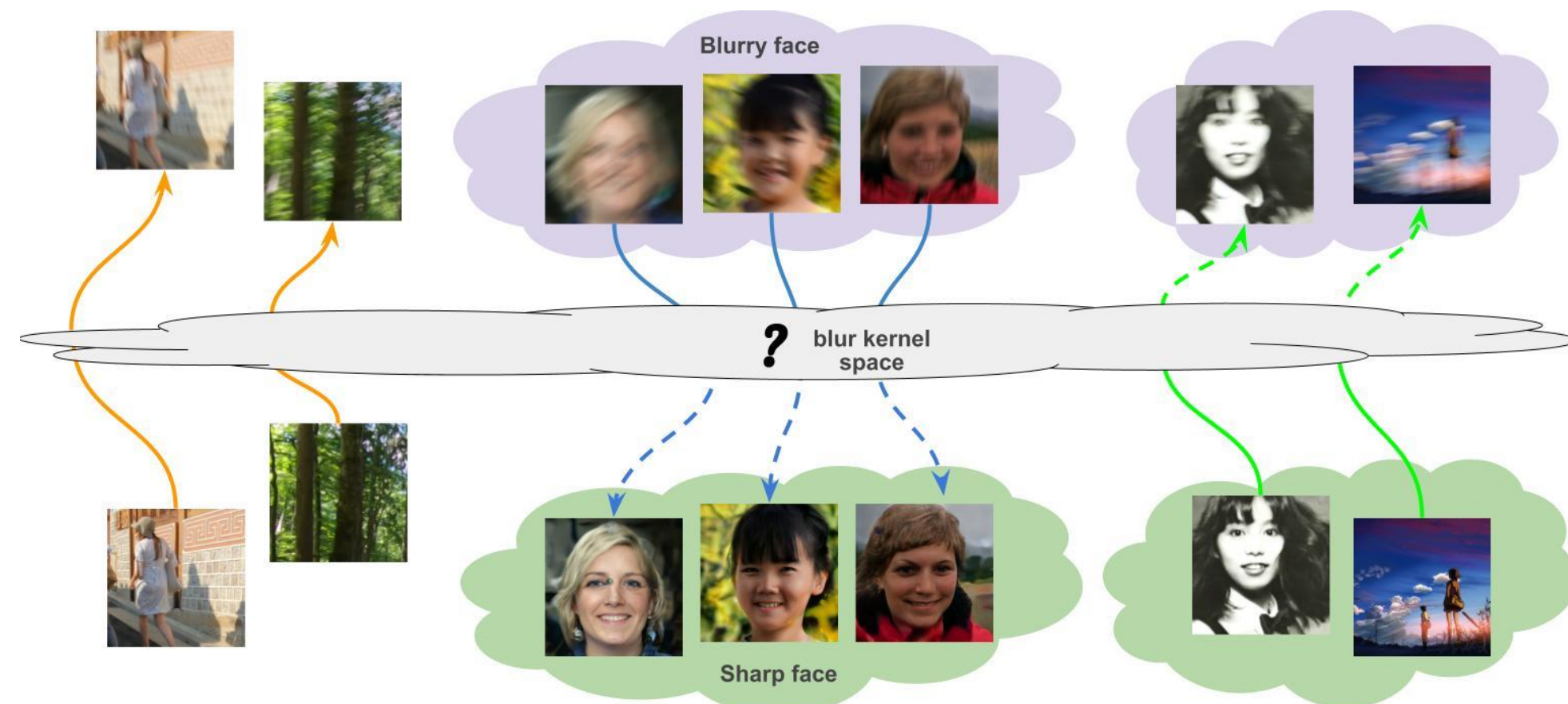


1. Introduction

- We propose a method to model the **blur kernel space** of a given dataset.
- Using this blur kernel space, we can perform **image deblurring** and **blur synthesis**.



2. Limitation of existing methods

Blur model:

$$y = \hat{\mathcal{F}}(x, k) + \eta \approx \hat{\mathcal{F}}(x, k)$$

Blur img. Noise Blur func. Sharp img. Blur kernel

Classical methods:

Linear convolution

Linear and uniform
→ too simple

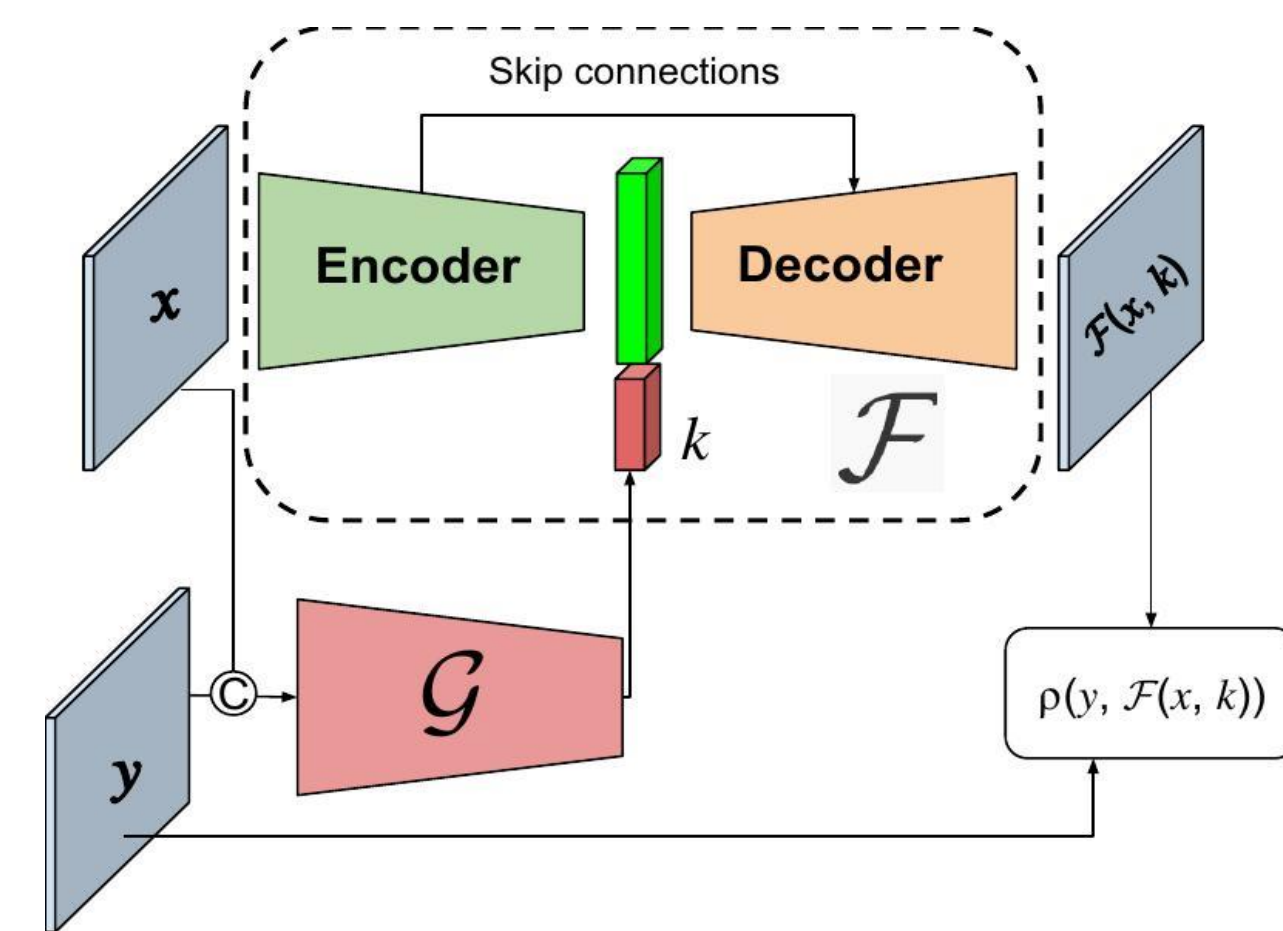
Deep learning methods:



3. Blur kernel encoding

- Find two functions F and G such that:
$$y = \mathcal{F}(x, k) \quad \text{and} \quad k = \mathcal{G}(x, y)$$
- Learn F and G by optimizing the objective function, given training data $\{(x_i, y_i)\}$
$$\sum_{i=1}^n \rho(y_i, \mathcal{F}(x_i, \mathcal{G}(x_i, y_i)))$$

Charbonnier loss
- F and G are implemented by two neural networks.



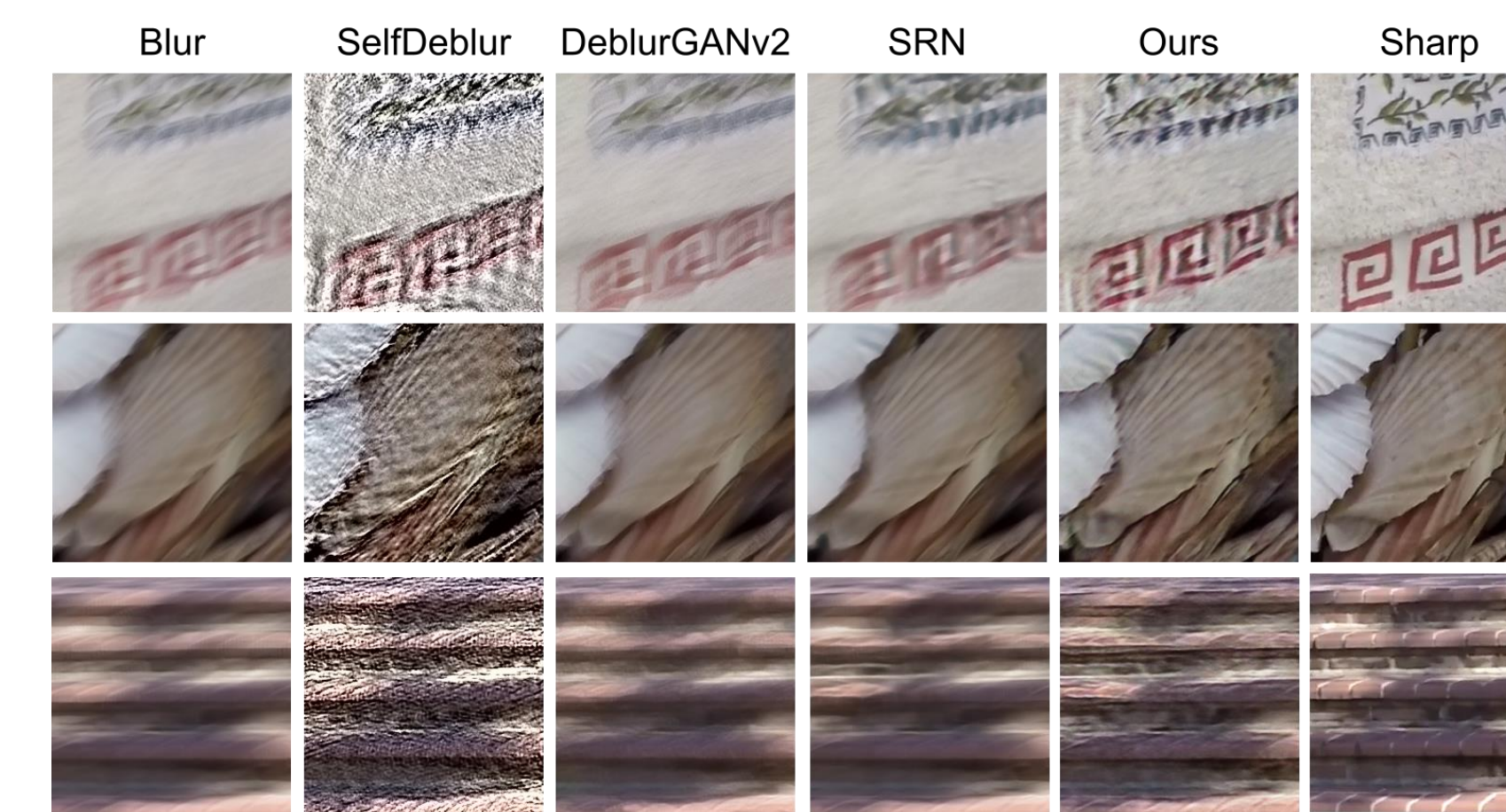
4. Image Deblurring

- General Image Deblurring**
Given F , a blurry image y , we can **alternatively** search for x and k via an objective function:
$$\rho(y, \mathcal{F}(x, k)) + \lambda \|k\|_2 + \gamma (g_u^2(x) + g_v^2(x))^{\alpha/2}$$

Kernel norm reg Gradient penalty
- To stabilize the optimization, we reparameterize x and k by Deep Image Prior (DIP)⁽¹⁾
- Domain-specific Deblurring**
 - Replace DIP of x with $G_{\text{style}}(z)$ in which G_{style} is the pretrained StyleGAN.

5. Experiments

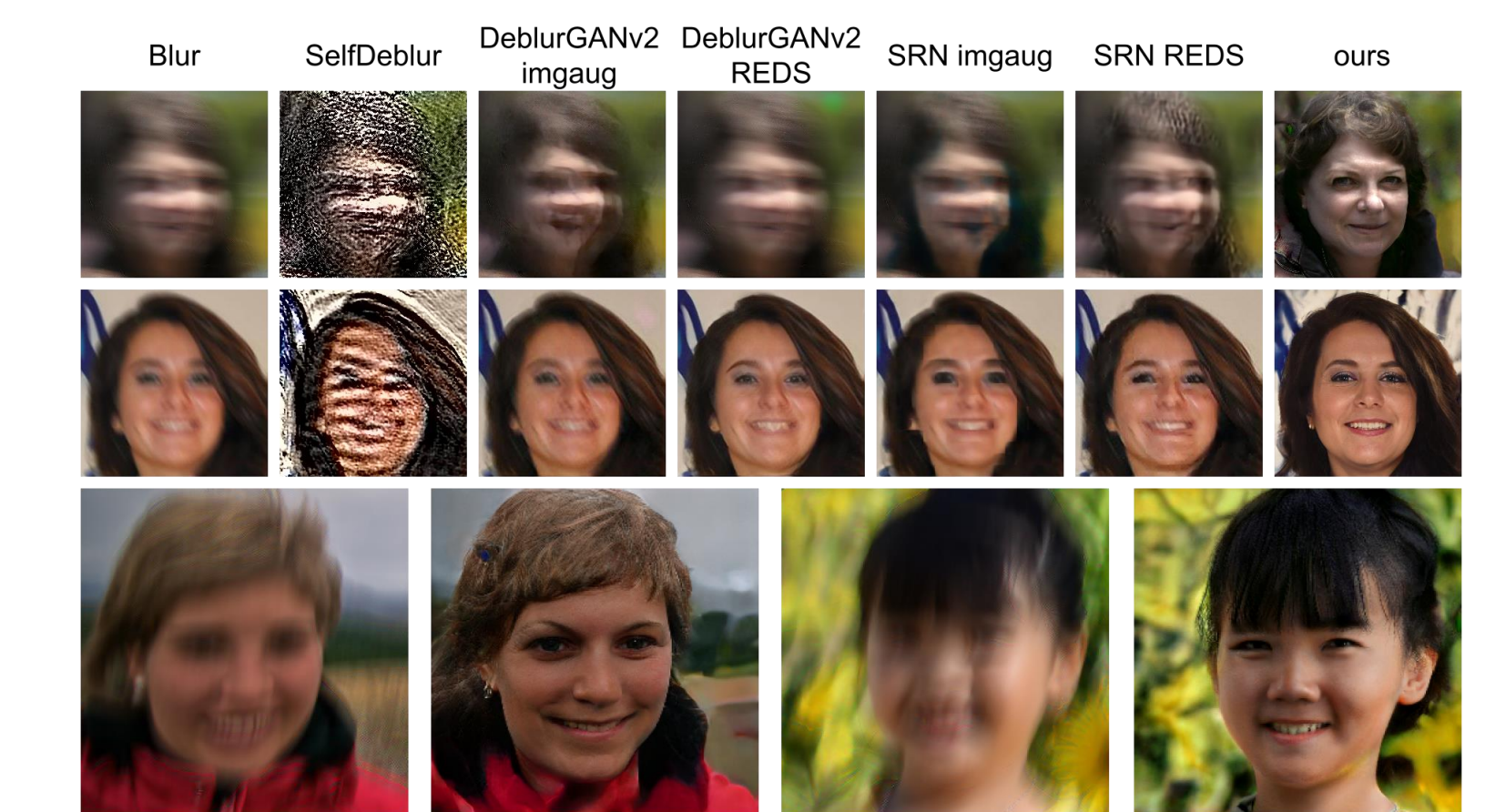
Image Deblurring



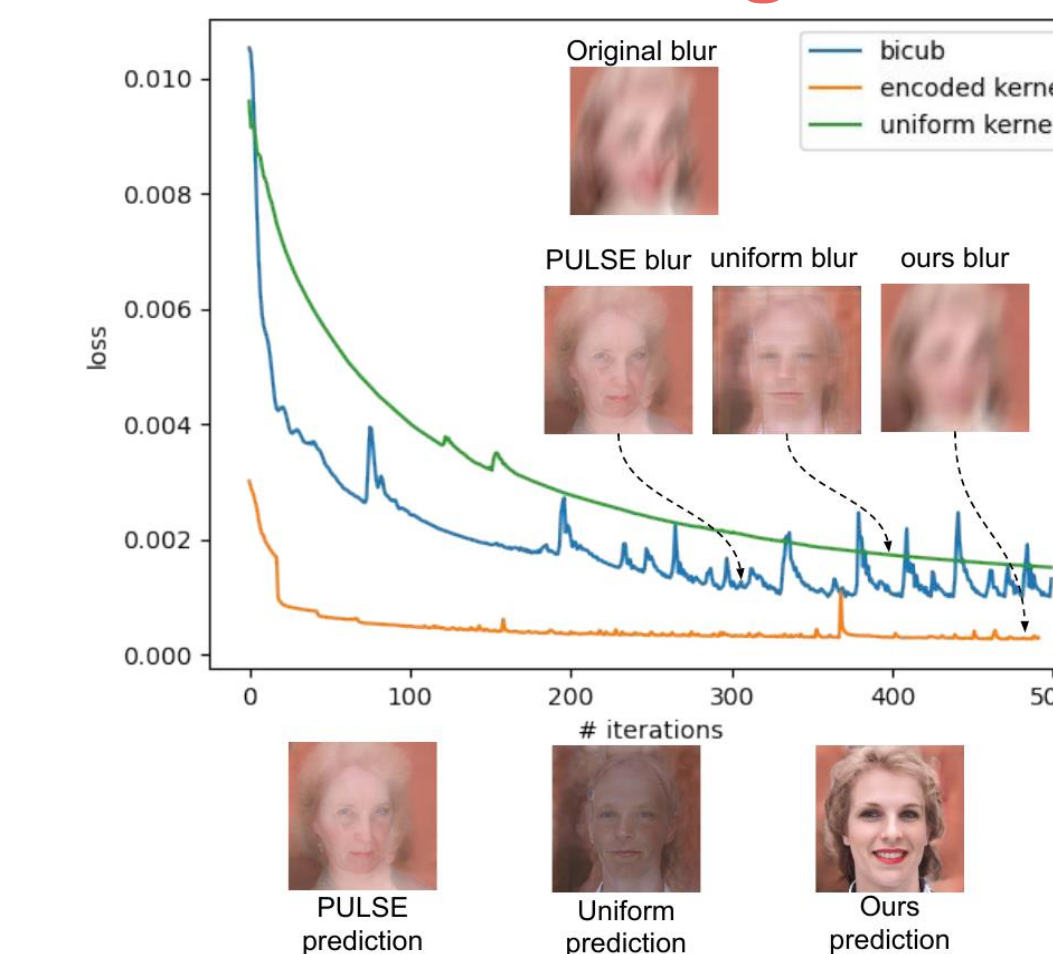
Blur Swapping



Face Deblurring



Loss Convergence



6. Data augmentation

- Apply blurs learned from a reference sharp-blur dataset
- Improve SRN-Deblur performance

Training kernels	Test kernels		
	imgaug	REDS	GOPRO
imgaug	28.64	24.22	22.96
comb.	28.30	28.37	23.92

7. Conclusion

- Propose a method to **encode the blur kernel space** of a deblurring dataset.
- Propose some **applications** of the blur kernel space.

