

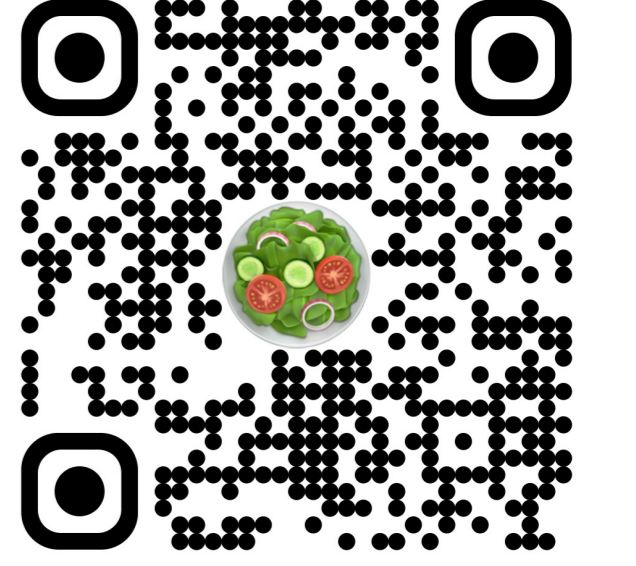
# SALAD: Part-Level Latent Diffusion for 3D Shape Generation and Manipulation



Juil Koo\* Seungwoo Yoo\* Minh Hieu Nguyen\* Minhyuk Sung

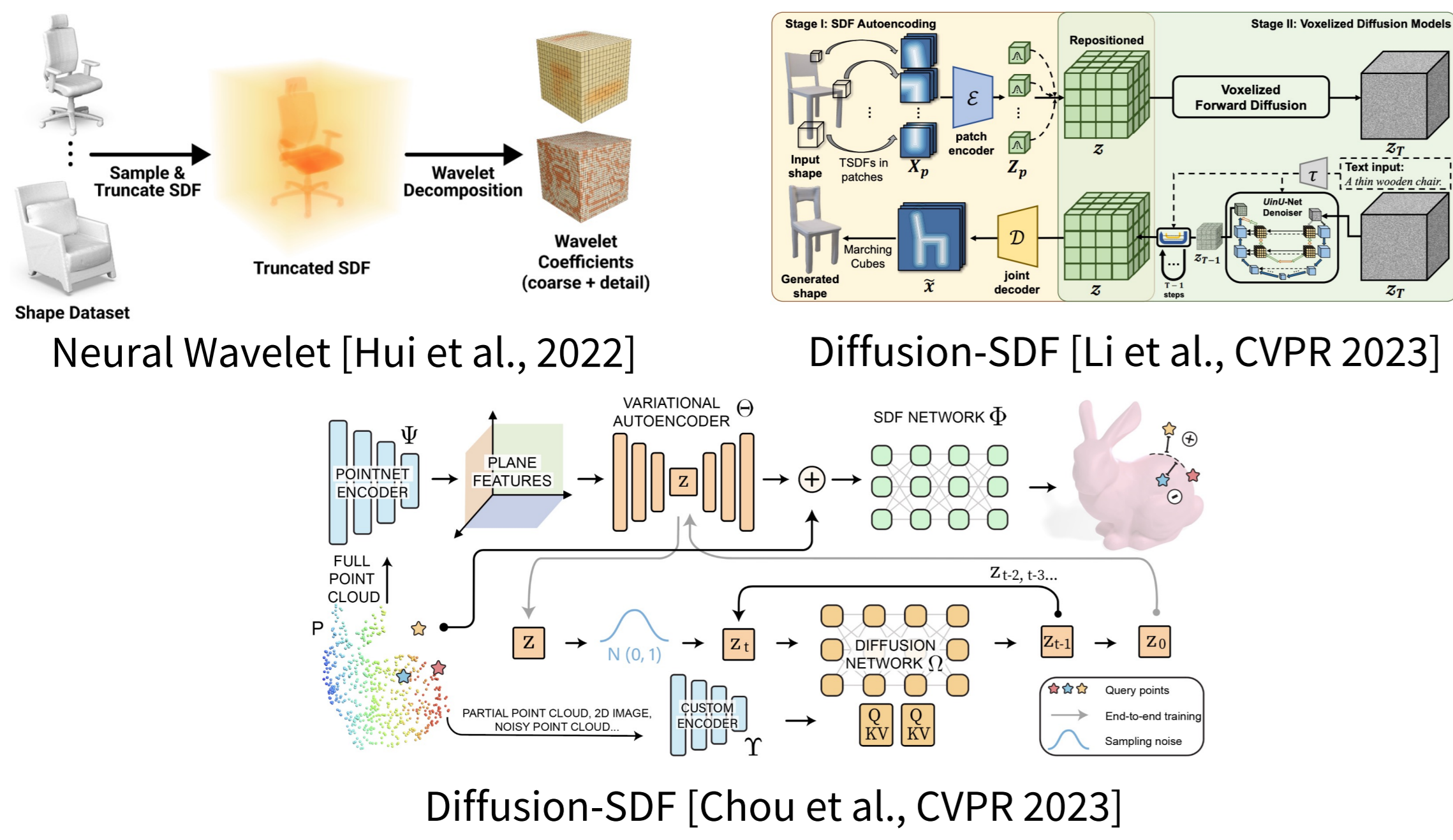
KAIST

\* equal contribution.



## Motivation

The existing 3D diffusion models are based on either voxel grid features or global latent features.



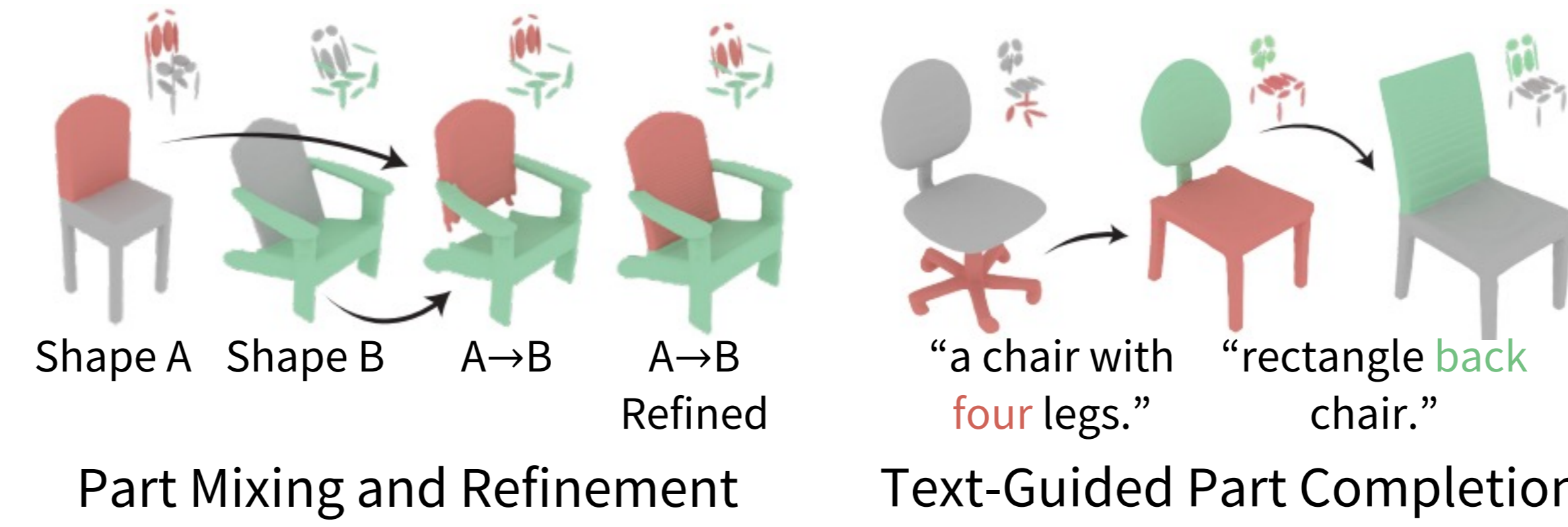
Due to the data representation, they do **not fully realize the zero-shot editing capability of diffusion models** in shape manipulation. For this, it is essential to leverage a part-level representation.

## Goal

Achieve state-of-the-art shape generation quality and zero-shot part-level shape manipulation.

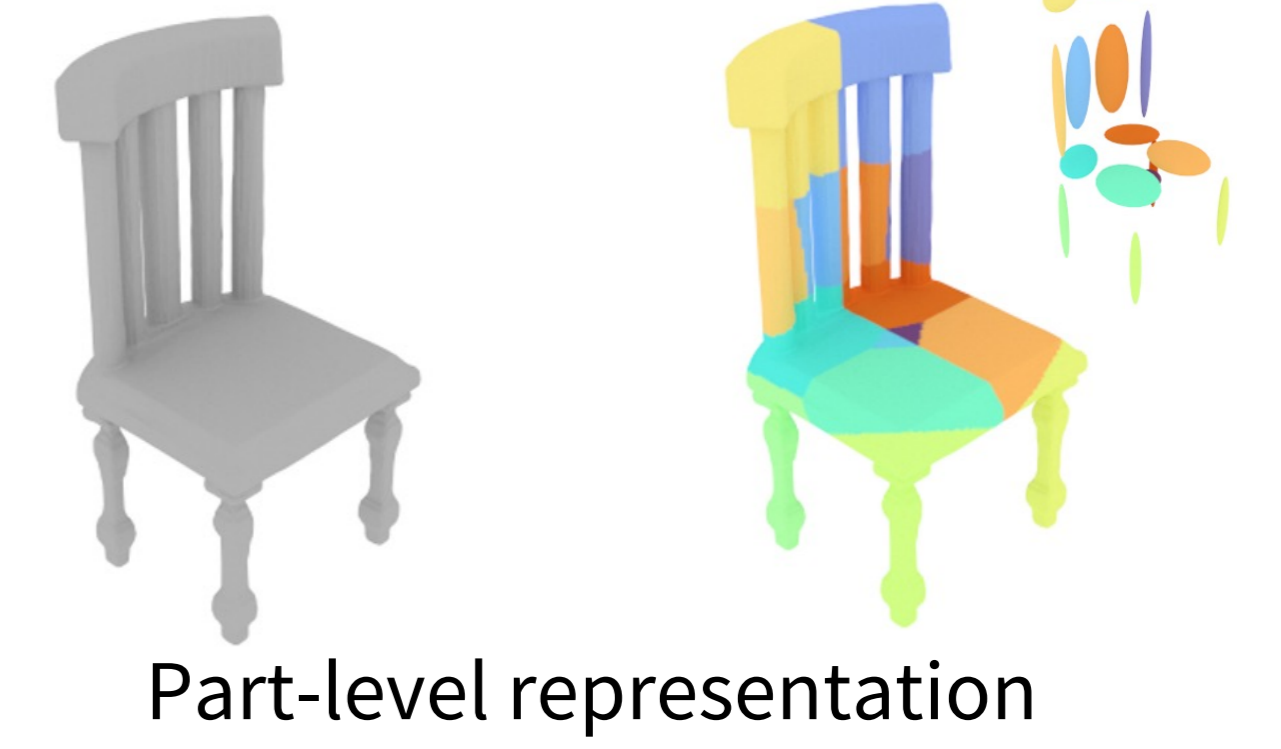


Shape Generation

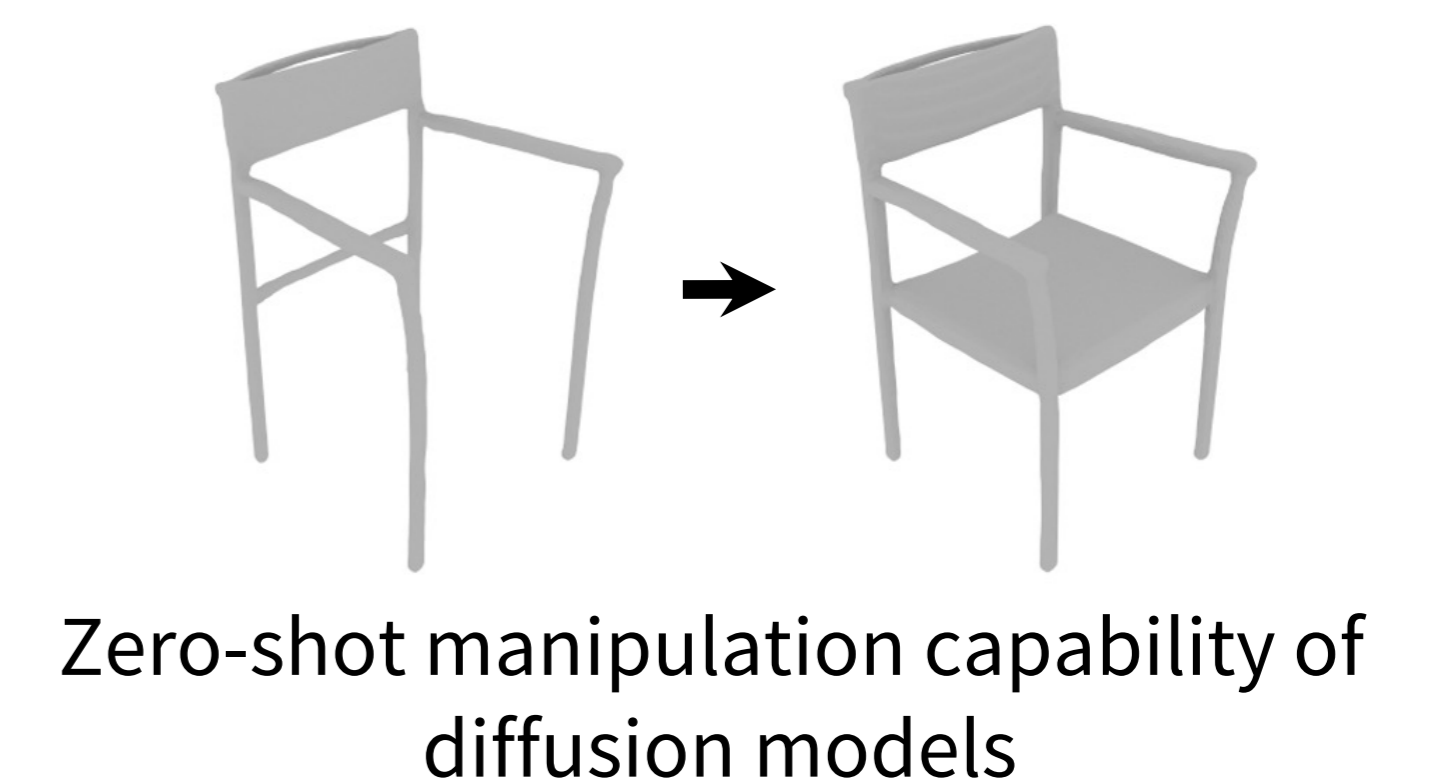


## Key Idea

Combine the **expressivity of part-level implicit representation** with **flexible manipulation capabilities of diffusion models**.

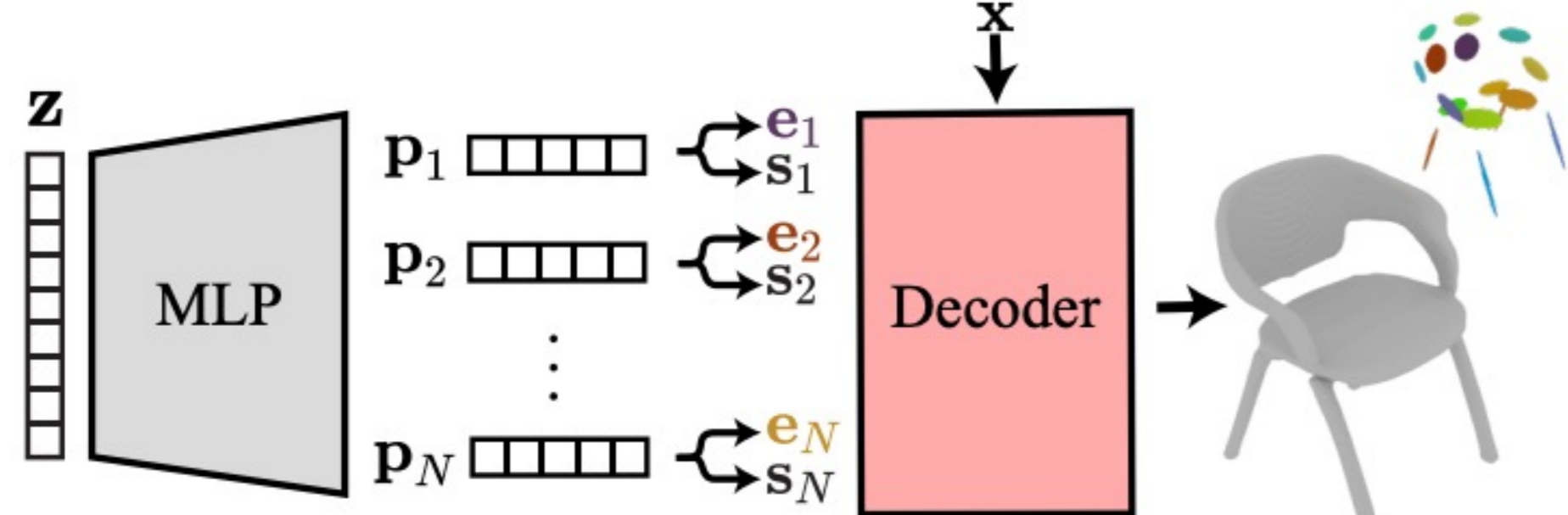


Part-level representation



## Part-Level Implicit Representation

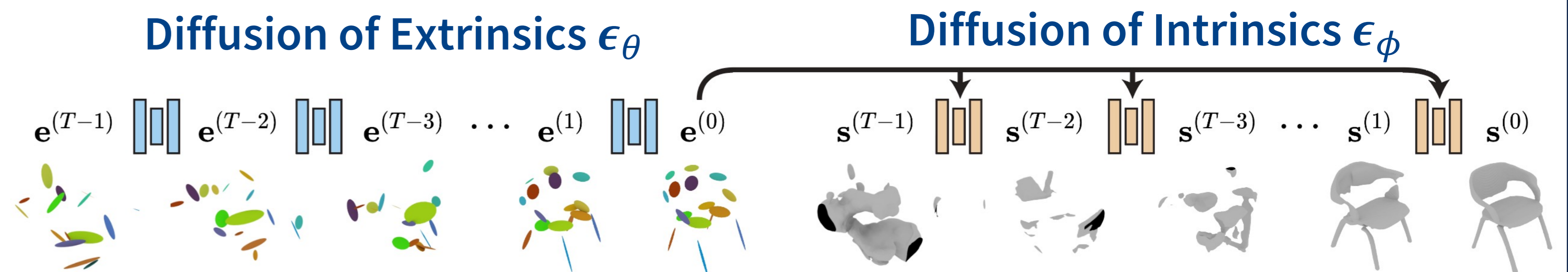
Hertz et al. [SPAGHETTI, SIGGRAPH 2022] proposes a part-level implicit representation for 3D shapes.



A 3D shape is represented by a set of extrinsics  $\{e_i\}_{i=1}^N$  and a set of intrinsics  $\{s_i\}_{i=1}^N$ .  $e_i \in \mathbb{R}^{16}$  represents a 3D gaussian primitive and  $s_i$  encodes fine details of shapes in a 512-dimensional space. The decoder finally predicts an occupancy value at point  $x$  given  $\{e_i, s_i\}_{i=1}^N$ .

## Cascaded Diffusion Models

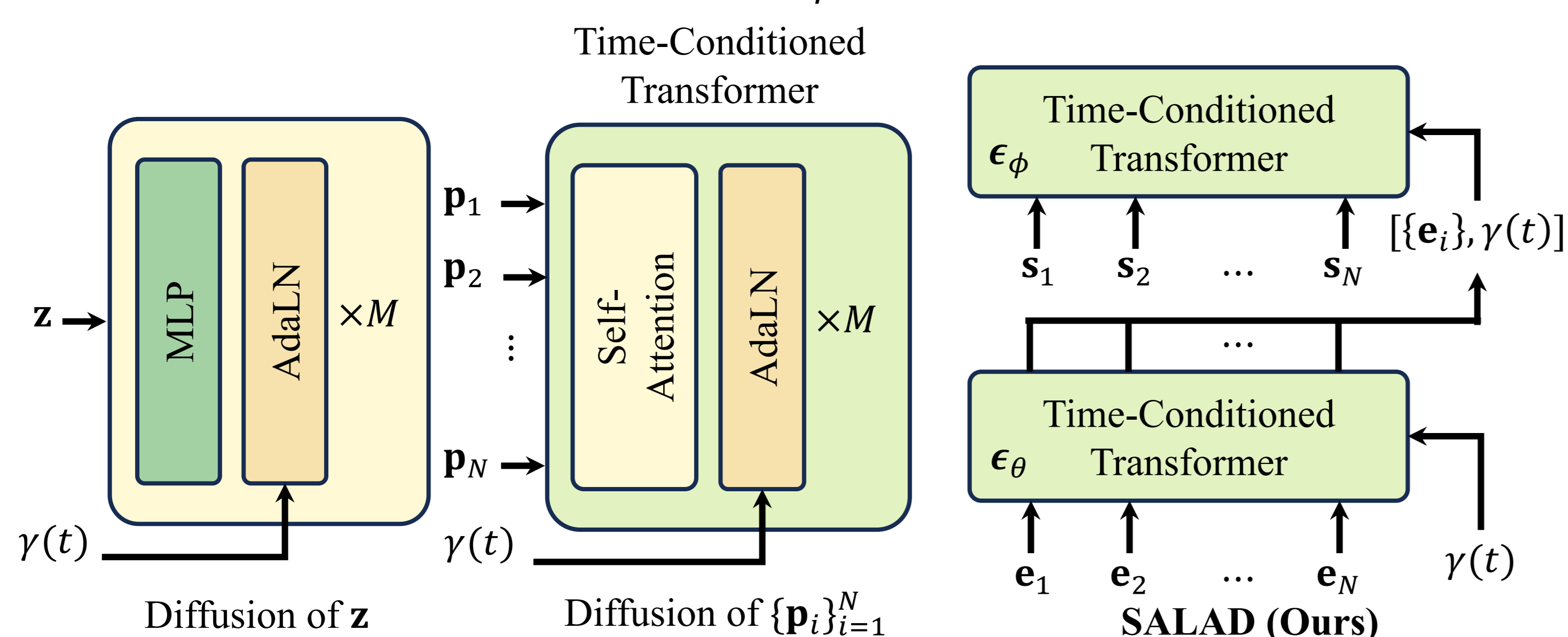
We propose a two-phase cascaded diffusion training framework, learning diffusion first in a low-dimensional subspace and subsequently in the other high-dimensional subspace.



In the first phase, SALAD learns the **rough structures of shapes** encoded with extrinsics. In the second phase, it captures the **fine details of shape surfaces** encoded with intrinsics. To ease the training of the diffusion of intrinsics in a high-dimensional space, we feed extrinsics as condition.

## SALAD Architecture Diagrams

We employ Transformers to process embeddings represented as set. SALAD consists of two cascaded latent diffusion models,  $\epsilon_\theta$  for the diffusion of extrinsics and  $\epsilon_\phi$  for the diffusion of intrinsics.



## SALAD Shape Manipulation Method

### Part Completion

$$\begin{aligned} \mathbf{x}^{(t-1)} &= \text{add\_noise}(\mathbf{x}^{(0)}, t-1) \\ \tilde{\mathbf{x}}^{(t-1)} &= \text{denoise}(\tilde{\mathbf{x}}^{(t)}, t) \\ \tilde{\mathbf{x}}^{(t-1)} &= \text{combine}(\mathbf{x}^{(t-1)}, \tilde{\mathbf{x}}^{(t-1)}, m) \end{aligned}$$

Given a data  $\mathbf{x}^{(0)}$  and a part mask  $m$ , the completed shape  $\tilde{\mathbf{x}}^{(t-1)}$  at  $t-1$  is obtained by combining the original and generated data.

### Part Mixing and Refinement

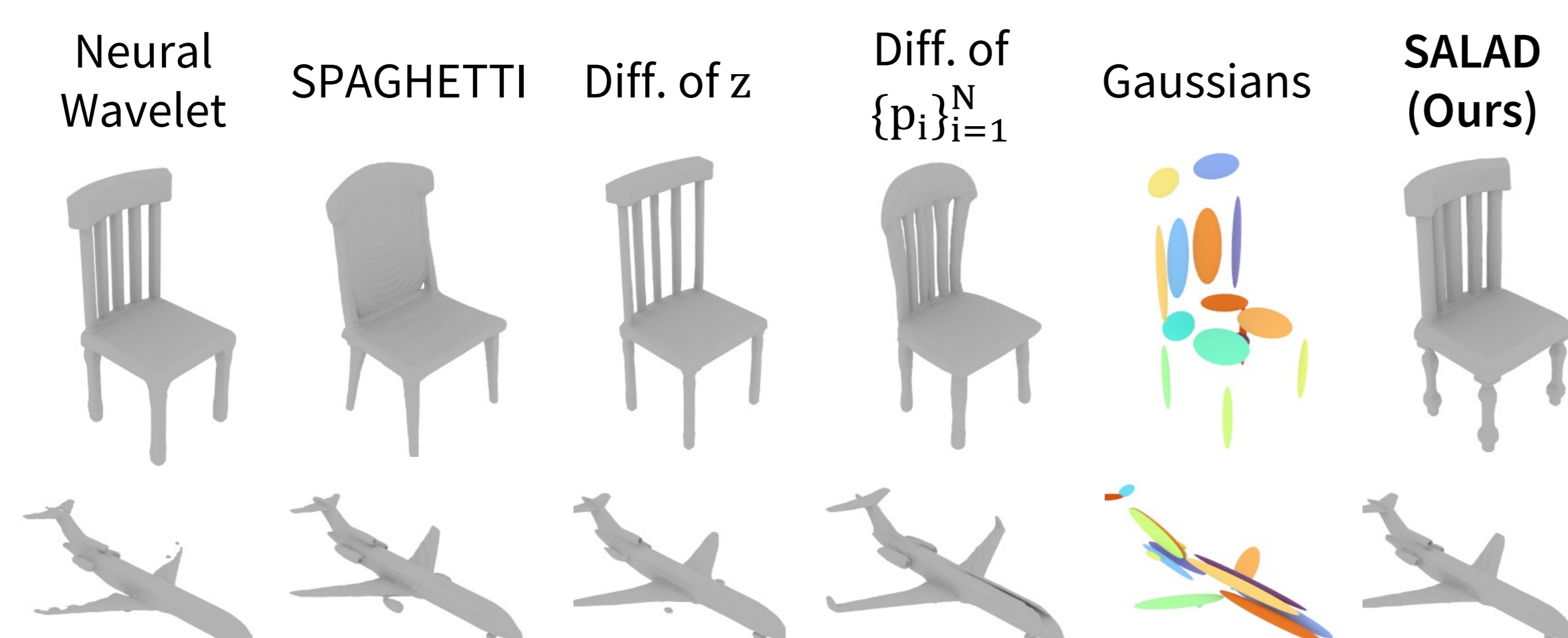
$$\begin{aligned} \tilde{\mathbf{x}}^{(0)} &= \text{combine}(\mathbf{x}_a^{(0)}, \mathbf{x}_b^{(0)}, m) \\ \tilde{\mathbf{x}}^{(S)} &= \text{add\_noise}(\tilde{\mathbf{x}}^{(0)}, S) \\ \text{for } t = S, \dots, 1 \text{ do} \\ &\quad \tilde{\mathbf{x}}^{(t-1)} = \text{denoise}(\tilde{\mathbf{x}}^{(t)}, t) \\ \text{end for} \end{aligned}$$

Given the mixed data  $\tilde{\mathbf{x}}^{(0)}$  from  $\mathbf{x}_a^{(0)}$  and  $\mathbf{x}_b^{(0)}$ , we add noise sampled at  $t = S \leq T$  to  $\tilde{\mathbf{x}}^{(0)}$  and run the reverse process to refine  $\tilde{\mathbf{x}}^{(0)}$ .

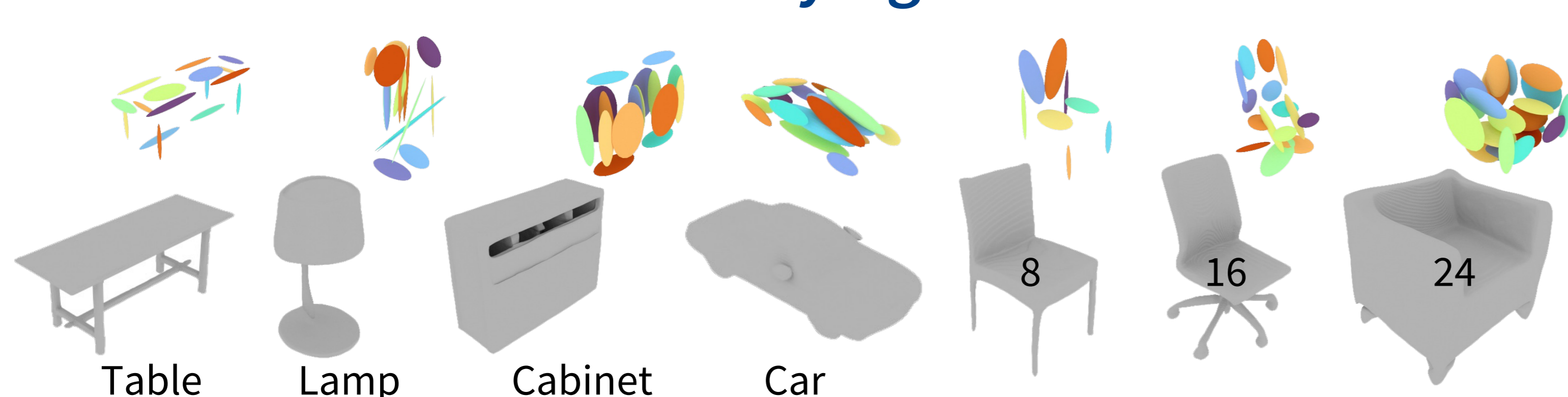
## Shape Generation

SALAD achieves **state-of-the-art shape generation** across widely used metrics while capturing fine details.

Method	Chair			Airplane		
	COV $\uparrow$	MMD $\downarrow$	1-NNA $\downarrow$	COV $\uparrow$	MMD $\downarrow$	1-NNA $\downarrow$
Neural Wavelet	50.15	<b>14.25</b>	62.87	59.09	<b>7.964</b>	72.93
<b>SALAD (Ours)</b>	<b>55.16</b>	14.29	<b>58.41</b>	<b>65.39</b>	8.238	<b>71.08</b>

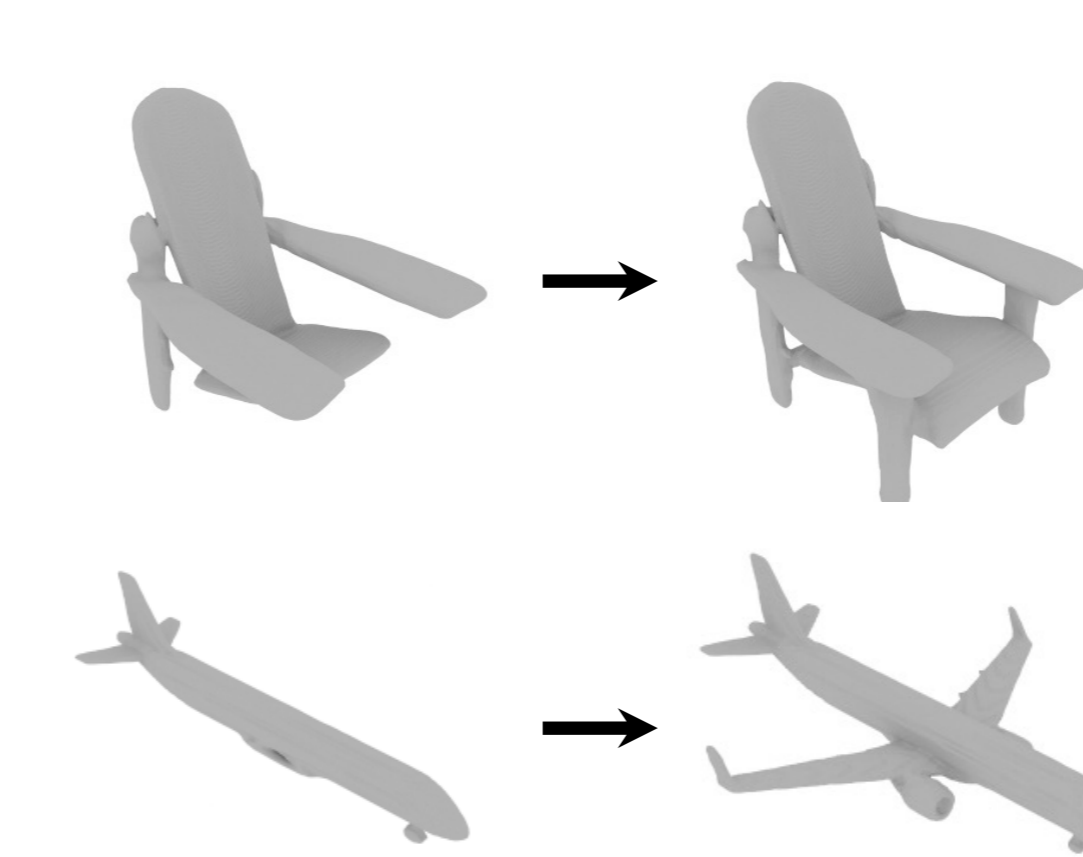


## More Classes and Varying Number of Parts



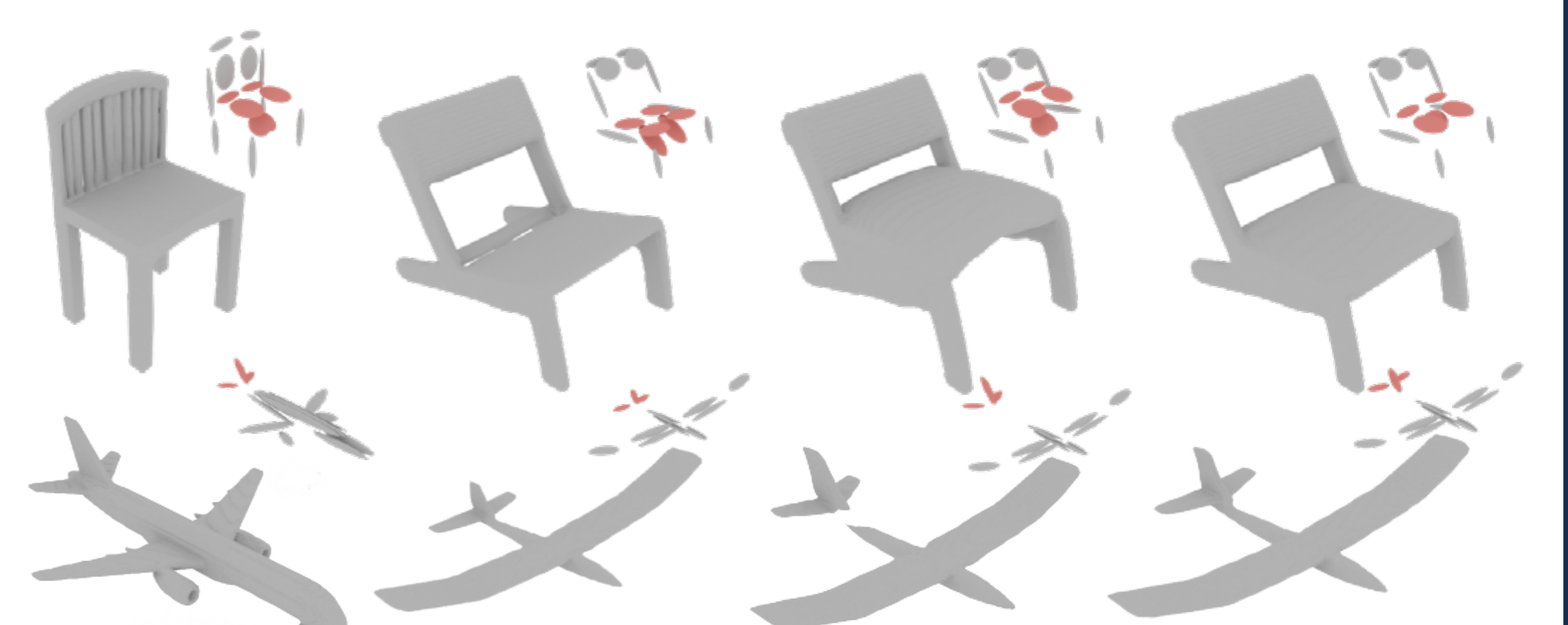
## Part Completion

Partial Shape Completed



## Part Mixing and Refinement

Shape A Shape B A  $\rightarrow$  B A  $\rightarrow$  B Refined



## Text-Guided Shape Generation and Part Editing

