Hypernetwork approach to generating point clouds

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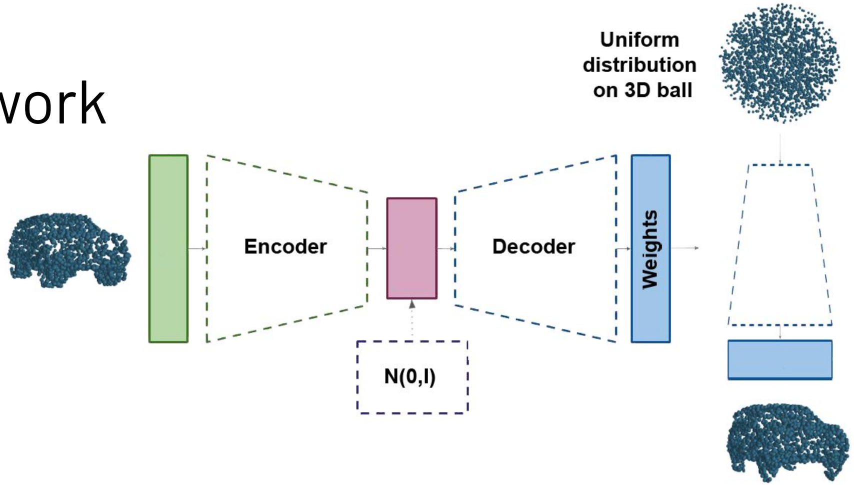
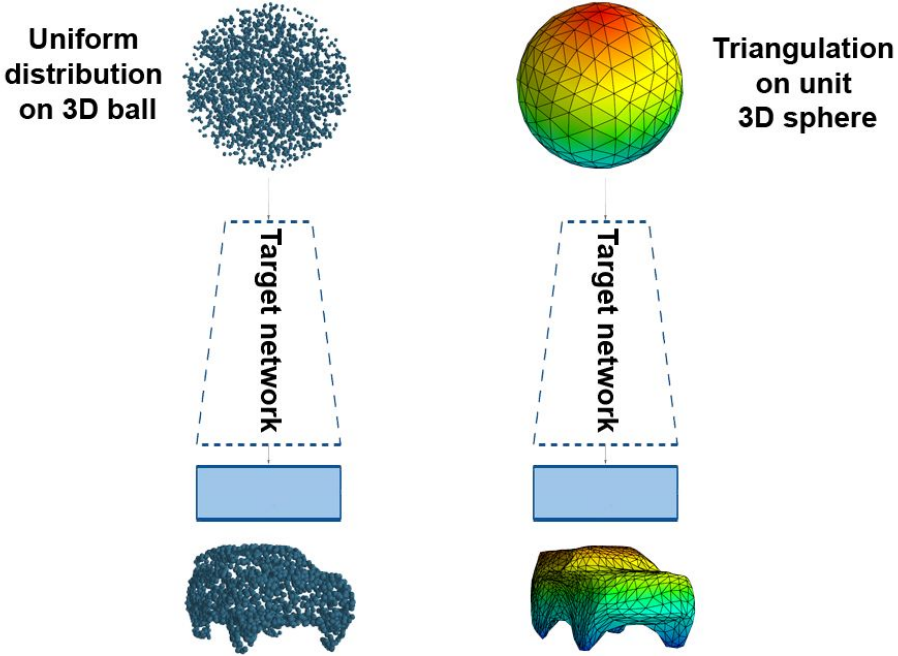
HyperCloud

- AAE architecture for hypernetwork
- PointNet as an Encoder
- Arbitrary prior on latent space
- Decoder produces weights for target network based on latent embedding
- Target network moves points from the uniform distribution on 3D ball to the 3D object



Easily extendible to meshes

- Use precomputed mesh instead of a point cloud
- Feeding vertices to the target network produces high-quality meshes
- No need for second mesh rendering



Experimental results

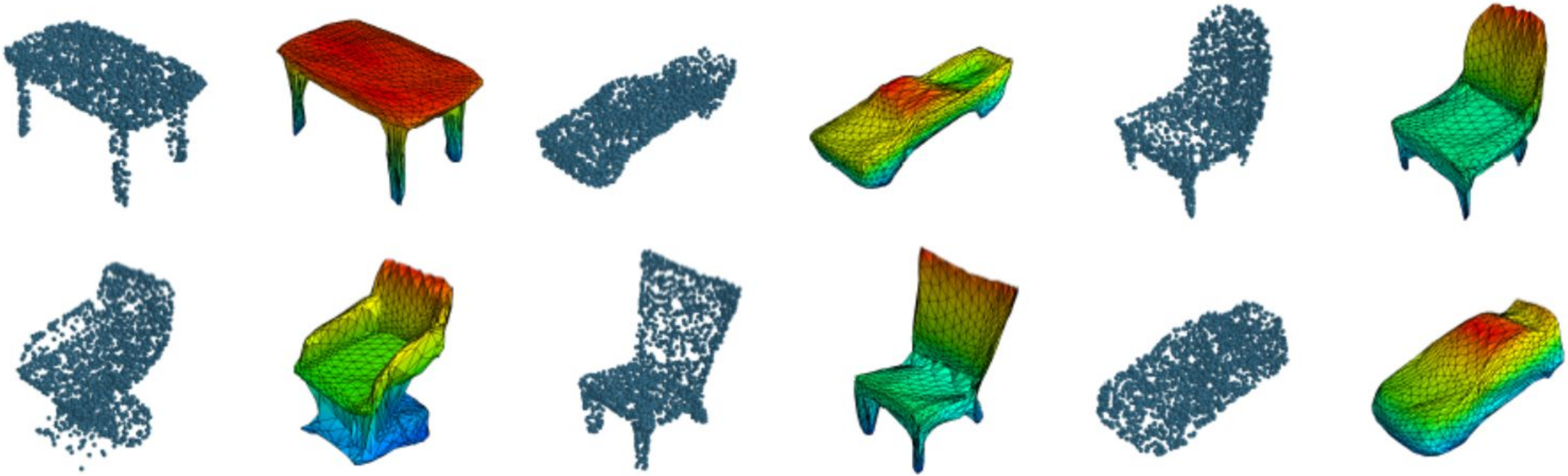


Figure: 3D point clouds and their mesh representations produced by HyperCloud

Experimental results

Table: Quality of representations by sampling from sphere (JSD ↓, MMD ↓, COV↑)

Class	Model	Sphere R	JSD	MMD		COV	
				CD	EMD	CD	EMD
Airplane	PointFlow	2.795	22.26	0.49	6.65	**44.69**	20.74
		3.136	26.46	0.60	6.89	39.50	19.01
		3.368	29.65	0.68	6.84	40.49	16.79
	HyperCloud	1.000	**9.51**	**0.45**	**5.29**	30.60	**28.88**
Chair	PointFlow	2.795	19.28	4.28	13.38	36.85	20.84
		3.136	22.52	4.89	14.47	32.47	17.22
		3.368	24.68	5.36	14.97	31.41	17.06
	HyperCloud	1.000	**4.32**	**2.81**	**9.32**	**40.33**	**40.63**
Car	PointFlow	2.795	16.59	1.60	8.00	20.17	17.04
		3.136	20.21	1.75	7.80	21.59	17.32
		3.368	24.10	1.96	8.35	18.75	17.04
	HyperCloud	1.000	**5.20**	**1.11**	**6.54**	**37.21**	**28.40**

Experimental results

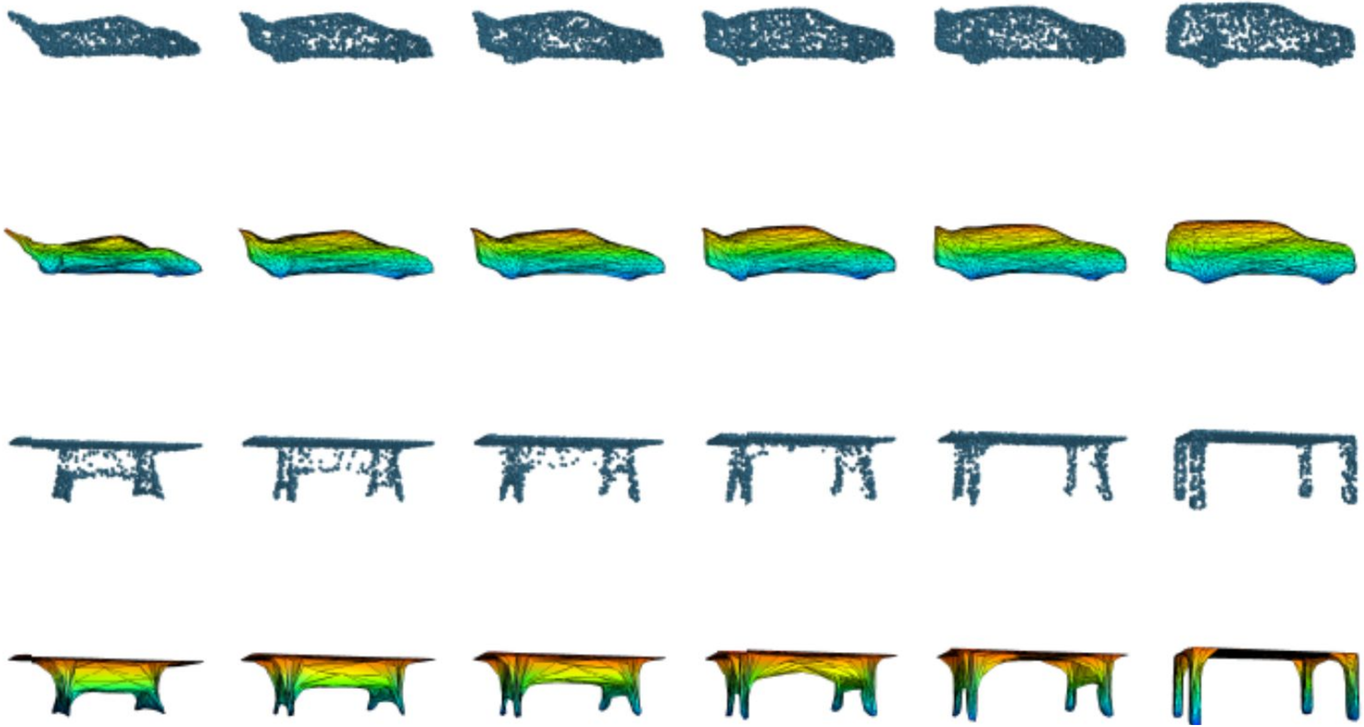


Figure: Interpolations between two 3D point clouds and their mesh representations

Conclusion

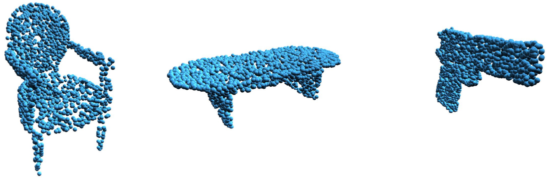
- We present a novel method for generating 3D point clouds
- Our approach is able to work not only on point clouds, but also on 3D meshes
- We leverage the hypernetworks to obtain simple architecture and fast end-to-end training
- Our model is able to generate shapes consisting of an arbitrary number of points or vertices

Point Clouds

- Objects represented as sets of real-valued points

$$= \begin{bmatrix} x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ \vdots & \vdots & \vdots \\ x_K & y_K & z_K \end{bmatrix} \in \mathbb{R}^{K \times 3}$$

- Unstructured
- Unordered - K! possible arrangements of K points
- One of the most common dataset is ShapeNet
  - 57k samples, 55 classes

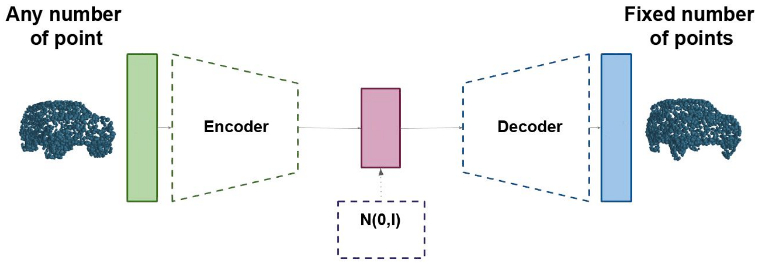


Related work: Hypernetworks

- Is training all parameters in (very) deep neural networks necessary?
- Instead train a smaller NN (hypernetwork) that generates weights for the (target) network
  - HyperNetworks (Ha et al. ICLR 2016)
  - Hypernetwork functional image representation (Klocek et al. ICANN 2019)

Related work: 3d Adversarial Autoencoders

- Adversarial Autoencoders adapted to point cloud data
  - Adversarial Autoencoders (Makhzani et al., ICLR 2016)
  - 3d Adversarial Autoencoders (Zamorski et al., CVIU 2019)
- Using PointNet as an Encoder
  - PointNet (Qi et al., CVPR 2017)
- Able to use an arbitrary prior
- Only generates a fixed number of points



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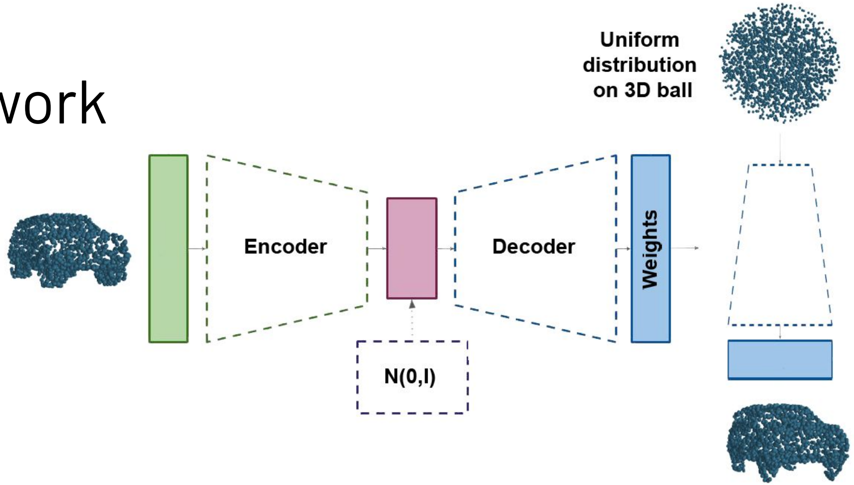

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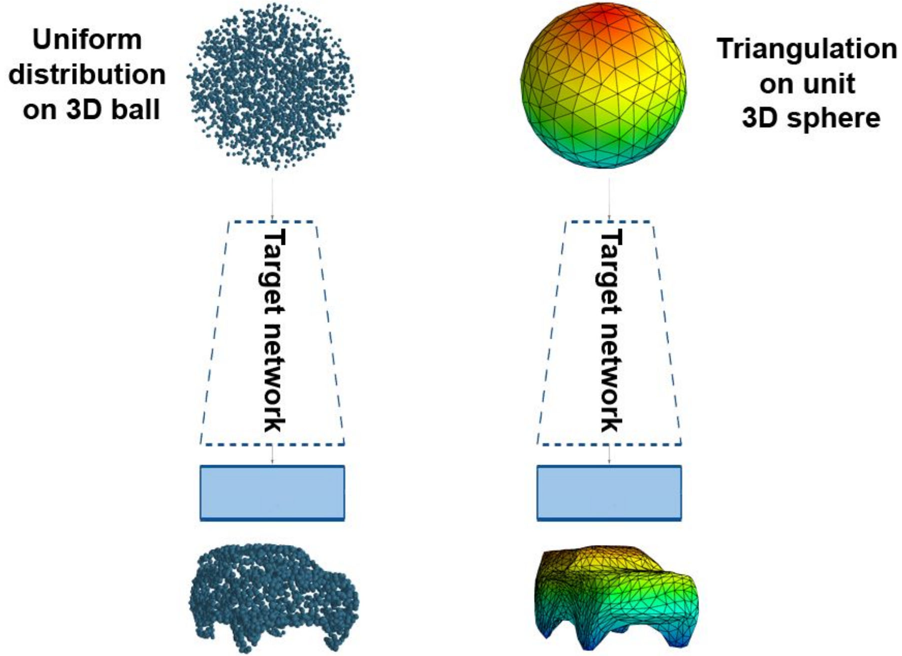

Experimental results

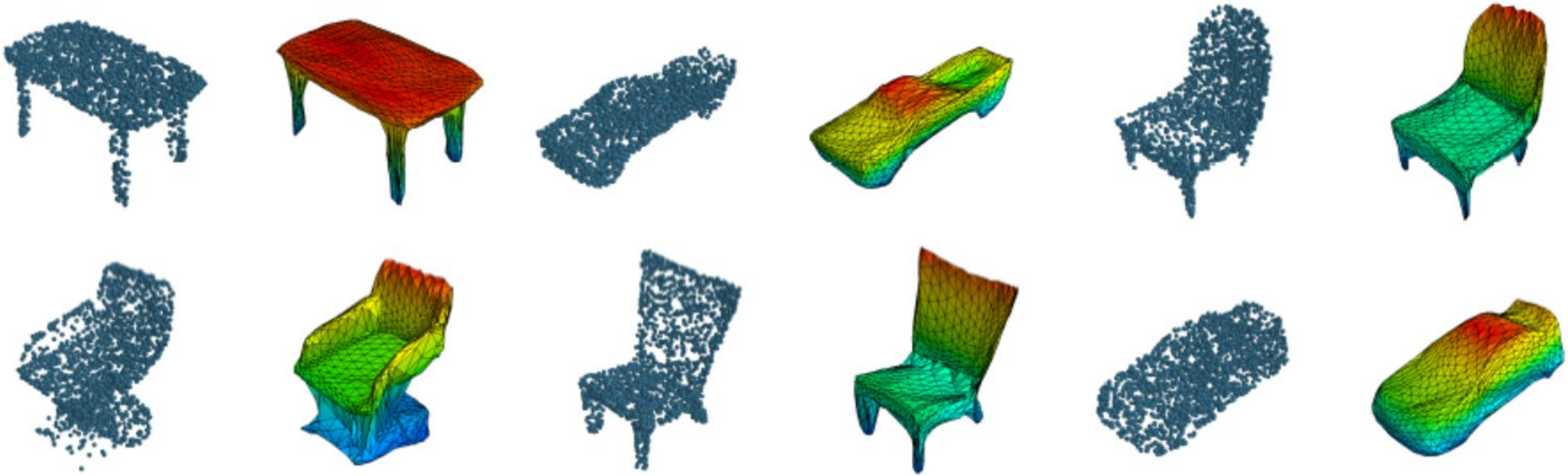

Figure: 3D point clouds and their mesh representations produced by HyperCloud

Evaluation

- Jensen-Shannon Divergence
  - The distance between two distributions
- Coverage
  - A portion of the reference data distribution that is covered by generated samples
- Minimum Matching Distance
  - Similarity of generated samples with respect to the reference set
- 1-Nearest Neighbour Accuracy
  - Are sample and reference test sets indistinguishable to simple classifier?

Experimental results

Table: Generation results (JSD ↓, MMD ↓, COV↑ , 1-NNA)

Class	Model	JSD	MMD		COV		1-NNA	
			CD	EMD	CD	EMD	CD	EMD
Airplane	r-GAN	7.44	0.261	5.47	42.72	18.02	93.58	99.51
	l-GAN (CD)	4.62	0.239	4.27	43.21	21.23	86.30	97.28
	l-GAN (EMD)	**3.61**	0.269	3.29	**47.90**	**50.62**	87.65	85.68
	PC-GAN	4.63	0.287	3.57	36.46	40.94	94.35	92.32
	PointFlow	4.92	**0.217**	**3.24**	46.91	48.40	**75.68**	**75.06**
	HyperCloud	4.84	0.266	3.28	39.75	43.70	93.80	88.95
	Training set	6.61	0.226	3.08	42.72	49.14	70.62	67.53
Chair	r-GAN	11.5	2.57	12.8	33.99	9.97	71.75	99.47
	l-GAN (CD)	4.59	2.46	8.91	41.39	25.68	64.43	85.27
	l-GAN (EMD)	2.27	2.61	7.85	40.79	41.69	64.73	65.56
	PC-GAN	3.90	2.75	8.20	36.50	38.98	76.03	78.37
	PointFlow	**1.74**	**2.42**	7.87	**46.83**	**46.98**	**60.88**	**59.89**
	HyperCloud	2.73	2.56	**7.84**	41.54	46.67	68.20	68.80
	Training set	1.50	1.92	7.38	57.25	55.44	59.67	58.46
Car	r-GAN	12.8	1.27	8.74	15.06	9.38	97.87	99.86
	l-GAN (CD)	4.43	1.55	6.25	38.64	18.47	63.07	88.07
	l-GAN (EMD)	2.21	1.48	5.43	39.20	39.77	69.74	68.32
	PC-GAN	5.85	1.12	5.83	23.56	30.29	92.19	90.87
	PointFlow	**0.87**	**0.91**	**5.22**	**44.03**	**46.59**	**60.65**	**62.36**
	HyperCloud	3.09	1.07	5.38	40.05	40.05	84.65	77.27
	Train set	0.86	1.03	5.33	48.30	51.42	57.39	53.27

Able to use EMD loss

Produce an arbitrary number of points

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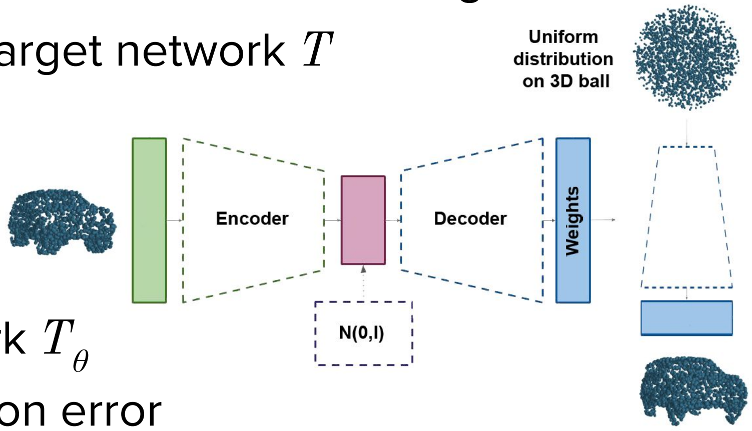
Training details

- Use point cloud X as an input to the encoder E to obtain encoding z
- Based on z, we generate weights θ for the target network T
- Sample same number of points from the 3D prior as in X
- To obtain reconstruction X' pass sampled points through parameterized target network T_θ
- Calculate the loss consisting of reconstruction error and latent space regularization

$$L(X; E, D, P) = Err(X, D(E(X))) + Reg(E(X), P)$$



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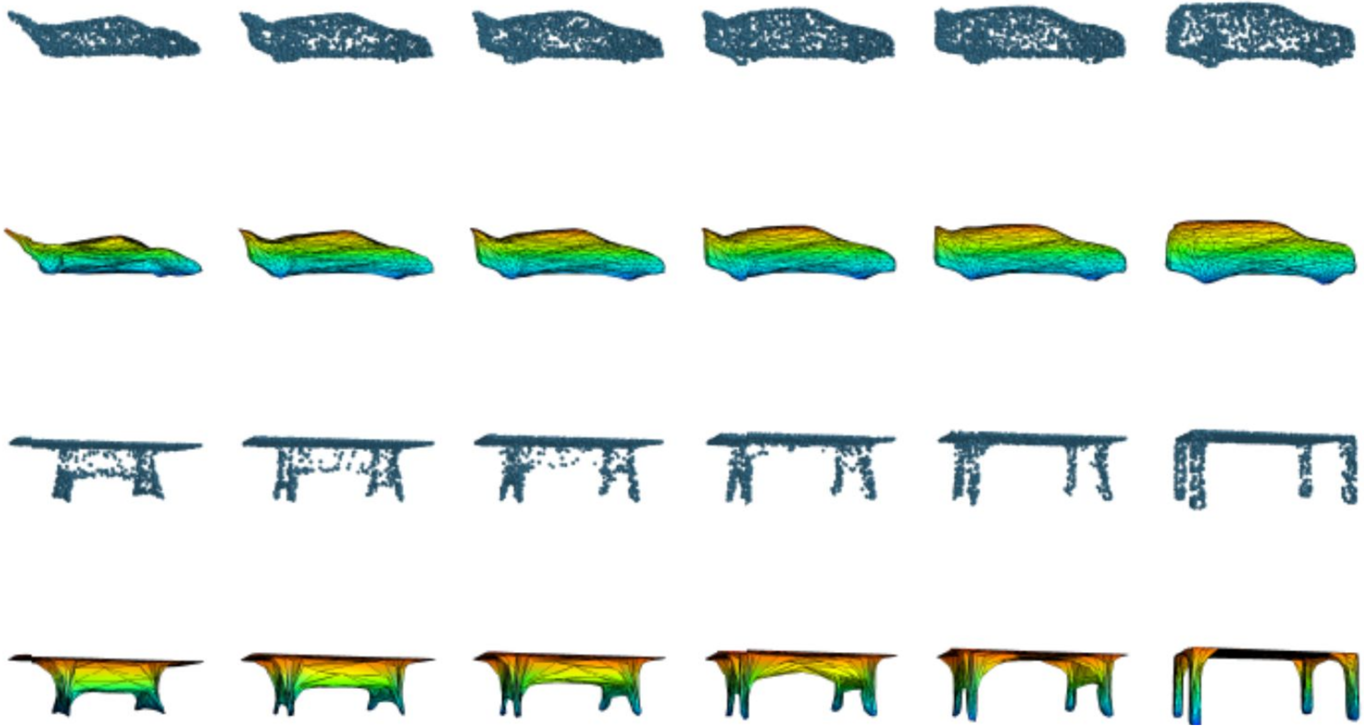

Figure: Interpolations between two 3D point clouds and their mesh representations

More experimental results

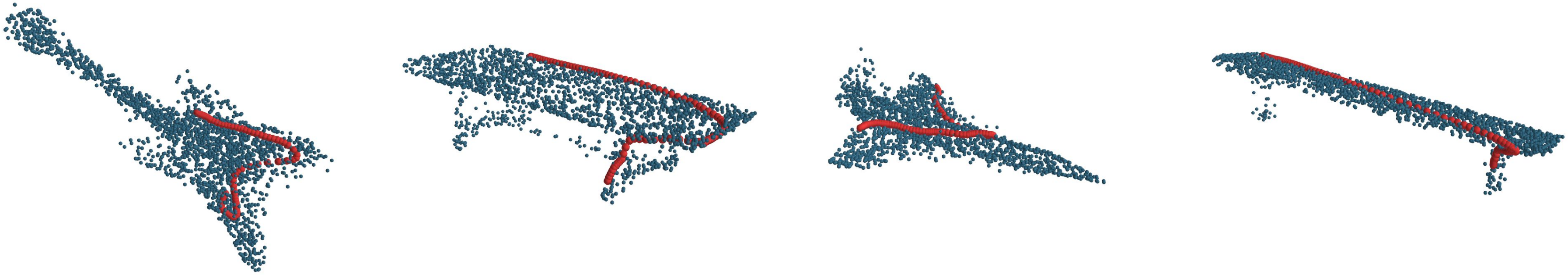

Figure: Interpolation between two points sampled from the 3D ball prior

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