Challenge:
Learning Large Encoder

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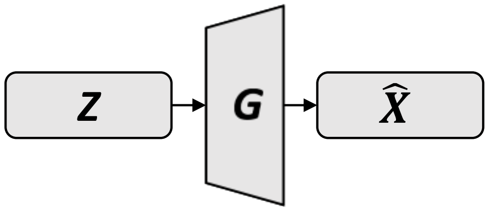
Peking University

Challenge: Learning Large Encoder

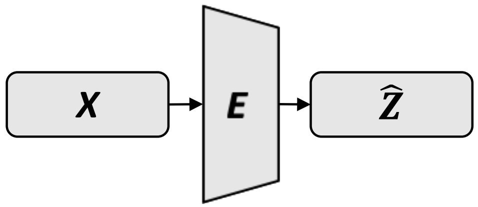
Previous Lecture: Large Image

Scalable



This Lecture: Large Encoder

Reversable



We use images for demonstration

Unsupervised Representation Learning!

Challenge: Learning Large Encoder

- VAE vs. GAN
- A Naïve Approach
- Another Naïve Approach
- Without Encoder
- Recap: BiGAN
- Adversarial Autoencoder
- VAE+GAN
- α-GAN
- BigBiGAN
- Multi-code GAN prior
- Implicit vs. Explicit Encoder
- Summary

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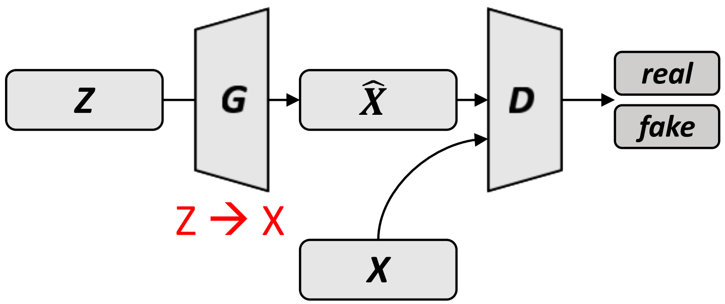
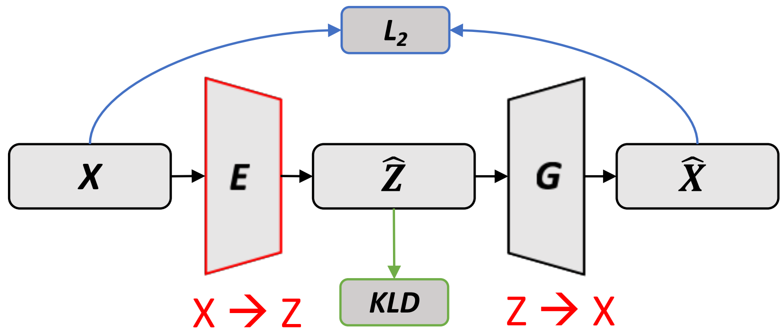
VAE vs. GAN

Vanilla GAN

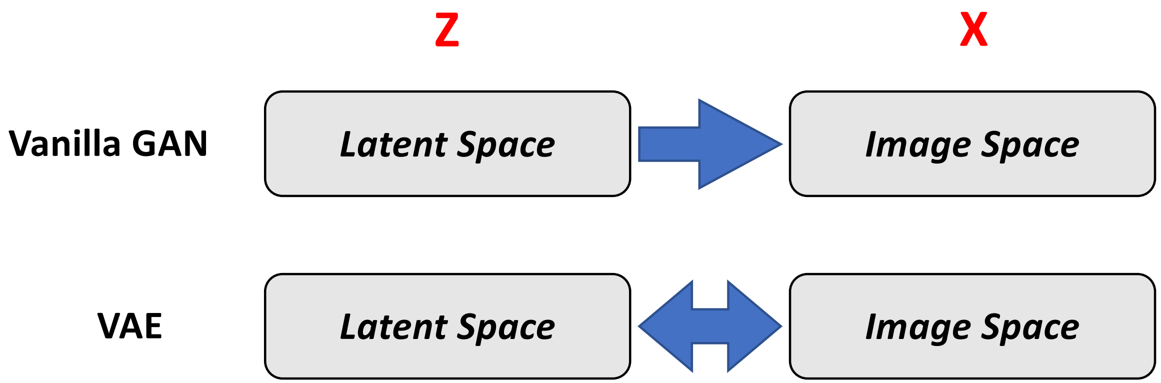


VAE variational autoencoder



VAE has an Encoder that can map x to z

VAE vs. GAN



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

VAE vs. GAN

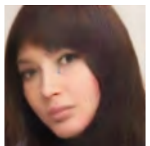
- **Without Encoder:**

Input vector $\boldsymbol{z_a}$ $\qquad G((1-\alpha) * z_a + \alpha * z_b), \quad \alpha \in [0, 1]$ $\qquad$ **Input vector $\boldsymbol{z_b}$**

$G(z_a)$ $\xrightarrow{\text{Interpolation}}$ $G(z_b)$

- **With Encoder:**

Input image $\boldsymbol{x_a}$



Input image $\boldsymbol{x_b}$

$$G((1-\alpha) * z_a + \alpha * z_b), \quad \alpha \in [0, 1]$$

$z_a = E(x_a)$ →  ← $z_b = E(x_b)$

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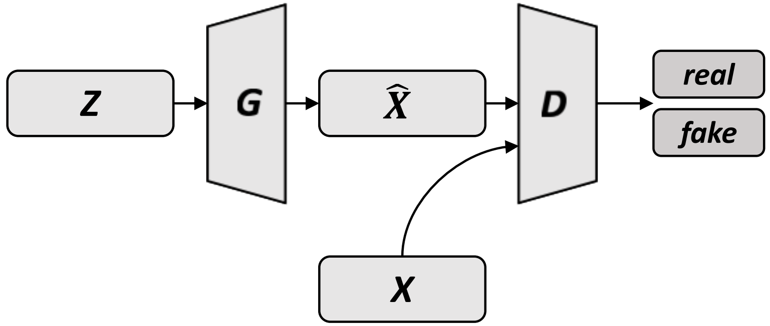
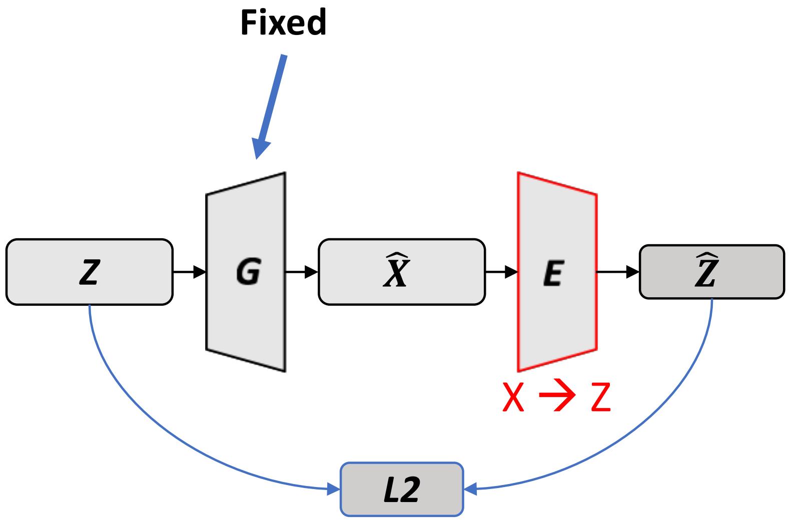
A Naïve Approach



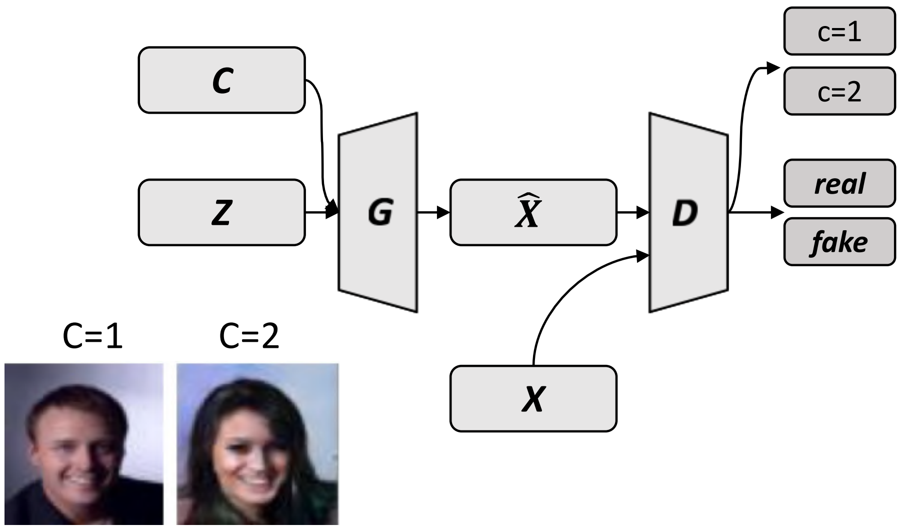
Step 1: Pre-trained G



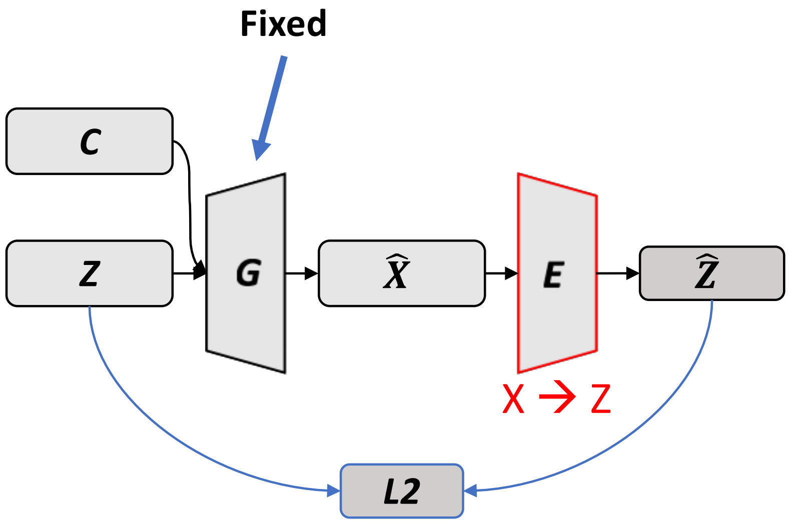
Step 2: Fix G and Train E

A Naïve Approach

- Application: Unsupervised/Unpaired Image-to-Image Translation



Given an ACGAN



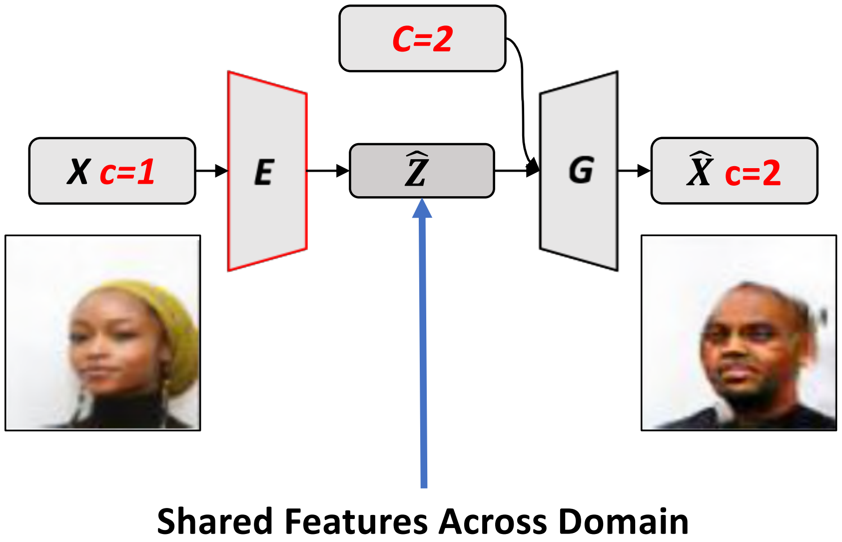
Learning the Encoder in a Brute Force Way

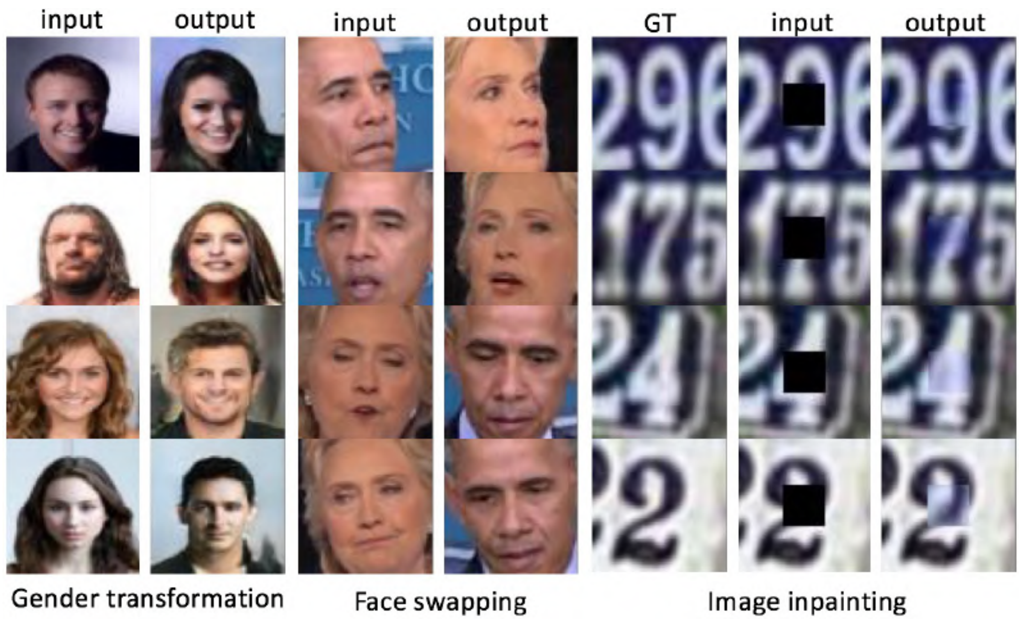
Z : shared latent representation across two domains

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

A Naïve Approach

- Application: Unsupervised/Unpaired Image-to-Image Translation





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

A Naïve Approach

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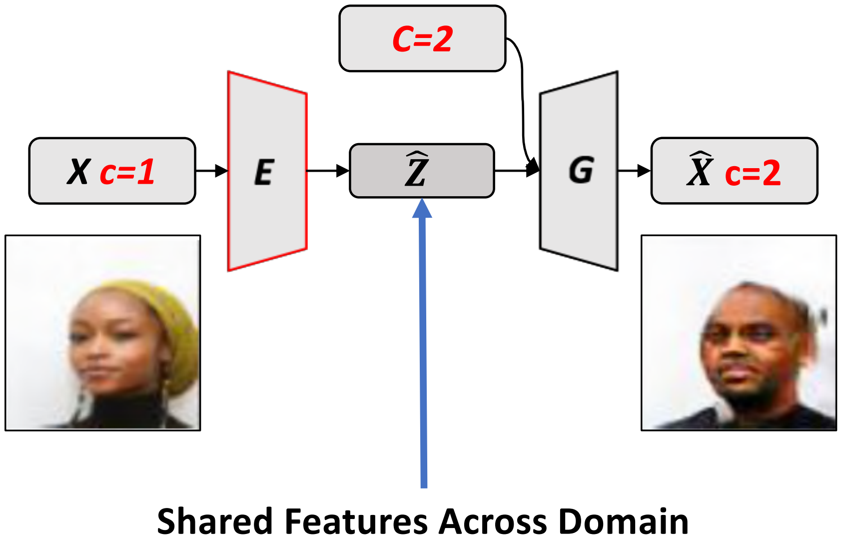
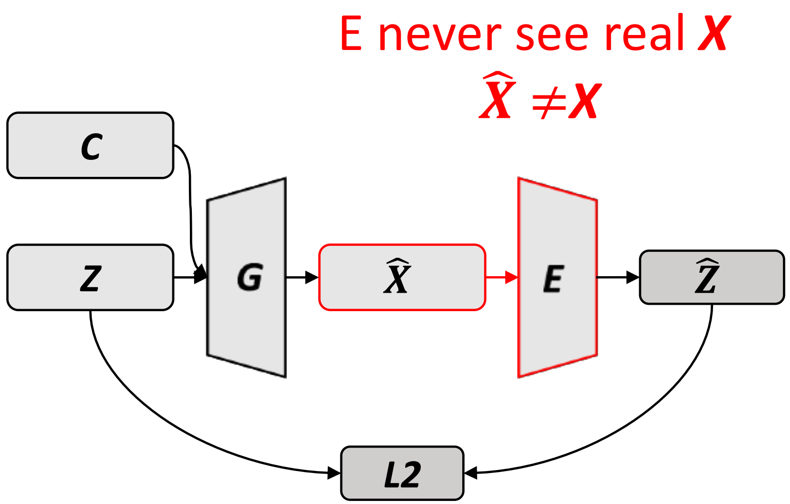


Only Work Well for Simple Image with Small Size

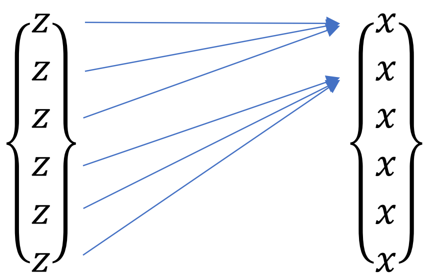
A Naïve Approach

- Limitation: Encoder never see real data sample !

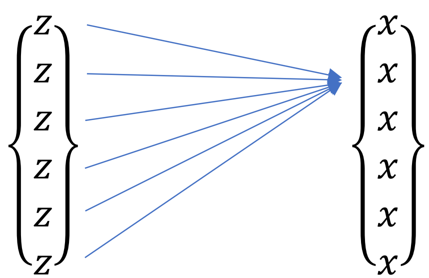


A Naïve Approach

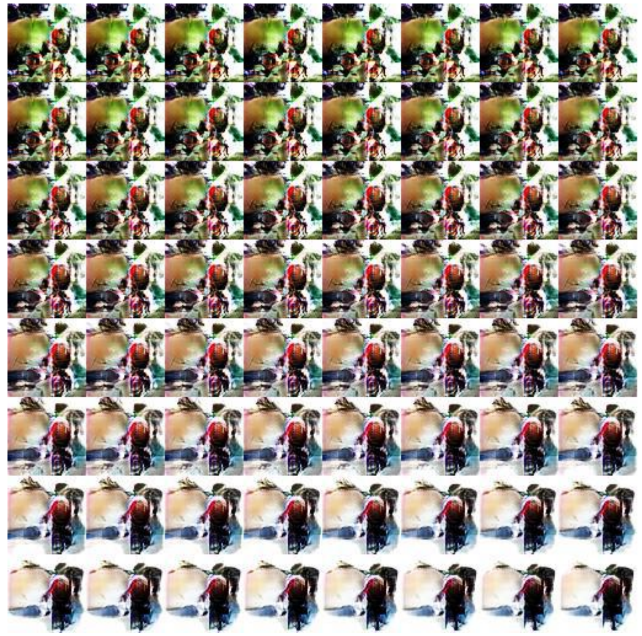
- Limitation: Encoder never see real data sample
  and the synthesized data distribution != real data distribution
- Mode Collapse



G can only synthesis some part of the dataset x
and can fool D



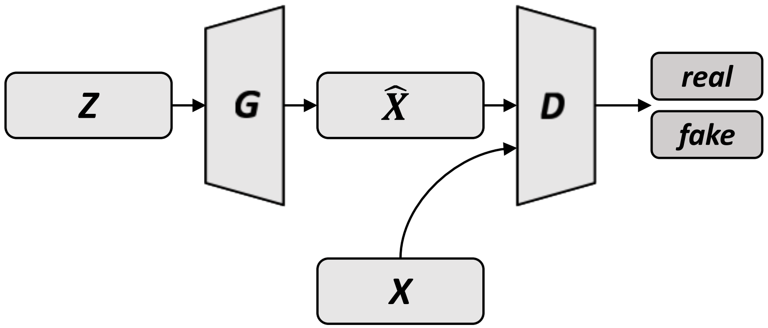
G can even only synthesis one data
and can fool D



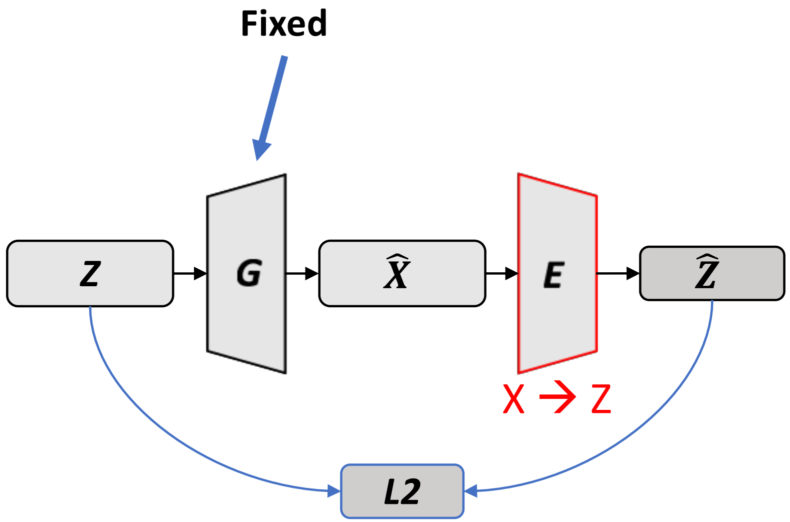
Examples of GAN collapse

A Naïve Approach

- Only work well if only if the fake distribution == the real distribution, but it is impossible in practice.



Step 1: Pre-trained G



Step 2: Fix G and Train E

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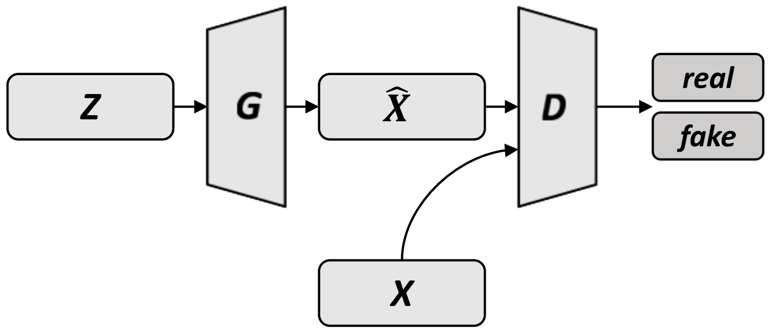
Another Naïve Approach

- Could E see real data sample?



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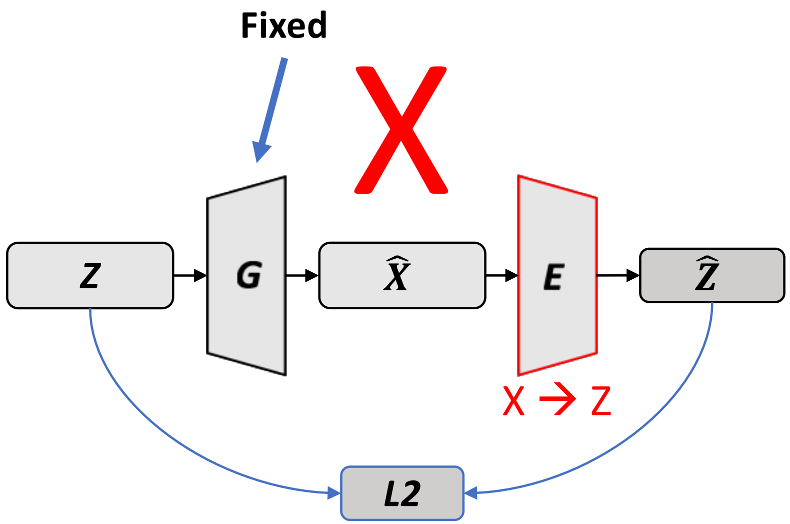
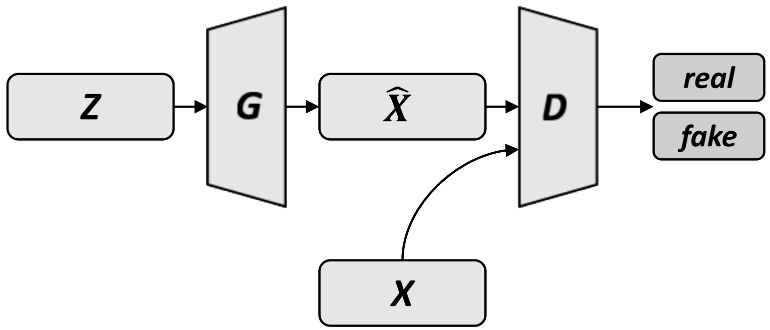


Step 2: Fix G and Train E

Another Naïve Approach

- Could E see real data sample?

E can see real data sample now



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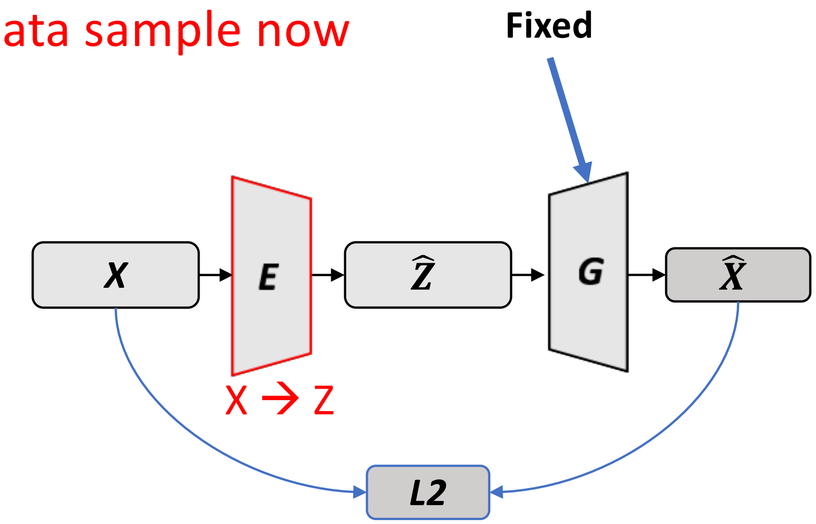


Step 2: Fix G and Train E

Another Naïve Approach

- Problem:
  Difficult to converge (even using a super-deep E)

- Reason:
  Model Collapse: G cannot synthesize the input image, so the loss cannot be reduced

  The quality of synthesized images != real images, so the loss cannot be reduced

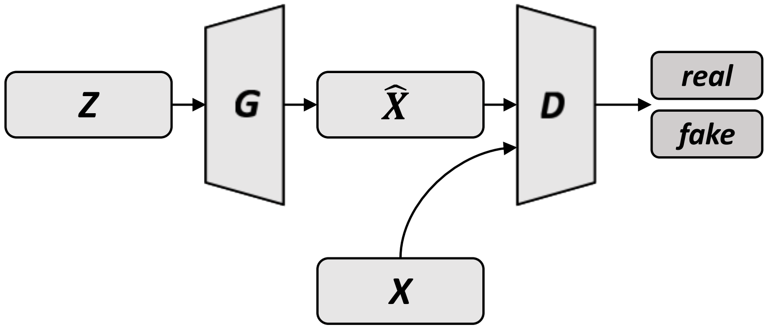
Another Naïve Approach

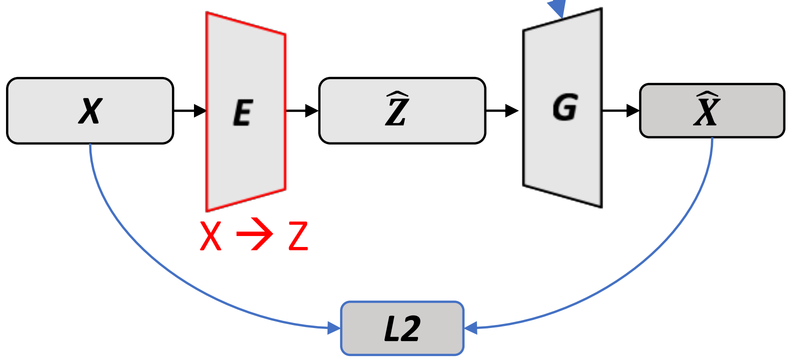
- Only work well if only if the fake distribution == the real distribution, but it is impossible in practice.

E can see real data sample now,

but G cannot always generate the input samples

Fixed





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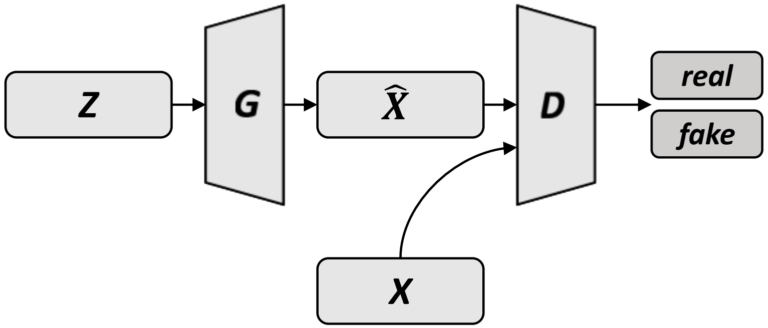
Without Encoder

- Optimisation-based method: find the optimal z iteratively



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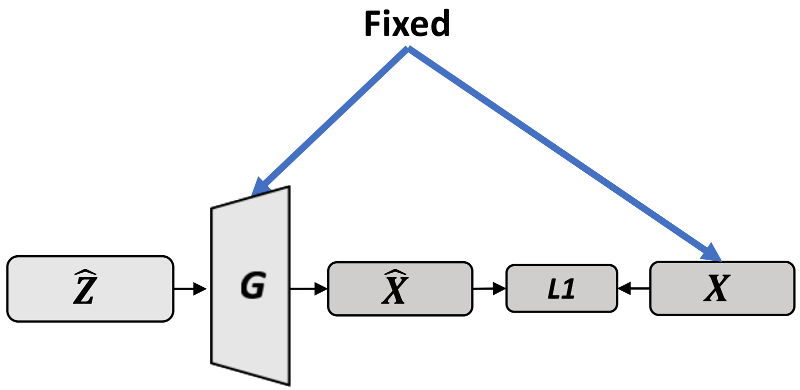

Step 2: Fix G and X, Train Z

Without Encoder

- Limitation?

SLOW

A naïve way to speed up this method is to:

use one of the previous naïve way to pretrain an encoder, then

step 1: use the encoder to initialize the latent code z when given an image x
step 2: find the optimal z iteratively

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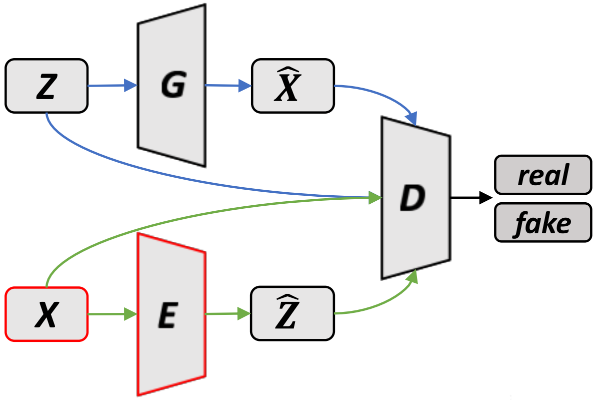
Recap: Bidirectional GAN



BiGAN

Bidirectional GAN

$$\{X, \hat{Z}\} - \{\hat{X}, Z\}$$

Consider a BiGAN discriminator input pair $(\mathbf{x}, \mathbf{z})$. Due to the sampling procedure, $(\mathbf{x}, \mathbf{z})$ must satisfy at least one of the following two properties:

$$\text{(a) } \mathbf{x} \in \hat{\Omega}_{\mathbf{X}} \ \wedge \ E(\mathbf{x}) = \mathbf{z} \qquad\qquad \text{(b) } \mathbf{z} \in \hat{\Omega}_{\mathbf{Z}} \ \wedge \ G(\mathbf{z}) = \mathbf{x}$$

If *only* one of these properties is satisfied, a perfect discriminator can infer the source of $(\mathbf{x}, \mathbf{z})$ with certainty: if only (a) is satisfied, $(\mathbf{x}, \mathbf{z})$ must be an encoder pair $(\mathbf{x}, E(\mathbf{x}))$ and $D^*_{EG}(\mathbf{x}, \mathbf{z}) = 1$; if only (b) is satisfied, $(\mathbf{x}, \mathbf{z})$ must be a generator pair $(G(\mathbf{z}), \mathbf{z})$ and $D^*_{EG}(\mathbf{x}, \mathbf{z}) = 0$.

Therefore, in order to fool a perfect discriminator at $(\mathbf{x}, \mathbf{z})$ (so that $0 < D^*_{EG}(\mathbf{x}, \mathbf{z}) < 1$), E and G must satisfy *both* (a) and (b). In this case, we can substitute the equality $E(\mathbf{x}) = \mathbf{z}$ required by (a) into the equality $G(\mathbf{z}) = \mathbf{x}$ required by (b), and vice versa, giving the inversion properties $\mathbf{x} = G(E(\mathbf{x}))$ and $\mathbf{z} = E(G(\mathbf{z}))$.

BiGAN: Adversarial Feature Learning. Jeff Donahue, Philipp Krahenbuhl, Trevor Darrell. ICLR 2017.

ALI: Adversarially Learned Inference. Vincent Dumoulin, Ishmael Belghazi, Ben Poole, Olivier Mastropietro, Alex Lamb, Martin Arjovsky, Aaron Courville. ICLR 2017.

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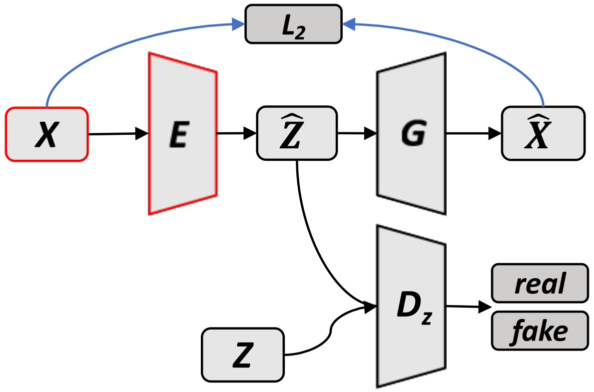
Adversarial Autoencoder



AAE
Adversarial Autoencoder

$$\{\hat{Z}\} - \{Z\}$$

AAE: Adversarial Autoencoder. Alireza Makhzani, Jonathon Shlens, Navdeep Jaitly. ICLR 2016.

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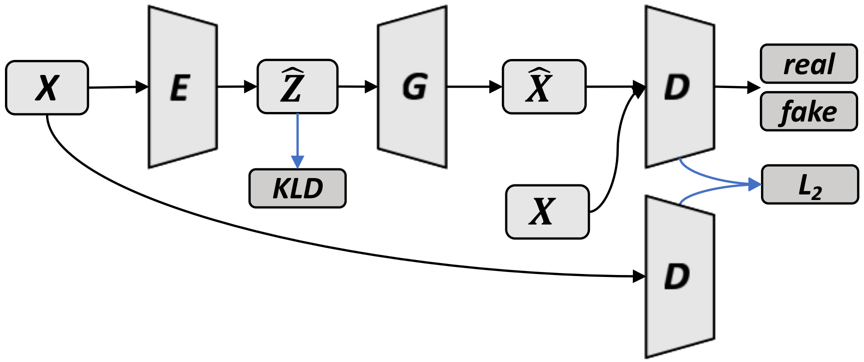
VAE+GAN



VAE+GAN

$$\{\hat{X}\} - \{X\}$$

Discriminator as the feature extractor

VAE-GAN: Autoencoding Beyond Pixels Using a Learned Similarity Metric. Andres Boesen Lindbo Larsen, Soren Kaae Sonderby, Hugo Larochelle, Ole Winther. ICML 2016.

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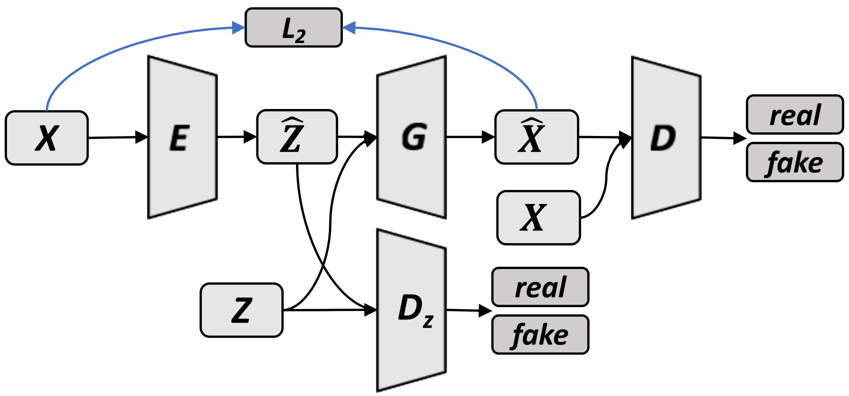
$\boldsymbol{\alpha}$-GAN



α-GAN

$$\{\hat{X}\} - \{X\}$$

$$\{\hat{Z}\} - \{Z\}$$

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

α-GAN: Variational Approaches for Auto-Encoding Generative Adversarial Networks. Mihaela Rosca, Balaji Lakshminarayanan, David Warde-Farley, Shakir Mohamed. arXiv preprint arXiv:1706.04987.

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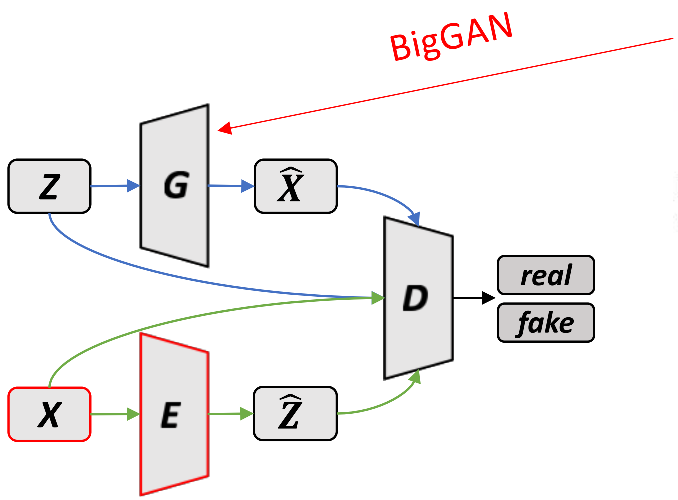
BigBiGAN

- Work on large images
- Combine BigGAN and BiGAN



BiGAN

Bidirectional GAN

(a) 128×128 (b) 256×256 (c) 512×512 (d)

Figure 4: Samples from our BigGAN model with truncation threshold 0.5 (a-c) and an example of class leakage in a partially trained model (d).

BigBiGAN: Large Scale Adversarial Representation Learning. Jeff Donahue, Karen Simonyan. NIPS 2019.

BigBiGAN

- Limitation

image size of 512x512x3 → Latent code with size of 1x512

$$\frac{512}{512\times 512\times 3} = 0.000651$$

Difficult to be lossless ….

BigBiGAN: Large Scale Adversarial Representation Learning. Jeff Donahue, Karen Simonyan. NIPS 2019.

BigBiGAN

- Limitation

Figure 2: Selected reconstructions from an unsupervised BigBiGAN model (Section 3.3). Top row images are real data $\mathbf{x} \sim P_{\mathbf{x}}$; bottom row images are generated reconstructions of the above image $\mathbf{x}$ computed by $\mathcal{G}(\mathcal{E}(\mathbf{x}))$. Unlike most explicit reconstruction costs (e.g., pixel-wise), the reconstruction cost implicitly minimized by a (Big)BiGAN [4, 7] tends to emphasize more semantic, high-level details. Additional reconstructions are presented in Appendix B.

BigBiGAN: Large Scale Adversarial Representation Learning. Jeff Donahue, Karen Simonyan. NIPS 2019.

BigBiGAN

- Limitation

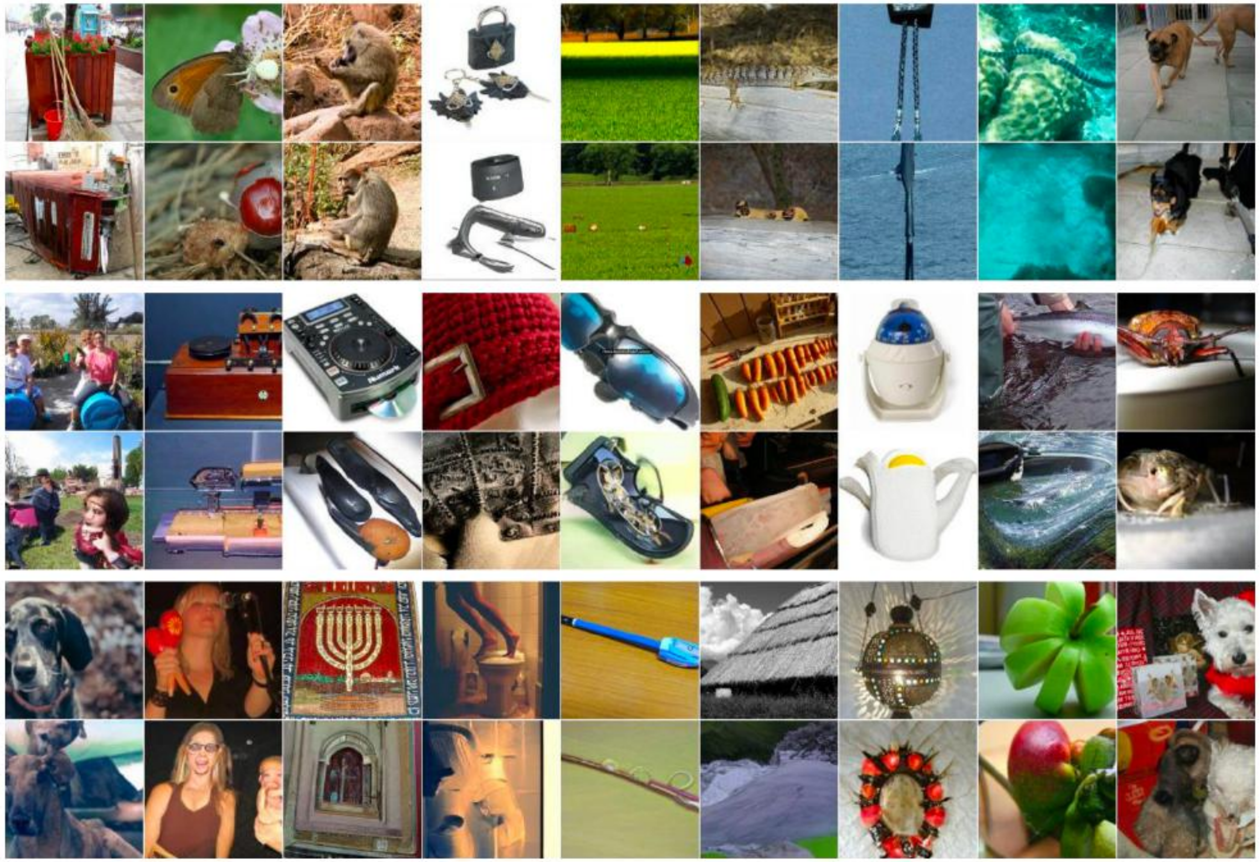


Figure 7: 128 × 128 reconstructions from an unsupervised BigBiGAN model, trained using the lighter augmentation from [24] with generation results reported in Table 3. The top rows of each pair are real data $\mathbf{x} \sim P_{\mathbf{x}}$, and bottom rows are generated reconstructions computed by $\mathcal{G}(\mathcal{E}(\mathbf{x}))$.

BigBiGAN: Large Scale Adversarial Representation Learning. Jeff Donahue, Karen Simonyan. NIPS 2019.

BigBiGAN

- Main Goal: Large Scale Adversarial Representation Learning

	Top-1 / Top-5 Acc. (%)			
Metric	$k=1$	$k=5$	$k=25$	$k=50$
D_1	38.09 / -	41.28 / 58.56	43.32 / 65.12	42.73 / 66.22
D_2	35.68 / -	38.61 / 55.59	40.65 / 62.23	40.15 / 63.42

Table 6: Accuracy of k nearest neighbors classifiers in BigBiGAN feature space on the ImageNet validation set. We report results under the normalized ℓ_1 distance D_1 as well as the normalized ℓ_2 (cosine) distance D_2.

BigBiGAN: Large Scale Adversarial Representation Learning. Jeff Donahue, Karen Simonyan. NIPS 2019.

BigBiGAN

- Main Goal: Large Scale Adversarial Representation Learning

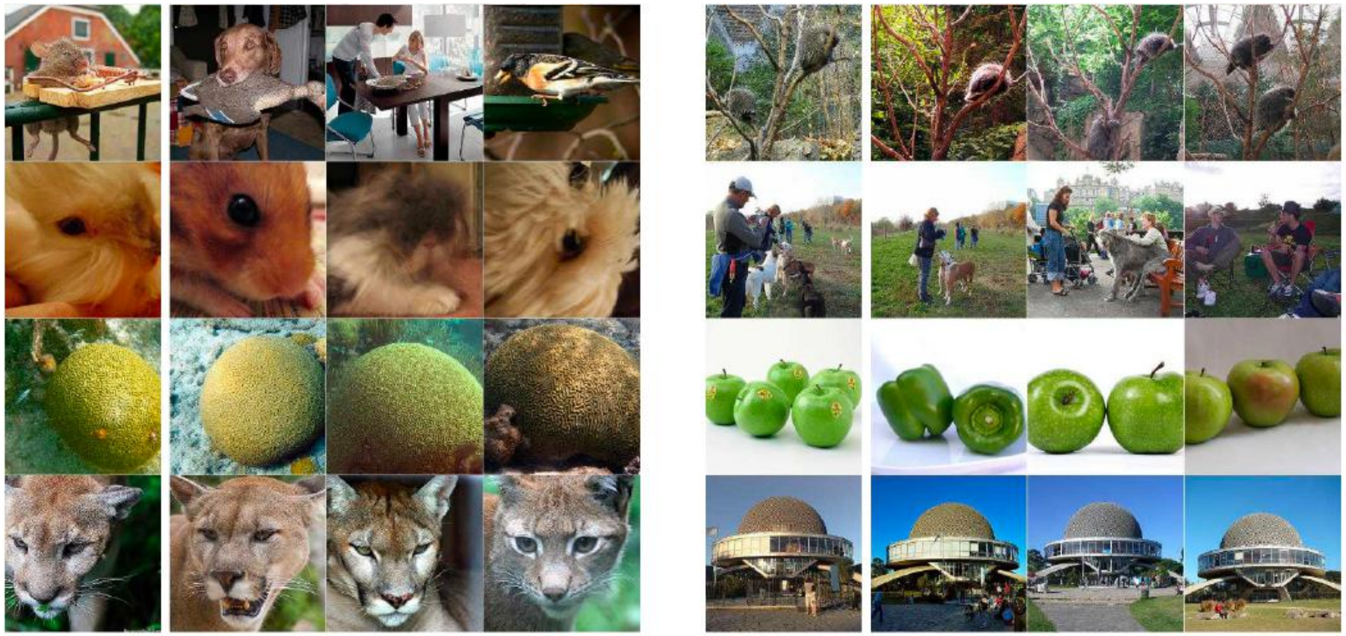


Figure 12: Nearest neighbors in BigBiGAN $\mathcal{E}$ feature space, from our best performing model (*RevNet* $\times 4$, $\uparrow \mathcal{E}$ *LR*). In each row, the first (left) column is a query image, and the remaining columns are its three nearest neighbors from the training set (the leftmost being the nearest, next being the second nearest, etc.). The query images above are the first 24 images in the ImageNet validation set.

BigBiGAN: Large Scale Adversarial Representation Learning. Jeff Donahue, Karen Simonyan. NIPS 2019.

BigBiGAN

- Summary

  - A single latent code cannot represent a high-resolution image
    - Other information inside the generator
    - High compression rate

  - Next: any solution?

BigBiGAN: Large Scale Adversarial Representation Learning. Jeff Donahue, Karen Simonyan. NIPS 2019.

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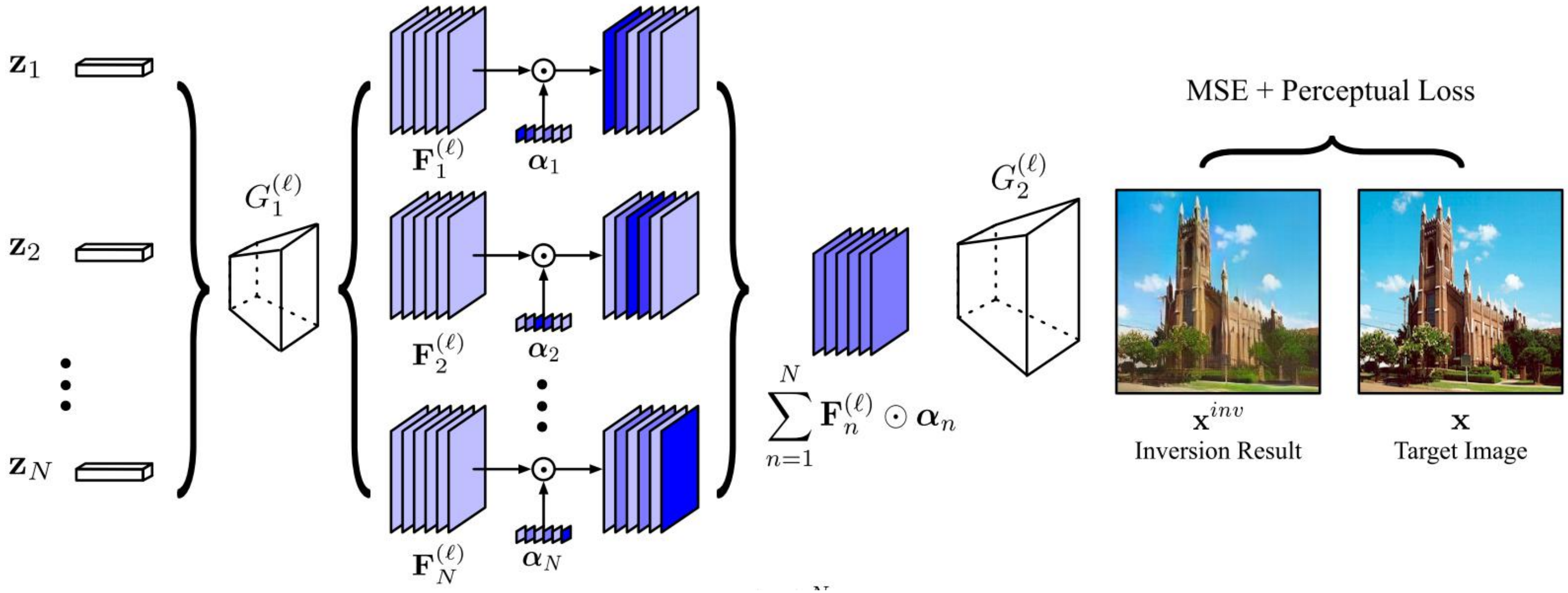
Multi-code GAN prior

- An Optimisation-based Method



A single latent code is not enough to recover all detailed information.
We can use multiple latent codes to recover different feature maps.

Image Processing Using Multi-Code GAN Prior. Gu, Jinjin. Shen, Yujun. Zhou, Bolei. arXiv 2019.

Multi-code GAN prior

- Reconstruction

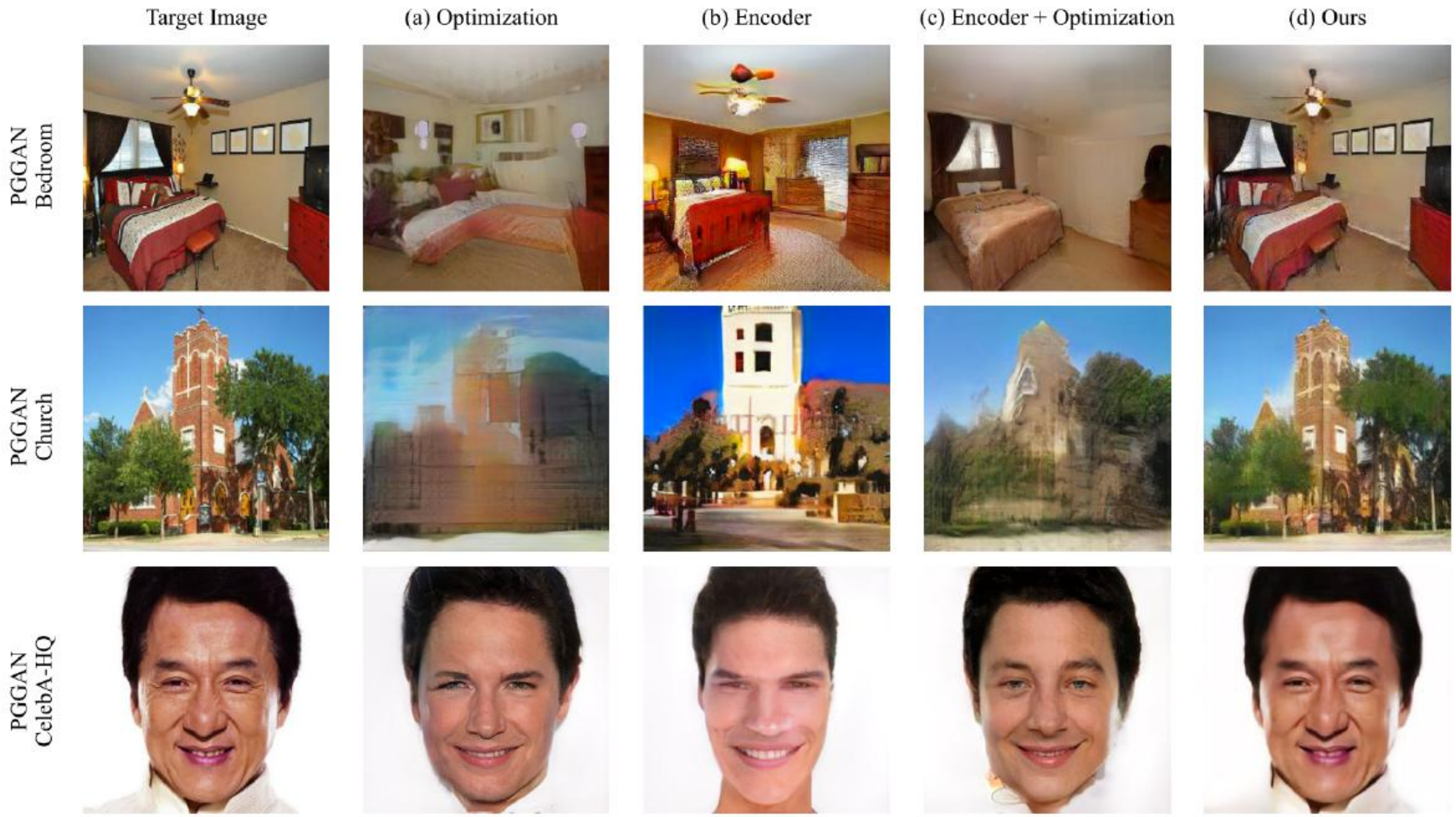


Image Processing Using Multi-Code GAN Prior. Gu, Jinjin. Shen, Yujun. Zhou, Bolei. arXiv 2019.

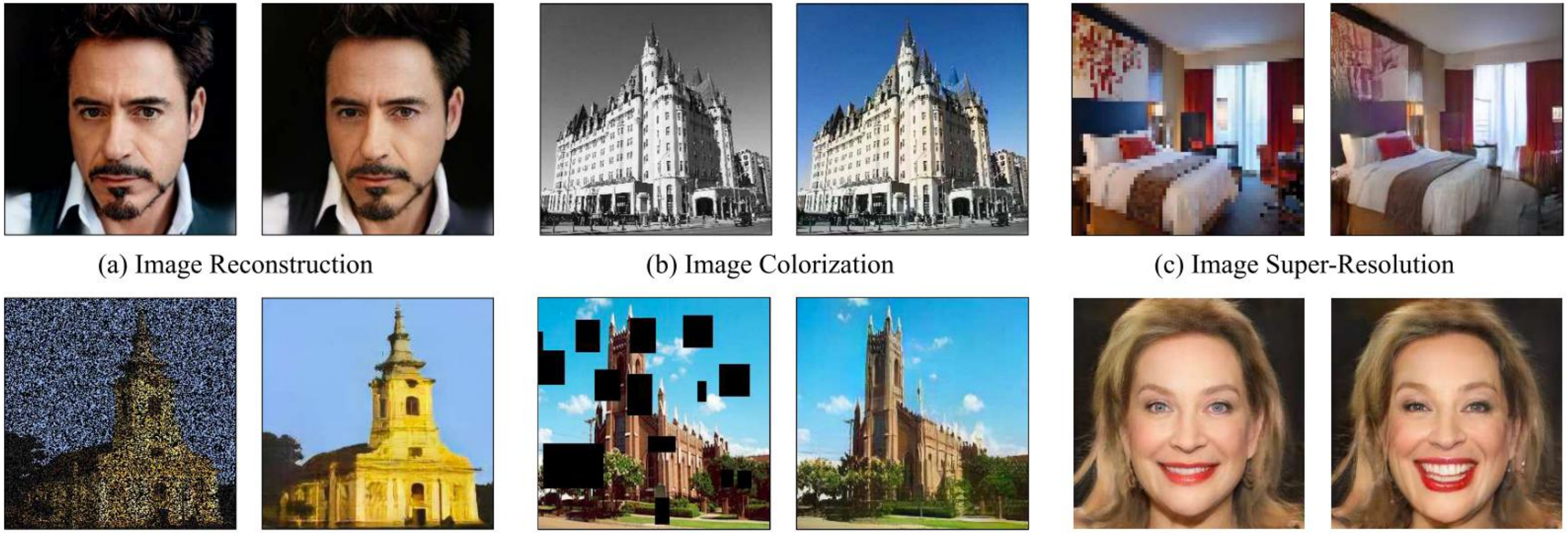
Multi-code GAN prior

- Inpainting

Image Processing Using Multi-Code GAN Prior. Gu, Jinjin. Shen, Yujun. Zhou, Bolei. arXiv 2019.

Multi-code GAN prior

- More



(a) Image Reconstruction (b) Image Colorization (c) Image Super-Resolution

(d) Image Denoising (e) Image Inpainting (f) Semantic Manipulation

Image Processing Using Multi-Code GAN Prior. Gu, Jinjin. Shen, Yujun. Zhou, Bolei. arXiv 2019.

Multi-code GAN prior

- Discussion
  - Why it works?
  - Limitations?

Image Processing Using Multi-Code GAN Prior. Gu, Jinjin. Shen, Yujun. Zhou, Bolei. arXiv 2019.

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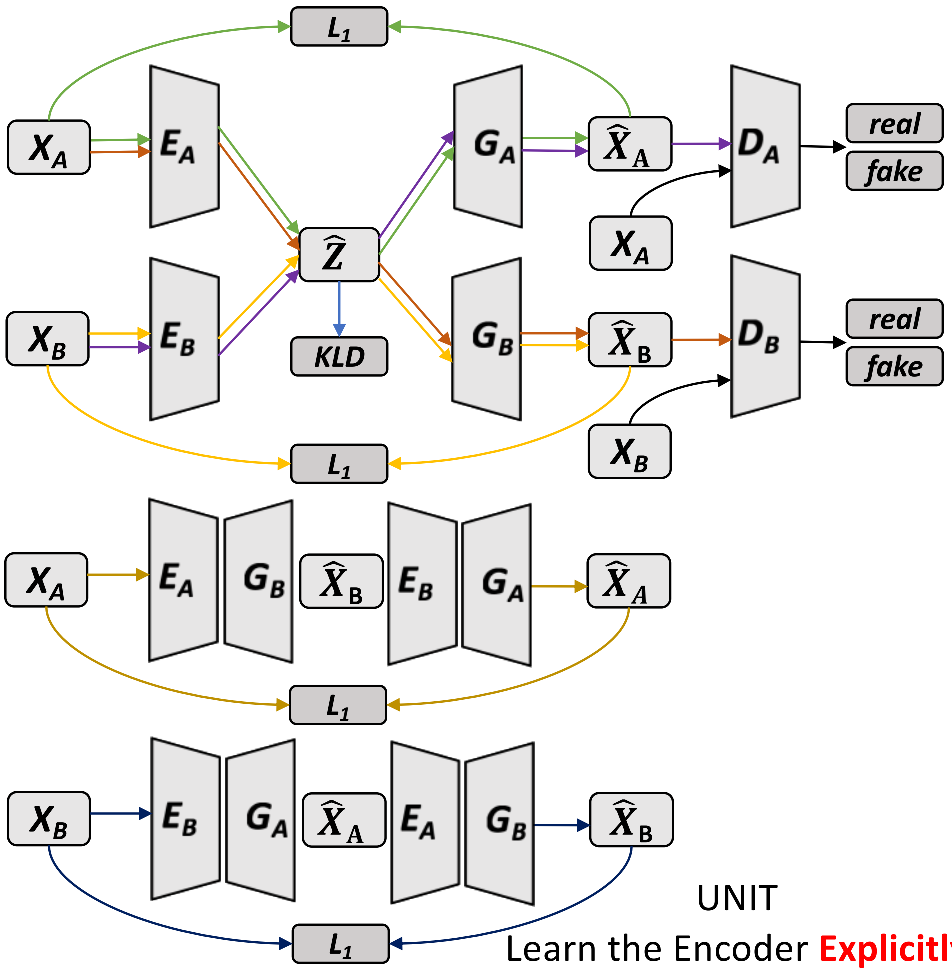
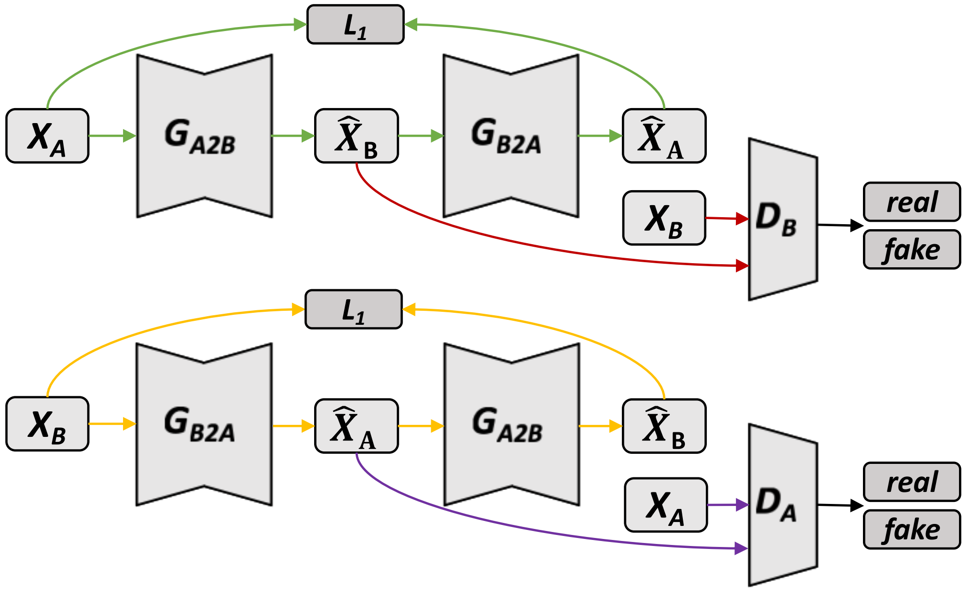
Implicit vs. Explicit Encoder



UNIT

Learn the Encoder **Explicitly**



CycleGAN

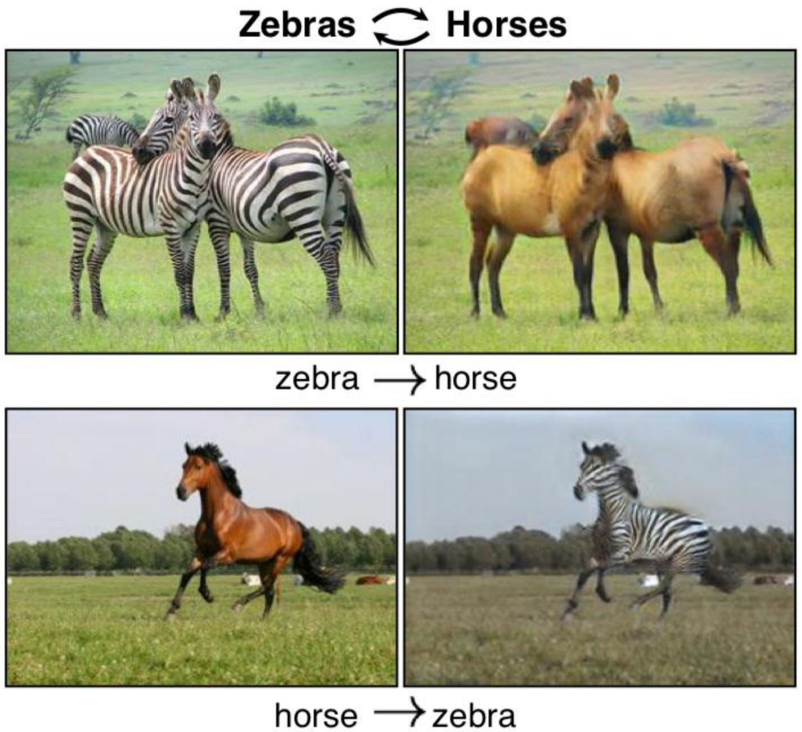
Learn the Encoder **Implicitly**

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.*

Implicit vs. Explicit Encoder

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



CycleGAN
Learn the Encoder **Implicitly**

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Implicit vs. Explicit Encoder

Input GTA5 CG

Output image with German street view style

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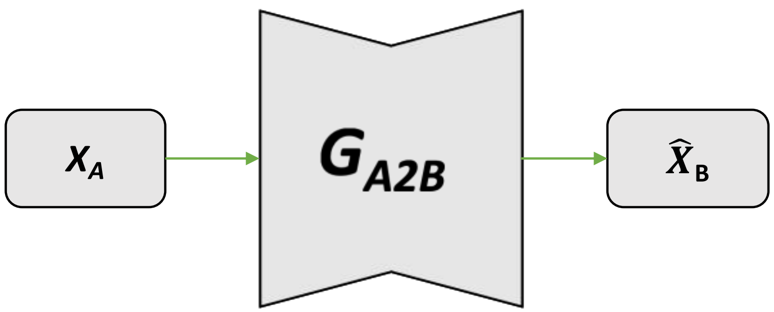
Implicit vs. Explicit Encoder

- 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
- ….

- VAE vs. GAN
- A Naïve Approach
- Another Naïve Approach
- Without Encoder
- Recap: BiGAN
- Adversarial Autoencoder
- VAE+GAN
- α-GAN
- BigBiGAN
- Multi-code GAN prior
- Implicit vs. Explicit Encoder
- Summary

Summary

- GAN : G + D → G + D + E
- Learning E from real data is important
- GAN mode collapse
- BiGAN, AAE, VAE+GAN, α-GAN, BigBiGAN
- Autoencoder can help to avoid mode collapse
- Learning E implicitly
- The E can be extended to text and any other data type
- Still on the way …

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Thanks