Image Generation from Texts and Multimodal Models

ESILV
ENGINEERING SCHOOL
DE VINCI PARIS

Apparition & Evolution of generative image from text

2014

Apparition des GAN
Ian Goodfellow et al. [1]

2016

First generated image with GAN
Reed Scott, Akata, Yan et al. [2]

2018

First transformers models:
Bert - Devlin et al.
GPT - Radford et al.
RoBERTa - Liu et al.

2021

Large language models
GPT - OpenAI
PaLM - Google
BLOOM
Popularized text-to-image:
DALL-E **-** Ramesh et al [3]

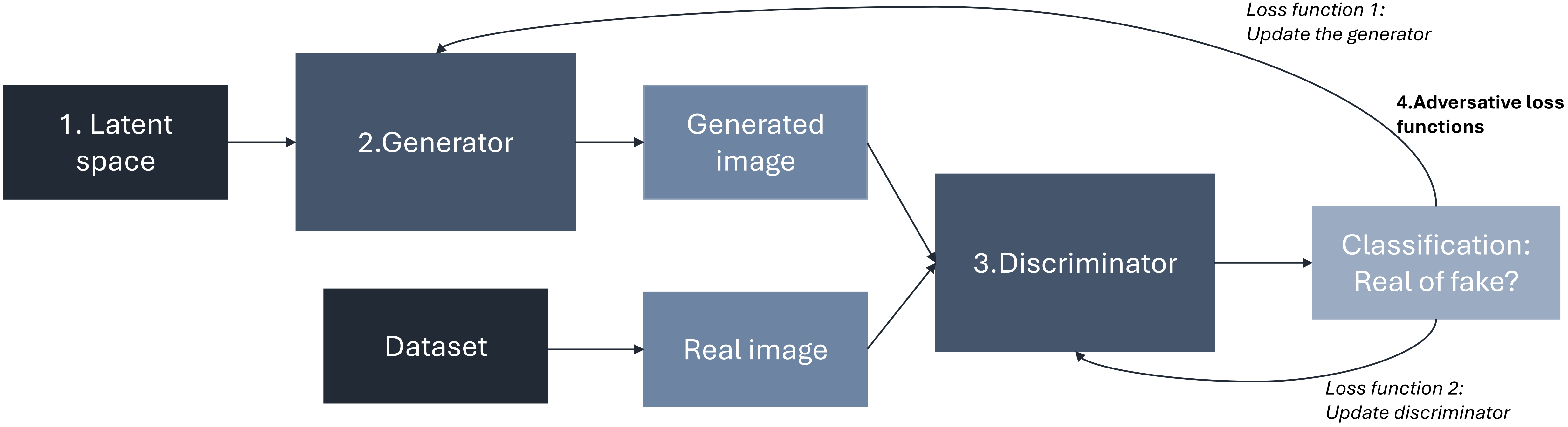
2022

Stable diffusion
R Rombach et al. [4]

> 2023

Text to slides
Text to video
Text to 3D images
Etc...

General idea of text-to-image network architecture



1. Create latent space
- Create dense vectors
- Employ LSTM, GRU, or Transformers (BERT, GPT) for contextual treatment (conditioning and attention mechanism)

2. Generator network:
- Generates images, the quality is progressively enhance through the training.

3.Discriminator Network:
- Evaluates whether the images are authentic or not and how well tehy match the text.

4. Adversative loss functions:
- The first aims to minimize the loss by producing realistic images.
- The second aims to maximize the number of accurately classified images.

Key figures of generatives IA

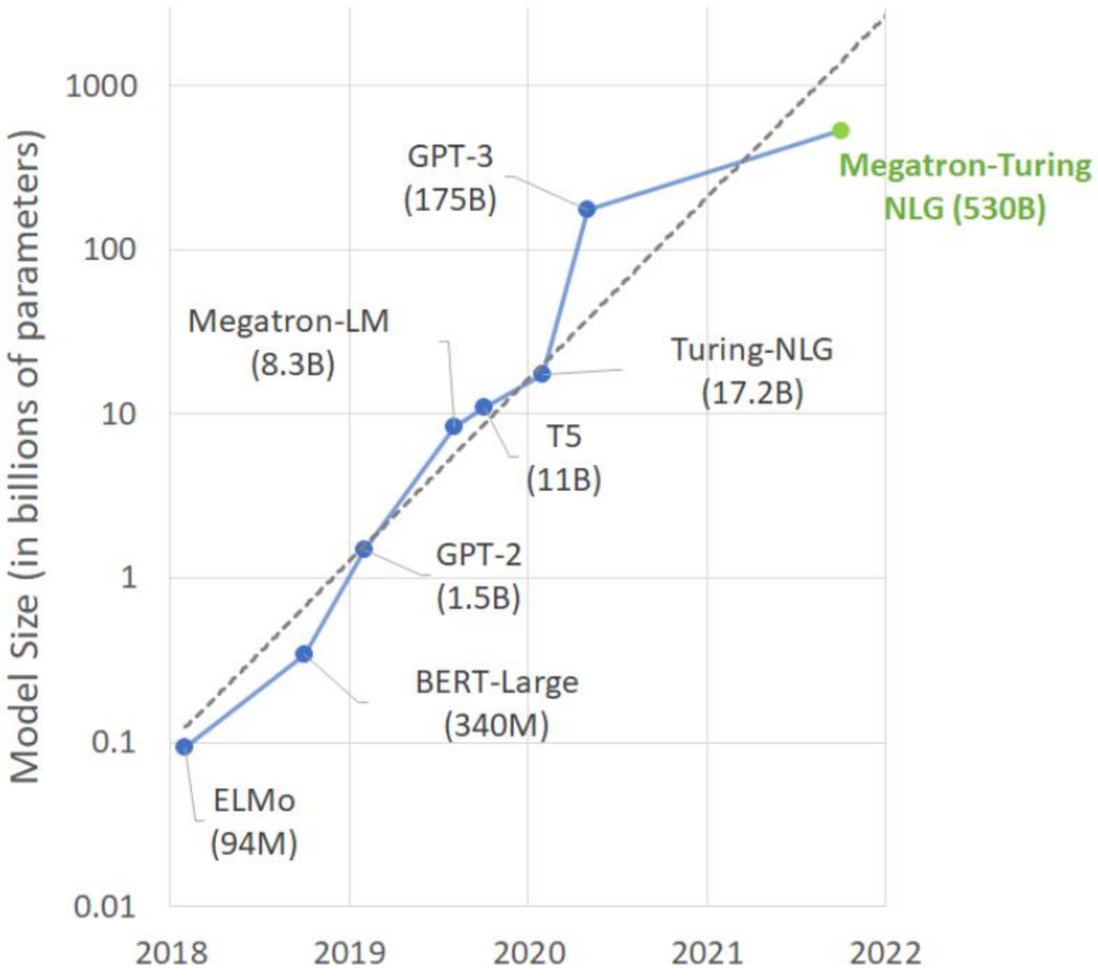


Figure 1 : Number of parameters for several pre trained models (NVIDIA, 2021)

Financial valorisation M$	
Open AI	90 000
Stable diffusion	1 000
Investment in IA M$	
1. EU	250
2. Chine	90
3. Royaume Unis	18
...	
6. France	6.5

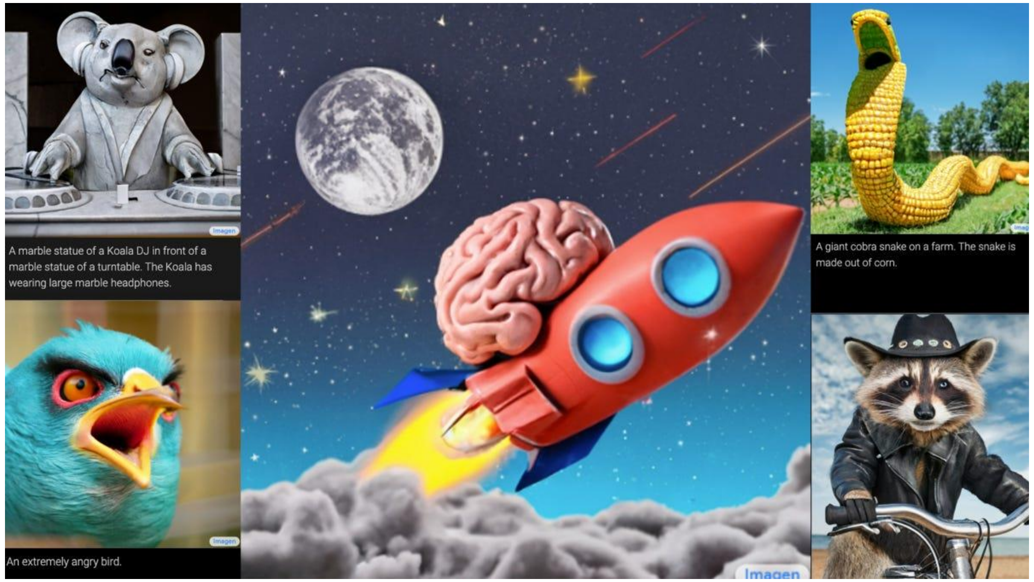
Expressive Text-to-Image Generation with Rich Text, Ge et al., 2023 [5]

Classical models:
Use of **plain text**

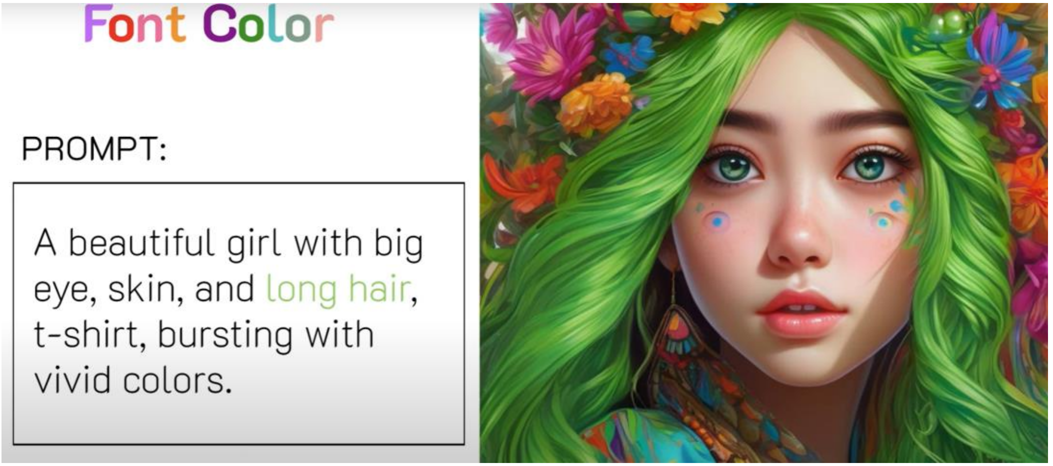
PROMPT:

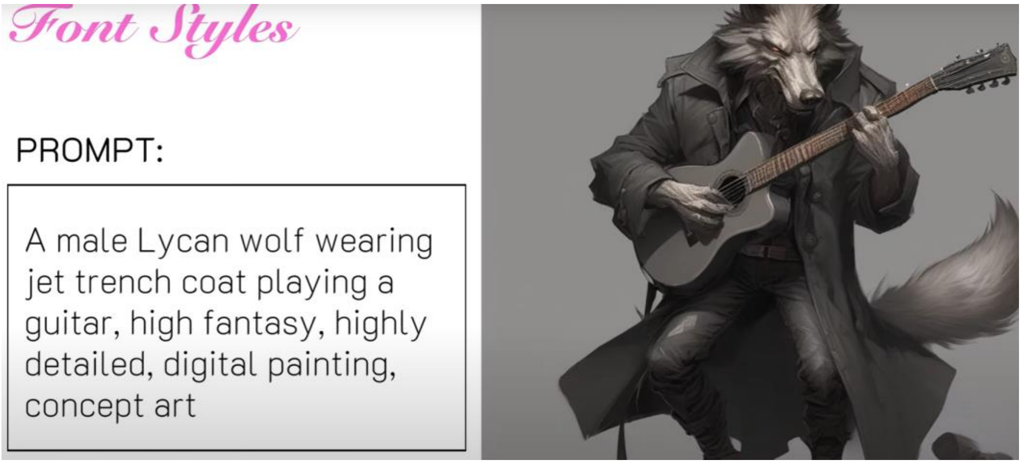
A photo of a Corgi dog riding a bike in Times square. It is wearing sunglasses and a beach hat.

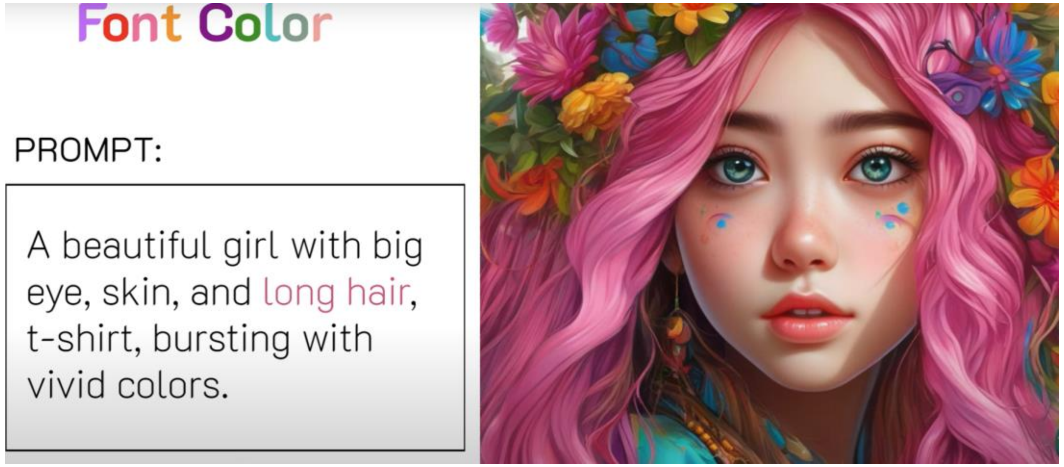
Use of **Rich and expressive texts :**
Front, style, links, footnotes

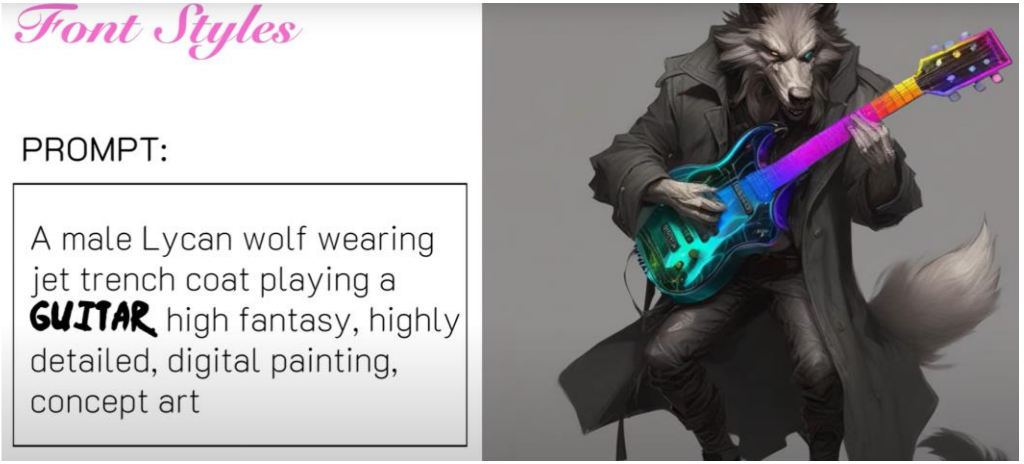


Expressive Text-to-Image Generation with Rich Text, Ge et al., 2023 [5]





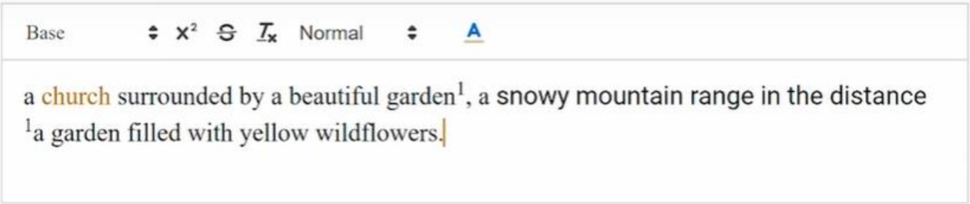




Expressive Text-to-Image Generation with Rich Text, Ge et al., 2023 [5]

Expressive Text-to-Image Generation with Rich Text, Ge et al., 2023 [5]

Rich Text editor

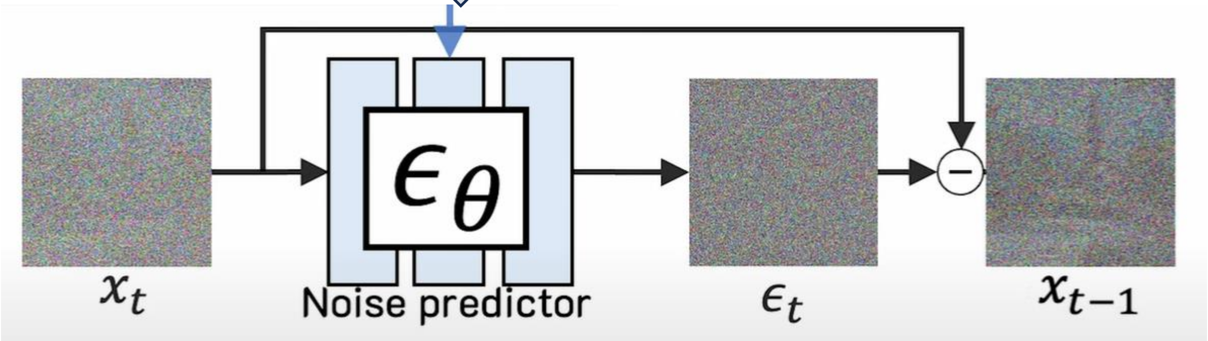


Raw text

Extraction

A church surrounded by a beautiful garden, a snowy mountain range in the distance

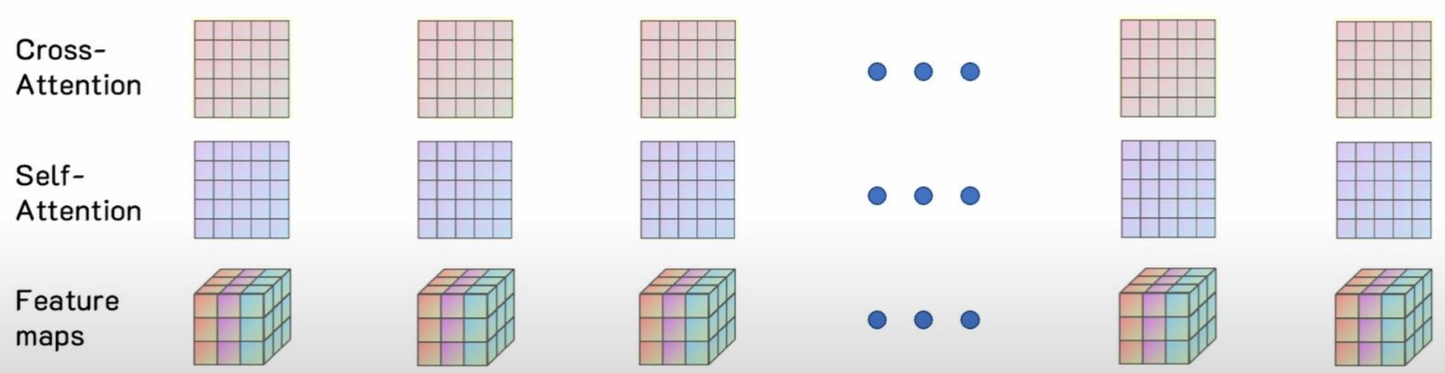
Denoising



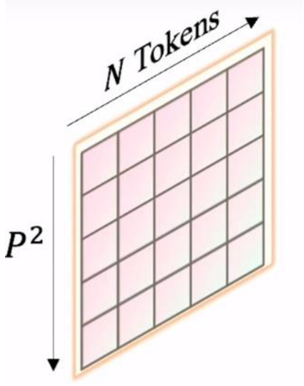
x1 x0

Expressive Text-to-Image Generation with Rich Text, Ge et al., 2023 [5]

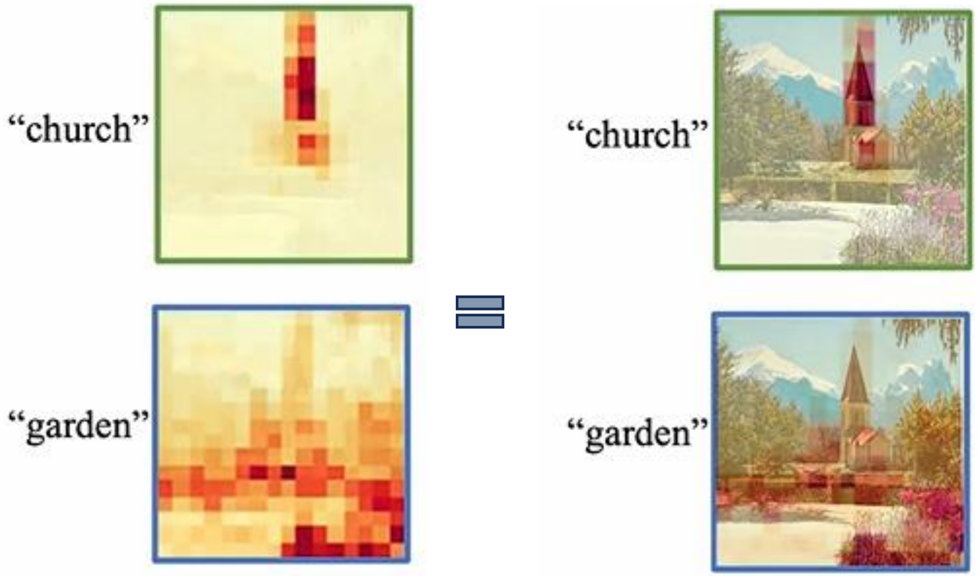
In parallel, collect of "maps"



In particular : Cross-Attention

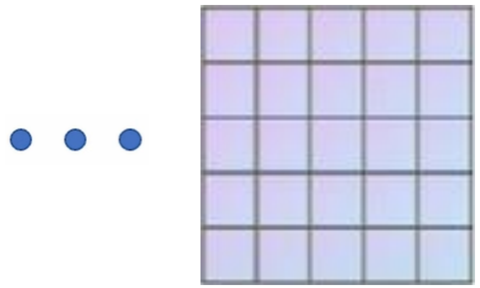


Info of token + location in image

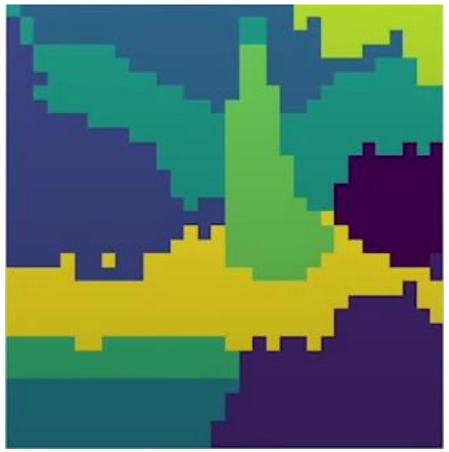


Expressive Text-to-Image Generation with Rich Text, Ge et al., 2023 [5]

To renforce the detection : self-attention



Spectral clustering

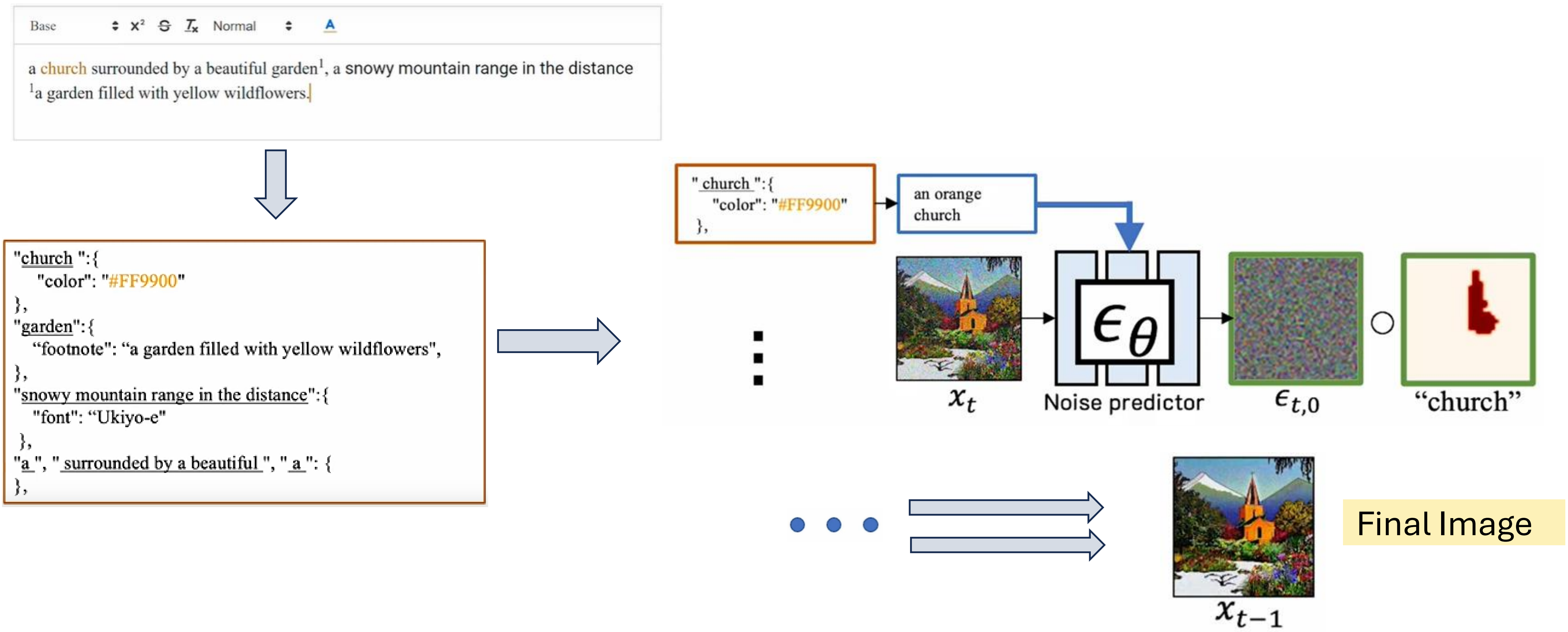


Cross + Self map

labelling

Expressive Text-to-Image Generation with Rich Text, Ge et al., 2023 [5]

Token map



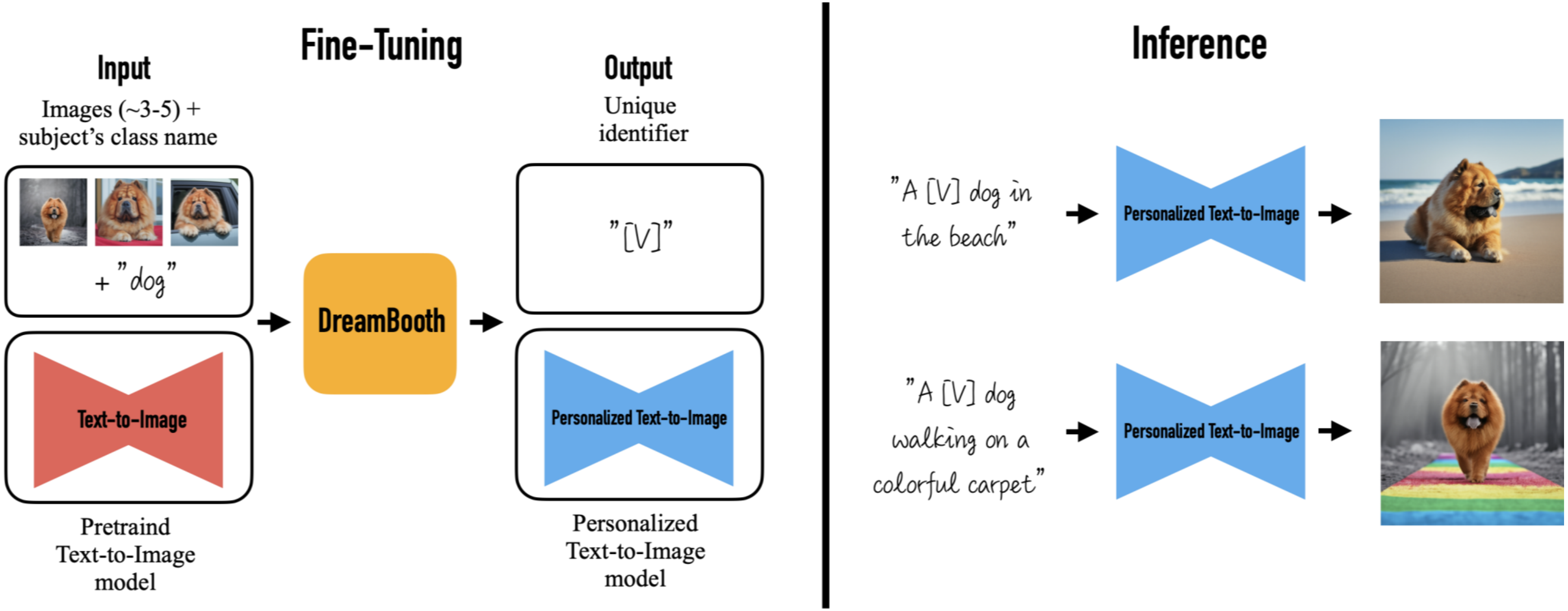
DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation, N. Ruiz et al, 2023 [10]

A new approach for personalization of text-to-image diffusions models

https://arxiv.org/pdf/2208.12242.pdf

DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation, N. Ruiz et al, 2023 [10]

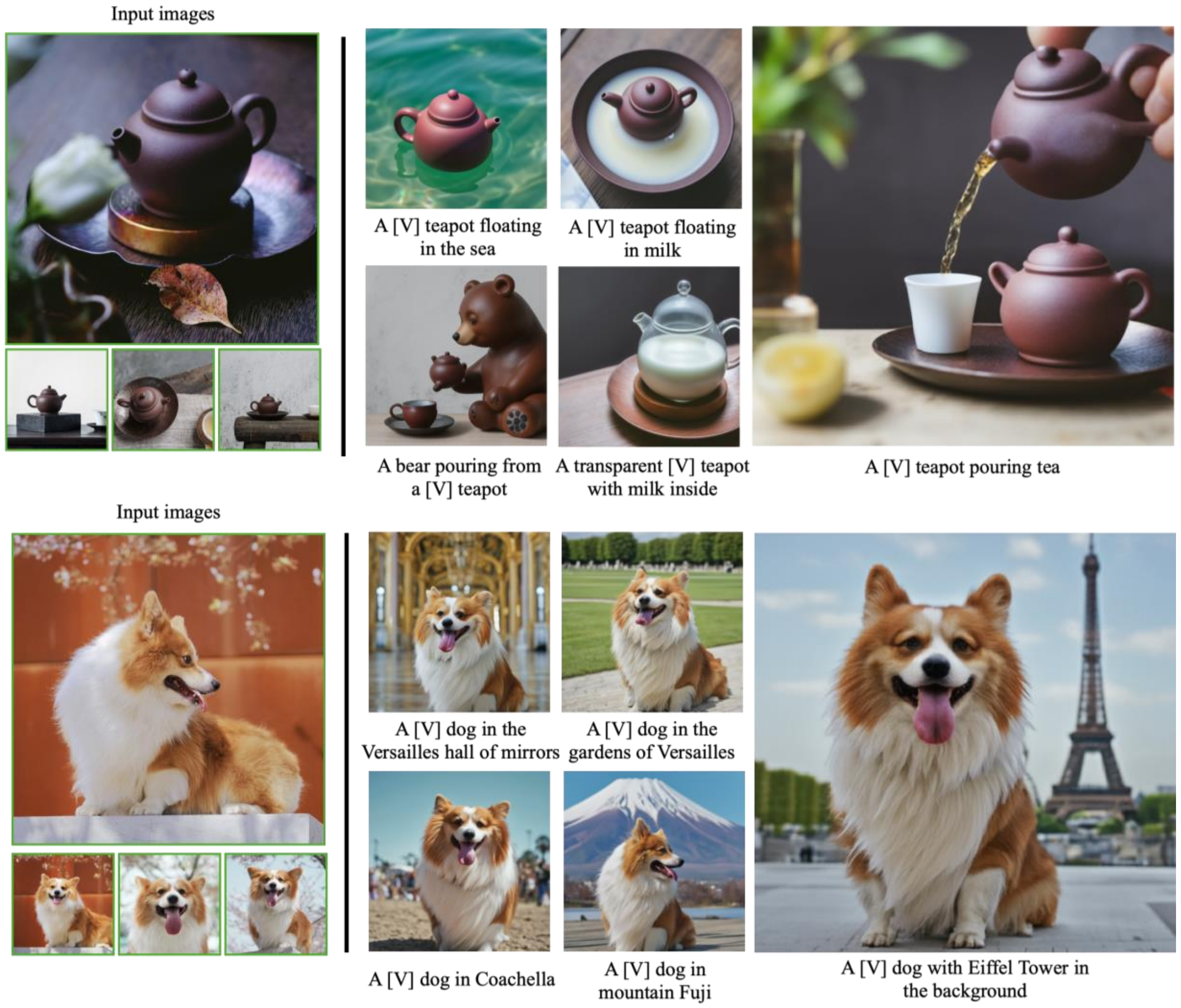
Takes as input a few images of a subject and a class name
Returns a fine-tuned text-to-image model with that encodes an unique identifier referring to the subject
In this work they used Imagen for the pretrained model as the base model



DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation, N. Ruiz et al, 2023 [10]

Recontextualization :

a [V] [class noun] [context description]



DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation, N. Ruiz et al, 2023 [10]

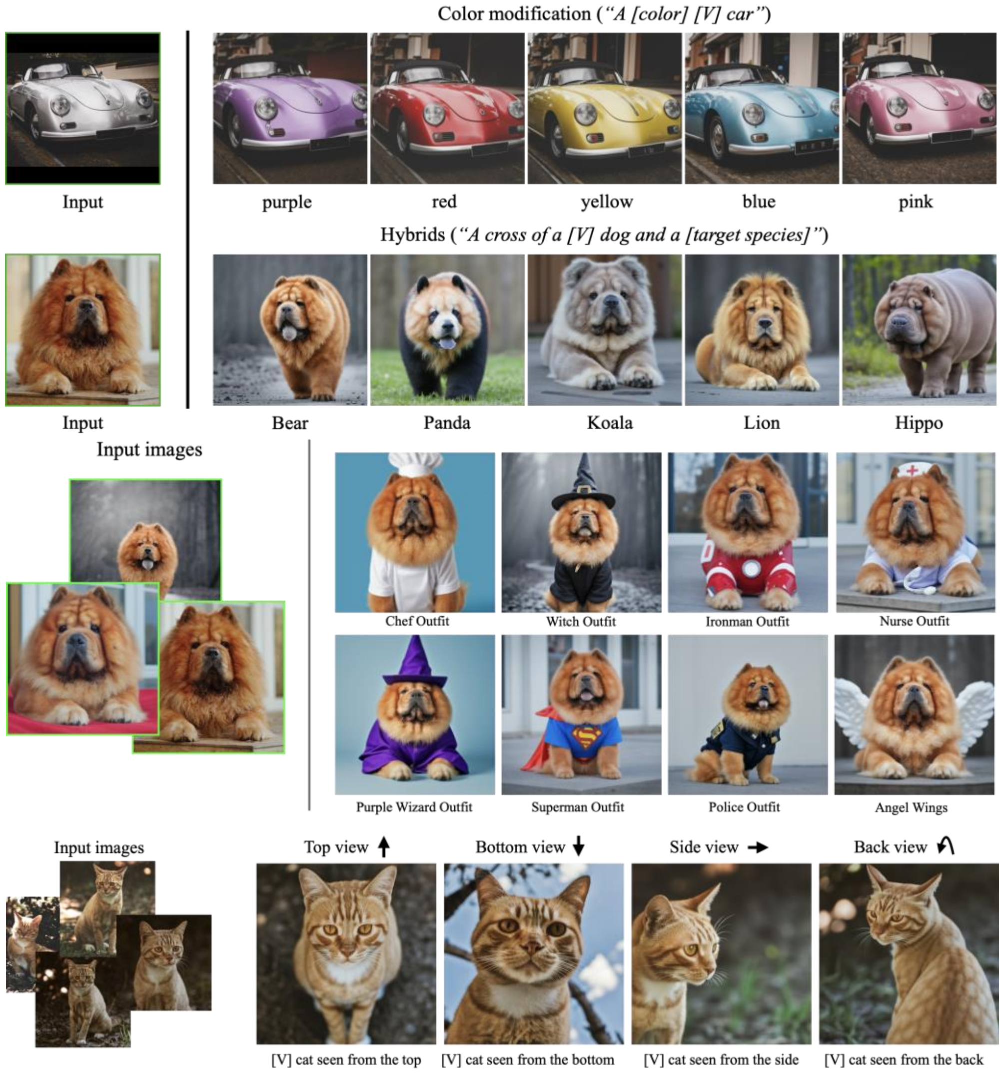
Art Rendition :

a painting/sculpture of a [V] [class noun] in the style of [famous painter/sculptor]

DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation, N. Ruiz et al, 2023 [10]

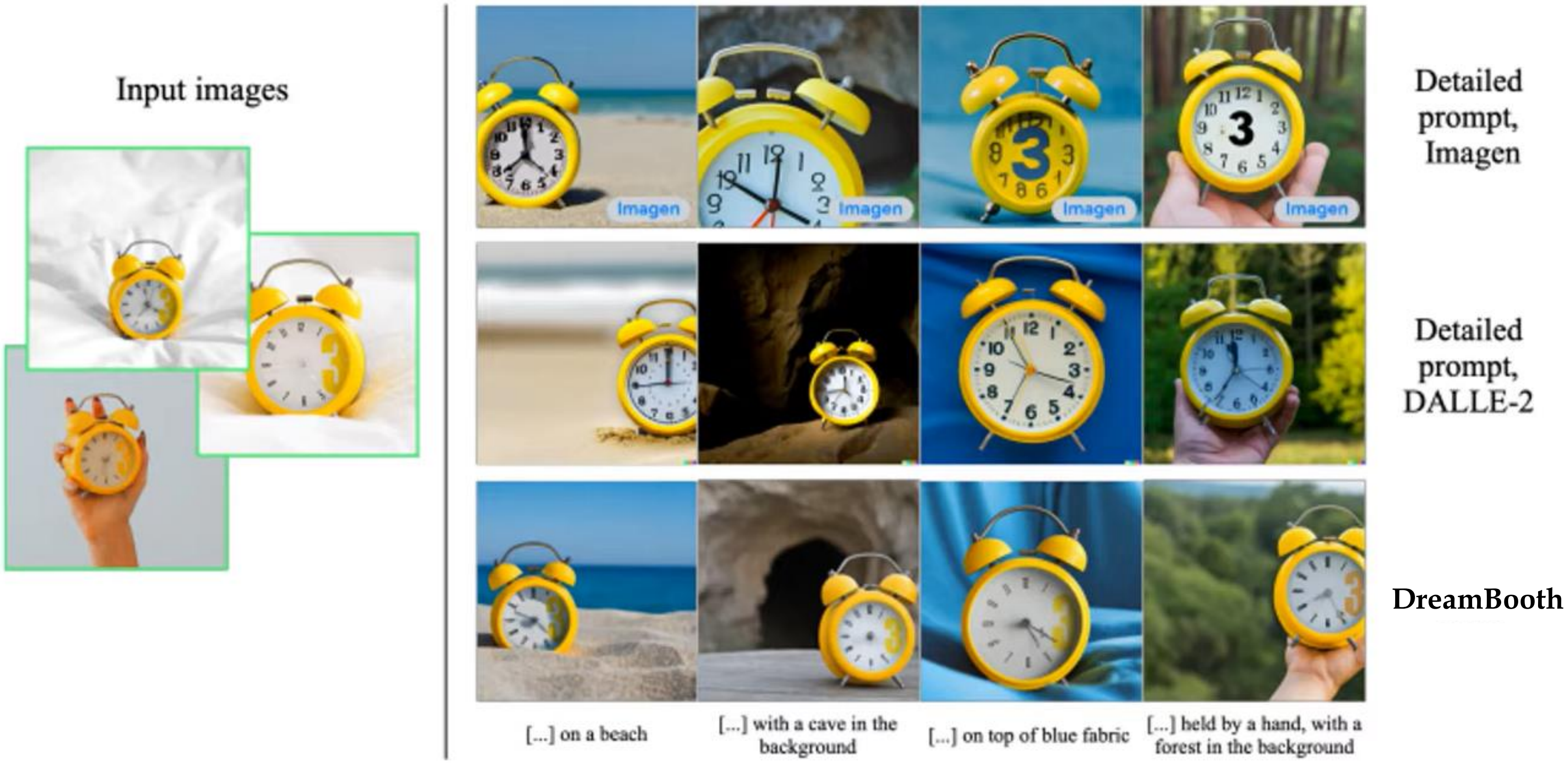
Property modification :

Color modification
Hybridation
Accessorization
Text-Guided View Synthesis



DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation, N. Ruiz et al, 2023 [10]

Comparison with other models :



Prompt : "retro style yellow alarm clock with a white clock face and a yellow number three on the right part of the clock face"

DALL-E : Zero-Shot Text-to-Image Generation, A. Ramesh et al., 2021, [11]

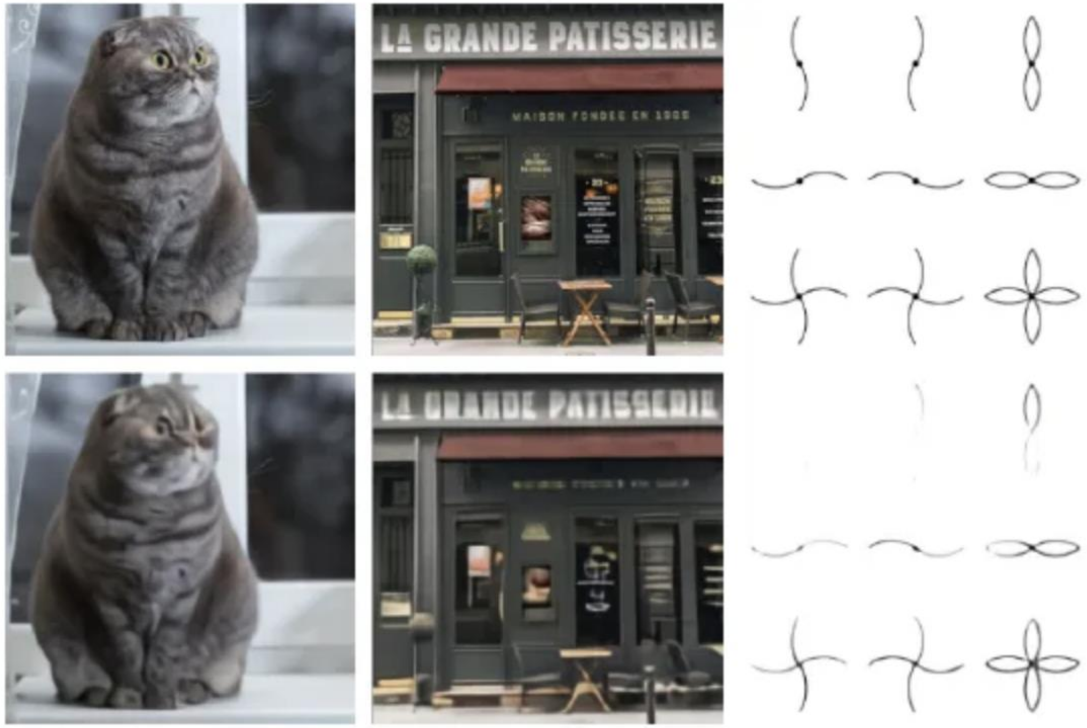
Goal : Train a Transformer (GPT-3) to autoregressively model the text and image tokens as a single stream of data.

Stage 1

Compress each 256*256 RGB image into a 32×32 (factor 64) grid of image tokens using a **VAE**.

Each element can take 8192 possible values to ensure a diversity.

Objective : Reduce the input space of the **transformer** by a factor of 192 (64*3)



Comparison of original images (top) and reconstructions from the discrete VAE (bottom)

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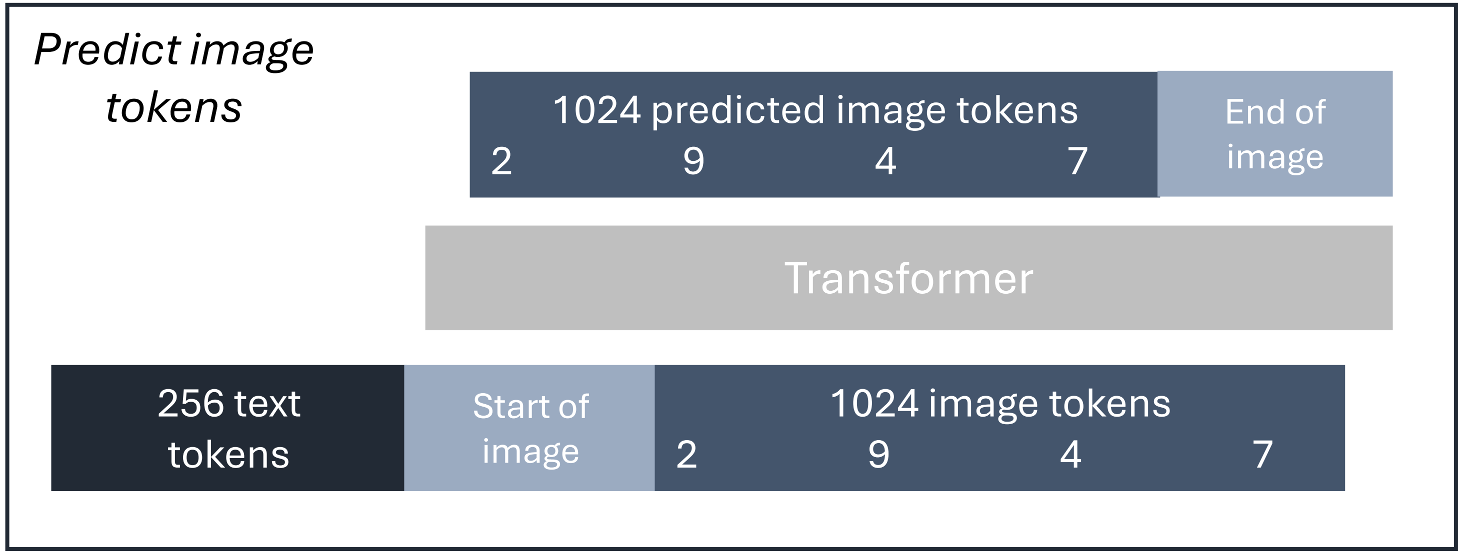
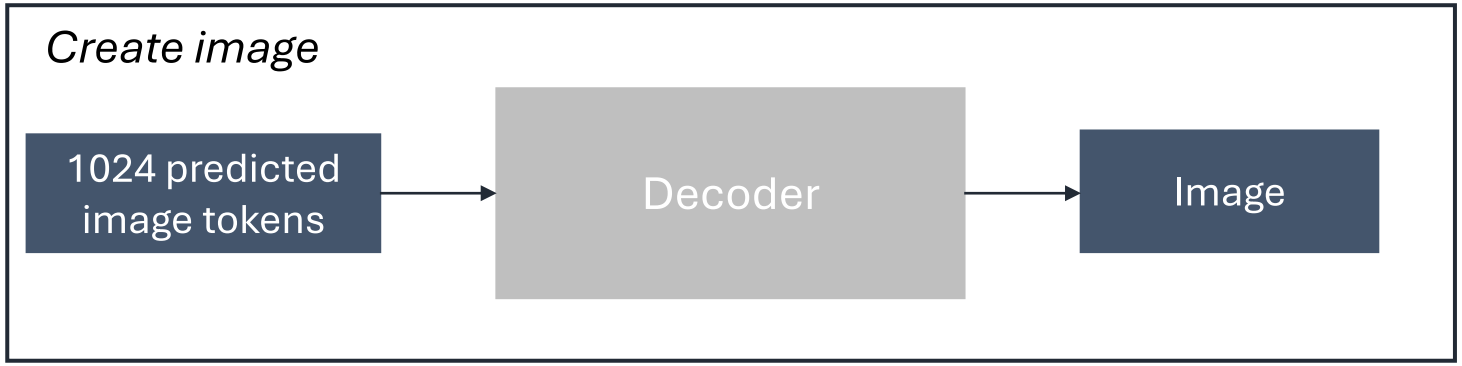
Stage 2

Concatenate in one sequence the 256 BPE-encoded **text** tokens and the 32×32=1024 **images** tokens.

« Finally, the text and image tokens are concatenated and modeled autoregressively as a single stream of data »





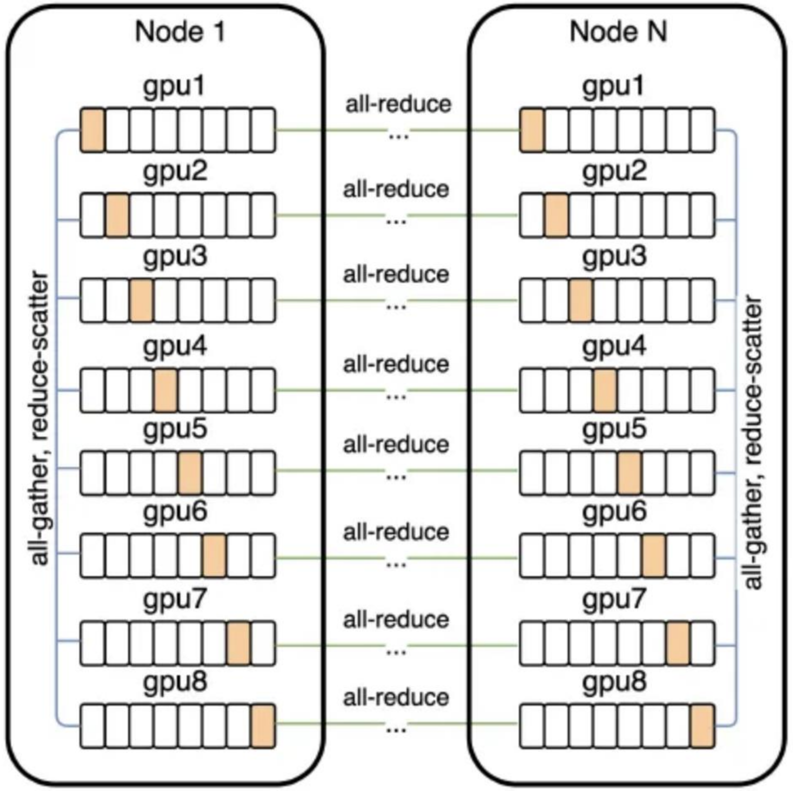
DALL-E : Zero-Shot Text-to-Image Generation, A. Ramesh et al., 2021, [11]

Goal : Train a Transformer (GPT-3) to autoregressively model the text and image tokens as a single stream of data.

Dataset : 250 millions text-images pairs from the internet.

Model : 12-billion parameters, it consumes about 24 GB of memory which exceeds 16 GB NVIDIA V100 GPU

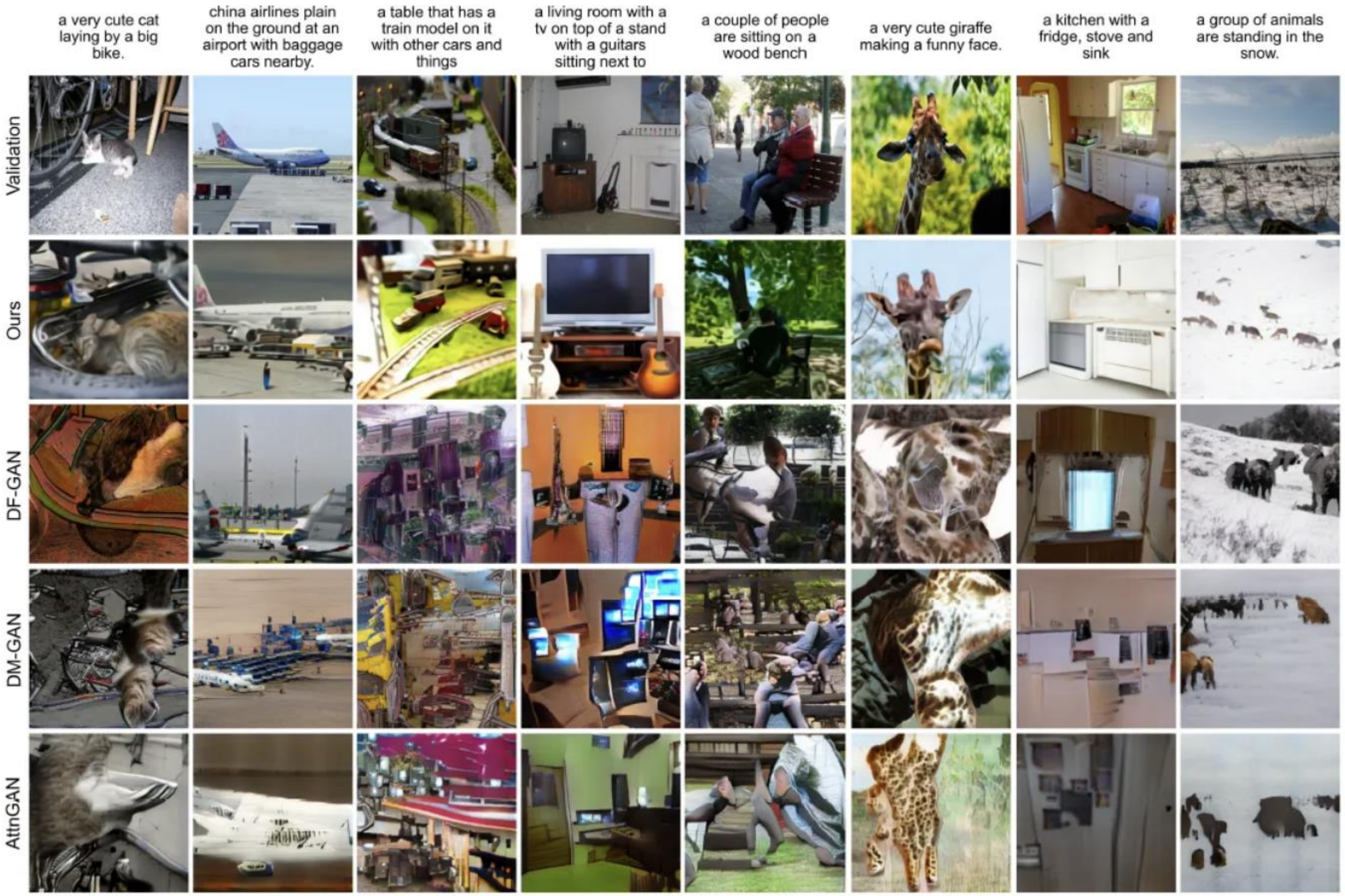
Optimization: Each parameter array is sharded among the eight GPUs on each machine and the gradient is compressed *(Vogels et al., 2019)*



vCommunication patterns used for distributed training

DALL-E : Zero-Shot Text-to-Image Generation, A. Ramesh et al., 2021, [11]

DALL-E's generated images are ranked with a contrastive model *(Radford et al., 2021)*. It was the best to create 512 images samples



Comparison of samples from DALL-E model to those from prior approaches on captions from MS-COCO

Electricity consumption of GPT

- 1.287 MWh for its training - 564 MWh per day for 3.500 servers - 30,000 GPUs
- **Future Scenario**: Implementing an AI in Google search - 500,000 servers - 4 million GPUs
  => Annual consumption of 29.2 TWh > Ireland's annual consumption of 29.3 TWh.

GPT's Carbon Footprint

- 260-522T of CO2e : 270 flights between Paris and New York - electrical operation (50%) - server manufacturing - refrigerant gas leaks (per year).
- 8,4 tCO2e/an : Daily execution

=> Paris Agreement's goal is 2T CO2eq per person and actual consumptions is 8T CO2eq in 2021.

Cost of GPT

=> 700,000 dollars per day for OpenAI.

Water consumption of GPT

- 700 cubic meters of water already used
- 25 to 50 interactions require half a liter of water
- GPT-4 is even more demanding in terms of water consumption

- LaMDa and Bard required over 8.7 million cubic meters of water in 2019 in just three U.S. states.

Deep Fake & GANS :

- Legal void
- Plagiarism and intellectual property
- Fraud
- Use of private data
- Infringement of someone else's privacy,
- Violation of the right to one's image.
- Lake of transparency (source…)

=> IA act: regulating the use of artificial intelligence throughout the European Union

CONTEXTE

[1] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets. In *Advances in Neural Information Processing Systems*, Vol. 27. 139–144

[2] R. Scott, A. Zeynep, Y. Xinchen, L. Lajanugen, S. Bernt, L. Honglak, Generative adversarial text to image synthesis, in *ICML* 2016

[3] A. Ramesh, P. Dhariwal, A. Nichol, C. Chu, M. Chen Hierarchical Text-Conditional Image Generation with CLIP Latents, *arXiv:2204.06125v1*, 2022

[4] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, High-Resolution Image Synthesis with Latent Diffusion Models, in *CVPR*, 2022

CURRENT TECHNIQUES : RICH TEXT

[5] S. Ge, T. Park, JY. Zhu, JB. Huang, Expressive Text-to-Image Generation with Rich Text, *Ge et al.*, 2023

[6] A. Hertz, R. Mokady, J. Tenenbaum, K. Aberman, Y. Pritch, and D. Cohen-Or. Prompt-to-prompt image editing with cross attention control. *arXiv:2208.01626*, 2022.

[7] T. Brooks, A. Holynski, and A. Efros. Instructpix2pix: Learning to follow image editing instructions. *CVPR*, 2023

[8] H. Chefer, Y. Alaluf, Y. Vinker, L. Wolf, and D. Cohen-Or. Attend-and-excite: Attention-based semantic guidance for text-to-image diffusion models.arXiv preprint *arXiv:2301.13826*, 2023.

[9] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, B. Ommer. High-resolution image synthesis with latent diffusion models.*CVPR*, 2022

CURRENT TECHNIQUES : DREAMBOOTH

[10] N. Ruiz, Y. Li, V. Jampani, Y. Pritch, M. Rubinstein, and K. Aberman, DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation, arXiv:2208.12242, in *CVPR* 2023

CURRENT TECHNIQUES : ZERO SHOT

[11] R. Aditya, P. Mikhail, G. Gabriel, G. Scott, V. Chelsea, R. Alec, C. Mark, S. Ilya. 2021. Zero-shot text-to-image generation. In *International Conference on Machine Learning*. 8821–8831.

Carbon Footprint and energy consumption

- https://towardsdatascience.com/the-carbon-footprint-of-chatgpt-66932314627d
- https://www.hellowatt.fr/blog/chat-gpt-empreinte-carbone/

Water consumption

- https://www.bfmtv.com/tech/intelligence-artificielle/une-bouteille-par-conversation-chat-gpt-est-un-gouffre-de-consommation-d-eau-fraiche_AV-202304120278.html

ChatGPT cost

- https://www.20minutes.fr/high-tech/4034128-20230424-chatgpt-fonctionnement-chatbot-coute-pres-700-000-dollars-jour

Deep Fake and IA act

- https://www.challenges.fr/high-tech/ai-act-pour-les-entreprises-la-fin-du-systeme-d-pour-utiliser-l-ia-risque-de-couter-cher_876982
- https://linc.cnil.fr/dossier-ia-generative-quelles-regulations-pour-la-conception-des-ia-generatives