ETH zürich


# Group 13
# Final presentation

## 3D Feature Point Learning for Fractured Object Reassembly

**Team:** Chaoyu Du, Ulrich Steger, Eshaan Mudgal, Florian Hürlimann **Supervisors:** Danda Pani Paudel, Martin Oswald

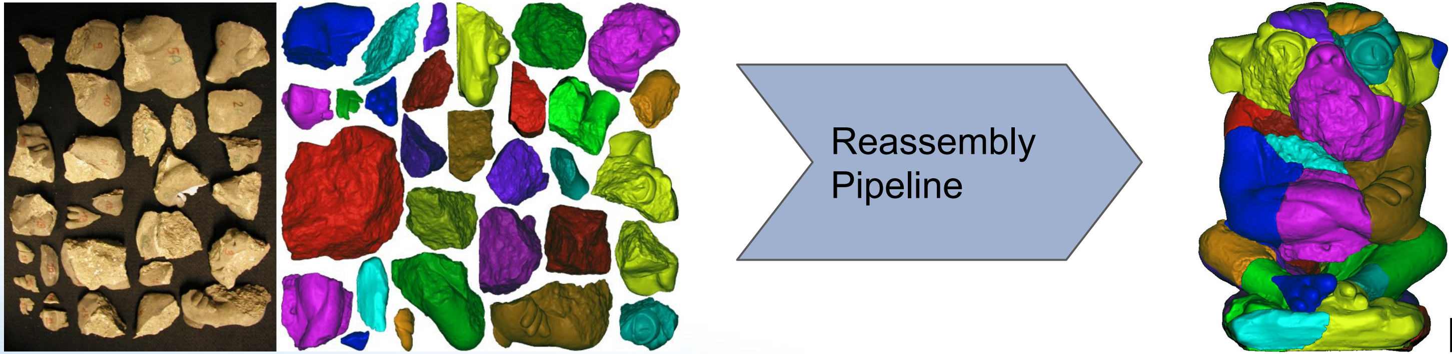
# 3D Feature Point Learning for Fractured Object Reassembly

## Fundamental problem

Given a 3D object consisting of n fragments with arbitrary position and orientation, each represented as a point cloud, determine the matching fragments and transformation matrices $T_n$ for reassembly of the object

## Scope of this project

Using 3D feature detection with Neural Networks(s), implement a fragment matching algorithm for reassembly of 3D objects. For this purpose a library of fragmented objects shall be created




[1]

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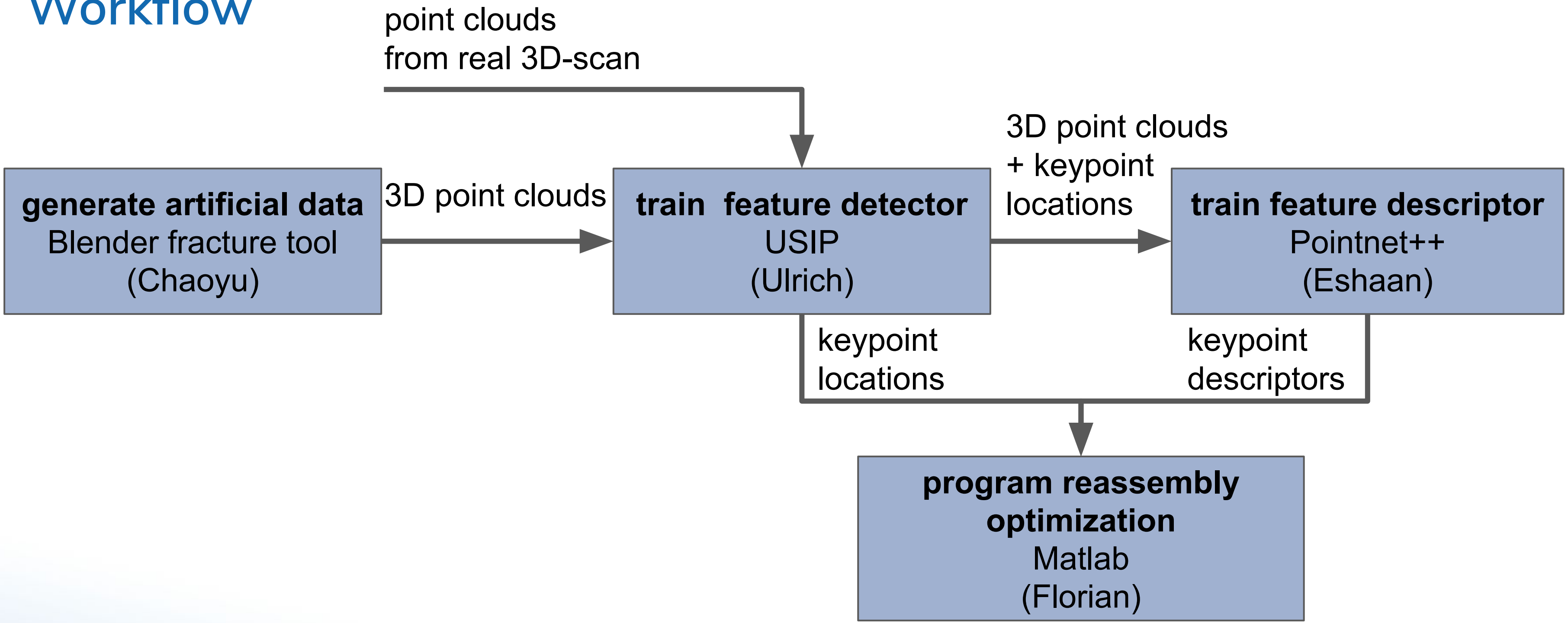
# Workflow


point clouds
from real 3D-scan
generate artificial data
Blender fracture tool
(Chaoyu)
3D point clouds
train feature detector
USIP
(Ulrich)
3D point clouds
+ keypoint
locations
train feature descriptor
Pointnet++
(Eshaan)
keypoint
locations
keypoint
descriptors
program reassembly
optimization
Matlab
(Florian)

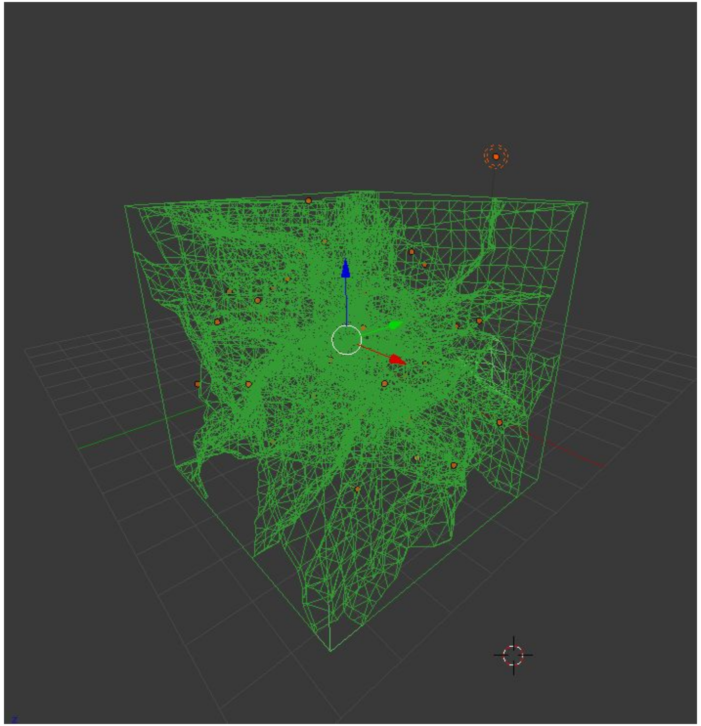
# Generation of library of fragmented objects

**Blender Algorithm: Voronoi + Fractal Boolean**
(Real surfaces fractures can be described by fractal geometry. B. B. Mandelbrot, D. E. Passoja, and A. J. Paullay, “Fractal Character of Fracture Surfaces of Metals,” Nature (London), 308 [5961] 721-22 (1984).)

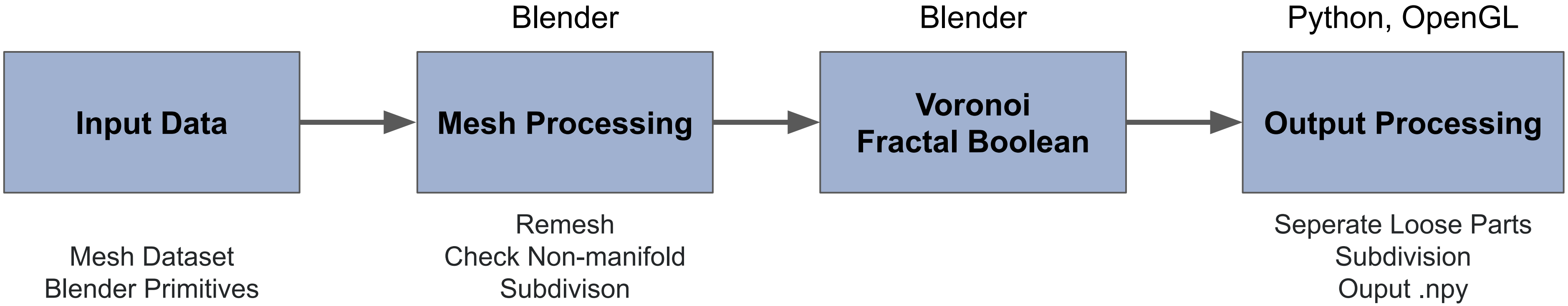
**Input**: Mesh

**Output: n * 6 .npy**
(points and normals in three-dimensional Euclidean space of a fragmented piece)

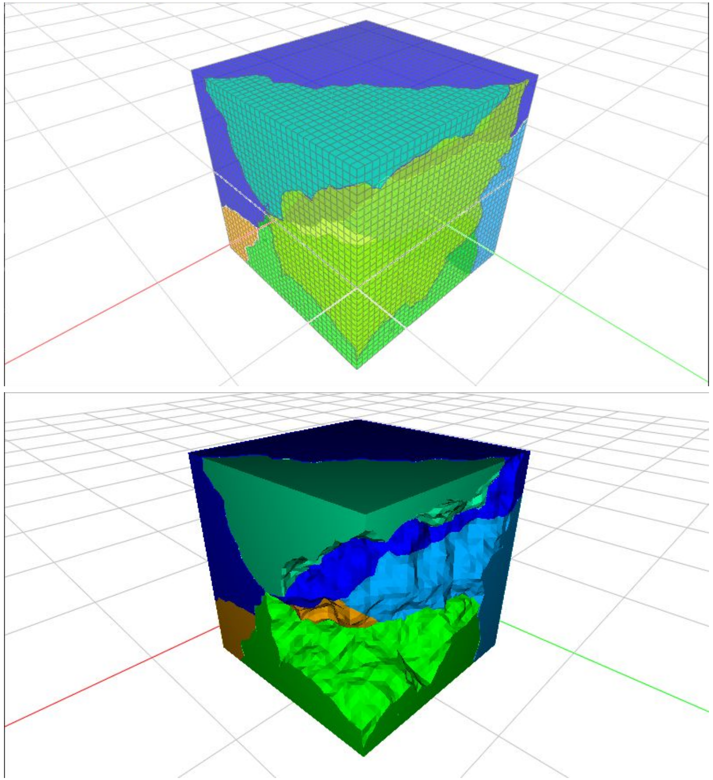
~400 pairs of 1-to-N fragmented objects in total for training



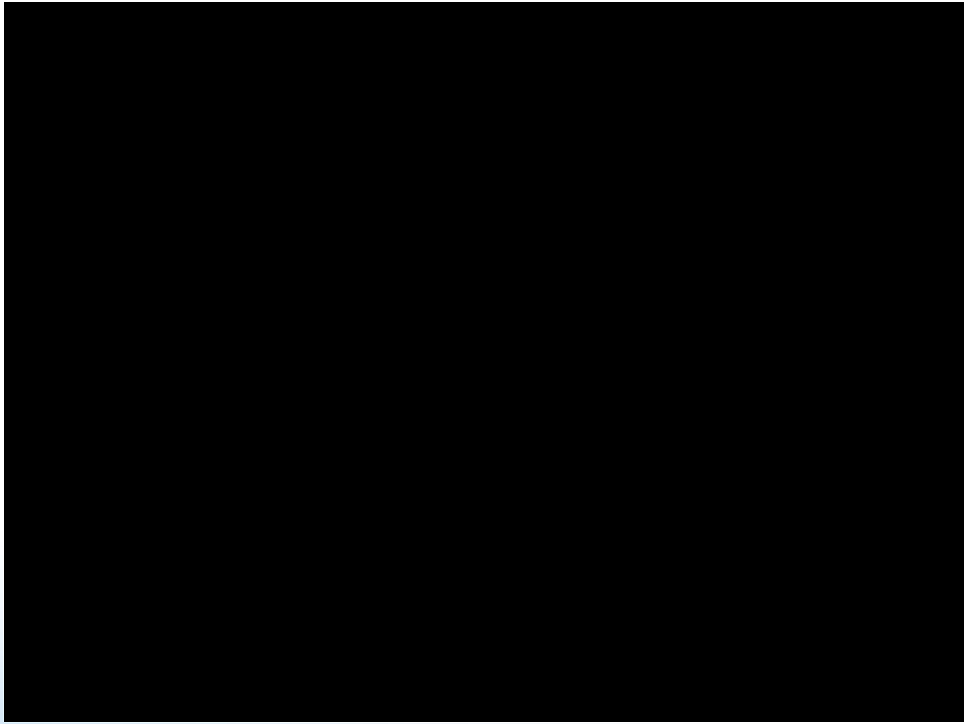
# Generation of library of fragmented objects

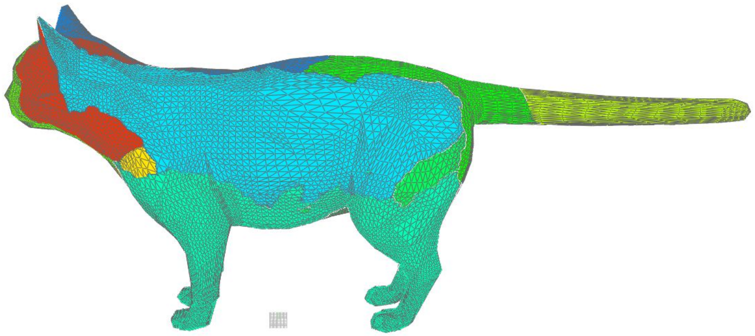


# Generation of library of fragmented objects



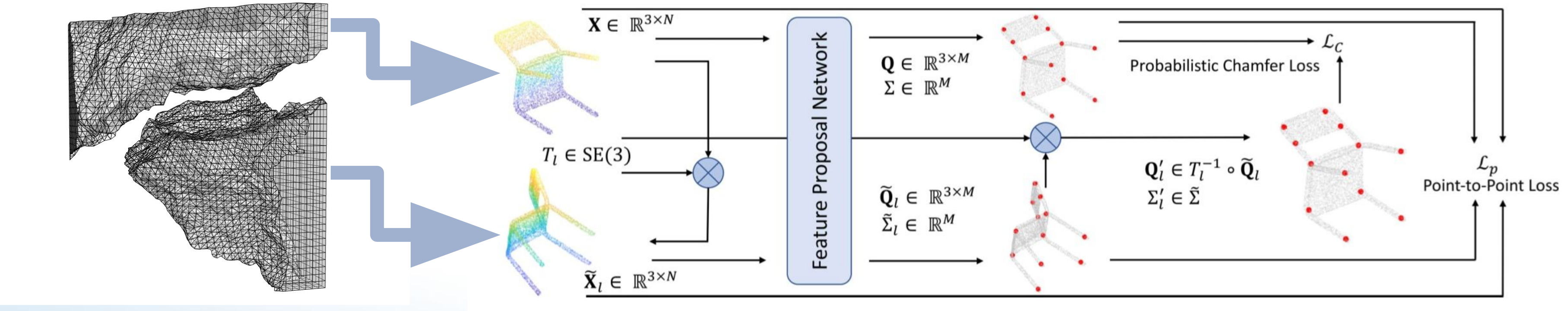
# Generation of library of fragmented objects



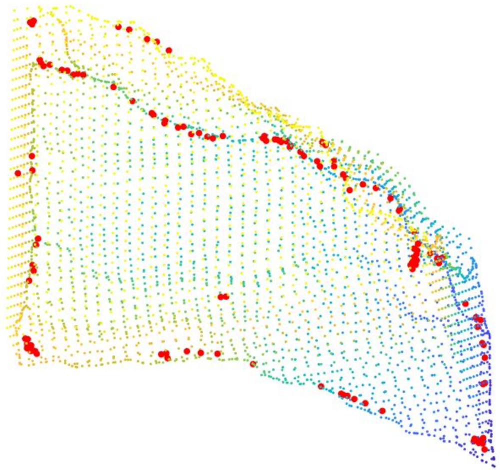


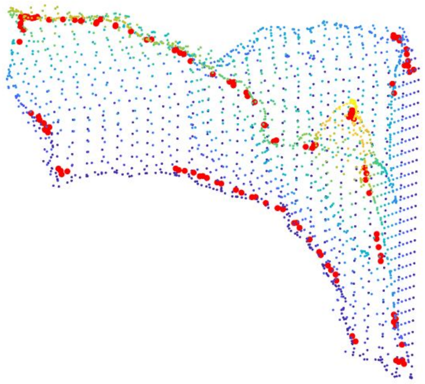
# Train feature detector: USIP[2]

- Used Unsupervised Stable Interest Point Detection (USIP)[2], pretrained on ModelNet[3].
- Retrained the whole network
- Training data: Fragments from generated data, 2 input channels
  - 1 fragment and all fragments touching it as the other input (+ modified loss)
  - **twice the same fragment, one has flipped surface normals => negative shape**



# Train feature detector: results





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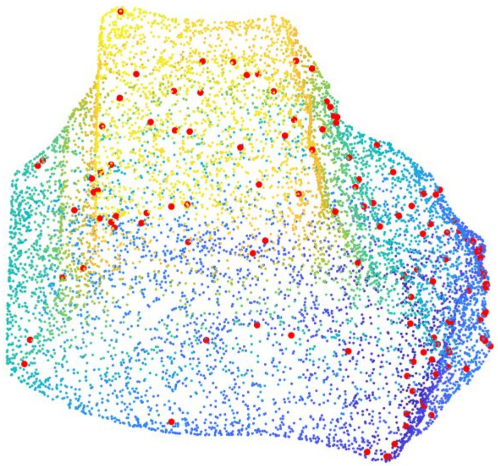
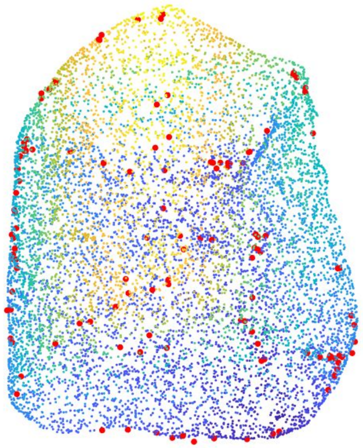
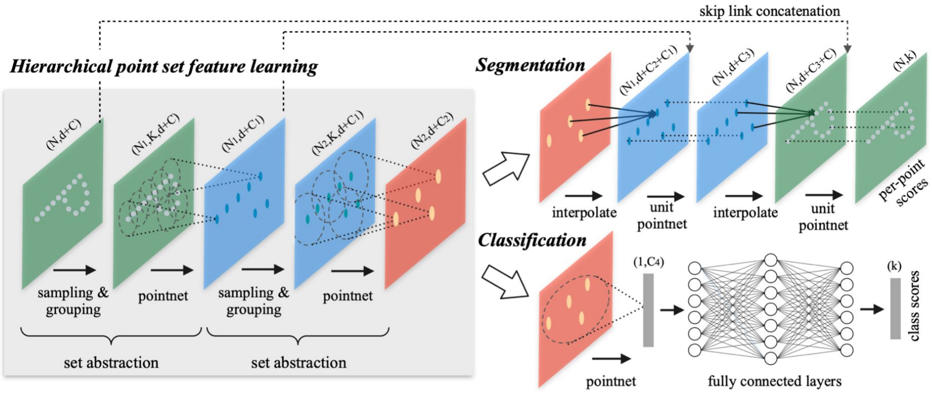




# Getting Feature Descriptors

- Leverage existing point cloud segmentation architectures to get key-point descriptors
  - PointNet ++
- Input → key point coordinates (Nx6)
- Output → Descriptors to these key points → facilitate final fragment reassembly



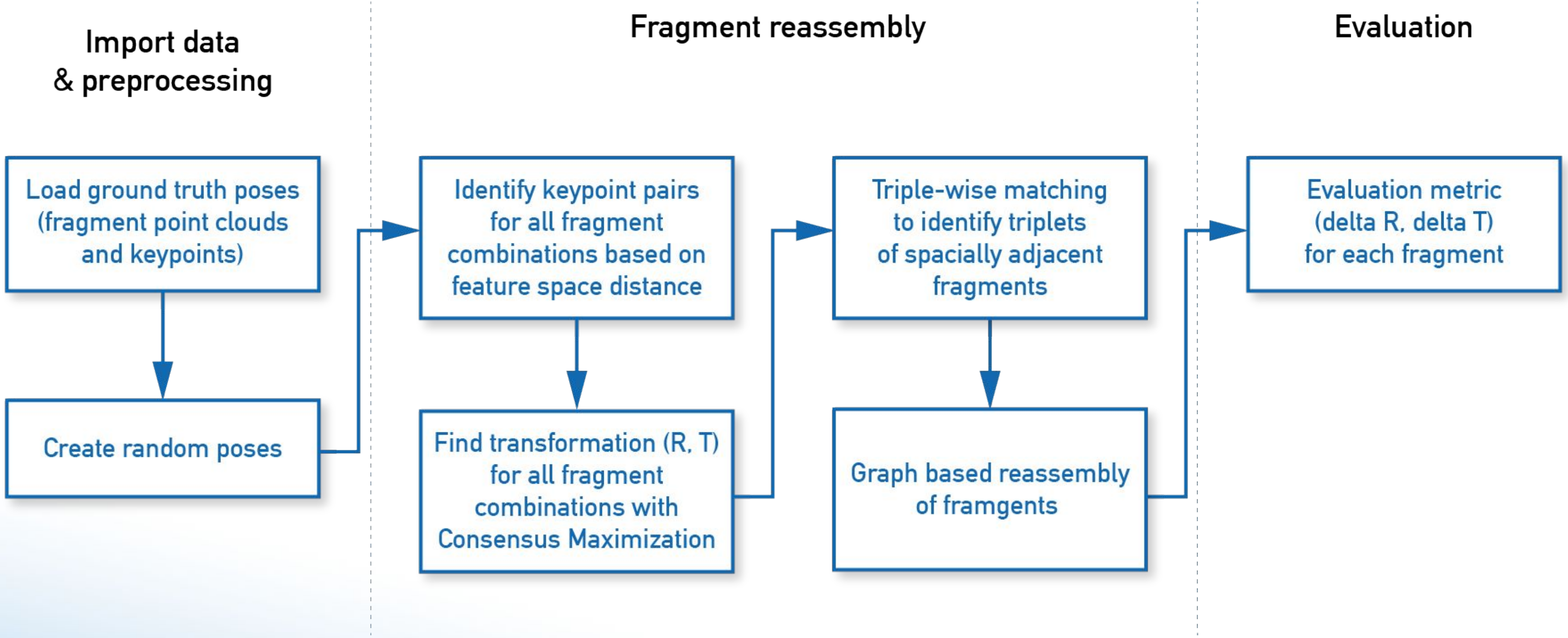
# Getting Feature Descriptors

- Extracting the features right before the fully connected layers → (Nx128)
- Inverse distance based average of features for keypoints (KP):

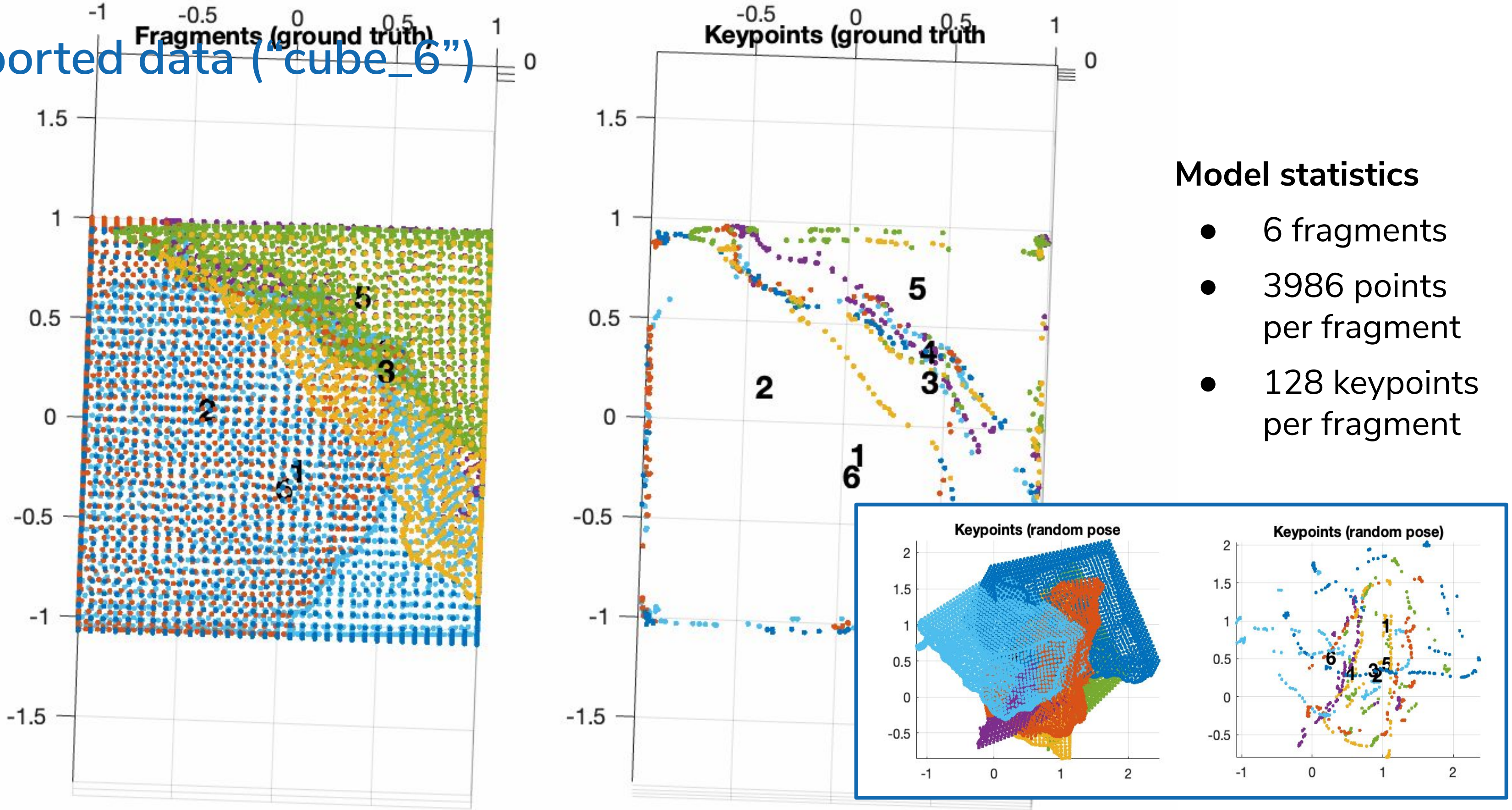
$$f^{(j)}(x) = \frac{\sum_{i=1}^{k} w_i(x) f_i^{(j)}}{\sum_{i=1}^{k} w_i(x)} \quad \text{where} \quad w_i(x) = \frac{1}{d(x, x_i)^p}, \; j = 1, \ldots, C$$

- Contrastive margin loss based training on descriptors
    - Reduce the distance for positive key-point correspondences
    - Increase distance for hardest negative key-point

# Reassembly optimization workflow



# Imported data ("cube_6")

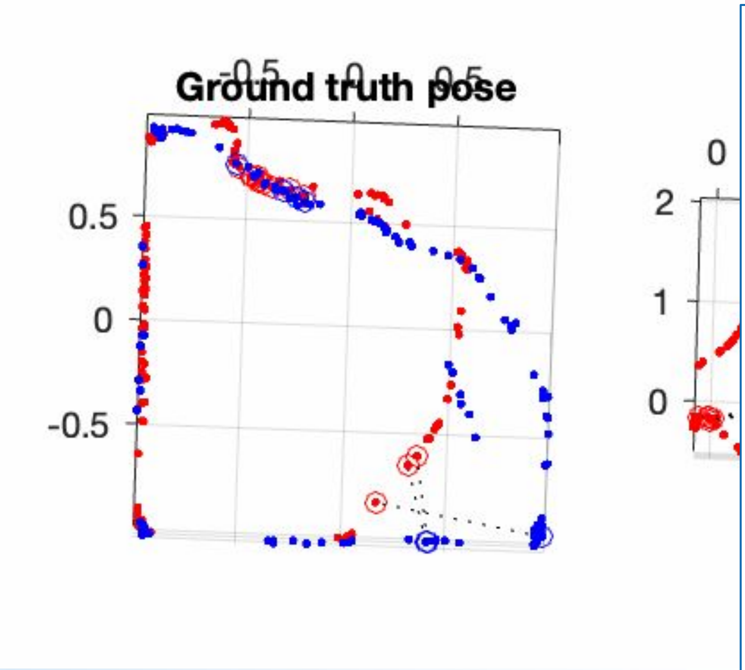


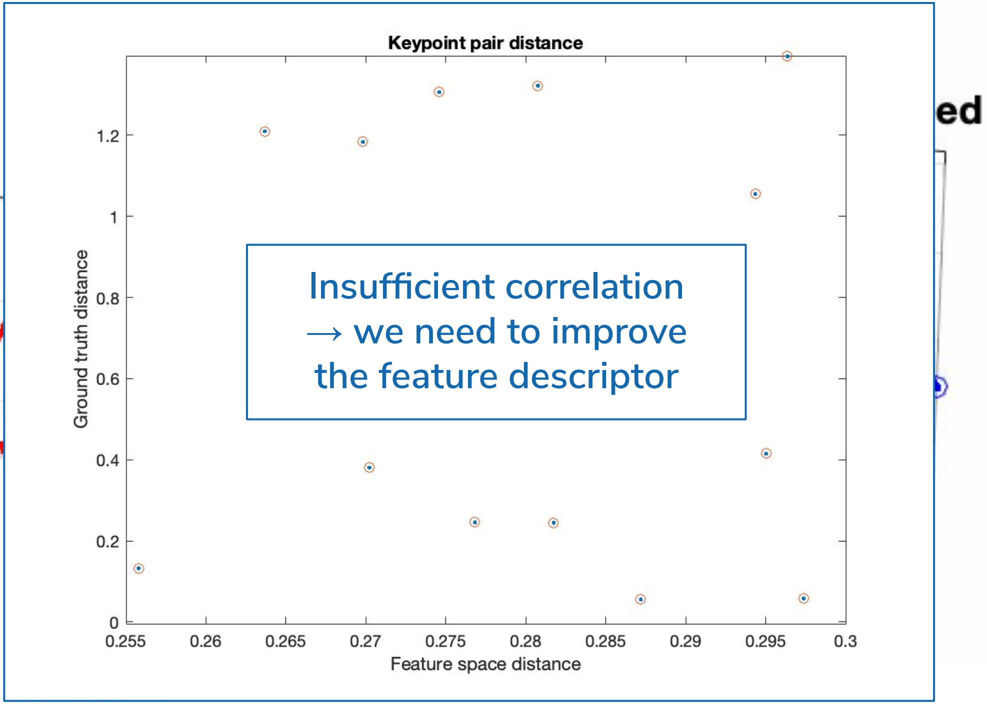

**Model statistics**

- 6 fragments
- 3986 points per fragment
- 128 keypoints per fragment

# Fragment reassembly: Pairwises pose estimation

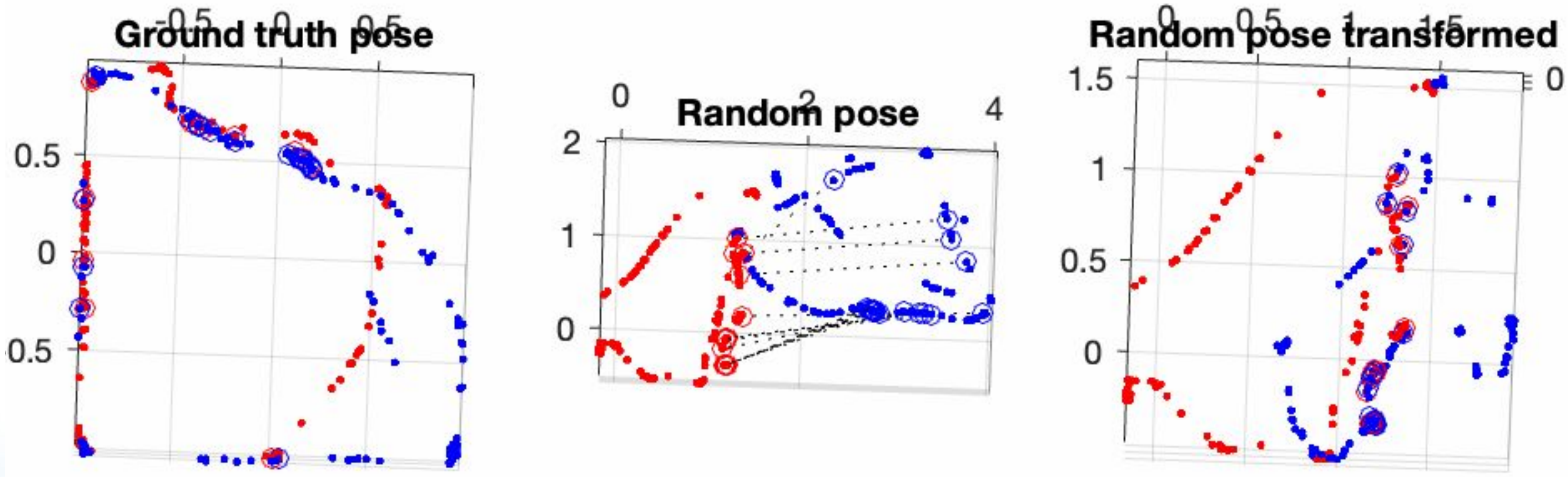
Keypoint pairs determined by random pose **keypoint feature space euclidean distance**



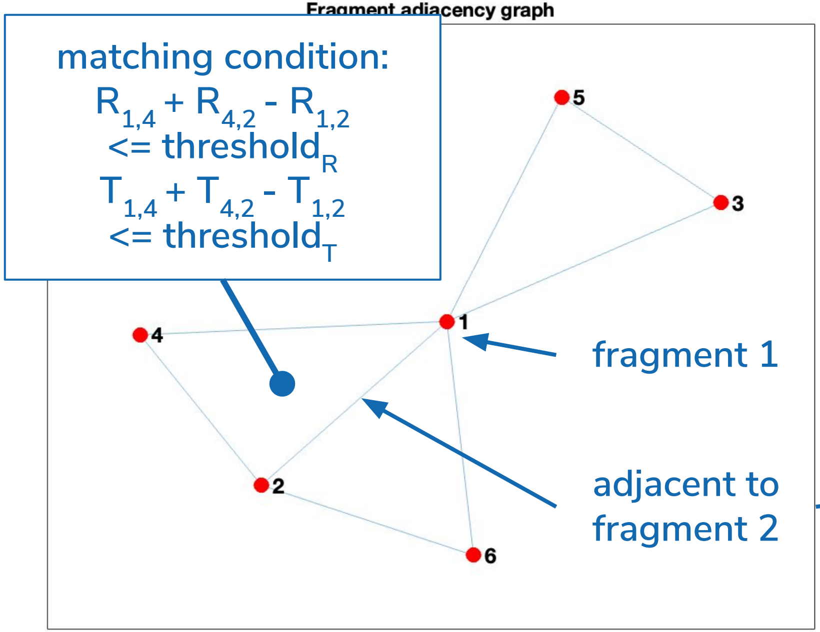



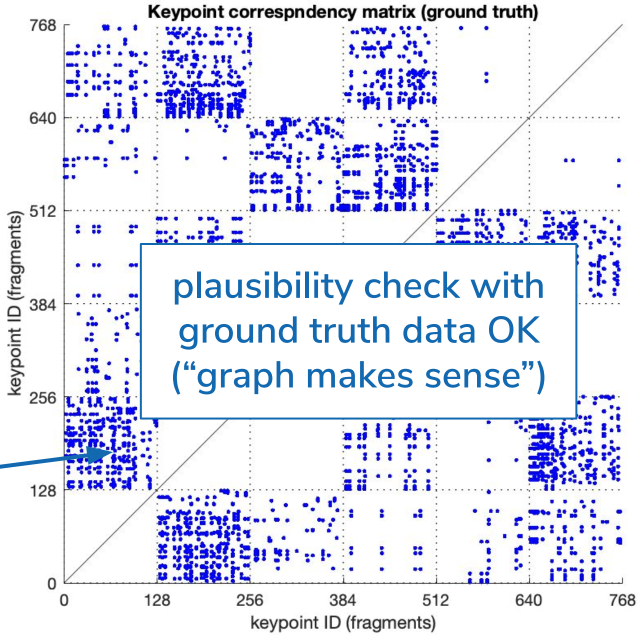
# Fragment reassembly: Pairwises pose estimation

Keypoint pairs determined by **ground truth keypoint euclidean distance**

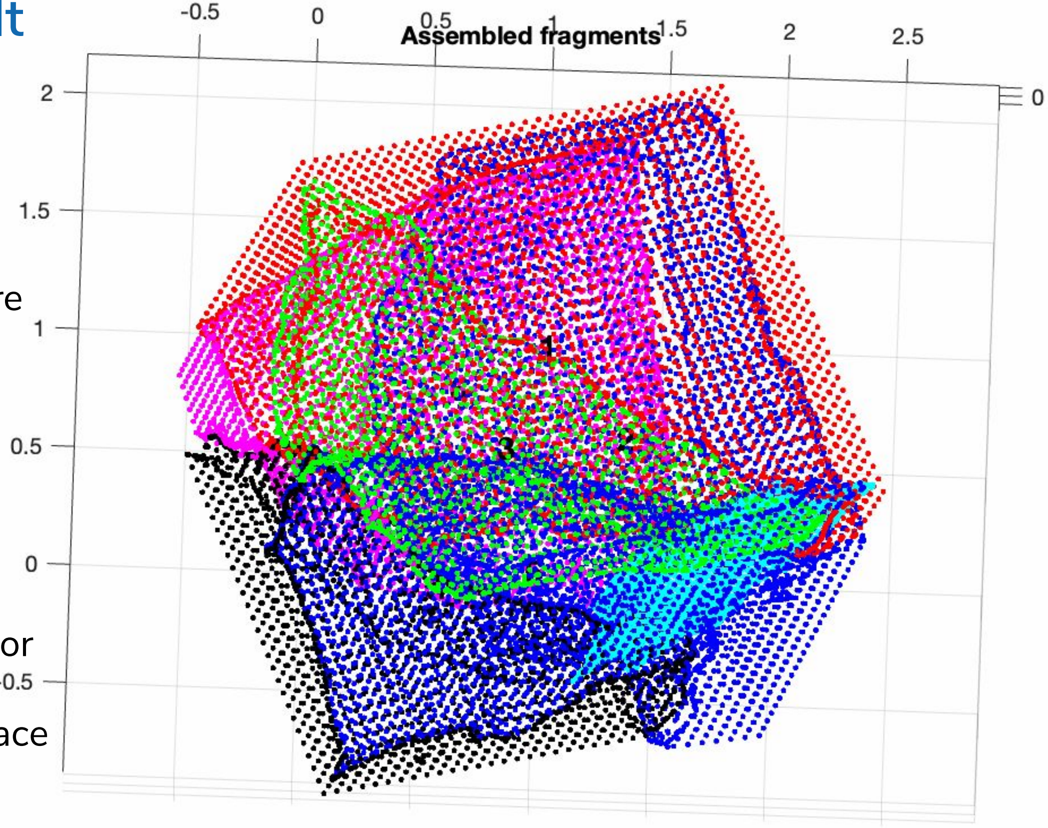


# Fragment reassembly: Triple-wise matching for adjacency detection



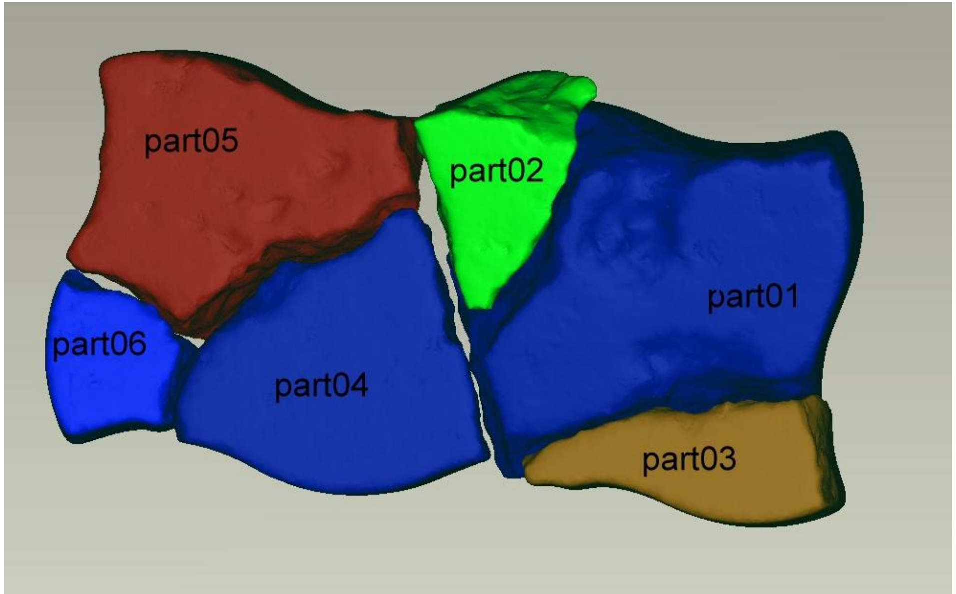
# Fragment reassembly: Result



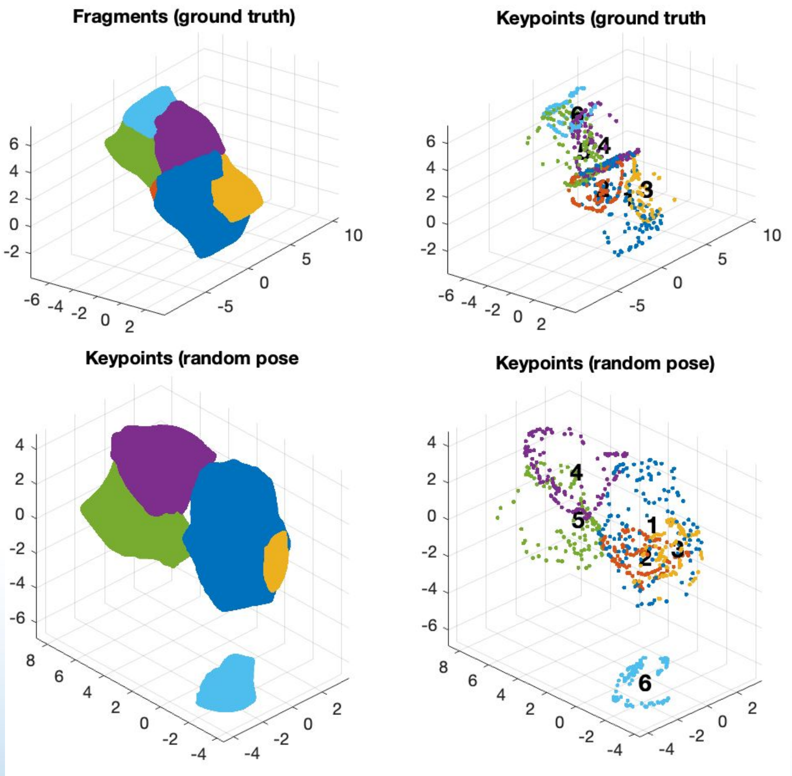

**Summary of reassembly**

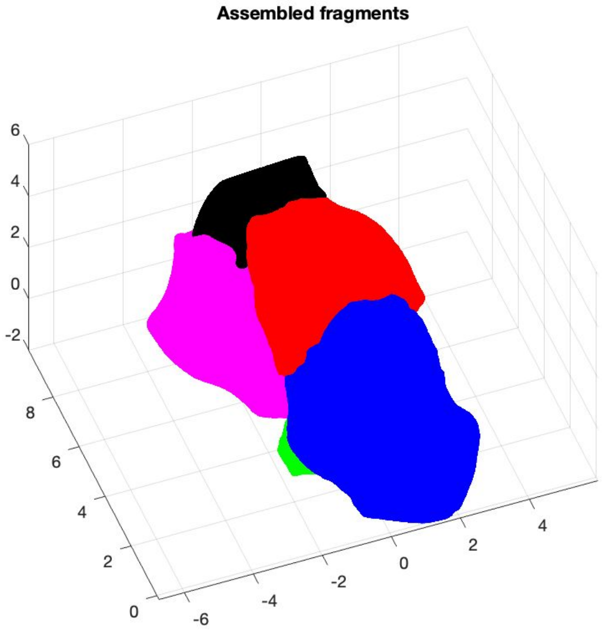
- Reassembly workflow generally working with keypoints locations detected by USIP feature detector network
- **Current limitations:** Keypoint pairs of two spatially adjacent fragments are found with help of ground truth pose
- **Planned improvements:** Optimization of keypoint descriptor network to allow identification of keypoint pairs close in feature space

# Fragment reassembly: Result (3D scanned brick)

# Fragment reassembly: Result (3D scanned brick)

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# Future Work / Possible Improvements

- Getting better descriptors
- Alternative to hardest sample training
- Trainable threshold for negative keypoints
- Generate training data with more complicated shapes
- Fuse keypoint detection and description network; simultaneous learning
- Refine reassembly by combining already solved clusters of fragments
- Implement intersection test in reassembly
- Exhaustive testing of different approaches; compare rotation and translation to ground truth

# References


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2. Li, J. and G. H. Lee (2019). USIP: Unsupervised stable interest point detection from 3d point clouds. Proceedings of the IEEE/CVF International Conference on Computer Vision
3. Z. Wu, S. Song, A. Khosla, F. Yu, L. Zhang, X. Tang and J. Xiao (2015): 3D ShapeNets: A Deep Representation for Volumetric Shapes. Proceedings of 28th IEEE Conference on Computer Vision and Pattern Recognition (CVPR2015)
4. Luxiao Cui (2019), 2D Fragment Reassembly, Master Thesis, Computer Vision and Geometry Lab, ETH Zurich
5. A. Alzaid, S. Dogramadzi (2019), Reassembly of Fractured Object Using Fragment Topology
6. P. Speciale; D. Paudel, M. Oswald (2017), Consensus Maximization with Linear Matrix Inequality Constraints, IEEE Conference on Computer Vision and Pattern Recognition

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# Thanks for your attention!

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# Final Pipeline