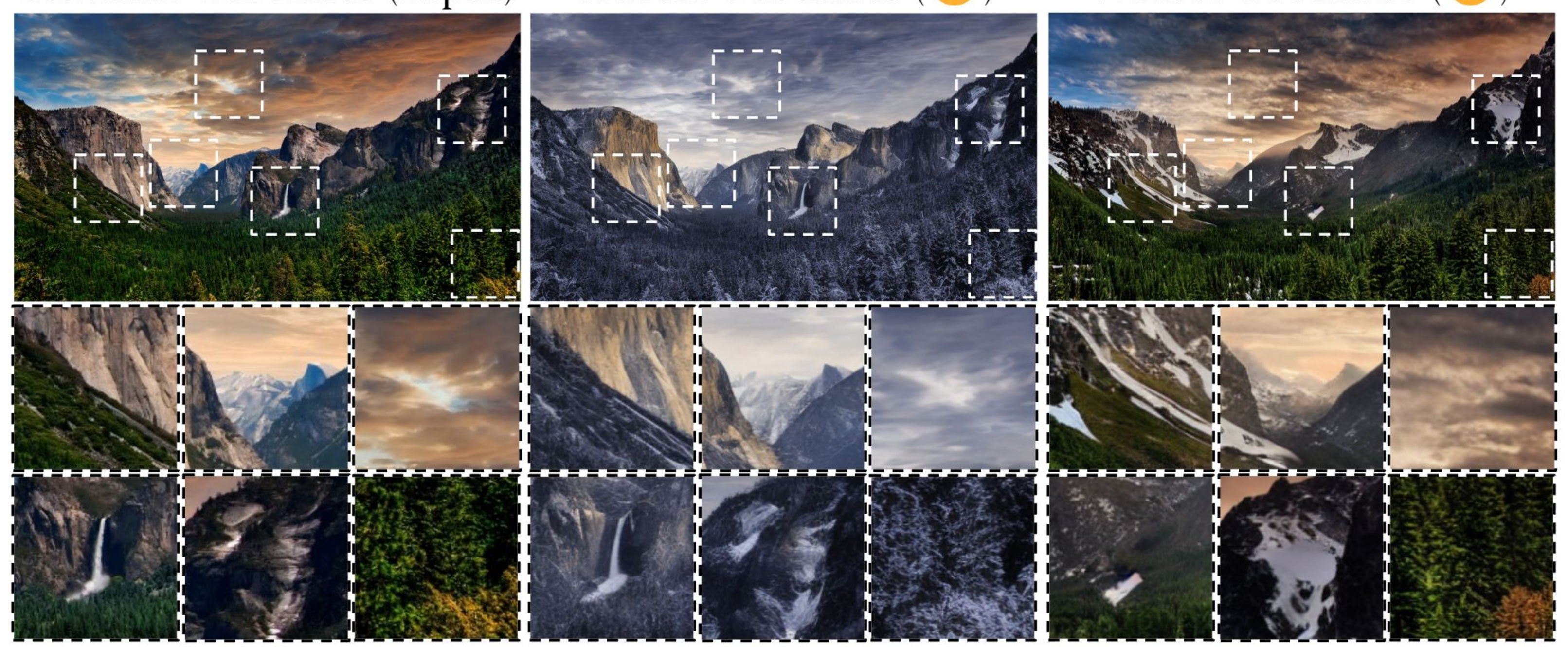
CycleNet: Rethinking Cycle Consistency in Text-Guided Diffusion for Image Manipulation

Sihan Xu*[1], Ziqiao Ma*[1], Yidong Huang[1], Honglak Lee[1,2], Joyce Chai[1] (*equal contributions)

1 COMPUTER SCIENCE AND ENGINEERING, UNIVERSITY OF MICHIGAN
2 LG AI Research

NEURAL INFORMATION PROCESSING SYSTEMS

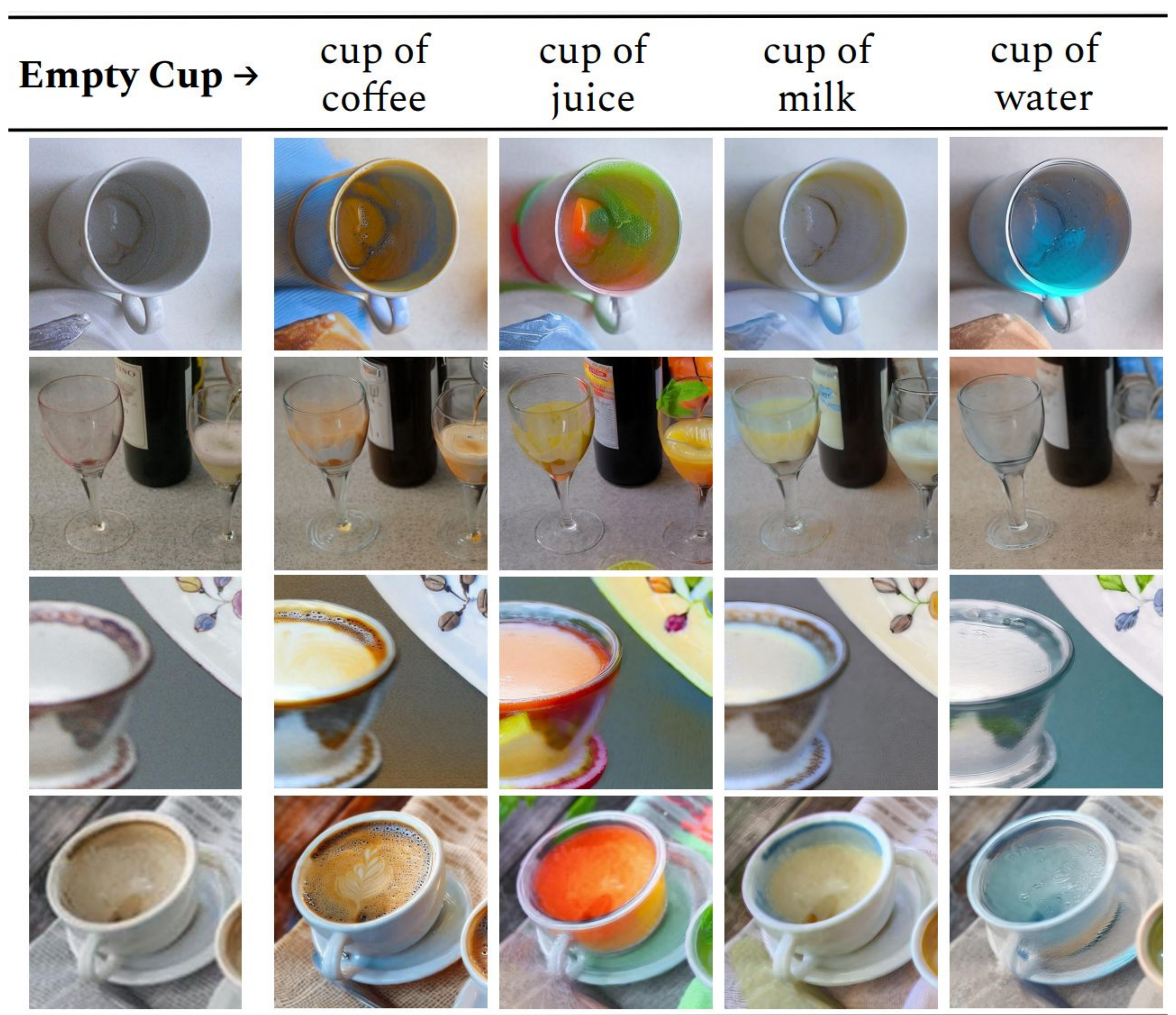
Motivation



- *Consistency* is a desirable property in image manipulation, especially in unpaired I2I scenarios as there is no guaranteed correspondence between images in the source and target domains.
- Pre-trained diffusion models (DMs) are effective in various image synthesis tasks. Still, it remains an open challenge to adapt them in unpaired I2I translation with a consistency guarantee.

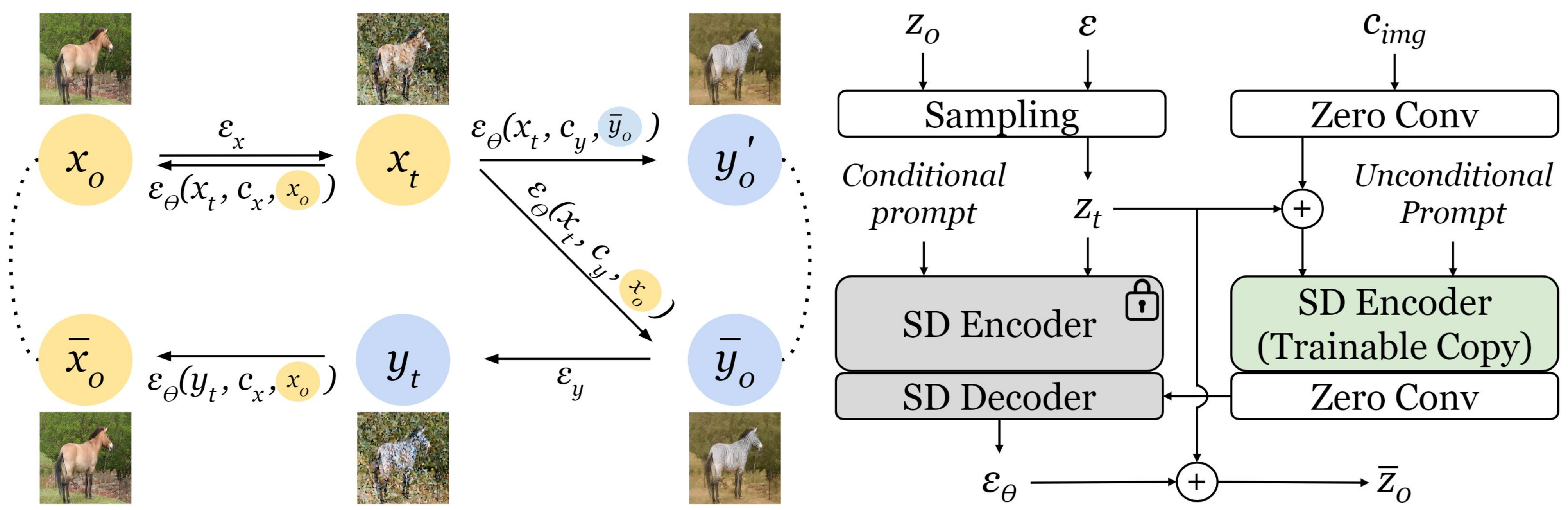
ManiCups: Editing Object-State Changes

A dataset of state-level image manipulation that tasks models to manipulate cups by filling or emptying liquid to/from containers.



CycleNet

CycleNet adopts ControlNet for conditioning and define a translation cycle as follows.



DDPM noted that the forward process allows the sampling of z_t at any time step t using a closed-form sampling function:

$$z_t = S(z_0, \varepsilon, t) := \sqrt{\bar{\alpha}_t} z_0 + \sqrt{1-\bar{\alpha}_t}\varepsilon,\ \varepsilon \sim \mathcal{N}(0, \mathbf{I}) \text{ and } t \sim [1, T]$$

The reverse process can be carried out with a network ε_θ that predicts the noise ε. One could estimate the original source image z_0 given a noised latent z_t. Under conditioning, the reconstructed image can be given by:

$$\bar{z}_0 = G(z_t, c_{\text{text}}, c_{\text{img}}) := \left[z_t - \sqrt{1-\bar{\alpha}_t}\varepsilon_\theta(z_t, c_{\text{text}}, c_{\text{img}})\right] / \sqrt{\bar{\alpha}_t}$$

With the translation cycle, a set of consistency losses is given by:

$$\mathcal{L}_{x\to x} = \mathbb{E}_{x_0,\varepsilon_x} \|\varepsilon_\theta(x_t, c_x, x_0) - \varepsilon_x\|_2^2$$

$$\mathcal{L}_{y\to y} = \mathbb{E}_{x_0,\varepsilon_x,\varepsilon_y} \|\varepsilon_\theta(y_t, c_y, \bar{y}_0) - \varepsilon_y\|_2^2$$

$$\mathcal{L}_{x\to y\to x} = \mathbb{E}_{x_0,\varepsilon_x,\varepsilon_y} \|\varepsilon_\theta(y_t, c_x, x_0) + \varepsilon_\theta(x_t, c_y, x_0) - \varepsilon_x - \varepsilon_y\|_2^2$$

$$\mathcal{L}_{x\to y\to y} = \mathbb{E}_{x_0,\varepsilon_x} \|\varepsilon_\theta(x_t, c_y, x_0) - \varepsilon_\theta(x_t, c_y, \bar{y}_0)\|_2^2$$

The simplified objective is given by

$$\mathcal{L}_x = \lambda_1 \mathcal{L}_{x\to x} + \lambda_2 \mathcal{L}_{x\to y\to y} + \lambda_3 \mathcal{L}_{x\to y\to x} \qquad \mathcal{L}_{\text{CycleNet}} = \mathcal{L}_x + \mathcal{L}_y$$

Experiments

- **Types of tasks**: scene level, object type level, object state level.
- **Types of evaluation**: qualitative and quantitative (image quality, translation quality, translation consistency)

Tasks	summer→winter (Scene level, 256 × 256)							horse→zebra (Object level, 256 × 256)						
Metrics	FID↓	FID_{clip}↓	CLIP↑	LPIPS↓	PSNR↑	SSIM↑	$L2^{\times 10^4}$↓	FID↓	FID_{clip}↓	CLIP↑	LPIPS↓	PSNR↑	SSIM↑	$L2^{\times 10^4}$↓
GAN-based Methods														
CycleGAN	133.16	18.85	22.07	0.20	16.27	0.39	3.62	77.18	27.69	28.07	0.25	18.53	0.67	1.39
CUT	180.09	23.45	24.21	0.19	20.05	0.71	1.15	45.50	21.00	29.15	0.46	13.71	0.35	2.44
Mask-based Diffusion Methods														
Inpaint + ClipSeg	246.56	79.70	21.85	0.57	12.63	0.19	2.83	187.63	40.03	26.32	0.30	15.45	0.43	2.31
Text2LIVE	100.63	22.59	26.03	0.22	16.51	0.67	1.74	128.21	24.46	30.51	0.14	21.05	0.81	1.03
Mask-free Diffusion Methods														
ControlNet + Canny	338.24	83.26	21.77	0.59	6.05	0.09	11.30	397.71	77.68	23.88	0.61	7.37	0.07	3.89
ILVR	105.19	37.24	22.91	0.59	10.06	0.16	3.62	148.45	40.80	25.95	0.57	10.24	0.17	3.57
EGSDE	131.00	38.74	22.96	0.44	17.68	0.27	1.53	97.61	27.79	27.31	0.41	18.05	0.29	1.44
SDEdit	330.98	79.70	21.85	0.57	12.63	0.19	2.83	398.60	83.21	24.17	0.66	9.75	0.11	4.01
Pix2Pix-Zero	311.03	81.54	22.03	0.57	14.31	0.32	5.08	377.44	86.21	24.37	0.67	11.18	0.19	3.85
MasaCtrl	106.91	52.38	20.79	0.36	16.22	0.36	3.71	333.17	68.31	21.15	0.40	16.31	0.37	1.83
P2P + NullText	160.00	41.12	23.31	0.37	16.84	0.39	1.73	287.45	48.93	23.91	0.36	17.20	0.41	1.68
CycleDiffusion	243.98	62.96	22.32	0.44	15.06	0.31	2.20	347.27	66.80	25.04	0.57	11.51	0.21	3.46
FastCycleNet	**82.48**	17.61	**23.62**	0.14	**22.45**	**0.57**	0.91	**80.75**	**27.23**	27.36	0.32	19.29	0.51	1.31
CycleNet	82.52	**17.54**	23.32	**0.13**	22.42	**0.57**	**0.90**	81.69	28.11	**28.91**	**0.27**	**20.42**	**0.52**	**1.14**

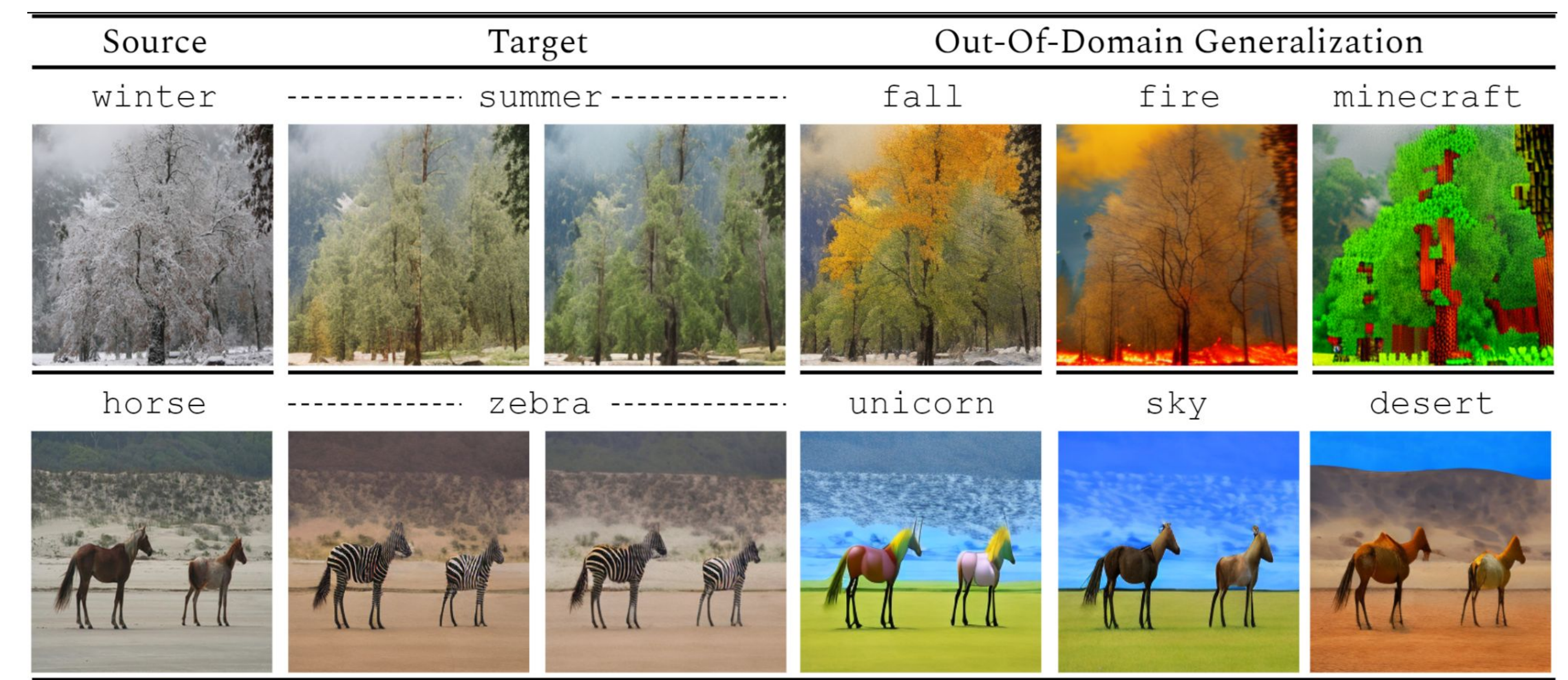
Ablation Study

An ablation study on the role of each loss terms.

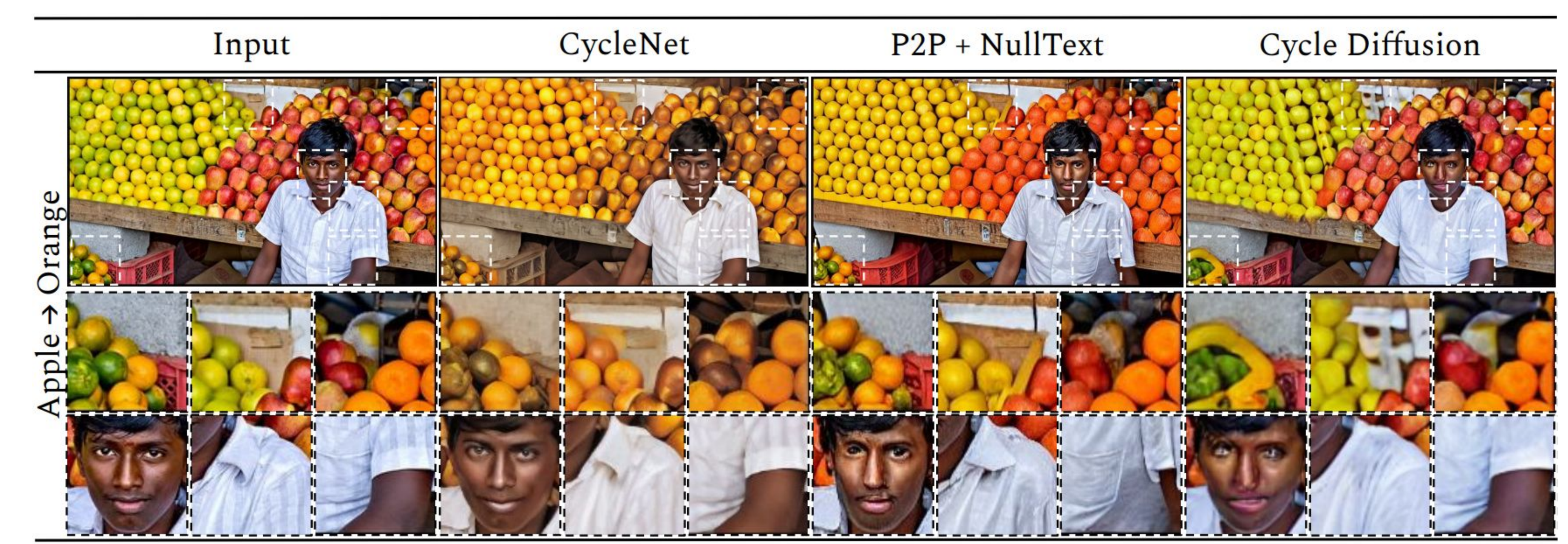
- Cycle consistency loss
  $L_{x\to y\to x}$
- Invariance loss
  $L_{x\to y\to y}$

summer→winter	FID ↓	CLIP ↑	LPIPS ↓
CycleNet	**77.16**	24.15	**0.15**
Invariance Only	**76.23**	**25.13**	0.23
Consistency Only	84.18	19.89	**0.14**
None	211.26	24.35	0.61

Diversity and Generalization to OOD



Quantitative Examples



Limitations and Follow-ups