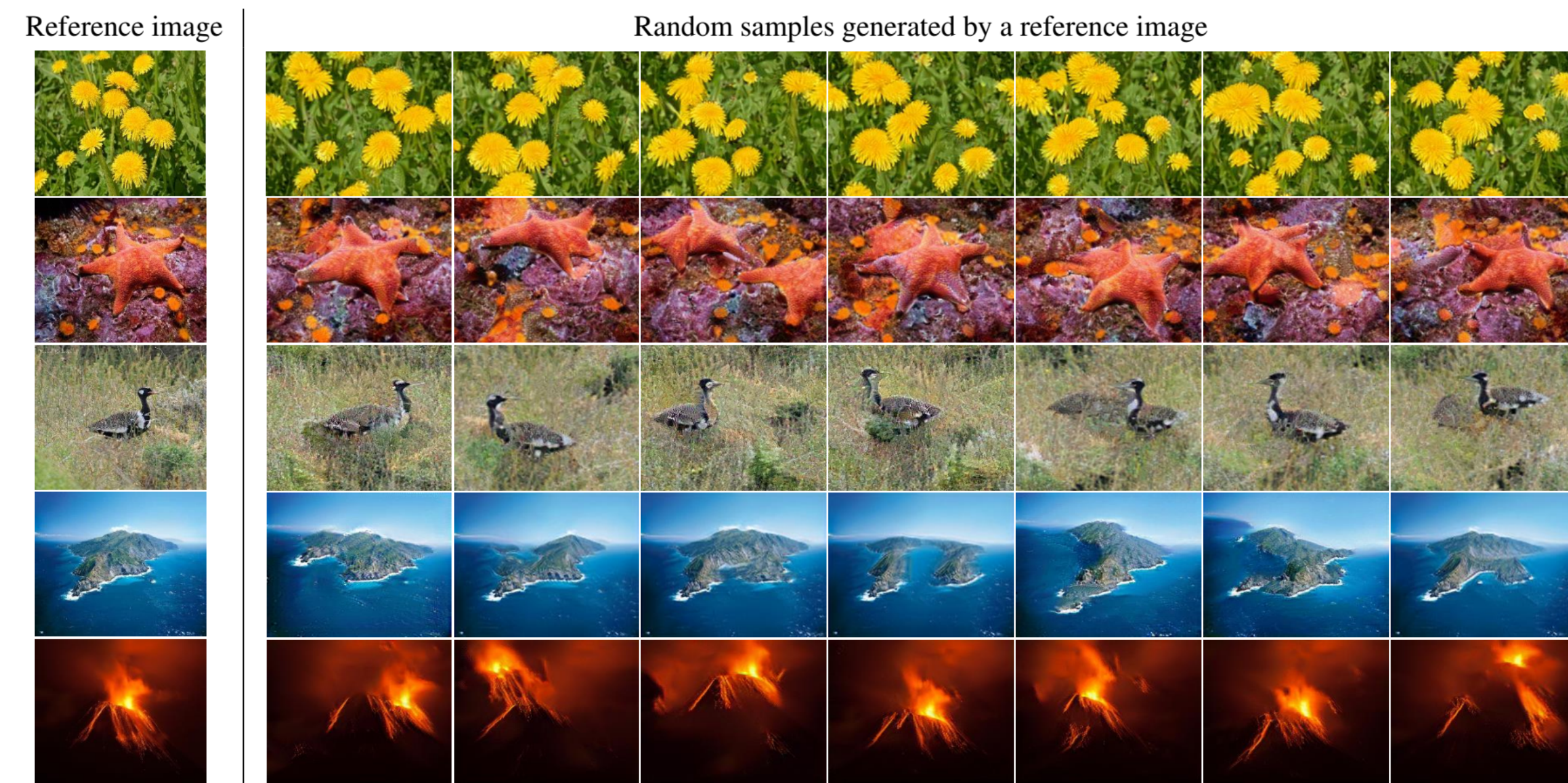
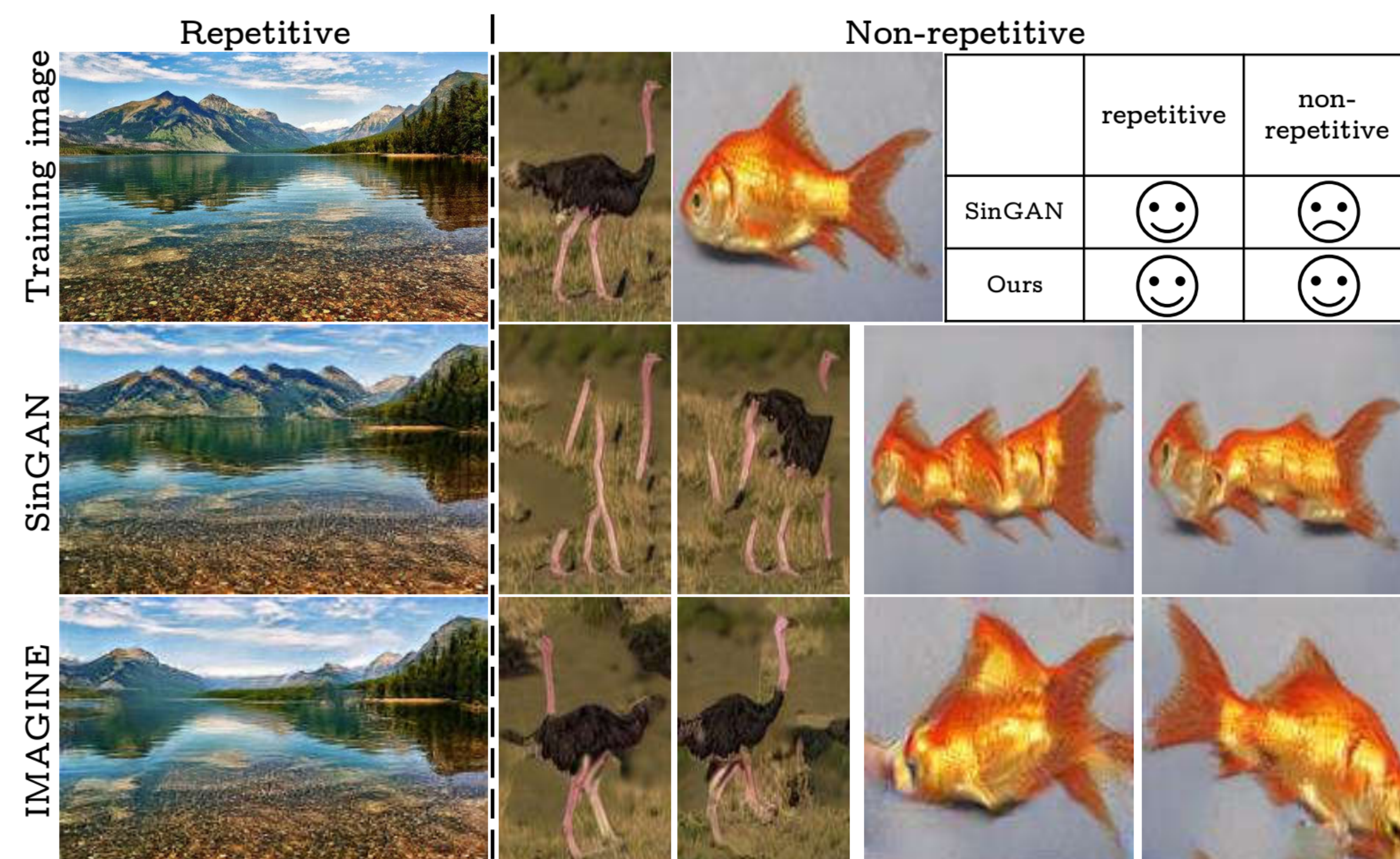


## Introduction

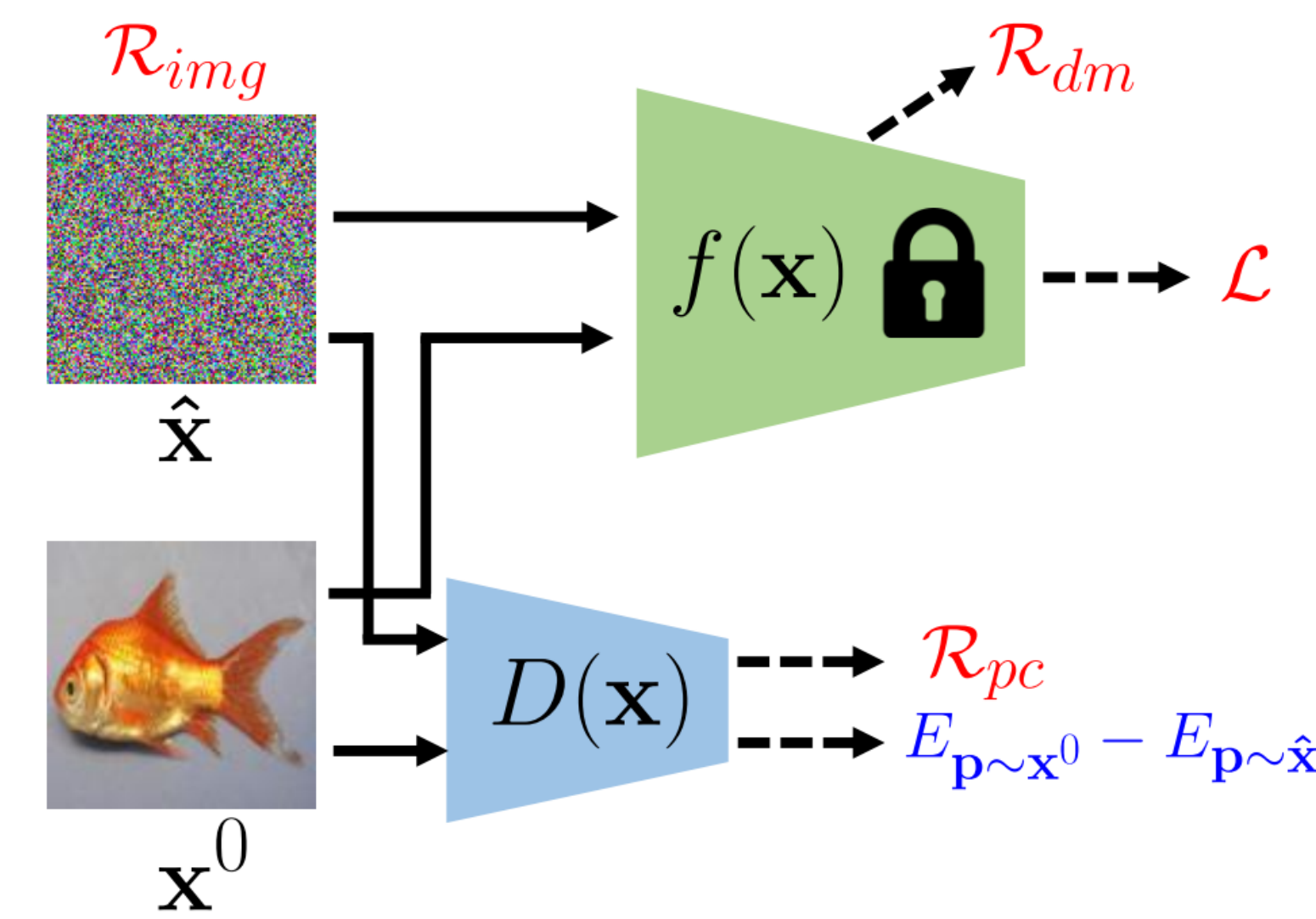
- We consider the problem of generating images from one single reference.



- Previous work mainly use GAN inversion, e.g., DGP or learning individual GANs for individual target images, e.g., SinGAN
- Training of generators is not easy
- One generator per reference image
- Cannot handle non-repetitive images



## Proposed Method



- Given a well-trained frozen classifier, an image is optimized from a noise under a couple of constraints.

$$\mathbf{x}^* = \arg \min_{\hat{\mathbf{x}}} \mathcal{L}(f(\hat{\mathbf{x}}), y^*) + \mathcal{R}(\hat{\mathbf{x}})$$

$$\mathcal{R}(\hat{\mathbf{x}}; \mathbf{x}^0, \Phi) = \mathcal{R}_{img}(\hat{\mathbf{x}}) + \lambda \mathcal{R}_{dm}(\hat{\mathbf{x}}; \mathbf{x}^0, \Phi) + \gamma \mathcal{R}_{pc}(\hat{\mathbf{x}})$$

- Basic regularizer
- Feature distribution matching regularizer

$$\mathcal{R}_{img}(\hat{\mathbf{x}}) = \alpha R_{TV}(\hat{\mathbf{x}}) + \beta \|\hat{\mathbf{x}}\|^2$$

$$\mathcal{R}_{dm}(\hat{\mathbf{x}}; \mathbf{x}^0, \Phi) = \sum_{l \in \Phi} \|\mu_l(\hat{\mathbf{x}}) - \mu_l(\mathbf{x}^0)\|_2 + \|\sigma_l(\hat{\mathbf{x}}) - \sigma_l(\mathbf{x}^0)\|_2$$

- Adversarial loss

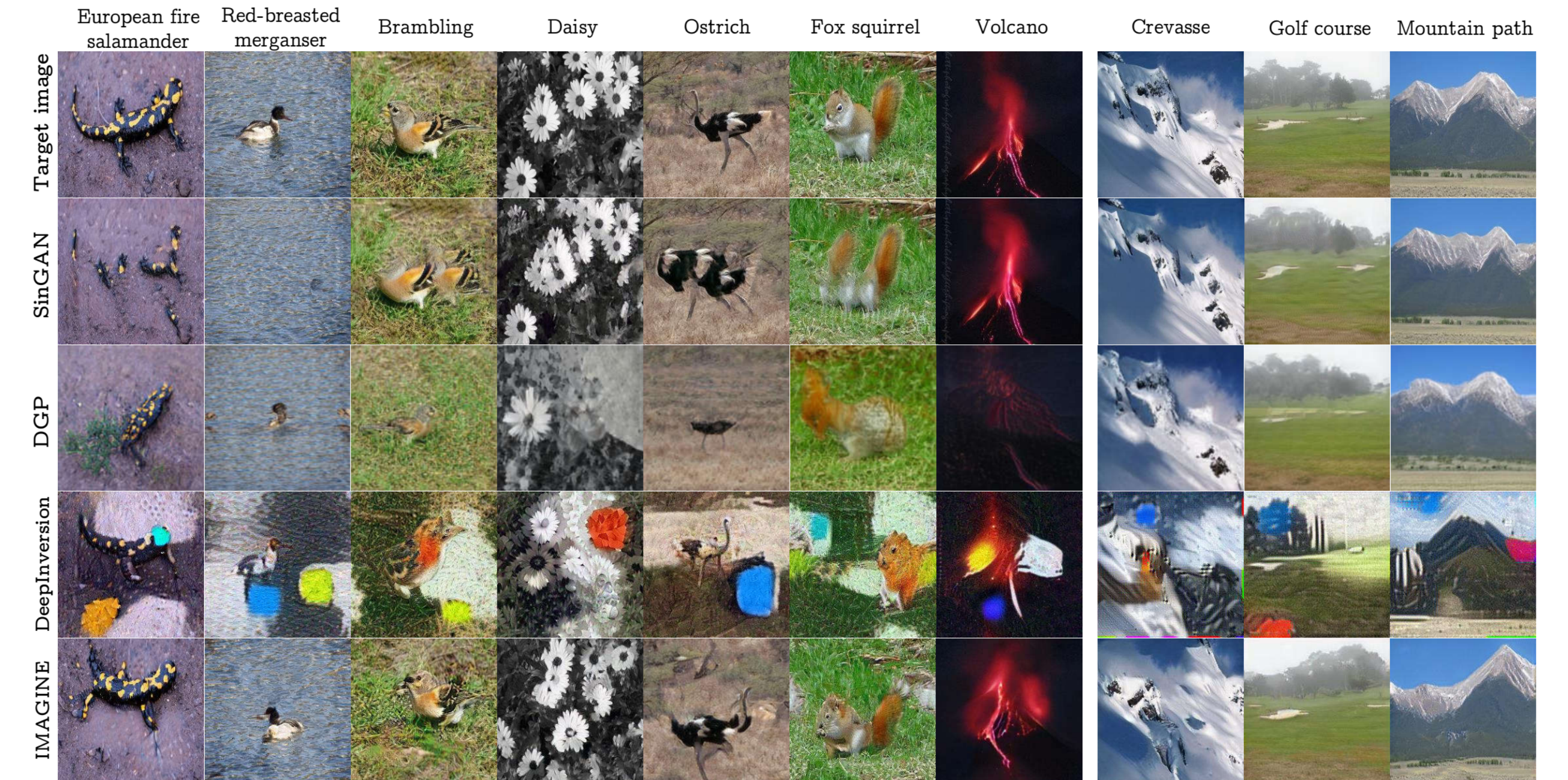
$$\mathcal{R}_{pc}(\hat{\mathbf{x}}) = -D(\hat{\mathbf{x}})$$

$$D(\hat{\mathbf{x}}) = E_{\mathbf{p} \sim \hat{\mathbf{x}}} [d^*(\mathbf{p})] \quad d^* = \arg \max_d E_{\mathbf{p} \sim \mathbf{x}^0} [d(\mathbf{p})] - E_{\mathbf{p} \sim \hat{\mathbf{x}}} [d(\mathbf{p})]$$

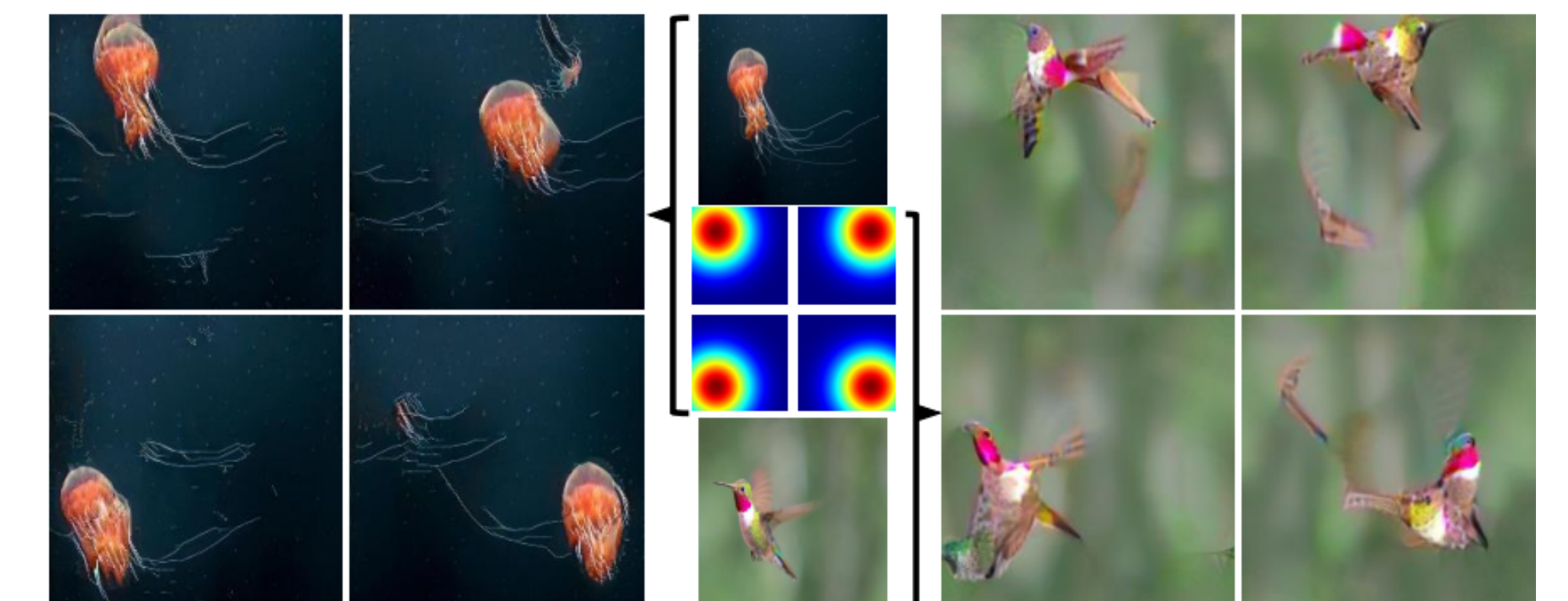
## Reference

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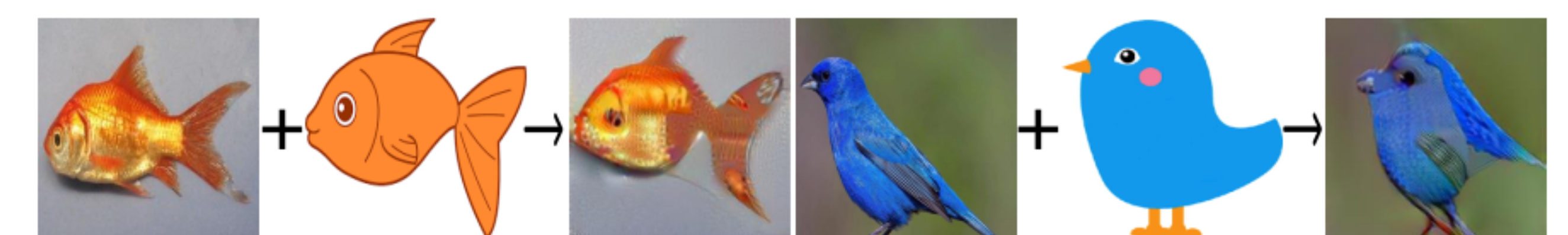
## Image Synthesis



## Position Control



## Shape Control



## Conclusion

- First attempt to utilize model inversion for image-guided synthesis
- Introduce adversarial training to improve the image quality of optimization-based model inversion
- Demonstrate the superiority of IMAGINE over GAN counterparts
- Show multiple multifaceted image control applications