

RePrompt: Reasoning-Augmented Reprompting for Text-to-Image Generation via Reinforcement Learning



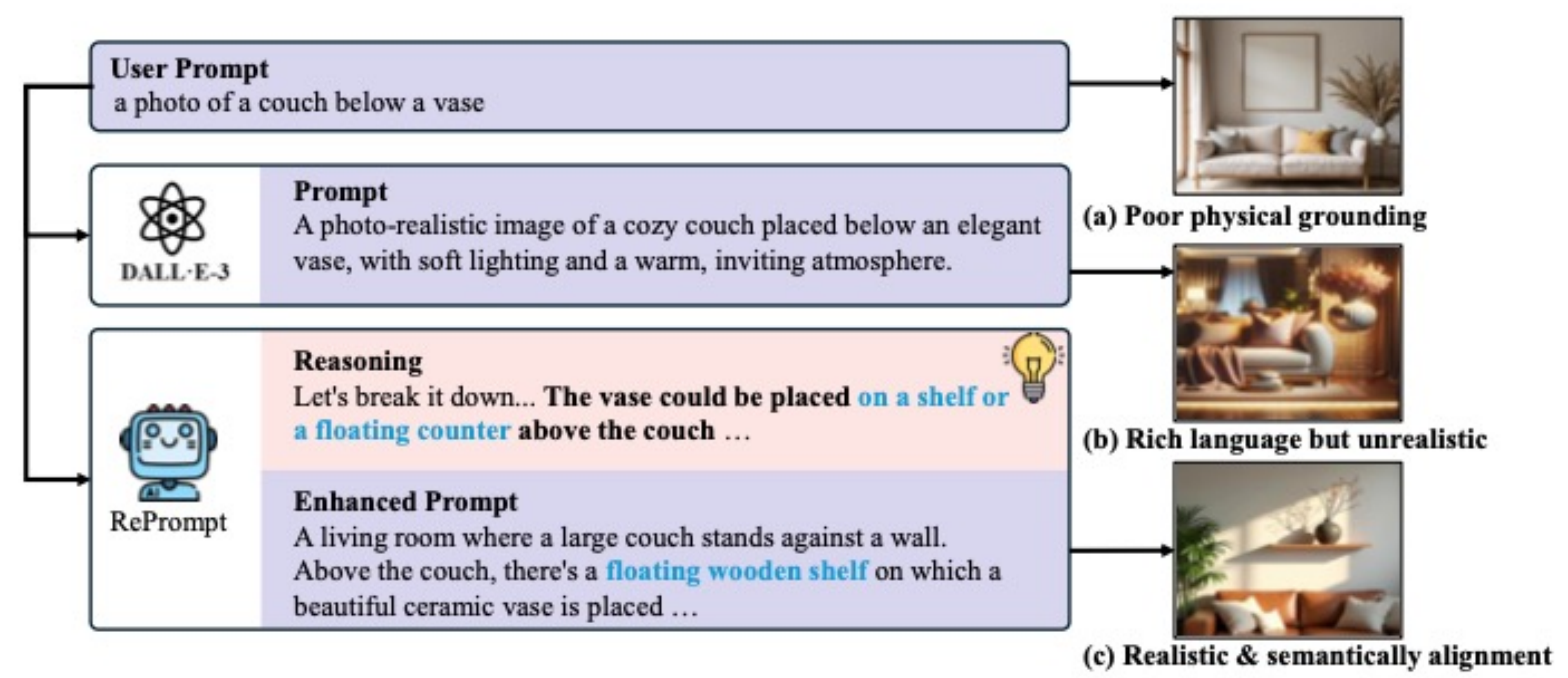
Generation via Reinforcement Learning

Mingrui Wu^{1,3*}, Lu Wang^{2†}, Pu Zhao^{2†}, Fangkai Yang^{2†}, Jianjin Zhang², Jianfeng Liu², Yuefeng Zhan², Weihao Han², Hao Sun², Jiayi Ji^{1‡}, Xiaoshuai Sun¹, Qingwei Lin², Weiwei Deng², Dongmei Zhang², Feng Sun², Qi Zhang², Rongrong Ji¹
 1 Key Laboratory of Multimedia Trusted Perception and Efficient Computing, Ministry of Education of China, Xiamen University, 361005, P.R. China.
 2 Microsoft. 3 Zhongguancun Academy, Beijing, China.100094.

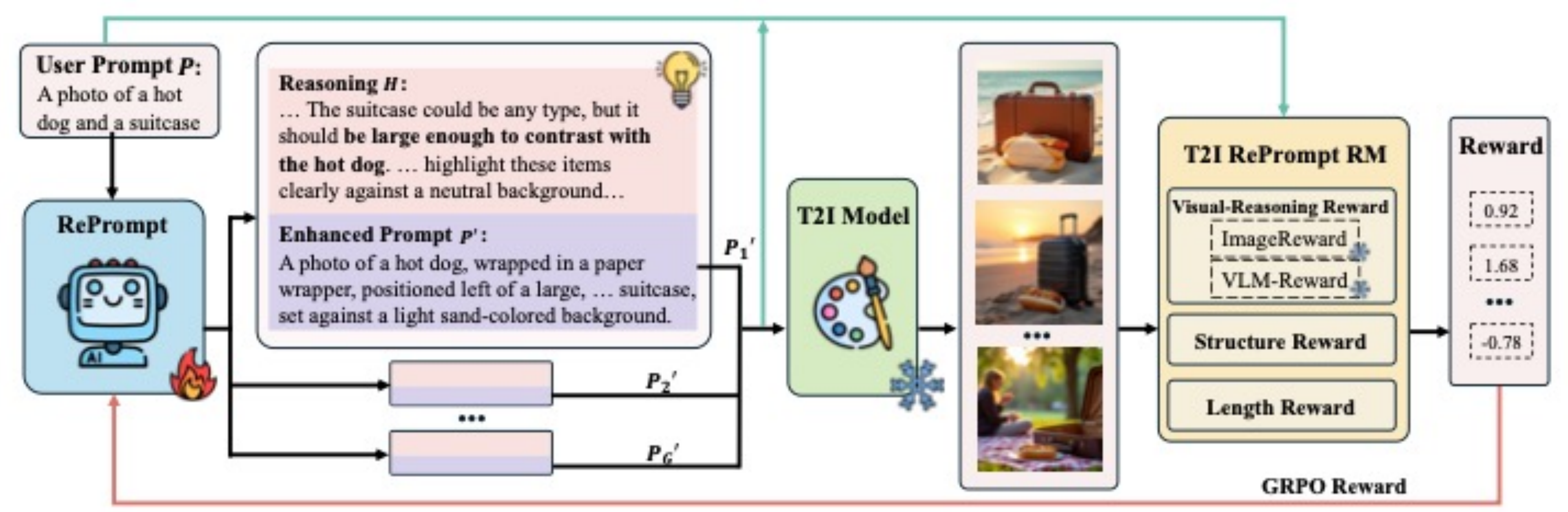


Introduction & Method

Challenge: Existing models often struggle to faithfully capture user intentions from short and underspecified prompts.



Our Contribution: We propose RePrompt, a novel reprompting framework that introduces explicit reasoning into the prompt enhancement process via reinforcement learning. Instead of relying on handcrafted rules or stylistic rewrites, our method trains a language model to generate structured, self-reflective prompts by optimizing for image-level outcomes.



Results

- Our approach shows substantial gains in **spatial position understanding** over Qwen2.5 3B-enhanced baselines.
- Our RePrompt improves spatial layout and object relations by generating enhanced prompts with explicit reasoning, leading to more faithful compositions.

Method	Single object	Two object	Counting	Colors	Position	Attribute binding	Overall ↑
FLUX Labs (2024)	0.99	0.79	0.75	0.78	0.18	0.45	0.66
+ Promptist Hao et al. (2023)	0.98	0.72	0.70	0.78	0.21	0.44	0.66
+ PAG Yun et al. (2025)	0.97	0.74	0.73	0.80	0.36	0.46	0.69
+ GPT4	0.99	0.79	0.68	0.84	0.51	0.52	0.72
+ GPT5	1.00	0.81	0.70	0.85	0.51	0.51	0.73
+ GPTo3	0.98	0.76	0.65	0.83	0.48	0.50	0.70
+ Deepseek-r1	1.00	0.81	0.56	0.78	0.47	0.43	0.67
+ Qwen2.5 7B	0.99	0.83	0.62	0.84	0.36	0.51	0.69
+ Qwen2.5 3B	0.99	0.84	0.63	0.81	0.35	0.48	0.68
+ Ours (train w/ FLUX)	0.98	0.87	0.77	0.85	0.62	0.49	0.76
Improvement over Qwen2.5 3B	-1.0%	+3.6%	+22.2%	+4.9%	+77.1%	+2.1%	+11.8%
SD3 Esser et al. (2024)	1.00	0.85	0.62	0.88	0.22	0.58	0.69
+ Promptist	0.99	0.84	0.66	0.84	0.45	0.52	0.69
+ PAG	0.99	0.85	0.68	0.85	0.49	0.53	0.71
+ GPT4	1.00	0.84	0.51	0.85	0.48	0.54	0.70
+ GPT5	1.00	0.85	0.53	0.85	0.47	0.50	0.70
+ GPTo3	0.99	0.82	0.50	0.84	0.41	0.52	0.68
+ Deepseek-r1	0.99	0.82	0.53	0.80	0.44	0.46	0.67
+ Qwen2.5 7B	1.00	0.82	0.49	0.85	0.34	0.58	0.68
+ Qwen2.5 3B	1.00	0.86	0.53	0.84	0.33	0.55	0.68
+ Ours (train w/ FLUX)	0.99	0.86	0.60	0.86	0.59	0.60	0.75
Improvement over Qwen2.5 3B	-1.0%	0.0%	+13.2%	+2.4%	+78.8%	+9.1%	+10.3%
Pixart-Σ Chen et al. (2024b)	0.99	0.60	0.47	0.81	0.10	0.26	0.54
+ Promptist	0.98	0.60	0.49	0.80	0.20	0.27	0.55
+ PAG	0.98	0.63	0.52	0.80	0.28	0.29	0.56
+ GPT4	0.96	0.67	0.48	0.84	0.36	0.31	0.60
+ GPT5	0.97	0.68	0.49	0.84	0.37	0.31	0.61
+ GPTo3	0.96	0.67	0.48	0.83	0.35	0.31	0.60
+ Deepseek-r1	0.99	0.63	0.43	0.78	0.24	0.27	0.56
+ Qwen2.5 7B	0.96	0.67	0.43	0.83	0.20	0.32	0.57
+ Qwen2.5 3B	0.99	0.68	0.48	0.82	0.18	0.32	0.58
+ Ours (train w/ FLUX)	0.98	0.64	0.56	0.81	0.40	0.35	0.62
Improvement over Qwen2.5 3B	-1.0%	-5.9%	+16.7%	-1.2%	+122.2%	+9.4%	+6.9%



- Our approach consistently improves performance across most aspects, particularly in Spatial compositions.
- Our method consistently improves the compositional understanding across all base models.

Method	Color	Shape	Texture	Spatial	Numeracy	Complex
FLUX	0.7223	0.4796	0.6522	0.2494	0.6101	0.3616
+ Qwen2.5 3B	0.7149	0.5103	0.6012	0.2579	0.5982	0.3325
+ Ours (train w/ FLUX)	0.7501	0.5276	0.6515	0.3301	0.6499	0.3721
SD3	0.7941	0.5812	0.7224	0.2815	0.5871	0.3714
+ Qwen2.5 3B	0.7227	0.5478	0.6581	0.2549	0.5934	0.3307
+ Ours (train w/ FLUX)	0.7866	0.5891	0.7184	0.3315	0.6289	0.3744
Pixart-Σ	0.5682	0.4717	0.5622	0.2497	0.5366	0.3655
+ Qwen2.5 3B	0.6618	0.4814	0.5662	0.2481	0.5443	0.3335
+ Ours (train w/ FLUX)	0.6665	0.5011	0.6190	0.2913	0.5716	0.3680

