CSC2547 3D & Geometric Deep Learning

Learning Delaunay Surface Elements for Mesh Reconstruction

Marie-Julie Rakotosanoa, Paul Guerrero, Noam Aigerman, Niloy Mitra, Maks Ovsjanikov

Date: 2021/3/15

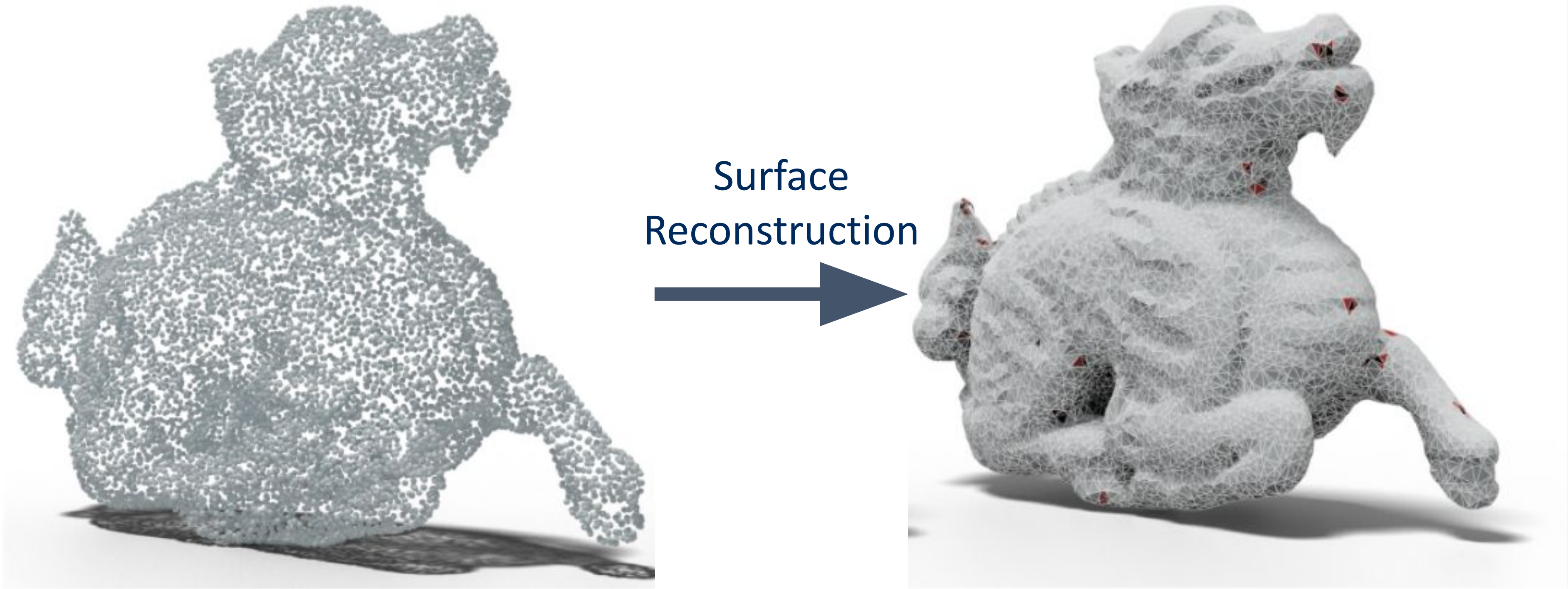
Presenter: Brendan Duke

Instructor: Animesh Garg

UNIVERSITY OF TORONTO

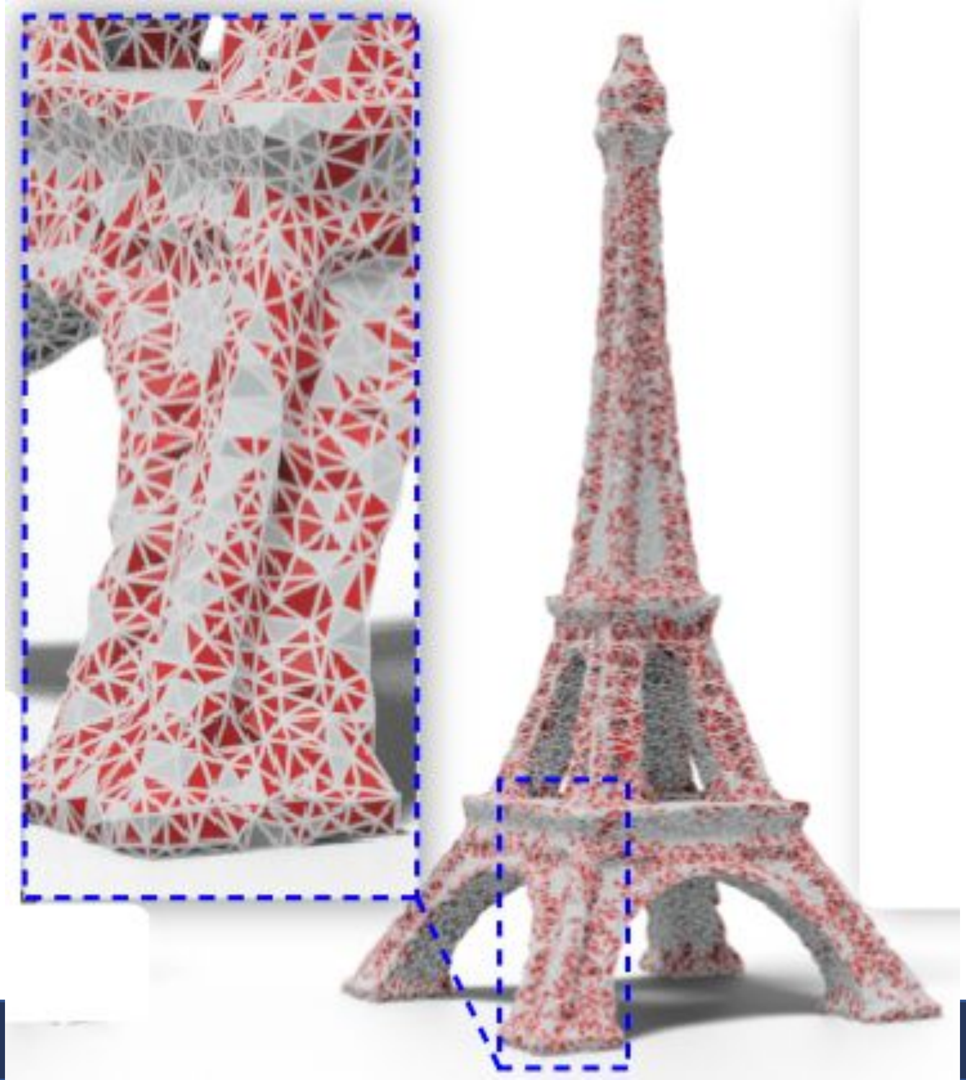
Main Problem

- Reconstructing triangle meshes from point clouds

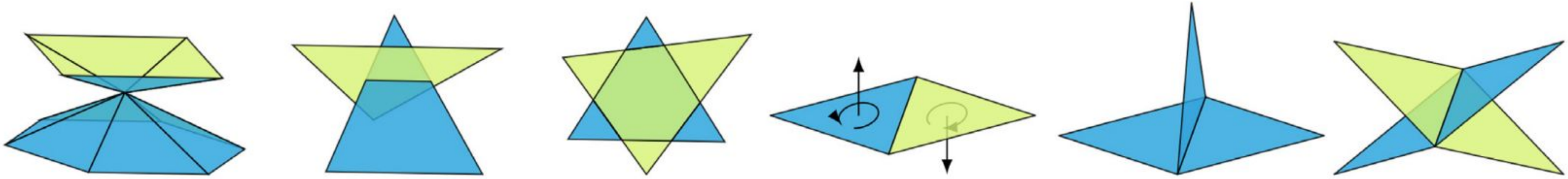


Challenges

- Detailed / thin surfaces
- Non-unformly sampled point clouds
- Manifoldness!

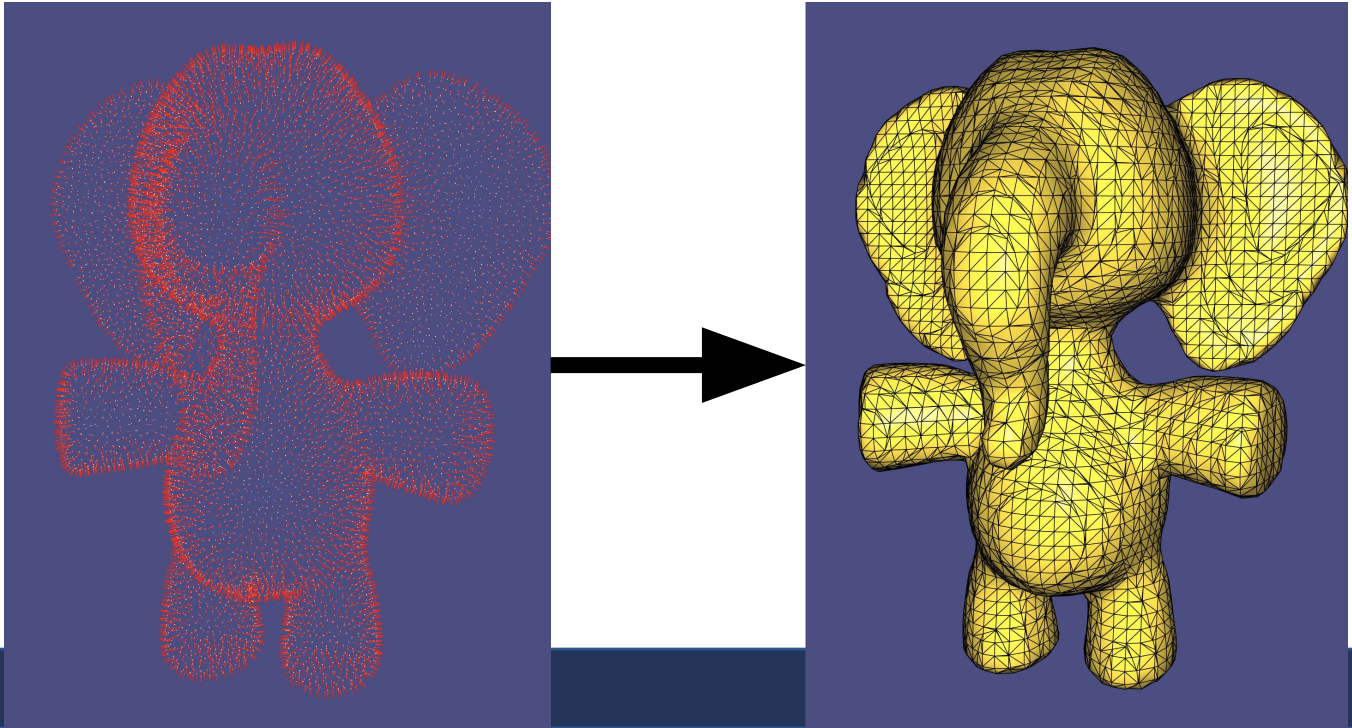


Challenges: Manifoldness

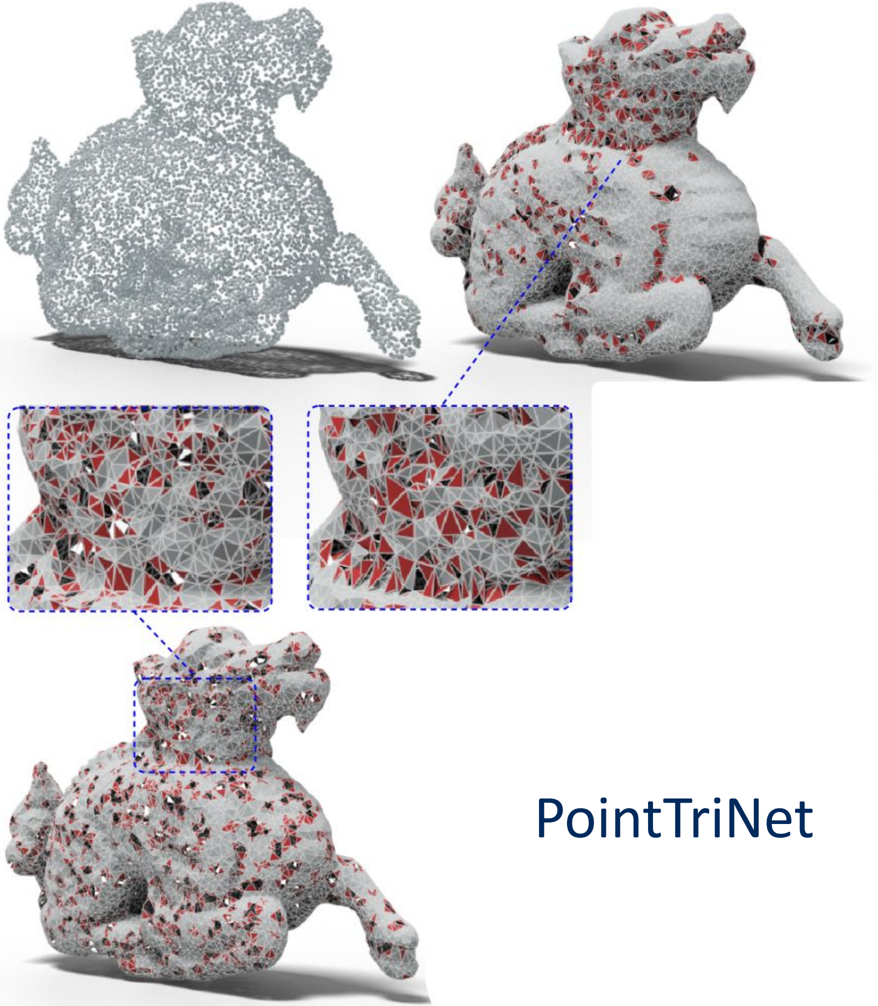


Prior Work

- Oriented normals -> Poisson surface reconstruction -> Marching Cubes



Prior Work



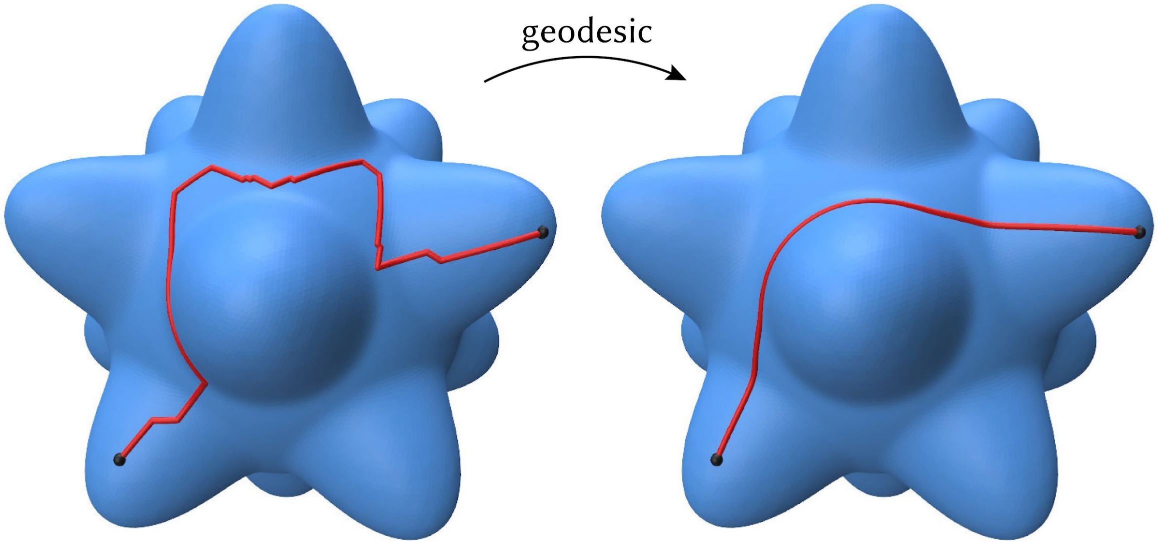
IER: Meshing Point Clouds with Intrinsic-Extrinsic Ratio Guidance

PointTriNet

Contributions

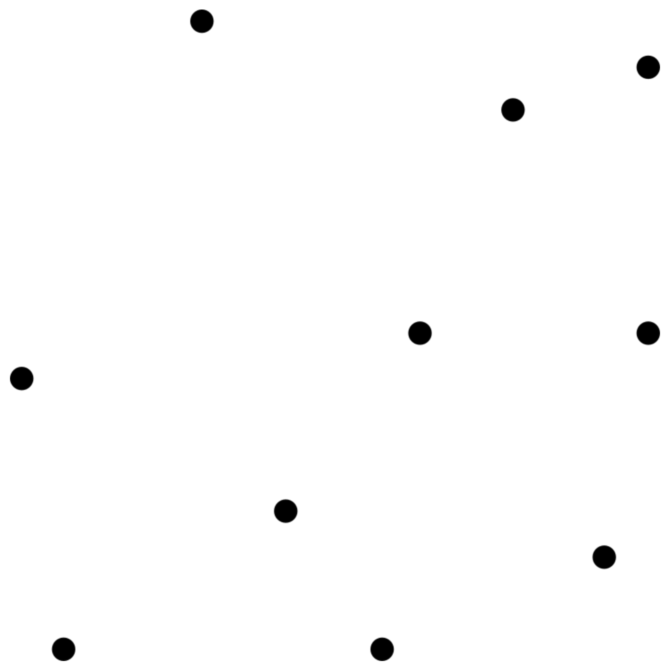
- Combine classic methods with learning-based data priors
- Core idea: combine Delaunay triangulations and learned log maps
- Delaunay triangulations are guaranteed manifold
- Log maps parametrize complex geometry

General Background: Geodesics

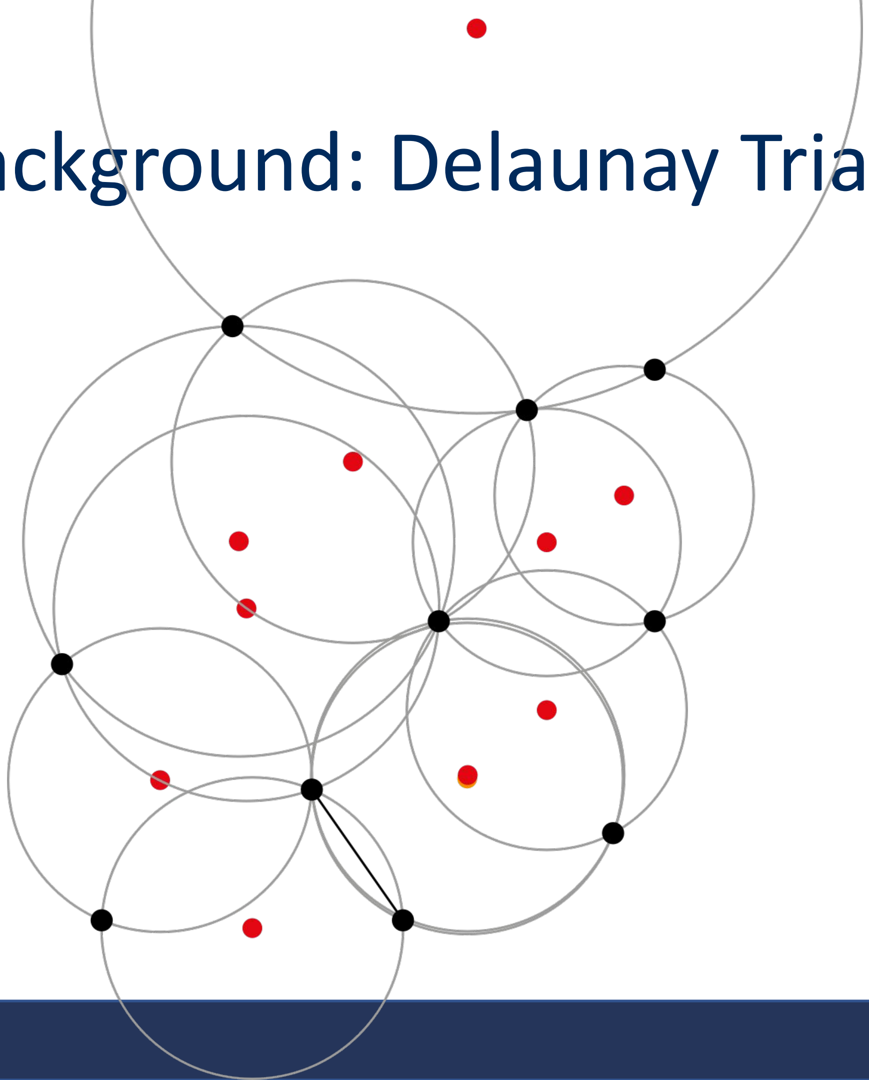


- Geodesics connect two points along a shortest path on the surface

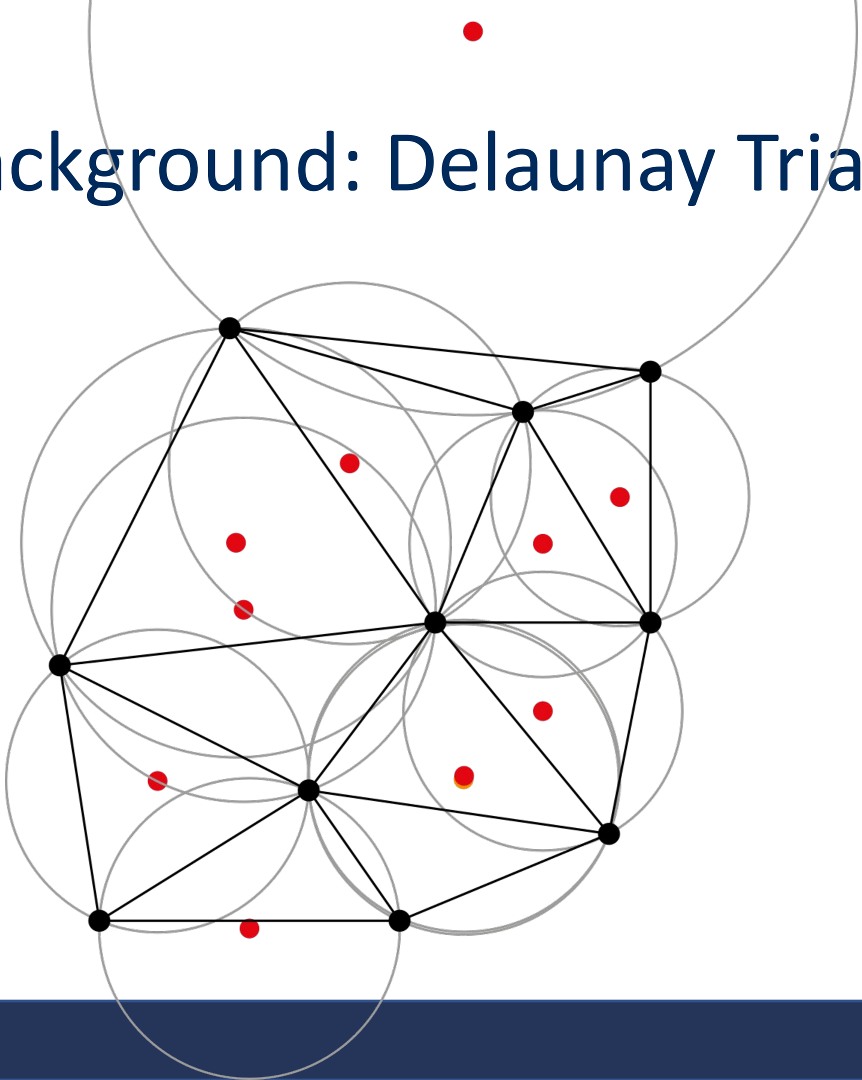
General Background: Delaunay Triangulation



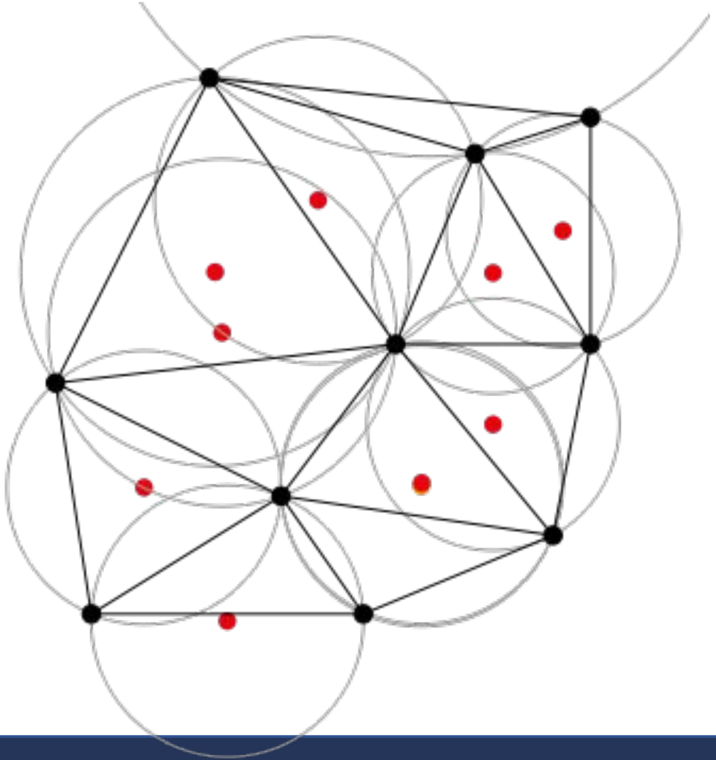
General Background: Delaunay Triangulation

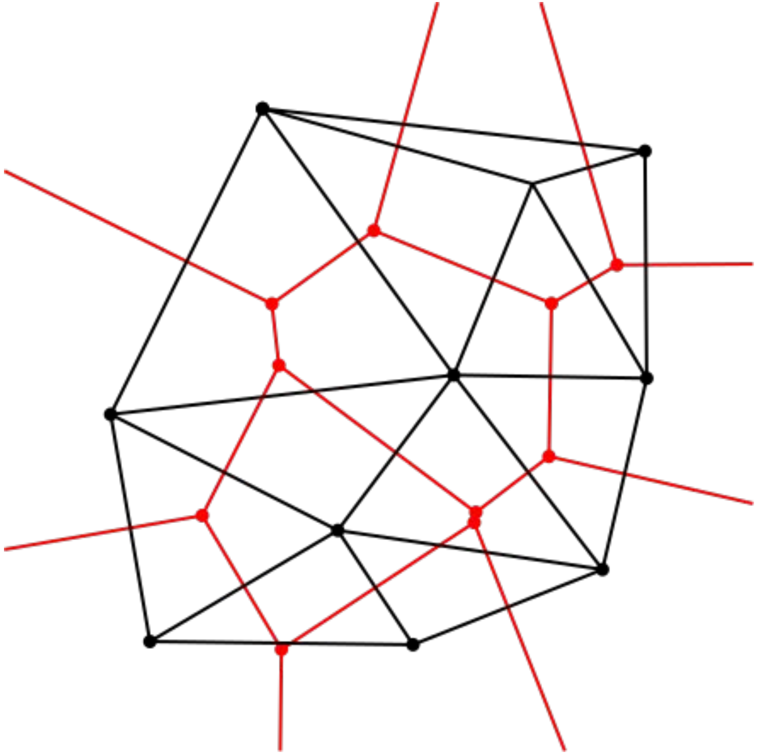


General Background: Delaunay Triangulation

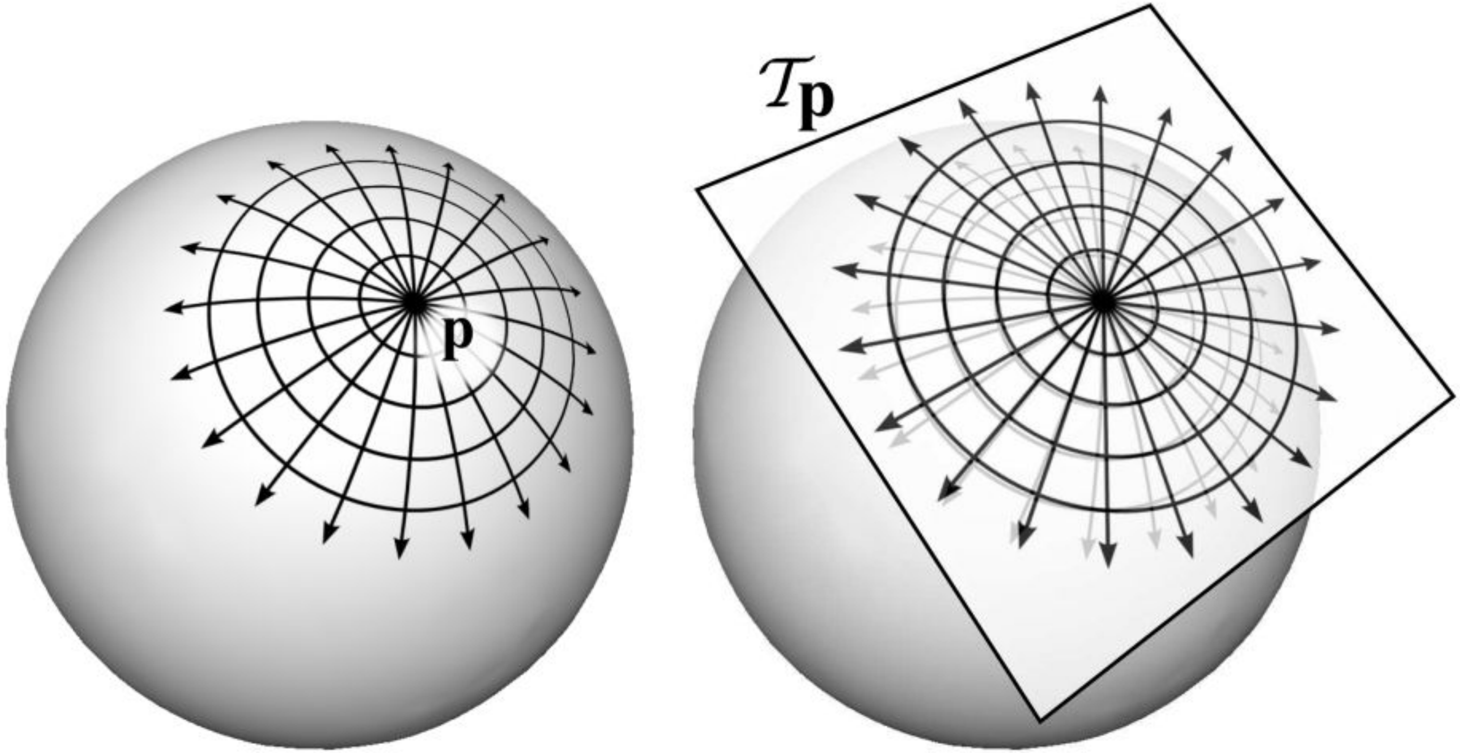


General Background: Delaunay Triangulation

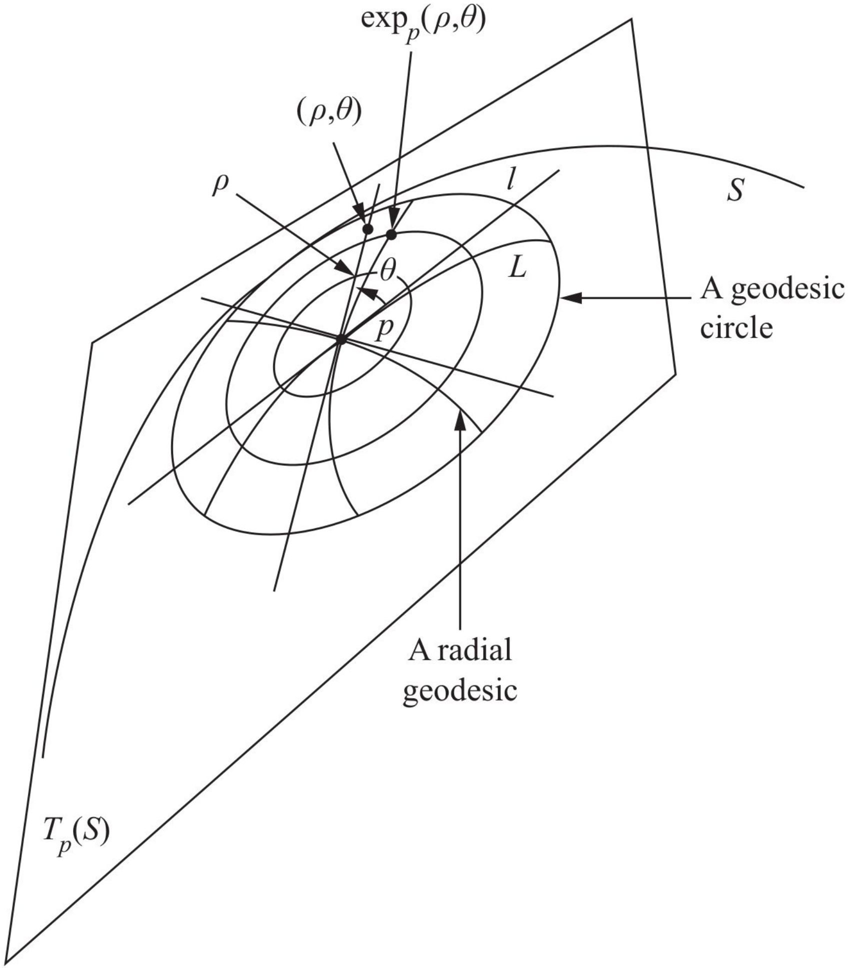




General Background: Log Maps



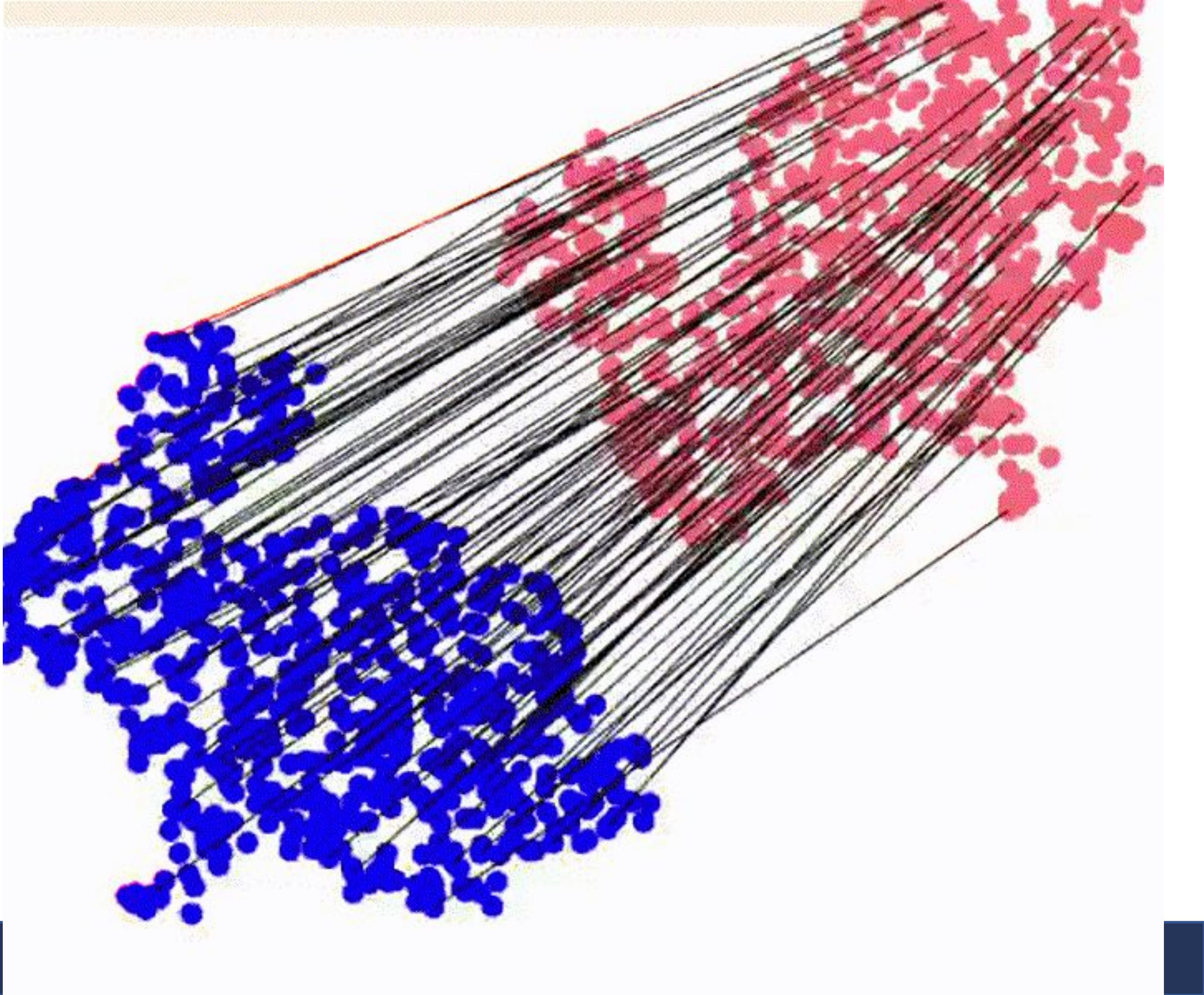
General Background: Log Maps



General Background: Kabsch Algorithm

For corresponding point clouds

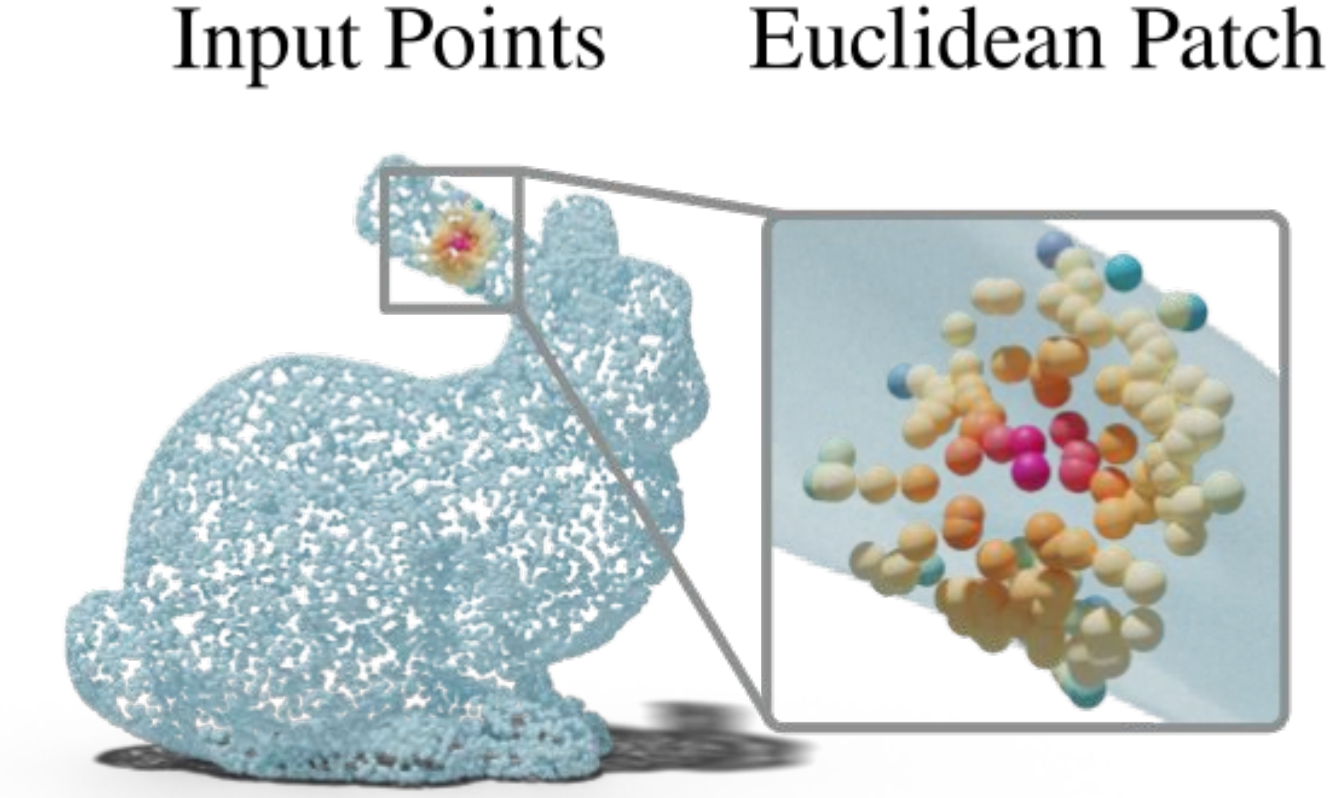
1. Translation
2. Covariance matrix
3. Optimal rotation via SVD



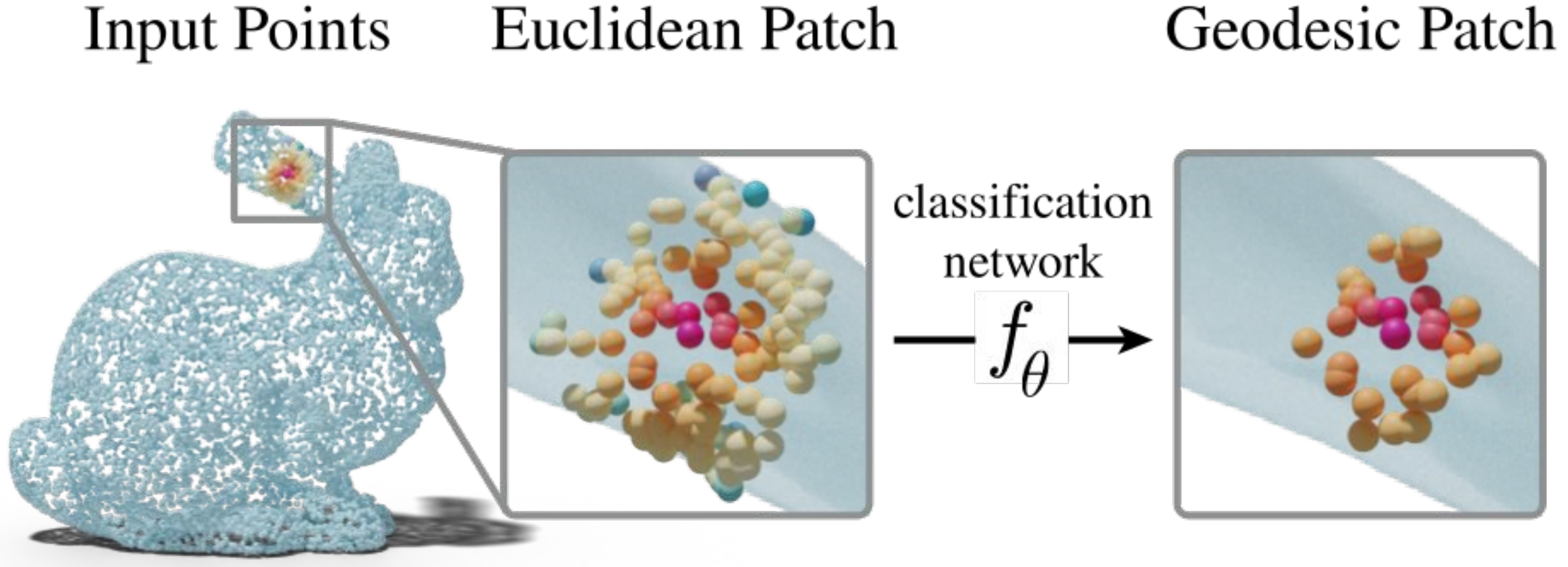
Approach: Overview

1. For each point extract a geodesic patch
2. Projection to log map (2D embedding of the patch)
3. Align log map embeddings
4. Delaunay triangulation ---> Delaunay Surface Element (DSE)
5. DSEs vote for candidate triangles ---> mesh

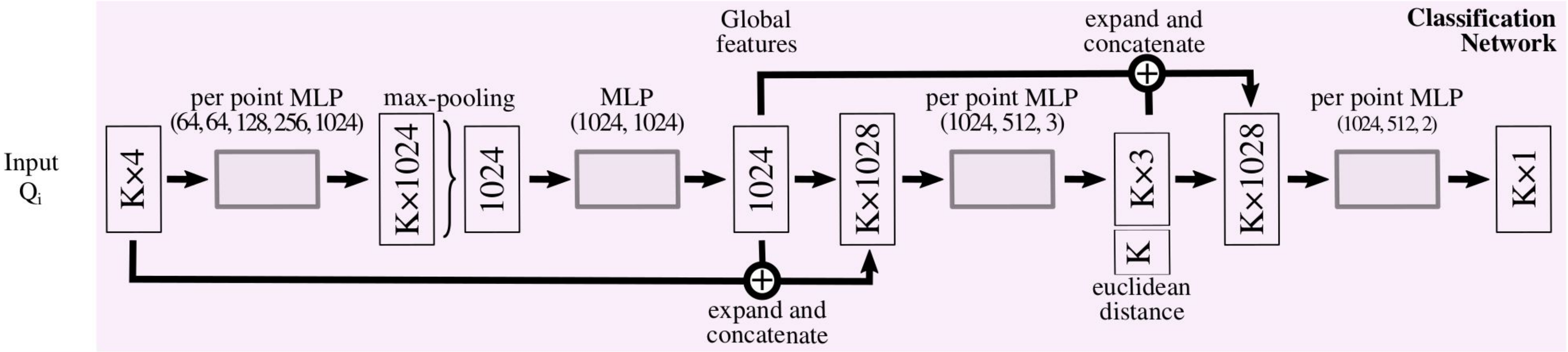
Approach: Pipeline



Approach: Pipeline

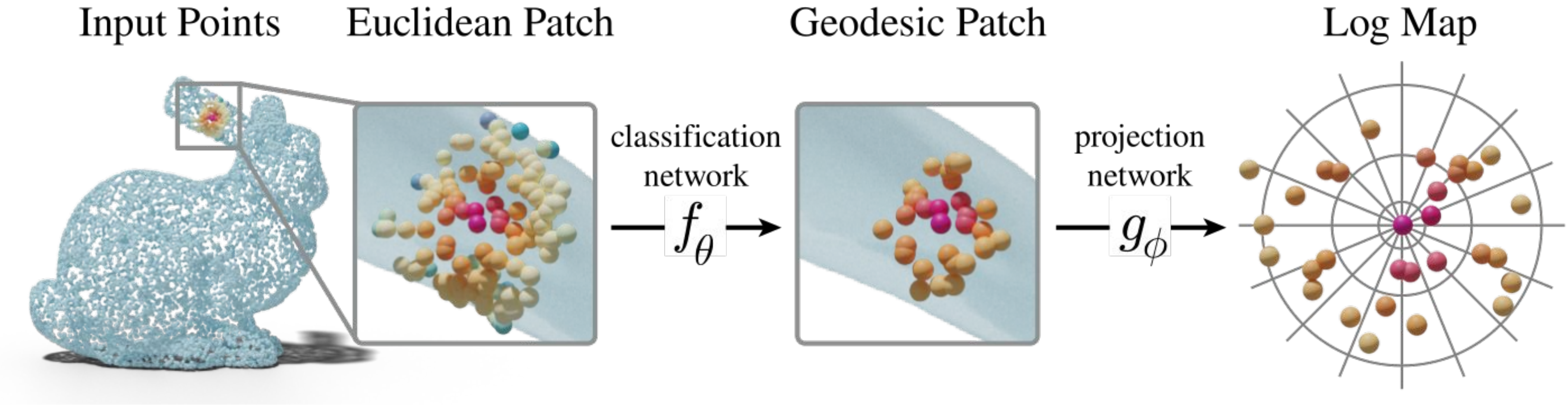


Approach: Geodesic Classification



FoldingNet. Yang et al, 2018.

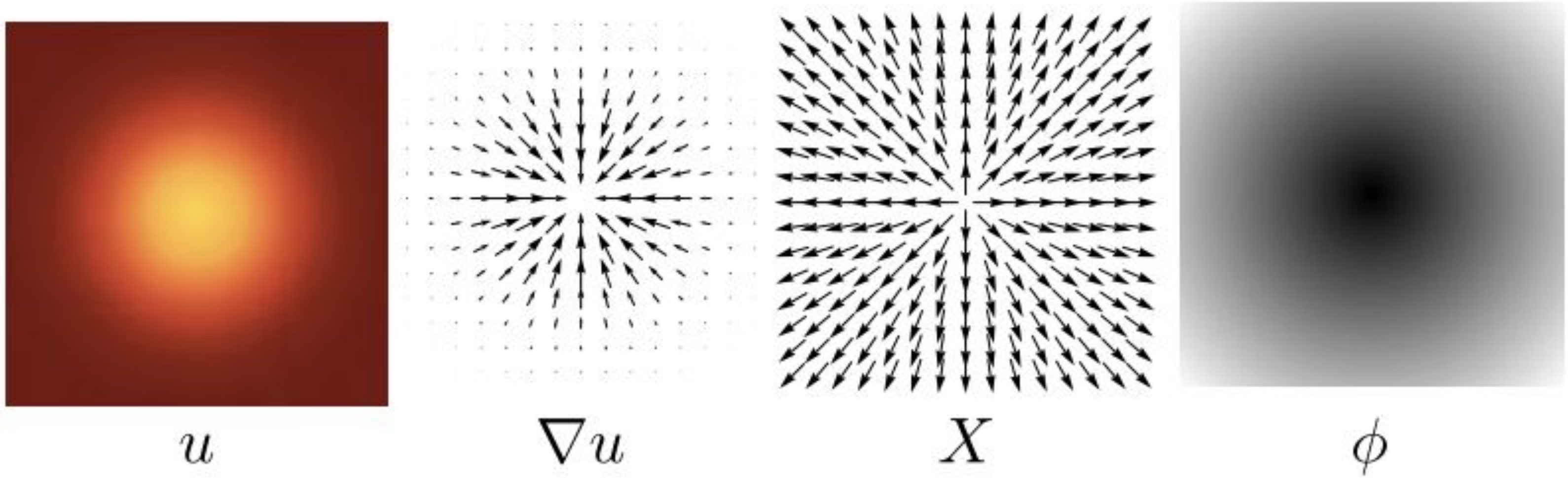
Approach: Pipeline



Approach: Ground Truth Log Maps

The Vector Heat Method. Sharp et al, 2020.

Approach: Vector Heat Method



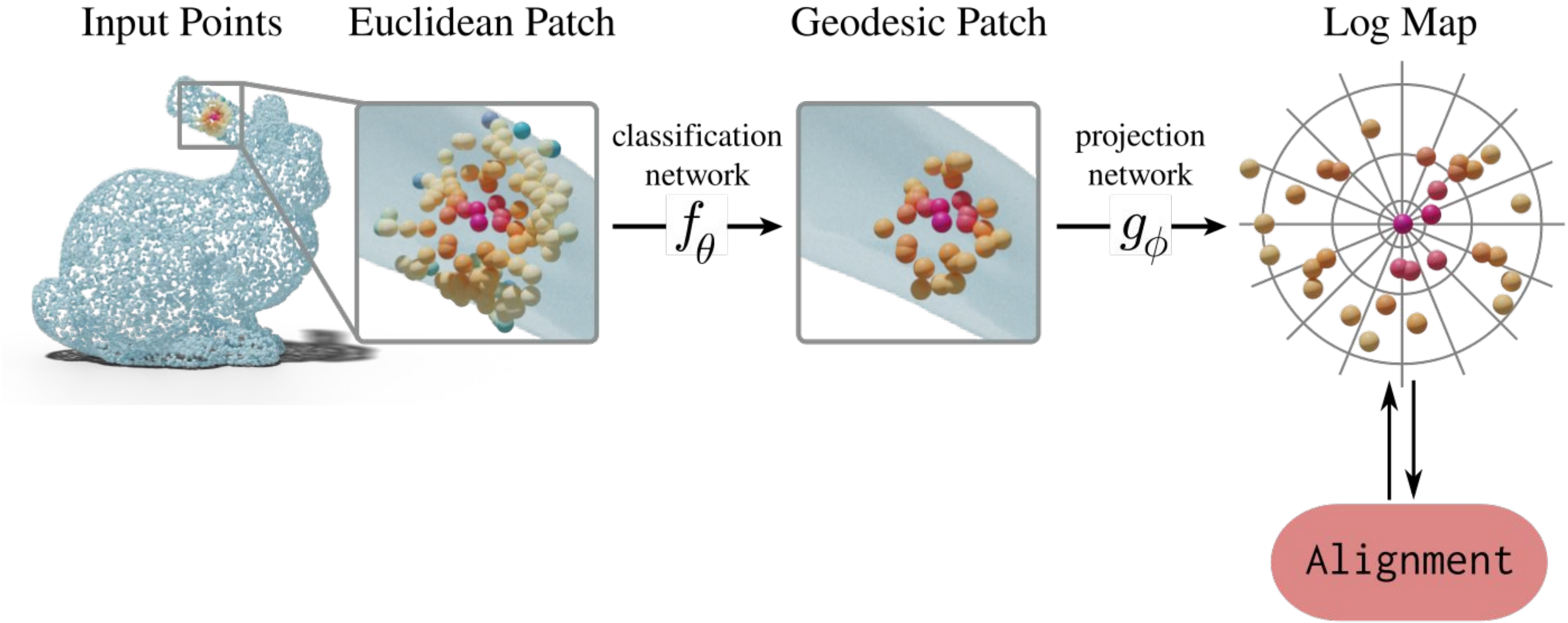
Algorithm 1 The Heat Method

I. Integrate the heat flow $\dot{u} = \Delta u$ for some fixed time t.

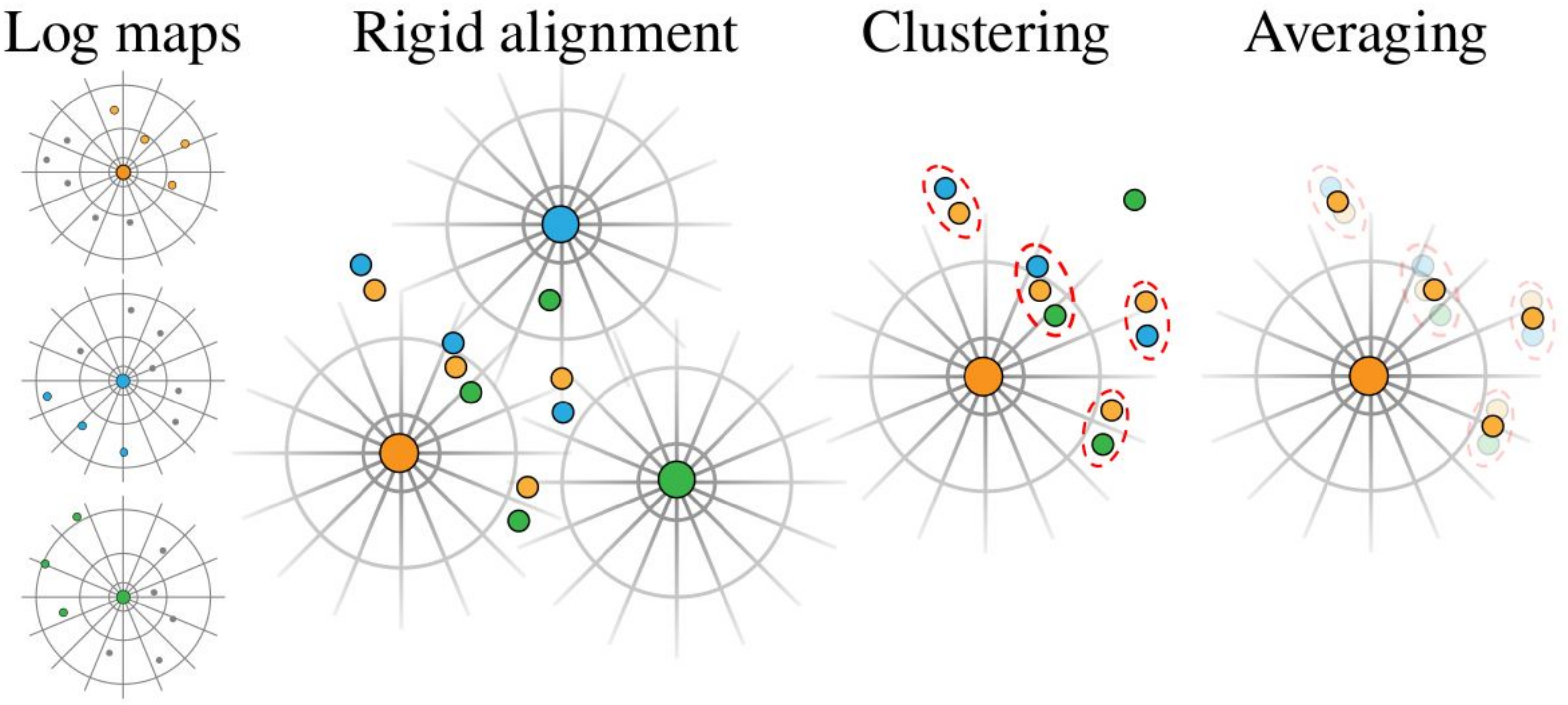
II. Evaluate the vector field $X = -\nabla u / |\nabla u|$.

III. Solve the Poisson equation $\Delta \phi = \nabla \cdot X$.

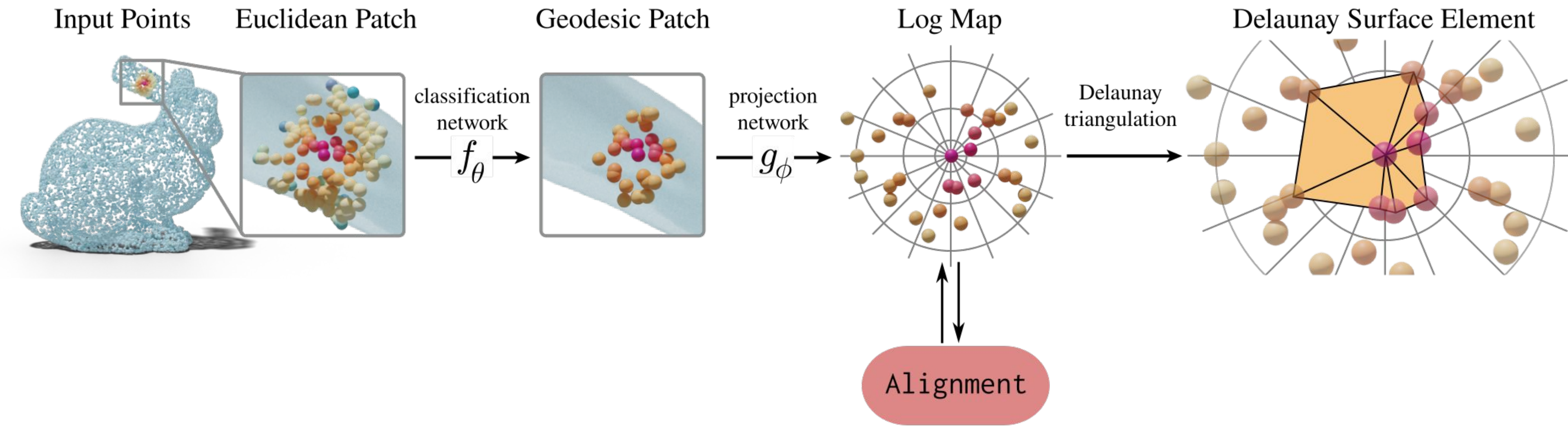
Approach: Pipeline



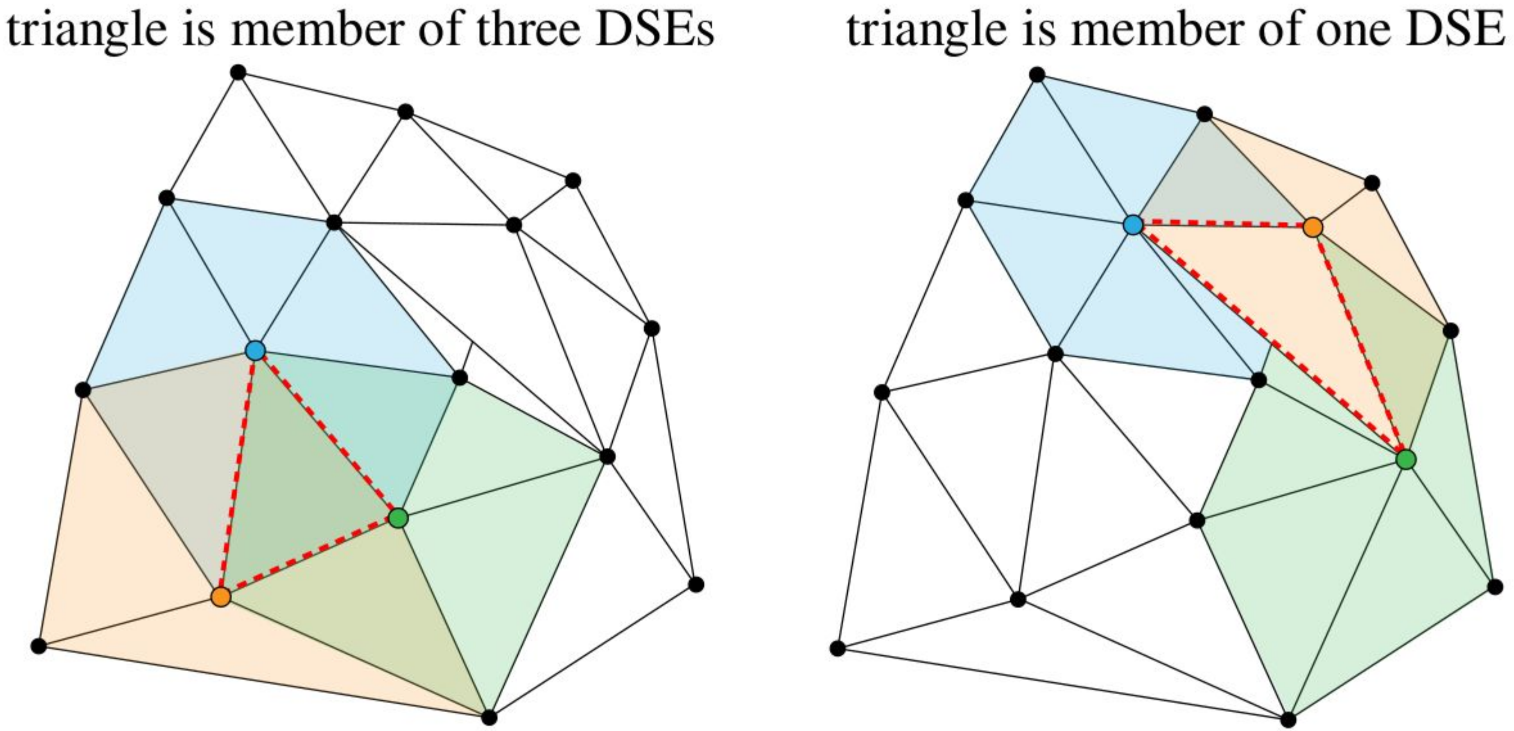
Approach: Log Map Alignment



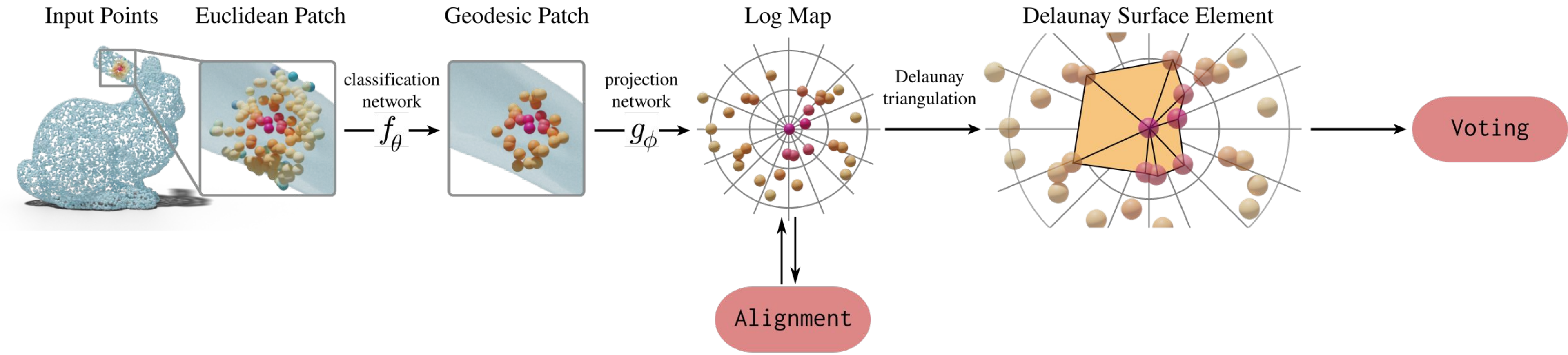
Approach: Pipeline



Approach: Triangle Voting

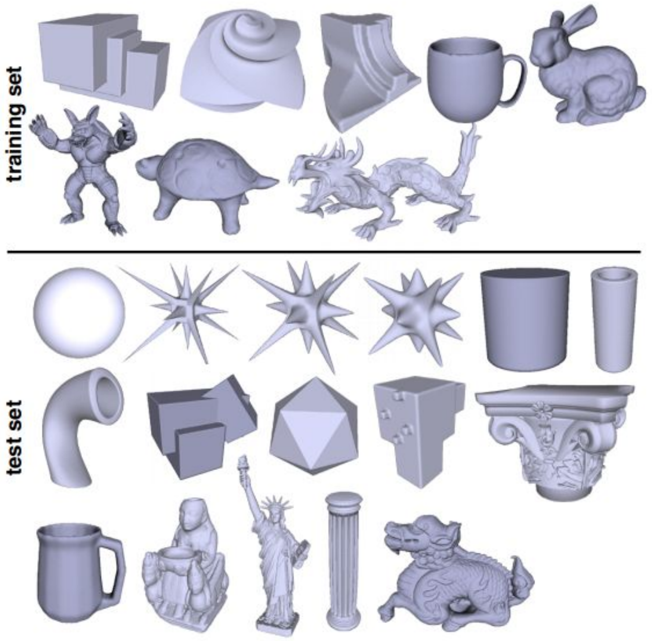


Approach: Pipeline



Experimental Setup: Datasets

Thingi10k



"FamousThingi"

Experimental Setup: Baselines

- Ball pivoting and Alpha shapes
  - Classic algorithms
  - “Roll a ball on the surface” to deduce connectivity
- Restricted Voronoi Estimation (RVE)
  - Estimate Voronoi regions by projecting to tangent planes
  - Closest to “Learning DSEs”
- PointTriNet and Intrinsic-Extrensic Ratio Guidance Meshing
  - Learning based methods

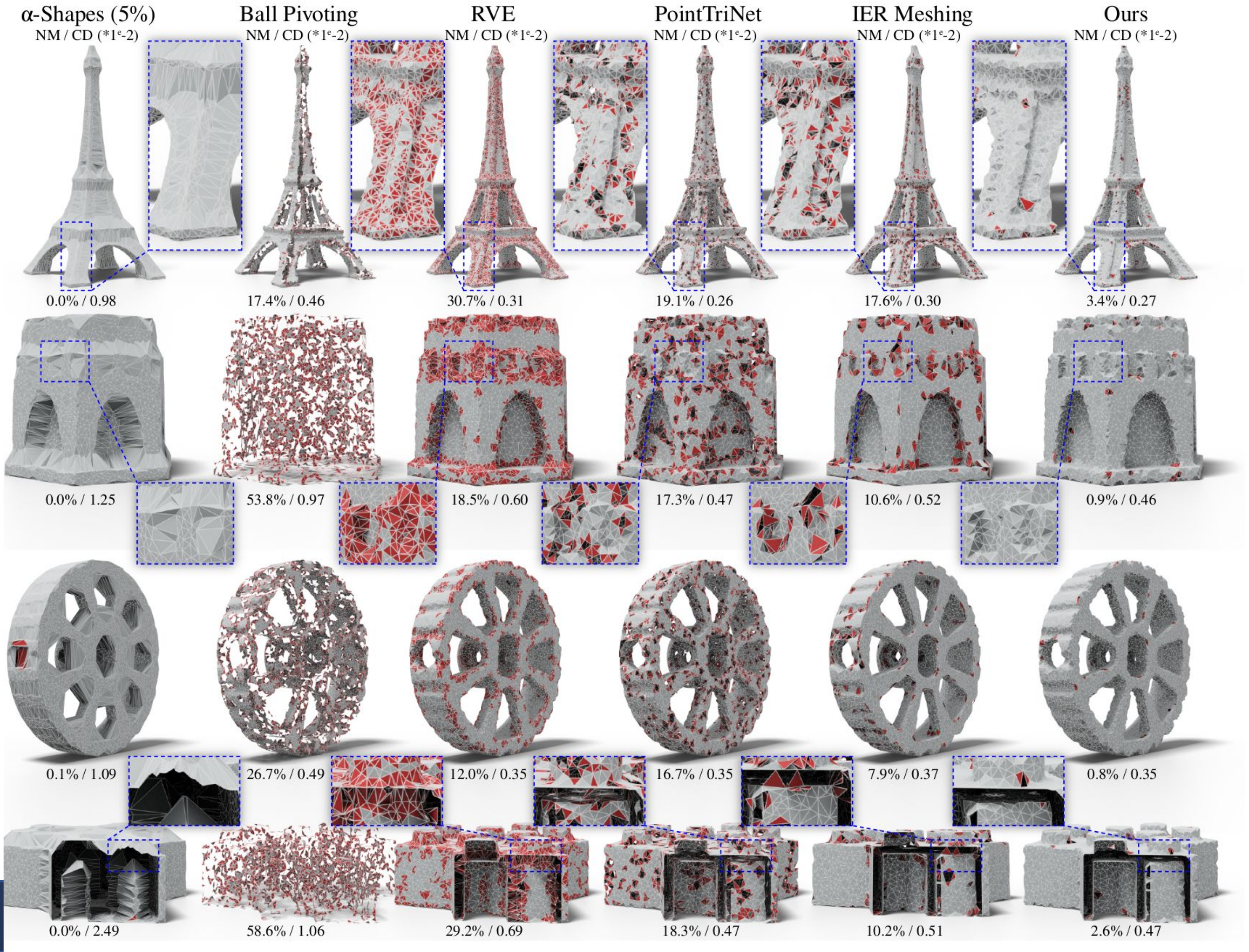
Experimental Setup: Metrics

- Chamfer Distance

$$\mathrm{CD}(P,Q) = \frac{1}{N}\sum_{p\in P}\min_{q\in Q}\|p-q\|_2 + \frac{1}{N}\sum_{q\in Q}\min_{p\in P}\|q-p\|_2$$

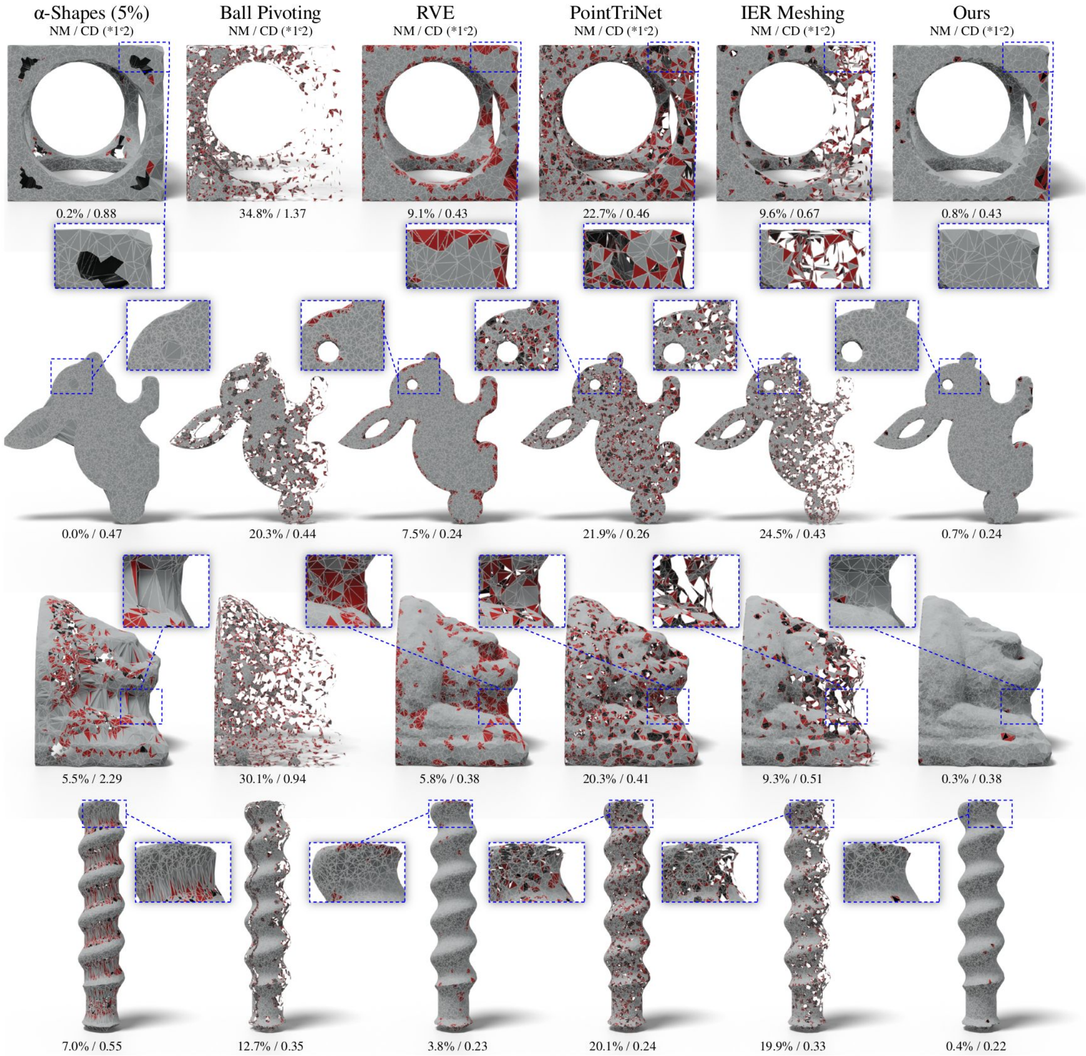
- Percentage of non-manifold triangles
- Standard deviation of triangle angles

Results


α-Shapes (5%)
NM / CD (*1e-2)
Ball Pivoting
NM / CD (*1e-2)
RVE
NM / CD (*1e-2)
PointTriNet
NM / CD (*1e-2)
IER Meshing
NM / CD (*1e-2)
Ours
NM / CD (*1e-2)
0.0% / 0.98
17.4% / 0.46
30.7% / 0.31
19.1% / 0.26
17.6% / 0.30
3.4% / 0.27
0.0% / 1.25
53.8% / 0.97
18.5% / 0.60
17.3% / 0.47
10.6% / 0.52
0.9% / 0.46
0.1% / 1.09
26.7% / 0.49
12.0% / 0.35
16.7% / 0.35
7.9% / 0.37
0.8% / 0.35
0.0% / 2.49
58.6% / 1.06
29.2% / 0.69
18.3% / 0.47
10.2% / 0.51
2.6% / 0.47

Results

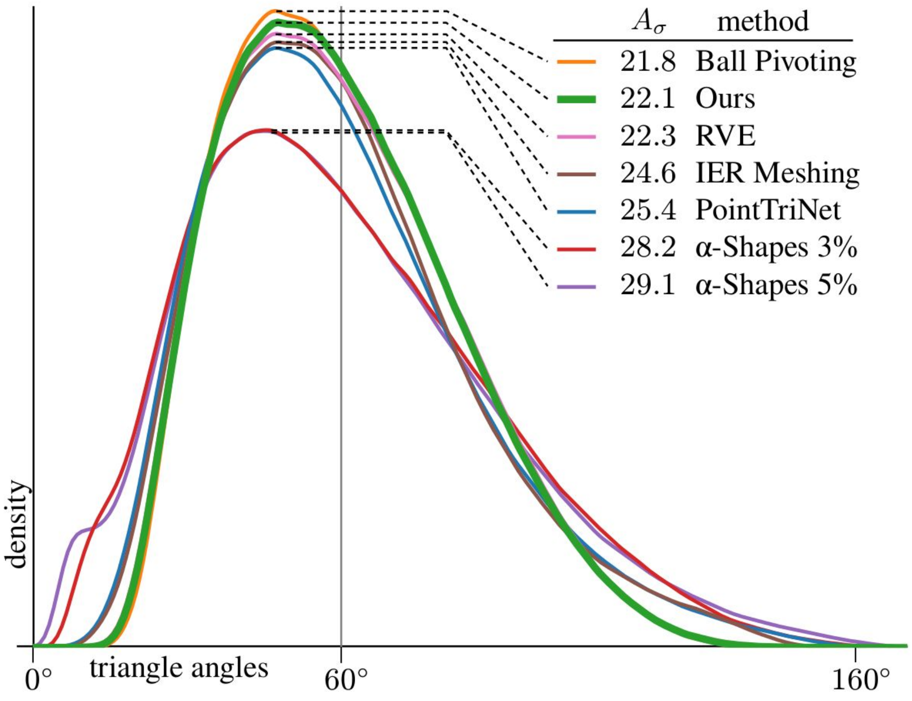
Results

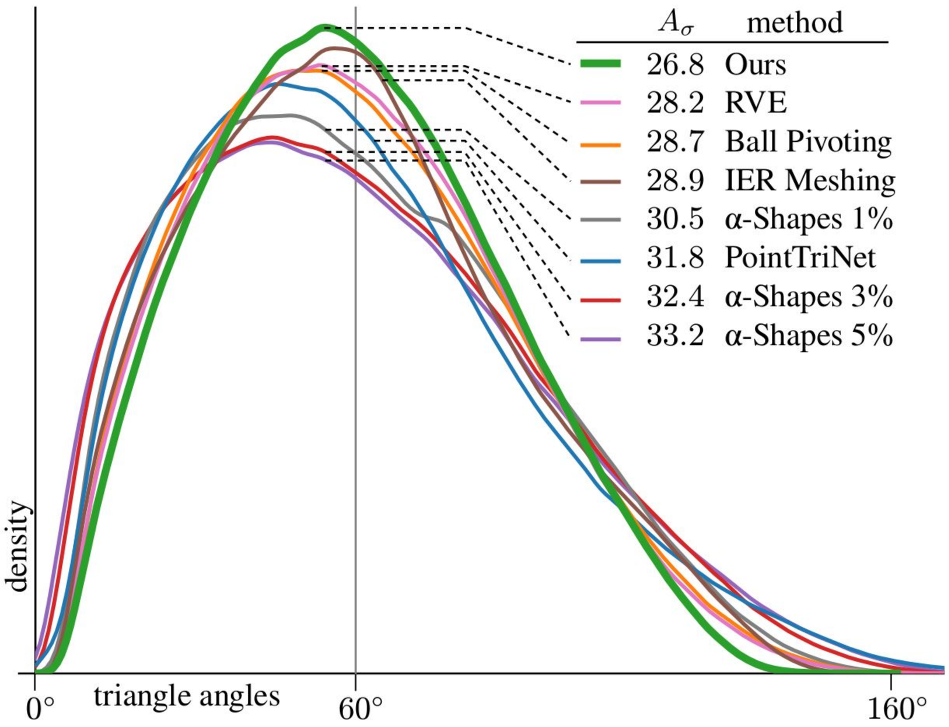

α-Shapes (5%)
NM / CD (*1e2)
Ball Pivoting
NM / CD (*1e2)
RVE
NM / CD (*1e2)
PointTriNet
NM / CD (*1e2)
IER Meshing
NM / CD (*1e2)
Ours
NM / CD (*1e2)
0.2% / 0.88
34.8% / 1.37
9.1% / 0.43
22.7% / 0.46
9.6% / 0.67
0.8% / 0.43
0.0% / 0.47
20.3% / 0.44
7.5% / 0.24
21.9% / 0.26
24.5% / 0.43
0.7% / 0.24
5.5% / 2.29
30.1% / 0.94
5.8% / 0.38
20.3% / 0.41
9.3% / 0.51
0.3% / 0.38
7.0% / 0.55
12.7% / 0.35
3.8% / 0.23
20.1% / 0.24
19.9% / 0.33
0.4% / 0.22

Results: Quantitative

Method	NM (%)	CD $*1^{e-2}$
ball pivoting	25.7	0.524
PointTriNet [41]	17.2	0.337
RVE [10]	9.2	0.344
IER meshing [33]	5.3	0.343
α-shapes 3%	2.5	0.939
α-shapes 5%	1.7	1.064
Ours	**0.9**	**0.328**

Results: Quantitative





Results: Quantitative

Method	NM (%)	CD $*1^{e-2}$
Ours w/o align, select	32.0	0.332
Ours w/o select	14.6	0.346
Ours w/o log maps	12.1	0.348
Ours w/o align	1.9	**0.328**
Ours	**0.9**	**0.328**

Limitations and Open Problems

- Dealing with noise?
- Missing direct comparison with Poisson surface reconstruction
- Learned triangle selection

Contributions (Recap)

- Combine classic methods with learning-based data priors
- Core idea: combine Delaunay triangulations and learned log maps
- Delaunay triangulations are guaranteed manifold
- Log maps parametrize complex geometry

Thank you!

Questions?

UNIVERSITY OF TORONTO