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Improved StyleGAN-v2 based Inversion for Out-of-Distribution Images

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Pre-trained StyleGANs have Emerged as Powerful Priors for Solving In-Domain Image Restoration

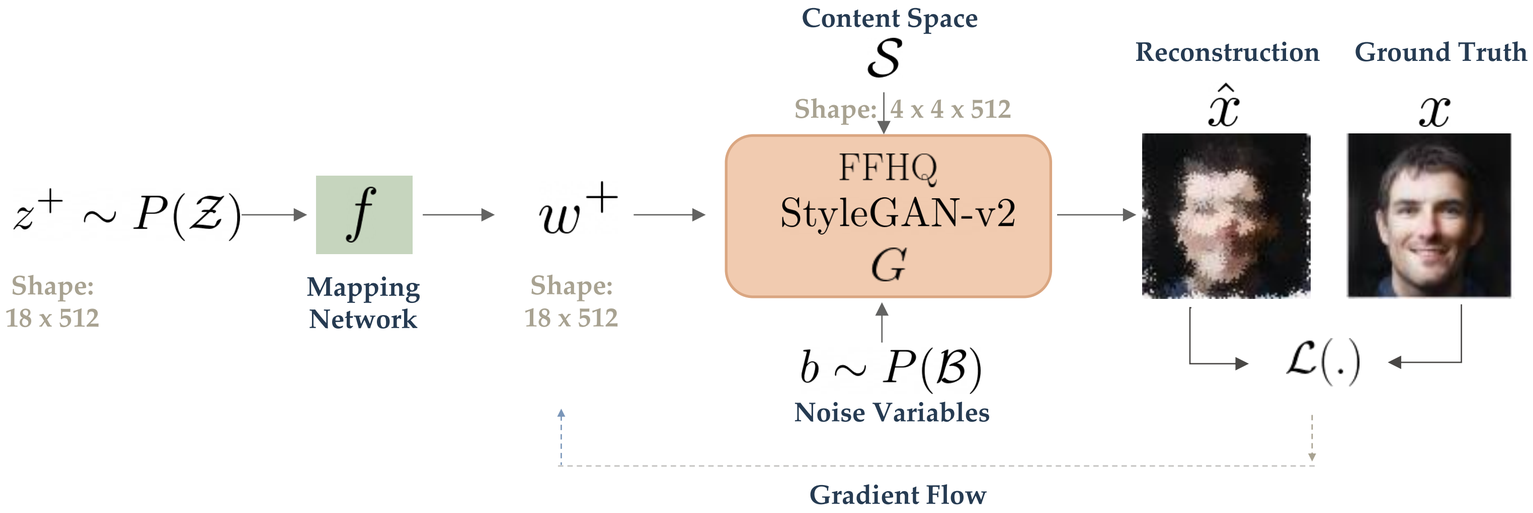
GAN Inversion

Ill-posed problem of inferring a latent code for a given image using a pre-trained generator (e.g., StyleGAN).

Mathematically,

$$w_*^+ = arg\min_{w^+} \mathcal{L}(x, G(w^+)) + \mathcal{R}(G(w^+))$$

MSE | LPIPS — Regularizer



Inversion

Semantic Editing (Age)

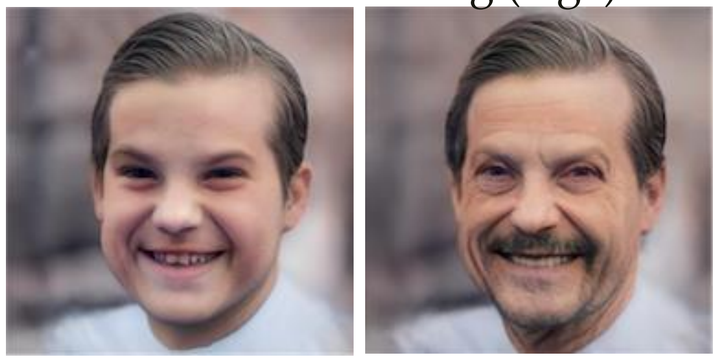
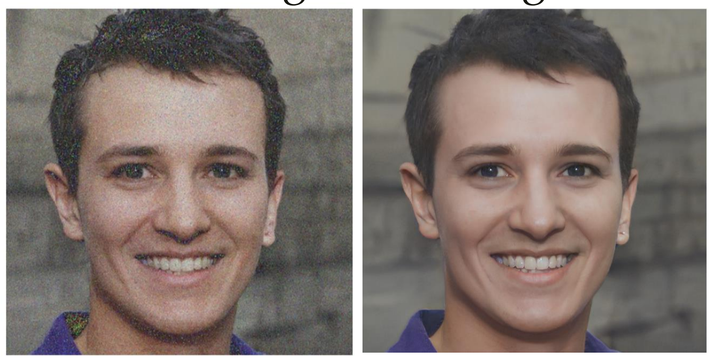


Image Denoising



Innately Leveraging Such Priors for Inverting Out-of-Distribution Images is Significantly Challenging

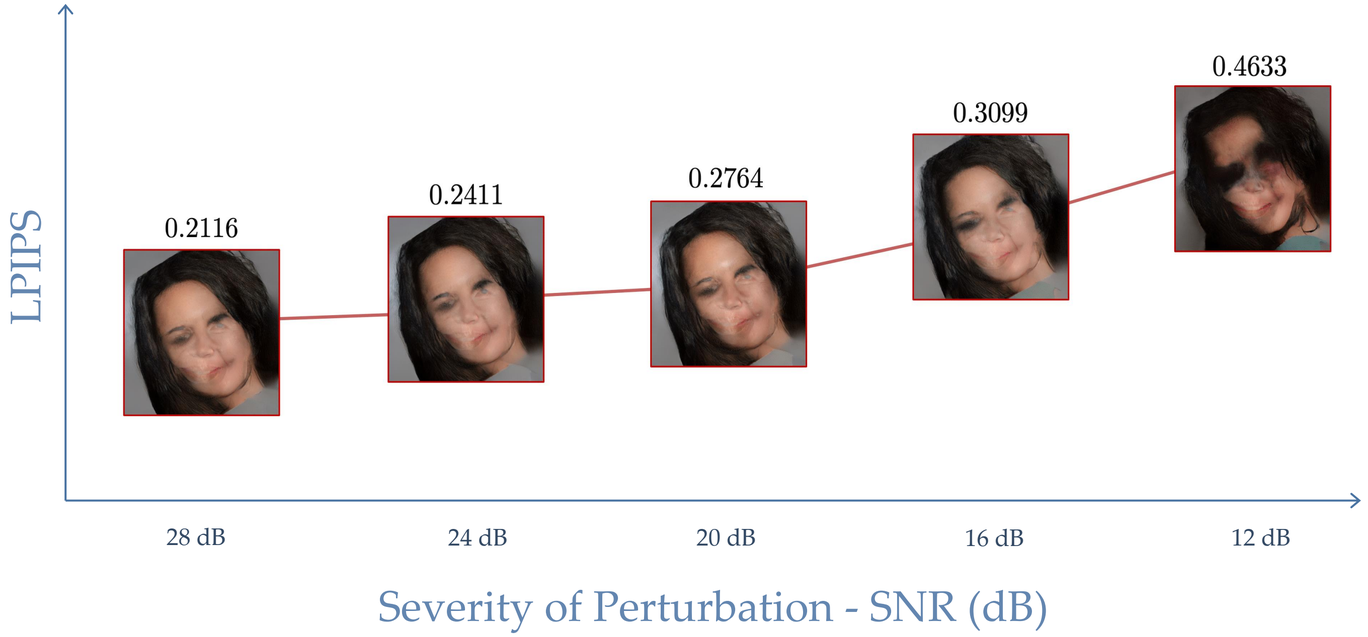
Input $\mathcal{W}+$

Geometrically Altered Face

28.9 dB / 0.23
PSNR/LPIPS

Inversion of out-of-distribution (OOD) images on to the $\mathcal{W}+$ latent space of a pre-trained StyleGAN generator produces low fidelity reconstructions

Solutions introduce in-domain artifacts to the reconstructed images !



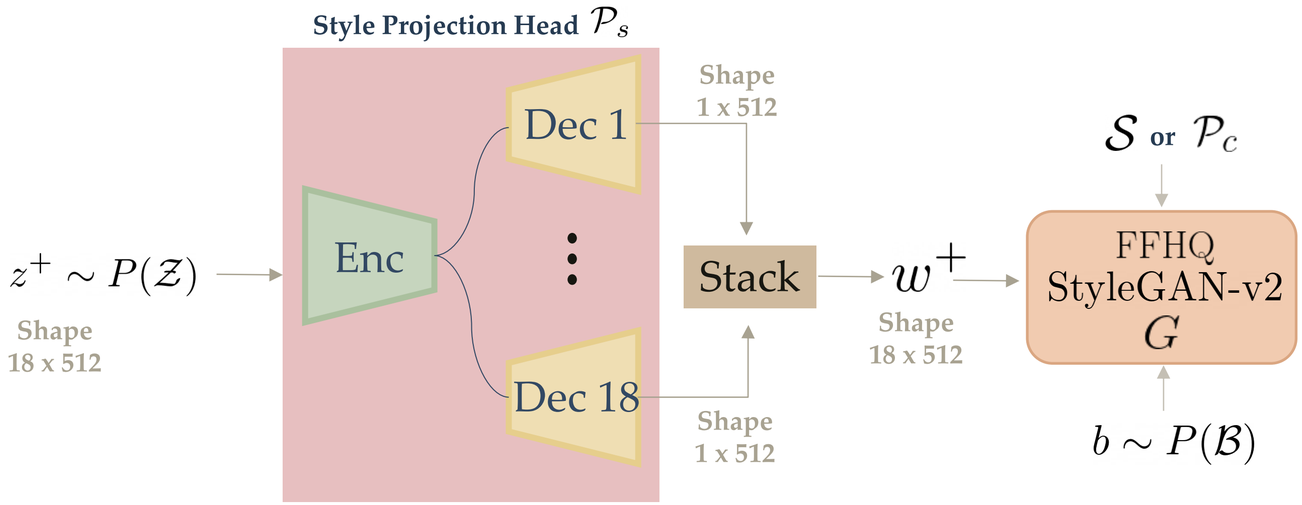
Why is such an optimization non-trivial ?

- Lack of known priors in $\mathcal{W}+$ to regularize the inversion

- Non-robust $\mathcal{W}+$ space optimization

  Inverted latent codes are sensitive to minor perturbations producing perceptually inferior reconstructions

SPHInX – StyleGAN with Projection Head for Inverting X
A Novel Strategy for Robust StyleGAN Inversion of OOD Images



Central Ideas Behind SPHInX

- SPHInX replaces the existing mapping network f with a style projection head $\mathcal{P}_s$

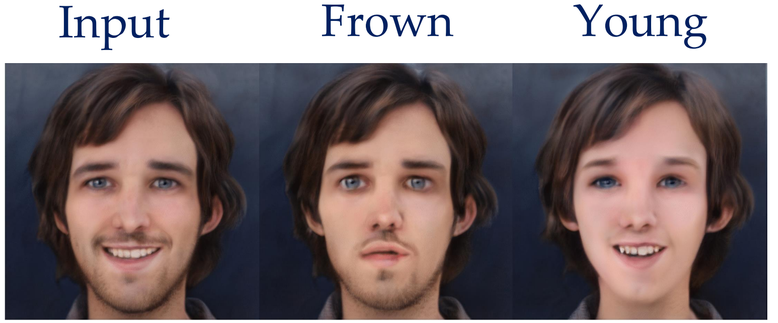
  Enc. Multi-Dec. → Decouples different layers in the $\mathcal{W}+$ space

- SPHInX transforms any $z^+ \sim P(\mathcal{Z})$ to $P(\mathcal{W}+)$ such that every realization from $P(\mathcal{W}+)$ produces the same reconstruction.

  Vicinal regularization that produces a robust estimate of $P(\mathcal{W}+)$

SPHInX improves the fidelity of OOD Inversion

SPHInX can repurpose existing StyleGAN attributes to support semantic editing for aligned OOD



SPHInX Optimizes Additional StyleGAN Latent Codes to Enhance Restoration Fidelity of Complex OOD Images

In addition to Ps, SPHInX optimizes S (realized via a content projection head Pc) and noise B

$\mathcal{S}$: Captures the semantic structure of images

$\mathcal{B}$: Improves overall textural quality

Inversion Reconstruction

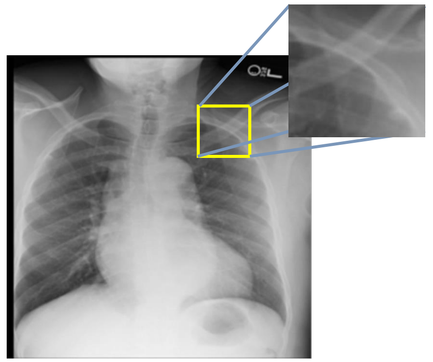
SPHInX produces significant improvements in perceptual quality and fidelity

Semantic Interpolation b/w Two Images

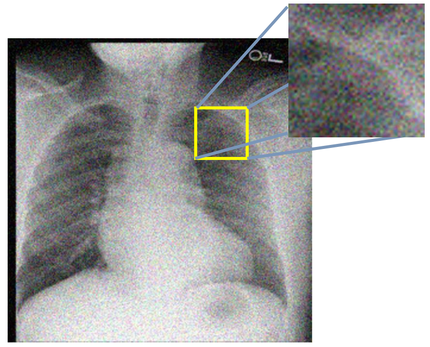
SPHInX synthesizes meaningful interpolations even for OOD images for which existing StyleGAN attributes cannot be adopted !

SPHInX Can Repurpose StyleGANs Pre-trained on FFHQ for Ill-posed Restoration of Novel Domains with Scarce Data Access

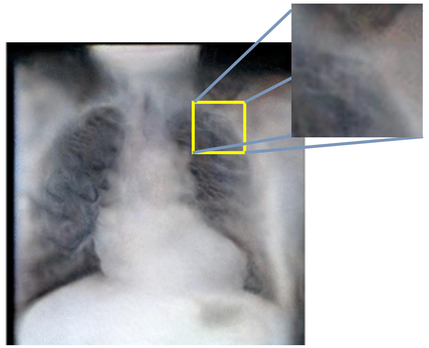
Application 1: Denoising



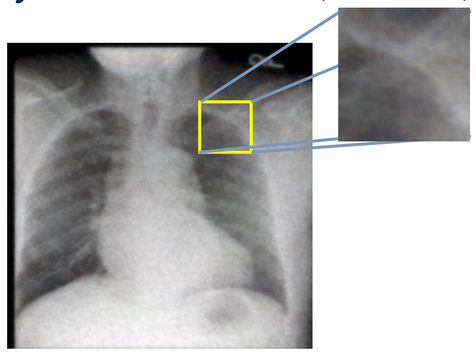
Ground Truth



Noisy Observation (Std 0.2)



Denoising $(\mathcal{W}+, \mathcal{S}, \mathcal{B})$



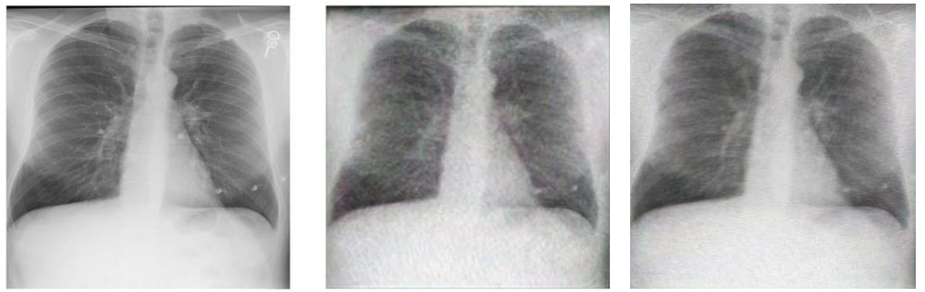
Denoising SPHInX

While improving denoising, SPHInX effectively preserves image specific semantics

Application 2: Compressed Sensing

Compressed recovery with 1% measurement factor

Ground Truth $(\mathcal{W}+, \mathcal{S}, \mathcal{B})$ SPHInX



SPHInX produces high-fidelity reconstructions even at severe compression factors

Thank You

https://github.com/Rakshith-2905/SPHInX

References

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