WarpingGAN: Warping Multiple Uniform Priors for Adversarial 3D Point Cloud Generation (Supplementary Materials)

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In this supplementary material, we provided the detailed network architecture of our WarpingGAN (Section 1), the subjective evaluation of different methods (Section 2), and more visual results including results of ablation Studies on *Airplane* (Section 3.1), results of more shapes generated by our method (Section 3.2), the video demo (Section 3.3 and the *demo https://youtu.be/GY1EeGI6jZ0* video), and results of failure cases (Section 3.4).

1. Details of the Network Architecture

Table 1 shows the detailed network architecture of the proposed WarpingGAN, including the code enhancement module and unified local-warping module in the generator and also the discriminator. In Table 1, we presented the input and output dimensions of each layer, where *Shared MLP* denotes one unified set of MLP parameters is applied to N points in parallel. Note that we utilized LeakyReLU with the slope equal to 0.2 as the activation function.

Module	Architecture
Code Enhancement	MLP(128, 128)+LeakyReLU MLP(128, 128)+LeakyReLU MLP(128, 256)+LeakyReLU MLP(256, 256)+LeakyReLU MLP(256, 512)+LeakyReLU
1^{st} Unified Local-warping	Concat(512+512/16+3)→547 Shared MLP(547,256)+LeakyReLU Shared MLP(256,64)+LeakyReLU Shared MLP(64,3)
2^{nd} Unified Local-warping	Concat(512+512/16+3)→547 Sharec MLP(547,256)+LeakyReLU Shared MLP(256,64)+LeakyReLU Shared MLP(64,3)
Discriminator	Shared MLP(3,64)+LeakyReLU Shared MLP(64,128)+LeakyReLU Shared MLP(128,256)+LeakyReLU Shared MLP(256,512)+LeakyReLU Shared MLP(512,512)+LeakyReLU MaxPooling→ 512 MLP(512,1)

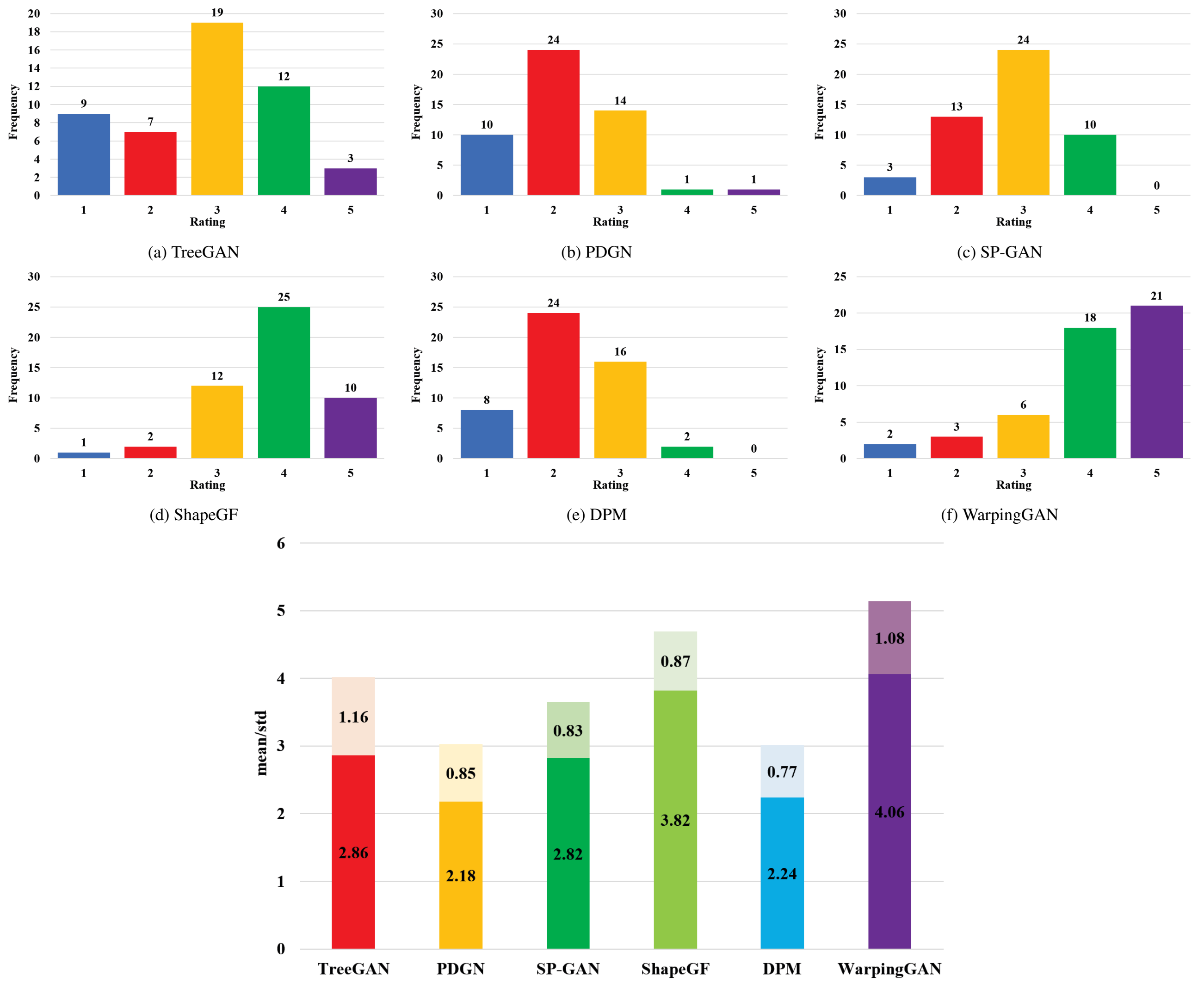
Table 1. Network architecture of WarpingGAN.

2. Subjective Evaluation

As argued in our manuscript, the MMD and COV-based quantitative evaluations may not faithfully reflect the quality of generated data. Thus, we conducted subjective evaluation to compare different methods quantitatively Specifically, We invited 50 volunteers covering undergraduate students, postgraduate students with various research background, and researchers and engineers from industry to do the evaluation on *Chair*, *Airplane* and *Car* three categories of ShapeNet. For each method, we displayed the video rendered from 20 randomly generated point clouds and asked the volunteers to rate the method with the score in the range of 1 and 5, based on the quality of the generated shapes, i.e., 1: bad, 2: poor, 3: fair, 4: good, 5:excellent.

Besides, the point clouds randomly selected from the real dataset were displayed for reference. We refer the readers to the submitted video demo named *demo.mp4* to examine the shapes in this subjective evaluation. Note that the names of methods are blind to volunteers, and we randomly displayed the videos of different methods for the three categories.

Figs. 1, 2, and 3 show the results of the subjective evaluation, where we provided the score distribution of each method and the mean value and the standard deviation (std) of the scores. It can be seen that our WarpingGAN consistently obtains the highest mean scores for all three categories. Particularly, for *Chair* and *Airplane*, most volunteers rated our WarpingGAN with 5, while rating the other methods with $2 \sim 4$. For *Car*, the compared methods only obtain the mean scores around 2, while the mean score of our WarpingGAN is about 4. This subjective evaluation convincingly demonstrate the advantage of our WarpingGAN over state-of-the-art methods in terms of the quality of generated data.



(a) TreeGAN (b) PDGN (c) SP-GAN

(d) ShapeGF (e) DPM (f) WarpingGAN

(g) Overall performance. The upper and bottom numbers are the std and mean values, respectively.

Figure 1. Results of the subjective evaluation on *Chair*.

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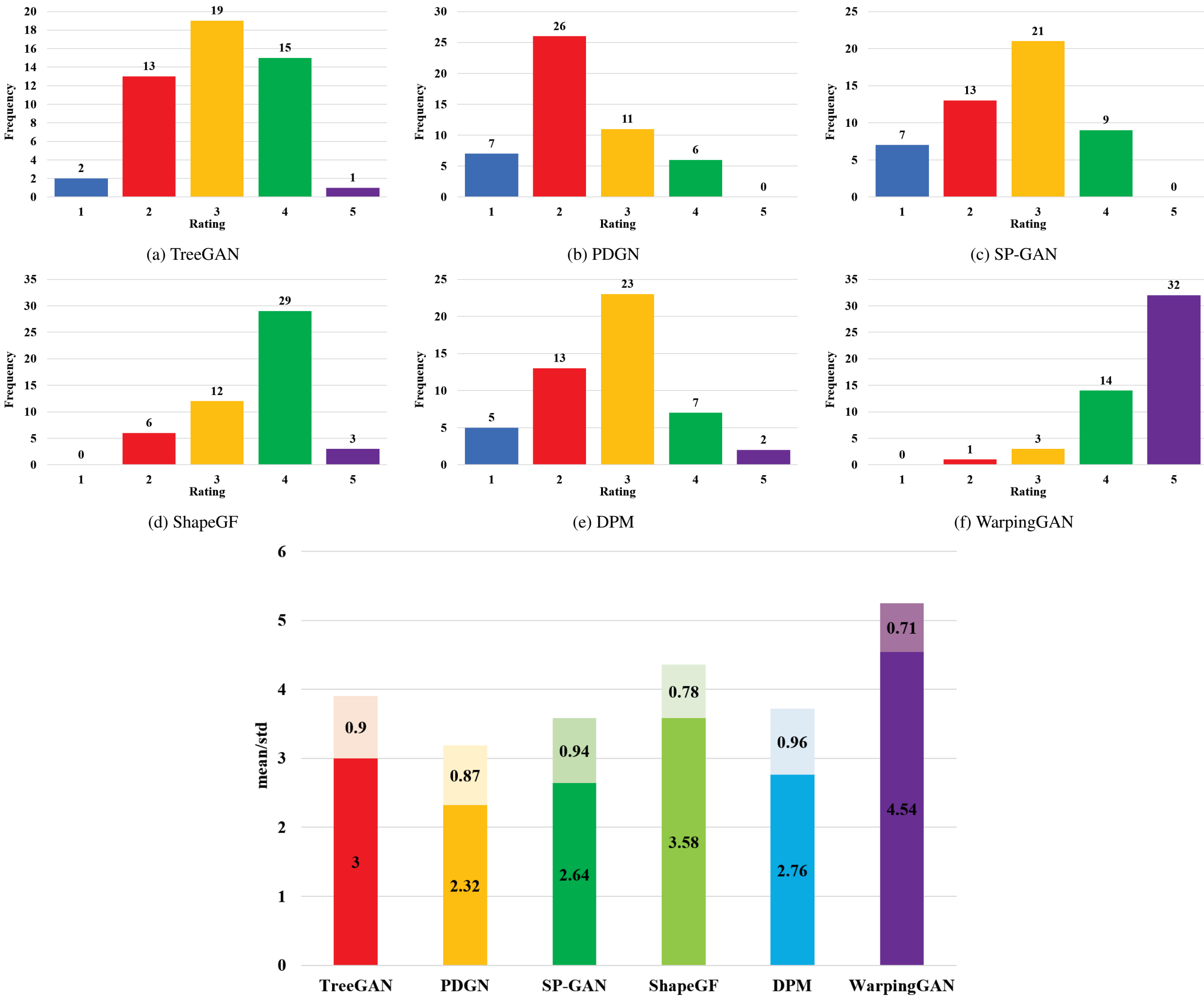
3. More Visual Results

3.1. Visual Results of Ablation Studies on Airplane

In Section 4.3 of the manuscript, we conducted the ablation studies of the proposed WarpingGAN quantitatively and visually over the *Chair* category. Here, we also provided the visual results of the ablation studies on the *Airplane* category.



(a) TreeGAN (b) PDGN (c) SP-GAN

(d) ShapeGF (e) DPM (f) WarpingGAN

(g) Overall performance. The upper and bottom numbers are the std and mean values, respectively.

Figure 2. Results of the subjective evaluation on *Airplane*.

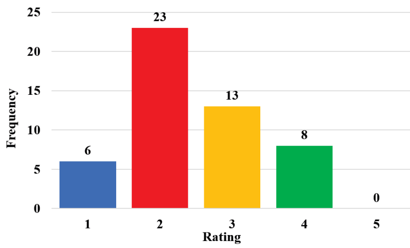
We followed the settings of Section 4.3, including the ablation studies towards the code enhancement module (Fig. 4), the global shape code (Fig. 5), the 2D vs. 3D priors (Fig. 6), and the non-uniform vs. uniform priors (Fig. 7). Here we omitted the ablation study towards the stitching loss on *Airplane*, since it has already been demonstrated in the manuscript (i.e., Section 4.3 **The effectiveness of the stitching loss** of the manuscript). These results further demonstrate the effectiveness of each module of our WarpingGAN.

3.2. Visual Illustration of More Shapes

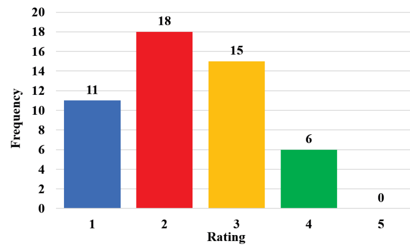
We provided visual results of generated 3D point clouds by our WarpingGAN for more categories, including *Sofa* (Fig. 8), *Cabinet* (Fig. 9), *Vessel* (Fig. 10), *Guitar* (Fig. 11), *Lamp* (Fig. 12), *Can* (Fig. 13) and *Human* (Fig. 14).

3.3. Video Demo

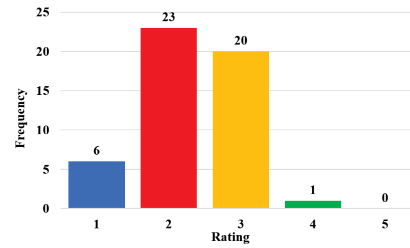
We provided a video demo (*demo.mp4*) to compare the quality of generated shapes by different methods. Note that we also utilized the shapes in this video for the subjective evaluation.



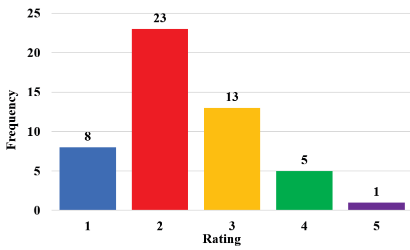
(a) TreeGAN



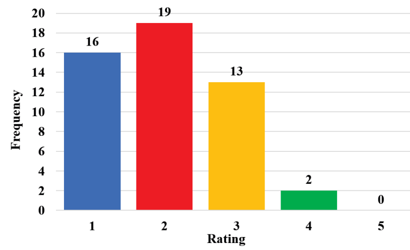
(b) PDGN



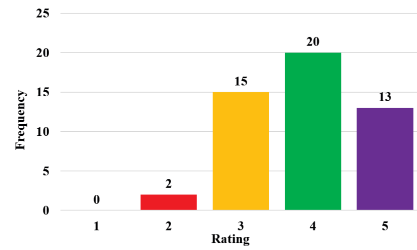
(c) SP-GAN



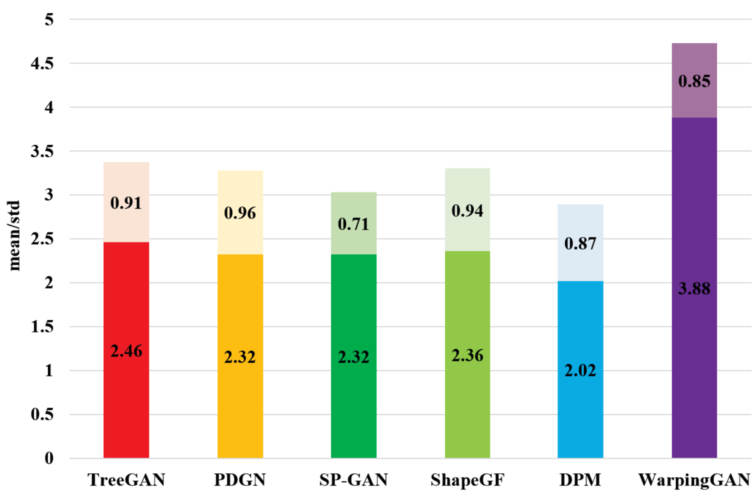
(d) ShapeGF



(e) DPM

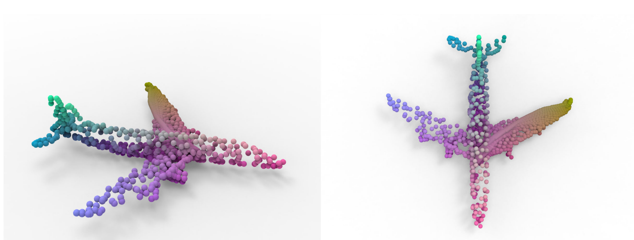


(f) WarpingGAN

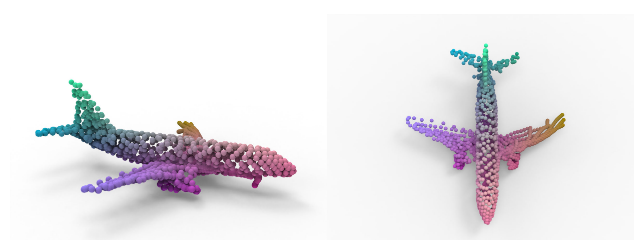


(g) Overall performance. The upper and bottom numbers are the std and mean values, respectively.

Figure 3. Results of the subjective evaluation on *Car*.



(a) without code enhancement

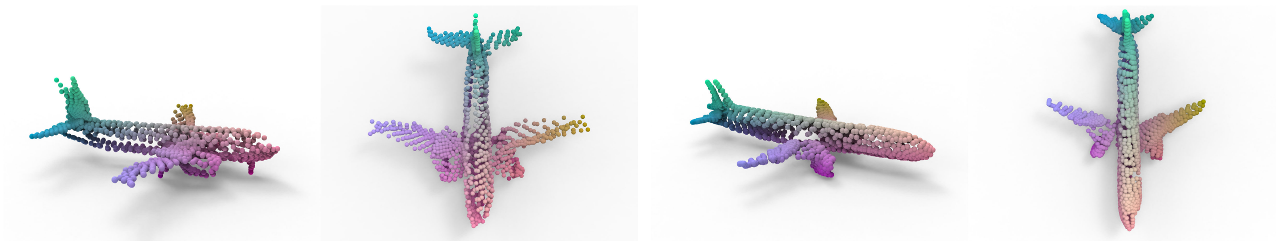


(b) with code enhancement

Figure 4. Visual comparison of our WarpingGAN (a) without and (b) with code enhancement.

3.4. Failure and Low-Quality Cases

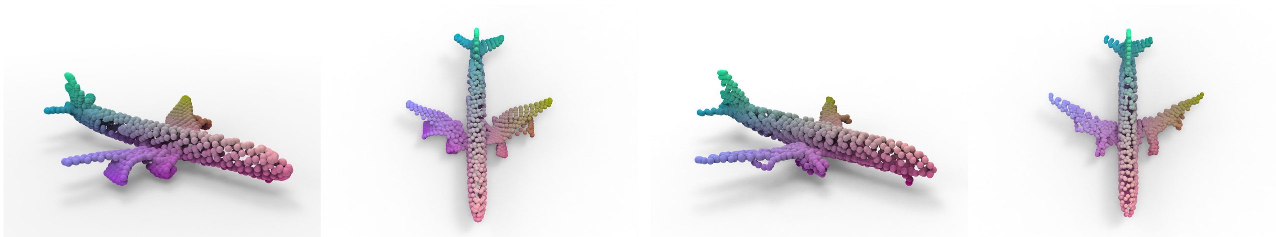
Although our WarpingGAN achieves better performance than state-of-the-art methods, failure and low-quality cases still occur, as GAN-based 3D point cloud generation is a pretty challenging problem and is difficult to train, especially equipped with the weak discriminator PointNet. Thus, WarpingGAN sporadically fails to generate shapes and cannot learn local details



(a) without global shape code

(b) with global shape code

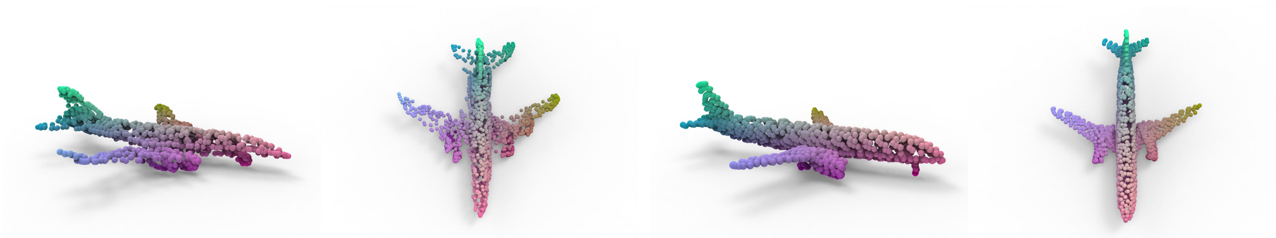
Figure 5. Visual comparison of our WarpingGAN (a) without and (b) with global shape code.



(a) 2D prior

(b) 3D prior

Figure 6. Visual comparison of our WarpingGAN equipped with (a) 2D and (b) 3D priors.



(a) non-uniform priors

(b) uniform priors

Figure 7. Visual comparison of our WarpingGAN equipped with (a) non-uniform and (b) uniform 3D priors.

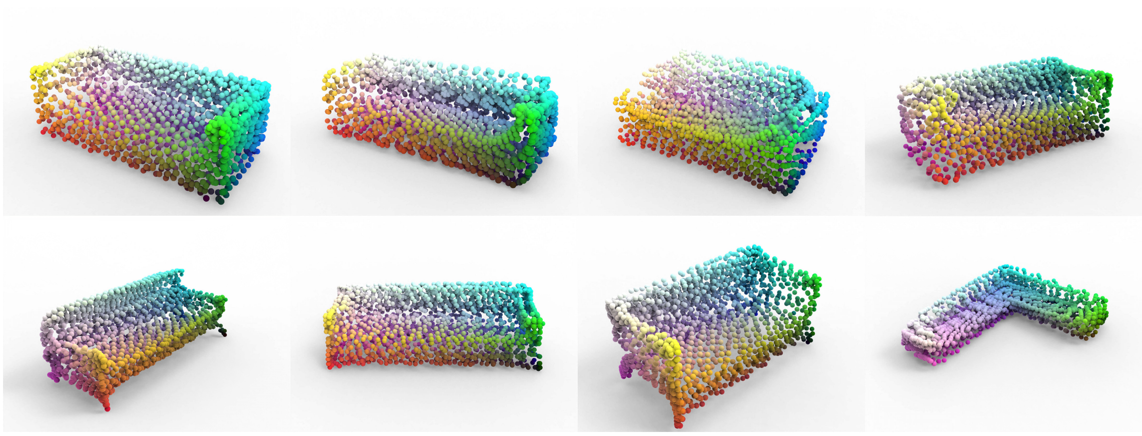


Figure 8. *Sofa* generated by WarpingGAN.

well. In Fig. 15, we presented several failure and low-quality cases of our WarpingGAN, which may bring motivations to the subsequent studies along this stream.

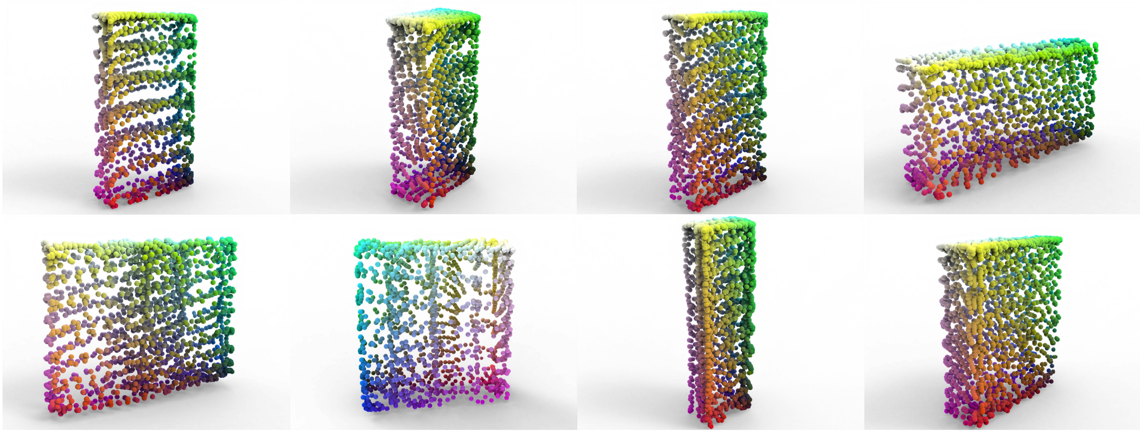


Figure 9. *Cabinet* generated by WarpingGAN.

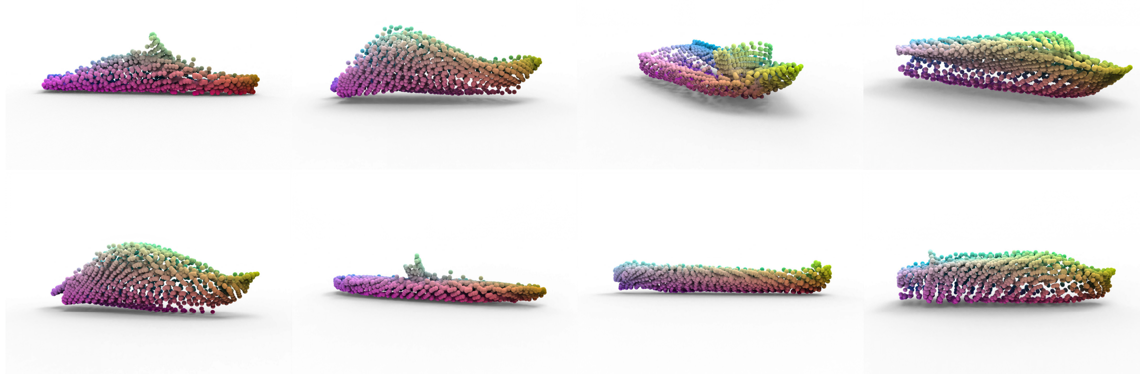


Figure 10. *Vessel* generated by WarpingGAN.

Figure 11. *Guitar* generated by WarpingGAN.

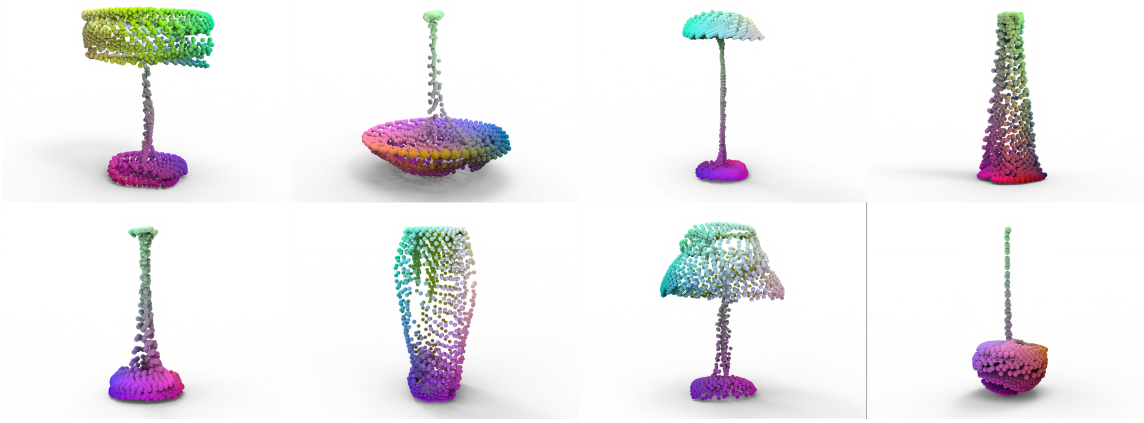


Figure 12. *Lamp* generated by WarpingGAN.

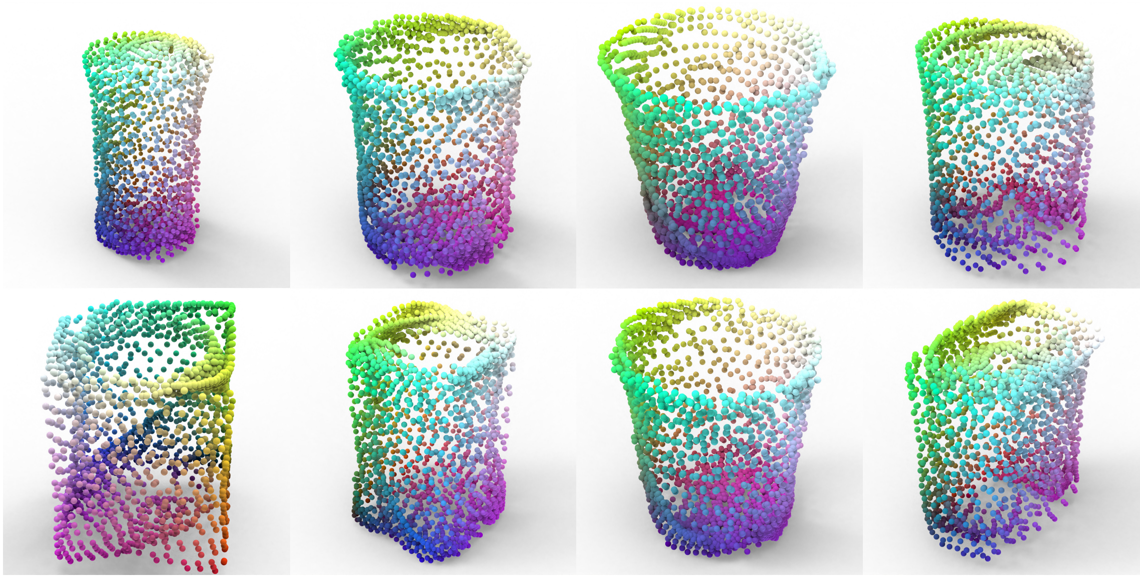


Figure 13. *Can* generated by WarpingGAN.

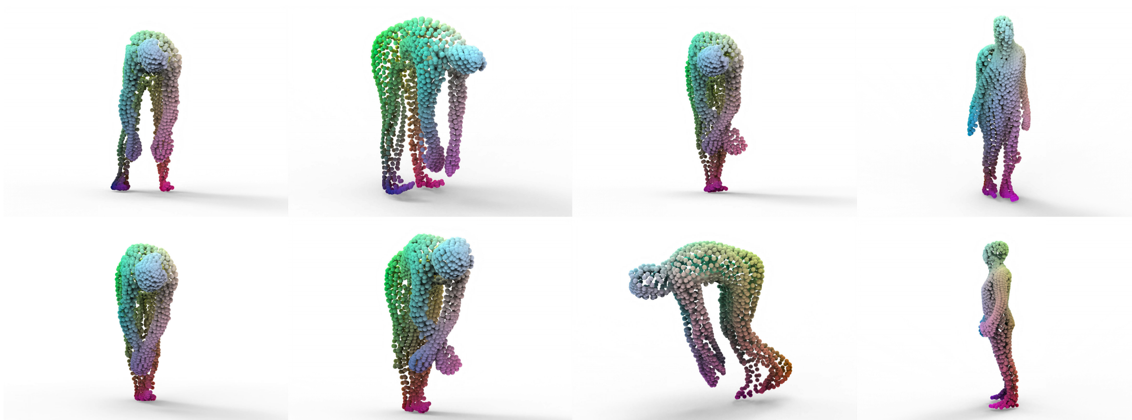
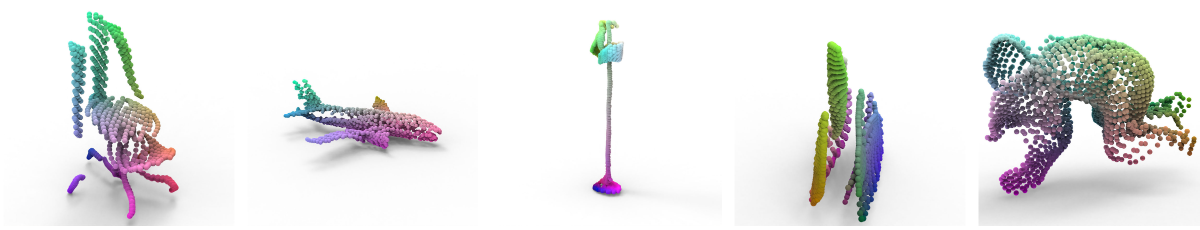


Figure 14. *Human Body* generated by WarpingGAN.



(a) Chair (b) Airplane (c) Lamp (d) Vessel (e) Human

Figure 15. Failure and low-quality cases of (a) *chair*, (b) *airplane*, (c) *lamp*, (d) *vessel* and (e) *human*.