Introduction

- Point clouds are a popular and versatile way represent 3D scenes
- However, raw sensor data (LiDAR, RGB-D) is sparse and irregular, making it difficult to use deep networks or where photo-realism matt
- We explore upsampling both the geometric structure and photo-realistic visual informat a sparse colored 3D point cloud
- We enable key applications in areas like VR, understanding, and autonomous driving

Related Work

- Partial convolutions (Liu et al., 2018) demon impressive results for 2D image inpainting a super-resolution
- Pointwise convolutions (Hua et al., 2018) pro a simple convolution operator for 3D point
- PU-Net (Yu et al., 2018) uses recent methods 3D deep learning to upsample the geometr structure of single object point clouds

Dataset

- Matterport3D dataset contains 3D textured meshes from **90** indoor scenes
- Preprocessing pipeline converts meshes to point clouds, creates (1.5m)³ chunks, and extracts patches of 4096 points from each



Pointwise Partial Convolutions for Photo-Realistic Point Cloud Upsampling Mihir Garimella, Prathik Naidu {mihirg, prathikn}@stanford.edu

Technical Approach

y to	We define a new operator called t ("pconv3p") that can operate direc	h tl
s often se with ters ic tion in	1 Kernel multiplication 2 3D m \checkmark	
, scene	Center voxel grid kernel at each point •, multiply feature values of valid neighbors • with kernel weights	≥s gh ı − g f
nstrate	For photo-realistic visual upsamplin architecture, an adaptation of U-N downsampling/upsampling in U-N (implemented as pointwise feature	n ● ●
ropose clouds ls in ric	For visual upsampling task: $n = 14$ (28 layers), perceptua per point at each intermediate layer	sk pc s
	For geometric upsampling, we monor of entire scenes. Then, we combined visual upsampling network to creat upsampling both geometric and v	d e te

Concatenate

ne pointwise partial convolution ly on 3D point clouds with



valid if it had at least nbor during kernel → network incrementally feature values 🔵

Forward Pass $x_{i}^{\ell} = \sum_{k} \left(\frac{w_{k}}{\sum_{p_{j} \in \Omega_{i}(k)} m_{j}^{\ell-1}} \sum_{p_{j} \in \Omega_{i}(k), m_{j} \neq 0} x_{j}^{\ell-1} \right)$ $m_i^{\ell} = \begin{cases} 1 & \text{if } \sum_{p_j \in \Omega_i(k)} m_j^{\ell-1} \neq 0\\ 0 & \text{otherwise} \end{cases}$ **Backward Pass** $\frac{\partial L}{\partial x_j^{\ell-1}} = \sum_k \sum_{i \in \Omega_j(k)} \frac{\partial L}{\partial x_i^{\ell}} \frac{\partial x_i^{\ell}}{\partial x_j^{\ell-1}}$ $\frac{\partial x_i^\ell}{\partial x_j^{\ell-1}} = \sum_k \left(\frac{w_k}{\sum_{p_j \in \Omega_i(k)} m_j^{\ell-1}} \sum_{p_j \in \Omega_i(k), m_j \neq 0} 1 \right)$ $\frac{\partial L}{\partial w_k} = \sum_i \frac{\partial L}{\partial x_i^\ell} \frac{\partial x_i^\ell}{\partial w_k}$ $\frac{\partial x_i^\ell}{\partial w_k} = \frac{1}{\sum_{p_j \in \Omega_i(k)} m_j^{\ell-1}} \sum_{p_j \in \Omega_i(k), m_j \neq 0} x_j^{\ell-1}$ (implemented as **custom TF op**, ~800 lines of CUDA)

ng, we design a "flattened U-Net" et for point clouds. It removes the et but preserves skip links concatenation + mask addition).



loss function (Lab color difference per point), 9 features

dify PU-Net to work on point clouds our modified PU-Net with our e an **end-to-end pipeline** for sual details of point clouds.











After training for just 3 epochs, same operator and architecture demonstrate **impressive preliminary results** on point cloud hole filling task

Results

Conclusion

• First to explore photo-realistic upsampling in 3D • Learned deep feature representations for 3D point clouds with novel operator and architecture • Future: train geometric and visual upsampling

networks together for higher accuracy, hole filling

