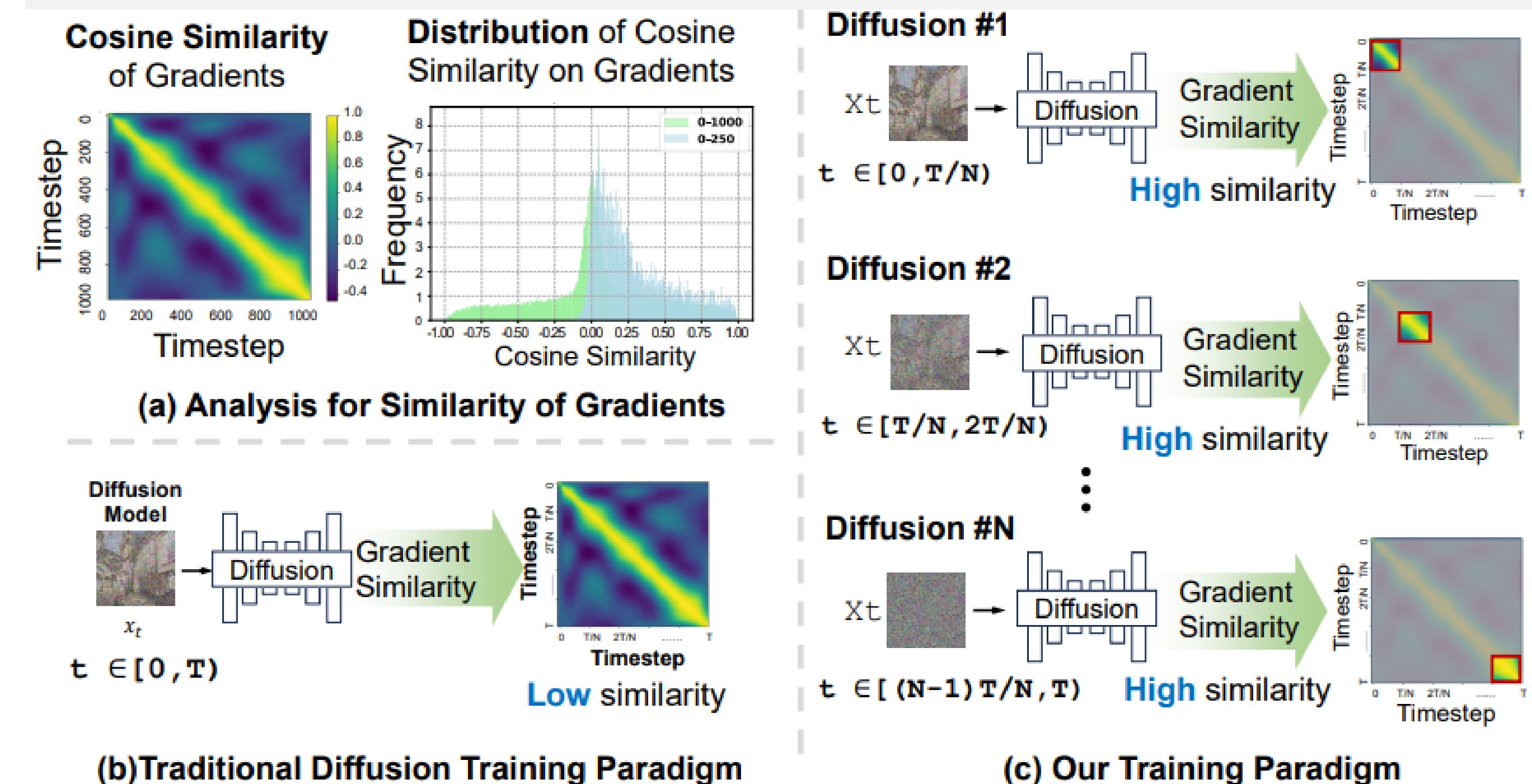
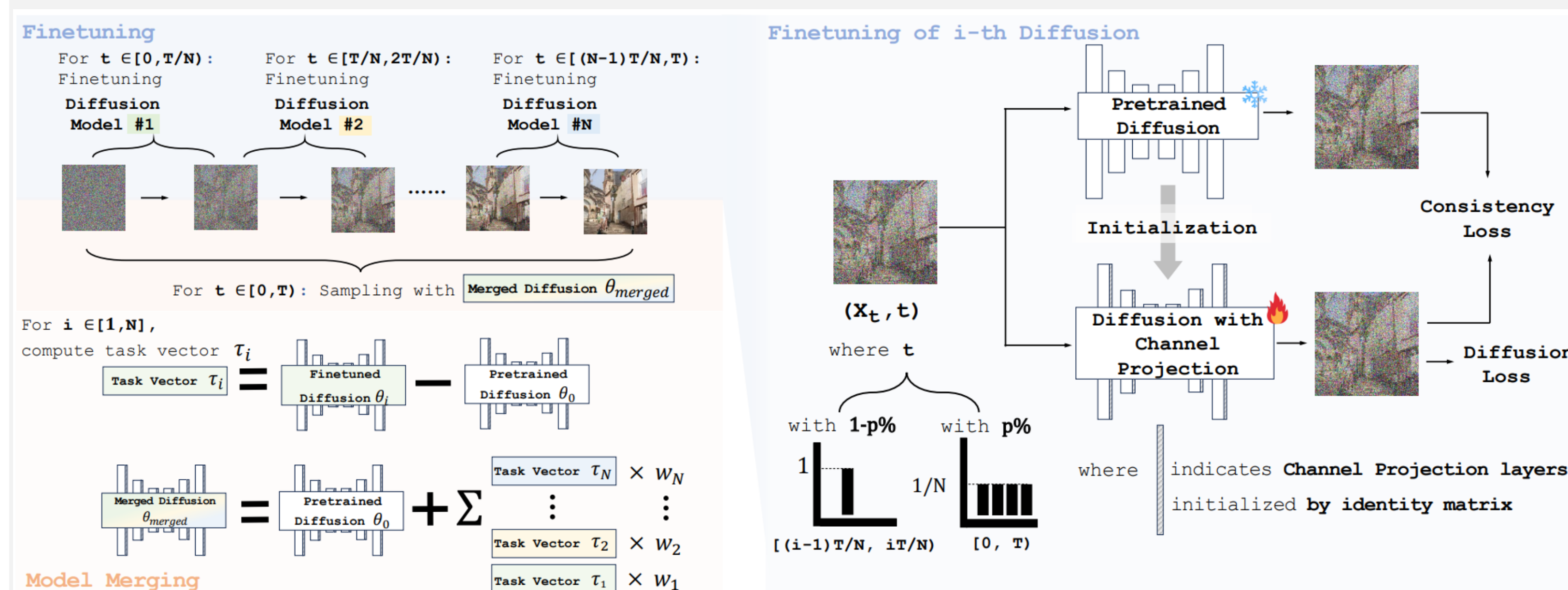


## Introduction

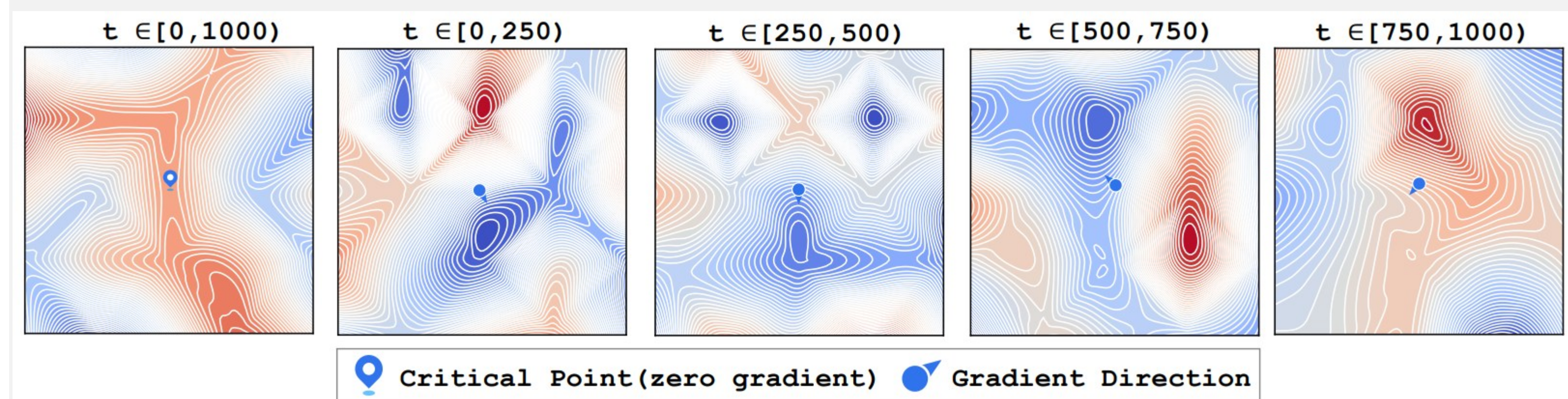


- Diffusion model learns to denoise across multiple timesteps. However, training a single diffusion model across all timesteps can cause **gradient conflicts**, leading to suboptimal performance.
- To solve this, we propose Decouple-then-Merge (DeMe), a novel finetuning framework that **decouples** training across different timestep ranges to reduce interference, and then **merges** the models in parameter space to retain efficiency. With simple techniques like consistency loss, probabilistic sampling and channel-wise projection, DeMe significantly improves generation quality without extra inference cost.
- We further provide theoretical analysis and conduct extensive experiments to demonstrate its effectiveness

## Method: Decouple Training & Models Merging



- In Decoupled training process, **Channel-wise Projection** enables the model to capture the channel-wise difference in different timesteps. **Consistency Loss** preserves the initial knowledge of the diffusion model. **Probabilistic Sampling** enables the finetuned model to mainly learn from its corresponding timestep range, but still possible to preserve the knowledge in the other timestep ranges
- Finally, we **merge** multiple fine-tuned diffusion models into single diffusion model in the parameter space, obtain an enhanced merged model without extra inference cost.



## Comparison Experiments

Method	MS-COCO		ImageNet		PartiPrompts	
	FID↓	CLIP Score↑	FID↓	CLIP Score↑	CLIP Score↑	#Iterations
Before-finetuning [41]	13.42	29.88	27.62	27.07	29.78	-
SNR+1 [46]	13.92	29.96	27.56	27.03	29.86	80K
Trun-SNR [46]	13.93	29.95	27.60	27.05	29.85	80K
Min-SNR- $\gamma$ [13]	13.92	29.93	27.59	27.02	29.87	80K
P2 Weighting [3]	13.23	29.93	26.92	26.44	29.50	80K
ANT-NashMTL [10]	13.39	29.81	27.41	26.99	29.90	80K
ANT-UW [10]	13.17	29.94	26.91	26.78	29.98	80K
DeMe (Before Merge)	12.78 (-0.64)	29.85 (-0.03)	26.36 (-1.26)	26.90 (-0.17)	30.02 (+0.24)	20K×4
DeMe (After Merge)	<b>13.06</b> (-0.36)	<b>30.11</b> (+0.23)	<b>27.23</b> (-0.39)	<b>27.09</b> (+0.02)	<b>29.98</b> (+0.20)	20K×4

Method	CIFAR10	LSUN-Church	LSUN-Bedroom	#Iterations
Before-finetuning [15]	4.42	10.69	6.46	-
SNR+1 [46]	5.41	10.80	6.41	80K
Trun-SNR [46]	4.49	10.81	6.42	80K
Min-SNR- $\gamma$ [13]	5.77	10.82	6.41	80K
P2 Weighting [3]	5.63	10.77	6.53	80K
ANT-NashMTL [10]	4.24	10.45	6.43	80K
ANT-UW [10]	4.21	10.43	6.48	80K
DeMe (Before Merge)	3.79 (-0.63)	9.57 (-1.12)	5.87 (-0.59)	20K×4
DeMe (After Merge)	<b>3.51</b> (-0.91)	<b>7.27</b> (-3.42)	<b>5.84</b> (-0.62)	20K×4

$N$	Probabilistic Sampling	Consistency Loss	Channel-wise Projection	FID ↓
1	✗	✗	✓	4.40 4.45
8	✓ ✓ ✓	✗ ✓ ✓	✗ ✗ ✓	4.32 4.27 3.87

**Prompt I:** “A graceful white horse galloping through a field of wildflowers, its mane flowing in the wind *as the sun sets behind it.*”

Before Finetuning: Loss of text-image alignment: *as the sun sets behind it* 😞  
After Finetuning: Superb text-image alignment, lifelike horse 🥰



**Prompt II:** “A tropical beach with *crystal-clear turquoise water gently lapping against white sandy shores*, tall palm trees swaying in the breeze under a clear blue sky.”

Before Finetuning: Loss of text-image alignment: *white sandy shores* 😞  
After Finetuning: Superb text-image alignment, excellent coastal view 🥰



**Prompt III:** “A dolphin leaping out of the ocean in perfect harmony, water splashing around it *as the sun sets on the horizon, casting a golden glow on the sea.*”

Before Finetuning: Loss of text-image alignment: *sun sets on the horizon.* 😞  
After Finetuning: Superb text-image alignment, photorealistic illustration 🥰



**Prompt IV:** “A foggy morning in a quiet countryside, *a small wooden cabin surrounded by wildflowers and tall grass, the sun just beginning to rise through the mist.*”

Before Finetuning: Loss of text-image alignment: *a small wooden cabin* 😞  
After Finetuning: Superb text-image alignment, serene landscape 🥰

