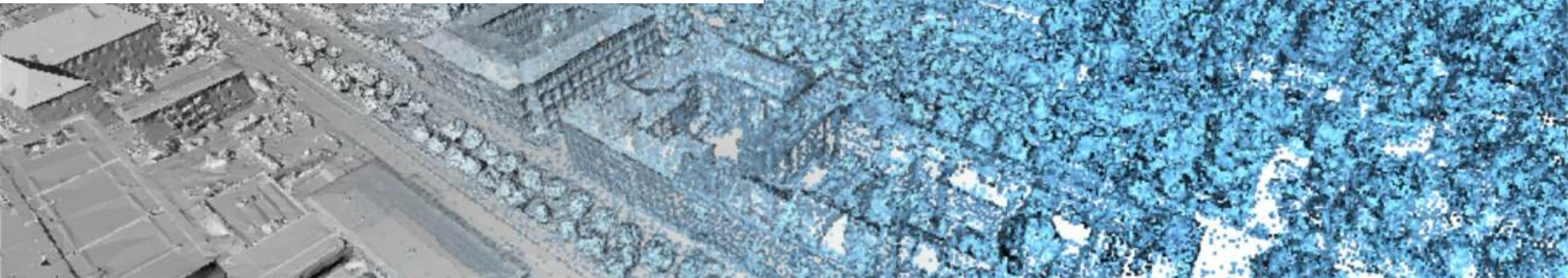


Learning Surface Reconstruction from Point Clouds in the Wild

PhD Defense of Raphael SULZER

Thesis Co-supervisor: Loic LANDRIEU

Thesis Supervisors: Bruno VALLET, Renaud MARLET

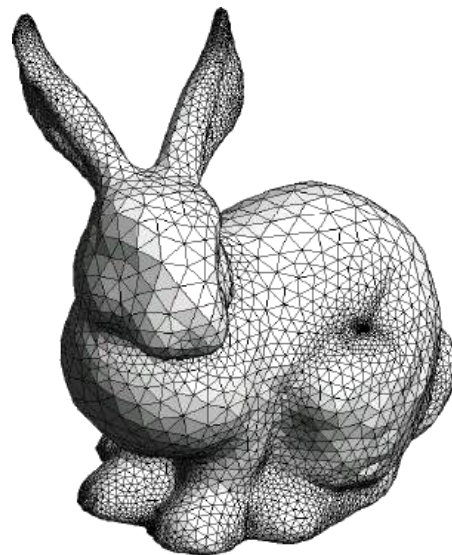


Learning Surface Reconstruction from Point Clouds in the Wild

How to create a digital copy of a real object?



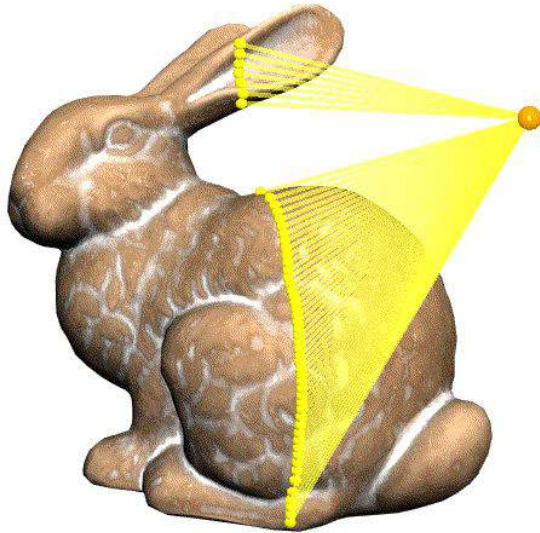
Real object



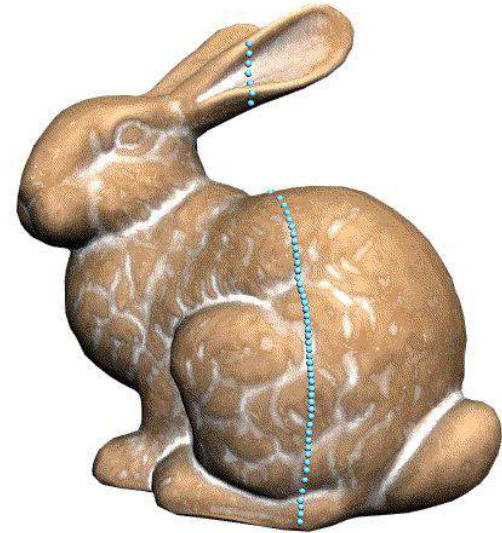
Digital copy

Learning Surface Reconstruction from Point Clouds in the Wild

Scan object to create a 3D point cloud



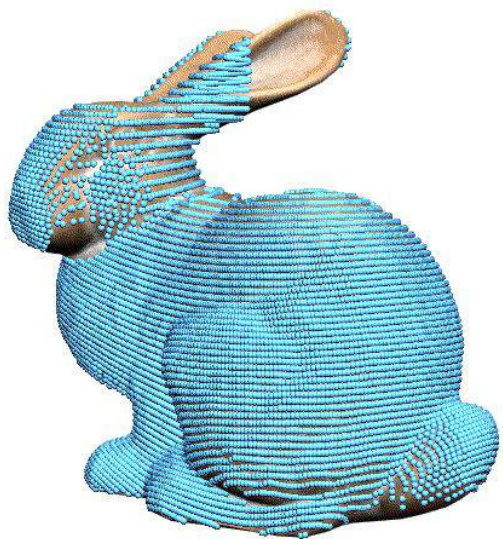
Scanning



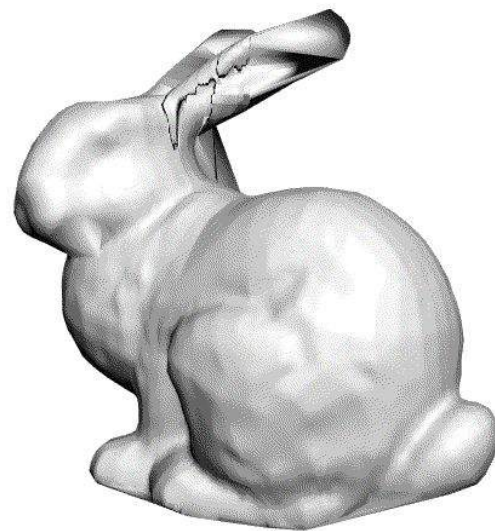
3D point cloud

Learning Surface Reconstruction from Point Clouds in the Wild

Approximate the surface given the point cloud



$$\mathcal{P} \in \mathbb{R}^{3 \times P}$$



$$\mathcal{S} \subset \mathbb{R}^3$$

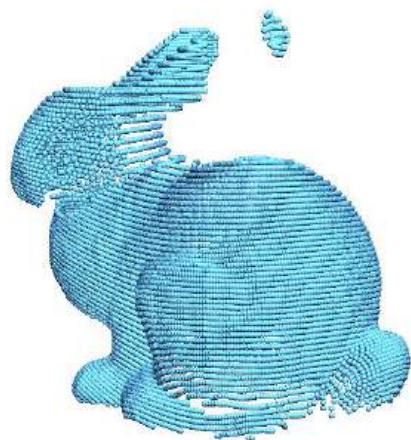
Learning Surface Reconstruction from Point Clouds in the Wild

Motivation:

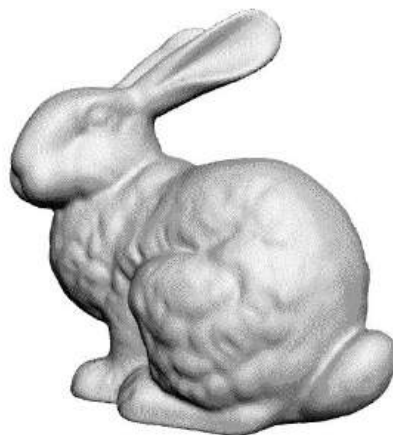
- Visualization



Real Image



Point cloud



Mesh



Textured Mesh

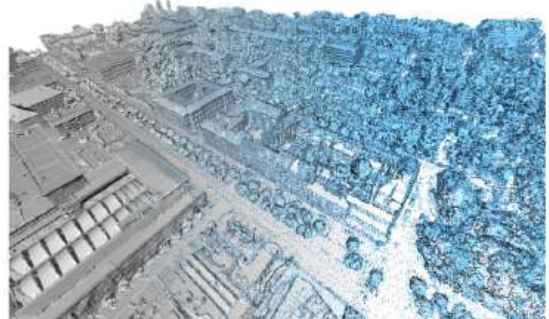
Learning Surface Reconstruction from Point Clouds in the Wild

Motivation:

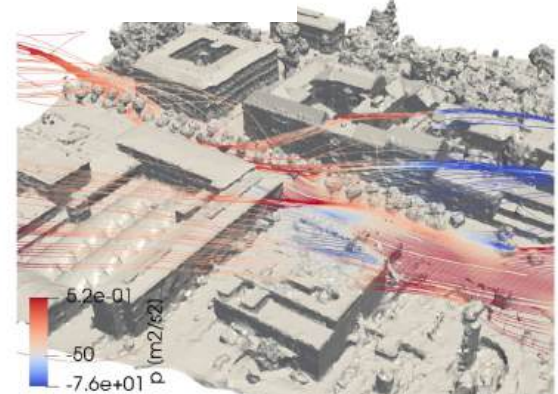
- Visualization
- Analysis
 - Mechanical engineering
 - Environmental science
 - Urban planning
 - Robotics
 - ...



(a) Point cloud acquisition



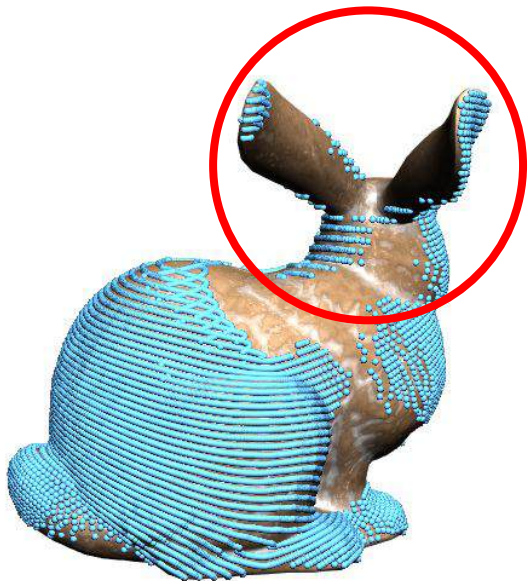
(b) Surface reconstruction



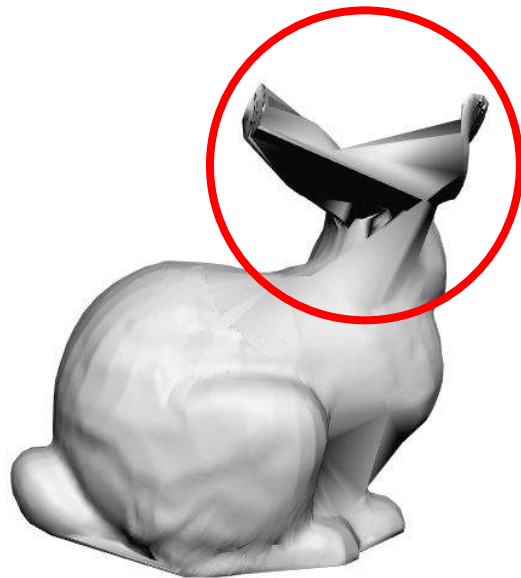
(c) Wind simulation with OpenFOAM

Learning Surface Reconstruction from Point Clouds in the Wild

Problem: We do not know what lies between the points!



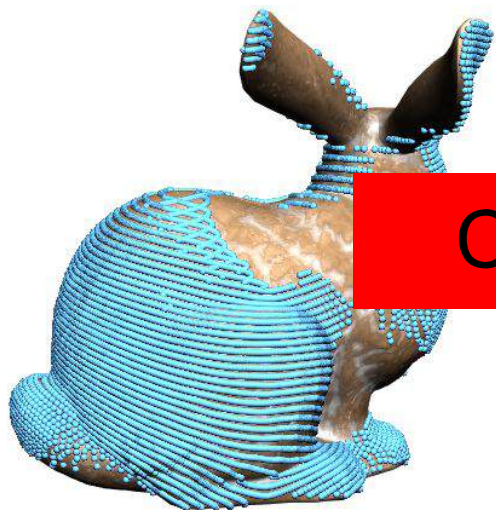
$$\mathcal{P} \in \mathbb{R}^{3 \times P}$$



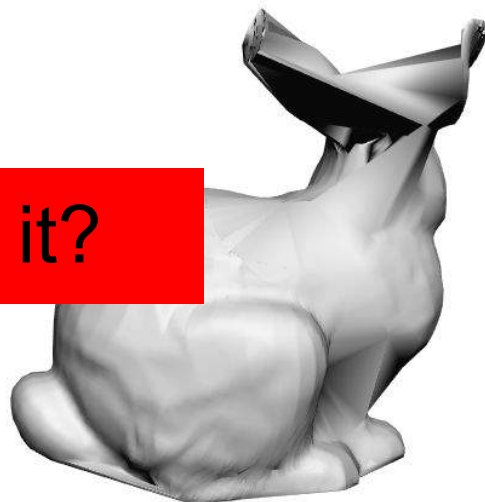
$$\mathcal{S} \subset \mathbb{R}^3$$

Learning Surface Reconstruction from Point Clouds in the Wild

Problem: We do not know what lies between the points!



Can we learn it?

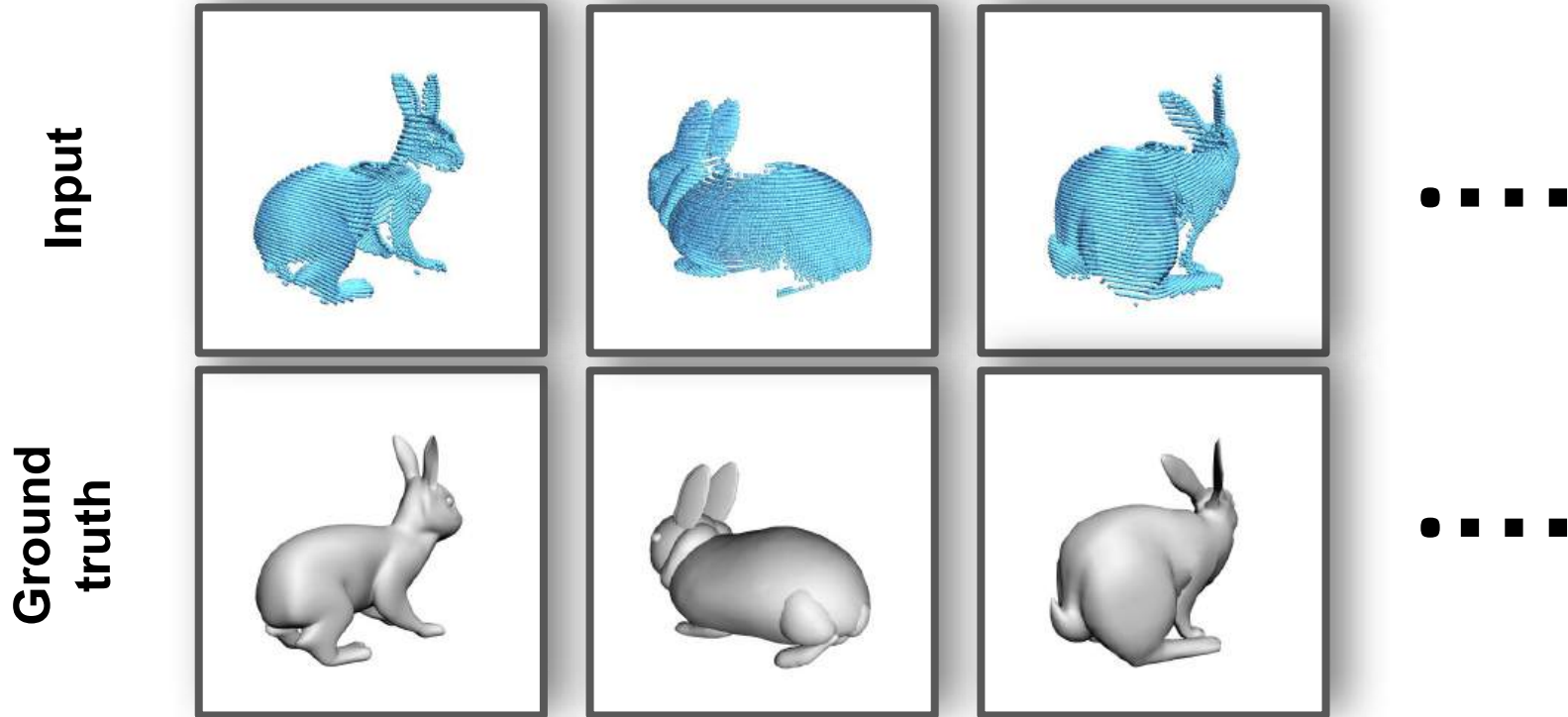


$$\mathcal{P} \in \mathbb{R}^{3 \times P}$$

$$\mathcal{S} \subset \mathbb{R}^3$$

Formulate surface reconstruction as a supervised learning problem

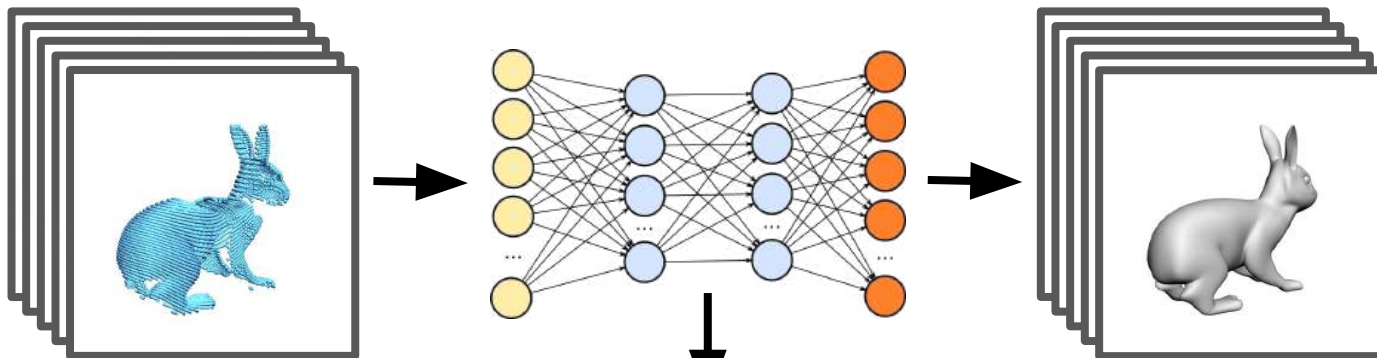
Train on many point cloud - surface pairs



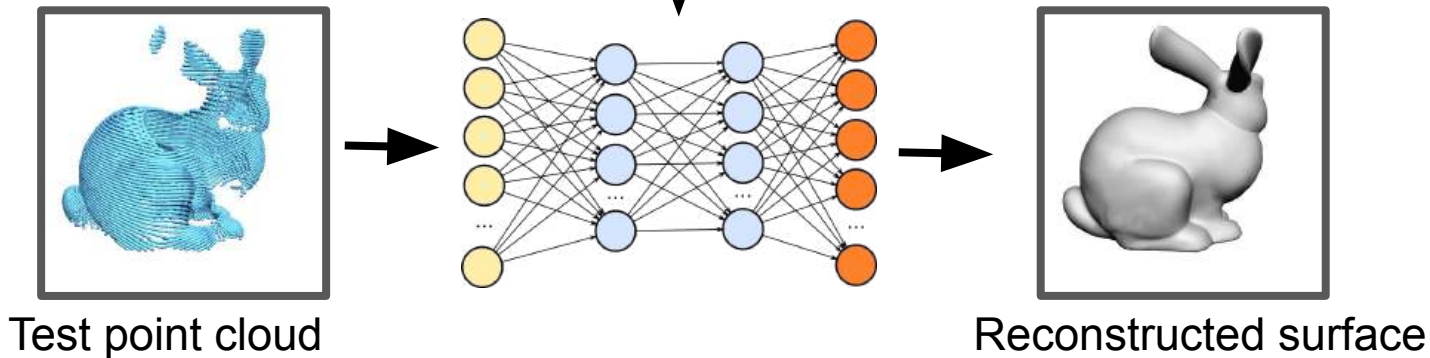
Formulate surface reconstruction as a supervised learning problem

Train on many point cloud - surface pairs

Training



Testing



Can we *learn* to reconstruct surfaces from point clouds in the wild?



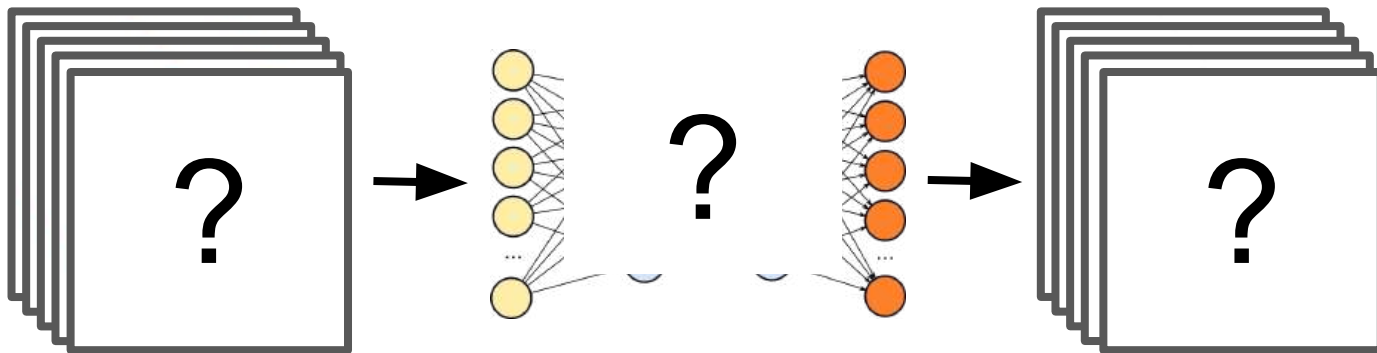
Difficulties:

- Point cloud defects
 - Missing data
 - Outliers
 - Noise
 - Non-uniform density
- Multiple modalities
 - LiDAR
 - Multi-View Stereo (MVS)
- Large scale (>1M points)
- No training data

Formulate surface reconstruction as a supervised learning problem

Train on many point cloud - surface pairs

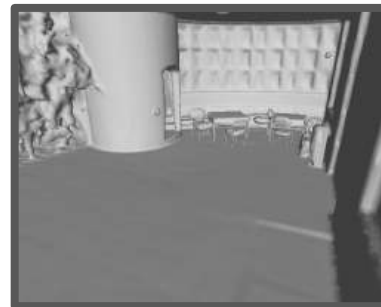
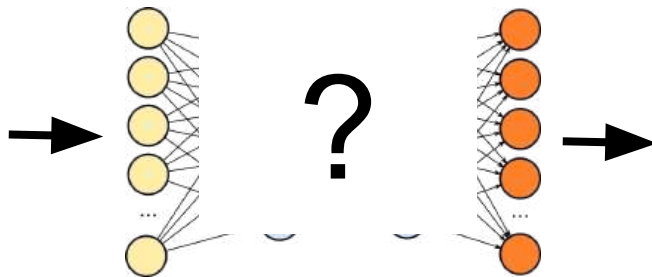
Training



Testing



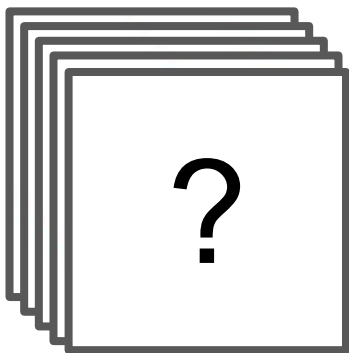
Test point cloud



Reconstructed surface

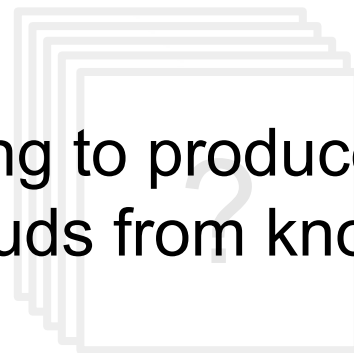
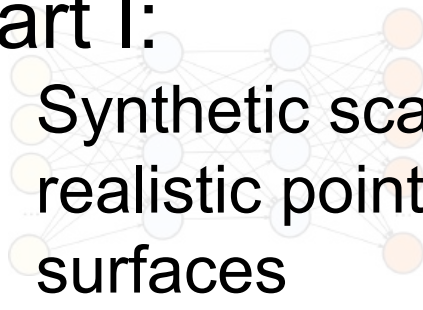
Outline

Training



Part I:

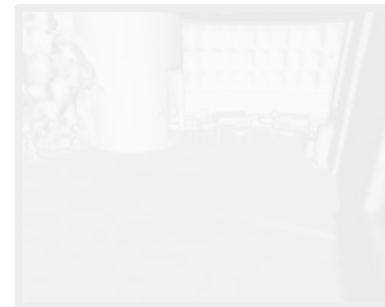
- Synthetic scanning to produce realistic point clouds from known surfaces



Testing



Test point cloud



Reconstructed surface

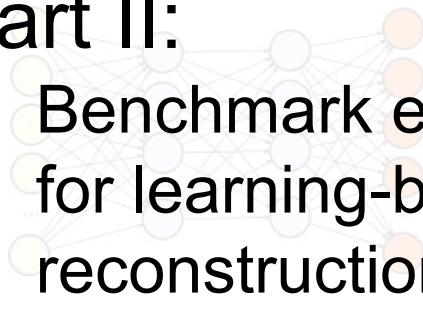
Outline

Training



Part II:

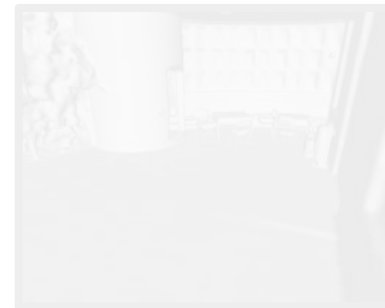
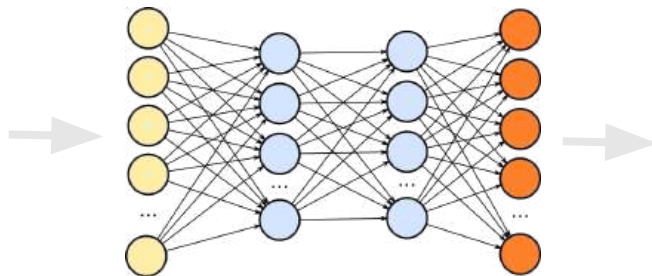
- Benchmark existing architectures for learning-based surface reconstruction



Testing



Test point cloud



Reconstructed surface

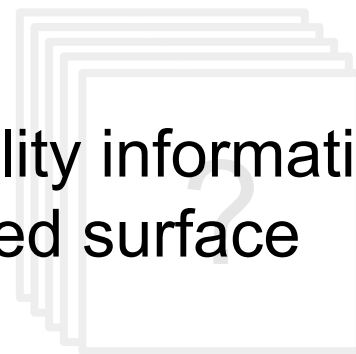
Outline

Training

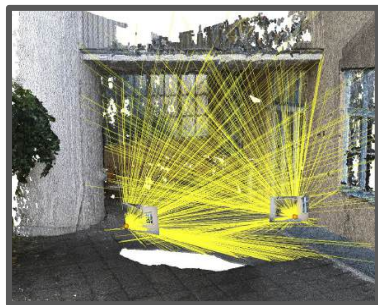


Part III:

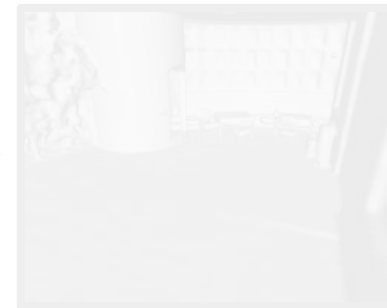
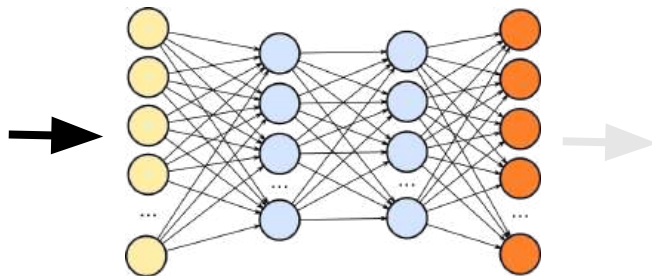
- Incorporate visibility information into learning-based surface reconstruction



Testing



Test point cloud



Reconstructed surface

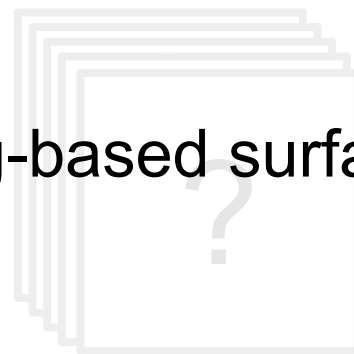
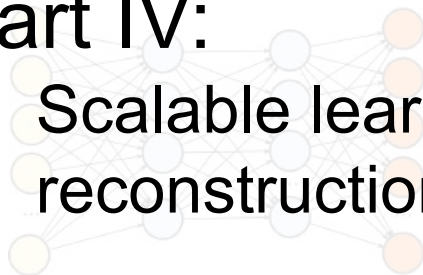
Outline

Training



Part IV:

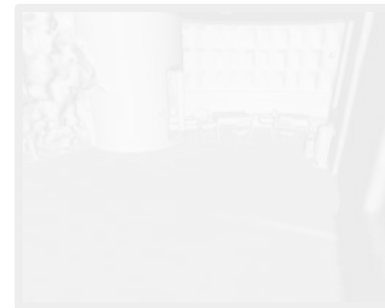
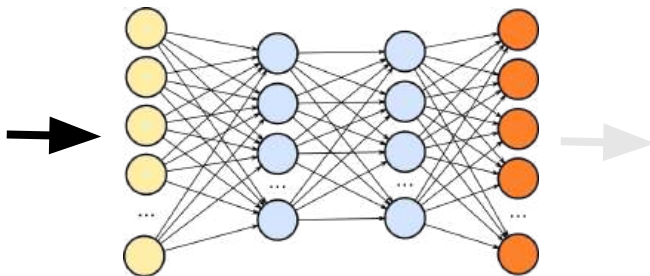
- Scalable learning-based surface reconstruction



Testing



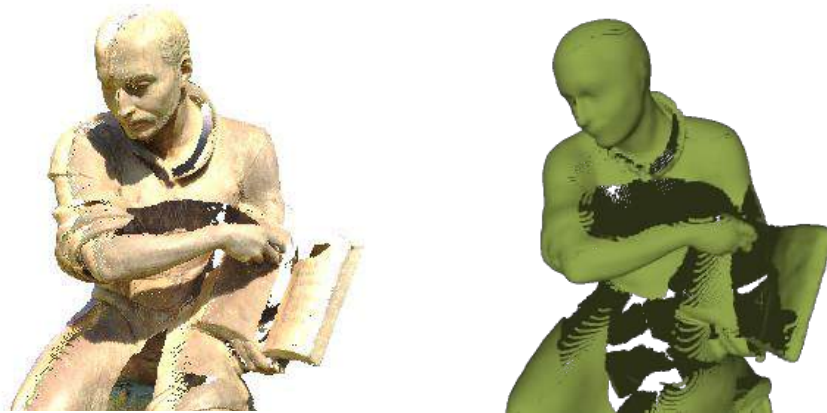
Test point cloud



Reconstructed surface

Part I

Synthetic scanning to produce realistic point clouds from known surfaces



Point clouds in the wild



MVS 40 views



MVS 260 views



LIDAR 3 views

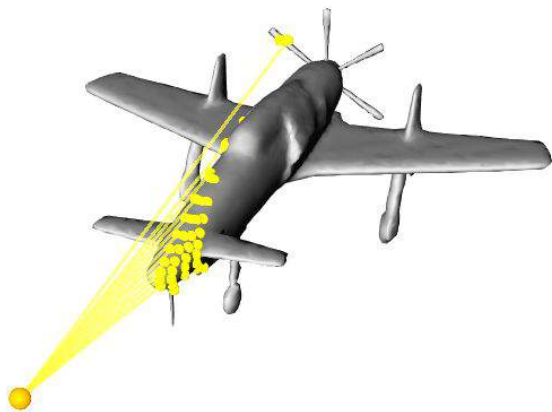


LIDAR 9 views

Scanning an object in the wild requires dense viewpoints
→ Does not scale

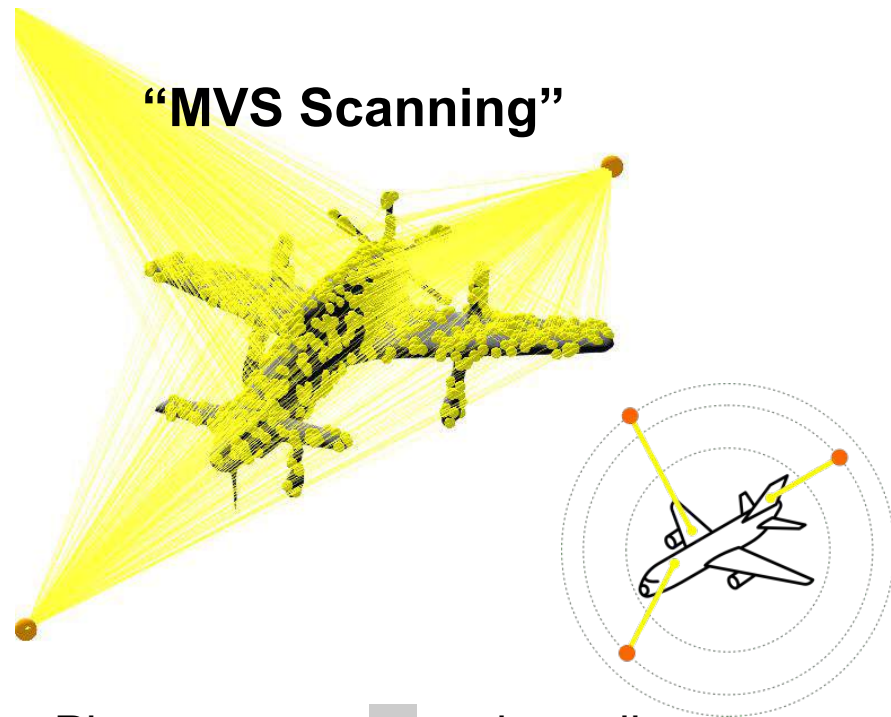
Synthetic Range and MVS Scans



Range Scanning



- Range scanning simulation of Berger *et al.*

“MVS Scanning”



- Place sensors  on bounding spheres with different radii
- Shoot rays  to unit sphere



High quality mesh



Uniform sampling



MVS



Synthetic MVS



Range scan



Synthetic range scan

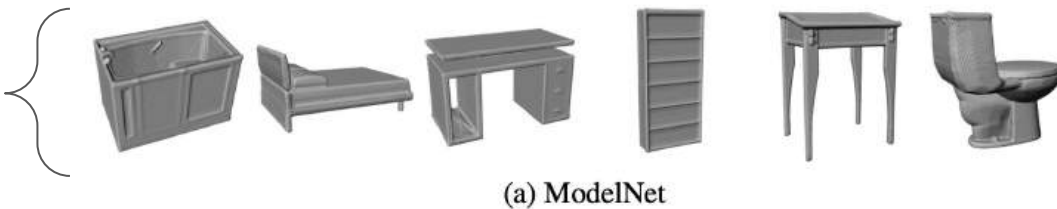
→ Synthetic scans produce point clouds with *real characteristics*

Datasets

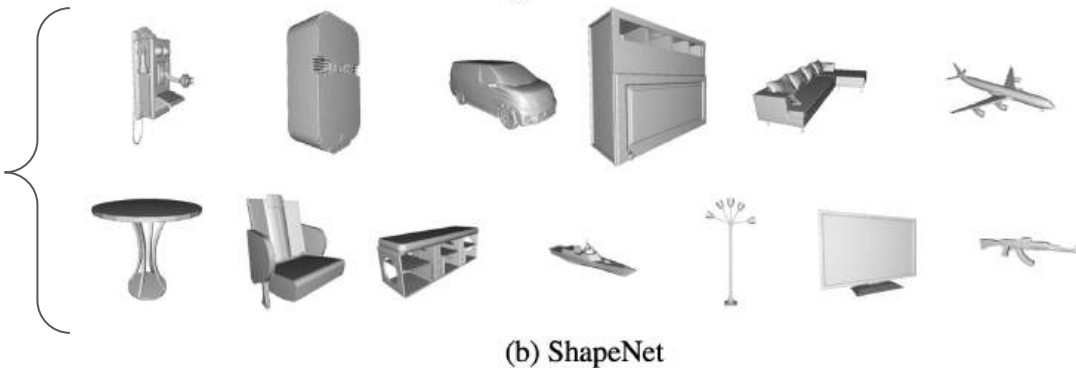
- We create synthetically scanned point clouds with real characteristics to train learning-based reconstruction algorithms
 - We provide scanned versions of four different datasets
 - ModelNet10 [Wu *et al.* 2015]
 - ShapeNet [Chang *et al.* 2015]
 - Reconbench [Berger *et al.* 2011]
 - Synthetic Rooms [Peng *et al.* 2020]
 - All dataset include point clouds with sensor position for each point and a watertight ground truth surface

Datasets

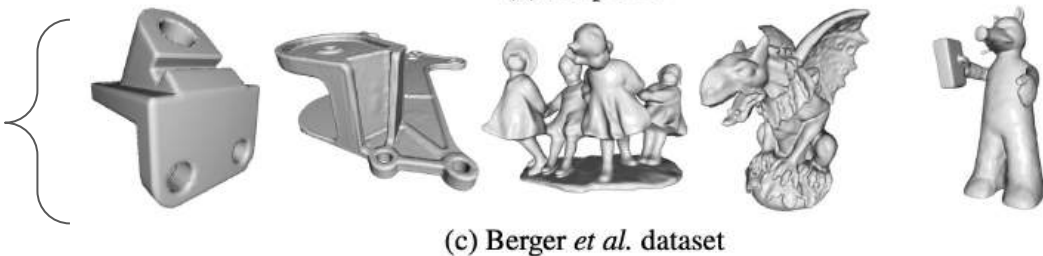
ModelNet:
5000 shapes w/ low complexity



ShapeNet:
13000 shapes w/ high complexity

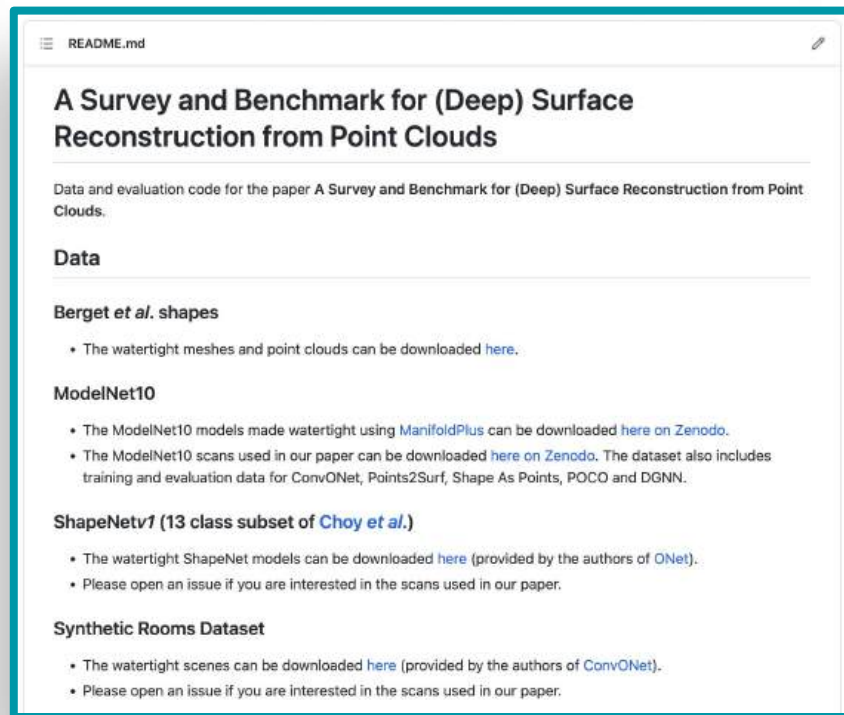


Berger *et al.* dataset:
5 shapes w/ high complexity



Datasets

<https://github.com/raphaelsulzer/dsr-benchmark>



The image shows a screenshot of a GitHub README file. The title is "A Survey and Benchmark for (Deep) Surface Reconstruction from Point Clouds". Below the title, there is a paragraph of text: "Data and evaluation code for the paper A Survey and Benchmark for (Deep) Surface Reconstruction from Point Clouds." followed by a section header "Data". Under "Data", there are three sub-sections: "Berget et al. shapes", "ModelNet10", and "ShapeNetv1 (13 class subset of Choy et al.)". Each sub-section has a list of bullet points providing links to download data. The final section is "Synthetic Rooms Dataset", also with a list of bullet points.

☰ README.md ✎

A Survey and Benchmark for (Deep) Surface Reconstruction from Point Clouds

Data and evaluation code for the paper A Survey and Benchmark for (Deep) Surface Reconstruction from Point Clouds.

Data

Berget et al. shapes

- The watertight meshes and point clouds can be downloaded [here](#).

ModelNet10

- The ModelNet10 models made watertight using [ManifoldPlus](#) can be downloaded [here on Zenodo](#).
- The ModelNet10 scans used in our paper can be downloaded [here on Zenodo](#). The dataset also includes training and evaluation data for ConvONet, Points2Surf, Shape As Points, POCo and DGNN.

ShapeNetv1 (13 class subset of [Choy et al.](#))

- The watertight ShapeNet models can be downloaded [here](#) (provided by the authors of [ONet](#)).
- Please open an issue if you are interested in the scans used in our paper.

Synthetic Rooms Dataset

- The watertight scenes can be downloaded [here](#) (provided by the authors of [ConvONet](#)).
- Please open an issue if you are interested in the scans used in our paper.

Part II

A Survey and Benchmark of (Deep) Surface Reconstruction from Point Clouds

to be submitted: Sulzer, R., Landrieu, L., Marlet, R., & Vallet, B. (2022). A Survey and Benchmark of (Deep) Surface Reconstruction from Point Clouds



Survey

Method	learning	normals req.	pose req.	RF	output
<i>Surface-based</i>					
BPA [11]				local	triangle mesh
Sharf <i>et al.</i> [108]				both	triangle mesh
AtlasNet [53]	✓			local	triangle mesh
IER [78]	✓			both	triangle mesh
PointTriNet [109]	✓			local	triangle mesh
DSE [102]	✓			local	triangle mesh
P2M [56]				both	triangle mesh
<i>Volume-based</i>					
SPSR [69]		✓		both	implicit field
Labatut <i>et al.</i> [75]			✓	global	triangle mesh
ONet [85]	✓			global	implicit field
DeepSDF [96]	✓			global	implicit field
IM-Net [37]	✓			global	implicit field
ConvONet [99]	✓			both	implicit field
IGR [52]	(✓)	(✓)		global	implicit field
LIG [67]	✓	✓		local	implicit field
DGNN [117]	✓		✓	both	triangle mesh
P2S [48]	✓			both	implicit field
SAP [98]	(✓)			both	implicit field
POCO [21]	✓	(✓)		local	implicit field

Benchmark

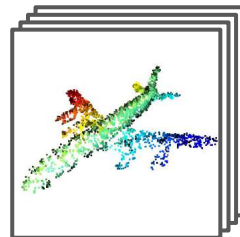
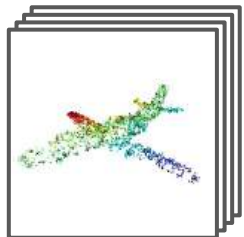
Experiment

Train

Test

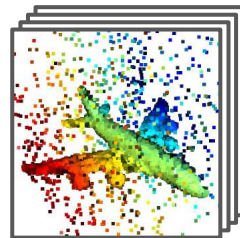
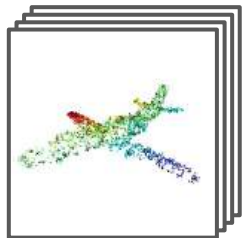
1

in-distribution



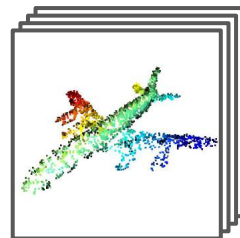
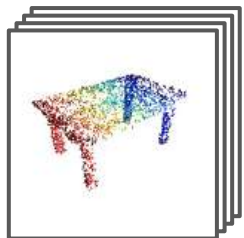
2

out-of-distribution





3

out-of-distribution






Benchmark

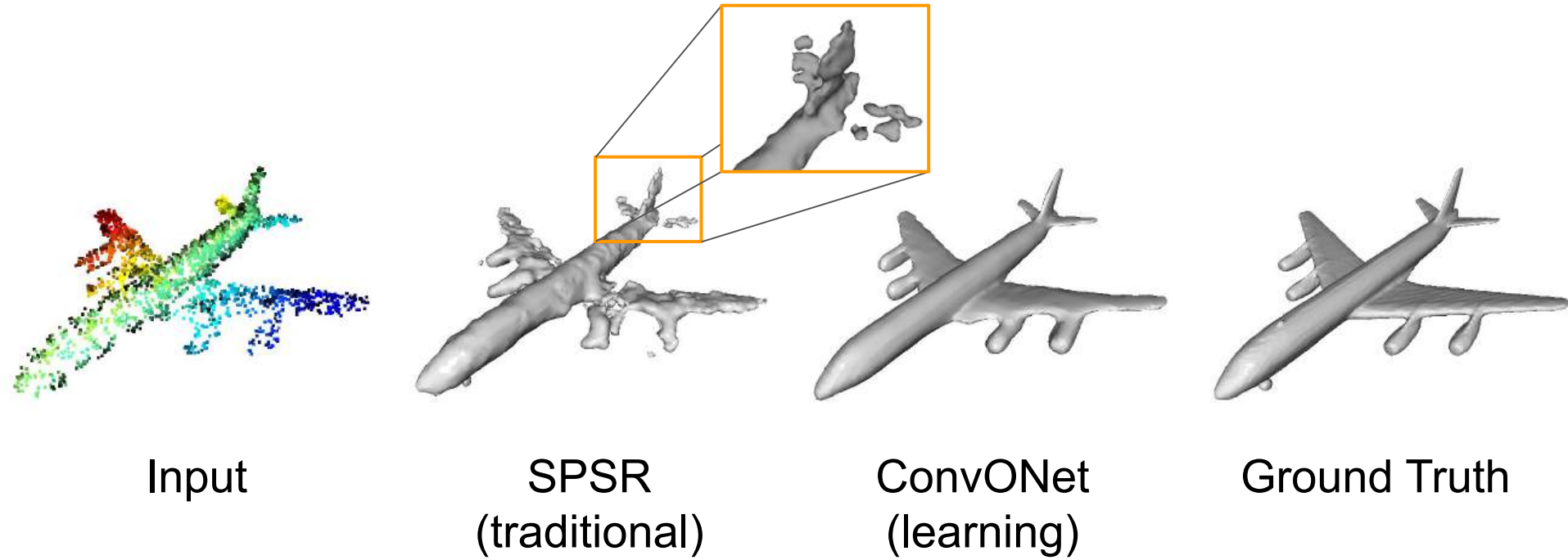
traditional methods

-  Screened Poisson Surface Reconstruction (SPSR) [Kazhdan *et al.* 2013]
-  Robust and Efficient Surface Reconstruction (Labatut *et al.*) [Labatut *et al.* 2009]

learning-based methods

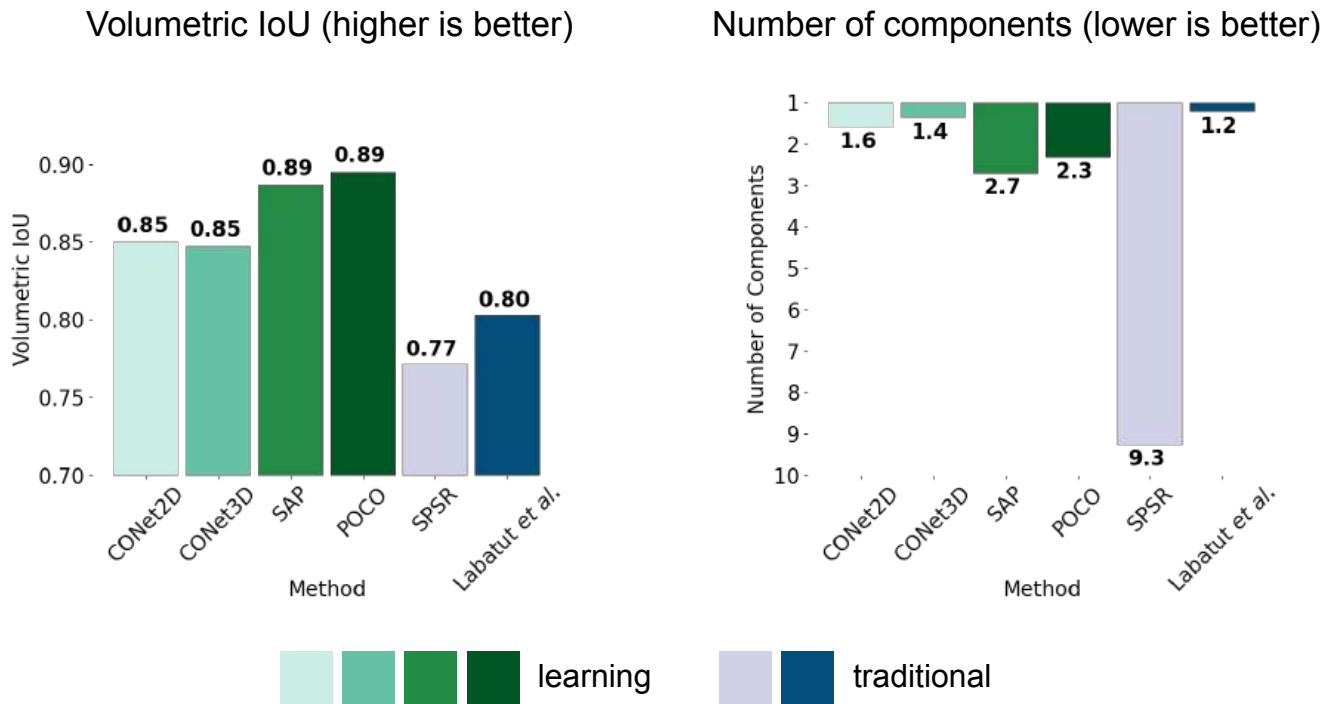
-  Convolutional Occupancy Networks (ConvONet) [Peng *et al.* 2020]
-  Shape-As-Points (SAP) [Peng *et al.* 2021]
-  Point Convolution for Surface Reconstruction (POCO) [Boulch & Marlet 2022]

1. Known sampling defects and known shape categories



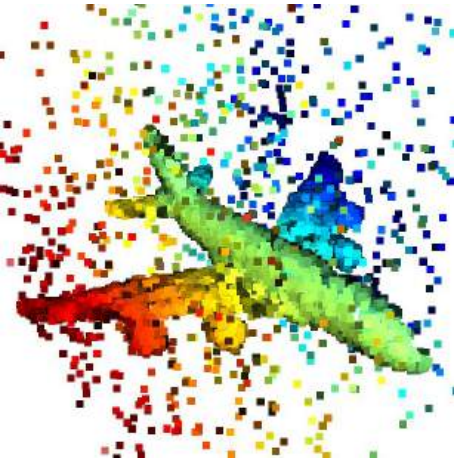
→ Learning-based methods provide more accurate reconstructions

1. Known sampling defects and known shape categories

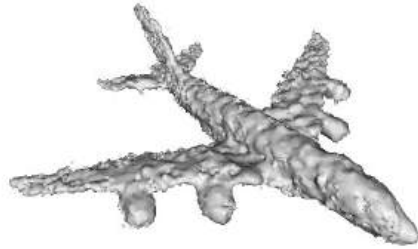


→ Learning-based methods provide more accurate reconstructions

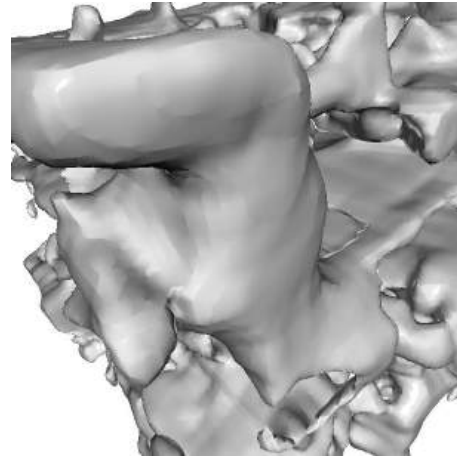
2. Unknown sampling defects and known shape categories



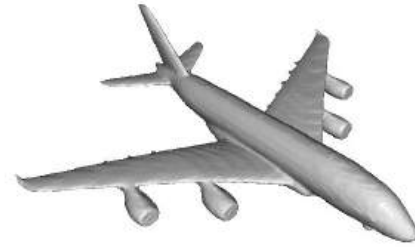
Input



SPSR
(traditional)



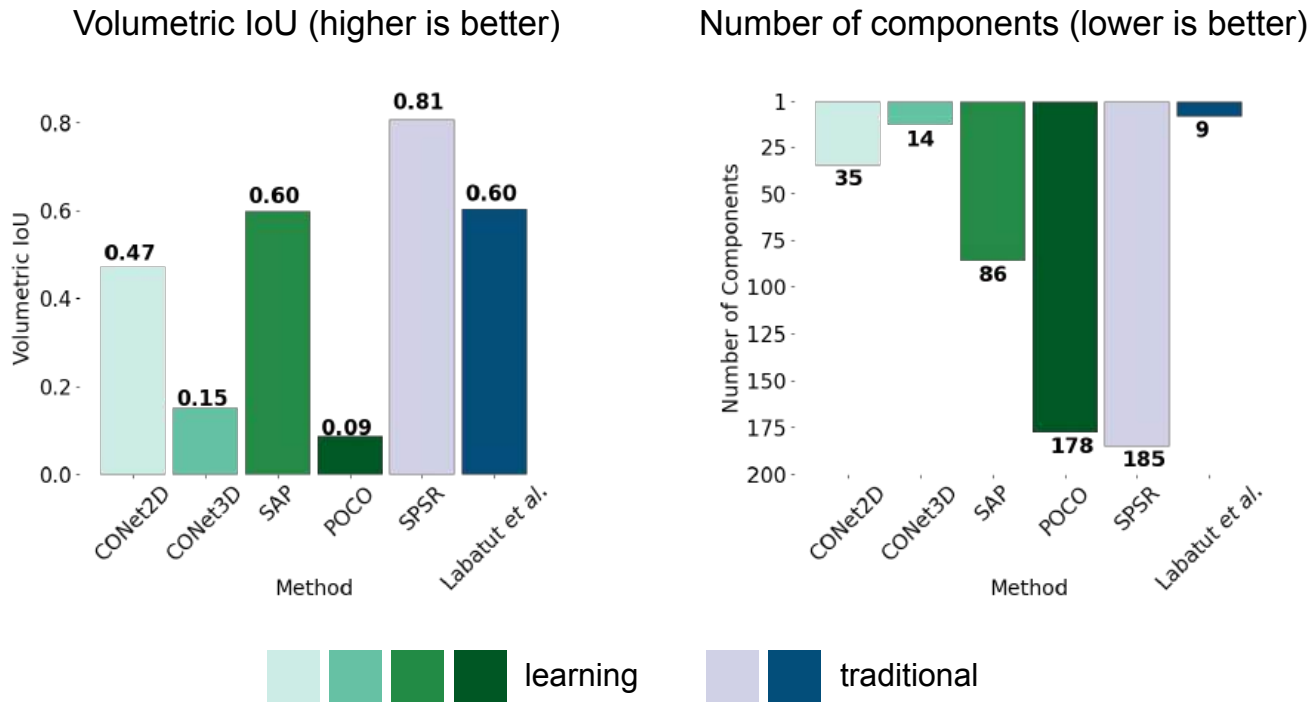
ConvONet
(learning)



Ground Truth

→ Traditional methods provide more accurate reconstructions

2. Unknown sampling defects and known shape categories

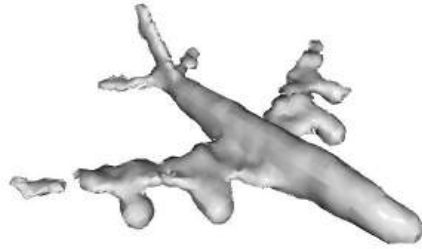


→ Traditional methods provide more accurate reconstructions

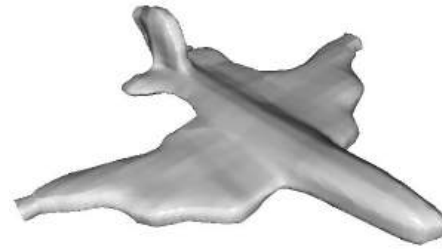
3. Known sampling defects and unknown shape categories



Input



SPSR
(traditional)



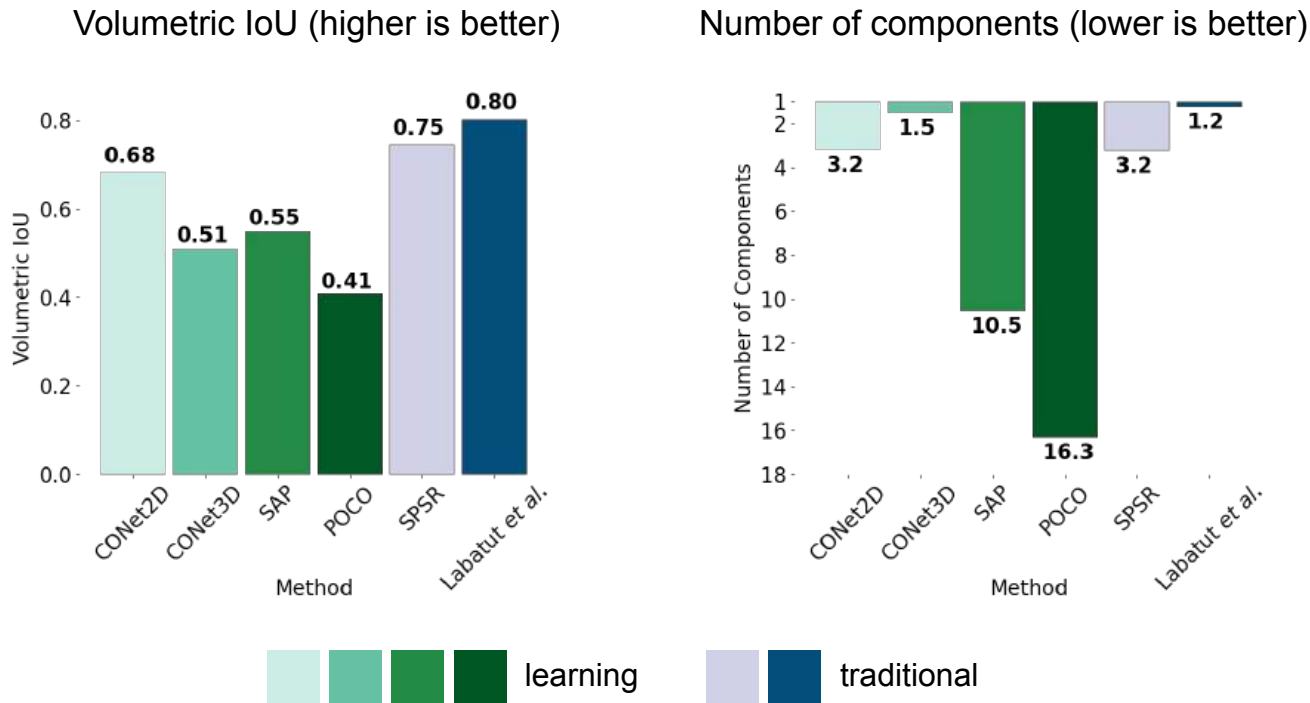
ConvONet
(learning)



Ground Truth

→ Traditional methods provide more accurate reconstructions

3. Known sampling defects and unknown shape categories



→ Traditional methods provide more accurate reconstructions

Conclusion

Learning-based surface reconstruction...

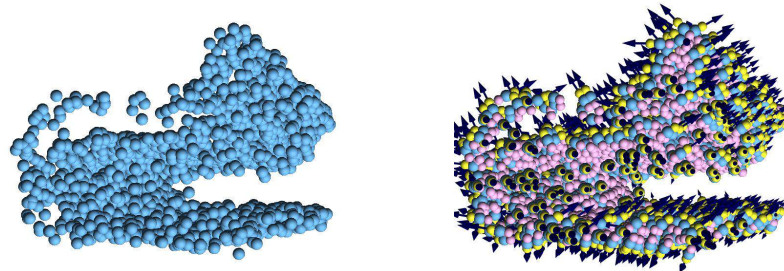
1. ...outperforms traditional reconstruction methods when sampling and shape categories are known
2. ...does not work well for unknown sampling defects
3. ...needs a large training set with complex shapes

→ We address issues 2. and 3. in Part III + IV

Part III

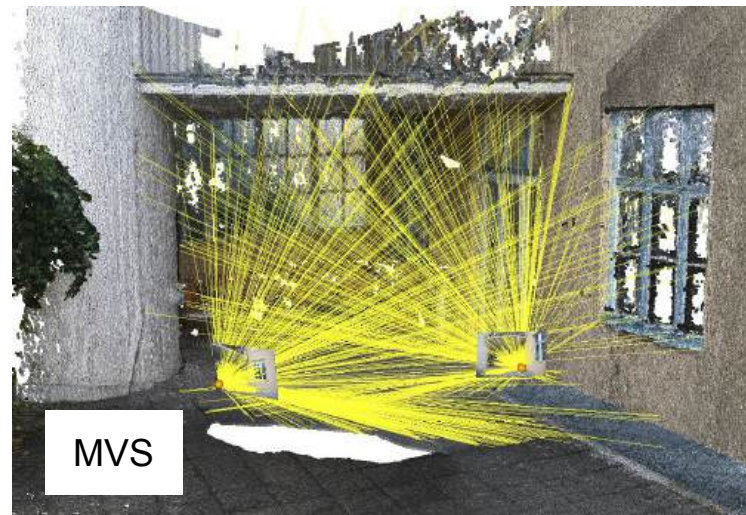
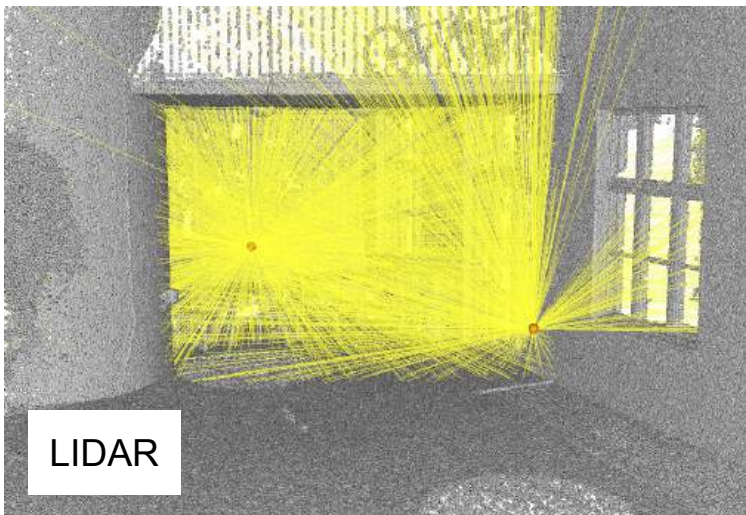
Deep Surface Reconstruction from Point Clouds with Visibility Information

Sulzer, R., Landrieu, L., Boulch, A., Marlet, R., & Vallet, B. (2022). Deep Surface Reconstruction from Point Clouds with Visibility Information. In *International Conference on Pattern Recognition (ICPR)*

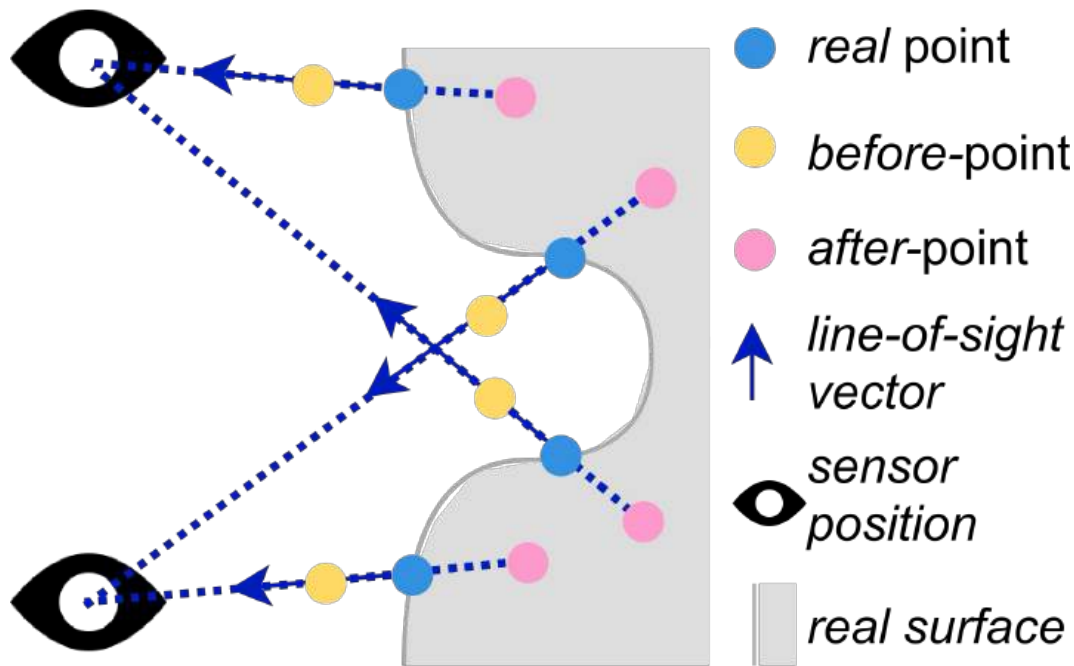


Deep Surface Reconstruction from Point Clouds with Visibility Information

- 3D scanning allows to recover sensor position from acquisition
- Sensor position can be used to relate each observed point with a line-of-sight

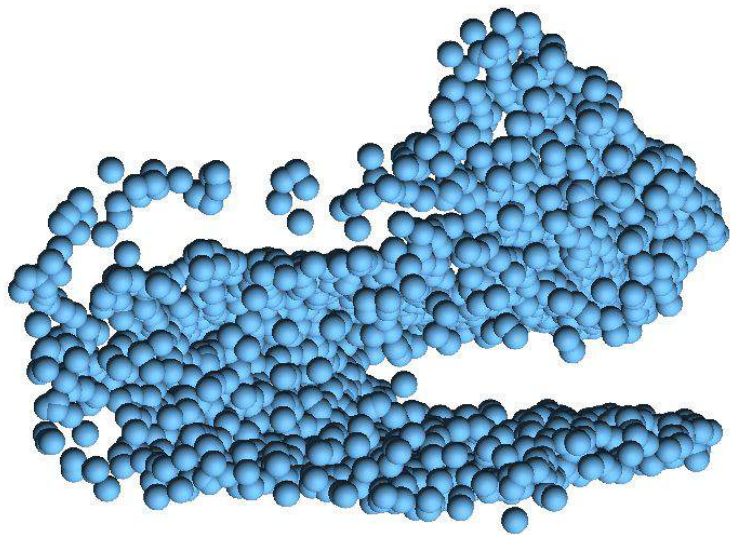


Deep Surface Reconstruction from Point Clouds with Visibility Information

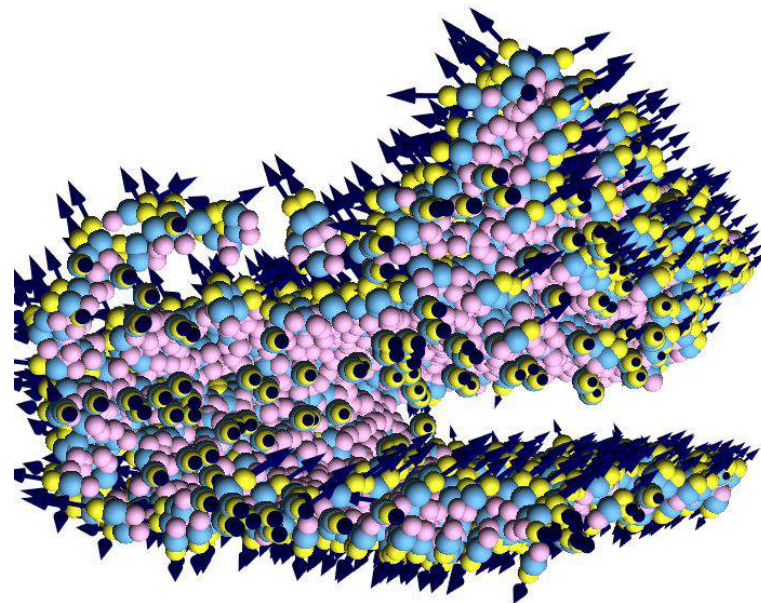


→ Make visibility information useable for surface reconstruction networks

Deep Surface Reconstruction from Point Clouds with Visibility Information



Bare point cloud

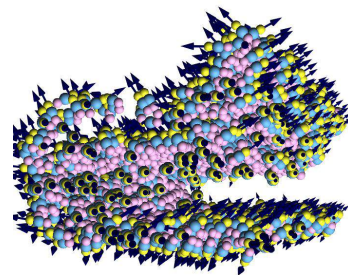
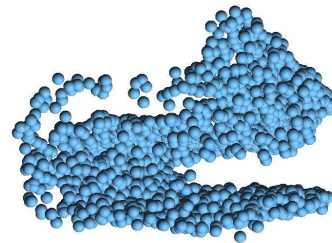


Visibility-augmented point cloud

Deep Surface Reconstruction from Point Clouds with Visibility Information

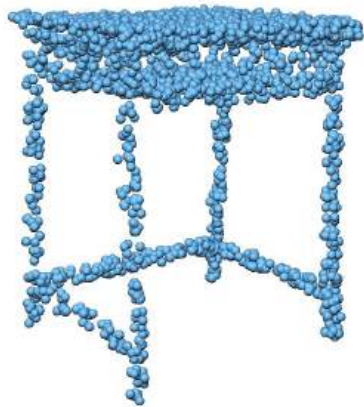
Only two small modifications to network

- Increase number of channels of first layer by 5
 - +3 channels for sightline vector coordinates
 - +2 channels for point type identifier (real / before / after)
- Directly add auxiliary points to input
 - → adjust batch size to handle 3x larger point cloud

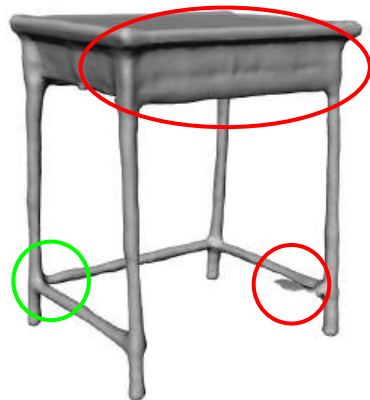


→ Modifications can be applied to almost any surface reconstruction network

Bare



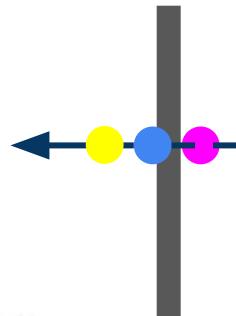
Point cloud



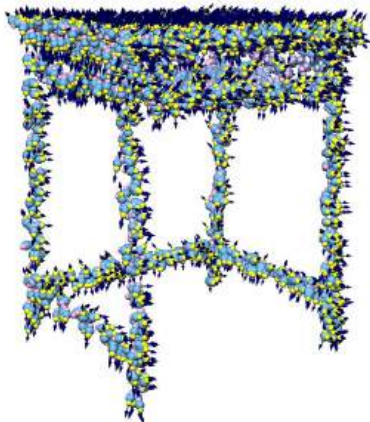
ConvONet



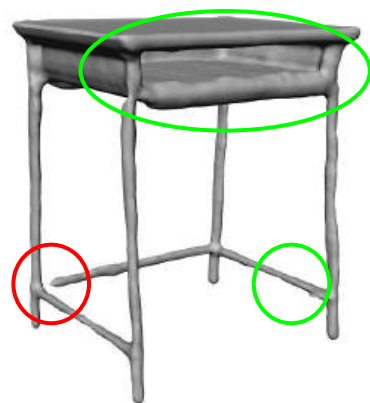
Ground truth



Augmented



Point cloud



ConvONet

Bare



ConvONet



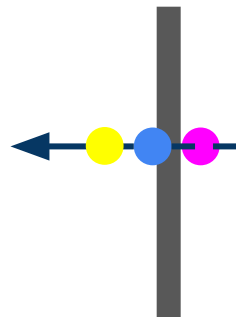
Points2Surf



Shape As Points



POCO



Augmented



ConvONet



Points2Surf



Shape As Points

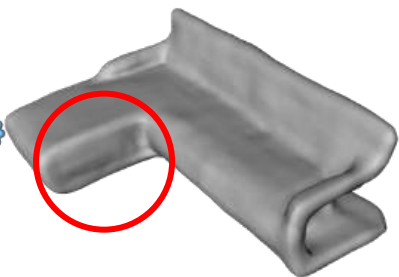
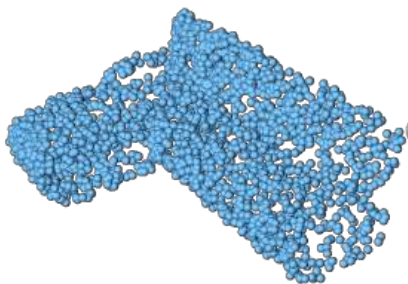


POCO



Ground truth

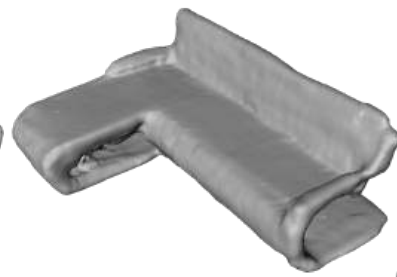
Bare



Points2Surf



Shape As Points

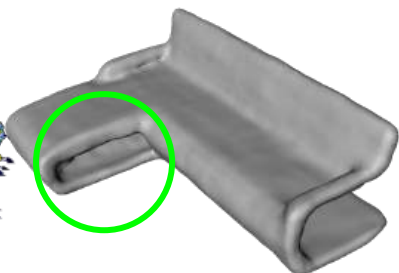
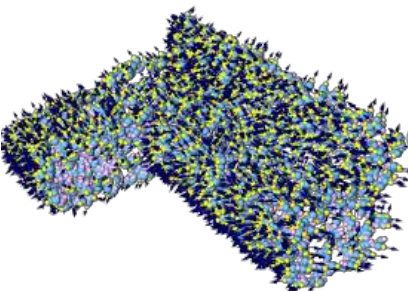


POCO

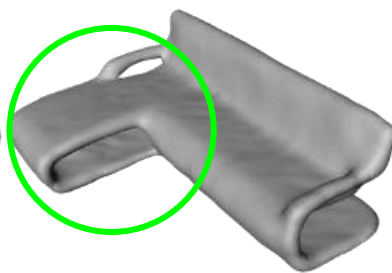


Ground truth

Augmented



Points2Surf



Shape As Points



POCO

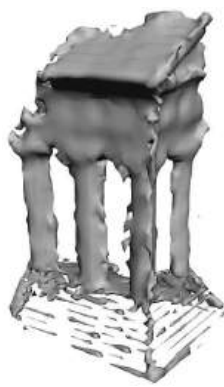
Bare



Input



ConvONet



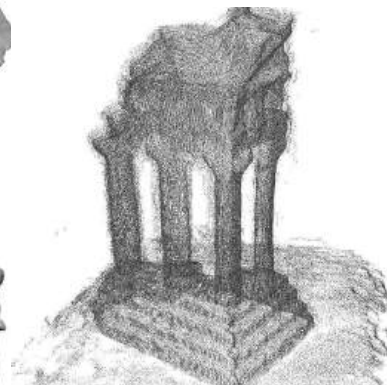
Points2Surf



Shape As Points

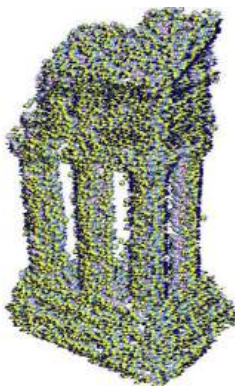


POCO



HD Scan

Augmented



Input



ConvONet



Points2Surf

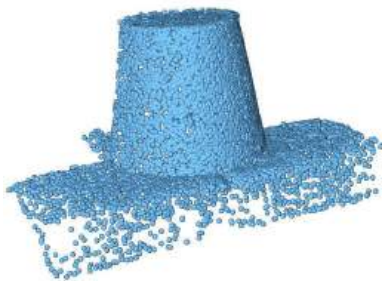


Shape As Points



POCO

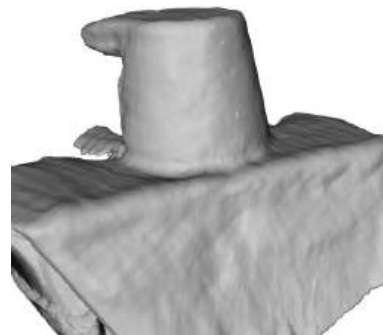
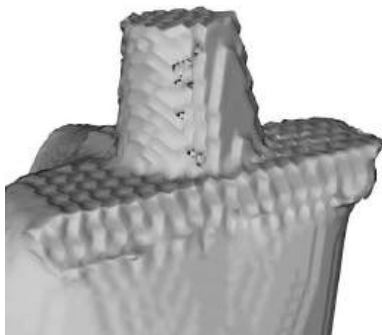
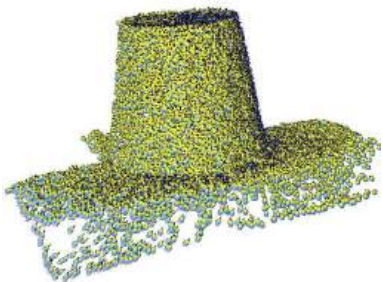
Bare



Points2Surf

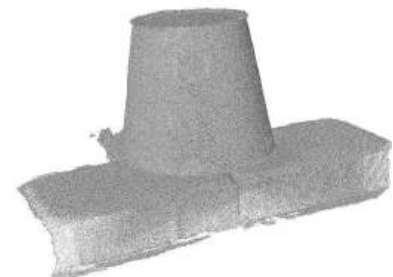
POCO

Augmented



Points2Surf

POCO



HD Scan

Bare



ConvONet



Points2Surf



Shape As Points

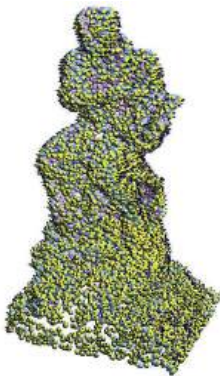


POCO



HD Scan

Augmented



ConvONet



Points2Surf



Shape As Points

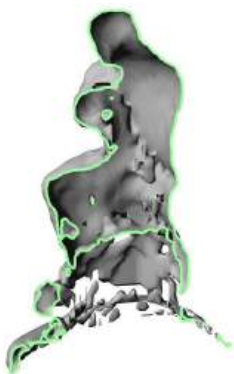


POCO

Bare



ConvONet



Points2Surf



Shape As Points

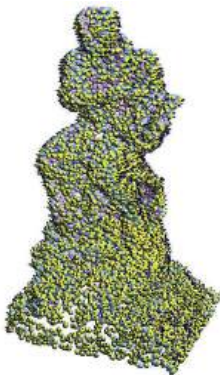


POCO

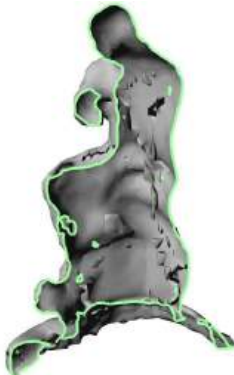


HD Scan

Augmented



ConvONet



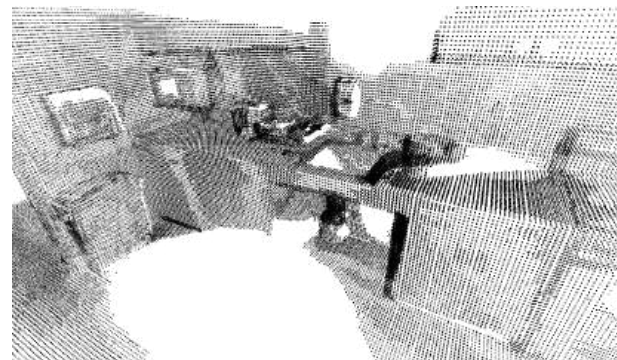
Points2Surf



Shape As Points



POCO



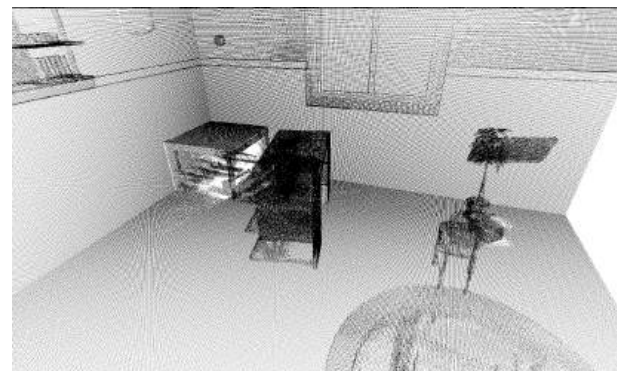
Point cloud



Reconstruction (Bare PC)



Reconstruction (Augmented PC)



Point cloud

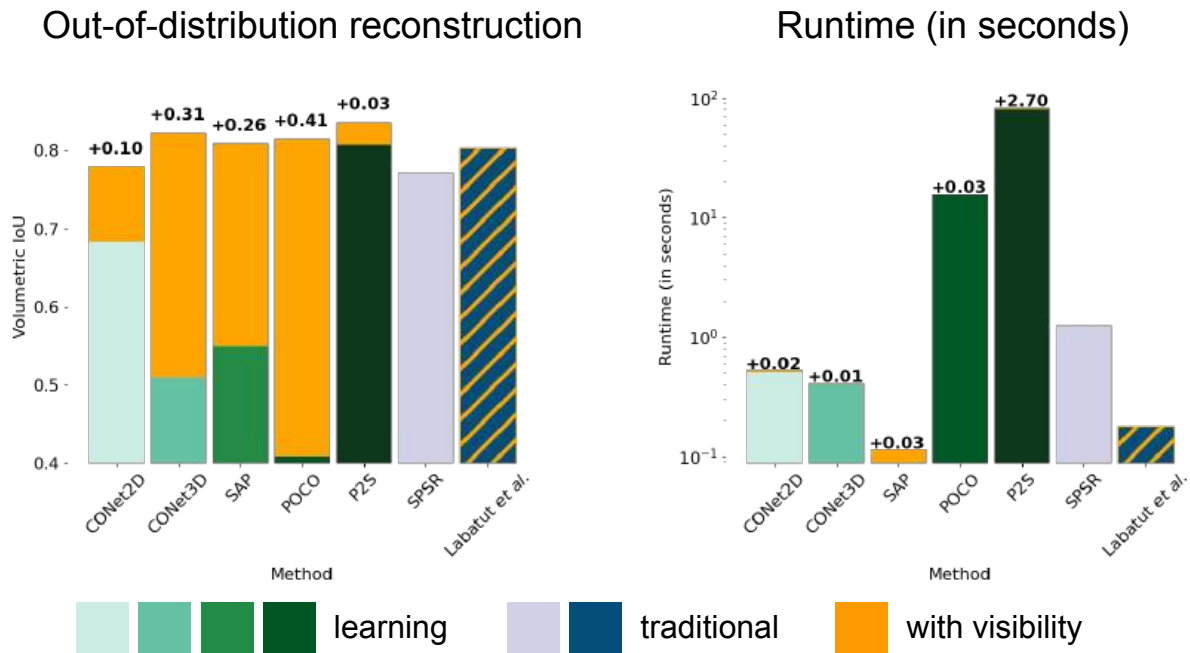


Reconstruction (Bare PC)



Reconstruction (Augmented PC)

Deep Surface Reconstruction with Visibility Information



→ Adding visibility information leads to more accurate reconstructions

Deep Surface Reconstruction from Point Clouds with Visibility Information

Ablation study (with ConvONet on ModelNet)

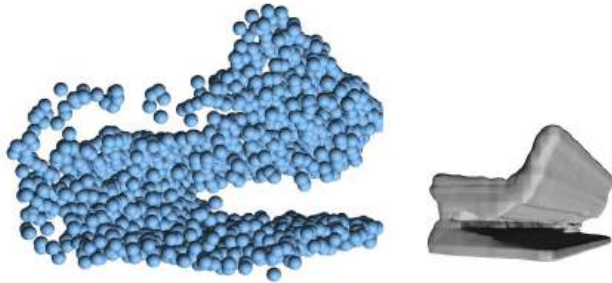
Model	volumetric IoU
ConvONet-2D	85.3
+sightline vectors (SV)	+1.8
+auxiliary points (AP)	+2.8
+SV and AP	+3.6
+true normals	+2.6

Conclusion

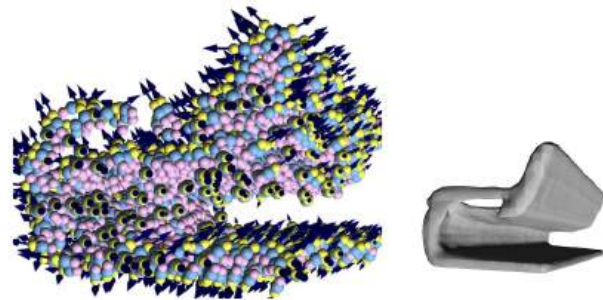
Visibility Information...

- ...can be added to most surface reconstruction networks with very little modification and little to no added runtime
- ...consistently improves the reconstruction quality as well as the robustness of surface reconstruction networks

→ Do not throw away sensor positions



(a) Reconstruction using only the points position.



(b) Reconstruction with visibility augmented point cloud.

Deep Surface Reconstruction from Point Clouds with Visibility Information



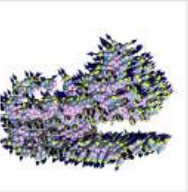

<https://github.com/raphaelsulzer/dsrv-data>

☰ README.md

Deep Surface Reconstruction from Point Clouds with Visibility Information

Paper

Data, code and pretrained models for the paper **Deep Surface Reconstruction from Point Clouds with Visibility Information**.

			
Point cloud	Reconstruction	Point cloud with Visibility	Reconstruction

Data

ModelNet10

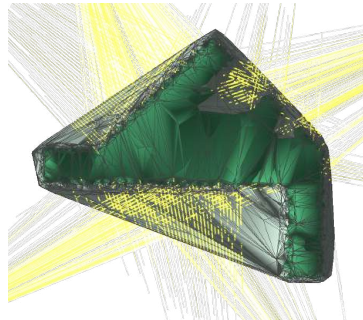
- The ModelNet10 models made watertight using [ManifoldPlus](#) can be downloaded [here on Zenodo](#).
- The ModelNet10 scans used in our paper can be downloaded [here on Zenodo](#). The dataset also includes training and evaluation data for CorvONet, Points2Surf, Shape As Points, POCO and DGNN.

ShapeNetv1 (13 class subset of [Choy et al.](#))

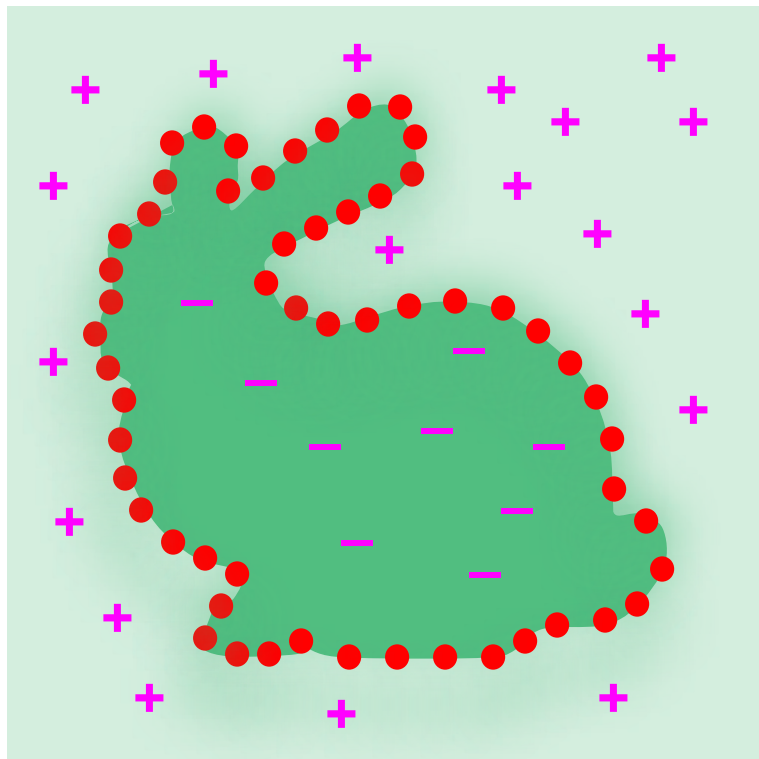
Part IV

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Sulzer, R., Landrieu, L., Marlet, R., & Vallet, B. (2021). Scalable Surface Reconstruction with Delaunay-Graph Neural Networks. *Eurographics Symposium on Geometry Processing (SGP)*.



Learning-based global reconstruction



- Condition NN input on \mathcal{P}
- Use NN to classify query points x to lie inside or outside of surface
- Surface is decision boundary of NN:
$$\mathcal{S} = \{x \in \mathbb{R}^3 \mid F_{\theta}(x, \mathcal{P}) = 0\}$$
- Examples:
 - ONet [Mescheder *et al.* 2019]
 - DeepSDF [Park *et al.* 2019]
 - IM-Net [Chen & Zhang 2019]

Learning-based global reconstruction: Architecture

Input

Output



Point cloud \mathcal{P}

Encoder

low-dimensional
shape code c

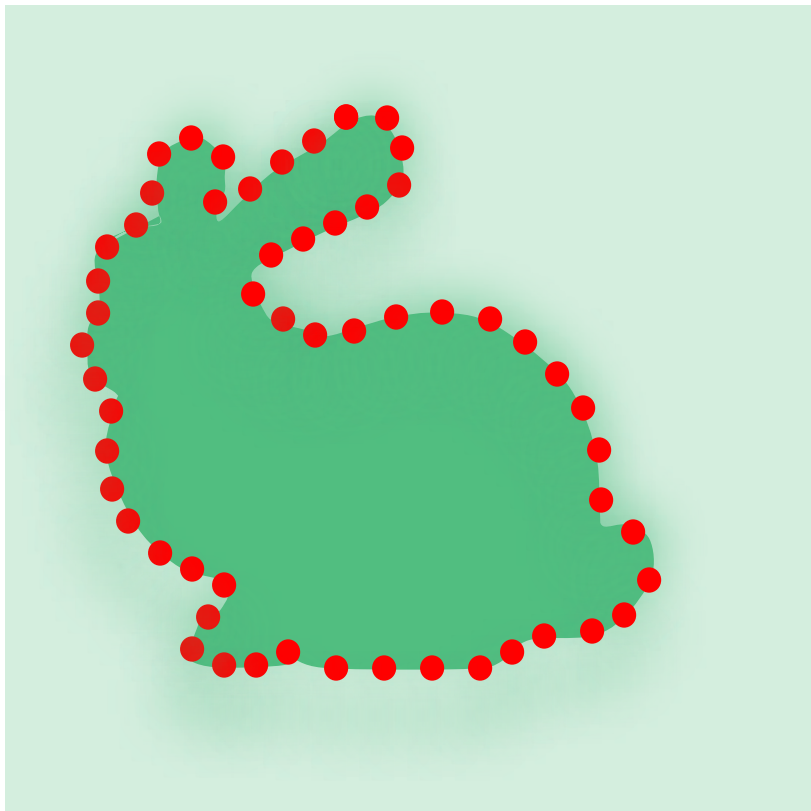
c

Decoder

Query point x

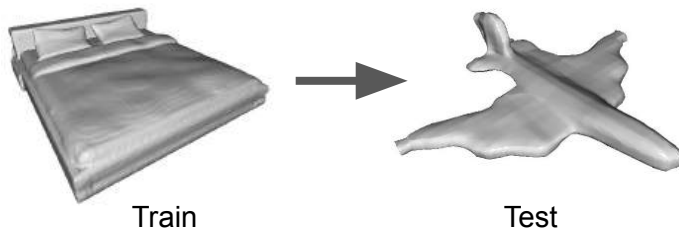
Occupancy o

Learning-based global reconstruction

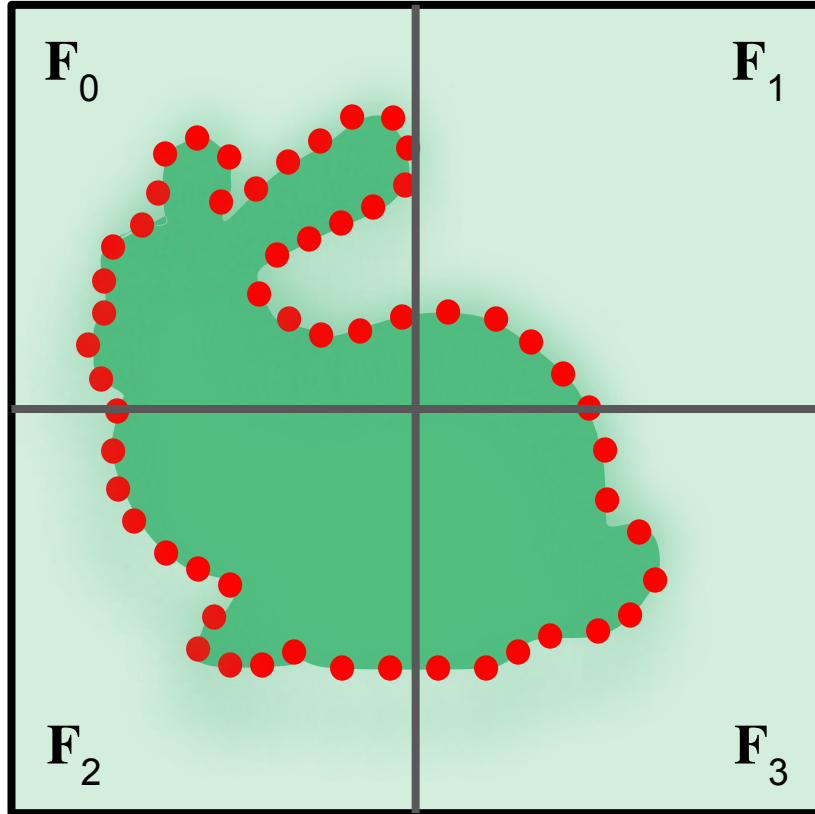


- Problem:

- Encoding entire \mathcal{P} does not scale to large point clouds
- NN specializes to shapes categories of training set



Local reconstruction

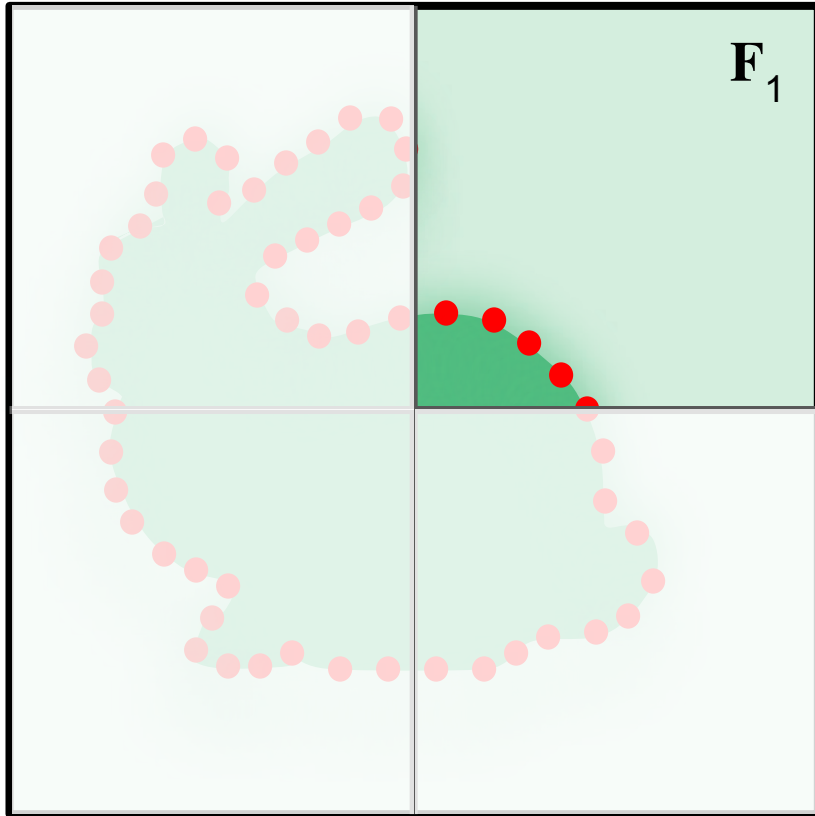


- Surface is defined as level set of multiple scalar valued functions

$$F_i : \mathbb{R}^3 \mapsto \mathbb{R} :$$

$$\mathcal{S} = \{\mathbf{x} \in \mathbb{R}^3 \mid F_i(\mathbf{x}) = c\} \forall i$$

Local reconstruction

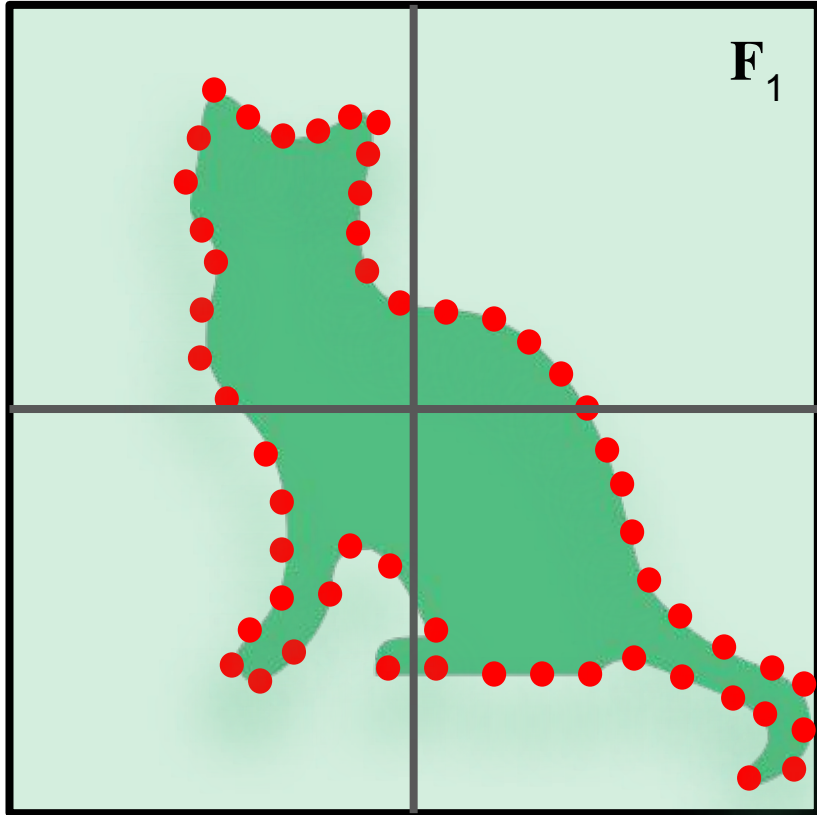


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$$F_i : \mathbb{R}^3 \mapsto \mathbb{R} :$$

$$\mathcal{S} = \{\mathbf{x} \in \mathbb{R}^3 \mid F_i(\mathbf{x}) = c\} \forall i$$

Local reconstruction



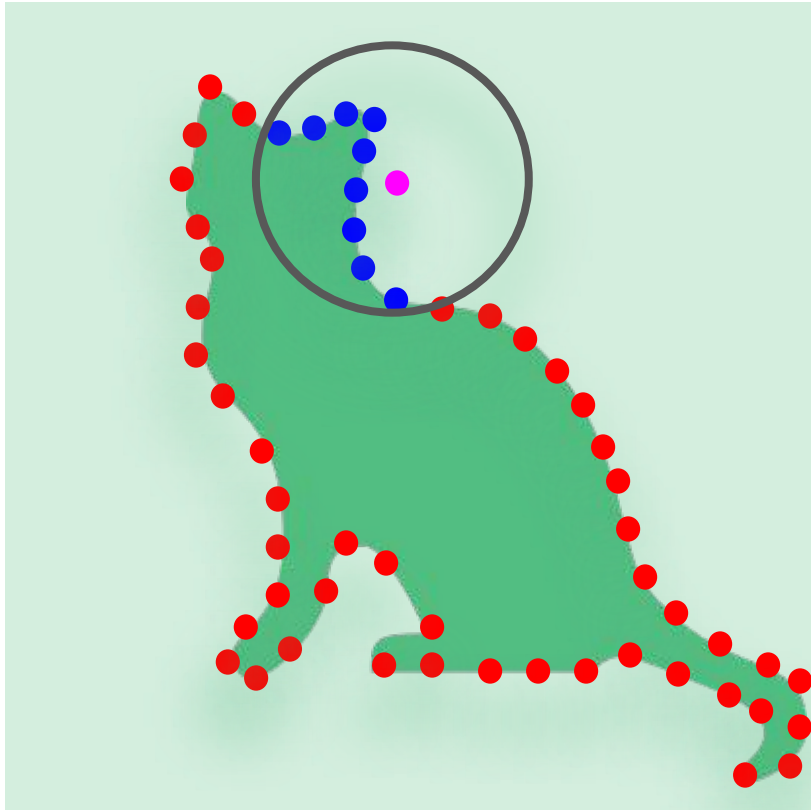
- Surface is defined as level set of multiple scalar valued functions

$$F_i : \mathbb{R}^3 \mapsto \mathbb{R} :$$

$$\mathcal{S} = \{\mathbf{x} \in \mathbb{R}^3 \mid F_i(\mathbf{x}) = c\} \forall i$$

- Example: LIG [Jiang *et al.* 2020]
- Problem:
 - Boundary effects
 - Need to process almost empty subspaces

Learning with local receptive field



- Encode local neighborhood around each point of \mathcal{P}
- Interpolate **query point** features in **latent space**
- Example: POCO [Boulch & Marlet 2022]
- Problem:
 - Expensive decoding
 - No global view

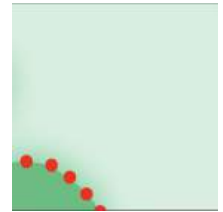
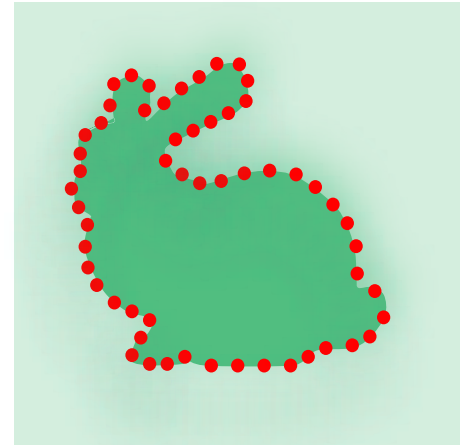
Global- vs. local learning

Global

- + allows for learning shape semantic
- memory intensive

Local

- + better memory and compute control
- + better generalization
- does not allow for learning shape semantic



Global- vs. local learning

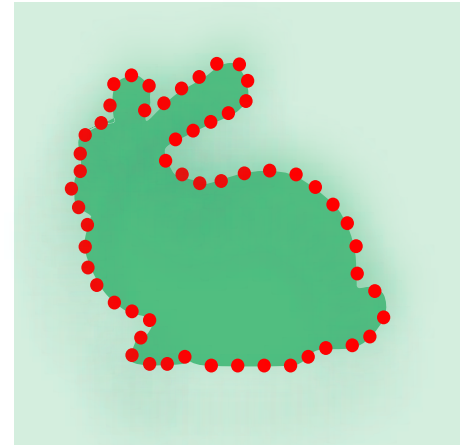
Global

- + allows for learning shape semantic
- memory intensive

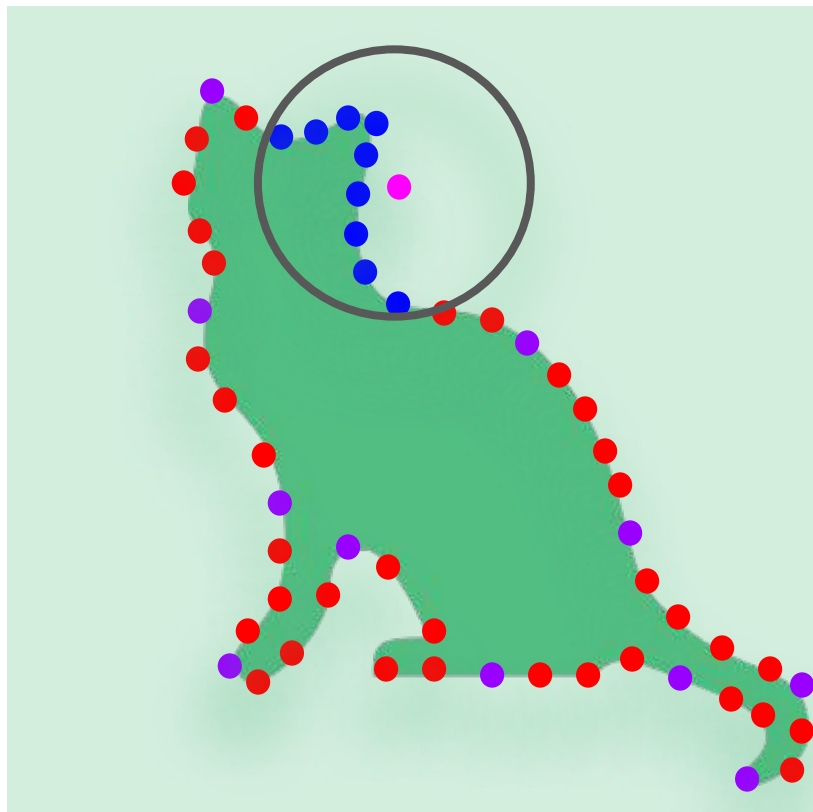
Local

- + better memory and compute control
- + better generalization

→ Important for reconstructing point clouds in the wild

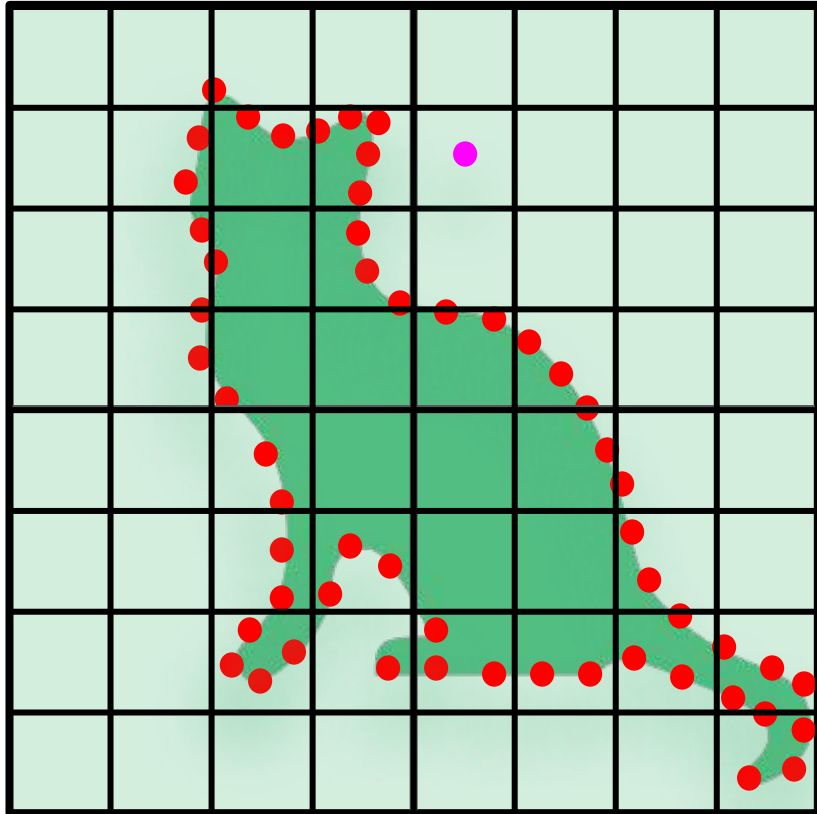


Learning with local and global receptive field



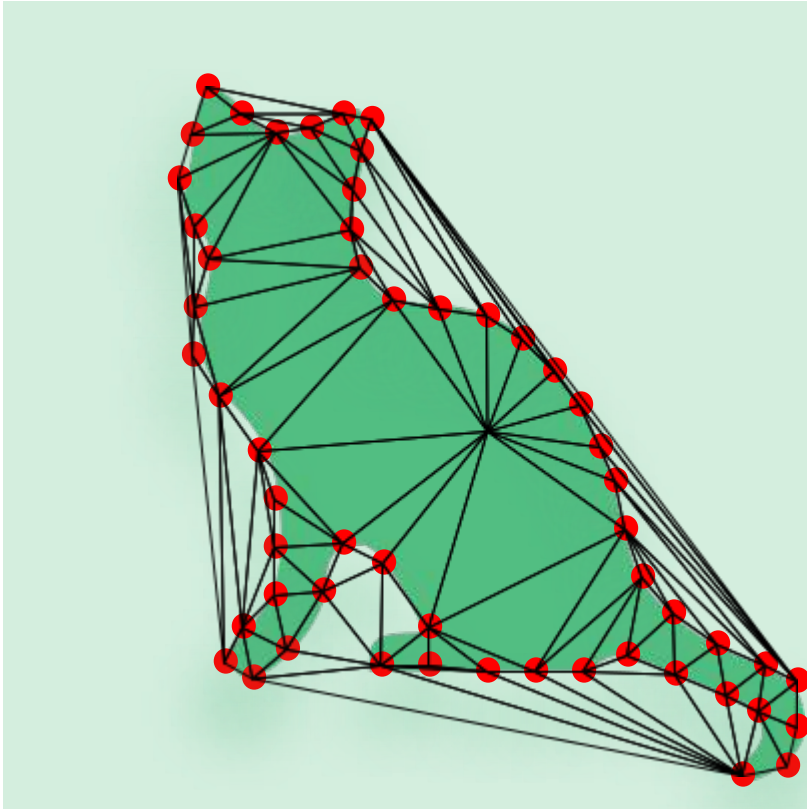
- Encode local neighborhood of **query point**
- Encode **global subsample** of \mathcal{P}
- Example: Points2Surf [Erler *et al.* 2020]
- Problem:
 - Expensive encoding
 - Expensive decoding

Convolutional - Regular Grid



- Aggregate local point features in grid cells
- Use CNN architecture to process features
- Interpolate **query point** features from grid nodes
- Example: ConvONet [Peng *et al.* 2020]
- Problem:
 - Choice of input grid size

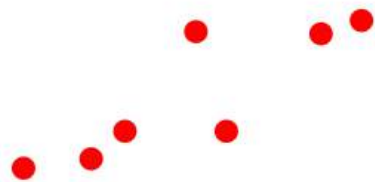
Convolutional - Adaptive Grid



- Triangulate \mathcal{P} using a 3DT
- Encode local neighborhood in the form of subgraphs
- Classify cells as empty or full
- Extract surface as interface
- Problem:
 - Interpolating approach
→ Hard to filter noise

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

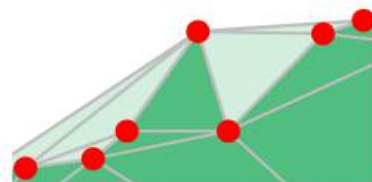
Delaunay based **Surface Reconstruction** using empty / full classification and explicit visibility modeling



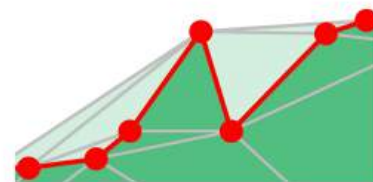
1. Input point set



2. Delaunay triangulation



3. Empty / full classification



4. Surface as interface

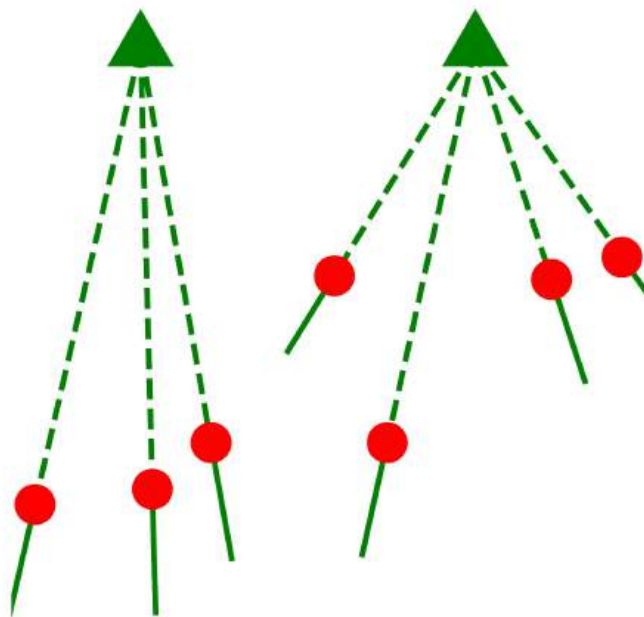
Previous work:

- Labatut *et al.* 2009
- Vu *et al.* 2011
- Jancosek *et al.* 2014

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Input

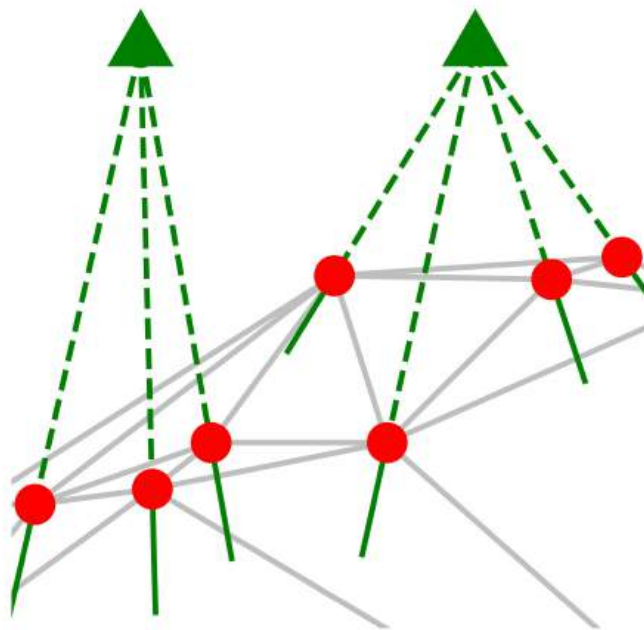
Input **Point Cloud** with **Visibility Information**



Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

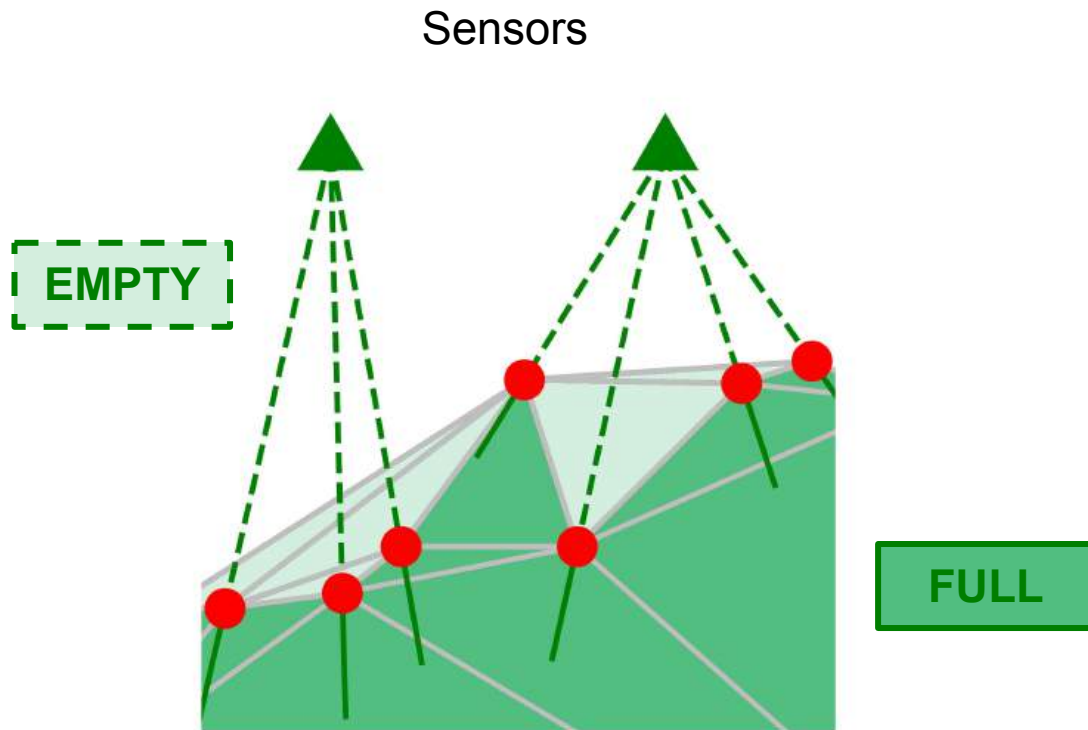
Tessellated point set with visibility information

Sensors



Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Empty / full classification of Delaunay tetrahedra



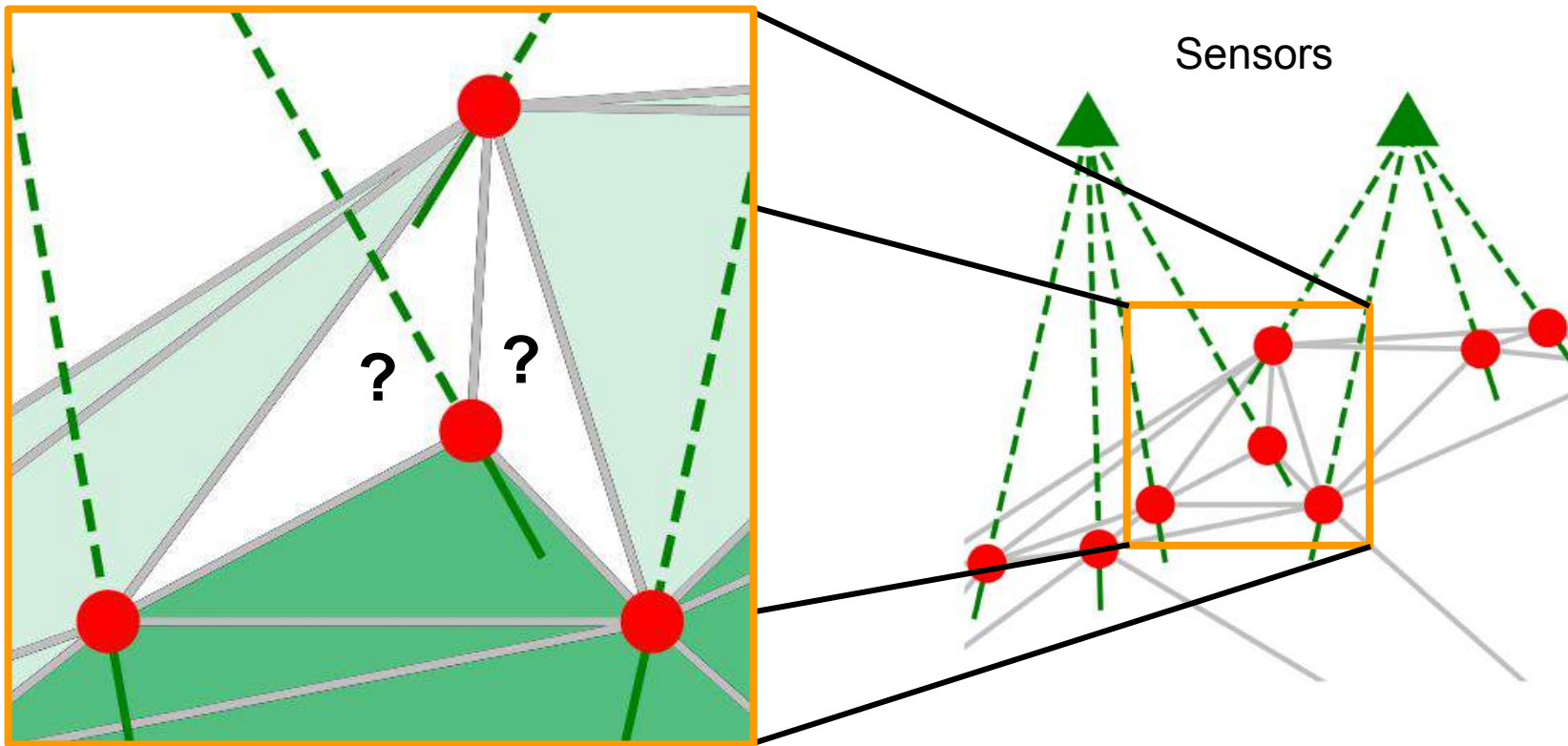
Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Point cloud acquisition with noise



Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

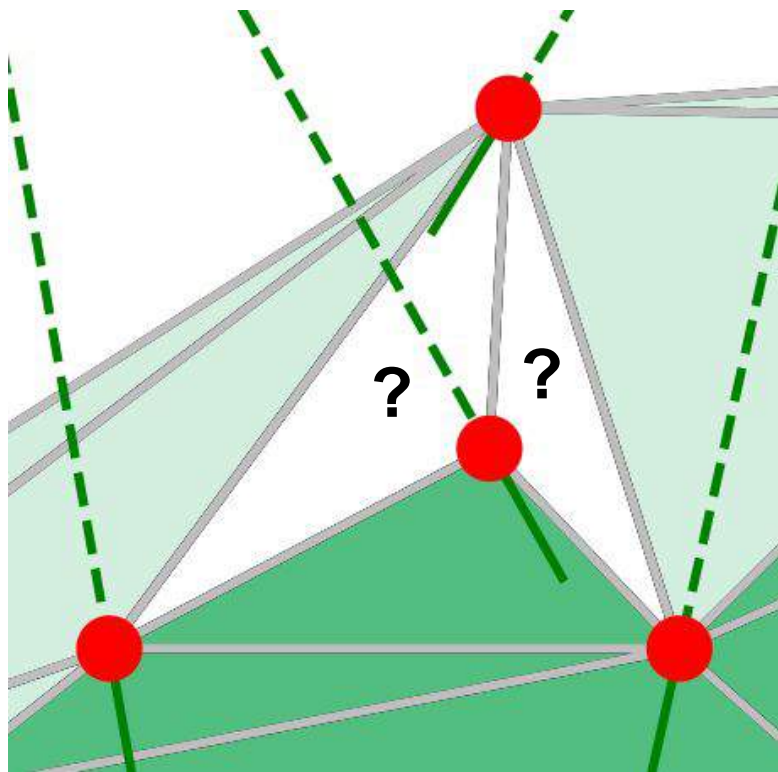
Point cloud acquisition with noise



Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Energy formulation for tetrahedron labelling

Labatut *et al* 2009



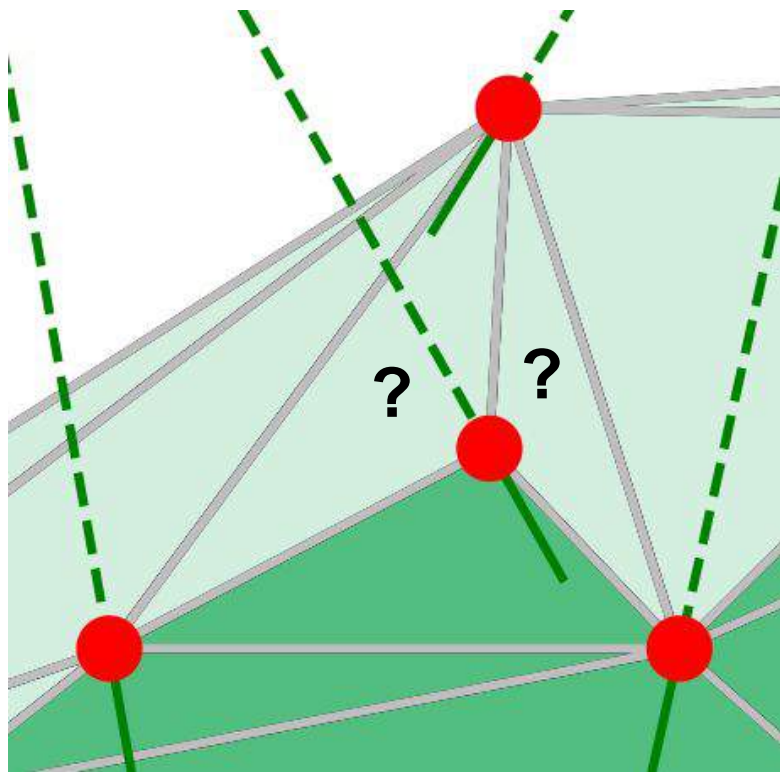
$$E(S) = \underbrace{E_{\text{vis}}(S, \mathbf{P}, \mathbf{v})}_{\text{Data term}} + \lambda E_{\text{smooth}}(S)$$

Data term assigning **empty** or **full** likelihood to each tetrahedron depending on local visibility

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Energy formulation for tetrahedron labelling

Labatut *et al* 2009



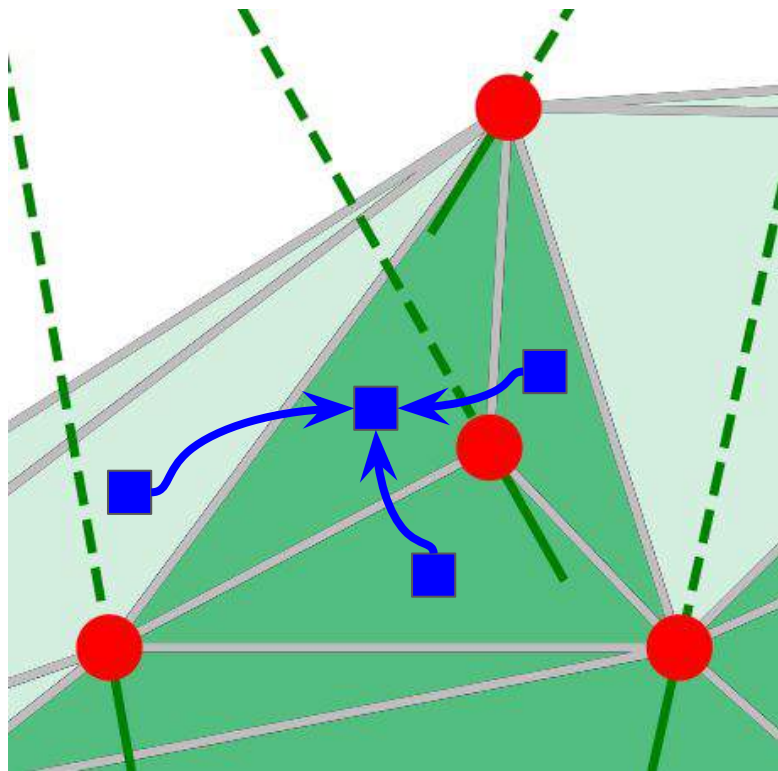
$$E(S) = E_{\text{vis}}(S, \mathbf{P}, \mathbf{v}) + \lambda E_{\text{smooth}}(S)$$



Favour a smooth surface.

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Energy formulation for tetrahedron labelling with learned likelihood



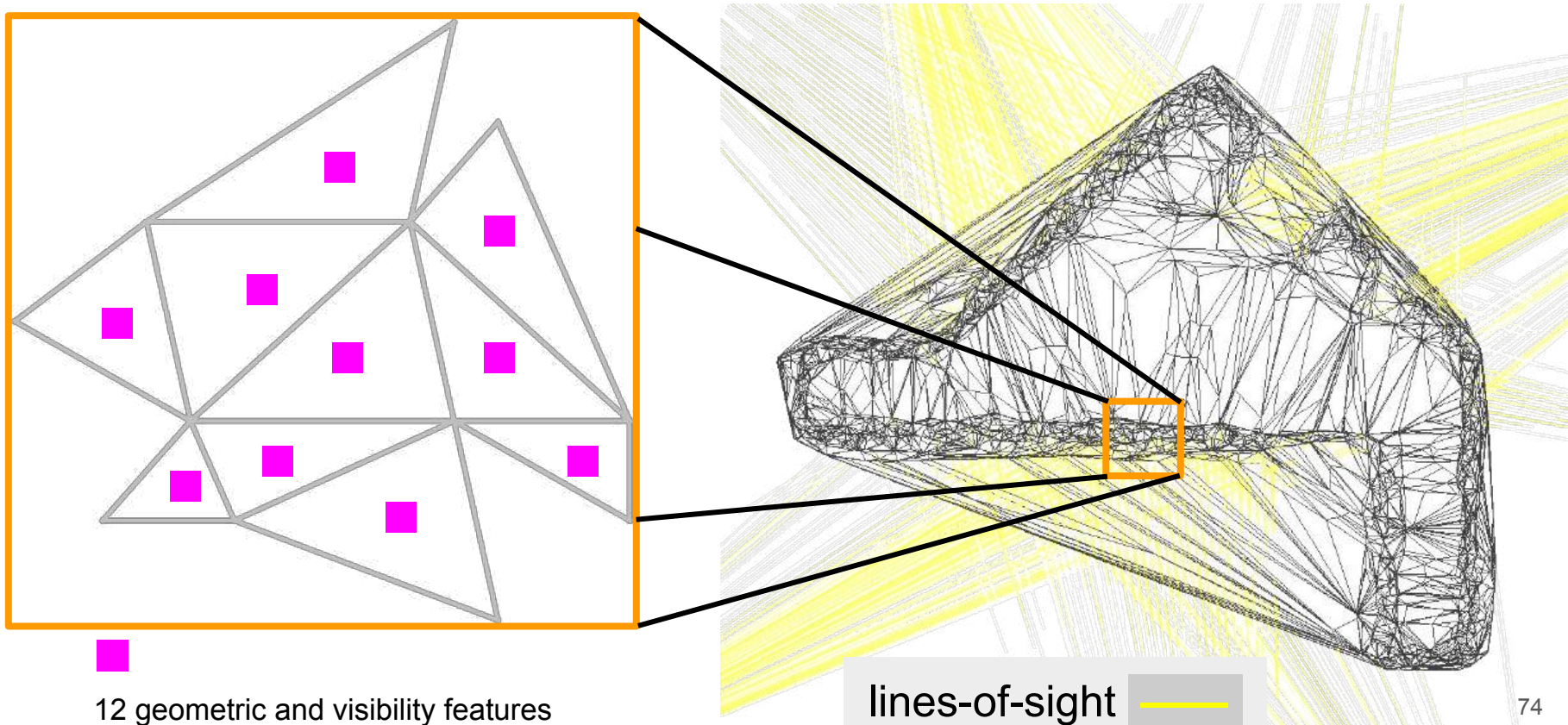
Labatut et al 2009

$$E(S) = \underbrace{E_{\text{vis}}(S, \mathbf{P}, \mathbf{v})}_{\text{learned}} + \lambda E_{\text{smooth}}(S)$$

- Apply **graph convolutions** on dual graph of Delaunay triangulation
 - Aggregate **geometric** and **visibility information** from local neighborhood
 - Infer **empty** / **full** likelihood

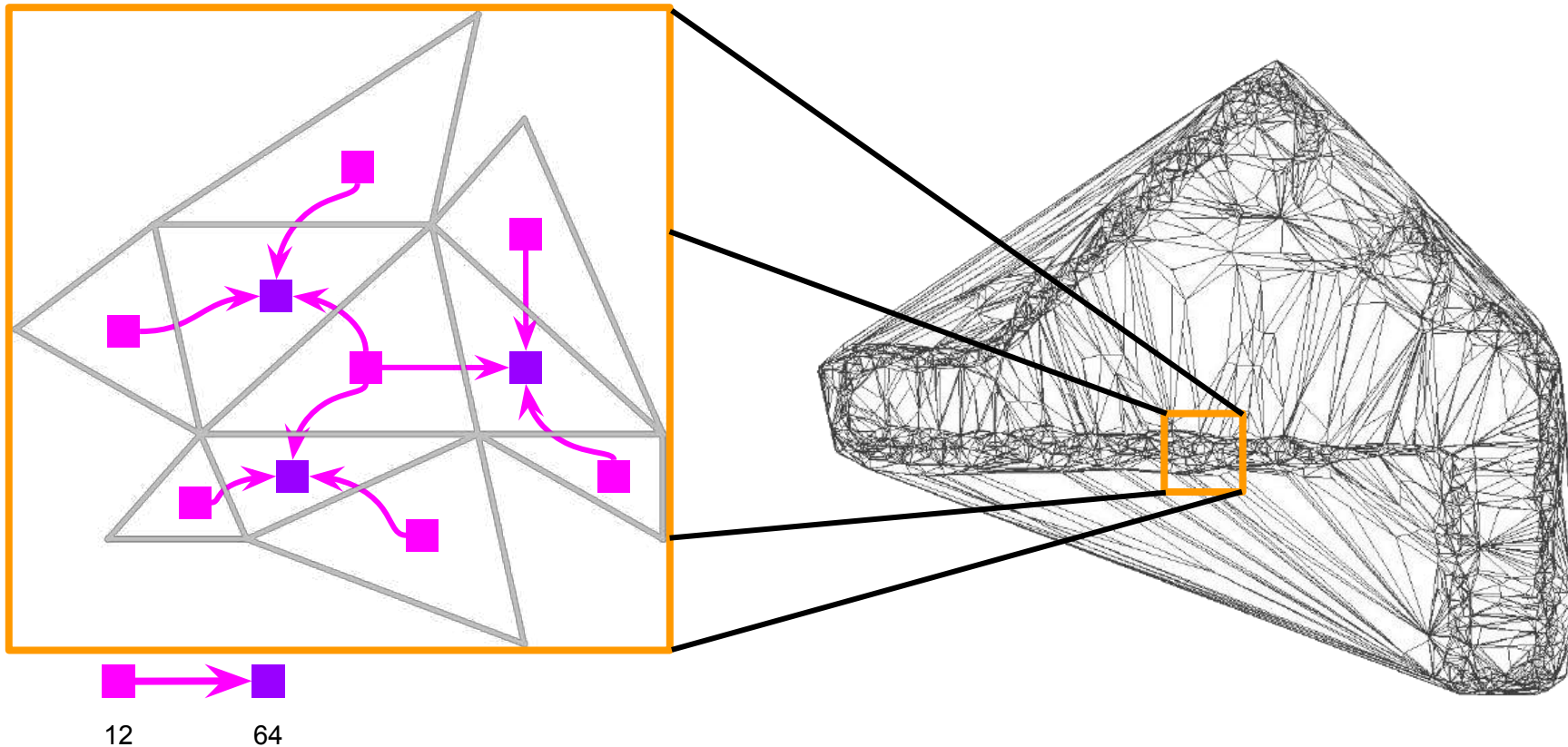
Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Graph Neural Network operating on dual graph of Delaunay triangulation



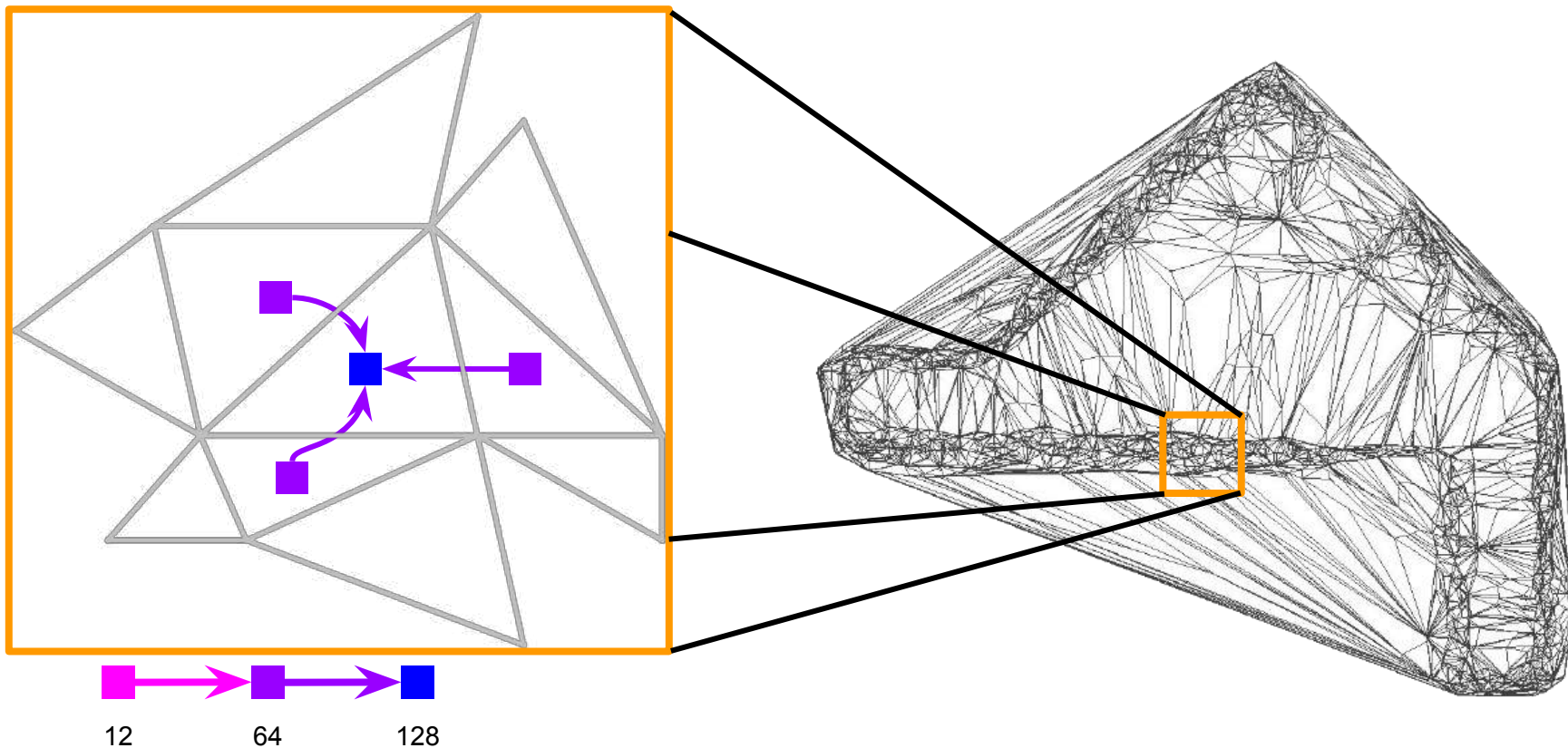
Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Graph Neural Network operating on dual graph of Delaunay triangulation



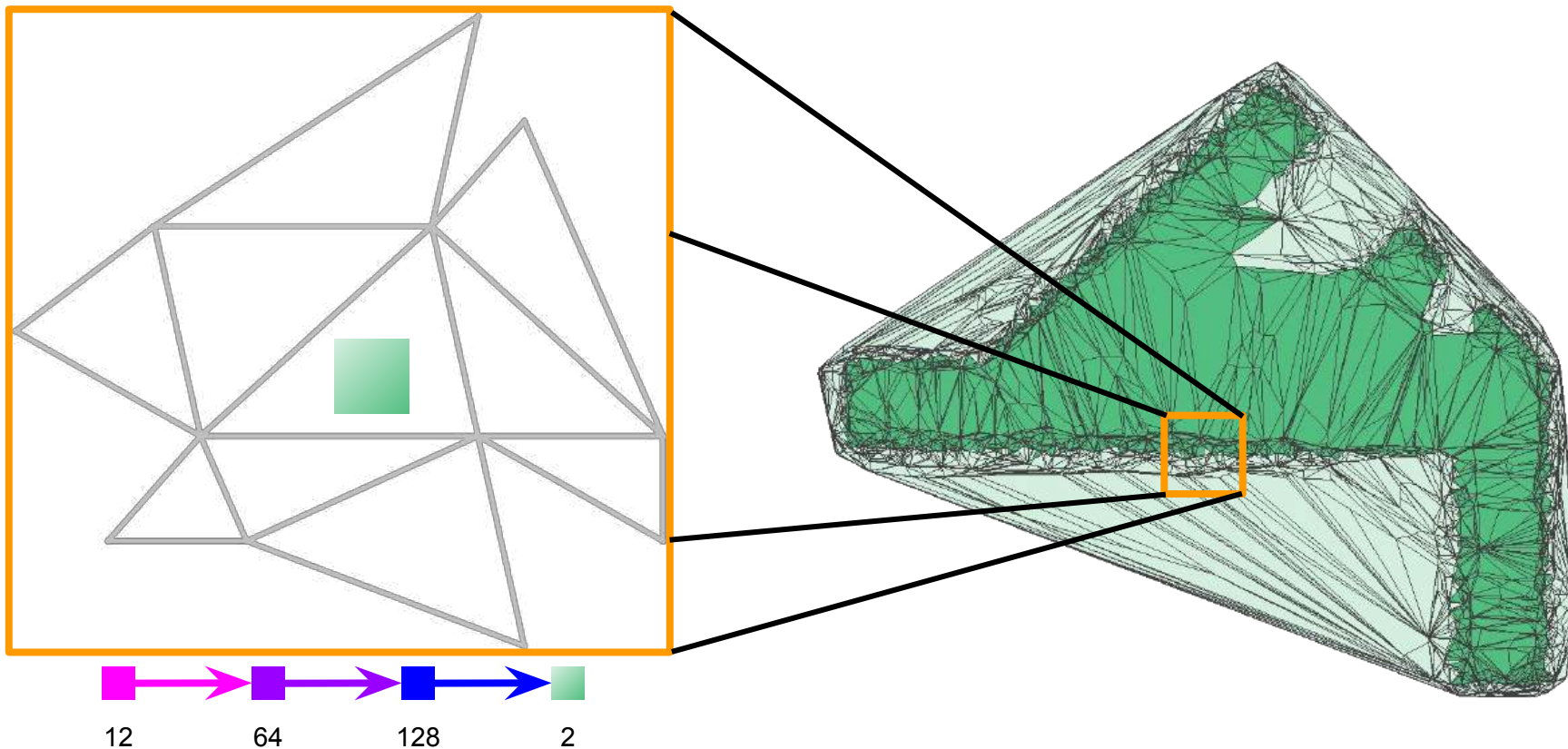
Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Graph Neural Network operating on dual graph of Delaunay triangulation



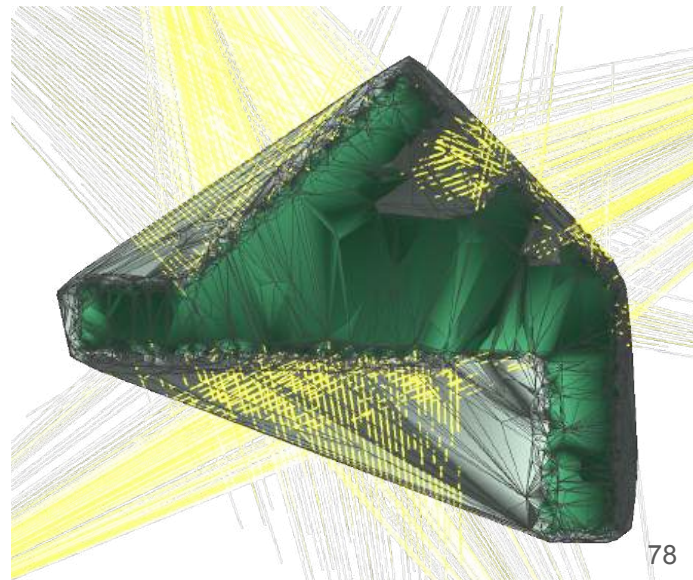
Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Graph Neural Network operating on dual graph of Delaunay triangulation



Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

- Delaunay-Graph Neural Network
 - Adaptive to local point density
 - Fast neighborhood search
- Local prediction
 - High memory and compute control
 - Good generalization
- Global regularization
 - Provides additional robustness



Scalable Surface Reconstruction with Delaunay-Graph Neural Networks



Ground truth

Test on 5 different defects:



Low resolution (LR)

High resolution (HR)

HR + noise (HRN)

HR + outliers (HRO)

HR + noise + outliers

→ Train on 130 shapes from ShapeNet with all of the above defects

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

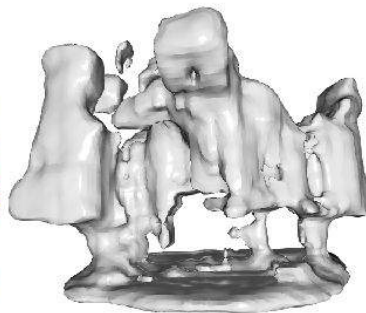


Ground truth

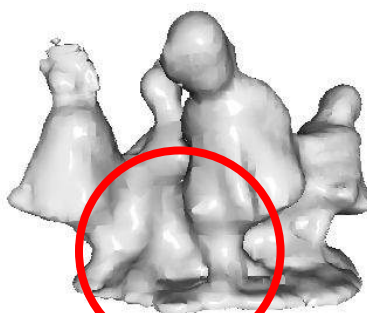
Low resolution:



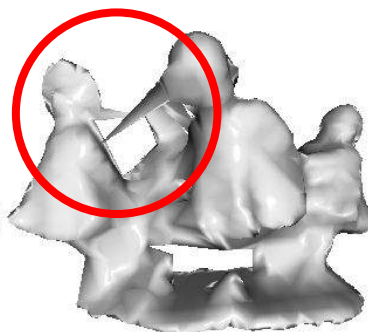
Low resolution (LR)



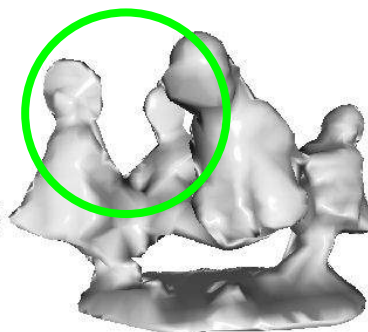
ConvONet
(learning)



SPSR
(traditional)



Labatut *et al.*
(traditional)



DGNN
(ours)

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

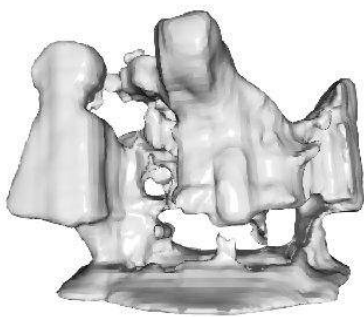


Ground truth

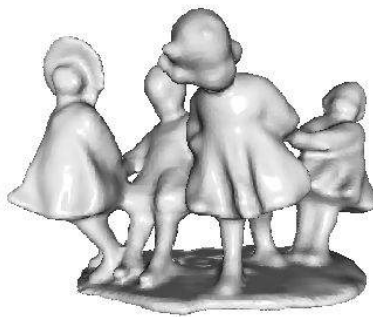
High resolution:



High resolution (LR)



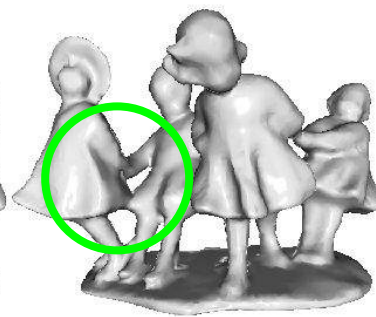
ConvONet
(learning)



SPSR
(traditional)



Labatut *et al.*
(traditional)



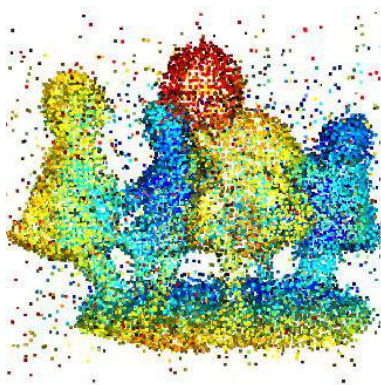
DGNN
(ours)

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

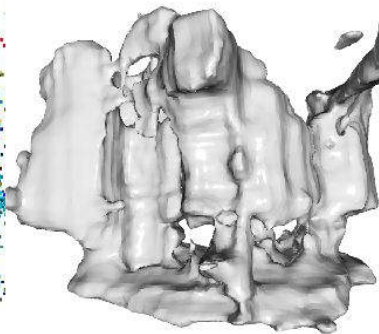


Ground truth

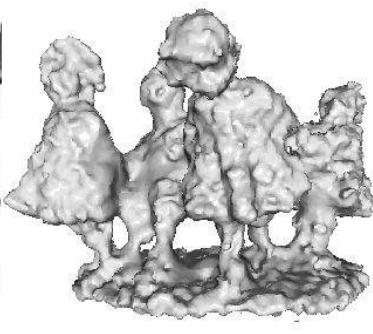
High resolution with noise and outliers:



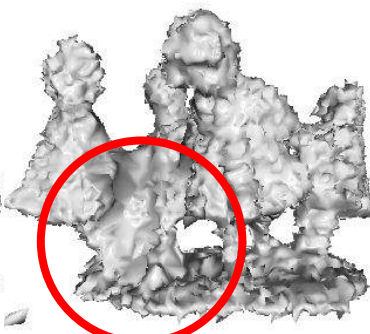
HR + noise + outliers



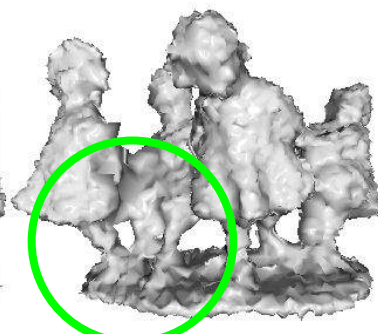
ConvONet
(learning)



SPSR
(traditional)



Labatut *et al.*
(traditional)



DGNN
(ours)

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Results on ETH3D dataset with 1.1 M points



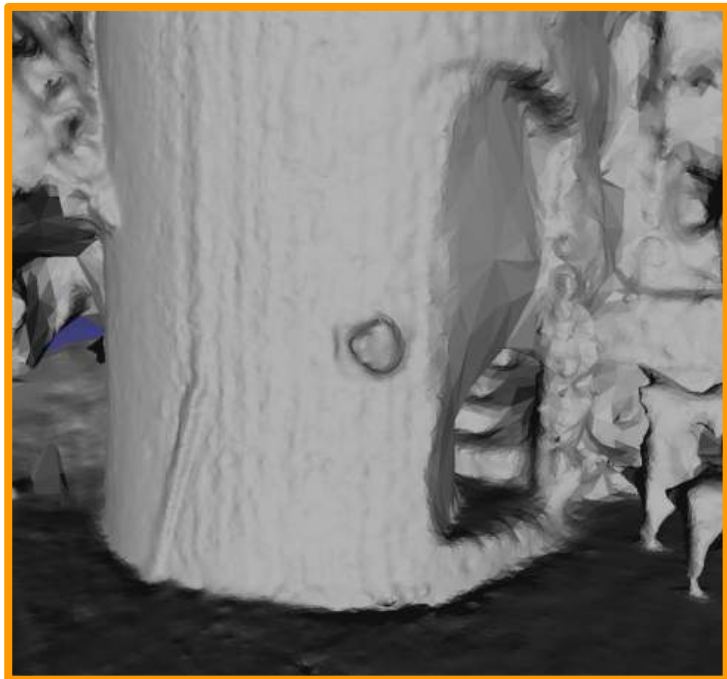
Point cloud



Our reconstruction textured

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Results on ETH3D dataset with 1.1 M points



Our reconstruction



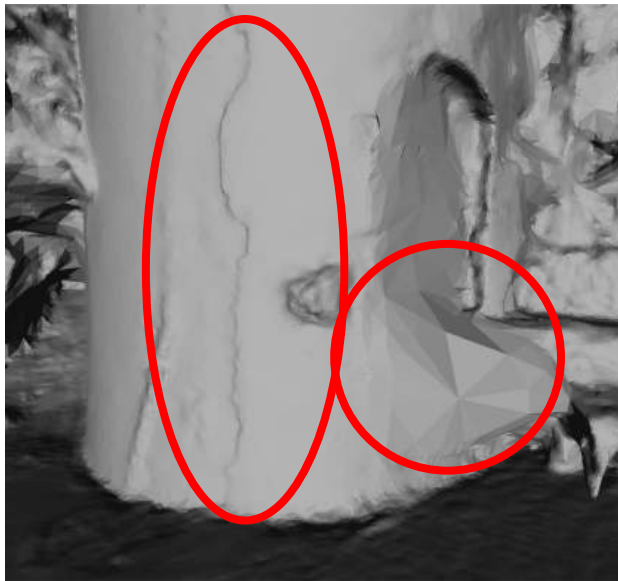
Our reconstruction textured

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

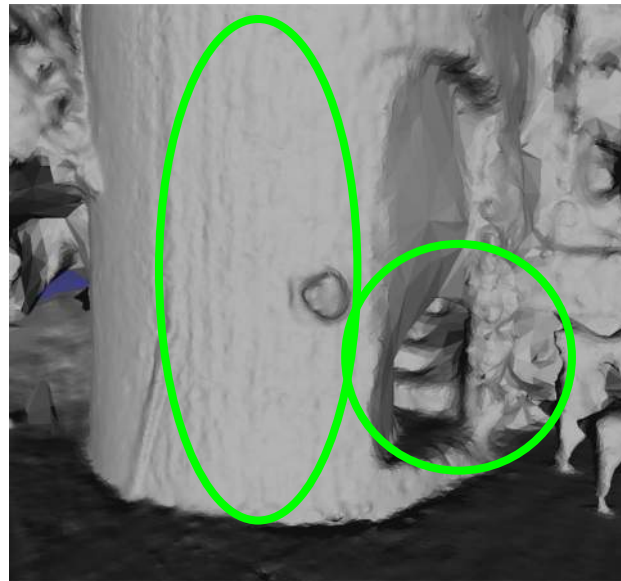
Results on ETH3D dataset with 1.1 M points



Image



Jancosek *et al.* (traditional)



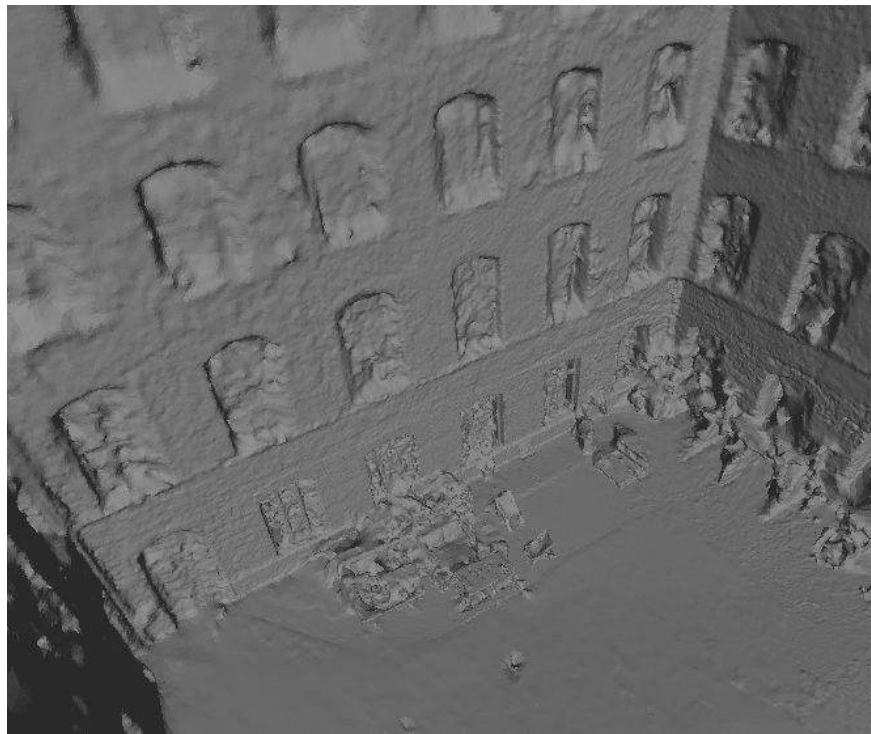
DGNN (ours)

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Results on **ETH3D dataset** with 2.5 M points



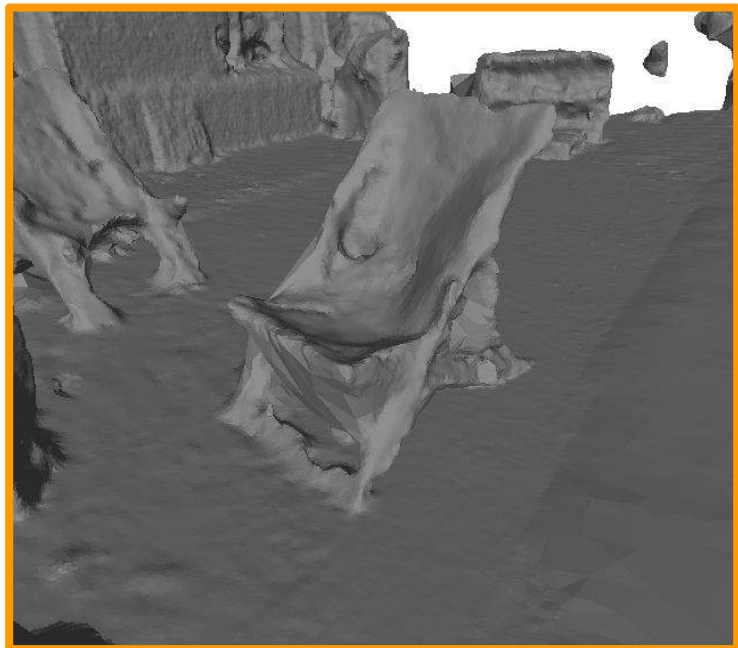
Point cloud



Our reconstruction

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Results on ETH3D dataset with 2.5 M points



Our reconstruction



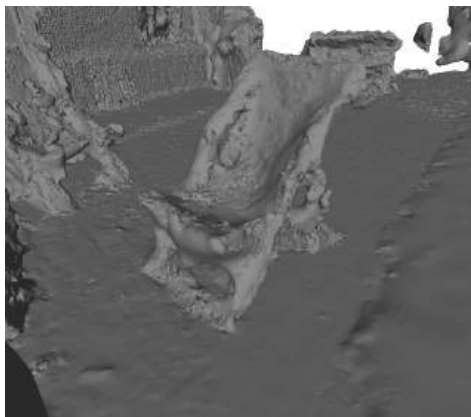
Our reconstruction

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Results on ETH3D dataset with 2.5 M points



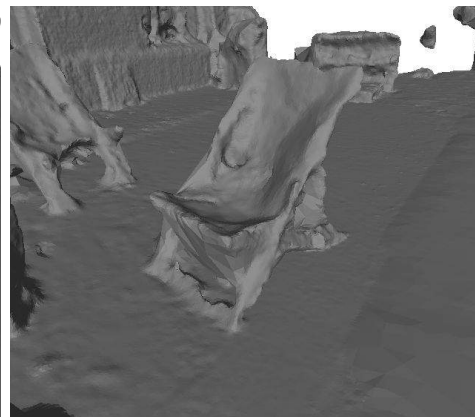
Point cloud



SPSR (traditional)



Vu *et al.* (traditional)



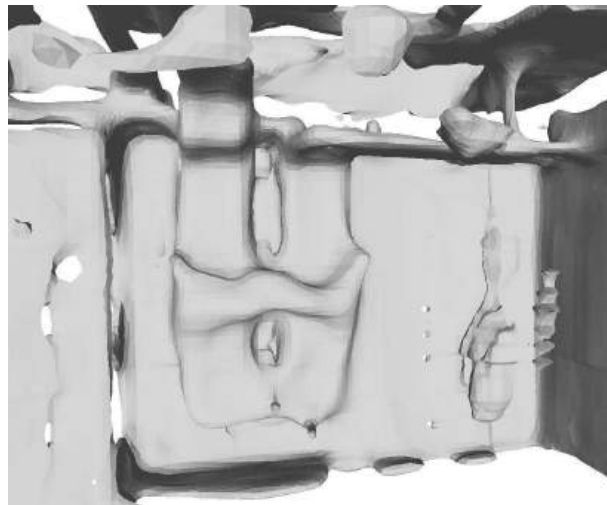
DGNN (ours)

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

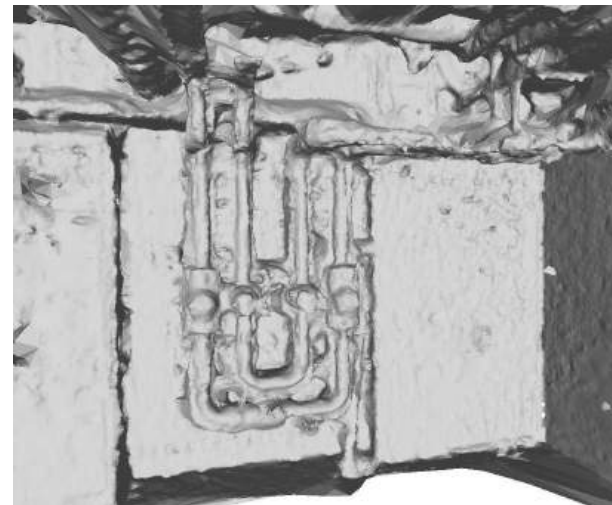
Results on ETH3D dataset with 1 M points



Point cloud

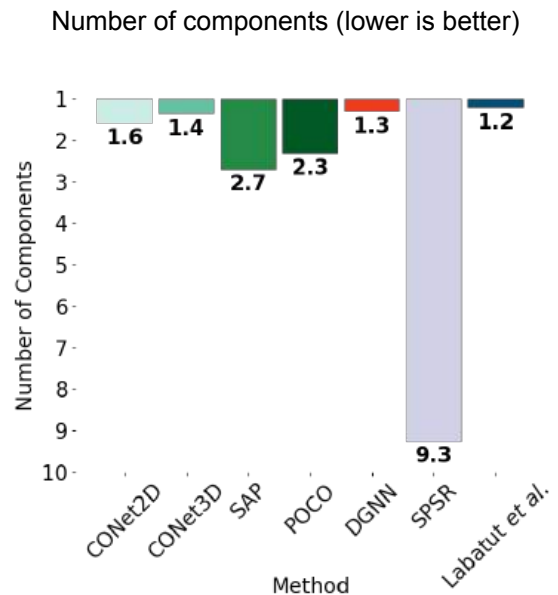
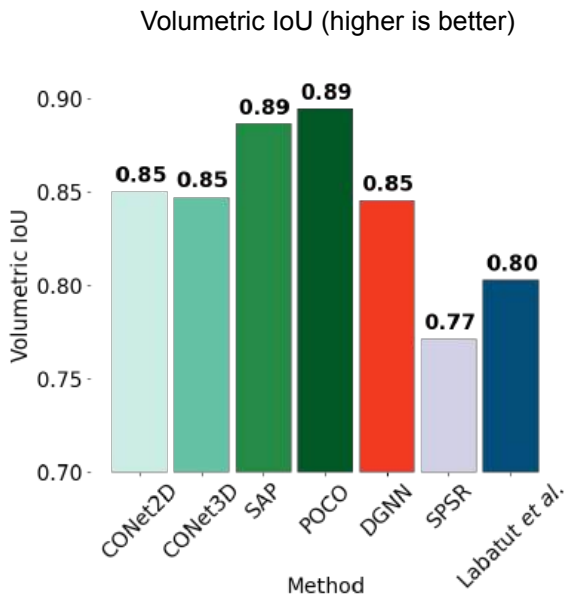
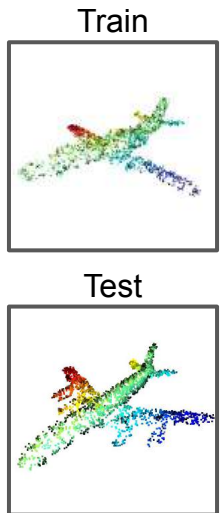


ConvONet (learning)



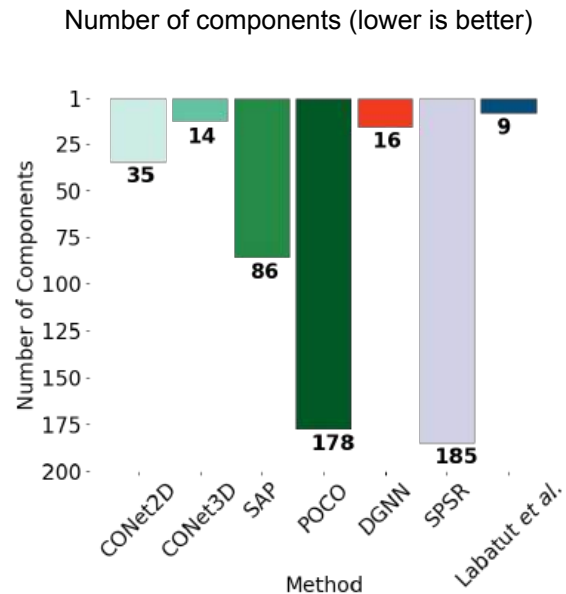
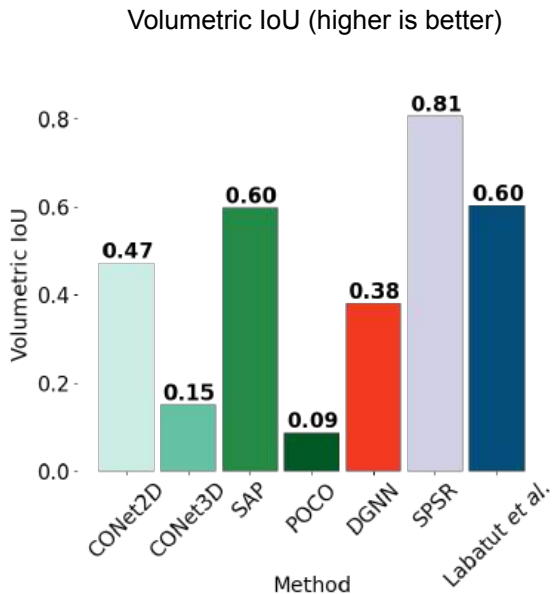
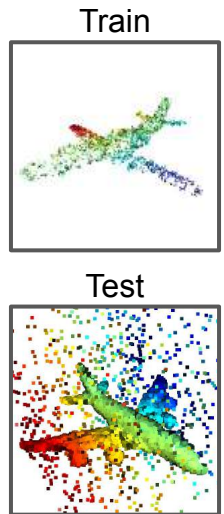
DGNN (ours)

1. Known sampling defects and known shape categories



→ SAP & POCO provide most accurate reconstructions

2. Unknown sampling defects and known shape categories



learning

DGNN

traditional

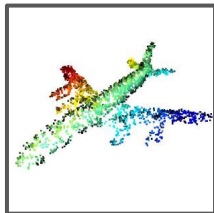
→ Traditional methods provide more accurate reconstructions

3. Known sampling defects and unknown shape categories

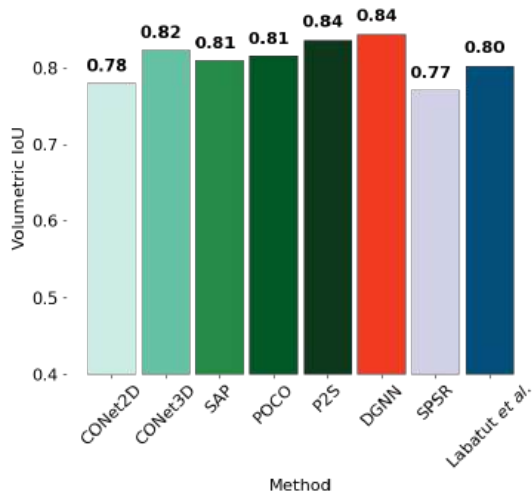
Train



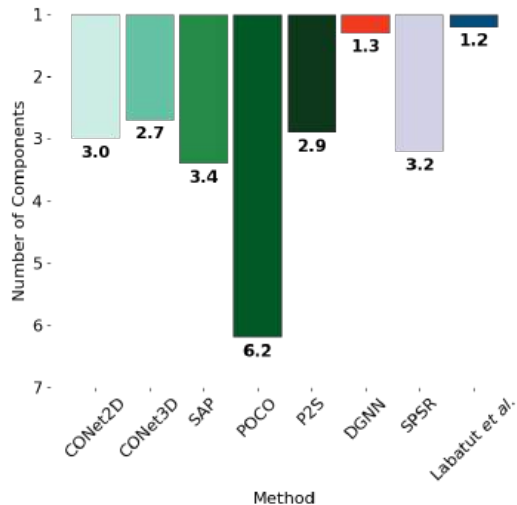
Test



Volumetric IoU (higher is better)



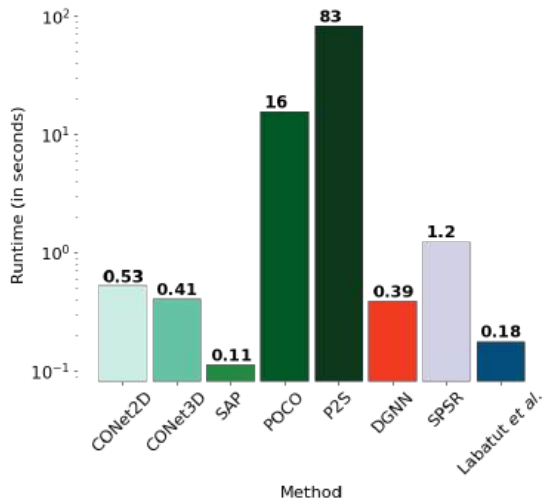
Number of components (lower is better)



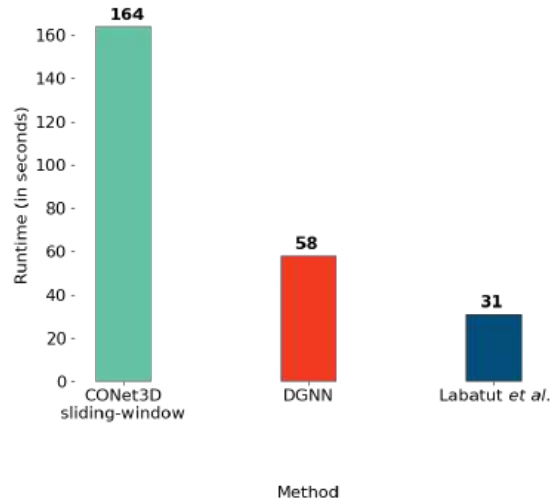
→ DGNN provides most accurate reconstructions

Runtimes (in seconds)

Object with 3,000 points



Scenes with 500k points



- SAP fastest object-level reconstruction
- DGNN fastest scene-level reconstruction

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

Ablation study

Model	volumetric IoU	
	ModelNet (in-distribution)	ShapeNet (out-of-distribution)
Vanilla Model	86.1	84.1
No visibility features	-4.5	-6.4
No graph-cut	+0.1	-0.3

Conclusion


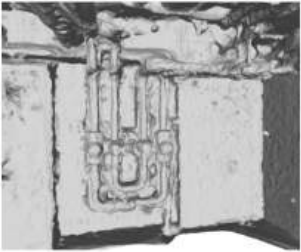
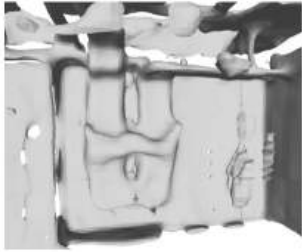
- DGNN combines...
 - an efficient and adaptive data structure (3DT)
 - with a powerful class of learning algorithms (GNN)
- This allows us to scale learning-based surface reconstruction to process real-world point clouds with millions of points

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks

<https://github.com/raphaelsulzer/dgnn>

☰ README.md ✎

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks [SGP 2021]

		
MVS point cloud	Ours	ConvONet [1]

[Paper](#) | [Video](#)

This repository contains the implementation of the paper:

Scalable Surface Reconstruction with Delaunay-Graph Neural Networks
Raphael Sulzer, Loic Landrieu, Renaud Marlet, Bruno Vallet
[SGP 2021](#)

Mesh-tools

<https://github.com/raphaelsulzer/mesh-tools>

☰ README.md ✎

mesh-tools

This repository contains tools for reconstructing, processing and evaluating point clouds and triangular surface meshes. The code is based on several scientific publications and makes heavy use of [CGAL](#).

Common interface for all tools

All tools have a couple of common command line parameters. To get a more complete and detailed list of all possible parameters use the help command.

Command	Description
<code>-h</code>	Display a help message, explaining all command line options of the specific tool.
<code>-w path/to/workingDir</code>	All input and output files are located inside the specified directory.
<code>-i inputFileName</code>	The file name of the input for the tool. The file ending does not have to be specified.
<code>-o outputFileName</code>	The file name of the output file(s). If left empty, the input file name is used.
<code>-e exportOptions</code>	Specify which files and which properties should be exported.

Available tools

`scan`

Contributions

Publications

- A benchmark for learning-based and traditional surface reconstruction algorithms
 - Sulzer, R., Marlet, R., Vallet, B., & Landrieu, L. (2024). A survey and benchmark of automatic surface reconstruction from point clouds. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 47(3), 2000-2019.
- A method to incorporate visibility information into learning-based surface reconstruction algorithms
 - Sulzer, R., Landrieu, L., Boulch, A., Marlet, R., & Vallet, B. (2022). Deep Surface Reconstruction from Point Clouds with Visibility Information. In *International Conference on Pattern Recognition (ICPR)*
- A method for large-scale learning-based surface reconstruction
 - Sulzer, R., Landrieu, L., Marlet, R., & Vallet, B. (2021). Scalable Surface Reconstruction with Delaunay-Graph Neural Networks. *Eurographics Symposium on Geometry Processing (SGP)*.

Datasets

- Scanned versions of 4 different datasets
 - ModelNet10
 - ShapeNet
 - Reconbench
 - Synthetic Rooms

Code

- 4 public Github repositories
 - <https://github.com/raphaelsulzer/dsr-benchmark>
 - <https://github.com/raphaelsulzer/dsrv-data>
 - <https://github.com/raphaelsulzer/dgnn>
 - <https://github.com/raphaelsulzer/mesh-tools>

Thank you

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Github: [@raphaelsulzer](https://github.com/raphaelsulzer)

