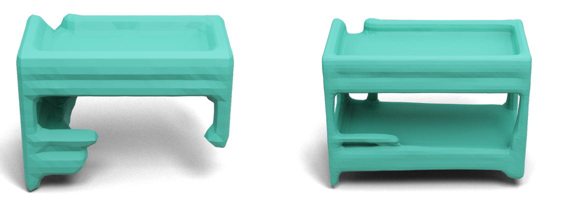
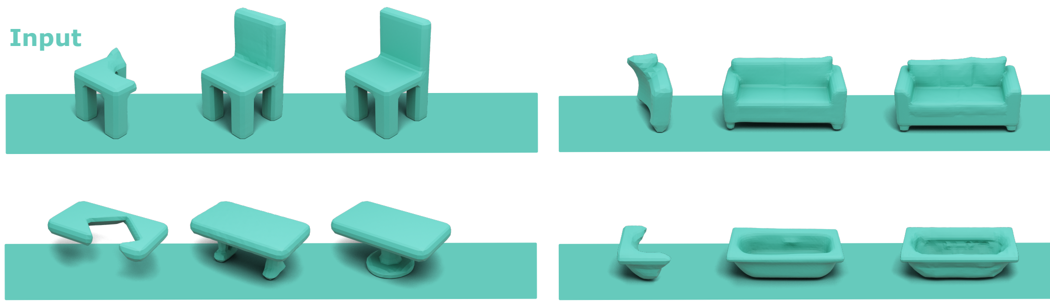
# GENERATIVE MODELS FOR 3D SHAPE COMPLETION

BRNO UNIVERSITY OF TECHNOLOGY
FACULTY OF INFORMATION TECHNOLOGY

**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. This work has potential for extensive use in medicine, especially with regards to dental crown scans, cranial implants, etc. Researchers from Canada have already shown interest in this thesis to apply it on dental crowns generation.

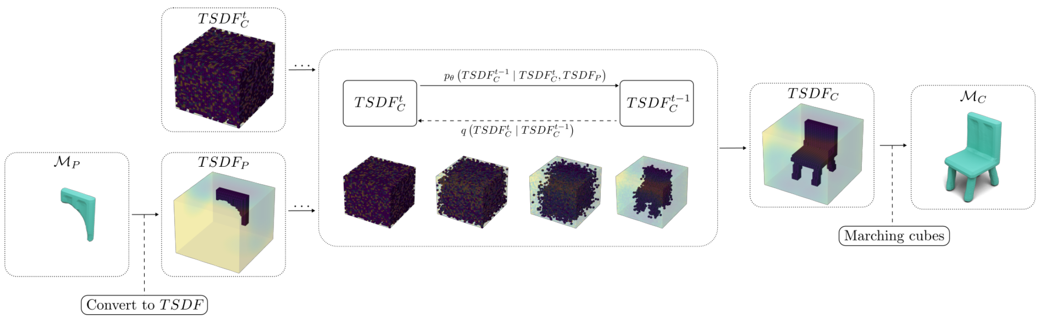
The **proposed solution** is to use a **diffusion-based model** and handle the task as a generative problem to create a complete shape from the incomplete one.

Forward process:

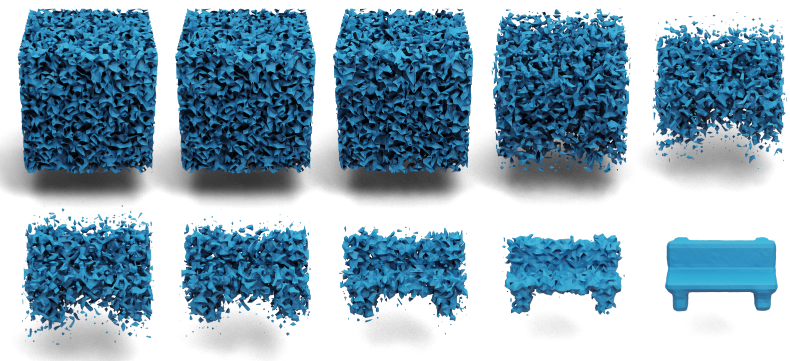
$$q\left(x_{0:T}\right) = q\left(x_0\right)\prod_{t=1}^{T} q\left(x_t \mid x_{t-1}\right), \quad q\left(x_t \mid x_{t-1}\right) := \mathcal{N}\left(\sqrt{1-\beta_t}x_{t-1}, \beta_t\mathbf{I}\right).$$

Backward process:

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




## Diffusion Process



**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.

| Dataset | Metrics | | |
|---|---|---|---|
| | $IoU\uparrow(\times 10^2)$ | $CD\downarrow(\times 10^2)$ | $\mathcal{L}_1\downarrow$ |
| 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 |