Taming Diffusion Prior for Image Super-Resolution with Domain Shift SDEs

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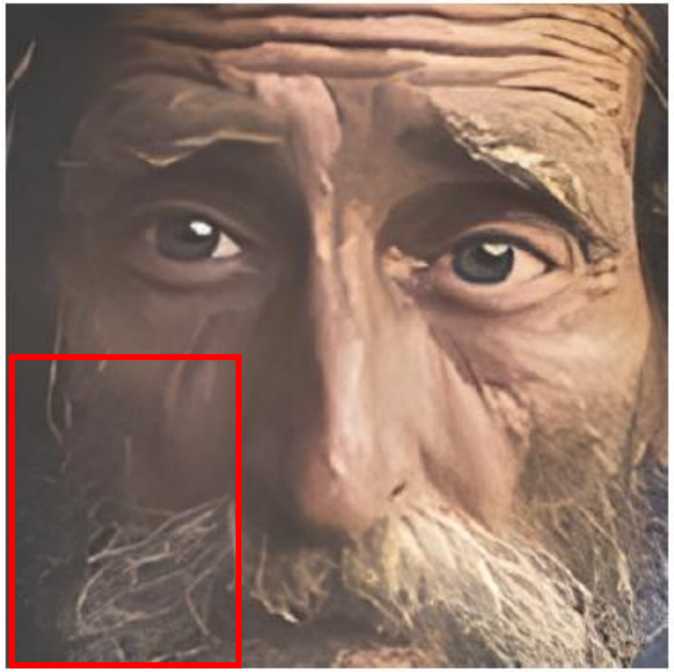
Motivation

- Image Super Resolution(SR): Traditional models aim to learn a mapping from low-resolution (LR) images to high-resolution(HR) image.

- Diffusion-based SR models have attracted substantial interest due to their powerful image restoration capabilities. However , prevailing diffusion models often struggle to strike an optimal balance between ***efficiency and performance*.**

LR image



Previous SR method

SD-based model

Motivation

- ❑ Currently, diffusion-based SR strategies can be broadly categorized into two approaches:

1) Follow the traditional diffusion process (High resolution images ⟷ Random Gaussian Noise):
   - Achieves good performance: leverage large-scale pretrained models(e.g. Stable Diffusion) as generative prior
   - Efficiency limitation due to the long transition path (start from noise)
   - eg: StableSR(IJCV’24)

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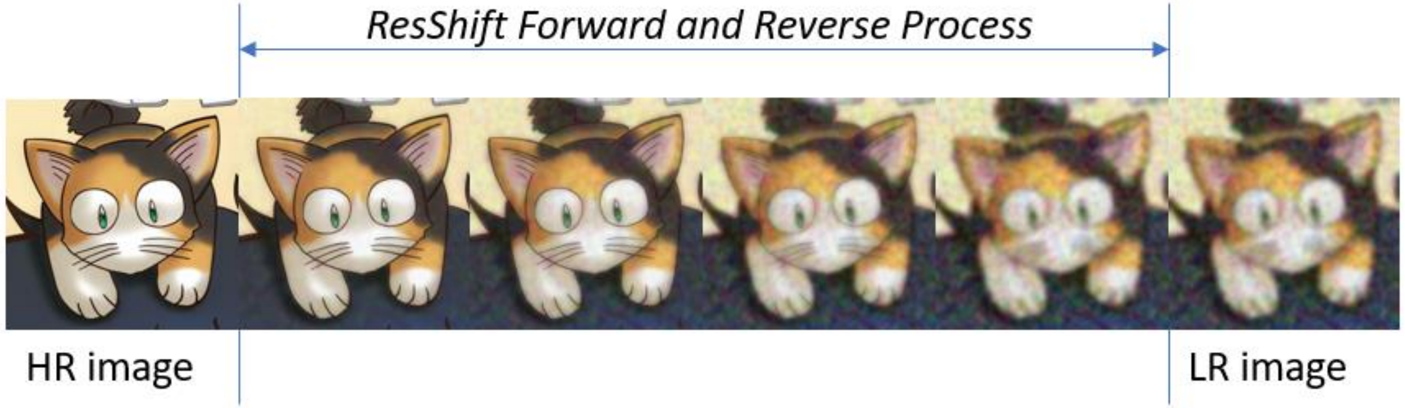
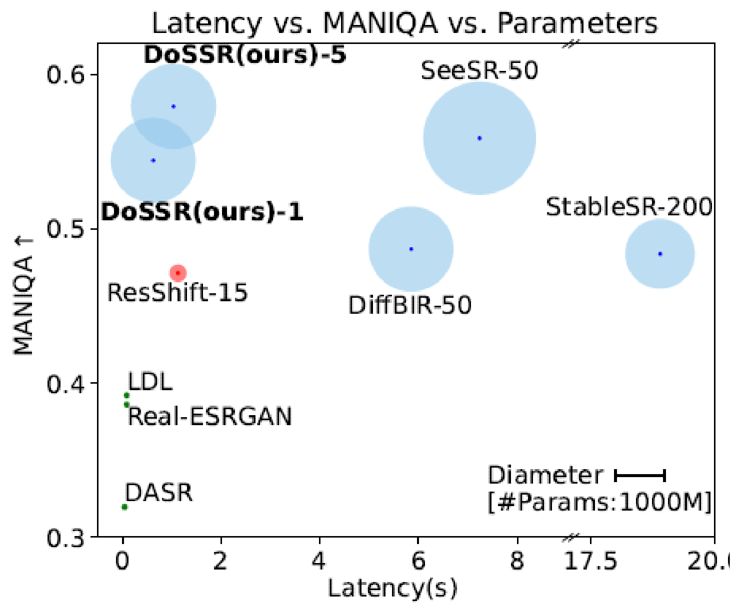
2) Redefine the diffusion process (High resolution images ⟷ Low resolution image):
   - poorer results: retraining a model from scratch for the SR task
   - Faster: start from LR image rather than gauss noise
   - eg: ResShift (NeurIPS' 23), FlowIE(CVPR' 24)

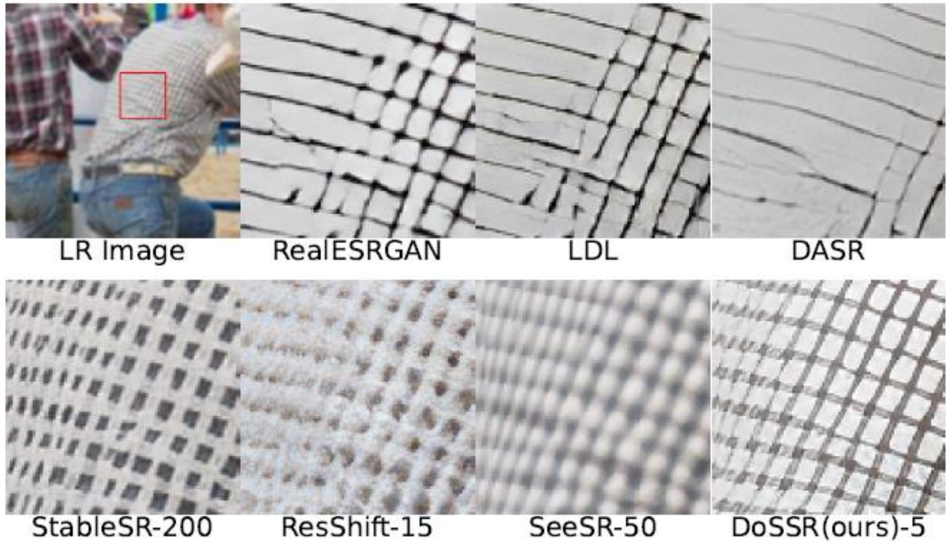


Contributions

- **Domain shift SDEs (DoS-SDE):** We propose a novel diffusion equation that improves efficiency while keeping good generative capability
  - Leveraging Stable Diffusion prior
  - Denoise starting from LR images rather than random Gaussians
- **Solvers for DoS-SDEs:** We design customized fast sampler, resulting in even higher efficiency



	Leverage SD Prior	Start from LR	Generative Capability	Efficiency
Category1 (StableSR)	✓		Good	Slow
Category2 (ResShift)		✓	Bad	Fast
DoSSR (ours)	✓	✓	Good	Fast



Method(*Domain Shift Equation*)

- Consider the SR task as a *gradual shift* from the *source domain* to the *target domain*.
  - source domain: the distribution of LR images $p_{data}(\hat{x}_0)$
  - target domain: the distribution of HR images $p_{data}(x_0)$

- How to describe this transition? Just *linear interpolation* is a simple and effective method !

$$\mathcal{D}(\hat{\boldsymbol{x}}_0, \boldsymbol{x}_0) = \eta_t \hat{\boldsymbol{x}}_0 + (1 - \eta_t)\boldsymbol{x}_0, \ 0 \leq \eta_t \leq 1, \ t = 1, 2, \cdots, T,$$

where drift coefficient η_t monotonically non-decreases with timestep t.

- To enable linear combination, we can interpolate $\hat{x}_0$to match the same dimensions as x_0 if necessary.
  - this operation applies similarly to the *latent space* as well

Method(*Diffusion Process with Domain Shift*)

- Combine this domain shift with the *Sable Diffusion* forward diffusion equation ?
  - *replace the "noise-added object" in diffusion equation*
  - *add noise while shifting from the HR to LR image distribution*

$$q(\boldsymbol{x}_t|\boldsymbol{x}_0) = \mathcal{N}(\boldsymbol{x}_t; \boxed{\alpha_t \boldsymbol{x}_0}, \sigma_t^2 \boldsymbol{I}),\ t = 1, 2, \cdots, T, \longrightarrow q(\boldsymbol{x}_t|\boldsymbol{x}_0, \hat{\boldsymbol{x}}_0) = \mathcal{N}(\boldsymbol{x}_t; \boxed{\alpha_t \mathcal{D}(\hat{\boldsymbol{x}}_0, \boldsymbol{x}_0)}, \sigma_t^2 \boldsymbol{I}),\ t = 1, 2, \cdots, T,$$

where $\alpha_t, \sigma_t \geq 0$ and $\alpha_t^2 + \sigma_t^2 = 1$, which are called *noise schedule*, $\boldsymbol{I}$ is identity matrix

- Maximally preserve the *diffusion prior* by keeping the *noise schedule* unchanged.
  - rearranging the noise schedule requires significant training cost and can disrupt the pretrained model

- However, keeping the *noise schedule* unchanged ensures *the noising process endpoint* remains approximately *Gaussian noise*, as in Stable Diffusion, but we ***aim to infer from LR***(+ little noise)
  - when $t = T, \alpha_T \to 0, \sigma_T \to 1, x_T \to N(0; I)$

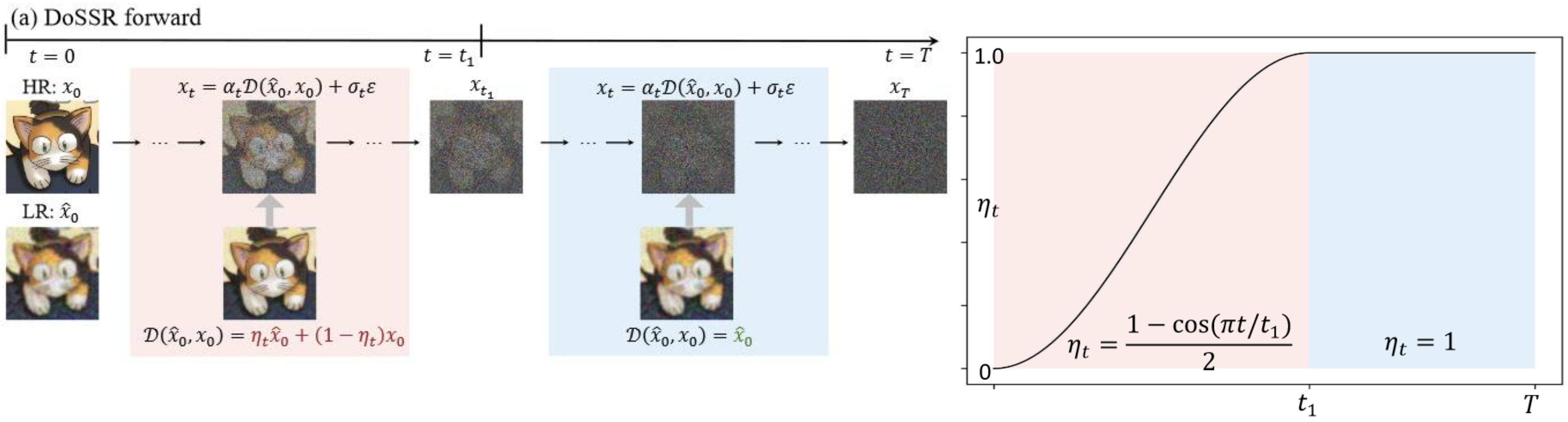
Solve this by designing the shifting sequence $\{\eta_t\}_{t=1}^{T}$!

Method(*Shifting Sequence Design*)

- Given that LR and noise are **known** prior distributions, we can use the shifting sequence to *shorten the unknown diffusion path length*.

- Segmented shifting sequence in two parts: $$\eta_t = \frac{1 - \cos(\pi \frac{t}{t_1})}{2} \text{ if } t \in [0, t_1], \quad \eta_t = 1 \text{ if } t \in [t_1, T].$$

  - ✓ Values of x_t for $t \in [t_1, T]$ are known and can be obtained through the forward process equation.
  - ✓ Inference can start at time step t_1 instead of T



Method(*Diffusion DoS-SDEs*)

- Extend the discrete diffusion process to an SDE to enable efficient sampler design.

Forward SDE(HR → LR)

$$\mathbf{x}(0) \longrightarrow d\boldsymbol{x}_t = [f(t)\boldsymbol{x}_t + h(t)\hat{\boldsymbol{x}}_0]\, dt + g(t)d\boldsymbol{w}_t \longrightarrow \mathbf{x}(t_1)$$

$$\mathbf{x}(0) \longleftarrow d\boldsymbol{x}_t = [f(t)\boldsymbol{x}_t + h(t)\hat{\boldsymbol{x}}_0 - g^2(t)\boxed{\nabla_x \log q_t(\boldsymbol{x}_t)}]\, dt + g(t)d\boldsymbol{w}_t \longleftarrow \mathbf{x}(t_1)$$

Reverse SDE(HR ← LR)

***Do**main **S**hift SDEs (DoS-SDEs)*

- Transition is a linear Gaussian:

$$q(\boldsymbol{x}_t|\boldsymbol{x}_0, \hat{\boldsymbol{x}}_0) = \mathcal{N}(\boldsymbol{x}_t; \alpha_t(\eta_t\hat{\boldsymbol{x}}_0 + (1-\eta_t)\boldsymbol{x}_0), \sigma_t^2\boldsymbol{I}),$$

- Training by score matching:

$$\begin{aligned}\boldsymbol{\theta}^* &= \arg\min_{\boldsymbol{\theta}} \mathbf{E}_t\Big\{w(t)\mathbf{E}_{q_t(\boldsymbol{x}_t)}\big[||\boldsymbol{\epsilon}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, \hat{\boldsymbol{x}}_0, t) + \sigma_t\nabla_{\boldsymbol{x}}\log q_t(\boldsymbol{x}_t)||\big]\Big\} \\ &= \arg\min_{\boldsymbol{\theta}} \mathbf{E}_t\Big\{w(t)\mathbf{E}_{q_0(\boldsymbol{x}_0)}\mathbf{E}_{q(\boldsymbol{\epsilon})}\big[||\boldsymbol{\epsilon}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, \hat{\boldsymbol{x}}_0, t) - \boldsymbol{\epsilon}||\big]\Big\},\end{aligned}$$

Method(*Solvers for Diffusion DoS-SDEs*)

❖ Design efficient samplers by solving the diffusion DoS-SDEs.

❑ Exact solution of Diffusion DoS-SDEs:

$$\boldsymbol{x}_t = \frac{\alpha_t(1-\eta_t)}{\alpha_s(1-\eta_s)}\frac{\lambda_t^2}{\lambda_s^2}\boldsymbol{x}_s + \alpha_t(1-\eta_t)\left(\frac{\eta_t}{1-\eta_t} - \frac{\eta_s}{1-\eta_s}\frac{\lambda_t^2}{\lambda_s^2}\right)\hat{\boldsymbol{x}}_0$$

nonlinear integral term

$$- \alpha_t(1-\eta_t)\int_{\lambda_s}^{\lambda_t}\frac{2\lambda_t^2}{\lambda^3}\boldsymbol{x}_\theta(\boldsymbol{x}_\lambda, \hat{\boldsymbol{x}}_0, \lambda)d\lambda + \alpha_t(1-\eta_t)\sqrt{\lambda_t^2 - \frac{\lambda_t^4}{\lambda_s^2}}\boldsymbol{z}_s, \qquad \text{where } \lambda_t = \frac{\sigma_t}{\alpha_t(1-\eta_t)} \text{ and } \boldsymbol{z}_s \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}).$$

first-order approximate(Euler method)

❑ Sampler(approximate exact solution):

$$\tilde{\boldsymbol{x}}_t = \frac{\alpha_t(1-\eta_t)}{\alpha_s(1-\eta_s)}\frac{\lambda_t^2}{\lambda_s^2}\boldsymbol{x}_s + \boxed{\underbrace{\alpha_t(1-\eta_t)\left(\frac{\eta_t}{1-\eta_t} - \frac{\eta_s}{1-\eta_s}\frac{\lambda_t^2}{\lambda_s^2}\right)\hat{\boldsymbol{x}}_0}_{\text{Domian Shift Guidance(DoSG)}}}$$

$$+ \alpha_t(1-\eta_t)\left(1 - \frac{\lambda_t^2}{\lambda_s^2}\right)\boldsymbol{x}_\theta(\boldsymbol{x}_s, \hat{\boldsymbol{x}}_0, s) + \alpha_t(1-\eta_t)\sqrt{\lambda_t^2 - \frac{\lambda_t^4}{\lambda_s^2}}\boldsymbol{z}_s.$$

<u>Do</u>main <u>S</u>hift <u>G</u>uidance(DoSG)

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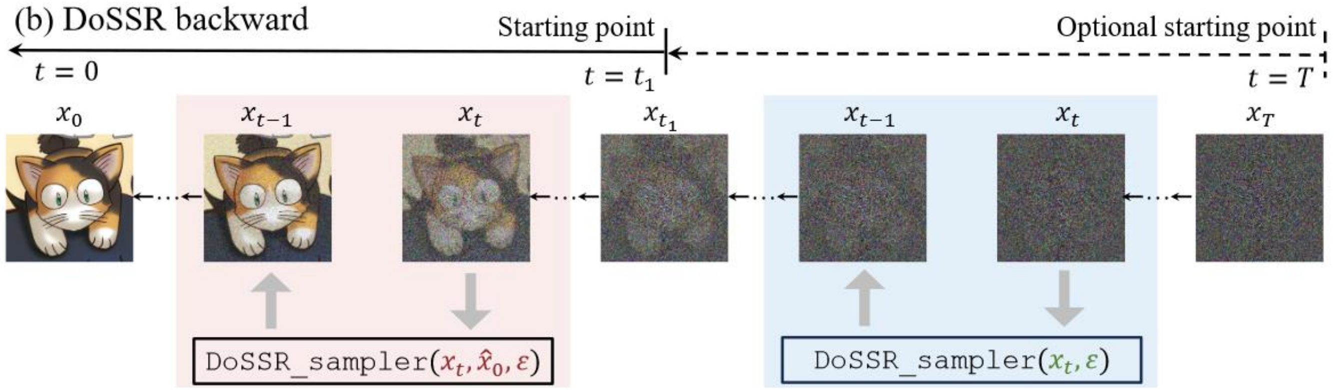
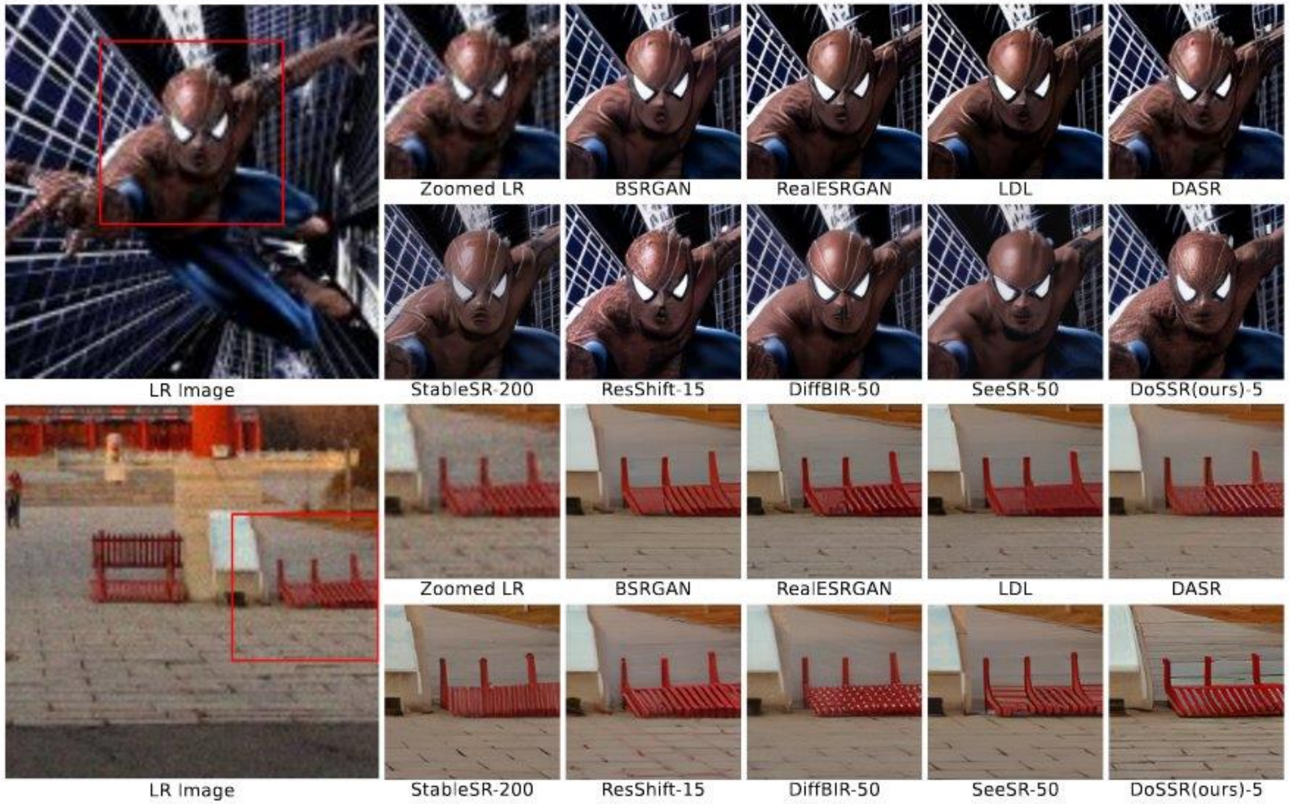
❑ Inference:



Experiments

- ✓ SOTA performance on synthetic and real-world datasets.
- ✓ Requiring ***only 5 sampling steps,*** *achieves a remarkable speedup of **5-7 times.***

Qualitative Comparison



Quantitative Comparison

Datasets	Metrics	BSRGAN	Real-ESRGAN	LDL	DASR	StableSR	ResShift	DiffBIR	SeeSR	DoSSR
DIV2k-Val	PSNR ↑	24.58	24.29	23.83	24.47	23.36	**24.65**	23.67	23.68	23.98
	SSIM ↑	0.6241	**0.6338**	0.6312	0.6277	0.5654	0.6148	0.5592	0.5987	0.6073
	LPIPS ↓	0.3351	**0.3112**	0.3256	0.3543	0.3114	0.3349	0.3516	0.3195	0.3371
	CLIPIQA ↑	0.5246	0.5276	0.5179	0.5036	0.6771	0.6065	0.6693	0.6935	**0.7014**
	MUSIQ ↑	61.19	61.06	60.04	55.19	65.92	61.07	65.78	**68.68**	66.54
	MANIQA ↑	0.3547	0.3795	0.3736	0.3165	0.4193	0.4107	0.4568	0.5041	**0.5294**
	TOPIQ ↑	0.5456	0.5294	0.5142	0.4530	0.5974	0.5383	0.6142	**0.6854**	0.6766
RealSR	PSNR ↑	26.38	25.69	25.28	**27.02**	24.65	26.26	24.81	25.14	24.18
	SSIM ↑	0.7655	0.7615	0.7565	**0.7714**	0.7060	0.7404	0.6571	0.7194	0.6839
	LPIPS ↓	**0.2656**	0.2709	0.2750	0.3134	0.3002	0.3469	0.3607	0.3007	0.3374
	CLIPIQA ↑	0.5114	0.4485	0.4556	0.3198	0.6234	0.5473	0.6448	0.6699	**0.7025**
	MUSIQ ↑	63.28	60.37	60.93	41.21	65.88	58.47	64.94	**69.82**	69.42
	MANIQA ↑	0.3764	0.3733	0.3792	0.2461	0.4260	0.3836	0.4539	0.5406	**0.5781**
	TOPIQ ↑	0.5502	0.5147	0.5124	0.3207	0.5743	0.4883	0.5722	0.6887	**0.6985**
DRealSR	PSNR ↑	28.74	28.62	28.17	**29.72**	28.03	28.42	26.67	27.89	26.82
	SSIM ↑	0.8033	0.8050	0.8126	**0.8264**	0.7523	0.7629	0.6548	0.7565	0.7298
	LPIPS ↓	0.2858	0.2818	**0.2792**	0.3099	0.3284	0.4036	0.4517	0.3273	0.3689
	CLIPIQA ↑	0.5091	0.4507	0.4473	0.3813	0.6357	0.5286	0.6391	0.6708	**0.6776**
	MUSIQ ↑	57.16	54.28	53.95	42.41	58.51	49.73	60.91	**65.09**	64.40
	MANIQA ↑	0.3424	0.3436	0.3444	0.2845	0.3867	0.3322	0.4486	0.5115	**0.5214**
	TOPIQ ↑	0.5058	0.4621	0.4518	0.3482	0.5320	0.4380	0.5819	0.6574	**0.6618**
Real200	CLIPIQA ↑	0.5910	0.5554	0.5508	0.5157	0.7272	0.6759	0.7170	0.7167	**0.7437**
	MUSIQ ↑	67.65	66.12	65.80	61.26	70.63	66.98	68.92	**72.14**	71.62
	MANIQA ↑	0.3882	0.3861	0.3921	0.3196	0.4838	0.4713	0.4869	0.5588	**0.5794**
	TOPIQ ↑	0.5966	0.5530	0.5478	0.4793	0.6517	0.6124	0.6235	0.7142	**0.7176**
NFE ↓		-	-	-	-	200	15	50	50	**5**
# Parameters		16.70M	16.70M	16.70M	8.07M	1409.1M	173.9M	1716.7M	2283.7M	1716.6M
Latency/Image ↓		0.06s	0.08s	0.08s	0.04s	18.90s	1.12s	5.85s	7.24s	1.03s

Conclusion

- We present *DoSSR*, a diffusion-based super-resolution framework that significantly ***enhances both efficiency and performance*** by integrating a domain shift strategy with pretrained diffusion models.

- Empirical validation on diverse SR benchmarks confirms that DoSSR ***achieves a 5-7 times speed improvement*** over existing methods, setting a new state-of-the-art.

Thanks!

Code: https://github.com/QinpengCui/DoSSR