Deep Generative Models: Latent Diffusion Models

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Outline

- Markov Hierarchical Variational Auto Encoders (MHVAEs)
  - Autoregressive Encoder and Autoregressive Decoder of an MHVAE
  - Derivation of the ELBO of an MHVAE

- Diffusion Models as MHVAEs with a Linear Gaussian Autoregressive Latent Space
  - Forward Diffusion Process
  - Reverse Diffusion Process
  - ELBO for Diffusion Models as a particular case of the ELBO for MHVAEs
  - Implementation Details: UNet Architecture, Training and Sampling Strategies

- **Application of Diffusion Models**
  - Stable Diffusion: Text-Conditioned Diffusion Model
  - ControlNet: Multimodal Control for Consistent Synthesis
  - Image Editing

Stable Diffusion

- DDPM operates in pixel space: optimization takes hundreds of GPU days and inference is expensive.
  - 50k sample takes around 5 days on a single A100 GPU.

- To enable training on limited computational resources, while retaining quality and flexibility, Stable Diffusion performs denoising in the latent space of powerful pretrained autoencoders.

- Benefits of Stable Diffusion:
  1. Denoising in the latent space enables spatial complexity reduction and detail preservation.
  2. Introducing cross-attention layers enables conditional input such as texts.

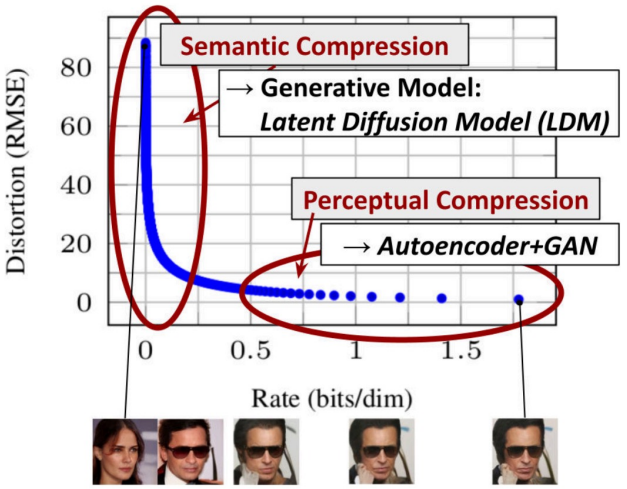
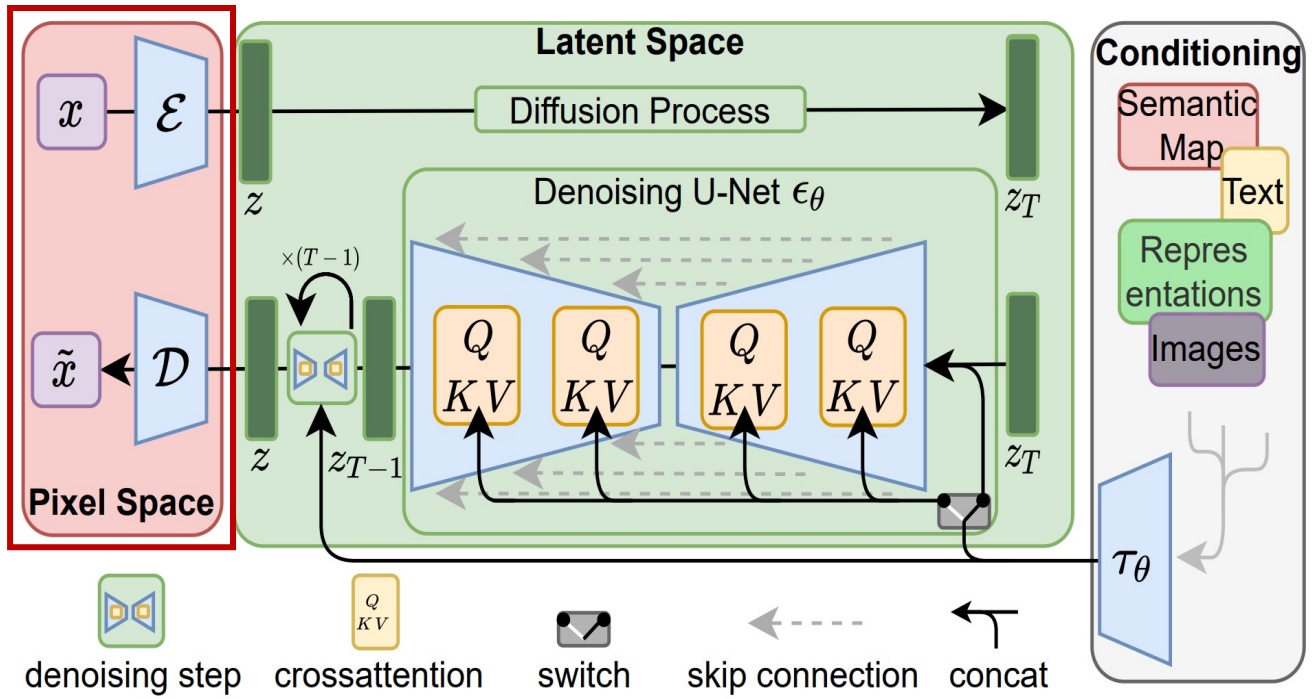


Figure 2. Illustrating perceptual and semantic compression: Most bits of a digital image correspond to imperceptible details. While DMs allow to suppress this semantically meaningless information by minimizing the responsible loss term, gradients (during training) and the neural network backbone (training and inference) still need to be evaluated on all pixels, leading to superfluous computations and unnecessarily expensive optimization and inference. We propose *latent diffusion models (LDMs)* as an effective generative model and a separate mild compression stage that only eliminates imperceptible details. Data and images from [29].

Stable Diffusion: Two-Stage Image Synthesis

- **(Stage 1) Perceptual Image Compression**: The SD framework uses a pre-trained VAE to map data into a low-dimensional space and back to the pixel space.
- Compared to the high-dimensional pixel space, the low-dimensional latent space is more suitable for likelihood-based generative models, as
  I. it focuses on the important, semantic bits of the data and
  II. trains in a low dimensional and computationally efficient space.

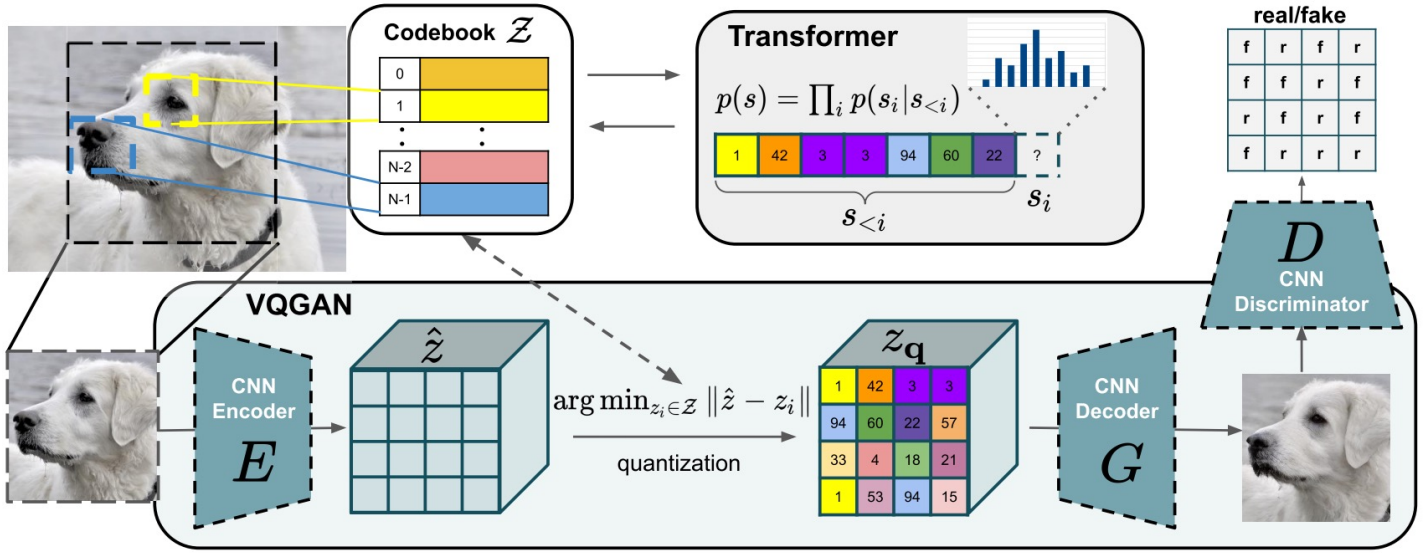


Stable Diffusion: Two-Stage Image Synthesis

- **(Stage 1) Perceptual Image Compression**: The VAE is trained by a combination of a reconstruction loss and a patch-based adversarial loss.
- It deploys a VQGAN to learn a codebook of context-rich visual parts, whose composition is modeled with an autoregressive transformer architecture.

$$L_{VQGAN} = \min_{E,G} \max_{D} \Big(L_{rec}(x, \mathrm{G}(\mathrm{E}(x))) - L_{synthetic}(\mathrm{D}(\mathrm{G}(\mathrm{E}(x)))) + L_{real}\, D(x) + L_{reg}(x; \mathrm{E}, \mathrm{G}) \Big)$$

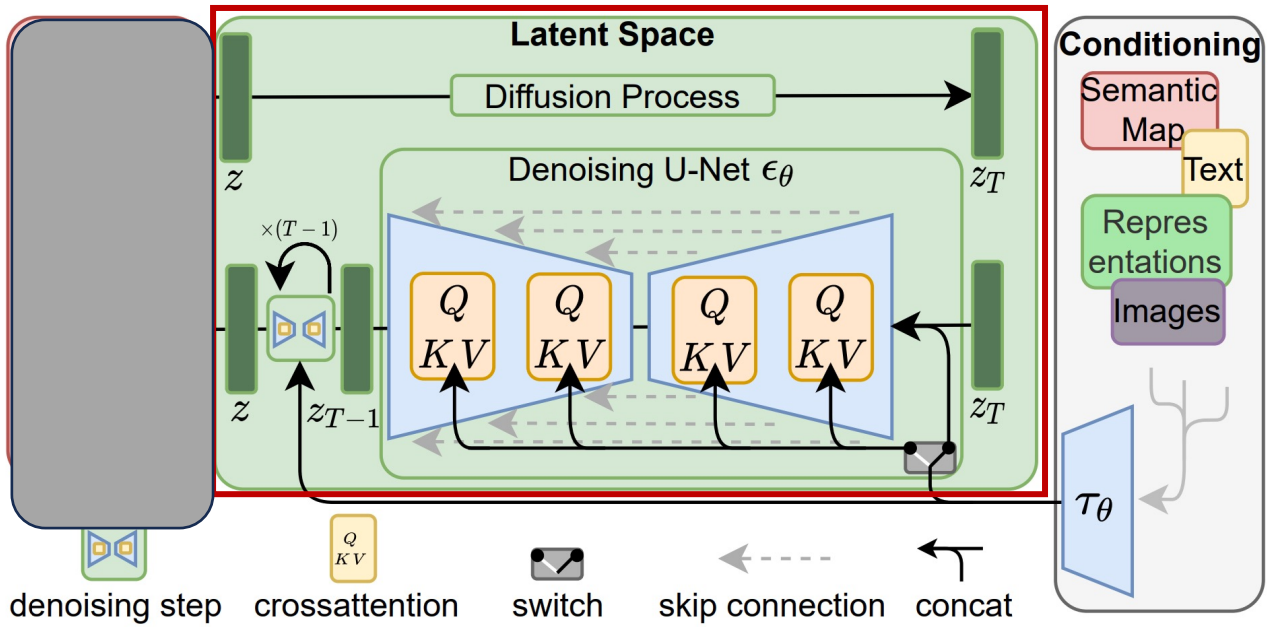
image reconstruction — differentiate original images from reconstructions



Stable Diffusion: Two-Stage Image Synthesis

- **(Stage 2) Denoising Latent Representations**: the denoising process happens in the compressed latent space of Stage 1.
- Recall that DDPM denoises the input in the image space, while the SD performs denoising for the latent code.
- The forward process deterministically adds T Gaussian noises to the original latent code z, and the reverse process learns to denoise.

Encoder and Decoder are from the Stage 1.



Stable Diffusion: Two-Stage Image Synthesis

- The neural backbone of SD is a time-conditional U-Net $\epsilon_\phi(z_t, t, \tau_\theta(\mathrm{y}))$ trained to predict the noise to be removed from the latent code z_t.
- SD augments the U-Net backbone with the cross-attention mechanism to receive conditions $\tau_\theta(\mathrm{y})$ such as textual prompts or semantic segmentations.

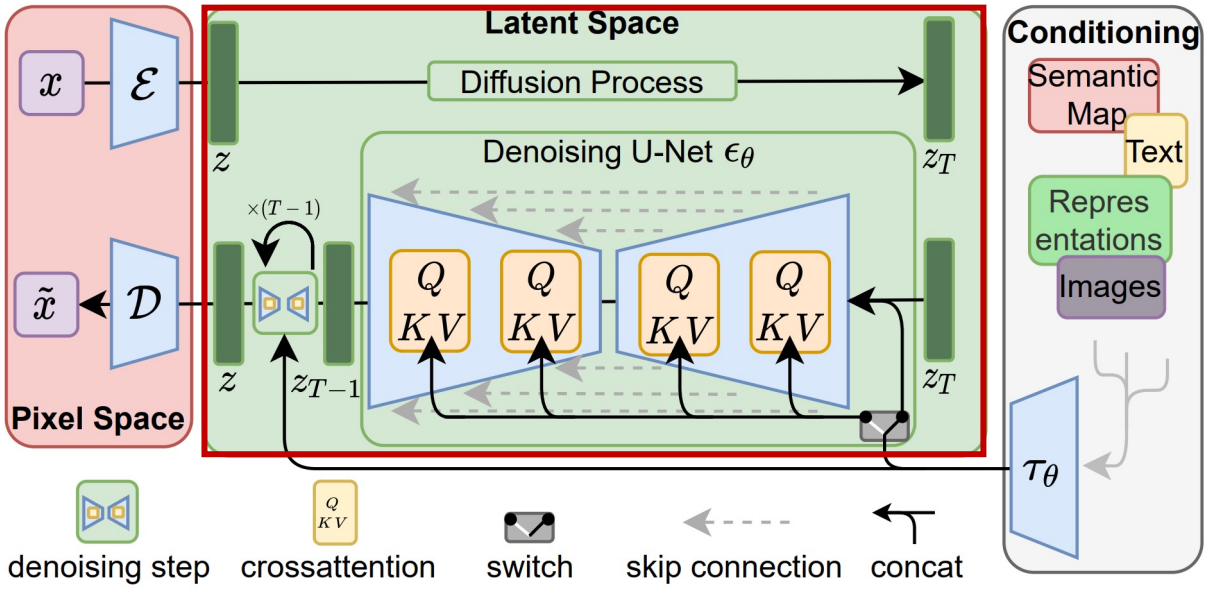
$$L_{LDM} = \mathbb{E}_{\mathcal{E}(x),\epsilon\sim\mathcal{N}(0,1),t}\left[\| \epsilon - \epsilon_\phi(z_t, t, \tau_\theta(\mathrm{y})) \|_2^2\right]$$

(flattened) visual representation from the U-Net ϵ_ϕ

Cross-attention Modules

$$Q = W_Q^{(i)} \cdot \varphi_i(z_t),$$
$$K = W_K^{(i)} \cdot \tau_\theta(y),$$
$$V = W_V^{(i)} \cdot \tau_\theta(y)$$

conditional representation such as textual prompt



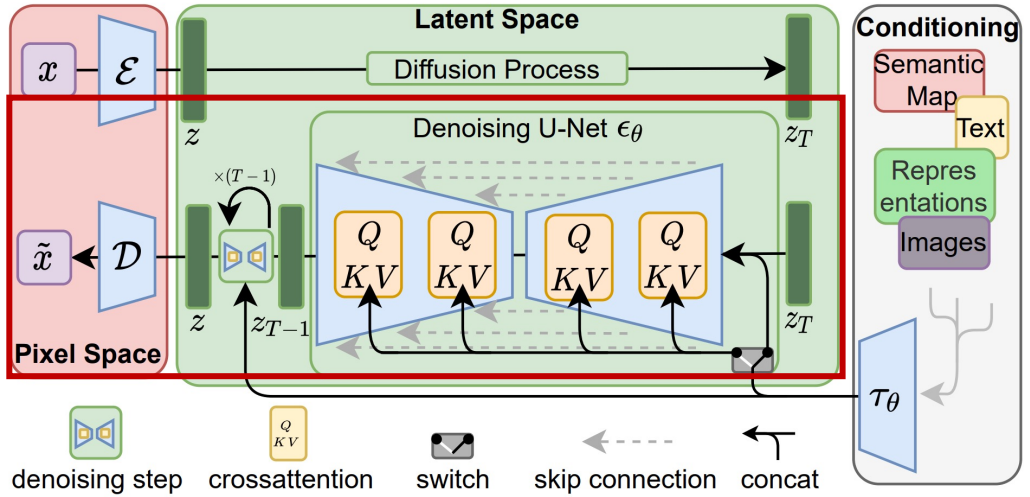
Stable Diffusion: Two-Stage Image Synthesis

- (Stage 2) **Generative Modeling of Latent Representations**: denoising happens in the compressed latent space given by Stage 1.
- Sampling of the latent code

$$z_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(z_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\,\epsilon_\phi(z_t, t, \tau_\theta(\mathrm{y}))\right) + \sqrt{\beta_t}\,\epsilon_t$$

where y is the conditioning (e.g., textual prompt, semantic segmentation).

- Generating (decoding) the image is performed using $\tilde{x} = D(z_0)$.



Unconditional Generation

- One can train a SD on a dataset of a visual domain without imposing extra conditions.
- In this case, the training of SD is similar to DDPM except that SD learns the denoising in a quantized latent space.
- Exemplary samples are provided from five unconditional stable diffusion models, each trained on a separate dataset.

Image Generation Conditioned on Layout

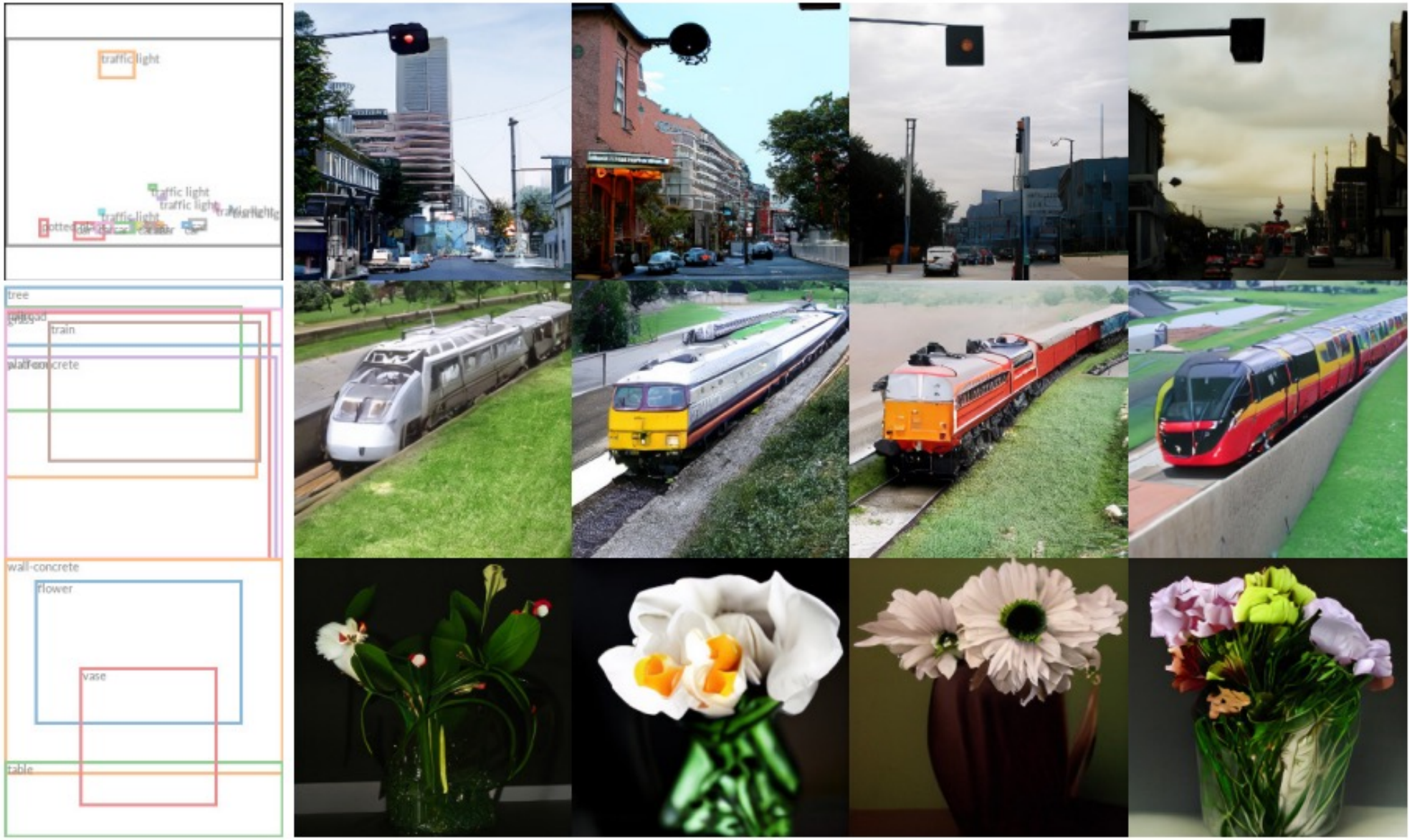
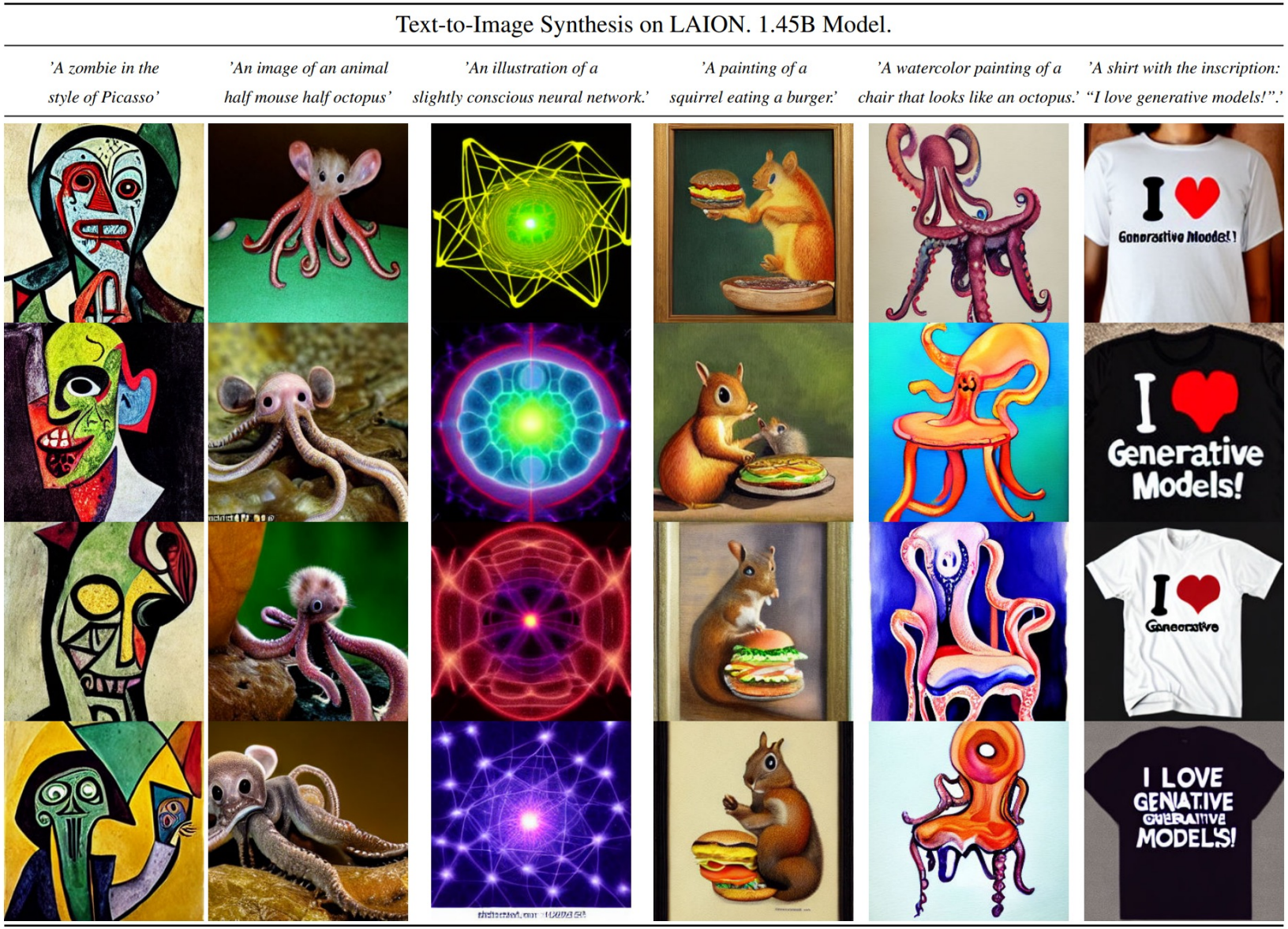


Image Generation Conditioned on Text

Details of this 1.45B Model
Training: KL-regularized
Text Conditioner: CLIP-like
Dataset: LAION-400M



Hyper-Parameters for Implementation

Task	Text-to-Image	Layout-to-Image		Class-Label-to-Image	Super Resolution	Inpainting	Semantic-Map-to-Image
Dataset	LAION	OpenImages	COCO	ImageNet	ImageNet	Places	Landscapes
f	8	4	8	4	4	4	8
z-shape	$32 \times 32 \times 4$	$64 \times 64 \times 3$	$32 \times 32 \times 4$	$64 \times 64 \times 3$	$64 \times 64 \times 3$	$64 \times 64 \times 3$	$32 \times 32 \times 4$
$\|\mathcal{Z}\|$	-	8192	16384	8192	8192	8192	16384
Diffusion steps	1000	1000	1000	1000	1000	1000	1000
Noise Schedule	linear	linear	linear	linear	linear	linear	linear
Model Size	1.45B	306M	345M	395M	169M	215M	215M
Channels	320	128	192	192	160	128	128
Depth	2	2	2	2	2	2	2
Channel Multiplier	1,2,4,4	1,2,3,4	1,2,4	1,2,3,5	1,2,2,4	1,4,8	1,4,8
Number of Heads	8	1	1	1	1	1	1
Dropout	-	-	0.1	-	-	-	-
Batch Size	680	24	48	1200	64	128	48
Iterations	390K	4.4M	170K	178K	860K	360K	360K
Learning Rate	1.0e-4	4.8e-5	4.8e-5	1.0e-4	6.4e-5	1.0e-6	4.8e-5
Conditioning	CA	CA	CA	CA	concat	concat	concat
(C)A-resolutions	32, 16, 8	32, 16, 8	32, 16, 8	32, 16, 8	-	-	-
Embedding Dimension	1280	512	512	512	-	-	-
Transformer Depth	1	3	2	1	-	-	-

Stable Diffusion as the Foundation Model

Representatives of generative vision works that take SD as the backbone:

DreamFusion: Text-to-3D using 2D Diffusion

Ben Poole[1], **Ajay Jain**[2], **Jonathan T. Barron**[1], **Ben Mildenhall**[1]
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Text2Video-Zero: Text-to-Image Diffusion Models are Zero-Shot Video Generators

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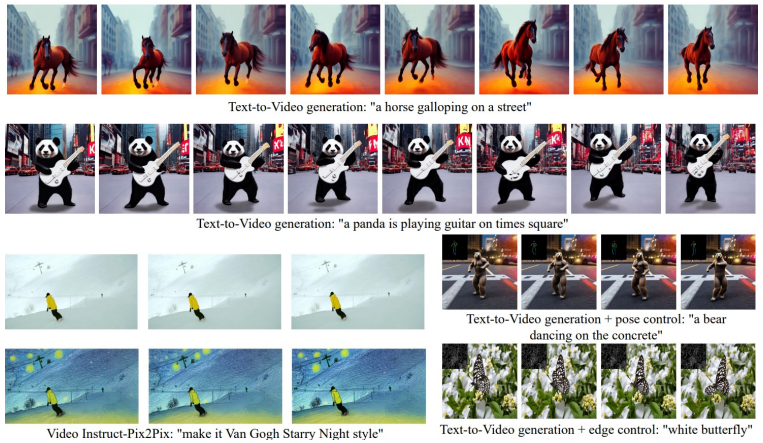
Zhangyang Wang[1,2] Shant Navasardyan[1] Humphrey Shi[1,3,4]
[1]Picsart AI Resarch (PAIR) [2]UT Austin [3]U of Oregon [4]UIUC
https://github.com/Picsart-AI-Research/Text2Video-Zero



Zero-1-to-3: Zero-shot One Image to 3D Object

Ruoshi Liu[1] Rundi Wu[1] Basile Van Hoorick[1] Pavel Tokmakov[2] Sergey Zakharov[2] Carl Vondrick[1]
[1] Columbia University [2] Toyota Research Institute
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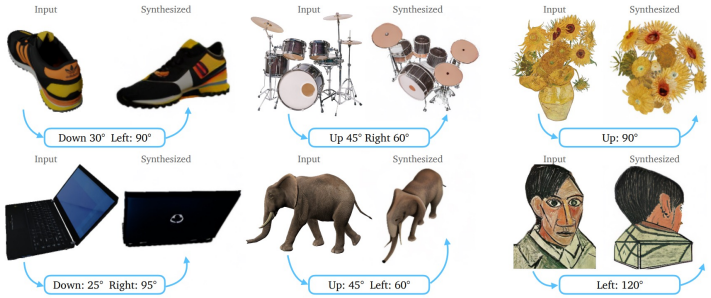


SDXL: Improving Latent Diffusion Models for High-Resolution Image Synthesis

Dustin Podell **Zion English** **Kyle Lacey** **Andreas Blattmann** **Tim Dockhorn**
Jonas Müller **Joe Penna** **Robin Rombach**
Stability AI, Applied Research

Code: https://github.com/Stability-AI/generative-models *Model weights*: https://huggingface.co/stabilityai/

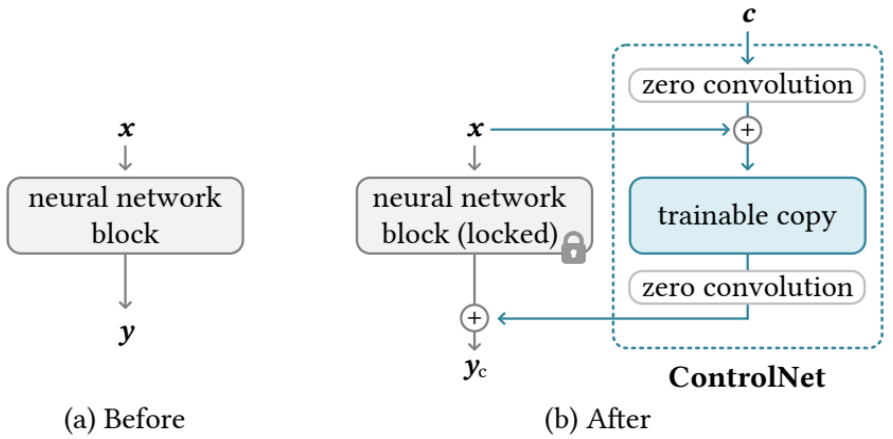
Adding Conditional Control to Text-to-Image Diffusion Models

- ControlNet is a neural network architecture that adds spatial conditioning to large pre-trained text-to-image diffusion models (e.g., Stable Diffusion).
- ControlNet allows users to add conditions like Canny edges or human pose to control the text-to-image synthesis.

Key Intuitions of ControlNet

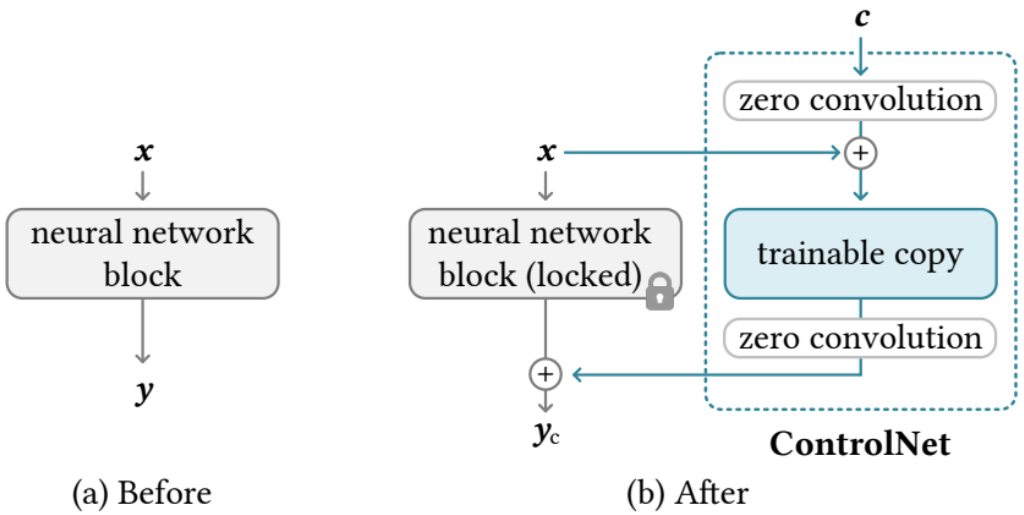
- Core idea:
  - ControlNet freezes the parameters Θ of the original generative neural block F_Θ and simultaneously clones the block to a trainable copy with parameters Θ_c.
  - The trainable copy takes an external conditioning vector c as input.

- Why it works well?
  - The locked parameters of a large model preserve the production-ready information with billions of images, while the trainable copy establishes a flexible learning paradigm for handling diverse input conditions.



MLP Layers with Zero Initialization

- The trainable copy is connected to the locked model with zero convolution layers, denoted $Z(\cdot;\cdot)$.
- Specifically, $Z(\cdot;\cdot)$ is a convolution or MLP layer with both weight and bias initialized to zeros.



$$\boldsymbol{y}_c = \mathcal{F}(\boldsymbol{x};\Theta) + \mathcal{Z}(\mathcal{F}\left(\boldsymbol{x} + \mathcal{Z}\left(\mathbf{c};\Theta_{z_1}\right);\Theta_c\right);\Theta_{z_2})$$

Gradient Calculation of A Zero Initialization Layer

- Consider a linear layer with weight W and bias $\boldsymbol{B}$ at spatial position p and channel-wise index i. Given an input map $\boldsymbol{I} \in R^{h \times w \times c}$, the forward pass can be written as

$$\mathcal{Z}(\boldsymbol{I}; \{\boldsymbol{W}, \boldsymbol{B}\})_{p,i} = \boldsymbol{B}_i + \sum_j^c \boldsymbol{I}_{p,j} W_{i,j}$$

- A zero Initialization layer is initialized with $\boldsymbol{W} = \boldsymbol{0}$ and $\boldsymbol{B} = \boldsymbol{0}$. The gradient for anywhere that $\boldsymbol{I}_{p,i} \neq 0$ is that:

$$\begin{cases} \dfrac{\partial \mathcal{Z}(\boldsymbol{I}; \{\boldsymbol{W}, \boldsymbol{B}\})_{p,i}}{\partial \boldsymbol{B}_i} = 1, \\ \dfrac{\partial \mathcal{Z}(\boldsymbol{I}; \{\boldsymbol{W}, \boldsymbol{B}\})_{p,i}}{\partial \boldsymbol{I}_{p,i}} = \sum_j^c W_{i,j} = 0 \\ \dfrac{\partial \mathcal{Z}(\boldsymbol{I}; \{\boldsymbol{W}, \boldsymbol{B}\})_{p,i}}{\partial \boldsymbol{W}_{i,j}} = \boldsymbol{I}_{p,j} \neq \boldsymbol{0} \end{cases}$$

- The gradients for updating the weight and bias are not always zero.

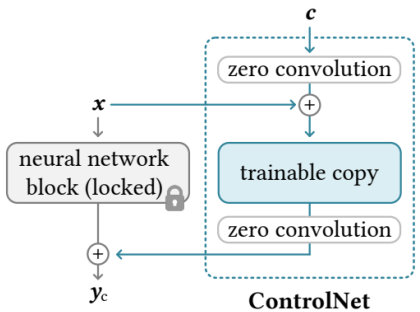
ControlNet for Stable Diffusion

- The ControlNet structure is applied to each encoder level of the U-Net.

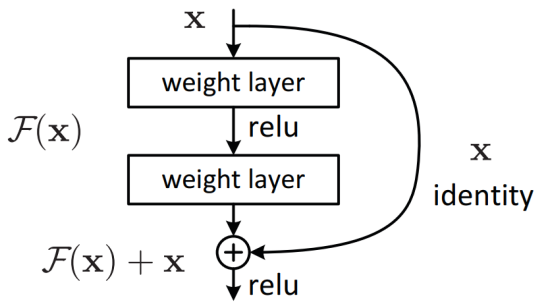
- An analogy with Residual Learning:

  Original SD: Y = Generator(X)

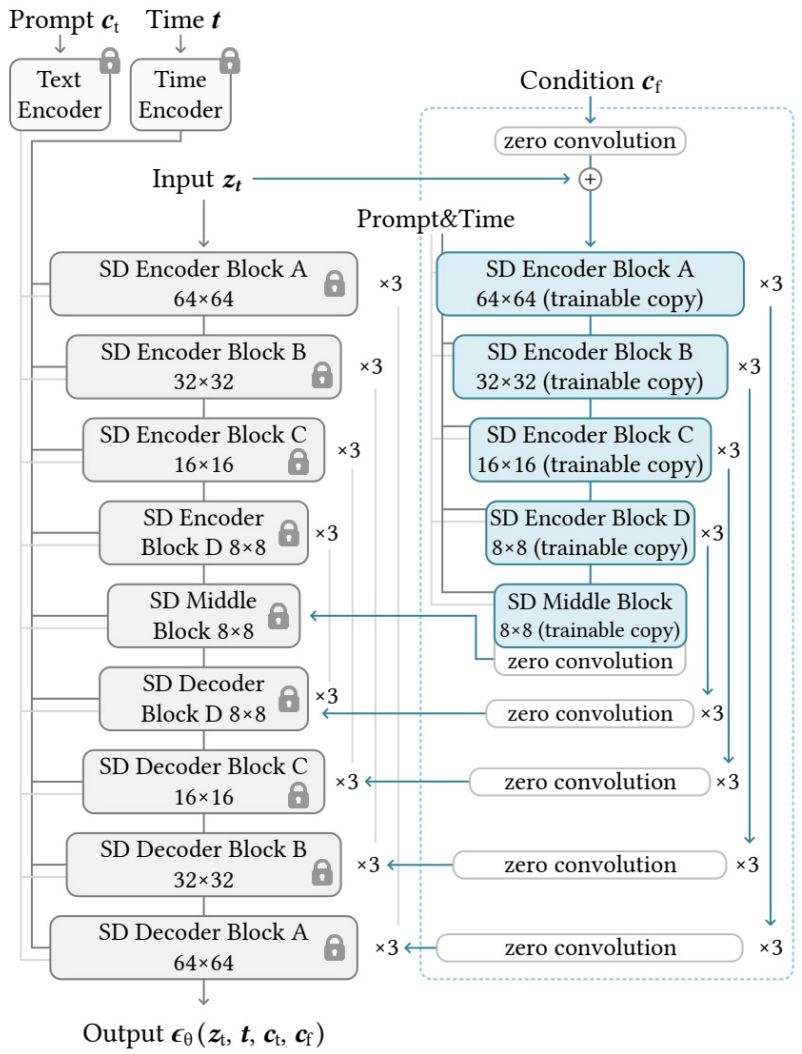
  ControlNet: Y = Generator(X) + ControlNet(X, C)



ControlNet

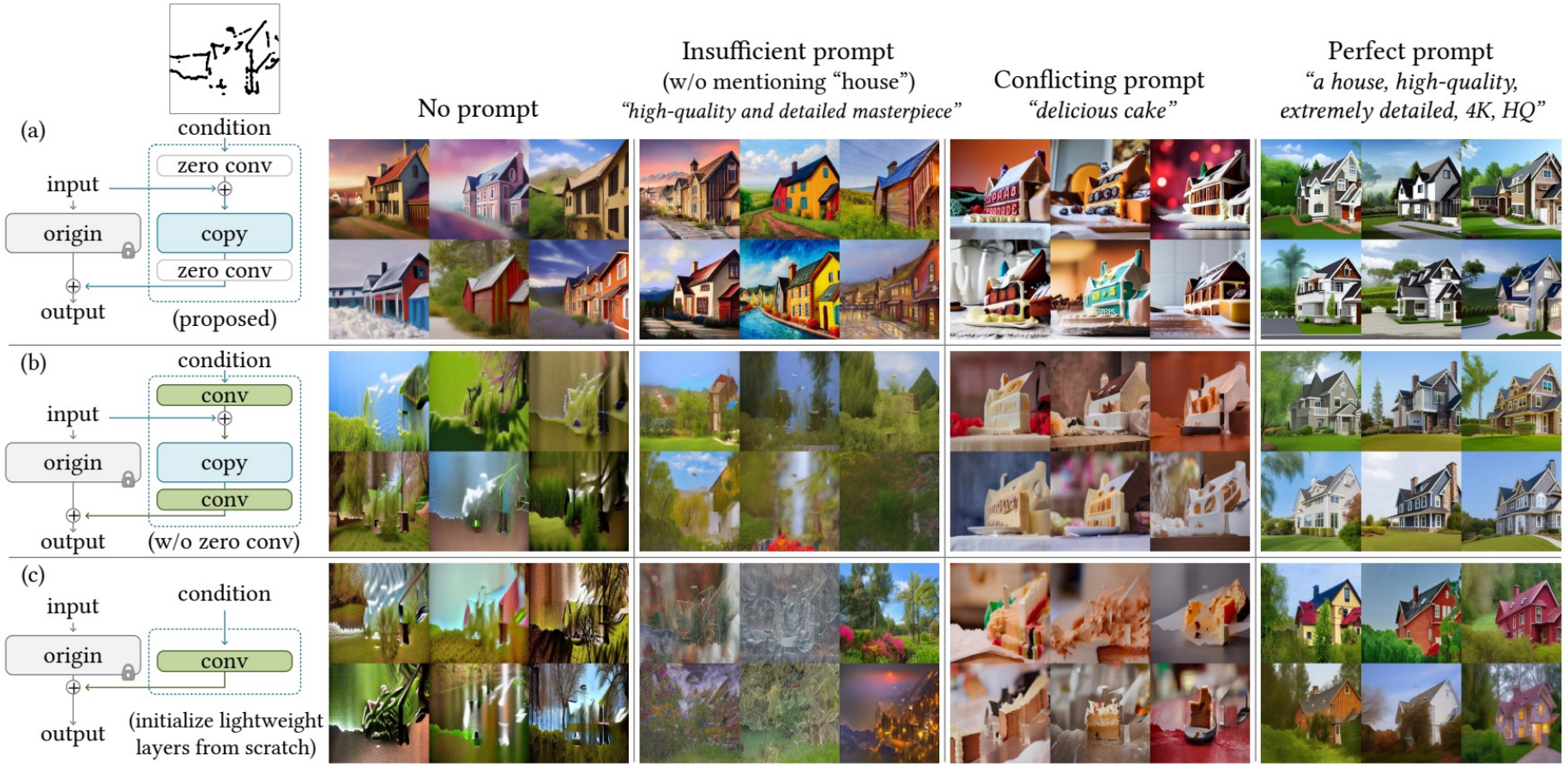


Residual Learning
[He et al., 2015]



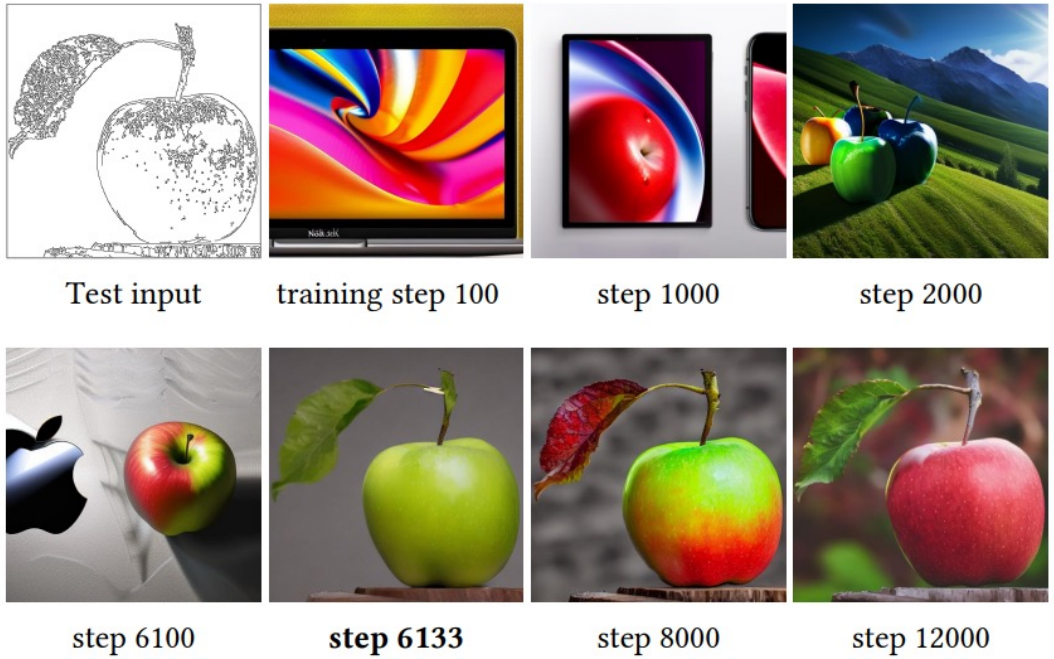
Does Zero Initialization Help?

- The ablation study indicates that zero initialization is beneficial for ControlNet.



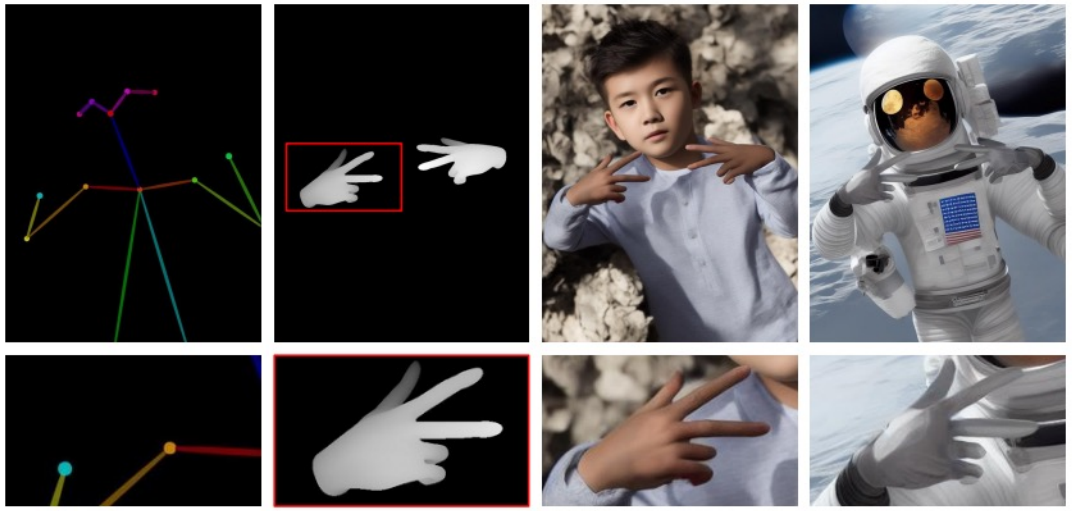
Training Results

- ControlNet supports conditioning on multiple modalities.
- Examples: Canny edge, human pose.



(a) Input Canny map (b) W/o CFG (c) W/o CFG-RW (d) Full (w/o prompt)

Figure 5: Effect of Classifier-Free Guidance (CFG) and the proposed CFG Resolution Weighting (CFG-RW).



Multiple condition (pose&depth) "boy" "astronaut"

Figure 6: Composition of multiple conditions. We present the application to use depth and pose simultaneously.

Hough Lines and User Scribble

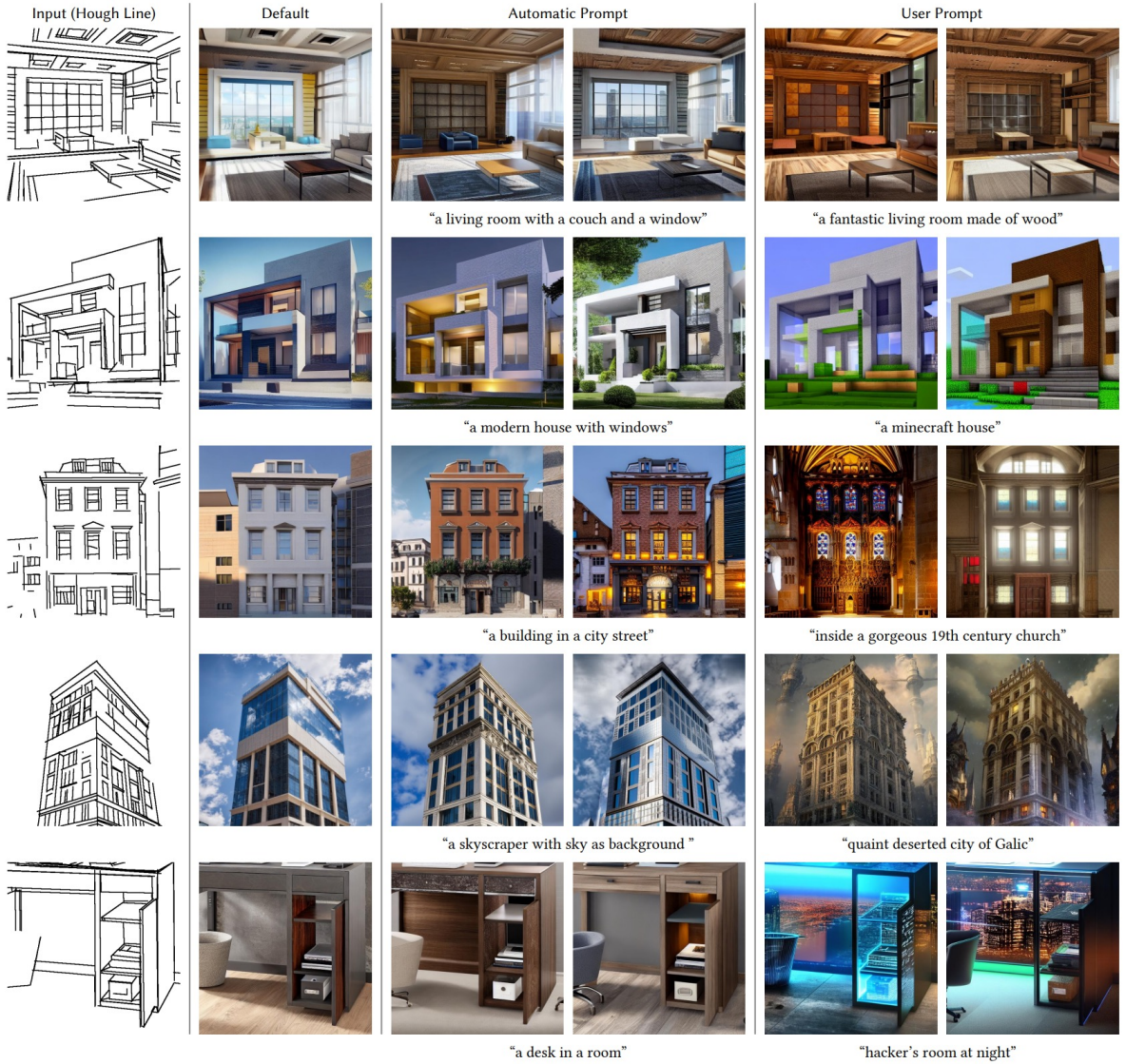


Figure 9: Controlling Stable Diffusion with Hough lines (M-LSD). The “automatic prompts” are generated by BLIP based on the default result images without using user prompts. See also the Appendix for source images for line detection.

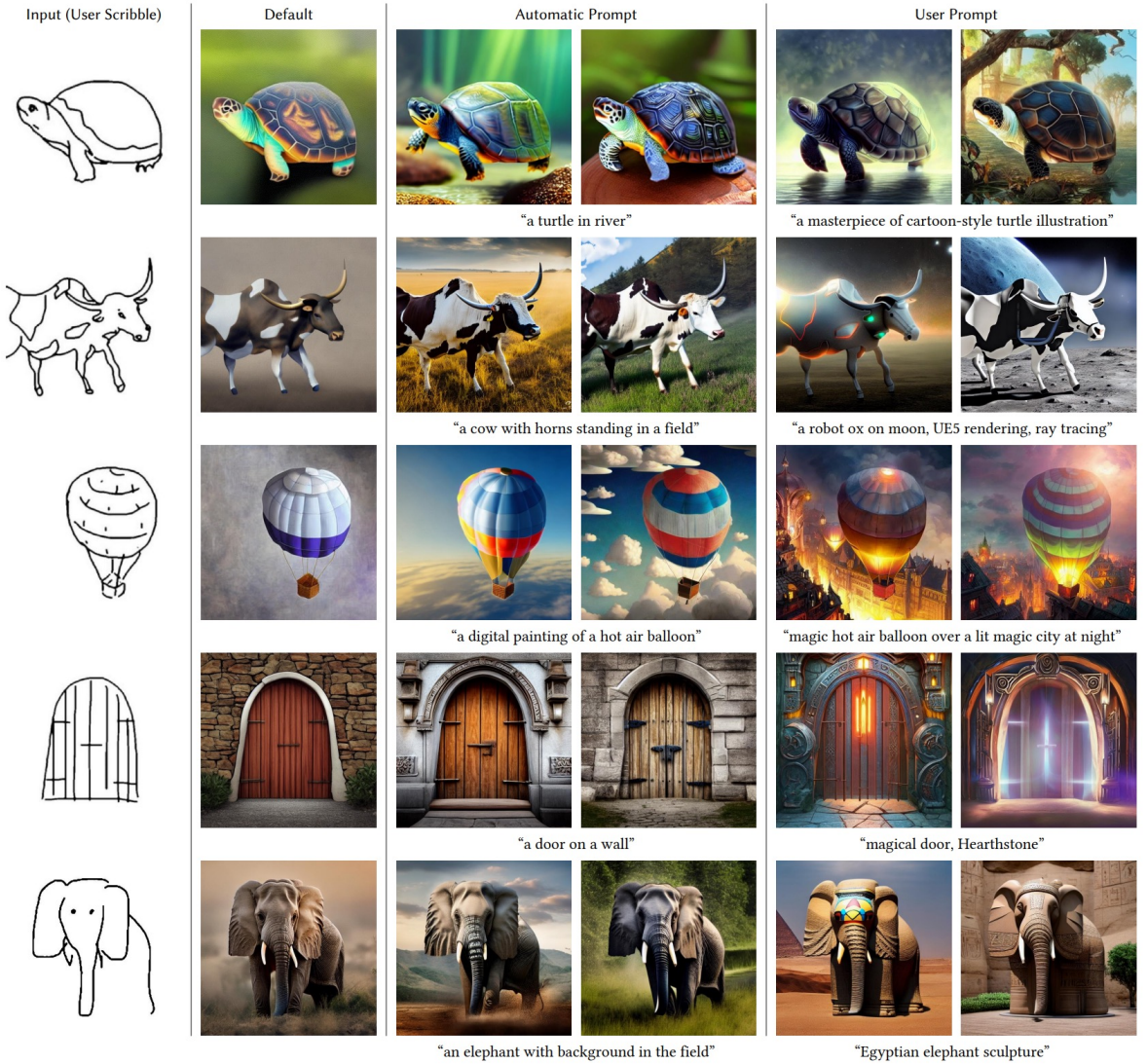


Figure 10: Controlling Stable Diffusion with Human scribbles. The “automatic prompts” are generated by BLIP based on the default result images without using user prompts. These scribbles are from [19].

Segmentation and Human Pose

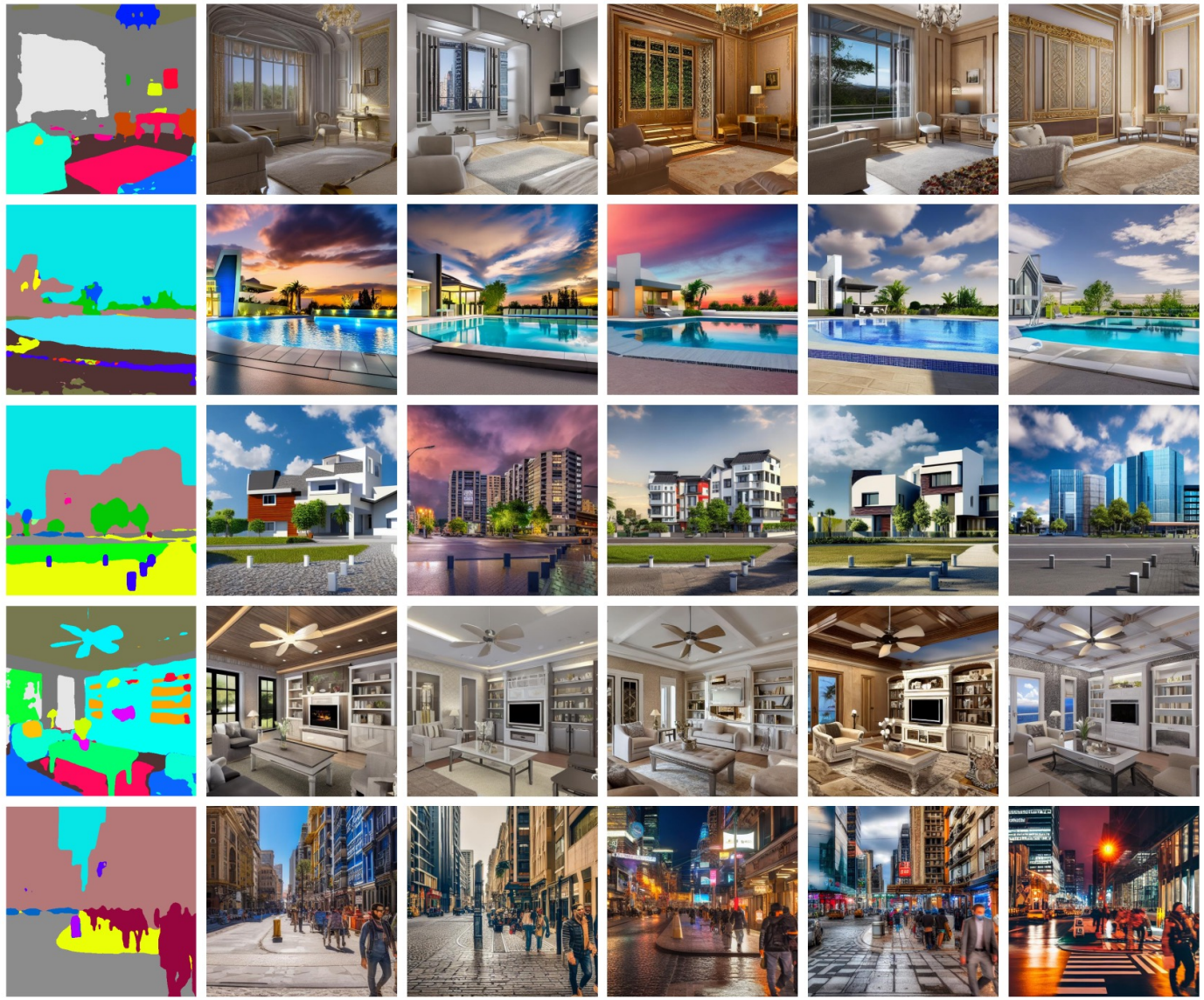


Figure 15: Controlling Stable Diffusion with ADE20K segmentation map. All results are achieved with default prompt. See also the Appendix for source images for semantic segmentation map extraction.

"Michael Jackson's concert"