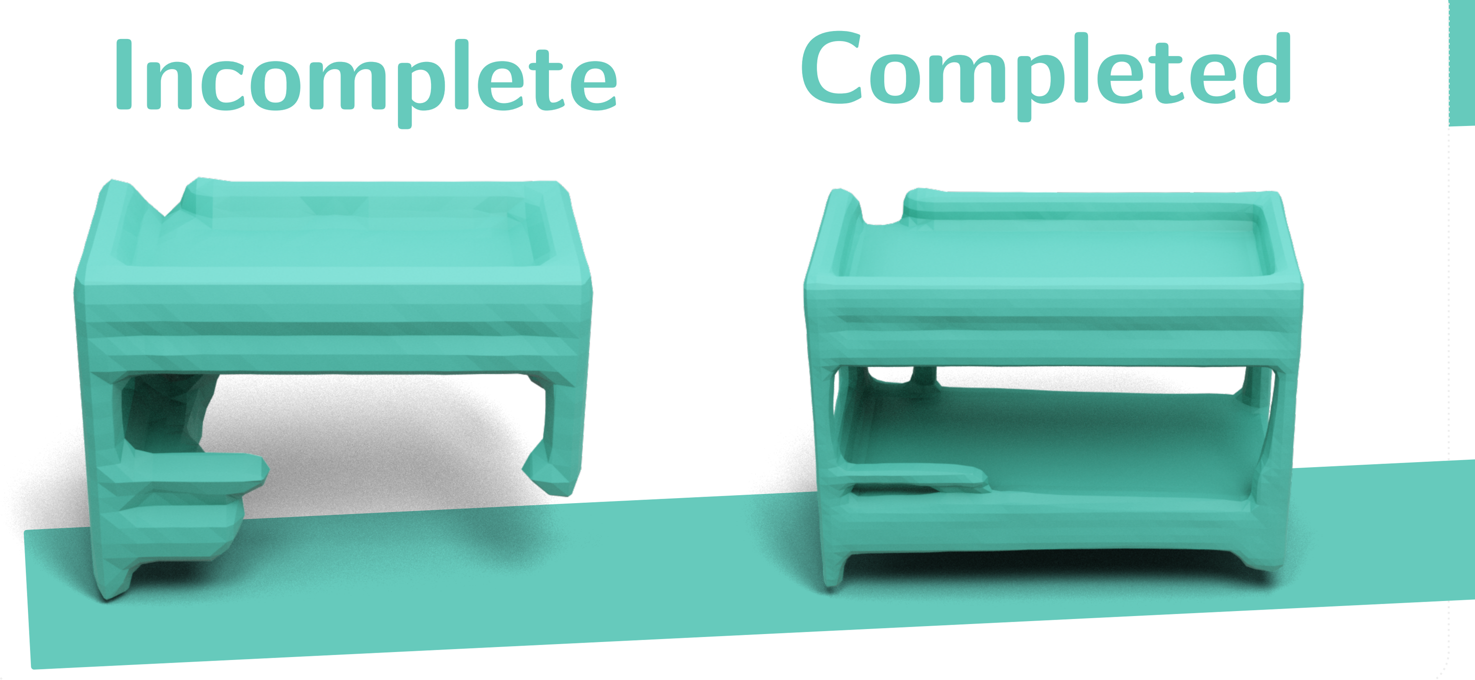
GENERATIVE MODELS FOR 3D SHAPE COMPLETION

Author: Peter Zdravecký
Supervisor: Tibor Kubík



Motivation and Proposed Method

The **goal** is to **automatically complete 3D shapes** based on the incomplete input using deep learning techniques. In many real world scenarios, scanned 3D models contain missing parts due to **occlusion**, **scanning errors** or the **incomplete nature** of the data itself.

The **proposed solution** is to use a **diffusion-based model** and handle the task as a generative problem to create a complete shape from the incomplete one.

Forward process:

$$q(x_{0:T}) = q(x_0)\prod_{t=1}^{T} q(x_t \mid x_{t-1}), \quad q(x_t \mid x_{t-1}) := \mathcal{N}\left(\sqrt{1-\beta_t}x_{t-1}, \beta_t \mathbf{I}\right).$$

Equation 1.

Backward process:

$$p_\theta(x_{0:T}, c) = p(x_T)\prod_{t=1}^{T} p_\theta(x_{t-1} \mid x_t, c), \quad p_\theta(x_{t-1} \mid x_t) := \mathcal{N}\left(\mu_\theta(x_t, t, c), \sigma_t^2 \mathbf{I}\right).$$

Equation 2.

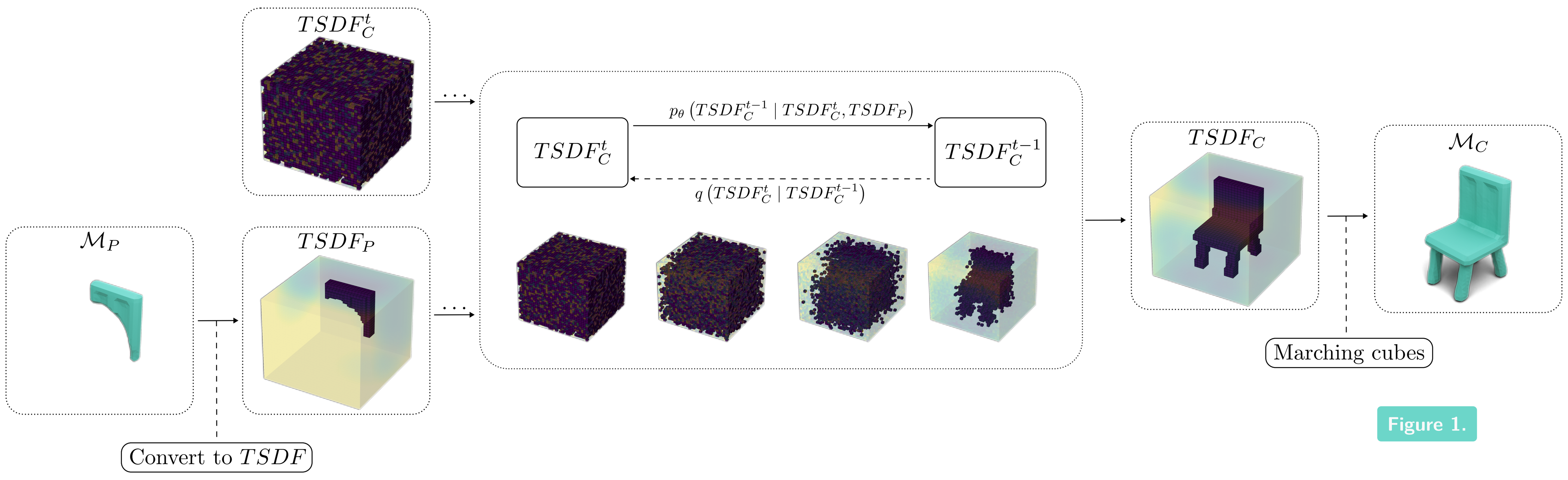


Figure 1.

Backward process is modeled using a **two-branch** architecture utilizing **3D Unet**, to handle the input and condition.

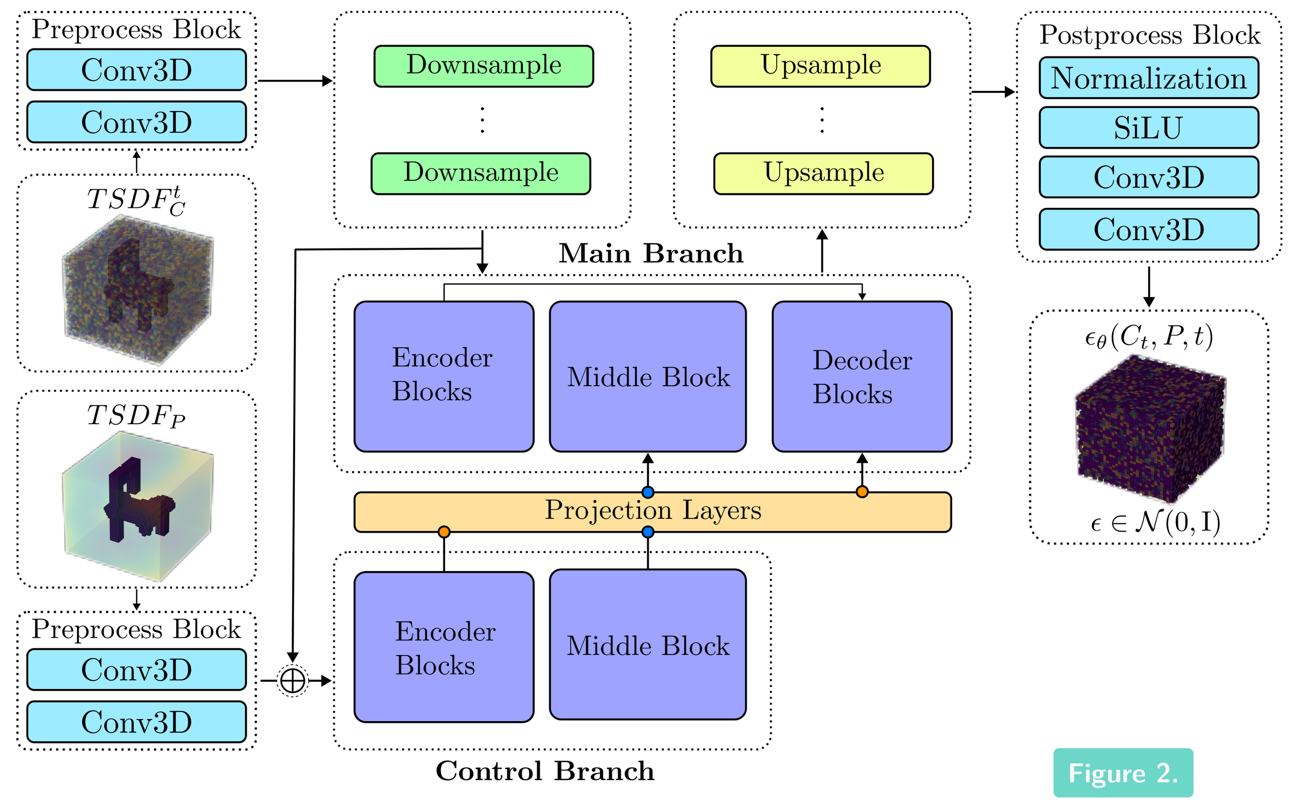


Figure 2.

1. Preprocess the input to a higher-dimensional space.
2. Downsample the input to spatial resolution of condition.
3. Process input/condition using two-branch 3D UNet.
4. Upsample output back to the original resolution.
5. Cast output to a lower-dimensional space.

Results and Conclusion

Experimental results show **high capability** of this model in **shape completion** task with high score of IoU for chosen datasets. The model possesses a strong ability to make use of the repetitive shape parts to adapt to data out of the training distribution. To enhance the generative process, the **Region of Interest** can be utilized to define the area of the missing parts. Additional experiments focused on generating results in higher resolution. A method was proposed for this purpose that uses **low-resolution processing** followed by upscaling process.

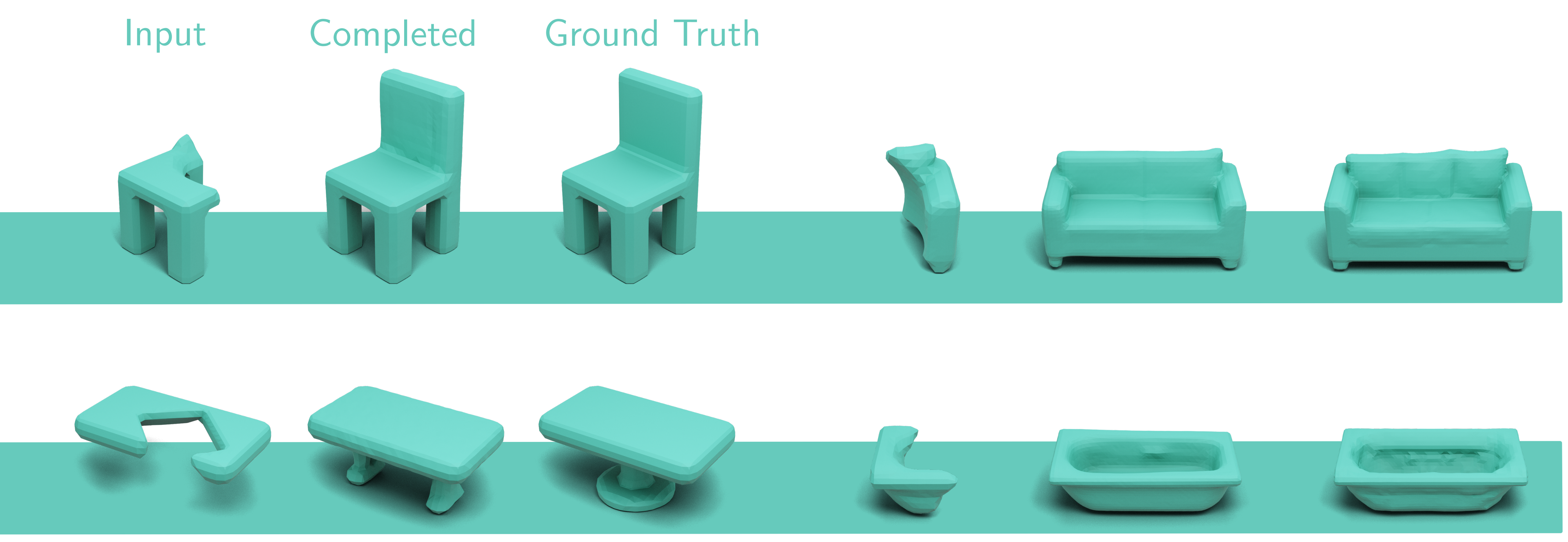


Figure 3.

The produced **results** from the automated shape completion are **very promising** for **real world** use. However, the inference time takes approximately **3-5 seconds**, therefore shape completion in real time is currently impossible.

Dataset	Metrics		
	$IoU\uparrow(\times10^2)$	$CD\downarrow(\times10^2)$	$\mathcal{L}_1\downarrow$
Objaverse – Furniture	81.62	3.53	0.026
Objaverse – Vehicles	76.05	4.21	0.035
Objaverse – Animals	70.46	5.48	0.052
ModelNet	63.34	5.93	0.055
ShapeNet	73.93	5.52	0.048

Quantitative results on multiple datasets.

Table 1.

Diffusion Process

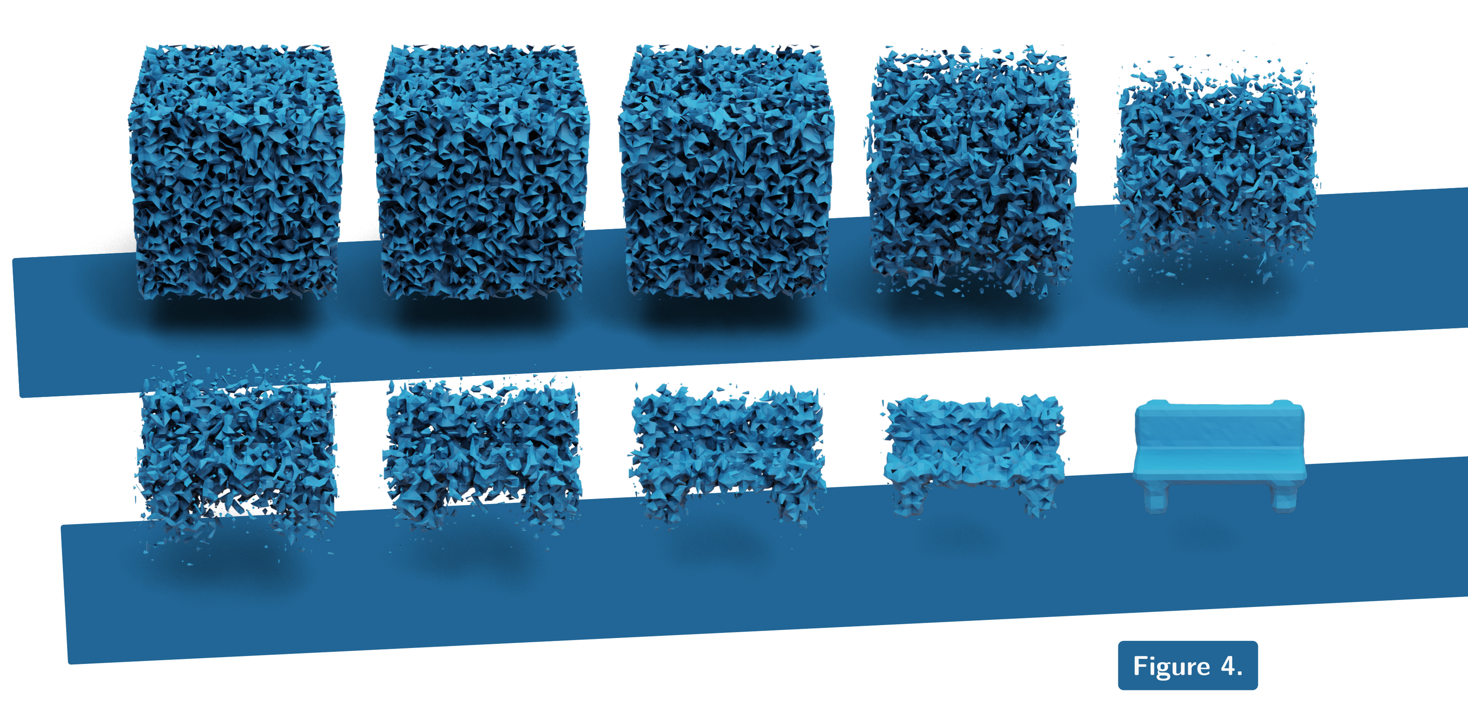


Figure 4.

Inference caputerd in different timestamp of backward diffusion process.

BRNO UNIVERSITY OF TECHNOLOGY
FACULTY OF INFORMATION TECHNOLOGY

Excel@FIT 2024