Learning Embedding of 3D Models with Quadric Loss

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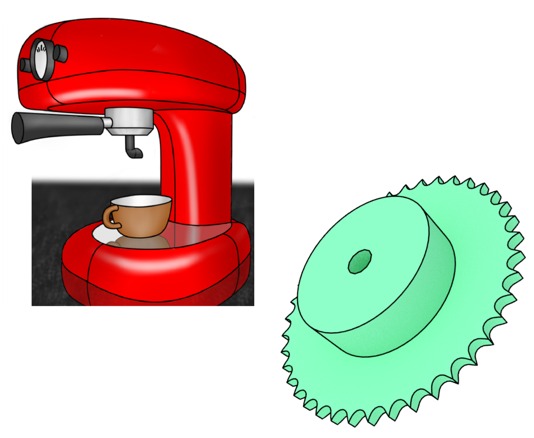
Project Webpage - https://www.ics.uci.edu/~agarwal/quadricLoss

Motivation

Sharp features such as edges, corners and boundaries are important for human visual perception. Current loss functions for reconstructing 3D objects, especially for point or mesh based networks, focus on either the overall shape or the input point distribution.

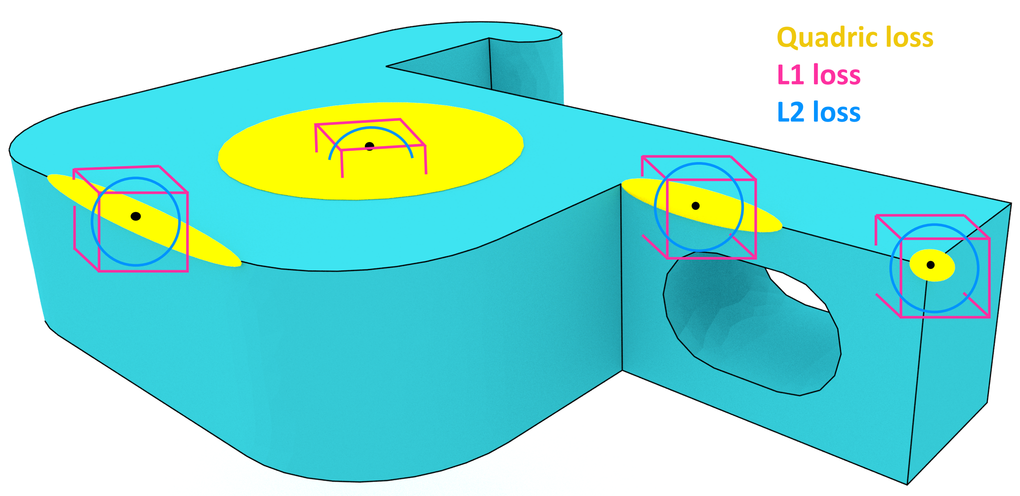


Our loss function encourages points to lie along sharp features.

Contributions

We propose a new loss function namely, **Quadric loss**:

- A point-surface loss function.
- It **preserves sharp features** - edges, corners and boundaries.
- Works with any point/mesh based architecture for 3D reconstruction.
- No Hyperparameters.
- Differentiable.
- Fast and easy to optimize.



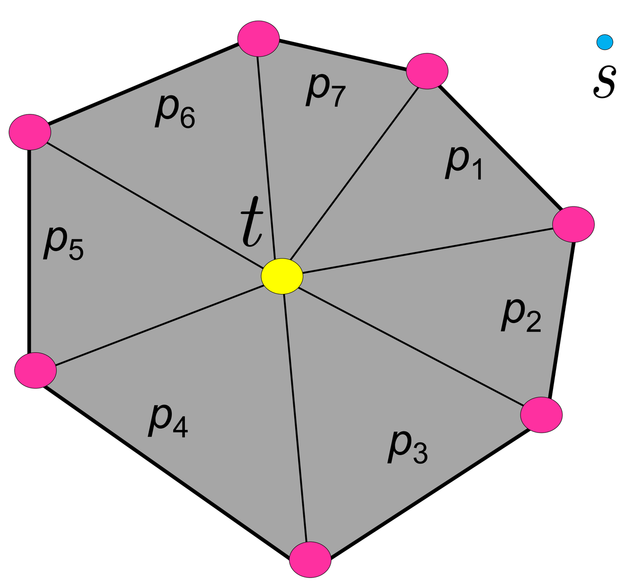
Iso-value surface

The code and data are available on project page

SCAN ME

Quadric Loss

Background:



$$\dot{s} = [x, y, z, 1]^T$$

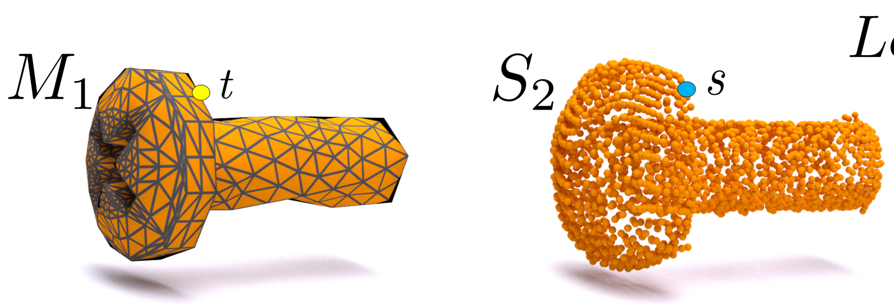
$$\Delta(t) = 0$$

$$p_i = [a, b, c, d]^T$$

$$\text{where } a^2 + b^2 + c^2 = 1$$

$$\Delta(s) = \sum_{i \in \mathcal{N}(t)} (p_i^T s)^2 = \sum_{i \in \mathcal{N}(t)} s^T (p_i p_i^T) s = s^T \Big(\sum_{i \in \mathcal{N}(t)} Q_{P_i} \Big) s = s^T \mathbf{Q_t}\, s$$

Computation:



Input Surface Reconstruction

$$Loss_{quad}(S_2, M_1) = \sum_{s \in S_2} s^T Q_t s$$

$$\sum \underset{(B \times N \times 16)}{(s^T \otimes s^T)} \cdot \underset{(B \times N \times 16)}{Q_t}$$

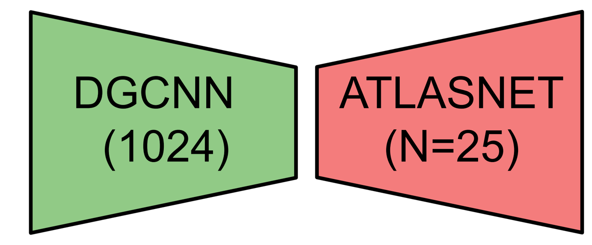
Comparison:

	Focus	Optimizes	No Manual Annotations	Differentiable	Fast & Efficient
Surface Loss	overall shape	point-triangle	✓	✓	✗
Edge Loss	sharp features	point-edge	✗	✓	✓
Normal Loss	high order features	inner-product	✓	✓	✗
Quadric Loss	sharp features	point-plane	✓	✓	✓

Garland et al., Surface Simplification using Quadric Error Metrics, SIGGRAPH 1997
Yu et al., EC-Net: an Edge-aware Point set Consolidation Network, ECCV 2018
Wang et al., Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images, ECCV 2018

Reconstruction Results from ABC Dataset

Using an autoencoder network, we study the effect of various loss functions on reconstruction quality of models from ABC dataset. All hyperparameters were kept constant.

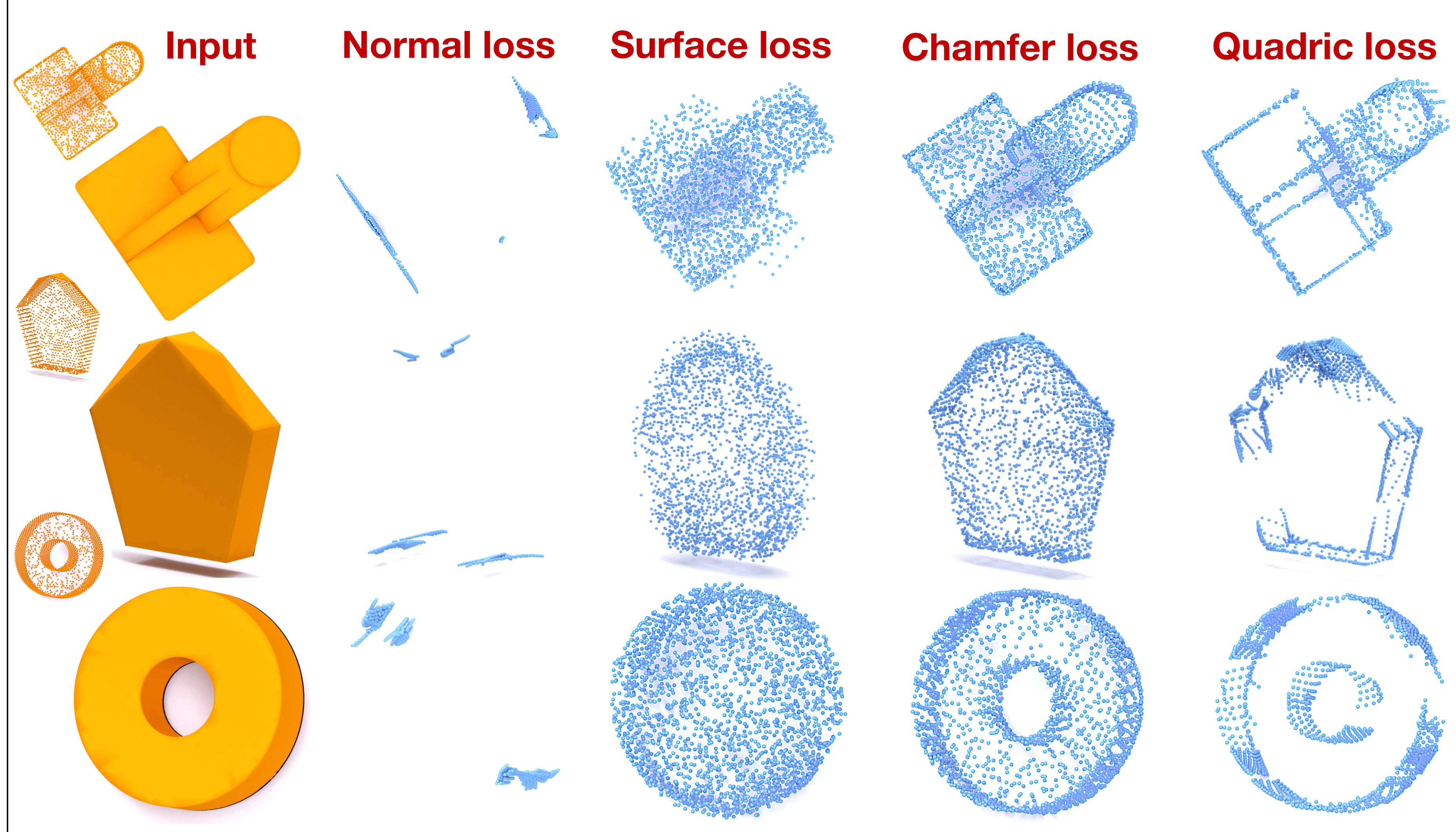


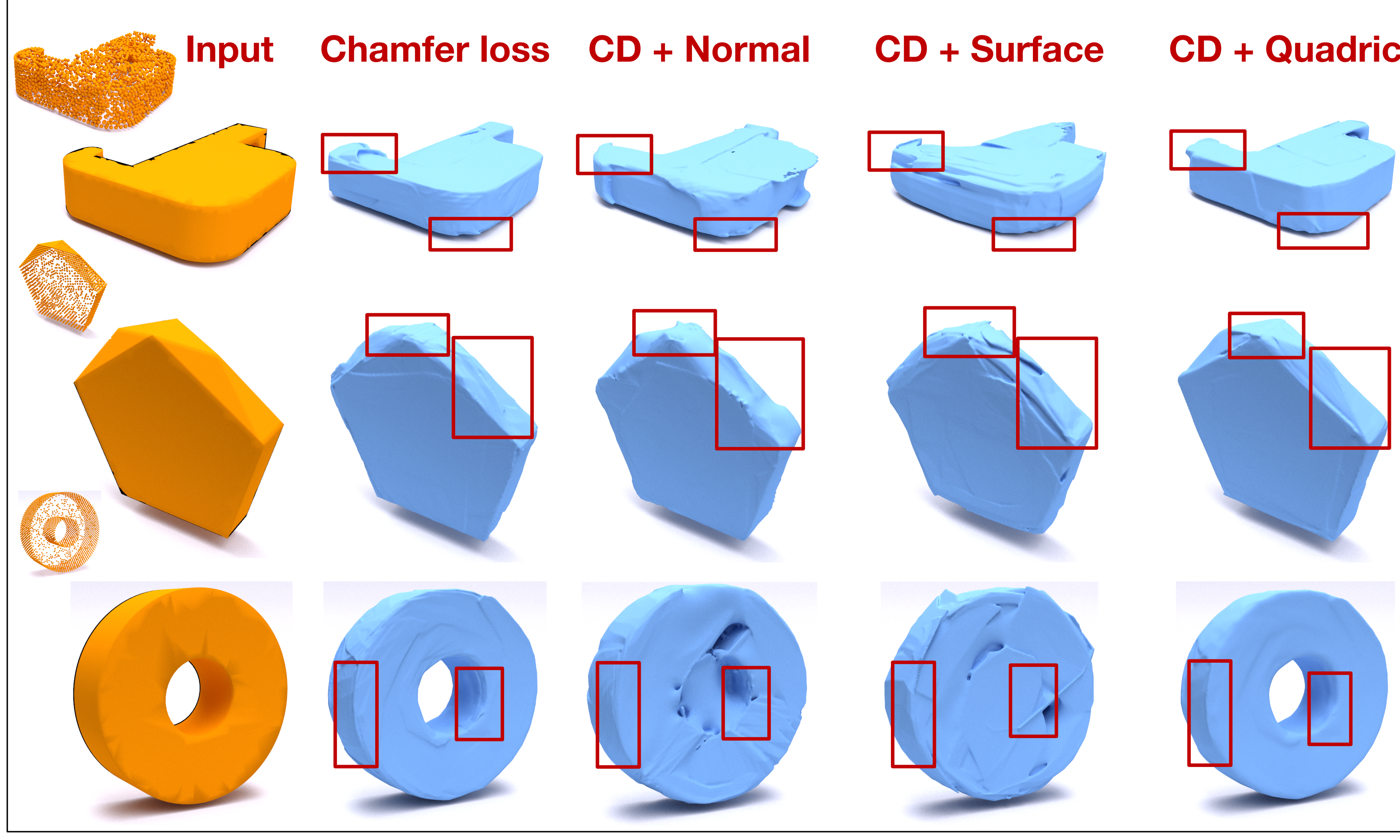
Result without Chamfer Loss

Losses	CD median	CD max	Metro median	Metro max
Normal loss	397.09	1750.6	10.65	28.38
Surface loss	21.86	398.85	6.11	24.93
Quadric loss	9.44	217.5	3.18	20.80
Chamfer loss	**1.97**	40.87	3.13	19.08

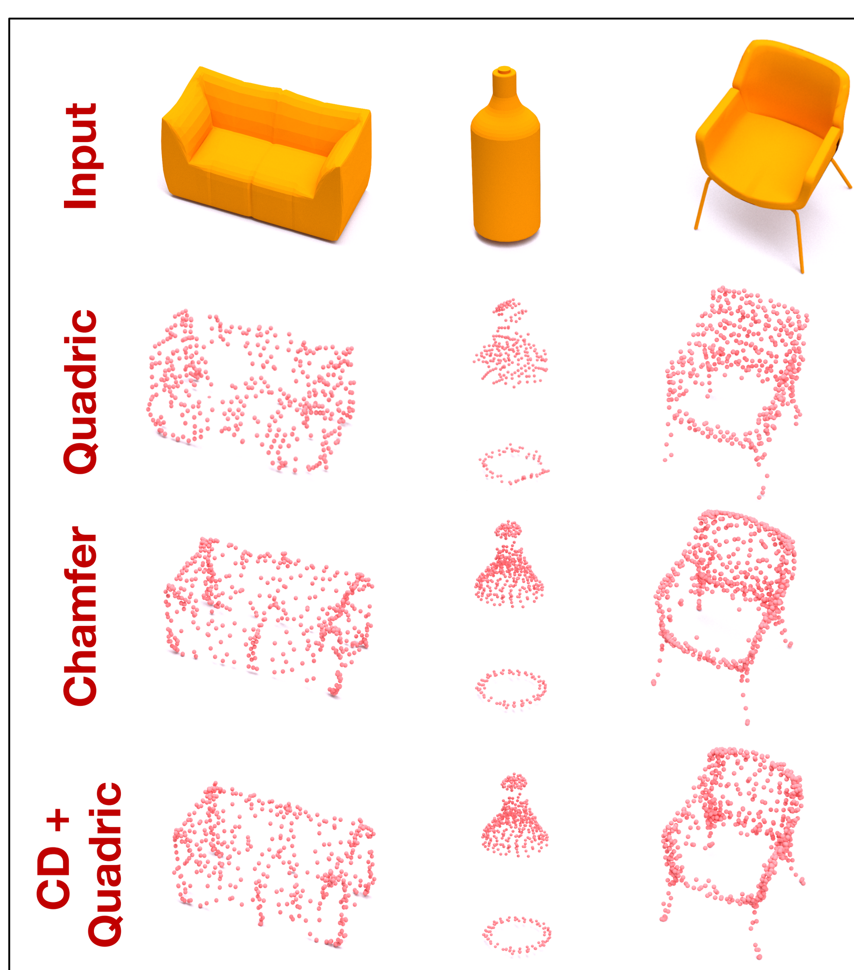
Result with Chamfer Loss

Losses	CD median	CD max	Metro median	Metro max
Normal loss	2.97	39.83	3.38	19.21
Surface loss	2.23	37.04	3.16	18.87
Quadric loss	2.21	**36.78**	**2.96**	**18.80**

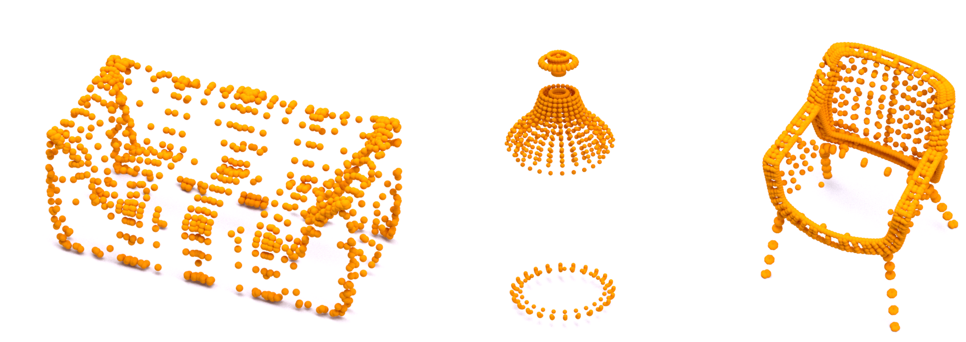




Reconstruction Results from ModelNet40 Dataset



Using the same autoencoder we also test quadric loss on shapes from ModelNet40.



Losses	CD median	CD max	Metro median	Metro max
Quadric loss	51.92	400.02	3.18	11.25
Chamfer loss	**4.51**	96.76	**3.05**	13.60
Quadric + Chamfer	5.59	**89.46**	3.09	**11.10**