SketchSampler: Sketch-based 3D Reconstruction via View-dependent Depth Sampling –Supplementary Material–

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1 Further Experimental Details

Evaluation details. To quantitatively compare the quality of the generated 3D shapes, we first sampled 2048 points on the surface of the 3D mesh reconstructed by Sketch2Mesh [2], Sketch2Model [10], and DISN [9]. The number of output points of PCDNet and our approach are also set to 2048. We use the source code provided by the baseline works and train all the models based on our proposed Synthetic-Linedrawing dataset. For Sketch2Model and Sketch2Mesh, we follow their original settings to train individual model for each category. Because the released code of Sketch2Point [8] does not allow us to adjust the number of output points, we follow its code and use 1024 points for Sketch2Point. We use a ground-truth (GT) point cloud with 2048 points to calculate CD, EMD, FPD for all methods (except for Sketch2Point which uses a GT point cloud with 1024 points). Chamfer distance between two point sets $\mathcal{X}, \mathcal{Y} \subseteq \mathcal{R}^3$ is defined as in Eq. (1).

$$d_{CD}(\mathcal{X}, \mathcal{Y}) = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \min_{y \in \mathcal{Y}} \|x - y\|_2^2 + \frac{1}{|\mathcal{Y}|} \sum_{y \in \mathcal{Y}} \min_{x \in \mathcal{X}} \|y - x\|_2^2 \tag{1}$$

EMD is defined as in Eq. (2). We use the implementation provided by [4] to compute the EMD.

$$d_{EMD}(\mathcal{X}, \mathcal{Y}) = \frac{1}{|\mathcal{X}|} \min_{\phi: \mathcal{X} \to \mathcal{Y}} \sum_{x \in \mathcal{X}} \|x - \phi(x)\|_2 \tag{2}$$

where $\phi : \mathcal{X} \to \mathcal{Y}$ is a bijection.

FPD does not evaluate the generation quality of individual samples, but the overall quality of the generated distribution. We refer the readers to [7] for more details. To compute Voxel-IOU, we used a similar method as in [5,6]. We first

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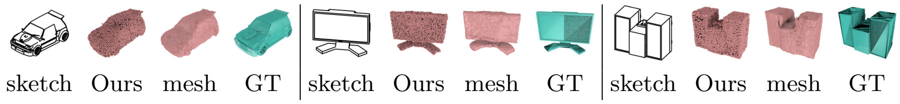

Fig. A. Our estimated meshes on the Synthetic-LineDrawing dataset.

voxelize 3D shapes $\mathcal{P}$ and $\mathcal{Q}$ to $32 \times 32 \times 32$ voxels, then calculate the IOU of two voxelized 3D shapes by using Eq. (3).

$$\text{Voxel-IOU}(\mathcal{P}, \mathcal{Q}) = \frac{\text{intersection } (\mathcal{V}(\mathcal{P}), \mathcal{V}(\mathcal{Q}))}{\text{union}(\mathcal{V}(\mathcal{P}), \mathcal{V}(\mathcal{Q}))} \tag{3}$$

where $\mathcal{V}$ denotes the voxelization process.

2 More Qualitative Results

More results on Synthetic-LineDrawing dataset. In Fig. B, we provide more reconstructed results of our proposed method and baseline methods on the *Synthetic-LineDrawing* dataset. It is clear to see that our proposed method can reconstruct 3D shapes with higher quality, e.g., the reconstructed results of our proposed method can reflect the structure of target objects more accurately and be more aligned with the input sketches.

More results on hand-drawn sketch datasets. Fig. C shows three examples of each category from the ShapeNet-Sketch dataset [10]. Fig. D and Fig. E illustrate the reconstructed results on sketches from the ProSketch-3DChair [11] dataset and AmateurSketch dataset [11], respectively.

Mesh generation. While our proposed method is designed to produce point clouds, it can be easily extended to generate mesh via the post-processing operations. Given a generated point cloud, we can use the Poisson surface reconstruction [3] and existing normal estimation methods such as [1] to convert a point cloud to its mesh representation. Several examples are illustrated in Fig. A.

Results of predicted density map. On Synthetic-LineDrawing, the average PSNR and SSIM of the predicted density map over all categories is 29.769 and 0.951, respectively. Fig. F shows more qualitative results of the predicted density map.

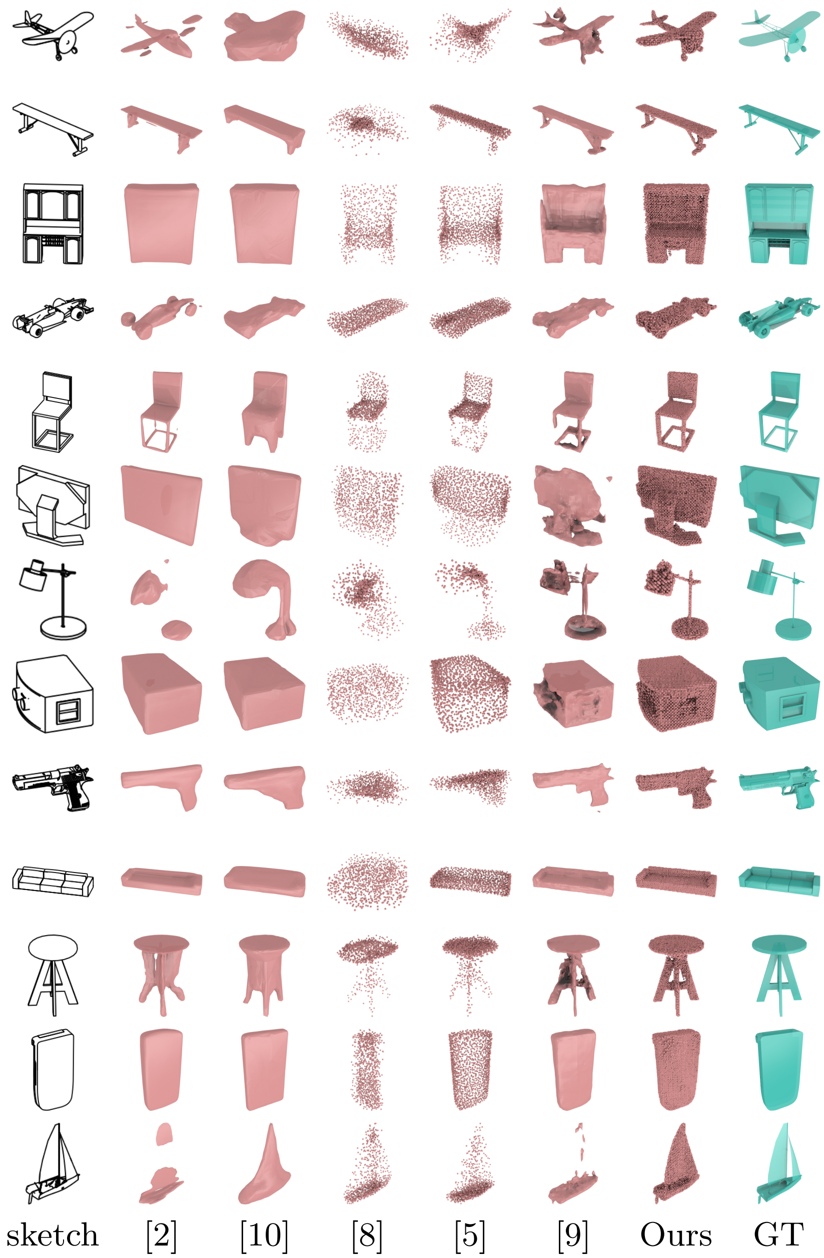

Fig. B. Reconstructed results of our method and different baseline methods on the ShapeNet-LineDrawing dataset. The baseline methods are Sketch2Mesh[2], Sketch2Model[10], Sketch2Point[8], PCDNet[5], and DISN[9]. "GT" means ground-truth.

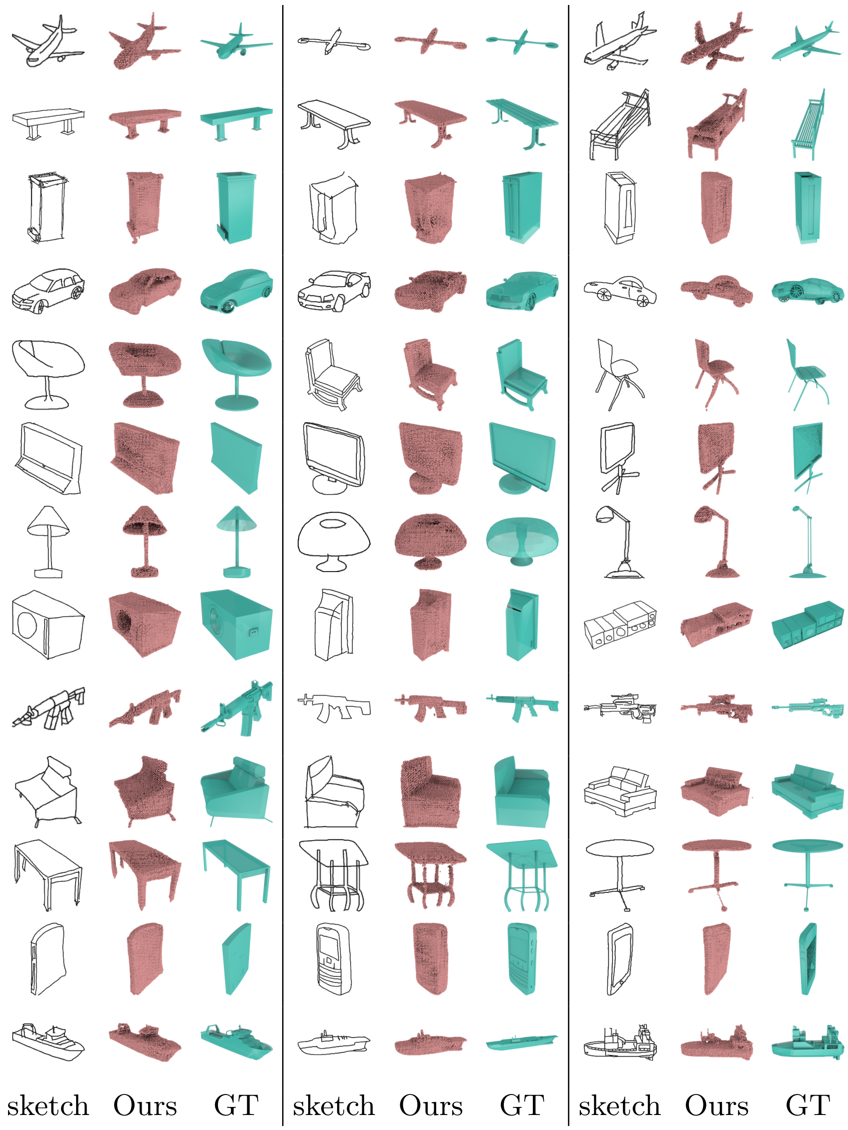

Fig. C. Reconstructed results of our method on the ShapeNet-Sketch dataset. "GT" means ground-truth.

Fig. D. Reconstructed results of our method on the ProSketch-3DChair dataset. "GT" means ground-truth.

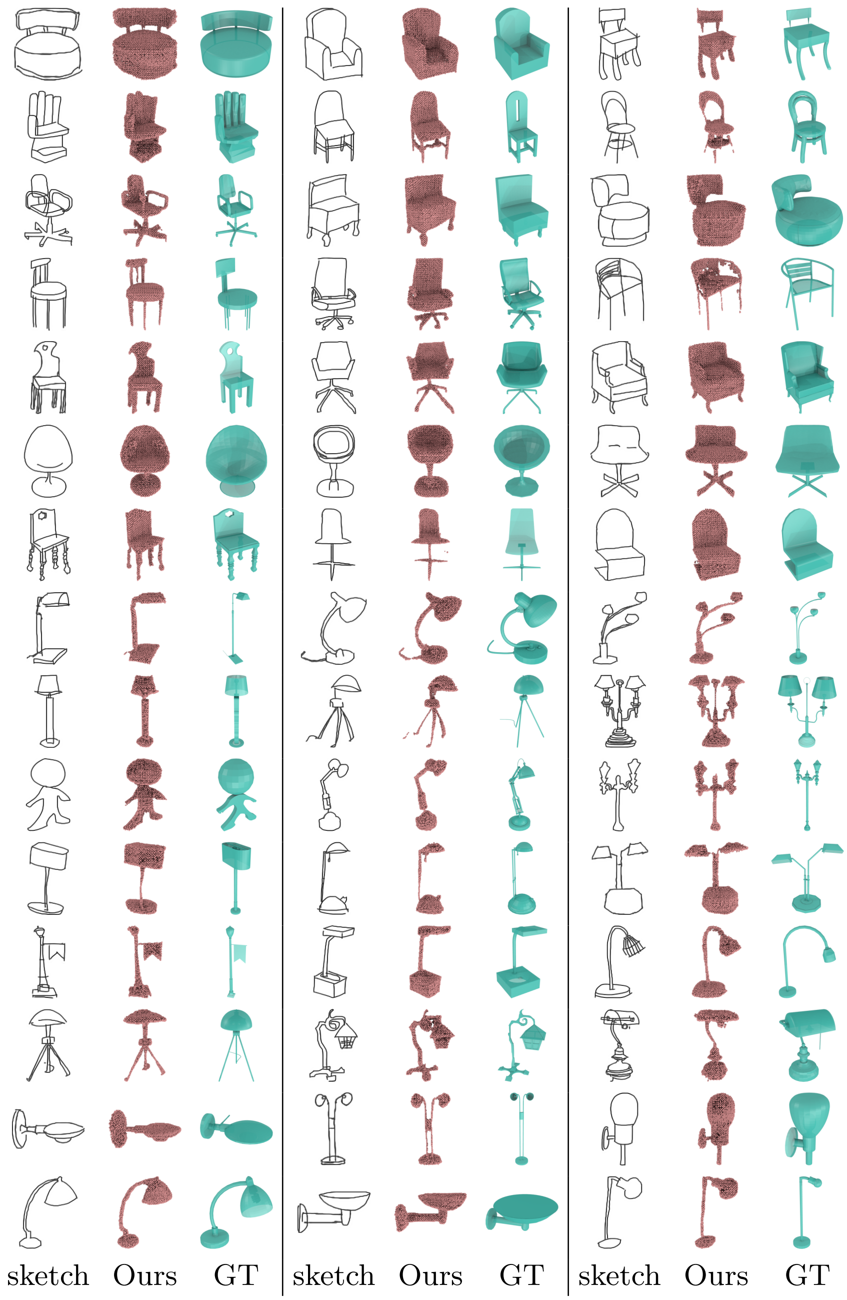

Fig. E. Reconstructed results of our method on the AmateurSketch dataset. “GT” means ground-truth.

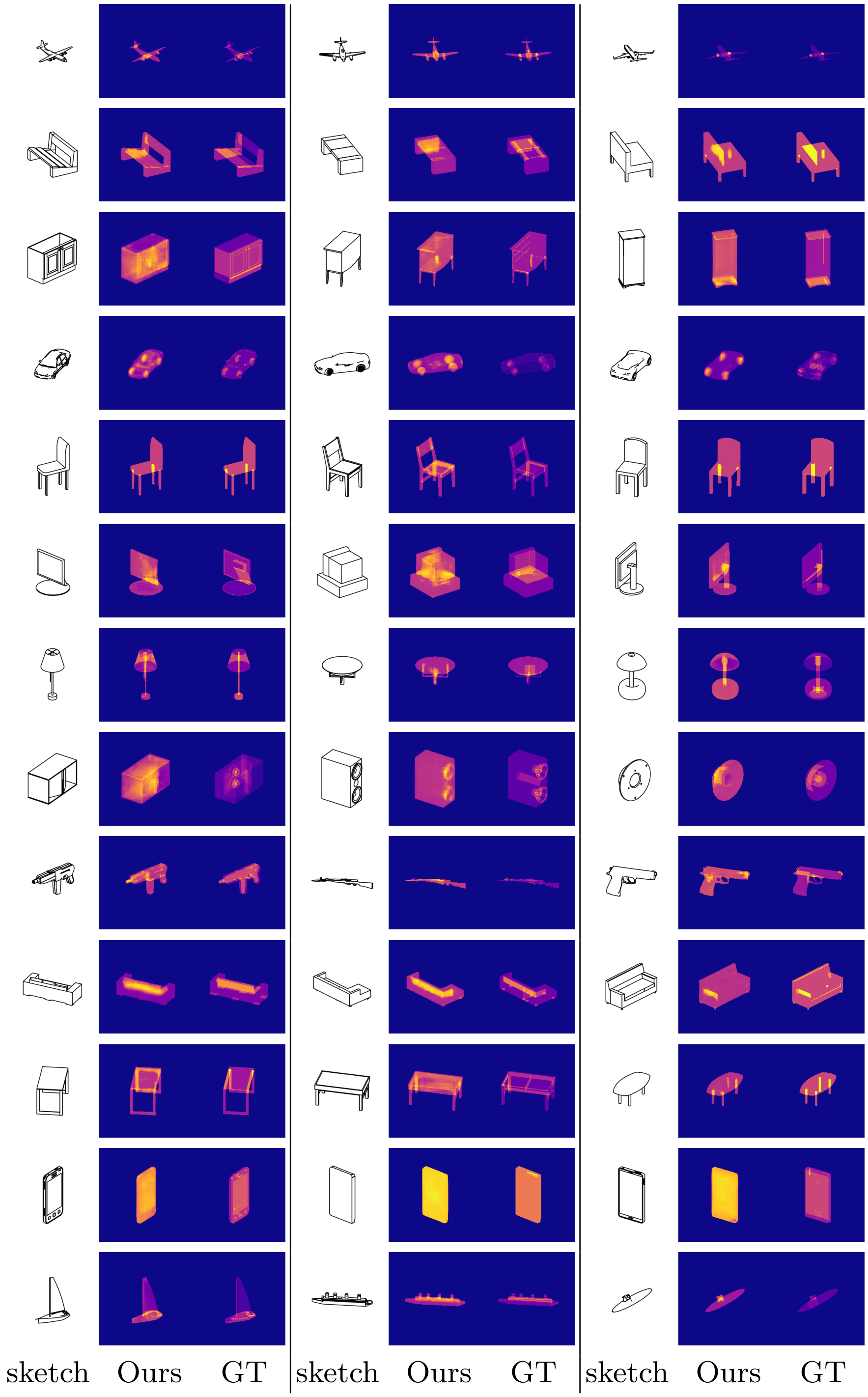

Fig. F. Density maps predicted by our method on the ShapeNet-LineDrawing dataset. “GT” means ground-truth.

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