Adapt and Diffuse: Sample-adaptive Reconstruction via Latent Diffusion Models

Zalan Fabian*, Berk Tinaz*, Mahdi Soltanolkotabi

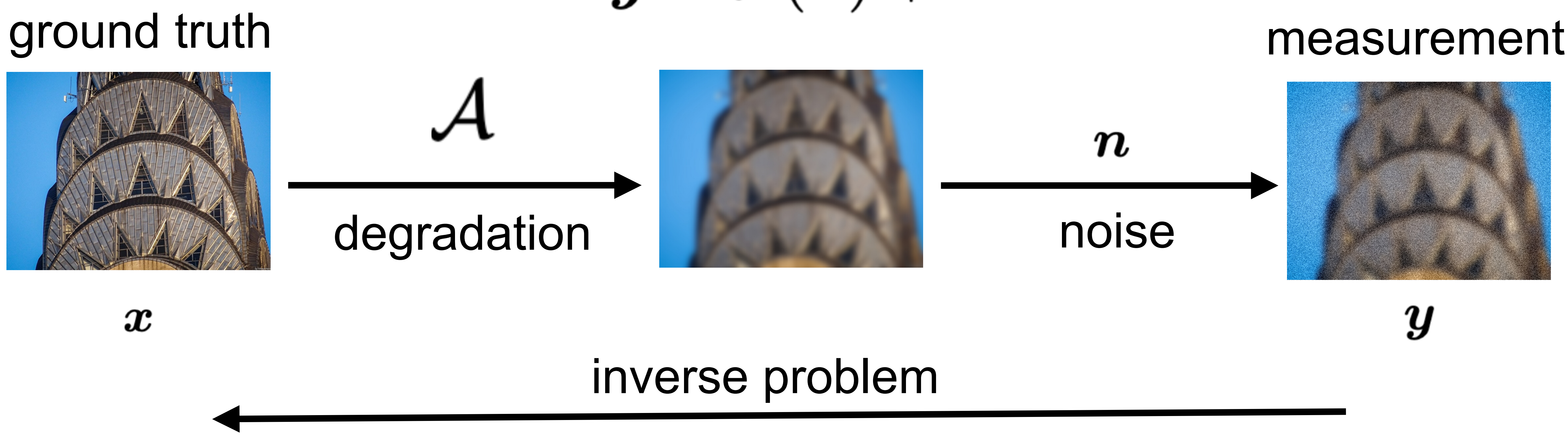
ICML
International Conference
On Machine Learning

USC

USC Center on AI Foundations for the Sciences

Inverse Problems

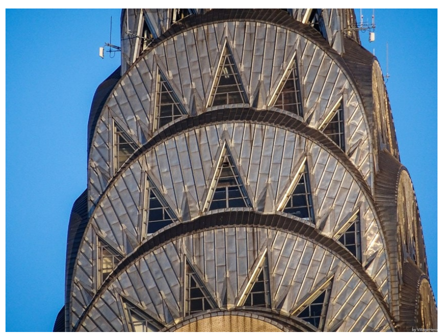
$$\boldsymbol{y} = \mathcal{A}(\boldsymbol{x}) + \boldsymbol{n}$$



Inverse Problems

$$\boldsymbol{y} = \mathcal{A}(\boldsymbol{x}) + \boldsymbol{n}$$

ground truth



$\boldsymbol{x}$

$\mathcal{A}$

degradation

$\boldsymbol{n}$

noise

measurement

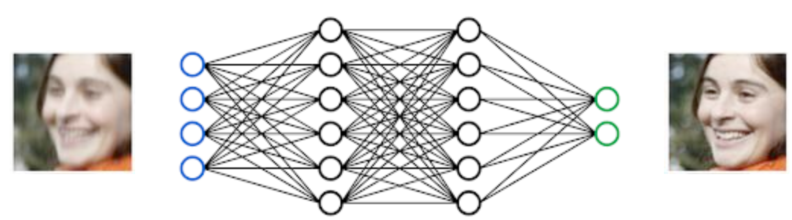
$\boldsymbol{y}$

inverse problem

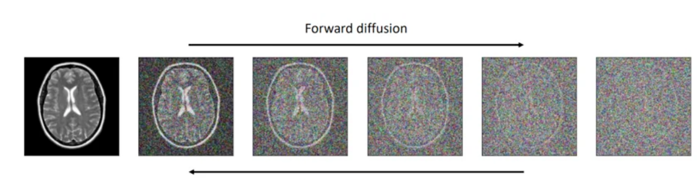
- Solving inverse problems

$$\hat{x} = arg \min_{x} \|\mathscr{A}(x) - y\|^2 + \mathscr{R}(x)$$

Classical approaches



End-to-end deep learning



Diffusion solvers

Reconstruction difficulty

- **Sample-by-sample variation in reconstruction difficulty**

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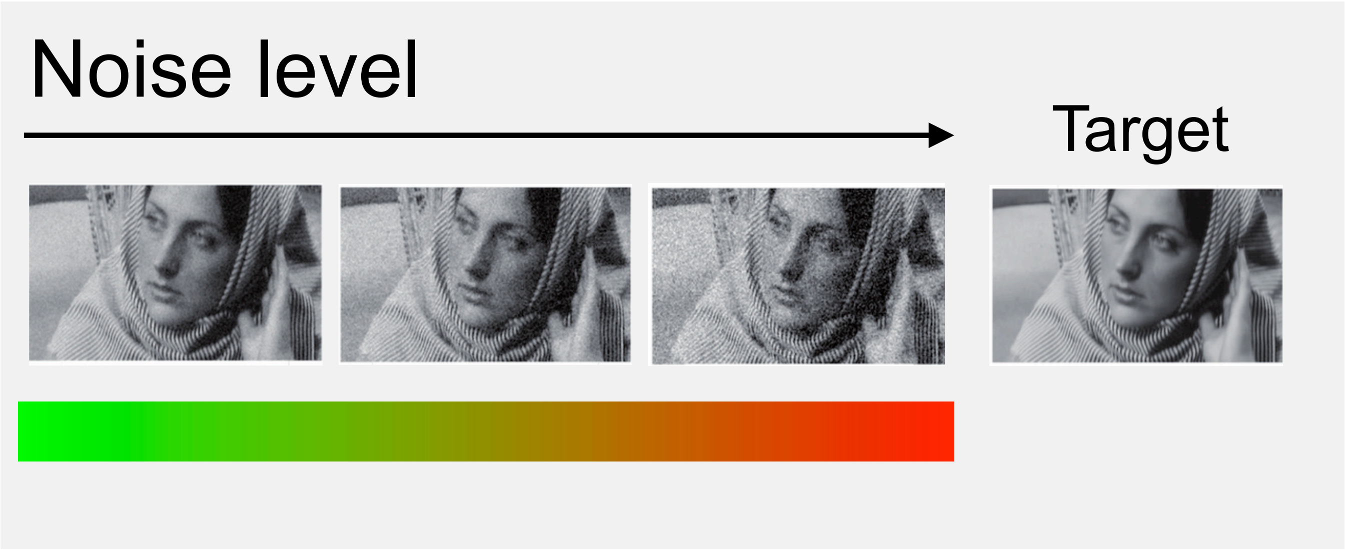

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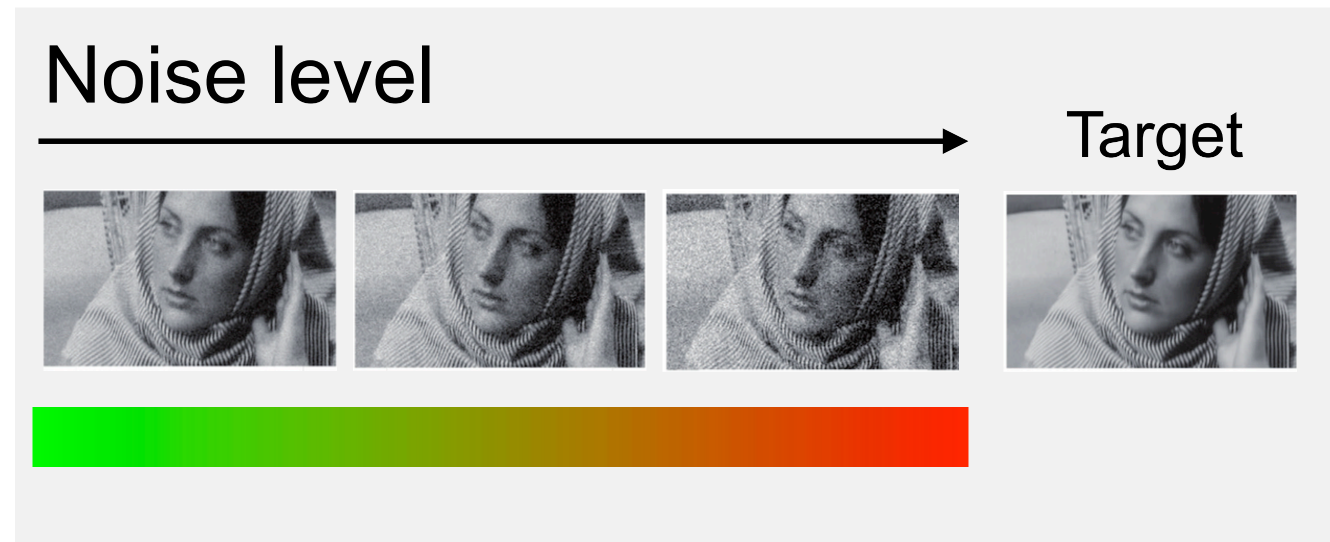

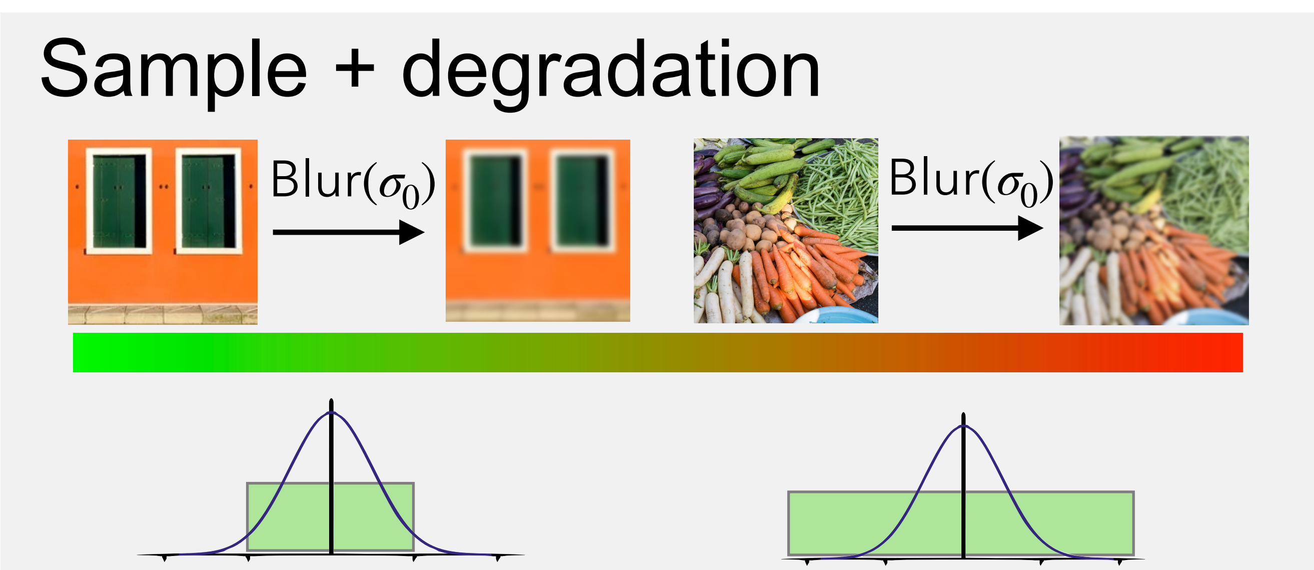

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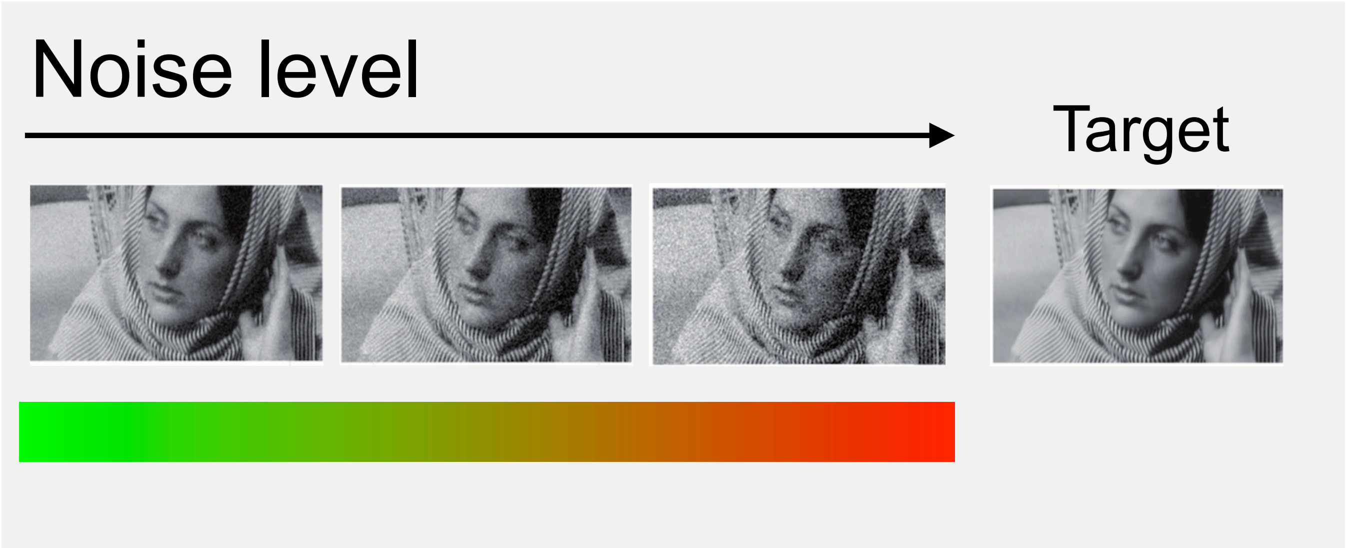
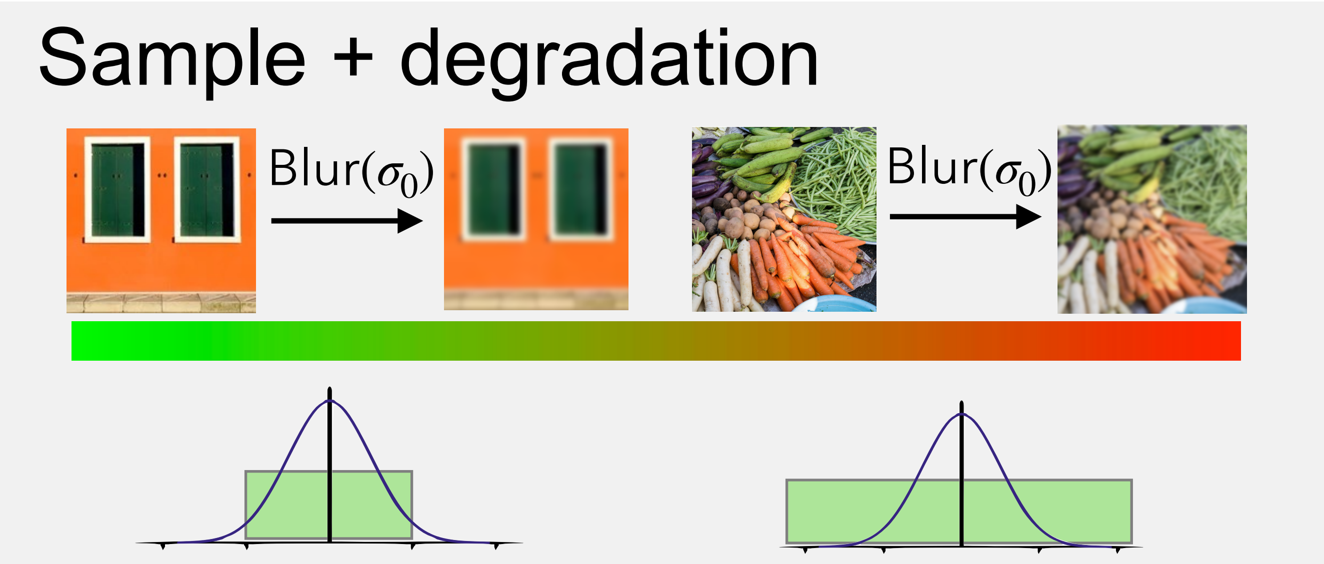
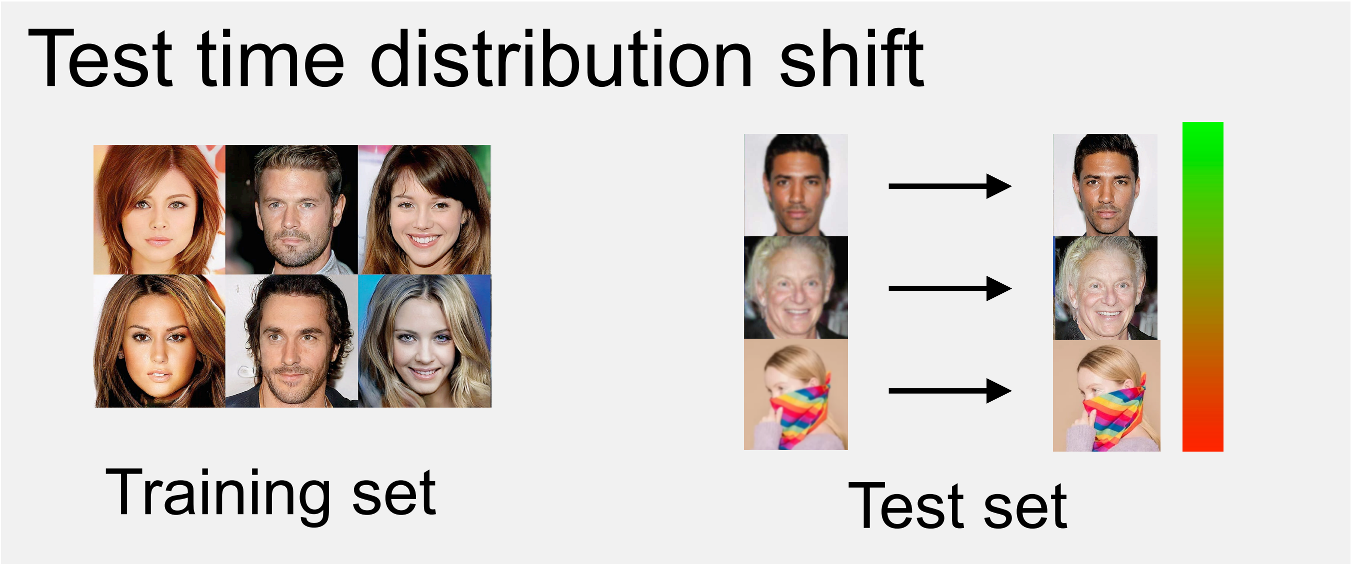
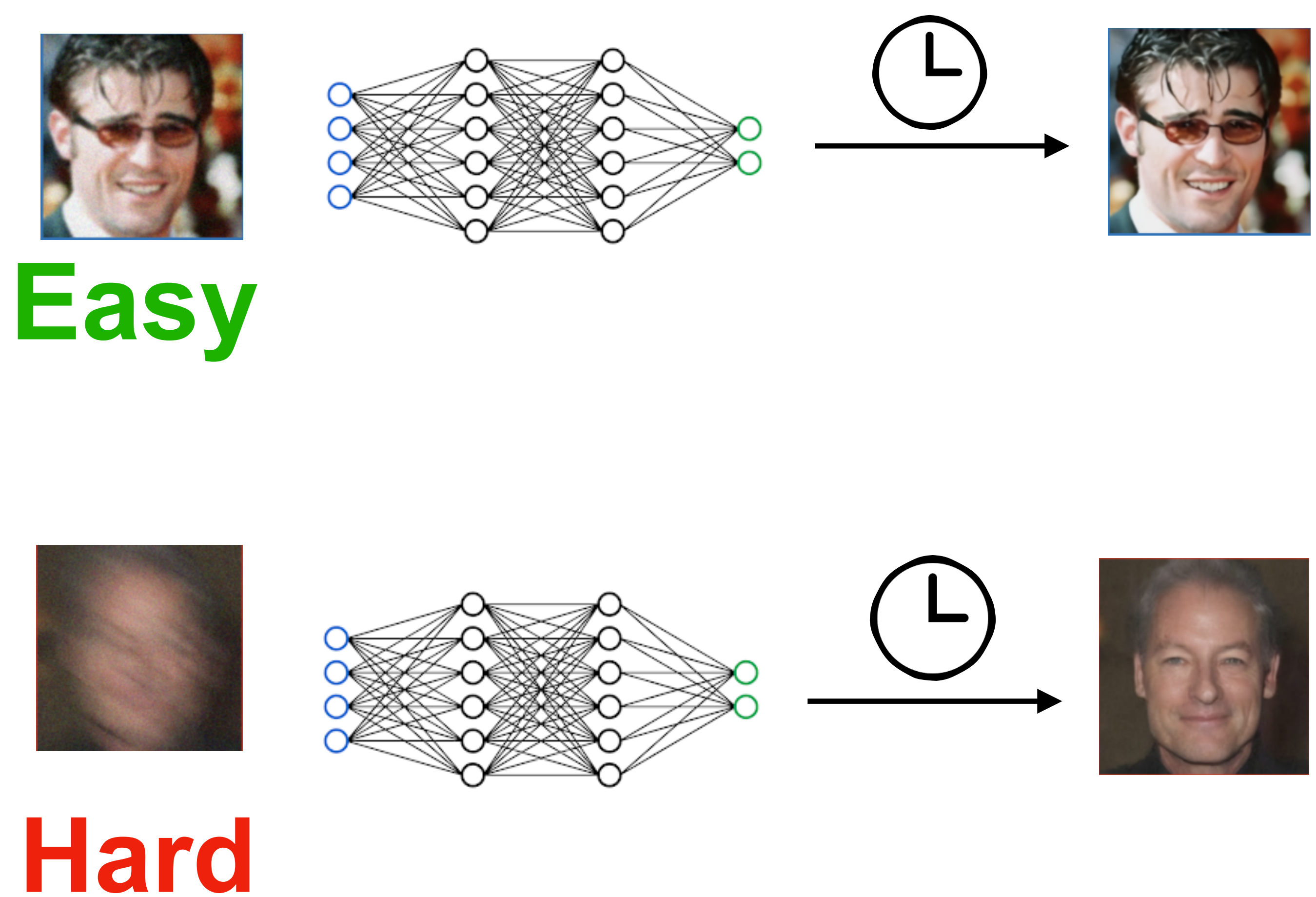






Sample-adaptive compute

- **Expending the same amount of resources to reconstruct any sample (easy or hard) is potentially wasteful.**



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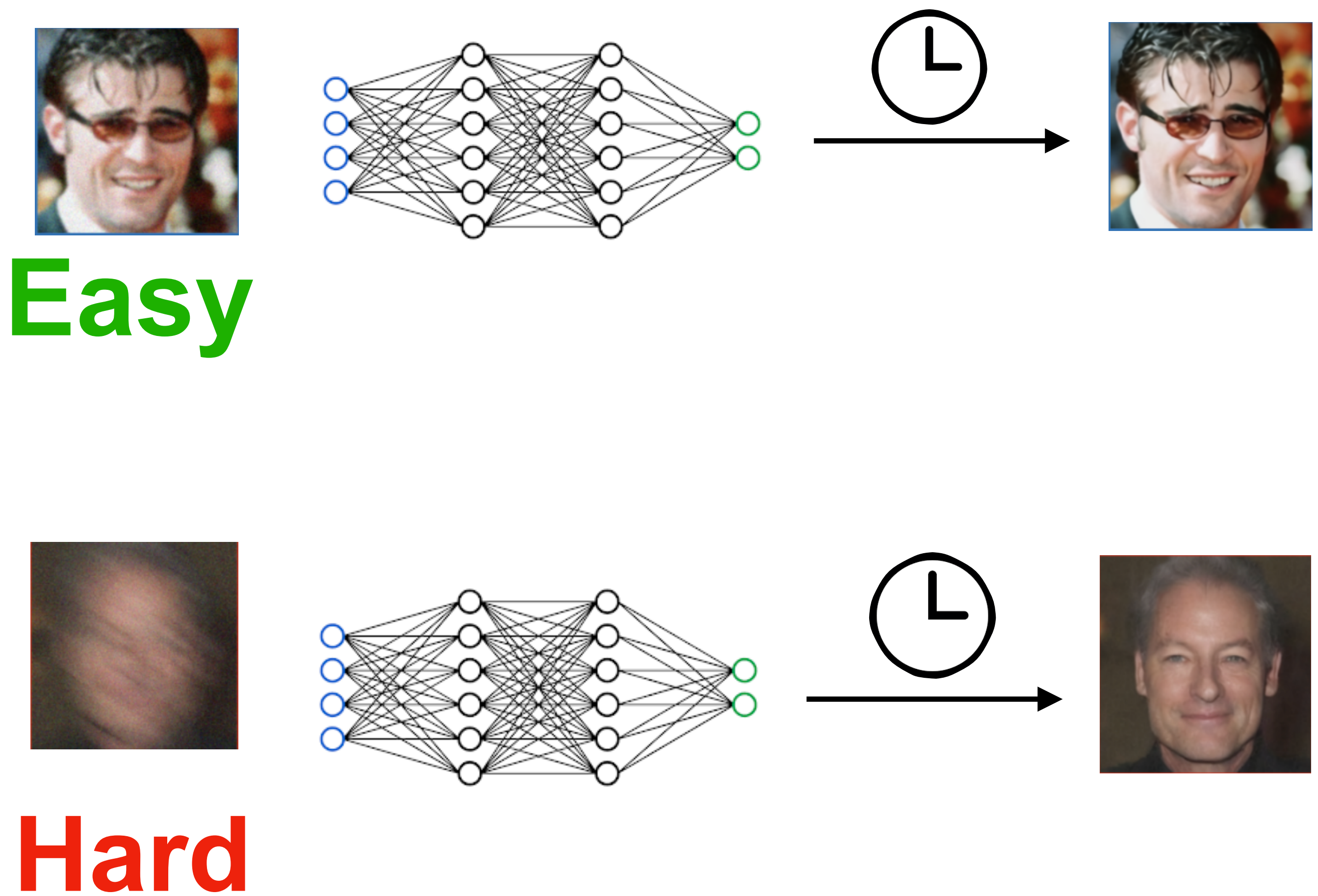

Idea: adapt the compute allocation based on the difficulty of the problem on a **sample-by-sample** basis in test time!

Adapt…

Quantifying difficulty

Image space

$y = c \cdot x, \quad c \in \mathbb{R}^+$

- arbitrarily high perturbation
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Idea: quantify severity of degradation **in the latent space** of an autoencoder

Severity Encoding

- **Estimate degradation severity given corrupted image**

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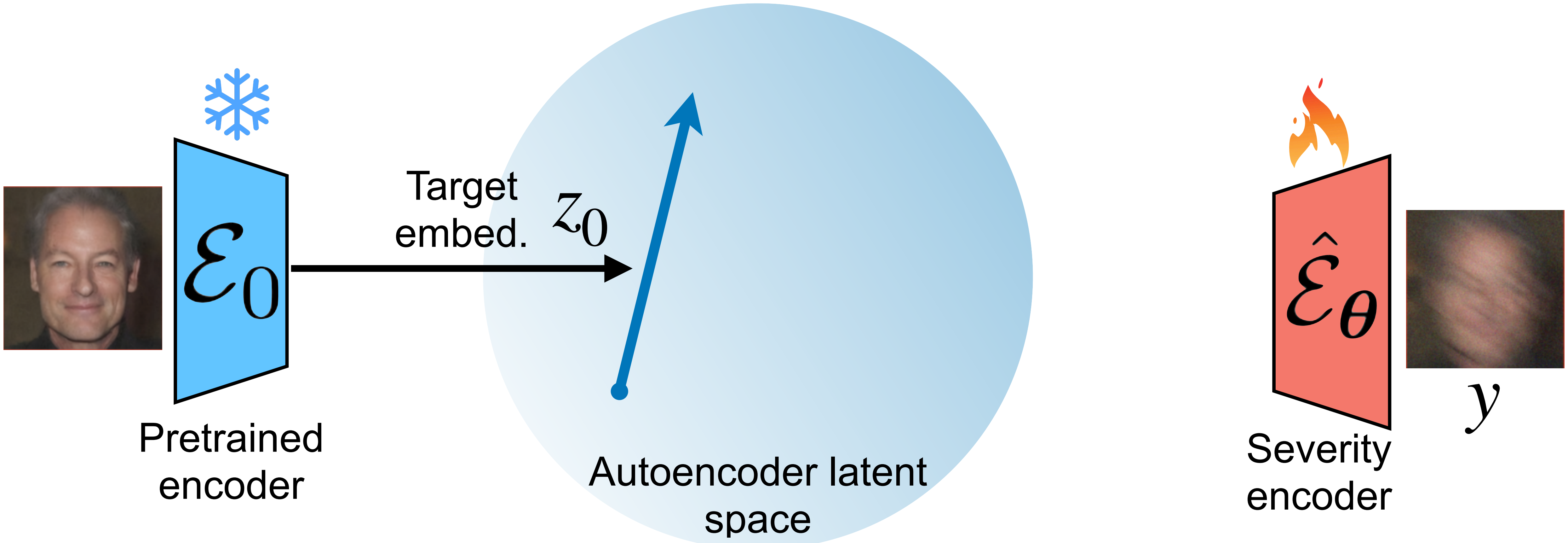

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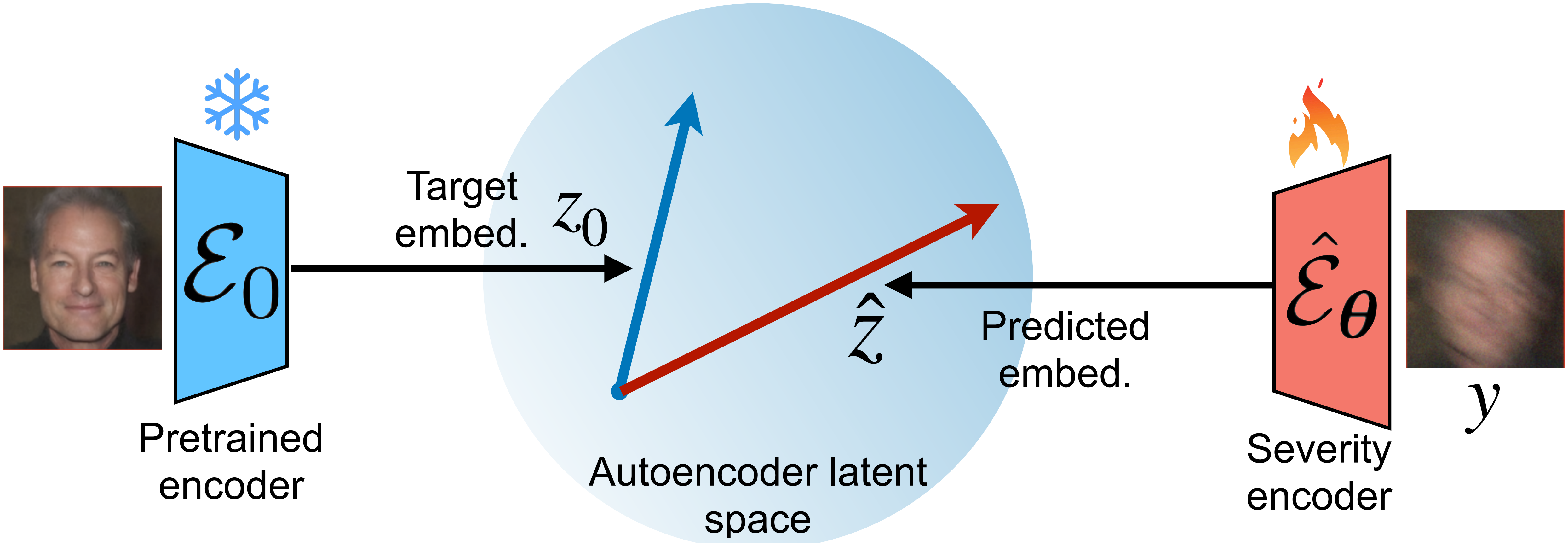

Objectives:

1. Predict latent of clean image

Severity Encoding

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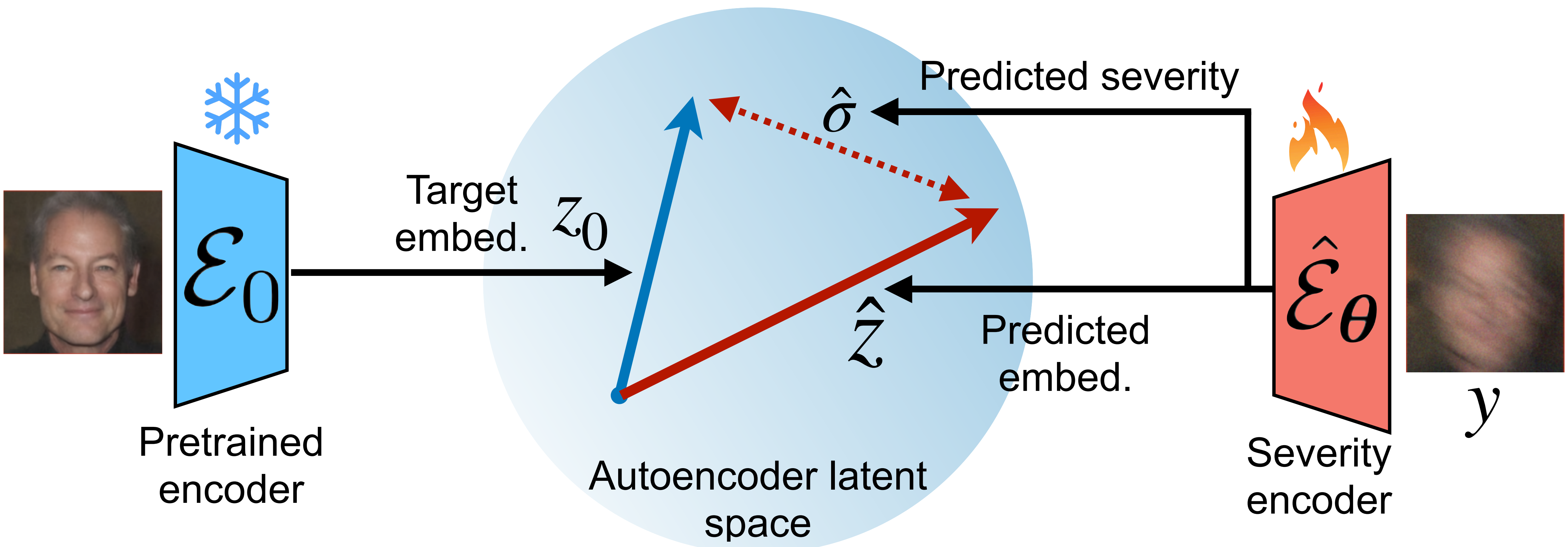

<u>Objectives:</u>

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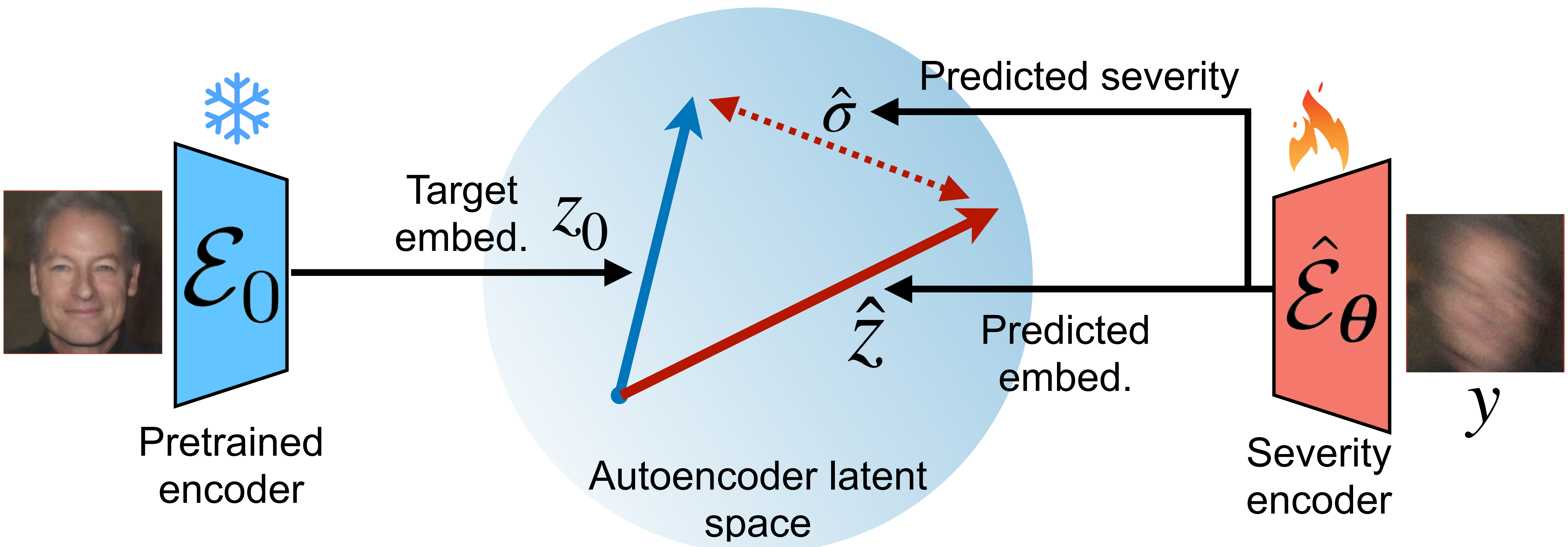

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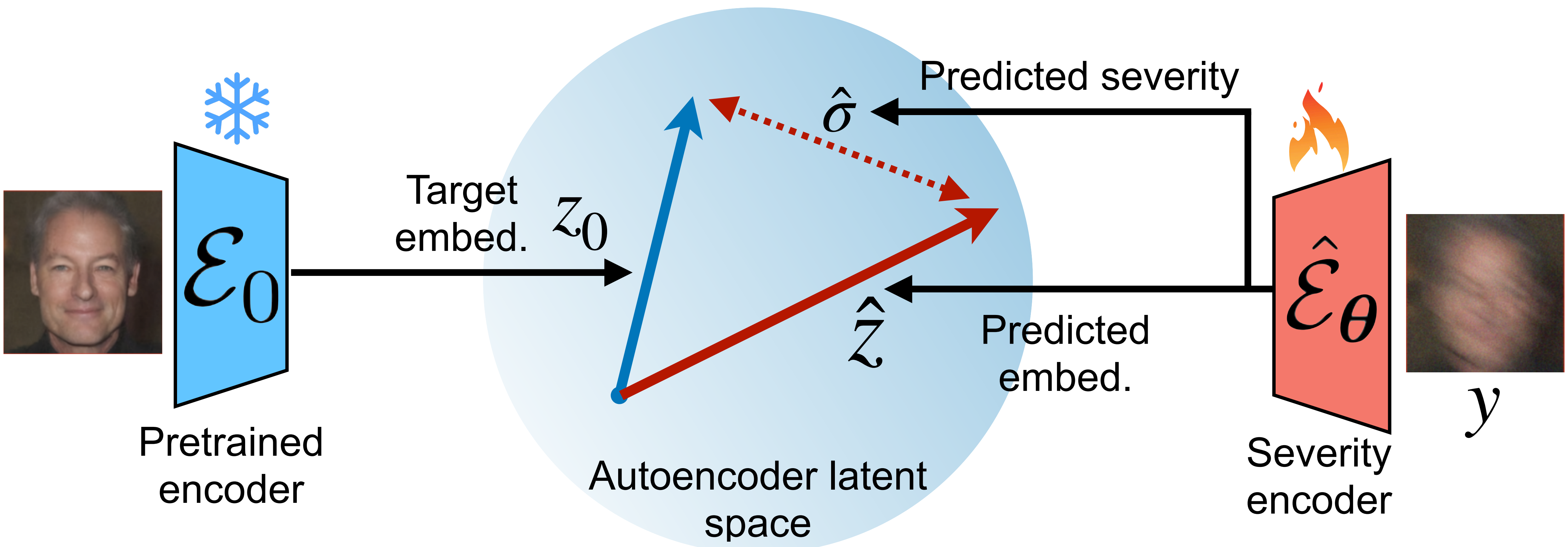

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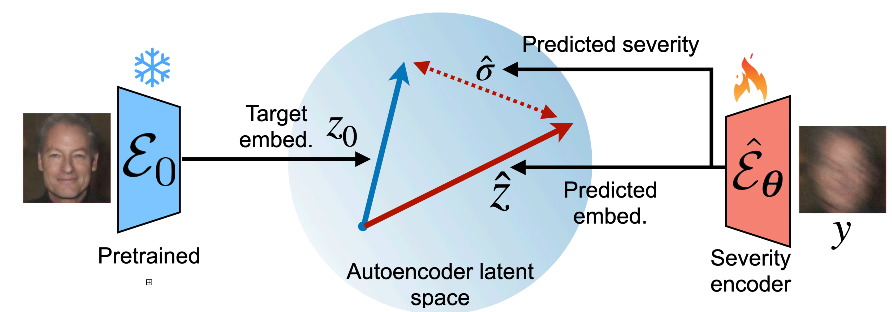
We leverage **latent prediction error as a proxy** for degradation severity!

Training objective

- **We minimize the following loss:**



$$\min_{\theta} \mathbb{E}_{\boldsymbol{x}_0 \sim q_0(\boldsymbol{x}_0), \boldsymbol{y} \sim \mathcal{N}(\mathcal{A}(\boldsymbol{x}_0), \sigma_y^2 \mathbf{I})} \left[\left\| \boldsymbol{z}_0 - \hat{z}(y;\theta) \right\|^2 + \lambda_\sigma \left\| \bar{\sigma}(y;z_0) - \hat{\sigma}(y;\theta) \right\|^2 \right]$$

reconstruction　　　　error prediction

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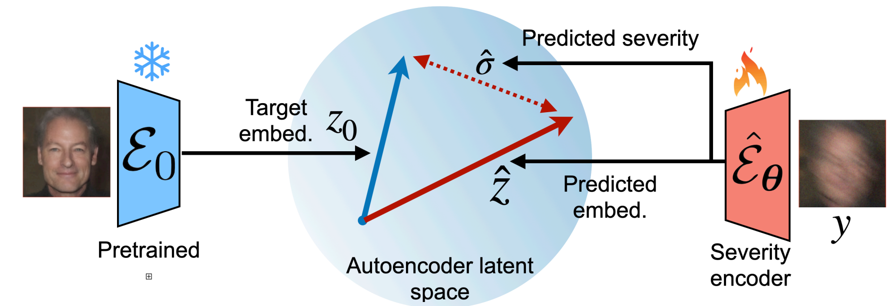

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reconstruction error prediction

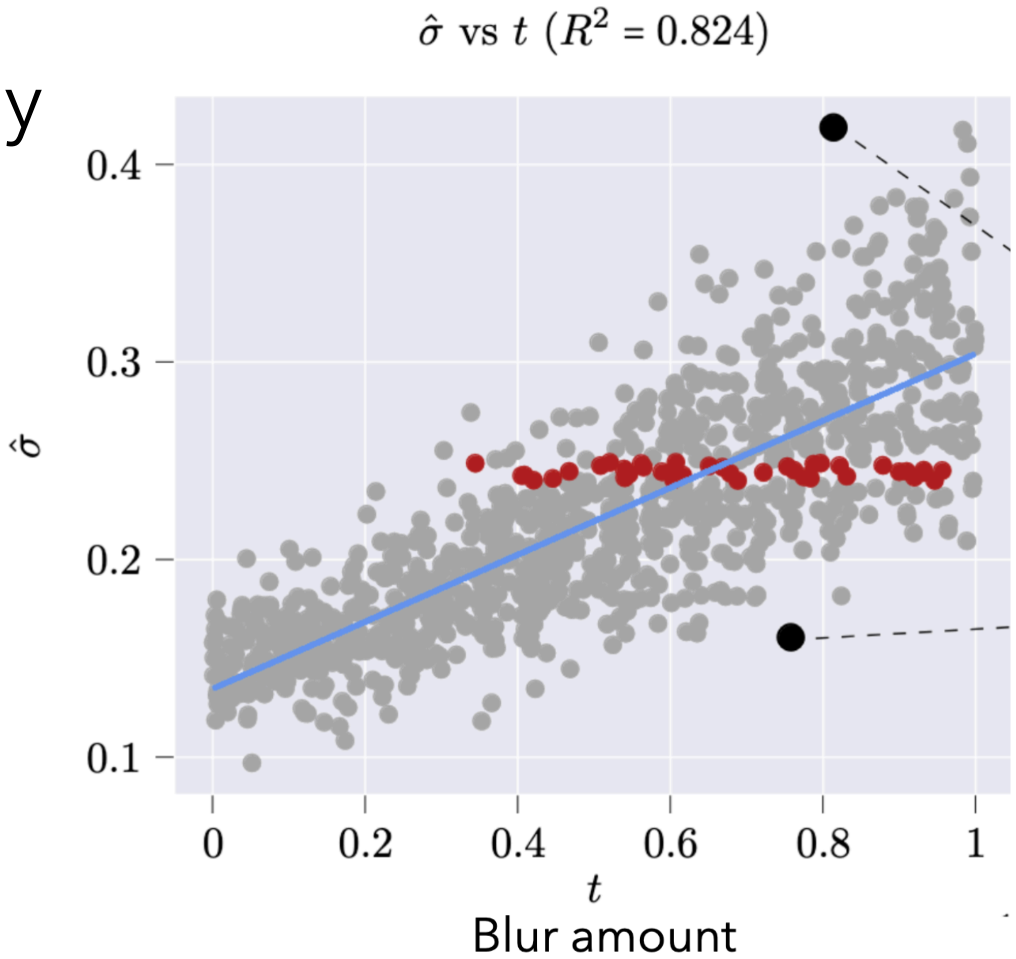
<u>Assumption</u>: prediction error is zero-mean i.i.d. Gaussian:

$$\boldsymbol{e}(\boldsymbol{y}) = \hat{\boldsymbol{z}} - \boldsymbol{z}_0 \sim \mathcal{N}(\mathbf{0}, \sigma_*^2(\boldsymbol{y})\mathbf{I})$$

$$\bar{\sigma}^2(\boldsymbol{y}, \boldsymbol{z}_0) = \frac{1}{d-1} \sum_{i=1}^{d} (\boldsymbol{e}^{(i)} - \frac{1}{d} \sum_{j=1}^{d} \boldsymbol{e}^{(j)})^2$$

Severity experiments

- Predicted severity strongly correlates with blur level



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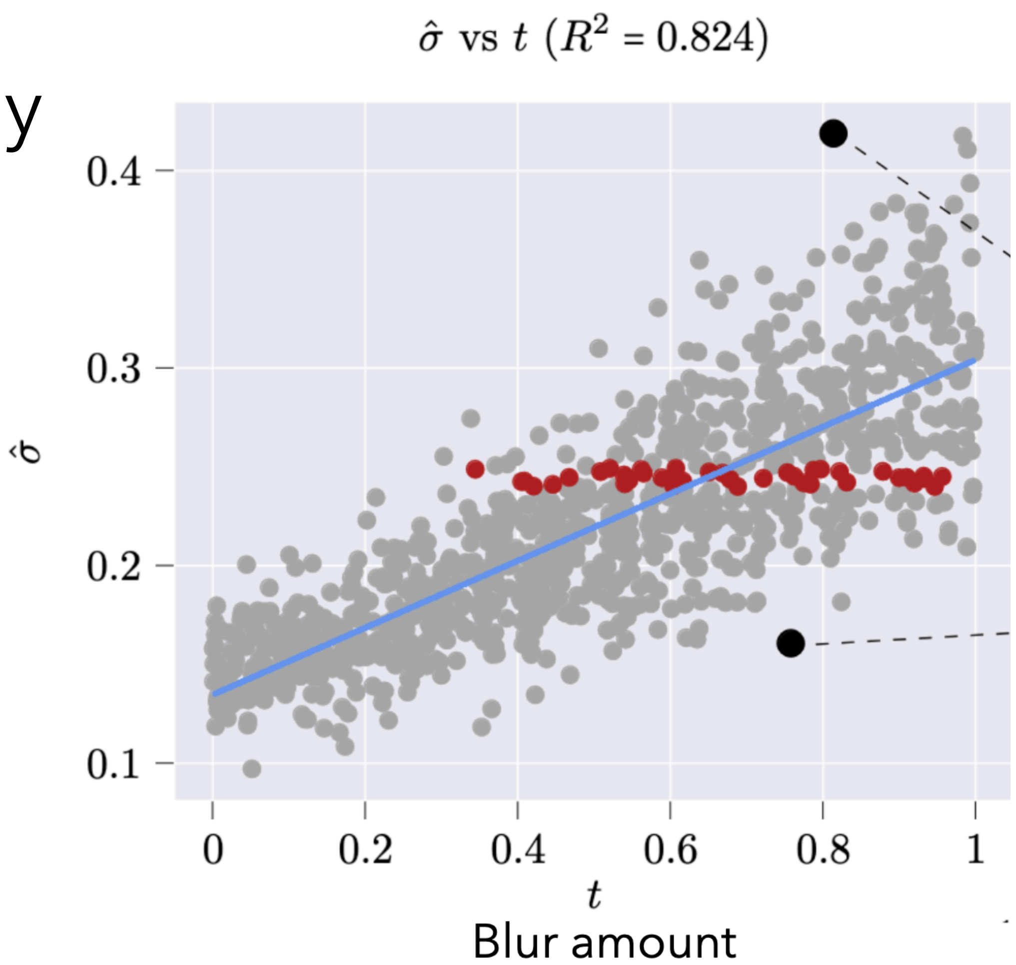

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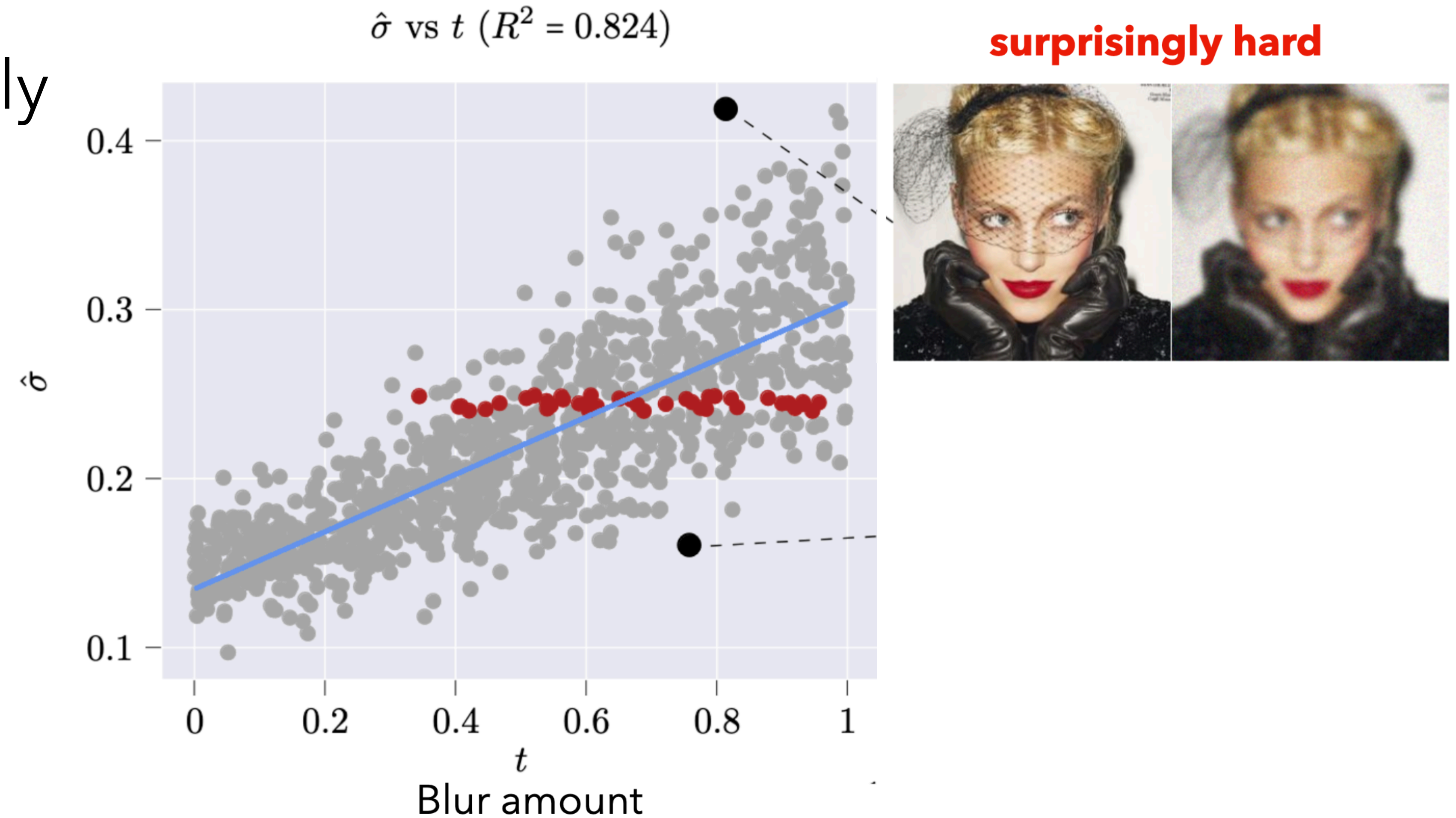

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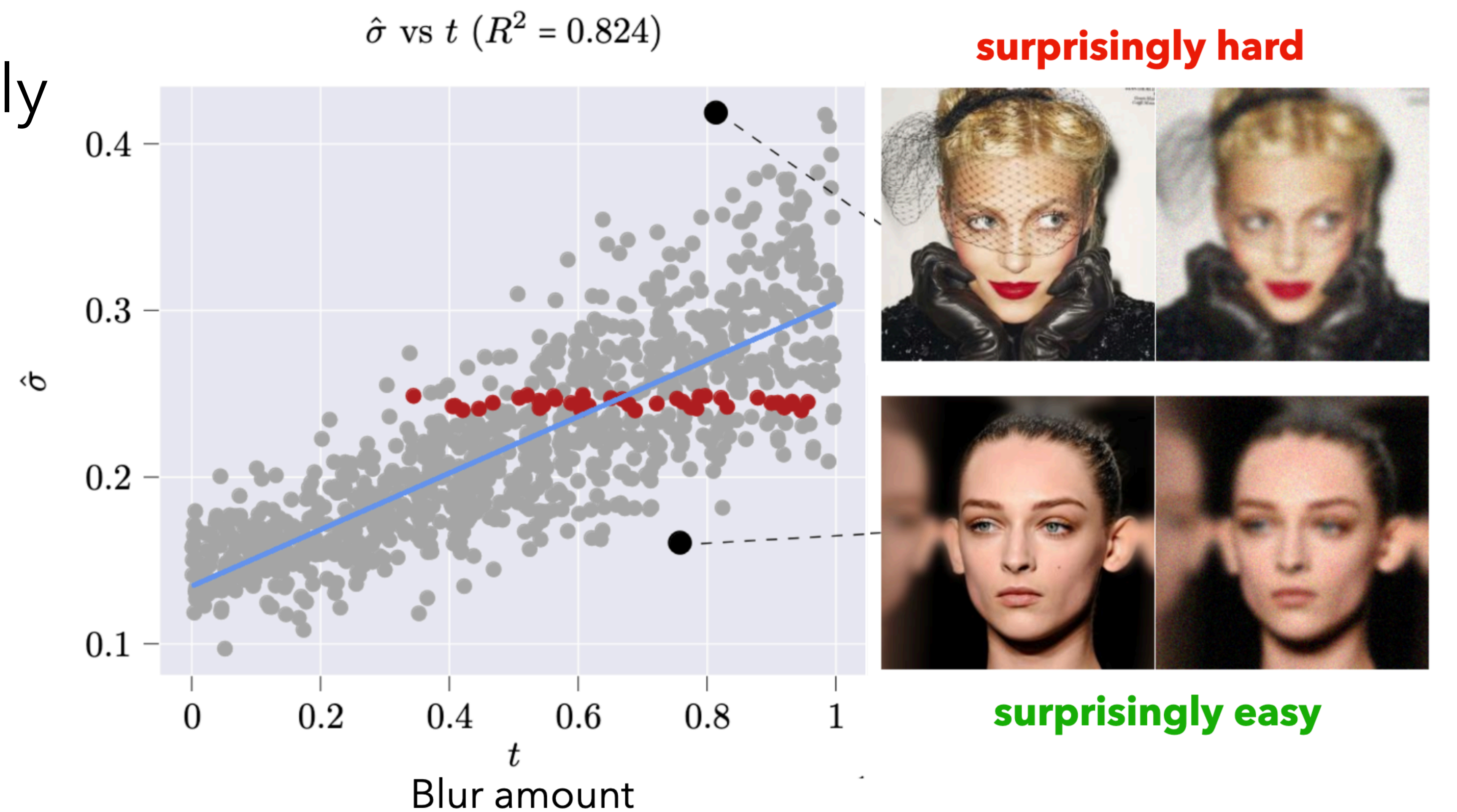

… and diffuse

Diffusion-based Inverse Problem Solving

- **Bayesian framework**

$$\boldsymbol{y} = \mathcal{A}(\boldsymbol{x}) + \boldsymbol{n}$$

solve inverse problem = sample from posterior

$$p_\theta(\boldsymbol{x}|\boldsymbol{y}) \propto p_\theta(\boldsymbol{x})p(\boldsymbol{y}|\boldsymbol{x})$$

$$\nabla_{\boldsymbol{x}} \log p_\theta(\boldsymbol{x}|\boldsymbol{y}) = \nabla_{\boldsymbol{x}} \log p_\theta(\boldsymbol{x}) + \nabla_{\boldsymbol{x}} \log p(\boldsymbol{y}|\boldsymbol{x})$$

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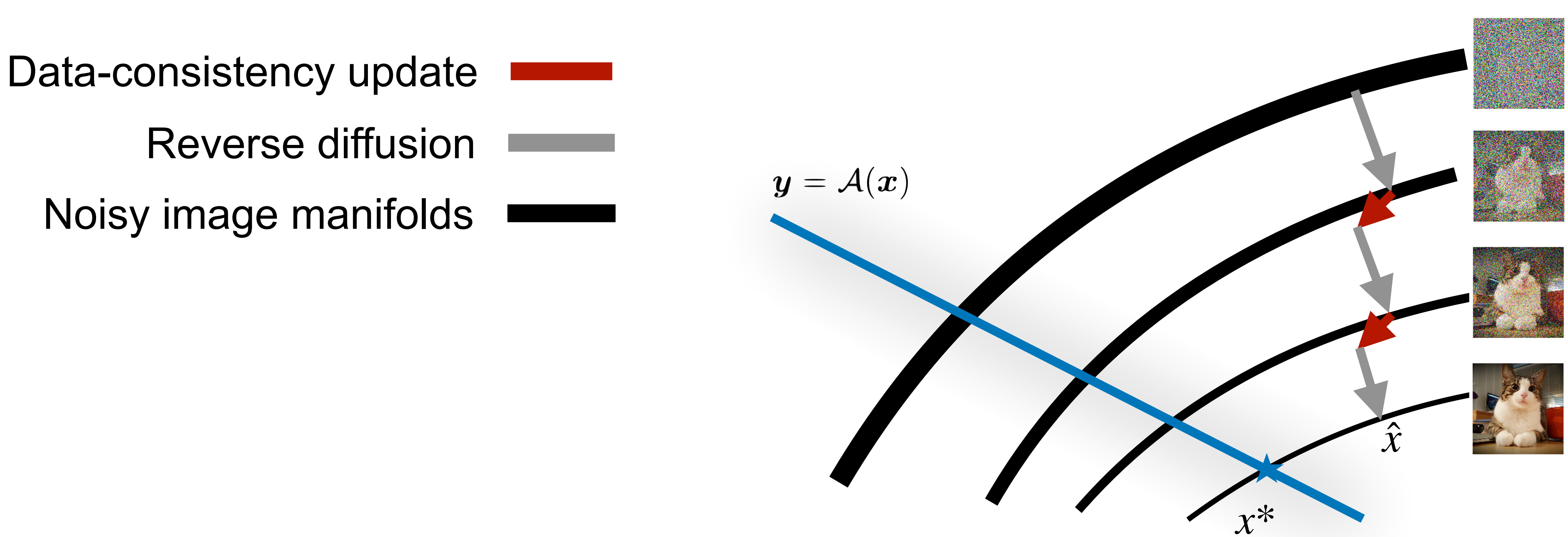
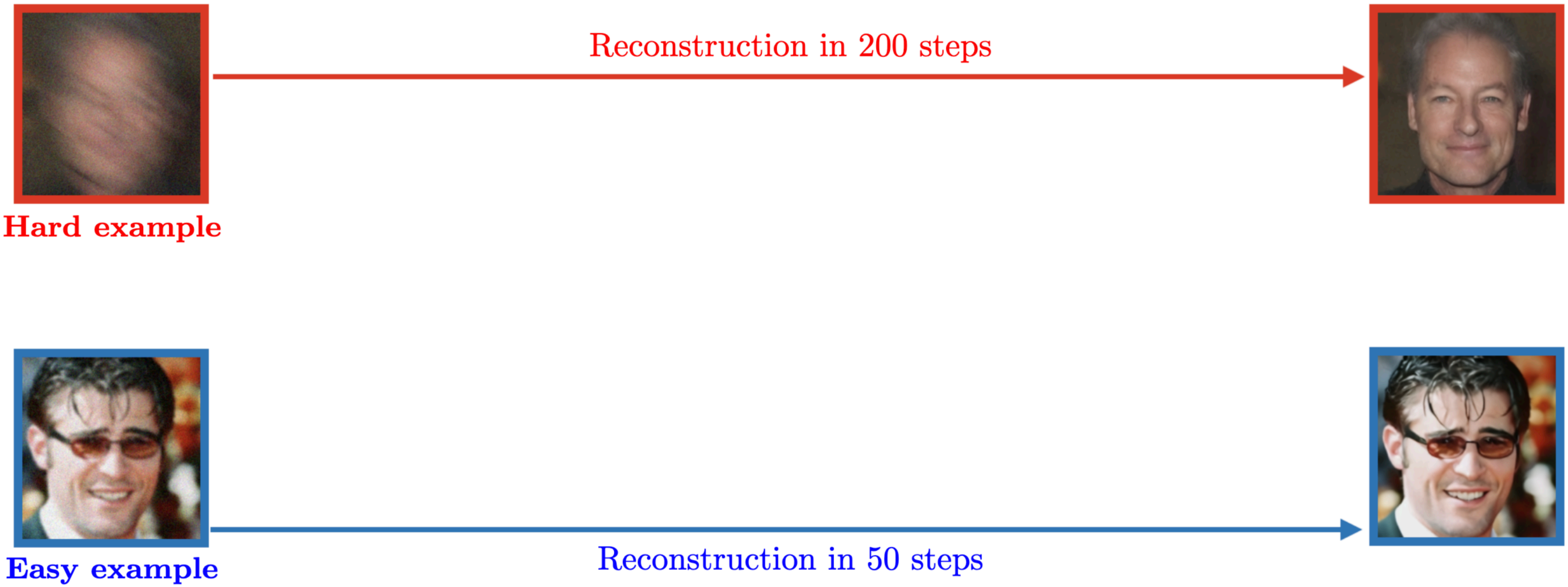


Flash-Diffusion



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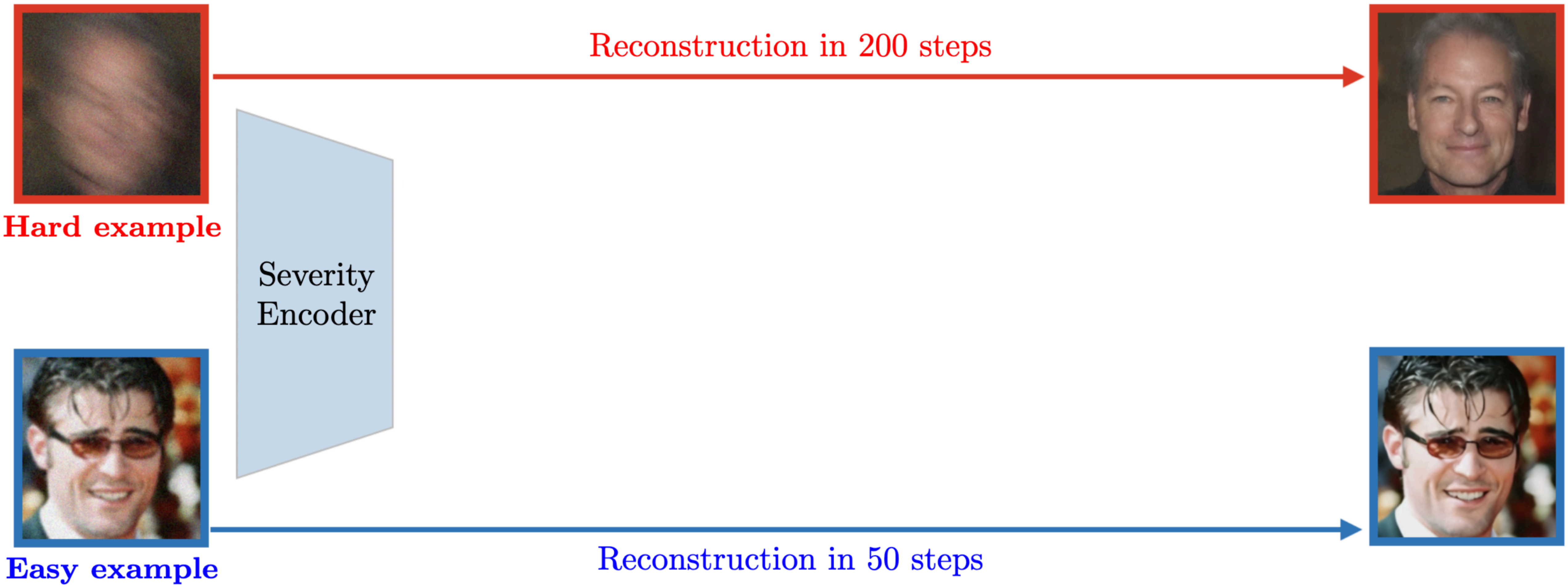

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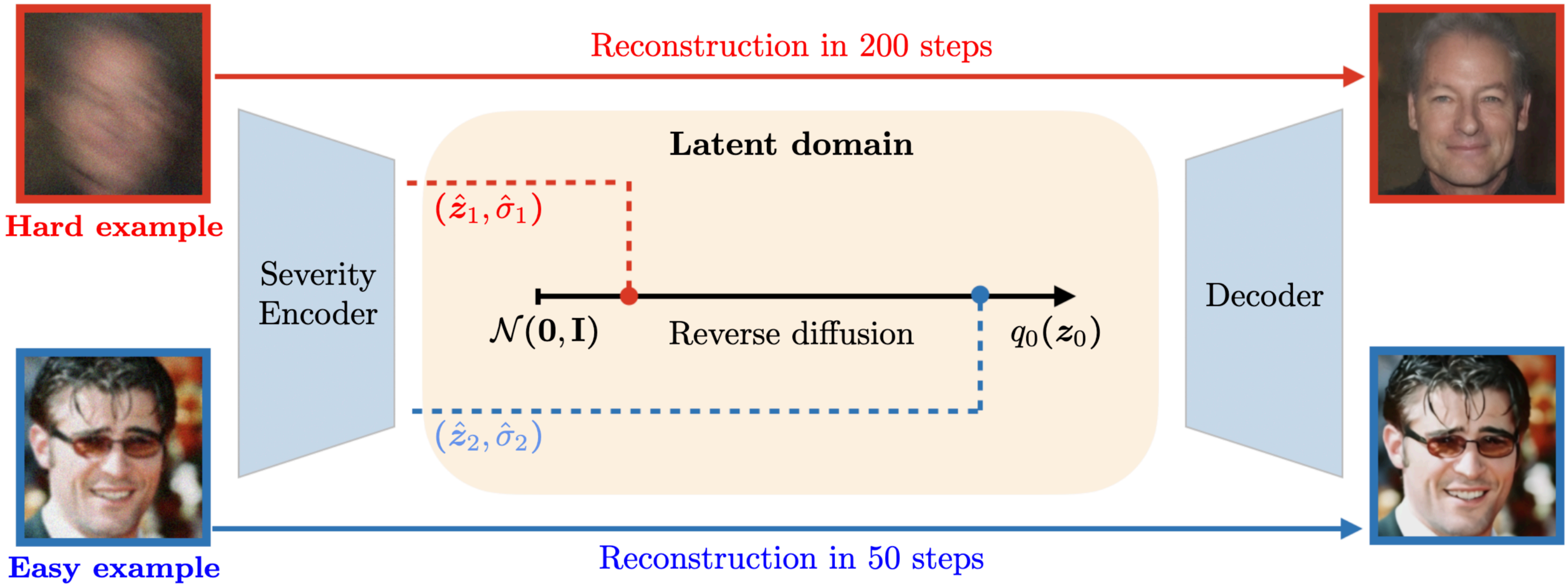

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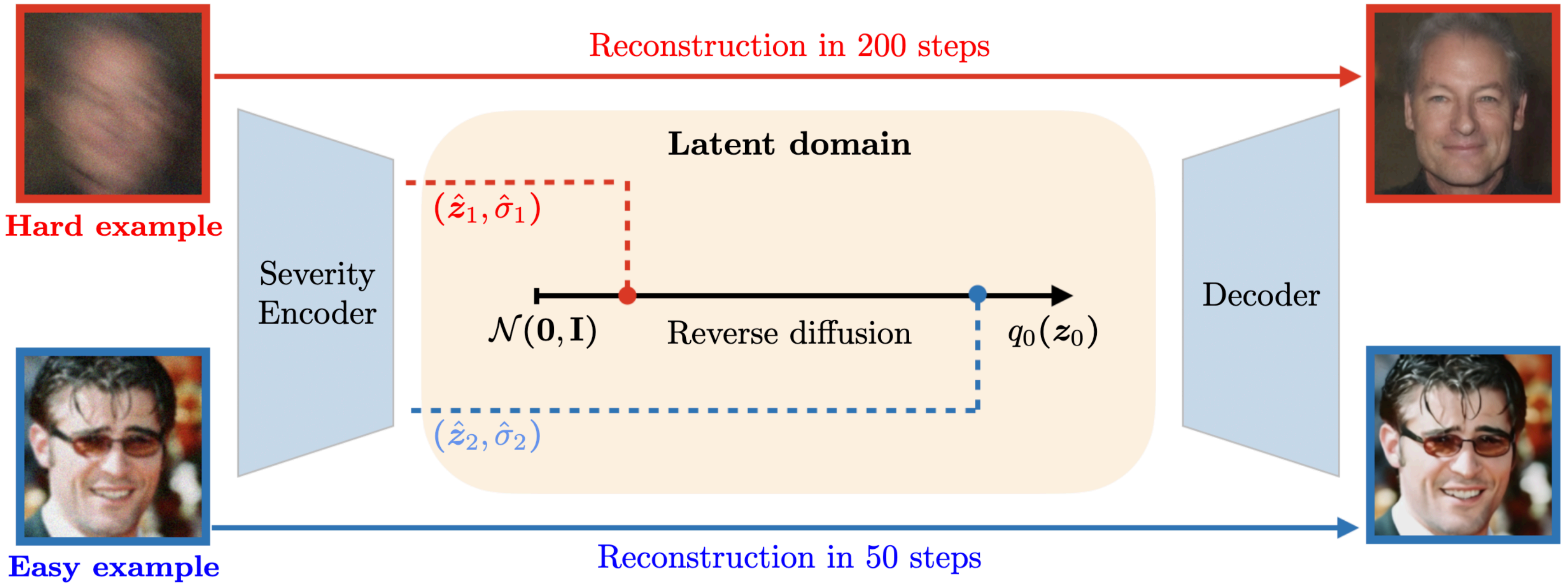
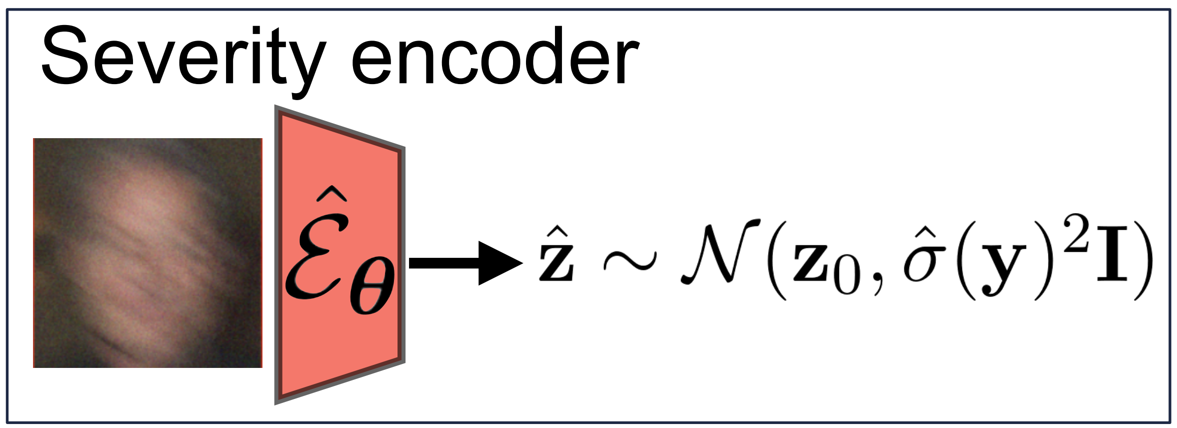


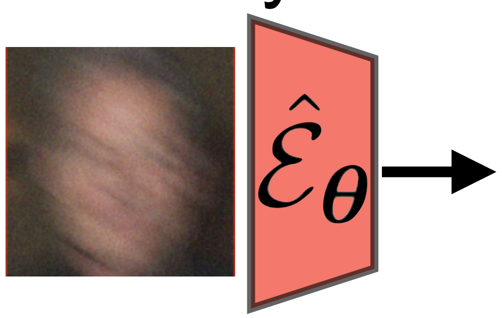
Flash-Diffusion **acts as a wrapper** around *any* baseline latent diffusion solver, imbuing it with sample-adaptivity.

Finding optimal starting time



Finding optimal starting time

Severity encoder



$\hat{\mathbf{z}} \sim \mathcal{N}(\mathbf{z}_0, \hat{\sigma}(\mathbf{y})^2\mathbf{I})$

Latent diffusion process

$$q_i(\boldsymbol{z}_i|\boldsymbol{z}_0) \sim \mathcal{N}(a_i\boldsymbol{z}_0, b_i^2\mathbf{I})$$

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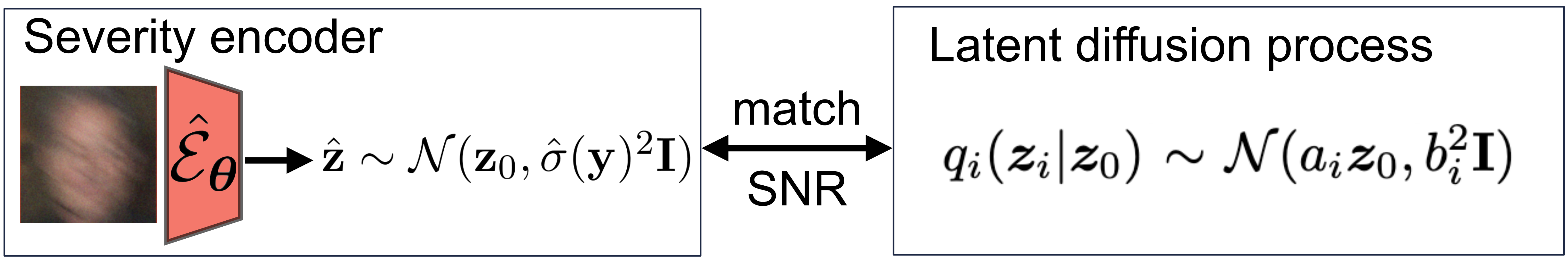

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$\rightarrow \hat{\mathbf{z}} \sim \mathcal{N}(\mathbf{z}_0, \hat{\sigma}(\mathbf{y})^2 \mathbf{I})$

$\xleftrightarrow[\text{SNR}]{\text{match}}$

Latent diffusion process

$$q_i(\boldsymbol{z}_i | \boldsymbol{z}_0) \sim \mathcal{N}(a_i \boldsymbol{z}_0, b_i^2 \mathbf{I})$$

Adaptive starting time: $$i_{start}(\mathbf{y}) = \arg \min_{i \in [1,2,\ldots,N]} \left| \frac{1}{\hat{\sigma}(\mathbf{y})^2} - \frac{a_i^2}{b_i^2} \right|$$

Experiments

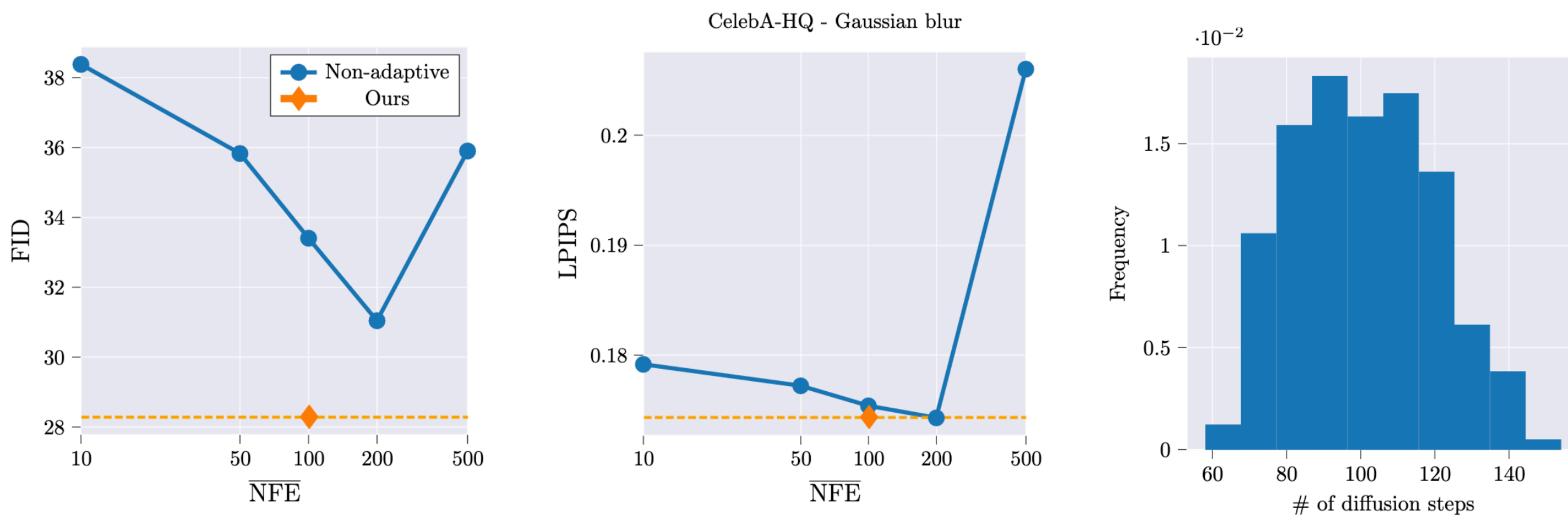
- **Comparison with baseline solvers**

FFHQ	Gaussian Deblurring (Varying)					Gaussian Deblurring (Fixed)					Nonlinear Deblurring					Random Inpainting				
Method	PSNR(↑)	SSIM(↑)	LPIPS(↓)	FID(↓)	NFE	PSNR(↑)	SSIM(↑)	LPIPS(↓)	FID(↓)	NFE	PSNR(↑)	SSIM(↑)	LPIPS(↓)	FID(↓)	NFE	PSNR(↑)	SSIM(↑)	LPIPS(↓)	FID(↓)	NFE
Latent-DPS	23.69	0.6418	0.3579	87.26	1000	22.88	0.6136	0.3690	89.38	1000	22.07	0.5974	0.3814	90.89	1000	23.96	0.6566	0.3666	93.65	1000
`Flash`(Latent-DPS)	29.17	0.8182	0.2240	55.57	100.3	27.44	0.7691	0.2823	80.44	127.7	27.17	0.7659	0.2695	69.78	136.1	29.21	0.8414	**0.1945**	**53.95**	104.7
PSLD (Rout et al., 2024)	25.06	0.6769	0.3194	79.79	1000	23.72	0.6183	0.3324	88.45	1000	-	-	-	-	-	24.94	0.6617	0.3672	85.64	1000
`Flash`(PSLD)	29.26	0.8205	**0.2203**	**53.27**	100.3	27.44	0.7657	**0.2797**	**65.35**	127.7	-	-	-	-	-	27.06	0.8018	0.2185	55.12	104.7
GML-DPS (Rout et al., 2024)	24.98	0.6884	0.3471	100.27	1000	24.01	0.6574	0.3621	102.80	1000	23.00	0.6426	0.3812	108.79	1000	25.20	0.7044	0.3527	103.3	1000
`Flash`(GML-DPS)	29.21	0.8276	0.2274	69.16	100.3	27.47	0.7699	0.2816	69.81	127.7	27.11	0.7640	0.2756	81.93	136.1	28.95	0.8437	0.1957	59.39	104.7
ReSample (Song et al., 2023)	28.77	0.8219	0.2587	81.96	500	27.62	0.7789	0.3148	102.47	500	26.61	0.7318	0.2838	68.57	500	27.51	0.7892	0.2460	63.39	500
`Flash`(ReSample)	29.07	0.8330	0.2383	74.76	49.9	27.77	0.7845	0.3092	100.84	63.6	26.88	0.7660	**0.2667**	**64.57**	67.8	28.13	0.8260	0.2045	56.67	52.1
AE	29.46	0.8358	0.2671	89.29	-	27.69	0.7820	0.3396	110.56	-	27.17	0.7786	0.3364	111.24	-	29.23	0.8432	0.2515	85.87	-
SwinIR (Liang et al., 2021)	**30.69**	**0.8583**	0.2409	87.61	-	**28.41**	**0.8021**	0.3091	108.49	-	**27.60**	**0.7928**	0.3093	99.56	-	**30.08**	**0.8654**	0.2223	78.32	-
DPS (Chung et al., 2022a)	28.34	0.7791	0.2465	81.70	1000	25.49	0.6829	0.3035	97.89	1000	22.77	0.6191	0.3601	109.58	1000	28.30	0.8049	0.2451	82.78	1000

Flash-Diffusion accelerates the baseline solver by a factor of up to 10x on average and greatly improves reconstruction quality.

Experiments

- **Adaptivity**



FlashDiffusion achieves best perceptual quality compared to any non-adaptive starting time.

Conclusion

1. Difficulty of a reconstruction problem may vary greatly on a **sample-by-sample** basis.



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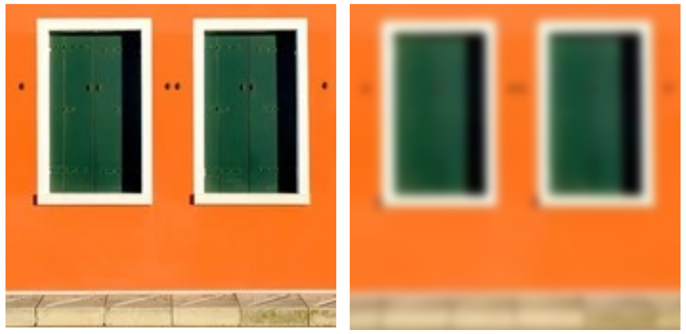
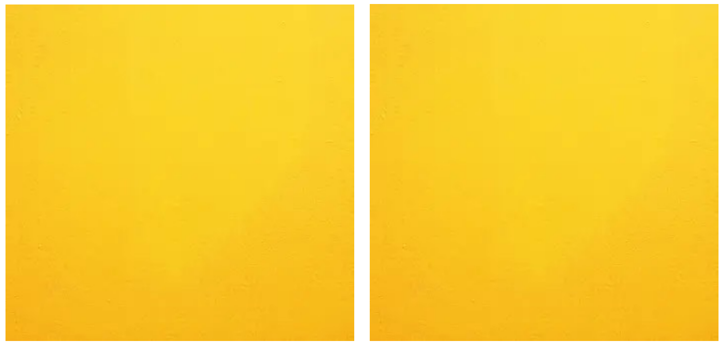
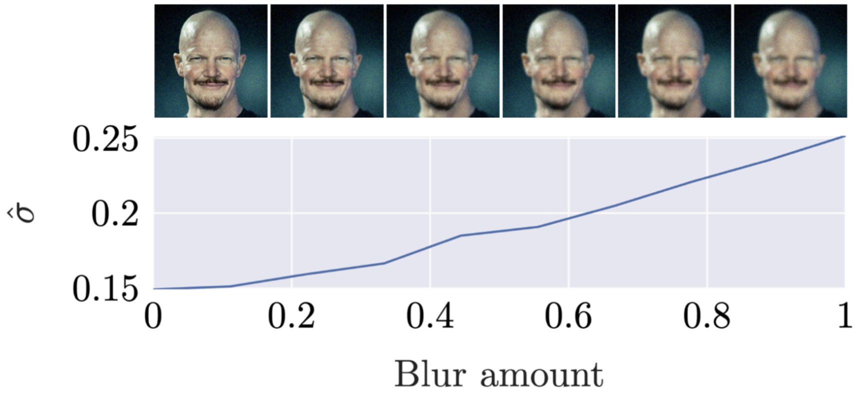



2. We propose **Severity Encoding** to estimate degradation severity in test-time.



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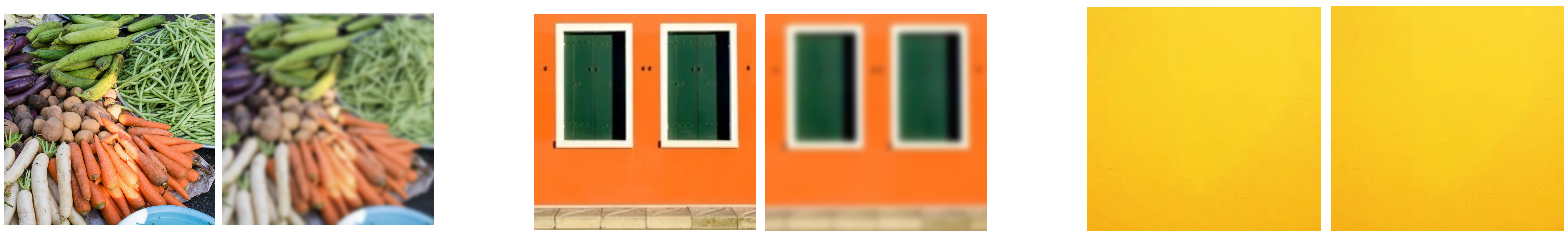

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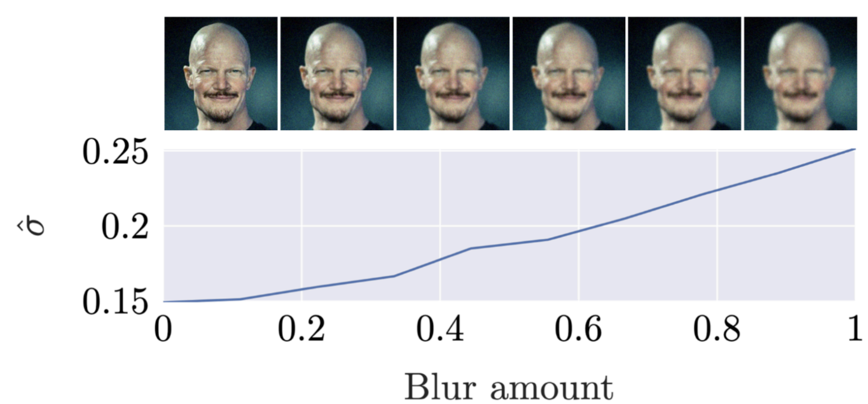
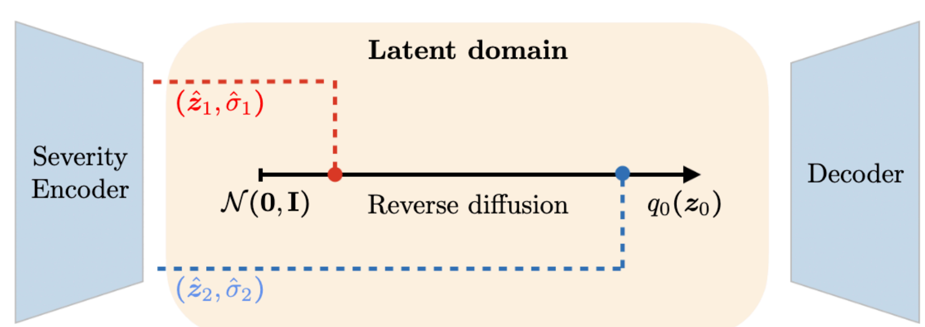


3. Flash-Diffusion **automatically scales reconstruction effort** with degradation severity via latent diffusion.



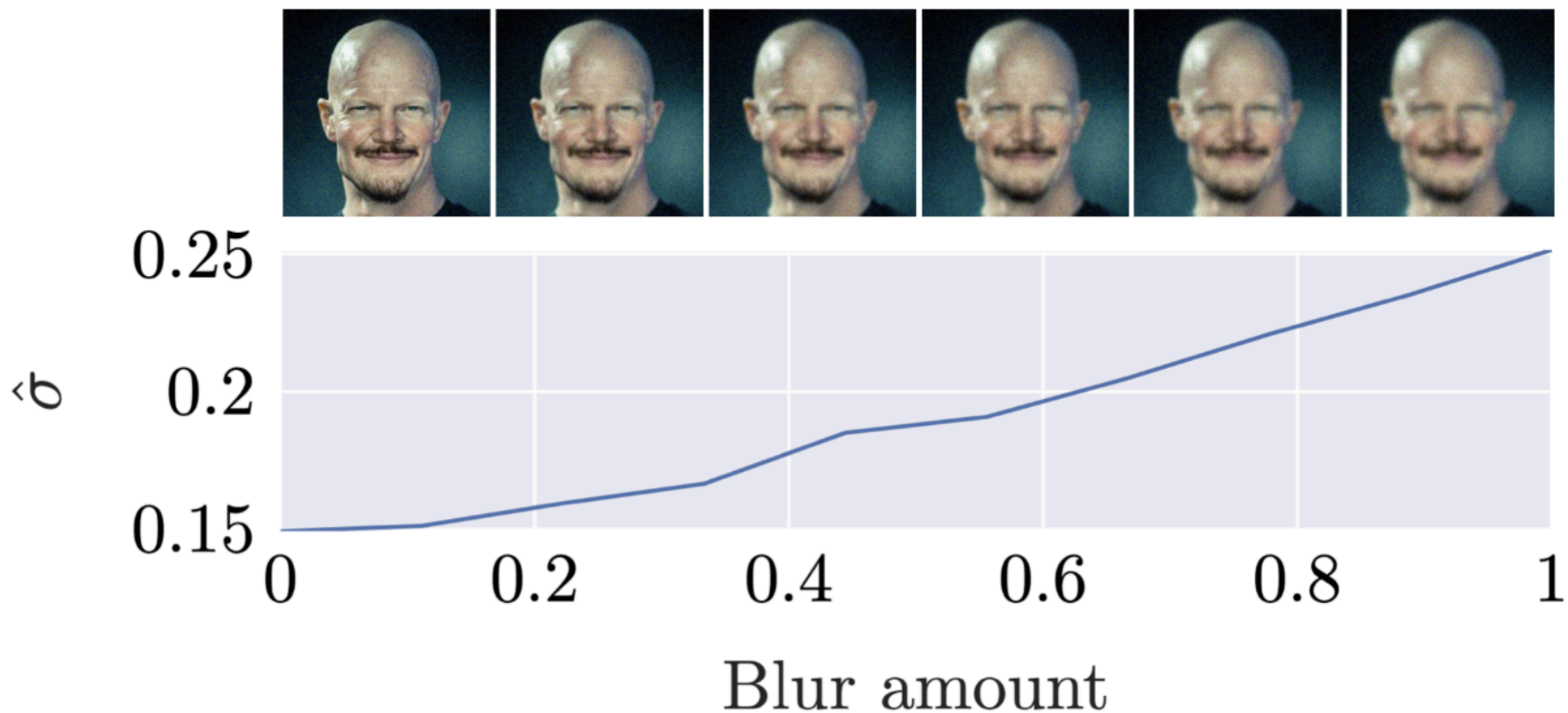
Thank you for your attention!

Paper

Code

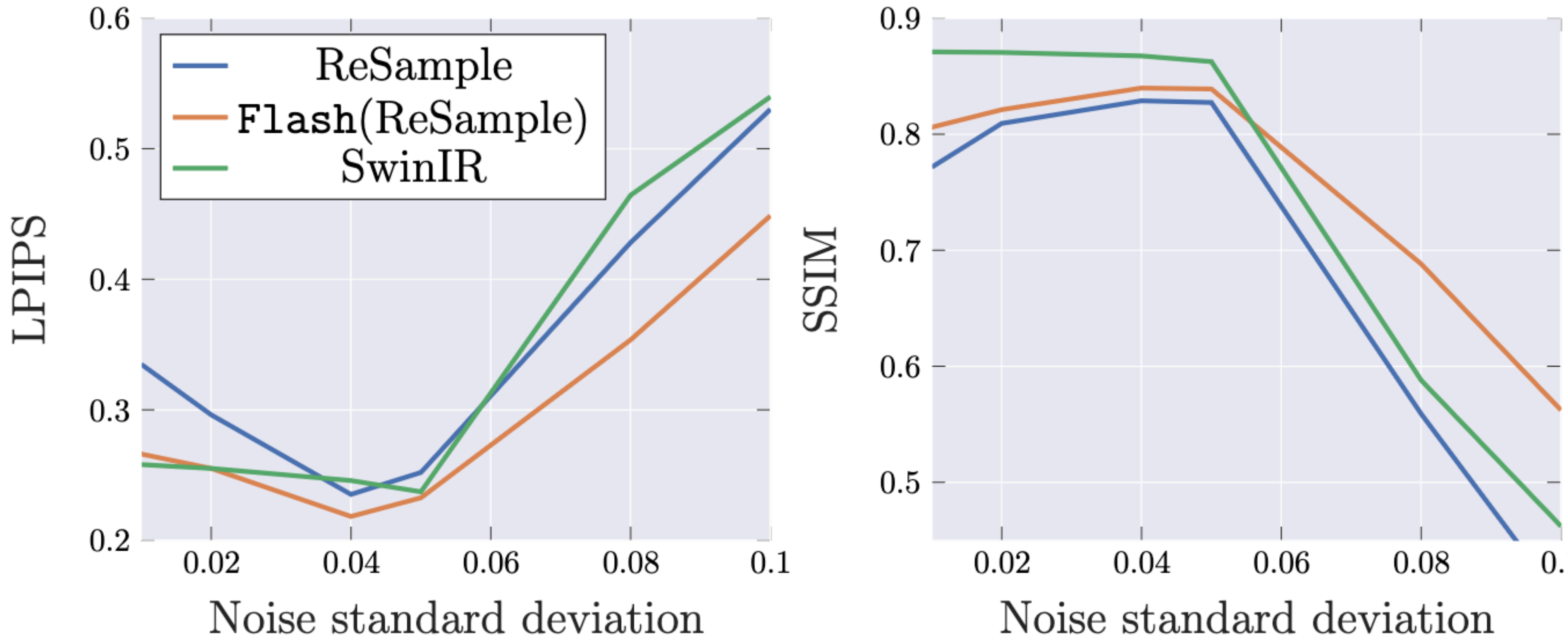
https://github.com/z-fabian/flash-diffusion

Severity experiments



Experiments

- **Robustness**



Flash-Diffusion performance degrades more gracefully than the baseline solver's performance.