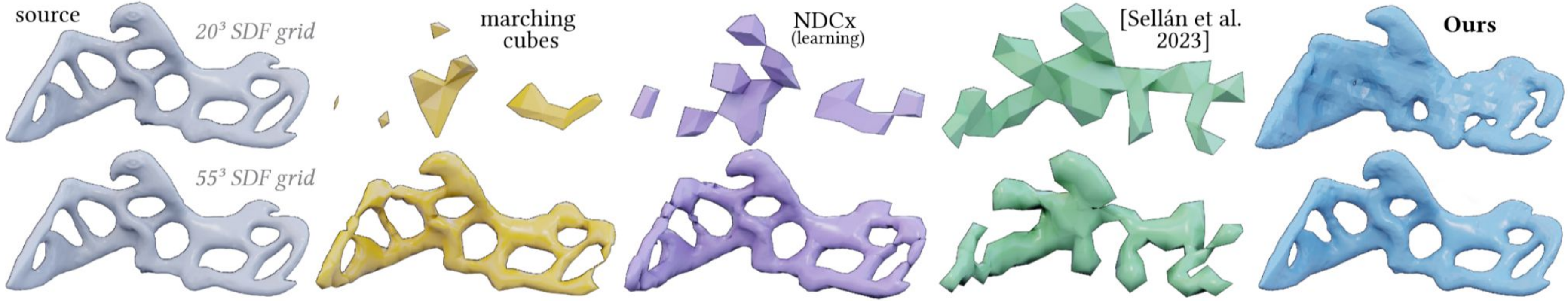
Reach for the Arcs: Reconstructing Surfaces from SDFs via Tangent Points

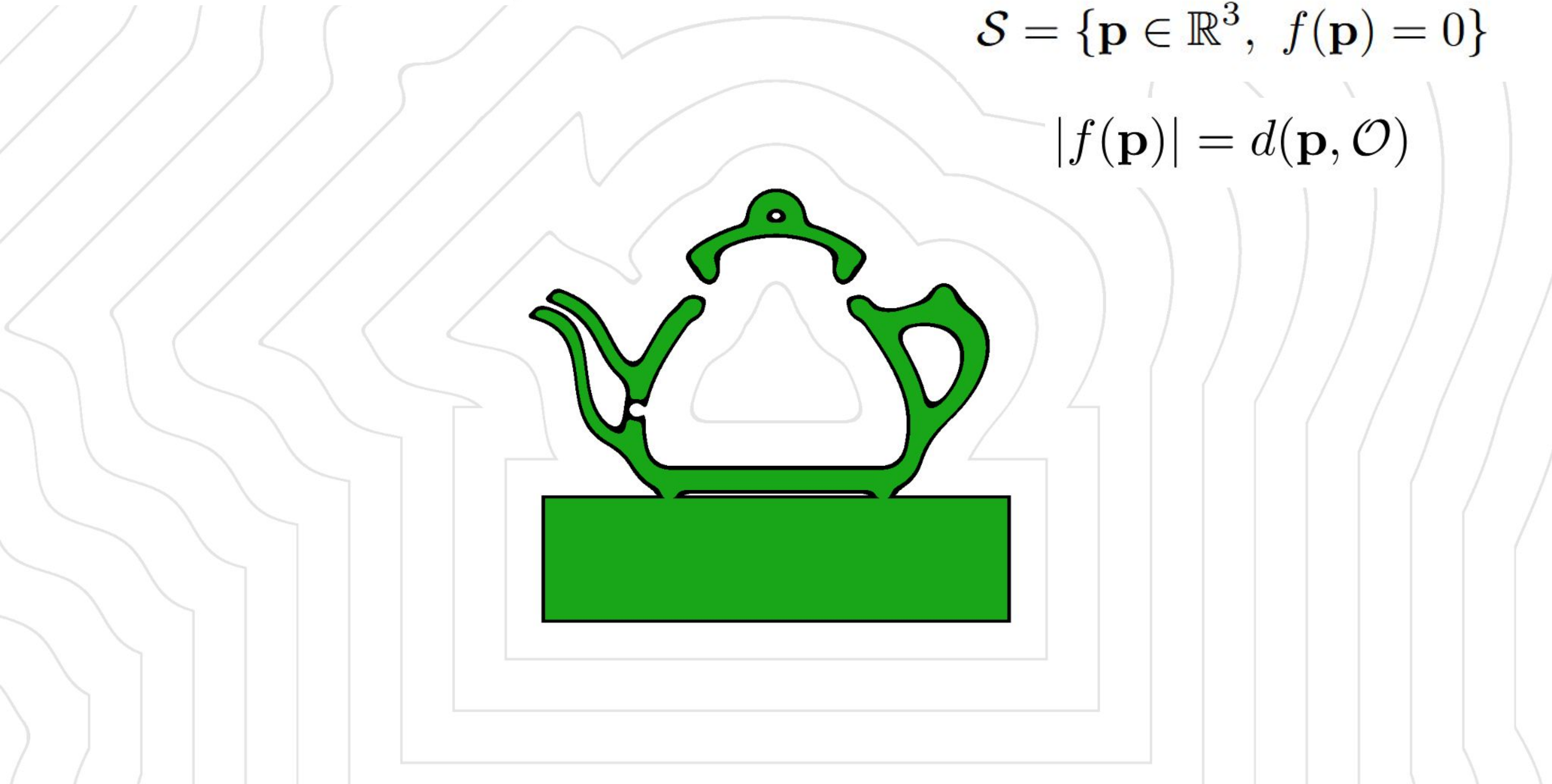


Silvia Sellán   Yingying Ren   Christopher Batty   Oded Stein

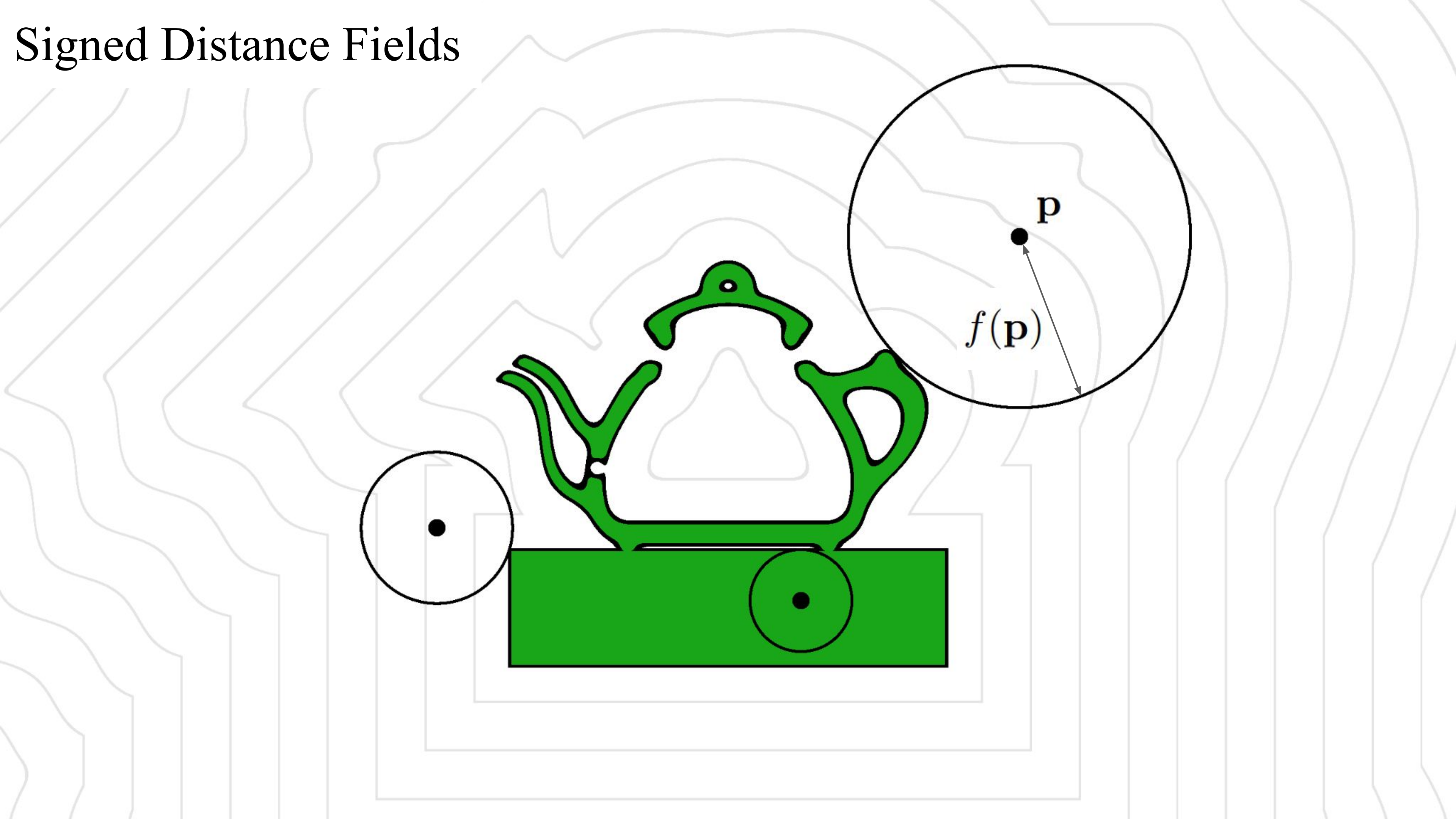
Signed Distance Fields

$$\mathcal{S} = \{\mathbf{p} \in \mathbb{R}^3,\ f(\mathbf{p}) = 0\}$$

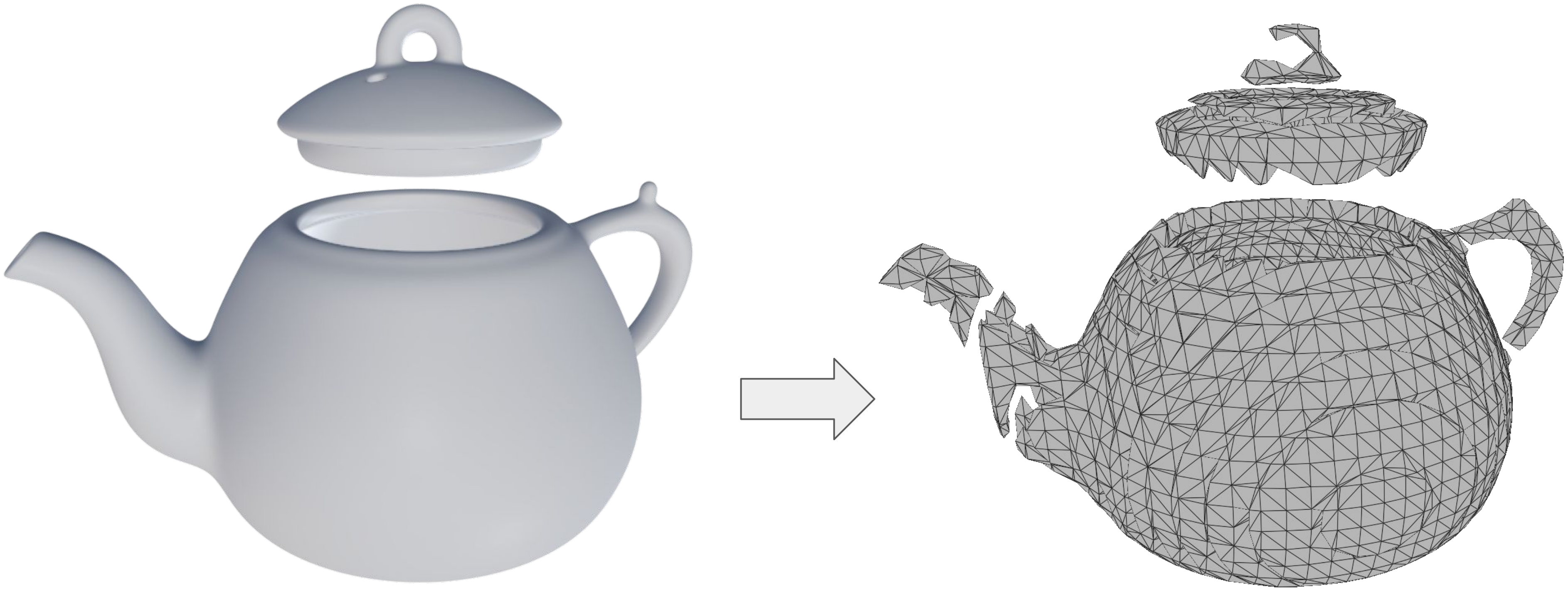
$$|f(\mathbf{p})| = d(\mathbf{p}, \mathcal{O})$$



Signed Distance Fields



Signed Distance Fields to Mesh



Surface reconstruction - Marching Cubes

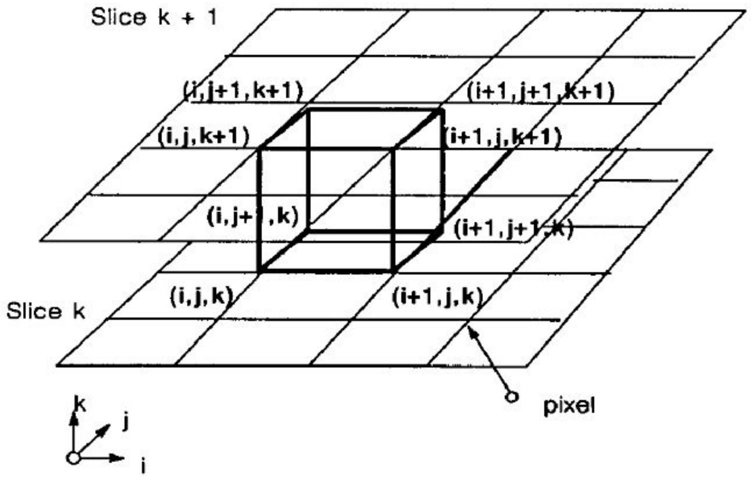


Figure 2. Marching Cube.

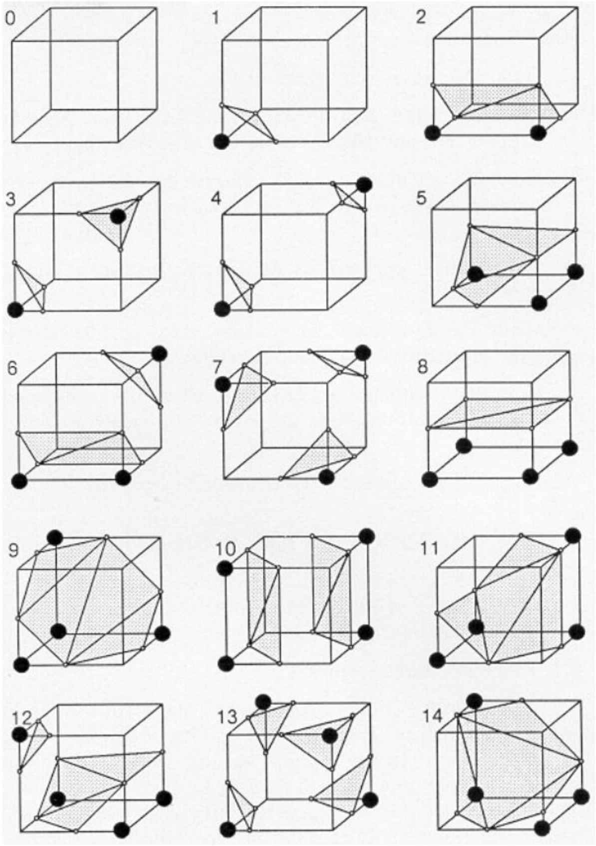
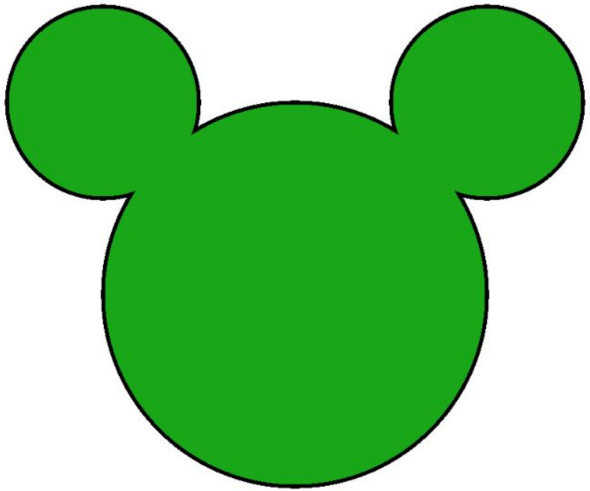
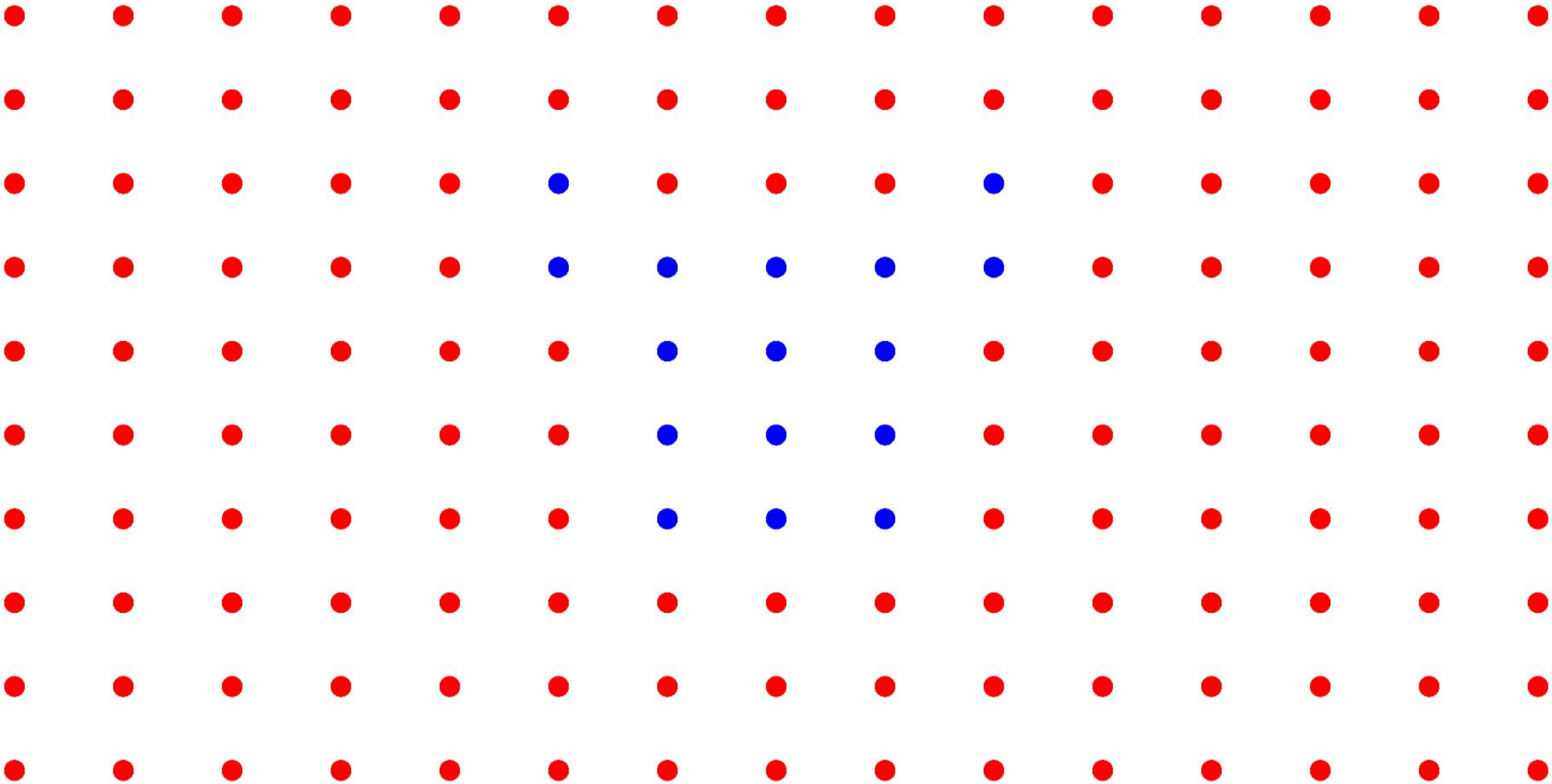


Figure 3. Triangulated Cubes.

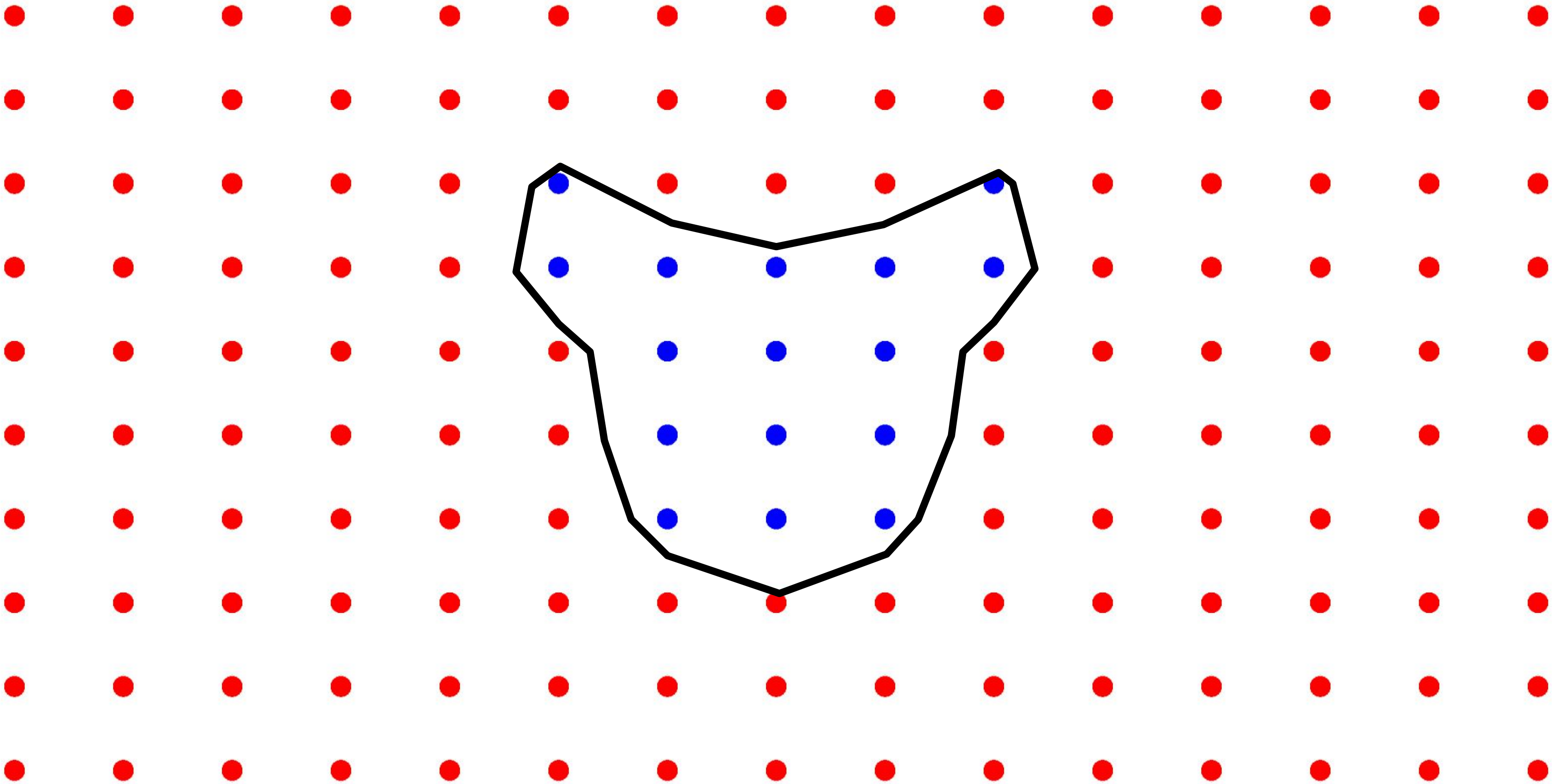
Surface reconstruction - Marching Cubes



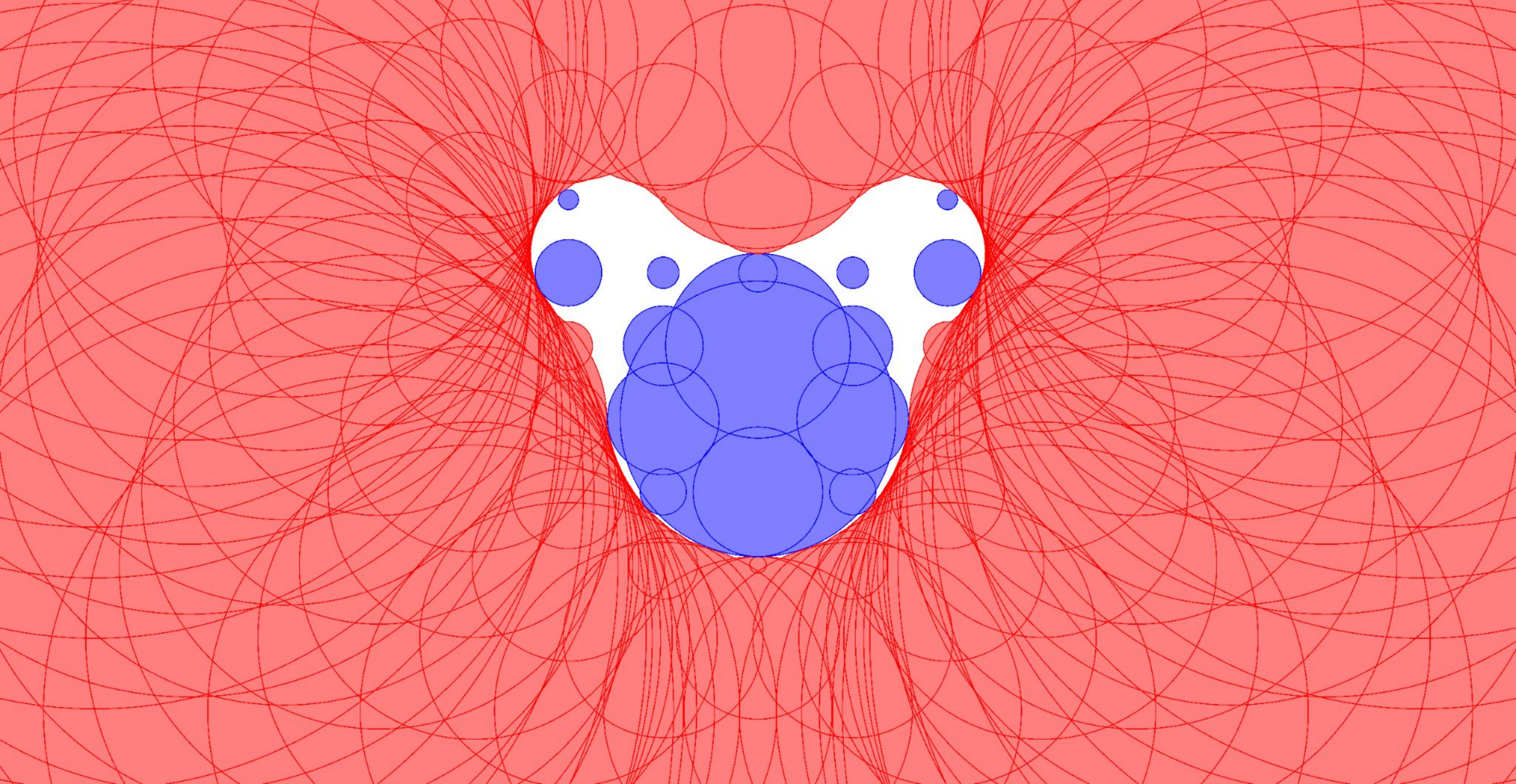
Surface reconstruction - Marching Cubes



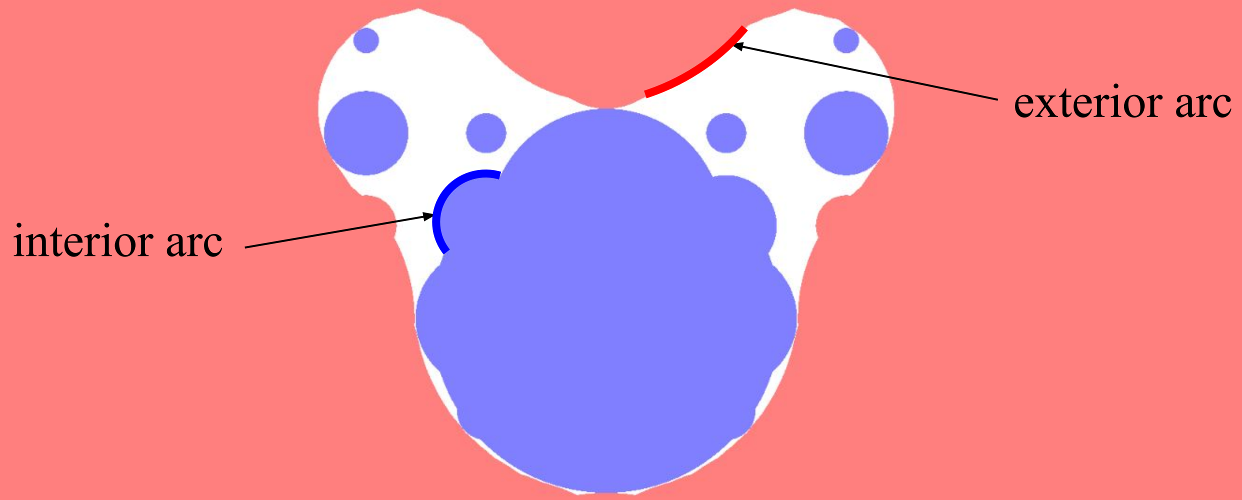
Surface reconstruction - Marching Cubes



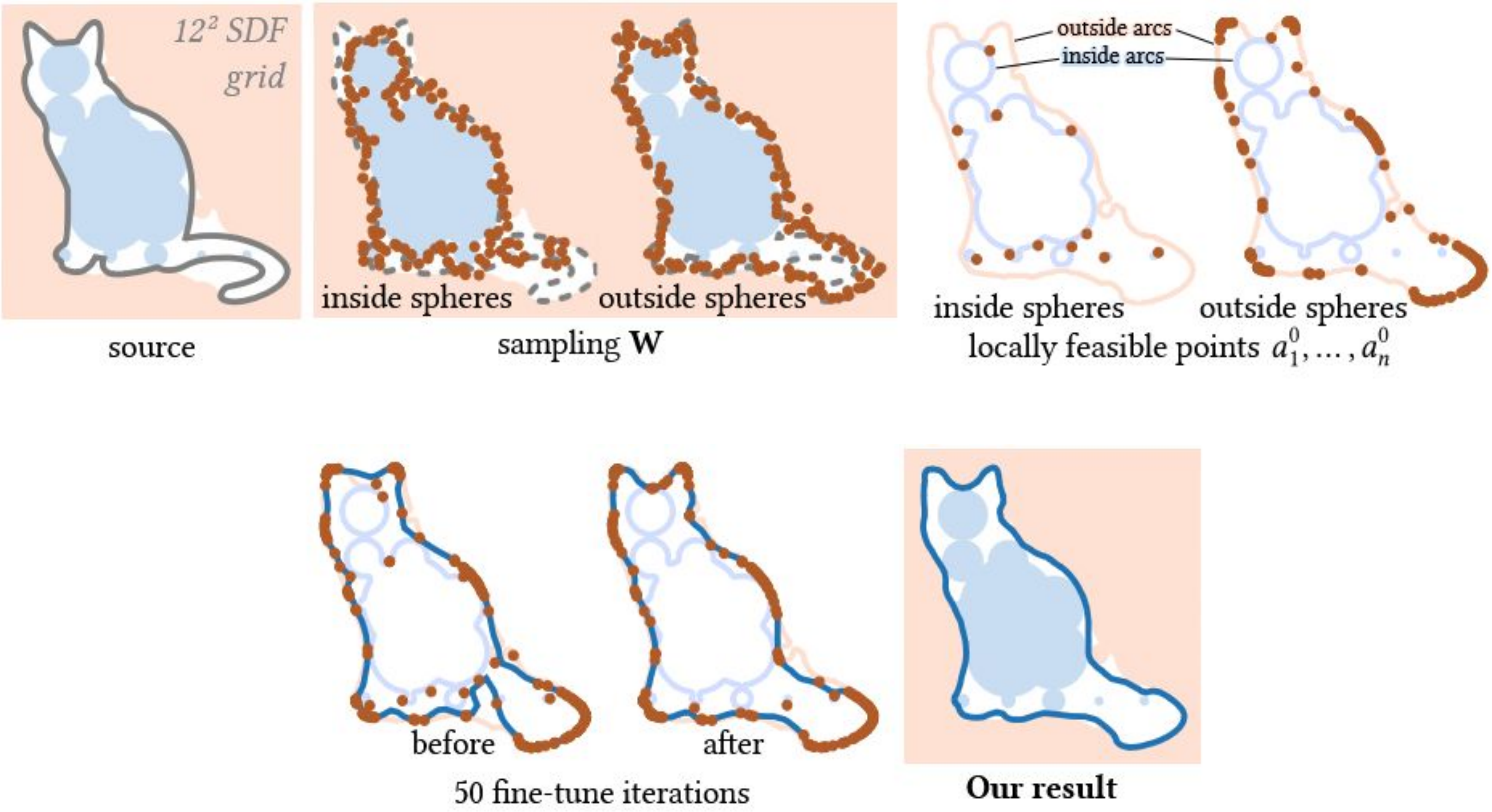
Surface reconstruction - Reach for the Arcs



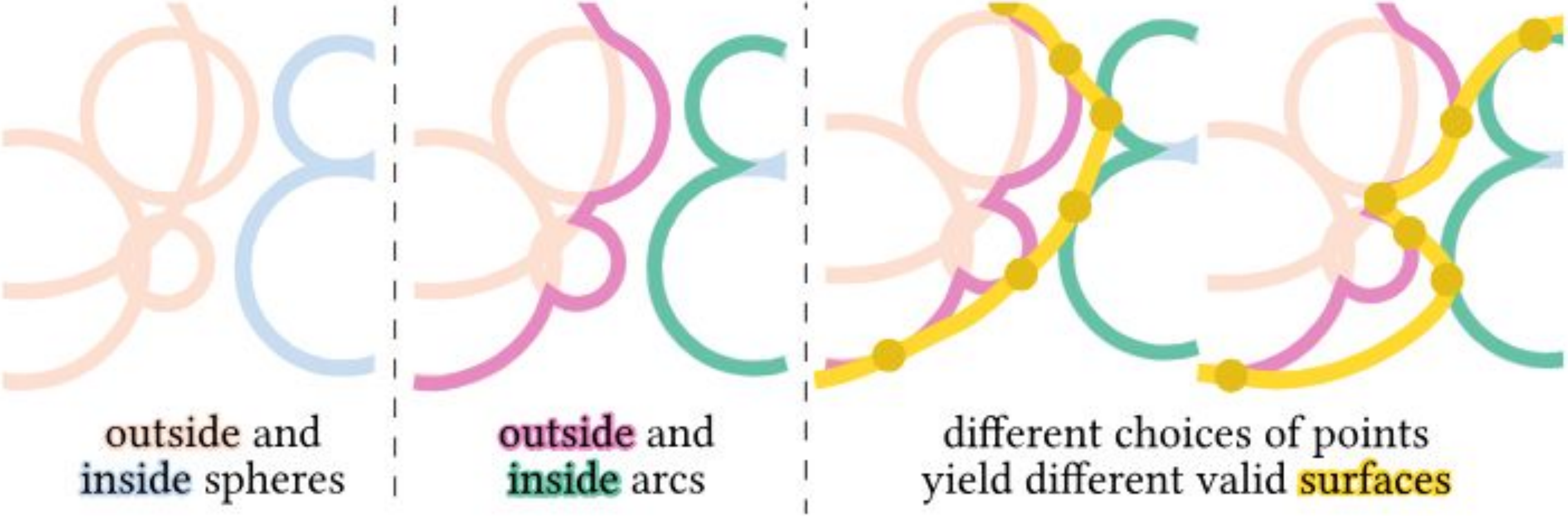
Surface reconstruction - Reach for the Arcs



Reach for the Arcs



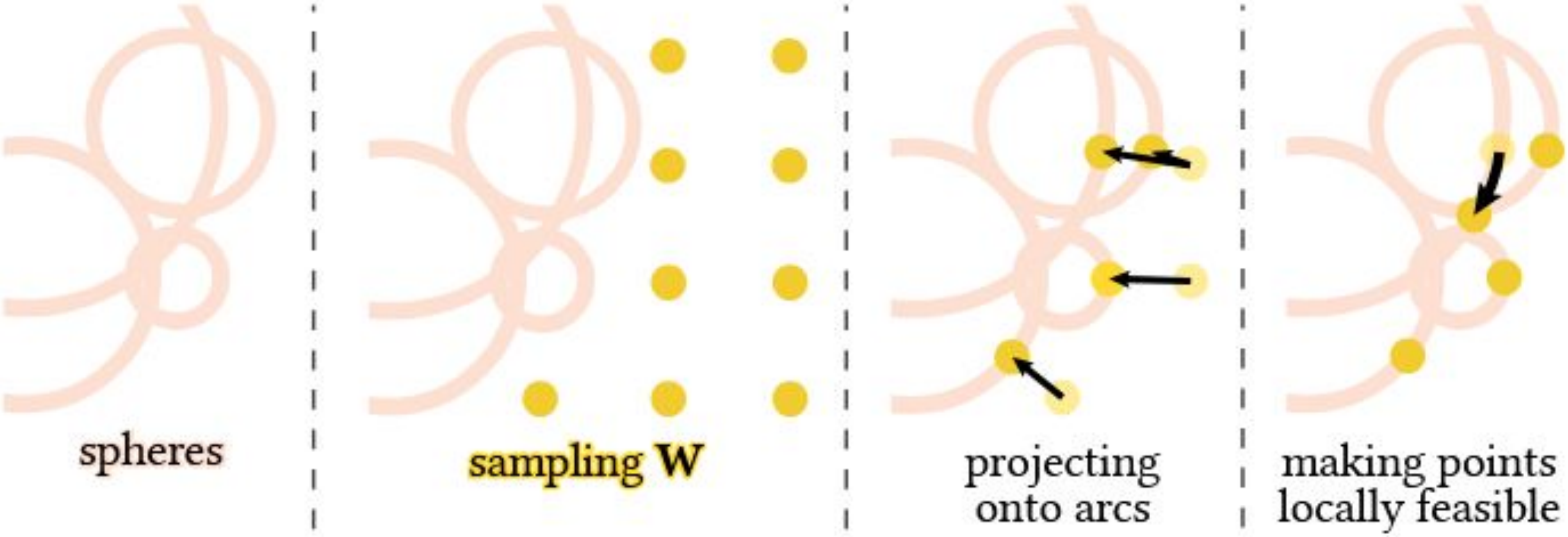
Feasible surfaces & Feasibility arcs



In other words, a feasible surface must be tangent to every *feasibility arc*

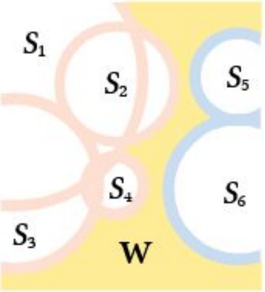
$$\mathcal{A}_i = \mathcal{S}_i \setminus \bigcup_{j \neq i} \mathcal{S}_j ,$$

Sampling feasibility arcs



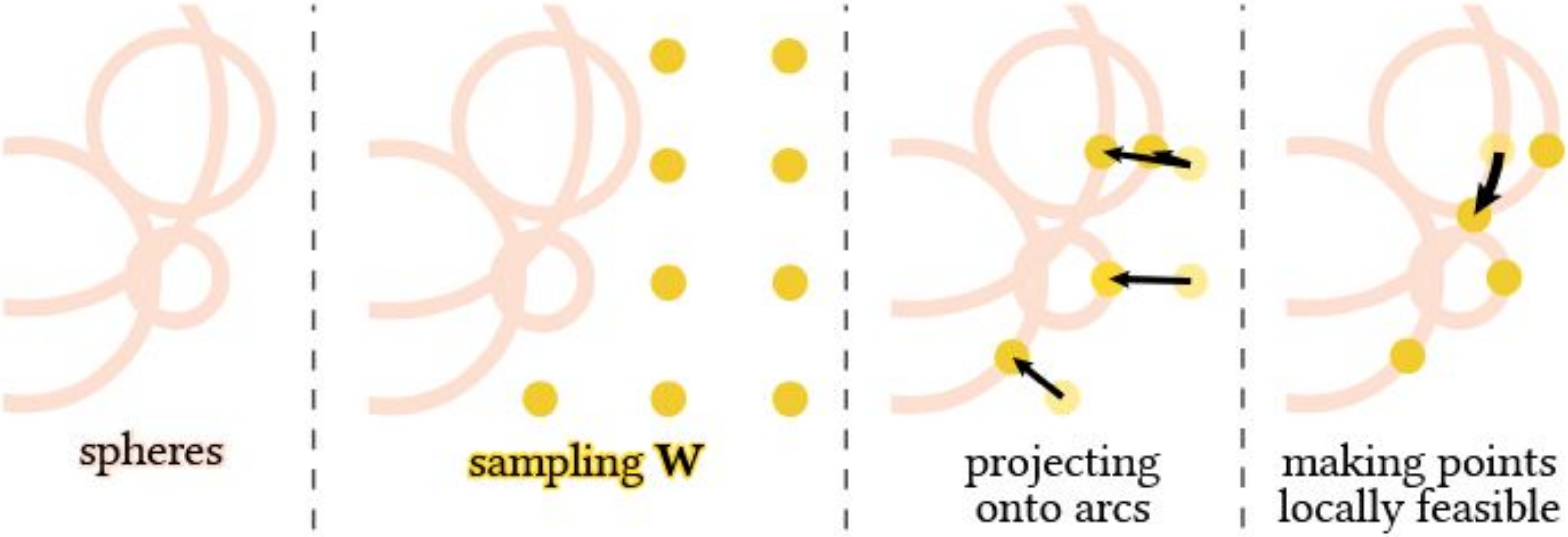
$$\mathbf{W} = \mathbf{B} \setminus \bigcup_{i=1}^{n} \mathrm{int}(\mathcal{S}_i)$$

feasibility volume



to sample W, rasterize the spheres in a grid

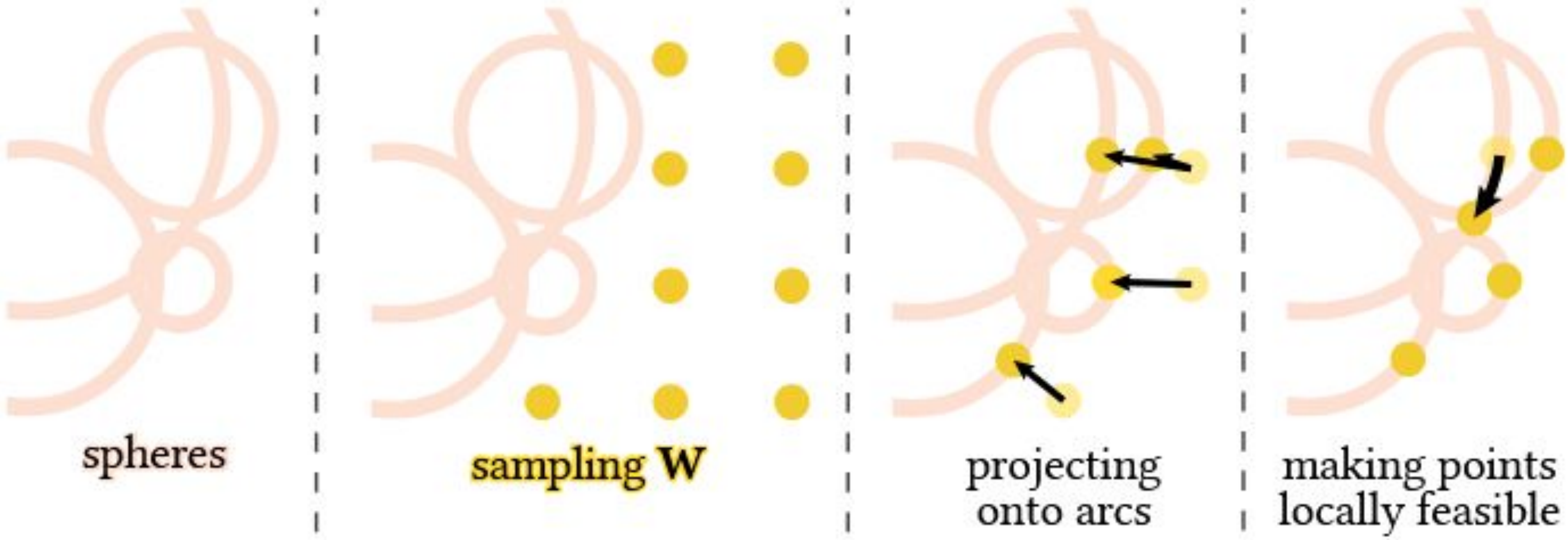
Sampling feasibility arcs



$$w^i = \text{argmin}_j d(w_j, S_i)$$

find the closest sample for
each sphere

Sampling feasibility arcs



If we sampled **W** perfectly and with infinite density, then simply selecting w^i as the closest point to the i-th sphere would yield a point on its feasibility arc $\mathcal{A}_i$. I

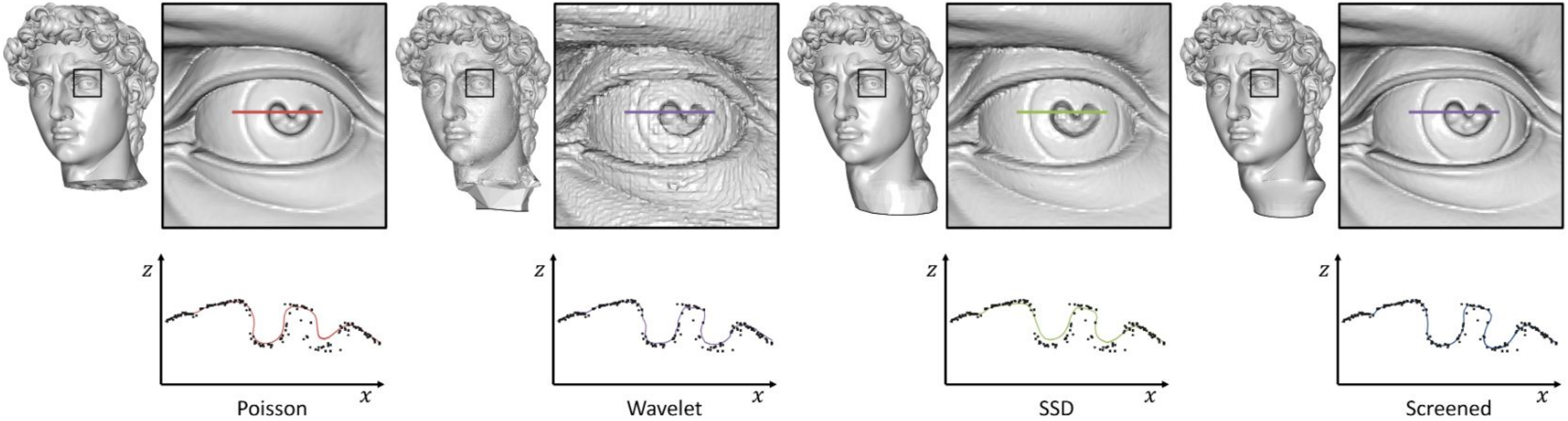
Replace with other candidates : intersection of spheres that also contain the wrong point

Surface reconstruction

Screened Poisson Surface Reconstruction

Michael Kazhdan and Hugues Hoppe. 2013

The problem of point cloud reconstruction is not too dissimilar from the task considered in this paper, in which the incomplete surface information comes instead from a discrete set of SDF samples. By explicitly elucidating this duality, we reformulate SDF reconstruction as a modified point cloud reconstruction problem. As such, our work could theoretically employ any of the above listed methods and priors; however, in practice, we opt for the smoothness prior imposed by Poisson Surface Reconstruction (PSR) [Kazhdan et al. 2006] and its follow-ups [Hou et al. 2022; Kazhdan and Hoppe 2013; Sellán and Jacobson 2022, 2023].



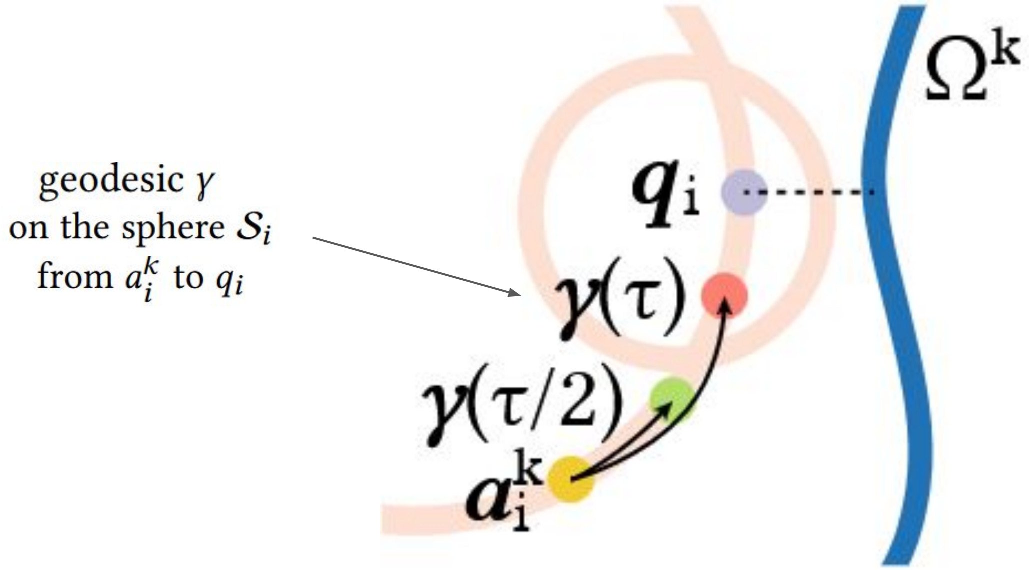
Fine-tuning the tangency set

initial tangency set

$$\mathbf{a}^0 = \{a_1^0, \ldots, a_n^0\}$$

reconstructed surface
at iteration k

$$\Omega^k = \Omega(\mathbf{a}^k)$$

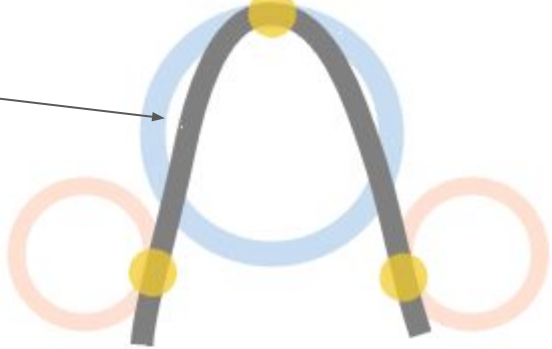


move the tangency point of
each S toward its closest point
on the surface

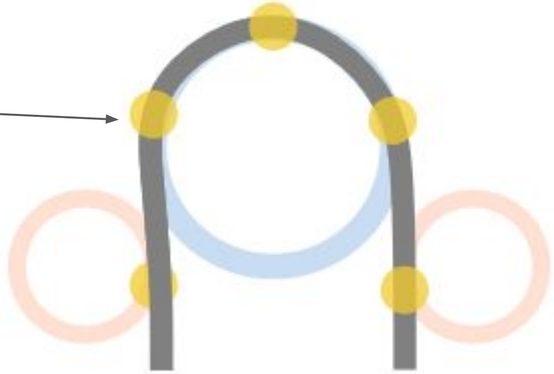
$$a_i^{k+1} = \gamma(\tau)$$

Preventing intersections

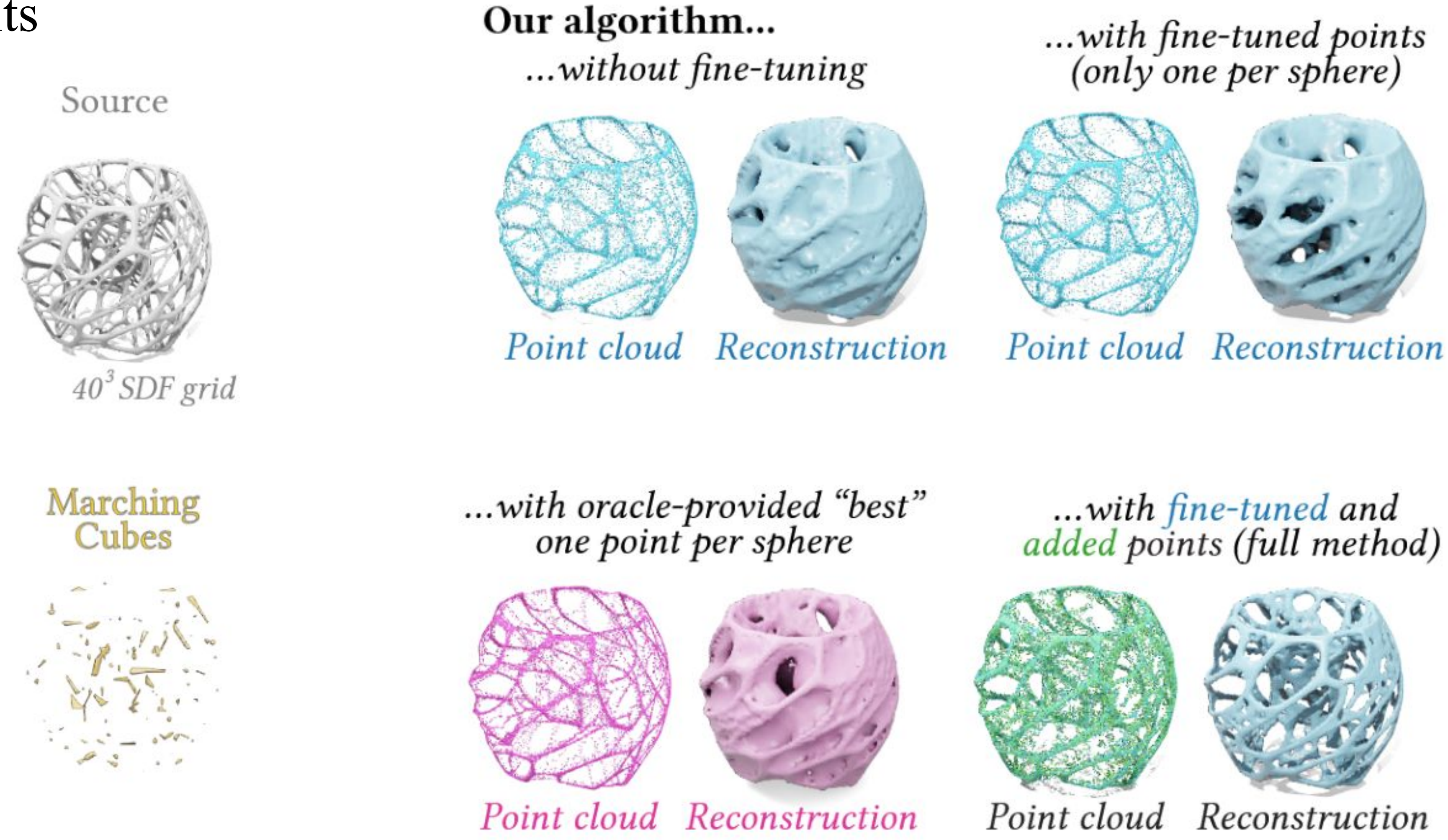
The closest surface point to S is inside S: intersection detected



Multiple tangency point for one sphere



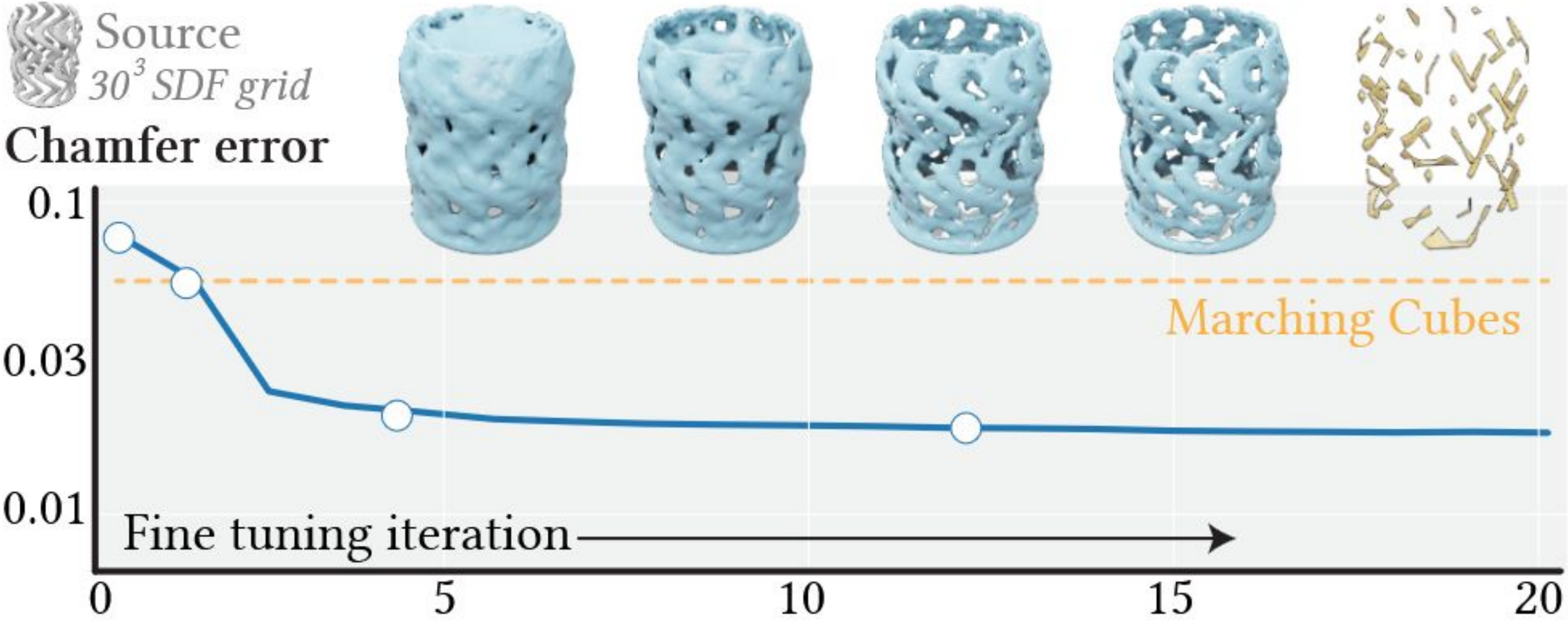
Results


Our algorithm...
...without fine-tuning
...with fine-tuned points (only one per sphere)
Source
40^3 SDF grid
Point cloud
Reconstruction
Point cloud
Reconstruction
Marching Cubes
...with oracle-provided "best" one point per sphere
...with fine-tuned and added points (full method)
Point cloud
Reconstruction
Point cloud
Reconstruction

Results

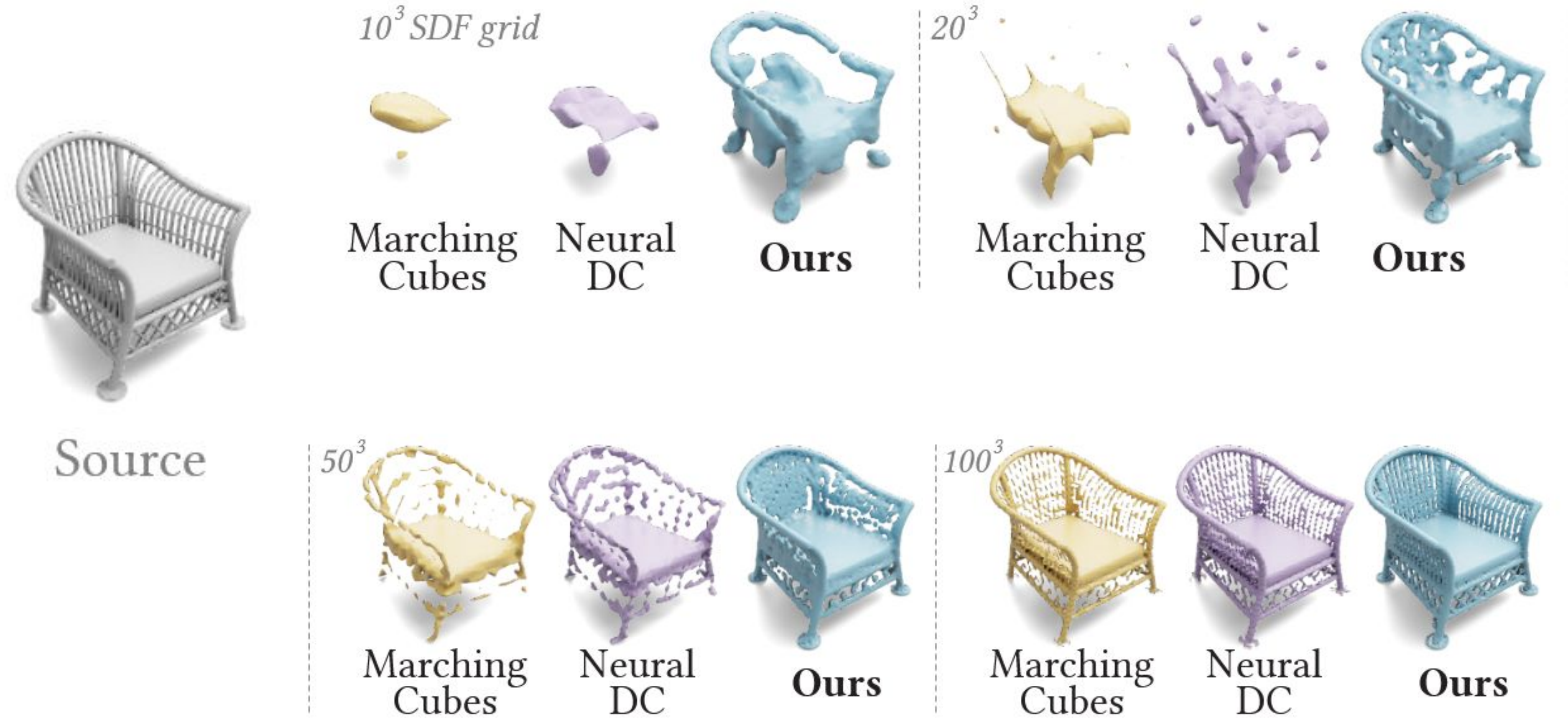

20³ SDF grid
source
marching cubes
NDCx (learning)
[Sellán et al. 2023]
Ours
55³ SDF grid

Results



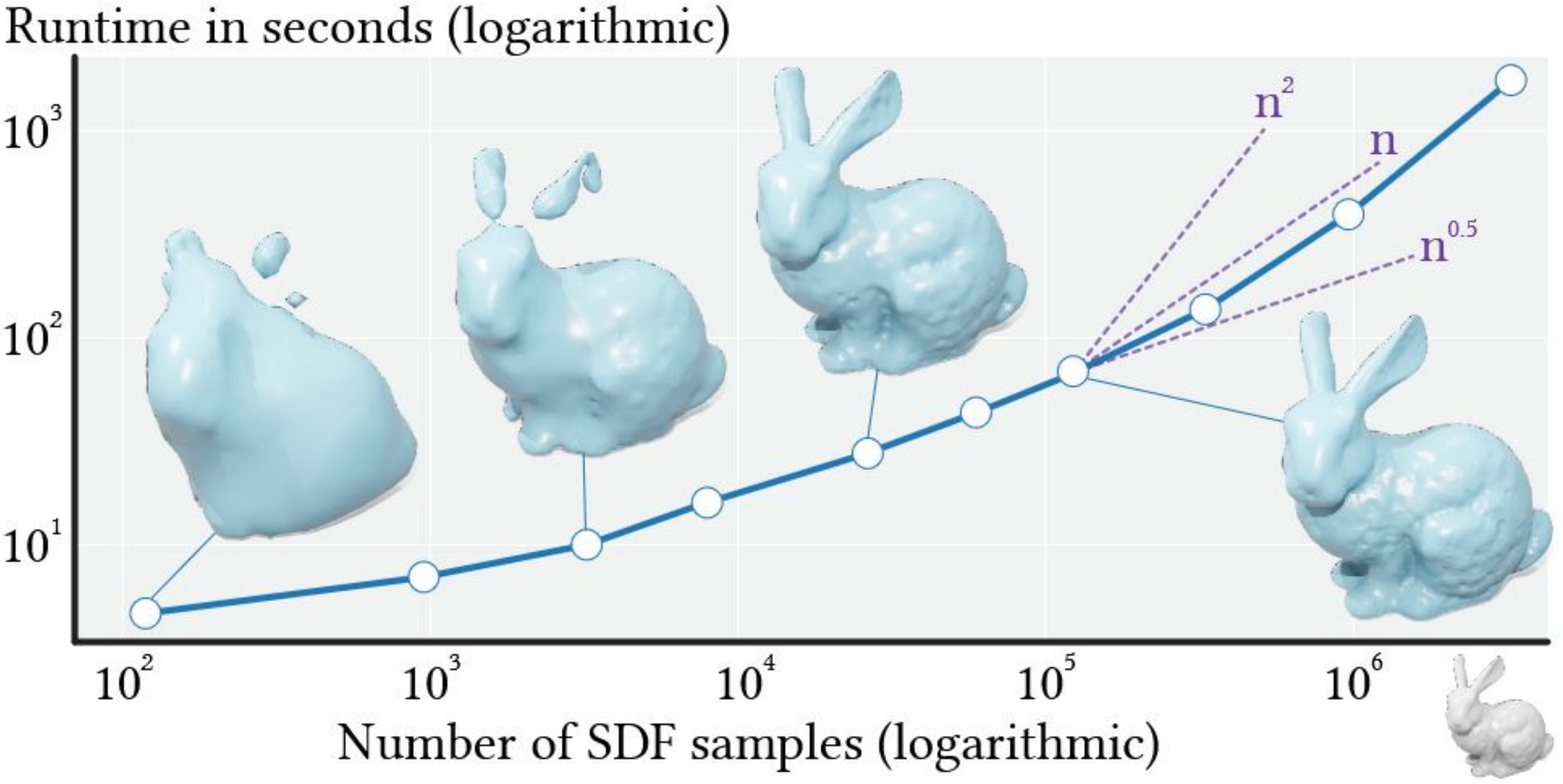
Source
30^3 SDF grid
Chamfer error
0.1
0.03
0.01
Marching Cubes
Fine tuning iteration
0
5
10
15
20

Results



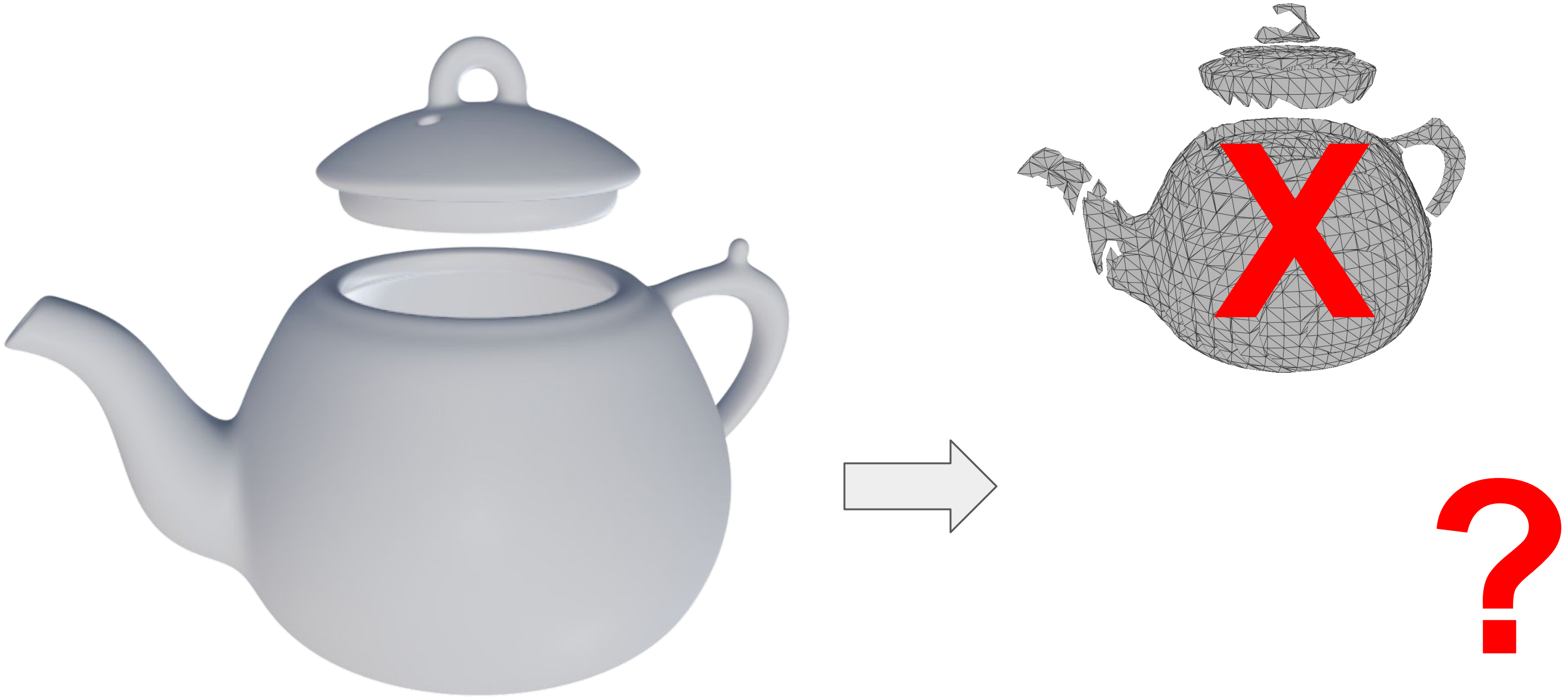
10³ SDF grid
Marching Cubes
Neural DC
Ours
20³
Marching Cubes
Neural DC
Ours
Source
50³
Marching Cubes
Neural DC
Ours
100³
Marching Cubes
Neural DC
Ours

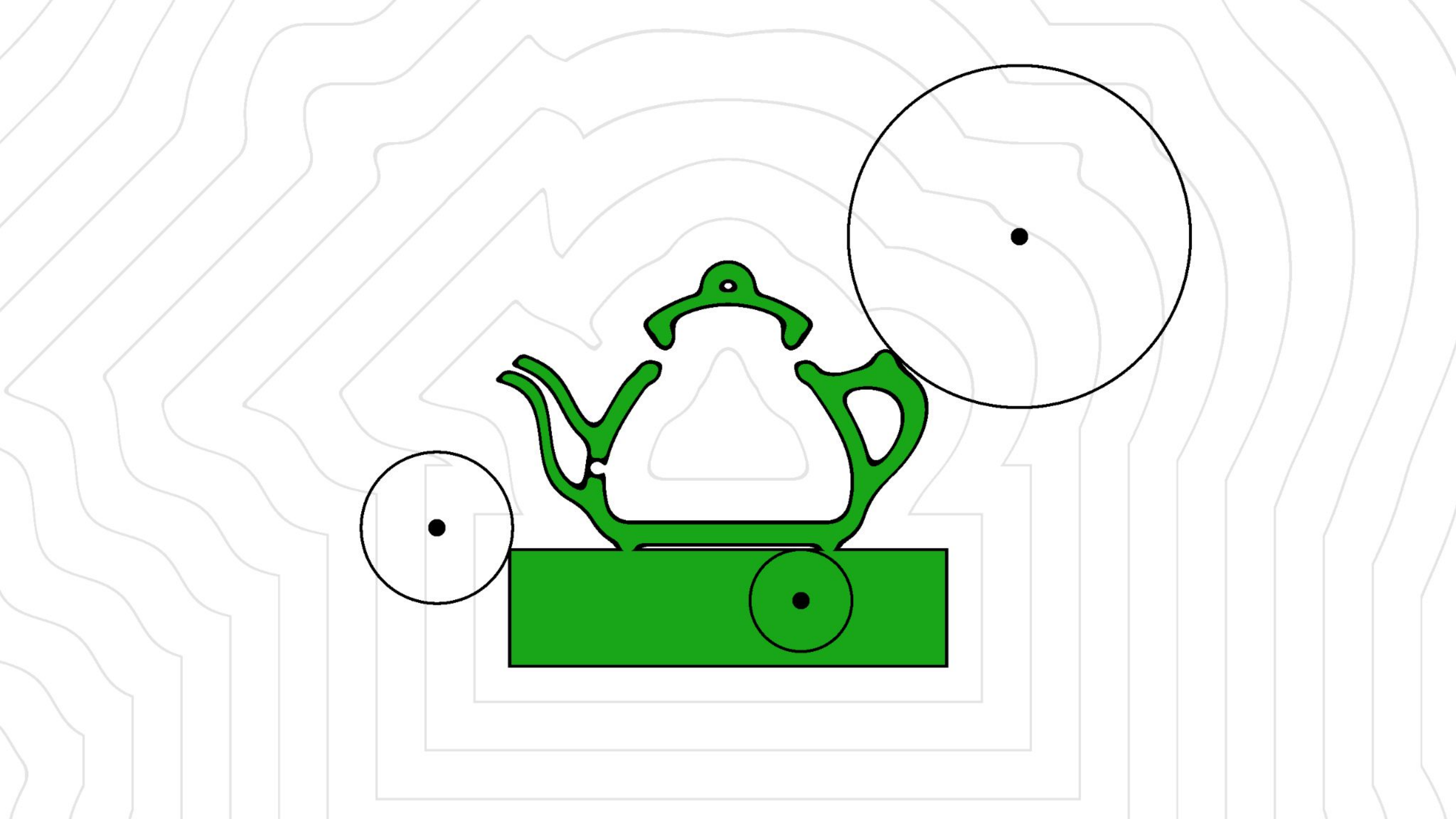
Results

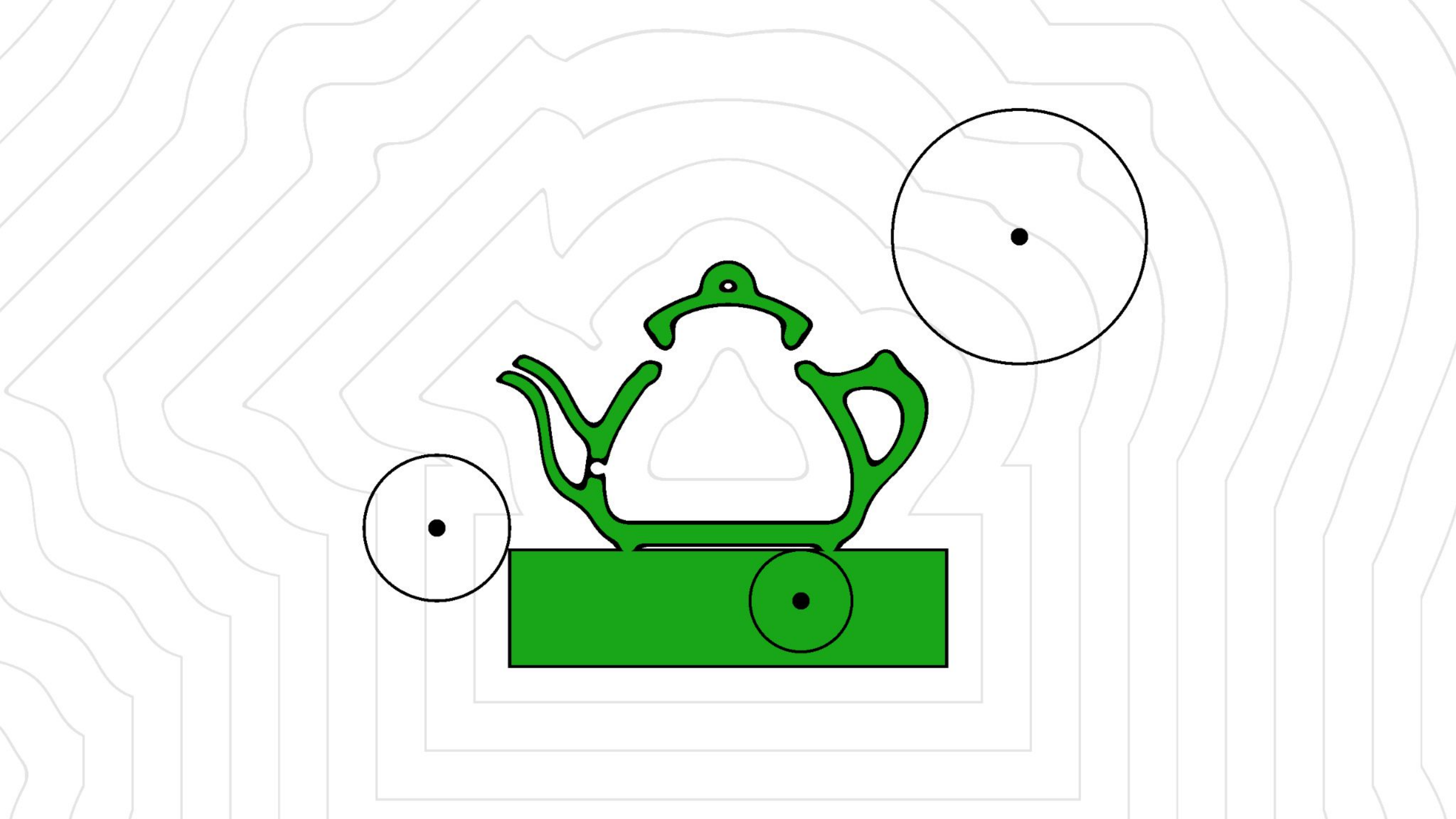


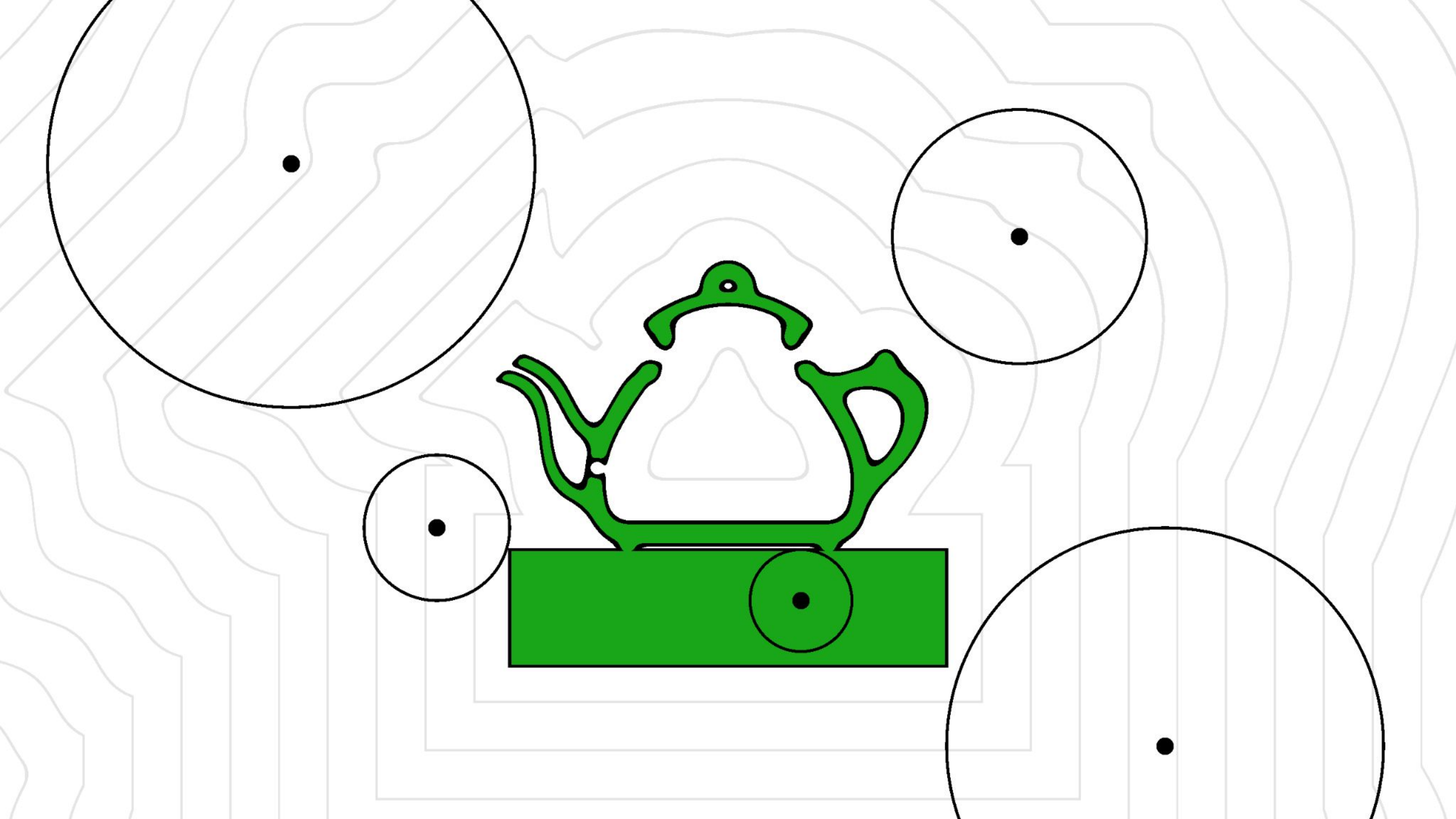
Runtime in seconds (logarithmic)
10^3
10^2
10^1
n^2
n
$n^{0.5}$
10^2
10^3
10^4
10^5
10^6
Number of SDF samples (logarithmic)

Signed Distance Fields to Mesh









Error between SDF and correct euclidean distance