Paper Review

Palette: Image-to-Image Diffusion Models

YeongHyeon Park

Department of Electrical and Computer Engineering

SungKyunKwan University

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Google Research

Palette: Image-to-Image Diffusion Models

Chitwan Saharia
Google Research, Brain Team
Toronto, ON, Canada
sahariac@google.com

William Chan
Google Research, Brain Team
Toronto, ON, Canada
williamchan@google.com

Huiwen Chang
Google Research
New York, NY, USA
huiwenchang@google.com

Chris A. Lee
Google Research
Mountain View, CA, USA
chrisalee@google.com

Jonathan Ho
Google Research, Brain Team
New York, NY, USA
jonathanho@google.com

Tim Salimans
Google Research, Brain Team
Amsterdam, Netherlands
salimans@google.com

David Fleet
Google Research, Brain Team
Toronto, ON, Canada
davidfleet@google.com

Mohammad Norouzi
Google Research, Brain Team
Toronto, ON, Canada
mnorouzi@google.com

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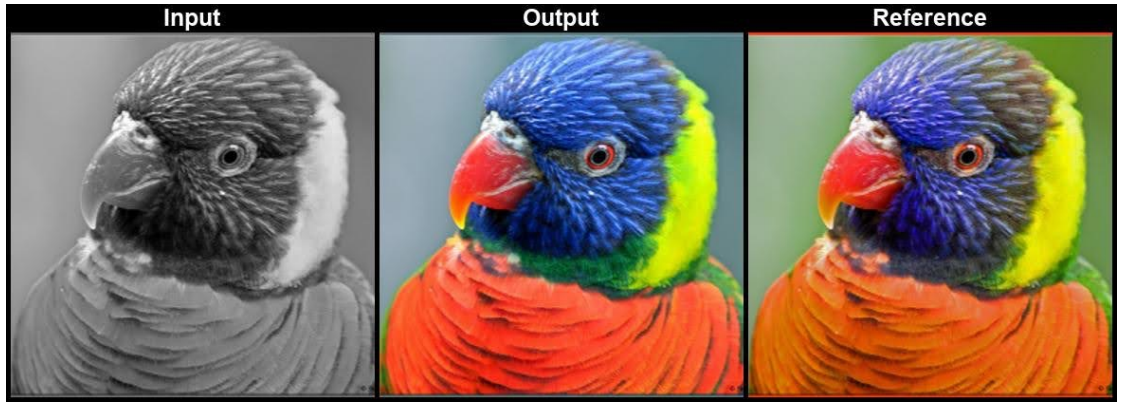
mnorouzi@google.com

Ho et al. 'Denoising Diffusion …'
NeurIPS, 2020

Preview of Palette

https://diffusion-palette.github.io/

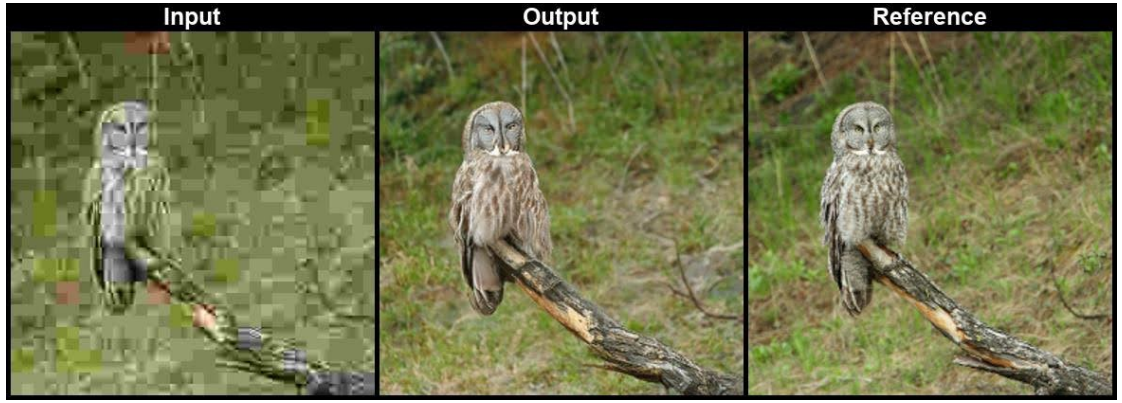
Image-to-image Translation



Colorization

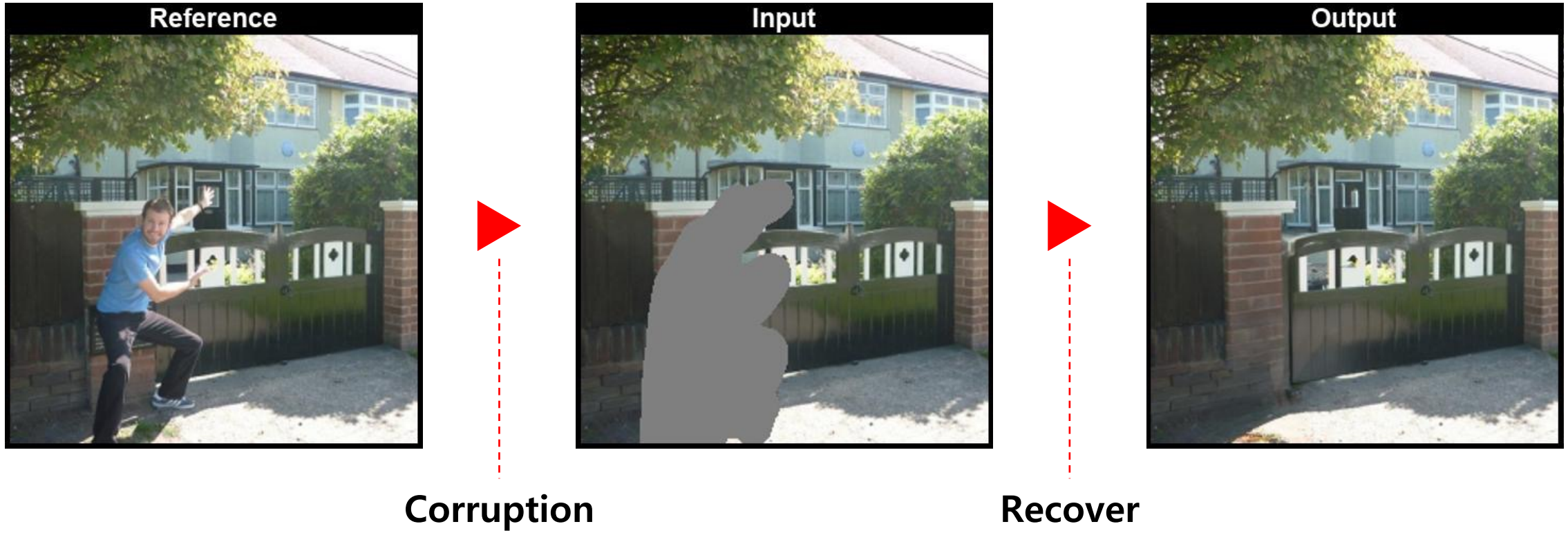
Inpainting

Uncropping (=outpainting)



JPEG restoration

How to Translate?



Contribution: Unified X

- A unified diffusion-based image-to-image translation (i2i) framework for four tasks.
  - No hyperparameter tuning required
  - No task-specific neural networks required

- A unified evaluation protocol on i2i translation tasks based on visual perception.
  - Inception Score (IS)
  - Fréchet Inception Distance (FID)
  - Classification Accuracy (CA)
  - Perceptual Distance (PD)

Why Diffusion?

Xiao, Zhisheng et al. "Tackling the generative learning trilemma with denoising diffusion GANs." *arXiv preprint*. 2021.

Why Diffusion?

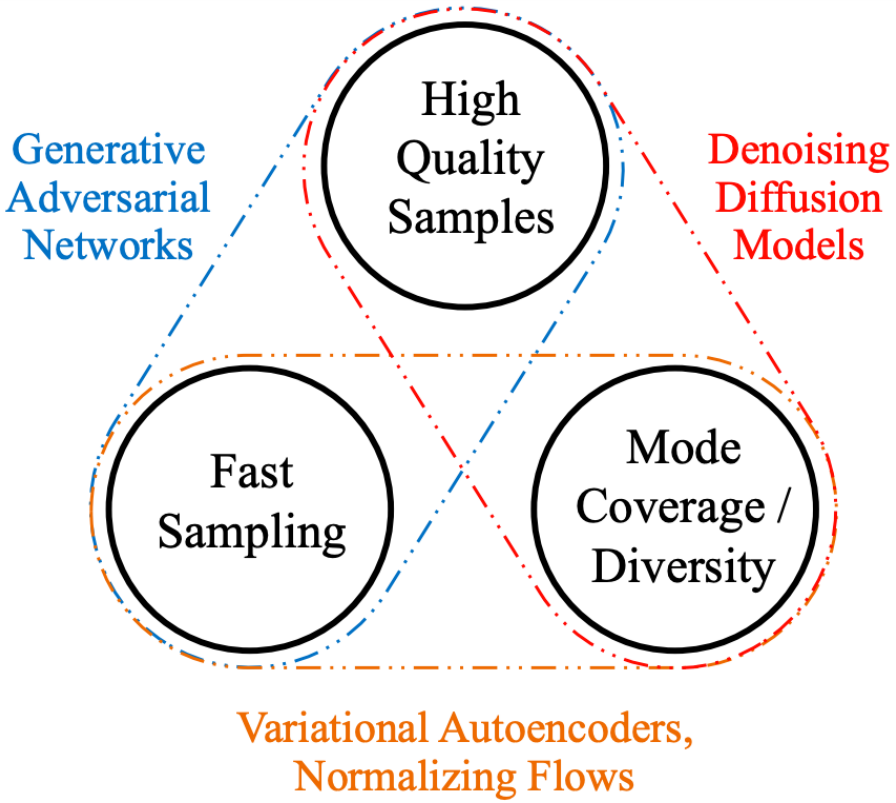


Figure 1: Generative learning trilemma.

Xiao, Zhisheng et al. "Tackling the generative learning trilemma with denoising diffusion GANs." *arXiv preprint*. 2021.

Why Diffusion?

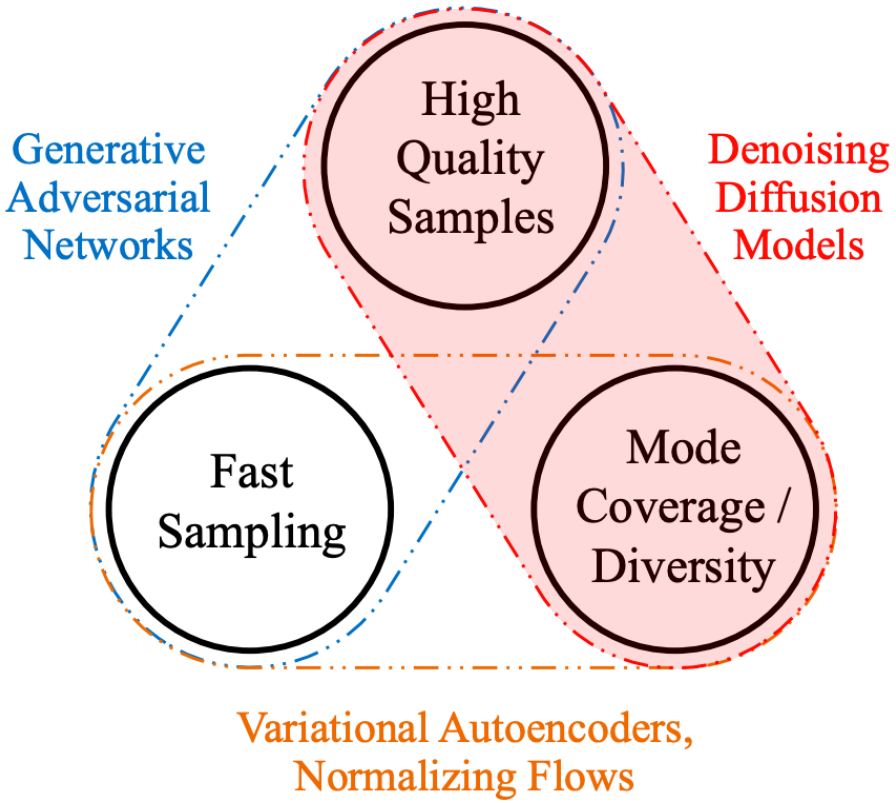


Figure 1: Generative learning trilemma.

Xiao, Zhisheng et al. "Tackling the generative learning trilemma with denoising diffusion GANs." *arXiv preprint*. 2021.

Mode Coverage / Diversity

- **Coverage** : Infer each mode without missing.
- **Diversity** : Infer all the different modes without exception.

Diffusion

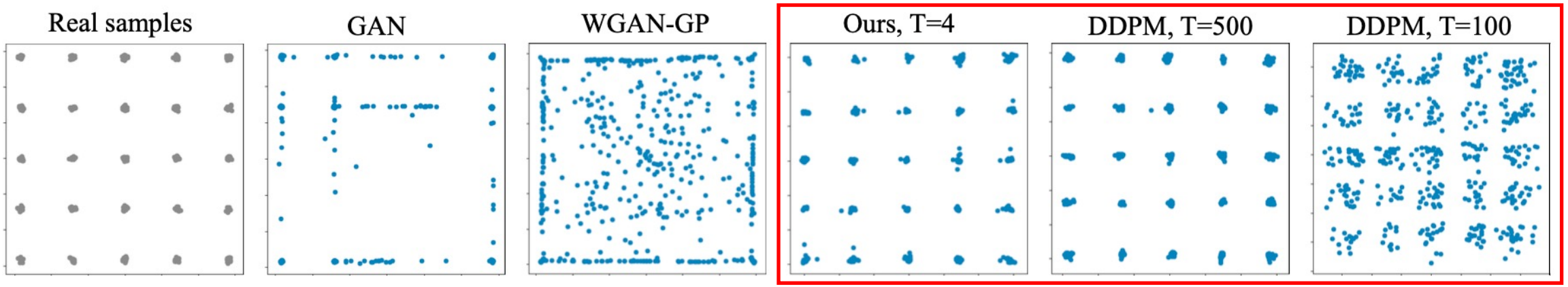
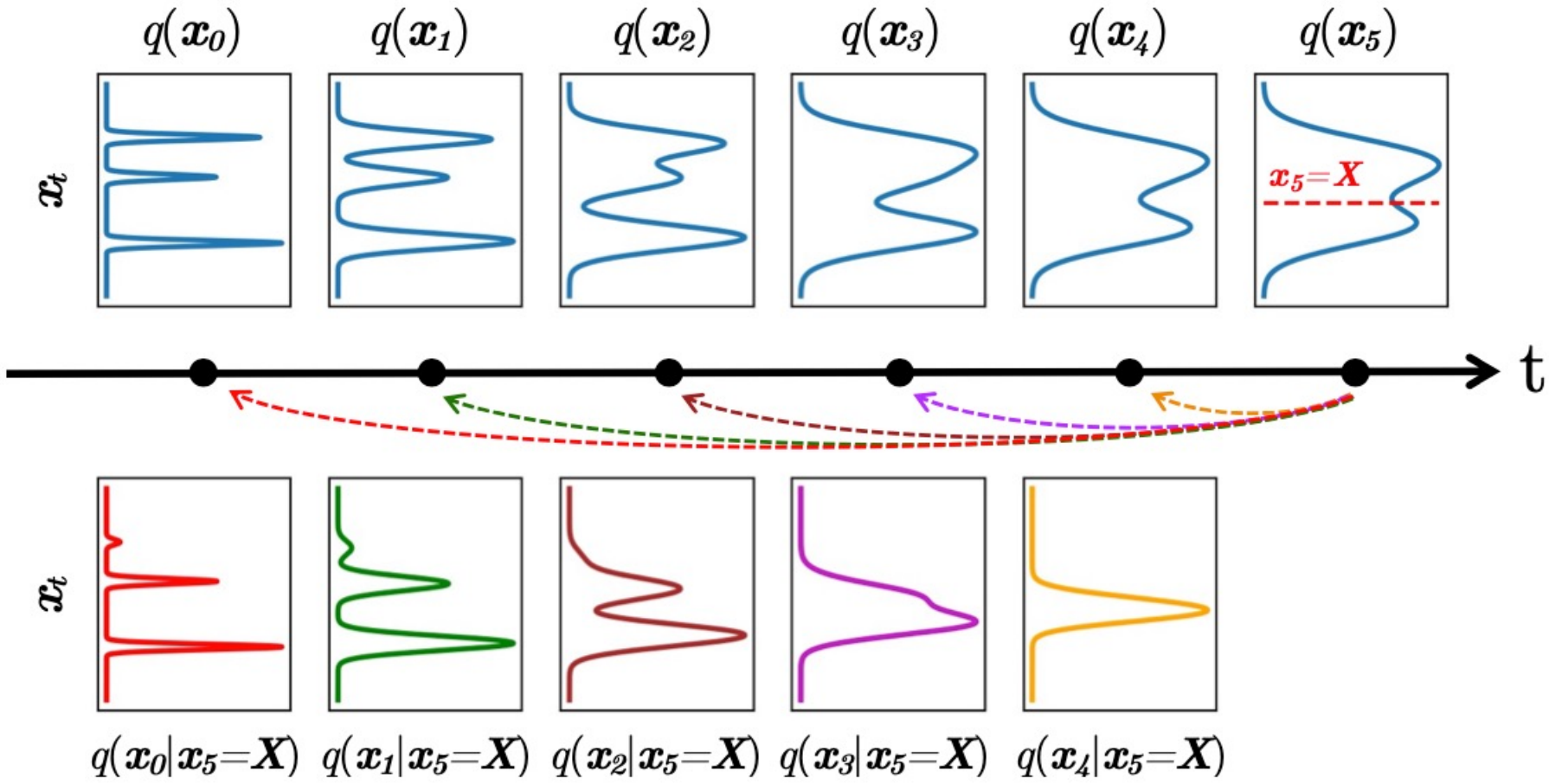


Figure 6: Qualitative results on the 25-Gaussians dataset.

Xiao, Zhisheng et al. "Tackling the generative learning trilemma with denoising diffusion GANs." *arXiv preprint*. 2021.

Diffusion Model

- x_0 : original sample
- x_t : noise injected sample (diffused sample)

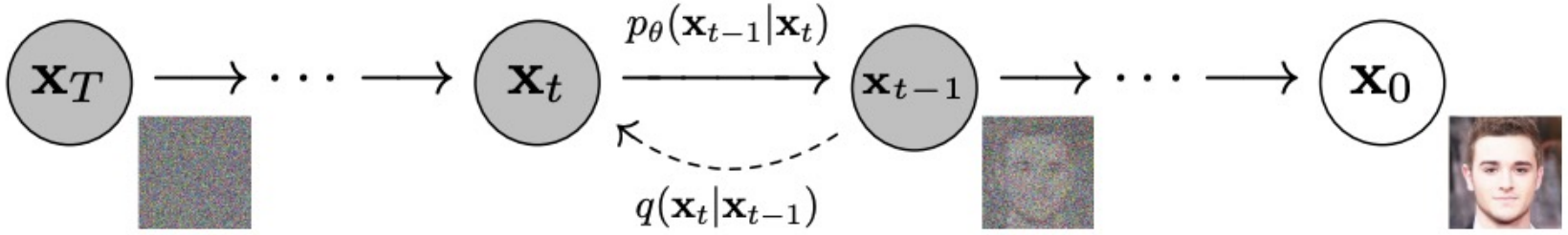


Ho, Jonathan et al. "Denoising diffusion probabilistic models." *Advances in Neural Information Processing Systems (NeurIPS)*. 2020.

Denoising Diffusion (Ho et al, 2020)

$$q(x_t|x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t I)$$

Reverse Denoising Process



Diffusion Process
(Noise Injection)

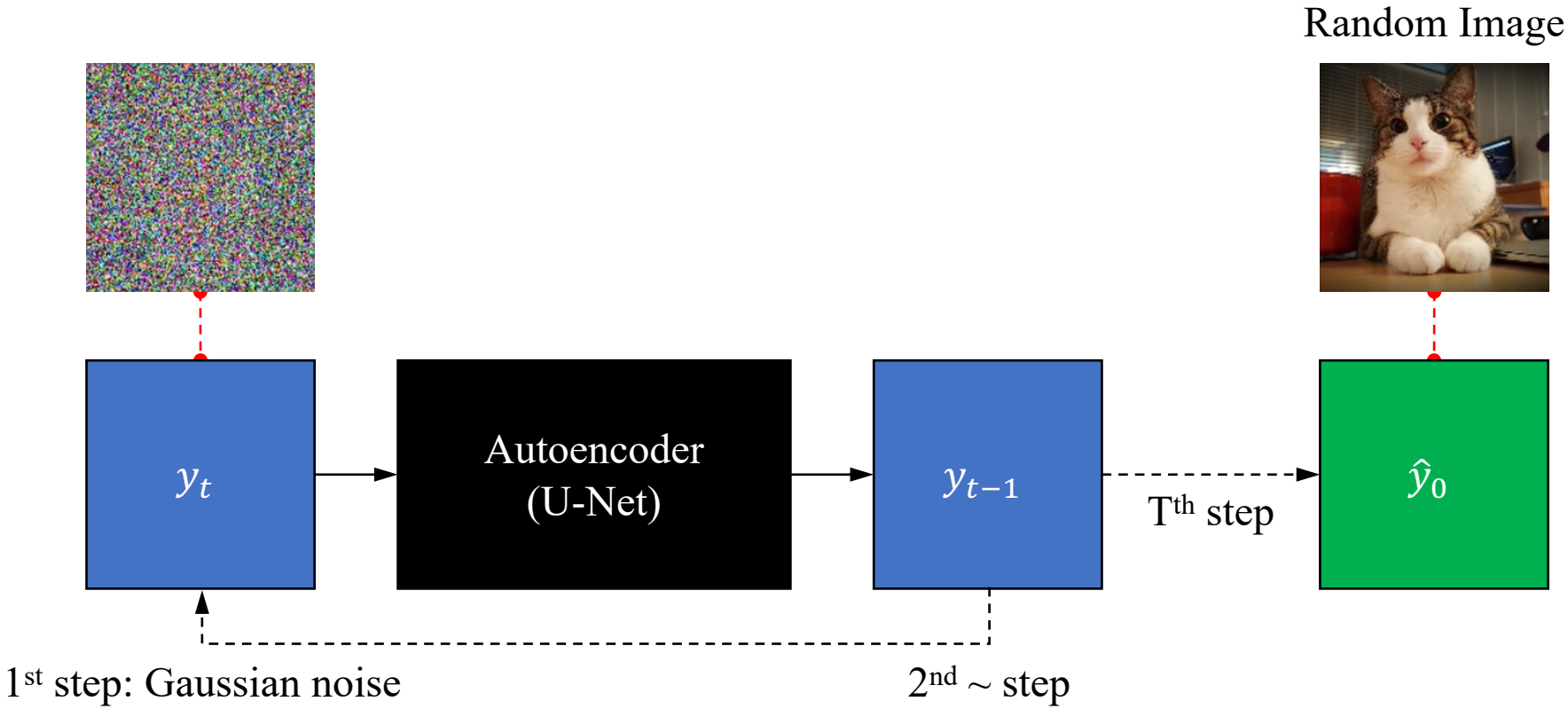
Gaussian Noise

Reference Image

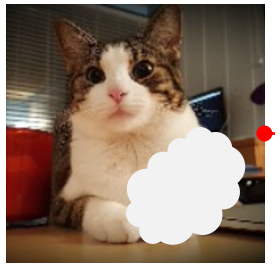
Palette

Image-to-Image Diffusion Models

Unconditional Diffusion



Conditional Diffusion



x

Condition

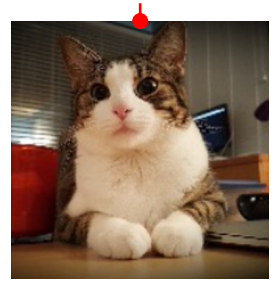
x

Autoencoder
(U-Net)

y_{t-1}

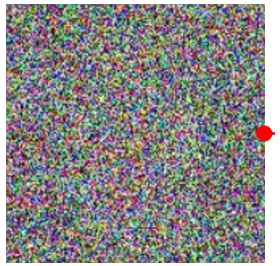
Tth step

$\hat{y}_0$



Conditional Output

2nd ~ step



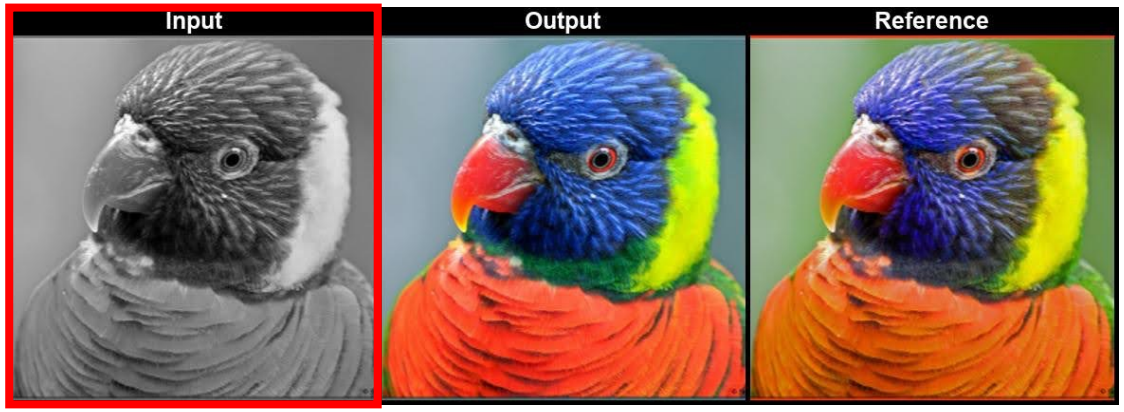
y_t

1st step: Gaussian noise

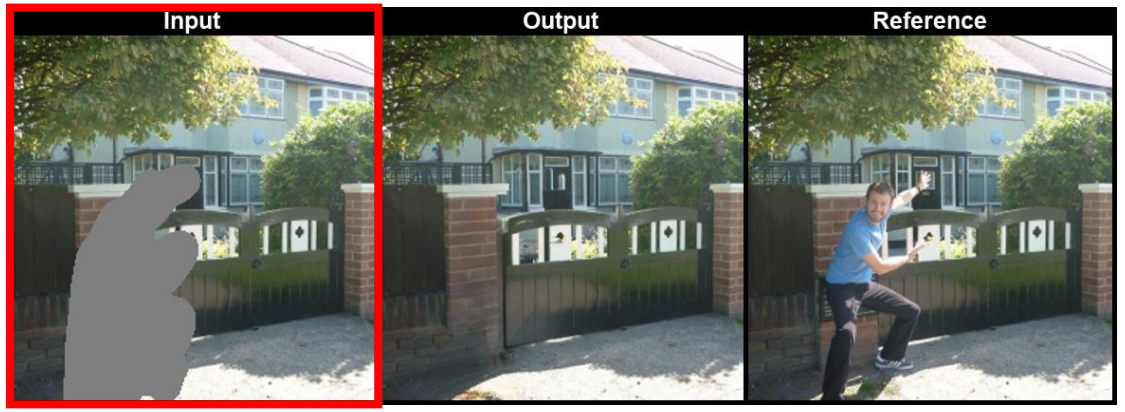
The only difference is the conditional information!

Image-to-image Translation

Conditional information in each task.

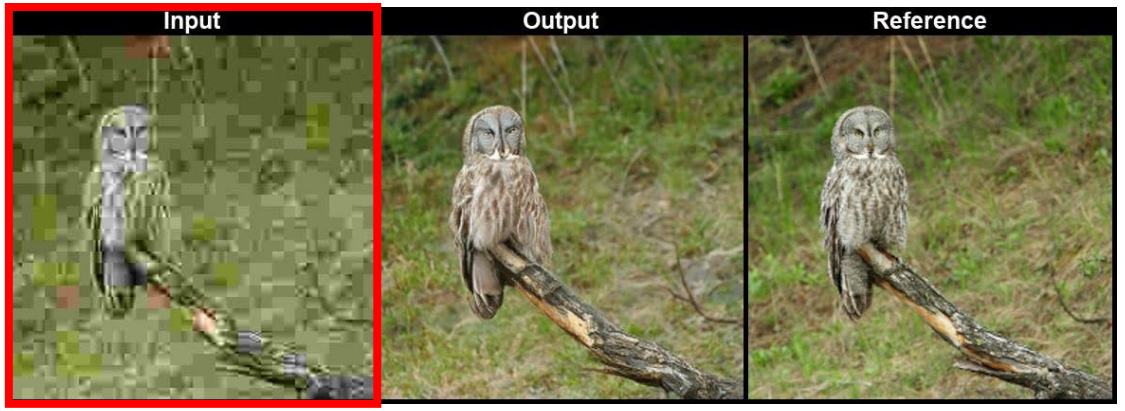


Colorization



Inpainting

Uncropping (=outpainting)



JPEG restoration

Evaluation Protocols

- **Fréchet Inception Distance (FID)** ↓
  - Measure the feature map similarity (e.g. covariance) between ground truth and generated sample.
  - Basically, a pre-trained neural network is used for measurement.

- **Perceptual Distance (PD)** ↓
  - Measure the feature map distance between ground truth and generated sample.
  - Basically, a pre-trained neural network is used for measurement.

- **Inception Score (IS)** ↑
  - Measure that the generated samples have both diversity and clarity.

- **Classification Accuracy (CA)** ↑
  - Confirm that the generated sample contains proper information to classify accurately.
  - The classification will be conducted with a pre-trained classifier.

Kumar, Manoj, Dirk Weissenborn, and Nal Kalchbrenner. "Colorization transformer." *International Conference on Learning Representations (ICLR)*. 2021.
Yu, Jiahui, et al. "Free-form image inpainting with gated convolution." *Proceedings of the IEEE/CVF international conference on computer vision (CVPR)*. 2019.
Teterwak, Piotr, et al. "Boundless: Generative adversarial networks for image extension." *Proceedings of the IEEE/CVF International Conference on Computer Vision (CVPR)*. 2019.

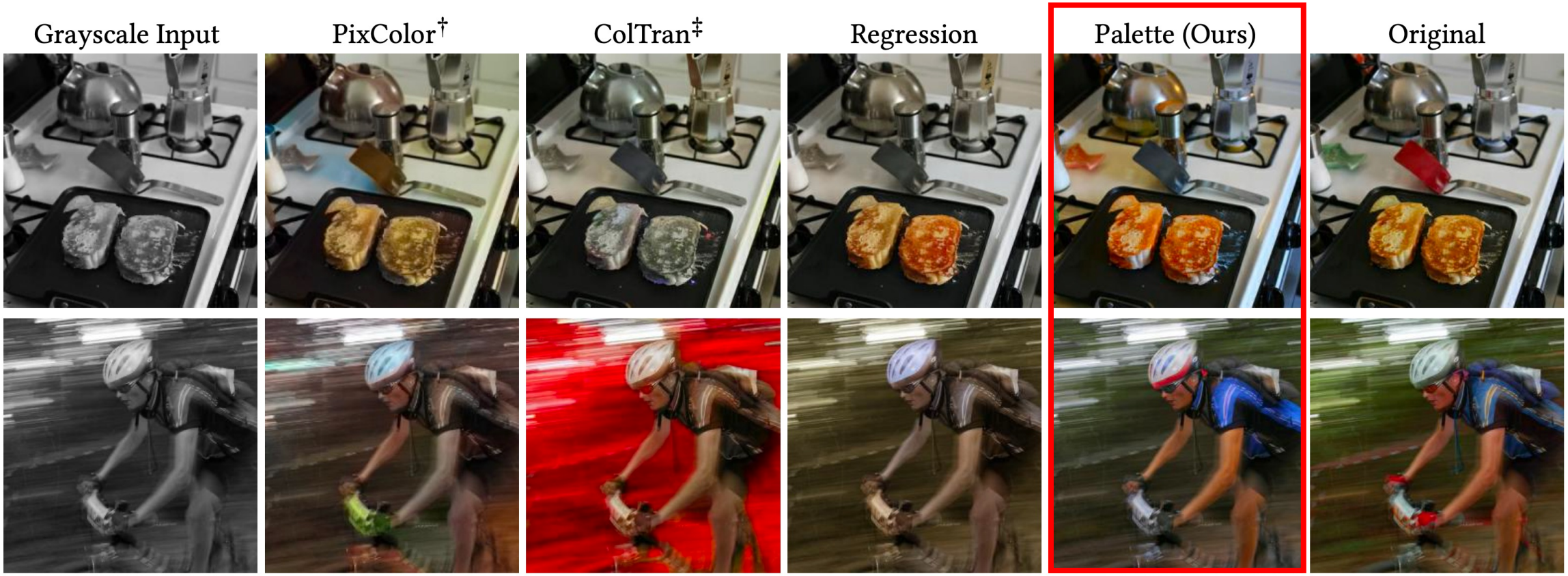
Summarized Performance

- **Task-specific** : Each model is trained only for the specific task.
- **Multi-task** : The unified model trained on all four tasks.

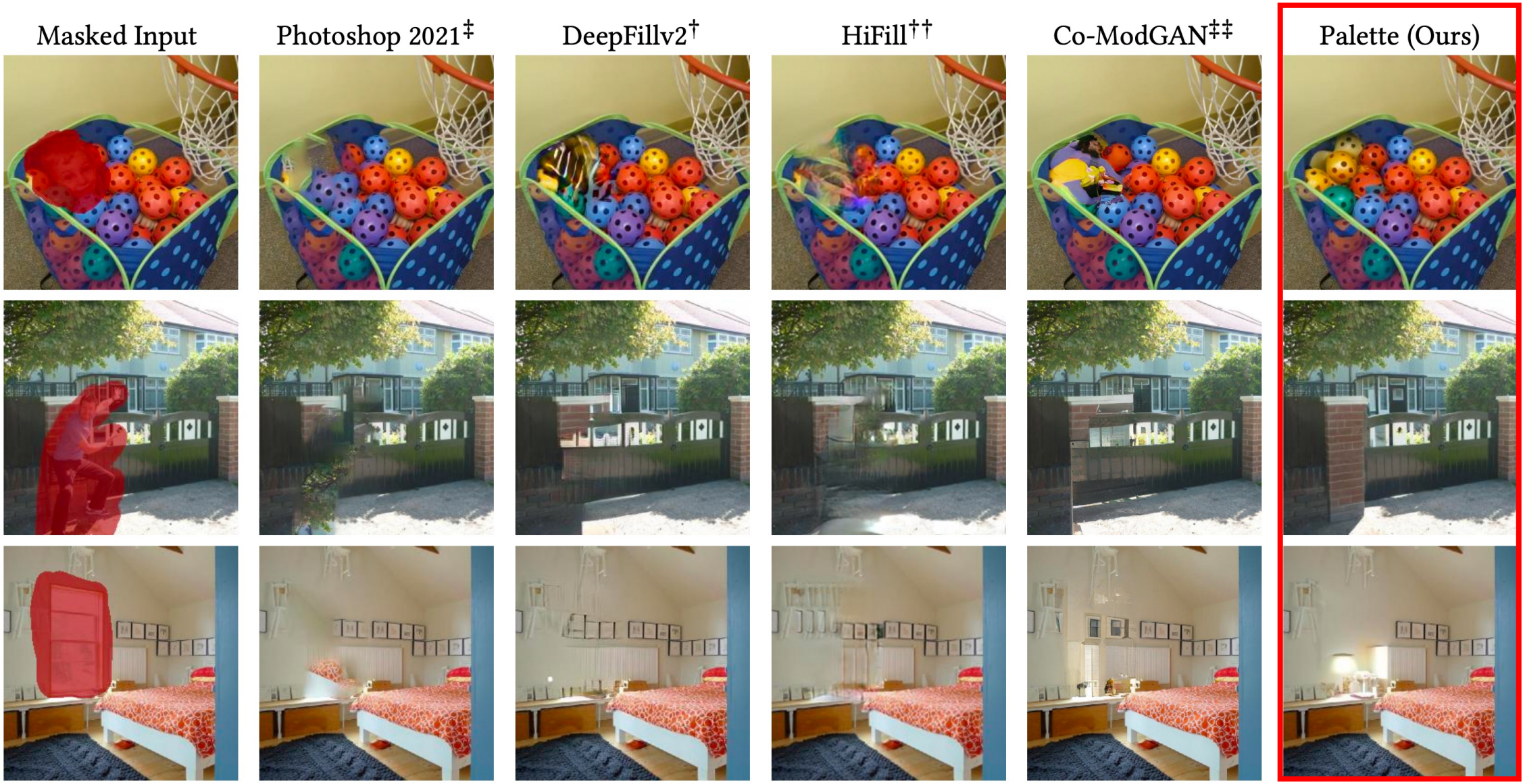
Summarized from Table 1, 2, 3, 4 and 7.

Task	Model	FID↓	PD↓	IS↑	CA↑
Colorization	Coltran	19.37	-	-	-
	Palette (Task-specific)	**3.4**	**48.0**	**212.9**	**72.0%**
	Palette (Multi-task)	3.7	57.1	187.4	69.4%
Inpainting	DeepFillv2	18.0	117.2	135.3	64.3%
	Palette (Task-specific)	**6.6**	**59.5**	**173.9**	**69.3%**
	Palette (Multi-task)	6.8	65.2	165.7	68.9%
Uncropping	Boundless	18.7	127.9	104.1	58.8%
	Palette (Task-specific)	**5.8**	**85.9**	**138.1**	**63.4%**
	Palette (Multi-task)	-	-	-	-
JPEG restoration (QF=5)	Regression	29.0	155.4	73.9	52.8%
	Palette (Task-specific)	8.3	95.5	133.6	64.2%
	Palette (Multi-task)	**7.0**	**92.4**	**137.8**	**64.7%**

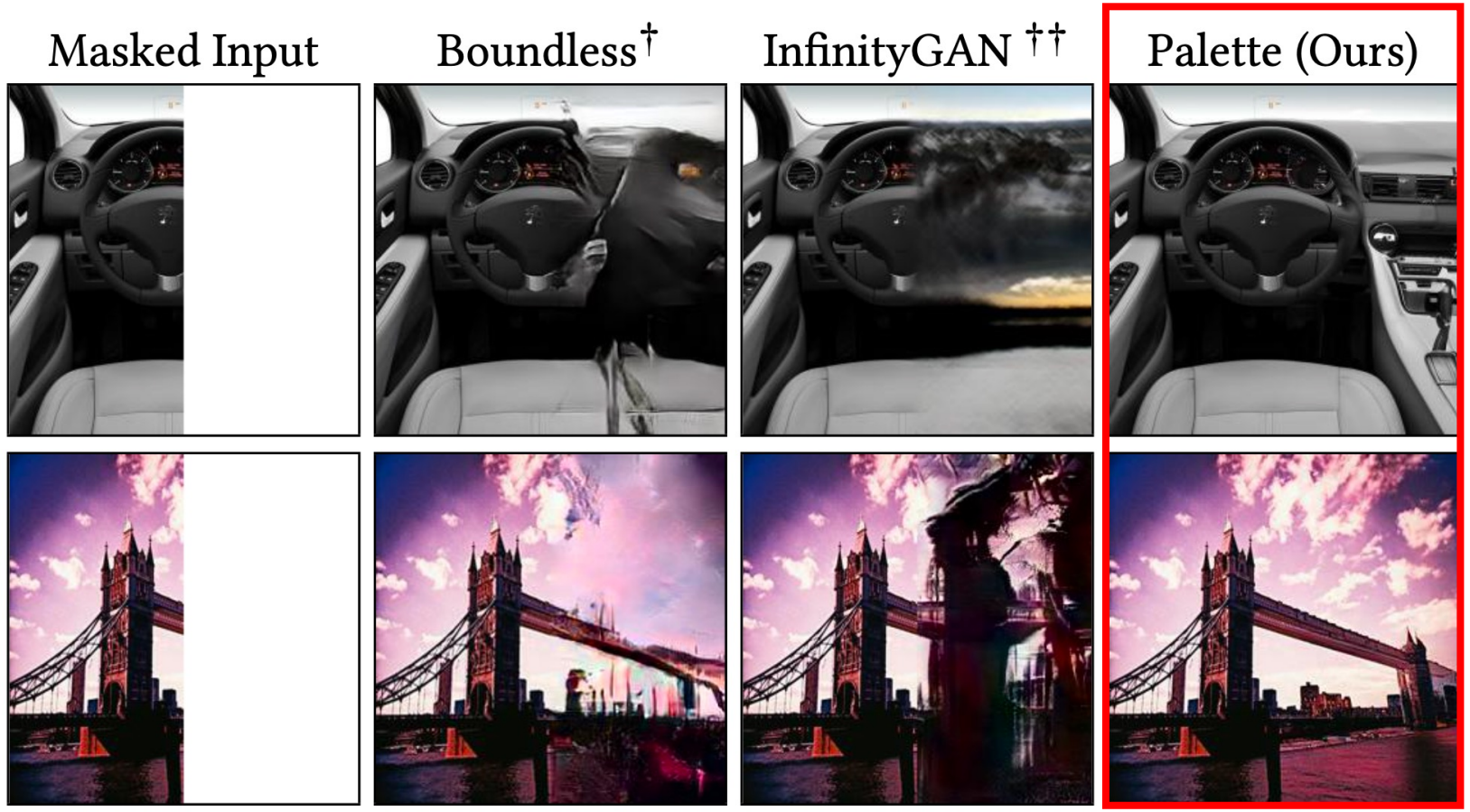
Quality – Colorization



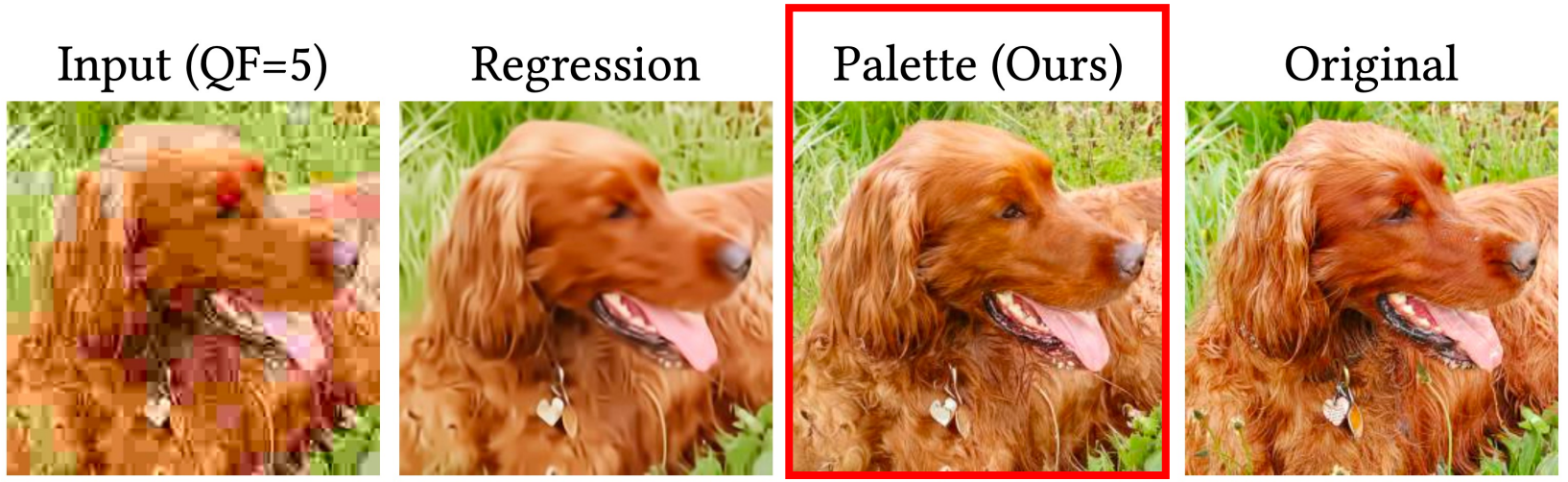
Quality – Inpainting



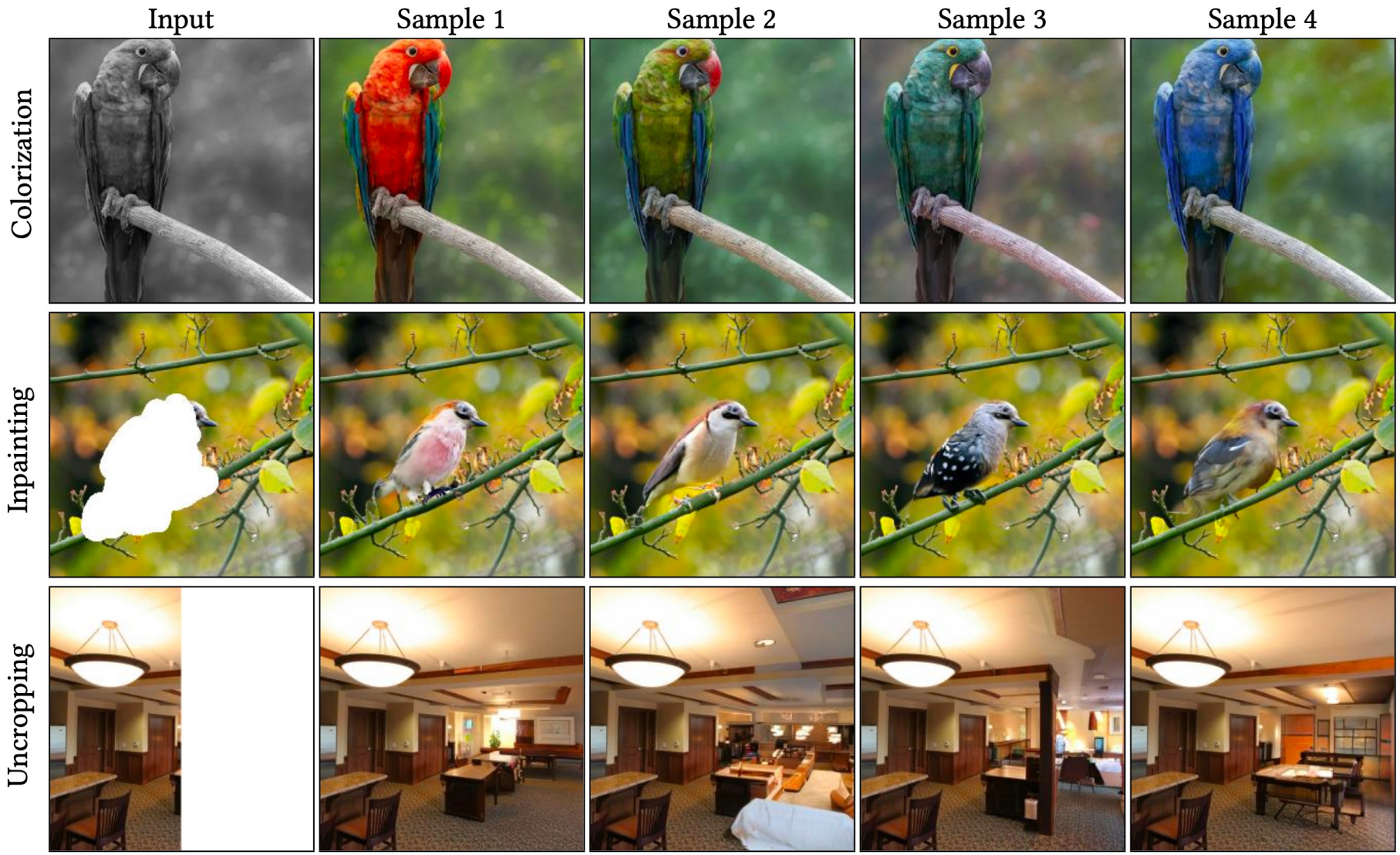
Quality – Uncropping (Outpainting)



Quality – JPEG restoration



Generative Diversity of Palette



Panorama Generation by Palette

Conclusion

Unified diffusion based i2i framework

- Diversity is improved based on diffusion.
- By conditional input, there is no need to construct each task-specific model.
- Moreover, the Palette outperforms existing task-specific models.

Unified evaluation protocol

- The performance can be evaluated from various viewpoints with the proposed protocol.
- It enables performance comparison with other studies easier and more reliable.