

# Surface Reconstruction

## *Power Diagrams, the Medial Axis Transform and the Power Crust Algorithm*

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6.838 Geometric Computation

Lecture 19 — 13 November 2001

# Overview

- Introduction
- Weighted distance and power diagrams
- Medial Axis Transform
- PowerCrust Algorithm

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# Introduction



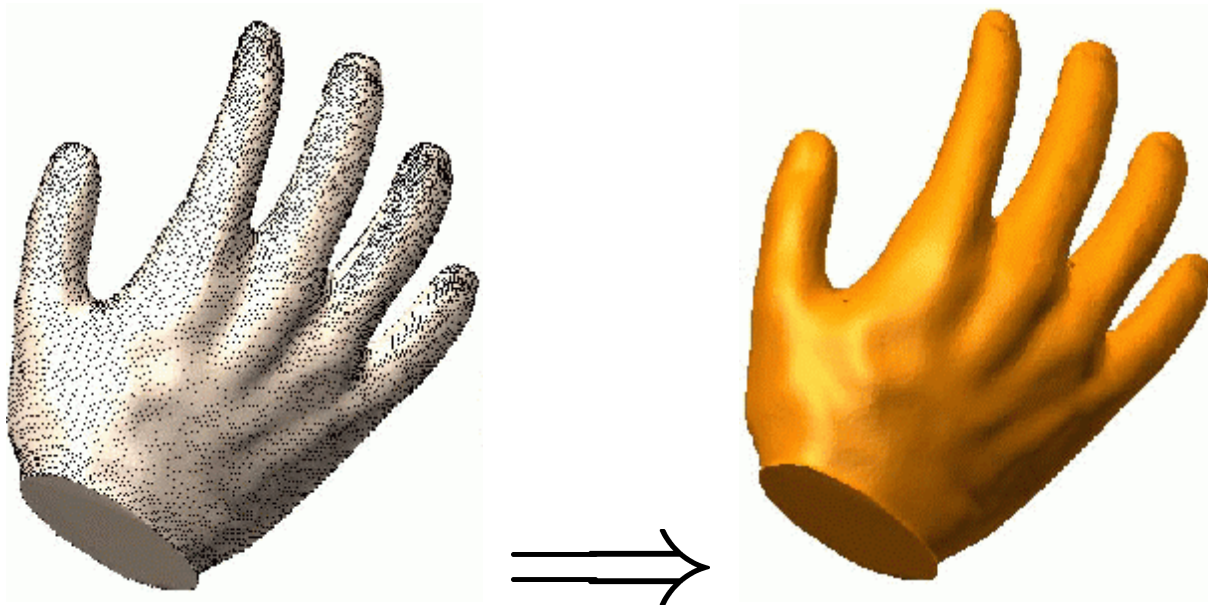
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# Introduction

- What is Surface Reconstruction?
- Applications
- Difficulties
- Survey of techniques

# Surface Reconstruction

Given a set of points  $X$  assumed to lie near an unknown surface  $U$ , construct a surface model  $S$  approximating  $U$ .



# How it usually works

- Input points sampled from the surface either “by hand” or via a physical process (e.g. 3D scanning).
- Assume:
  - Real surface  $U$  is “nice” (= “smooth”)
  - Samples  $X$  are “dense enough”, especially near features such as edges, points, bumps, etc.
- Output  $S$  in usable format for processing
  - Triangulation of  $S$
  - Fitted “splines” (i.e. low-dimensional surfaces)
  - CSG model

# Applications of 3D Scanning

- Reverse engineering / Industrial design

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- Performance analysis and simulations (e.g. drag)



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- Reverse engineering / Industrial design
- Performance analysis and simulations (e.g. drag)
- Realistic virtual environments

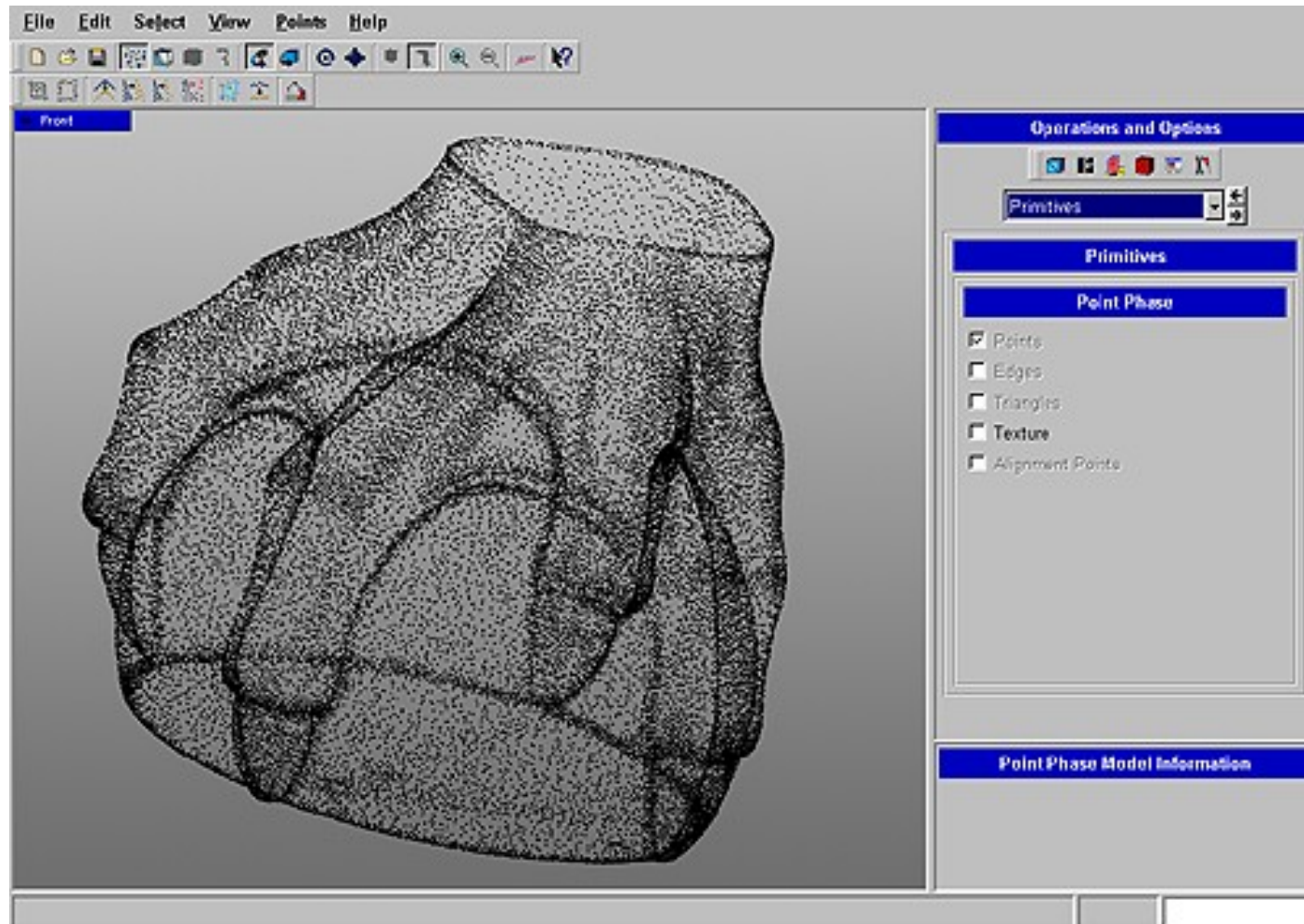
# Applications of 3D Scanning

- Reverse engineering / Industrial design
- Performance analysis and simulations (e.g. drag)
- Realistic virtual environments
- Medical Imaging

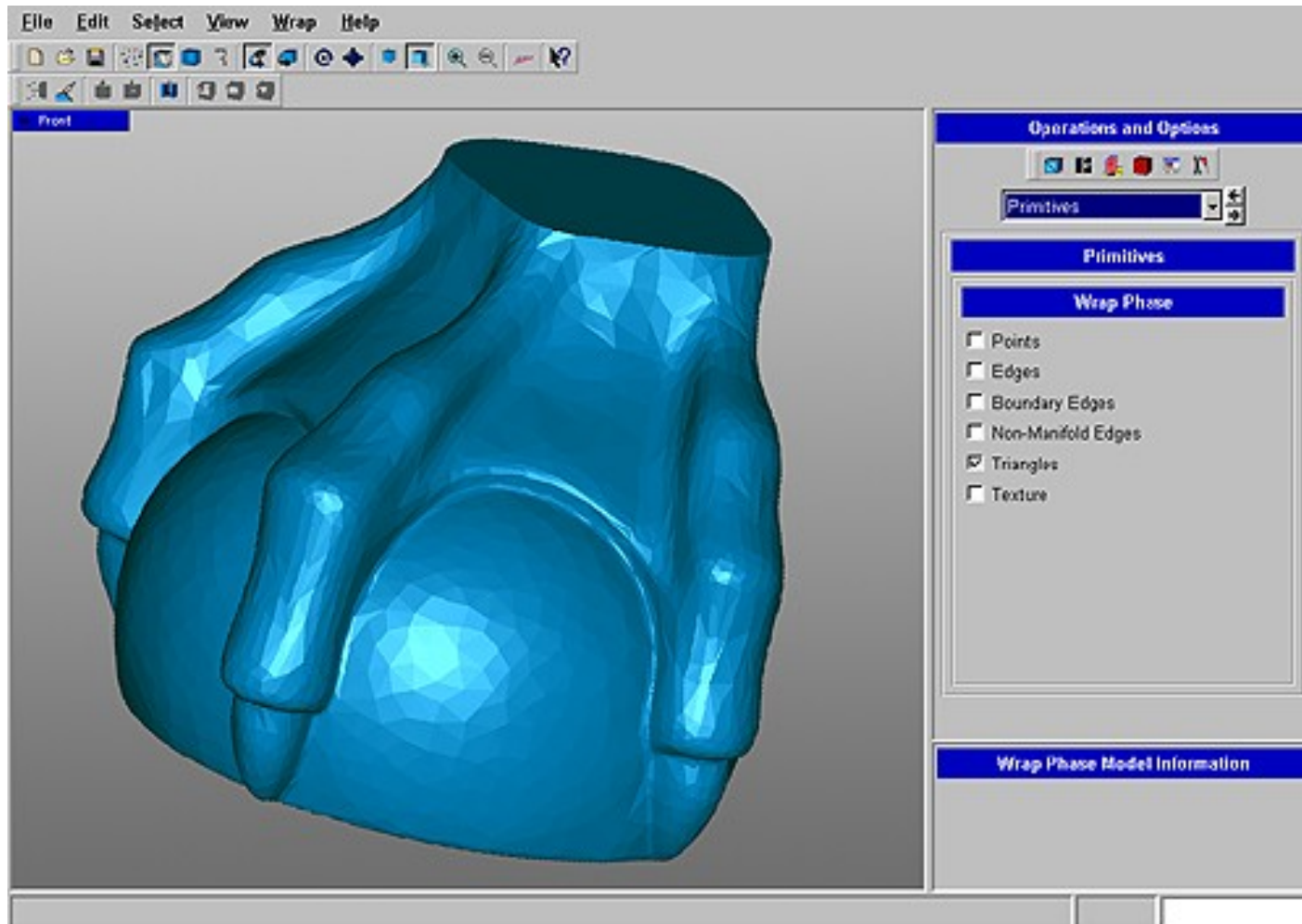
# Applications of 3D Scanning

- Reverse engineering / Industrial design
- Performance analysis and simulations (e.g. drag)
- Realistic virtual environments
- Medical Imaging
- ...

# Modeling a claw I



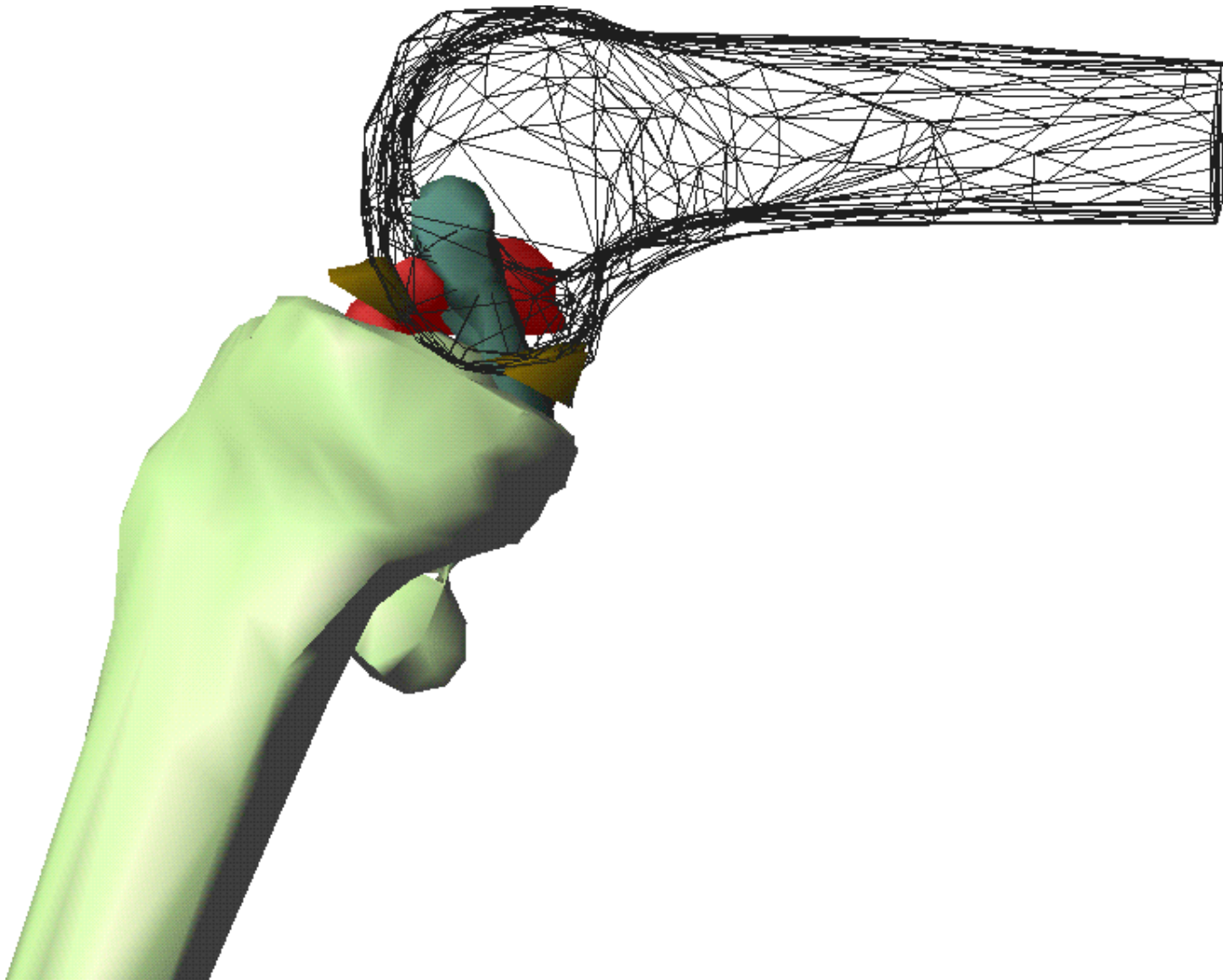
# Modeling a Claw II



# Modeling hand-made parts



# Medical Shape Reconstruction



# Difficulties

- Surface not smooth
- Noisy data
- Lack of orientation data
- Surface not watertight



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# Techniques

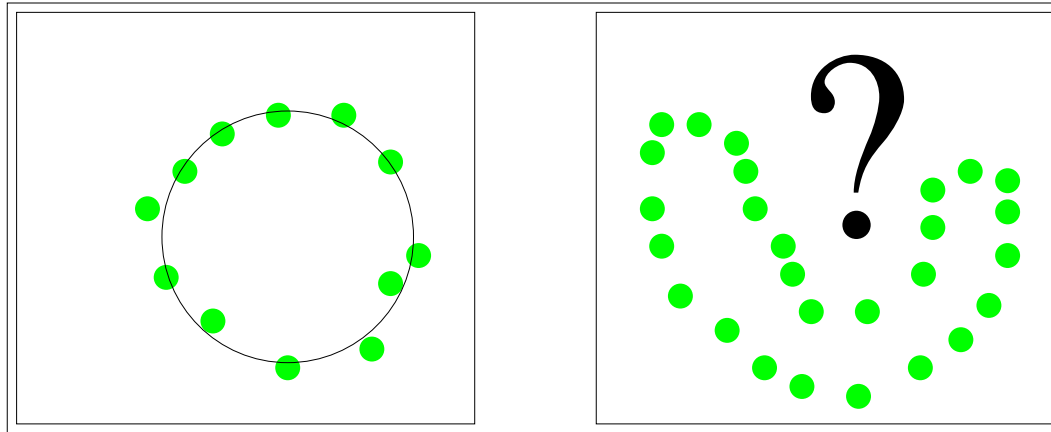


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# Techniques for Surface Reconstruction

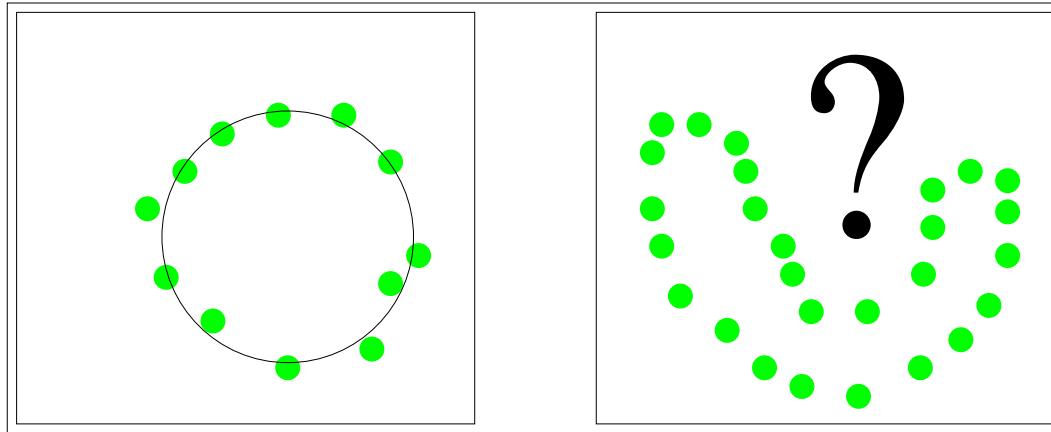
Technique	Assumptions
Fit parametric surface	

# Fitting Parametric Surfaces



- Assume surface is from some known family (e.g. sphere, cylinder, plane, hyperboloid, etc)
- Find best parameters to fit data

# Fitting Parametric Surfaces



- Fast, accurate for good data
- Useless when data is of unknown type

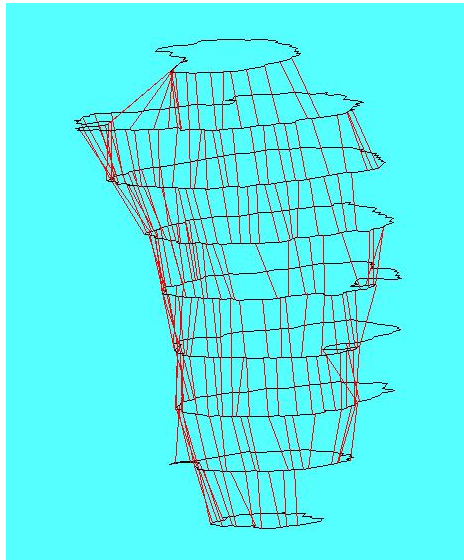
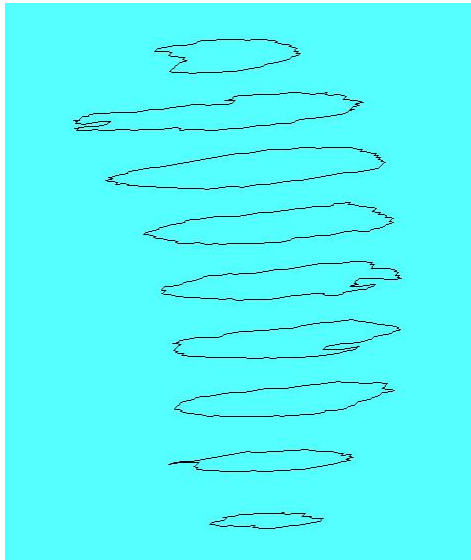
# Techniques for Surface Reconstruction

Technique	Assumptions
Fit parametric surface	Data fits model

# Techniques for Surface Reconstruction

Technique	Assumptions
Fit parametric surface	Data fits model
Piece together parallel contours	

# Contour Data Reconstruction



- Piece together image from parallel slices
- Assumes data is “pre-structured”
- Applications: **medical**, **topographic terrain maps**

# Techniques for Surface Reconstruction

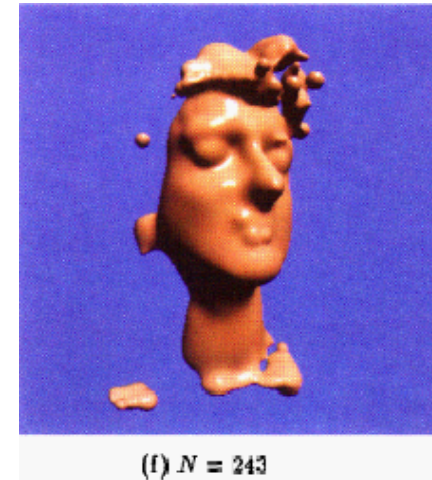
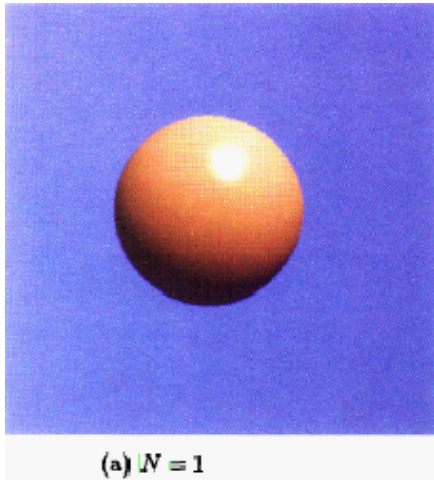
Technique	Assumptions
Fit parametric surface	Data fits model
Piece together parallel contours	Data from known device



# Techniques for Surface Reconstruction

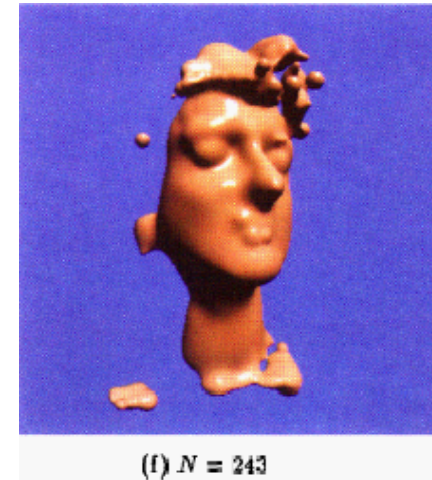
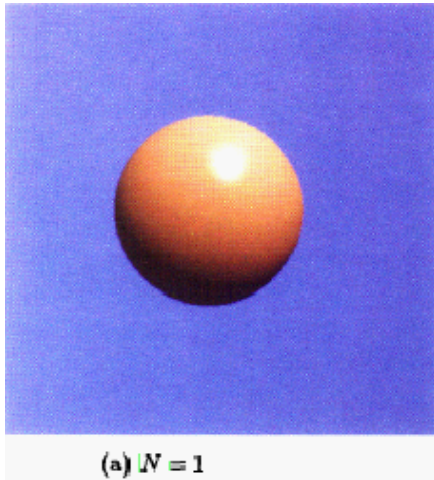
Technique	Assumptions
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Piece together parallel contours	Data from known device
Fit Gaussian Kernels	

# Fitting Gaussian balls



- Take linear combination of 3D Gaussians
$$f(\vec{x}) = \sum c_i e^{((\vec{x}-\vec{\mu})^\top K_i (\vec{x}-\vec{\mu}))}$$
- Surface  $S = \{\vec{s} \mid f(\vec{s}) = 0\}$   
(inside = positive, outside = negative)

# Fitting Gaussian balls



Problems:

- Must know surface normal at each point
- Output always watertight, bubbly-shaped
- Useful for range scanner data

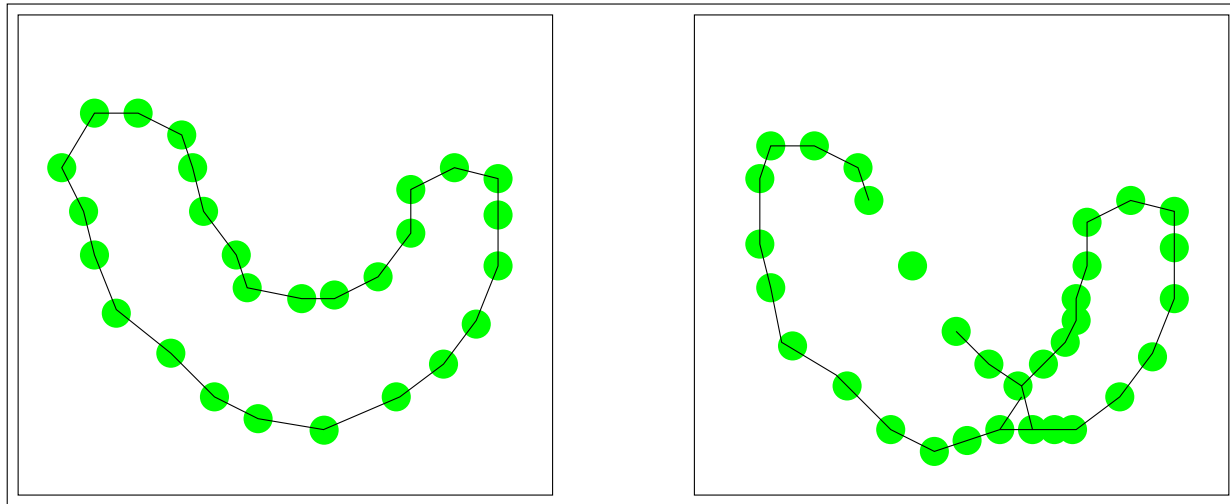
# Techniques for Surface Reconstruction

Technique	Assumptions
Fit parametric surface	Data fits model
Piece together parallel contours	Data from known device
Fit Gaussian Kernels	Given normal at each point

# Techniques for Surface Reconstruction

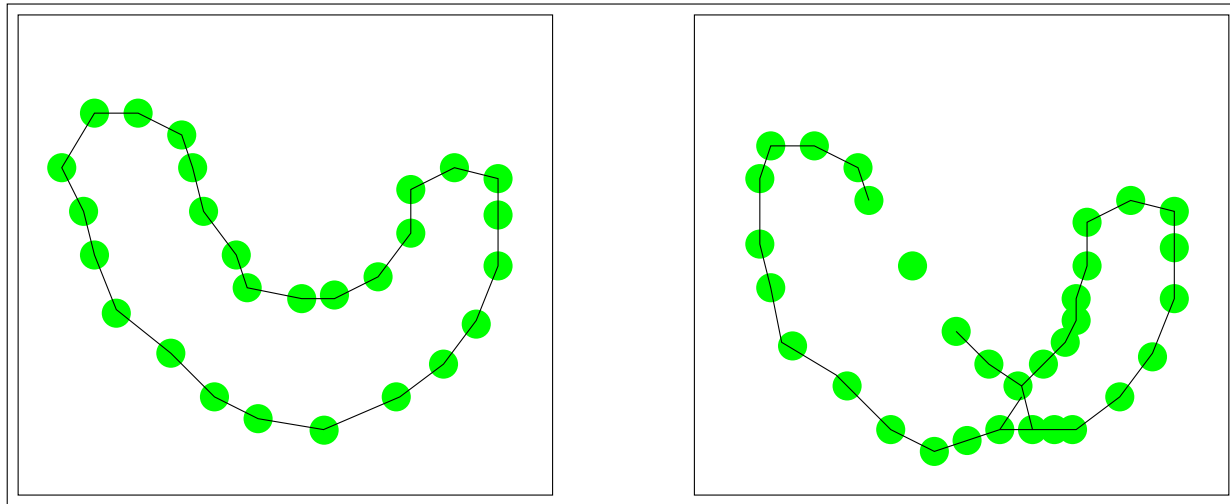
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$\alpha$ -shape Triangulation	

# $\alpha$ -shape triangulation



- Start with Delaunay triangulation
- Take subset of the edges “on” the surface  $S$   
(In fact, just take shortest edges in graph)

# $\alpha$ -shape triangulation



- Bad when samples unevenly spaced (can be fixed using weights on sample points)
- Works only for noise-free data

# Techniques for Surface Reconstruction

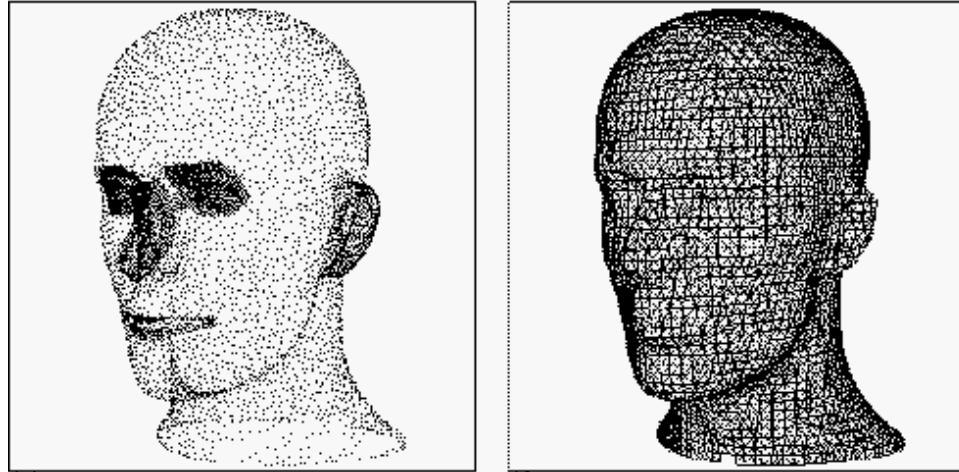
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# Techniques for Surface Reconstruction

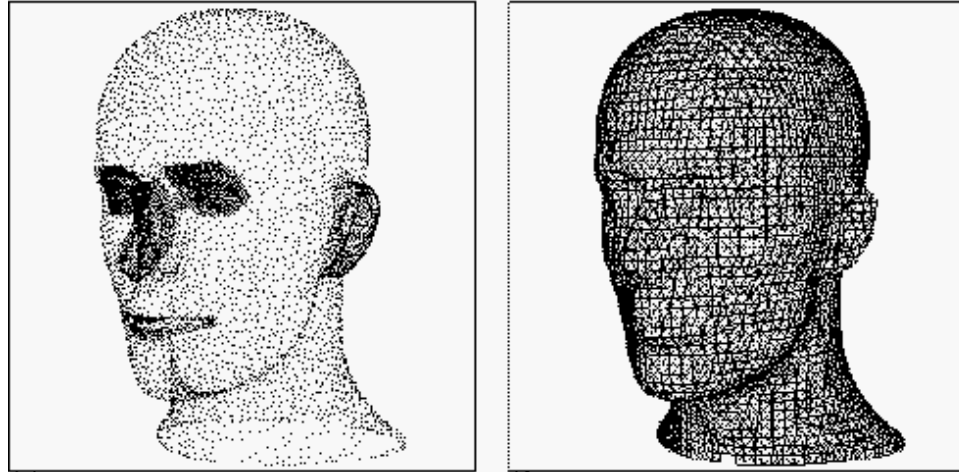
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$\alpha$ -shape Triangulation	Noise-free
“Mesh” methods	

# Mesh methods



- Exploit local information to find a mesh  $S$  approximating surface  $U$
- Simplify mesh afterwards

# Mesh methods



- Handles noisy data
- Assumes only sample dense near features (edges, bumps)
- Methods ad hoc; Rigorous analysis difficult

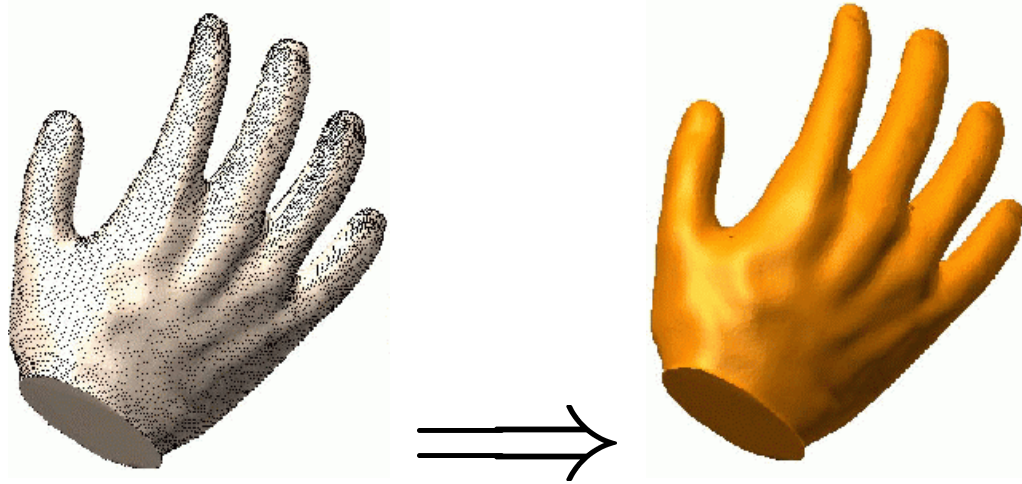
# Techniques for Surface Reconstruction

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Fit parametric surface	Data fits model
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“Mesh” methods	Sample Dense near Features

# Techniques for Surface Reconstruction

Technique	Assumptions
Fit parametric surface	Data fits model
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Fit Gaussian Kernels	Given normal at each point
$\alpha$ -shape Triangulation	Noise-free
“Mesh” methods	Sample Dense near Features
Crust Methods	

# Crust methods



- Focus of this lecture
- Assume only dense sampling
- Provide other information on  $S$ :  
Volume, Skeletal Structure

# Techniques for Surface Reconstruction

Technique	Assumptions
Fit parametric surface	Data fits model
Piece together parallel contours	Data from known device
Fit Gaussian Kernels	Given normal at each point
$\alpha$ -shape Triangulation	Noise-free
“Mesh” methods	Sample Dense Near Features
Crust Methods	Sample Dense Near Features

# Overview

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- Weighted distance and power diagrams
- Medial Axis Transform
- PowerCrust Algorithm





# Weighted Distance and Power Diagrams

# Weighted Distance and Power Diagrams

- Weighted distance
- Power Diagrams ( = Weighted Voronoi)
- $\alpha$ -shapes

# Unions of balls

Key concept:

Solids can be roughly approximated (exact in the limit) as a union of balls (discs in 2D).

Given a set of points  $X$ , we can view  $X$  as *centers* of balls. How can we use this?

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Try to visualize “shape” of  $X$ .

# Adding weights

Some points are “bigger” than others.

- $X$  sampled from a surface  $\implies$  points where sampling is less dense are “bigger”.
- $X$  = centers of atoms in a molecule  $\implies$  heavier atoms are “bigger”.
- In **Power Crust (later)**, this will be crucial.

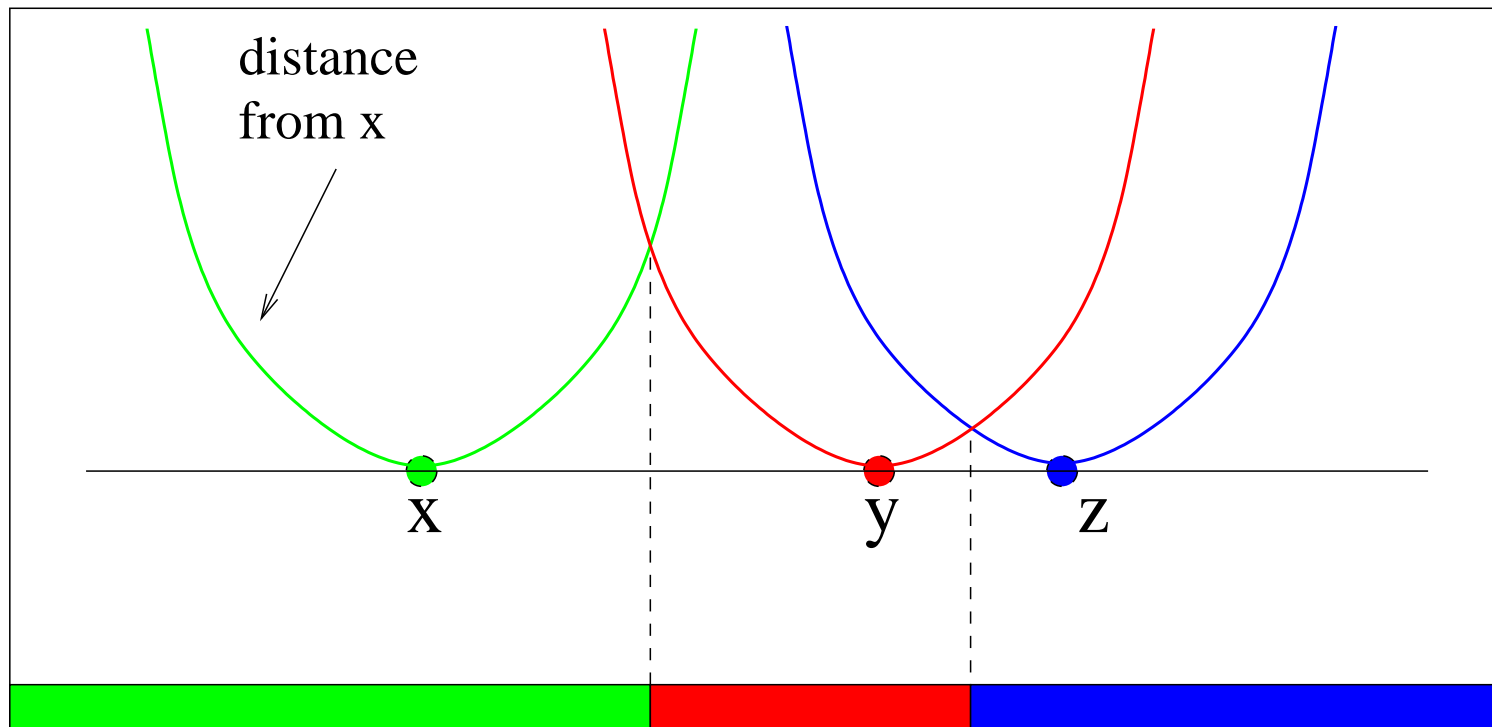
Each point  $x \in X$  gets a weight  $r_x$  (its **radius**).

# Weighted Distance

- Work with **weighted distance**. Distance from a point  $p$  to a ball  $(x, r_x)$ :

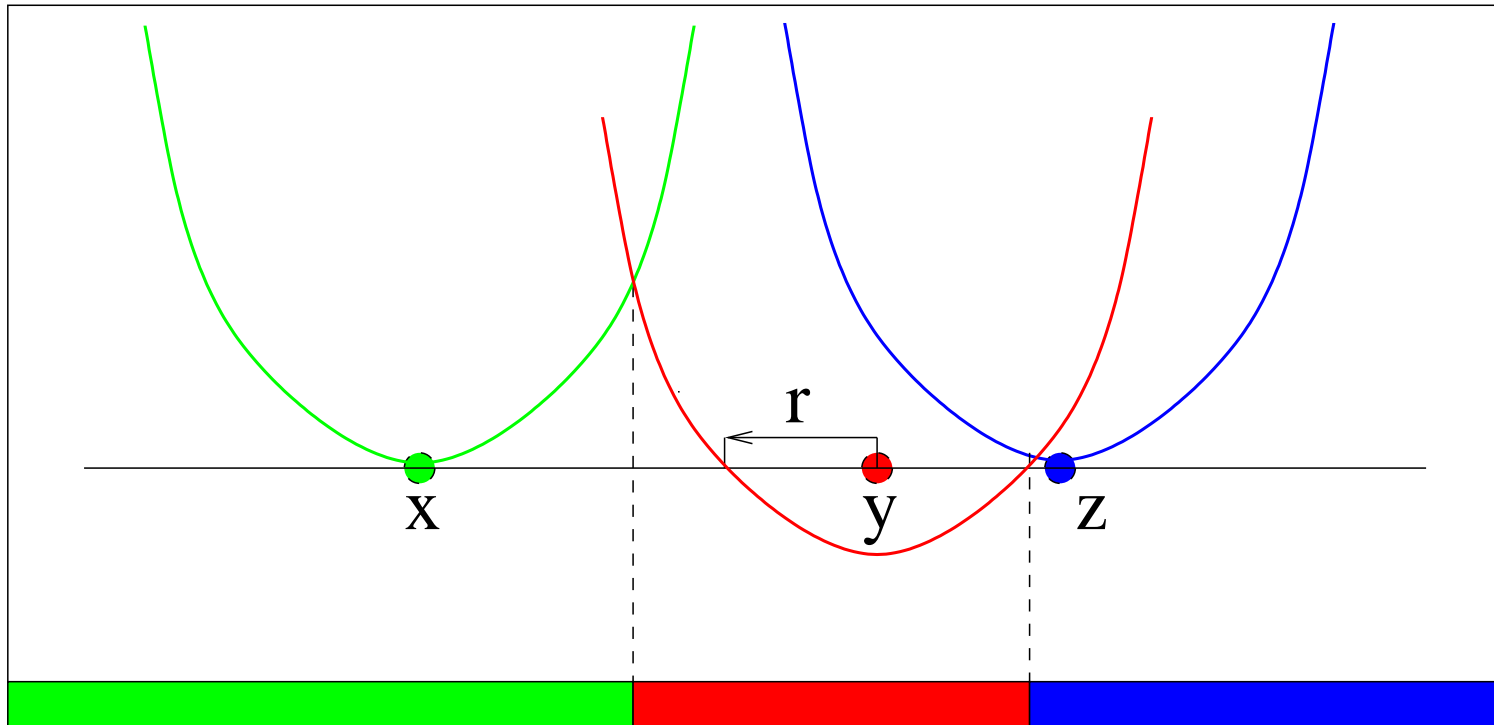
$$d_{r_x}(x, p) = d(x, p)^2 - r_x^2$$

# Normal Distance: $(p - x)^2$



In 1D, the (normal) squared distance induced by each point  $x$  gives a parabola centered at  $x$ .

$$d_r(y, p) = (p - y)^2 - r^2$$



Point  $y$  has radius  $r_y \implies$  parabola gets lowered to intersect axis at distance  $r$  from  $y$ .



# Power Diagram

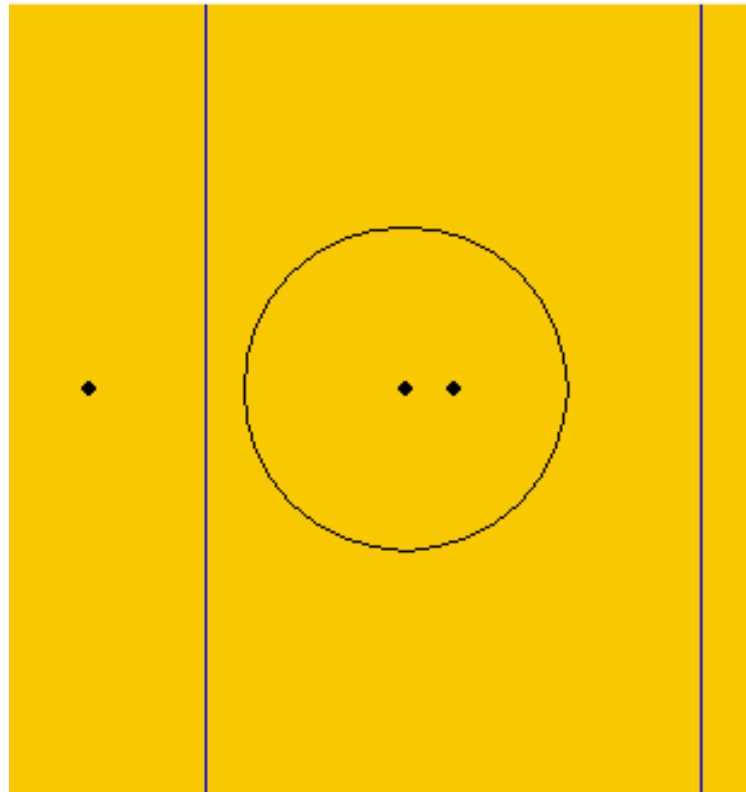
- Distance:  $d_{r_x}(x, p) = d(x, p)^2 - r_x^2$
- Weighted Voronoi cell of  $(x, r_x)$  is set of points  $p$  that have smaller weighted distance to  $x$  than to any other point in  $X$ :

$$\text{cell}(x) = \{p \mid d_{r_x}(x, p) \leq d_{r_{x'}}(x', p) \text{ for all } x' \in X\}$$

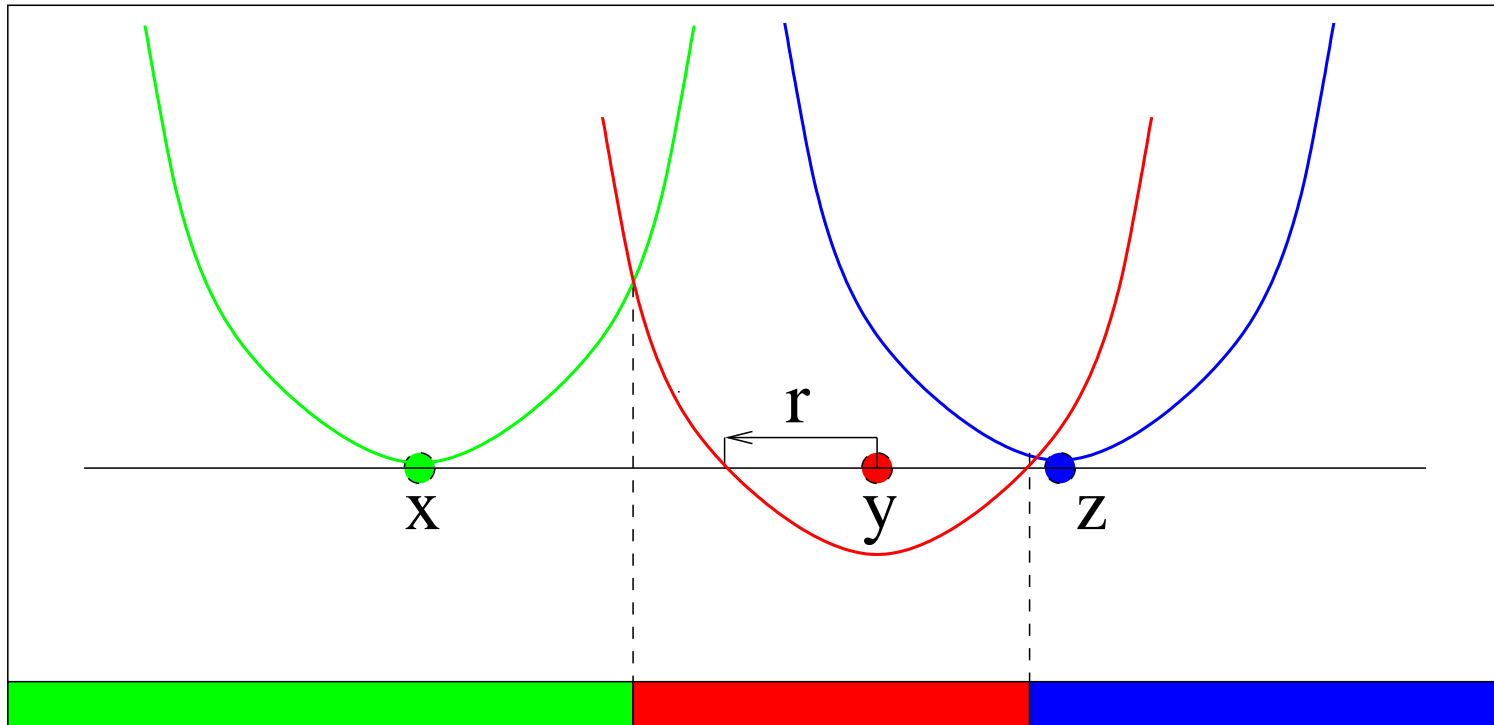
- When all weights are equal, get the usual Voronoi diagram.

# Power Diagram Demo

Demo

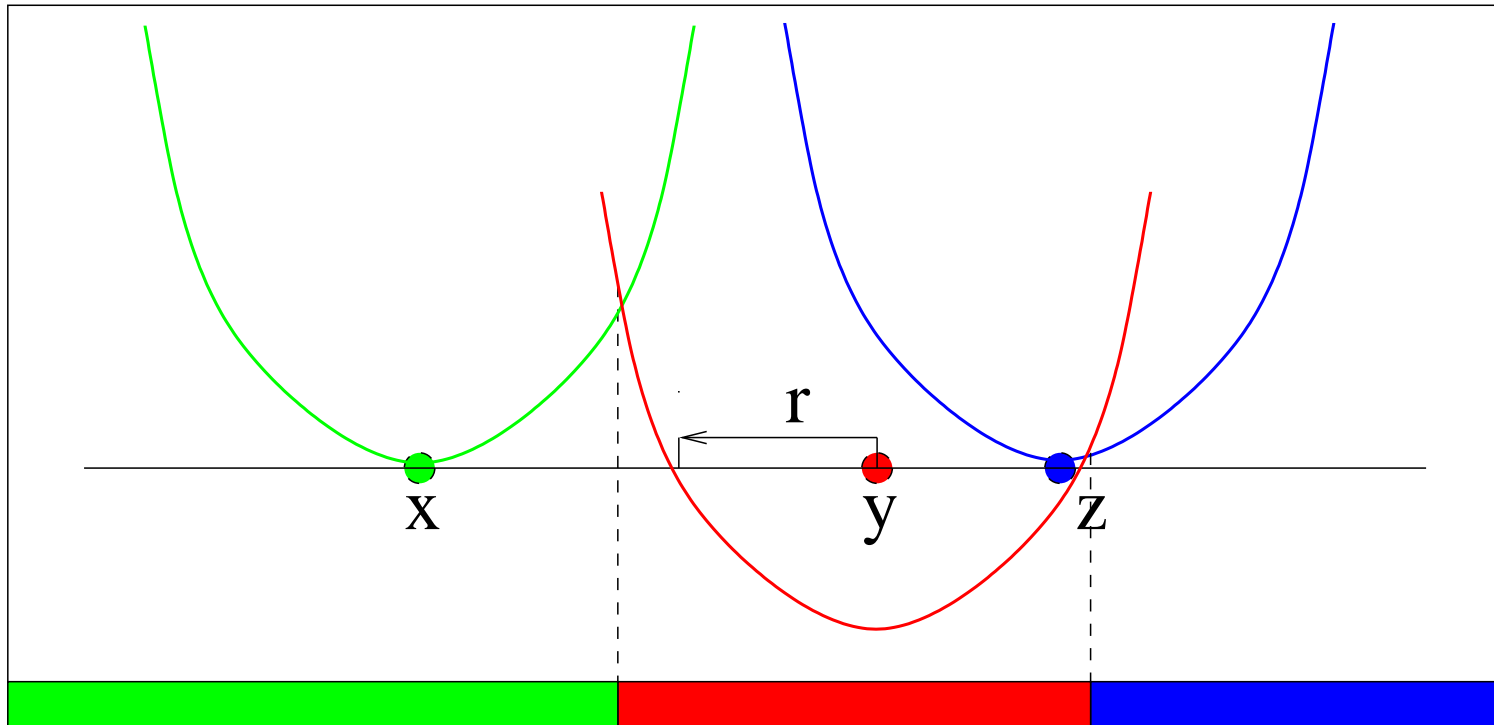


$$d_r(y, p) = (p - y)^2 - r^2$$



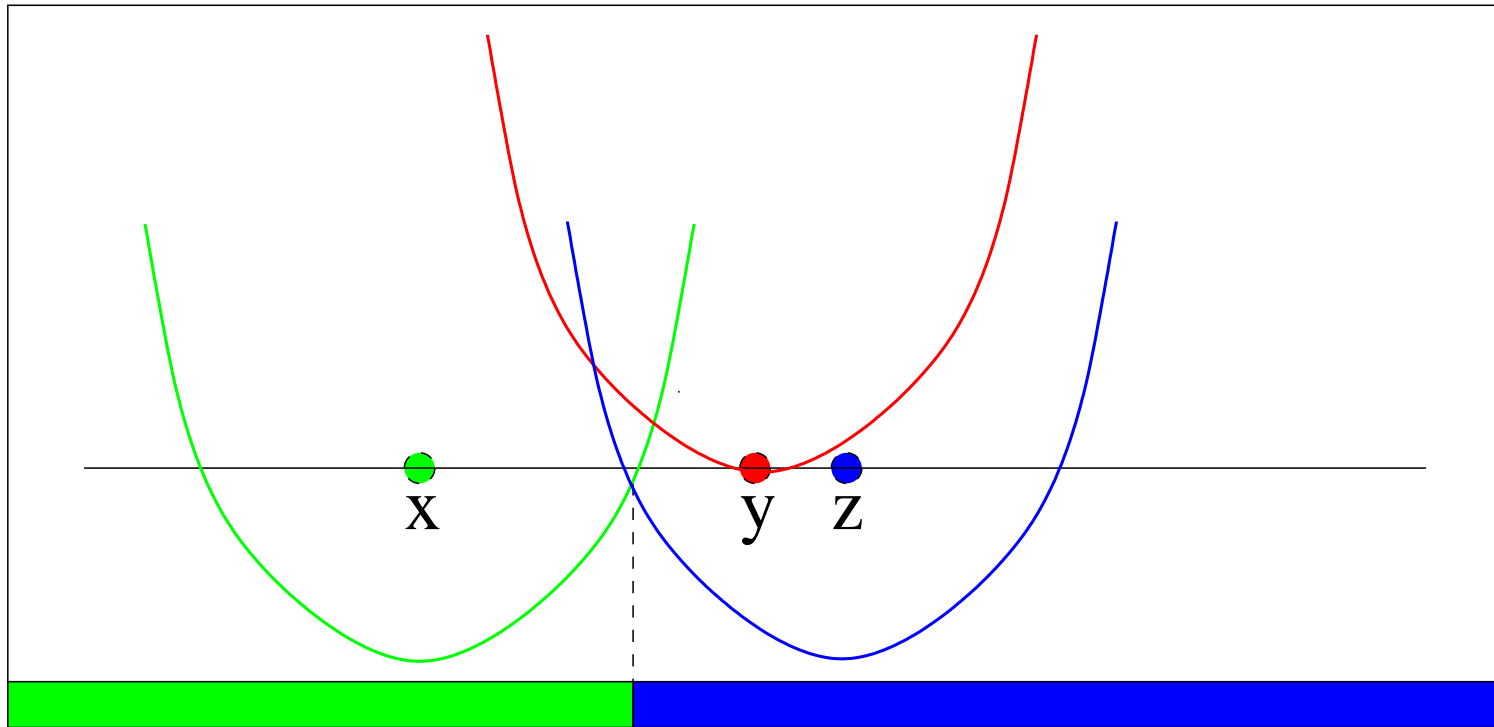
Point  $y$  has radius  $r_y \implies$  parabola gets lowered to intersect axis at distance  $r$  from  $y$ .

$$d_r(x, y) = (x - y)^2 - r^2$$



Weighted Voronoi cell for  $z$  doesn't necessarily contain  $z$ .

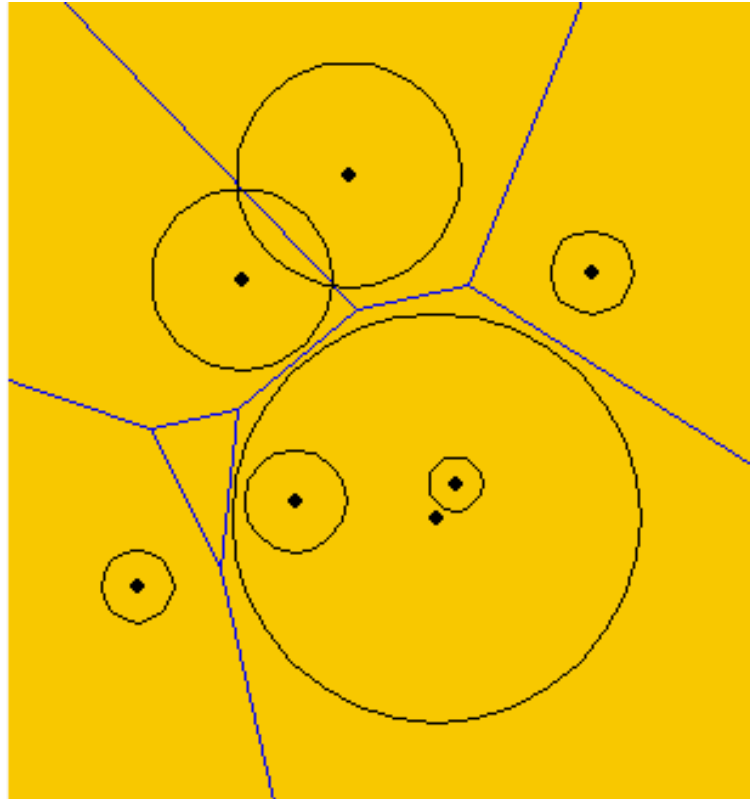
$$d_r(x, y) = (x - y)^2 - r^2$$



Some Voronoi cells may be empty!

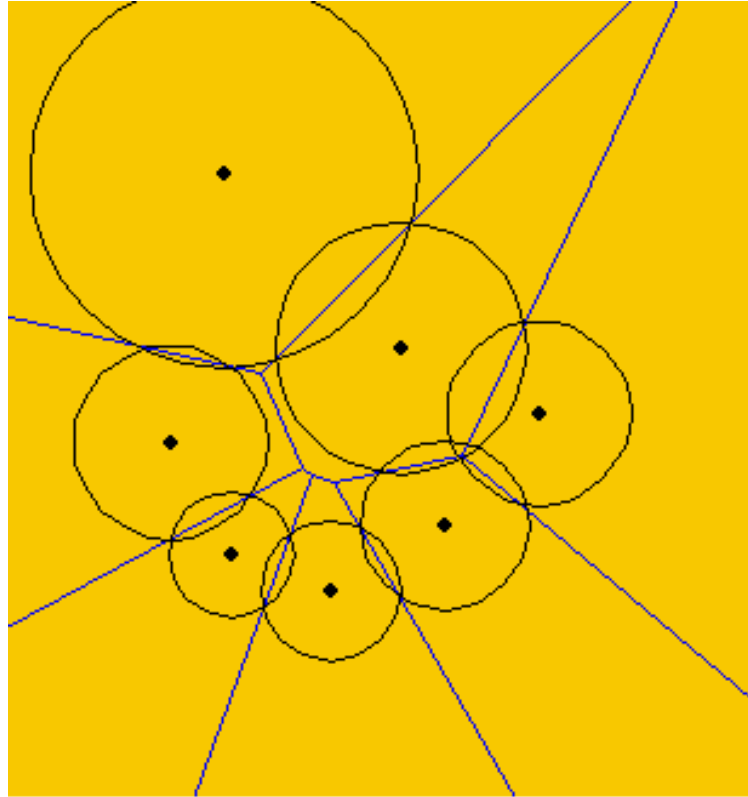
# Power Diagram Demo

More Demo



# Intersections

Power diagram edges always go through the intersections of circles



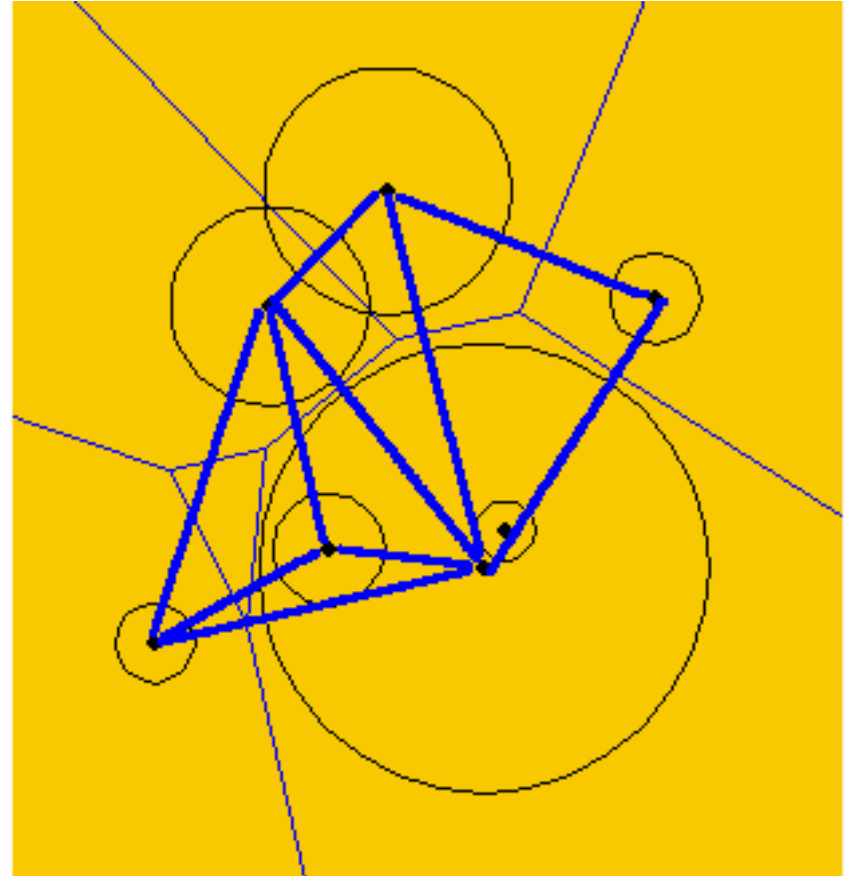
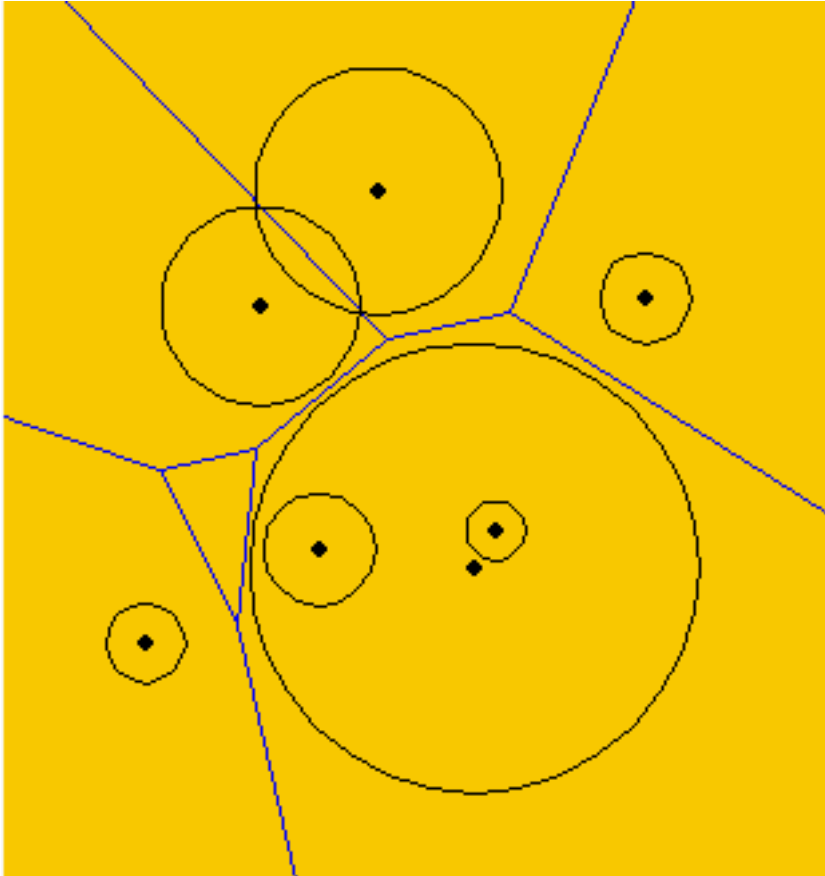
# Weighted Delaunay Complex

Weighted Delaunay Complex  
= Dual of Power Diagram

- Add an edge  $\{x, y\}$  if cells of  $x, y$  intersect
- Add a triangle  $\{x, y, z\}$  if cells of  $x, y, z$  intersect
- Add a tetrahedron...



# Weighted Delaunay Complex

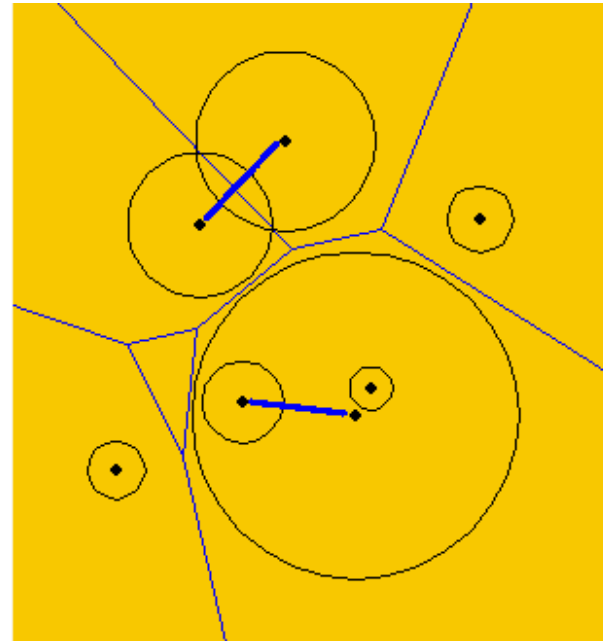
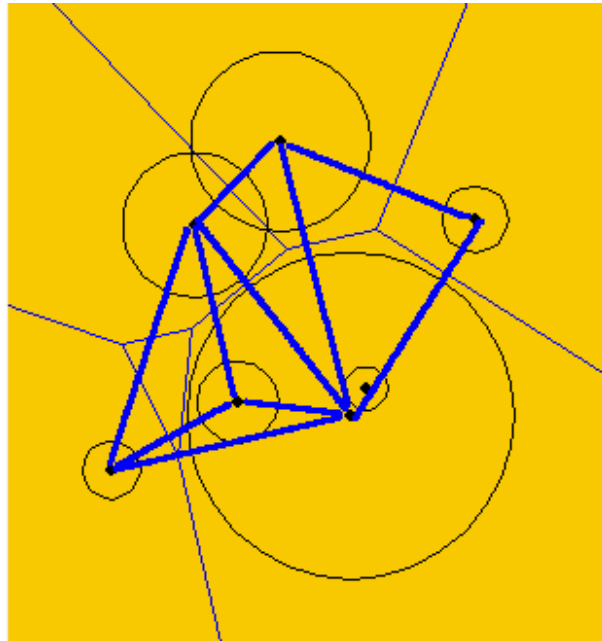


# Weighted Distance and Power Diagrams

- Weighted distance
- Power Diagrams ( = Weighted Voronoi)
- $\alpha$ -shapes

# Dual Complex

- **Subset** of weighted Delaunay graph
- Only keep edge  $(x, y)$  if balls at  $x, y$  intersect:  
 $d(x, y) \leq r_x + r_y$ .

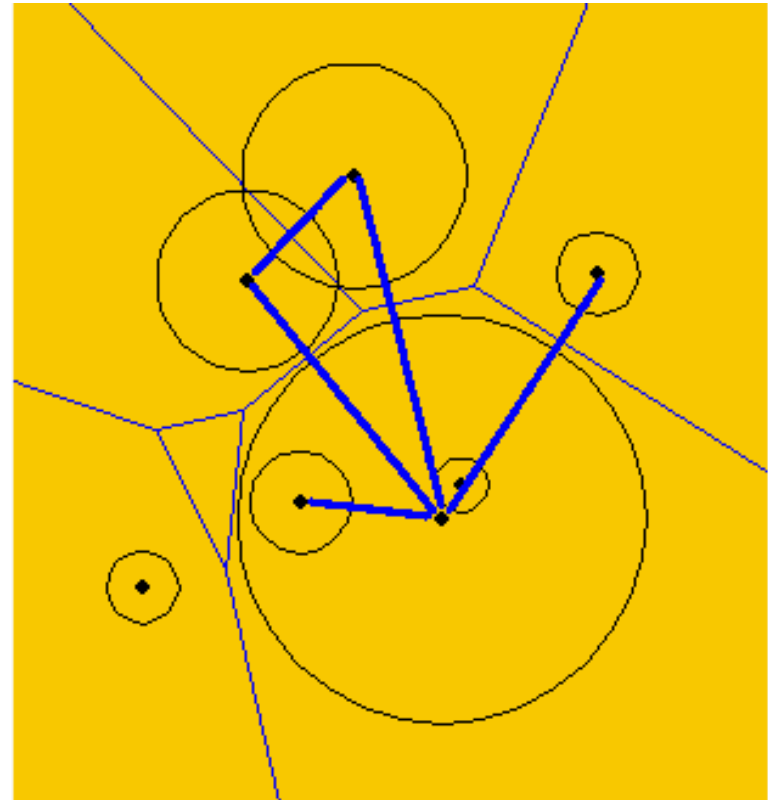
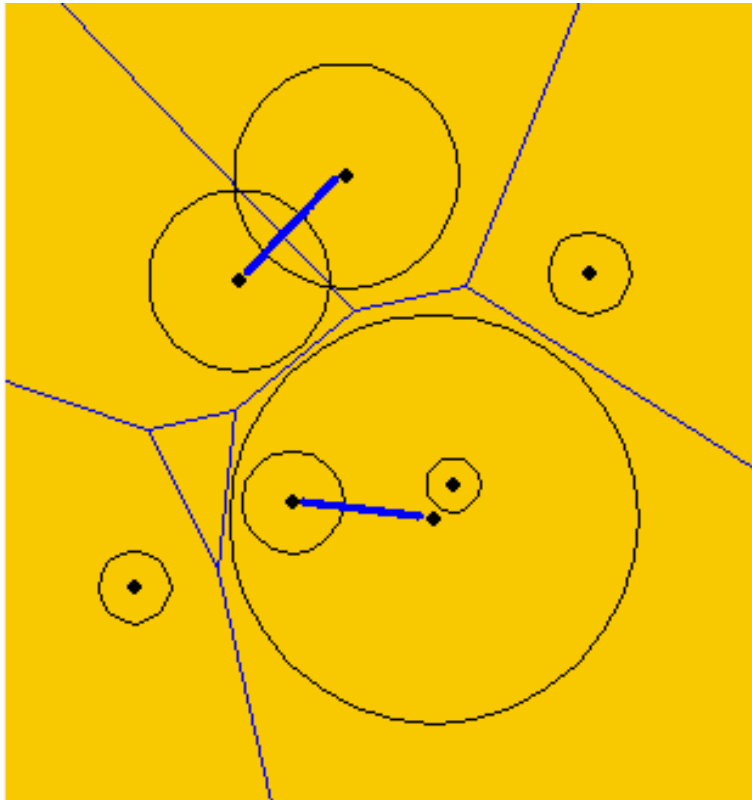


# Changing the radii

- Fix a parameter  $\alpha^2 \in (-\infty, \infty)$  (i.e.  $\alpha \in \mathbb{C}$ )
- Consider new radii  $r'_x = \sqrt{r_x^2 + \alpha^2}$
- Power diagram stays the same since  $d_{r'}(x, p) = d_r(x, p) - \alpha^2$ .
- Weighted Delaunay graph stays the same.
- Dual Complex
  - grows if  $\alpha^2 > 0$
  - shrinks if  $\alpha^2 < 0$

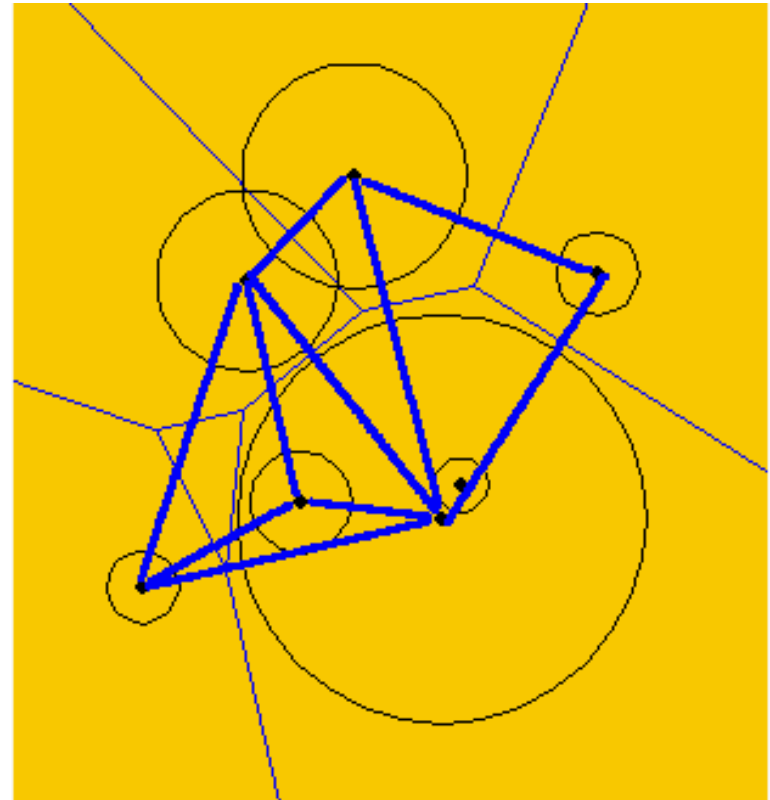
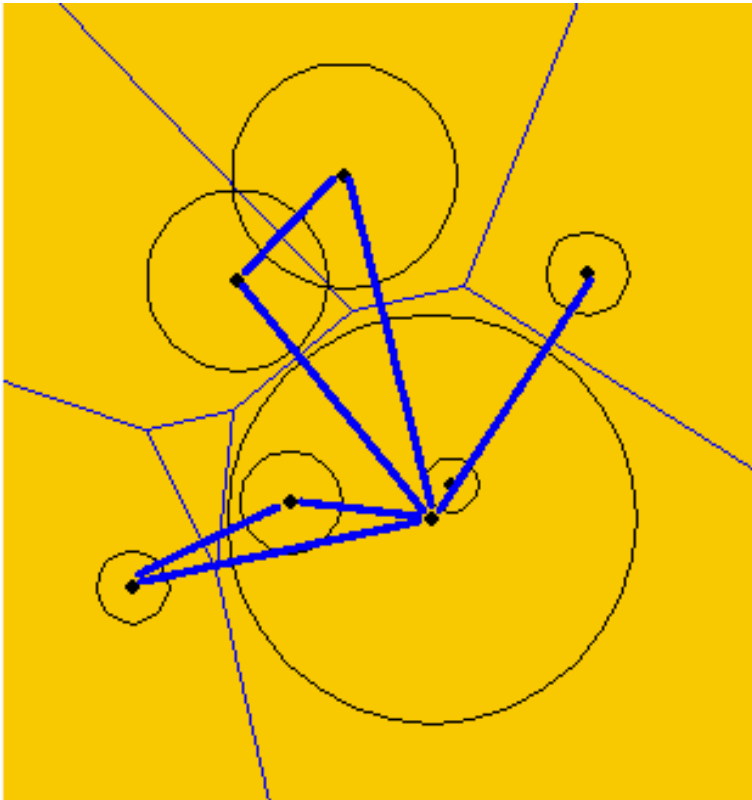
# $\alpha$ -shapes

As  $\alpha^2$  grows from  $-\infty$  to  $\infty$ , progress from empty graph to full weighted Delaunay graph:

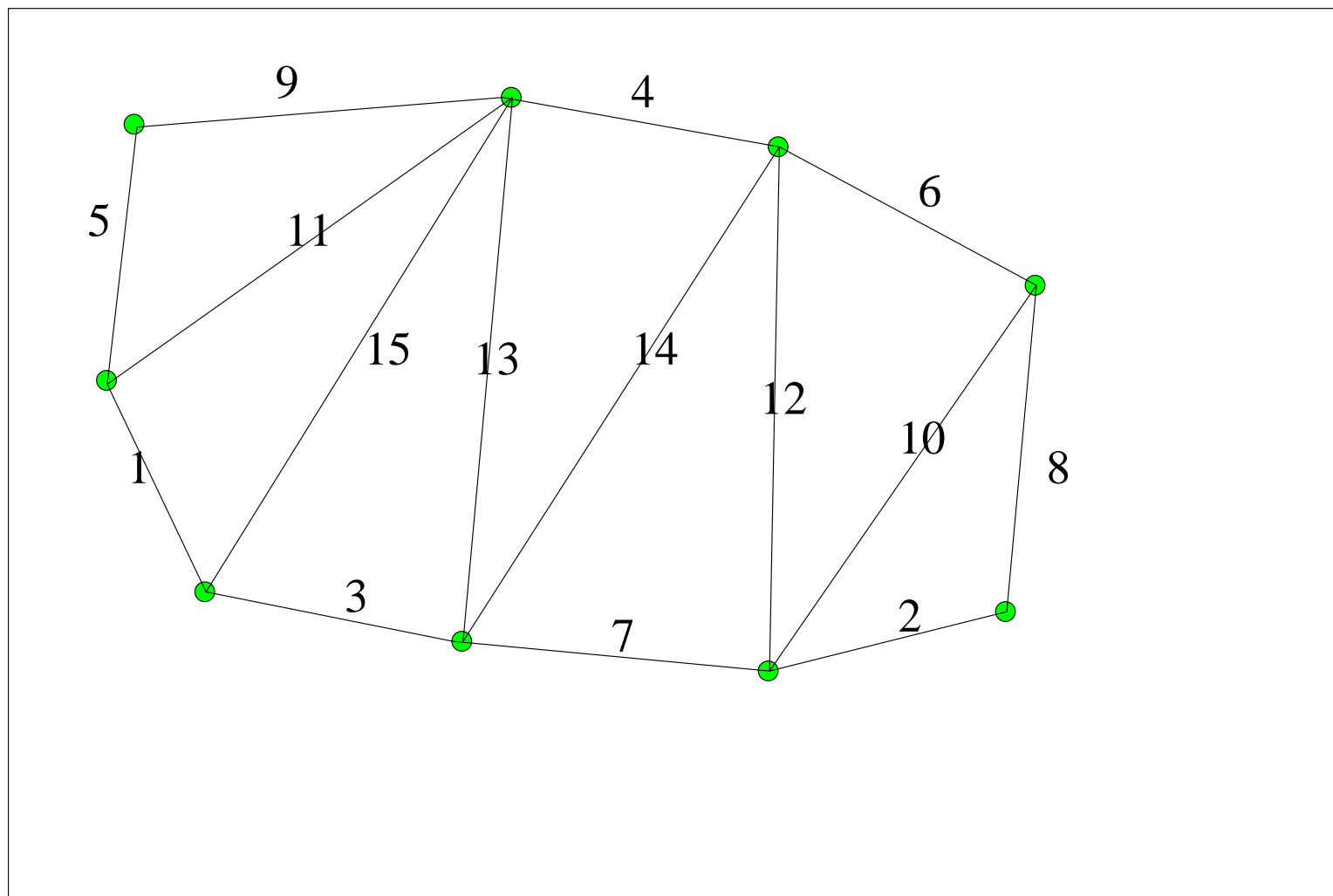


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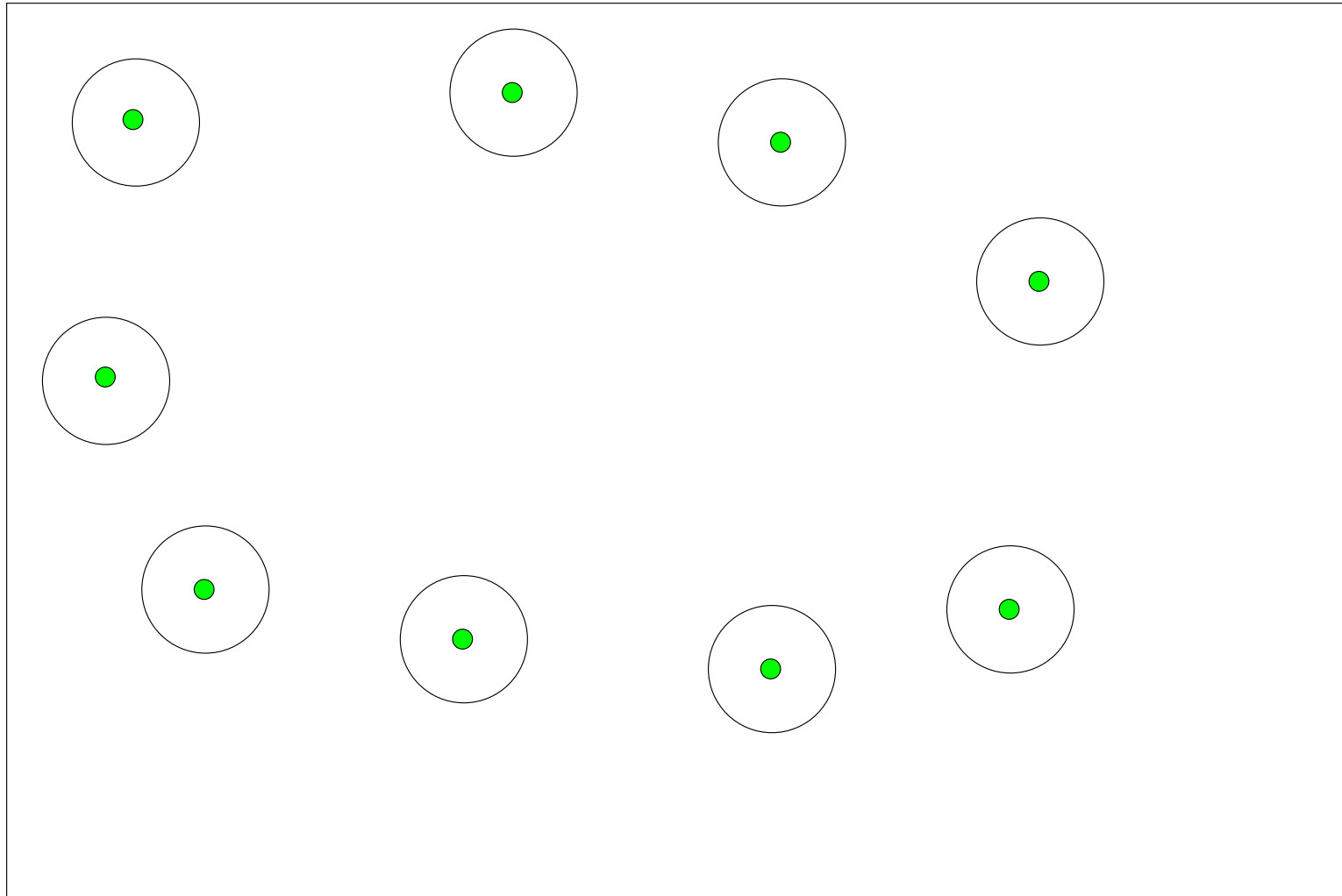
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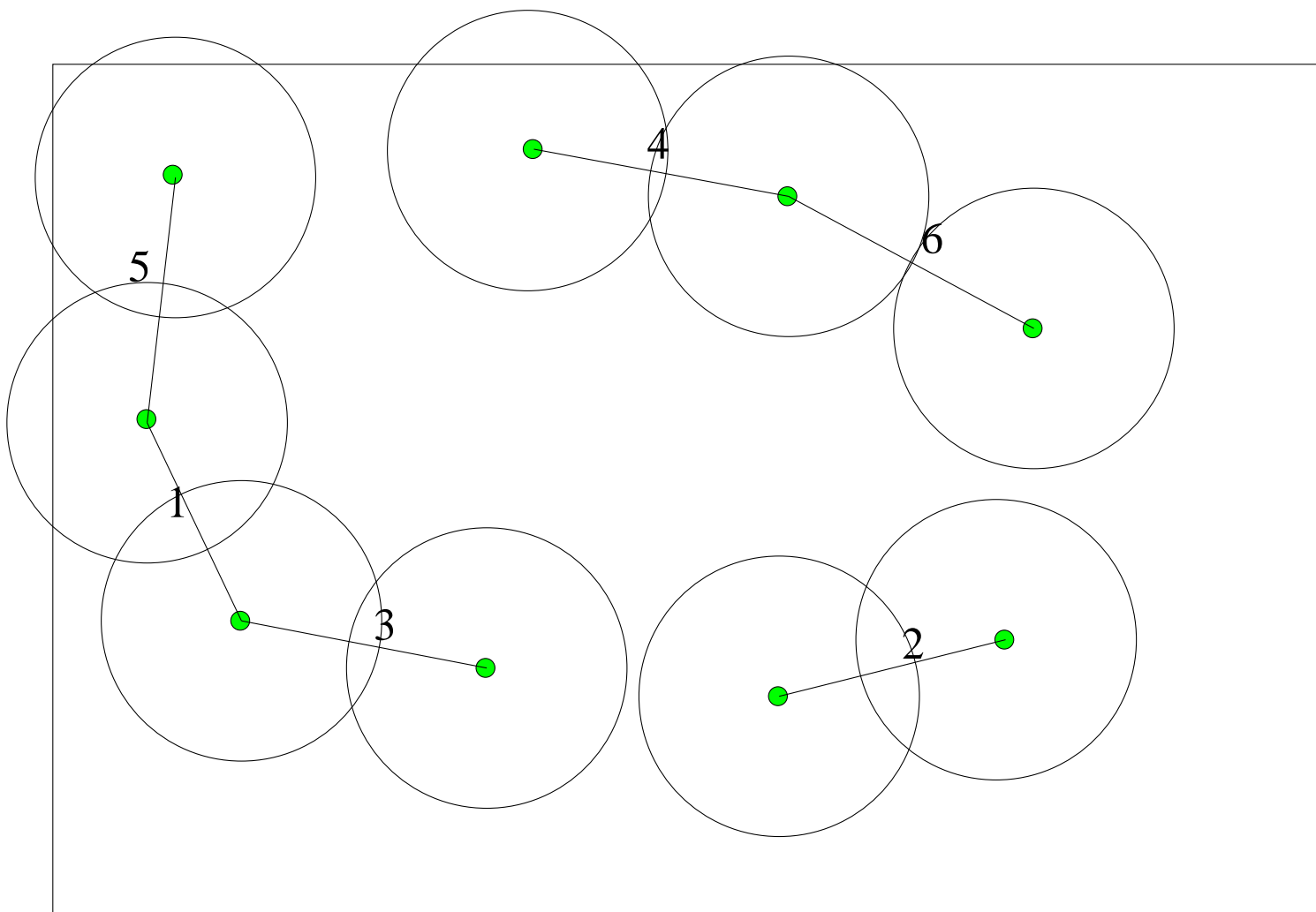


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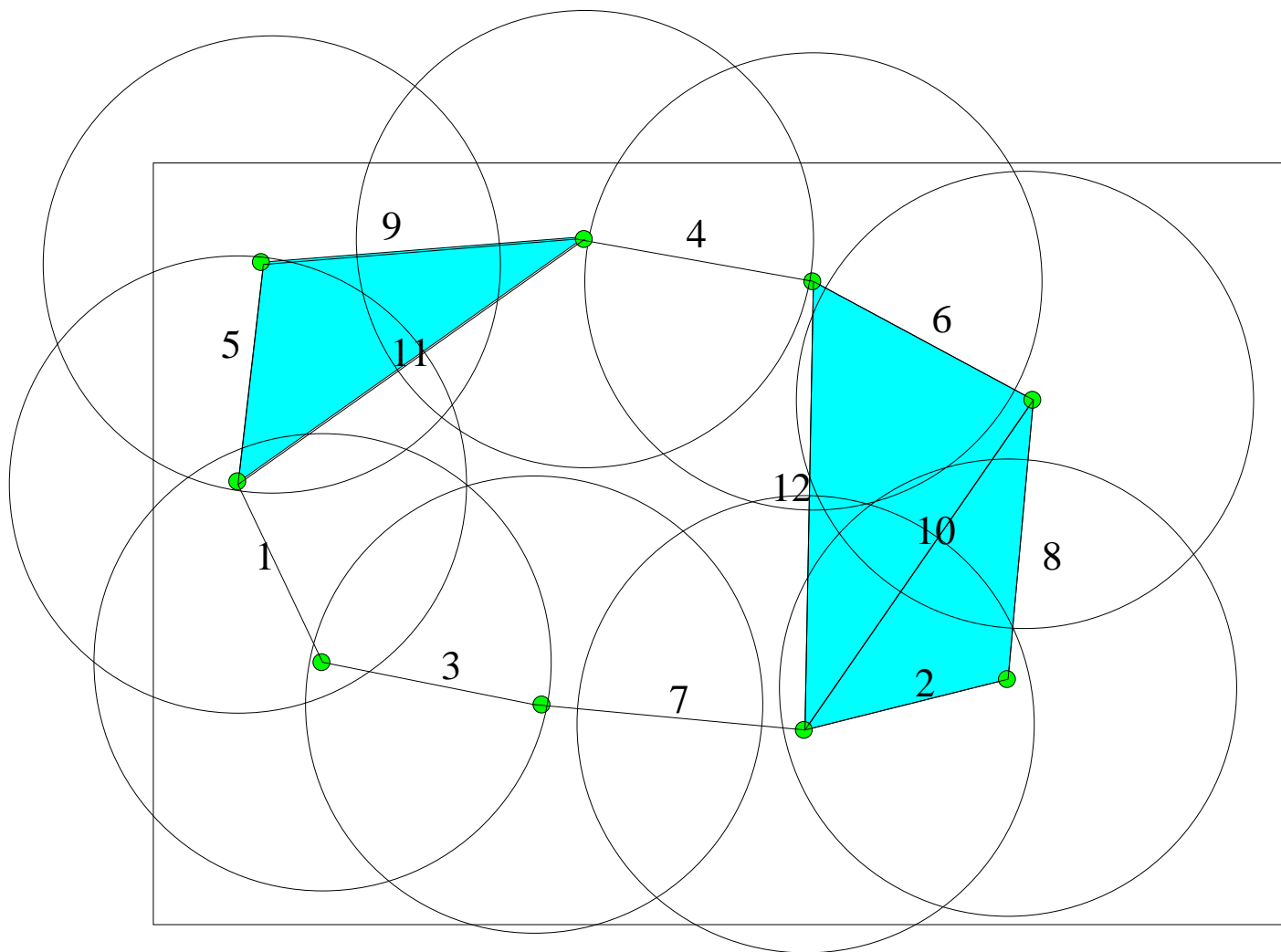




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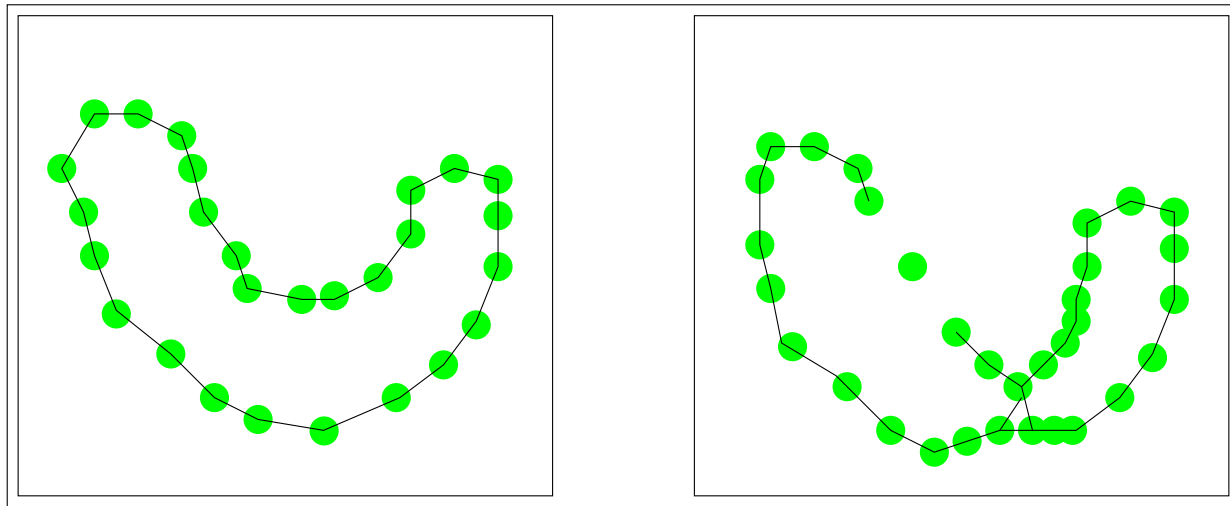
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# Who cares?

This ordering is useful for visualizing structure of the point set.

Example: Simple surface reconstruction



Other apps: chemical modeling, visualization

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# Selected References

- Hughes Hoppe. *Surface reconstruction from unorganized points*. Ph.D. Thesis, University of Washington, June 1994.
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- <http://pages.cpsc.ucalgary.ca/~laneb/Power/>