
Additional Experiments

Method (vs SDv1.5)	Aesthetic ↑	Brightness ↑	Darkness ↑
DNO	37.8	35.6	53.3
PRNO	42.2	75.5	66.7
MIRA (Ours)	60.0	91.1	88.9

Table 1. GPT-4 win rates of MIRA, DNO and PRNO vs SDv1.5 on Simple Animals dataset. We report GPT-4 win rates of DNO, PRNO, and MIRA with respect to three objectives (Aesthetic Score, brightness, darkness). As seen from the table, MIRA outperforms both the other baselines.

MIRA (Ours) vs ...	Aesthetic ↑	Brightness ↑	Darkness ↑
SDv1.5	57.58	80.30	90.91
DDPO	57.58	60.61	83.33
Diffusion-DPO	66.67	81.82	84.85
D3PO	63.64	68.18	74.24
BoN (N=50)	62.12	71.21	92.42
InitNO	65.15	78.79	83.33
DyMO	56.06	80.30	87.98
DNO	77.27	57.58	66.67

Table 2. GPT-4 win rates of MIRA vs baselines on Animal-Animal dataset. Using SDv1.5 as the base model, we report GPT-4 win rates with respect to three objectives (Aesthetic, brightness, darkness). InitNO, DyMO, and DNO are inference-time optimization methods. As seen from the results, MIRA outperforms all the other baselines in win-rate comparisons.

MIRA (Ours) vs ...	Aesthetic ↑	Brightness ↑	Darkness ↑
SDv1.5	61.11	88.19	90.28
DDPO	54.86	68.06	81.25
Diffusion-DPO	63.19	82.64	89.58
D3PO	68.06	77.78	83.33
BoN (N=50)	54.86	83.33	93.06
InitNO	57.64	84.03	80.56
DyMO	46.53	84.81	87.50
DNO	68.06	77.78	71.53

Table 3. GPT-4 win rates of MIRA vs baselines on Animal-Object dataset. Using SDv1.5 as the base model, we report GPT-4 win rates with respect to three objectives (Aesthetic, brightness, darkness). InitNO, DyMO, and DNO are inference-time optimization methods. As seen from the results, MIRA outperforms all the other baselines in win-rate comparisons.

MIRA (Ours) vs ...	Aesthetic ↑	Brightness ↑	Darkness ↑
InitNO	61.11	72.22	82.22
DyMO	53.89	68.89	68.89

Table 4. GPT-4 win rates of MIRA vs InitNO and DyMO on Simple Animals dataset. Using SDv1.5 as the base model, we report GPT-4 win rates with respect to three objectives (Aesthetic, brightness, darkness). As depicted, MIRA outperforms InitNO and DyMO on all three rewards (Aesthetic, brightness, darkness).

MIRA (SDXL) vs ...	Win Rate (User Study) ↑	Win Rate (GPT-4) ↑
DNO (SDXL)	55.75	58.00
ReNO (SDXL-Turbo)	70.95	70.00

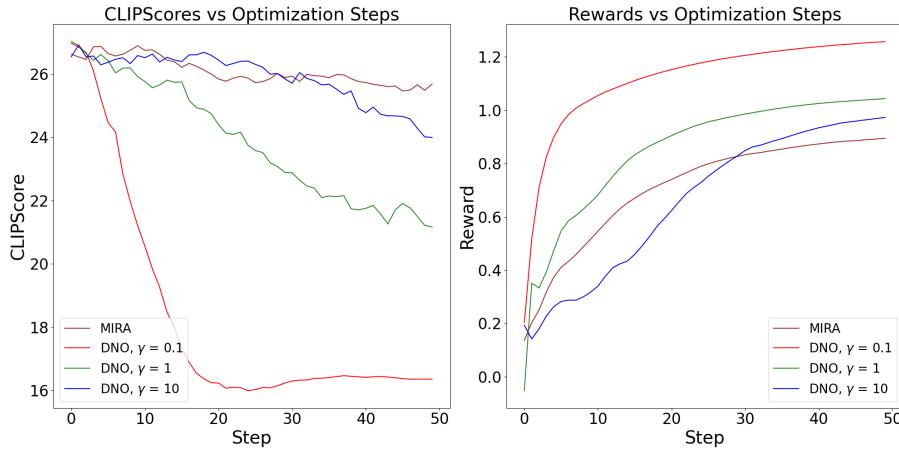
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060 **Table 5. Win rates of MIRA vs DNO and ReNO on 50 HPDv2 prompts.** Using SDXL as the base model for MIRA, we report both
061 user study and GPT-4 win rates with respect to HPSv2. We use ReNO, tailored for one-step models, with SDXL-Turbo for fair comparison.
062 Results show the proposed MIRA is preferred by both GPT-4 and humans over baselines.
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MIRA (SDv1.5) vs ...	Win Rate (User Study) ↑	Win Rate (GPT-4) ↑
DNO (SDv1.5)	80.30	80.00

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065 **Table 6. Win rate of MIRA vs DNO on Simple Animals dataset.** Using SDv1.5 as the base model, we report both user study and
066 GPT-4 win rates with respect to Aesthetic Score. Results show the proposed MIRA is preferred by both GPT-4 and humans over DNO.
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Method	TFLOPs	Memory (GB)	Runtime (min)
SDv1.5	24.7	2.63	0.04
SDv1.5 + BoN (N = 50)	1235	2.63	0.81
InitNO	146.2	15.36	0.5
DyMO	44.5	15.63	0.85
DNO (SDv1.5)	4446.1	9.17	3
MIRA (Ours, SDv1.5)	2223.1	8.97	3
DNO (SDXL)	16278.9	36.60	29
MIRA (Ours, SDXL)	8139.4	36.60	29

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070 **Table 7. Computational costs of inference-time methods for multi-step diffusion models.** For several inference-time time methods,
071 we report the number of operations in tera-FLOPs (TFLOPs), peak memory usage, and wall-clock runtime. Since MIRA is tailored for
072 multi-step diffusion models, we do not report results on methods applied to distilled or one-step diffusion. We observe
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084 **Figure 1. MIRA compared to DNO with different γ on darkness reward.** Here, we use $\beta = 0.8$, $\gamma = 1$ for MIRA. Each curve is the
085 mean curve over all 45 prompts in the Simple Animals dataset, optimized for ‘darkness’ reward. We observe that after 50 optimization
086 steps, MIRA has the highest CLIPScore despite lower reward. As discussed, higher reward is more likely to be overoptimized or hacked.
087 Furthermore, we observe DNO with $\gamma = 10$ overtakes MIRA in reward at step 30 at the cost of CLIPScore and prompt adherence. We
088 note that DNO with $\gamma = 1$ is their optimal setting and exhibits significant drops in CLIPScore over the course of optimization, whereas
089 MIRA balances reward optimization and prompt adherence.
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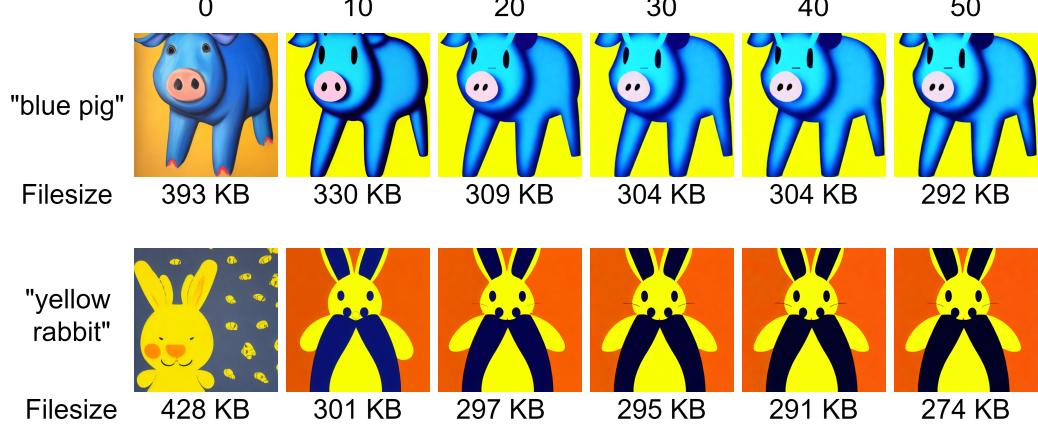


Figure 2. MIRA optimization with non-differentiable reward (JPEG compression) on SDv1.5. We observe a gradual reduction in file sizes over the course of 50 optimization steps while keeping the main subject in the images intact. We provide two examples, prompting with: “Generate an image of a blue pig” (top) and “Generate an image of a yellow rabbit” (bottom).

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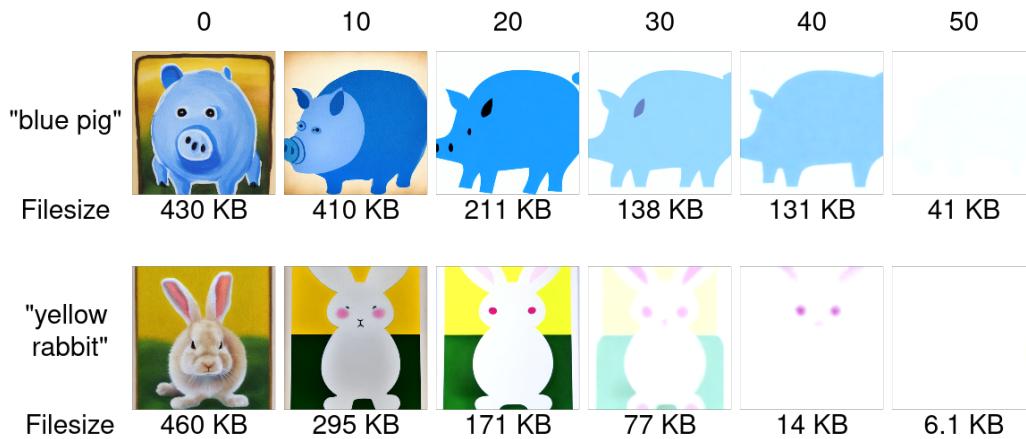


Figure 3. DNO optimization with non-differentiable reward (JPEG compression) on SDv1.5. We see optimizing for JPEG compression with DNO’s gradient approximation does reduce file sizes yet also causes the images lose essential details over the course of 50 optimization steps. We provide two examples, prompting with: “Generate an image of a blue pig” (top) and “Generate an image of a yellow rabbit” (bottom).