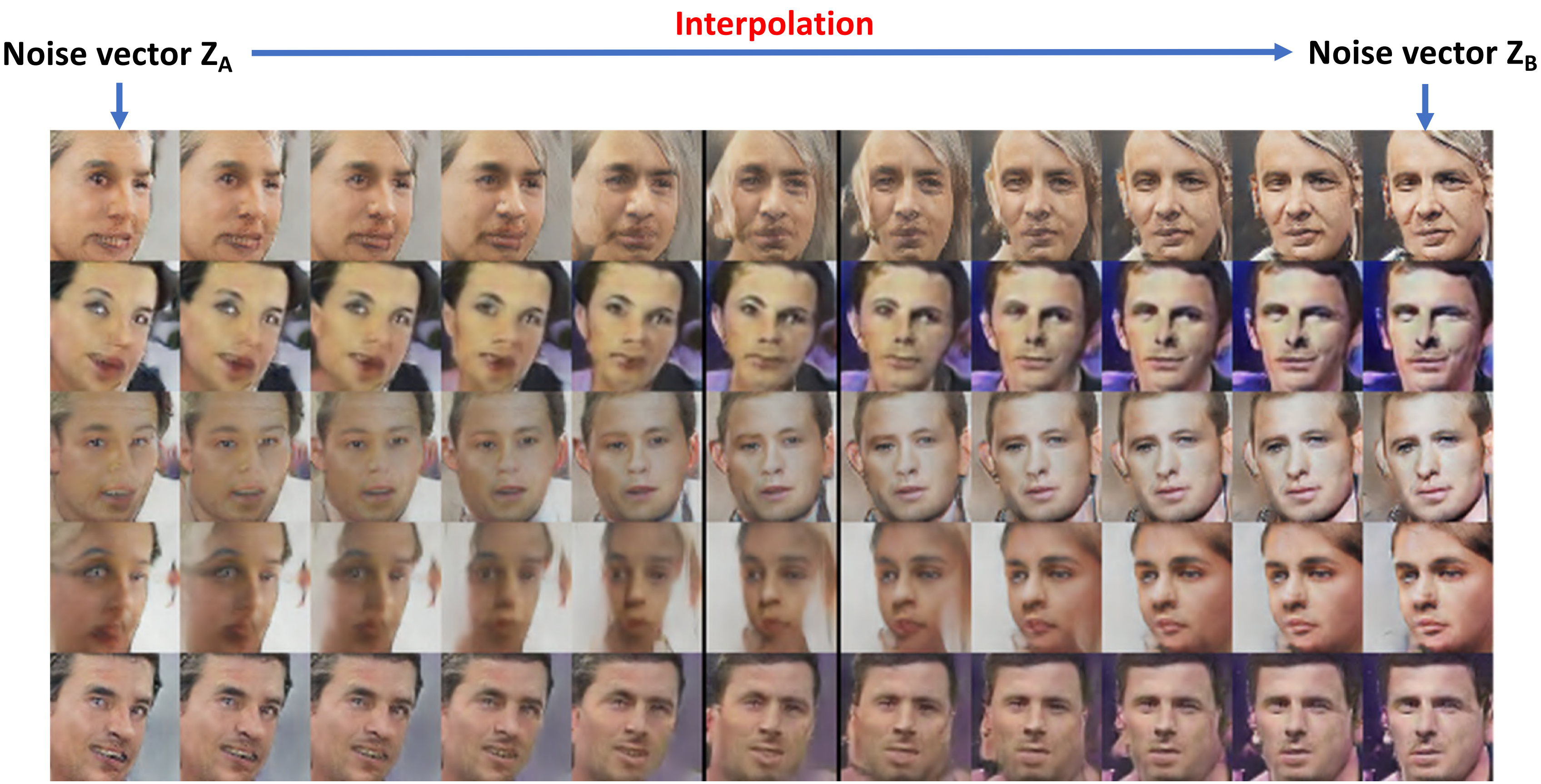
- Using the power of CNN



$\hat{X}$

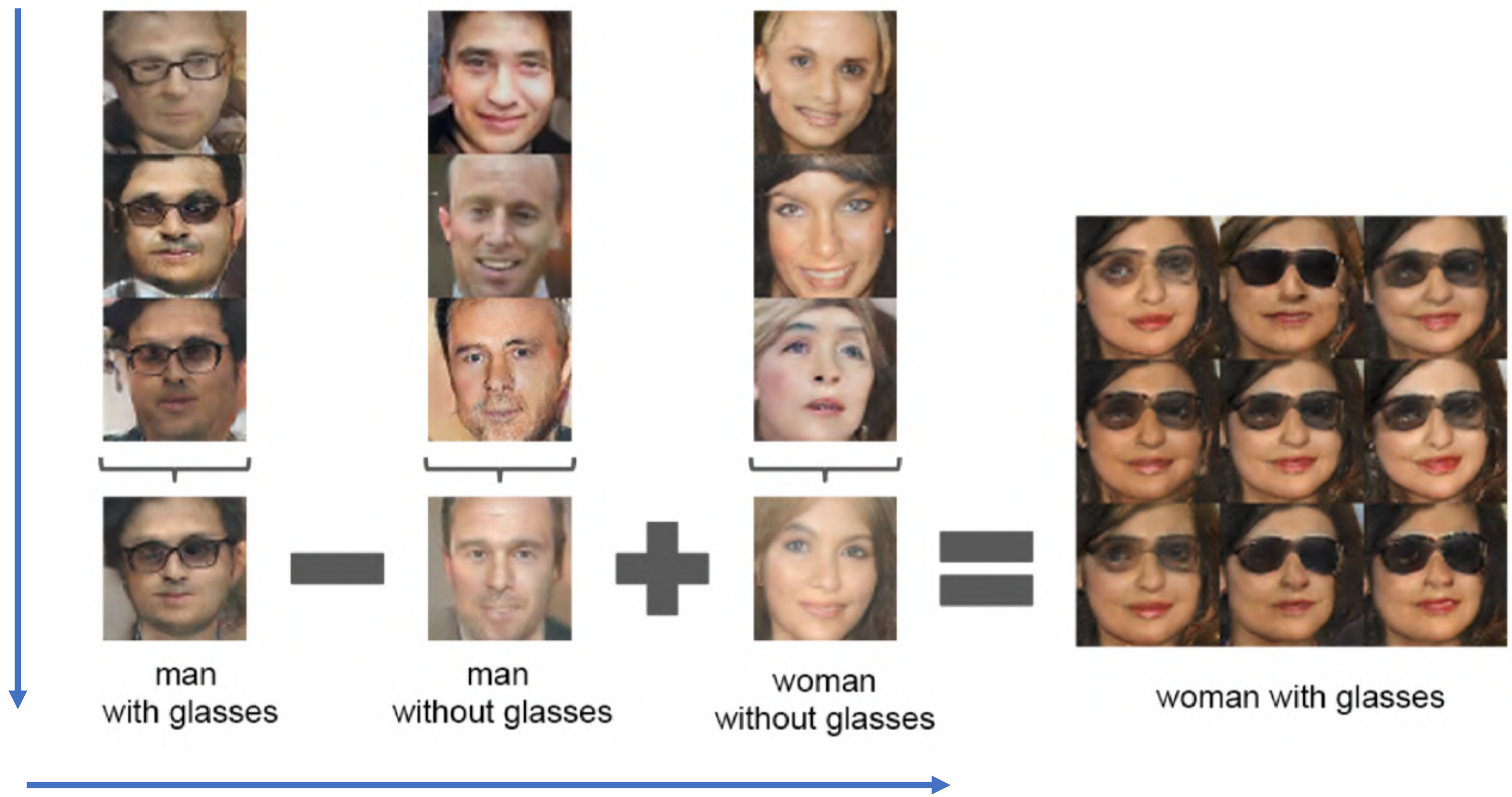
Vanilla GAN – Deep Convolutional GAN (DCGAN)

- Latent representation z



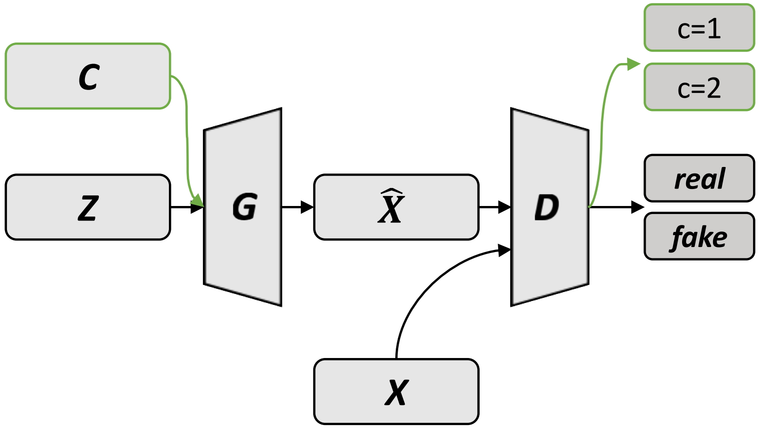
Vanilla GAN – Deep Convolutional GAN (DCGAN)

- Latent representation z



Vanilla GAN -- Conditional GAN

- Auxiliary Classifier GANs



$$\mathcal{L}_D = \mathbb{E}_{x \sim p_{data}}[log D_x(x)] + \mathbb{E}_{z \sim p_z}[log(1 - D_x(G(z,c)))]$$

$$\mathbb{E}_{x \sim p_{data}}[log D_c(x)] + \mathbb{E}_{z \sim p_z}[log(1 - D_c(G(z,c)))]$$

$$\mathcal{L}_G = \mathbb{E}_{x \sim p_{data}}[log D_x(G(z,c))] + \mathbb{E}_{z \sim p_z}[log D_c(G(z,c))]$$

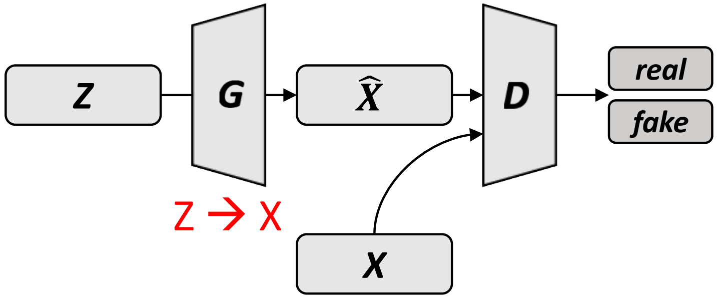
monarch butterfly goldfinch daisy

Multi-modal problem: one problem has multiple solutions
P(z, c)

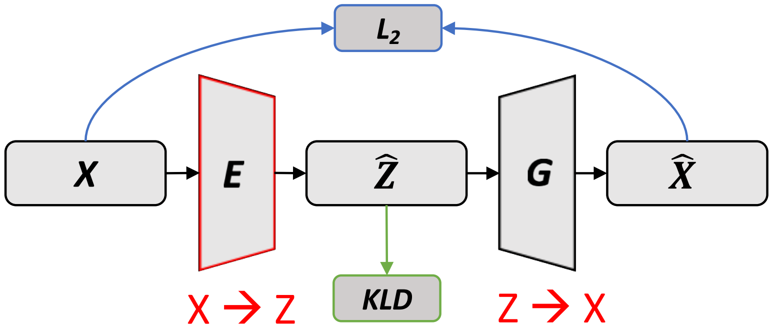
GAN with Encoder

GAN with Encoder – Vanilla GAN vs VAE

Vanilla GAN

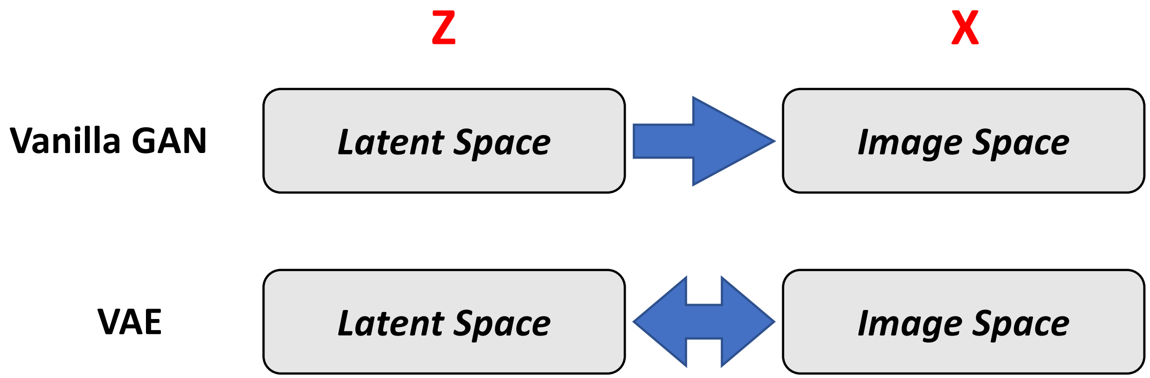


VAE variational autoencoder



VAE has an Encoder that can map x to z

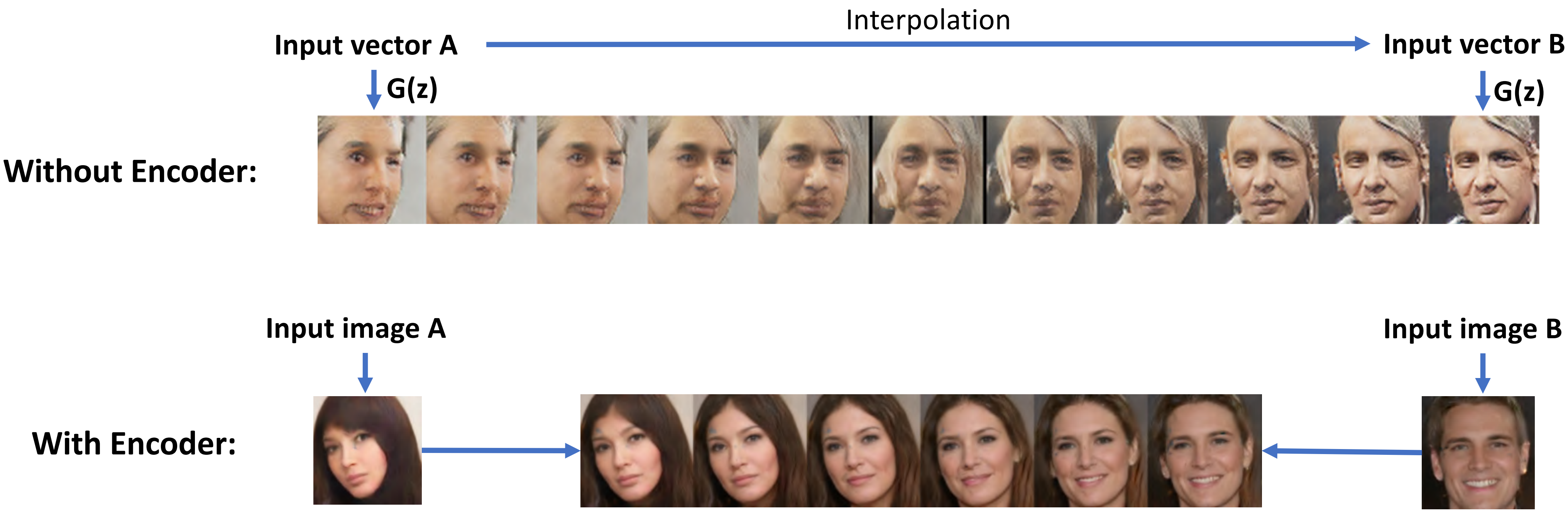
GAN with Encoder – Vanilla GAN vs VAE



- VAE = **G**enerator + **E**ncoder
- Vanilla GAN = **G**enerator + **D**iscriminator
- Better GAN = **G**enerator + **D**iscriminator + **Encoder**

GAN with Encoder – Why Encoder

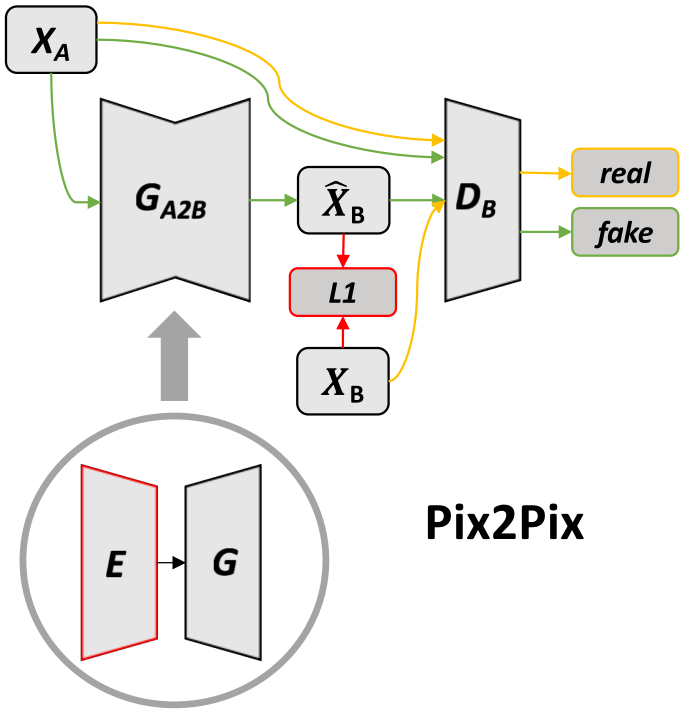
- Encoder allows GAN to receive images == More applications



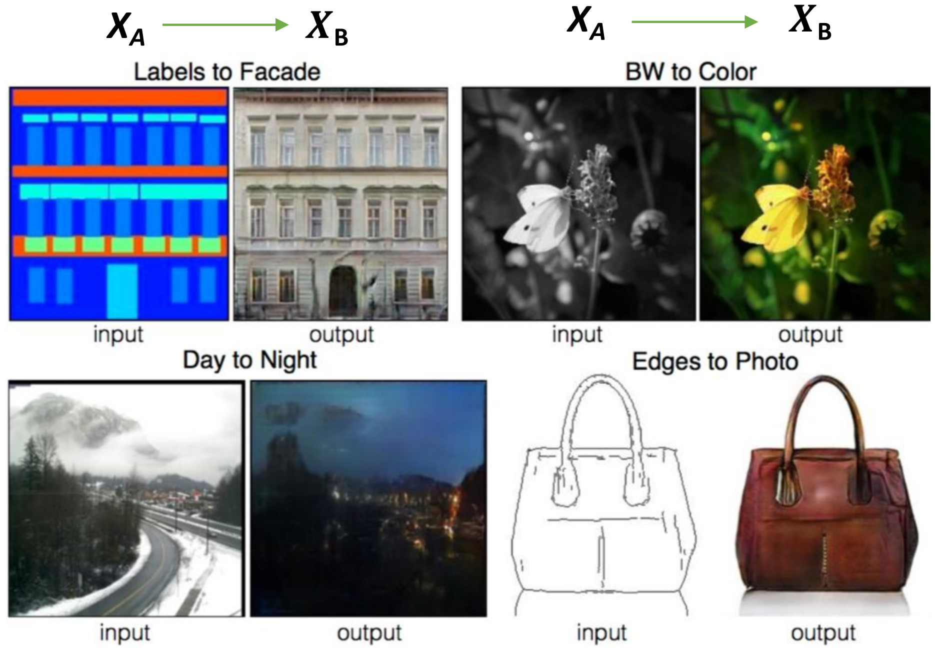
GAN with Encoder – Encoder as a part of the Generator

- Supervised image-to-image "translation"

Inputs can be images



Pix2Pix



$$\mathcal{L}_D = \boxed{\mathbb{E}_{x\sim p_{data}}[logD(x_A, x_B)]} + \boxed{\mathbb{E}_{x\sim p_{data}}[log(1 - D(x_A, G(x_A)))]}$$

$$\mathcal{L}_G = \boxed{\mathbb{E}_{x\sim p_{data}}[logD(x_A, G(x_A))]} + \boxed{\mathbb{E}_{x\sim p_{data}}\lambda||x_B - G(x_A)||}$$

Image-to-Image Translation with Conditional Adversarial Networks. *P. Isola, J. Zhu et al. CVPR 2017.*

GAN with Encoder – Encoder as a part of the Generator

- Supervised image-to-image “translation”

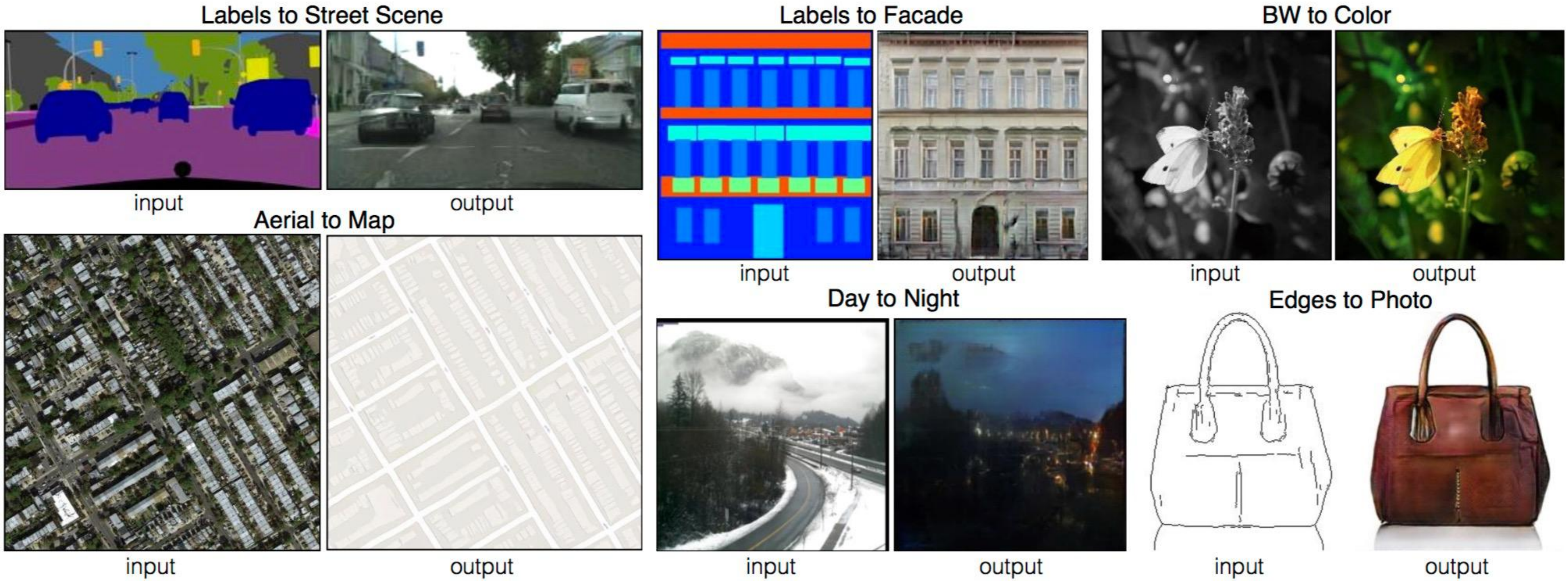


Image-to-Image Translation with Conditional Adversarial Networks. *P. Isola, J. Zhu et al. CVPR 2017.*

GAN with Encoder – Encoder as a part of the Generator

- Supervised image-to-image “translation”

Input Output

Input labels

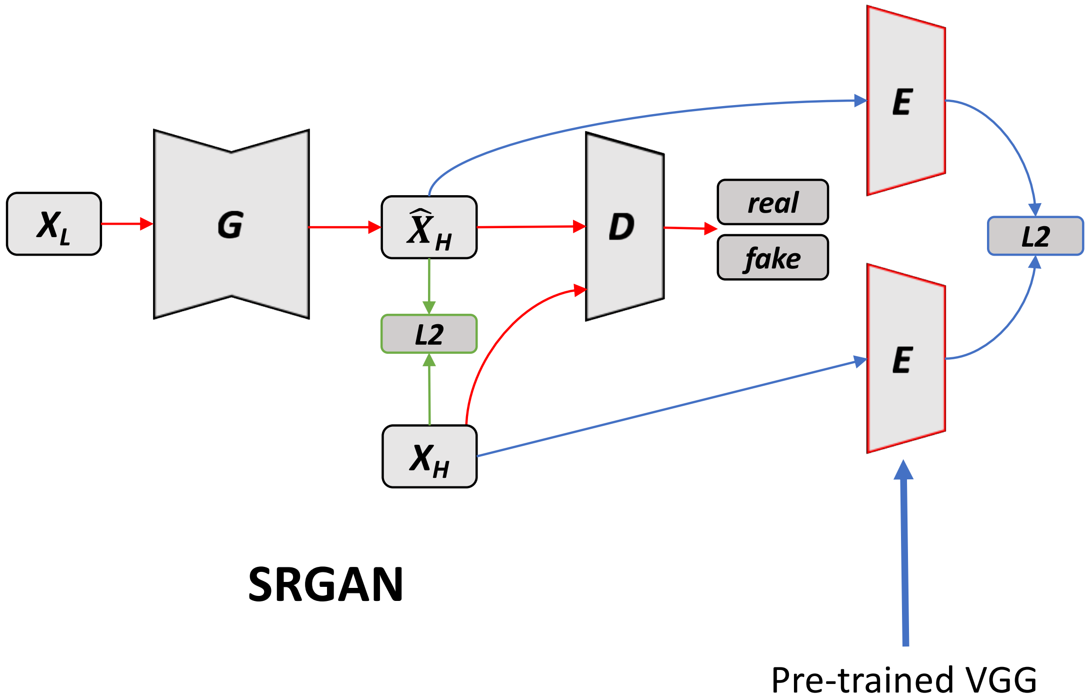
Synthesized image

Image-to-Image Translation with Conditional Adversarial Networks. *P. Isola, J. Zhu et al. CVPR 2017.*

GAN with Encoder – Encoder as the Feature Extractor

- Supervised image super resolution

Better feature reconstruction



SRGAN

Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. *C. Ledig, L. Theis et al. CVPR 2017.*

GAN with Encoder – Encoder as the Feature Extractor

- Supervised image super resolution

Input Output

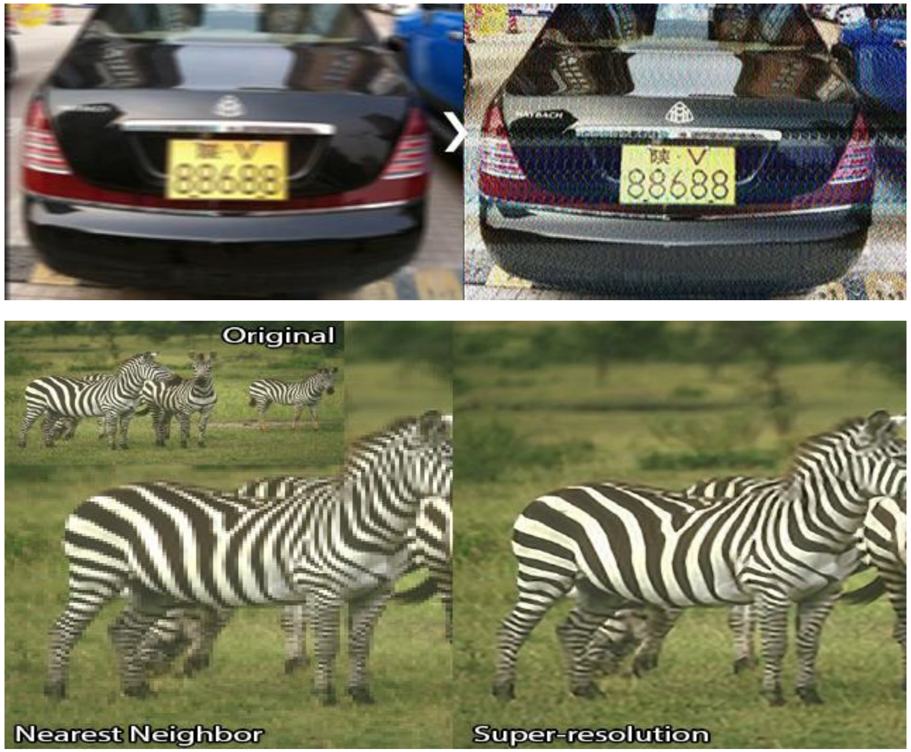
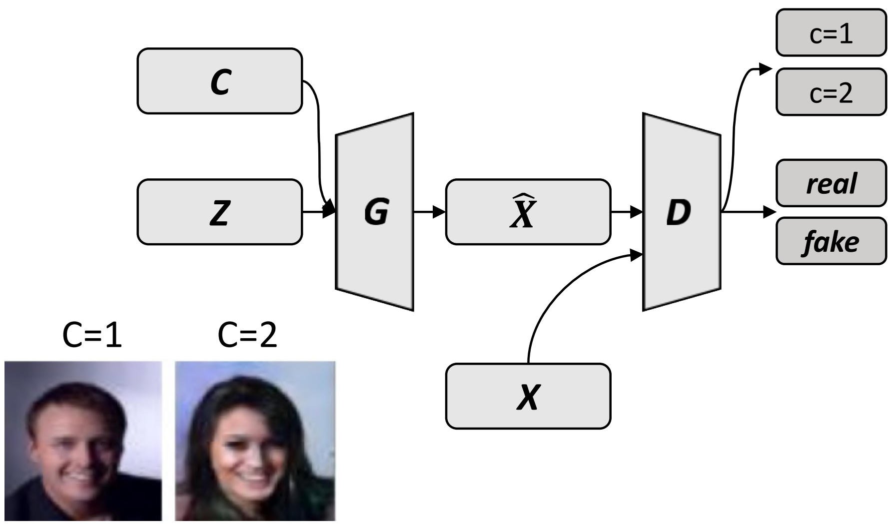


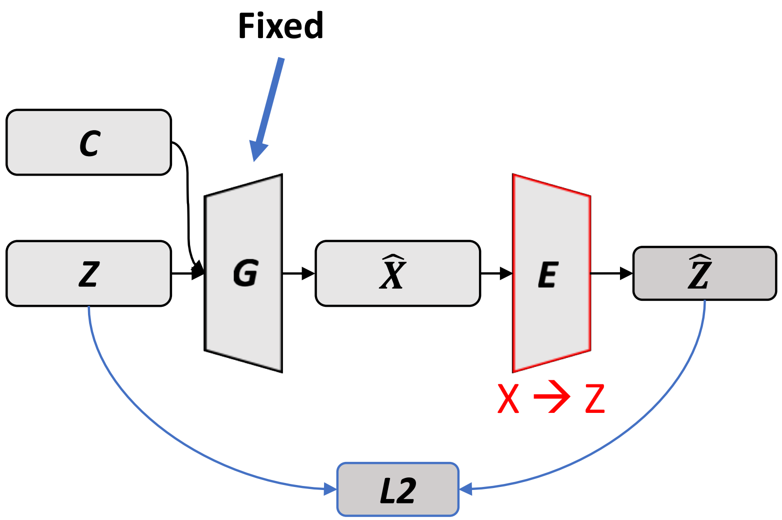
Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. *C. Ledig, L. Theis et al. CVPR 2017.*

GAN with Encoder – Learn the mapping from x to z like VAE

- Unsupervised image-to-image translation



Given an ACGAN

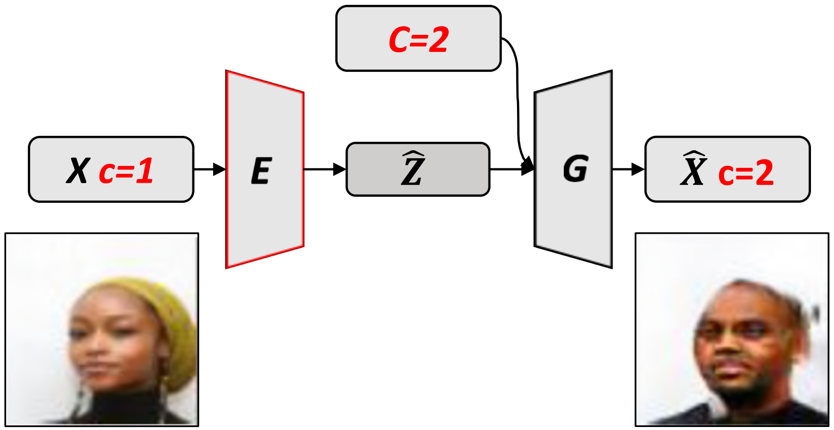


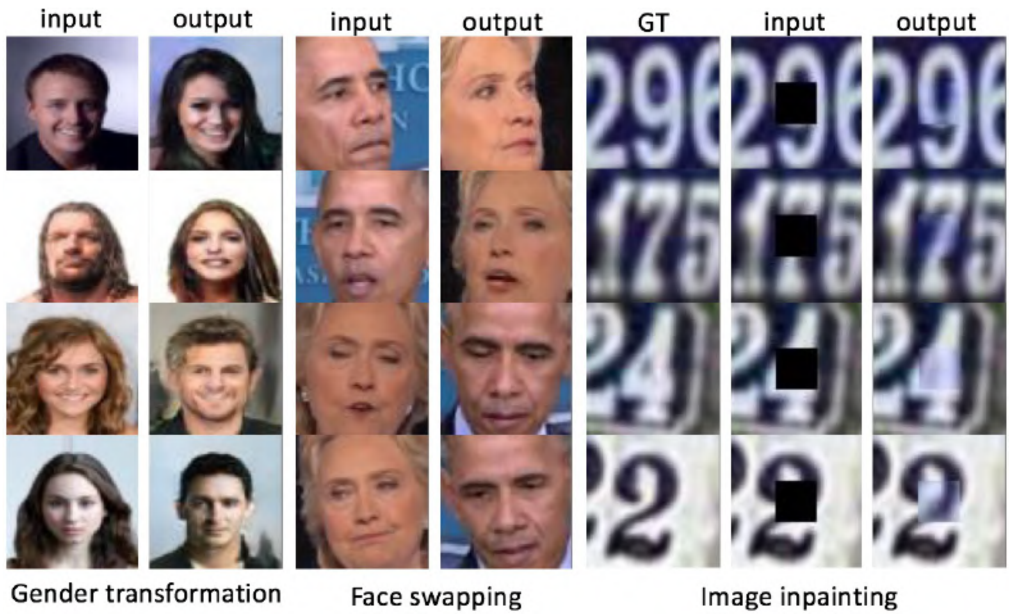
Learning the Encoder in a Brute Force Way

Unsupervised Image-to-Image Translation with Generative Adversarial Networks. *H. Dong, P. Neekhara et al. arXiv 2017.*

GAN with Encoder – Learn the mapping from x to z

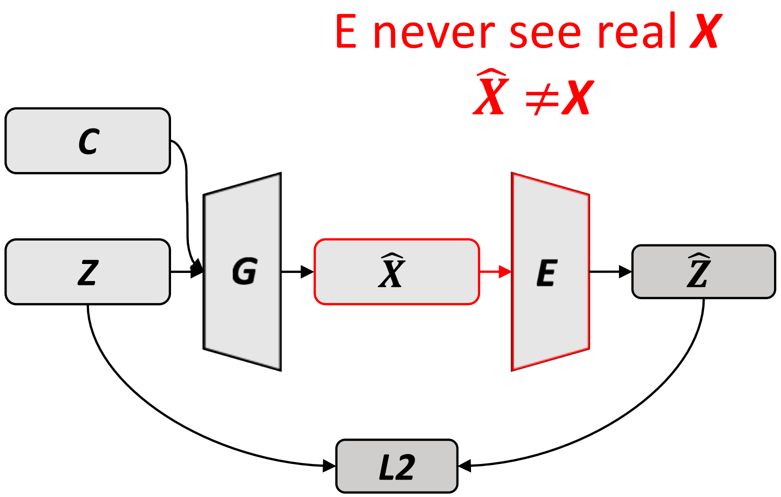
- Unsupervised image-to-image translation





GAN with Encoder – Learn the mapping from x to z

- Limitation of the brute force method : Encoder never see real data samples

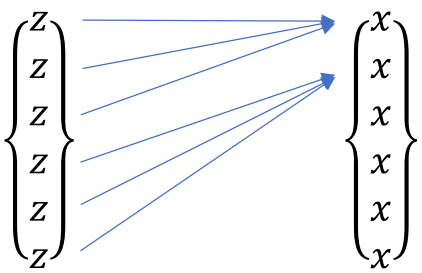


GAN with Encoder – Learn the mapping from x to z

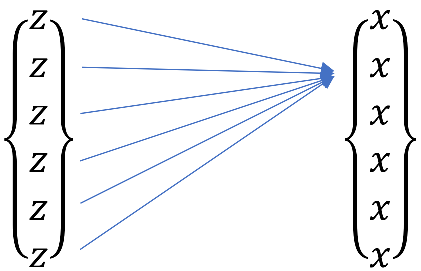
- Limitation of the brute force method : GAN Collapse

E never see real ***X***

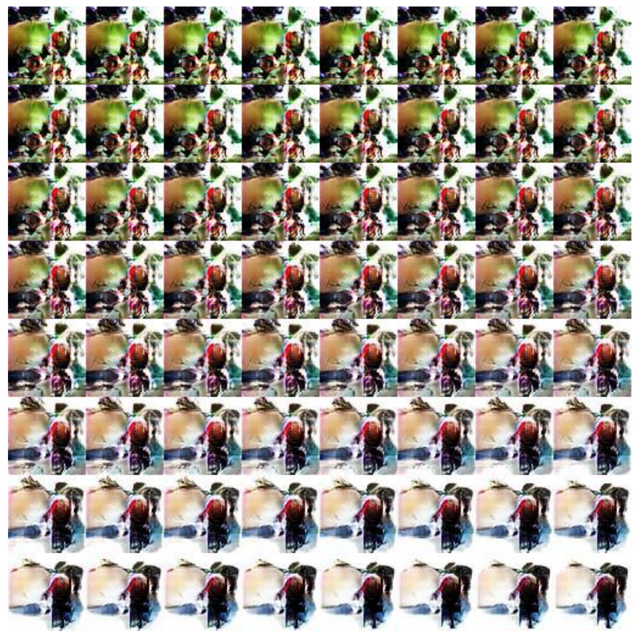
$\hat{\boldsymbol{X}} \neq \boldsymbol{X}$



G can only synthesis some part of the dataset x



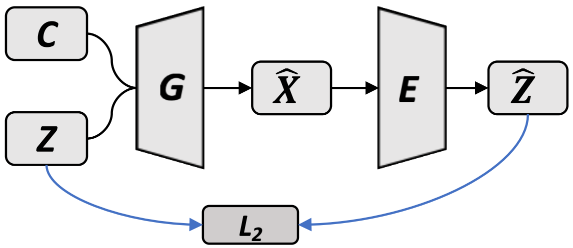
G can only synthesis one data



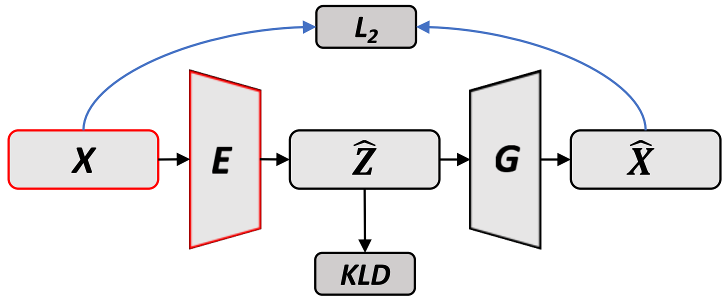
Examples of GAN collapse

GAN with Encoder -- Learn the Encoder from Real Data

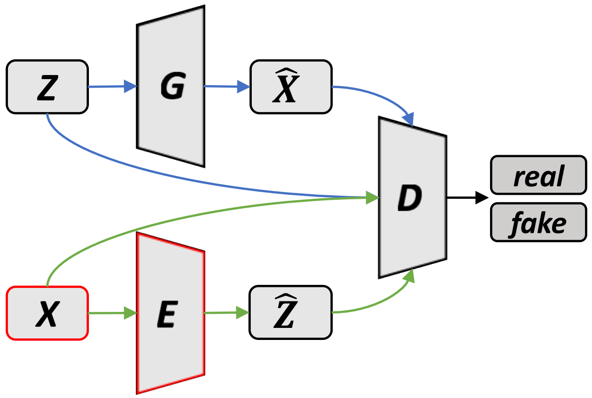
- Learn the Encoder



Brute Force

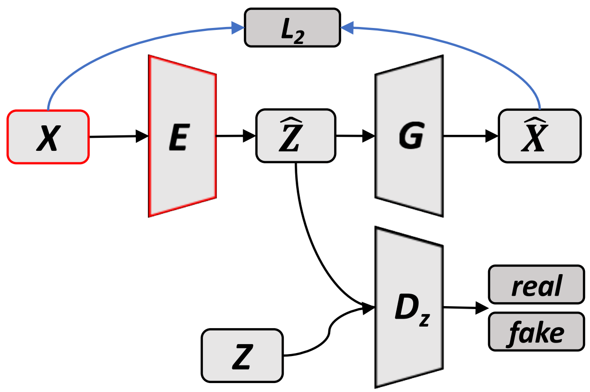


VAE



BiGAN

Bidirectional GAN



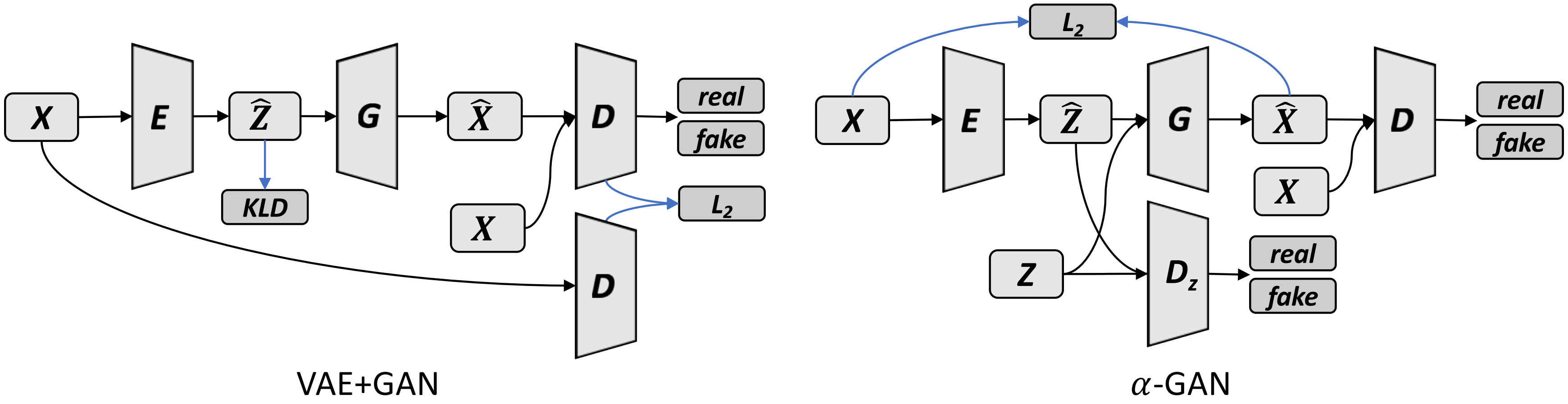
AAE

Adversarial Autoencoder

GAN with Encoder -- Learn the Encoder from Real Data

- Learn the Encoder

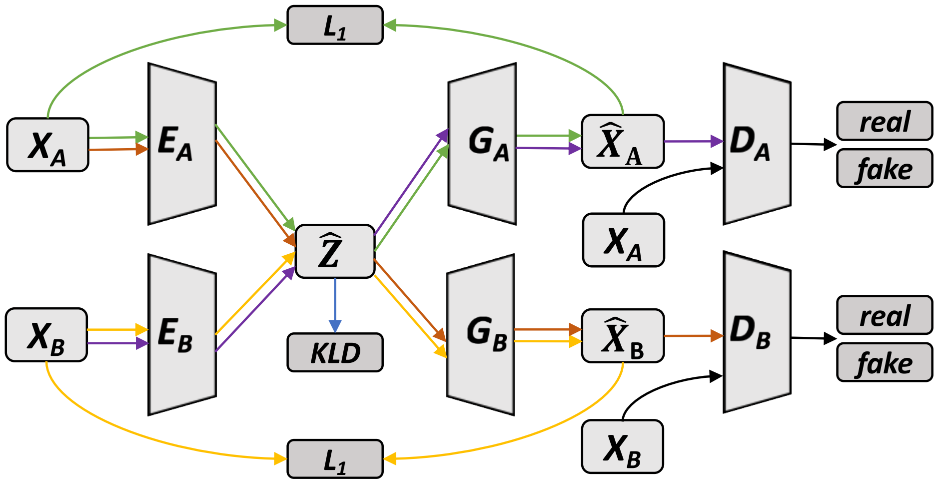
Avoid GAN collapse



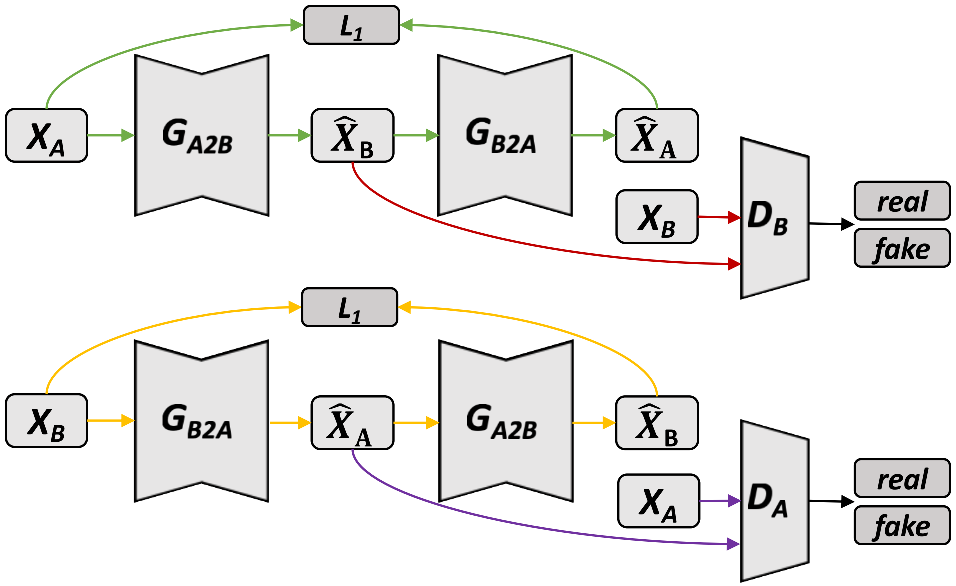
Discriminator as the feature extractor

- Training the *G* and *E* in Autoencoder way can force the G to be able to generate all *X, avoiding GAN collapse*

GAN with Encoder -- Unsupervised Image-to-Image Translation



Liu et al.
Learn the Encoder **Explicitly**



CycleGAN
Learn the Encoder **Implicitly**

Unsupervised image-to-image translation networks. *M.Y. Liu, T. Breuel, J. Kautz. NIPS. 2017*
Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. *J. Zhu, T. Park et al. ICCV 2017.*

GAN with Encoder -- Unsupervised Image-to-Image Translation

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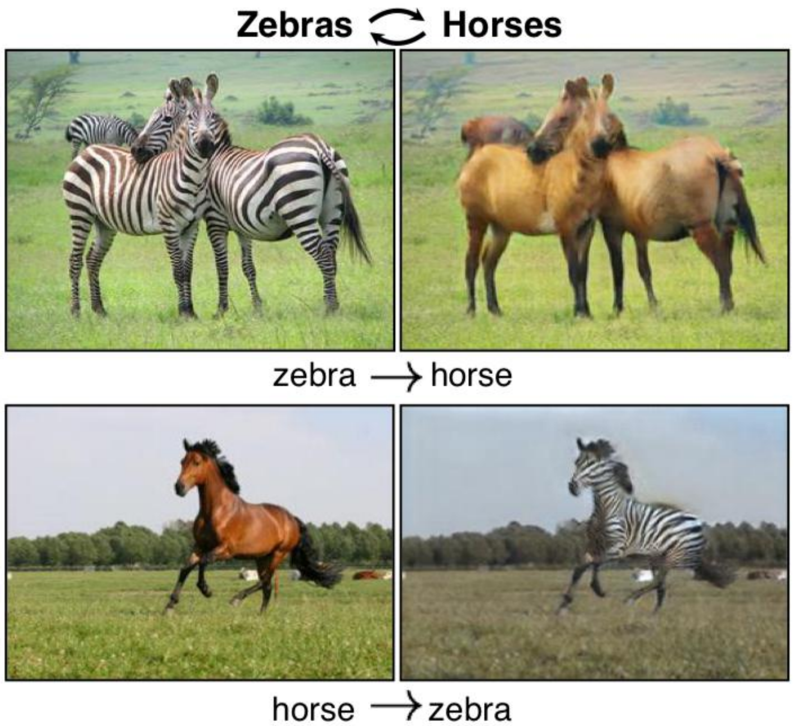
Liu et al.
Learn the Encoder **Explicitly**



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GAN with Encoder -- Unsupervised Image-to-Image Translation

Input GTA5 CG

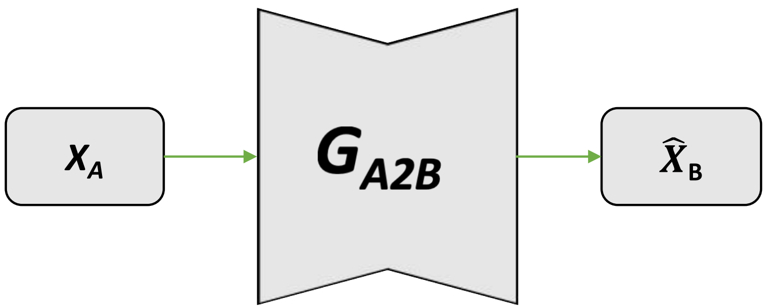
Output image with German street view style

Unsupervised image-to-image translation networks. *M.Y. Liu, T. Breuel, J. Kautz. NIPS. 2017*

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. *J. Zhu, T. Park et al. ICCV 2017.*

GAN with Encoder – Learn Encoder in Implicit or Explicit Ways?

- Simple normal distribution is difficult to model complex images
- 3D tensors can contain more spatial information than vectors
- Many applications do not need interpolation



- Image inpainting
- Image super resolution
- Image-to-image translation
- ….

Summary

Summary

This talk:

- GAN : G + D → G + D + E
- Learning E from real data is important
- Autoencoder can help to avoid GAN collapse
- Learning E implicitly is becoming more and more popular
- The E can be extended to text and any other data type

GAN applications:

- Image-to-image: Pix2Pix→CycleGAN→Attention CycleGAN
- Text-to-image: GAN-CLS → StackGAN → StackGAN++
- Text+image to image: …
- Video-to-video: …

Questions

Questions

- Q1. 如何解决GAN中，输入的normal distribution太简单的问题？
- Q2. 为什么G、D要来回对抗训练，而不是完全训练好D后再训练G？
- Q3. G是不是真的能创造出训练数据中没有的数据？