Summary 18.11.

Kevin Zien Qu

1) Xu et al.: OMNet: Learning Overlapping Mask for Partial-to-Partial Point Cloud Registration (ICCV 2021)

- OM-Net: Network for partial-to-partial point cloud registration
- Non-overlapping regions infer global feature extraction

→predict overlapping masks for the two inputs

- Given the accurate overlapping masks, the non-overlapping points are rejected during the aggregation of global features, which converts the partial-to-partial registration to the registration of the same shape

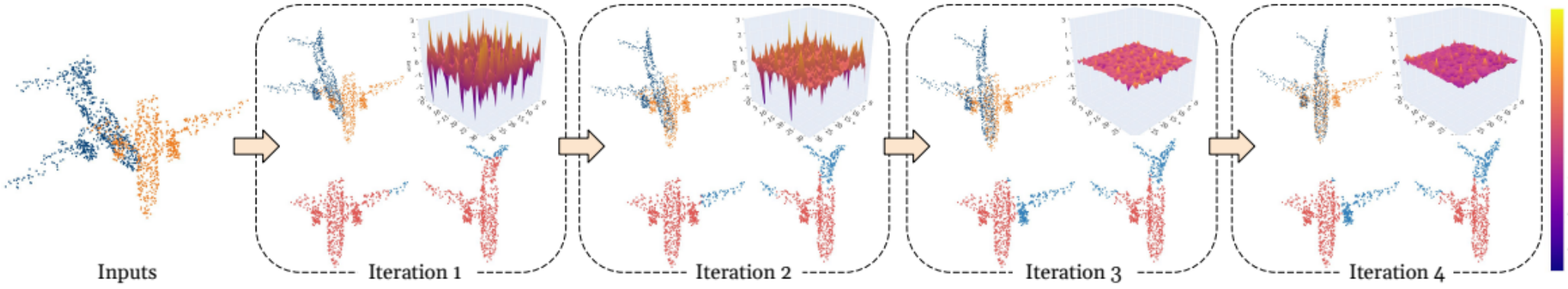

Figure 5. We show the registration result (top left), the difference between the global features of the inputs $\mathbf{X}$ and $\mathbf{Y}$ (top right), and the predicted masks (bottom) at each iteration. Red and blue indicate the predicted overlapping and non-overlapping regions respectively.

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Performance on unseen categories:

- The model is trained on the first 14 categories and tested on the other 18 categories

→ Still good performance

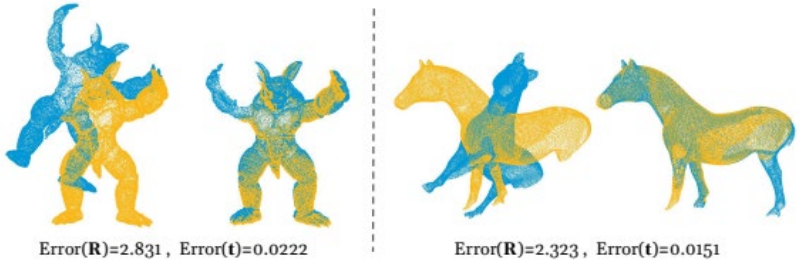


Figure 9. Example results on Stanford 3D Scan.

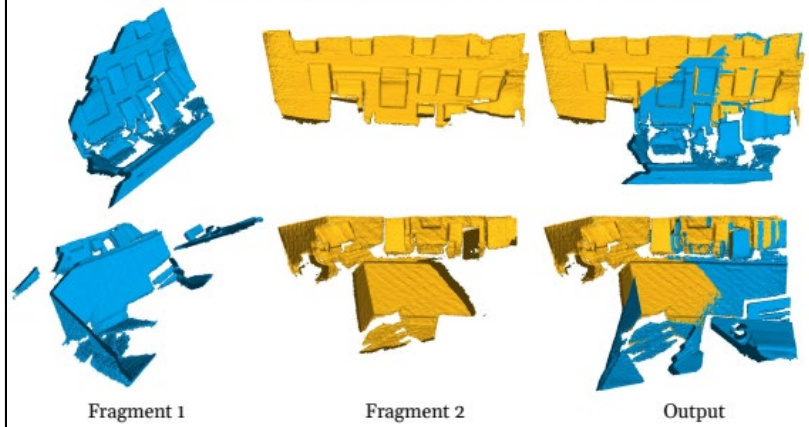


Figure 10. Example results on 7Scenes.

2) Huang et al.: PREDATOR: Registration of 3D Point Clouds with Low Overlap (CVPR 2021)

- PREDATOR, a neural architecture for pairwise 3D point cloud registration that learns to **detect the overlap region** between two unregistered scans, and to **focus on that region when sampling feature points**

- Different from previous work, the model is specifically designed to handle (also) point-cloud pairs with low overlap

- Existing literature and benchmarks consider only pairs of point clouds with ≥30% overlap to measure performance

2) Huang et al.: PREDATOR: Registration of 3D Point Clouds with Low Overlap (CVPR 2021)

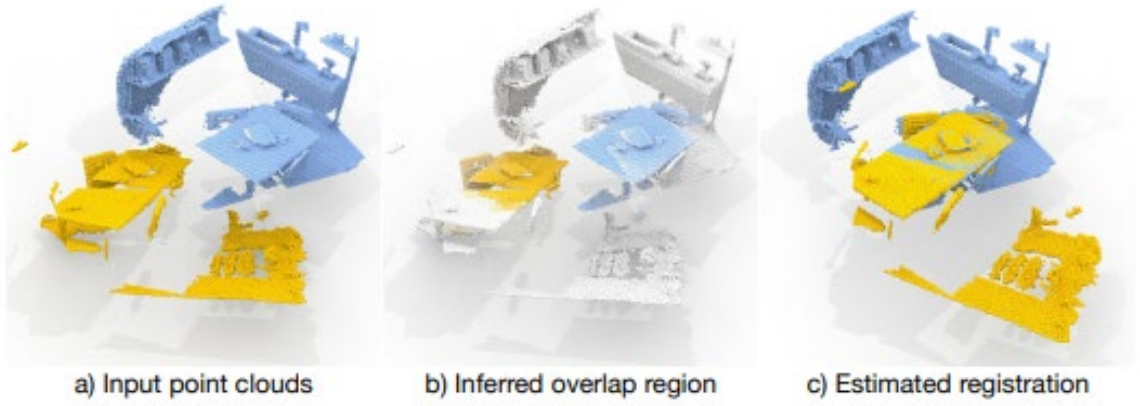


Figure 1: PREDATOR is designed to focus attention on the overlap region, and to prefer salient points in that region, so as to enable robust registration in spite of low overlap.

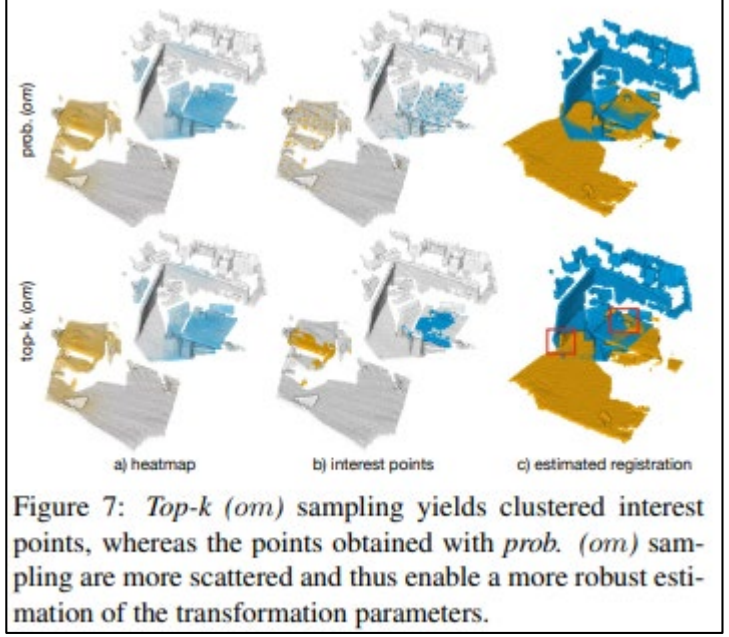


Figure 7: *Top-k (om)* sampling yields clustered interest points, whereas the points obtained with *prob. (om)* sampling are more scattered and thus enable a more robust estimation of the transformation parameters.

2) Huang et al.: PREDATOR: Registration of 3D Point Clouds with Low Overlap (CVPR 2021)

- Also experiments on object-centric dataset ModelNet40 (12,311 CAD models from 40 different categories)
- But: ModelNet40 average overlap of 73,5%
- They generate another dataset ModelLoNet with lower average overlap (53,6%)

3) Sarode et al.: MaskNet: A Fully-Convolutional Network to Estimate Inlier Points (3DV 2020)

- Fully-convolutional neural network that identifies which points in one point cloud are most similar (inliers) to the points in another

- In other words, the network learns to ‘mask-out’ outliers from the template point cloud, hence they call the approach MaskNet

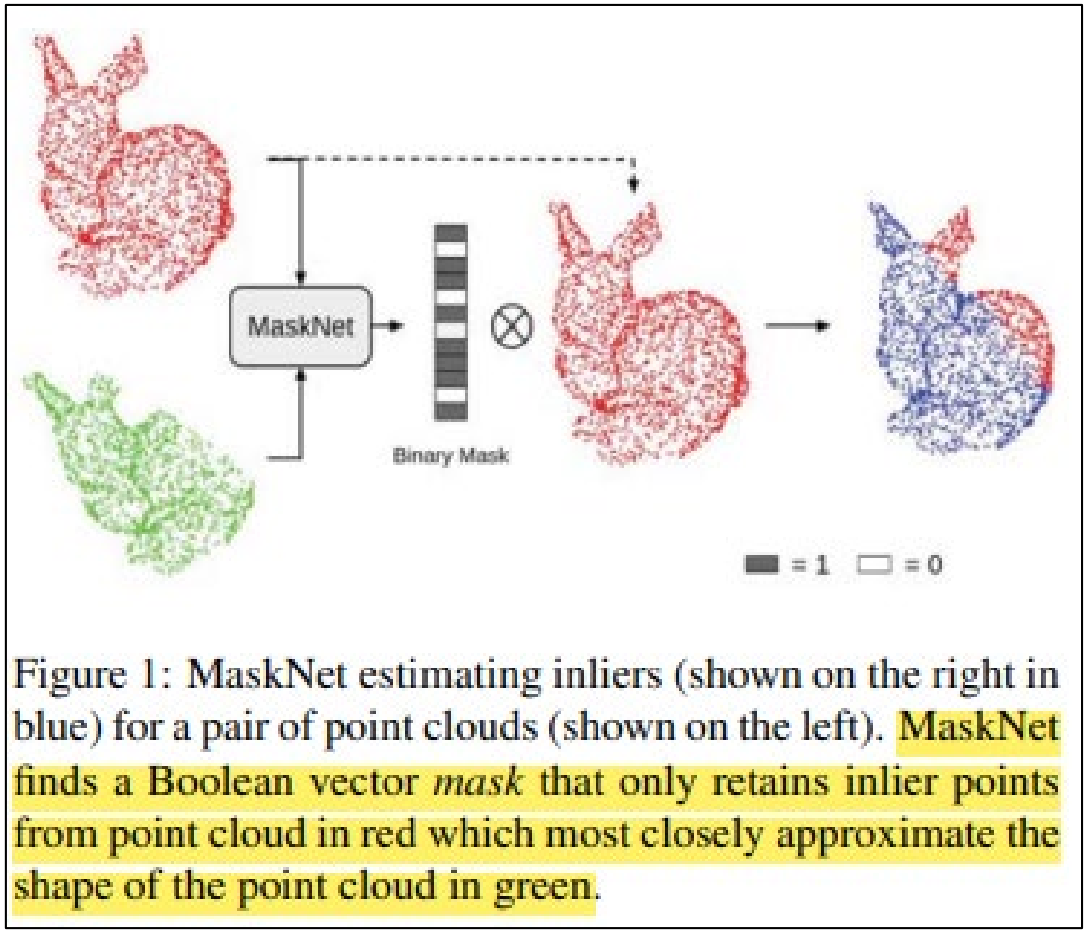
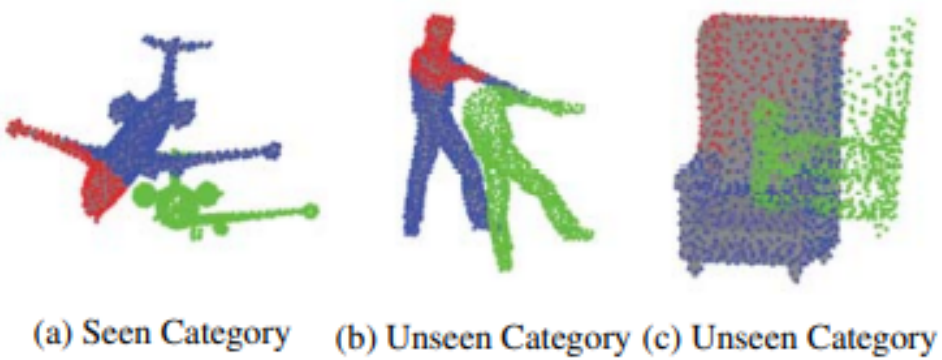


Figure 1: MaskNet estimating inliers (shown on the right in blue) for a pair of point clouds (shown on the left). MaskNet finds a Boolean vector *mask* that only retains inlier points from point cloud in red which most closely approximate the shape of the point cloud in green.

3) Sarode et al.: MaskNet: A Fully-Convolutional Network to Estimate Inlier Points (3DV 2020)

- Finding inlier points in a given pair of point clouds **describing the same object**, where one of them (source) has missing points compared to the other (template)



(a) Seen Category (b) Unseen Category (c) Unseen Category

Figure 6: Results showing the template point cloud $\mathcal{X}$ visualized as a CAD model, and source point cloud $\mathcal{Y}$ as green colored points. Blue point cloud represents $\mathcal{X}_1 = \mathcal{C} \otimes \mathcal{X}$ and points from $\mathcal{X}$ having $\mathcal{C}_i = 0$ are shown in red color.

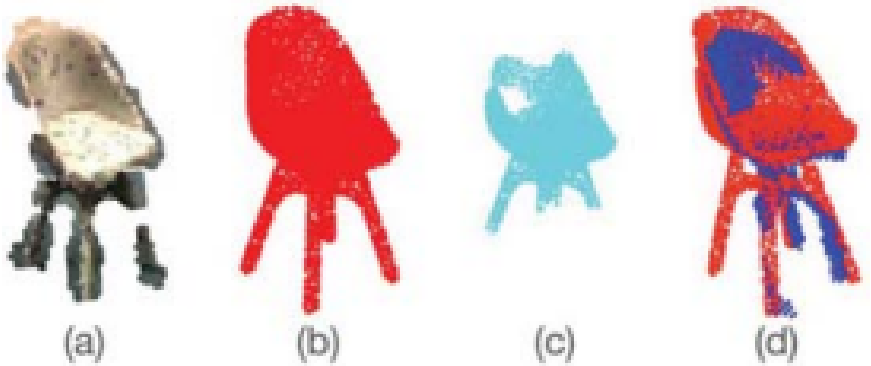


Figure 13: (a) Point cloud obtained from a RealSense sensor. (b) Template point cloud of the chair (red), (c) Result of MaskNet (cyan), (d) blue point cloud is the result of Mask-PointNetLK.

3) Sarode et al.: MaskNet: A Fully-Convolutional Network to Estimate Inlier Points (3DV 2020)

Generalization:

- They split ModelNet40 dataset into two parts – models of first 20 categories for training (seen categories) and the last 20 categories for testing (unseen categories)

- Good performance

3) Sarode et al.: MaskNet: A Fully-Convolutional Network to Estimate Inlier Points (3DV 2020)

Drawbacks:

- Two point clouds have to be from the same object
- They use a PointNet encoding in MaskNet (Prior works [2, 33, 48] show the sensitivity of PointNet to large initial misalignment between a given pair of point clouds)
- MaskNet is currently limited to removing points from only one of the input point clouds