SIGGRAPH2012

Exploring Collections of 3D Models using Fuzzy Correspondences

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Motivating Application

Exploring collections of 3D models

Google 3D Warehouse

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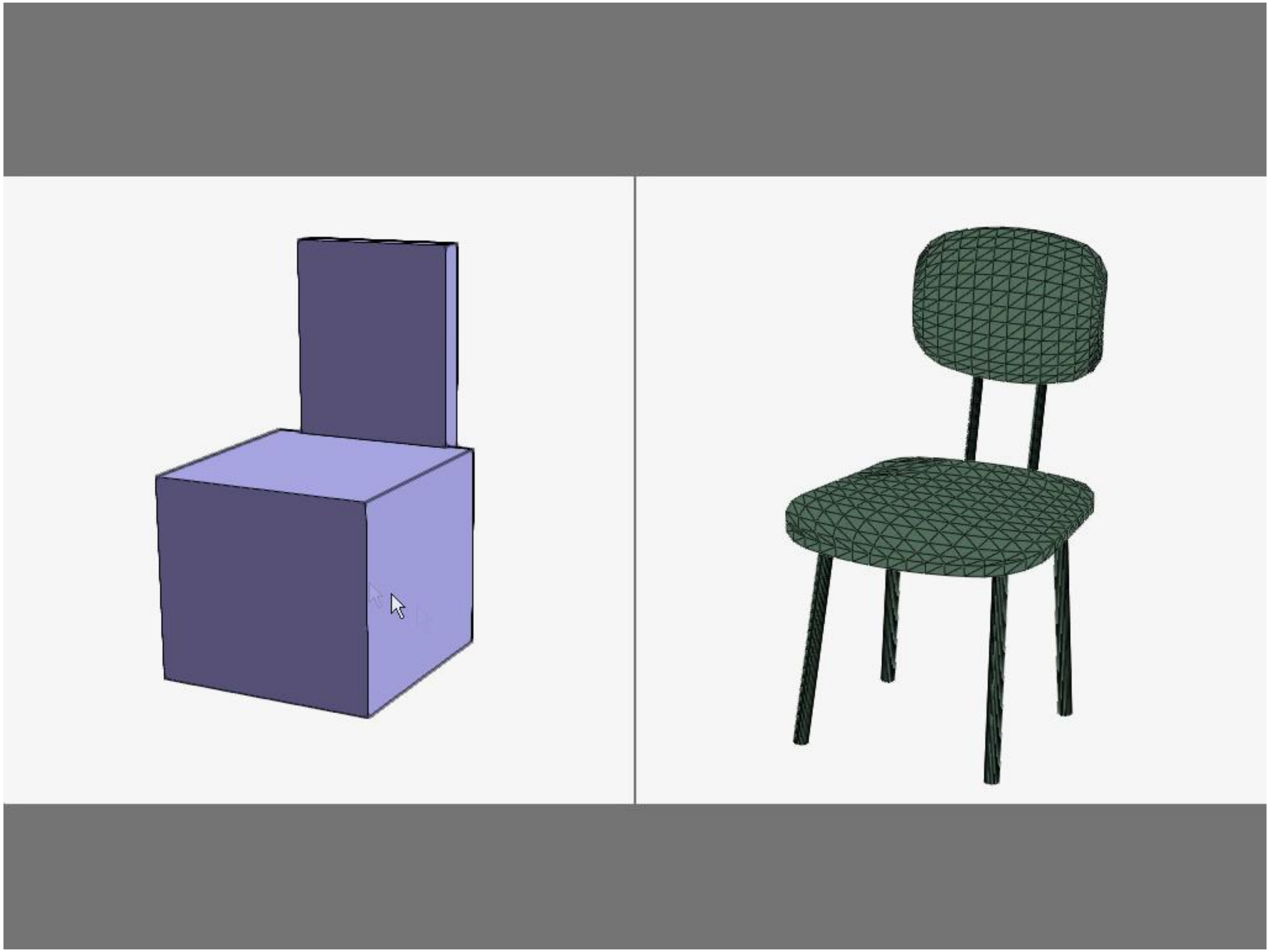
Previous Work



Ovsjanikov et al., SIGGRAPH 2011

Goal

Exploration tool for understanding **shape variations for arbitrary regions** of models in collections

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- Sort by similarity
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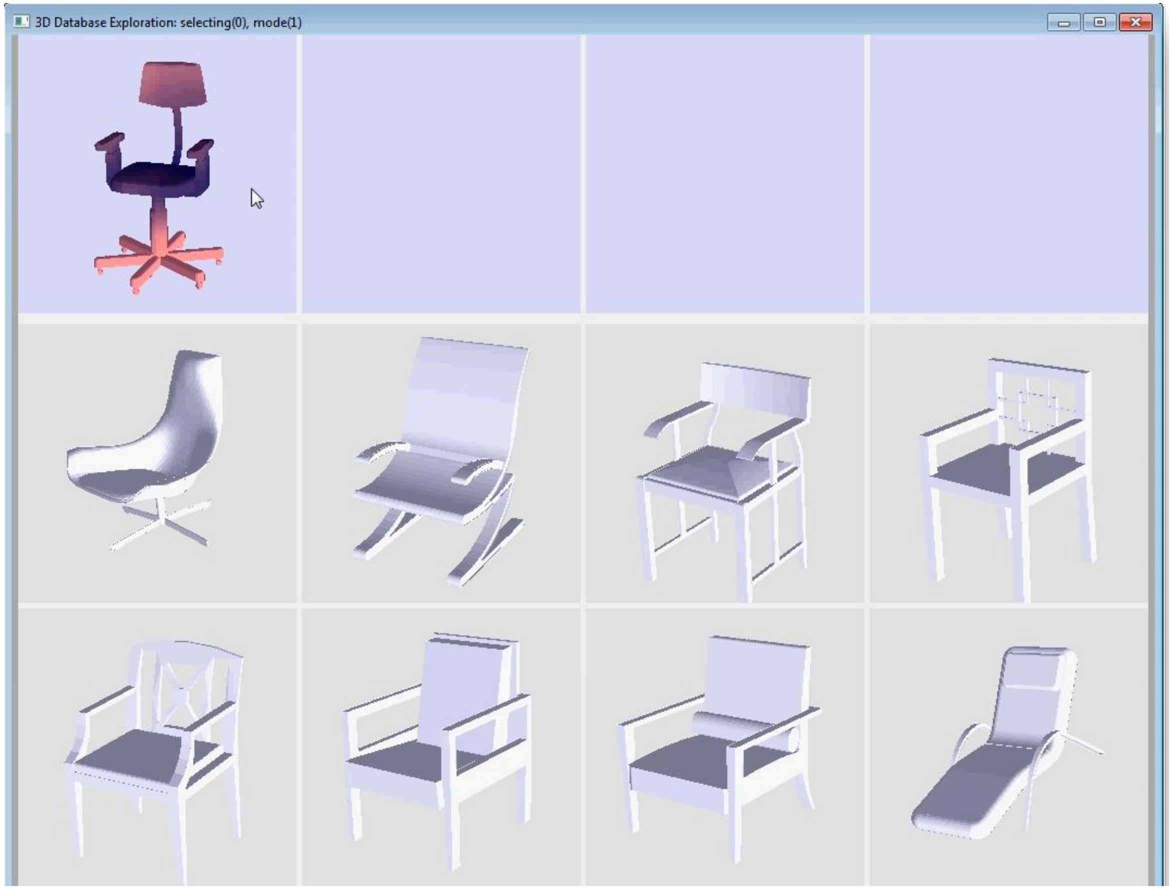

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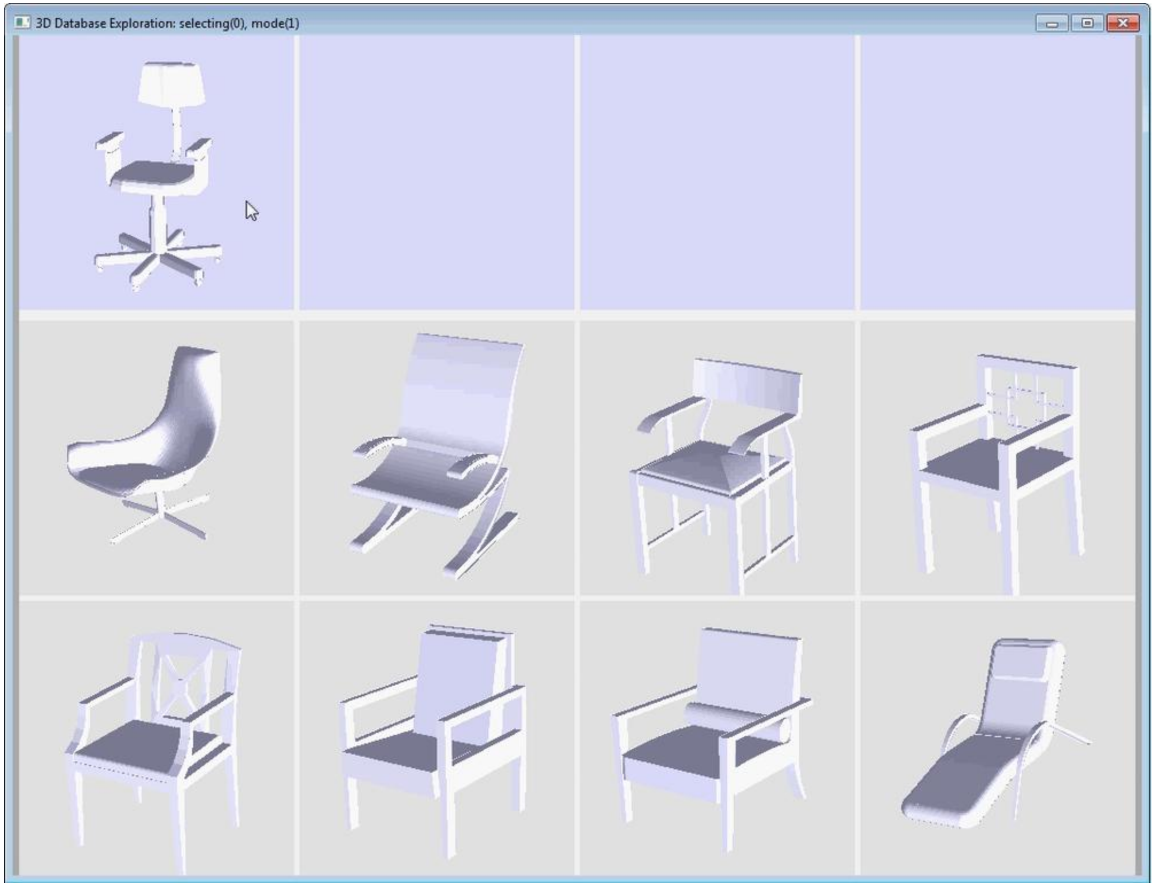

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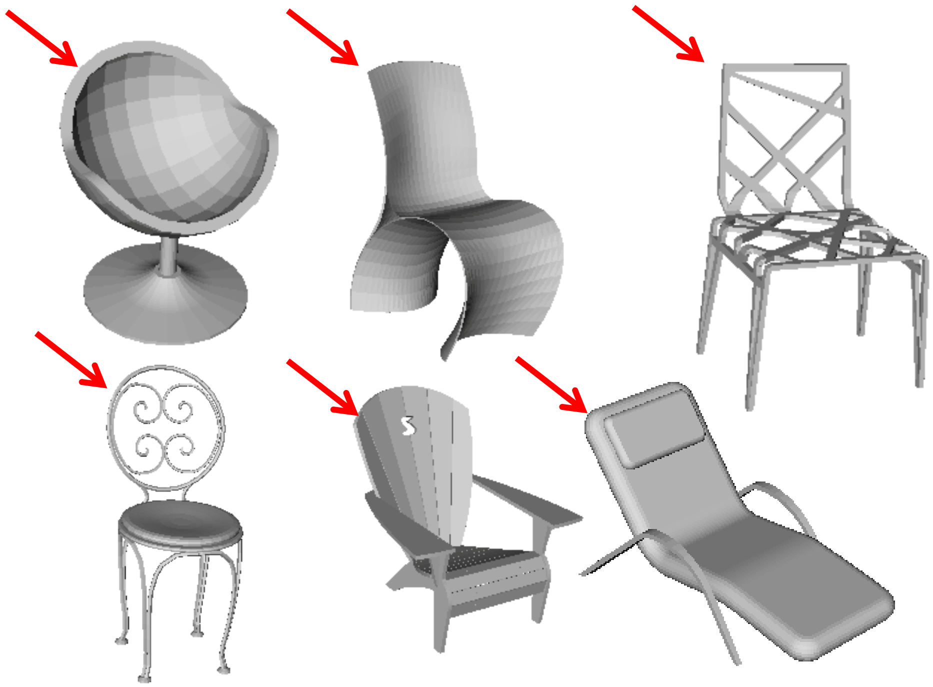
Approach

Compute correspondences between similar points on all models in the collection



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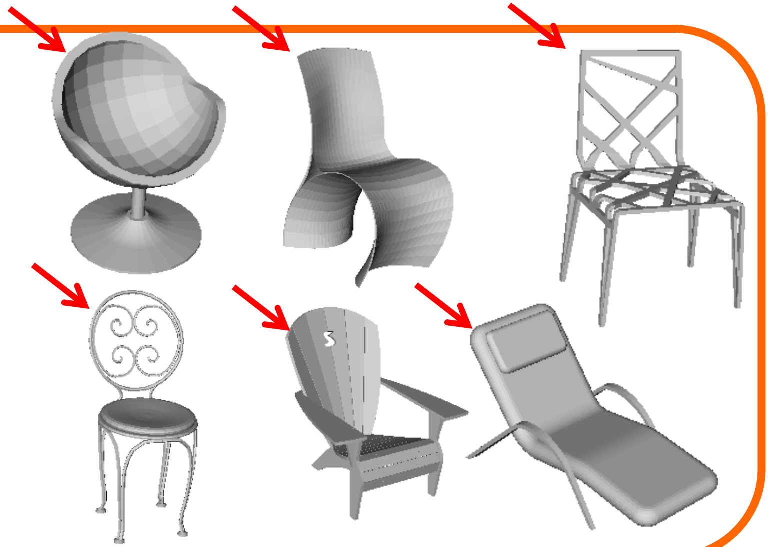
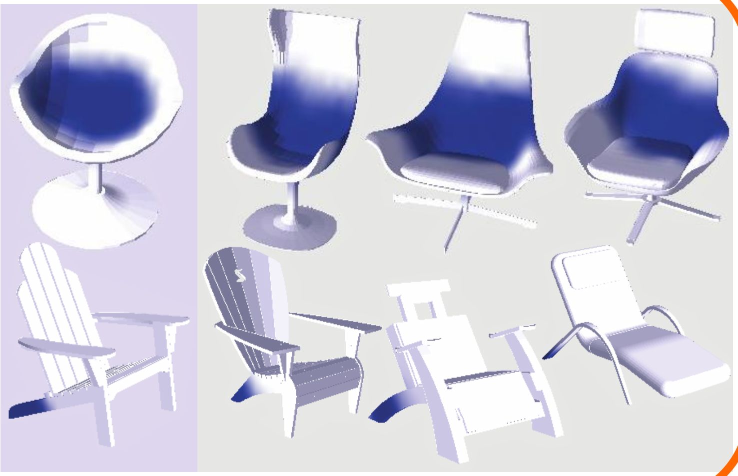


Exploration Tool



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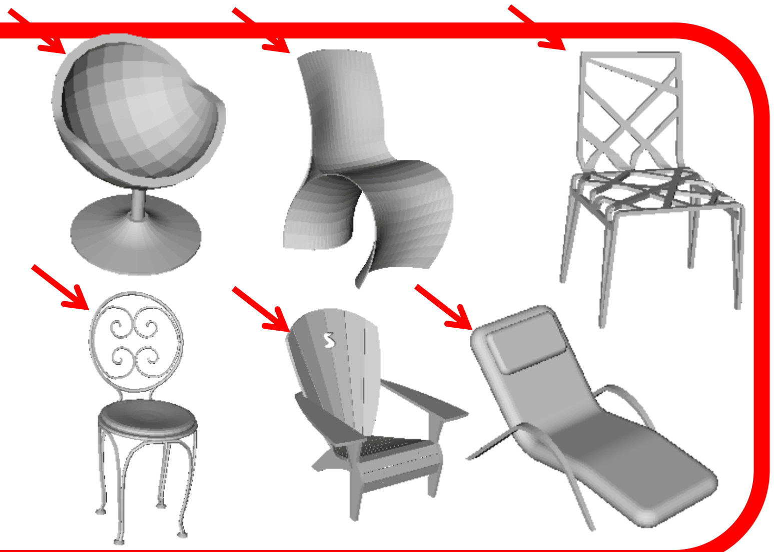

Exploration Tool

Related Work

Previous Methods

- Pairwise alignment
- Map optimization
- Template fitting

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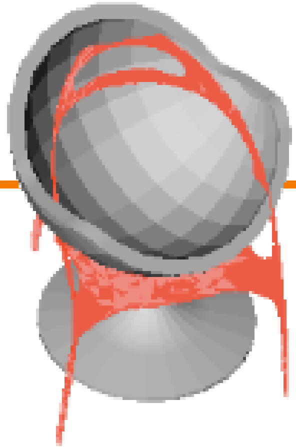

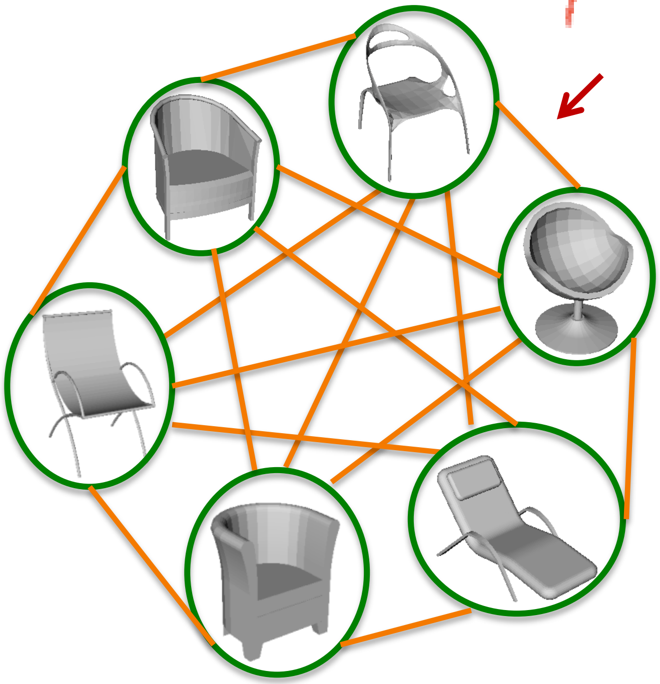

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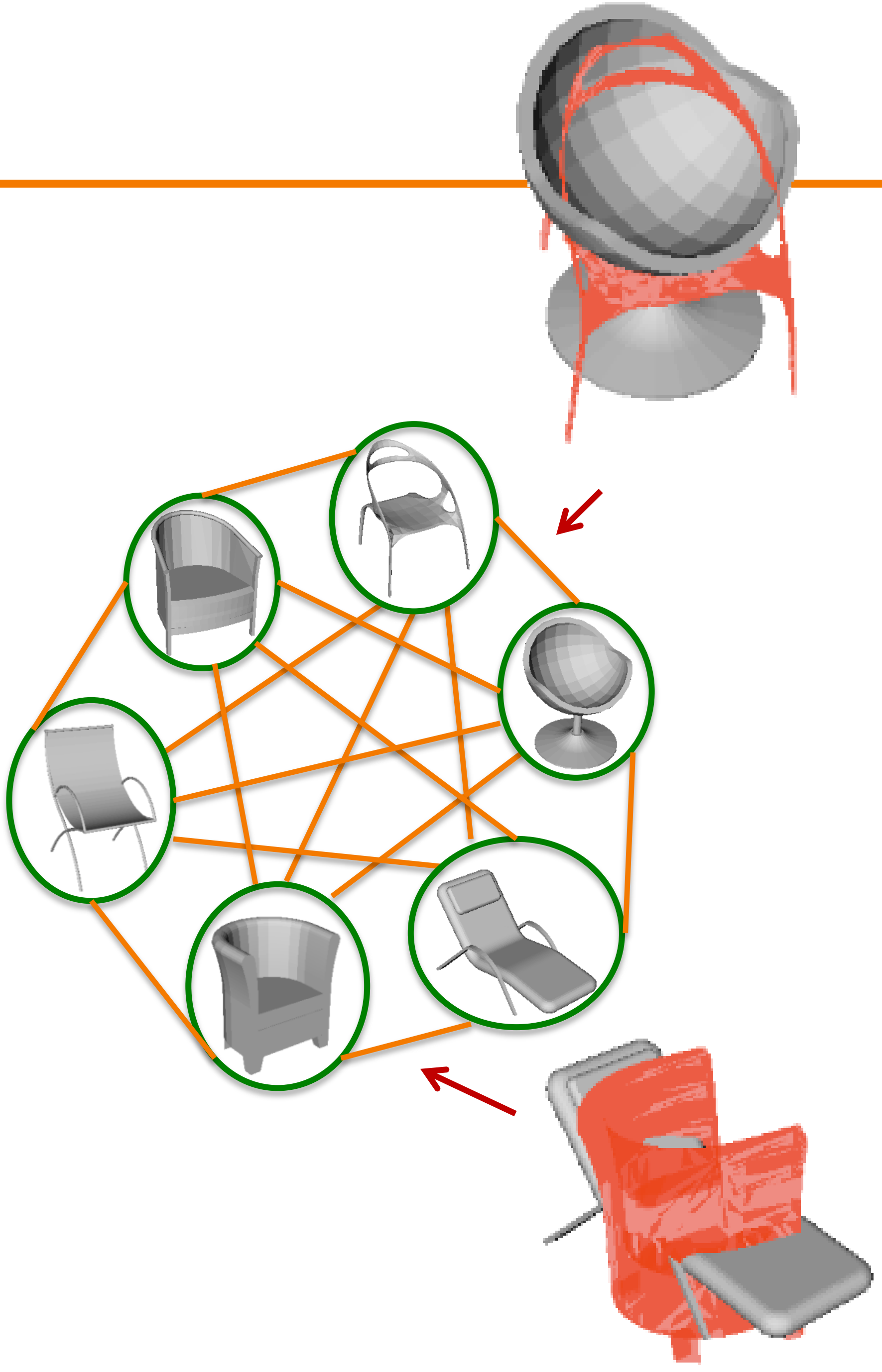

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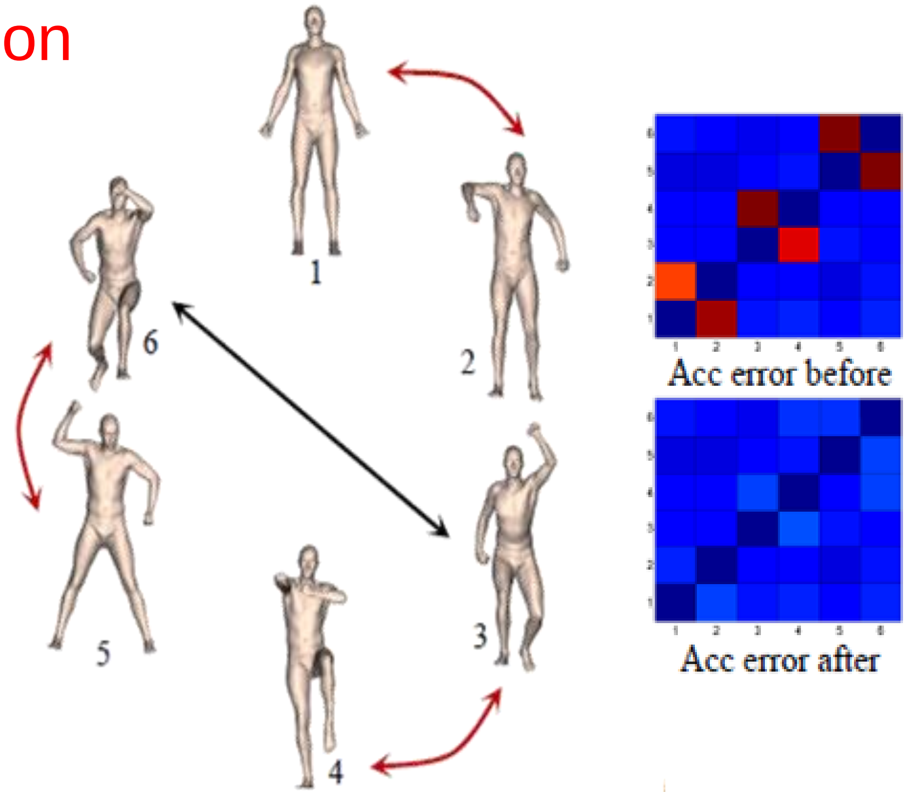

Nguyen et al., SGP 2011

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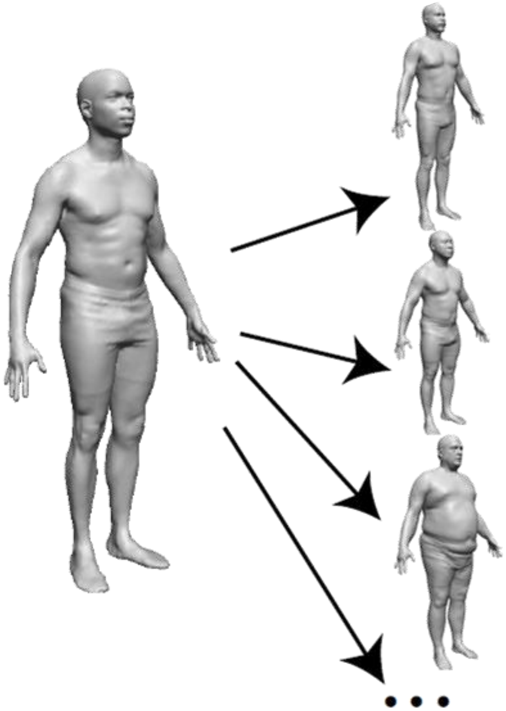
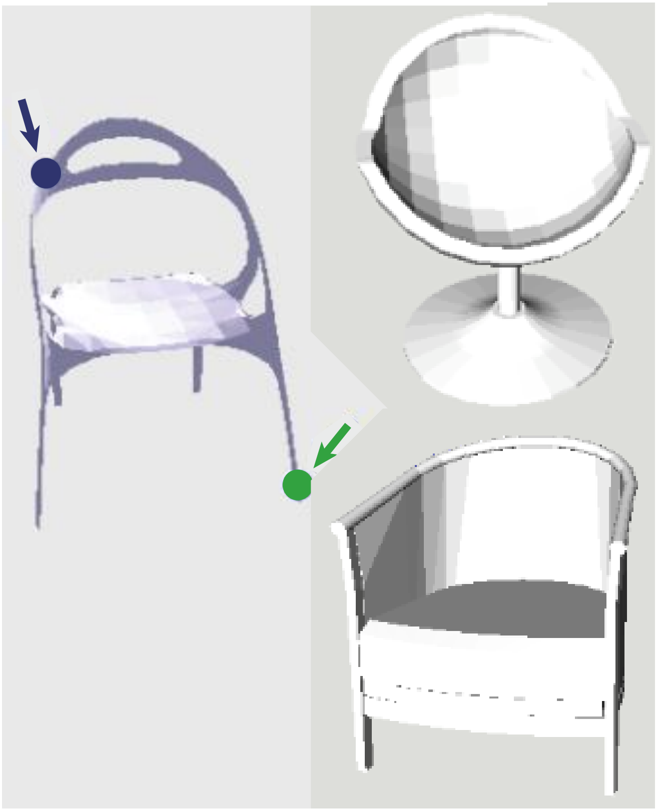


Allen et al., SIGGRAPH 2003.

Problem: Representing Correspondences

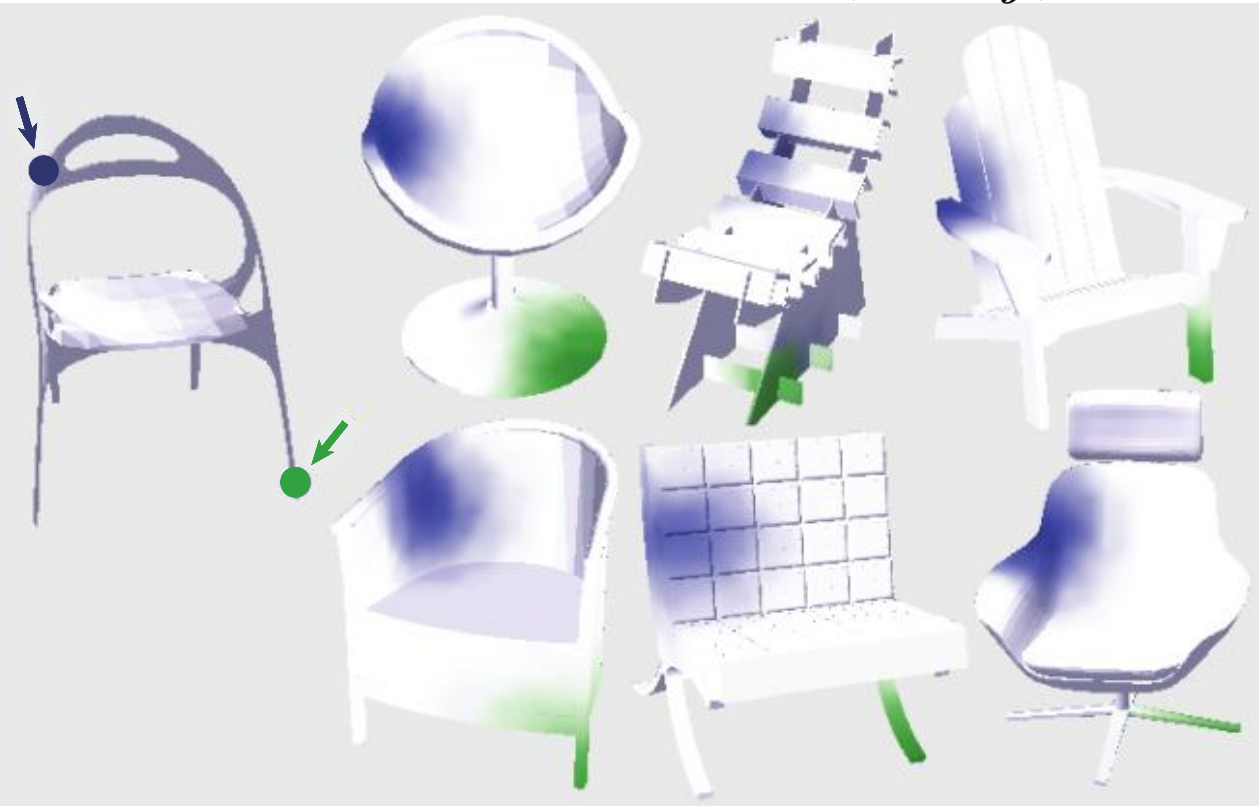
Point-to-point correspondences are not well-defined for all pairs of models



Solution: Fuzzy Correspondences

Continuous function measuring "how well" two points correspond

$$f(p_i, p_j) \in \mathbb{R}$$



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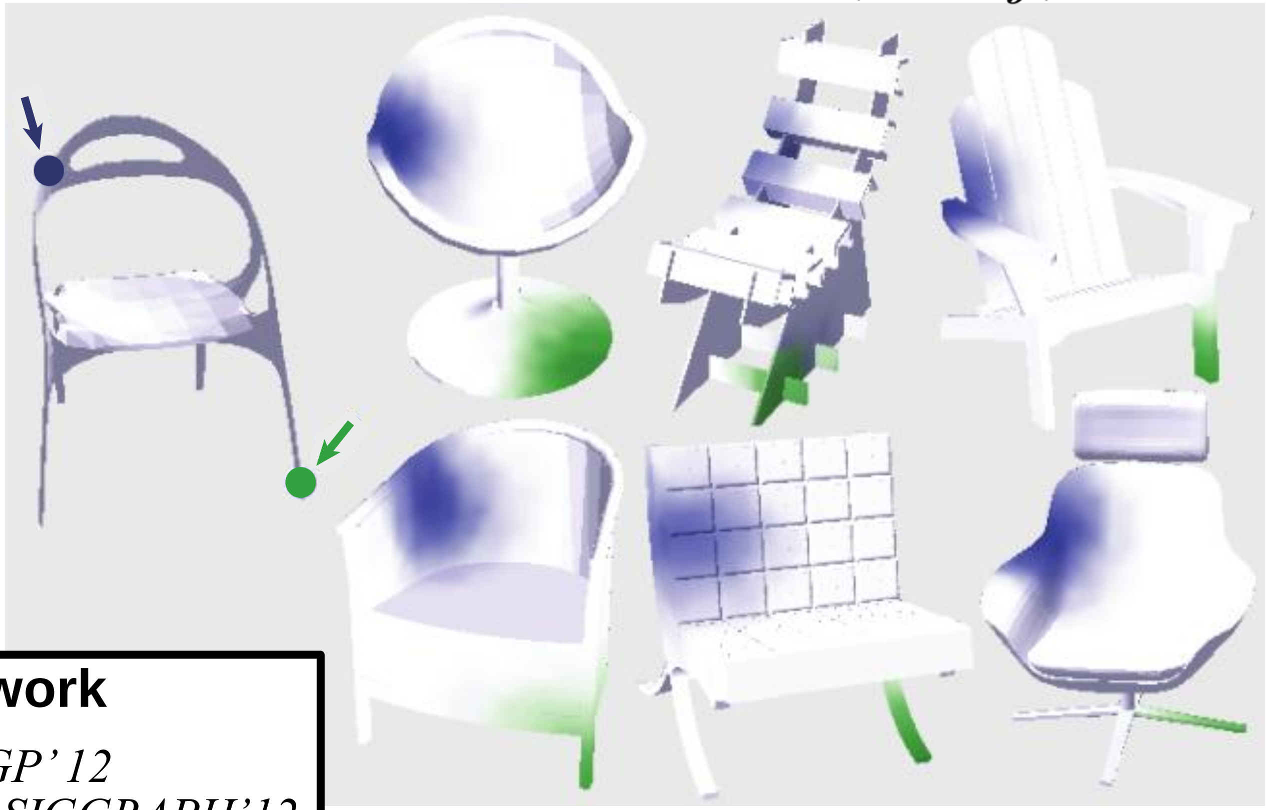
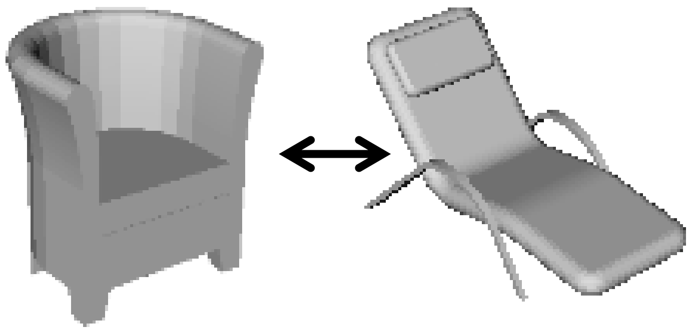


Concurrent work

Solomon et al., SGP’ 12
Ovsjanikov et al., SIGGRAPH’12

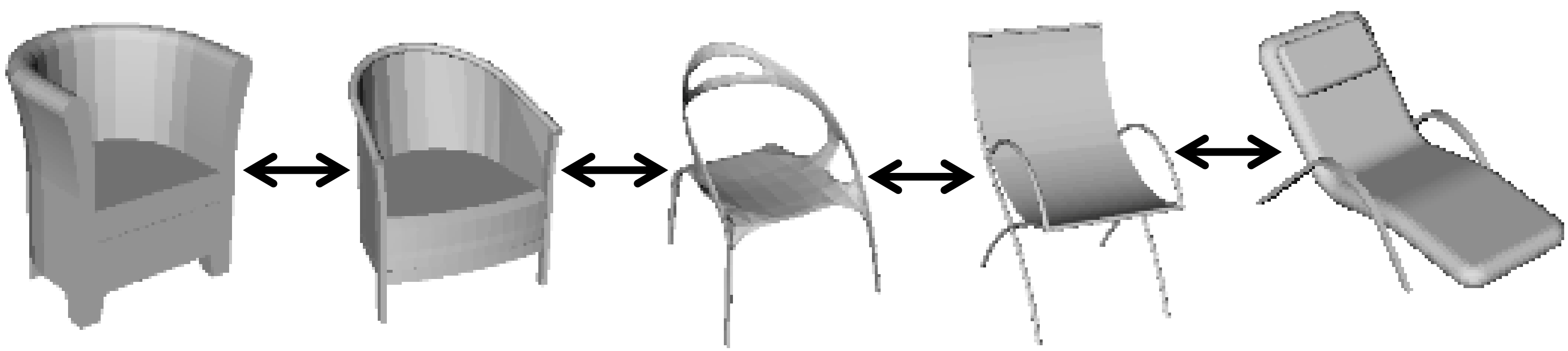
Problem: Matching Dissimilar Shapes

Geometric alignment algorithms work well only for similar pairs of shapes



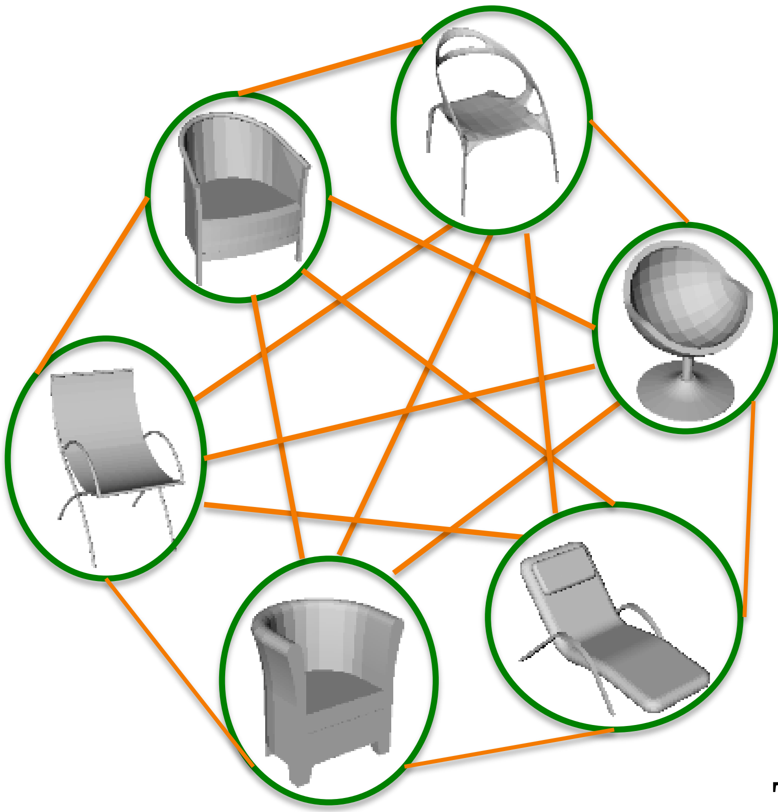
Solution: Transitivity

Leverage correspondences between similar shapes to reason about correspondences in dissimilar shapes



Problem: Handling N^2 Complexity

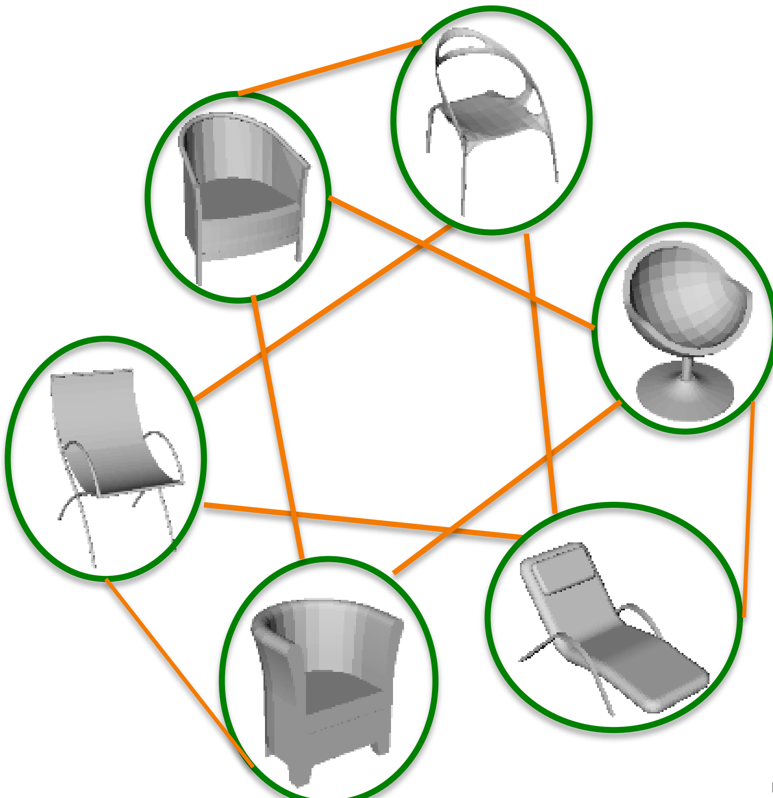
Computing pairwise alignments for all pairs is too expensive for large collections: $O(N^2)$ alignments



Typical: N=100

Solution: Diffusion

Compute alignments for small number of pairs (M) and diffuse correspondences to other pairs: O(MN))



A small amount of redundancy provides robustness to poor alignments

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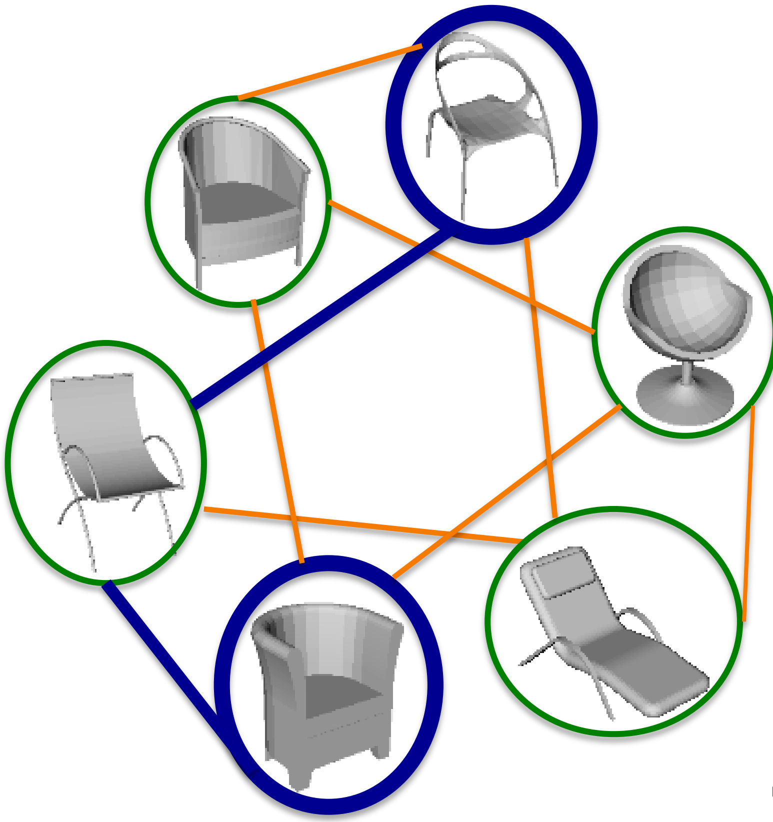

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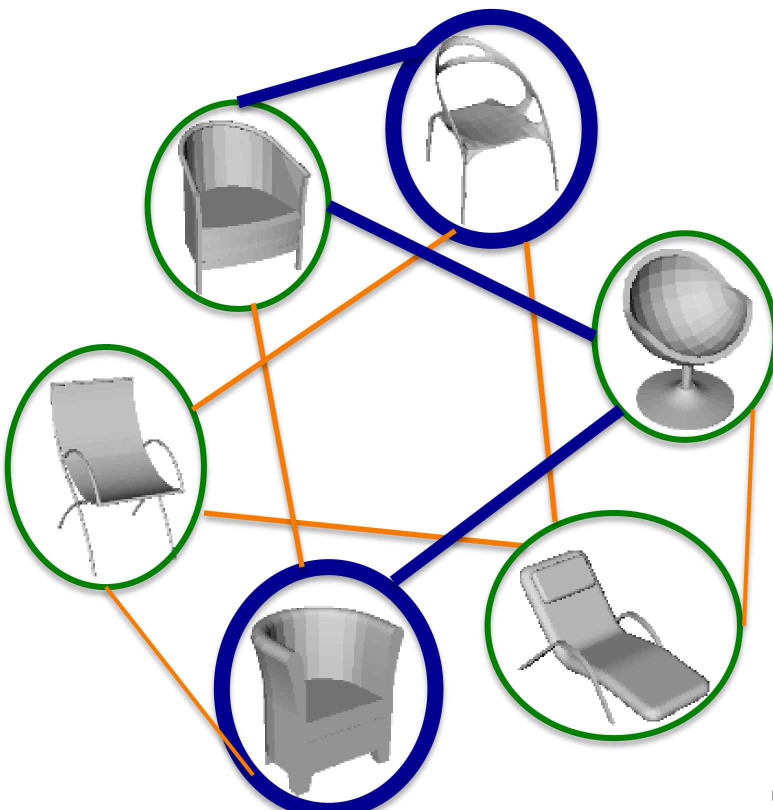

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Computing Fuzzy Correspondences

1. Sample points on each model
2. Select pairs of models to align
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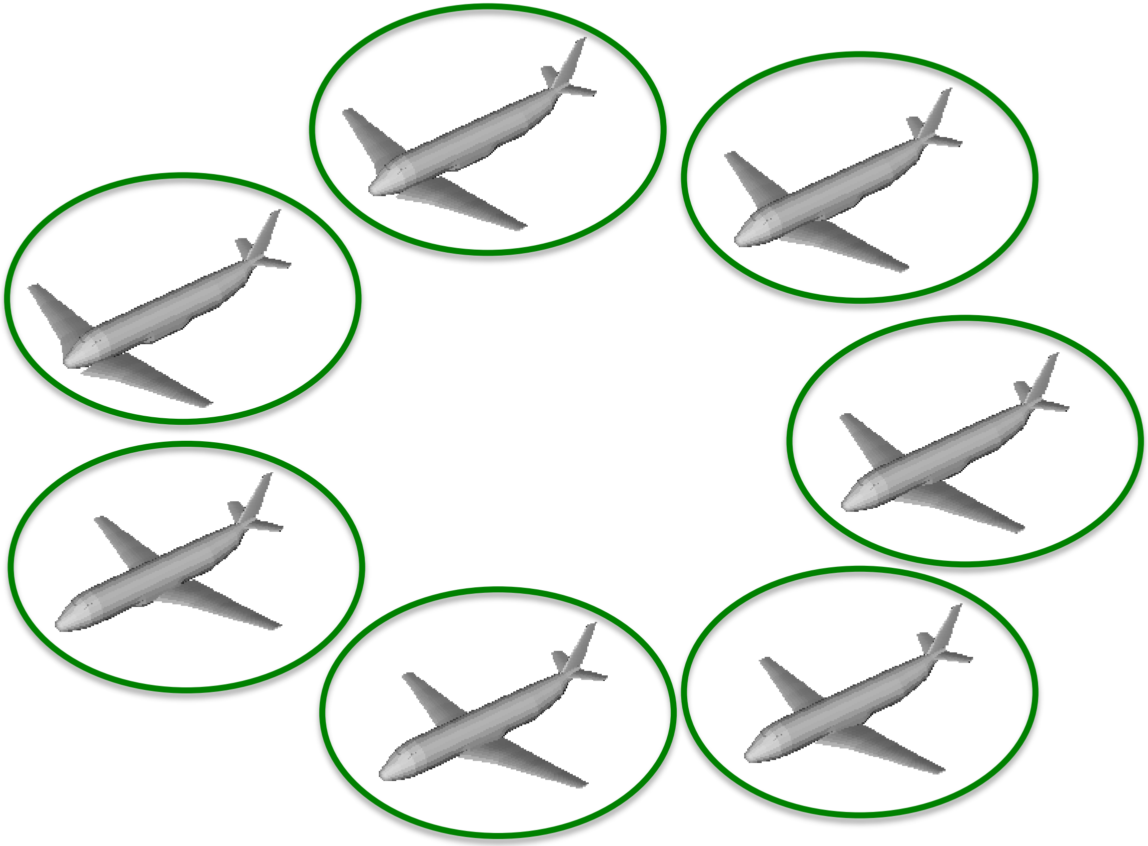
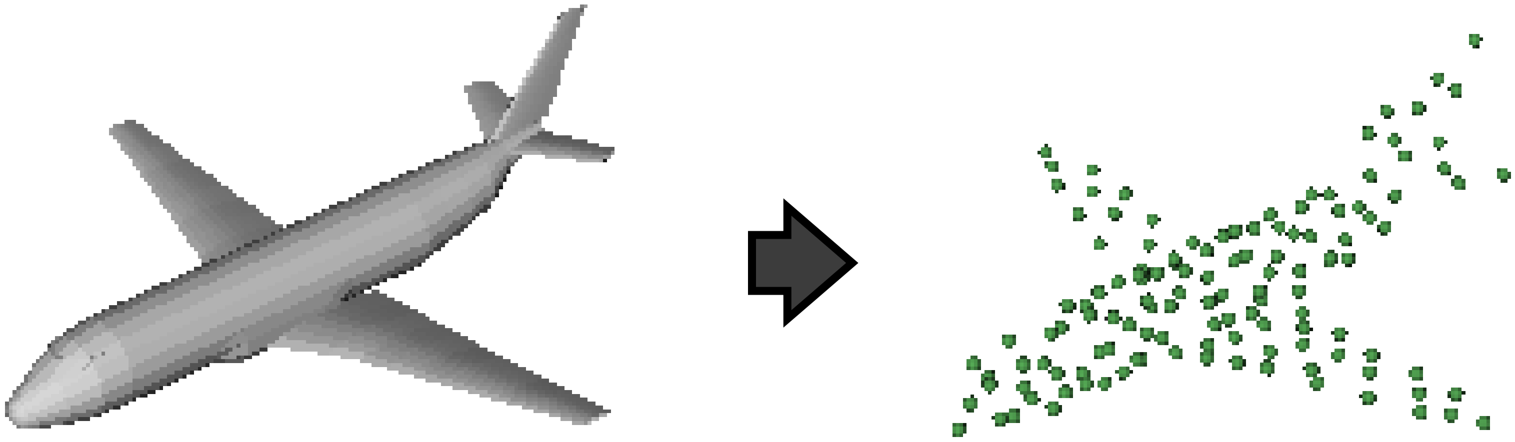
   Go to 4

Example Collection



Step 1: Sample Points

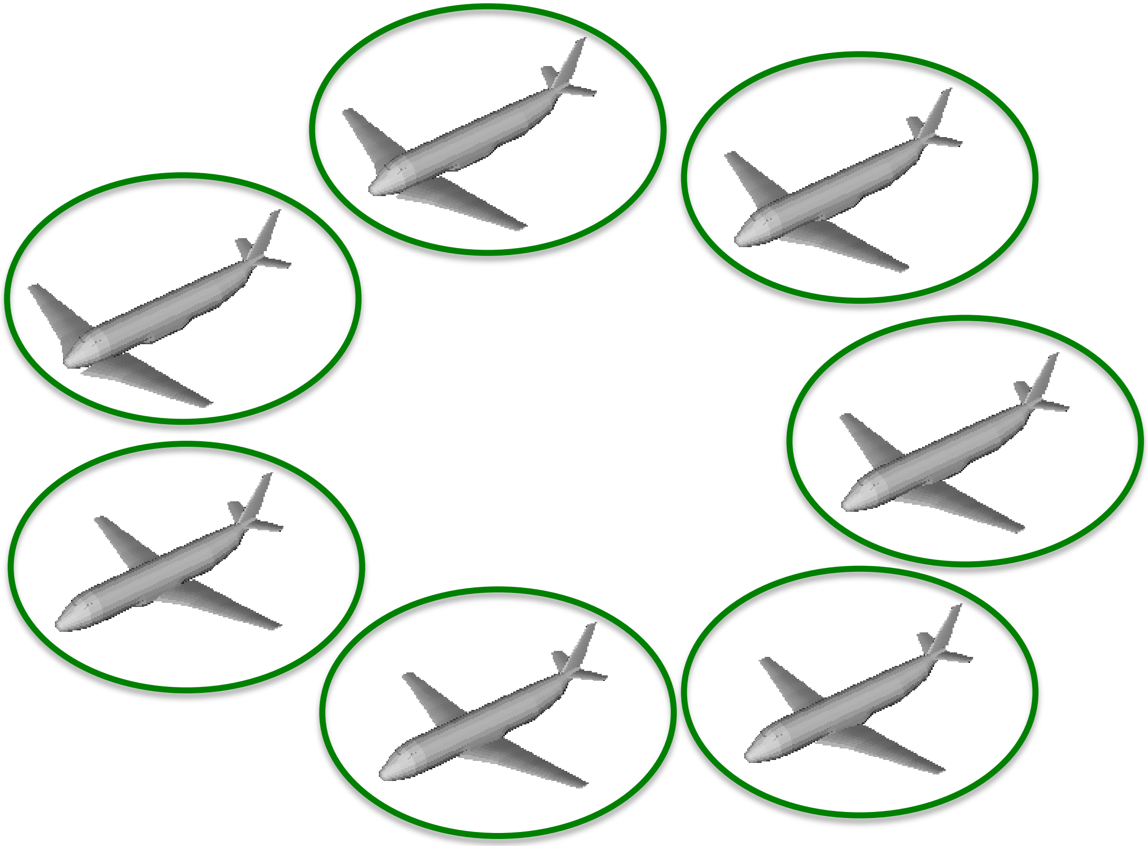


Input Model

K Points

Step 2: Select Models To Align

Find pairs of models that can be aligned robustly and form a well-connected graph



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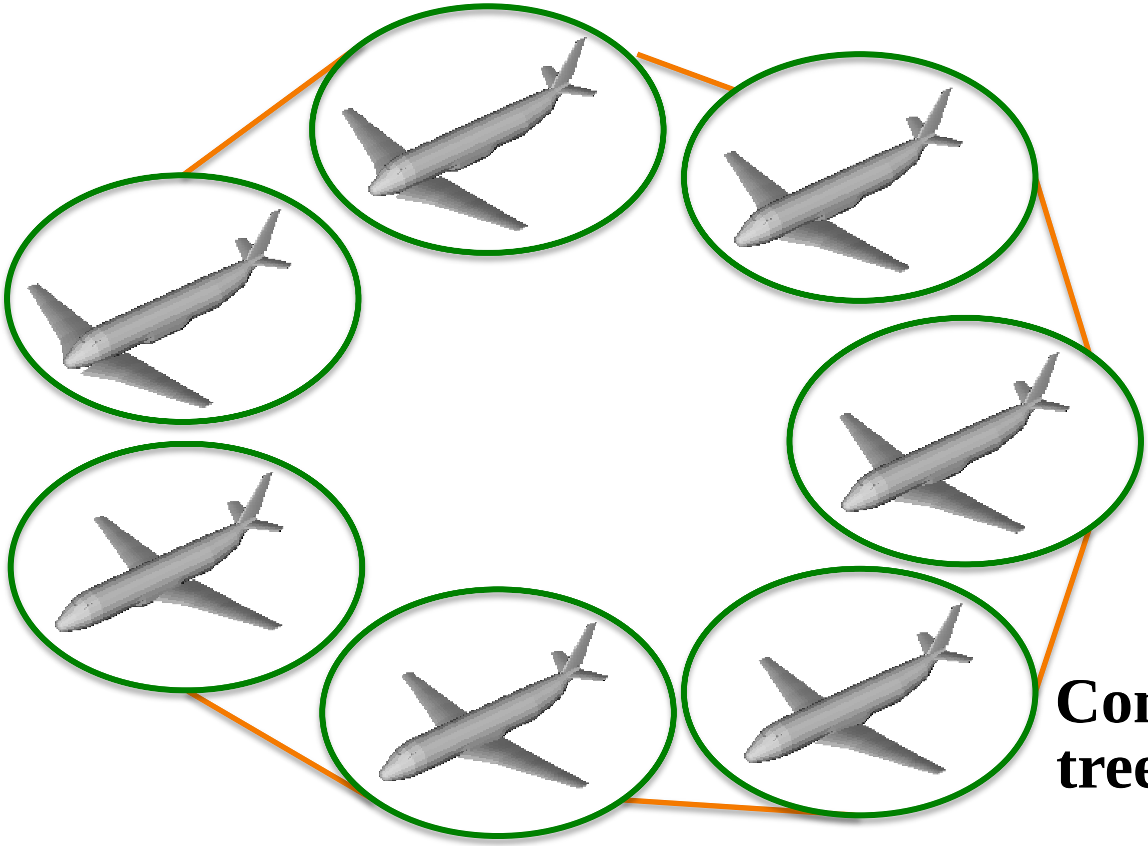

Compute minimum spanning tree based on shape similarity

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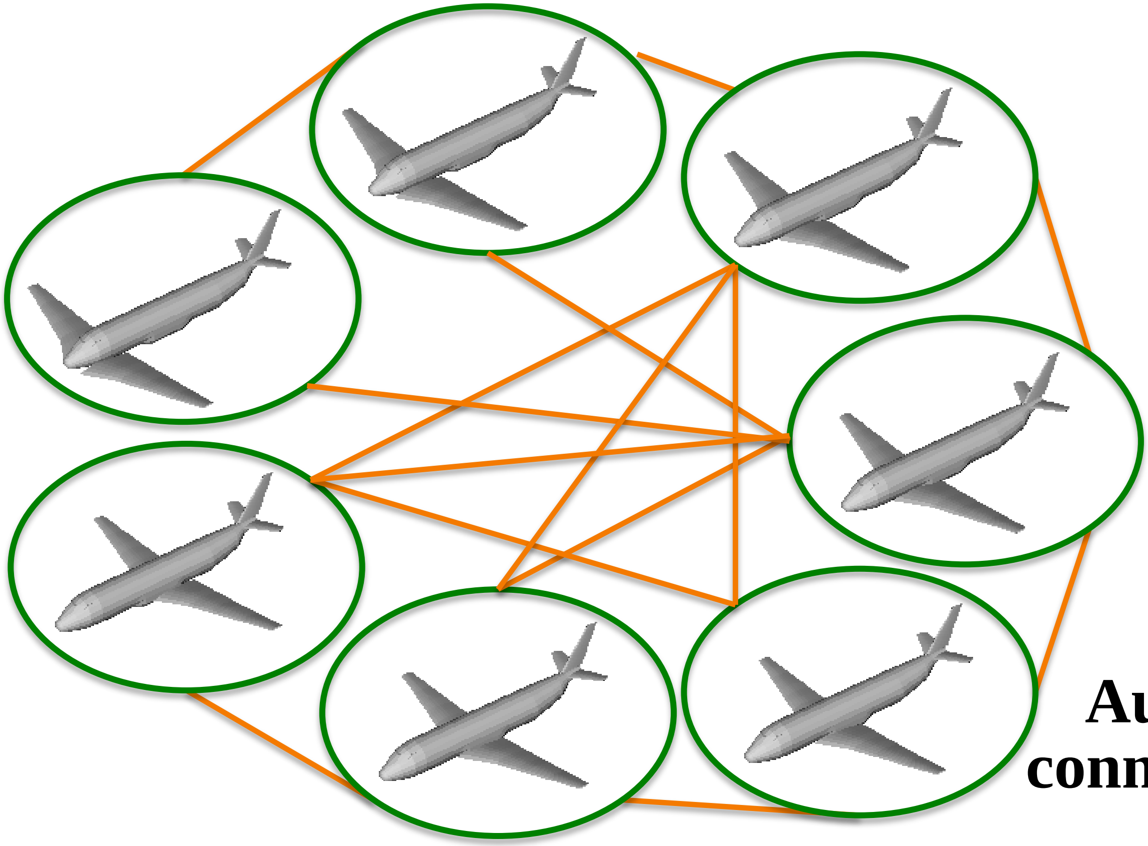

Augment graph to increase connectivity based on edge rank

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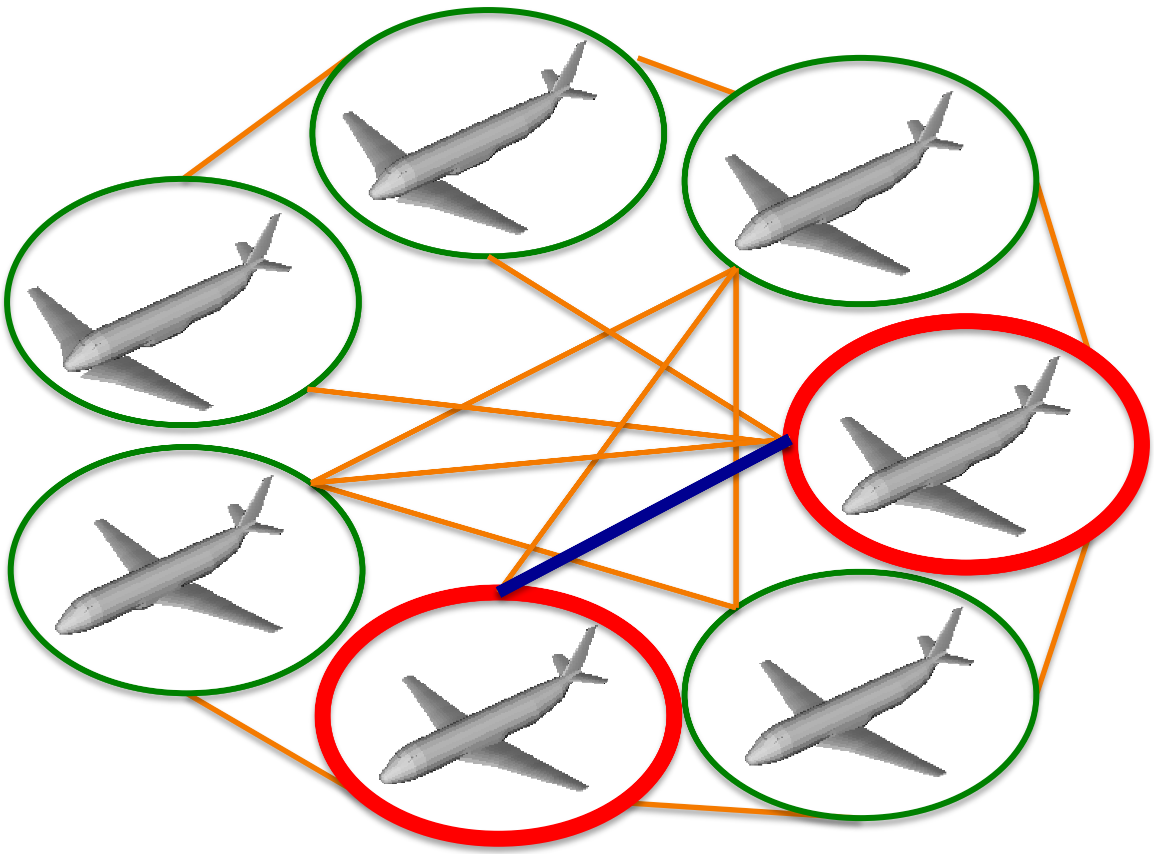
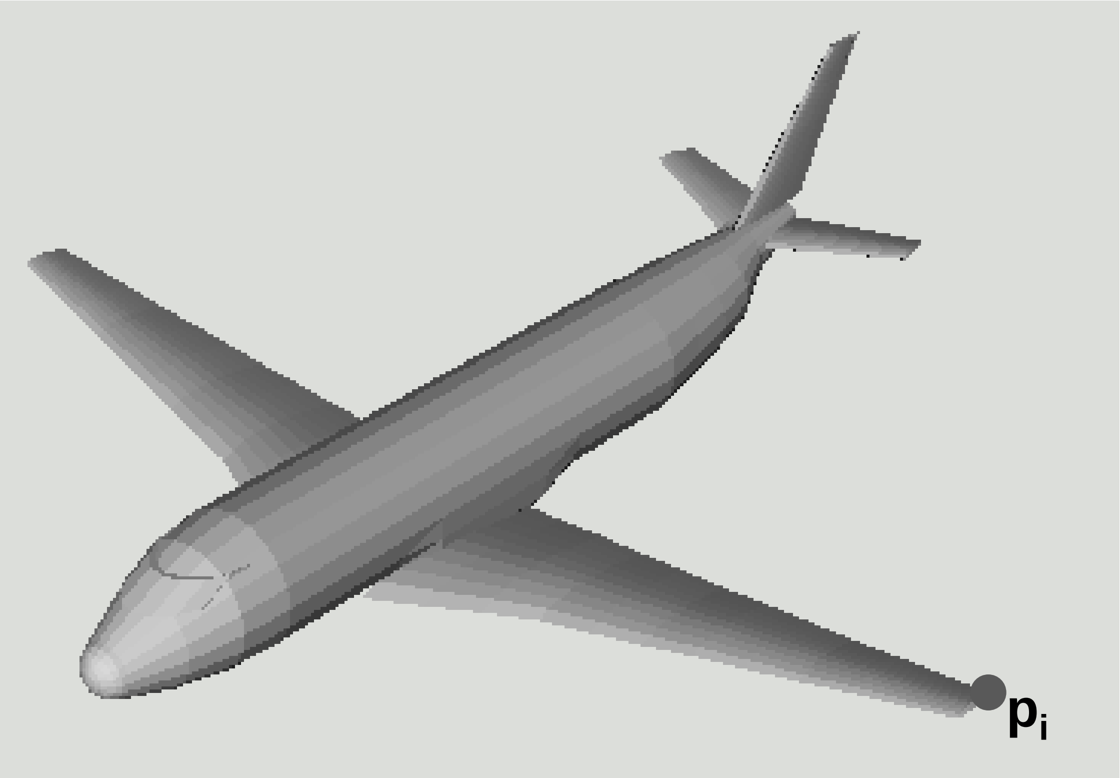


Step 3: Estimate Correspondence

Align selected pairs of models to estimate correspondence $C(p_i, p_j)$ between points



Rigid Alignment
PCA + ICP

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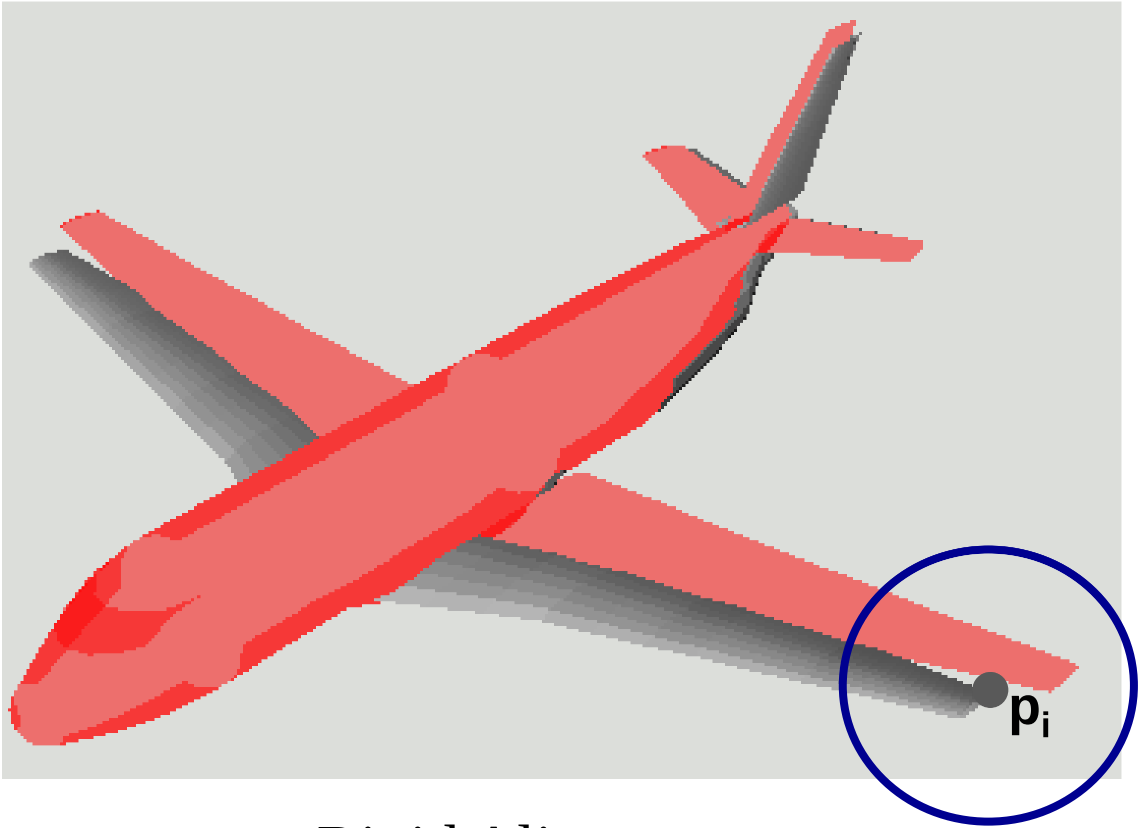

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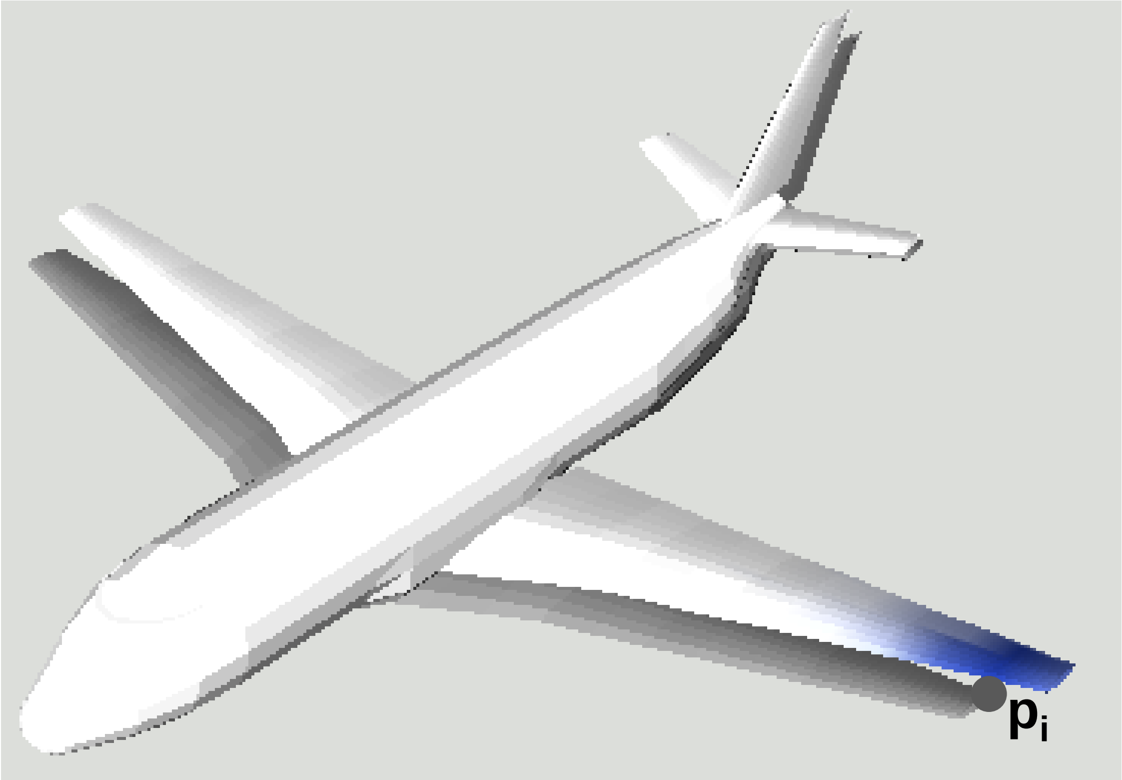

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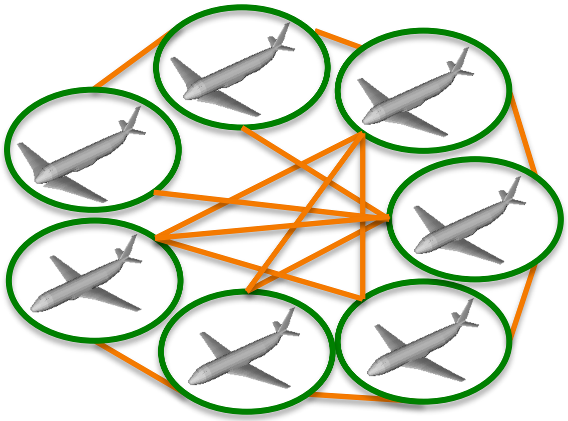

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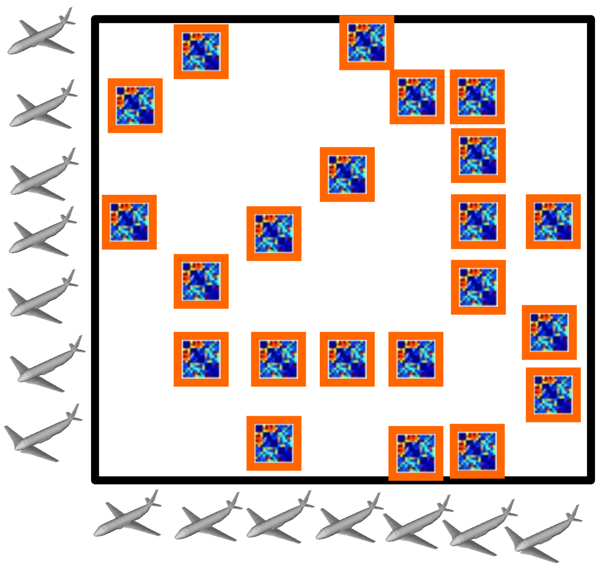

Sparse Correspondence Matrix $C(p_i,p_j)$

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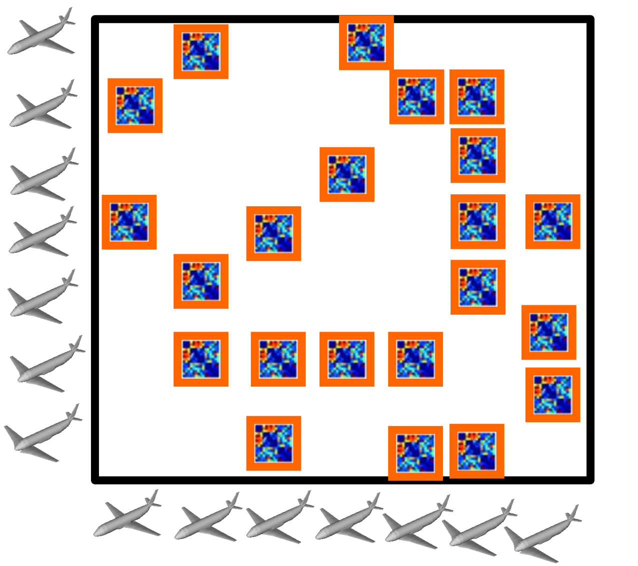

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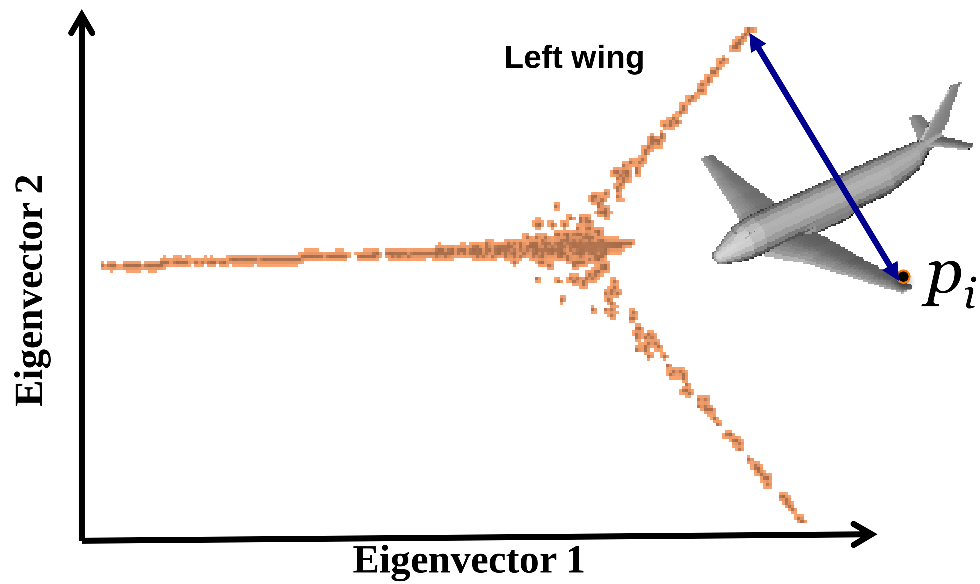

Spectral Embedding

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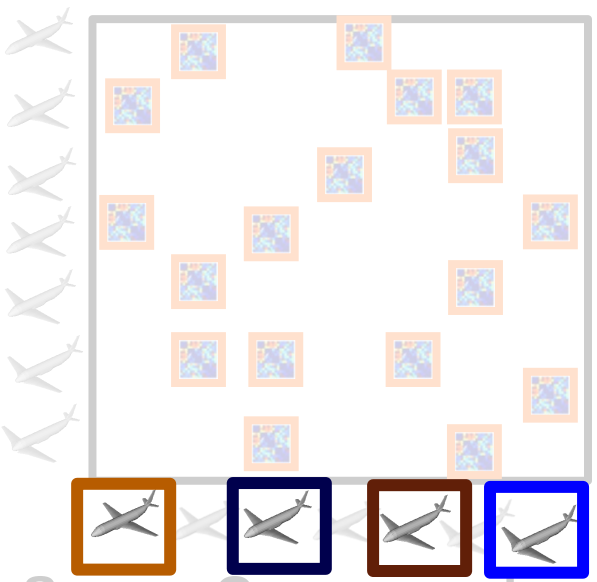

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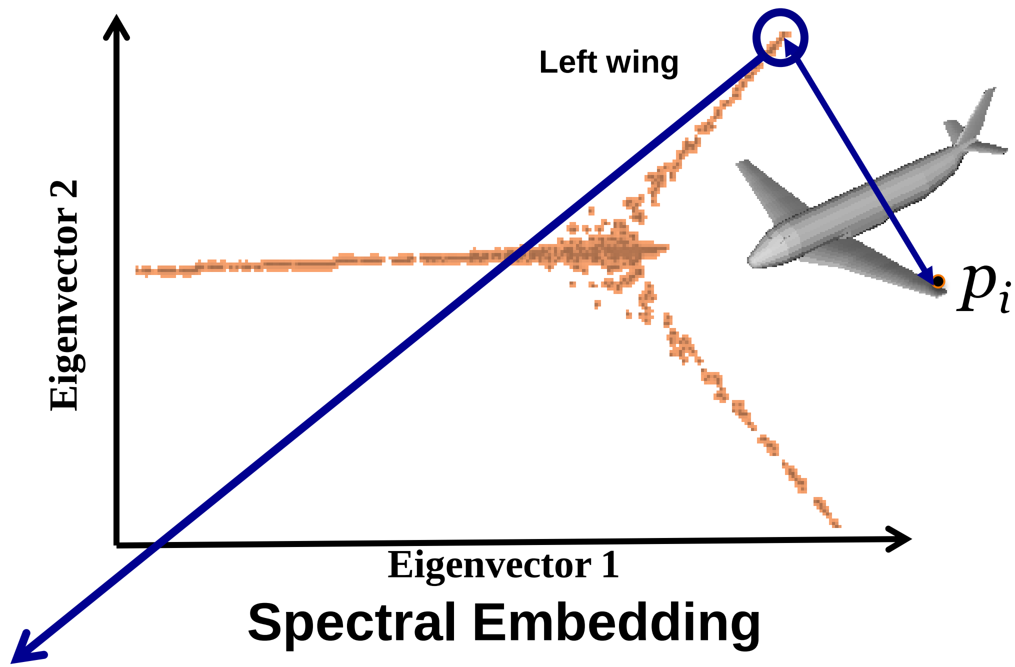

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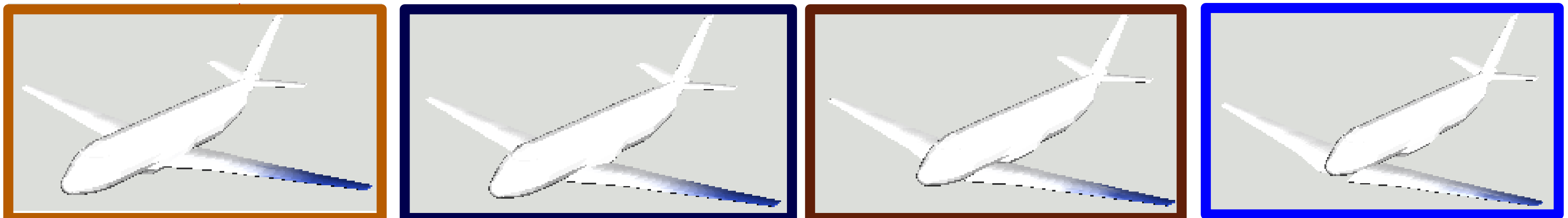

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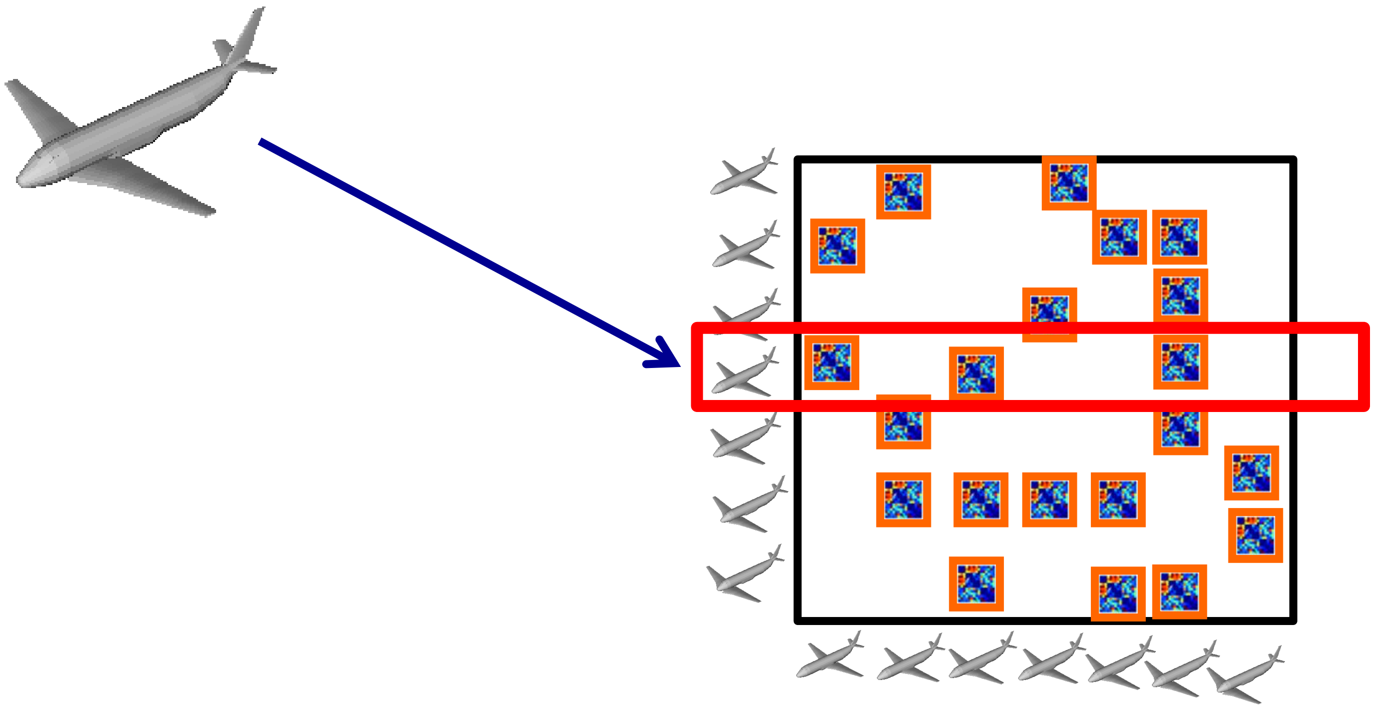

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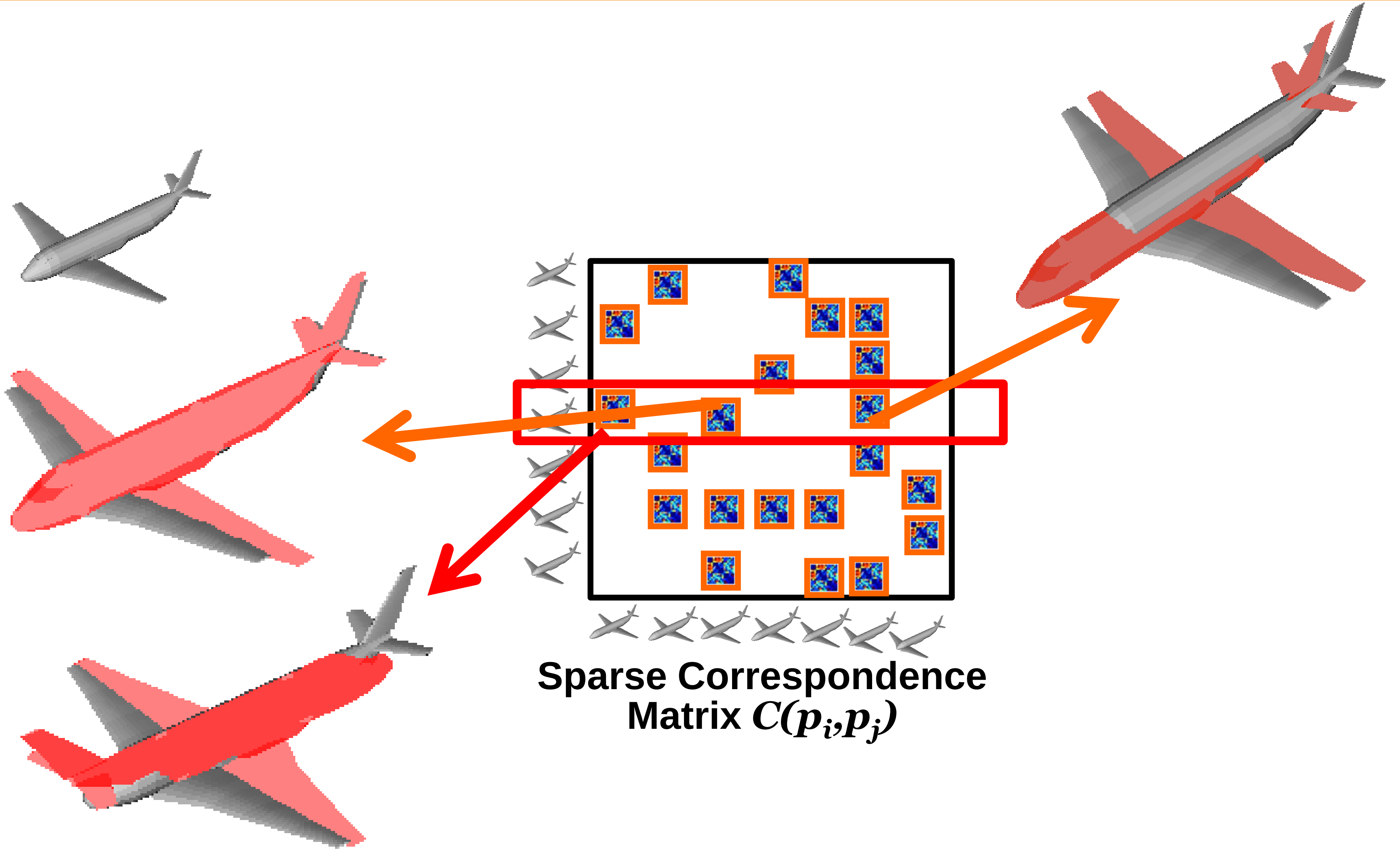

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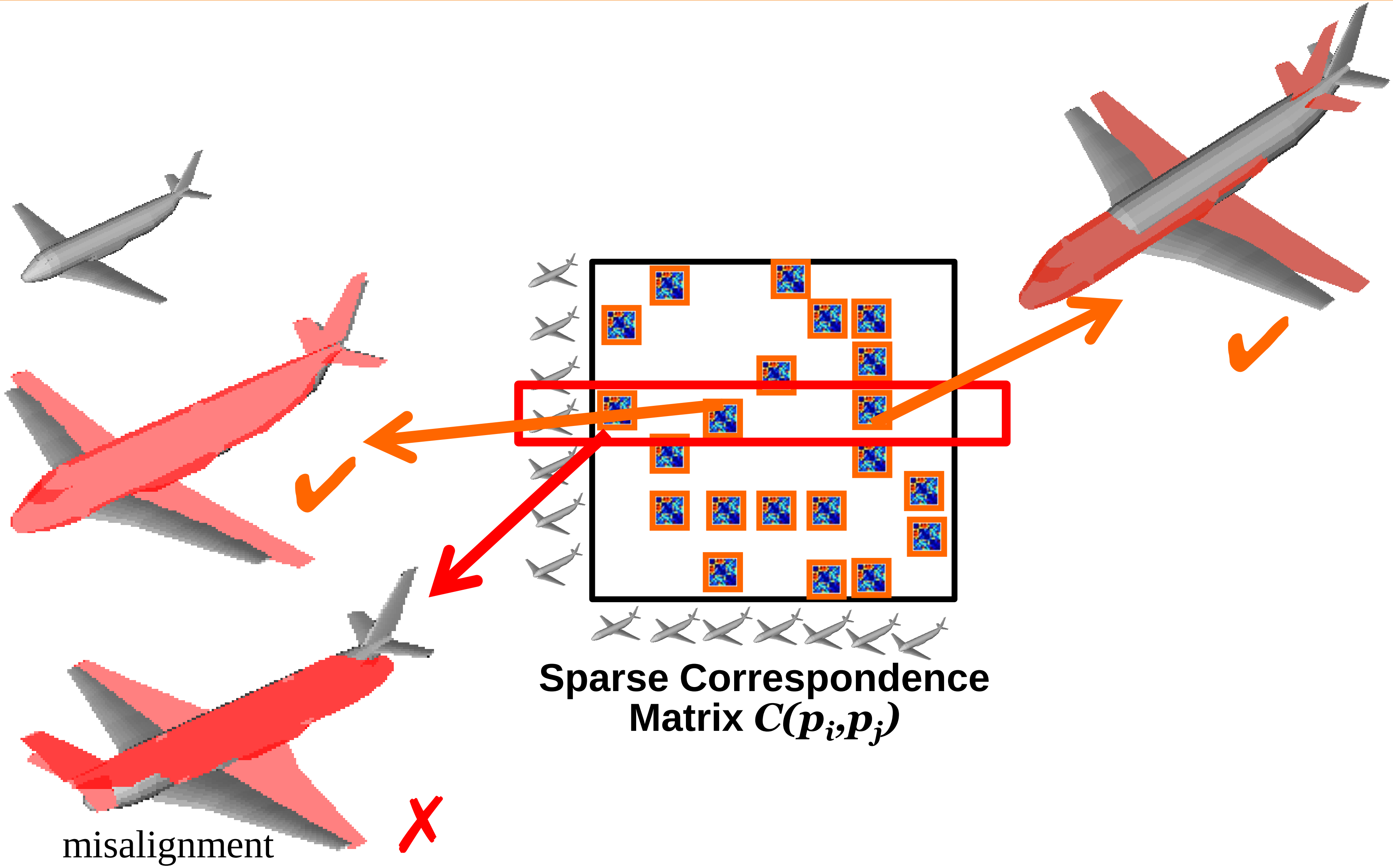

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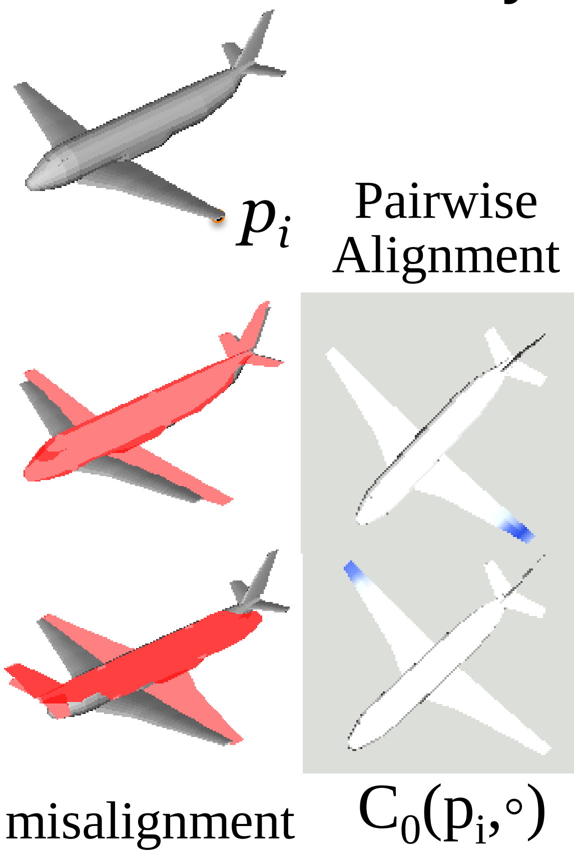

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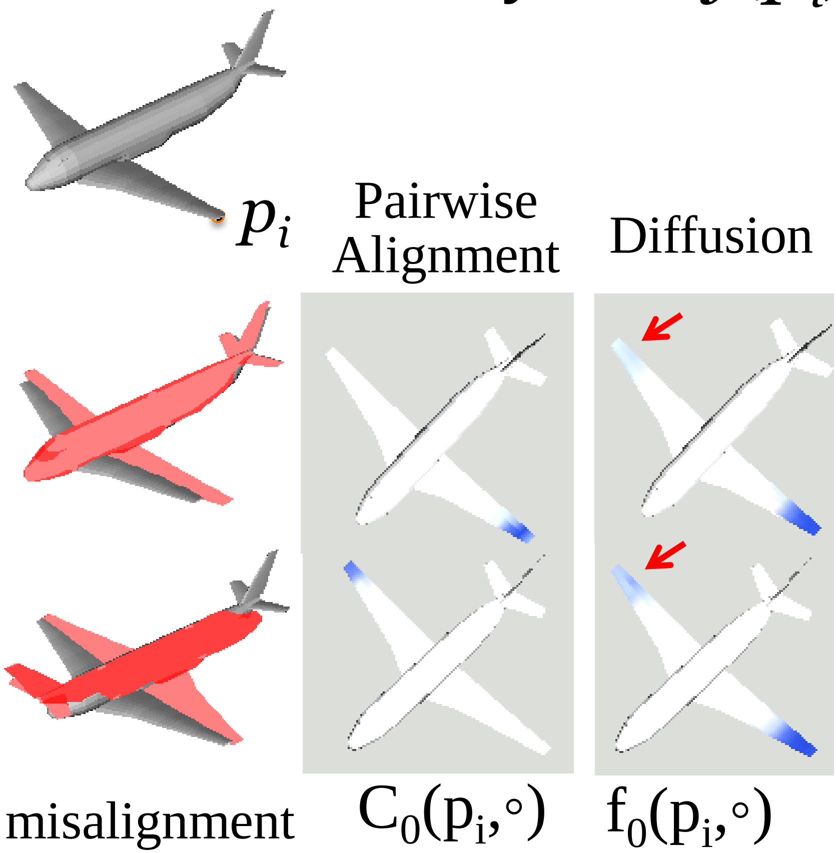

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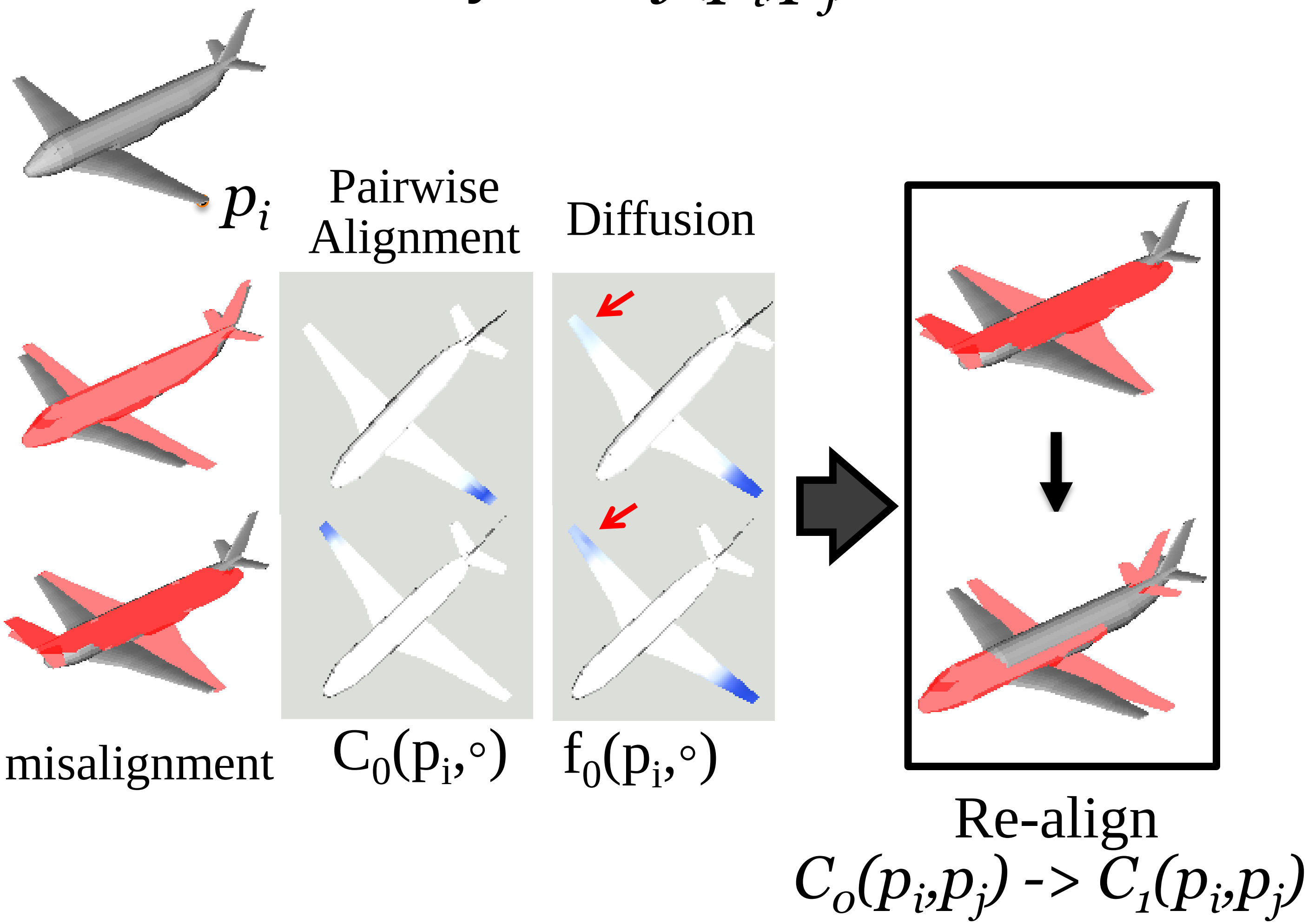

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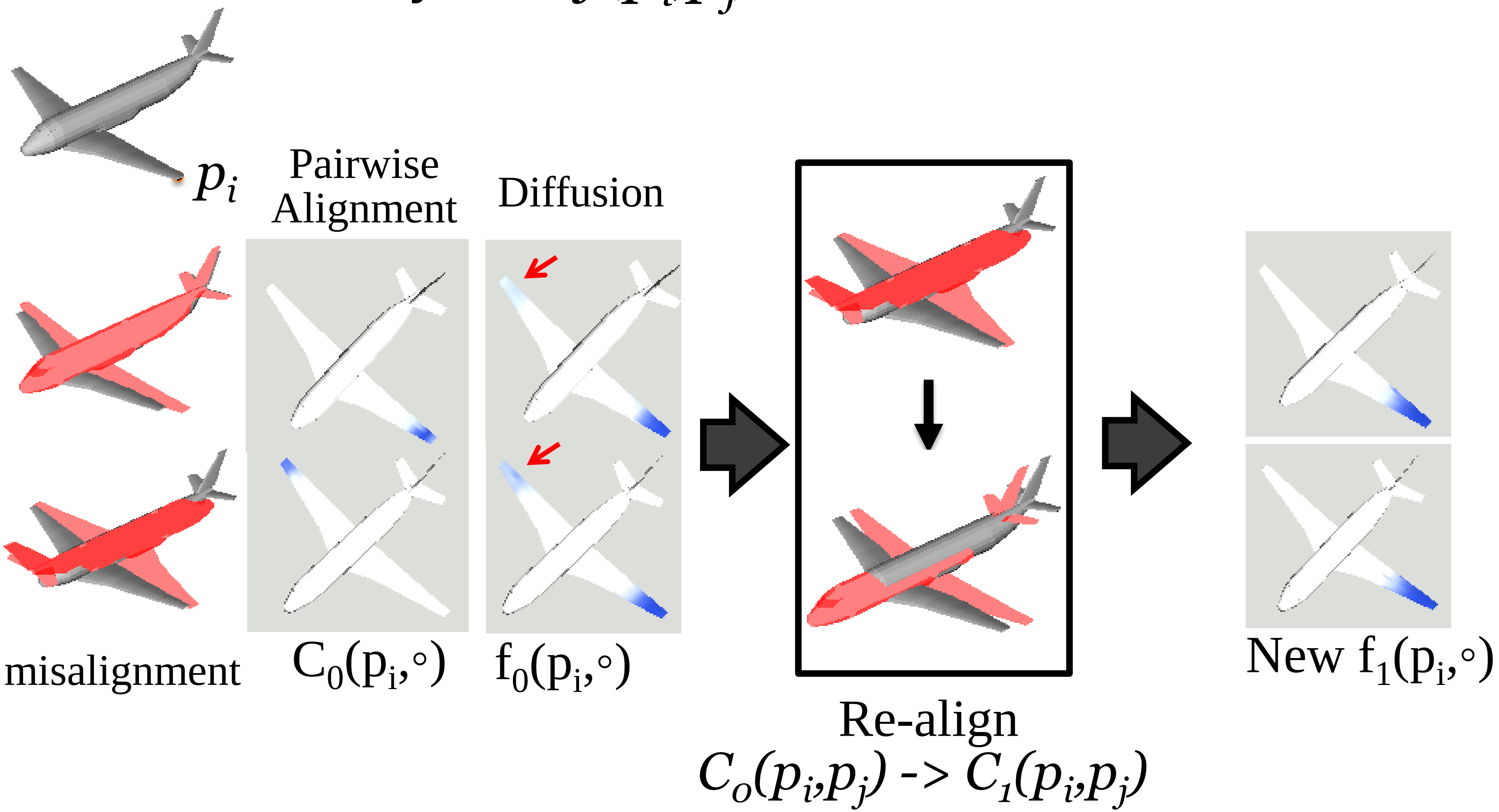

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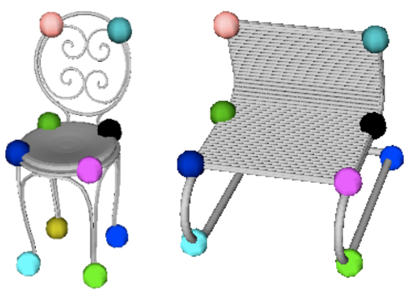
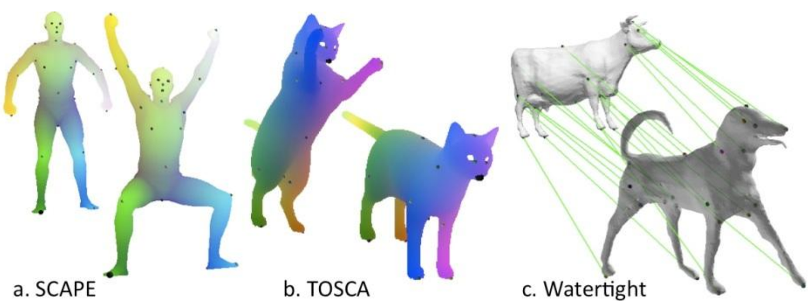
Quantitative Evaluation – refer to paper

Experiments:

- Diffusion and optimization improve correspondences
- Far less than N^2 alignments are necessary
- Larger collections yield better correspondences
- Our method compare favorably on benchmarks

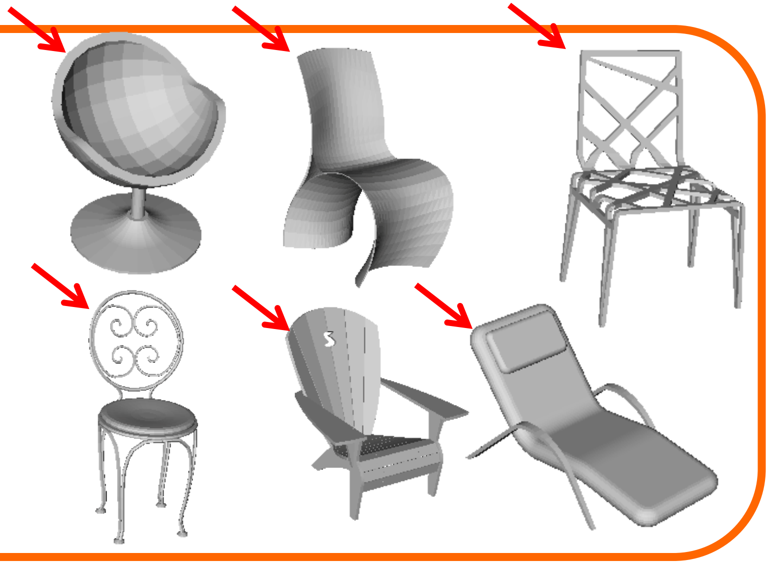


Chairs, Bikes, & Airplanes
from Google 3D Warehouse
[Kim et al. 2012]

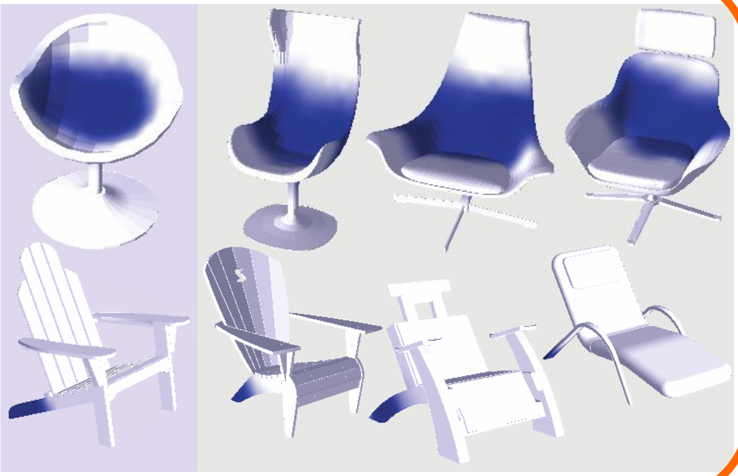


Nonrigid Surface Alignment Benchmarks
[Kim et al, 2011]
[Nguyen et al., 2011]

Correspondences



Exploration Tool



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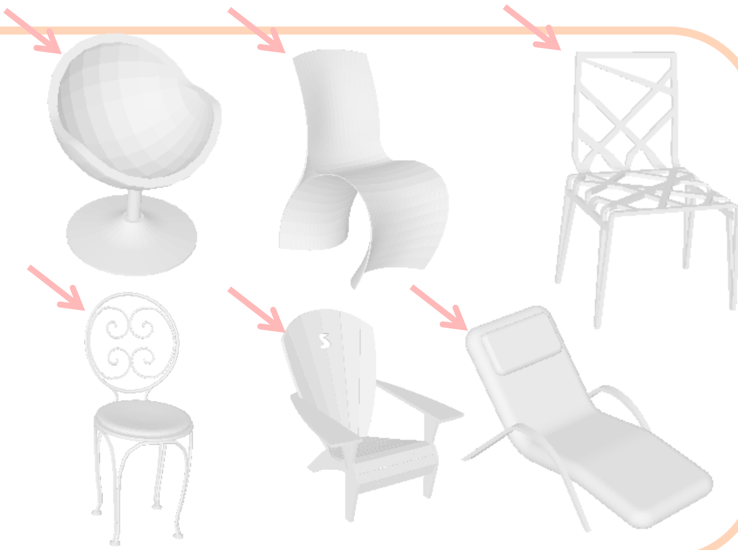

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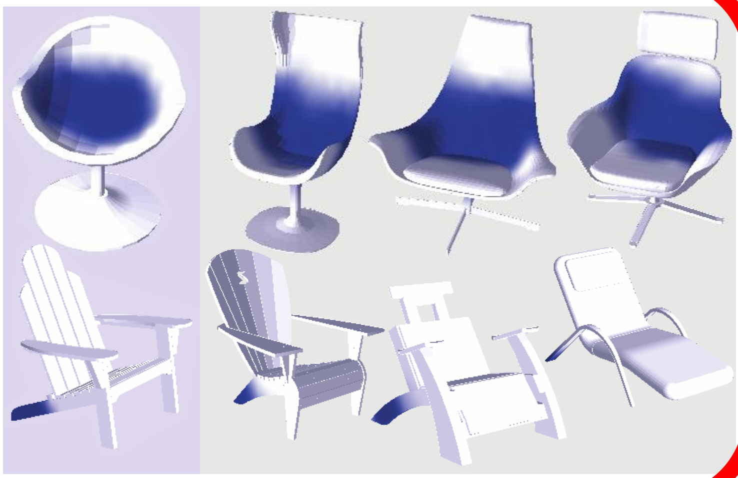


Exploration Tool

Key features enabled by fuzzy correspondences

- Find variations
- Align viewpoints
- Sort by similarity

Finding Variations

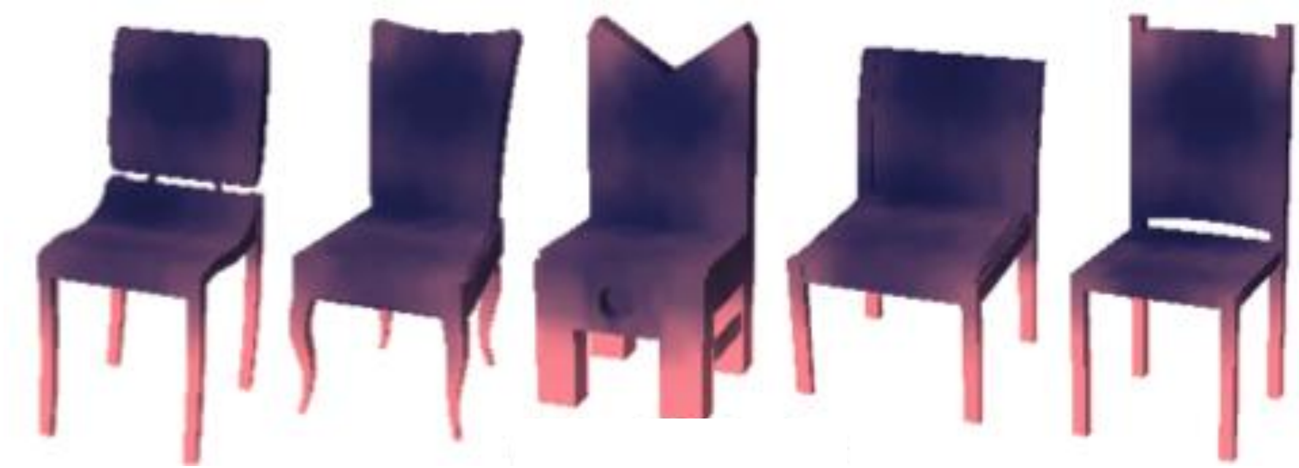
Finding Variations

Distance to Xth closest fuzzy correspondence can reveal amount of shape variation in data set

More Variation

Finding Variations

Distance to Xth closest fuzzy correspondence can reveal amount of shape variation in data set



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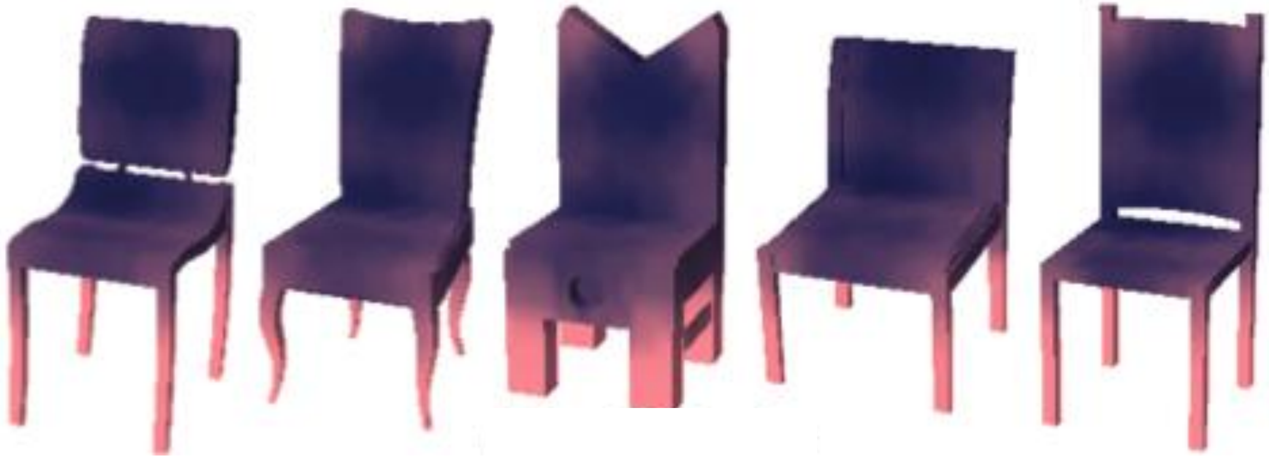
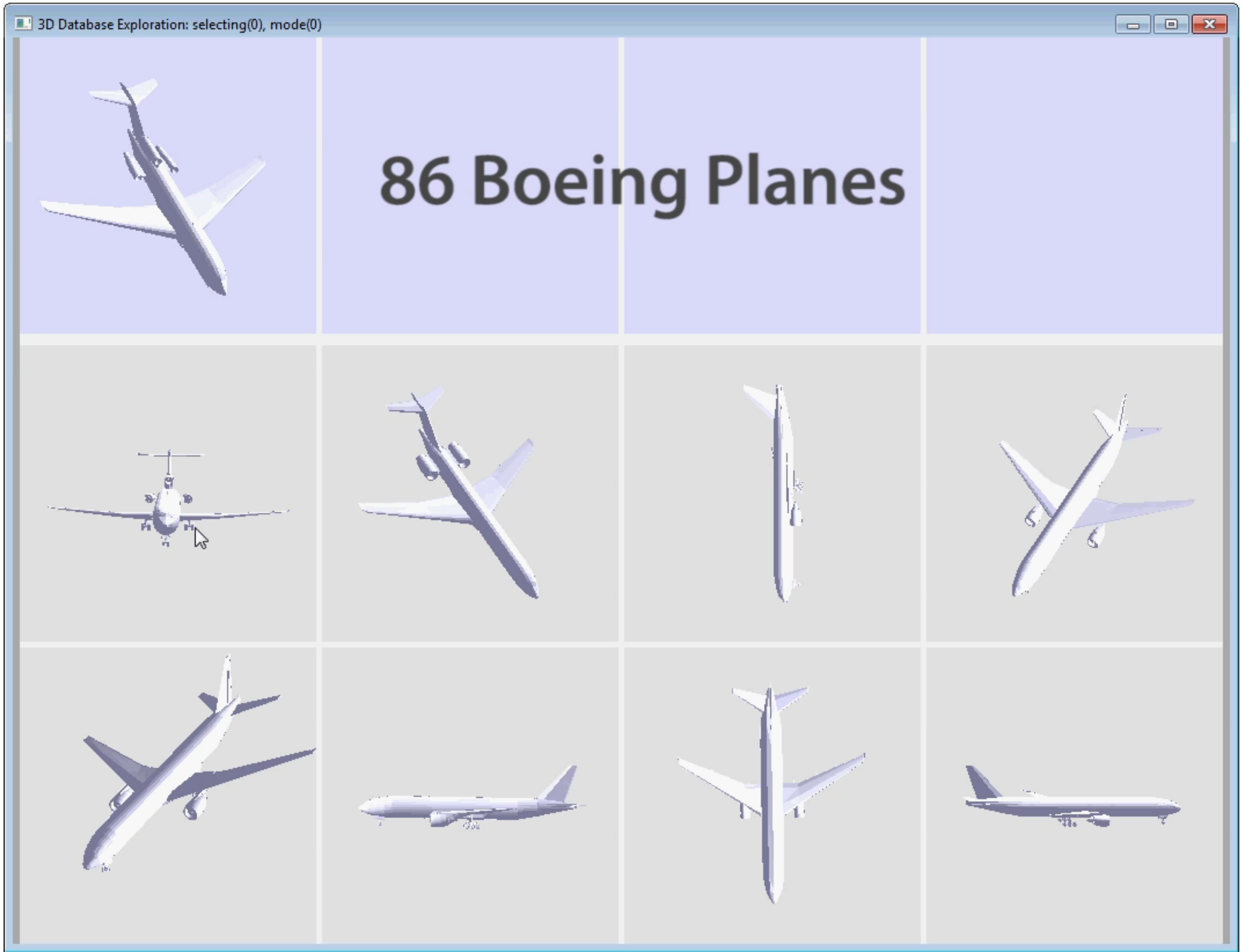


Collection 2:

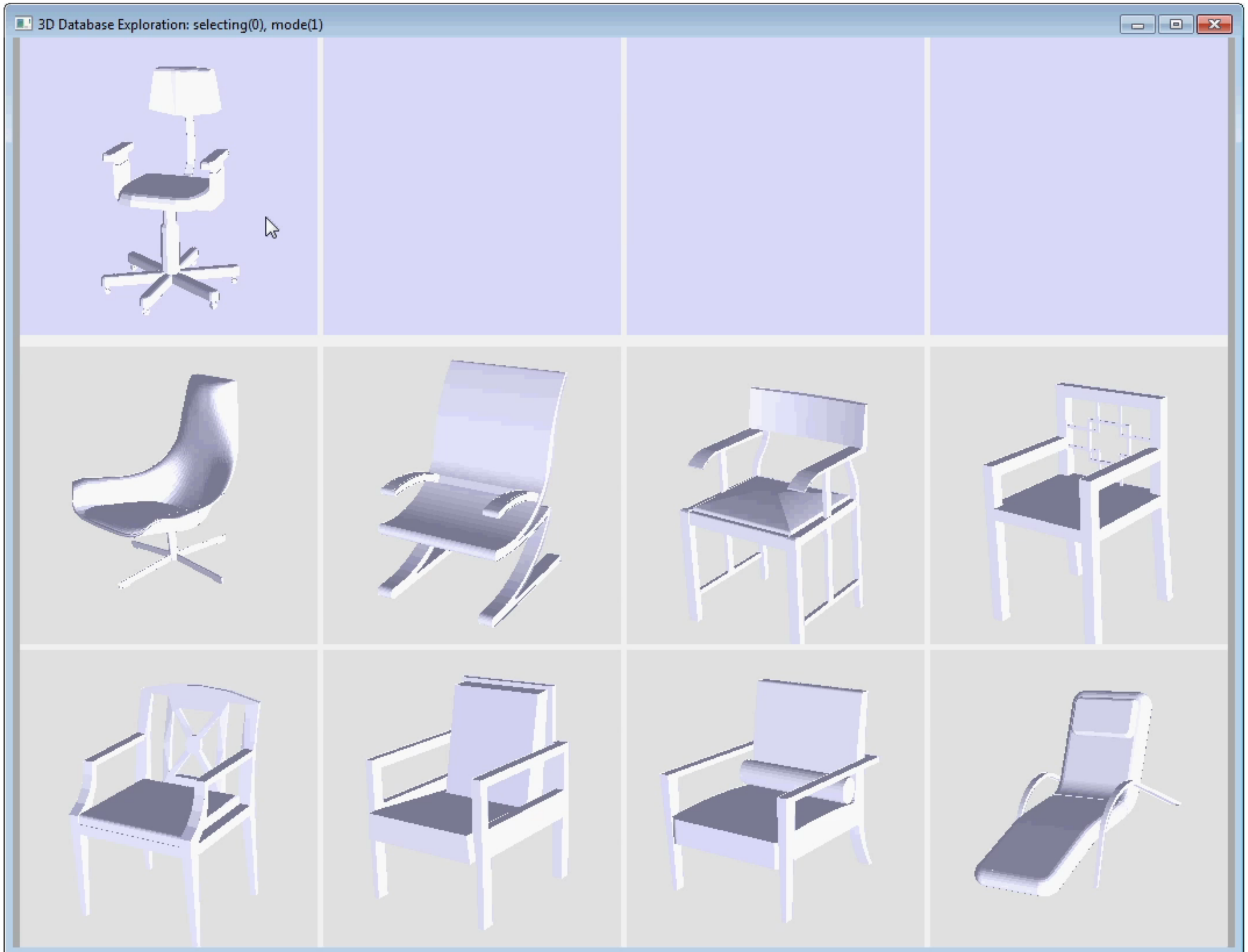
Aligning Models

Find best alignment weighted by fuzzy corrs.



Sorting by Similarity

Sort based on similarity in aligned regions



Sorting by Similarity: Intrinsic Matching

Sort based on similarity in aligned regions

Sorting with Multiple Facets

Provide several similarity objectives

Timing

Fuzzy Correspondences for 111 chairs

- Pairwise alignments ≈ 100s (602 / 6105 alignments)
- Iterative Optimization ≈ 800s (11 iterations)

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Fuzzy Correspondences for 71 SCAPE models

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Exploration tool

- Real time interaction

Summary

Fuzzy Correspondences via Diffusion

- Represent ambiguity in mapping
- More robust: easier to compare similar shapes
- Far less than N^2 pairwise alignments are required

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- Represent ambiguity in mapping
- More robust: easier to compare similar shapes
- Far less than N^2 pairwise alignments are required

Exploration with Fuzzy Correspondences

- Allows navigating in shape space by interactively selecting regions of interest

Future Work

Short-term

- Consistent bias in misalignments not always resolved by diffusion
- More diverse datasets (e.g. all classes jointly)
- Larger collections

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Long-term:

- Higher-level understanding of collections of shapes
- Data-driven Analysis: segmentation, labeling
- Data-driven Synthesis: assembly-based modeling

Acknowledgments + Our code

Data:

- Brown et al. (3D Warehouse), Giorgi et al. (SHREC Watertight), Anguelov et al. (SCAPE), Bronstein et al. (TOSCA)

Funding:

- NSERC, NSF, AFOSR, Intel, Google, Adobe, Marie Curie Career Integration Grant

Discussions and suggestions:

- Marc Alexa, Yaron Lipman, Amit Singer

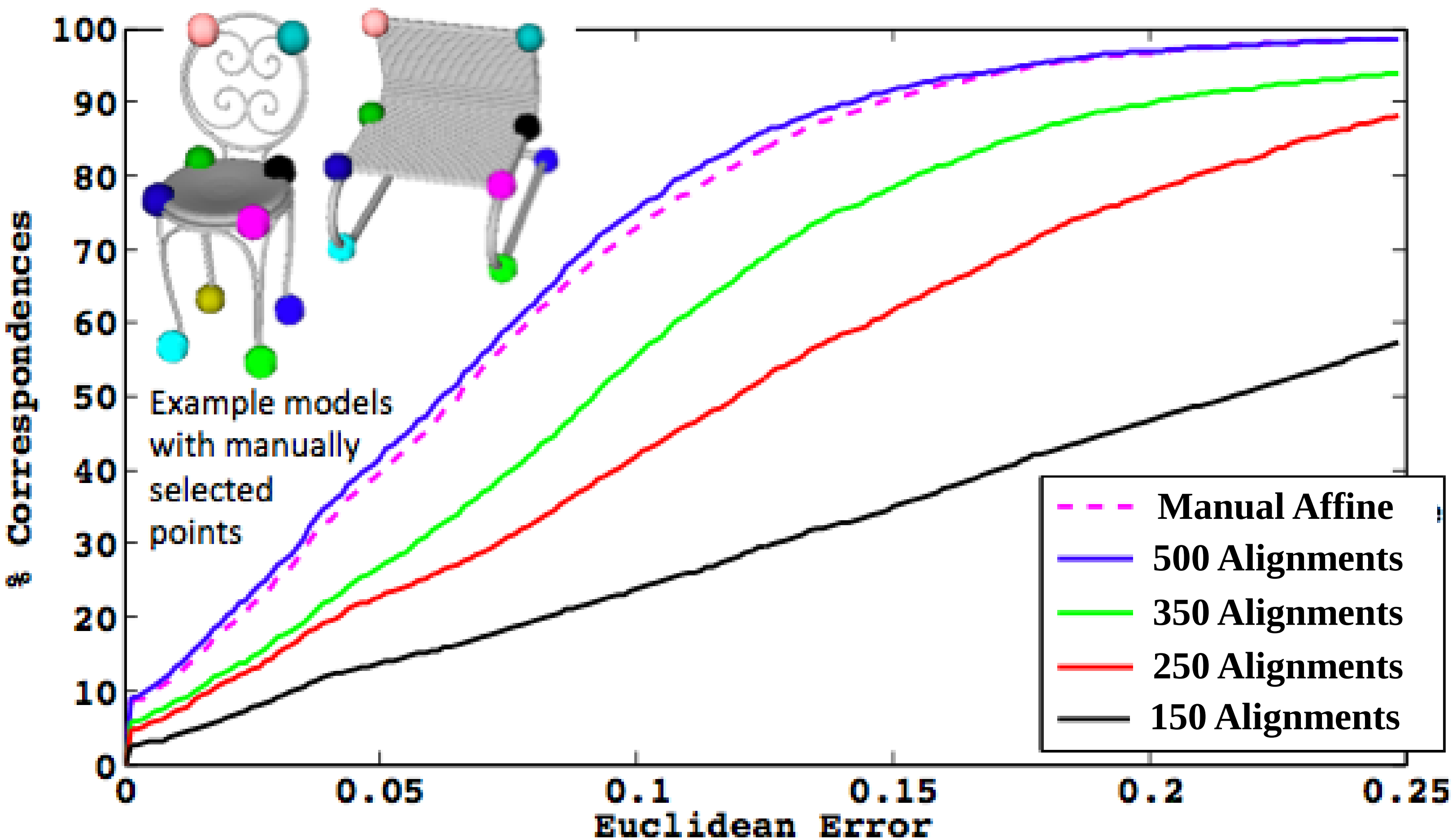
CODE AND DATA

http://www.cs.princeton.edu/~vk/CorrsFuzzy

Additional Slides

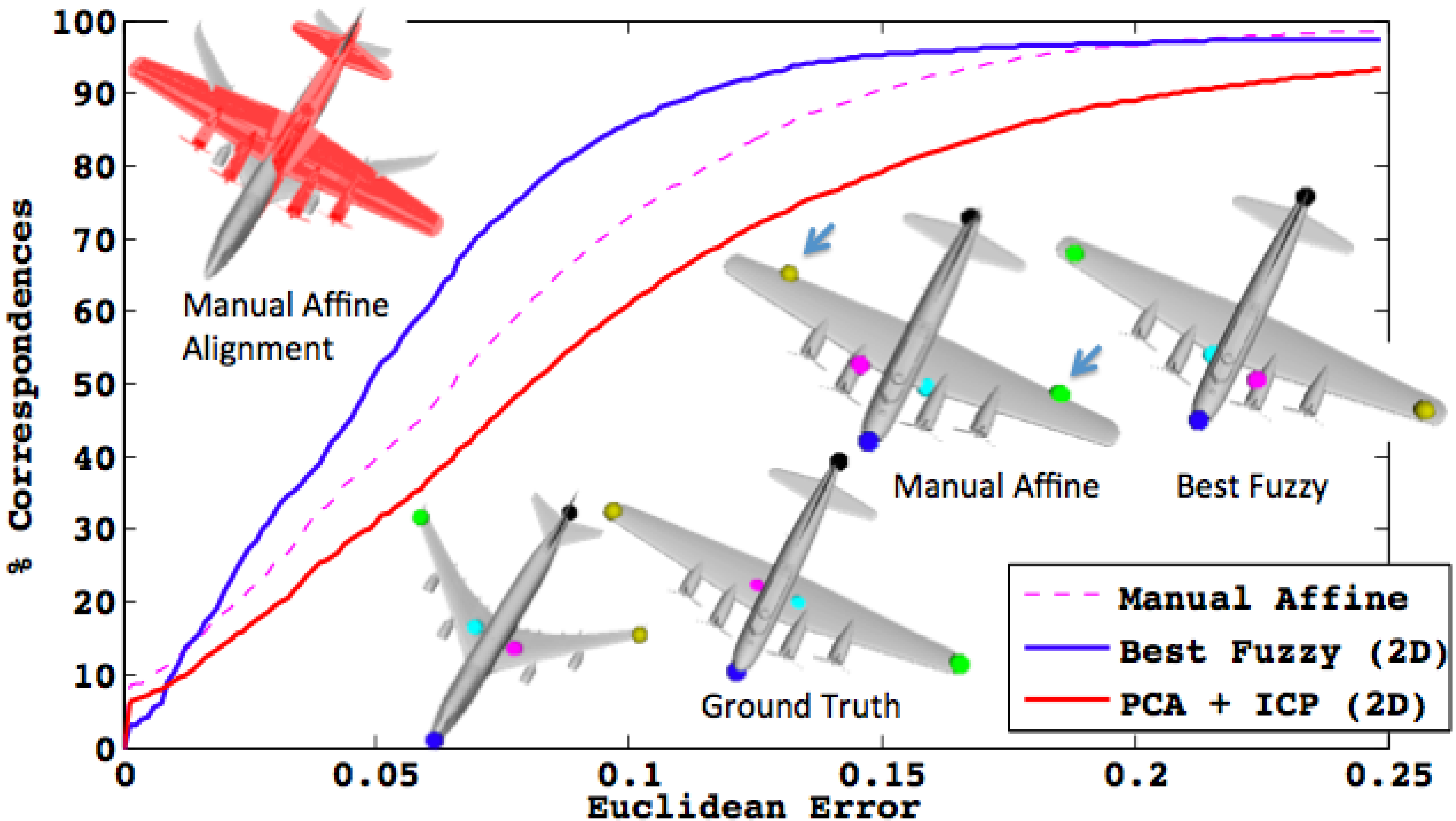
Results

A small subset of pairwise alignments suffices



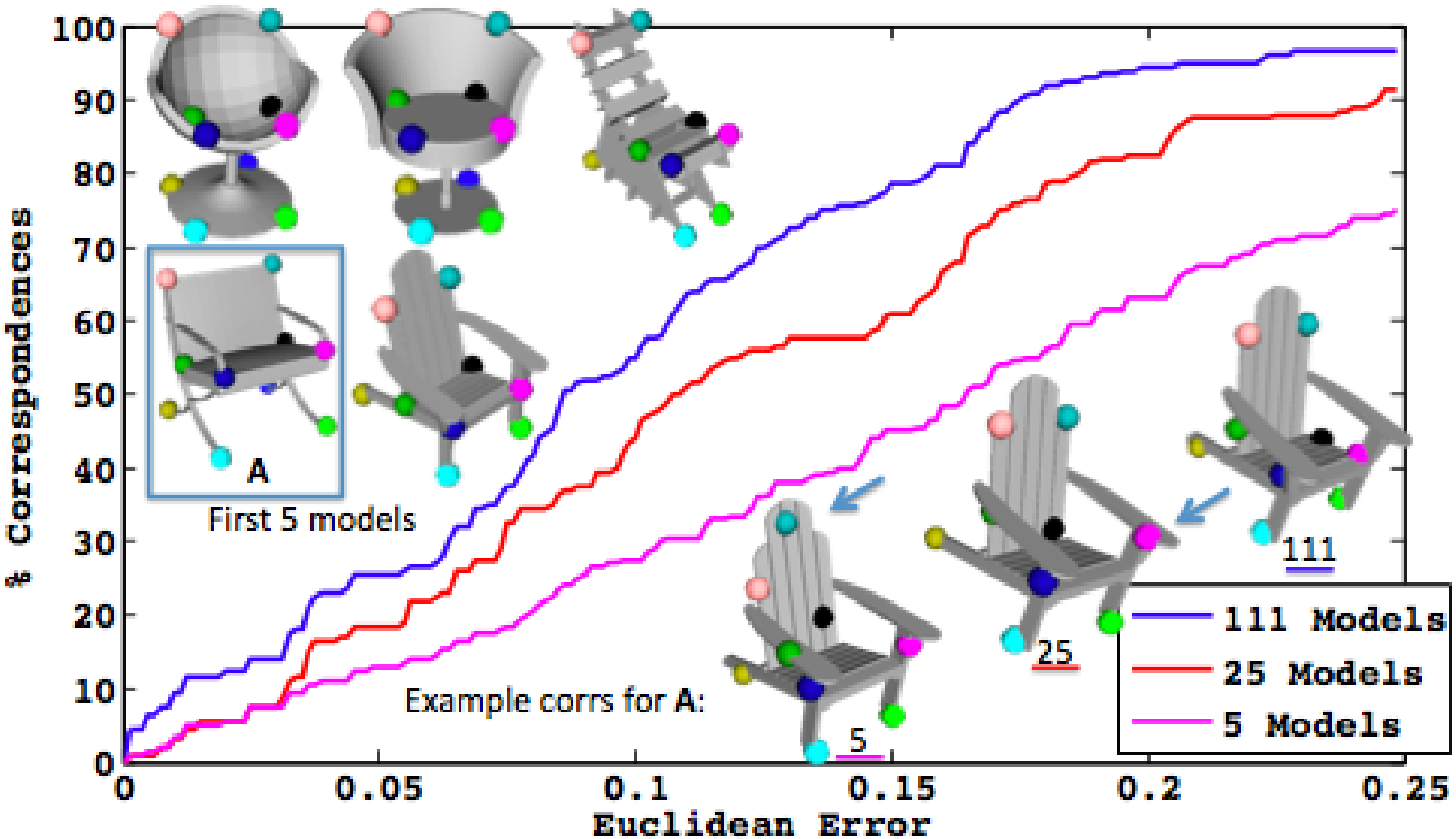
Results

Diffusion & optimization improve correspondences



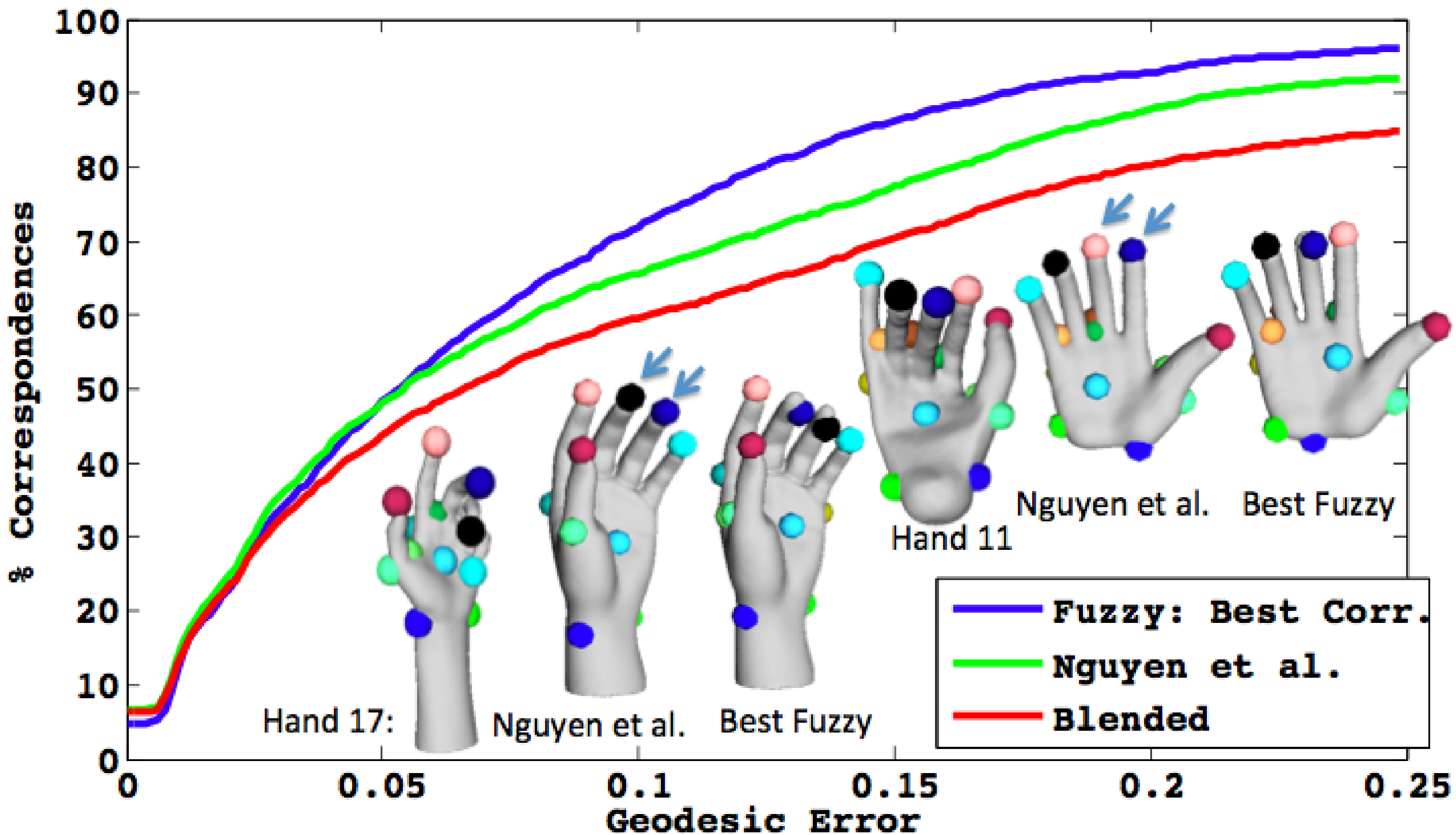
Results

Larger collections yield better correspondences



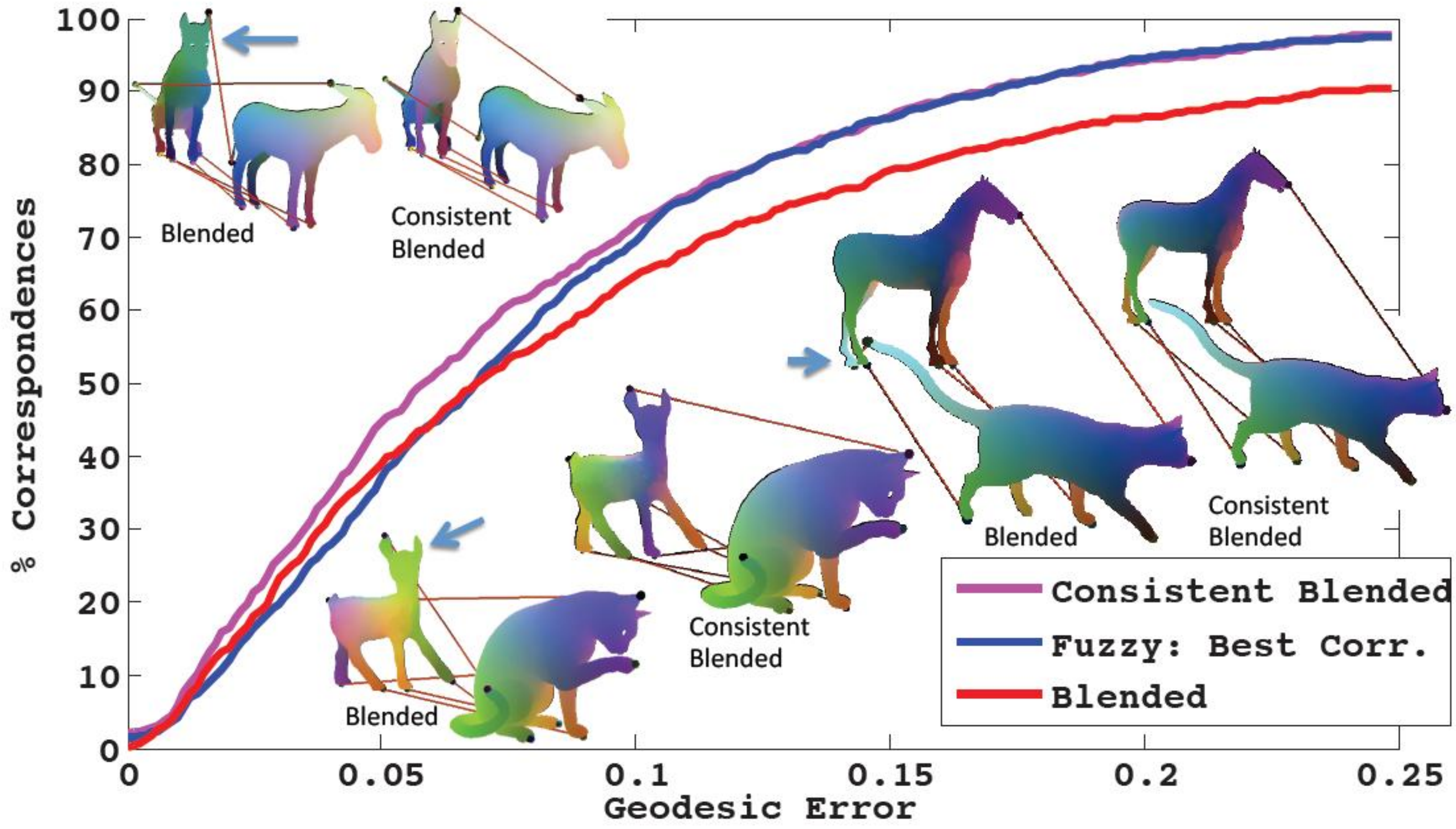
Results

Best results on examples in [Nguyen et al., 2011]



Results

Best results on benchmark in [Kim et al. 2011]



Future Work

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- More diverse datasets (e.g. all classes jointly)
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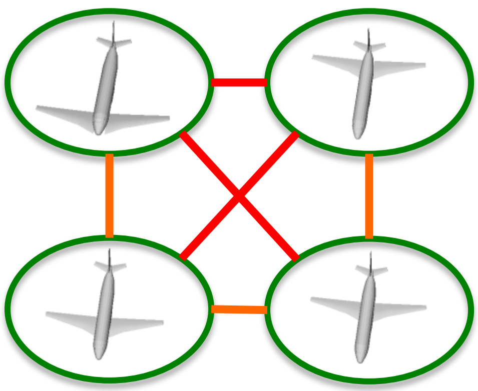
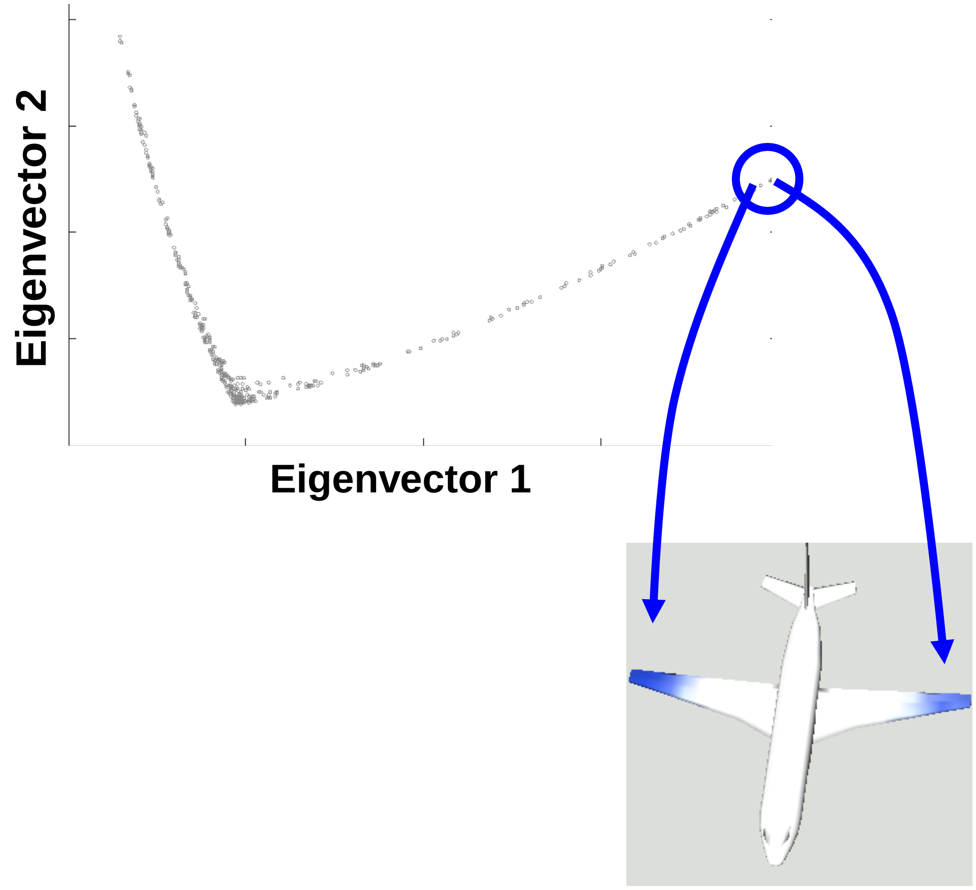
- (Near-)Symmetry





Future Work

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- Larger collections
- (Near-)Symmetry