Structure and Function
in Large Collections of 3D Shapes

Vladimir G. Kim

Stanford University

How Do We Use Computers?

Explore, Analyze, and Create Data

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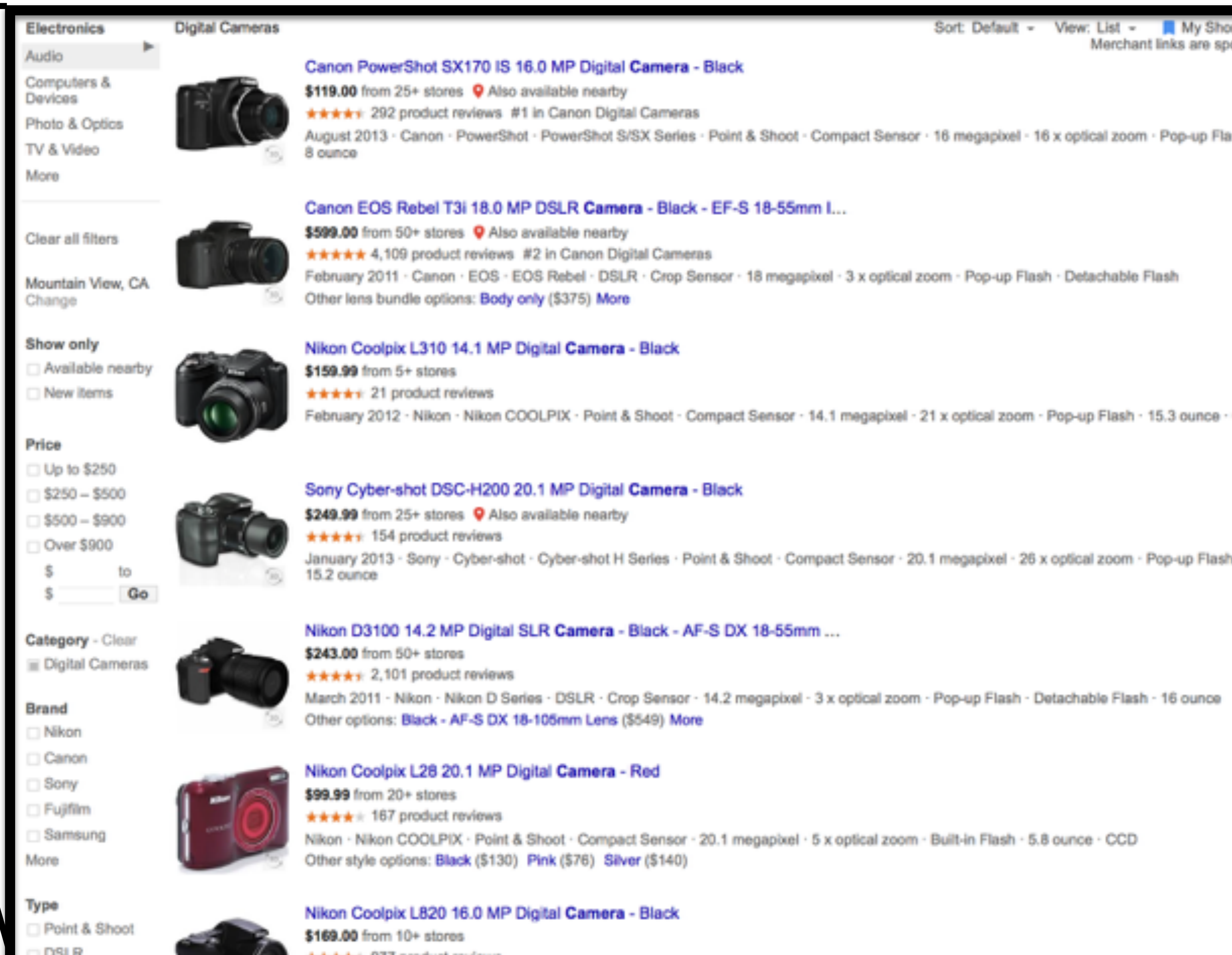
Online Shopping



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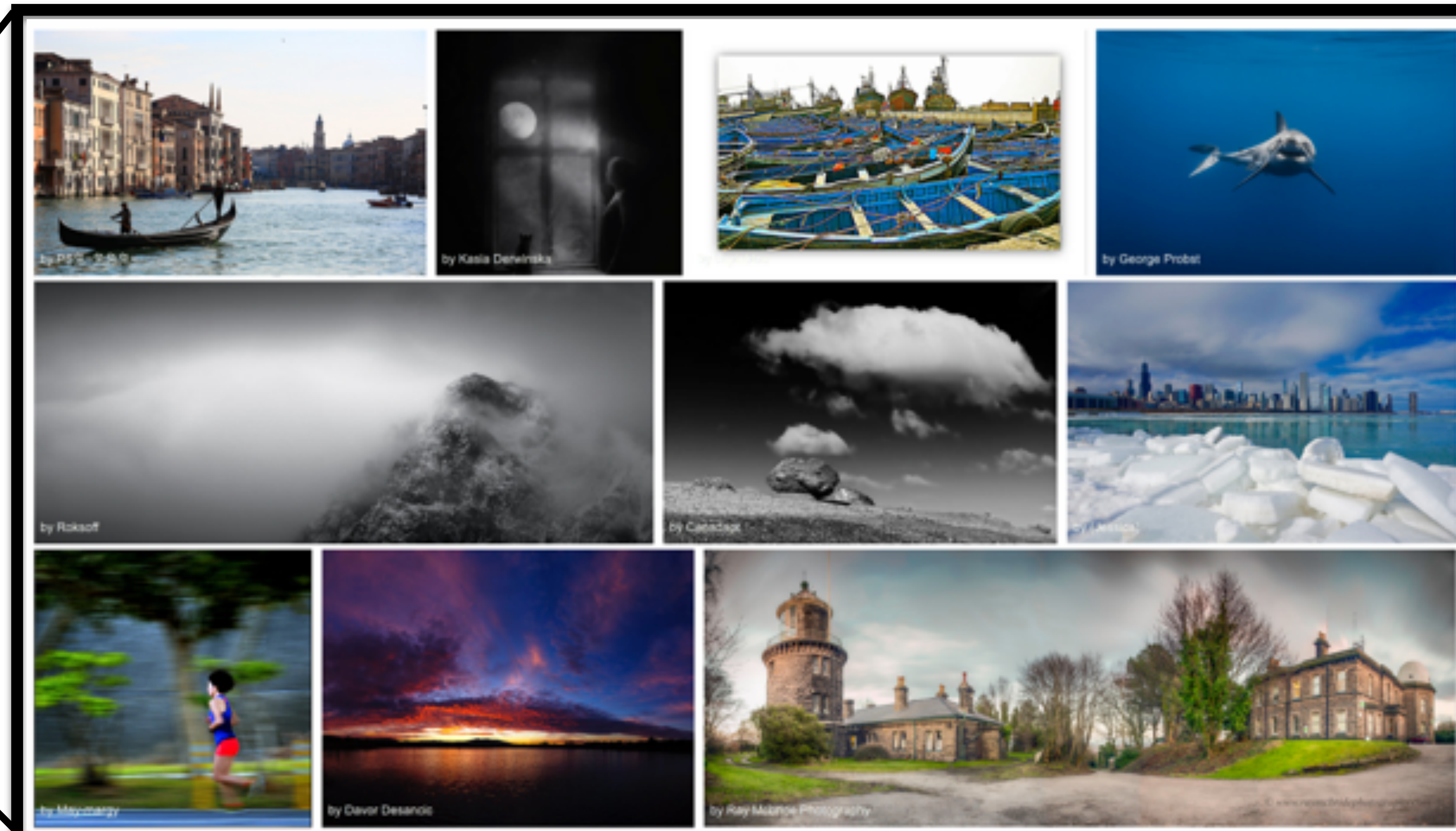
Personal Data



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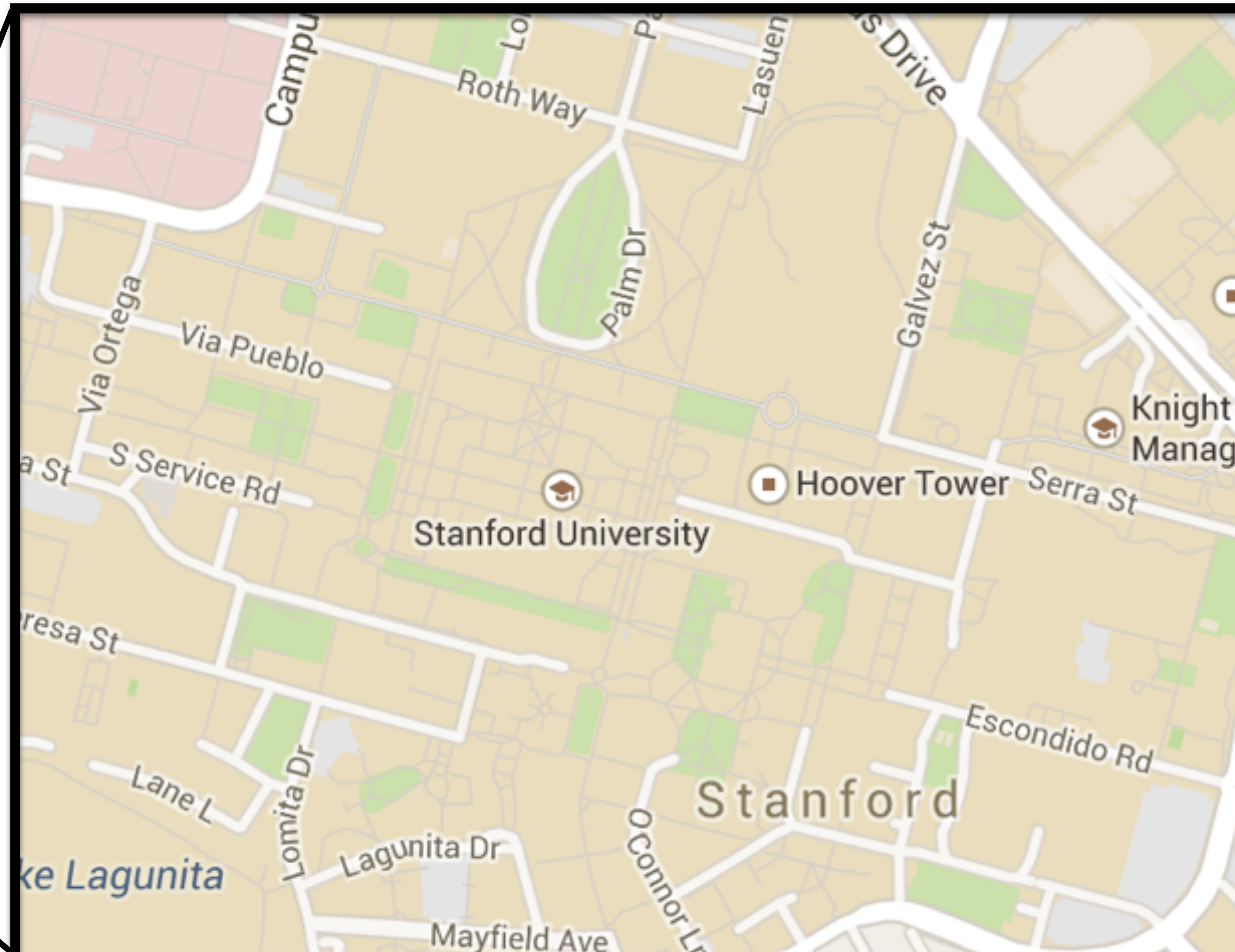

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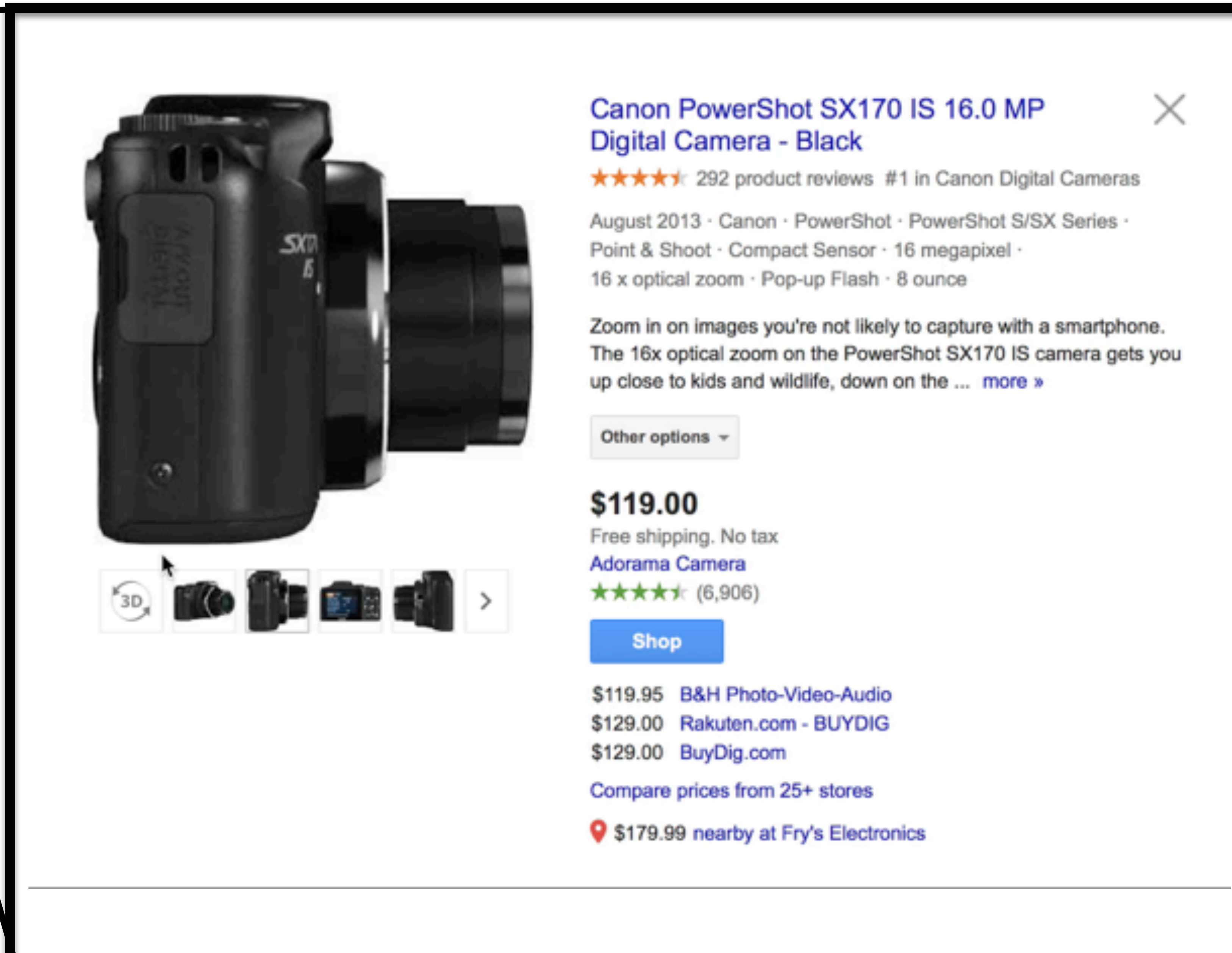

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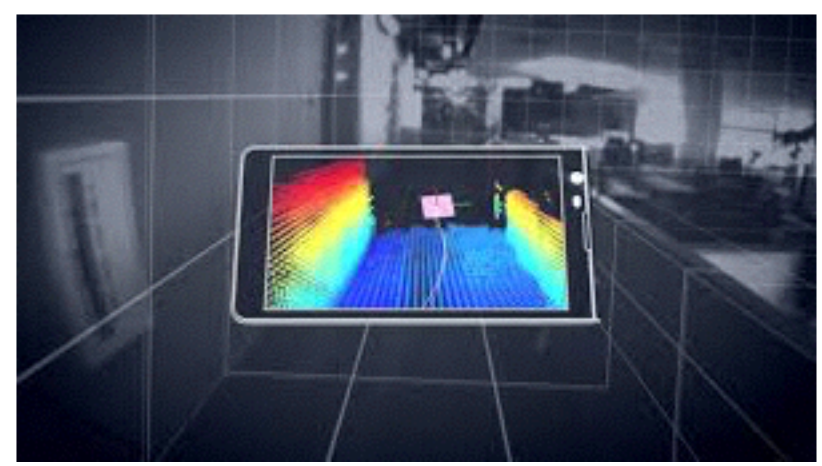
24 million MS Kinect devices!



Project Tango

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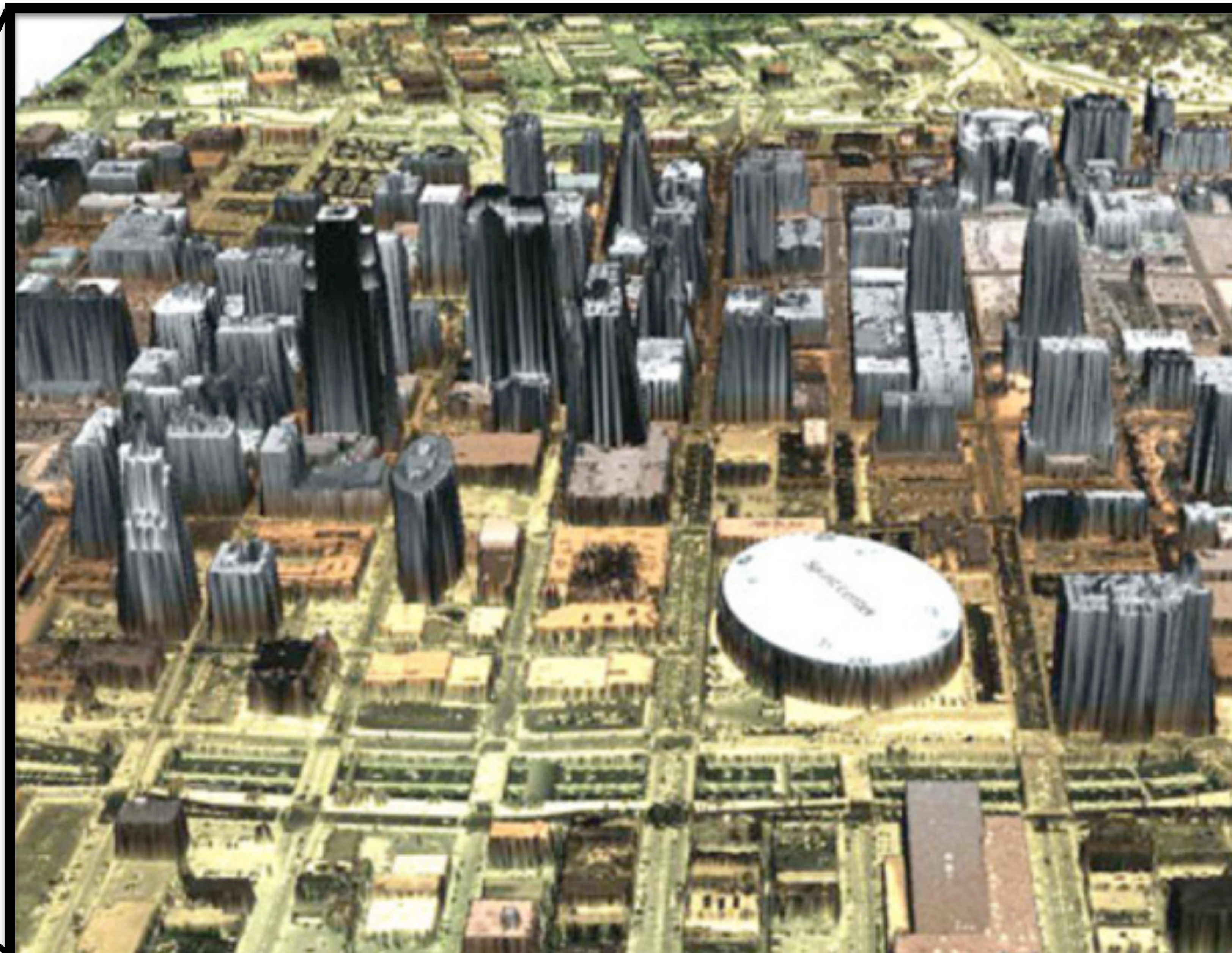

Google Streetview Point Cloud

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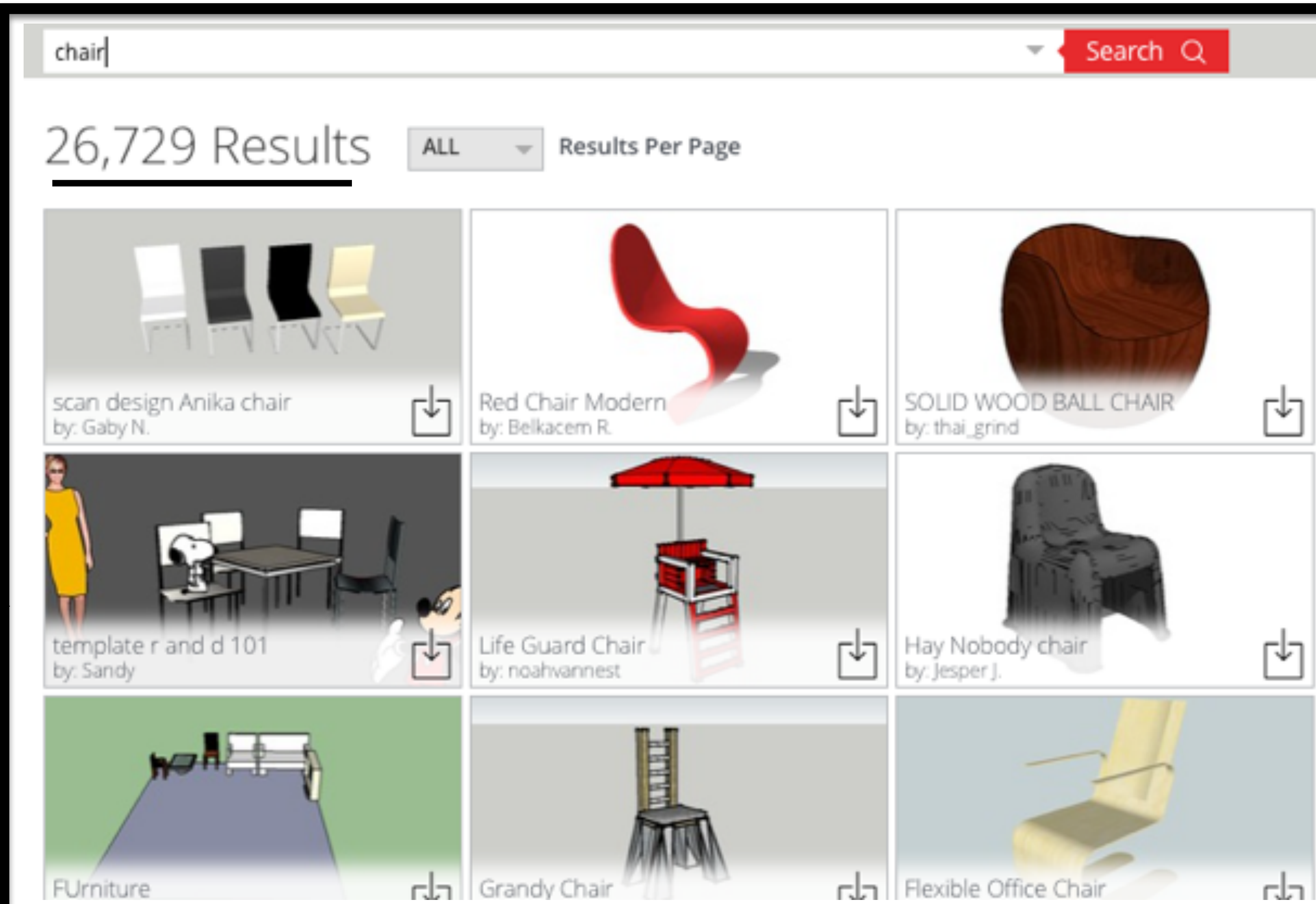
CG Data



3D Warehouse

How Do We Use Computers?

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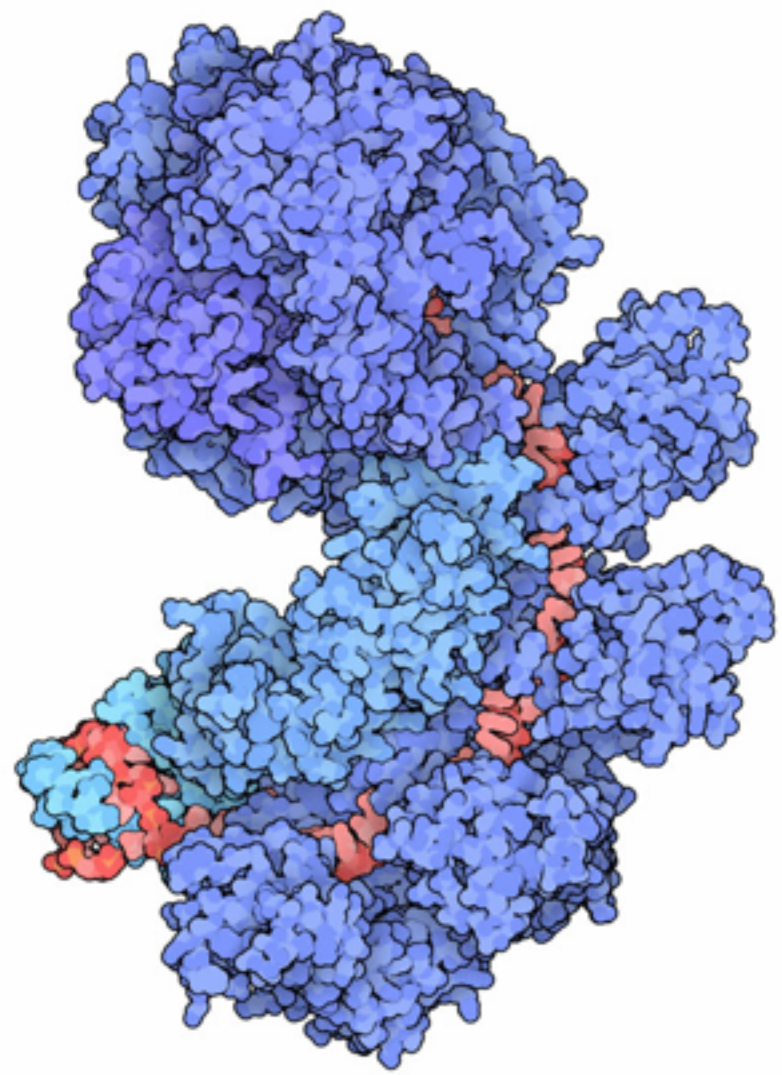
Scientific Data



Protein Data Bank

Medical Imaging

How Do We Use Computers?

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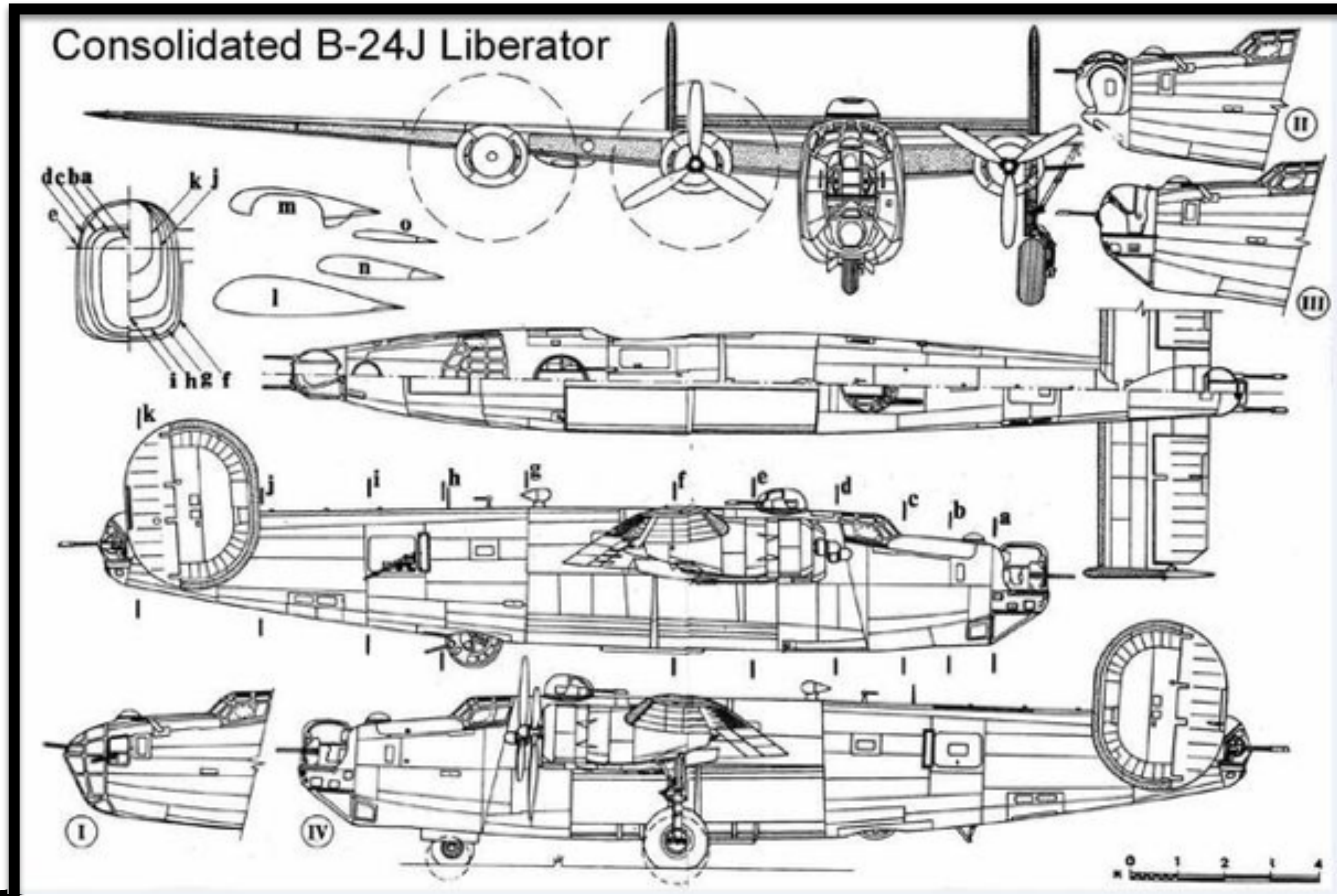


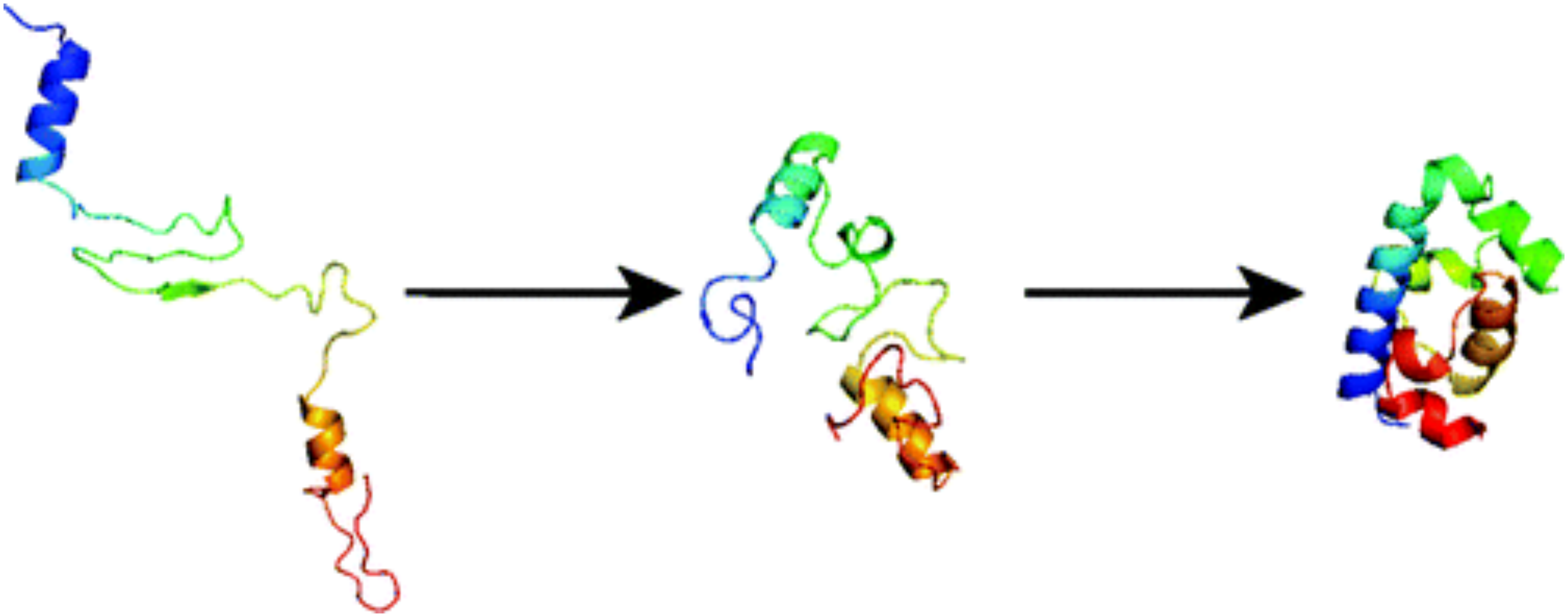
CAD Models

Geometry and Function

Explore, Analyze, and Create Geometric Data

Geometry and Function

Explore, Analyze, and Create Geometric Data



3D Geometry is essential to understand functionality

Geometry and Function

Explore, Analyze, and Create Geometric Data

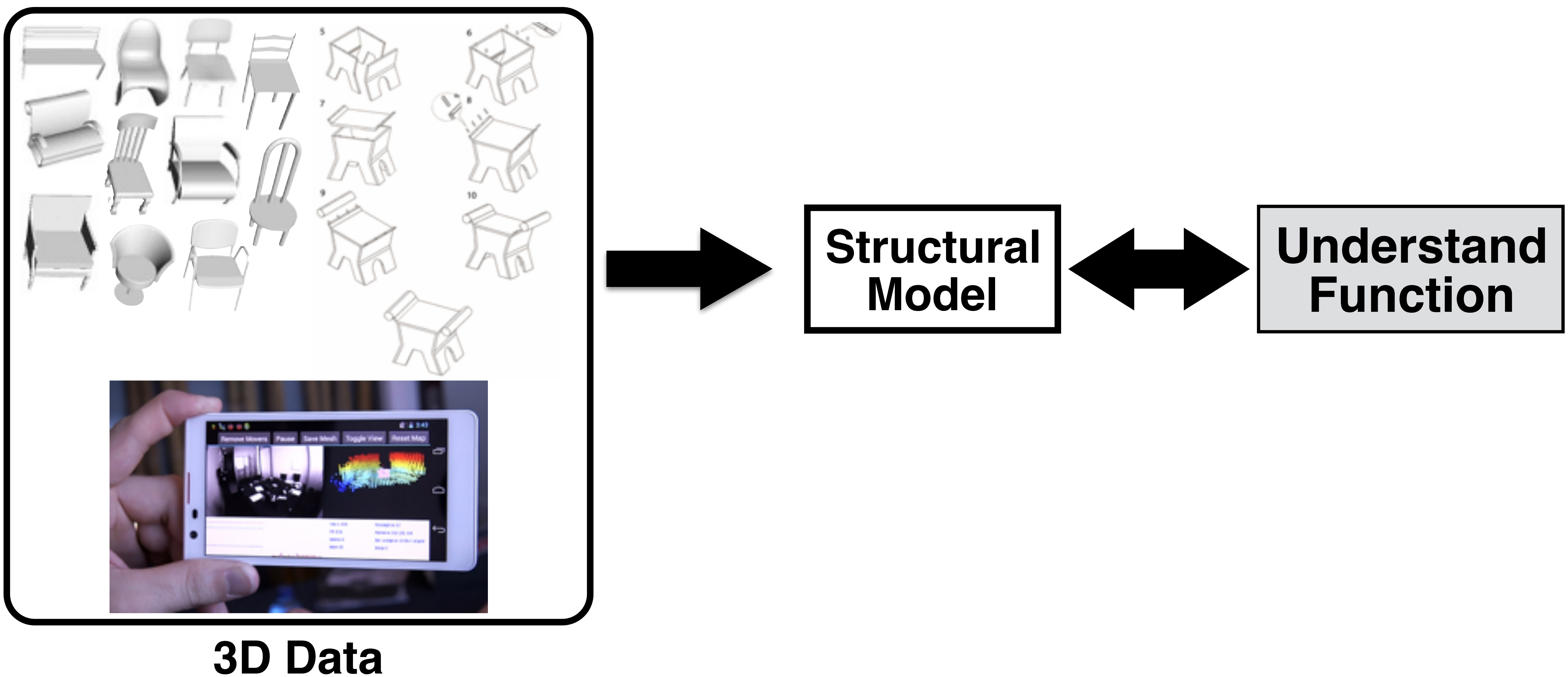
**Image from Mathieu Aubry*

3D Geometry is essential to understand functionality

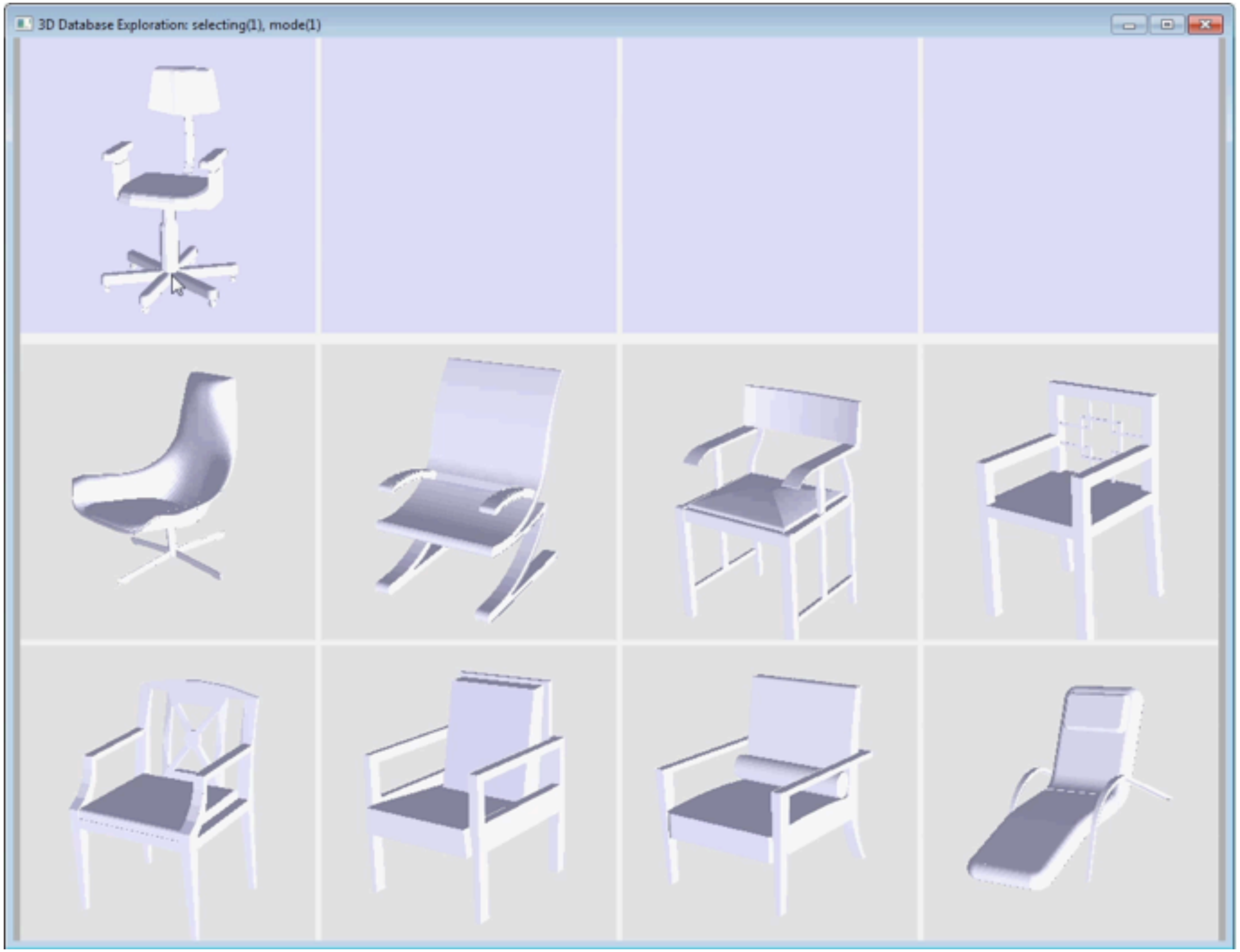
Research Agenda

Find structure in 3D data to

- Understand similarities
- Detect important regions
- Learn structural variations



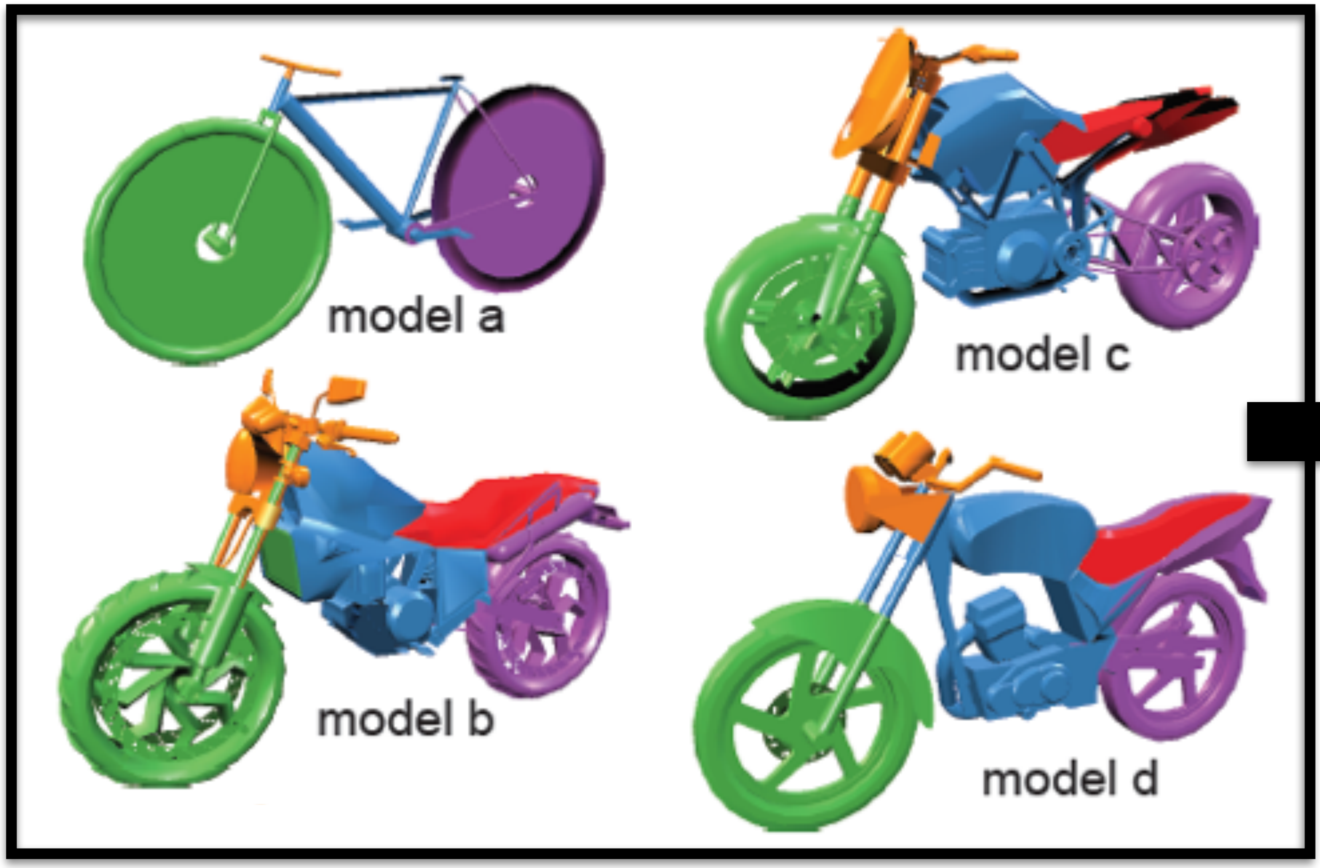
Motivating Applications

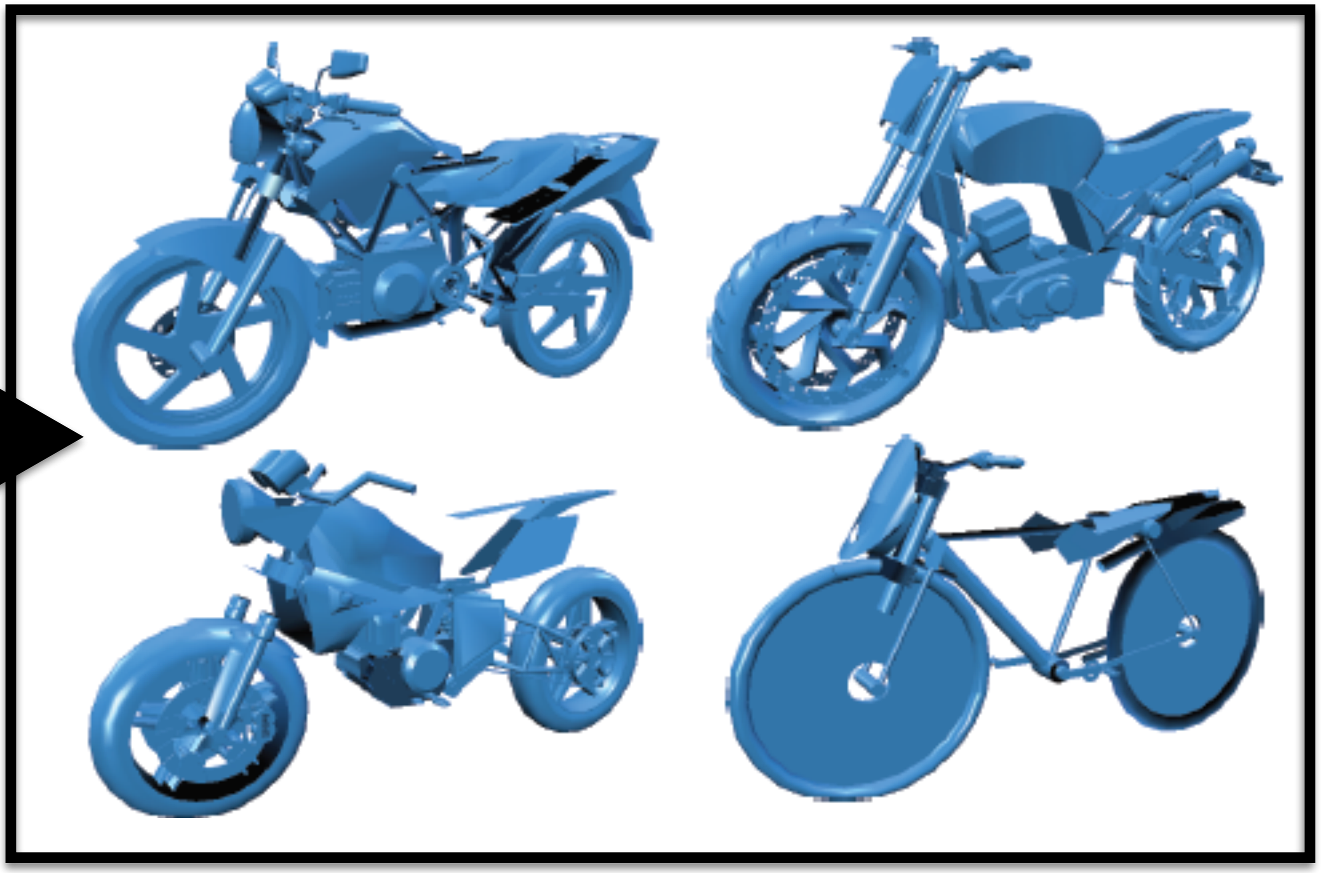


Understand Similarity to Explore Collections of Objects

Exploring Collections of 3D Models using Fuzzy Correspondences.
V. Kim, W. Li, N. Mitra, S. Chaudhuri, S. DiVerdi, T. Funkhouser, SIGGRAPH 2012

Motivating Applications





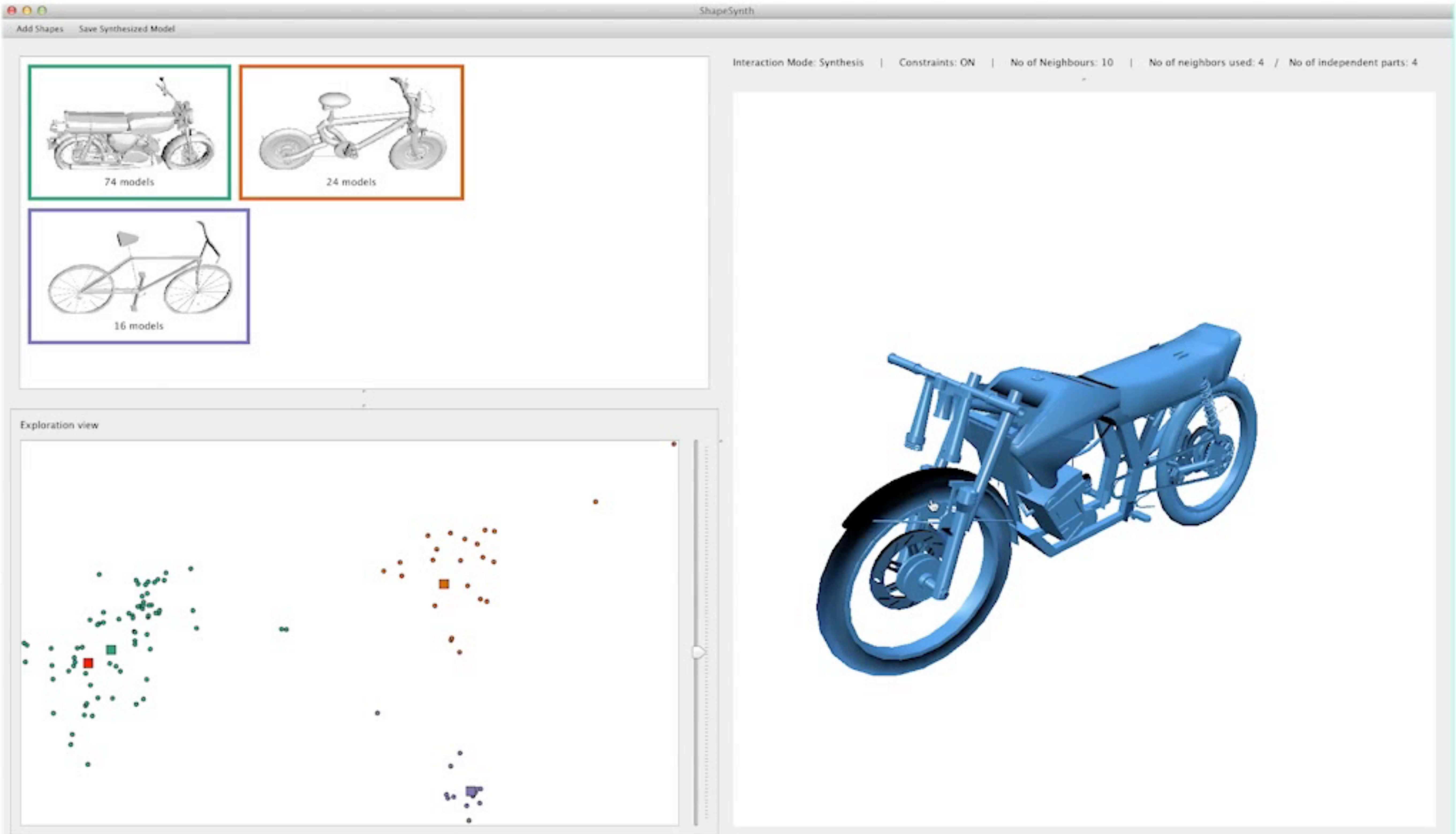
Database of 3D Objects (takes hours to create a model)

User-created ≈1 minute

Learn Structural Variations to Synthesize Plausible Shapes

ShapeSynth: Parameterizing Model Collections for Coupled Shape Exploration and Synthesis
M. Averkiou, V. Kim, Y. Zheng, and N. Mitra, Eurographics 2014

Motivating Applications

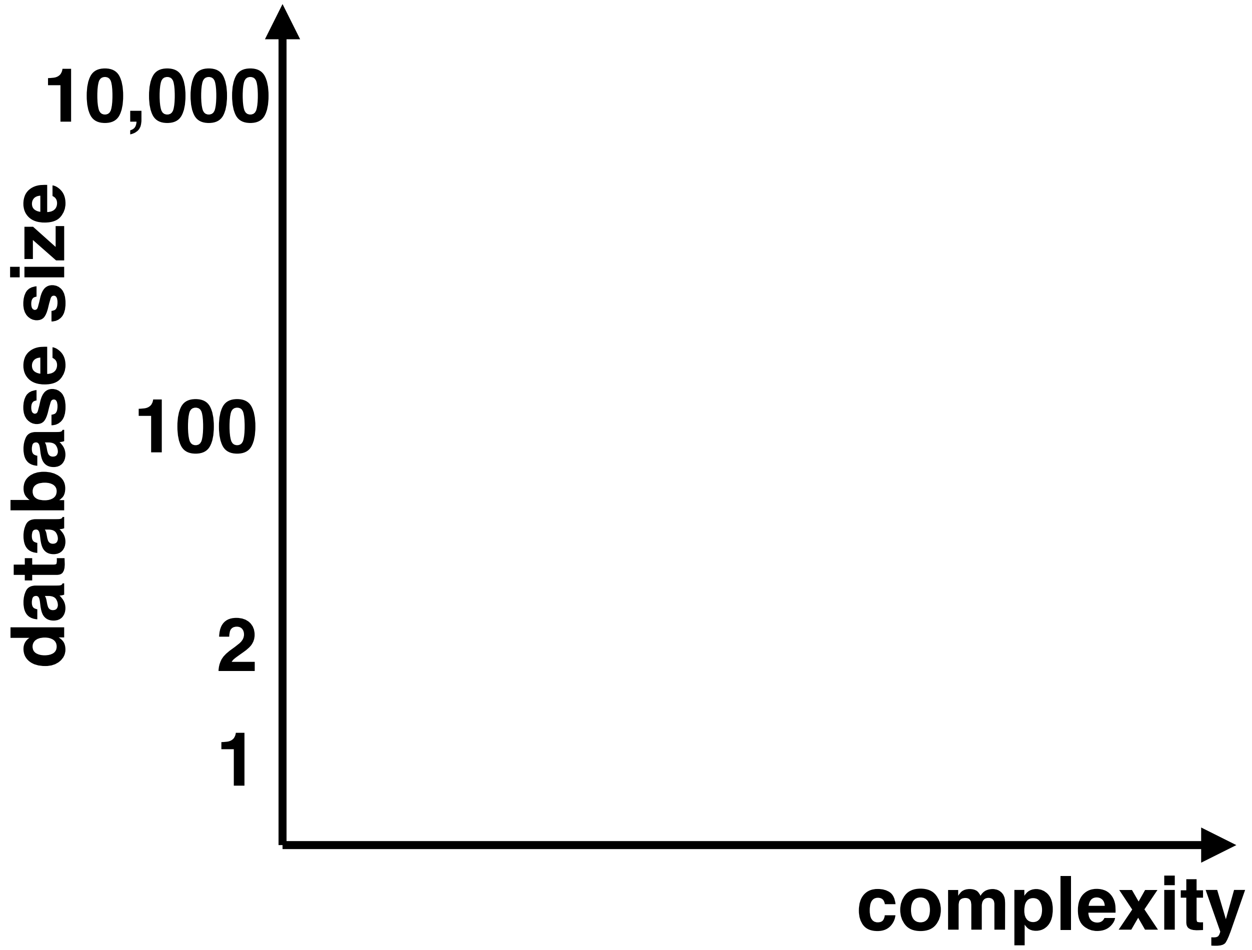


ShapeSynth: Parameterizing Model Collections for Coupled Shape Exploration and Synthesis
M. Averkiou, V. Kim, Y. Zheng, and N. Mitra, Eurographics 2014

Previous Work

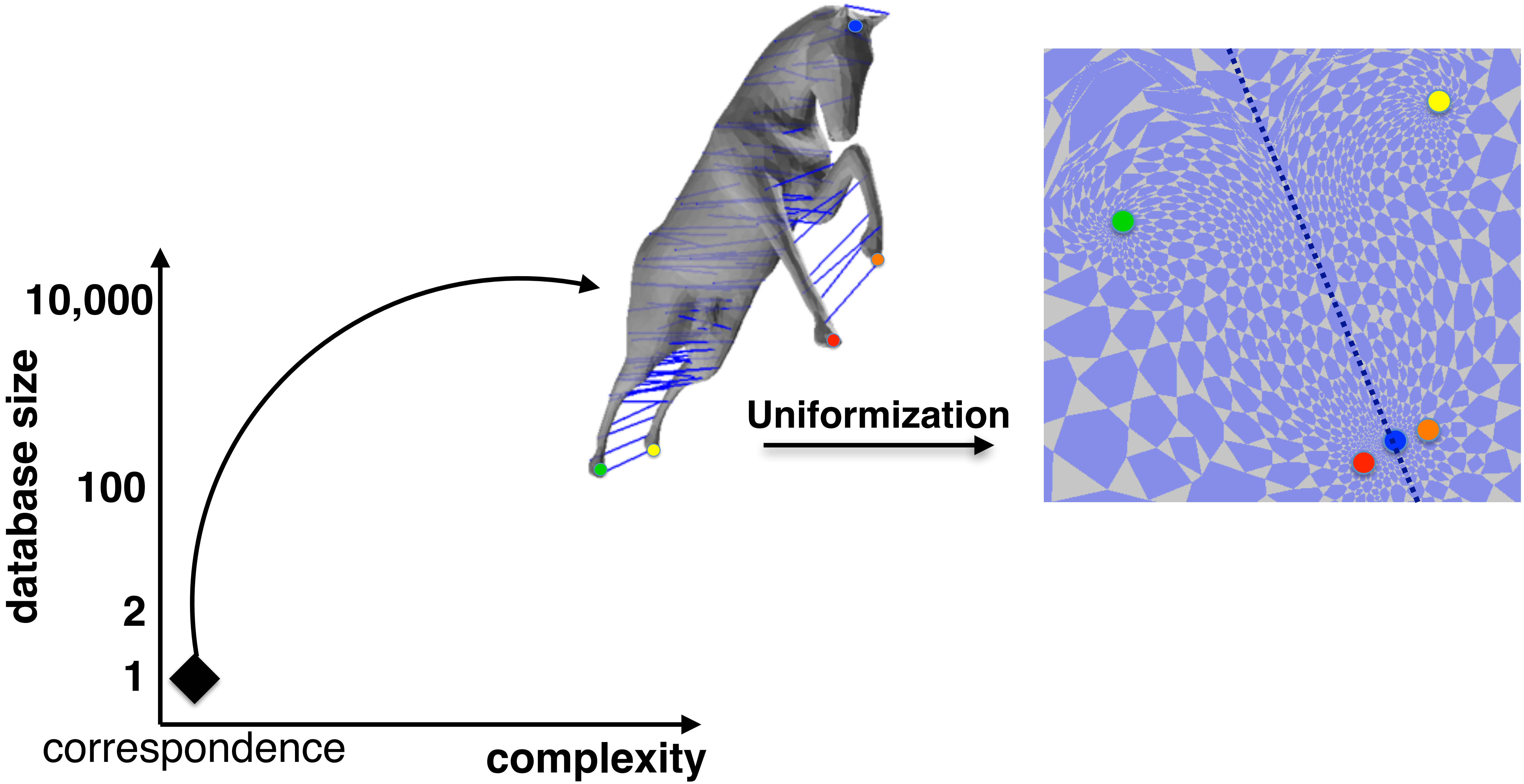
Geometry analysis to understand structure:
(self-serving overview)

- Symmetry
- Correspondences
- Probabilistic structural models



Symmetry

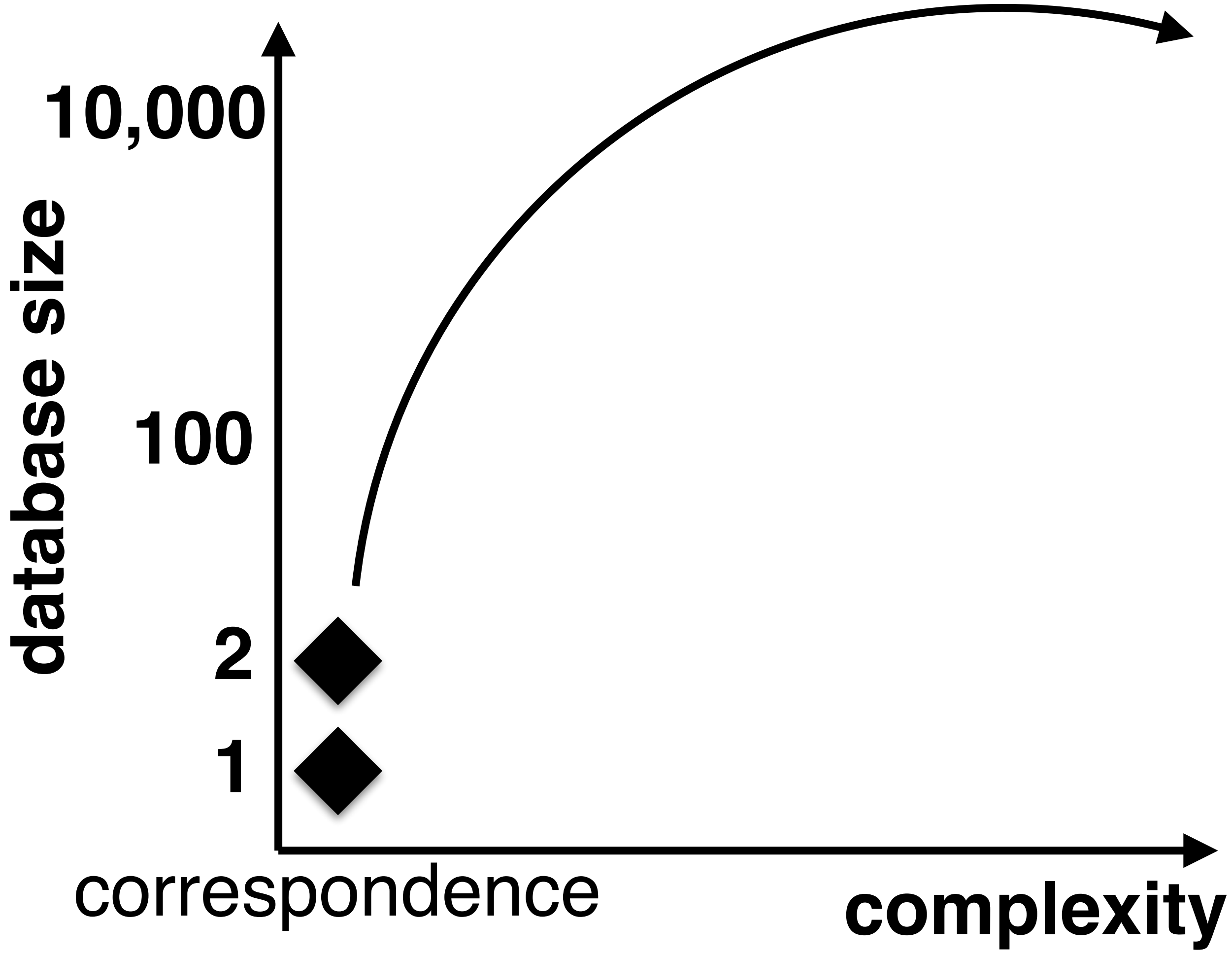
Key Idea: find a symmetric conformal embedding

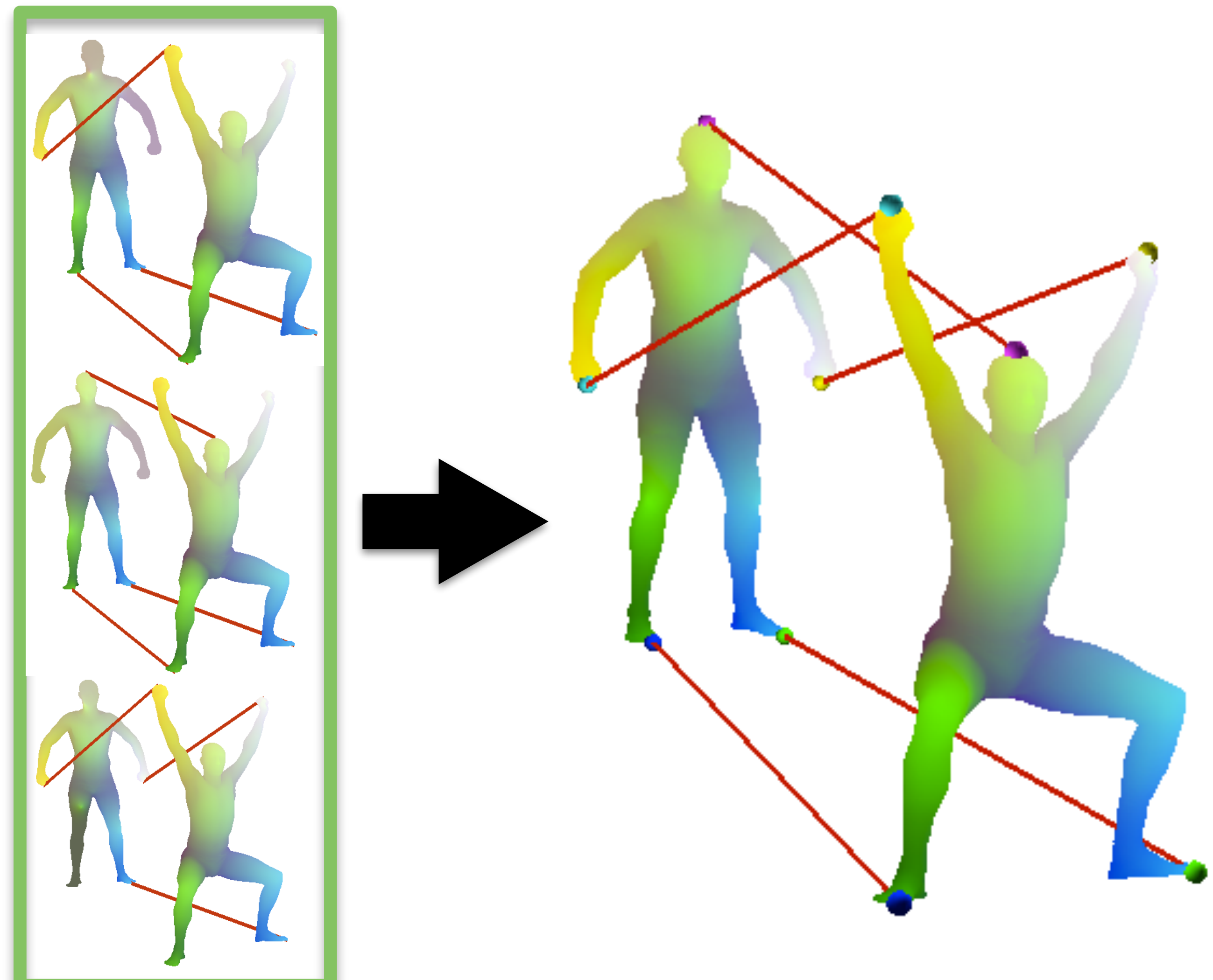


E.g., Möbius Transformations For Global Intrinsic Symmetry Analysis
V. Kim, Y. Lipman, X. Chen, and T. Funkhouser, SGP'10

Correspondences

Key Idea: blend partial intrinsic maps





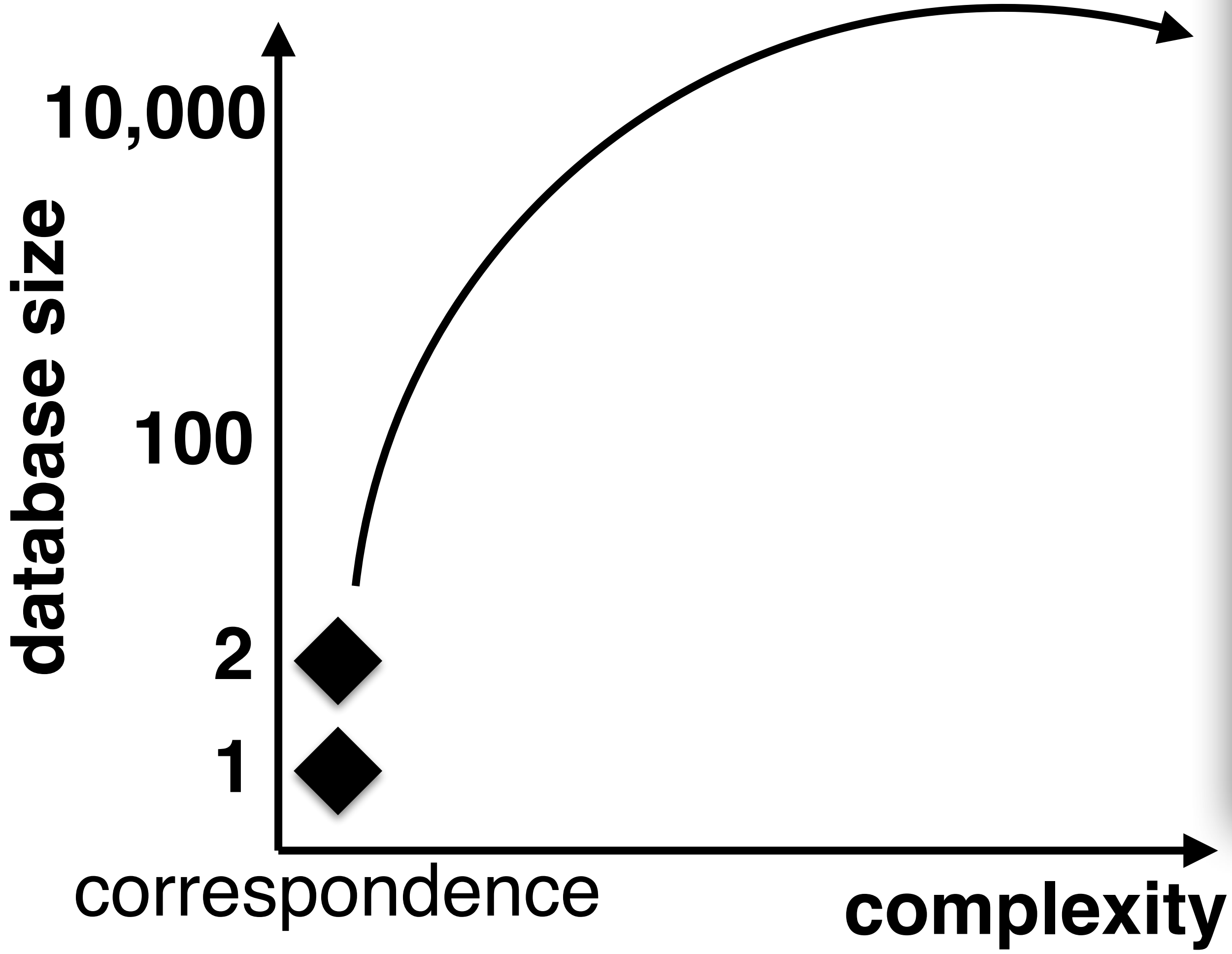
Conformal Maps

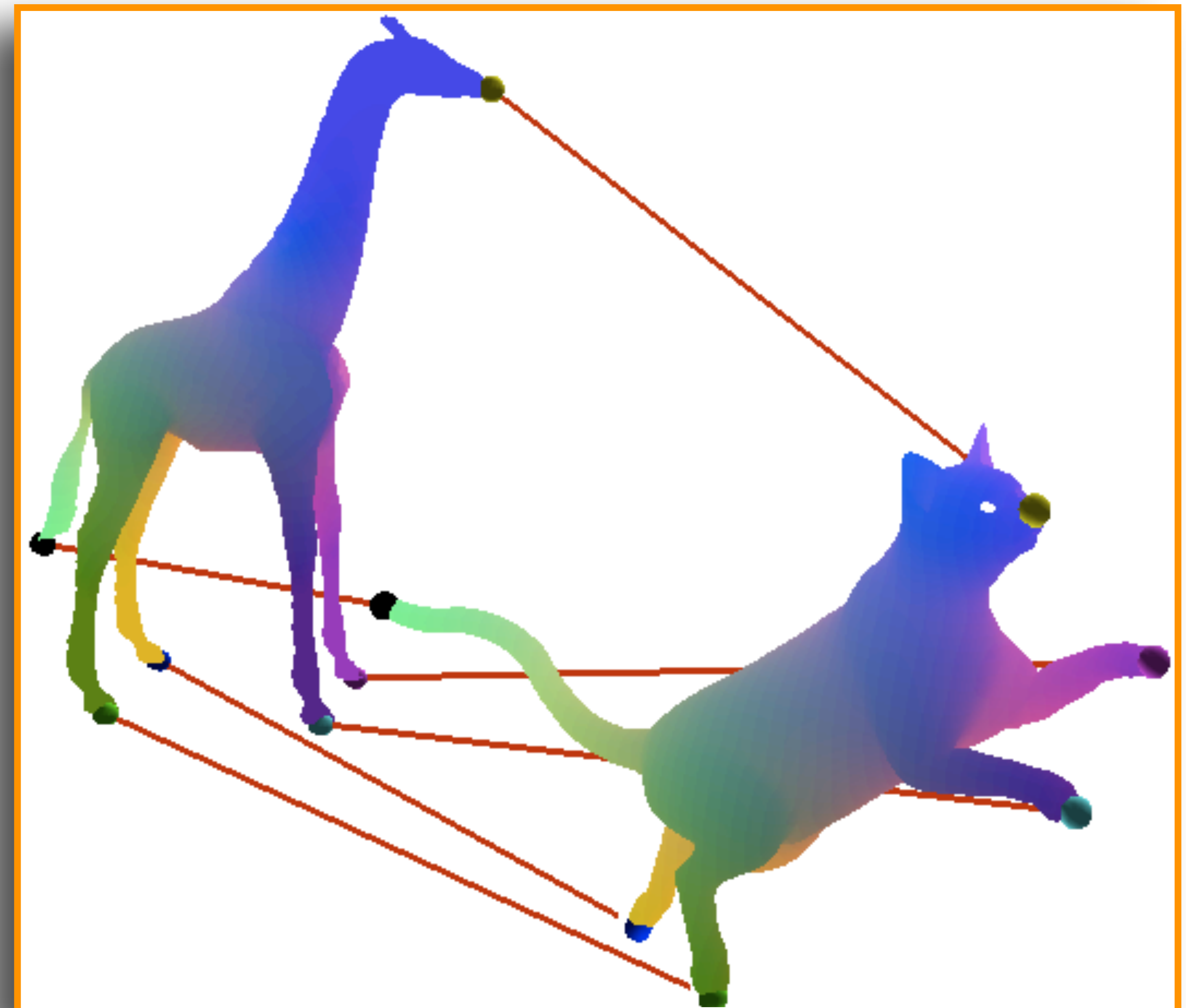
Final Map

E.g., Blended Intrinsic Maps
V. Kim, Y. Lipman, and T. Funkhouser, SIGGRAPH'11

Correspondences

Key Idea: blend partial intrinsic maps



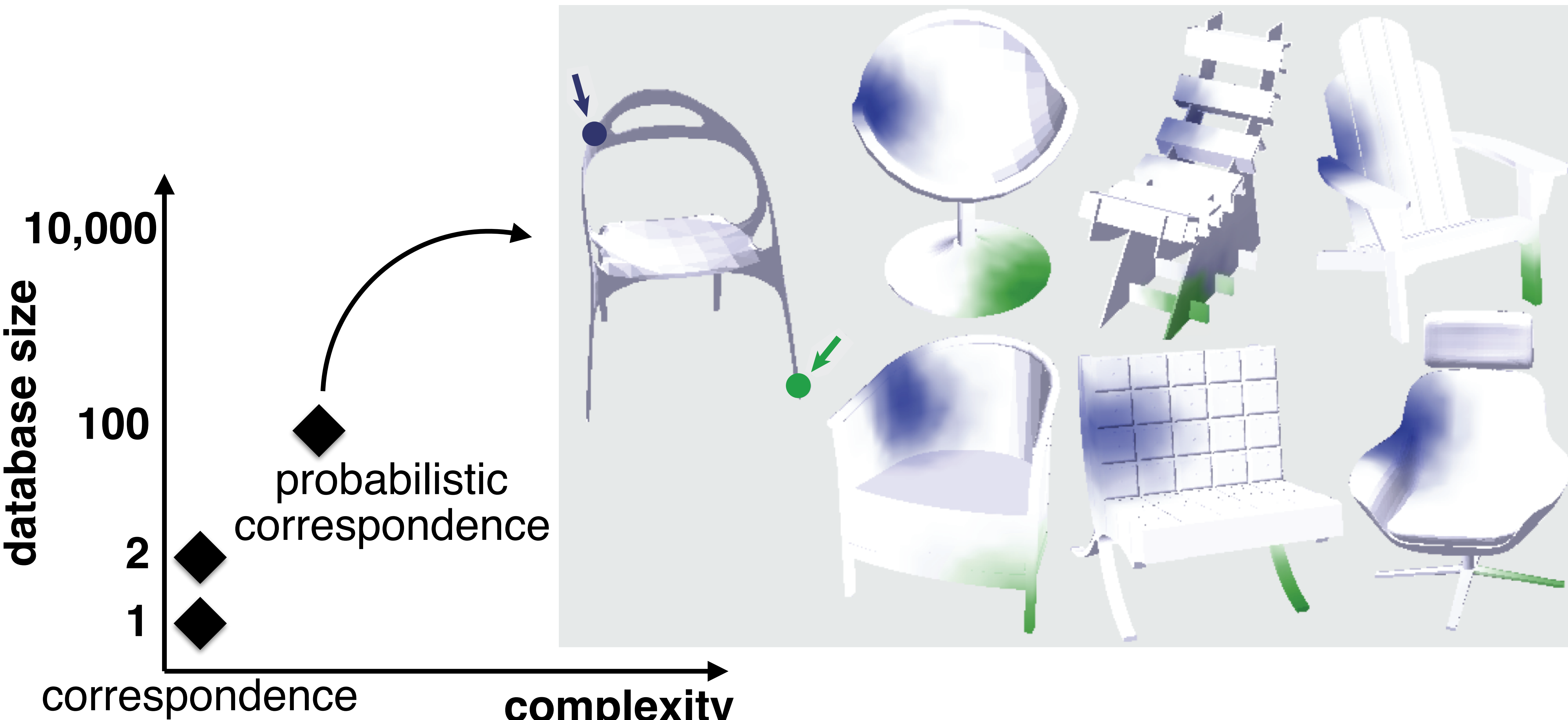


NOTE: state-of-the-art for mapping non-isometric surfaces

E.g., Blended Intrinsic Maps
V. Kim, Y. Lipman, and T. Funkhouser, SIGGRAPH'11

Correspondences in Collections

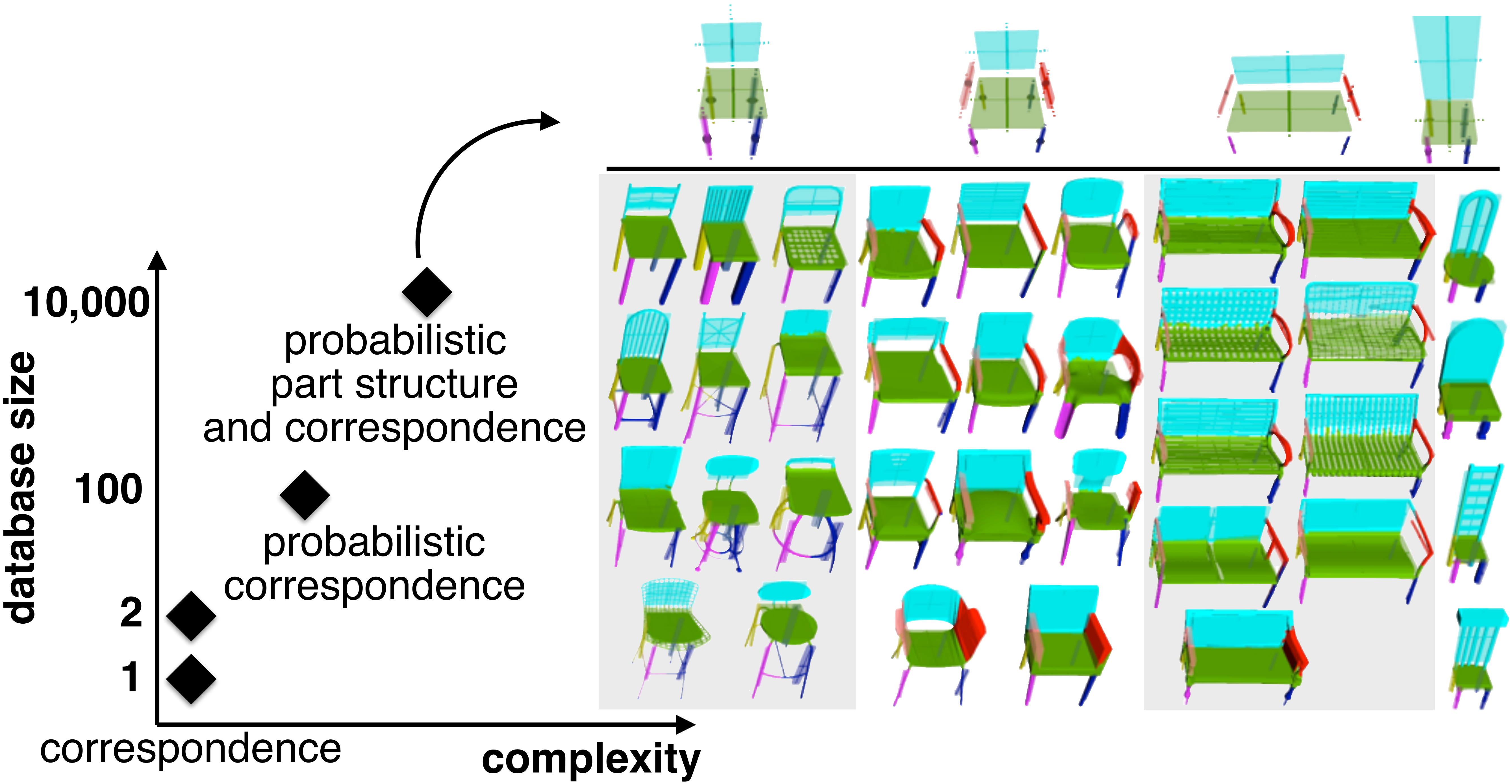
Key Ideas: represent ambiguity in mapping, leverage consistency and transitivity of correspondences



E.g, Exploring Collections of 3D Models using Fuzzy Correspondences
V. Kim, W. Li, N. Mitra, S. DiVerdi, T. Funkhouser, SIGGRAPH'12

Probabilistic Part Models

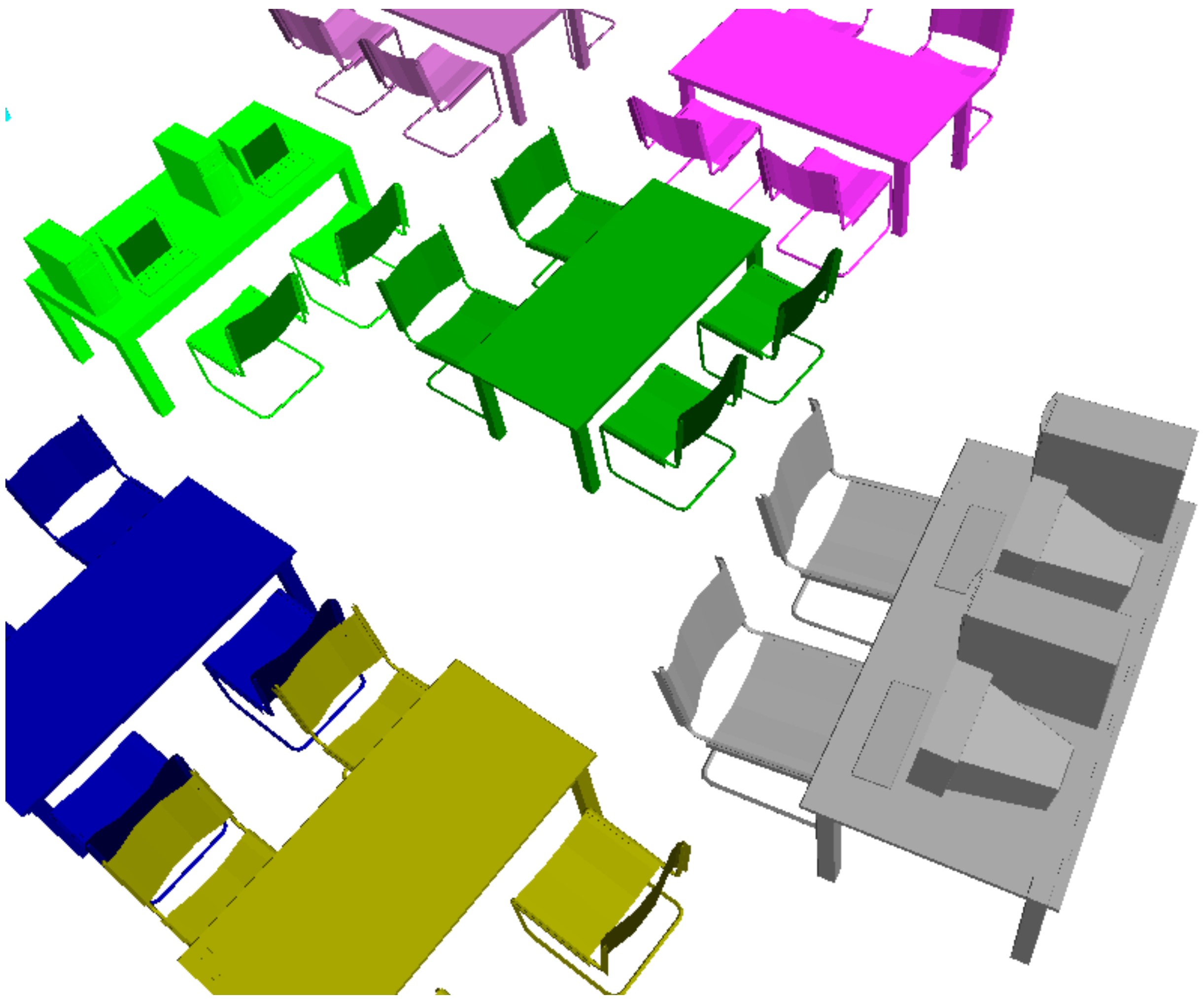
Key Idea: learn deformable templates



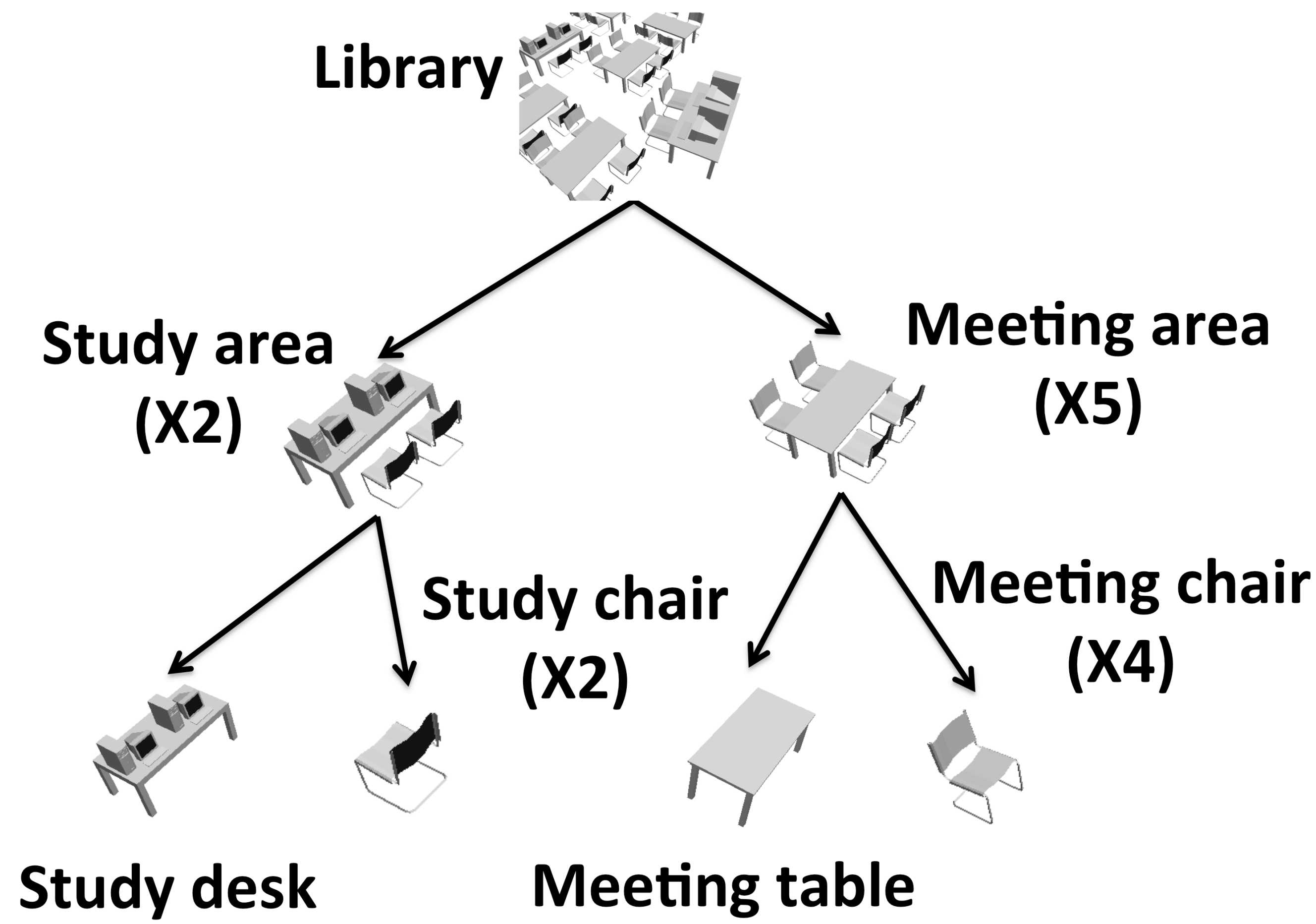
E.g., Learning Part-based Templates from Large Collections of 3D Shapes
V. Kim, W. Li, N. Mitra, S. Chaudhuri, S. DiVerdi, T. Funkhouser, SIGGRAPH'13

Hierarchical Probabilistic Models

Key Idea: group related elements into hierarchies



Scene from 3D Warehouse



Semantic Hierarchy

E.g., Creating Consistent Scene Graphs Using a Probabilistic Grammar
T. Liu, S. Chaudhuri, V. Kim, Q. Huang, N. Mitra, and T. Funkhouser, SIGGRAPH Asia'14

Two low-probability chairs

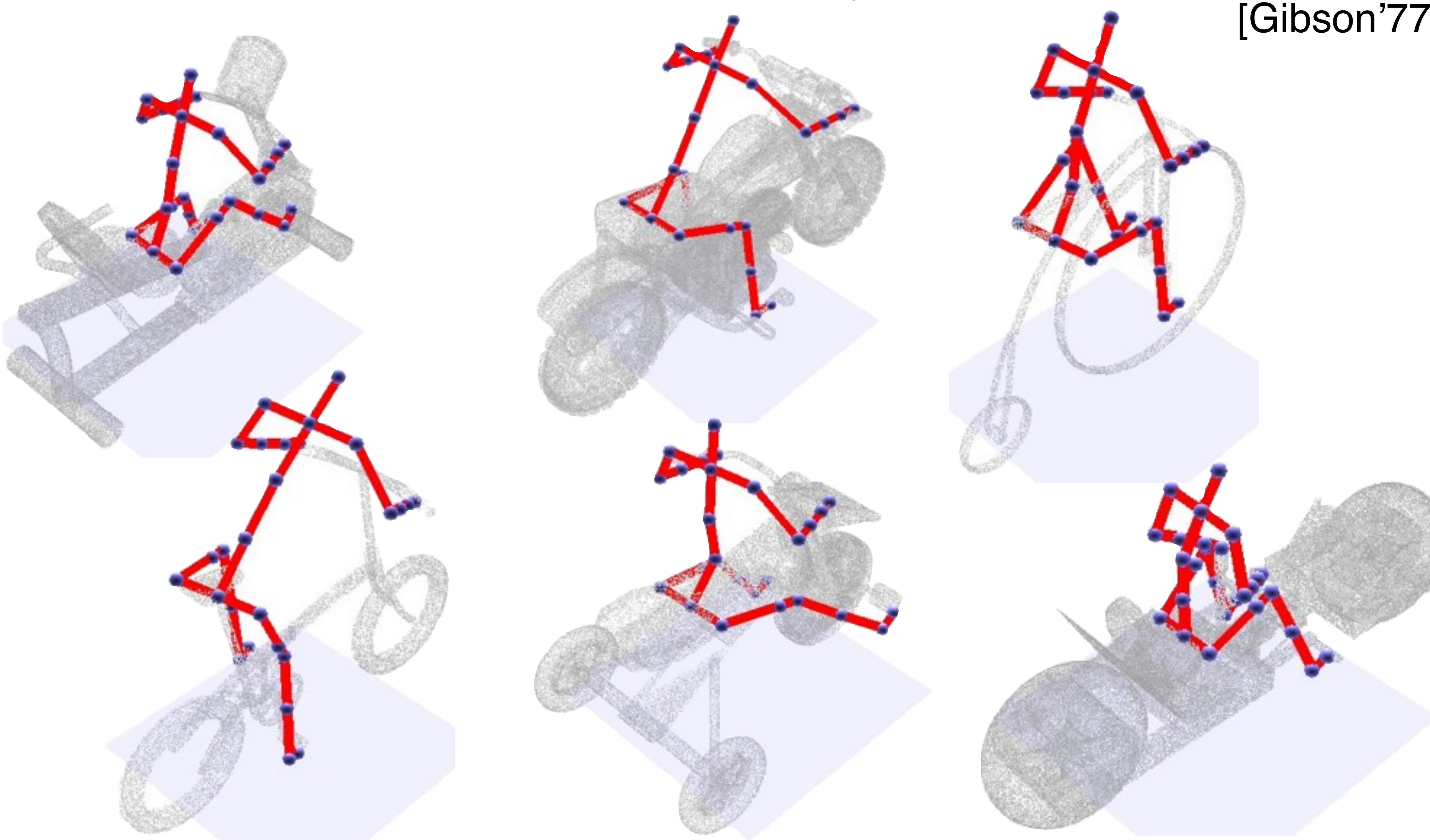
Challenge

Find common structure

Observation

Affordance is an intrinsic property of a shape

[Gibson'77]



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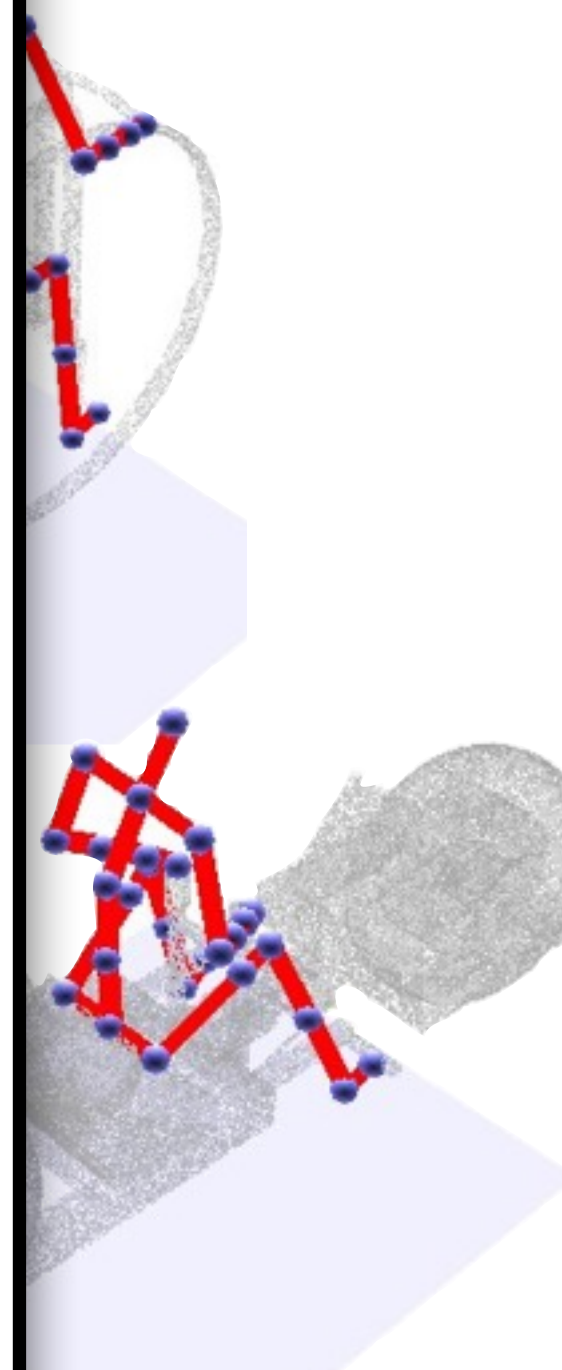
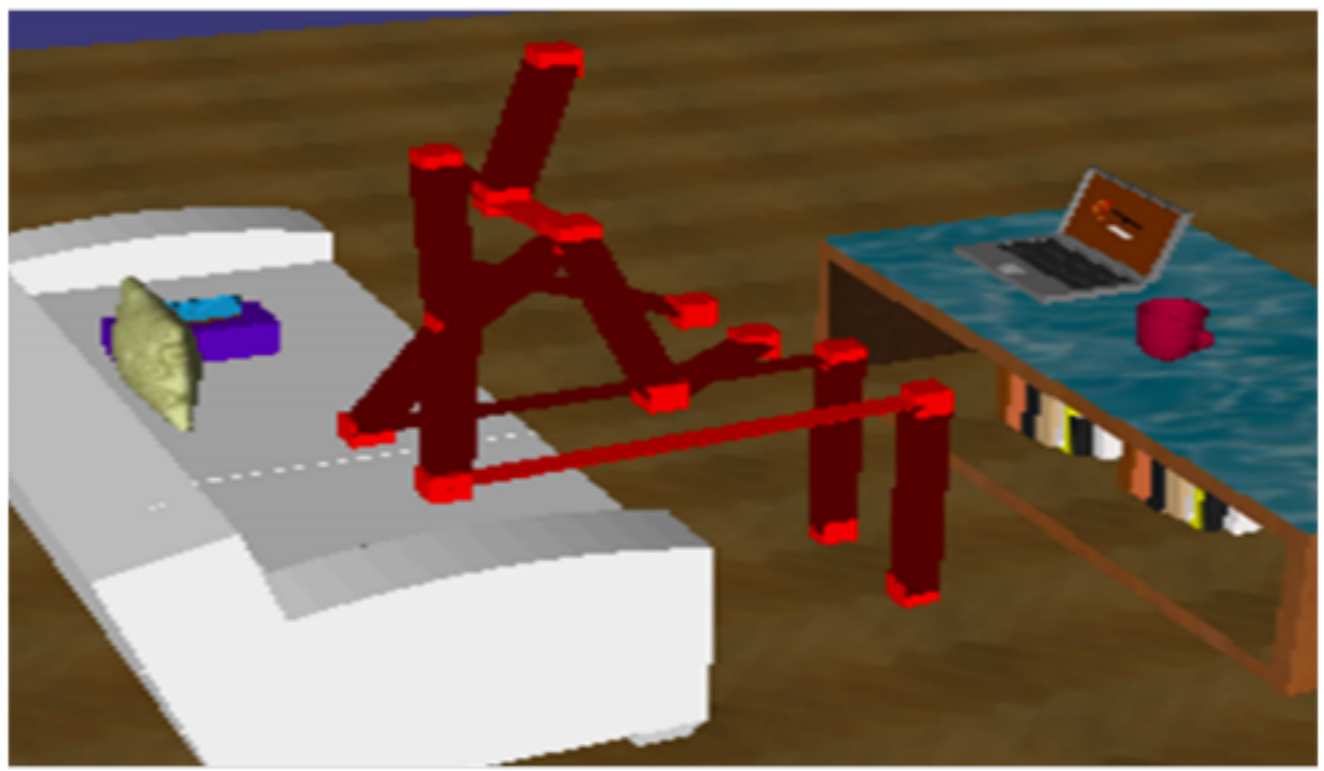
[Gibson’77]

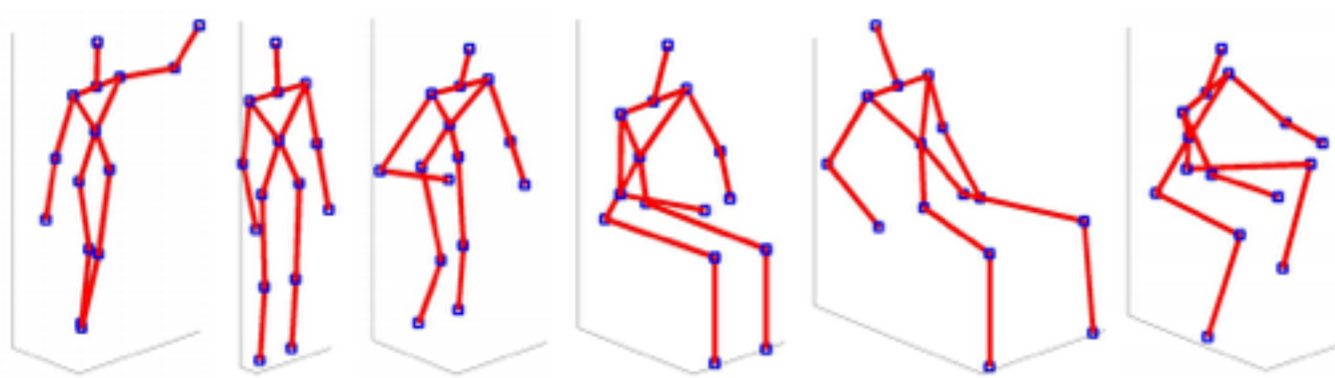


Previous work: classification



Jiang et al.

Rigid poses:

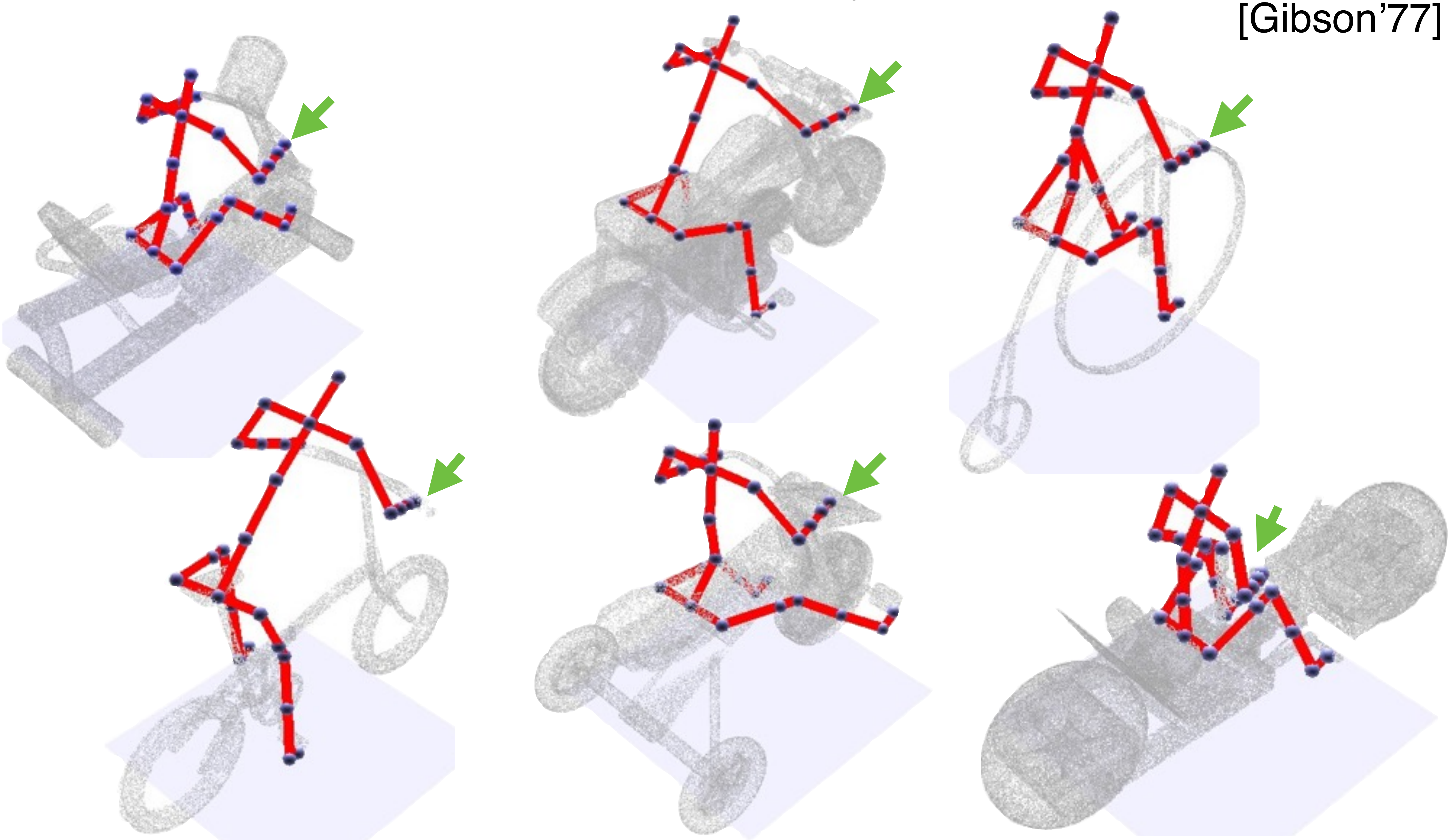


Observation

✓ Correspondence
✷ Saliency
✷ Structural Variations

Affordance is an intrinsic property of a shape

[Gibson'77]



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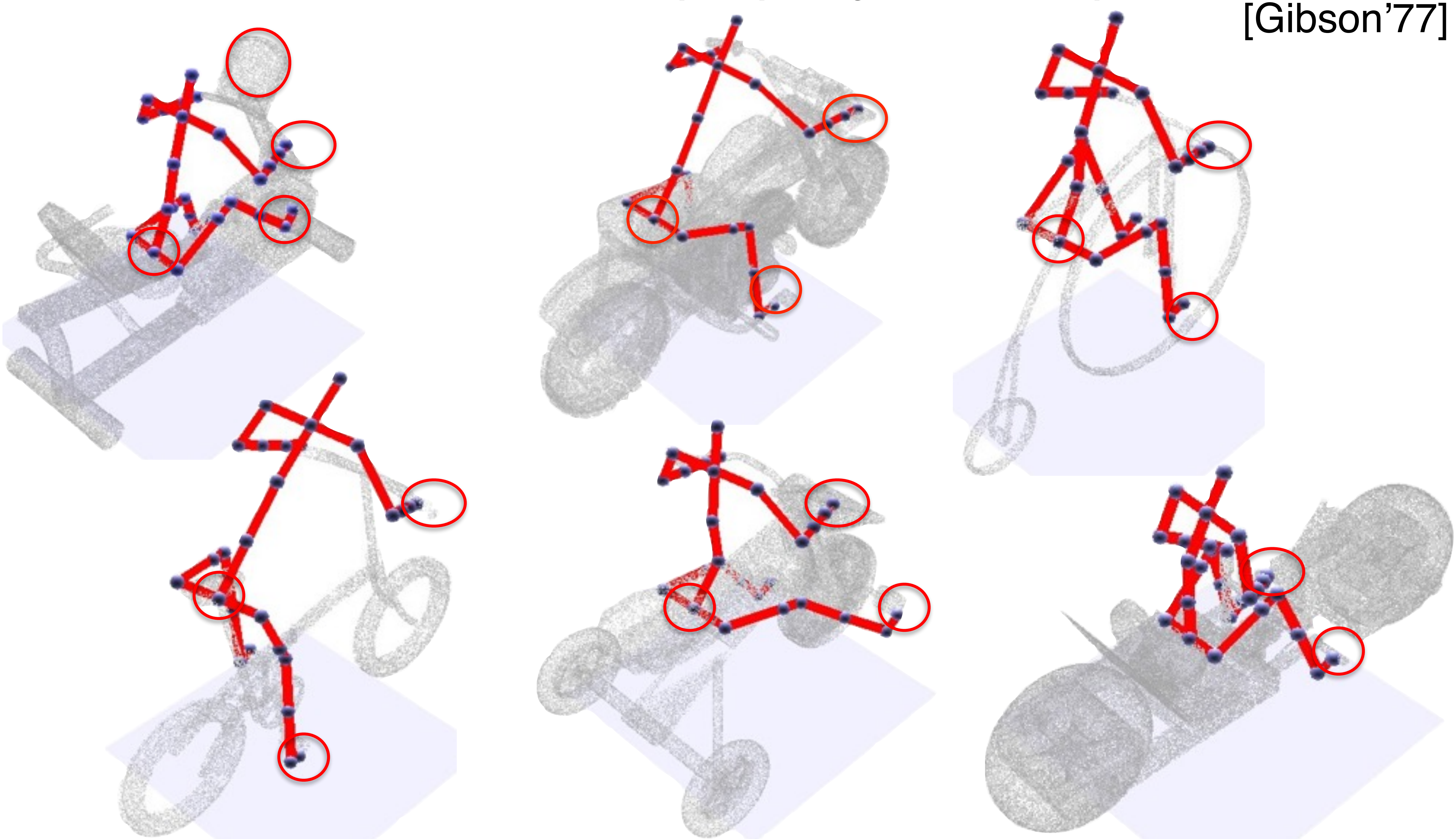

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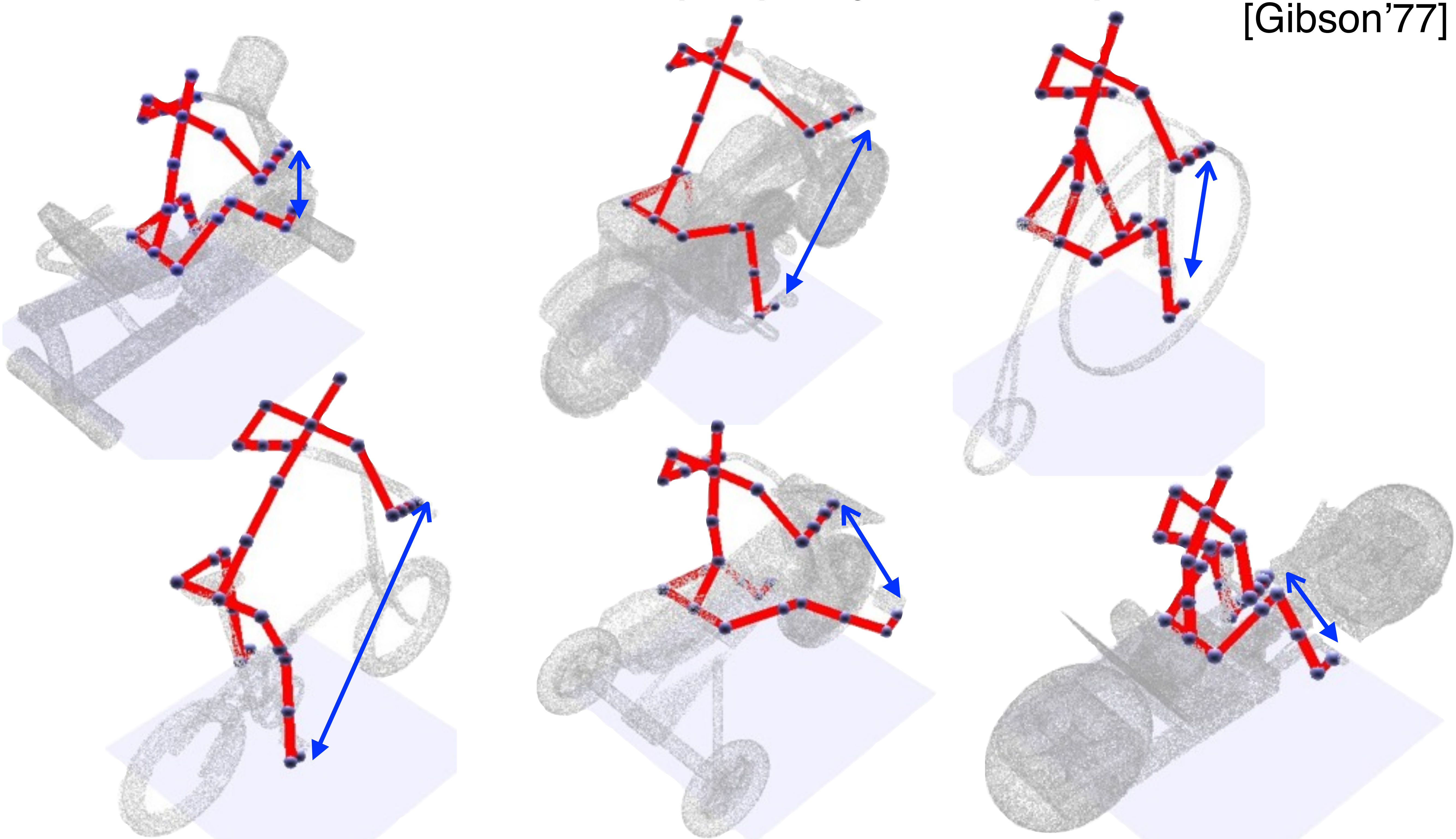
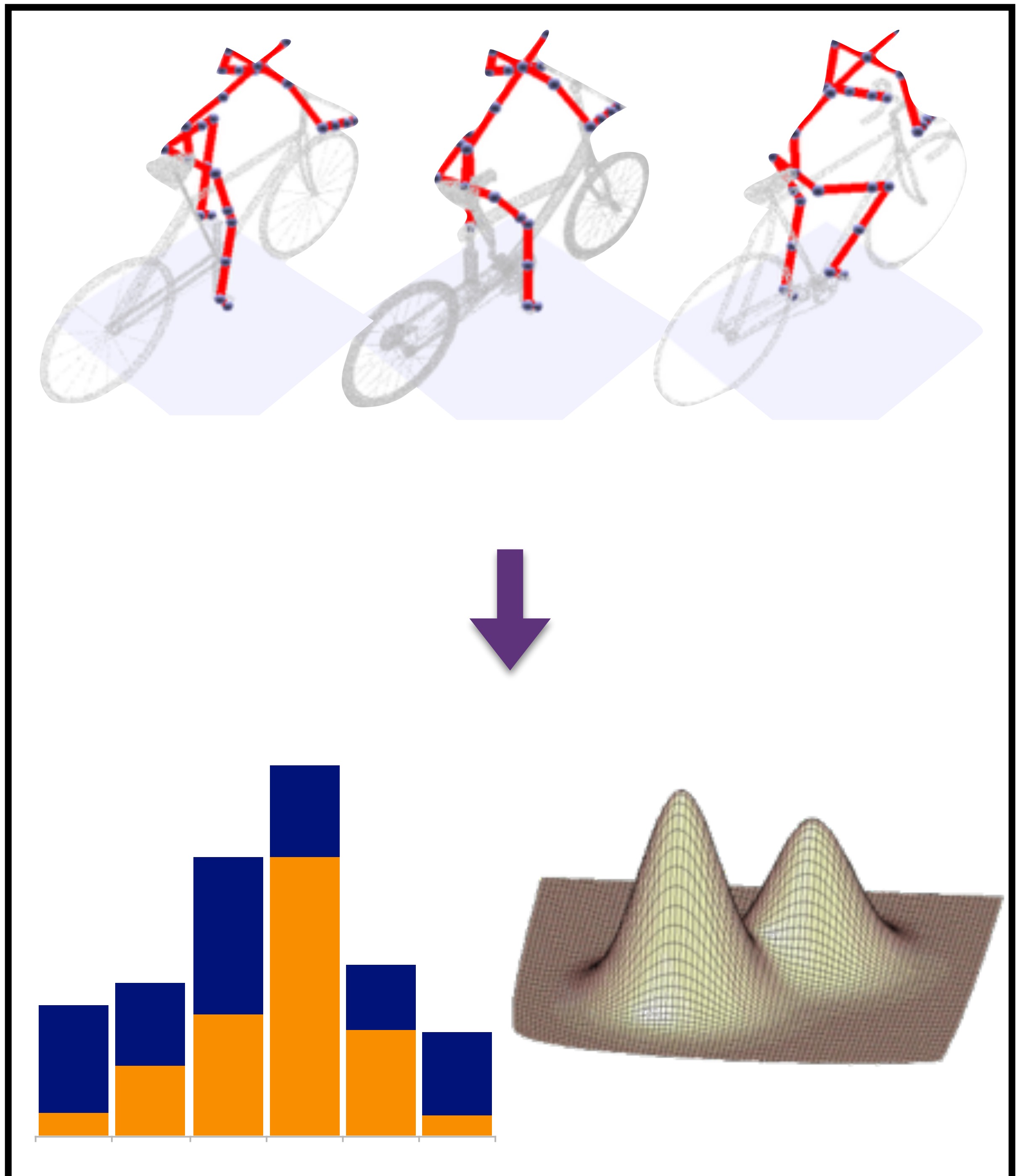
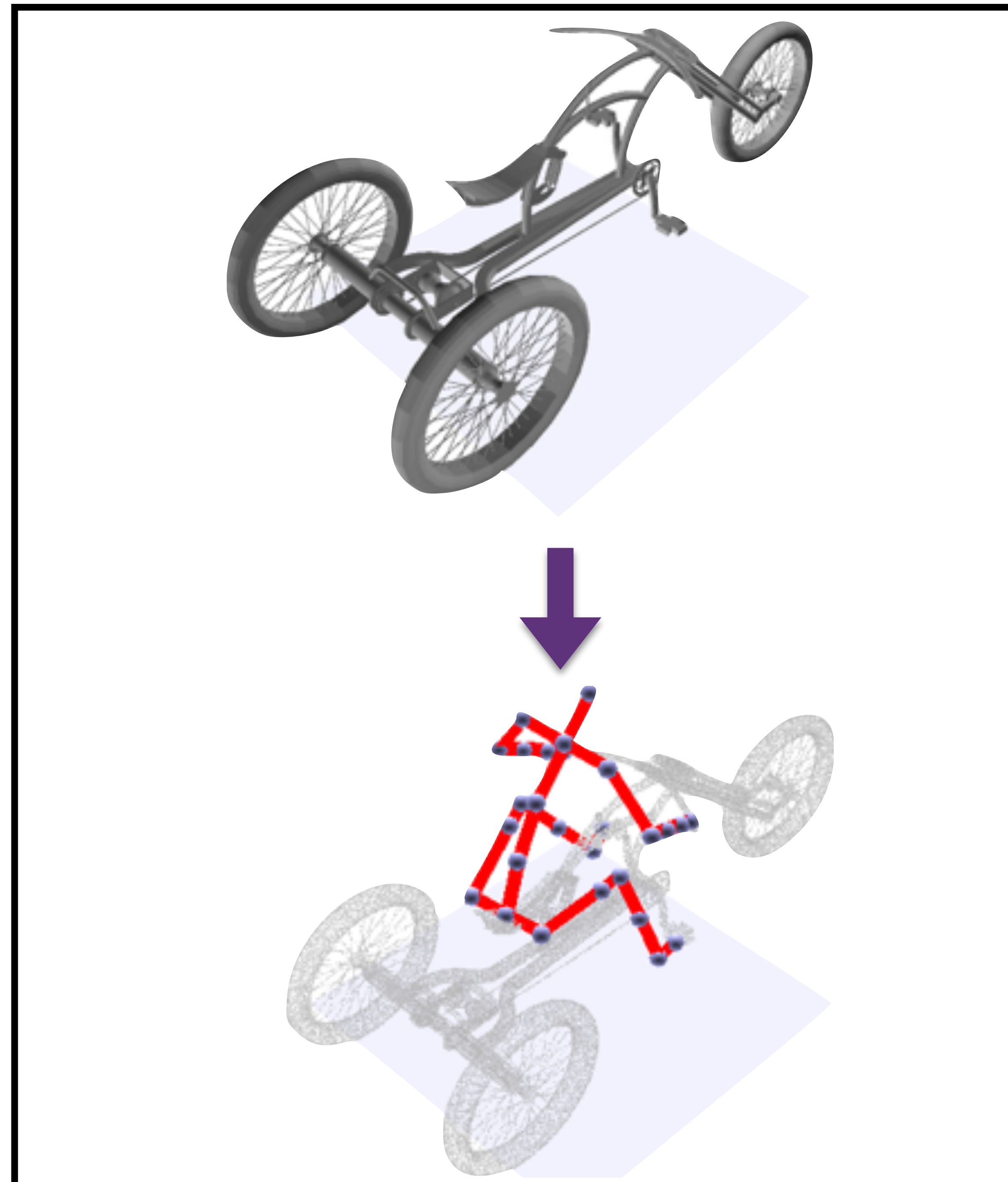


Affordance Model and Pose Prediction

Affordance Model Learning



Pose Prediction



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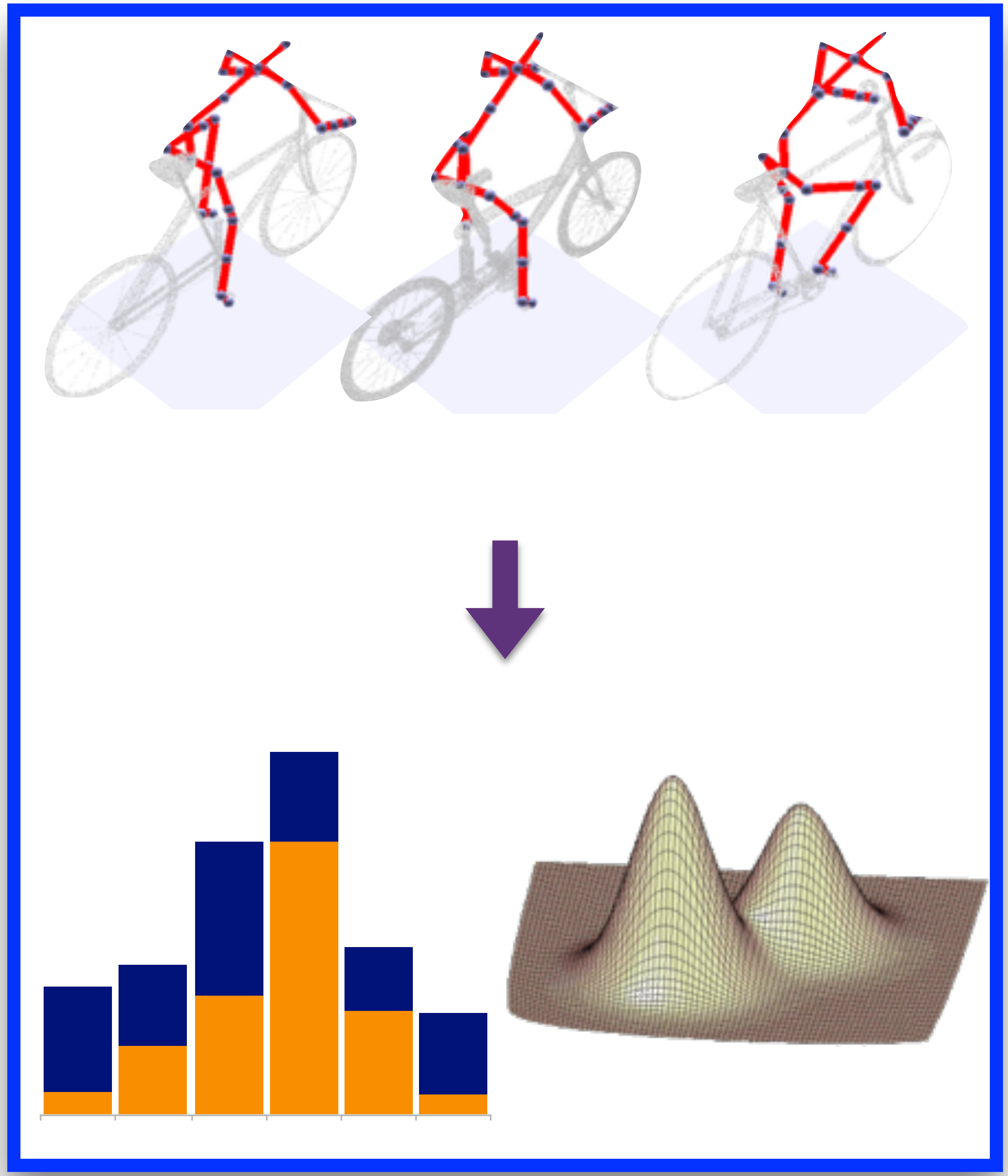


Pose Prediction

Affordance Model

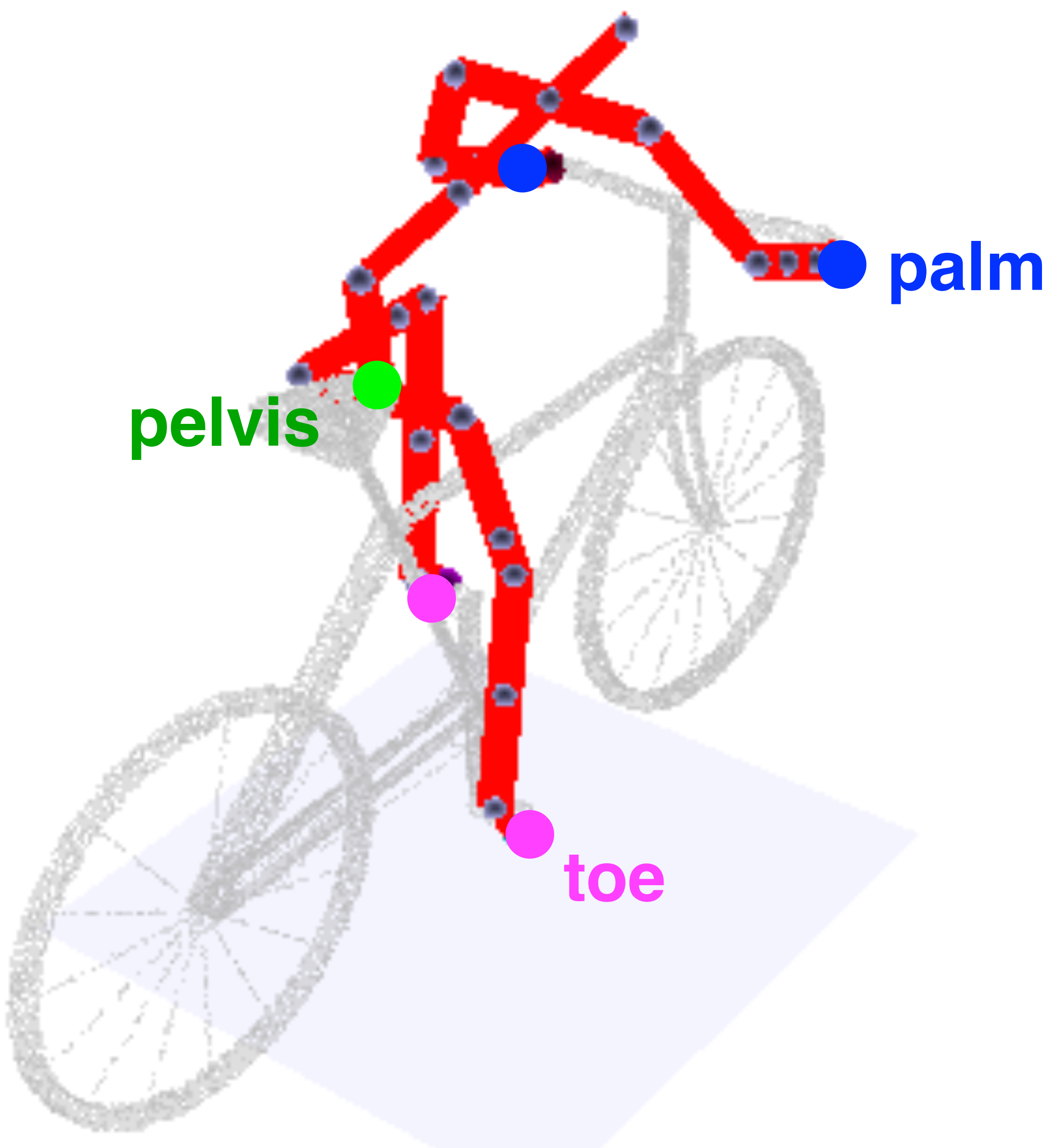
Learn from training data

- Geometry of contact points
- Plausibility of poses

Affordance Model

Learn from training data

- ➡ Geometry of contact points
- o Plausibility of poses



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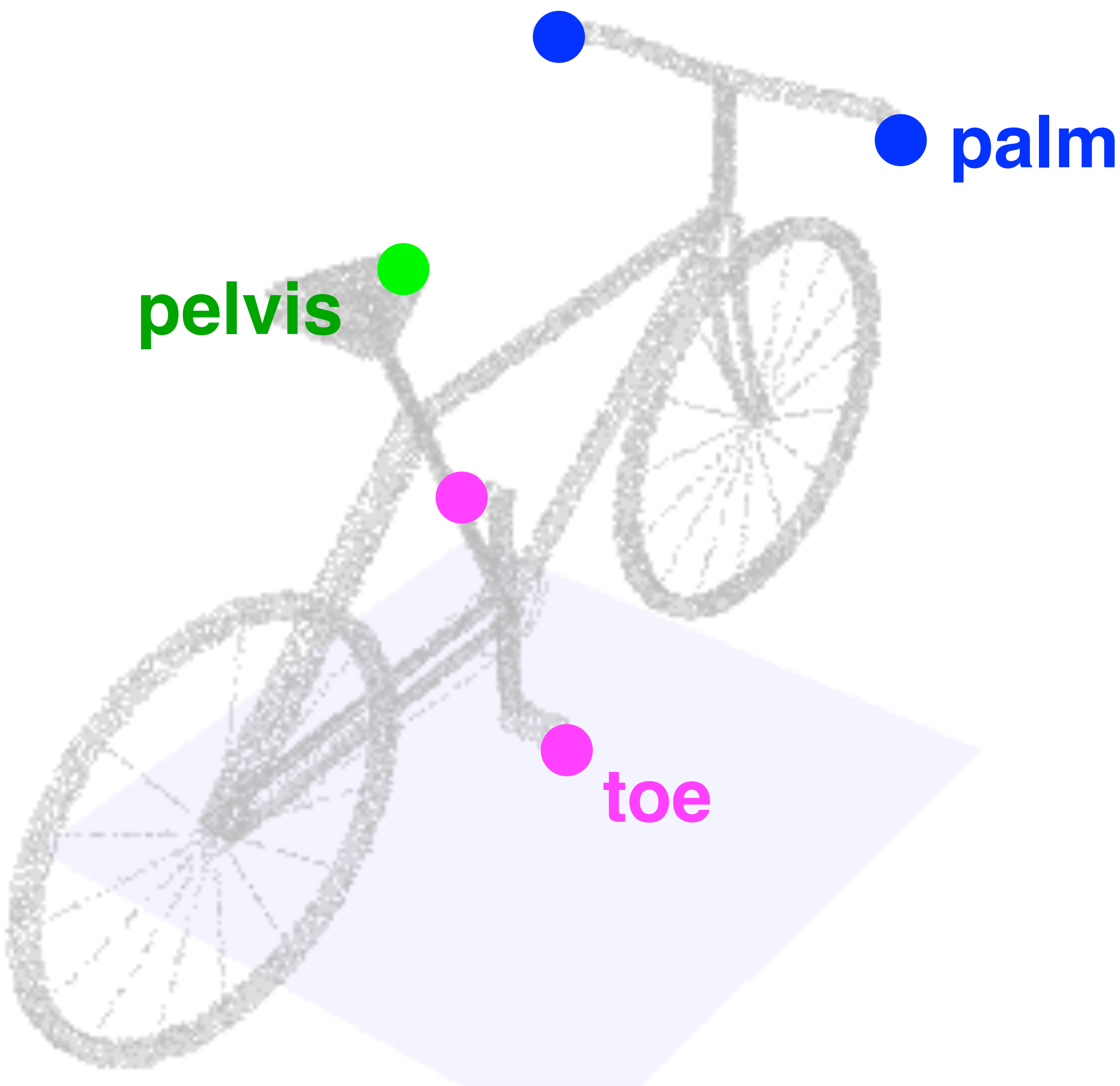

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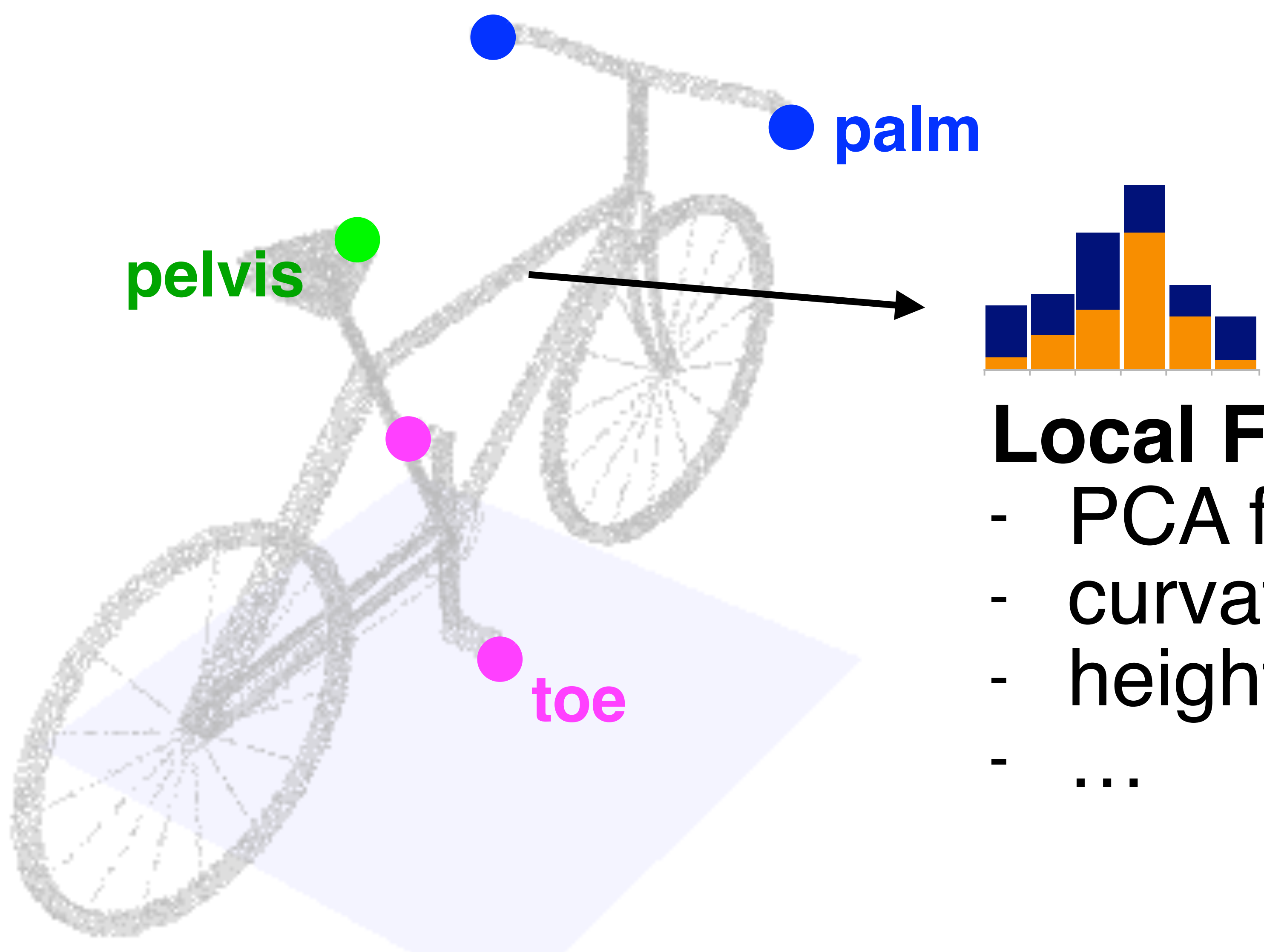

Local Features:

- PCA features
- curvature
- height
- …

Affordance Model

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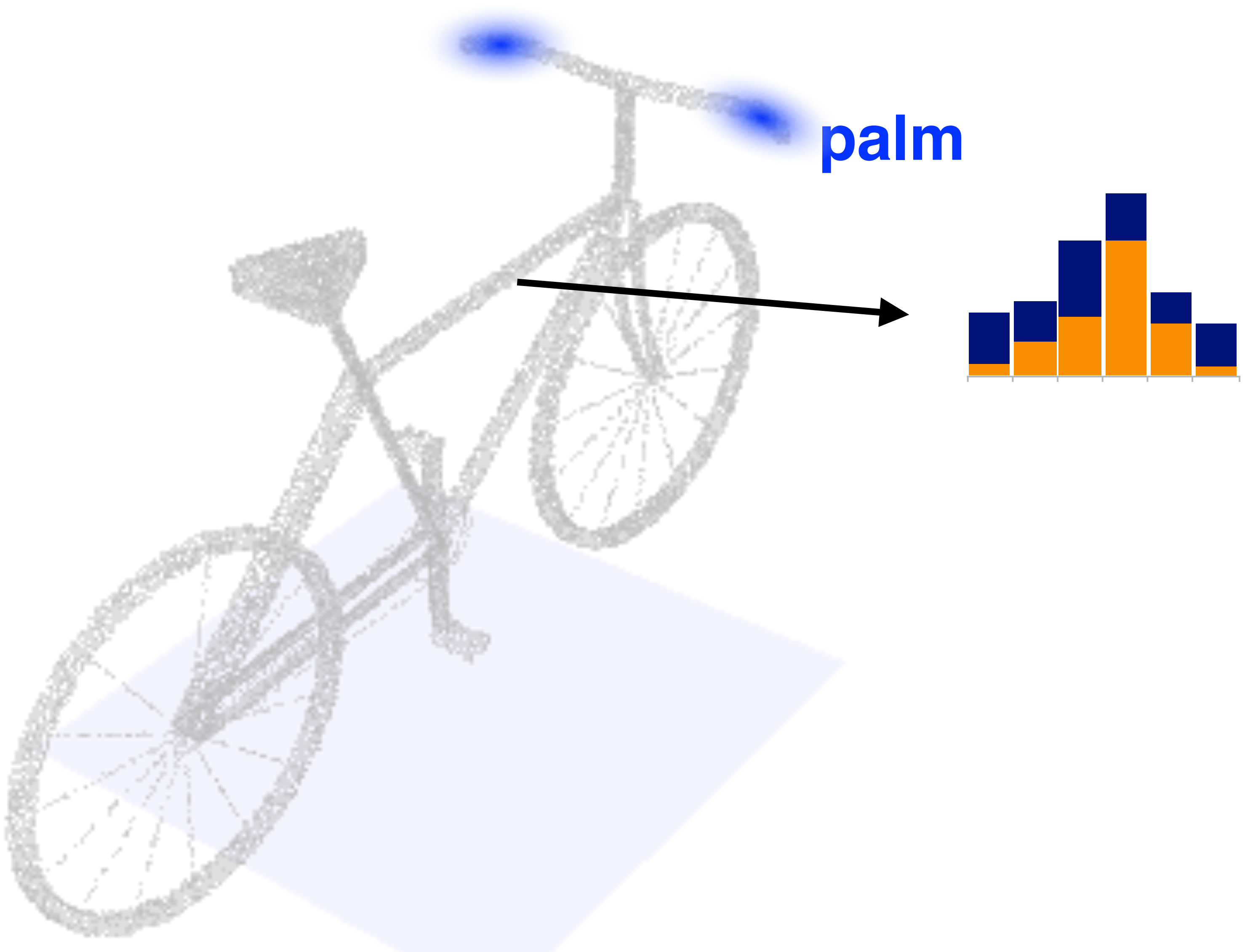

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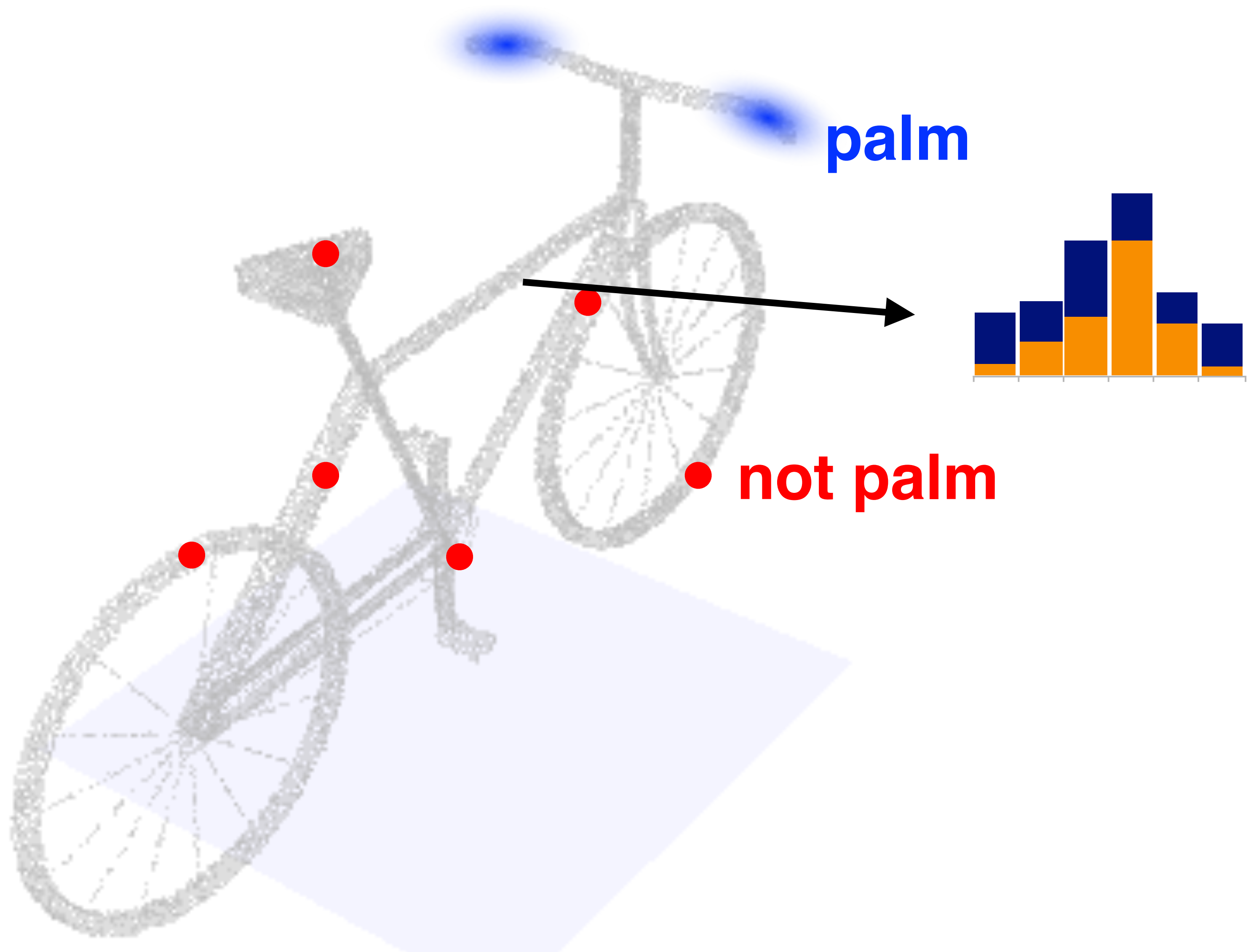

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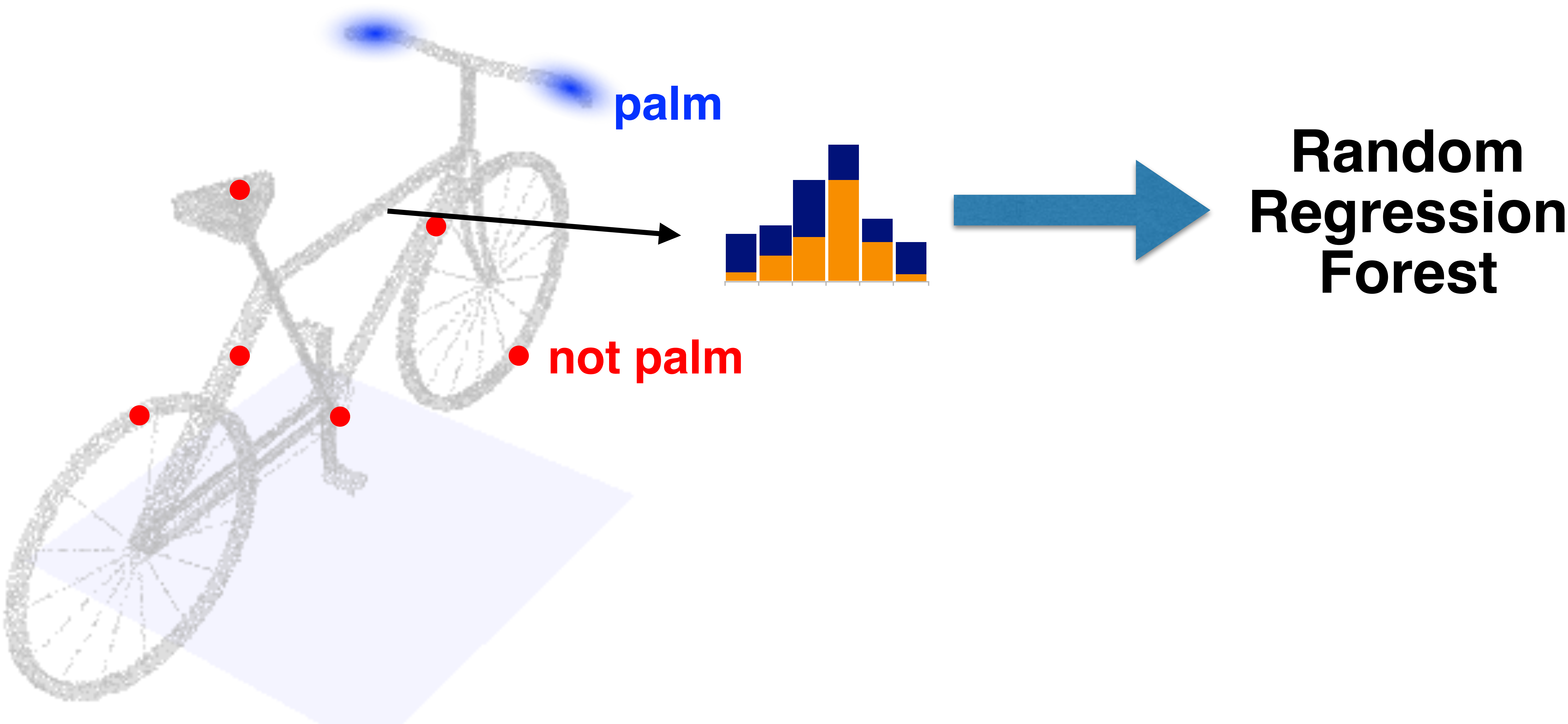

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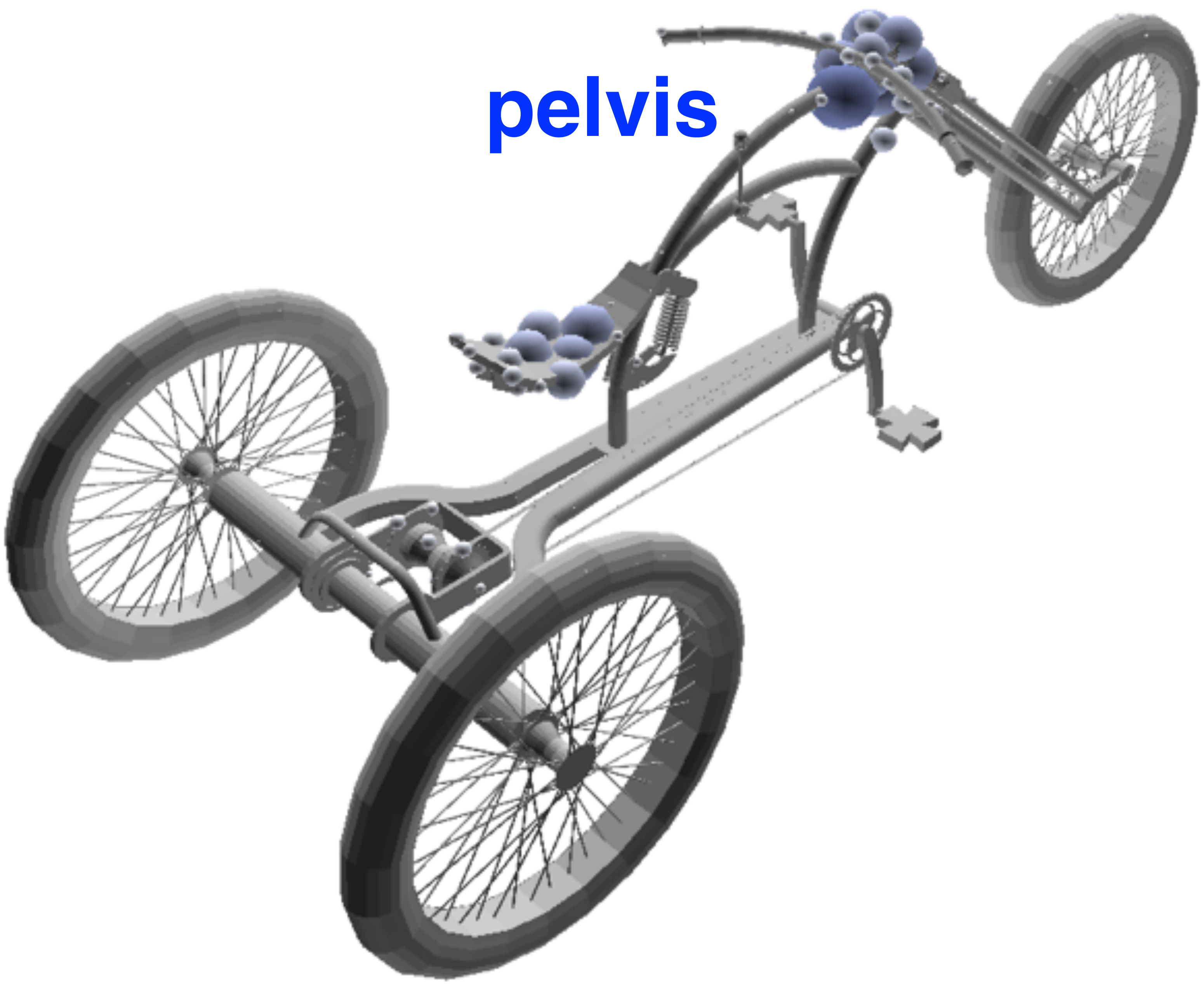

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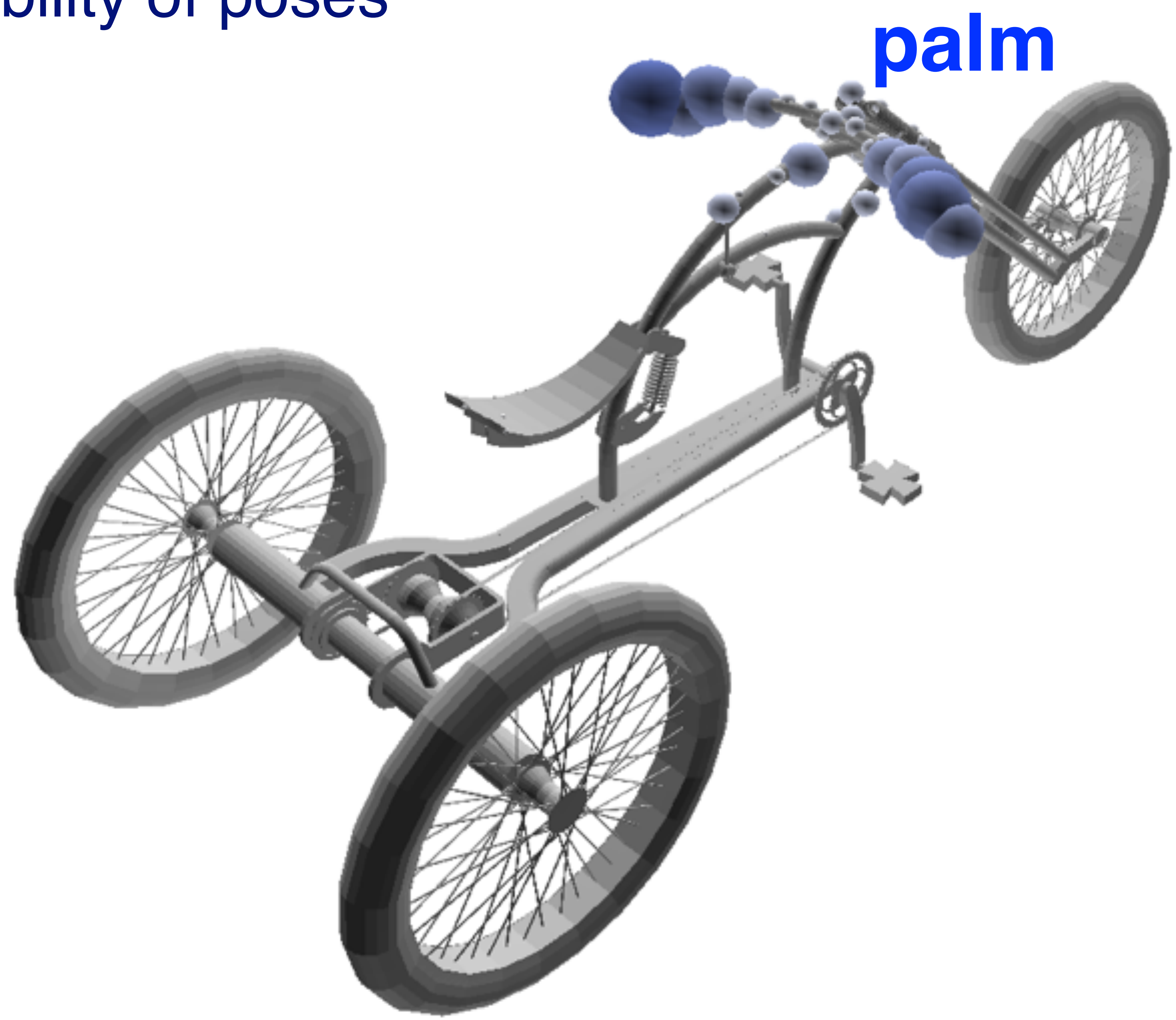

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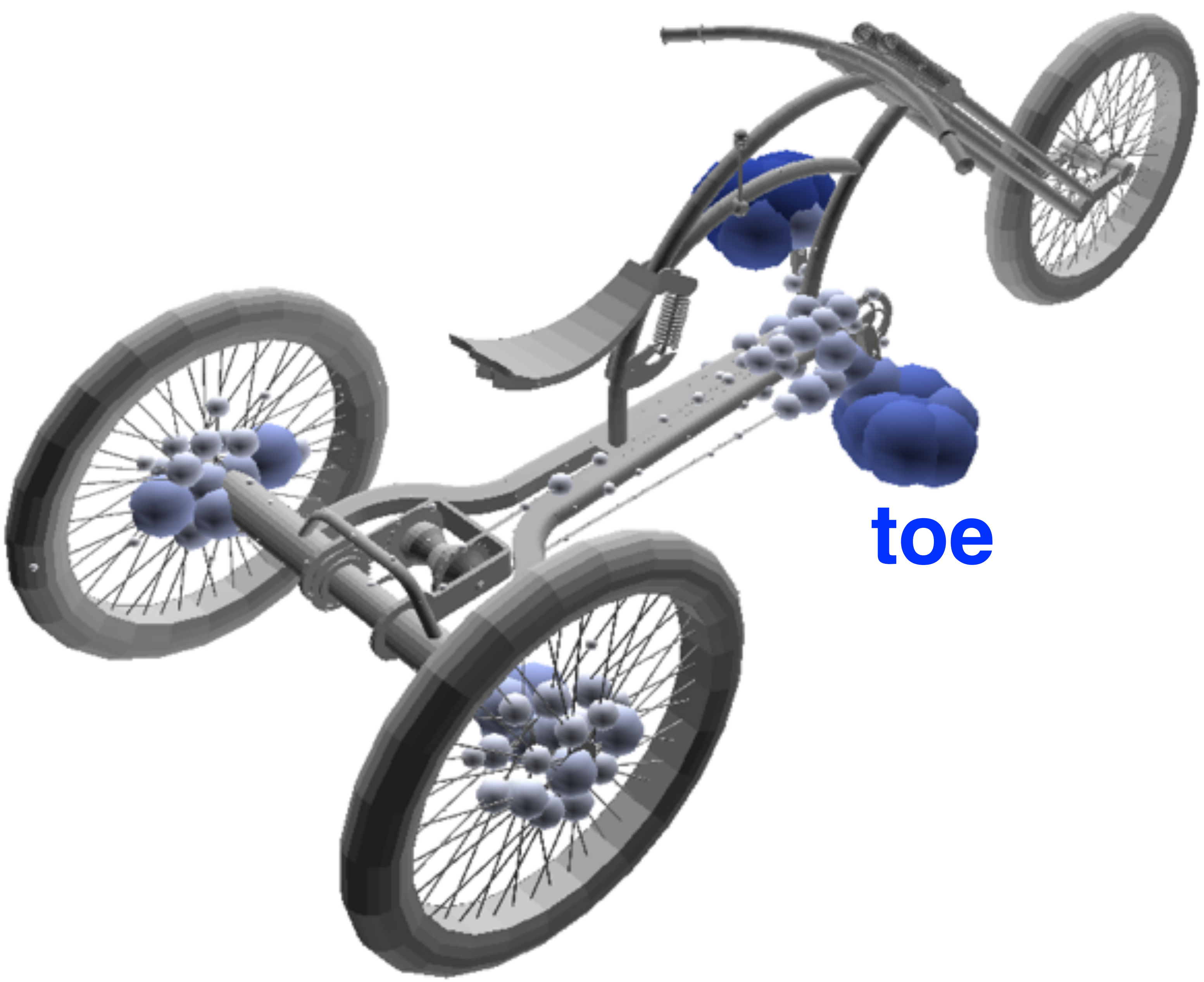

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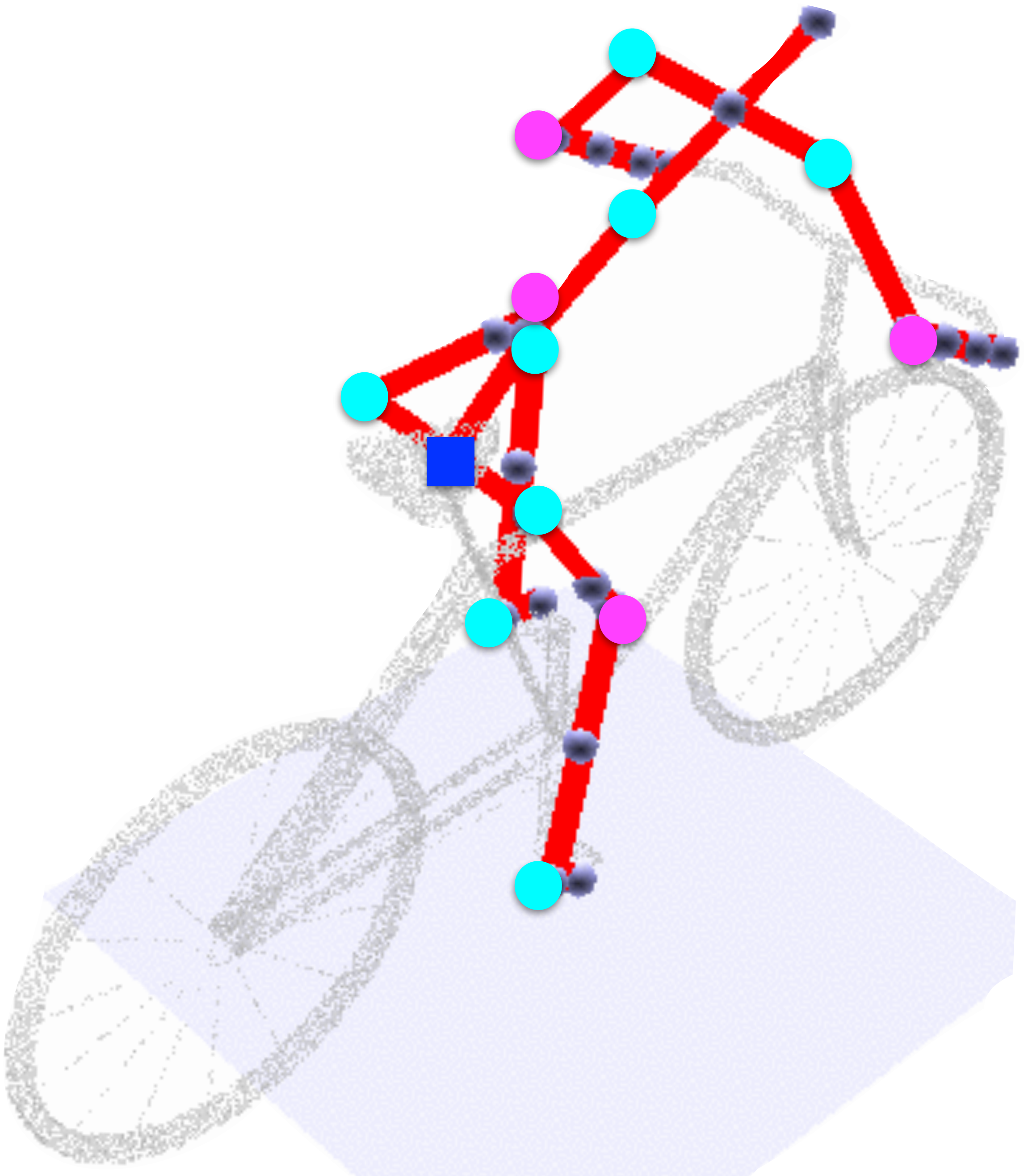

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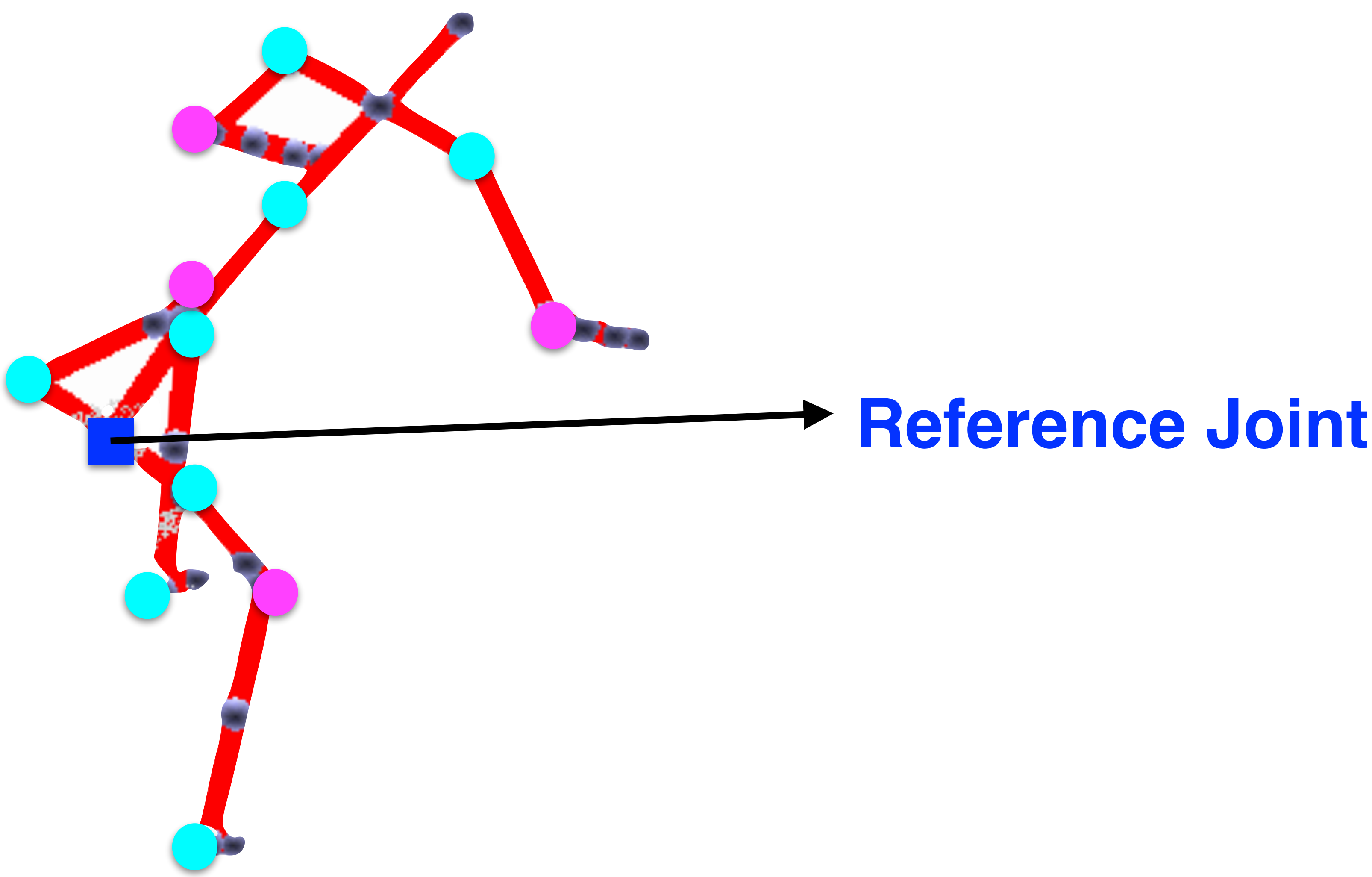

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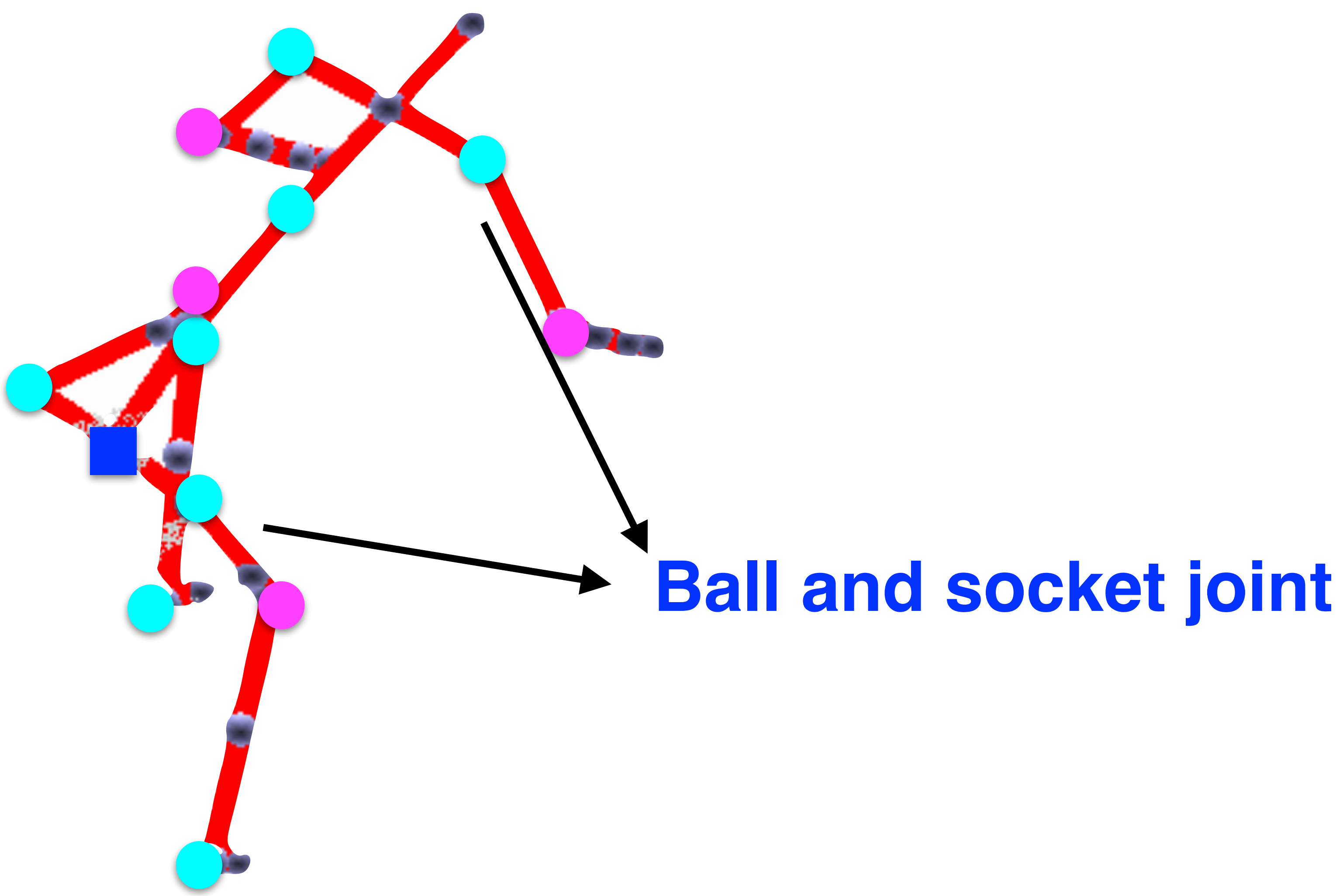

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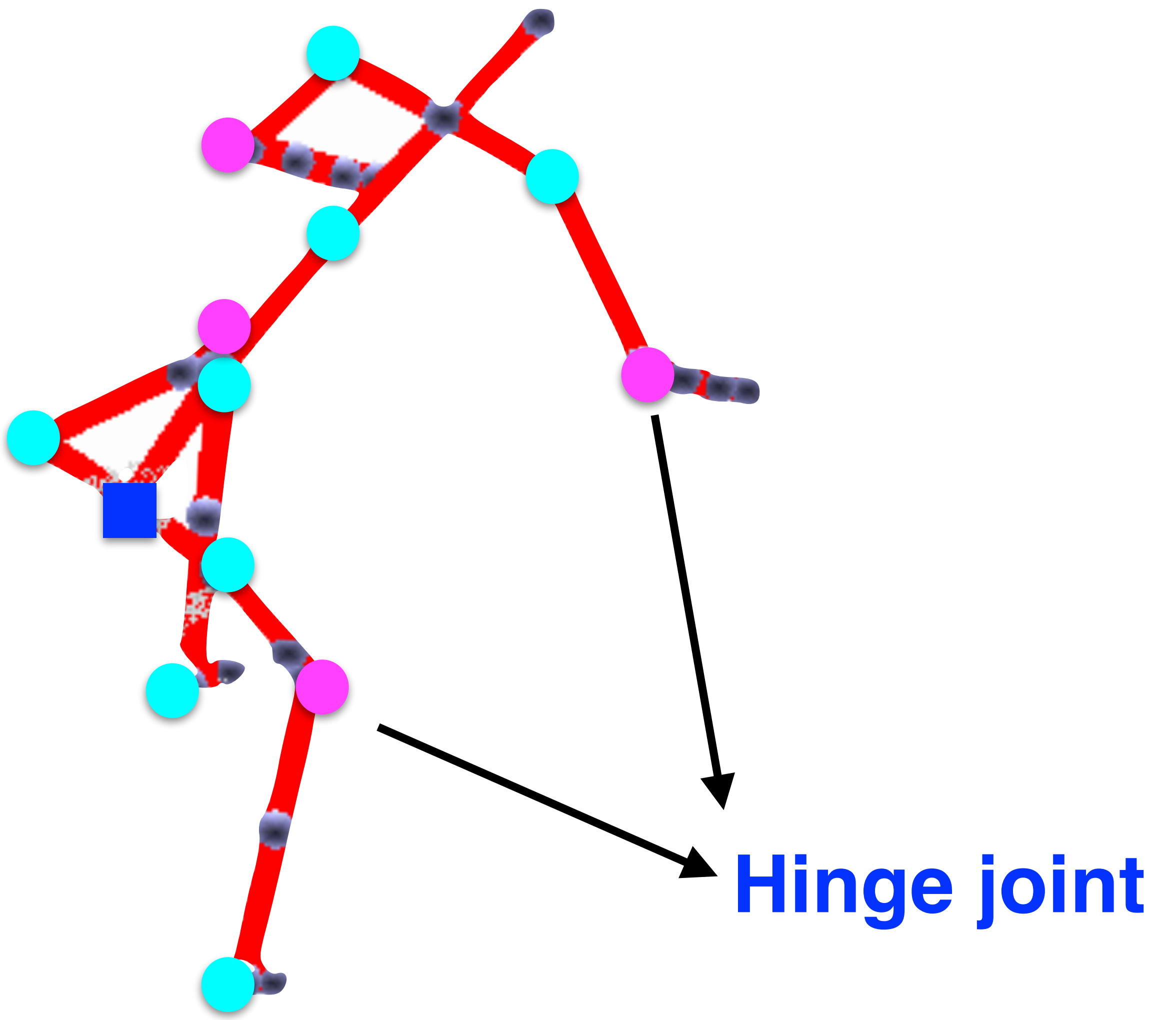

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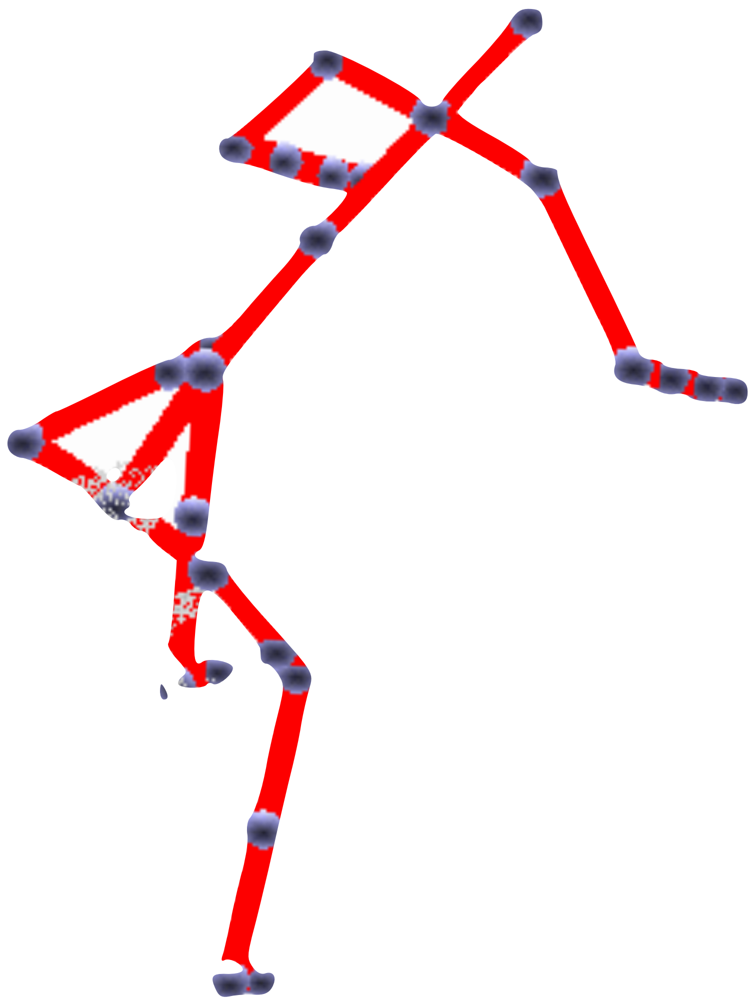
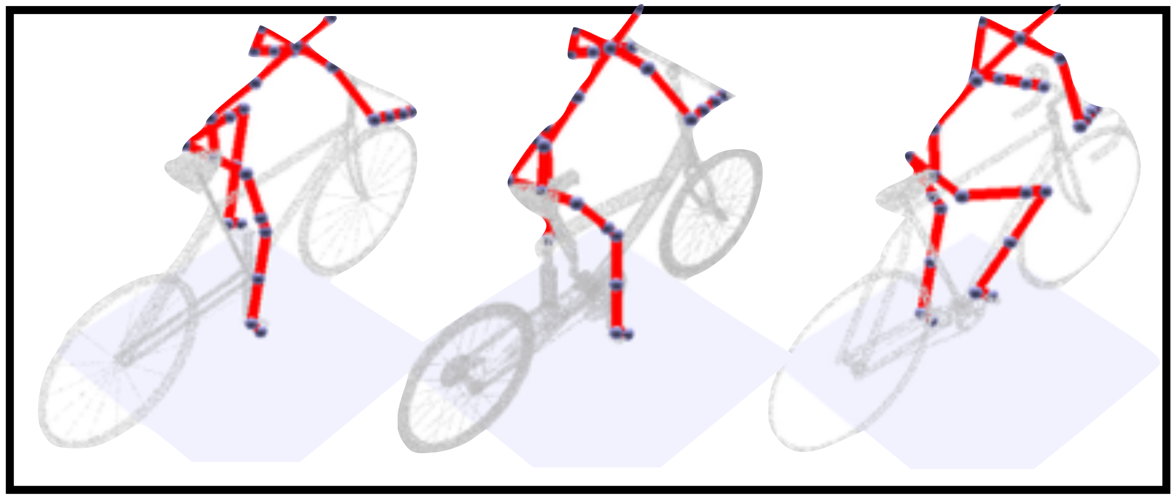
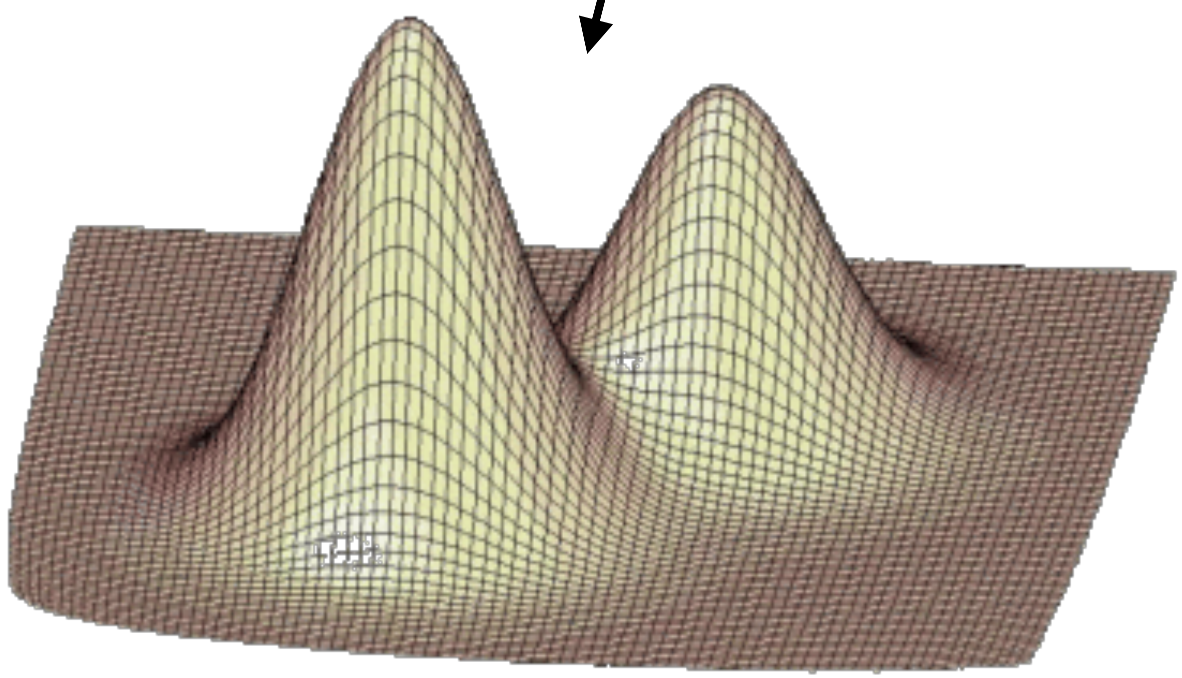




Training Data



Mixture of multi-variate Gaussians

Affordance Model

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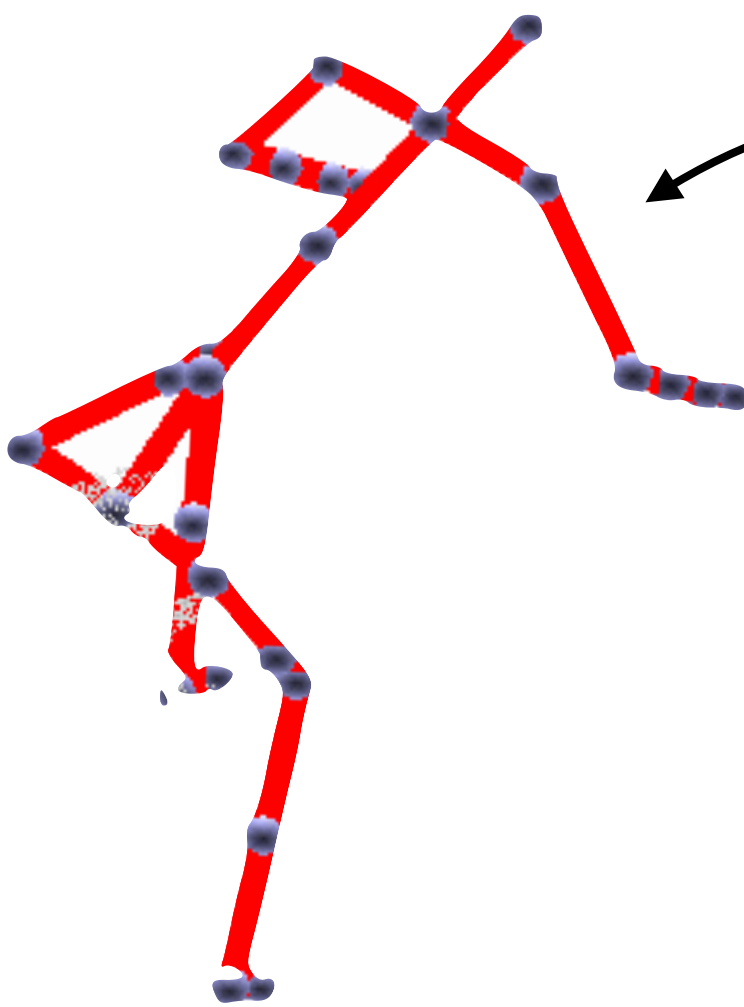
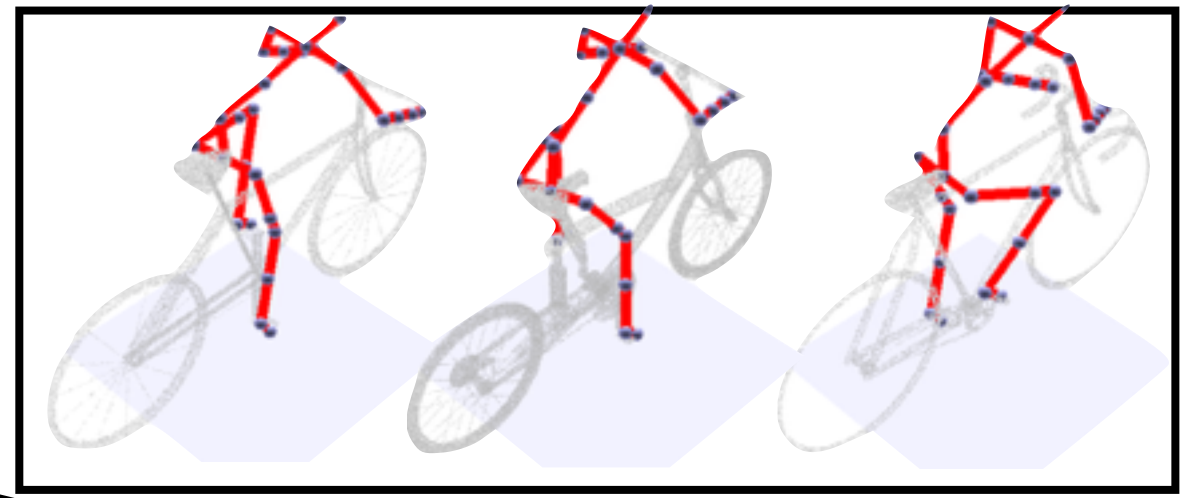
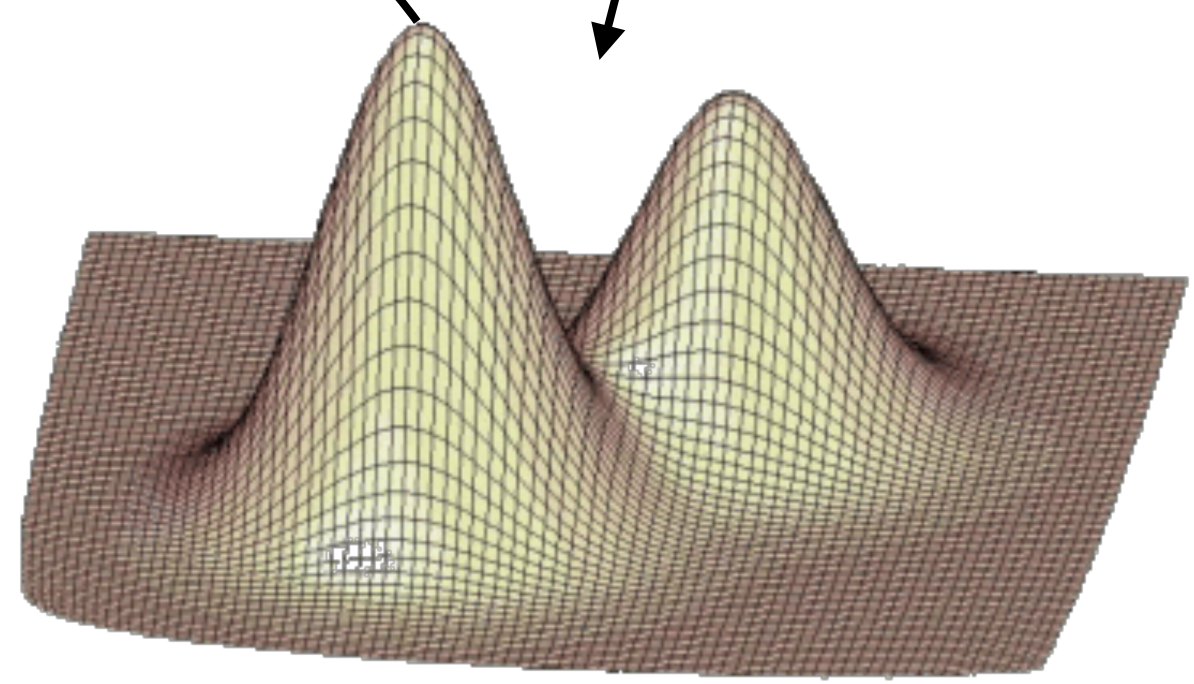
- ➡ Plausibility of poses





Training Data



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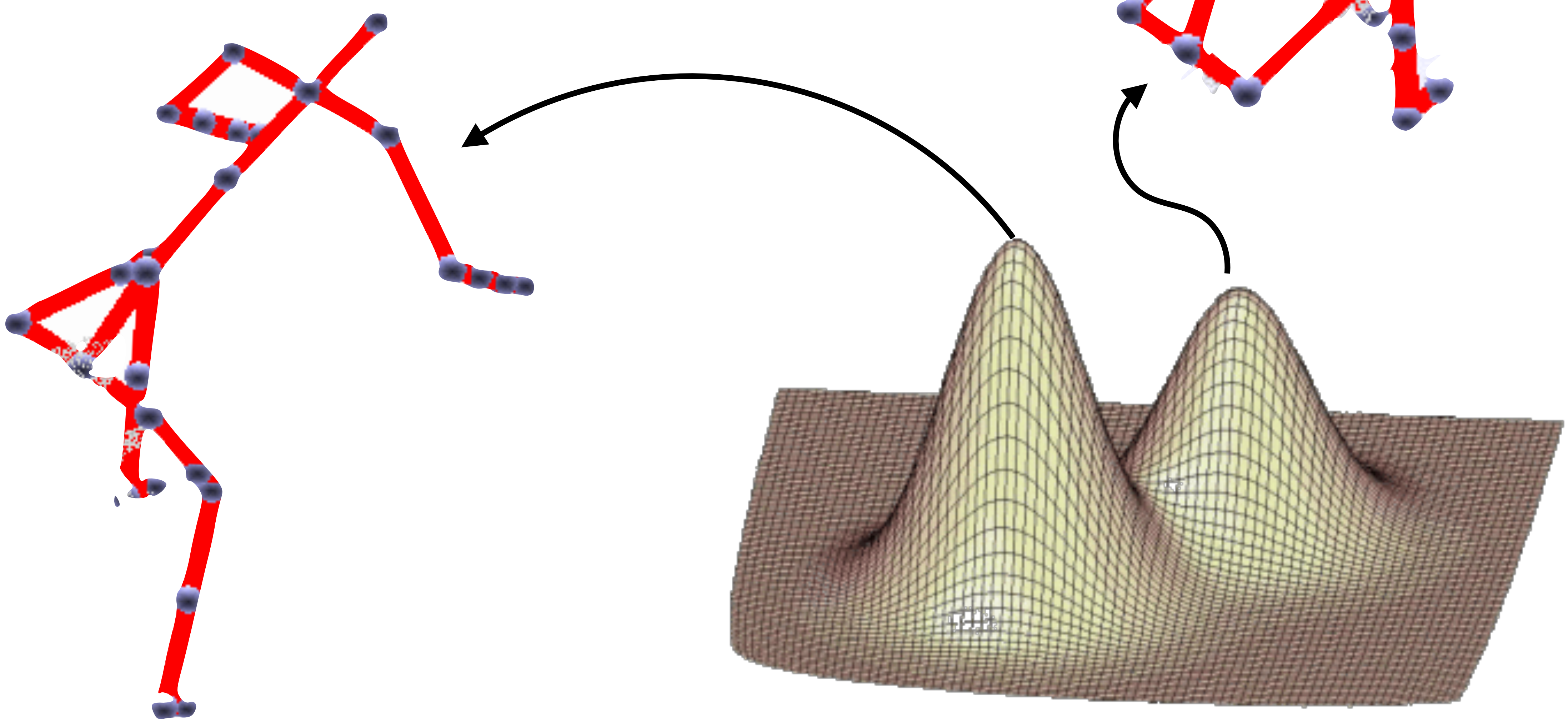

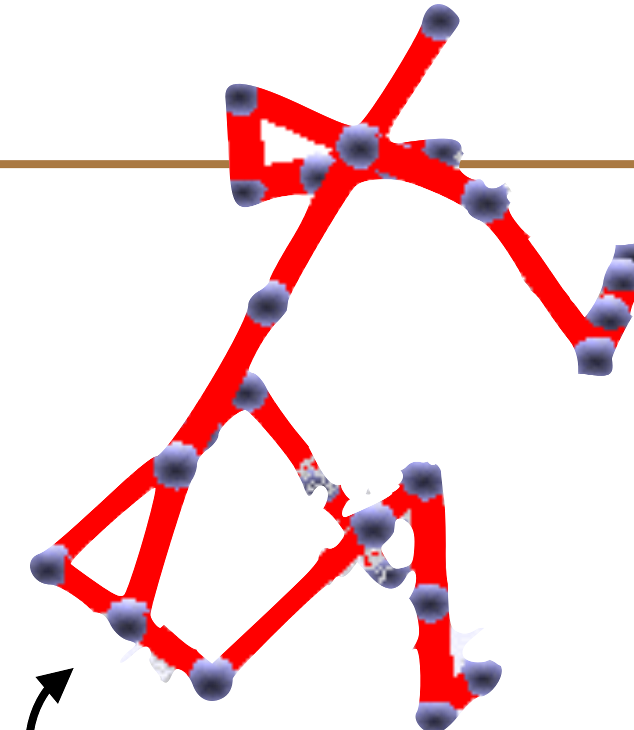

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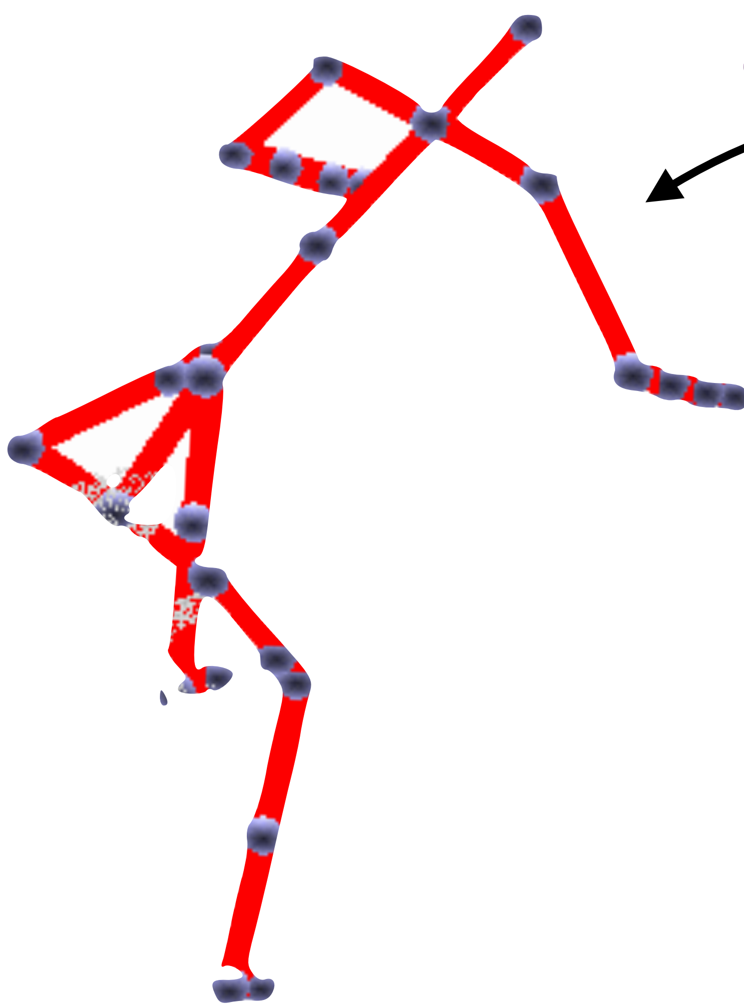
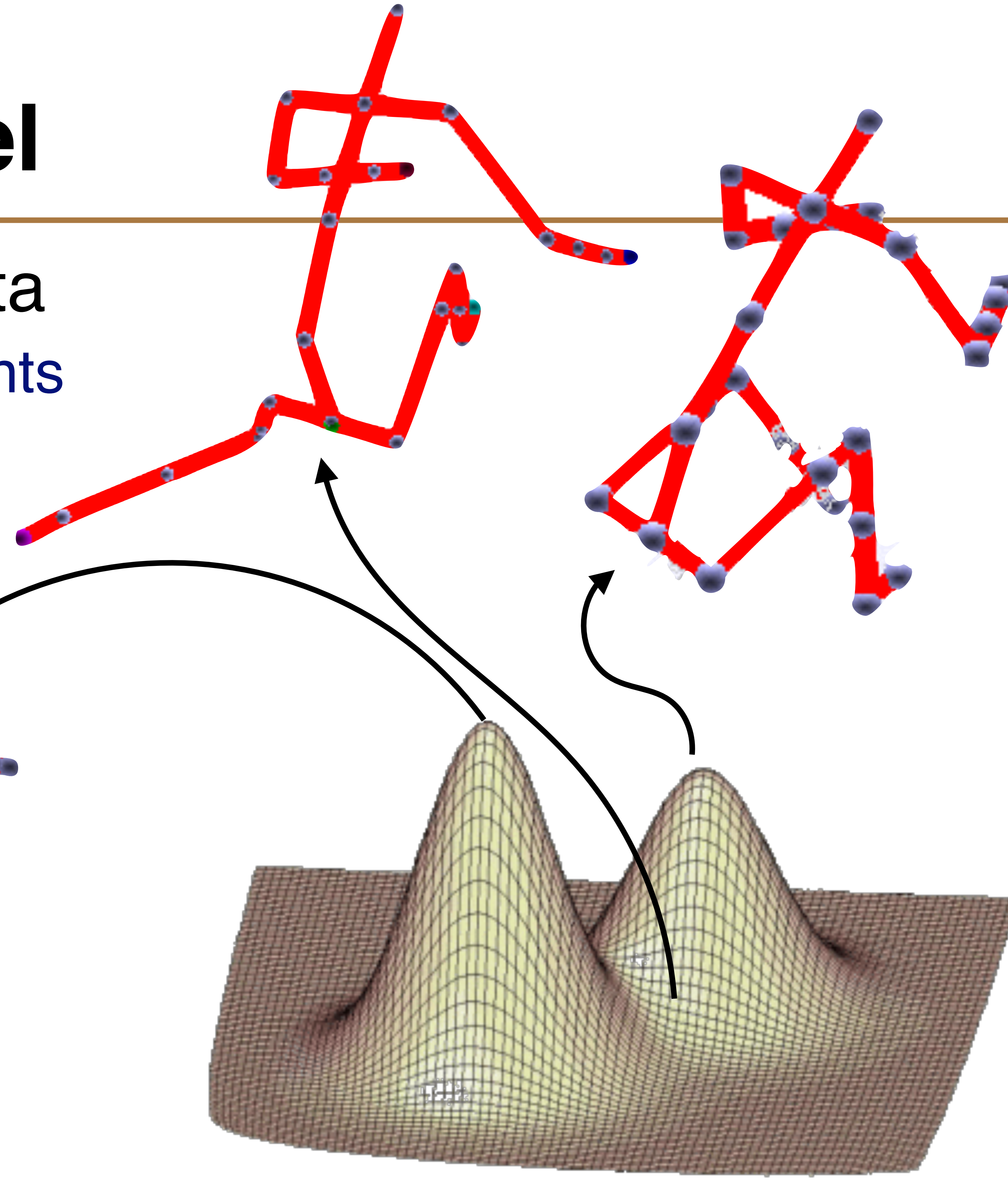


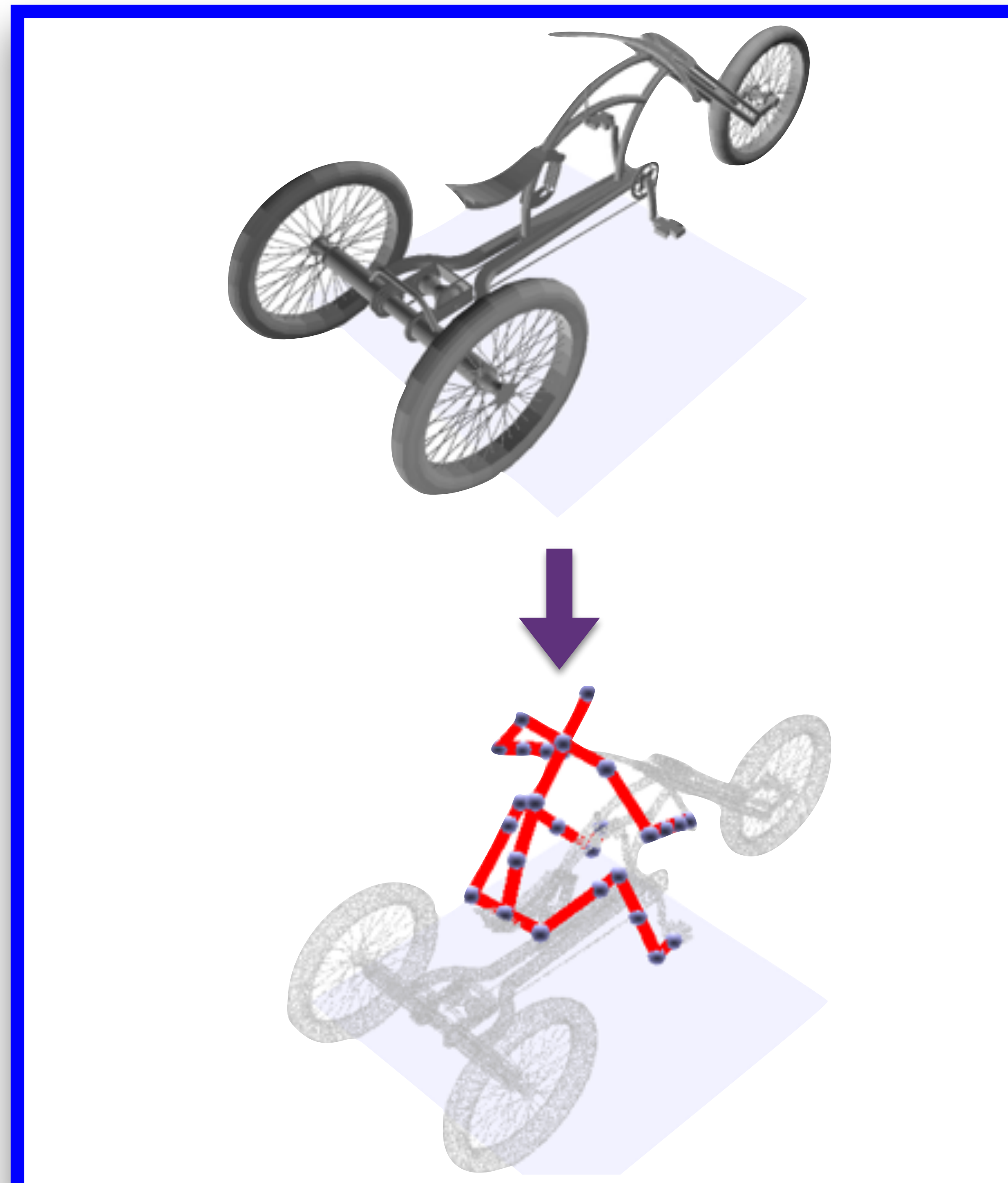


Mixture of multi-variate Gaussians

Affordance Model and Pose Prediction

Affordance Model Learning

Pose Prediction



Pose Prediction

Objective function for each pose-model fit:

$$E = E_{\mathrm{dist}} + E_{\mathrm{feat}} + E_{\mathrm{pose}} + E_{\mathrm{symm}} + E_{\mathrm{isect}}$$

Solve for:

- Contact points $m : \underbrace{P}_{\text{Body parts}} \rightarrow \underbrace{S}_{\text{Shape}}$
- Joint angles θ, T

Pose Prediction

Objective function for each pose-model fit:

$$E = \boxed{E_{\text{dist}}} + E_{\text{feat}} + E_{\text{pose}} + E_{\text{symm}} + E_{\text{isect}}$$

$$E_{\text{dist}} = \sum_{p \in P} ||T\mathbf{p}_\theta - m(p)||^2$$

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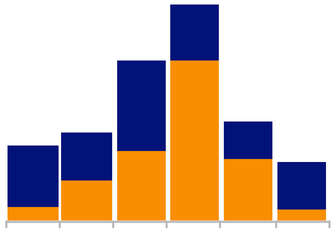


$$E_{\text{feat}} = \sum_{p \in P} -\log V_p(m(p))$$

Regression Model

Solve for:

Body parts Shape

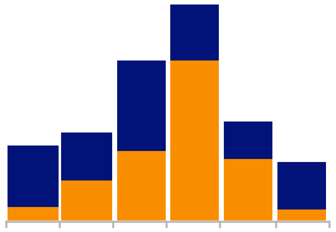
- Contact points $m : P \to S$
- Joint angles θ, T

Pose Prediction

Objective function for each pose-model fit:

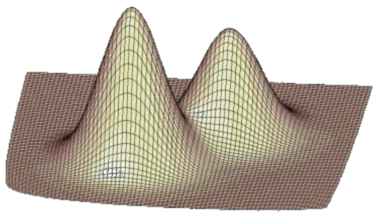
$$E = E_{\text{dist}} + E_{\text{feat}} + \boxed{E_{\text{pose}}} + E_{\text{symm}} + E_{\text{isect}}$$

$$E_{\text{dist}} = \sum_{p \in P} ||T\mathbf{p}_\theta - m(p)||^2$$



$$E_{\text{feat}} = \sum_{p \in P} -\log V_p(m(p))$$

Regression Model



$$E_{\text{pose}} = \min_{l \in L} \sum_{i}^{40} \frac{|\theta_i - \mu_l^l|^2}{(\sigma_i^l)^2}$$

Solve for:

Body parts **Shape**

- Contact points $m : P \rightarrow S$
- Joint angles θ, T

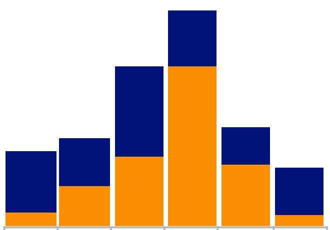
Pose Prediction

Objective function for each pose-model fit:

$$E = \boxed{E_{\text{dist}} + E_{\text{feat}} + E_{\text{pose}}} + E_{\text{symm}} + E_{\text{isect}}$$

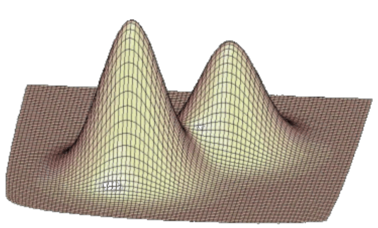
$$E_{\text{dist}} = \sum_{p \in P} ||T\mathbf{p}_\theta - m(p)||^2$$

Hard Constraint



$$E_{\text{feat}} = \sum_{p \in P} -\log V_p(m(p))$$

Regression Model



$$E_{\text{pose}} = \min_{l \in L} \sum_{i}^{40} \frac{|\theta_i - \mu_l^l|^2}{(\sigma_i^l)^2}$$

Key Optimization Terms

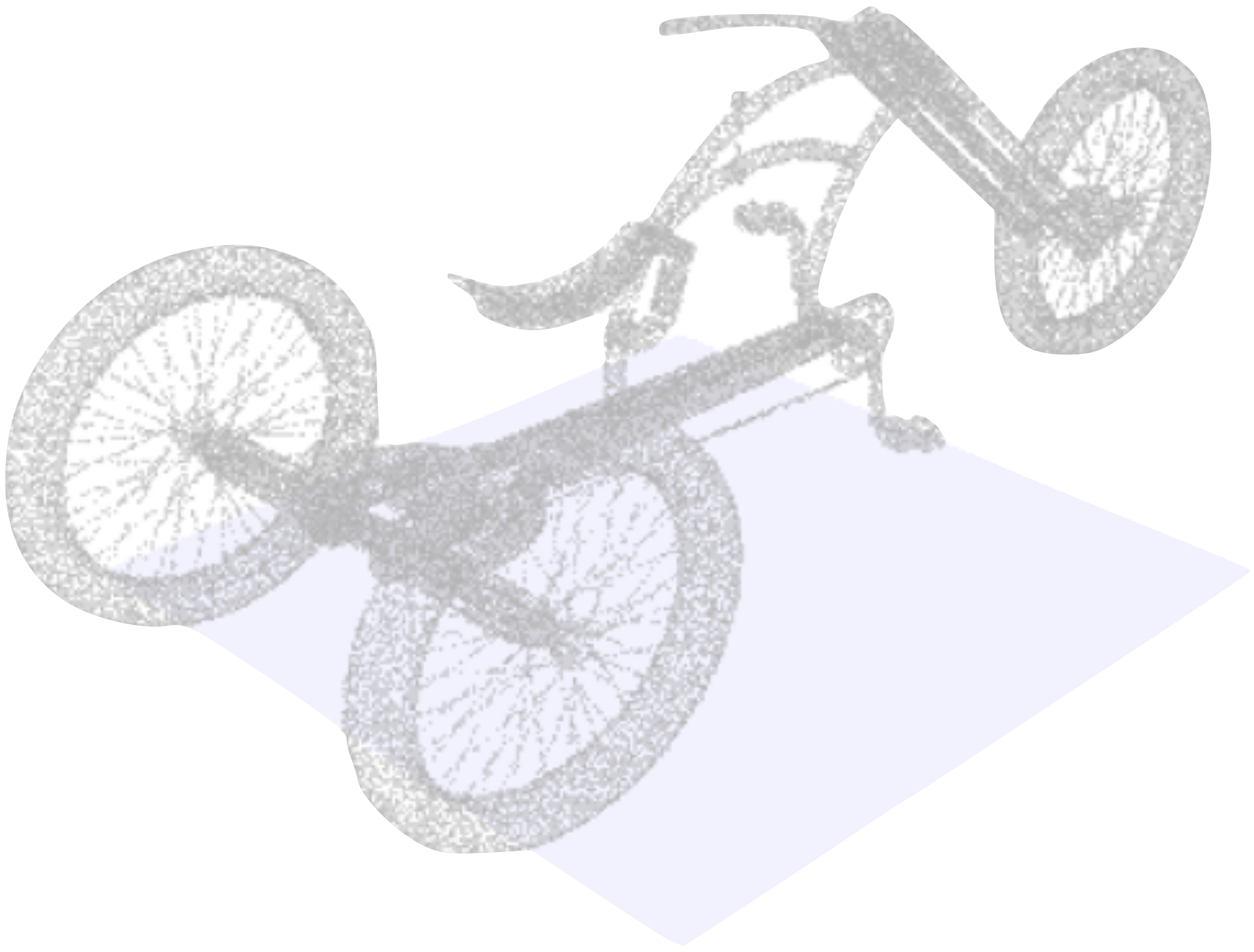
Solve for:

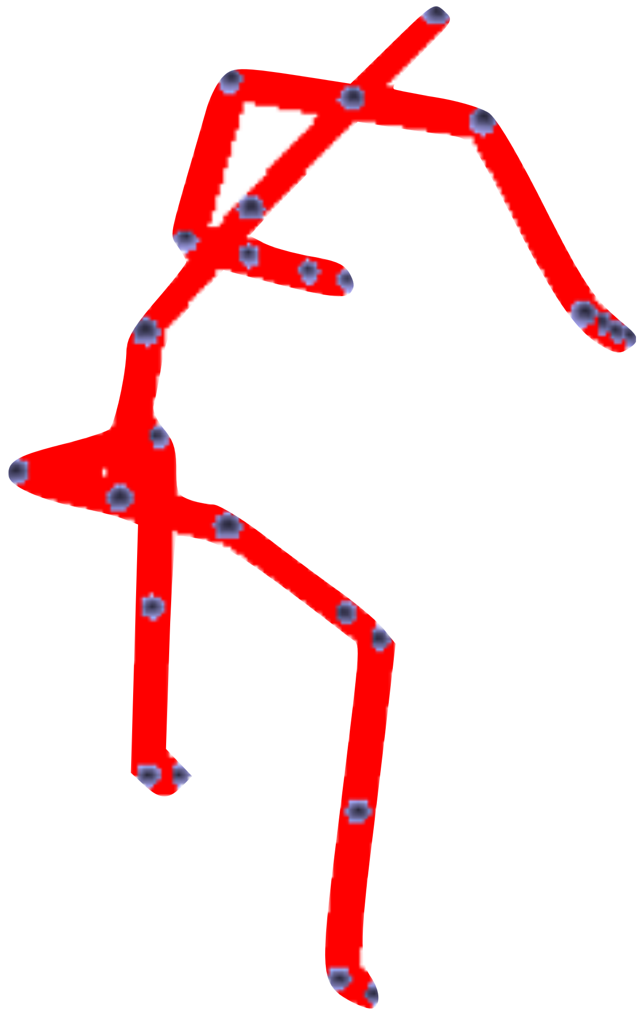
Body parts **Shape**

- Contact points $m : P \to S$
- Joint angles θ, T

Pose Prediction Algorithm

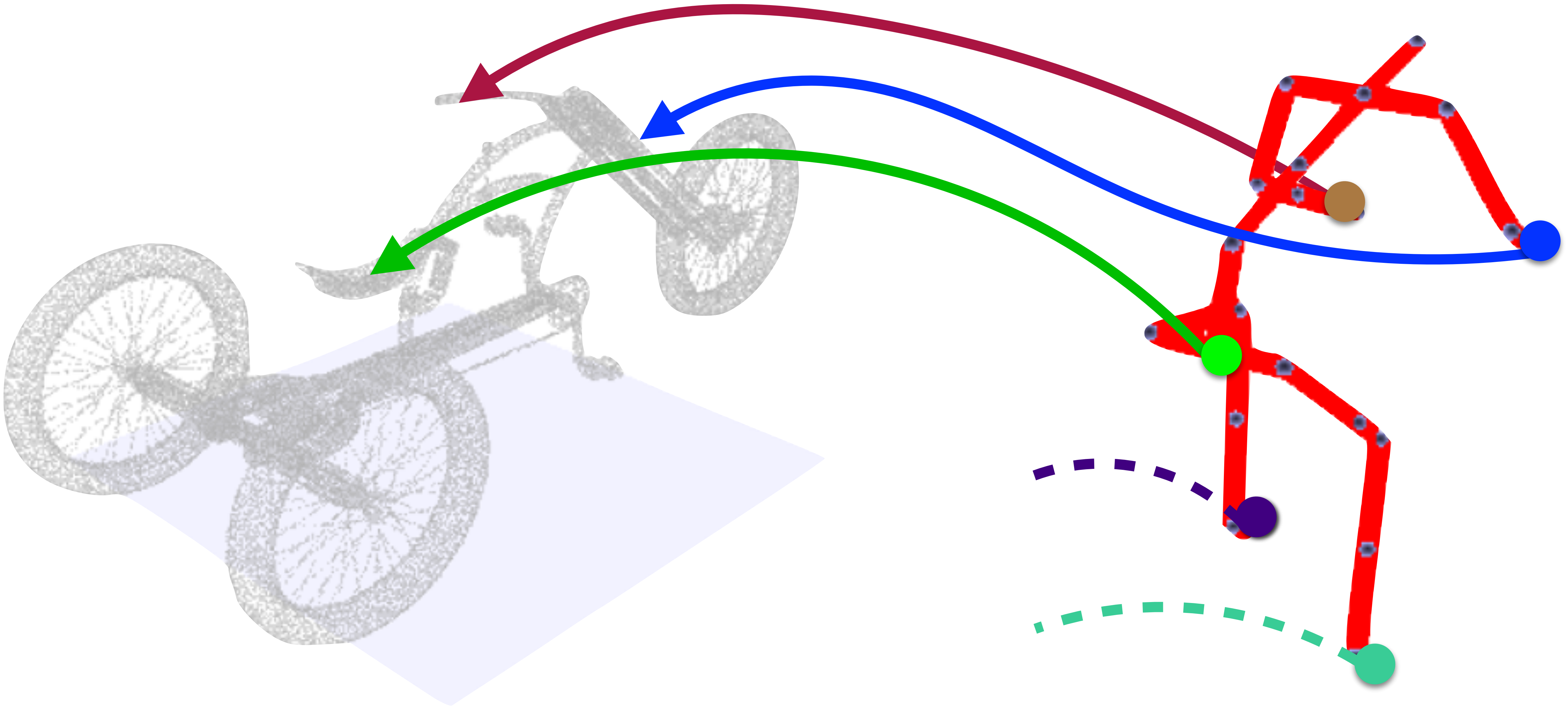
Input





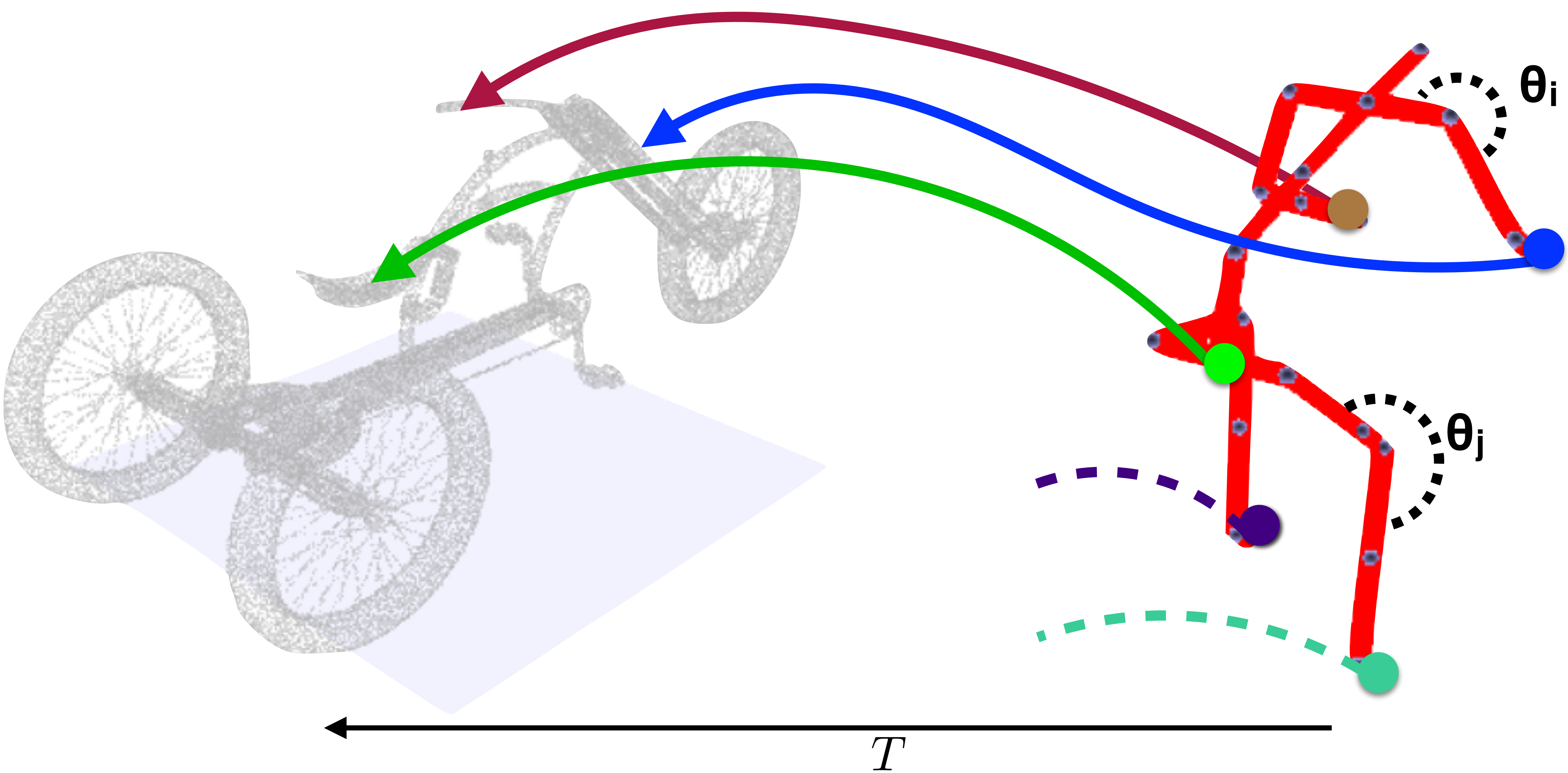
Pose Prediction Algorithm

Output: m



Pose Prediction Algorithm

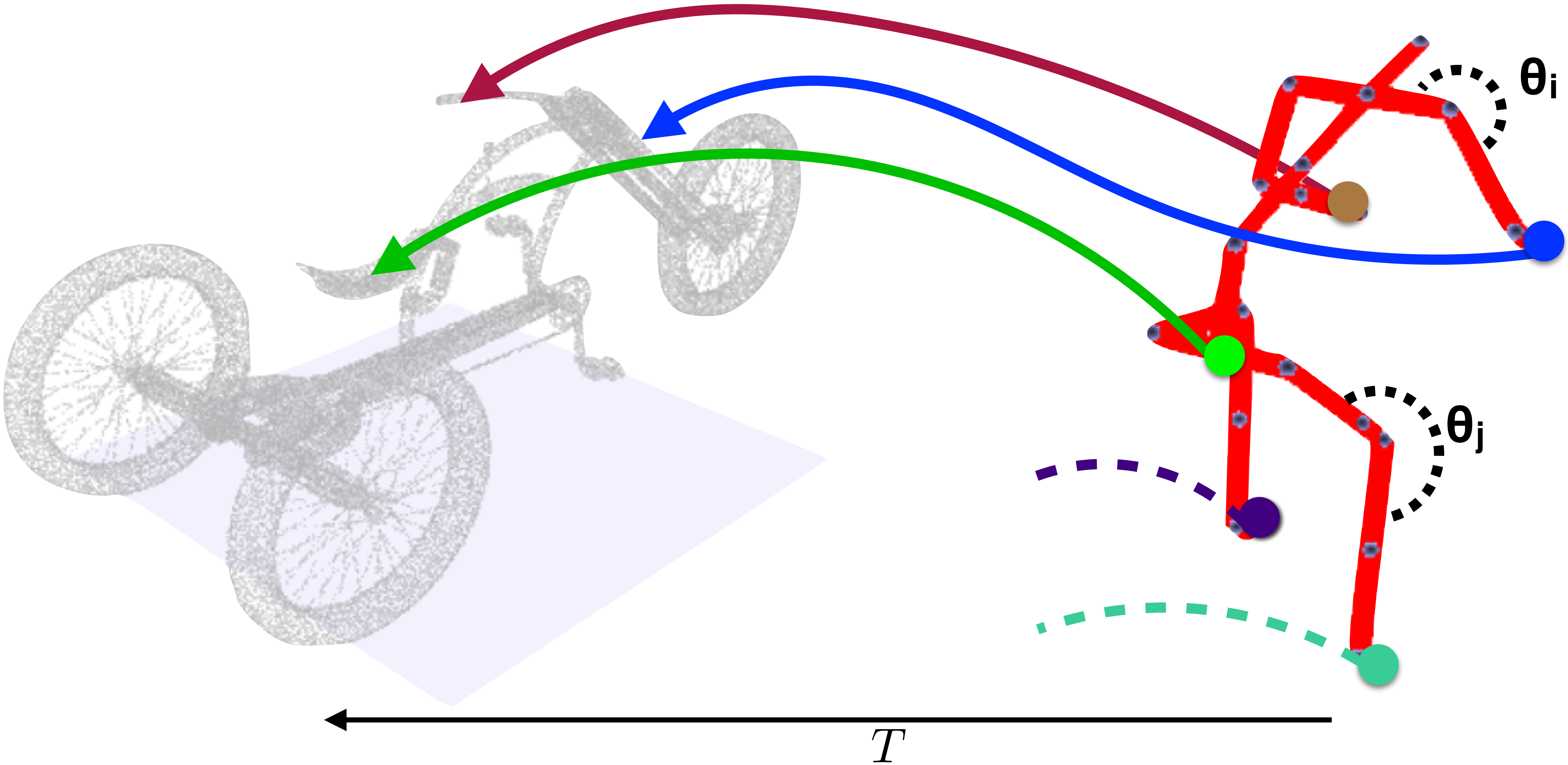
Output: m θ, T



Pose Prediction Algorithm

Output: $m \leftrightarrow \theta, T$

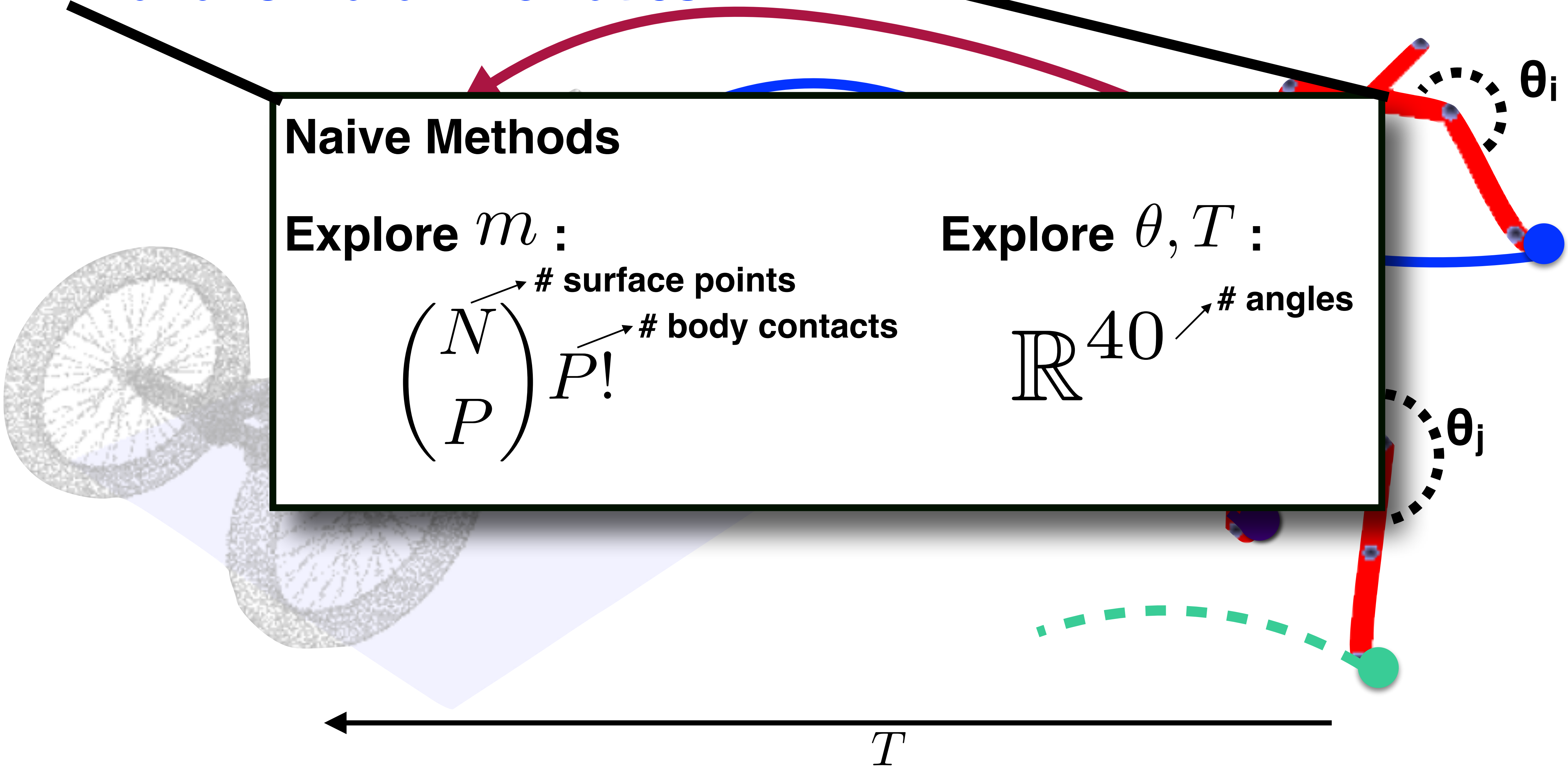
Related via inverse and forward kinematics



Pose Prediction Algorithm

Output: $m \longleftrightarrow \theta, T$

Related via inverse and forward kinematics



Naive Methods

Explore m **:**

surface points

body contacts

$$\binom{N}{P} P!$$

Explore θ, T **:**

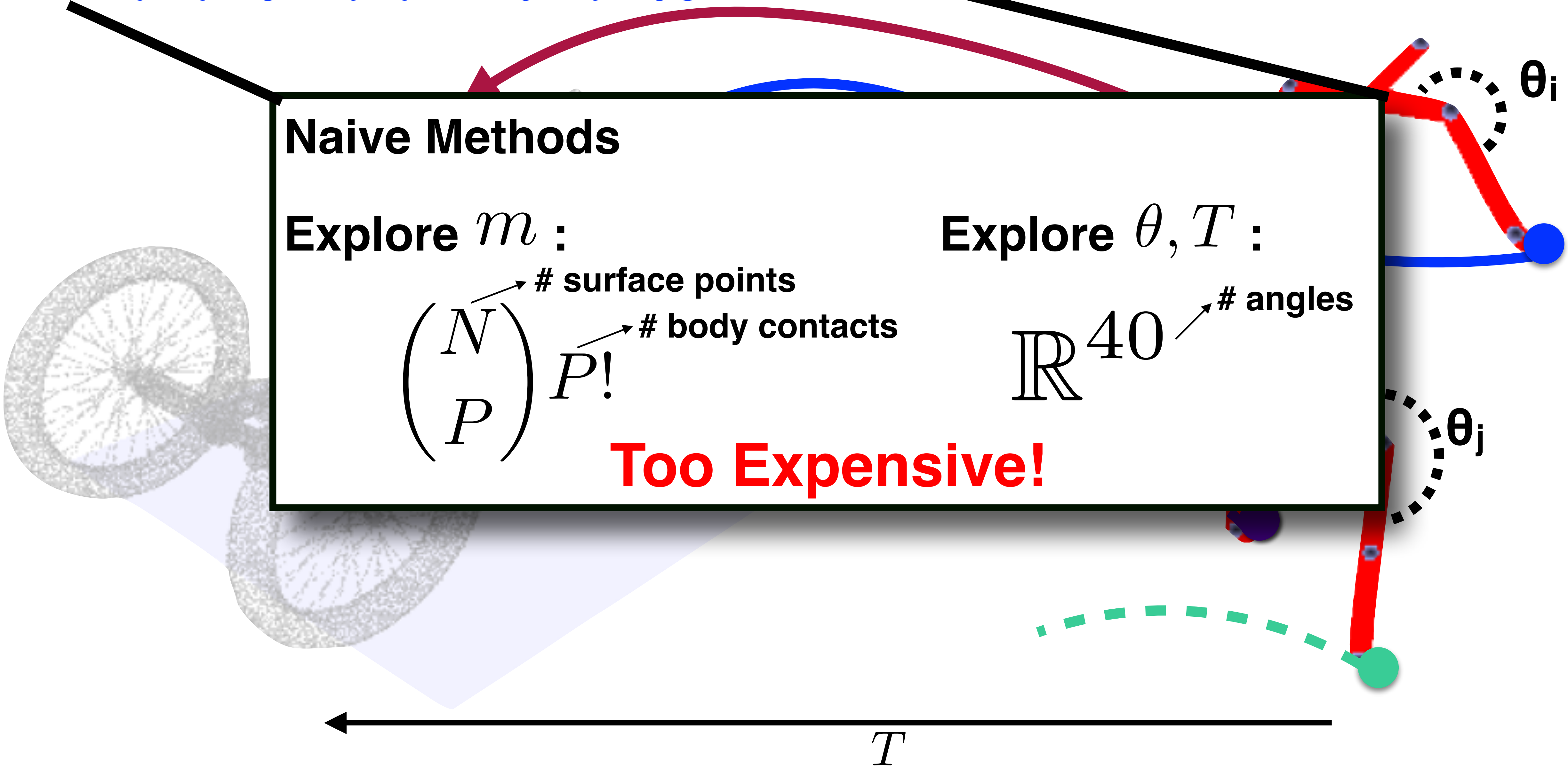
angles

$$\mathbb{R}^{40}$$

Pose Prediction Algorithm

Output: $m \leftrightarrow \theta, T$

Related via inverse and forward kinematics



Naive Methods

Explore m **:**

$$\binom{N}{P} P!$$

N: # surface points

P: # body contacts

Explore θ, T **:**

$$\mathbb{R}^{40}$$

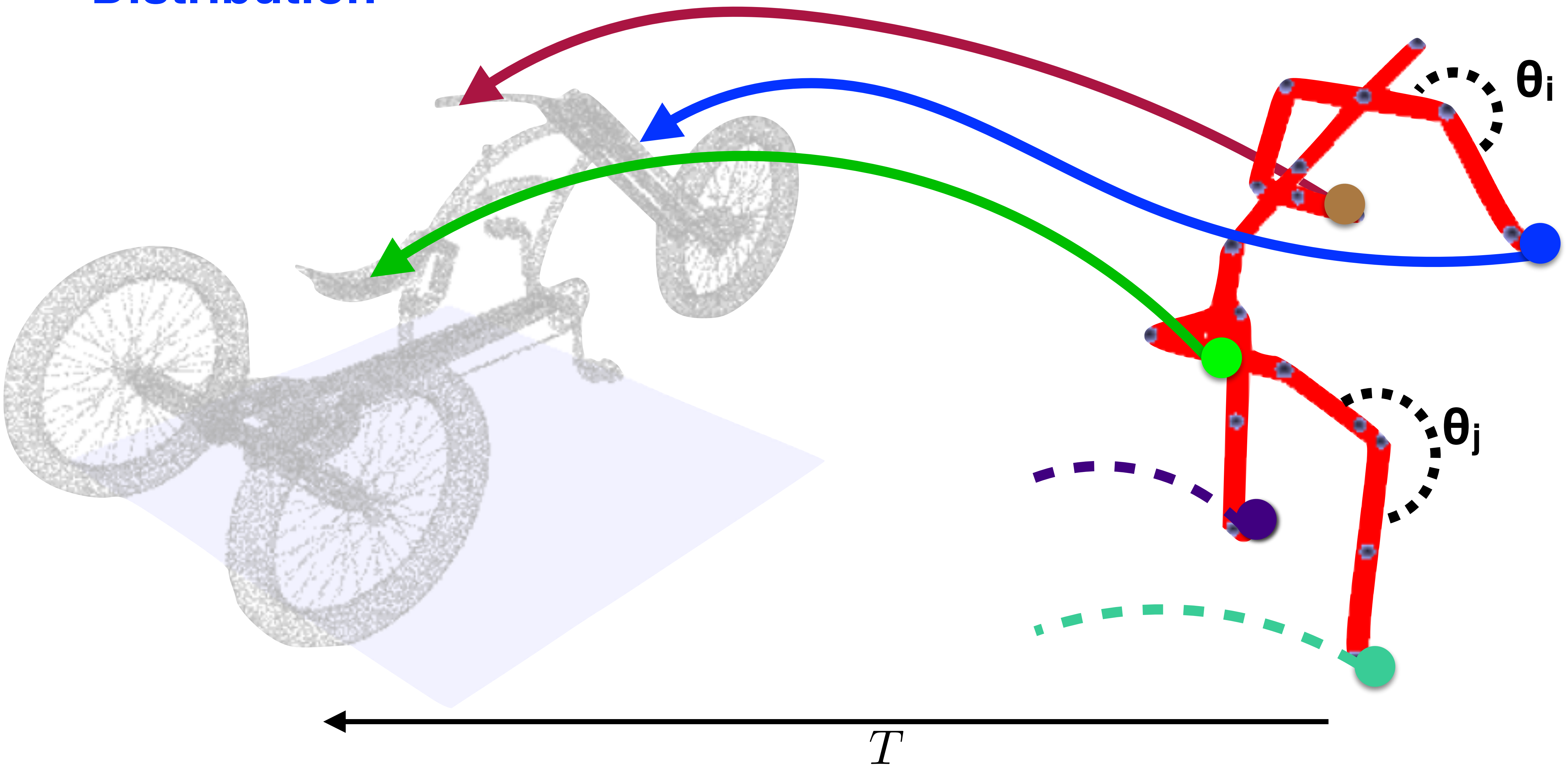
40: # angles

Too Expensive!

Pose Prediction Algorithm

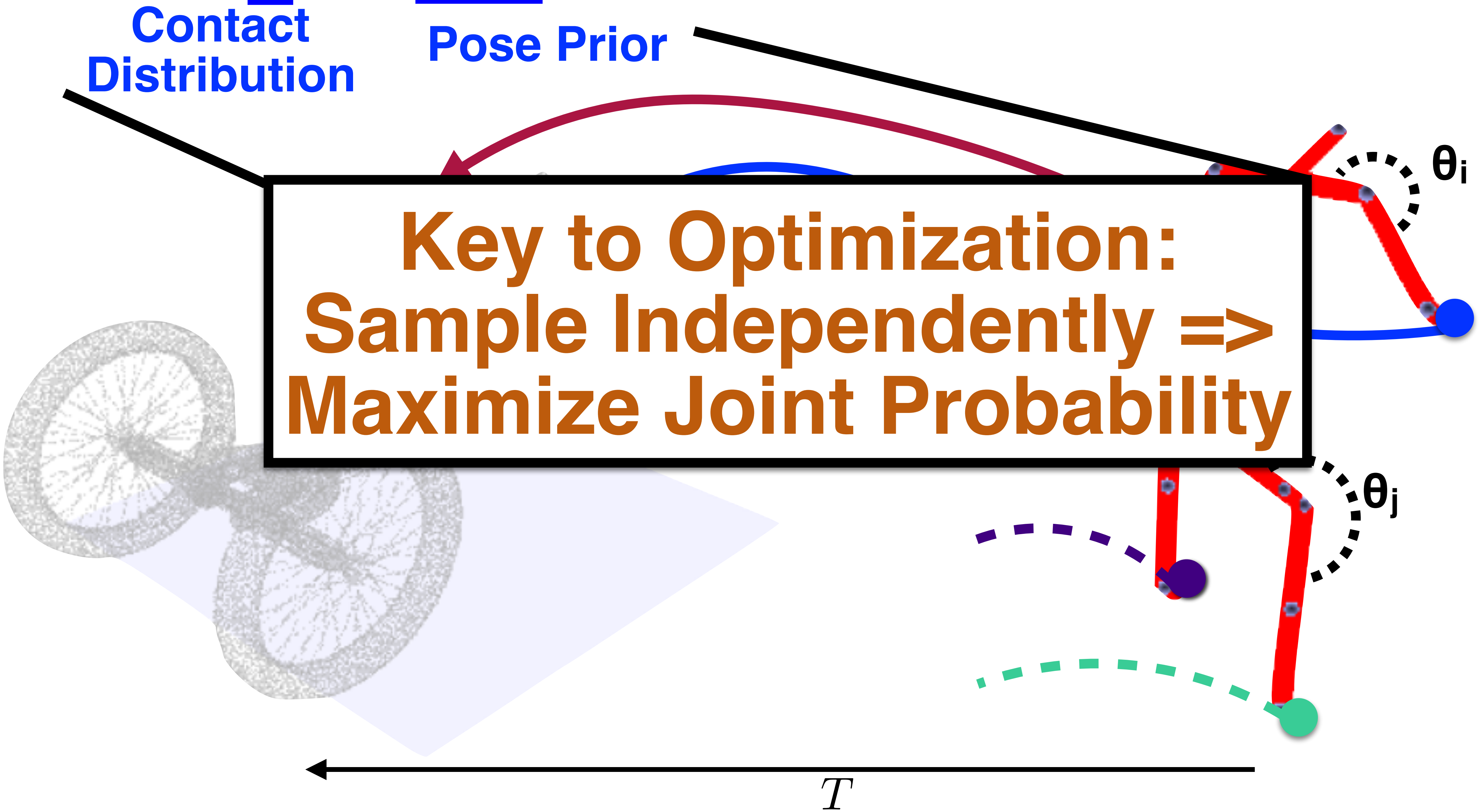
Output: $\underline{m}$ $\underline{\theta, T}$

Contact Distribution **Pose Prior**



Pose Prediction Algorithm

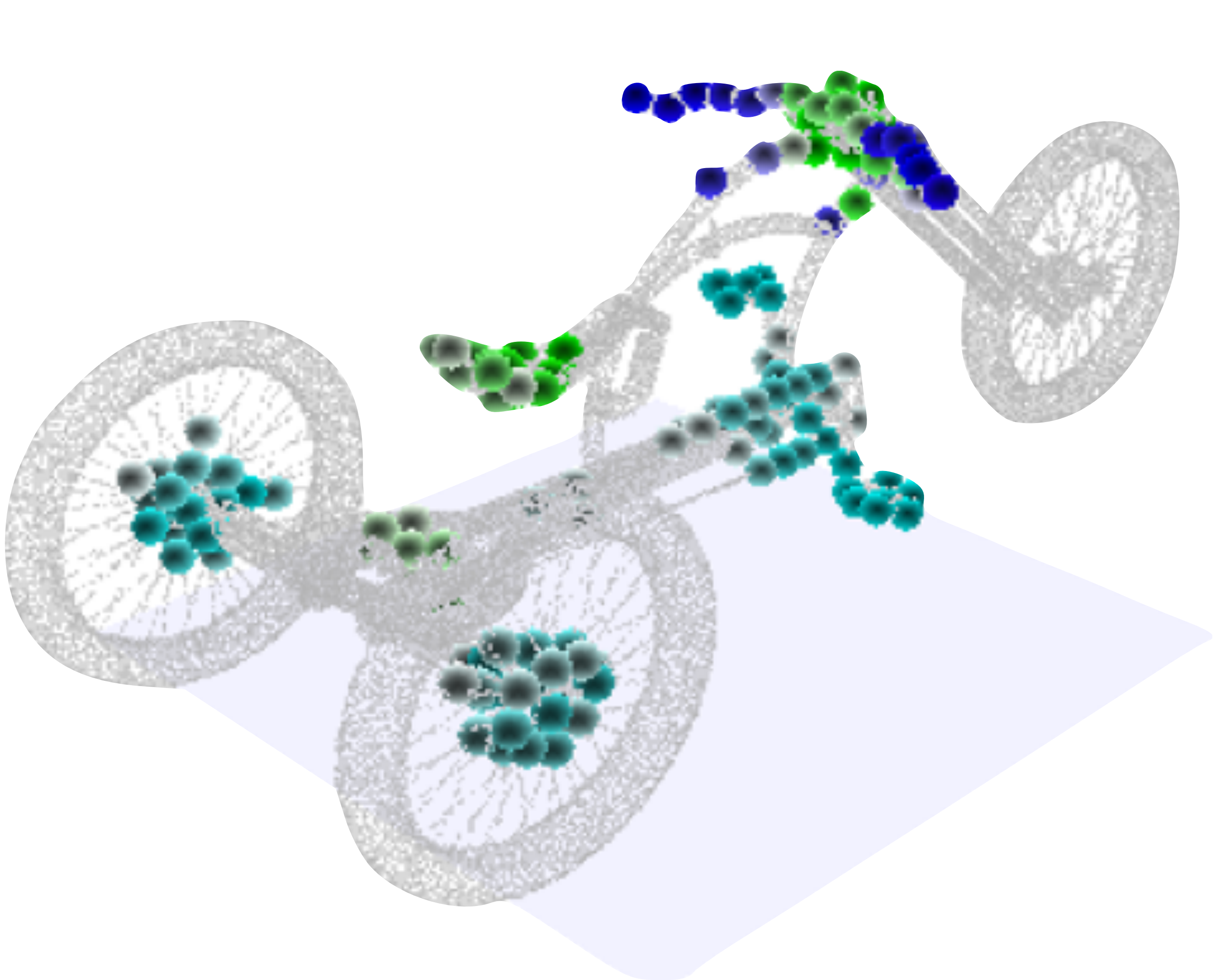
Output: $\underline{m}$ $\underline{\theta, T}$



Key to Optimization: Sample Independently => Maximize Joint Probability

Pose Prediction Algorithm

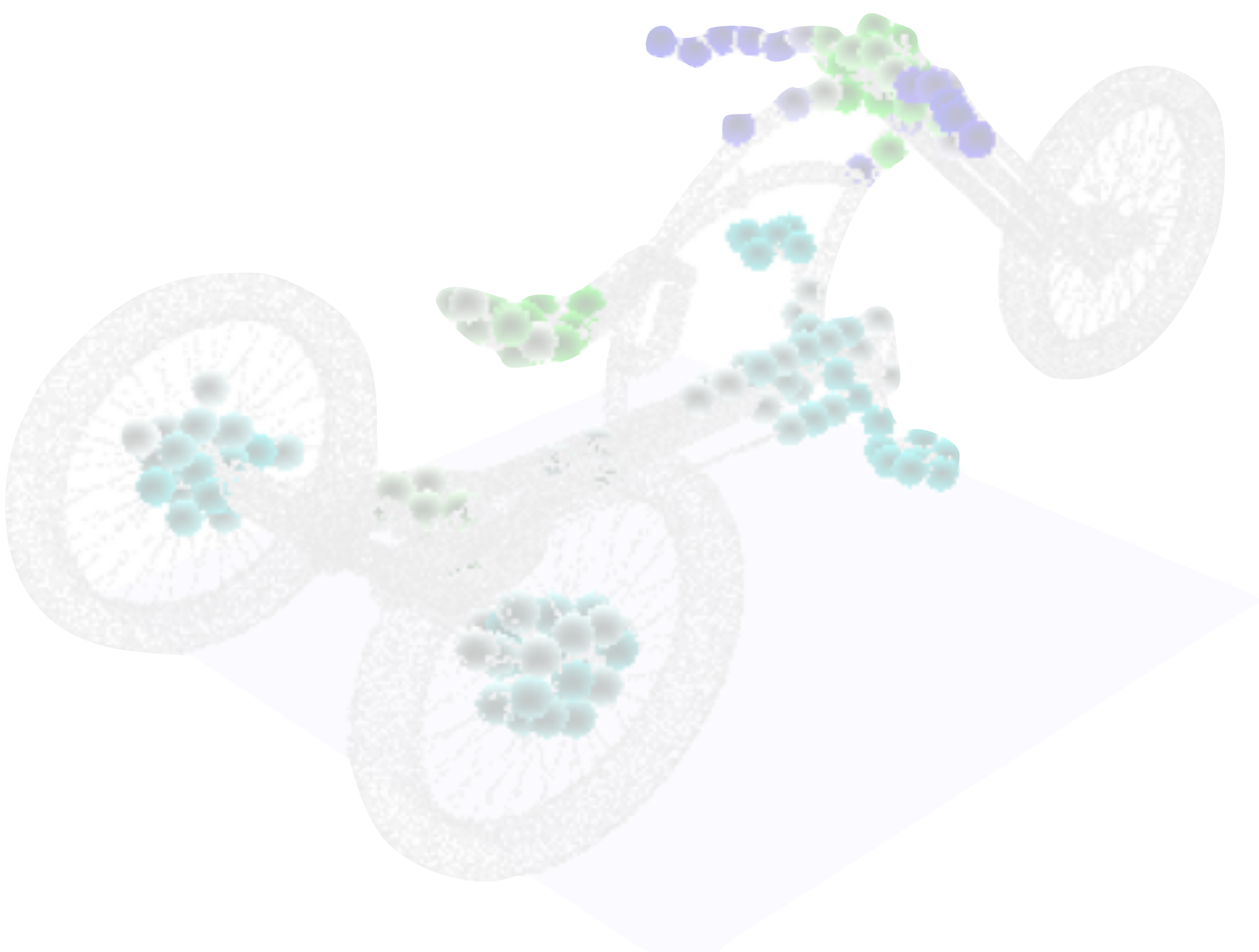
Sample m: classify surface based on local features

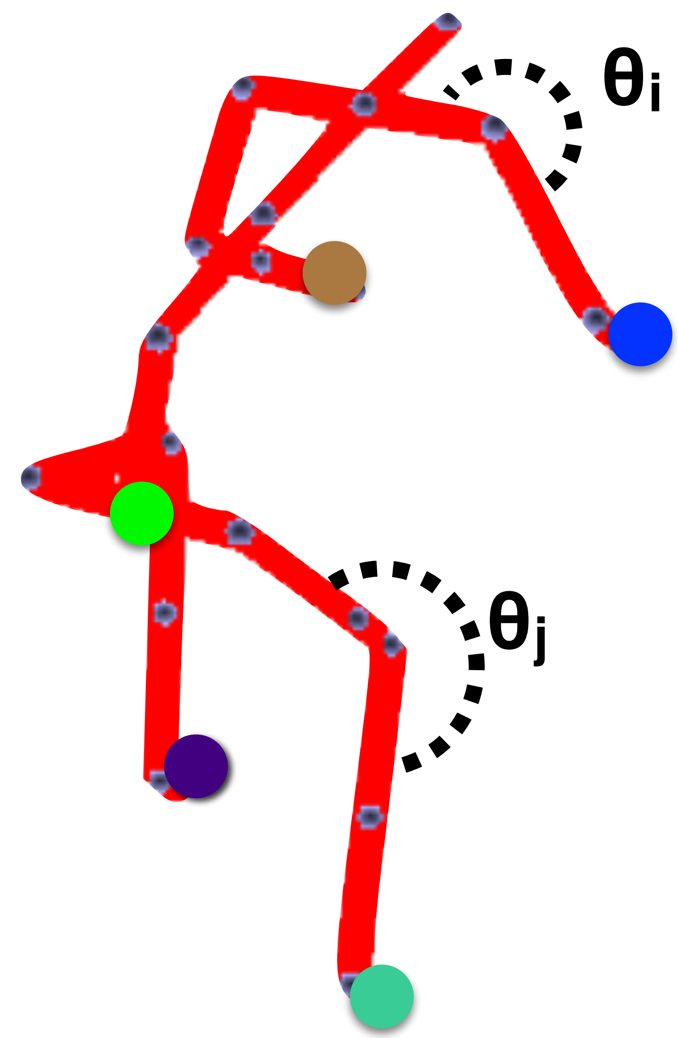


Contact Distribution

Pose Prediction Algorithm

Sample θ, T: Gaussian distributions

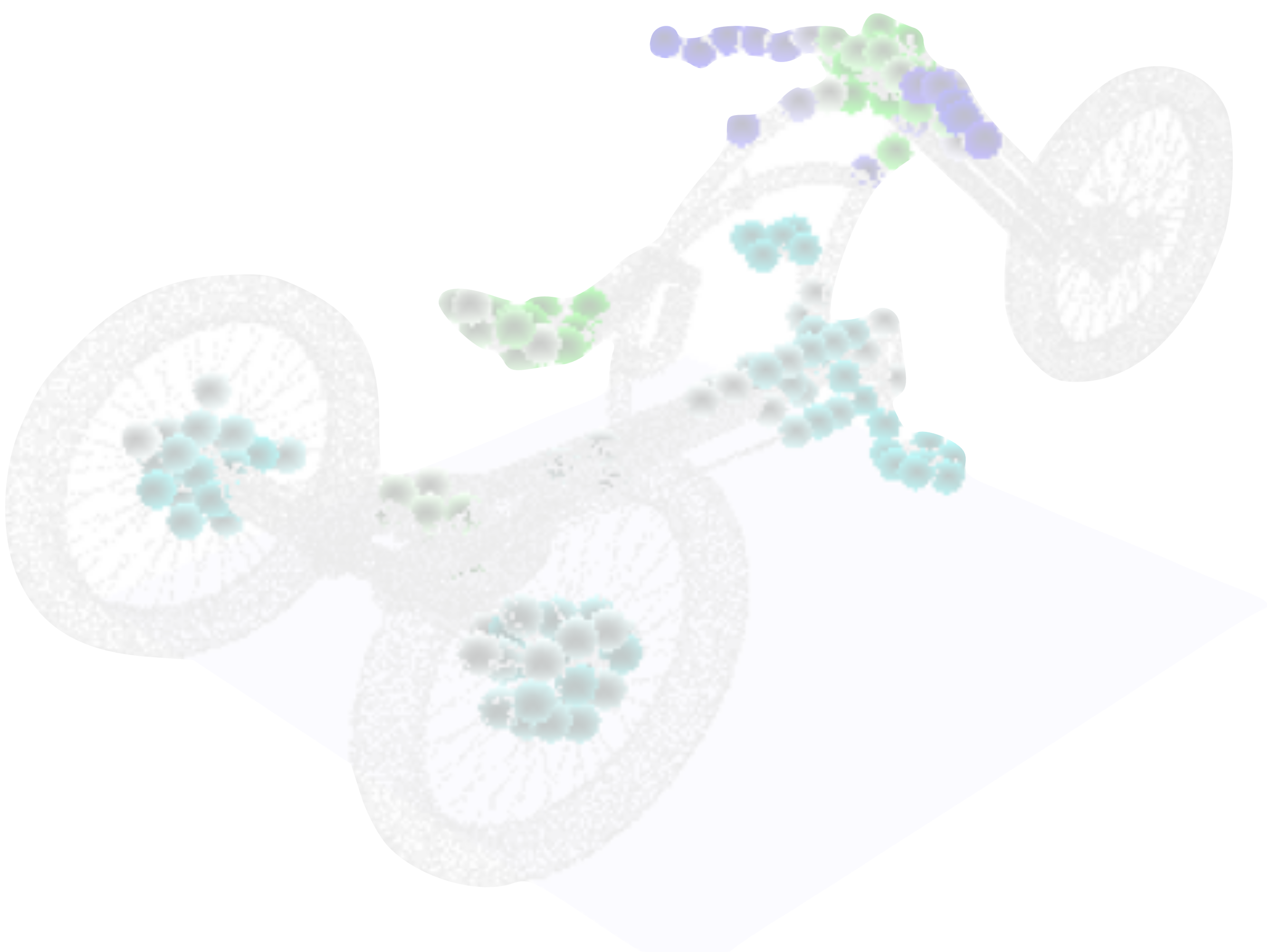




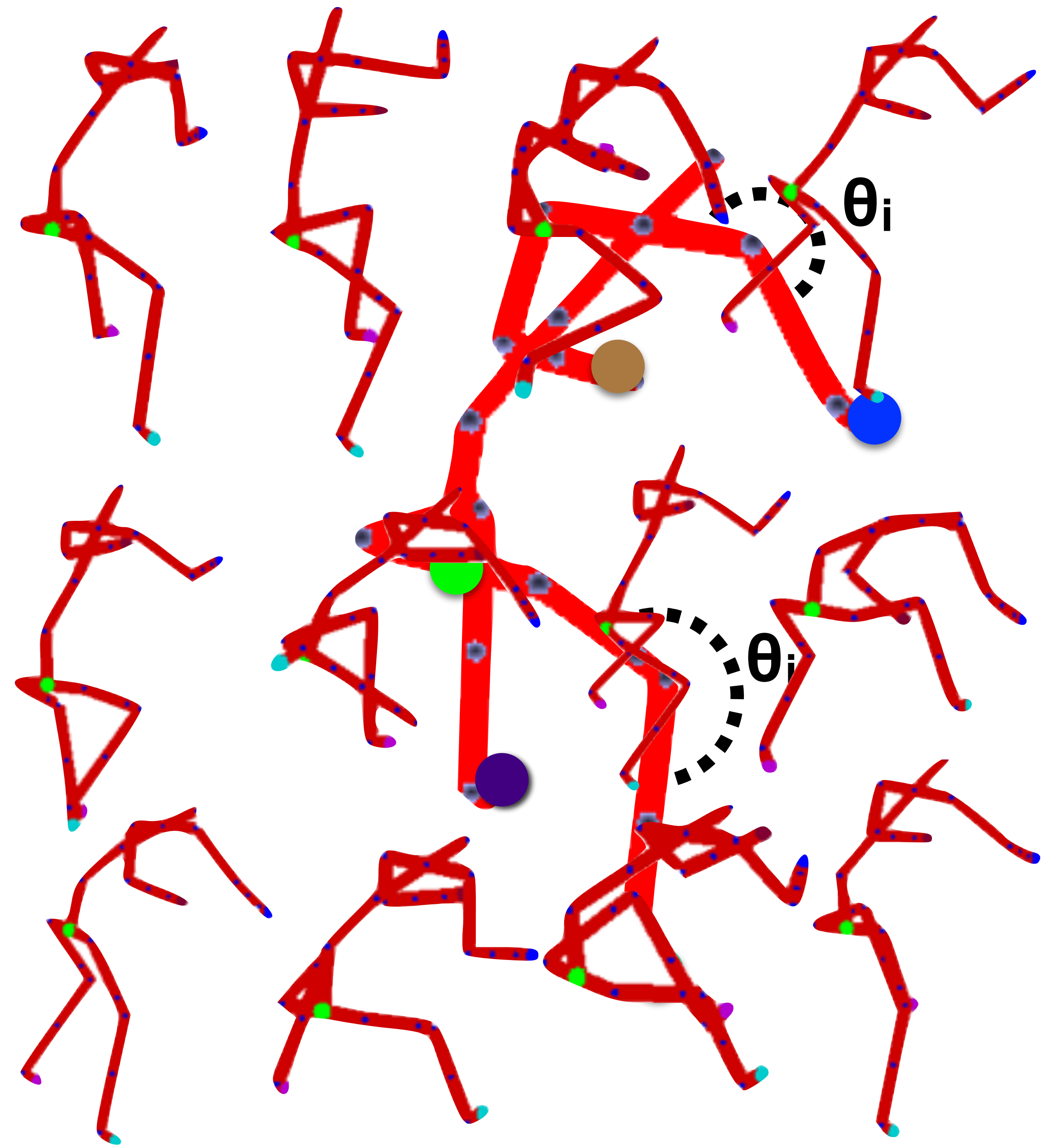
Contact Distribution

Pose Prediction Algorithm

Sample θ, T: Gaussian distributions



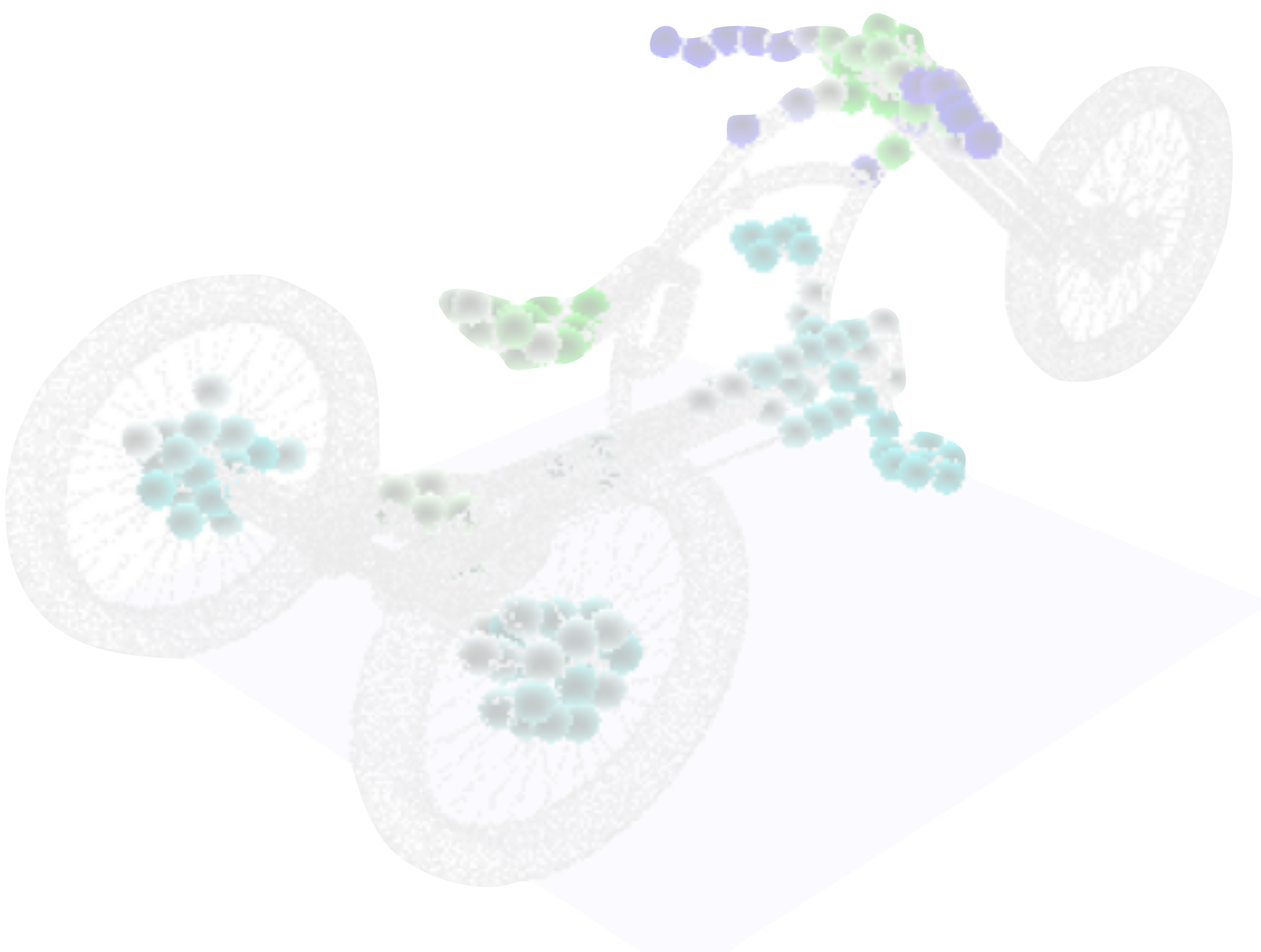
Contact Distribution



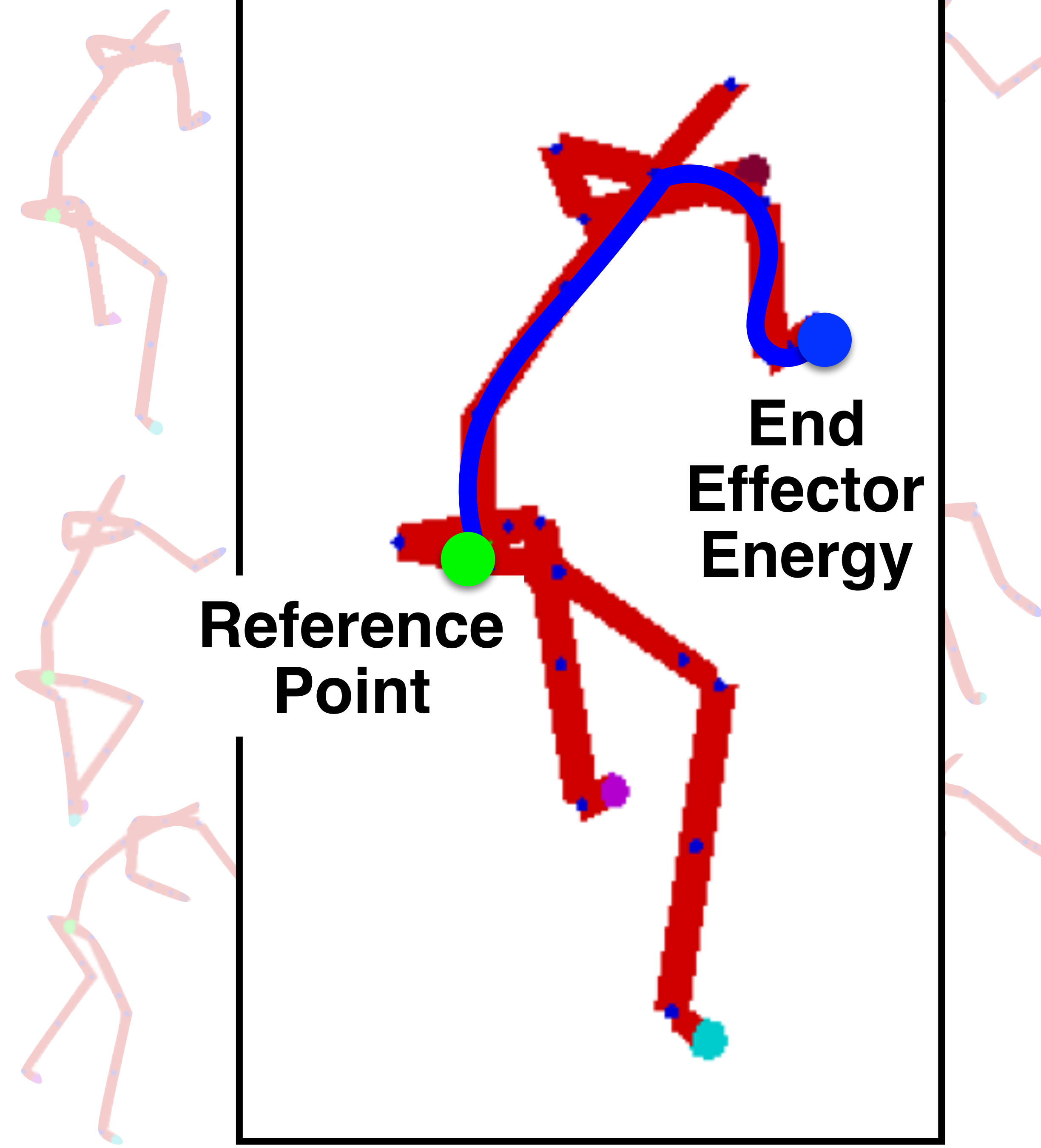
Sampled Poses

Pose Prediction Algorithm

Sample θ, T: Gaussian distributions



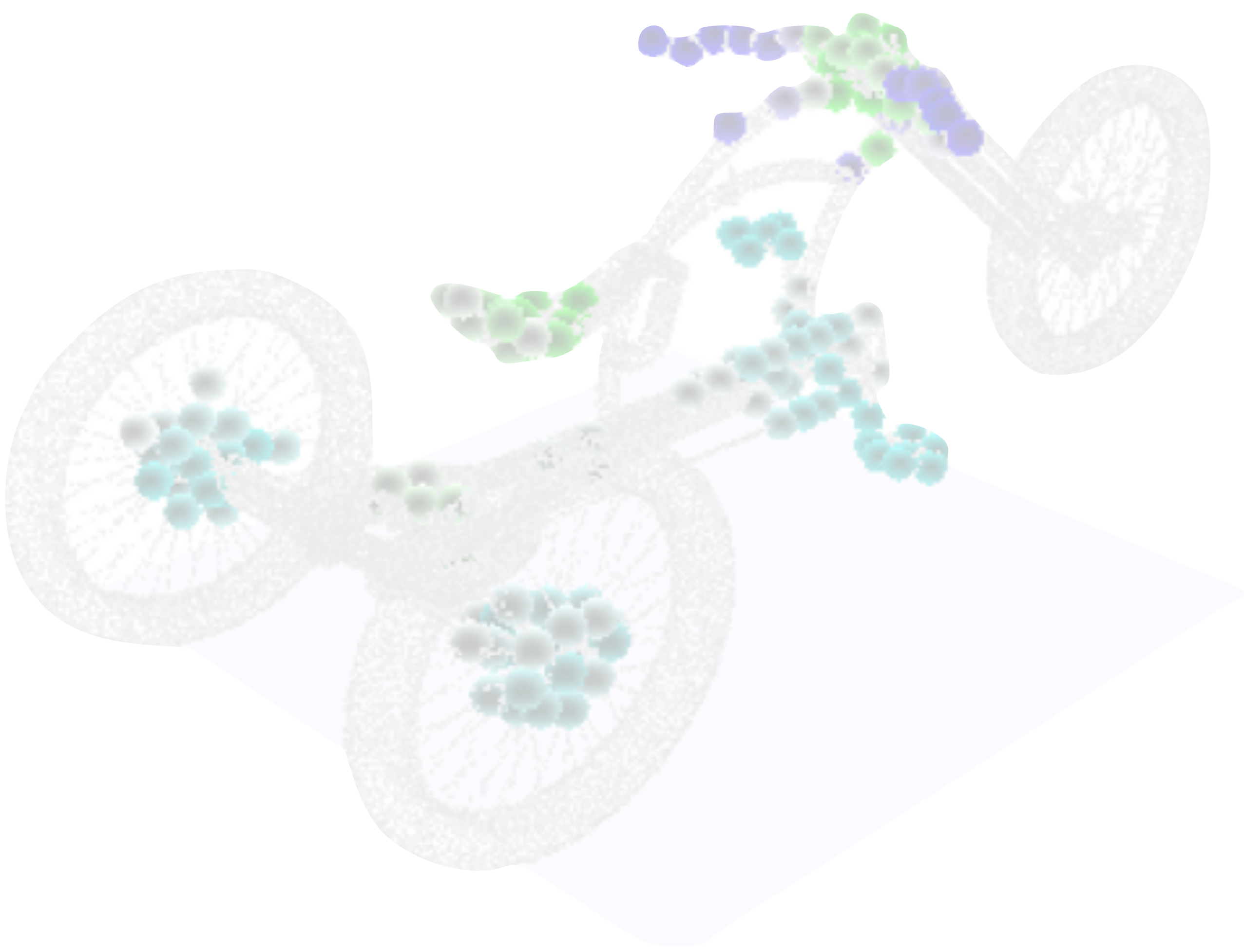
Contact Distribution

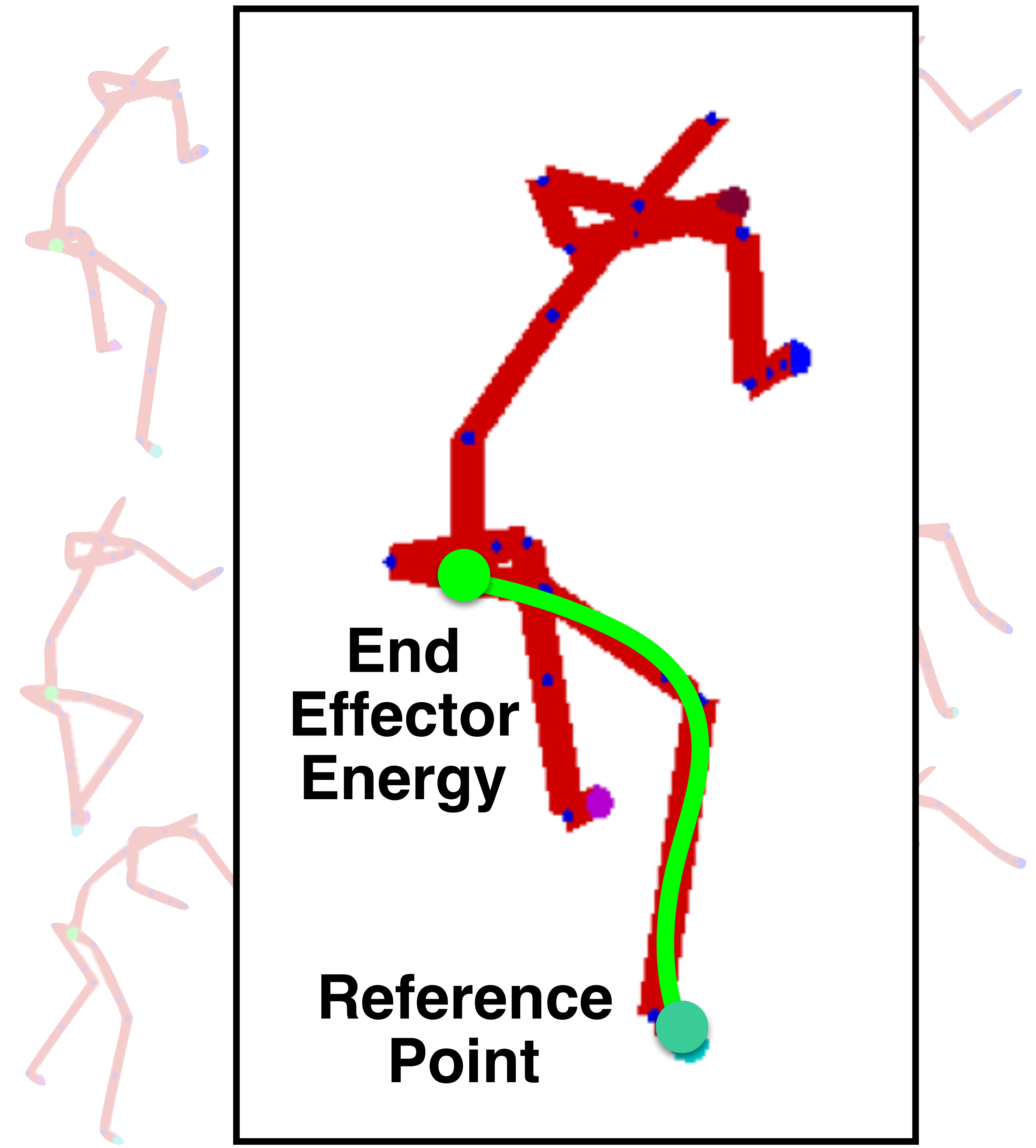


Sampled Poses

Pose Prediction Algorithm

Sample θ, T: Gaussian distributions





Contact Distribution

Sampled Poses

Pose Prediction Algorithm

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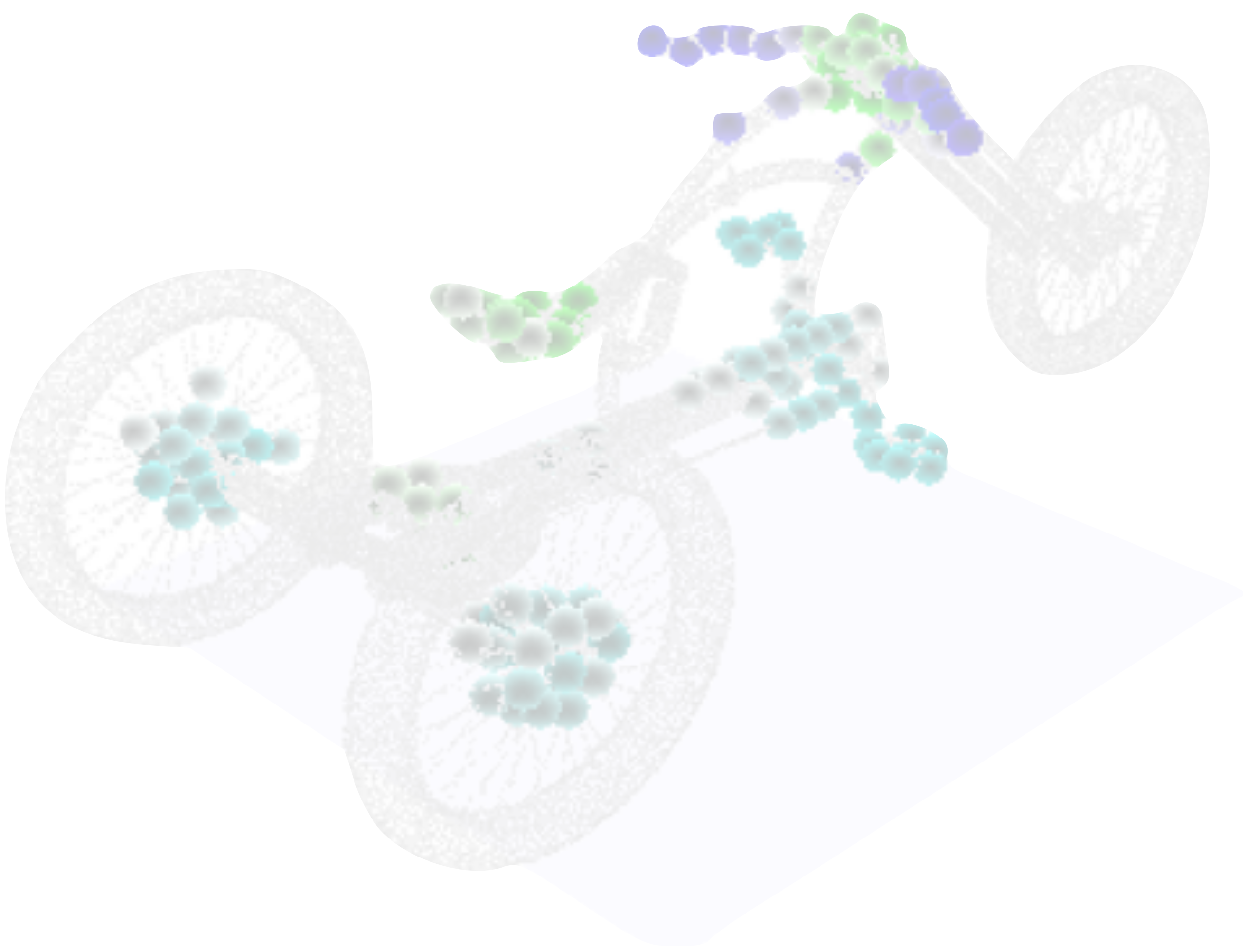
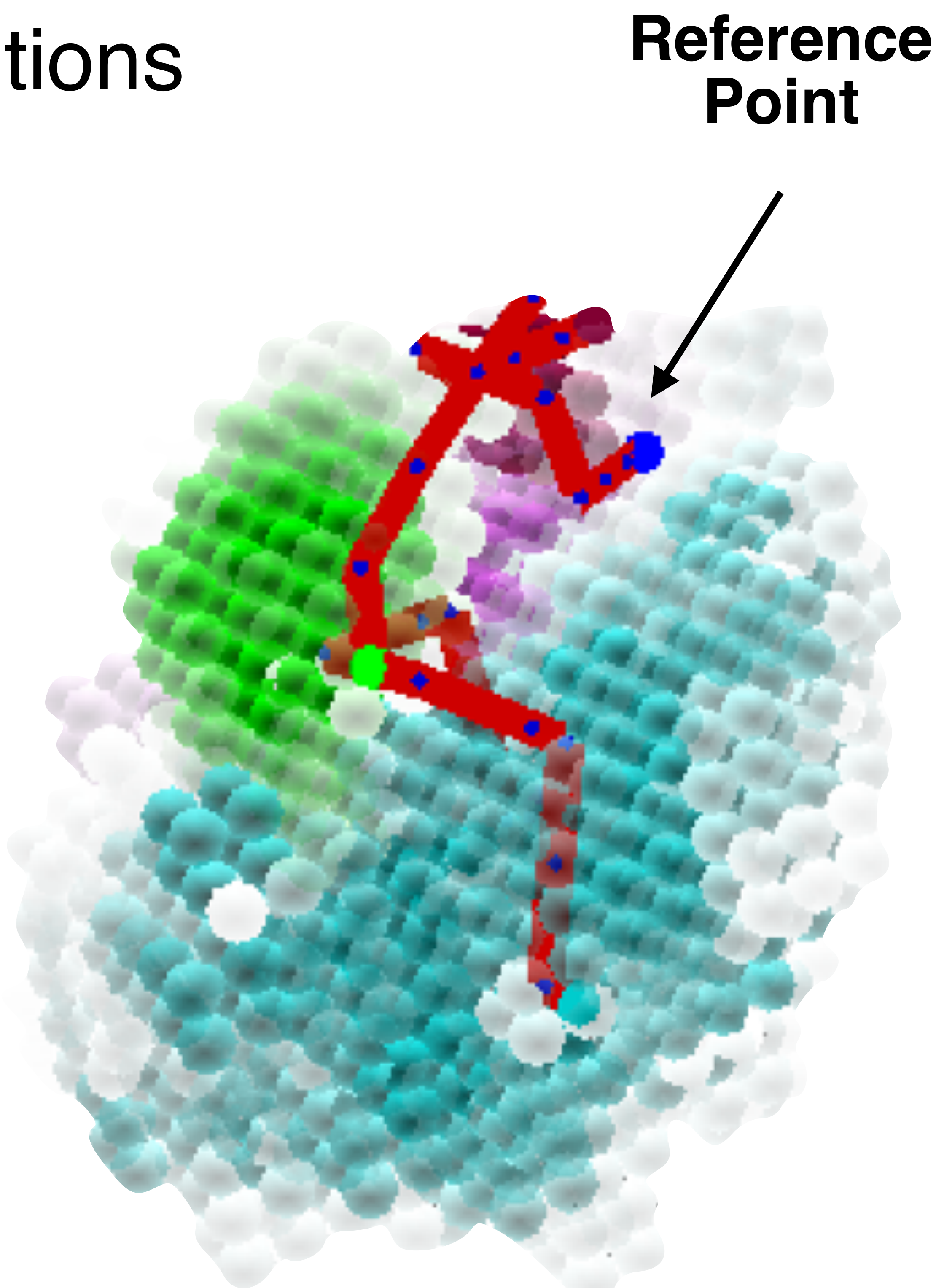


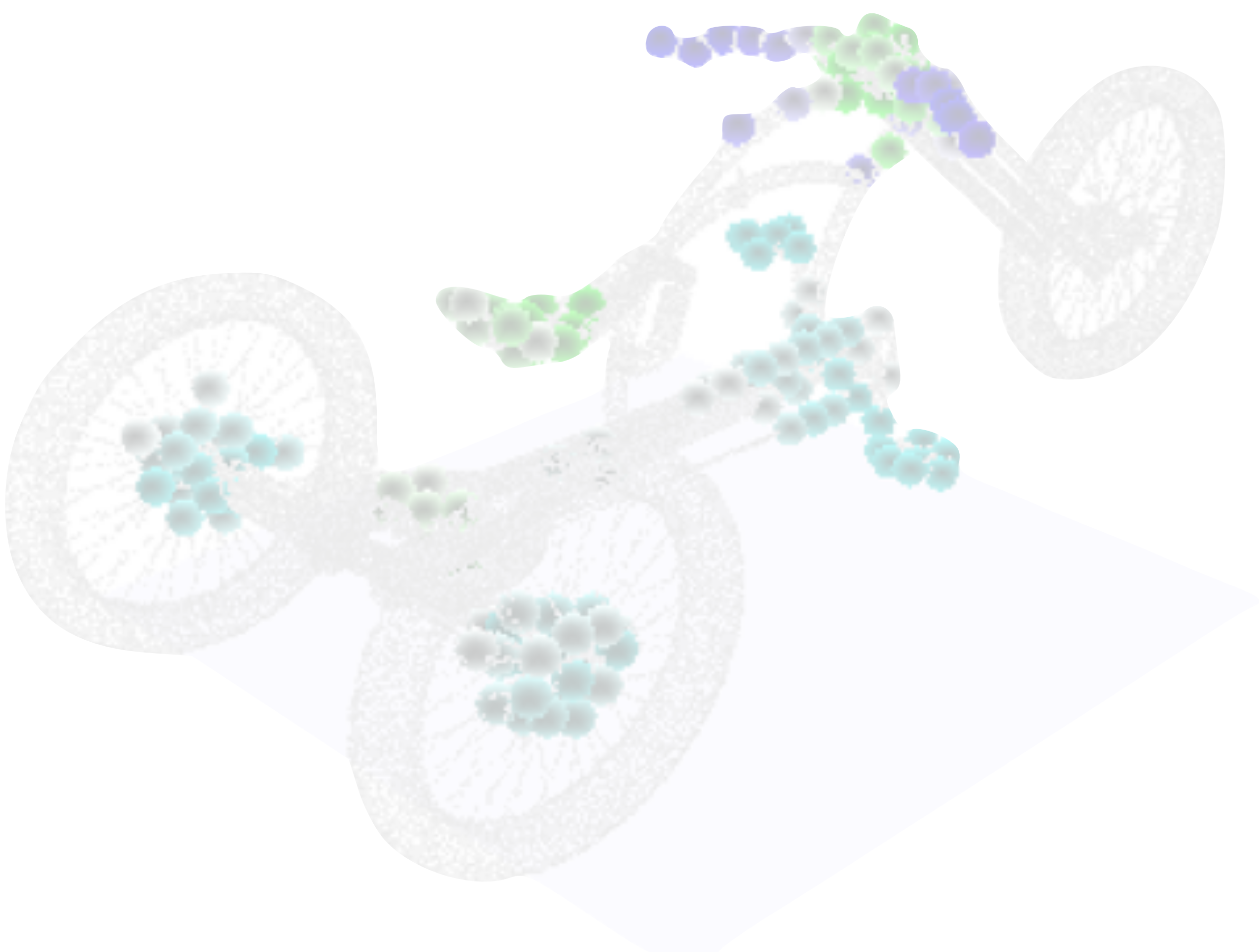
Contact Distribution

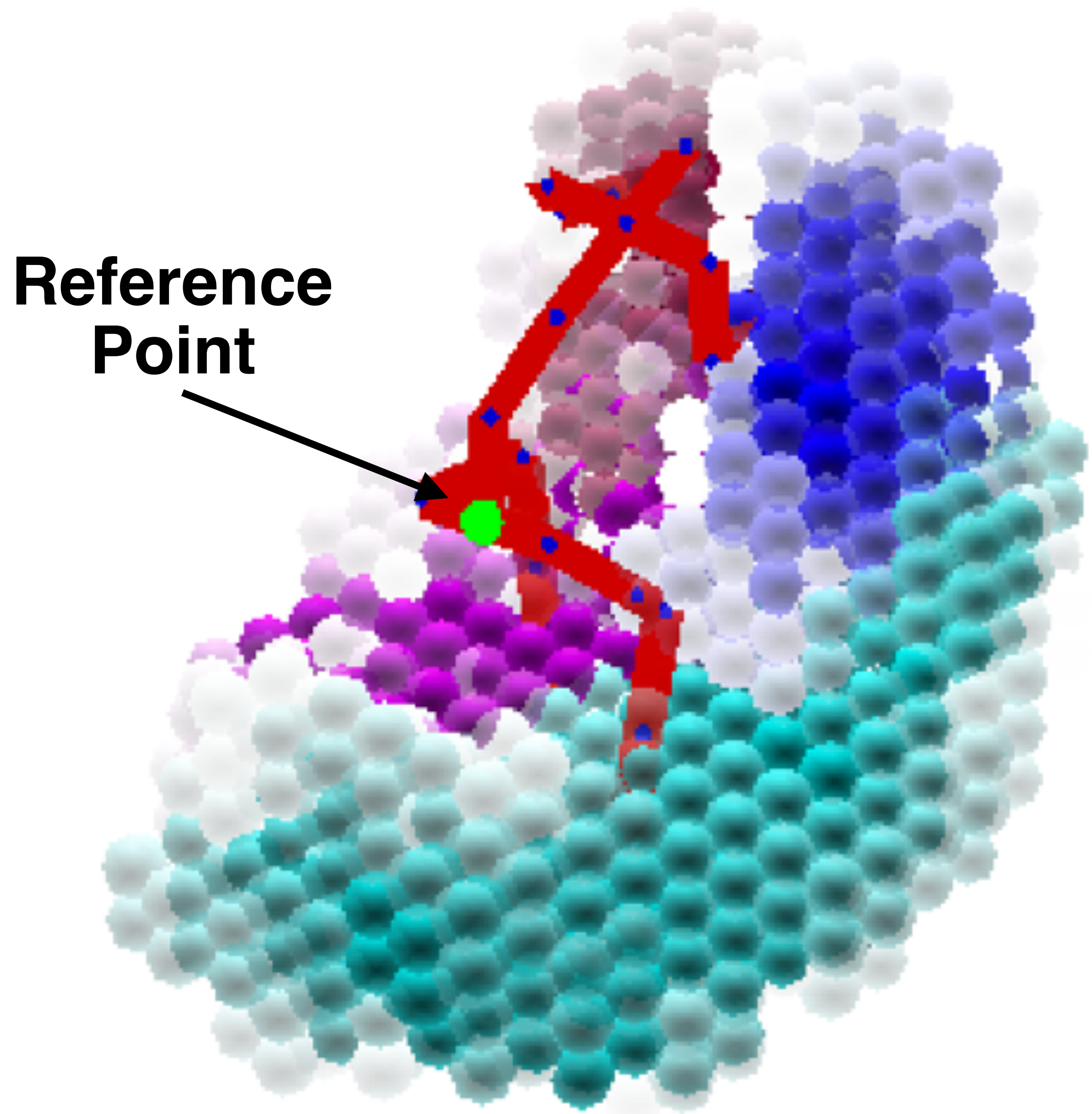


End Effector Distribution

Pose Prediction Algorithm

Sample θ, T: Gaussian distributions



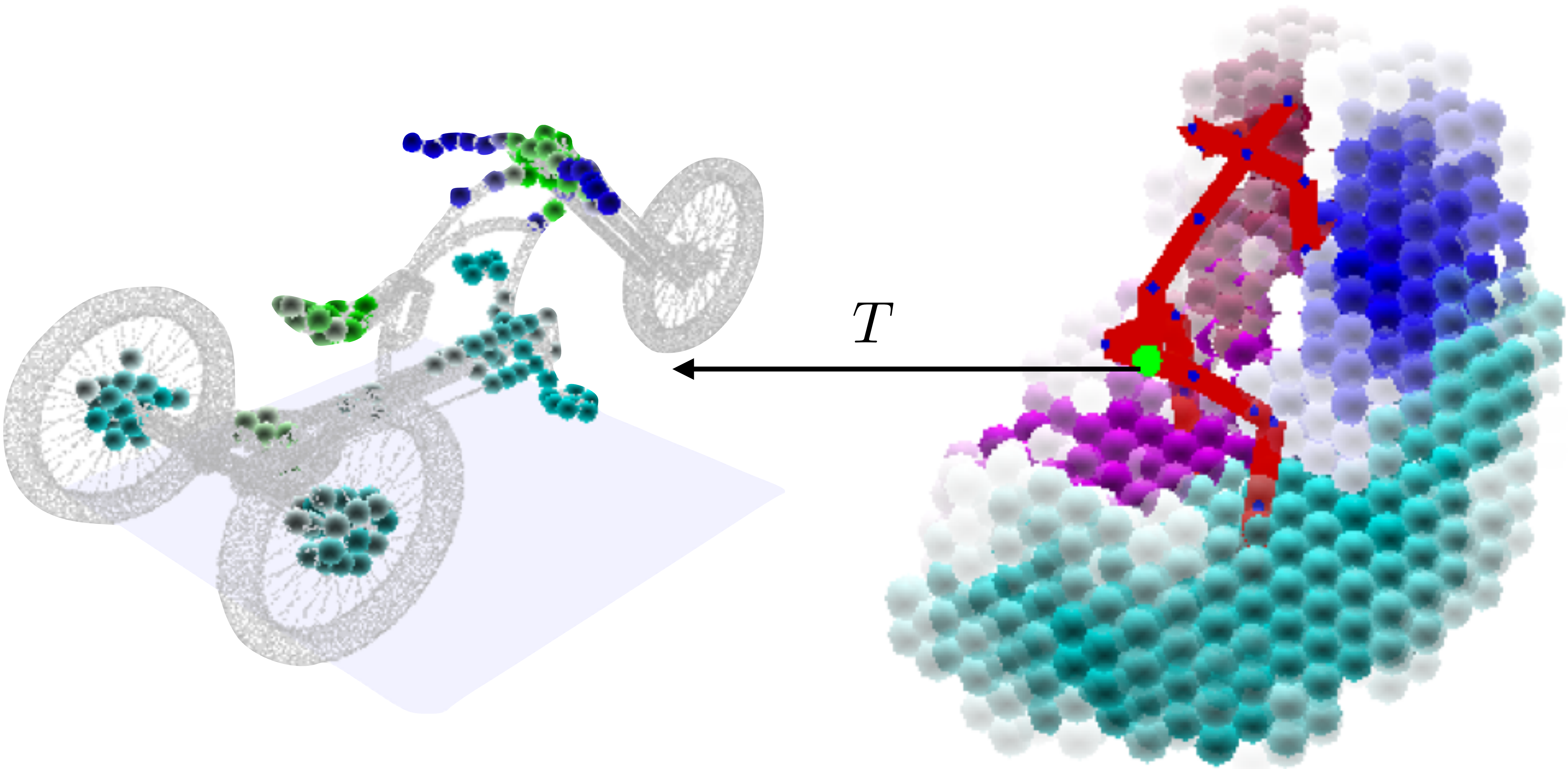


Contact Distribution

End Effector Distribution

Pose Prediction Algorithm

Sample θ, T: Gaussian distributions



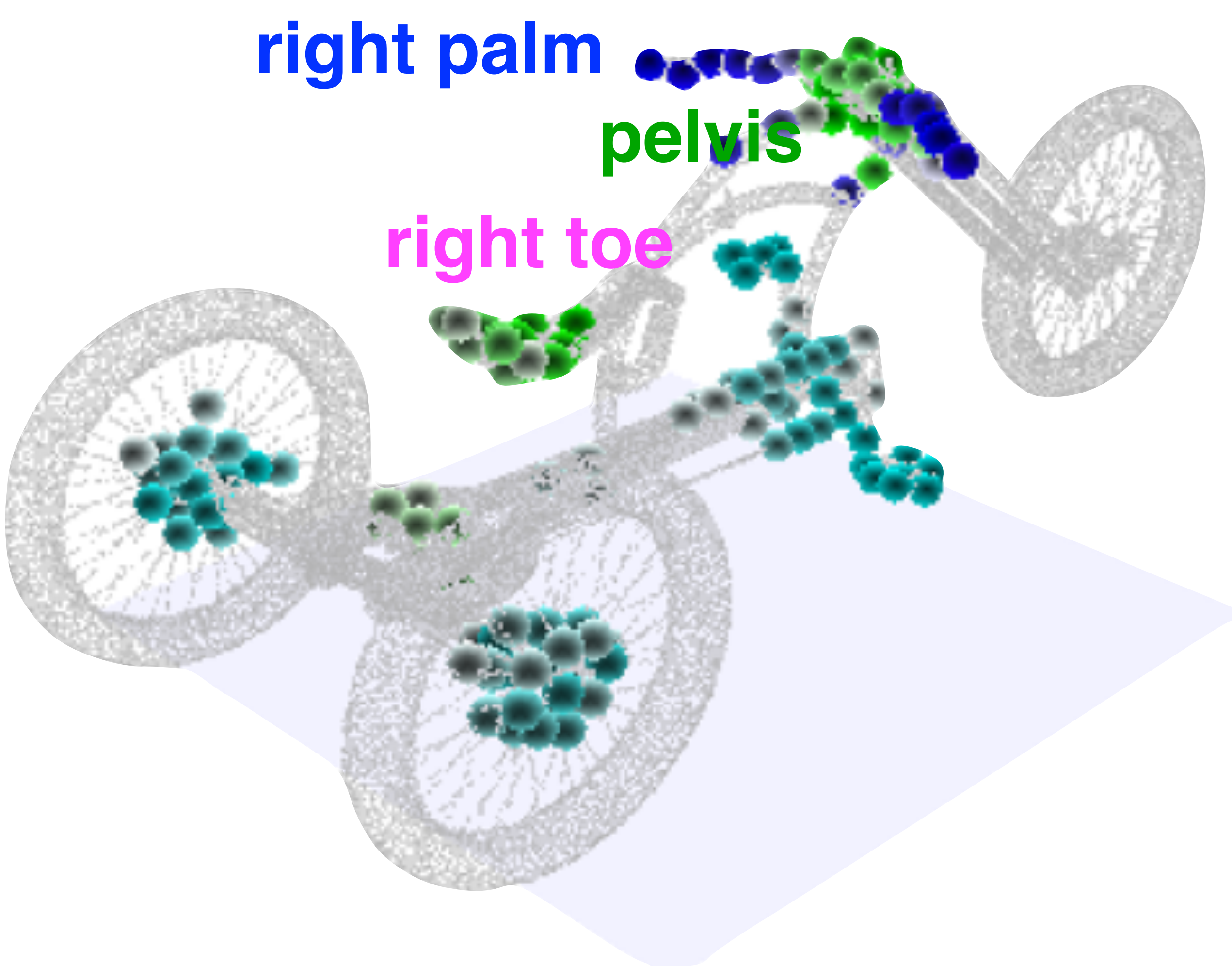
Contact Distribution

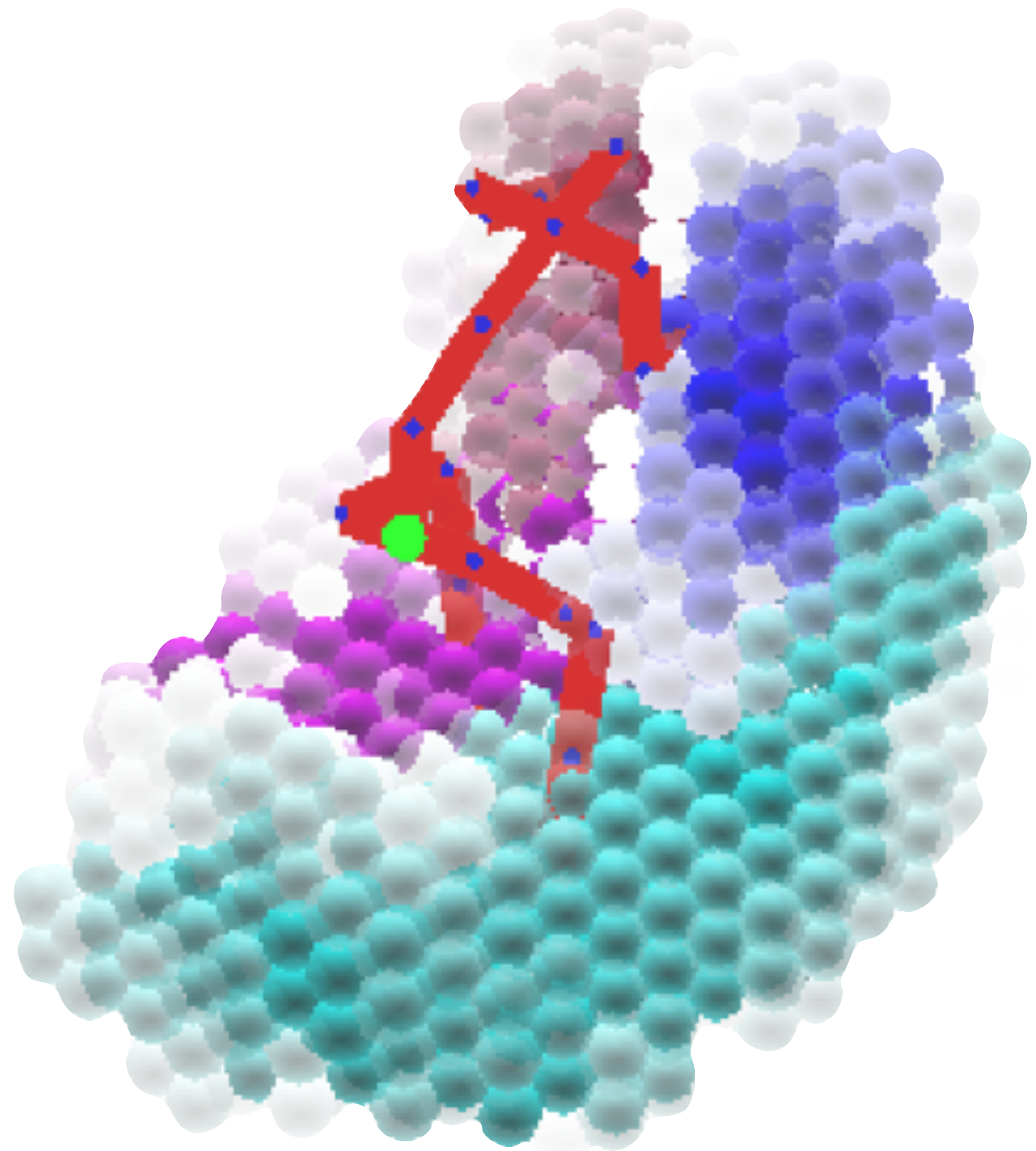
End Effector Distribution

Pose Prediction Algorithm

Sample global θ, T: Gaussian distributions

Pick peaks in the joint distribution





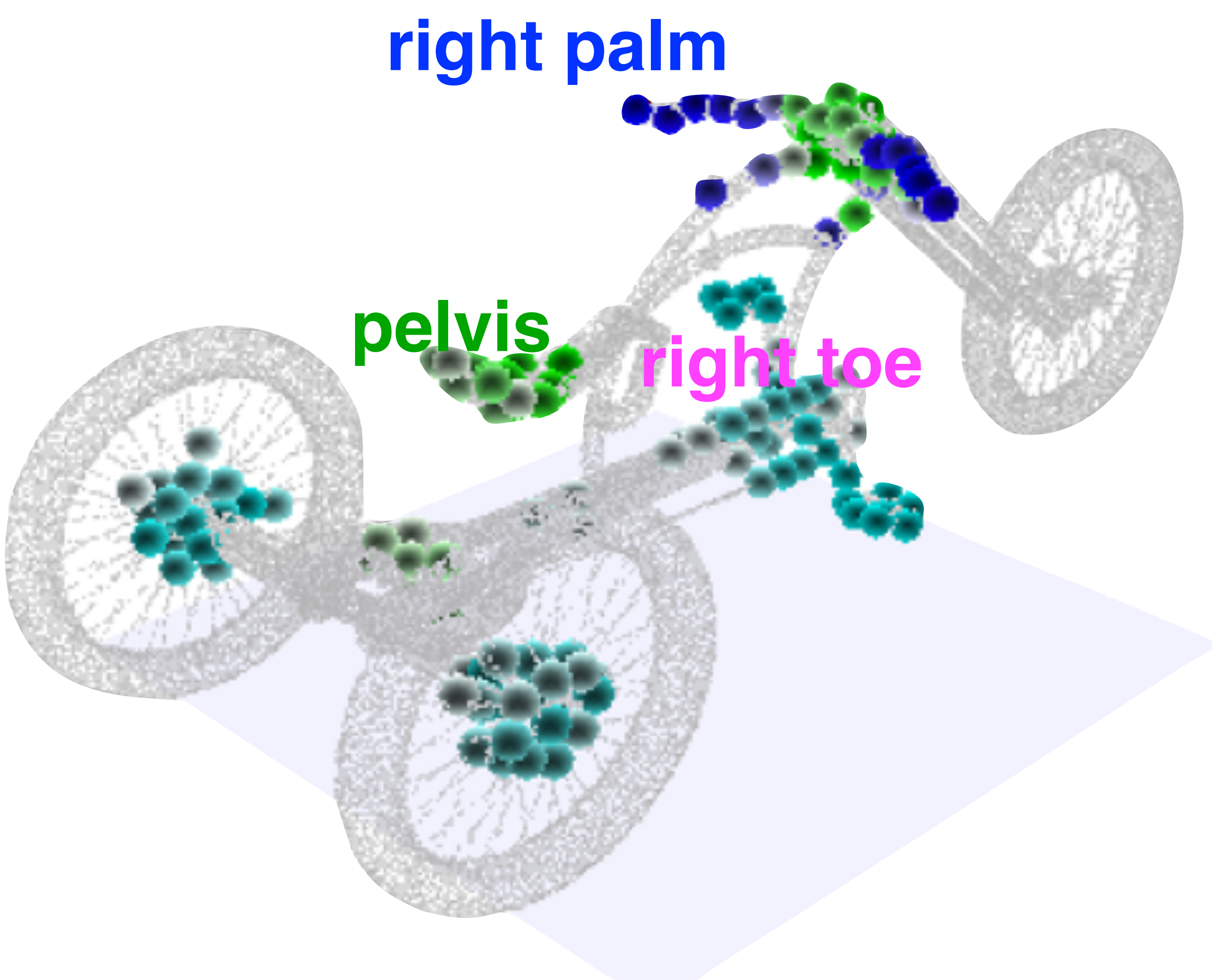
Contact Distribution

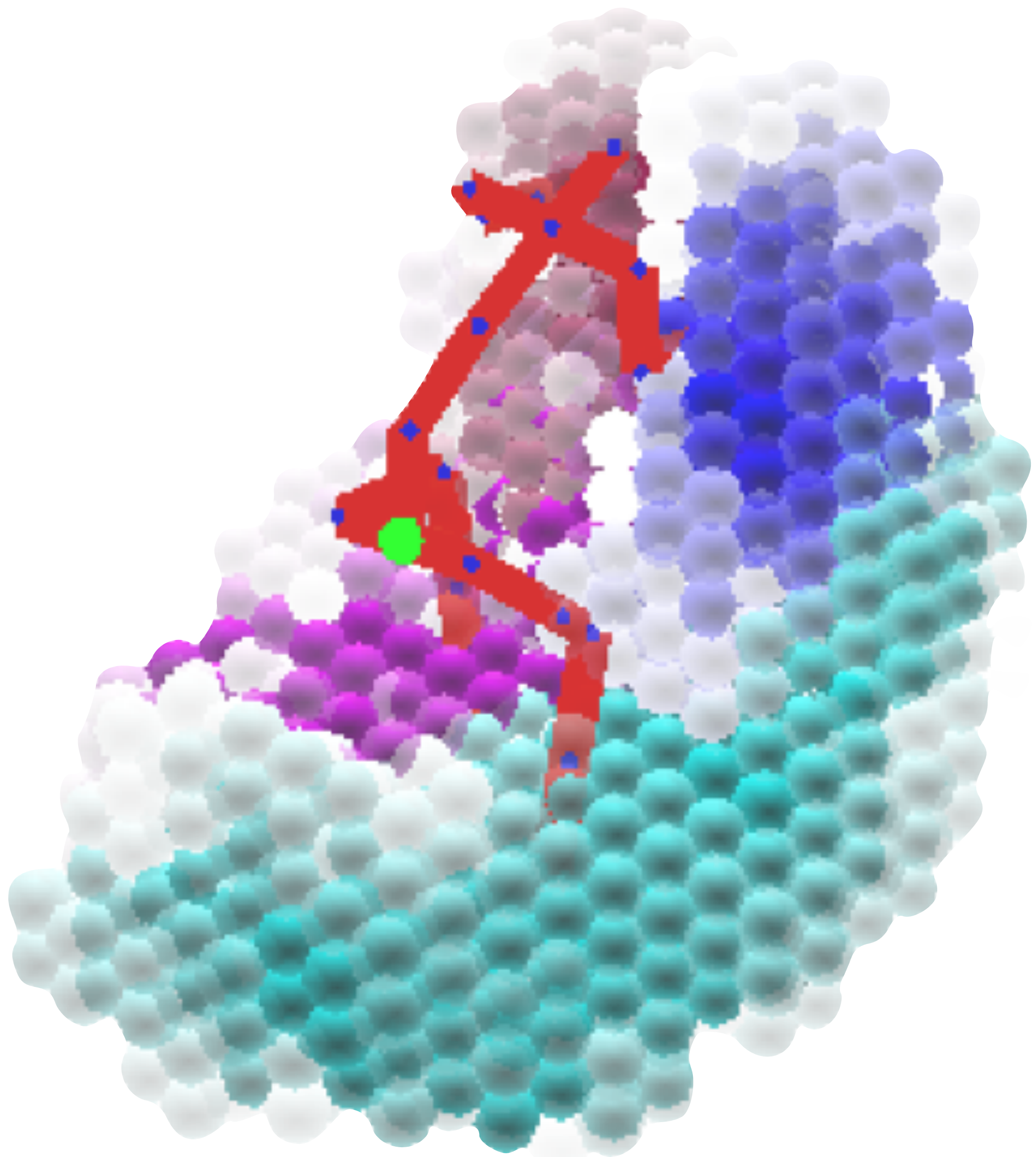
End Effector Distribution

Candidate pose with lower-bound on the energy

Pose Prediction Algorithm

Pick global peaks in the joint distribution

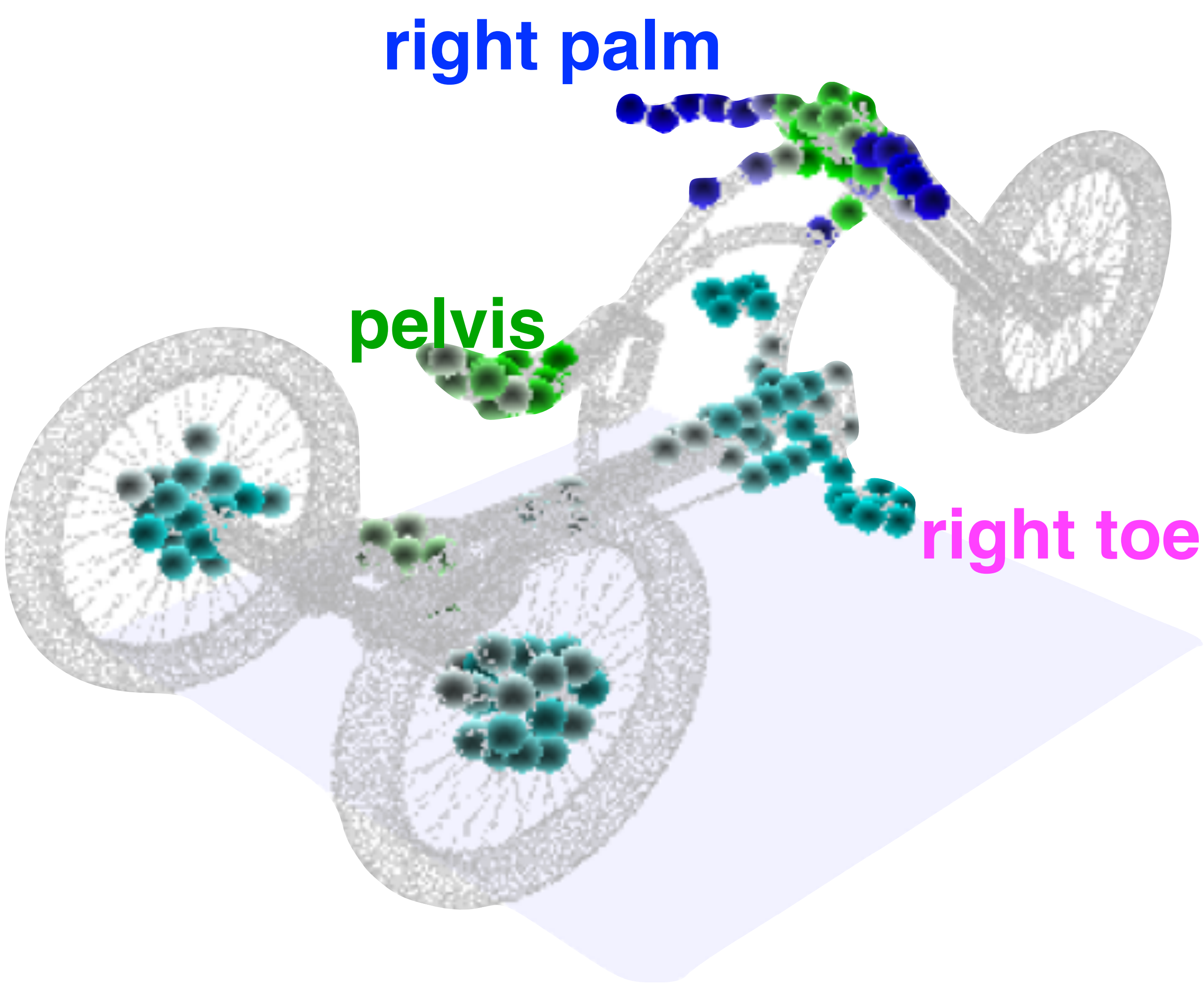


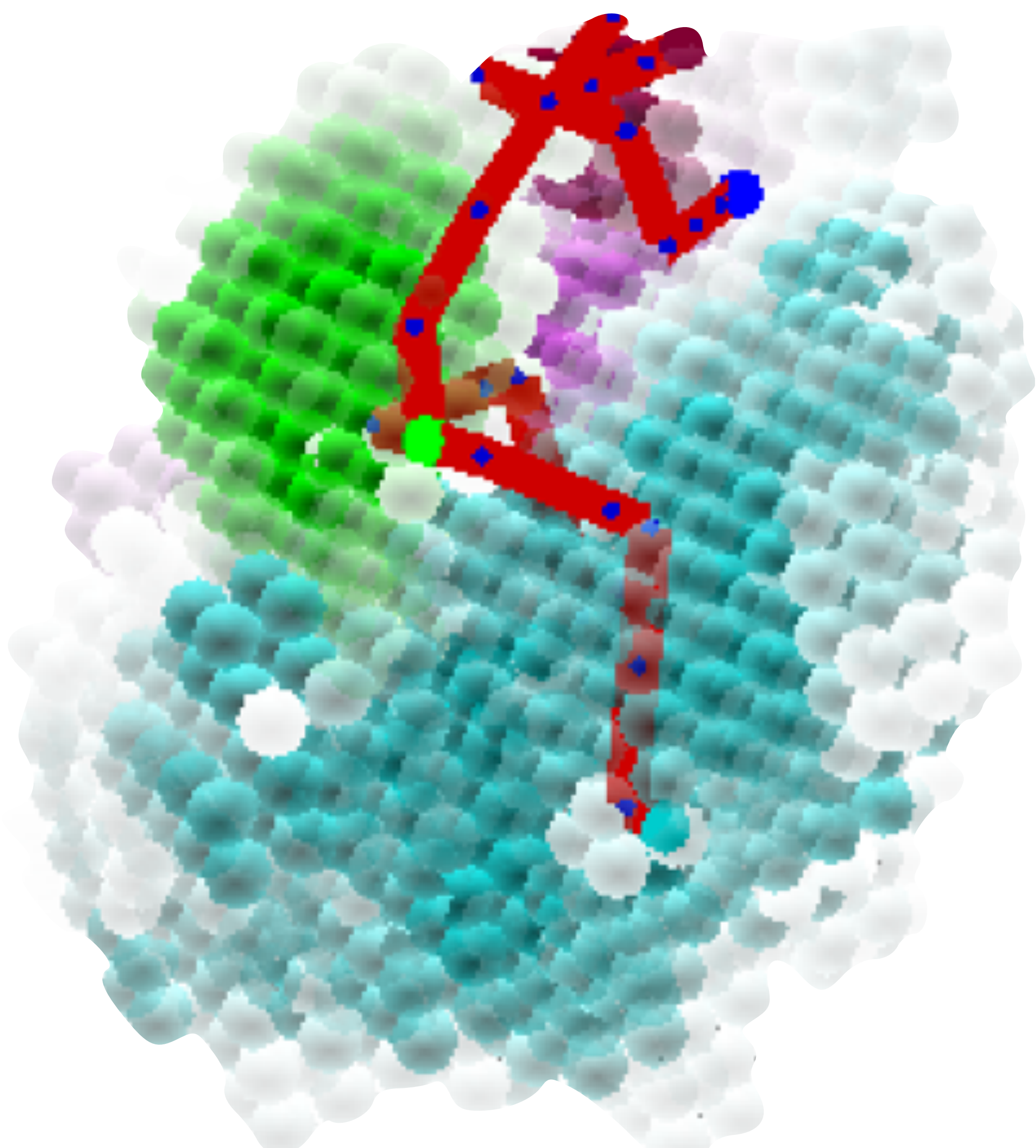


Candidate pose with lower-bound on the energy

Pose Prediction Algorithm

Pick global peaks in the joint distribution

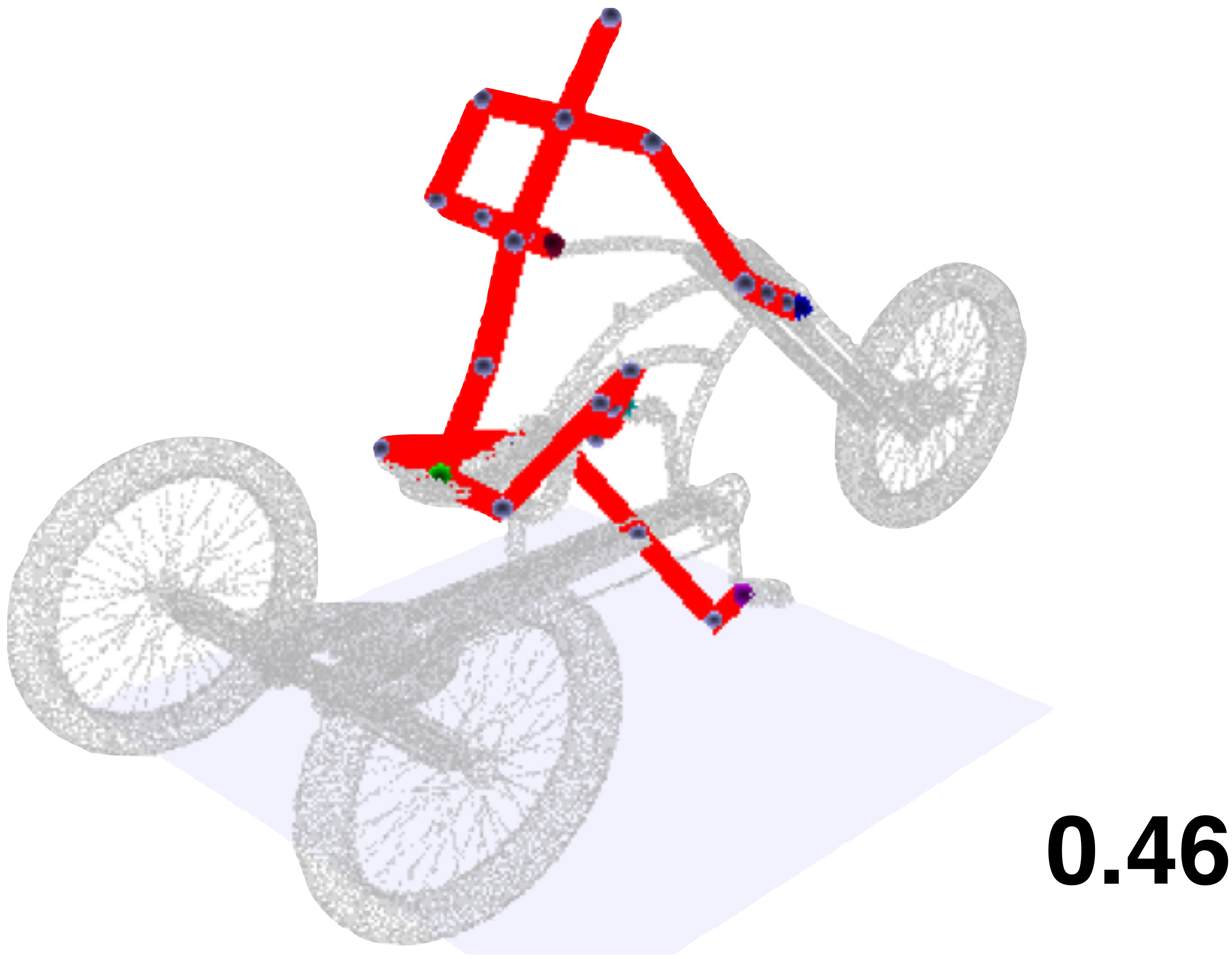




Candidate pose with lower-bound on the energy

Pose Prediction Algorithm

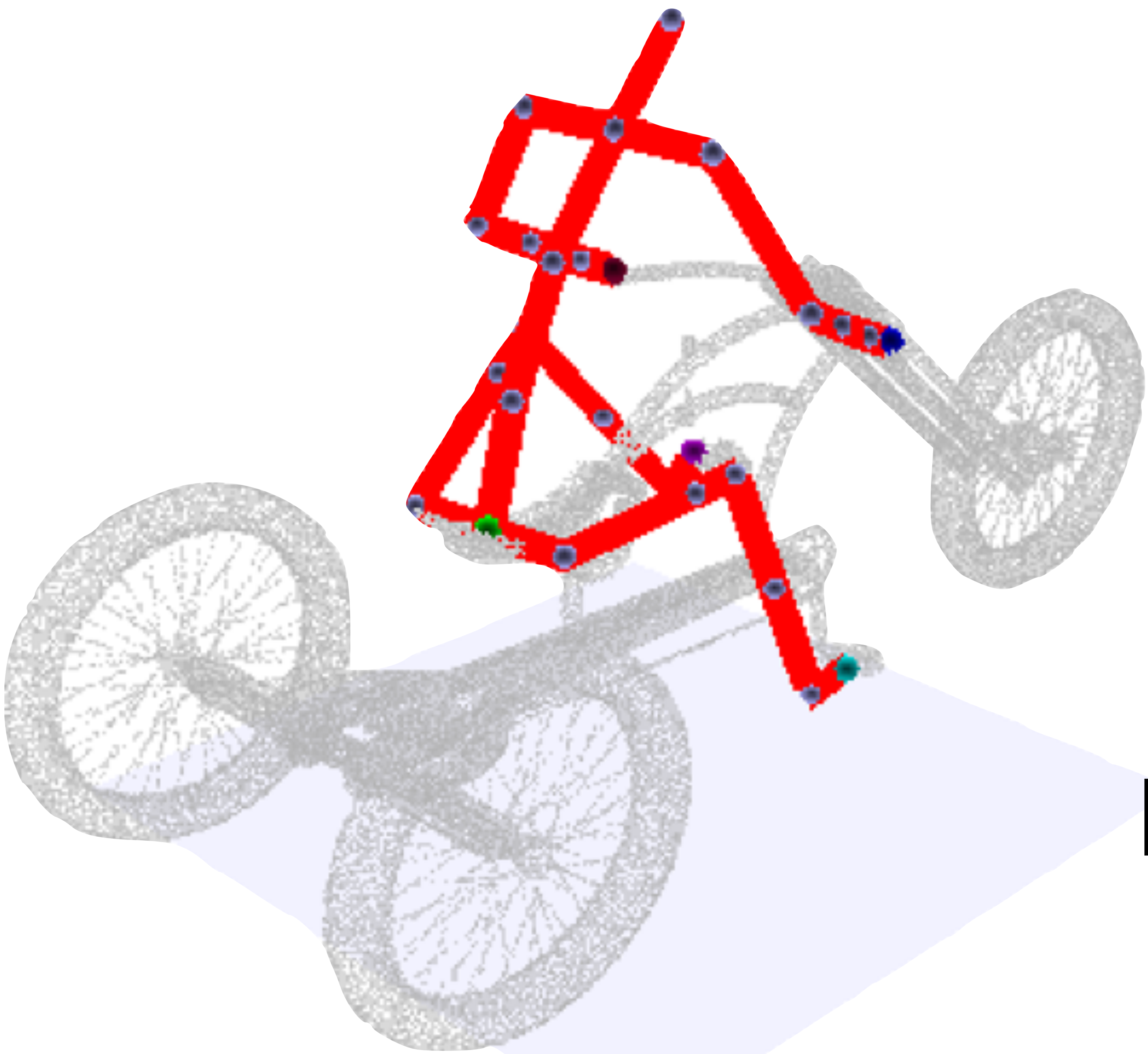
Run IK on best candidate poses to compute energy



Predicted pose with the final energy

Pose Prediction Algorithm

Run IK on best candidate poses to compute energy

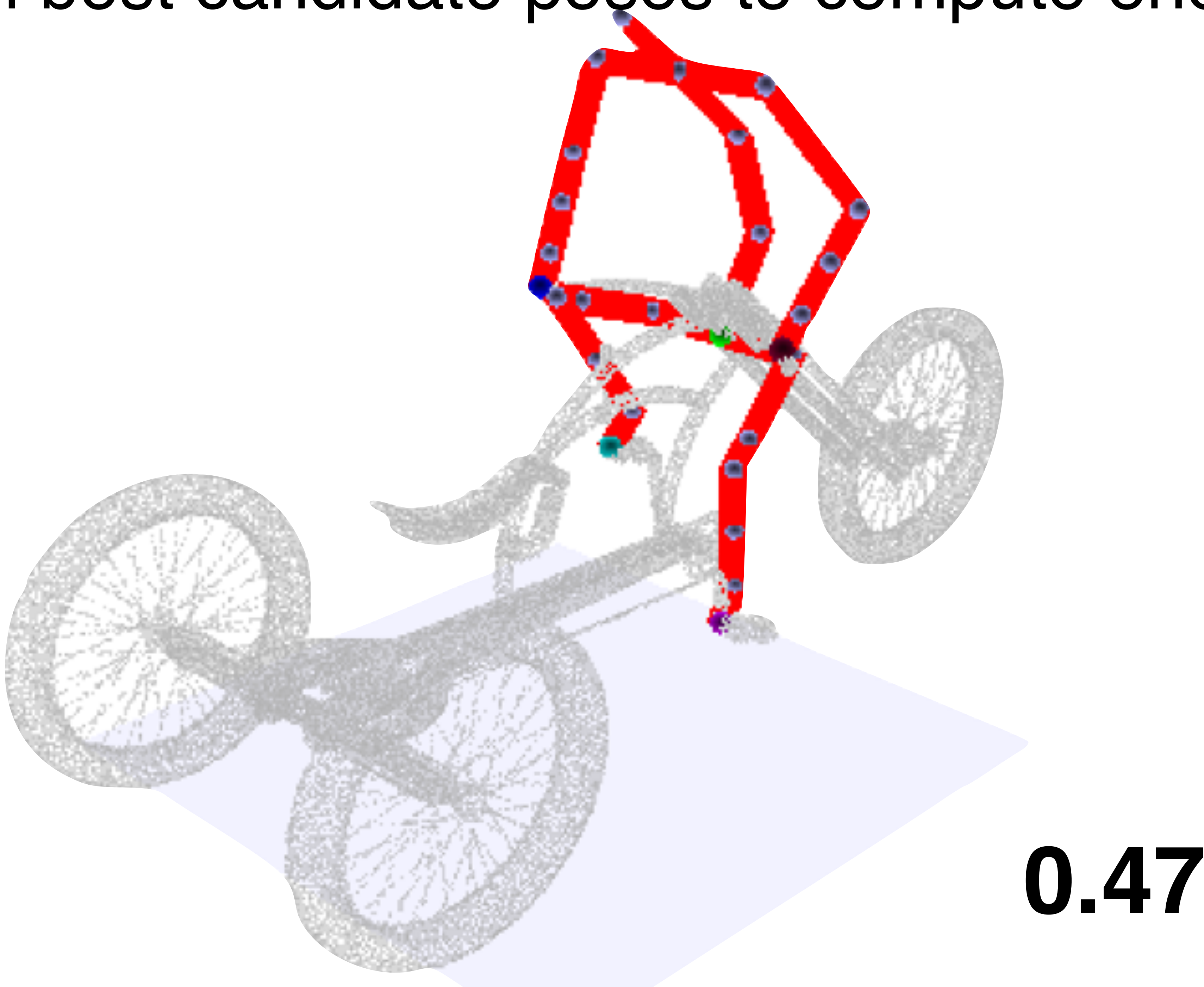


Best Pose!
0.36

Predicted pose with the final energy

Pose Prediction Algorithm

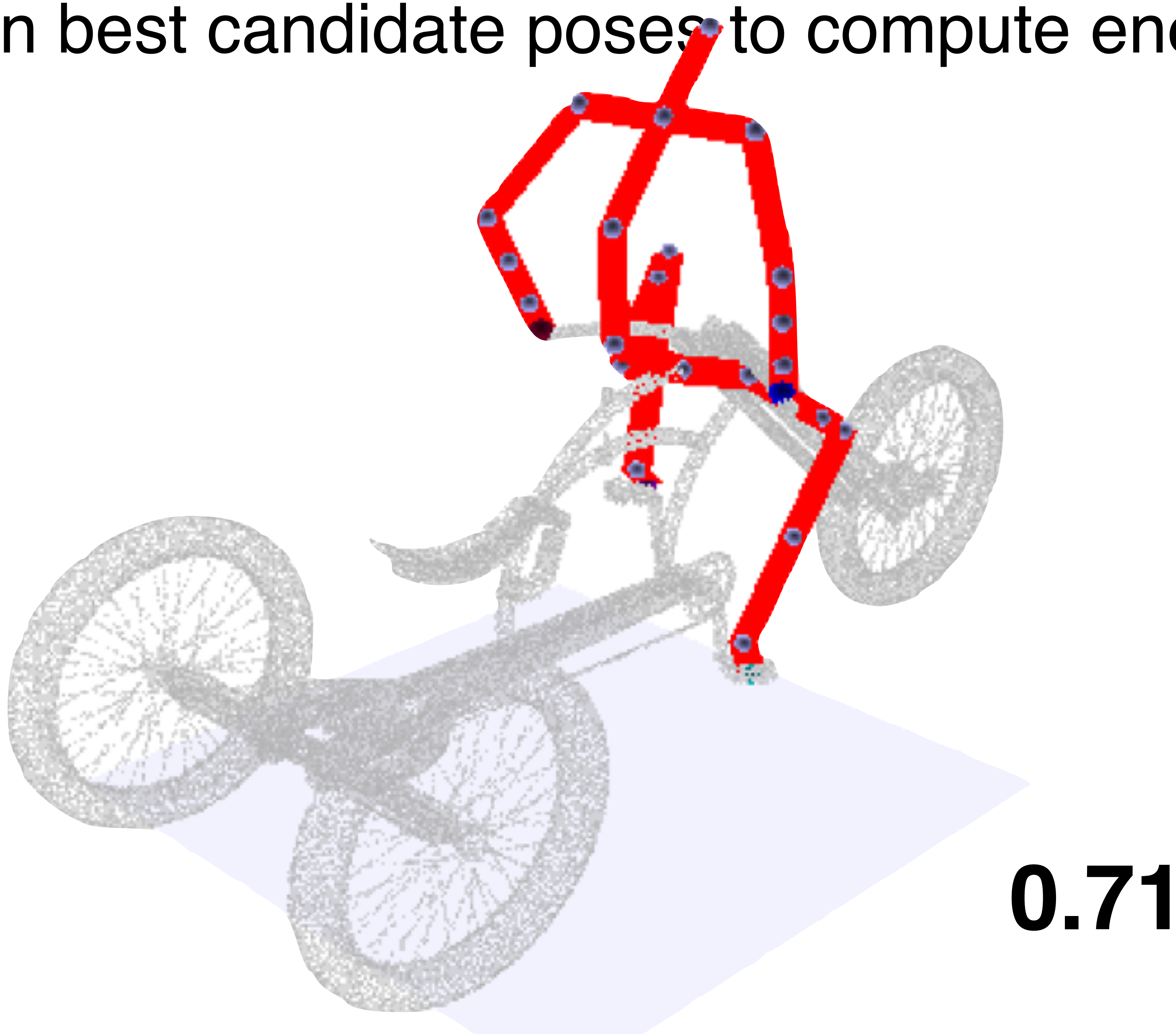
Run IK on best candidate poses to compute energy



Predicted pose with the final energy

Pose Prediction Algorithm

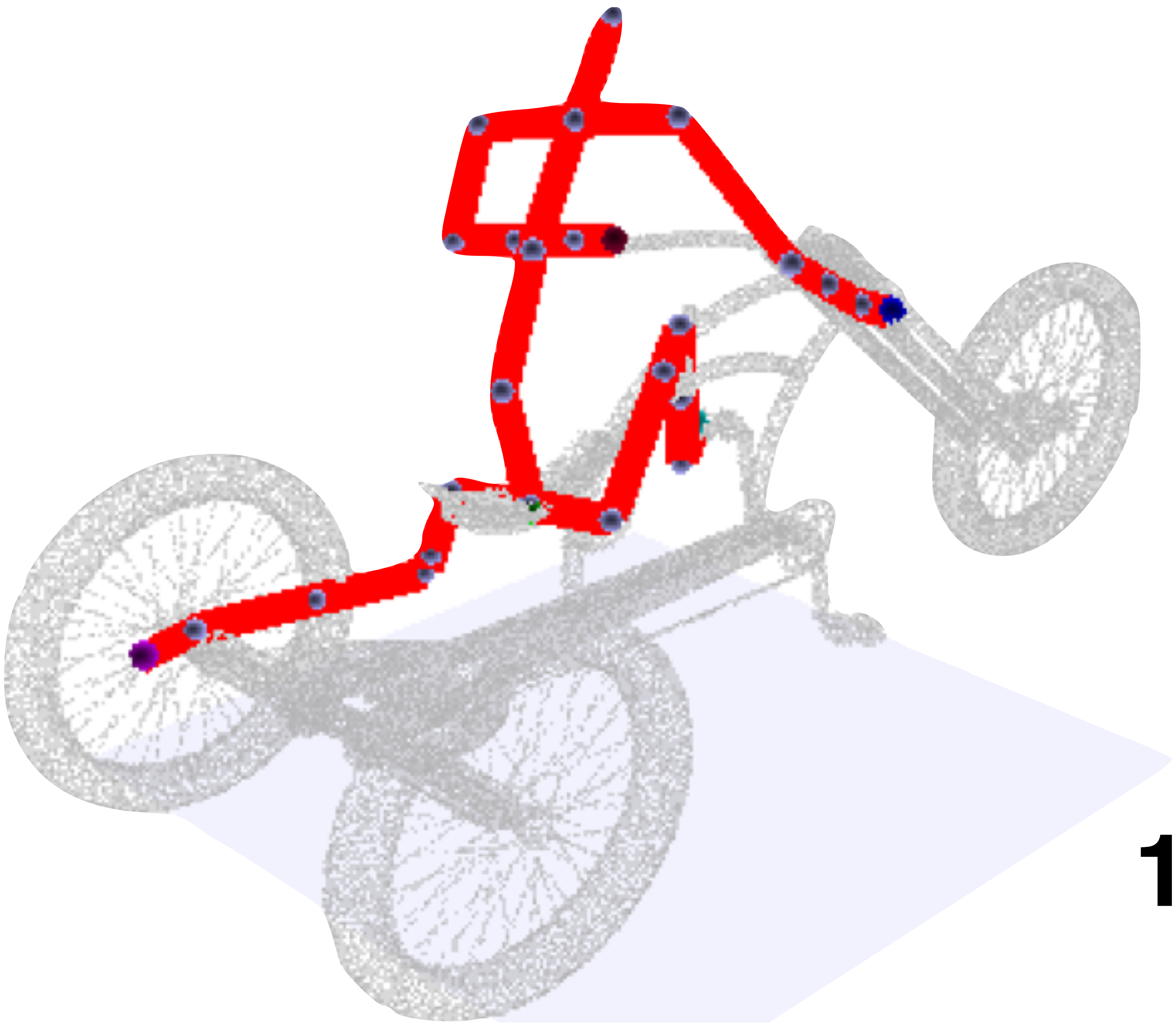
Run IK on best candidate poses to compute energy



Predicted pose with the final energy

Pose Prediction Algorithm

Run IK on best candidate poses to compute energy

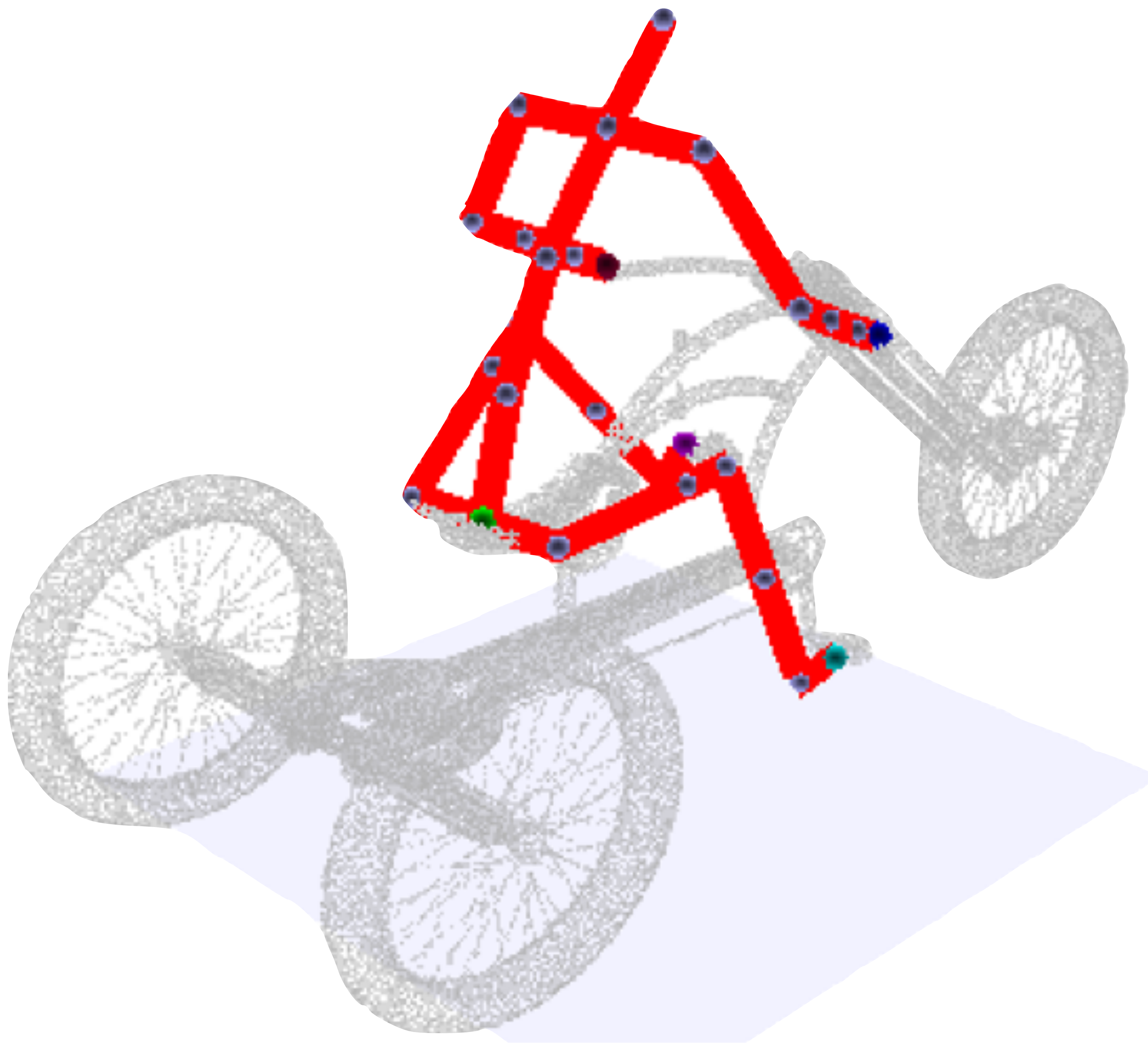


1.11

Predicted pose with the final energy

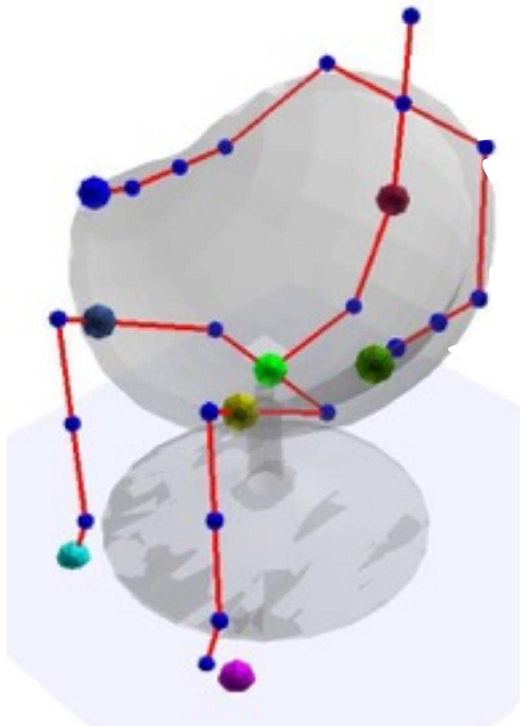
Pose Prediction Algorithm

Run IK on best candidate poses to compute energy

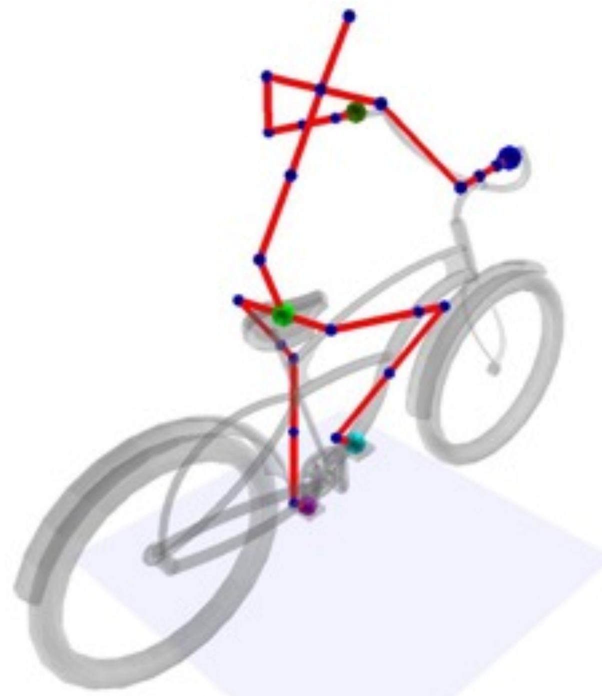


Final Predicted Pose

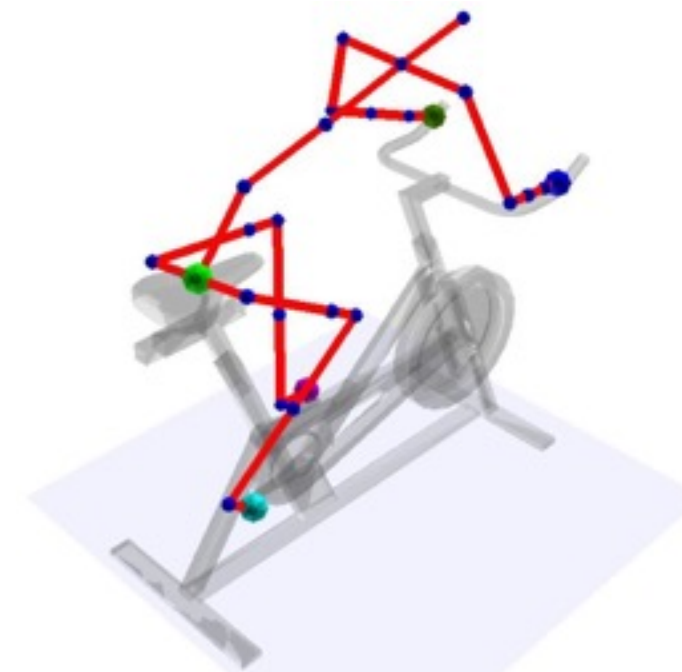
Human-centric Model Evaluation



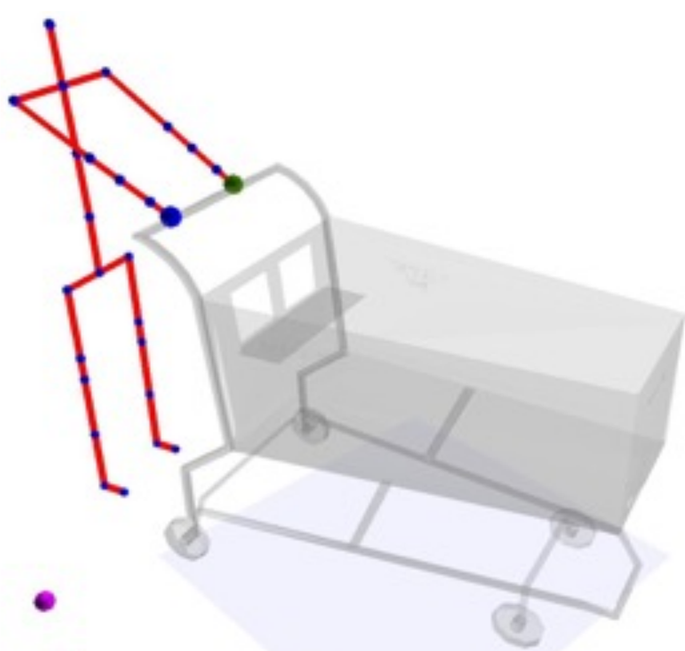
Chairs



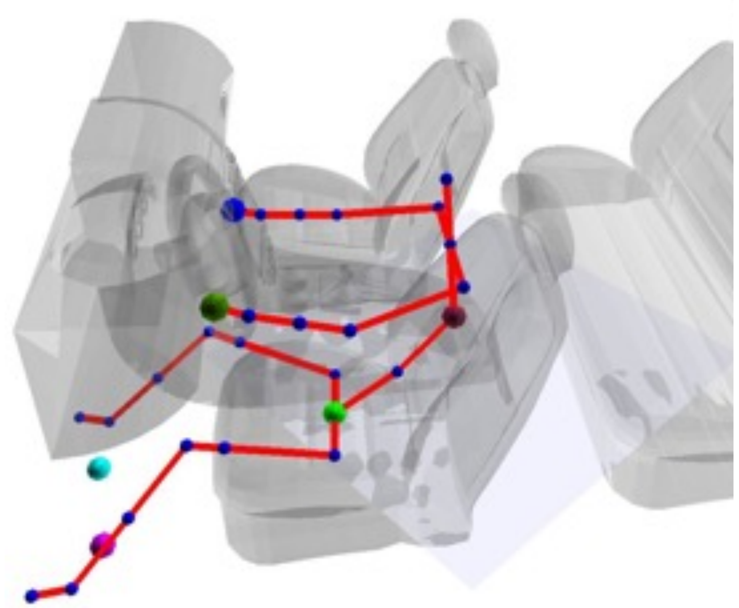
Bicycles



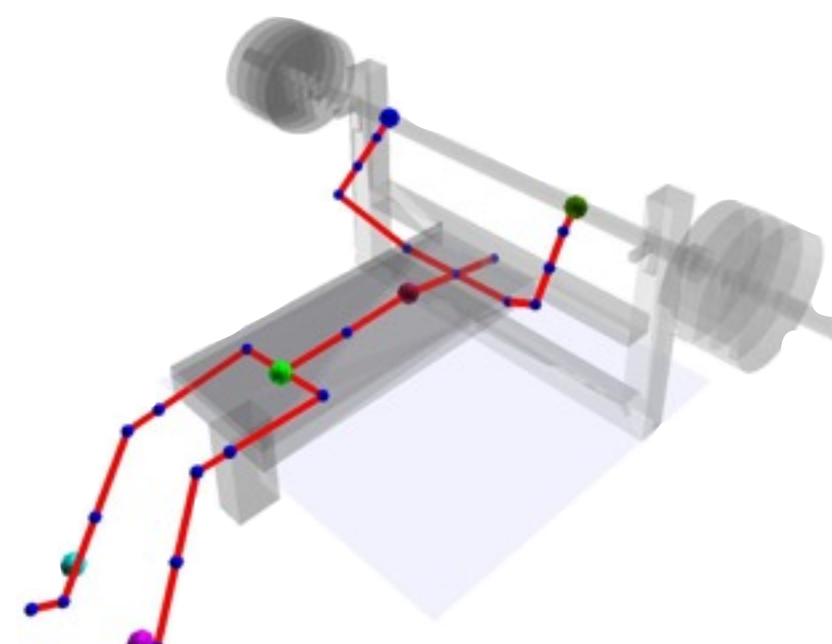
Bipedals



Carts

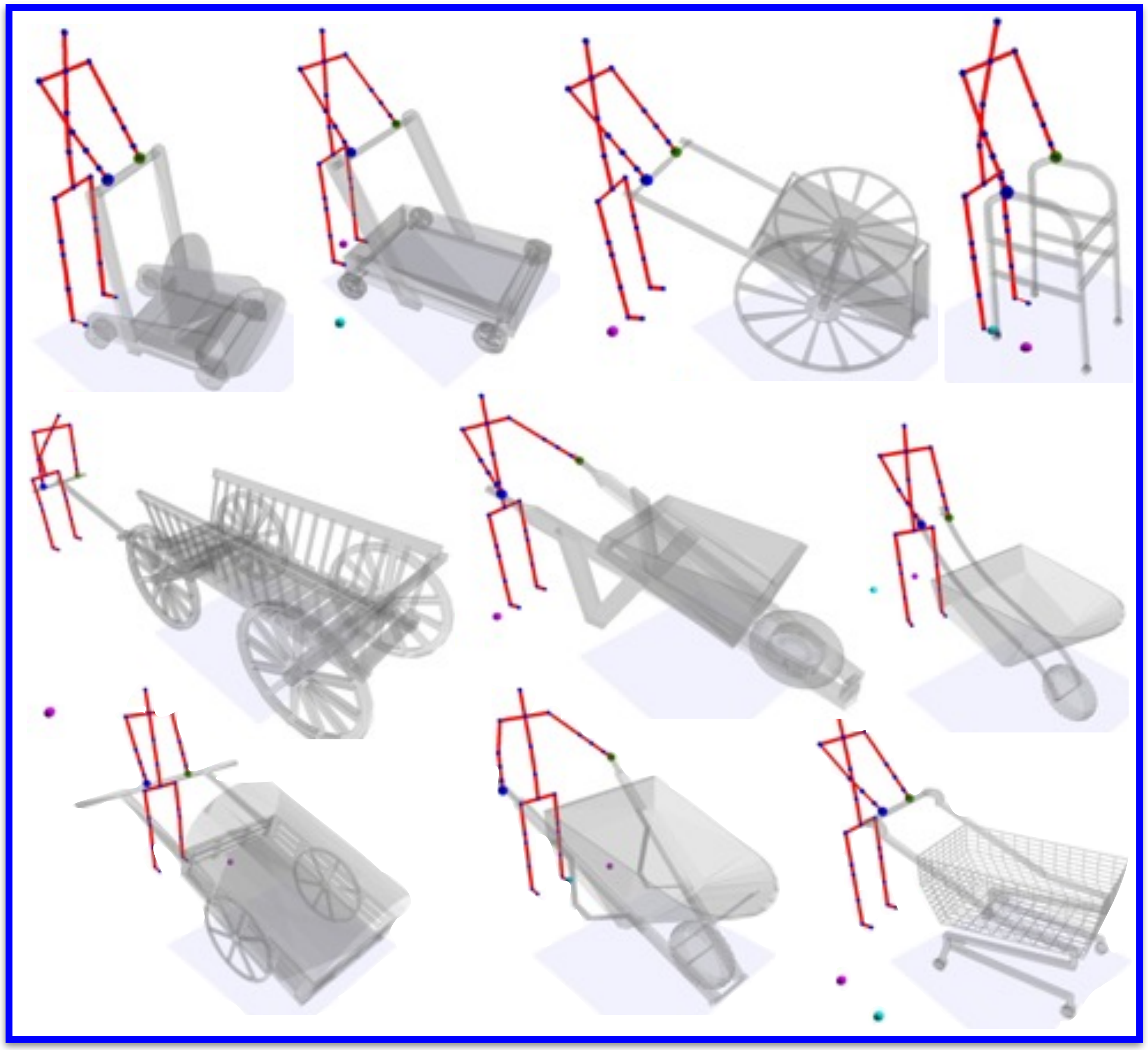


Cockpits



Gym

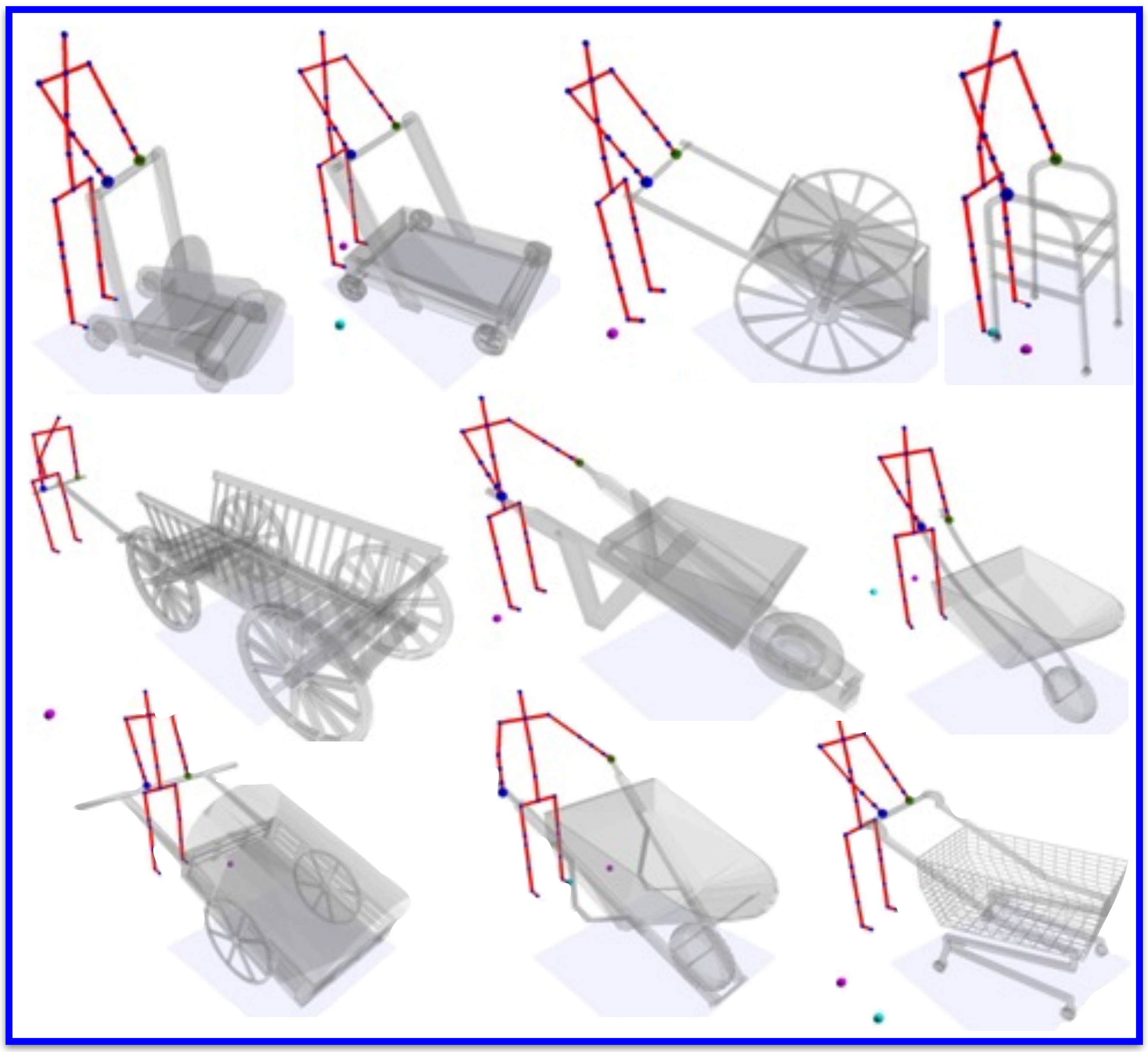
Leave-one-out Evaluation



Training Data

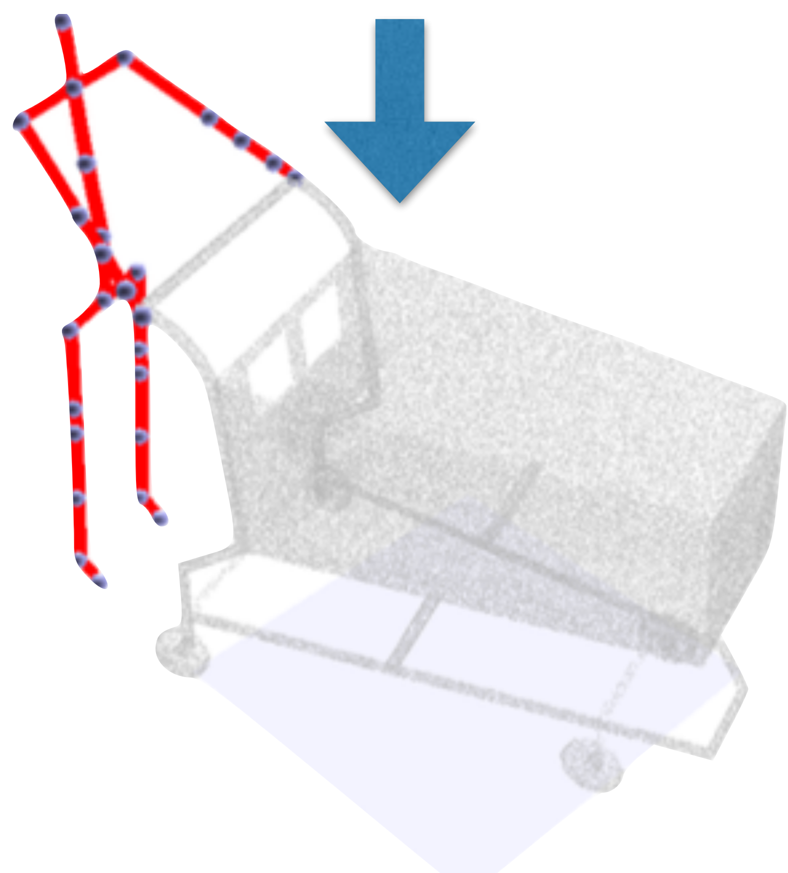
Test Data

Leave-one-out Evaluation

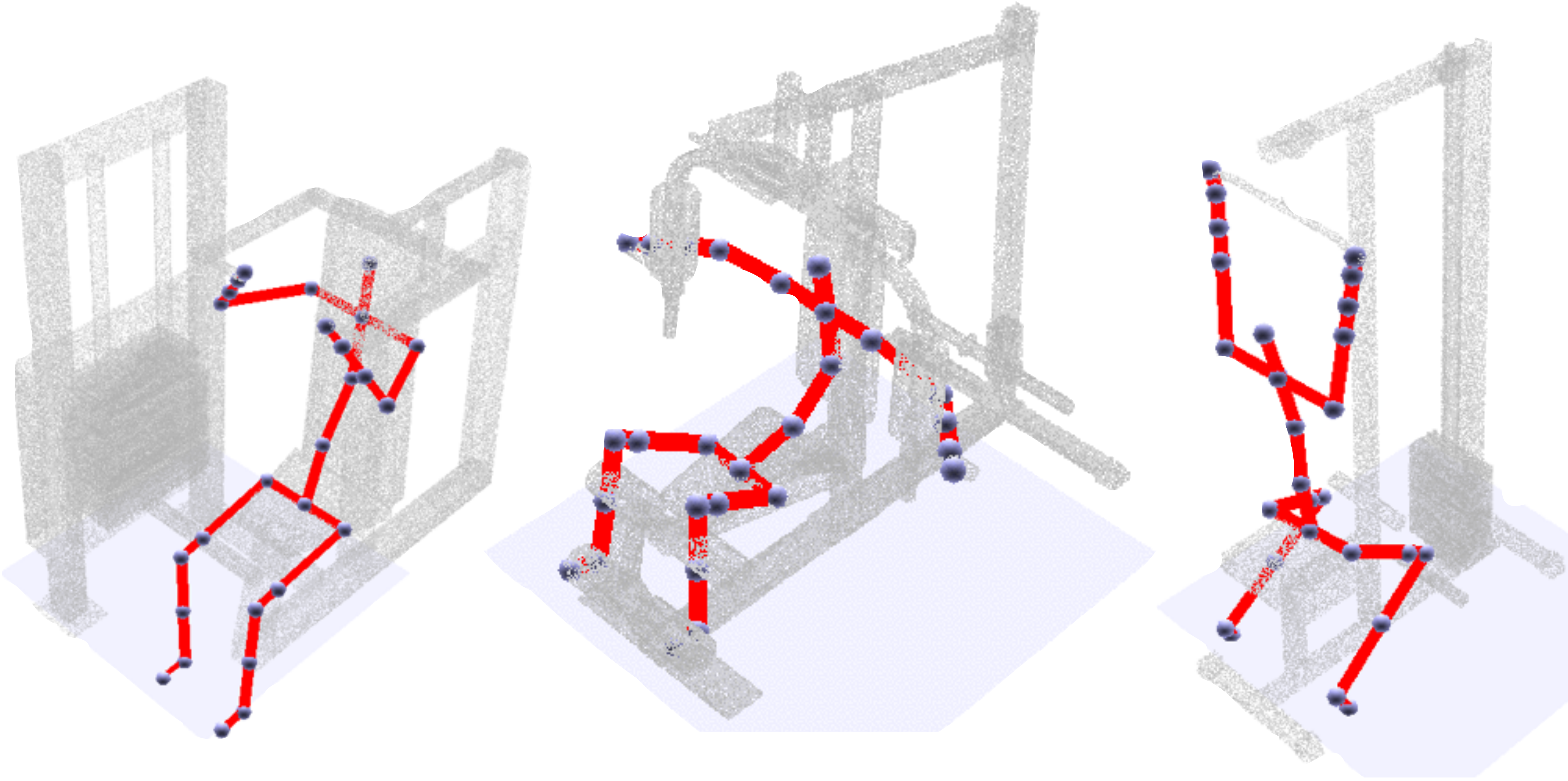


Training Data

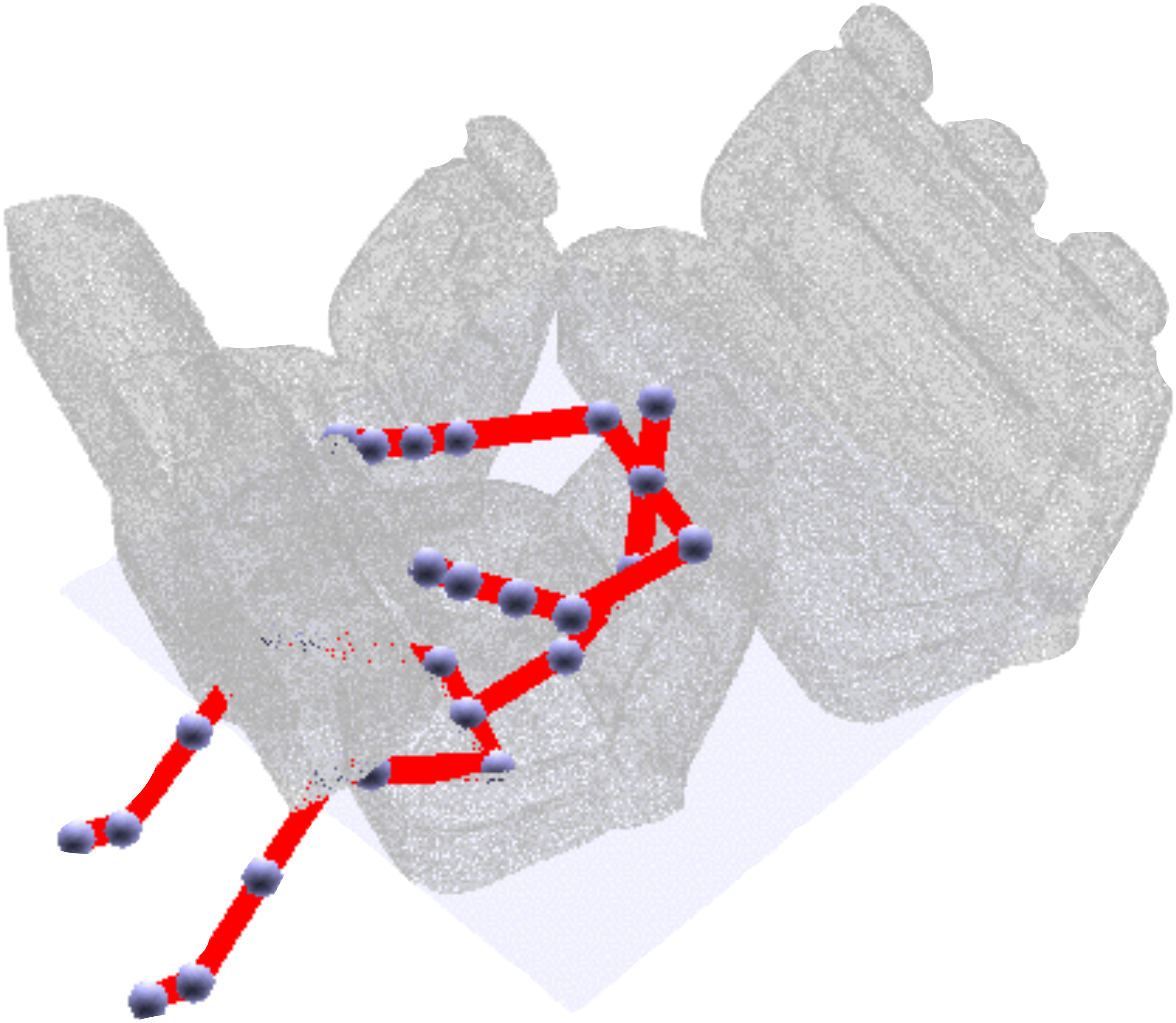
Test Data

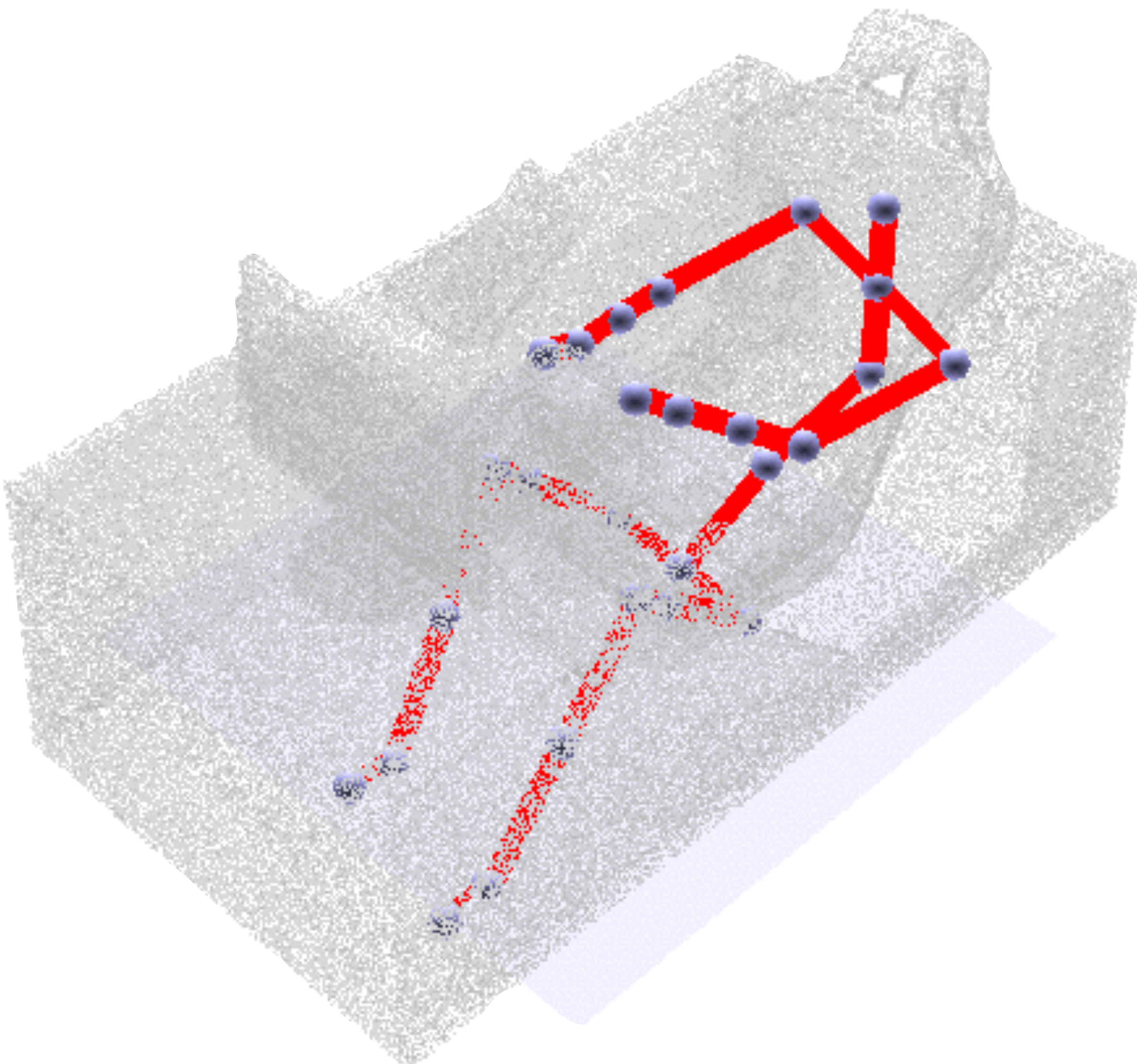


Pose Prediction Results

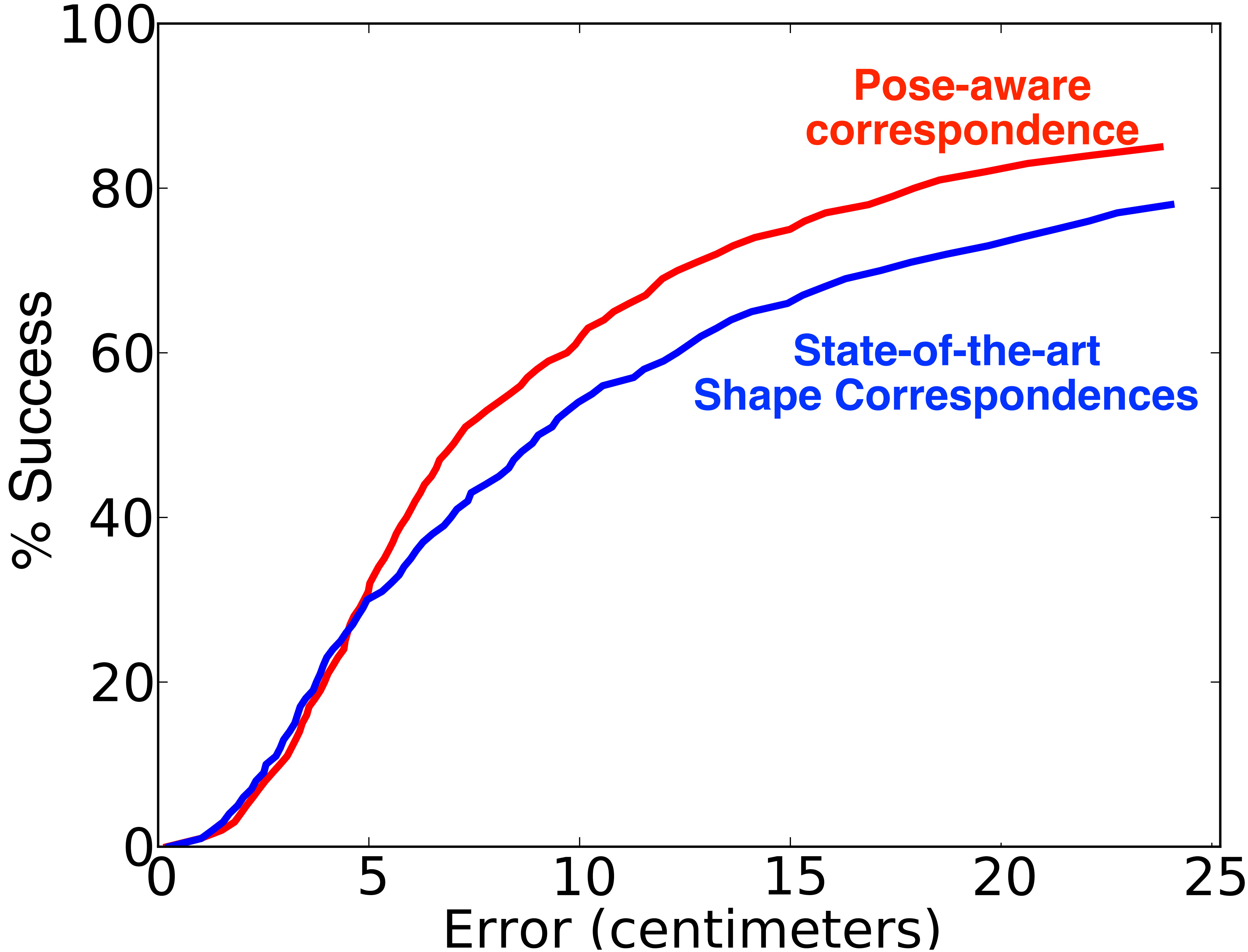


Pose Prediction Results





Shape Correspondence Results



Salience Estimation Results

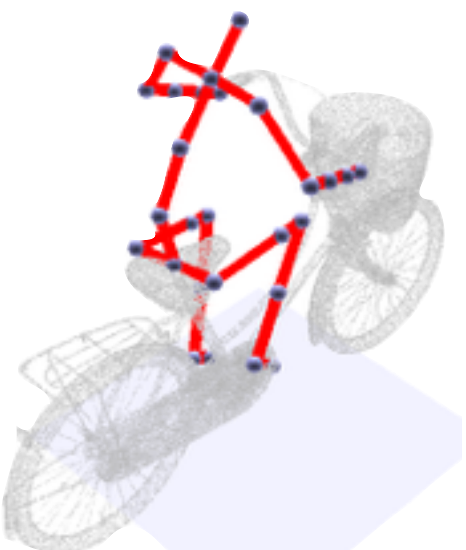
Mesh Saliency [Lee et al. 2005]

Salience Estimation Results

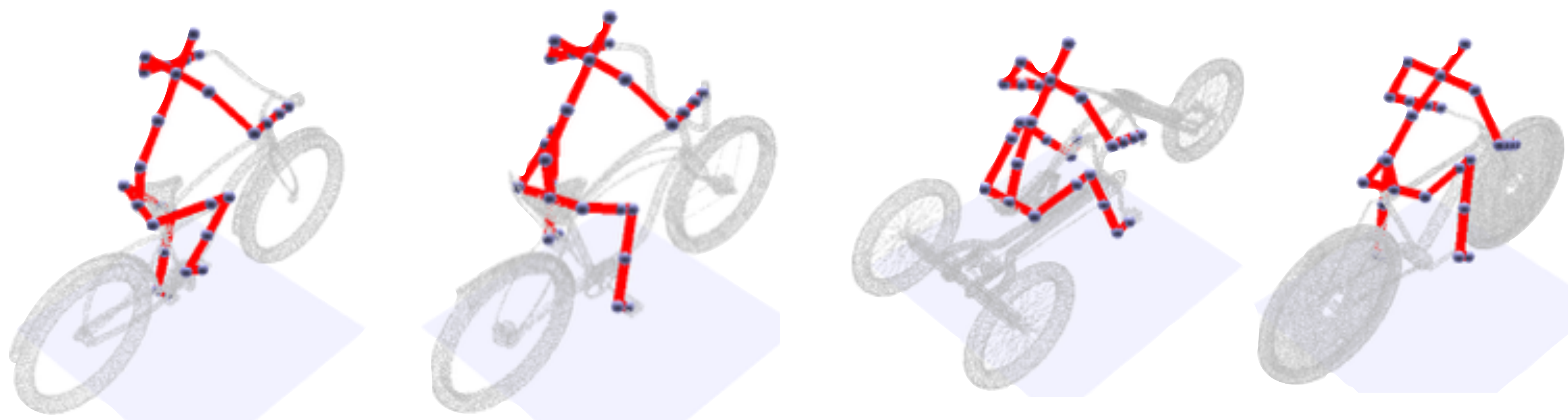
Human-centric Saliency [Our method]

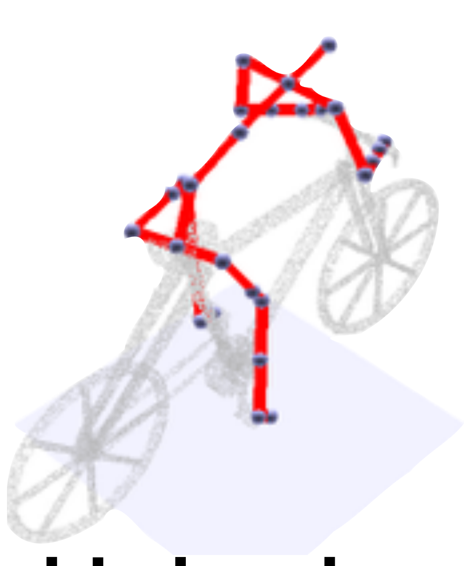
Shape Retrieval Results

Query | **Most Similar**

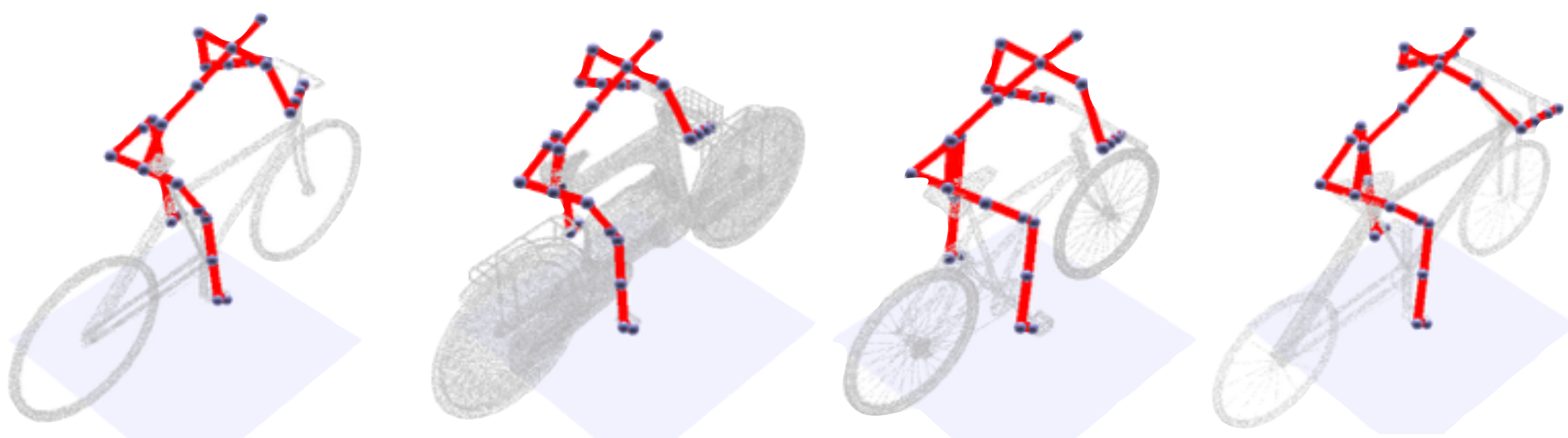


ride sitting up-right

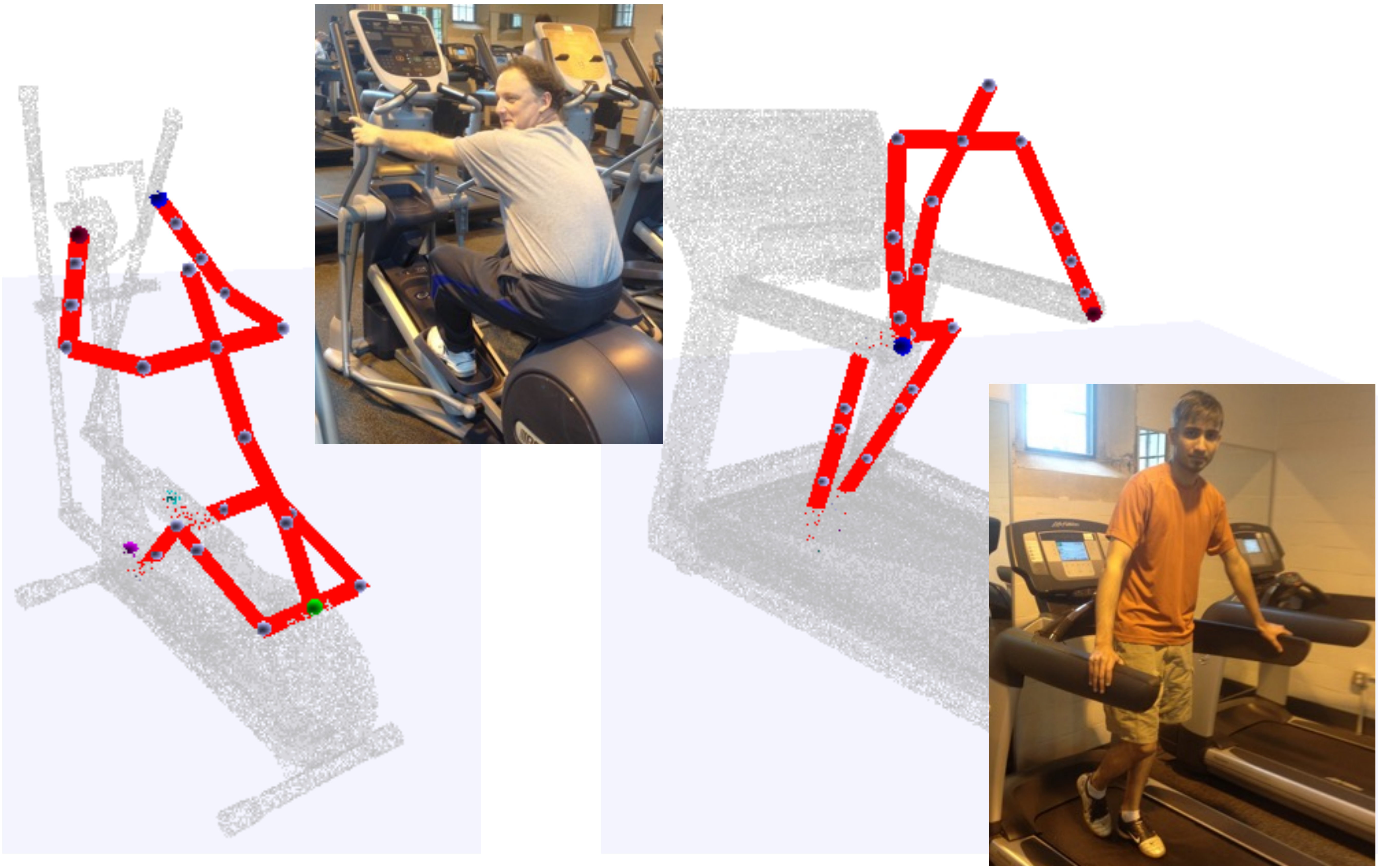




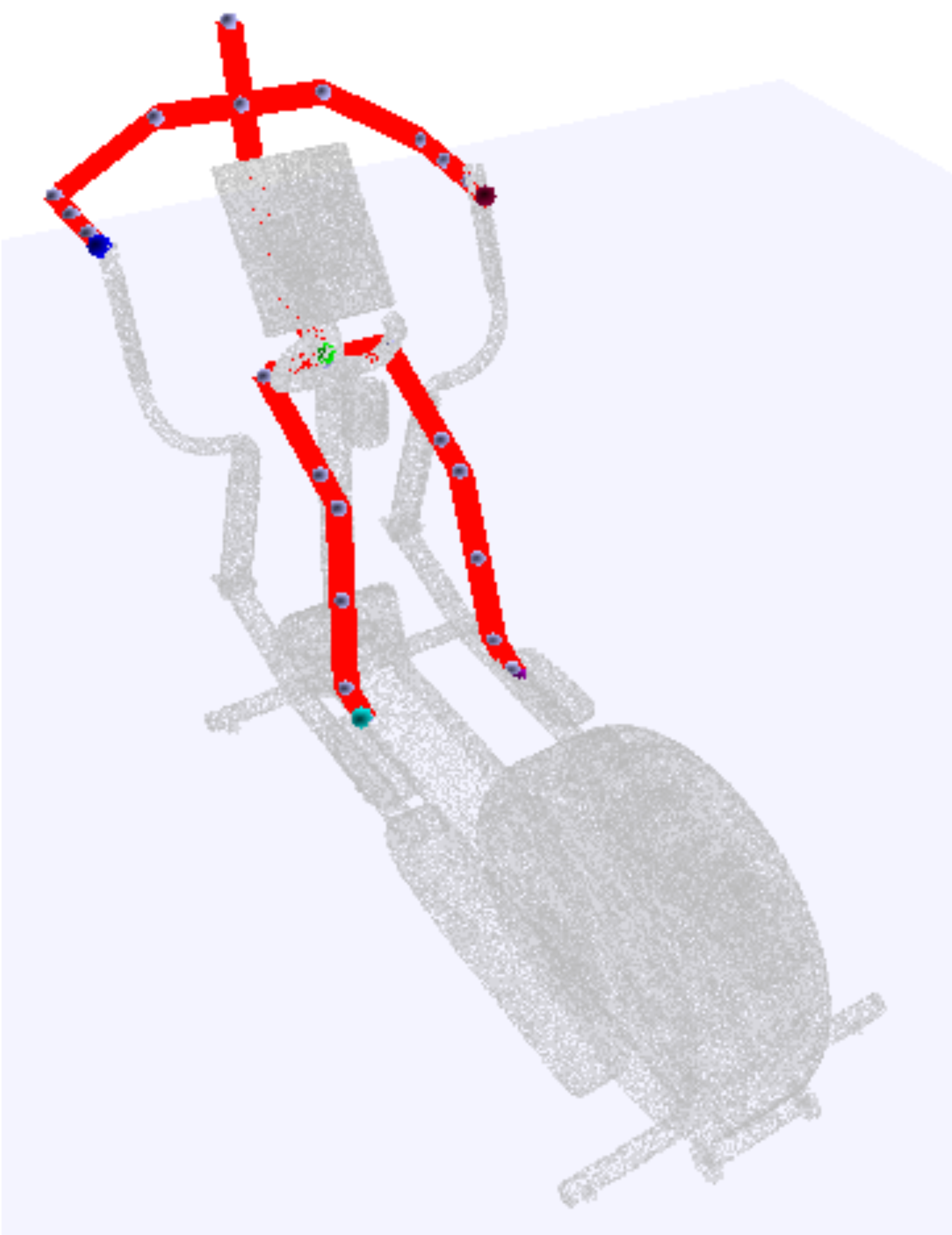
ride leaning forward



Failure Examples



Failure Examples



Research Agenda

Find Structure in 3D data to infer Function

- Better structural models
- Additional input to understand function
- Designing manufacturable objects
- Scene understanding

Research Agenda

Find Structure in 3D data to infer Function

➡ Better structural models

- Additional input to understand function
- Designing manufacturable objects
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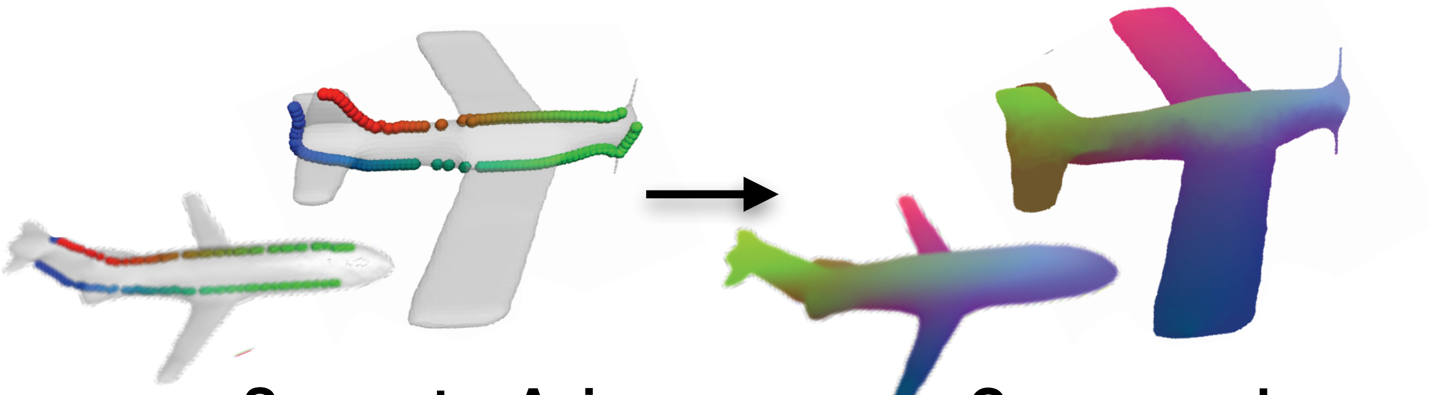
Correspondences

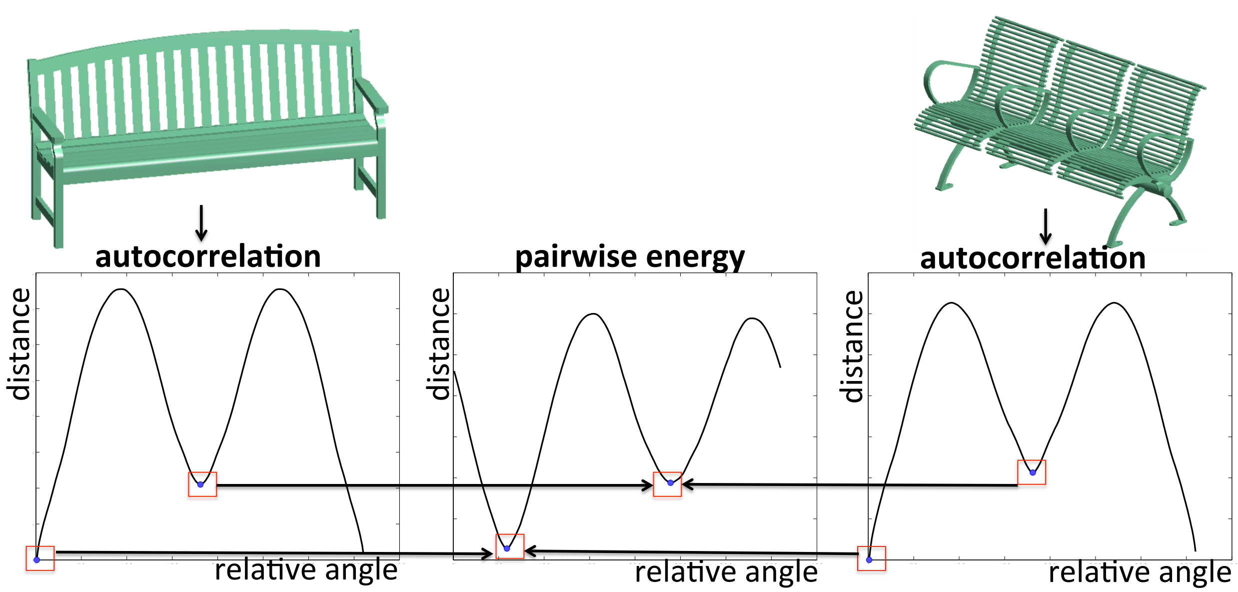
Find Structure in 3D data to infer Function

➡ Better structural models



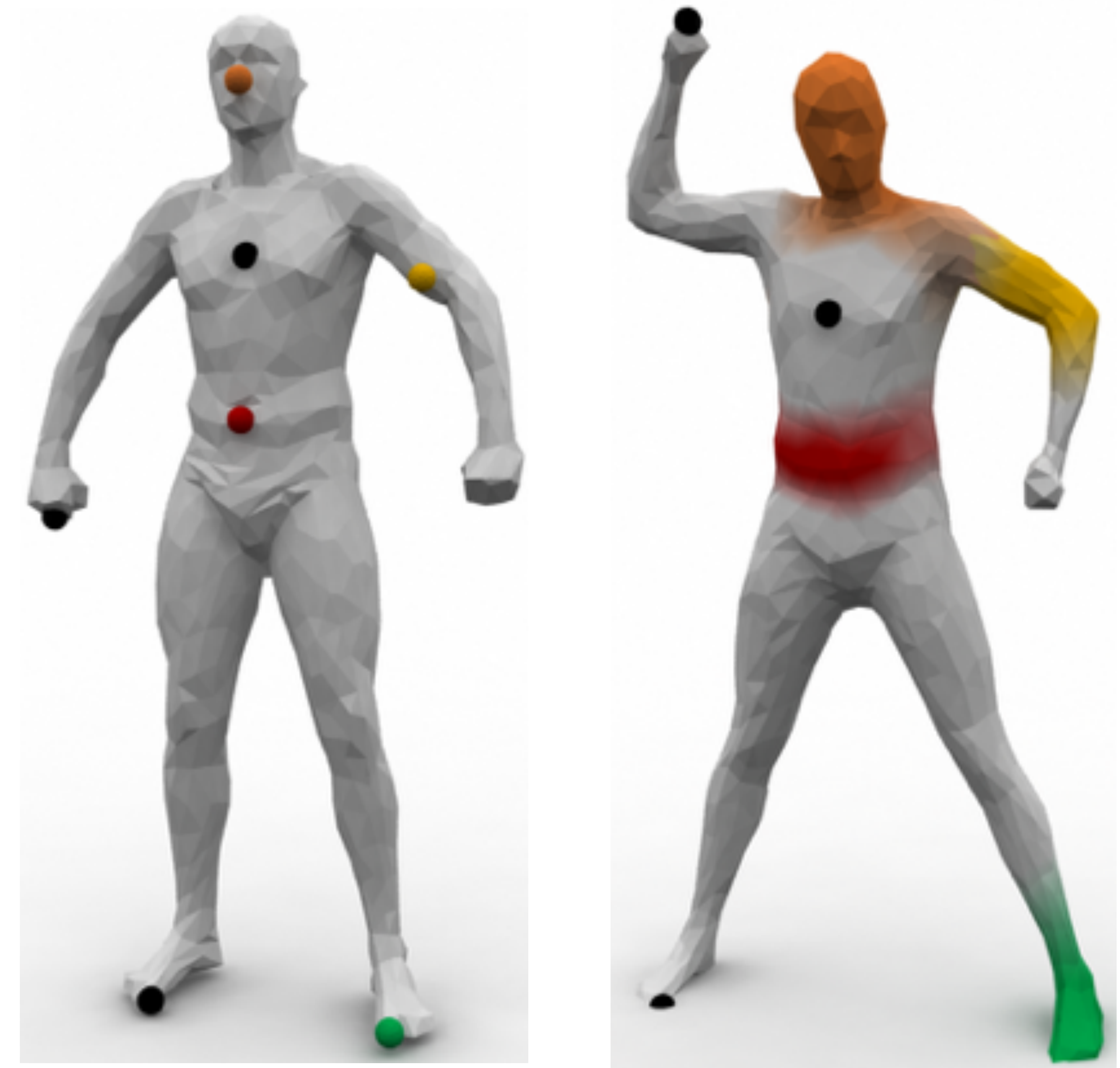
Symmetry Axis → **Correspondence**

with T. Liu and T. Funkhouser, SGP 2012



Autocorrelation → **Correspondence**

with M. Averkiou and N. Mitra, CGF 2015 (conditional)



with A. Nguyen, J. Solomon, L. Guibas

Symmetry And Correspondence

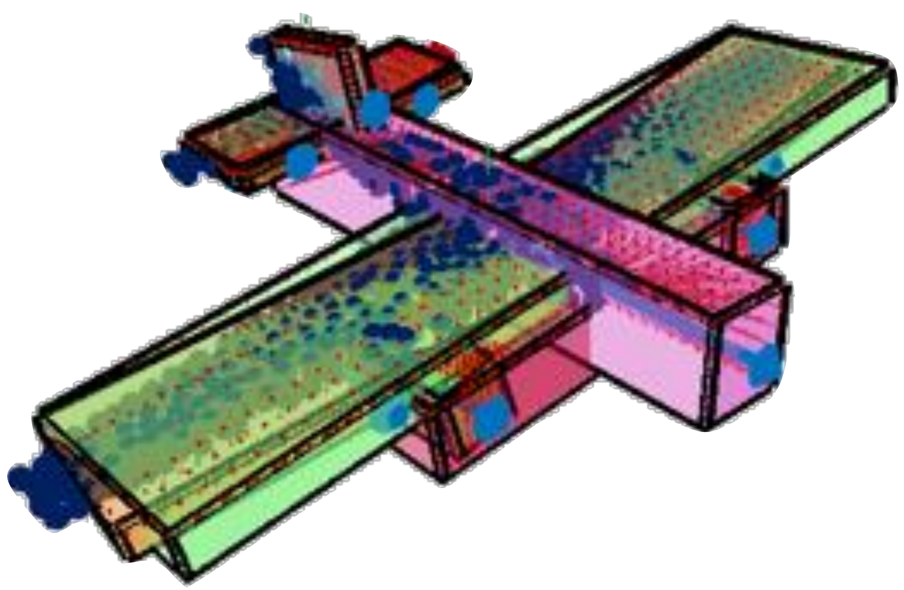
Probabilistic Correspondence

Probabilistic Part Model

Find Structure in 3D data to infer Function

- ➡ Better structural models

Input



Output

Handle partial observations

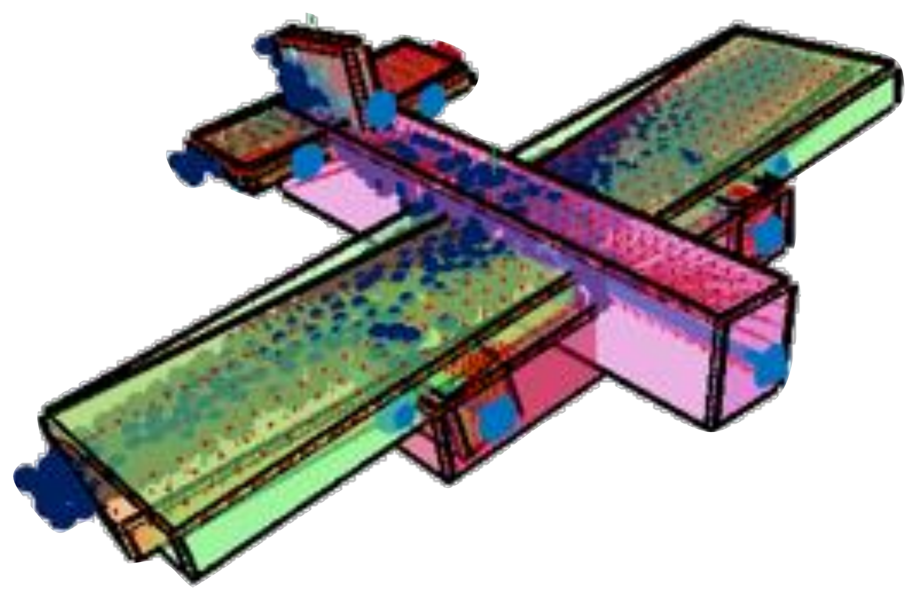
An on-going project with M. Sung, R. Angst, L. Guibas

Probabilistic Part Model

Find Structure in 3D data to infer Function

➡ Better structural models

Input



Output

Reconstruction

Handle partial observations

An on-going project with M. Sung, R. Angst, L. Guibas

Research Agenda

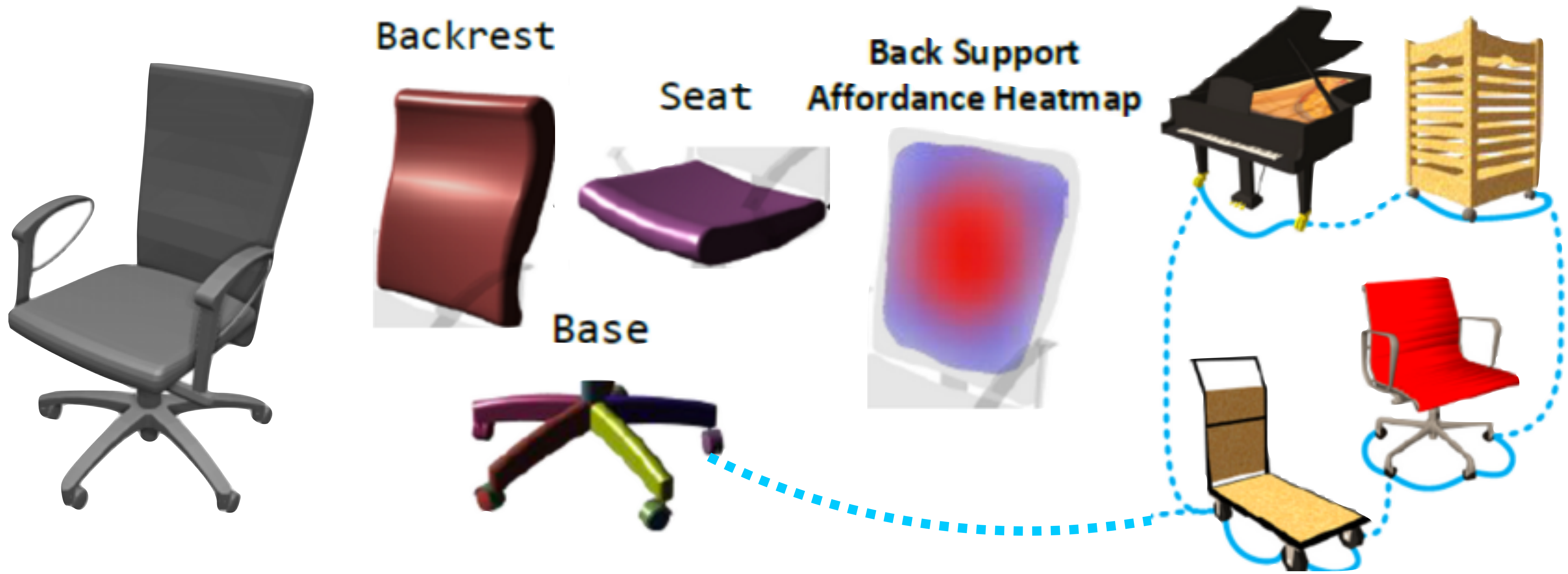
Find Structure in 3D data to infer Function

- Better structural models
- ➡ Additional input to understand function
- Designing manufacturable objects
- Scene understanding

Semantic Shape Network

Find Structure in 3D data to infer Function

➡ Additional input to understand function



Leverage crowdsourcing to detect functional relations among <u>MILLIONS</u> of 3D models

An on-going project with L. Yi, I. Shen, H. Su, Q. Huang, A. Sheffer, L. Guibas

Semantic Shape Network

Desiderata

- Crowdsourced
- Semi-supervised
- Handle diverse data
- Active

Semantic Shape Network

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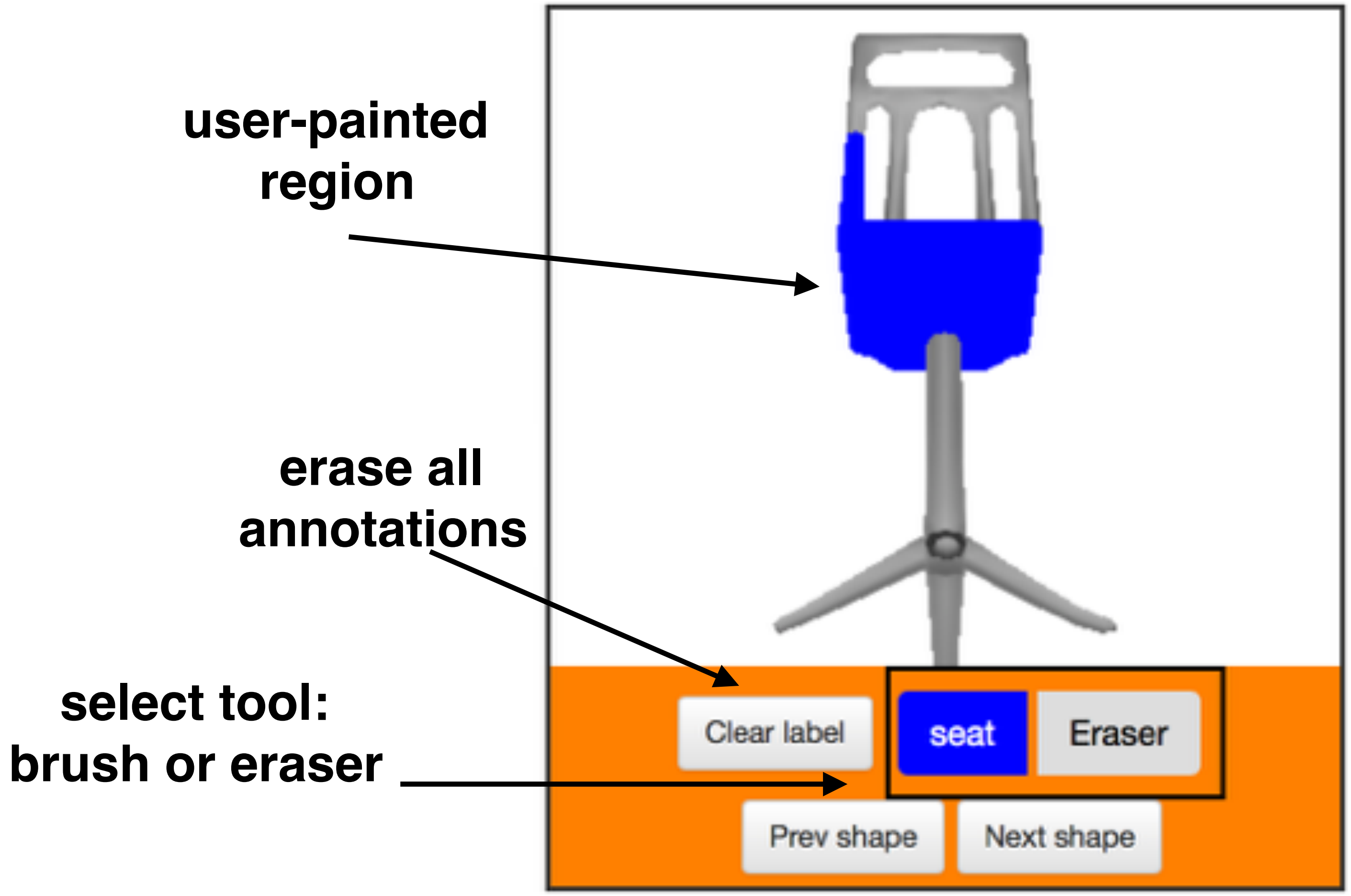


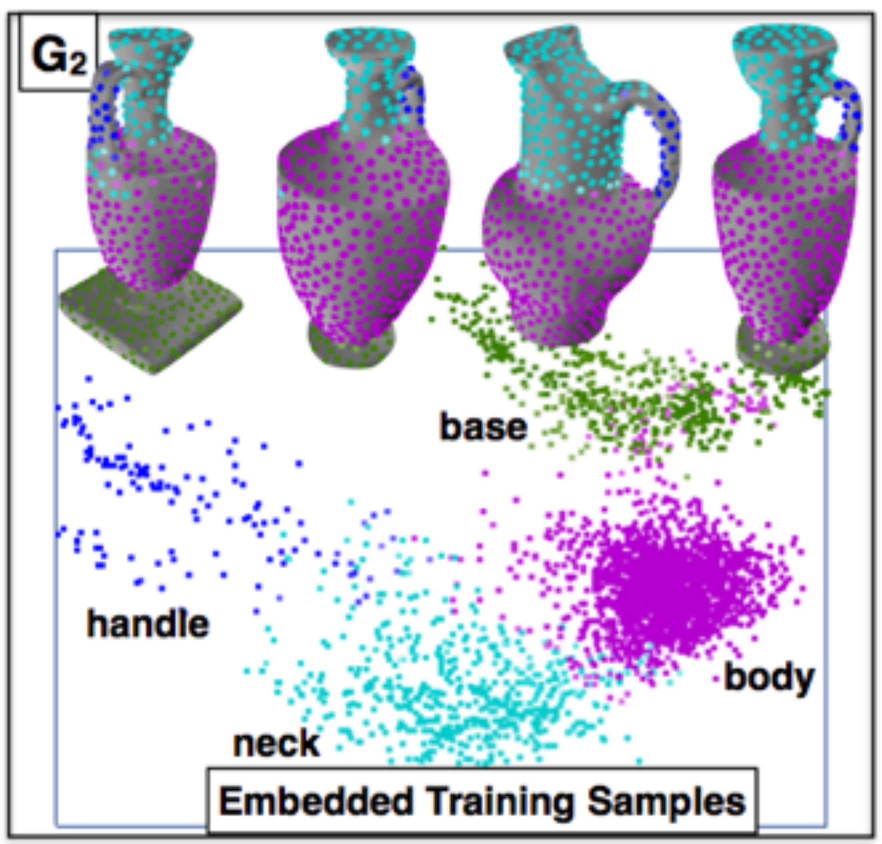
Simple 2D interface

Semantic Shape Network

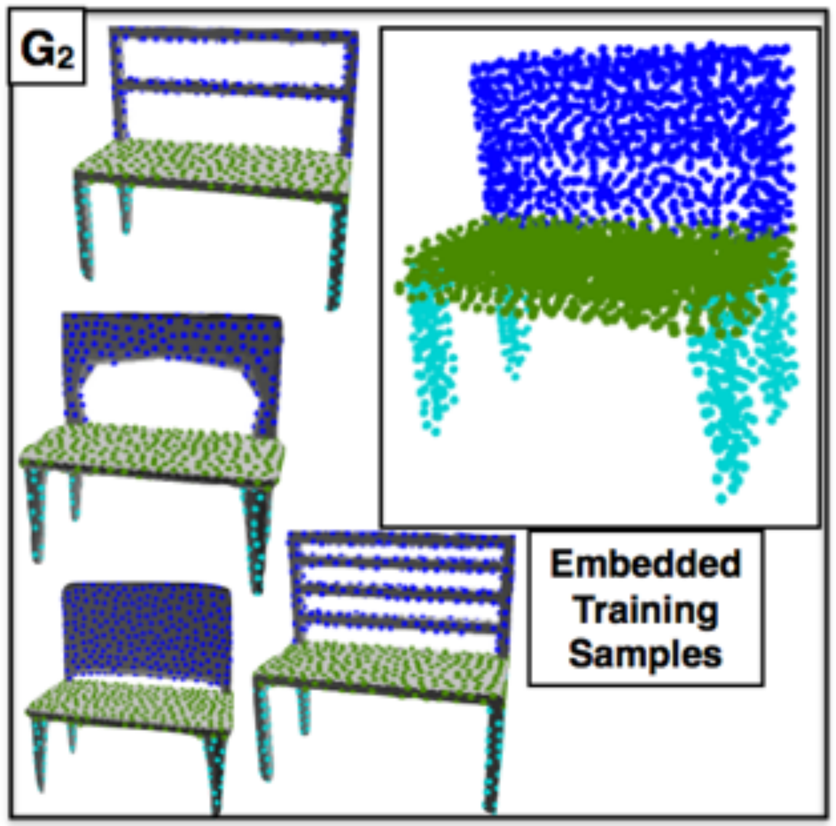
Desiderata

- Crowdsourced
- ➡ Semi-supervised
- Handle diverse data
- Active

Leverage geometry matching to propagate semantic information



Local Shape Features



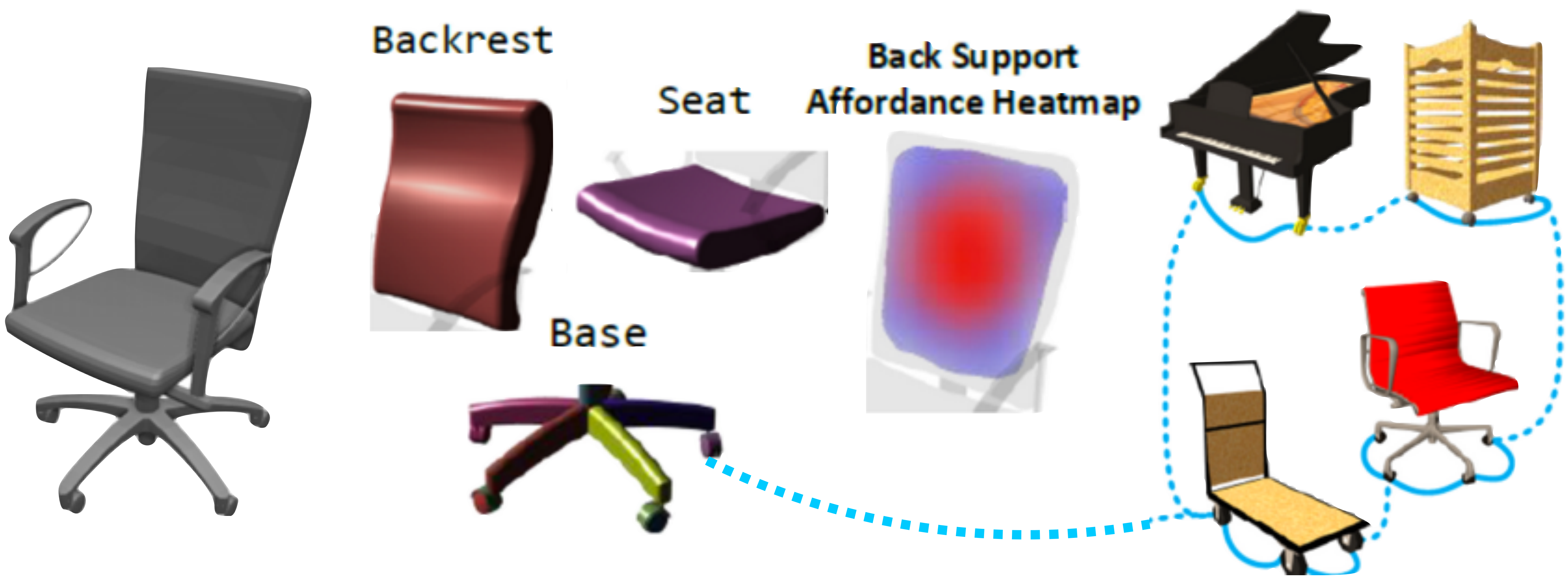
Global Correspondences

Semantic Shape Network

Desiderata

- Crowdsourced
- Semi-supervised
- ➡ Handle diverse data
- Active

Learn a network structure for propagating annotations

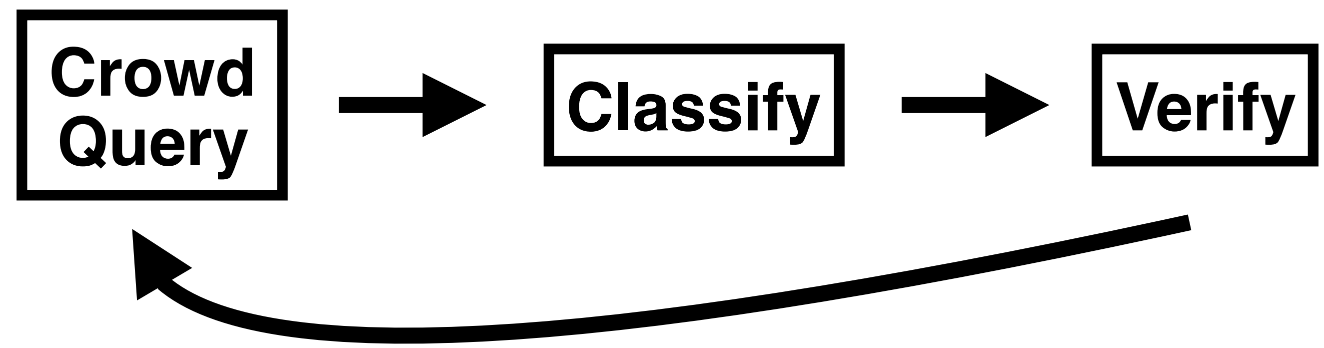


Semantic Shape Network

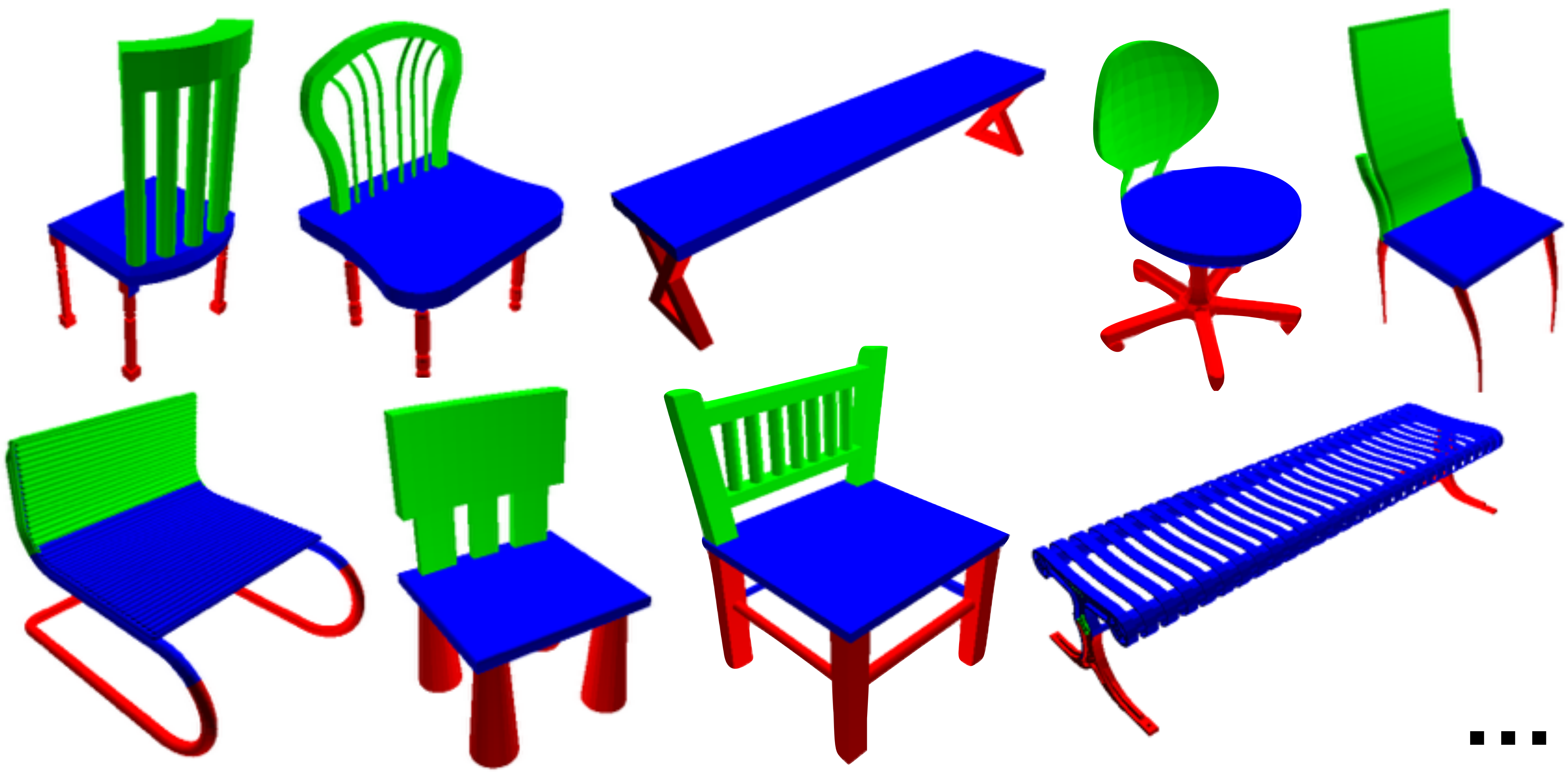
Desiderata

- Crowdsourced
- Semi-supervised
- Handle diverse data

➡ Active



preliminary results on 10K models



...

Model Dynamic Interactions

Find Structure in 3D data to infer Function

- ➡ Additional input to understand function

*image from: "Design of Everyday Things", D. Norman

An on-going project with K. Gibson, B. Araujo, K. Singh

Model Dynamic Interactions

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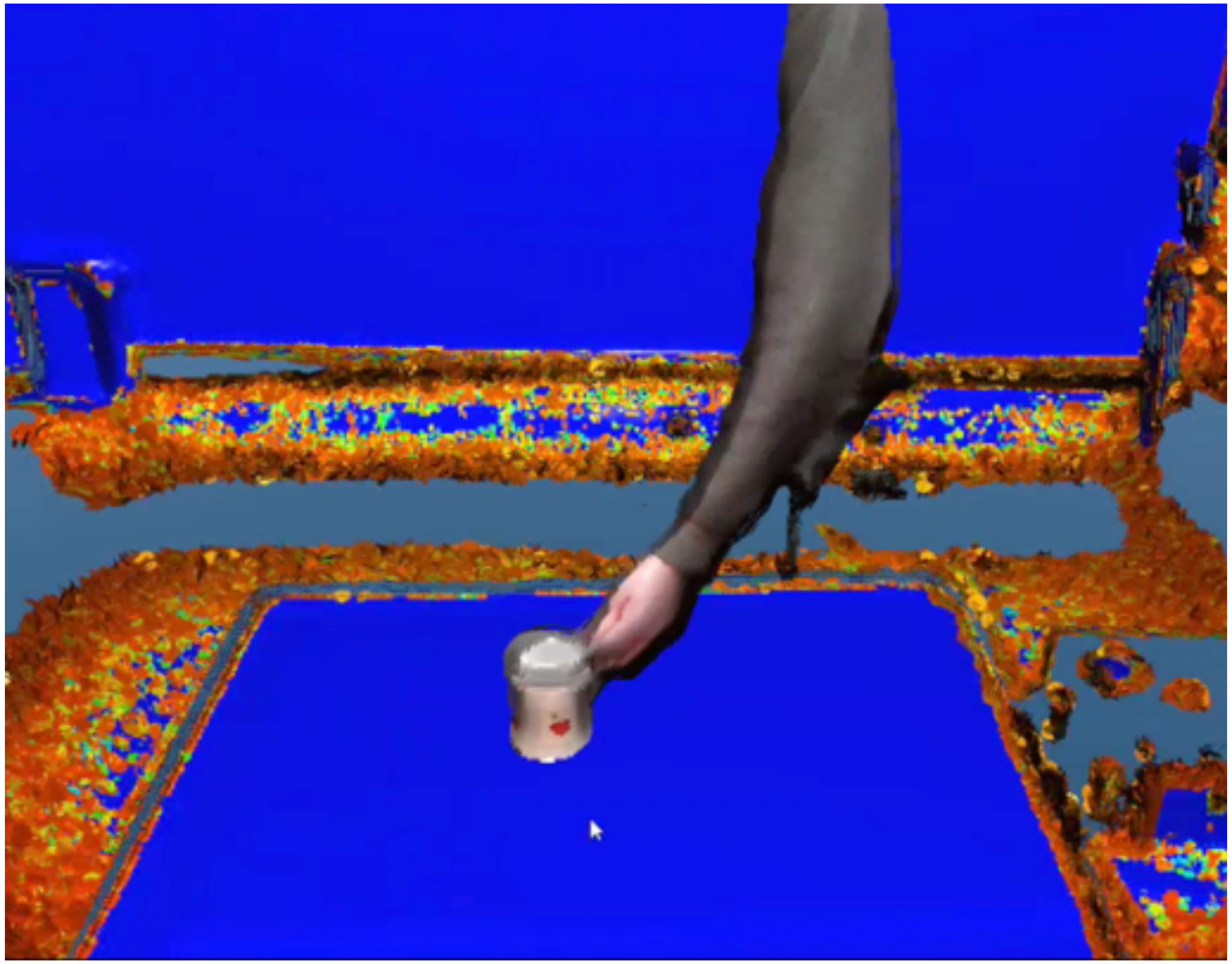


An on-going project with K. Gibson, B. Araujo, K. Singh

Research Agenda

Find Structure in 3D data to infer Function

- Better structural models
- Additional input to understand function
- ➡ Designing manufacturable objects
- Scene understanding

Furniture Design

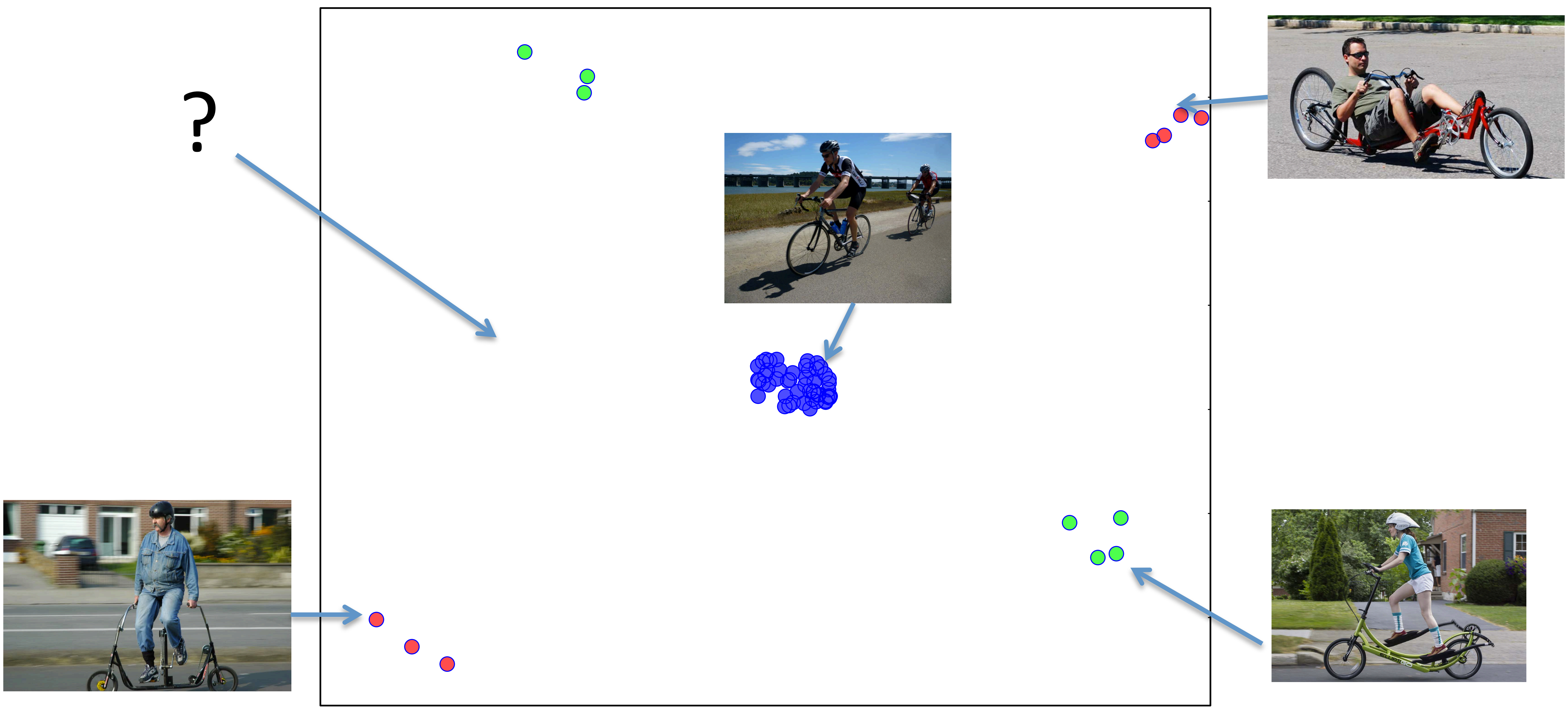
Find Structure in 3D data to infer Function

➡ Designing manufacturable objects

Design Mechanical Assemblies

Find Structure in 3D data to infer Function

- ➡ Designing manufacturable objects

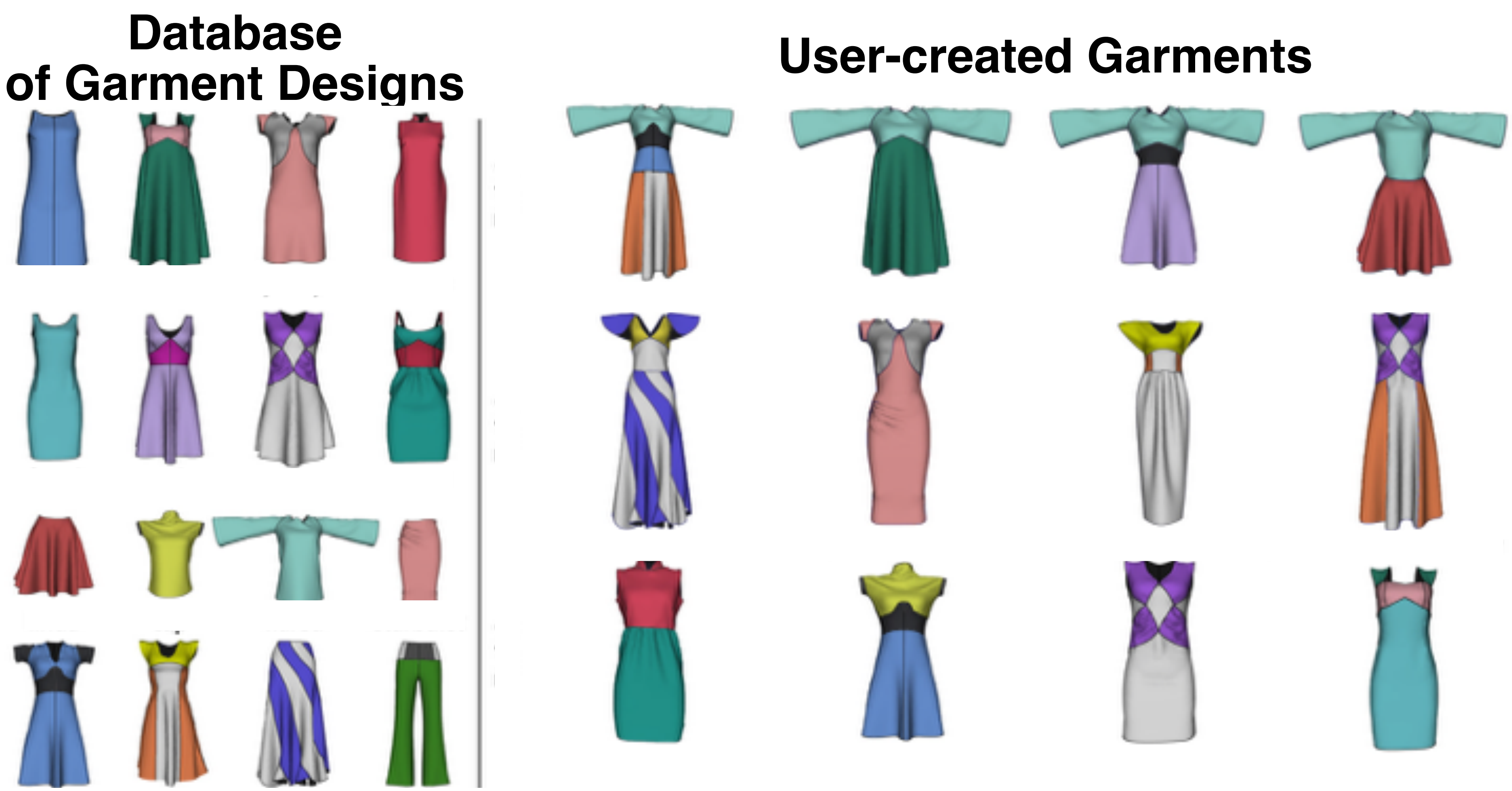


An on-going project with N. Mitra, M. Averkiou

Garment Design

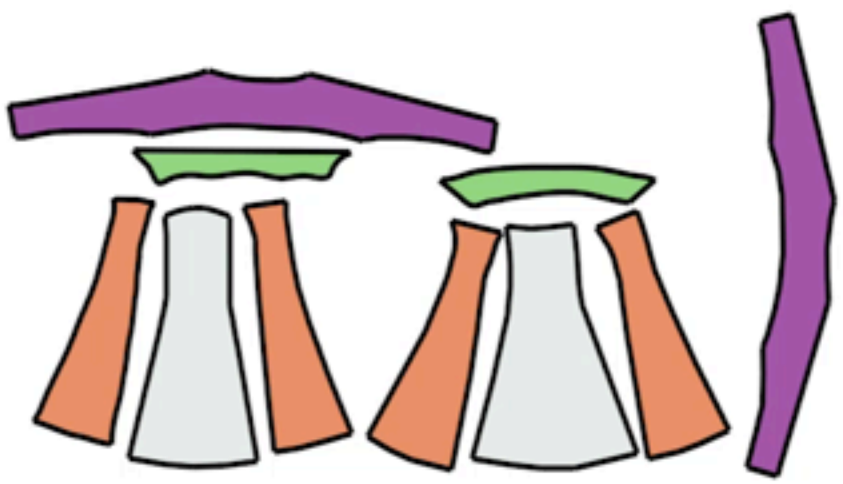
Find Structure in 3D data to infer Function

- ➡ Designing manufacturable objects



An on-going project with A. Bartle, A. Sheffer, F. Bertouzoz

Garment Design

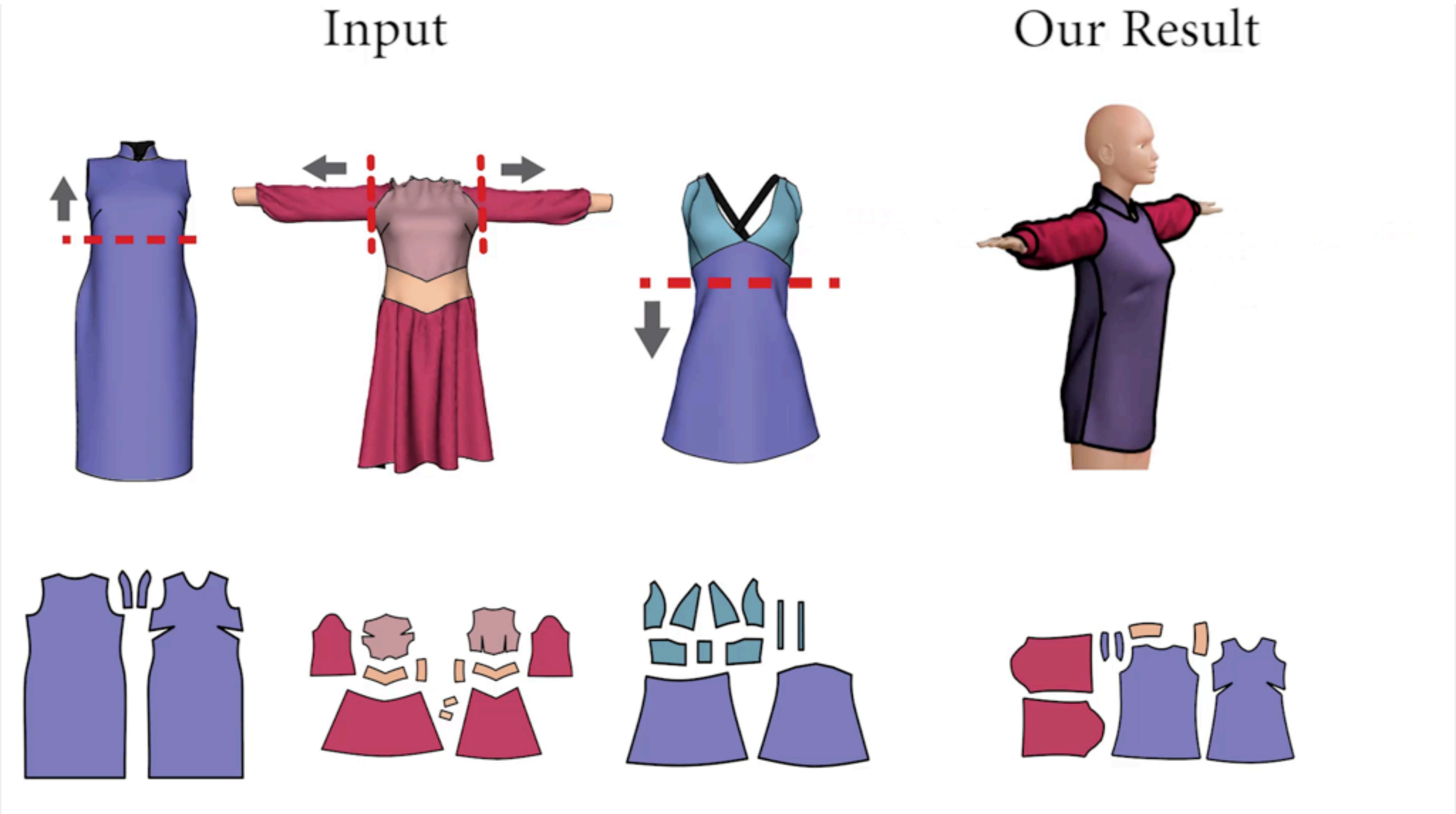


Pattern

Simulated

Manufactured

Garment Design



Garment Design

Research Agenda

Find Structure in 3D data to infer Function

- Better structural models
- Additional input to understand function
- Designing manufacturable objects

➡ Scene understanding

Research Agenda

Find Structure in 3D data to infer Function

- Better structural models
- Additional input to understand function
- Designing manufacturable objects
- ➡ Scene understanding
  - – Reason about function and semantics using 3D CG data
  - – Advantages: known lighting, camera, objects, functionality*

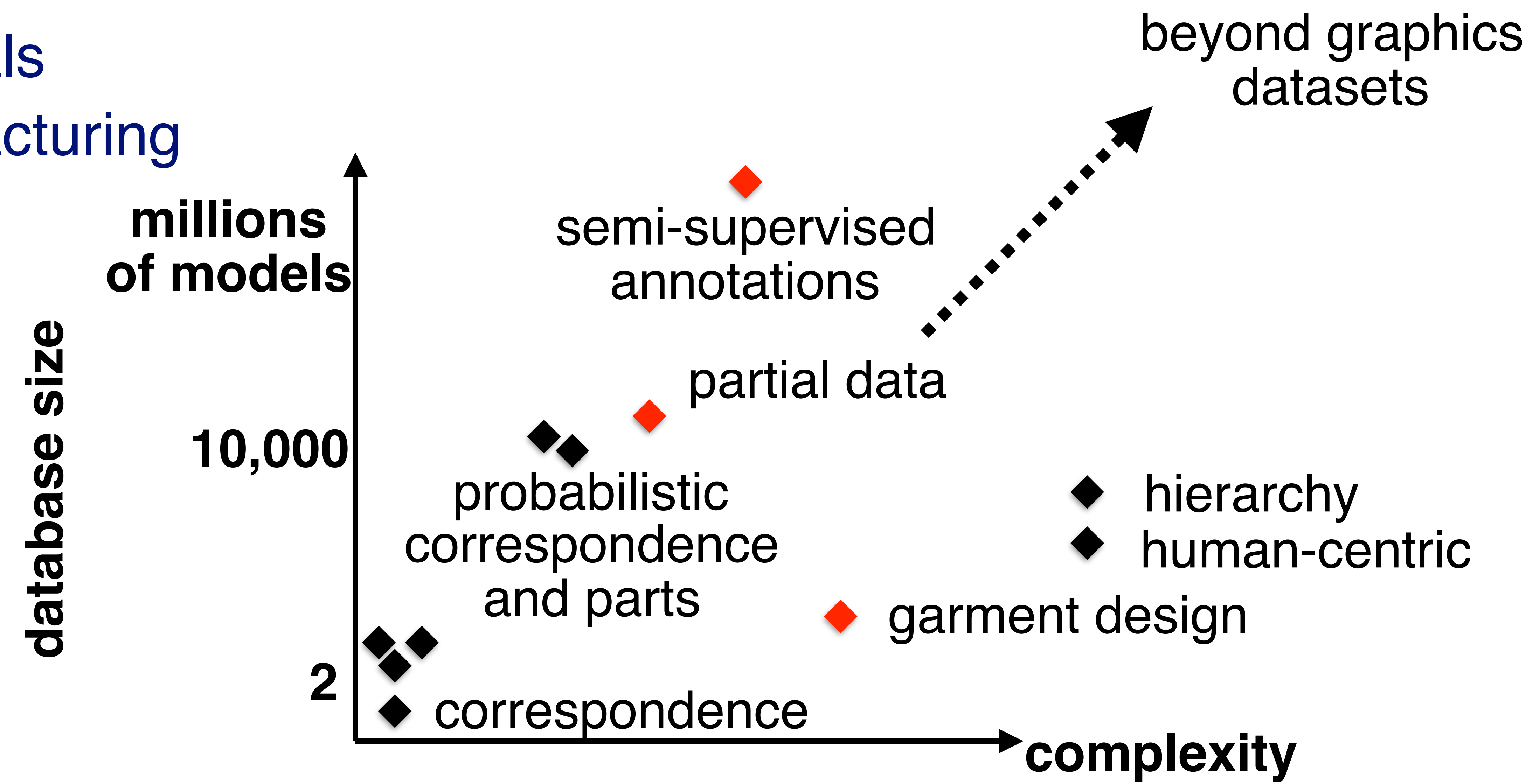
Real

Rendered

Beyond Geometry Analysis

Model object classes from large collections

- Geometry
- Semantics
- Function
- Appearance
- Materials
- Manufacturing



Summary

Large collections of 3D models are available (and more are coming!)

- 3D modeling repositories, Kinect scans, Google Streetview, online shopping catalogues, scientific datasets

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Finding structure in large 3D collections is useful to predict functional attributes

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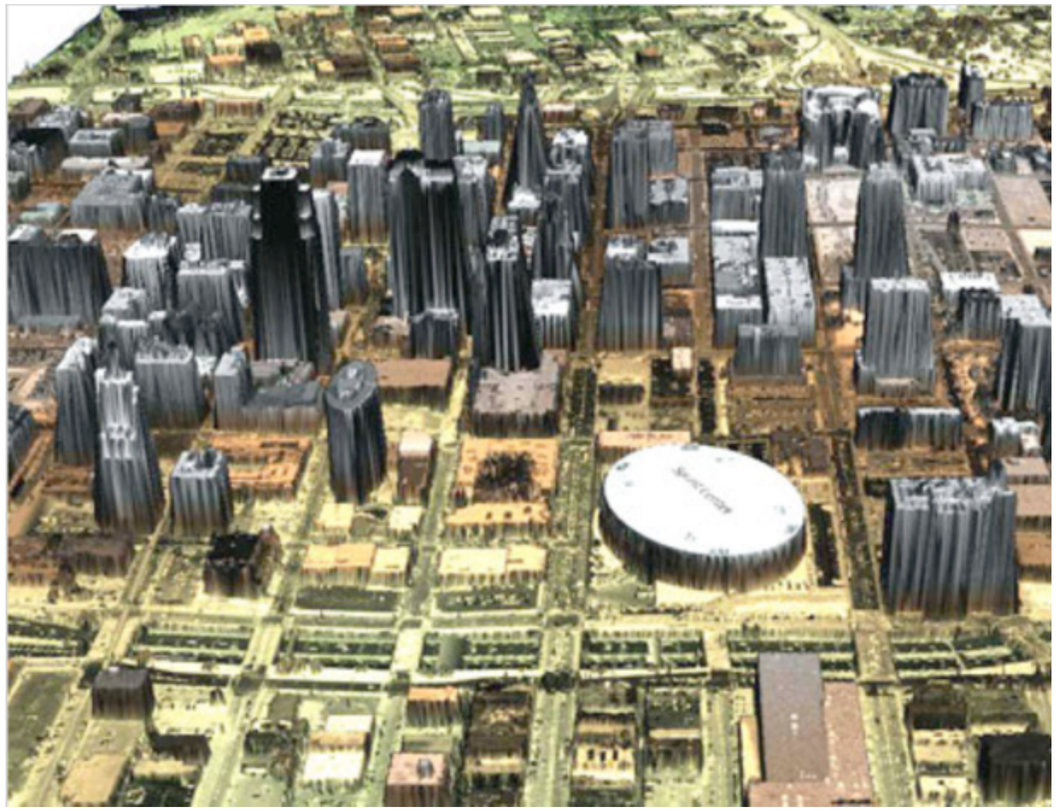
- 3D modeling repositories, Kinect scans, Google Streetview, online shopping catalogues, scientific datasets

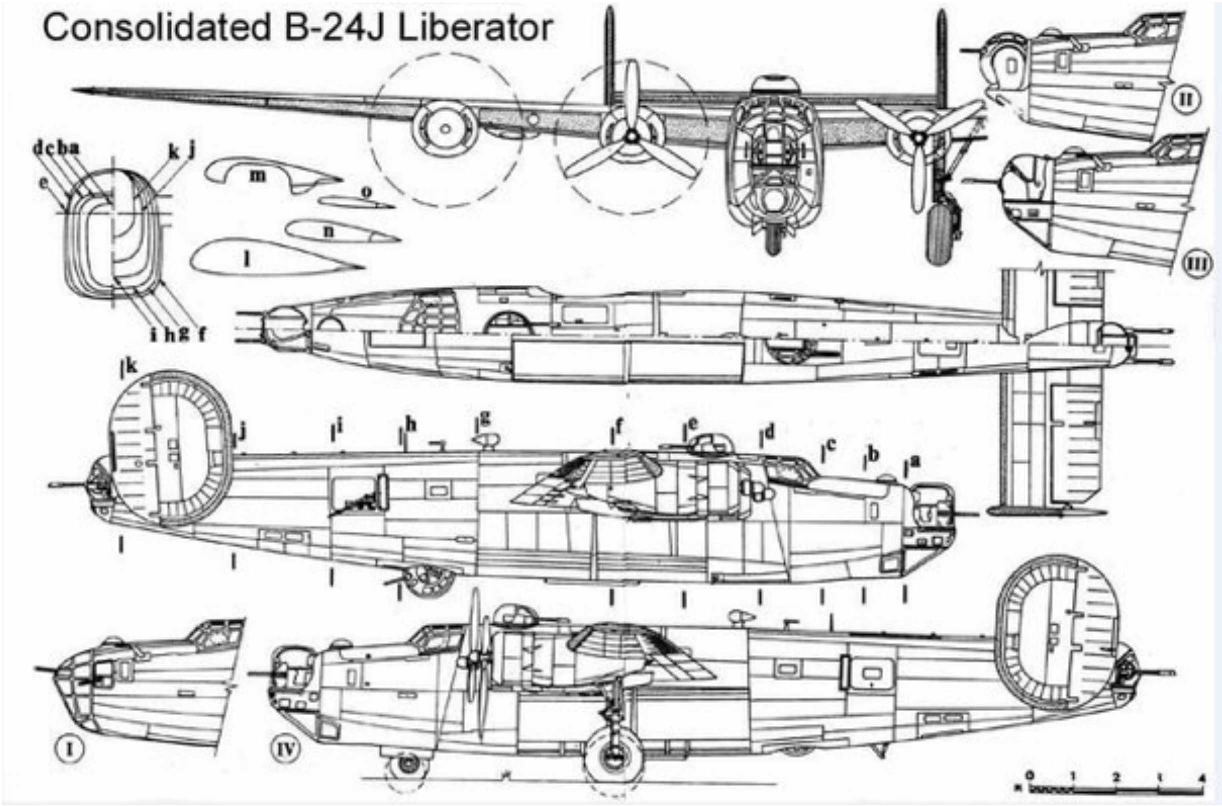
Finding structure in large 3D collections is useful to predict functional attributes

Understanding functionality is essential for

- Exploring and organizing the data
- Digital design
- Scene understanding

Explore, Analyze and Create Data





Scans of Cities **Medical Data** **CAD Models**

Understanding functionality is essential for

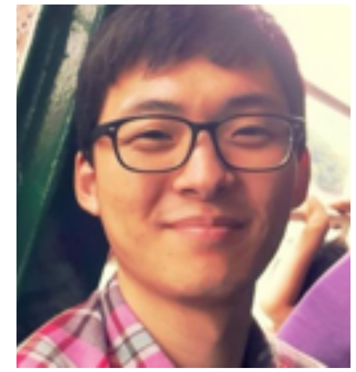
- Exploring and organizing the data
- Digital design
- Scene understanding

Collaborators

Stanford University

Leonidas Guibas

Roland Angst



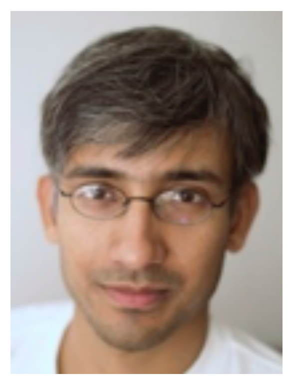
Minhyuk Sung

Hao Su

Li Yi

Princeton University

Thomas Funkhouser



Siddhartha Chaudhuri

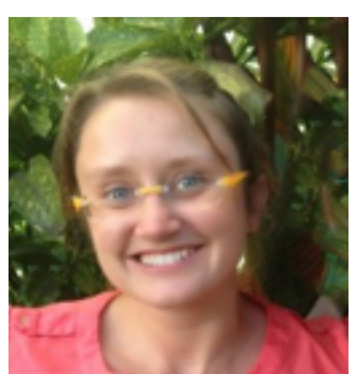
Tianqiang Liu

Xiaobai Chen

Aleksey Golovinskiy

Adobe

Wilmot Li

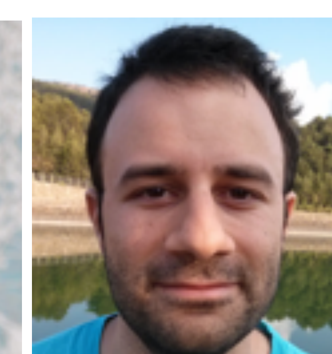


Floraine Berthouzoz

Stephan DiVerdi

UCL University College London

Niloy Mitra



Melinos Averkiou

Collaborators

University of British Columbia

Alla Sheffer

I-Chao Shen

TTIC

Qi-xing Huang

University of Toronto

Karan Singh

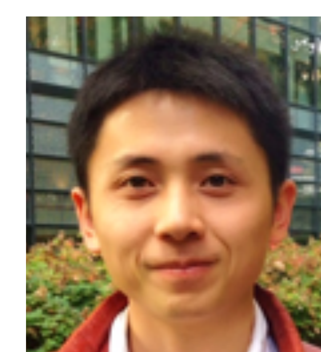
Bruno Rodrigues De Araujo

Kevin Gibson

Weizmann Institute of Science

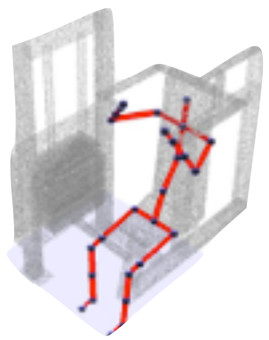
Yaron Lipman

Yale University

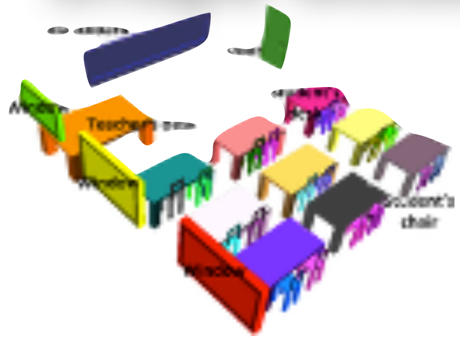


Youyi Zheng

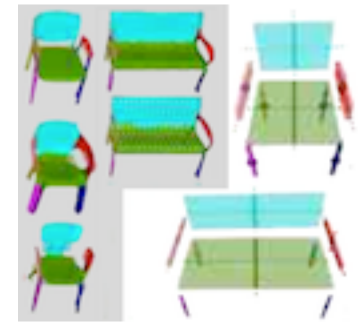
Shape Models



Human-centric
[SIGGRAPH'14]



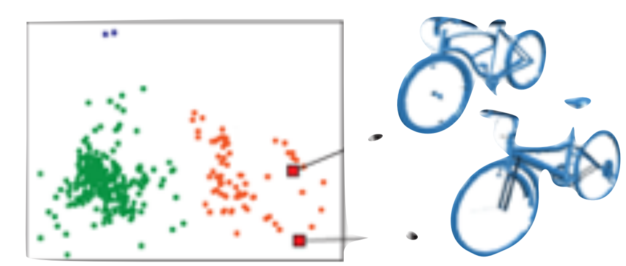
Hierarchical
[SIGGRAPH Asia'14]



Part-based
[SIGGRAPH'13]

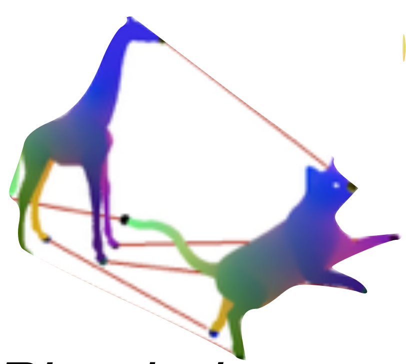
Exploration and Synthesis

Exploration via Fuzzy Correspondence
[SIGGRAPH'12]



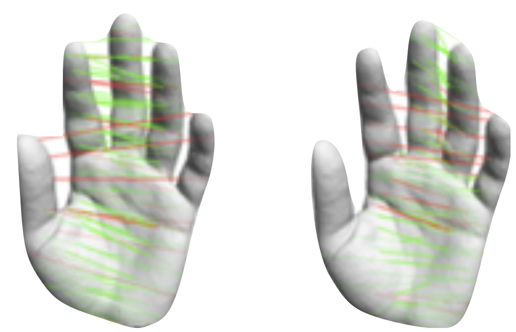
Coupled Exploration and Synthesis
[EG'14]

Shape Correspondence



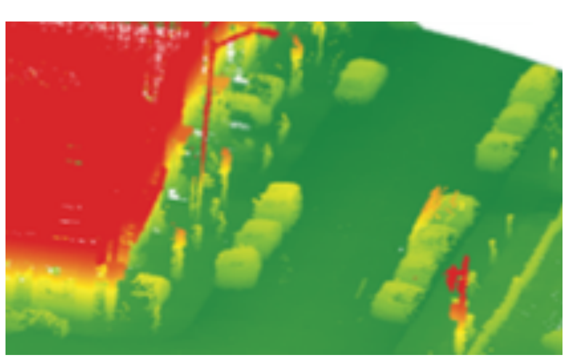
Blended maps
[SIGGRAPH'11]

Symmetry maps
[SGP'12]



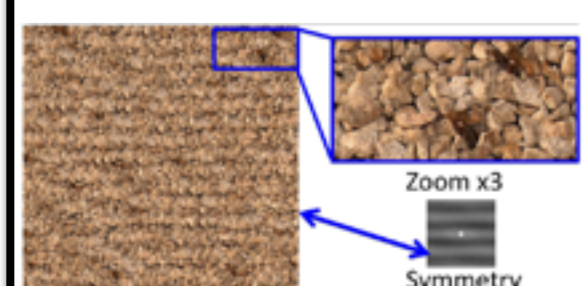
Intrinsic symmetry
[SGP'10]

Recognition

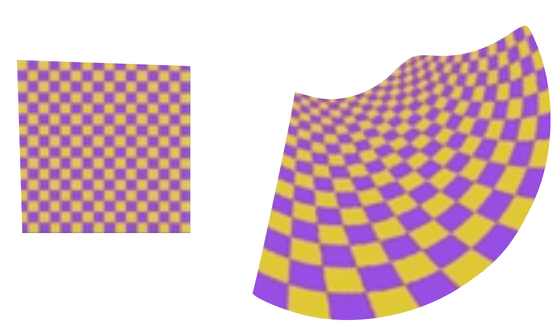


Urban point cloud
[ICCV'09]

Images and Textures

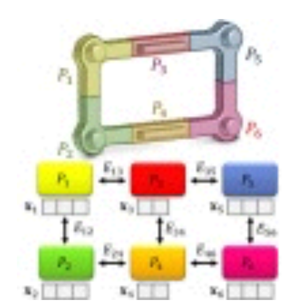


Symmetry-guided
[ToG'12]



Quasi-conformal
[ToG'12]

Courses



Structure-aware
[SIGGRAPH'14]
[SIGGRAPH Asia'14]