

**PrefPaint**



# PrefPaint: Aligning Image Inpainting Diffusion Model with Human Preference

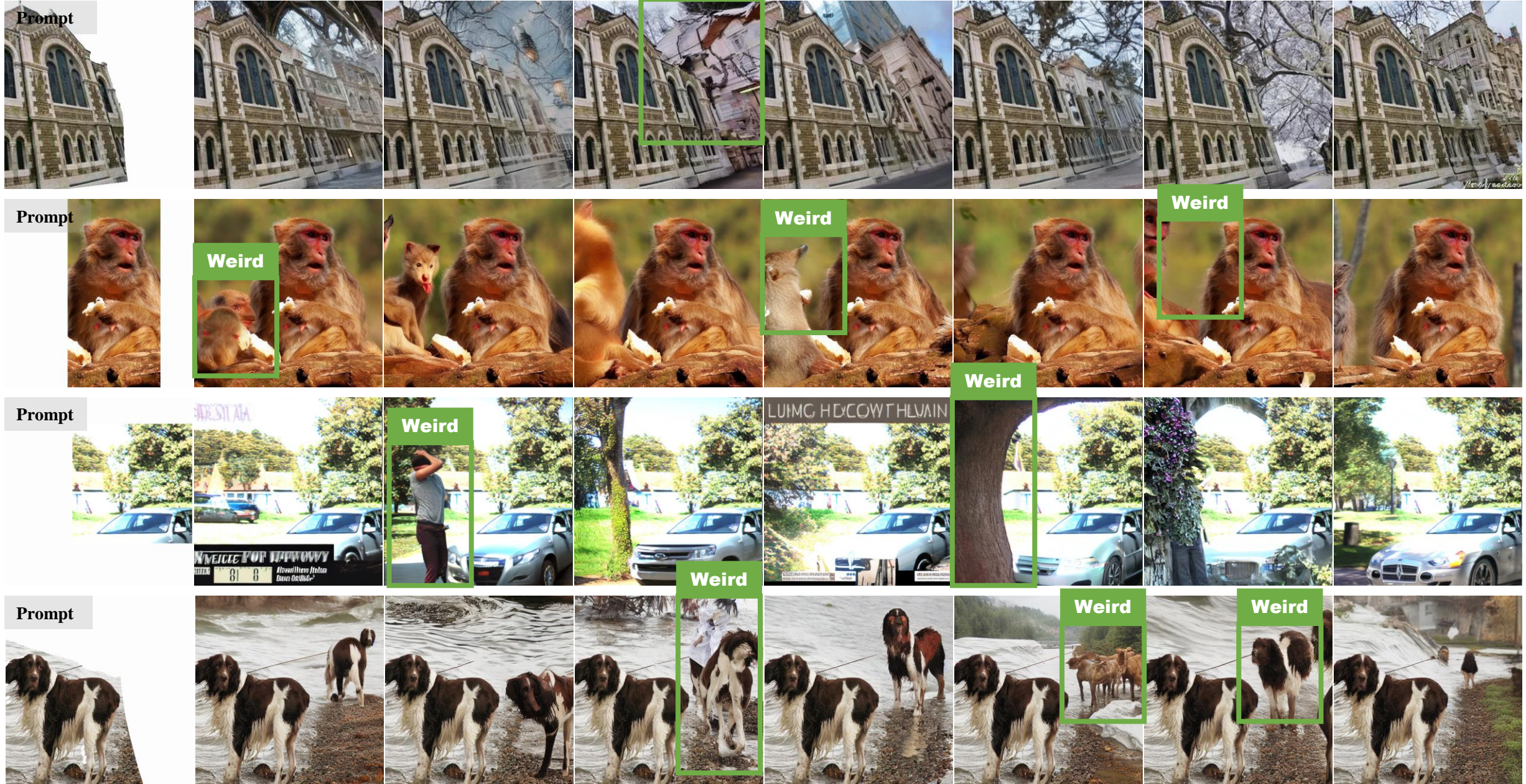
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<sup>4</sup>Huaqiao University, \* Equal Contribution

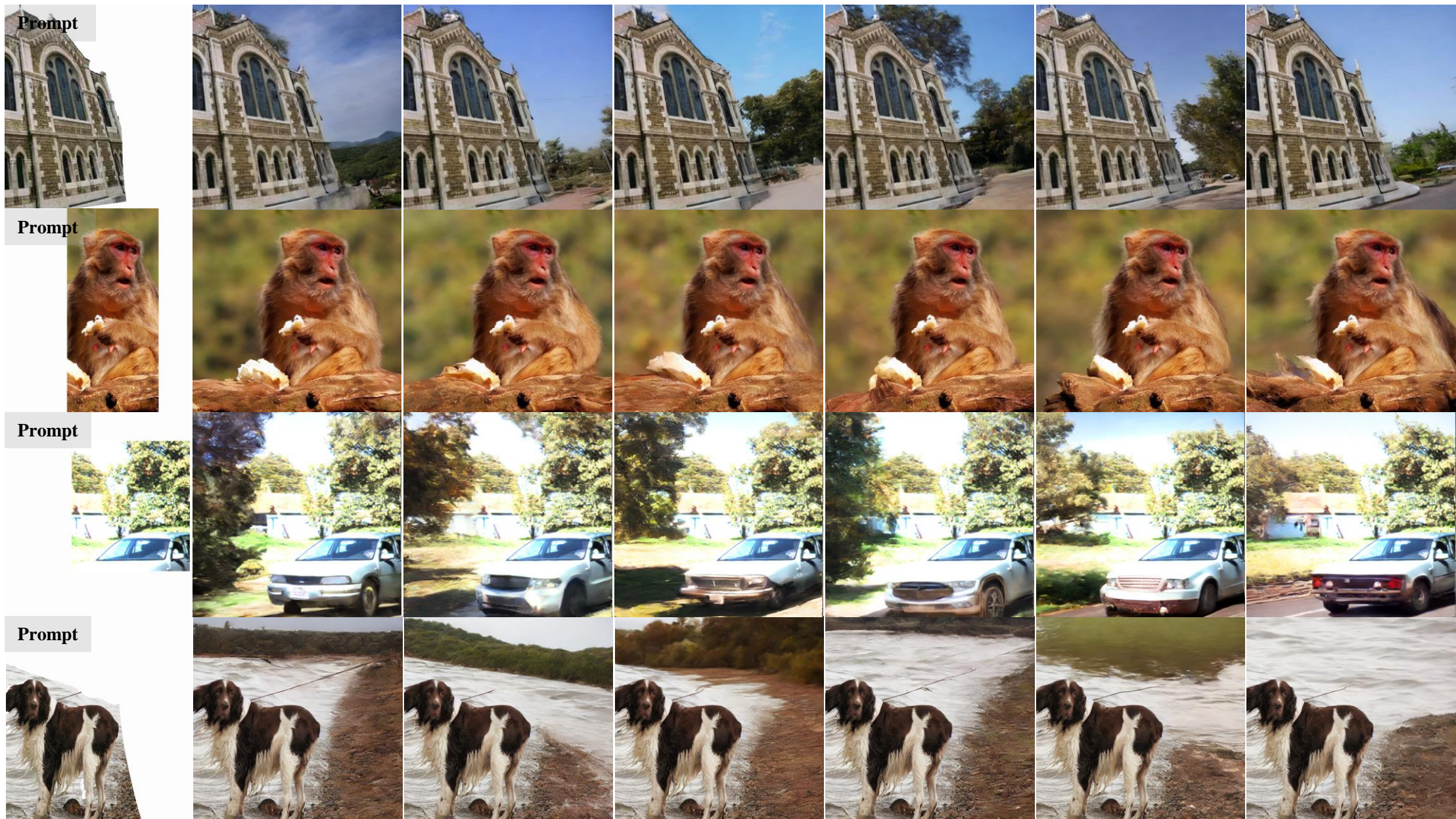


# Inpainting model cannot be aligned with human preferences



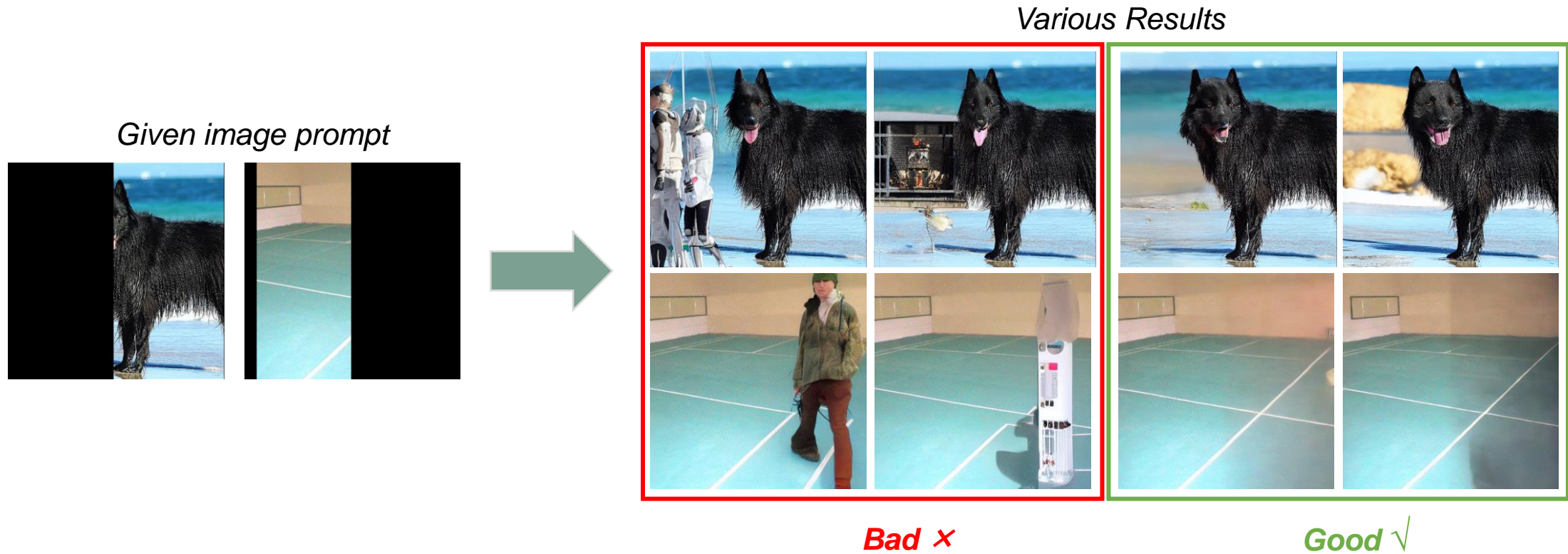


# After Alignment





# How to align the existing inpainting model with human preference?



*We train a reward model that can distinguish good from bad.*

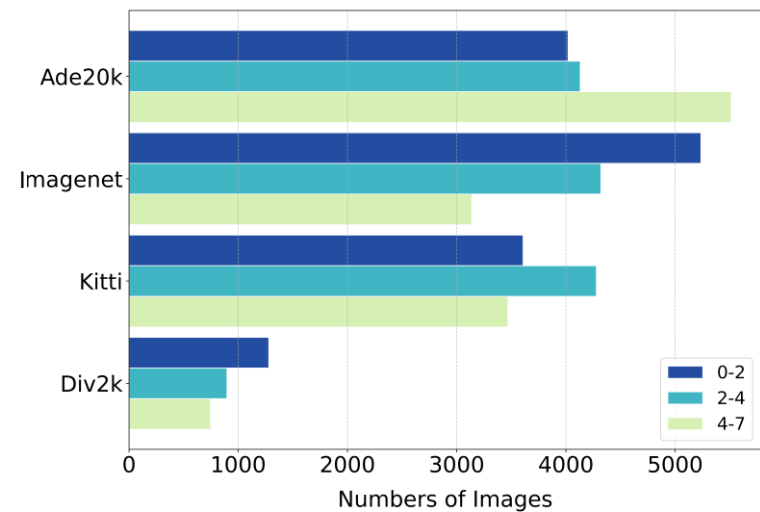
# HumanPreference-Centric Dataset for Reward

1. **Prepare prompts:** warping & outpainting

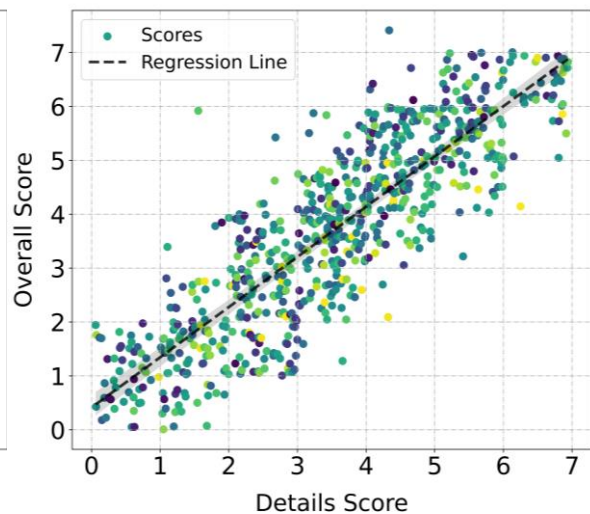
2. **Professional Labelling:** comprehensive criteria

3. **Dataset preprocess:** weighted scores & normalizations

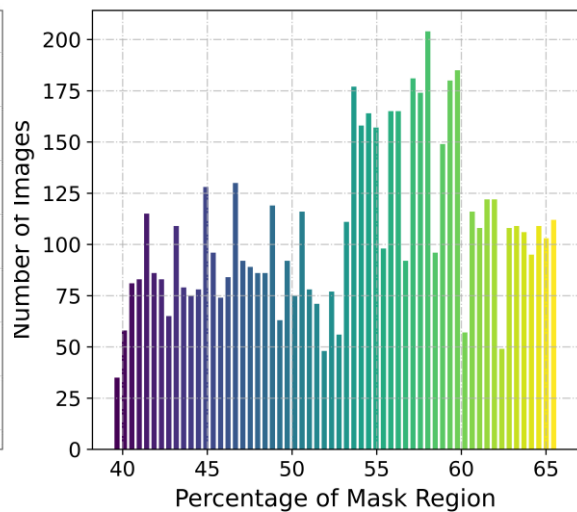
4. **Train a reward model:** regression or classification



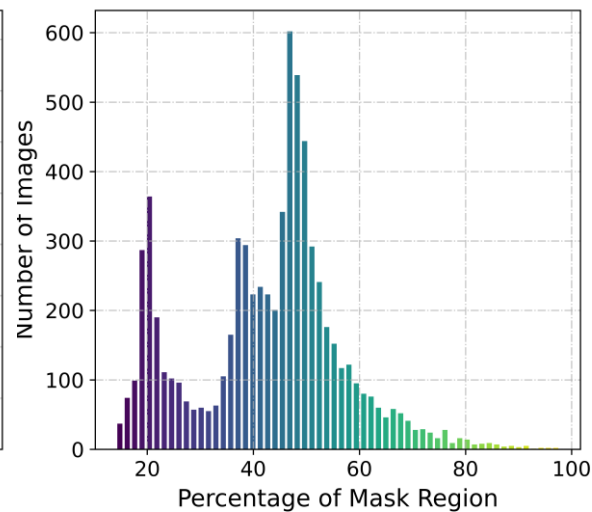
(a)



(b)

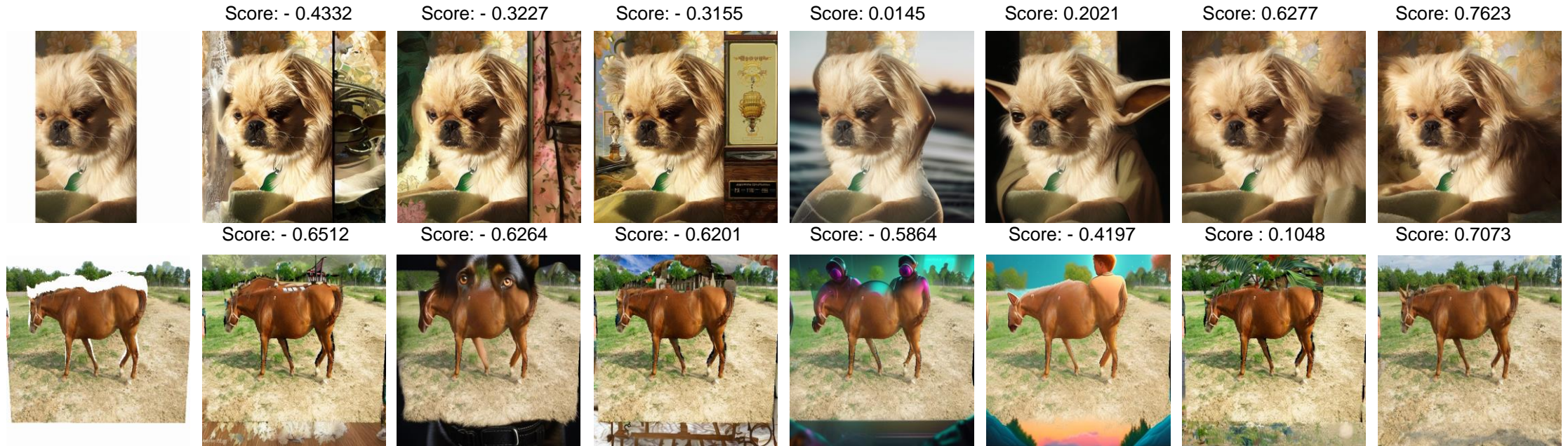


(c)



(d)

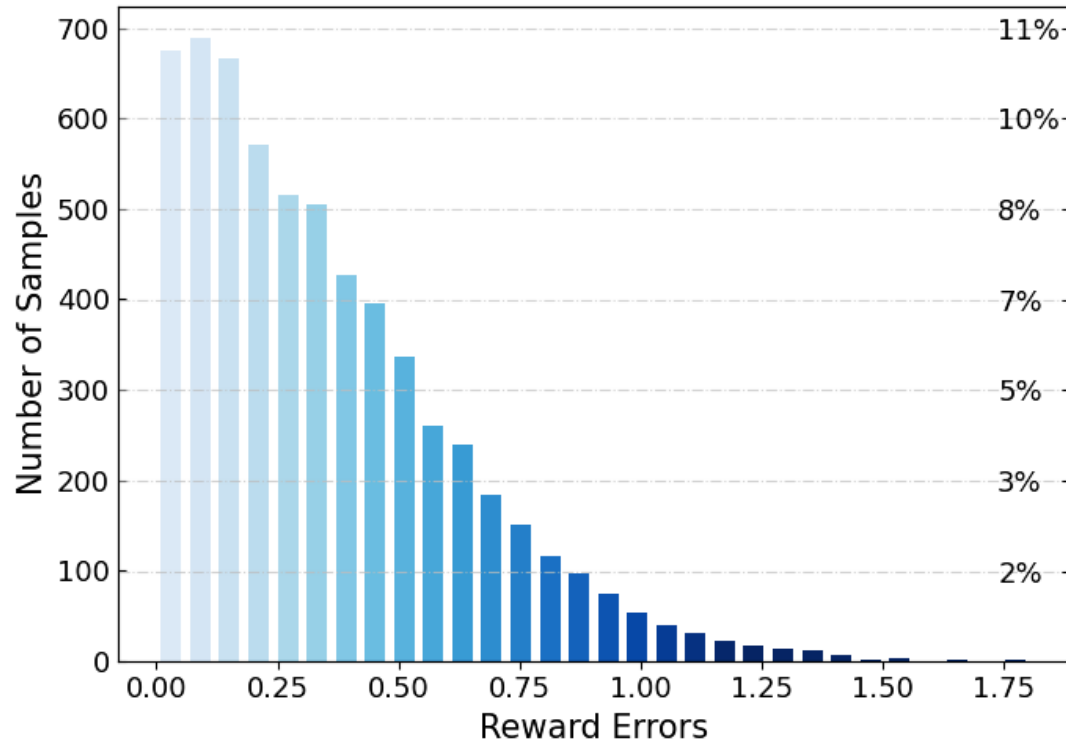
# HumanPreference-Centric Dataset for Reward



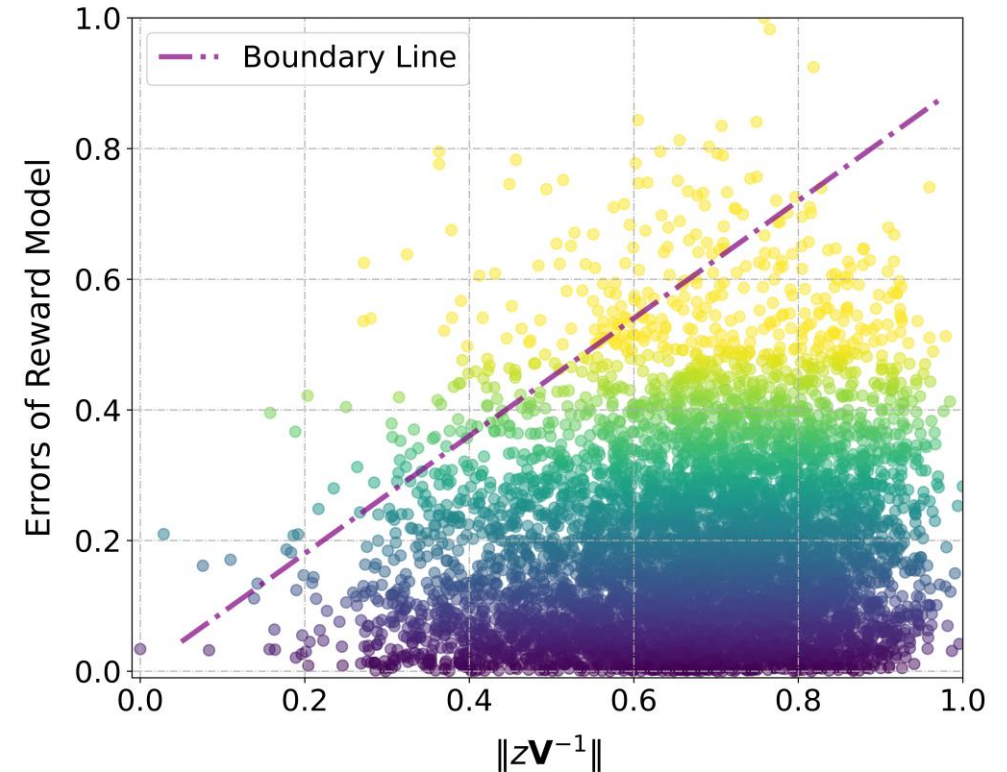
*Our reward model distinguishes between good from bad with high alignment with human preference.*



We adopt a reinforcement learning process to fine-tune the distribution of a pretrained diffusion model for image inpainting in the direction of higher reward.



The precision of the reward model assumes a pivotal function within this learning framework as it directs the optimization trajectory.



We theoretically derive its error upperbound, which can facilitate the enforced training process in terms of both efficacy and efficiency.



# Experiment Results

Table 1: Quantitative comparisons of different methods.  $\star$  indicates the small model (non SD-based); “ $S$ ” is the number of sampling times. For the calculation of WinRate, we first derive the best sample of the compared method among  $S$  sampling times. Then, we calculate it as  $\frac{T_w}{T}$ , where  $T_w$  indicates the number of compared samples that surpass the results of *Runway* ( $S = 1$ ) and  $T$  is the total number of prompts. “ $\uparrow$  (resp.  $\downarrow$ )” means the larger (resp. smaller), the better. We normalized the predicted reward values with the dataset distribution. “Var” calculates the variance of different sampling times, showing the consistency of generation quality. (See the *Supplementary Material* for more details.)

Prompt Methods	Outpainting Prompts					Warping Prompts				
	WinRate (%) $\uparrow$			Reward		WinRate (%) $\uparrow$			Reward	
Metrics	$S = 1$	$S = 3$	$S = 10$	Mean $\uparrow$	Var $\downarrow$	$S = 1$	$S = 3$	$S = 10$	Mean $\uparrow$	Var $\downarrow$
Runway [62]	--	73.40	89.32	--	0.07	--	75.74	91.42	--	0.06
SD v1.5 [63]	11.95	20.67	30.24	-0.43	0.05	11.38	21.22	32.85	-0.38	0.06
SD v2.1 [64]	10.73	18.51	26.82	-0.44	0.04	11.68	22.11	34.22	-0.36	0.06
SD xl [65]	14.56	22.58	31.09	-0.31	0.04	15.43	25.43	36.77	-0.26	0.05
SD xl ++ [66]	21.15	33.25	45.51	-0.13	0.05	18.66	30.53	43.07	-0.18	0.04
Compvis [67]	50.51	66.39	78.21	+0.03	0.03	47.35	65.08	78.01	-0.01	0.04
Kandinsky [68]	14.06	22.73	32.16	-0.37	0.04	11.38	19.46	29.20	-0.42	0.05
MAT $\star$ [69]	15.06	17.97	20.51	-0.40	0.01	7.17	9.97	12.96	-0.56	0.01
Palette $\star$ [41]	10.96	16.92	21.37	-0.38	0.02	13.41	20.18	27.37	-0.34	0.03
<b>Ours</b>	<b>70.16</b>	<b>84.65</b>	<b>93.14</b>	<b>+0.38</b>	<b>0.01</b>	<b>72.38</b>	<b>87.10</b>	<b>93.85</b>	<b>+0.36</b>	<b>0.01</b>

*We compared our PrefPaint with SOTA methods both quantitatively to demonstrate the advantage of our method.*

# Experiment Results

Metric \ Model	T2I	CLIP	BLIP	Aes.	CA	IS	Rank
	[54]	[70]	[71]	[72]	[73]	[74]	
SDv1.5	-1.67	0.19	0.44	4.52	0.38	17.07	5.17
SDv2.1	-1.37	0.20	0.45	4.62	0.39	17.07	4.33
Kand.	-3.49	0.18	0.39	<b>5.19</b>	0.39	17.06	5.33
SD xl ++	0.63	0.21	0.46	4.77	0.40	18.95	3.17
Runway	3.16	0.22	0.48	4.61	0.43	20.30	2.33
Platte	-1.76	0.22	0.46	4.08	0.37	16.24	5.33
<b>Ours</b>	<b>4.49</b>	<b>0.23</b>	<b>0.49</b>	4.55	<b>0.45</b>	<b>23.71</b>	<b>1.67</b>

Table 2: Comparison across metrics: higher values are better for all metrics except "Rank".

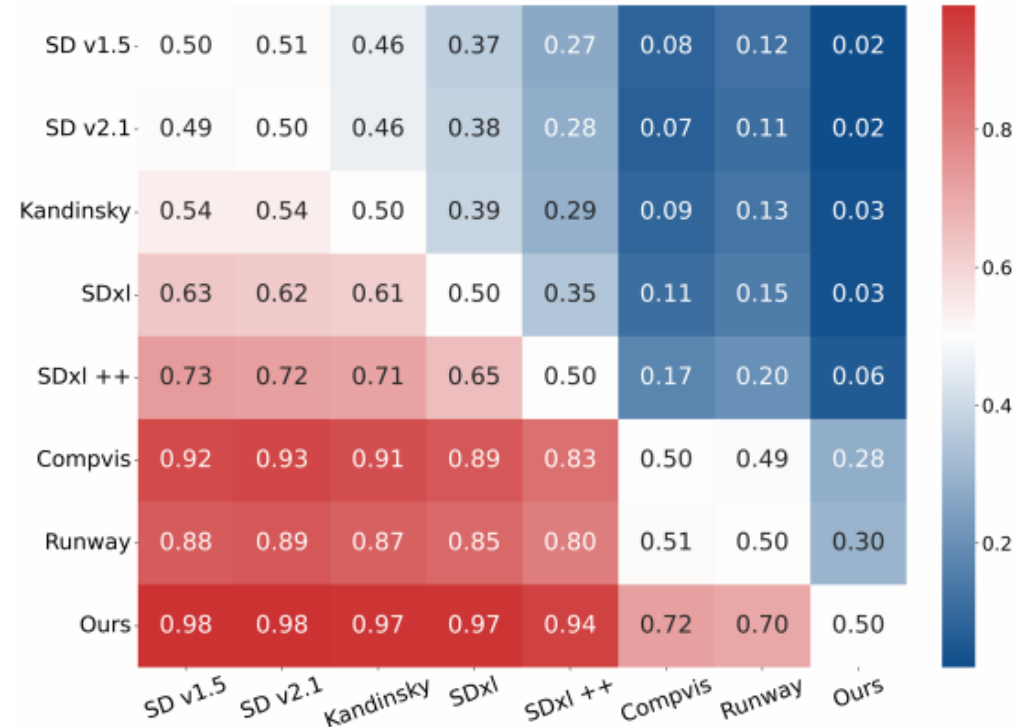
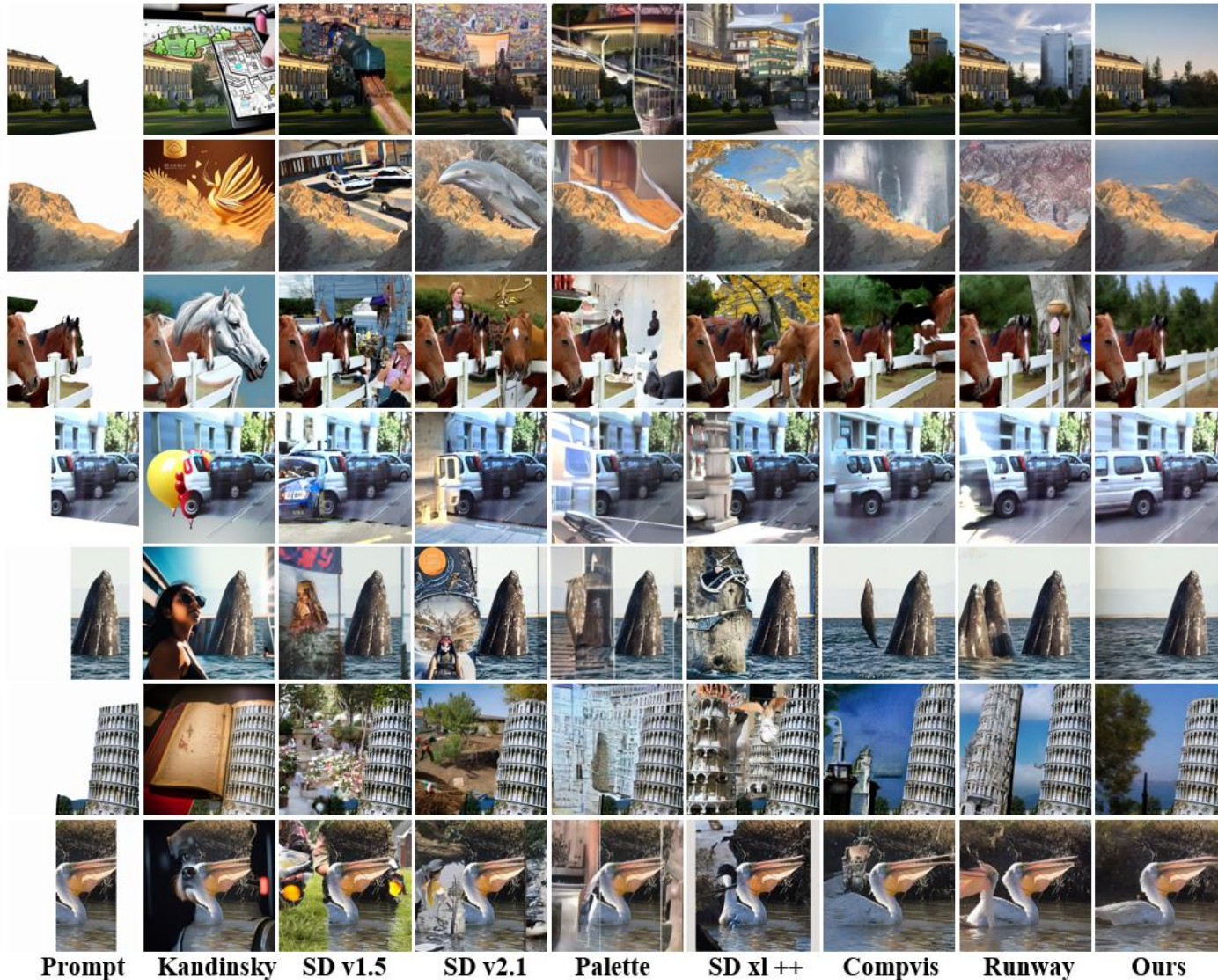


Figure 4: WinRate comparison heat-map between different methods.

*We compared our PrefPaint with SOTA methods both quantitatively to demonstrate the advantage of our method.*



# Experiment Results



*We compared our PrefPaint with SOTA methods both qualitatively to demonstrate the advantage of our method.*

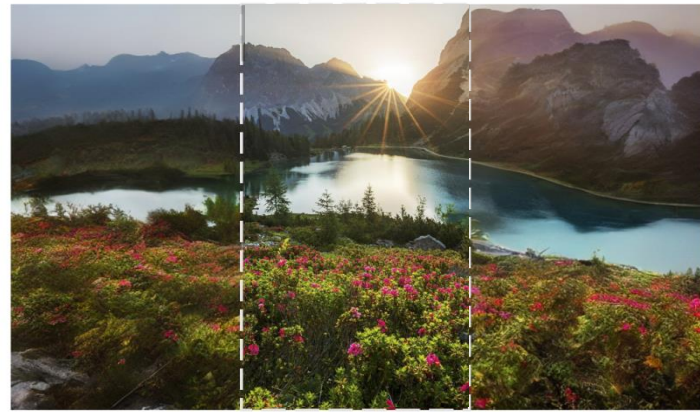


# For Novel View Synthesis





# For Image FOV Enlargement



# PrefPaint

**Project page: <https://prefpaint.github.io/>**