


Lecture 7

Surface Reconstruction

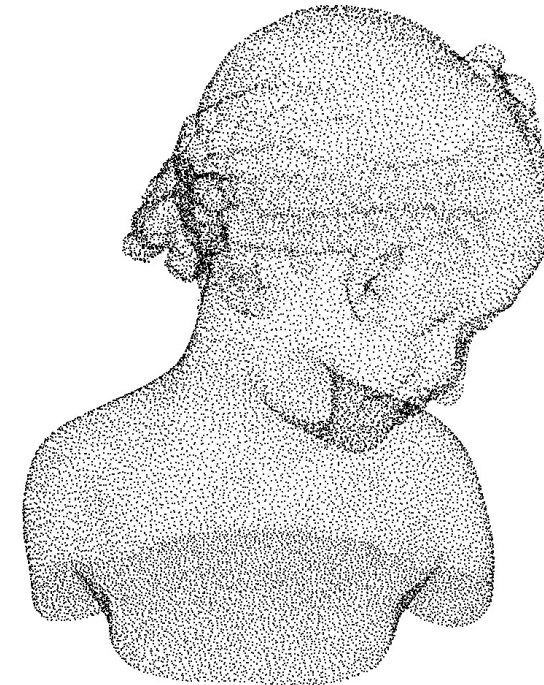
Liangliang Nan

Today's Agenda

- Introduction 
- Smooth object reconstruction
 - The pioneer work of [Hoppe *et al.* \(1992\)](#)
 - Poisson reconstruction [[Kazhdan *et al.* 2006](#)]
 - Piecewise smooth reconstruction
- Piecewise planar object reconstruction [[Nan and Wonka. 2017](#)]

Introduction

- Data sources
 - Laser scanning



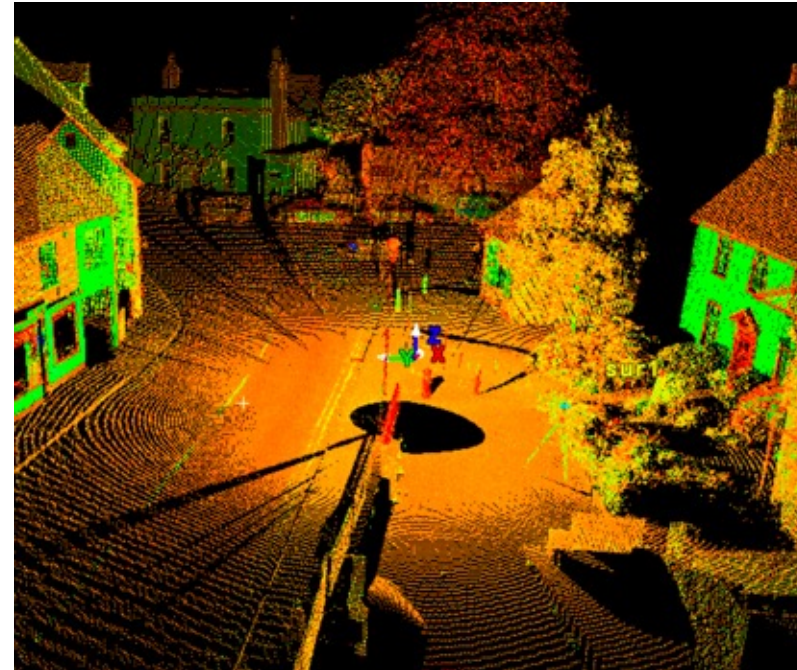
Introduction

- Data sources
 - Laser scanning



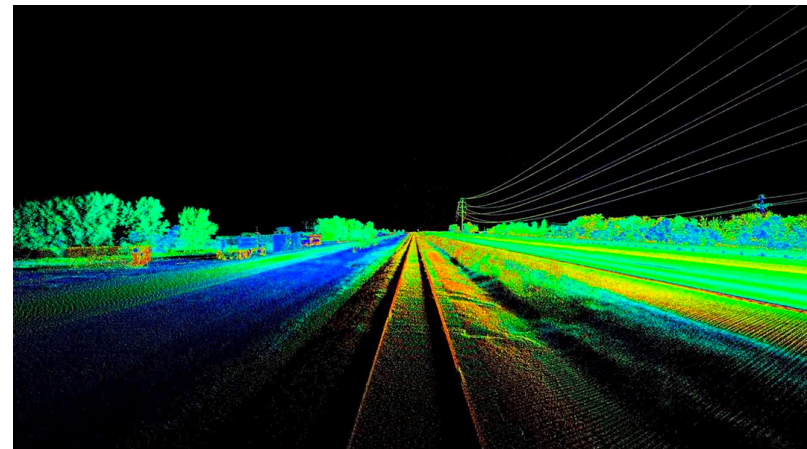
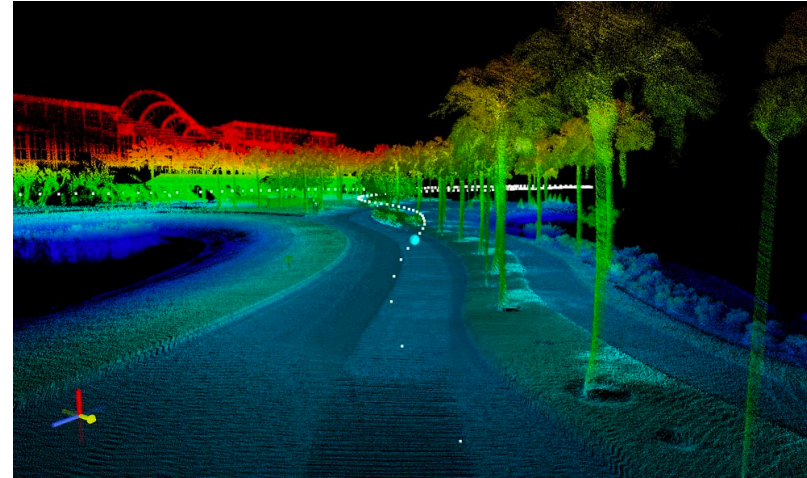
Introduction

- Data sources
 - Laser scanning



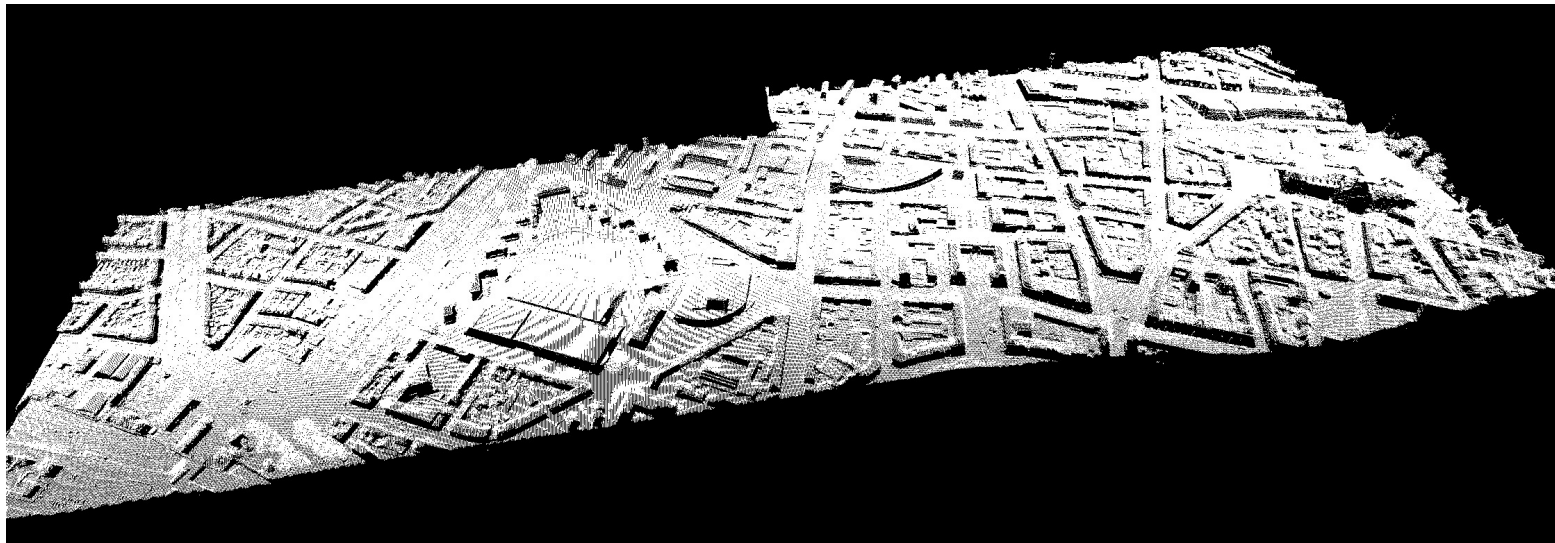
Introduction

- Data sources
 - Laser scanning



Introduction

- Data sources
 - Laser scanning



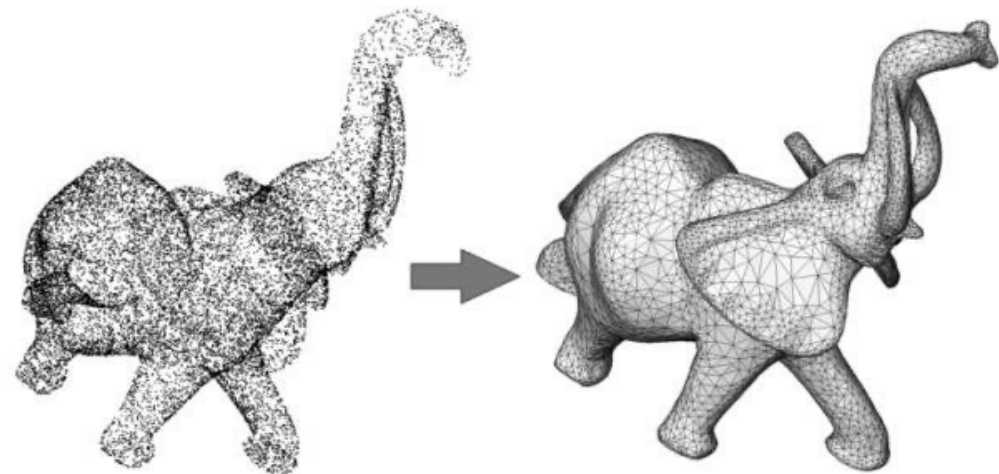
Introduction

- Data sources
 - Laser scanning
 - Structure from Motion (SfM) and Multi-view stereo (MVS)



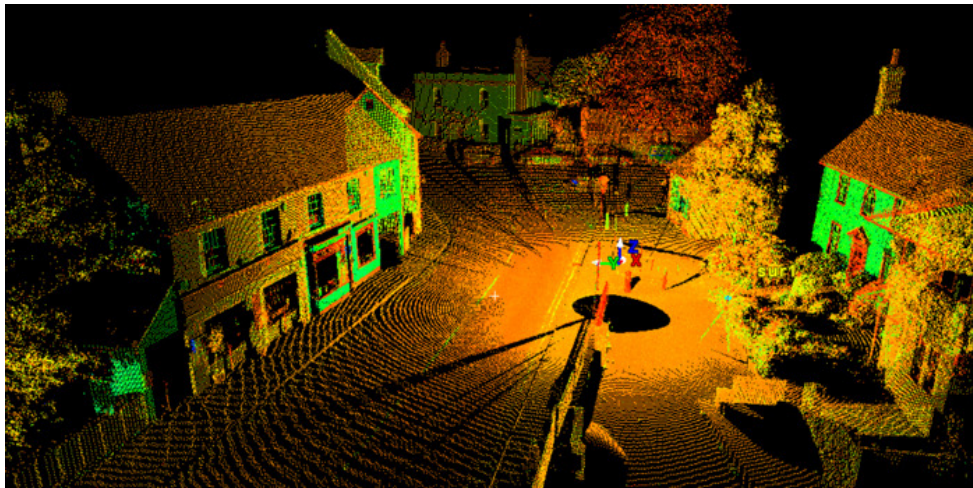
Introduction

- Surface reconstruction
 - Input: point set P sampled over a surface S
 - Non-uniform sampling
 - With holes
 - With uncertainty (noise)
 - Output: surface approximating S in terms of topology and geometry
 - Desired
 - Watertight
 - Intersection free



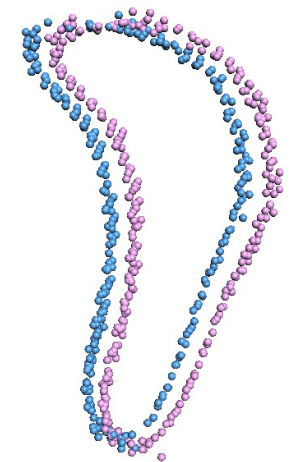
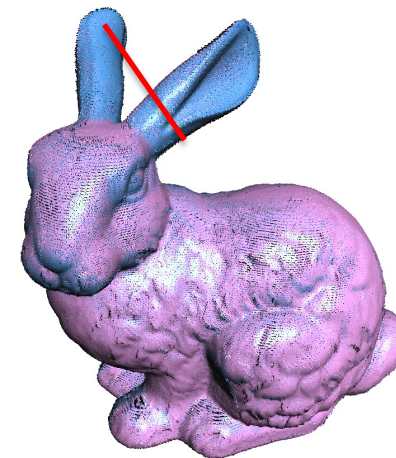
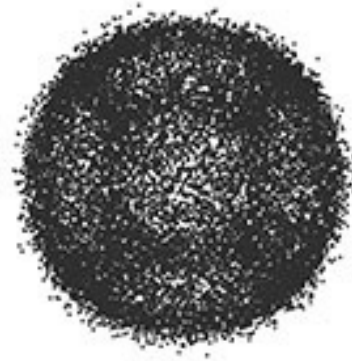
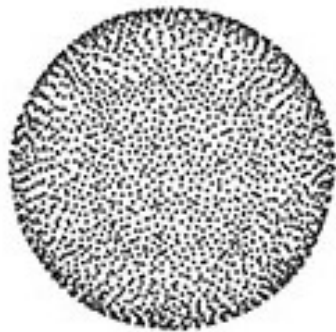
Introduction

- Challenges
 - The point samples may not be uniformly distributed
 - Oblique scanning angles
 - Laser energy attenuation



Introduction

- Challenges
 - The point samples may not be uniformly distributed
 - The positions and normals are generally noisy
 - Sampling inaccuracy
 - Scan misregistration



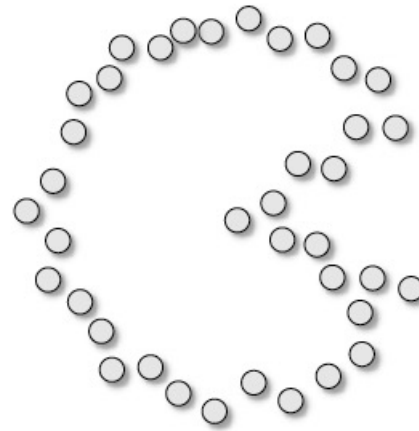
Introduction

- Challenges
 - The point samples may not be uniformly distributed
 - The positions and normals are generally noisy
 - Missing data
 - Material properties, inaccessibility, occlusion, etc.



Introduction

- Challenges
 - The point samples may not be uniformly distributed
 - The positions and normals are generally noisy
 - Missing data
 - Ill-posed problem

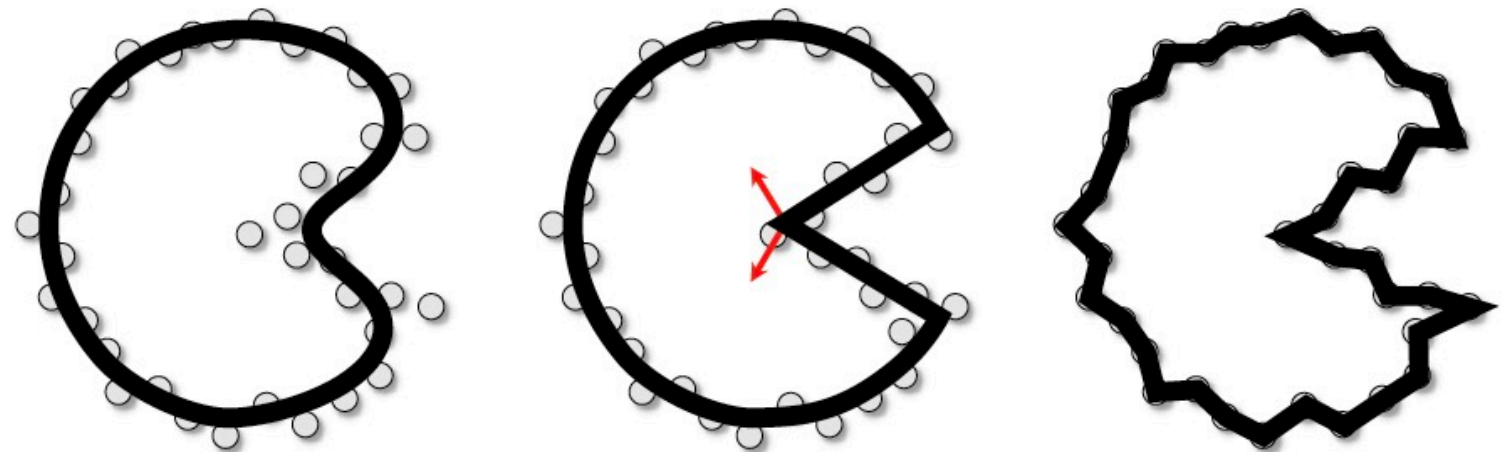


Many candidate surfaces for the reconstruction problem!

Introduction

- Challenges
 - The point samples may not be uniformly distributed
 - The positions and normals are generally noisy
 - Missing data
 - Ill-posed problem

How to pick?

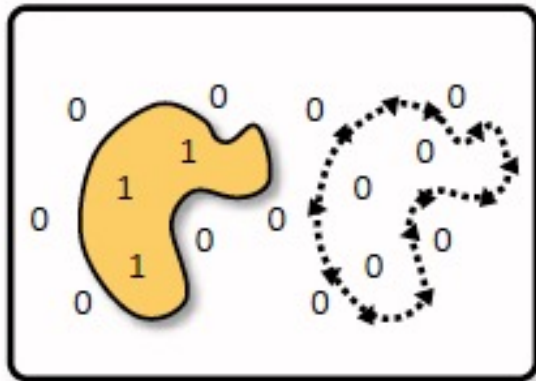


Many candidate surfaces for the reconstruction problem!

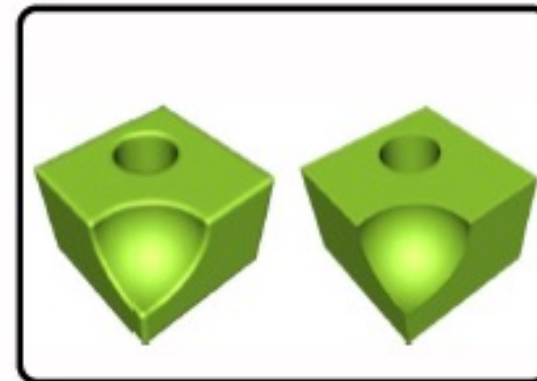
General Ideas

- Surface Smoothness Priors

Global Smoothness



Piecewise Smoothness

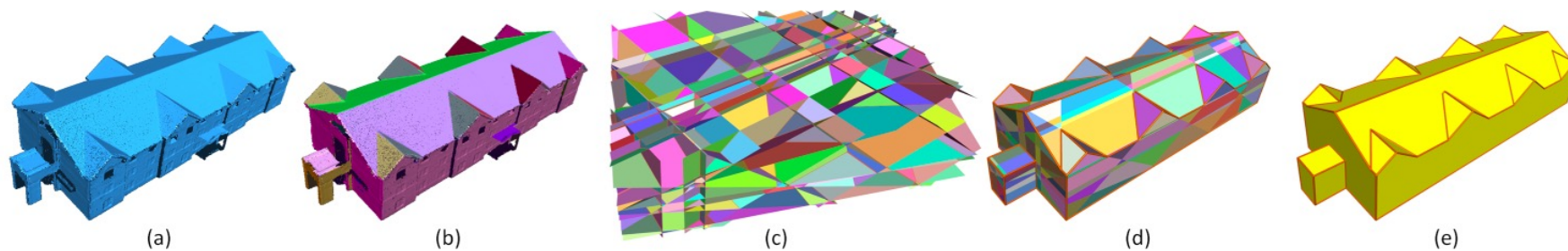


General Ideas

- Domain-Specific Priors



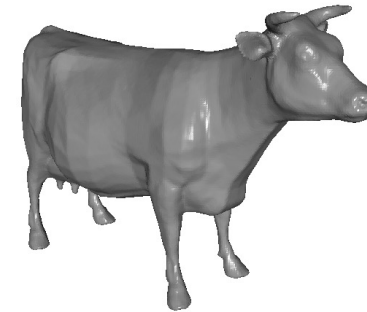
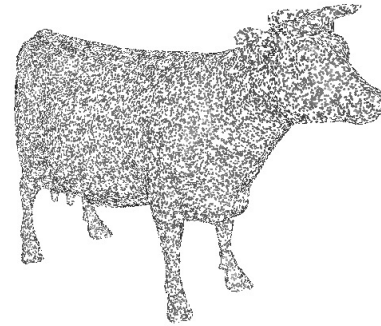
[Verdie et al, 2015]



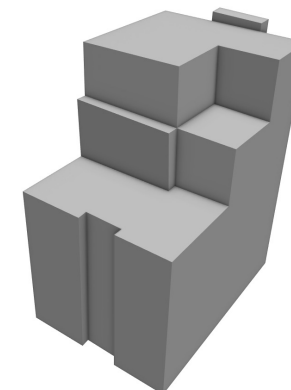
[Nan and Wonka 2017]

Introduction

- Smooth surface reconstruction



- Piecewise-planar object reconstruction



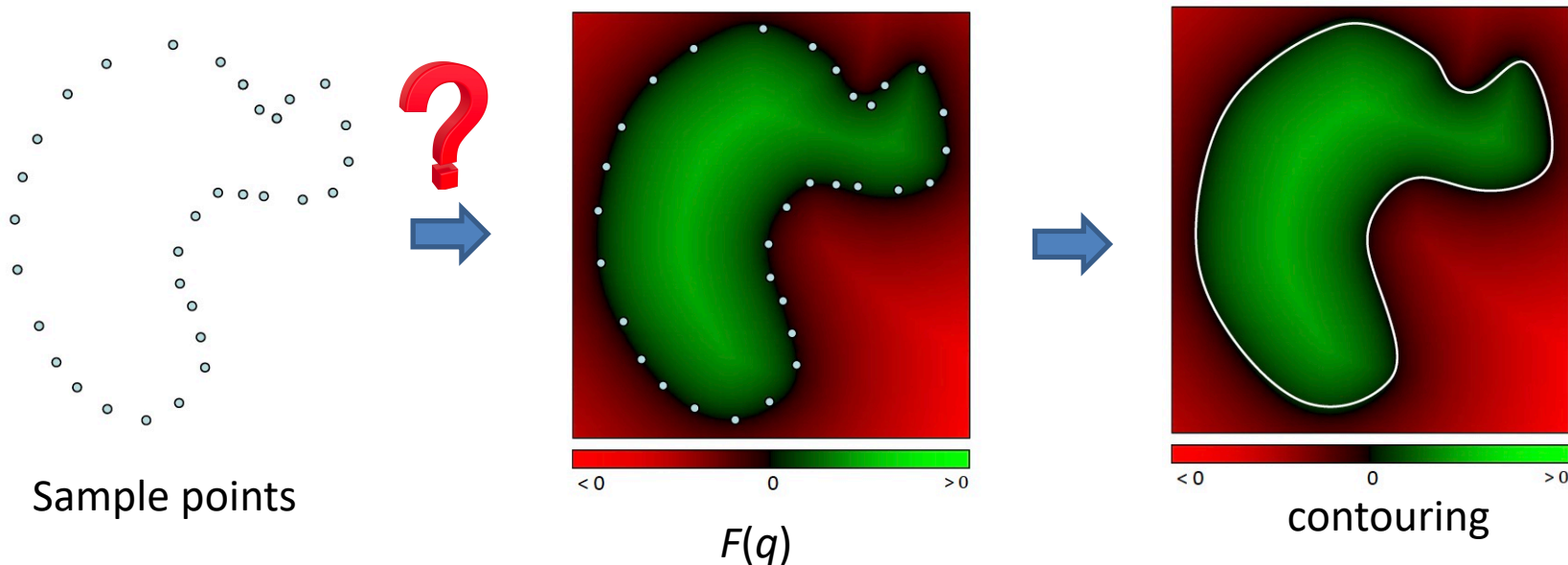
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 - The pioneer work of [Hoppe *et al.* \(1992\)](#)
 - Poisson reconstruction [[Kazhdan *et al.* 06](#)]
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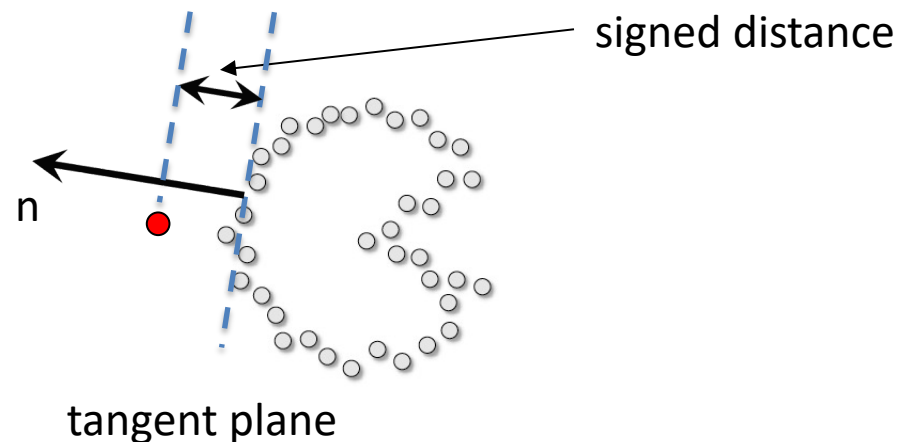
The pioneer work of Hoppe *et al.* (1992)

- Two main steps
 - Estimate signed geometric distance to the unknown surface
 - Extract the zero-set of the distance field using a contouring algorithm



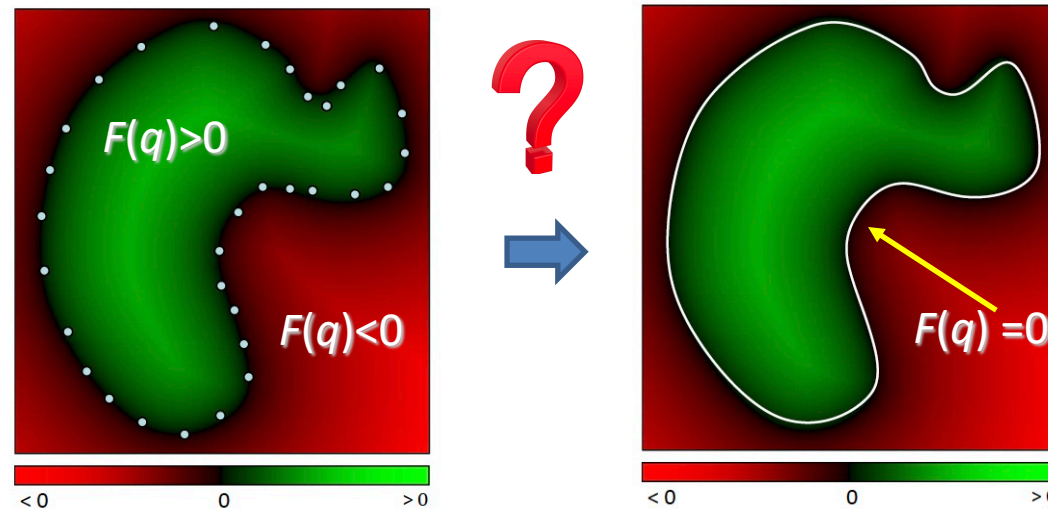
The pioneer work of Hoppe *et al.* (1992)

- Define a signed distance function (SDF)
 - Associate an oriented plane (tangent plane) with each of the data points
 - Tangent plane is a local linear approximation to the surface.
 - Used to define signed distance function to surface.



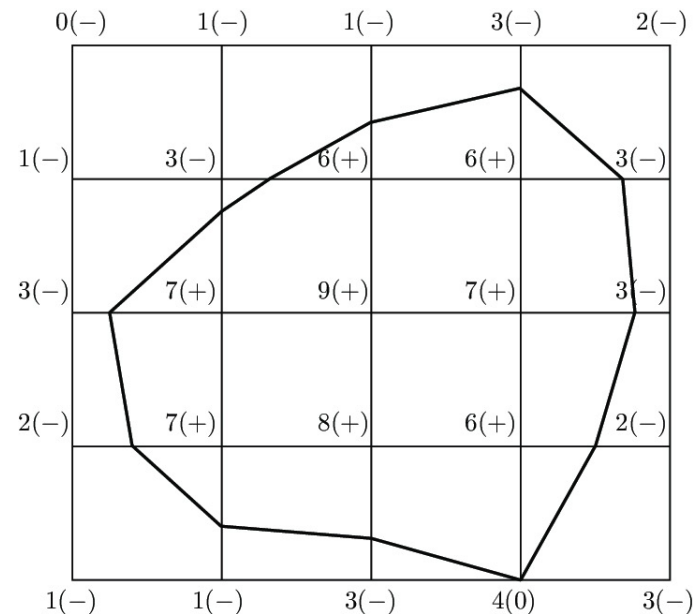
The pioneer work of Hoppe *et al.* (1992)

- Contour tracing
 - Extract 0-set iso-surface from the scalar field
 - Marching cubes

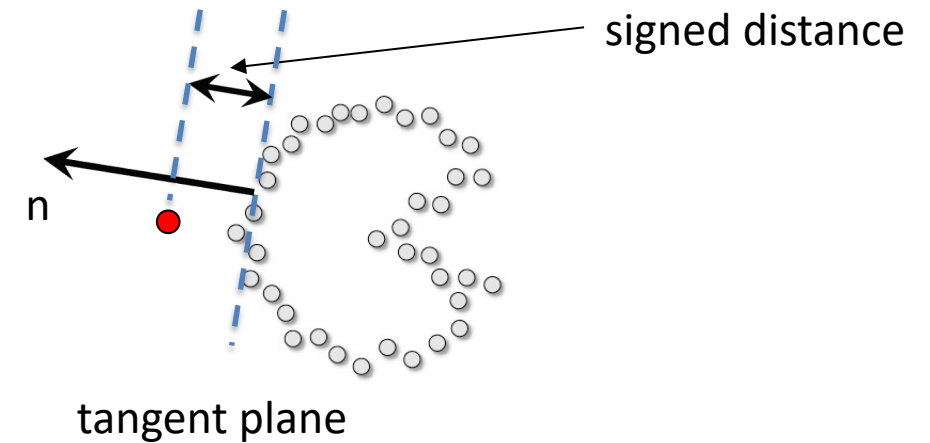


The pioneer work of Hoppe *et al.* (1992)

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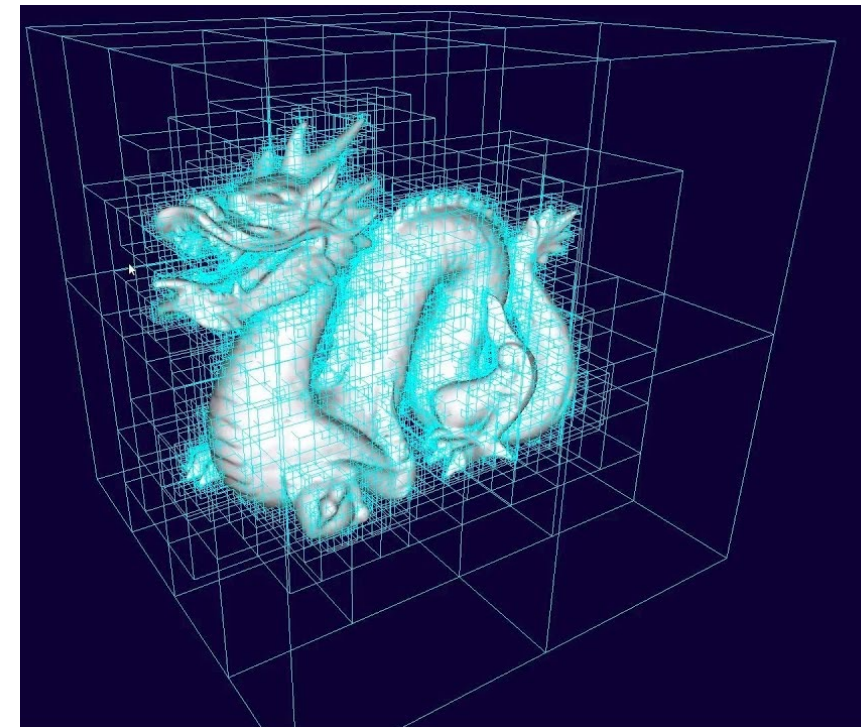
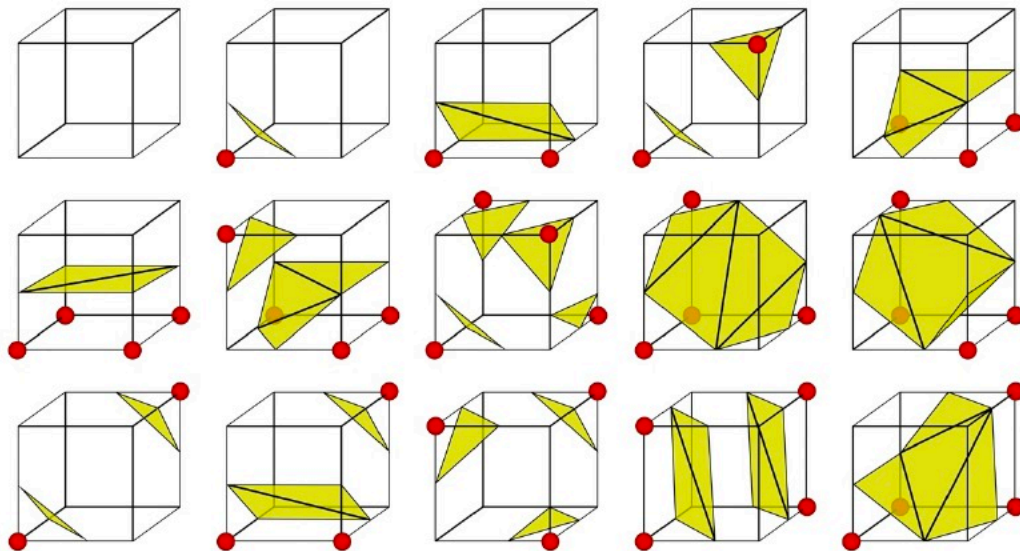


Marching squares (2D version of marching cubes)



The pioneer work of Hoppe *et al.* (1992)

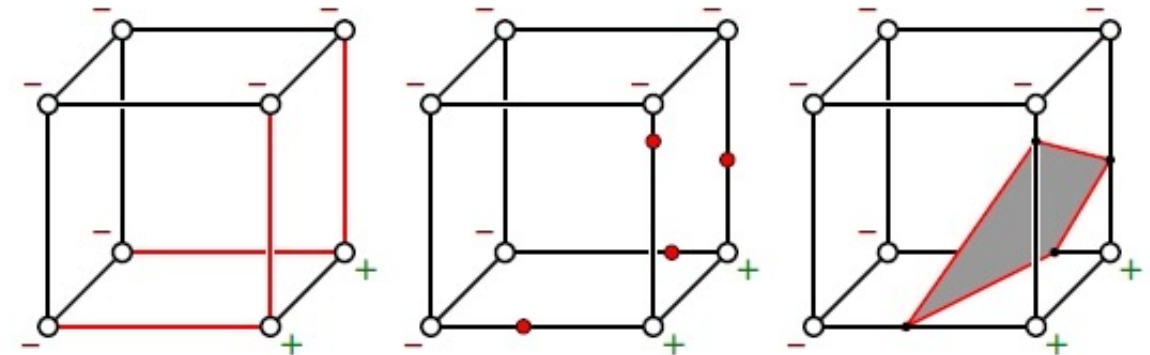
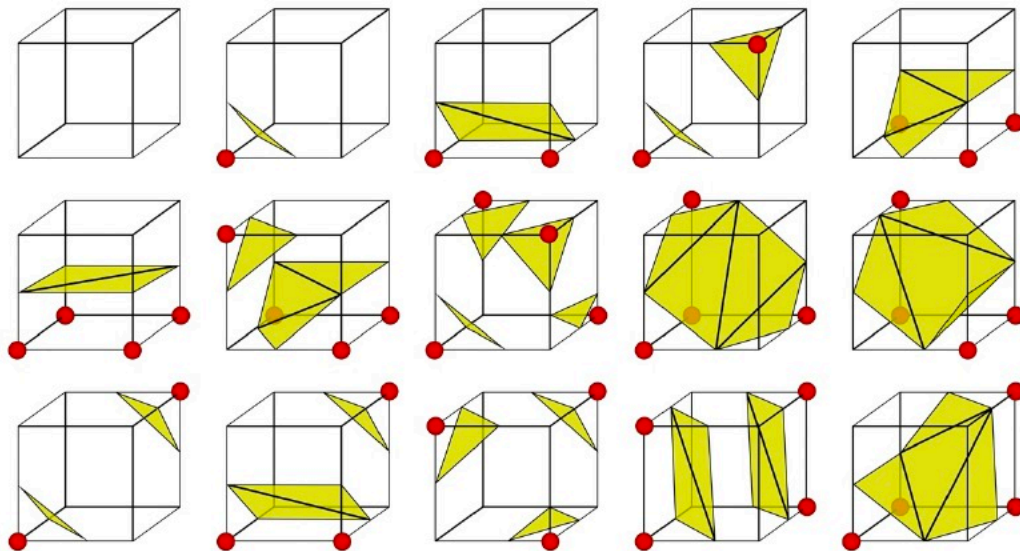
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Marching cubes

The pioneer work of Hoppe *et al.* (1992)

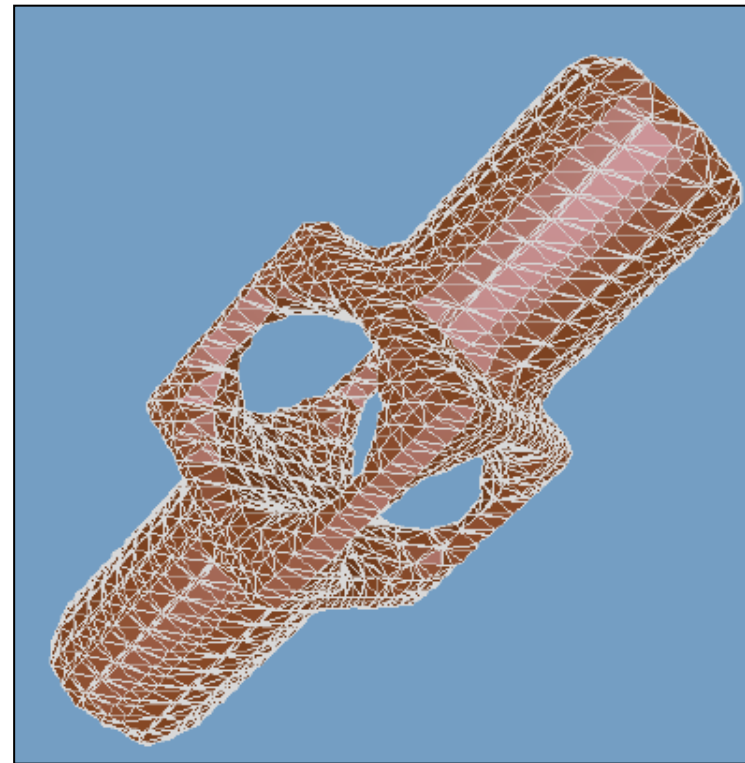
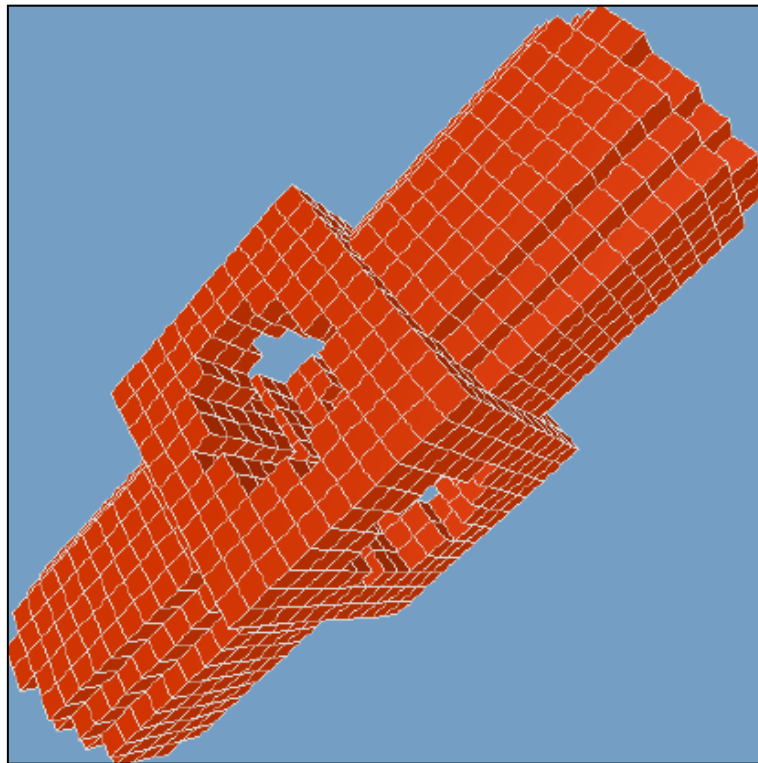
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Marching cubes

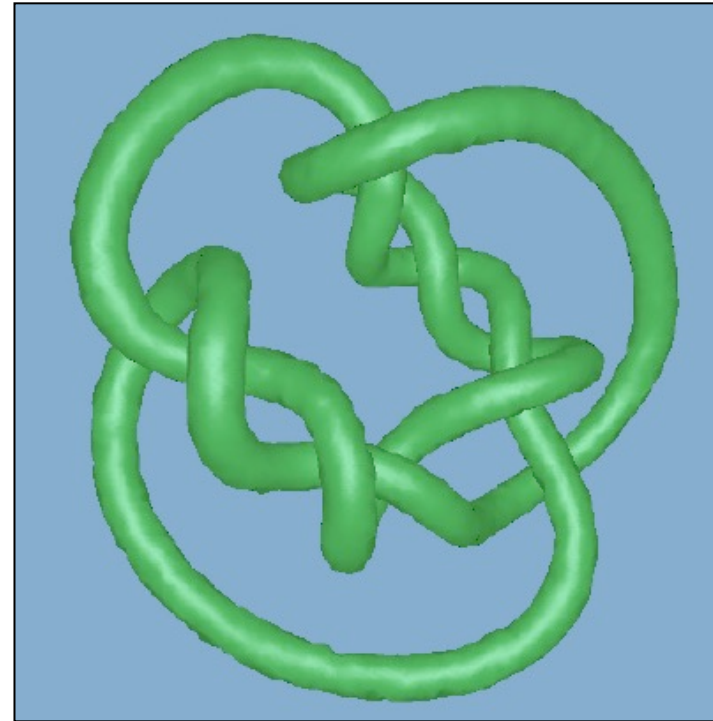
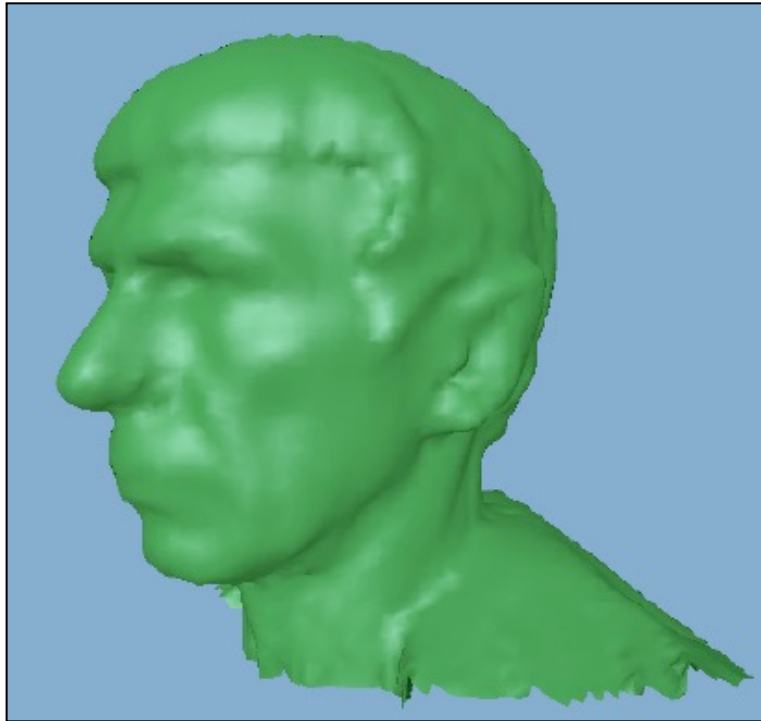
The pioneer work of Hoppe *et al.* (1992)

- Contour tracing



The pioneer work of Hoppe *et al.* (1992)

- Reconstruction results



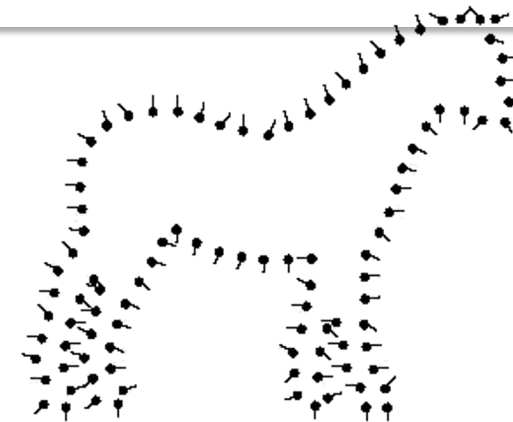
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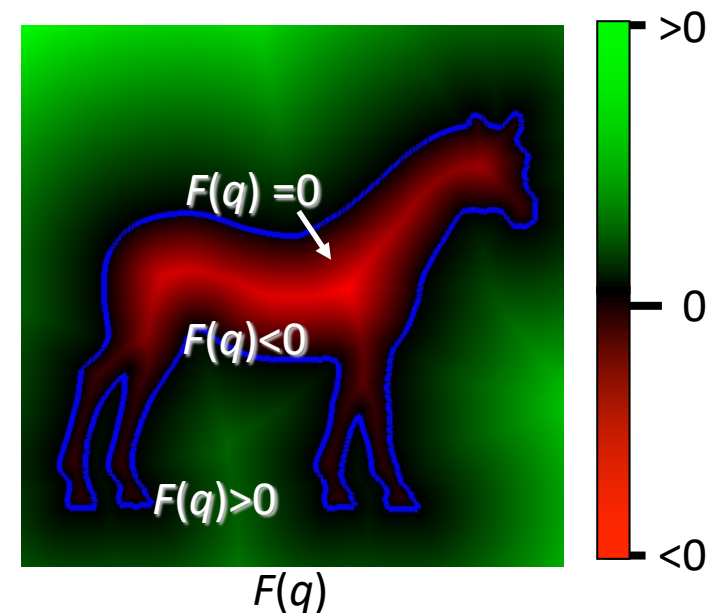


Poisson Reconstruction

- Implicit function fitting
 - Define a 3D scalar function
 - Zero values at the points
 - Positive values outside
 - Negative values inside
 - Extract the zero isosurface

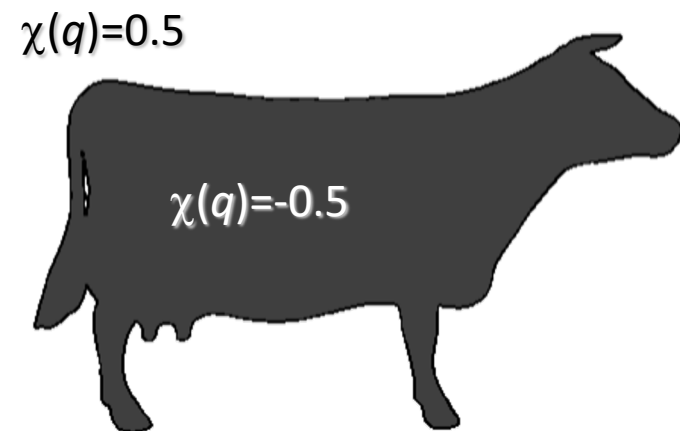


Sample points



Poisson Reconstruction

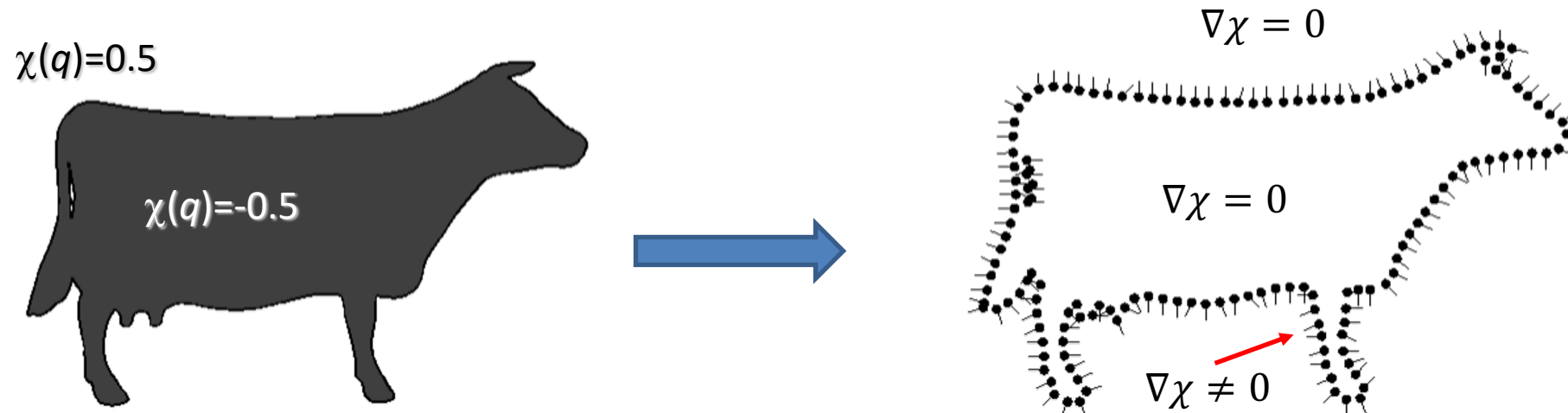
- The idea
 - The indicator function (χ)
 - Interior: constant negative value
 - Exterior: constant positive value



Poisson Reconstruction

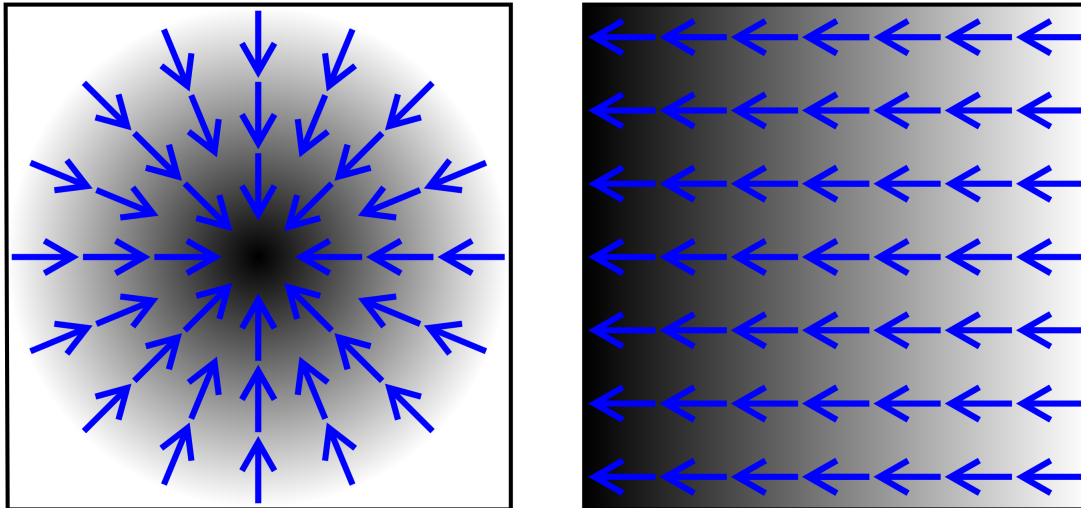
- The idea
 - The indicator function (χ)
 - The gradient of the indicator function ($\nabla\chi$)
 - Zero everywhere except close to the boundary

Gradient?



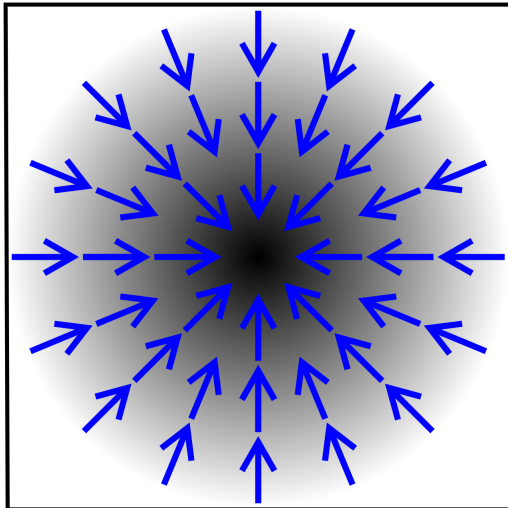
- Gradient (∇f) is a vector at a point
 - Direction: the greatest rate of increase of f
 - Magnitude: the rate of increase in that direction

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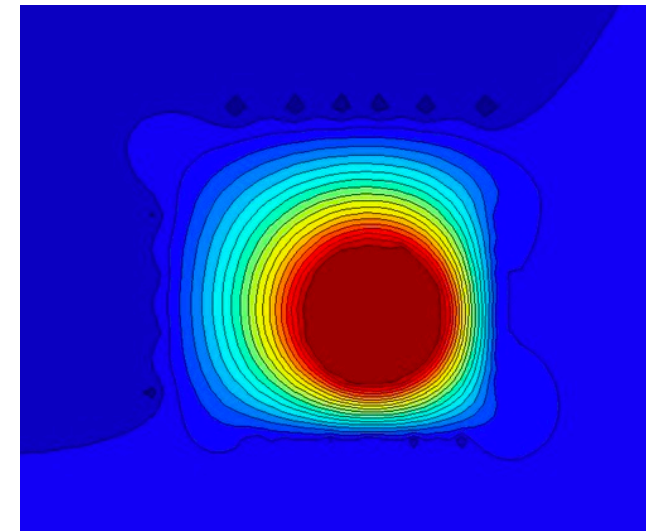
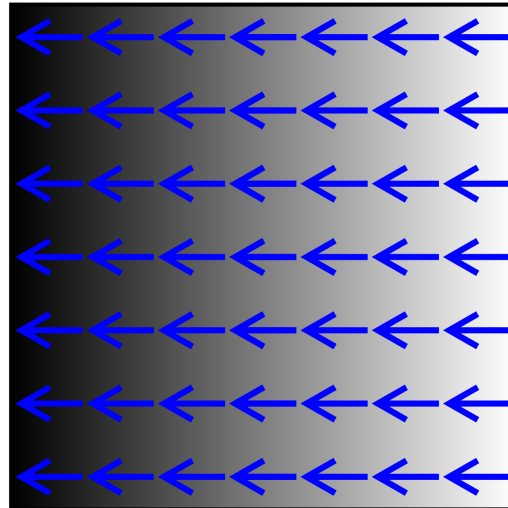


Gradient of colors

- Gradient (∇f) is a vector at a point
 - Direction: the greatest rate of increase of f
 - Magnitude: the rate of increase in that direction



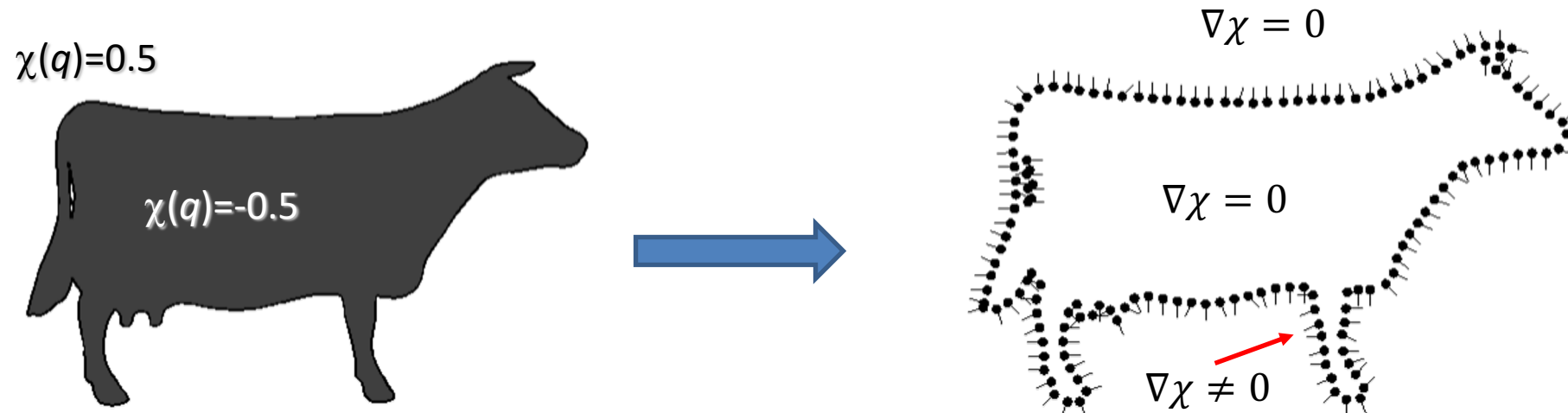
Gradient of colors



Heat source (2D)

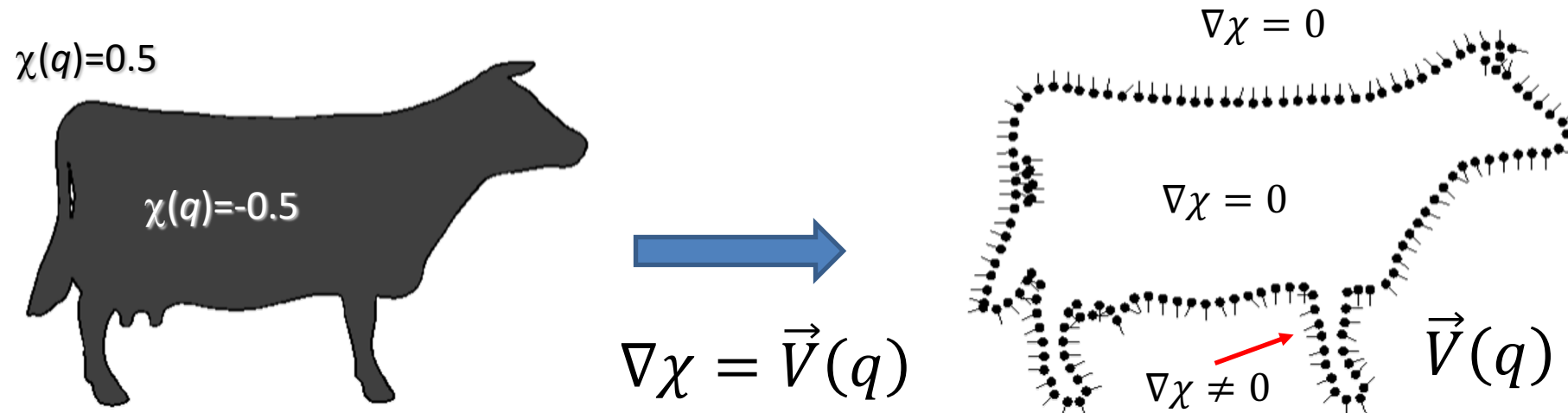
Poisson Reconstruction

- The idea
 - The indicator function (χ)
 - The gradient of the indicator function ($\nabla\chi$)
 - Zero everywhere except close to the boundary



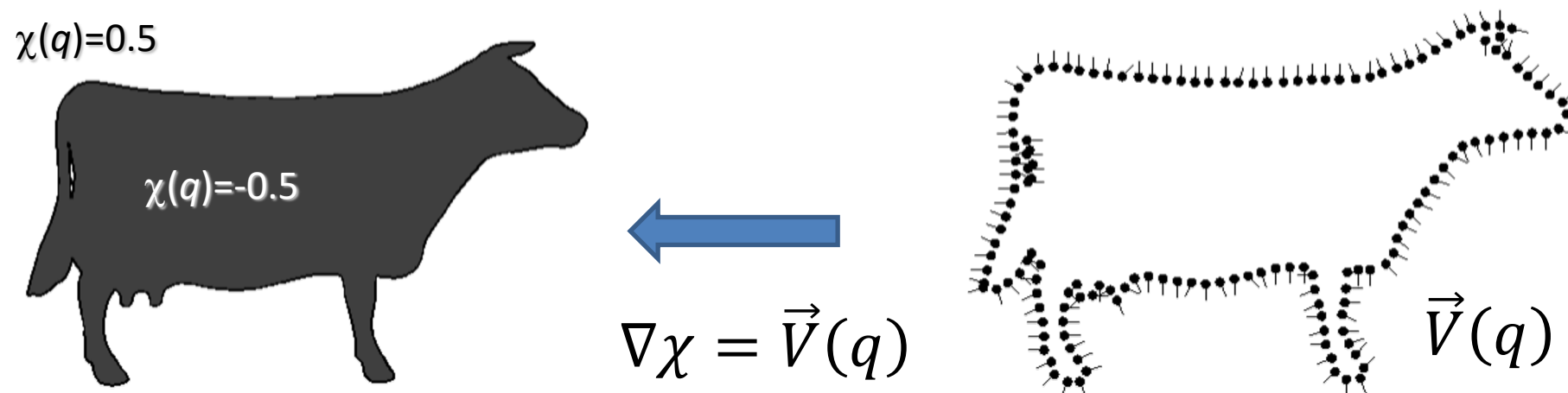
Poisson Reconstruction

- The idea
 - The indicator function (χ)
 - The gradient of the indicator function ($\nabla\chi$)
 - Oriented points $\vec{V}(q) \approx$ samples of gradient



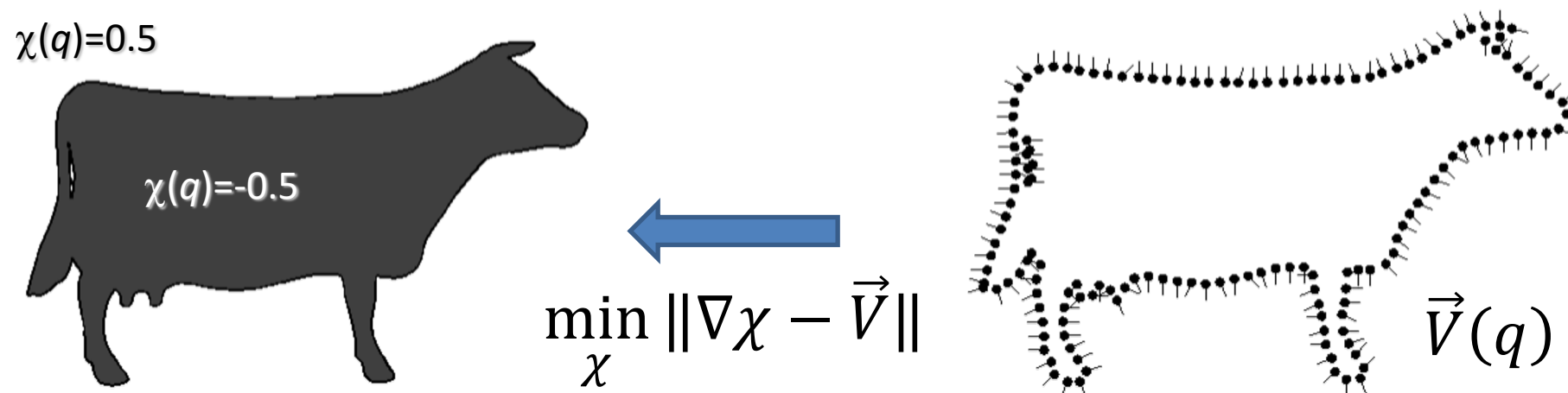
Poisson Reconstruction

- The idea
 - The indicator function (χ)
 - The gradient of the indicator function ($\nabla\chi$)
 - Oriented points $\vec{V}(q) \approx$ samples of gradient
 - Reconstruction



Poisson Reconstruction

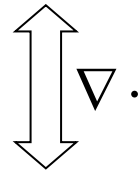
- The idea
 - The indicator function (χ)
 - The gradient of the indicator function ($\nabla\chi$)
 - Oriented points $\vec{V}(q) \approx$ samples of gradient
 - Reconstruction: finding the indicator function



Poisson Reconstruction

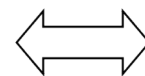
- Reconstruction: finding the indicator function
 - Continues vector field? $\nabla\chi = \vec{V}(q)$
 - The best least-squares approximate solution
 - Apply the divergence operator

$$\min_{\chi} \|\nabla\chi - \vec{V}\|$$



$$\nabla \cdot \nabla\chi = \nabla \cdot \vec{V}$$

?



$$\Delta\chi = \nabla \cdot \vec{V}$$

Poisson equation

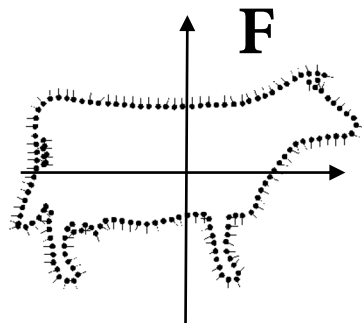


Laplace operator (or Laplacian): $\nabla \cdot \nabla$, ∇^2 , or Δ
 - Divergence of the gradient of a function

Poisson Reconstruction

- Pipeline
 - Point samples \rightarrow Continuous vector field

$$\mathbf{F} = U \vec{i} + V \vec{j} + W \vec{k}$$



Poisson Reconstruction

- Pipeline

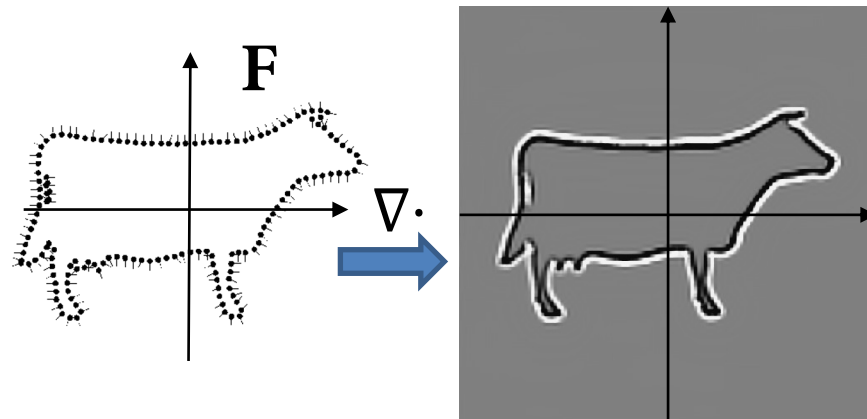
- Point samples -> Continuous vector field

$$\mathbf{F} = U \vec{i} + V \vec{j} + W \vec{k}$$

- Compute the divergence ($\nabla \cdot$)

$$\text{div } \mathbf{F} = \nabla \cdot \mathbf{F} = \left(\frac{\partial}{\partial x}, \frac{\partial}{\partial y}, \frac{\partial}{\partial z} \right) \cdot (U, V, W) = \frac{\partial U}{\partial x} + \frac{\partial V}{\partial y} + \frac{\partial W}{\partial z}$$

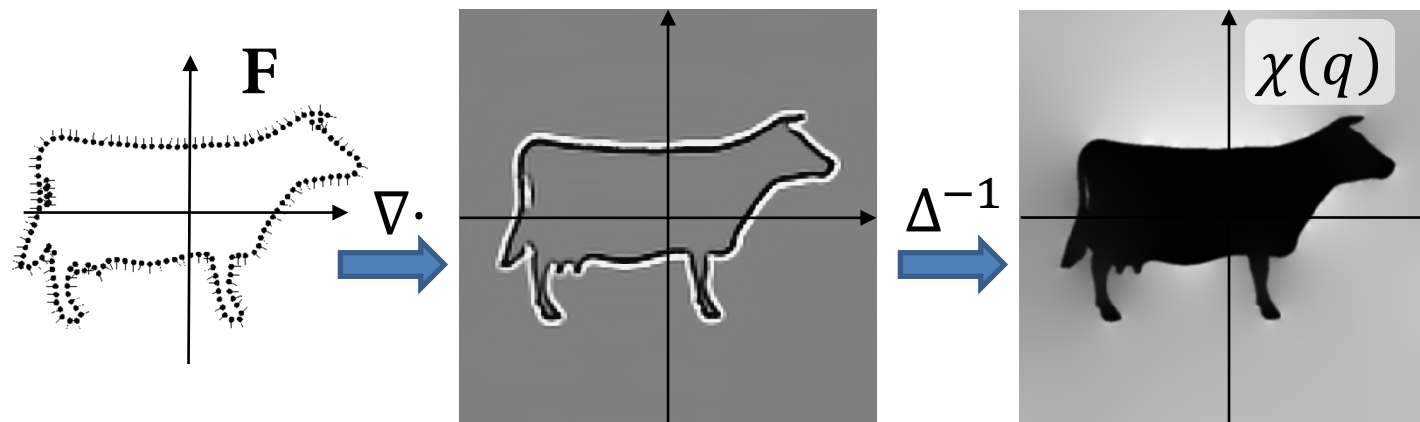
the sum of the first-order partial derivative



Poisson Reconstruction

- Pipeline
 - Point samples -> Continuous vector field
 - Compute the divergence ($\nabla \cdot$)
 - Solve the Poisson equation

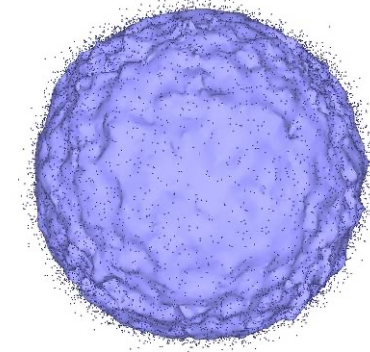
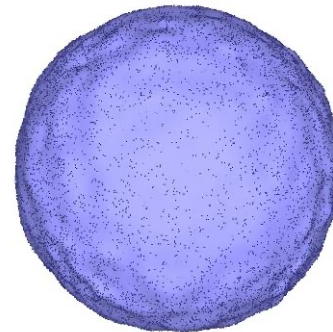
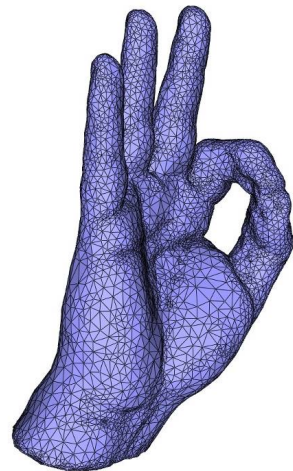
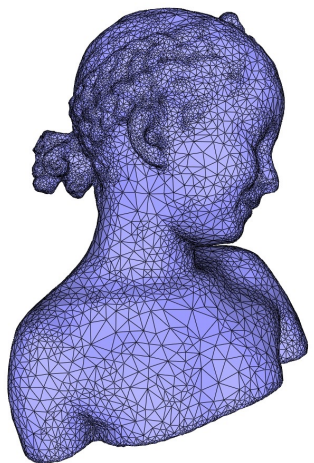
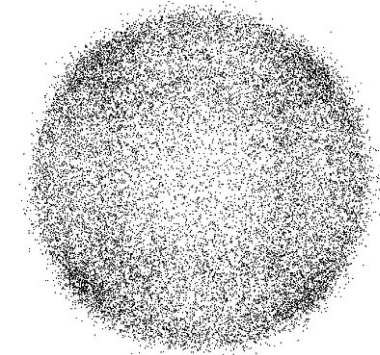
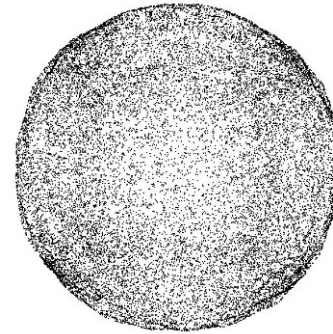
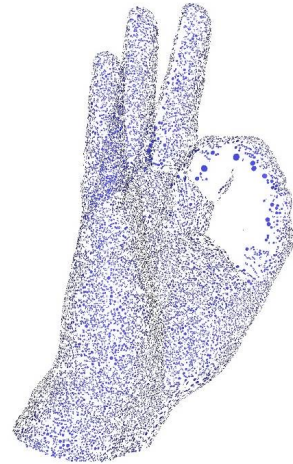
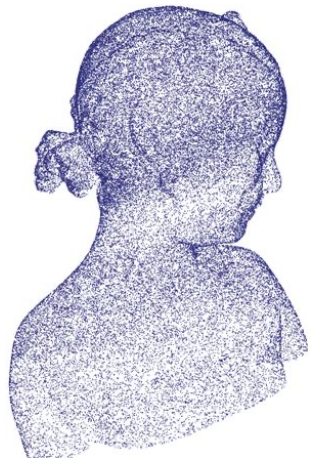
$$\Delta \chi = \nabla \cdot \mathbf{F}$$



Poisson Reconstruction

- Pipeline
 - Point samples -> Continuous vector field
 - Compute the divergence ($\nabla \cdot$)
 - Solve the Poisson equation
 - Iso-surface extraction
 - Marching cubes

Poisson Reconstruction



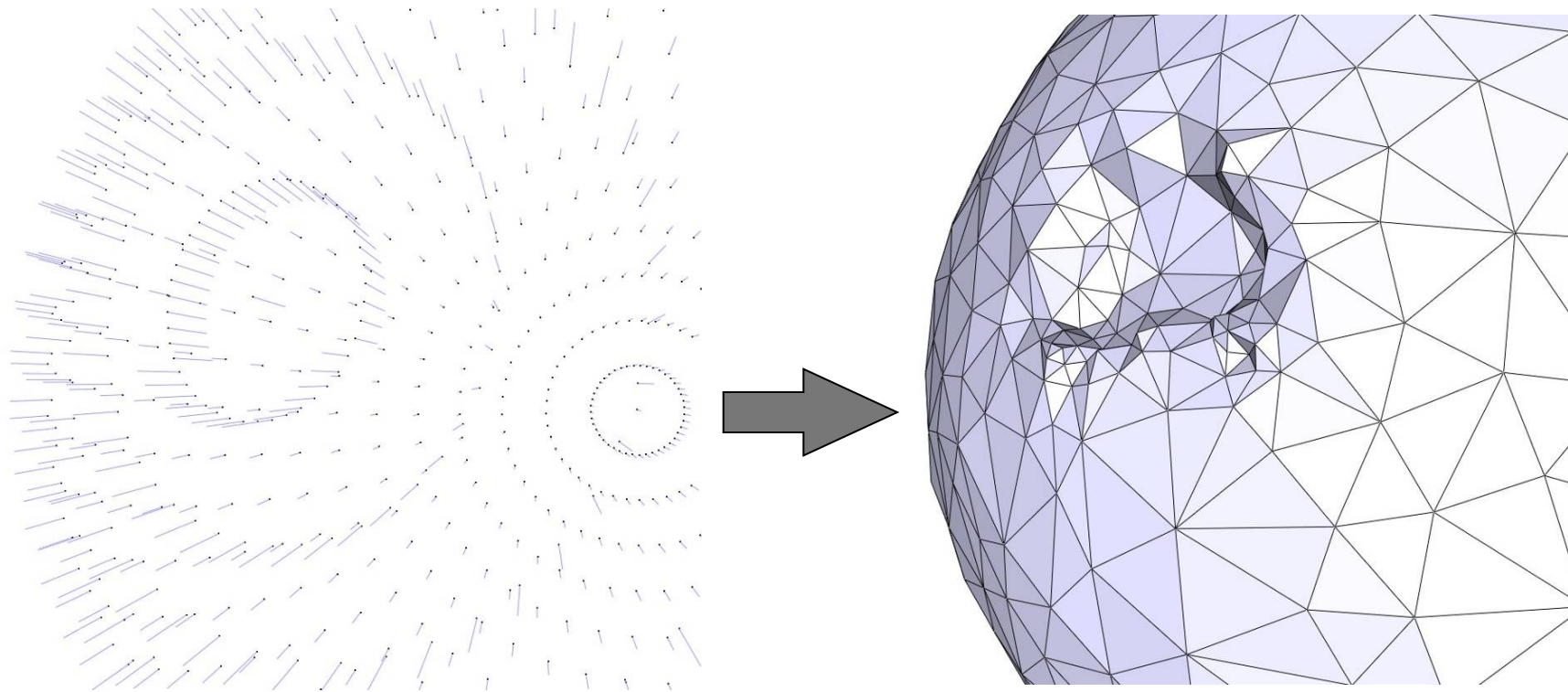
Poisson Reconstruction



Left: 50K points sampled on
Neptune trident

Right: point set simplified to 1K
then reconstructed

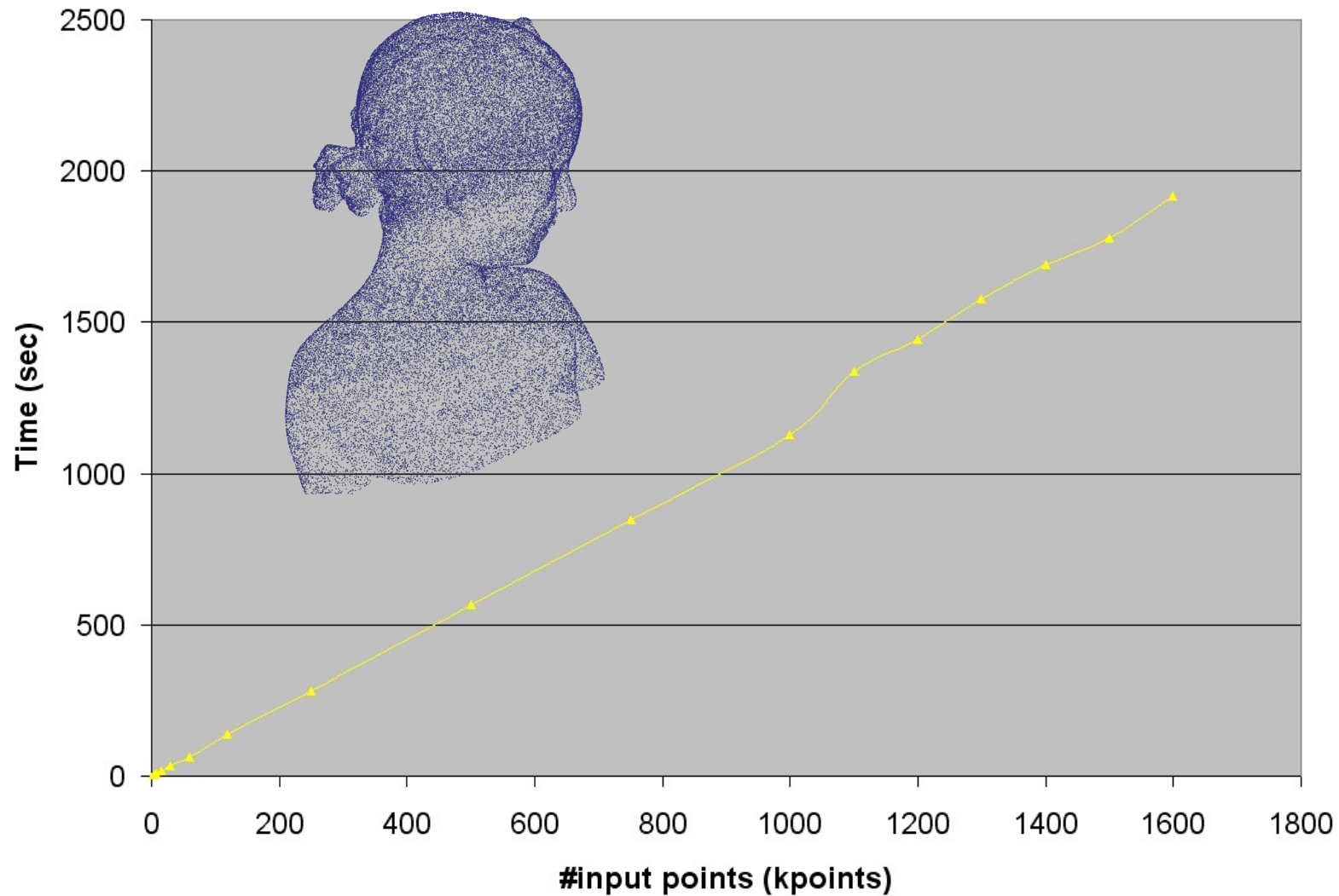
Poisson Reconstruction



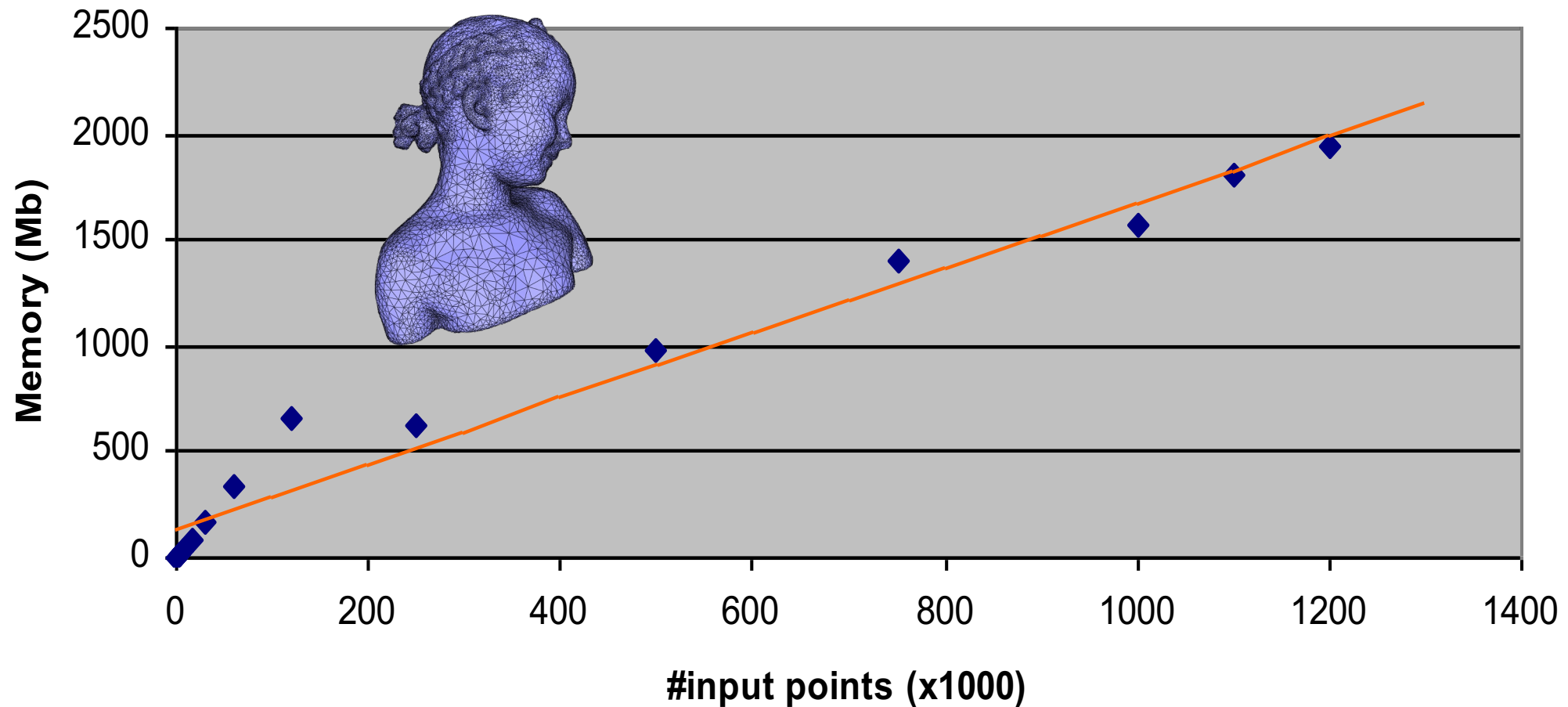
Left: points sampled on a sphere
with flipped normals

Right: reconstructed surface

Poisson duration wrt #input points

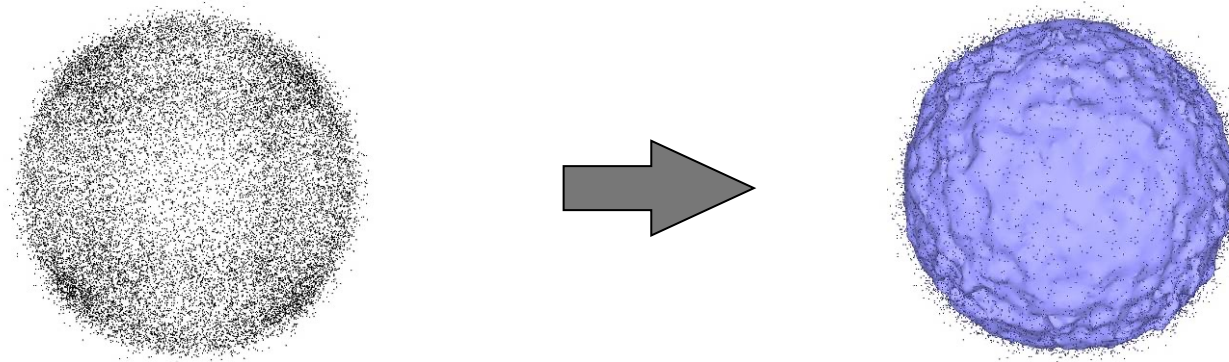


Memory wrt #input points



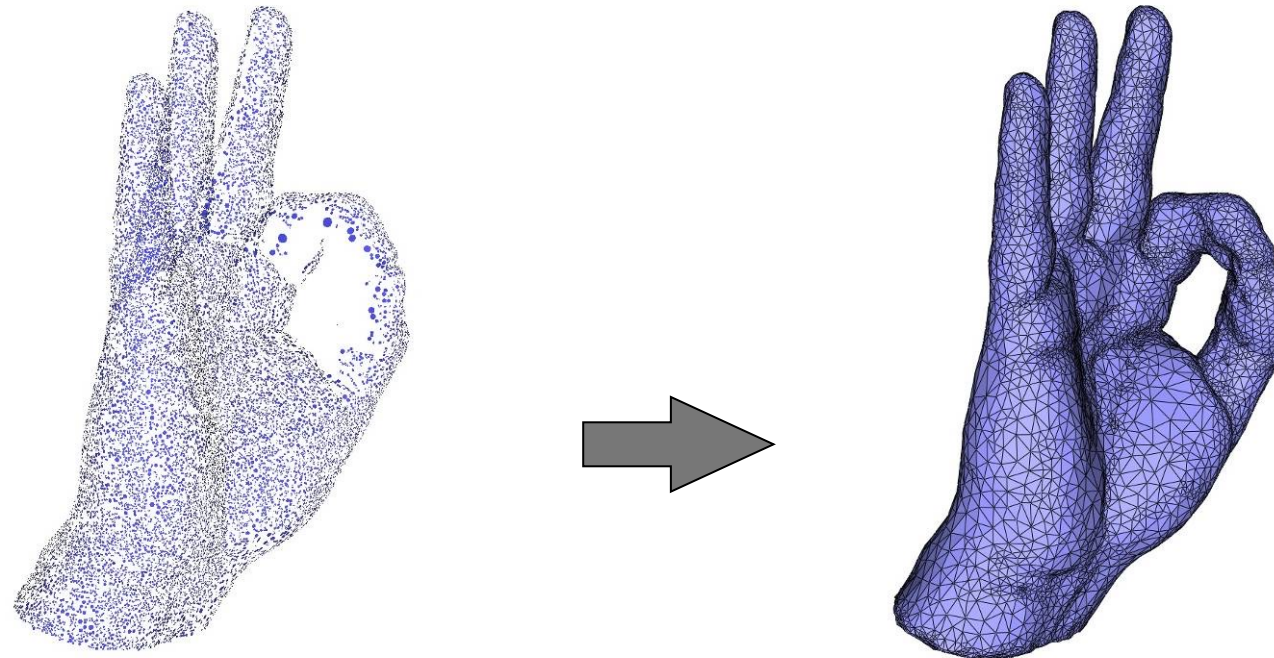
Poisson Reconstruction

- Properties
 - ✓ Supports noisy, non-uniform data



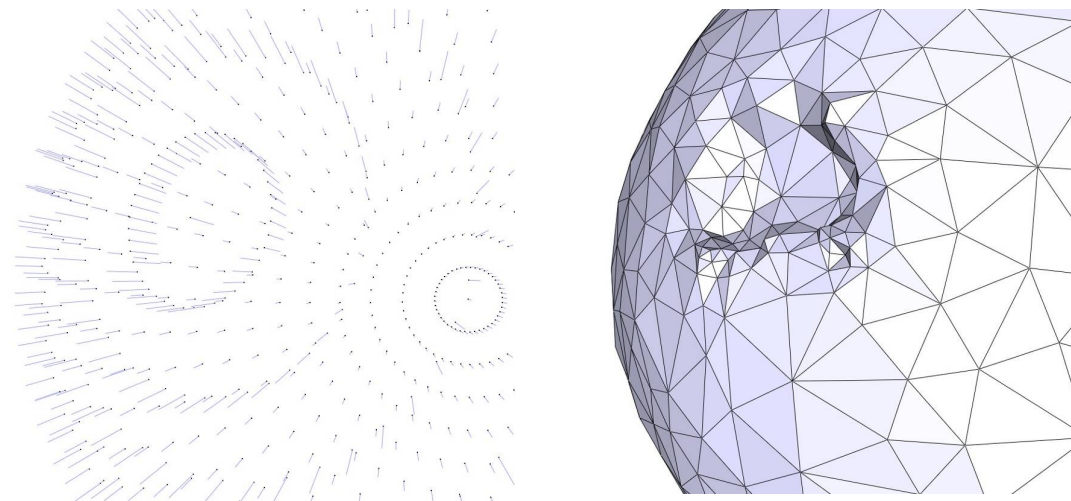
Poisson Reconstruction

- Properties
 - ✓ Supports noisy, non-uniform data
 - ✓ Can fill reasonably large holes



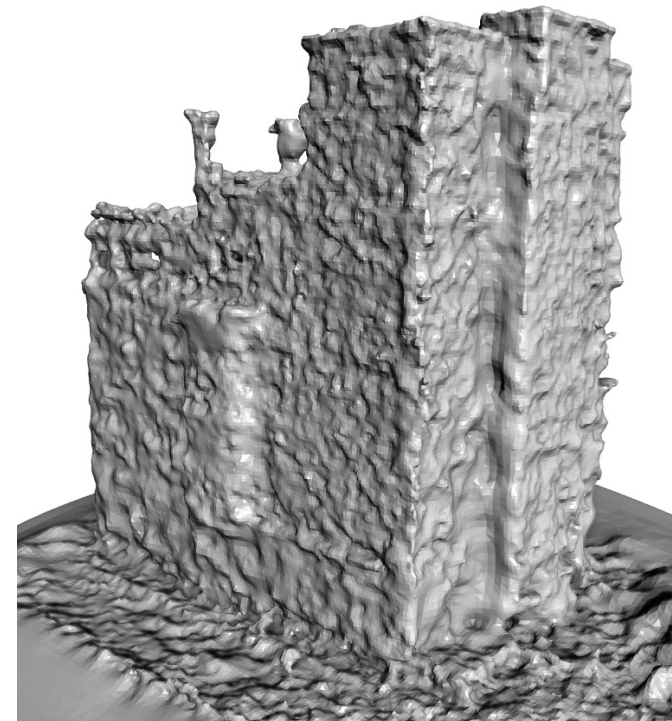
Poisson Reconstruction

- Properties
 - ✓ Supports noisy, non-uniform data
 - ✓ Can fill reasonably large holes
- Limitations
 - It requires good normal information




Poisson Reconstruction

- Properties
 - ✓ Supports noisy, non-uniform data
 - ✓ Can fill reasonably large holes
- Limitations
 - It requires good normal information
 - Sharp features are oversmoothed
 - Not good for piecewise planar objects

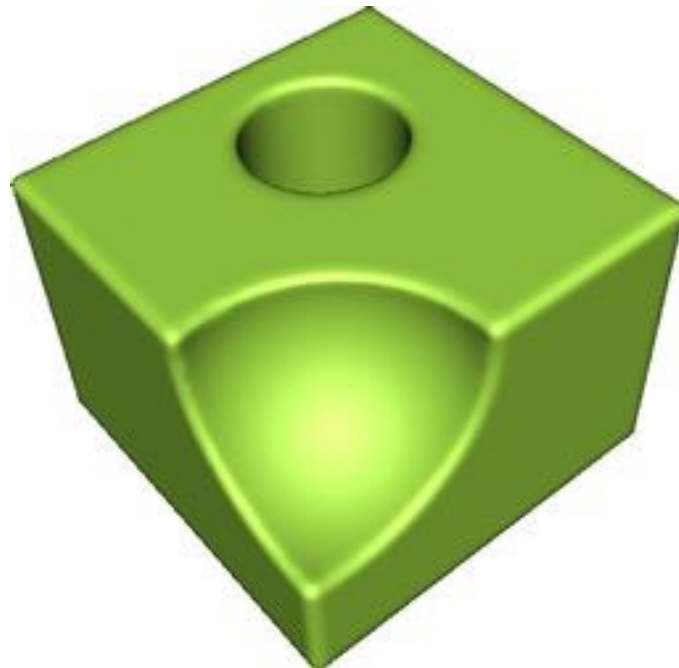


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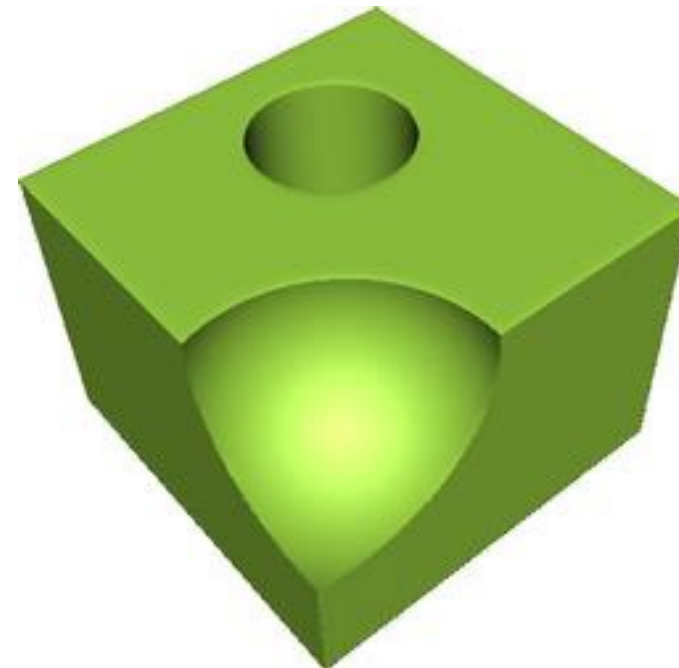
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Piecewise Smooth Reconstruction

- Piecewise-smooth



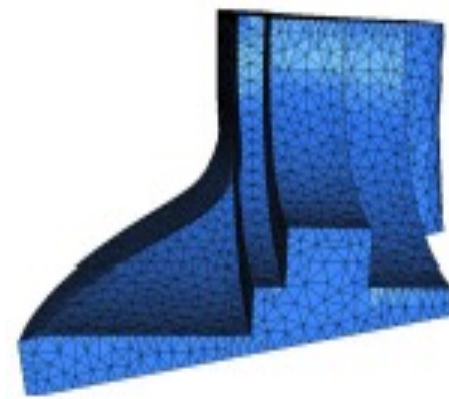
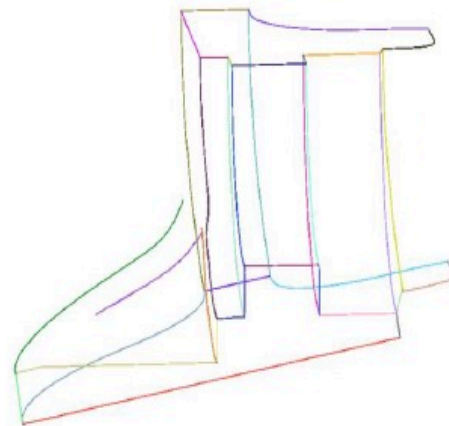
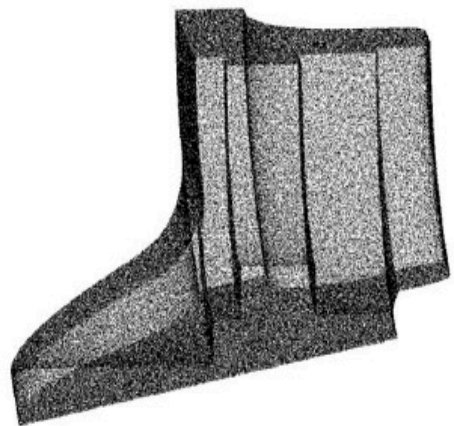
smooth



piecewise-smooth

Piecewise Smooth Reconstruction

- Feature detection
 - Extract a set of sharp features
 - Decompose the point cloud into smooth patches
- Smooth reconstruction patch by patch
- Stitch the patches



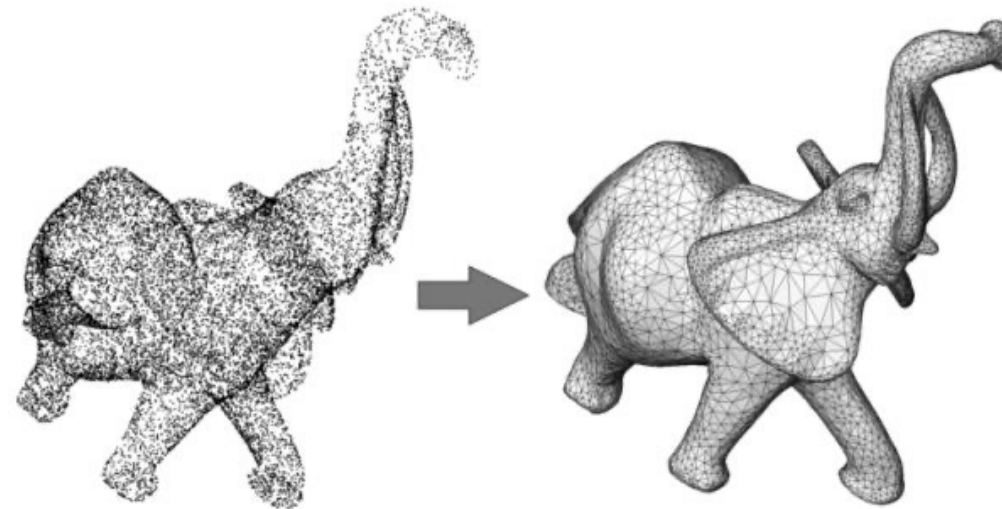
Today's Agenda

- Introduction
- Smooth object reconstruction
 - The pioneer work of [Hoppe *et al.* \(1992\)](#)
 - Poisson reconstruction [[Kazhdan *et al.* 06](#)]
 - Piecewise smooth reconstruction
- Piecewise planar object reconstruction



Polygonal Surface Reconstruction

- Surface Reconstruction Methods
 - Smooth surfaces
 - Fit noisy data; infer topology; fill (small) holes



Poisson Surface Reconstruction [[Kazhdan et al. 06](#)]

Polygonal Surface Reconstruction

- Surface Reconstruction Methods
 - Smooth surfaces
 - Piecewise planar objects



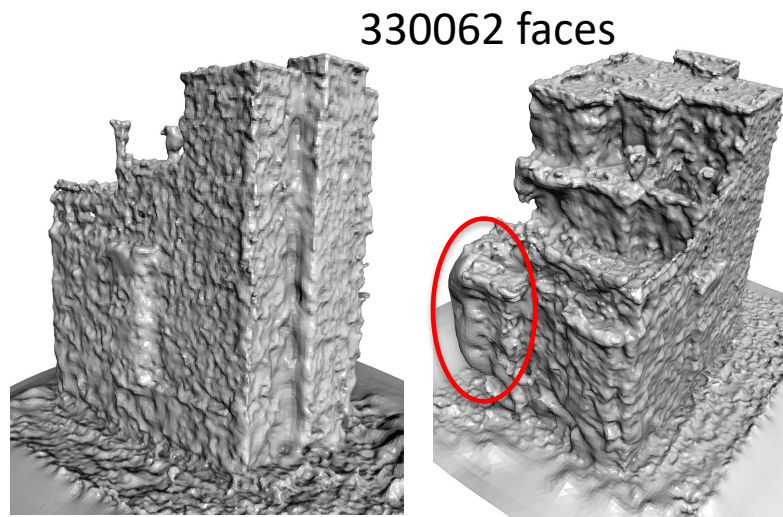
Polygonal Surface Reconstruction

- Surface Reconstruction Methods
 - Smooth surfaces
 - Piecewise planar objects



Polygonal Surface Reconstruction

- Surface Reconstruction Methods
 - Smooth surfaces
 - Piecewise planar objects

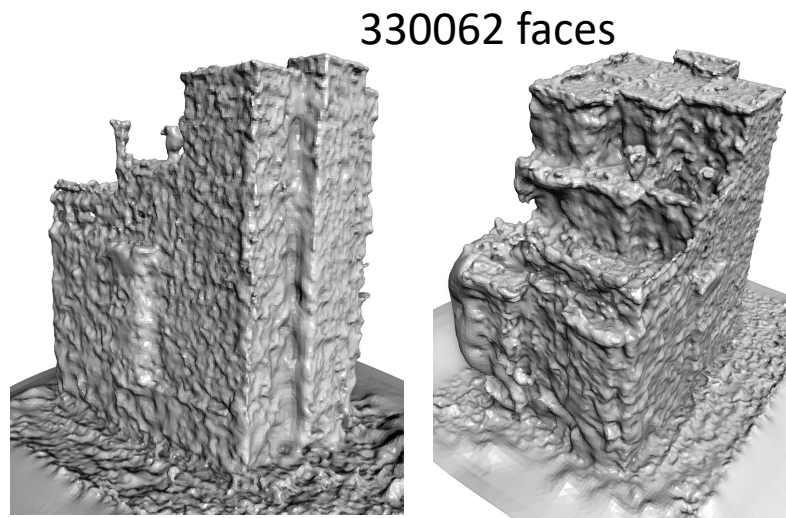


Result of [Kazhdan *et al.* 06]

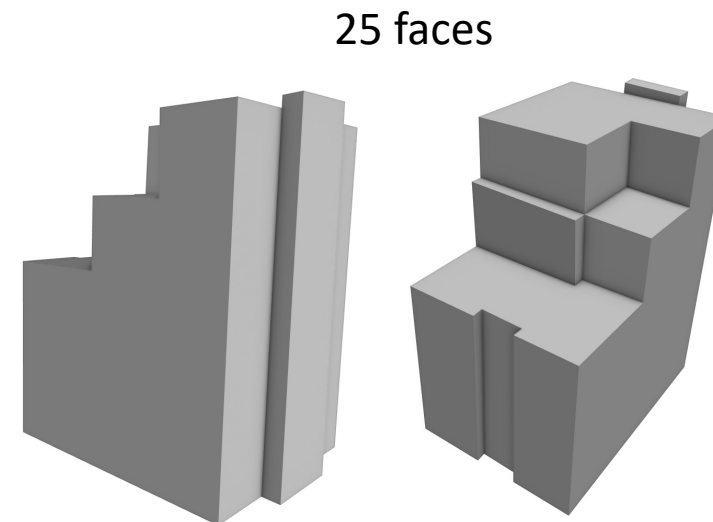
- Unsatisfied results
 - Bumpy
 - Large number of faces
 - Unacceptable hole filling
- Rare direct applications
 - Post-processing required
 - Topologically correct
 - Simplified

Polygonal Surface Reconstruction

- Surface Reconstruction Methods
 - Smooth surfaces
 - Piecewise planar objects



Result of [Kazhdan *et al.* 06]



[Nan and Wonka 17]

Polygonal Surface Reconstruction

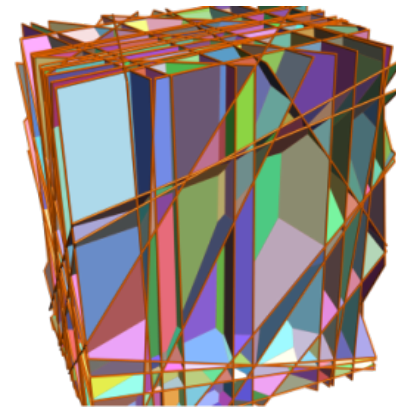
- Overview



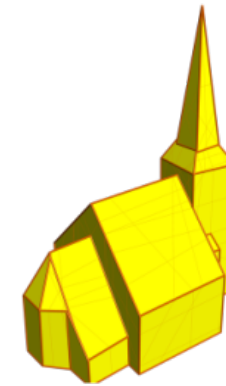
Input



Planar segments



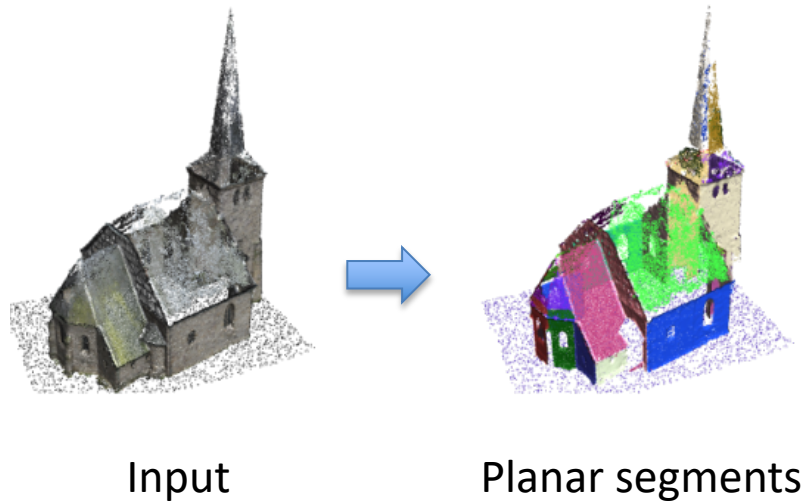
Candidate faces



Result

Polygonal Surface Reconstruction

- Overview



RANSAC algorithm

- Random 3 points -> plane
- Scoring, accept or reject
- Repeat
 - Plane from the remaining points
 - Stop if no plane can be extracted

Polygonal Surface Reconstruction

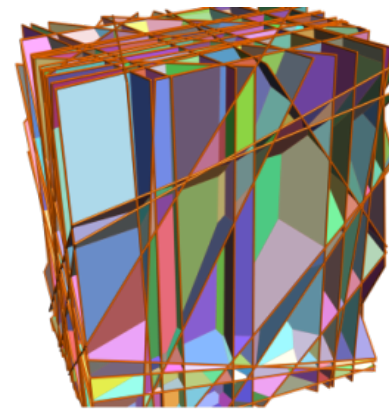
- Candidate Generation
 - Supporting plane clipping
 - Pairwise intersection



Input



Planar segments



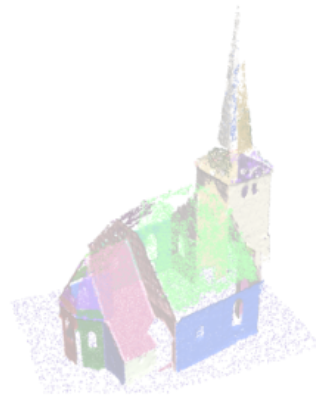
Candidate faces

Polygonal Surface Reconstruction

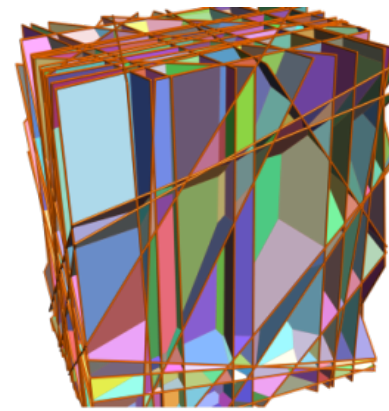
- Face Selection



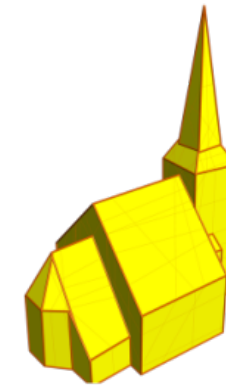
Input



Planar segments



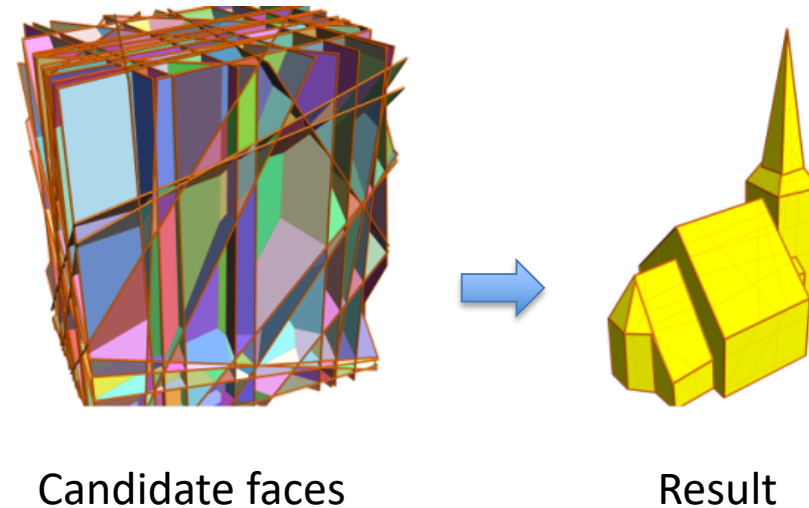
Candidate faces



Result

Polygonal Surface Reconstruction

- Face Selection
 - Labeling problem
 - Linear integer program



N candidate faces $F = \{f_i | 1 \leq i \leq N\}$

Variables: $x_i = \begin{cases} 1, & \text{face } f_i \text{ will be chosen} \\ 0, & \text{face } f_i \text{ will **not** be chosen} \end{cases}$

Polygonal Surface Reconstruction

- Objective Function
 - Data fitting
 - Favors selecting faces with more support
 - Percentage of unused points

$$E_f = 1 - \frac{1}{|P|} \sum_{i=1}^N x_i \cdot support(f_i)$$

Polygonal Surface Reconstruction

- Objective Function

- Data fitting

- Favors selecting faces with more support
- Percentage of unused points

$$E_f = 1 - \frac{1}{|P|} \sum_{i=1}^N x_i \cdot support(f_i)$$

Confidence weighted
number of supporting point

$$support(f) = \sum_{p, f | dist(p, f) < \epsilon} \left(1 - \frac{dist(p, f)}{\epsilon}\right) \cdot conf(p)$$

Polygonal Surface Reconstruction

- Objective Function

- Data fitting

- Favors selecting faces with more support
- Percentage of unused points

$$E_f = 1 - \frac{1}{|P|} \sum_{i=1}^N x_i \cdot support(f_i)$$

Confidence weighted
number of supporting point

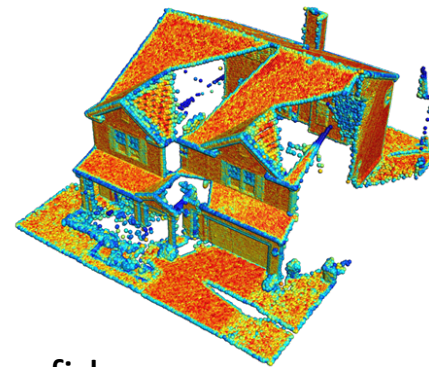
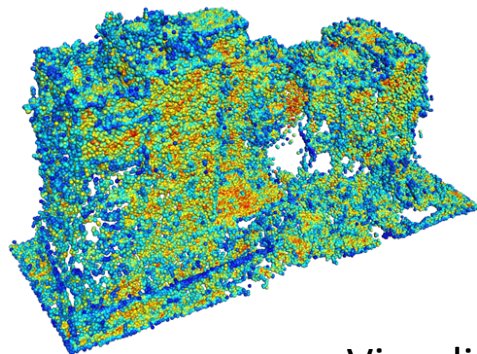
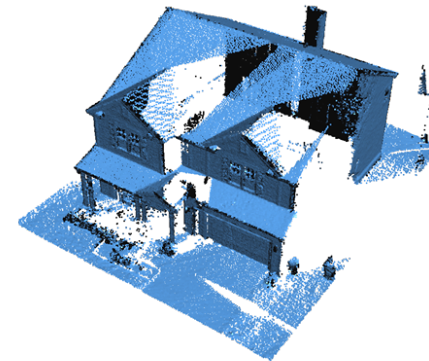
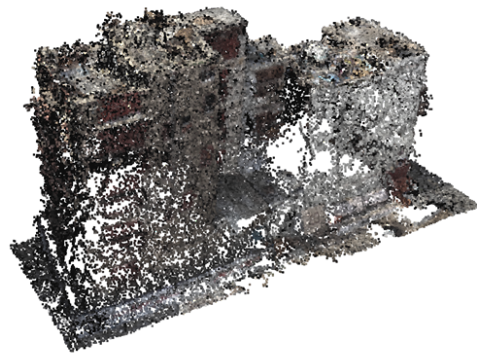
$$support(f) = \sum_{p, f | dist(p, f) < \epsilon} \left(1 - \frac{dist(p, f)}{\epsilon}\right) \cdot conf(p)$$

Point confidence

$$conf(p) = \frac{1}{3} \sum_{i=1}^3 \left(1 - \frac{3\lambda_i^1}{\lambda_i^1 + \lambda_i^2 + \lambda_i^3}\right) \cdot \frac{\lambda_i^2}{\lambda_i^3} \quad \lambda_i^1 \leq \lambda_i^2 \leq \lambda_i^3$$

Polygonal Surface Reconstruction

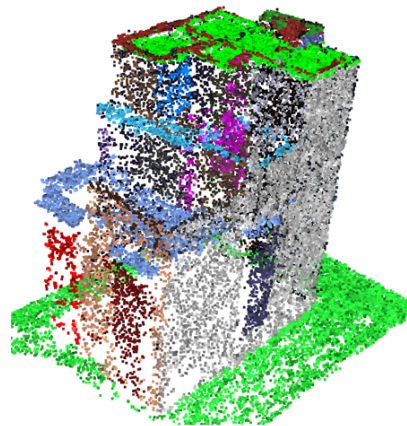
- Objective Function
 - Data fitting



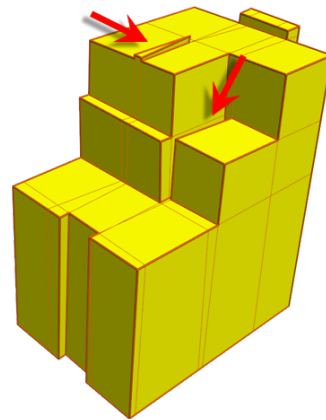
Visualization of point confidences

Polygonal Surface Reconstruction

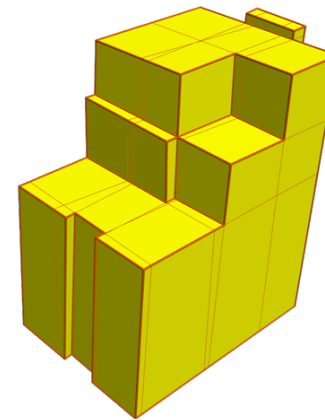
- Objective Function
 - Data fitting
 - Model complexity
 - Penalize sharp corners



(a)



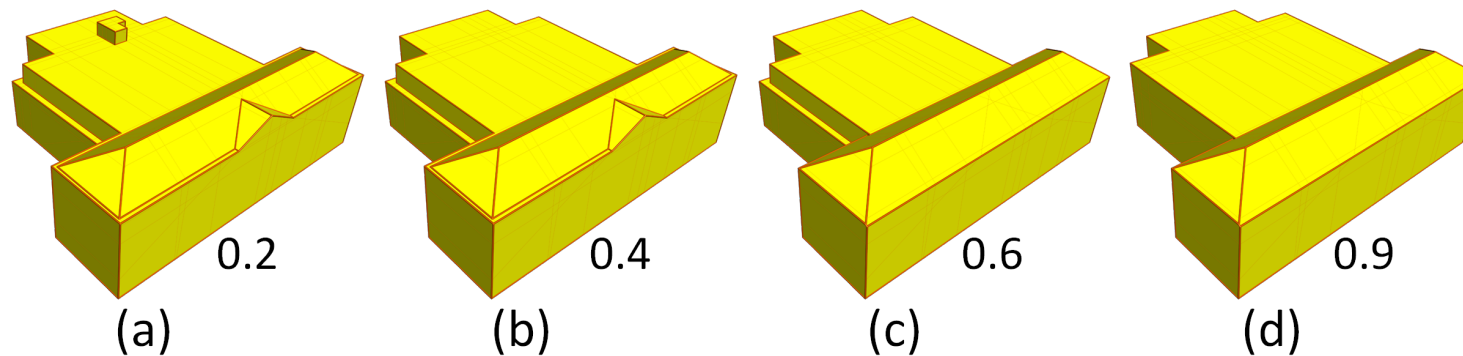
(b)



(c)

Polygonal Surface Reconstruction

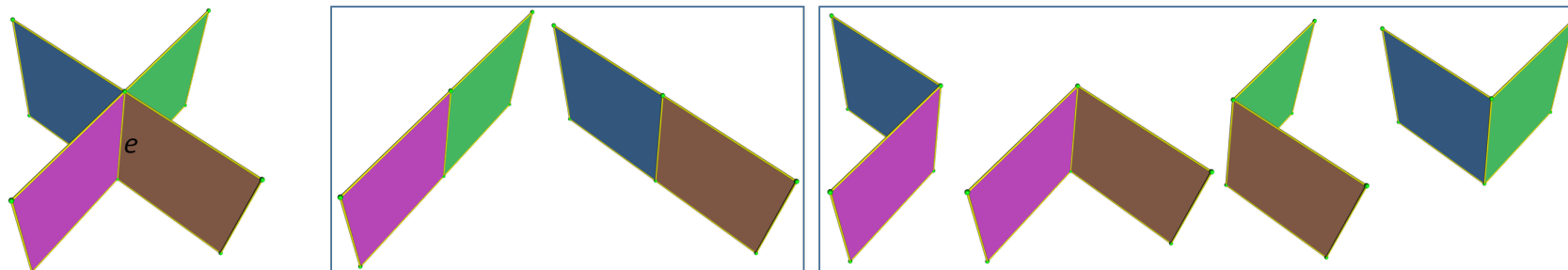
- Objective Function
 - Data fitting
 - Model complexity
 - Penalize sharp corners



Polygonal Surface Reconstruction

- Objective Function
 - Data fitting
 - Model complexity
 - Penalize sharp corners

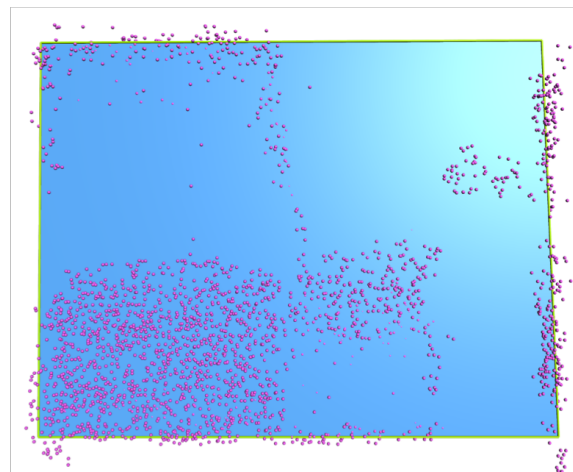
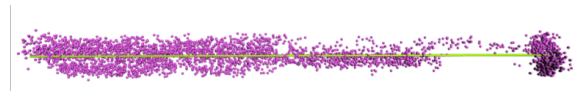
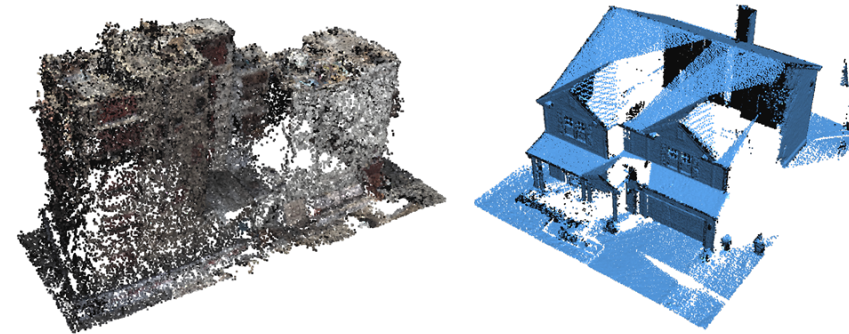
$$E_m = \frac{1}{|E|} \sum_{i=1}^{|E|} \text{corner}(e_i)$$



Intersecting two faces

Polygonal Surface Reconstruction

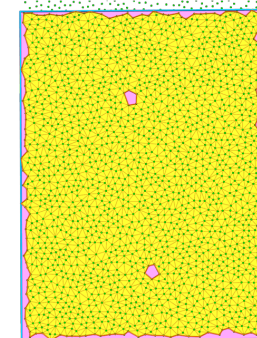
- Objective Function
 - Data fitting
 - Model complexity
 - Point coverage



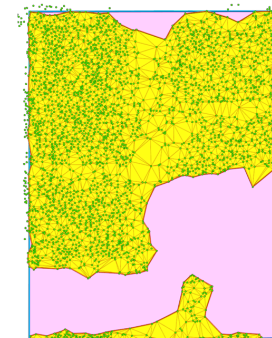
Polygonal Surface Reconstruction

- Objective Function
 - Data fitting
 - Model complexity
 - Point coverage

$$E_c = \frac{1}{\text{area}(M)} \sum_{i=1}^N x_i \cdot (\text{area}(f_i) - \text{area}(M_i^\alpha)),$$



0.93



0.65

Polygonal Surface Reconstruction

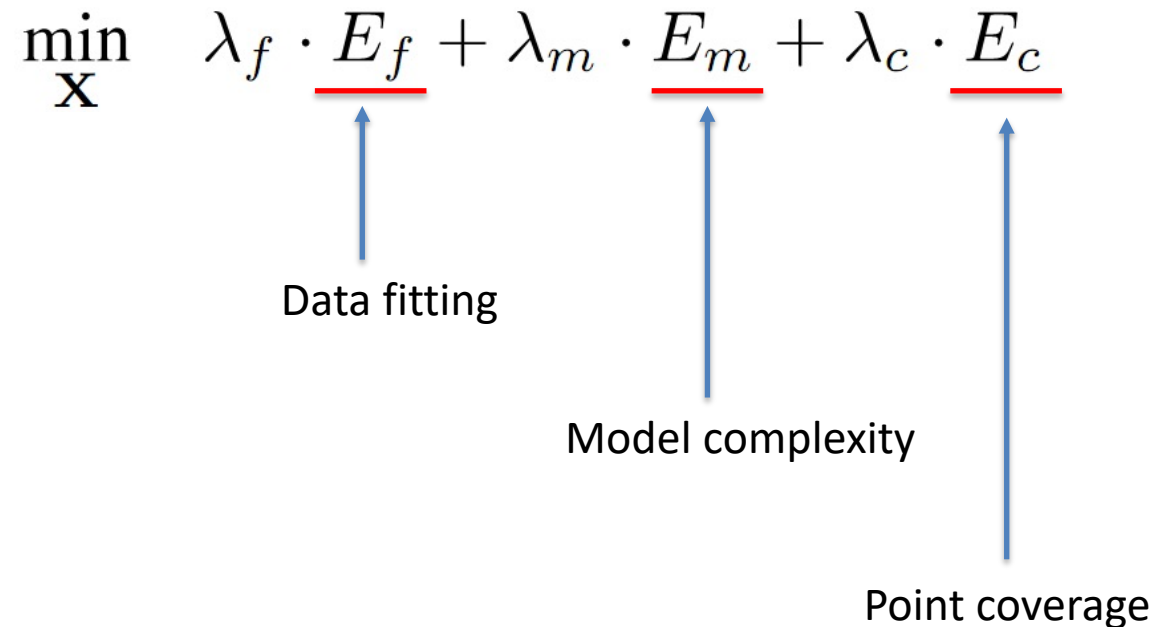
- Face Selection
 - Linear integer program

$$\min_{\mathbf{X}} \quad \lambda_f \cdot \underline{E_f} + \lambda_m \cdot \underline{E_m} + \lambda_c \cdot \underline{E_c}$$

Data fitting

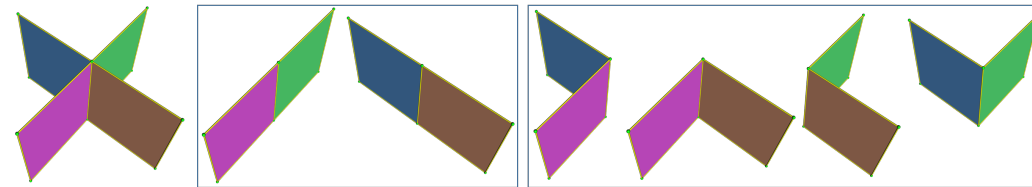
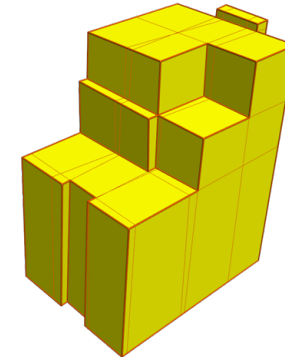
Model complexity

Point coverage

The diagram shows the objective function $\min_{\mathbf{X}} \lambda_f \cdot \underline{E_f} + \lambda_m \cdot \underline{E_m} + \lambda_c \cdot \underline{E_c}$. Three blue arrows point upwards from labels below to the underlined terms in the equation: 'Data fitting' points to $\underline{E_f}$, 'Model complexity' points to $\underline{E_m}$, and 'Point coverage' points to $\underline{E_c}$.

Polygonal Surface Reconstruction

- Face Selection
 - Linear integer program
 - Constraints
 - Watertight
 - Manifold



$$\min_{\mathbf{X}} \lambda_f \cdot E_f + \lambda_m \cdot E_m + \lambda_c \cdot E_c$$

$$\text{s.t.} \begin{cases} \sum_{j \in \mathcal{N}(e_i)} x_j = 2 \text{ or } 0, & 1 \leq i \leq |E| \\ x_i \in \{0, 1\}, & 1 \leq i \leq N \end{cases}$$

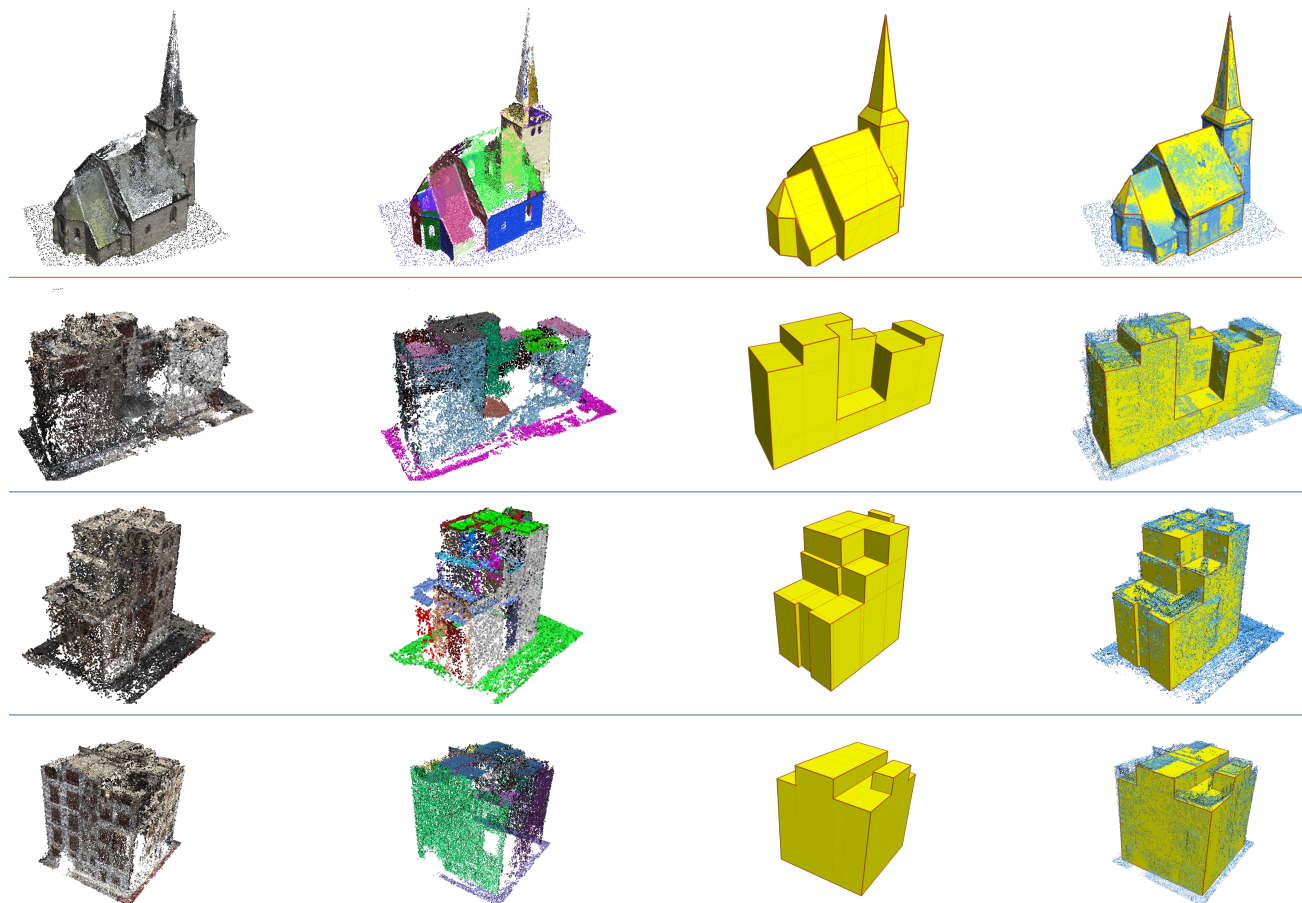
Polygonal Surface Reconstruction

- Face Selection
 - Linear integer program
 - Constraints
 - Solvers (SCIP, CBC, GLPK, Gurobi...)

$$\begin{aligned} \min_{\mathbf{x}} \quad & \lambda_f \cdot E_f + \lambda_m \cdot E_m + \lambda_c \cdot E_c \\ \text{s.t.} \quad & \begin{cases} \sum_{j \in \mathcal{N}(e_i)} x_j = 2 \quad \text{or} \quad 0, & 1 \leq i \leq |E| \\ x_i \in \{0, 1\}, & 1 \leq i \leq N \end{cases} \end{aligned}$$

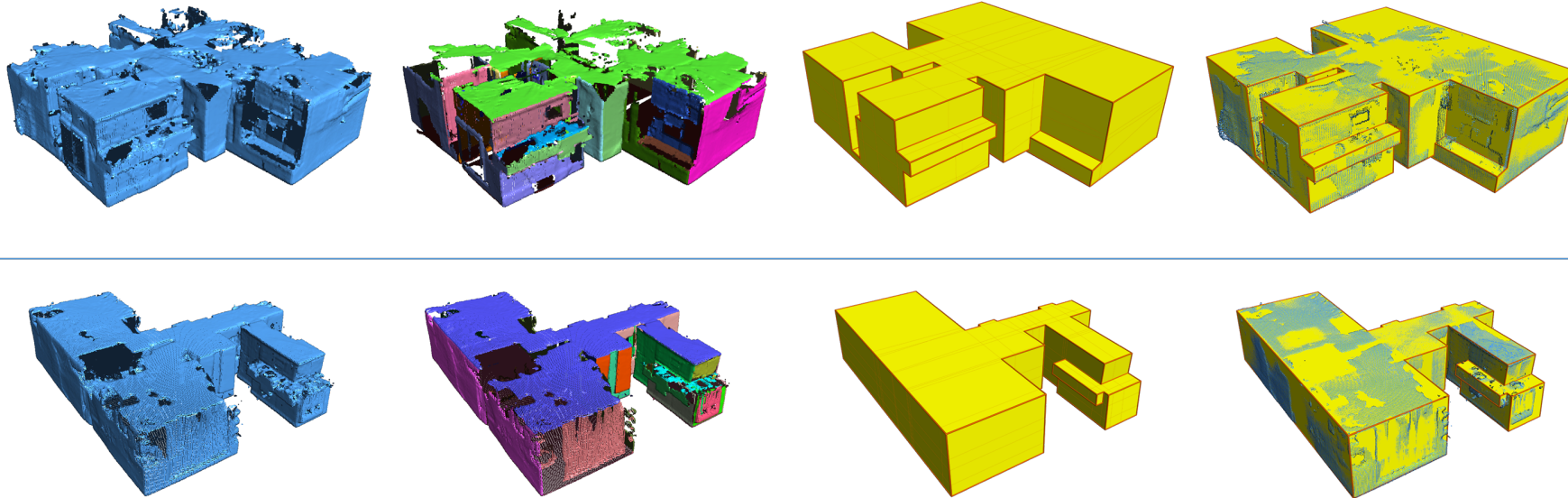
Polygonal Surface Reconstruction

- Reconstruction Results



Polygonal Surface Reconstruction

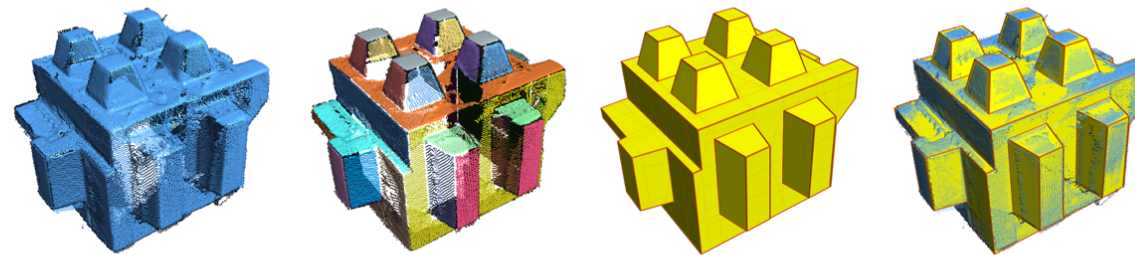
- Reconstruction Results



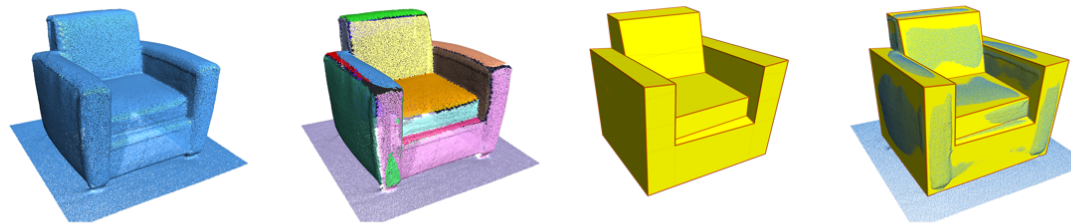
Piecewise Planar Reconstruction

- Reconstruction Results

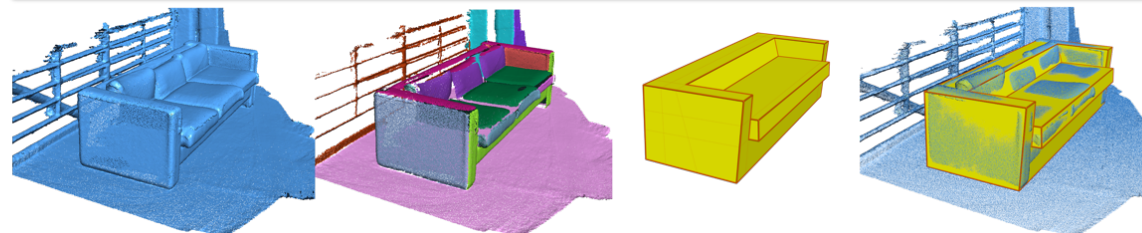
Packing foam box



Chair

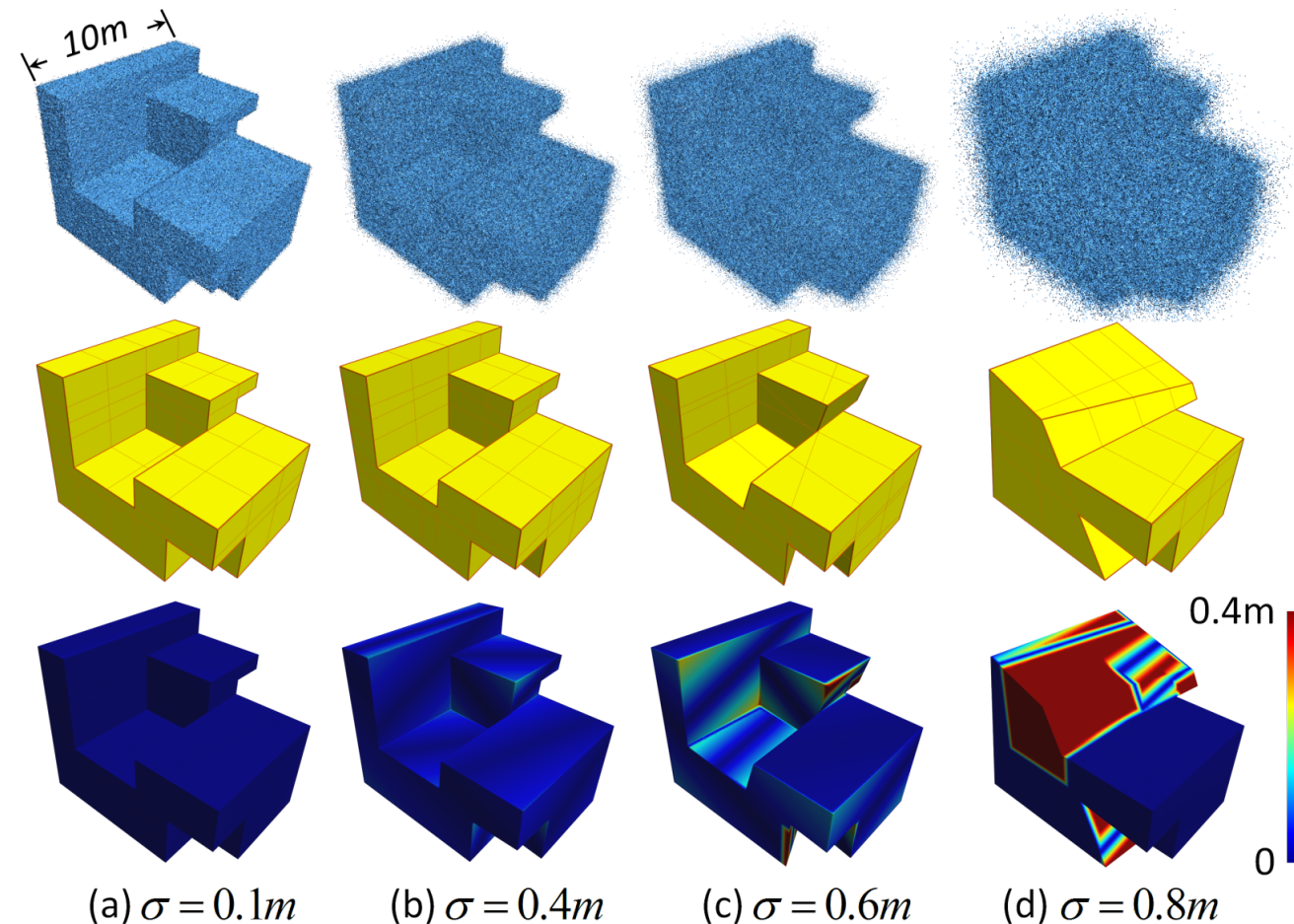


Sofa



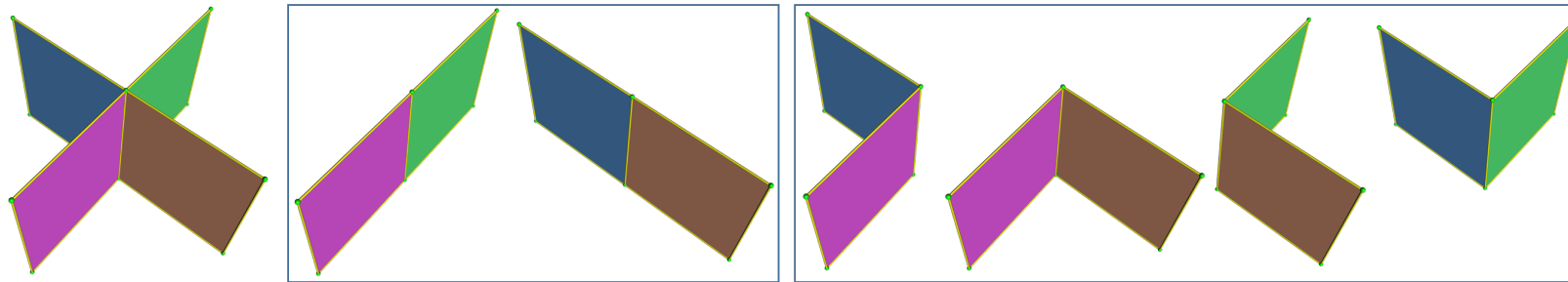
Piecewise Planar Reconstruction

- Robustness to noise



Limitations

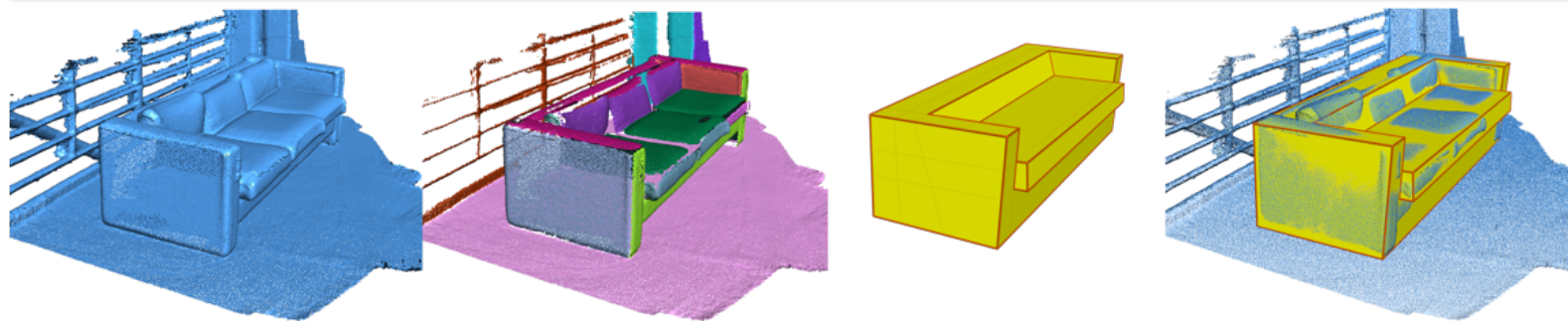
- Open surfaces



$$\text{s.t. } \begin{cases} \sum_{j \in \mathcal{N}(e_i)} x_j = 2 \text{ or } 0, & 1 \leq i \leq |E| \\ x_i \in \{0, 1\}, & 1 \leq i \leq N \end{cases}$$

Limitations

- Open surfaces



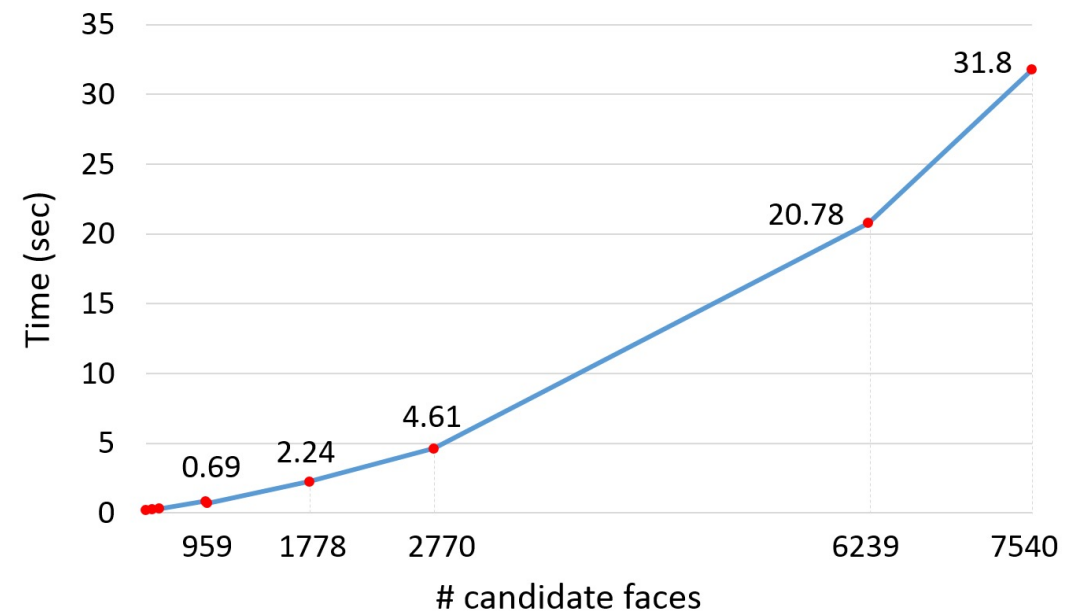
$$\text{s.t. } \begin{cases} \sum_{j \in \mathcal{N}(e_i)} x_j = 2 \text{ or } 0, & 1 \leq i \leq |E| \\ x_i \in \{0, 1\}, & 1 \leq i \leq N \end{cases}$$

Limitations

- Open surfaces
- Finer surface details
 - Fence
 - Façade decorations
 - Door handle
 - ...

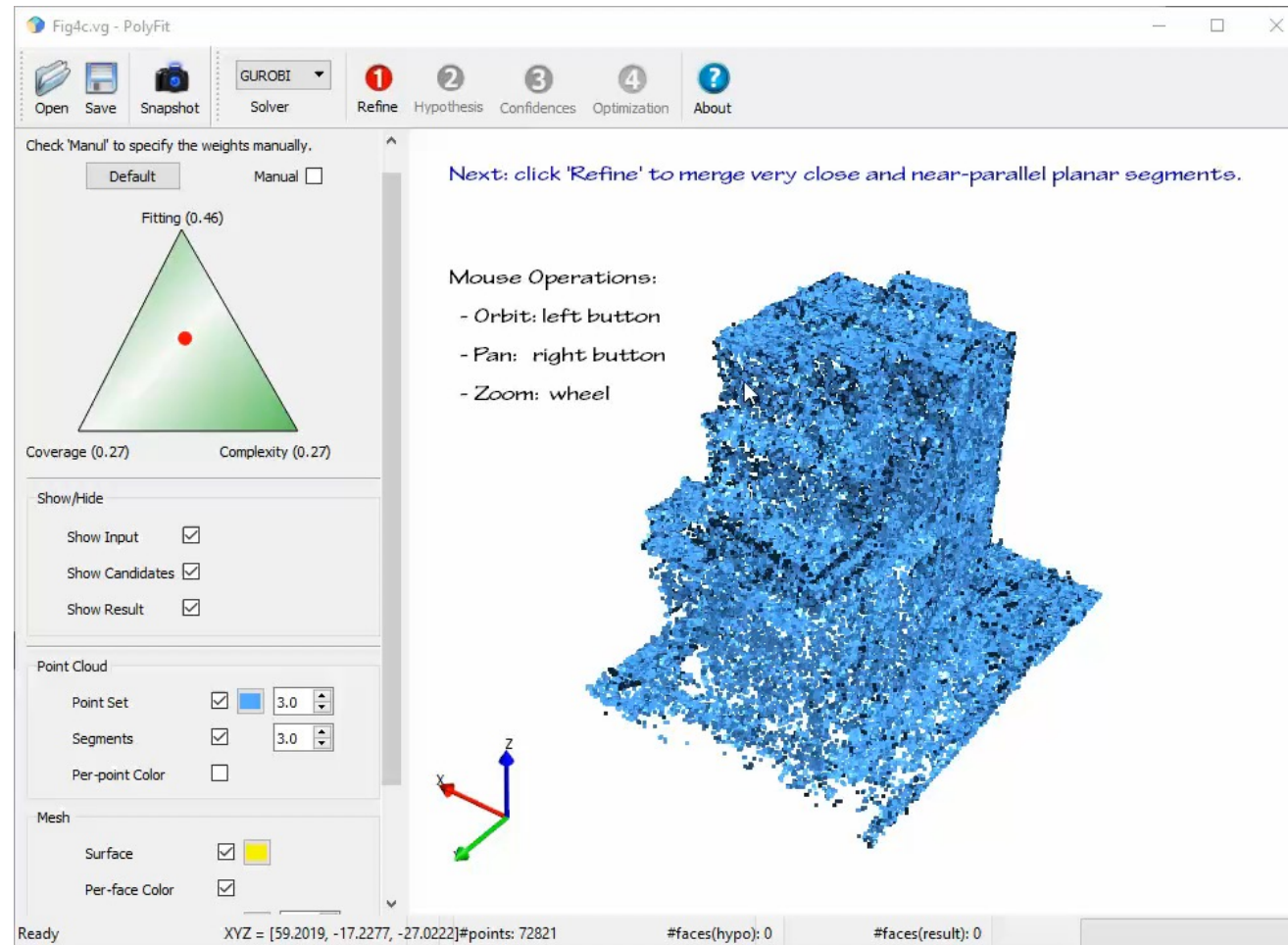
Limitations

- Open surfaces
- Finer surface details
- Complexity of the algorithm



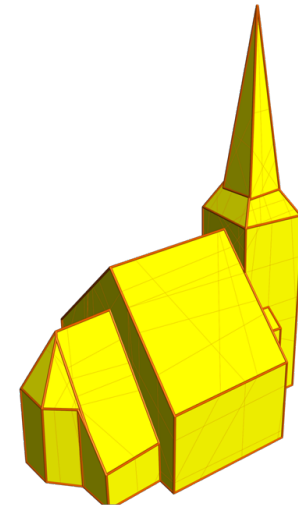
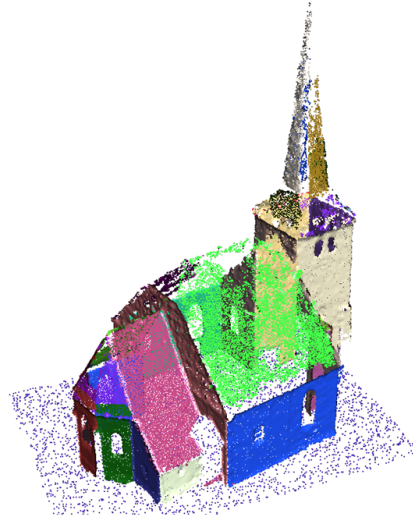
Polygonal Surface Reconstruction

- Demo



Source Code (in C++) <https://github.com/LiangliangNan/PolyFit>

Questions?



Next Lecture

- Machine learning for point cloud segmentation/classification

