TP-NoDe: Topology-aware Progressive Noising and Denoising of Point Clouds towards Upsampling

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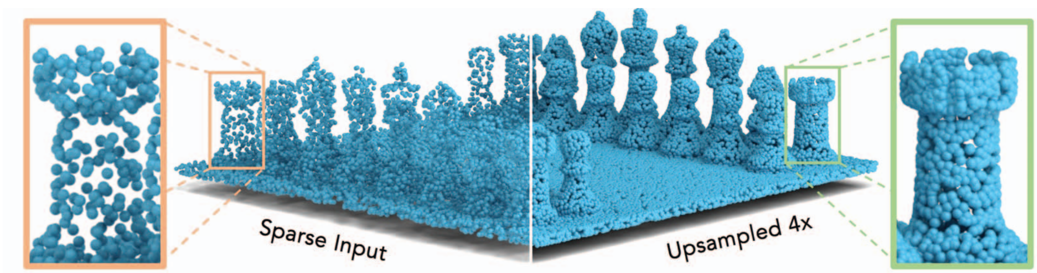

Figure 1: We demonstrate the superiority of our proposed method TP-NoDe on a sparse and incomplete point cloud of chess board; It can upsample the sparse point cloud with intricate geometric details, effortlessly recovering the underlying data. the **Left** presents a sparse input point cloud, the **right** section showcases the upsampled point cloud, accurately capturing the underlying surface with remarkable precision. Observe the intricate details of the recovered information, exemplified by the successful reconstruction of the Rook piece.

Abstract

In this paper, we propose TP-NoDe, a novel Topology-aware Progressive Noising and Denoising technique for 3D point cloud upsampling. TP-NoDe revisits the traditional method of upsampling of the point cloud by introducing a novel perspective of adding local topological noise by incorporating a novel algorithm Density-Aware k nearest neighbour (DA-kNN) followed by denoising to map noisy perturbations to the topology of the point cloud. Unlike previous methods, we progressively upsample the point cloud, starting at a $2\times$ upsampling ratio and advancing to a desired ratio. TP-NoDe generates intermediate upsampling resolutions for free, obviating the need to train different models for varying upsampling ratios. TP-NoDe mitigates the need for task-specific training of upsampling networks for a specific upsampling ratio by reusing a point cloud denoising framework. We demonstrate the supremacy of our method TP-NoDe on the PU-GAN dataset and compare it with state-of-the-art upsampling methods. The code is publicly available at https://github.com/Akash-Kumbar/TP-NoDe.

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1. Introduction

Point clouds are a widely used form of 3D data representation obtained through various technologies like LiDAR sensors and photogrammetry software. The versatility of point cloud data enables it to be utilized in various fields such as 3D city reconstruction [25, 38], cultural heritage reconstruction [37, 54], geophysical information systems [41, 40], and AR/VR/XR [16, 49] applications among others. Additionally, point clouds have a remarkably low memory footprint compared to other forms of data representation such as Voxels, Mesh, and Multi-view images, making them ideal for 3D immersive telepresence [48]. There has been a massive surge in technological development in sensing of 3D data [15, 24]. Despite such technological development in sensing technologies, they are considered not reliable in fast decision-making tasks like self-driving cars and robotics due to memory and latency issues of deep learning models. This challenge can be solved by processing sparse and low-resolution point clouds which can be later interpolated to dense and highly detailed point clouds as a requirement of the downstream task. To address this critical need for accurate and detailed point cloud data, we must shift our focus towards software development rather than relying solely on hardware-based solutions.

Towards providing software-based solutions authors in [60] proposed to use optimization-based methods to upsample the point clouds, yet these methods find challenges due to slow computation and limited upsampling factor. To address this issue, authors in PU-NET [60] introduced a parametric-based deep upsampling network that achieved comparable results. However, PU-NET still faces challenges in producing fine-detailed upsampled point clouds. To overcome this limitation, PU-GAN [26] and PUGeo-NET [46] introduced more accurate deep upsampling networks by utilizing GANs and tangent-plane-based sampling respectively. All of the aforementioned methods are inspired by image super-resolution techniques such as [36, 1]. Recent work in image super-resolution; ProGAN [23] introduced a novel approach of progressively upsampling images, which brings both generalizability and less latency.

Inspired by ProGAN's [23] progressive ideology in the 2D realm, we propose TP-NoDe: a Topology-aware Progressive Noising and Denoising of 3D Point Clouds towards Upsampling. We propose and employ Density-Aware k Nearest Neighbour (DA-kNN) for adding local topological noise followed by denoising as shown in Figure 1. We propose to employ score-based denoising [33] in the work proposed framework. The coupled noising and denoising framework yields an upsampled point cloud. Unlike previous upsampling methods that use k-nearest neighbours, our method is robust and generalizable for upsampling due to the incorporation of DA-kNN. In contrast to conventional deep upsampling networks, we progressively upsample the point cloud, starting at a 2 $\times$ upsample ratio and advancing up to a desired ratio. This allows us to obtain all intermediate upsampling ratios for free, making it more suitable for edge devices, while also mitigating the challenge of memory footprint by reusing a single deep denoising network that serves for both point cloud denoising and all x-resolution upsampling of point clouds. Furthermore, we conduct ablation studies to investigate the effect of generating different noisy perturbations of various statistical distributions and evaluate the performance of our proposed method on various local region extraction algorithms. TP-NoDe achieves good results on benchmark datasets while maintaining high efficiency.

we summarize our contributions as:

- We propose TP-NoDe: a novel perspective of noising and denoising of point cloud towards robust and generalized upsampling.
  - We propose Density-Aware k Nearest Neighbour algorithm(DA-kNN), that selects the number of neighbours(k) based on a Gaussian kernel density score.
  - We propose a new perspective of adding local topological noise towards upsampling by incorporating density-aware kNN.
  - We propose a novel methodology that progressively upsamples point cloud, commencing at a 2 $\times$ upsample ratio and advancing up to a desired ratio.
- We demonstrate the results of proposed methodology on PU-GAN [26] dataset and compare with state-of-the-art techniques.

2. Related works

In this section, we provide a detailed review of the existing methods for point cloud denoising and upsampling. It covers optimization-based methods like Laplacian smoothing, bilateral filtering, and non-local means filtering, for denoising and LOP [28], EAR [21] for upsampling as well as recent deep learning-based approaches like PU-Net [60] and its variants for upsampling, and DMR-Denoise [32], and score-based denoisng [33] for denoising. The strengths and weaknesses of each approach are discussed, and potential future research directions are highlighted.

2.1. Denoising

Optimization-based point cloud denoising has commonly relied on incorporating explicit geometric priors. Optimization-based denoising approaches can be classified into four categories: density-based, local-surface-fitting-based, sparsity-based, and graph-based methods. Outliers are removed using density-based approaches [61, 14], they model the distribution of points and use kernel density estimation technique. Methods based on local-surface fitting [3, 14, 9, 10, 21] approximate the point cloud with a smooth surface and project points onto it. Sparsity-based approaches [7, 53, 57, 35] rebuild normals and update point coordinates depending on them. Graph-based approaches [51, 17, 63, 19, 18] employ graph filters to denoise point clouds that are represented on graphs. Yet, there is a trade-off between preserving detail and increasing denoising effectiveness.

Deep learning-based approaches use neural networks to estimate the displacement of each point and then apply the inverse displacement to each point. Such approaches are PointCleanNet [47] and GPDNet [2]. DMR Denoise [32]suggested that the underlying manifold (surface) of a noisy point cloud can be learned for reconstruction in a downsample-upsample procedure. Displacement prediction approaches, on the other hand, may suffer from shrinkage and outliers, and understanding the underlying manifold may result in over-smoothing. Score-based denoising [33] proposes a novel framework that is motivated by the distribution model of noisy point clouds and distinguishes itself significantly from the proposed techniques, which uses score matching which is a technique for training energy-based models. [33], [22, 52] entails reducing the squared distance between the model-predicted gradients and the data log-density gradients.

2.2. Upsampling

Optimization-based point cloud upsampling methods are not usually driven by data and instead rely on prior assumptions. They also encounter difficulties in preserving multiscale structures. The first point cloud upsampling algorithm was introduced in 2003 by Alexa et al [4] and involved creating a Voronoi diagram on an MLS(Moving least squares) surface using three points as input. later, Lipman et al. [28] presented a non-parameterized approach for point resampling and surface reconstruction, which was also applied to point cloud upsampling. Their technique used the locally optimal projection operator (LOP) too approximate the surface. Huang et al [20] proposed the weighted LOP (WLOP), which added local adaptive density weights to LOP to achieve a more even distribution of the original point cloud. Preiner et al. [42] proposed the continuous LOP (CLOP), which described the input point density based on a Gaussian mixture. Huang et al. [21] also introduced the edge-aware resampling (EAR) method, and Wu et al [56] proposed a consolidation method based on deep points. Dinesh et al. [11] proposed a 3D point cloud super-resolution local algorithm based on the graph total variation(GTV).

Deep learning-Based point cloud methods like pointnet [43], Pointnet++ [44], DGCNN [55] were successfully introduced on point clouds, it became great research area to upsample point cloud using deep learning methods. Yu et al. [60] were the first to propose a deep learning model for point cloud upsampling, using hierarchical feature learning from PointNet++ [44]. Similar feature extraction strategies were used by DensePCR [34] and EC-Net [59]. Zeng et al. [62] introduced the spatial feature extractor (SFE) block to replace PointNet++ [44] for local feature extraction. Wang et al. [58] proposed the multi-step point cloud upsampling network (MPU) inspired by dynamic graph convolution to define local neighbourhoods in feature space. PU-GCN [45] introduced node shuffle, which uses graph convolution layers to expand features and rearrange them through shuffle operations. Li et al. [26] introduced the up-and-down sampling mechanism in PU-GAN. While Li et al. [27] proposed Dis-PU, which upsamples the point cloud in two steps using a feature expansion unit and a spatial refinement unit. PU-EVA [31] decouples the upsampling rate from the network structure and uses an approximate solution based on edge vectors. PUGeo-Net [46] achieves point cloud upsampling through a purely geometric sampling method. The approaches described above are sensitive to noise and are not generalizable, whereas we propose a novel perspective for which our approach is both robust to noise and generalizable.

3. TP-NoDe

In this study, we introduce TP-NoDe, a novel approach for upsampling point clouds through topology-aware progressive noising and denoising technique. Building upon the foundations of score-based denoising [33], our method employs a density-aware k-nearest neighbour(DA-kNN) to extract local neighbourhoods based on their geometric complexity, then we concatenate perturbed points to this neighbourhood, taking into account its underlying topological structure.

We progressively perform the aforementioned topological noising followed by parameterized denoising process (f_θ), which is repeated $\log_2(r)$ times, where r represents the upsampling factor as shown in Figure 2. By incorporating topology awareness into our noising and denoising strategy, we aim to enhance the quality and accuracy of the upsampled point cloud data.

Note that our methods rely on the assumption that the denoising framework provides a faithful reconstruction of the underlying geometry of the point cloud.

3.1. Topological Perturbations

Global noise on point clouds indiscriminately alters the morphology of the point cloud data, resulting in uniform perturbations that smooth out vital features such as edges and corners during denoising. To overcome this, we propose a novel approach that utilizes topological perturbations based on the local neighbourhoods. By incorporating local topological priors into our perturbation strategy, we can selectively introduce perturbations that retain the intricate details of the point cloud, preserving its morphology and underlying structure. This method allows us to effectively denoise point clouds without sacrificing important features towards upsampling.

Local Neighbourhood in point cloud processing is a crucial step in feature extraction. Two common methods for computing local neighbourhoods in point clouds are K-nearest neighbours (k-NN) [43, 44] and ball query [44]. However, these methods have limitations as they are not

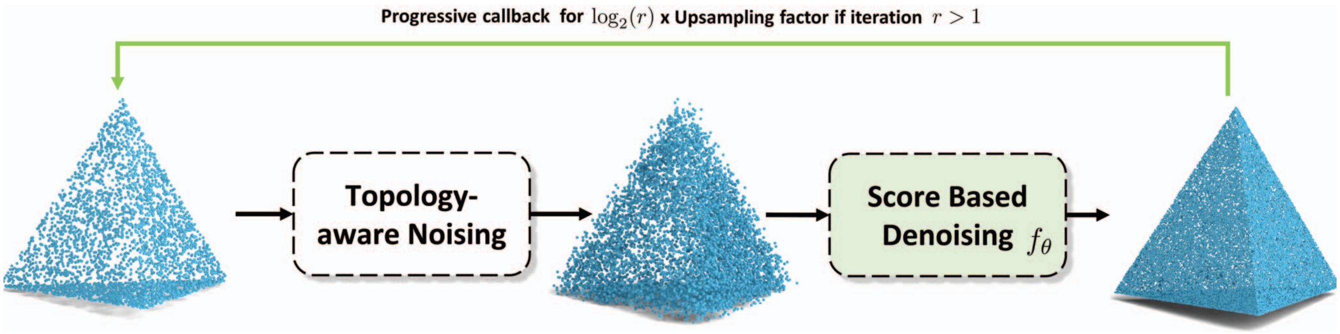

Figure 2: Depicts our methodology TP-NoDe, which involves concatenating a sparse point cloud with topology-aware noisy perturbations. The resulting concatenated point cloud is then passed through a denoising function f_θ that fits these perturbed points to the surface of the point cloud, thereby upsampling it. Our method is also depicted in Algorithm 1

density-aware and are not dynamically adaptable to varying geometric structures. As a result, setting hyperparameters can become a challenging task that requires trial and error. To mitigate these challenges we propose Density-aware kNN (DA-kNN) a simple yet effective approach to understanding the local topology of a point cloud [5, 6] while being density-aware. The Density-aware kNN is a simple extension of the kNN algorithm where the fixed k in the kNN algorithm is replaced by per-point dynamic number of neighbours kd_i and is given by,

$$kd_i = k_b + (k_{max} - k_b) * s_i \tag{1}$$

where r_b is base k, k_{max} is maximum number of neighbours and s_i is the kernel density score for the euclidean distance $d()$ between points given by,

$$s_i = \frac{1}{Mh} \sum_{j=0}^{N} \frac{1}{\sqrt{2\pi}} e^{-\frac{d(p_i, p_j)}{2h^2}} \tag{2}$$

The expression can be stated as follows: The value of density d for each point in p_i, where there are a total of M points, is influenced by a bandwidth parameter h. The density value reflects the likelihood of π being situated in flat areas of the object, signifying the degree of dilation.
The local patch extracted using DA-kNN models local topological noise/perturbation, facilitating superior upsampling of the point clouds via denoising.

Modeling Perturbation
After extracting p_i using density-aware kNN, we concatenate a noisy perturbation x_i of the given local neighbourhood and pass the resulting point cloud to a denoising network. The network outputs an upsampled version of the p_i, denoted as q_i. Specifically, let f_θ denote the denoising network parameterized by θ, then we have:

$$\mathcal{Q} = f_\theta(\mathcal{P} \oplus \mathcal{X})$$

where $\oplus$ denotes the concatenation operation.

To enhance the upsampling performance, we investigate the effect of different types of noise perturbations, represented by $\mathcal{X}$, added to the neighbourhood of $\mathcal{P}$. By analyzing the impact of various noise distributions, we identify the optimal distribution that improves the quality of the resulting upsampled point cloud $\mathcal{Q}$.

We evaluate our approach using various types of noise, including Gaussian, Laplacian, Discrete, Uniform, and Covariance noise.

3.2. Progressive Upsampling

Inspired by the ideology of ProGAN [23], we model the progressive upsampling technique for the point cloud. Specifically, given a sparsely populated point cloud with M points as input, we apply independent perturbations to the data progressively followed by denoising algorithm [33] $\log_2(r)$ times. This generates a dense/ upsampled point cloud with rM points as best depicted in Algorithm 1 and figure 4.

4. Experiments

In this section, we investigate the effectiveness of the topological perturbations incorporated with score-based denoising [33] towards progressive upsampling. We use score-based denoising [33] as f_θ in Algorithm 1. Compared to all other point cloud upsampling methods [60, 46, 26, 39, 50] we leverage pre-trained weights from [33] to construct a robust and effective upsampling framework via denoising.

4.1. Dataset

We build upon the work of [33] by utilizing their denoising network as the only learning-based component in our

Algorithm 1: Progressive noising and denoising of point cloud towards upsampling

Input: $\mathcal{P} = \{(x_1, y_1, z_1), ..., (x_M, y_M, z_M)\}$, r, k_b

/* where P is the sparse point cloud with M points, r is the upsampling factor, and k_b is the base number of neighbouring points for density aware kNN. */

Output: $\mathcal{Q} = \{(x_1, y_1, z_1), ..., (x_{rM}, y_{rM}, z_{rM})\}$

/* where $\mathcal{Q}$ is the upsampled version of $\mathcal{P}$, with r times more points */

$iterations \leftarrow \lceil \log_2(r) \rceil$

// $\lceil\rceil$ denotes ceil operation

for $i = 1$ **to** $iterations$ **do**

  // Cluster centroids for each iteration

  $centroids \leftarrow \phi(\mathcal{P}_i$, int(M*3/256))

  $dist \leftarrow calculate\_distance(centroids, \mathcal{P}_i)$

  $kd, kd\_dist \leftarrow density\_aware\_kNN(dist, k_b, max\_k \leftarrow k_b * 3)$

  $mask \leftarrow (dist < kd\_dist)$

  $denoised\_patches = list()$

  for $j = 1$ **to** $len(centroids)$ **do**

    $p_j \leftarrow \mathcal{P}_i[mask[j] = 1]$

    $n_j \leftarrow p_j + noise(0, \sigma)$

    $q_j \leftarrow f_\theta(n_j \oplus p_j)$

    $add\_to\_list(denoised\_patches, q_j)$

  $r_b \leftarrow r_b/2$

  $\mathcal{Q}_i := concatenate(denoised\_patches)$

$\mathcal{Q}_r \leftarrow \phi(\mathcal{Q}_i$, int($r * \mathcal{M}$))

/* ϕ is farthest point sampling operation */

/* f_θ is the denoising function and our proposed algorithm is Illustrated in Figure 2 */

approach. Specifically, we incorporate pre-trained weights from the network, which can be found at [1], to facilitate effective denoising of perturbed points. **Note**: we do not train the denoising network ourselves, but rather leverage the existing weights provided by [33].

The Score-based denoising network data consisted of 40 meshes for training from the training set of PU-Net [60] and then they used Poisson disk sampling to sample points from the meshes, at resolutions ranging from 10K to 50K points. The points are then normalized into the unit sphere. Then, they are only perturbed by Gaussian noise with a standard deviation from 0.5 % to 2.0% of the bounding sphere's radius.

To facilitate effective evaluation and comparison of our results, we employ the test dataset provided by PU-GAN [26], as previously used in [64]. This dataset represents a common benchmark for evaluating point cloud generation methods, and its use enables a straightforward comparison of our approach with other state-of-the-art techniques.

[1] https://github.com/luost26/score-denoise

Table 1: Quantitative comparison of different SOTA network models on PUGAN benchmark dataset. We efficacy of our proposed method TP-NoDe; outperforms PU-Net [60] by 2 folds in all point cloud upsampling evaluation metrics while being the only method not train task specifically. We demonstrate **bold underline** as best and **bold** as second best. The metrics are in the power of 10^{-3}.

Methods	CD	HD	P2f
EAR [21]	0.52	7.37	5.82
MPU [58]	0.49	6.11	3.96
PU-GAN [26]	0.28	4.64	$\underline{\mathbf{2.33}}$
PU-GCN [45]	$\underline{\mathbf{0.25}}$	$\underline{\mathbf{1.85}}$	**2.94**
Dis-PU [27]	0.31	4.21	4.14
PU-EVA [31]	**0.27**	3.07	-
L2G-AE [29]	6.31	63.23	39.37
SPU-NET [30]	0.41	**2.18**	6.85
PU-NET [60]	0.72	8.94	6.84
Ours (k-NN)	**0.40**	**3.96**	**5.38**
Ours (DA-BQ)	**0.35**	**3.55**	**5.26**
Ours (DA-kNN)	**0.33**	**3.49**	**5.21**

4.2. Comparison with State-of-the-art Methods

Our novel upsampling methodology, TP-NoDe, is highly robust and performs exceptional grade upsampling. To demonstrate the efficacy of our proposed approach, we present both qualitative and quantitative comparisons on the PU-GAN dataset [26]. Specifically, we compare our results with those obtained from PU-Net [60] and PUGeo-Net [46] for an input of 5000 points and an upsampling factor of $r = 4$, resulting in 20000 points. Our approach can achieve superior results, as shown in Figure 3, which showcases the visual supremacy of TP-NoDe on a 4 $\times$ upsampling task. In contrast, PU-Net [60] fails to upsample areas with natural holes and instead fills them with geometry. On the other hand, while PUGeo-Net [46] maintains the geometry, it fails to produce uniform upsampling. Our proposed method, TP-NoDe, can perform upsampling while maintaining finer details when compared to all other methods. Furthermore, to provide a more comprehensive evaluation of the actual geometry, we also show the ground truth with 20000 points, which corresponds to 4 $\times$ the input size of 5000 points. It is evident that our method achieves outstanding results, which demonstrates the robustness and superiority of TP-NoDe over existing upsampling methods.

In addition to the qualitative evaluation, we also con-

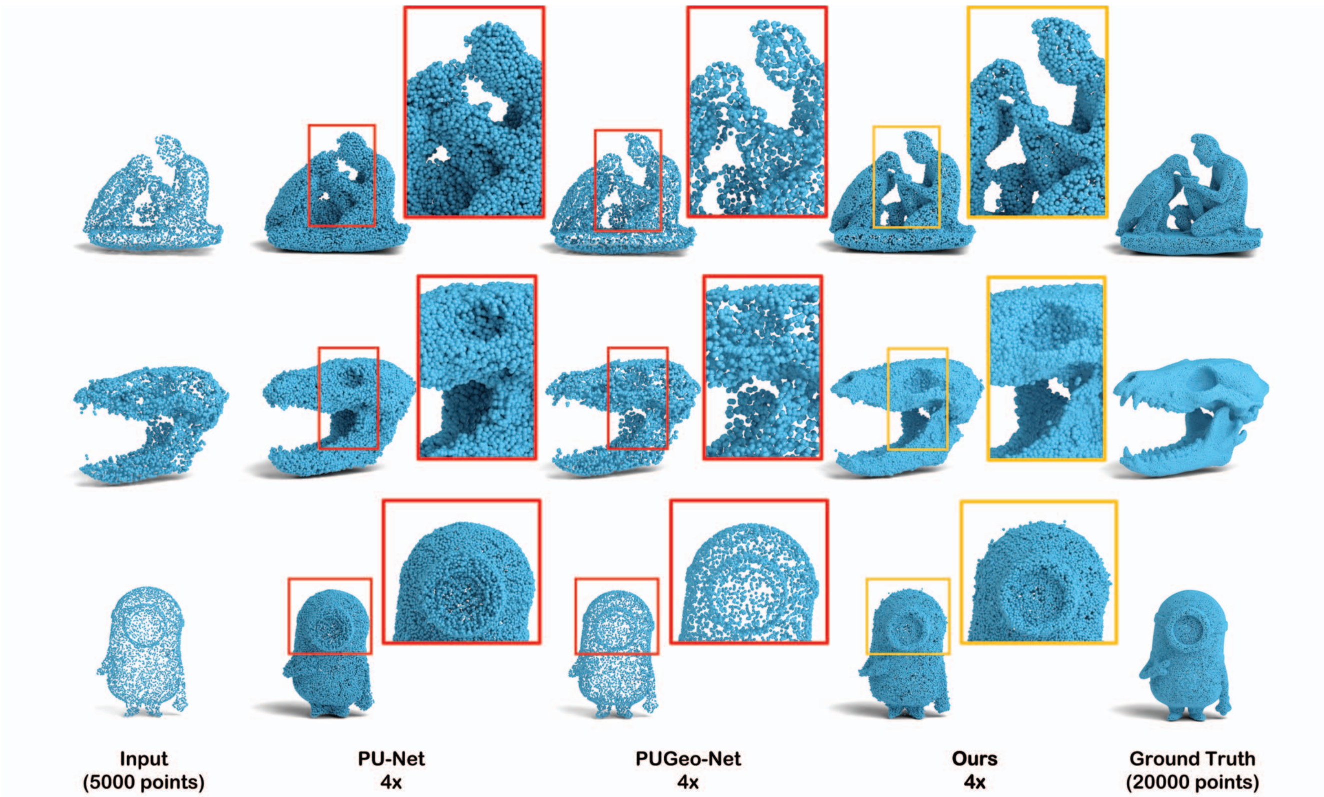

Figure 3: In this comparison, we evaluate our method against other state-of-the-art approaches using a selection of intriguing point clouds with intricate geometric structures which are a statue of a man giving water to a bird, a fox skull and a minion. The red highlighted regions represent other methods, while the yellow highlighted regions represent the results of our proposed method TP-NoDe. Our results demonstrate that our approach is capable of retaining missing information in complex structures while effectively upsampling the point cloud.

ducted a quantitative comparison of our proposed methodology on the PU-GAN dataset for point cloud upsampling. The performance of our approach is reported in Table 1. Notably, all values in the table, except for ours, are taken from [64]. When compared to PU-Net, our proposed TP-NoDe with Density Aware kNN (DA-kNN) achieves superior performance with a significant decrease of 0.39 in Chamfer Distance [13], 5.45 in Hausdorff Distance [12], and 1.63 in Point to Surface Distance [8]. These results confirm the robustness and effectiveness of our proposed approach over existing upsampling methods.

In summary, our novel methodology, TP-NoDe, has demonstrated exceptional performance in point cloud upsampling. We have presented both qualitative and quantitative comparisons with existing methods, showcasing the superior results achieved by TP-NoDe.

4.3. Ablation Study

This section describes the ablation studies conducted to analyze the impact of different designs of our proposed methodology on point cloud upsampling. We conducted an in-depth analysis of our proposed methodology, TP-NoDe, by evaluating it on various types of noise (Gaussian, Laplace, Uniform, Covariance, Discrete) and different topologies, including global and local topologies (k-NN, DA-BQ, DA-kNN), as described in Section 3.1. The results of our ablation studies are reported in Table 2. The table demonstrates that our proposed TP-NoDe with proposed DA-kNN (Density Aware kNN) performs the best with Gaussian noise, with a dynamic number of neighbours varying from 64 to 512. These findings highlight the effectiveness of our proposed approach and its ability to handle various types of noise, as well as its adaptability to different topologies. Overall, the ablation studies provide valuable insights into the design choices of our proposed methodology and their impact on point cloud upsampling. The results confirm the robustness and effectiveness of TP-NoDe with DA-kNN in handling noise and adapting to different topologies by varying the number of neighbours respectively.

In Figure 4, we showcase the qualitative analysis of our proposed progressive upsampling methodology. Our methodology involves starting with a $2\times$ upsample ratio

Table 2: Quantitative comparison of our ablation studies where we test our algorithm, with the noise of various statistical distributions and different neighbourhood search algorithms. Here all the metrics are in the power of 10^{-3}. We demonstrate **bold underline** as best and **bold** as second best. The ablations show that our proposed method TP-NoDe incorporated with DA-kNN topological grouping and Gaussian noise performs the best also presented in Table 1

Noise		Discrete			Laplacian			Gaussian			Uniform Ball			Covariance		
		CD	HD	P2F	CD	HD	P2F	CD	HD	P2F	CD	HD	P2F	CD	HD	P2F
Global		0.4415	5.4466	5.1549	0.5068	13.8065	5.2873	0.4327	5.5879	5.2768	**0.4404**	5.1157	5.3333	0.4808	4.9309	5.8065
	128	0.4529	5.0474	5.5524	**0.4078**	5.1854	5.5549	0.4212	5.3688	5.4005	0.4564	5.1915	5.6116	0.4680	5.6051	**5.3744**
k-NN	**256**	0.4818	4.3008	6.0210	**0.4321**	**4.3858**	6.1196	0.4443	4.0442	5.7025	0.4853	4.8119	6.0666	0.50057	4.6757	6.0730
	512	0.4894	4.1077	6.6383	0.4370	**4.4739**	6.4390	0.4492	4.2634	6.3644	0.4894	4.1077	6.6383	0.5087	**3.966**	6.5592
	64	0,4645	**4.0303**	5.4615	0.5099	16.4335	5.7810	0.4219	**3.9940**	5.4940	0.4692	**3.9828**	5.4005	0.4886	4.2917	**5.3166**
DA-kNN	**128**	**0.4332**	**3.9509**	**4.9731**	0.7437	23.494	**5.1536**	**0.3585**	**3.5555**	**5.3662**	0.4465	**3.9653**	**4.9579**	**0.4545**	**3.9032**	5.6548
	256	**0.4385**	5.0608	**4.8240**	0.6025	19.6728	**5.2518**	**0.3834**	4.3078	**5.2638**	**0.4462**	4.9196	**5.1982**	**0.4674**	4.8866	5.6668

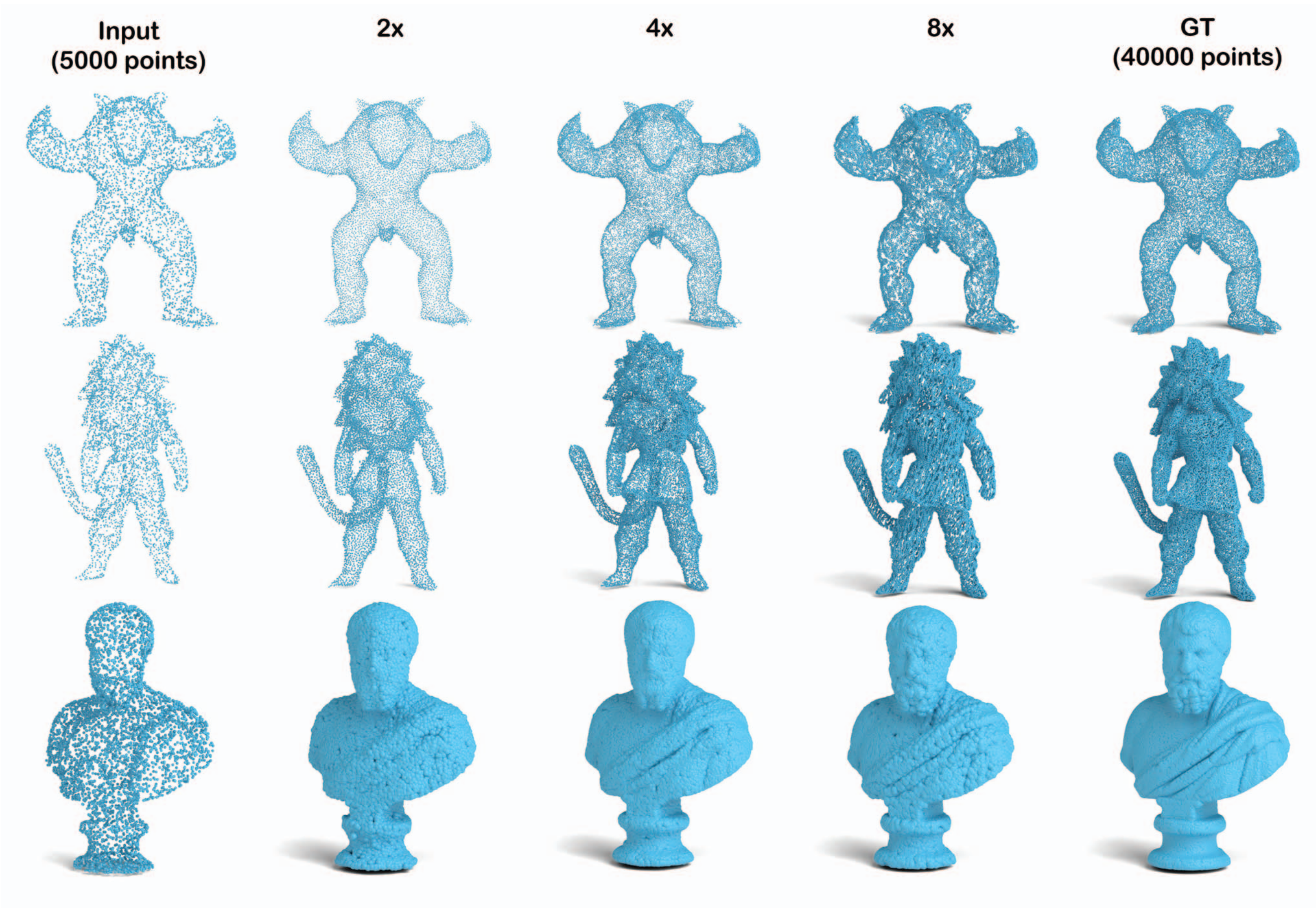

Figure 4: We showcase the effectiveness and robustness of our TP-NoDe method for upsampling sparse point clouds with complex structures. We demonstrate the upsampling of a point cloud with only 5000 points by a factor of 8, the intermediate factors 2, and 4 are also visualized, using point clouds with intricate details such as Stanford's Armadillo, Super Saiyan Goku, and a figure of Reuther. Our method generates detailed and uniform upsampling results with high fidelity, without requiring different models for different upsampling ratios.

and gradually increasing it until the desired ratio, which we set to 8× in Figure 4. Our approach involves progressively upsampling the point cloud, and we present all intermediate outputs and the final 8× upsampling of the actual geometry. Additionally, we provide the ground truth with 40000 points, which corresponds to 8× the input size of 5000 points of point clouds. As one can observe in Figure 4 results of 2× upsampling capture global-coarser upsampling and local topological with finer detailed upsampling for 8× resolution. One potential reason for this is due to our proposed Algorithm 1 progressive reduces the number of neighbours in DA-kNN that facilitates superior upsampling of point cloud via noising and denoising.

4.4. Limitations

Despite achieving promising outcomes in our research, we acknowledge several limitations that require attention. Initially, our current approach utilizes local grouping algorithms such as k-NN and density-aware kNN to extract geometrically meaningful regions. However, these methods involve numerous hyperparameters, which can affect their efficiency. To tackle this, we suggest incorporating a learning-based model that can augment points based on specific requirements, enhancing the accuracy and efficacy of our region extraction methodology. Furthermore, we utilized a score-based denoising framework as our denoising backbone, which was solely trained on Gaussian noise. This can restrict the application of our technique in real-time lidar point cloud analysis as they comprise a mixture of multiple noise sources.

Despite these limitations, we believe that our study offers valuable insights into point cloud upsampling via denoising. We hope that our findings will inspire further research to address these limitations and lead to the development of more robust and effective methods for point cloud upsampling.

5. Conclusions

We have proposed TP-NoDe, a novel approach for upsampling 3D point clouds using topology-aware progressive noising and denoising. We introduce and leverage Density-Aware kNN (DA-kNN) to introduce local topological noise and score-based denoising to map the noisy perturbations to the topology of the point cloud. Unlike traditional deep upsampling networks, TP-NoDe progressively upsamples the point cloud, starting at a 2 × upsample ratio and advancing up to a desired ratio, enabling us to generate intermediate upsampling resolutions for free. TP-NoDe also reuses a single deep denoising network that serves for both point cloud denoising and all x-resolution upsampling of point clouds, mitigating the challenge of memory footprint. We have demonstrated the effectiveness of TP-NoDe on the PU-GAN dataset, achieving state-of-the-art results while maintaining high efficiency. Our proposed methodology offers a promising solution for achieving accurate and detailed point cloud data, essential for a variety of applications.

6. Broader Impact

This study explores the intersection of local topological perturbations and denoising algorithms for realistic point cloud upsampling. Point cloud upsampling is a critical technique in academia and industry as it allows for improved accuracy and resolution in 3D scanning and virtual reality applications. Integrating local topological perturbations into denoising algorithms can prove pivotal, unlocking fresh possibilities for modelling and simulation in construction and beyond. Our investigation also indicates that our work on topological perturbations could enhance downstream point cloud analysis tasks such as object classification and part segmentation. This research has the potential to provide robustness and improve accuracy in point cloud analysis. The exciting implications of this work cannot be overstated, making it a fascinating area for exploration and advancement.

7. Acknowledgement

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