

Structure and Function **in Large Collections of 3D Shapes**

Vladimir G. Kim




**Stanford
University**

How Do We Use Computers?

Explore, Analyze, and Create Data

How Do We Use Computers?

Explore, Analyze, and Create Data



Online Shopping

Electronics Digital Cameras Sort: Default View: List My Shortlist Merchant links are sponsored

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Mountain View, CA
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Price
☐ Up to \$250
☐ \$250 – \$500
☐ \$500 – \$900
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\$ to \$ Go

Category - Clear
☒ Digital Cameras

Brand
☐ Nikon
☐ Canon
☐ Sony
☐ Fujifilm
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More

Type
☐ Point & Shoot
☐ DSLR

Canon PowerShot SX170 IS 16.0 MP Digital Camera - Black
\$119.00 from 25+ stores Also available nearby
★★★★★ 292 product reviews #1 in Canon Digital Cameras
August 2013 · Canon · PowerShot · PowerShot S/SX Series · Point & Shoot · Compact Sensor · 16 megapixel · 16 x optical zoom · Pop-up Flash · 8 ounce

Canon EOS Rebel T3i 18.0 MP DSLR Camera - Black - EF-S 18-55mm I...
\$599.00 from 50+ stores Also available nearby
★★★★★ 4,109 product reviews #2 in Canon Digital Cameras
February 2011 · Canon · EOS · EOS Rebel · DSLR · Crop Sensor · 18 megapixel · 3 x optical zoom · Pop-up Flash · Detachable Flash
Other lens bundle options: [Body only \(\\$375\)](#) [More](#)

Nikon Coolpix L310 14.1 MP Digital Camera - Black
\$159.99 from 5+ stores
★★★★★ 21 product reviews
February 2012 · Nikon · Nikon COOLPIX · Point & Shoot · Compact Sensor · 14.1 megapixel · 21 x optical zoom · Pop-up Flash · 15.3 ounce · C

Sony Cyber-shot DSC-H200 20.1 MP Digital Camera - Black
\$249.99 from 25+ stores Also available nearby
★★★★★ 154 product reviews
January 2013 · Sony · Cyber-shot · Cyber-shot H Series · Point & Shoot · Compact Sensor · 20.1 megapixel · 26 x optical zoom · Pop-up Flash · 15.2 ounce

Nikon D3100 14.2 MP Digital SLR Camera - Black - AF-S DX 18-55mm ...
\$243.00 from 50+ stores
★★★★★ 2,101 product reviews
March 2011 · Nikon · Nikon D Series · DSLR · Crop Sensor · 14.2 megapixel · 3 x optical zoom · Pop-up Flash · Detachable Flash · 16 ounce
Other options: [Black - AF-S DX 18-105mm Lens \(\\$549\)](#) [More](#)

Nikon Coolpix L28 20.1 MP Digital Camera - Red
\$99.99 from 20+ stores
★★★★★ 167 product reviews
Nikon · Nikon COOLPIX · Point & Shoot · Compact Sensor · 20.1 megapixel · 5 x optical zoom · Built-in Flash · 5.8 ounce · CCD
Other style options: [Black \(\\$130\)](#) [Pink \(\\$76\)](#) [Silver \(\\$140\)](#)

Nikon Coolpix L820 16.0 MP Digital Camera - Black
\$169.00 from 10+ stores
★★★★★ 977 product reviews

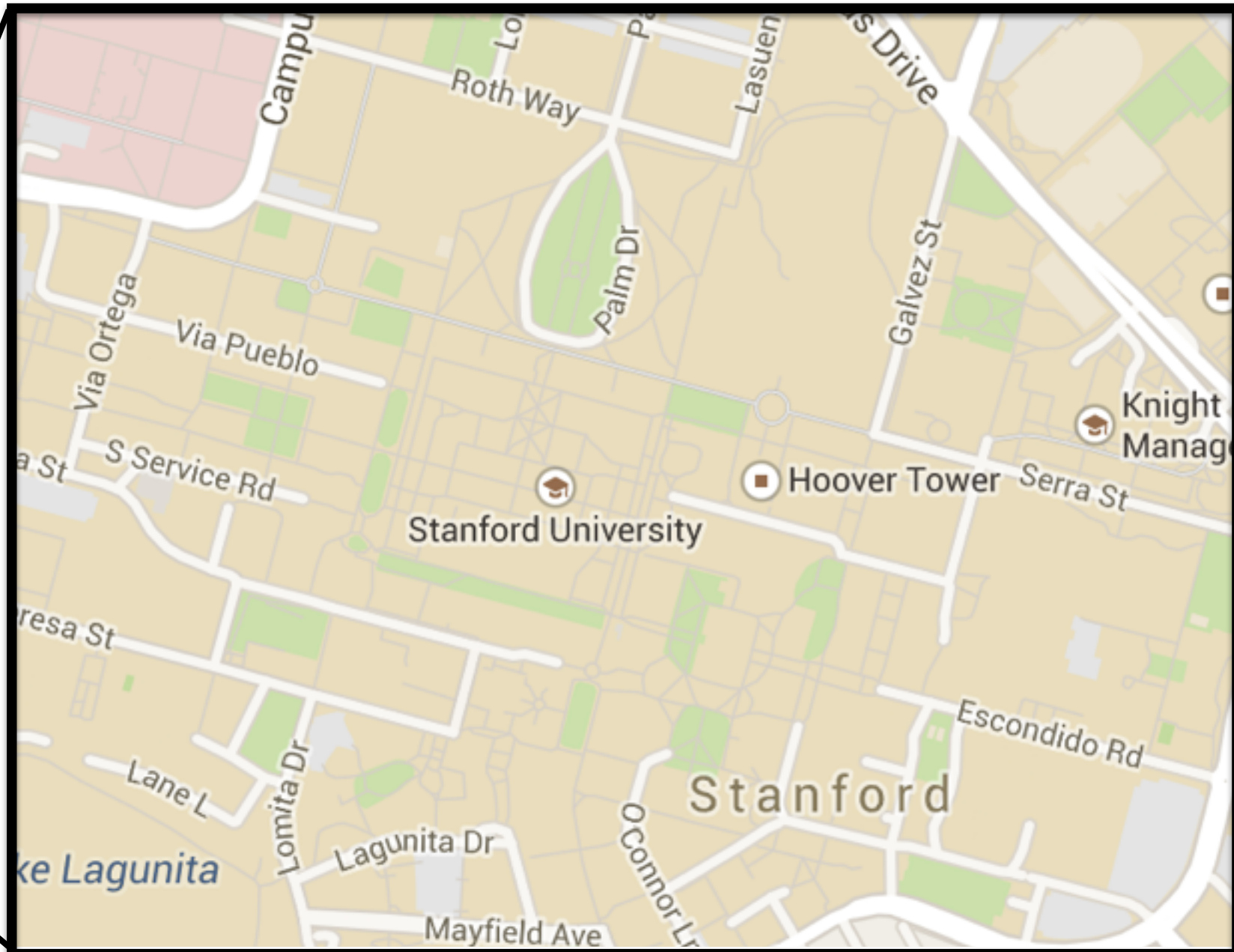
How Do We Use Computers?

Explore, Analyze, and Create Data




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How Do We Use Computers?

Explore, Analyze, and Create Data



Canon PowerShot SX170 IS 16.0 MP Digital Camera - Black

★★★★★ 292 product reviews #1 in Canon Digital Cameras

August 2013 · Canon · PowerShot · PowerShot S/SX Series · Point & Shoot · Compact Sensor · 16 megapixel · 16 x optical zoom · Pop-up Flash · 8 ounce

Zoom in on images you're not likely to capture with a smartphone. The 16x optical zoom on the PowerShot SX170 IS camera gets you up close to kids and wildlife, down on the ... [more »](#)

Other options ▾

\$119.00
Free shipping. No tax
[Adorama Camera](#)
★★★★★ (6,906)

[Shop](#)

\$119.95 [B&H Photo-Video-Audio](#)
\$129.00 [Rakuten.com - BUYDIG](#)
\$129.00 [BuyDig.com](#)

Compare prices from 25+ stores

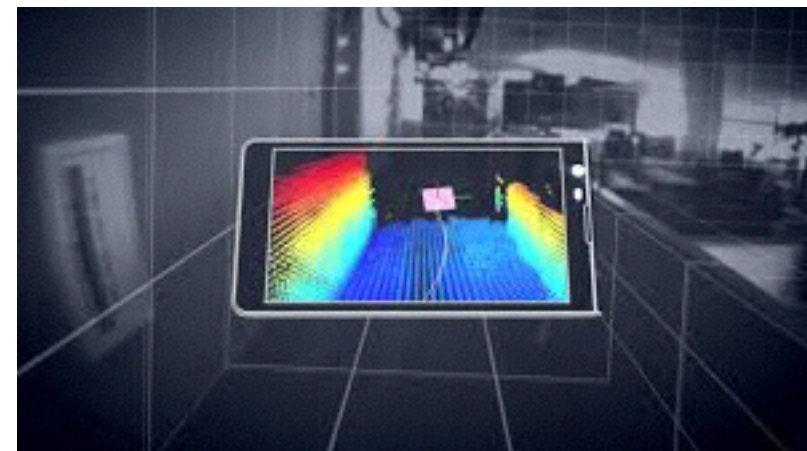
📍 \$179.99 nearby at Fry's Electronics

How Do We Use Computers?

Explore, Analyze, and Create Data



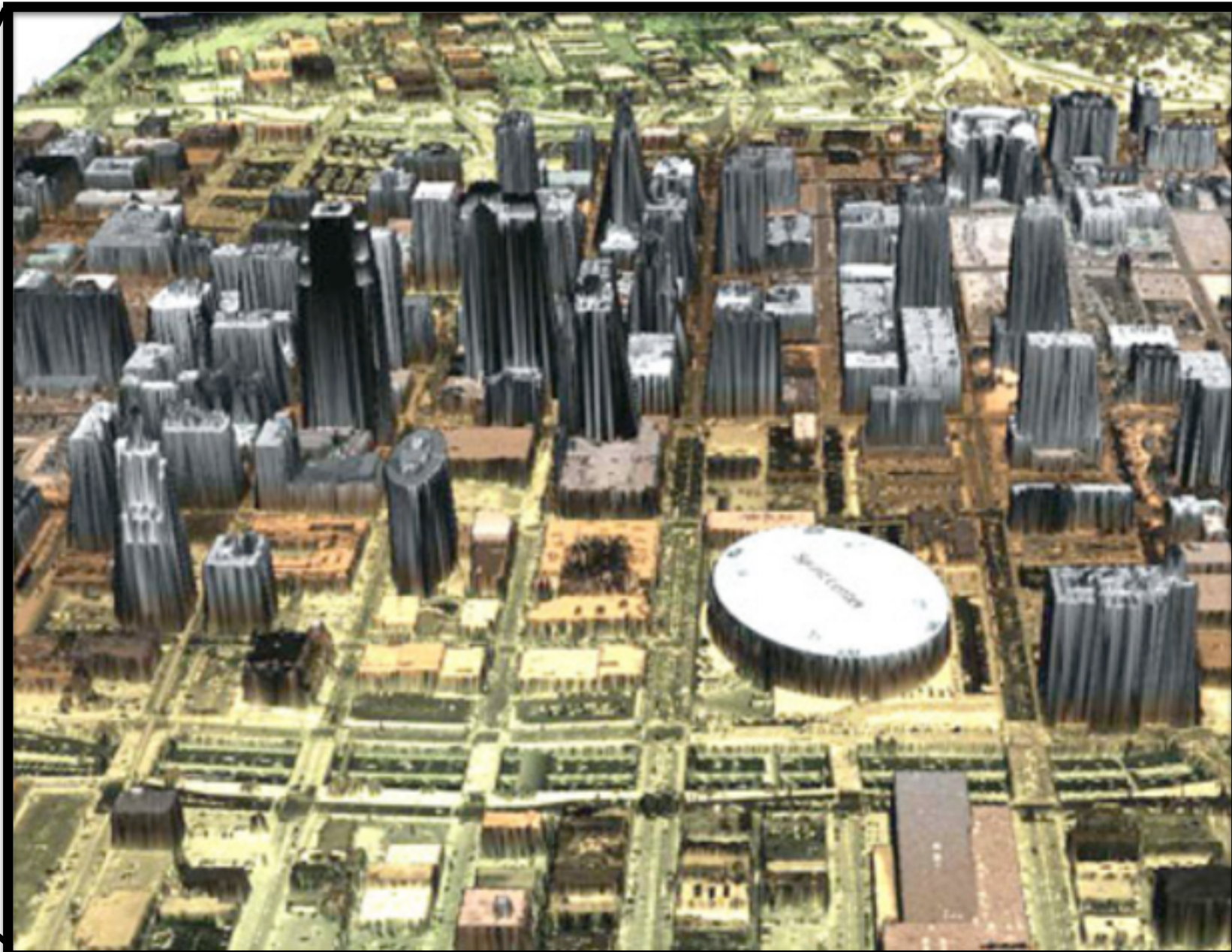
24 million MS Kinect devices!



Project Tango

How Do We Use Computers?

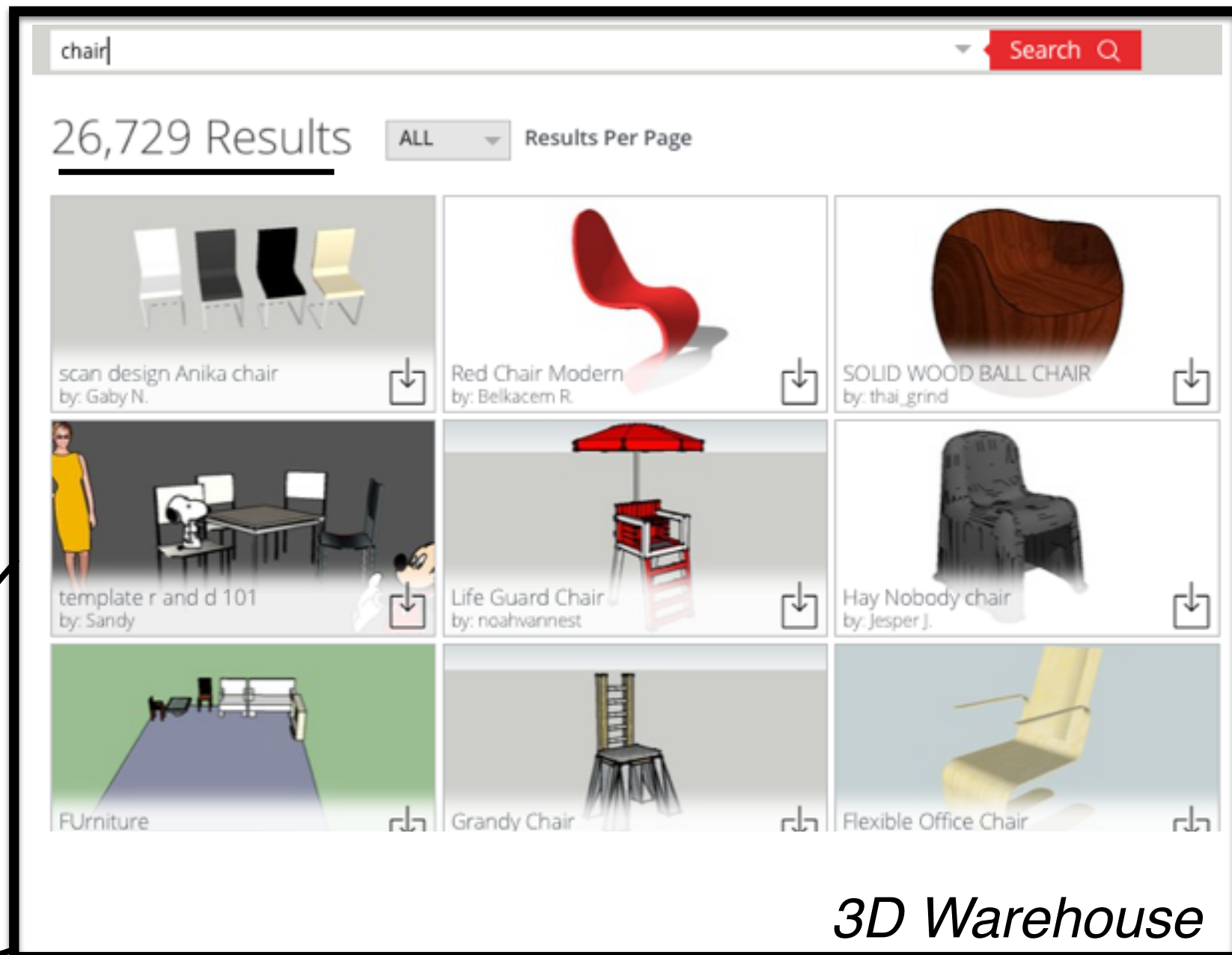
Explore, Analyze, and Create Data



Google Streetview Point Cloud

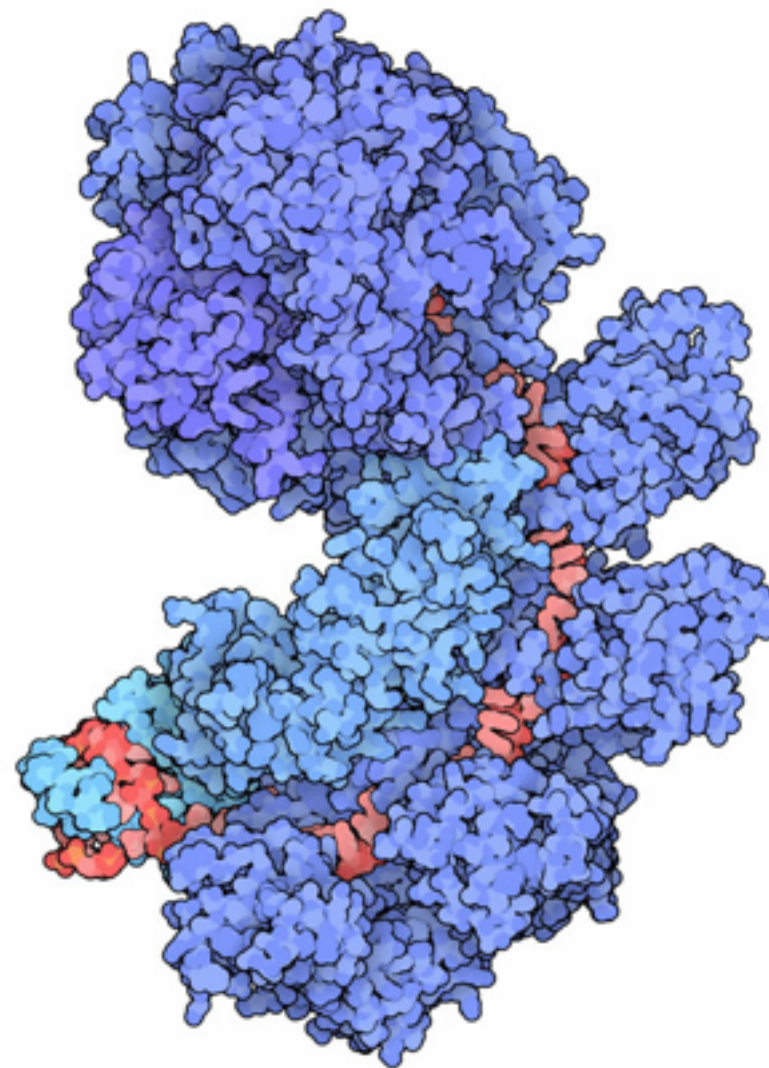
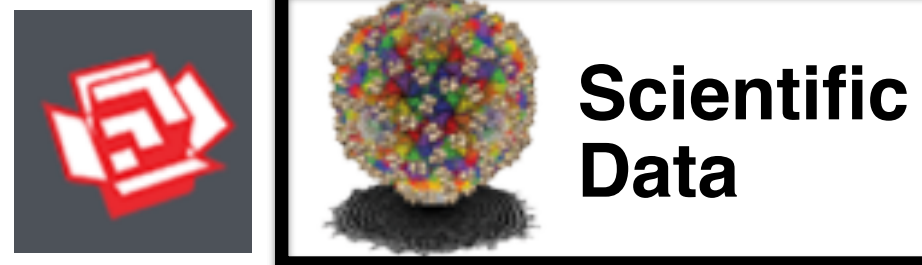
How Do We Use Computers?

Explore, Analyze, and Create Data



How Do We Use Computers?

Explore, Analyze, and Create Data



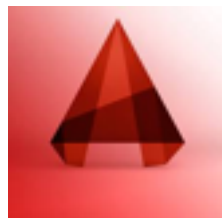
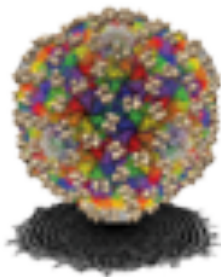
Protein Data Bank



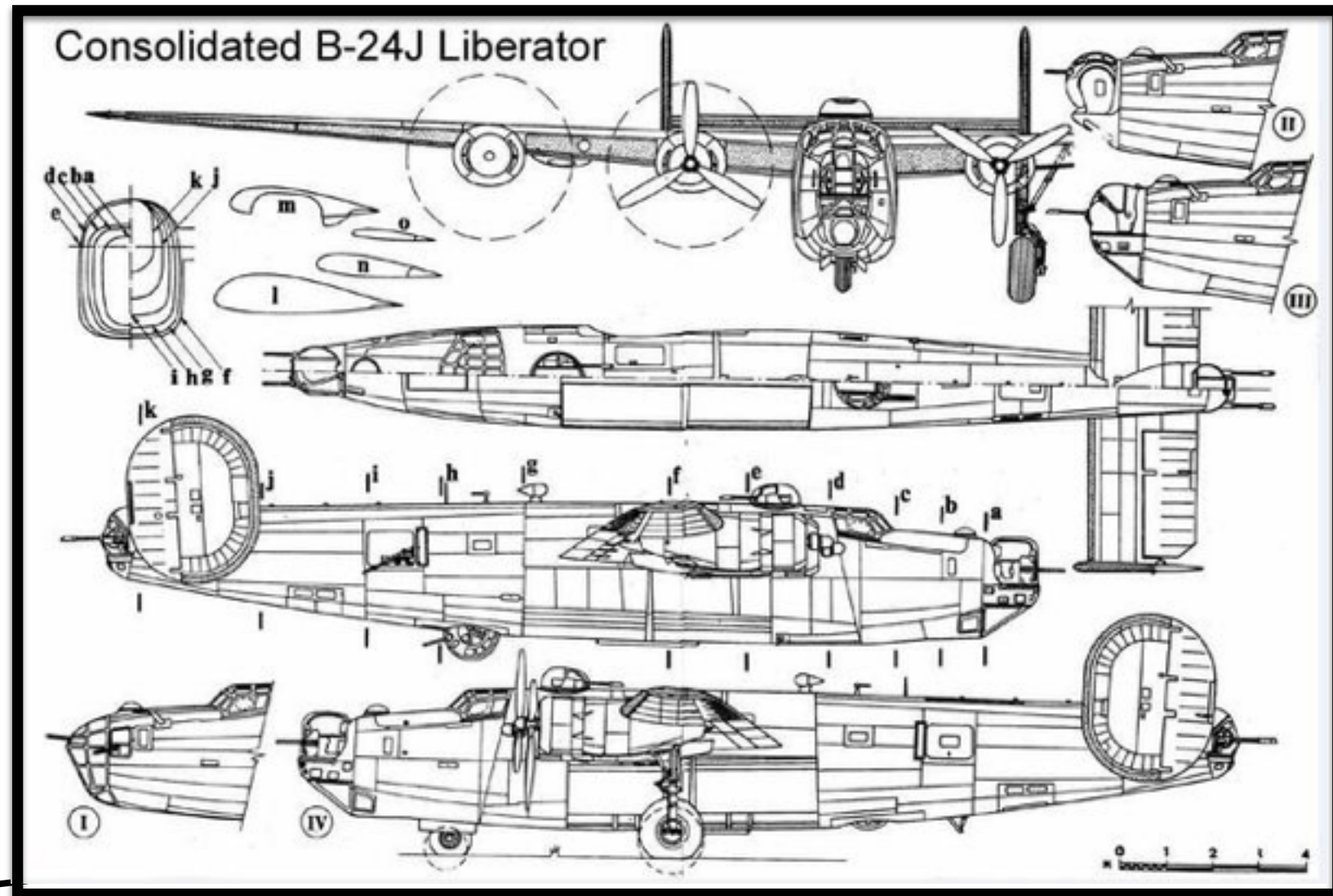
Medical Imaging

How Do We Use Computers?

Explore, Analyze, and Create Data



**CAD
Models**

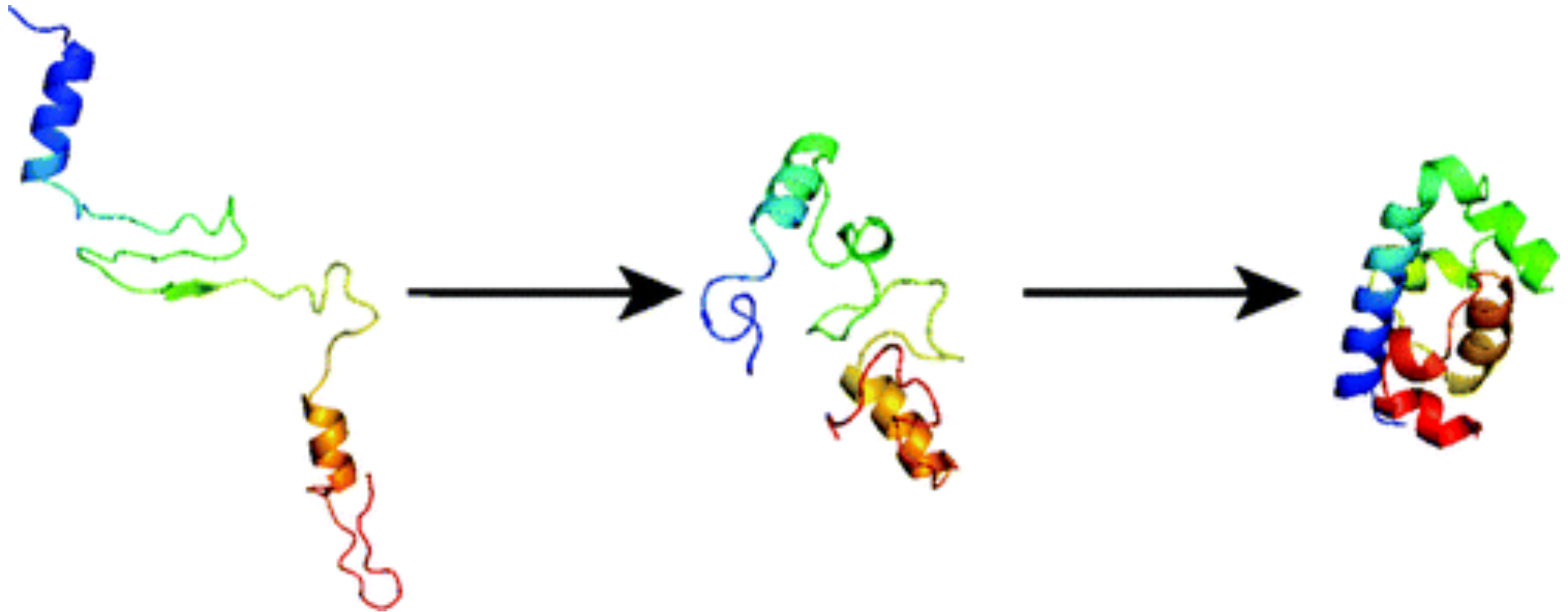


Geometry and Function

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



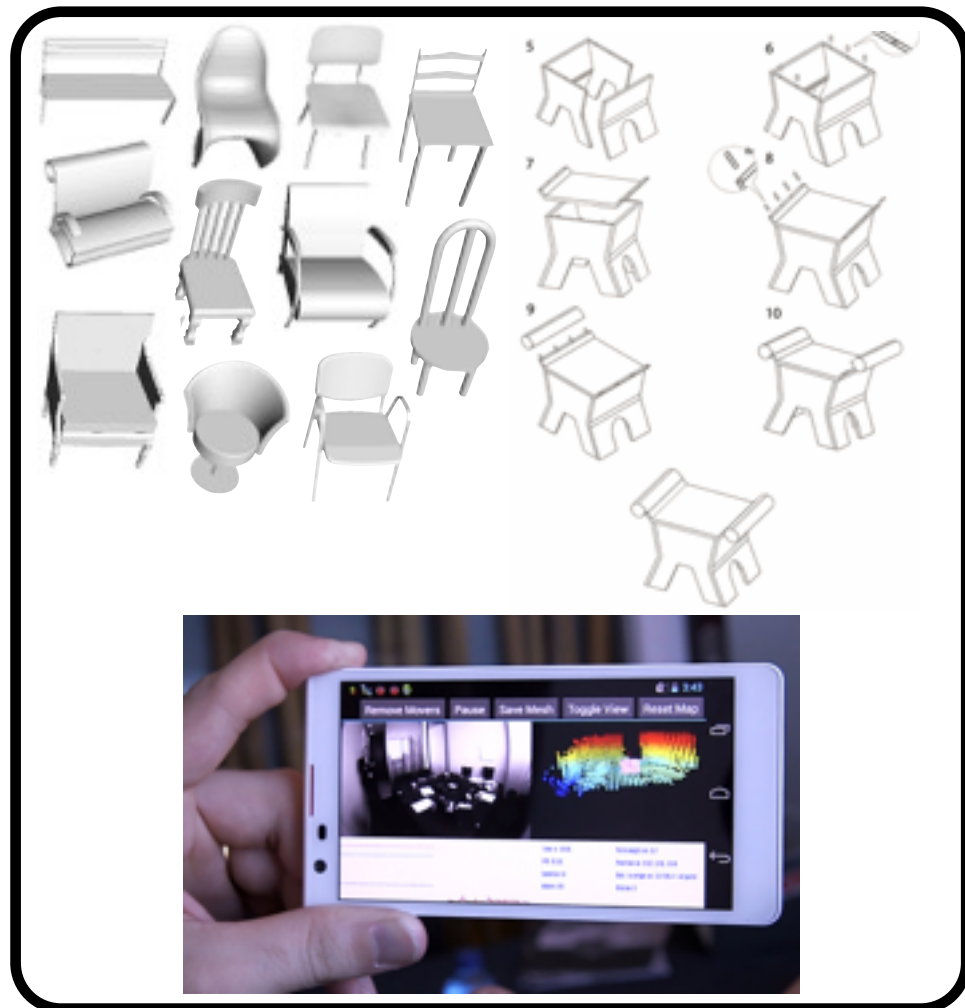
**Image from Mathieu Aubry*

3D Geometry is essential to understand functionality

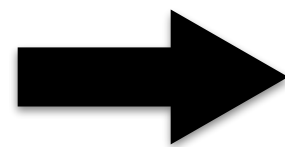
Research Agenda

Find structure in 3D data to

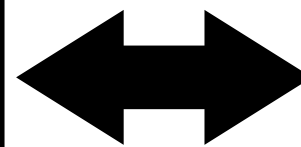
- Understand similarities
- Detect important regions
- Learn structural variations



3D Data

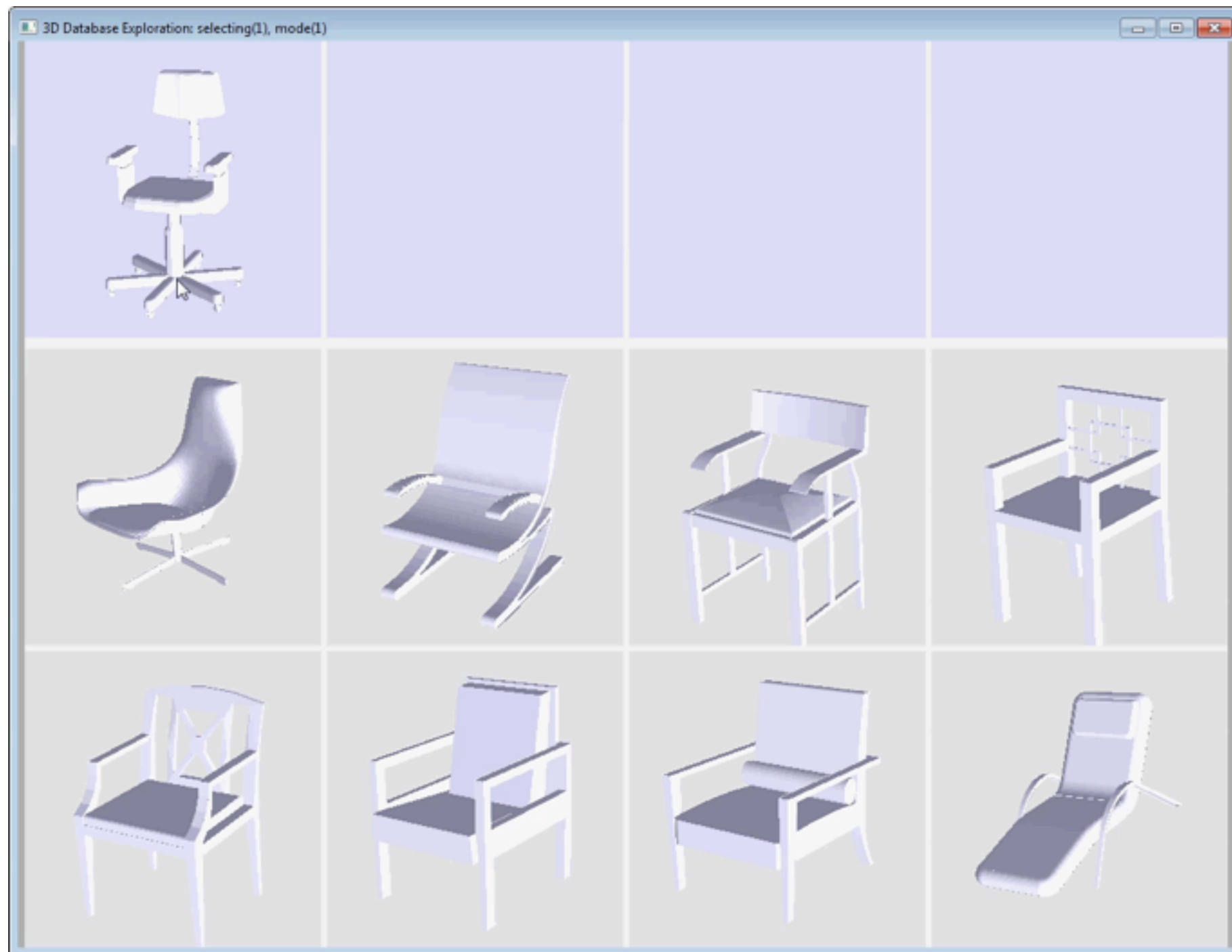


**Structural
Model**



**Understand
Function**

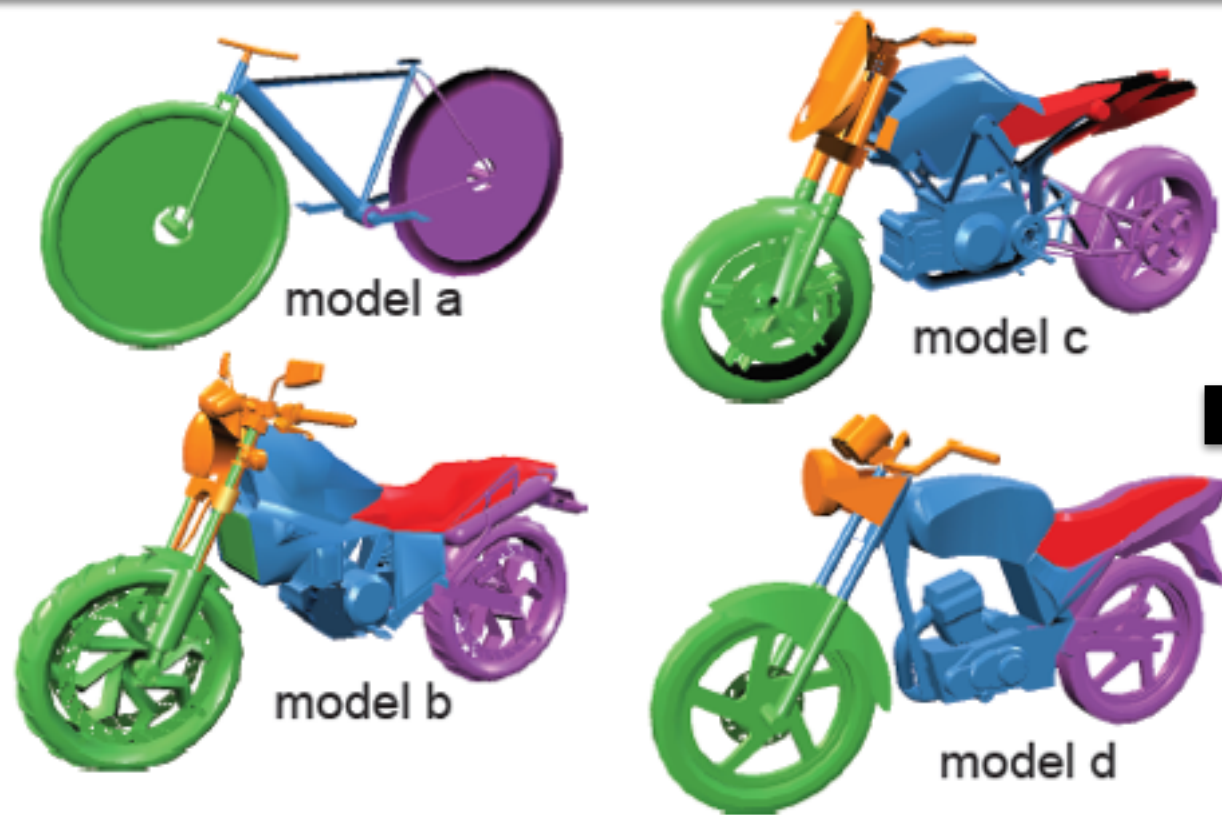
Motivating Applications



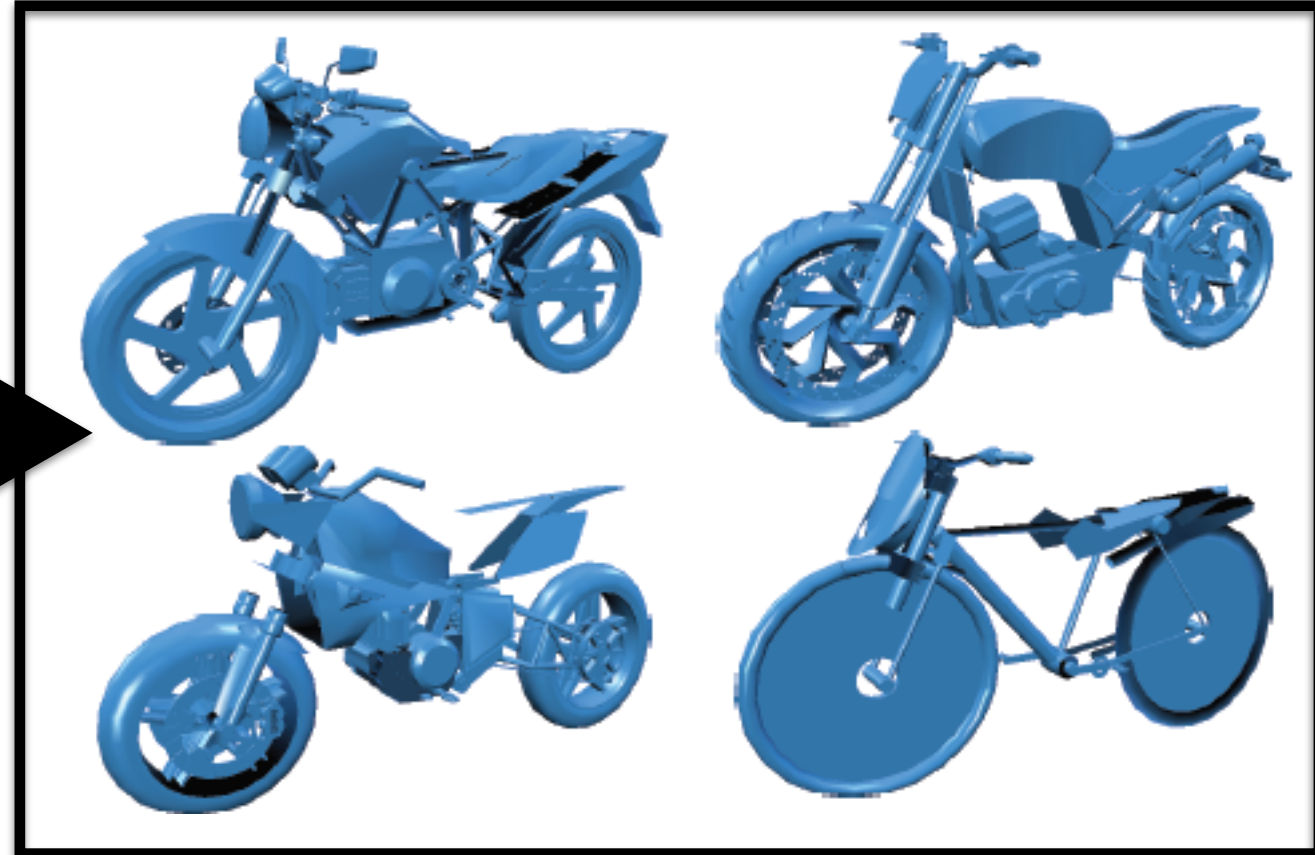
**Understand
Similarity
to Explore
Collections
of Objects**

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

Motivating Applications



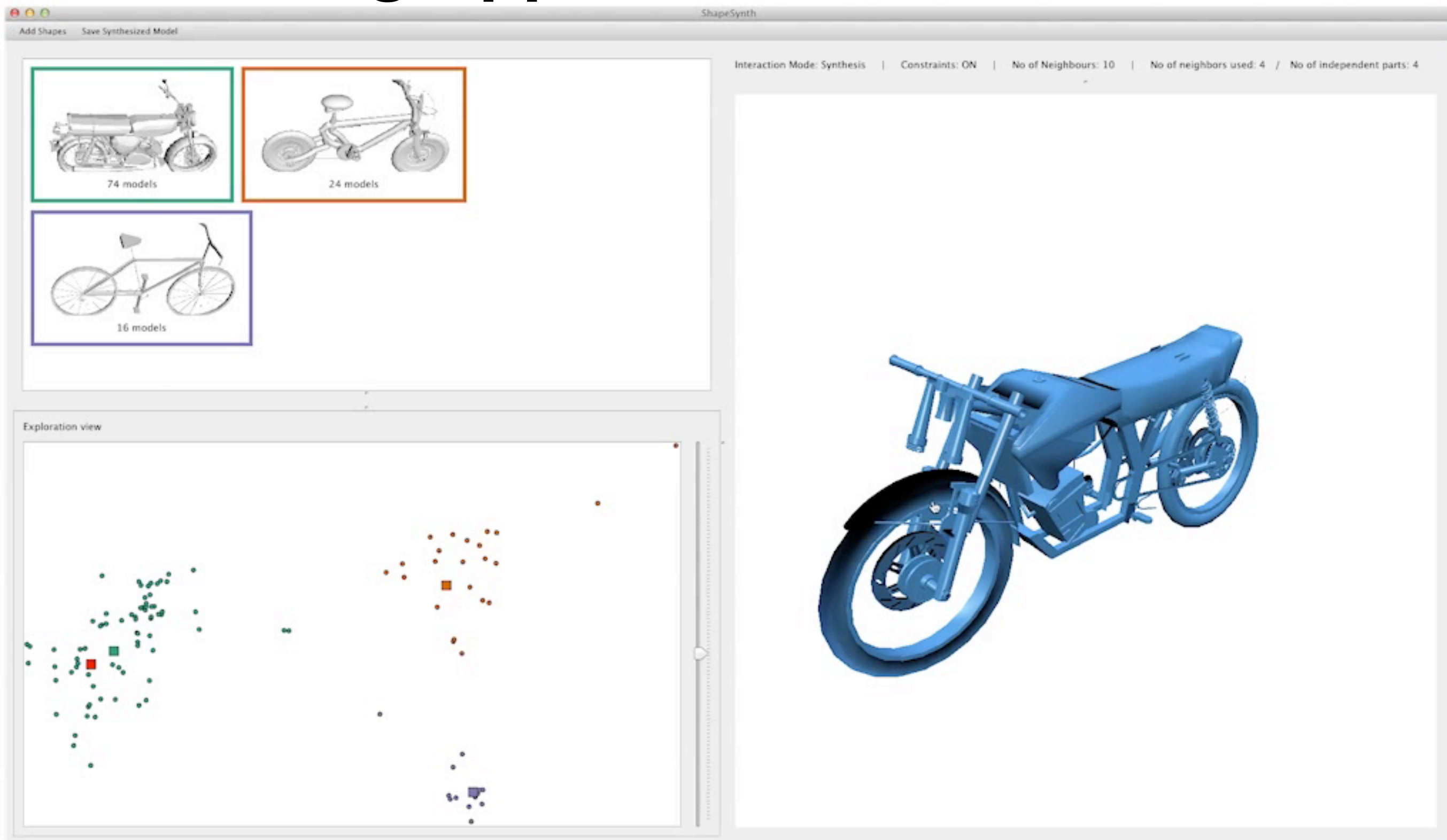
Database of 3D Objects
(takes hours to create a model)



User-created
 ≈ 1 minute

**Learn
Structural
Variations
to Synthesize
Plausible
Shapes**

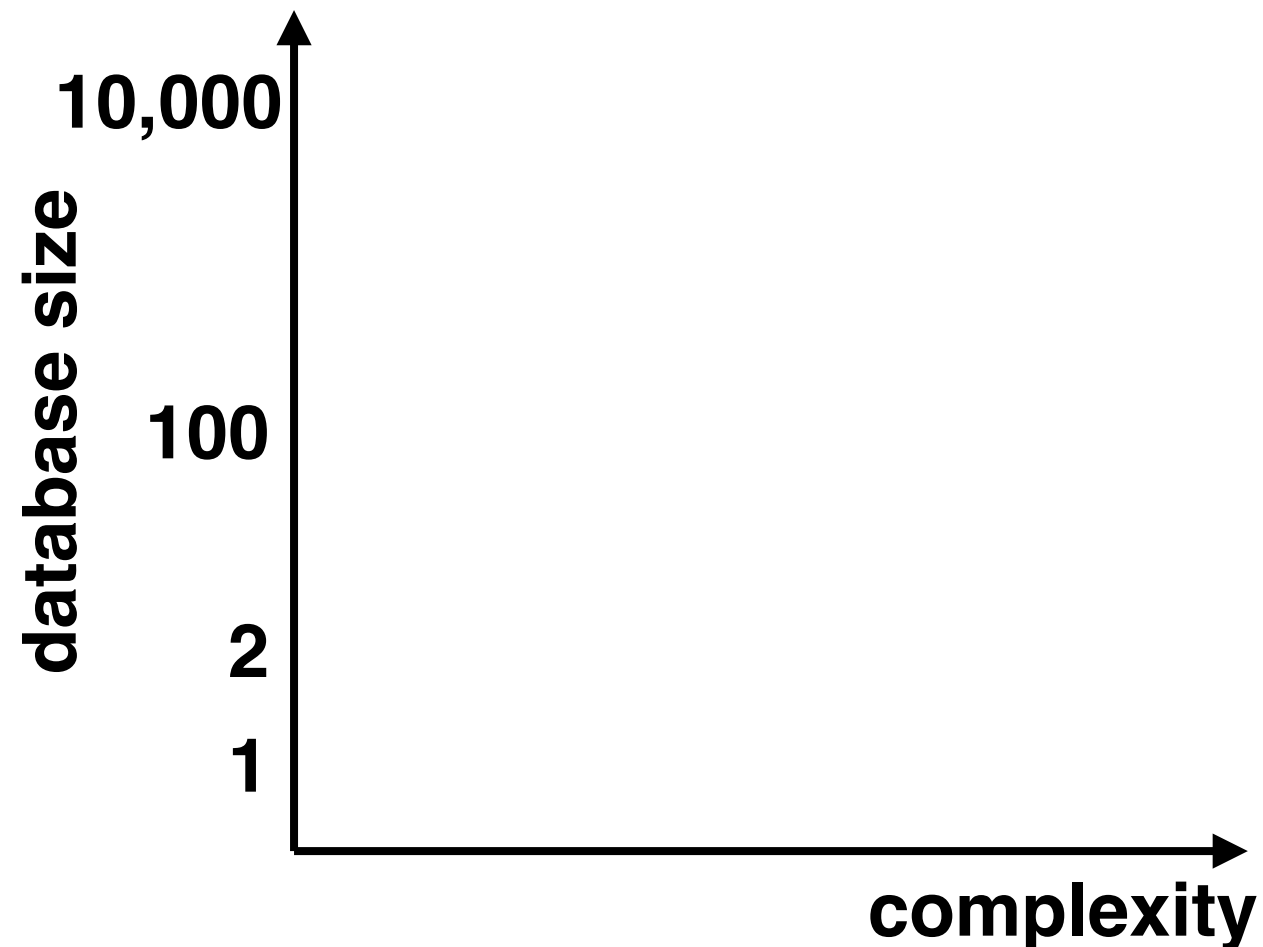
Motivating Applications



Previous Work

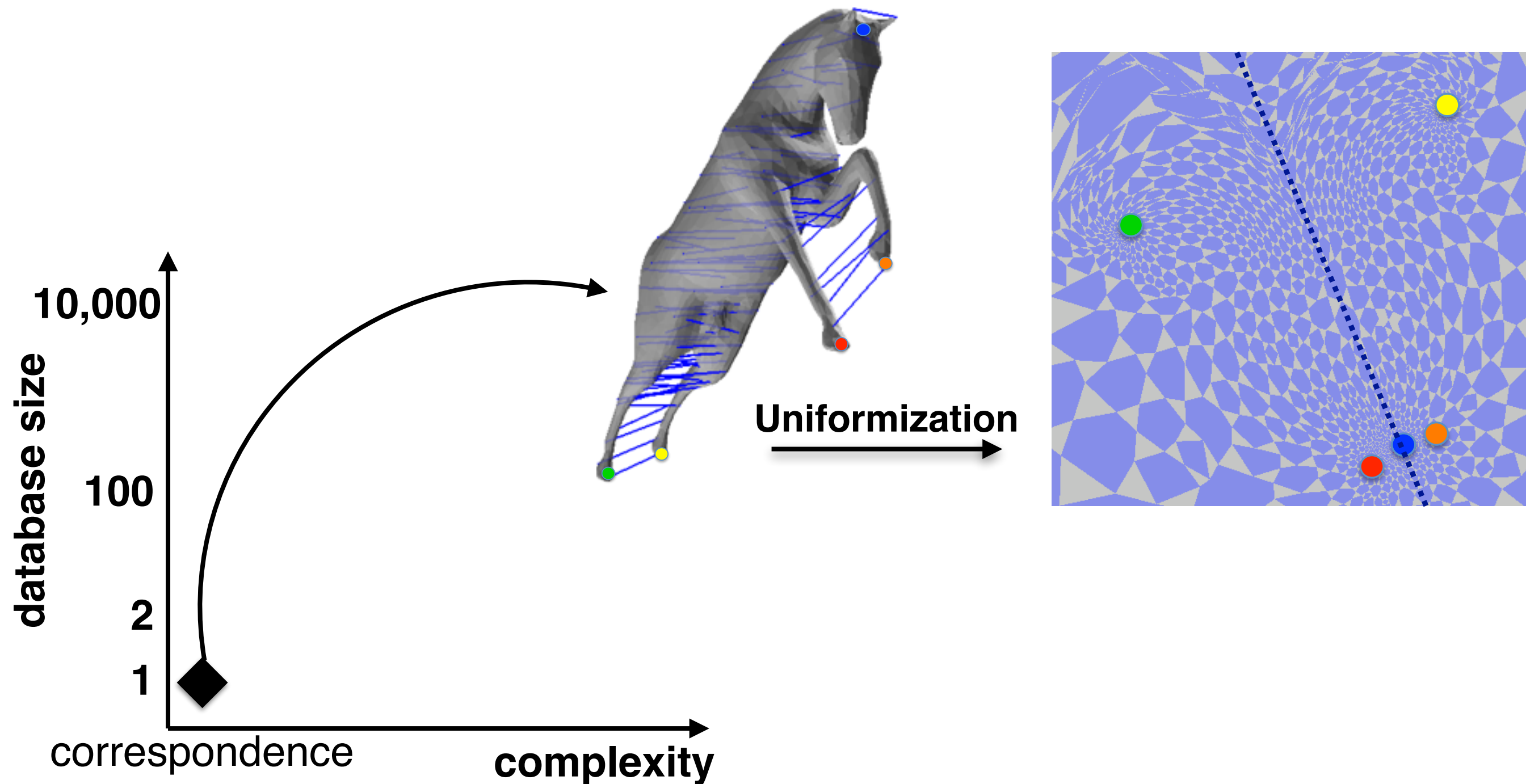
Geometry analysis to understand structure:
(self-serving overview)

- Symmetry
- Correspondences
- Probabilistic structural models



Symmetry

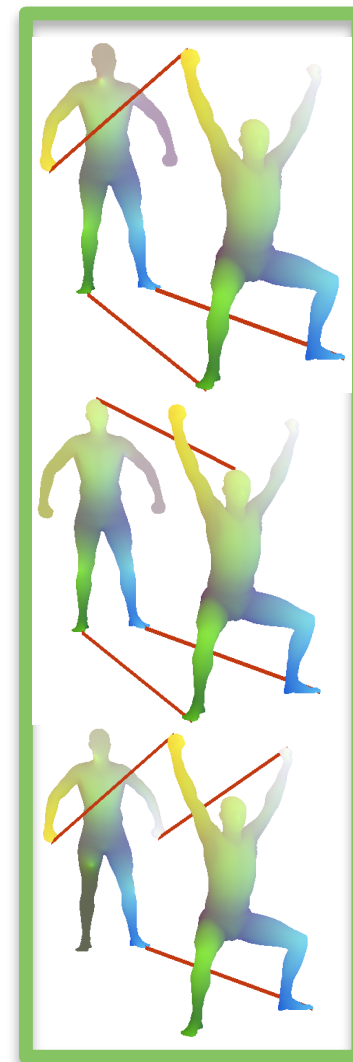
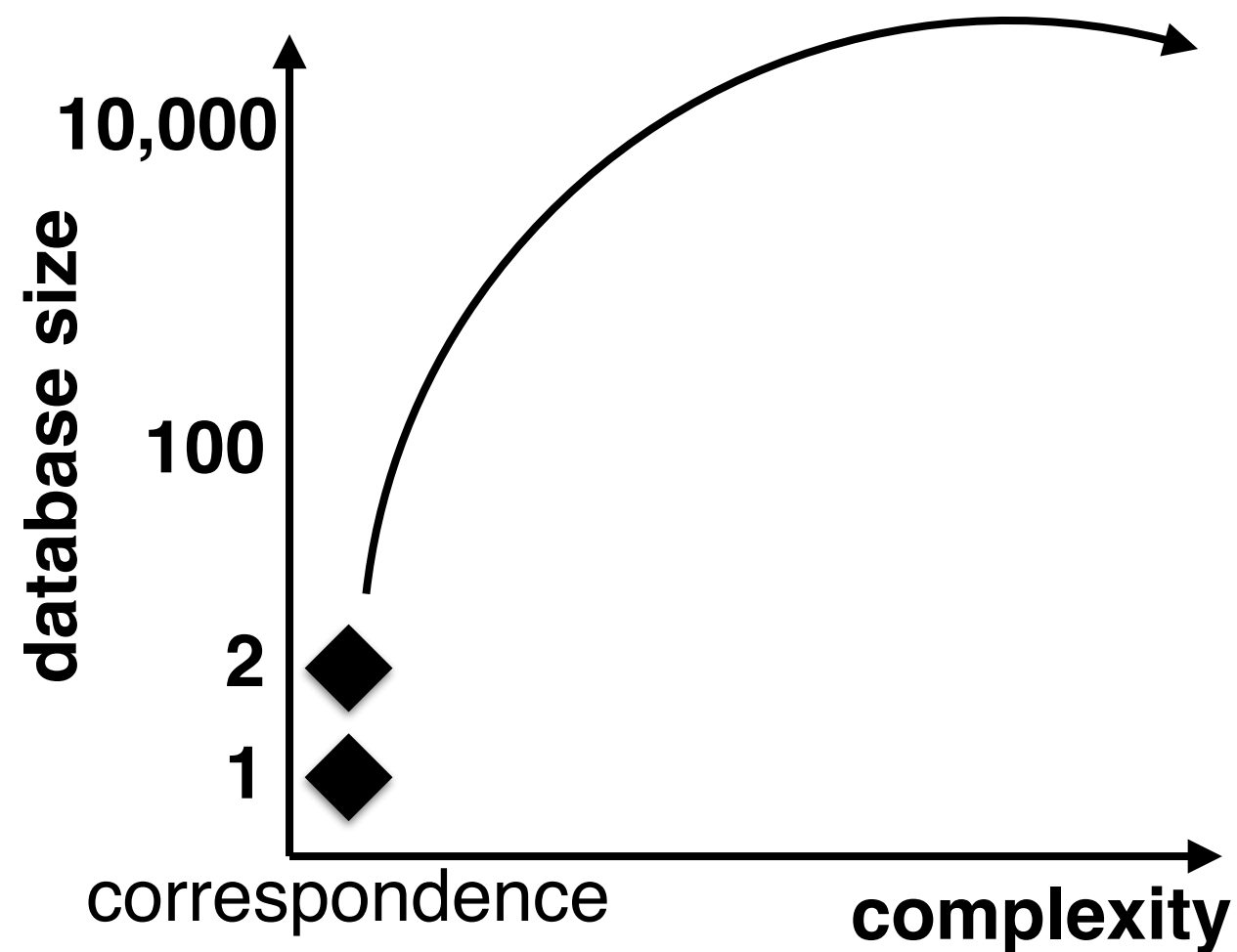
Key Idea: find a symmetric conformal embedding



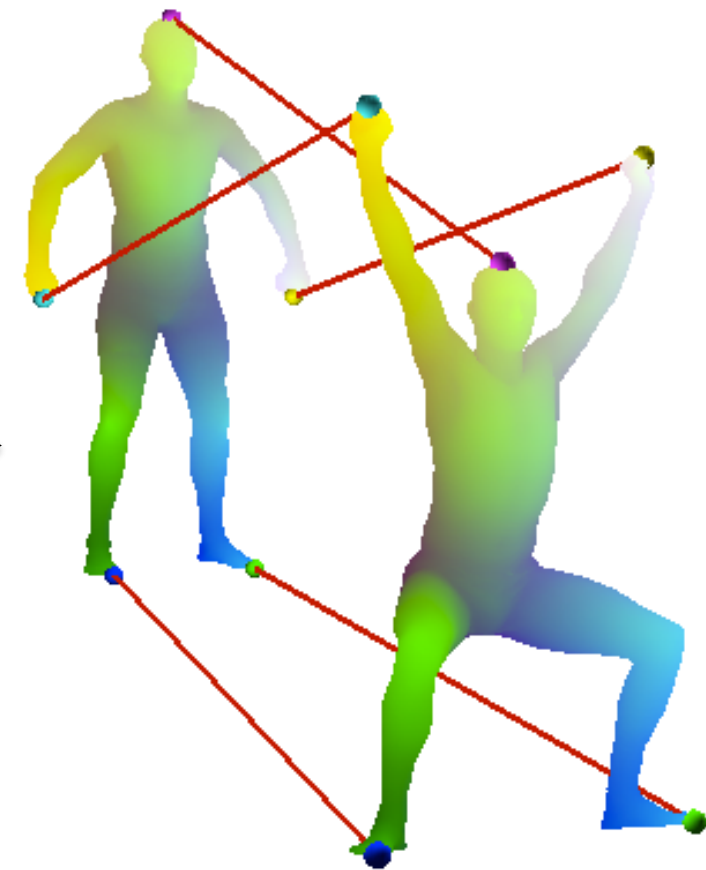
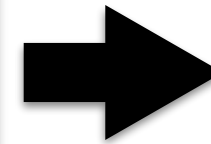
E.g., Möbius Transformations For Global Intrinsic Symmetry Analysis
V. Kim, Y. Lipman, X. Chen, and T. Funkhouser, SGP'10

Correspondences

Key Idea: blend partial intrinsic maps



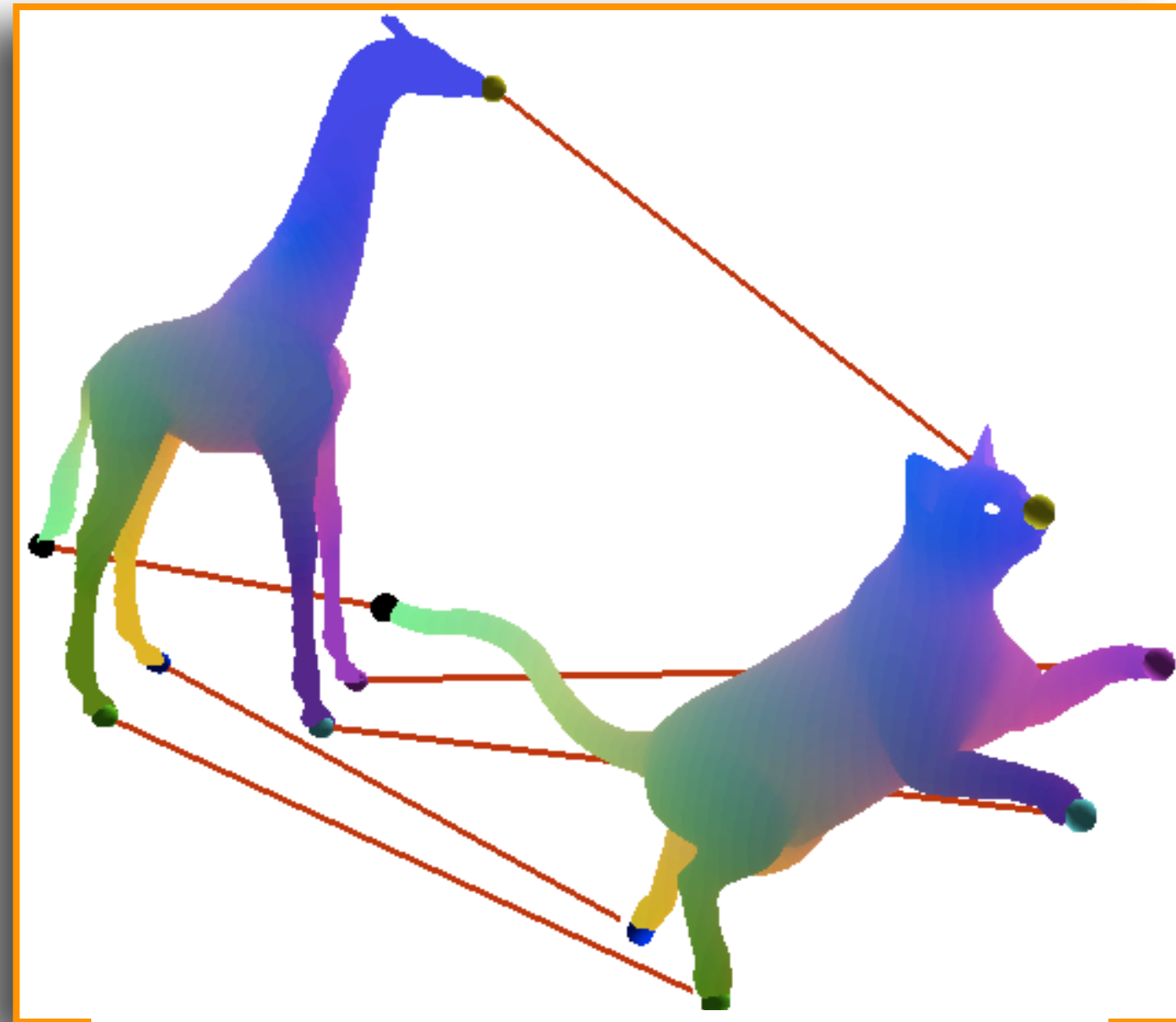
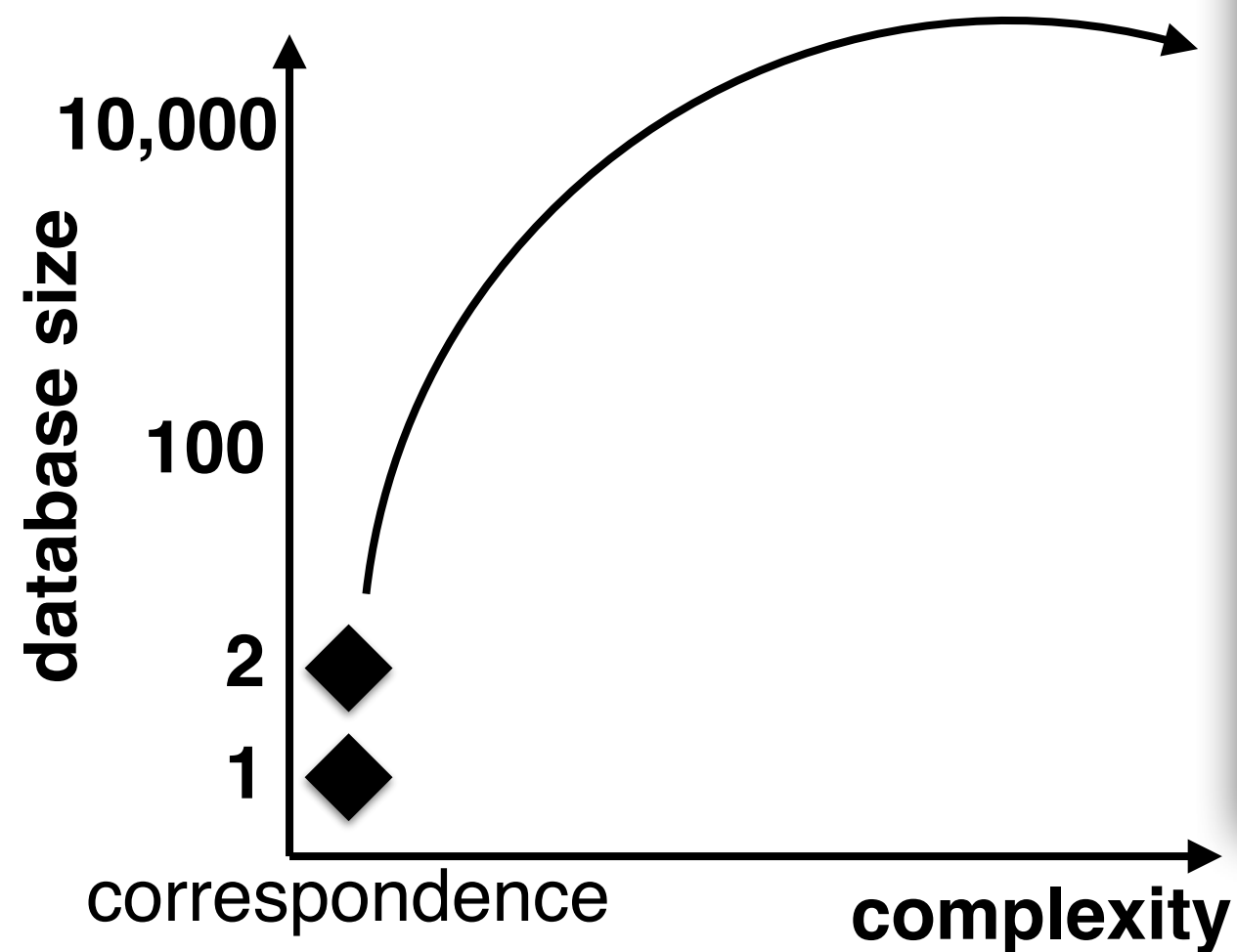
**Conformal
Maps**



Final Map

Correspondences

Key Idea: blend partial intrinsic maps

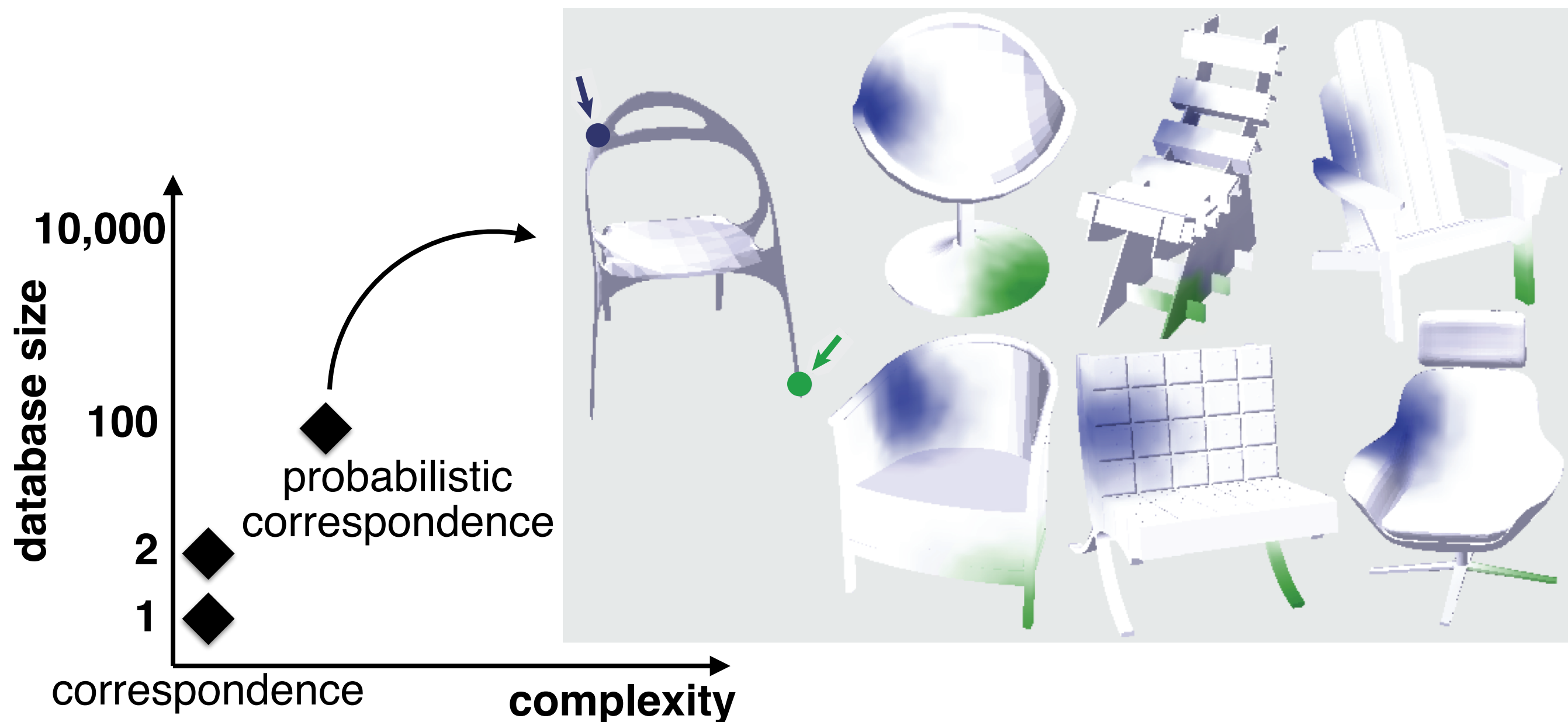


NOTE: state-of-the-art for mapping non-isometric surfaces

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

Correspondences in Collections

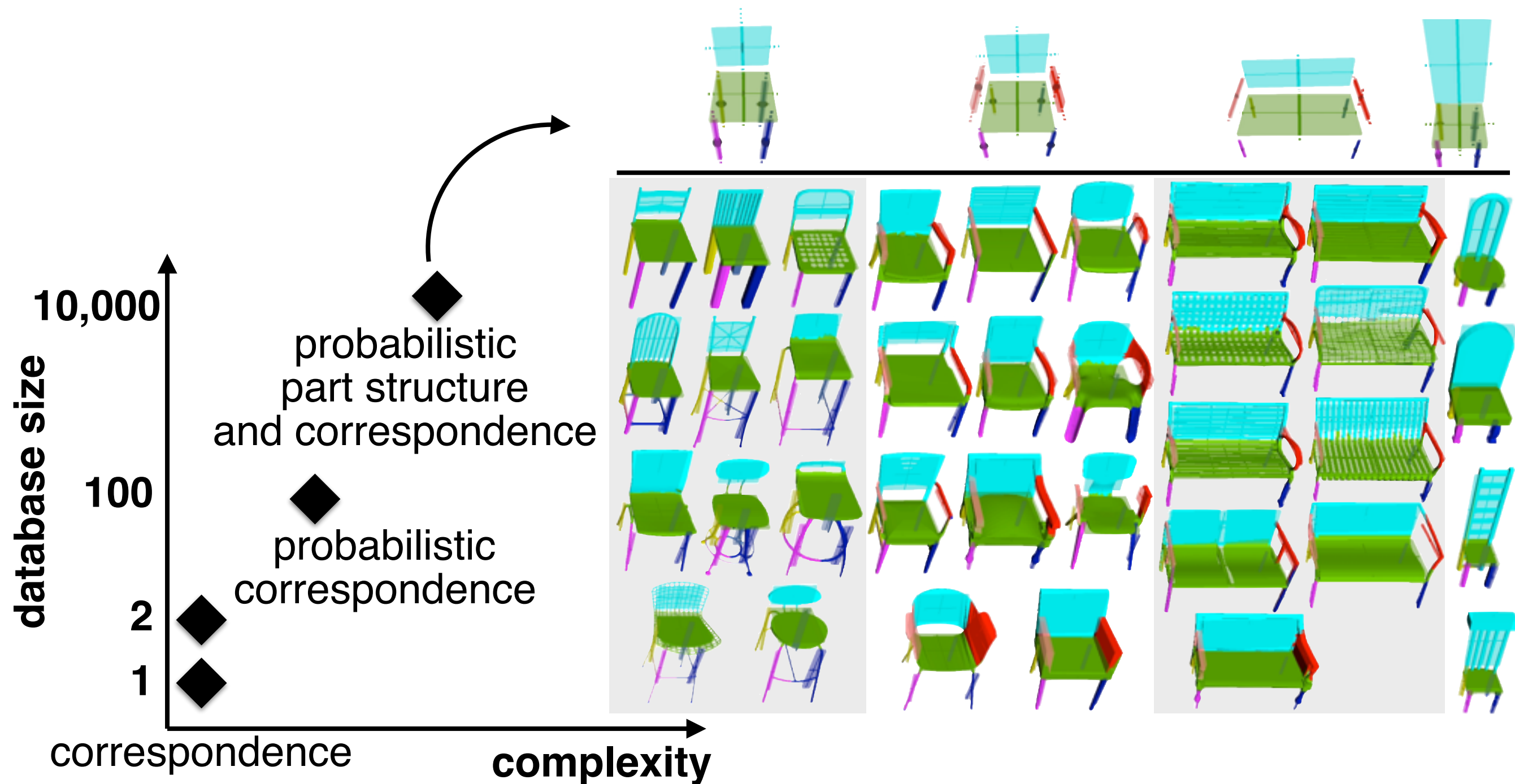
Key Ideas: represent ambiguity in mapping, leverage consistency and transitivity of correspondences



*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

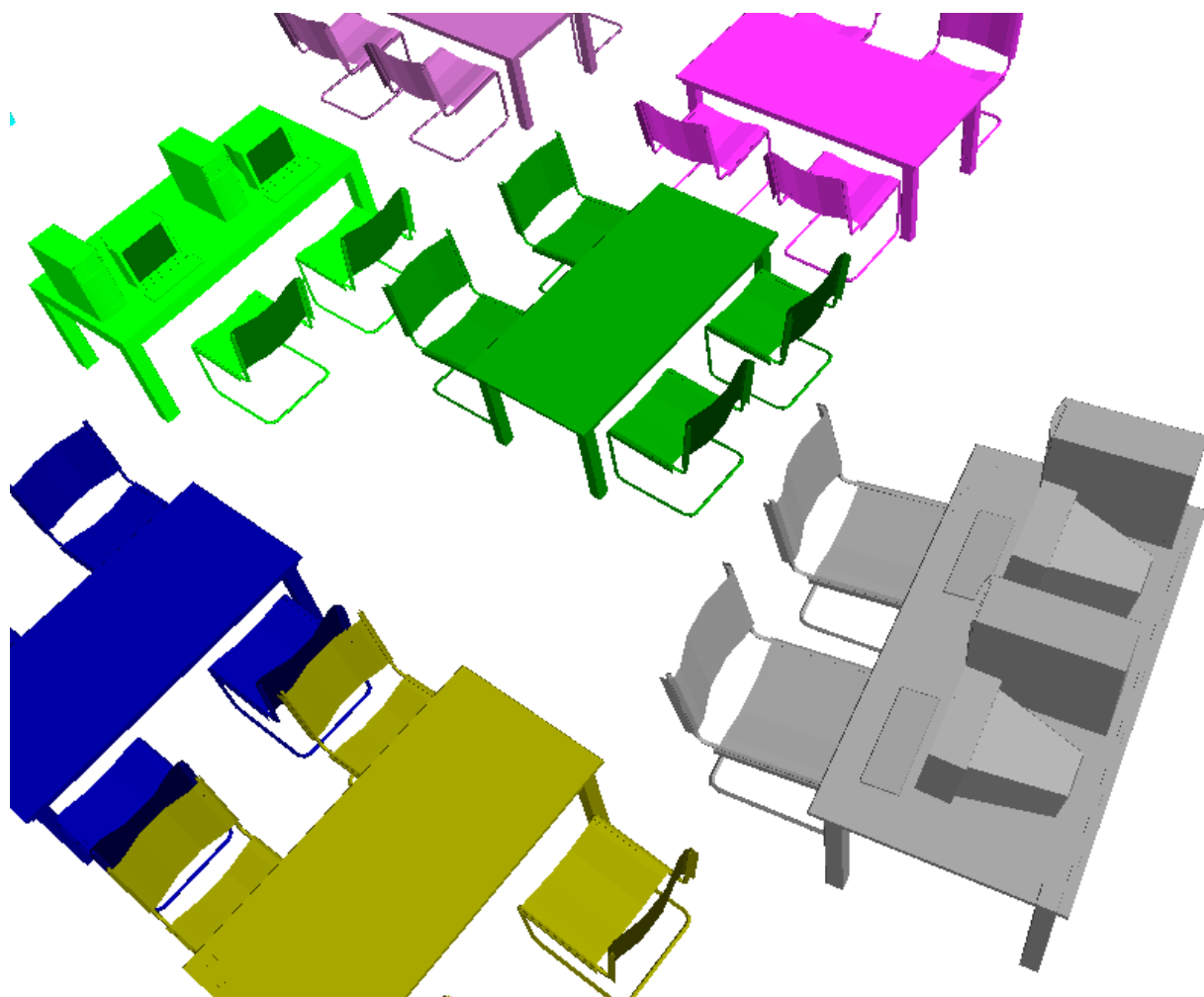
Key Idea: learn deformable templates



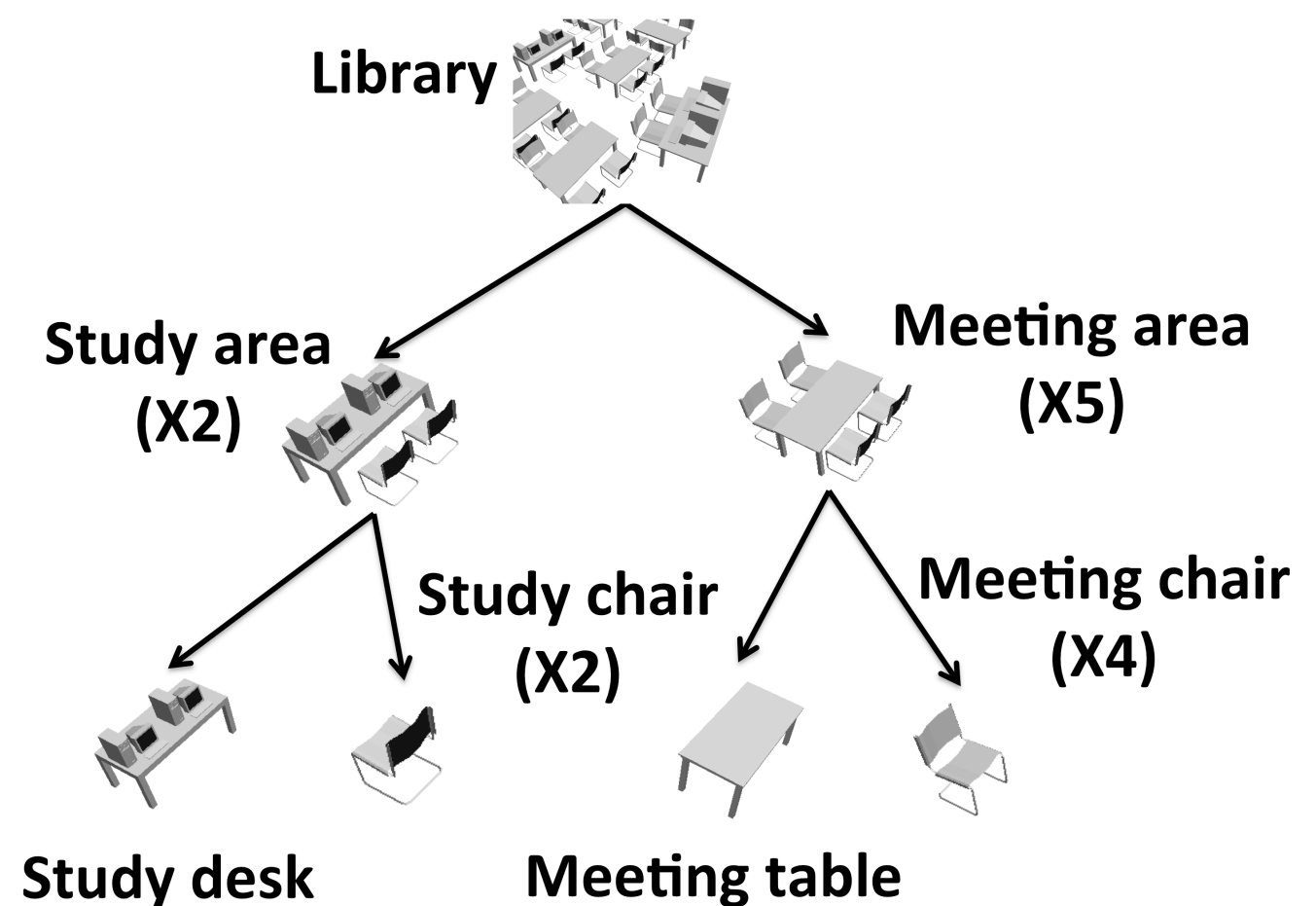
E.g., Learning Part-based Templates from Large Collections of 3D Shapes
V. Kim, W. Li, N. Mitra, S. Chaudhuri, S. DiVerdi, T. Funkhouser, SIGGRAPH'13

Hierarchical Probabilistic Models

Key Idea: group related elements into hierarchies



Scene from 3D Warehouse



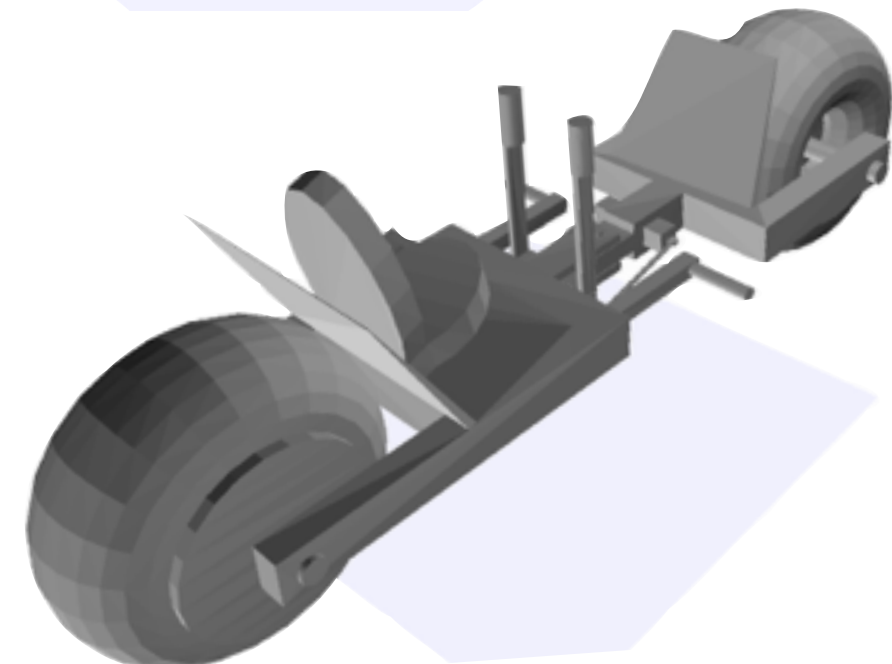
Semantic Hierarchy

Two low-probability chairs



Challenge

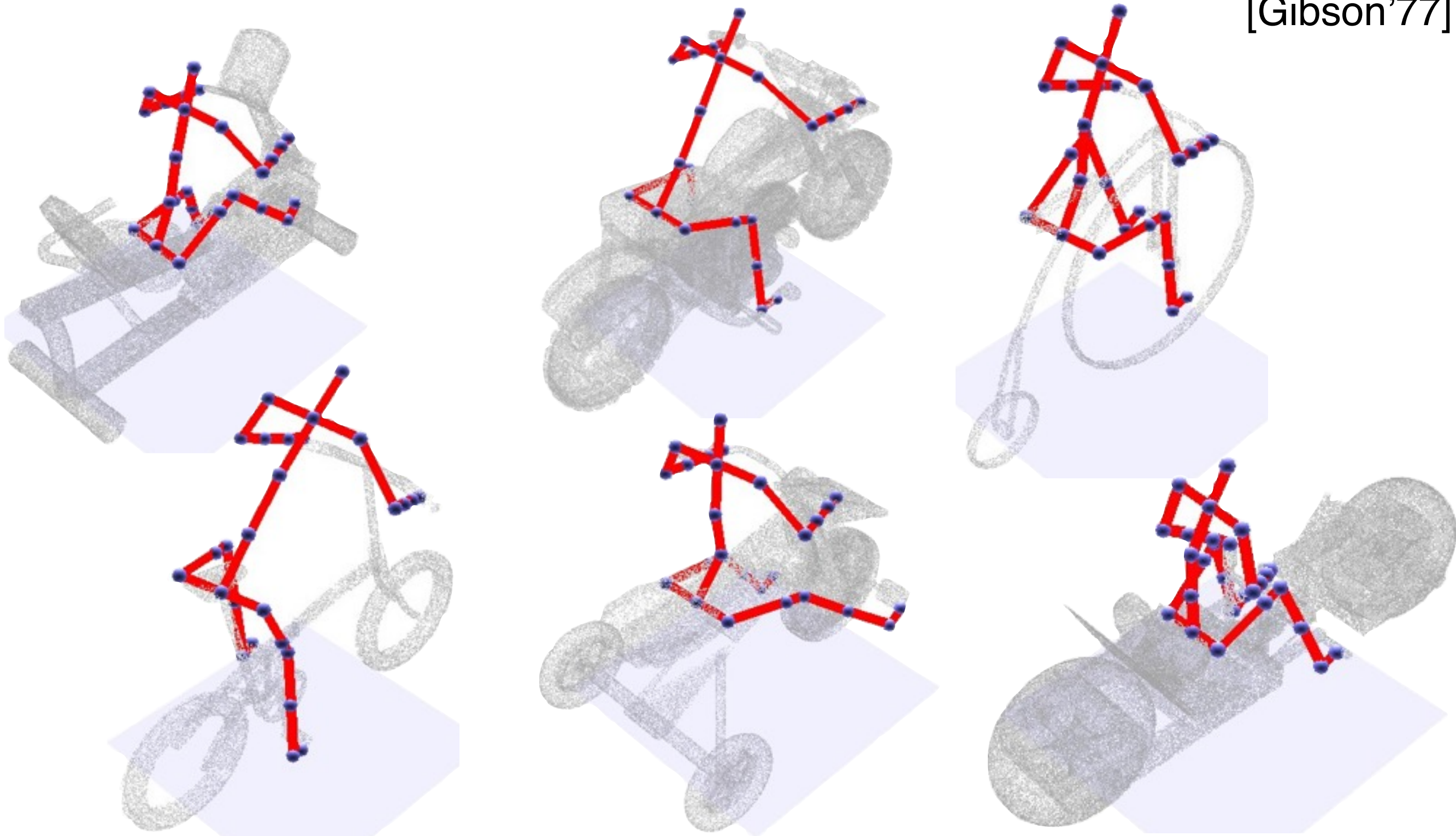
Find common structure



Observation

Affordance is an intrinsic property of a shape

[Gibson'77]

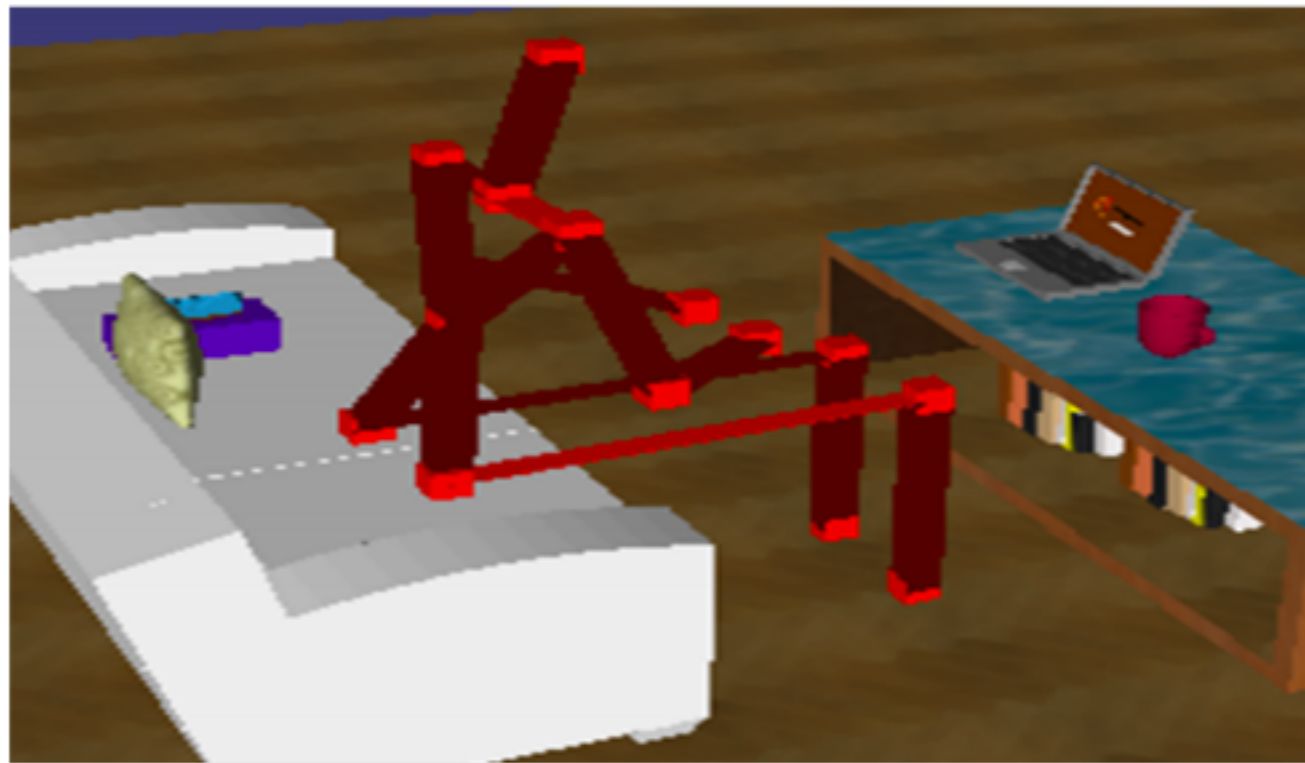


Observation

Affordance is an intrinsic property of a shape

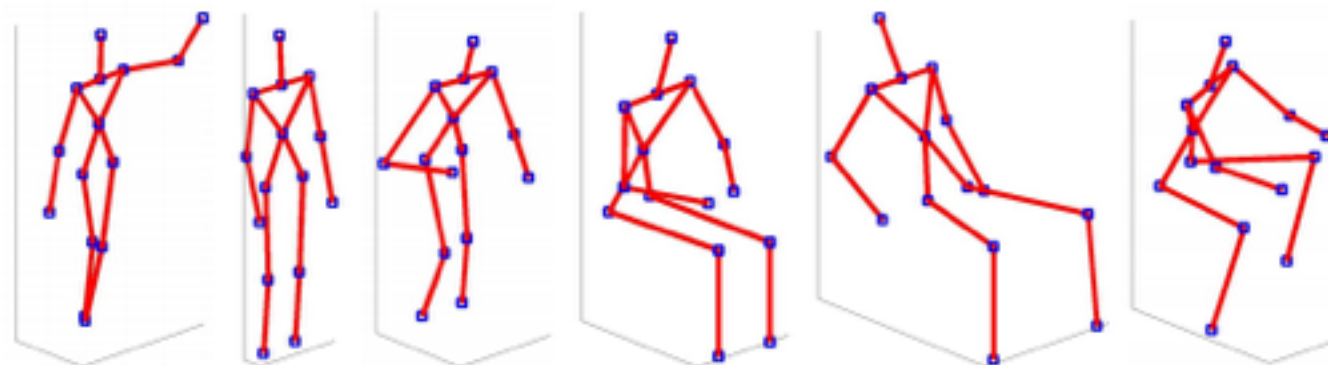
[Gibson'77]

Previous work: classification



Jiang et al.

Rigid poses:

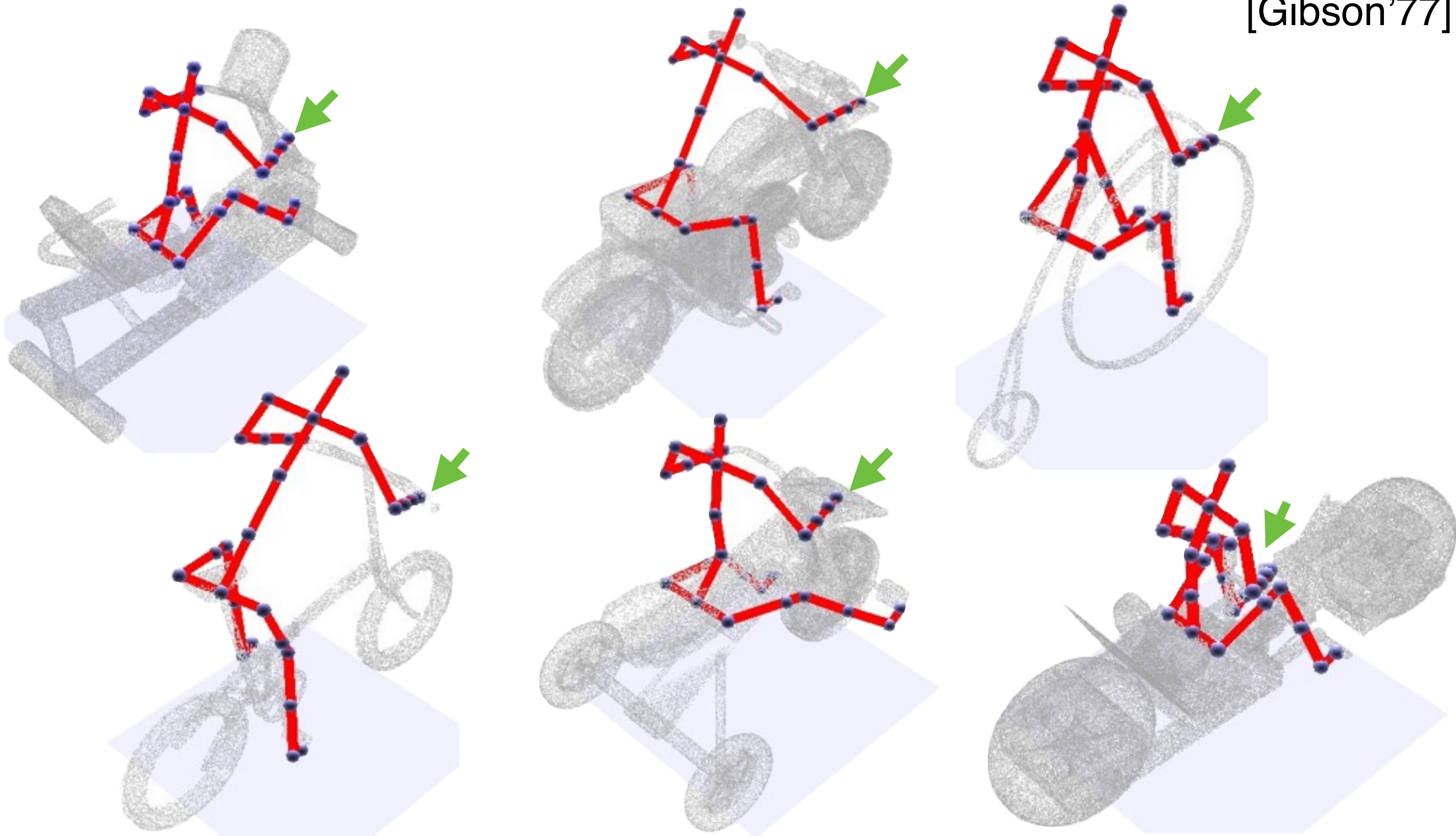


Observation

- ✓ Correspondence
- ✱ Saliency
- ✱ Structural Variations

Affordance is an intrinsic property of a shape

[Gibson'77]

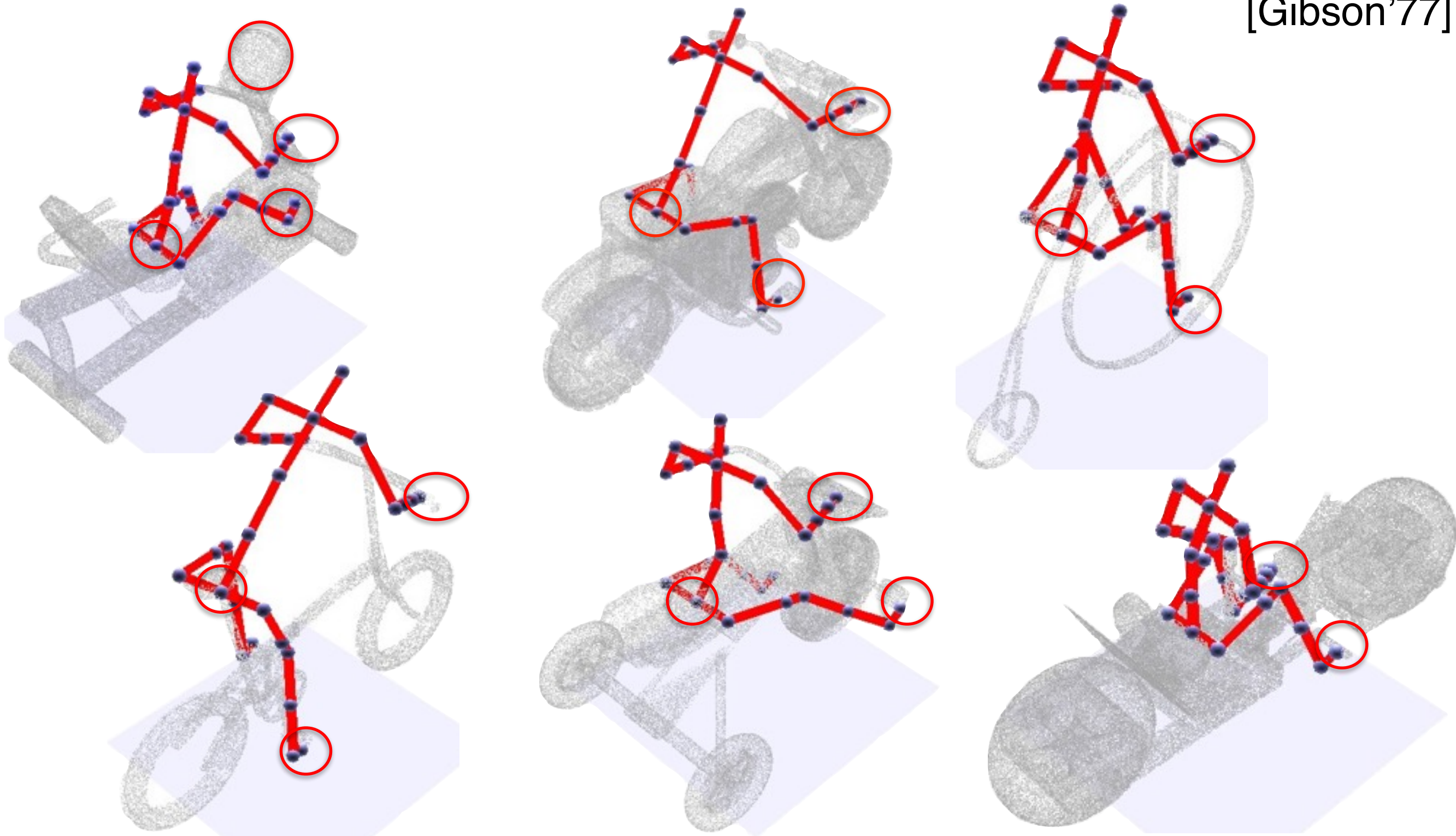


Observation

- ✓ Correspondence
- ✓ **Saliency**
- ✱ Structural Variations

Affordance is an intrinsic property of a shape

[Gibson'77]

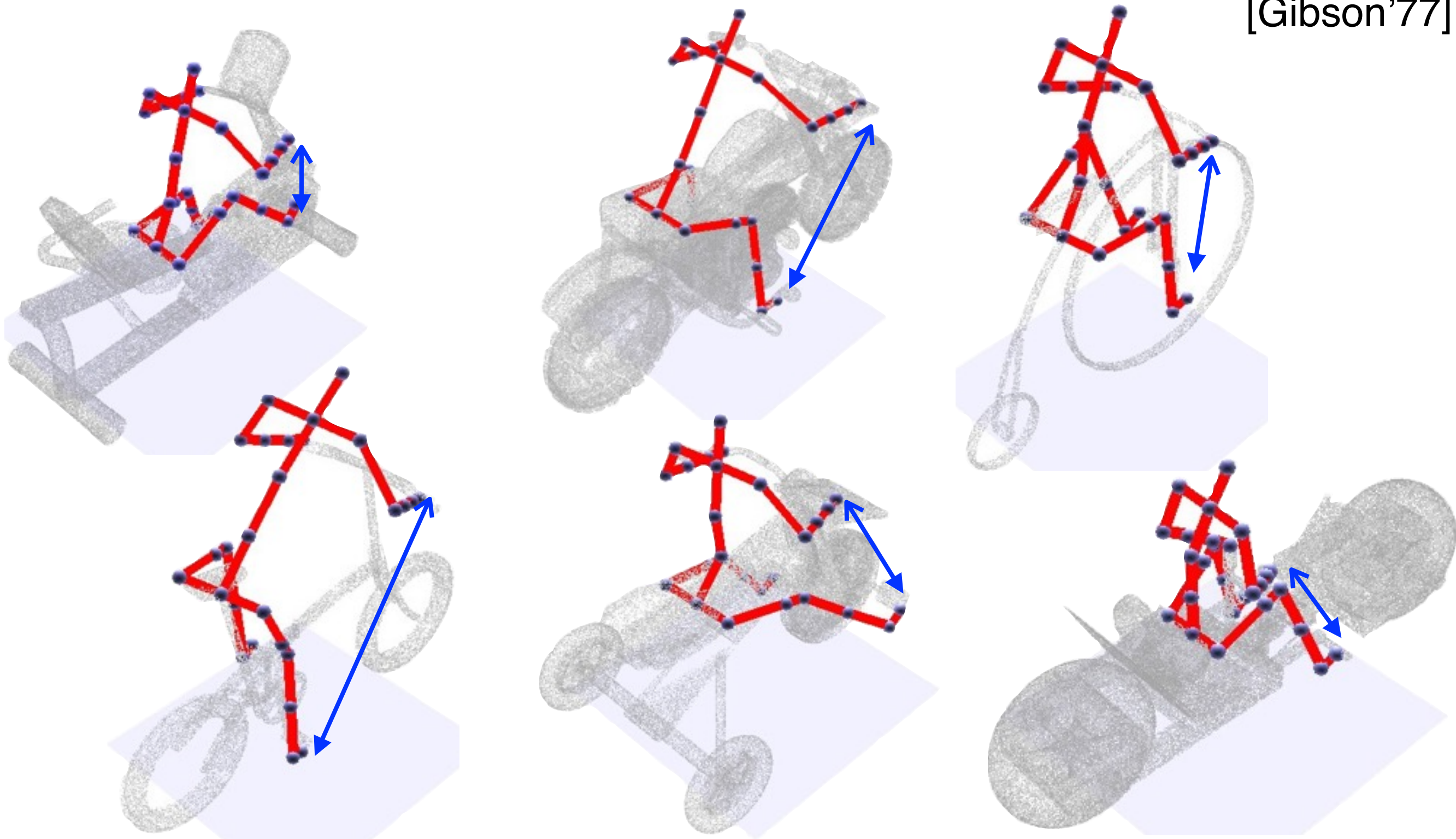


Observation

- ✓ Correspondence
- ✓ Saliency
- ✓ **Structural Variations**

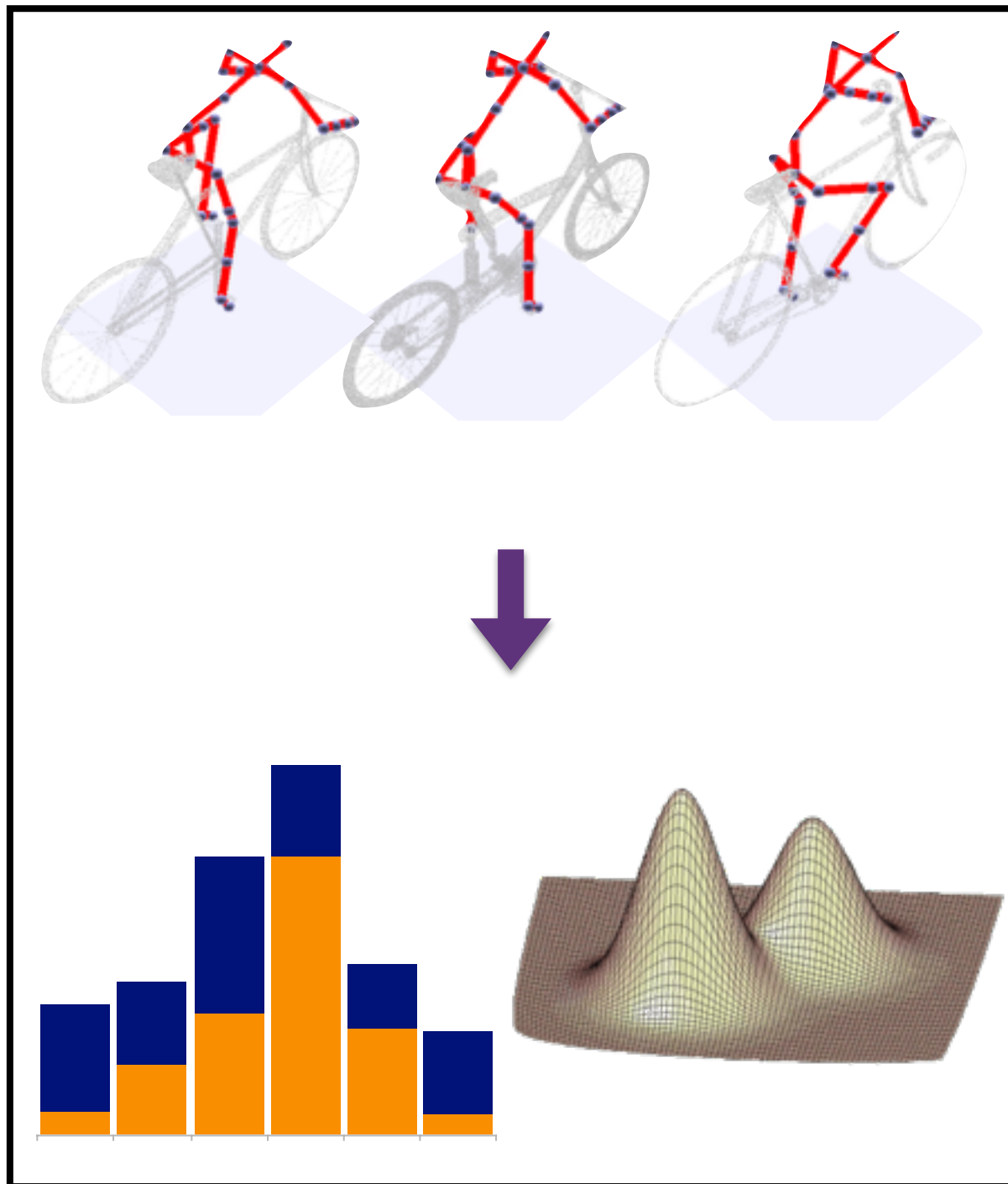
Affordance is an intrinsic property of a shape

[Gibson'77]

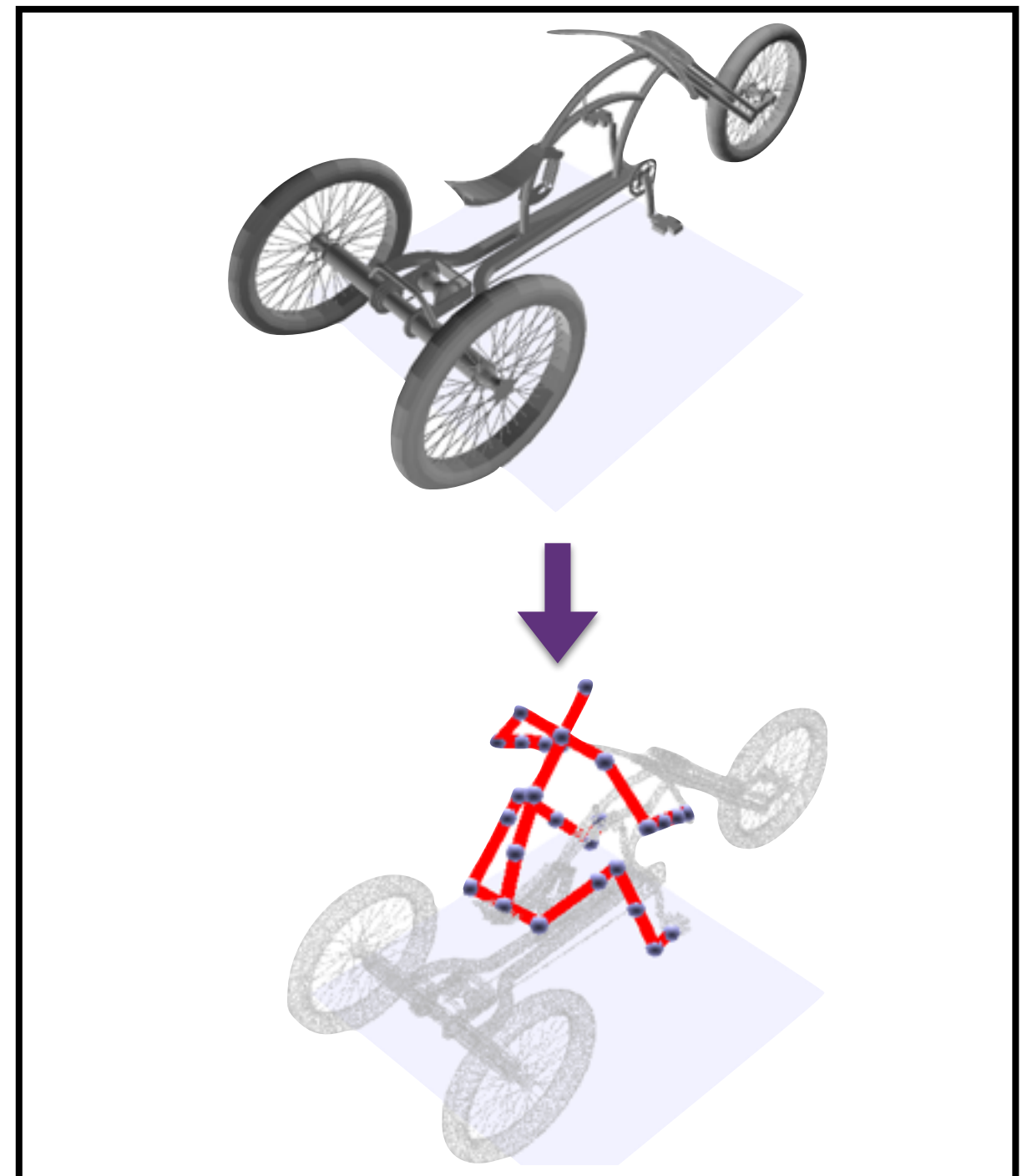


Affordance Model and Pose Prediction

Affordance Model Learning

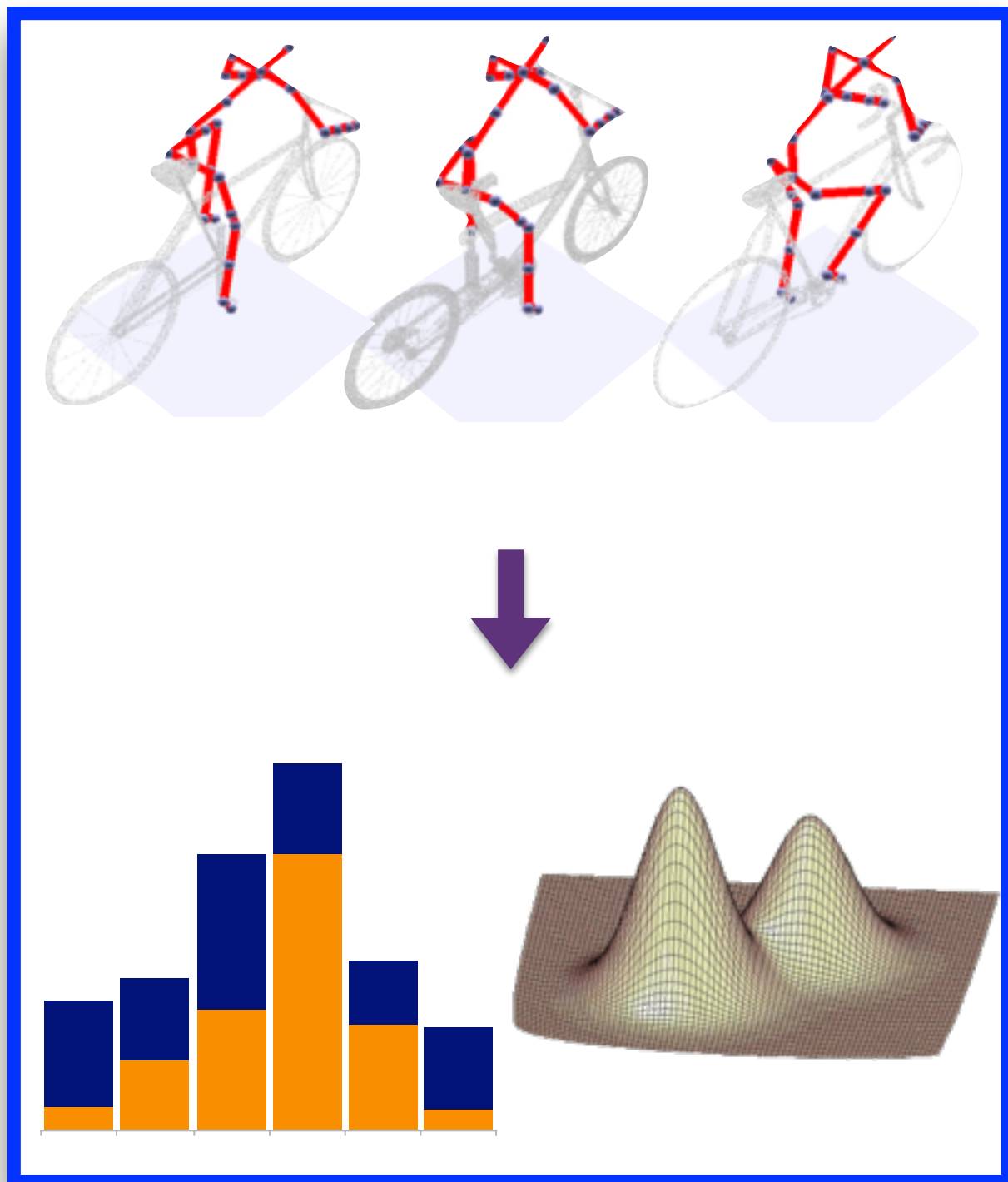


Pose Prediction

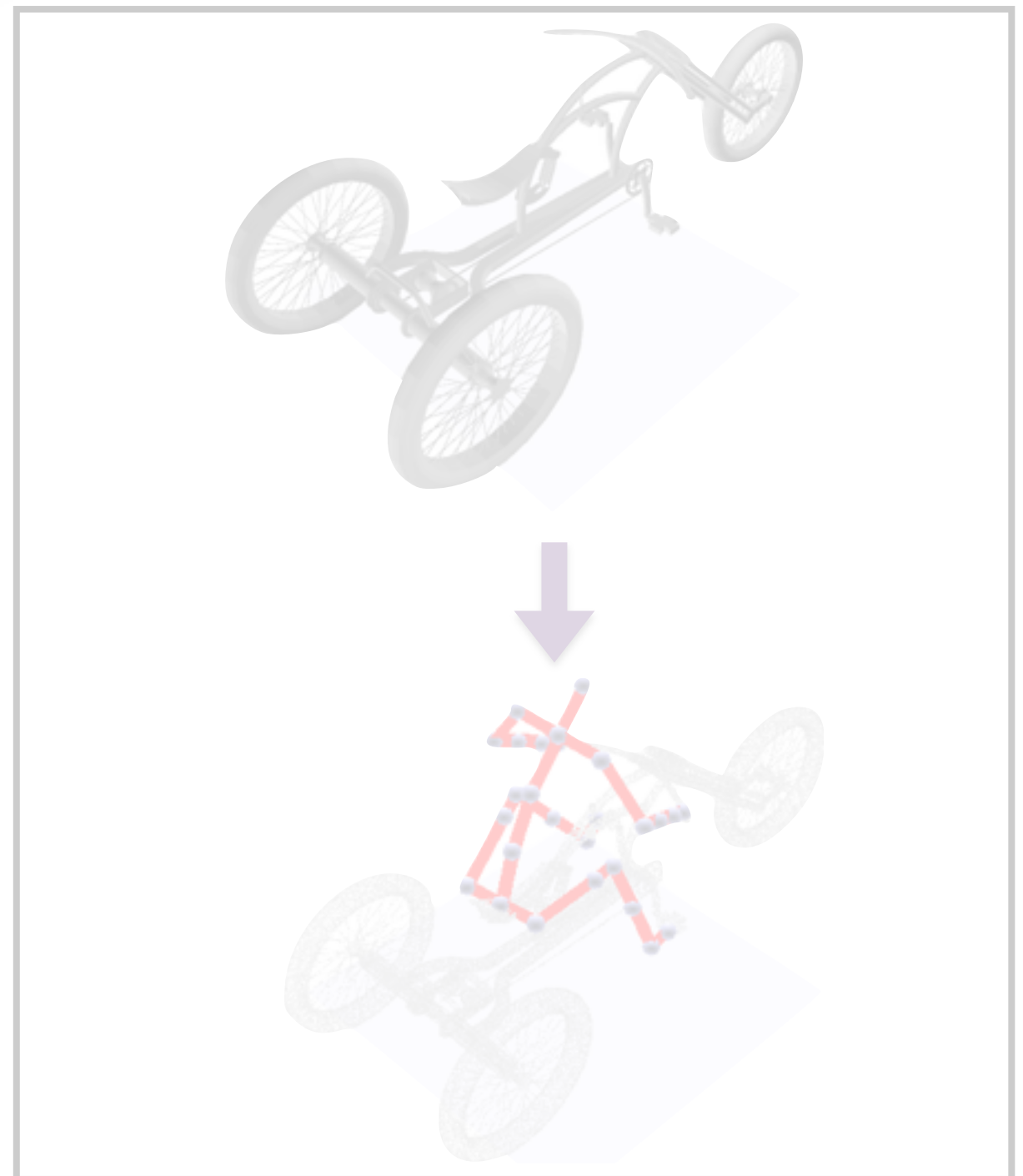


Affordance Model and Pose Prediction

Affordance Model Learning



Pose Prediction



Affordance Model

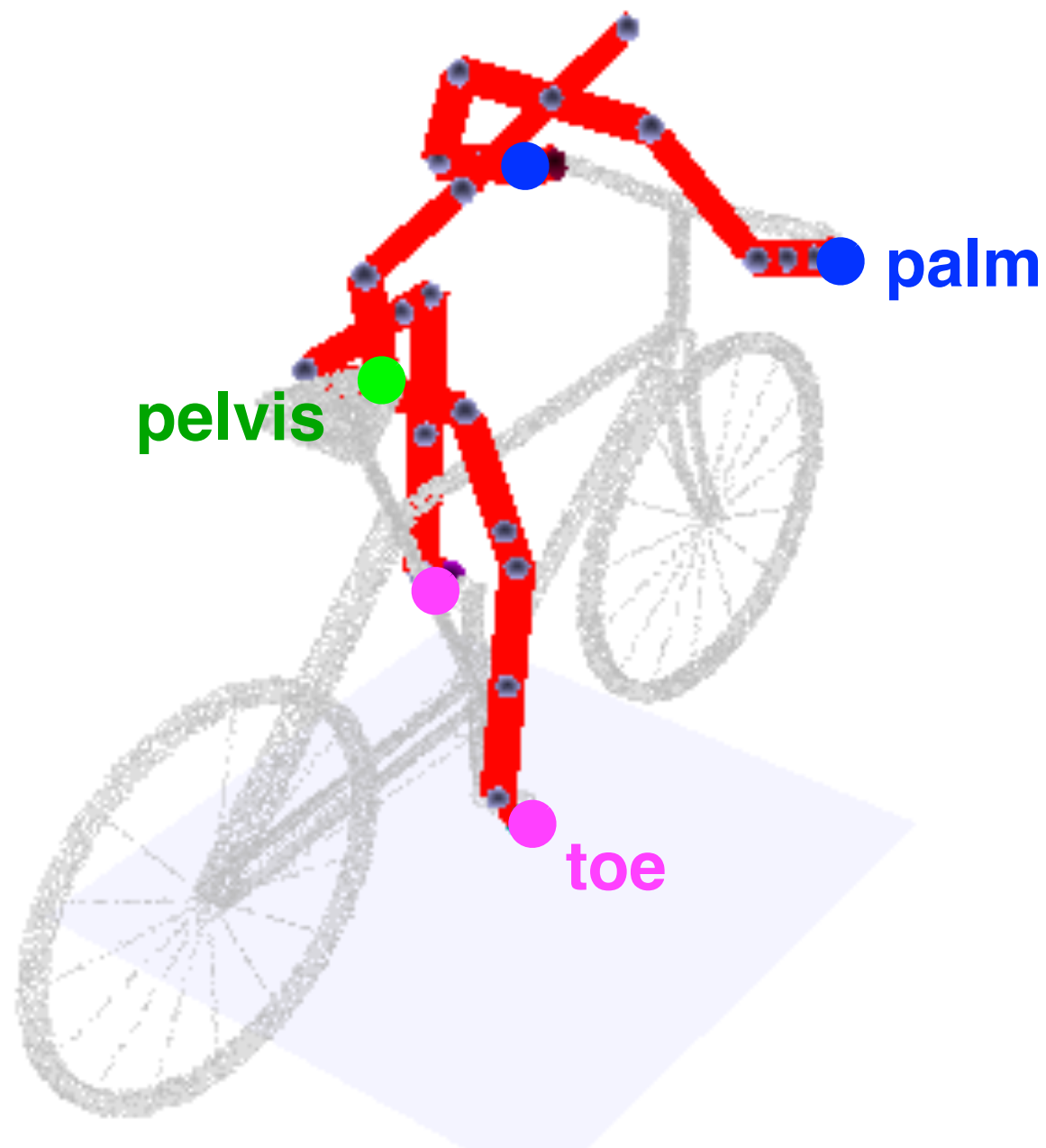
Learn from training data

- Geometry of contact points
- Plausibility of poses

Affordance Model

Learn from training data

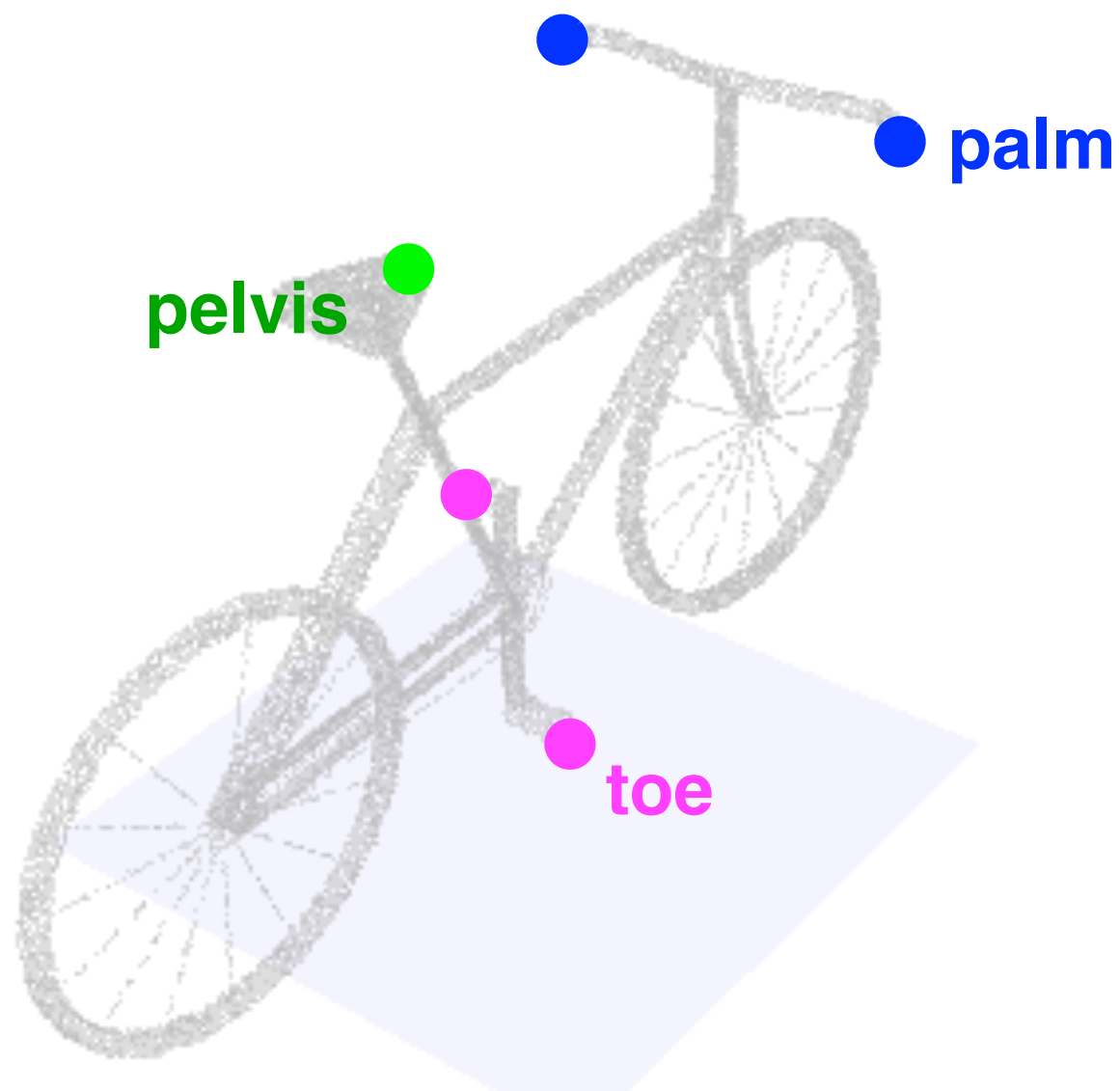
- Geometry of contact points
- Plausibility of poses



Affordance Model

Learn from training data

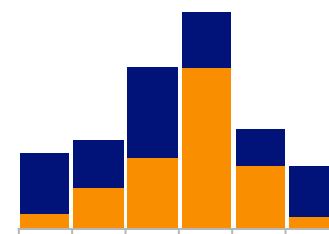
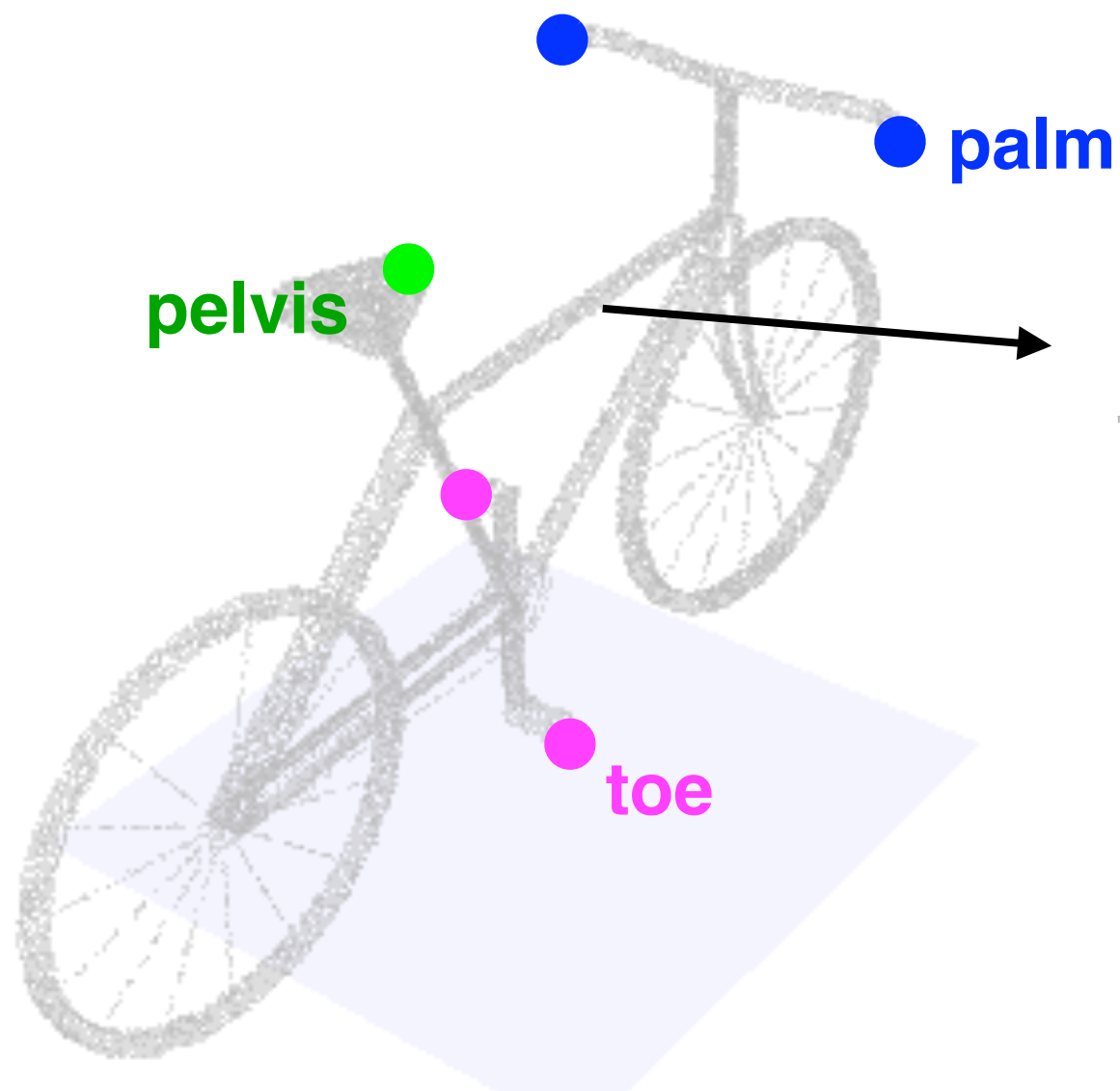
- Geometry of contact points
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Affordance Model

Learn from training data

- Geometry of contact points
- Plausibility of poses



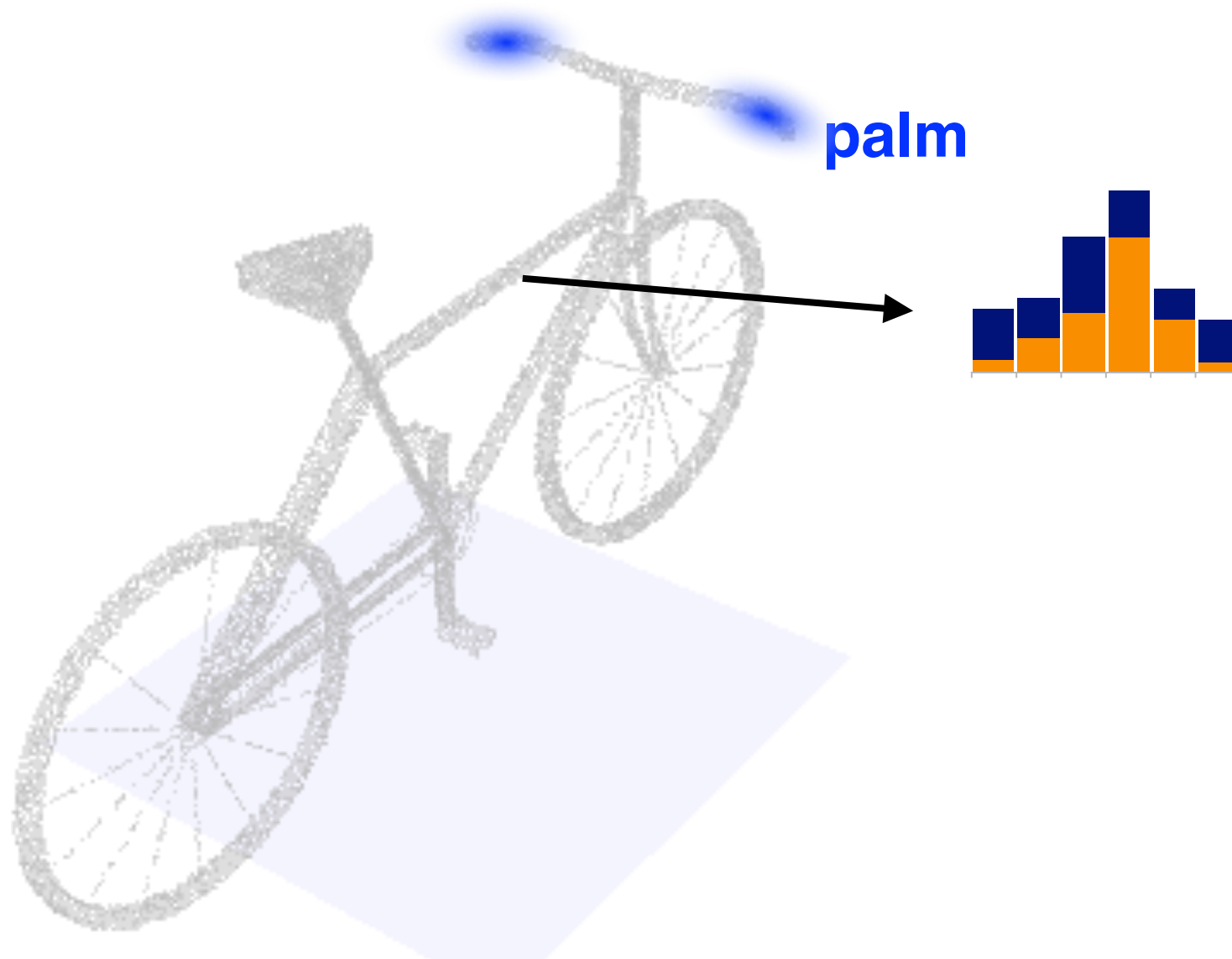
Local Features:

- PCA features
- curvature
- height
- ...

Affordance Model

Learn from training data

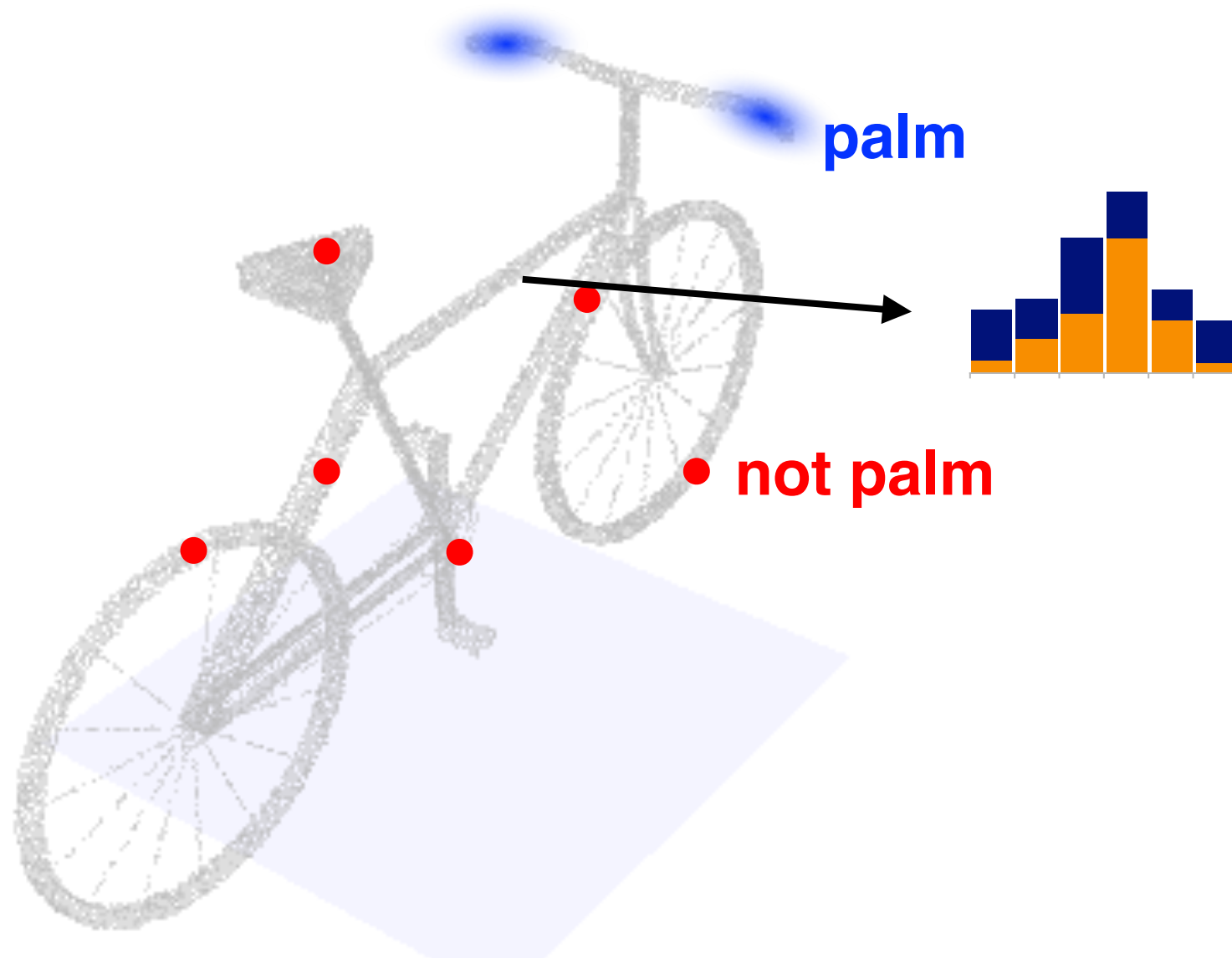
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Affordance Model

Learn from training data

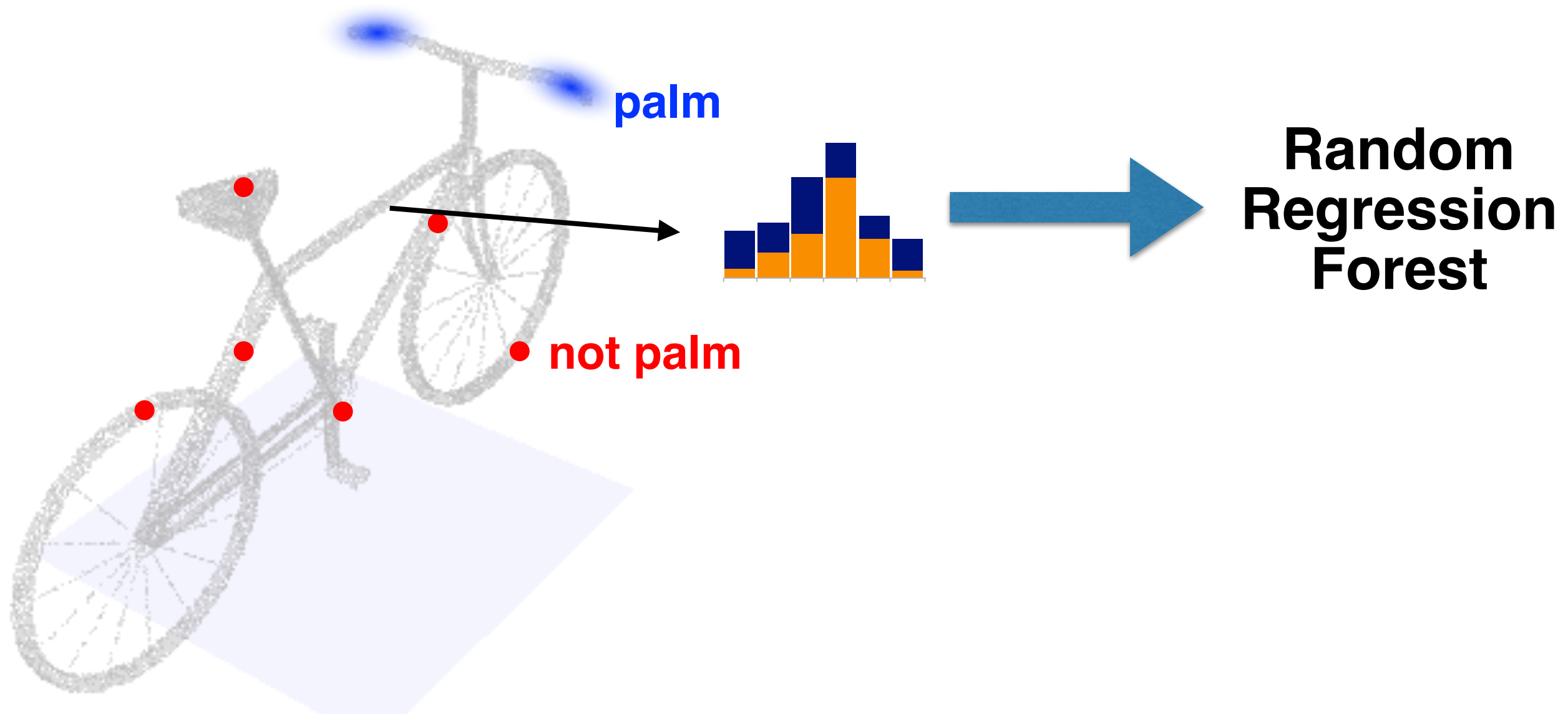
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Affordance Model

Learn from training data

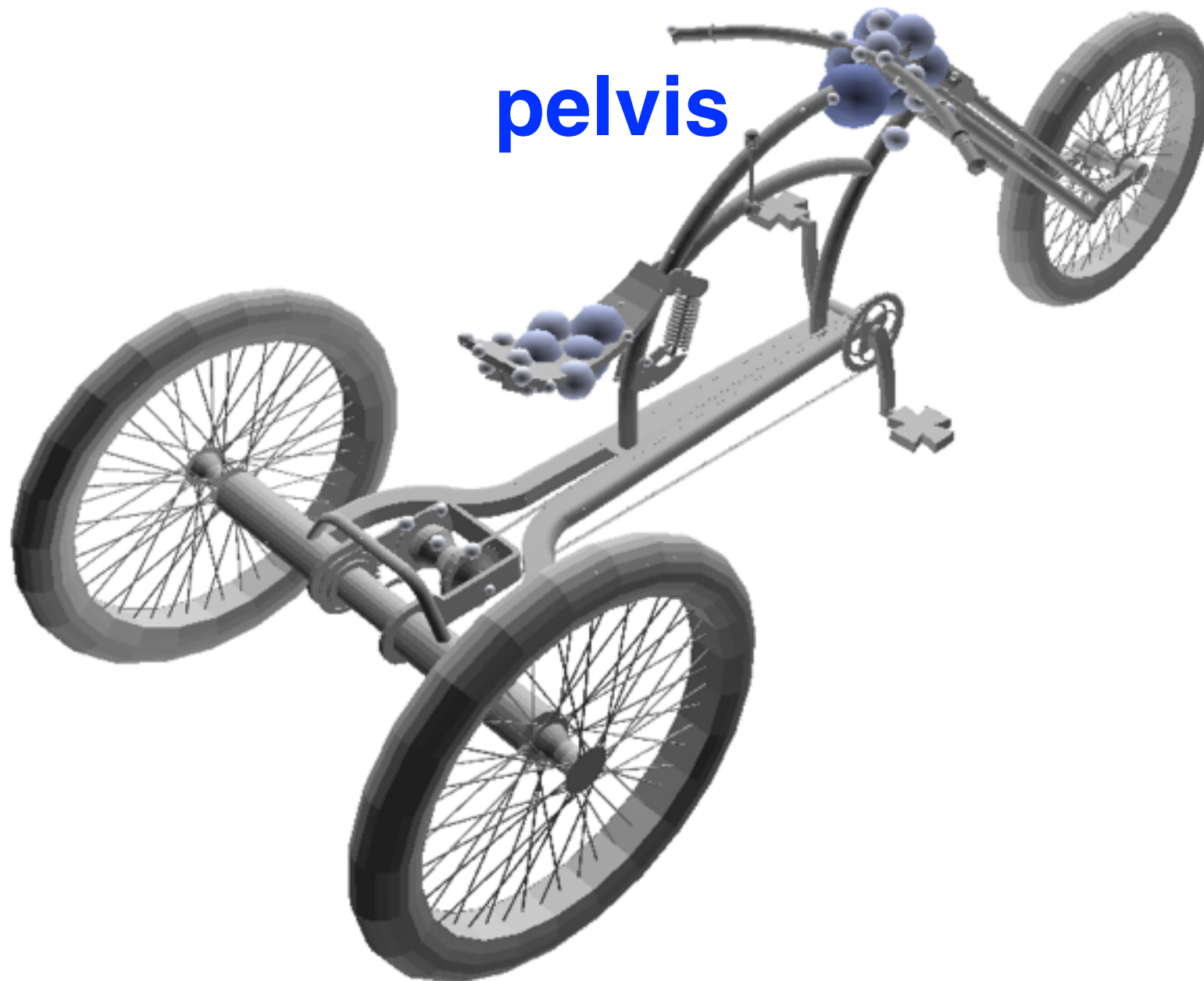
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Affordance Model

Learn from training data

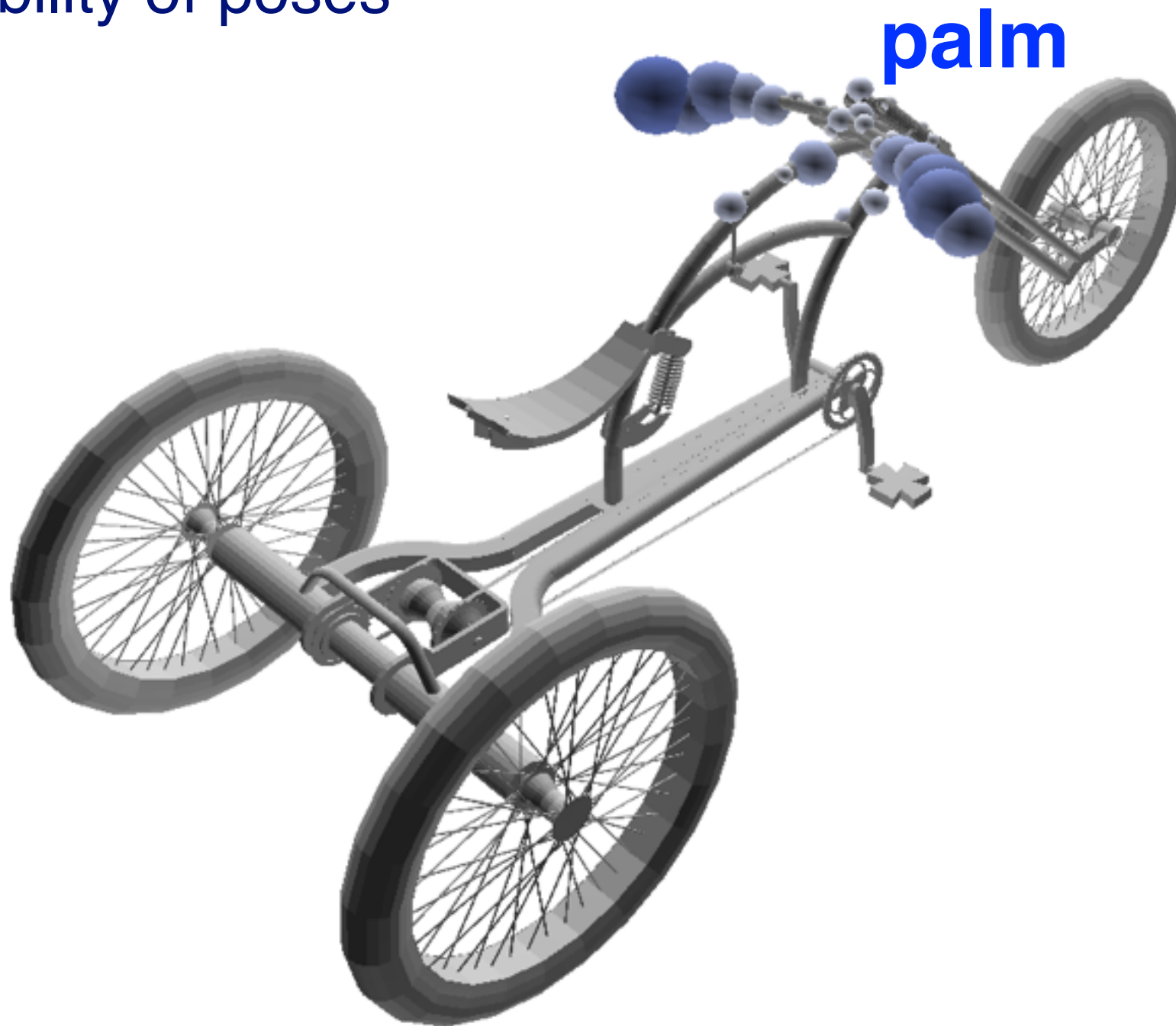
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Affordance Model

Learn from training data

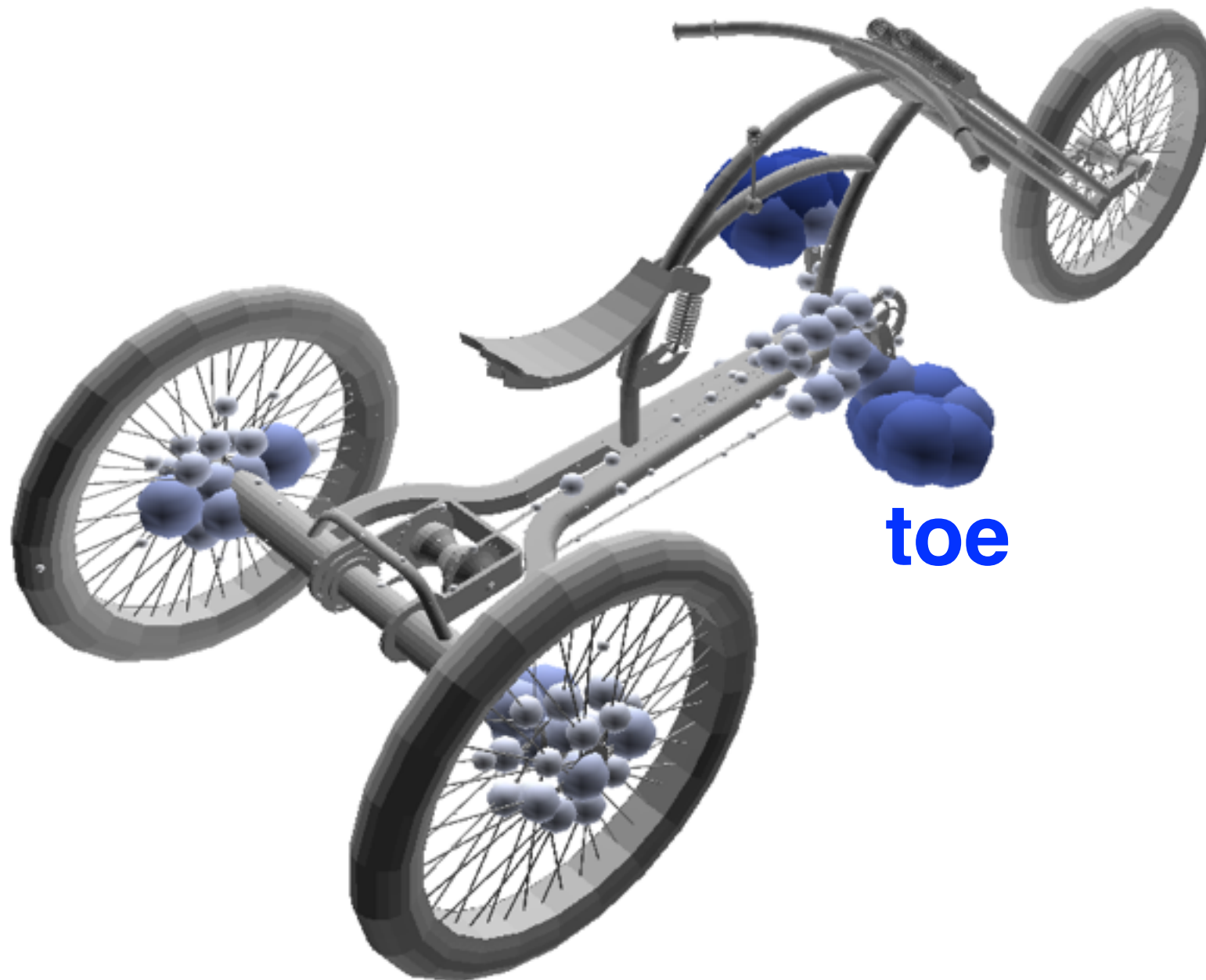
- Geometry of contact points
- Plausibility of poses



Affordance Model

Learn from training data

- Geometry of contact points
- Plausibility of poses

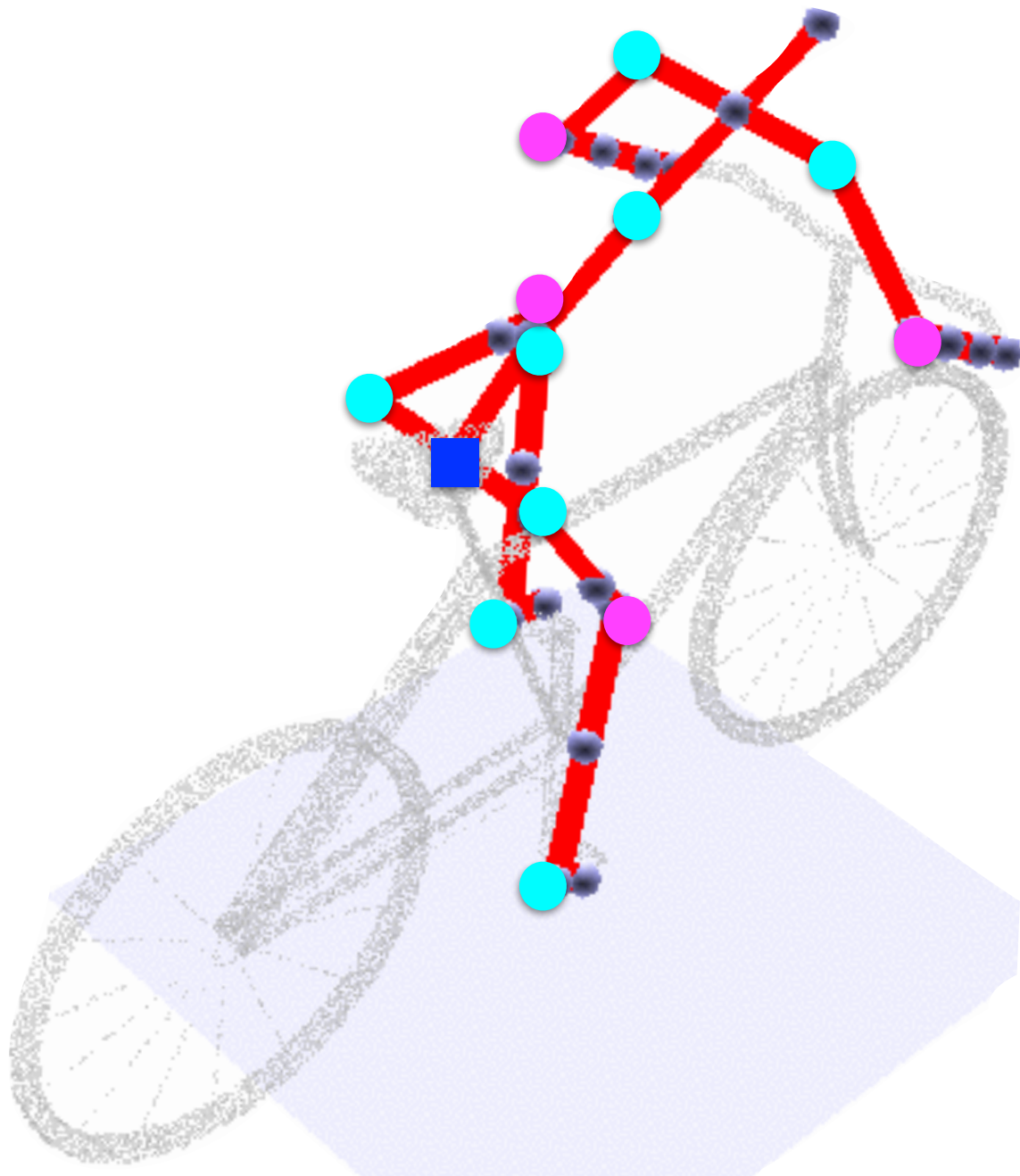


Affordance Model

Learn from training data

- Geometry of contact points

→ Plausibility of poses

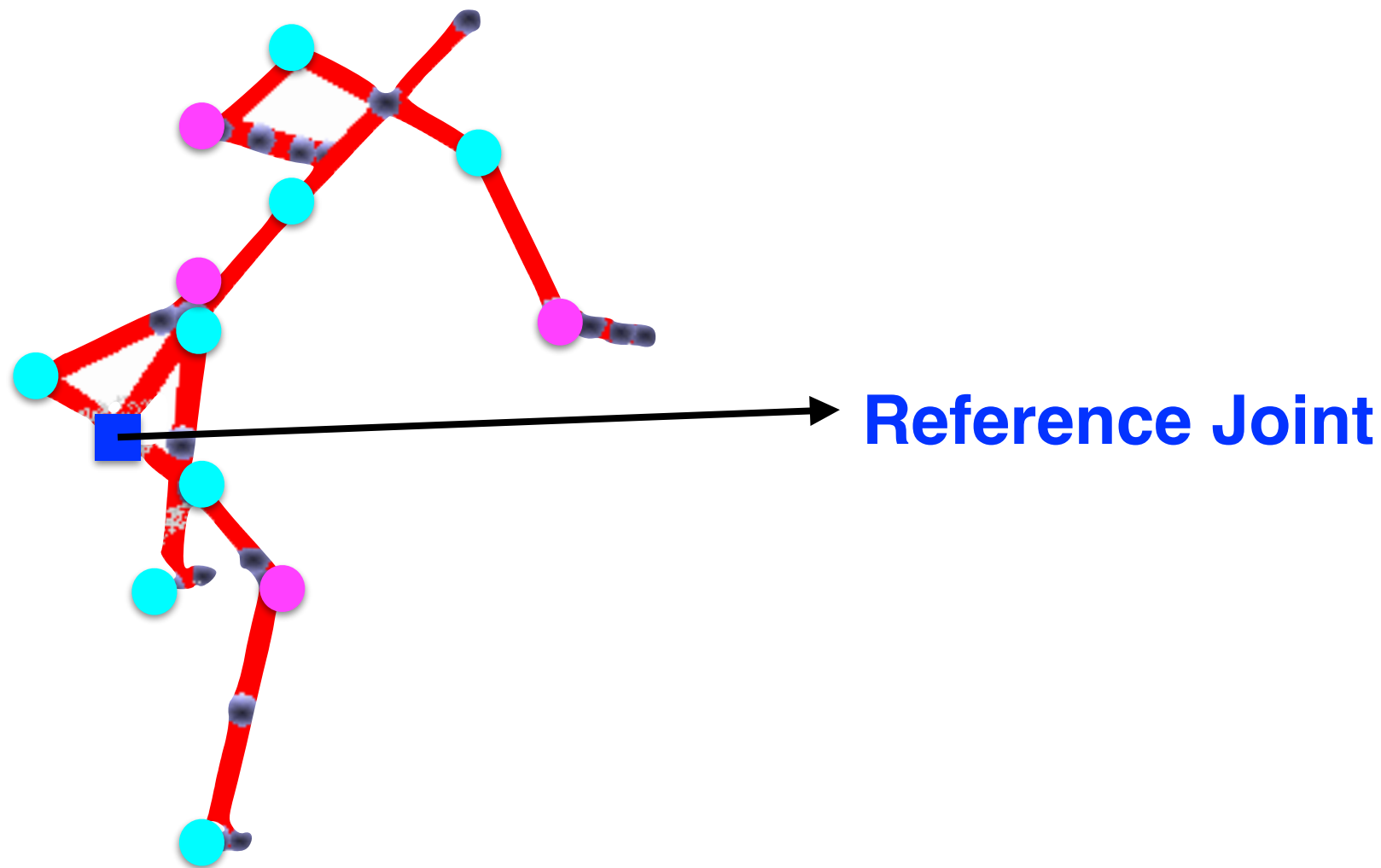


Affordance Model

Learn from training data

- Geometry of contact points

→ Plausibility of poses

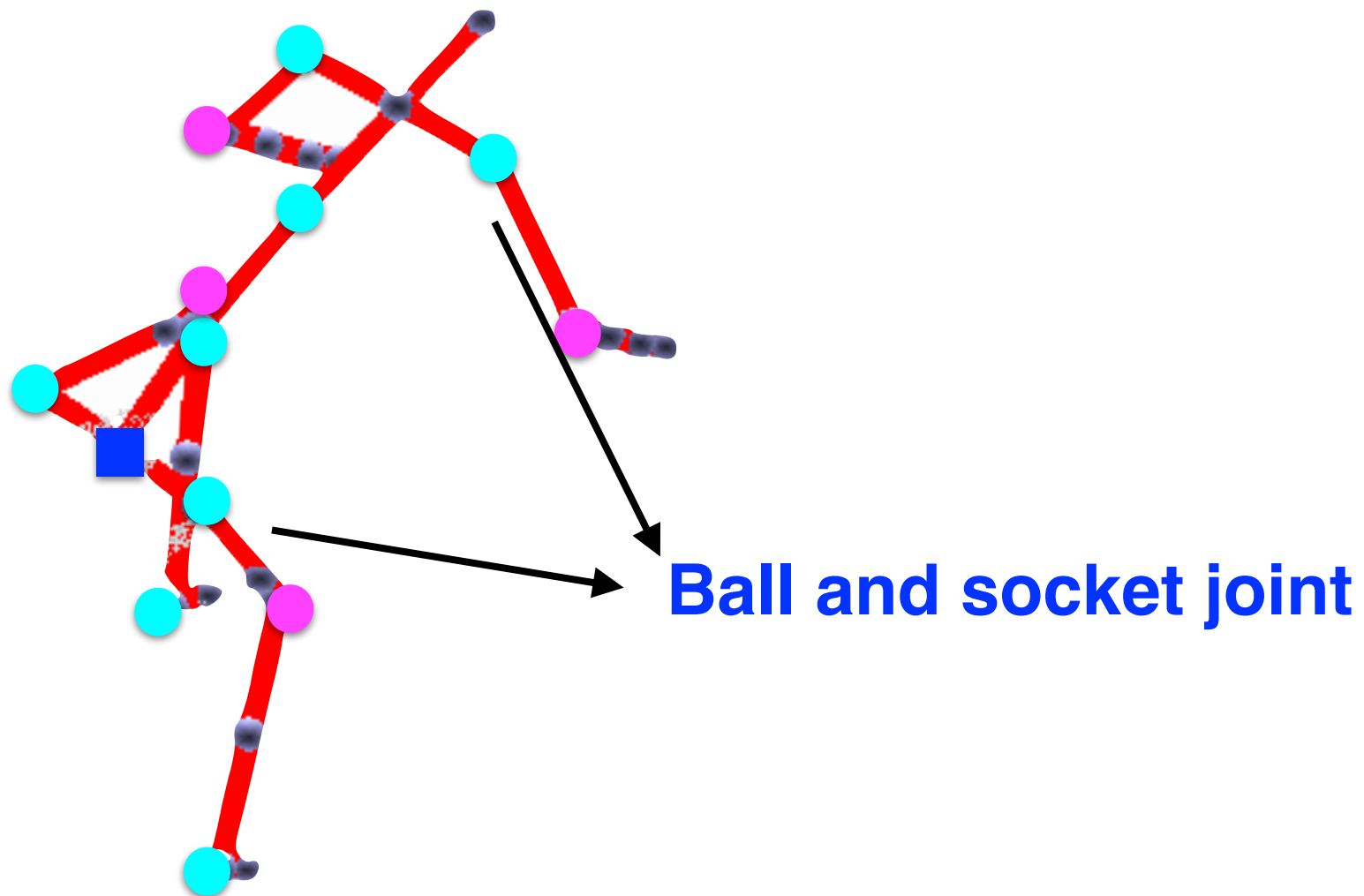


Affordance Model

Learn from training data

- Geometry of contact points

→ Plausibility of poses

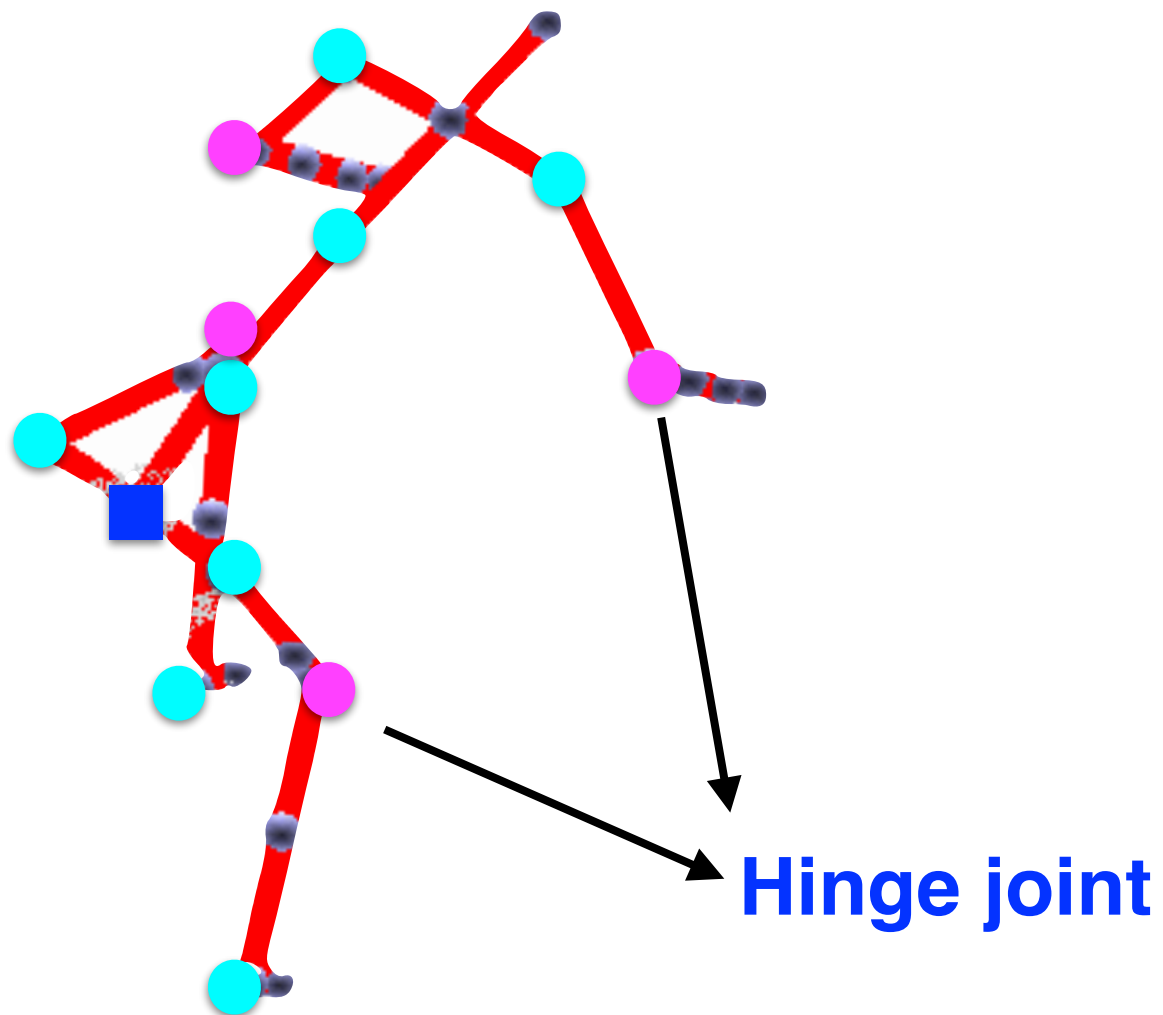


Affordance Model

Learn from training data

- Geometry of contact points

→ Plausibility of poses

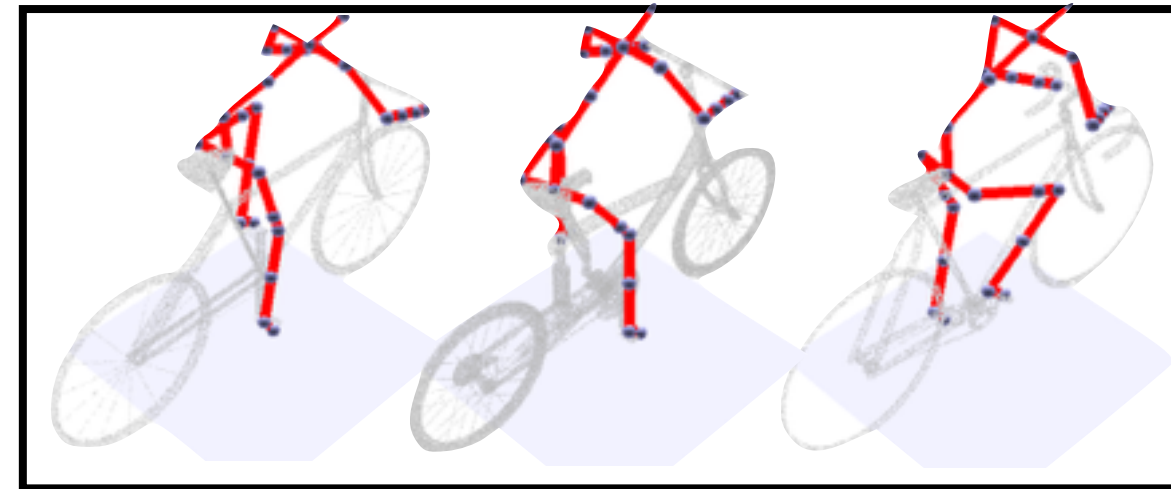
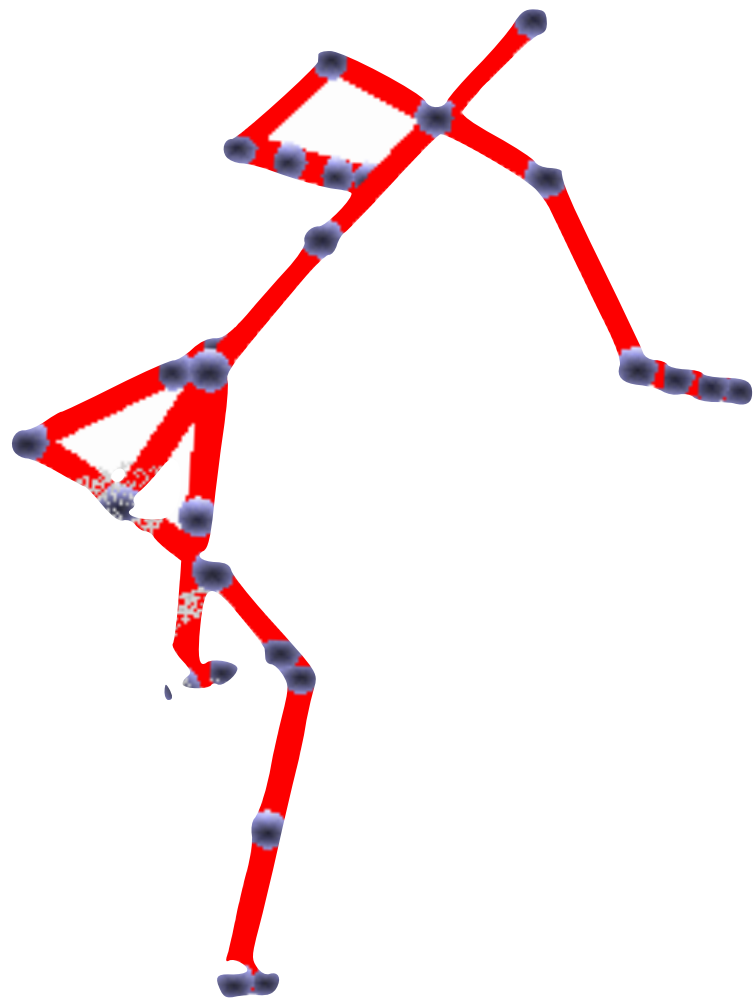


Affordance Model

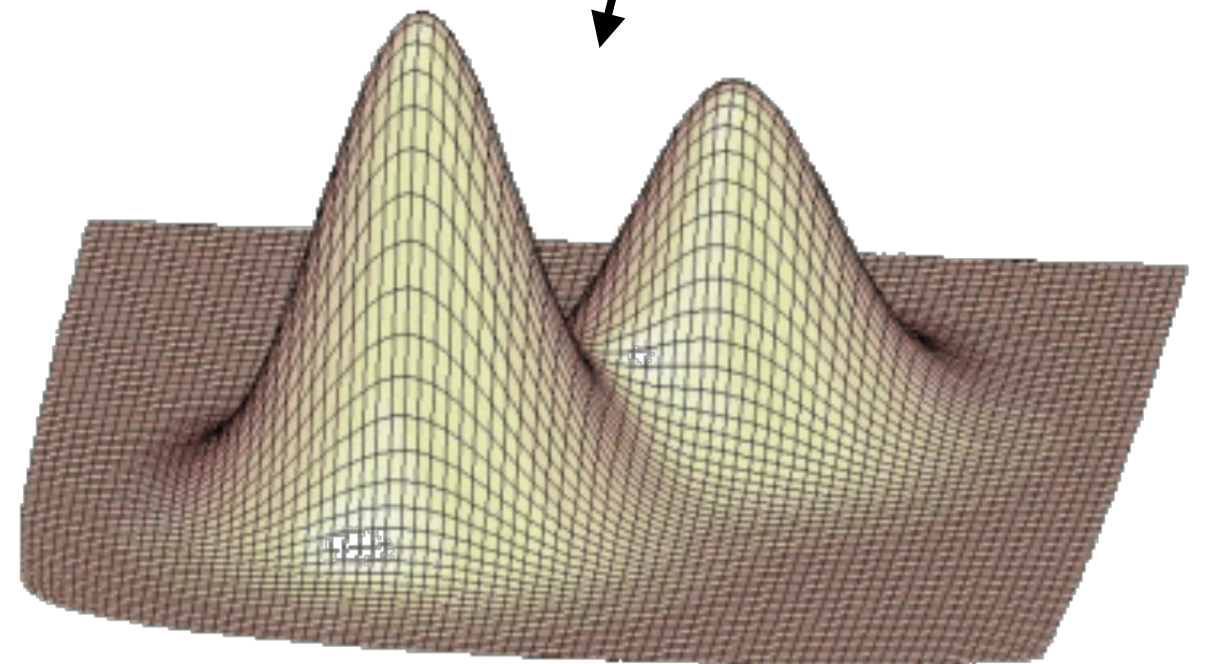
Learn from training data

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Training Data



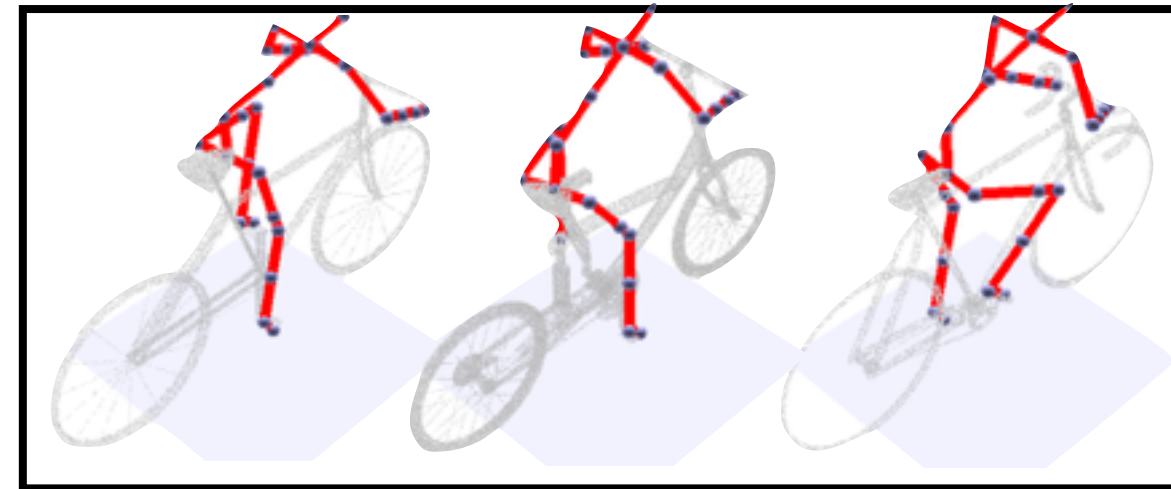
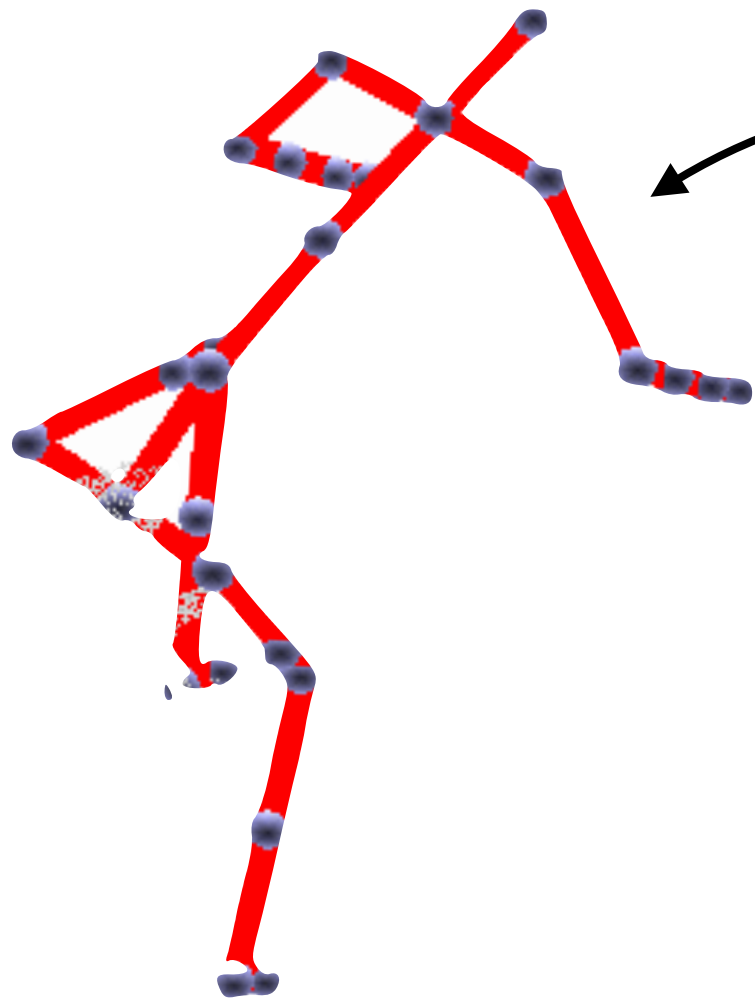
Mixture of multi-variate Gaussians

Affordance Model

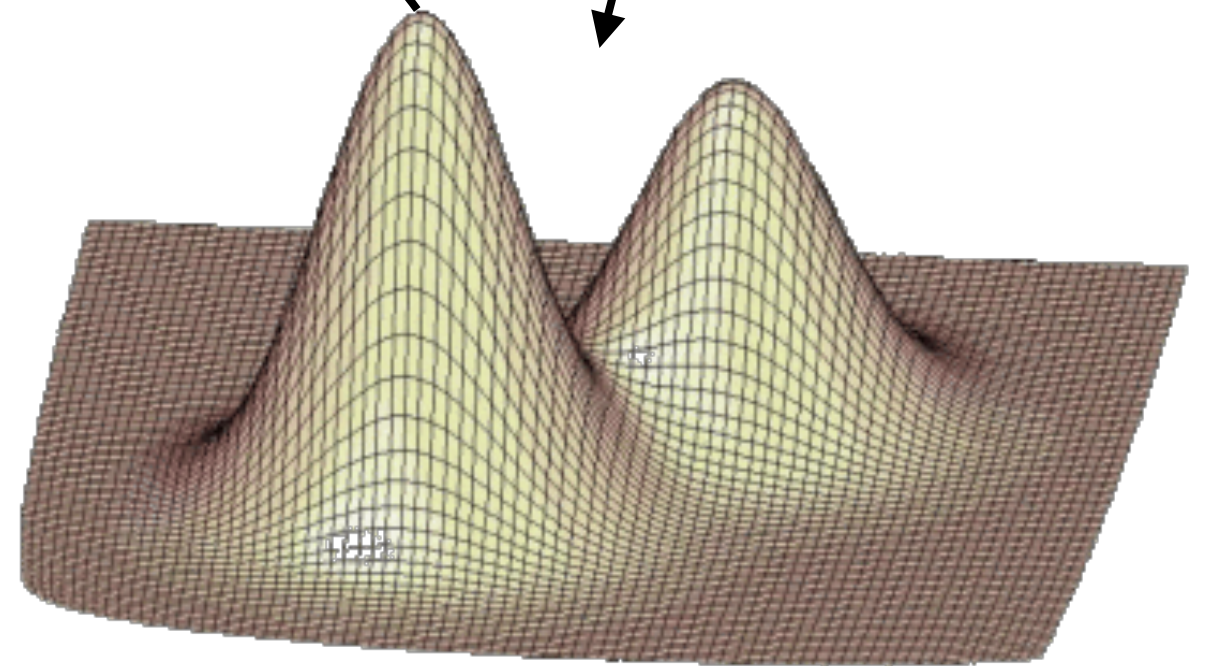
Learn from training data

- Geometry of contact points

→ Plausibility of poses



Training Data



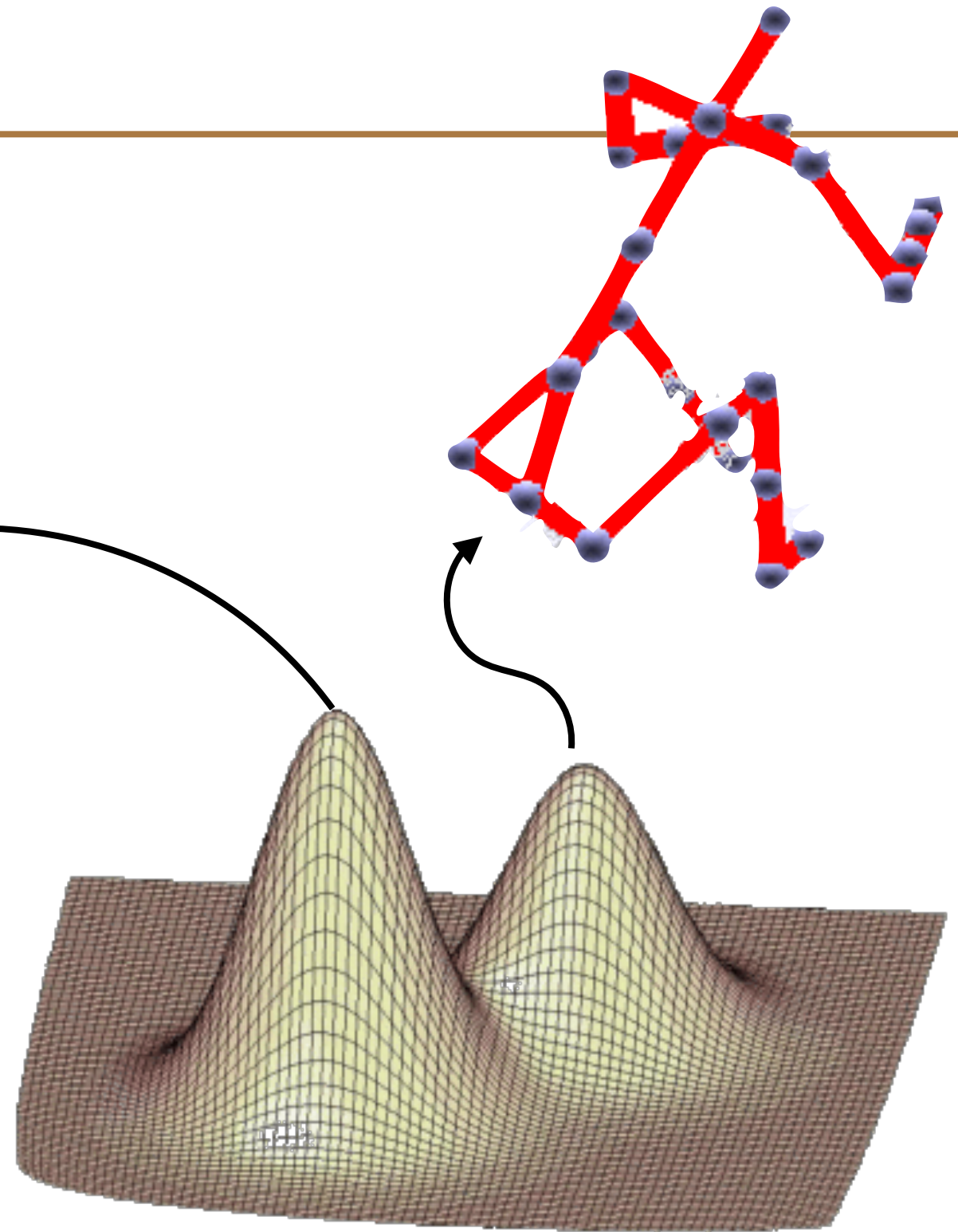
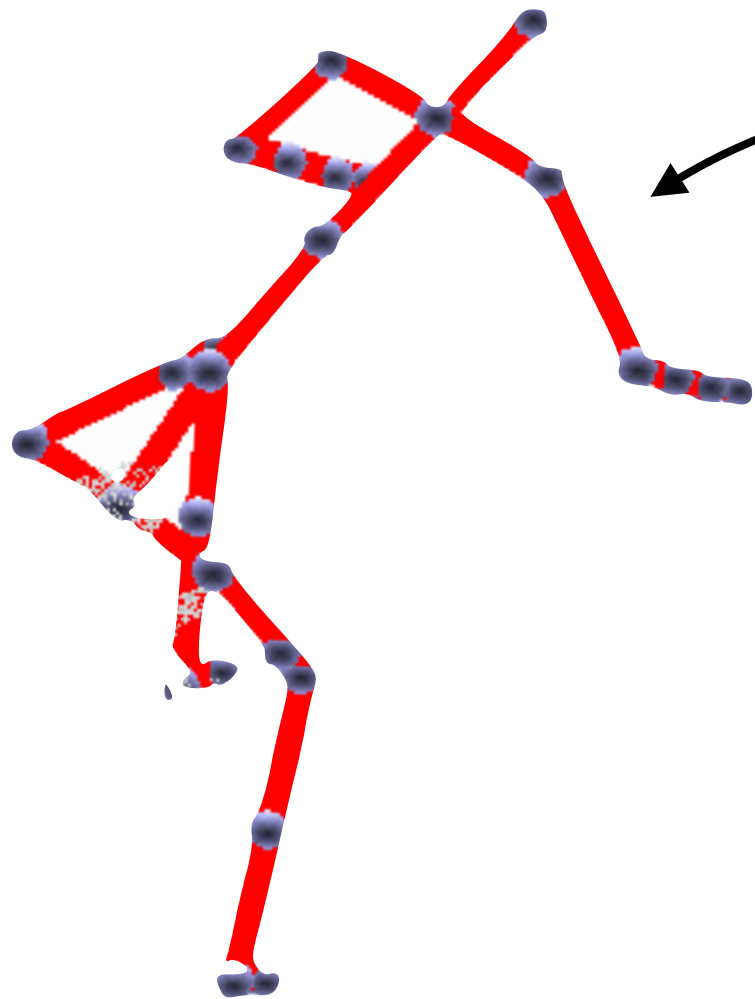
Mixture of multi-variate Gaussians

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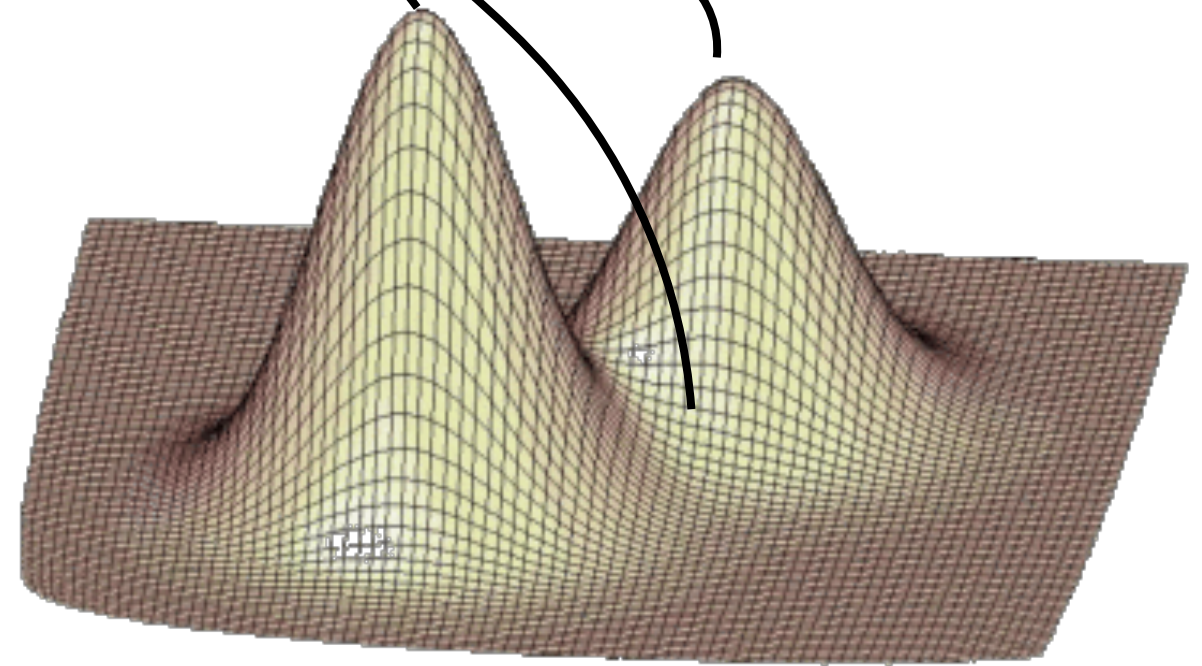
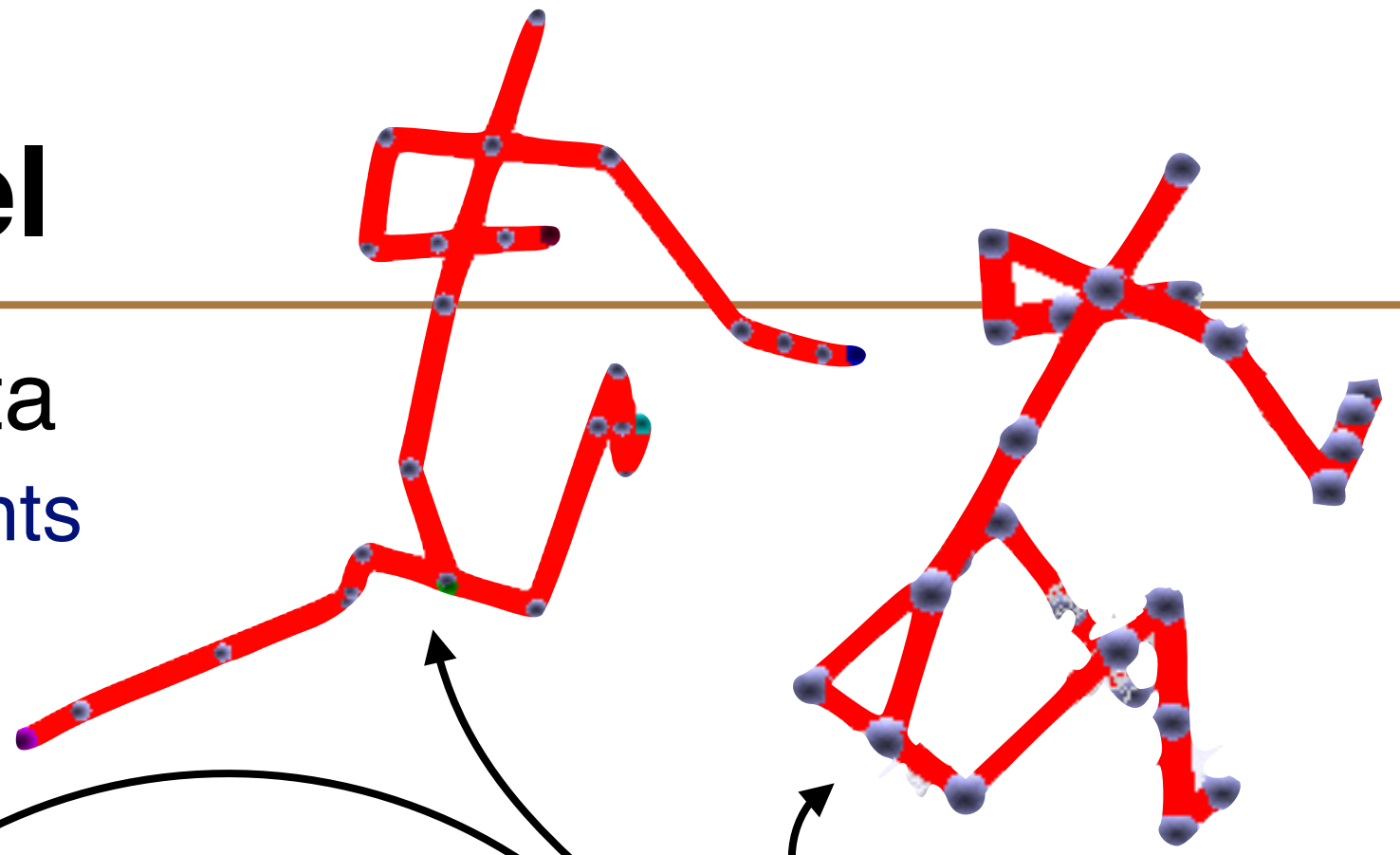
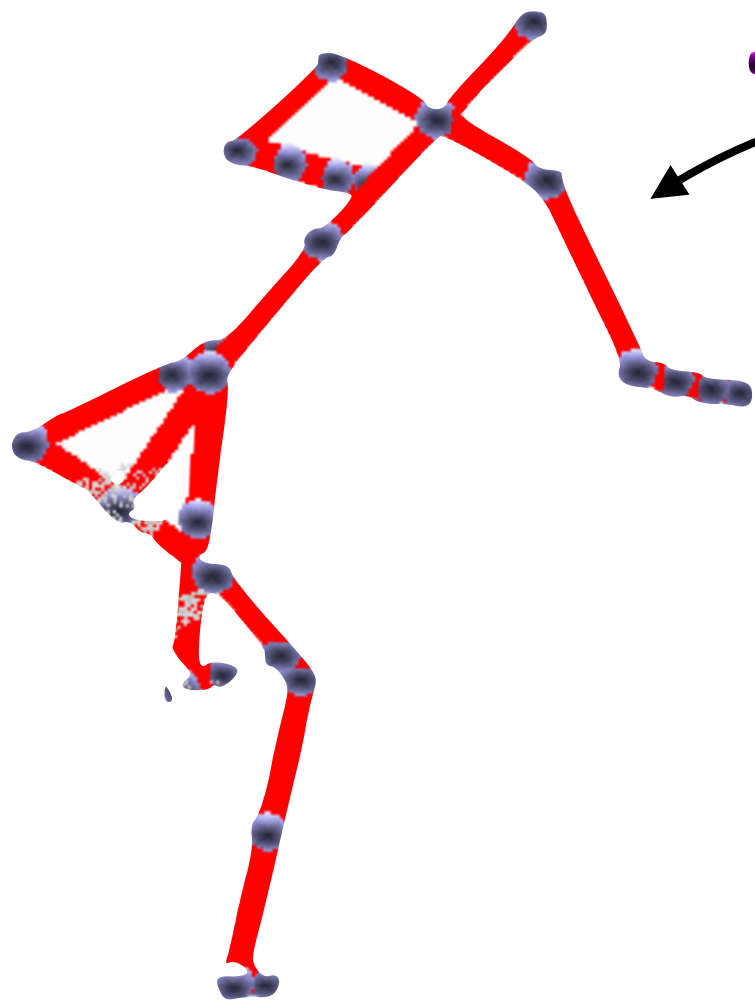
Mixture of multi-variate Gaussians

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Learn from training data

- Geometry of contact points

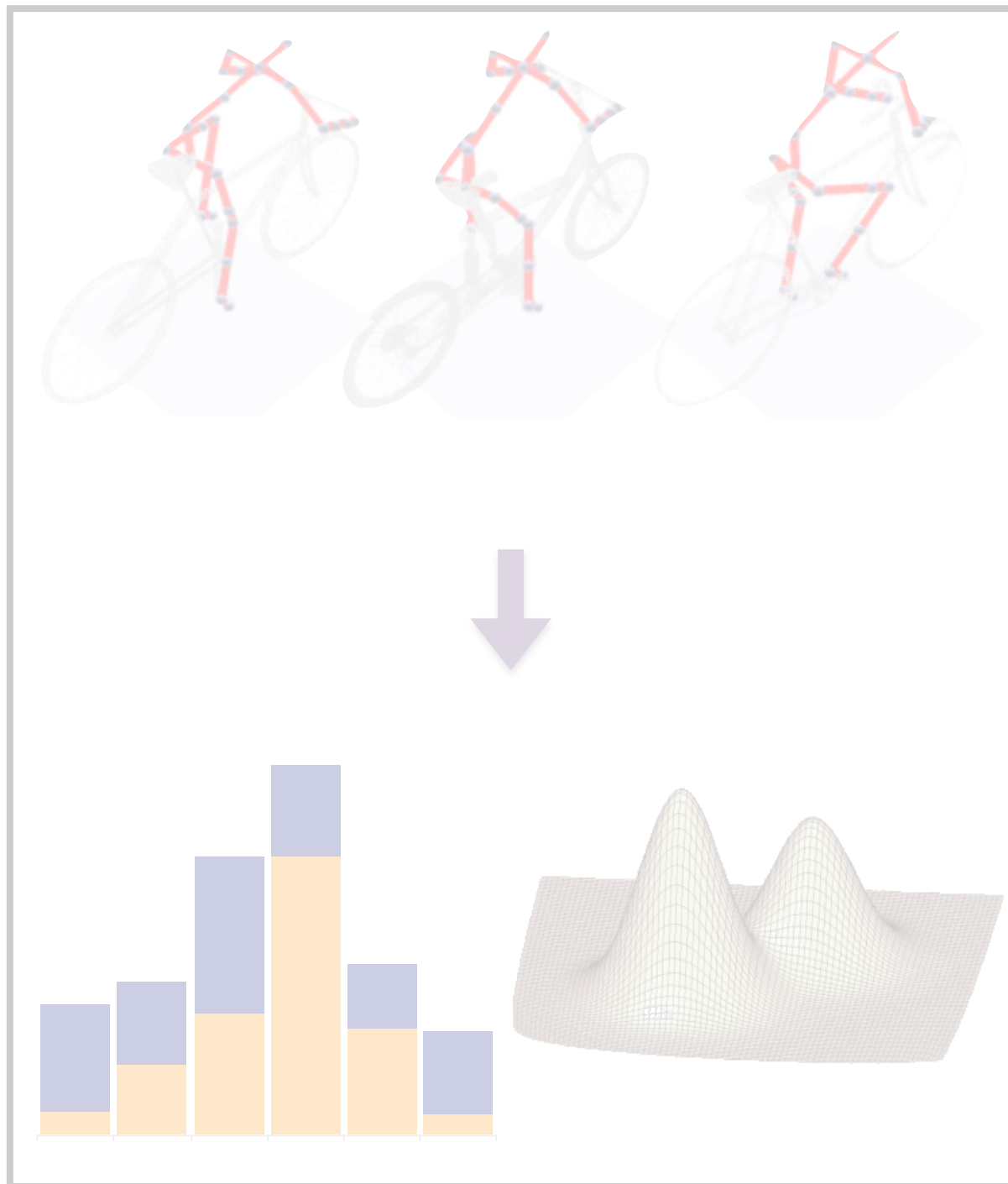
→ Plausibility of poses



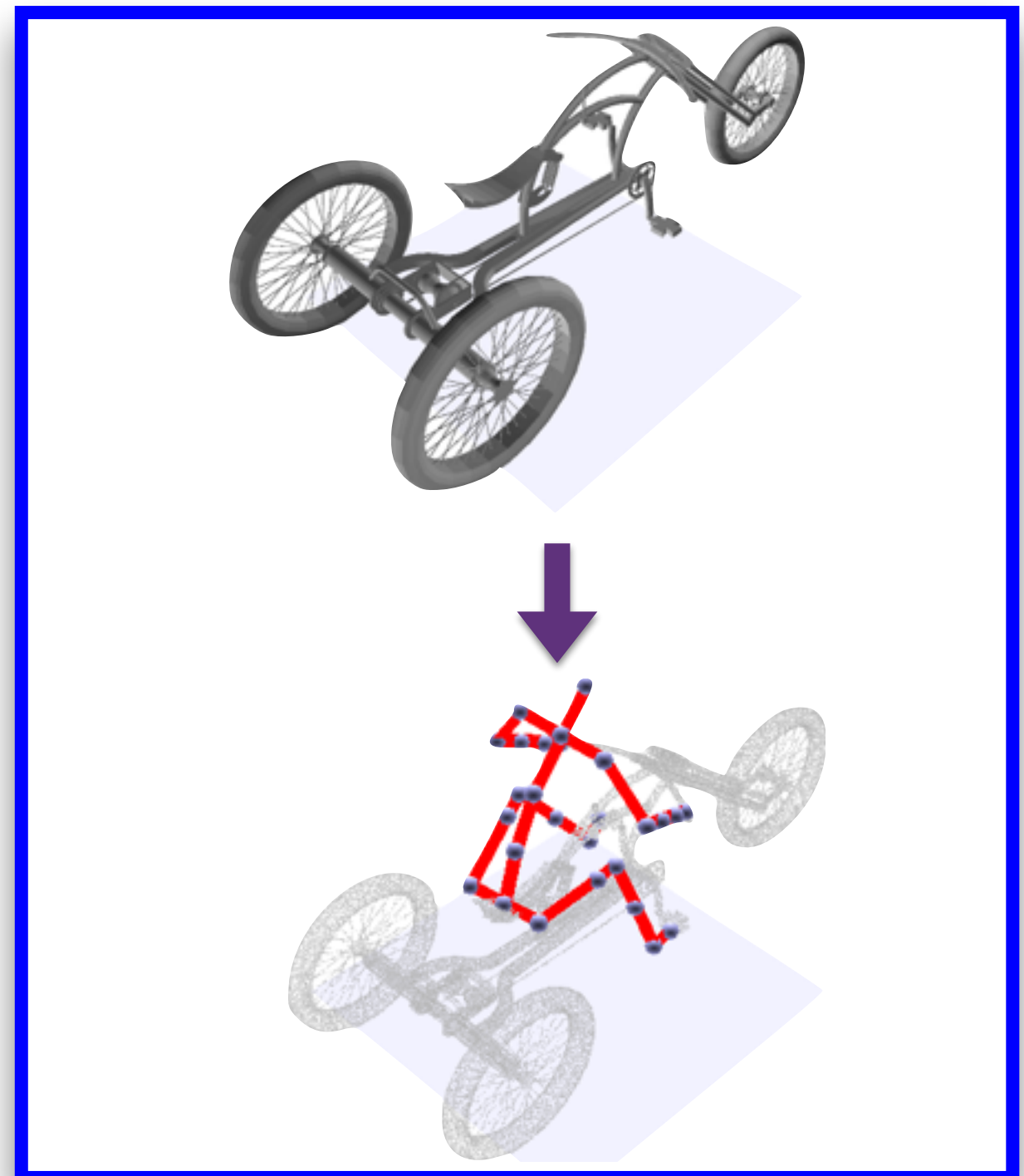
Mixture of multi-variate Gaussians

Affordance Model and Pose Prediction

Affordance Model Learning



Pose Prediction



Pose Prediction

Objective function for each pose-model fit:

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

Solve for:

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

Pose Prediction

Objective function for each pose-model fit:

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

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

Solve for:

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

Pose Prediction

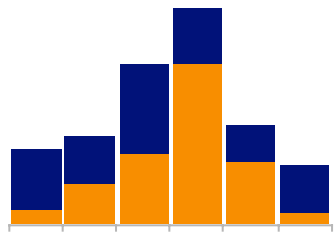
Objective function for each pose-model fit:

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

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

Regression Model



Solve for:

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

Pose Prediction

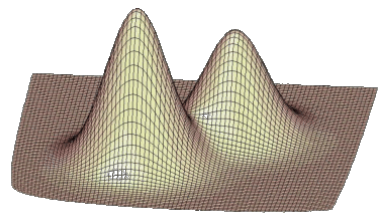
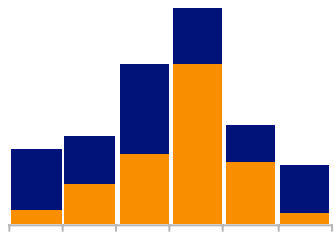
Objective function for each pose-model fit:

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

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

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

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:

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

Body parts Shape

Pose Prediction

Objective function for each pose-model fit:

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

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

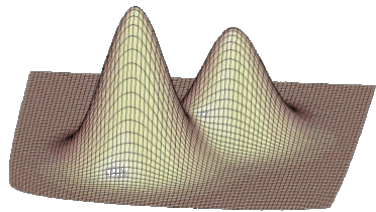
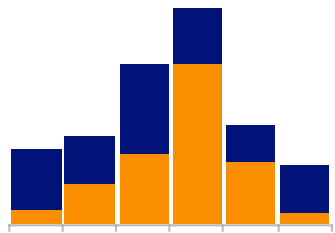
Hard Constraint

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

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:

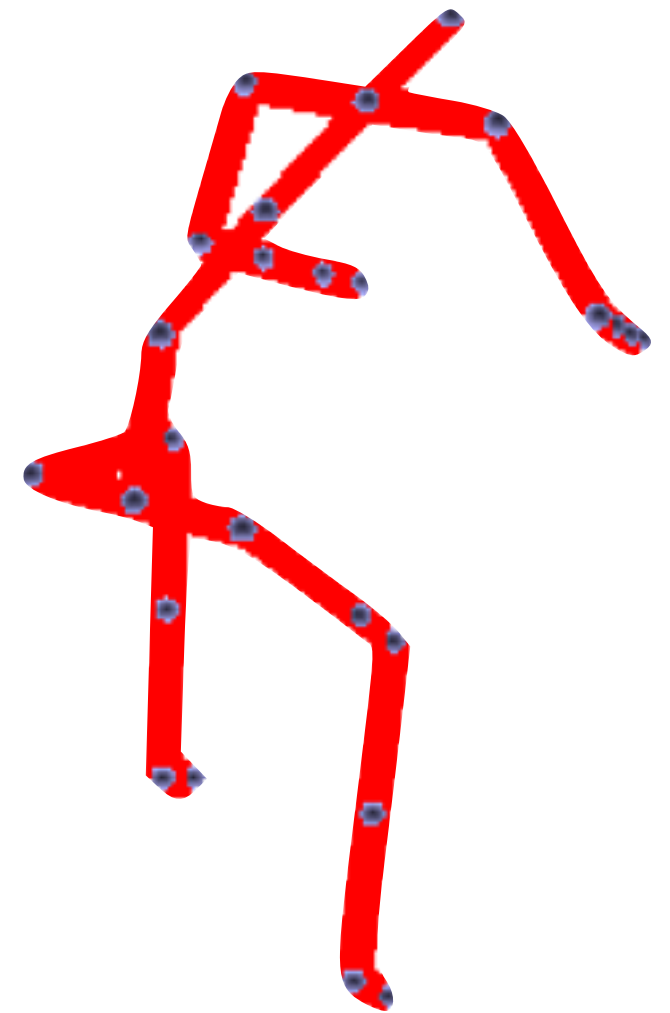
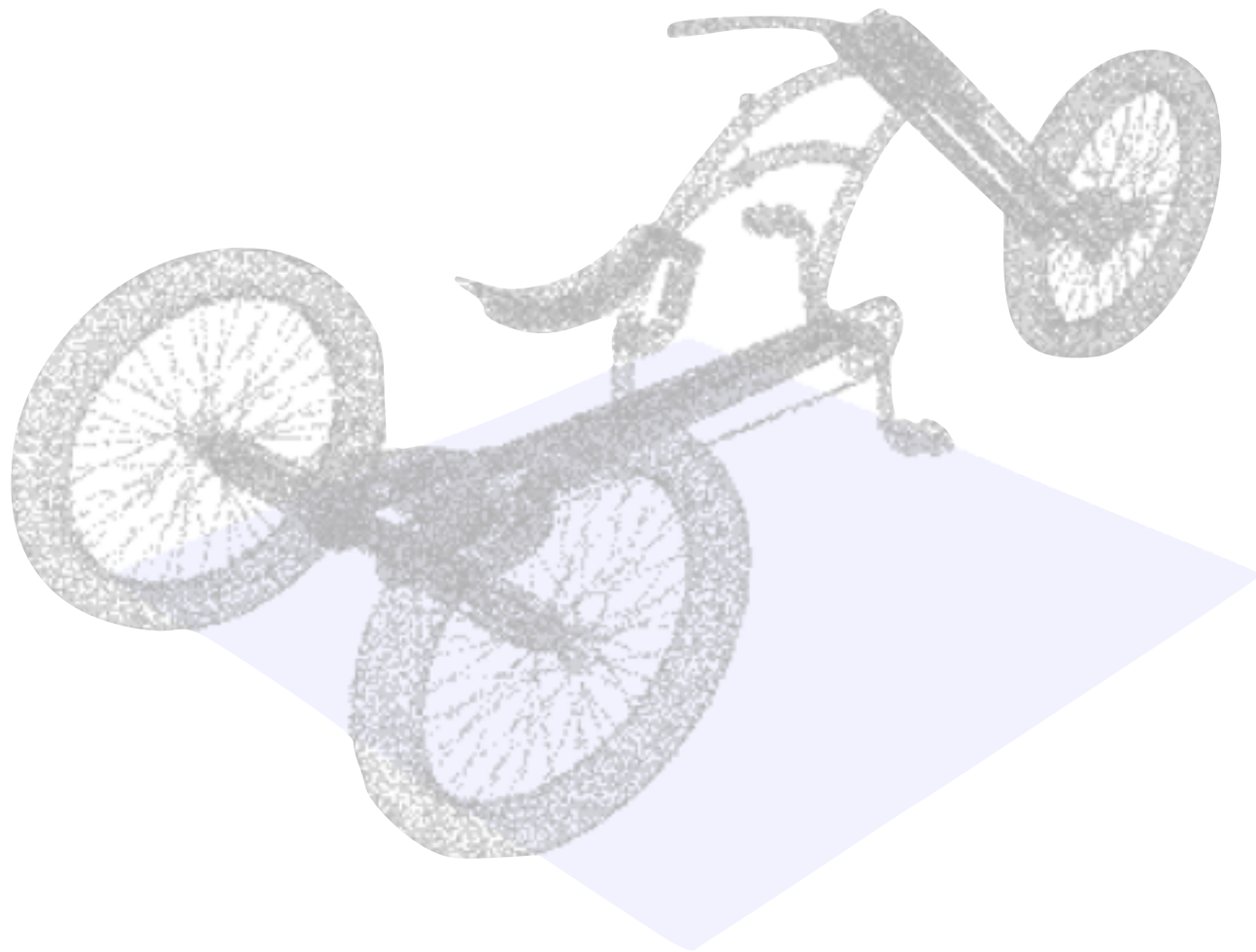
- Contact points $m : P \rightarrow S$
- Joint angles θ, T

Body parts

Shape

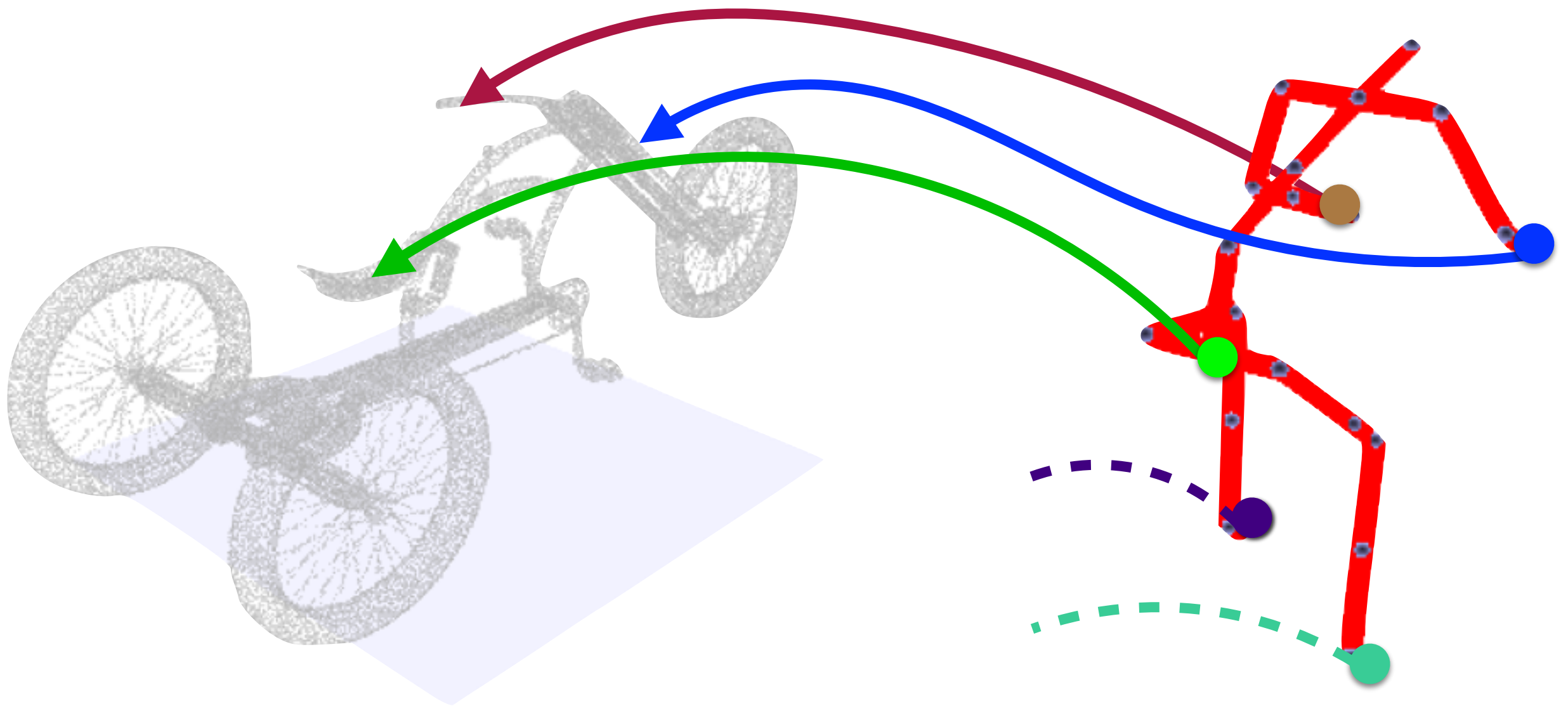
Pose Prediction Algorithm

Input



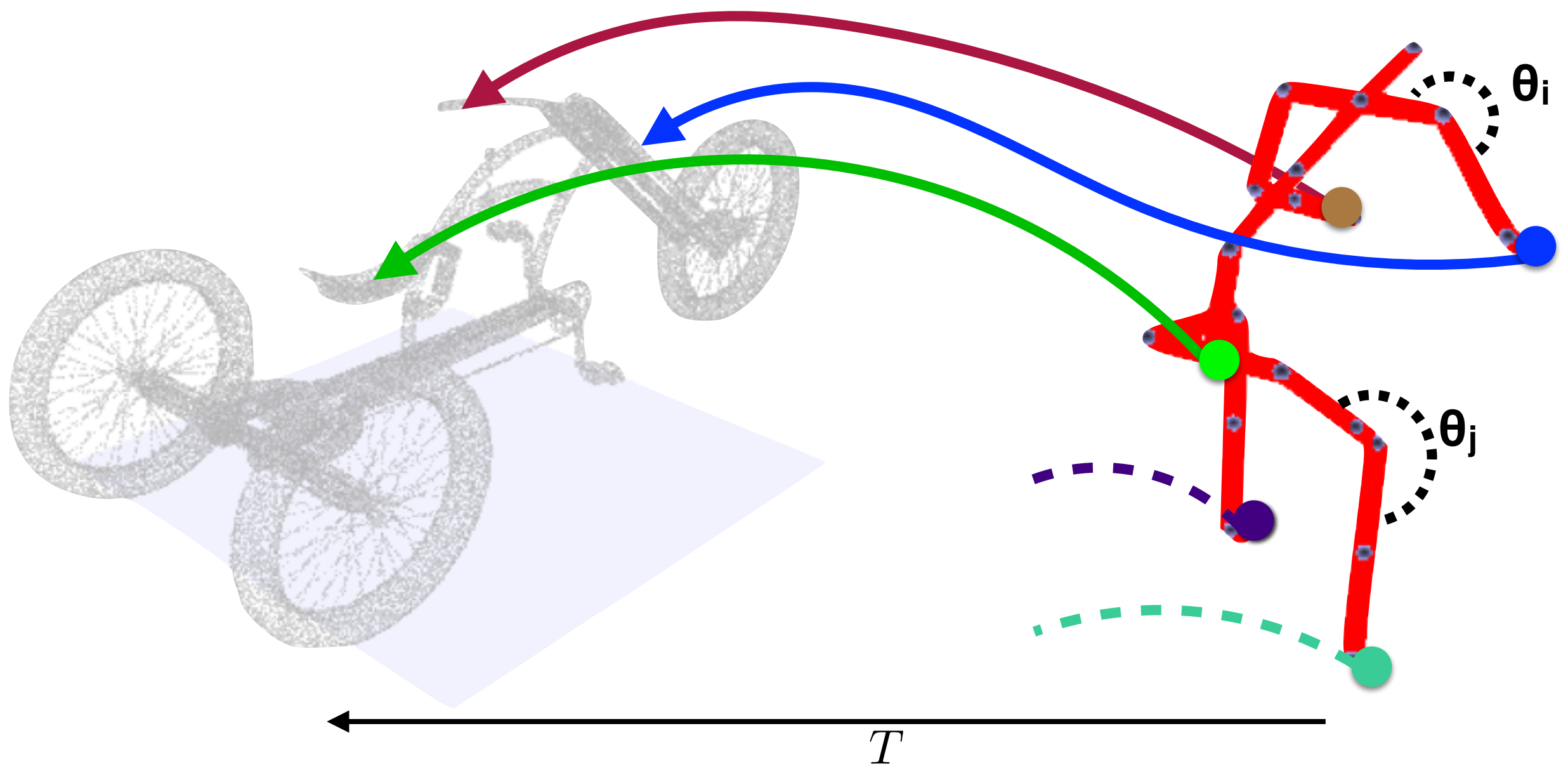
Pose Prediction Algorithm

Output: m



Pose Prediction Algorithm

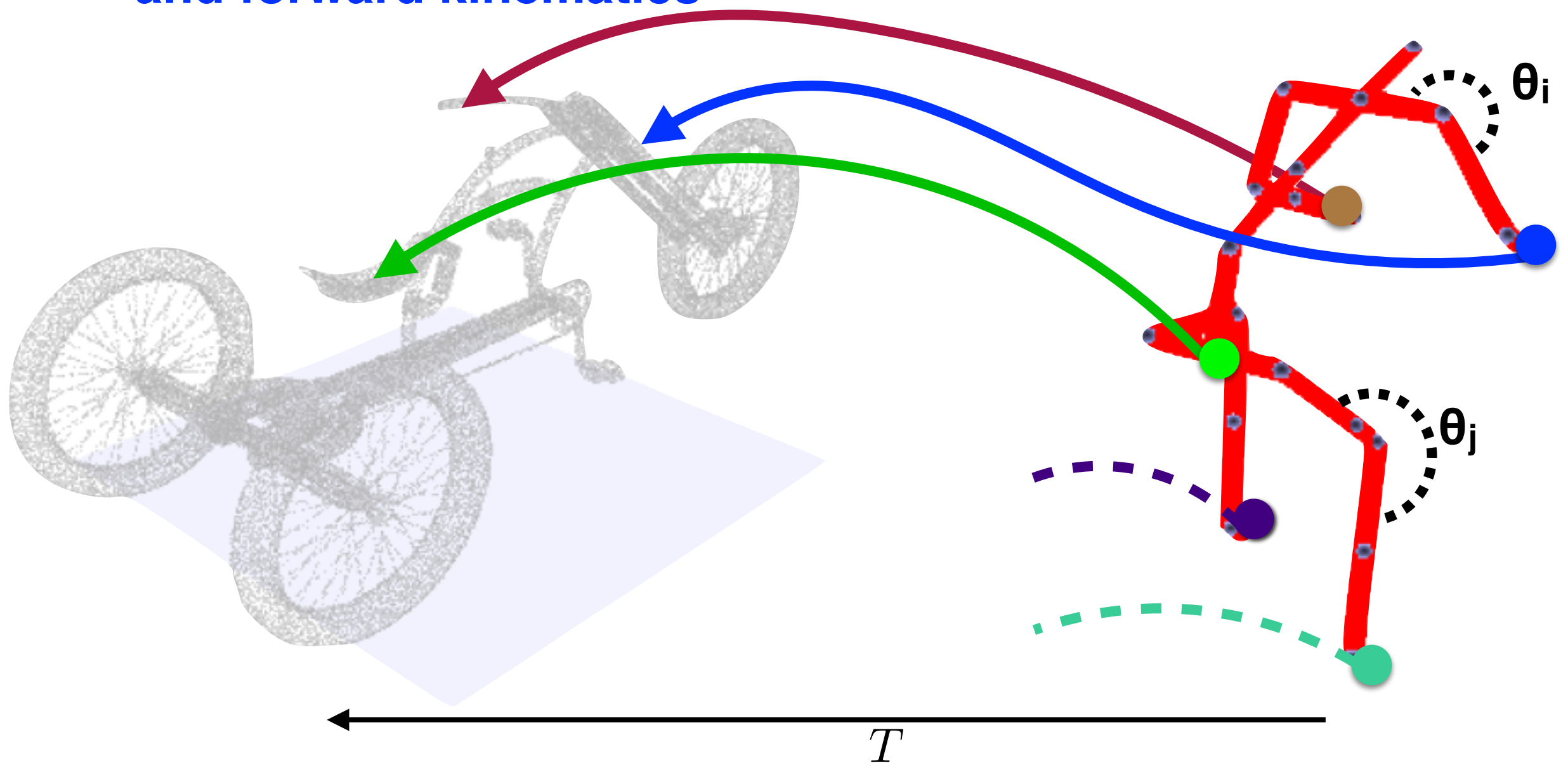
Output: m θ, T



Pose Prediction Algorithm

Output: $m \leftrightarrow \theta, T$

Related via inverse
and forward kinematics



Pose Prediction Algorithm

Output: $m \leftrightarrow \theta, T$

Related via inverse
and forward kinematics

Naive Methods

Explore m :

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

surface points
body contacts

Explore θ, T :

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

angles

T



The diagram illustrates a robotic arm with multiple joints, each labeled with an angle θ_i and θ_j . The arm is shown in a red color, with joints represented by blue and green circles. A dashed green line indicates a path or trajectory. A horizontal arrow at the bottom is labeled T , representing time. The background features a faint image of a wheel and a light blue triangular shape.

Pose Prediction Algorithm

Output: $m \leftrightarrow \theta, T$

Related via inverse
and forward kinematics

Naive Methods

Explore m :

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

surface points
body contacts

Explore θ, T :

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

angles

Too Expensive!

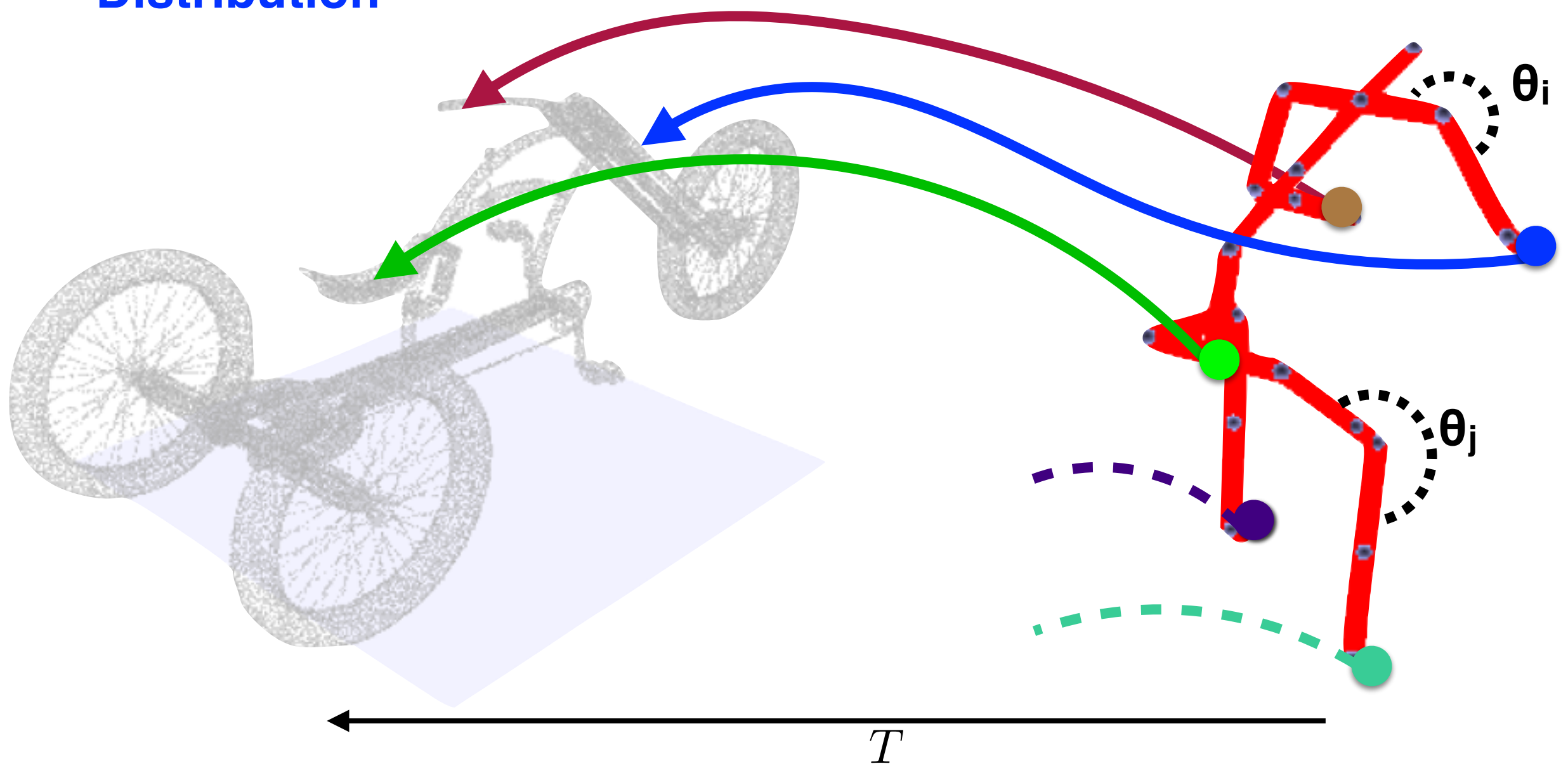
T

A diagram of a robotic arm with multiple joints, some labeled with angles theta_i and theta_j. A horizontal arrow at the bottom is labeled T, representing time. A box labeled 'Naive Methods' is overlaid on the diagram, containing text about exploring m and theta, T. The text 'Too Expensive!' is written in red. The background shows a faint image of a wheel.

Pose Prediction Algorithm

Output: \underline{m}
**Contact
Distribution**

$\underline{\theta, T}$
Pose Prior

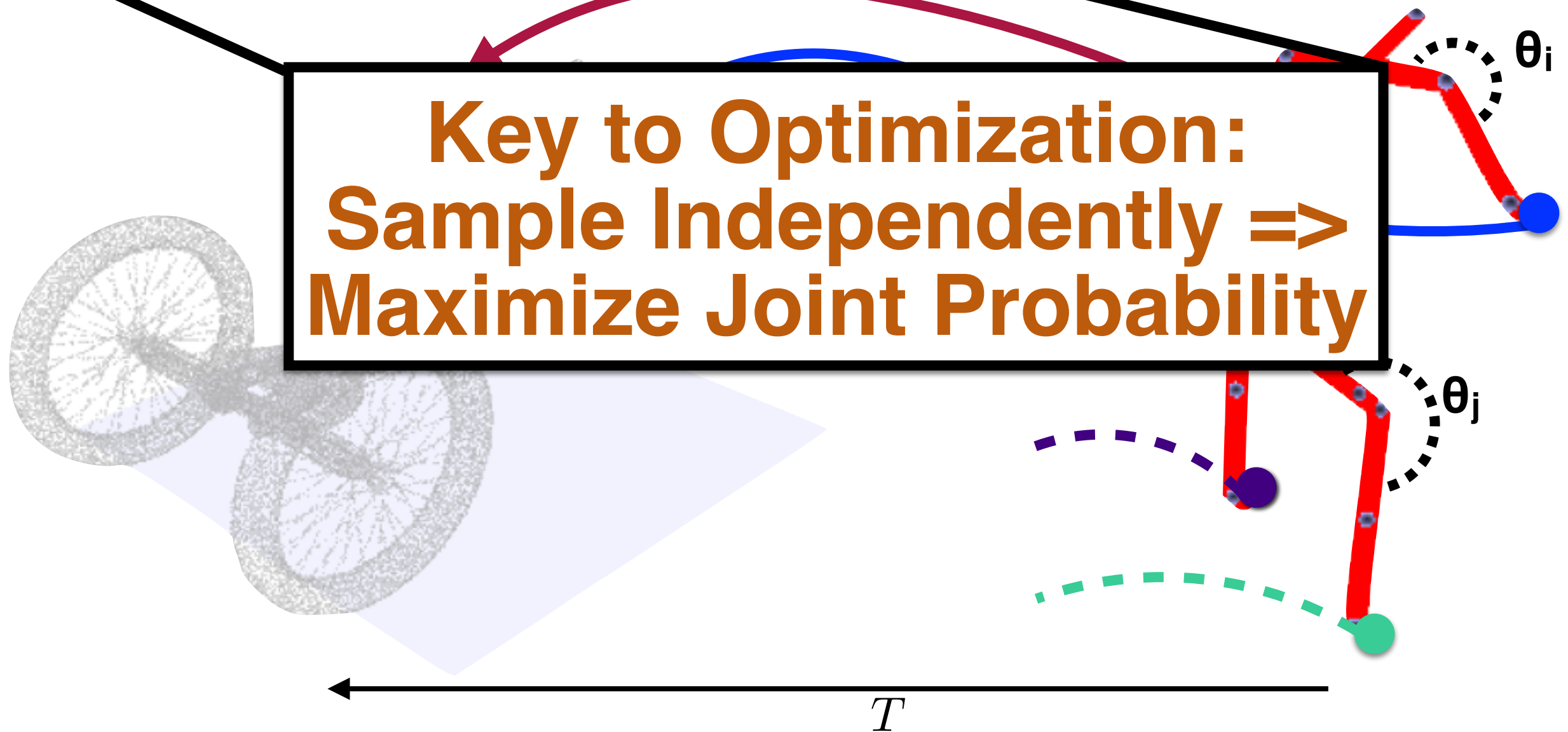


Pose Prediction Algorithm

Output: \bar{m}
Contact
Distribution

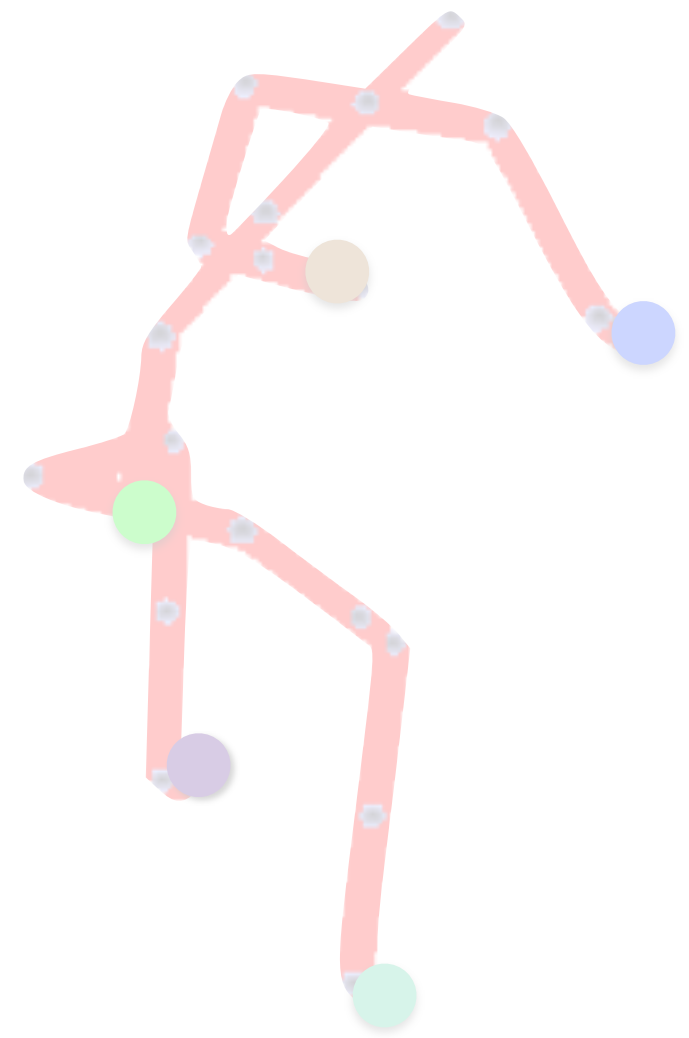
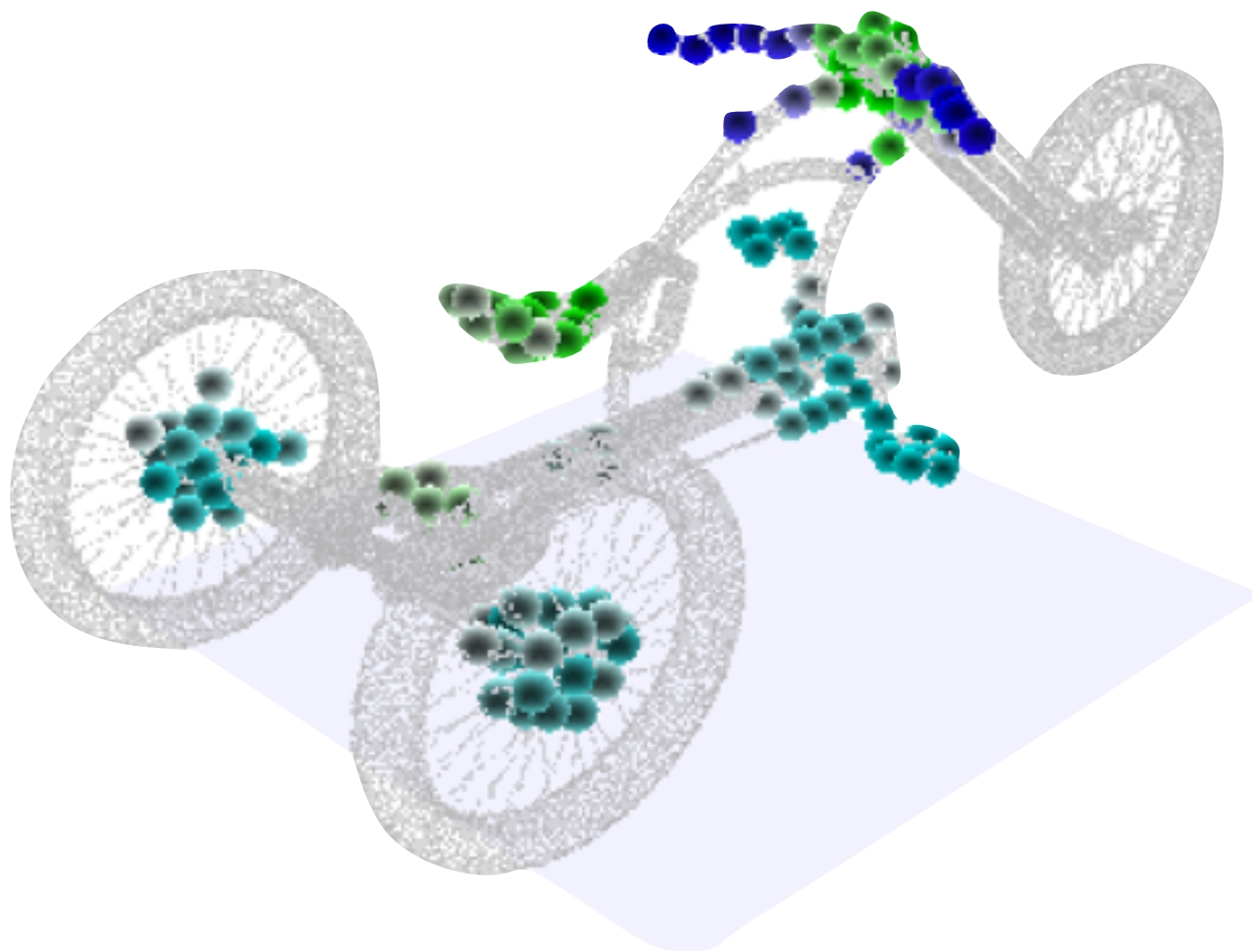
θ, T
Pose Prior

**Key to Optimization:
Sample Independently =>
Maximize Joint Probability**



Pose Prediction Algorithm

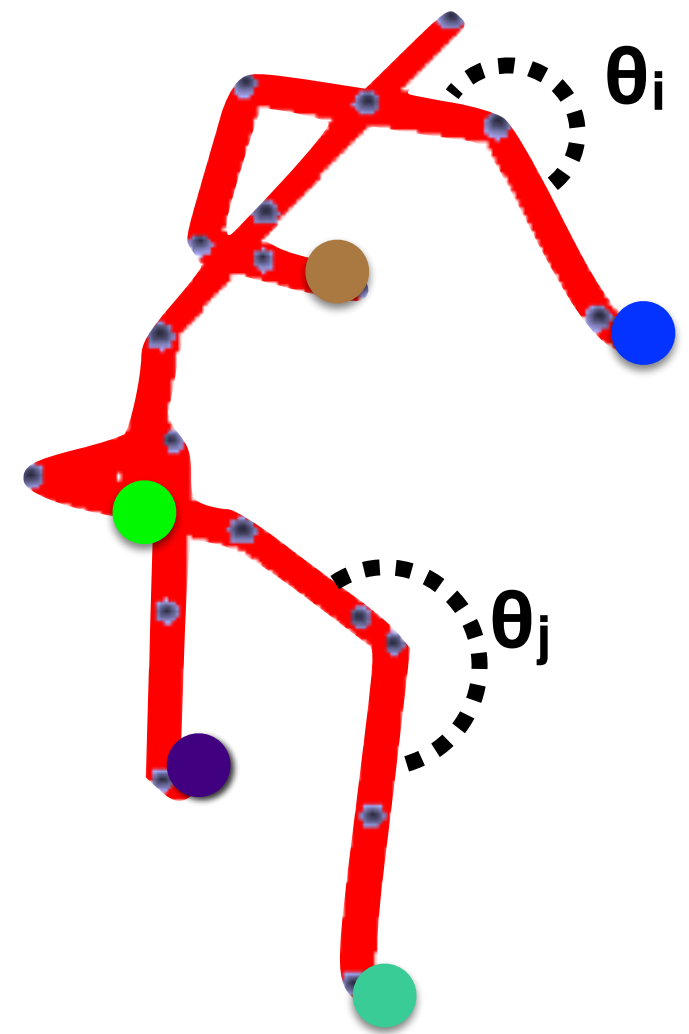
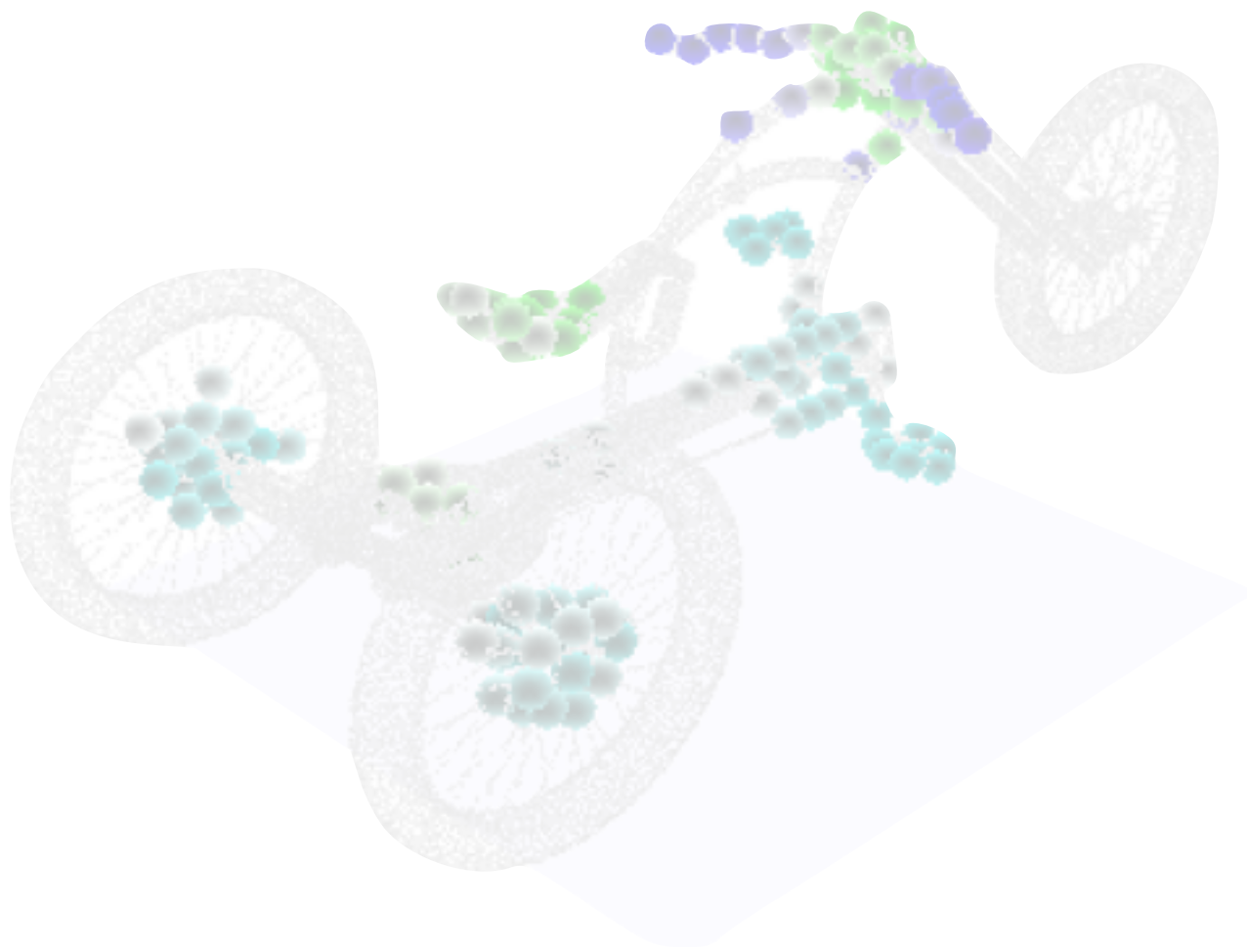
Sample m : classify surface based on local features



Contact Distribution

Pose Prediction Algorithm

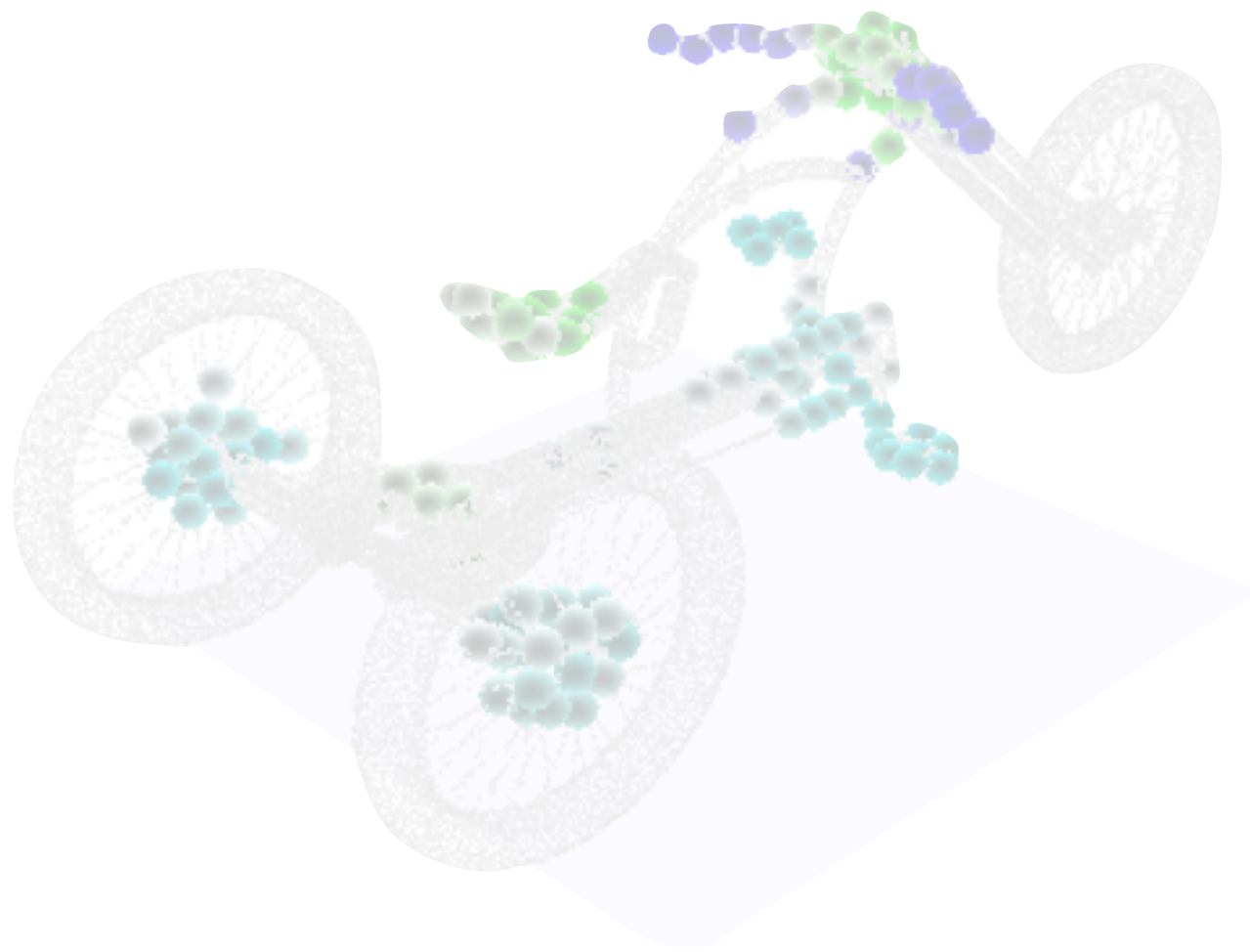
Sample θ, T : Gaussian distributions



Contact Distribution

Pose Prediction Algorithm

Sample θ, T : Gaussian distributions



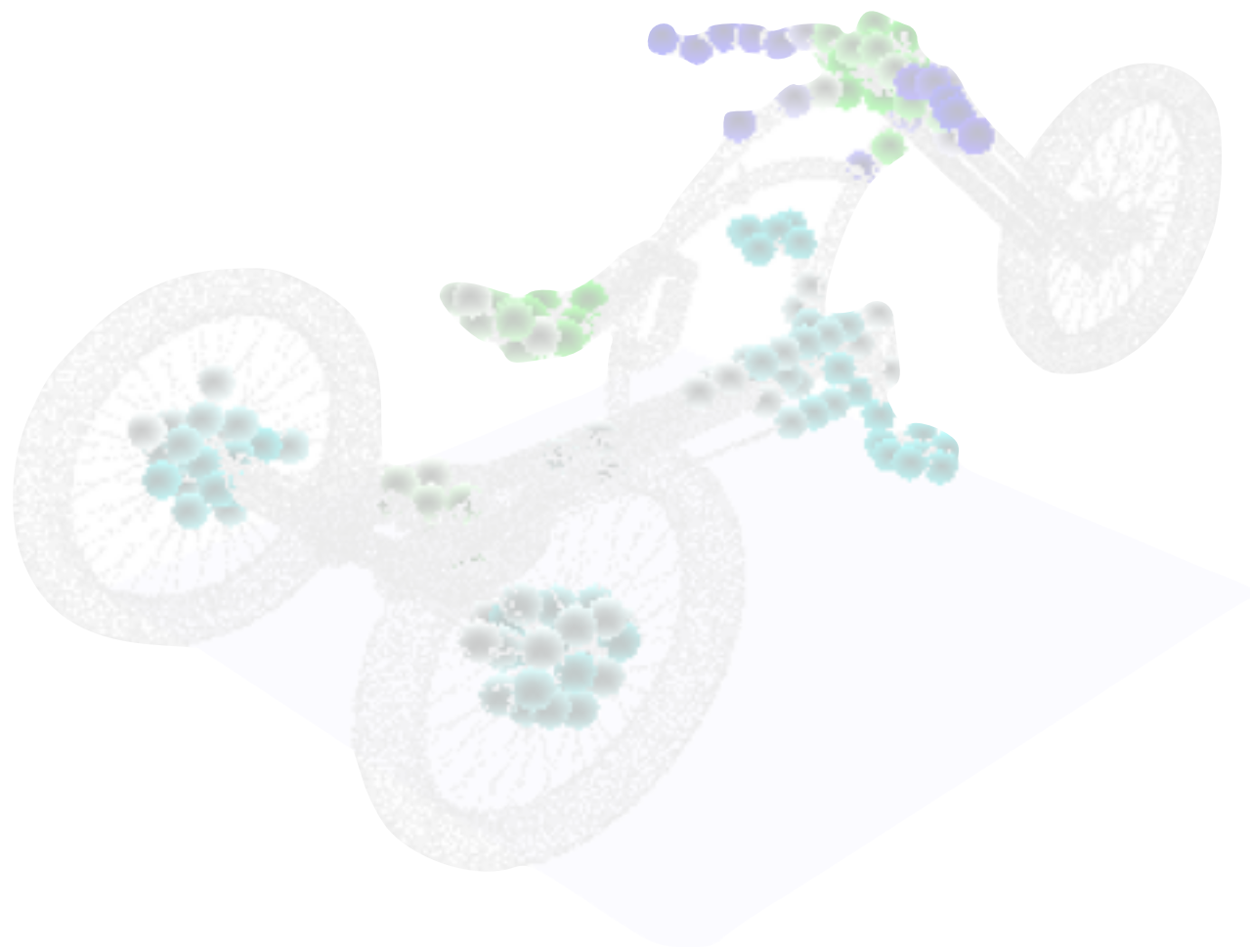
Contact Distribution



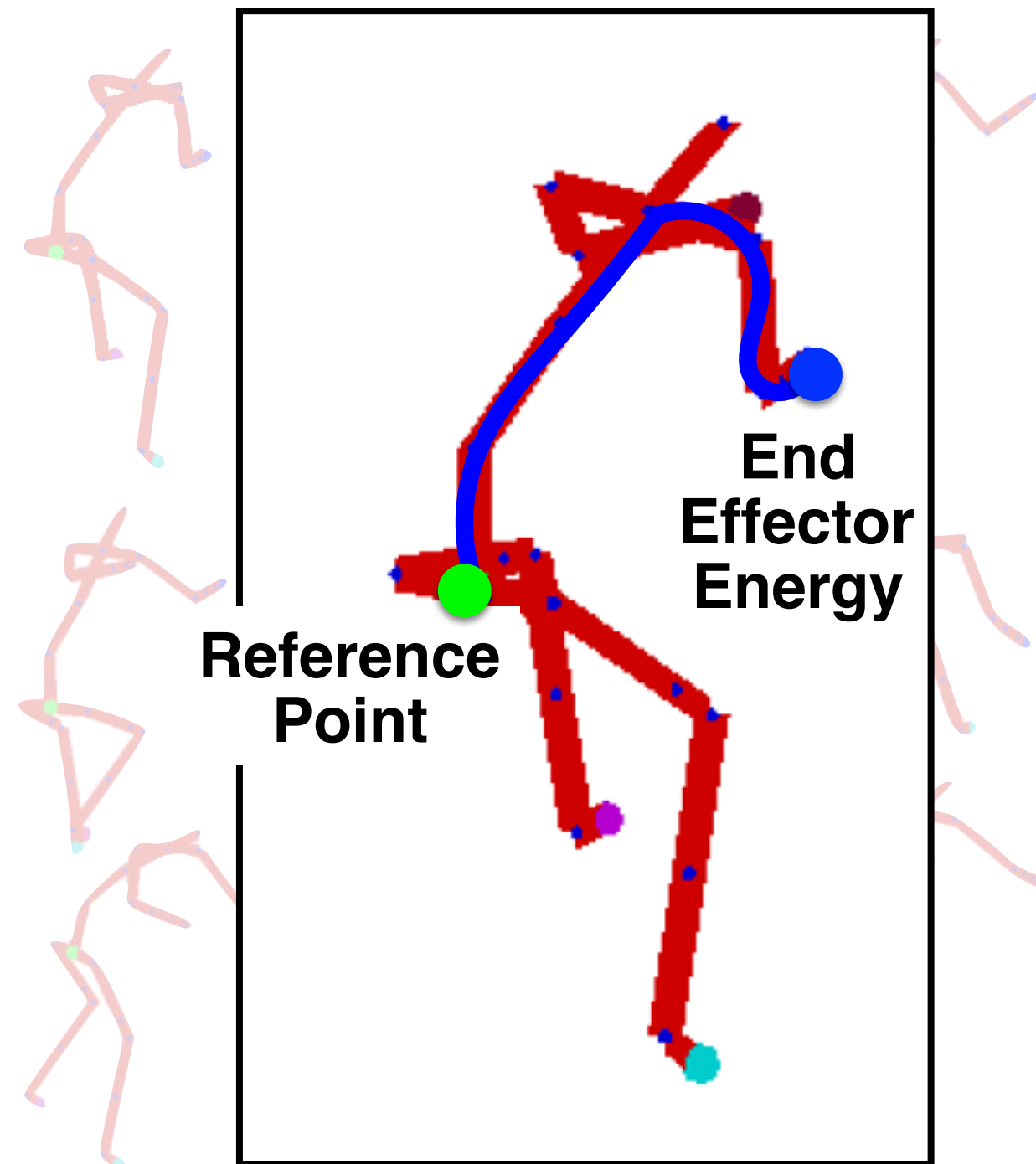
Sampled Poses

Pose Prediction Algorithm

Sample θ, T : Gaussian distributions



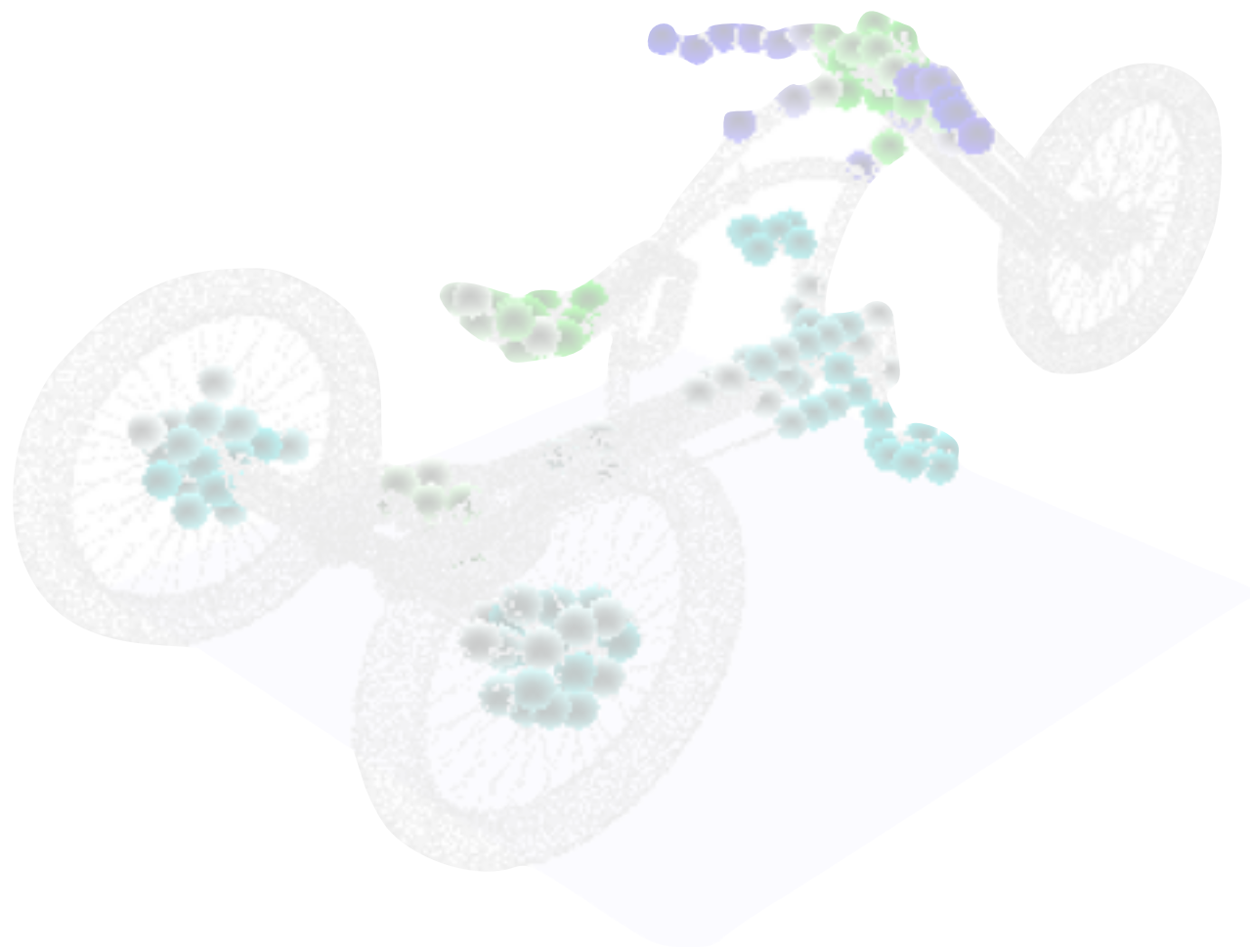
Contact Distribution



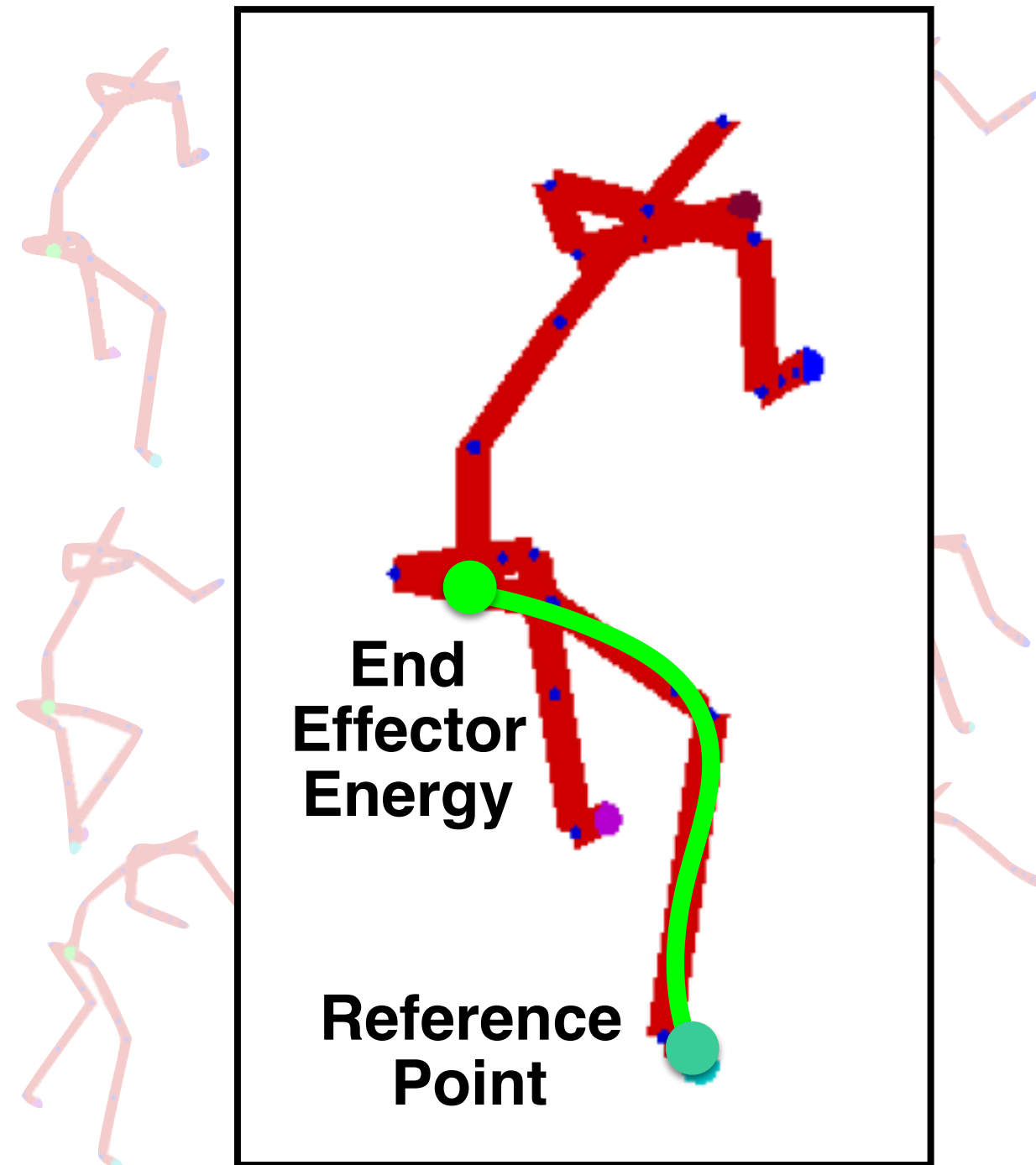
Sampled Poses

Pose Prediction Algorithm

Sample θ, T : Gaussian distributions



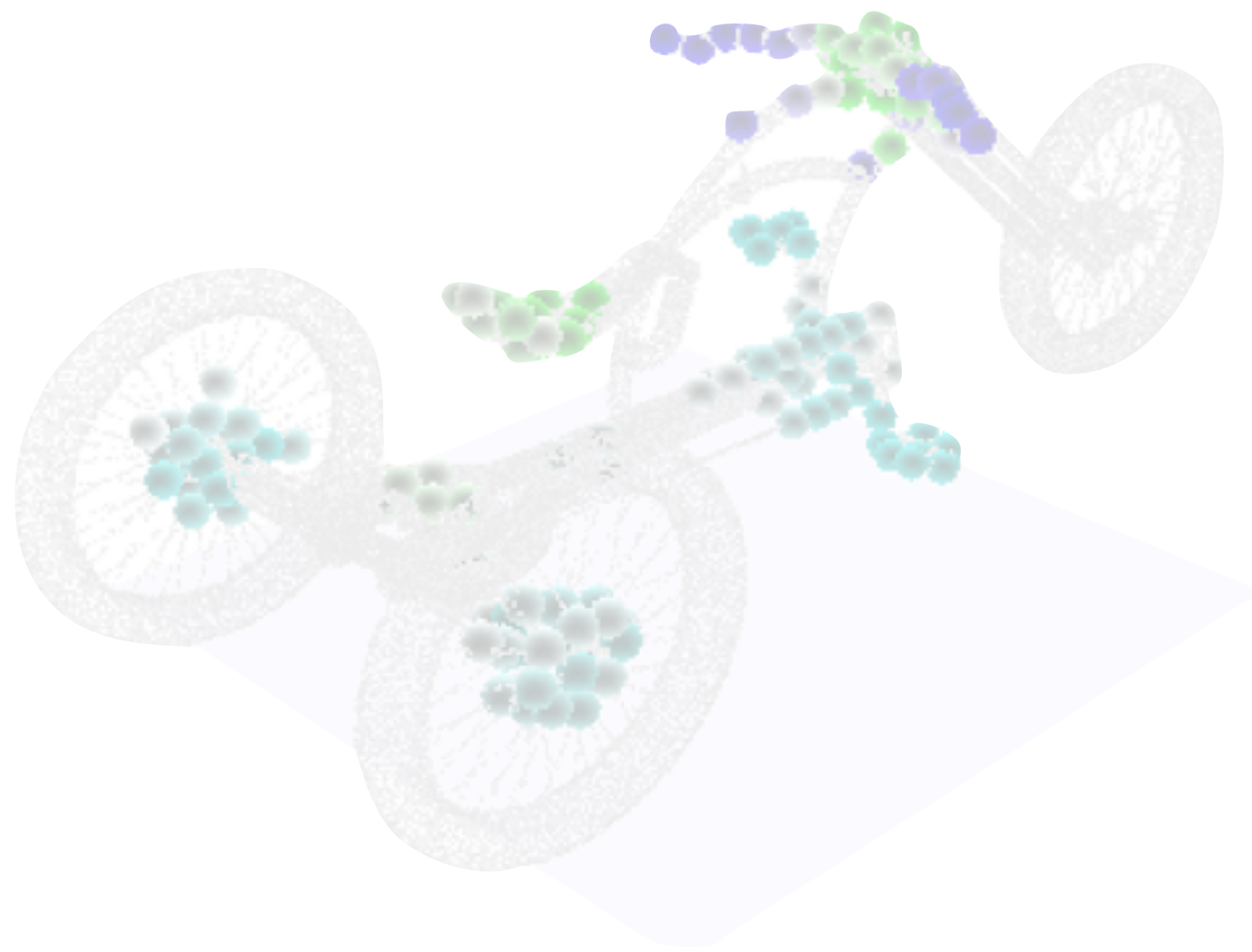
Contact Distribution



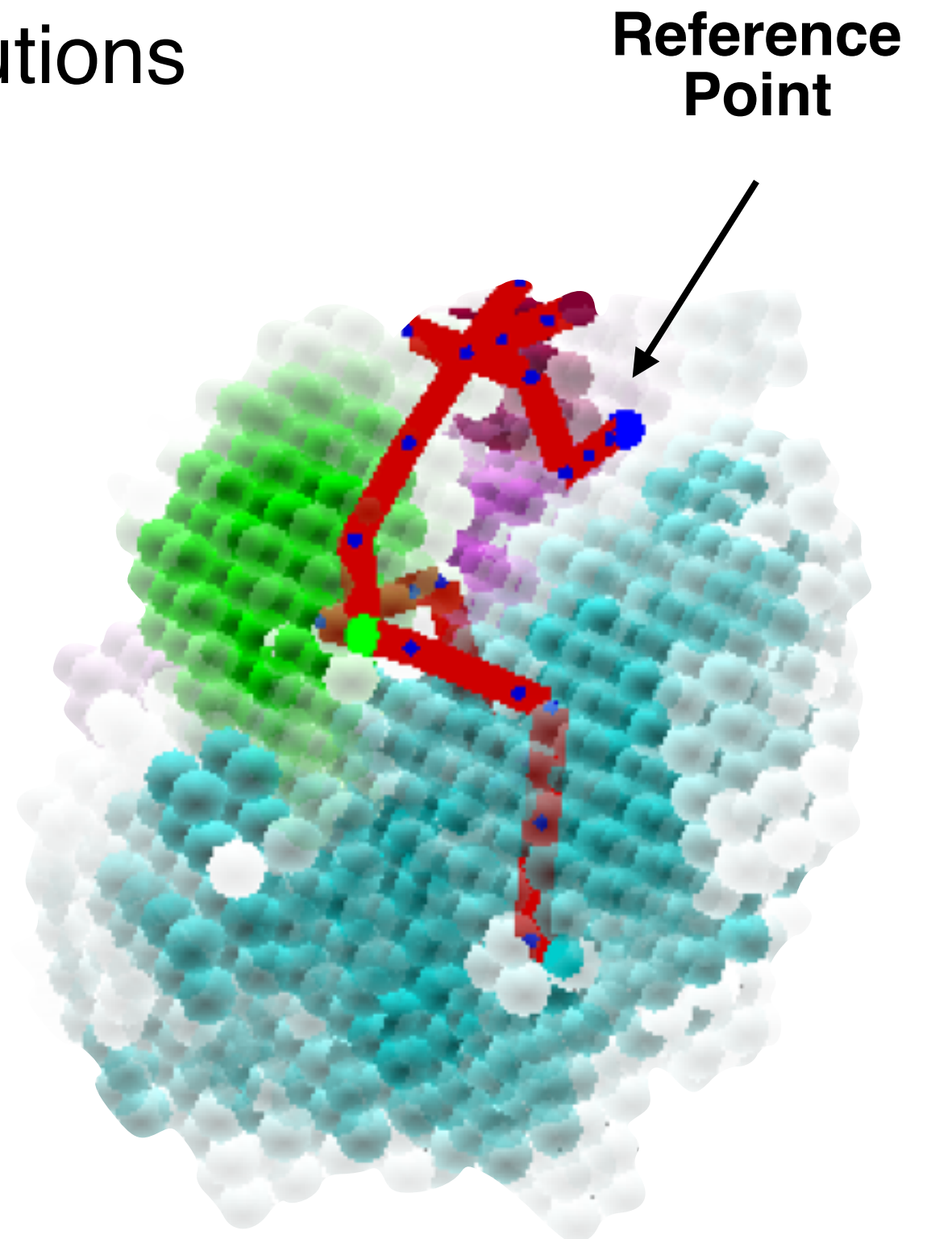
Sampled Poses

Pose Prediction Algorithm

Sample θ, T : Gaussian distributions



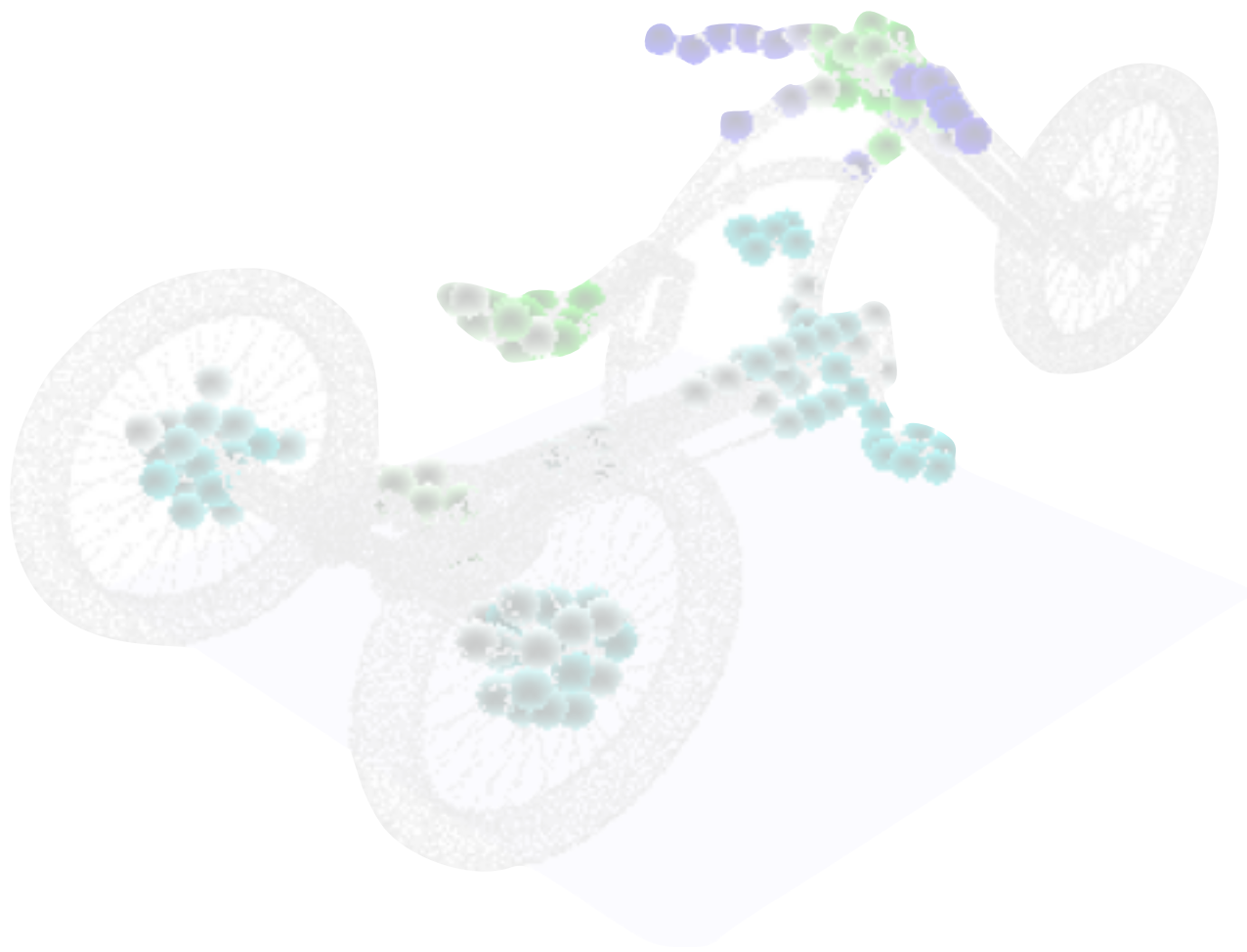
Contact Distribution



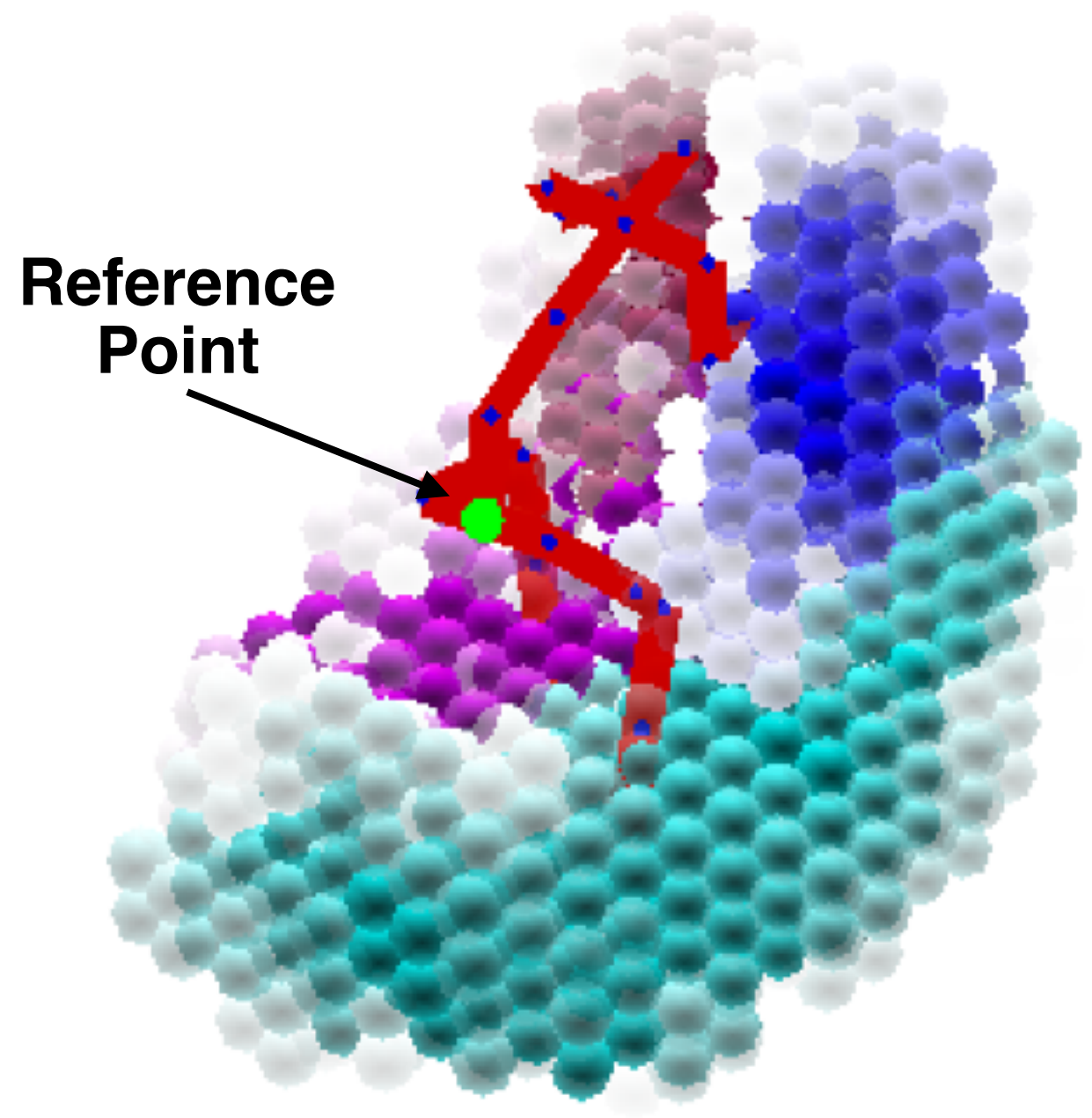
End Effector Distribution

Pose Prediction Algorithm

Sample θ, T : Gaussian distributions



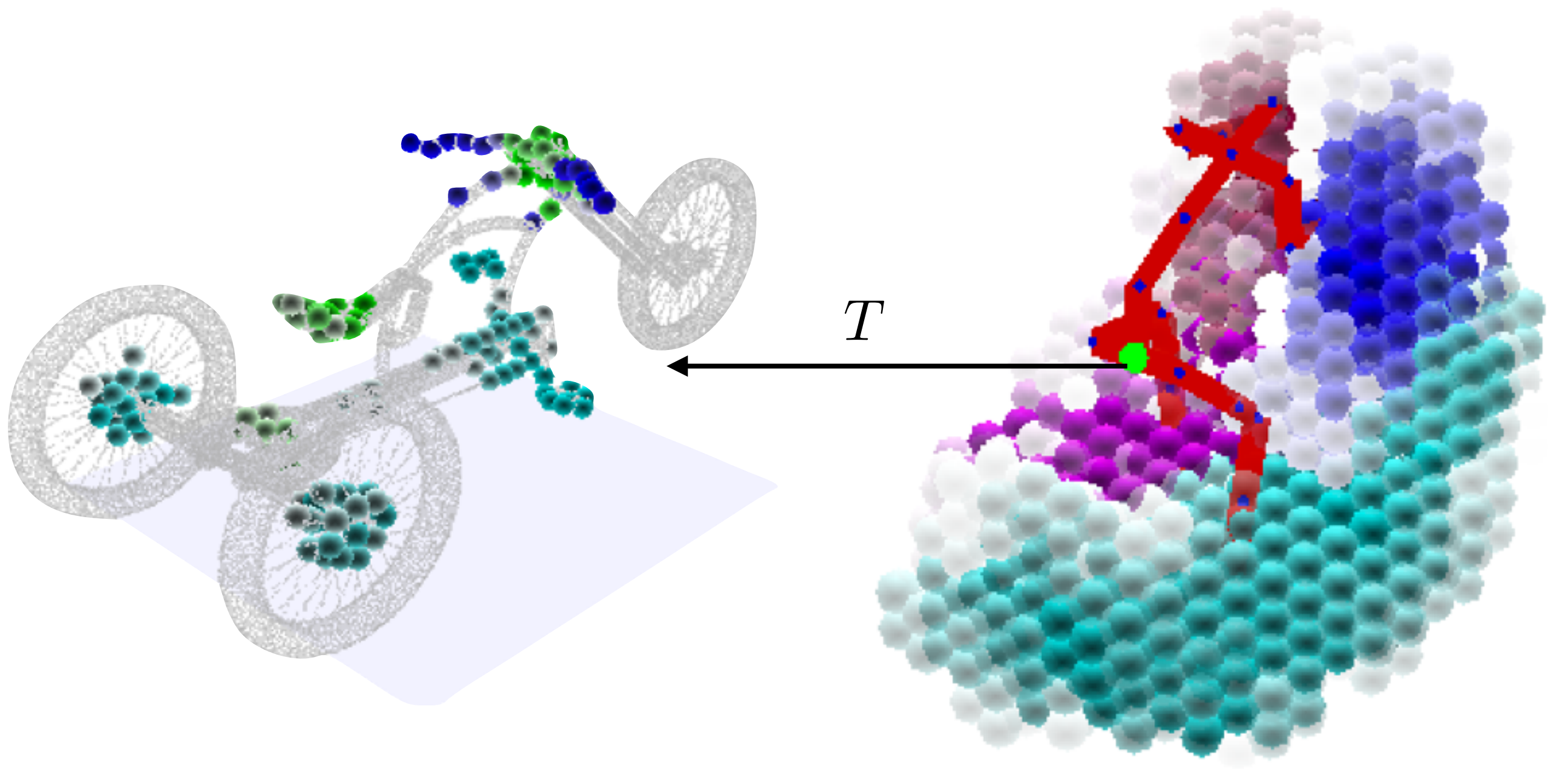
Contact Distribution



End Effector Distribution

Pose Prediction Algorithm

Sample θ, T : Gaussian distributions

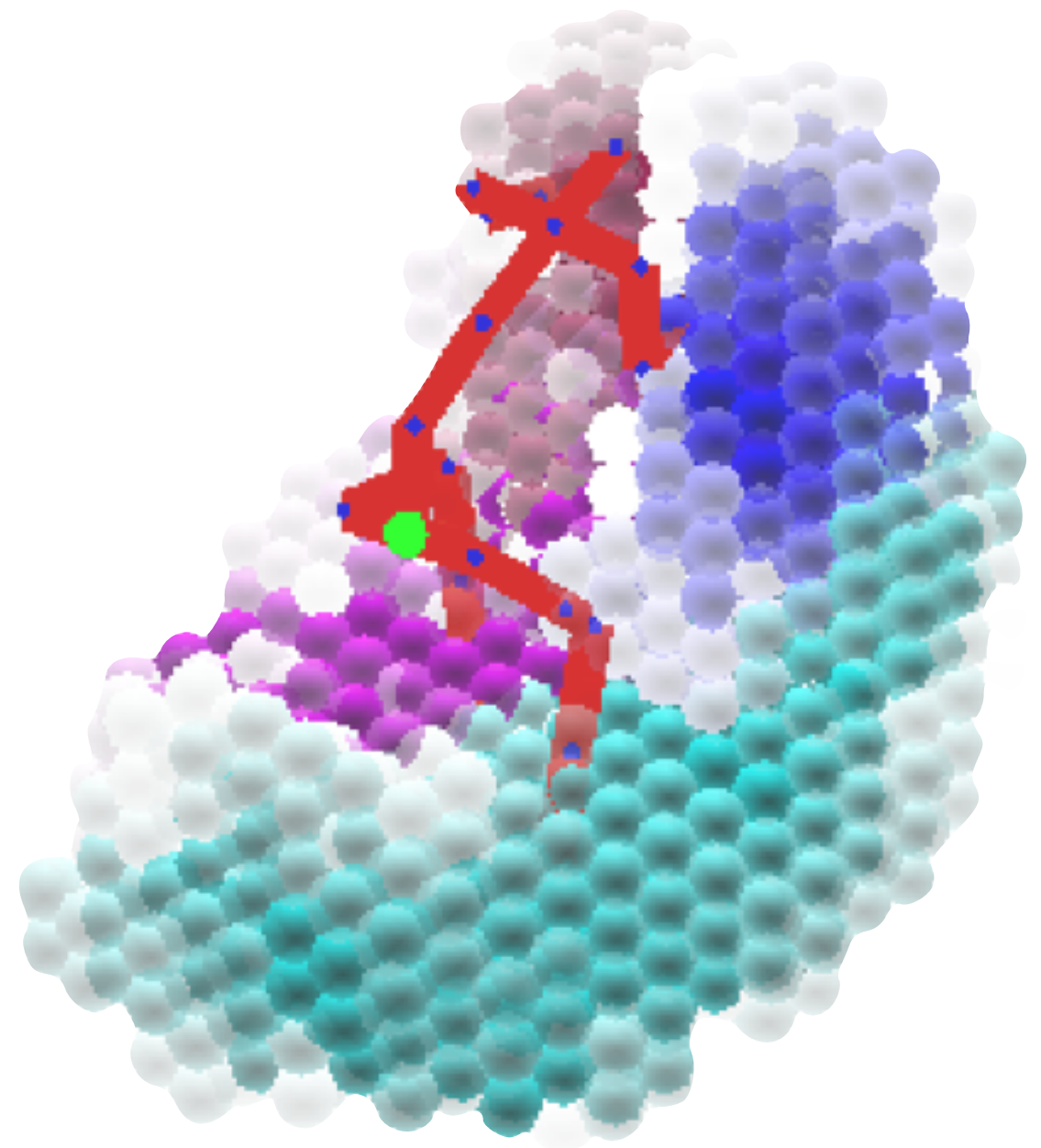
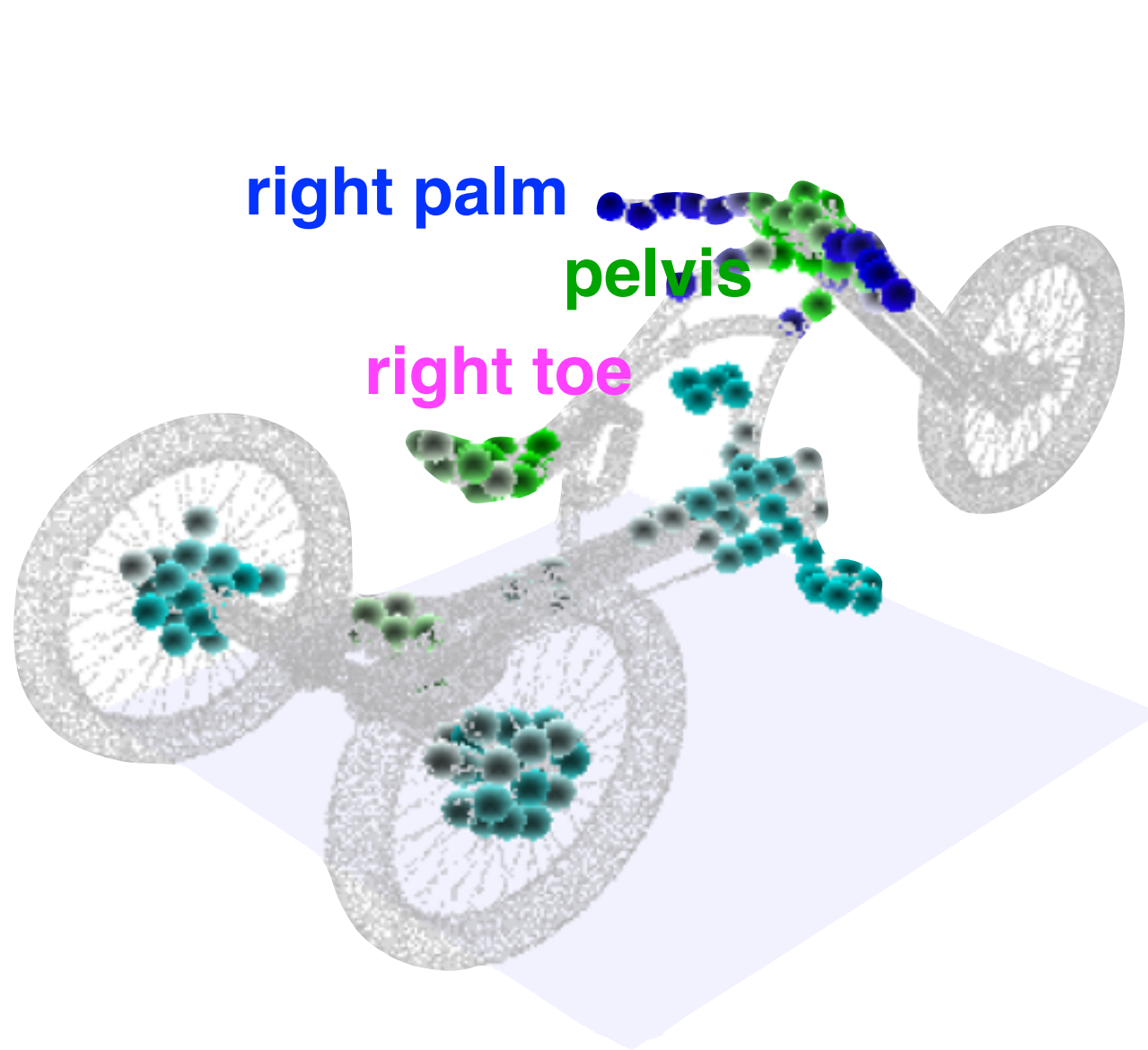


Contact Distribution

End Effector Distribution

Pose Prediction Algorithm

Example of a 2D Gaussian distribution



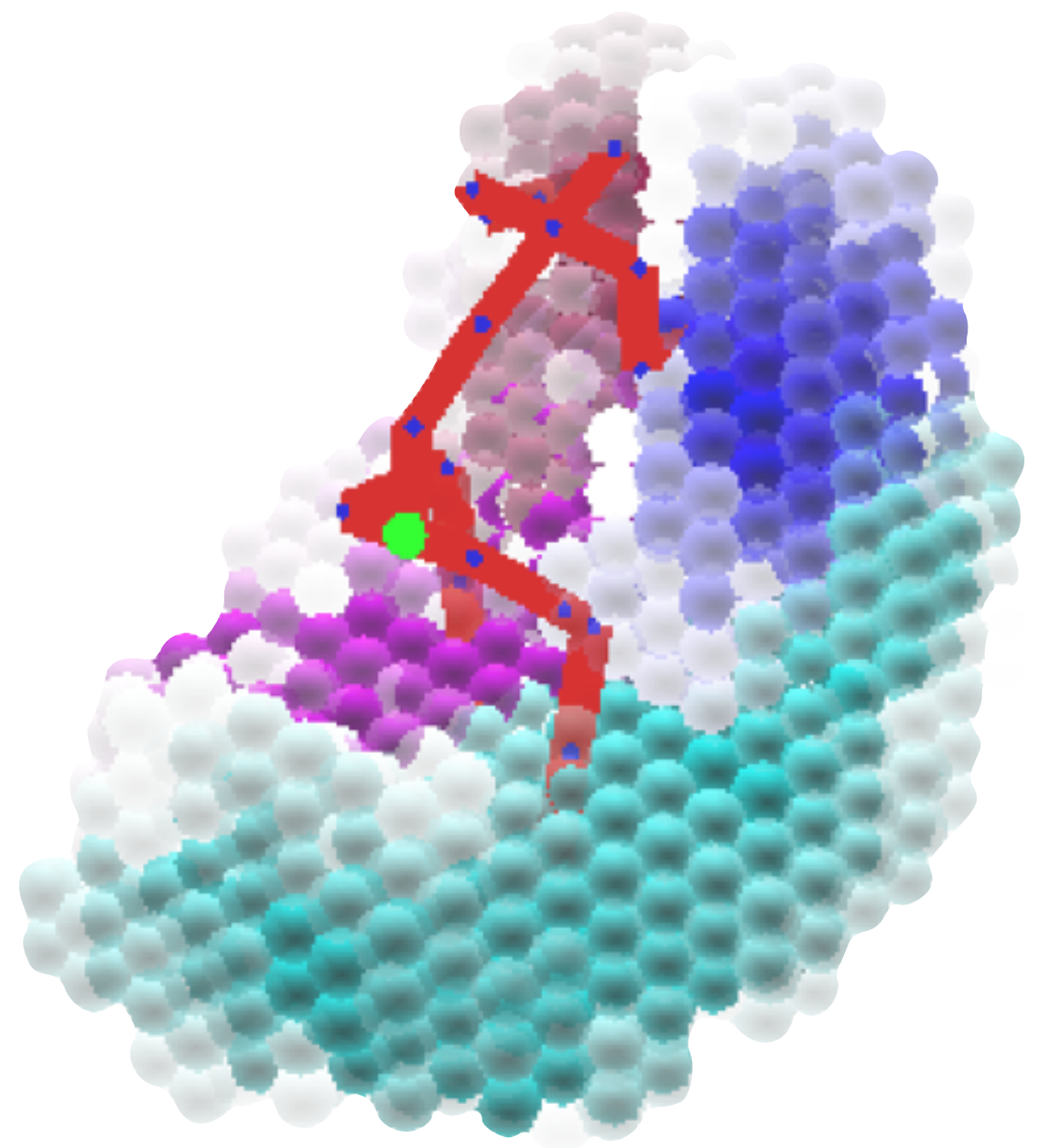
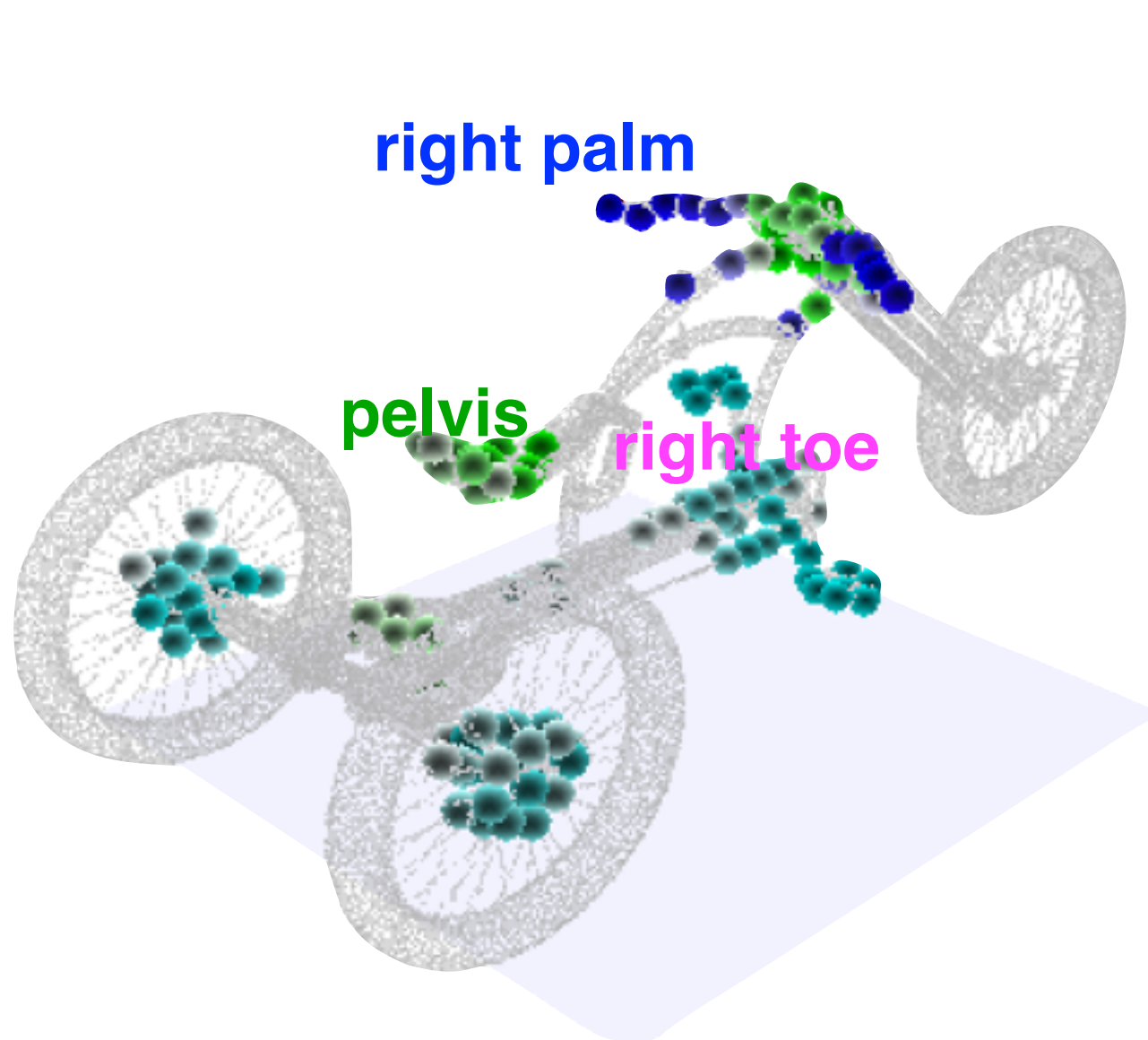
Candidate pose with lower-bound on the energy

Contact Distribution

End Effector Distribution

Pose Prediction Algorithm

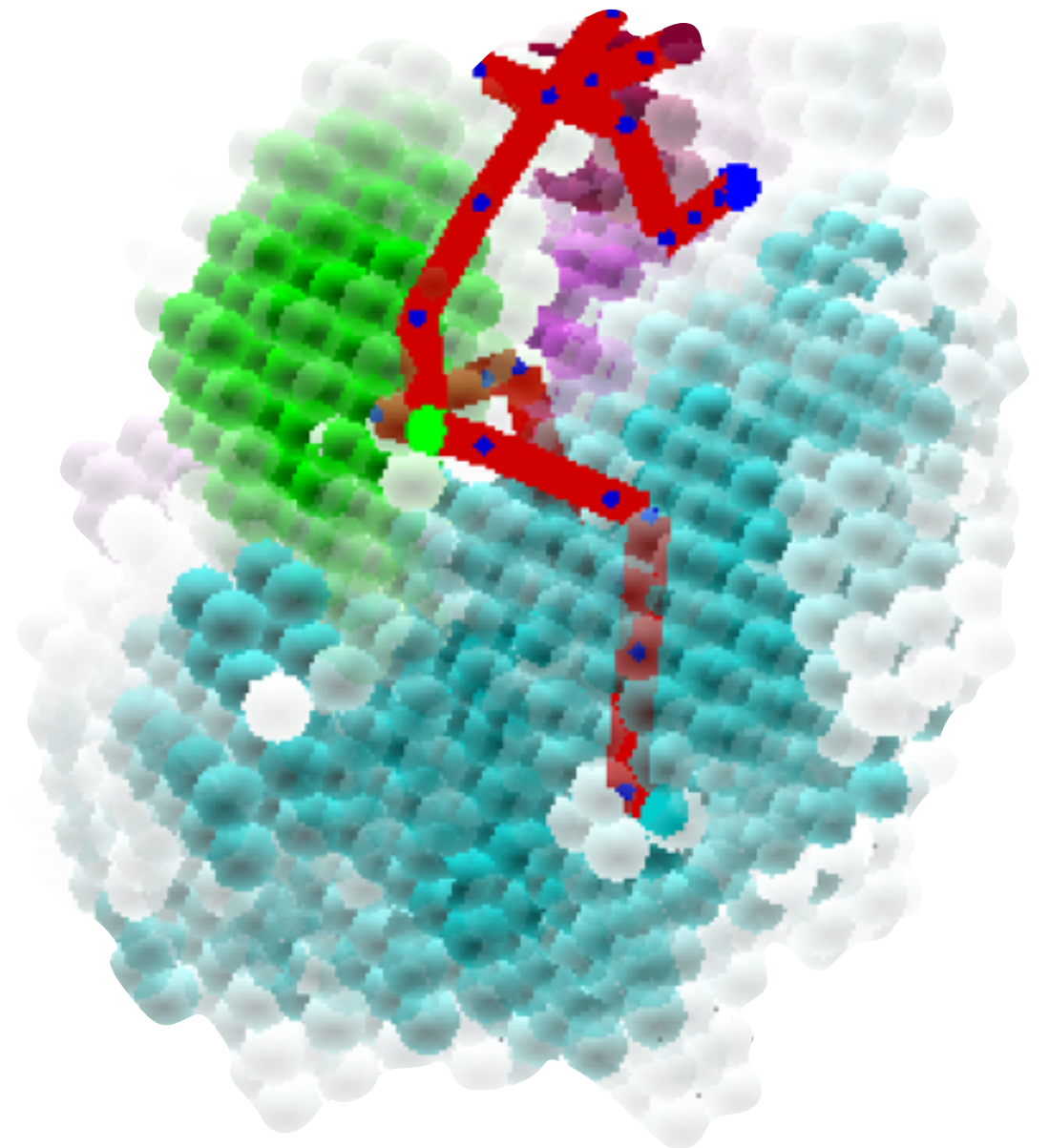
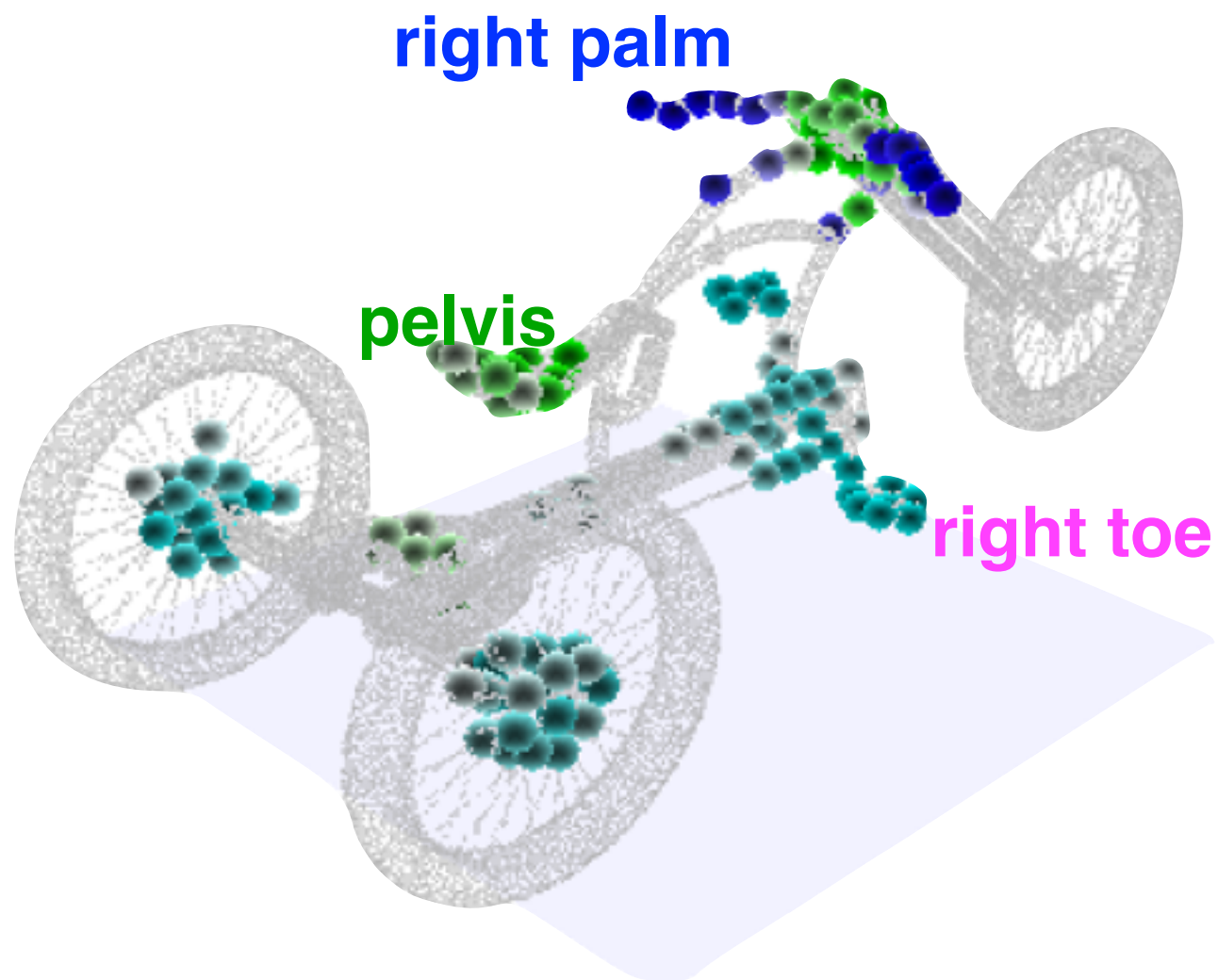
Pick global peaks in the joint distribution



Candidate pose with lower-bound on the energy

Pose Prediction Algorithm

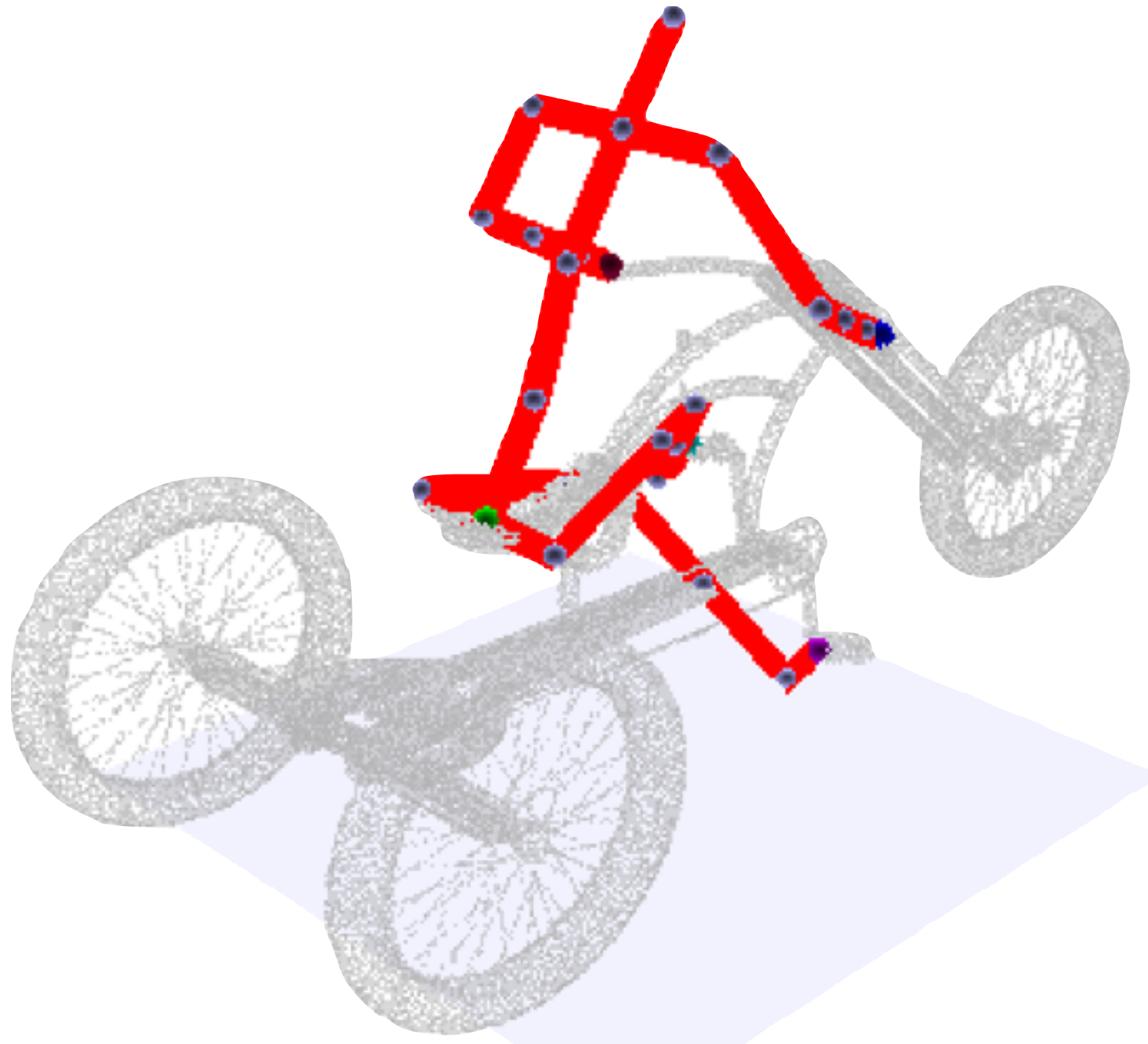
Pick global peaks in the joint distribution



Candidate pose with lower-bound on the energy

Pose Prediction Algorithm

Run IK on best candidate poses to compute energy

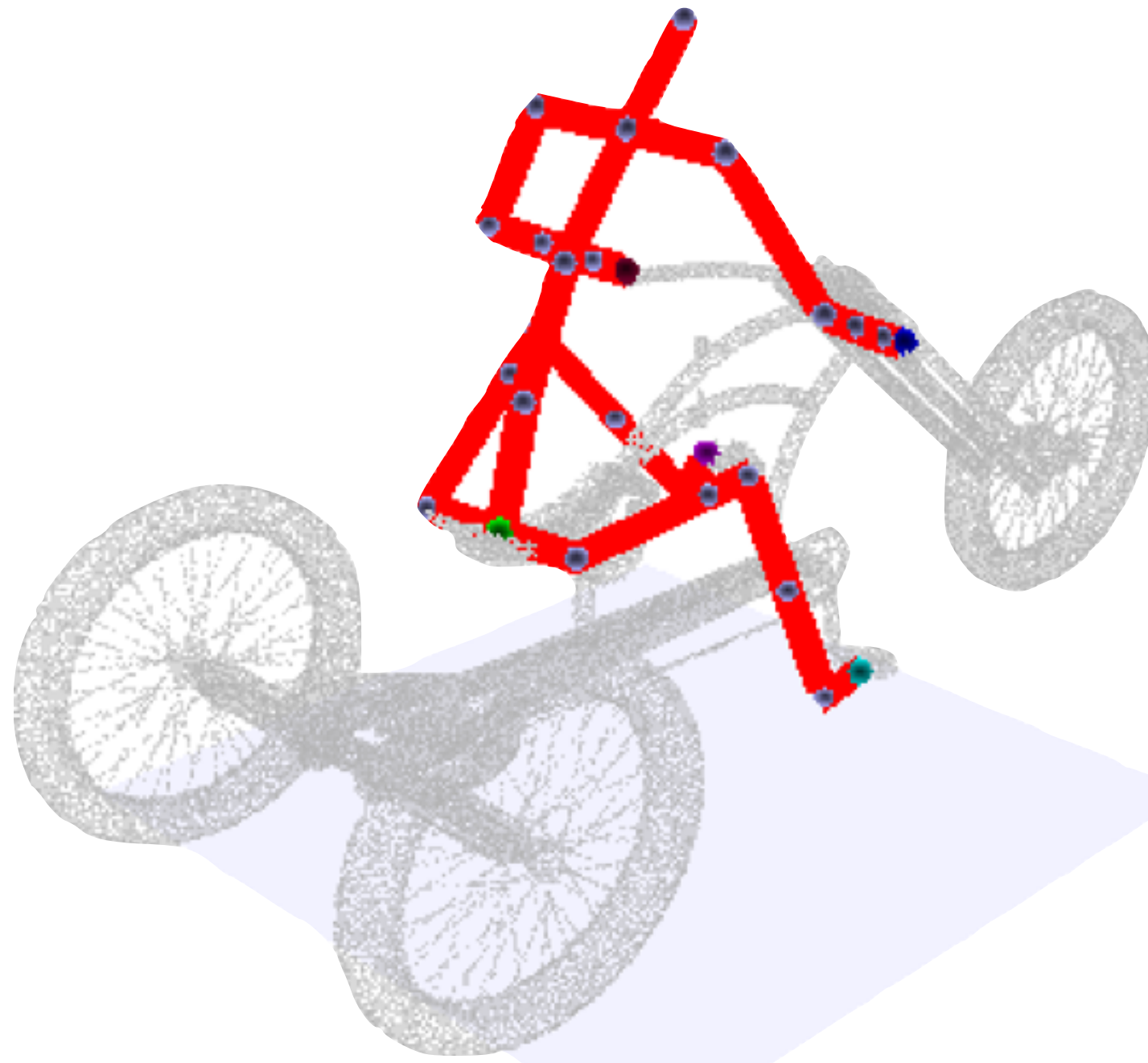


0.46

Predicted pose with the final energy

Pose Prediction Algorithm

Run IK on best candidate poses to compute energy

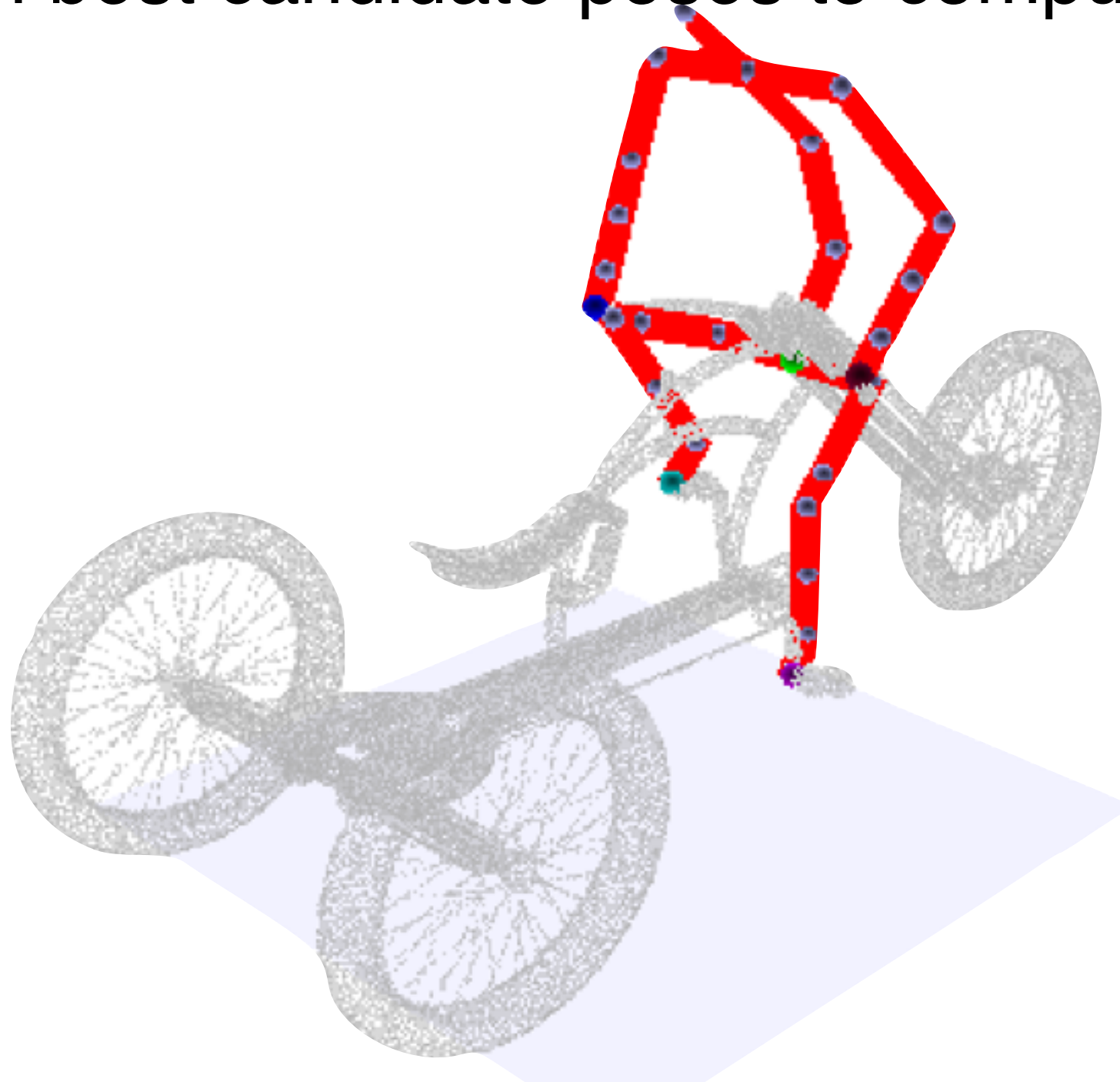


Best Pose!
0.36

Predicted pose with the final energy

Pose Prediction Algorithm

Run IK on best candidate poses to compute energy

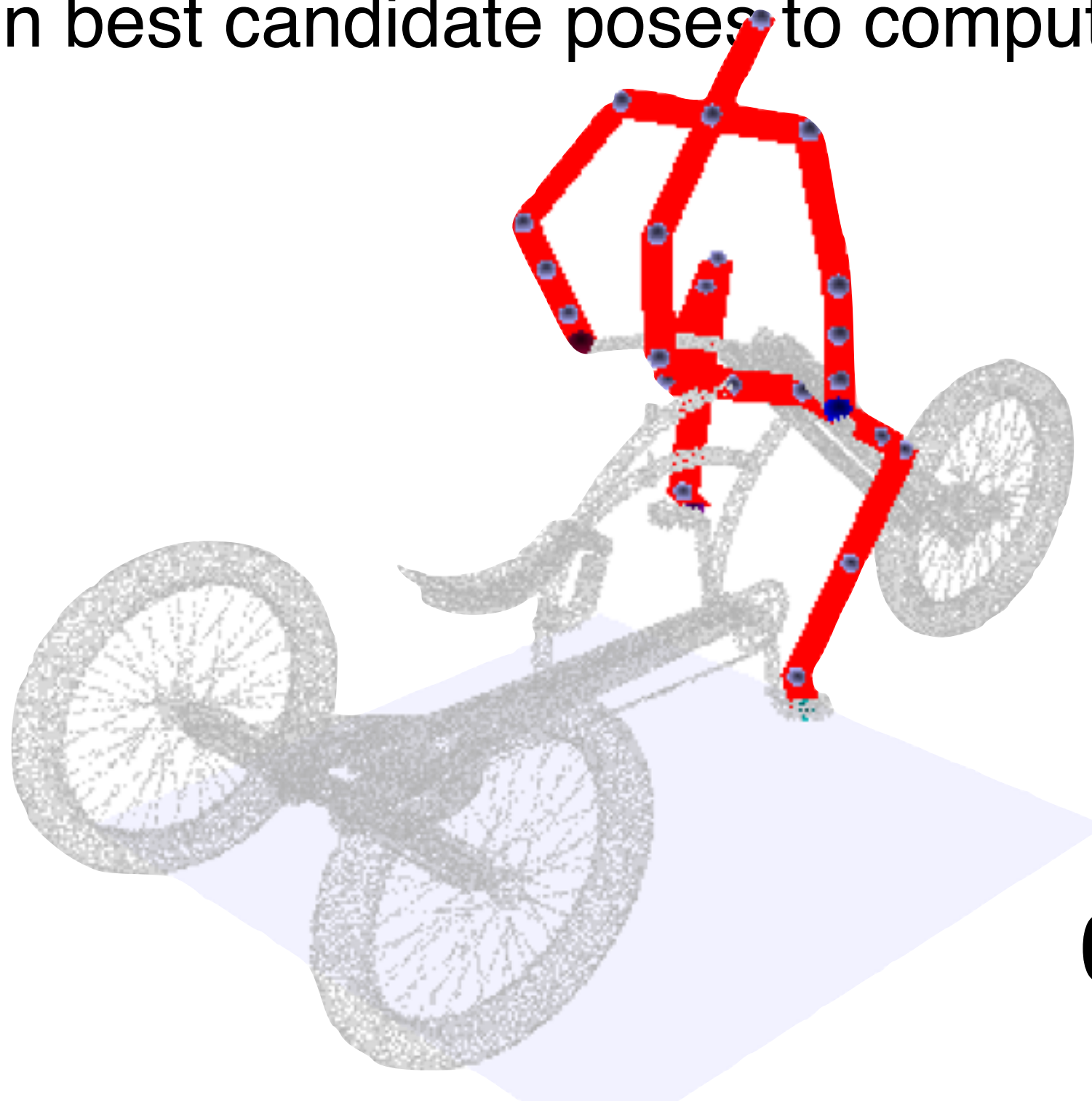


0.47

Predicted pose with the final energy

Pose Prediction Algorithm

Run IK on best candidate poses to compute energy

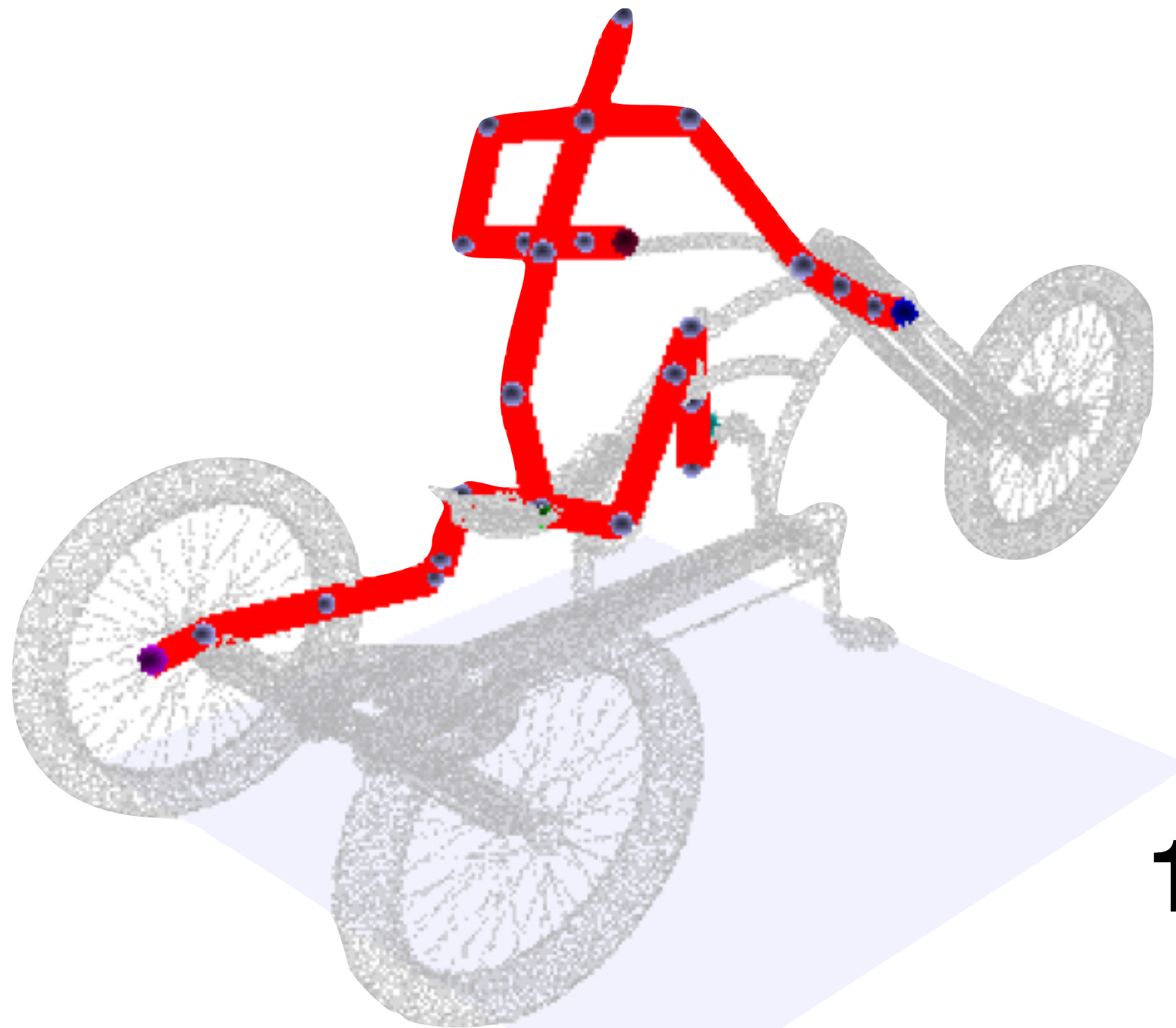


0.71

Predicted pose with the final energy

Pose Prediction Algorithm

Run IK on best candidate poses to compute energy

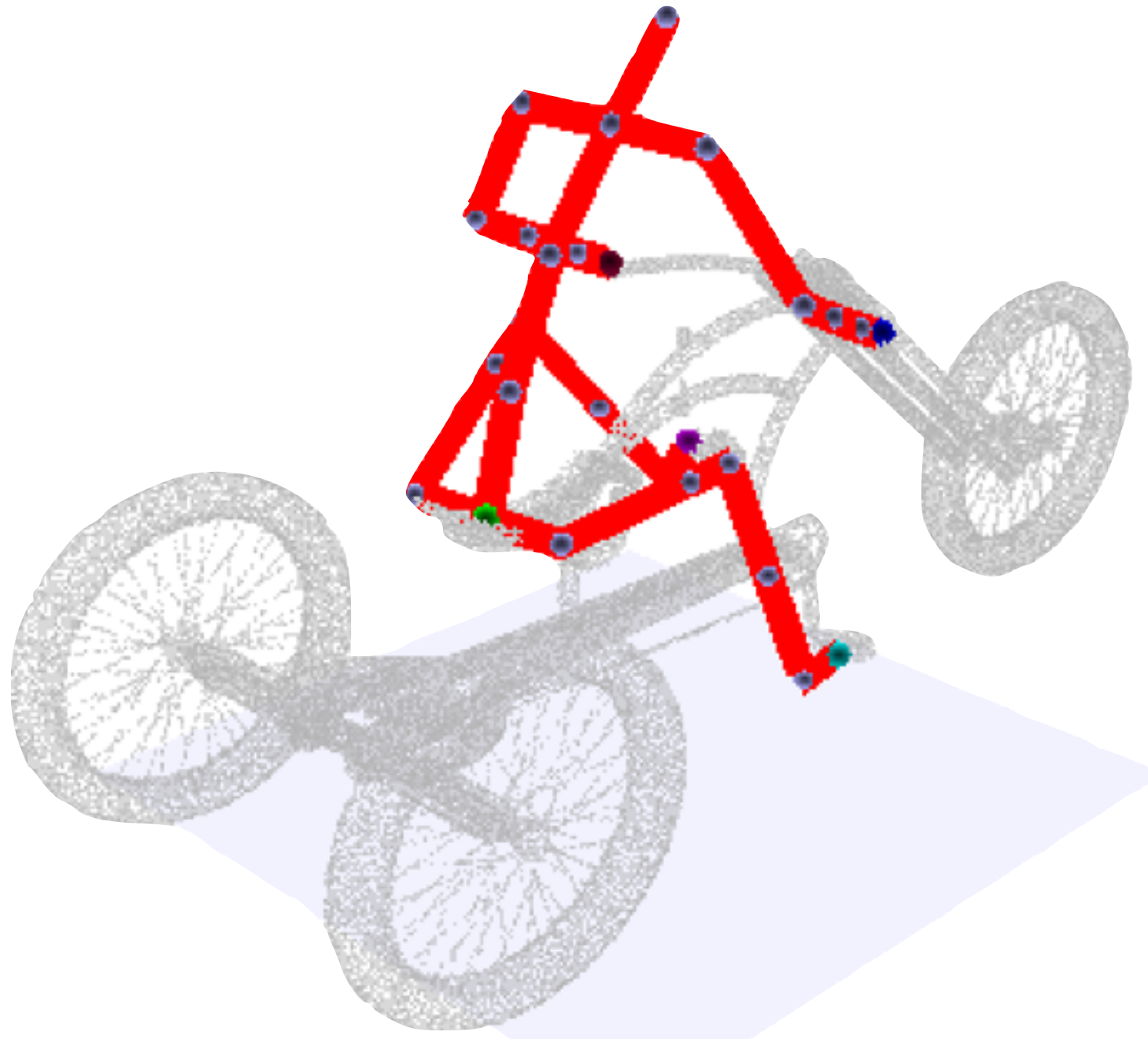


1.11

Predicted pose with the final energy

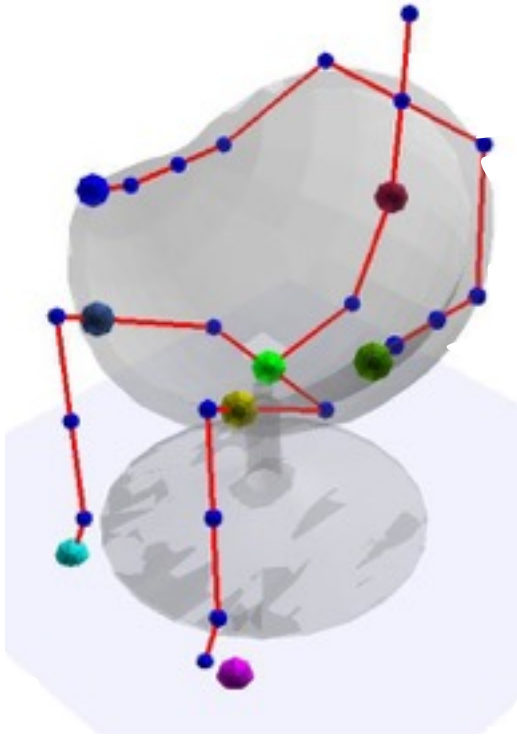
Pose Prediction Algorithm

Run IK on best candidate poses to compute energy

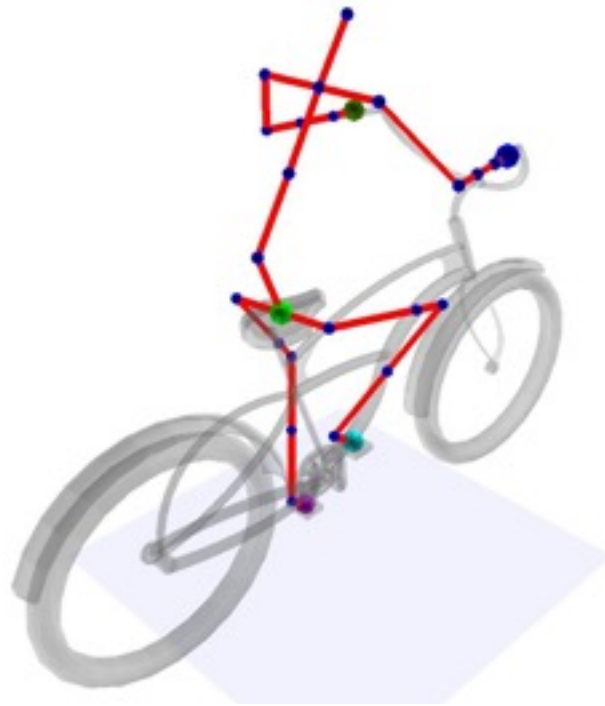


Final Predicted Pose

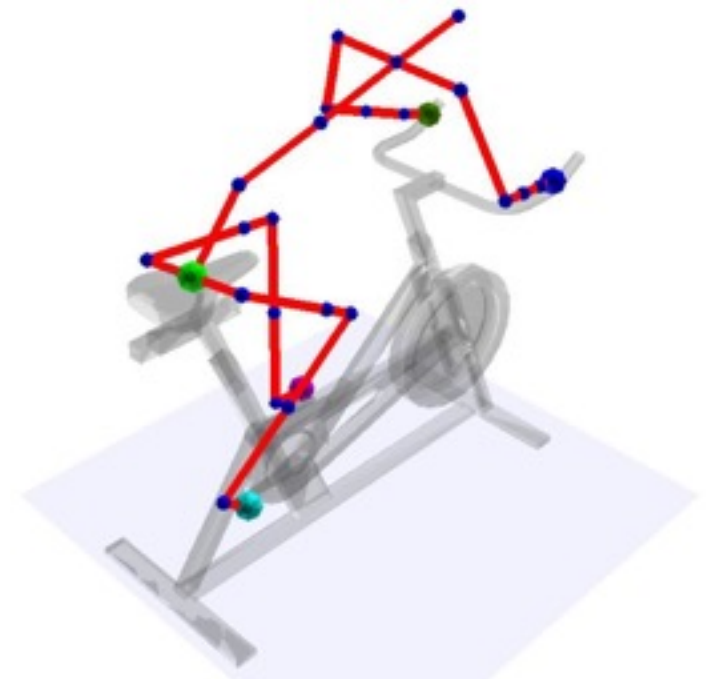
Human-centric Model Evaluation



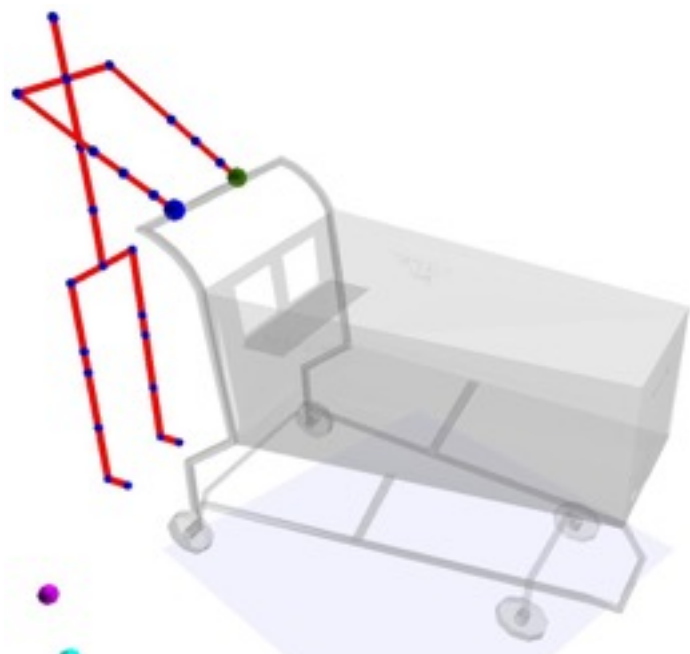
Chairs



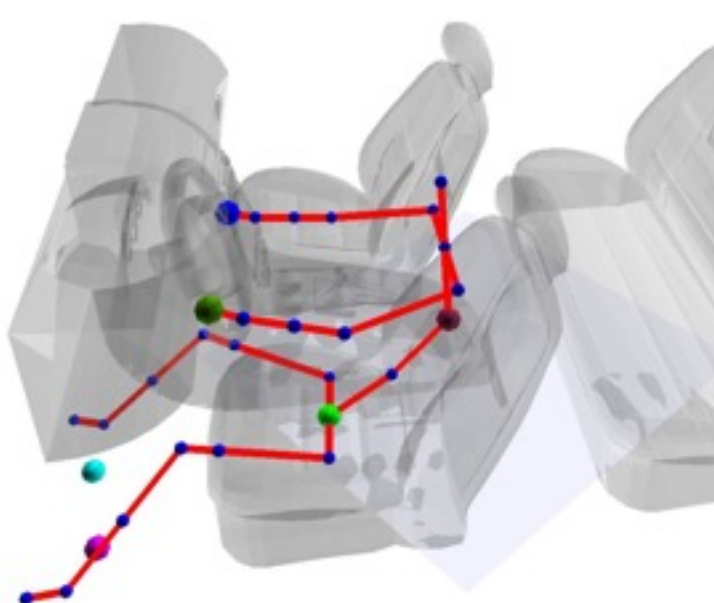
Bicycles



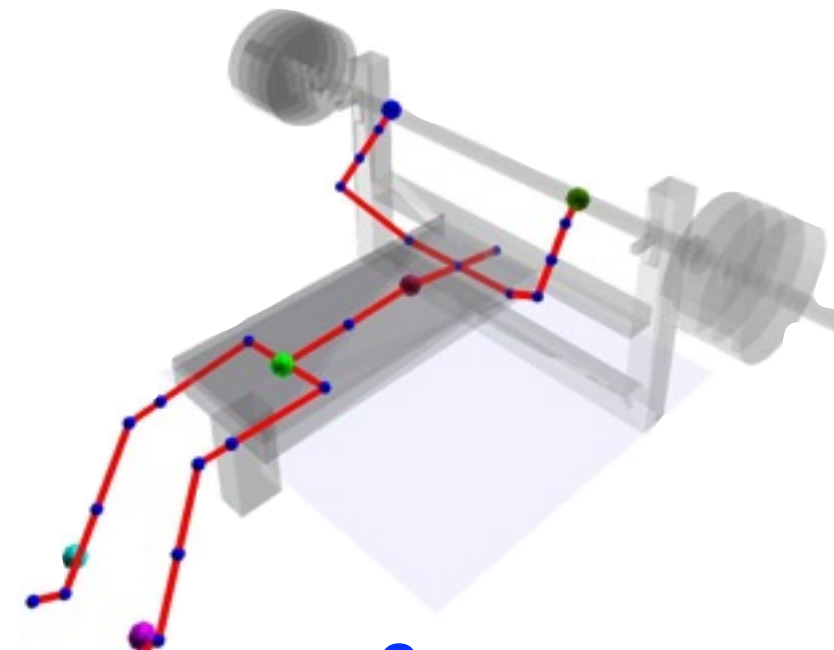
Bipedals



Carts

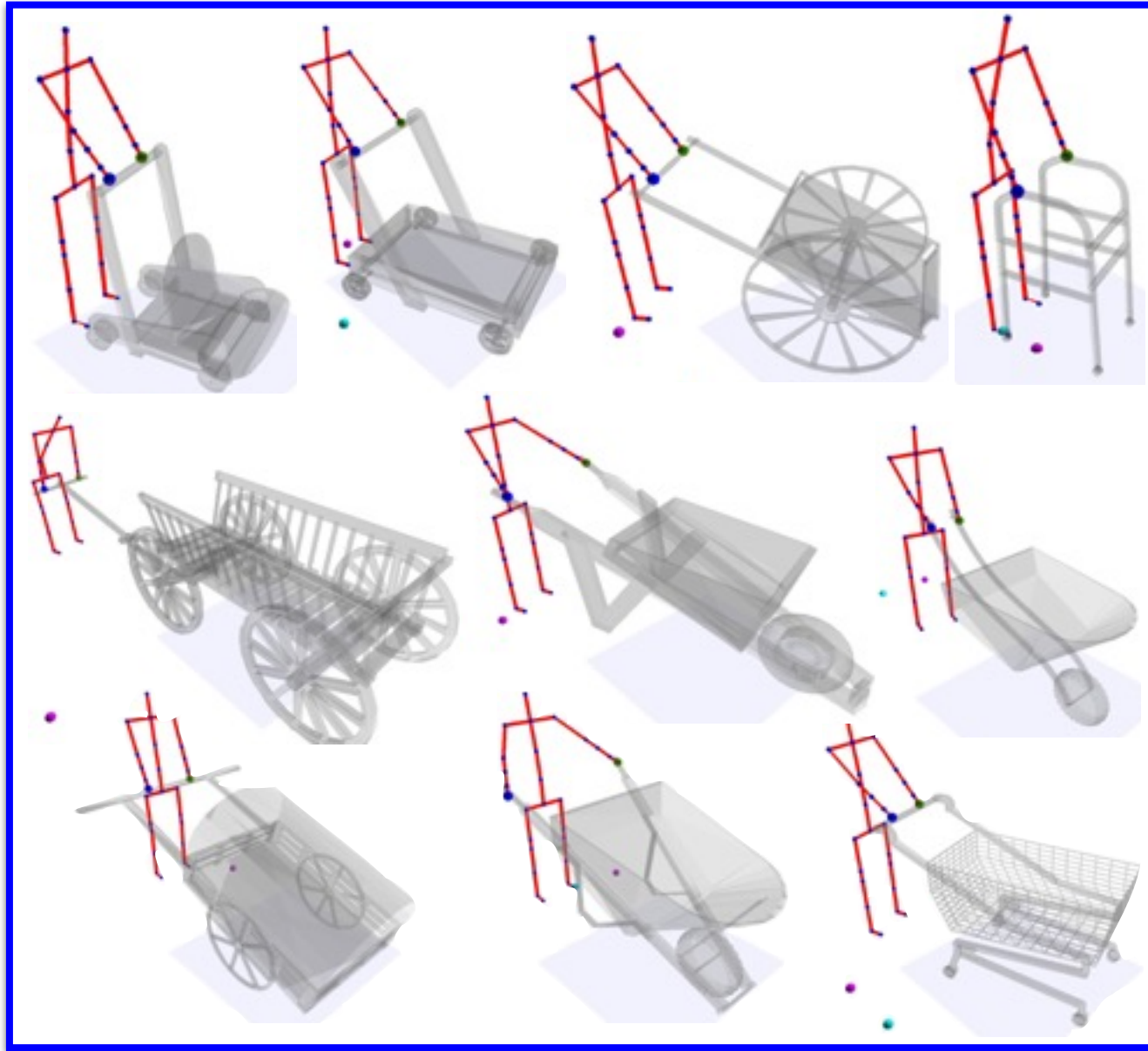


Cockpits



Gym

Leave-one-out Evaluation

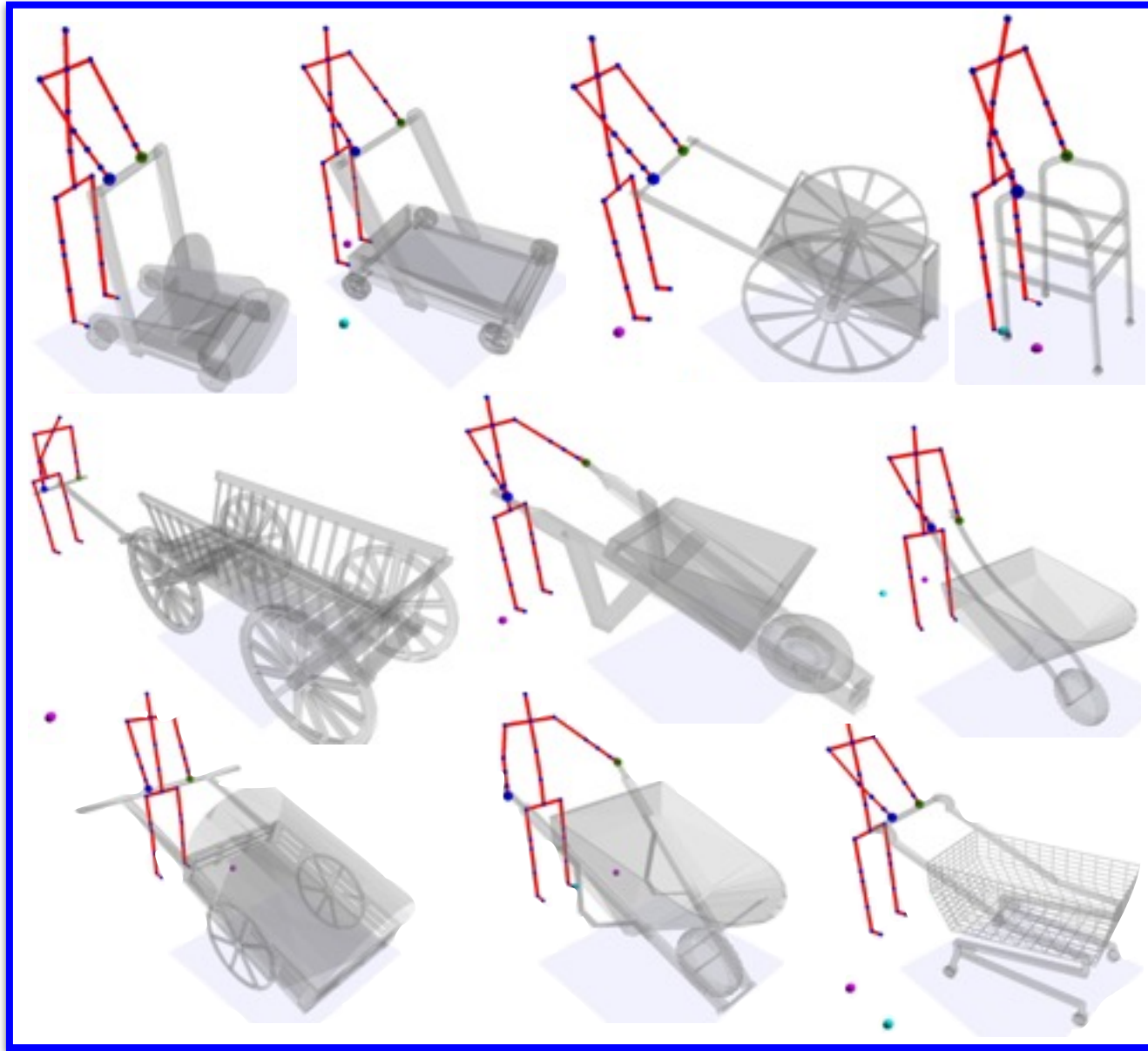


Training Data



Test Data

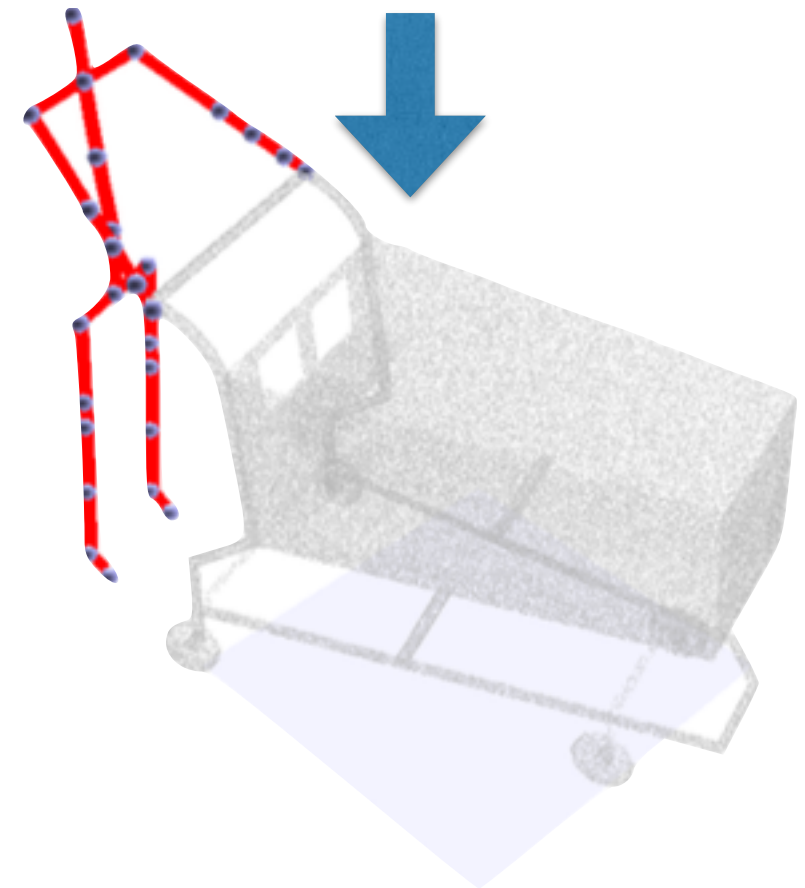
Leave-one-out Evaluation



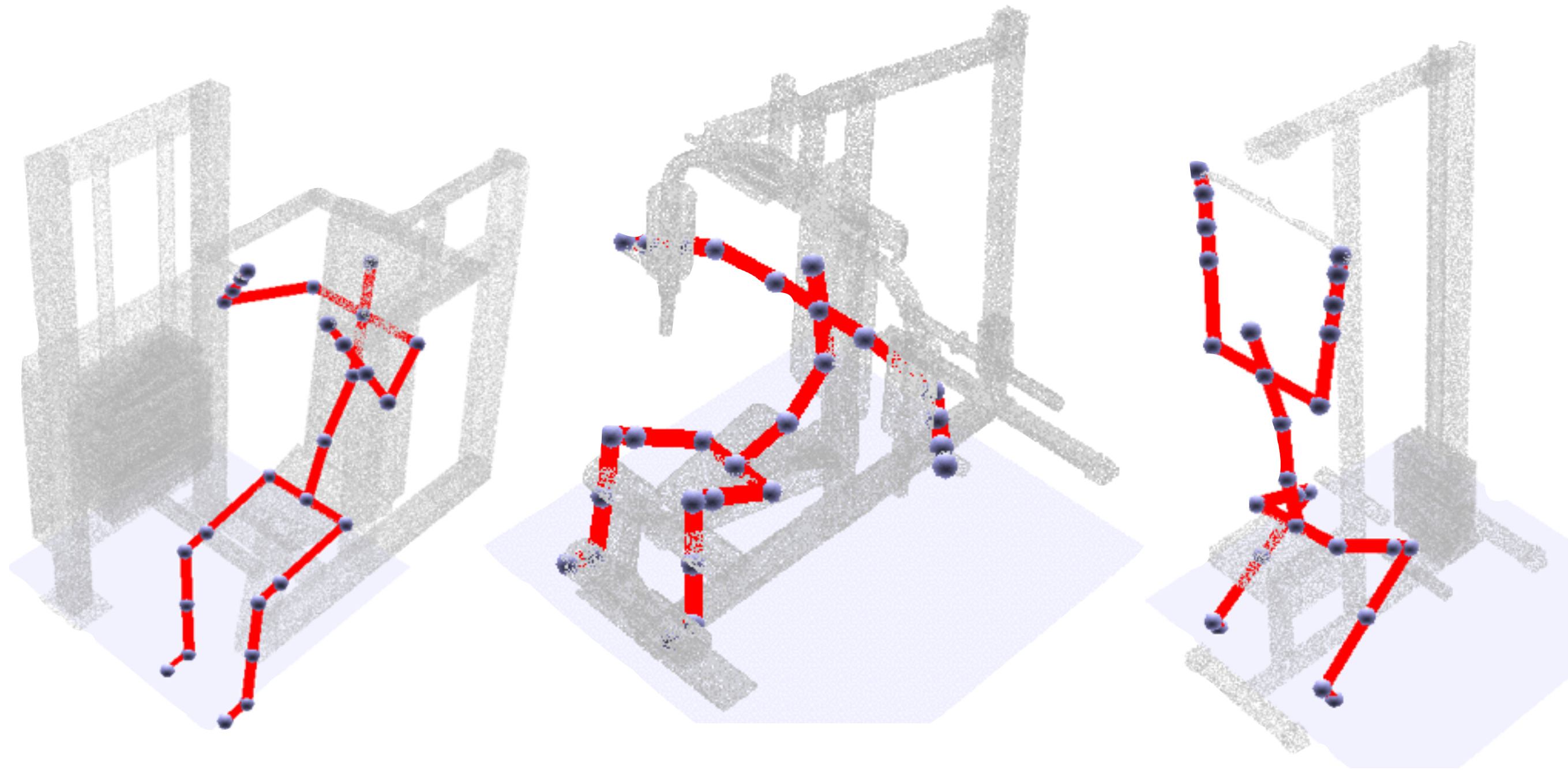
Training Data



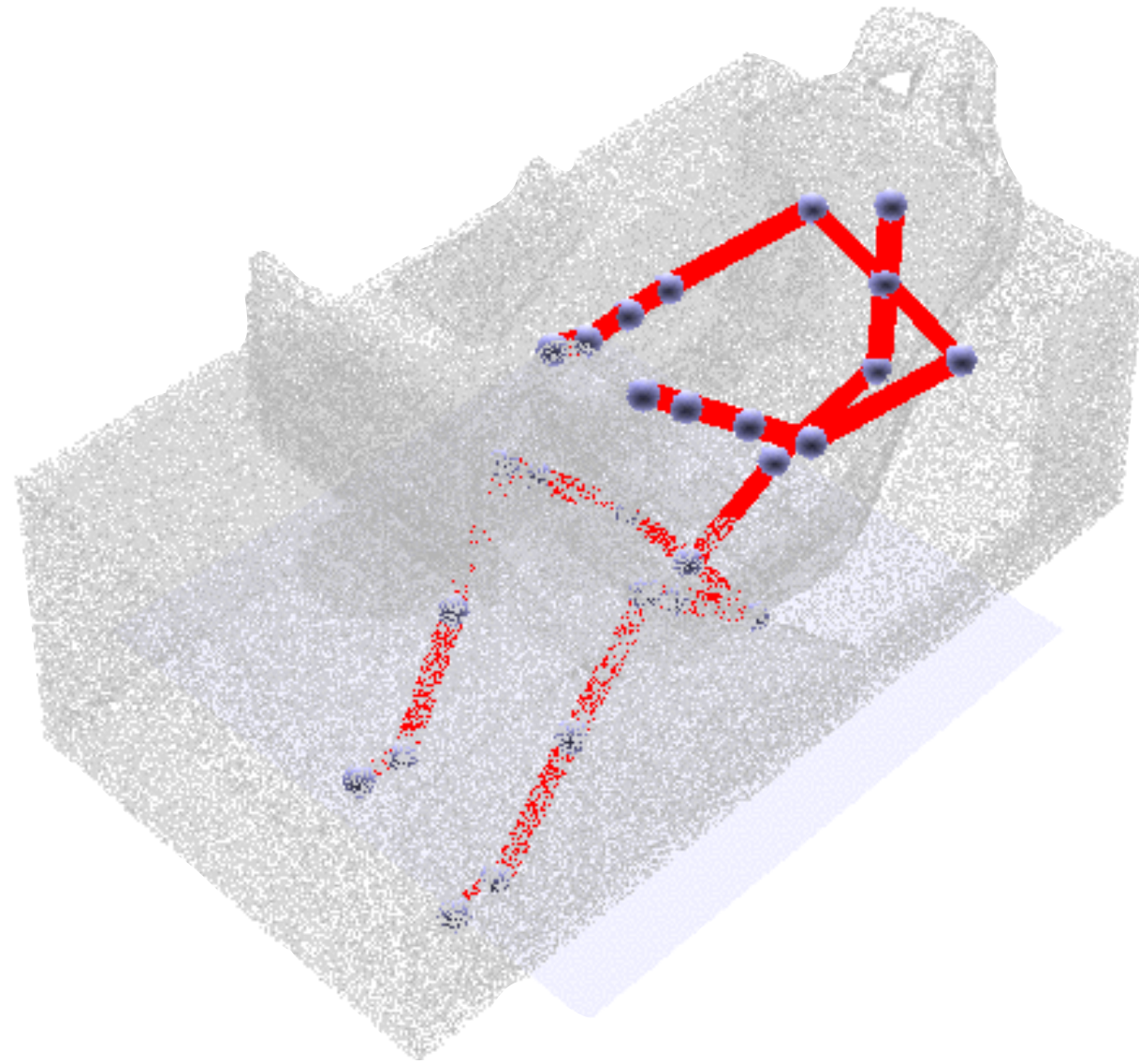
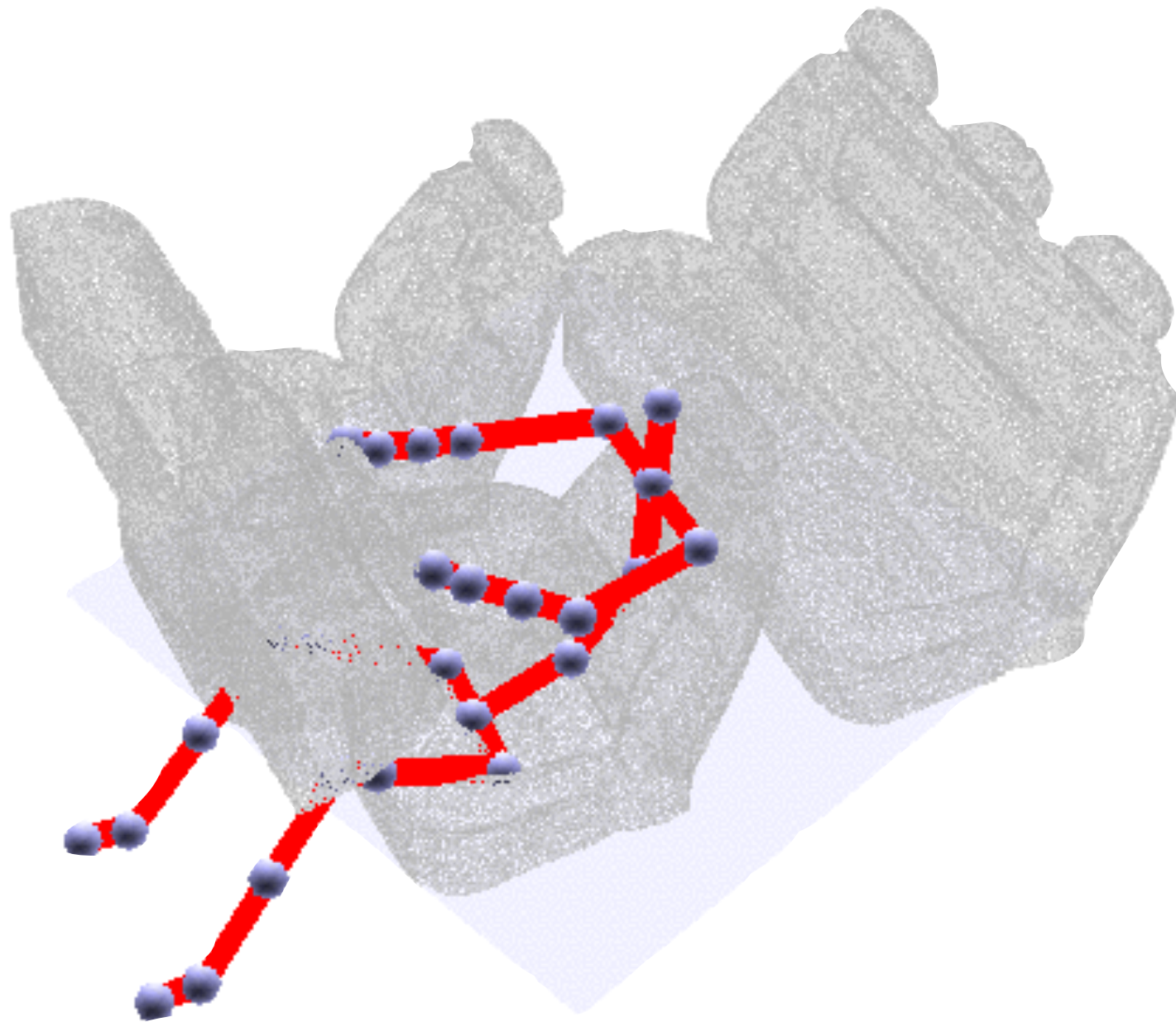
Test Data



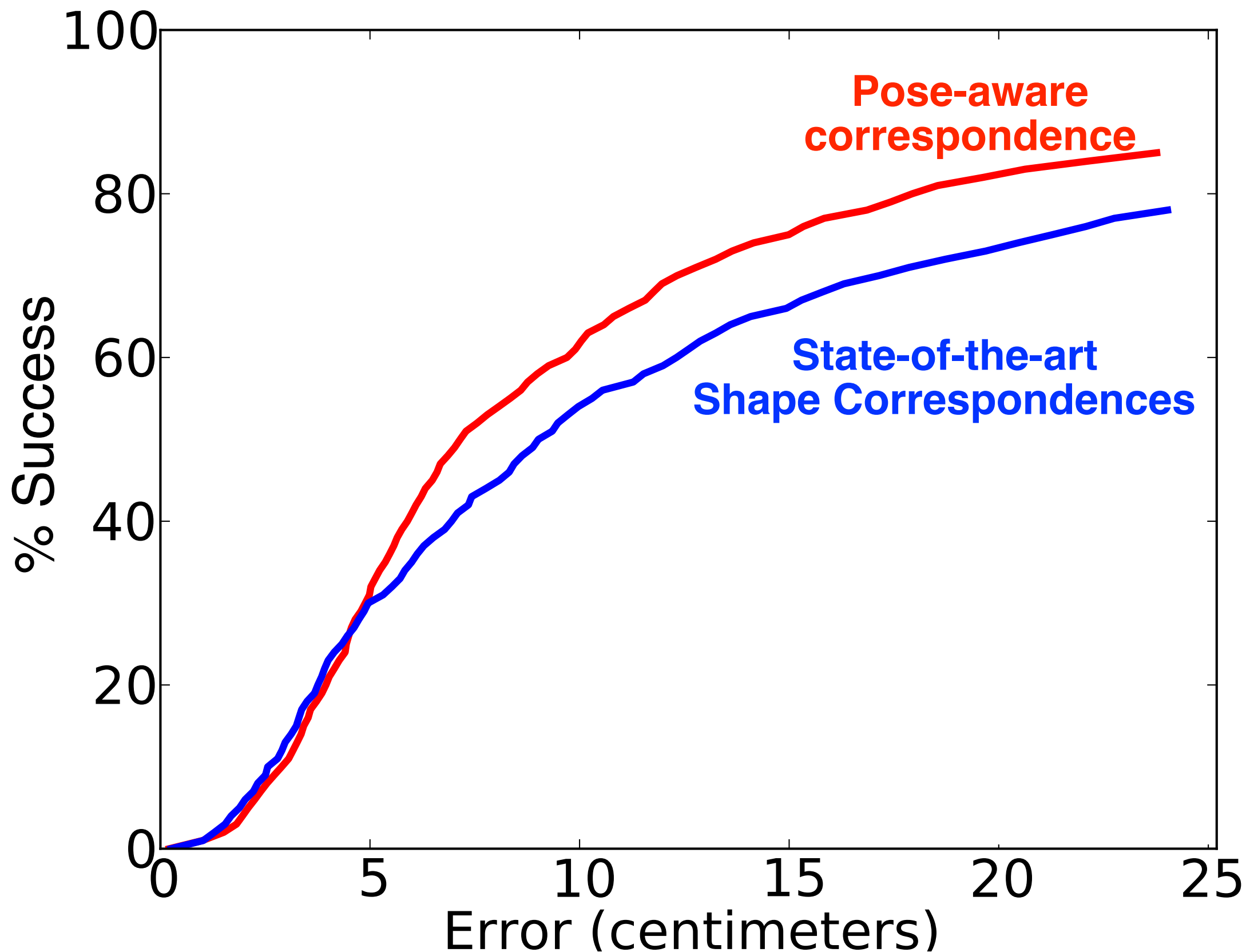
Pose Prediction Results



Pose Prediction Results



Shape Correspondence Results



Saliency Estimation Results



Mesh Saliency [Lee et al. 2005]

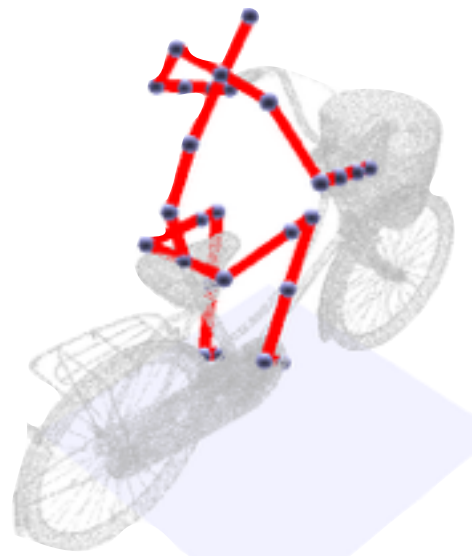
Saliency Estimation Results



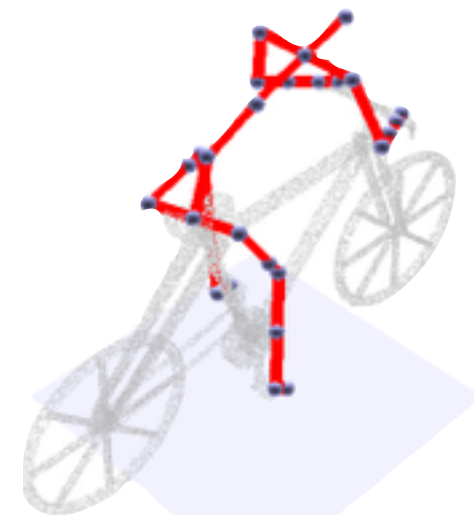
Human-centric Saliency [Our method]

Shape Retrieval Results

Query

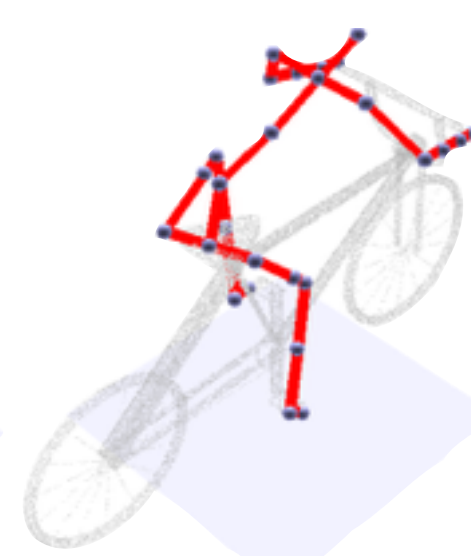
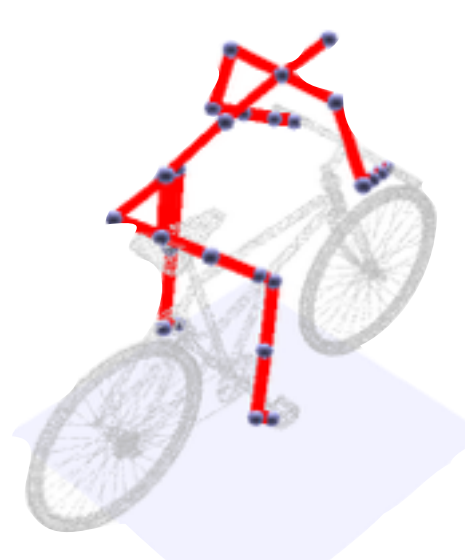
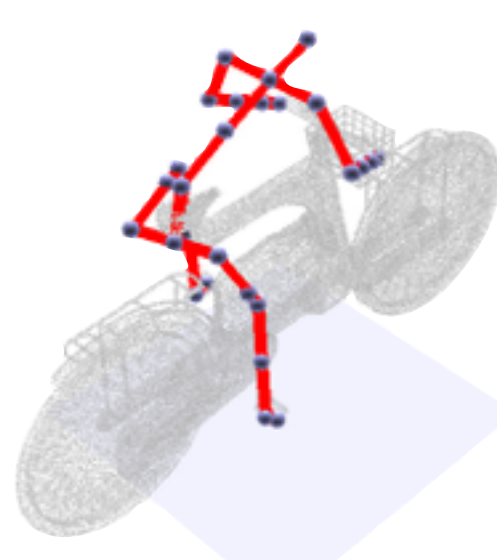
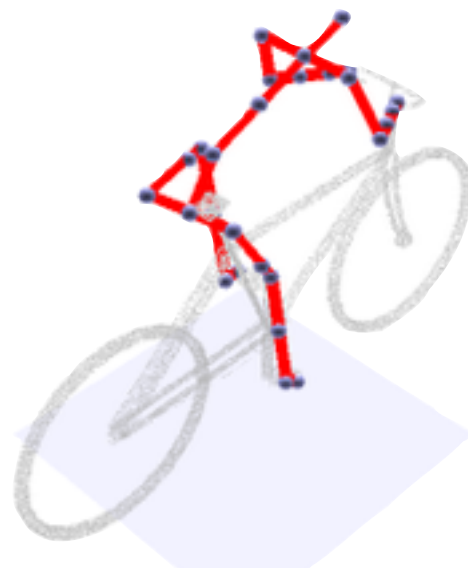
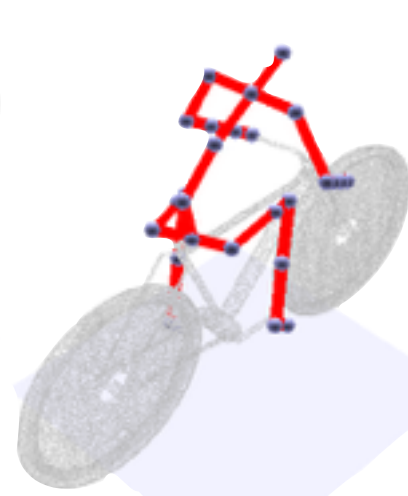
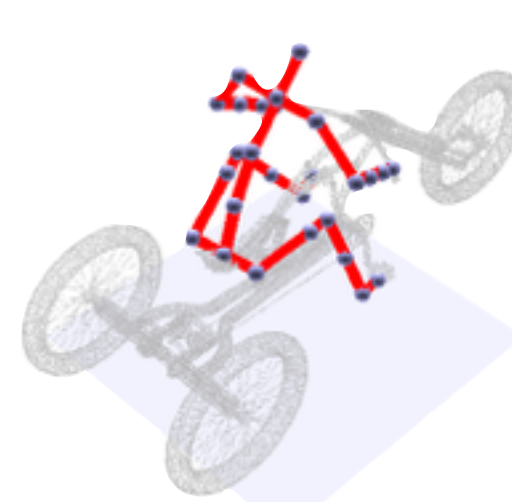
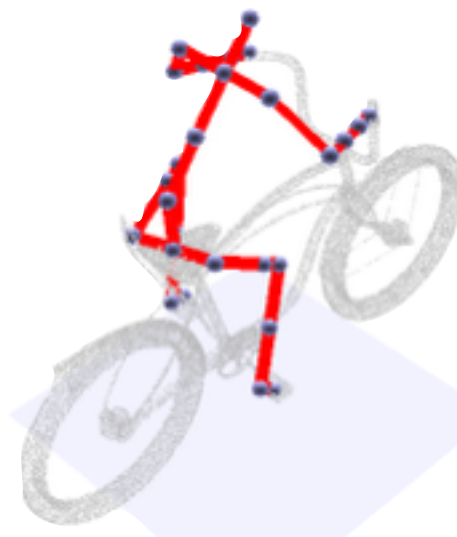
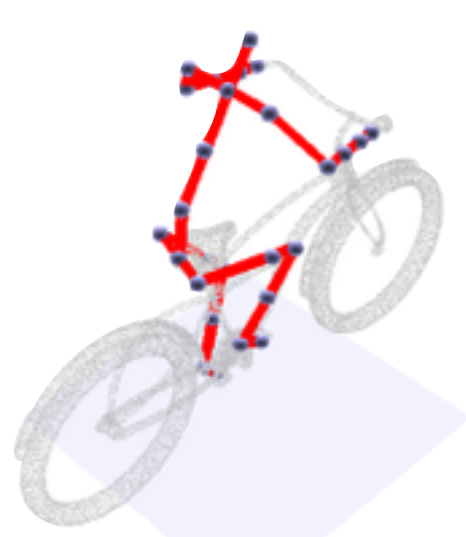


ride sitting
up-right

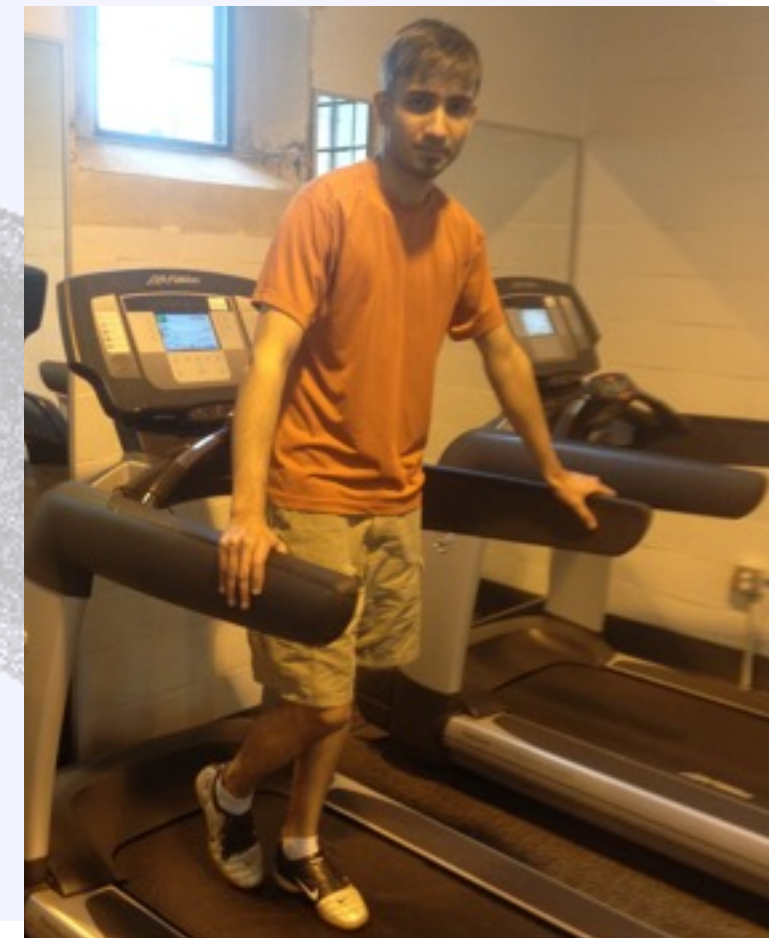
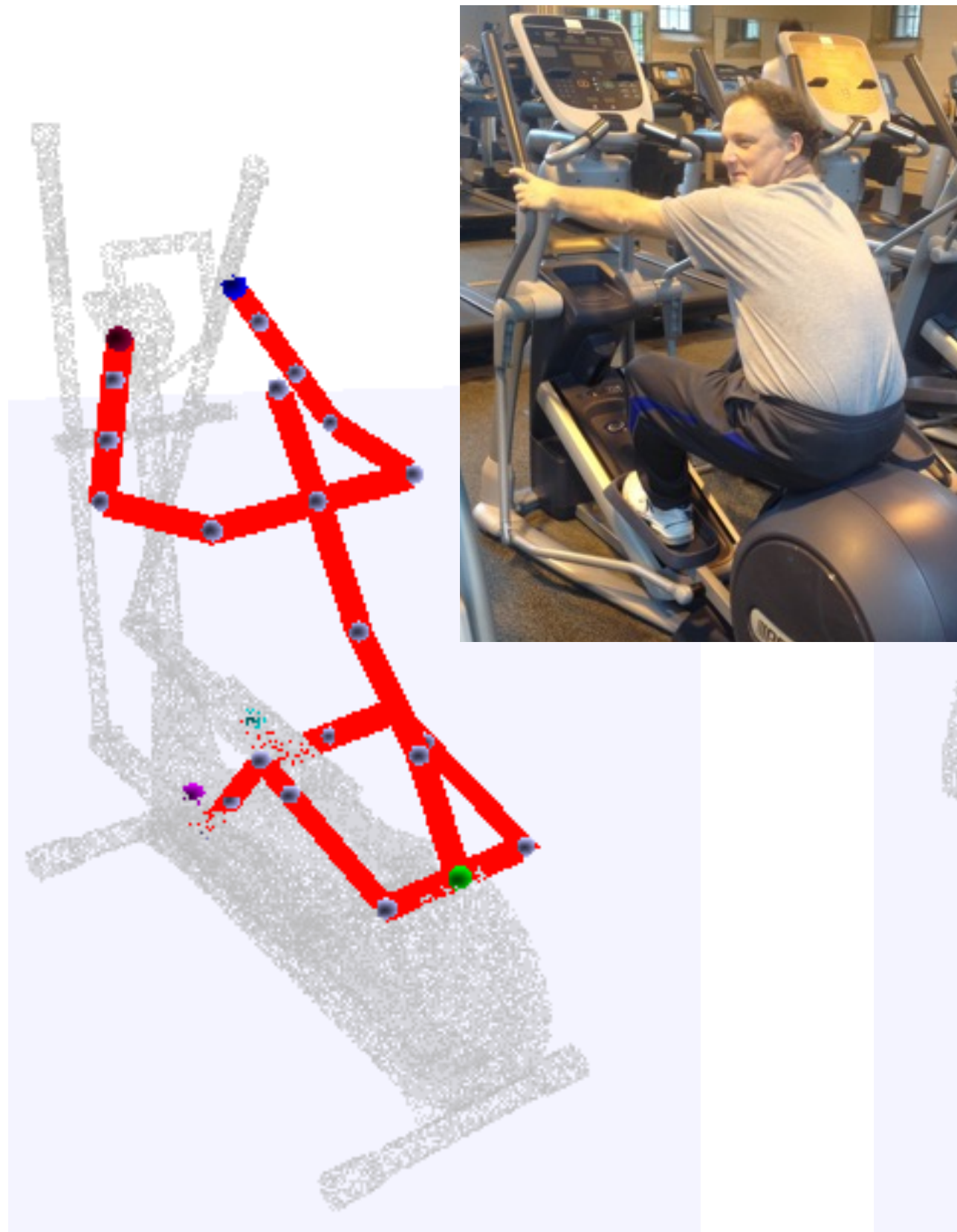


ride leaning
forward

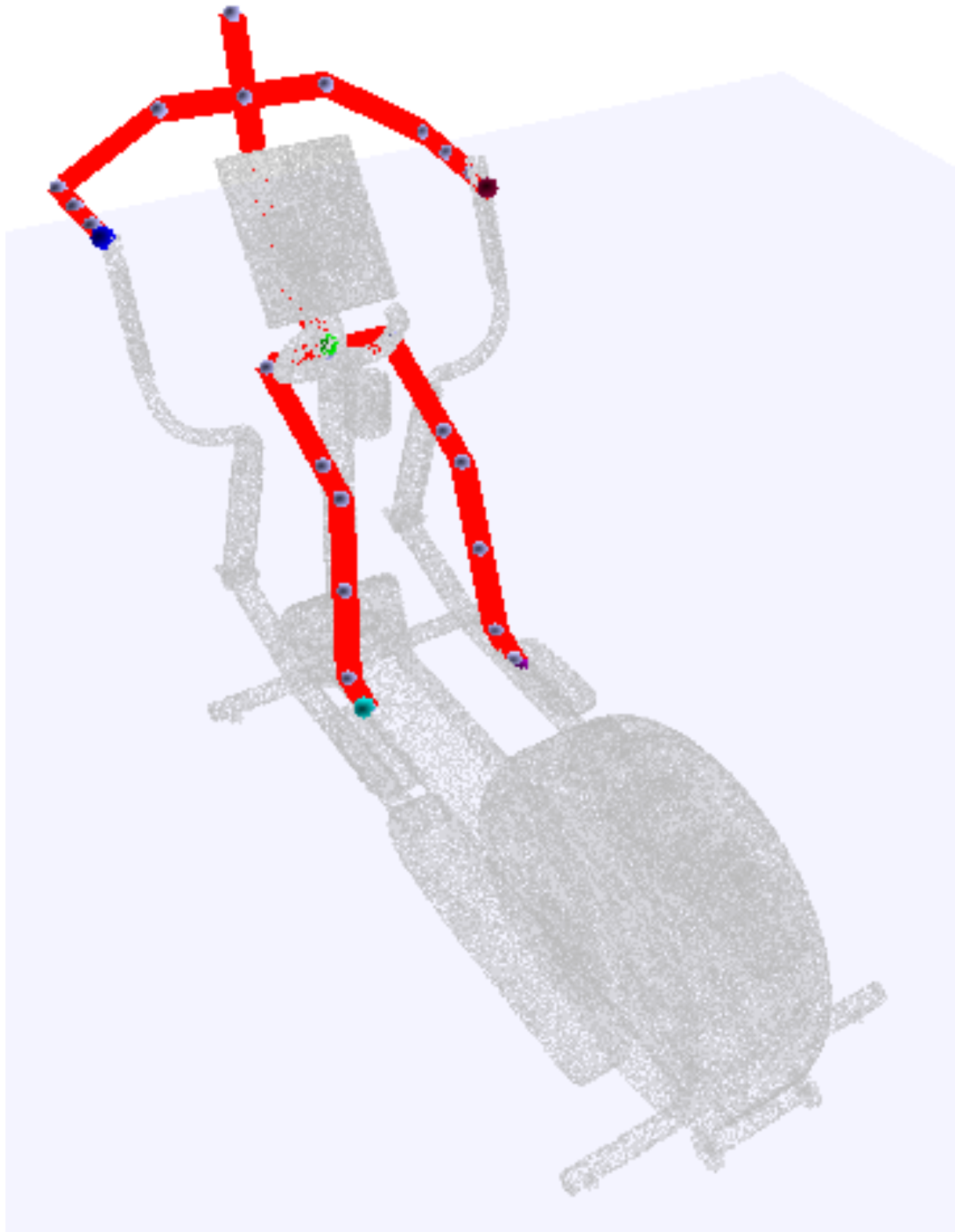
Most Similar



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

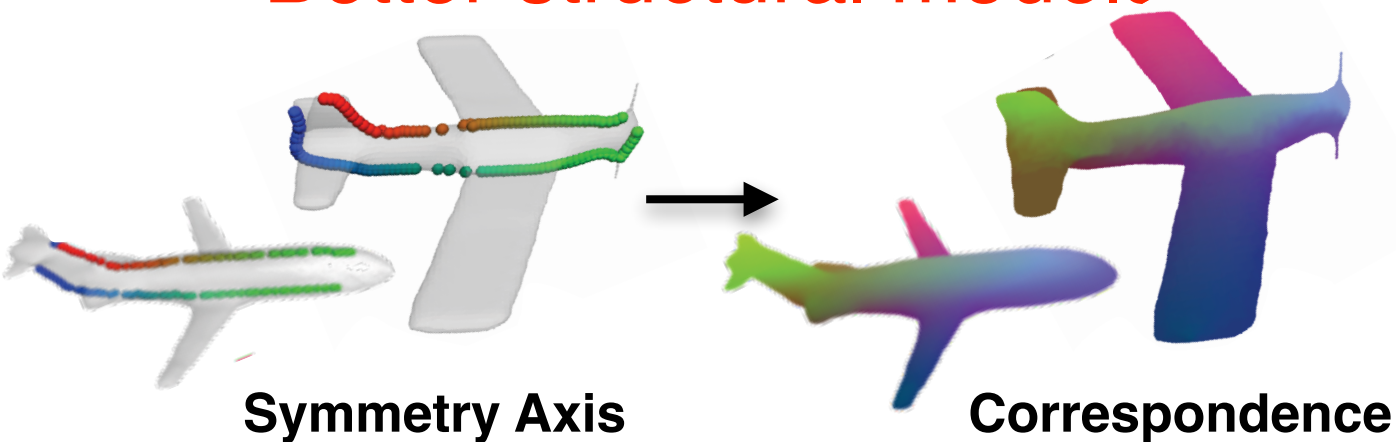
➔ Better structural models

- Additional input to understand function
- Designing manufacturable objects
- Scene understanding

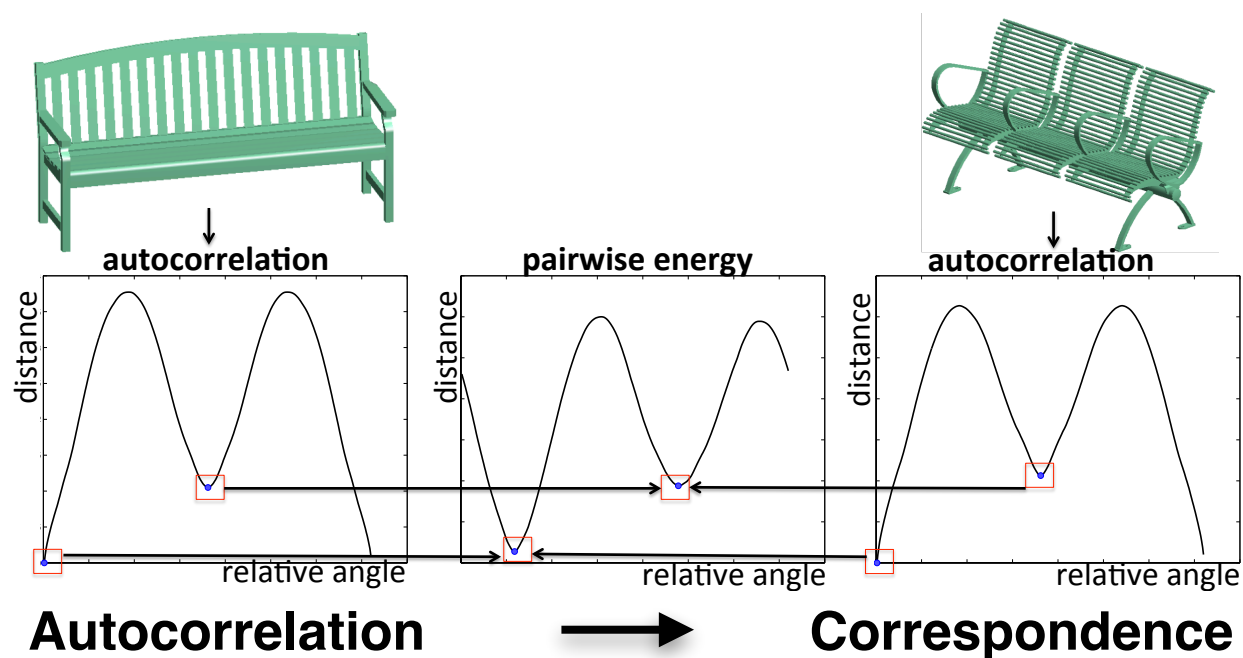
Correspondences

Find Structure in 3D data to infer Function

→ Better structural models

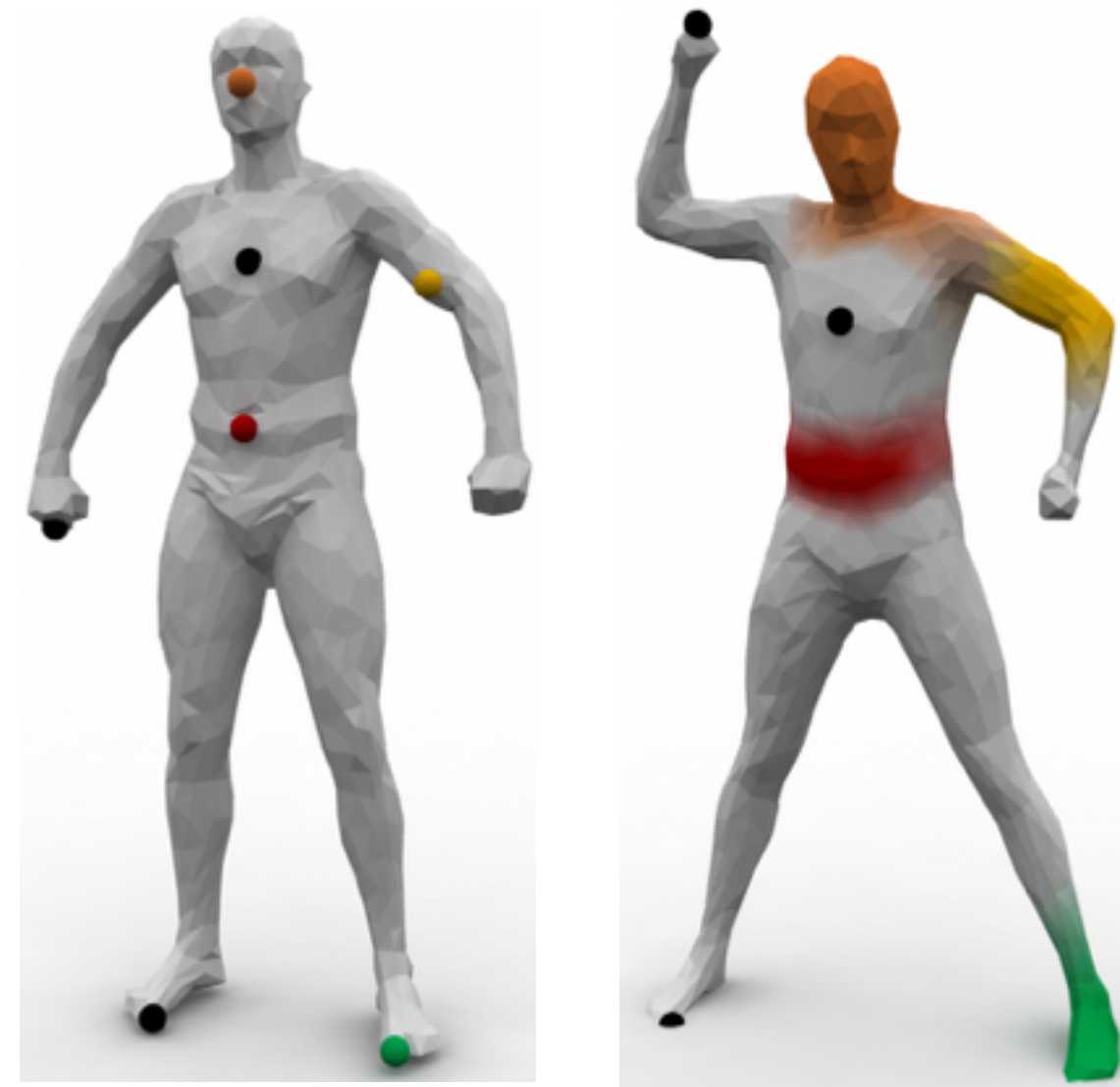


with T. Liu and T. Funkhouser, SGP 2012



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

Symmetry And Correspondence



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

Probabilistic Correspondence

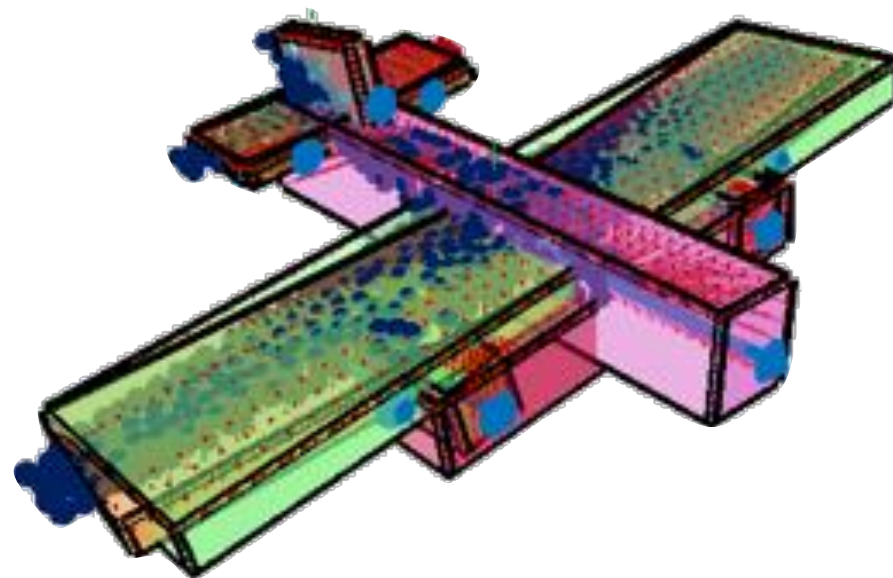
Probabilistic Part Model

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

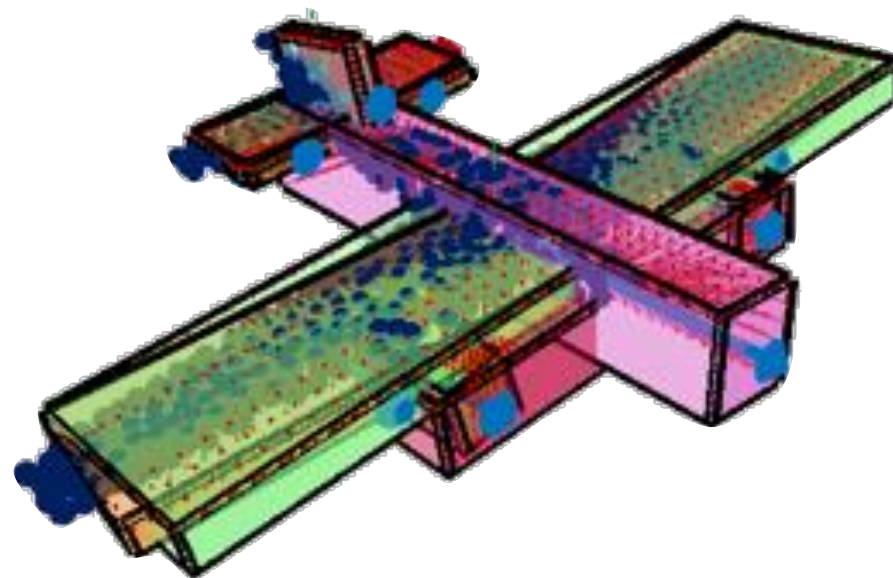
Probabilistic Part Model

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

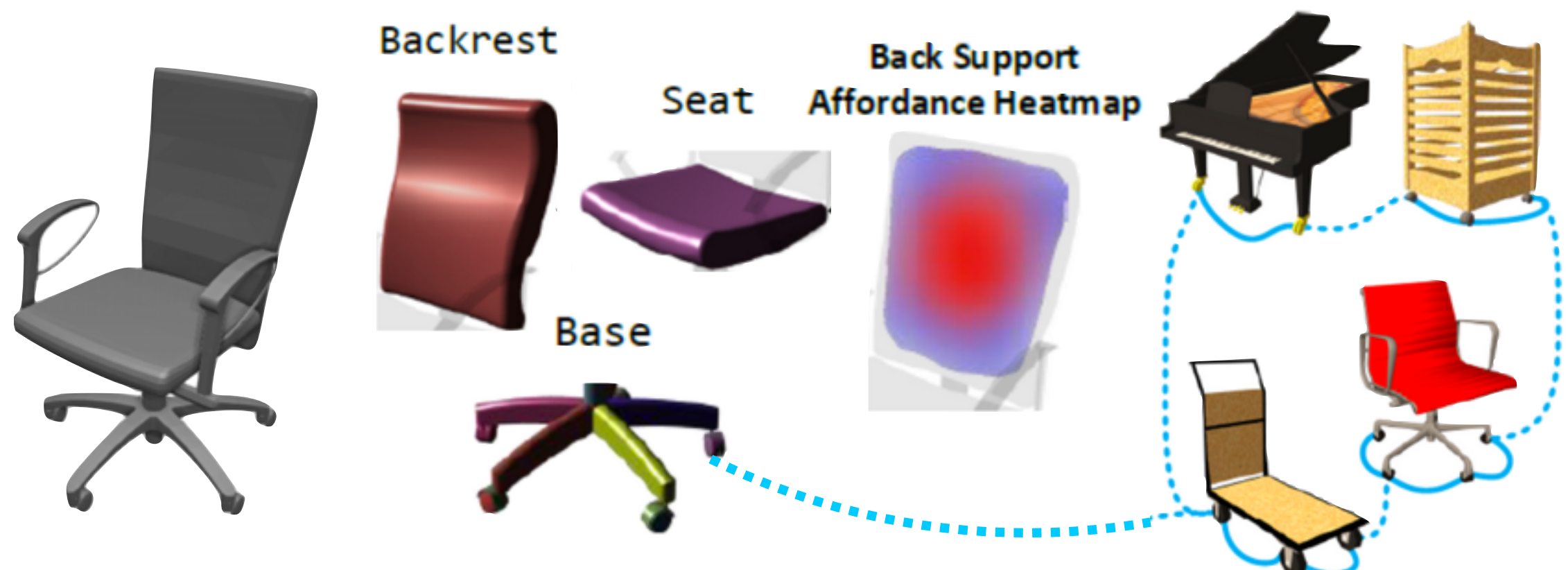
Find Structure in 3D data to infer Function

- 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 MILLIONS of 3D models



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

Semantic Shape Network

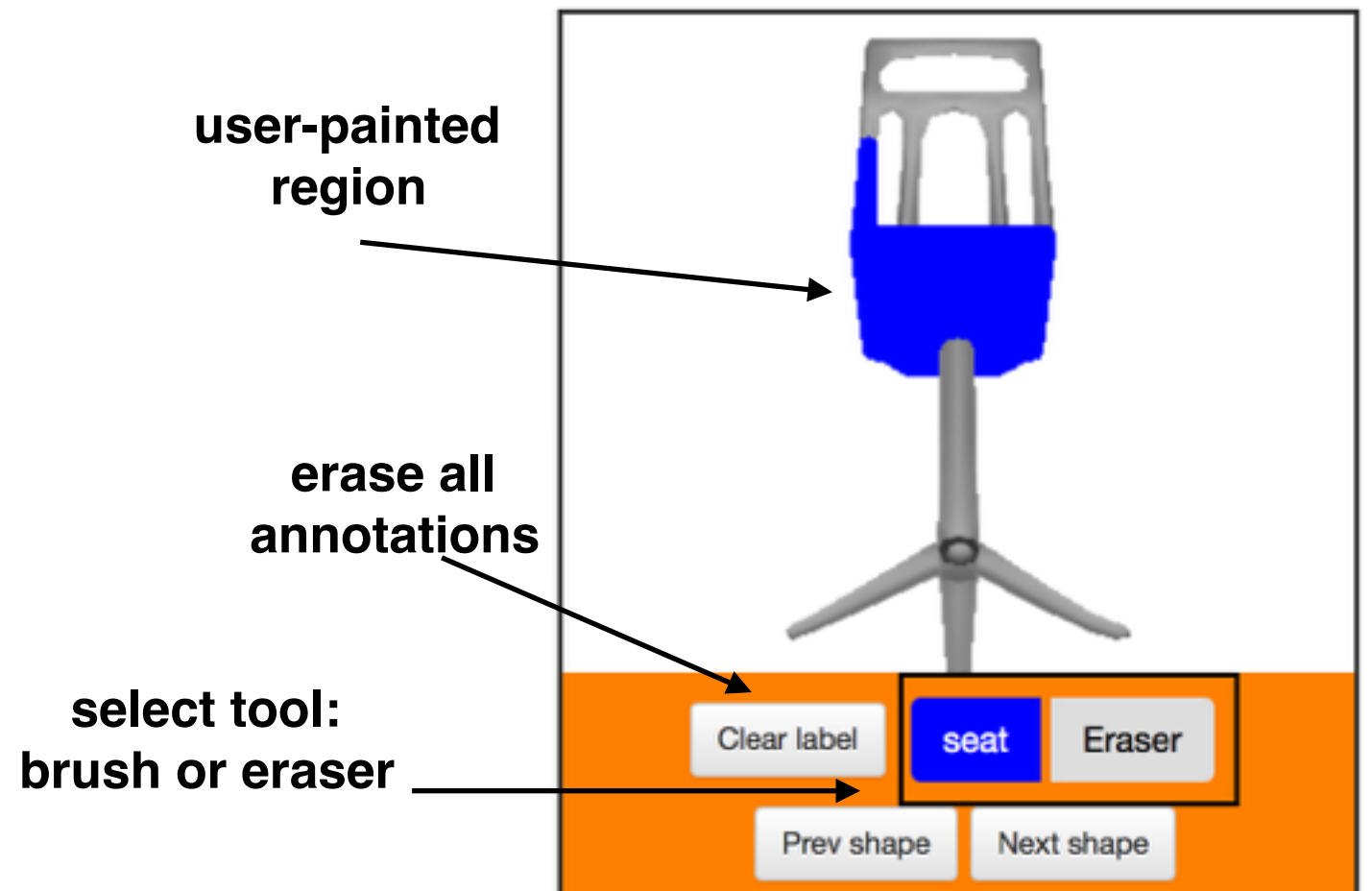
Desiderata

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

Semantic Shape Network

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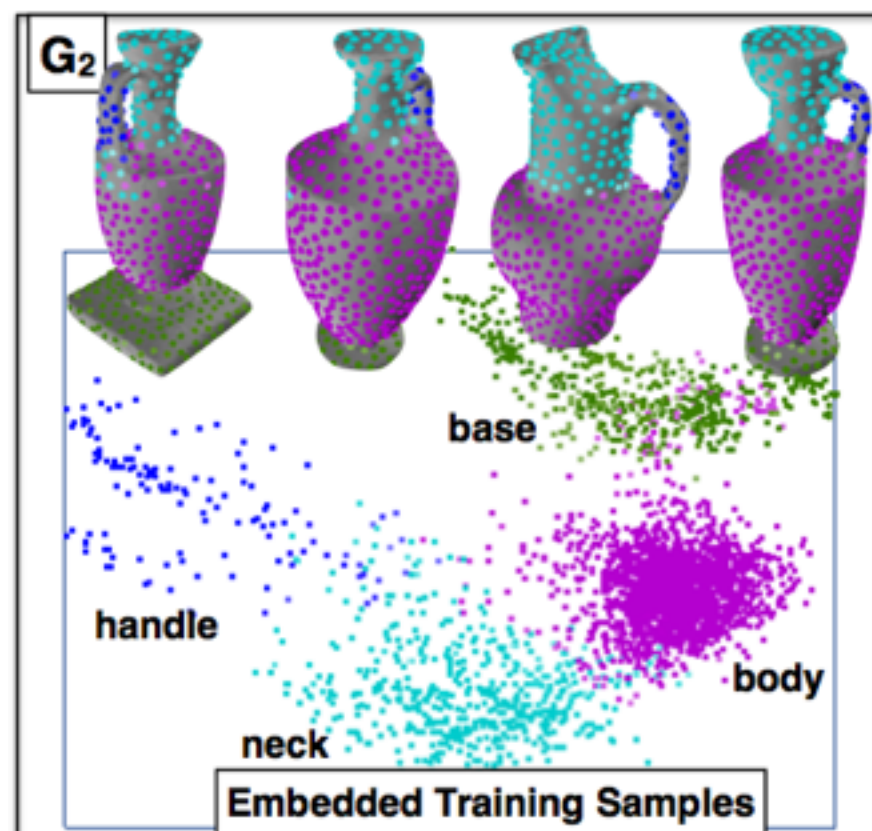
Simple 2D interface

Semantic Shape Network

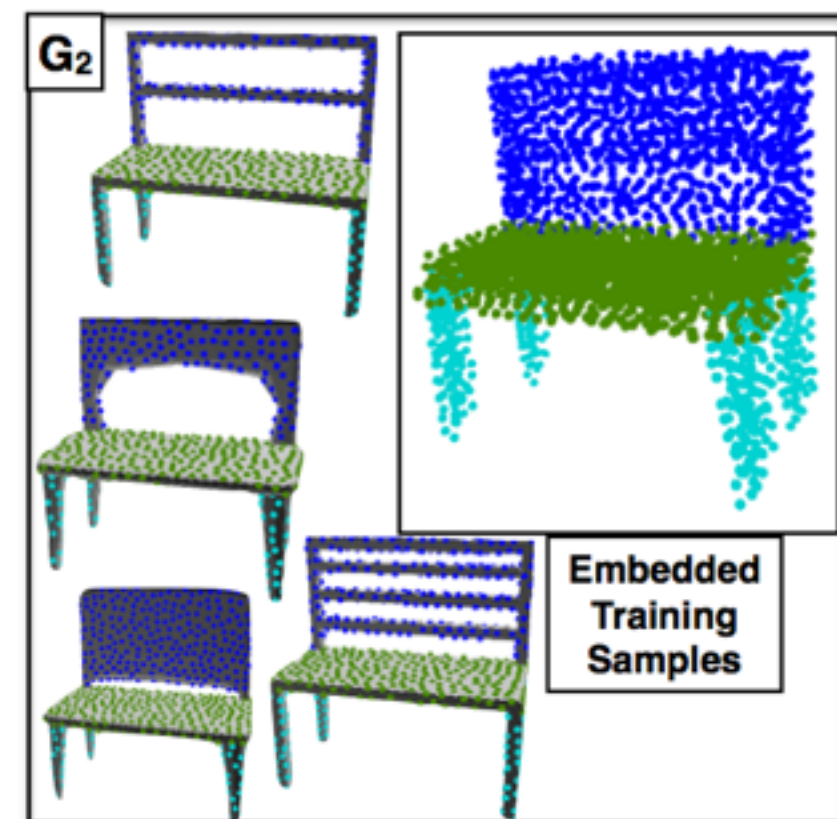
Desiderata

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

**Leverage geometry matching
to propagate semantic information**



Local Shape Features



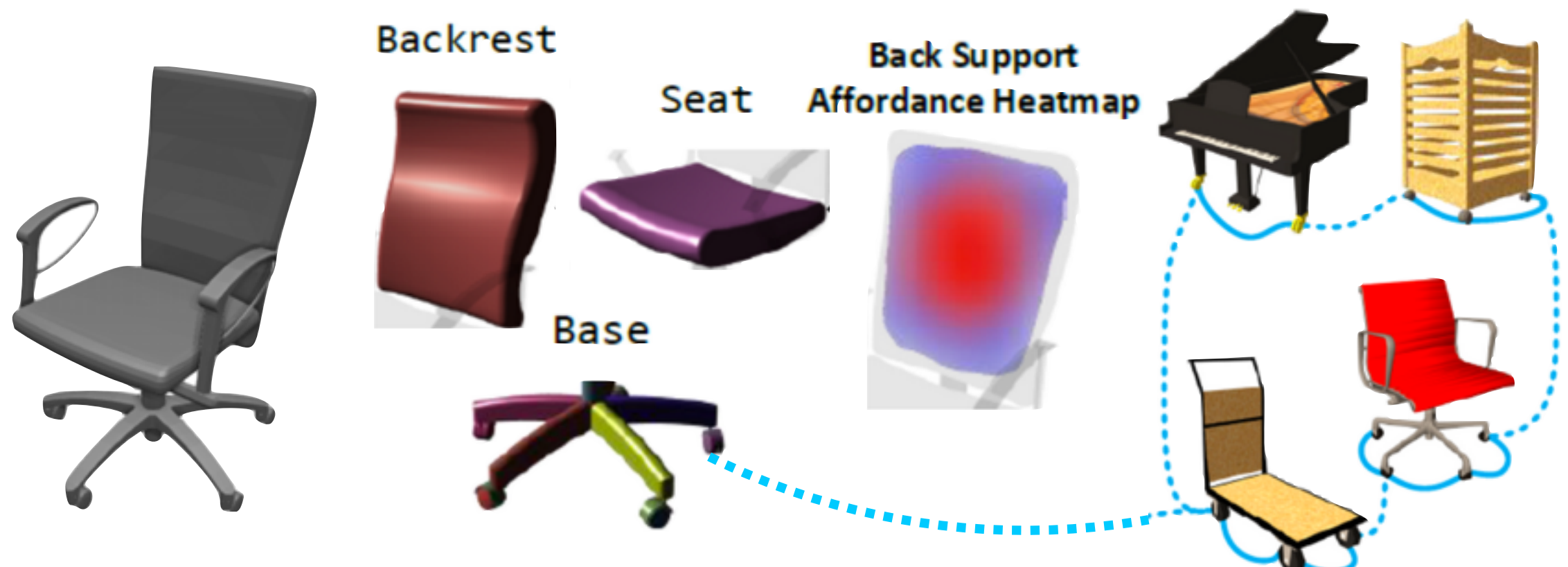
Global Correspondences

Semantic Shape Network

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- ➔ Handle diverse data
- Active

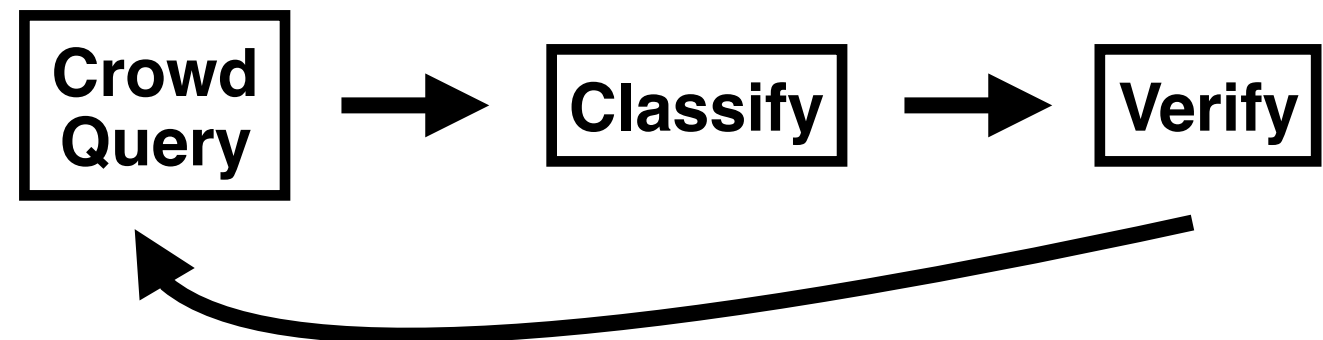
Learn a network structure for propagating annotations



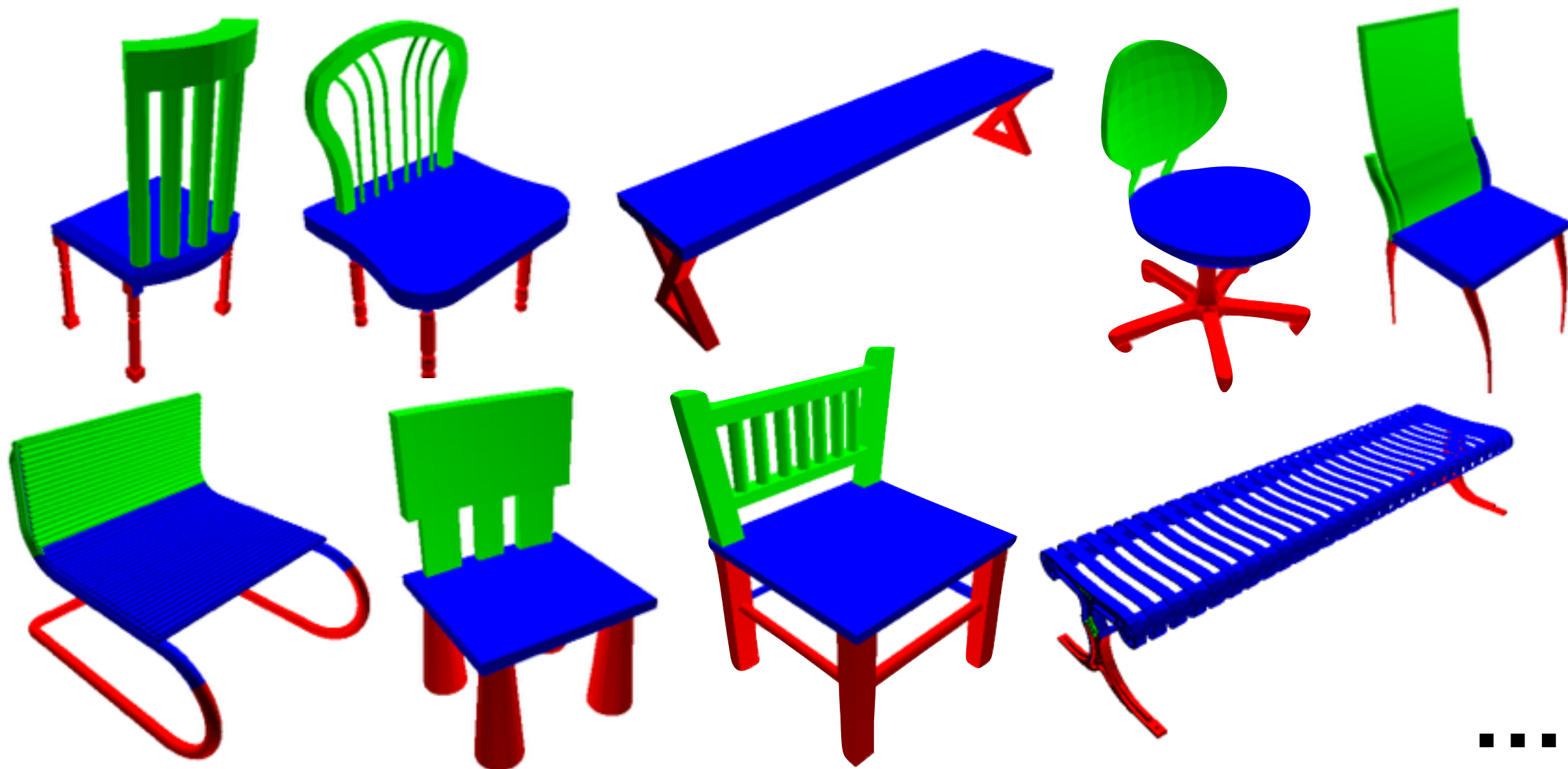
Semantic Shape Network

Desiderata

- Crowdsourced
 - Semi-supervised
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preliminary
results on
10K models



Model Dynamic Interactions

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



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

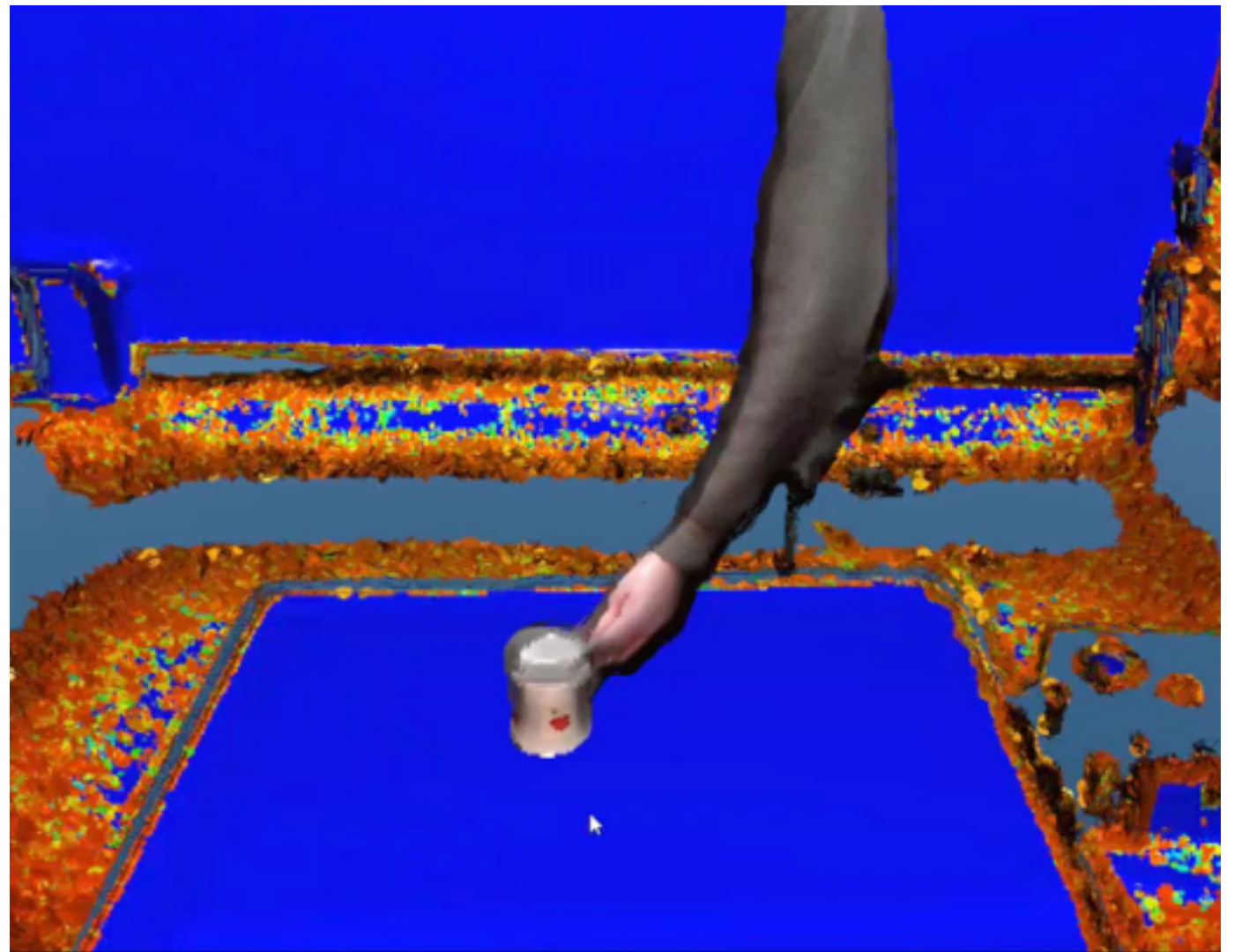
Model Dynamic Interactions

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



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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



Garment Design

Find Structure in 3D data to infer Function

→ Designing manufacturable objects

Database
of Garment Designs

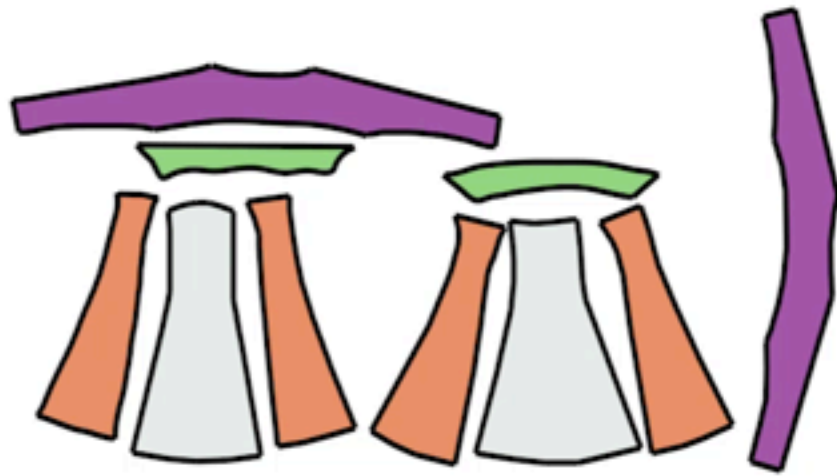


User-created Garments



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

Garment Design



Pattern



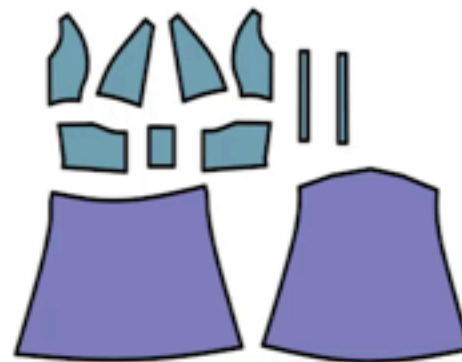
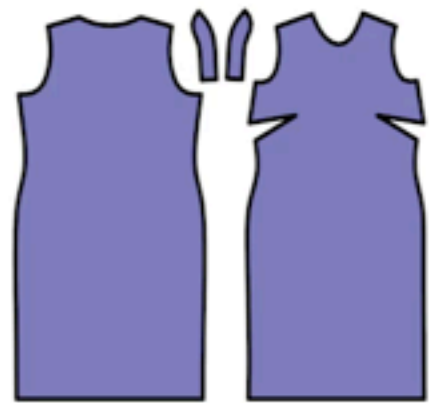
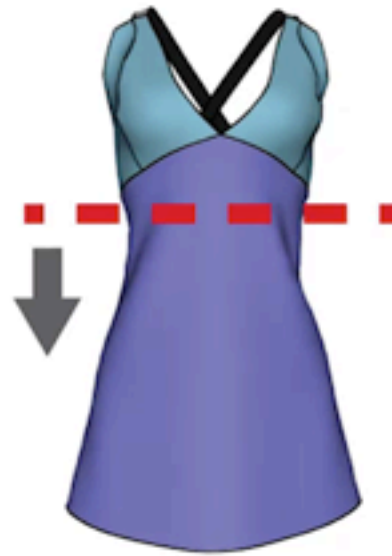
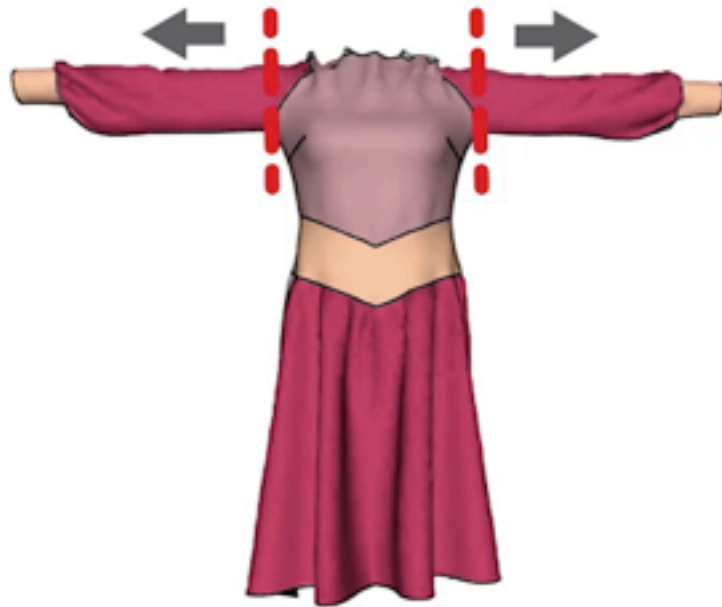
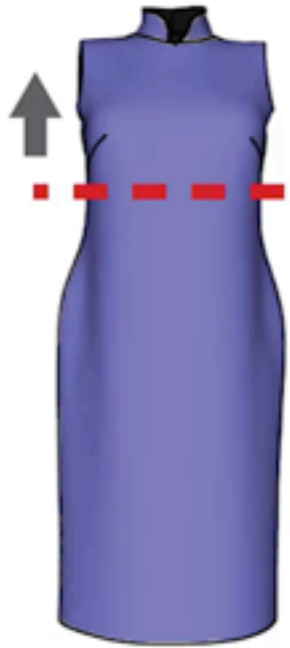
Simulated



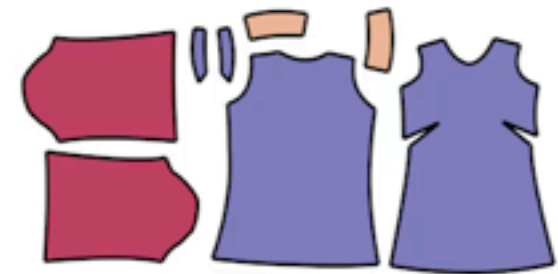
Manufactured

Garment Design

Input



Our Result



Garment Design



User study

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

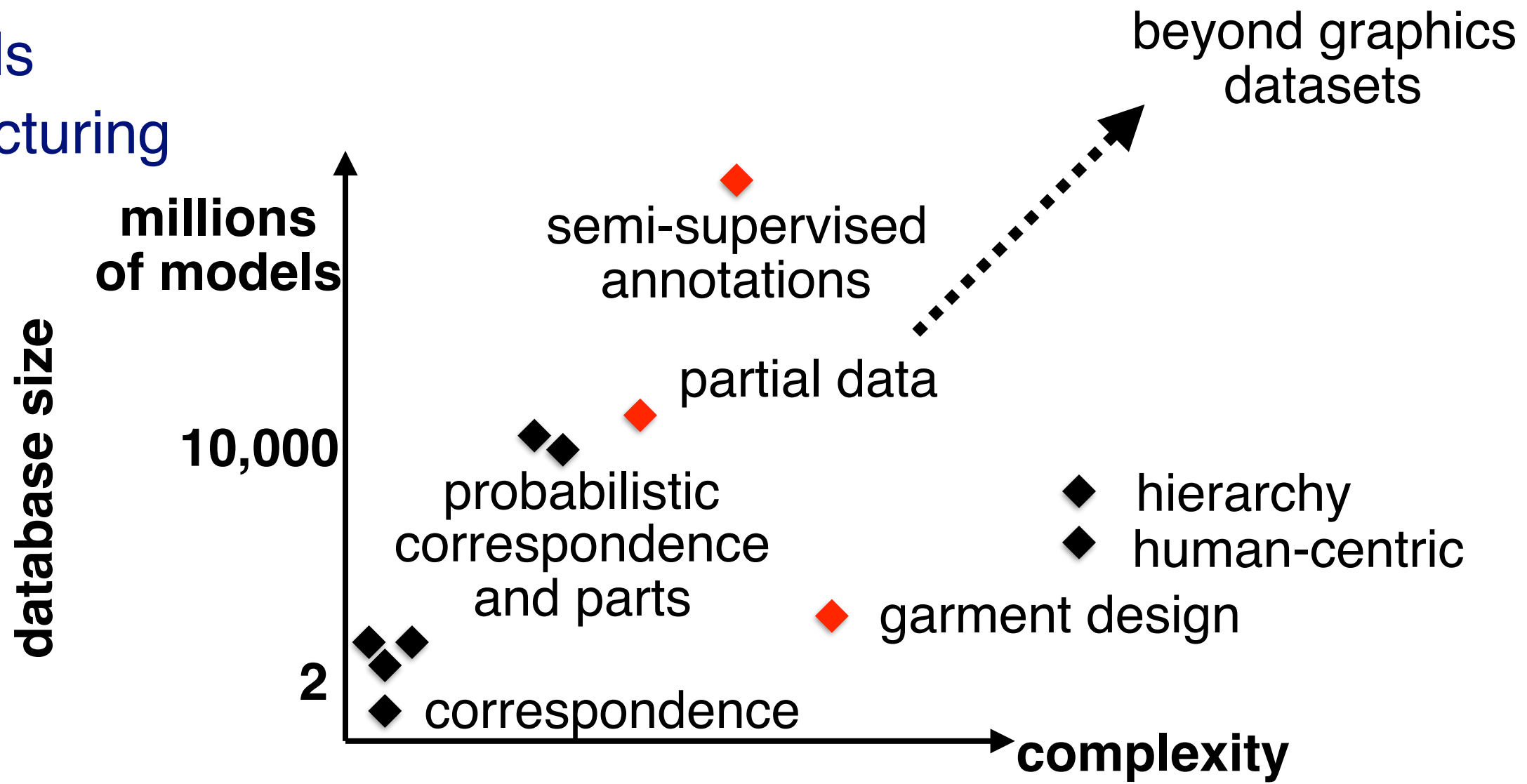
- Better structural models
 - Additional input to understand function
 - Designing manufacturable objects
- ➔ **Scene understanding**
- Reason about function and semantics using 3D CG data
 - Advantages: known lighting, camera, objects, functionality*



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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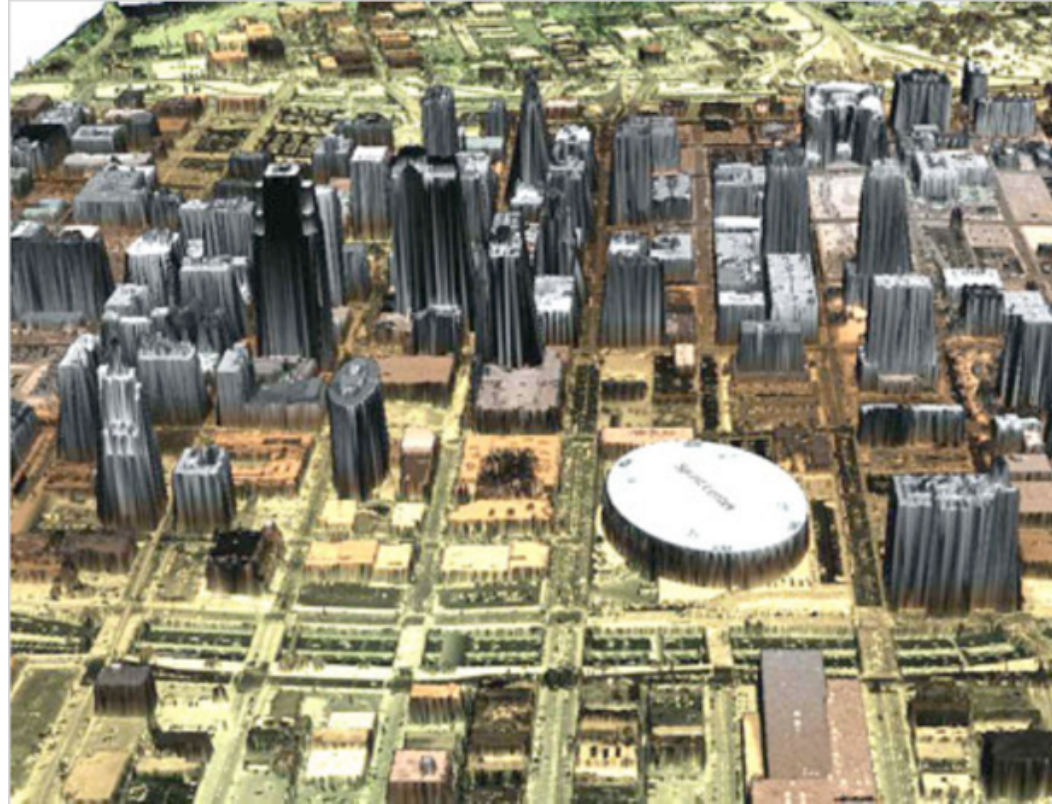
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Finding structure in large 3D collections is useful to
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Understanding functionality is essential for

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

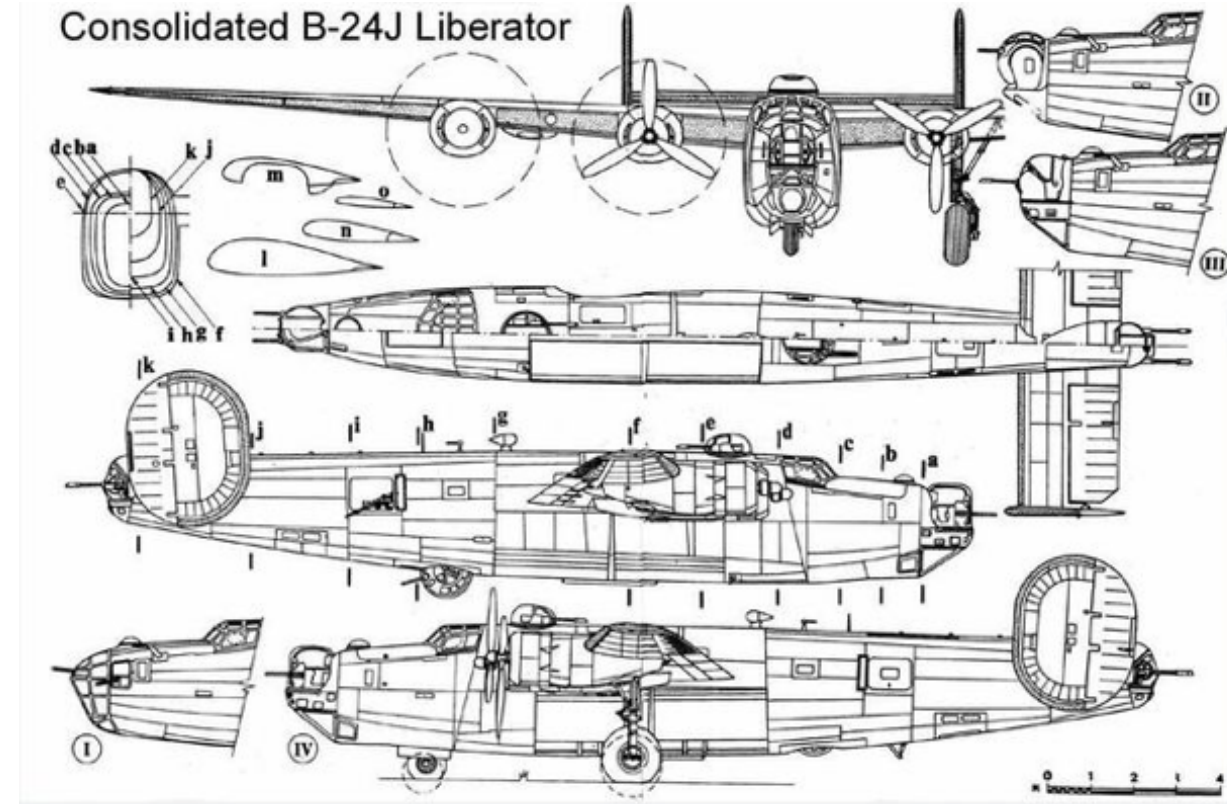
Explore, Analyze and Create Data



Scans of Cities



Medical Data



CAD Models

Understanding functionality is essential for

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

Collaborators



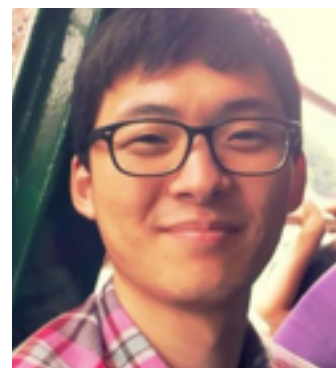
**Stanford
University**



**Leonidas
Guibas**



**Roland
Angst**



**Minhyuk
Sung**



Hao Su

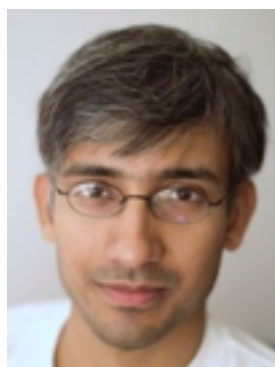
Li Yi



**Princeton
University**



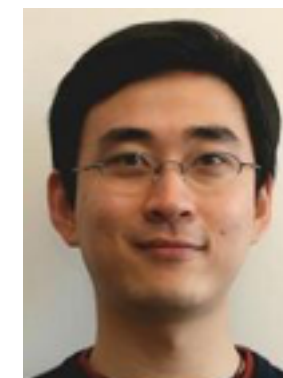
**Thomas
Funkhouser**



**Siddhartha
Chaudhuri**



**Tianqiang
Liu**

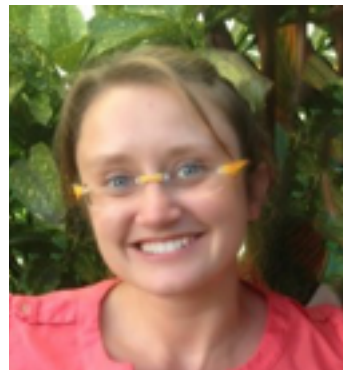


**Xiaobai
Chen**

**Aleksey
Golovinskiy**



Wilmot Li



**Floraine
Berthouzoz**



**Stephan
DiVerdi**



Niloy Mitra



**Melinos
Averkiou**

Collaborators



**University of
British Columbia**



Alla Sheffer



I-Chao Shen



TTIC



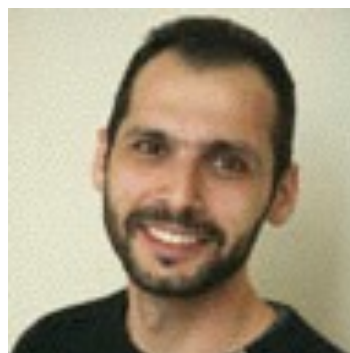
**Qi-xing
Huang**



**University of
Toronto**



Karan Singh



**Bruno
Rodrigues
De Araujo**



**Kevin
Gibson**



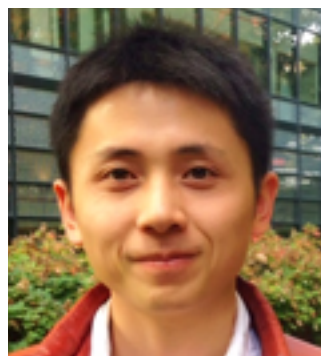
**Weizmann
Institute
of Science**



**Yaron
Lipman**

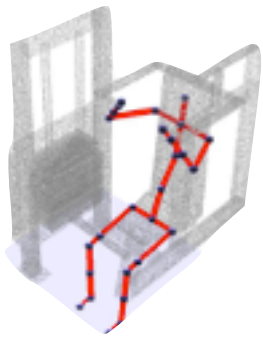


**Yale
University**

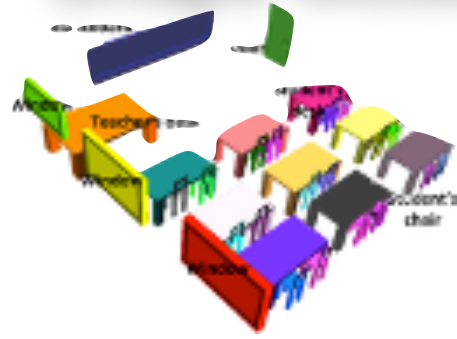


**Youyi
Zheng**

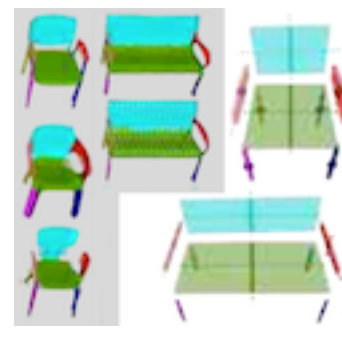
Shape Models



Human-centric
[SIGGRAPH'14]

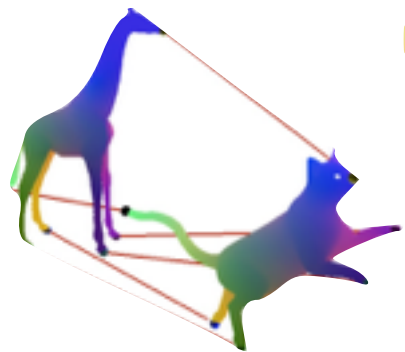


Hierarchical
[SIGGRAPH Asia'14]



Part-based
[SIGGRAPH'13]

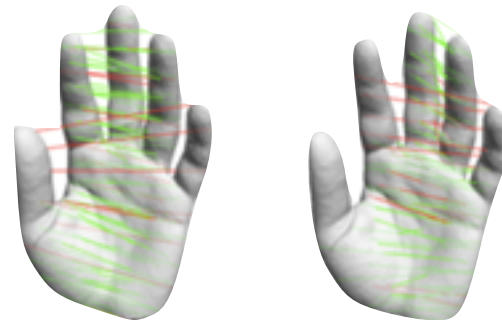
Shape Correspondence



Blended maps
[SIGGRAPH'11]



Symmetry maps
[SGP'12]

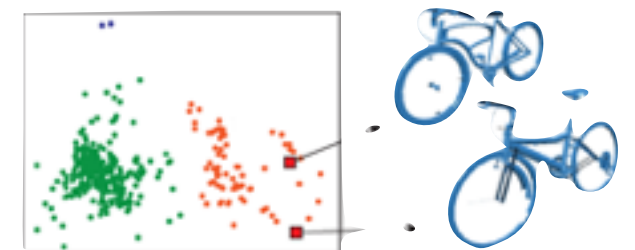


Intrinsic symmetry
[SGP'10]

Exploration and Synthesis

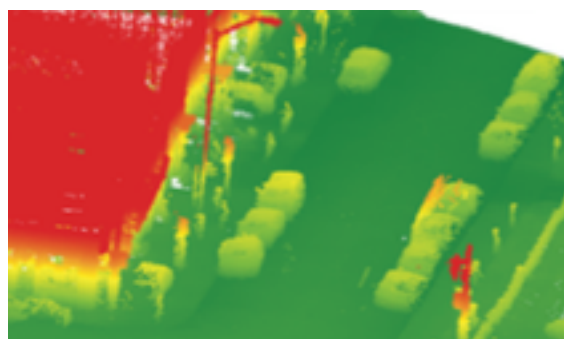


*Exploration via
Fuzzy Correspondence*
[SIGGRAPH'12]



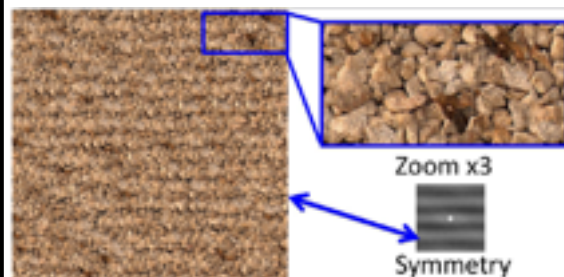
*Coupled
Exploration and Synthesis*
[EG'14]

Recognition

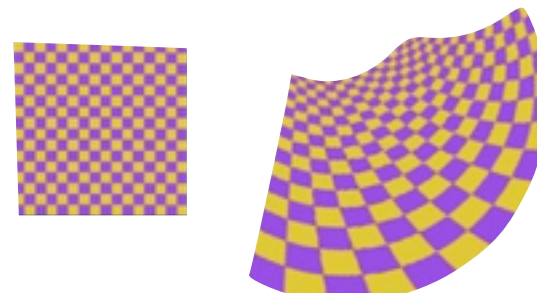


Urban point cloud
[ICCV'09]

Images and Textures

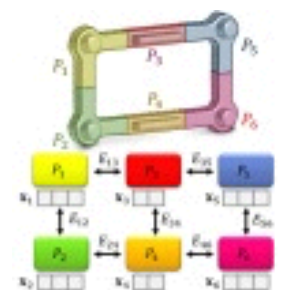


Symmetry-guided
[ToG'12]



Quasi-conformal
[ToG'12]

Courses



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