ControlNet

Links

https://learnopencv.com/controlnet/#How-ControlNet-Works? - Кратко

https://arxiv.org/abs/2302.05543 - Статья

https://lllyasviel.github.io/misc/202309/cnet_supp.pdf - supplementary materials.

Проблема

The largest datasets for various specific problems (e.g., object shape/normal, human pose extraction, etc.) are usually about 100K in size, which is 50,000 times smaller than the LAION-5B [79] dataset

The direct finetuning or continued training of a large pretrained model with limited data may cause overfitting and catastrophic forgetting

Общая идея

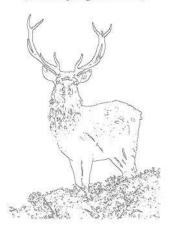
- разработать стратегию fine-tune для больших моделей не требующую огромных выч. мощ.
- как можно более четко управлять доменом

Решение:

- end-to-end архитектура для обучения моделей специфическим задачам
- скопируем веса (не все) и будем учить не их, а их копии



Source image (for canny edge detection)



Canny edge (input)

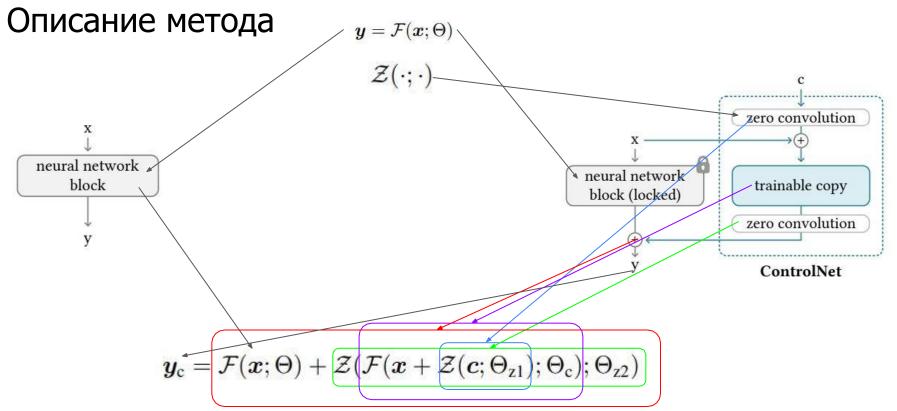








Generated images (output)



where non-zero gradients are obtained and the neural network begins to learn. In this way, the zero convolutions become a unique type of connection layer that progressively grows parameters from zero to optimized values in a learned way.

Gradient Calculation of Zero Convolution Layers

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

$$\begin{cases} \mathcal{Z}(c; \Theta_{z1}) = \boldsymbol{0} \\ \mathcal{F}(\boldsymbol{x} + \mathcal{Z}(c; \Theta_{z1}); \Theta_c) = \mathcal{F}(\boldsymbol{x}; \Theta_c) = \mathcal{F}(\boldsymbol{x}; \Theta) \\ \mathcal{Z}(\mathcal{F}(\boldsymbol{x} + \mathcal{Z}(c; \Theta_{z1}); \Theta_c); \Theta_{z2}) = \mathcal{Z}(\mathcal{F}(\boldsymbol{x}; \Theta_c); \Theta_{z2}) = \boldsymbol{0} \end{cases}$$

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

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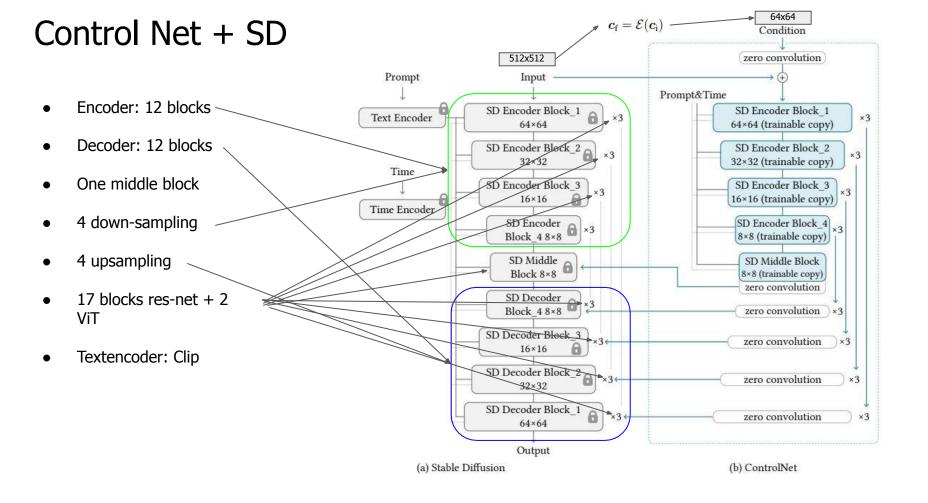
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Обучение

- z_0 начальное изображение
- z_{t} зашумленное изображение на последнем шаге
- t кол-во шагов зашумления
- $oldsymbol{c}_t$ текстовый промт
- \mathbf{c}_{f} наше условие которому учим
- $\epsilon_{ heta}$ семейство зашумляющих сетей

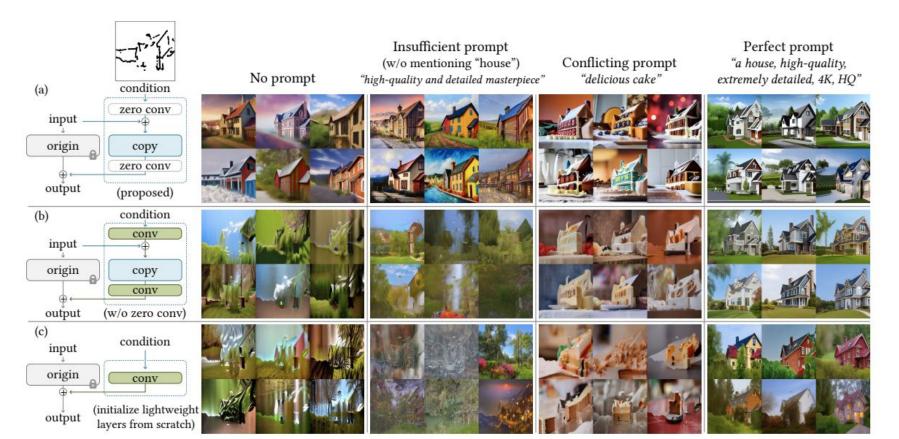
лосс функция

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

Детали обучения:

- рандомно меняем промты на пустые
- Small-Scale Training
 - "SD Middle Block" and "SD Decoder Block 1,2,3,4"
 - убрать skip-connect из D
 увеличит скорость в 1.6 (потом можно вернуть и дотюнить)
- Large-Scale Training
 - если много GPU
 - если много данных (пару лимонов)
 - можно учить ControlNet 50k
 итераций, а потом разлочить и
 учить всю диффузию

Ablation Study Zero Convolution



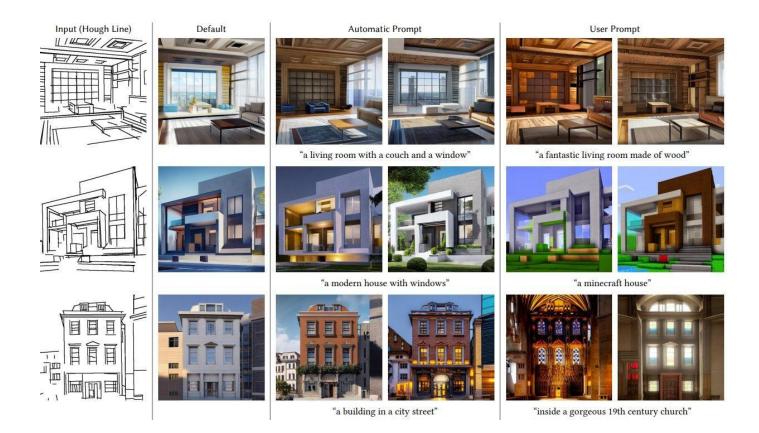
Результаты

- имеем подход позволяющий сократить ресурсы при дообучении
- можно брать небольшой датасет и не оверфитнуться!
- бери доп. условие которое надо и тюнь диффузию
- на 23% нужно больше GPU и на 34% больше времени на 1 итерацию по сравнению со SD

Canny Edge



Hough lines



Human scribbles



Controlling Stable Diffusion with Openpose

