University of Massachusetts Amherst

TECHNICAL UNIVERSITY OF CRETE

WACV 2026
TUCSON, AZ 3/6 - 3/10

SOPHY: Generating Simulation-Ready Objects with PHYsical Materials

Junyi Cao[1], Evangelos Kalogerakis[1,2]

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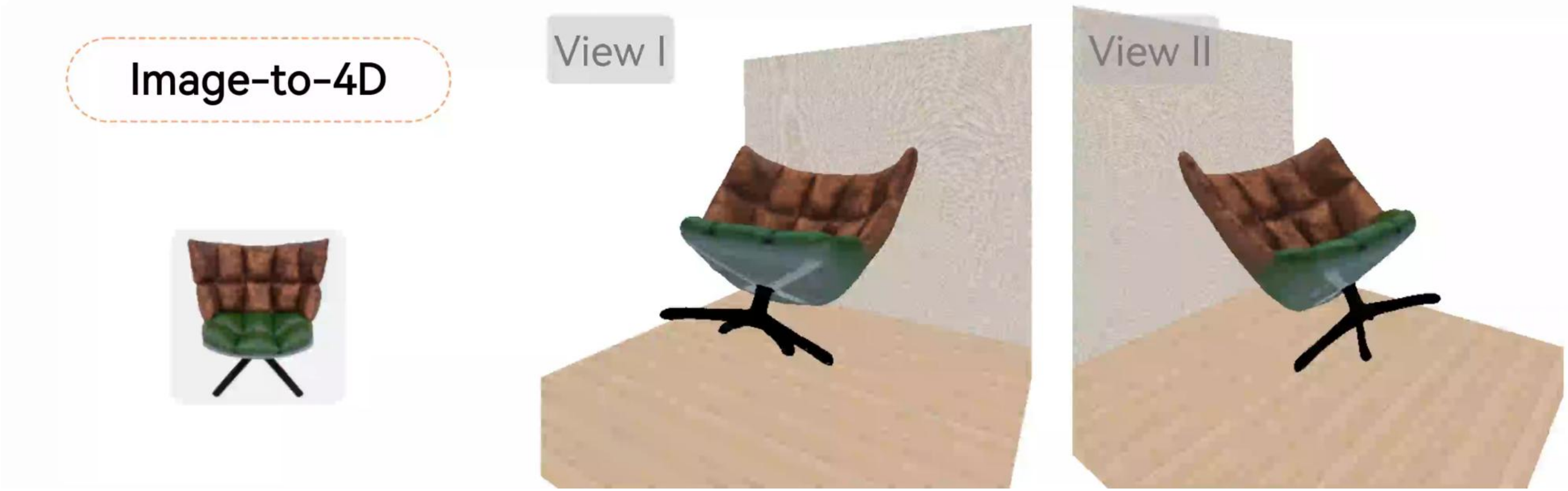
Project Page



Code

Feb. 23, 2026

Contents

Contents

Background

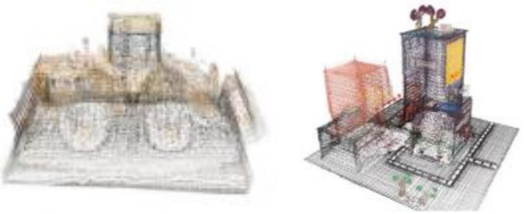
Triangular Mesh

MeshAnything V2
Chen *et al*, arXiv 24

NeRF

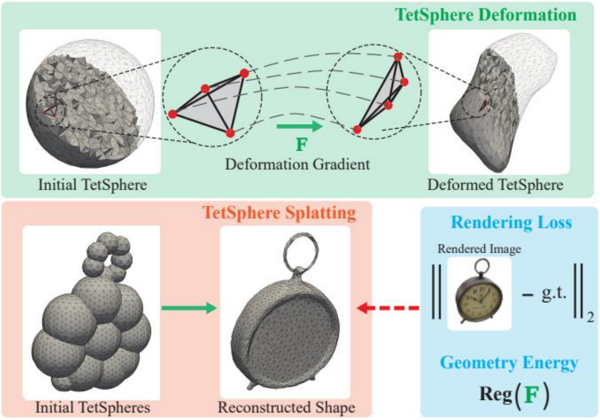
Latent-NeRF
Metzer *et al*, CVPR 23

3D Gaussians



GRM
Xu *et al*, ECCV 24

Tetrahedral Mesh



TetSphere Splatting
Guo *et al*, ICLR 25

Textured Mesh

Meta 3D AssetGen
Siddiqui *et al*, NeurIPS 24

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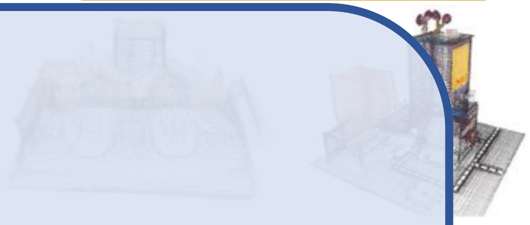
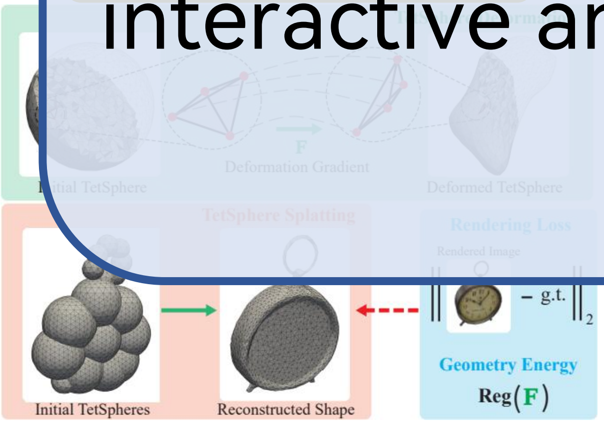


GRM
Xu *et al*, ECCV 24

Problem: Overlook physical properties of generated 3D objects that are essential to interactive and simulation-based scenarios.

Tetrahedral Mesh



TetSphere Splatting
Guo *et al*, ICLR 25

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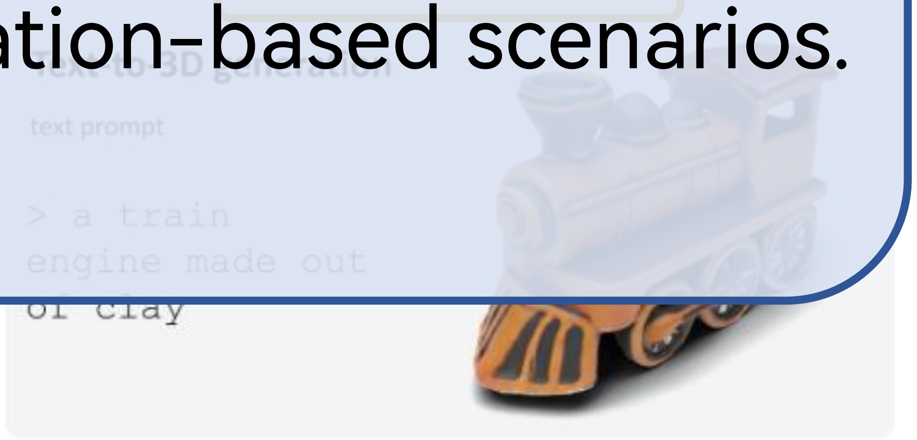
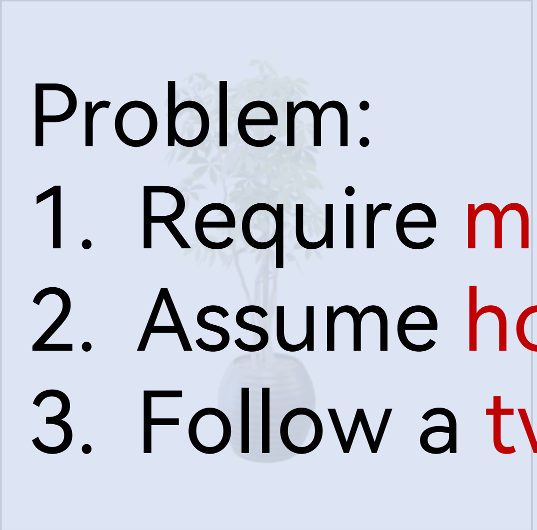


Meta 3D AssetGen
Siddiqui *et al*, NeurIPS 24

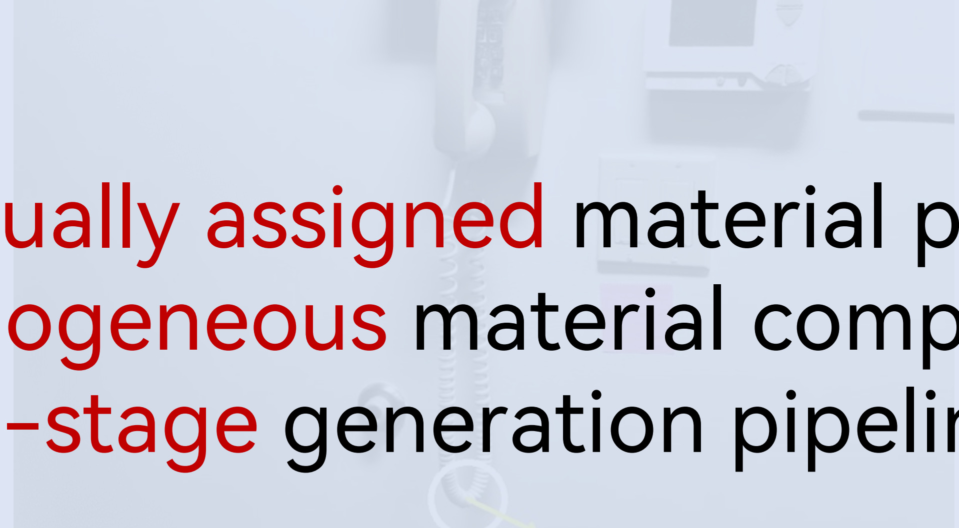
Background

Problem:

1. Require manually assigned material parameters
2. Assume homogeneous material compositions
3. Follow a two-stage generation pipeline



PhysGaussian



PhysDreamer

Phys4DGen

PhysGaussian: Physics-integrated 3D Gaussians for Generative Dynamics. CVPR 2024.
PhysDreamer: Physics-Based Interaction with 3D Objects via Video Generation. ECCV 2024.
Phys4DGen: Physics-Compliant 4D Generation with Multi-Material Composition Perception. ACM MM 2025.

Question

How can we generate simulation-ready objects with diverse material compositions that are compatible in geometry, textures, and physical properties?

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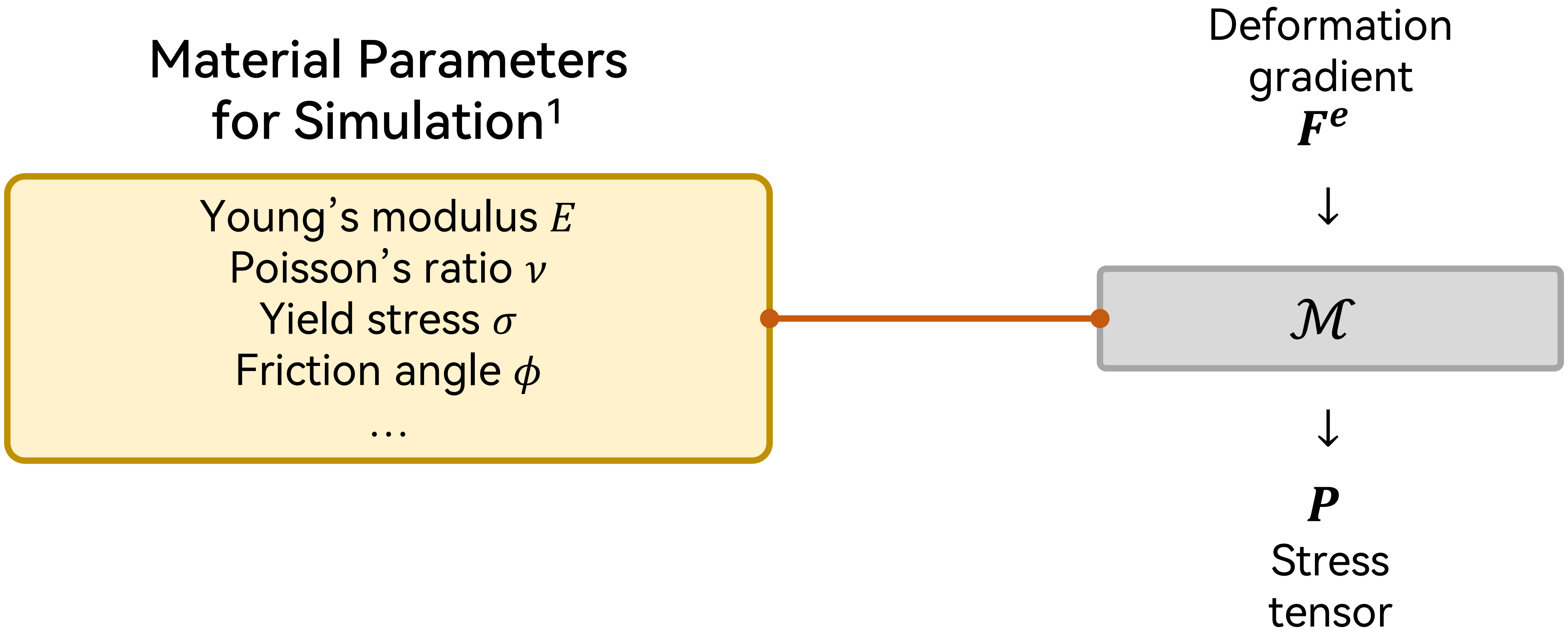
How can we generate simulation-ready objects with diverse material compositions that are compatible in geometry, textures, and physical properties?

Challenges

1. Lack of available datasets that include detailed material parameters.



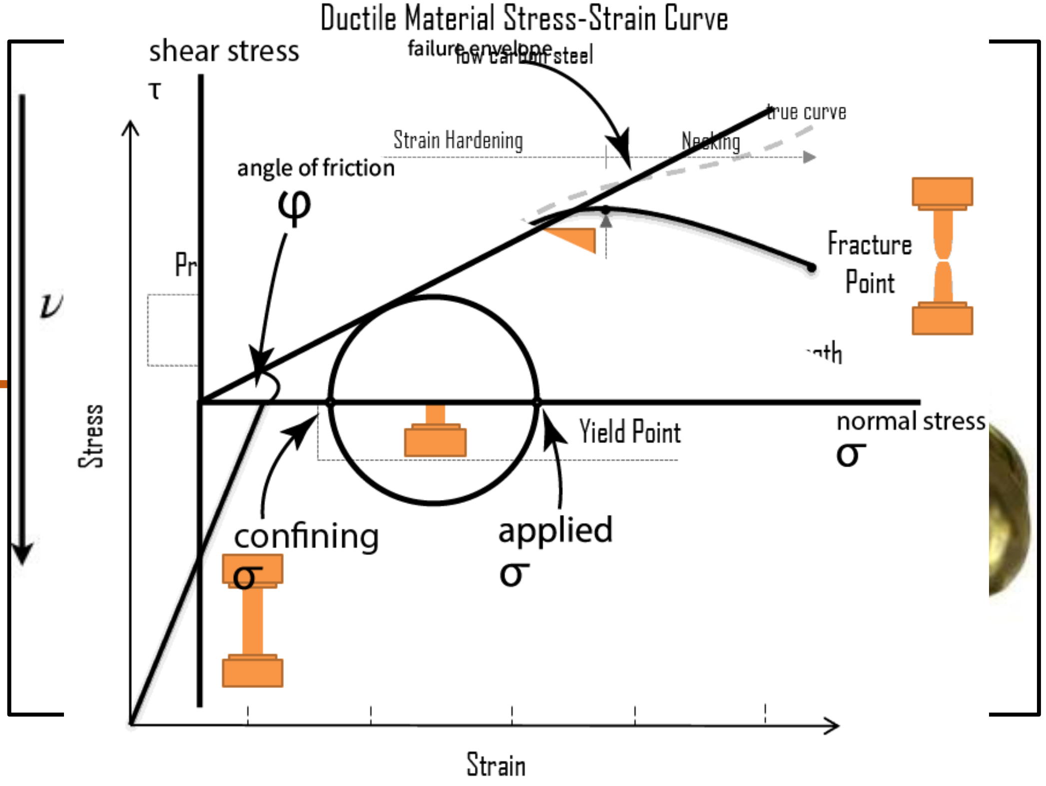
1: We consider the Material Point Method in our work. $\mathcal{M}$: Material models (*a.k.a* constitutive models)

Challenges

1. Lack of available datasets that include detailed material parameters.

Material Parameters for Simulation[1]

Young's modulus E
Poisson's ratio ν
Yield stress σ
Friction angle ϕ
…



1. We consider the Material Point Method in our work. $\mathcal{M}$: Material models (a.k.a constitutive models)

Credit to: https:// … friction angle … CVPR 2024.

Challenges

1. Lack of available datasets that include detailed material parameters.

ShapeNet
Chang *et al*, arXiv 15

Objaverse
Deitke *et al*, CVPR 23

Amazon Berkeley Objects
Collins *et al*, CVPR 22

Challenges

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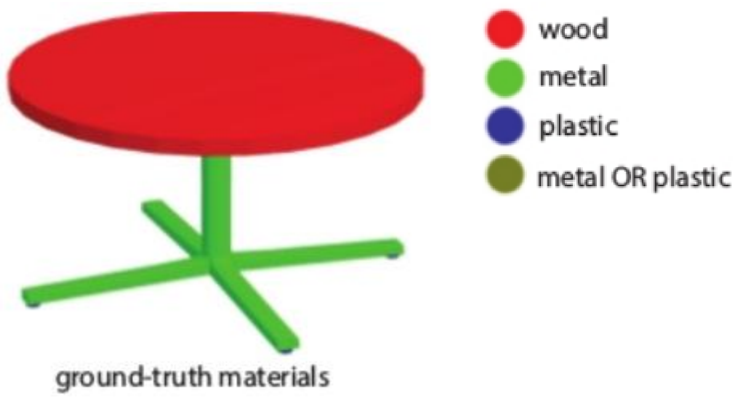
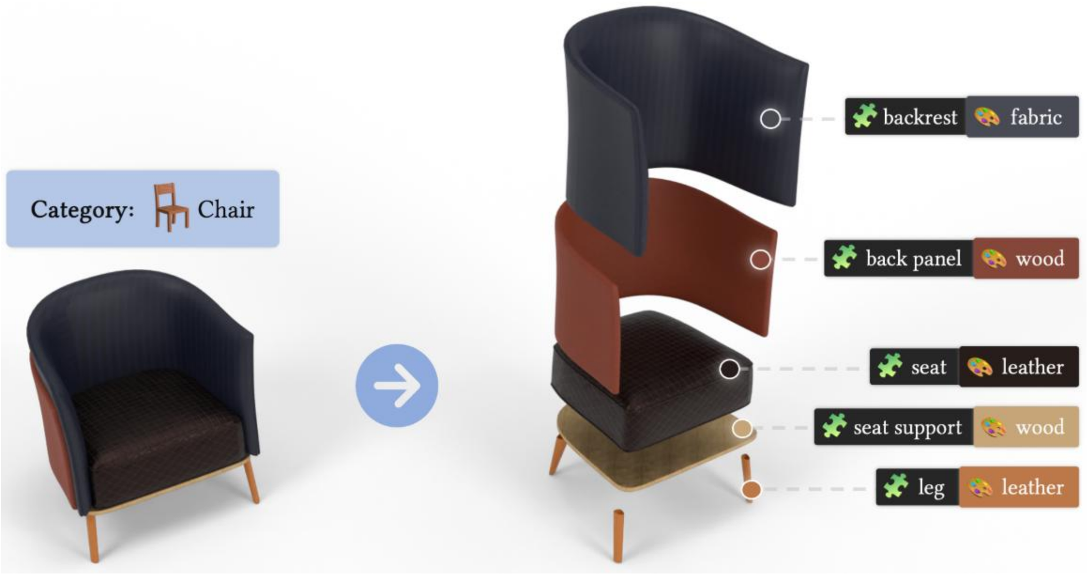




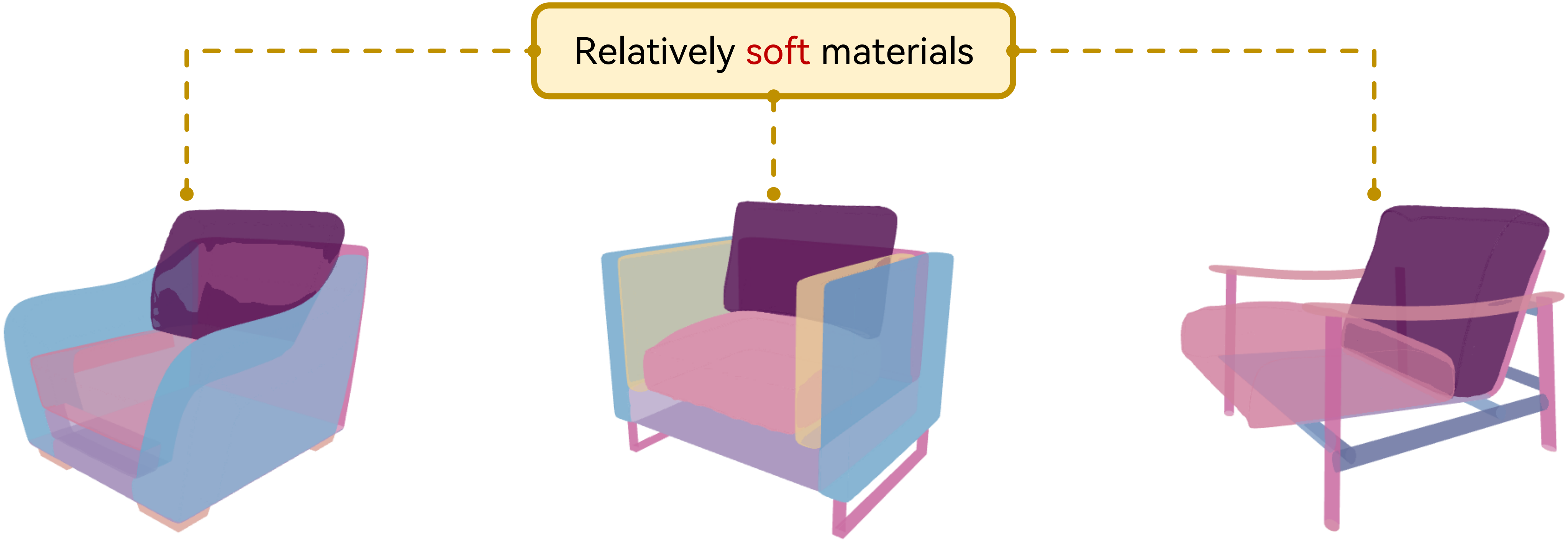
ShapeNet-Mat
Lin *et al*, 3DV 18

3DCoMPaT/++/200
ECCV 22/arXiv 23/NeurIPS 24

Challenges

2. How to jointly model the interplay of shape and material in generation?

Regarding the material of backrest …



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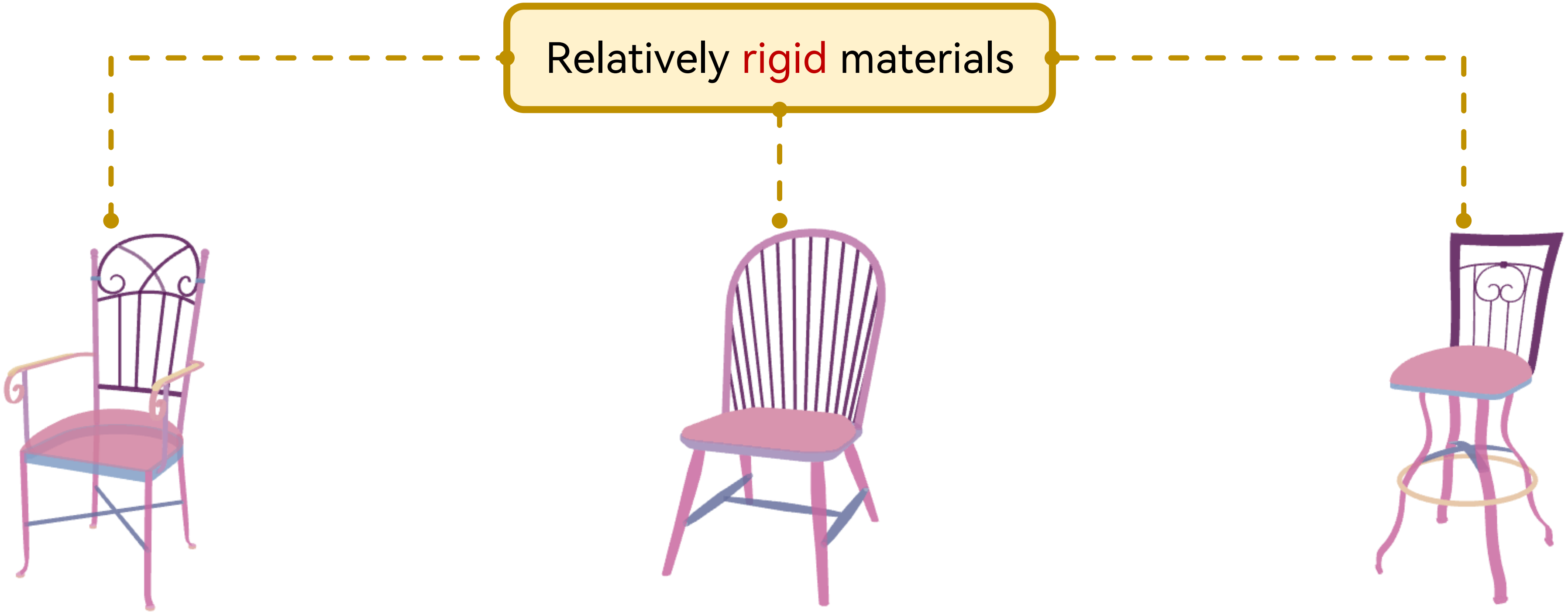


Challenges

2. How to jointly model the interplay of shape and material in generation?

Certain materials are associated with certain geometric structures.

Contents

- Background
- Material-annotated Dataset
- Generative Model
- Experiment

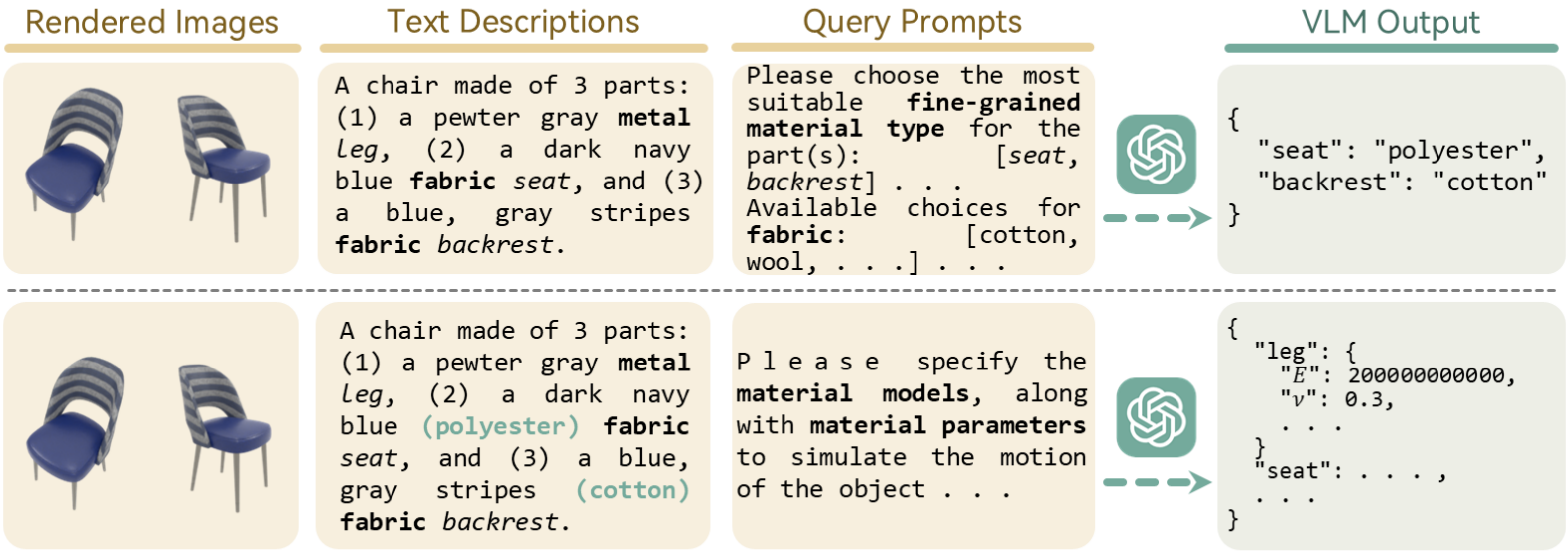
Material-annotated Dataset

A planter made of 3 parts: (1) a brown with speckles **soil** 'soil', (2) a light gray **metal** 'planter_container', and (3) a light green **plant** 'plant'.

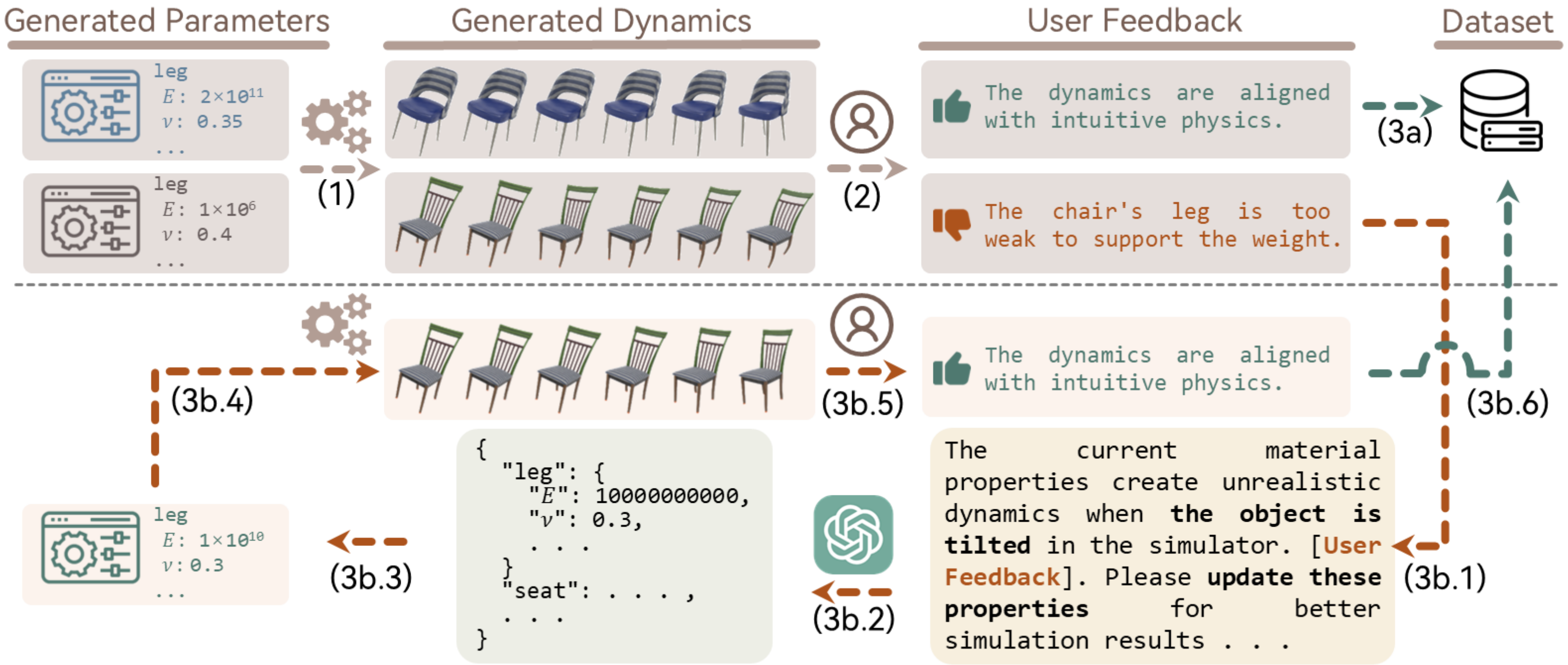

```
"soil": {
    "E": 1000000.0,
    "nu": 0.3,
    "phi": 30,
    "mmid": "M5",
    "elasticity": "stvk",
    "plasticity": "drucker_prager",
    "mat_name": "soil_02",
    "mat_id": 10
}

"plant": {
    "E": 100000.0,
    "nu": 0.4,
    "mmid": "M3",
    "elasticity": "fixed_corotated",
    "plasticity": "identity",
    "mat_name": "plant_00",
    "mat_id": 7
}

"planter_container": {
    "E": 200000000000.0,
    "nu": 0.3,
    "sigma_y": 300000000.0,
    "mmid": "M1",
    "elasticity": "neo_hookean",
    "plasticity": "von_mises",
    "mat_name": "metal_09",
    "mat_id": 6
}
```


3DCoMPaT200: Language-grounded compositional understanding of parts and materials of 3D shapes. NeurIPS 2024.

VLM-guided material annotation of shape parts



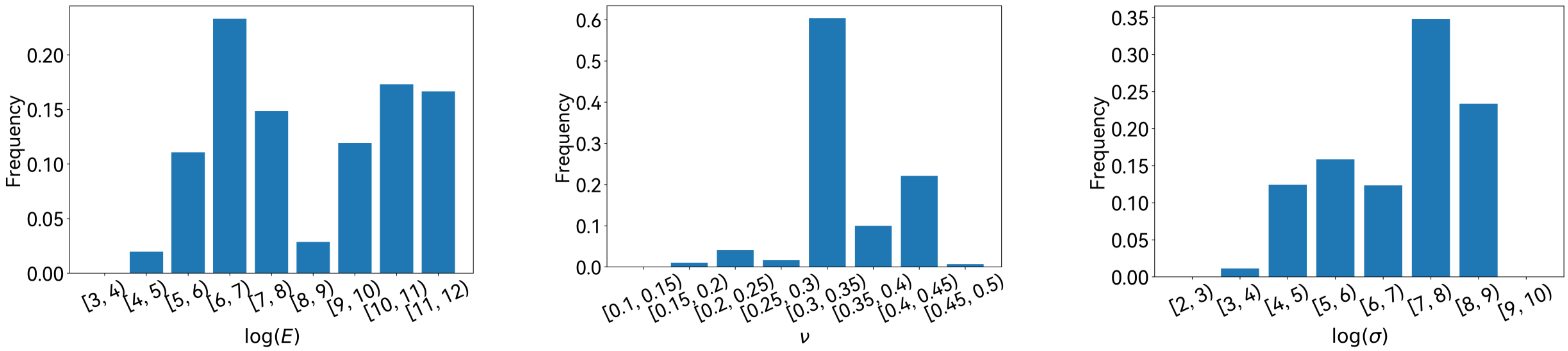
Expert verification of material annotations



Material-annotated Dataset

In total: 12 shape categories, 3K objects, 15K parts

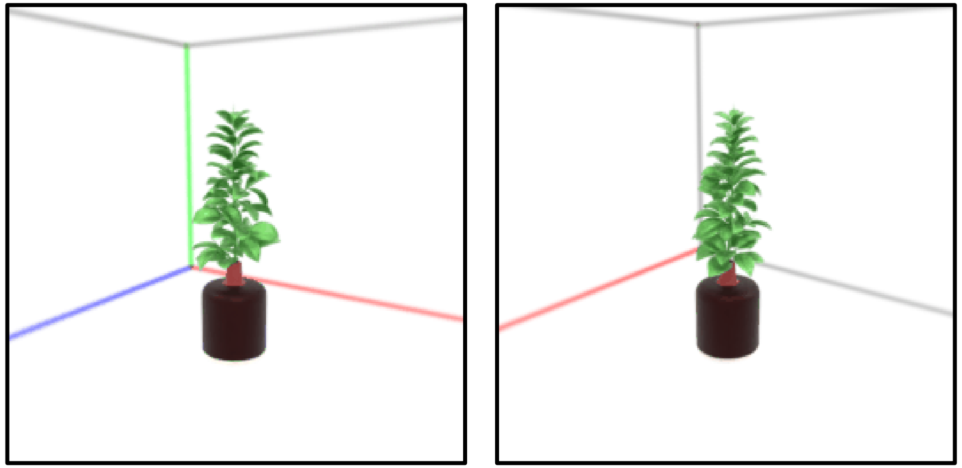
	bag	bed	chair	crib	hat	headband	love_seat	pillow	planter	sofa	teddy_bear	vase	Total
Train	75	418	898	27	18	27	139	71	383	278	37	91	2462
Valid	10	26	52	5	2	5	21	11	21	18	6	3	180
Test	24	48	106	8	7	10	39	18	46	31	11	14	362



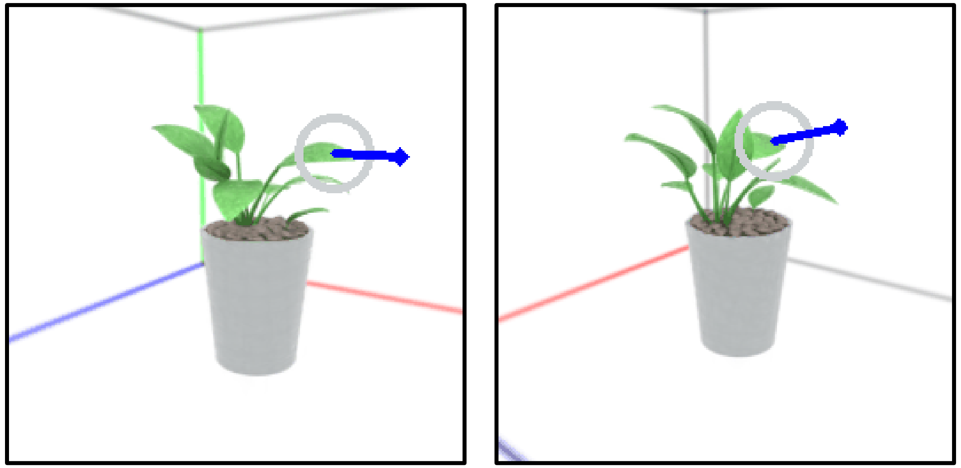
Data Distribution of Material Parameters

Material-annotated Dataset

Simulation Samples – Testcase: Drag



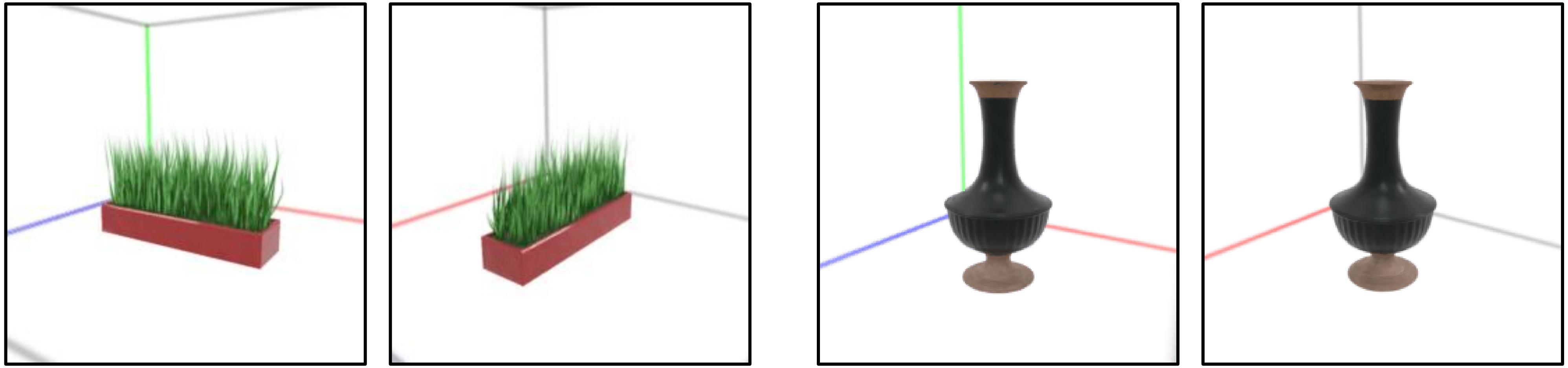
Planter



Planter

Material-annotated Dataset

Simulation Samples – Testcase: Wind

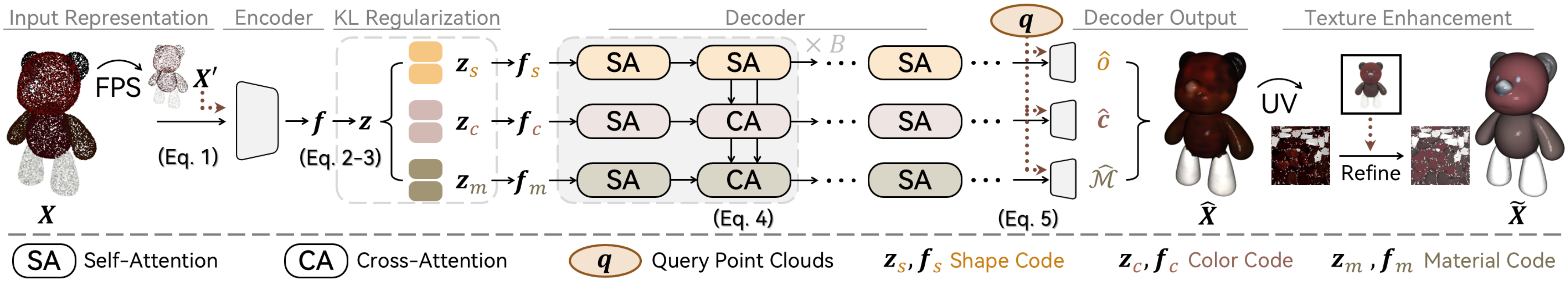


Planter Vase

Contents

Generative Model

Overall Structure (VAE)



Check our code 👉

https://github.com/XJay18/SOPHY

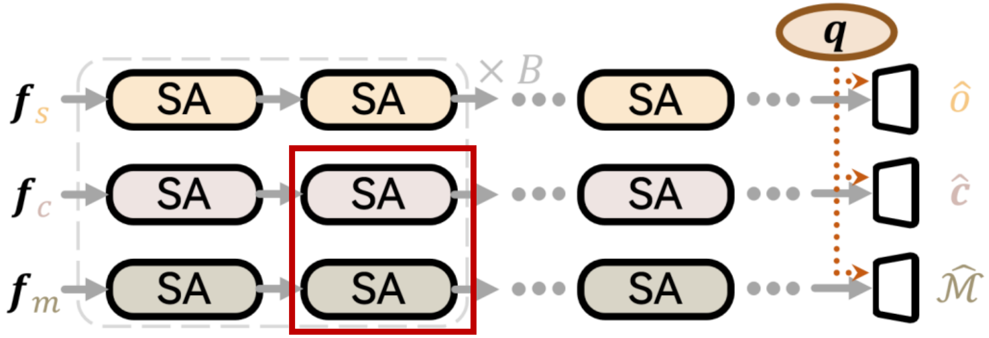
Contents

Auto-encoding Experiment

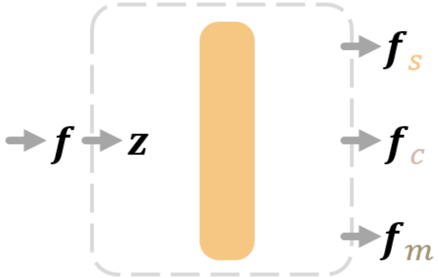
1. Comparison Methods

a) Baseline (B. Dec.) X → Shape-only VAE → $\hat{o}$ → Color Decoder → $\hat{c}$ → Material Decoder → $\hat{\mathcal{M}}$

b) w/o CA



c) Fused

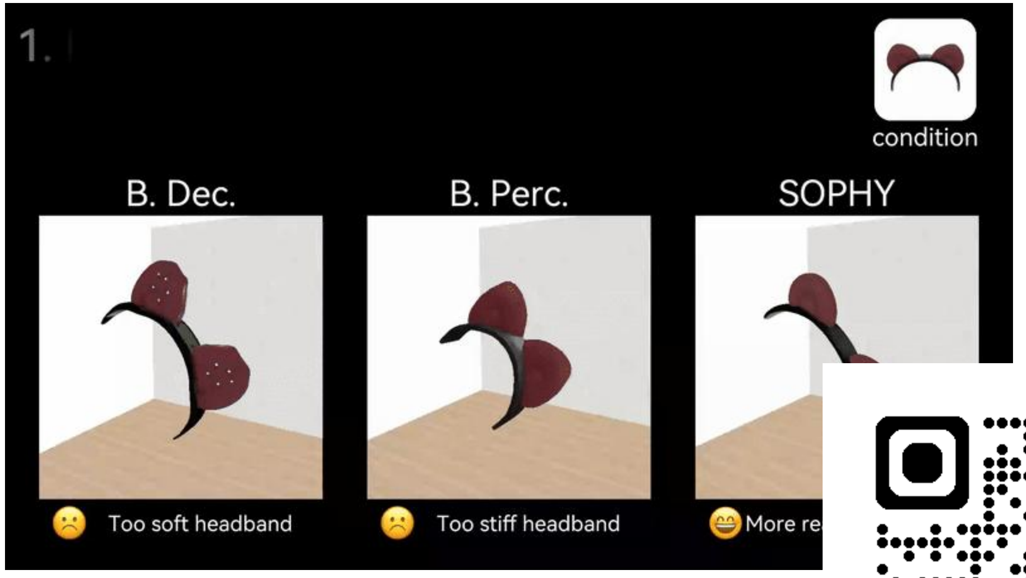


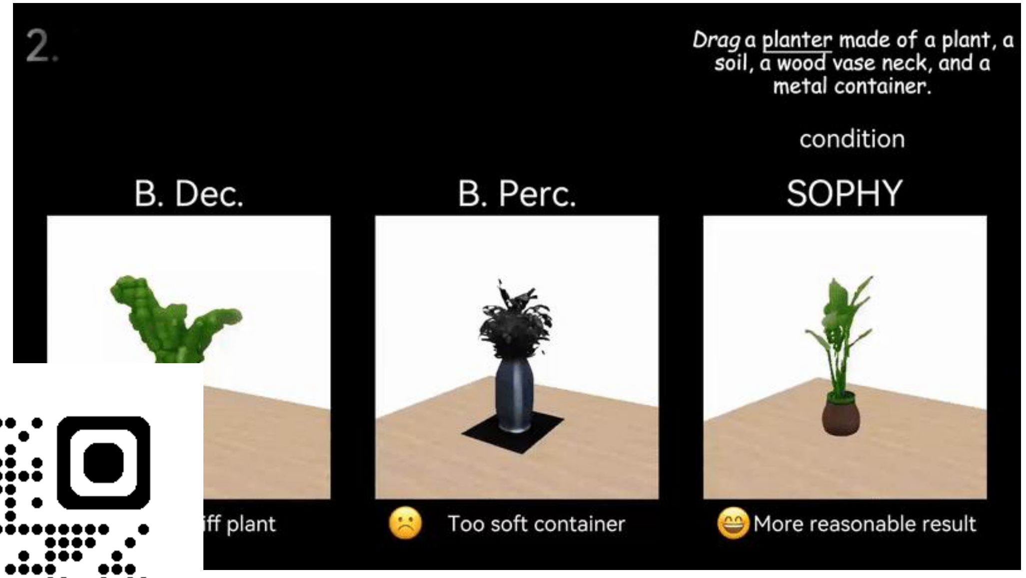
Auto-encoding Experiment

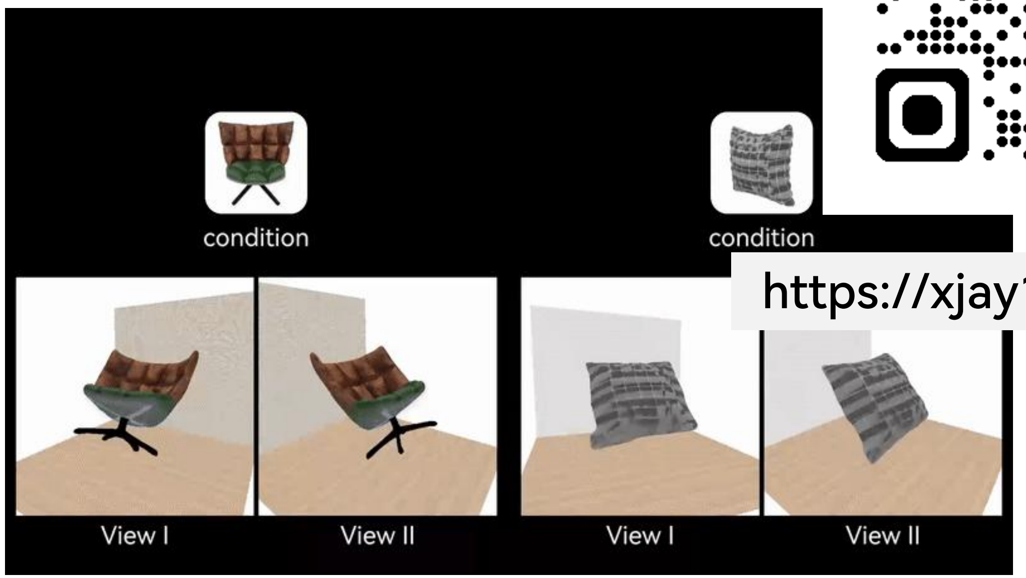
2. Results

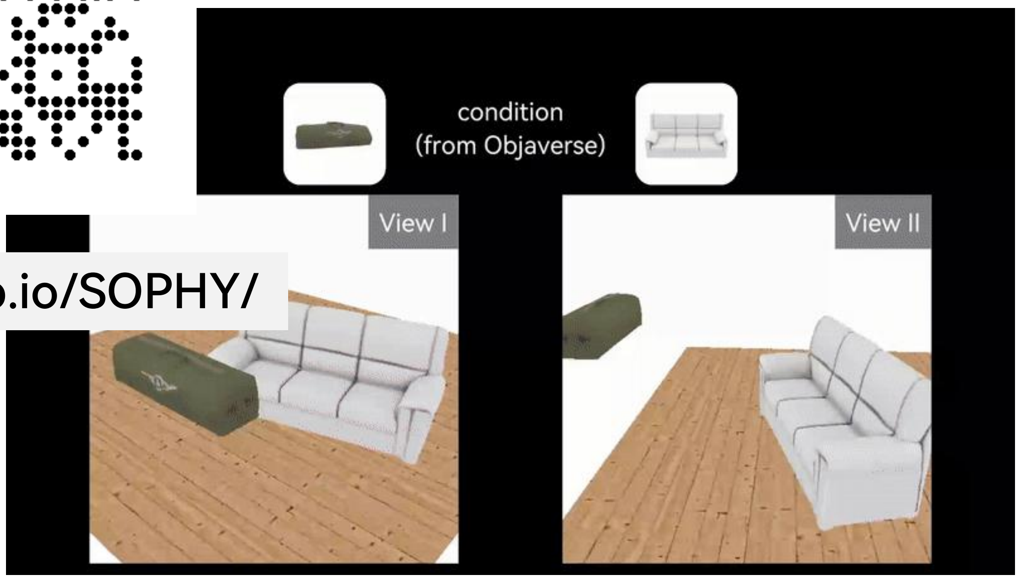
Metric	B. Dec.	w/o CA	Fused	SOPHY
M.B. Acc(%) ↑	71.04	92.77	93.23	**93.55**
MAE-log(E) ↓	1.18	0.50	0.47	**0.45**
MAE-ν($\times 10^{-2}$) ↓	4.10	3.06	**2.98**	3.06
MAE-log(σ) ↓	1.07	0.41	0.32	**0.29**
MAE-ϕ ($\times 10^{-2}$) ↓	5.45	1.89	**1.22**	1.28
MAE-ρ ↓	0.16	0.14	0.13	**0.09**
Sim-CD ($\times 10^{-3}$) ↓	53.84	17.47	10.05	**8.72**
MAE-c($\times 10^{-2}$) ↓	8.75	8.47	8.35	**8.13**
IoU(%) ↑	90.69	90.75	90.66	**90.89**
CD($\times 10^{-4}$) ↓	3.51	3.34	3.30	**3.02**
F-Score(%) ↑	93.65	93.77	93.79	**93.85**

M.B. Acc: Material Behavior Type Accuracy. MAE: Mean Absolute Error.









https://xjay18.github.io/SOPHY/

Limitation and Future Work

1. Limitation

- Our annotated dataset is currently a small-scale dataset.

- The considered test scenarios for material parameter verification may still be insufficient to validate the annotation correctness comprehensively.

- There is room for improvement in thin structure generation and texture enhancement.

Limitation and Future Work

2. Future Work

- A more efficient/automatic pipeline for material parameter annotation.
- Consider improved shape/texture generation techniques.
- Consider the Finite Element Method for more accurate simulations

Thanks for watching!