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WEAKLY SUPERVISED POINT CLOUD UPSAMPLING VIA OPTIMAL TRANSPORT


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Outlines

- Introduction
- Methodology
- Experiments
- Summary

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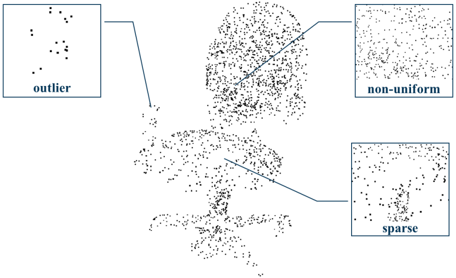
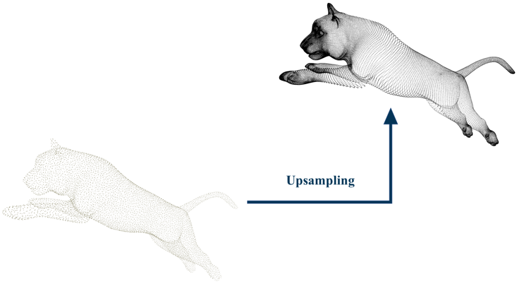
Introduction



In real world, the raw point clouds produced from depth cameras and LiDAR sensors are often sparse, noisy, and non-uniform.

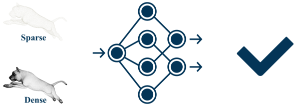
Introduction



The point cloud upsampling technology that aims at generating dense, uniform and complete point clouds.

Problems

1. Previous methods require paired sparse-dense data in the network training, these supervised methods cannot be trained with real-scanned datasets such as ScanNet and KITTI where paired dense point clouds are unavailable.

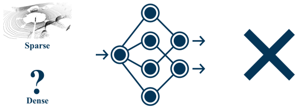


— PU-Net

— PU-GAN

— MPU

— Dis-PU



2. The distributions gap between synthetic point cloud data and real scans usually degrades the performance of the model trained on synthetic data when applied to real scans.

Motivation

To resolve the above problems, we cast point cloud sampling as the OT problem and propose PU-CycGAN. Through the design of Densifier, Sparsifier and consistency loss, self-restraint loss, our model can be trained with unpaired point sets. In addition, based on OT quadratic transport cost, our upsampling model can converge to a local equilibrium point.

Contribution

1. We propose a weakly supervised point cloud upsampling framework that trains the model with unpaired point clouds.
2. We notably regard point cloud upsampling as an OT problem, and design a quadratic Wasserstein distance to stabilize GAN's training.
3. We introduce consistency loss and self-restraint loss to improve the performance of the model in underlying surface representation.
4. Extensive experiments demonstrate that our method achieves comparable results to the SOTA supervised methods, especially on real data.

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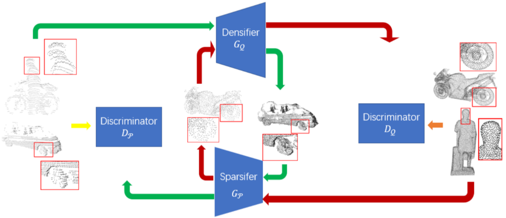
Methodology

Given M sparse point sets $\mathcal{P} = \{\{p_i^j\}_{j=1}^{N}\}_{i=1}^{M}$ and unpaired dense point sets $\mathcal{Q} = \{\{q_i^k\}_{k=1}^{rN}\}_{i=1}^{M}$, we aim to learn a map which transports the sparse point sets to dense and uniformly distributed point set. Where N denotes the number of points in each sparse point set, r is the upsampling rate.

Methodology

The diagram of the proposed PU-CycGAN



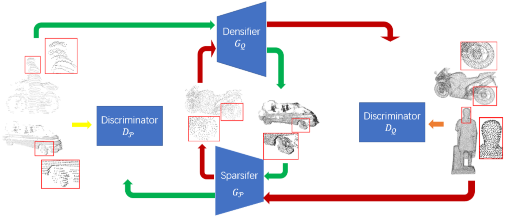
- Densifier $G_{\mathcal{Q}}$ and Sparsifer $G_{\mathcal{P}}$ are generators which are used to fit the map $\mathcal{P} \rightarrow \mathcal{Q}$ and $\mathcal{Q} \rightarrow \mathcal{P}$.
- Sparse discriminator $D_{\mathcal{P}}$ and Dense discriminator $D_{\mathcal{Q}}$.

where $D_{\mathcal{P}}$ aims to distinguish between $\mathcal{P}$ and generated sparse point sets $G_{\mathcal{P}}(\mathcal{Q})$, $D_{\mathcal{Q}}$ aims to discriminate between $\mathcal{Q}$ and $G_{\mathcal{Q}}(\mathcal{P})$.

Methodology

The diagram of the proposed PU-CycGAN

- sparse-dense-sparse (green)
- dense-sparse-dense (red)



Through the data cycles, our model is expected to capture the inherent upsampling patterns and generate dense patches that are uniformly distributed on the target surface.

Methodology

We regard point cloud upsampling as an OT problem

GANs accomplish two major tasks:

1. manifold learning
2. probability distribution transformation

Specifically,

- the generator computes the OT map
- the discriminator computes the Wasserstein distance between the generated and the real distribution

Methodology

We regard point cloud upsampling as an OT problem

discrete Monge-Kantorovich dual problem:

$$\max_{\phi,\psi} \frac{1}{m} \sum_{y_i \in Y} \phi(y_i) - \frac{1}{n} \sum_{x_j \in X} \psi(x_j)$$
$$s.t.\ \psi(y_i) - \phi(x_j) \le c(x_j, y_i) \ \ \forall y_i \in Y, \forall x_j \in X \tag{1}$$

Liu et al. proposed WGAN-QC which is based on the quadratic transport cost:

$$c(x_j, y_i) = \frac{1}{2} \|x_j - y_i\|_2^2 \tag{2}$$

When Equation (2) is applied, the optimal objective in Equation (1) equals to the quadratic Wasserstein distance

Methodology

We regard point cloud upsampling as an OT problem

Quadratic Wasserstein Loss

$$\min_{w} \frac{1}{2}\left(\frac{1}{B}\sum_{i=1}^{B} D_w(y_i) - \frac{1}{B}\sum_{i=1}^{B}\phi(y_i)\right)^2 + \frac{1}{2}\left(\frac{1}{B}\sum_{i=1}^{B}(D_w(y_i) - \psi(y_i))^2\right) + \frac{\gamma}{B}\sum_{i=1}^{B}(\|\nabla_x D_w(x_i)\| - d_{EM}(x_i, y_i))^2$$

Further, to stabilize the optimization of the generator, we set the adversarial loss of the generators $G_{\mathcal{Q}}$ and $G_{\mathcal{P}}$ as a quadratic function, which is

$$\mathcal{L}_{adv}(x_i, y_i) = \left(\frac{1}{B} \sum_{i=1}^{B} D_w(y_i) - \frac{1}{B} \sum_{i=1}^{B} D_w(x_i) \right)^2$$

Here, when

- $x_i = G_{\mathcal{Q}}(G_{\mathcal{P}}(q_i))$and $y_i = q_i,\ D_w$ is $D_{\mathcal{Q}}$.
- $x_i = G_{\mathcal{P}}(G_{\mathcal{Q}}(p_i))$and $y_i = p_i,\ D_w$is$D_{\mathcal{P}}$.

Cycle Consistency Loss

To eliminates the need of paired data, we proposed an point cloud upsampling consistency loss which is defined as follows:

$$\mathcal{L}_{cyc} = d_{EM}(p_i, G_P(G_Q(p_i))) + d_{EM}(q_i, G_Q(G_P(q_i)))$$

Self Restraint Loss

Without paired point sets as the supervision, we define a self-restraint loss to ensure that the generated points are distributed on the underlying surface. Herein, self-restraint loss uses the Chamfer distance to measure the loss between sparsified or densified point set and the original one, which is

$$\mathcal{L}_{sel}(x_i, z_i) = \frac{1}{N}\sum_{j=1}^{N}\min_{x_{ik}\in x_i}\|z_{ij} - x_{ik}\|_2^2 + \frac{1}{rN}\sum_{k=1}^{rN}\min_{z_{ij}\in z_i}\|z_{ij} - x_{ik}\|_2^2$$

Methodology

Loss Function

The final total loss of PU-CycGAN's generator Densifier and Sparsifier is the weighted sum of consistency loss, self-restraint loss, uniform loss and adversarial loss:

$$
\begin{aligned}
\mathcal{L}_G = {} & \lambda_{cyc}\mathcal{L}_{cyc} \\
& + \lambda_{sel}(\mathcal{L}_{sel}(G_Q(p_i), p_i)) + \lambda_{sel}(\mathcal{L}_{sel}(G_P(q_i), q_i)) \\
& + \lambda_{uni}(\mathcal{L}_{uni}(G_Q(p_i))) + \mathcal{L}_{uni}(G_Q(G_P(q_i))) \\
& + \lambda_{adv}(\mathcal{L}_{adv}(q_i, G_Q(G_P(q_i)))) + \mathcal{L}_{adv}(p_i, G_P(G_Q(p_i)))
\end{aligned}
$$

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Experiments

Datasets

To compare with baseline methods, we first train models on PU1K and PU-GAN's datasets which are cropped into dense and downsampled sparse point clouds patches respectively. Then we train a model with upaired real-scanned sparse KITTI and dense SEMANTIC3D data to demonstrate the capability and advantages of our method in the real applications with unpaired data.

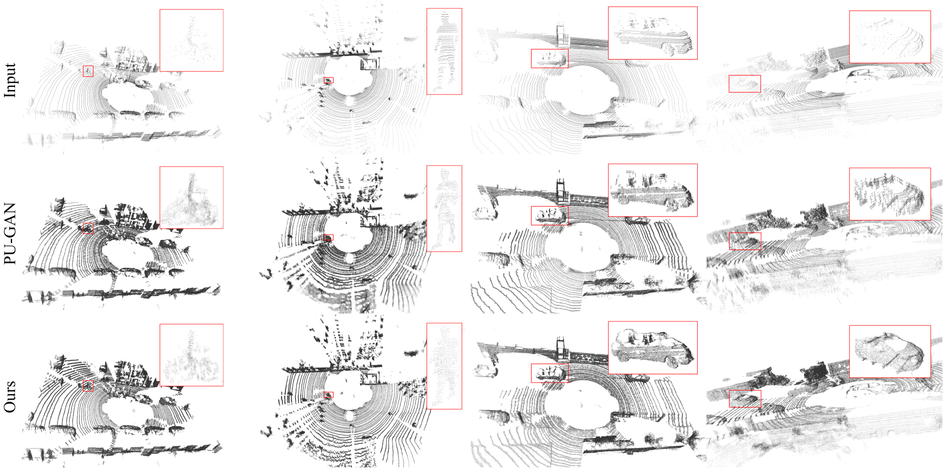
Experiments

Comparisons on PU1K against supervised methods.

Method	P2F(10^{-3})	CD(10^{-3})	HD(10^{-3})
PU-Net [1]	4.834	1.155	15.170
MPU [3]	3.551	0.935	13.327
PU-GAN [4]	**1.590**	**0.420**	<u>5.390</u>
PU-GCN [5]	2.499	0.585	7.577
Dis-PU [6]	3.143	1.151	14.680
Ours	<u>2.080</u>	<u>0.551</u>	**2.919**

Experiments

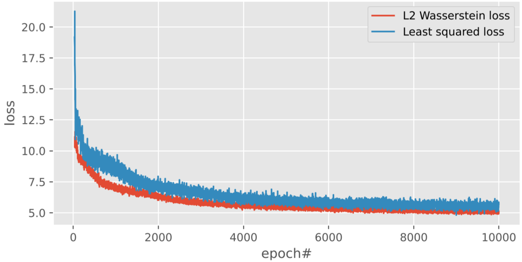
Qualitative comparisons on KITTI



Experiments

Ablation Study

Model	l_2	$\mathcal{L}_{sel}$	CD(10^{-3})
A	✓		24.197
B		✓	0.774
C			27.577
Full	✓	✓	**0.551**



Summary

- Through the design of Densifier, Sparsifier and consistency loss, self-restraint loss, our PU-CycGAN can be trained on unpaired point clouds.
- Moreover, by using quadratic transport cost, our method greatly improved in stability and convergence speed.
- Especially, we can train with sparse and dense point clouds from different scenes, so as to overcome the demand for high-density point clouds in the real scene and improve the generalization ability of the model.

Thank you from your time and attention!

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