《物理与人工智能》

11. 扩散模型

授课教师：马滟青

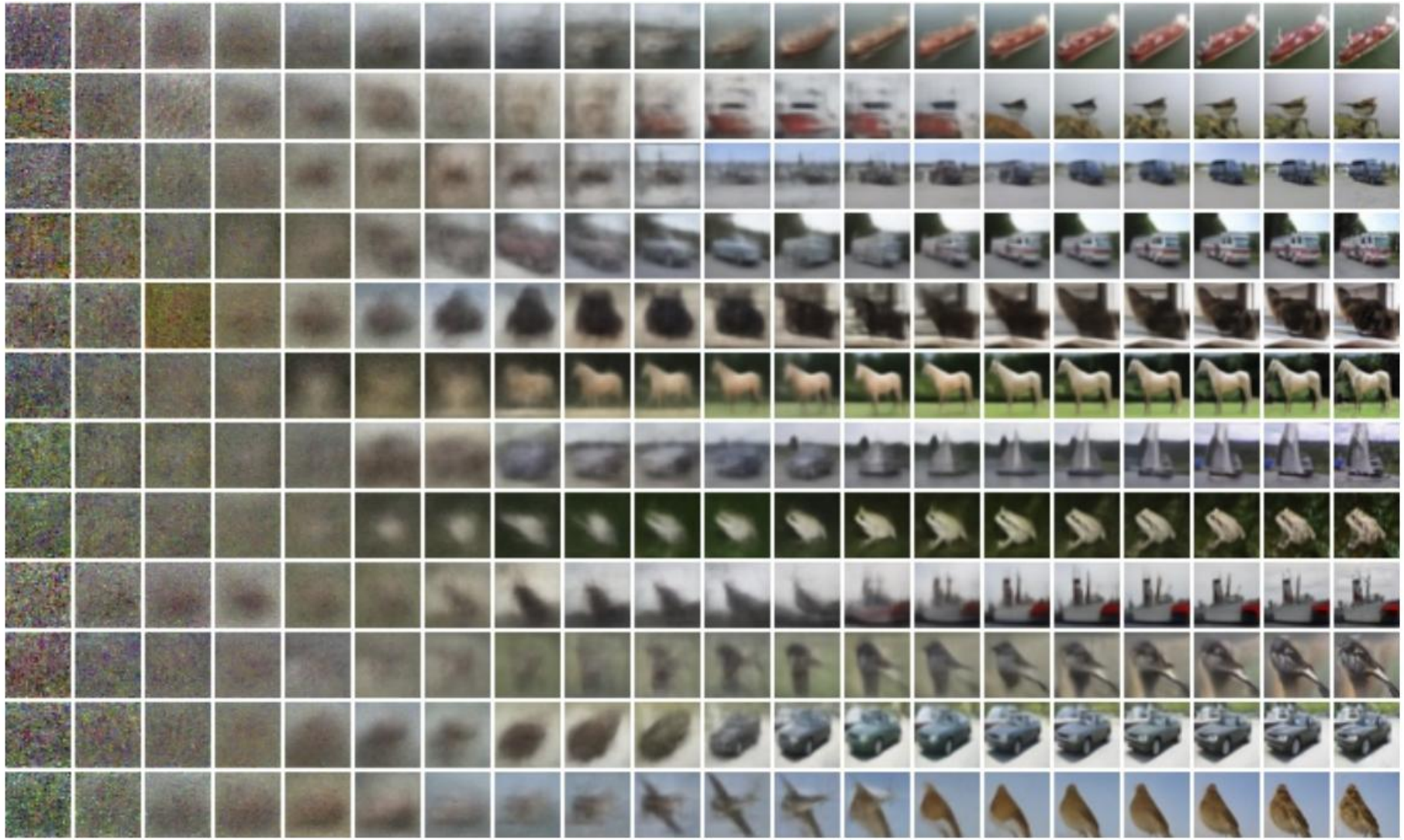
2026/10/12（第五周）

鸣谢：基于Viraj Shah幻灯片

北京大学



Diffusion models



Diffusion models





https://www.nytimes.com/2023/04/08/technology/ai-photos-pope-francis.html

Outline

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- **Part 1: Basics**
  - Denoising diffusion probabilistic models (DDPMs)
  - Conditional diffusion models
  - Large-scale models: DALL-E 2, Stable Diffusion, Imagen
- **Part 2: Advances**
  - Denoising diffusion implicit models (DDIMs)
  - Stable Diffusion XL, Stable Diffusion 3
  - Progressive Distillation
  - Latent Consistency Models (LCM)
  - Emu3

Denoising diffusion probabilistic models (DDPMs)

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Denoising Diffusion Probabilistic Models

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Abstract

We present high quality image synthesis results using diffusion probabilistic models, a class of latent variable models inspired by considerations from nonequilibrium thermodynamics. Our best results are obtained by training on a weighted variational bound designed according to a novel connection between diffusion probabilistic models and denoising score matching with Langevin dynamics, and our models naturally admit a progressive lossy decompression scheme that can be interpreted as a generalization of autoregressive decoding. On the unconditional CIFAR10 dataset, we obtain an Inception score of 9.46 and a state-of-the-art FID score of 3.17. On 256x256 LSUN, we obtain sample quality similar to ProgressiveGAN. Our implementation is available at `https://github.com/hojonathanho/diffusion`.

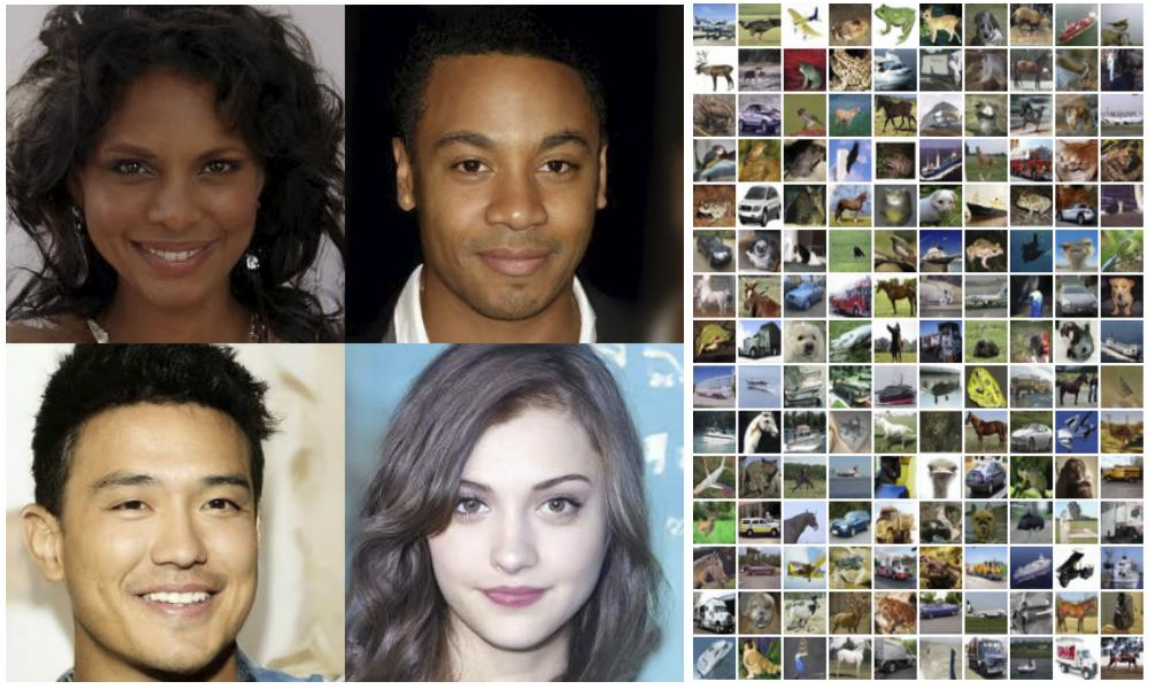
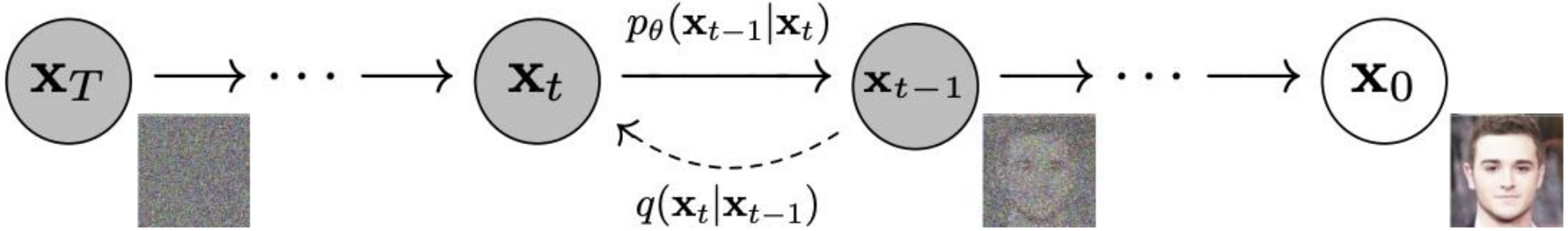


Figure 1: Generated samples on CelebA-HQ 256 × 256 (left) and unconditional CIFAR10 (right)

J. Ho et al. Denoising diffusion probabilistic models. NeurIPS 2020

DDPMs: Basic idea



Unconditional CIFAR10 sample generation

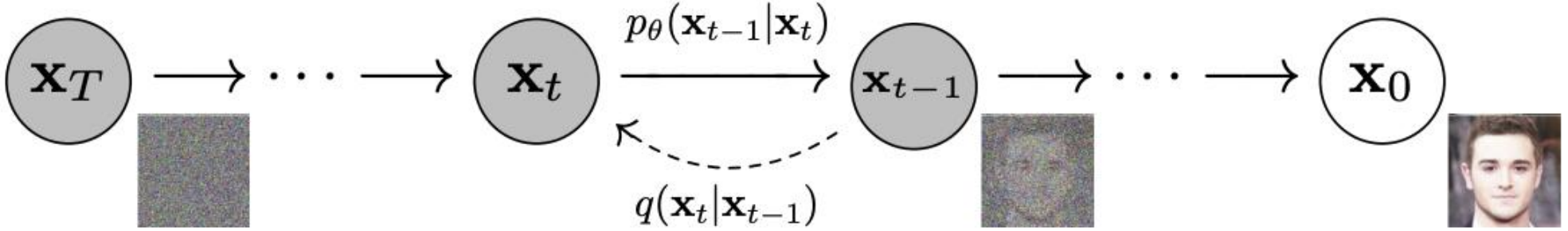


J. Ho et al. Denoising diffusion probabilistic models. NeurIPS 2020

Blog introduction: https://lilianweng.github.io/posts/2021-07-11-diffusion-models/

CVPR 2022 tutorial

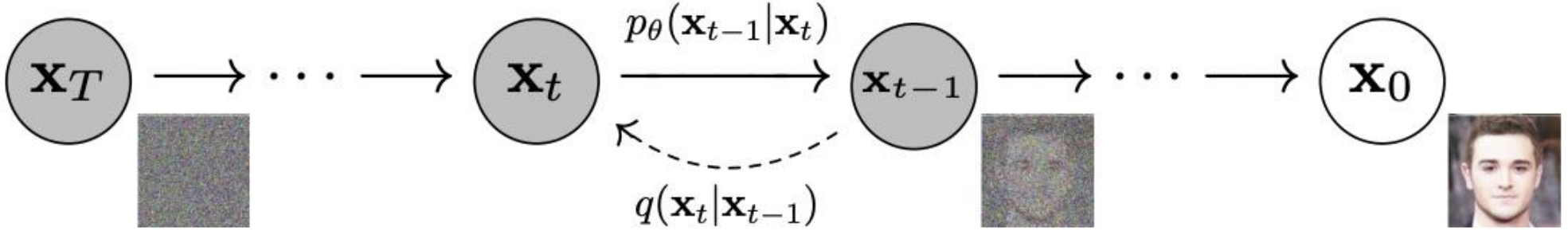
DDPMs: Basic idea



- *Forward process* q turns images into Gaussian noise
- *Reverse process* p turns noise into images
- Provided the increments of t are small enough, $p_\theta(x_{t-1}|x_t)$ is Gaussian and we can train a neural network to estimate the mean of x_{t-1} given x_t

J. Ho et al. Denoising diffusion probabilistic models. NeurIPS 2020

DDPMs: Basic idea



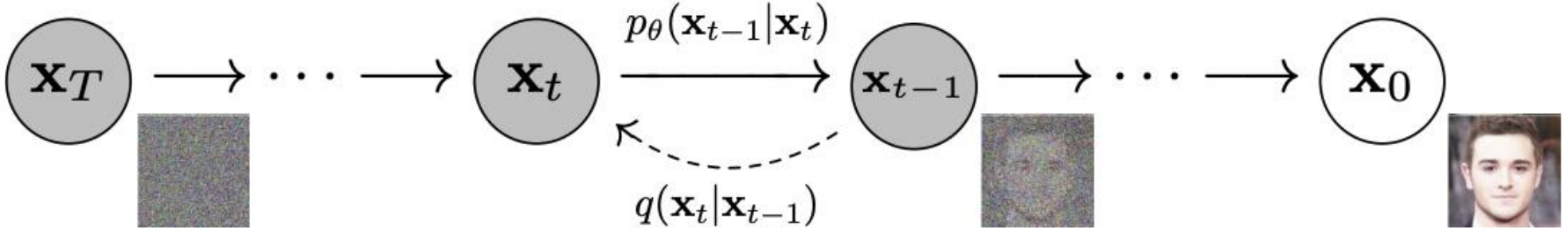
Algorithm 1 Training

1: **repeat**
2: $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
3: $t \sim \text{Uniform}(\{1, \dots, T\})$
4: $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
5: Take gradient descent step on
$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\boxed{x_t} , t) \right\|^2$
6: **until** converged

- $\epsilon_\theta(x_t, t)$ is the predicted noise component of image x_t given noise level t
- Network parameters θ are updated to reduce L2 error between actual noise ϵ and predicted noise $\epsilon_\theta(x_t, t)$

J. Ho et al. Denoising diffusion probabilistic models. NeurIPS 2020

DDPMs: Basic idea



Algorithm 1 Training

1: **repeat**
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4: $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
5: Take gradient descent step on
$$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$$
6: **until** converged

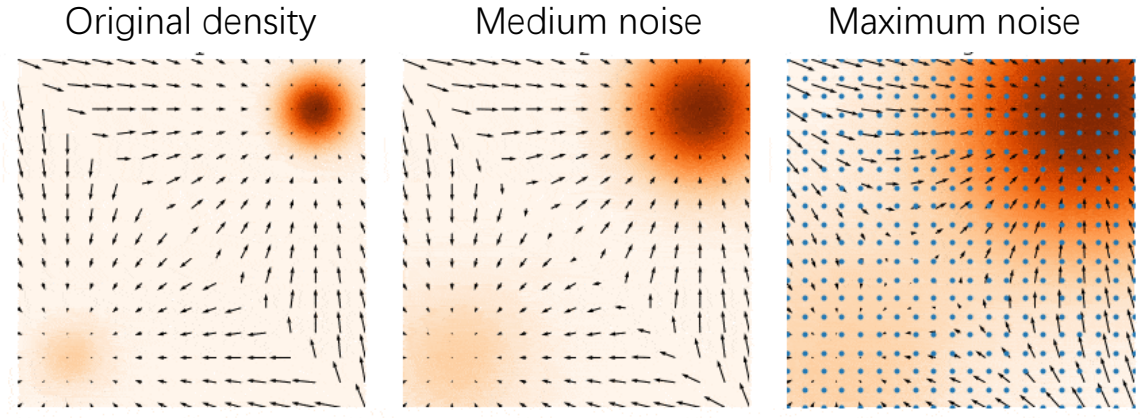
Algorithm 2 Sampling

1: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
2: **for** $t = T, \dots, 1$ **do**
3: $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ if $t > 1$, else $\mathbf{z} = \mathbf{0}$
4: $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$
5: **end for**
6: **return** $\mathbf{x}_0$

J. Ho et al. Denoising diffusion probabilistic models. NeurIPS 2020

Alternate viewpoint: Score-based generative modeling

- It can be shown that $\epsilon_\theta(x_t, t) \approx -\nabla_{x_t} \log q(x_t)$, where $\nabla_{x_t} \log q(x_t)$ is the *score function* of the (noisy) data distribution
- To sample from the original data density $q(x_0)$, we can use *annealed Langevin dynamics,* i.e., start by sampling from noise-perturbed versions of the data distribution and gradually reduce the amount of noise



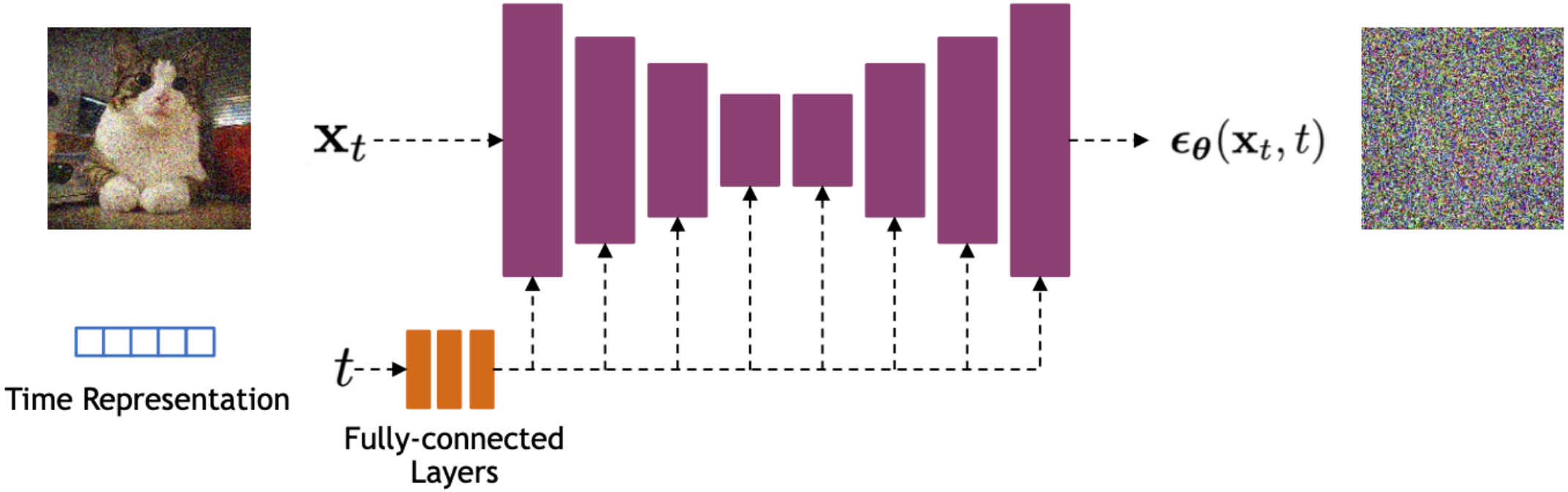
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for $t = T, \ldots, 1$ **do**
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end for
return $\mathbf{x}_0$

Y. Song and S. Ermon. Generative Modeling by Estimating Gradients of the Data Distribution. NeurIPS 2019
https://yang-song.net/blog/2021/score/

DDPMs: Implementation

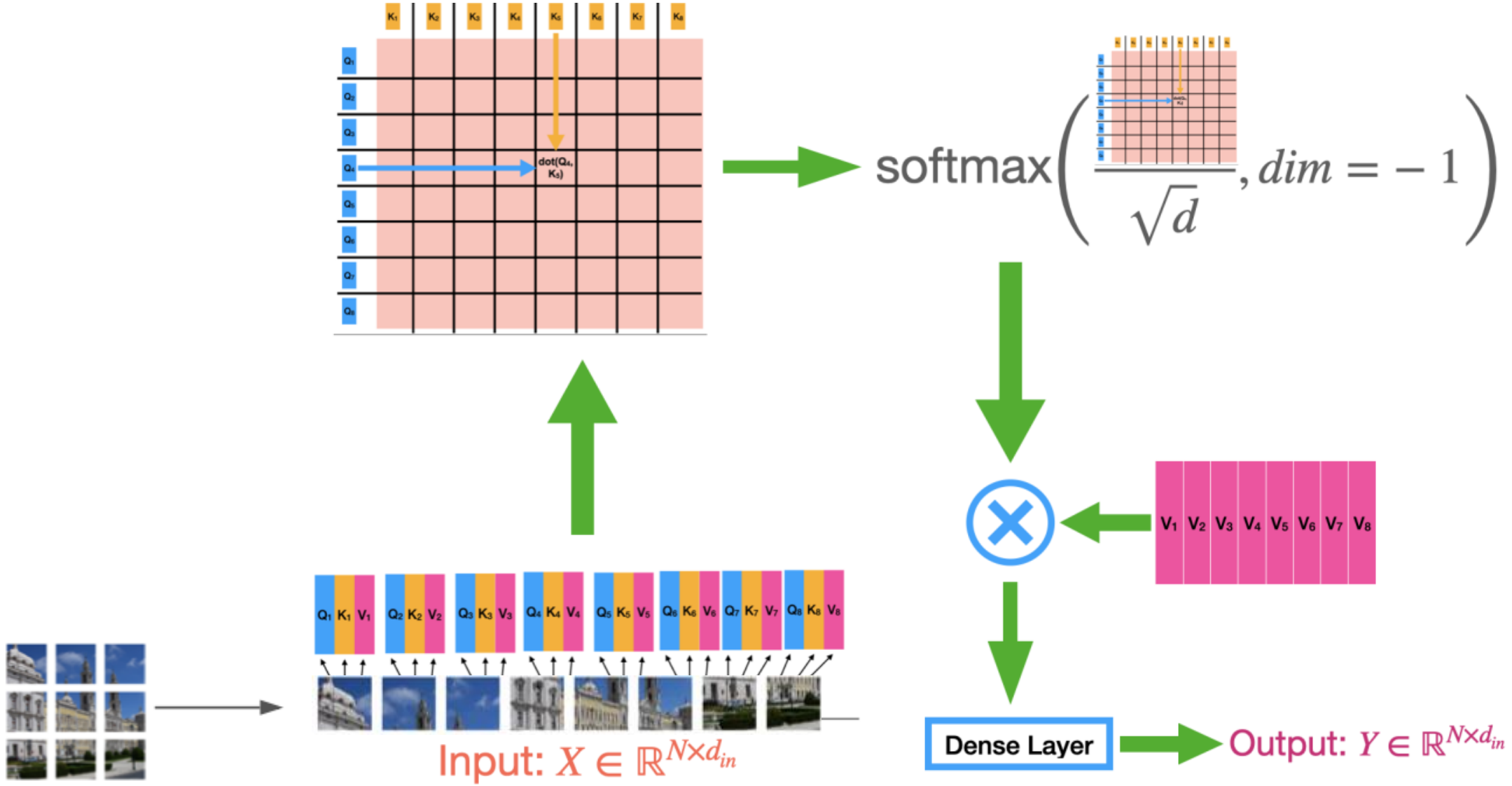
- U-Net architectures are typically used to represent $\epsilon_\theta(x_t, t)$
  - Bells and whistles: residual blocks, self-attention



- Time is encoded using sinusoidal positional embeddings or random Fourier features, fed into the U-Net using addition or adaptive normalization

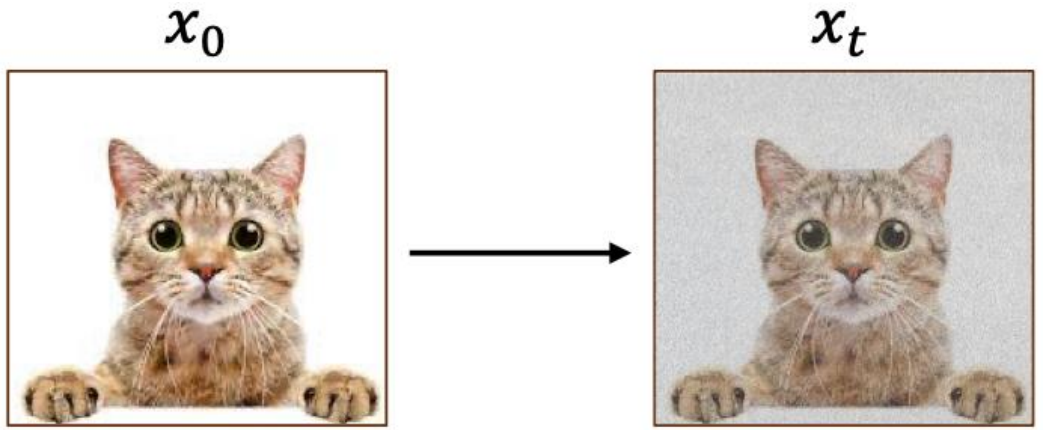
Source: CVPR 2002 DM tutorial

Attention Module

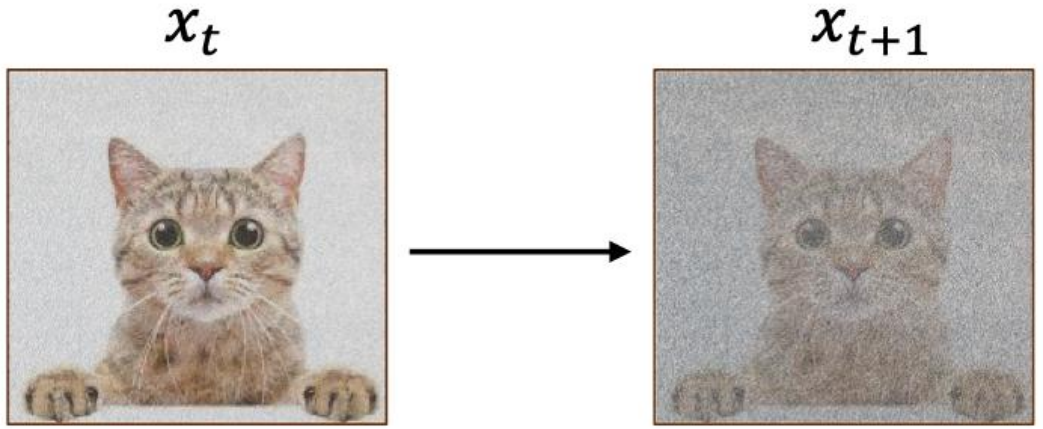


How do we do this in practice?

- Step 1: Sample image from the dataset, generate noisy image using forward process



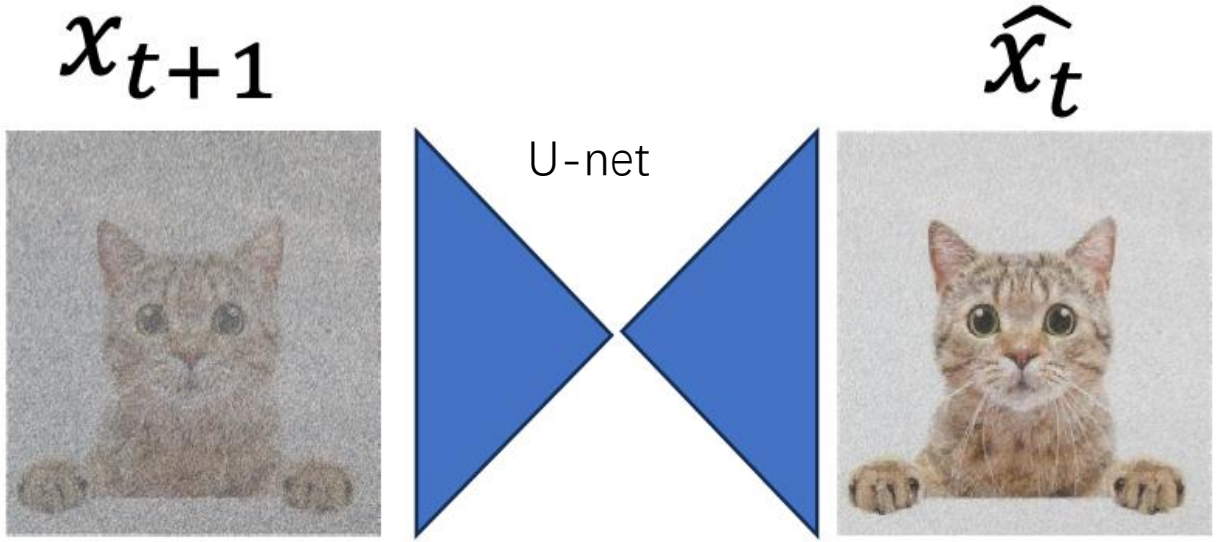
- Step 2: Given noisy image, generate slightly noisier image



https://www.eecs.umich.edu/courses/eecs442-ahowens/fa23/slides/lec11-diffusion.pdf

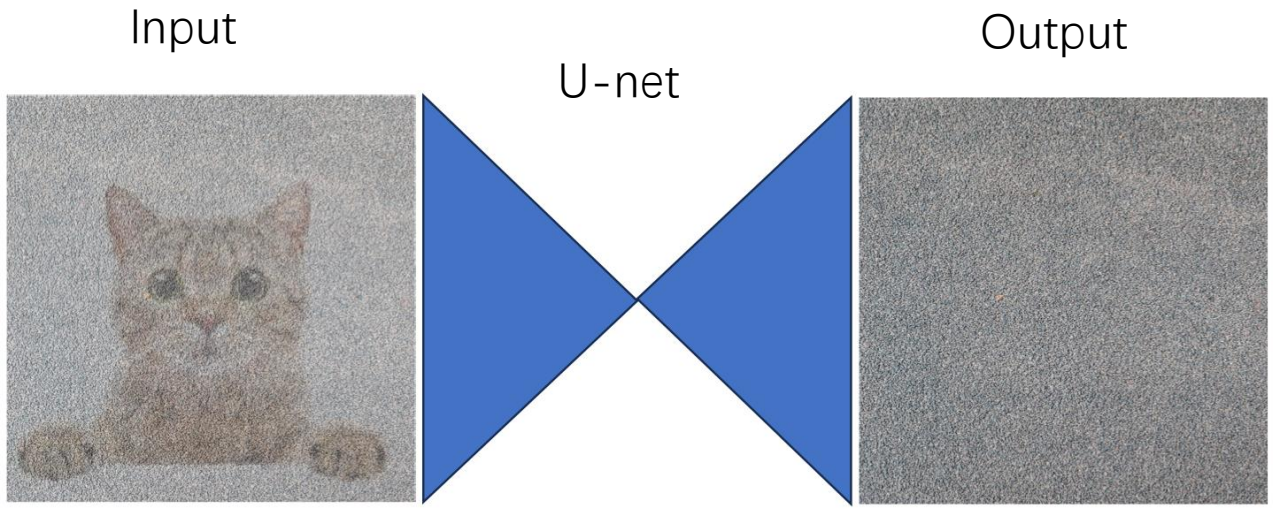
How do we do this in practice?

During Training



Loss: MSE$(x_t, \hat{x}_t)$

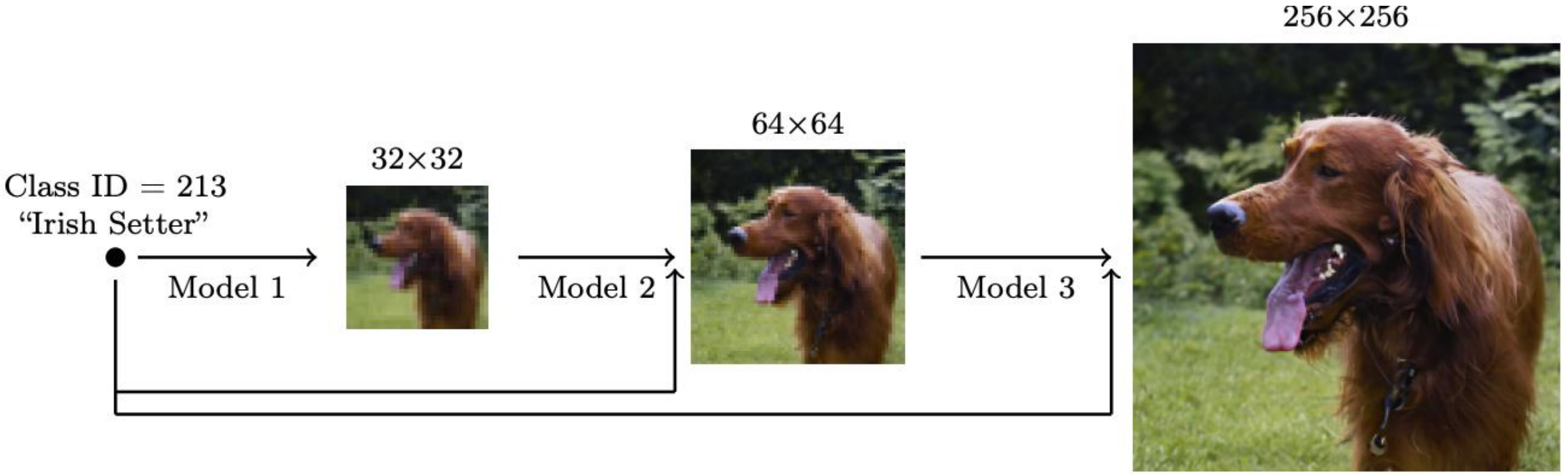
During Inference



U-net predicts the noise

https://www.eecs.umich.edu/courses/eecs442-ahowens/fa23/slides/lec11-diffusion.pdf

Efficient sampling at high resolutions: Cascaded generation



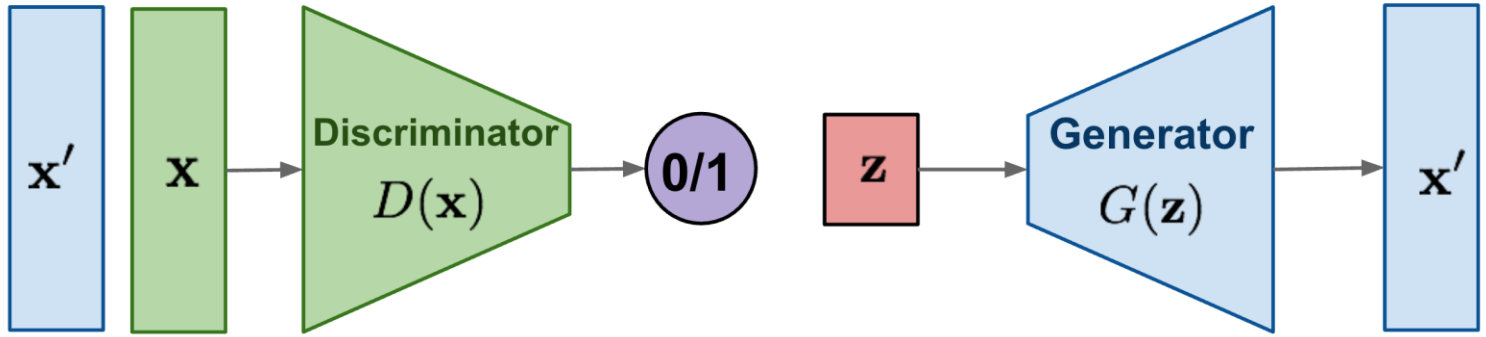
- In practice, data augmentation for inputs to upsampling models is crucial (esp. adding Gaussian noise or early stopping for base model)

J. Ho et al. Cascaded Diffusion Models for High Fidelity Image Generation. JMLR 2022

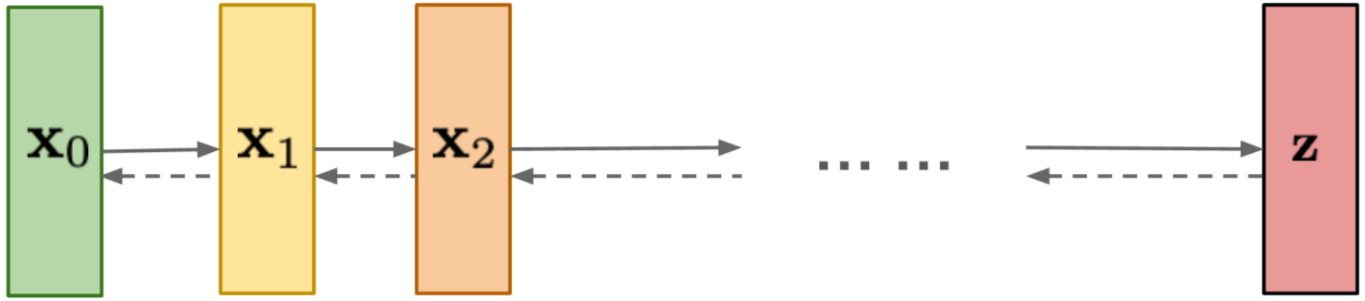
GANs vs. Diffusion Models

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GAN: Adversarial training



Diffusion models: Gradually add Gaussian noise and then reverse



Outline

- **Part 1: Basics**
  - Denoising diffusion probabilistic models (DDPMs)
  - Conditional diffusion models

Class-conditioned DDPMs

- "We can sample with as few as 25 forward passes while maintaining FIDs comparable to BigGAN"

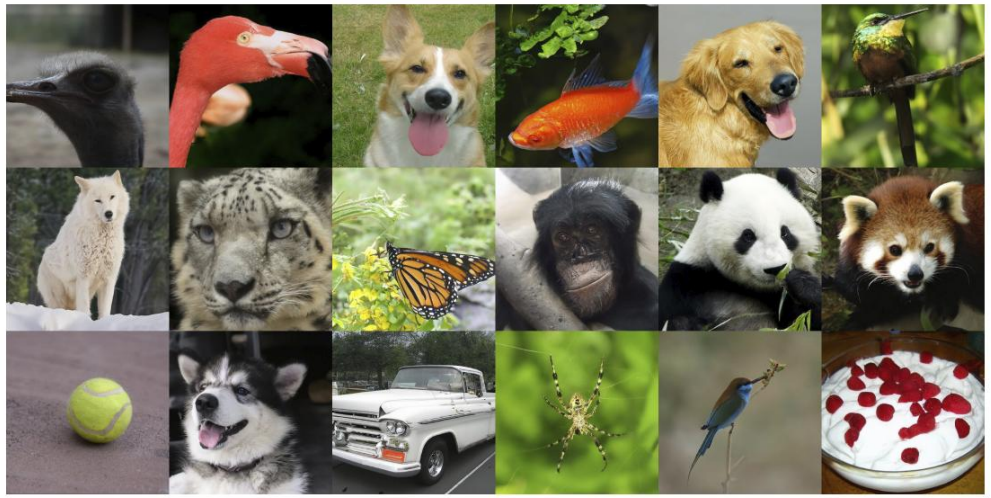


Figure 1: Selected samples from our best ImageNet 512×512 model (FID 3.85)

Abstract

We show that diffusion models can achieve image sample quality superior to the current state-of-the-art generative models. We achieve this on unconditional image synthesis by finding a better architecture through a series of ablations. For conditional image synthesis, we further improve sample quality with classifier guidance: a simple, compute-efficient method for trading off diversity for fidelity using gradients from a classifier. We achieve an FID of 2.97 on ImageNet 128×128, 4.59 on ImageNet 256×256, and 7.72 on ImageNet 512×512, and we match BigGAN-deep even with as few as 25 forward passes per sample, all while maintaining better coverage of the distribution. Finally, we find that classifier guidance combines well with upsampling diffusion models, further improving FID to 3.94 on ImageNet 256×256 and 3.85 on ImageNet 512×512. We release our code at `https://github.com/openai/guided-diffusion`.

P. Dhariwal and A. Nichol. Diffusion Models Beat GANs on Image Synthesis. NeurIPS 2021

Classifier guidance

- We can sample from the class-conditional density $q(x_t|c)$ with the help of a pre-trained classifier $P(c|x_t)$
- Bayes rule:

$$q(x_t|c) \propto P(c|x_t)q(x_t)$$

$$\log q(x_t|c) = \log P(c|x_t) + \log q(x_t) + \text{const.}$$

$$\nabla_{x_t} \log q(x_t|c) = \nabla_{x_t} \log P(c|x_t) + \nabla_{x_t} \log q(x_t)$$

conditional score function — obtained from classifier output — unconditional *score function* (pre-trained)

- To sample from class c, steer sample in the modified direction $\nabla_{x_t}[\log q(x_t) + w \log P(c|x_t)]$

Classifier-free guidance

- Instead of training an additional classifier, get an "implicit classifier" by jointly training a conditional and unconditional diffusion model: $P(c|x_t) \propto q(x_t|c)/q(x_t)$
- Both $q(x_t|c)$ and $q(x_t)$ are represented using the same network, trained by dropping out c with some probability (corresponding to the unconditional case)
- The modified score function corresponding to this implicit classifier is

$$\nabla_{x_t}[\log q(x_t) + w \log P(c|x_t)]$$
$$= \nabla_{x_t}[\log q(x_t) + w(\log q(x_t|c) - \log q(x_t))]$$

Sample is steered away from the unconditional distribution in the direction of the conditional one

J. Ho and T. Salimans. Classifier-Free Diffusion Guidance. arXiv 2021

Classifier-free guidance



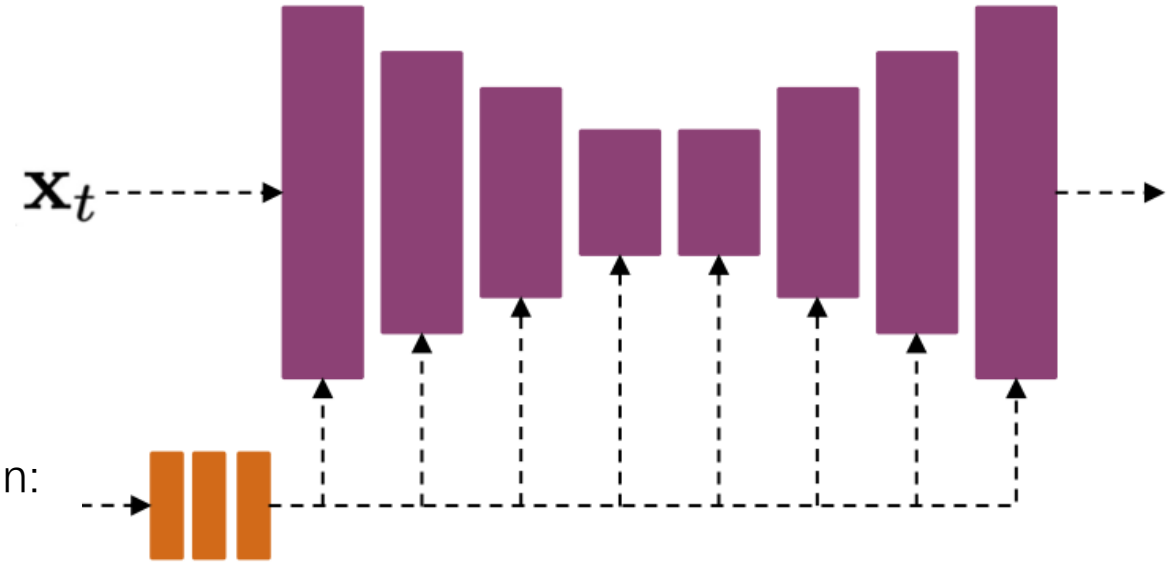
Figure 1: Classifier-free guidance on the malamute class for a 64x64 ImageNet diffusion model. Left to right: increasing amounts of classifier-free guidance, starting from non-guided samples on the left.

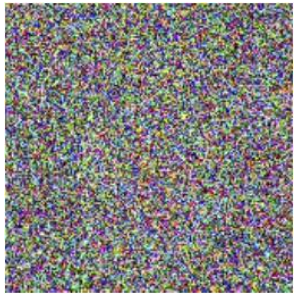
J. Ho and T. Salimans. Classifier-Free Diffusion Guidance. arXIv 2021

Text-guided diffusion

- Instead of a class label, c can be an encoded text prompt, injected into the U-Net using *cross-attention*



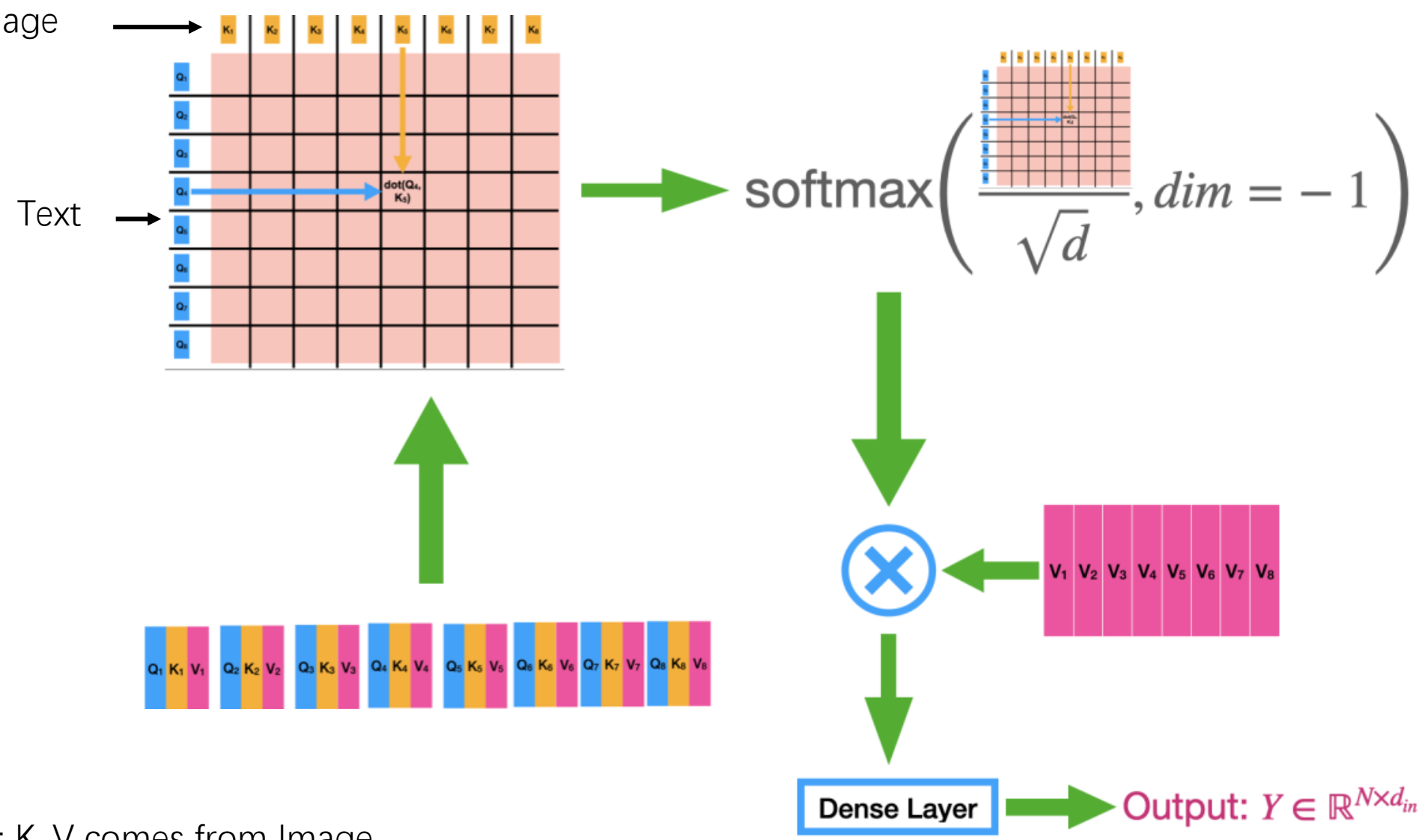




Conditioning information:
text c, time t

Image source

Cross Attention Module



Q comes from Text; K, V comes from Image

Text-guided diffusion

- Instead of a class label, c can be an encoded text prompt, injected into the U-Net using *cross-attention*

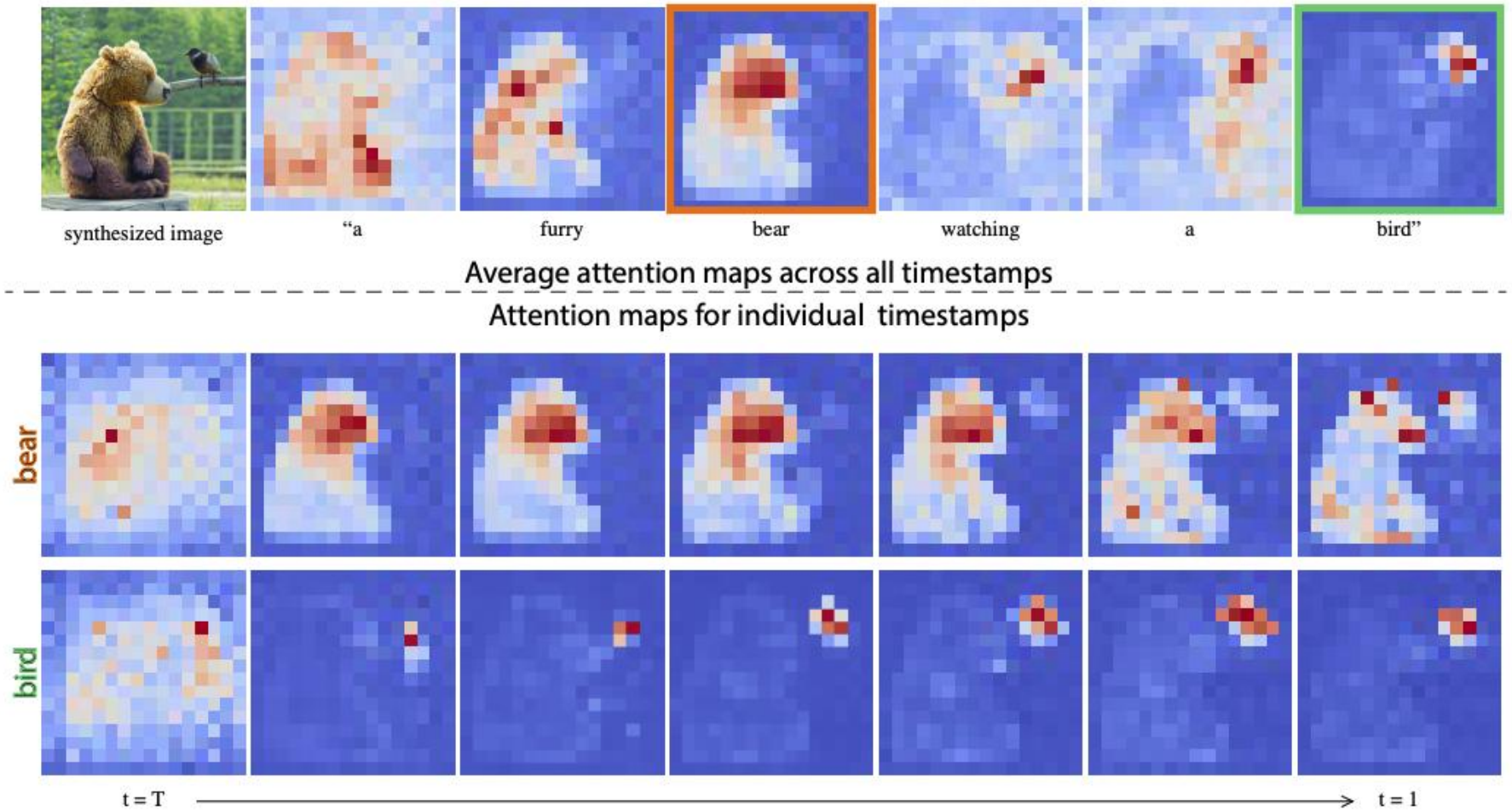
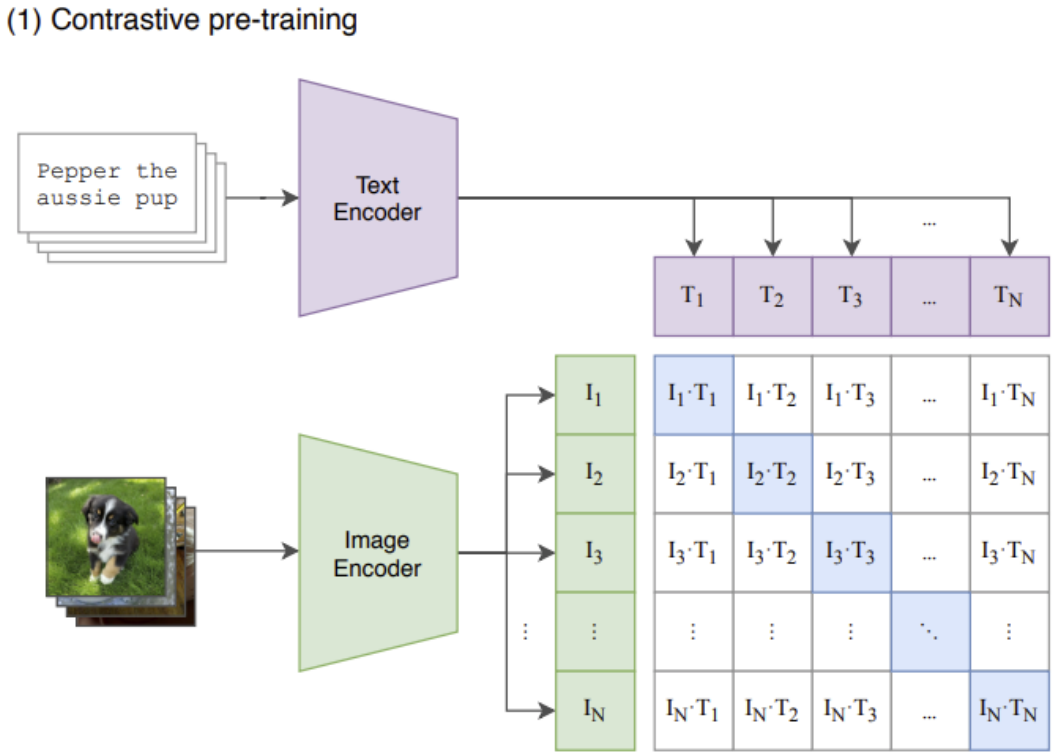


Image source

Text-guided diffusion

- Instead of a class label, c can be an encoded text prompt, injected into the U-Net using *cross-attention*
- Classifier-free guidance works the same way as before, by training both conditional and unconditional models using text dropout
- CLIP guidance: steer samples in the direction of $\nabla_{x_t} \text{CLIP}(x_t, c)$
- Note: both classifier and CLIP must be *noise-aware* (trained on noised images)

CLIP



Contrastive objective: in a batch of N image-text pairs, classify each text string to the correct image and vice versa

A. Radford et al., Learning Transferable Visual Models From Natural Language Supervision, ICML 2021
https://openai.com/blog/clip/

Outline

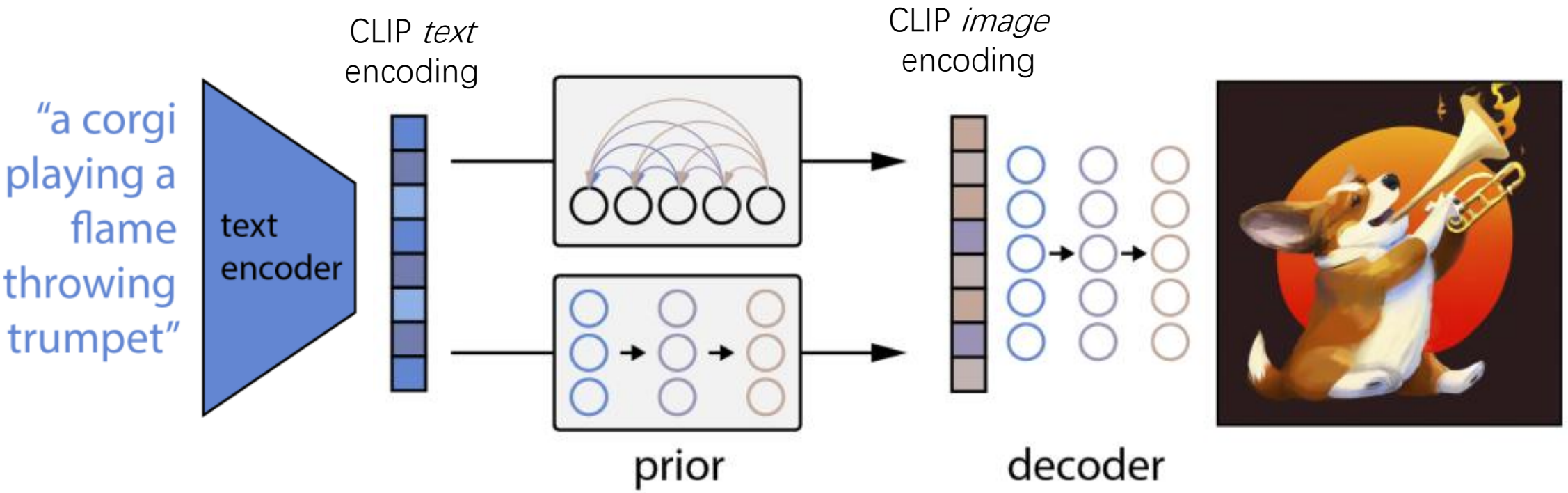
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DALL-E 2



A. Ramesh et al. Hierarchical text-conditional image generation with CLIP latents. Preprint 2022

DALL-E 2



Generative model to produce CLIP *image* encoding given CLIP *text* encoding

Diffusion model (GLIDE) conditioned on CLIP image embedding and text prompt

Generate at 64x64, upsample to 256x256, then upsample to 1024x1024

DALL-E 2: Results



Figure 19: Random samples from unCLIP for prompt "A close up of a handpalm with leaves growing from it."



Figure 18: Random samples from unCLIP for prompt "Vibrant portrait painting of Salvador Dali with a robotic half face"

DALL-E 2: Results



Figure 3: Variations of an input image by encoding with CLIP and then decoding with a diffusion model. The variations preserve both semantic information like presence of a clock in the painting and the overlapping strokes in the logo, as well as stylistic elements like the surrealism in the painting and the color gradients in the logo, while varying the non-essential details.

DALL-E 2: Results



Figure 4: Variations between two images by interpolating their CLIP image embedding and then decoding with a diffusion model. We fix the decoder seed across each row. The intermediate variations naturally blend the content and style from both input images.

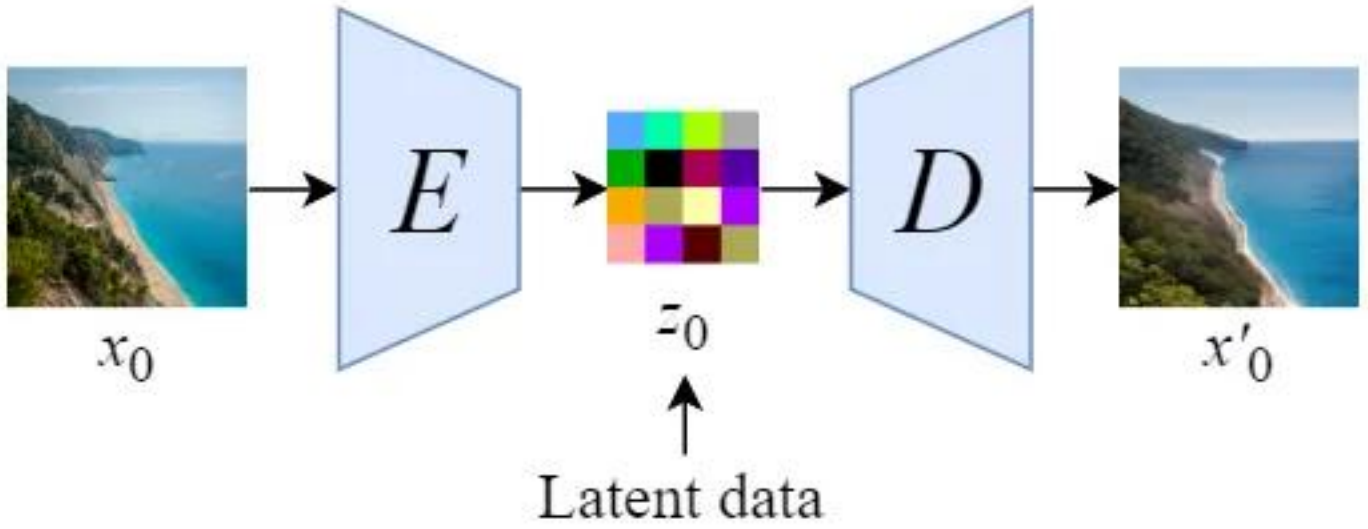
DALL-E 2: Limitations



Figure 15: Reconstructions from the decoder for difficult binding problems. We find that the reconstructions mix up objects and attributes. In the first two examples, the model mixes up the color of two objects. In the rightmost example, the model does not reliably reconstruct the relative size of two objects.

Latent diffusion model (basis of Stable Diffusion)

- Key idea: train a separate *encoder* and *decoder* to convert images to and from a lower-dimensional latent space, run conditional diffusion model in latent space

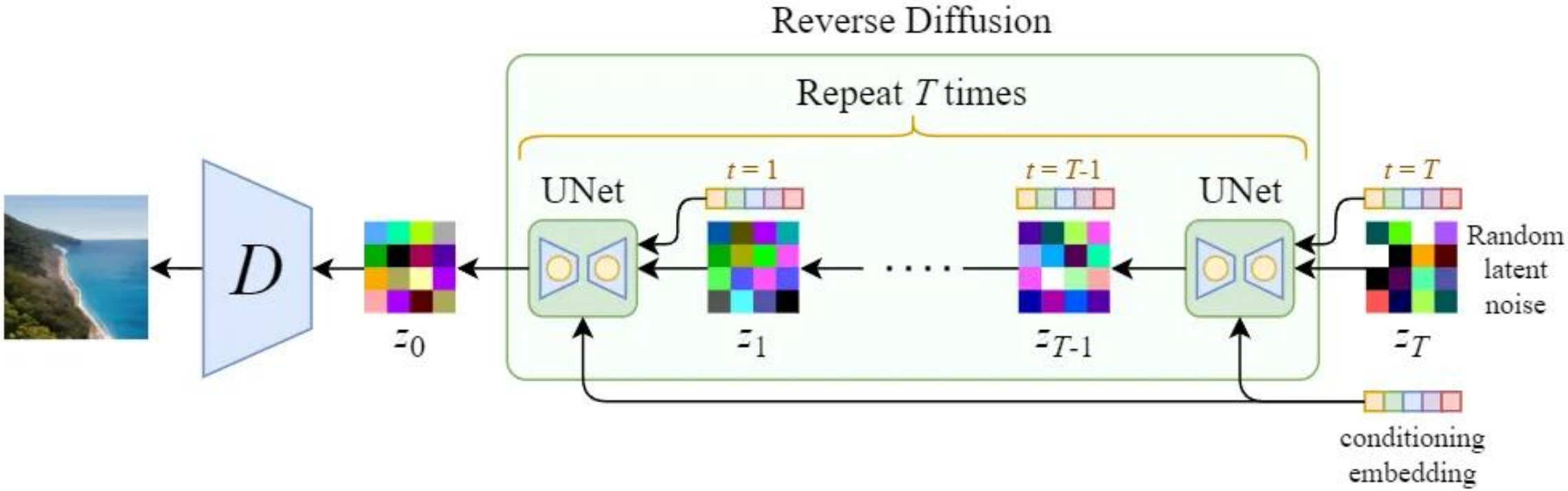


R. Rombach et al. High-Resolution Image Synthesis with Latent Diffusion Models. CVPR 2022

https://medium.com/@steinsfu/stable-diffusion-clearly-explained-ed008044e07e

Latent diffusion model (basis of Stable Diffusion)

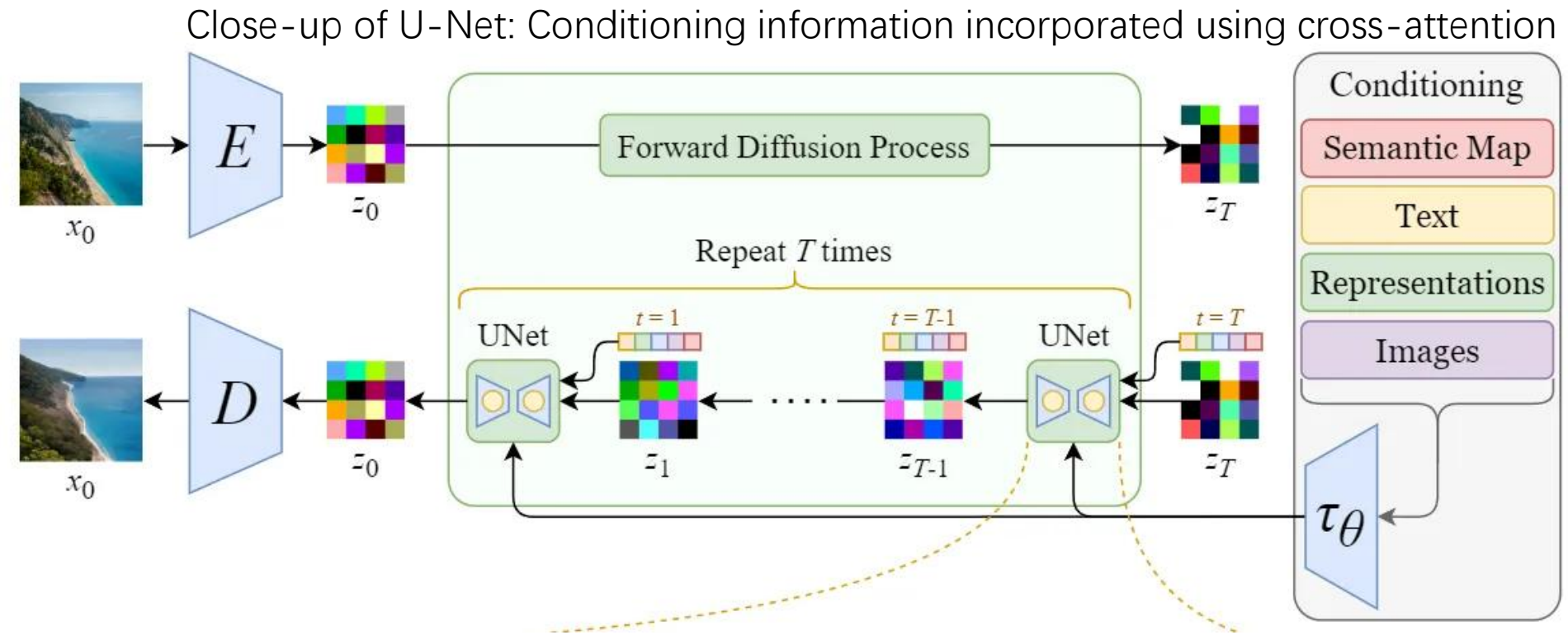
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https://medium.com/@steinsfu/stable-diffusion-clearly-explained-ed008044e07e

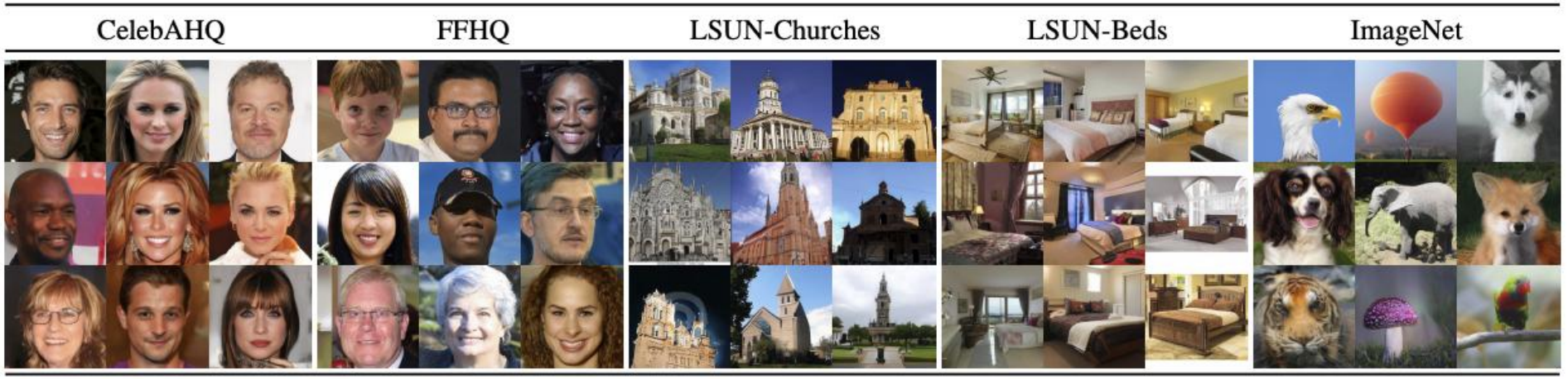
Latent diffusion model (basis of Stable Diffusion)

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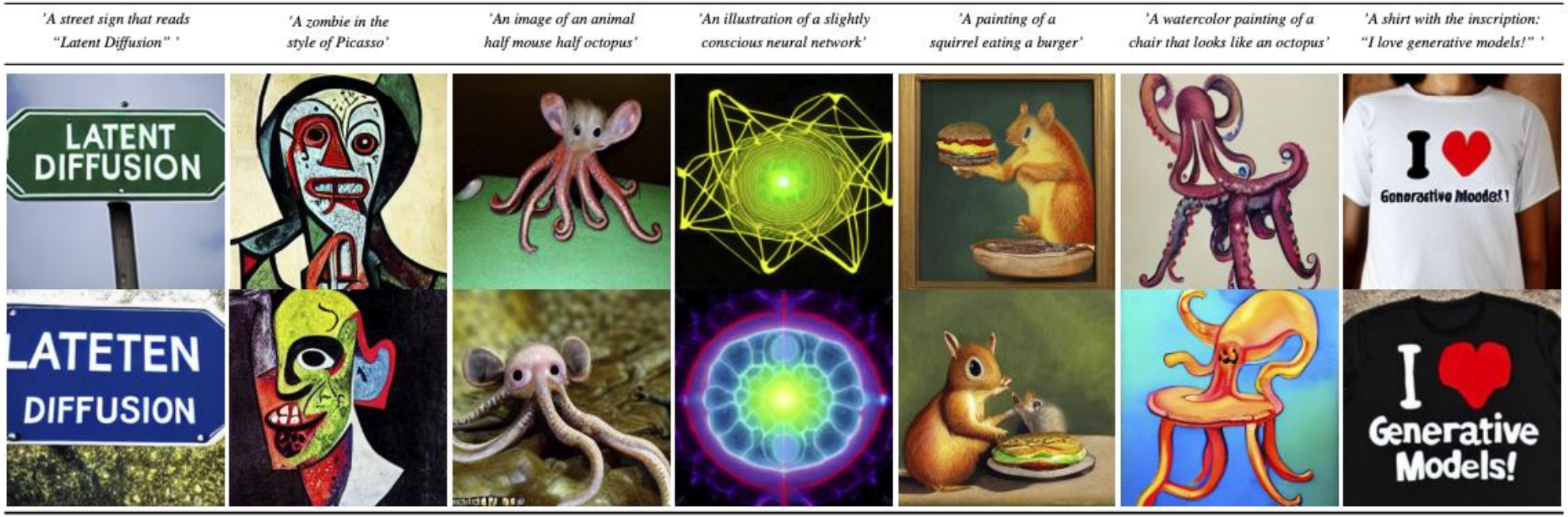


https://medium.com/@steinsfu/stable-diffusion-clearly-explained-ed008044e07e

Latent diffusion model (basis of Stable Diffusion)



Text-to-Image Synthesis on LAION. 1.45B Model.



Google Imagen (not public)



Sprouts in the shape of text 'Imagen' coming out of a fairytale book.



A photo of a Shiba Inu dog with a backpack riding a bike. It is wearing sunglasses and a beach hat.



A high contrast portrait of a very happy fuzzy panda dressed as a chef in a high end kitchen making dough. There is a painting of flowers on the wall behind him.



Teddy bears swimming at the Olympics 400m Butterfly event.



A cute corgi lives in a house made out of sushi.

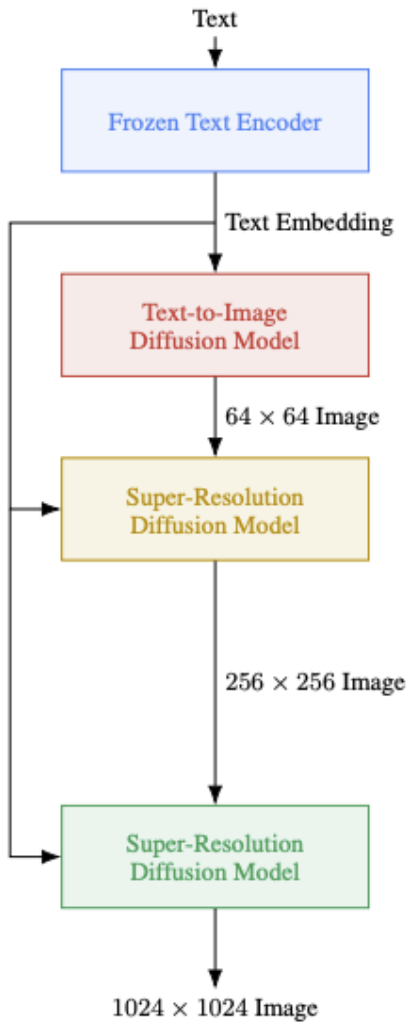


A cute sloth holding a small treasure chest. A bright golden glow is coming from the chest.

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

Google Imagen: Details

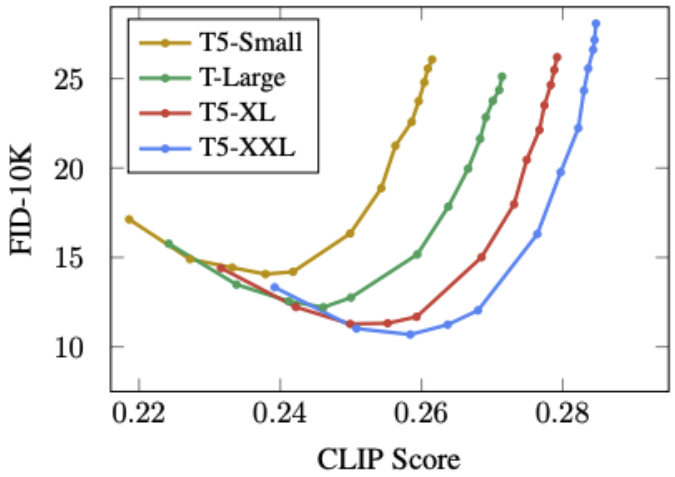
- Text encoder is a large language model (4.6B parameters) trained on text only
- Diffusion model to generate at 64x64, upsample to 256x256, then 1024x1024
  - Architecture: *efficient U-Net* (2B parameters): more parameters at lower resolutions, convolutions *after* downsampling and *before* upsampling
  - Classifier-free guidance with a *dynamic thresholding* technique, enabling good generation quality with high guidance weights
  - Training dataset: 460M image-text pairs (internally collected), 400M pairs from the LAION dataset



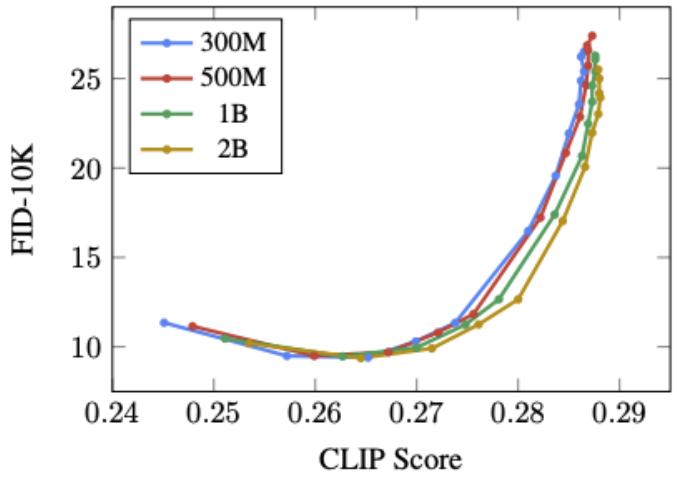
C. Saharia et al. Photorealistic Text-to-Image Diffusion Models with Deep Language Understanding. NeurIPS 2022

Google Imagen: Evaluation

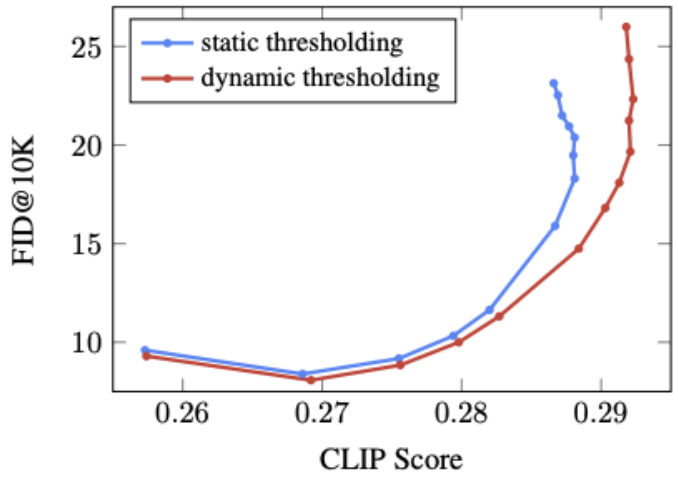
- Impact of model size, implementation choices



(a) Impact of encoder size.



(b) Impact of U-Net size.



(c) Impact of thresholding.

Curves are obtained by varying guidance weight
FID evaluated on COCO dataset by sampling prompts and generating images using the same prompts

Google Imagen: Evaluation

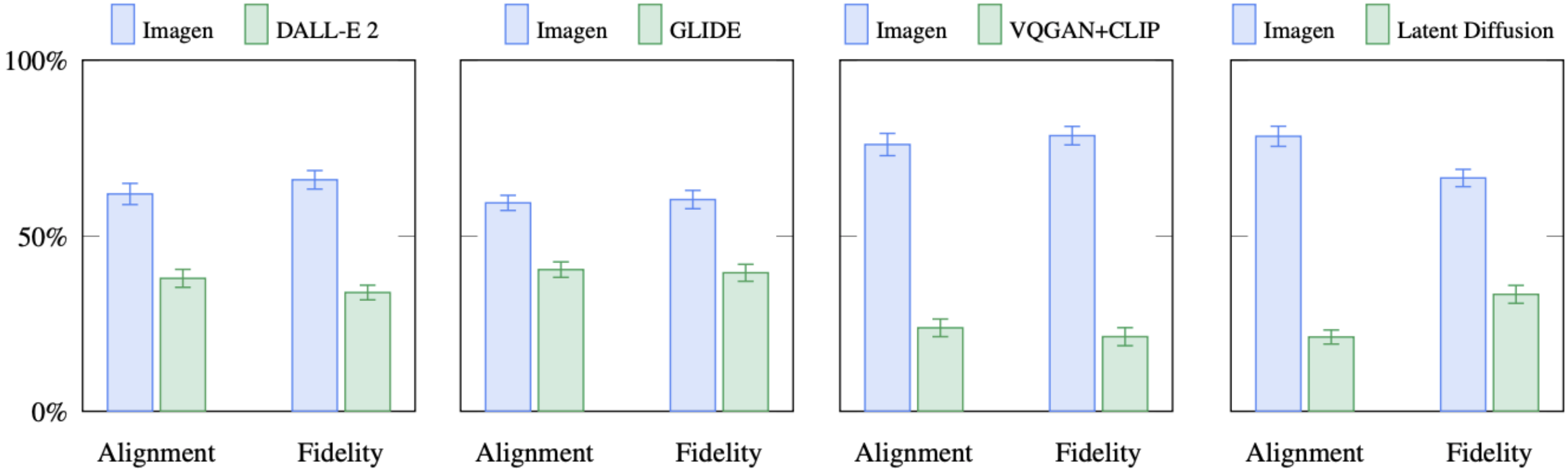


Imagen vs. DALL-E 2



“A yellow book and a red vase”

Imagen vs. DALL-E 2



"A black apple and a green backpack"

Imagen is better than DALL-E 2 in assigning the colors to the objects

Imagen vs. DALL-E 2



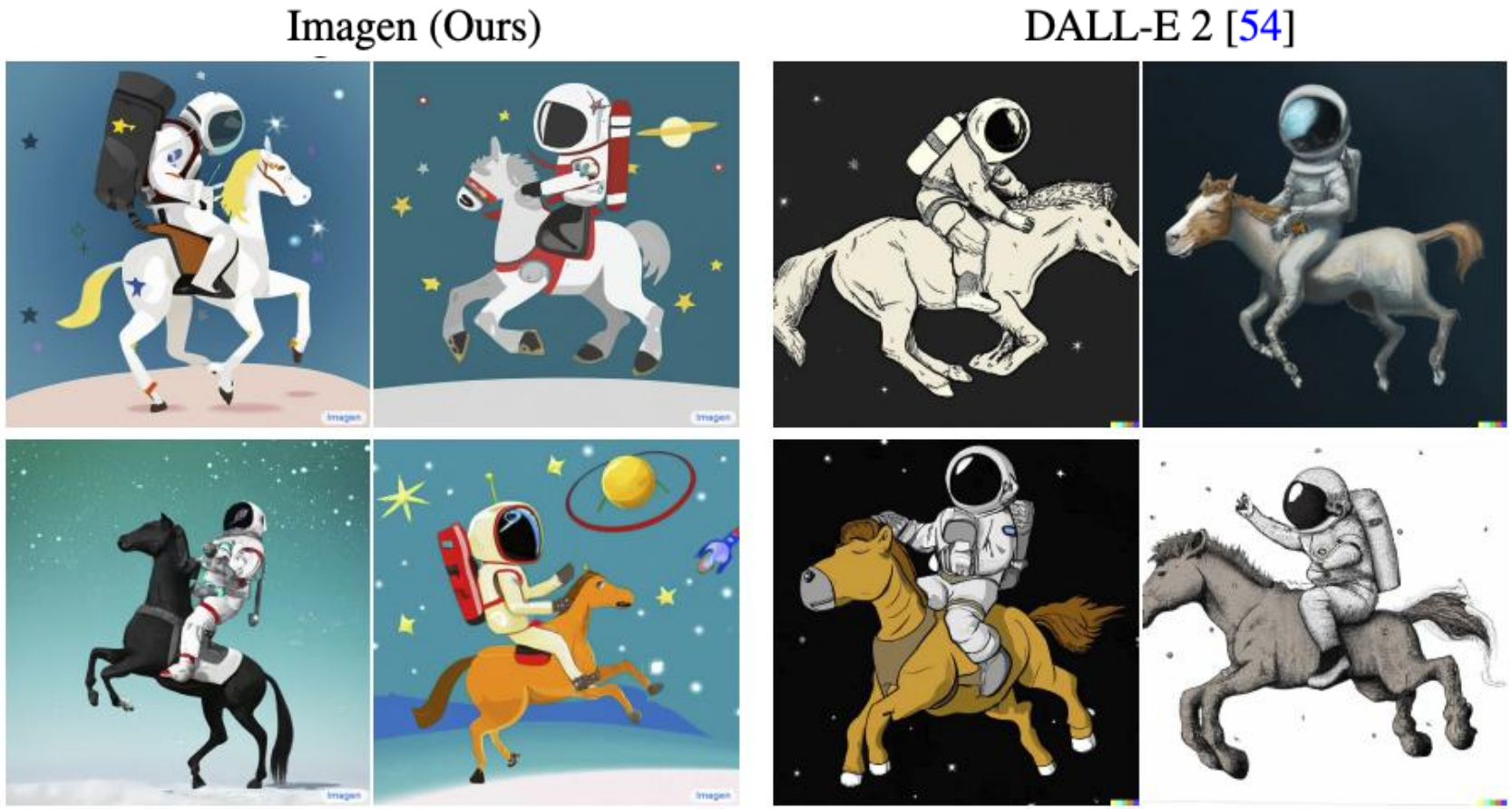
"A storefront with Text to Image written on it"

Imagen vs. DALL-E 2



“A panda making latte art”

Imagen vs. DALL-E 2



“A horse riding an astronaut”

Outline

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- **Part 1: Basics**
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Denoising Diffusion Implicit Models (DDIMs)

- **DDIM roughly sketches the final sample, then refine it with the reverse process**
  - **Key idea:**
    - Given $\mathbf{x}_t$, generate the rough sketch $\mathbf{x}_0$ and refine $p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0)$[1]
    - Unlike original diffusion model, it is not a Markovian structure

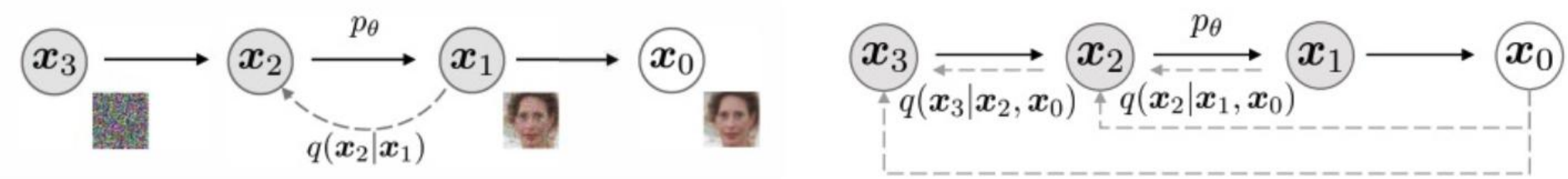
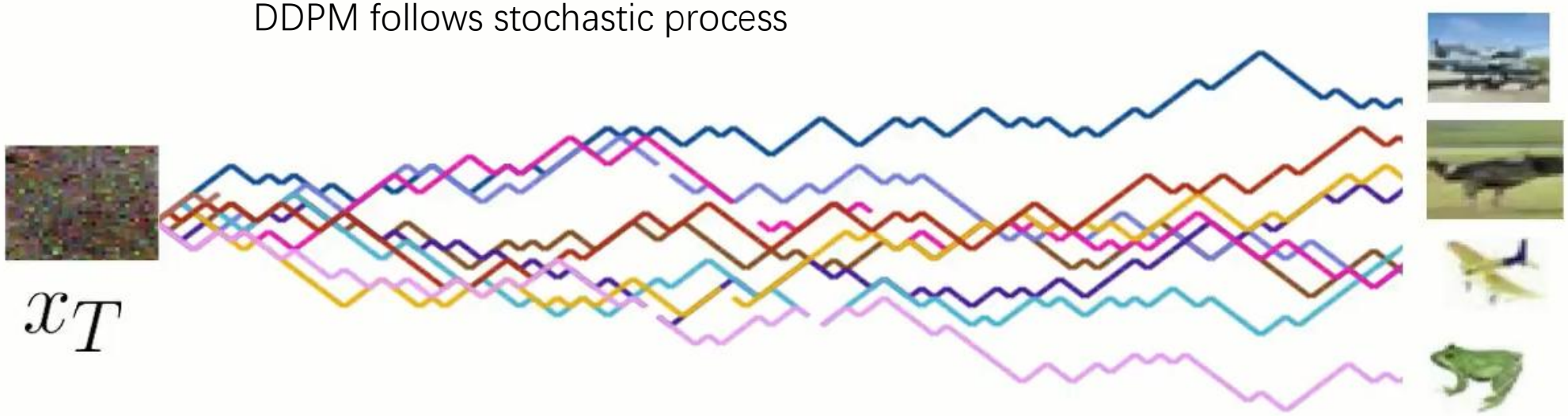


Figure 1: Graphical models for diffusion (left) and non-Markovian (right) inference models.

DDIM follows a deterministic process

DDPM follows stochastic process

DDPM



x_T

DDIM follows deterministic process

DDIM



x_T

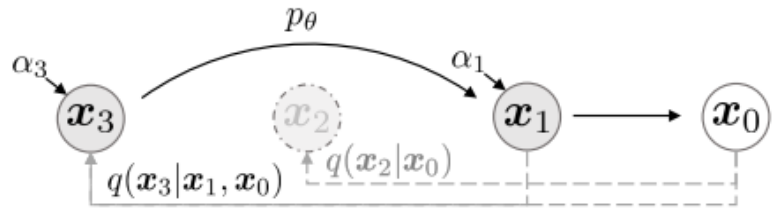
The same original noise $\boldsymbol{x_T}$ to same image $\boldsymbol{x_0}$

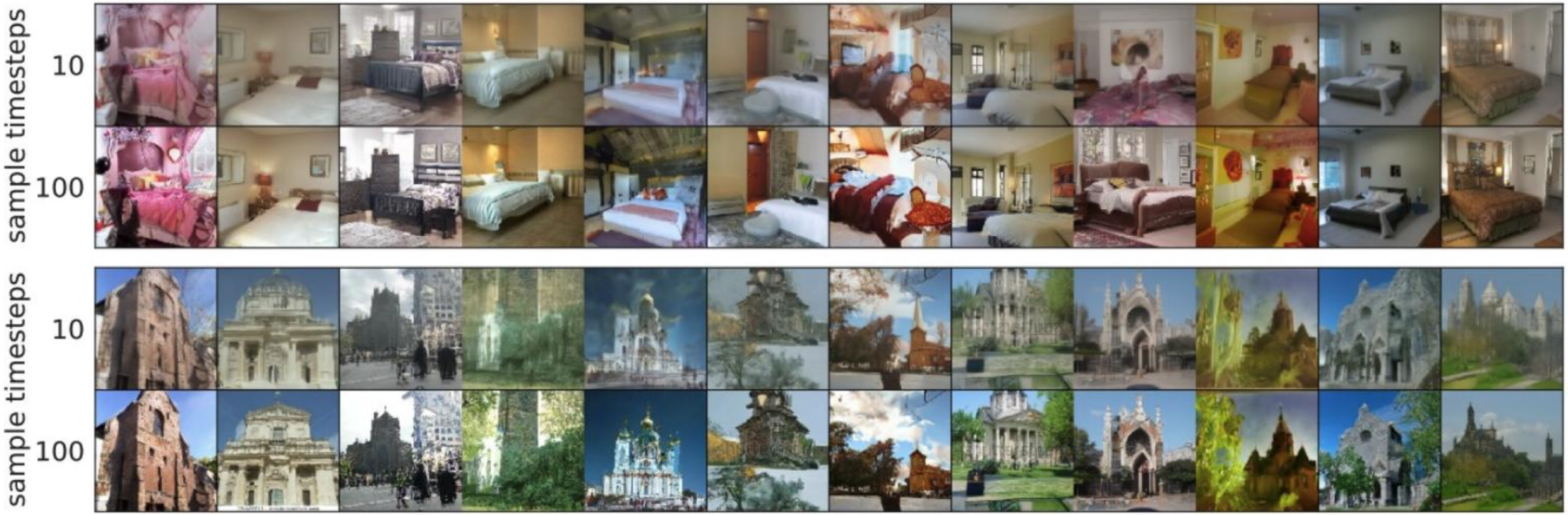
Tidiane Ndir, presentation on Faster diffusion, Uni of Freiburg

DDIM reduces the sampling steps significantly

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- Creates the outline of the sample after only 10 steps (DDPM needs hundreds)

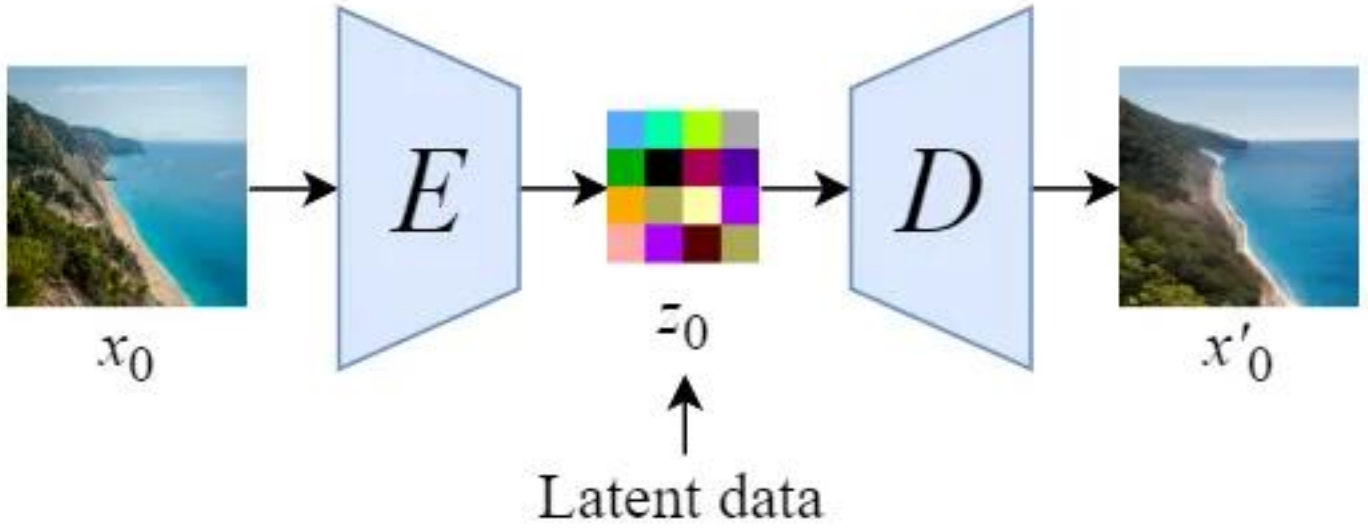




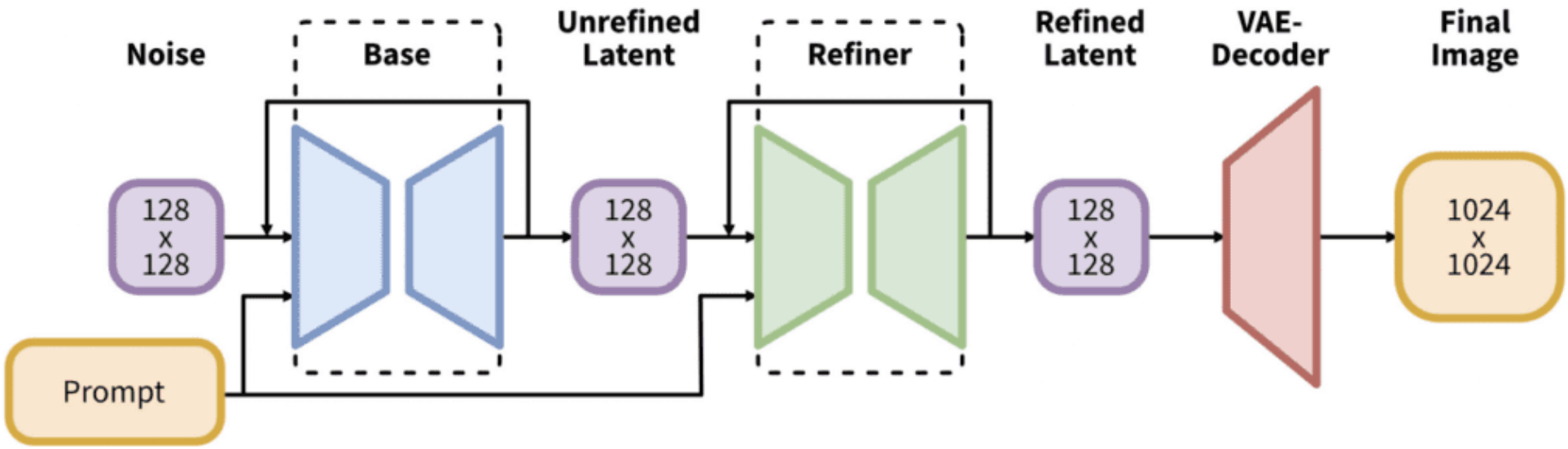
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Recall Stable Diffusion (SD v1.4, SD v1.5, SD v2.1)



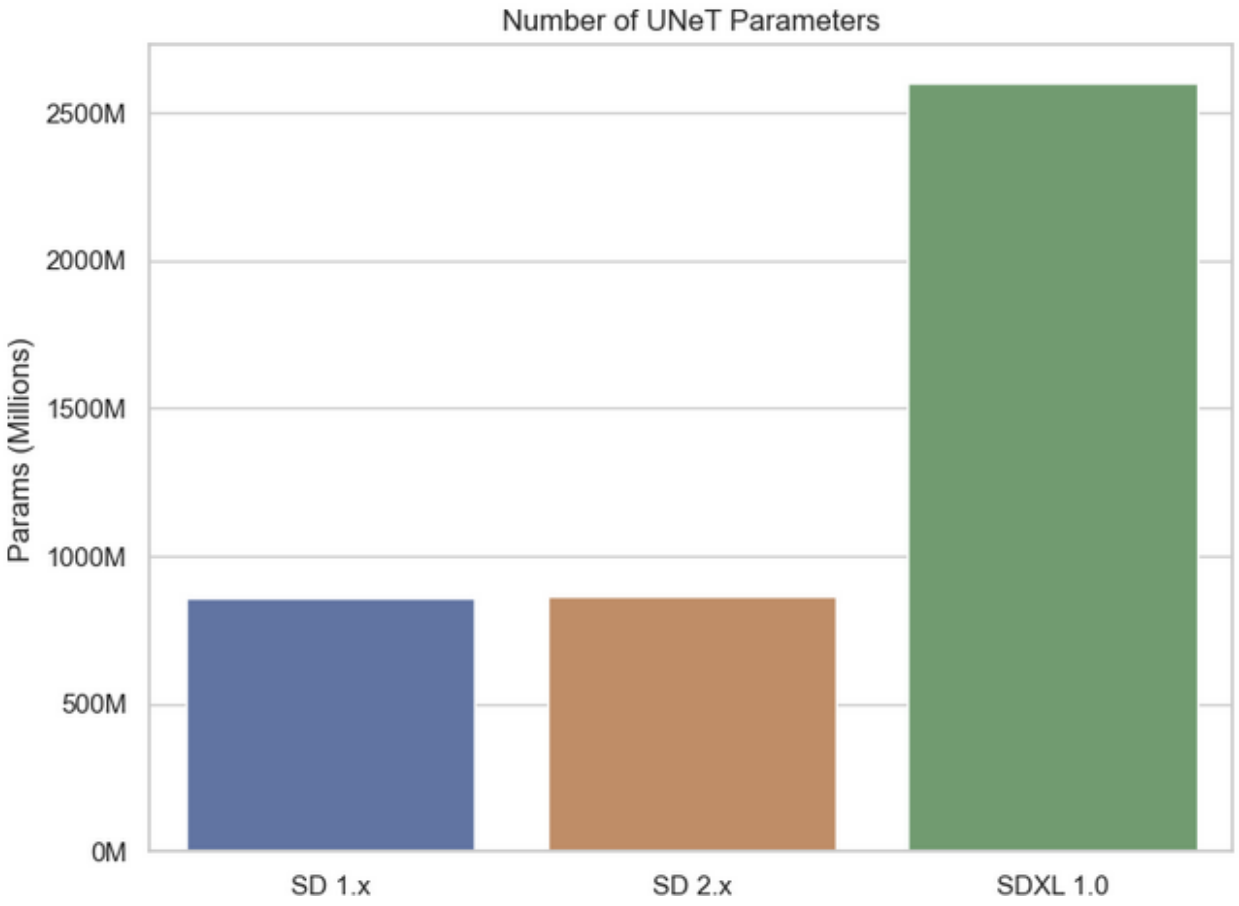
Improved SDXL pipeline

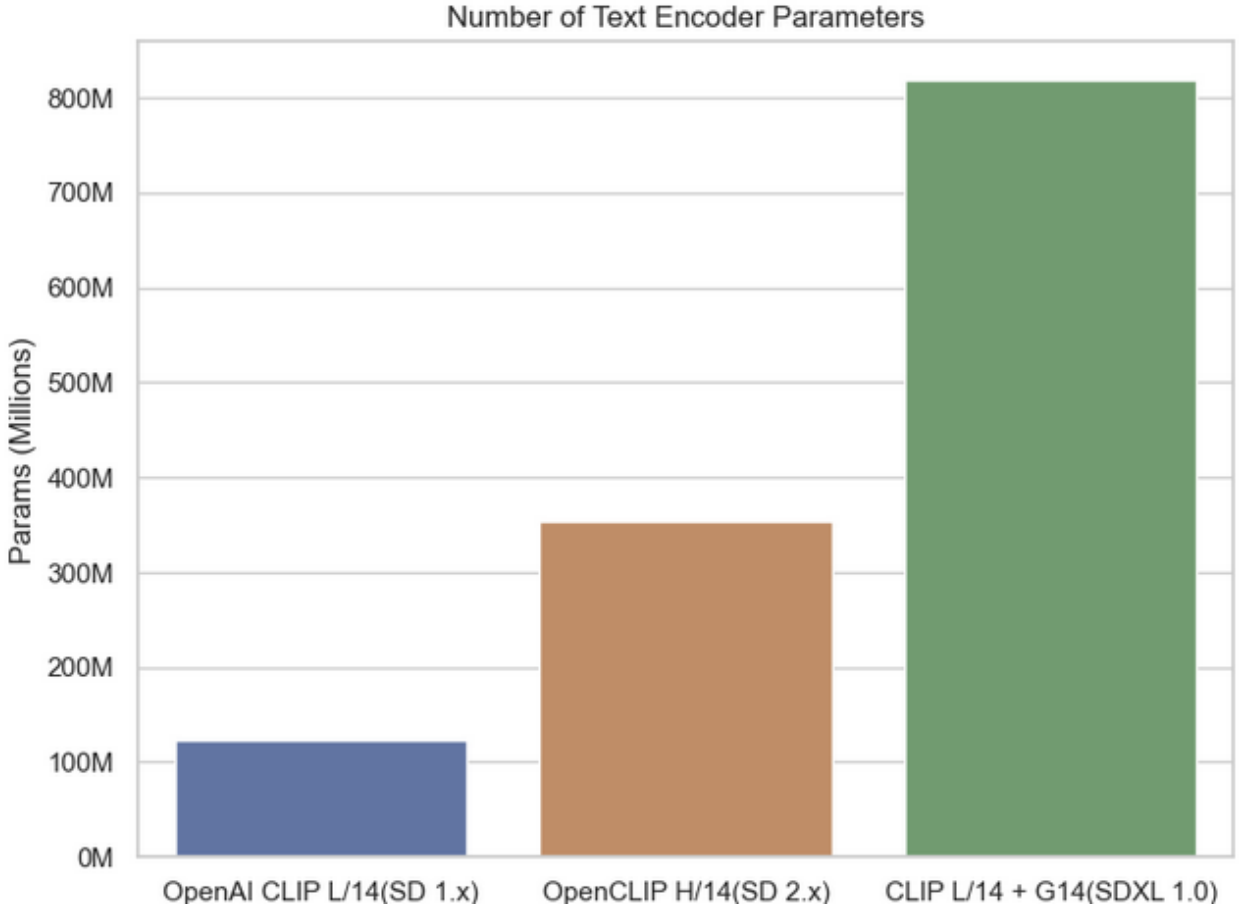


- Separate refiner model
- Two text-encoders
- Bigger U-net with more attention blocks and higher number of parameters

https://towardsdatascience.com/the-arrival-of-sdxl-1-0-4e739d5cc6c7

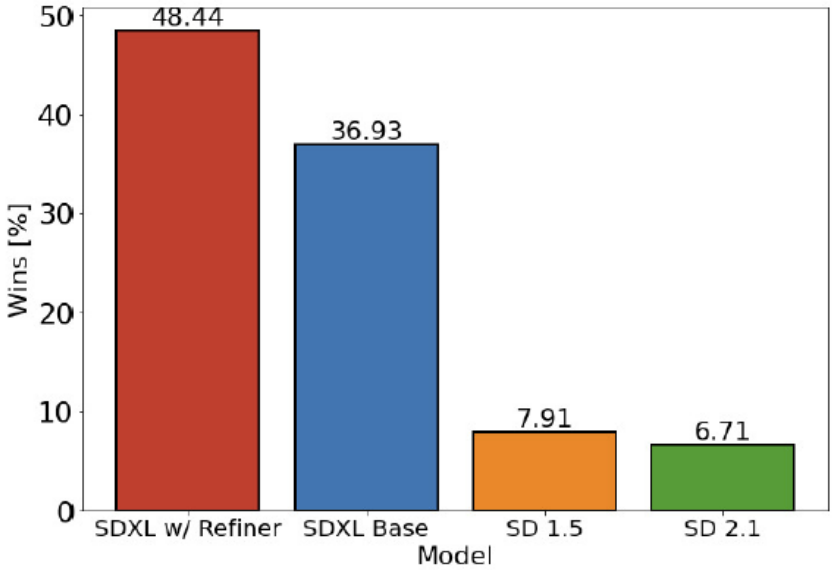
SDXL





https://towardsdatascience.com/the-arrival-of-sdxl-1-0-4e739d5cc6c7

SDXL: Improvements in generation quality



Comparing user preferences between SDXL and previous models.

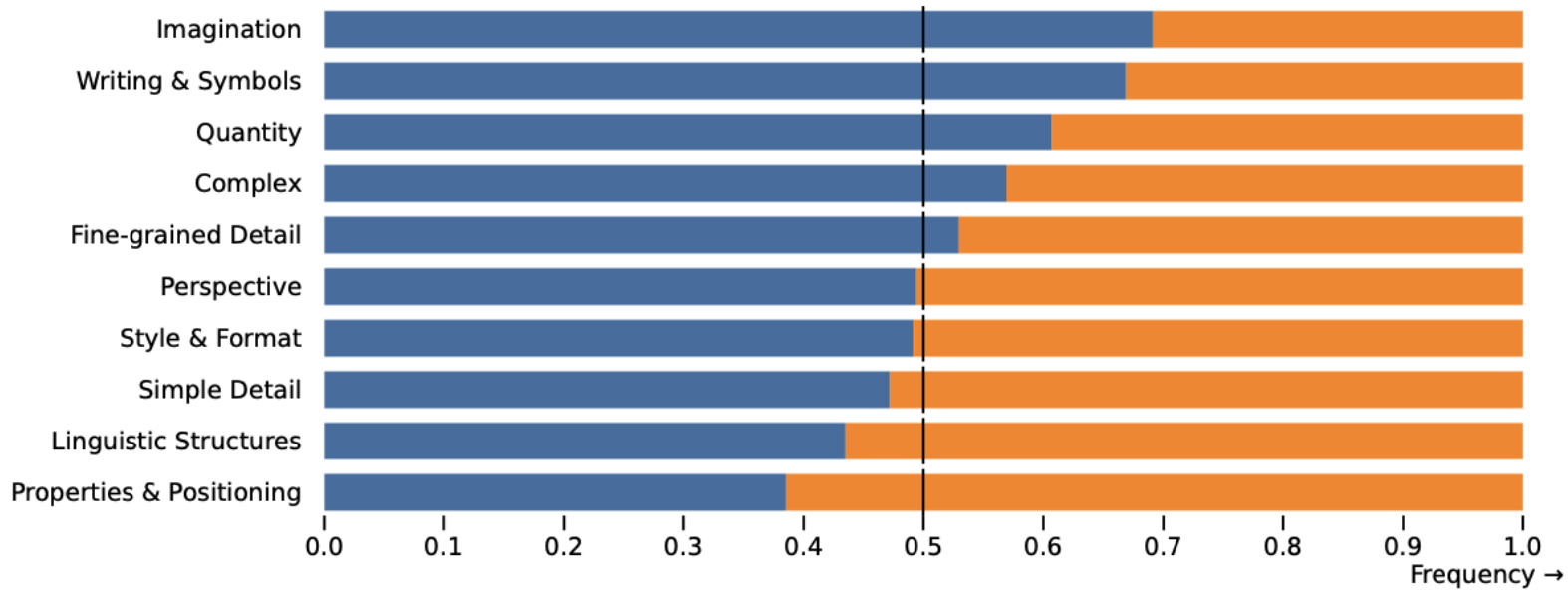


Figure 11: Preference comparisons of *SDXL* (with refinement model) to Midjourney V5.1 on complex prompts. *SDXL* either outperforms or is statistically equal to Midjourney V5.1 in 7 out of 10 categories.

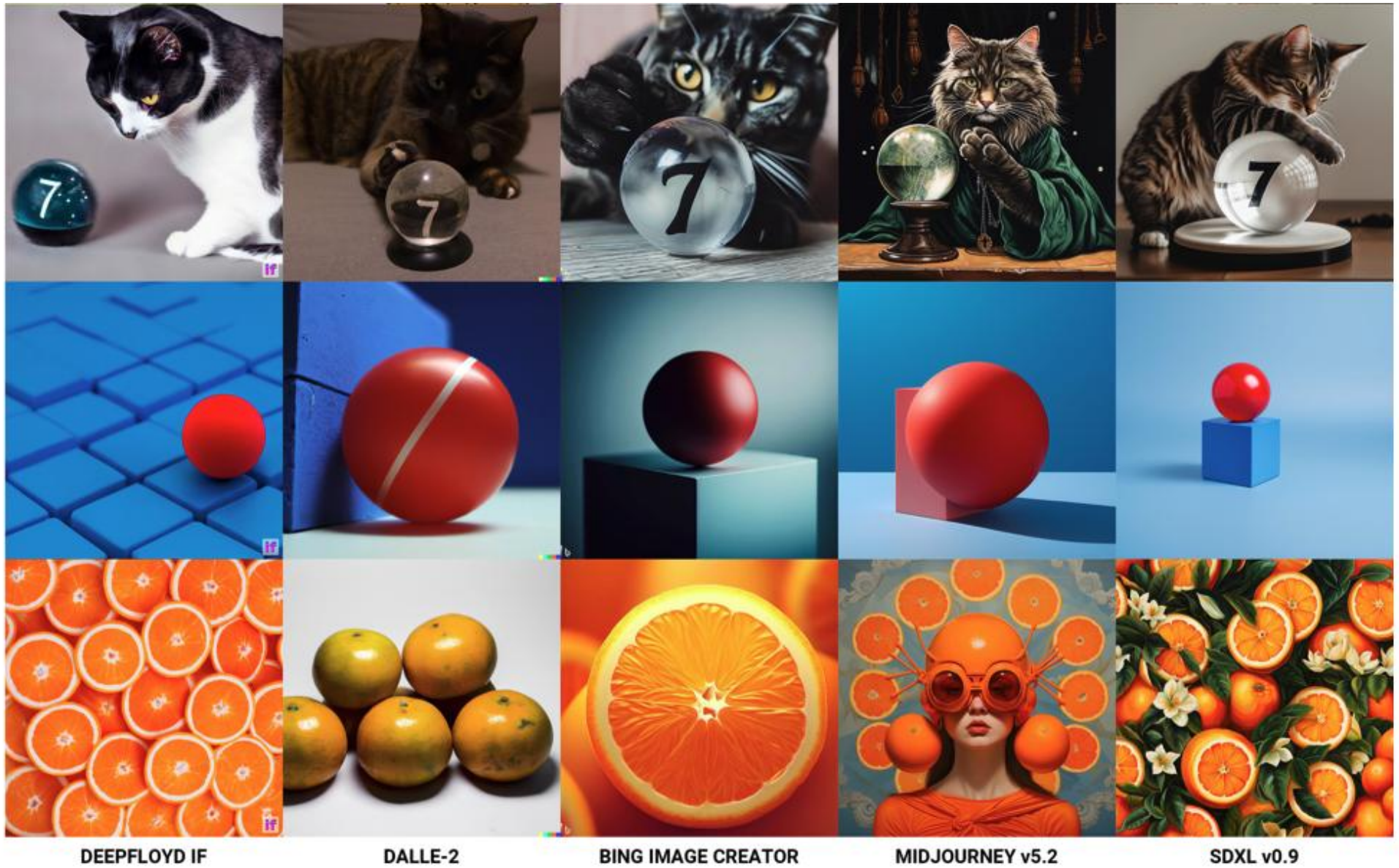
Improving Latent Diffusion Models for High-Resolution Image Synthesis

SDXL: Results



Figure 4: Comparison of the output of *SDXL* with previous versions of *Stable Diffusion*. For each prompt, we show 3 random samples of the respective model for 50 steps of the DDIM sampler [46] and cfg-scale 8.0 [13]. Additional samples in Fig. 14.

SDXL: Results



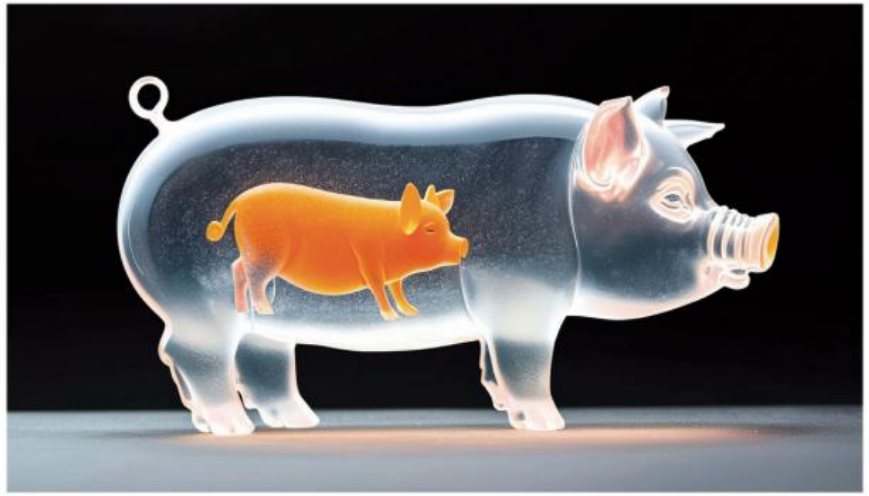
SD3



Prompt: A beautiful painting of flowing colors and styles forming the words "The SD3 research paper is here!", the background is speckled with drops and splashes of paint

https://stability.ai/news/stable-diffusion-3-research-paper

SD3: Results



Prompt: Translucent pig, inside is a smaller pig.



Prompt: A massive alien space ship that is shaped like a pretzel.



Prompt: A kangaroo holding a beer, wearing ski goggles and passionately singing silly songs.



Prompt: An entire universe inside a bottle sitting on the shelf at walmart on sale.



Prompt: A cheeseburger with juicy beef patties and melted cheese sits on top of a toilet that looks like a



Prompt: This dreamlike digital art captures a vibrant, kaleidoscopic bird in a lush rainforest



Prompt: A car made out of vegetables.

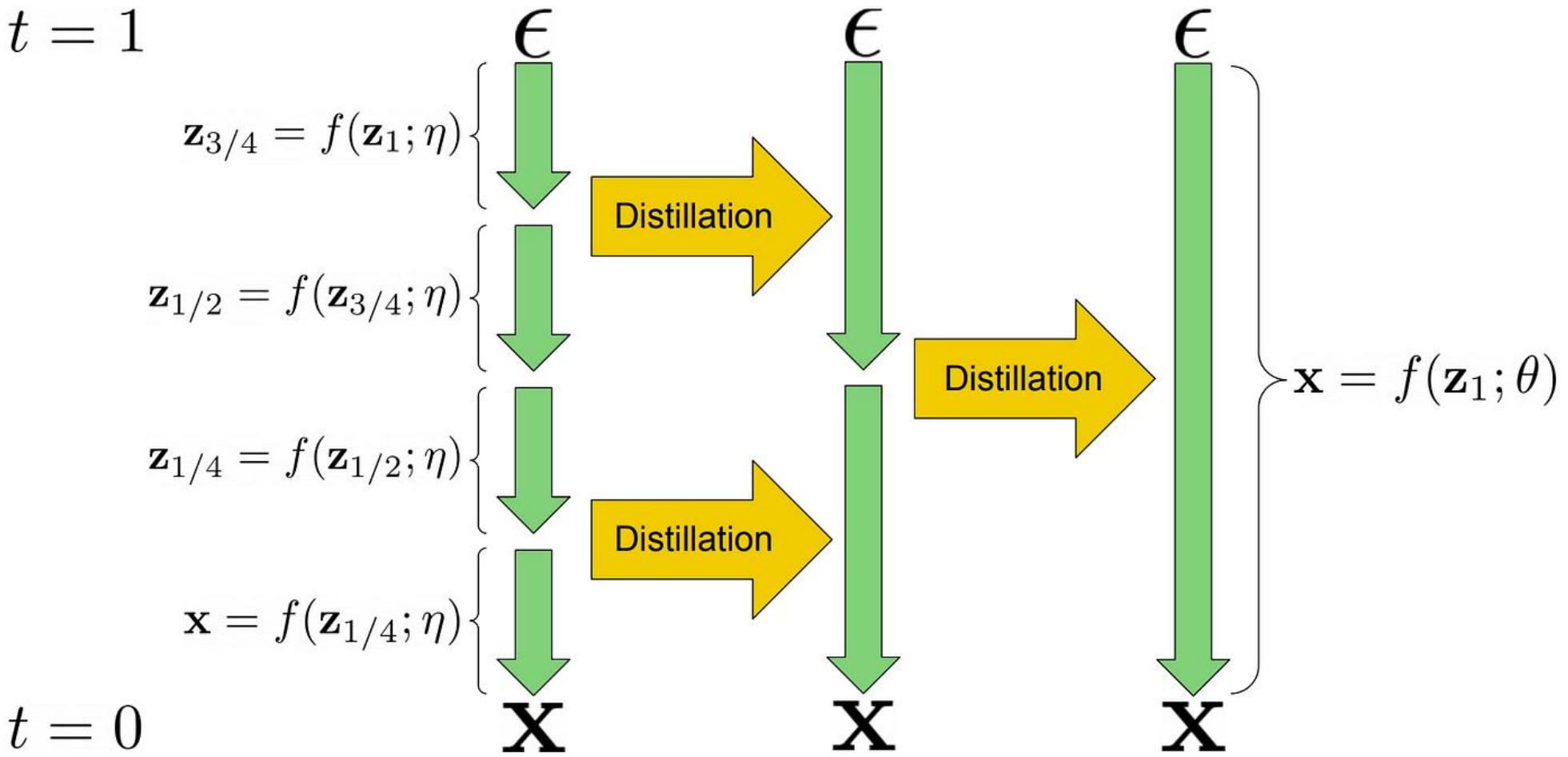


Prompt: Heat death of the universe line art

Outline

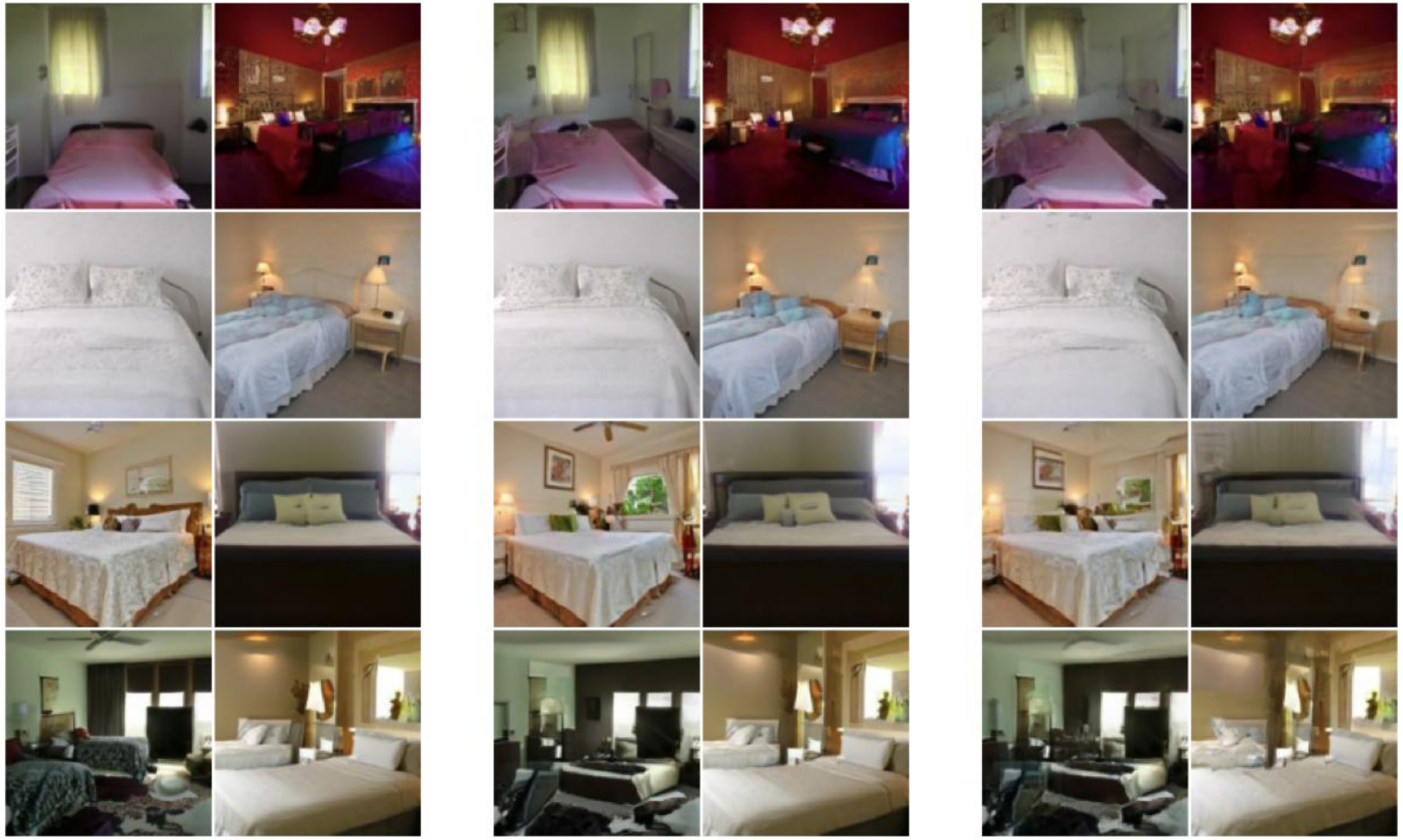
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  - Progressive Distillation

Progressive Distillation



Salimans et al, Progressive distillation for fast sampling of diffusion models

Progressive Distillation: Results



(a) 256 sampling steps (b) 4 sampling steps (c) 1 sampling step

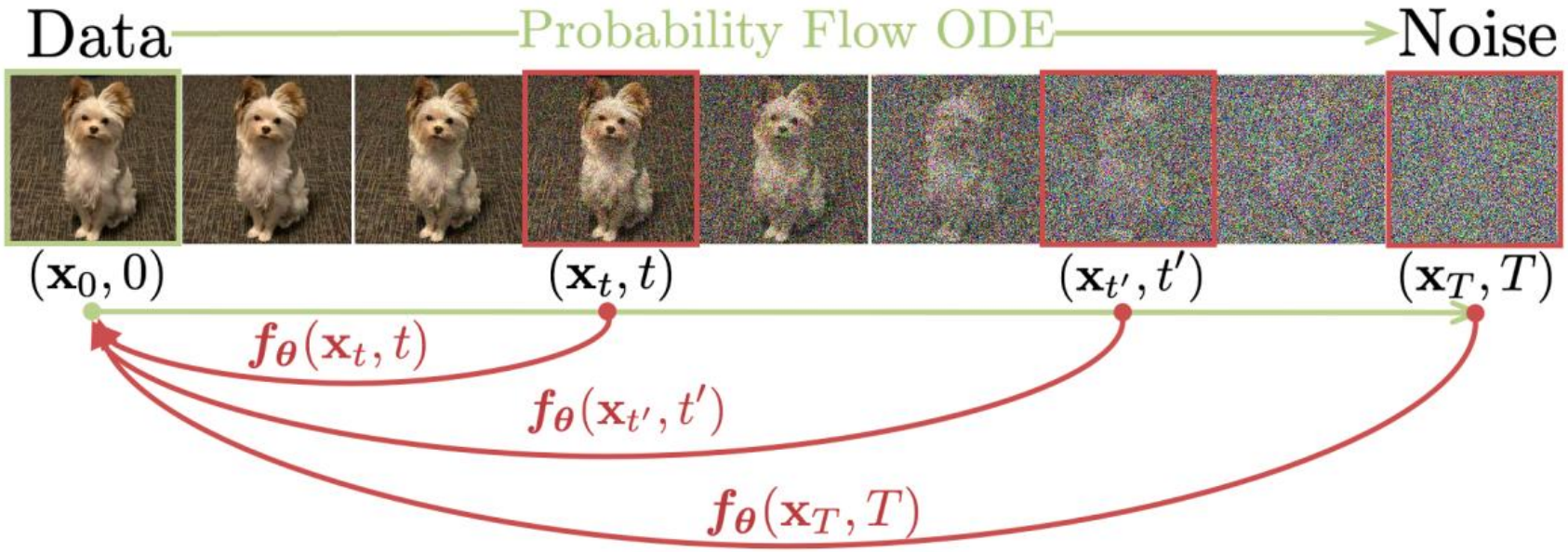
Figure 10: Random samples from our distilled LSUN bedrooms models, for fixed random seed and for varying number of sampling steps.

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  - Model Distillation
  - Latent Consistency Models (LCM)

Latent Consistency Models

Consistency Models

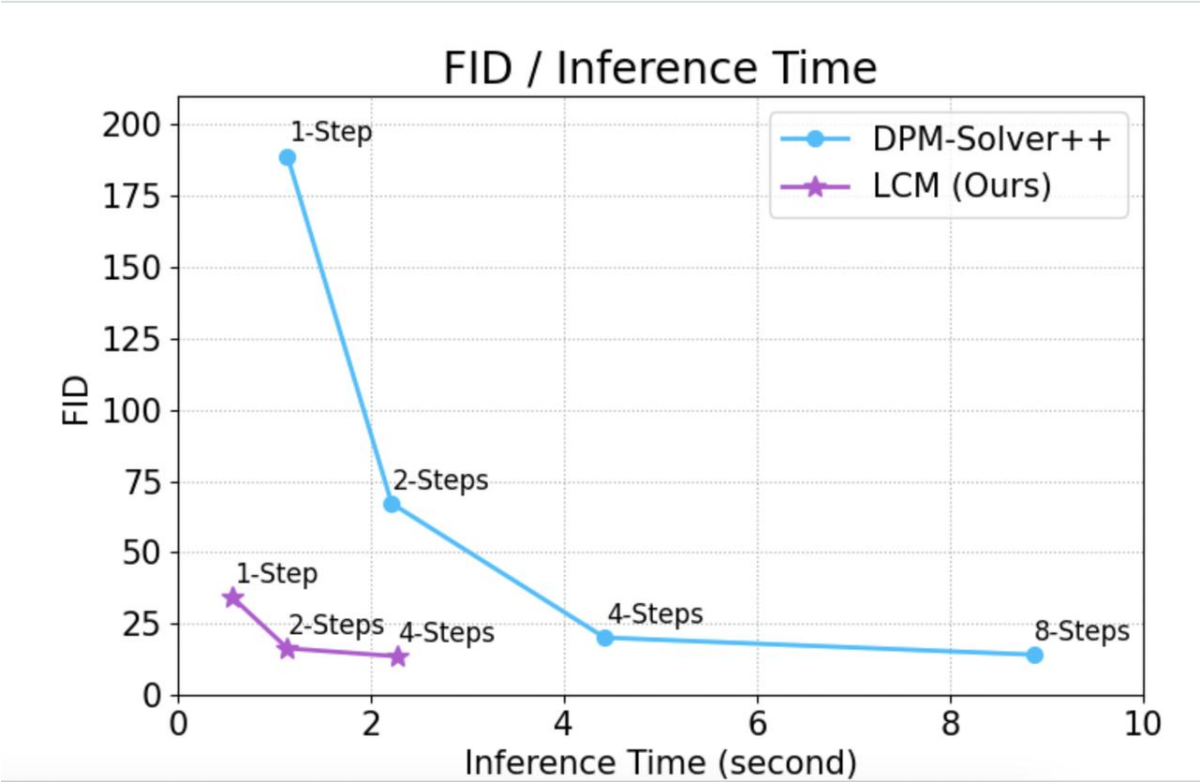


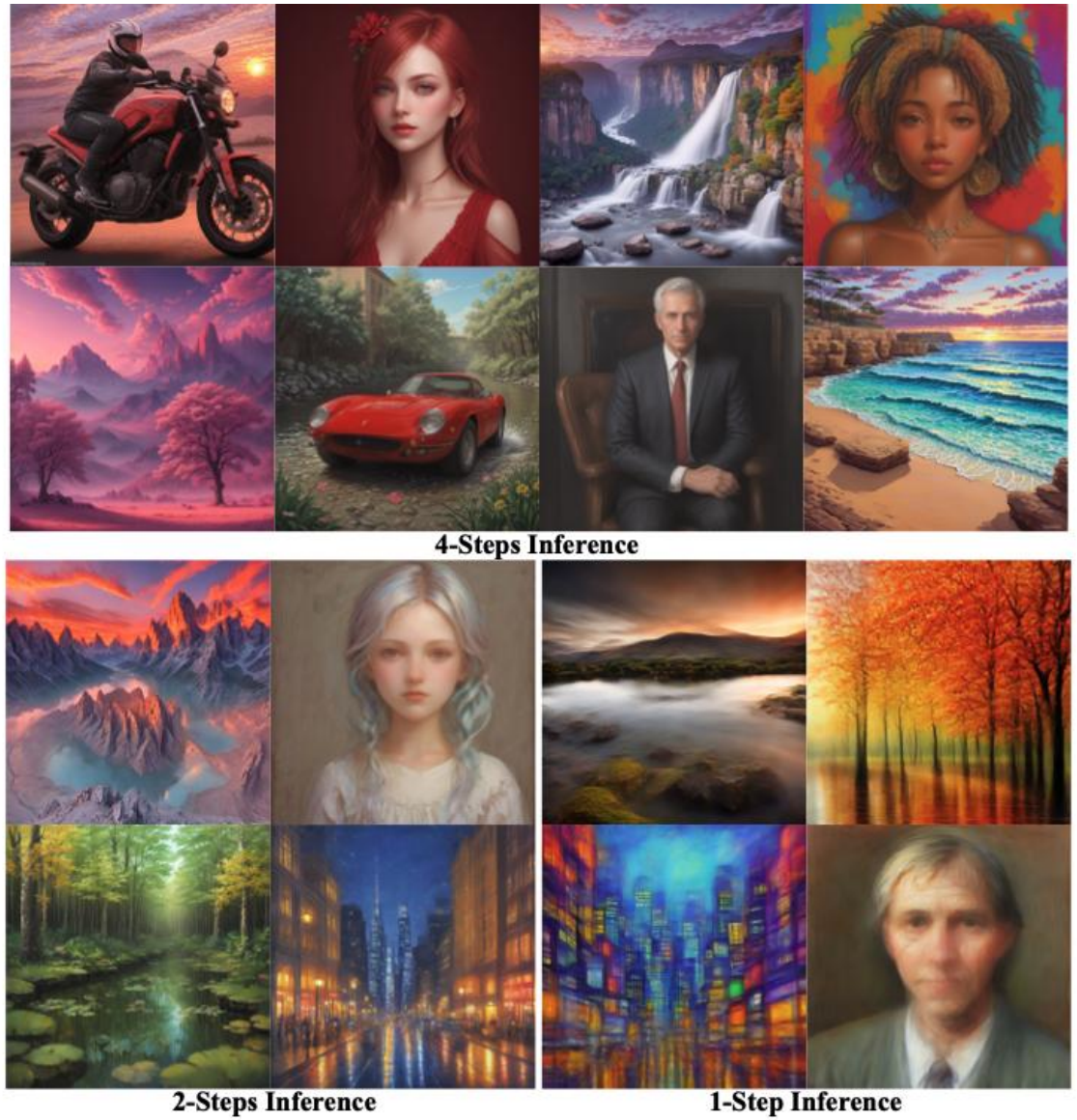
Latent Consistency Models: combine the above idea with Latent Diffusion Models

Song et al., Consistency Models

Luo et al, Latent Consistency Models: Synthesizing High-Resolution Images with Few-step Inference

Latent Consistency Models: Results





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  - Emu3

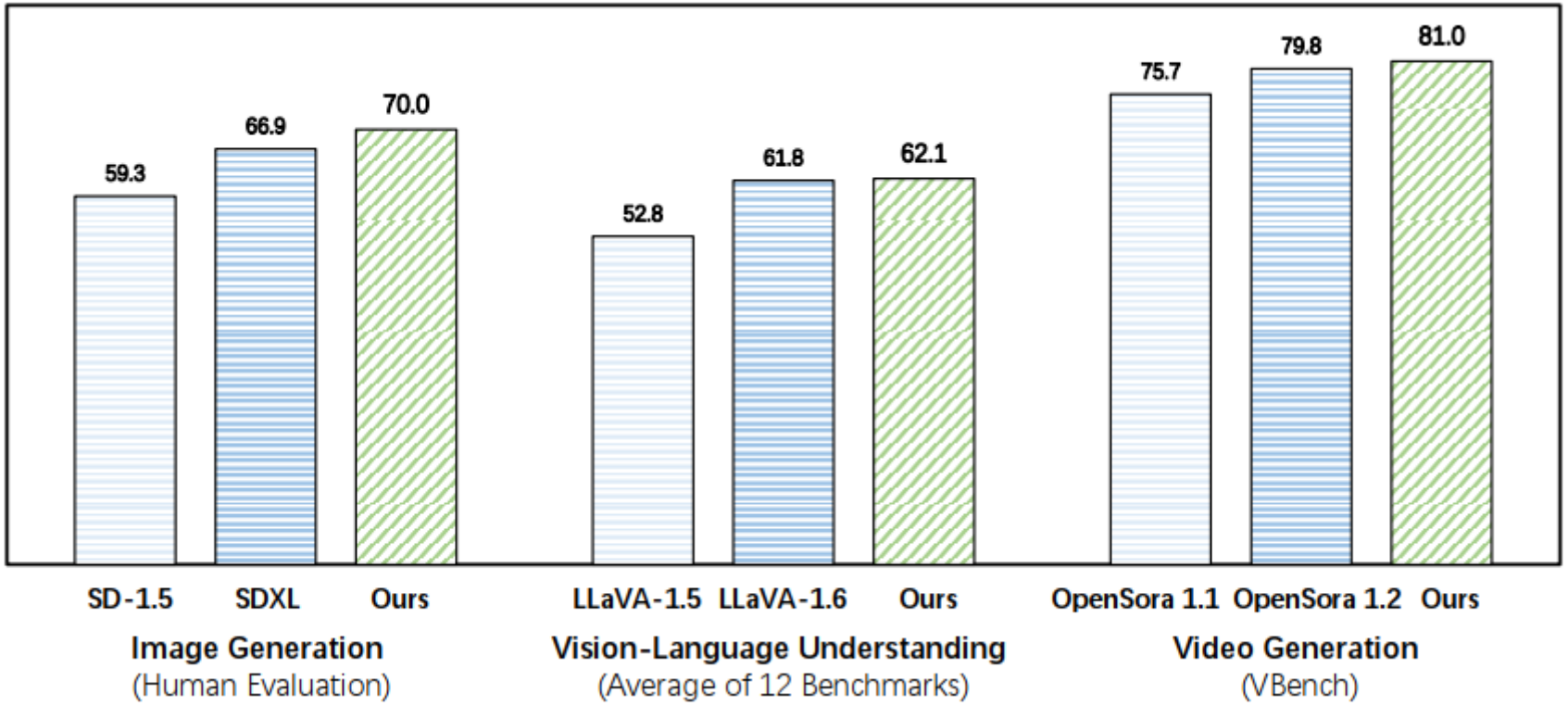
Emu3: Next-Token Prediction is All You Need



Figure 1: **Emu3** is trained to predict the next token with a single Transformer on a mix of video, image, and text tokens. **Emu3** achieves state-of-the-art performance compared to well-established task-specific models in generation and perception tasks.

arXiv:2409.18869

Emu3: Next-Token Prediction is All You Need



arXiv:2409.18869

谢谢

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