CONTROLLING VISION-LANGUAGE MODELS FOR MULTI-TASK IMAGE RESTORATION

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ICLR 2024

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Outline

- Preliminary
- Framework
- Method
- Experiment
- Conclusion

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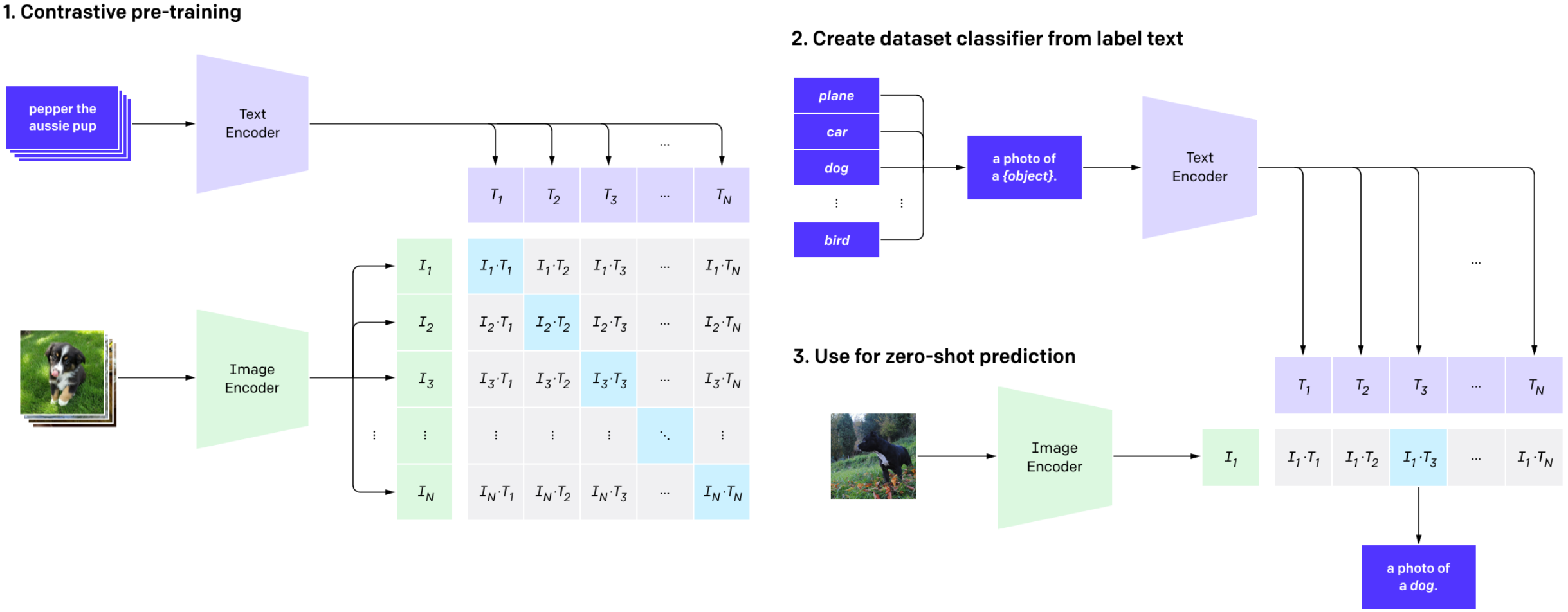
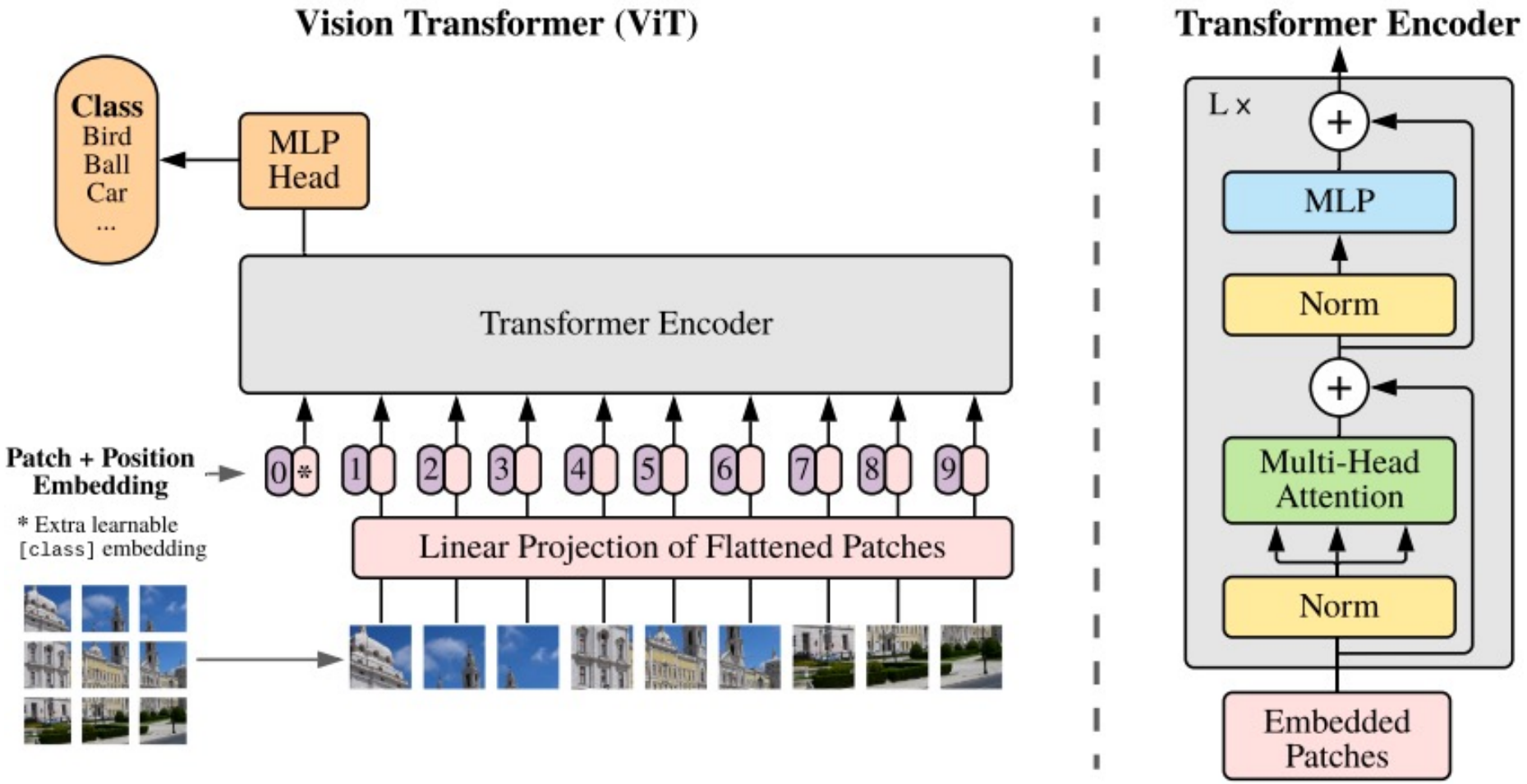
CLIP



Learning Transferable Visual Models From Natural Language Supervision, ICML 2021

Vision Transformer



An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale, ICLR 2021

Stochastic Differential Equations

$$dX_t = \mu(X_t, t)\, dt + \sigma(X_t, t)\, dW_t$$

$$dx_t = \left[\mu(t, x_t) - \sigma(t)^2 \nabla_{x_t} \log p_t(x_t)\right] dt + \sigma(t)\, d\bar{W}_t$$

IR-SDE

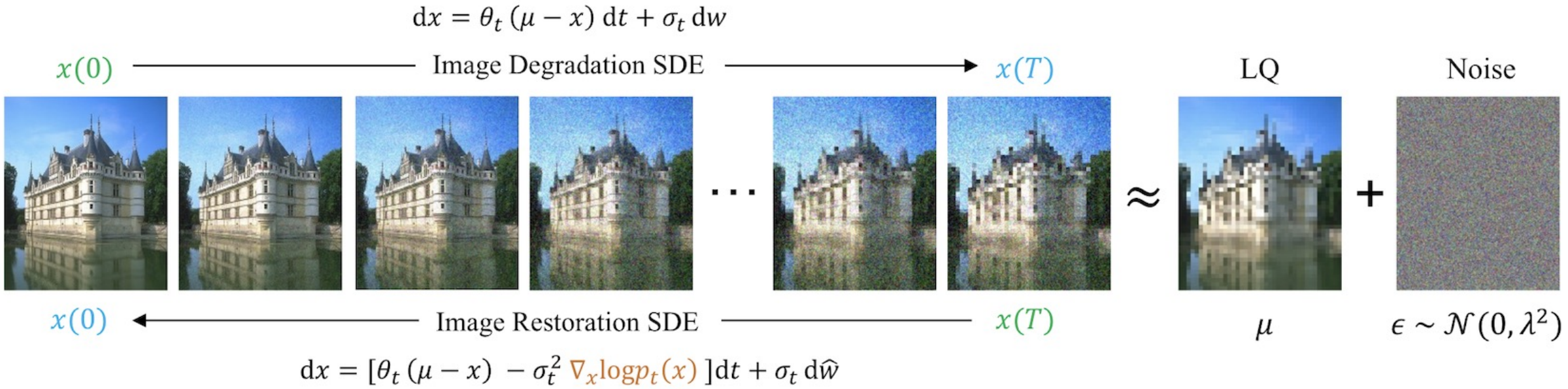


Image Restoration with Mean-Reverting Stochastic Differential Equations, ICML 2023

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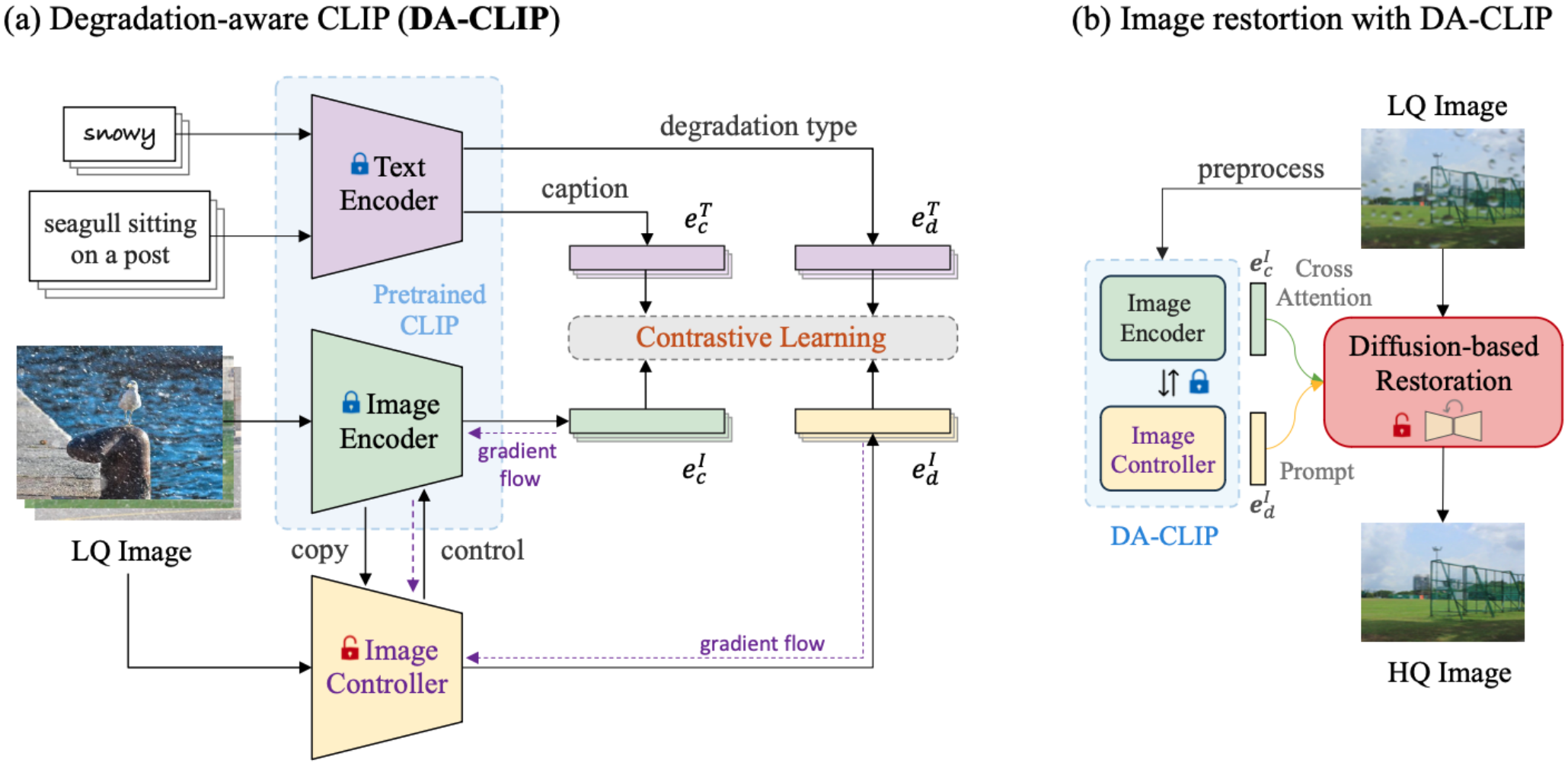
Introduction

- Present a degradation-aware vision-language model (**DA-CLIP**) to better transfer pretrained **vision-language models** to **low-level vision tasks** as a multi-task framework for image restoration.

- Trains an additional controller predict **HQ content embeddings** and **degradation embedding**. By integrating the embedding into an image restoration network.

- Advances **SOTA** performance on both degradation-specific and unified image restoration tasks, showing a promising direction of **prompting image restoration with large-scale pretrained vision-language models**.

Framework



e_c^T: Caption Embedding from Text-encoder

e_d^T: Degradation Embedding from Text-encoder

e_c^I: Content Embedding from Image-encoder

e_d^I: Degradation Embedding from Image-controller

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Image controller

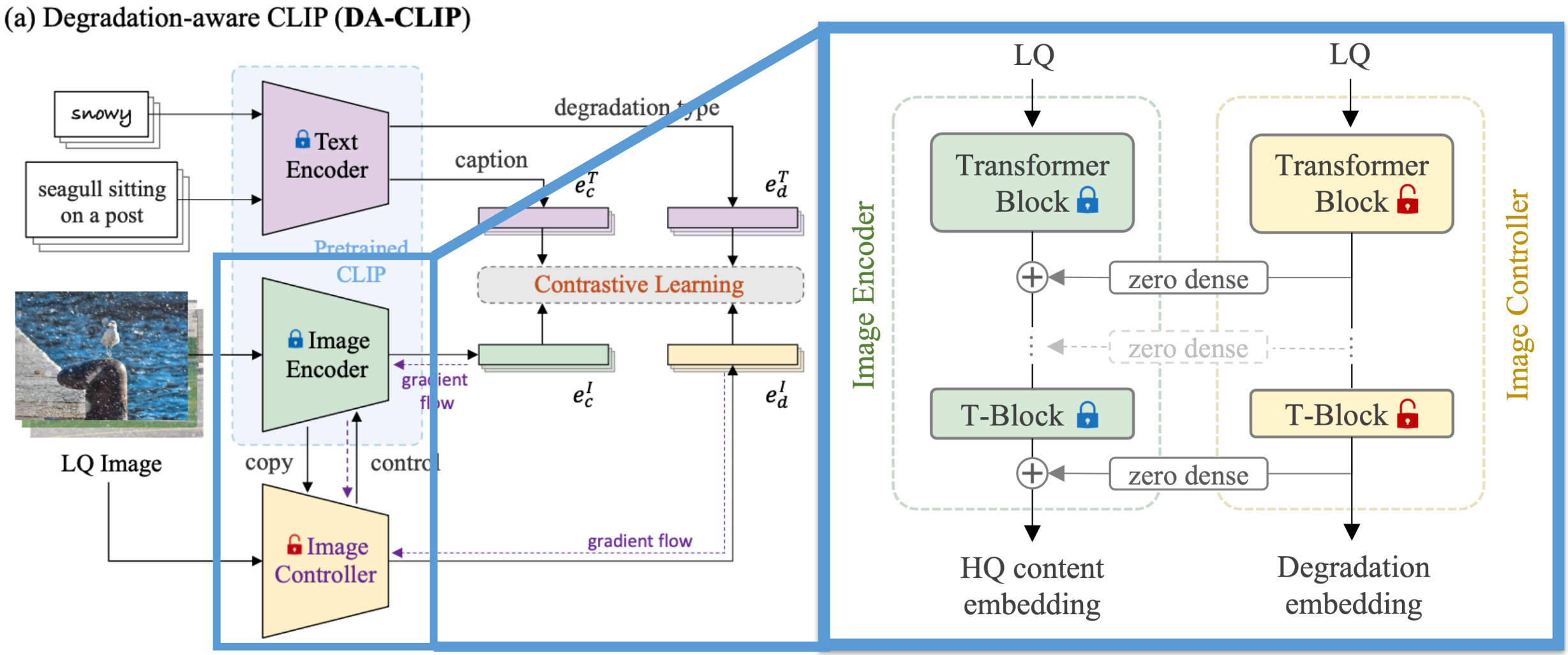


Image controller

$$\mathcal{L}_{\text{con}}(\boldsymbol{x}, \boldsymbol{y}) = -\frac{1}{N}\sum_{i=1}^{N}\log\left(\frac{\exp\left(\boldsymbol{x}_i^{\intercal}\boldsymbol{y}_i/\tau\right)}{\sum_{j=1}^{N}\exp(\boldsymbol{x}_i^{\intercal}\boldsymbol{y}_j/\tau)}\right),$$

$$\mathcal{L}_c(\omega) = \mathcal{L}_{\text{con}}(\boldsymbol{e}_c^I, \boldsymbol{e}_c^T; \omega) + \mathcal{L}_{\text{con}}(\boldsymbol{e}_d^I, \boldsymbol{e}_d^T; \omega),$$

- Learning to align these embeddings enables DA-CLIP to predict real degradation types and HQ content features for corrupted image inputs.

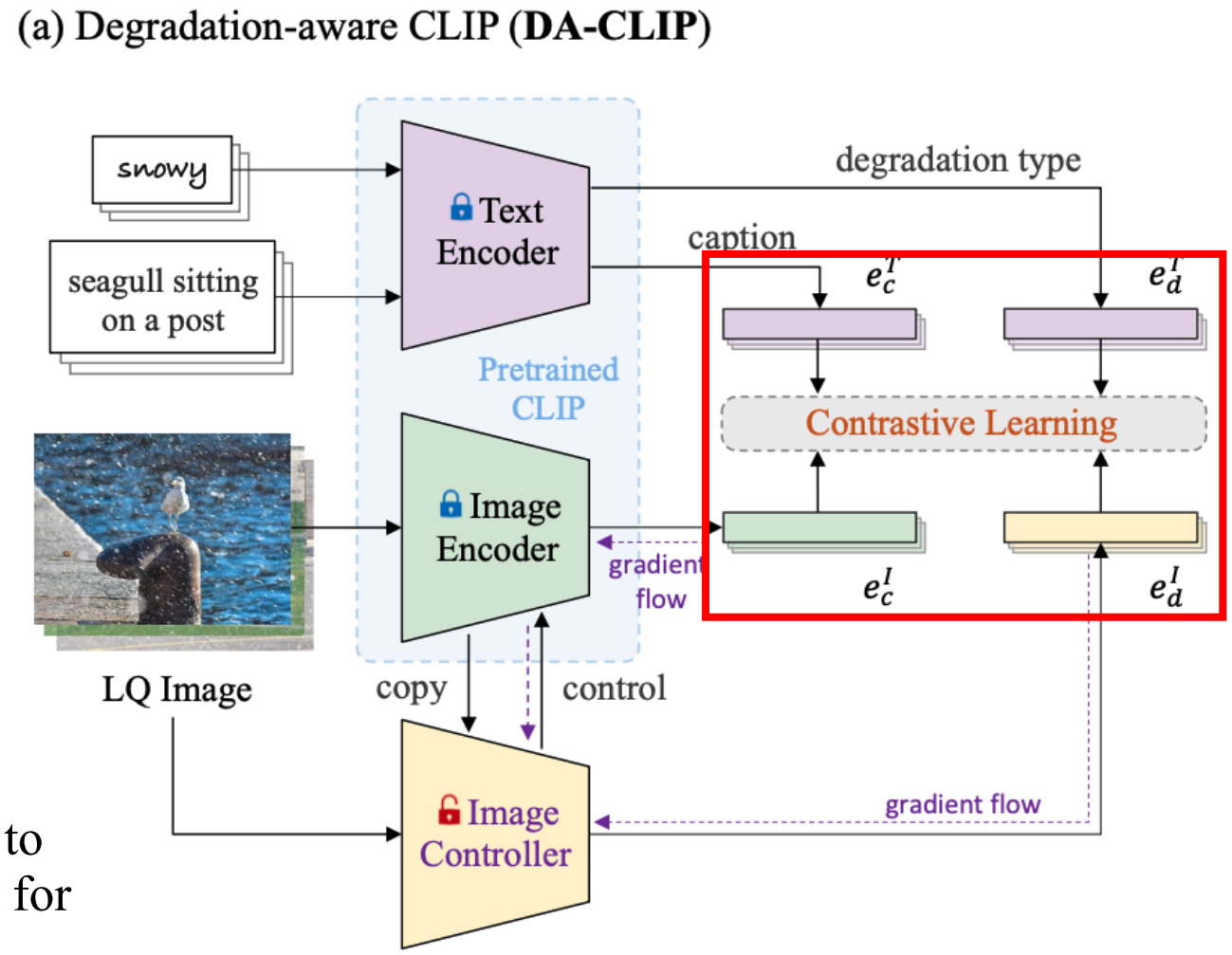
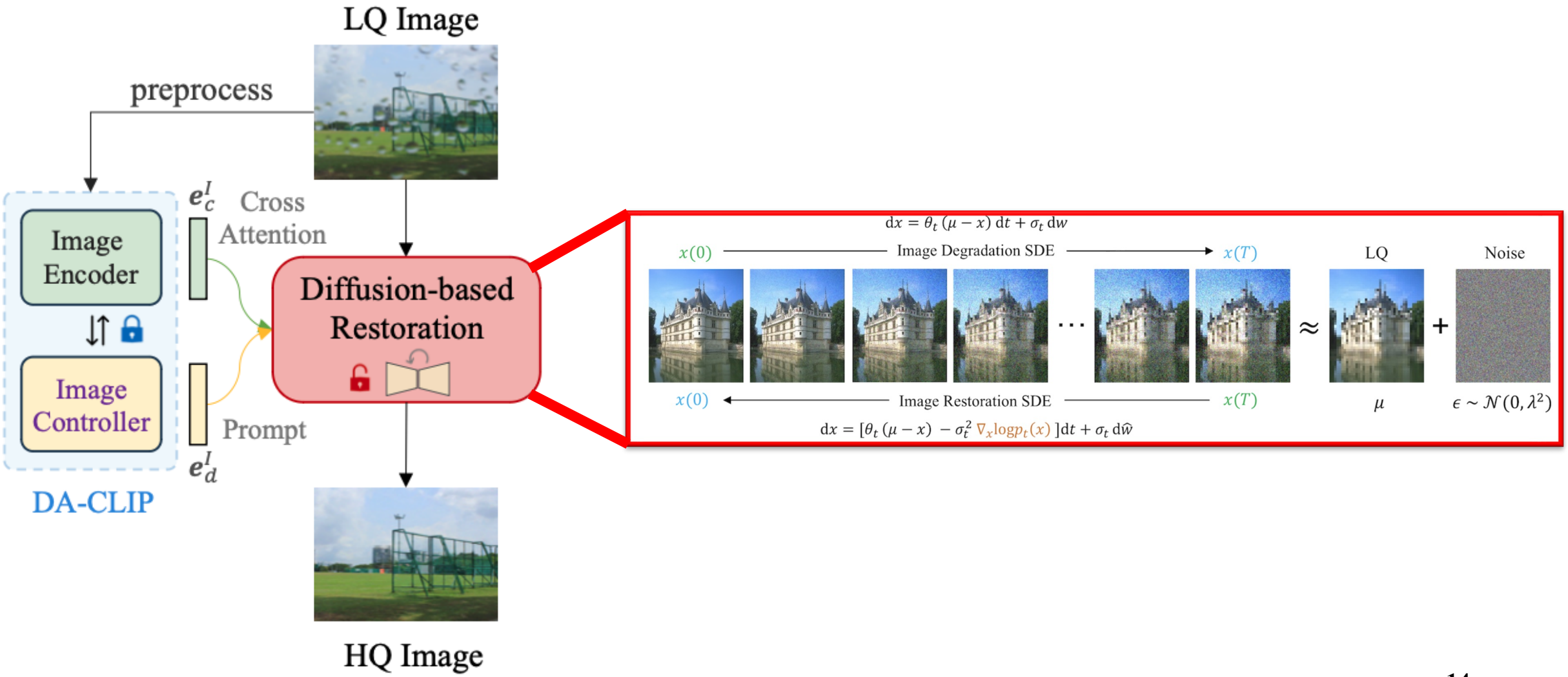
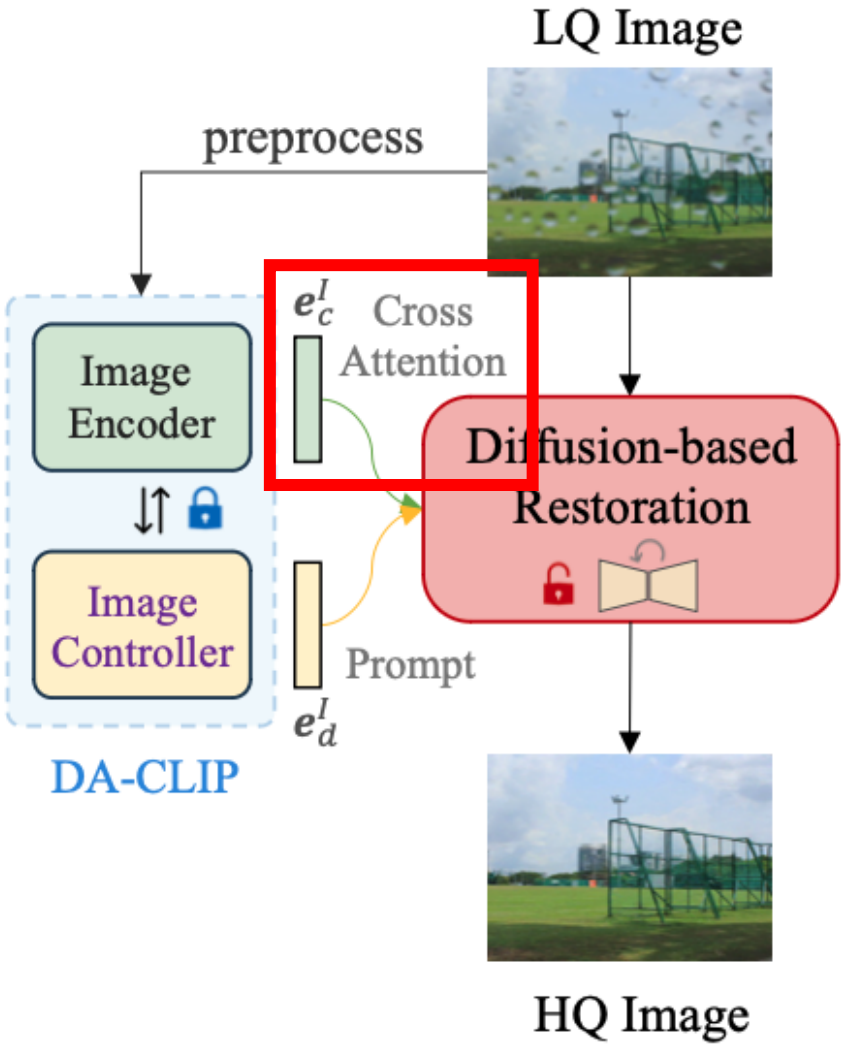
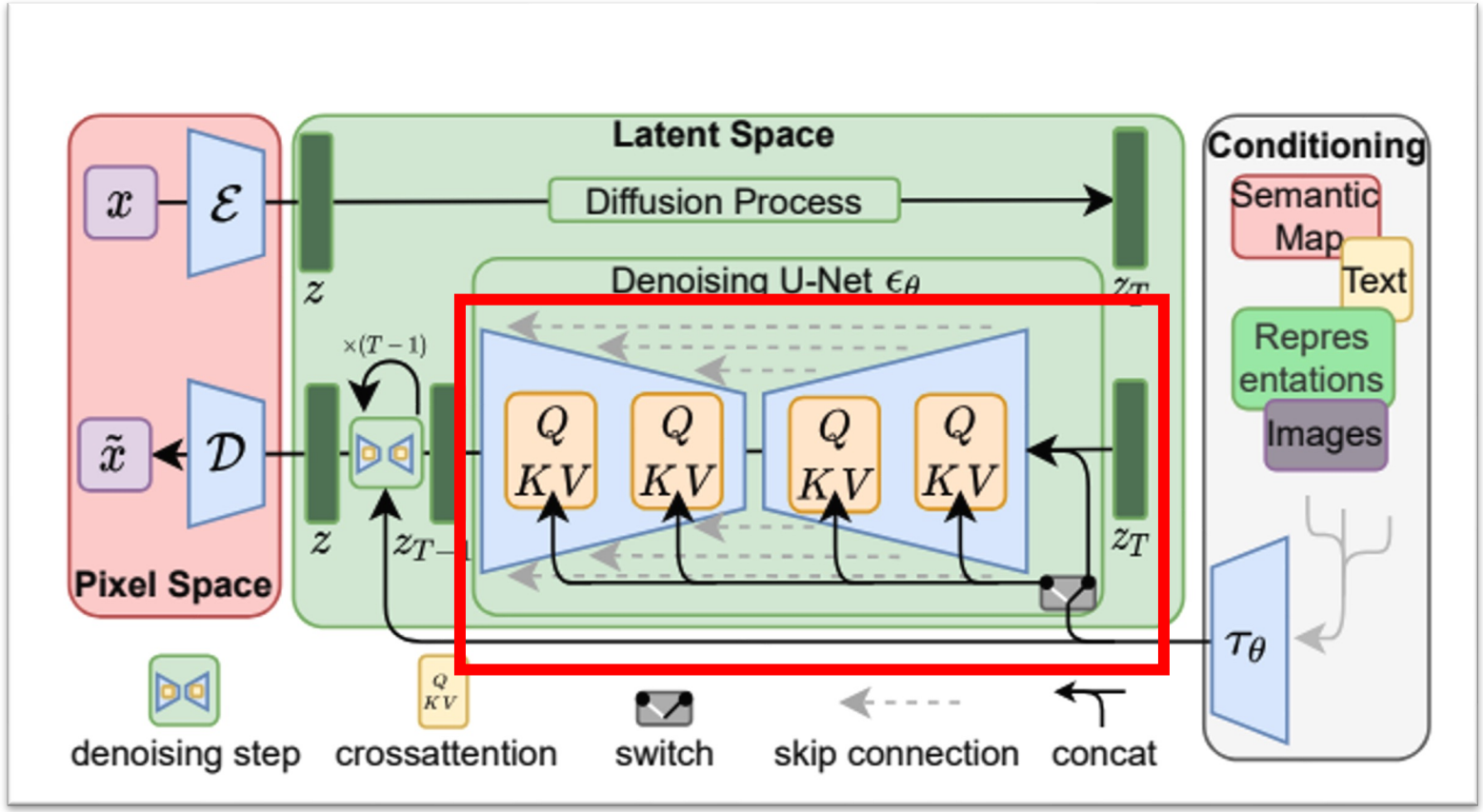


Image Restoration With DA-CLIP



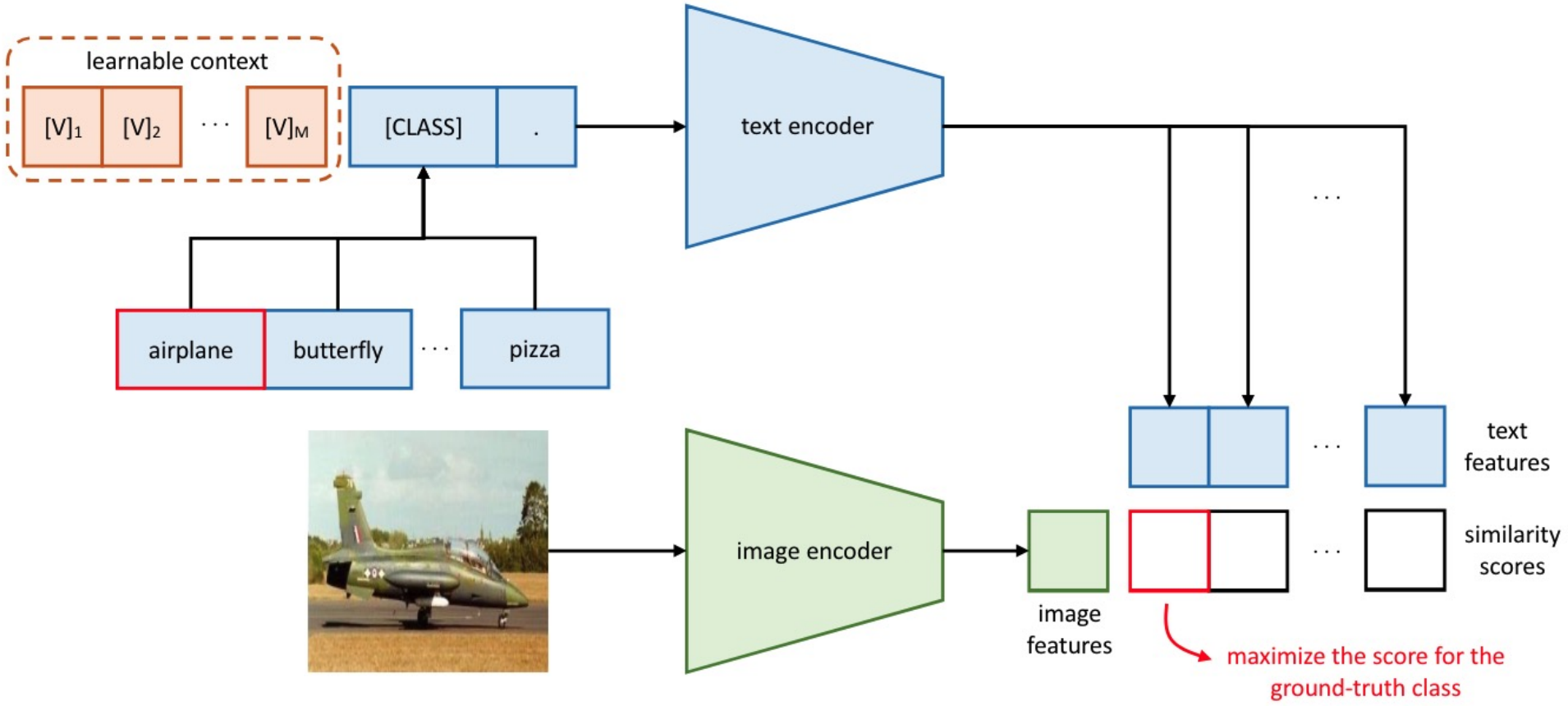
Cross attention





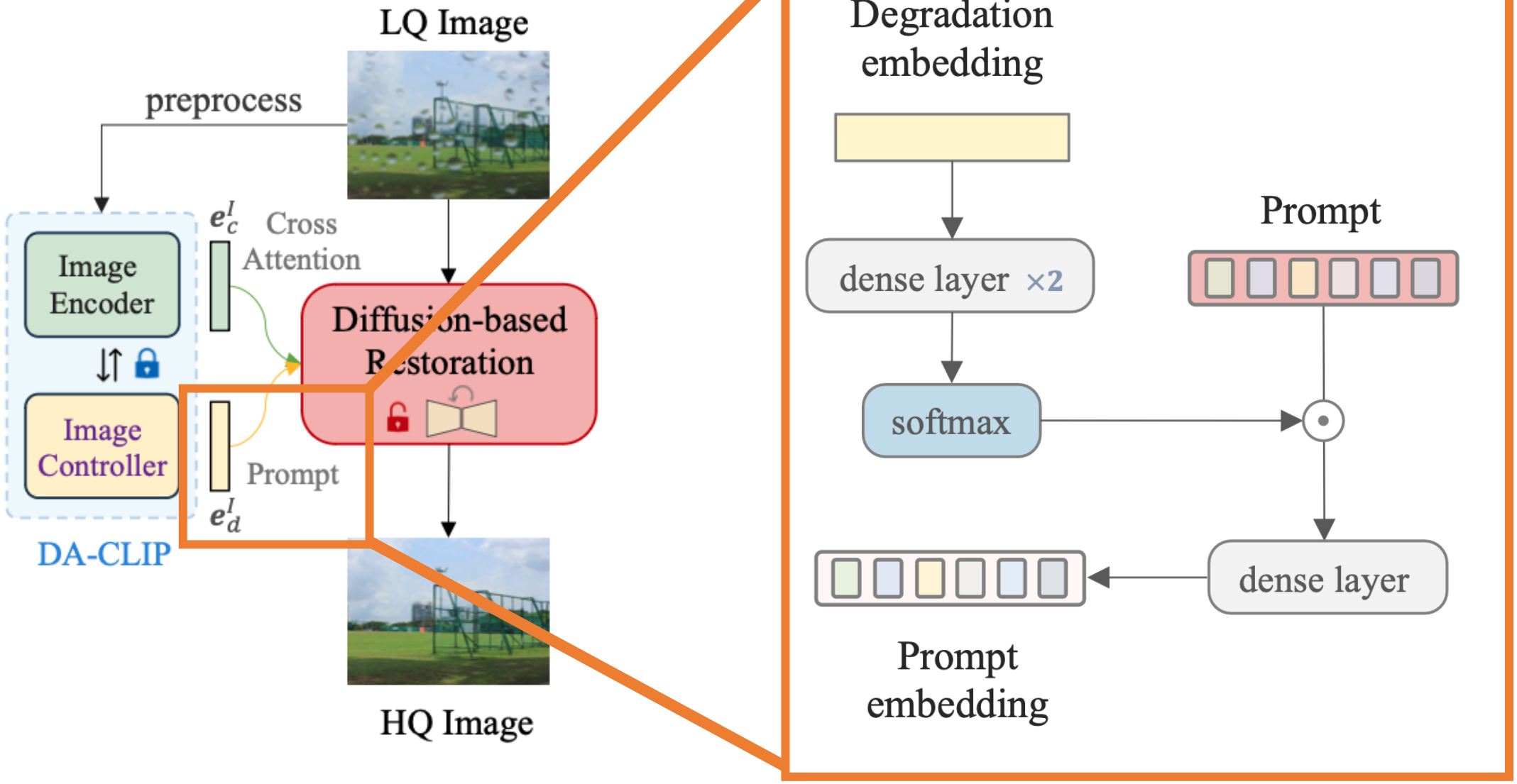
High-Resolution Image Synthesis with Latent Diffusion Models, CVPR2022

Prompt learning



Learning to Prompt for Vision-Language Models, IJCV 2022

Prompt module



Dataset Construction

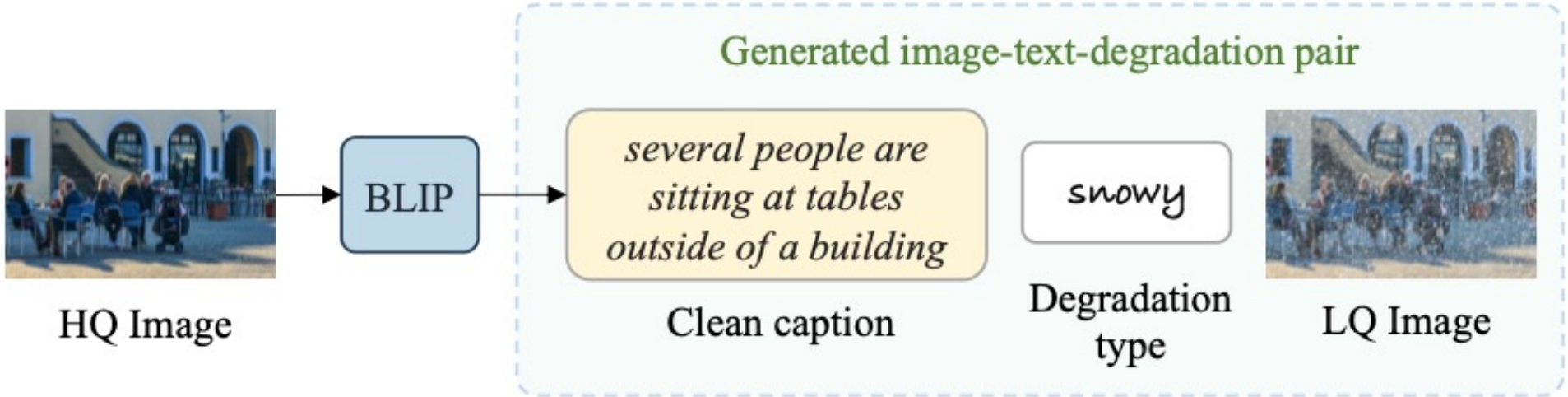


Table 1: Details of the collected training and testing datasets with different image degradation types.

Dataset	Blurry	Hazy	JPEG	Low-light	Noisy	Raindrop	Rainy	Shadowed	Snowy	Inpainting
#Train	2 103	6 000	3 550	485	3 550	861	1 800	2 680	1 872	29 900
#Test	1 111	1 000	29	15	68	58	100	408	601	100

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Degradation-Specific Image Restoration

Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
JORDER	26.25	0.835	0.197	94.58
PReNet	29.46	0.899	0.128	52.67
MPRNet	30.41	0.891	0.158	61.59
MAXIM	30.81	0.903	0.133	58.72
IR-SDE	31.65	0.904	0.047	18.64
Ours	**33.91**	**0.926**	**0.031**	**11.79**

(a) Deraining results on the Rain100H dataset.

Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
EnlightenGAN	17.61	0.653	0.372	94.71
MIRNet	**24.14**	0.830	0.250	69.18
URetinex-Net	19.84	0.824	0.237	52.38
MAXIM	23.43	**0.863**	0.098	48.59
IR-SDE	20.45	0.787	0.129	47.28
Ours	23.77	0.830	**0.083**	**34.03**

(b) Low-light enhancement on the LOL dataset.

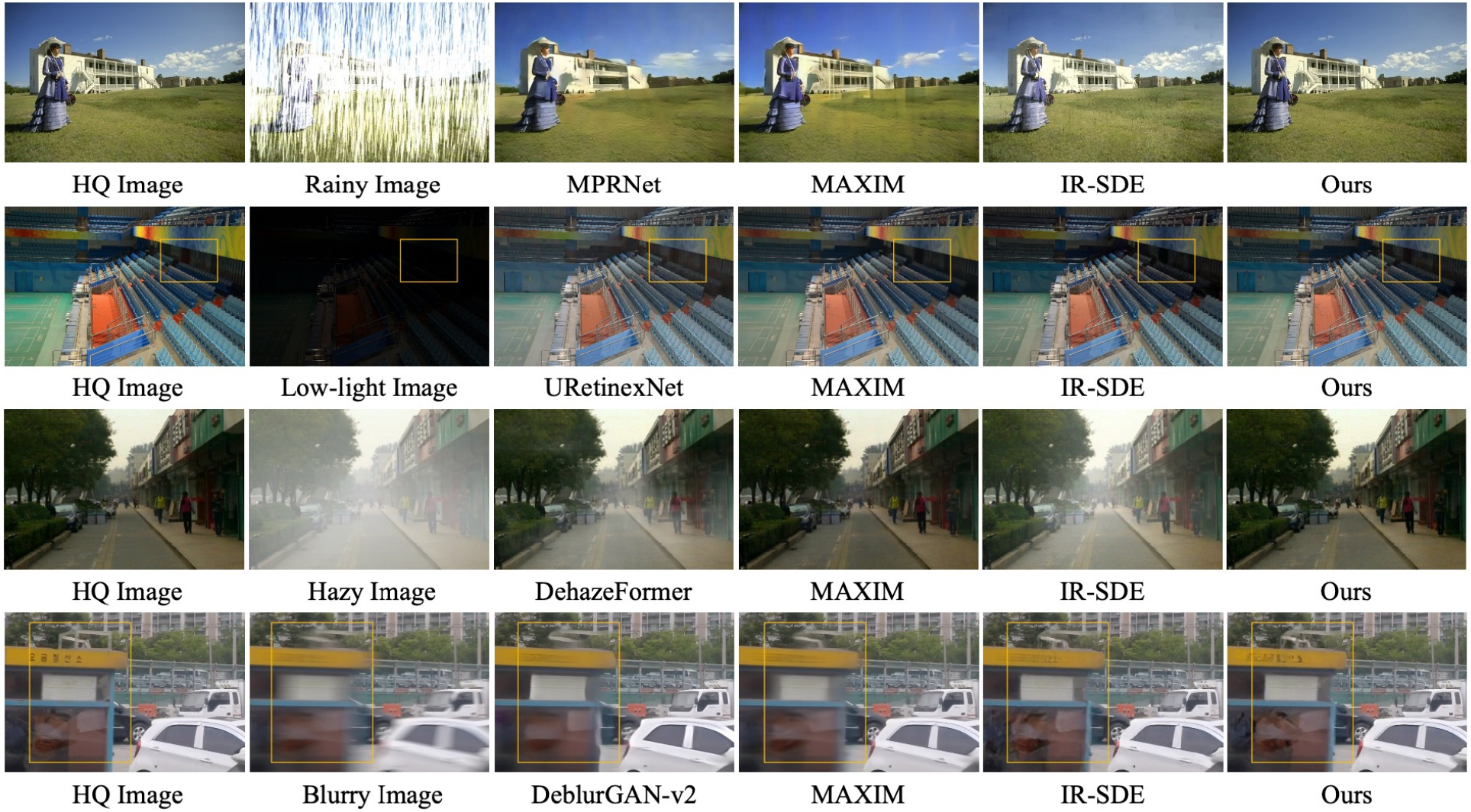
Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
DeepDeblur	29.08	0.913	0.135	15.14
DeblurGAN	28.70	0.858	0.178	27.02
DeblurGANv2	29.55	0.934	0.117	13.40
MAXIM	**32.86**	**0.940**	0.089	11.57
IR-SDE	30.70	0.901	0.064	6.32
Ours	30.88	0.903	**0.058**	**6.15**

(c) Deblurring results on the GoPro dataset.

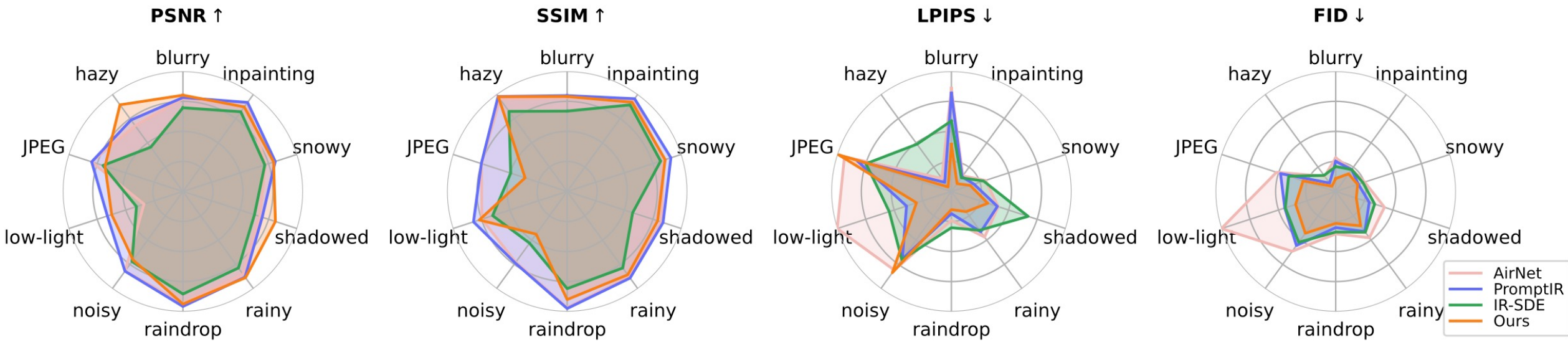
Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
GCANet	26.59	0.935	0.052	11.52
GridDehazeNet	25.86	0.944	0.048	10.62
DehazeFormer	**30.29**	**0.964**	0.045	7.58
MAXIM	29.12	0.932	0.043	8.12
IR-SDE	25.25	0.906	0.060	8.33
Ours	30.16	0.936	**0.030**	**5.52**

(d) Dehazing results on the RESIDE-6k dataset.

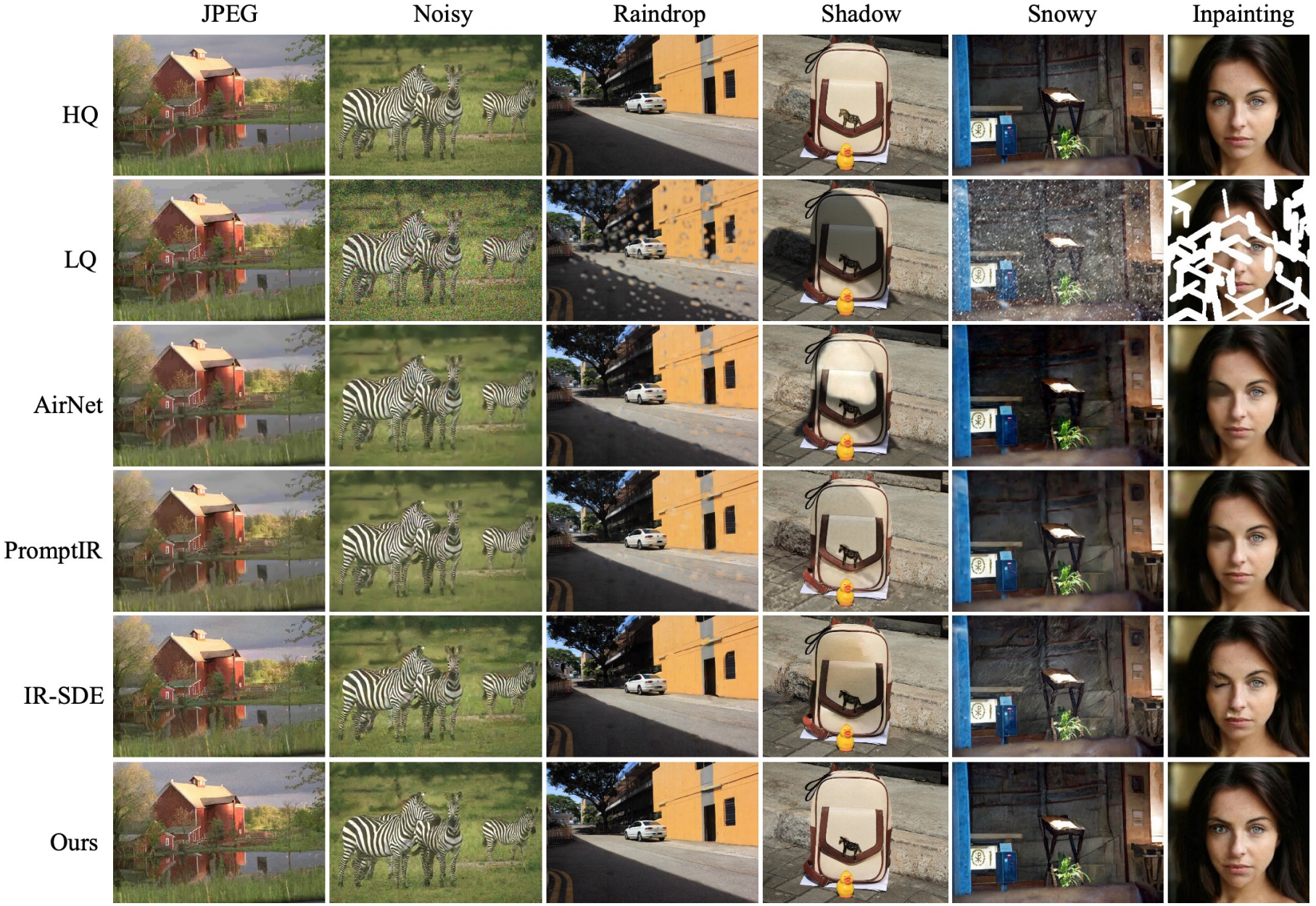
Degradation-Specific Image Restoration



Unified Image Restoration



Unified Image Restoration



Unified Image Restoration

PromptIR

Ours

Unified Image Restoration

Table 3: Comparison of the average results over ten different datasets on the *unified* image restoration task.

Method	Distortion		Perceptual	
	PSNR↑	SSIM↑	LPIPS↓	FID↓
NAFNet	26.34	0.847	0.159	55.68
NAFNet + Degradation	27.02	0.856	0.146	48.27
NAFNet + DA-CLIP	**27.22**	**0.861**	0.145	47.94
Restormer	26.43	0.850	0.157	54.03
AirNet	25.62	0.844	0.182	64.86
PromptIR	27.14	0.859	0.147	48.26
IR-SDE	23.64	0.754	0.167	49.18
Ours	27.01	0.794	**0.127**	**34.89**

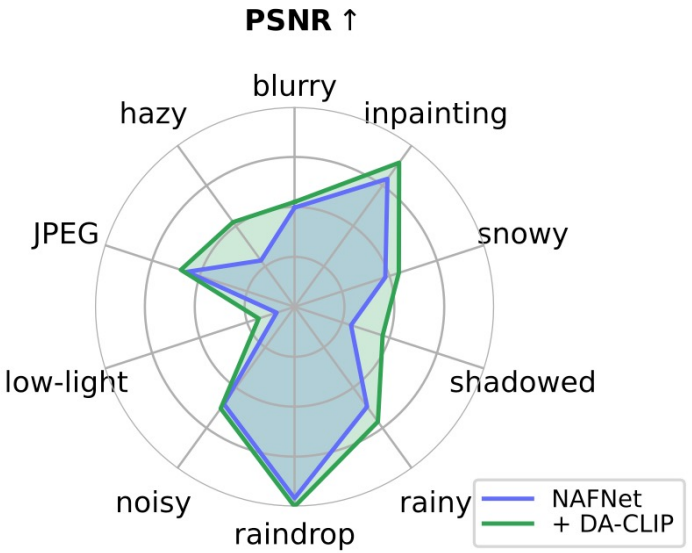


Figure 7: NAFNet with DA-CLIP for *unified* image restoration.

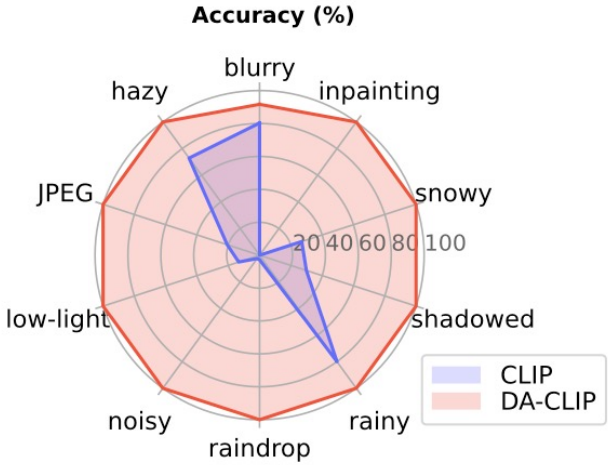
Discussion and Analysis

Image dehazing

Image deblurring

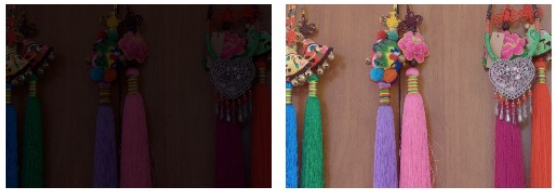
Face inpainting

JPEG artifact deduction



Degradation prediction

Image desnowing



Low-light image enhancement

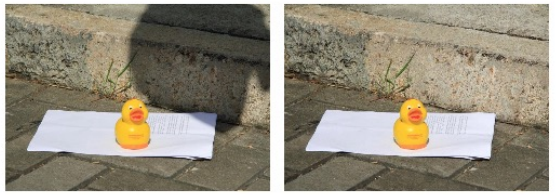


Image shadow removal

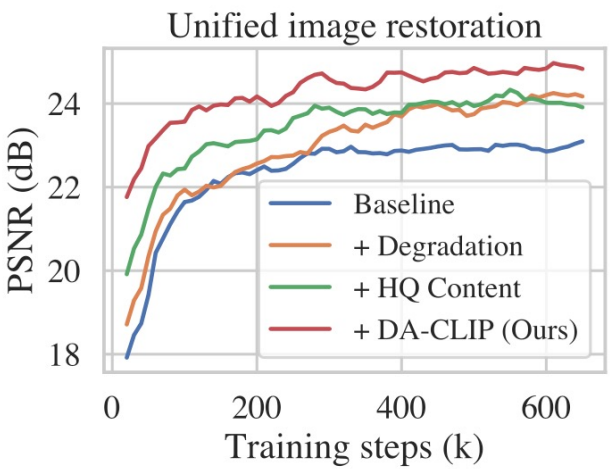
Image denoising

Image raindrop removal

Image deraining

- prompt is set to “a [degradation type] photo”

Discussion and Analysis



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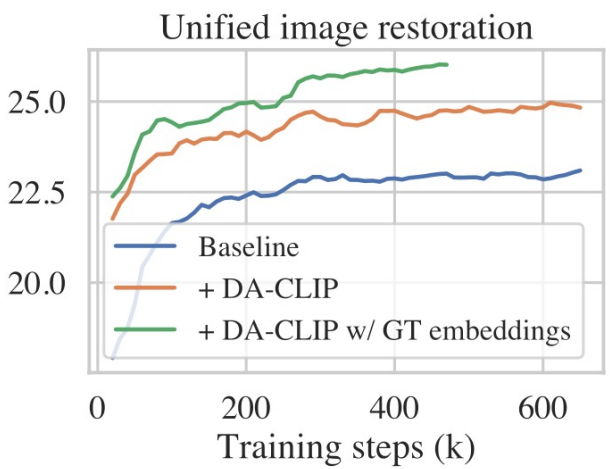

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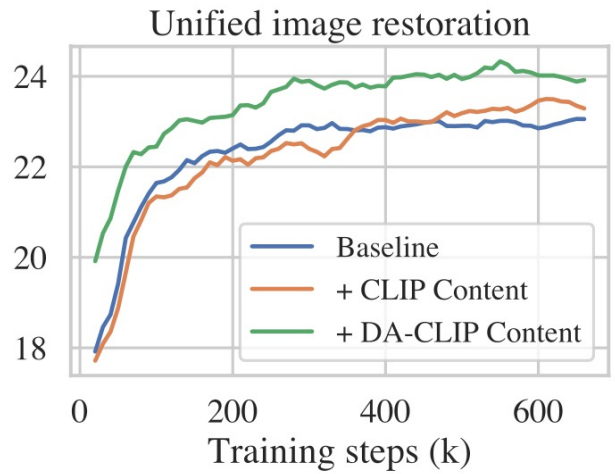
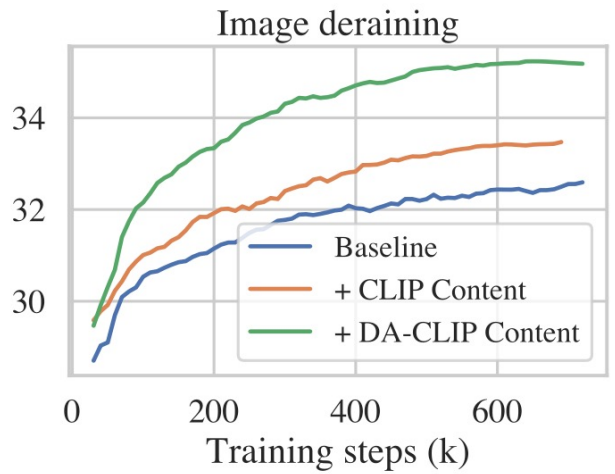


(c)



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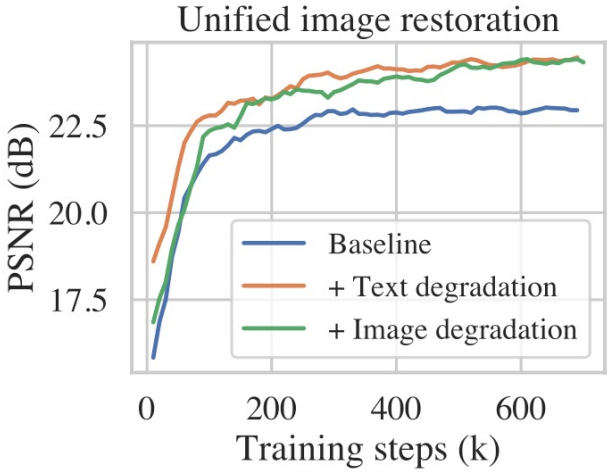

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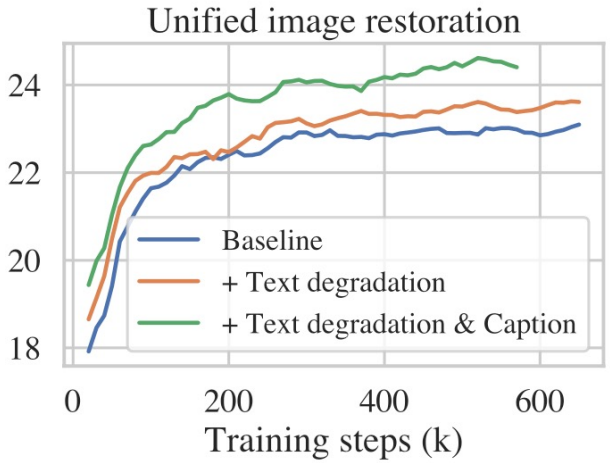

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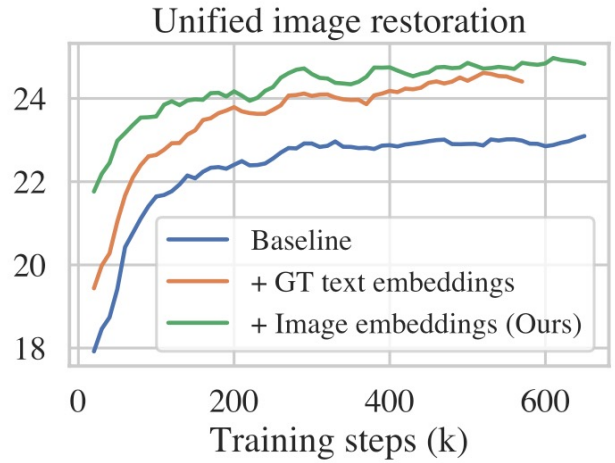

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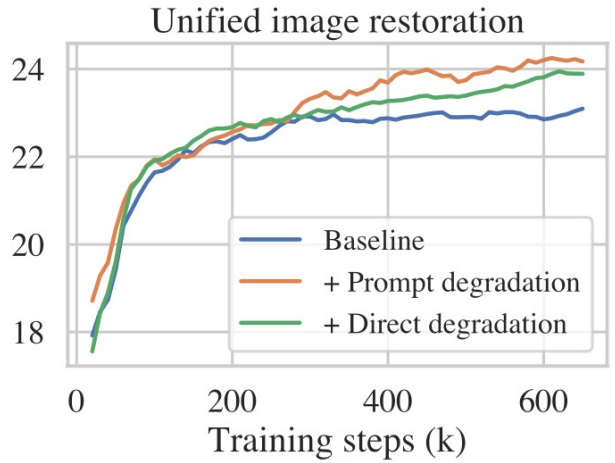

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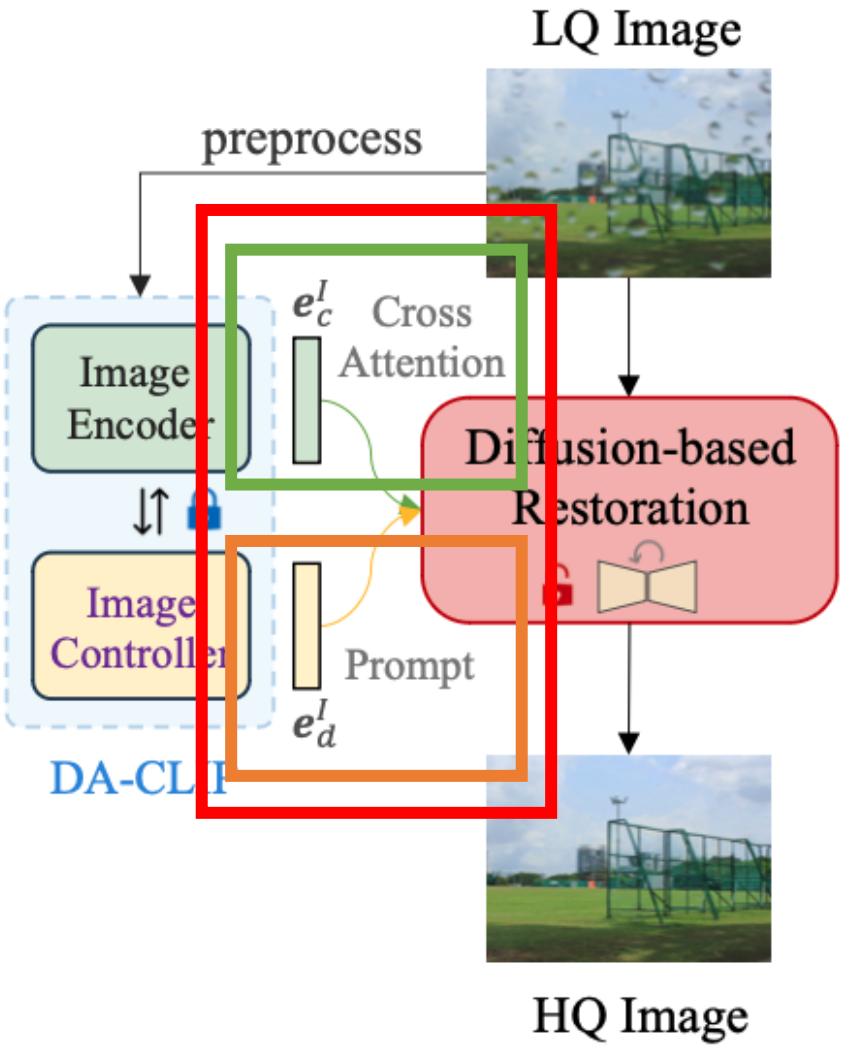
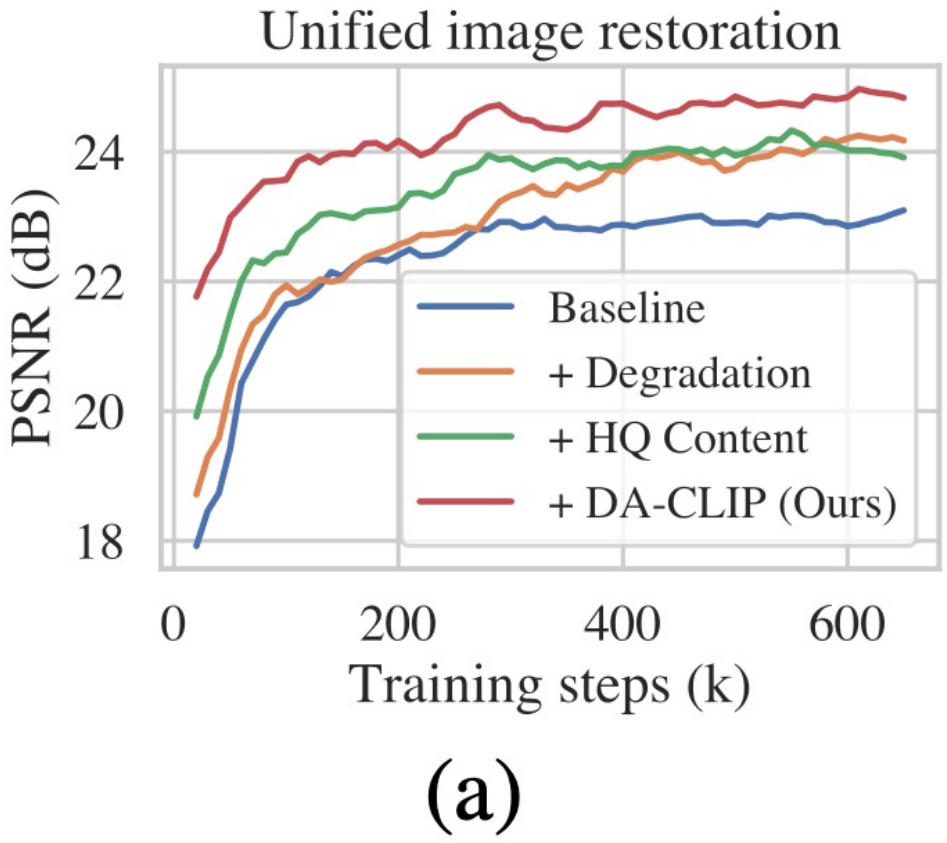
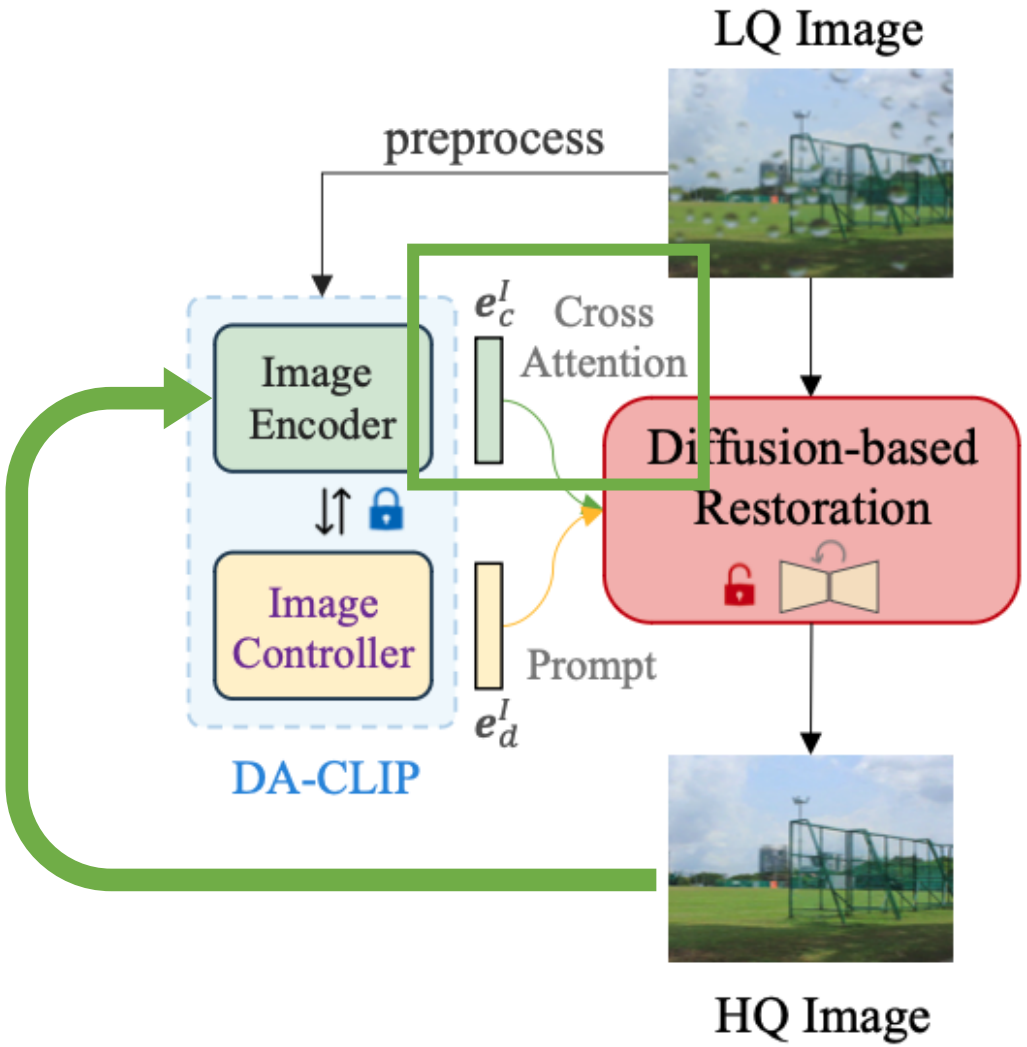
Discussion and Analysis

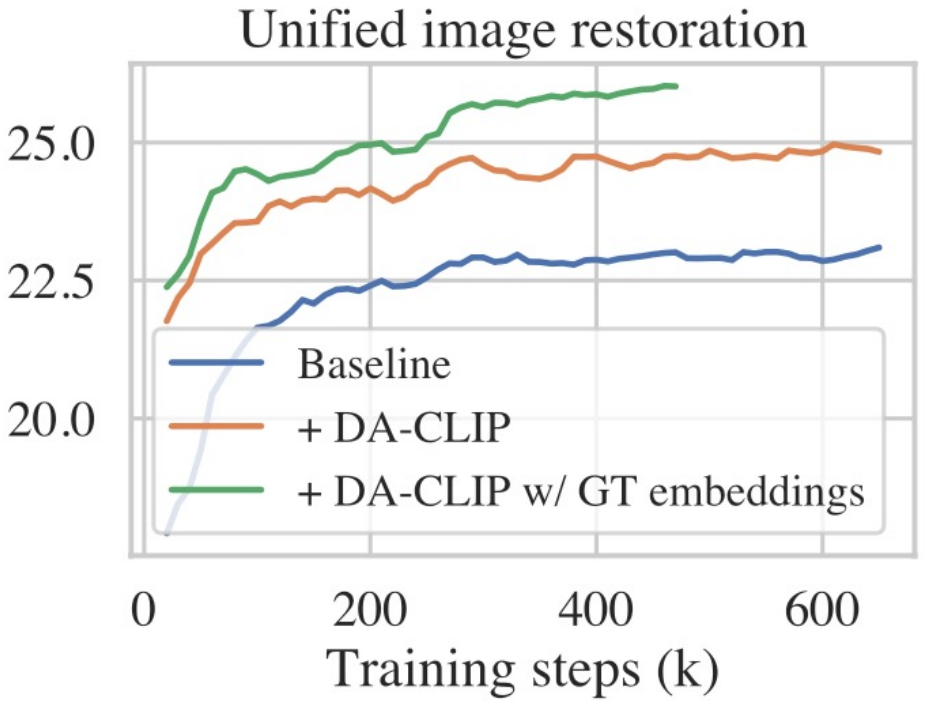




(a)

Discussion and Analysis





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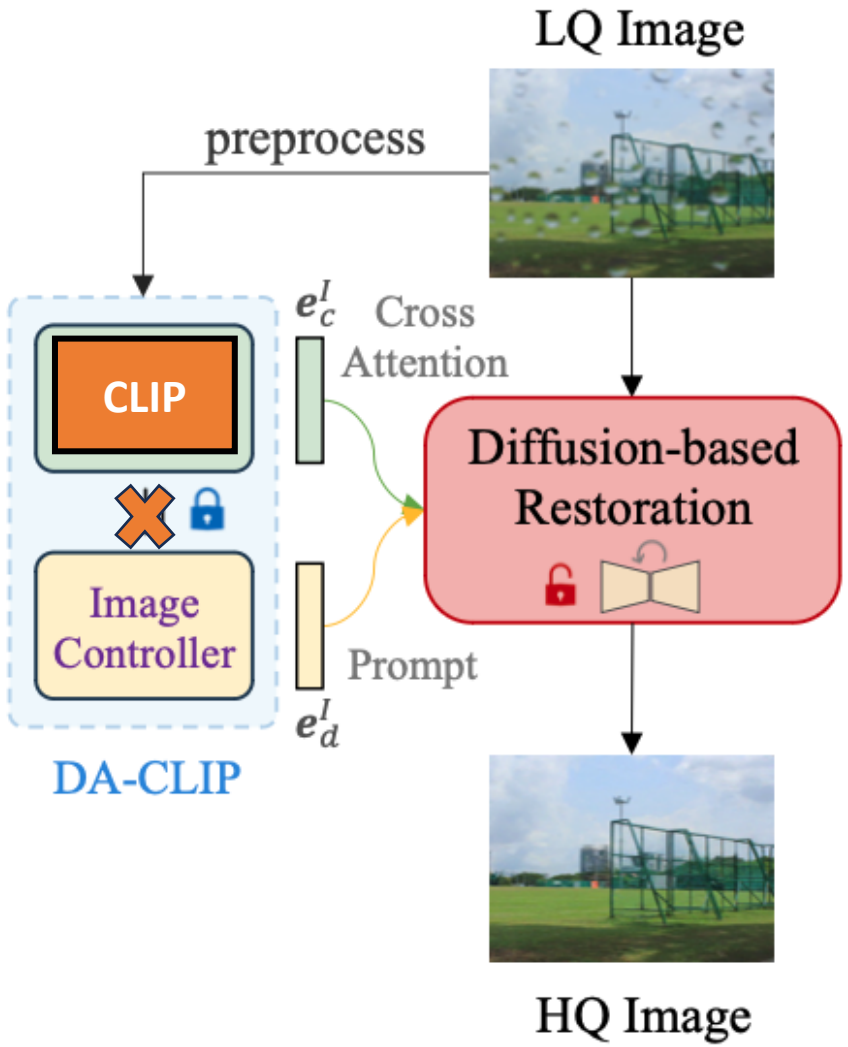
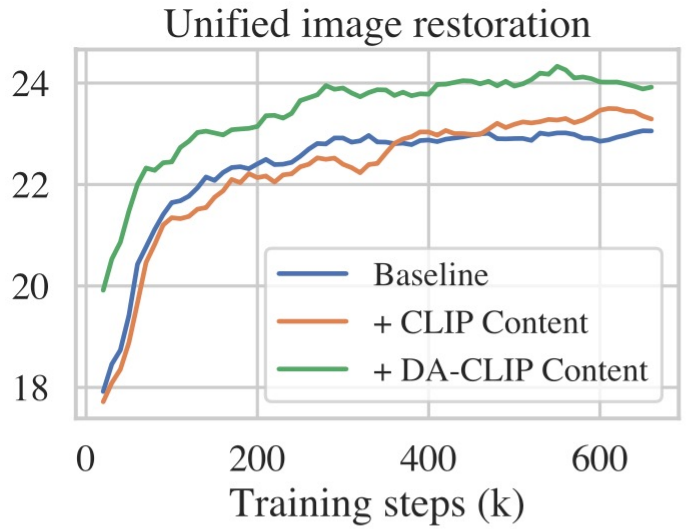
Discussion and Analysis





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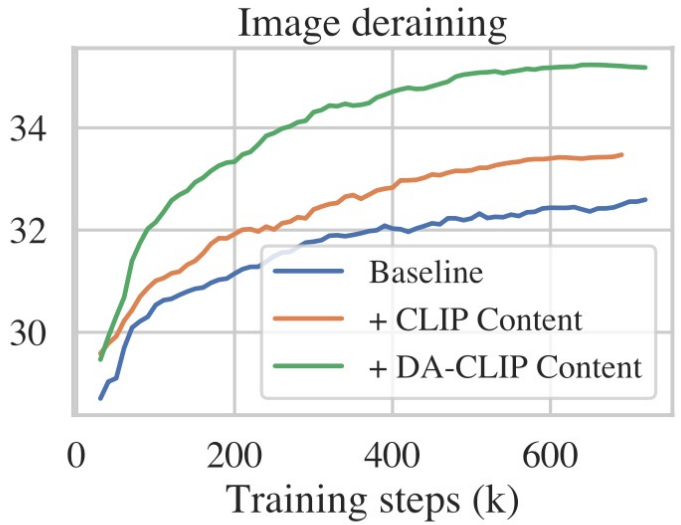
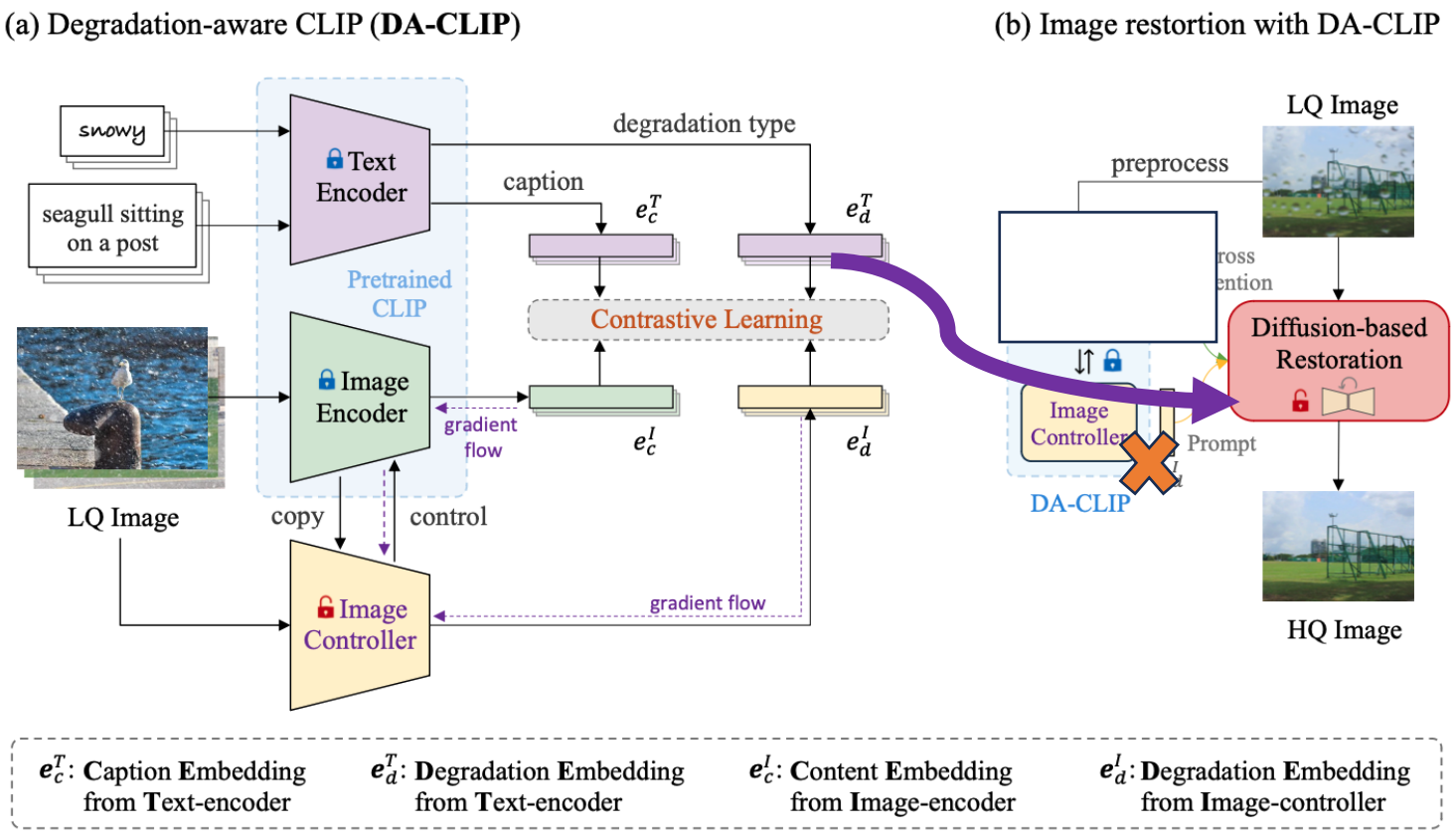
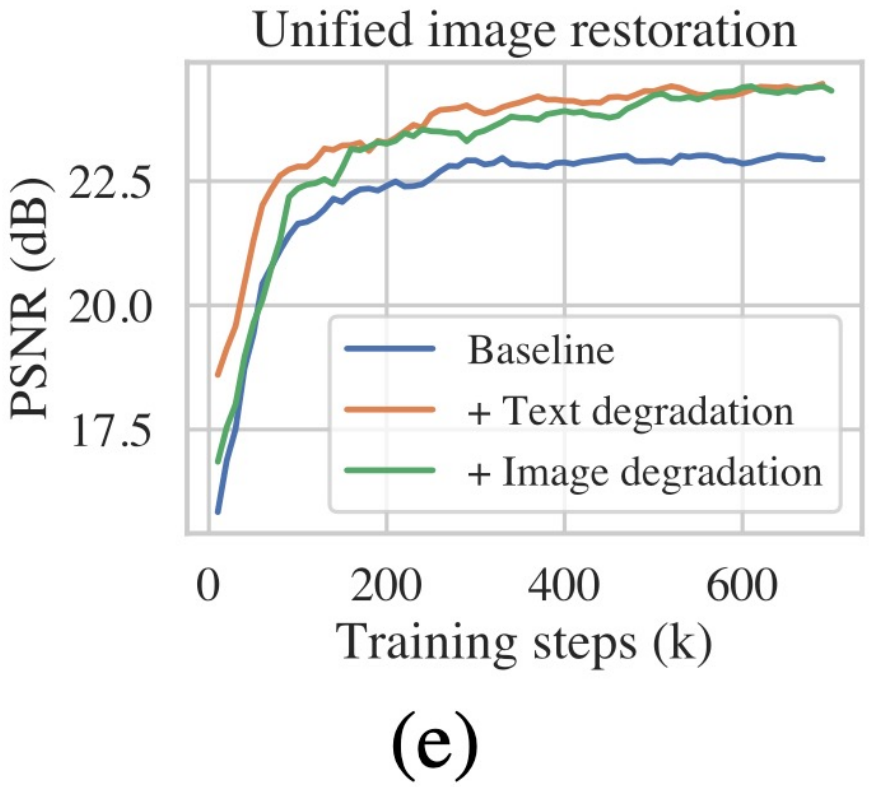


(d)

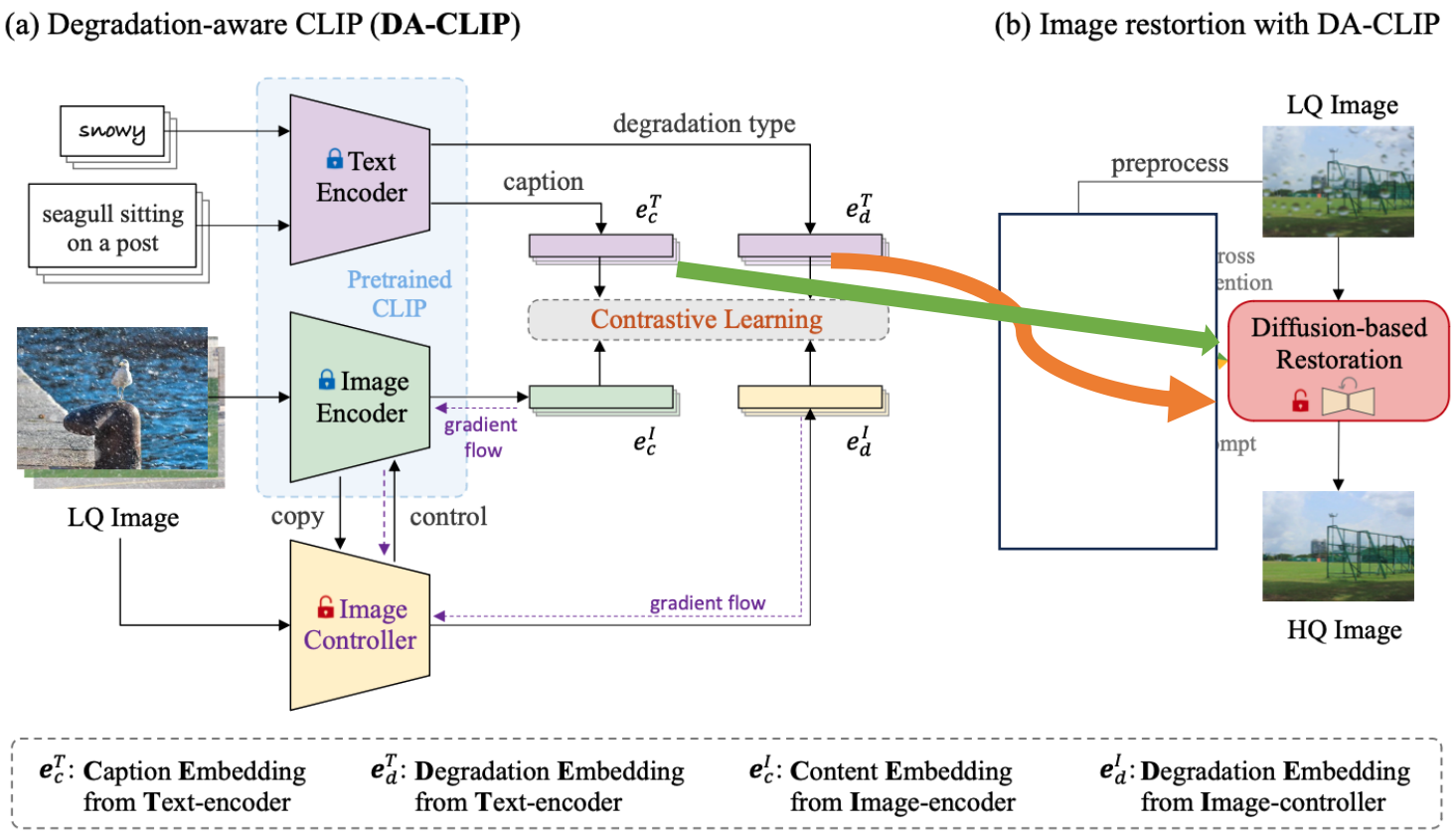
Discussion and Analysis

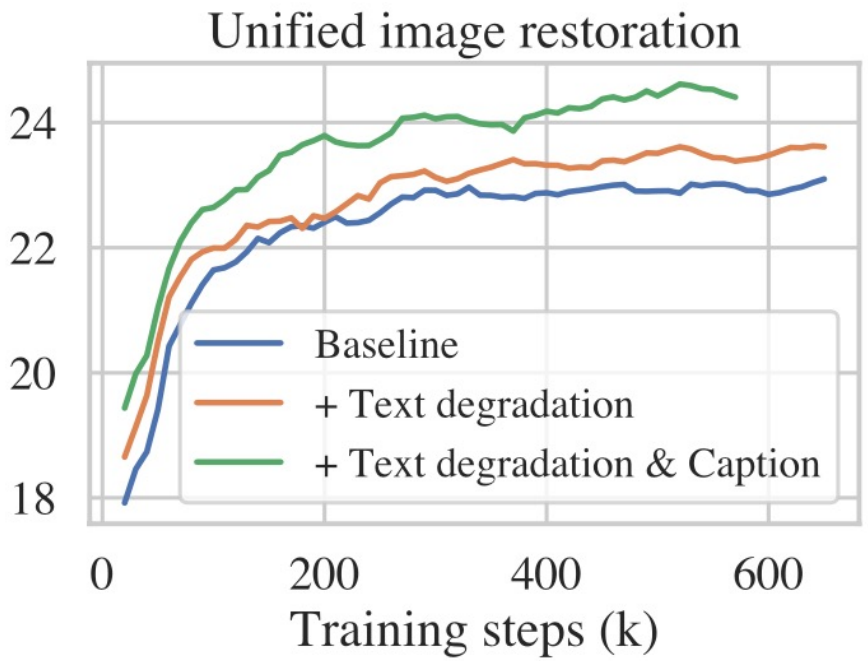




(e)

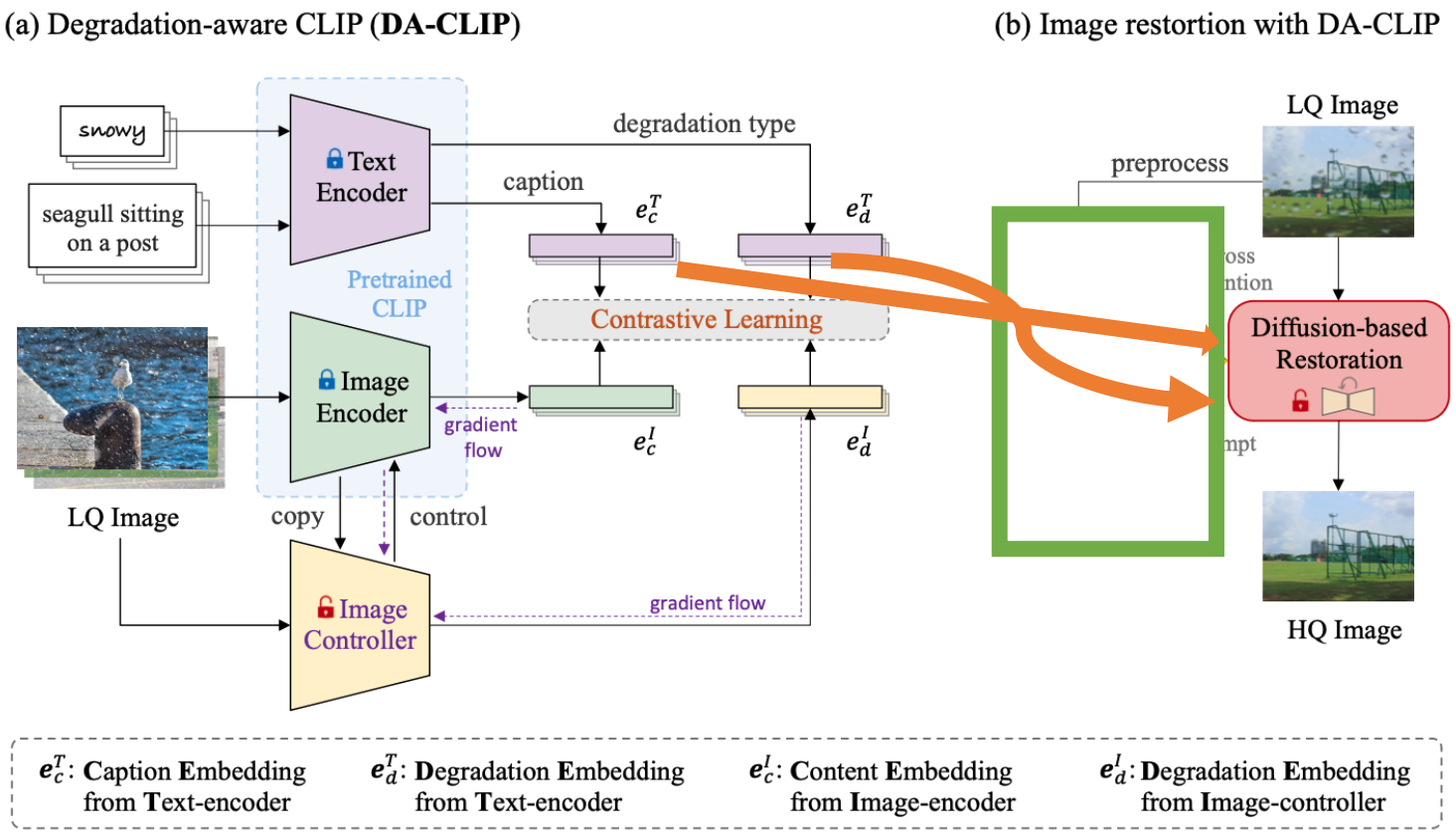
Discussion and Analysis

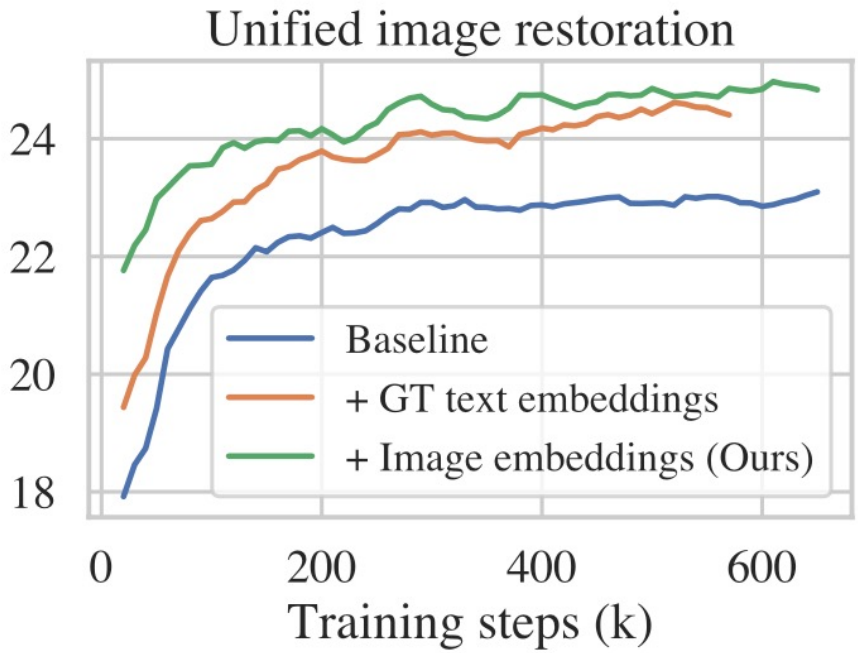




(f)

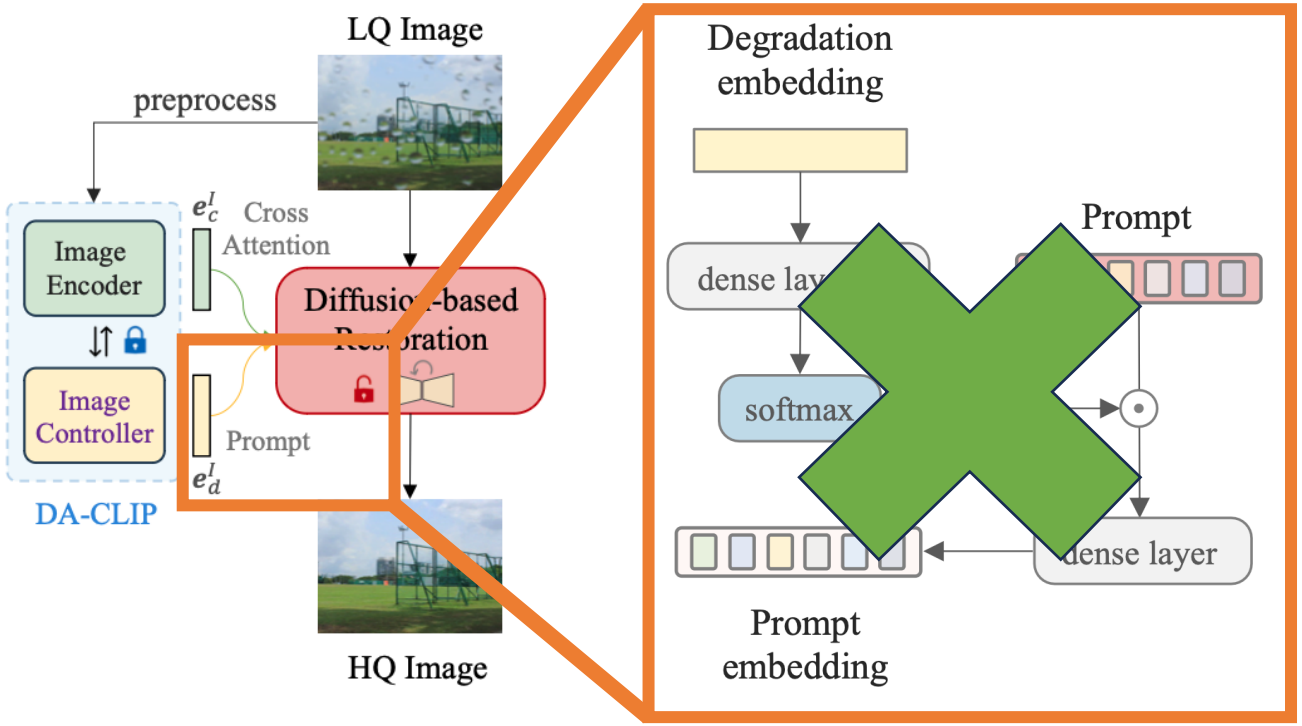
Discussion and Analysis

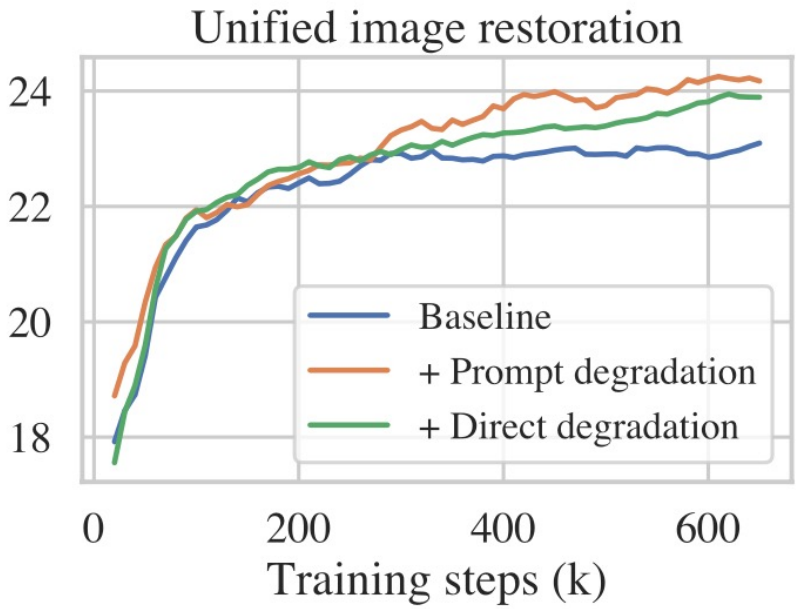




(g)

Discussion and Analysis





(h)

Outline

- Preliminary
- Framework
- Method
- Experiment
- Conclusion

Conclusion

- Present DA-CLIP to leverage **large-scale pretrained vision-language models** as a framework for image restoration. Image controller that predicts the **degradation** and **HQ content embeddings** from corrupted inputs.

- Use **cross-attention** to integrate the content embedding into restoration networks and **prompt learning module** to utilize the degradation context.

- Demonstrate the effectiveness of DA-CLIP by applying it to image restoration models for both degradation-specific and unified image restoration across all ten degradation types.