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# Adding Conditional Control to Text-to-Image Diffusion Models

*Zhang, L., Rao, A., & Agrawala, M. (2023)*

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# Abstract

- ControlNet, a neural network architecture to add spatial conditioning controls to large, pretrained text-to-image diffusion models.
- Reuses their deep and robust encoding layers pretrained with billions of images to learn a diverse set of conditional controls.
- Connected with “zero convolutions” (zero-initialized convolution layers) that progressively grow the parameters from zero and ensure that no harmful noise could affect the finetuning.
- Test various conditioning controls, e.g., edges, depth, segmentation, human pose, etc.
- The training of ControlNets is robust with small (<50k) and large (>1m) datasets.
- Extensive results show that ControlNet may facilitate wider applications to control image diffusion models.

# Introduction


Figure 1: Controlling Stable Diffusion with learned conditions. ControlNet allows users to add conditions like Canny edges (top), human pose (bottom), *etc*., to control the image generation of large pretrained diffusion models. The default results use the prompt "a high-quality, detailed, and professional image". Users can optionally give prompts like the "chef in kitchen".

# ControlNet

- ControlNet is a neural network architecture that can enhance large pretrained text-to-image diffusion models with spatially localized.
- ControlNet injects additional conditions into the blocks of a neural network.
- *network block* to refer to a set of neural layers that are commonly put together to form a single unit of a neural network.
- Suppose *F*(·; Θ) is such a trained neural block, with parameters Θ, that transforms an input feature map ***x***, into another feature map ***y*** as

$$\boldsymbol{y} = \mathcal{F}(\boldsymbol{x}; \Theta). \qquad (1)$$

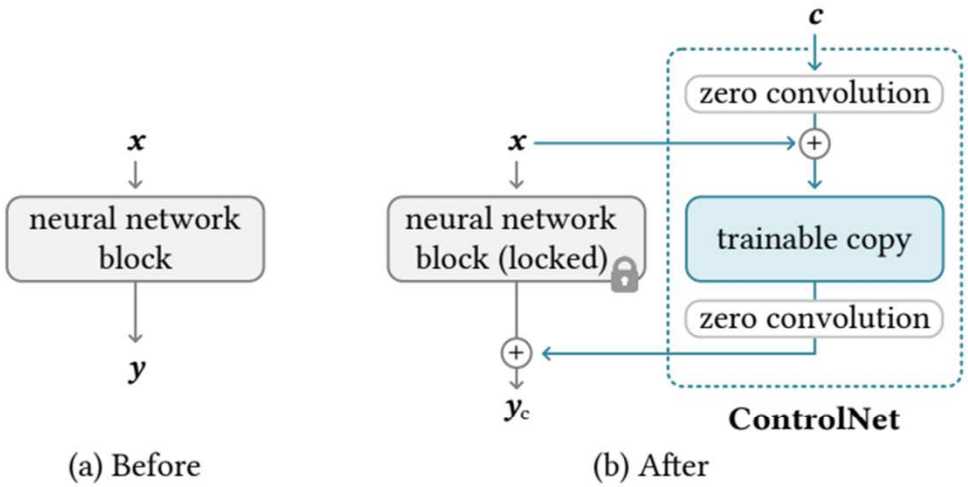
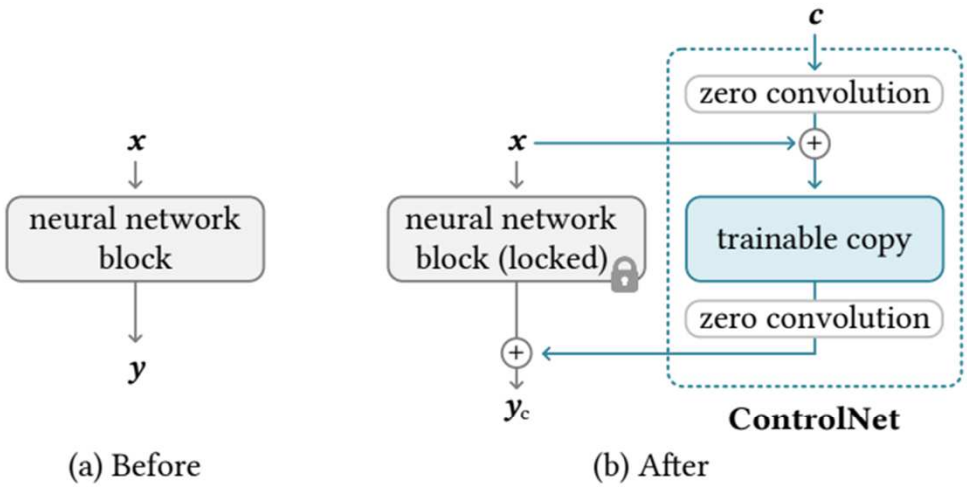



Figure 2: A neural block takes a feature map $x$ as input and outputs another feature map $y$, as shown in (a). To add a ControlNet to such a block we lock the original block and create a trainable copy and connect them together using zero convolution layers, *i.e.*, $1 \times 1$ convolution with both weight and bias initialized to zero. Here $c$ is a conditioning vector that we wish to add to the network, as shown in (b).

# ControlNet

- lock (freeze) the parameters Θ of the original block and simultaneously clone the block to a *trainable copy* with parameters Θc.
- Applied to large models Stable Diffusion, the locked parameters preserve the production-ready model trained with billions of images.
- The trainable copy is connected to the locked model with *zero convolution* layers, denoted $\mathcal{Z}(\cdot;\cdot)$. To build up a ControlNet, we use two instances of zero convolutions with parameters Θz1 and Θz2 respectively. The complete ControlNet then computes

$$\boldsymbol{y}_c = \mathcal{F}(\boldsymbol{x};\Theta) + \mathcal{Z}(\mathcal{F}(\boldsymbol{x} + \mathcal{Z}(\boldsymbol{c};\Theta_{z1});\Theta_c);\Theta_{z2}), \quad (2)$$

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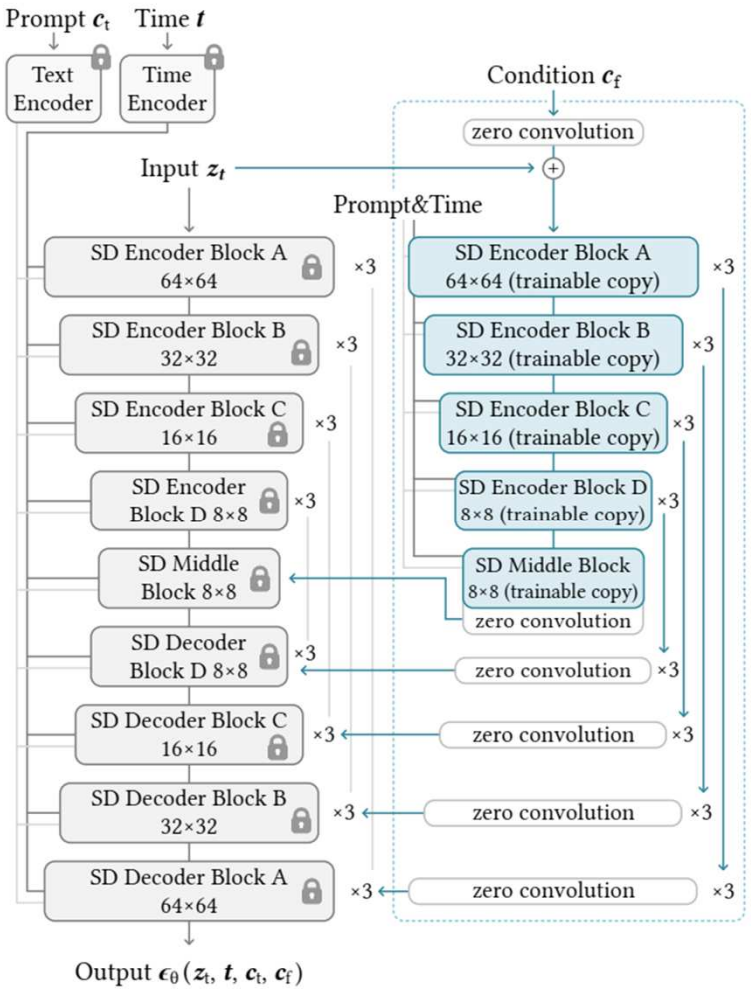
# ControlNet for Text-to-Image Diffusion




Both the encoder and decoder contain 12 blocks, and the full model contains 25 blocks, including the middle block.

Of the 25 blocks, 8 blocks are down-sampling or up-sampling convolution layers, while the other 17 blocks are main blocks that each contain 4 resnet layers and 2 Vision Transformers (ViTs)

“SD Encoder Block A” contains 4 resnet layers and 2 ViTs

Figure 3: Stable Diffusion’s U-net architecture connected with a ControlNet on the encoder blocks and middle block. The locked, gray blocks show the structure of Stable Diffusion V1.5 (or V2.1, as they use the same U-net architecture). The trainable blue blocks and the white zero convolution layers are added to build a ControlNet.

# Training

- Given an input image ***z***0, image diffusion algorithms progressively add noise to the image and produce a noisy image ***z****t*, where *t* represents the number of times noise is added. Given a set of conditions including time step ***t***, text prompts ***c****t*, as well as a task-specific condition ***c***f, image diffusion algorithms learn a network $\epsilon$ to predict the noise added to the noisy image ***z****t* with

$$\mathcal{L} = \mathbb{E}_{\boldsymbol{z}_0, \boldsymbol{t}, \boldsymbol{c}_t, \boldsymbol{c}_\mathrm{f}, \epsilon \sim \mathcal{N}(0,1)} \left[ \| \epsilon - \epsilon_\theta(\boldsymbol{z}_t, \boldsymbol{t}, \boldsymbol{c}_t, \boldsymbol{c}_\mathrm{f})) \|_2^2 \right],$$

- Where L is the overall learning objective of the entire diffusion model.
- Randomly replace 50% text prompts ct with empty strings. This approach increases ControlNet's ability to directly recognize semantics

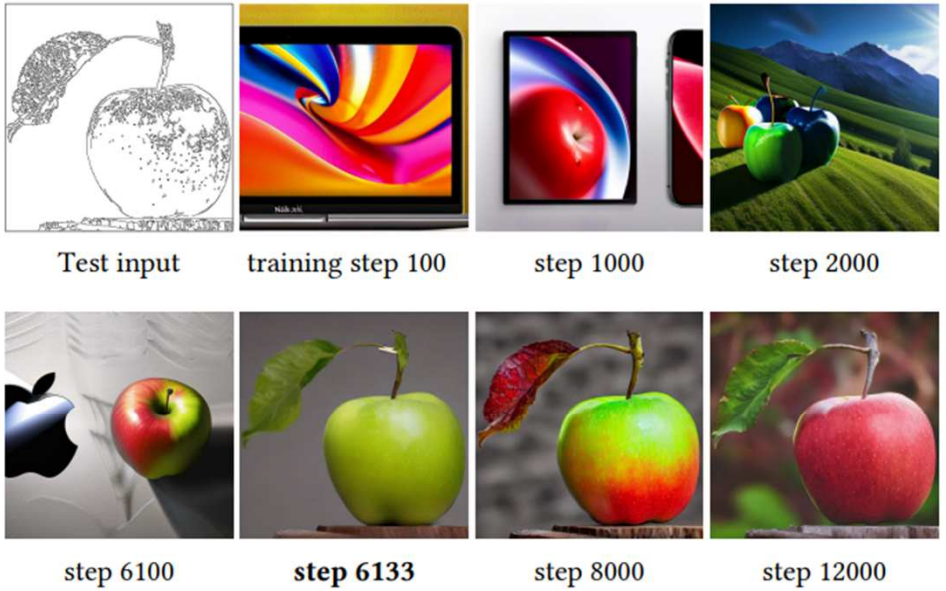


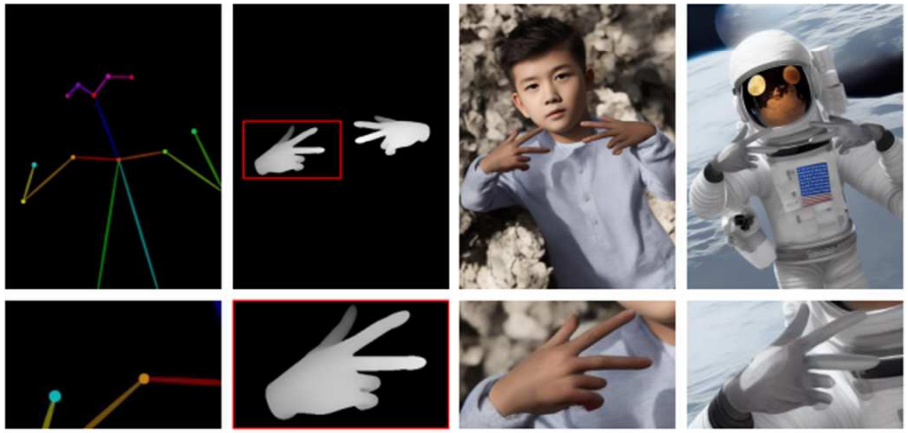

Figure 4: The sudden convergence phenomenon. Due to the zero convolutions, ControlNet always predicts high-quality images during the entire training. At a certain step in the training process (*e.g.*, the 6133 steps marked in bold), the model suddenly learns to follow the input condition.

# Inference

- We can further control how the extra conditions of ControlNet affect the denoising diffusion process in several ways.
- **Classifier-free guidance resolution weighting.** CFG is formulated as $\epsilon prd = \epsilon uc + \beta cfg(\epsilon c - \epsilon uc)$ where $\epsilon prd$, $\epsilon uc$, $\epsilon c$, $\beta cfg$ are the model's final output, unconditional output, conditional output, and a user-specified weight respectively.
- **Composing multiple ControlNets.** To apply multiple conditioning images (*e.g.*, Canny edges, and pose) to a single instance of Stable Diffusion

(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.

# Inference

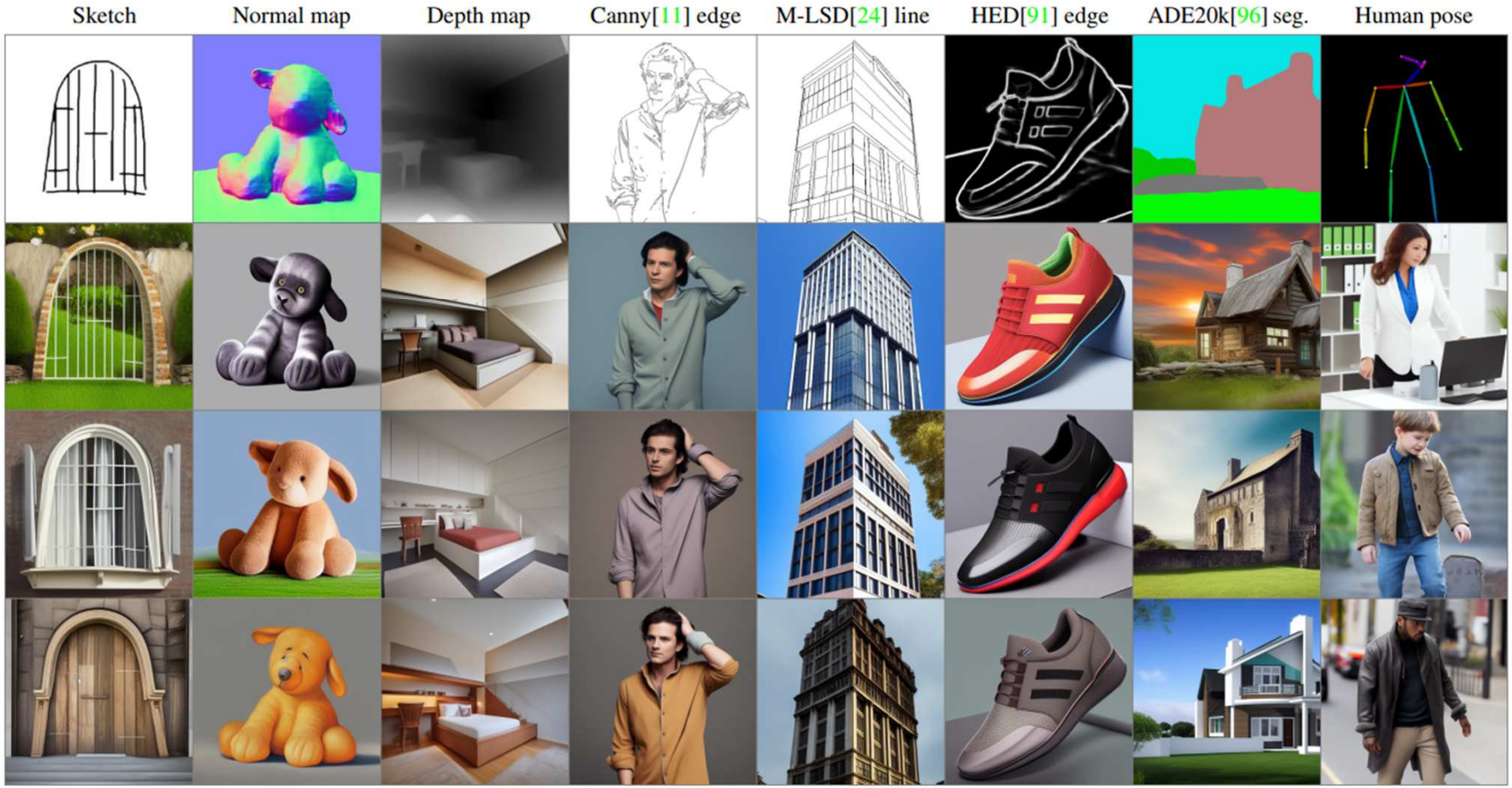



Figure 7: Controlling Stable Diffusion with various conditions **without prompts**. The top row is input conditions, while all other rows are outputs. We use the empty string as input prompts. All models are trained with general-domain data. The model has to recognize semantic contents in the input condition images to generate images.

# Experiment

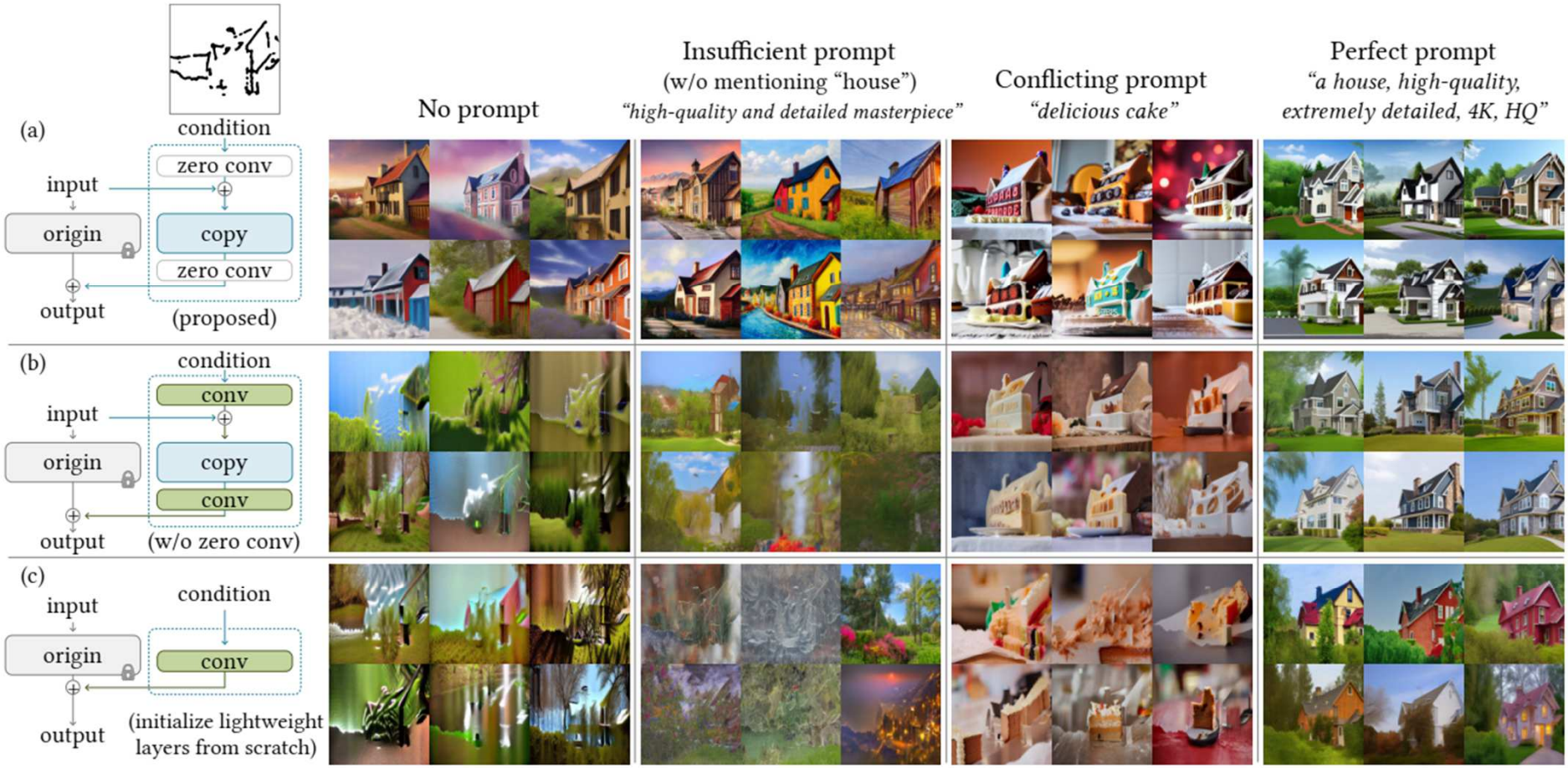



Figure 8: Ablative study of different architectures on a sketch condition and different prompt settings. For each setting, we show a random batch of 6 samples without cherry-picking. Images are at 512 × 512 and best viewed when zoomed in. The green "conv" blocks on the left are standard convolution layers initialized with Gaussian weights.

# Experiment

| Method | Result Quality ↑ | Condition Fidelity ↑ |
|---|---|---|
| PITI [89](sketch) | $1.10 \pm 0.05$ | $1.02 \pm 0.01$ |
| Sketch-Guided [88] ($\beta = 1.6$) | $3.21 \pm 0.62$ | $2.31 \pm 0.57$ |
| Sketch-Guided [88] ($\beta = 3.2$) | $2.52 \pm 0.44$ | $3.28 \pm 0.72$ |
| ControlNet-lite | $3.93 \pm 0.59$ | $4.09 \pm 0.46$ |
| ControlNet | $\mathbf{4.22 \pm 0.43}$ | $\mathbf{4.28 \pm 0.45}$ |

Table 1: Average User Ranking (AUR) of result quality and condition fidelity. We report the user preference ranking (1 to 5 indicates worst to best) of different methods.

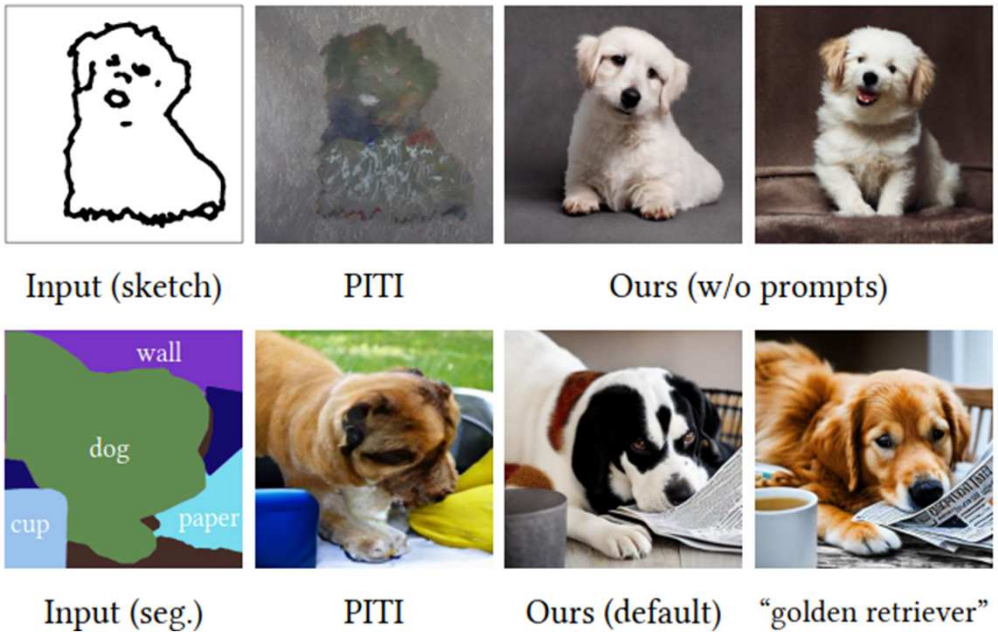
| ADE20K (GT) | VQGAN [19] | LDM [72] | PITI [89] | ControlNet-lite | ControlNet |
|---|---|---|---|---|---|
| $0.58 \pm 0.10$ | $0.21 \pm 0.15$ | $0.31 \pm 0.09$ | $0.26 \pm 0.16$ | $0.32 \pm 0.12$ | $\mathbf{0.35 \pm 0.14}$ |

Table 2: Evaluation of semantic segmentation label reconstruction (ADE20K) with Intersection over Union (IoU ↑).

| Method | FID ↓ | CLIP-score ↑ | CLIP-aes. ↑ |
|---|---|---|---|
| Stable Diffusion | 6.09 | 0.26 | 6.32 |
| VQGAN [19](seg.)* | 26.28 | 0.17 | 5.14 |
| LDM [72](seg.)* | 25.35 | 0.18 | 5.15 |
| PITI [89](seg.) | 19.74 | 0.20 | 5.77 |
| ControlNet-lite | 17.92 | 0.26 | 6.30 |
| ControlNet | 15.27 | 0.26 | 6.31 |

Table 3: Evaluation for image generation conditioned by semantic segmentation. We report FID, CLIP text-image score, and CLIP aesthetic scores for our method and other baselines. We also report the performance of Stable Diffusion without segmentation conditions. Methods marked with "*" are trained from scratch.

# Experiment



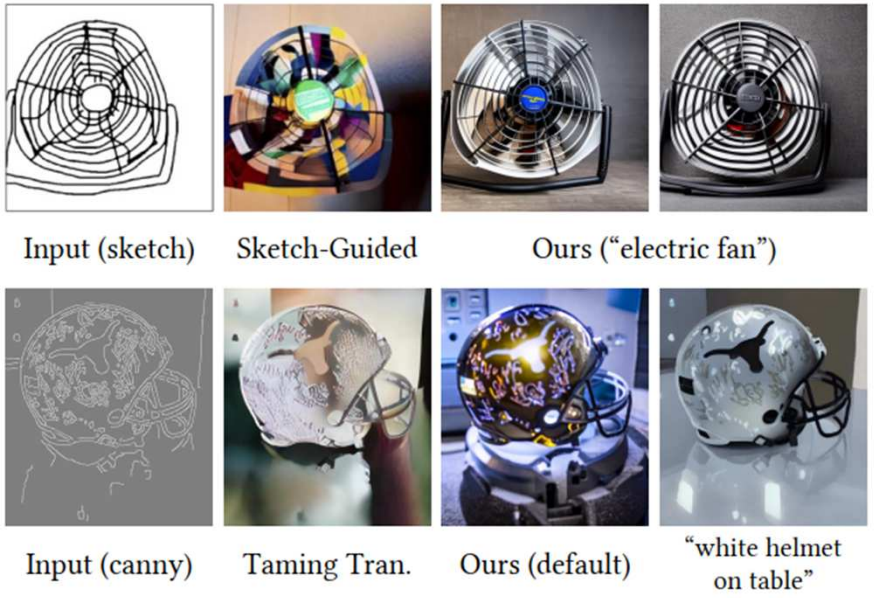
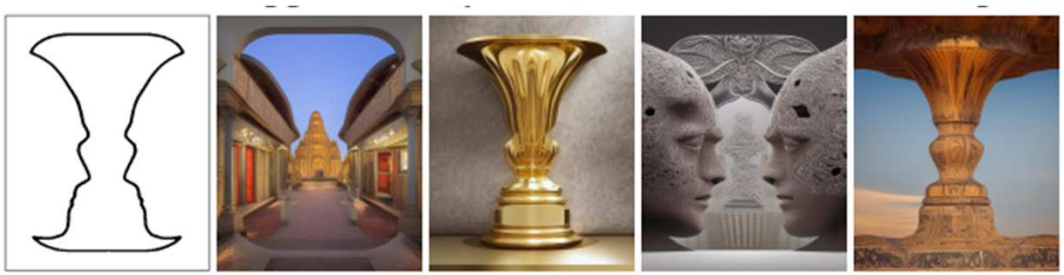




Figure 9: Comparison to previous methods.We present the qualitative comparisons to PITI [89], Sketch-Guided Diffusion [88], and Taming Transformers [19].

# Experiment

"Lion" 1k images 50k images 3m images

Figure 10: The influence of different training dataset sizes. See also the supplementary material for extended examples.



Input "a high-quality and extremely detailed image"

Figure 11: Interpreting contents. If the input is ambiguous and the user does not mention object contents in prompts, the results look like the model tries to interpret input shapes.

# Experiment


Figure 12: Transfer pretrained ControlNets to community models [16, 61] without training the neural networks again.

# THANK YOU

## Question & Answer