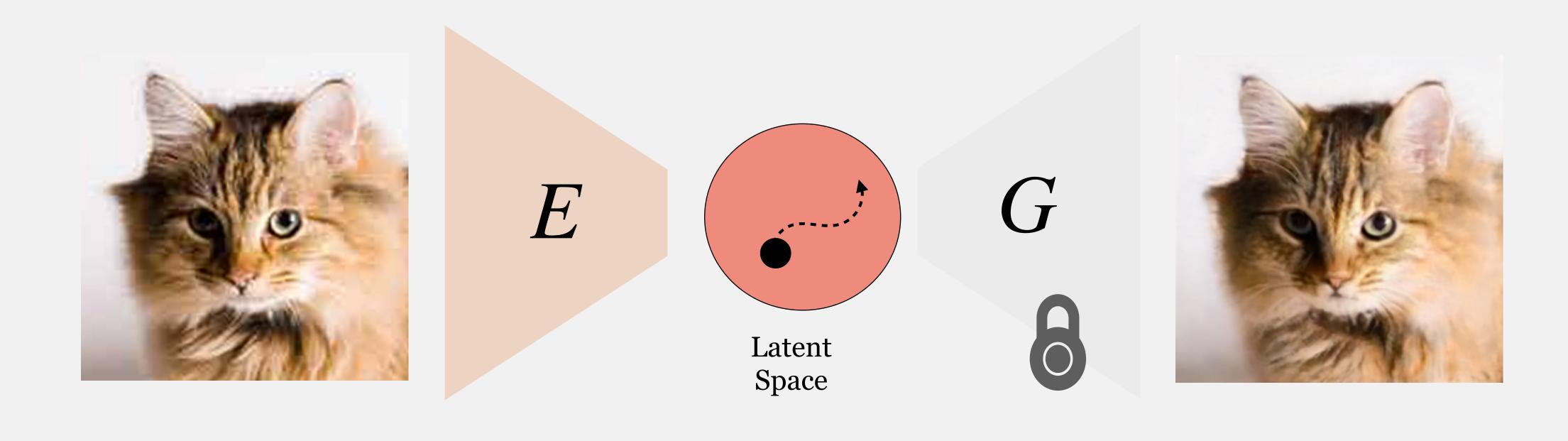
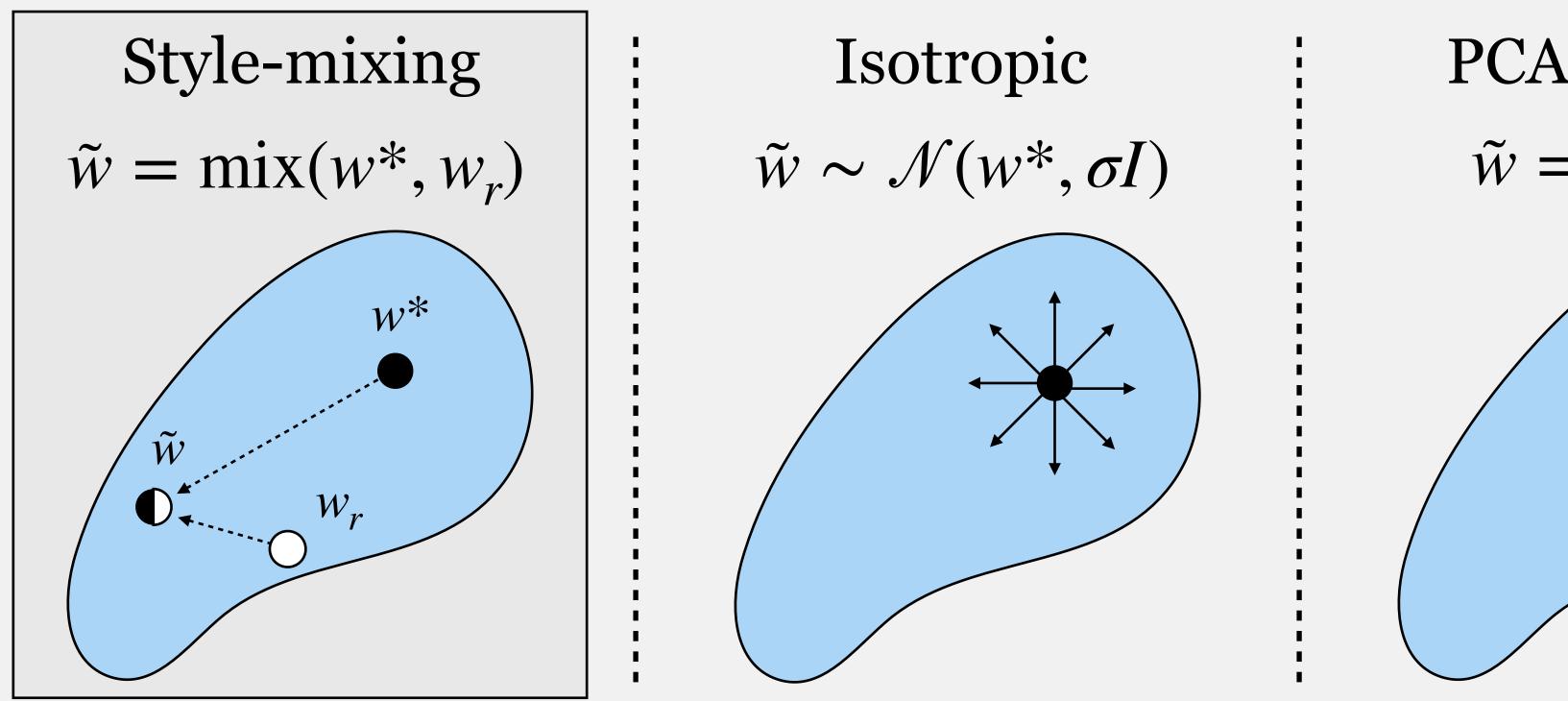


Creating GAN-generated Image Variants



- $w^* = \arg\min L_{img}(x, G(w)) + \lambda L_{latent}(w, E(x))$
- Encode and optimize to find image latent code, inversion required be fast and accurate

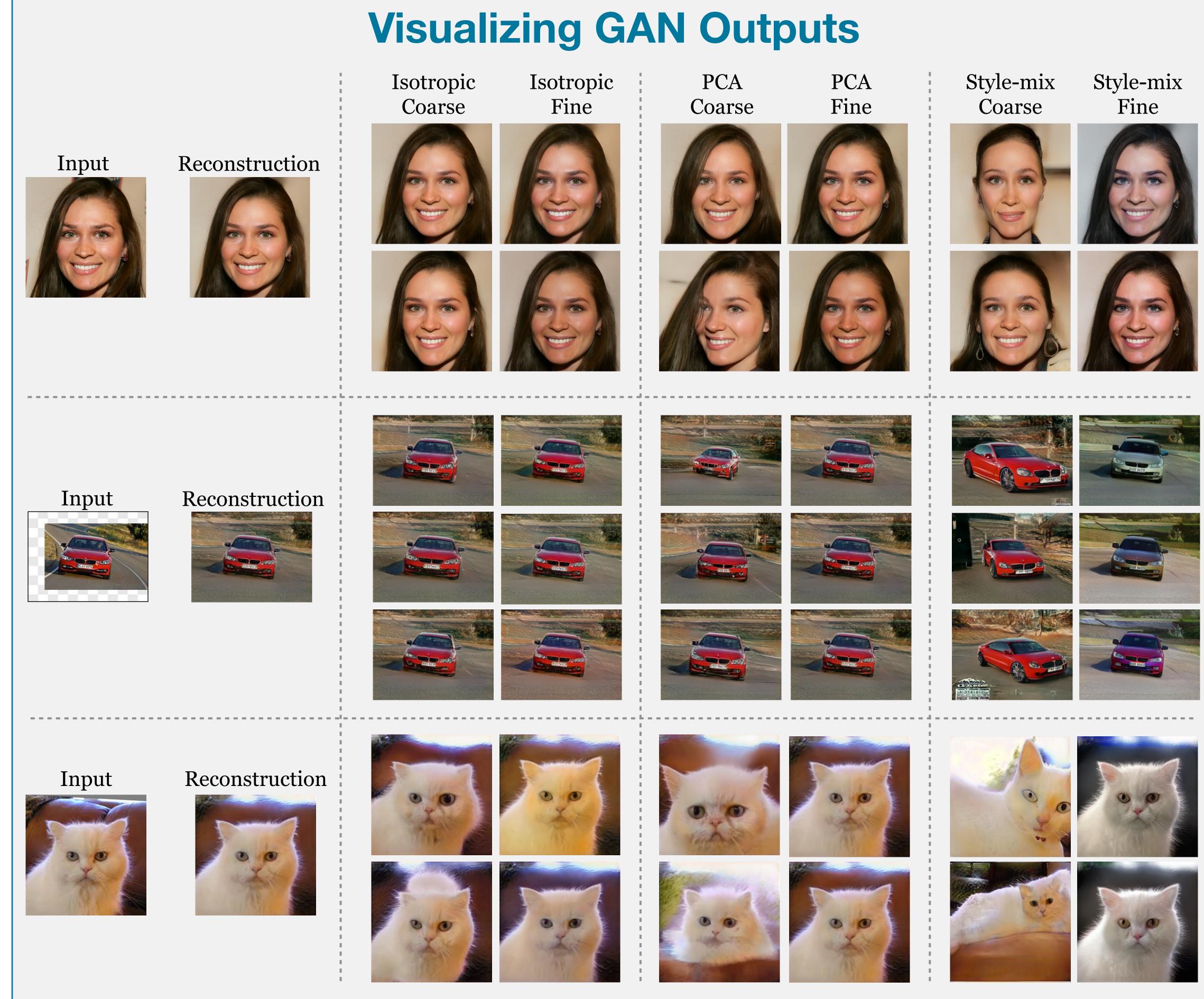


- Perturb optimized latent code in StyleGAN2 W+ space
- Style-mixing: swaps a random latent code at specified generator layers
- Style-mixing is more robust compared to isotropic or PCA perturbation

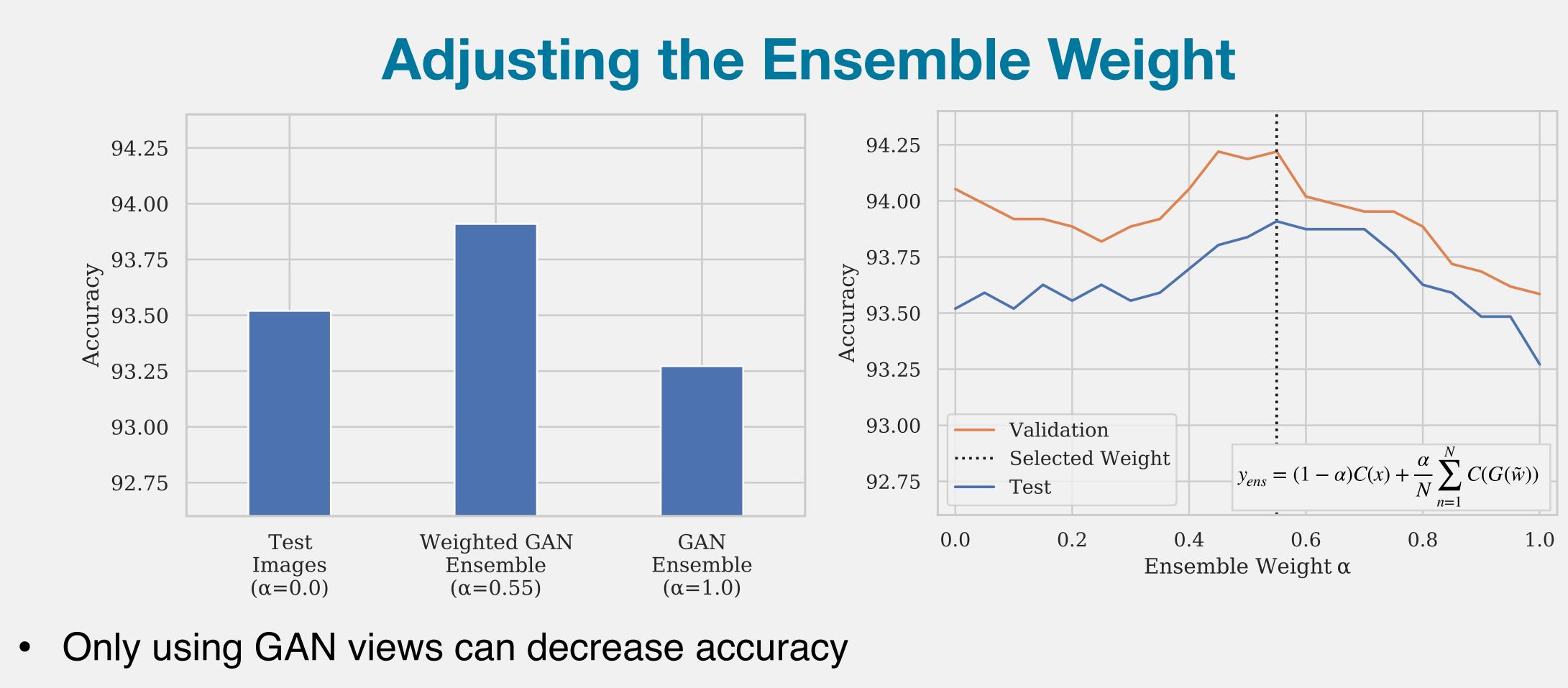
Ensembling with Deep Generative Views Lucy Chai, Jun-Yan Zhu, Eli Shechtman, Phillip Isola, Richard Zhang https://chail.github.io/gan-ensembling/

- due to classifier sensitivity to GAN

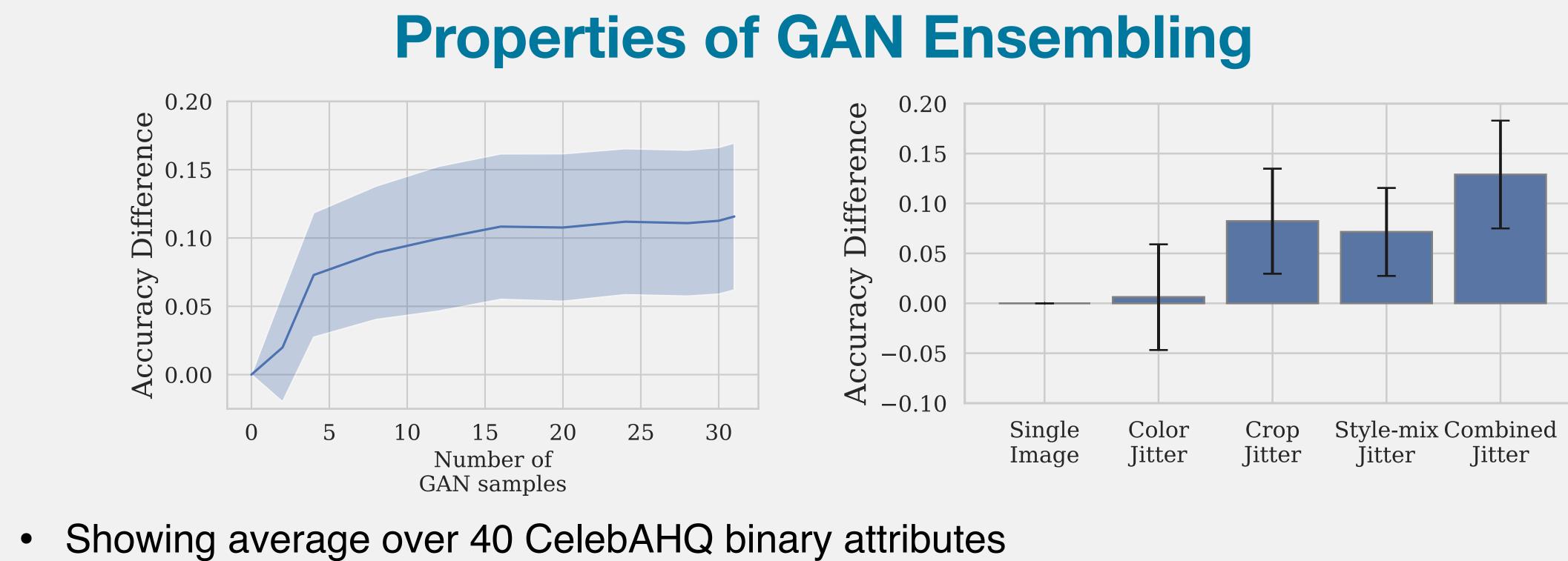
PCA Directions $\tilde{w} = w^* + \beta \tilde{v}_d$



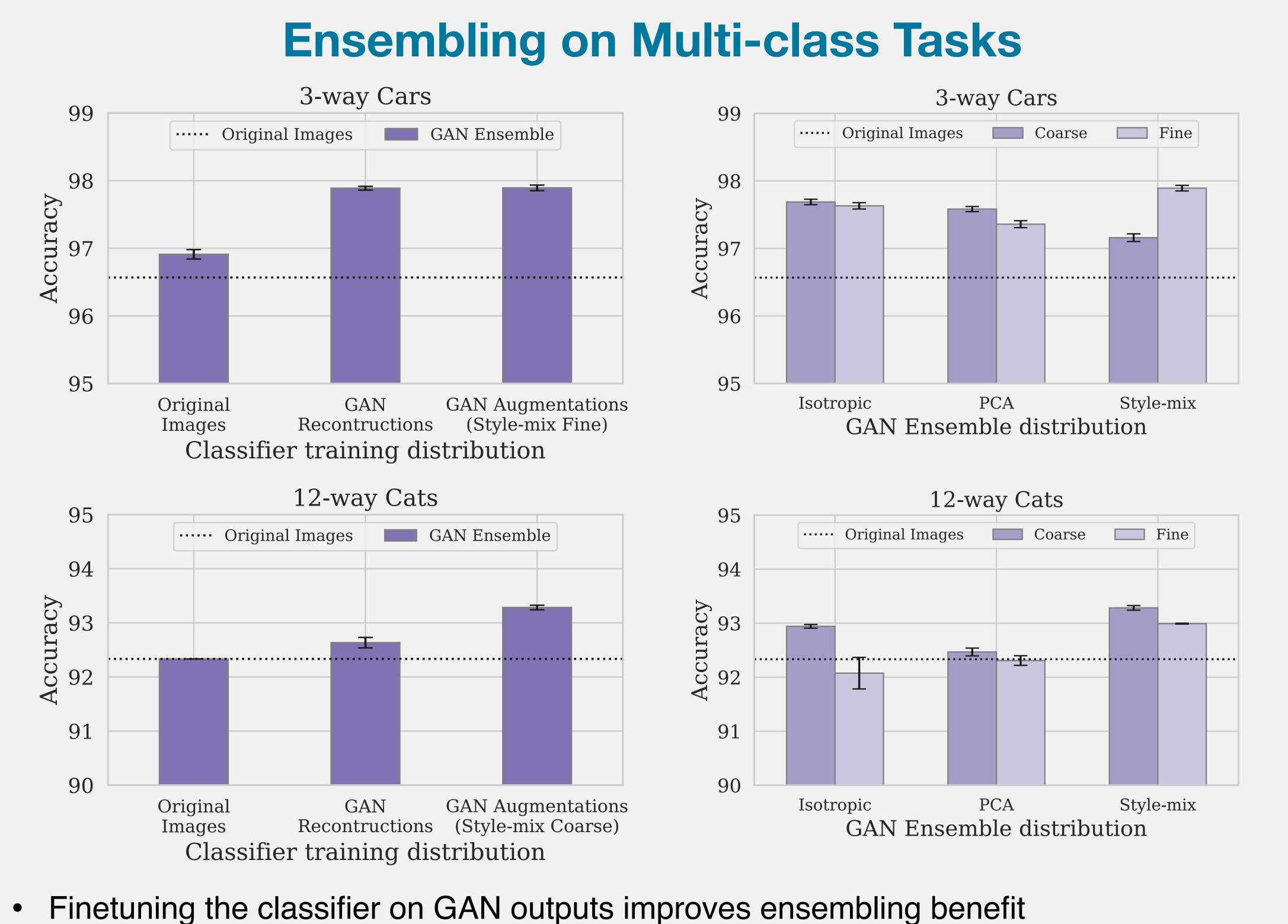
- Perturb coarse or fine layers of StyleGAN2 (middle layers change identity) Coarse layers change shape, fine layers change coloring
- Style-mixing causes larger visual changes compared to isotropic or PCA perturbations



- Softly weight between the dataset original and GAN views
- Weight selected based on validation data



- Increasing GAN ensemble size improves classification but saturates
- GAN style-mixing and traditional image cropping perform similarly
- Combining traditional and GAN views offers additional improvement



• Style-mixing perturbation at test time is best

Limitations of Ensembling with GANs

- GAN reconstruction capability: must preserve discriminative attributes
- GAN inversion efficiency: optimization time and reconstruction tradeoff
- Classifier sensitive to GAN artifacts
- Currently limited to simple tasks and small structured datasets
- Similar techniques may yield greater benefits in the future as GANs improve

