P2C: Self-Supervised Point Cloud Completion from Single Partial Clouds

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Introduction

Point cloud data is a fundamental representation of 3D geometry, contributing to numerous applications in robotics, auto-navigation, augmented reality, *etc*. Limited by viewing angle, occlusion, and acquisition resolution, raw point clouds are generally sparse and incomplete.

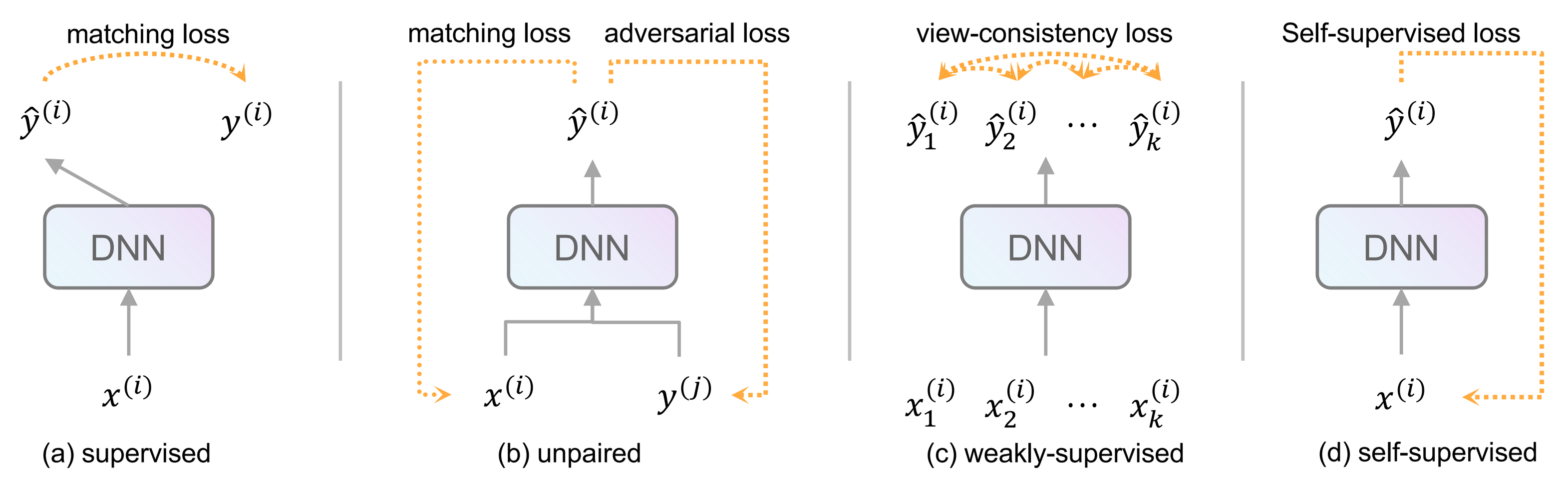

Figure 1. Conceptual comparison of point cloud completion schemes

We propose a new scheme to address the above challenge, namely **self-supervised point cloud completion**, aiming at recovering incomplete point clouds with only single partial clouds available.

Motivation

- **Self-Supervised Completion** Existing methods require either ground truth shapes, unpaired complete examples, or multi-view observations as supervision, which is expensive to collect compared with raw partial shape, so we leverage the observation that a collection of shapes with different incompleteness can represent the whole geometry and proposed the first self-supervised point cloud completion method.
- **Region-Aware Chamfer Distance** We notice that existing point set distance metrics limit the completion capability in self-supervised setting, so we designed a novel measure that is aware of missing regions via dynamically sampled skeleton points.
- **Normal Consistency Constraint** To further regularize our self-supervised method, we introduce a novel constraint that incorporates a local planarity assumption.

Contribution

Our main contributions are summarized below:

- We propose, **P2C**, the first self-supervised framework that is able to complete point clouds with only a single partial point cloud per object for learning.
- We design a novel distance measure, **Region-Aware Chamfer Distance**, which overcomes problems of restricting completion and insufficient supervision, by constructing local regions around dynamically constructed skeleton points.
- We present the **Normal Consistency Constraint** to refine shape predictions to follow the local surface manifold by minimizing a novel consistency metric, improving surface continuity and completeness.

Partial2Complete

Starting from the partial point cloud P_p, we divide it into patches and partition these patches into three groups $(G_{rec}, G_{com}, G_{latent})$. The encoder takes G_{rec} to produce features f then the decoder generates a predicted point cloud P_c based on f. G_{latent} is never observed by the encoder, we resample corresponding regions G'_{latent} in P_c to yield another feature embedding f'.

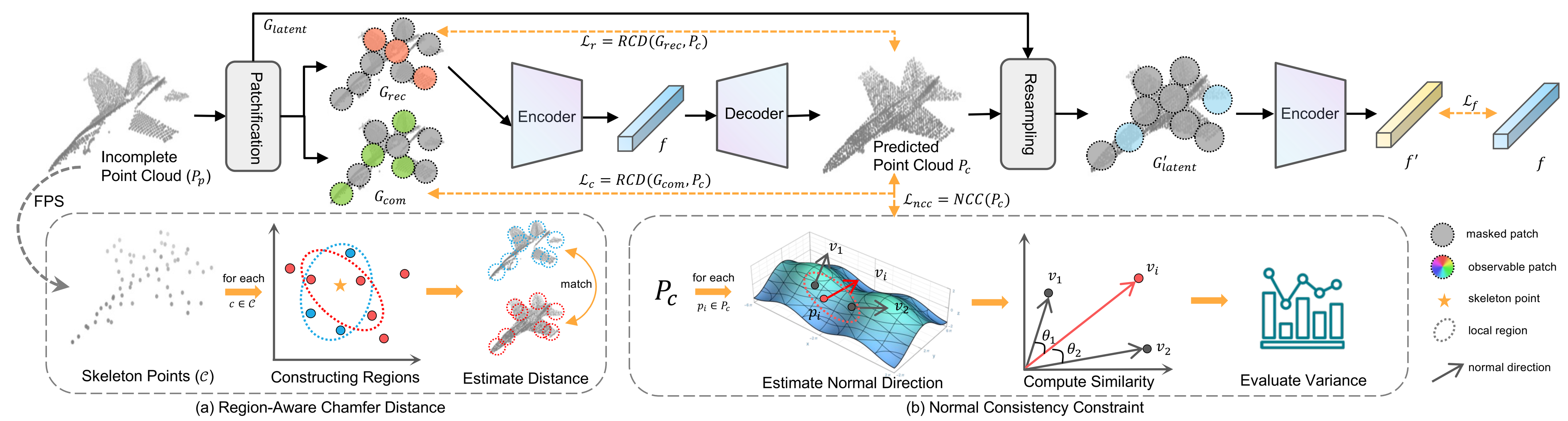

Figure 2. The Pipeline of P2C.

The overall loss has four components. The reconstruction loss $\mathcal{L}_r$ and completion loss $\mathcal{L}_c$ are realized by RCD. The latent reconstruction loss $\mathcal{L}_f$ and the normal consistency constraint $\mathcal{L}_{ncc}$ are introduced to regularize the inference.

Region-Aware Chamfer (RCD) Distance and Normal Consistency Constraint

Region-Aware Chamfer Distance as A Similarity Measure in the Self-Supervised Setting

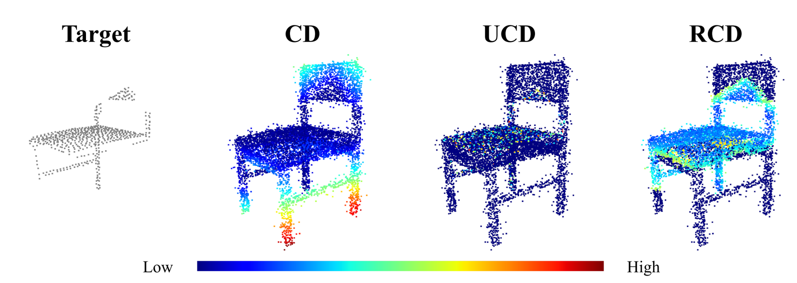

Figure 3. Visualization of per-point distance measures of CD, UCD, and RCD

RCD addresses the problem of seen/unseen region awareness by constructing local regions in both prediction and partial input centered at skeleton points that are dynamically sampled from the partial shape P_p. Given two point sets, P_p and P_c, m points are sampled from P_p as skeleton points $\mathcal{C} = \{c_i\}_{i=1}^m$, representing a rough observed shape. Then, the k-nearest neighbors in each point set are gathered for each skeleton point in $\mathcal{C}$, forming two sets that represent the matched regions R_p and R_c.

$$d_{RCD}(P_p, P_c) = d_{UCD}(R_p, R_c) + d_{UCD}(R_c, R_p), \tag{1}$$

Normal Consistency Constraint (NCC) as An Unsupervised Surface Regularization

we introduce the NCC to improve surface continuity. Given a point cloud $P = \{p_i\}_{i=1}^n$, we estimate the normal direction v_i of a tangent plane centered at p_i. We define the normal consistency of a point p_i as :

$$nc(p_i) = \left(\sum_{j=1}^{k} (v_i^T v_j - \mu_i)^T (v_i^T v_j - \mu_i) \right)^{1/2}, \tag{2}$$

where a dot product between two normal directions is applied as the similarity measure, and $\mu_i = \frac{1}{k}\sum_{j=1}^{k} v_i^T v_j$ is the mean of similarities between v_i and v_j. Further, NCC is formulated as: $NCC(P) = \frac{1}{n}\sum_{i=1}^{n} nc(p_i)$.

Experiments

Table 1. Quantitative comparison result of our method and other methods on the ShapeNet dataset using CD-$\ell_2 \downarrow (\times 10^4)$.

Method	Data	Average	Plane	Cabinet	Car	Chair	Lamp	Couch	Table	Boat
Folding	paired	6.8	2.6	7.6	4.8	8.3	9.7	7.4	8.0	5.8
PCN	paired	7.4	2.5	8.0	4.8	9.0	12.2	8.1	8.9	6.0
TopNet	paired	6.4	2.3	7.5	4.6	7.6	8.9	7.3	7.5	5.2
PoinTr	paired	4.3	1.2	6.5	4.0	5.1	4.5	5.4	5.4	2.6
Pcl2Pcl	unpaired	17.4	4.0	19.0	10.0	20.0	23.0	26.0	26.0	11.0
C4C	unpaired	14.3	3.7	12.6	8.1	14.6	18.2	26.2	22.5	8.7
Inv	complete	23.6	4.3	20.7	11.9	20.6	25.9	54.8	38.0	12.8
Cai *et al.*	unpaired	13.6	3.5	12.2	9.0	12.1	17.6	26.0	19.8	13.6
P2C*	unpaired	**10.9**	3.7	12.5	**7.7**	**11.3**	**15.3**	**13.2**	**15.2**	**8.0**
Gu *et al.*	multi-view	21.3	5.9	20.8	9.5	20.4	34.9	27.1	36.7	14.8
PPNet	multi-view	28.1	5.6	46.6	22.4	24.3	46.1	28.4	36.4	15.0
P2C	partial	**14.1**	**4.3**	**19.4**	**8.6**	**13.5**	**16.3**	**20.2**	**18.1**	**12.0**

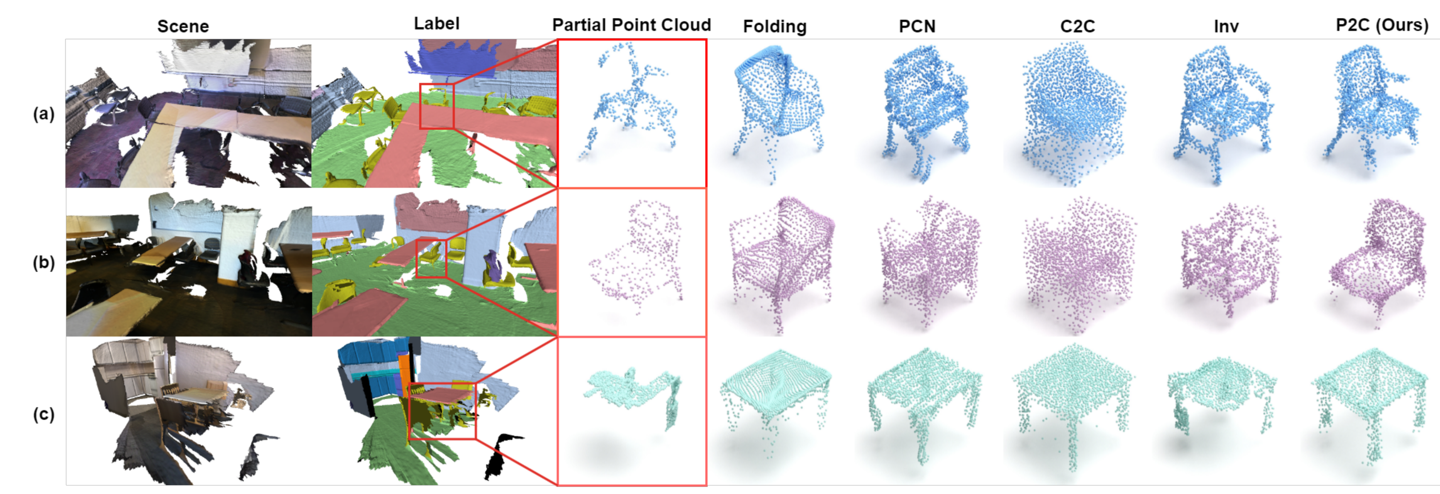

Figure 4. Visual comparison of point cloud completion results on the ScanNet dataset.

Conclusion

We propose P2C, the first self-supervised point cloud completion method that only requires a single partial point cloud observation per object for learning. Our method employs a novel Region-Aware Chamfer Distance to measure input-prediction similarity, and we design the Normal Consistency Constraint to enhance prediction completeness. Experimental results demonstrate that P2C exhibits state-of-the-art performance on both synthetic and real-world completion tasks, even outperforming models trained with known complete samples. Overall, our proposed method provides an effective solution for point cloud completion given only partial observation data.

Code is here!