MAY 2025

The University of Texas at Austin

SHARD: GLOBAL SHAPE-AWARE REASSEMBLY OF 3D FRACTURED OBJECTS

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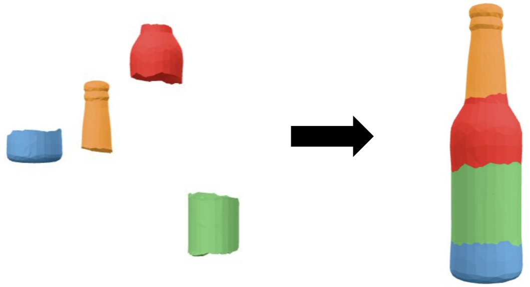
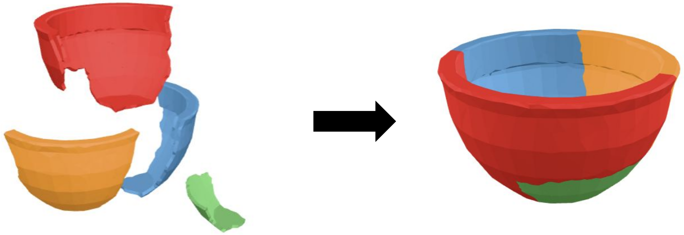
What is Reassembly?

- **<u>Task</u>**: Reconstructing physically broken 3D objects composed of multiple **fragments**
- Fragments typically have:
  - No knowledge of the original object (**global shape**)
  - No semantic / texture information
  - Extremely low overlap between fragments



Bottle Reassembly

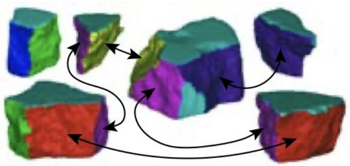


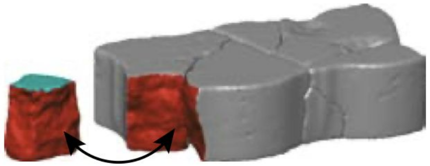
Bowl Reassembly

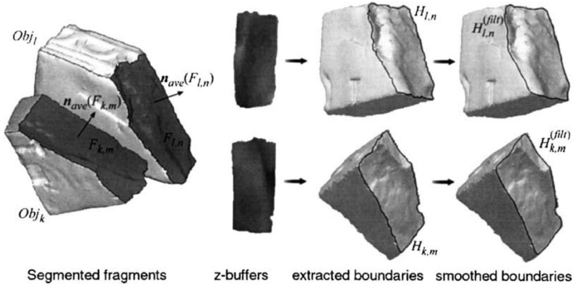
Silvia Sellan et al. "Breaking bad: A dataset for geometric fracture and re-assembly". In: Advances in Neural Information Processing Systems 35 (2022), pp. 38885–38898.

Early Approaches

- **Pairwise Approaches**
  - **No assumptions about the global shape**
  - **Handcrafted** geometric feature descriptors (roughness, curvature)
  - Fragment-fragment matching between **fractured surfaces**
  - **Greedy** & **global** strategies to minimize matching errors



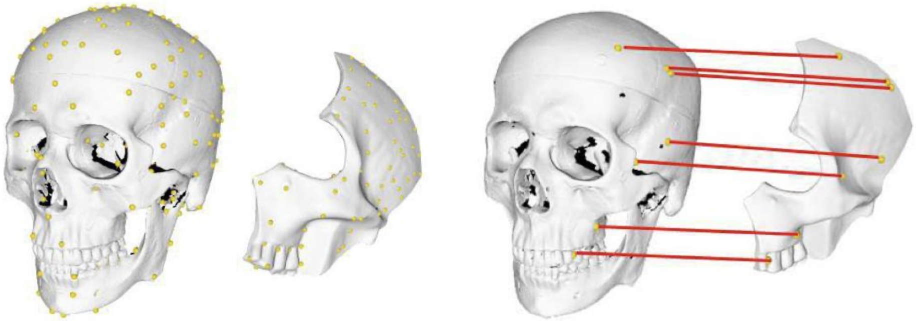




Qi-Xing Huang et al. “Reassembling fractured objects by geometric matching”. In: ACM Siggraph 2006 papers. 2006, pp. 569–578.
Georgios Papaioannou and Evaggelia-Aggeliki Karabassi. “On the automatic assemblage of arbitrary broken solid artefacts”. In: Image and Vision Computing 21.5 (2003), pp. 401–412.

Early Approaches

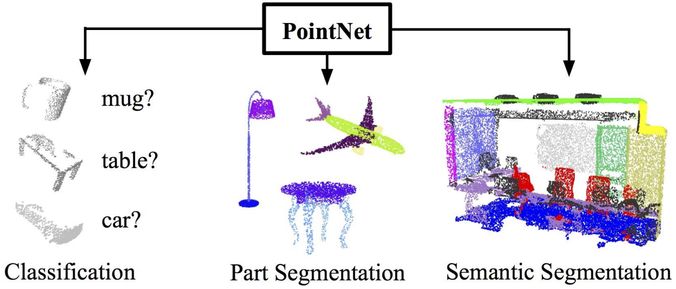
- **Template-Guided Approaches**
  - **Global shape is known,** acting as a **template**
  - Handcrafted geometric descriptors (SHOT, Intrinsic Shape Signatures)
  - Fragment-template & Fragment-fragment matching
  - **+ Unfractured surface reasoning** about how fragments conform to template
  - **+ Global consistency** to ensure fragments collectively create global shape



Kang Zhang et al. “3D fragment reassembly using integrated template guidance and fracture-region matching”. In: Proceedings of the IEEE international conference on computer vision. 2015, pp. 2138–214

Recent Works

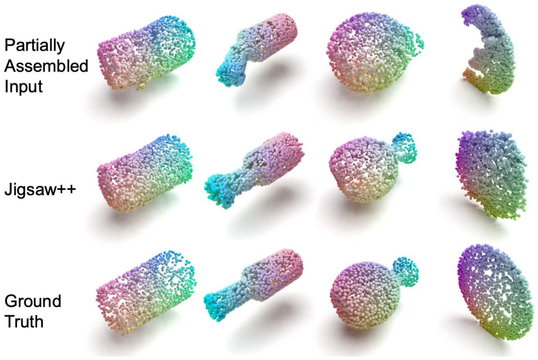
- **Breaking Bad**, large & diverse 3D geometric fracture dataset
- **Deep Learning Approaches**:
  - Embeddings + Matching Functions learned from data **directly**
  - **Powerful point cloud feature extractors** on fragments / global shape (PointNet, PointNet++, DGCNN, KPConv)
  - **Robust matching** across object categories using learned rich features



Silvia Sellan et al. "Breaking bad: A dataset for geometric fracture and re-assembly". In: Advances in Neural Information Processing Systems 35 (2022), pp. 38885–38898.
Charles R Qi et al. "Pointnet: Deep learning on point sets for 3d classification and segmentation". In: Proceedings of the IEEE conference on computer vision and pattern recognition. 2017, pp. 652–660.

Recent Works

- **Pairwise Approaches:**
    - **Jigsaw:** jointly learning fracture segmentation & multi-fragment matching
    - **PMT:** matching via point cloud matching through 2nd order convolutions
- **Template Guided Approaches**
    - **Jigsaw++:** generated a global shape prior using partially reassembled results

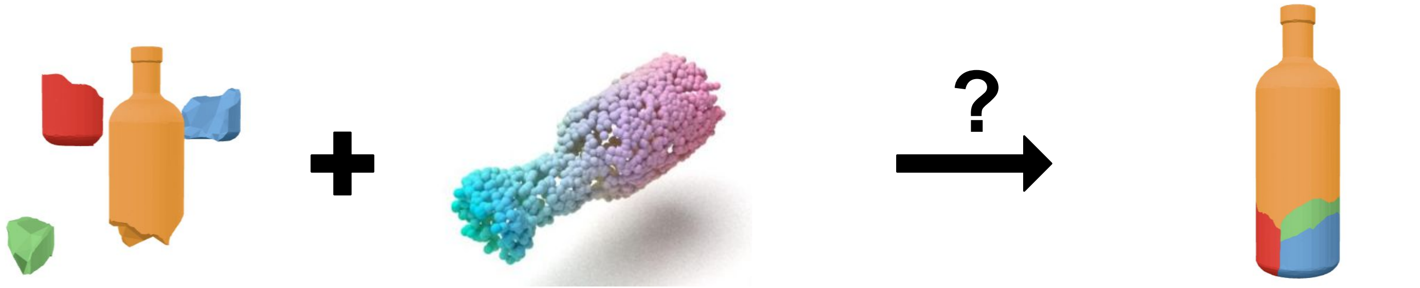


Jiaxin Lu, Yifan Sun, and Qixing Huang. “Jigsaw: Learning to assemble multiple fractured objects”. In: Advances in Neural Information Processing Systems 36 (2023), pp. 14969–14986.
Nahyuk Lee et al. “3D geometric shape assembly via efficient point cloud matching”. In: arXiv preprint arXiv:2407.10542 (2024).
Jiaxin Lu, Gang Hua, and Qixing Huang. “Jigsaw++: Imagining Complete Shape Priors for Object Reassembly”. In: arXiv preprint arXiv:2410.11816 (2024).

Motivation

- With **Jigsaw++**, we now roughly know what the original object looks like
- Given:
  - **Fragments** from an object
  - **Inferred global shape prior** from Jigsaw++

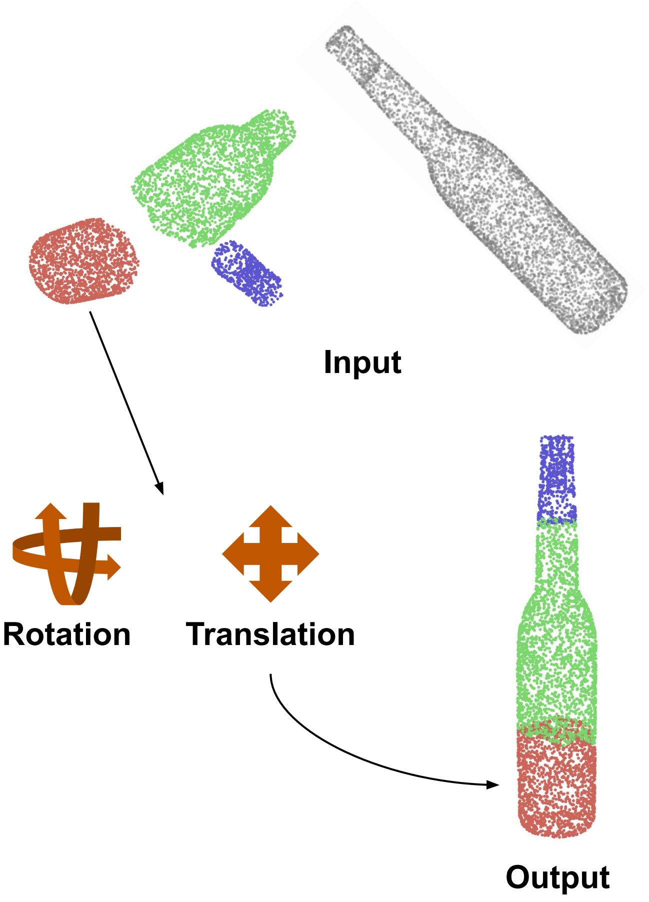
Can we improve reassembly using a <u>learned</u>, <u>template-guided</u> approach?



Fragments | Inferred Global Shape | Reconstruction

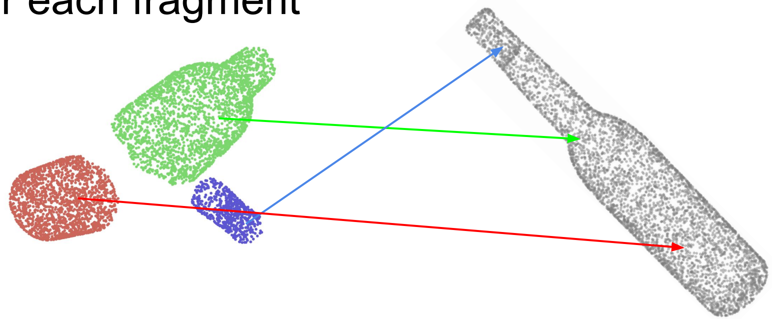
Problem Statement

- **Input**
  - Set of broken **fragments**, represented as 3D point clouds
  - **Inferred global shape**, represented as a 3D point cloud
- **Output**
  - Global rigid transformation (**rotation** & **translation**) for each fragment
- **Assumptions:**
  - No missing fragments
  - Inferred global shape is the same as the ground truth's (original object) shape
  - 3D Point Cloud is surface-only



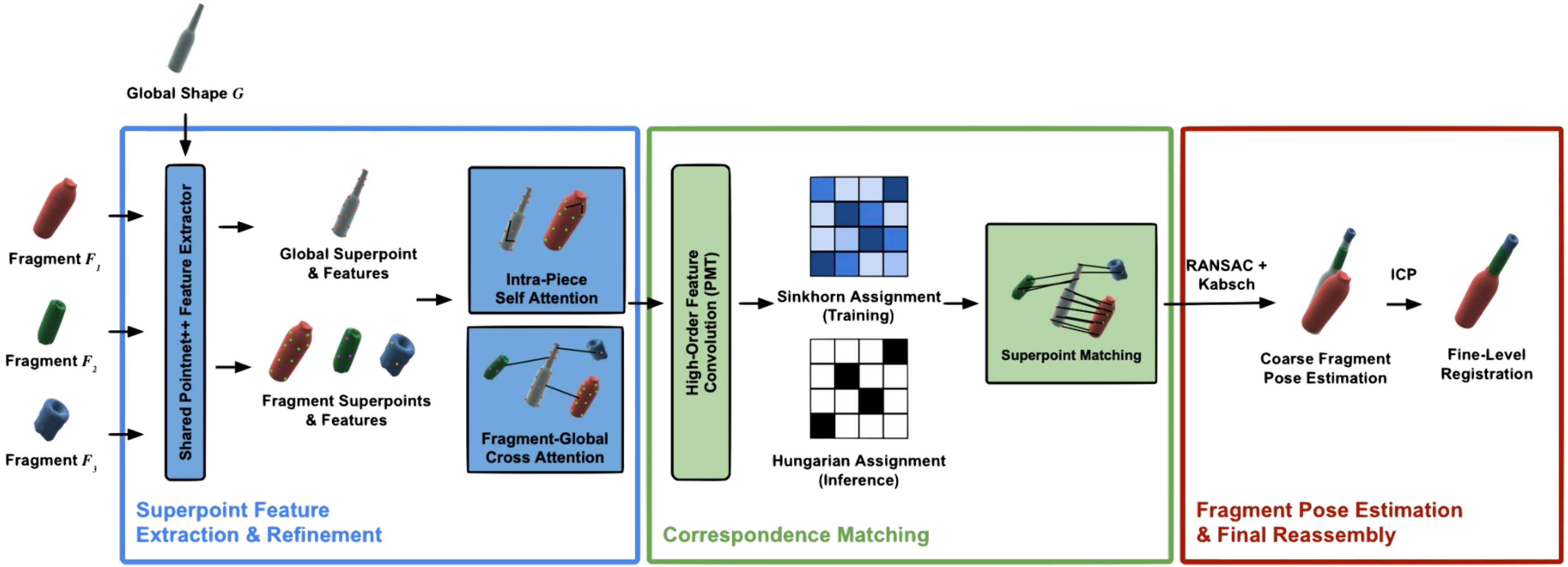
SHARD: General Approach & Task

- **Local-Global Alignment & Coarse-Matching Framework**
  - Reassemble fragments by **aligning fragments to their <u>corresponding region</u> on the global shape** using local geometry.
  - **Coarse & Fine Matching**
- **Correspondence-Based**
  1. Find correspondences between fragment and global shape points
  2. Use correspondences to estimate optimal rigid transformation (rotation & translation) for each fragment



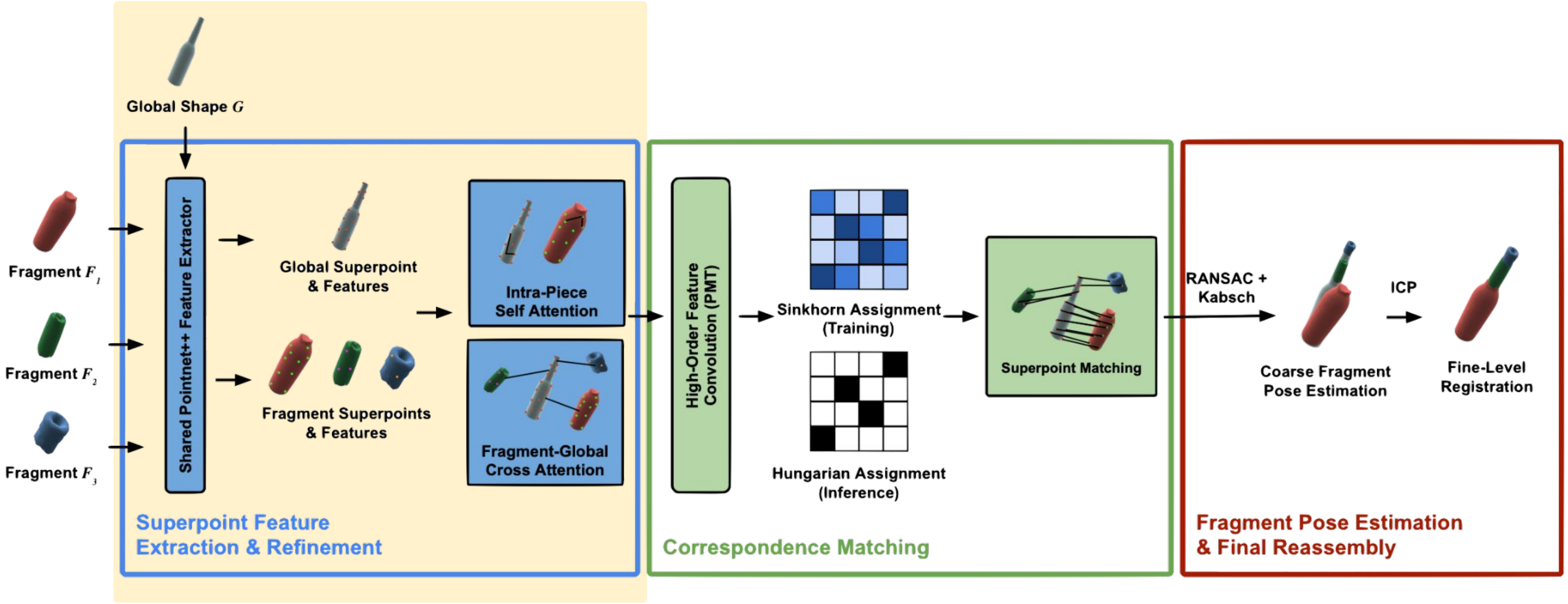
SHARD = Global **SH**ape **A**ware **R**eassembly of 3**D** Fractured Objects

SHARD: Approach



SHARD Model Architecture

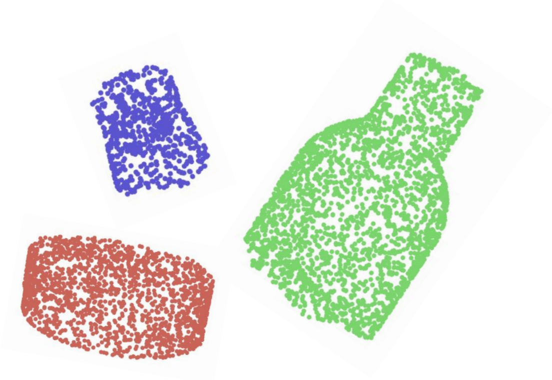
SHARD: Approach



SHARD Model Architecture

SHARD: Input

Global Shape



Fragments

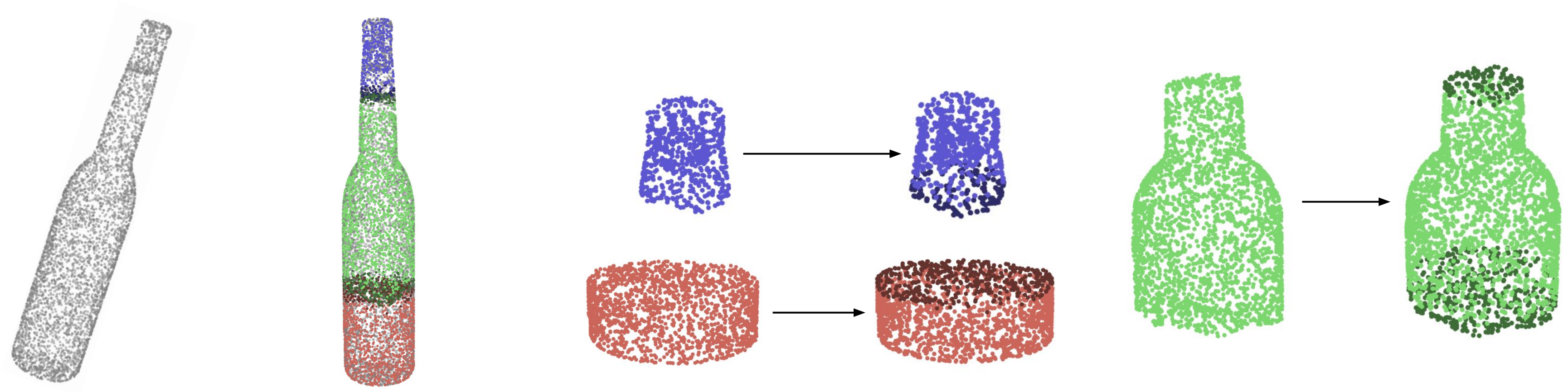
SHARD: Superpoints & Features

1 **Fractured Surface Segmentation**

- Global shape has an **unbroken surface**
- Fragments have **broken & unbroken surfaces**

$$\arg\min_{q \in G' \setminus F_i} \|p_{ij} - q\|_2 < \alpha$$

- **Label points as fractured / unfractured** with inter-piece distance thresholding

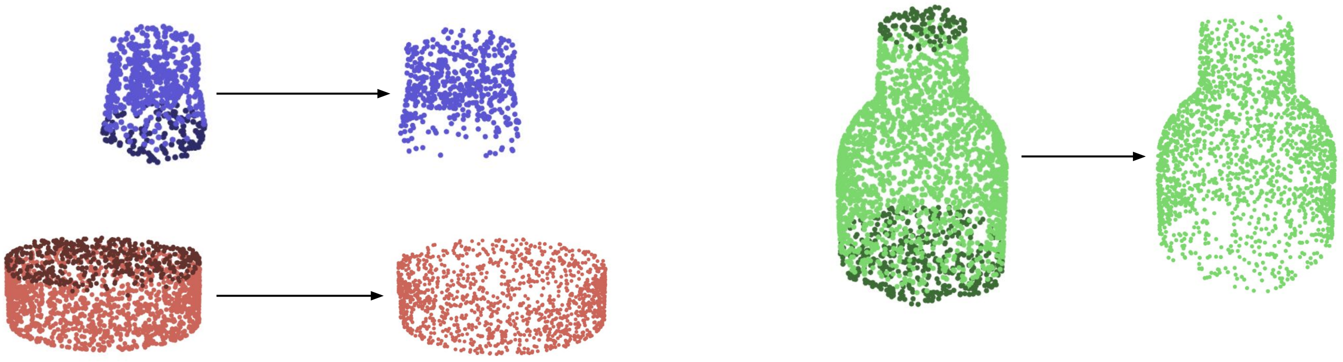


Global Shape Original Pose Fragments Segmented Fragments

SHARD: Superpoints & Features

1 Fractured Surface Segmentation

- **Filter fractured points out** to remove noisy false correspondences

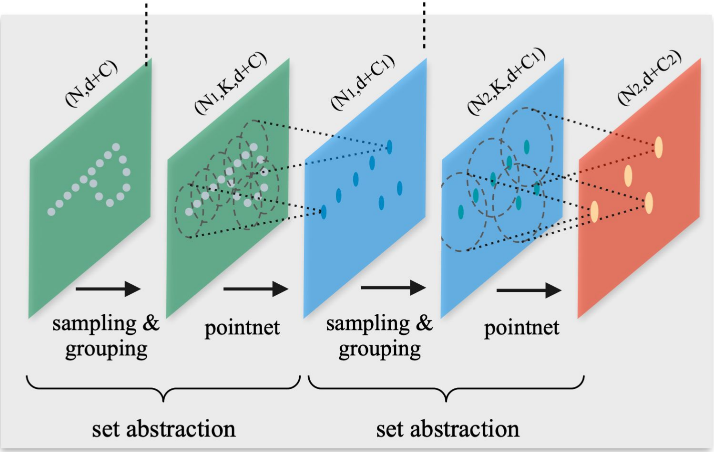


Fracture-less Fragments

SHARD: Superpoints & Features

2 PointNet++ Superpoint & Feature Extraction

- Simple, powerful hierarchical point cloud feature extractor
- Extracts reduced **superpoints** from global & fragment point clouds
- Each superpoint has **feature embedding** describing **local neighborhood geometry** around that point
- **Perfect for coarse matching**

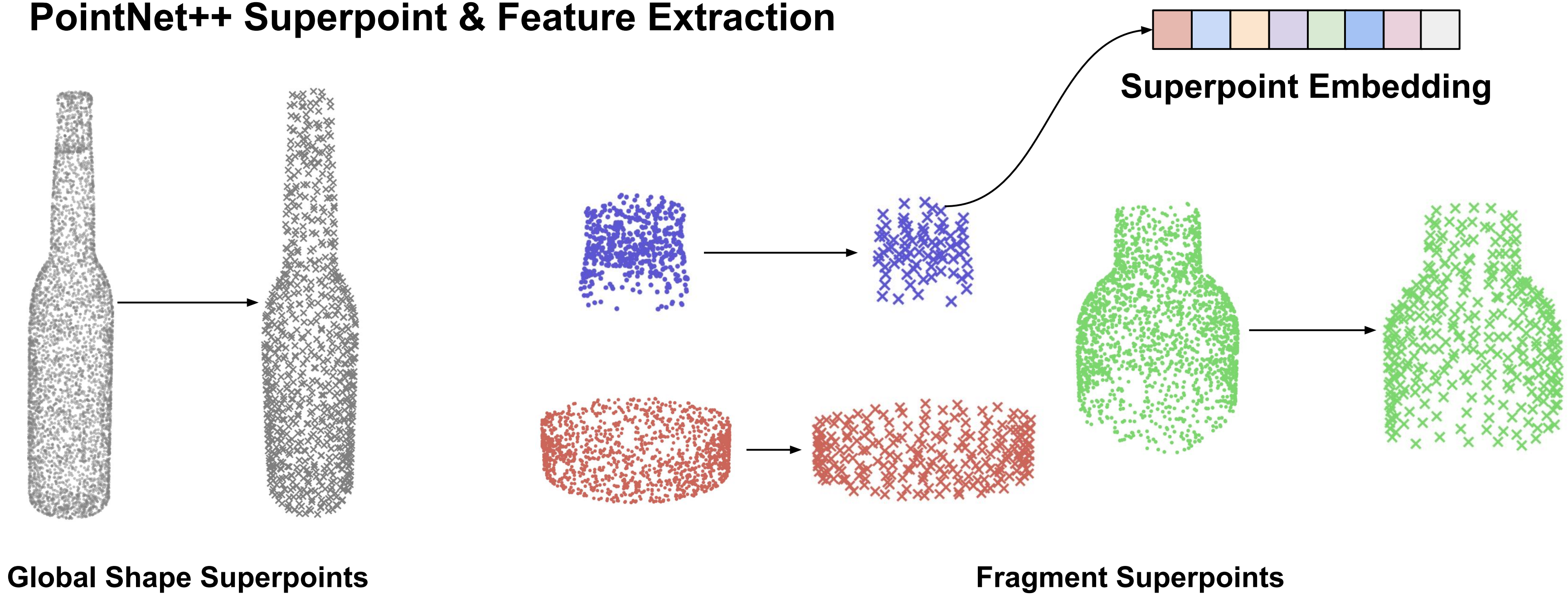


PointNet++ Layers

Charles Ruizhongtai Qi et al. “Pointnet++: Deep hierarchical feature learning on point sets in a metric space”. In: Advances in neural information processing systems 30 (2017).

SHARD: Superpoints & Features

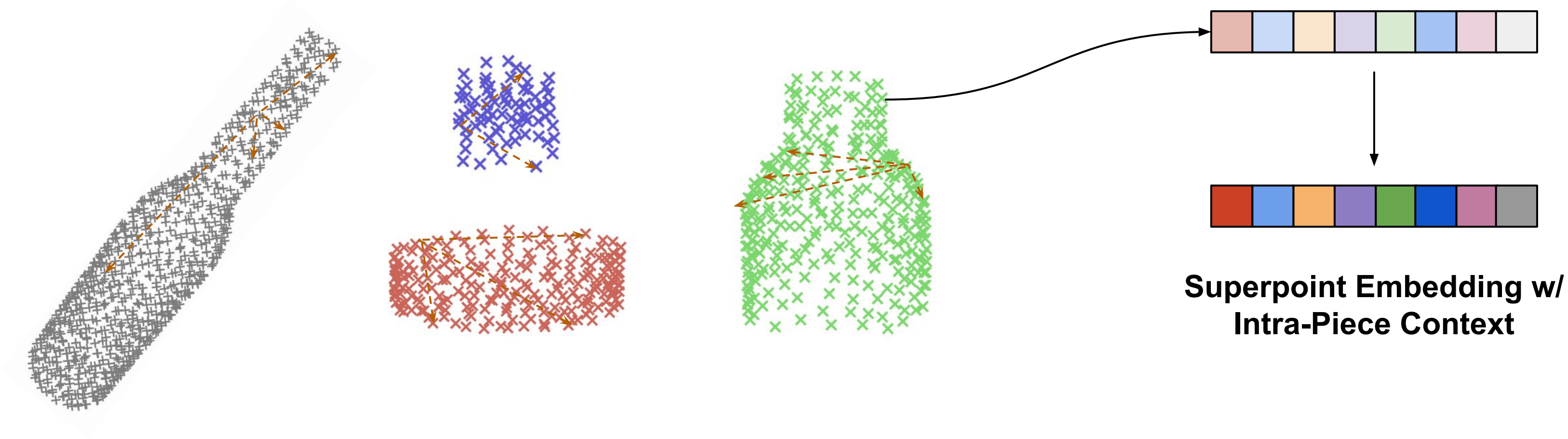
2 PointNet++ Superpoint & Feature Extraction



SHARD: Superpoints & Features

3 Intra-Piece Self Attention

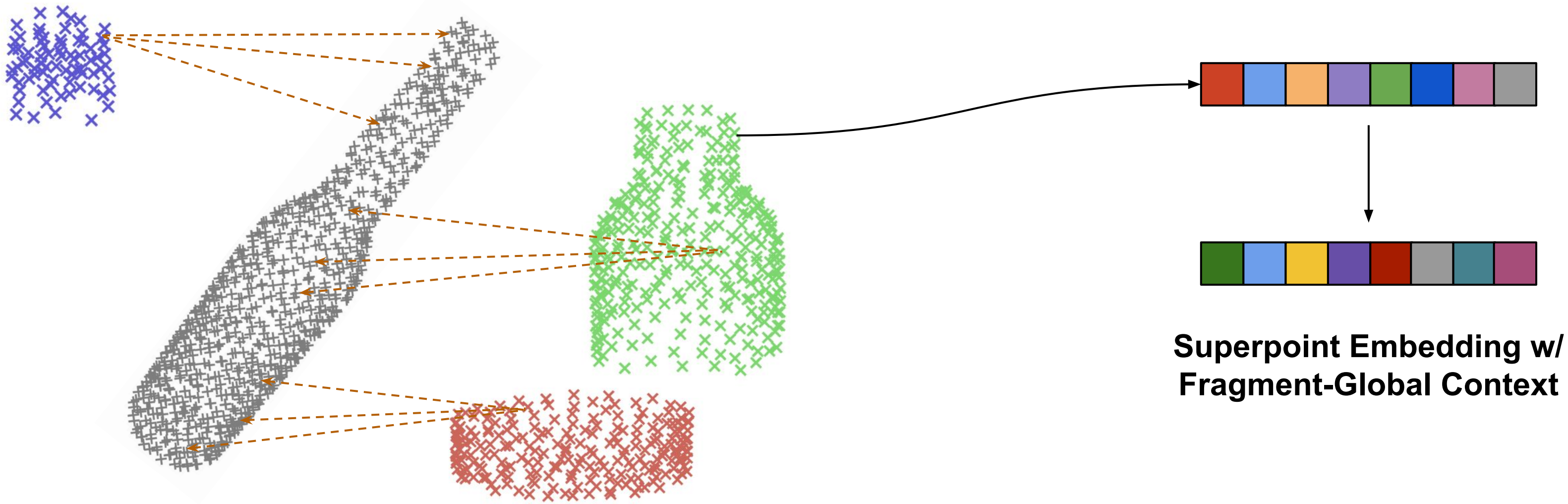
- Each superpoint's feature only has information about its local neighborhood
- **Self-attention** introduces **long-range structural context** about the piece it belongs to by integrating **feature similarity** & **spatial proximity**
- Applied to fragments & global shape



SHARD: Superpoints & Features

4 Fragment-Global Cross Attention

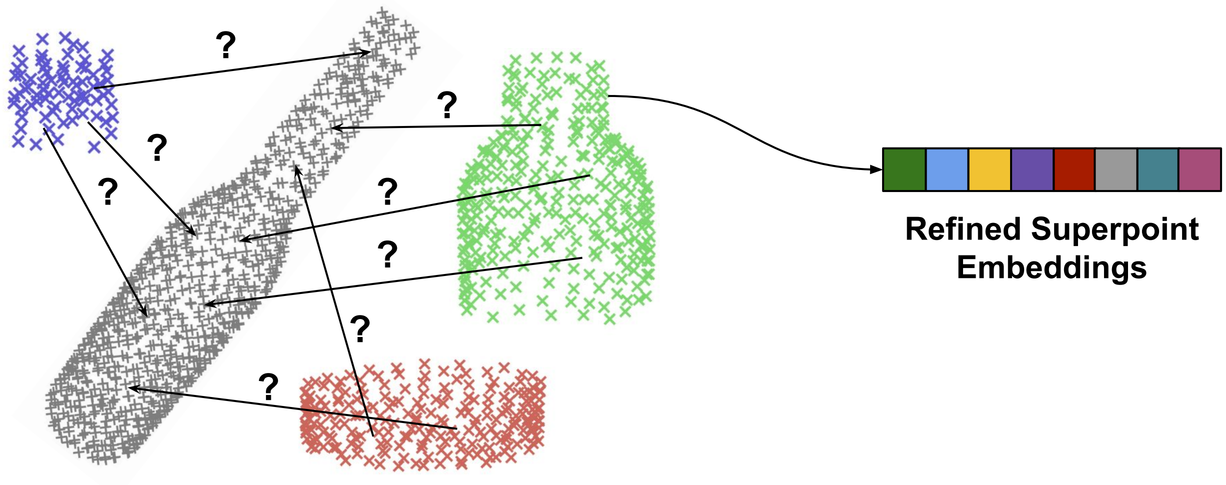
- **Introduces global context** to fragment superpoint embeddings
- **Cross-attention** to capture relationships **between fragments & global shape**
- Refines fragment embeddings for aligning fragments to global shape



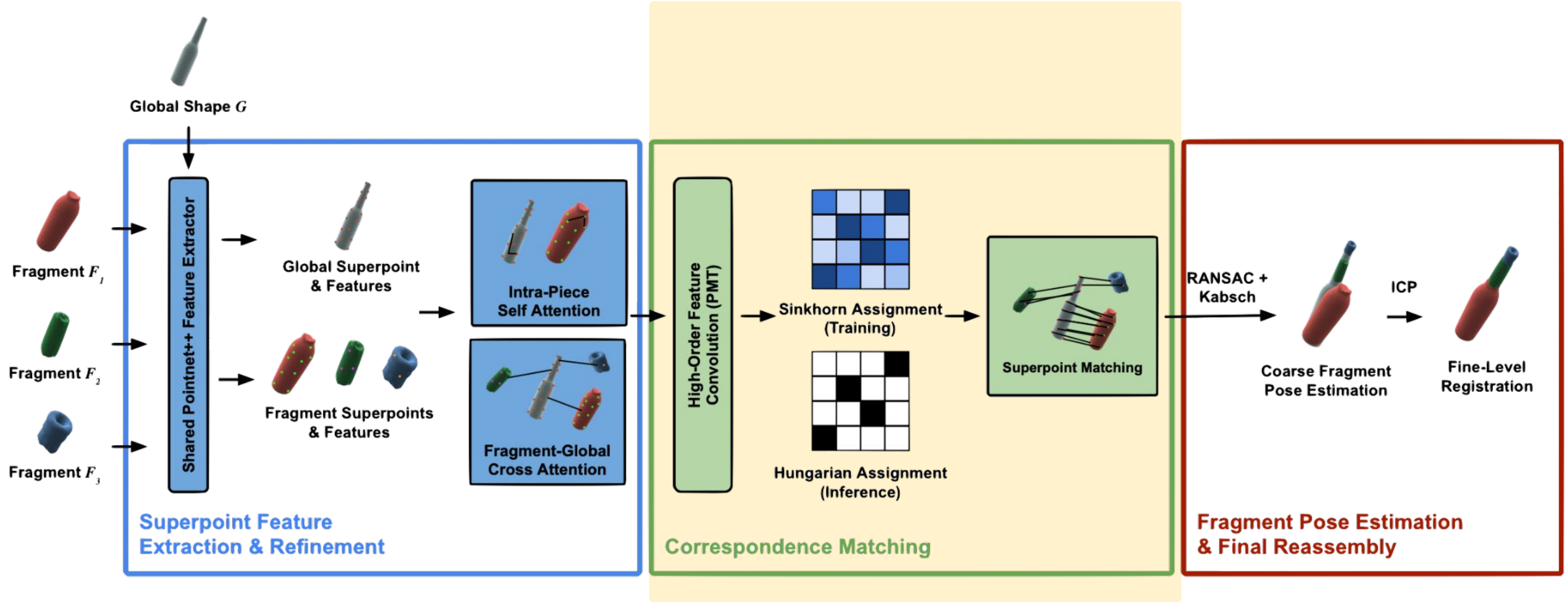
SHARD: Correspondence Matching

- We have:
  - Global Superpoints, each with an embedding
  - Fragment Superpoints, each with an embedding

How do we establish correspond fragment superpoints to global superpoints?



SHARD: Approach

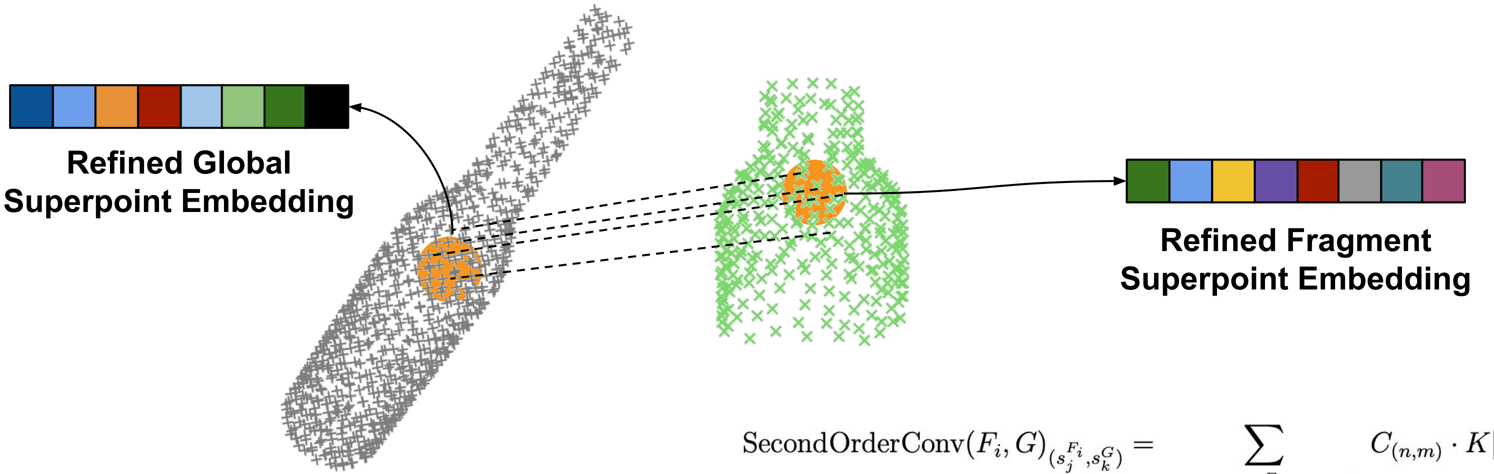


SHARD Model Architecture

SHARD: Correspondence Matching

5 Second-Order Feature Convolutions

- Promising at comparing fragment and global superpoint embeddings
- Computes **pairwise correlations** between neighborhoods of superpoints
- Sub-quadratic complexity with **ProxyMatchTransform (PMT)**



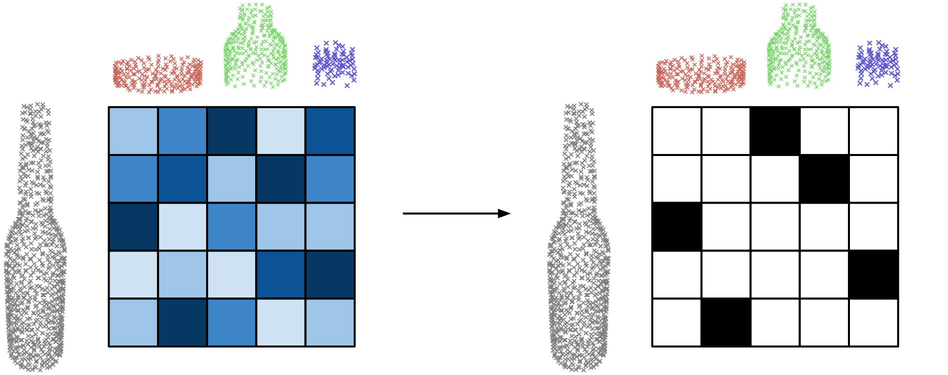
$$\mathrm{SecondOrderConv}(F_i, G)_{(s_j^{F_i}, s_k^G)} = \sum_{(n,m) \in N(s_j^{F_i}) \times N(s_k^G)} C_{(n,m)} \cdot K[n - s_j^{F_i}, m - s_k^G]$$

Nahyuk Lee et al. "3D geometric shape assembly via efficient point cloud matching". In: arXiv preprint arXiv:2407.10542 (2024).

SHARD: Correspondence Matching

6 1:1 Superpoint Matching

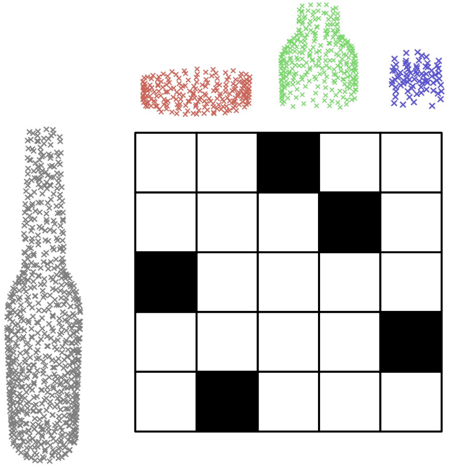
- From the previous step, we get an **affinity matrix** indicating how similar each fragment superpoint is with each global superpoint
- **Sinkhorn / Hungarian Algorithm:** find the optimal 1:1 assignment matching between fragment and global superpoints to maximize total affinity



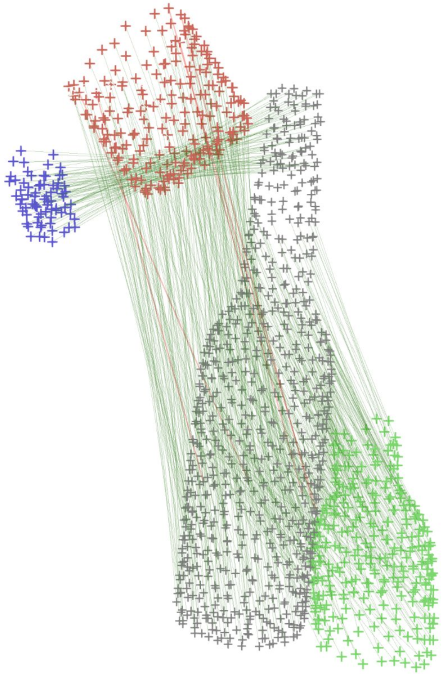
Affinity Matrix **1:1 Assignment Matrix**

SHARD: Correspondence Matching

6 1:1 Superpoint Matching

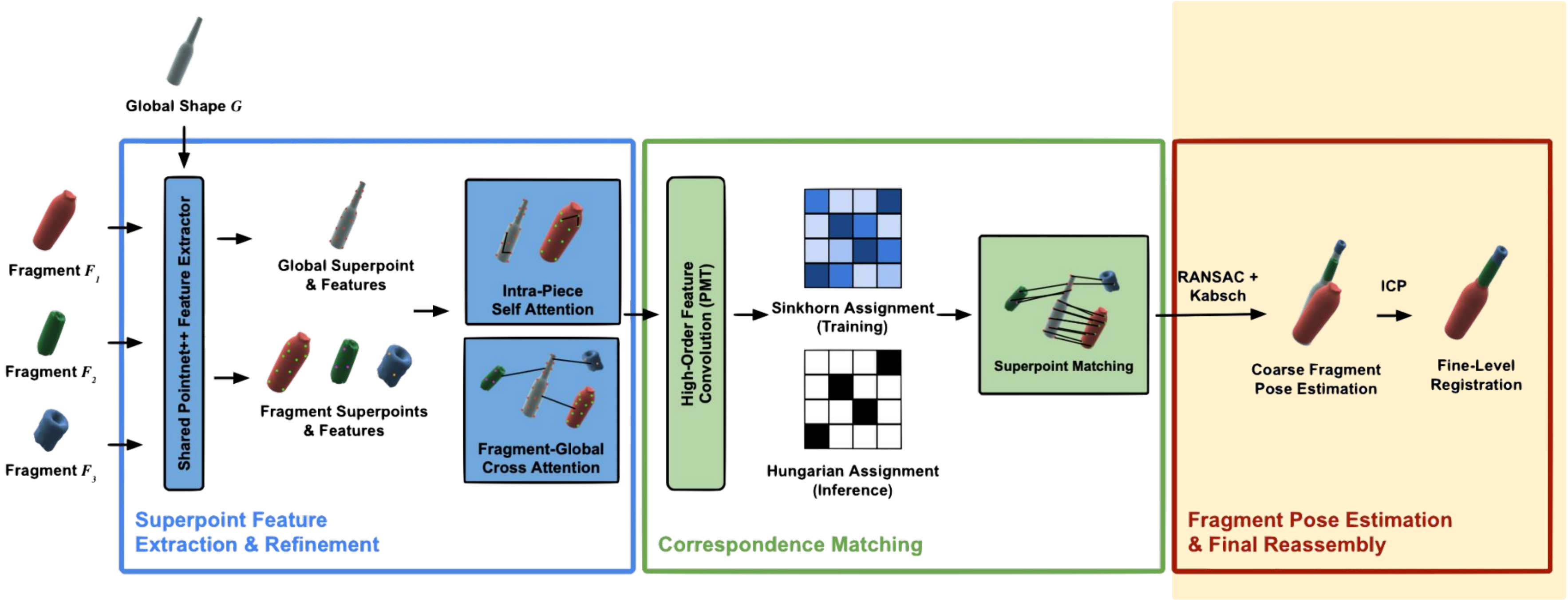


1:1 Assignment Matrix



Visualized Correspondences

SHARD: Approach

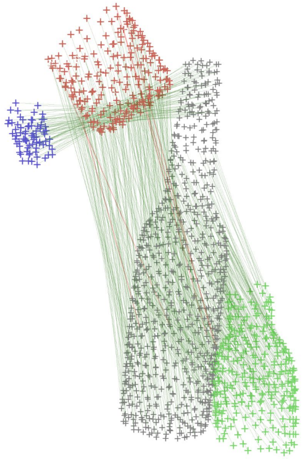


SHARD Model Architecture

SHARD: Correspondence Matching

7 Coarse Pose Estimation

- Use correspondences to find **best rigid transformation** for each fragment
- **Kabsch Algorithm** to compute optimal transformation + rotation
- **Random Sample Consensus (RANSAC)** to handle incorrect correspondences



Fragment-Global Correspondences

$$\arg\min_{R,t} \sum_{i=1}^{n} ||(Rx_i + t) - y_i||^2$$

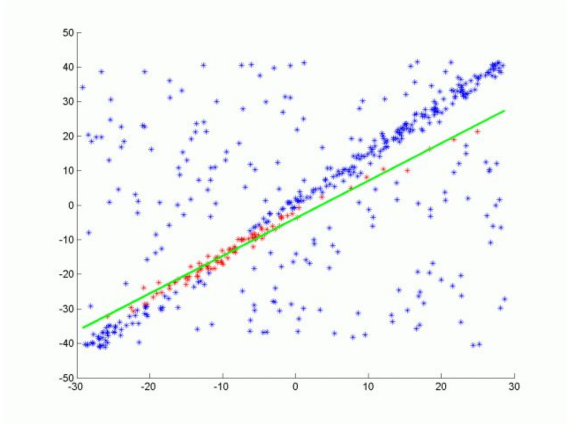
$$X_{\text{centered}} = x_i - \mu_x, \quad Y_{\text{centered}} = y_i - \mu_Y$$

$$U, \Sigma, V^\top = \text{SVD}(X_{\text{centered}} Y_{\text{centered}}^\top)$$

$$R = VU^\top \quad \text{s.t. } \det(R) = 1$$

$$t = \mu_Y - R\mu_x$$

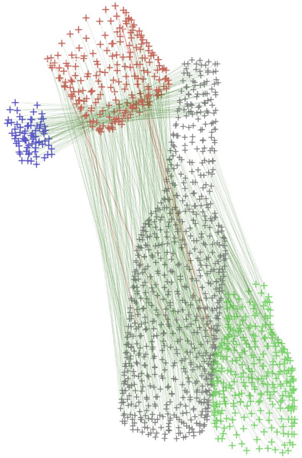
Kabsch Algorithm



RANSAC Algorithm

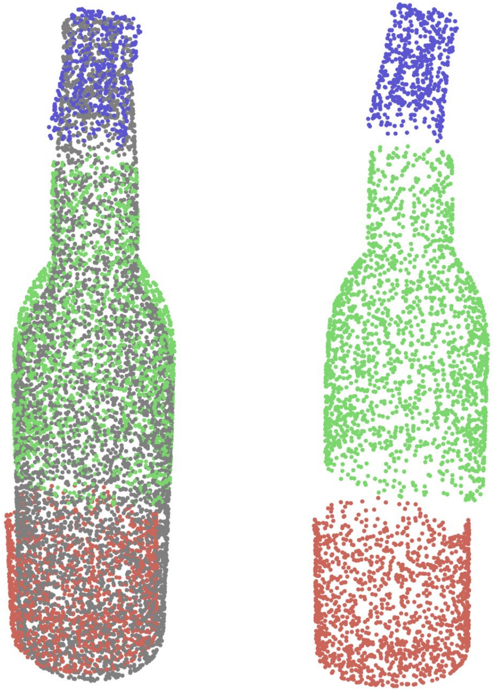
SHARD: Final Reassembly

7 Coarse Pose Estimation



Fragment-Global Correspondences

RANSAC +
Kabsch



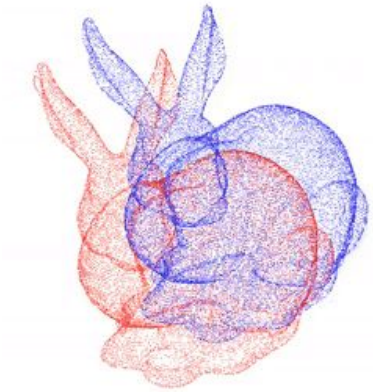
Coarsely Aligned Fragments

SHARD: Final Reassembly

8 Fine Pose Estimation

- **Iterative Closest Point (ICP)**
  - Simple, iterative algorithm to align (register) two point clouds
  - Uses nearest point information to compute optimal transformation per iteration
  - Requires a good initialization

$$\arg\min_{R,t} \sum_{i=0}^{N} [n_i^\top ((R_{x_i} + t) - y_i)]^2$$

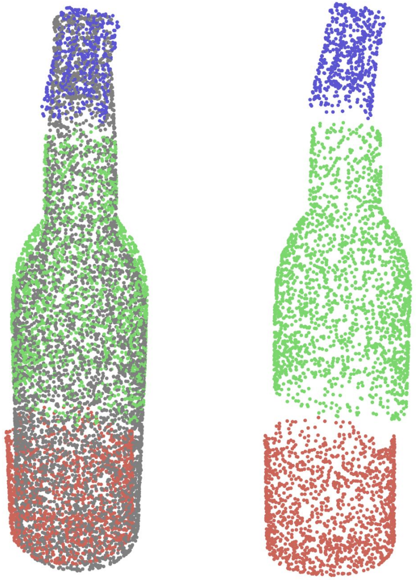


Point-to-Plane ICP

Jaykumaran. (2025, April 30). *Iterative closest point (ICP) for 3D explained with code*. LearnOpenCV. https://learnopencv.com/iterative-closest-point-icp-explained/

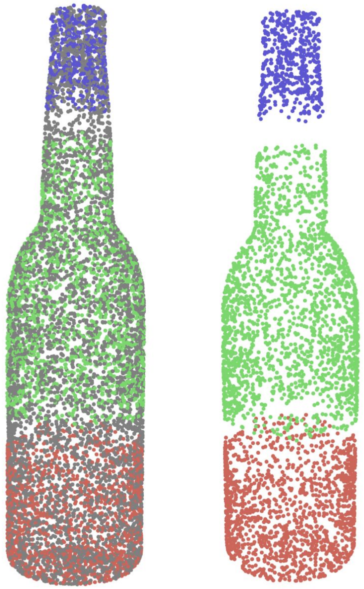
SHARD: Final Reassembly

8 Fine Pose Estimation



Coarsely Aligned Fragments

ICP →



Finely Aligned Fragments
(Final Reassembly)

Training

Data:

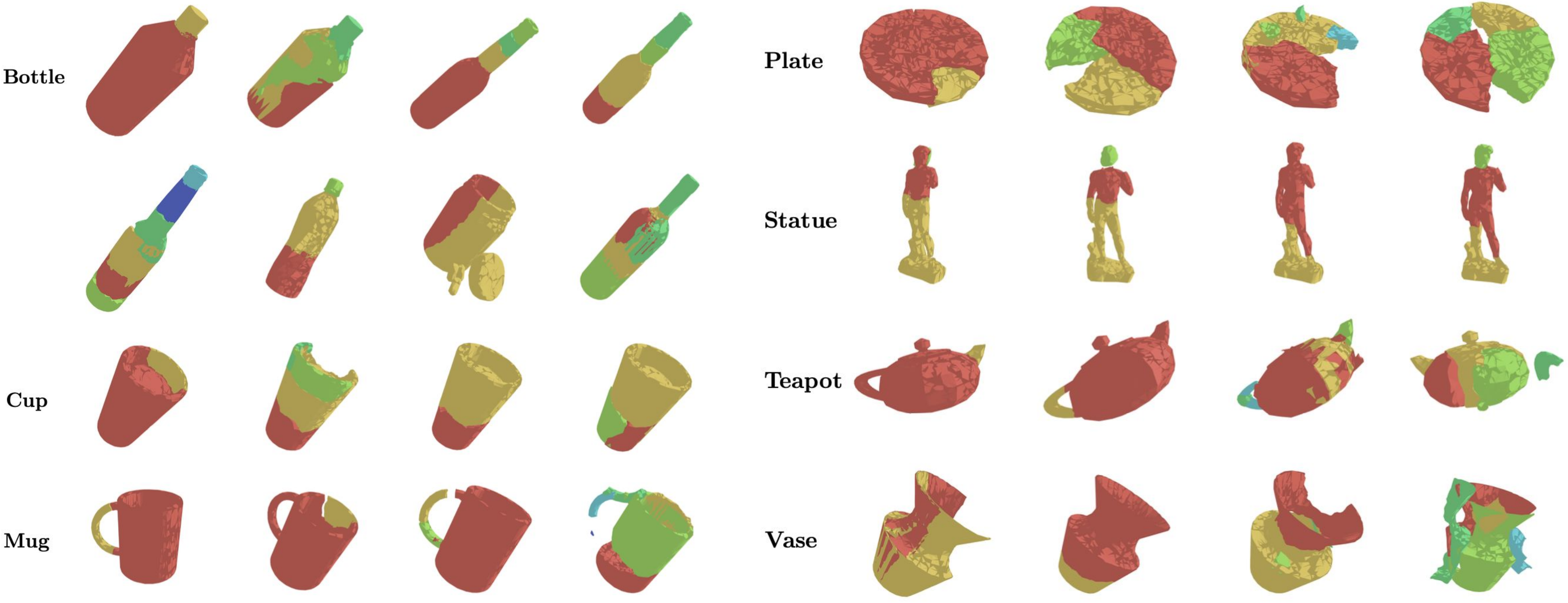
- `everyday` subset of Breaking Bad dataset

Training Objectives:

1. **Weighted Circle Loss**
   a. Encourages superpoints with **similar geometries to have similar features**, and superpoints with **different geometries to have different features**
   b. Insufficient for symmetric, ambiguous geometries
2. **KL Divergence**
   a. **Directly encourages** fragment superpoints to match to their actual corresponding global superpoint/region via **distribution alignment**

Silvia Sellan et al. "Breaking bad: A dataset for geometric fracture and re-assembly". In: Advances in Neural Information Processing Systems 35 (2022), pp. 38885–38898.

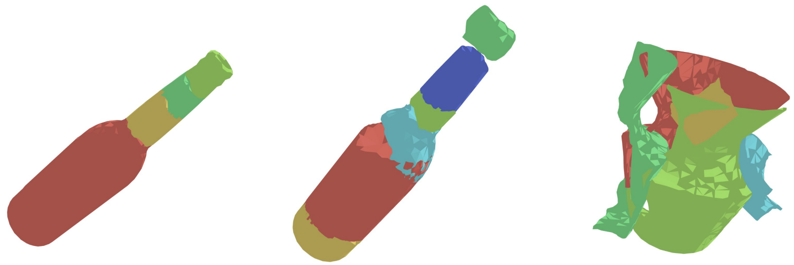
Results



Results

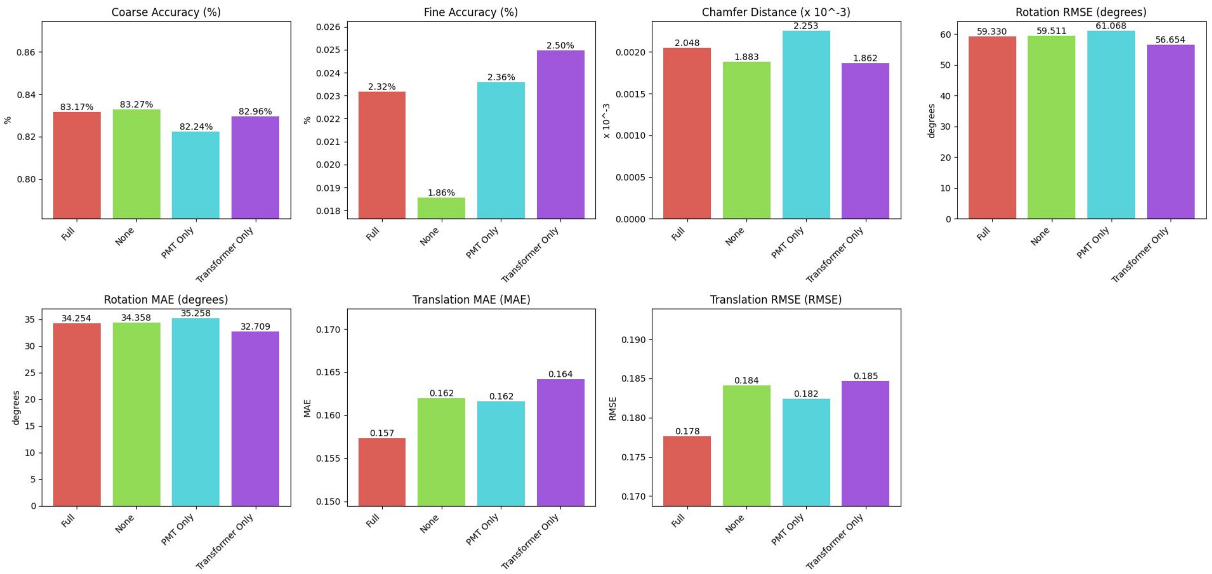
- **Fragments roughly aligned with their corresponding regions quite well.**
  - \+ High Coarse Accuracy
  - \+ Low Translation Error
- **Exact superpoint matches underperformed due to naive fine-level ICP.**
  - \- Mid Rotation Error
  - \- Low-Mid Fine Accuracy

Evaluation Metric	Reported Value
Coarse Accuracy (%)	83.03 %
Fine Accuracy (%)	2.31%
Chamfer Distance ($\times 10^{-3}$)	2.076801
Rotation RMSE (degrees)	59.346165
Rotation MAE (degrees)	34.263524
Translation MAE ($\times 10^{-2}$)	15.760097
Translation RMSE ($\times 10^{-2}$)	17.790916

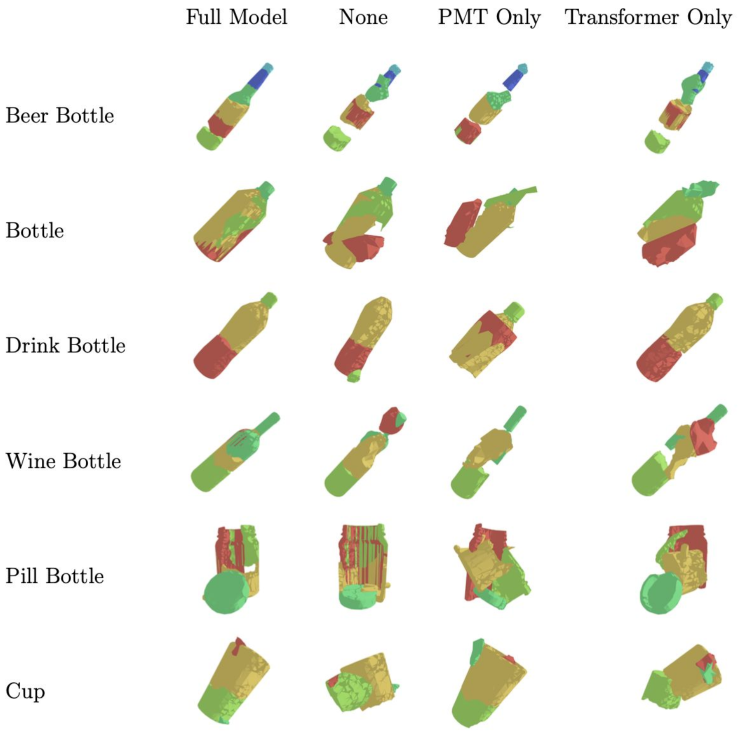


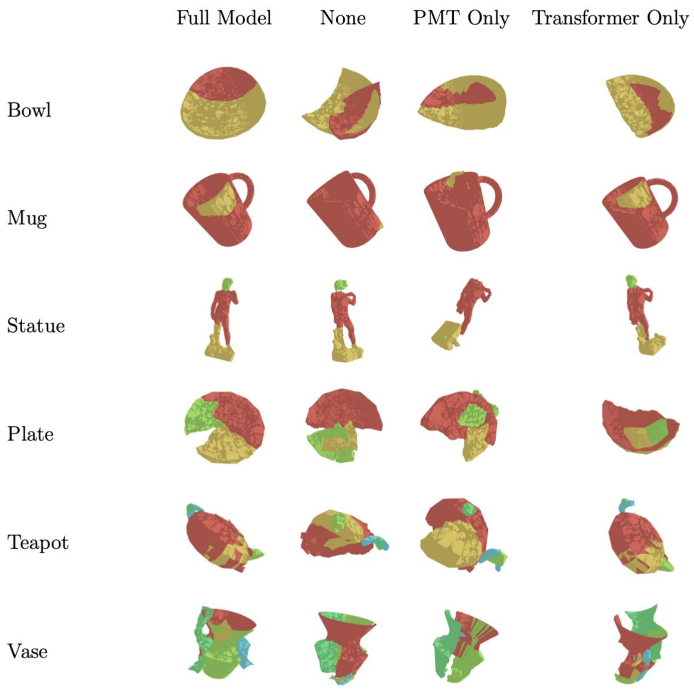
Model Architecture Ablations

- Removed Transformer / PMT components of SHARD to analyze their contributions
- **Transformer & PMT components outperform** no components
- Full Model is **competitive** but **hard to train** due to **increased parameter space**



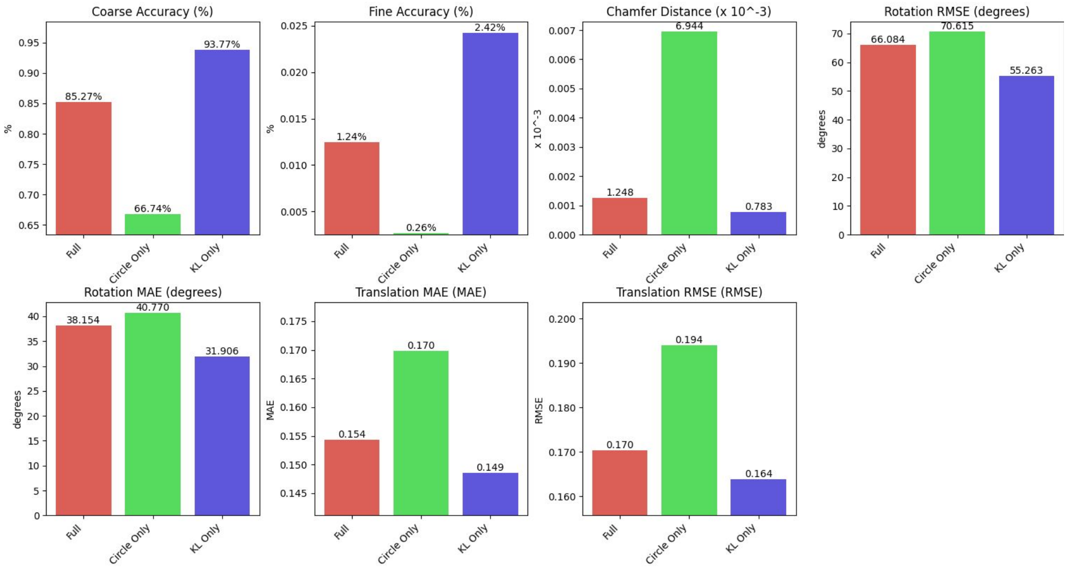
Model Architecture Ablations





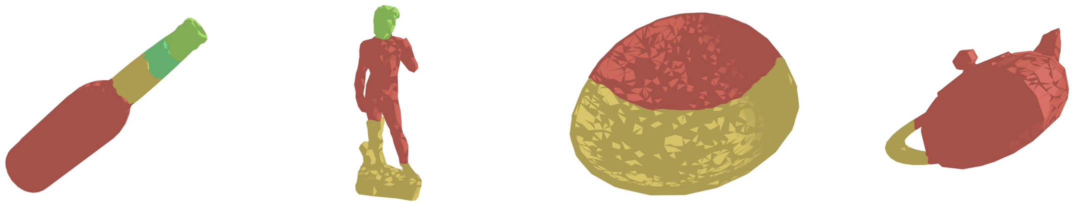
Loss Ablations

- Trained model on different combinations of loss terms to analyze contributions
- **Circle loss harder to train** as it lacks distribution guidance; **KL easy to train**
- Having both helps generalize by **preventing distribution overfitting**

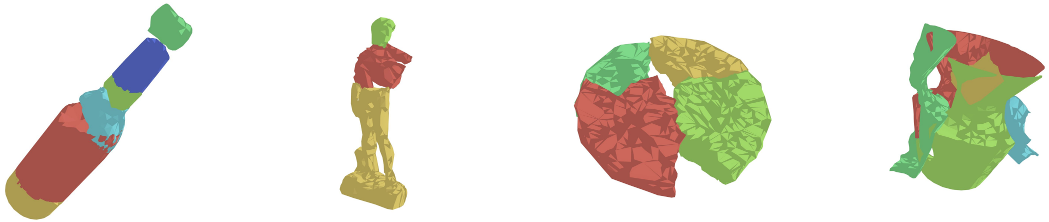


Conclusions & Limitations

- Introduced a **learned, template-guided** approach for 3D fracture reassembly
- **Strong coarse correspondence accuracy**
- **Promising coarse fragment pose estimation** & reconstruction results



- **Gaps & overlaps** between fragments in some reassembly results
- **Poor fine level pose estimation** with underpowered ICP



Thank you!