Unsupervised Deep Probabilistic Approach for Partial Point Cloud Registration

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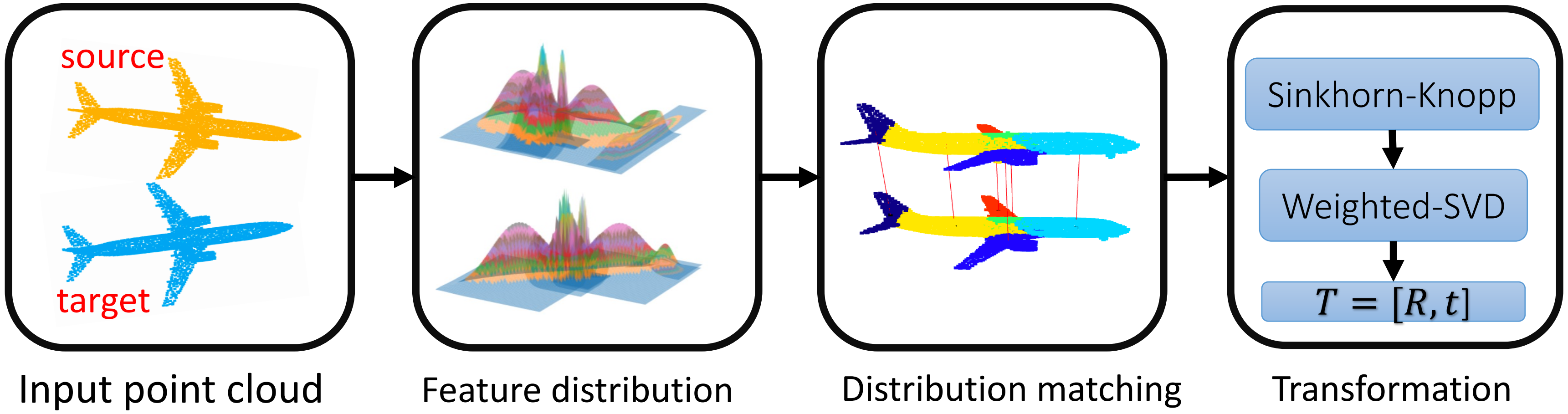
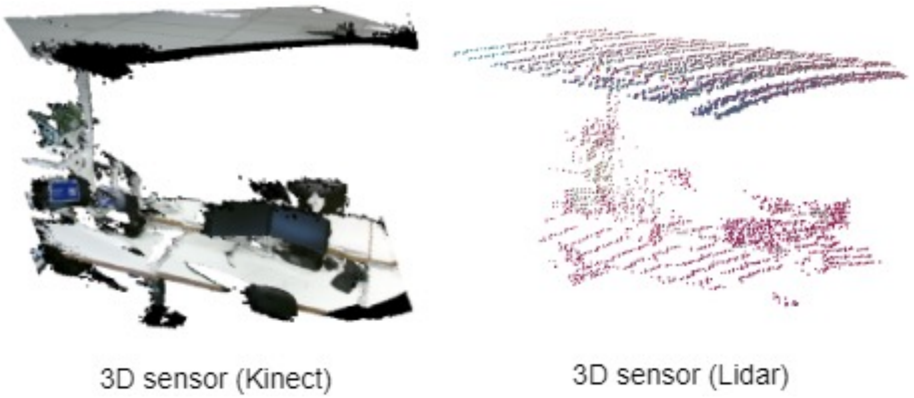
Poster: WED-PM-120

Background

Deep Probabilistic Registration





- It is suitable for point clouds with density variations;

Background

Challenges

- Deep point cloud registration methods depend on large amounts of ground truth transformations or correspondences;

- Underperform on point clouds with partial overlaps.

Our solution

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Our methods:

1. A point cloud should share an identical posterior distribution in coordinate and feature spaces – Self-Consistency Loss function.
2. The GMMs from two point clouds should be the almost same in their overlapped regions – Cross-consistency Loss function.
3. The detected overlapped regions should have the almost same clustering centroids – Contrastive Loss function.

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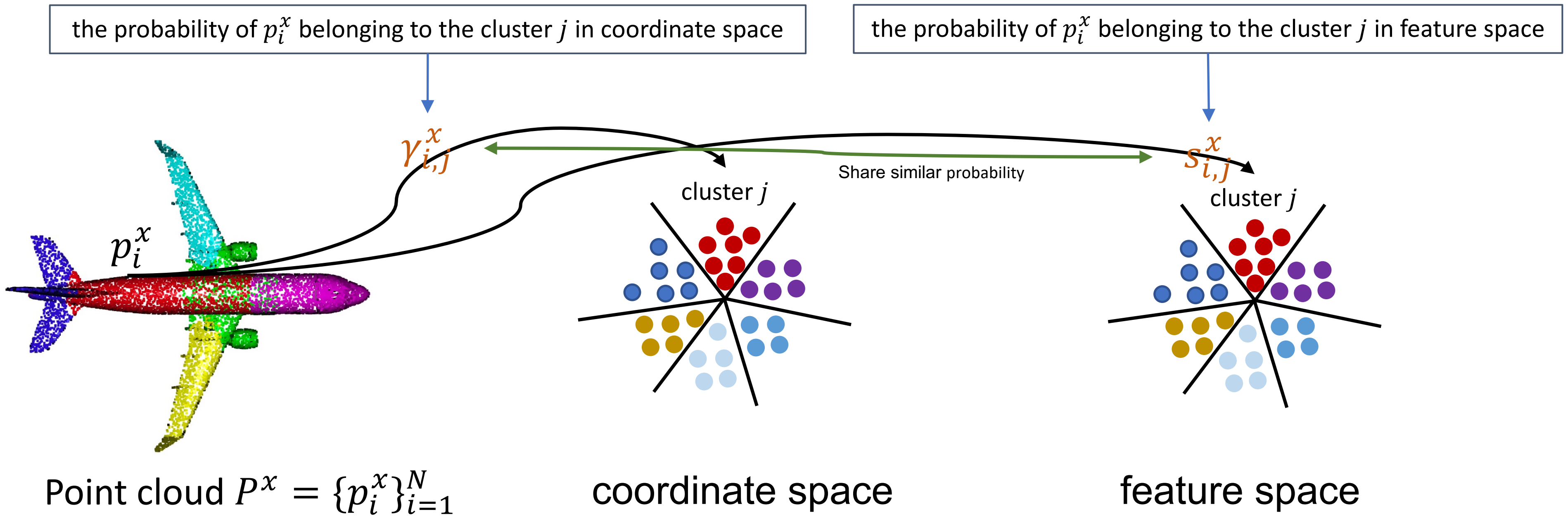
Self-consistency loss



Points of a point cloud share a similar posterior probability in feature and coordinate spaces ⟺ $min\ \mathcal{L}_{sc} = -\sum_{ij} \gamma_{i,j}^x \log(s_{i,j}^x)$

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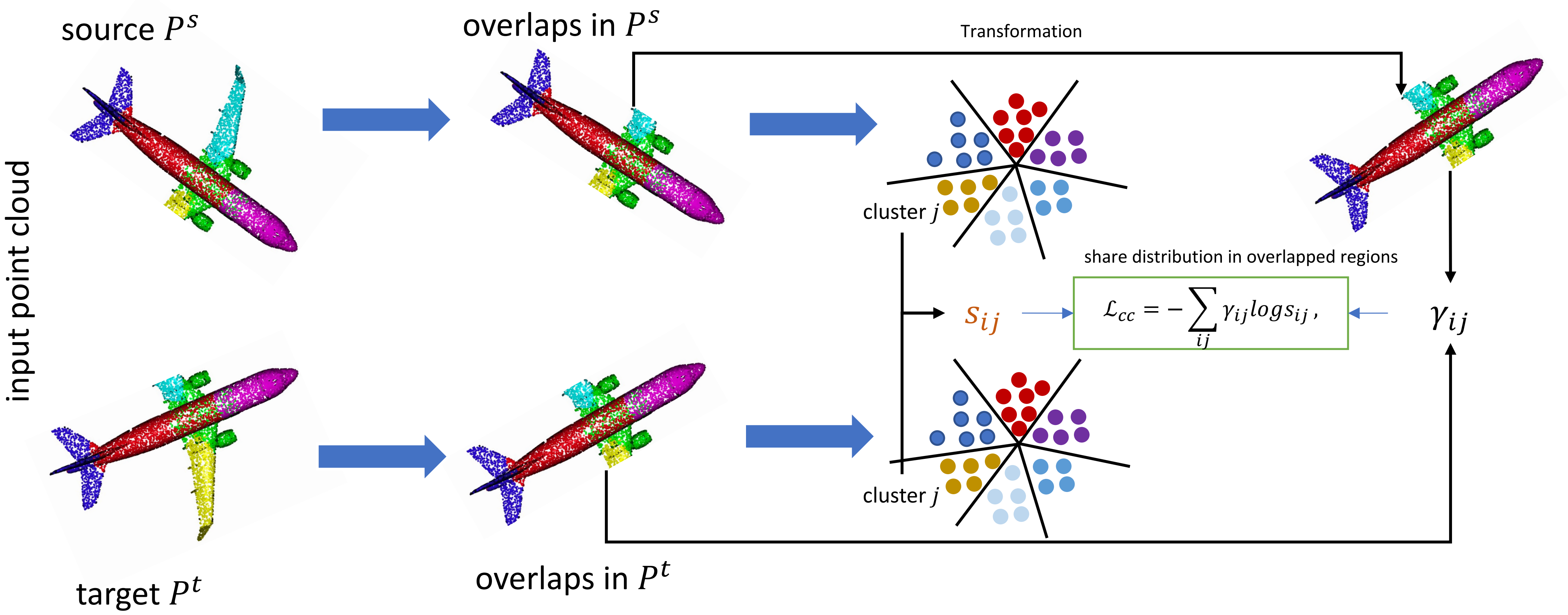
Cross-consistency loss



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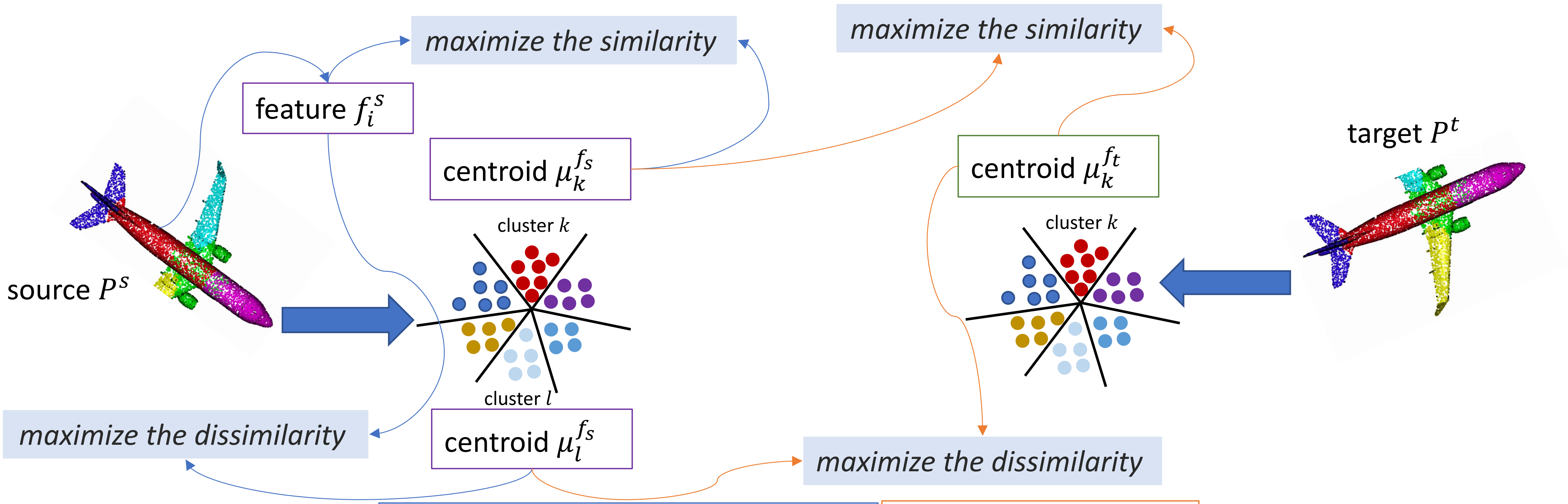
Local contrastive loss



$$min\mathcal{L}_{lc} = \boxed{-\frac{1}{L}\sum_{i=1}^{L} log \frac{\exp(\mu_i^{f_s} f_i^{s^T})\exp(\mu_i^{f_t} f_i^{t^T})}{\sum_{j=1}^{L}\exp\left(\mu_i^{f_s} f_j^{s^T}\right) \sum_{j=1}^{L}\exp\left(\mu_i^{f_t} f_j^{t^T}\right)}} \boxed{-\frac{1}{L}\sum_{i=1}^{L} log \frac{\exp(\mu_i^{f_s}\mu_i^{f_t^T})}{\sum_{j=1}^{L}\exp(\mu_i^{f_s}\mu_j^{f_t^T})}}$$

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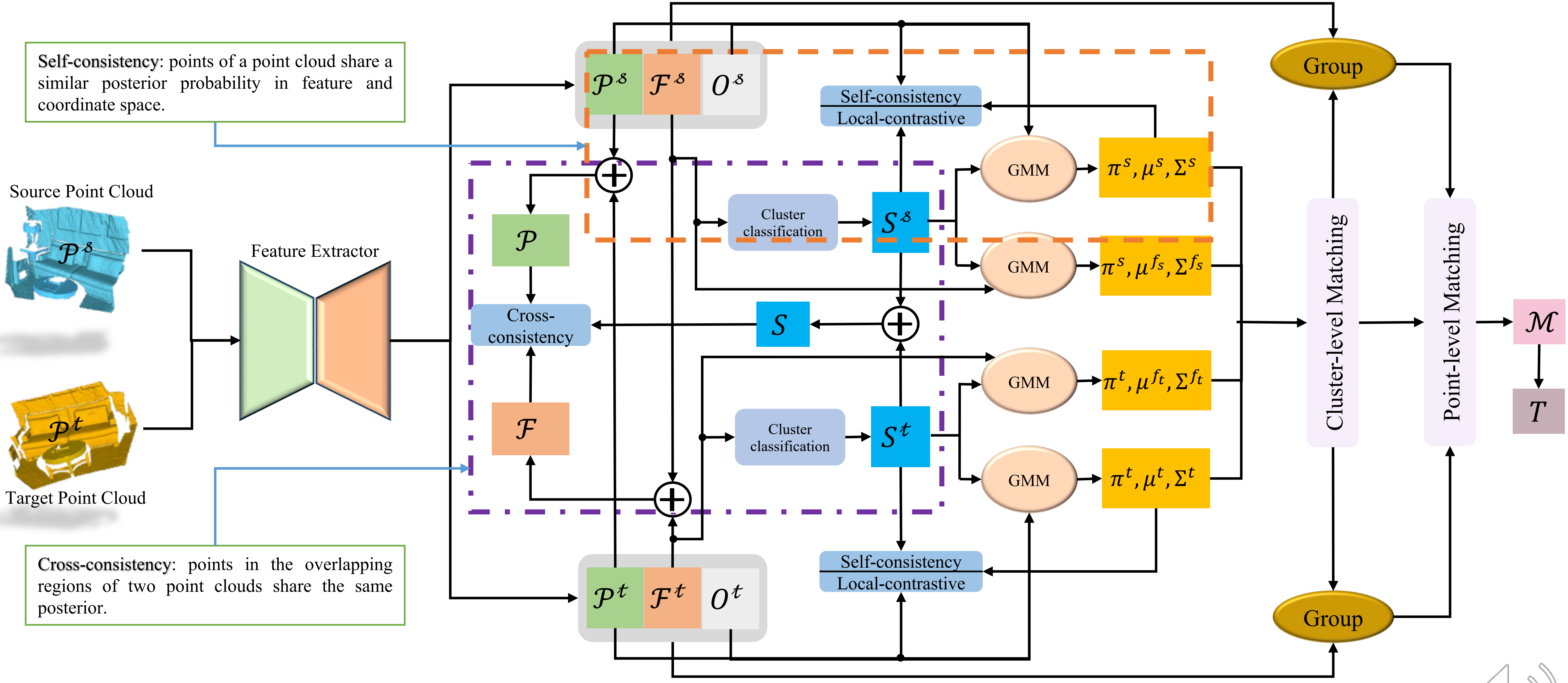
Self-consistency: points of a point cloud share a similar posterior probability in feature and coordinate space.



Cross-consistency: points in the overlapping regions of two point clouds share the same posterior.

Our solution

Experiments

Dataset

- Evaluation for real word dataset:
  - 3DMatch and 3DLoMatch
- Evaluation for synthesis dataset:
  - ModelNet40

Baselines

- Supervised methods
  - OMNet
- Unsupervised methods
  - SGP+R10K
  - UGMM

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Experiment

Results on both 3DMatch and 3DLoMatch datasets.

	3DMatch			3DLoMatch		
Method	RRE	RTE	CD	RRE	RTE	CD
	Supervised Methods					
FCGF	85.1%	1.949	0.066	40.1%	3.147	0.1
D3Feat	81.6%	2.161	0.067	37.2%	3.361	0.103
OMNet	35.9%	4.166	0.105	8.4%	7.299	0.151
	Unsupervised Methods					
PPFFoldNet	69.3%	3.021	0.089	24.8%	7.527	1.884
SGP+R10K	85.5%	1.986	0.079	39.4%	3.529	0.099
UDPReg(ours)	91.4%	1.642	0.064	64.3%	2.951	0.086

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Experiment

Results on both ModelNet and ModelLoNet datasets.

	ModelNet			**ModelLoNet**		
Method	RRE	RTE	CD	RRE	RTE	CD
	Supervised Methods					
DCP-v2	11.98	0.171	0.0117	16.5	0.3	0.0268
DeepGMR	7.871	0.108	0.0056	9.867	0.117	0.0064
OMNet	2.947	0.032	0.0015	6.517	0.129	0.0074
	Unsupervised Methods					
RIENet	2.447	0.018	0.0365	14.49	0.105	0.0828
UGMM	13.65	0.124	0.0753	17.39	0.161	0.0745
UDPReg(ours)	1.331	0.011	0.0306	3.578	0.069	0.0416

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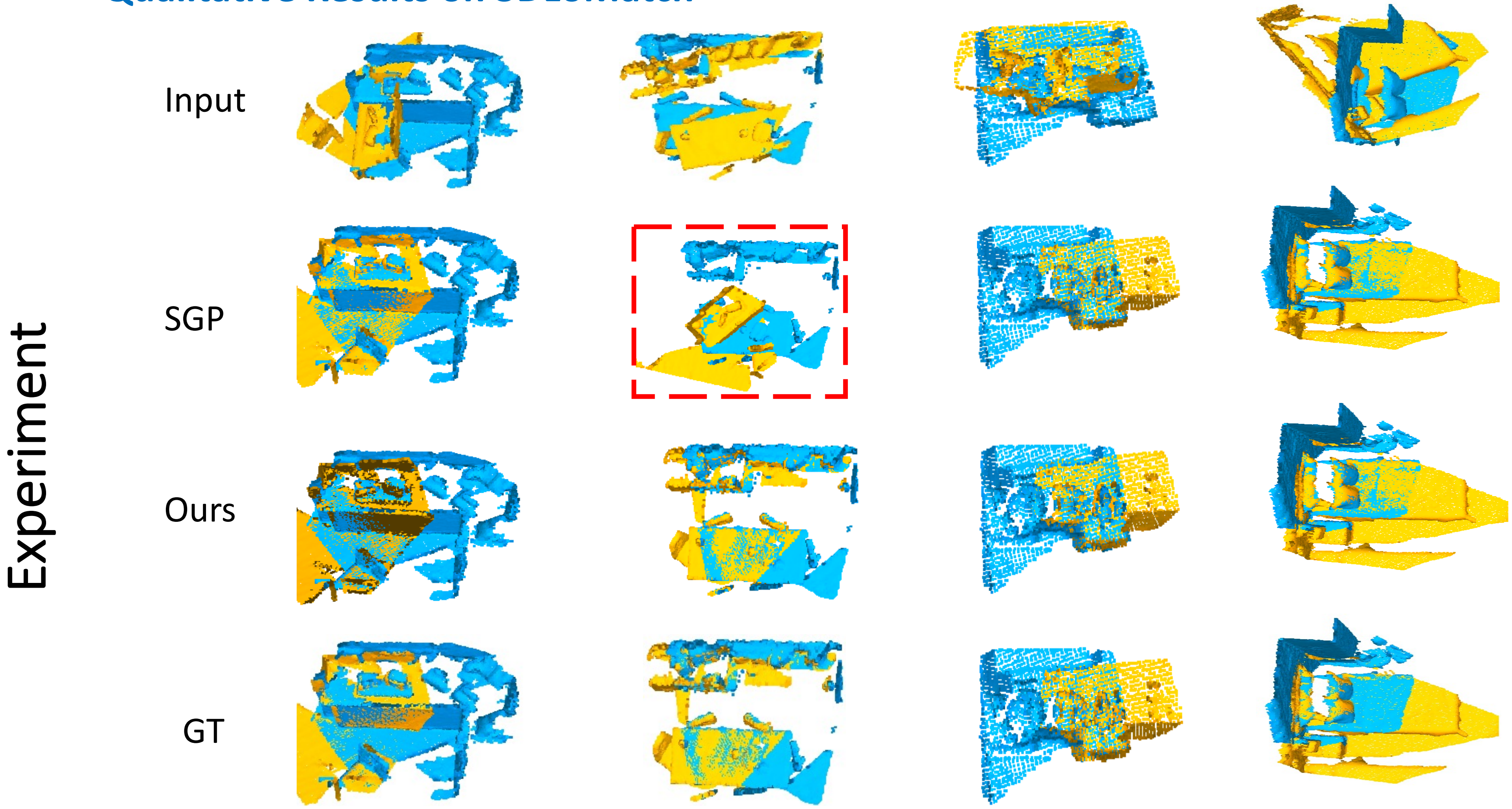
Qualitative Results on 3DLoMatch



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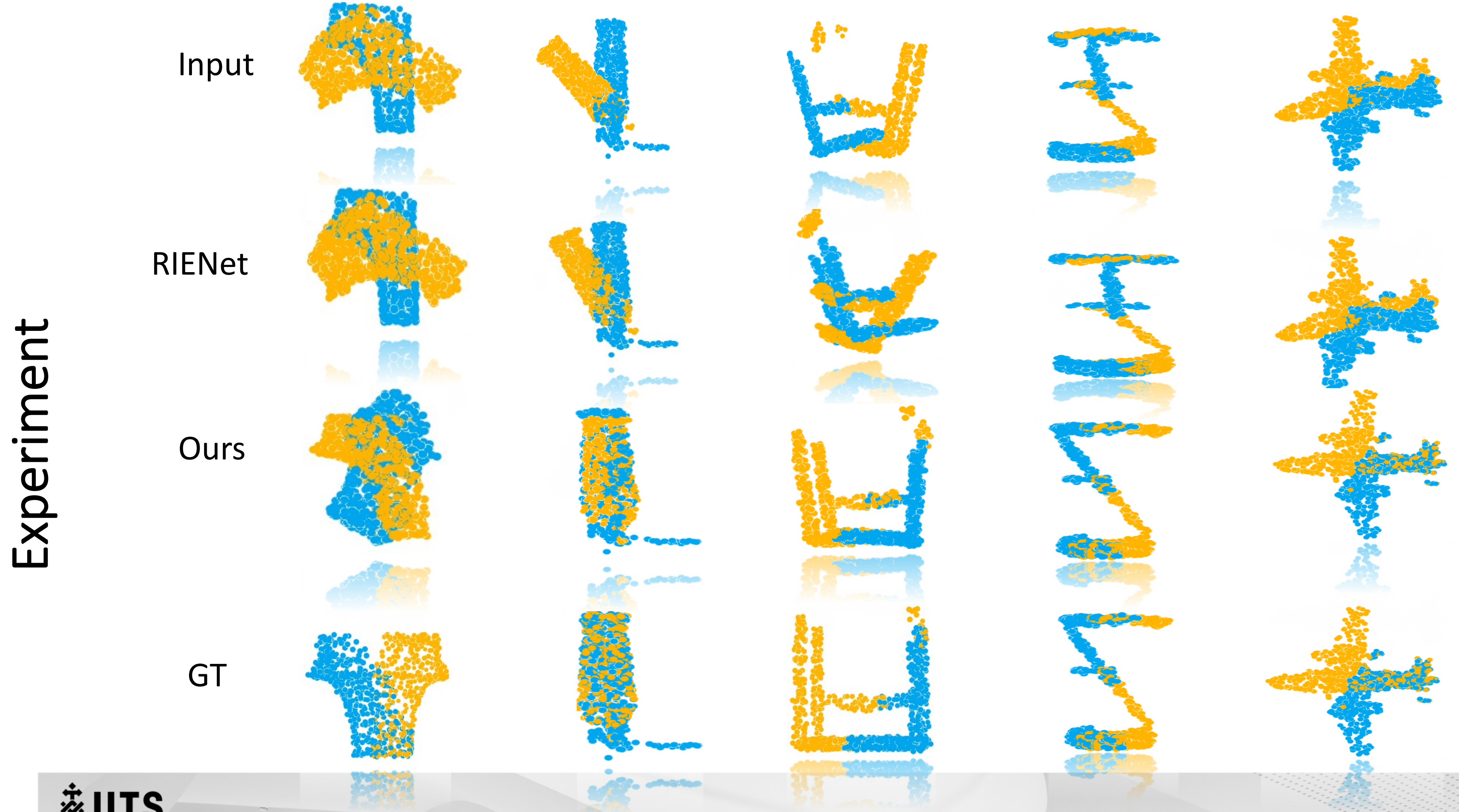
Qualitative Results on ModelLoNet



Thank You for Listening!