

A photograph of a modern wooden cabinet with a natural wood grain finish. The cabinet is positioned against a red brick wall. It features two large doors on the left side, both of which are open, revealing interior shelves. To the right of the doors are two drawers, each with a black handle. The cabinet sits on a dark wood floor. The text is overlaid on the image in a white, sans-serif font.

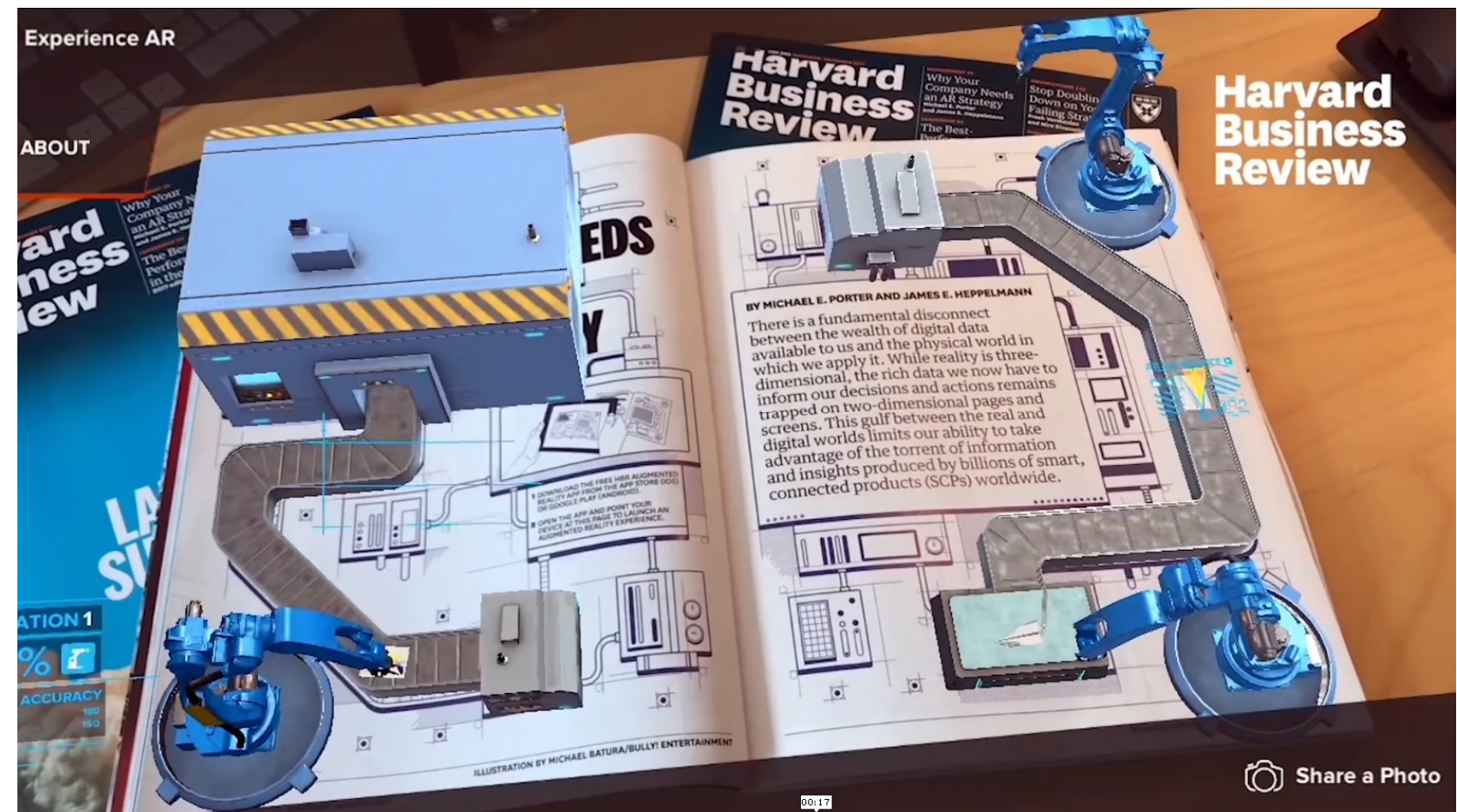
Towards 4D-aware generative models: *Creating dynamic, interactive 3D worlds with generative AI*

Evangelos Kalogerakis
TU Crete, CYENS, UMass Amherst

Living in the 3D Digital Era!



The Real Significance Of AR, VR And Mixed Reality [forbes.com]



Why Every Organization Needs an Augmented Reality Strategy [hbr.org]

3D Interactive Environments



A Simulated Part-based Interactive Environment [<https://sapien.ucsd.edu/>]



RoboDK - Guide to 3D Simulation Software [robodk.com]

3D Interactive Social Media & Entertainment

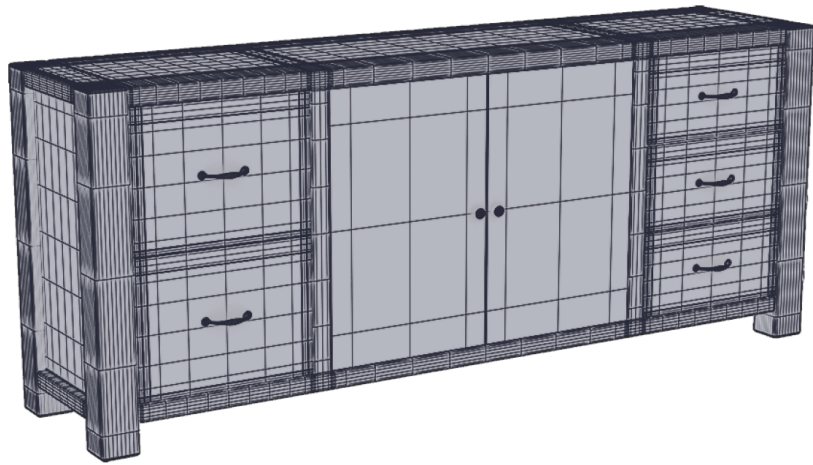


Entering The Metaverse [[popularmechanics.com](https://www.popularmechanics.com)]

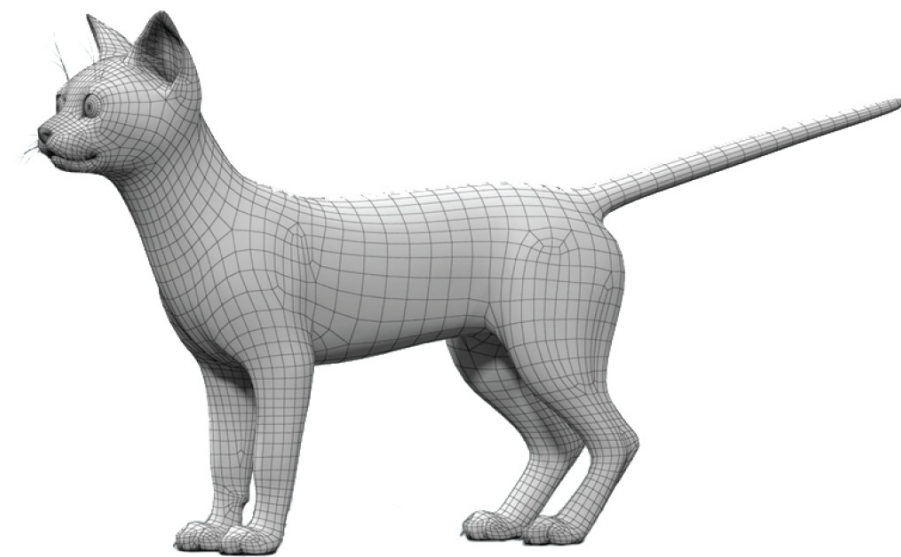


Animated Meerkat [[Weta Digital / Epic Games](#)]

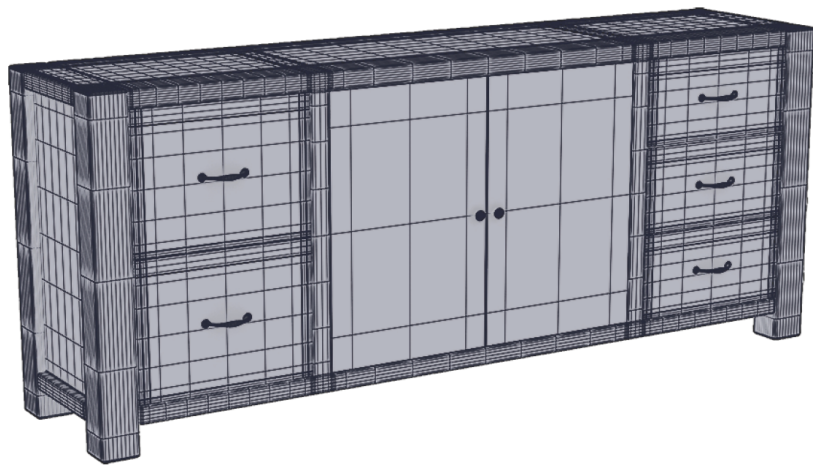
Crafting interactive 3D models



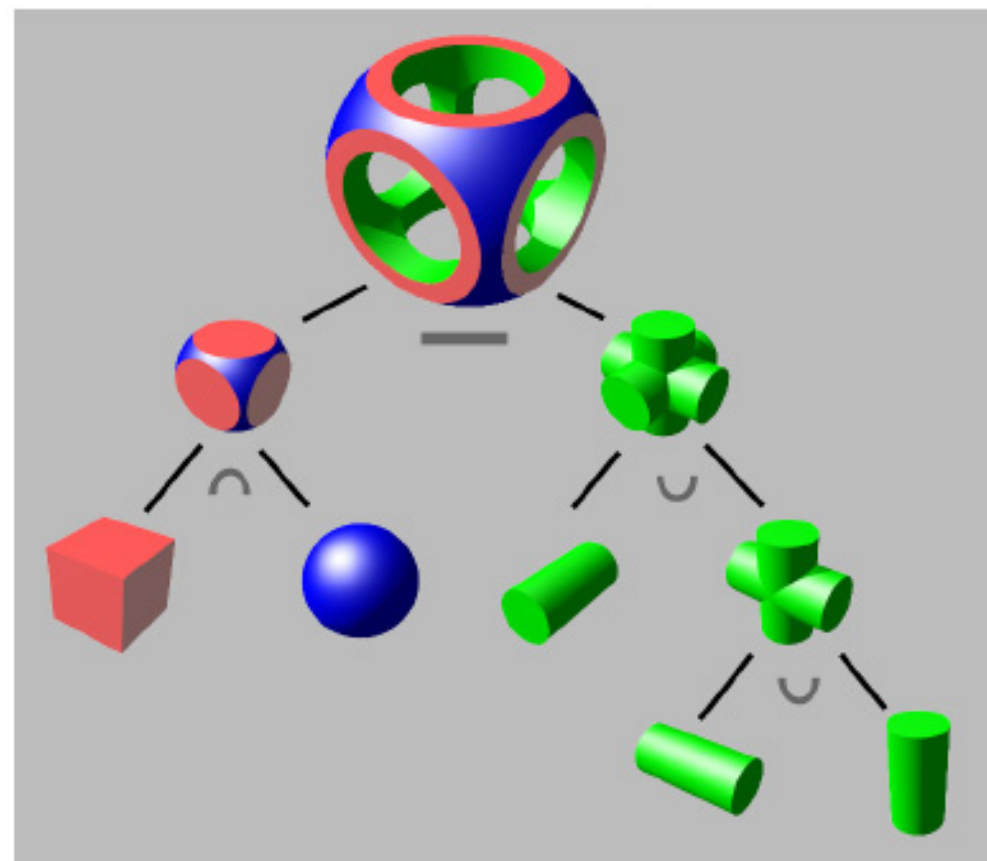
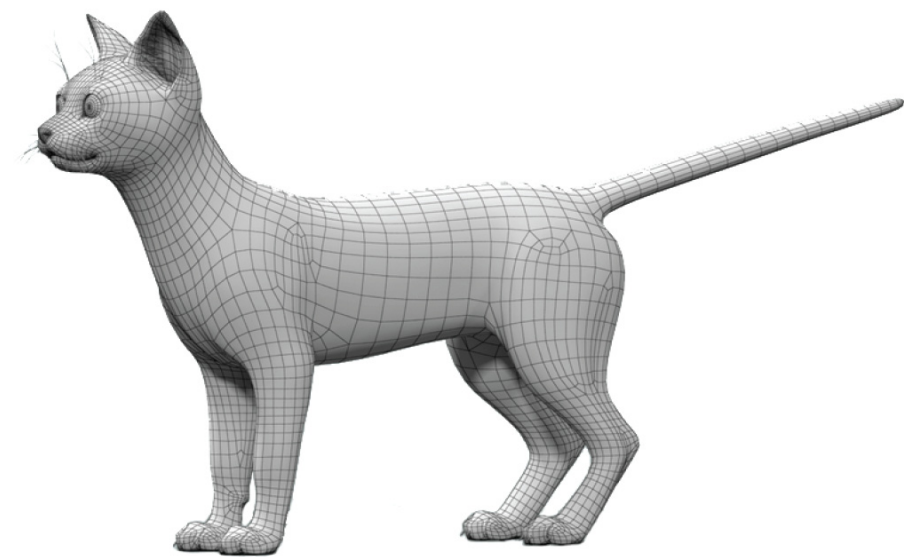
3D Geometry



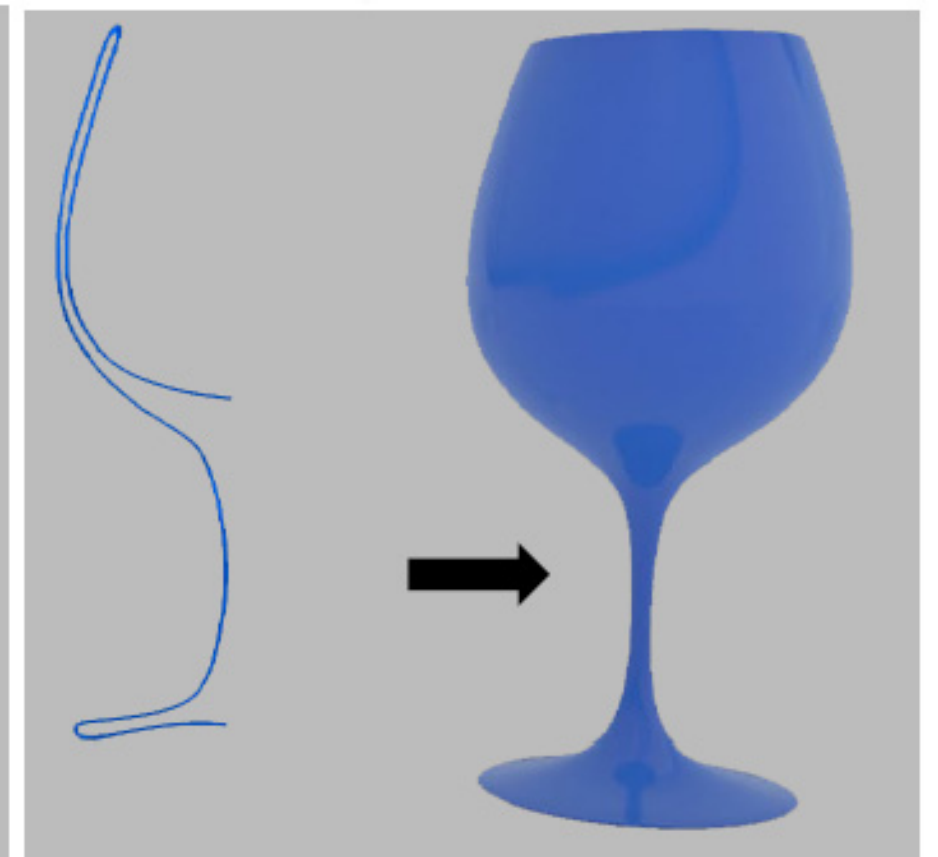
Crafting interactive 3D models



3D Geometry

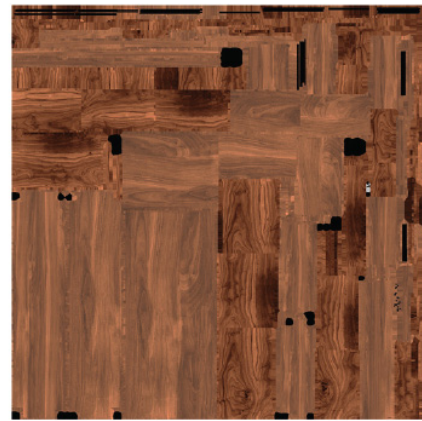
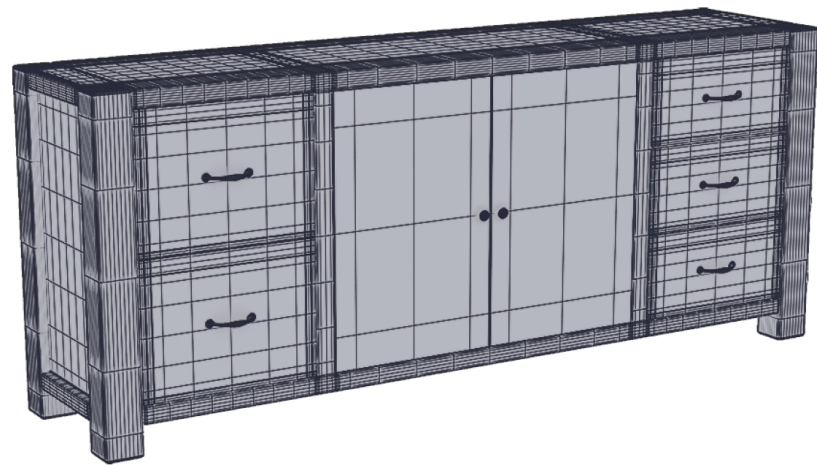


Constructive Solid Geometry

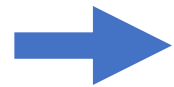


Parametric curves / surfaces

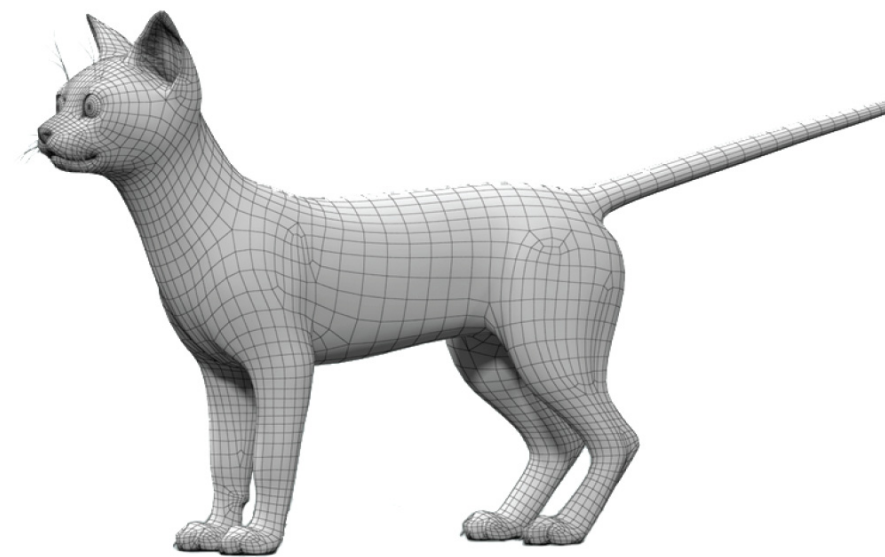
Crafting interactive 3D models



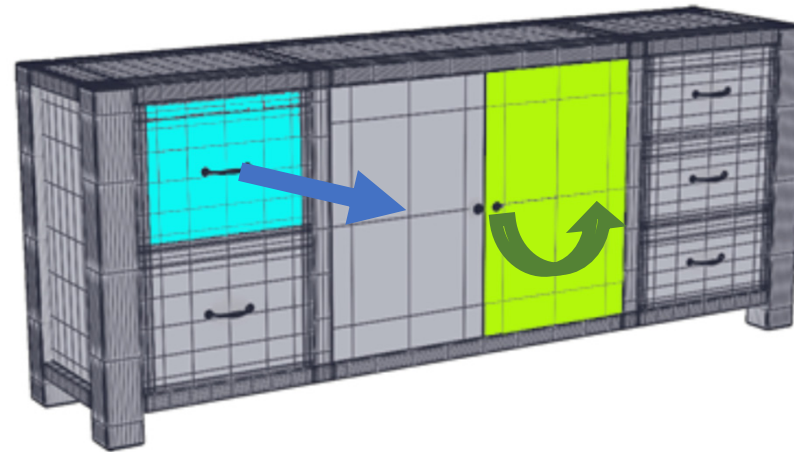
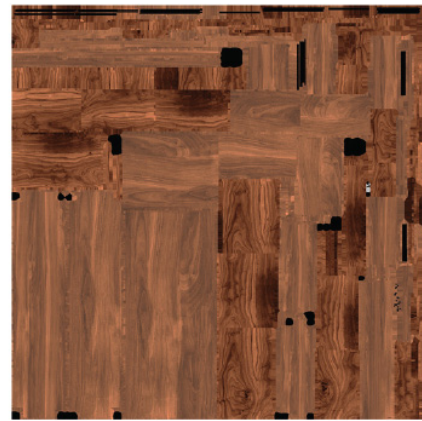
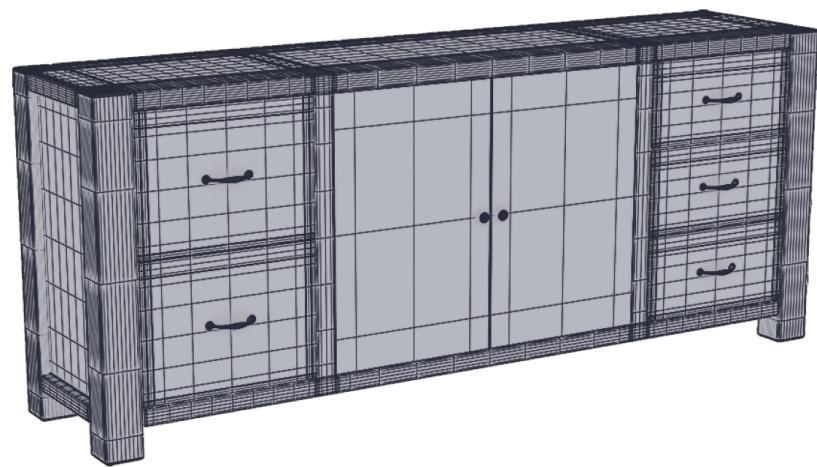
3D Geometry



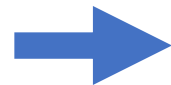
Textures



Crafting interactive 3D models



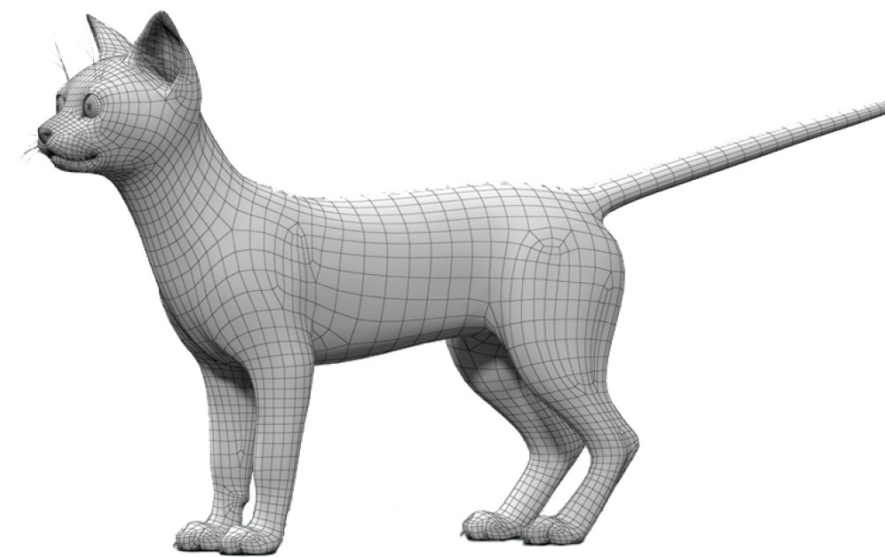
3D Geometry



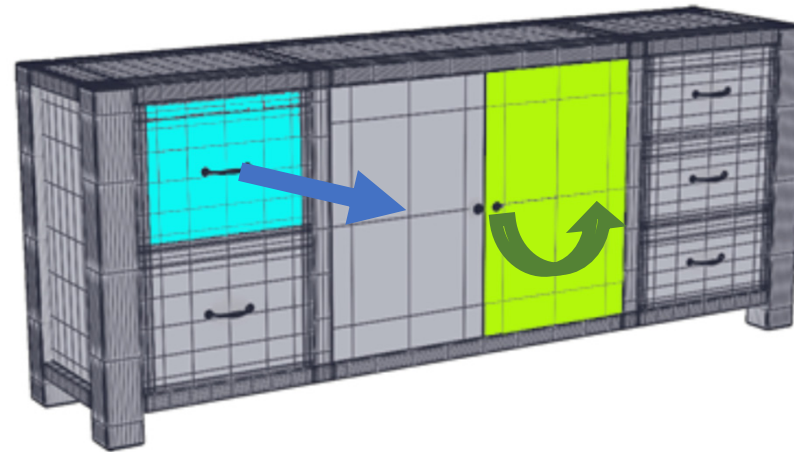
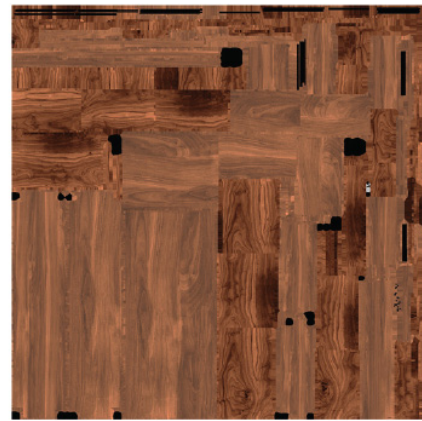
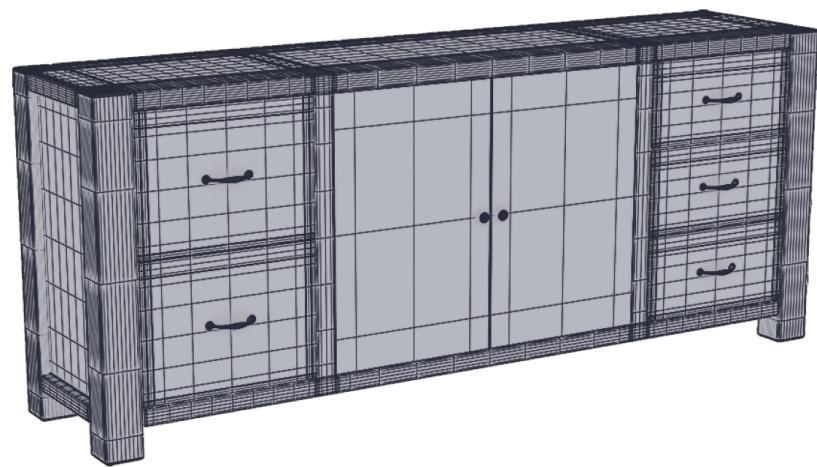
Textures



**Motion controller
& attributes**



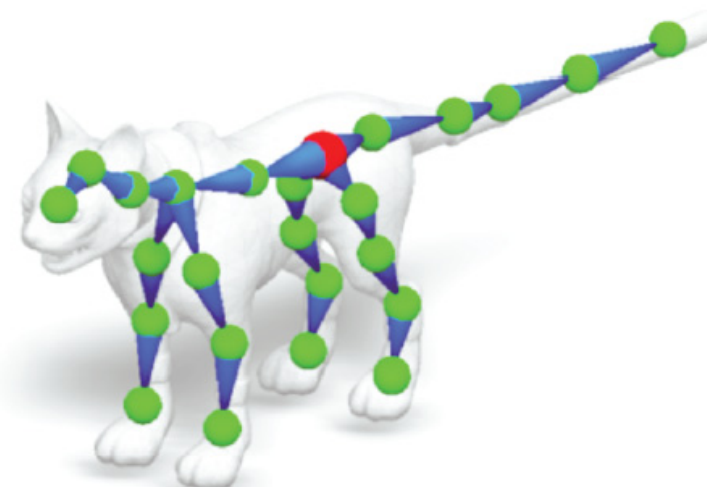
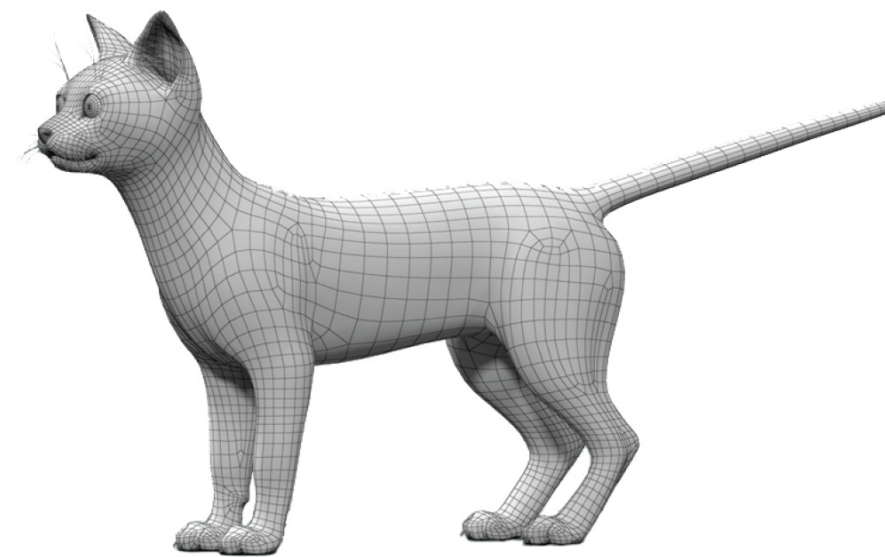
Crafting interactive 3D models



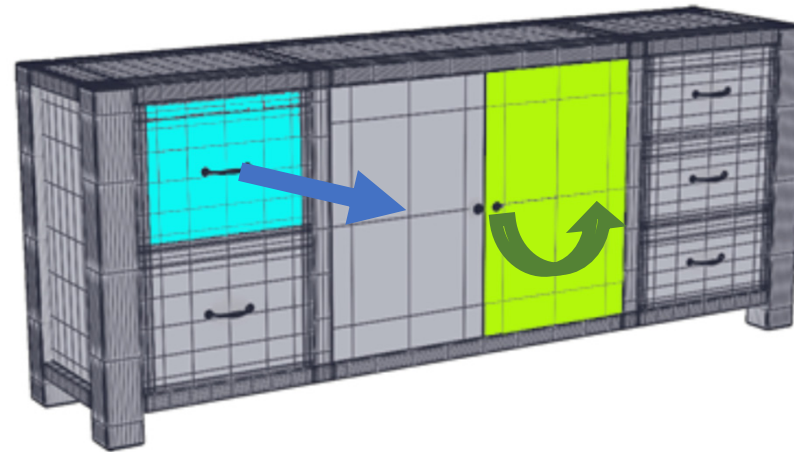
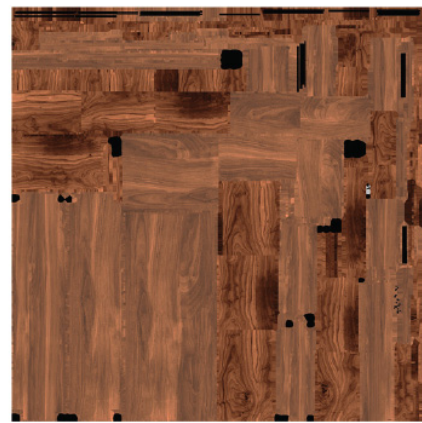
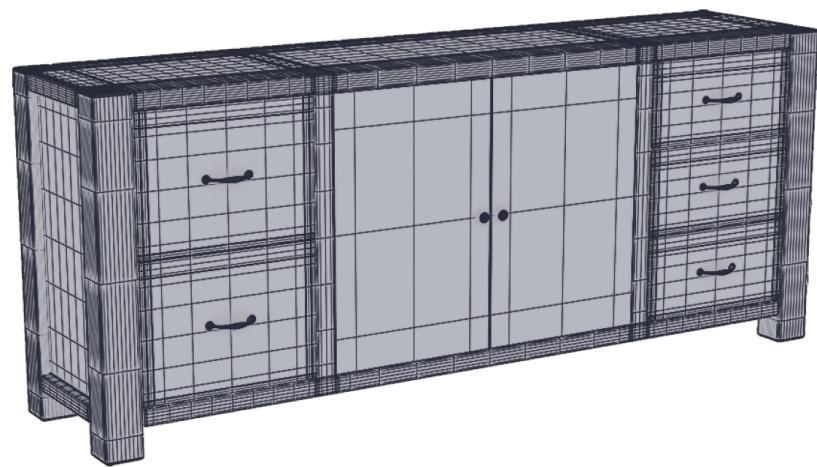
3D Geometry

Textures

**Motion controller
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Crafting interactive 3D models



3D Geometry



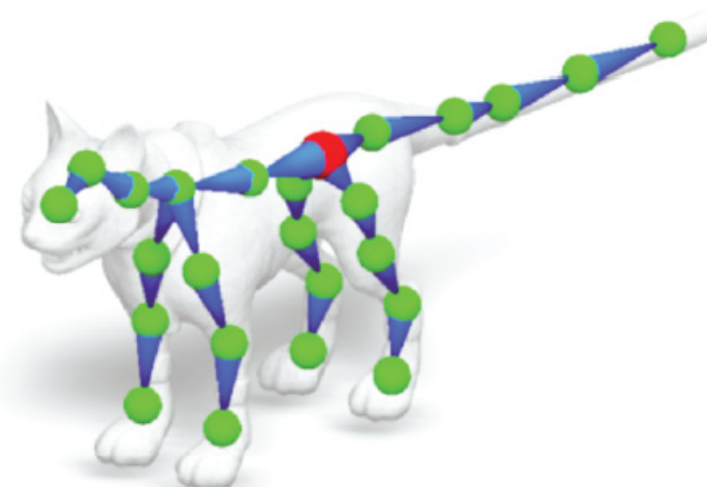
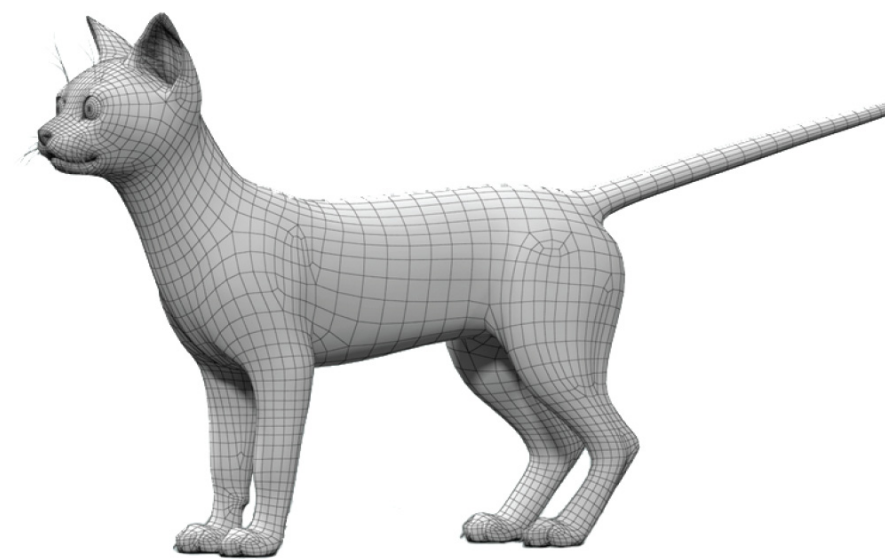
Textures



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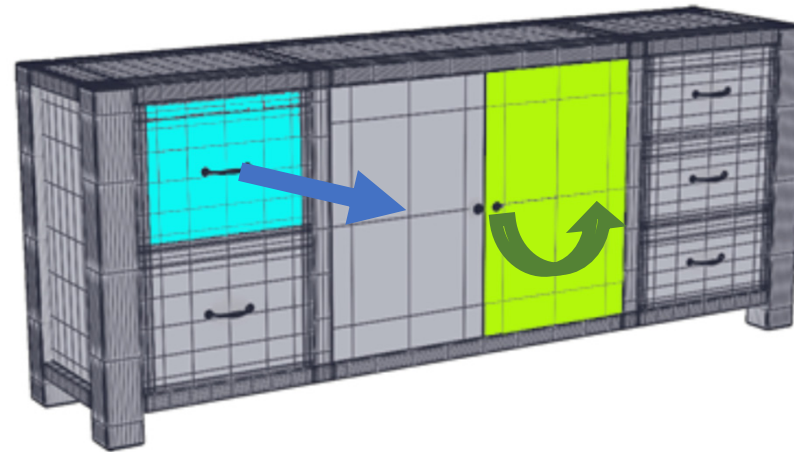
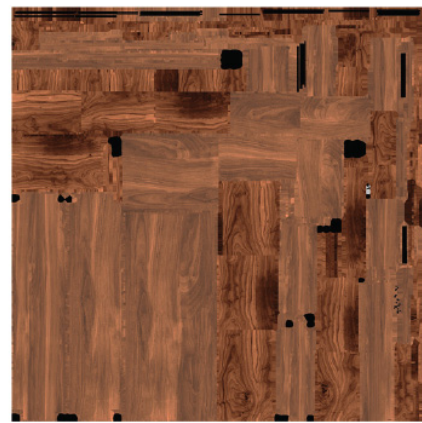
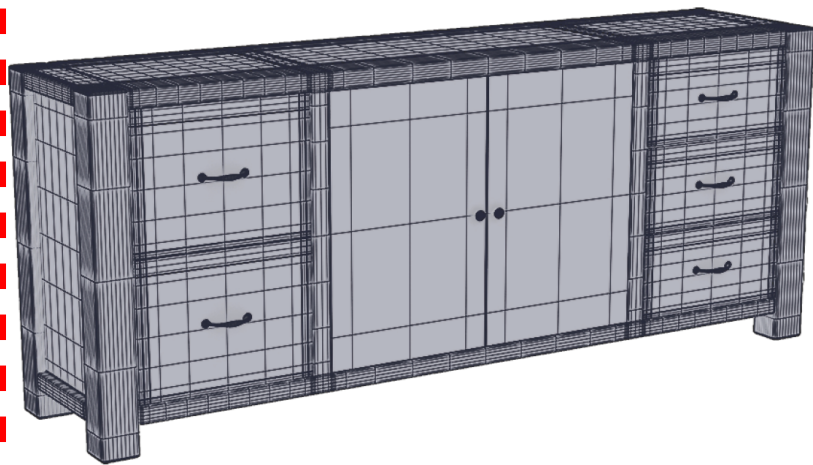


Interactive Model



[models from turbosquid]

Lots of AI progress here!

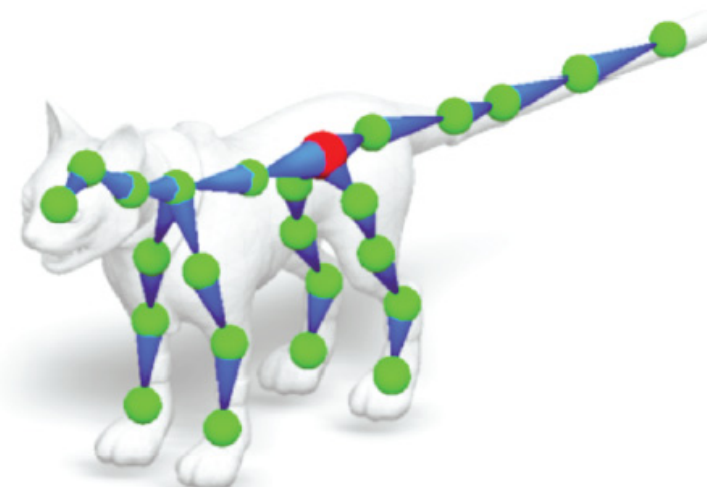
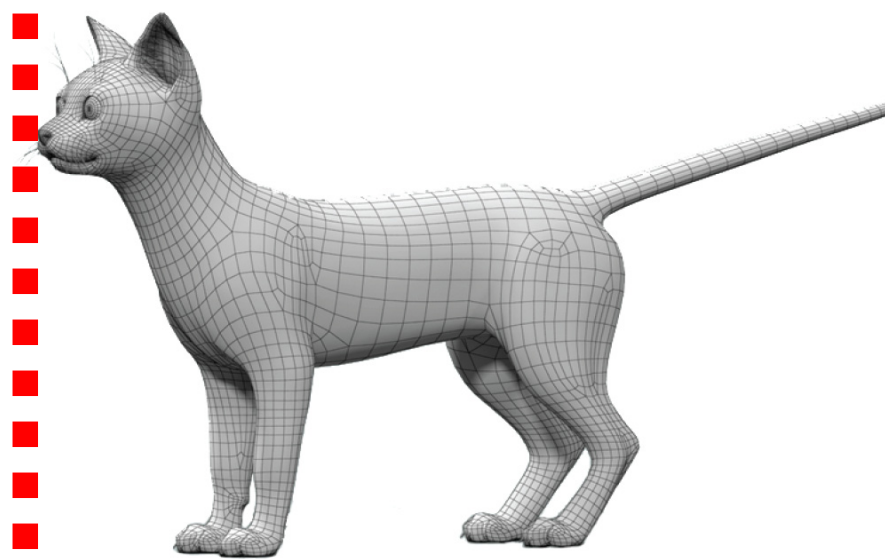


3D Geometry

Textures

**Motion controller
& attributes**

Interactive Model



[models from turbosquid]

Neural 3D Reconstruction & Generation

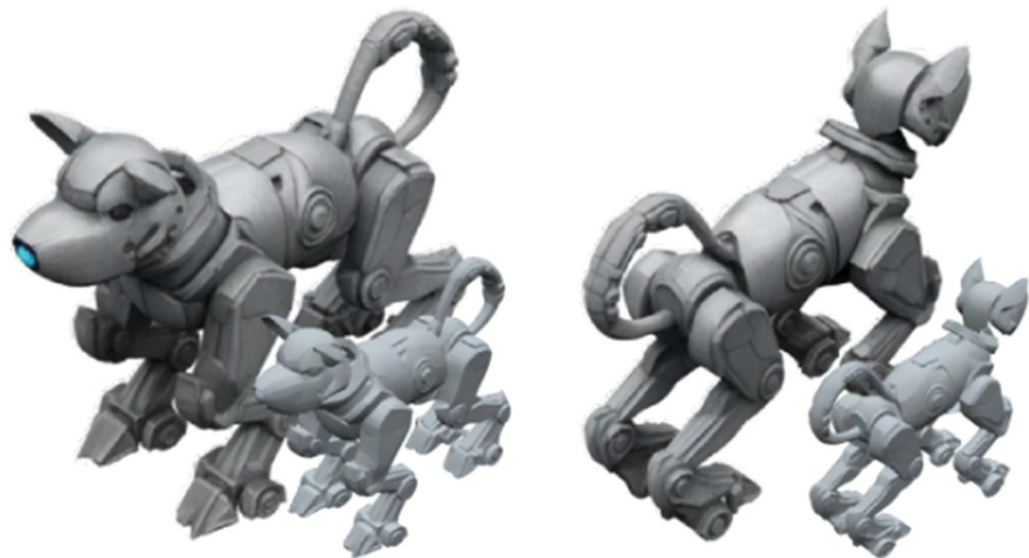
*Portable transistor radio, dark cover,
speaker grille, brand logo on front.*

*Metallic dog-like robot with articulated legs and
futuristic design elements.*

Neural 3D Reconstruction & Generation



Portable transistor radio, dark cover, speaker grille, brand logo on front.

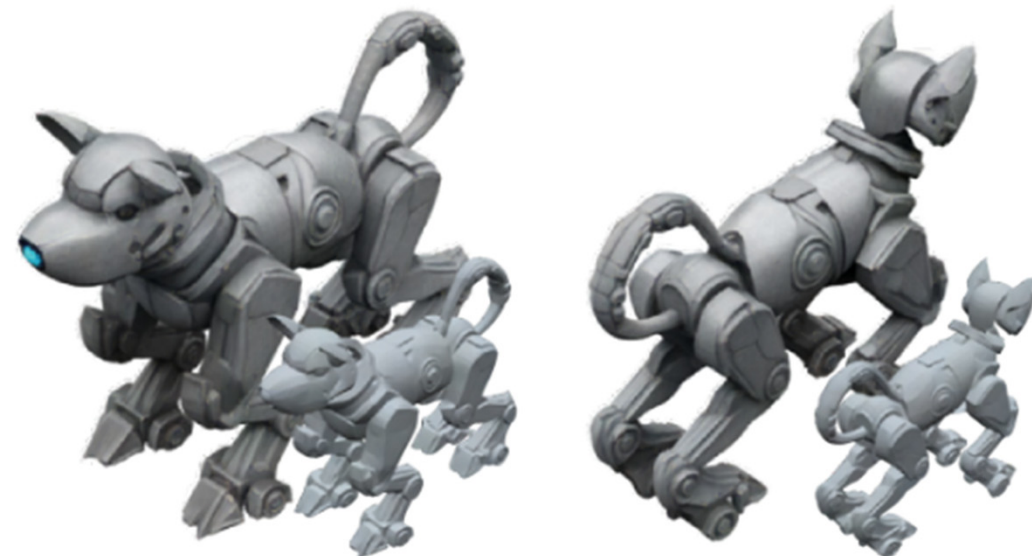


Metallic dog-like robot with articulated legs and futuristic design elements.

Neural 3D Reconstruction & Generation



Portable transistor radio, dark cover, speaker grille, brand logo on front.



Metallic dog-like robot with articulated legs and futuristic design elements.

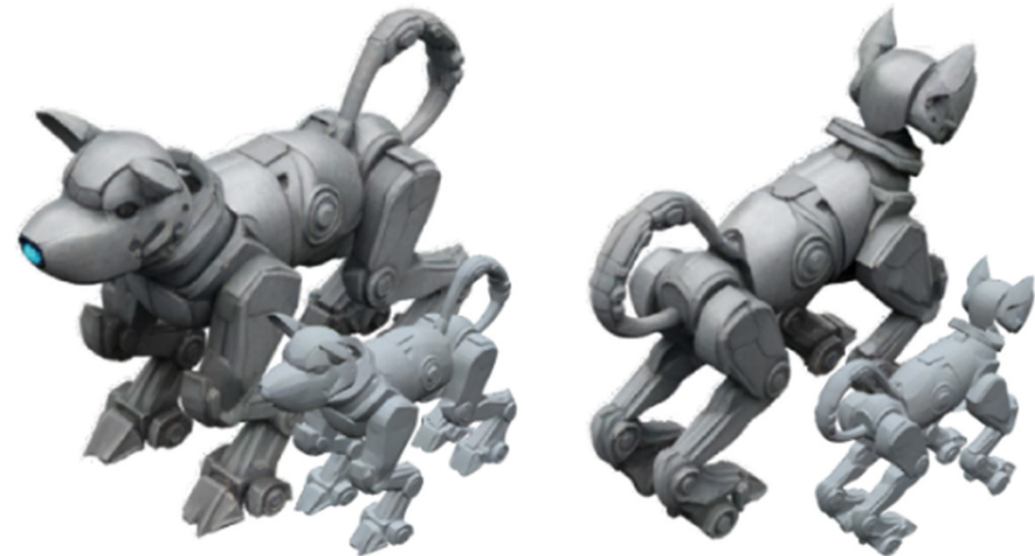
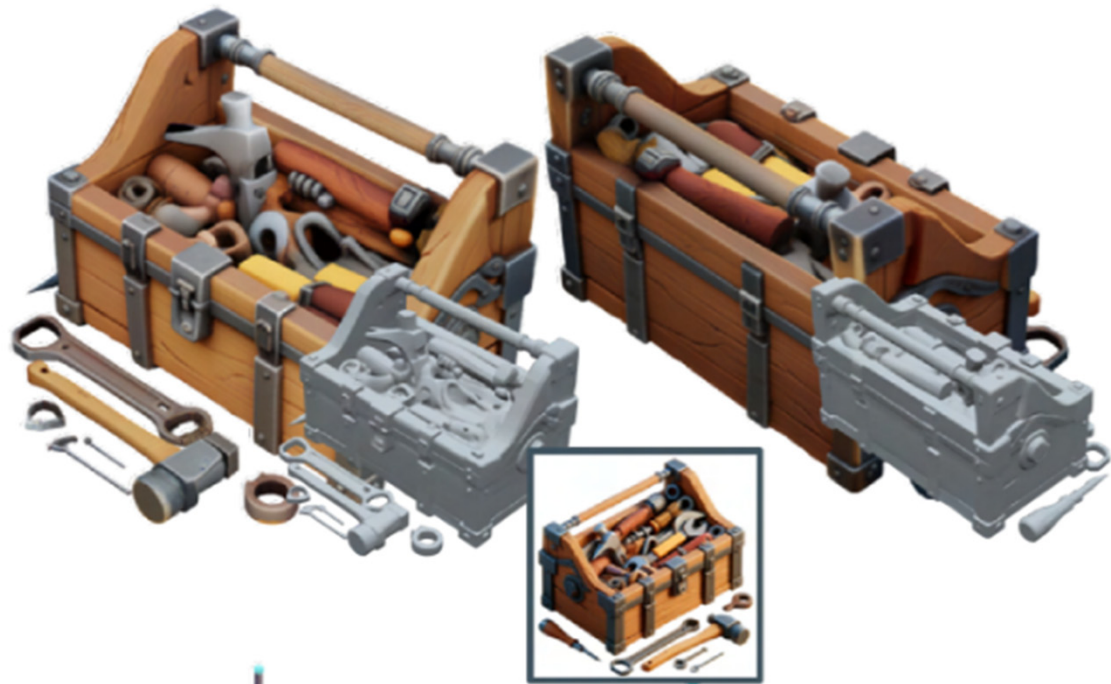


[TRELLIS, CVPR 2025]

Neural 3D Reconstruction & Generation



Portable transistor radio, dark cover, speaker grille, brand logo on front.

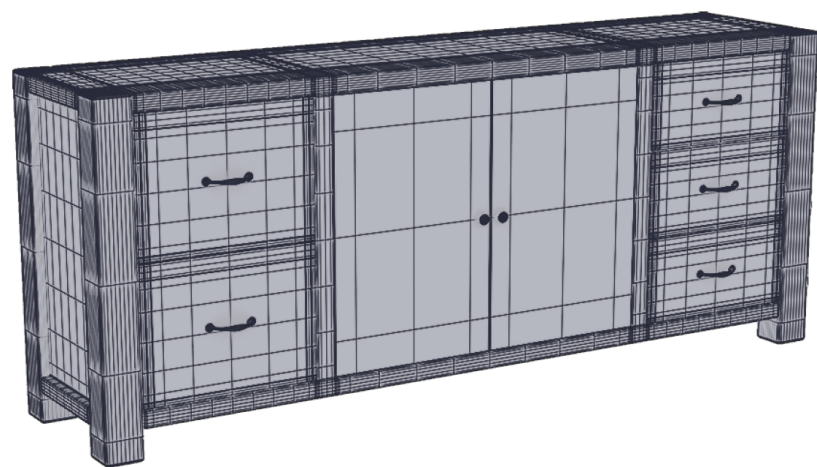


Metallic dog-like robot with articulated legs and futuristic design elements.



[TRELLIS, CVPR 2025]

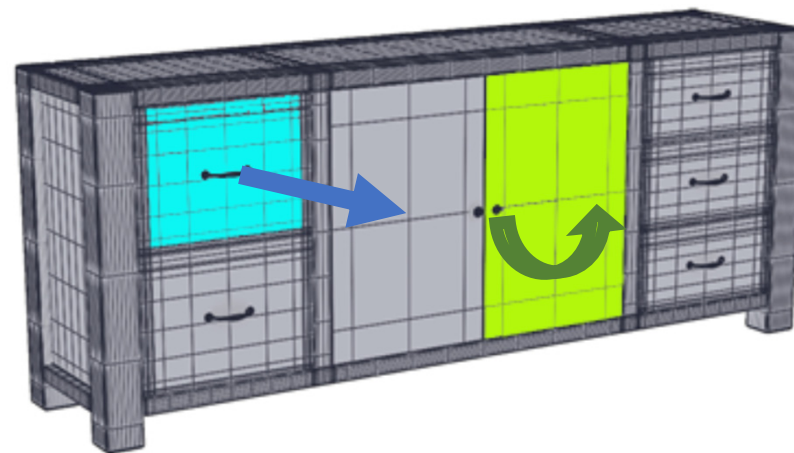
Need more AI progress here!



3D Geometry



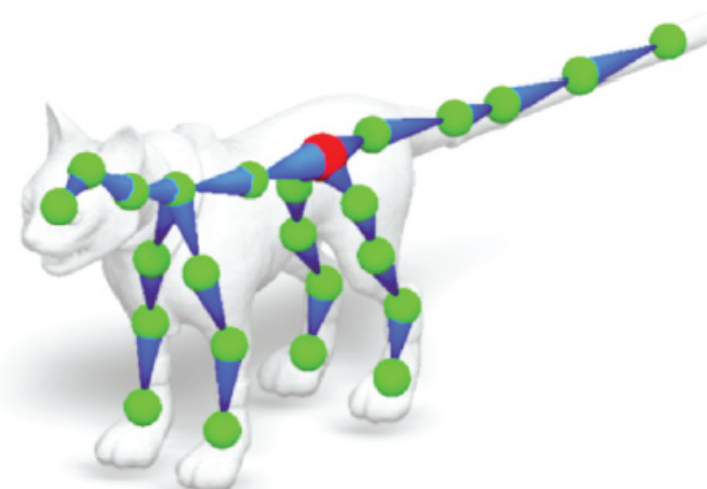
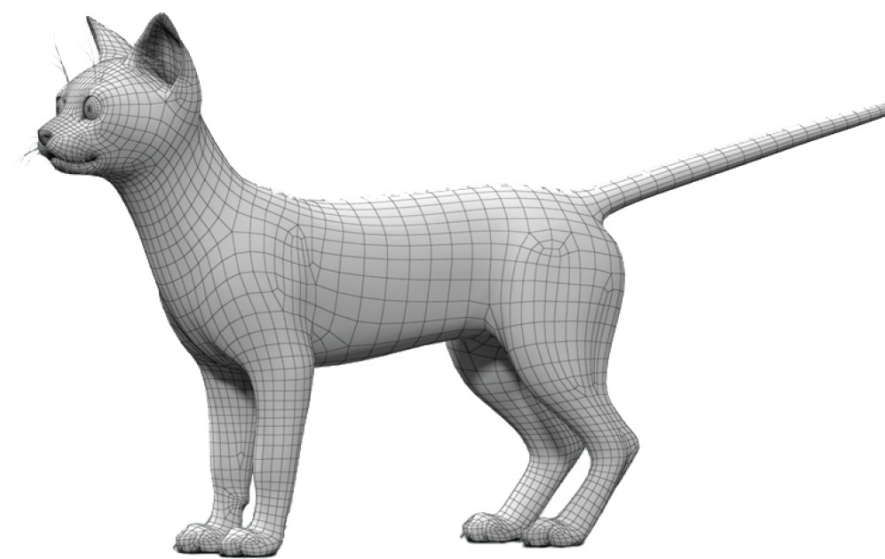
Textures



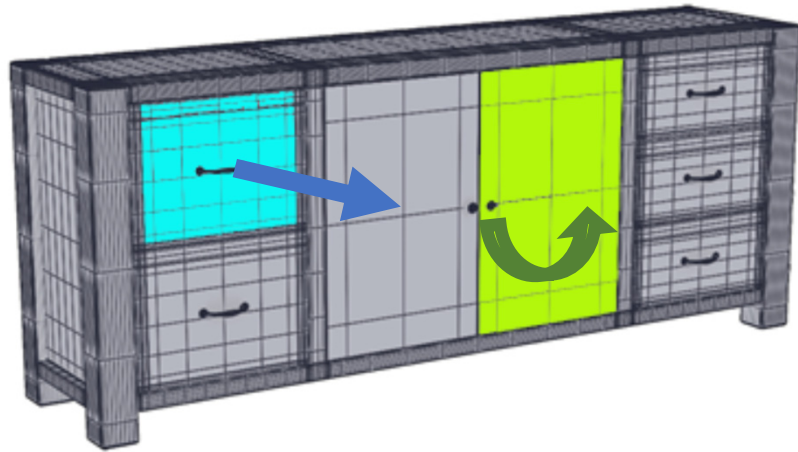
**Motion controller
& attributes**



Interactive Model



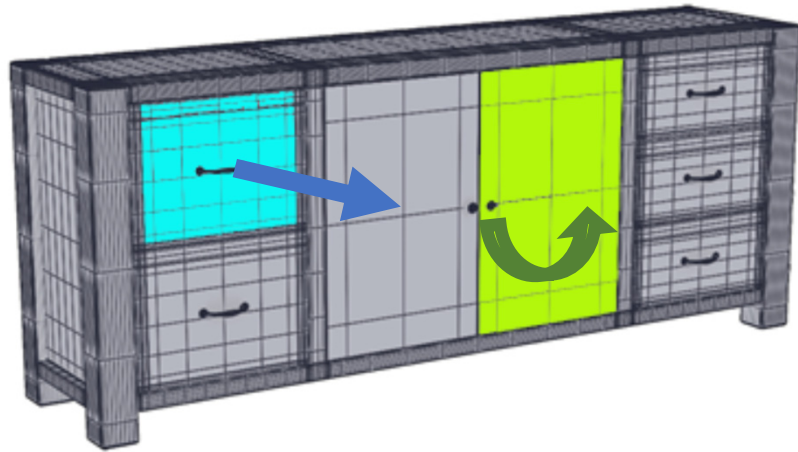
Learn motion controllers & interaction attributes



Given a 3D shape, infer:

- moving parts
- motion types
- motion axes

Learn motion controllers & interaction attributes



Given a 3D shape, infer:

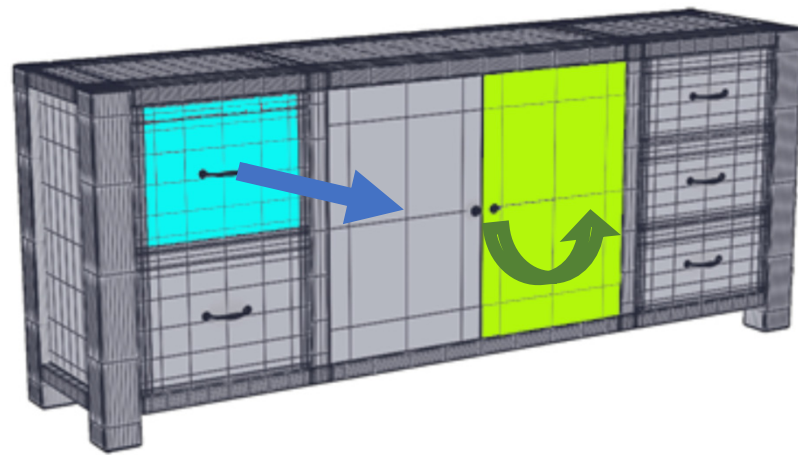
- moving parts
- motion types
- motion axes
- material types
- material properties



metal

wood

Learn motion controllers & interaction attributes



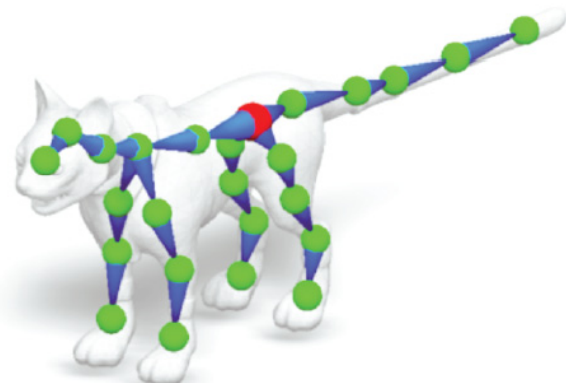
Given a 3D shape, infer:

- moving parts
- motion types
- motion axes
- material types
- material properties
- articulation hierarchy
- degrees of freedom
- deformations

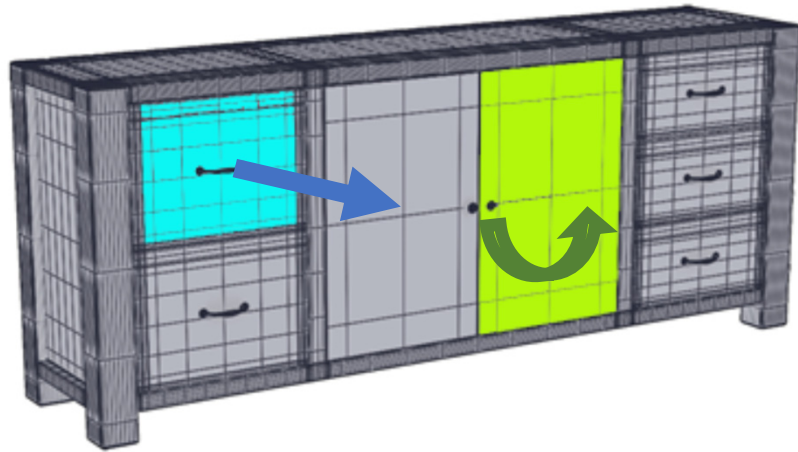


metal

wood

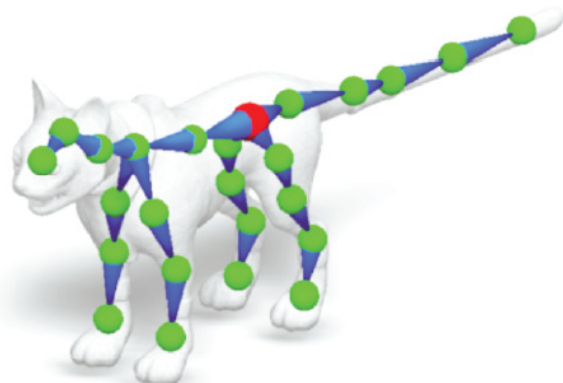


Learn motion controllers & interaction attributes



metal

wood



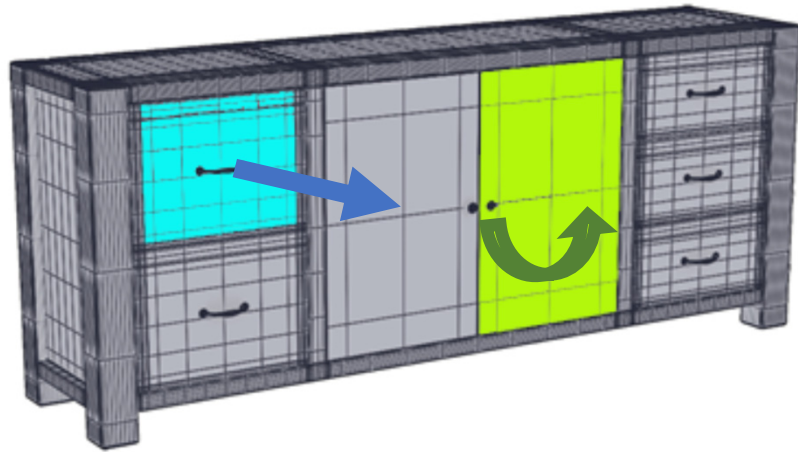
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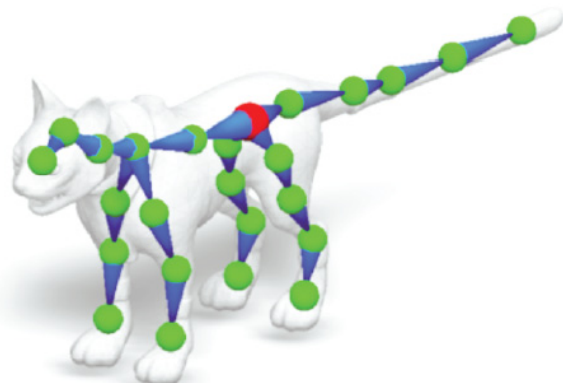
Challenges:

- Limited datasets/annotations
- Generalization

Learn motion controllers & interaction attributes



metal wood

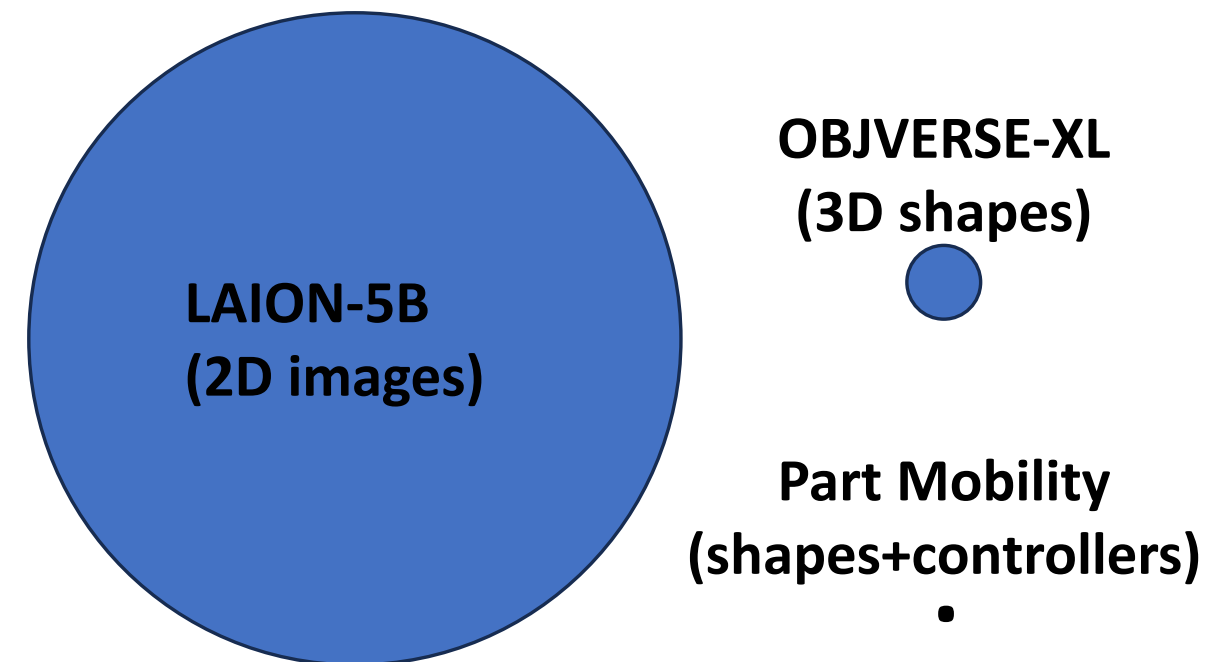


Given a 3D shape, infer:

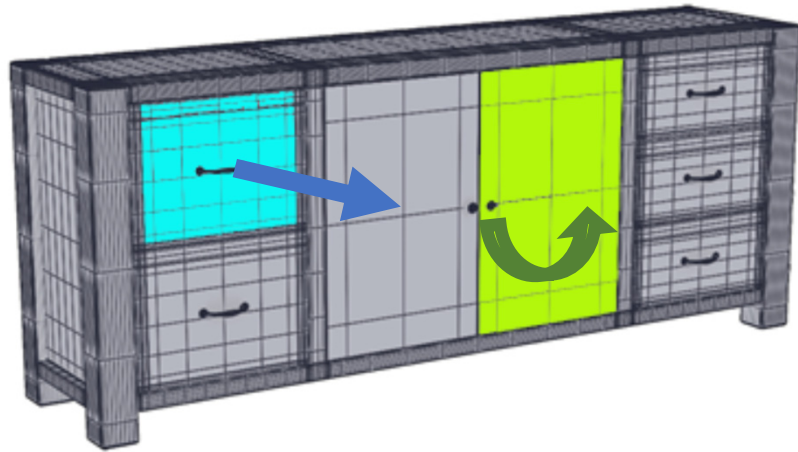
- moving parts
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Challenges:

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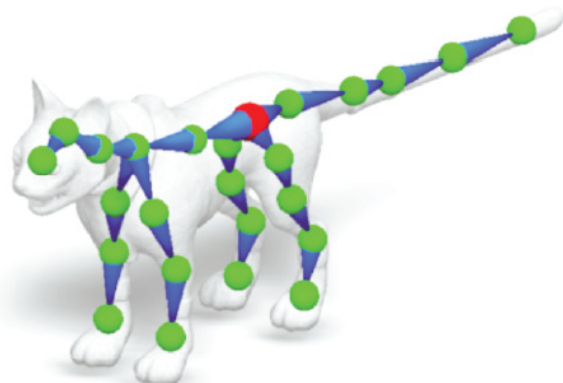


Learn motion controllers & interaction attributes



metal

wood



Given a 3D shape, infer:

- moving parts
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- degrees of freedom
- deformations

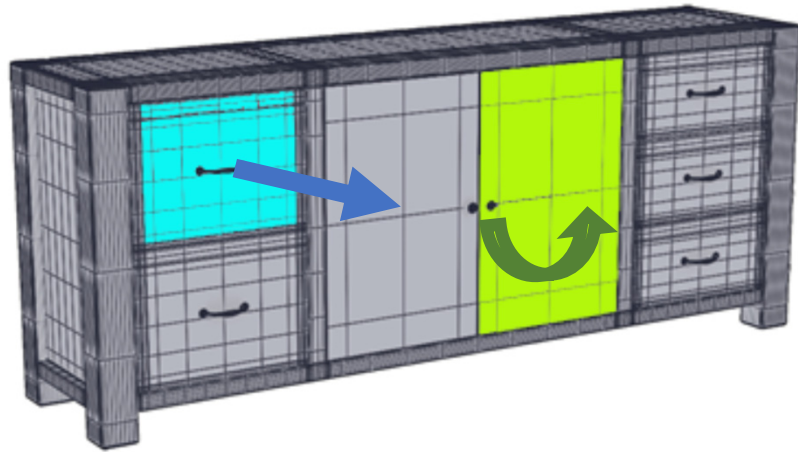
Challenges:

- Limited datasets/annotations
- Generalization

Methodology:

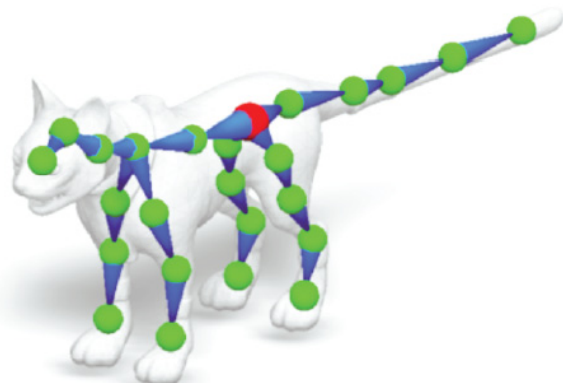
- Self-supervision

Learn motion controllers & interaction attributes



metal

wood



Given a 3D shape, infer:

- moving parts
- motion types
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- material types
- material properties
- articulation hierarchy
- degrees of freedom
- deformations

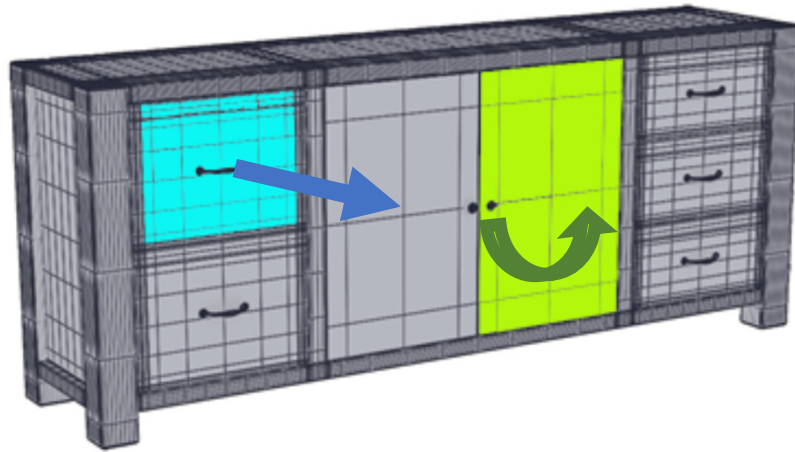
Challenges:

- Limited datasets/annotations
- Generalization

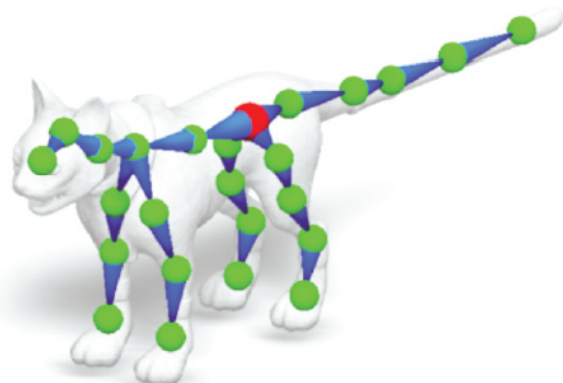
Methodology:

- Self-supervision
- Distillation from 2D models

Learn motion controllers & interaction attributes



metal wood



Generate objects with:

- moving parts
- motion types
- motion axes
- material types
- material properties
- articulation hierarchy
- degrees of freedom
- deformations

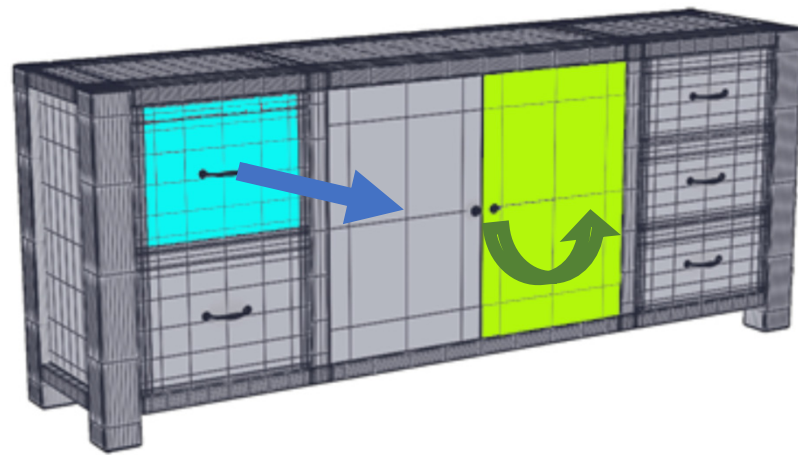
Challenges:

- Limited datasets/annotations
- Generalization
- Generate motion controllers compatible with geometry

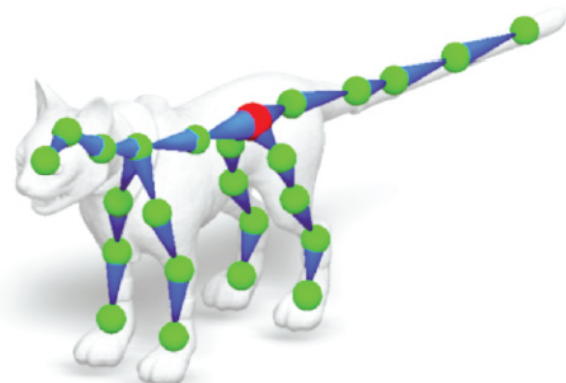
Methodology:

- Self-supervision
- Distillation from 2D models

Learn motion controllers & interaction attributes



metal wood



Generate objects with:

- moving parts
- motion types
- motion axes
- material types
- material properties
- articulation hierarchy
- degrees of freedom
- deformations

Challenges:

- Limited datasets/annotations
- Generalization
- Generate motion controllers compatible with geometry

Methodology:

- Self-supervision
- Distillation from 2D models
- Latent space encoding motion controllers & shape

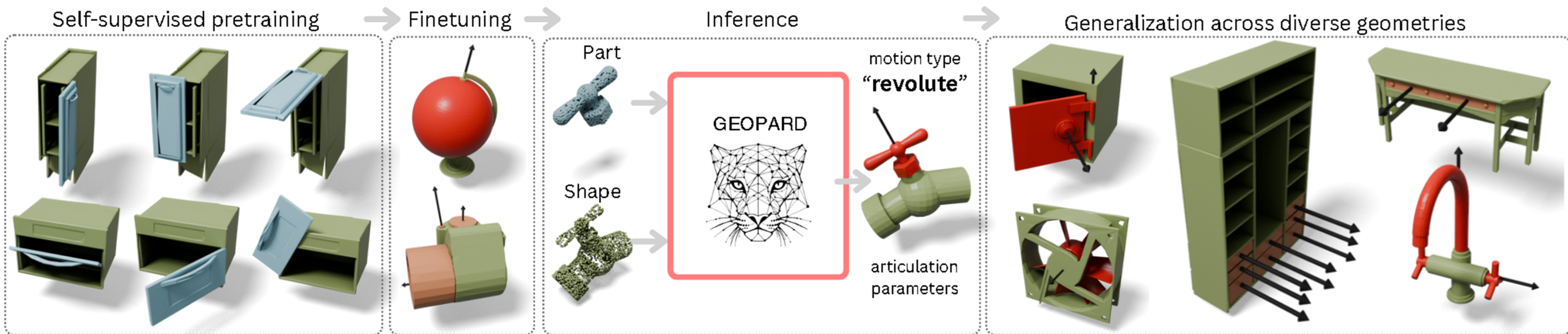
Part I:

GEOPARD: Geometric Pretraining for Articulation Prediction in 3D Shapes

Pradyumn Goyal¹ Dmitry Petrov¹ Sheldon Andrews² Yizhak Ben-Shabat³

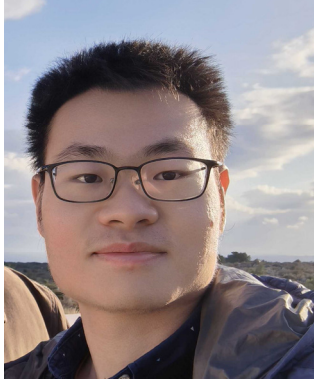
Hsueh-Ti Derek Liu³ Evangelos Kalogerakis⁴

¹UMass Amherst ²École de technologie supérieure ³Roblox ⁴TU Crete



Part II:

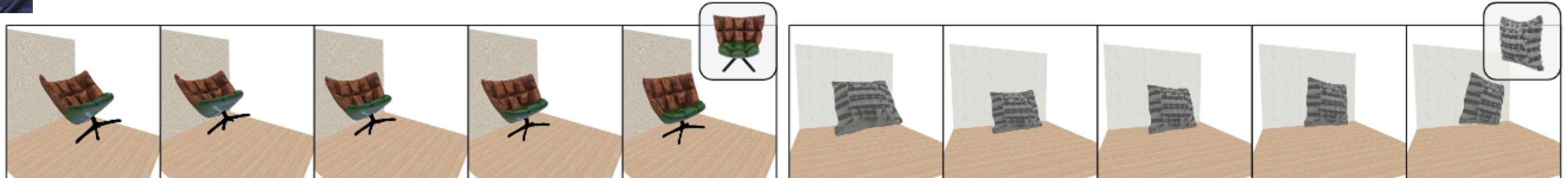
SOPHY: Learning to Generate Simulation-Ready Objects with PHYSical Materials



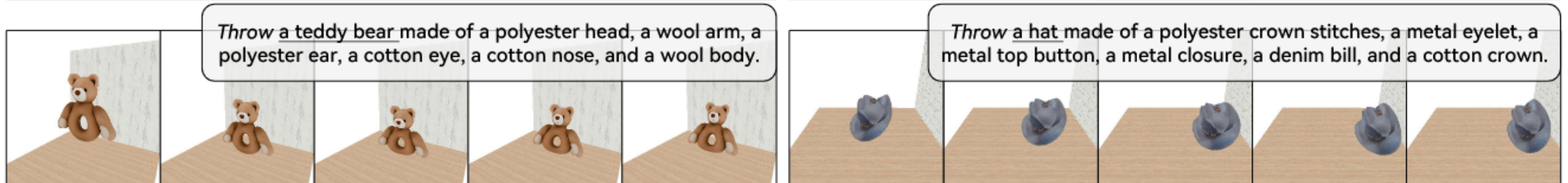
Junyi Cao

Evangelos Kalogerakis

Image-
conditioned
Generation



Text-
conditioned
Generation



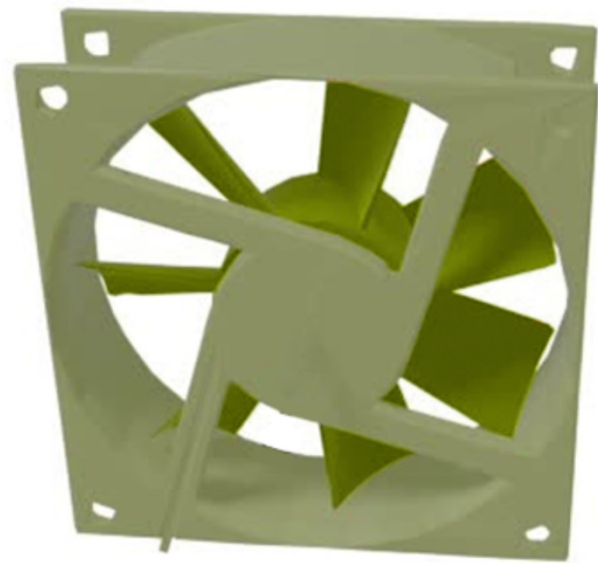
Physical
Virtual World



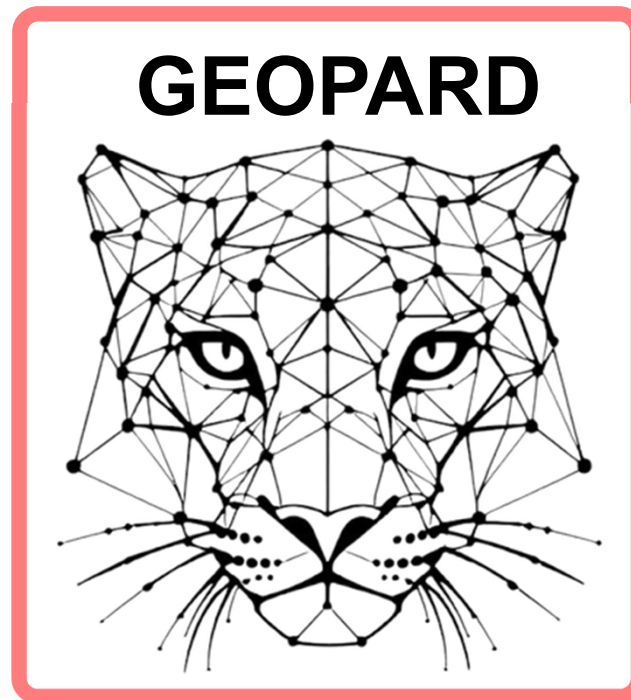
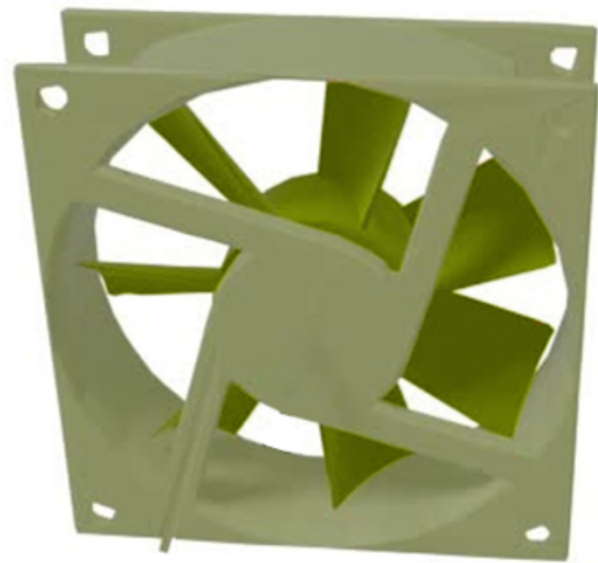
Outline

1. **GEOCARD: Geometric Pretraining for Articulation Prediction in 3D Shapes**
2. **SOPHY: Generating Simulation-Ready Objects with Physical Materials**
3. Future directions

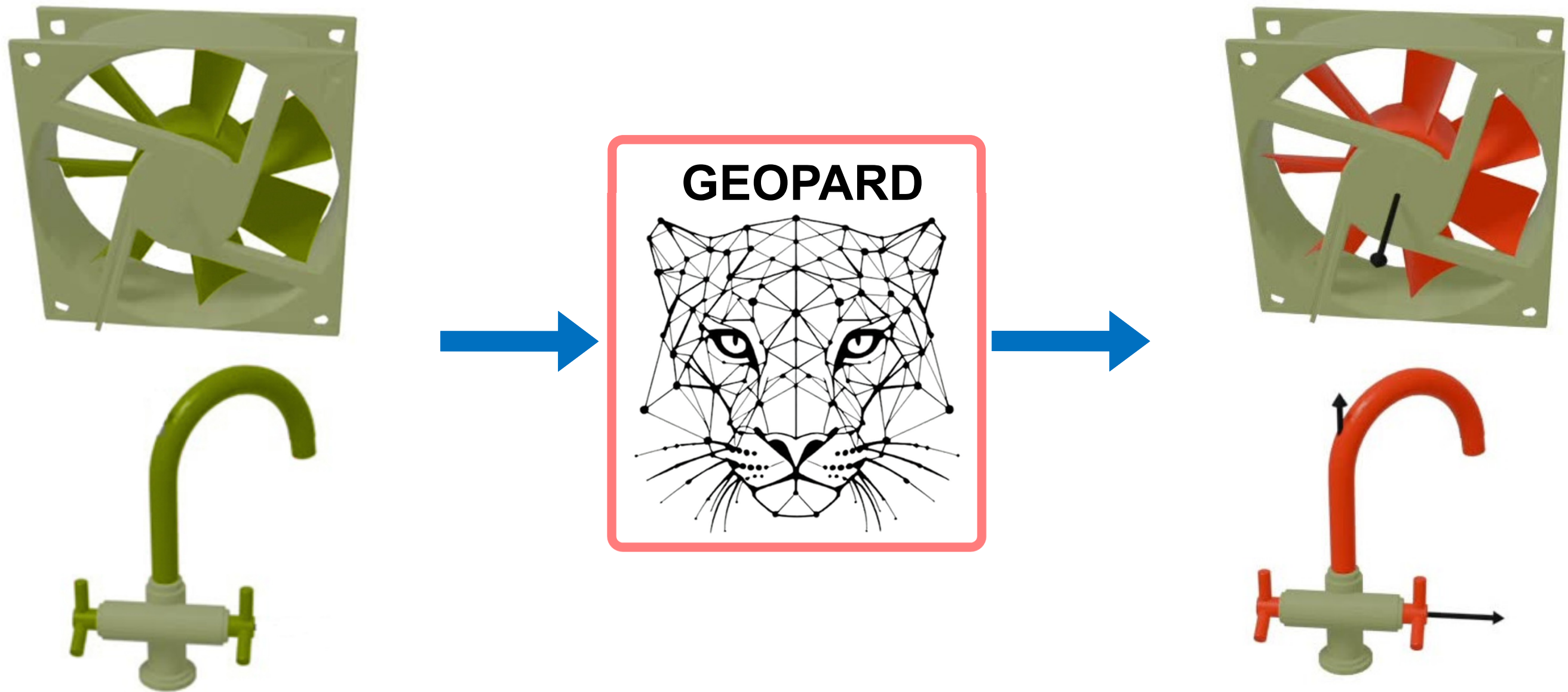
Goal: estimate articulation from a static shape



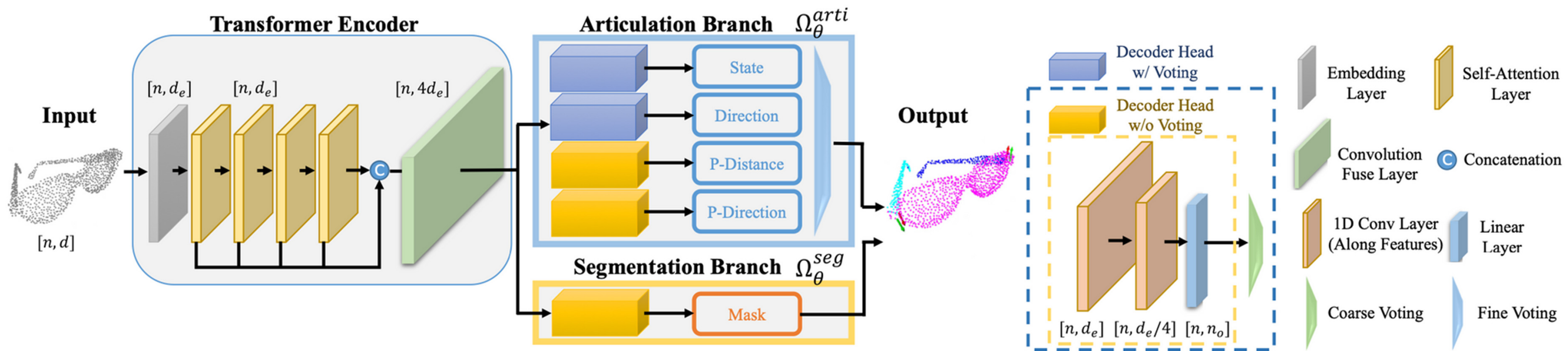
Goal: estimate articulation from a static shape



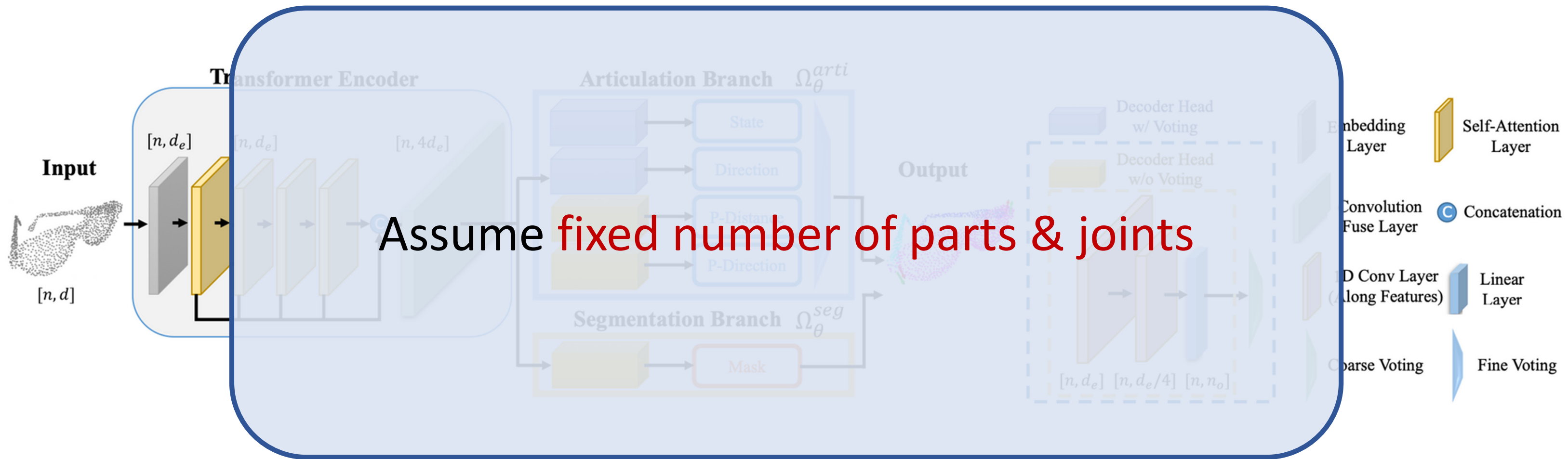
Goal: estimate articulation from a static shape



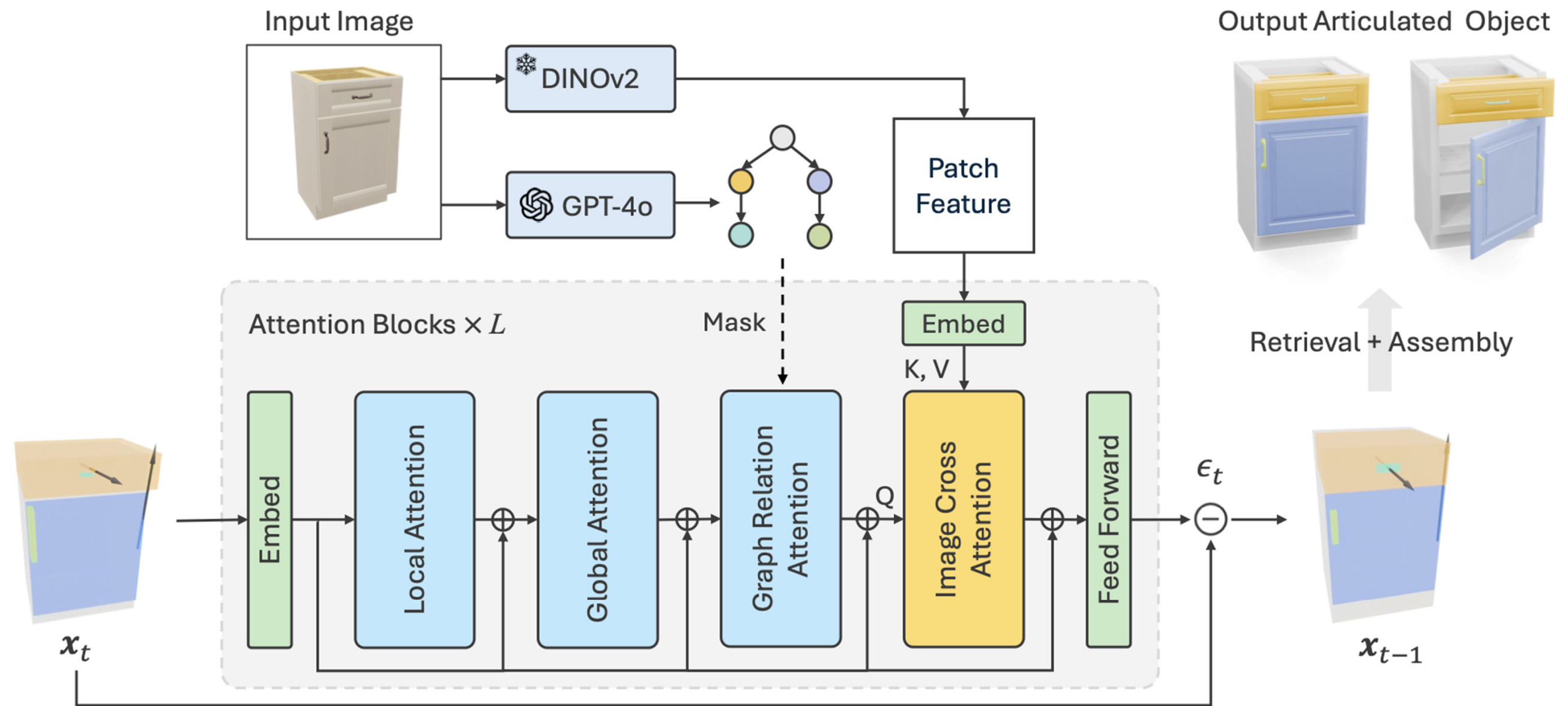
Prior Work



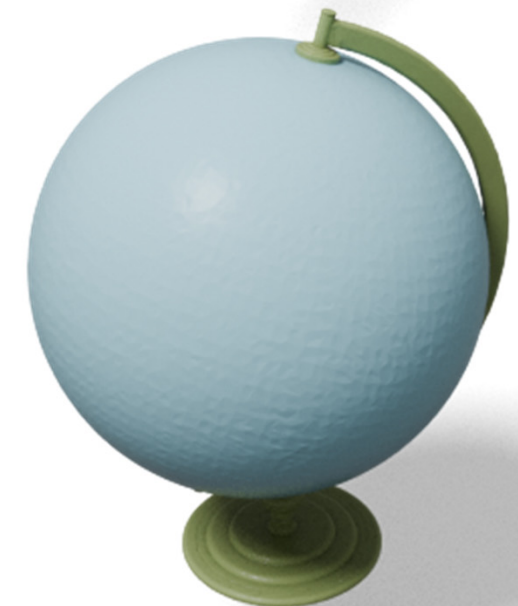
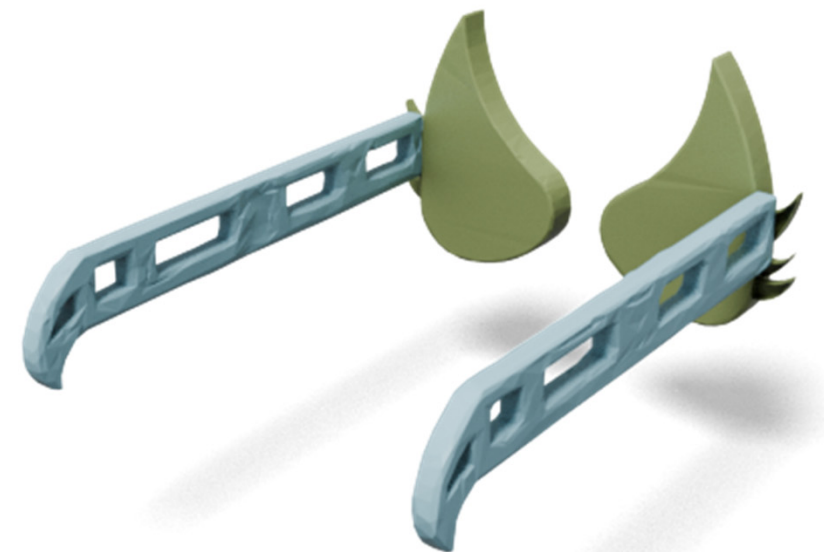
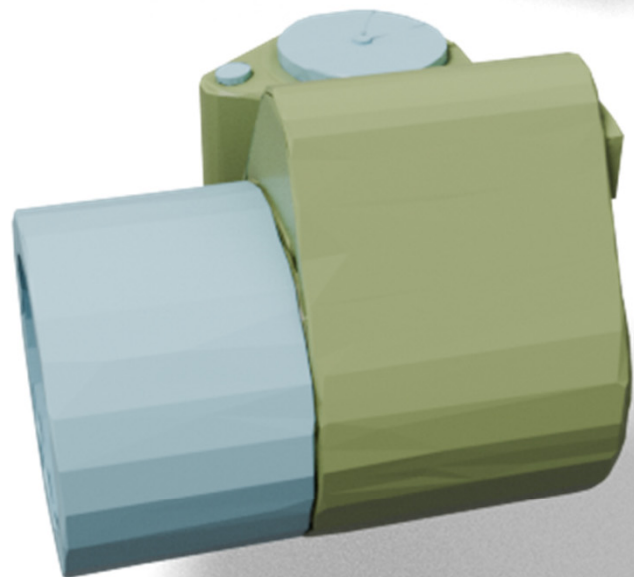
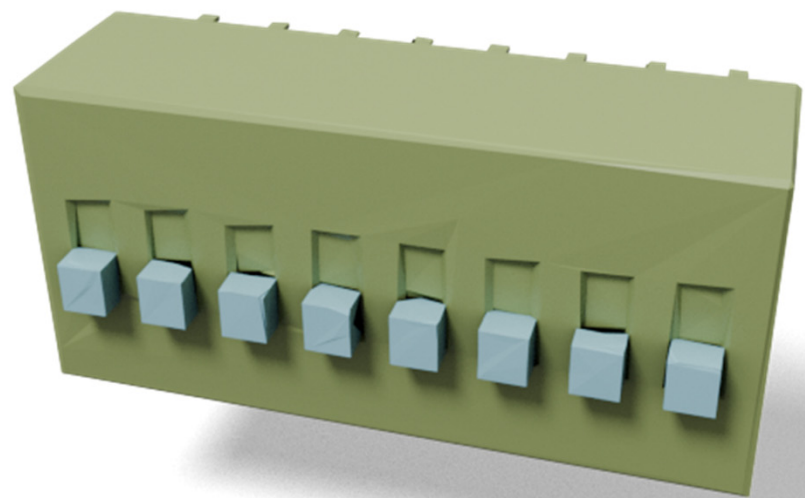
Prior Work



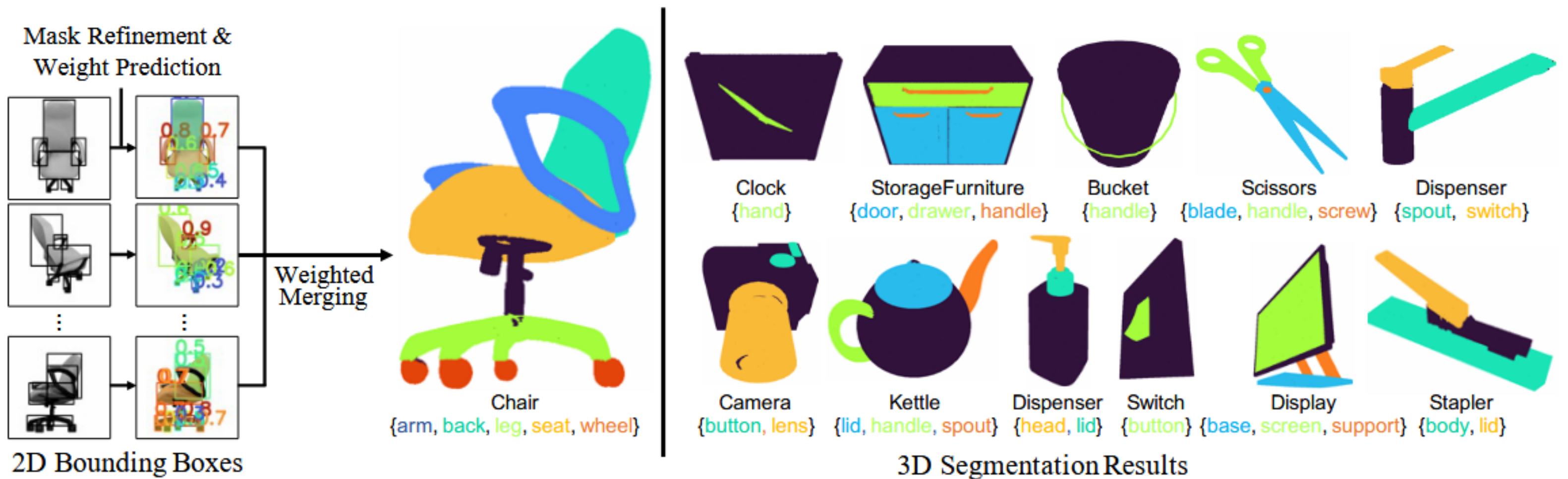
Prior Work



Input assumption: 3D segmented models

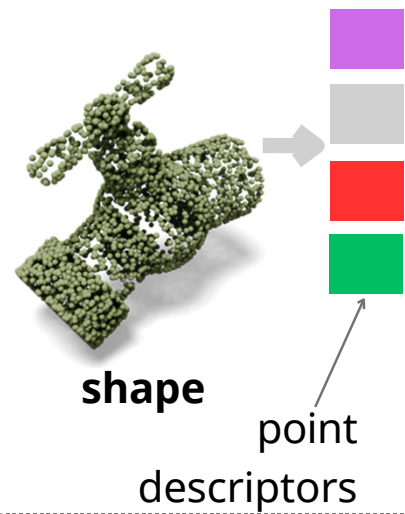
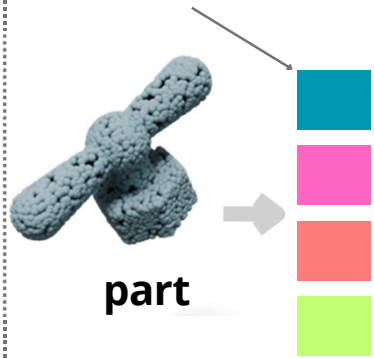


3D parts from 2D foundation model adaptation

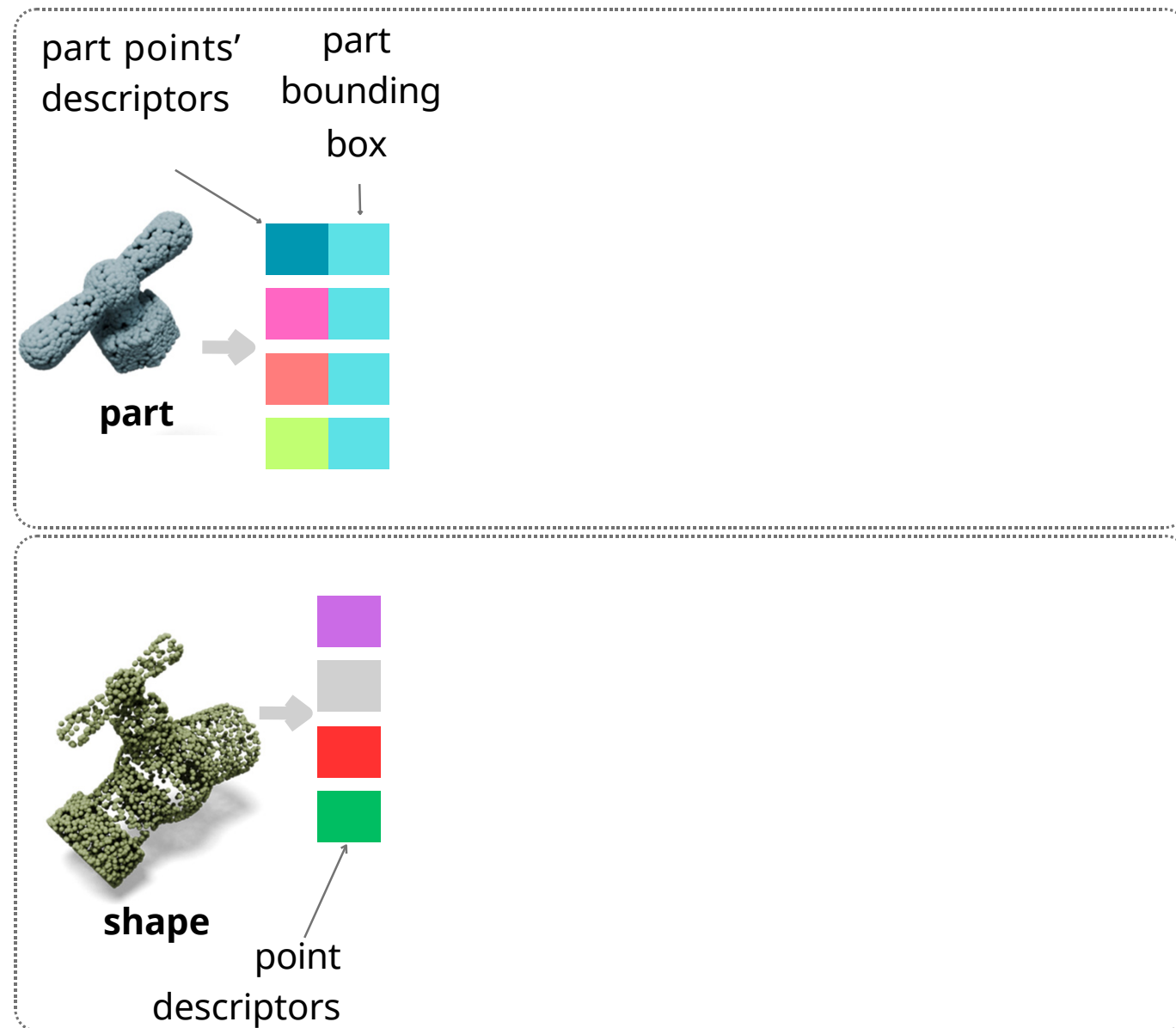


Network Architecture

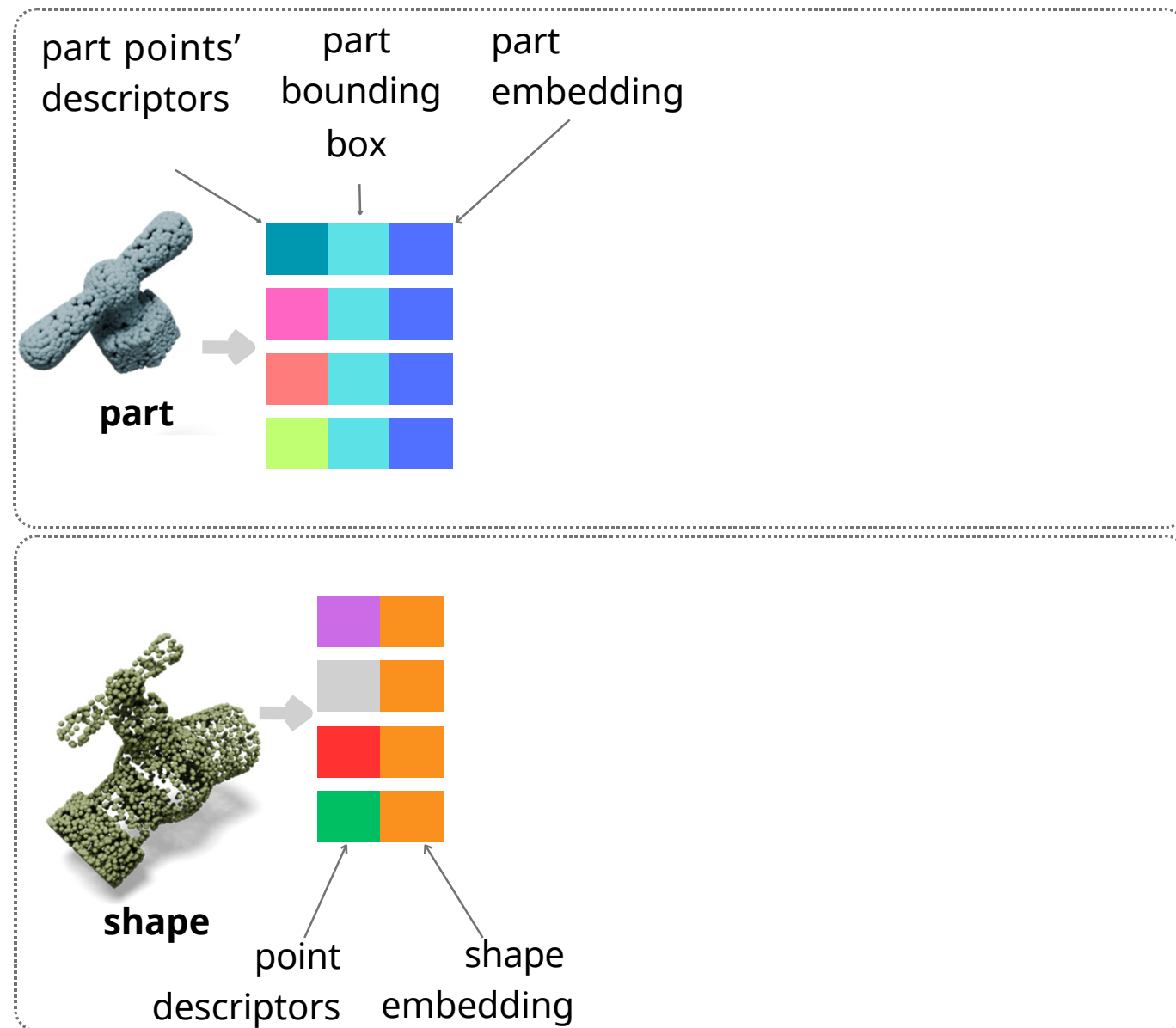
part points'
descriptors



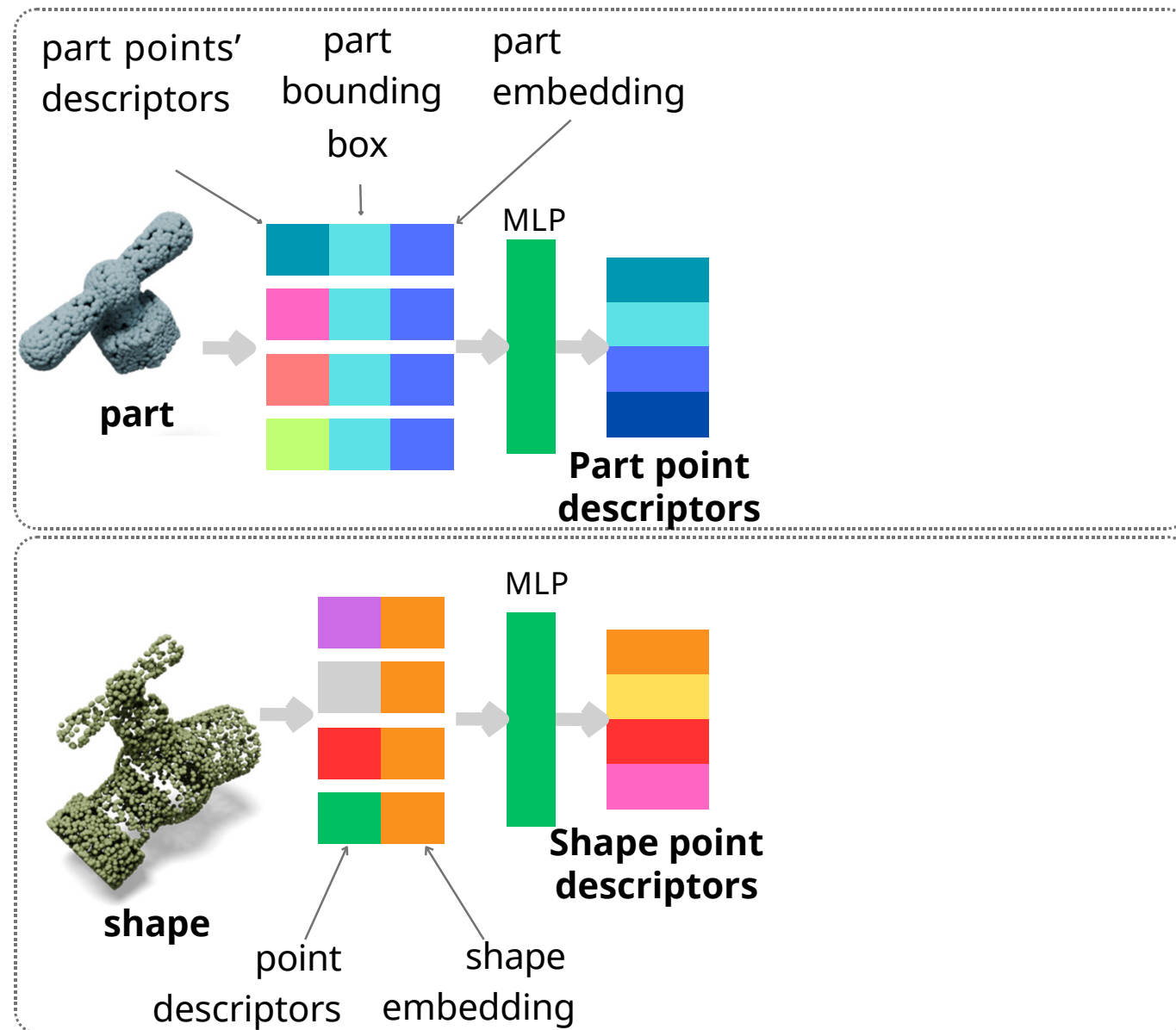
Network Architecture



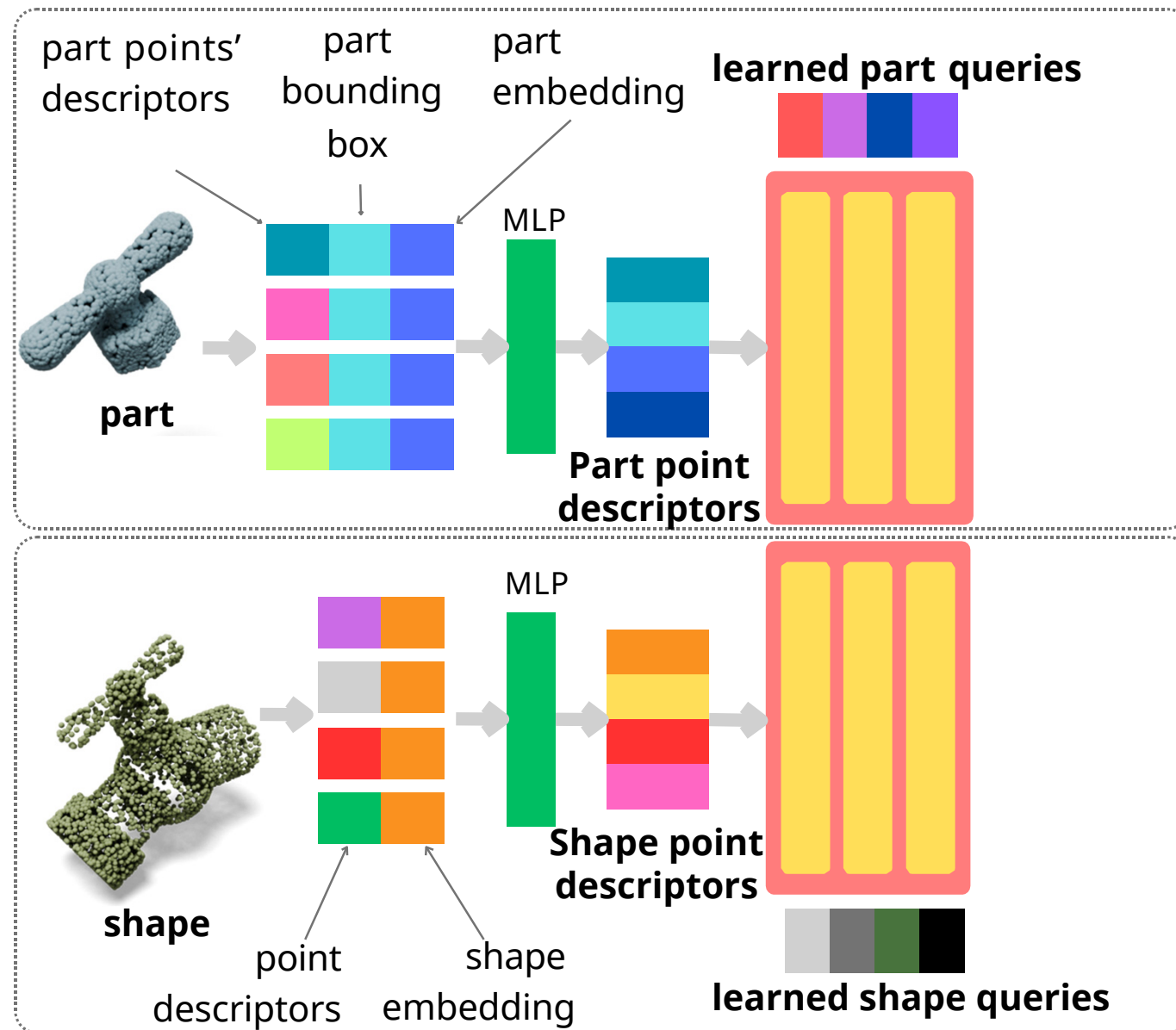
Network Architecture



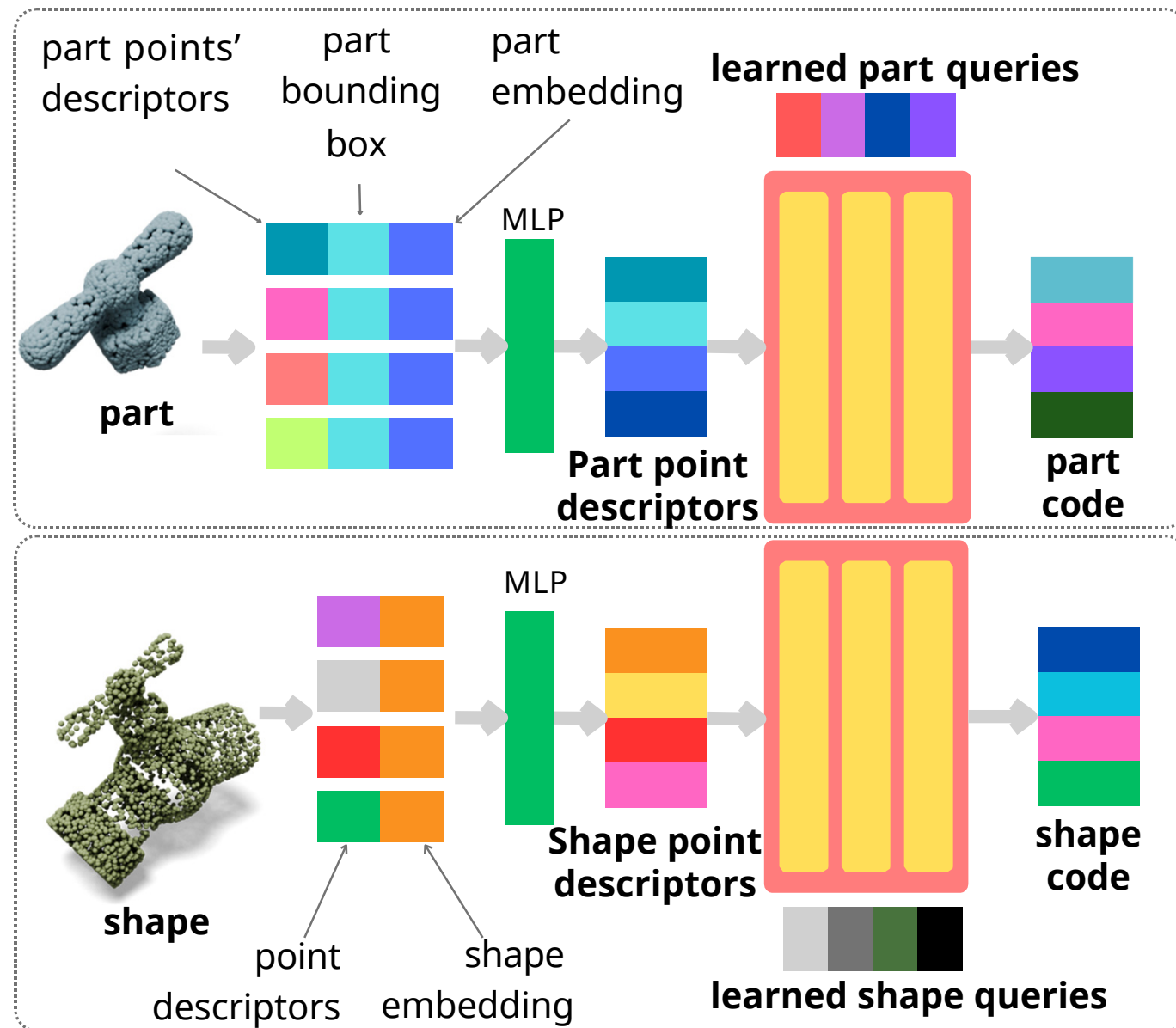
Network Architecture



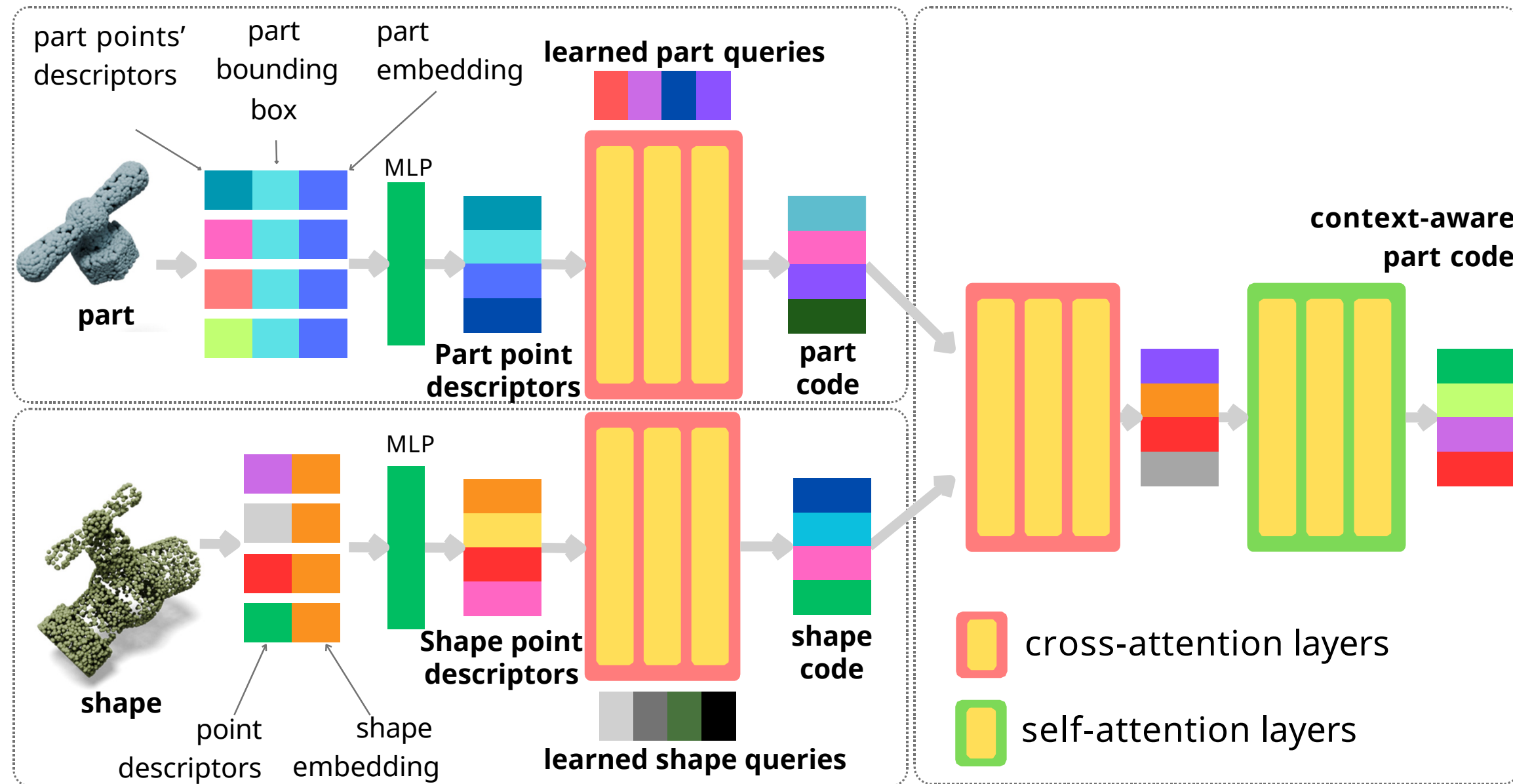
Network Architecture



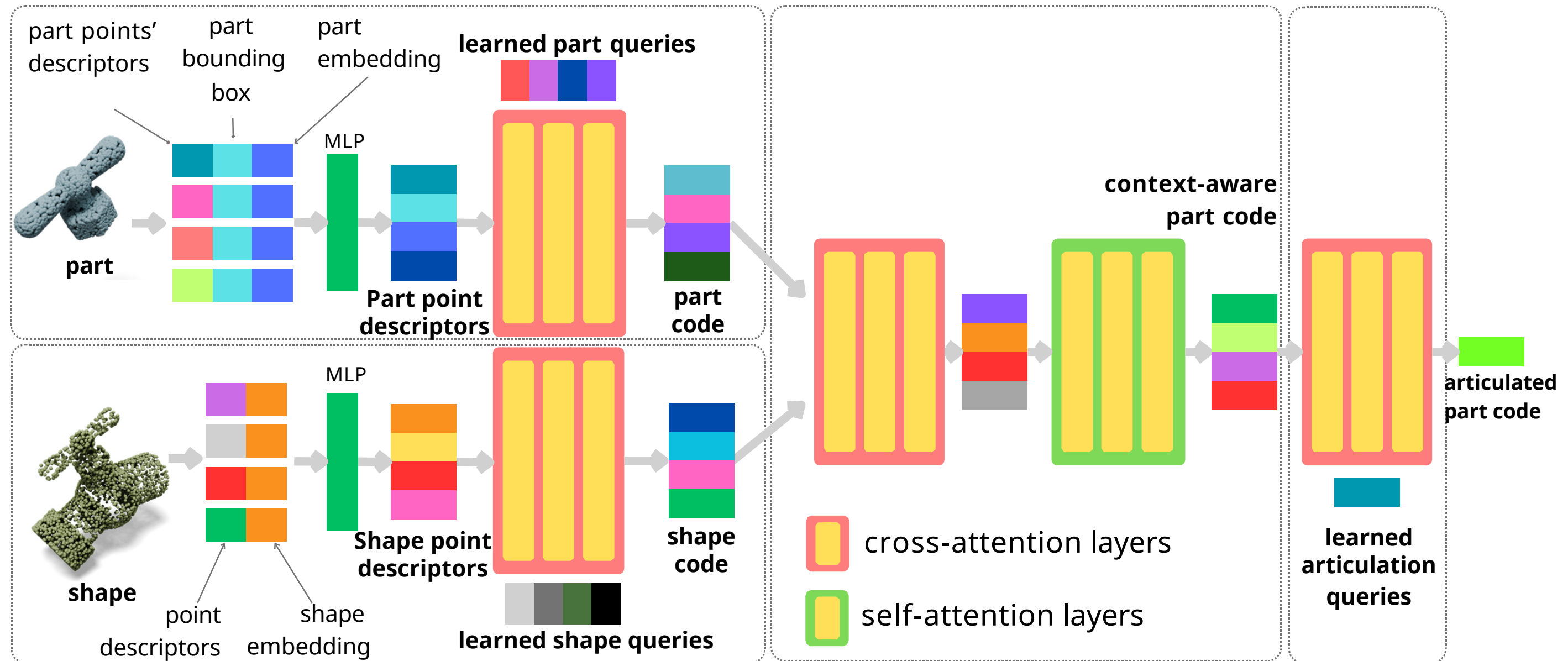
Network Architecture



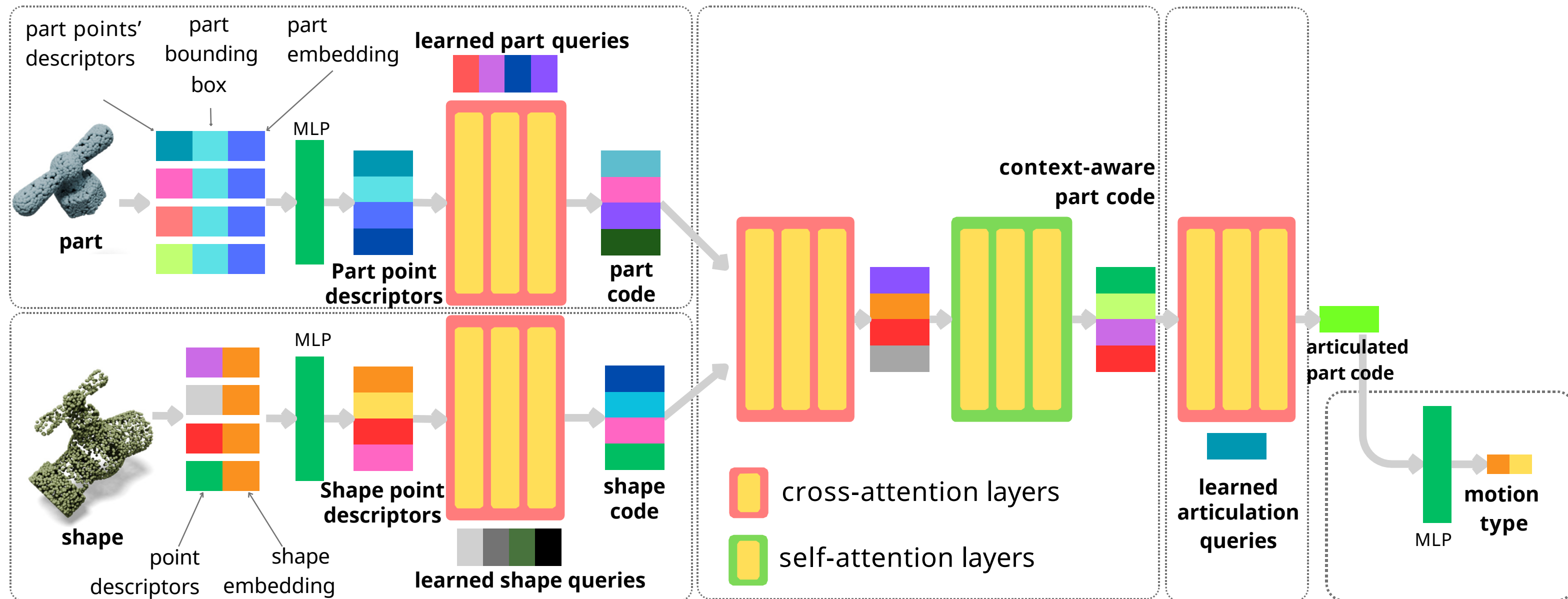
Network Architecture



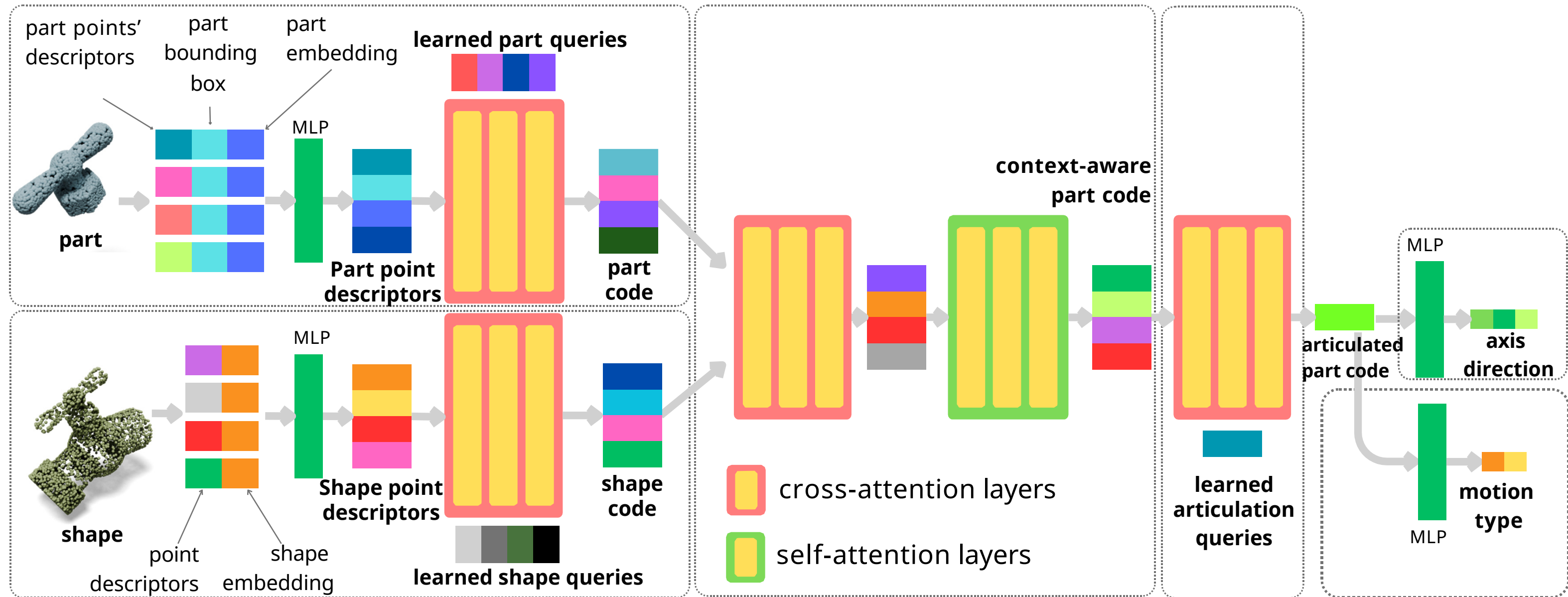
Network Architecture



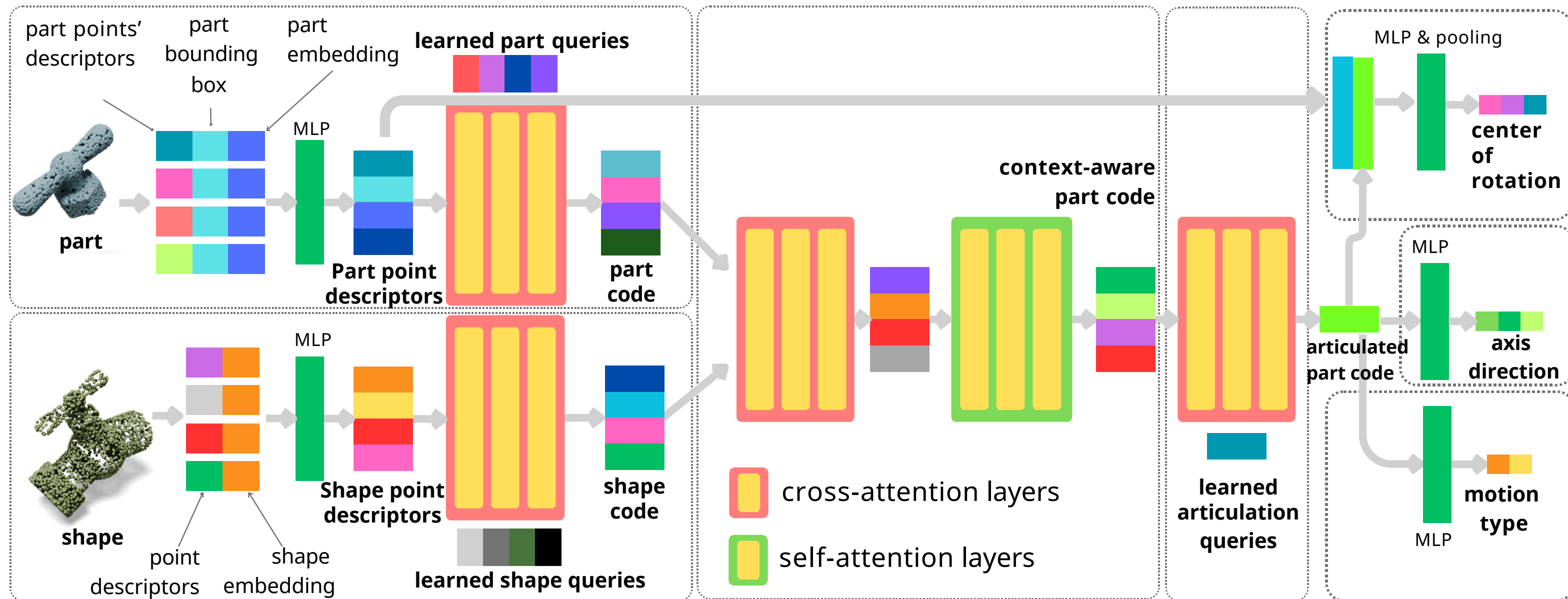
Network Architecture



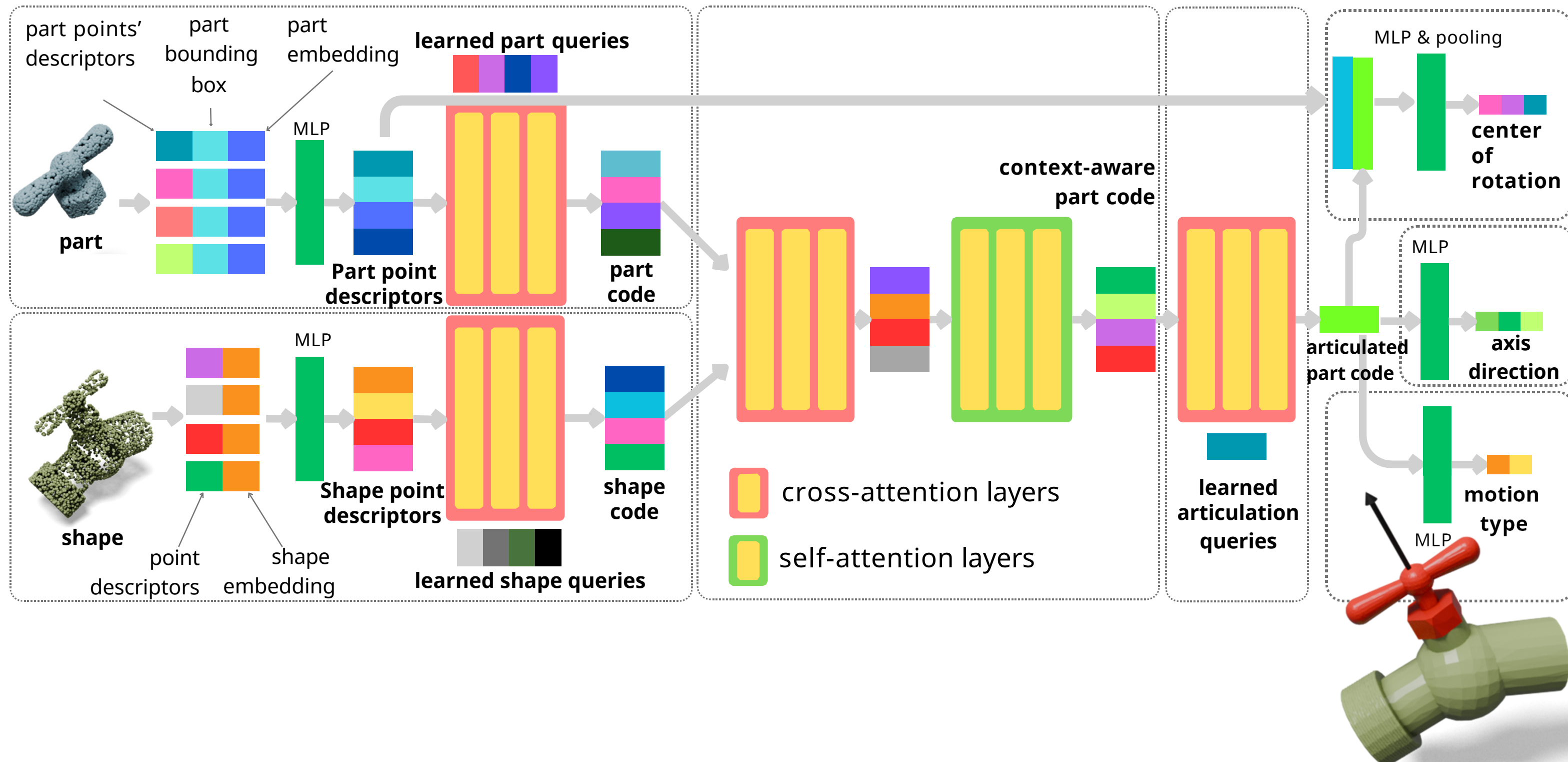
Network Architecture



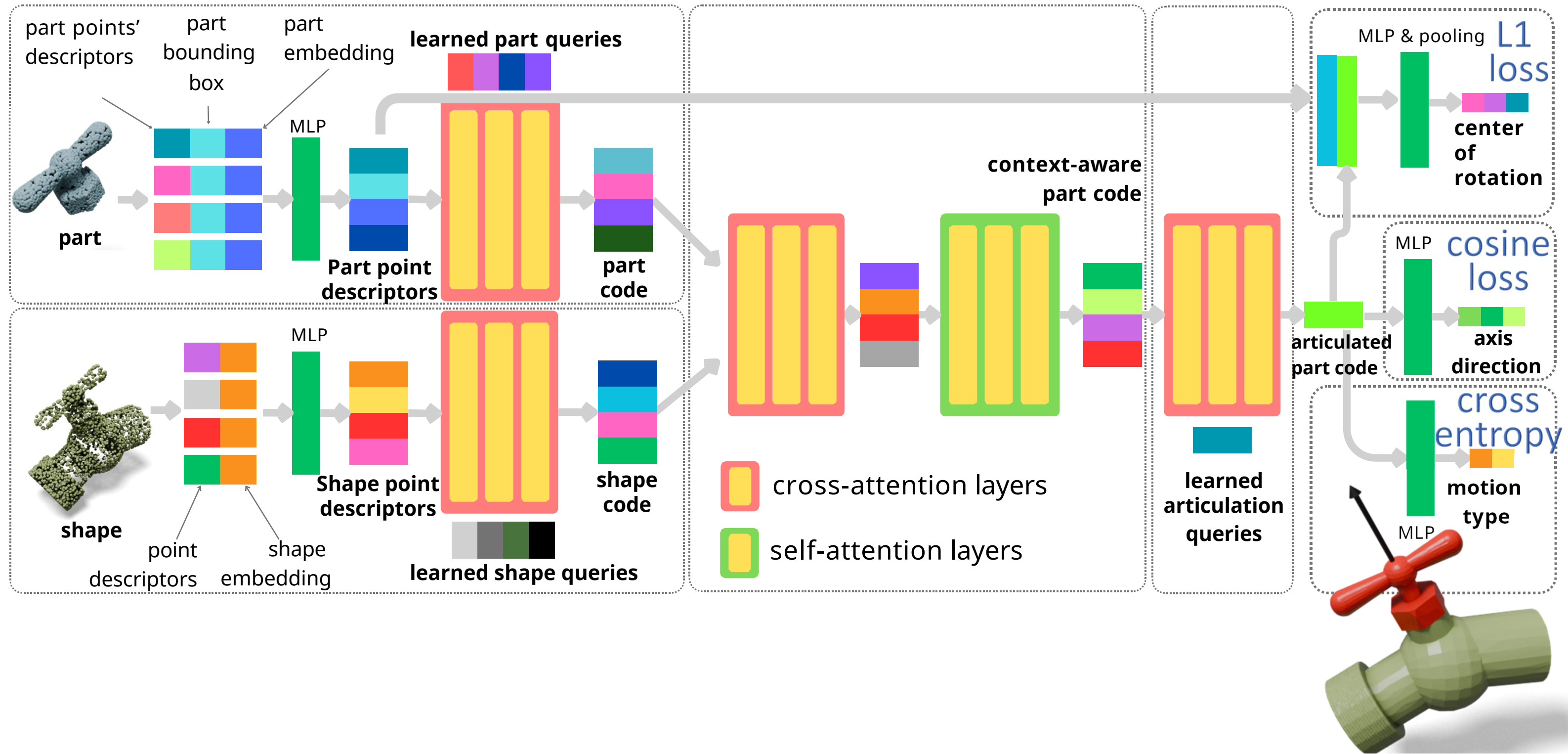
Network Architecture



Network Architecture



Training

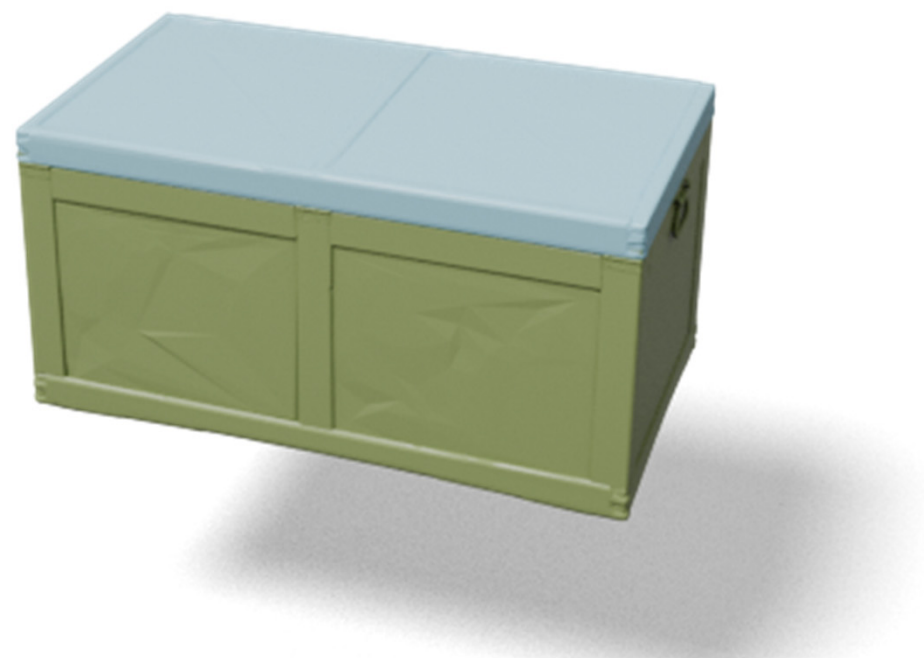


Datasets with annotated articulation are small!

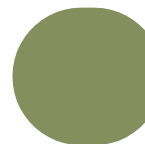


2.3K shapes, 46 object categories
PartNet-Mobility, CVPR 2020

Self-supervision: find possible motions

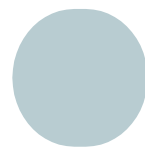
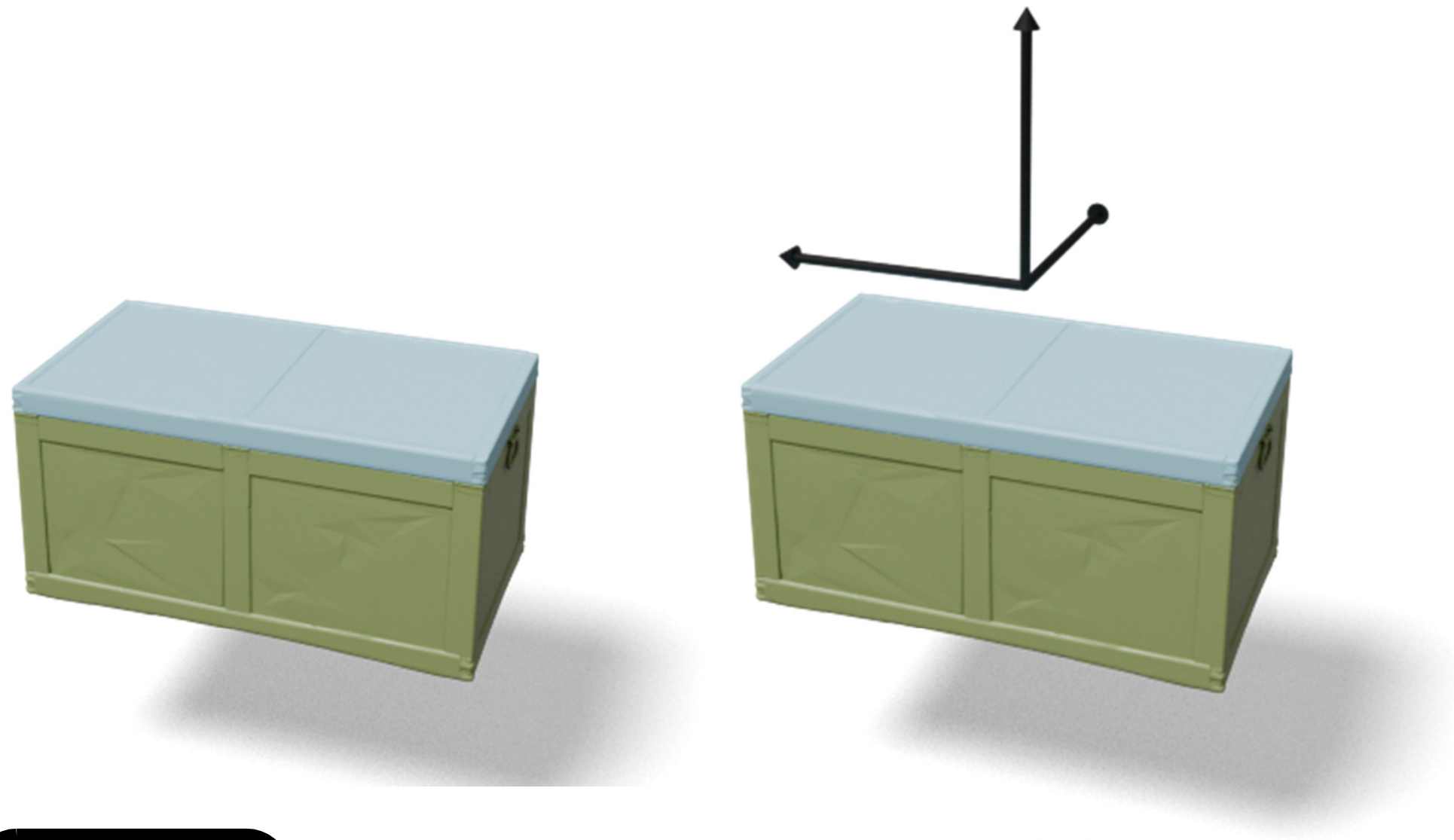


Part

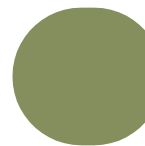


Shape

Self-supervision: find possible motions



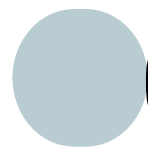
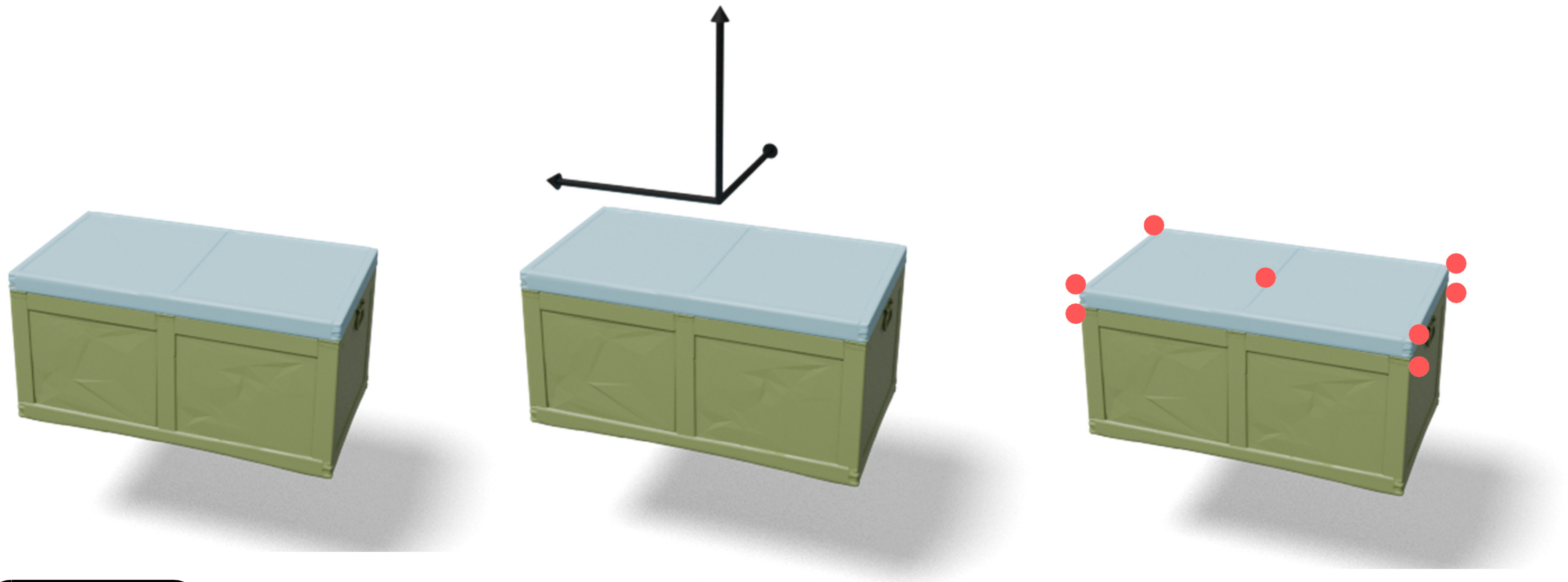
Part



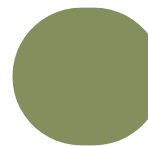
Shape

**Candidate
motion axes**

Self-supervision: find possible motions

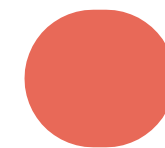


Part



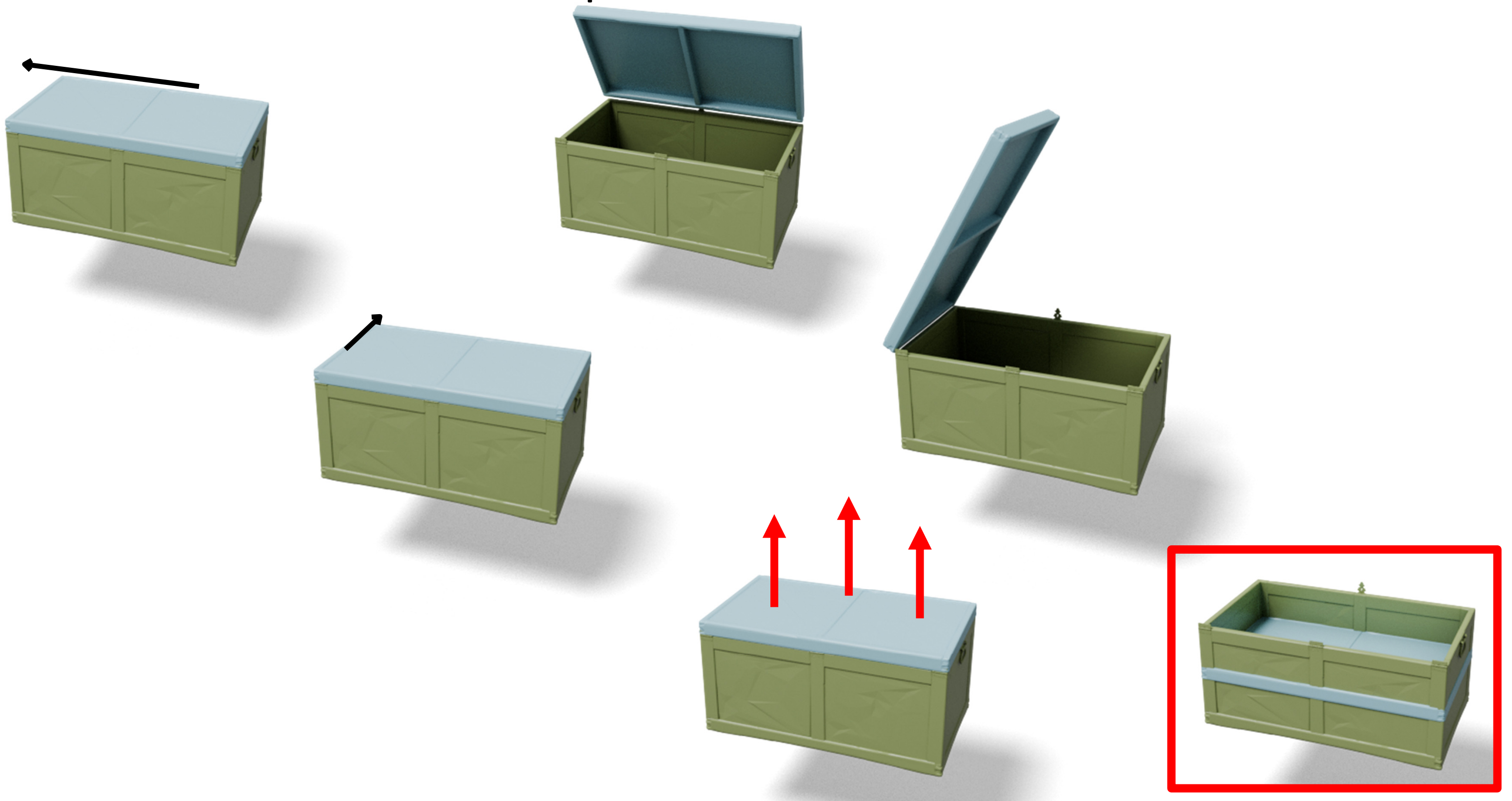
Shape

Candidate
motion axes



Candidate
rotation centers

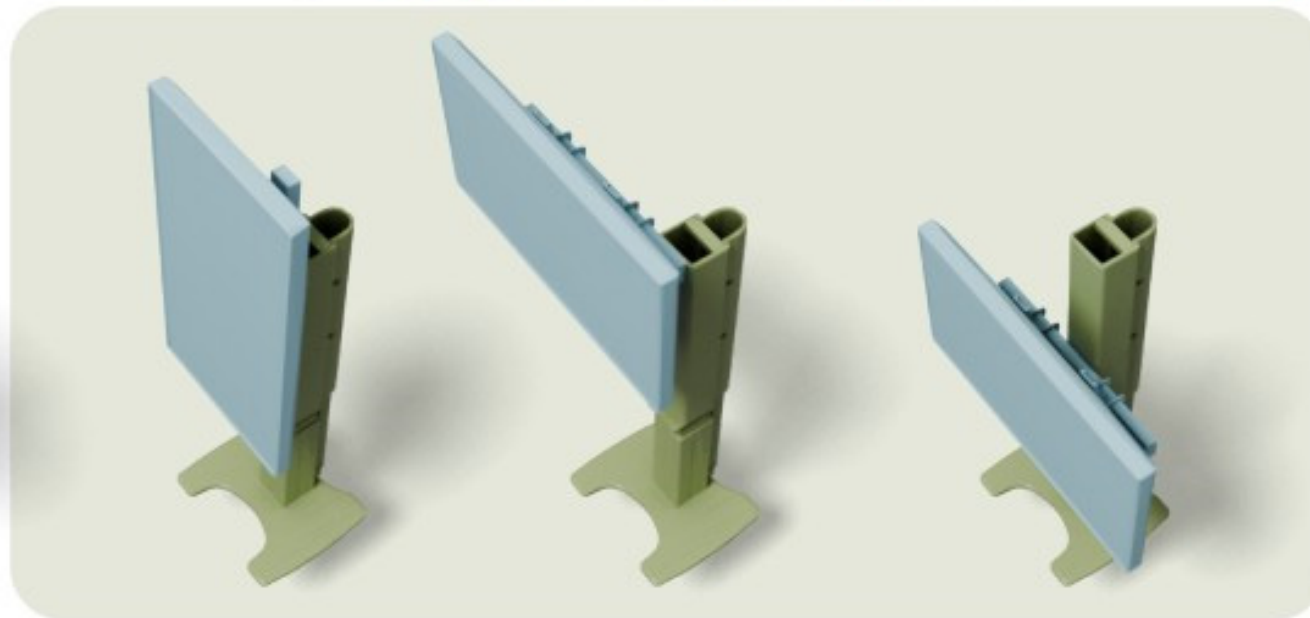
Self-supervision: simulator



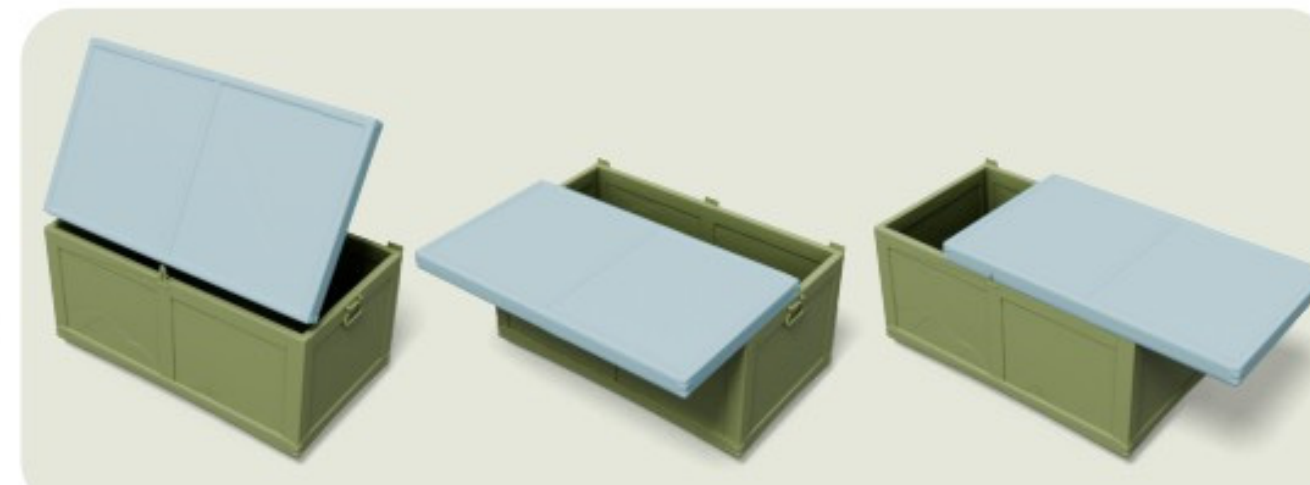
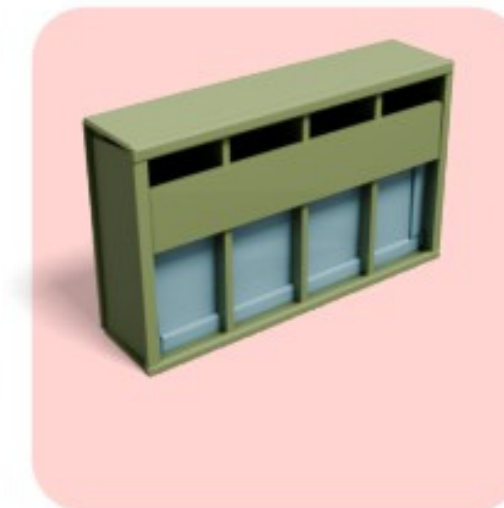
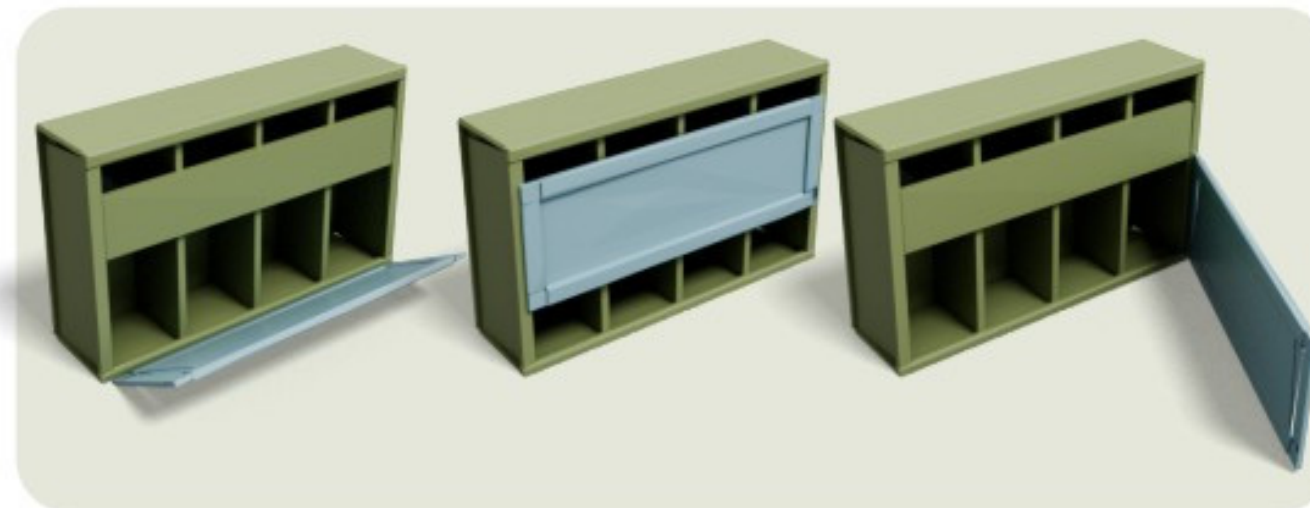
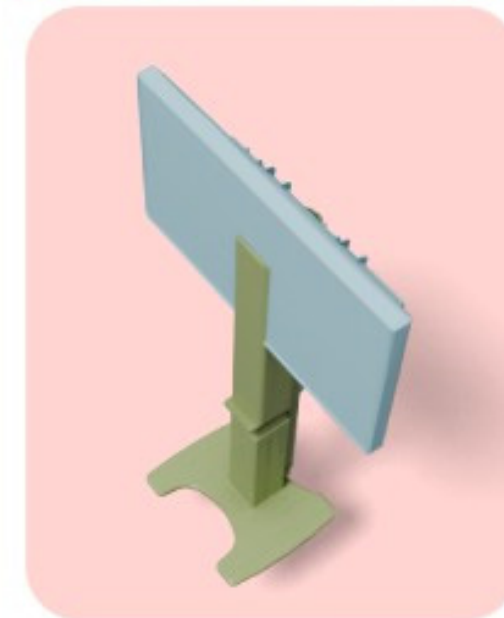
Input



Candidate Articulations



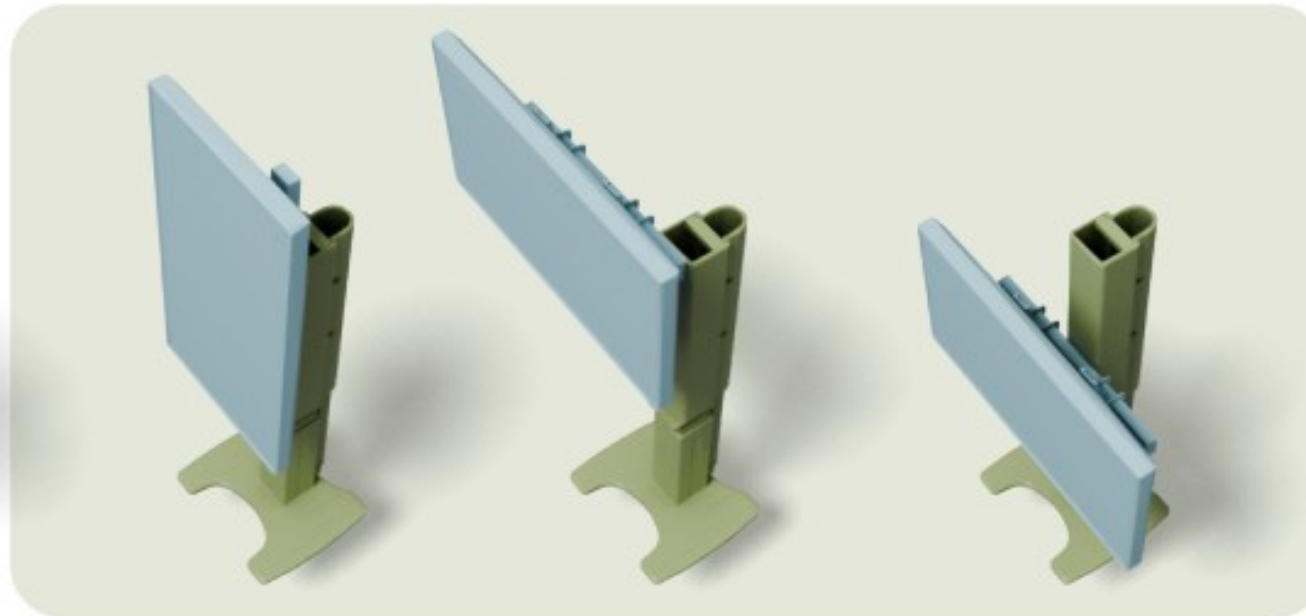
Invalid Articulations



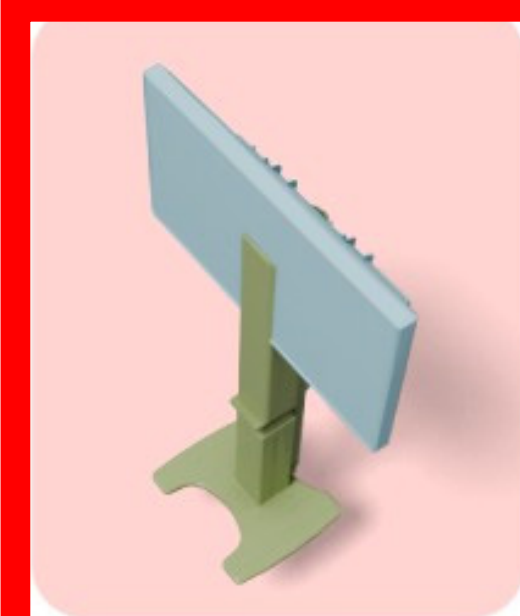
Input



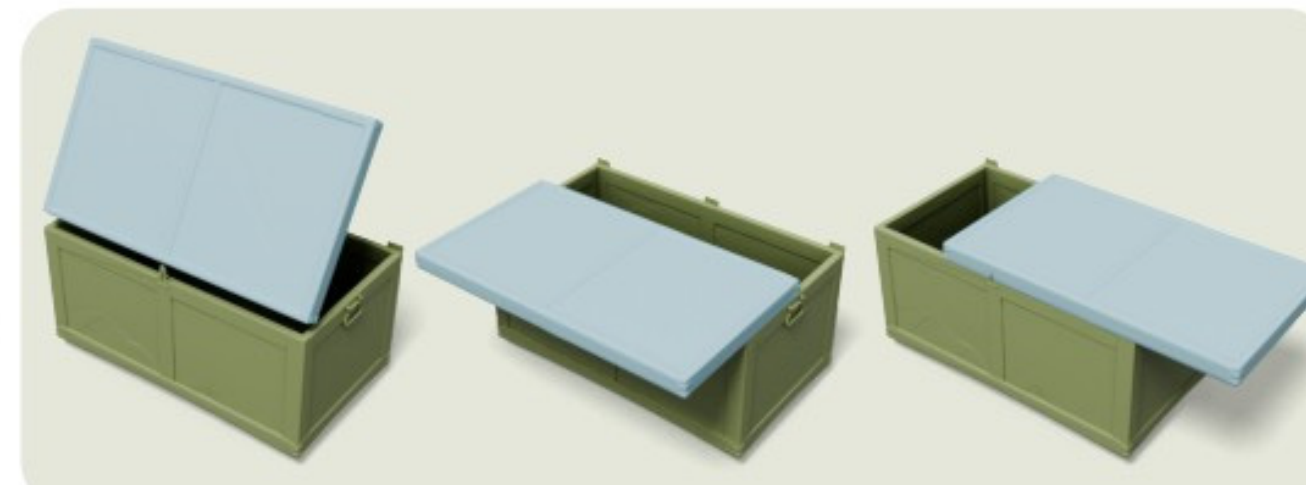
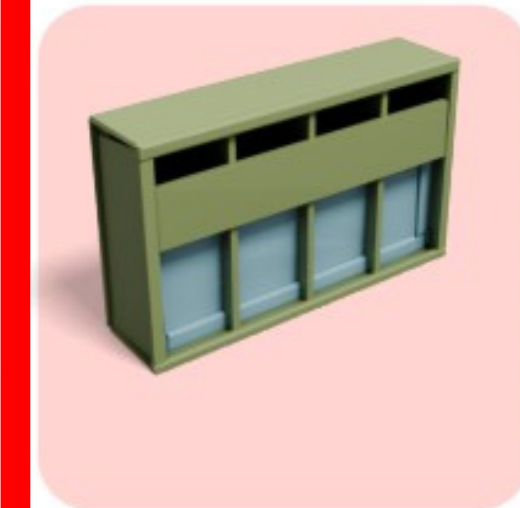
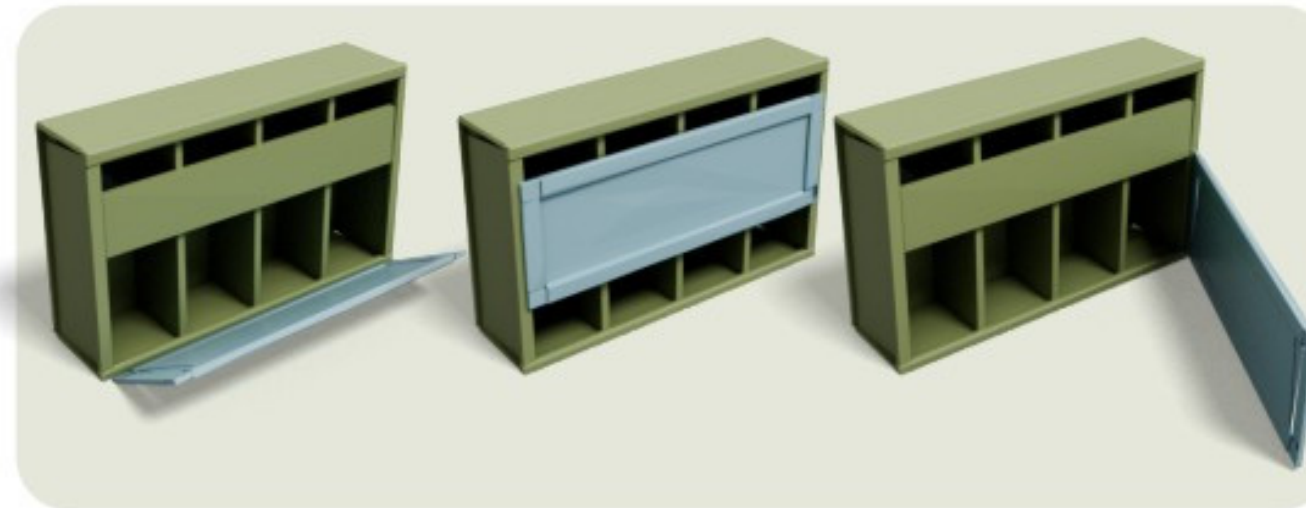
Candidate Articulations



Invalid Articulations



**reject
articulations
causing
detachment &
self-collisions**

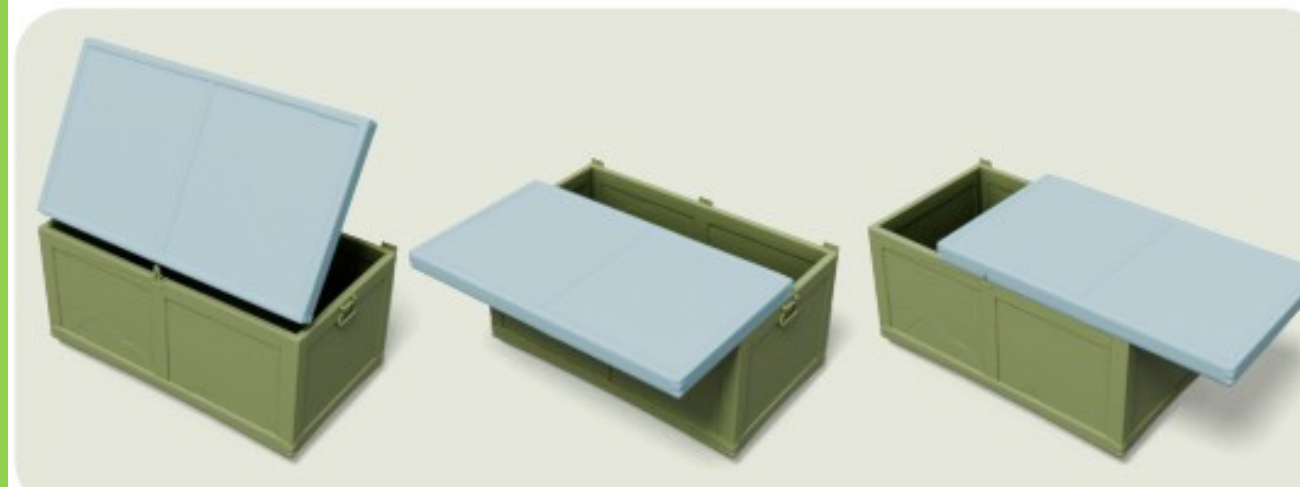
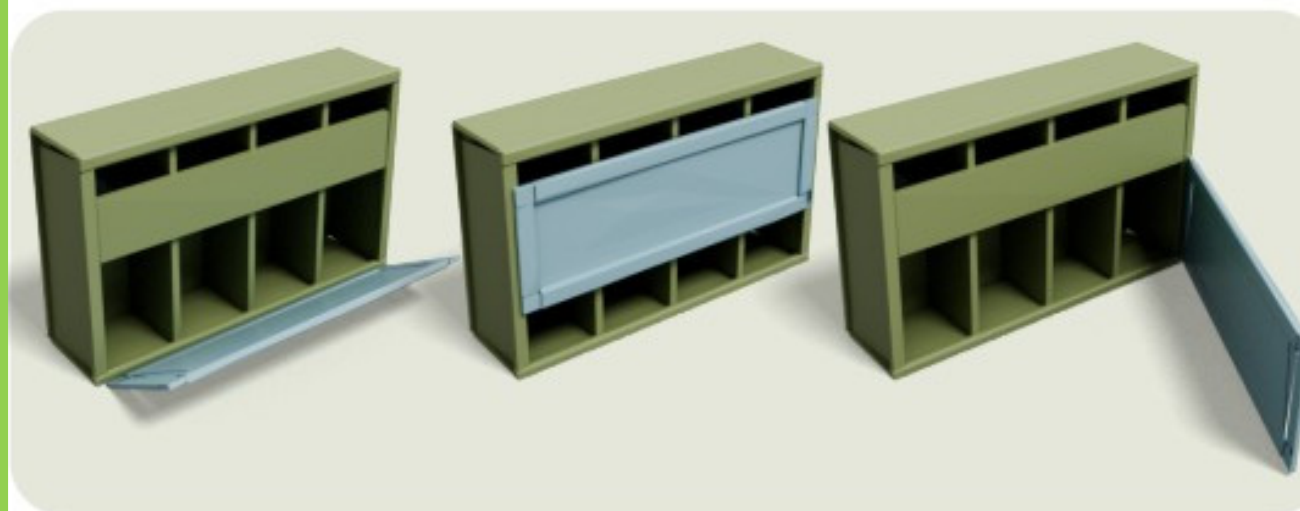
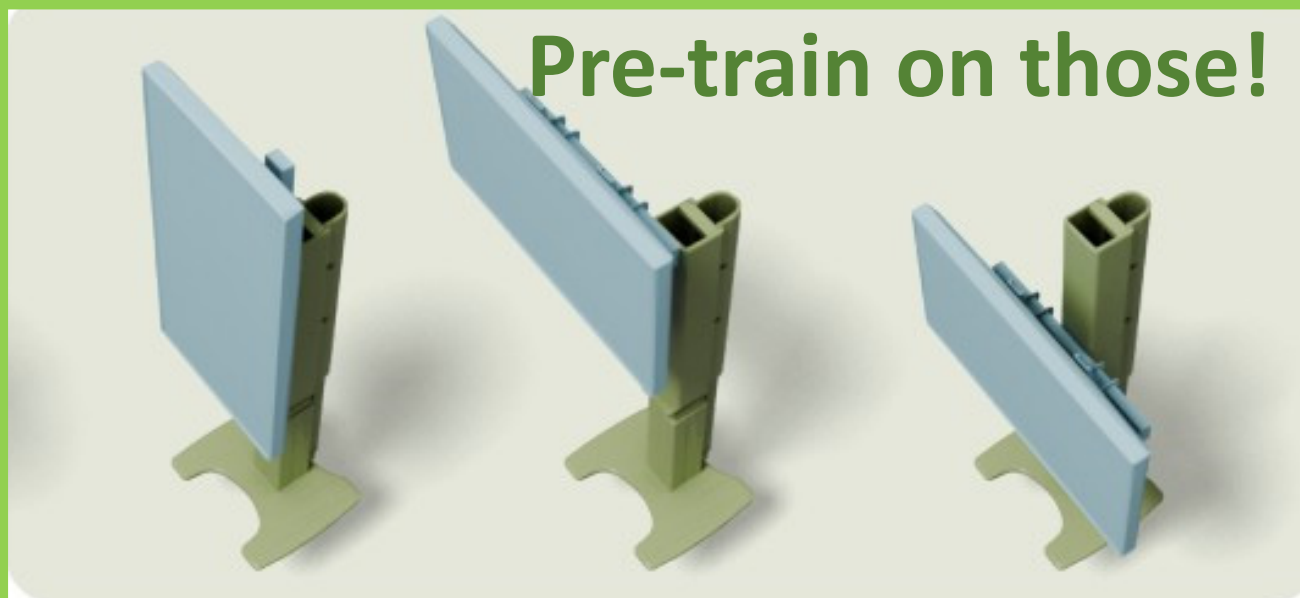


Input

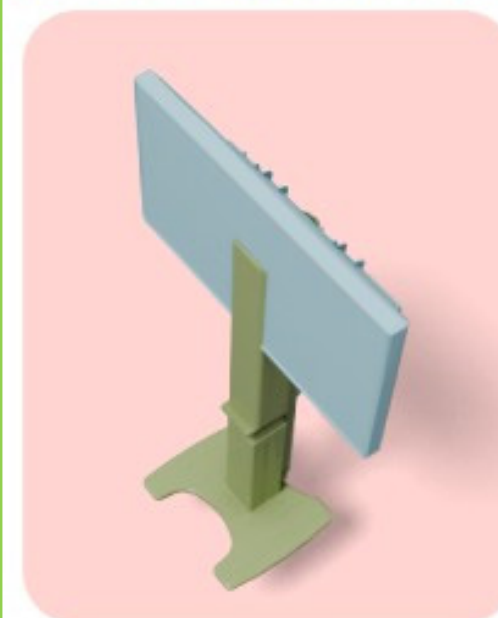


Candidate Articulations

Pre-train on those!

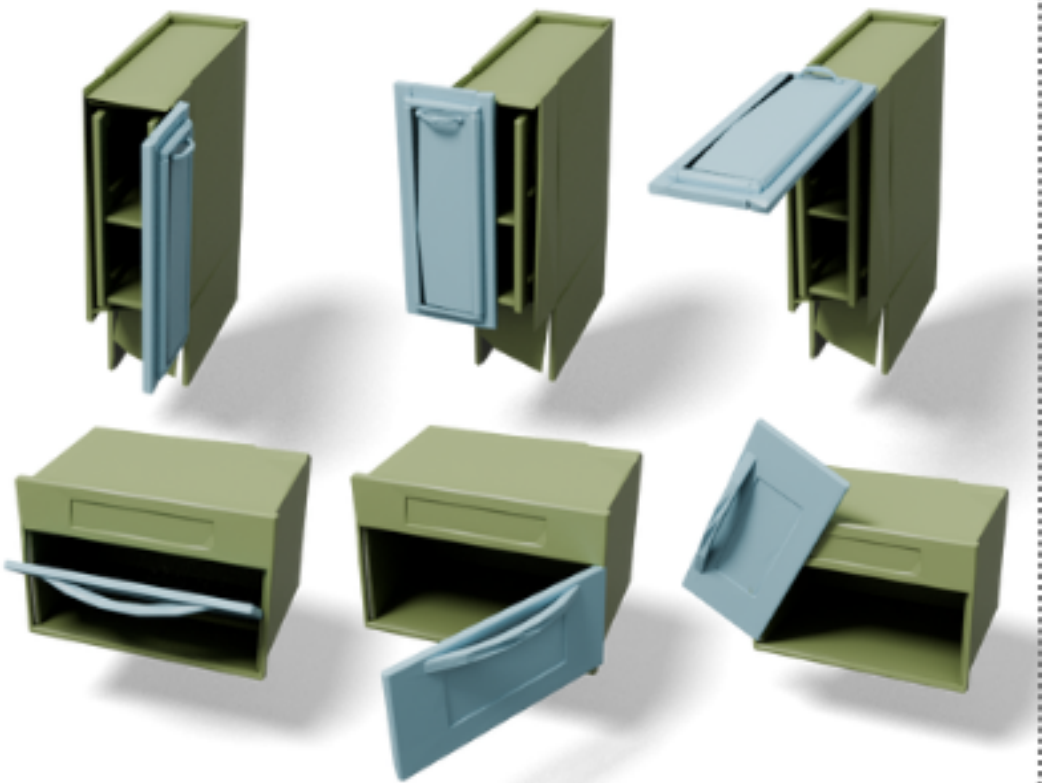


Invalid Articulations



GEOPARD in a nutshell

Self-supervised pretraining

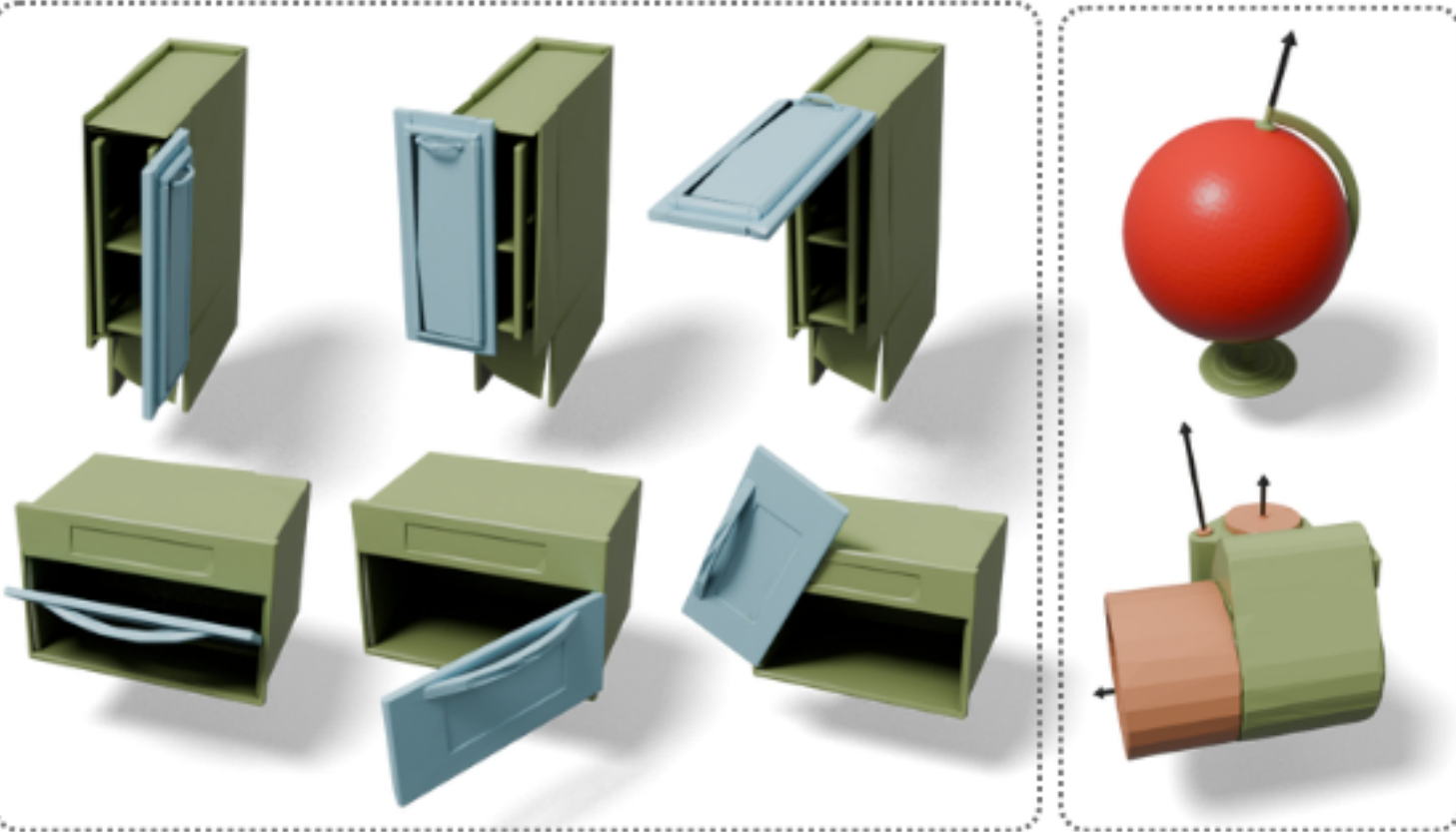


GEOPARD in a nutshell

Self-supervised pretraining

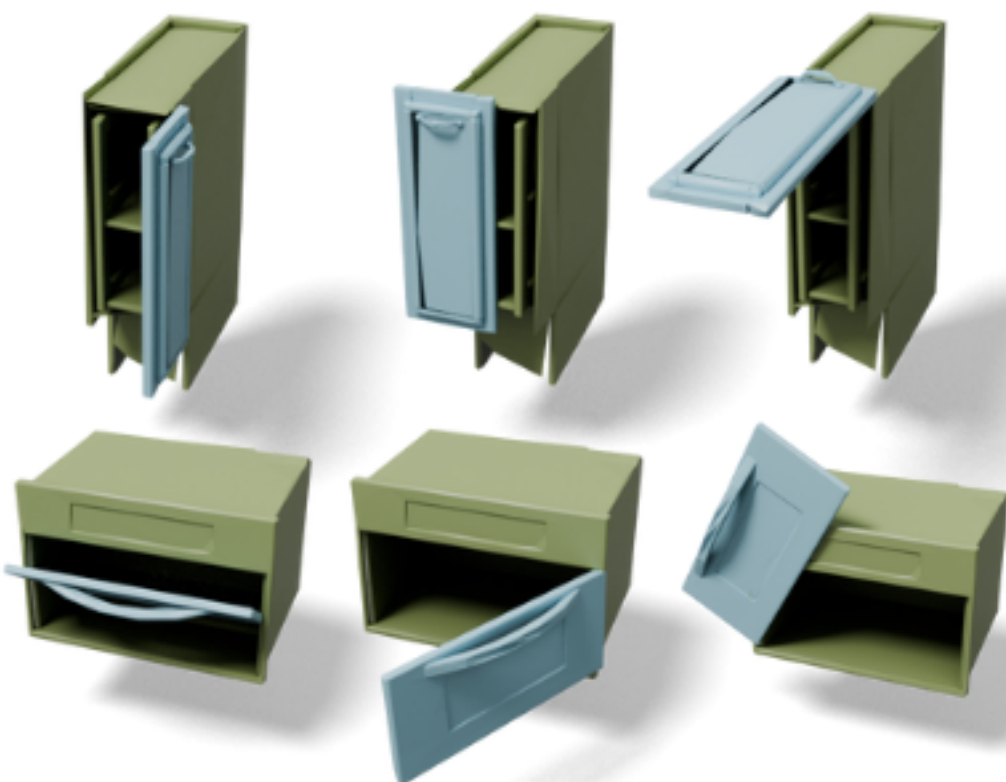


Finetuning

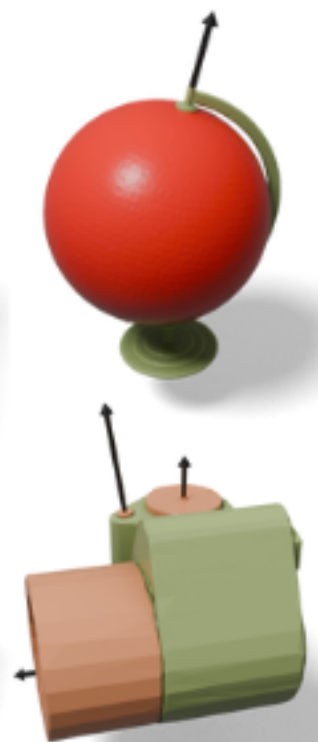


GEOPARD in a nutshell

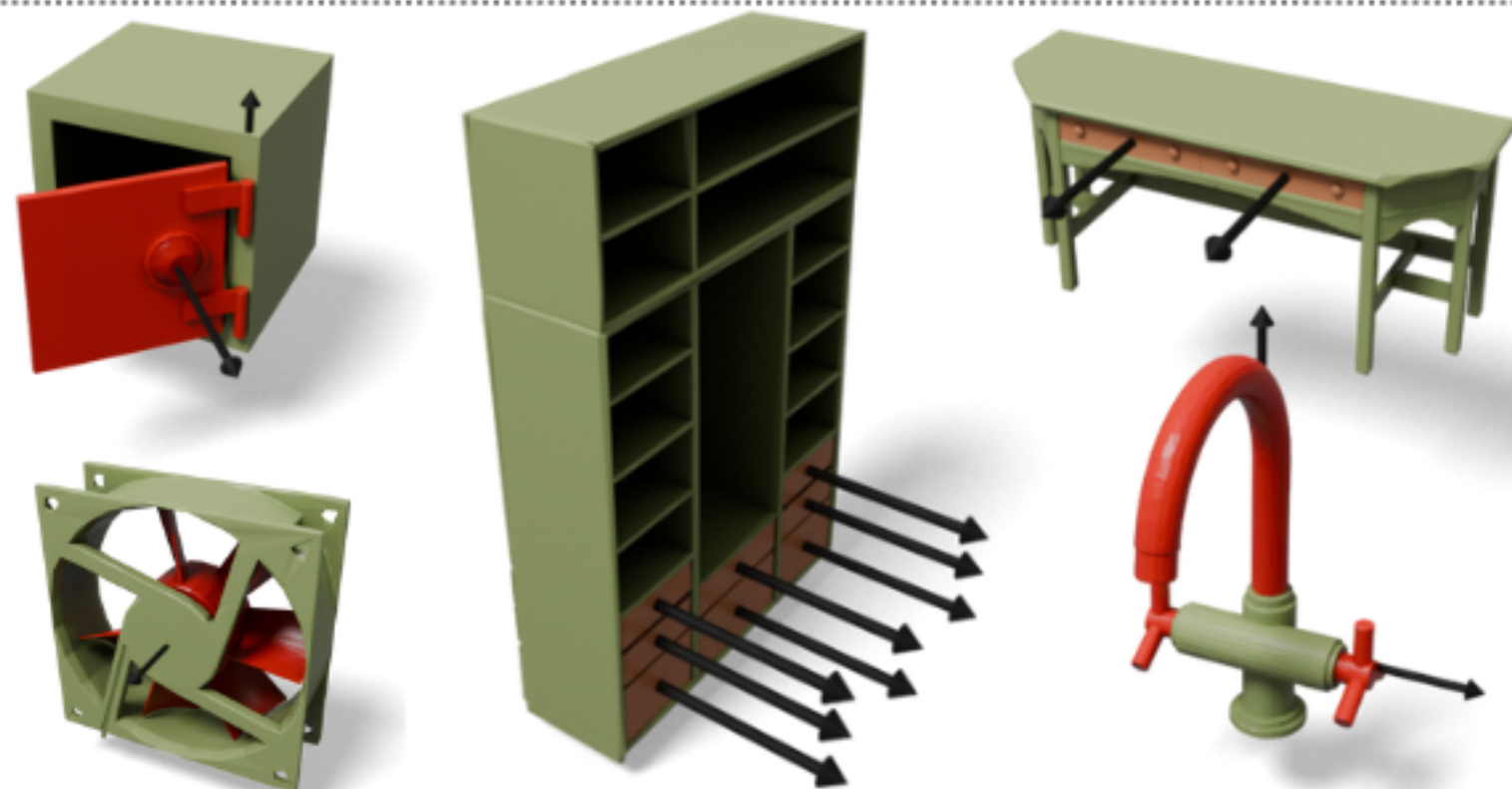
Self-supervised pretraining



Finetuning



Generalization across diverse geometries



Comparisons

Method	Axis Error ↓
CAGE	12.83
SINGAPO	11.20
GEOPARD	9.18

CAGE: Controllable Articulation Generation, Li et al. CVPR 24

SINGAPO: Single Image Controlled Generation of Articulated Parts in Objects, Liu et al, ICLR 25

Comparisons

Method	Axis Error ↓	Rot. Center Error ↓
CAGE	12.83	0.11
SINGAPO	11.20	0.12
GEOPARD	9.18	0.05

CAGE: Controllable Articulation Generation, Li et al. CVPR 24

SINGAPO: Single Image Controlled Generation of Articulated Parts in Objects, Liu et al, ICLR 25

Comparisons

Method	Axis Error ↓	Rot. Center Error ↓	Motion Type Precision ↑
CAGE	12.83	0.11	0.89
SINGAPO	11.20	0.12	0.90
GEOPARD	9.18	0.05	0.92

CAGE: Controllable Articulation Generation, Li et al. CVPR 24

SINGAPO: Single Image Controlled Generation of Articulated Parts in Objects, Liu et al, ICLR 25

Comparisons

Method	Axis Error ↓	Rot. Center Error ↓	Motion Type Precision ↑	Motion Type Recall ↑
CAGE	12.83	0.11	0.89	0.89
SINGAPO	11.20	0.12	0.90	0.91
GEOCARD	9.18	0.05	0.92	0.93

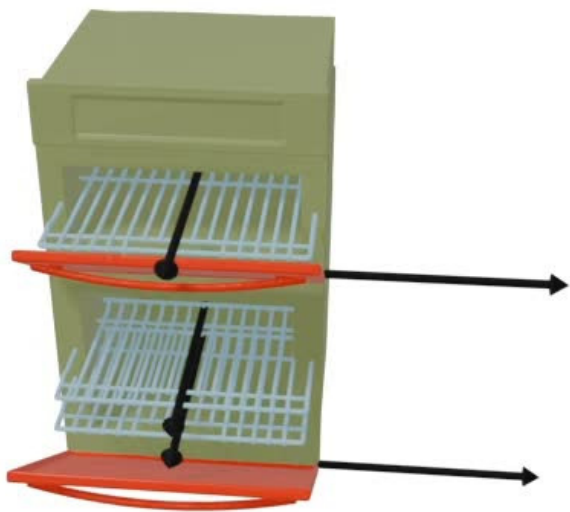
CAGE: Controllable Articulation Generation, Li et al. CVPR 24

SINGAPO: Single Image Controlled Generation of Articulated Parts in Objects, Liu et al, ICLR 25

Ablation

GEOPARD variant	Axis Error ↓	Rot. Center Error ↓	Motion Type Precision ↑	Motion Type Recall ↑
No pretrain.	10.67	0.06	0.87	0.88
With pretrain.	9.18	0.05	0.92	0.93

Generalization across diverse categories



Outline

1. GEOPARD: Geometric Pretraining for Articulation Prediction in 3D Shapes

2. SOPHY: Generating Simulation-Ready Objects with Physical Materials

3. Future directions

Goal: generate simulation-ready 3D objects



Input:
**image or/and
text prompt**

Goal: generate simulation-ready 3D objects



Input:
**image or/and
text prompt**

Output:
object geometry+texture+physical materials

Background

Triangular Mesh



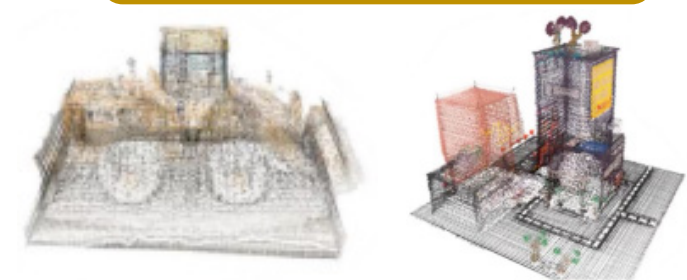
MeshAnything V2
Chen *et al*, arXiv 24

NeRF



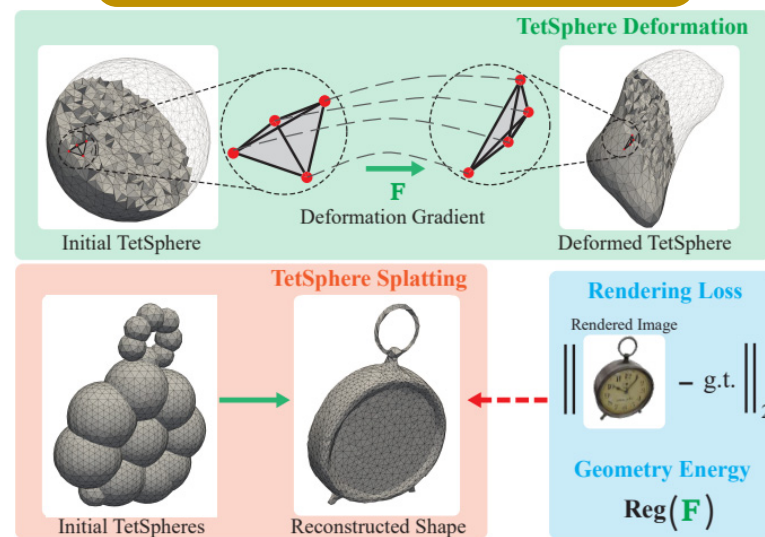
Latent-NeRF
Metzer *et al*, CVPR 23

3D Gaussians



GRM
Xu *et al*, ECCV 24

Tetrahedral Mesh



TetSphere Splatting
Guo *et al*, ICLR 25

Textured Mesh

Text-to-3D generation

text prompt

```
> a train  
engine made out  
of clay
```



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

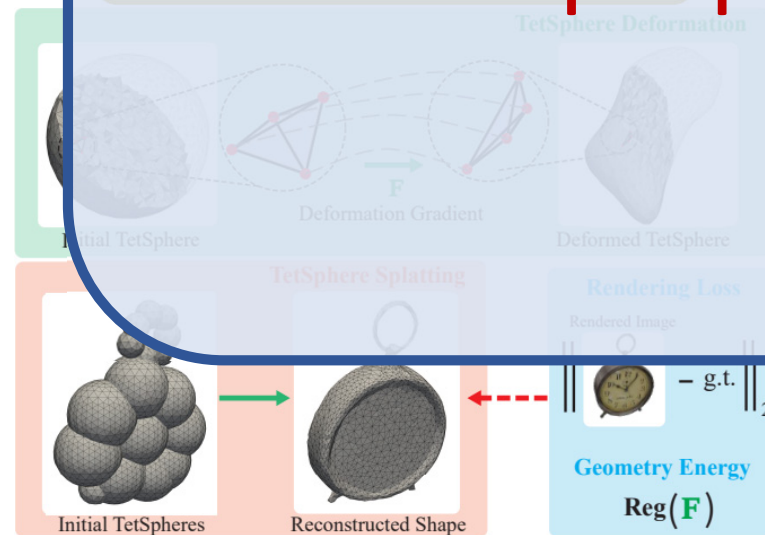
Background

Triangular Mesh

NeRF

3D Gaussians

Completely agnostic to physics & material properties i.e., “dead” objects



TetSphere Splatting
Guo *et al*, ICLR 25



Latent-NeRF



GRM

Text-to-3D generation

text prompt

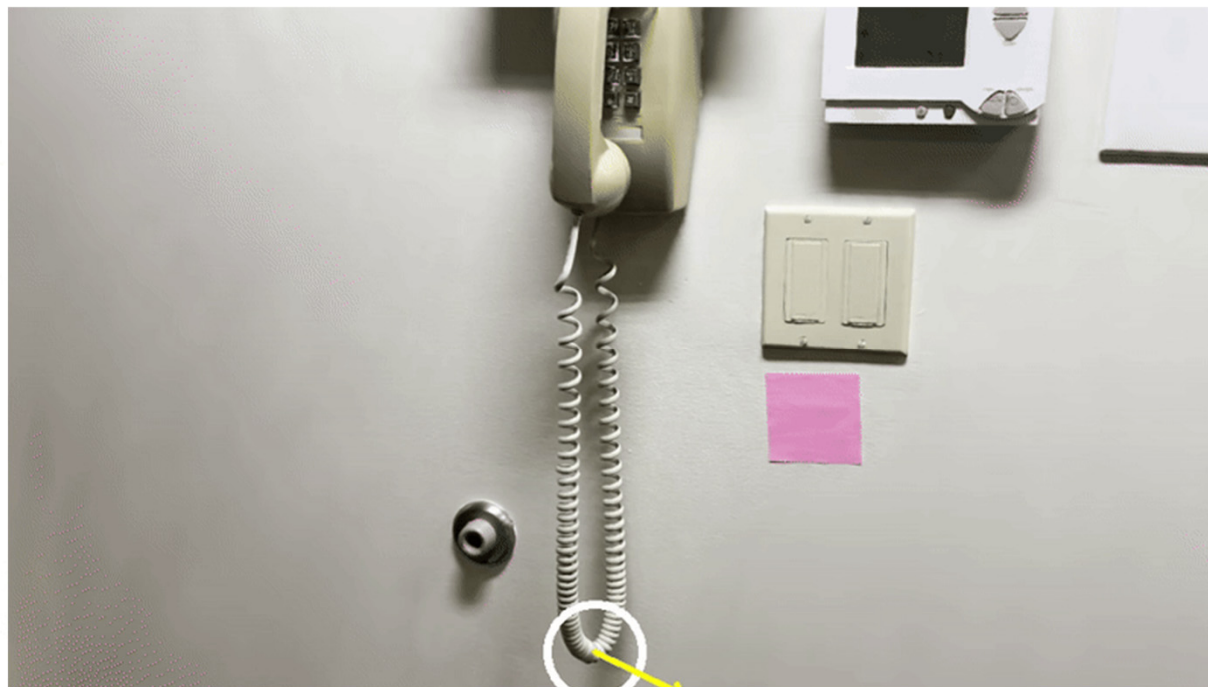
```
> a train  
engine made out  
of clay
```

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

Prior Work



PhysGaussian



PhysDreamer



PhysMotion

PhysGaussian: Physics-integrated 3D Gaussians for Generative Dynamics. CVPR 2024.

PhysDreamer: Physics-Based Interaction with 3D Objects via Video Generation. ECCV 2024.

PhysMotion: Physics-Grounded Dynamics From a Single Image. arXiv 2024.

Prior Work

Assume given **3D shapes & material properties**

PhysGaussian

PhysDreamer

PhysMotion

PhysGaussian: Physics-integrated 3D Gaussians for Generative Dynamics. CVPR 2024.

PhysDreamer: Physics-Based Interaction with 3D Objects via Video Generation. ECCV 2024.

PhysMotion: Physics-Grounded Dynamics From a Single Image. arXiv 2024.

Challenges

1. Lack of available datasets that include detailed material parameters

Material Parameters

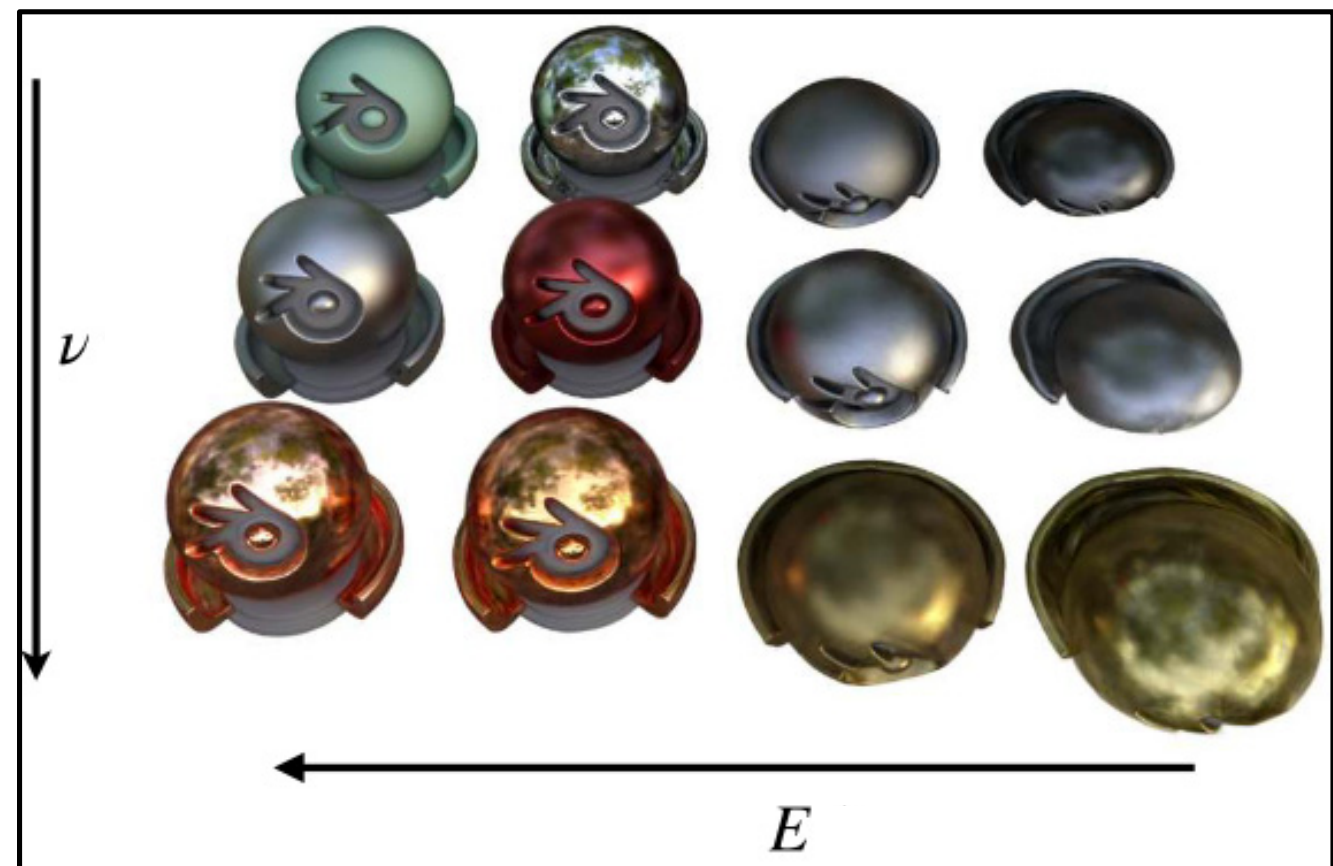
Young's modulus E

Poisson's ratio ν

Yield stress σ

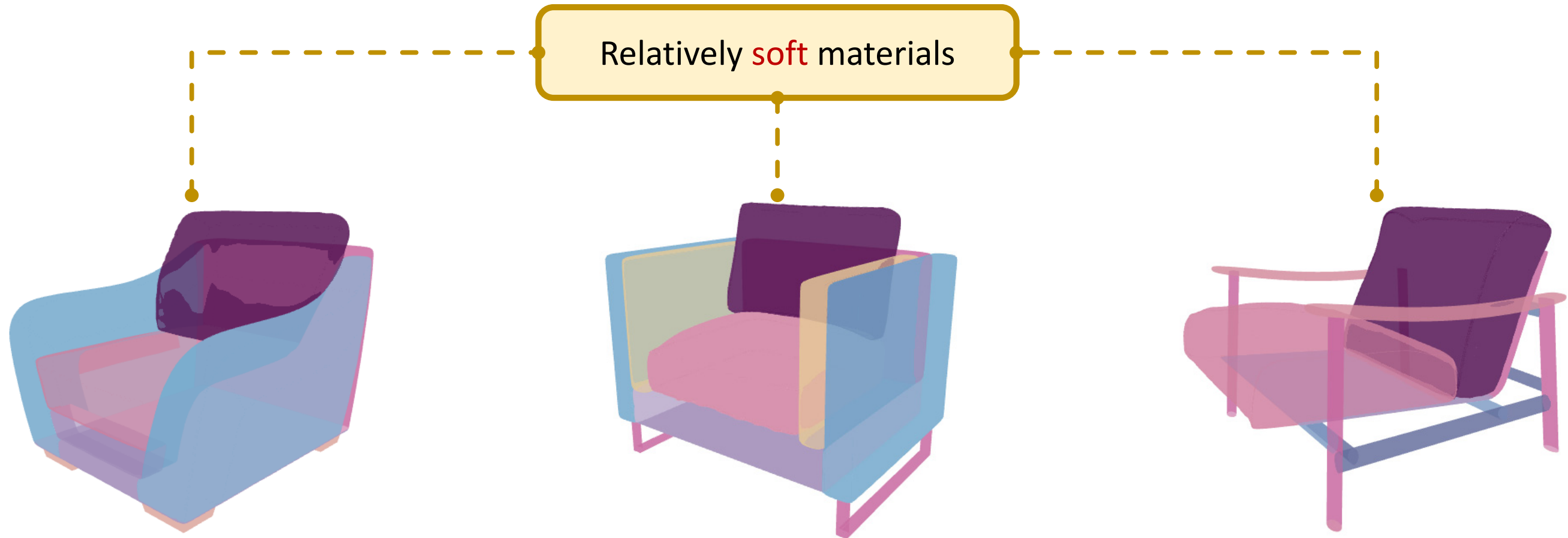
Friction angle ϕ

...



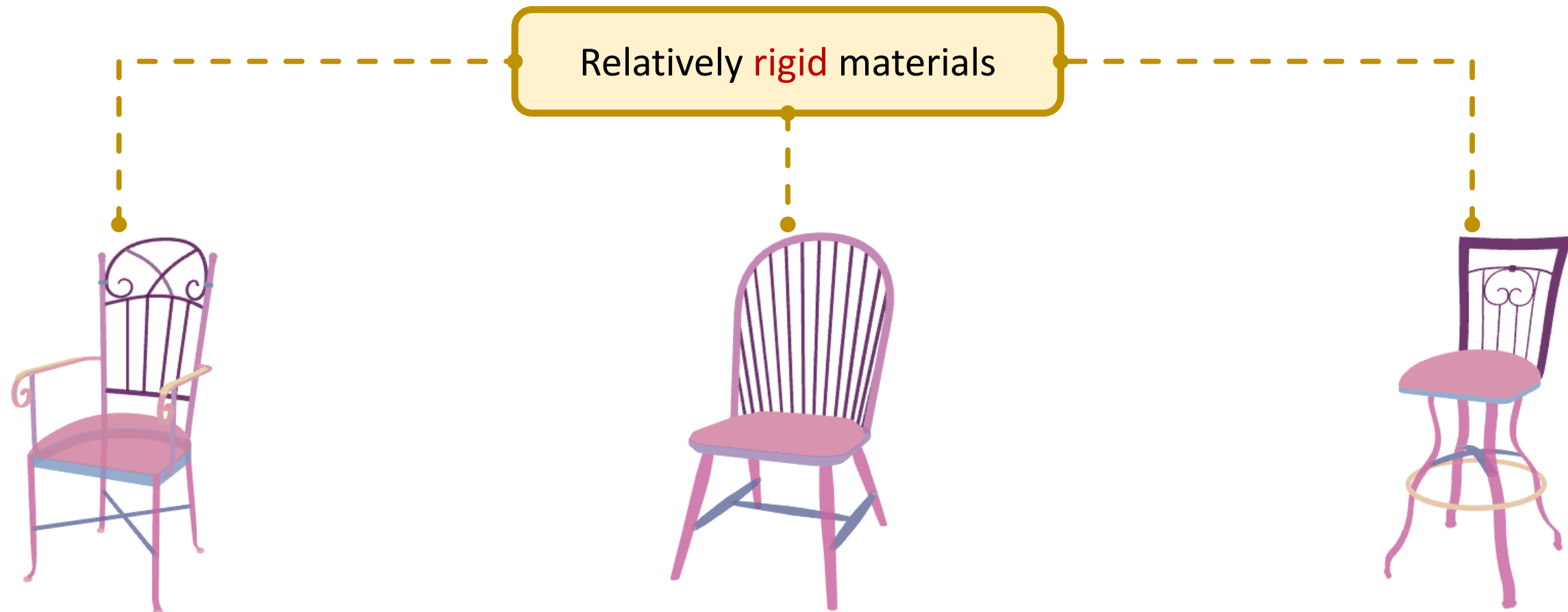
Challenges

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



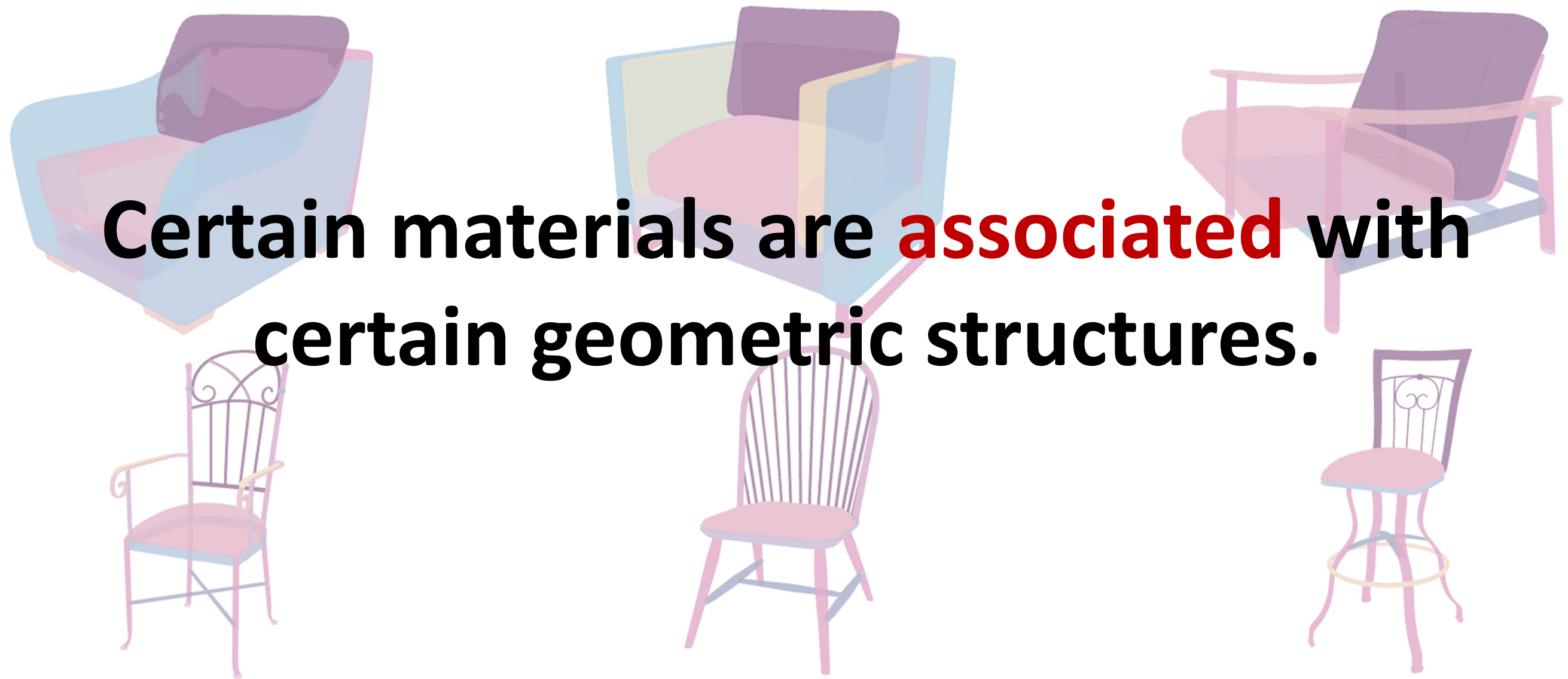
Challenges

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



Challenges

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



Certain materials are **associated** with certain geometric structures.

Material-annotated Dataset

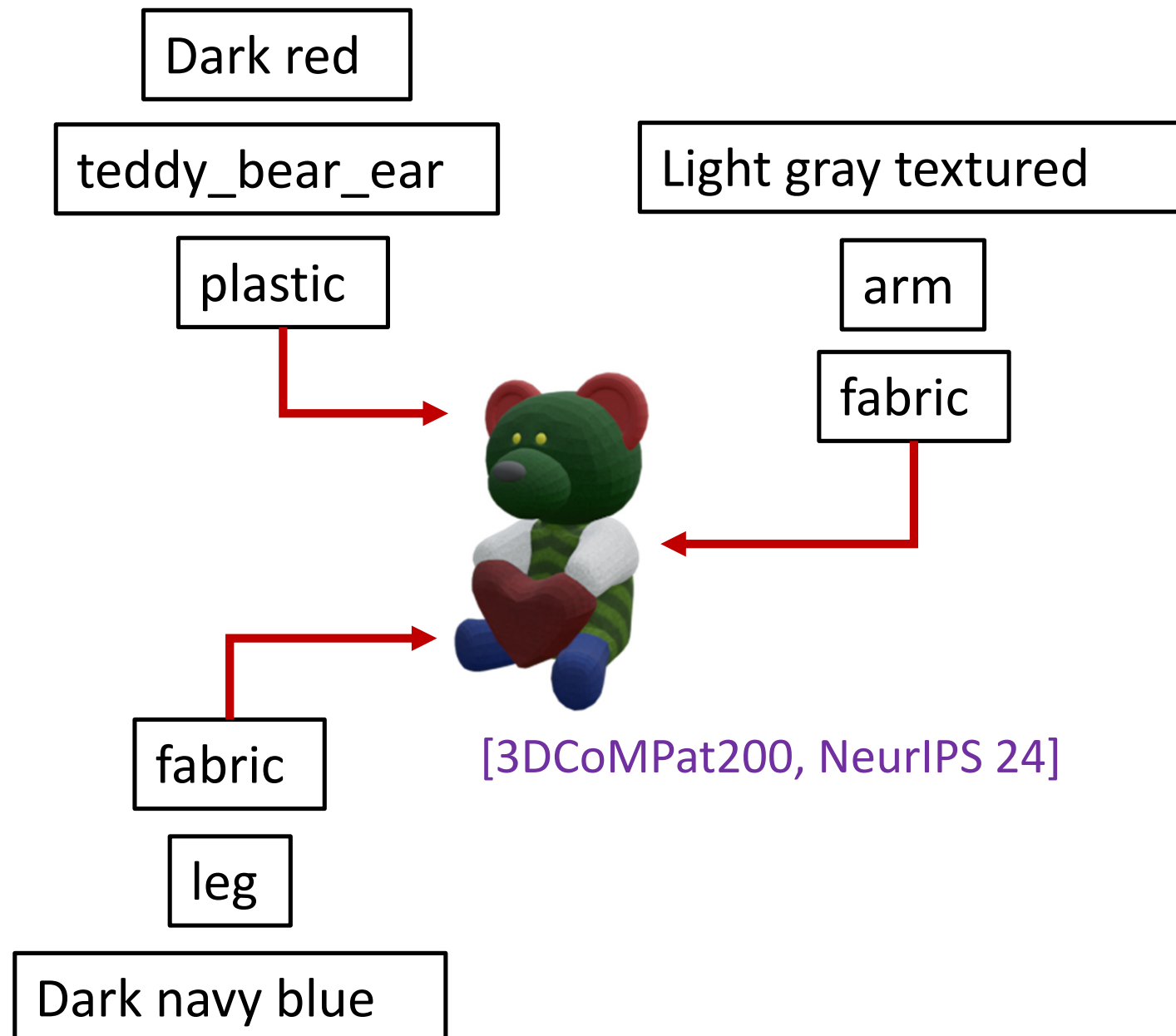
12 shape categories, 3K objects, 15K parts

bag	bed	chair	crib	hat	headband
-----	-----	-------	------	-----	----------

love_seat	pillow	planter	sofa	teddy_bear	vase
-----------	--------	---------	------	------------	------

Automated Assembled Text

The teddy bear is made of *a light gray fabric arm, a dark navy-blue fabric leg, a dark red fabric ear, ...*



Material-annotated Dataset

Assistance from Vision Language Models (VLMs)!

Rendered Images



Text Descriptions

A chair made of 3 parts:
(1) a pewter gray **metal**
leg, (2) a dark navy
blue **fabric** *seat*, and (3)
a blue, gray stripes
fabric *backrest*.

Query Prompts

Please choose the most
suitable **fine-grained**
material type for the
part(s): [seat,
backrest] . . .
Available choices for
fabric: [cotton,
wool, . . .] . . .



VLM Output

```
{  
  "seat": "polyester",  
  "backrest": "cotton"  
}
```

Material-annotated Dataset

Assistance from Vision Language Models (VLMs)!

Rendered Images



Text Descriptions

A chair made of 3 parts:
(1) a pewter gray **metal** leg,
(2) a dark navy blue **fabric** seat, and
(3) a blue, gray stripes **fabric** backrest.

Query Prompts

Please choose the most suitable **fine-grained material type** for the part(s): [seat, backrest] . . .
Available choices for **fabric**: [cotton, wool, . . .] . . .



VLM Output

```
{  
  "seat": "polyester",  
  "backrest": "cotton"  
}
```



A chair made of 3 parts:
(1) a pewter gray **metal** leg,
(2) a dark navy blue (**polyester**) **fabric** seat, and
(3) a blue, gray stripes (**cotton**) **fabric** backrest.

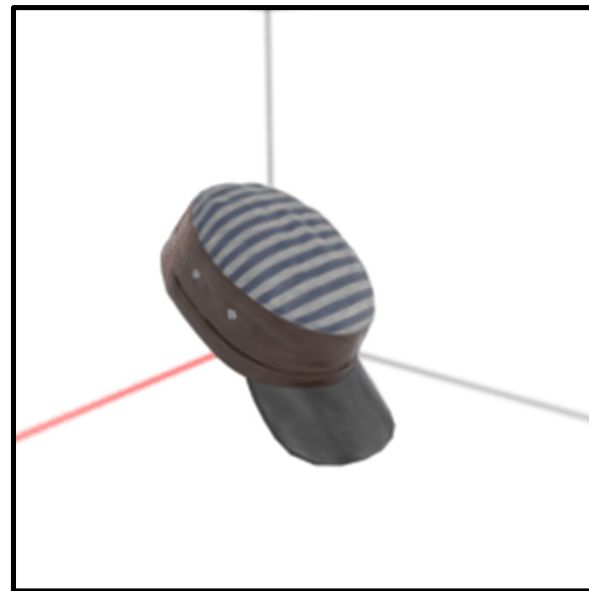
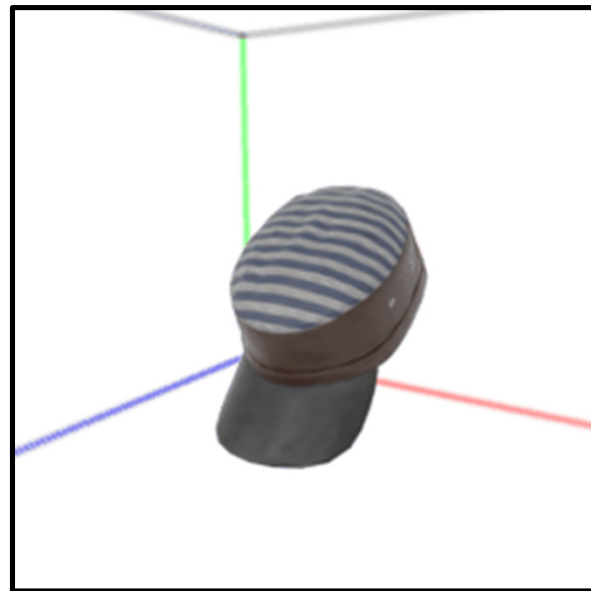
Please specify the **material models**, along with **material parameters** to simulate the motion of the object . . .



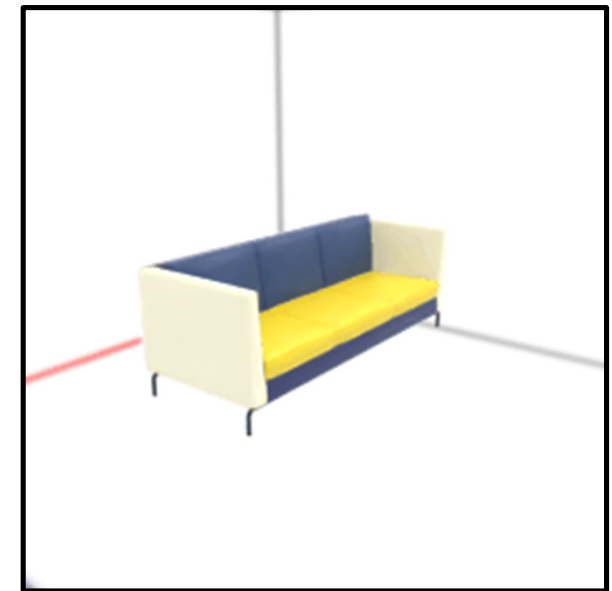
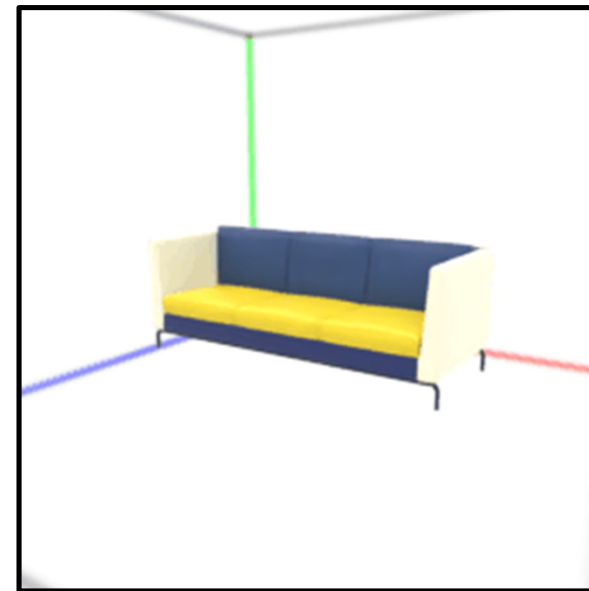
```
{  
  "leg": {  
    "E": 2000000000000,  
    "v": 0.3,  
    . . .  
  },  
  "seat": . . . ,  
  . . .  
}
```


Simulations

Test case: **Drop**



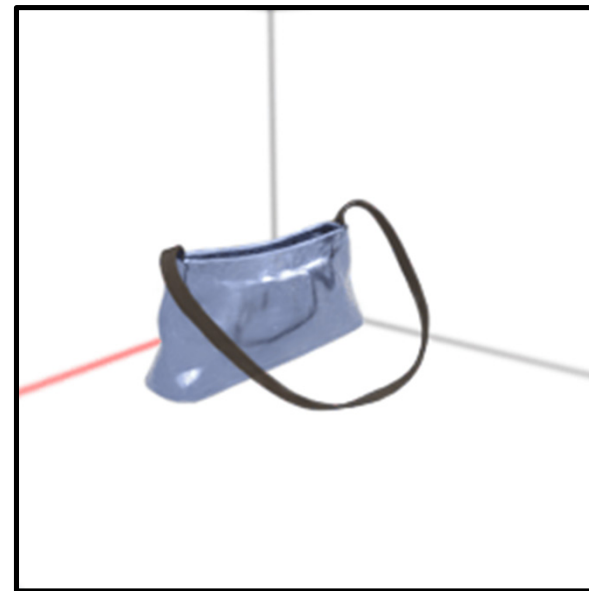
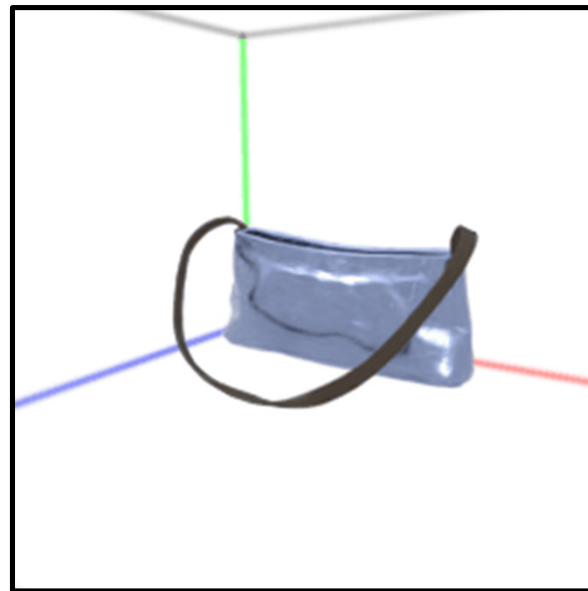
Hat



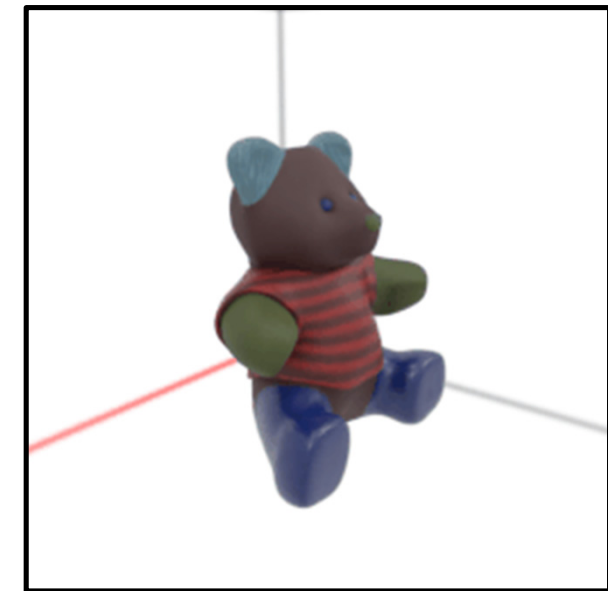
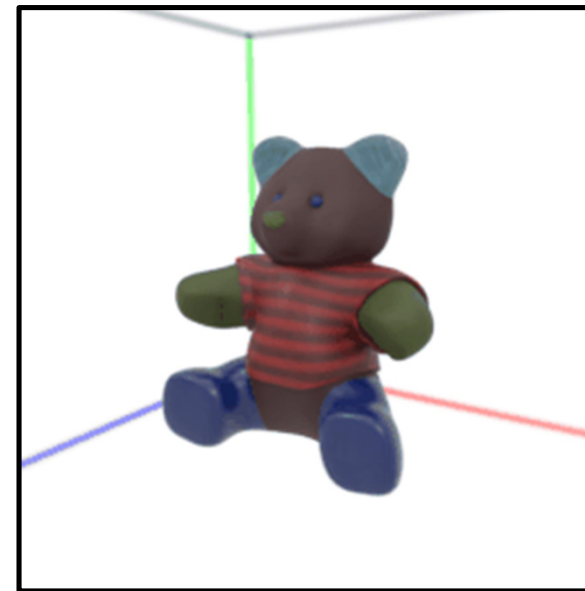
Sofa

Simulations

Test case: **Throw**



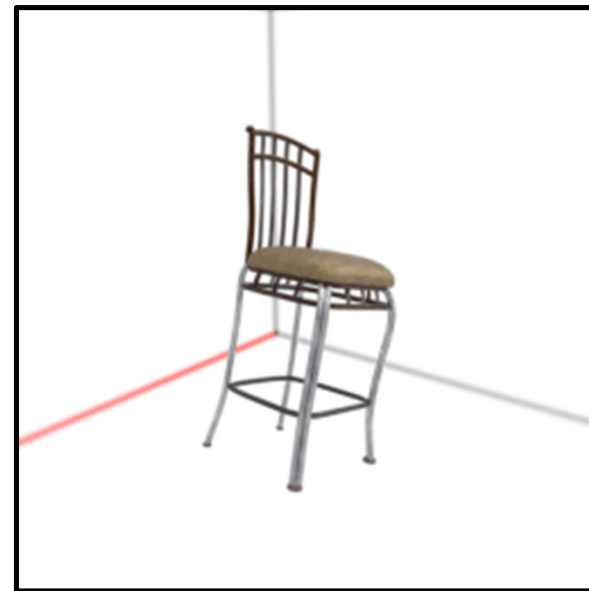
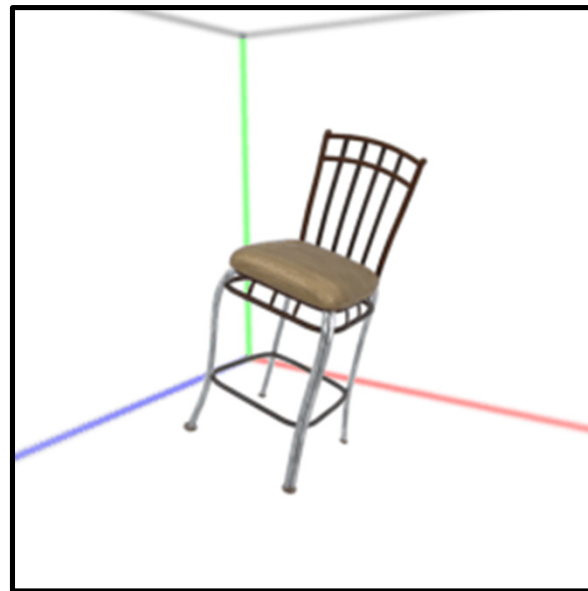
Bag



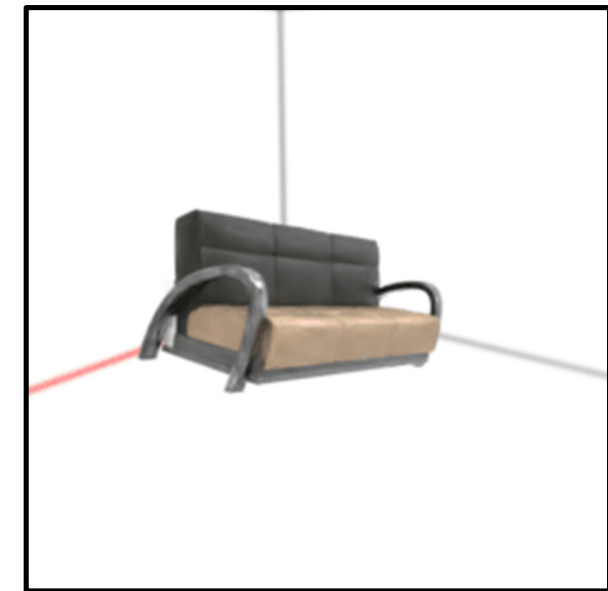
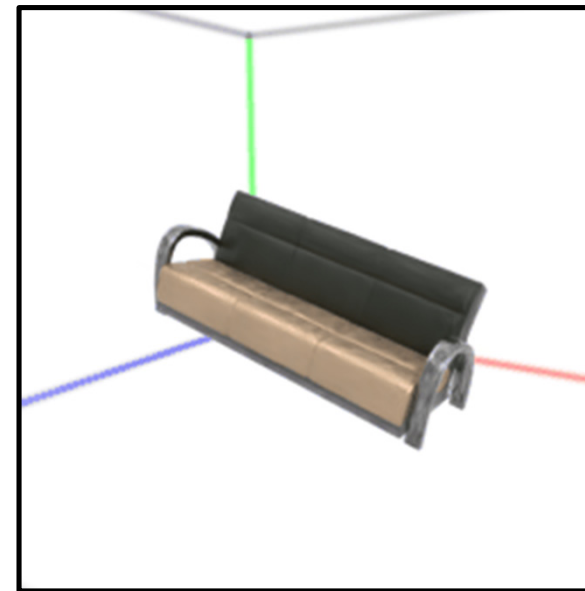
Teddy Bear

Simulations

Test case: **Tilt**



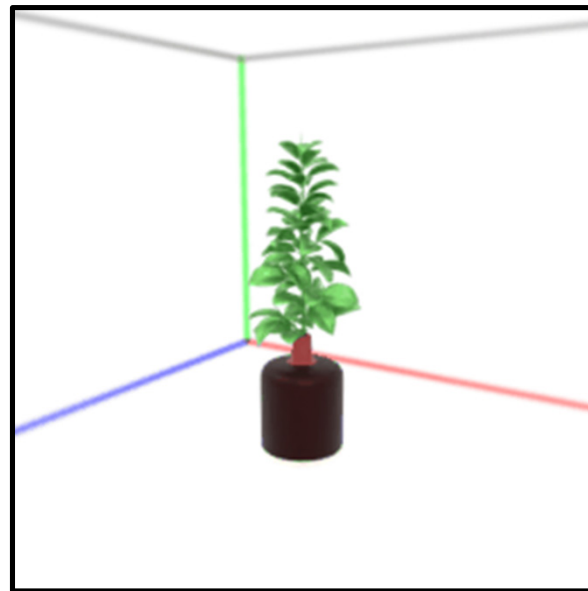
Chair



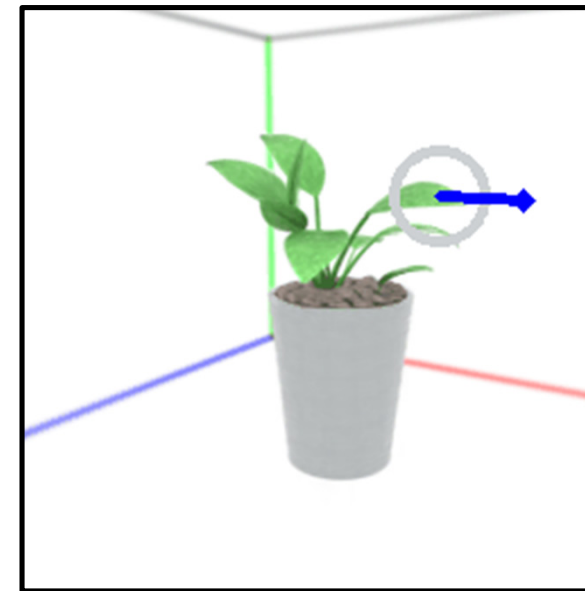
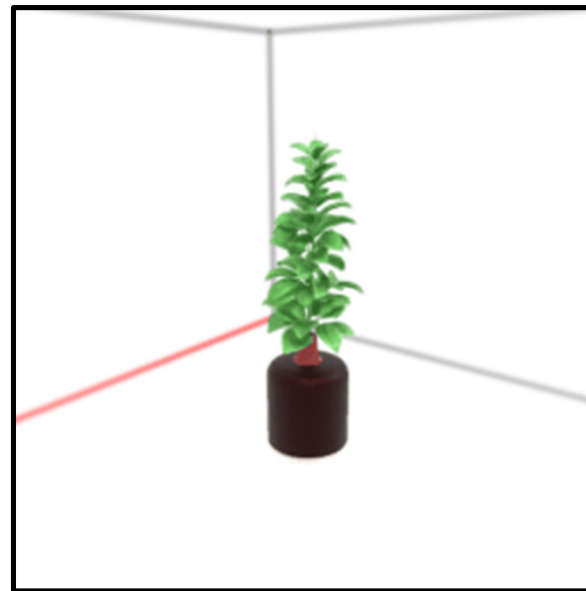
Sofa

Simulations

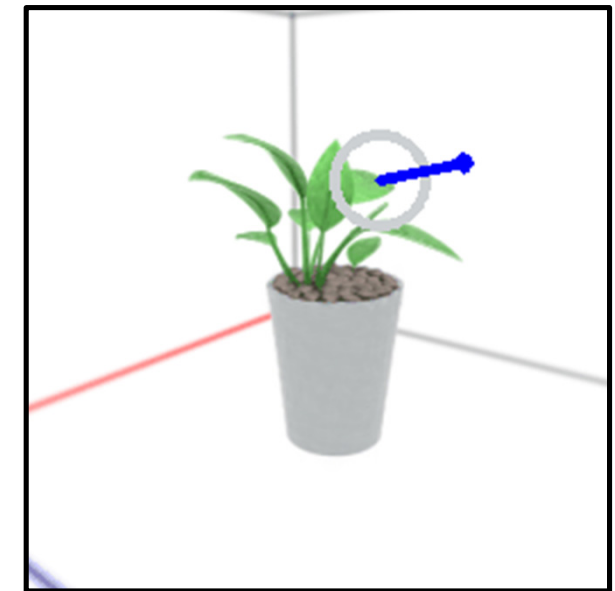
Test case: **Drag**



Planter

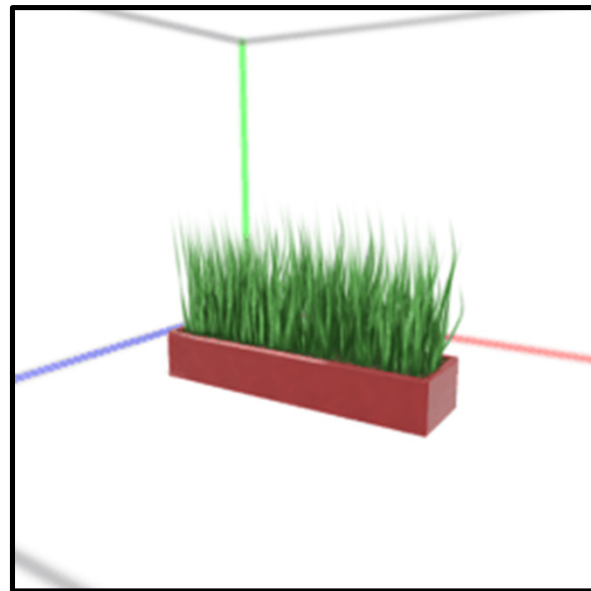


Planter

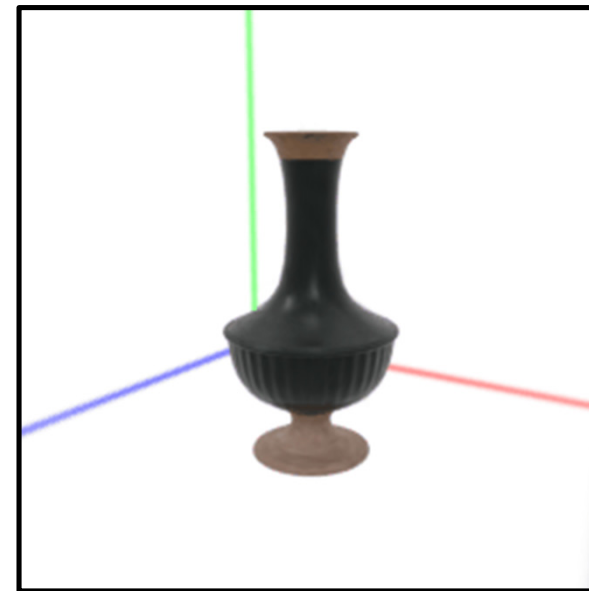
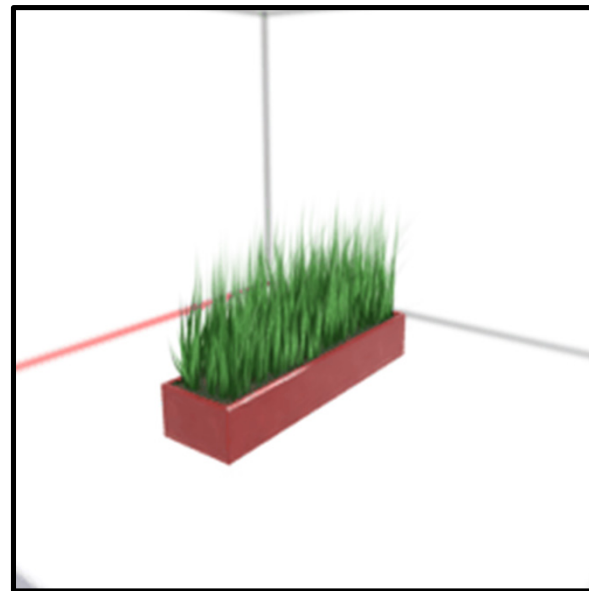


Simulations

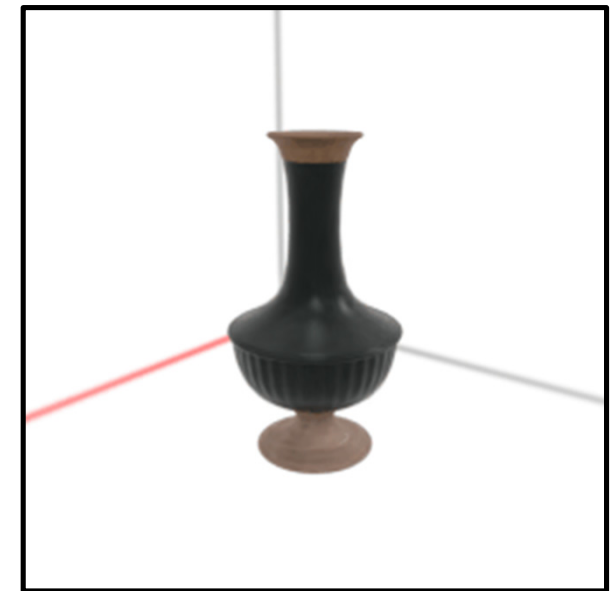
Test case: **Wind**



Planter

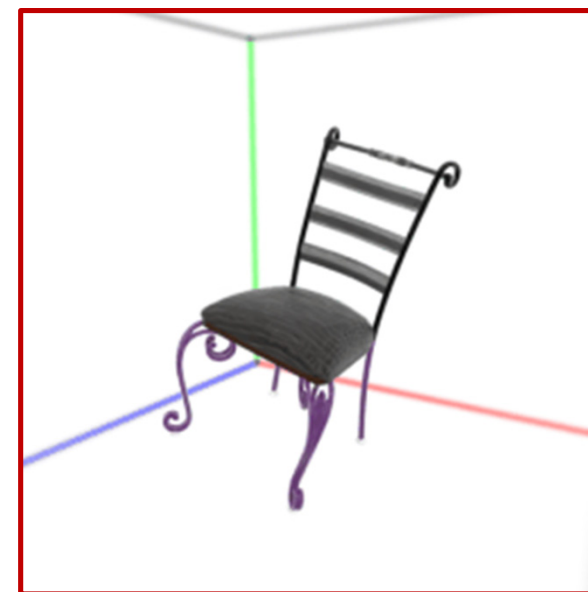
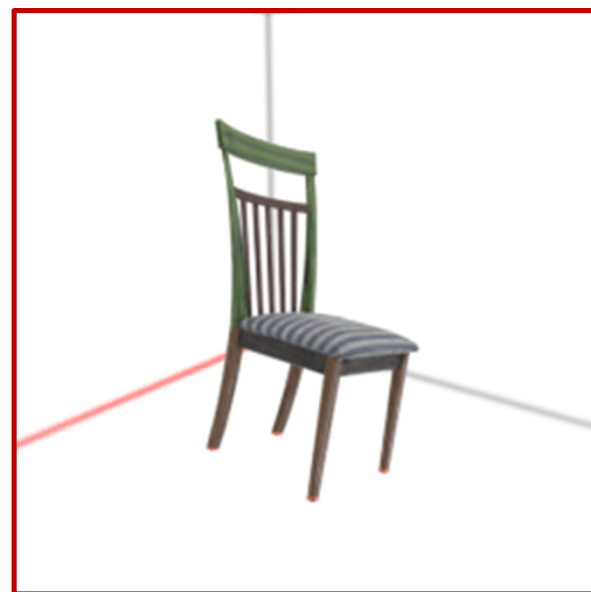
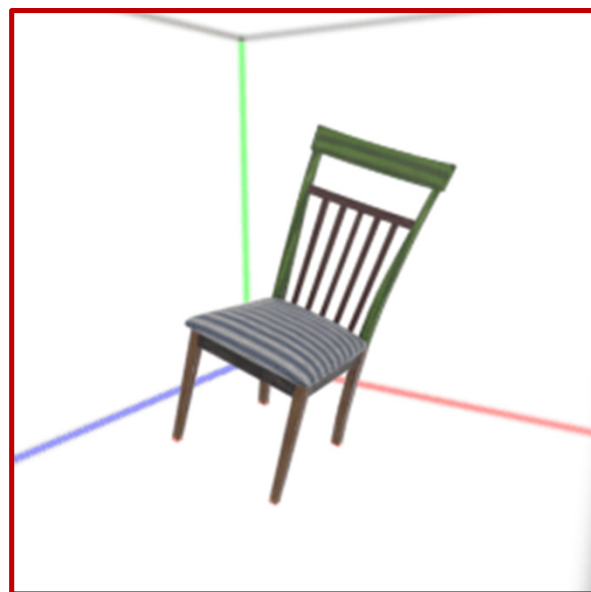


Vase

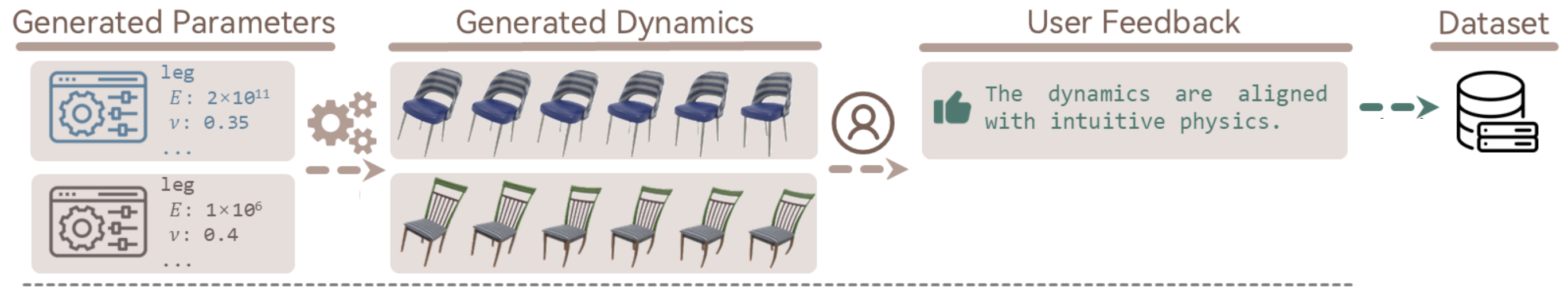


Material-annotated Dataset

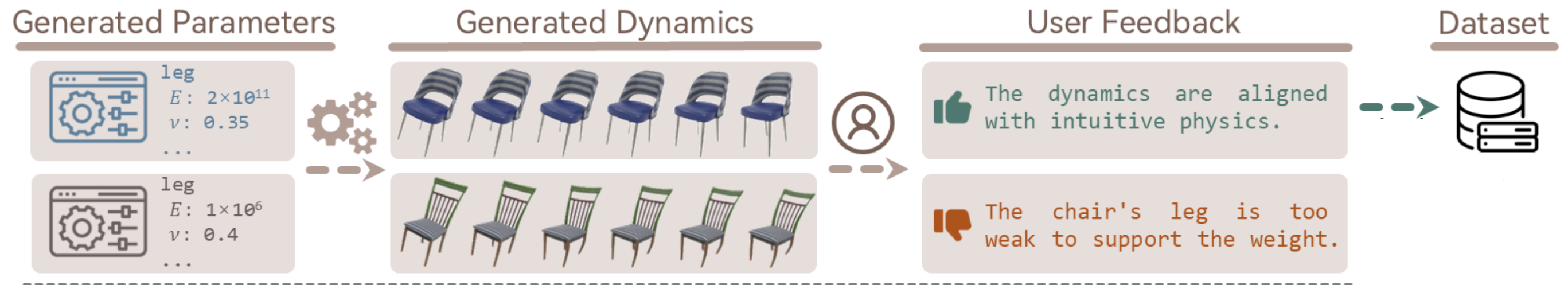
Expert verification for checking simulation results from the VLM parameters!



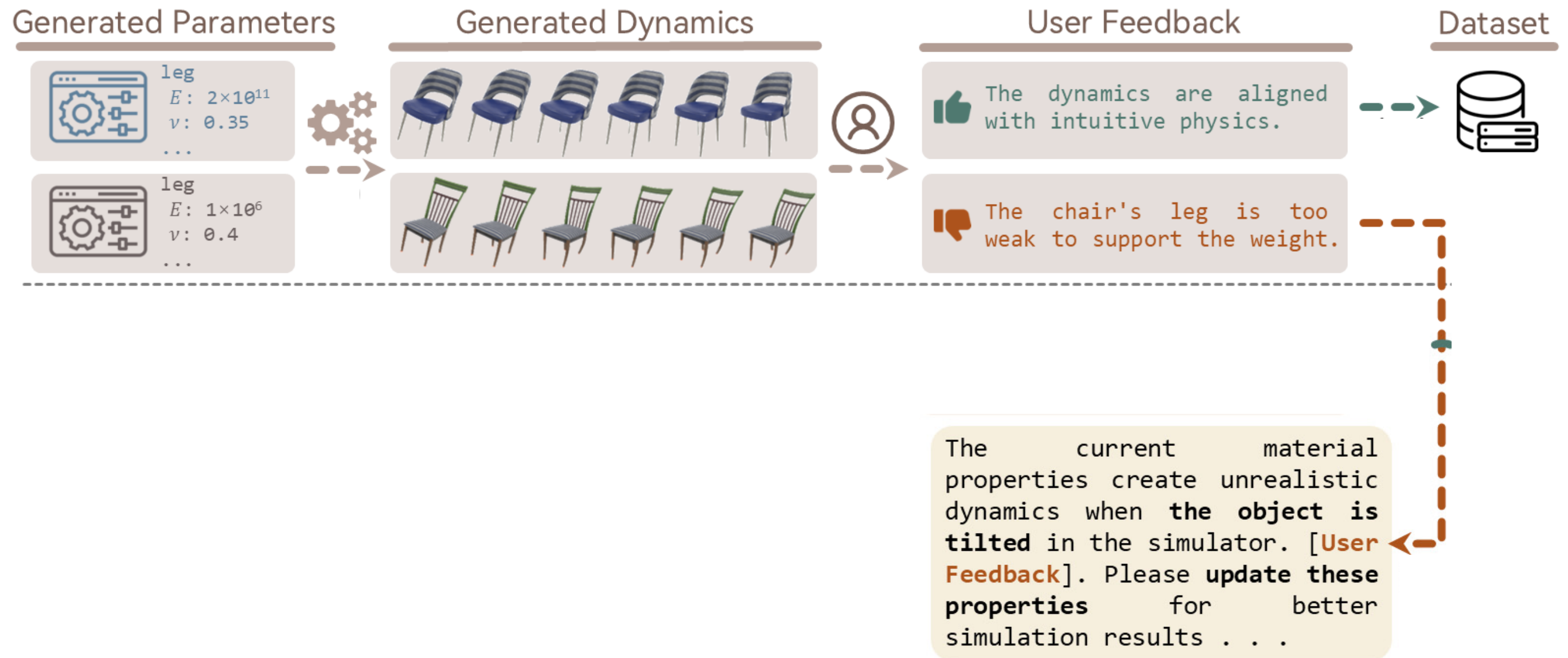
Annotation Pipeline



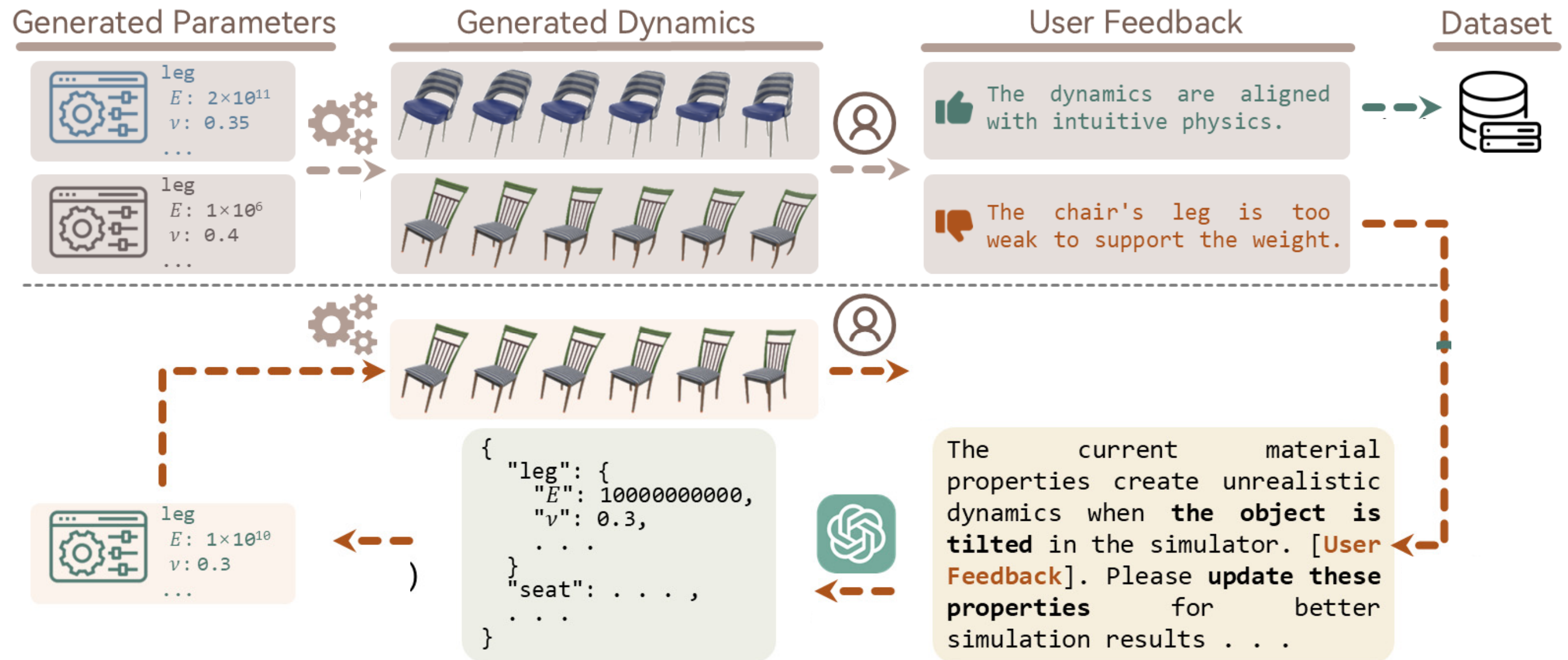
Annotation Pipeline



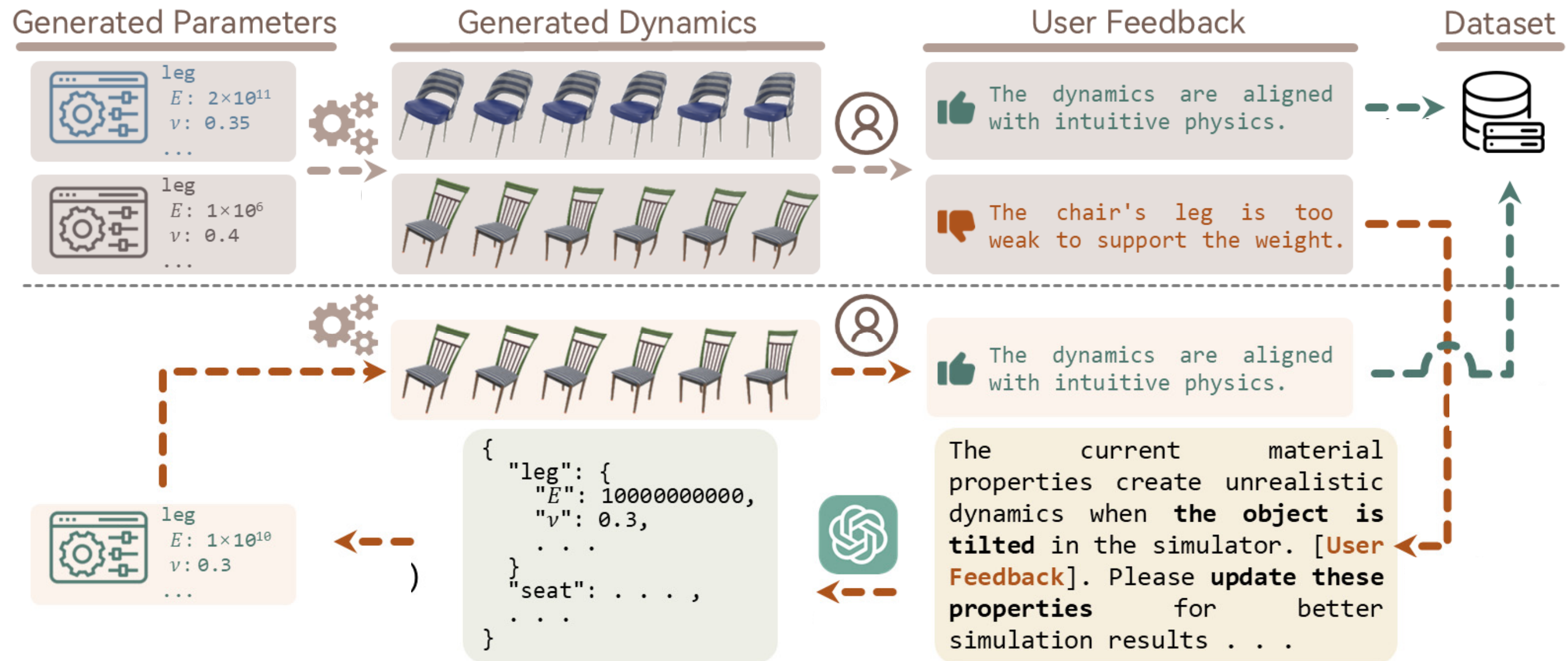
Annotation Pipeline



Annotation Pipeline



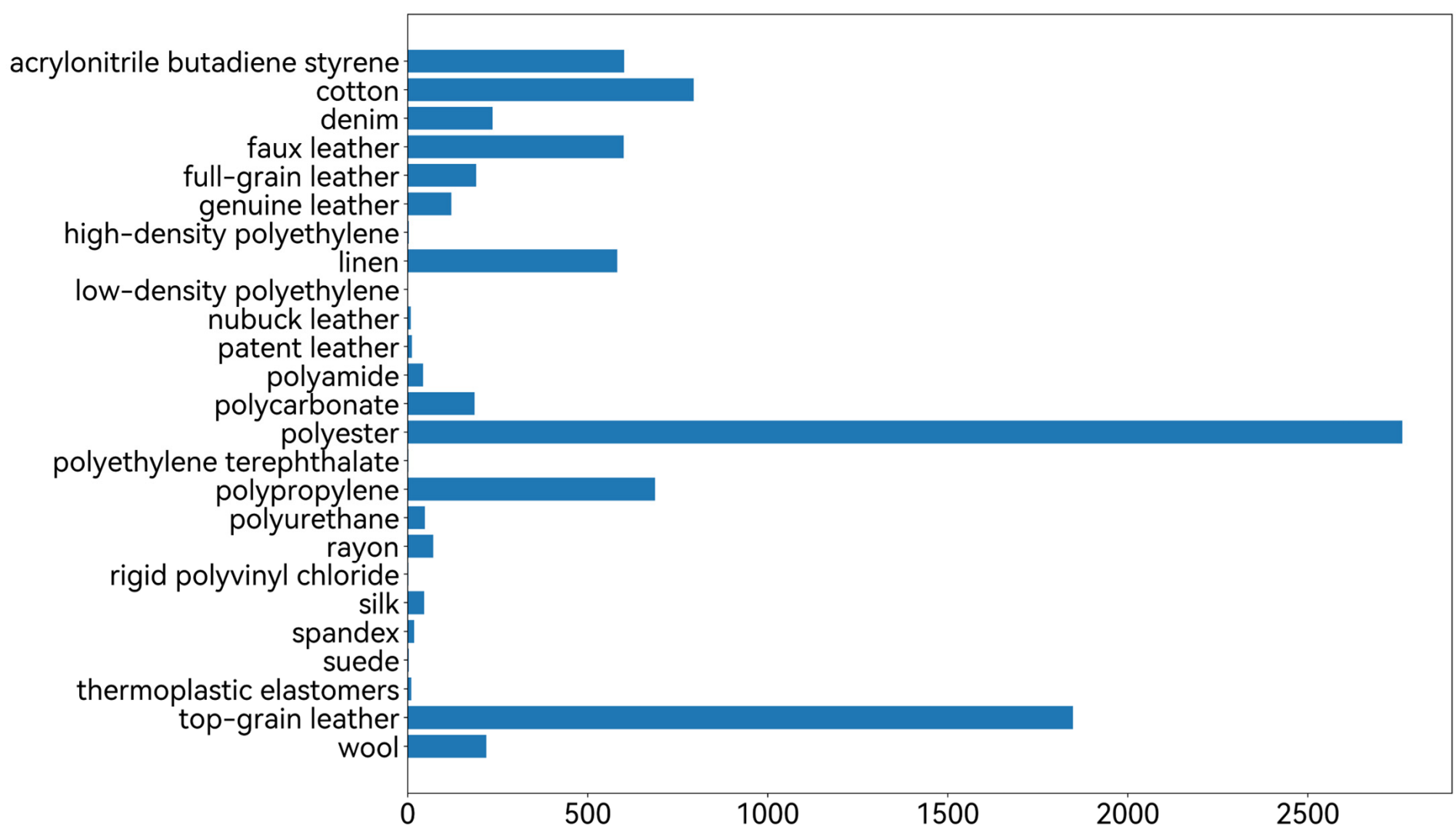
Annotation Pipeline



Dataset Statistics

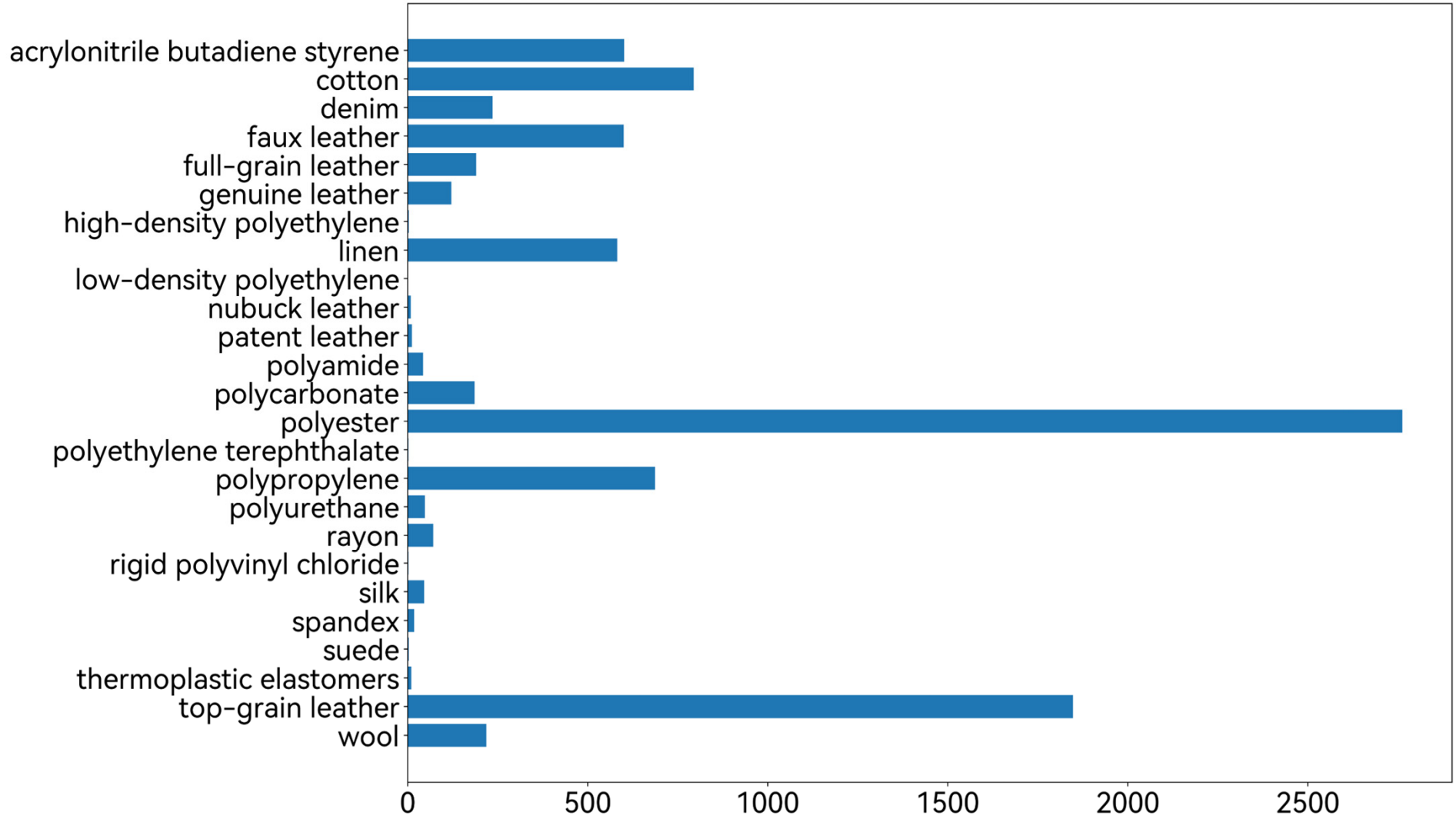
	bag	bed	chair	crib	hat	head-band	love seat	pillow	plant	sofa	teddy bear	vase	Total
Train	75	418	898	27	18	27	139	71	383	278	37	91	2462
Valid	10	26	52	5	2	5	21	11	21	18	6	3	180
Test	24	48	106	8	7	10	39	18	46	31	11	14	362

Dataset Statistics

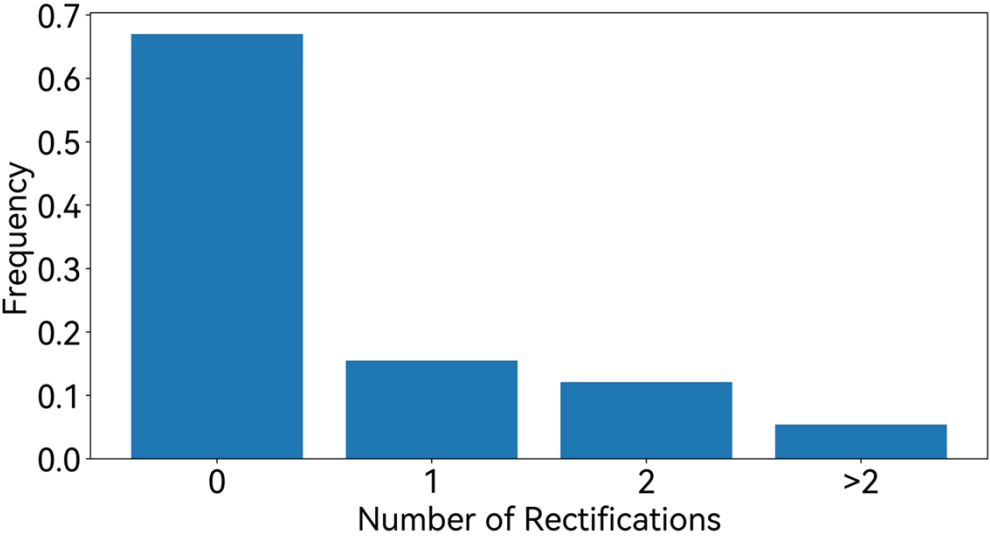


Statistics of fine-grained material types

Dataset Statistics



Statistics of fine-grained material types

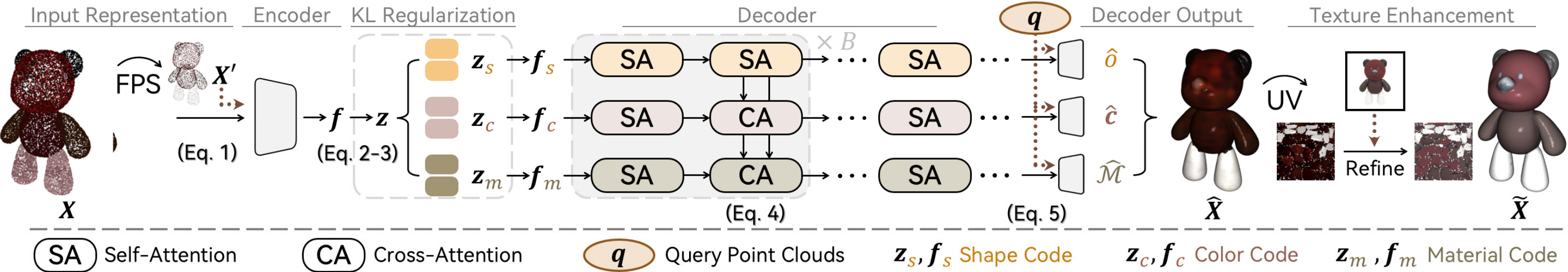


~ **1/3** of the data received at least one round of update

~ **5%** of the data received more than two rounds of updates

Statistics of expert rectification times

Learning latent spaces of geometry+texture+materials



Input Representation



For each surface point $p \in P...$

{

position,

rgb,

Young's modulus,

Poisson's ratio,

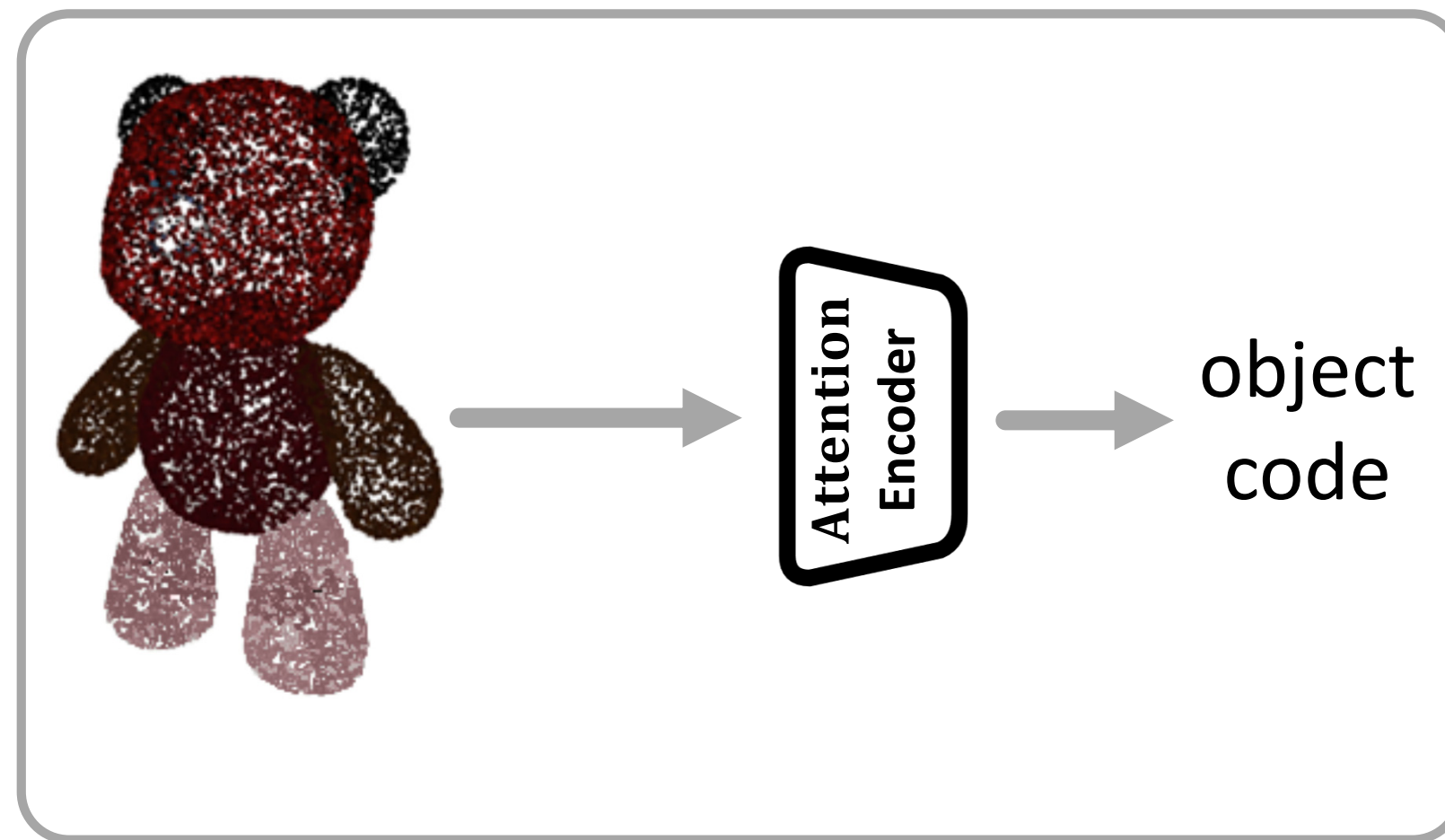
yield stress,

friction angle,

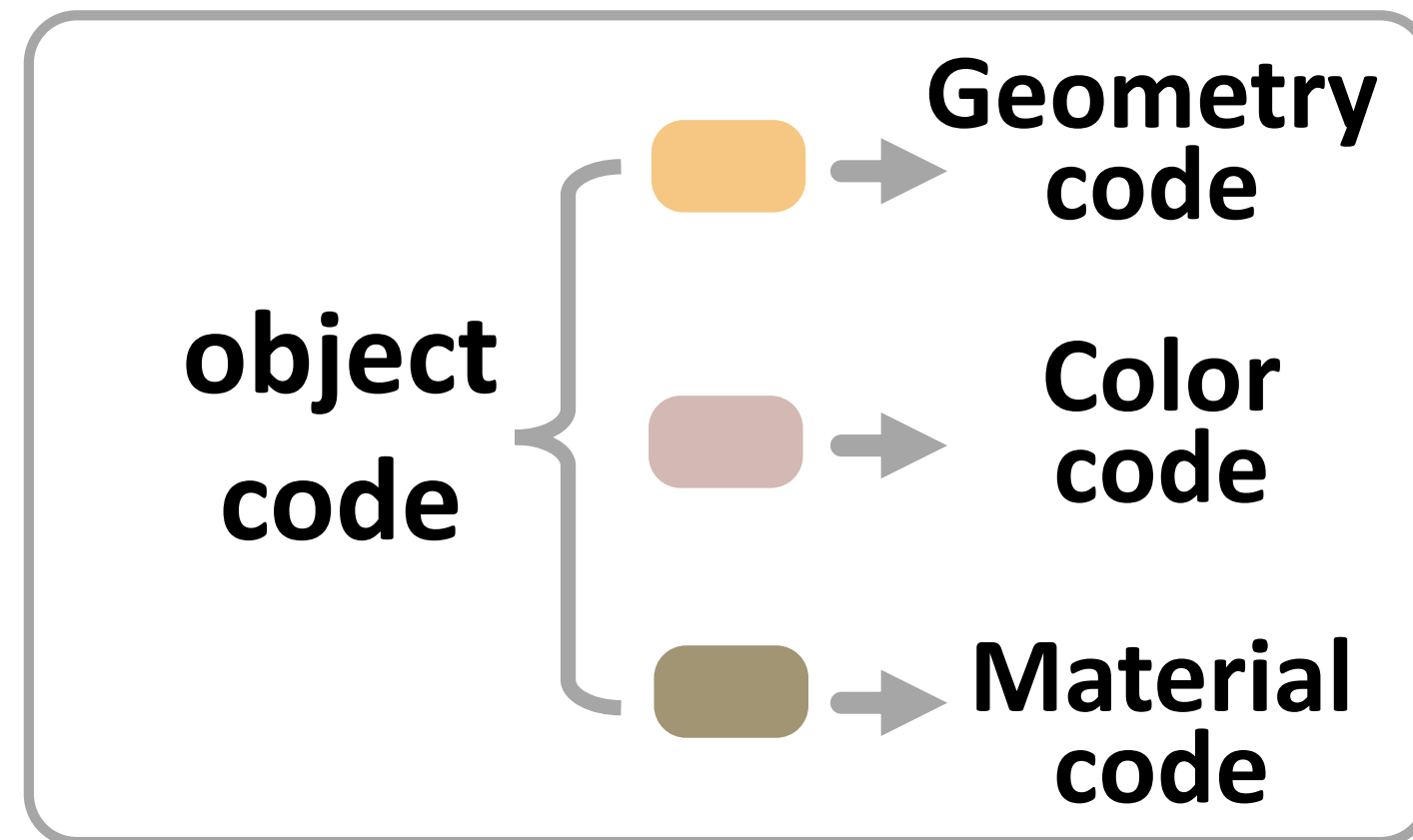
material type,

}

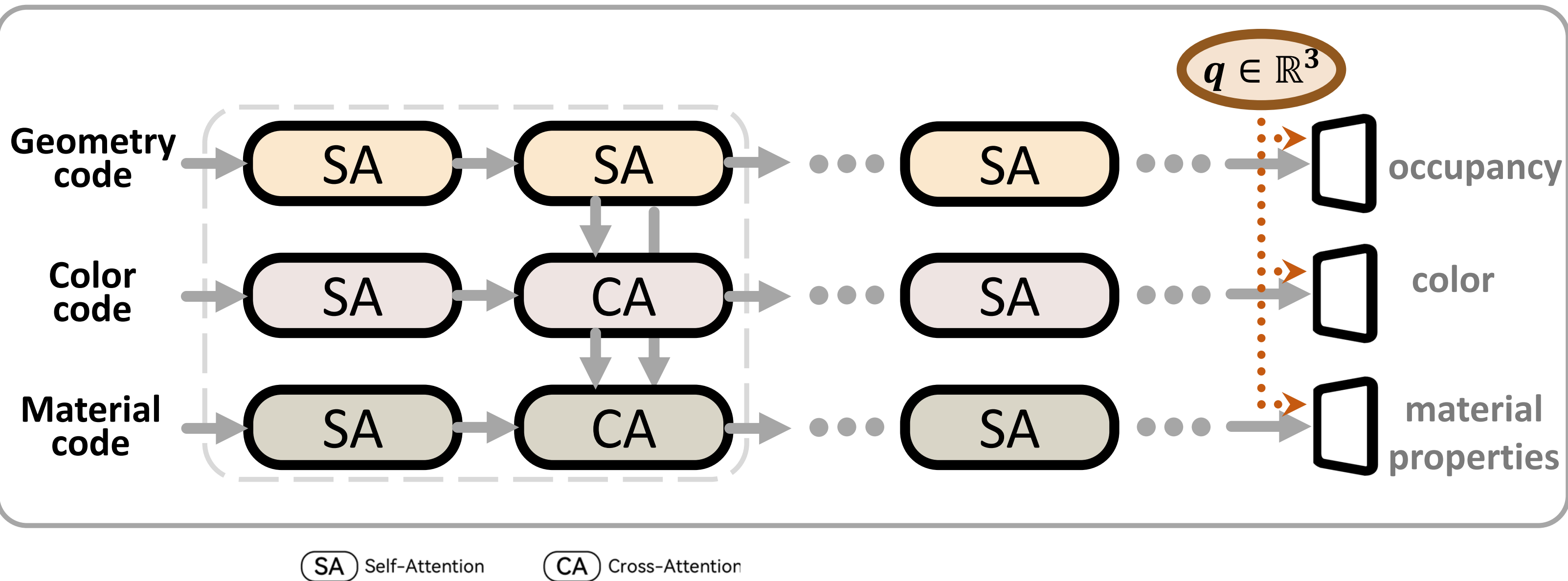
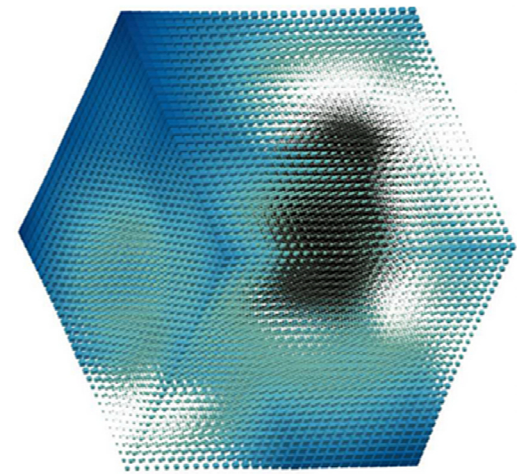
Shape & Texture & Material Encoder



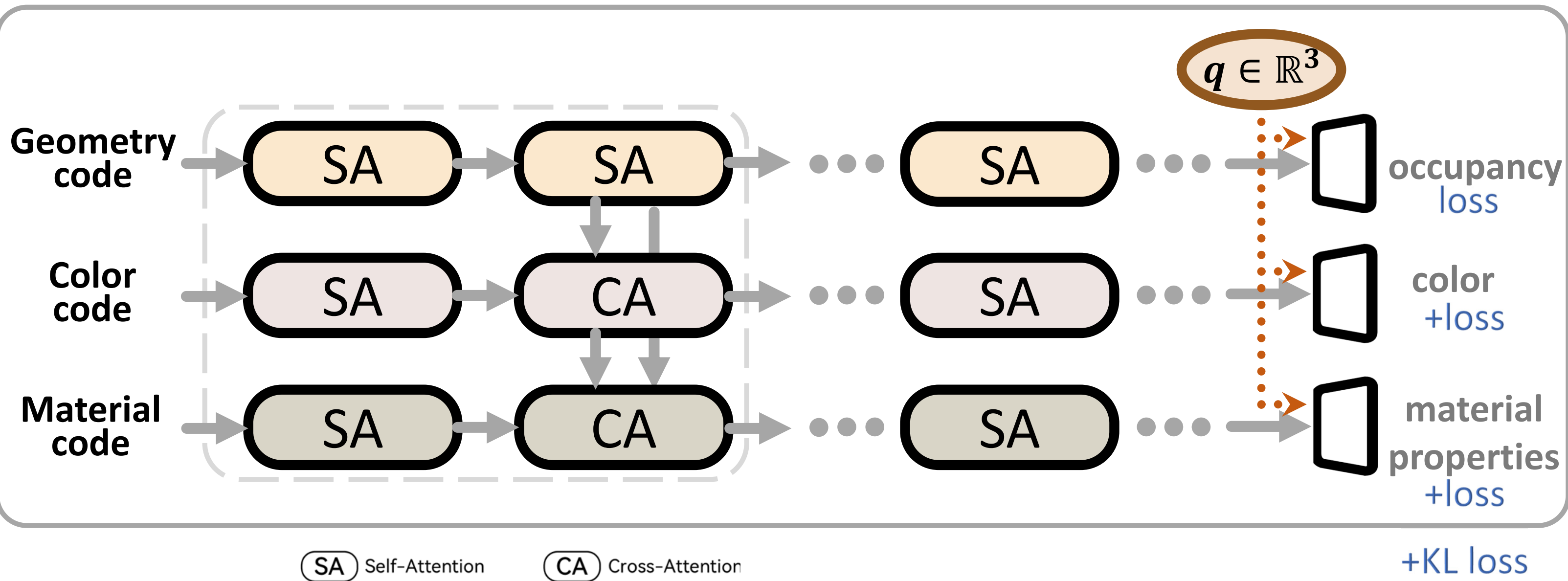
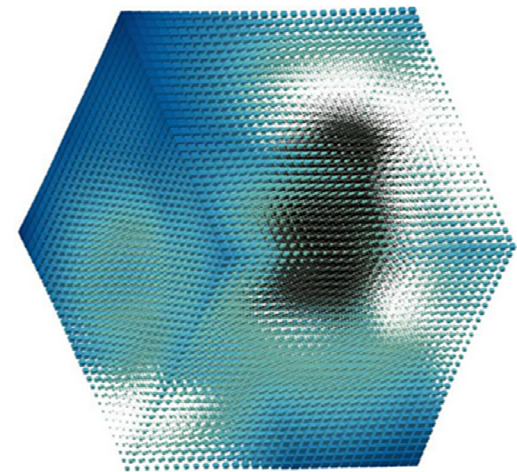
Generative Model: code decomposition



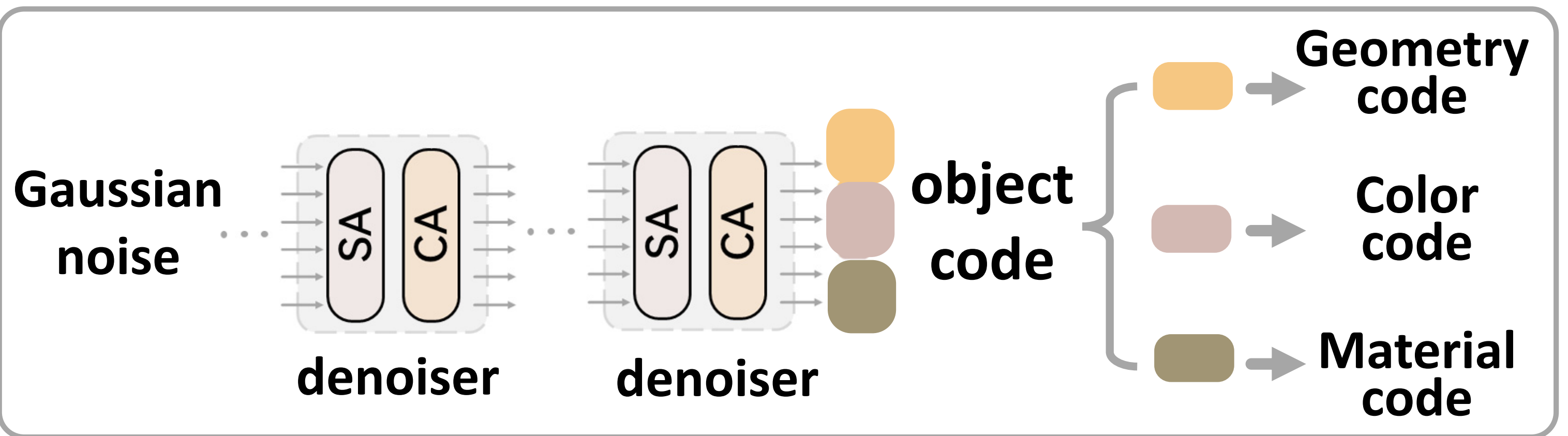
Decoder



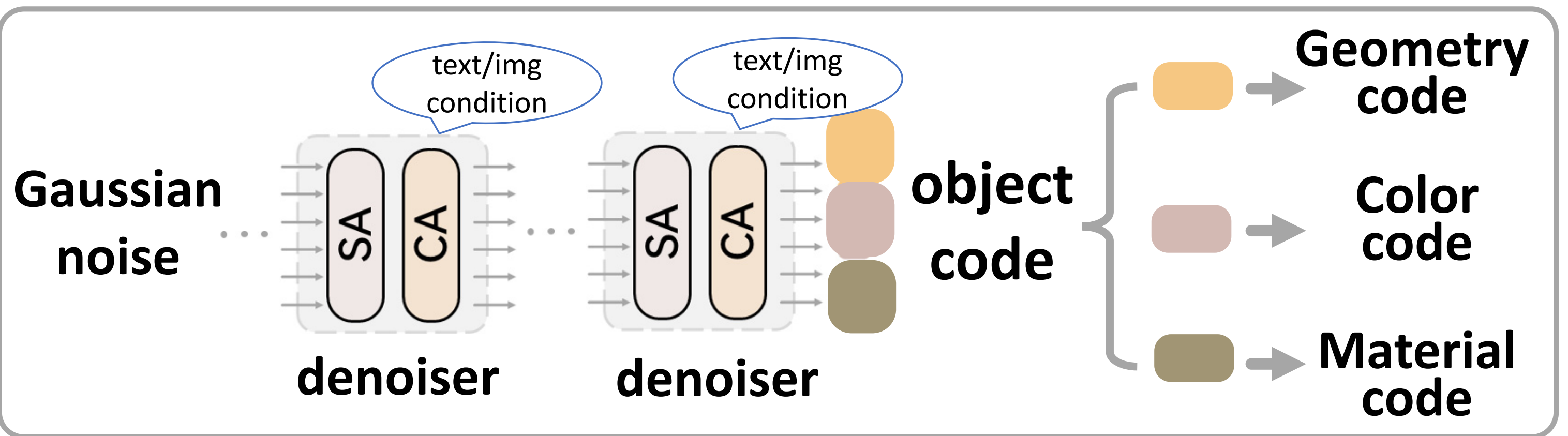
Losses



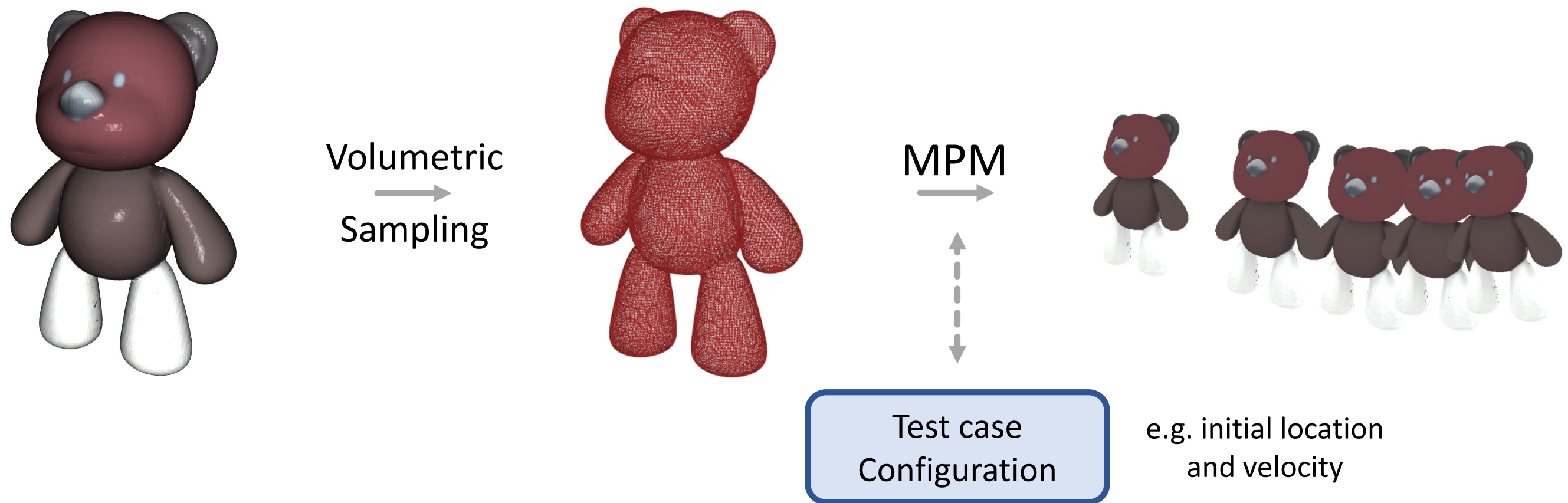
Generative Model: diffusion



Generative Model: diffusion



Dynamics Generation



The material point method for simulating continuum materials (MPM). SIGGRAPH 2016 courses.

Image-to-4D Experiments

Variant
“B. Dec”
“B. Perc”
SOPHY

B. Dec.: generates shape, then
uses a subsequent decoder for
predicting material properties

Image-to-4D Experiments

Variant
“B. Dec”
“B. Perc”
SOPHY

B. Perc.: off-the-shelf 3D generation followed by segmentation (Find3D) + ChatGPT-4o for material properties

Image-to-4D Experiments

Variant	Physical Commonsense [VideoPhy] 
“B. Dec”	-0.22
“B. Perc”	0.18
SOPHY	0.40

Image-to-4D Experiments

Variant	Physical Commonsense [VideoPhy] ↑	Text matching score [CLIP] ↑
“B. Dec”	-0.22	0.73
“B. Perc”	0.18	0.74
SOPHY	0.40	0.77

Image-to-4D Experiments

Variant	Physical Commonsense [VideoPhy] 	Text matching score [CLIP] 	Time (min) 
“B. Dec”	-0.22	0.73	5
“B. Perc”	0.18	0.74	7
SOPHY	0.40	0.77	5

Many ablations...

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

M.B. Acc: Material Behavior Type Accuracy.

MAE: Mean Absolute Error.

Image-to-4D Experiments

1. Image-to-4D Comparison



condition

B. Dec.



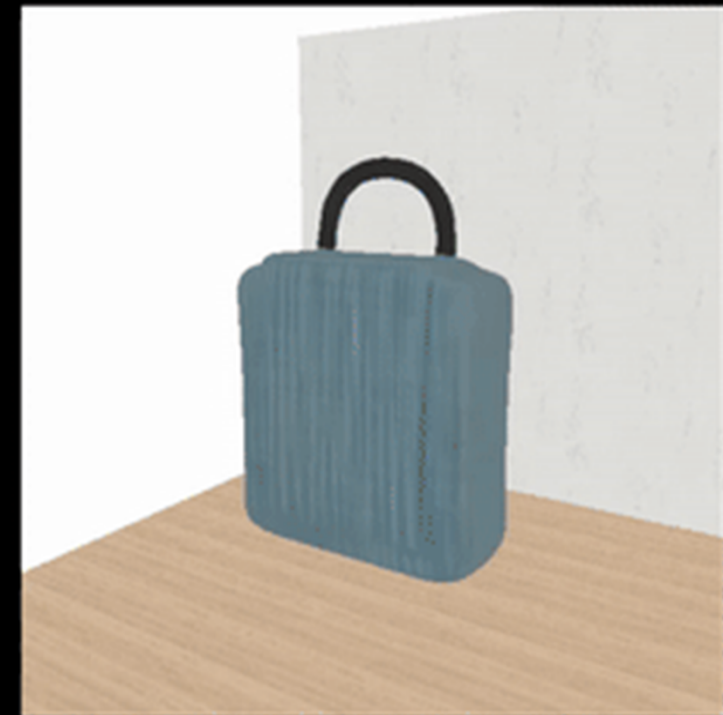
Too hard / Poor alignment

B. Perc.



Too hard / Poor alignment

SOPHY



More reasonable / better alignment

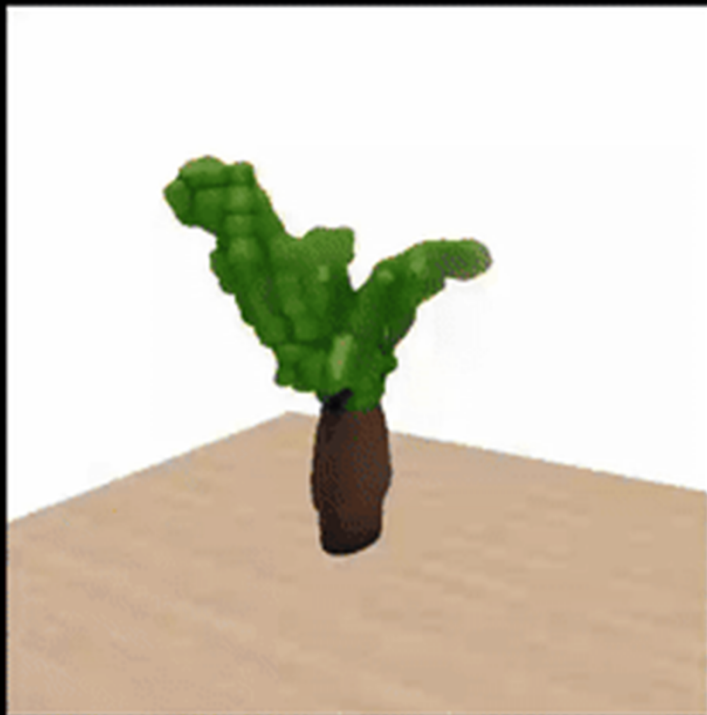
Text-to-4D Experiments

2.

Drag a planter made of a plant, a soil, a wood vase neck, and a metal container.

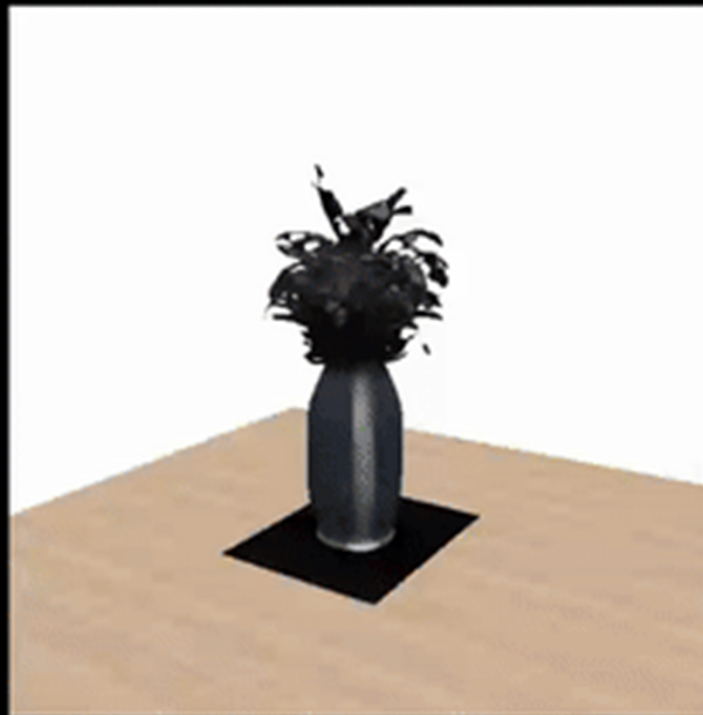
condition

B. Dec.



Too stiff plant

B. Perc.



Too soft container

SOPHY

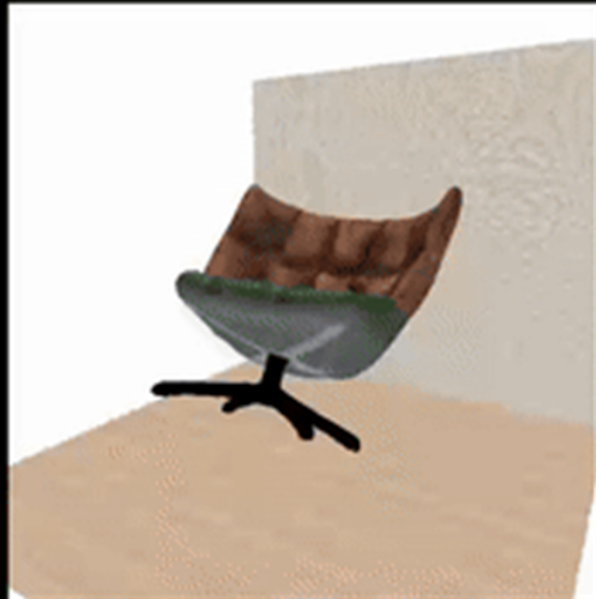


More reasonable result

More Results



condition



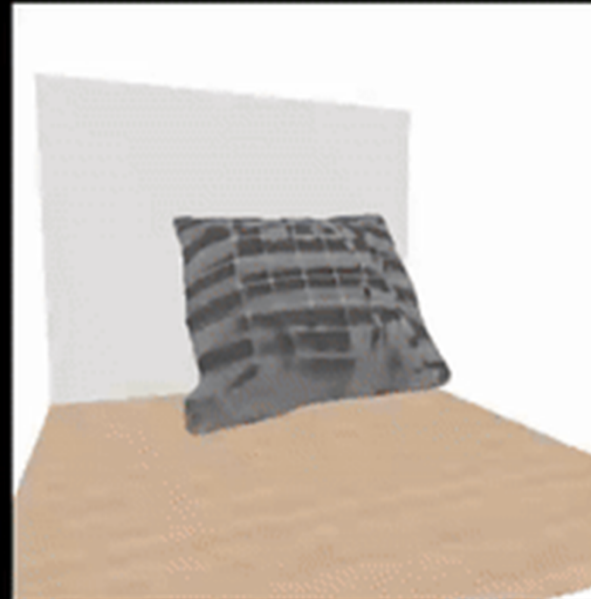
View I



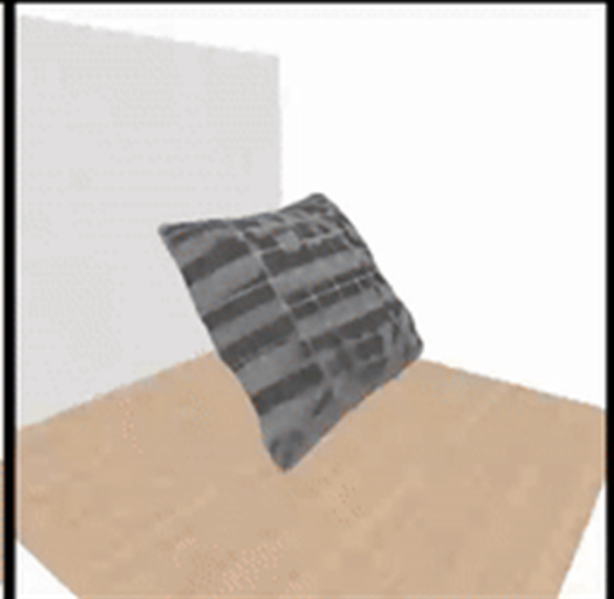
View II



condition



View I



View II

More Results

3. More Generation Results of SOPHY

condition



A tan leather love seat with plush back cushions, wide armrests, and a modern, slightly curved design.

View I



View II



More Results

3. More Generation Results of SOPHY

condition



This object is a rectangular handbag with a woven texture, dark brown leather-like material, metallic rivets, a central clasp, and two curved handles.

View I



View II



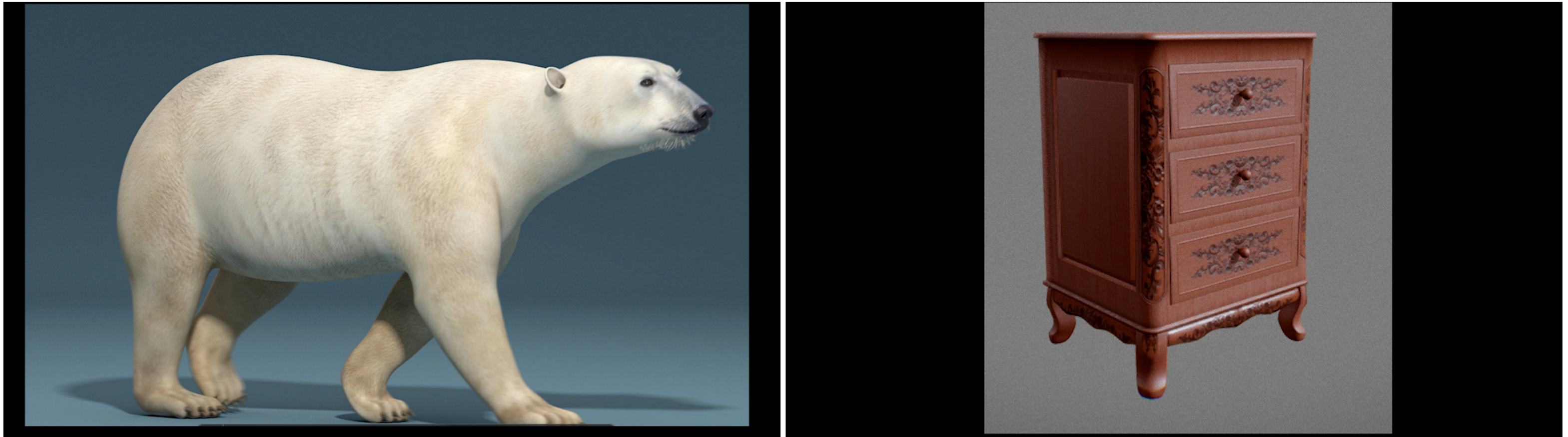
Outline

1. **GEOPARD: Geometric Pretraining for Articulation Prediction in 3D Shapes**
2. **SOPHY: Generating Simulation-Ready Objects with Physical Materials**
3. **Future directions**

Many more things to be done!

- Generative models of **object geometry+articulation hierarchy+motions**
- **Larger-scale datasets** with material annotations
- **Better material verification** strategies
- **4D scene generation** with multiple objects+agents interacting

[models from
turbosquid]



Thank you!

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(now @ Foundation)*



*Junyi Cao
PhD
UMass & TU Crete*



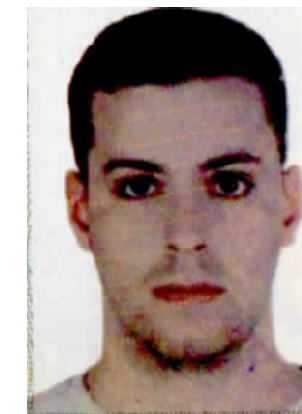
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Thank you!

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TU Crete & CYENS*

Funding:



Project pages & code:

<https://kalo-ai.github.io/>

