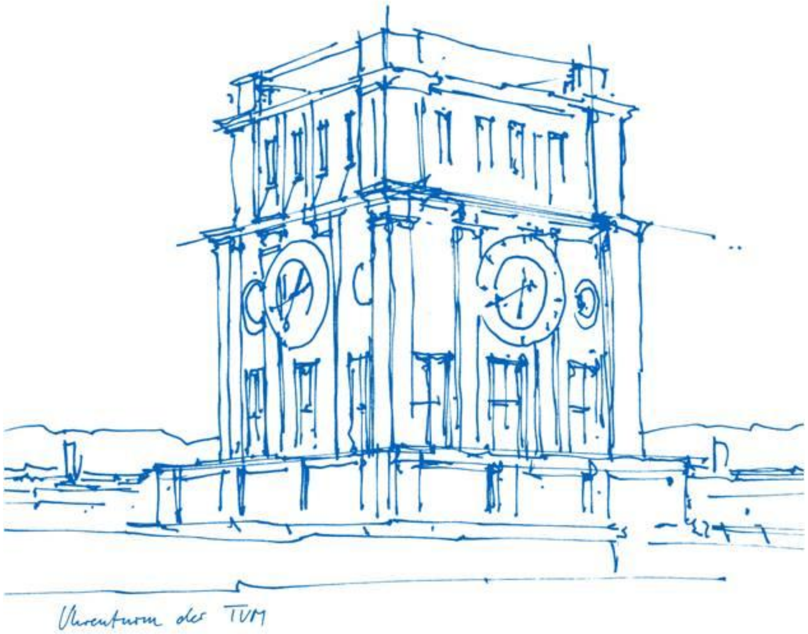
Deformation Generation via Autoregressive Models

Ran Ding

Barry Hu



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Agenda

- Self Introduction
- Motivation
- Related Work
- Method
- Results
- Discussion
- Next Steps

Self-Intro

Self-Intro

Ran Ding

- Bachelor of Computer Science, Dalian University of Technology, China
- Research Student, Visual Computing, TUM (2022 - Now)

Barry Hu

- Bachelor of Computer Science, University of Waterloo, Ontario, Canada
- Reseach student, Visual Computing, 3D AI, TUM (2021 - Now)

Motivation

Motivation

- NSDP uses a Transformer-based encoder to extract deformation, based on which the source points are transformed into the target points
- Can we generate these deformation?

Motivation

- Transformer based Autoregressive model has been widely used for generative tasks

- Generate unknown deformation
  Using Autoregressive model
  Based on existing deformation.

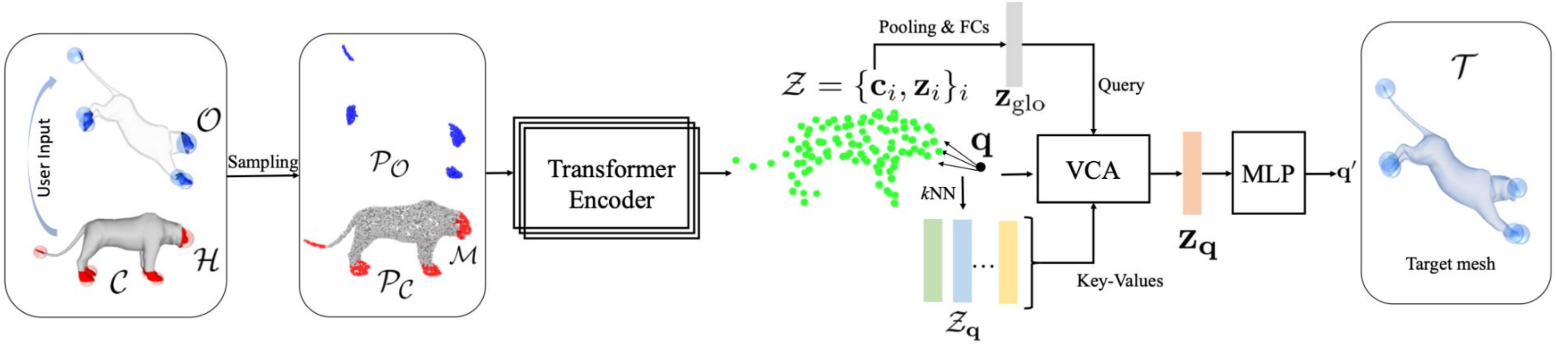
Motivation

Core Goal: Given partial deformation, aim to generate complete deformation.

Direct Application:

- 4D Completion and Generation
- Novel Deformation of Exiting Shapes
- Handle-based Shape Manipulation
- Text-based Deformation Editing
- Shape & Flow Completion

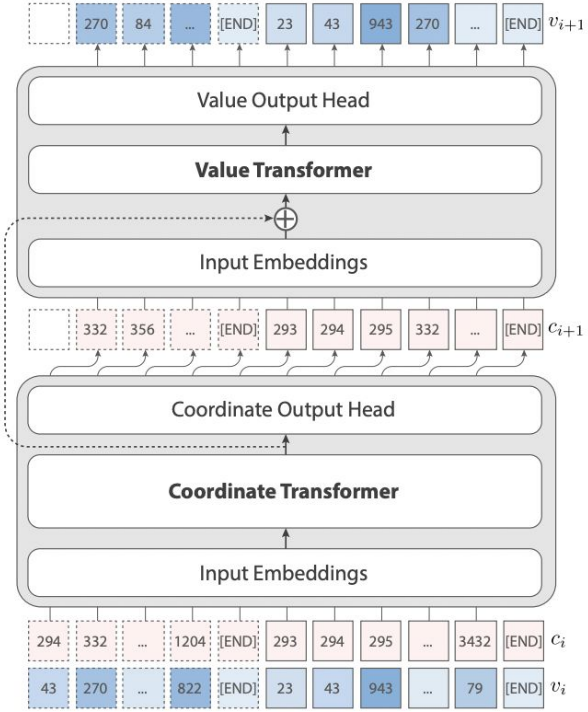
Related work



NSDP: encode deformation field

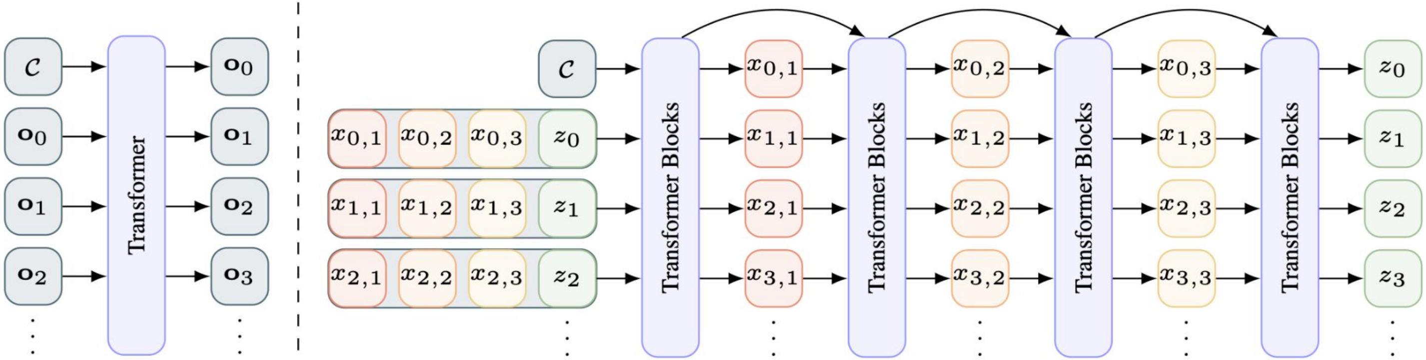
Tang et al. 2022. Neural Shape Deformation Prior. In NeurIPS 2022
https://arxiv.org/pdf/2210.05616.pdf

Related work



Yan, Xingguang, et al. "Shapeformer: Transformer-based shape completion via sparse representation."
https://arxiv.org/abs/2201.10326

Related work



3DILG: Irregular Latent Grids for 3D Generative Modeling

Zhang et al. 2021. 3DILG: Irregular Latent Grids for 3D Generative Modeling. In NeurIPS 2022
https://arxiv.org/pdf/2205.13914.pdf

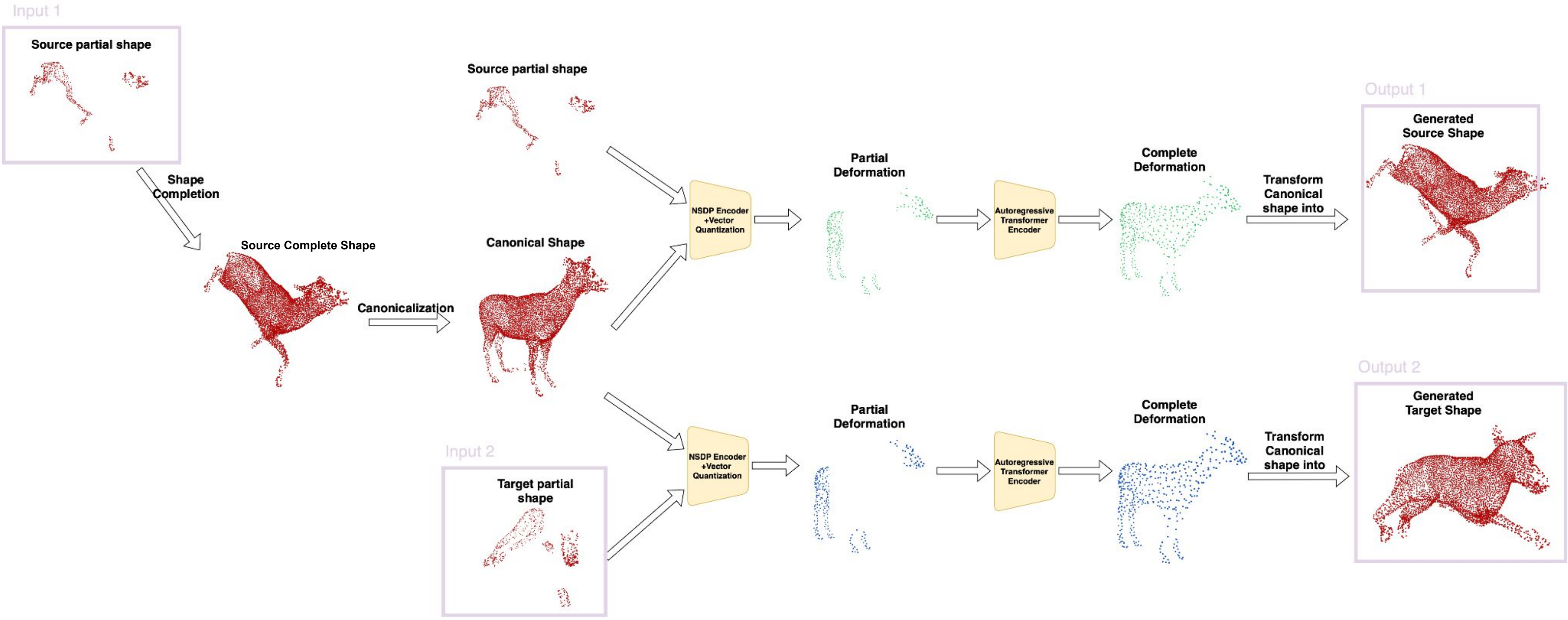
Method

Overview

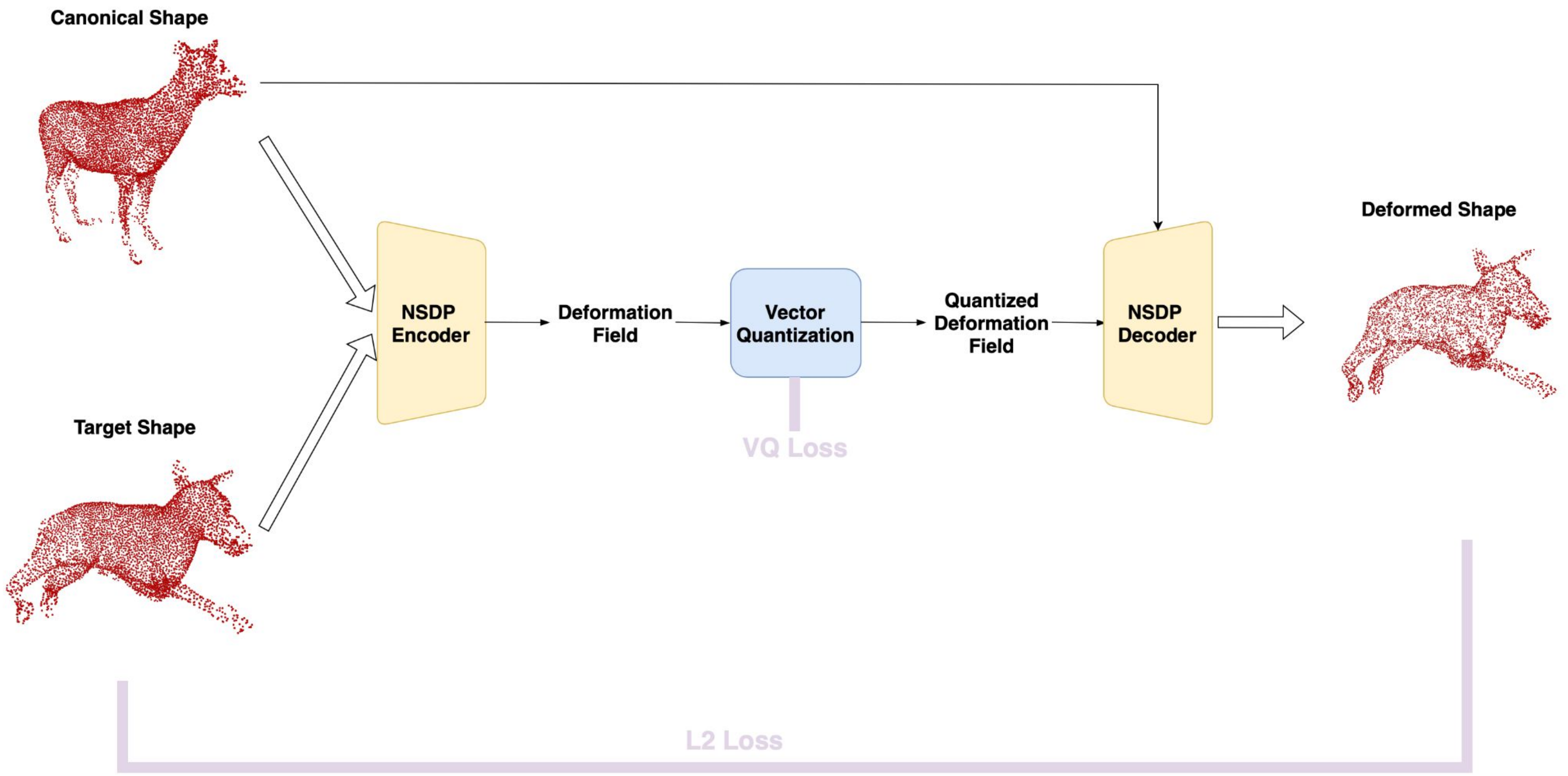
Deformation Quantization

Generate Deformation

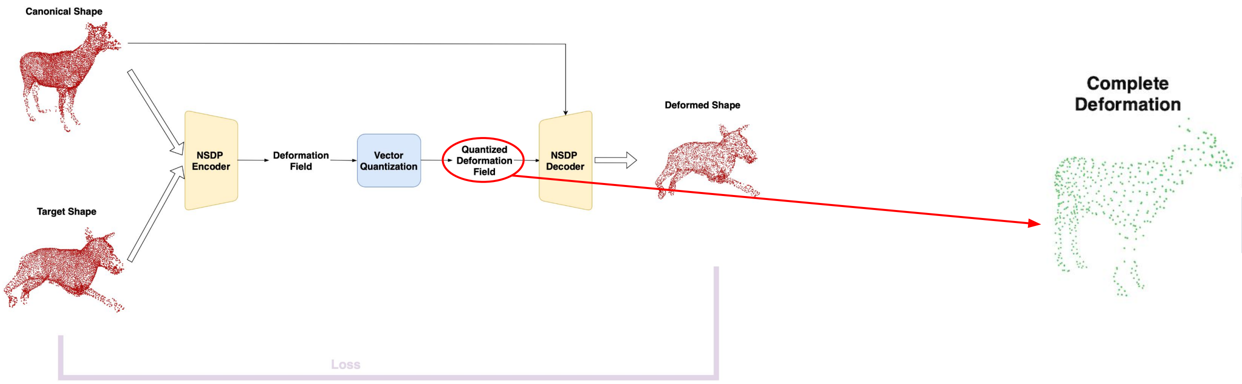
Method: Overview



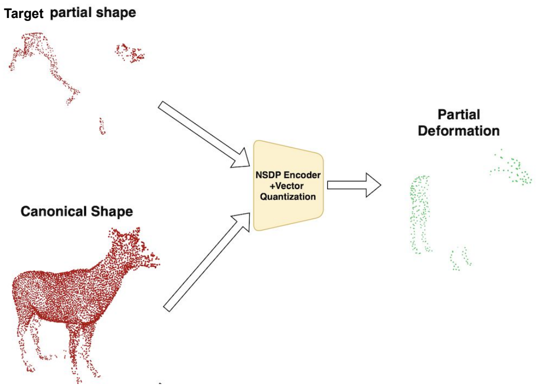
Method: Vector Quantized “Deformation”



Method: Vector Quantized “Deformation”

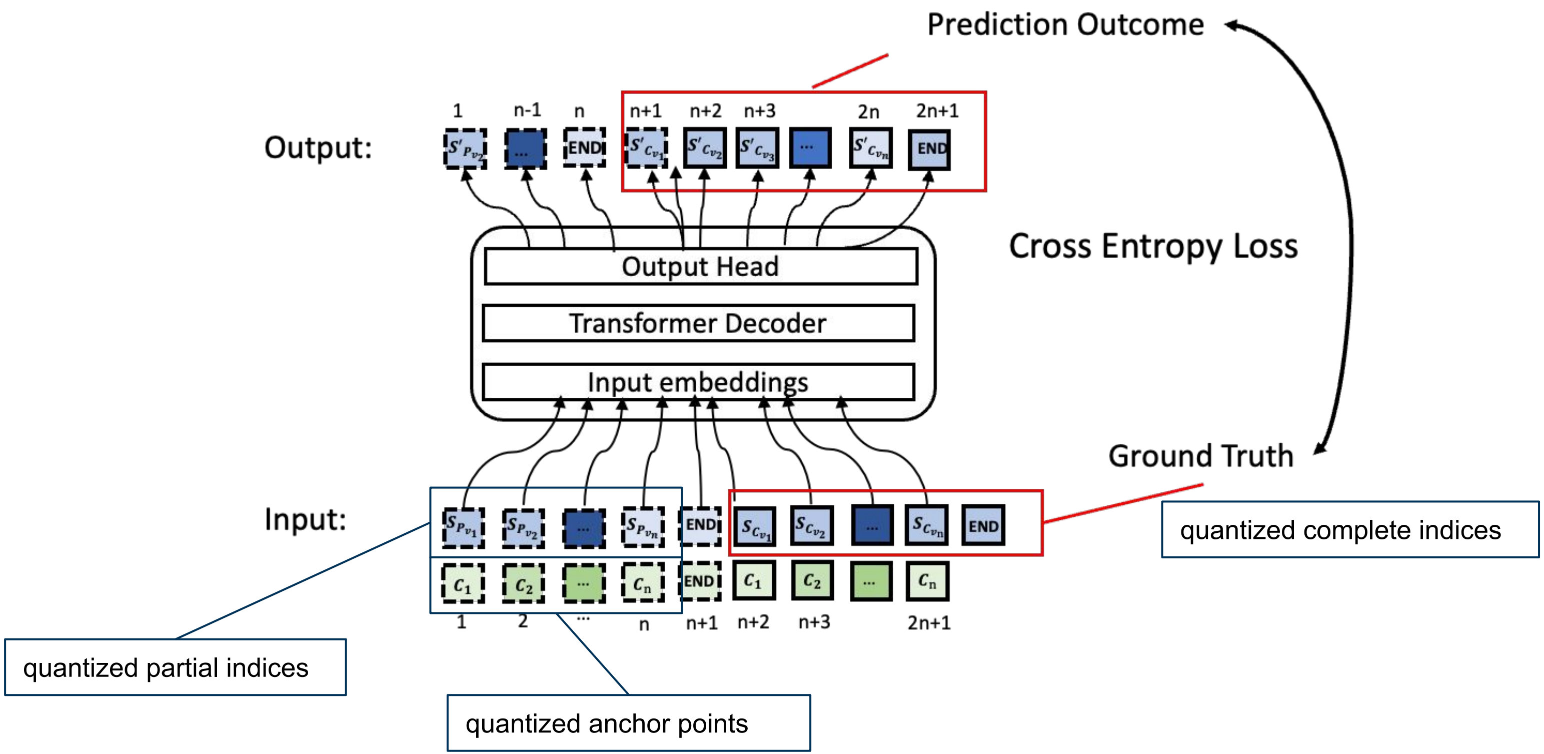


Used as Ground Truth

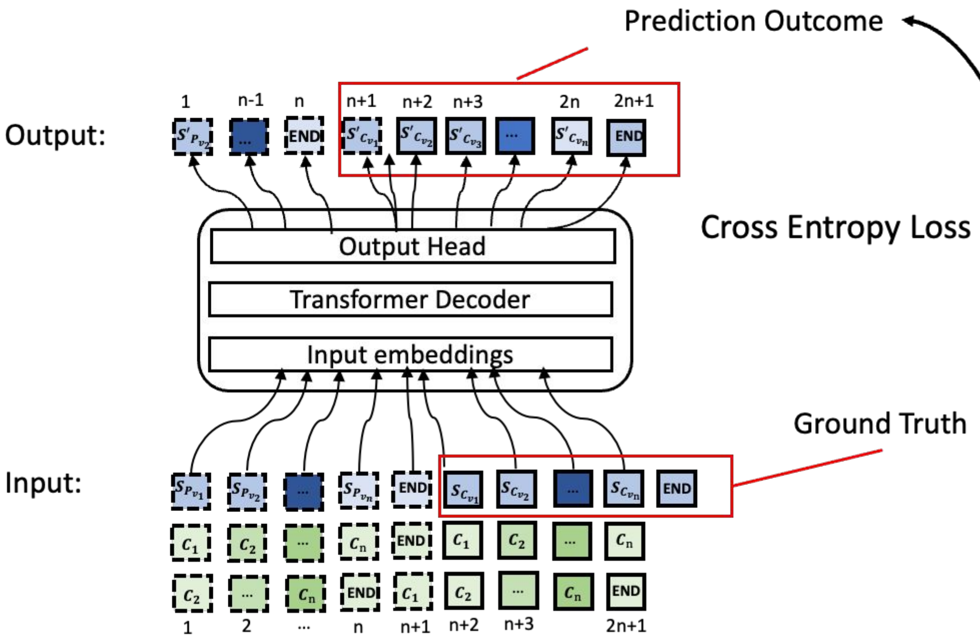


Used as Input to Autoregressive Model

Method: AutoRegressive Model



Method: AutoRegressive Model



Results

Shape Completion

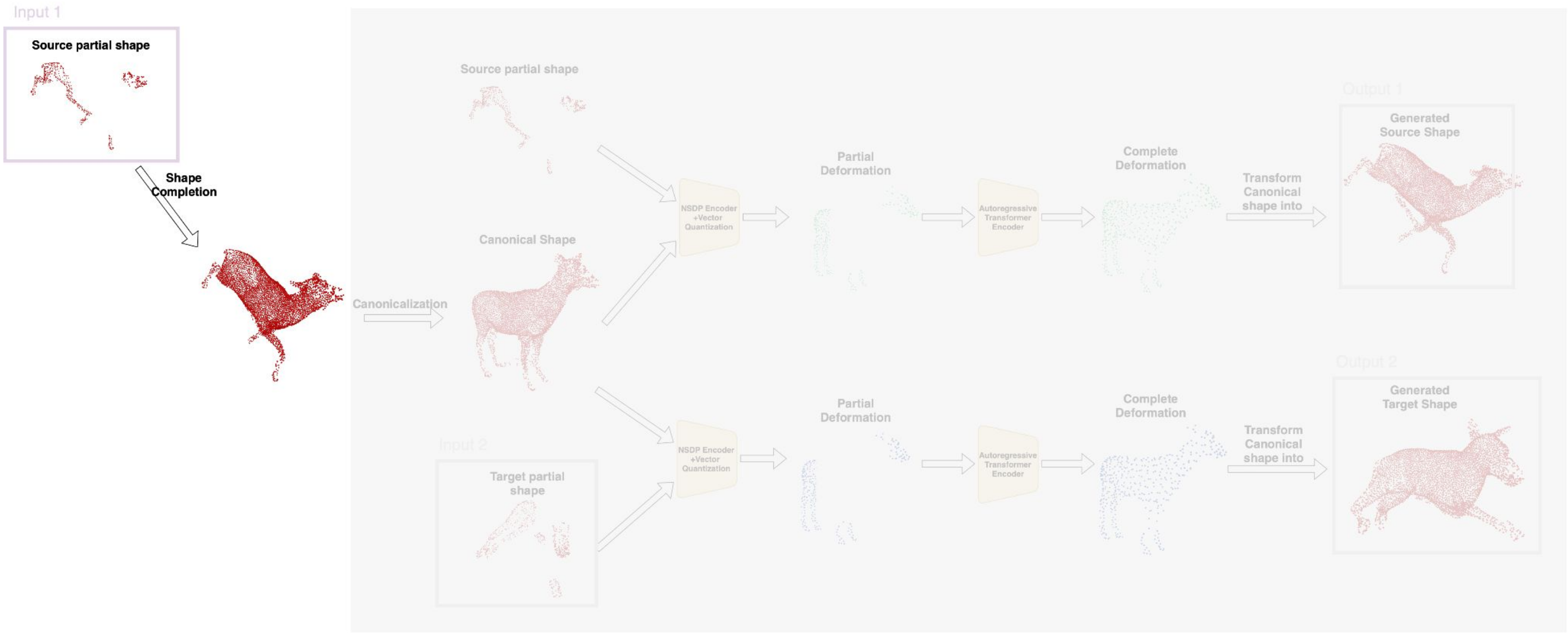
Shape Canonicalization

NSDP + VQ

Results: Shape Completion

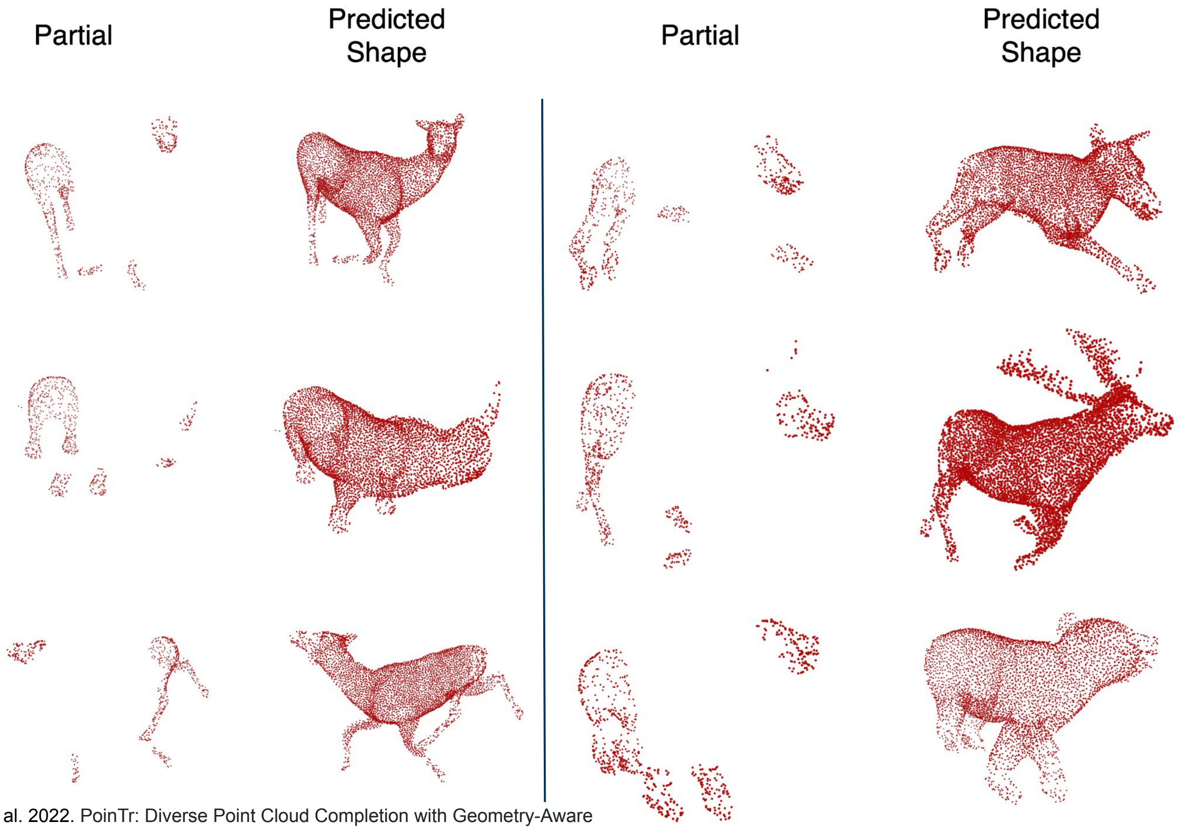
Input: Arbitrary partial shape

Output: Arbitrary complete shape



Yu et al. 2022. PoinTr: Diverse Point Cloud Completion with Geometry-Aware Transformers. In ICCV 2021 https://arxiv.org/abs/2108.08839

Results: Shape Completion

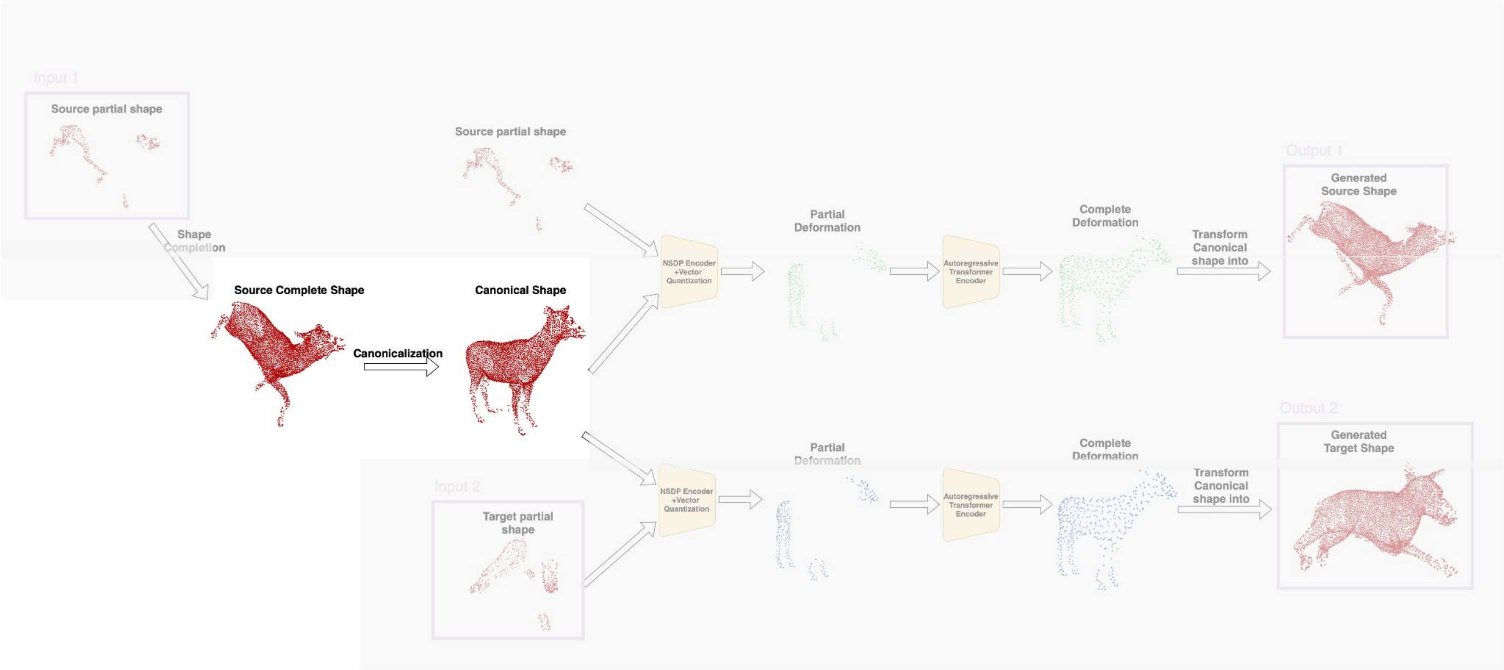


Yu et al. 2022. PoinTr: Diverse Point Cloud Completion with Geometry-Aware Transformers. In ICCV 2021 https://arxiv.org/abs/2108.08839

Visual: arbitrary pose to canonical (pretrained NSDP)

Input: Source complete shape

Output: Canonical complete shape



Tang et al. 2022. Neural Shape Deformation Prior. In NeurIPS 2022
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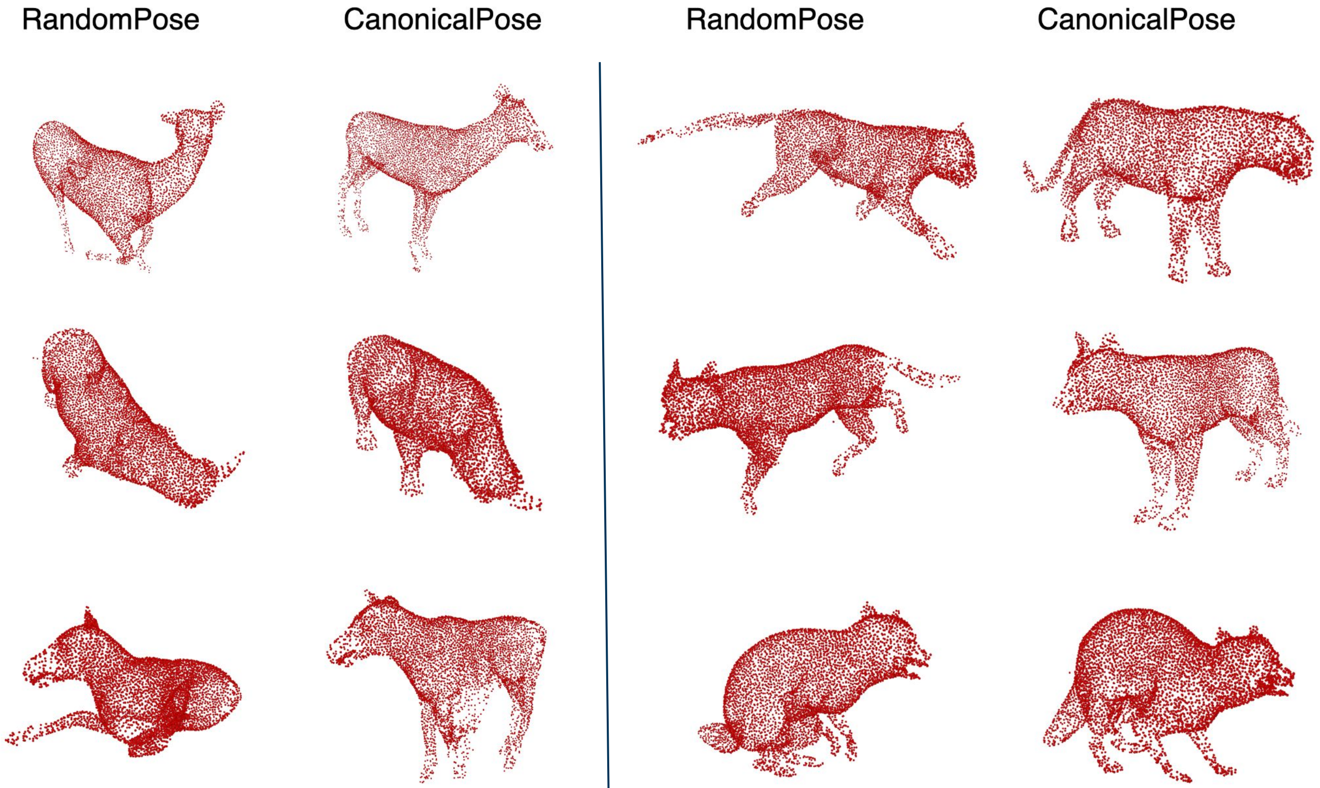
Visual: arbitrary pose to canonical (pretrained NSDP)



Tang et al. 2022. Neural Shape Deformation Prior. In NeurIPS 2022
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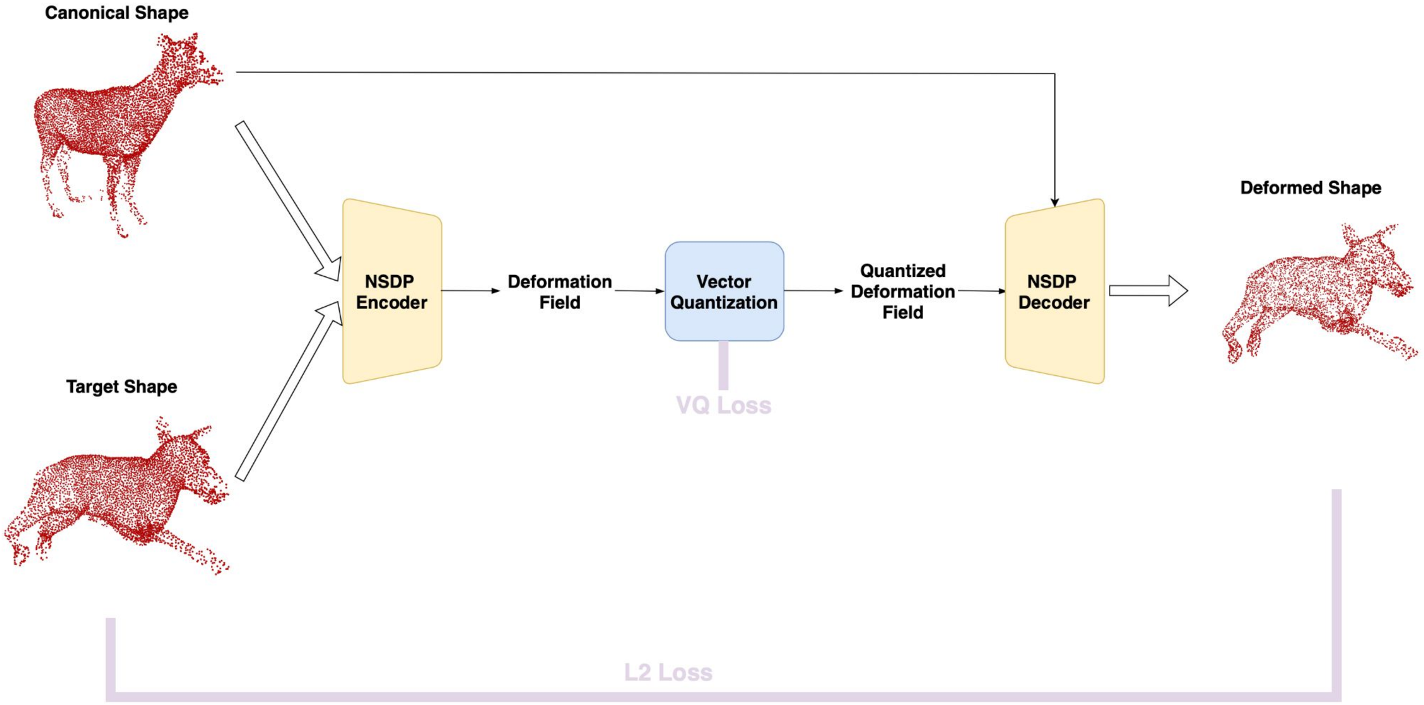
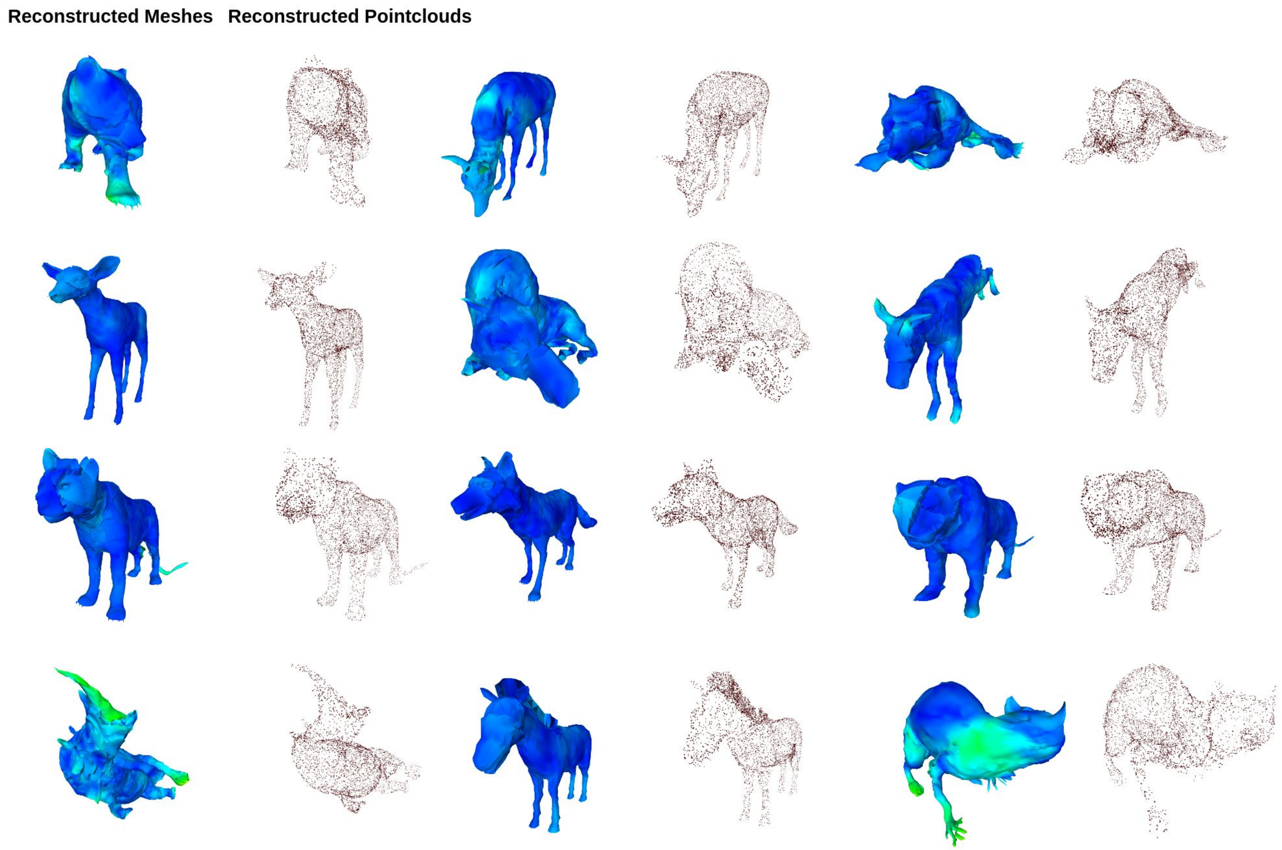
Results: NSDP + Vector Quantization

Input: Canonical + Target Shape

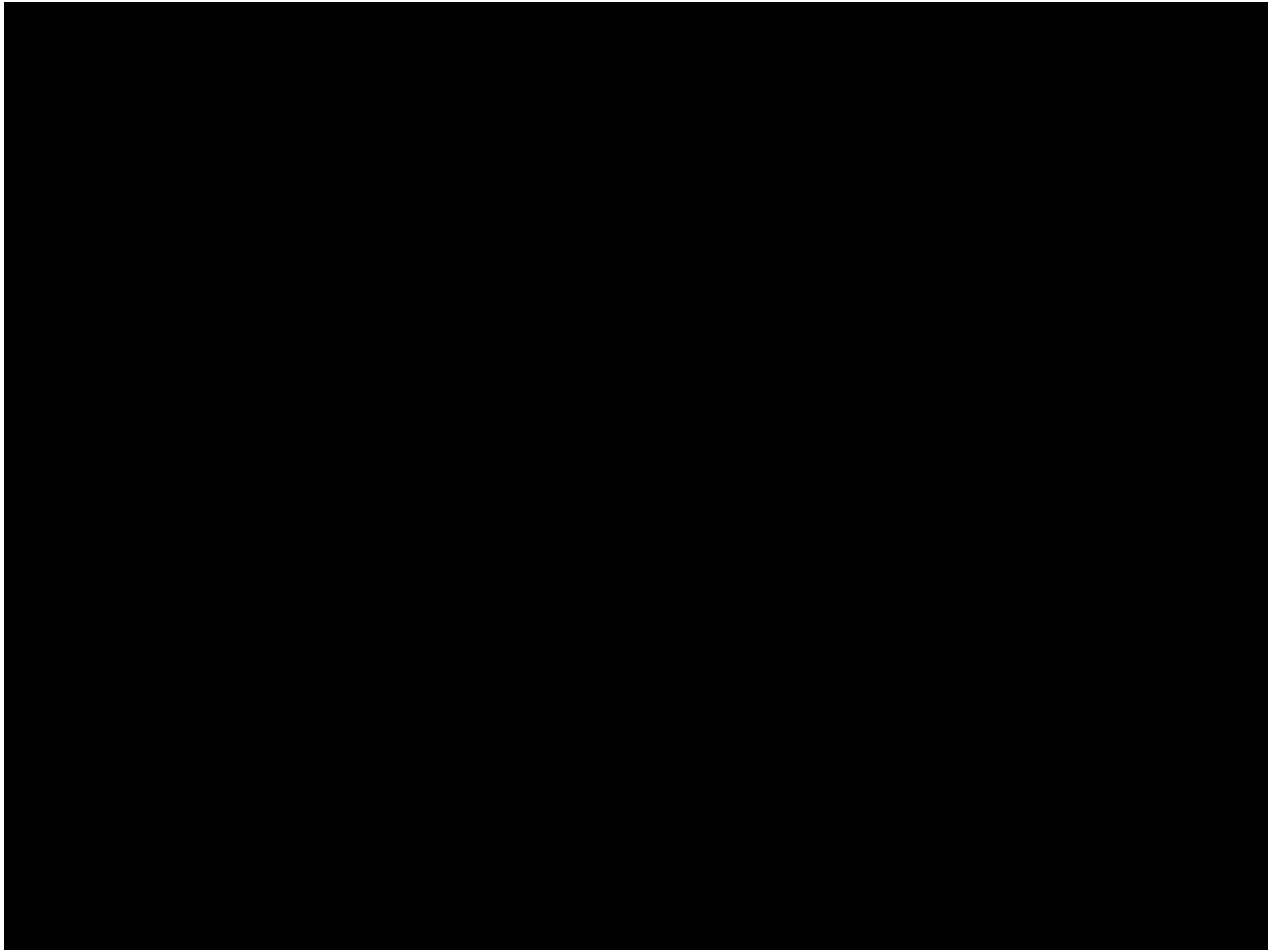
Output: Reconstructed target shape



Results: NSDP + VQ



Results: NSDP + VQ



Results: NSDP + VQ

	L2 x 0.001 (low)	CD x 0.01 (low)	FNC x 0.01 (high)
NSDP*	0.752	0.948	96.59
NSDP **	TBD	TBD	TBD
NSDP + VQ **	0.783	1.048	92.06
3DCNN + VQ **	1.39	1.131	94.97

*Complete Shape + Partial Deformation as input, tested on unseen motion
**Complete Shape + Complete Deformation as input, tested on unseen motion

Discussion

Vector Quantization

Autoregressive Model
- condition information
- number of transformer blocks
- geometry meaning of partial sequence

Next Steps

QnA

Thank you!