

## Take-Aways

1 Properly constrained weights exhibit **semantic structure** and serve as **effective data representations**;

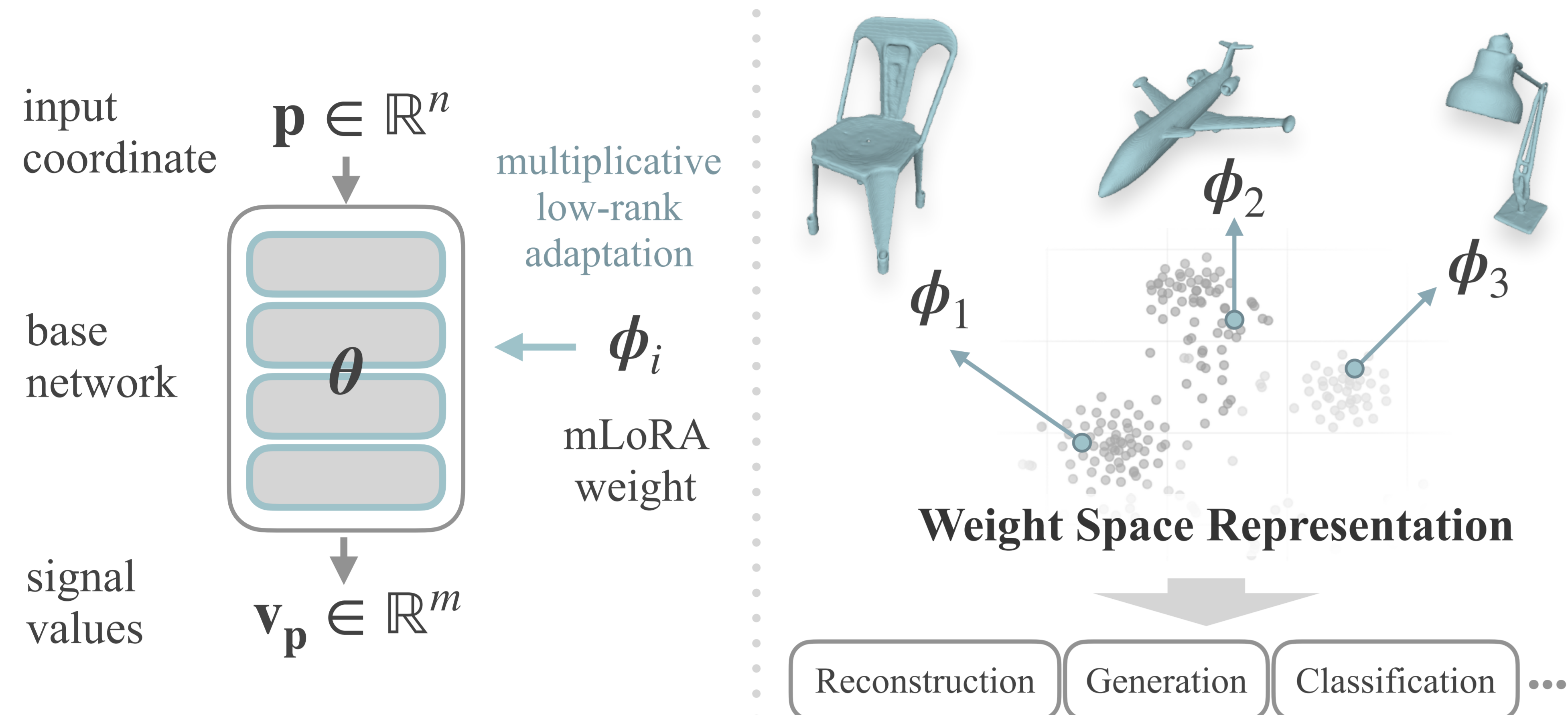
2 Weight-space geometry **correlates** strongly with diffusion **generation quality**.



Project Page

## 1 Can Weights Serve as Representations?

■ A **fitted neural field already encodes its data**. An image or shape lives entirely in its parameters.

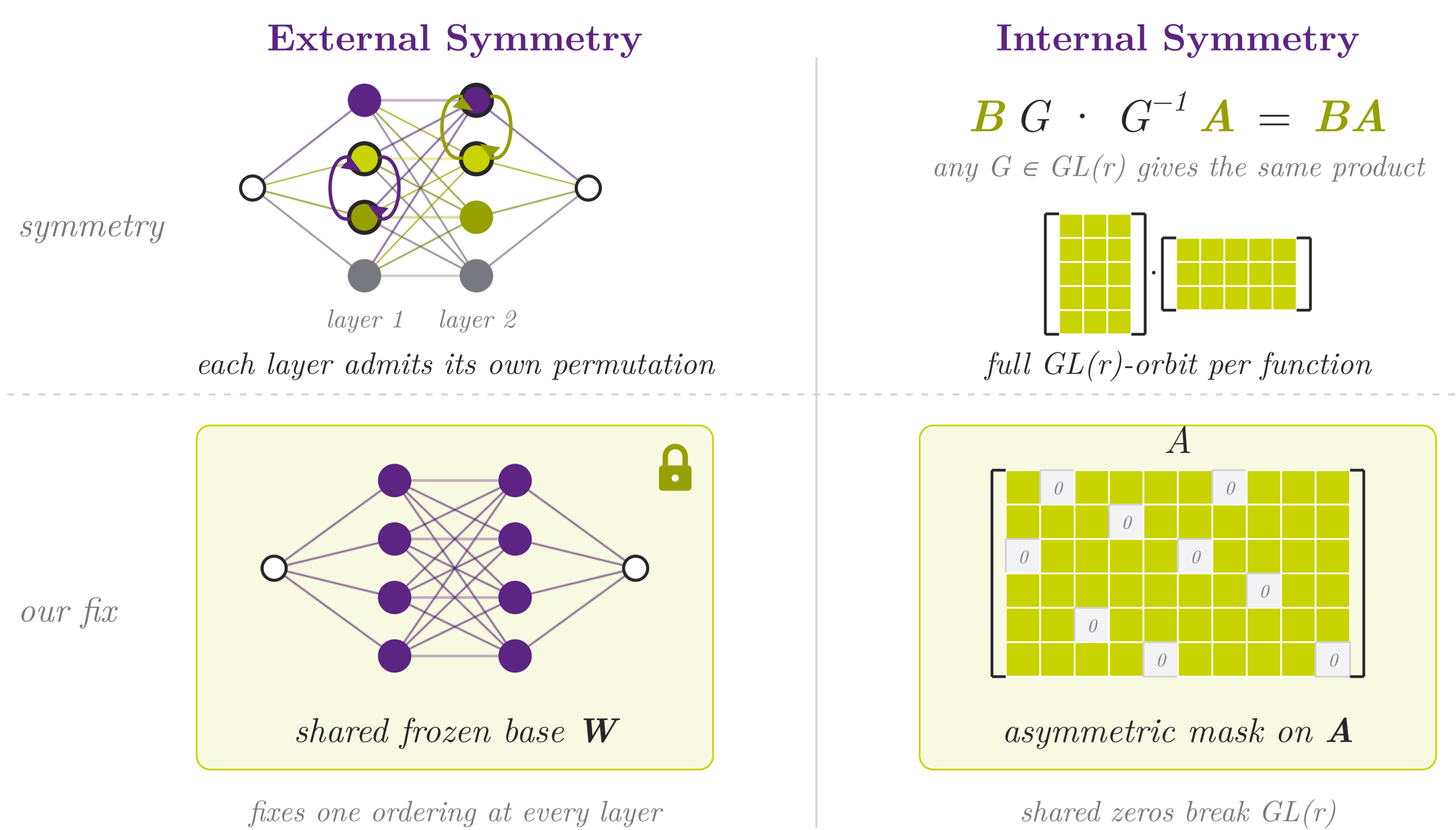


■ **Representation Paradigm** A frozen base neural field is adapted by per-instance mLoRA weights  $\phi_i$ ; those weights *are* the data representation.

## 3 Enforcing Structure in Weight Space

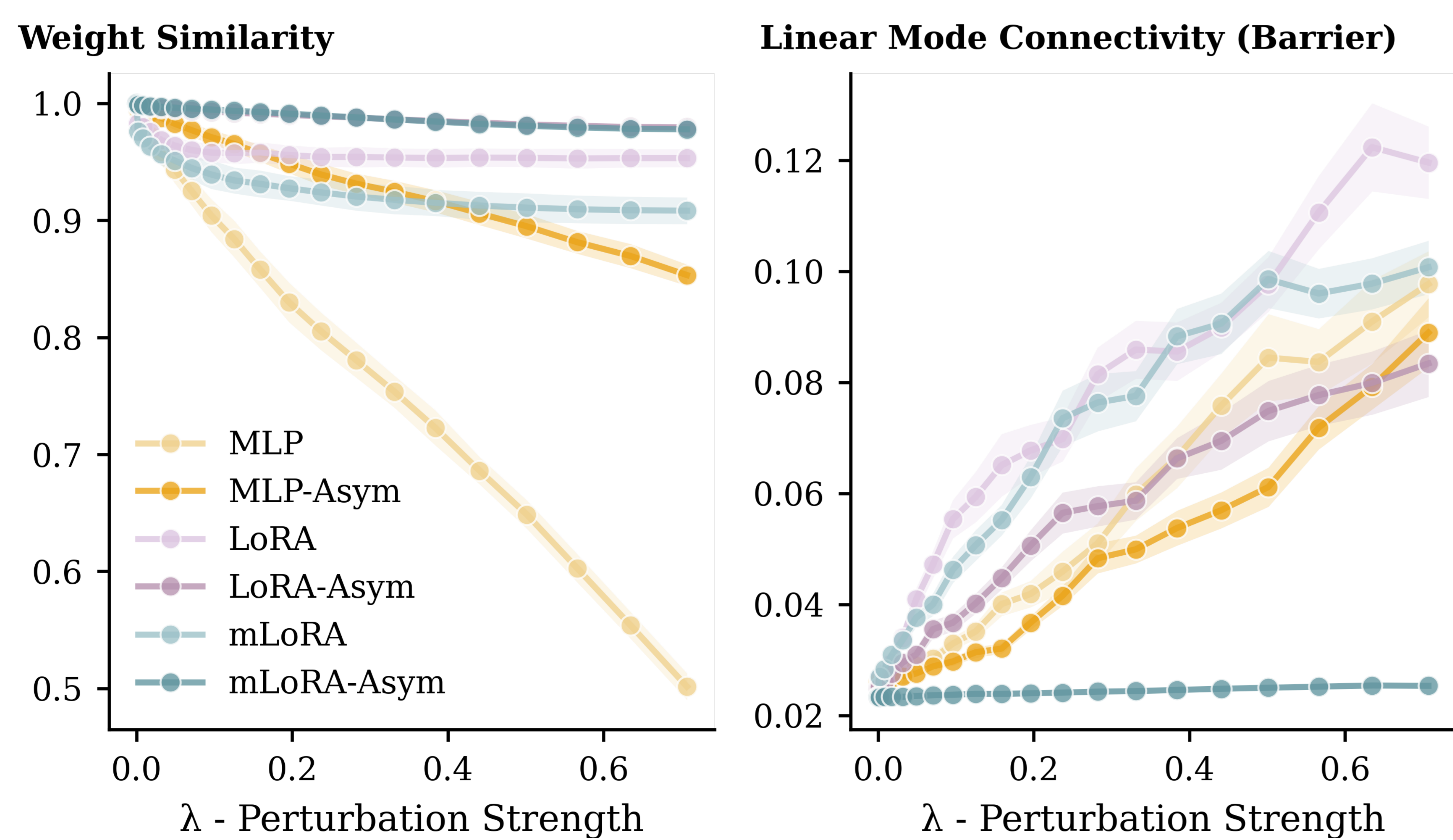
■ Each instance is a **multiplicative LoRA (mLoRA)** update over a shared base network:  $\mathbf{W}' = \mathbf{W} \odot \mathbf{B}\mathbf{A}$ .

■ We constrain the neural field optimization to **break symmetries**.

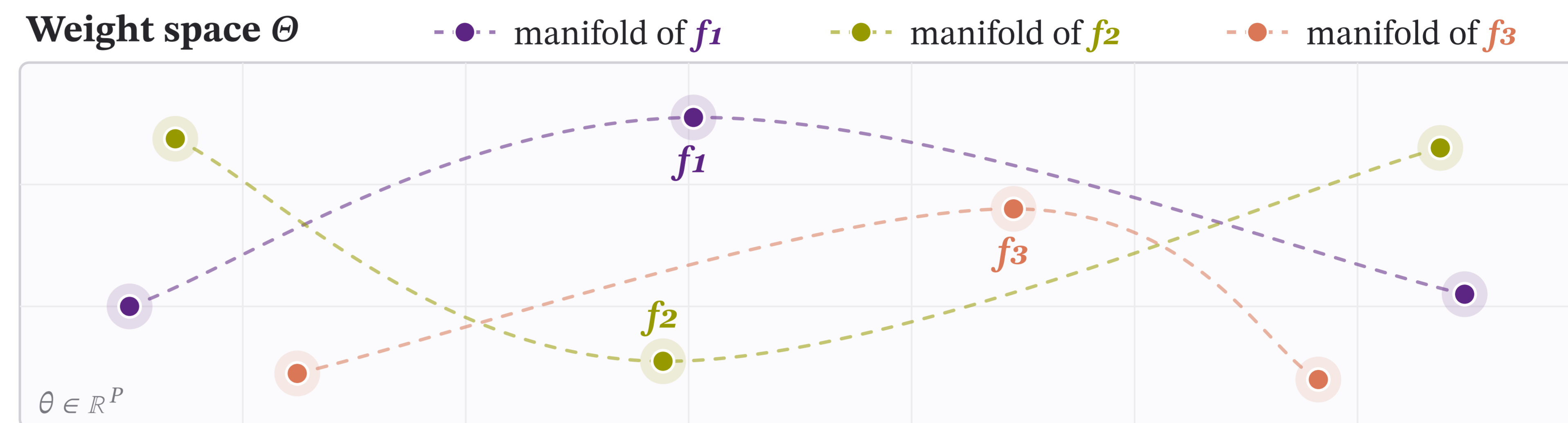


## 4 A Structured, Learnable Geometry

■ Across very different initializations, mLoRA-Asym fits converge to the **same linear mode**: high weight similarity, near-zero loss barrier. This smooth geometry is what makes the weight space **learnable** (right).



## 2 Challenge: Weight Space Symmetries



■ **Symmetries complicate weight space structure**. Transformations on the network weights (such as permuting neurons) sends **functionally identical** networks **arbitrarily far** apart in weight space. The distribution becomes wildly **multi-modal**.

## 5 Generating New Neural Fields

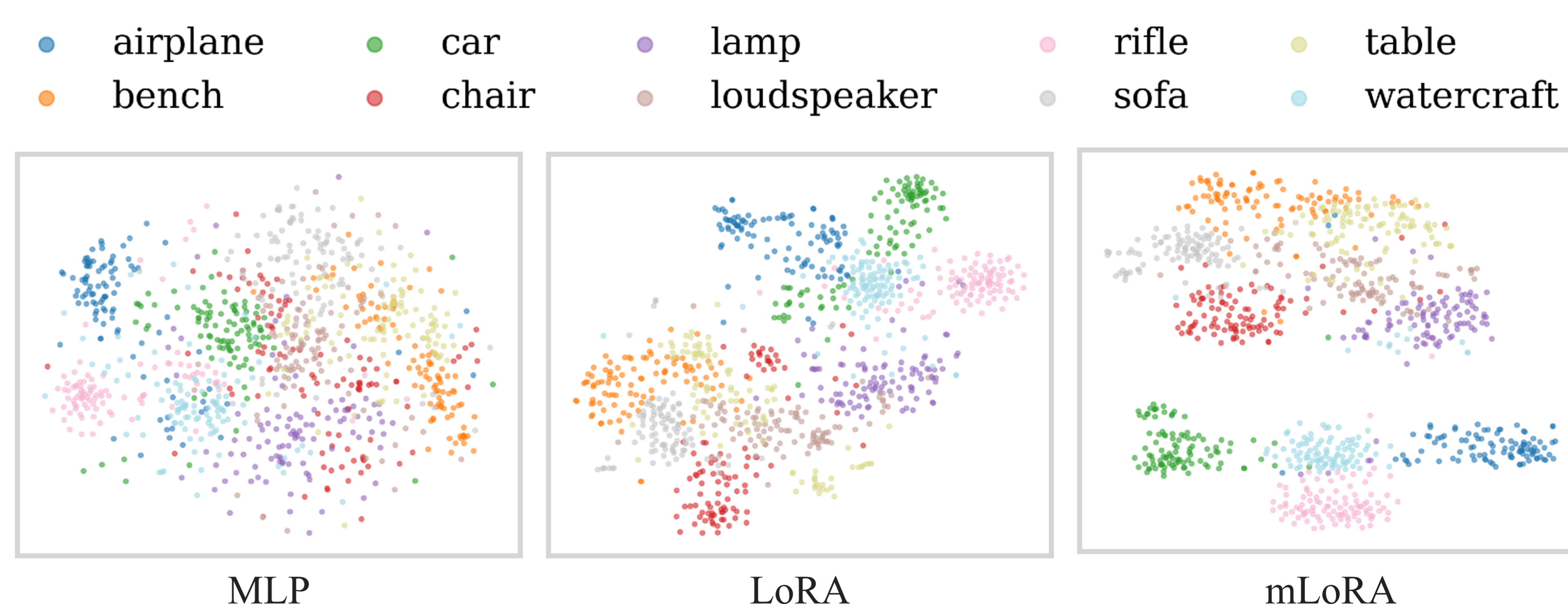
■ A **diffusion model** trained directly on the mLoRA weight set samples new weights, and therefore new neural fields: new images and new shapes.



First successful weight-space generation of **natural images** at  $128 \times 128$ .

## 6 Weights Encode Semantics

■ A linear classifier on raw mLoRA weights reaches **90% accuracy** over ten ShapeNet categories. The weight space carries **semantic structure**.



t-SNE of each weight space, colored by ShapeNet category.