Priors Guided Image Inpainting and Synthesis

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Tutorial Homepage: https://dqiaole.github.io/priors_guided_image_editing_synthesis/

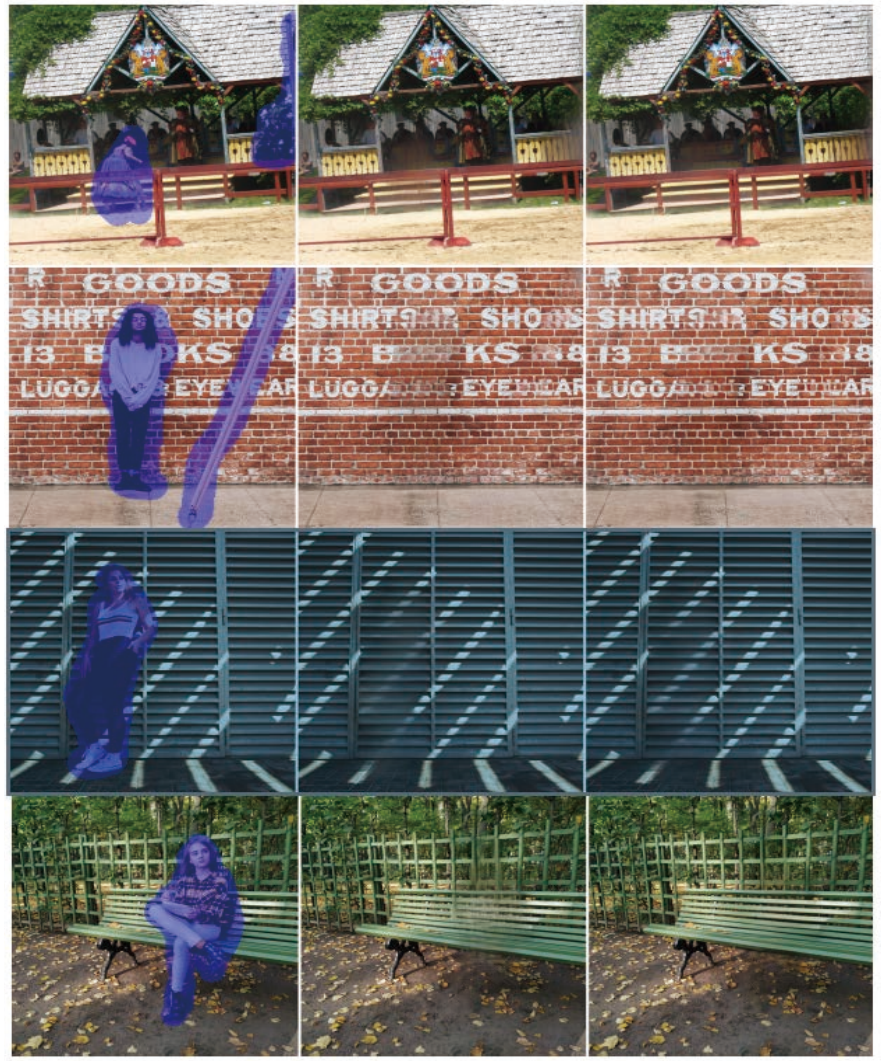
Contents

- Tasks and Motivation
- Image Synthesis/Generation Methods
  - GAN
    - Inpainting with GAN
    - GAN inversion
  - VAE and Flow
  - Transformer
  - Diffusion

Task1: Image Inpainting

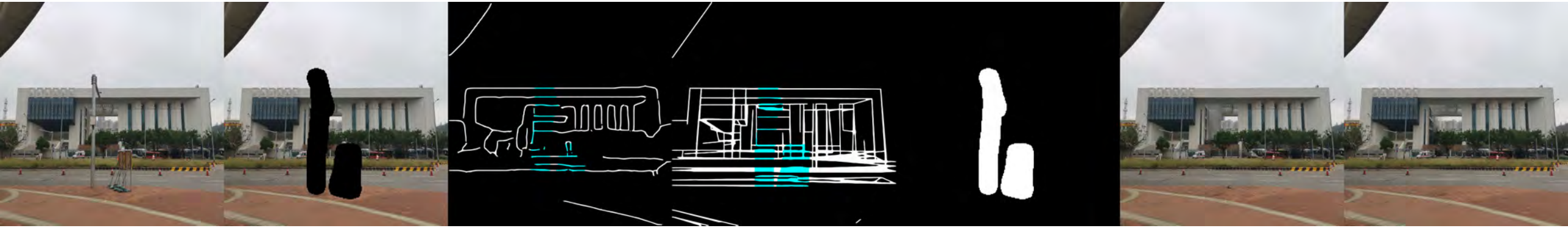
Original (2K) LAMA Our work

Original (1K) LAMA Our work



Original (1K) LAMA Our work

Chenjie Cao, Qiaole Dong, Yanwei Fu, ZITS++: Image Inpainting by Improving the Incremental Transformer on Structural Priors.



Original images | Masked images | Edge maps | Lines | Applied Mask | LaMa | **Our ZITS++**

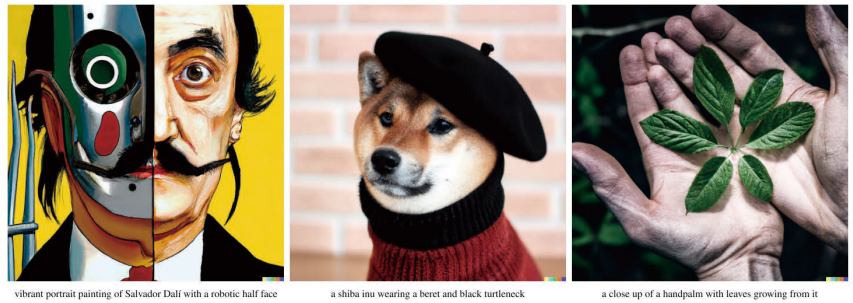
Task2: Image Synthesis/Generation

StyleGAN2

StyleGAN-XL

BIGGAN

DALLE2



Image

Unconditional

Class-conditional

Text-conditional

Prompt Engineering: A photo of {Class-label}

[StyleGAN2] Karras, Tero, et al. "Analyzing and improving the image quality of stylegan." *CVPR*. 2020.

[StyleGAN-XL] Sauer, Axel, Katja Schwarz, and Andreas Geiger. "Stylegan-xl: Scaling stylegan to large diverse datasets." *ACM Siggraph*. 2022.

[BIGGAN] Brock, Andrew, Jeff Donahue, and Karen Simonyan. "Large scale GAN training for high fidelity natural image synthesis." *ICLR2019*.

[DALLE 2] Ramesh, Aditya, et al. "Hierarchical text-conditional image generation with clip latents." (2022).

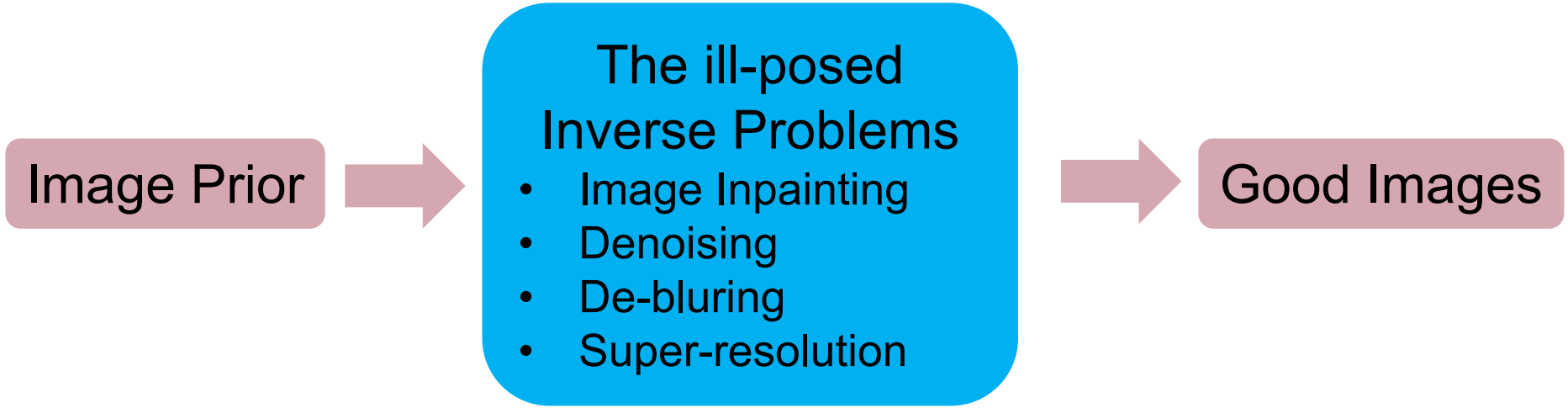
[Imagen] Saharia, Chitwan, et al. "Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding." arXiv preprint arXiv:2205.11487 (2022).

Priors: What are the Priors?

Prior probability, of an uncertain quantity (Bayesian statistical inference)

- probability distribution *expresses one's beliefs about this quantity* before some evidence is taken into account.
- $$Posterior = Likelihood * Prior + Evidence$$

- Inverse Problems in Computer Vision



https://en.wikipedia.org/wiki/Prior_probability

Priors: as the Guidance to Image Tasks

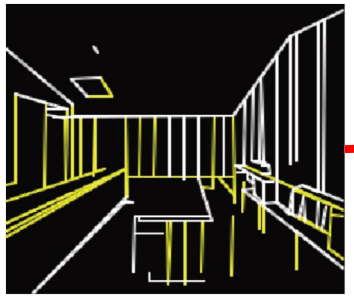
High-level (Semantic) Guidance

Text: This is an apple

Class: Dog

Deep Generative Model

Low-level (Structure) Guidance



Deep Generative Model

Fidelity: (high-level) Diffusion Models V.S. Inpainting Models

Ground truth | Masked Image | ZITS | Stable diffusion (0.8B)

Large capacity of model ⇏ Fidelitous and consistent inpainting results

[ZITS] Dong Qiaole, et al. " Incremental Transformer Structure Enhanced Image Inpainting with Masking Positional Encoding." *CVPR*. 2022.

[Stable diffusion] Robin Rombach, et al. "High-Resolution Image Synthesis with Latent Diffusion Models Robin." *CVPR*. 2022.

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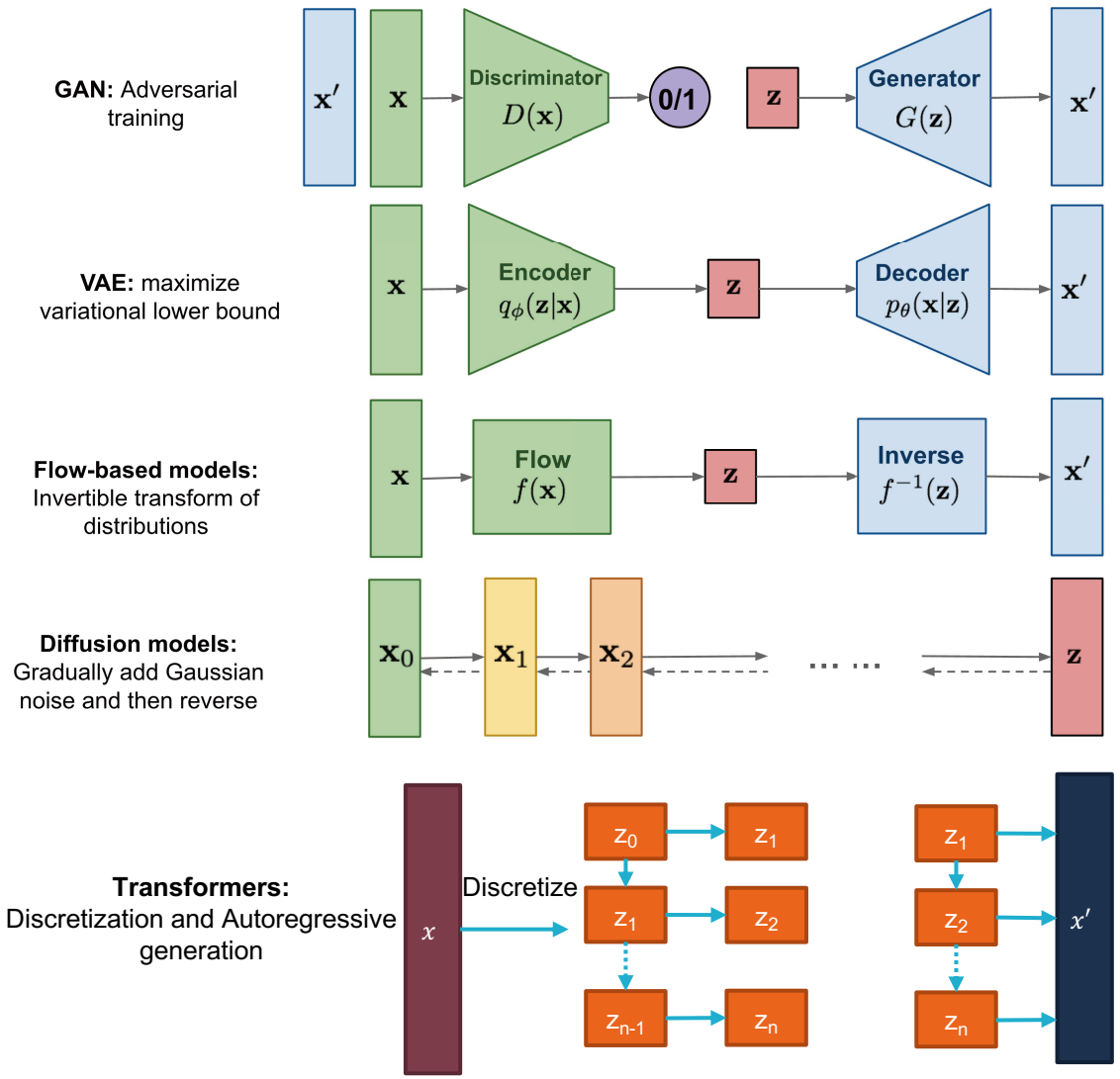

Weng, Lilian. (Jul 2021). What are diffusion models? Lil'Log. https://lilianweng.github.io/posts/2021-07-11-diffusion-models/

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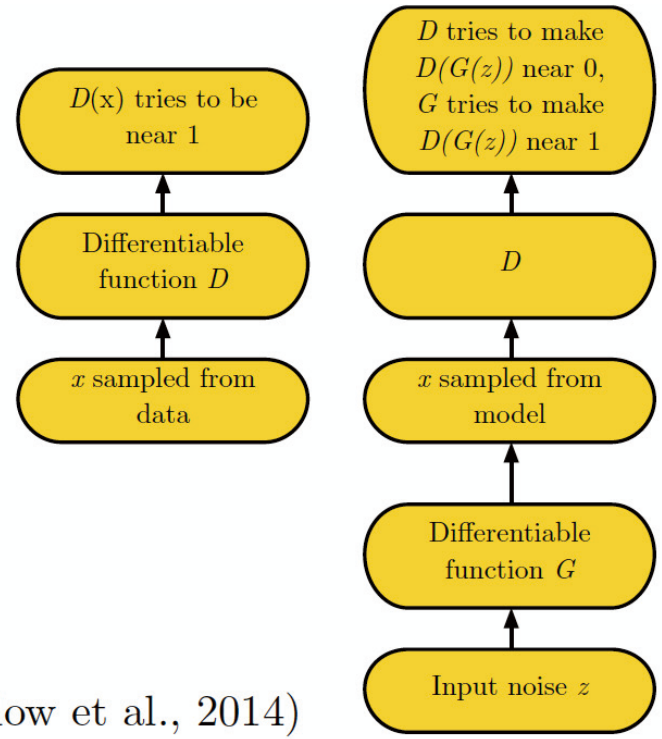
Generative Adversarial Networks (GANs)



(Goodfellow et al., 2014)

Improve the training of GANS:

- WGAN[2]
- WGAN-GP[3]
- Spectral normalization[4]

…

D and G play the following two-player minimax game with value function V(D, G)[1].

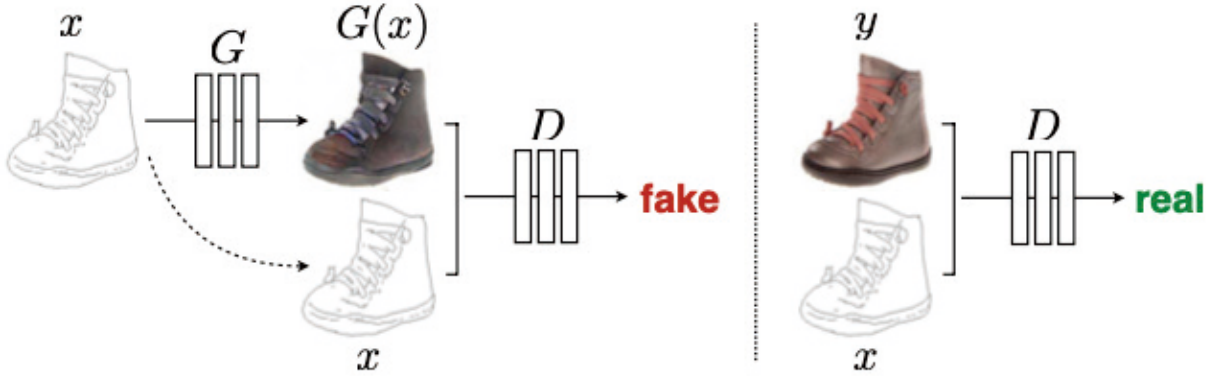
$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

[1] Ian J. Goodfellow et al. Generative Adversarial Nets. NeurIPS2014
[2] Arjovsky, Martin, Soumith Chintala, and Léon Bottou. "Wasserstein generative adversarial networks." *International conference on machine learning*. PMLR, 2017.
[3] Gulrajani, Ishaan, et al. "Improved training of wasserstein gans." Advances in neural information processing systems 30 (2017).
[4] Miyato, Takeru, et al. "Spectral normalization for generative adversarial networks." *arXiv preprint arXiv:1802.05957* (2018).

GANs for Image Synthesis

The adversarial training is critical for generating the high-frequency details.

Pixel2Pixel (2017)

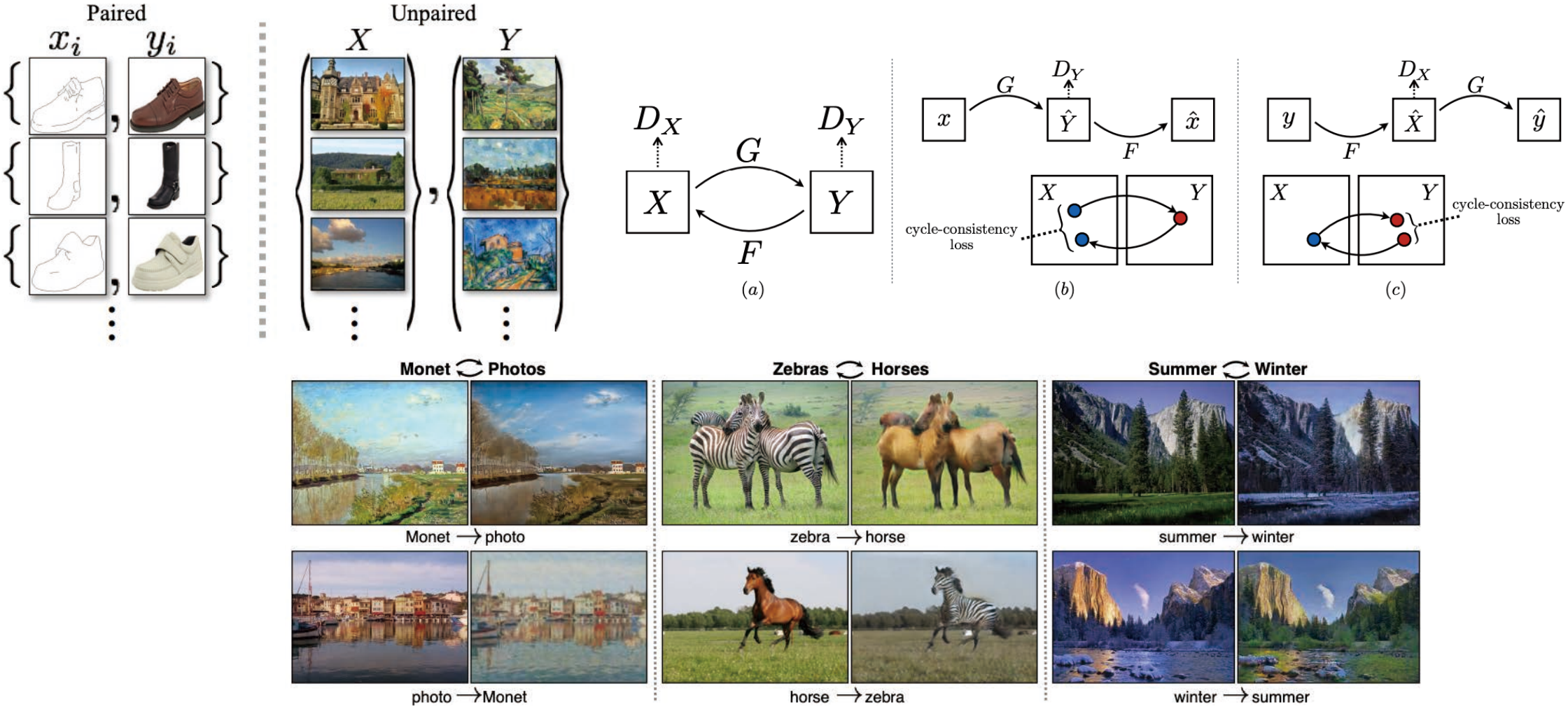


$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}_y[\log D(y)] + \mathbb{E}_{x,z}[\log(1 - D(G(x, z))].$$

Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." *CVPR*. 2017.

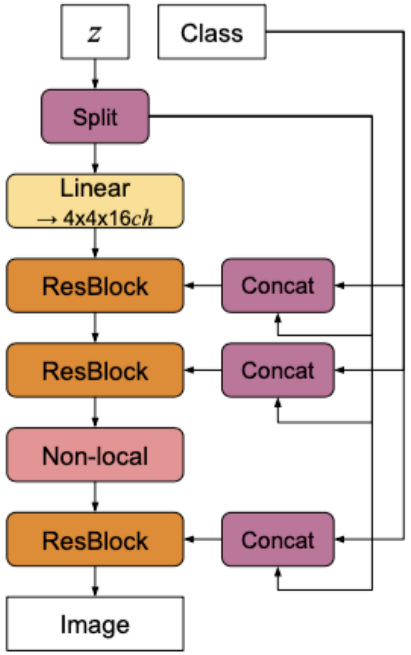
Cycle GANs

- The training can be trained with unpaired images of cycle-consistency loss.

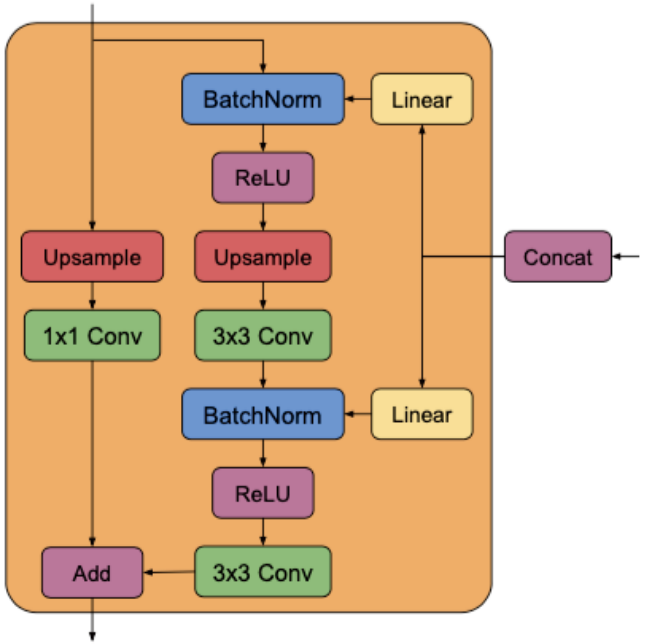


Jun-Yan Zhu et al. Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. ICCV 2017

BigGAN: Bigger GANs



Overview



Model Block

Figure 6: Samples generated by our BigGAN model at 512×512 resolution.

Scaling up the model and training for GANs

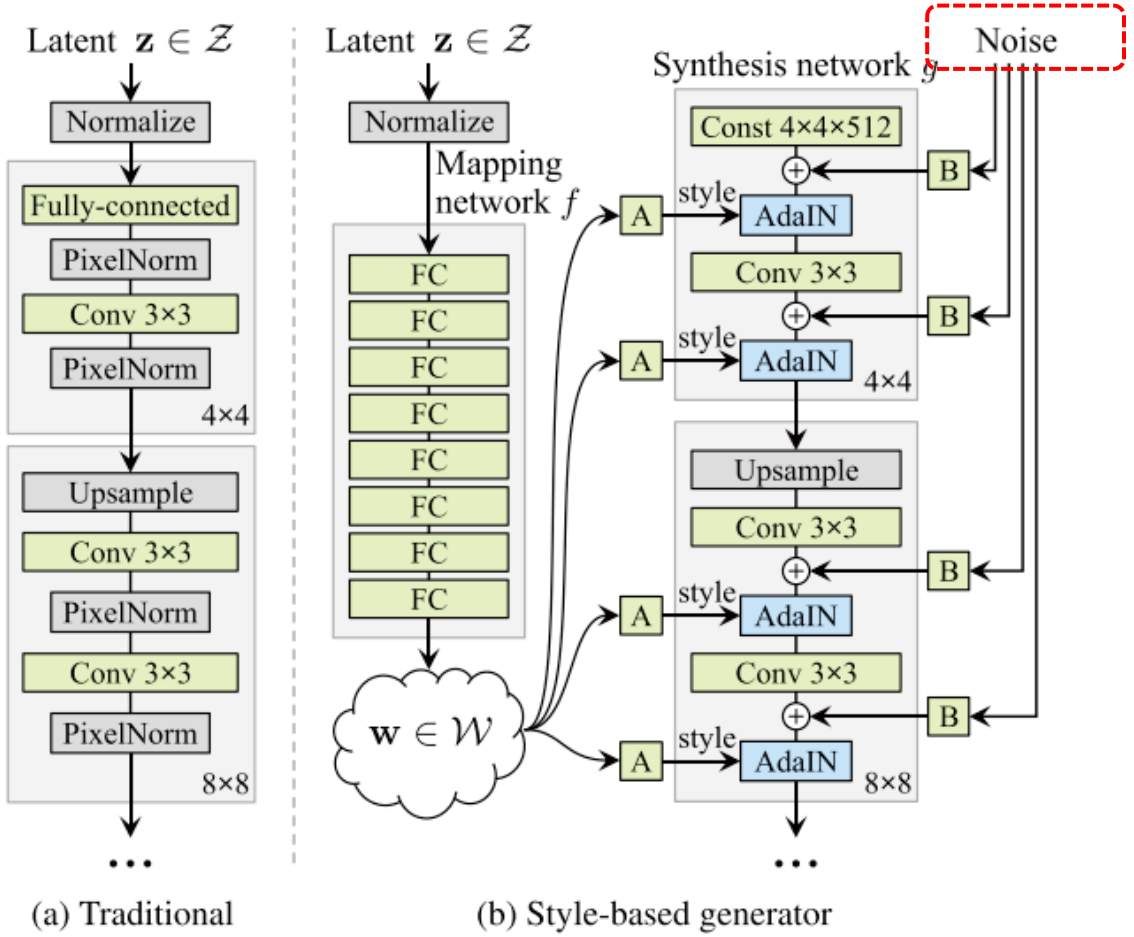
- Larger batch size (2048)
- Larger base channels (96)
- Truncation Trick

Very good results!

Brock, Andrew, Jeff Donahue, and Karen Simonyan. "Large scale GAN training for high fidelity natural image synthesis." *ICLR2019*

Style-based Generator: StyleGAN

Noise in multi-scale



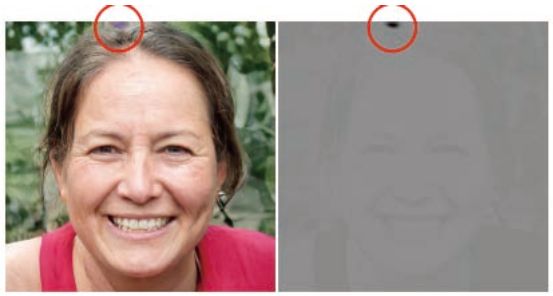
(a) Traditional (b) Style-based generator

AdaIn for style fusion: $\mathrm{AdaIN}(\mathbf{x}_i, \mathbf{y}) = \mathbf{y}_{s,i} \frac{\mathbf{x}_i - \mu(\mathbf{x}_i)}{\sigma(\mathbf{x}_i)} + \mathbf{y}_{b,i},$

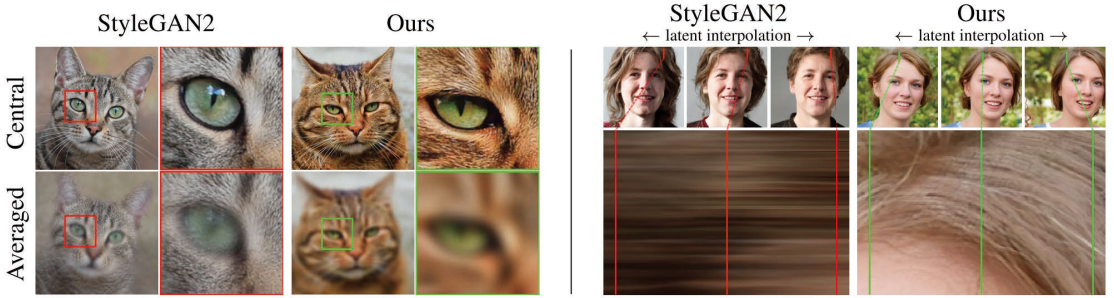
High-quality results in FFHQ and LSUN

Karras, Tero, Samuli Laine, and Timo Aila. "A style-based generator architecture for generative adversarial networks." *CVPR*2019.

Improved StyleGANs



StyleGAN2[1]: adjusting model architecture and training strategy to address water droplet and phase artifacts



StyleGAN3[2]: make stylegan's texture free-from image coordinates

StyleGAN-XL[3]: generalize stylegan on ImageNet

[1] Karras, Tero, et al. "Analyzing and improving the image quality of stylegan." *CVPR* 2020.

[2] Karras, Tero, et al. "Alias-free generative adversarial networks." *NeurIPS2021.*

[3] Sauer, Axel, Katja Schwarz, and Andreas Geiger. "Stylegan-xl: Scaling stylegan to large diverse datasets." *ACM Siggraph*. 2022.

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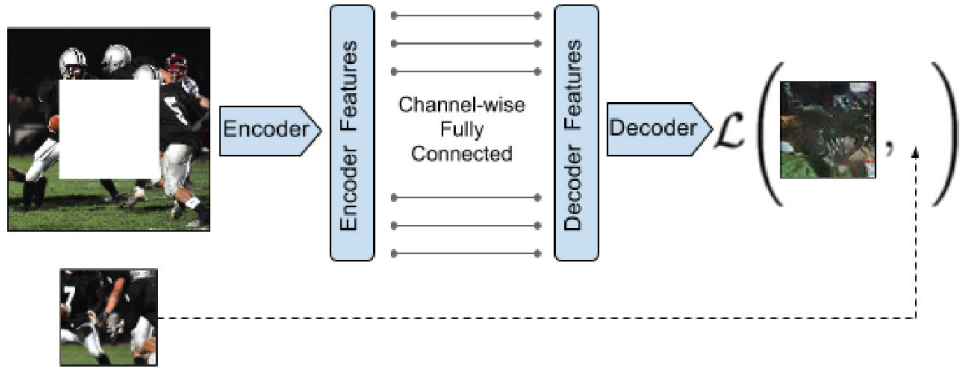
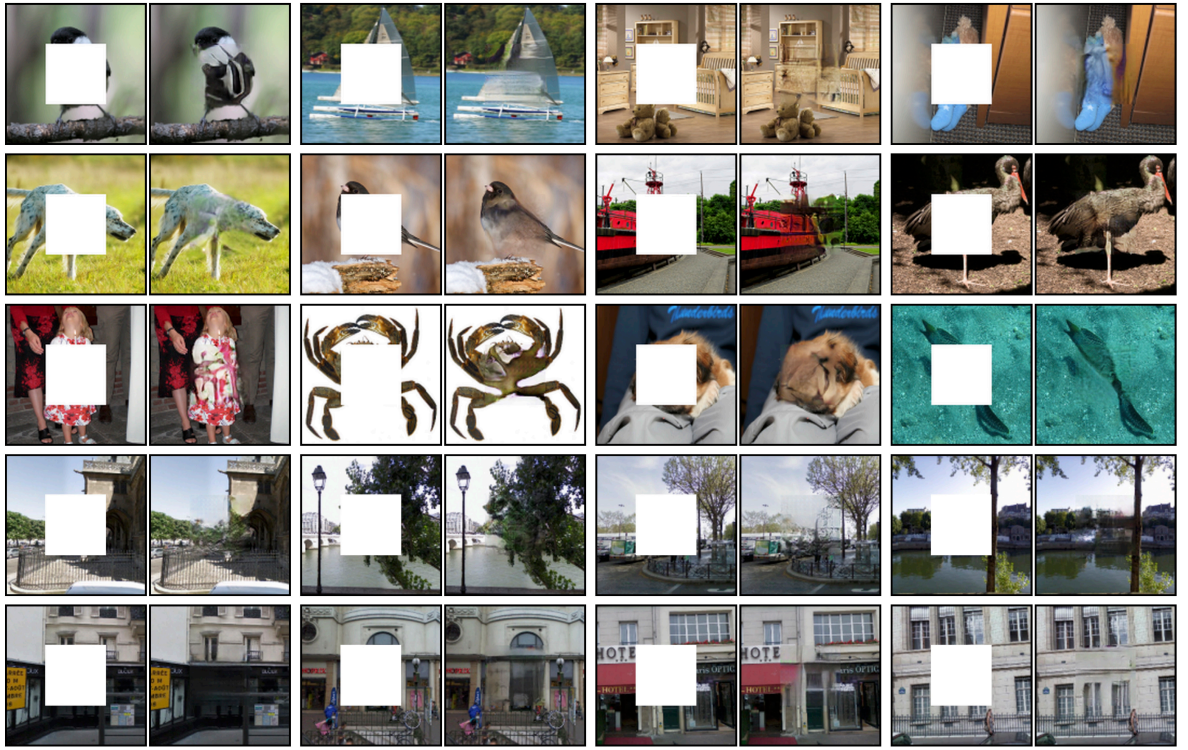
GANs for Image Inpainting

(a) Input context (b) Human artist

(c) Context Encoder ($L2$ loss) (d) Context Encoder ($L2$ + Adversarial loss)



Context Encoder



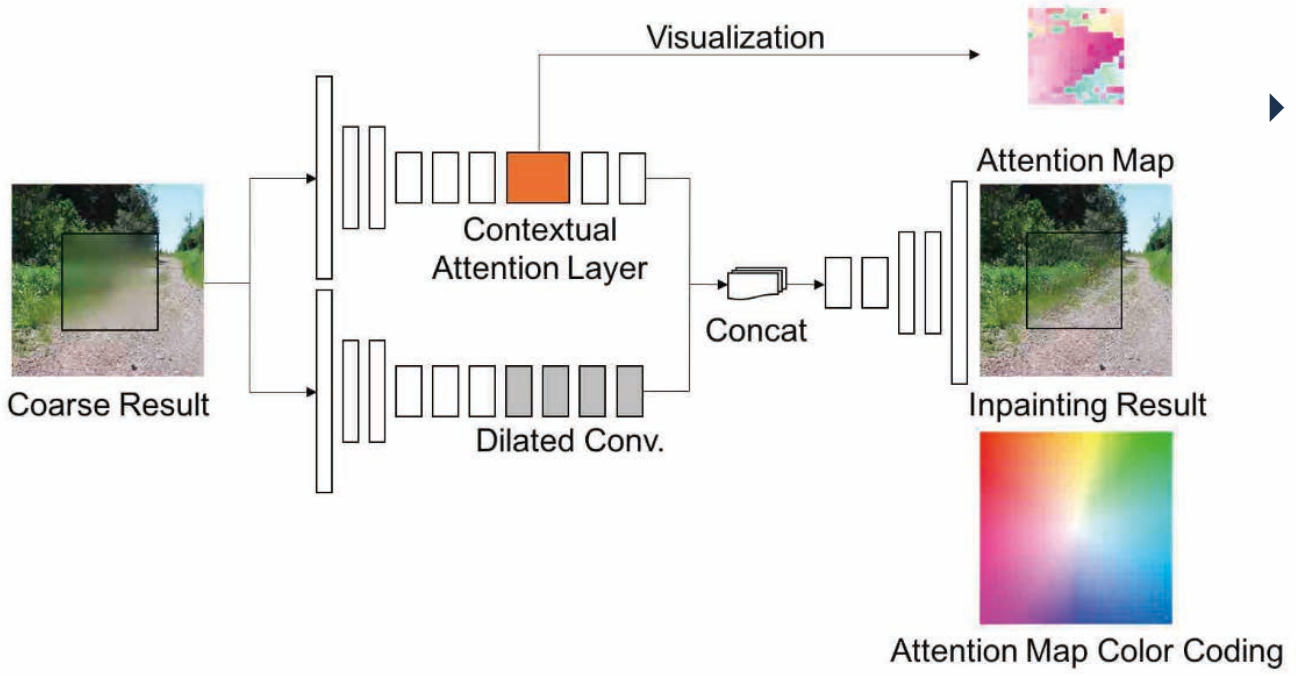
Semantic Inpainting results on held-out images by Context Encoder.
from https://www.cs.cmu.edu/~dpathak/context_encoder/#extraResults

Convolutional Designs for Inpainting in GANs

- Partial Convolution [2]
- Gated Convolution [3]

[1] Pathak, Deepak, et al. "Context encoders: Feature learning by inpainting." *CVPR*. 2016.
[2] Guilin Liu et al. Image Inpainting for Irregular Holes Using Partial Convolutions. ECCV2018
[3] Jiahui Yu et al. Free-Form Image Inpainting with Gated Convolution. ICCV2019

Attention for Inpainting in GANs



- Aggregating features from unmasked regions for masked ones largely improves the inpainting[1].
  - Guiding for the high-resolution inpainting[2,3].
  - Guiding for the texture and structure feature fusion[4].

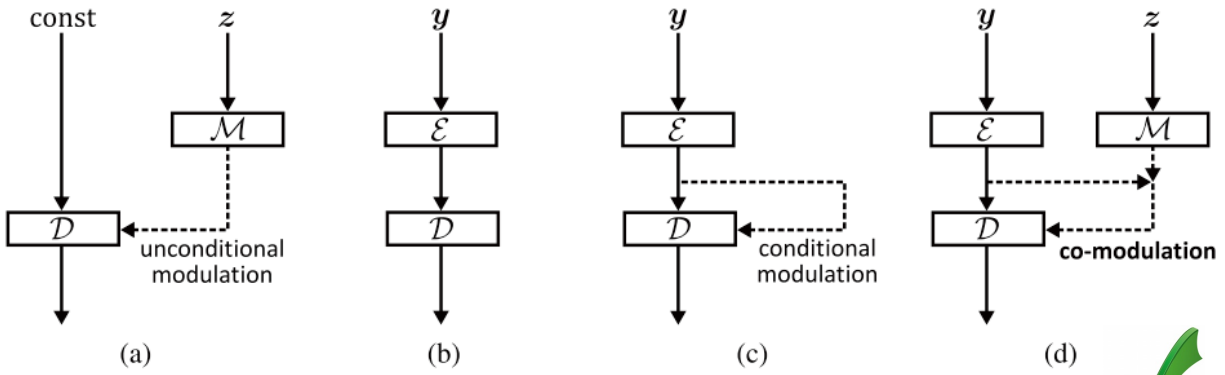
[1] Yu, Jiahui, et al. "Generative image inpainting with contextual attention." *CVPR*2018.

[2] Zeng, Yu, et al. "High-resolution image inpainting with iterative confidence feedback and guided upsampling." *ECCV*2020.

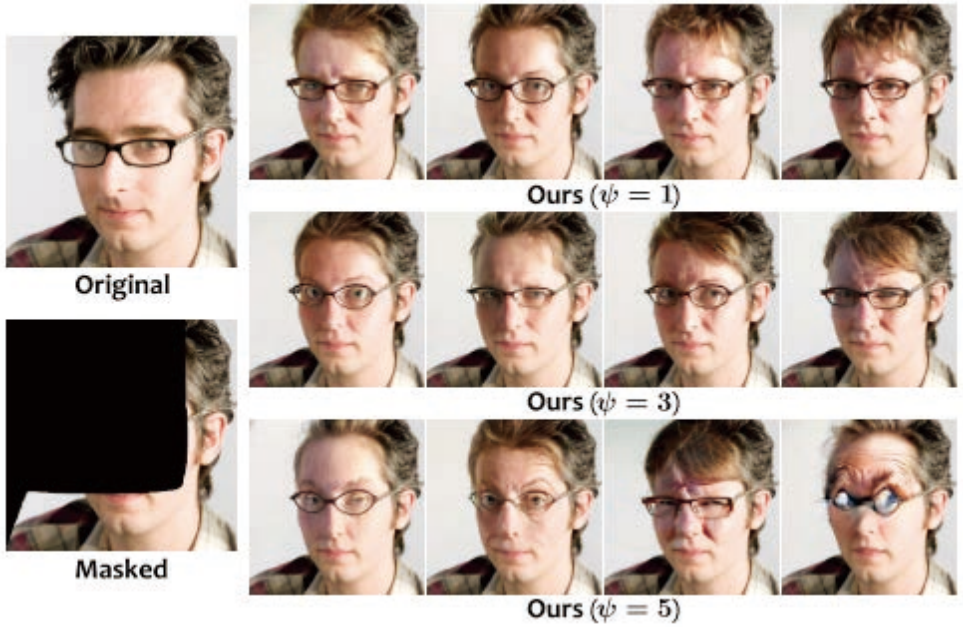
[3] Zili Yi et al. “Contextual Residual Aggregation for Ultra High-Resolution Image Inpainting.” CVPR2020

[4] Xiefan Guo et al. “Image Inpainting via Conditional Texture and Structure Dual Generation” CVPR2021

Co-Mod: StyleGAN for Inpainting



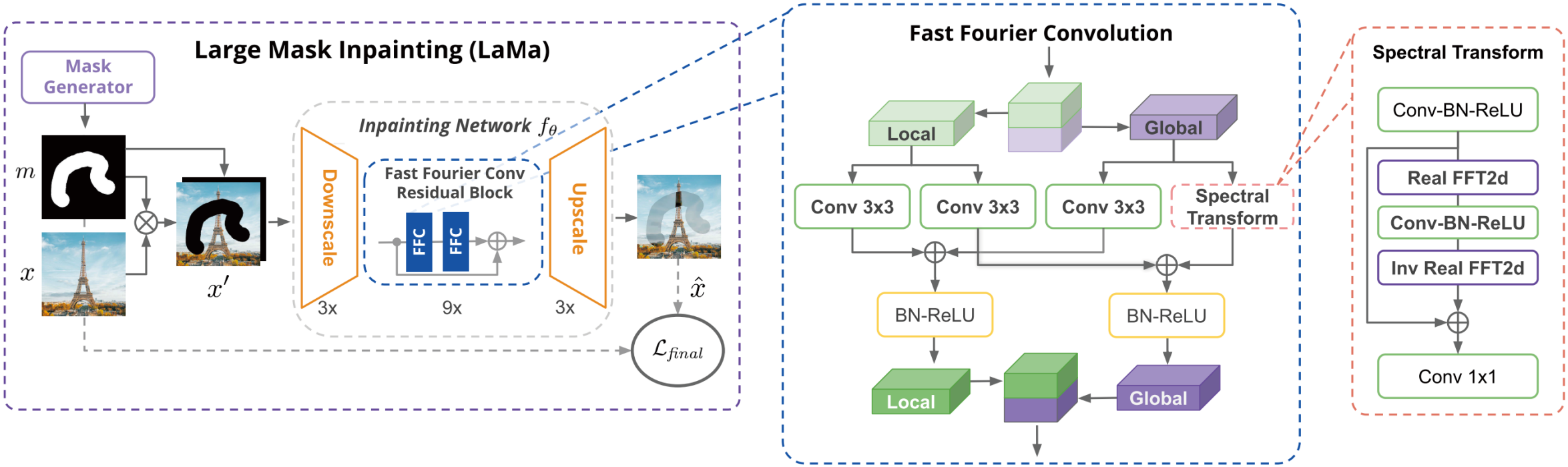
$$s = A(\mathcal{E}(y), \mathcal{M}(z)),$$



- Using Conditional (unmasked image) and unconditional modulated (style feature) generator.
- Co-mod is powerful but not faithful and stable enough for some inpainting cases.

Zhao, Shengyu, et al. "Large scale image completion via co-modulated generative adversarial networks." *arXiv preprint arXiv:2103.10428* (2021).

LaMa: Resolution-robust Large Mask Inpainting with Fourier Convolutions

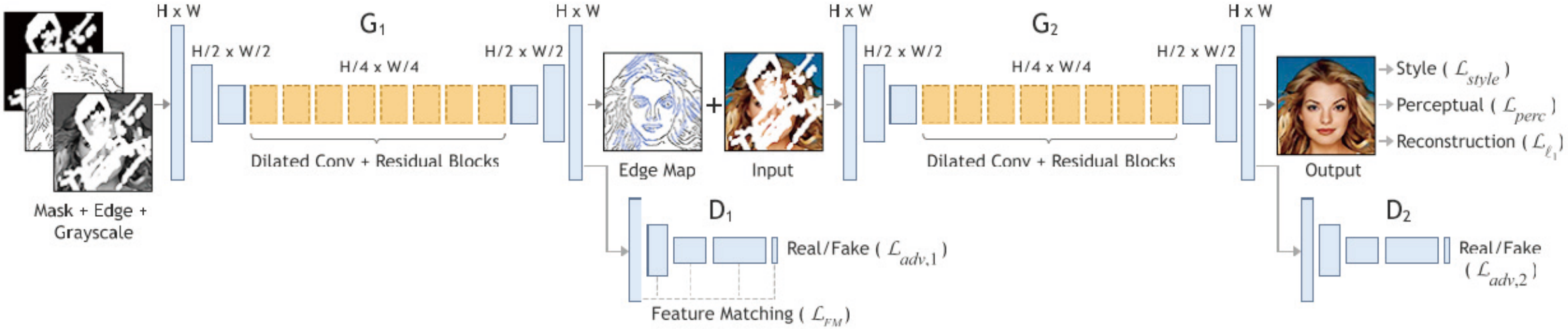


Fourier convolutions are used to for the high-resolution image inpainting

The 256x256 trained model can be generalized to high-resolution images!

Roman Suvorov, Elizaveta Logacheva, et al. Resolution-robust large mask inpainting with fourier convolutions. WACV 2022.

EdgeConnect: **Edge Prior** for Inpainting

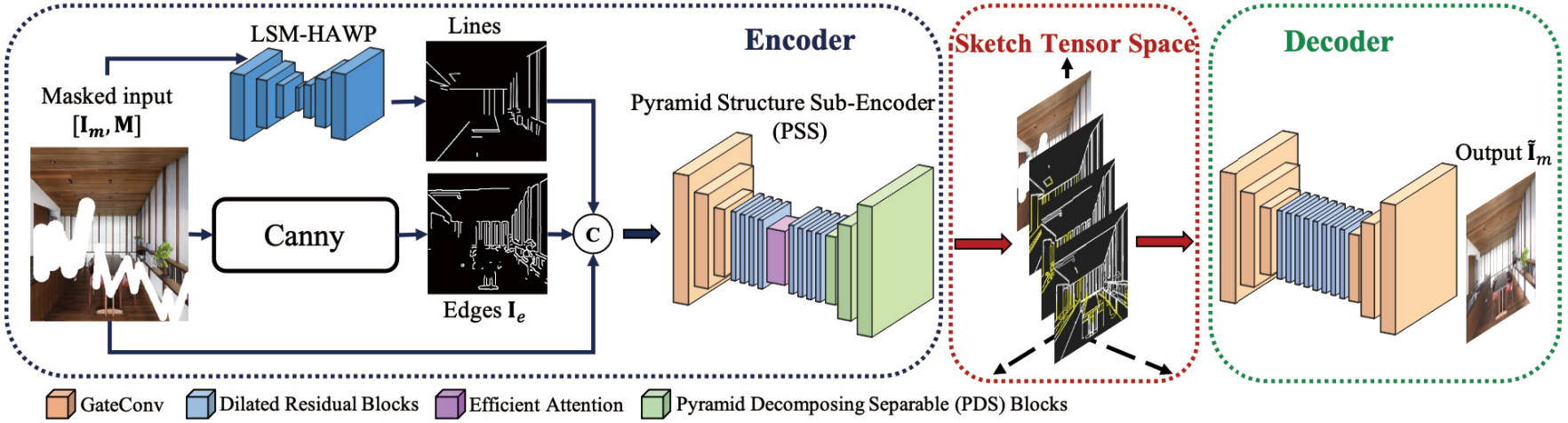


- Recovering Canny Edges at first, then recover colored images, i.e., “lines first, color next”

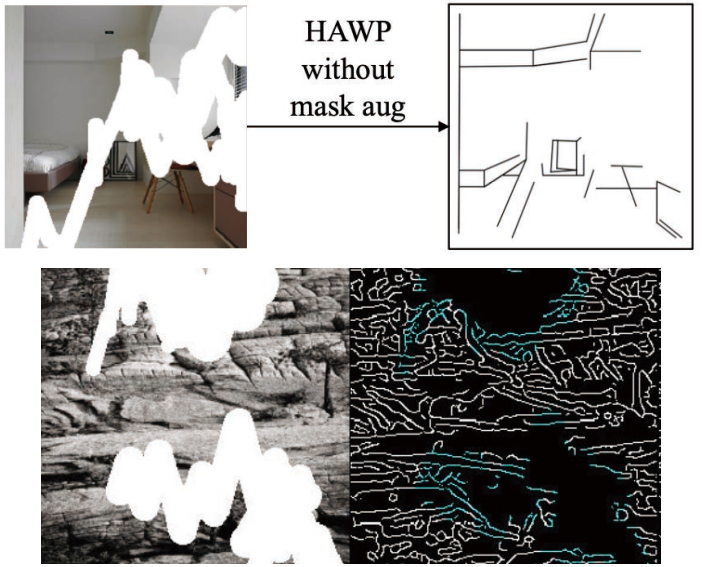
- Advantage: more faithful and stable generation with structural priors
- Limitations: Limited receptive fields for both edge and color generators.

Nazeri, Kamyar, et al. "Edgeconnect: Generative image inpainting with adversarial edge learning.”ICCV 2019- workshop.

MST: Learning a Sketch Tensor Space for Inpainting of Man-made Scenes



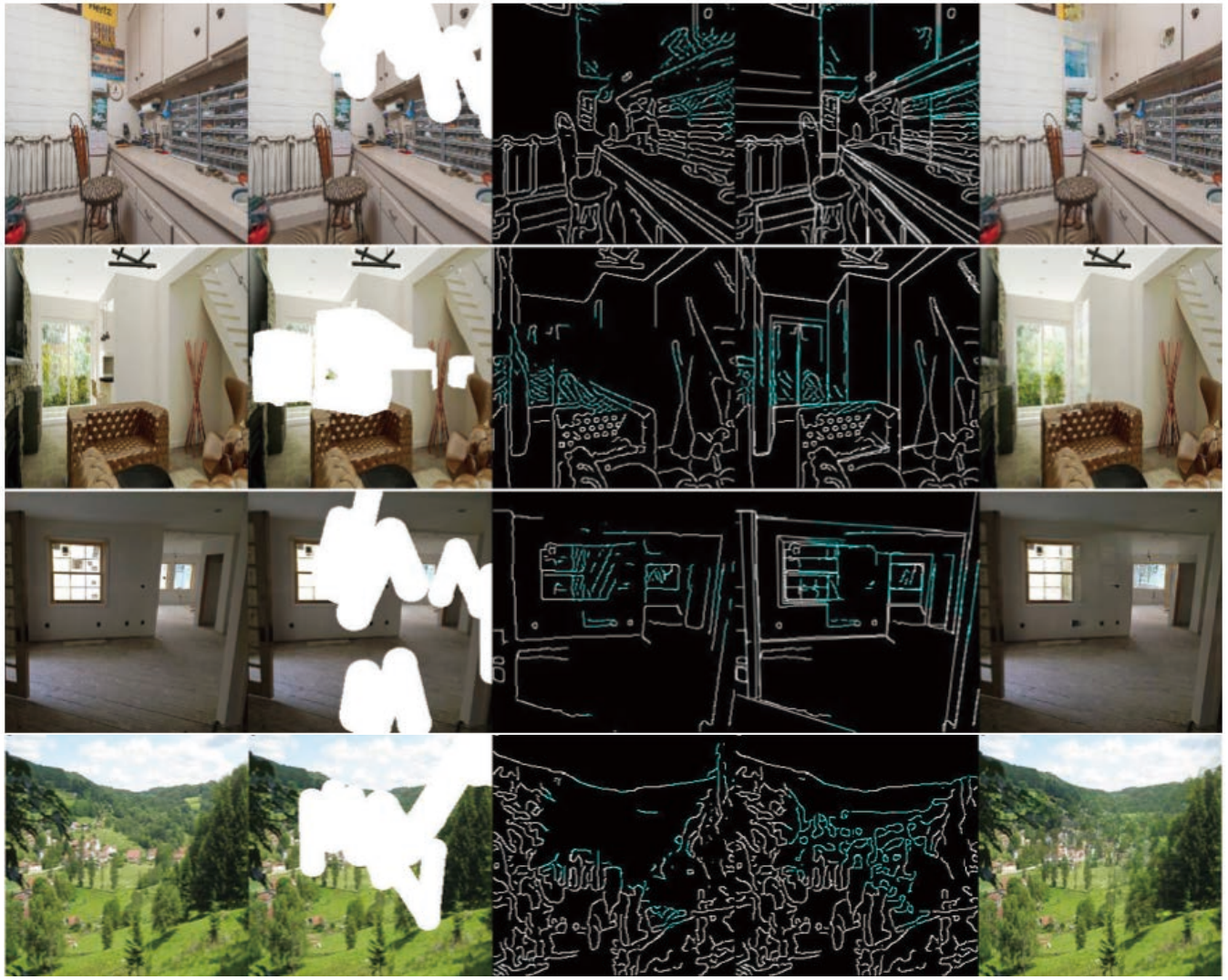

(a) Inputs (b) Exemplar-based (c) GateConv (d) EdgeConnect (e) Ours



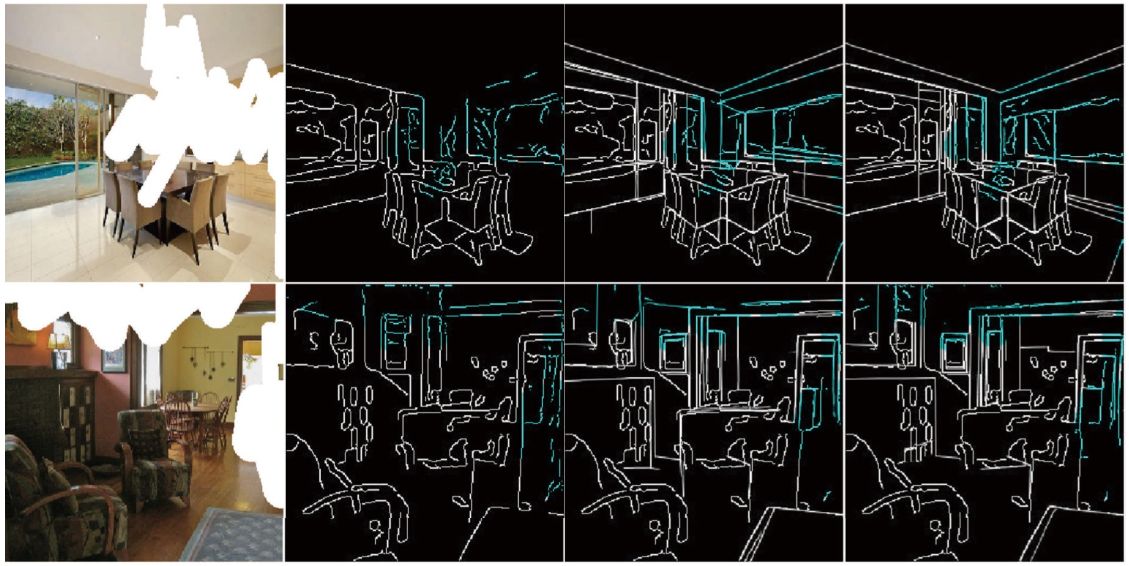
Cao, Chenjie, and Yanwei Fu. "Learning a sketch tensor space for image inpainting of man-made scenes." *ICCV*2021.

https://ewrfcas.github.io/MST_inpainting

Qualitative results



Ground truth | Masked input | EC edge | Ours edge | Ours results



(a) input | (b) Ours w/o lines | (c) Ours w/o PDS | (d) Ours

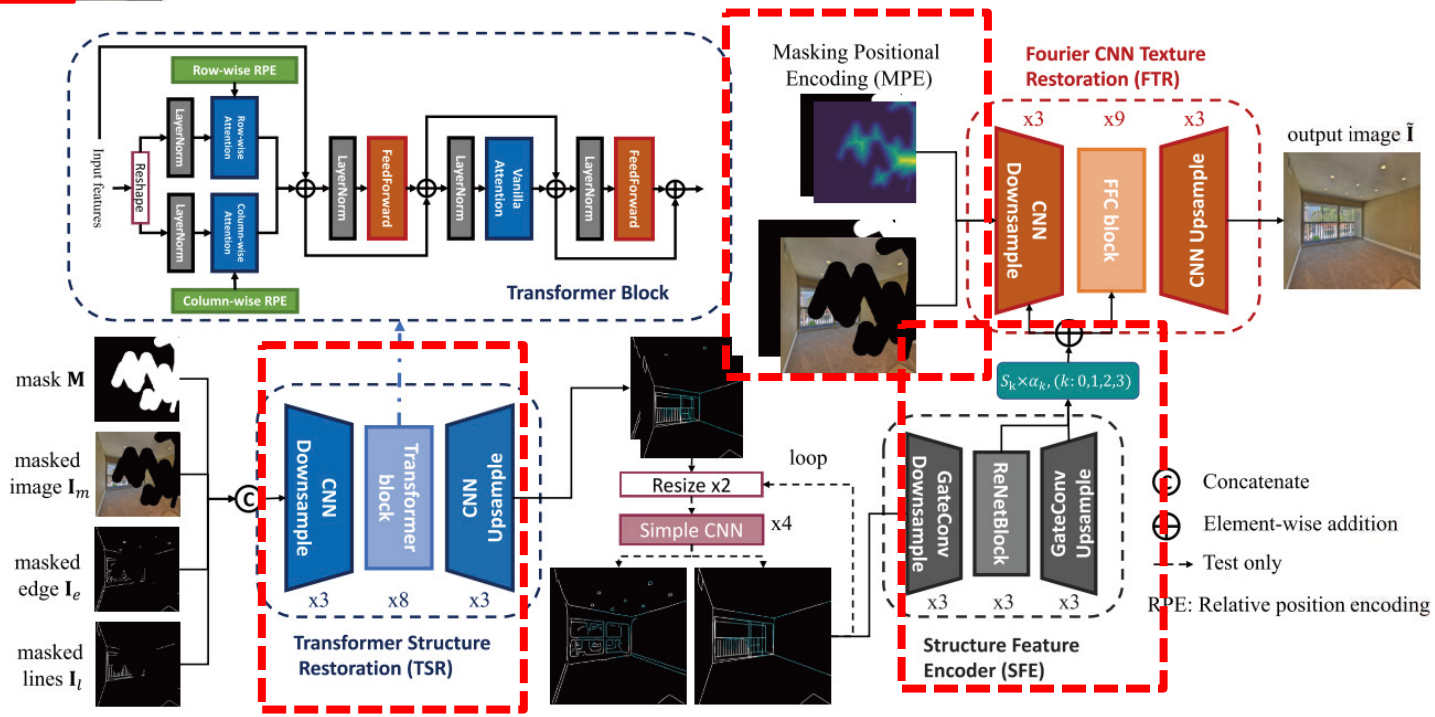
(a) input | (b) PSS (edge) | (c) PSS (edge+line)

Figure 4. Qualitative results w. and w./o. lines in ShanghaiTech.

ZITS: ZeroRA based Incremental Transformer Structure

- Incremental Transformer Structure for filling line priors
- Novel Masking Positional Encoding
- Incrementally training strategy to utilize pretrained LaMa.

(a) Masked input (b) Edges from MST (c) Lines from MST (d) Edges from ours (e) Lines from ours

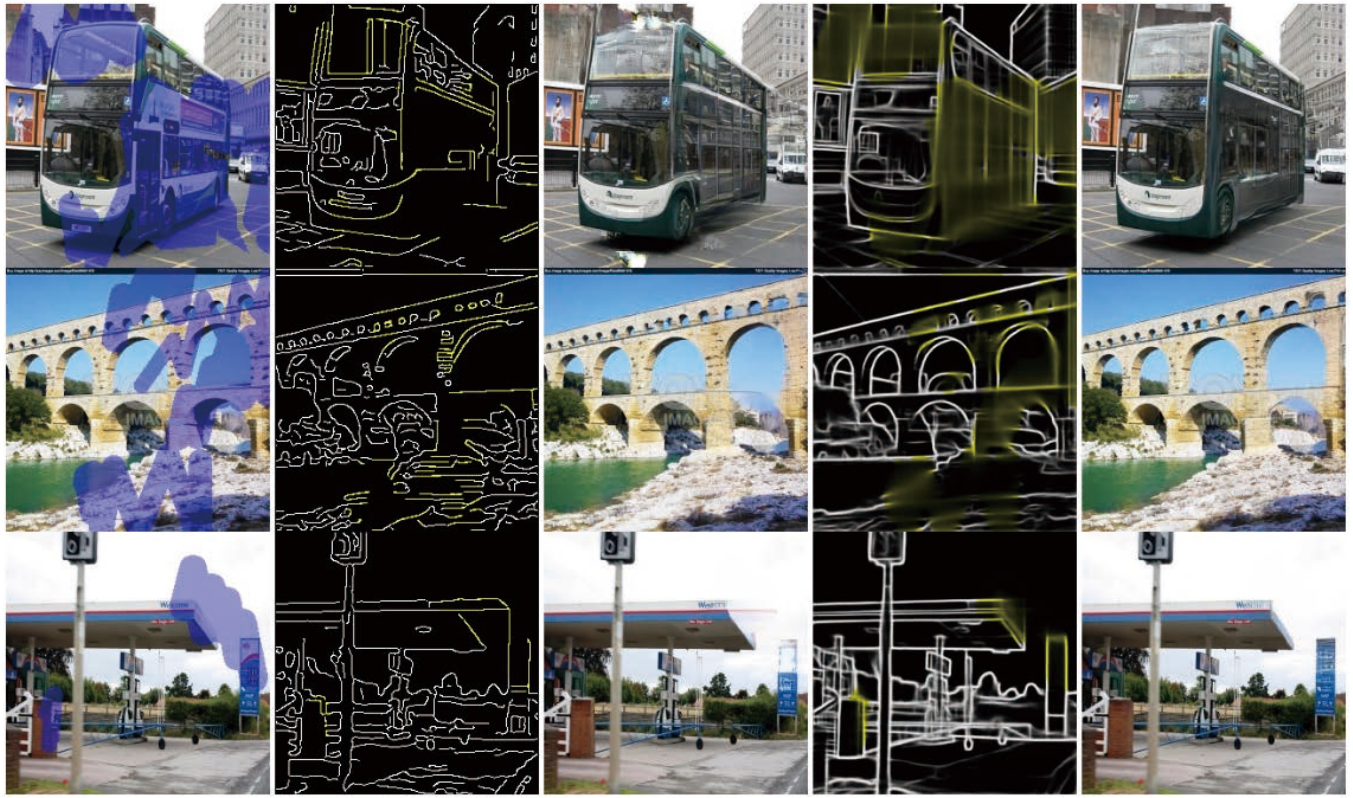


https://github.com/DQiaole/ZITS_inpainting

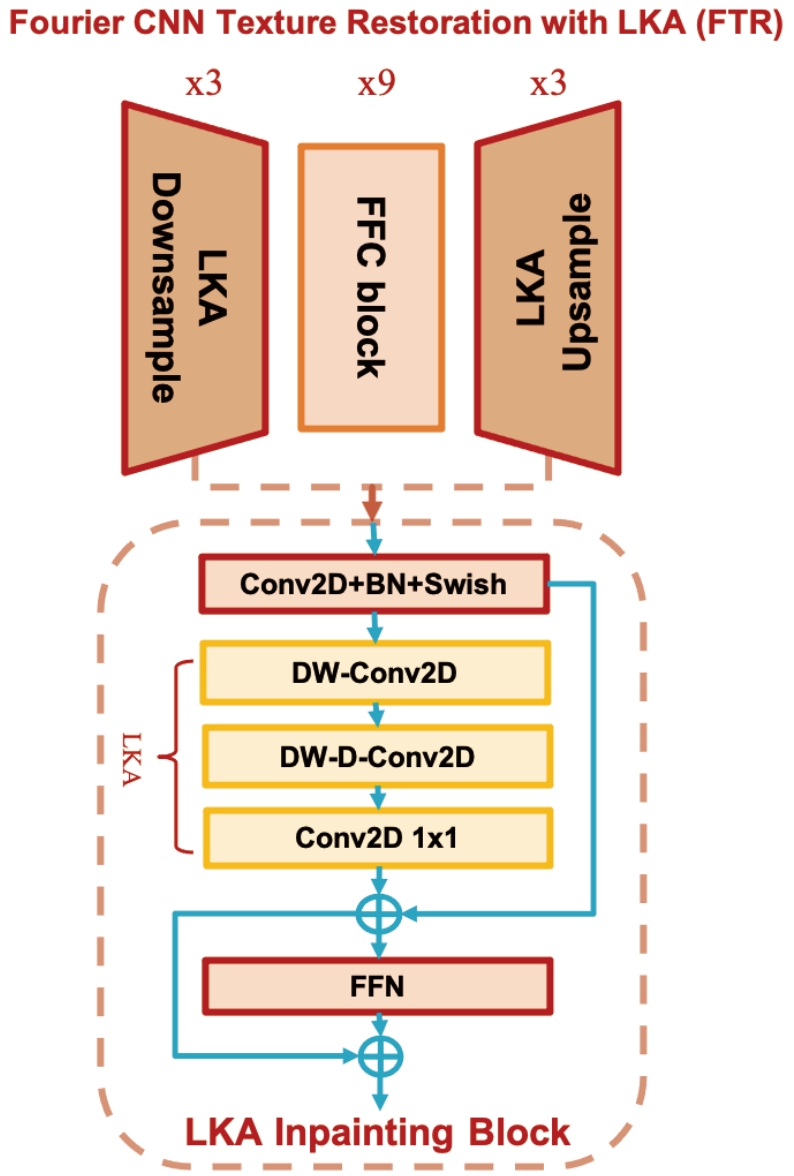
Dong, Qiaole, Chenjie Cao, and Yanwei Fu. "Incremental transformer structure enhanced image inpainting with masking positional encoding." *CVPR*2022.

ZITS++: Improved Incremental Transformer on Structural Priors

- Using Learning based Edges instead of Canny edge.
- Further improve the FTR training with large kernel attention (LKA)
- Discussing more about different priors for image inpainting



(a) Masked image (b) Canny from ZITS (c) ZITS results (d) CATS from ZITS++ (e) ZITS++ results



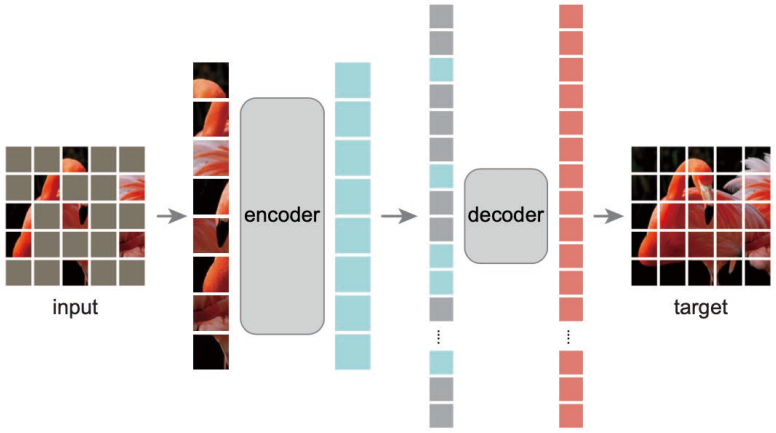
ZITS++, in submission to a journal

High resolution results of ZITS++

(f) High-resolution inpainting results compared with LaMa (first) and our ZITS++ (second).

1K and 4K resolution

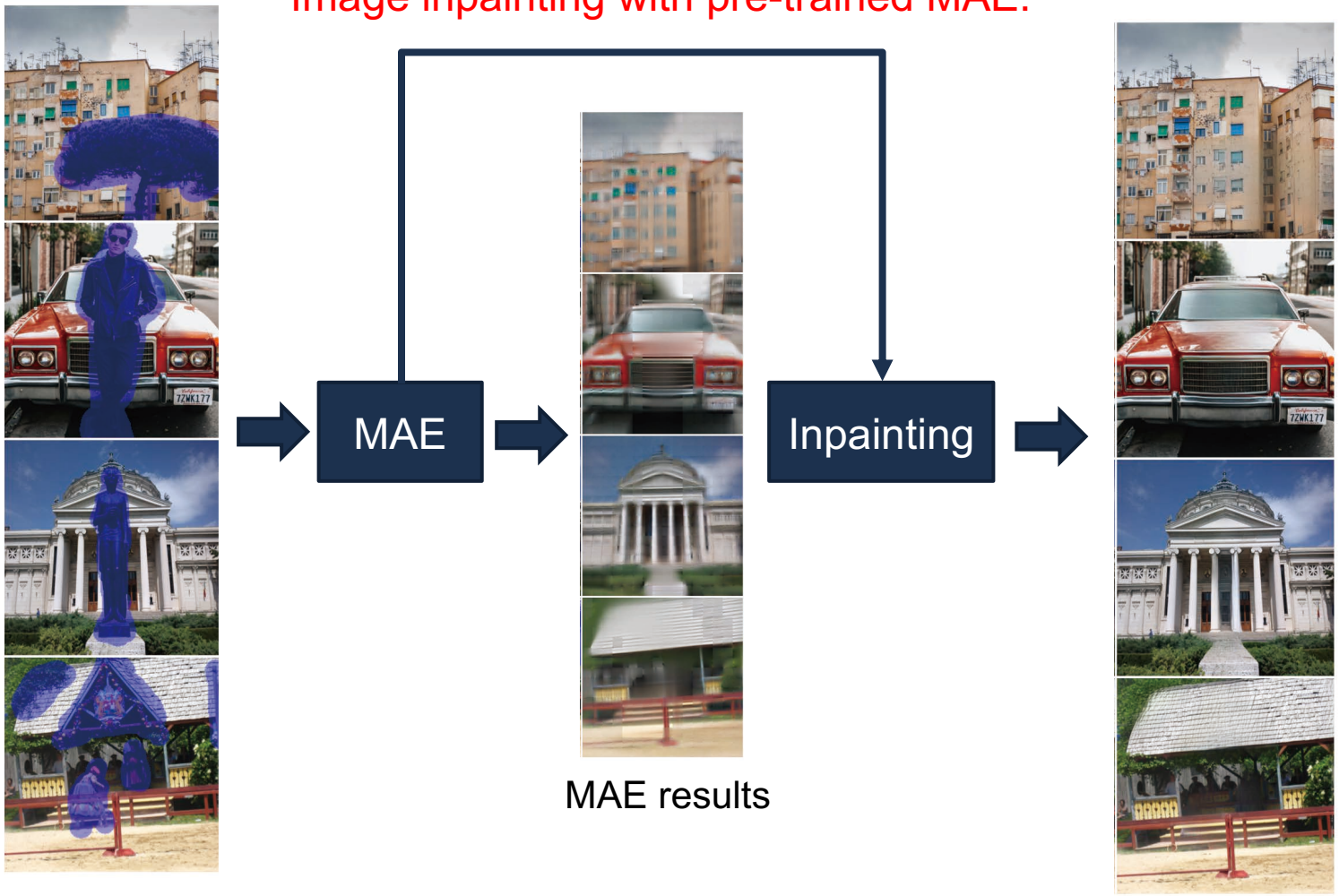
MAE-FAR: Learning Prior Feature and Attention Enhanced Image Inpainting



Masked AutoEncoder (MAE): A vision transformer that is pre-trained with 75% random masking prediction

https://github.com/ewrfcas/MAE-FAR

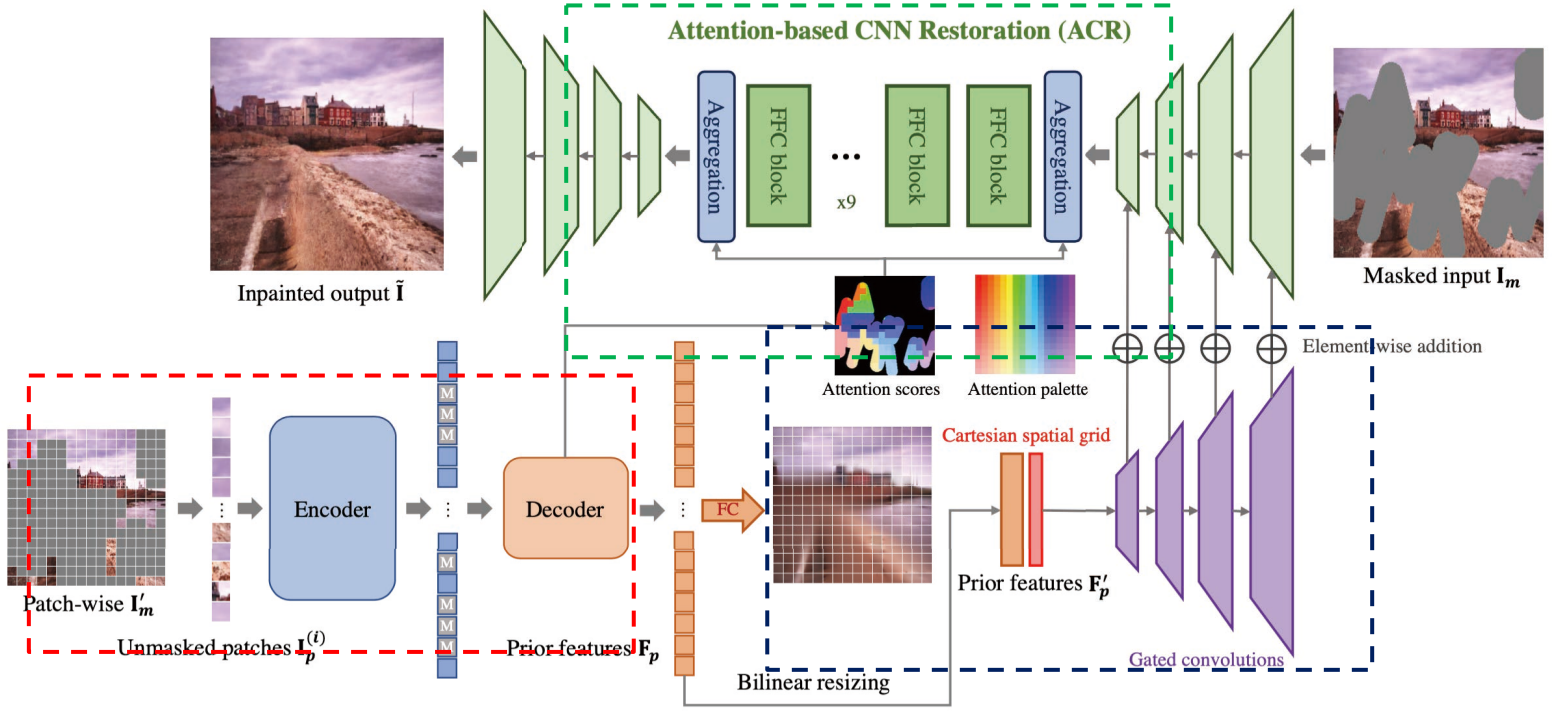
Our model provides proper priors for Image inpainting with pre-trained MAE.

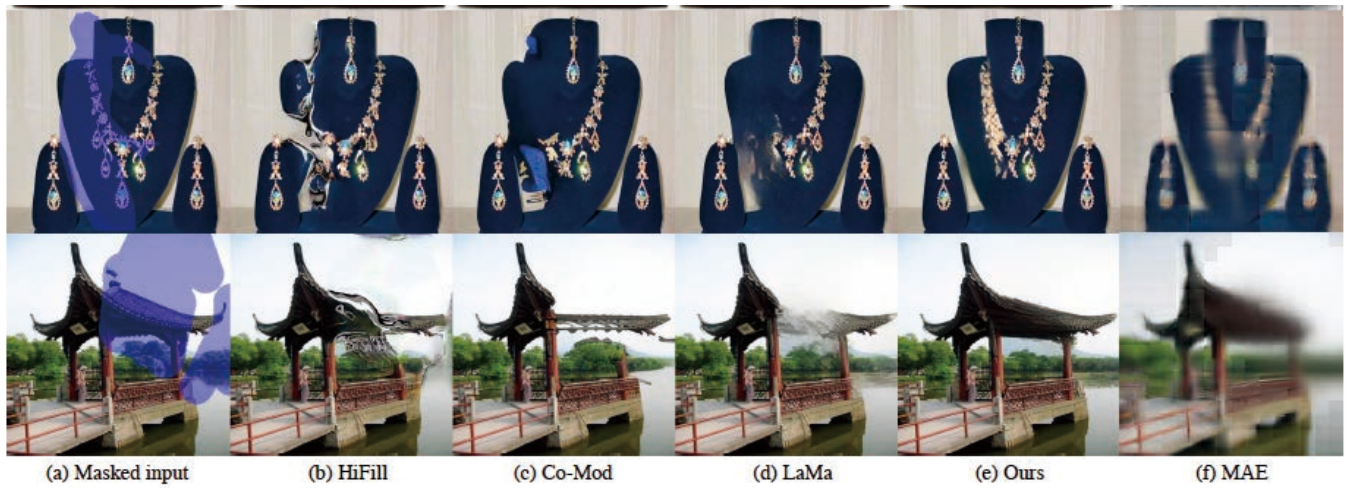


MAE results

He K, Chen X, Xie S, et al. Masked autoencoders are scalable vision learners CVPR2022.
Cao, Chenjie, Qiaole Dong, and Yanwei Fu. "Learning Prior Feature and Attention Enhanced Image Inpainting." *ECCV*2022.

Overview





(a) Masked input (b) HiFill (c) Co-Mod (d) LaMa (e) Ours (f) MAE

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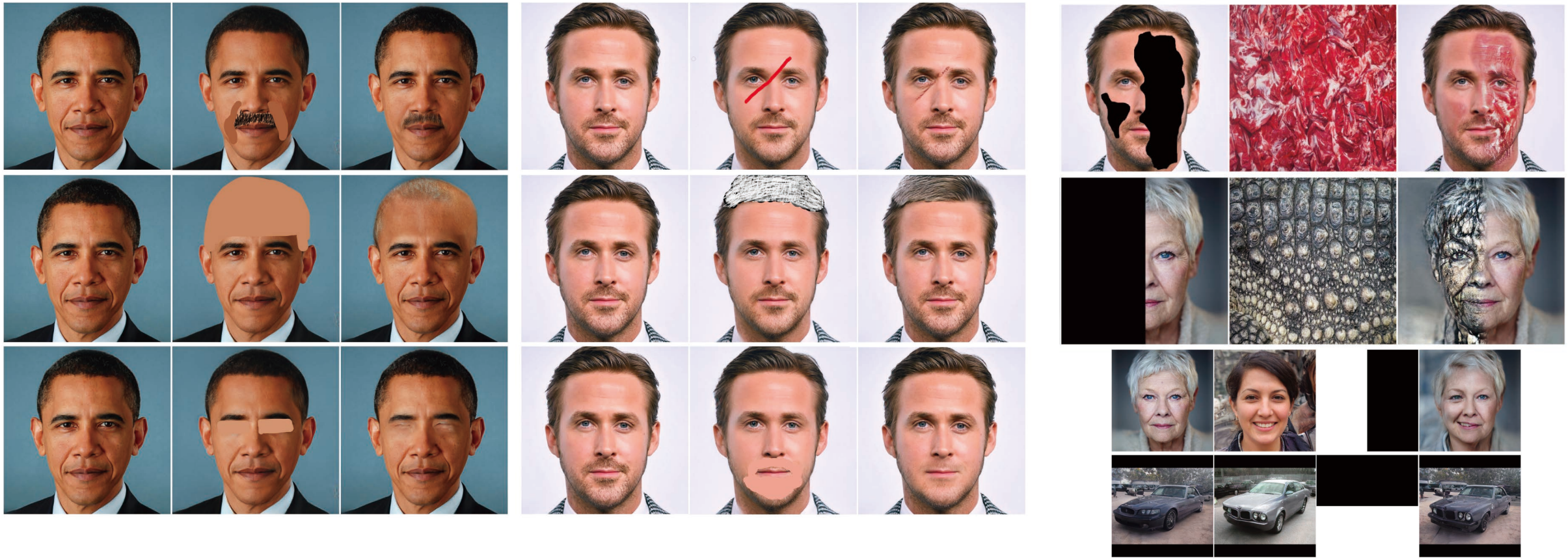
  - Transformer
  - Diffusion

GAN Inversion: A Survey. IEEE TPAMI 2022

Image2StyleGAN

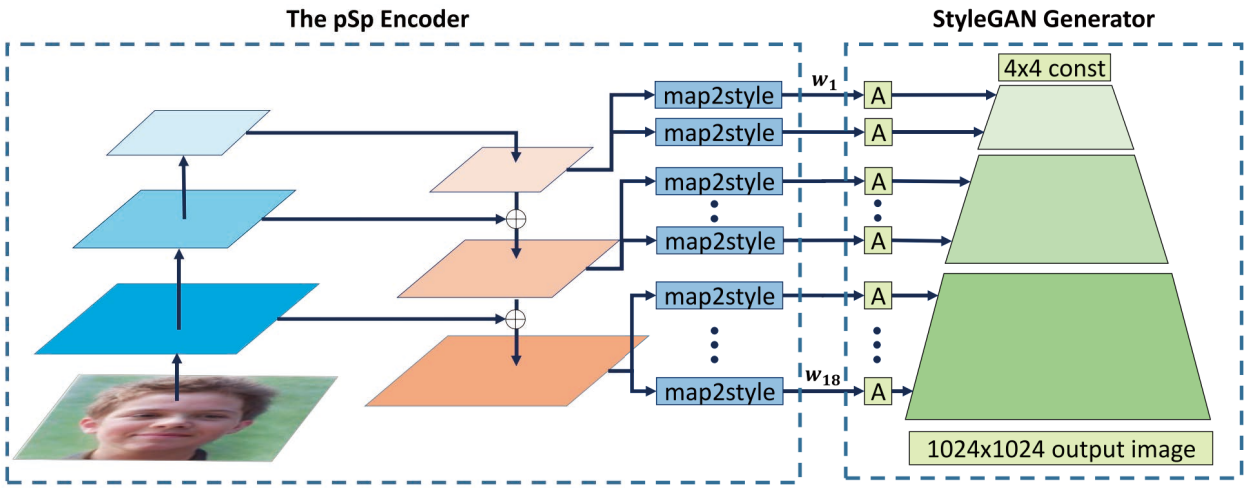
- Optimizing the latent space for an effective editing
- Embedding works well into the extended latent space W+

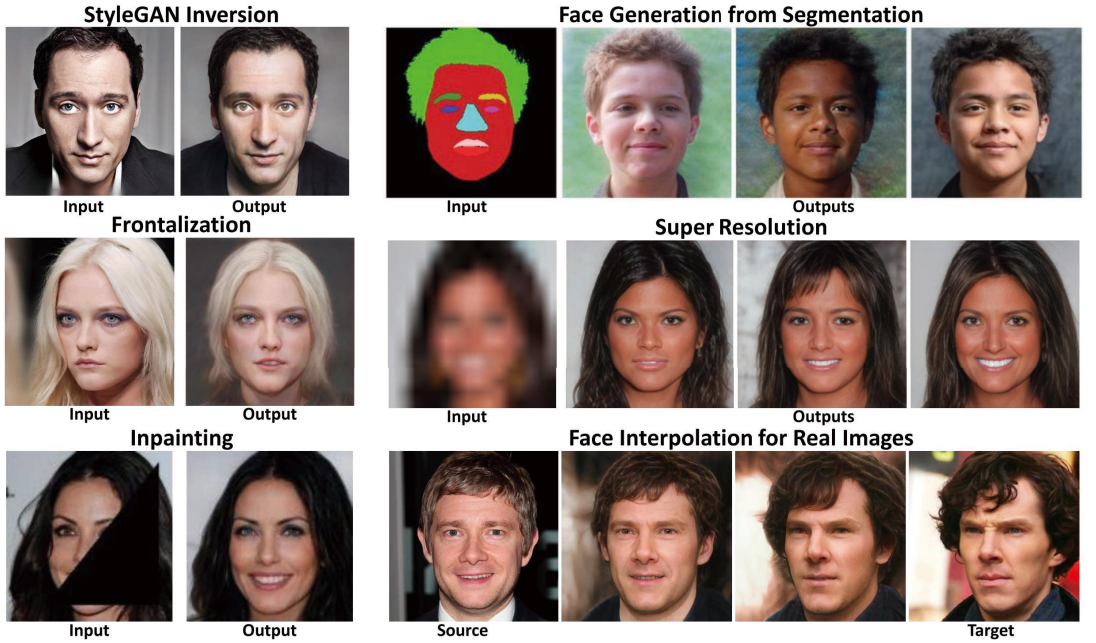


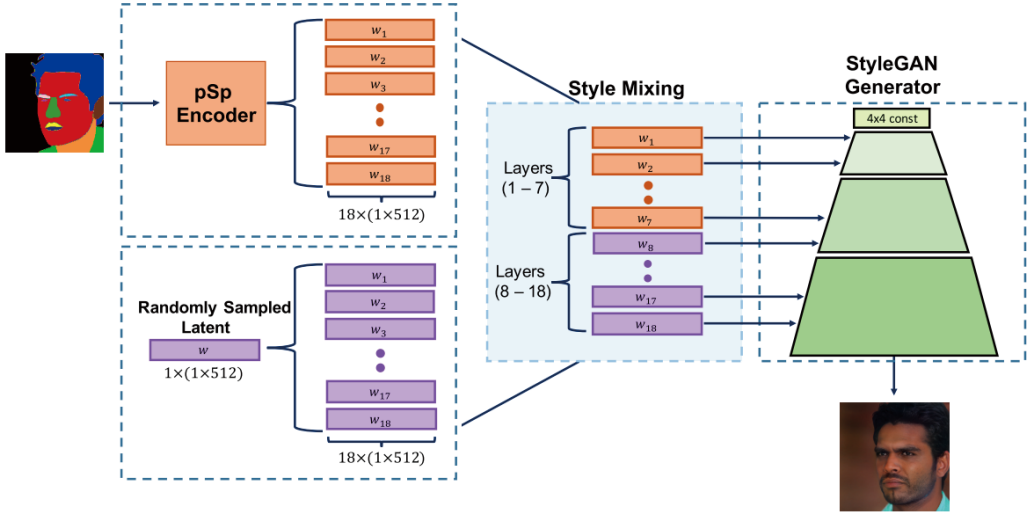
Rameen Abdal et al. Image2StyleGAN: How to Embed Images Into the StyleGAN Latent Space? ICCV2019
Rameen Abdal et al. Image2StyleGAN++: How to Edit the Embedded Images? CVPR2020

Encoding in Style: a StyleGAN Encoder for Image-to-Image Translation

- Using a pSp Encoder to learn for a latent space W+
- Combining with random latent codes and fuse for the mixed styles for stylegan

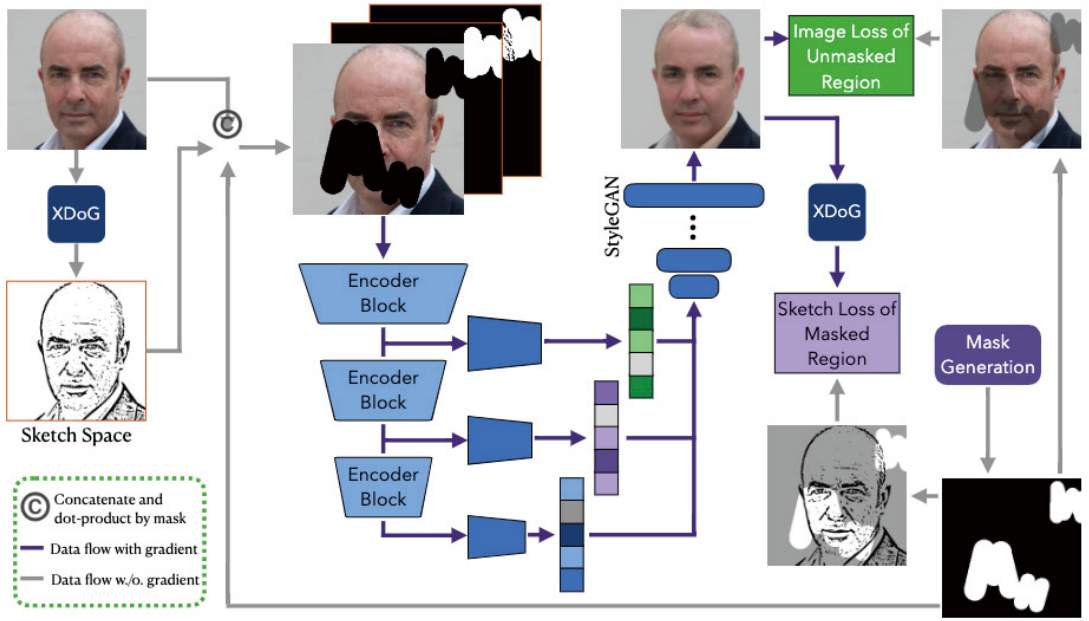


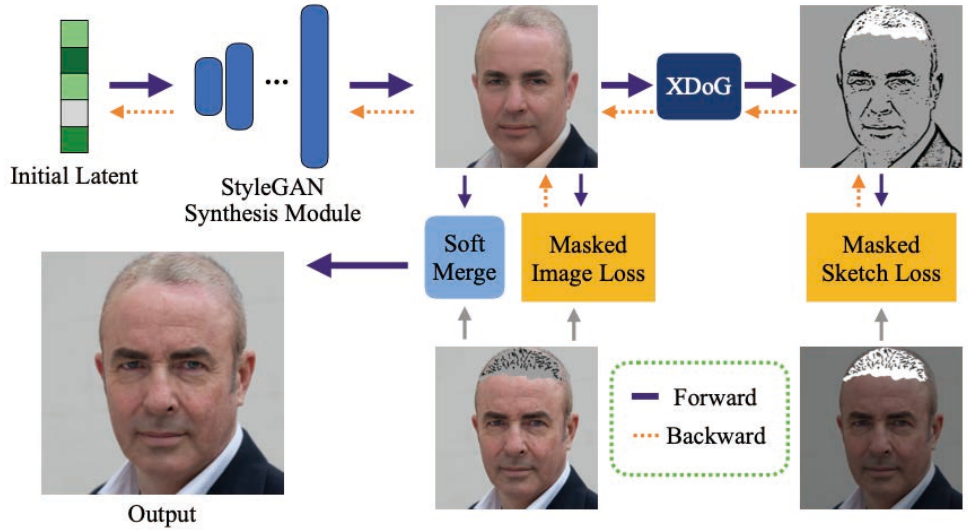




Richardson, Elad, et al. "Encoding in style: a stylegan encoder for image-to-image translation." *CVPR*2021.

Portrait Editing by Differentiable Guided Sketches from Latent Space





Unify both latent encoding and optimizing with differentiable sketch (XDoG operator)

Wang, Chengrong, et al. "High-Fidelity Portrait Editing Via Exploring Differentiable Guided Sketches from the Latent Space." *ICASSP*2022.

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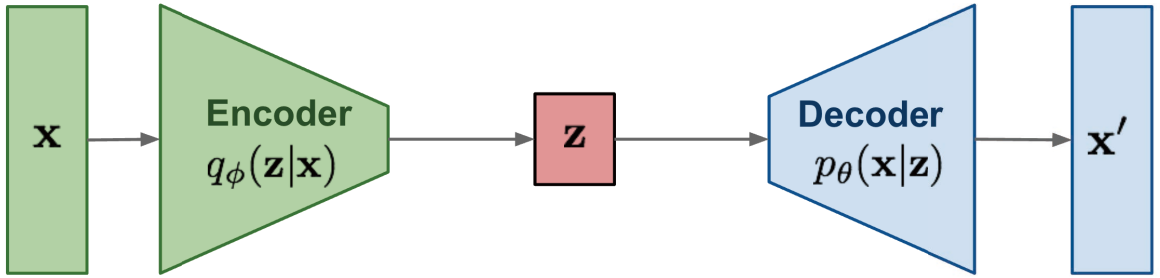
Variational Auto-Encoder (VAE)

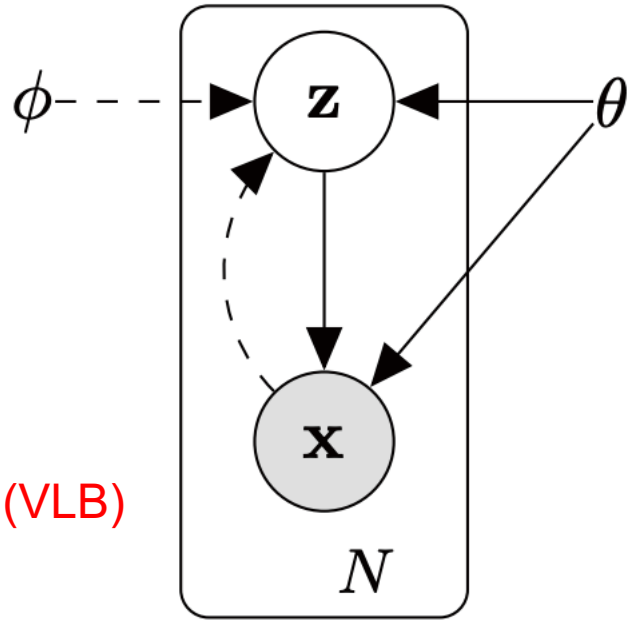
VAE: maximize variational lower bound



Generative model: $p_{\boldsymbol{\theta}}(\mathbf{z})p_{\boldsymbol{\theta}}(\mathbf{x}|\mathbf{z})$

Variational approximation $q_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x})$ to the posterior $p_{\boldsymbol{\theta}}(\mathbf{z}|\mathbf{x})$

$$p_\theta(z|x) \cong q_\phi(z|x)$$



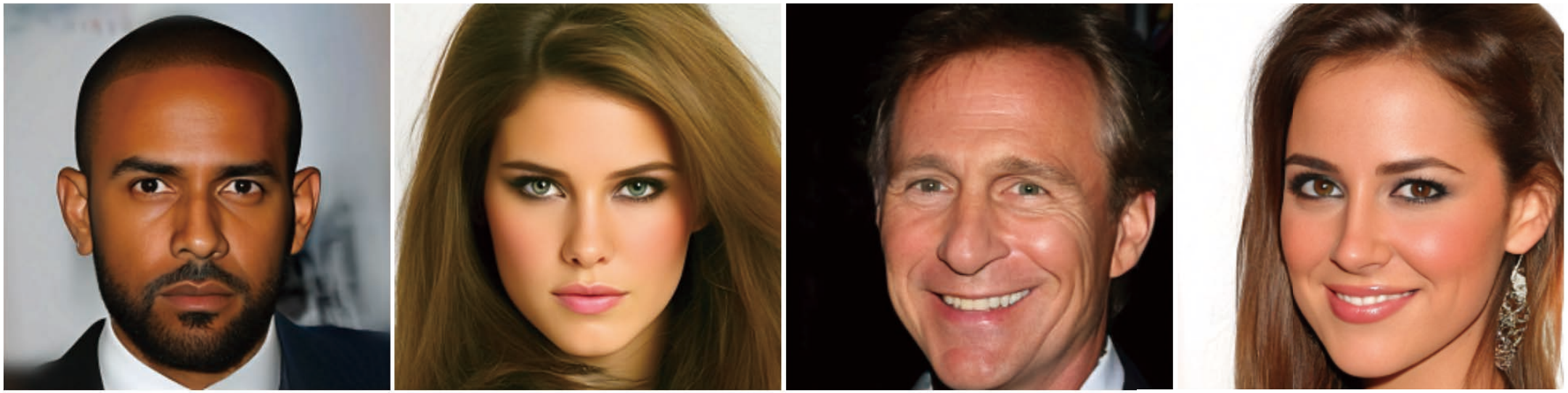
$$\log p_{\boldsymbol{\theta}}(\mathbf{x}^{(i)}) = D_{KL}(q_{\boldsymbol{\phi}}(\mathbf{z}|\mathbf{x}^{(i)})||p_{\boldsymbol{\theta}}(\mathbf{z}|\mathbf{x}^{(i)})) + \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\phi}; \mathbf{x}^{(i)})$$

Const — Non-negative — Variational Lower Bound (VLB)

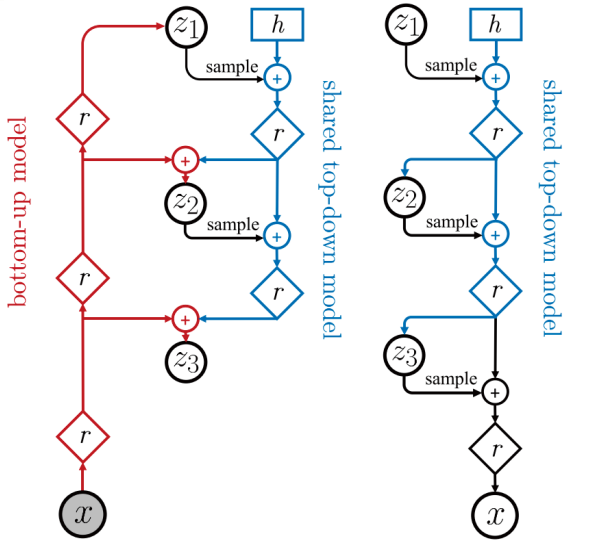
So when VLB is larger, KL is lower

Kingma D P, Welling M. Auto-encoding variational bayes, 2013.

NVAE: A Deep Hierarchical Variational Autoencoder



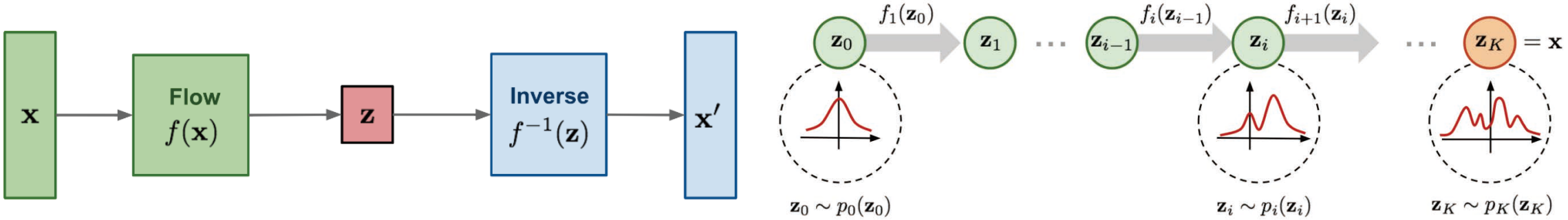
- VAE: Difficult to approximate p(z|x),q(z|x). Unstable to train very deep hierarchical VAE.
- NVAE:
  - Autoregressive and multi-scale residual normal distribution
  - Many architecture improvements
  - Scaling up the model design



(a) Bidirectional Encoder (b) Generative Model

Vahdat A, Kautz J. NVAE: A deep hierarchical variational autoencoder. NeurIPS2020.

Flow-based Generative Model



Normalizing Flows: A normalizing flow transforms a simple distribution into a complex one by applying a sequence of **invertible** transformation functions

$$p_i(\mathbf{z}_i) = p_{i-1}(f_i^{-1}(\mathbf{z}_i)) \left| \det \frac{df_i^{-1}}{d\mathbf{z}_i} \right|$$

- NICE: Affine coupling layer without the scale term, known as additive coupling layer
- RealNVP: Stacking a sequence of invertible bijective transformation functions
- Glow: Replacing the reverse operation on the channel ordering with invertible 1x1 convolutions

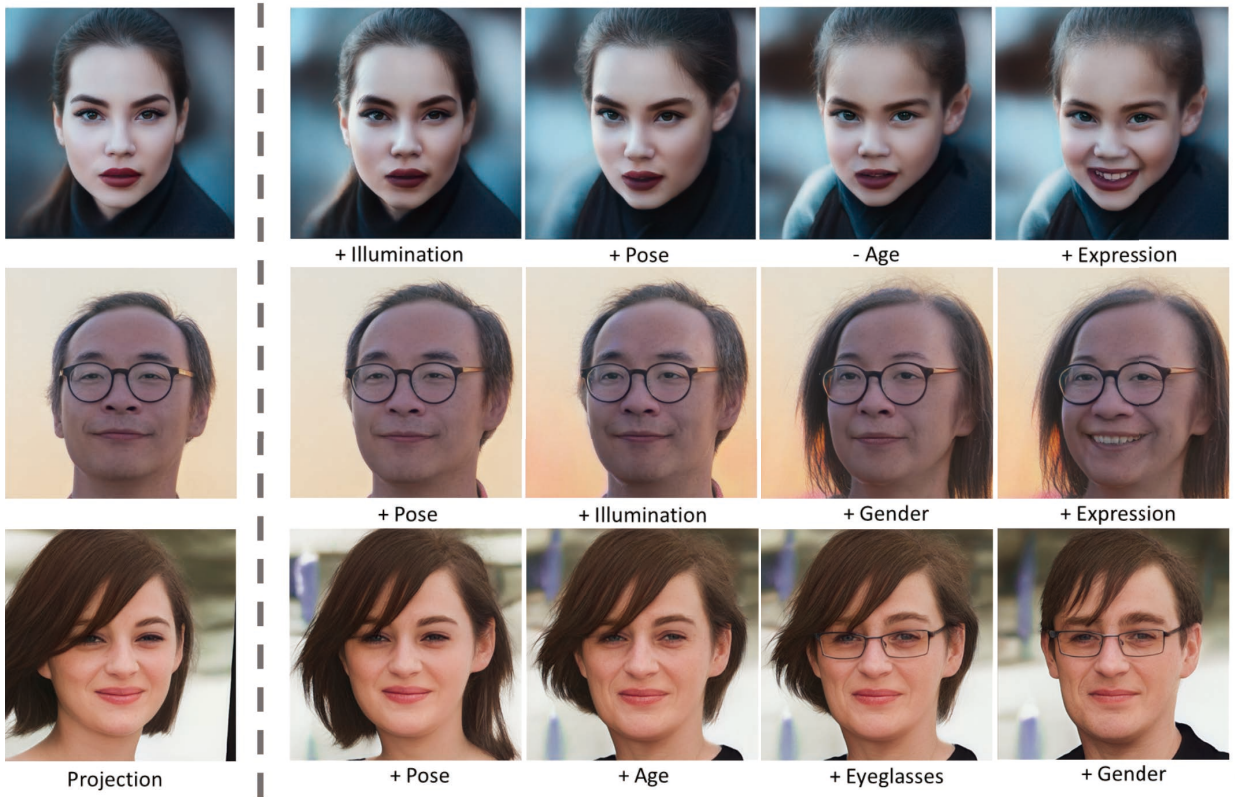
https://lilianweng.github.io/posts/2018-10-13-flow-models/

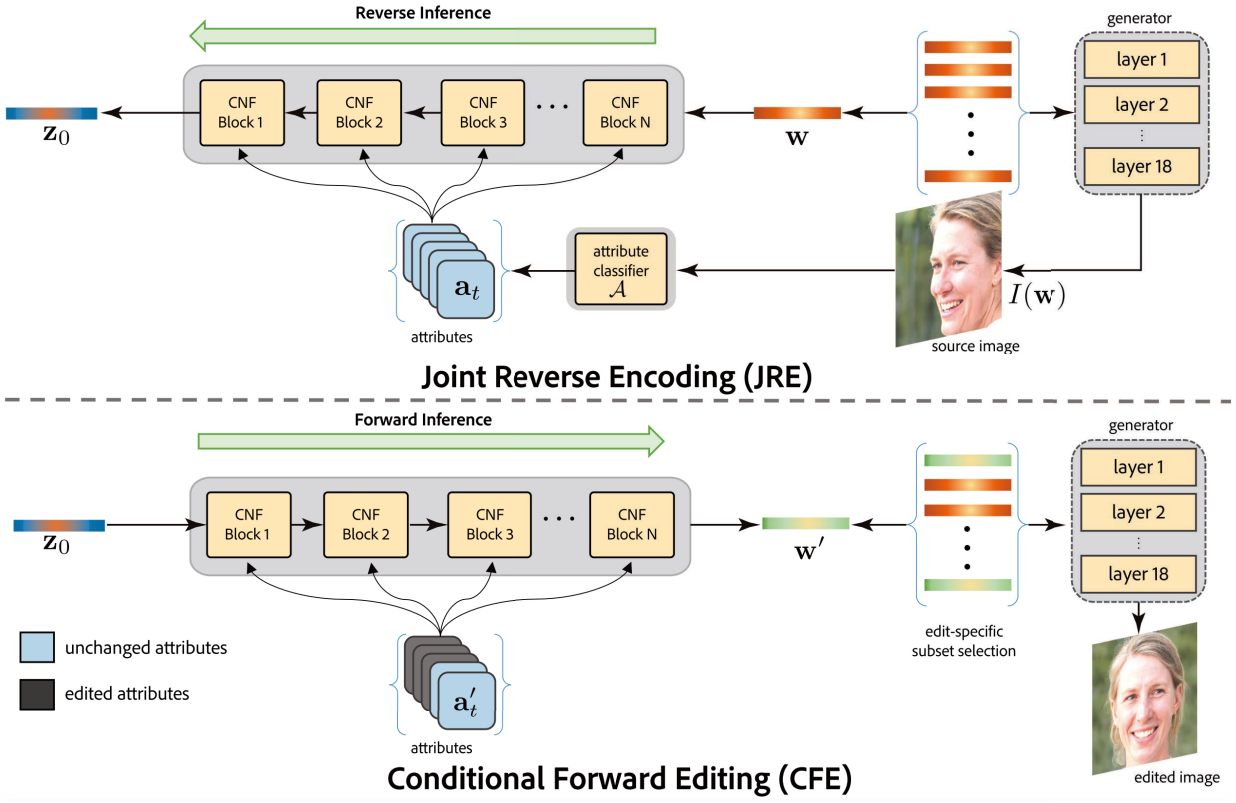
Dinh L, Krueger D, Bengio Y. Nice: Non-linear independent components estimation. ICLR2015.

Dinh L, Sohl-Dickstein J, Bengio S. Density estimation using real nvp. ICLR2017.

Kingma D P, Dhariwal P. Glow: Generative flow with invertible 1x1 convolutions. NeurIPS2018.

StyleFlow: Normalizing Flow and StyleGAN





- Flow enjoys good performance when combined with the stylegan through the conditional continuous normalizing flow

Abdal, Rameen, et al. "Styleflow: Attribute-conditioned exploration of stylegan-generated images using conditional continuous normalizing flows." *ToG2021*.

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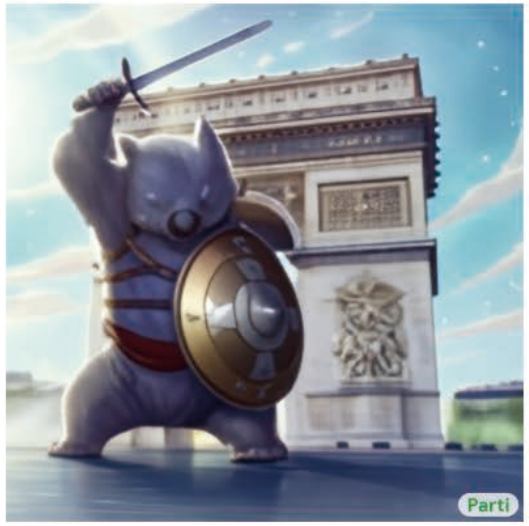
SOTA Synthesis Results from Transformers with VQGAN

Parti



A warrior wombat holding a sword and shield in a fighting stance. The wombat stands in front of the Arc de Triomphe on a day shrouded mist with the sun high in the sky. realistic anime illus-

A sloth in a go kart on a race track. The sloth is holding a banana in one hand. There is a banana peel on the track in the background. DSLR photograph.

A robot with a black visor and the number 42 on its chest. It stands proudly in front of an F1 race car. The sun is setting on a cityscape in the background. wide-angle view. comic book illustration.

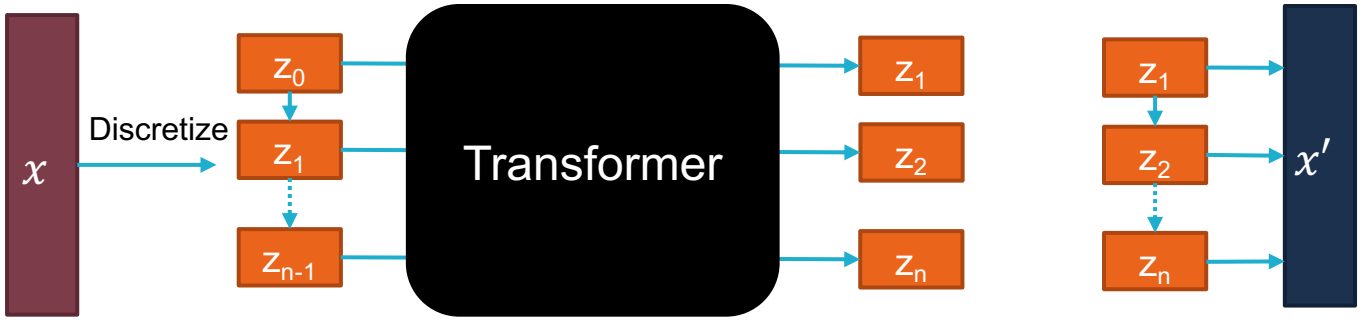
NUWA-infinity

Input: a field with a house and a cloudy sky

[1] Yu, Jiahui, et al. "Scaling autoregressive models for content-rich text-to-image generation." arXiv preprint arXiv:2206.10789 (2022).
[2] Wu, Chenfei, et al. "NUWA-Infinity: Autoregressive over Autoregressive Generation for Infinite Visual Synthesis." arXiv preprint arXiv:2207.09814 (2022).

Transformer for Image Generation

Transformers:
Discretization and
Autoregressive generation

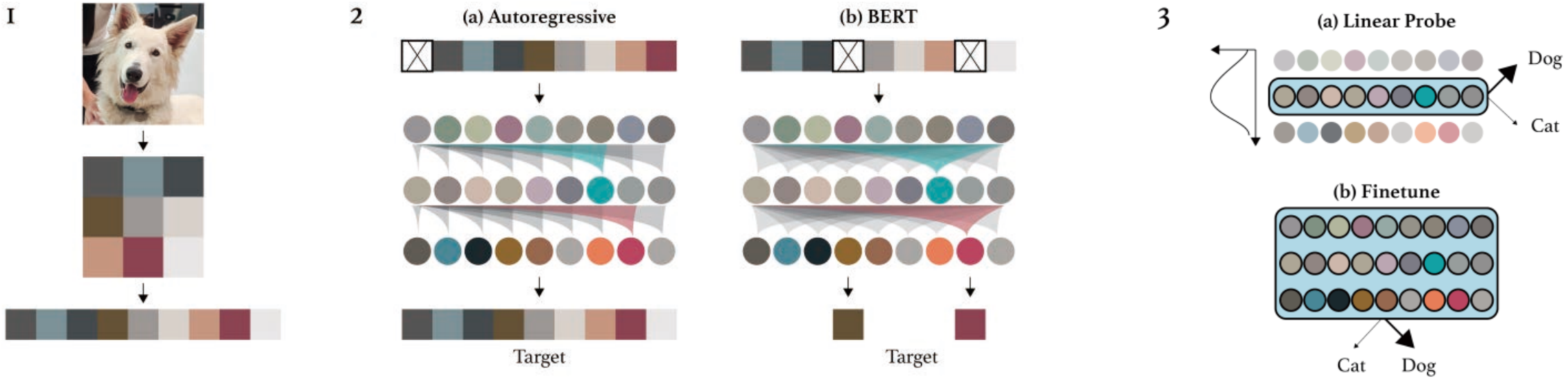


- Some classical works without discretization (**inefficient!**) :
- PixelCNN [1]
- Image Transformer[2]

[1] Van den Oord, Aaron, et al. "Conditional image generation with pixelcnn decoders." *NIPS* 2016.
[2] Parmar, Niki, et al. "Image transformer." International conference on machine learning. PMLR, 2018

iGPT: Generation Task for Model Pretraining

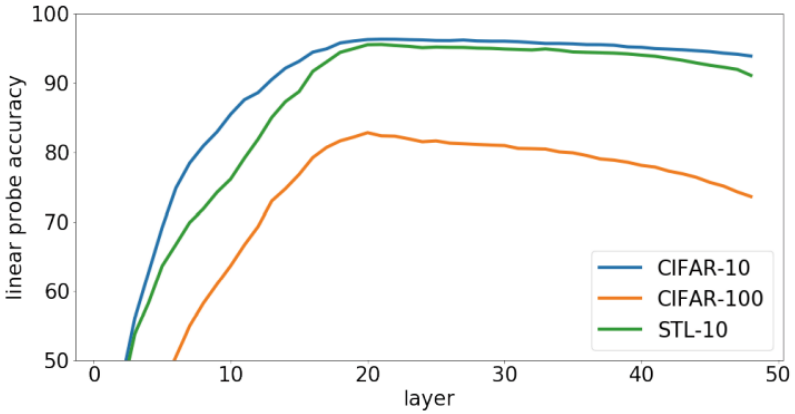
Discretizing RGB to 512 color index with K-means



- Autoregressive: $p(x) = \prod_{i=1}^{n} p(x_{\pi_i} | x_{\pi_1}, ..., x_{\pi_{i-1}}, \theta)$

$$L_{AR} = \mathop{\mathbb{E}}_{x \sim X} [-\log p(x)]$$

- BERT: $$L_{BERT} = \mathop{\mathbb{E}}_{x \sim X} \mathop{\mathbb{E}}_{M} \sum_{i \in M} \left[-\log p\left(x_i | x_{[1,n] \setminus M} \right) \right]$$



Chen, Mark, et al. "Generative pretraining from pixels." International conference on machine learning. PMLR, 2020.

DALLE：Zero-Shot Text-to-Image Generation

(a) a tapir made of accordion. a tapir with the texture of an accordion.

(b) an illustration of a baby hedgehog in a christmas sweater walking a dog

(c) a neon sign that reads "backprop". a neon sign that reads "backprop". backprop neon sign

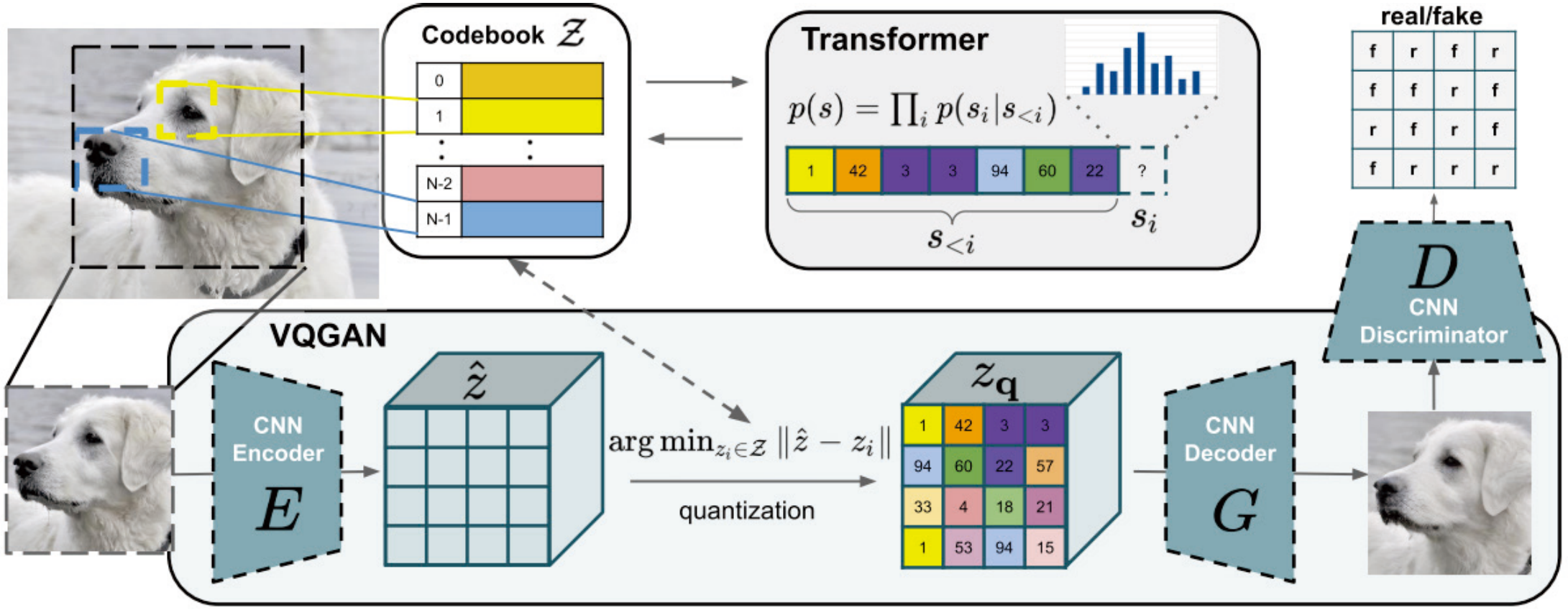
(d) the exact same cat on the top as a sketch on the bottom

- Stage 1. Training a **discrete Variational AutoEncoder (dVAE)**
  - compress each 256×256 image into a 32×32 grid of image tokens, assuming 8192 possible values
- Stage 2. Concating 256 BPE-encoded text tokens with the 32×32=1024 image tokens, and train an autoregressive transformer to model the joint distribution over text and image tokens.

Ramesh, Aditya, et al. "Zero-shot text-to-image generation." International Conference on Machine Learning. PMLR, 2021.

Taming Transformers for High-Resolution Image Synthesis

- Learning an Effective Codebook of Image Constituents for Use in Transformers (**Discretization:VQVAE**)
- Using an Autoregressive Transformer to learn/reconstruct sequential codebook tokens
- Improve VQVAE to VQGAN with adversarial training

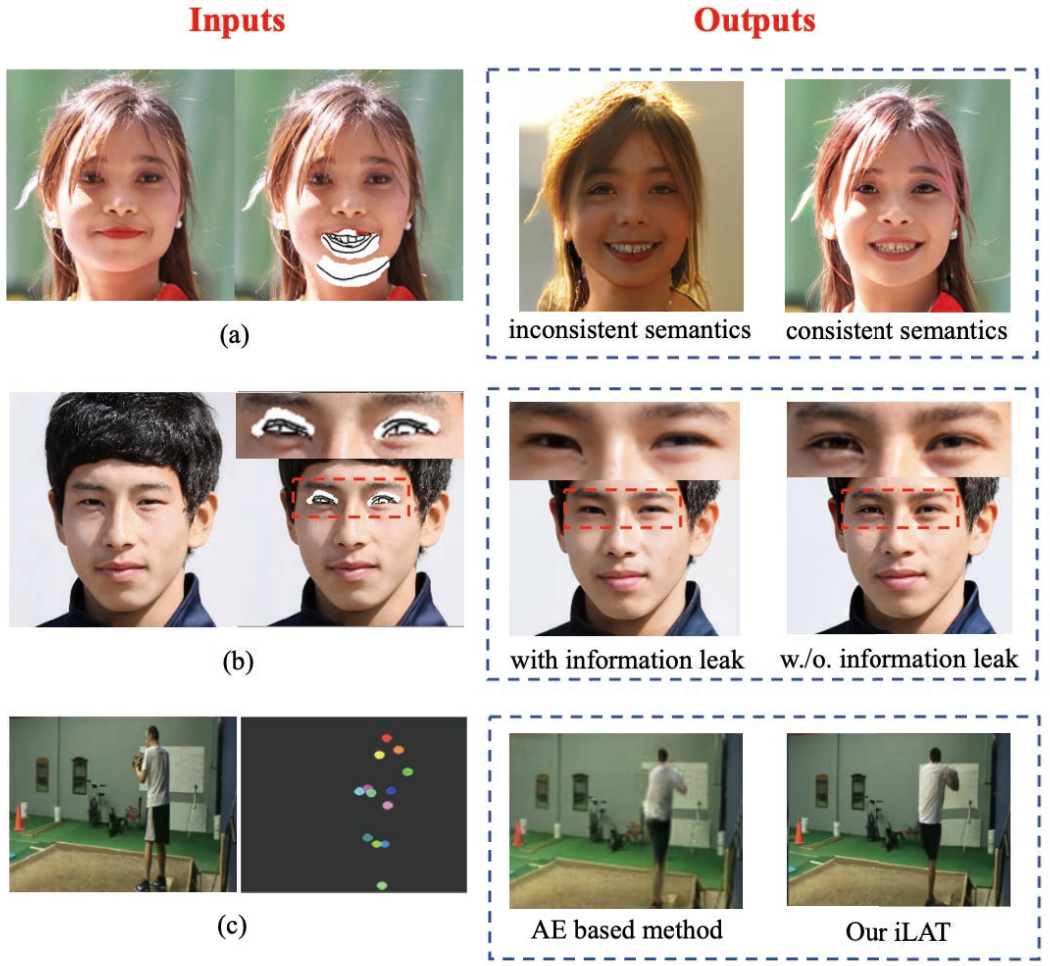


Esser, Patrick, Robin Rombach, and Bjorn Ommer. "Taming transformers for high-resolution image synthesis." CVPR 2021.

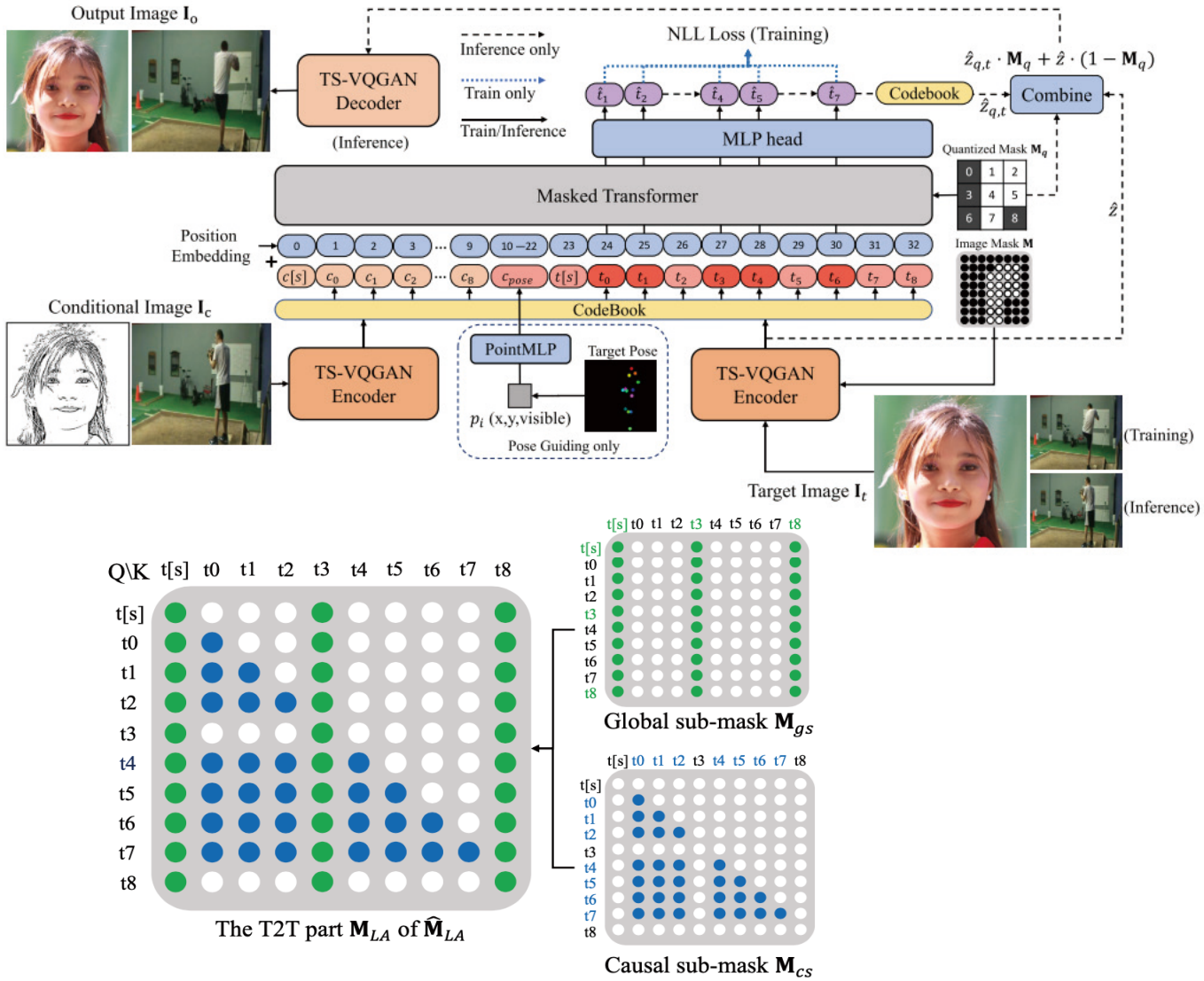
VQVAE VS VQGAN with large downsample scale(f=16)

Esser, Patrick, Robin Rombach, and Bjorn Ommer. "Taming transformers for high-resolution image synthesis." CVPR 2021.

Image Local Autoregressive Transformer

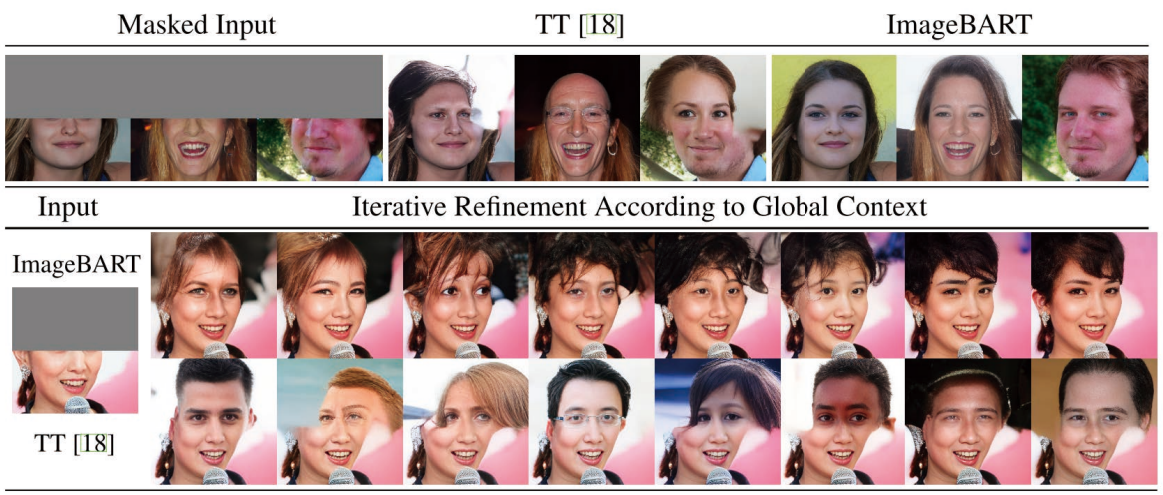


(A) Inputs and outputs of local generation compared with previous works

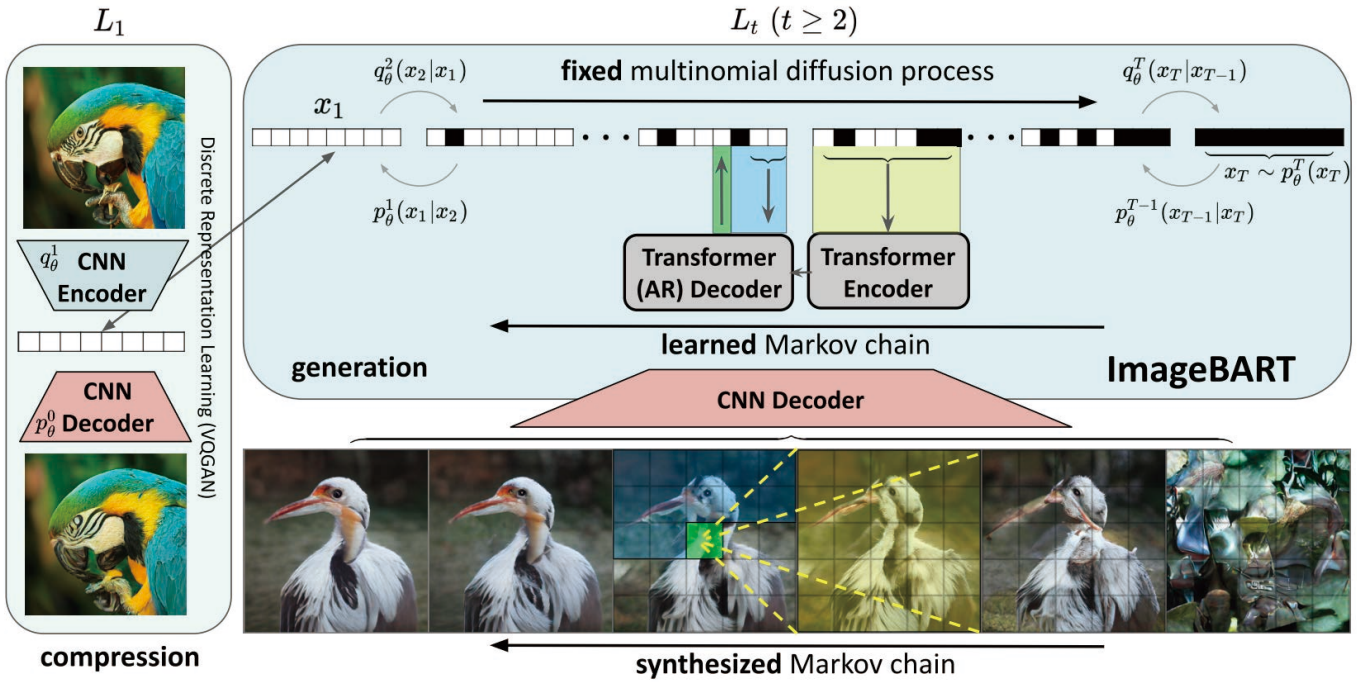


Cao, Chenjie, et al. "The image local autoregressive transformer." *NIPS 2021*

ImageBART



Taming Transformer (TT) Esser, Patrick et al. CVPR2021

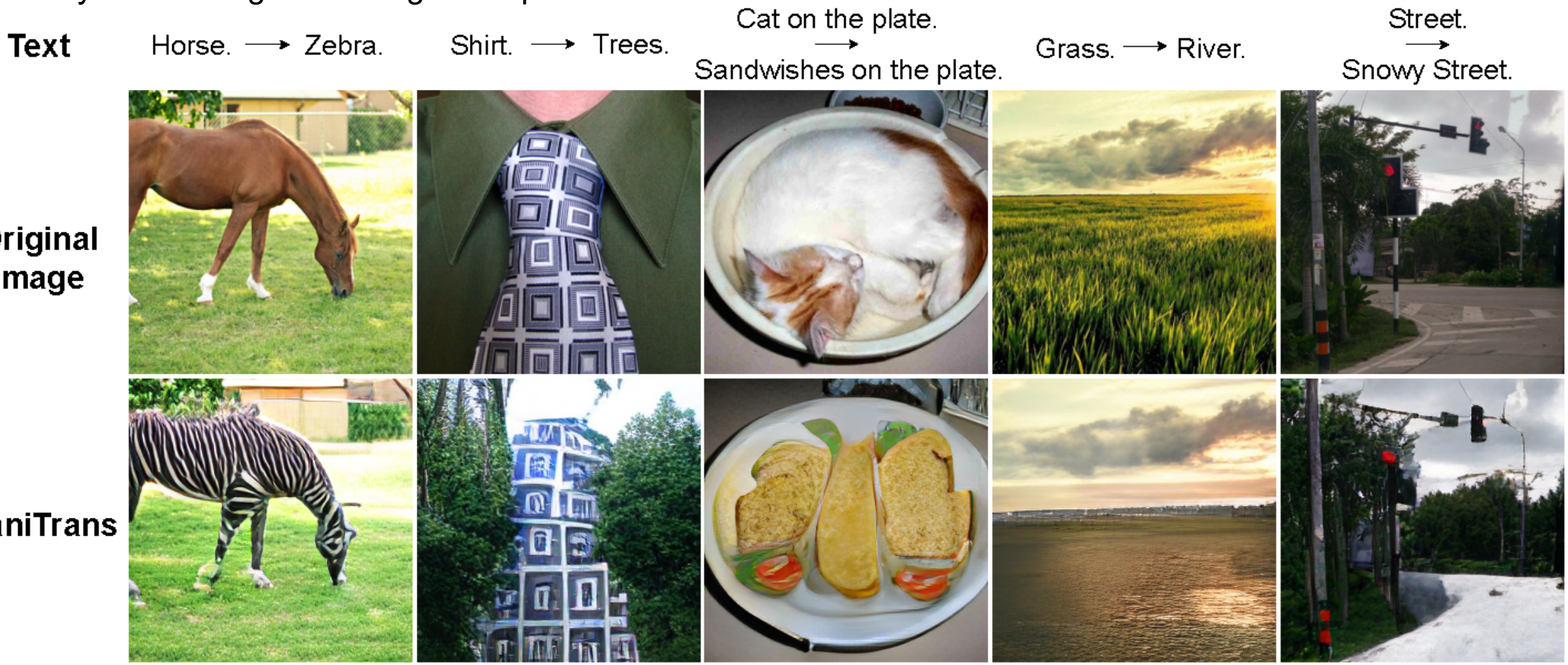


- Learning a compact, discrete representation for images (VQGAN)
- Multinomial diffusion for discrete sequence (extended from binomial diffusion)
- Diffusion encoder: bidirectional transformer (more layers)
- Diffusion decoder: autoregressive transformer (less layers)

Esser, Patrick, et al. "Imagebart: Bidirectional context with multinomial diffusion for autoregressive image synthesis." *NeurIPS2021*.

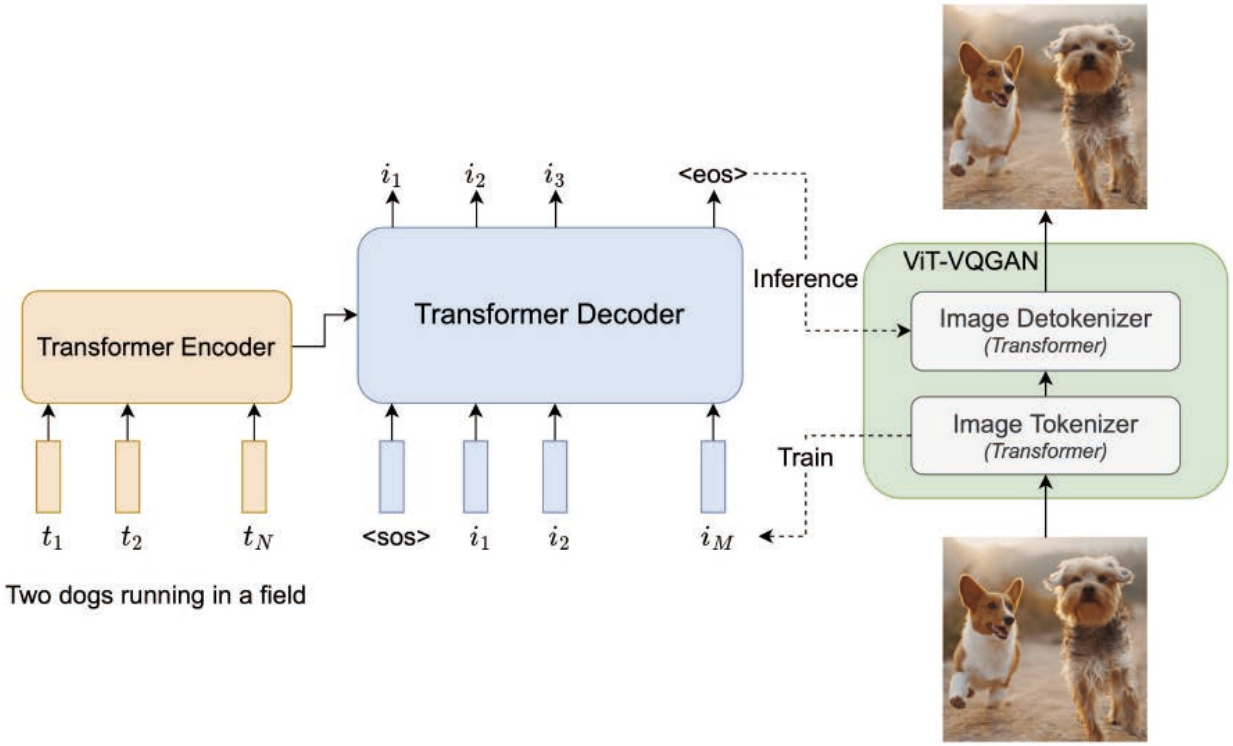
ManiTrans

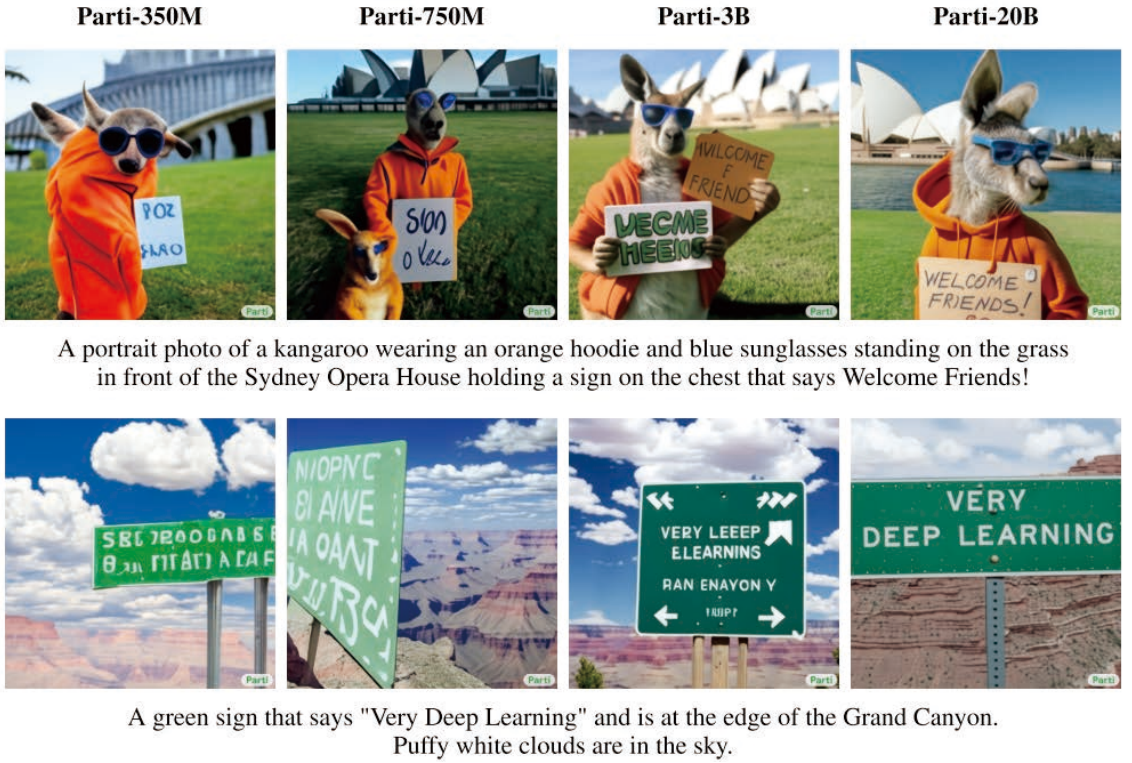
Entity-level Text-guided Image Manipulation



ManiTrans: Entity-Level Text-Guided Image Manipulation via Token-wise Semantic Alignment and Generation, CVPR 2022 (Oral)

Parti: Pathways Autoregressive Text-to-Image Model





- Use ViT-VQGAN with L2-normalization codes and factorized codes
- At the model scale of 350-million to 750-million parameters, the encoder-decoder variants of Parti outperformed decoder-only ones
- Pretrain the text encoder on large datasets

If model capacities are large enough, autoregressive models are still competitive compared with diffusion models!

Yu, Jiahui, et al. "Scaling autoregressive models for content-rich text-to-image generation." arXiv preprint arXiv:2206.10789 (2022).

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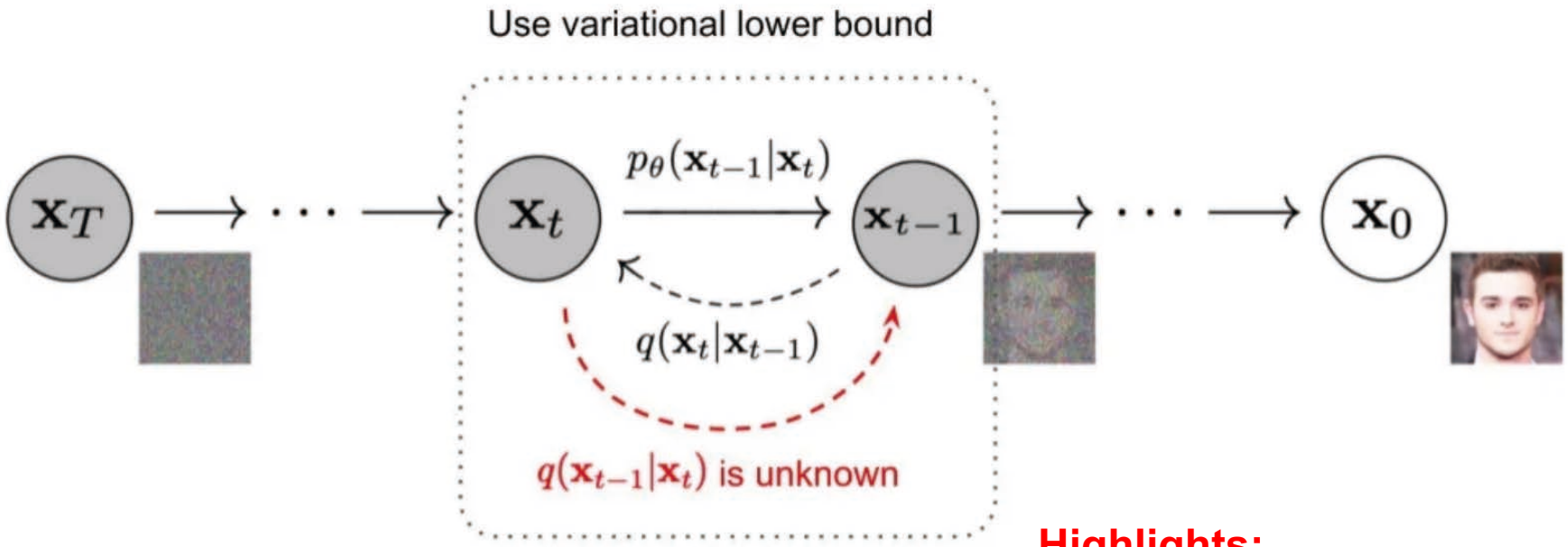
Denoising Diffusion Probabilistic Models



Denoising diffusion models consist of two processes:

- Forward diffusion process: gradually adding noise to input
- Reverse denoising process: learning to generate data by denoising

Highlights:

- **Typically using U-net for implementation**
- **Conditional Diffusion Models**

Denoising Diffusion Probabilistic Models, NIPS 2020
Sohl-Dickstein et al., Deep Unsupervised Learning using Nonequilibrium Thermodynamics, ICML 2015
Song et al., Score-Based Generative Modeling through Stochastic Differential Equations, ICLR 2021

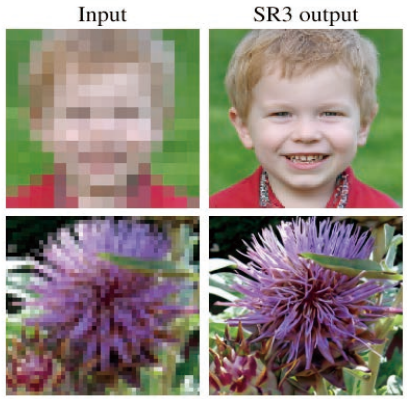
Denoising Diffusion Models

Emerging as powerful generative models, outperforming GANs

"Diffusion Models Beat GANs on Image Synthesis" Dhariwal & Nichol, OpenAI, 2021

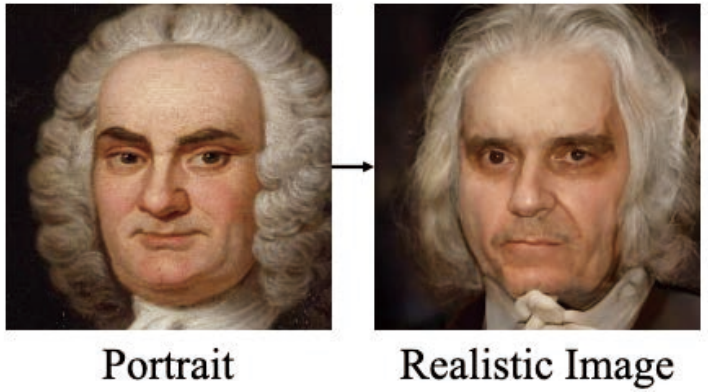
"Cascaded Diffusion Models for High Fidelity Image Generation" Ho et al., Google, 2021

Various Usages of Diffusion Models



Super-resolution

Saharia, Chitwan, et al. "Image super-resolution via iterative refinement." (2021).

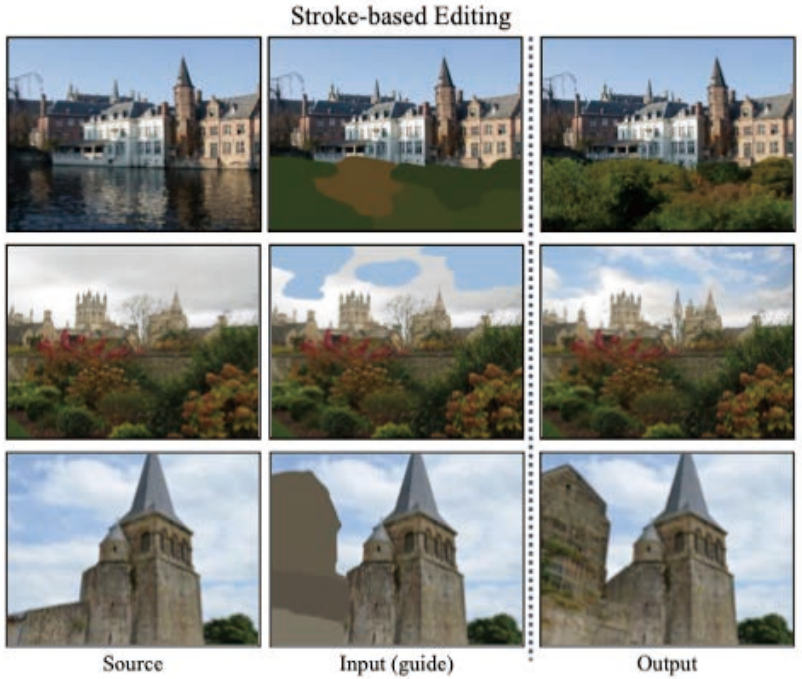


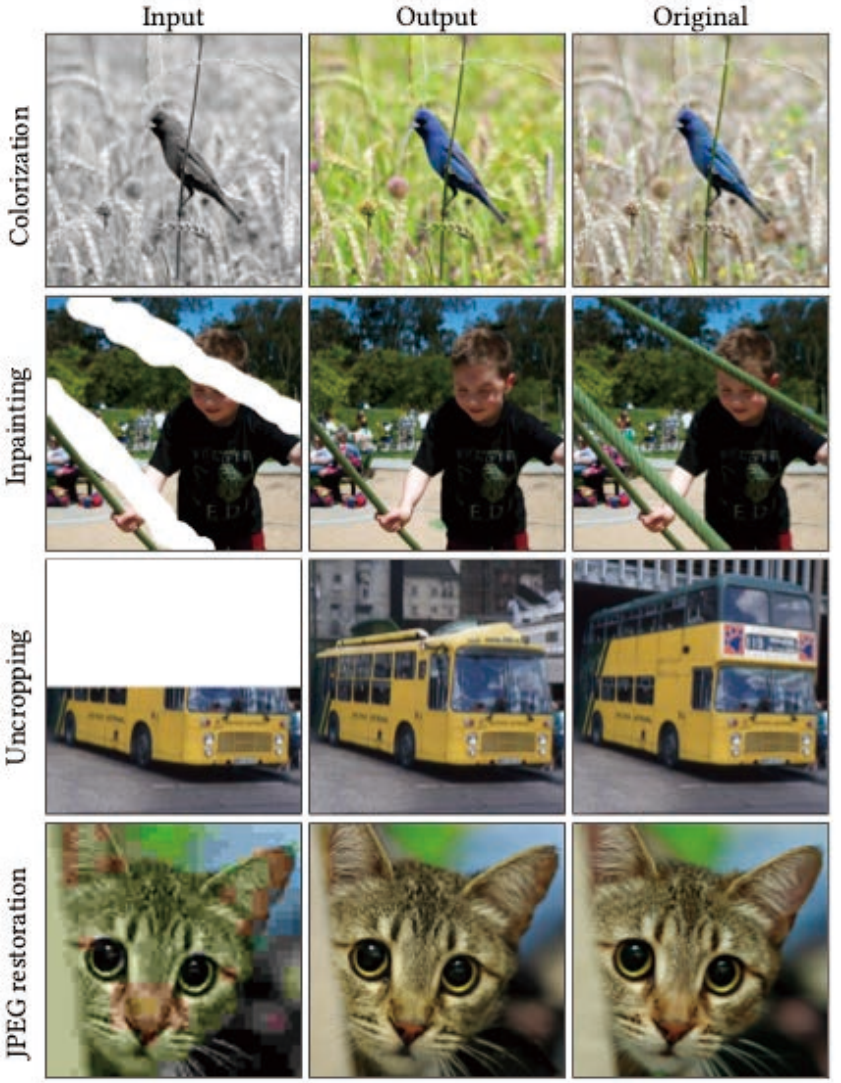
Domain Transfer

Choi, Jooyoung, et al. "Ilvr: Conditioning method for denoising diffusion probabilistic models." (2021).

Editing

Meng, Chenlin, et al. "Sdedit: Guided image synthesis and editing with stochastic differential equations." 2021.





Multi-task (colorization, inpainting, restoration)

Saharia, Chitwan, et al. "Palette: Image-to-image diffusion models.". 2022.

Text-to-Image Models

DALL·E 2

"a teddy bear on a skateboard in times square"

"Hierarchical Text-Conditional Image Generation with CLIP Latents" Ramesh et al., 2022

Imagen

A group of teddy bears in suit in a corporate office celebrating the birthday of their friend. There is a pizza cake on the desk.

"Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding", Saharia et al., 2022

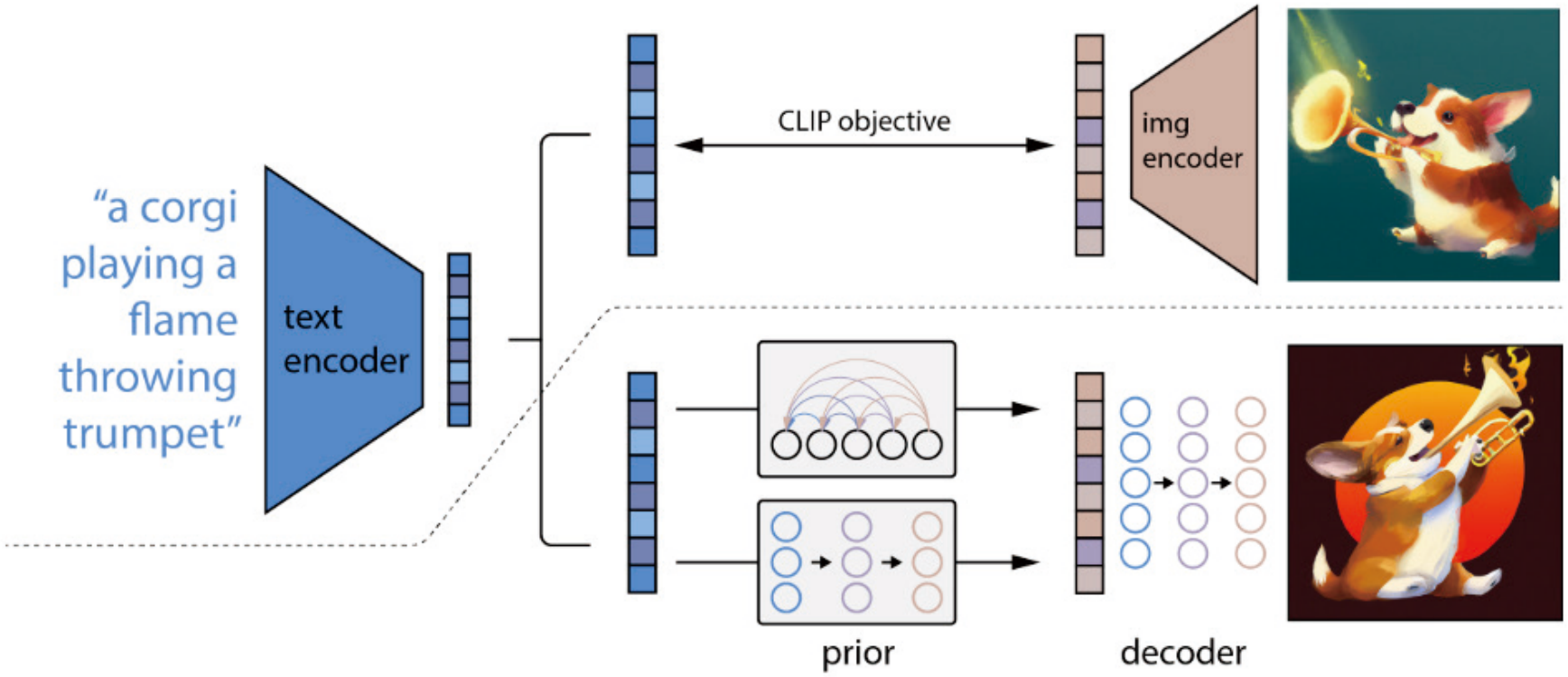
DALLE 2

a propaganda poster depicting a cat dressed as french emperor napoleon holding a piece of cheese

a teddy bear on a skateboard in times square

Hierarchical Text-Conditional Image Generation with CLIP Latents. arxiv 2022

DALLE 2 (unCLIP)

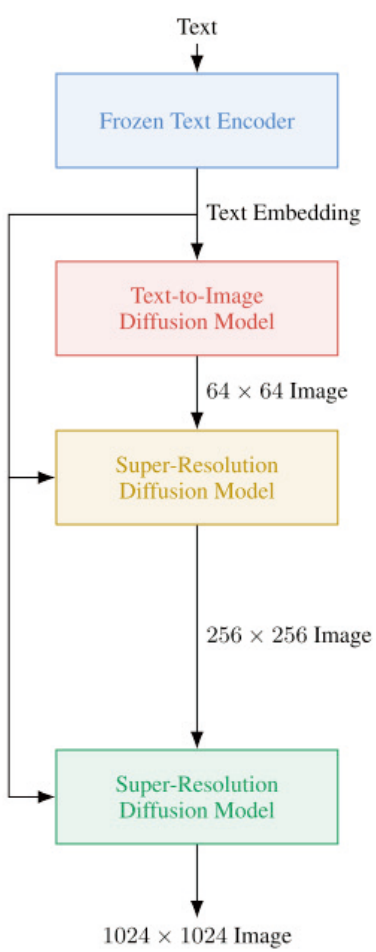


encode any given image x into a bipartite latent representation (z_i, x_T)

- A *prior* $P(z_i|y)$ that produces CLIP image embeddings z_i conditioned on captions y.
- A *decoder* $P(x|z_i, y)$ that produces images x conditioned on CLIP image embeddings z_i (and optionally text captions y).

Imagen

Pretrained text encoders are important for Text-to-Image!



Super-Resolution Diffusion Model for high-resolution synthesis

Figure A.4: Visualization of Imagen. Imagen uses a frozen text encoder to encode the input text into text embeddings. A conditional diffusion model maps the text embedding into a 64×64 image. Imagen further utilizes text-conditional super-resolution diffusion models to upsample the image, first $64 \times 64 \rightarrow 256 \times 256$, and then $256 \times 256 \rightarrow 1024 \times 1024$.

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Thanks!

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