QuadGPT: Native Quadrilateral Mesh Generation with Autoregressive Models

Jian Liu[1,2], Chunshi Wang[2], Song Guo[1*], Haohan Weng[2], Zhen Zhou[2], Zhiqi Li[2], Jiaao Yu[2], Yiling Zhu[2], Jing Xu[2], Biwen Lei[2], Zhuo Chen[2], Chunchao Guo[2*]

[1]Hong Kong University of Science and Technology [2]Tencent Hunyuan

[*]Corresponding Author

Project Page Hunyuan 3D Author WeChat

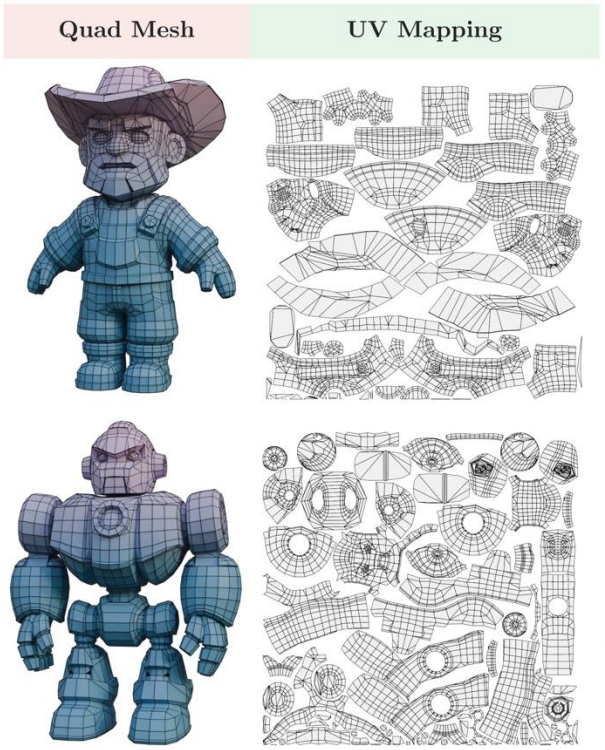
Introduction & Motivation — Why Quad Meshes?

Quad meshes are essential in engineering simulation, animation, and geometric modeling — **superior numerical properties and structural regularity**

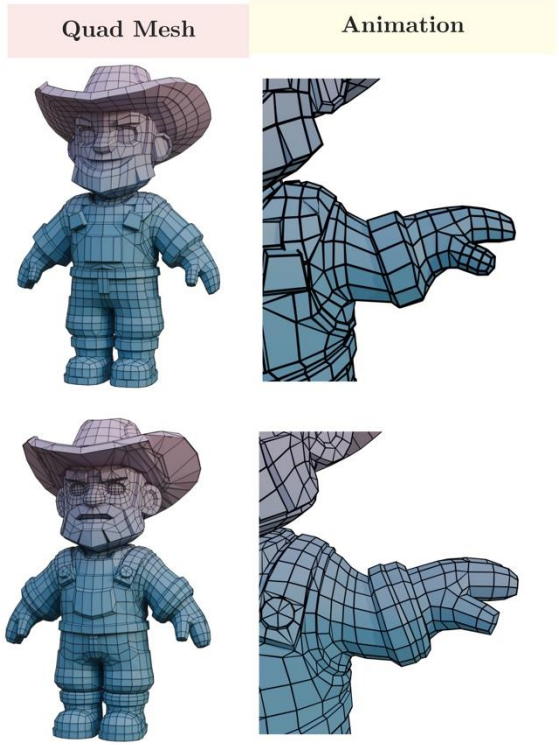
Compare with **Tri Mesh**

- Better accuracy in FEA
- Improved UV parameterization
- More natural deformation in animation

UV Mapping



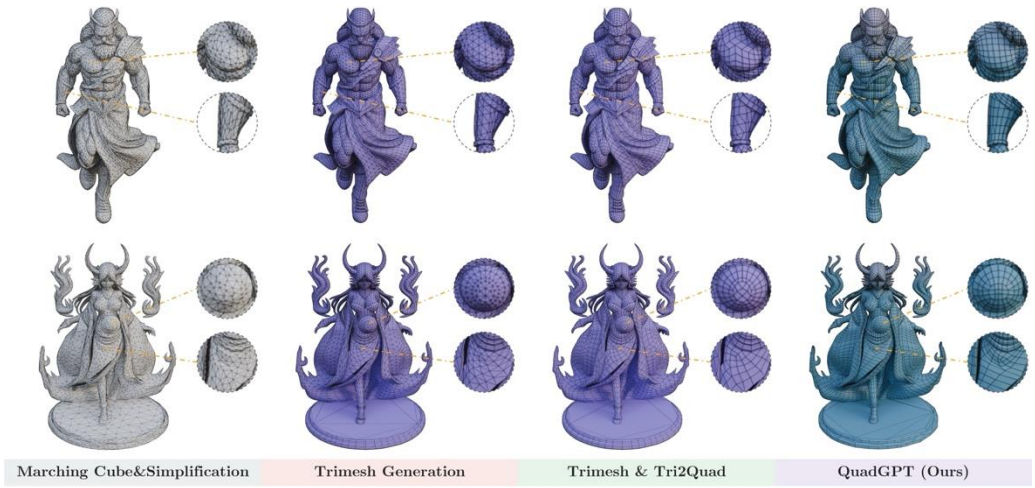
Animation



Introduction & Motivation — Why not Tri-Quad Conversion

- Conversion is the dominant paradigm
- Edge flow is not preserved during triangle-to-quad conversion
- Topology cannot be recovered post hoc

Comparison across different pipeline



Observation: Conversion-based pipelines fail to recover coherent edge loops and produce fragmented quad topology.

Insight: Quad topology must be modeled natively rather than reconstructed from triangles.

Introduction & Motivation

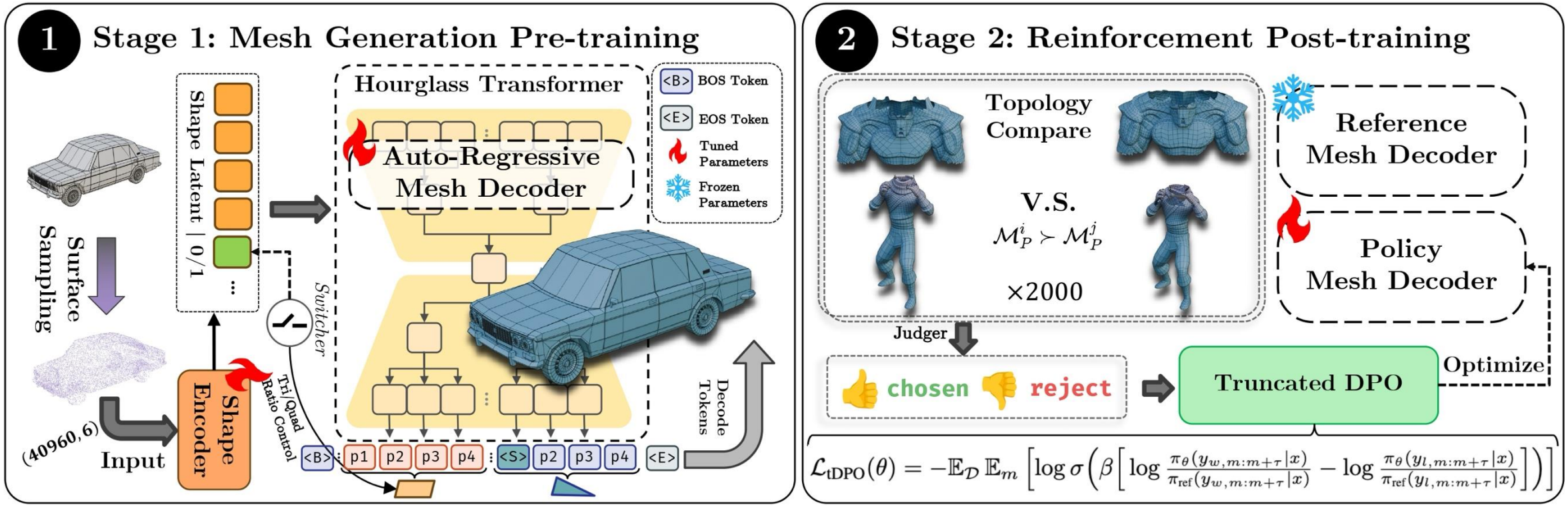
Native over conversion: directly generates quad meshes without post-processing

Unified representation: models mixed mesh topology in a single sequence space

Topology-aware learning: enforces coherent edge loops via tDPO

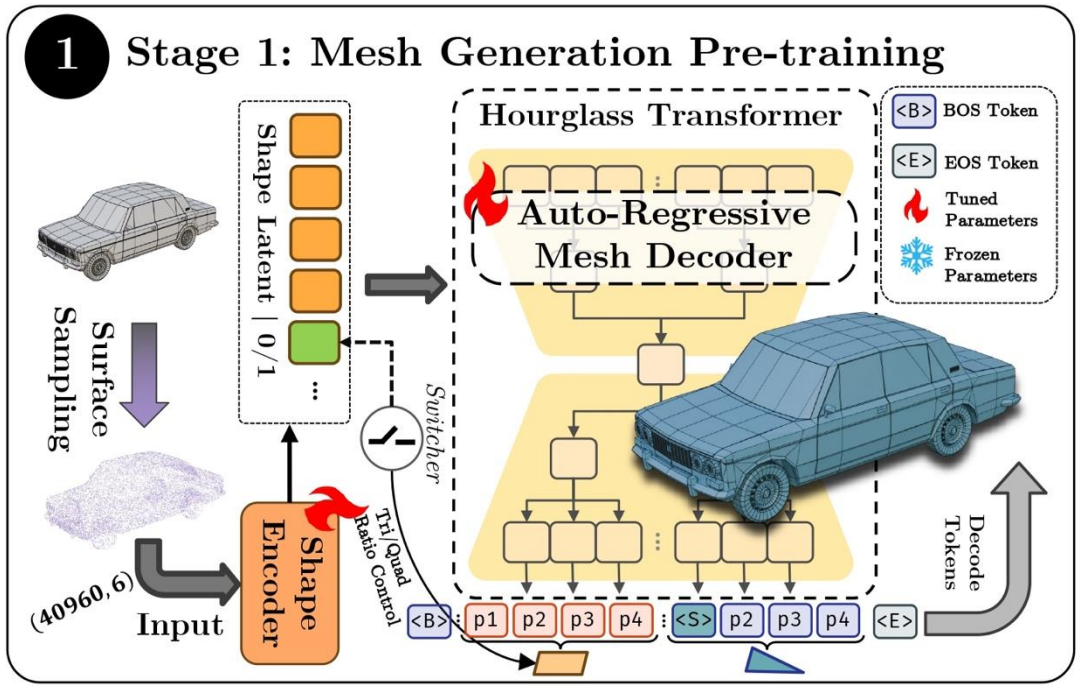
First Native Quad Mesh Autoregressive Framework

Methodology — Overall Framework



Overall framework of our native quad mesh generation

Methodology — Mesh Generation



Hierarchical Model Architecture

Hourglass shortening captures long-range structure in high-resolution mesh sequences

$$\mathbf{E}^{(1)} = \texttt{Shorten}_3(\texttt{TransformerBlock}_1(\mathbf{E}^{(0)})) \in \mathbb{R}^{(L/3)\times D_1}$$

$$\mathbf{E}^{(2)} = \texttt{Shorten}_4(\texttt{TransformerBlock}_2(\mathbf{E}^{(1)})) \in \mathbb{R}^{(L/12)\times D_2}$$

Training & Data Strategy

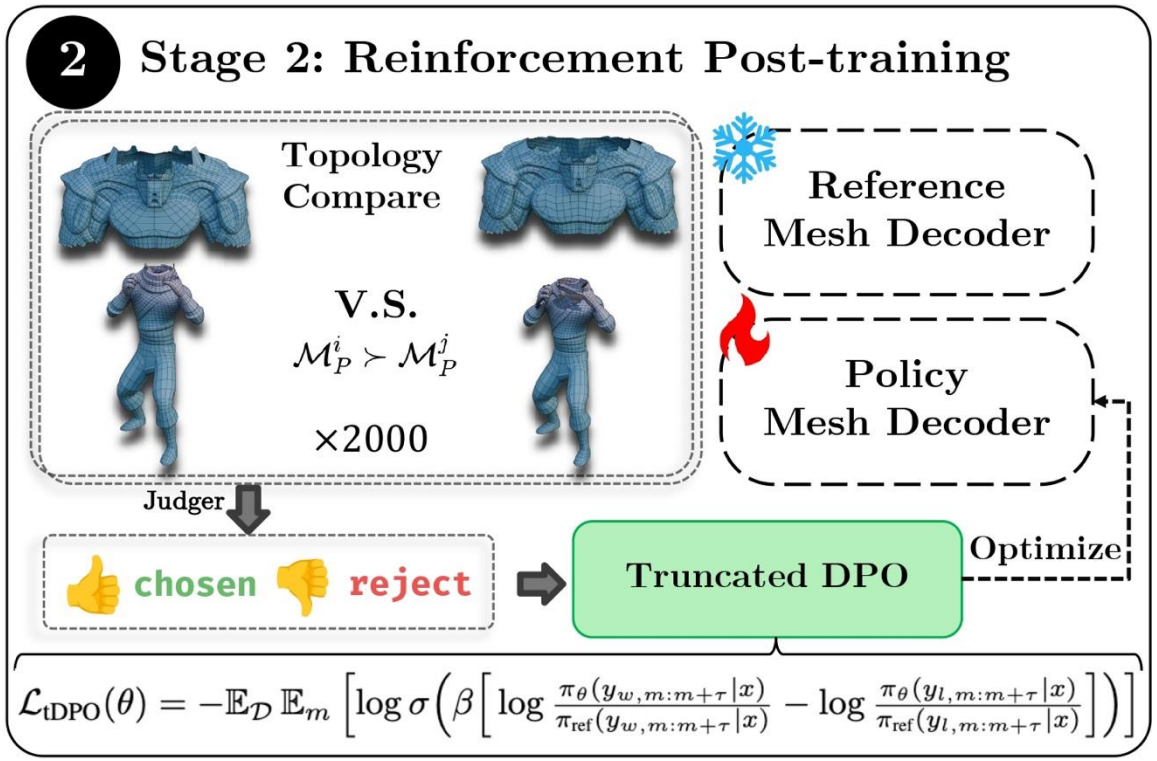
- **Training:** Curriculum learning that gradually transitions from triangle-only to quad-dominant data
- **Data:** 1.3M models via automated triangle-to-quad conversion and multi-stage filtering

Unified Serialization

$$\begin{aligned}\mathcal{M} &= \{\mathbf{f}^1, \mathbf{f}^2, \ldots \mathbf{f}^{N_f}\} \\ &= \{\mathcal{S}(\mathbf{f}^1), \mathcal{S}(\mathbf{f}^2), \ldots \mathcal{S}(\mathbf{f}^{N_f})\} \\ &= \{\tau_{\text{pad}}, \ldots, \underbrace{\mathbf{c}_1^1, \ldots, \mathbf{c}_3^1}_{\text{e.g., Triangle Block}}, \underbrace{\mathbf{c}_1^2, \ldots, \mathbf{c}_4^2}_{\text{e.g., Quad Block}}, \ldots\}\end{aligned}$$

- **Face level:** mesh as a sequence of faces
- **Token-block level:** each face as a structured token group
- **Coordinate level:** vertex coordinates as discrete tokens

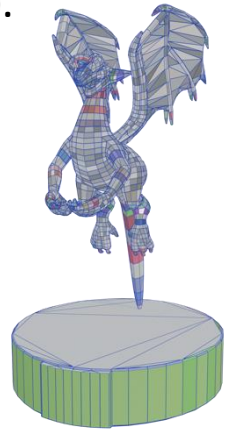
Methodology — Topology-Aware Refinement



Topology-Aware Rewards

Cross-entropy training is local and **fails to enforce global topology quality** (e.g., clean edge loops).

- **Topology-aware rewards** encourage long, structured edge loops while penalizing fractures.
- **Preference learning** ranks candidate meshes to construct pairwise supervision for optimization



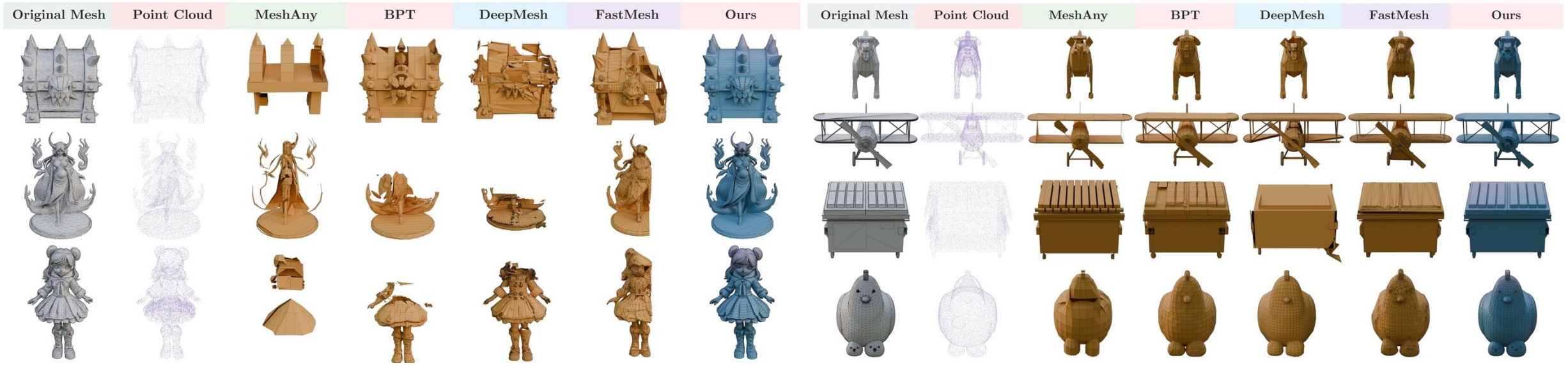
Truncated DPO

- Optimizes local face blocks for efficient training on long mesh sequences

$$\mathcal{L}_{\text{tDPO}}(\theta) = -\mathbb{E}_{\mathcal{D}}\,\mathbb{E}_m \left[\log \sigma\left(\beta\left[\log \frac{\pi_\theta(y_{w,m:m+\tau}|x)}{\pi_{\text{ref}}(y_{w,m:m+\tau}|x)} - \log \frac{\pi_\theta(y_{l,m:m+\tau}|x)}{\pi_{\text{ref}}(y_{l,m:m+\tau}|x)}\right]\right)\right].$$

Experimental Analysis — Qualitative Results

Qualitative Comparison against Indirect Autoregressive Pipelines



- Baseline methods followed by tri-to-quad conversion often produce **topological artifacts** and **lose geometric detail**.
- QuadGPT consistently generates meshes with **superior topological coherence and fidelity** across both domains.

Experimental Analysis — Qualitative Results

Qualitative Comparison against a Field-Guided Method

Experimental Analysis — Quantitative Results

Data Type	Dense Meshes				Artist Meshes			
Metrics	CD ↓	HD ↓	QR ↑	US ↑	CD ↓	HD ↓	QR ↑	US ↑
Quadriflow* (Huang et al., 2018)	**0.045**	**0.099**	**100%**	1.6	0.281	0.531	**100%**	0.3
MeshAnythingv2 (Chen et al., 2025c)	0.153	0.394	53%	1.4	0.096	0.251	60%	2.1
BPT (Weng et al., 2025)	0.115	0.283	43%	2.7	0.051	0.125	49%	3.1
DeepMesh (Zhao et al., 2025a)	0.246	0.435	64%	3.3	0.236	0.417	66%	2.8
FastMesh (Kim et al., 2025)	0.105	0.257	3%	1.1	0.052	0.141	17%	1.9
Ours	0.057	0.147	80%	**4.9**	**0.043**	**0.095**	78%	**4.8**

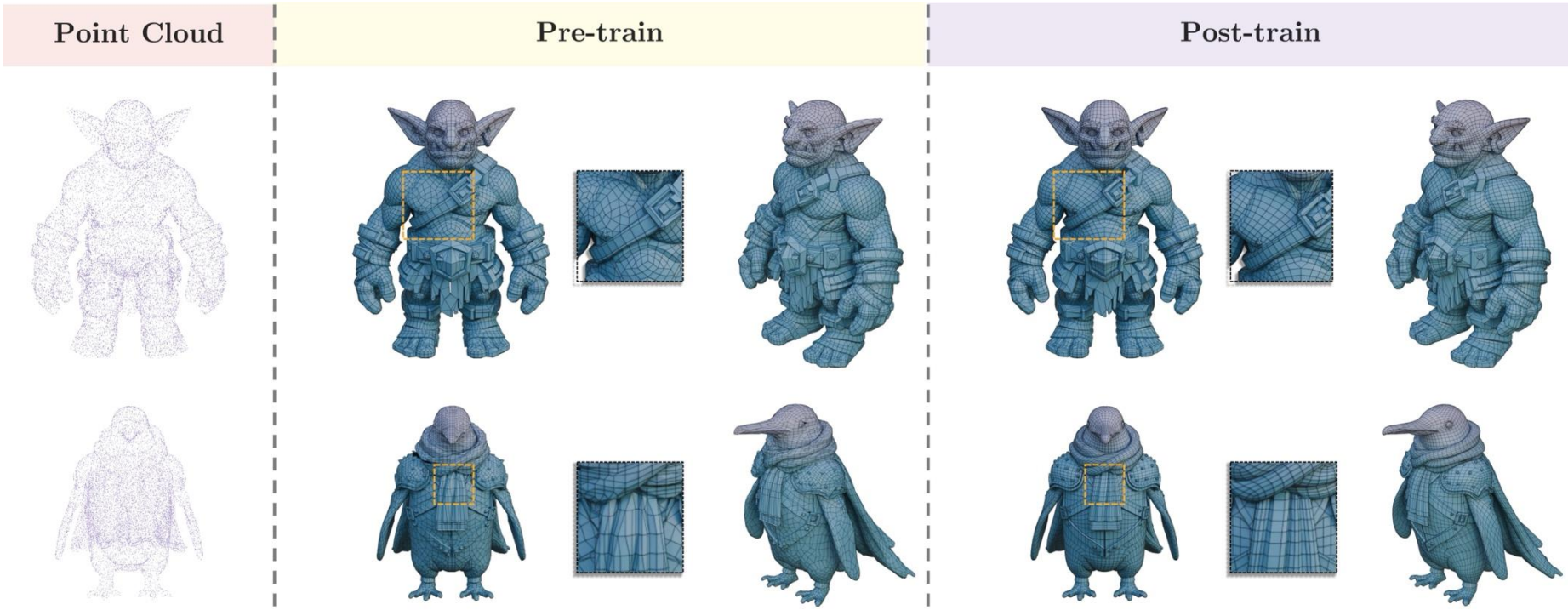
Three Different Evaluation Dimension

- Geometric Fidelity: CD & HD
- Topological Quality: Quad Ratio (QR)
- Perceptual Quality: User Study (US)

Conclusion: Our advantages in producing production-ready assets are not only quantitatively measurable but also perceptually significant.

Experimental Analysis — Ablation Studies

Effectiveness of tDPO



Our comprehensive training strategy significantly enhances both the geometric quality and structural integrity of the generated quad-meshes.

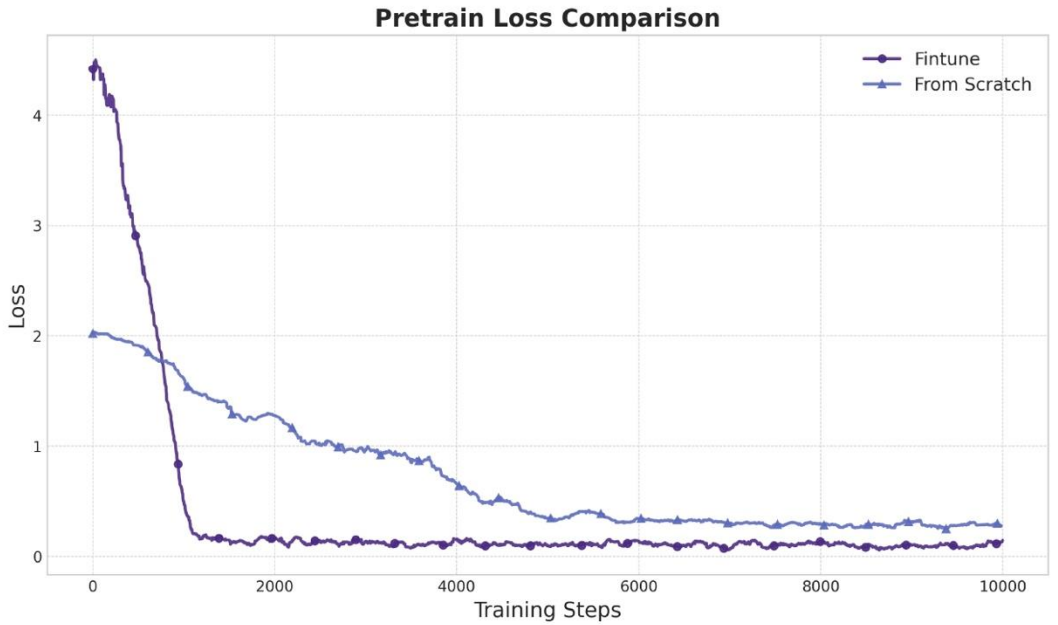
Experimental Analysis — Ablation Studies

Effectiveness of Curriculum-based Pre-Training

- **From Scratch** model struggles to converge, resulting in poor geometric fidelity
- Predicting a quad face is **topologically equivalent to predicting two correlated triangles**
- **Finetuning** from converged triangle weights yields significantly superior results

Conclusion: Curriculum strategy leveraging triangle generation as a warmup is essential for mastering quadrilateral topology

Method	CD ↓	HD ↓	QR ↑	US ↑
From Scratch	0.081	0.203	75%	0.6
Finetune	0.065	0.167	72%	1.3
DPO	0.073	0.188	74%	1.1
tDPO	0.061	0.156	78%	3.3
tDPO-Pro	**0.057**	**0.147**	**80%**	**3.7**



Experimental Analysis — Ablation Studies

Native Generation vs. Conversion Pipeline

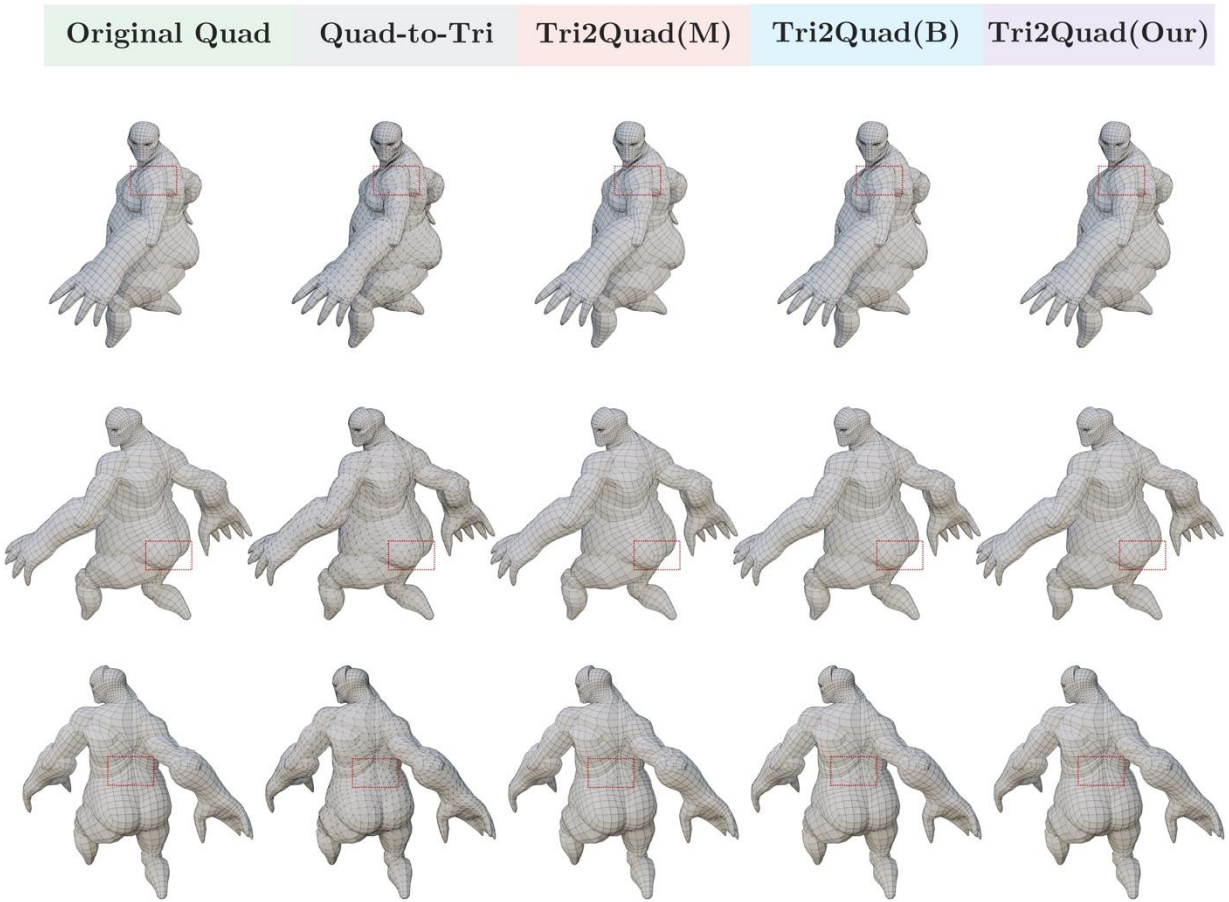
- TriGPT shares **identical architecture, dataset, and RL strategy**, differing only in generation paradigm
- TriGPT+RL achieves slightly better CD/HD, but **cannot match the topological quality** of native generation
- QuadGPT achieves substantially **higher QR** and **2.6× higher user preference**

Method	CD ↓	HD ↓	QR ↑	US ↑
TriGPT(Q)	0.062	0.160	70%	0.2
TriGPT+RL(Q)	**0.051**	**0.138**	72%	0.5
QuadGPT (Ours)	0.057	0.147	**80%**	**1.3**

Conclusion: Post-hoc conversion struggles to create coherent global structures. Native generation excels at learning artist-preferred topologies.

Experimental Analysis — Why Conversion Fails

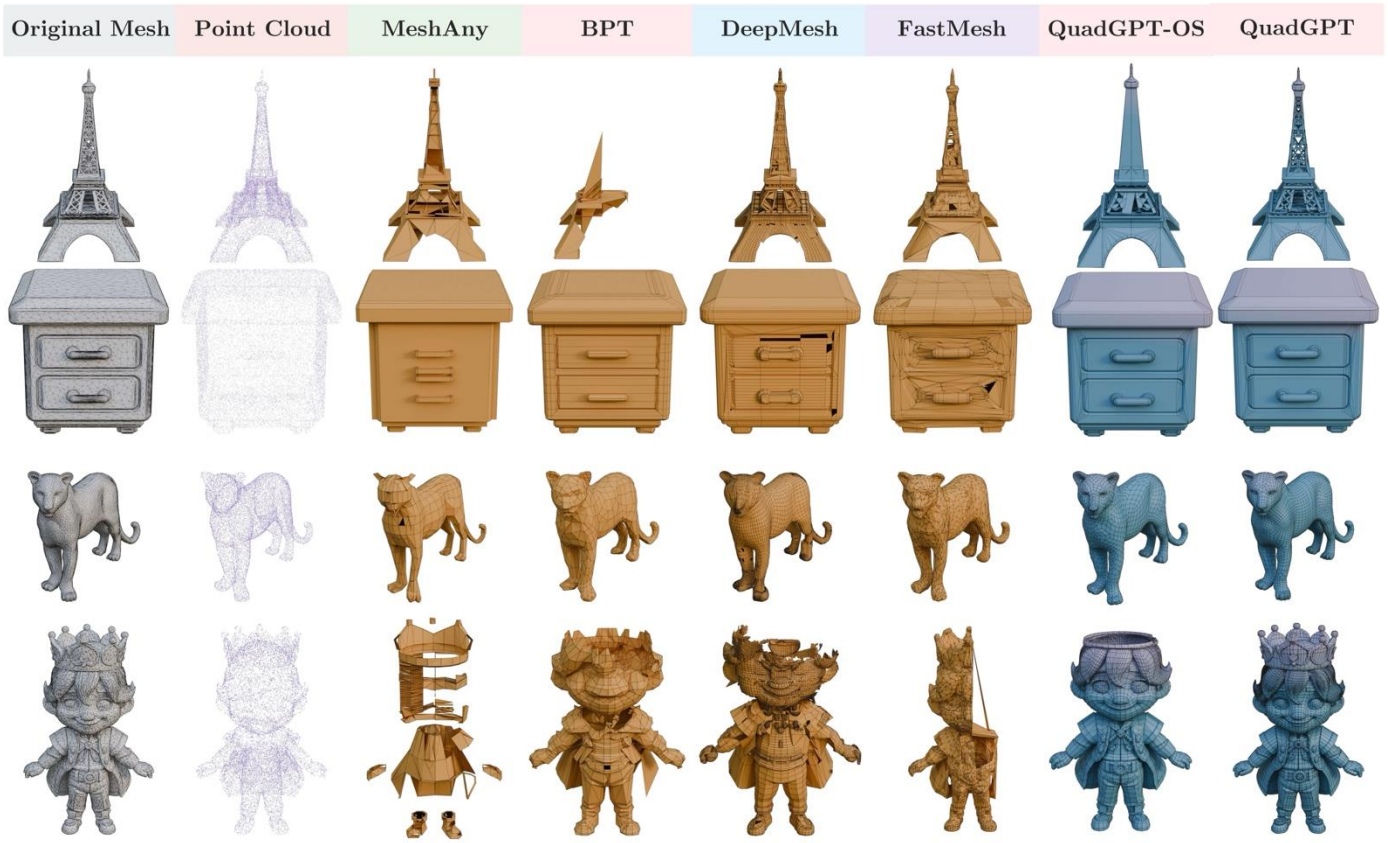
The Irreversibility of Triangulation



- Triangulation causes **irreversible information loss**. No conversion method can **perfectly recover** the original edge flow.
- This limitation is **amplified** on AI-generated triangle meshes, **reinforcing the necessity of native generation**.

Experimental Analysis — Data Ablation

Open-Source Data vs. Full Curated Dataset



- **QuadGPT-OS** (open-source data only) already **significantly outperforms** all prior baselines, confirming the methodology as the primary driver.
- Full dataset further improves quality, demonstrating the **scalability** of our approach with high-quality data.

Conclusion & Future Work

Native Quad Generation

- **First** autoregressive model for **native quad-dominant mesh** generation
- **Unified sequence representation** for mixed-element meshes via padding-based serialization
- **State-of-the-art** in both geometric fidelity and topological quality

Topology-Aware RL

- Introduce **tDPO** with a novel reward for global topological optimization
- Encourages formation of **structured edge loops** in generated meshes
- **Curriculum learning** from triangle generation ensures stable convergence

Limitations & Future Work

- Cannot explicitly control the **final polygon count** for LOD production
- Current reward cannot capture the full nuance of **artistic preference**
- Future directions: **end-to-end geometry-topology co-generation** and **part-aware generation**

THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

腾讯混元

QuadGPT: Native Quadrilateral Mesh Generation with Autoregressive Models

Jian Liu[1,2], Chunshi Wang[2], Song Guo[1*], Haohan Weng[2], Zhen Zhou[2], Zhiqi Li[2], Jiaao Yu[2], Yiling Zhu[2], Jing Xu[2], Biwen Lei[2], Zhuo Chen[2], Chunchao Guo[2*]

Thank You for Watching!

Project Page

Hunyuan 3D

Author WeChat