InstructPix2Pix: Learning to Follow Image Editing Instructions

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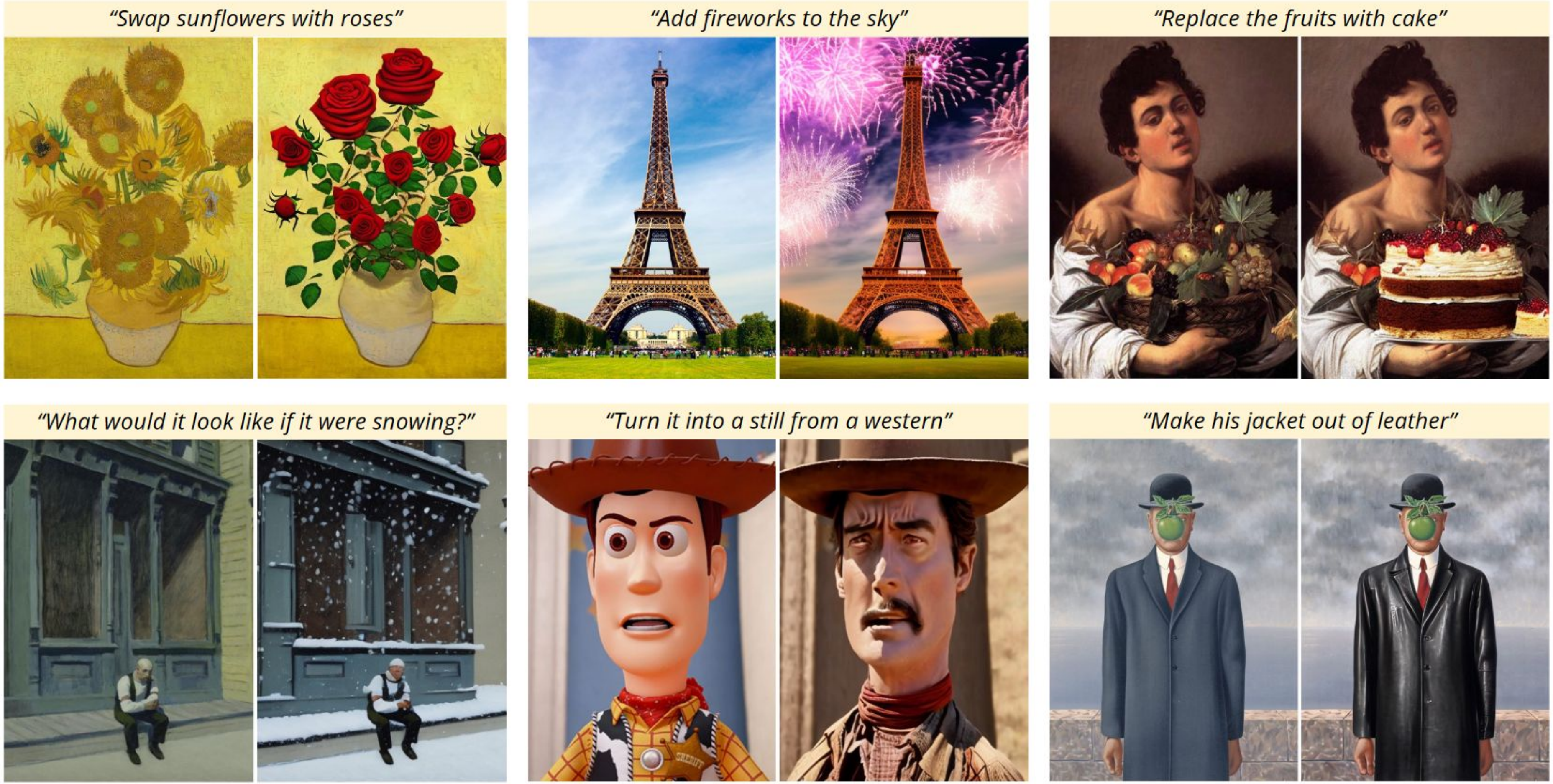


"Swap sunflowers with roses"

"Add fireworks to the sky"

"Replace the fruits with cake"

"What would it look like if it were snowing?"

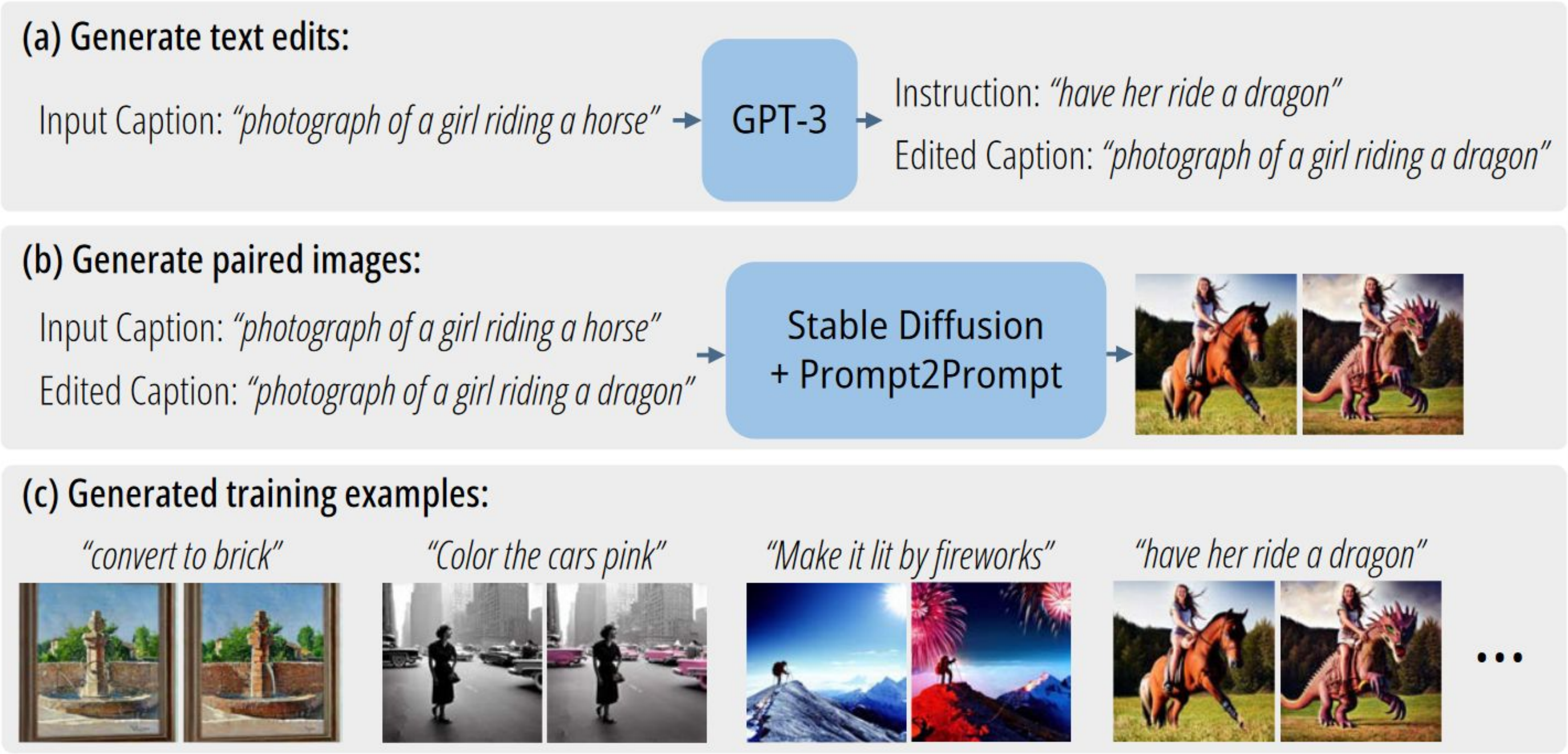
"Turn it into a still from a western"

"Make his jacket out of leather"

Генерация данных

Набор данных LAION-Aesthetics из картинок и подписей к ним.
(625K пар)

Генерация данных



(a) Generate text edits:

Input Caption: *"photograph of a girl riding a horse"* → GPT-3 →

Instruction: *"have her ride a dragon"*

Edited Caption: *"photograph of a girl riding a dragon"*

(b) Generate paired images:

Input Caption: *"photograph of a girl riding a horse"*

Edited Caption: *"photograph of a girl riding a dragon"*

→ Stable Diffusion + Prompt2Prompt →

(c) Generated training examples:

"convert to brick"

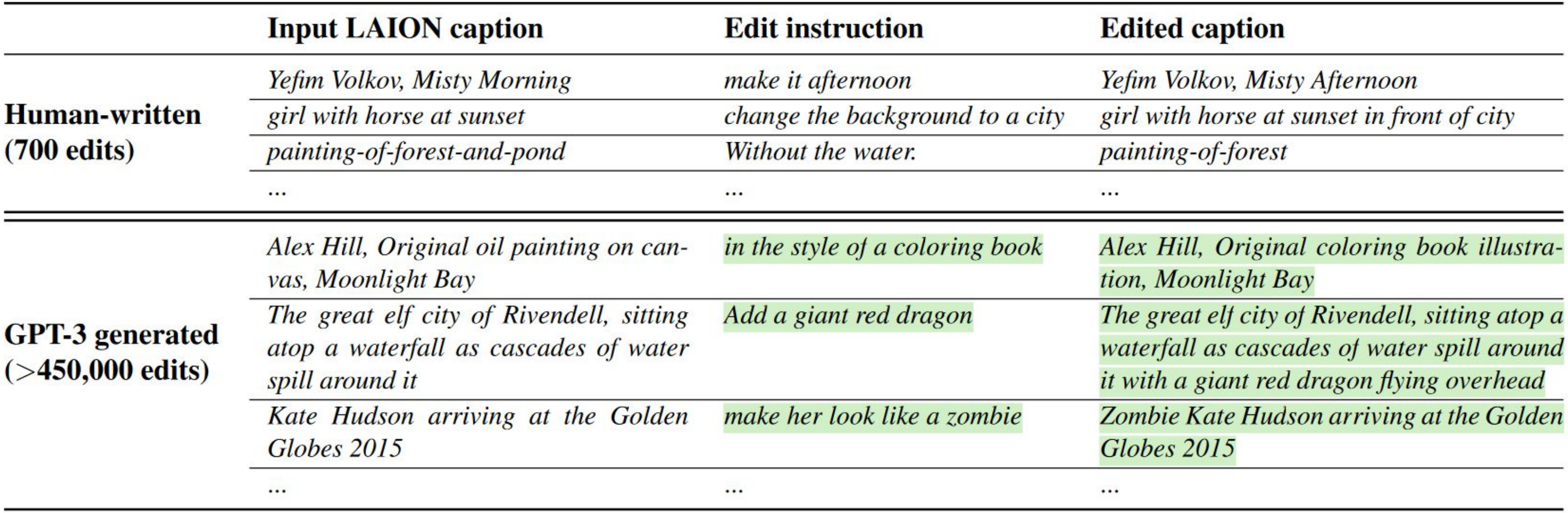
"Color the cars pink"

"Make it lit by fireworks"

"have her ride a dragon"

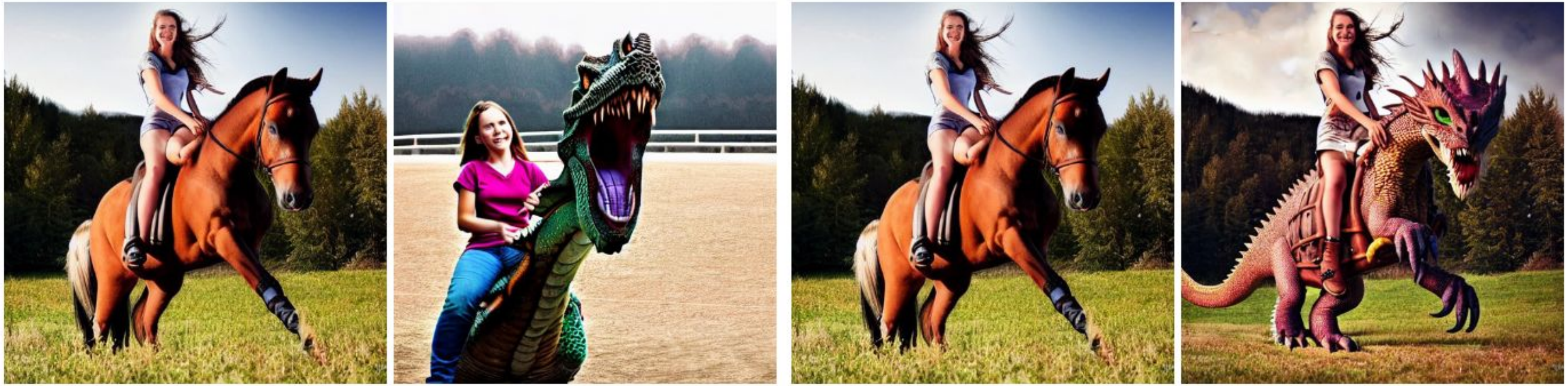
...

Генерация данных (a)



	Input LAION caption	Edit instruction	Edited caption
Human-written (700 edits)	*Yefim Volkov, Misty Morning*	*make it afternoon*	*Yefim Volkov, Misty Afternoon*
	girl with horse at sunset	*change the background to a city*	*girl with horse at sunset in front of city*
	painting-of-forest-and-pond	*Without the water.*	*painting-of-forest*
	...	...	...
GPT-3 generated (>450,000 edits)	*Alex Hill, Original oil painting on canvas, Moonlight Bay*	*in the style of a coloring book*	*Alex Hill, Original coloring book illustration, Moonlight Bay*
	The great elf city of Rivendell, sitting atop a waterfall as cascades of water spill around it	*Add a giant red dragon*	*The great elf city of Rivendell, sitting atop a waterfall as cascades of water spill around it with a giant red dragon flying overhead*
	Kate Hudson arriving at the Golden Globes 2015	*make her look like a zombie*	*Zombie Kate Hudson arriving at the Golden Globes 2015*
	...	...	...

Генерация данных (b)



(a) Without Prompt-to-Prompt.

(b) With Prompt-to-Prompt.

Генерация данных (b)

Для каждой пары подписей получают 100 пар картинок с разными значениями параметра p (отвечает за схожесть двух изображений).

Отбирают с помощью CLIP directional similarity (сравниваются разности текстов и картинок в пространстве CLIP)

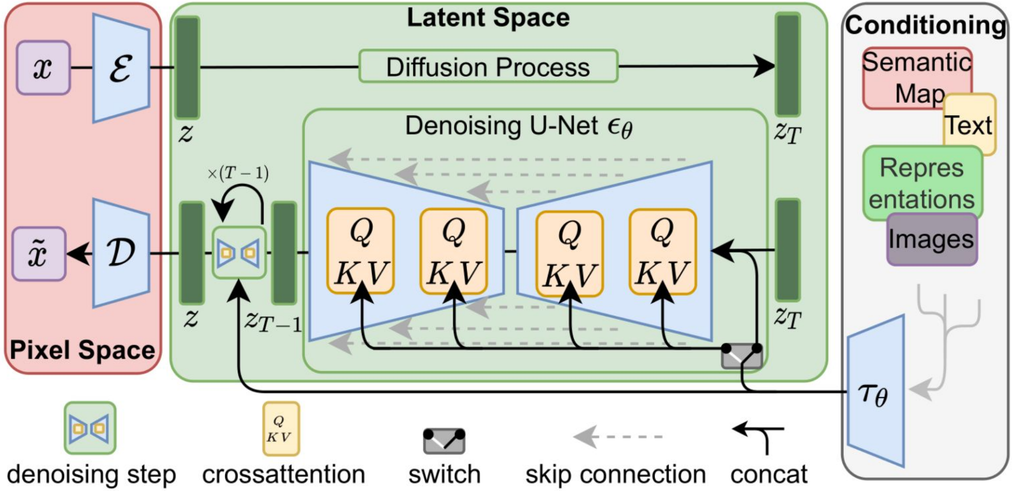
Получили более 450K примеров для обучения.

InstructPix2Pix

За основу взяли Stable Diffusion (веса тоже)

Особенности:

- Latent diffusion
- Classifier-free Guidance

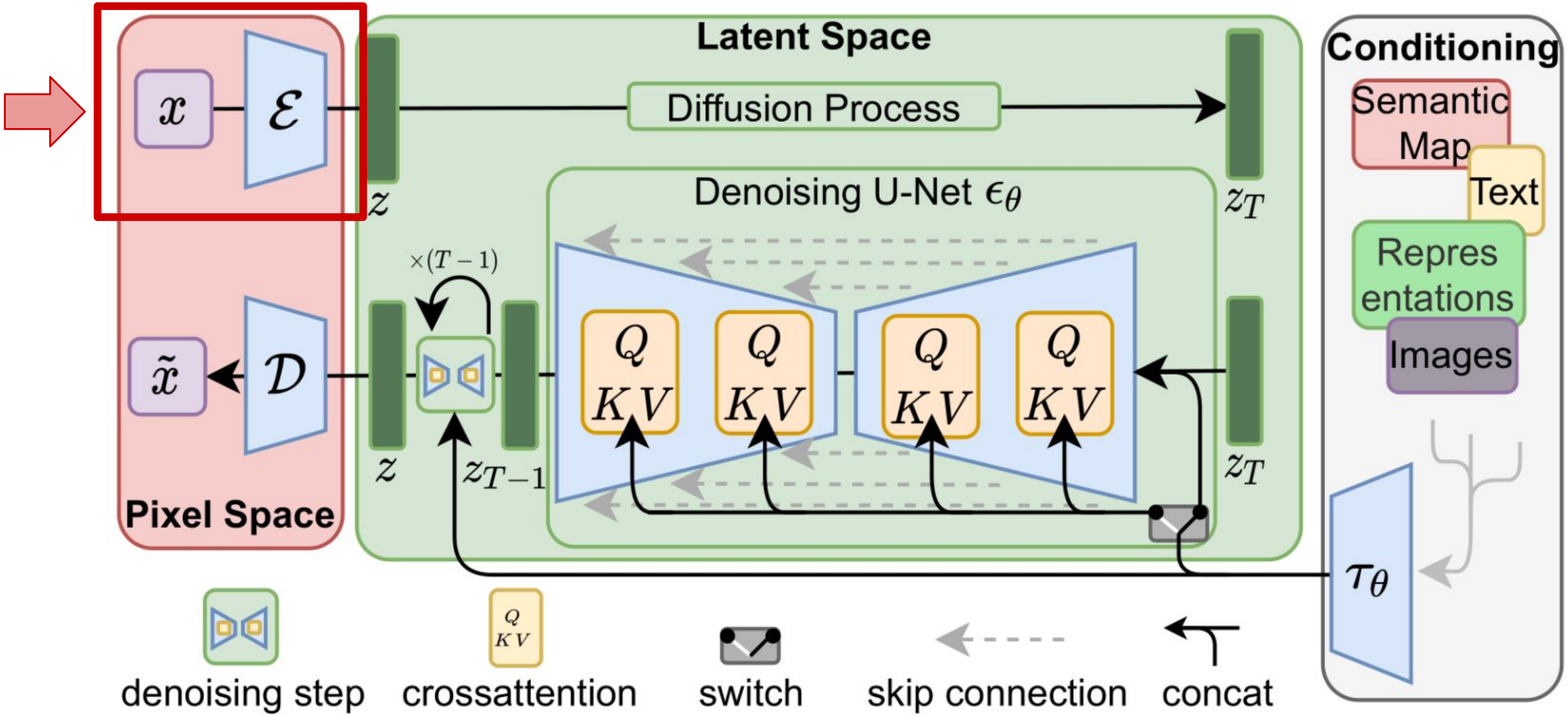


Latent diffusion

Кратко:

- Вместо картинок работаем с их представлениями.
- Для представлений предобученный автоэнкодер.

Latent diffusion



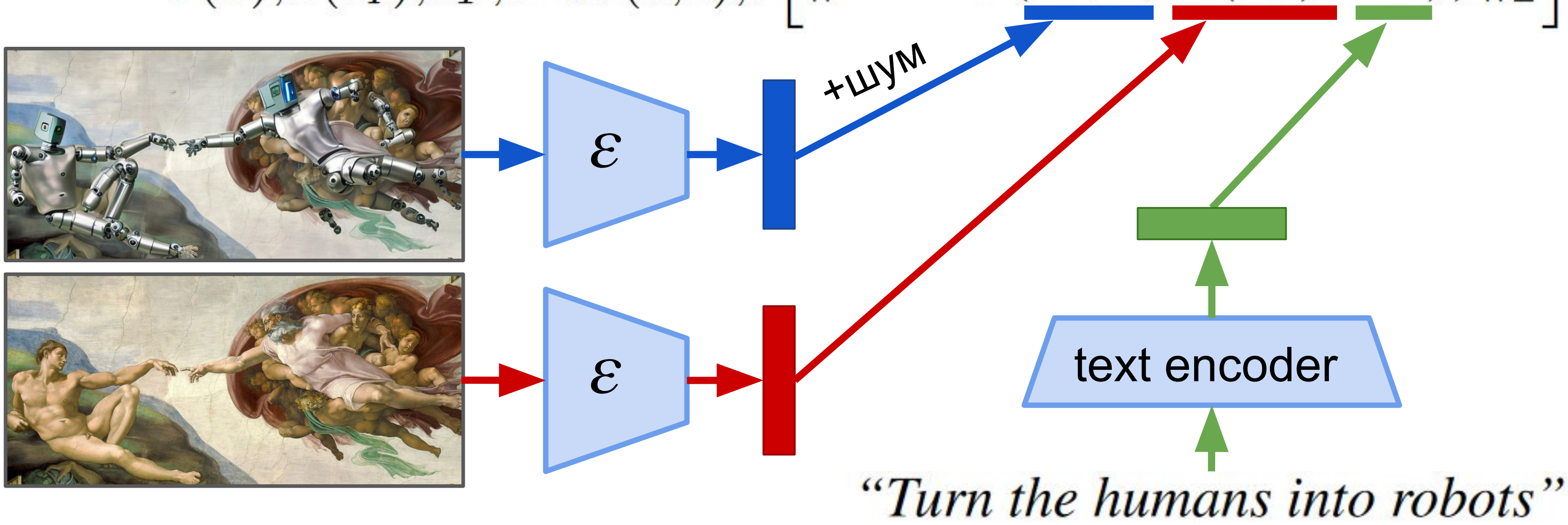
Latent diffusion

Зачем?

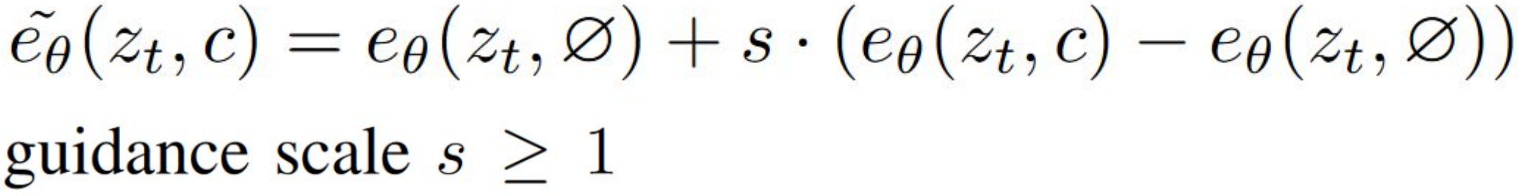
- Быстрее
- Лучше качество

Обучение

$$L = \mathbb{E}_{\mathcal{E}(x),\mathcal{E}(c_I),c_T,\epsilon\sim\mathcal{N}(0,1),t}\Big[\|\epsilon - \overbrace{\epsilon_\theta(z_t, t, \mathcal{E}(c_I), c_T))}^{\text{модель}}\|_2^2\Big]$$



Classifier-free Guidance



$$\tilde{e_\theta}(z_t, c) = e_\theta(z_t, \varnothing) + s \cdot (e_\theta(z_t, c) - e_\theta(z_t, \varnothing))$$

guidance scale $s \geq 1$

Чем больше коэффициент, тем “ближе” мы к конкретному классу и “дальше” от обобщённого предсказания.

Classifier-free Guidance

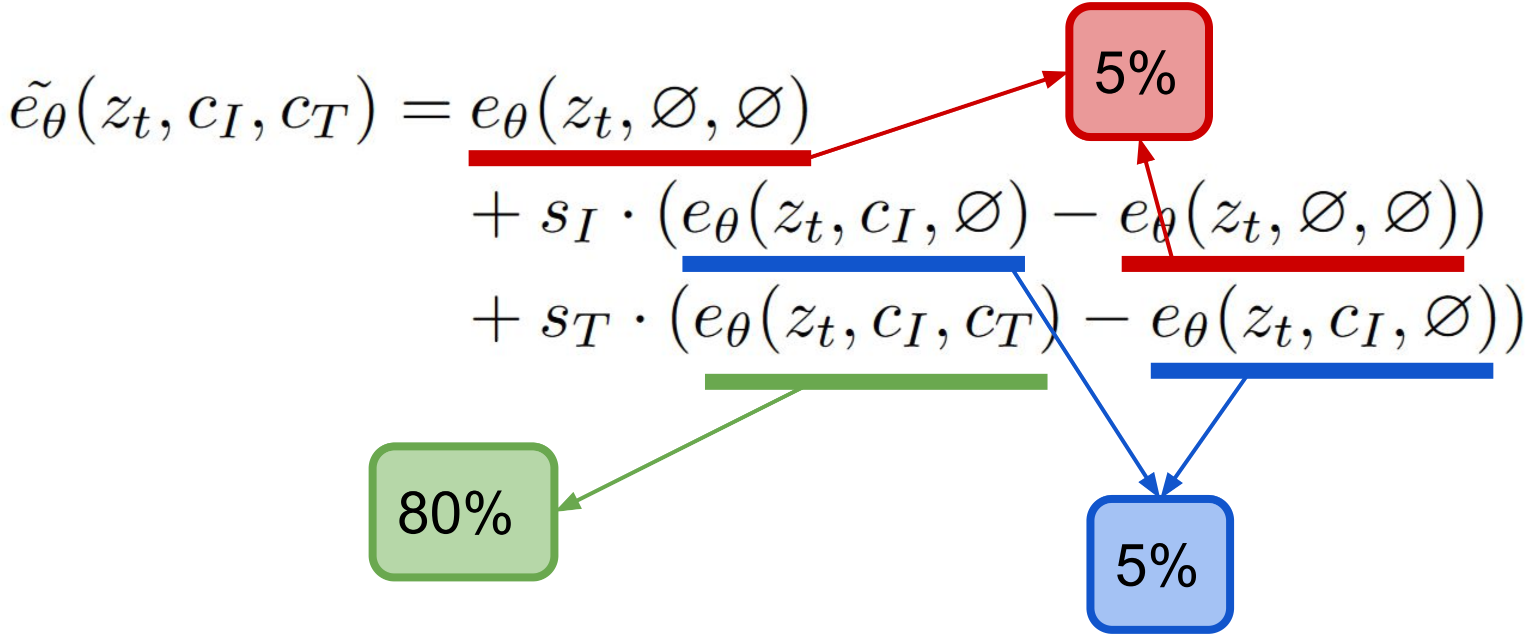
$$\begin{aligned}\tilde{e_\theta}(z_t, c_I, c_T) = e_\theta(z_t, \varnothing, \varnothing) \\ + s_I \cdot (e_\theta(z_t, c_I, \varnothing) - e_\theta(z_t, \varnothing, \varnothing)) \\ + s_T \cdot (e_\theta(z_t, c_I, c_T) - e_\theta(z_t, c_I, \varnothing))\end{aligned}$$

Согласно формулам получается:

$$s_I \longrightarrow p_\theta(c_I | z_t)$$

$$s_T \longrightarrow p_\theta(c_T | c_I, z_t)$$

Обучение

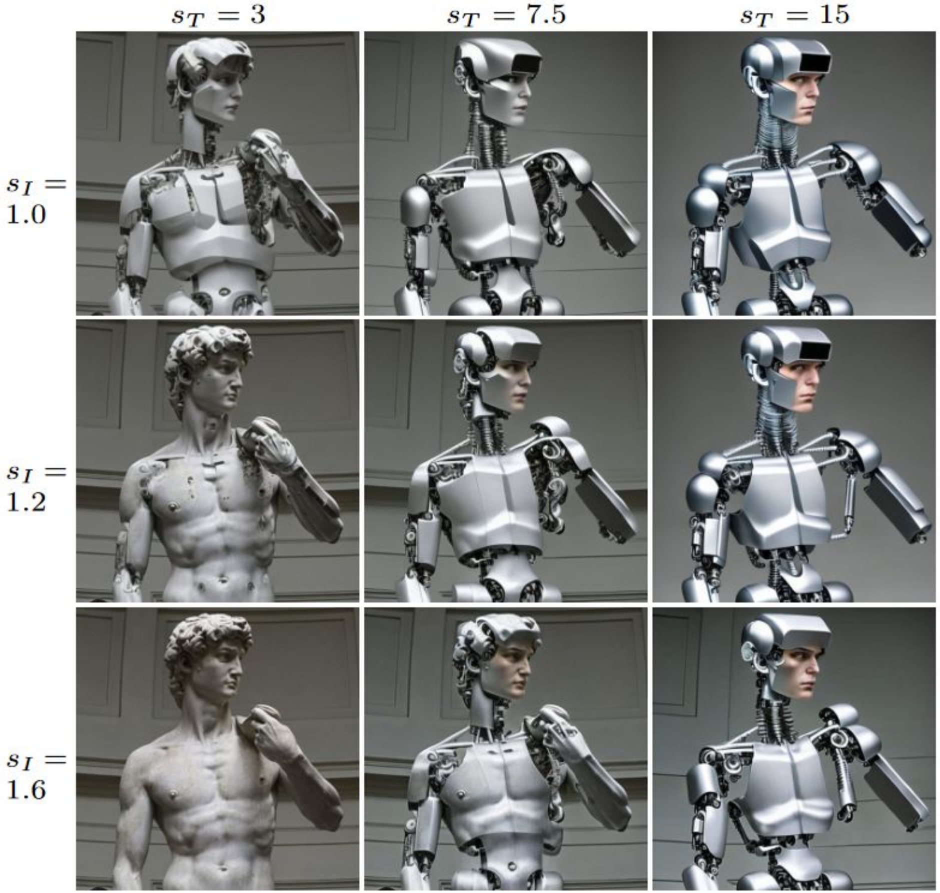


$$\tilde{e}_\theta(z_t, c_I, c_T) = e_\theta(z_t, \varnothing, \varnothing) + s_I \cdot (e_\theta(z_t, c_I, \varnothing) - e_\theta(z_t, \varnothing, \varnothing)) + s_T \cdot (e_\theta(z_t, c_I, c_T) - e_\theta(z_t, c_I, \varnothing))$$

5%

80%

5%



Edit instruction: *“Turn him into a cyborg!”*

Сравнение

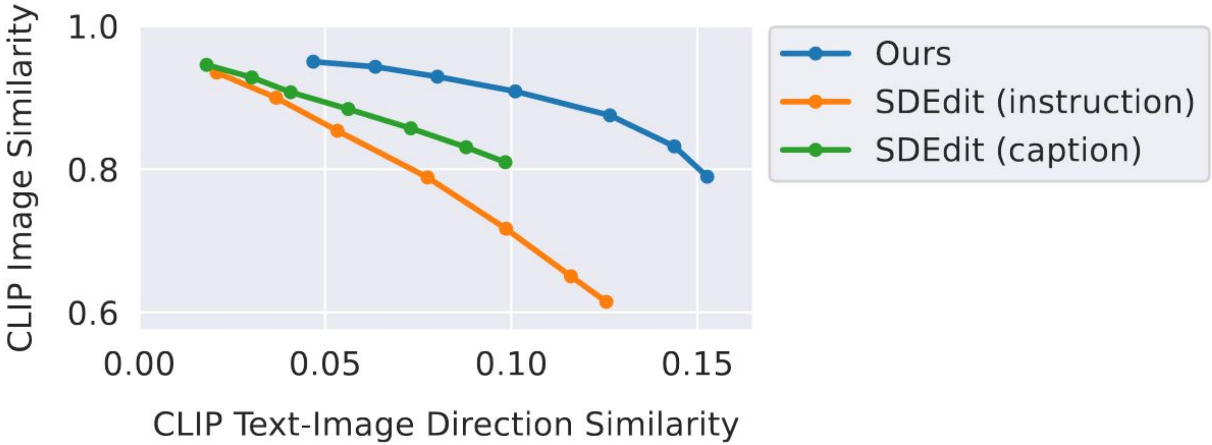
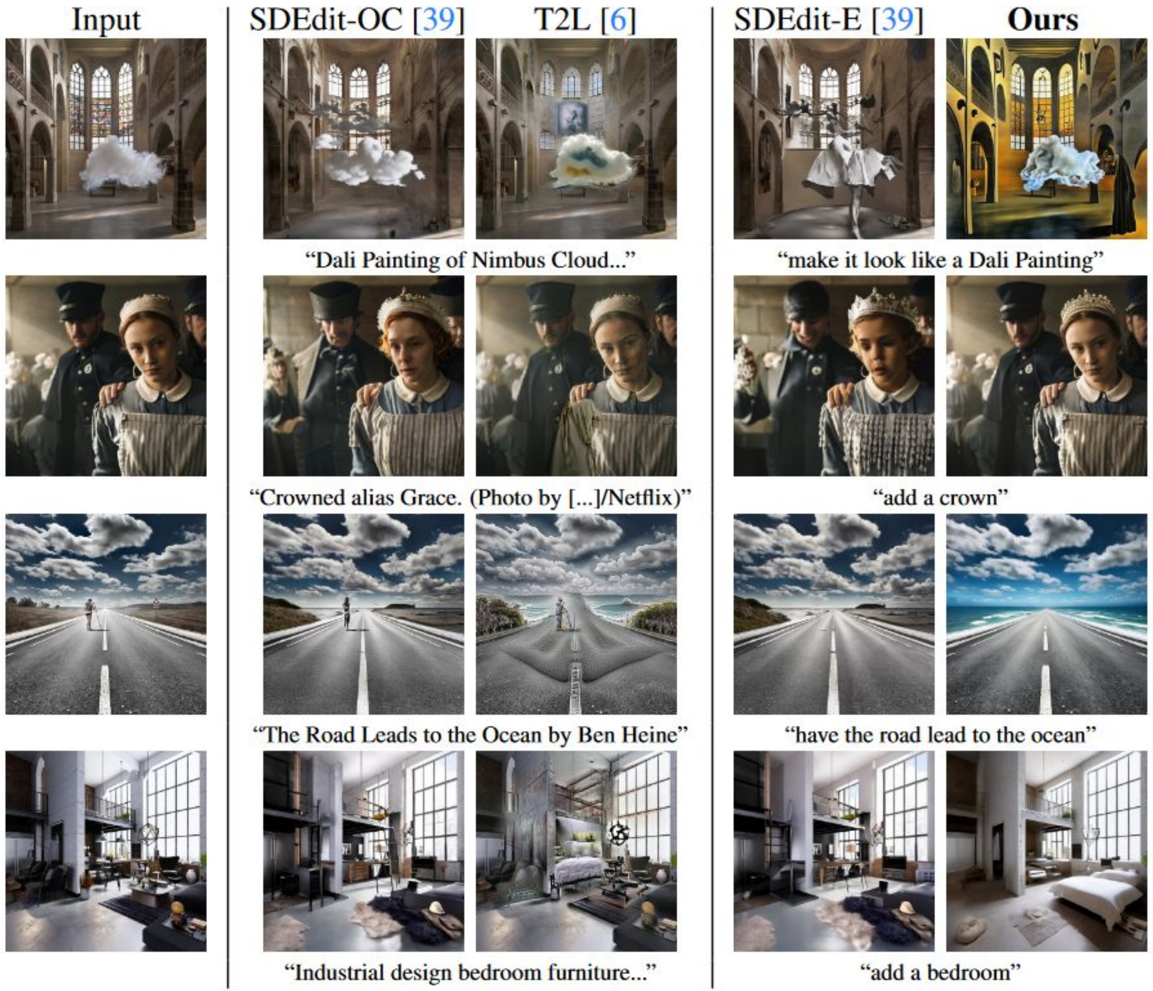
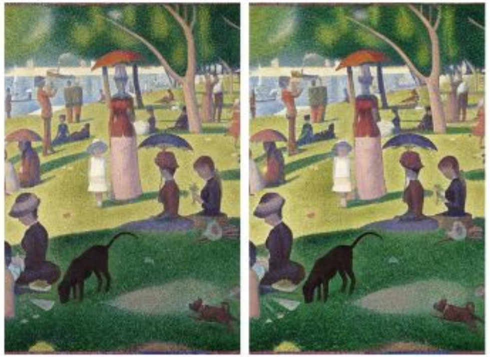


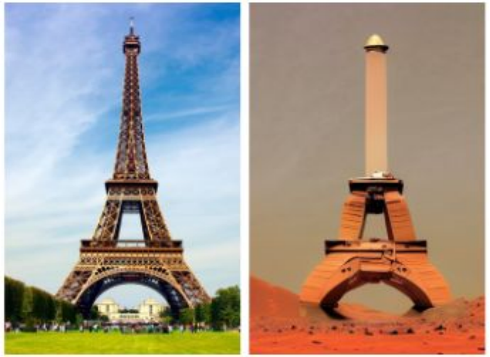
Figure 8. We plot the trade-off between consistency with the input image (Y-axis) and consistency with the edit (X-axis). For both metrics, higher is better. For both methods, we fix text guidance to 7.5, and vary our $s_I \in [1.0, 2.2]$ and SDEdit's strength (the amount of denoising) between $[0.3, 0.9]$.


Input
SDEdit-OC [39]
T2L [6]
SDEdit-E [39]
Ours
“Dali Painting of Nimbus Cloud...”
“make it look like a Dali Painting”
“Crowned alias Grace. (Photo by [...]/Netflix)”
“add a crown”
“The Road Leads to the Ocean by Ben Heine”
“have the road lead to the ocean”
“Industrial design bedroom furniture...”
“add a bedroom”

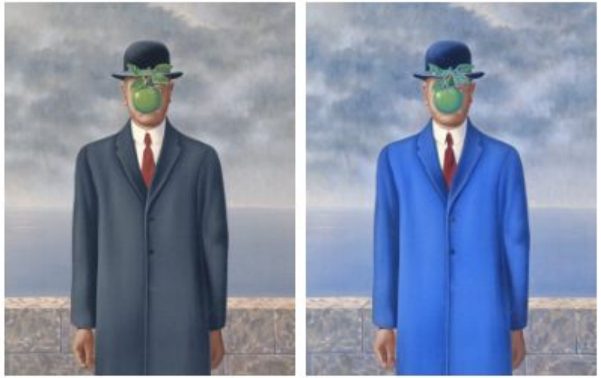
Что не получается



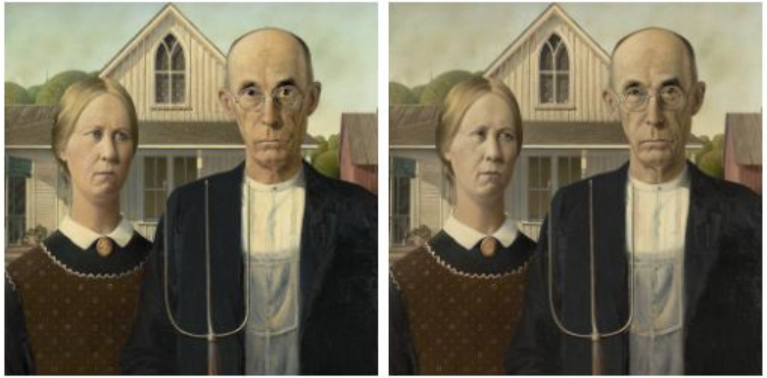
“Zoom into the image”



“Move it to Mars”



“Color the tie blue”



“Have the people swap places”

- https://arxiv.org/pdf/2211.09800.pdf
- https://arxiv.org/pdf/2112.10752.pdf