

Seeds of Structure: Patch PCA Reveals Universal Compositional Cues in Diffusion Models



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(1) The Noise-to-Image Map

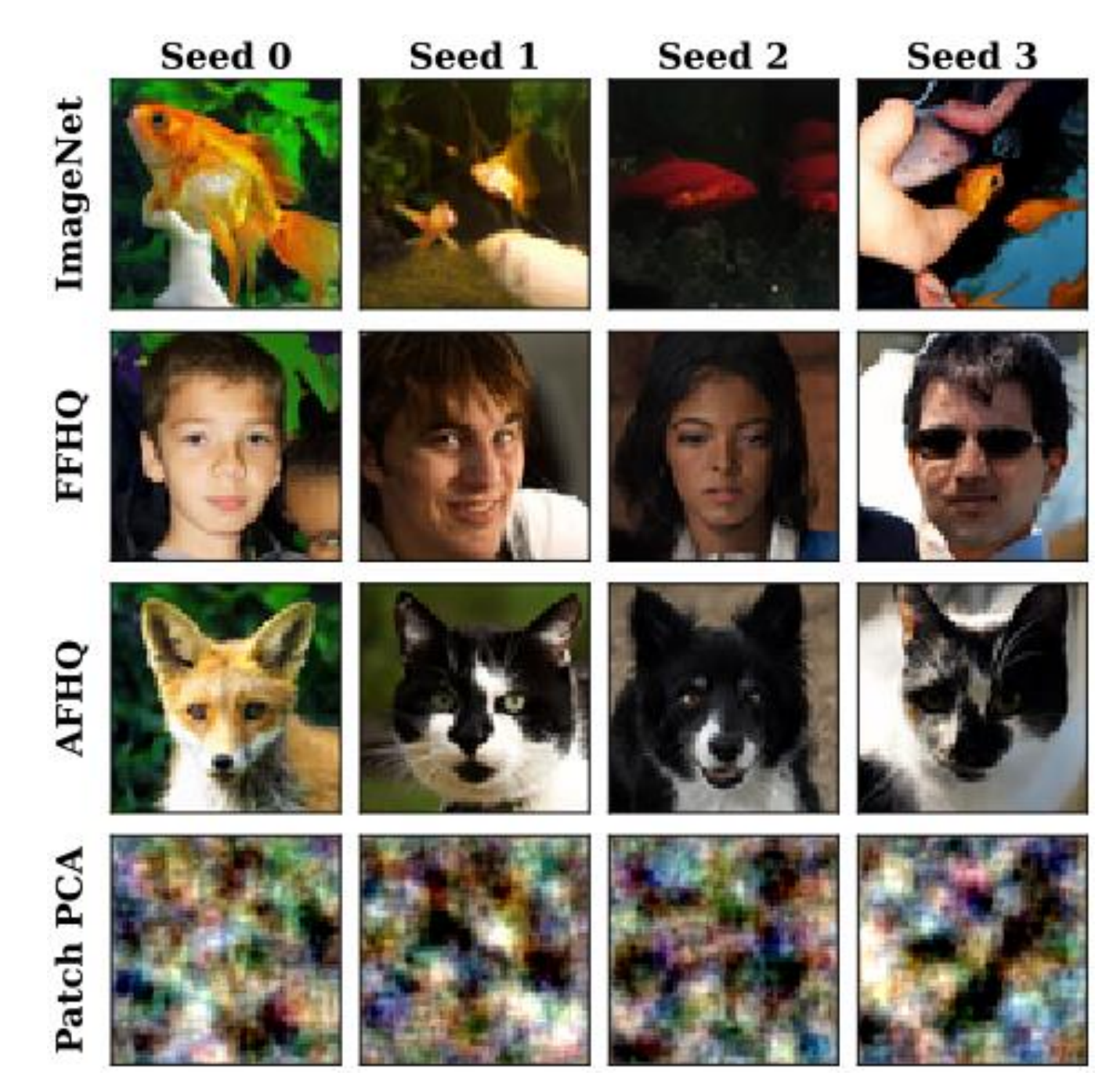
Diffusion model with an ODE sampler deterministically transforms noise into an image.

Question: What are the properties of this noise-to-image map?

- Our findings:**
- **Noise is not just random:** compositional structure of a generated image (e.g., layout, lighting) predominantly determined by the **low frequency part of the initial noise**.
 - **Patch PCA denoiser** effectively extracts the shared compositional cue in noise.
 - **Enable compositional control through noise editing.**

Similar Layout from the Same Seed

Same noise seed generates visually similar images with diffusion models trained on **different datasets**



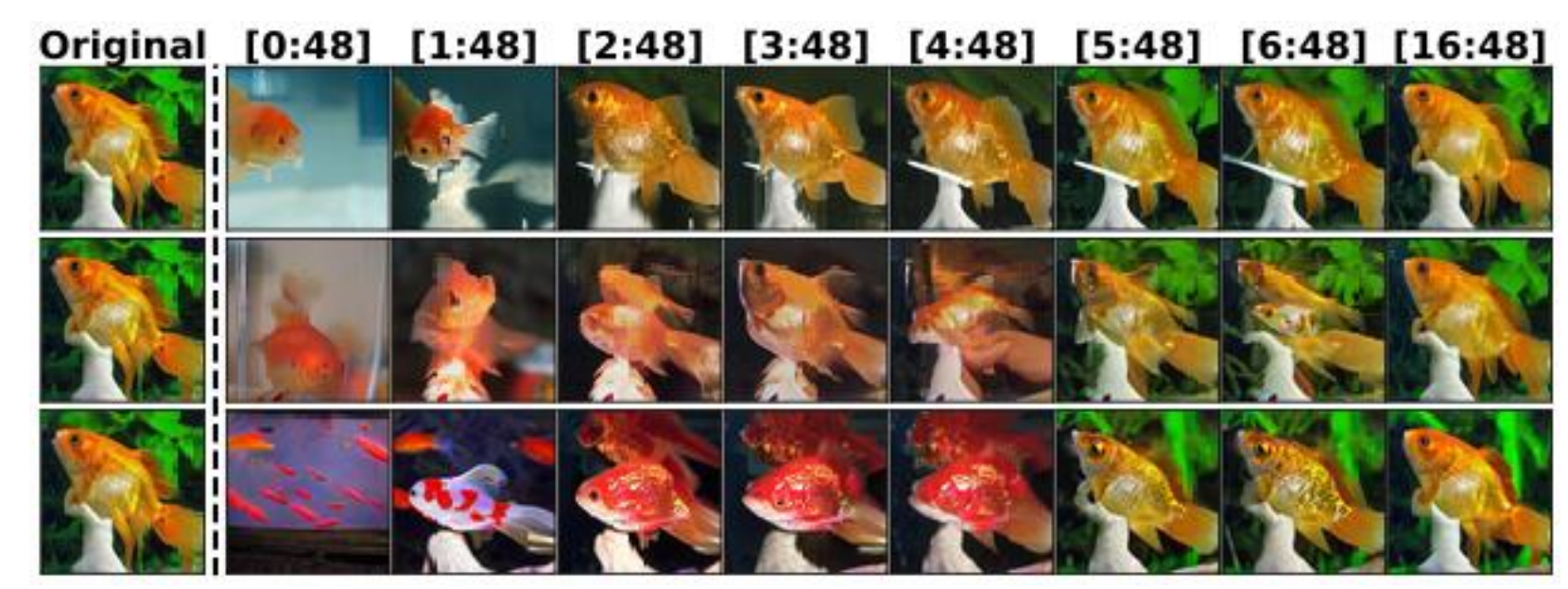
Images from identical seeds on ImageNet, FFHQ, AFHQ, and Patch PCA (to be introduced later)

Quantitative validation: high similarity score for the generated image from the same noise seed compared with randomly paired.

Network Pair	SSIM (higher is better)		MSE (lower is better)	
	Same Seed	Random	Same Seed	Random
ImageNet vs FFHQ	0.423 ± 0.087	0.065 ± 0.040	0.041 ± 0.017	0.136 ± 0.055
ImageNet vs AFHQ	0.447 ± 0.097	0.062 ± 0.039	0.038 ± 0.018	0.130 ± 0.055
FFHQ vs AFHQ	0.469 ± 0.074	0.054 ± 0.041	0.032 ± 0.012	0.128 ± 0.046

Sensitivity of the Noise-to-Image Map

Perturbing low-frequency Patch-PCA components in initial noise dramatically changes generated image, while high-frequency perturbation leaves layout and semantics nearly unchanged.



(2) The Patch PCA Denoiser

Extracting the compositional cue with **Patch PCA denoiser**:

1. **Patchify** the image into overlapping patches.
2. **Apply PCA denoiser for each patch** with PCA computed from a generic set of patches (μ is the mean and λ_i are eigenvalues and u_i are eigenvectors).

$$D_{PCA}(\mathbf{p}_i, \sigma) := \mu + \sum_{j=1}^{p^2c} \frac{\lambda_j}{\lambda_j + \sigma^2} \langle \mathbf{p}_i - \mu, \mathbf{u}_j \rangle \mathbf{u}_j$$

3. **Unpatchify** to reconstruct the image.

Theorem 5.1 (informal) Under a Gaussian patch assumption, the Patch PCA denoiser is optimal among all “patch-local” denoisers.

Qualitative validation of Patch PCA Denoiser:

Images (left) from identical seeds on ImageNet, FFHQ, and Patch PCA denoiser and their patch-wise projection to top-1 (middle) and top-2 (right) eigenspaces.

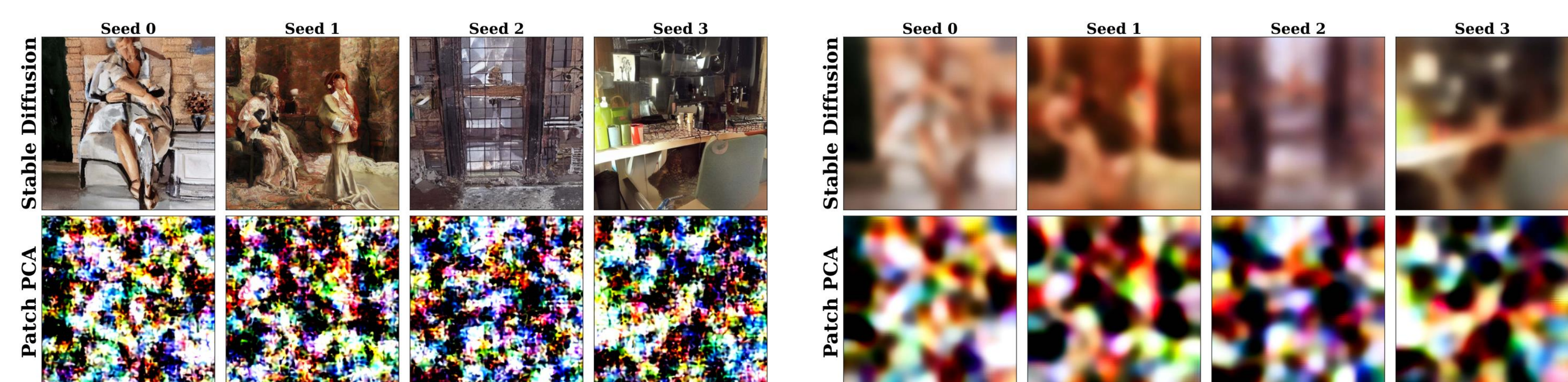


Quantitative validation of Patch PCA Denoiser

Network Pair	SSIM (higher is better)		MSE (lower is better)	
	Same Seed	Random	Same Seed	Random
Patch PCA vs ImageNet	0.474 ± 0.137	0.031 ± 0.027	0.049 ± 0.025	0.115 ± 0.037
Patch PCA vs FFHQ	0.473 ± 0.077	0.029 ± 0.033	0.045 ± 0.014	0.114 ± 0.027
Patch PCA vs AFHQ	0.548 ± 0.084	0.029 ± 0.034	0.036 ± 0.014	0.104 ± 0.029

Extension to Latent Diffusion model

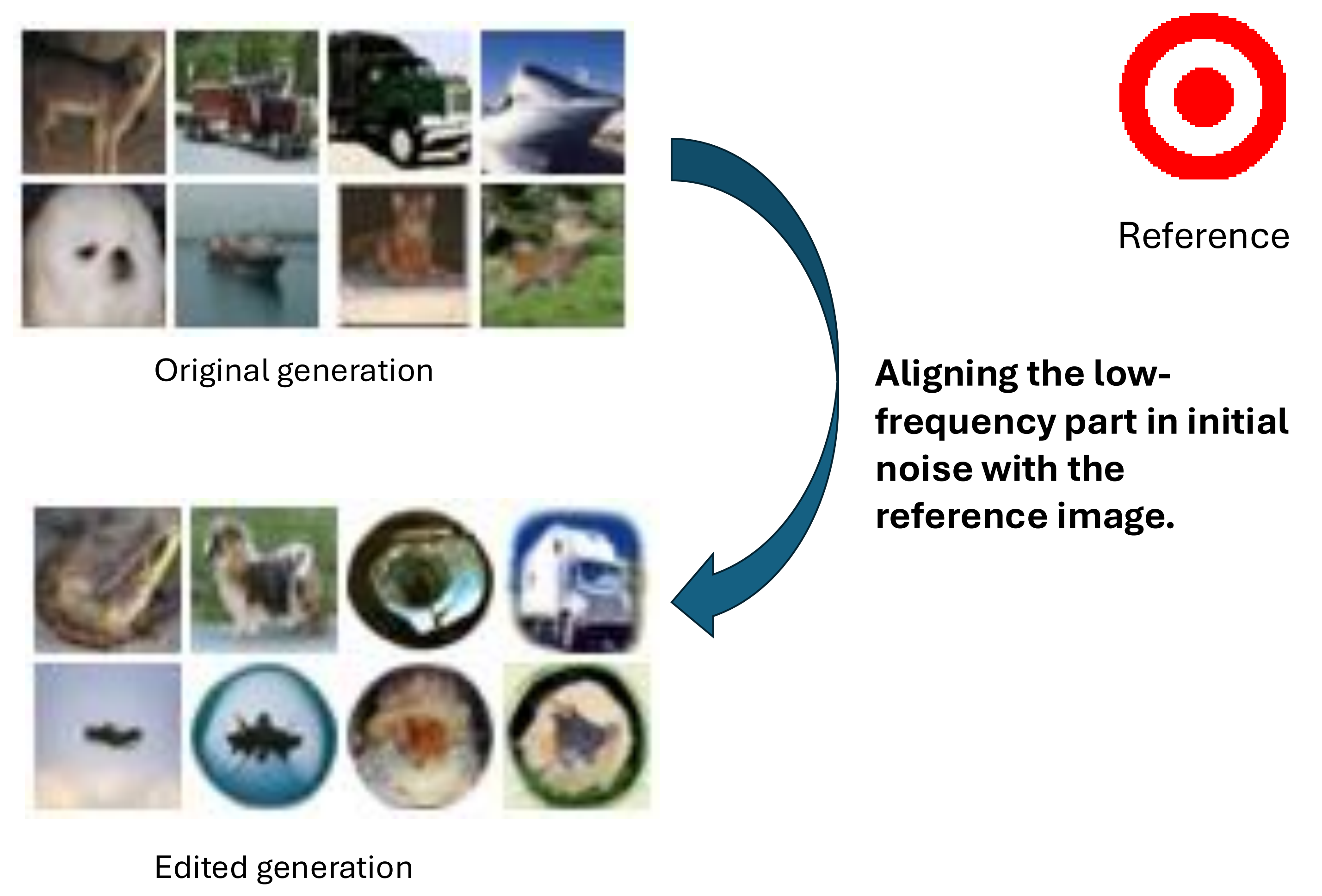
Our method extends to latent diffusion models. A PCA denoiser built from patch statistics of encoded images generates images with a similar layout to neural network outputs, as illustrated below and quantified in our paper.



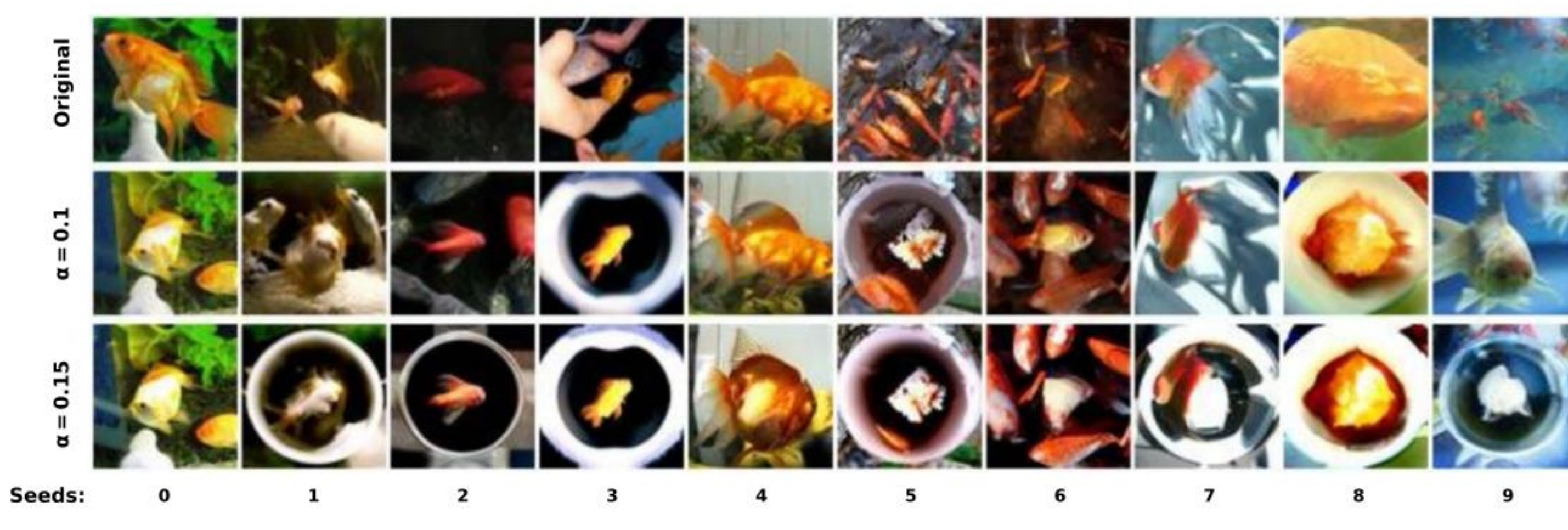
Stable Diffusion Generated Images Patch-wise projection to the top 2 eigenspaces

(3) Training-Free Image Editing by Noise Editing

Editing with CIFAR-10 diffusion model



Editing with ImageNet diffusion model (still use as reference) at different aligning strengths.



Takeaways

Noise is not just random

- **Compositional cues in noise are universal across models**
- **Patch PCA captures the compositional cue**
- **Training-free control via noise editing**

Acknowledgements

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