Reassembling Broken Objects using Breaking Curves

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CVPR 2023 Workshop on 3D Vision and Robotics

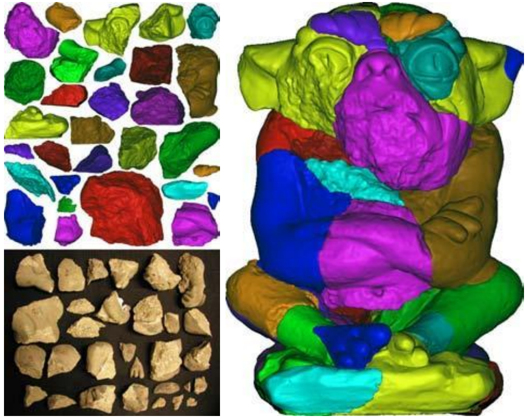
June 18th, 2023

Università
Ca'Foscari
Venezia

RePAIR

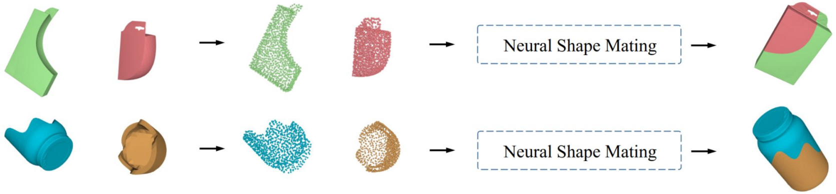
Related Work and SOTA

Geometric Methods



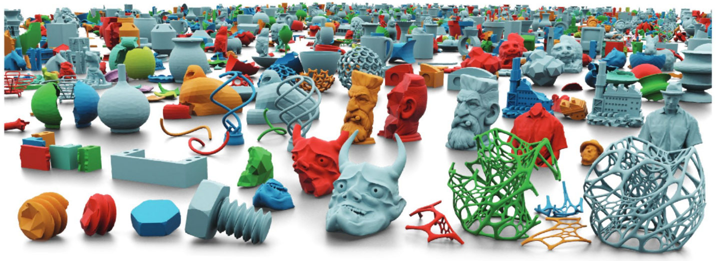
Reassembling Fractured Objects by Geometric Matching, Huang et al. SIGGRAPH 2006

Pairwise Assembly



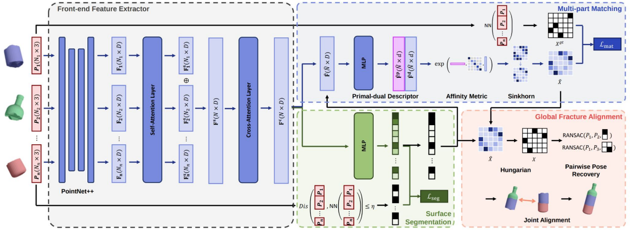
Neural Shape Mating: Self-Supervised Object Assembly with Adversarial Shape Priors, Chen et al, CVPR 2022

Benchmarking and Dataset



Breaking Bad: A Dataset for Geometric Fracture and Reassembly, Sellan, Chen, Wu et al., NeurIPS 2022 (Datasets and Benchmarks Track)

Assembling Objects Broken in Multiple Parts



Jigsaw: Learning to Assemble Multiple Fractured Objects, Lu, Sun and Quang,
Under Review 2023

Main Goal & Contributions

We aim at reassembling two parts of a broken object using point clouds:

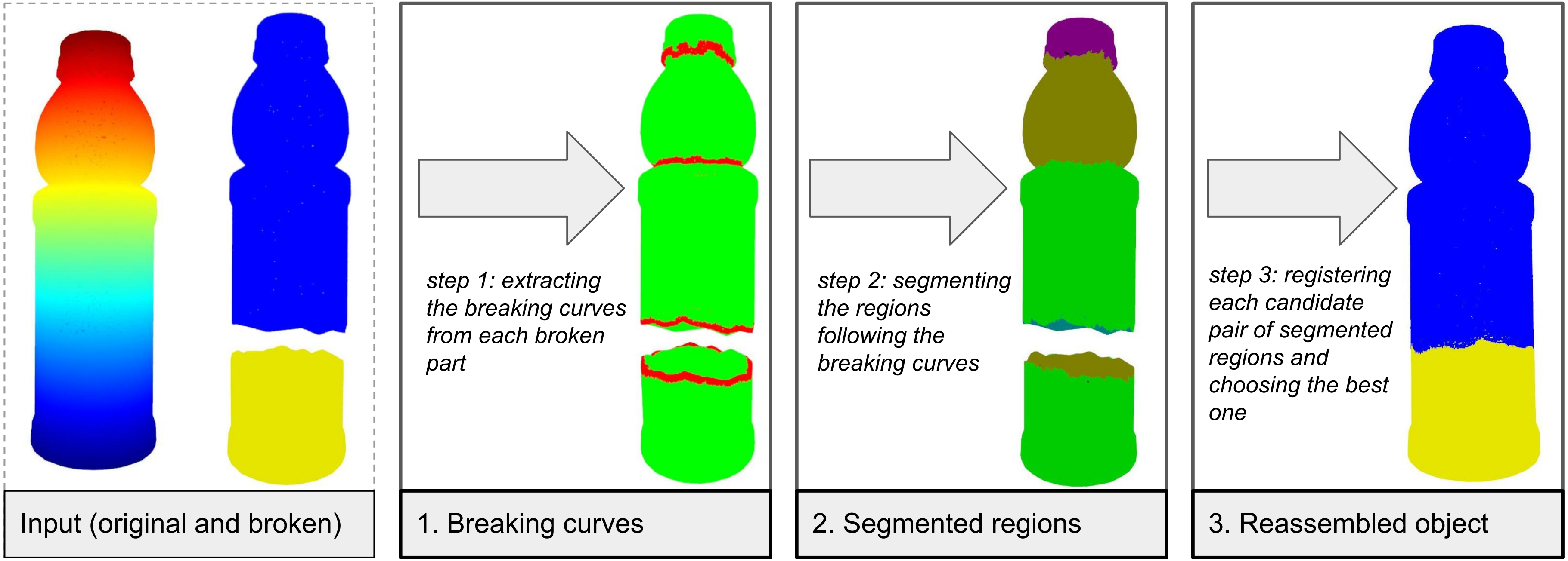
- assuming no prior information on the geometry of the broken objects
- without the need of surface reconstruction

Contributions:

- Creation of a flexible and modular framework for assembling broken objects
- The graph-based breaking curve extraction generalizes well to different shapes, allowing to use the same approach on real and synthetic objects without prior geometric assumptions

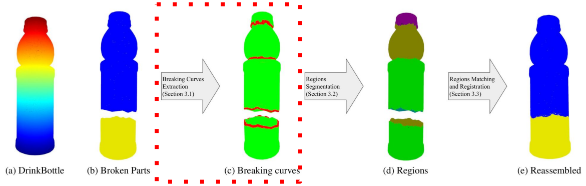
Pipeline

The pipeline is divided into 3 main steps



Extracting breaking curves, segmenting and registering segmented regions

Breaking Curves Extraction

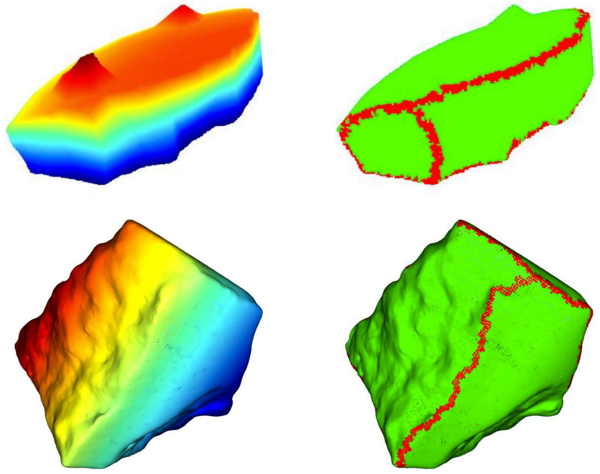


Breaking curves characterize object's fractures:

1. Represent a point cloud as an ε-graph
2. Compute for each vertex *p* a corner penalty [1]

$$\omega_{co}(p) = \frac{\lambda_2(p) - \lambda_0(p)}{\lambda_2(p)}$$

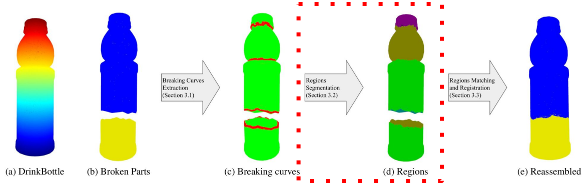
3. Select *p* nodes where $\omega_{co}(p) < \theta$
4. Pruning + Dilation to promote the creation of closed breaking curves



(a) Original (b) Breaking Curves

[1] Gumhold et.al. Feature extraction from point clouds. Proceedings of 10th international meshing roundtable, 2001, 11 2001

Region Segmentation



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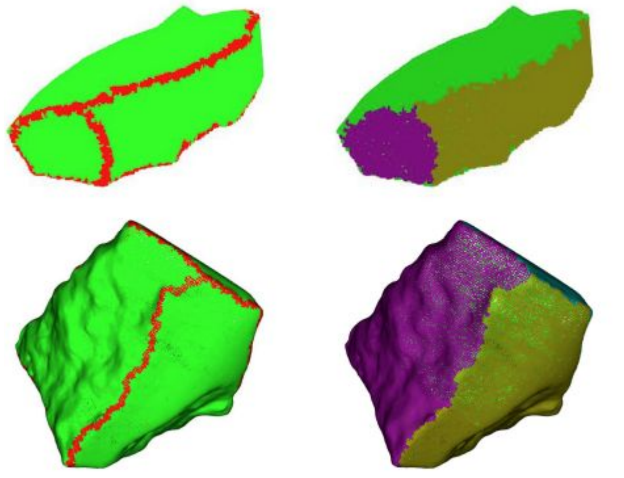


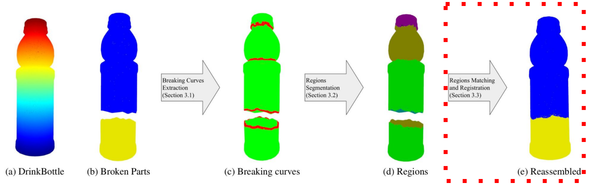
(b) Breaking Curves (c) Segmented Regions

Regions are part of the point cloud enclosed by a breaking curves

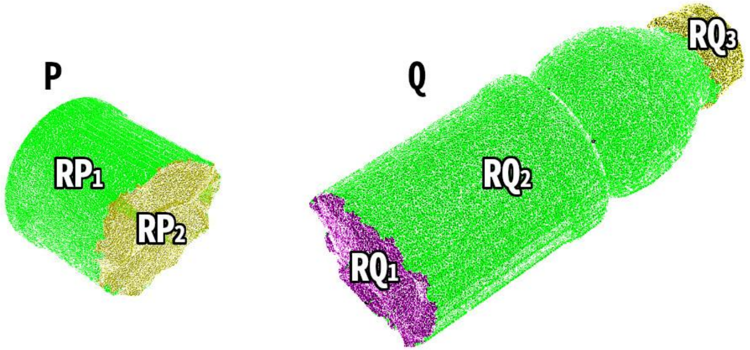
5. A B.C.-constrained region-growing technique extracts the regions.

[1] Gumhold et.al. Feature extraction from point clouds. Proceedings of 10th international meshing roundtable, 2001, 11 2001

Regions Registration



Given two segmented point clouds *P* and *Q* with regions $\mathcal{RP}$ and $\mathcal{RQ}$ the registration works by:



1. Discarding smaller regions
2. Perform ICP over all possible pair of regions
3. Assess alignment quality of each pair with the Chamfer distance
4. Select the registration with the best score and use it to align the two point clouds.

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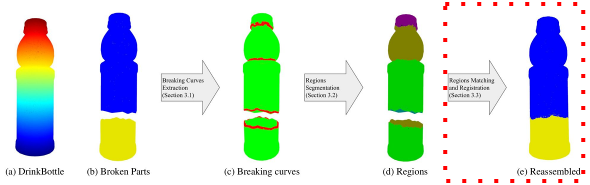

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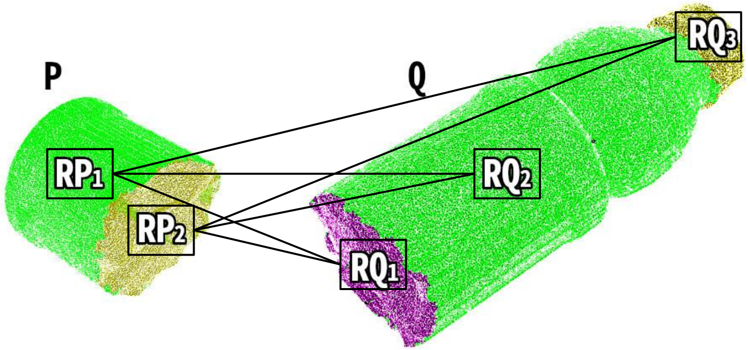

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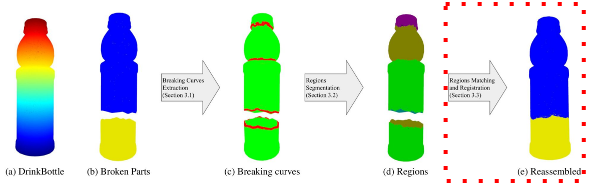

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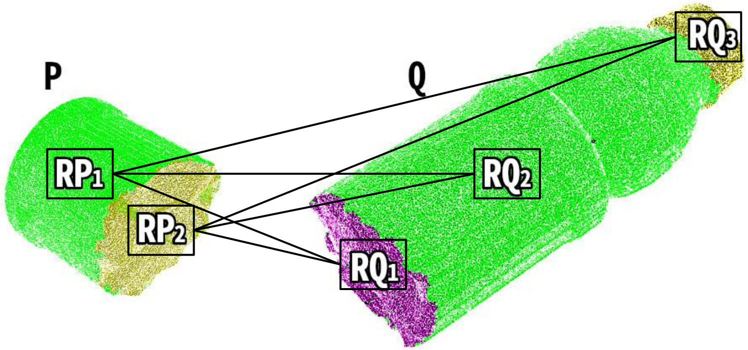
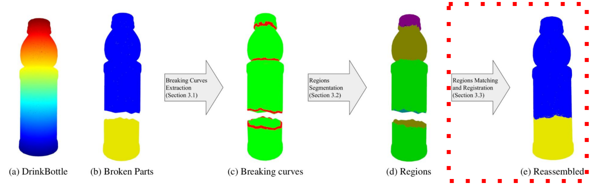


<u>*CD*</u>	RQ1	RQ2	RQ3
RP1	0.91	0.98	0.97
RP2	0.1	0.9	0.7

Regions Registration



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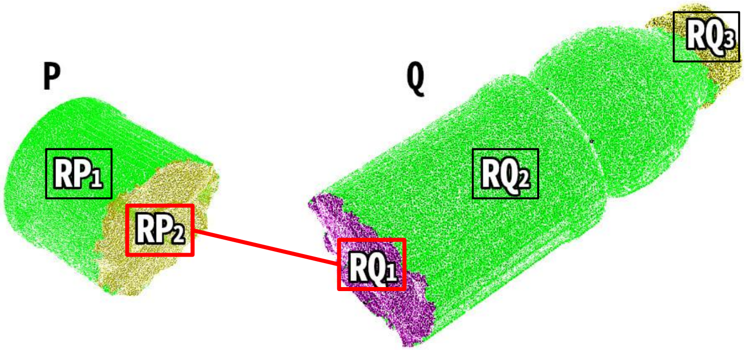

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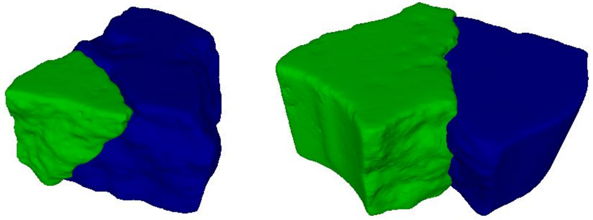
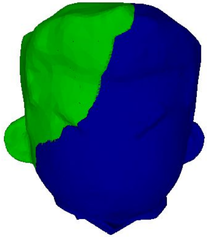
Qualitative Results

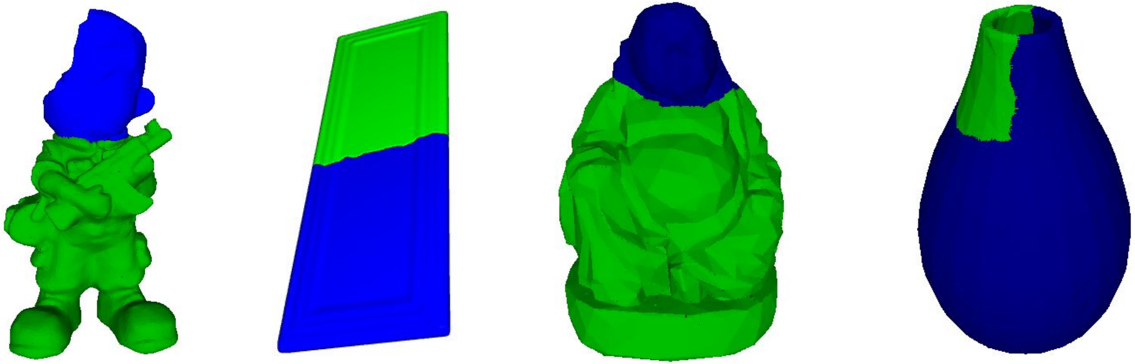
Broken Fresco from Pompeii National Park
(3D scan, *real* data, RePAIR Project)

Brick
(3D scan, *real* data, TUWien University)



Breaking Bad Dataset
(*synthetic* 3D models)





Quantitative Results

The proposed model reaches:

- Smaller RMSE in terms of rotation
- Smaller RMSE in terms of translation

No need for learning

	Relative RMSE (R)			RMSE (T)		
Category	ICP [2]	DGL♠ [7]	ours	ICP [2]	DGL♠ [7]	ours
BeerBottle	57.028	78.933	**1.62**	1.104	0.073	**0.02**
WineBottle	54.262	84.699	**1.58**	0.743	0.024	**0.02**
DrinkBottle	60.253	70.014	**1.89**	1.288	**0.008**	0.033
Bottle	68.125	76.802	**1.983**	1.198	0.078	**0.077**
Mug	$\boxed{5.041}$	$\boxed{86.221}$	$\boxed{\mathbf{1.12}}$	0.364	0.164	**0.025**
Cookie	12.594	85.707	**1.96**	0.632	0.159	**0.043**
Mirror	0.593	81.454	**0.111**	0.503	0.125	**0.001**
ToyFigure	208.333	87.972	**1.98**	4.123	0.159	**0.079**
Statue	105.582	89.605	**0.66**	2.159	0.149	**0.003**
Vase	30.756	82.218	**0.592**	1.496	0.109	**0.002**
Brick♣ [8]	11.577	62.820	**3.064**	2.356	1.684	**0.626**
Repair♣[2]	7.911	87.491	**3.466**	2.525	**0.076**	0.695

(a) Original (b) Input (c) Proposed (d) DGL [7] (e) ICP [2]

Conclusions

- Best results overall (both R and T)
- Generalization to different categories or model types (agnostic)

Code Available

https://repairproject.github.io/AAFR/

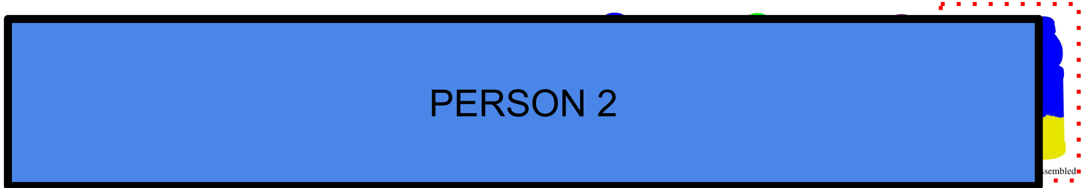
Future work:

1. Multi-part assembly
2. Enhancing breaking curve extraction methodology to make it more parameter-free

This work is part of a project that has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No.964854.

Regions Registration

PERSON 2



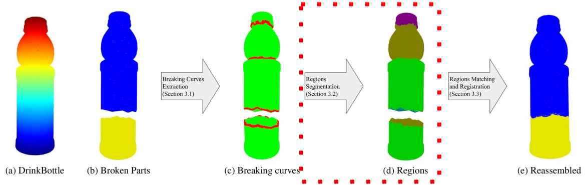
Given two segmented point clouds P and Q with regions RP and RQ
the registration works by:

1. discarding regions with a number of points below a certain threshold.

2. The registration is achieved with an exhaustive search of all the remaining regions matches.

3. Given a pair of regions RP i and R Q j , we register them with ICP [2] and compute the Chamfer Distance (CD) as their matching score. The pair with the best score is selected and their transformation is used for the final alignment.

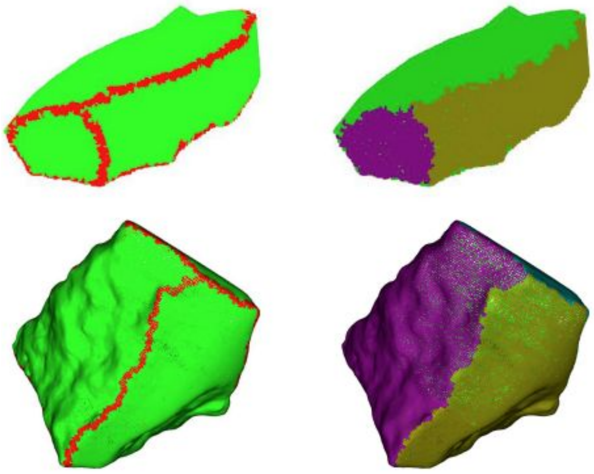
Region Segmentation



Given a point cloud P, let $\mathcal{B}^P$ be the the set of points in P that are part of a breaking curve.

Use region-growing constrained by breaking curves

1. Given $p \notin \mathcal{B}^P$ define the i-th region $\mathcal{R}_i^P$, assign *p* to it.
2. Include each $q \in \mathcal{N}_p$ in the region $\mathcal{R}_i$ if $q \notin \mathcal{B}^P$
3. Iterate until al $p \notin \mathcal{B}^P$ are considered.



(b) Breaking Curves (c) Segmented Regions

This results in segmenting the point cloud P into several regions RP enclosed by the breaking curves.

Quantitative Results

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- Smaller RMSE in terms of rotation
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Method	Eval	RMSE (R) degree	RMSE (T) $\times 10^{-2}$
ICP	BPC	60	13.6
DGL	BPC	82.4	10.5
Ours	BPC	1.3	3.0
DGL†	AVG	80.6	15.8
Jigsaw†	AVG	42.3	10.7

BPC = Best per category (averaging the best result for each category)
AVG = Averaging all the results for all categories.
†=Results from the Jigsaw paper