

Supplementary Materials for Submission 11223: TAG

Method	Deblur		Super-resolution		CIFAR10		ImageNet		Audio declipping		Audio inpainting	
	FID↓	LPIPS↓	FID↓	LPIPS↓	FID↓	Acc.↑	FID↓	Acc.↑	FAD↓	DTW↓	FAD↓	DTW↓
TFG	64.2	0.154	65.5	0.187	114.1	55.8	231.0	14.3	1.42	256	0.52	74
TFG + TAG (ours)	62.7	0.151	64.7	0.175	102.7	61.5	219.4	17.8	0.74	120	0.42	51
TCS [15]	96.5	0.350	188.7	0.518	160.5	63.7	297.9	15.1	20.03	549	6.25	446
Timestep Guidance [16]	469.8	0.951	483.8	0.973	371.5	11.3	536.5	25.0	33.67	112	21.96	900
Self-Guidance [17]	297.7	0.612	426.9	0.711	188.6	42.9	280.5	14.5	35.05	116	19.39	892

Method	Polarizability α		Dipole μ		Heat capacity C_v		ϵ_{HOMO}		ϵ_{LUMO}		Gap ϵ_{Δ}	
	MAE↓	Stab.↑	MAE↓	Stab.↑	MAE↓	Stab.↑	MAE↓	Stab.↑	MAE↓	Stab.↑	MAE↓	Stab.↑
TFG	8.91	19.2	2.41	26.3	2.65	96.2	0.55	14.6	1.33	10.8	1.40	16.1
TFG + TAG (ours)	4.46	43.6	1.28	94.3	2.67	96.7	0.43	93.9	0.89	92.5	0.78	82.8
TCS [15]	5.40	99.2	1.43	99.2	3.35	99.1	N/A	N/A	1.22	99.2	1.31	99.2
Timestep Guidance [16]	10.98	84.4	N/A	N/A	4.09	85.5	0.70	83.5	1.36	73.0	1.30	83.5
Self-Guidance [17]	7.66	80.2	32.54	80.3	3.80	80.3	N/A	N/A	1.32	80.3	1.27	80.4

Table R1: Comparison of TFG-based methods. The best result for each metric is highlighted in **bold**.

Method	FID ↓	Acc. ↑
DPS	217.1	57.5
TAG (ours)	190.4	63.2
TCS [15]	213.4	29.4
Timestep Guidance [16]	393.2	9.4
Self-Guidance [17]	205.4	51.6
Epsilon Scaling [10]	226.5	56.8
Time Shift Sampler [11]	247.7	56.4
Langevin Dynamics [13]	226.8	58.2

Table R2: Additional baselines when applying DPS on CIFAR-10.

Method	FID ↓	Acc. ↑
$\eta = 0$	332.0	28.5
$\eta = 0.05$	409.9	23.3
$\eta = 0.10$	376.6	25.4
$\eta = 0.15$	326.7	29.2

Table R3: Effect of Input perturbation on DPS, CIFAR-10.

Method	FID ↓	Acc. ↑
<i>512 samples</i>		
TFG	114.1	55.8
TFG + TAG (ours)	102.7	61.5
<i>50000 samples</i>		
TFG	77.5	54.3
TFG + TAG (ours)	47.1	84.4

Table R4: Evaluation with 50,000 samples on CIFAR-10. 100 inference steps.

Method	FID ↓	Acc. ↑
<i>Original Update Order</i>		
DPS + TAG	190.4	63.2
TFG + TAG	102.7	61.5
<i>Changed Update Order</i>		
DPS + TAG	203.5	60.1
TFG + TAG	116.4	54.1

Table R5: Effect of original vs. changed update order for Algorithm 1 (TAG) on CIFAR-10.

		Training Steps
		10K 30K
FID ↓	116.0	102.7
Acc. ↑	55.3	61.5

Table R6: Quantitative evaluation of TFG+TAG for varying training steps on CIFAR10.

Layers	W1 distance ↓
0 (No TAG)	6.458
1	1.716
2	1.681
3	1.975
4	1.714
5	1.713
6	1.788

Table R7: Robustness of time classifier network on toy experiment.



(a) Original images of corrupted reverse process

(b) Images after applying TAG

Figure R1: Comparison of images with different noise levels.

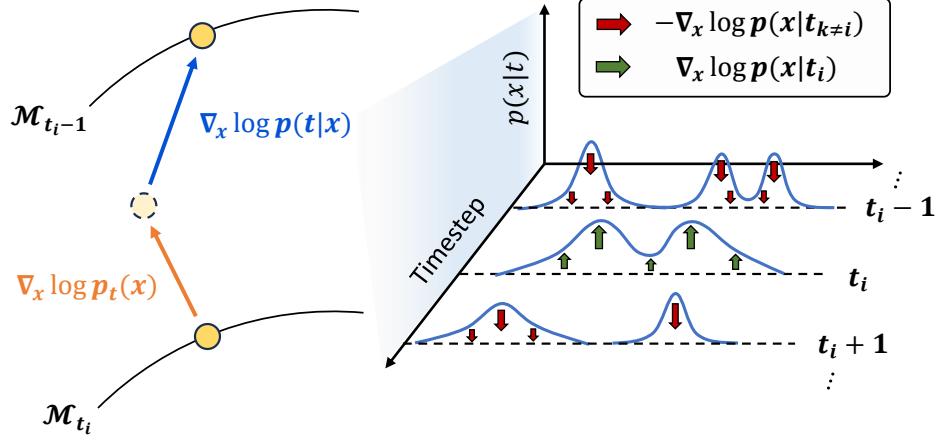


Figure R2: Overview of TAG algorithm. In the left figure, we specifically visualized the decomposition of $\nabla_x \log p(t_i|x)$ according to Eq. 11 in Lemma 3.3.

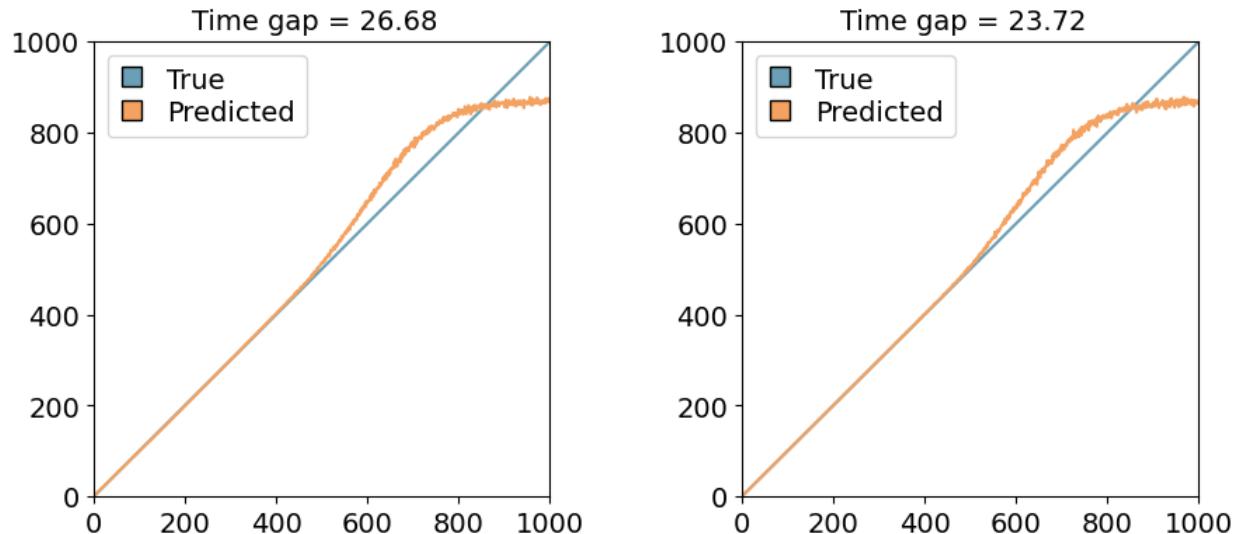


Figure R3: Time gap in CIFAR10. Training iterations are 10K (left) and 30K (right), respectively.

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