

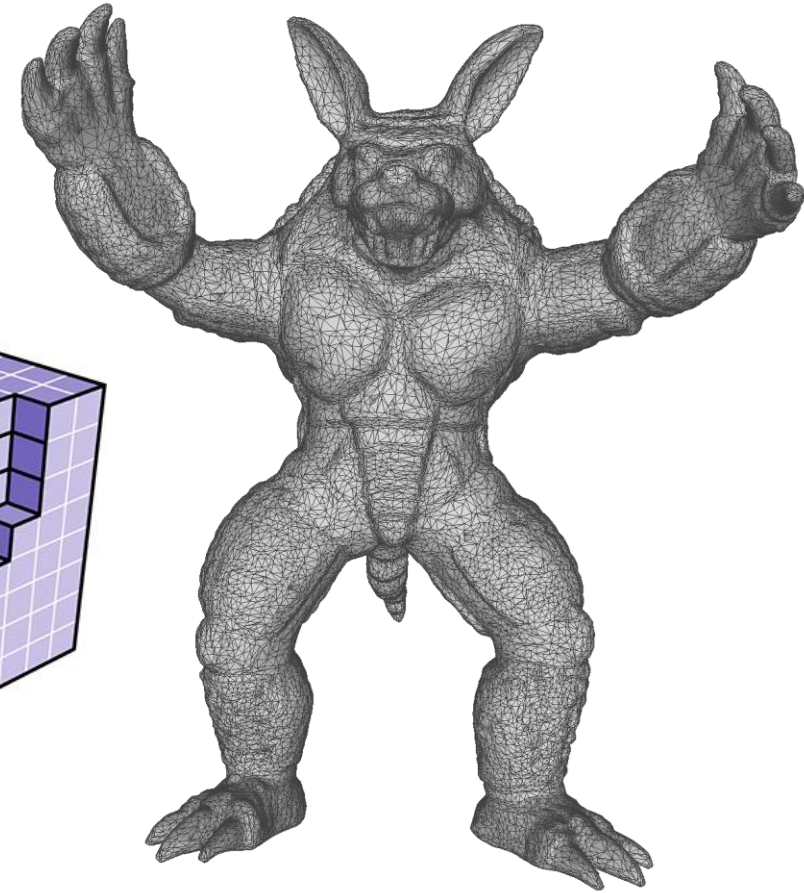
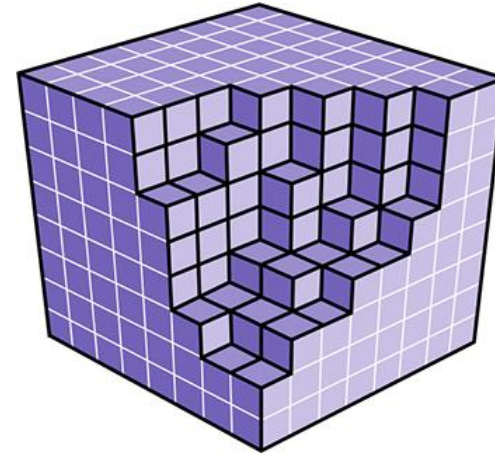
Visualization – Interpolation

J.-Prof. Dr. habil. Kai Lawonn

Data Representation

Data representation

- Discrete representations
 - Data samples (values) typically given on **meshes/grids** consisting of **cells**
 - Compact/efficient data representation

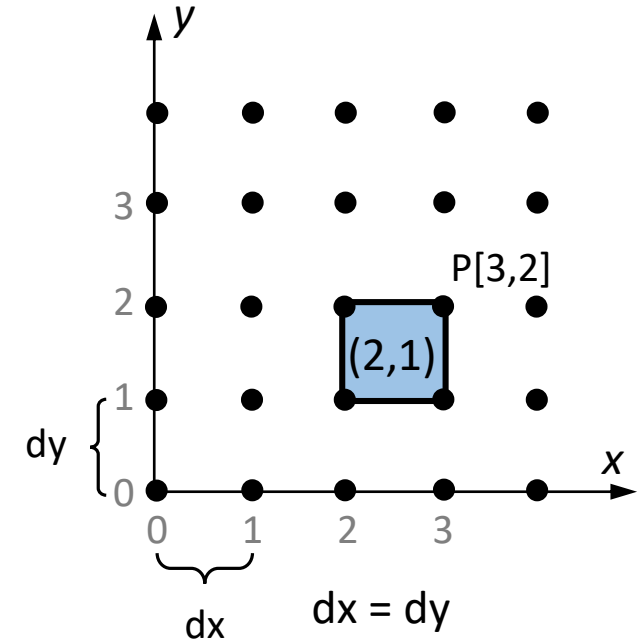


Primitives in different dimensions

dimension	cell	mesh
0D	points	polyline 2D mesh 3D mesh
1D	lines (edges)	
2D	triangles, quadrilaterals (rectangles)	
3D	tetrahedra, prisms, hexahedra	

Data representation

- Grids: Cartesian or equidistant grid
 - Samples at equidistant intervals along Cartesian coordinate axes
 - Neighboring samples are connected via edges
 - Cells formed by 4 (2D) or 8 (3D) samples
 - Cells and samples (grid vertices) are numbered sequentially with respect to increasing coordinates

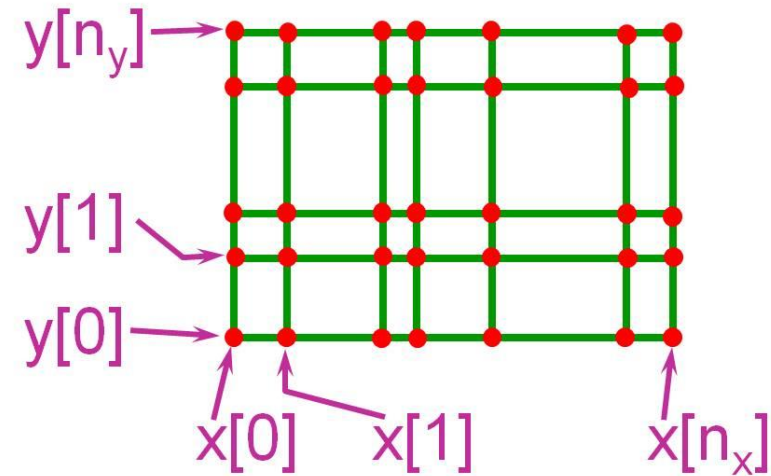
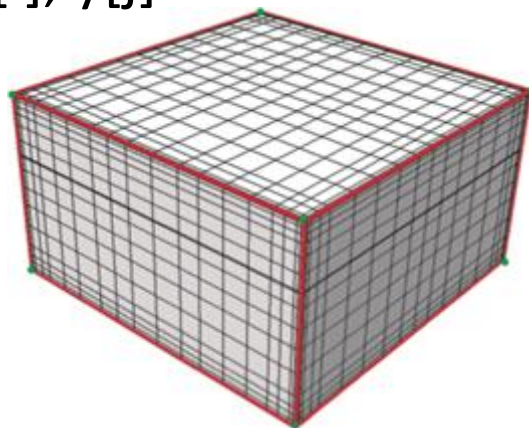
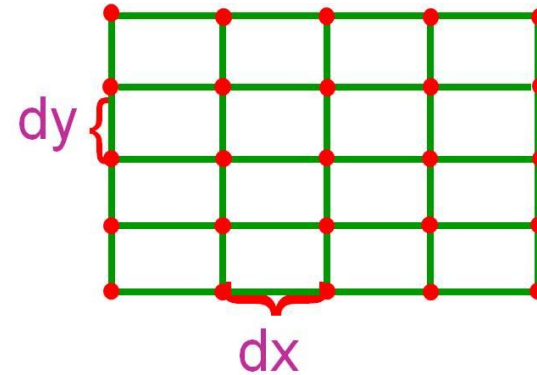


Data representation

- Some **properties** of Cartesian grids
 - Assuming N_x and N_y vertices along x- and y-axis
 - Number of **vertices** = $N_x \cdot N_y$
 - Number of **cells** = $(N_x - 1) \cdot (N_y - 1)$
 - Vertex positions are given **implicitly** from indices $[i,j]$:
 - $P[i,j].x = \text{origin} + i \cdot dx$
 - $P[i,j].y = \text{origin} + j \cdot dy$
 - It is a **structured grid**
 - Neighboring information (**topology**) is given implicitly
 - Neighbors obtained by incrementing/decrementing indices

Data representation

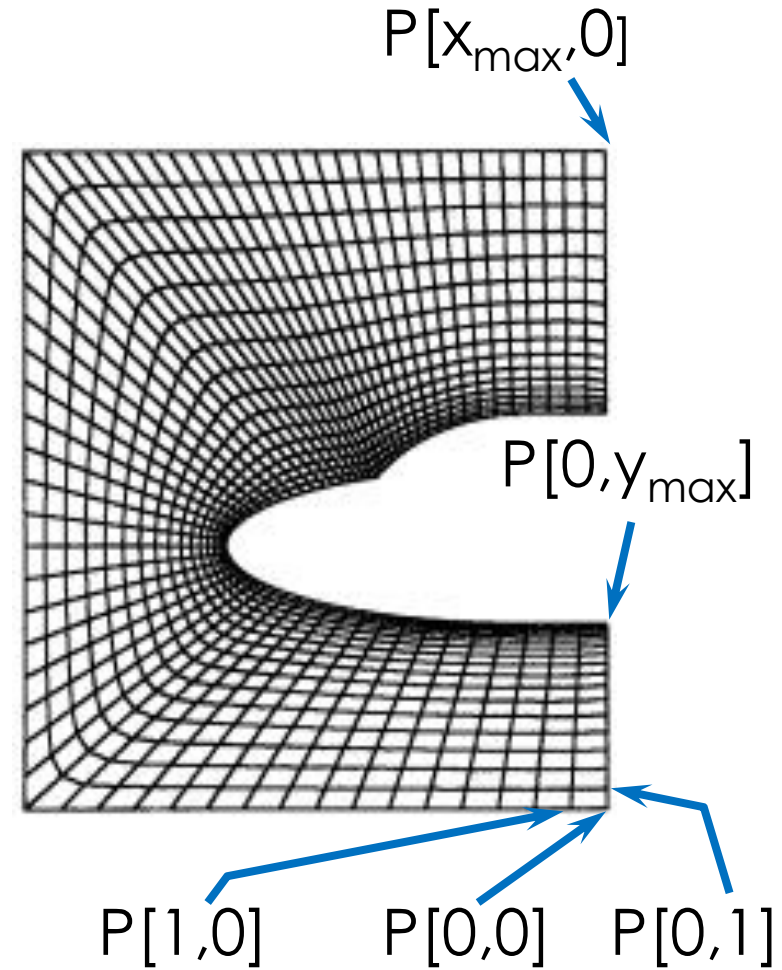
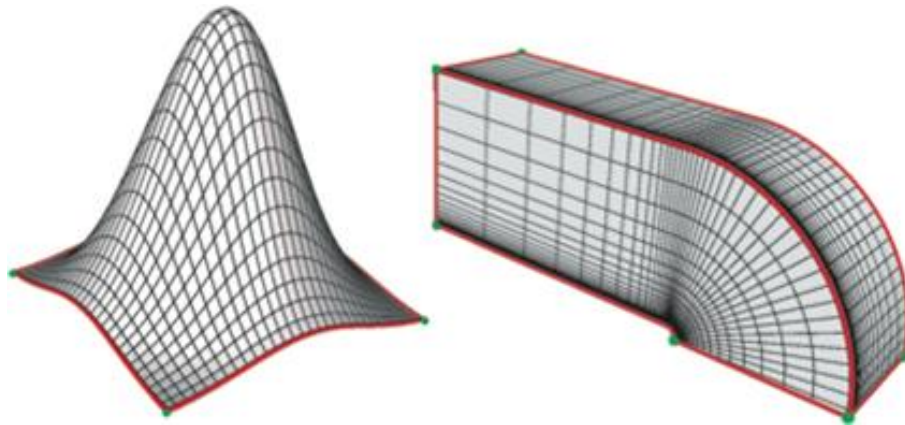
- Uniform or Regular Grid
 - Orthogonal, equidistant grid
 - $dx \neq dy$
- Rectilinear Grid
 - Varying sample-distances $x[i]$, $y[j]$



Data representation

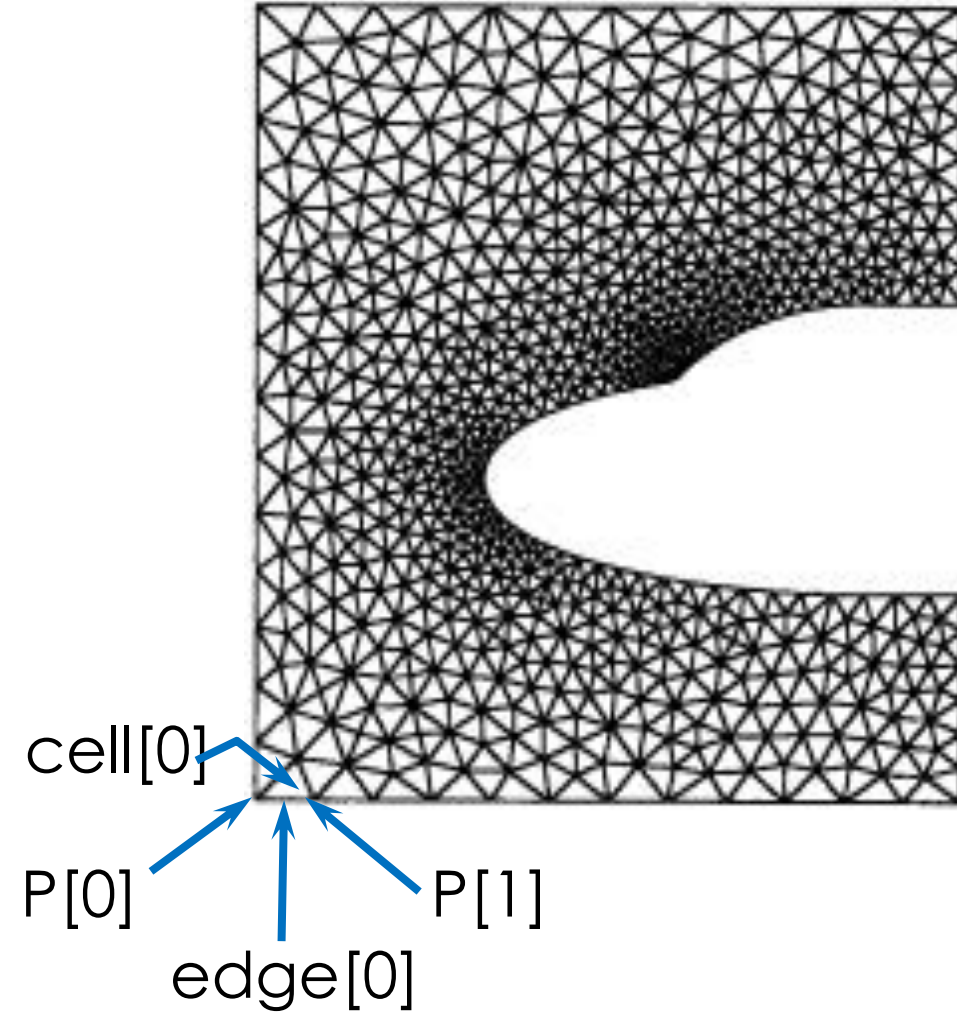
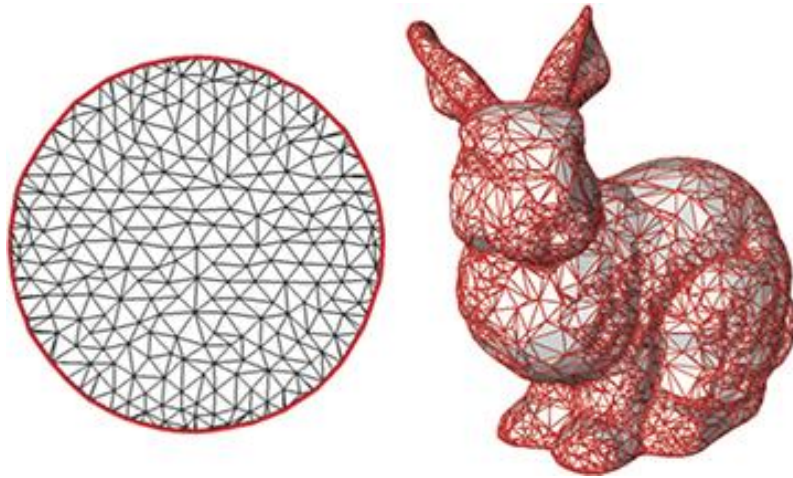
- **Curvilinear Grid**

- Non-orthogonal grid
- Grid-points specified explicitly ($P[i,j]$)
- Implicit neighborhood relationship



Data representation

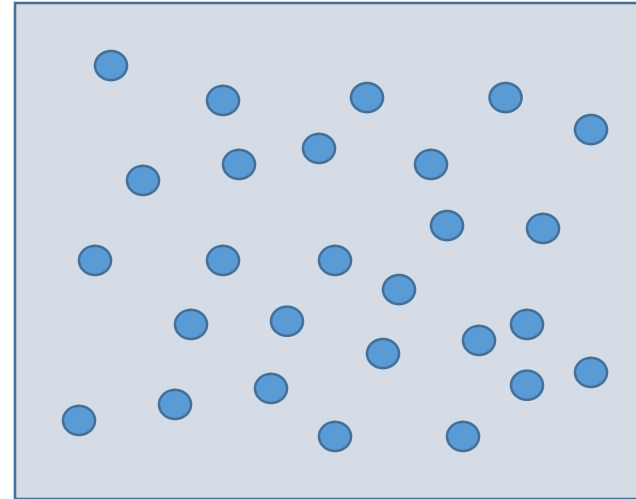
- **Unstructured grid**
 - Grid points and neighborhood specified explicitly
 - Cells: tetrahedra, hexahedra



Data representation

- Scattered Data

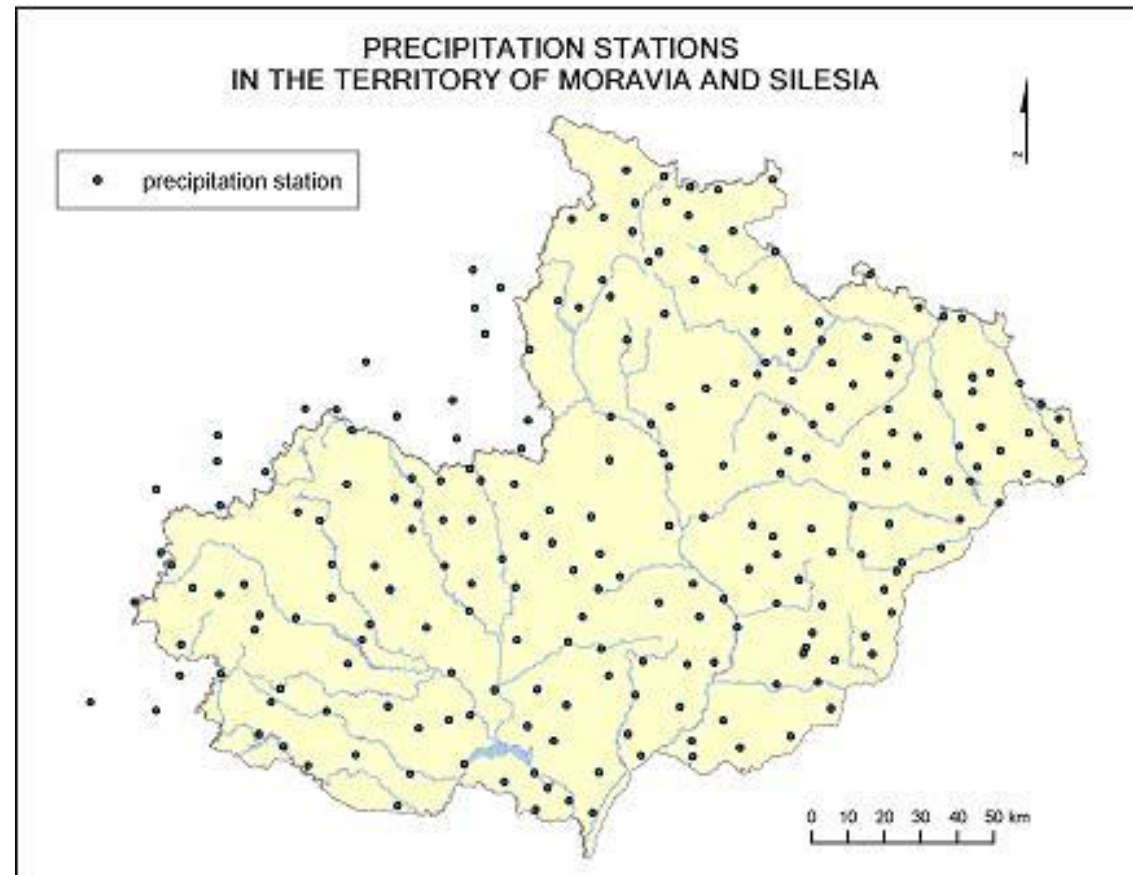
- Grid-free data
- Data points given without neighborhood-relationship
- Influence on neighborhood defined by spatial proximity
- Scattered data interpolation



Data Reconstruction

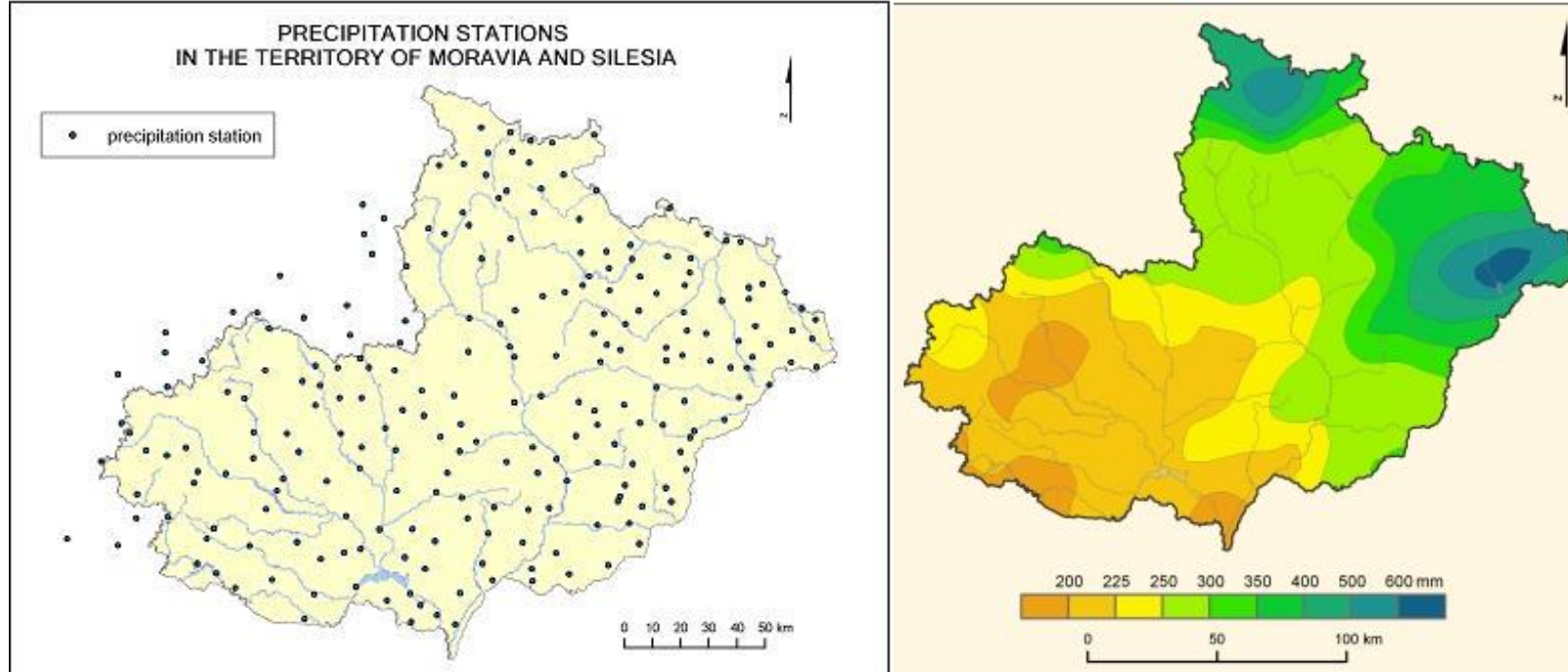
Data reconstruction

- Initial data often given at a discrete set of scattered points (samples) in the domain



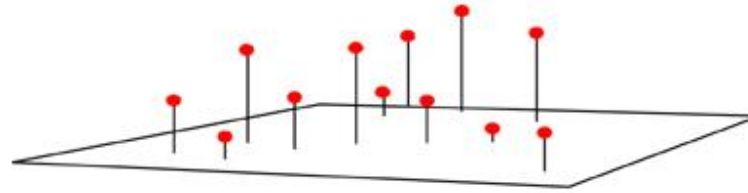
Data reconstruction

- Derive **continuous** representation from data given at scattered points
 - Better communication of spatial data distribution

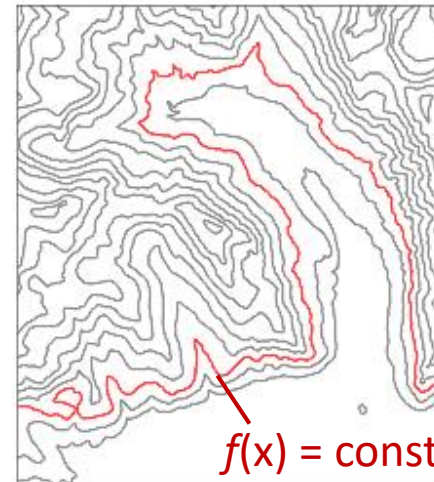
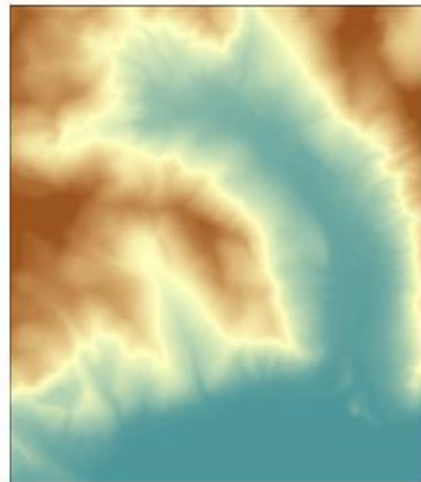


Data reconstruction

- Derive **continuous** representation from data given at scattered points
 - Some analysis techniques require a continuous representation



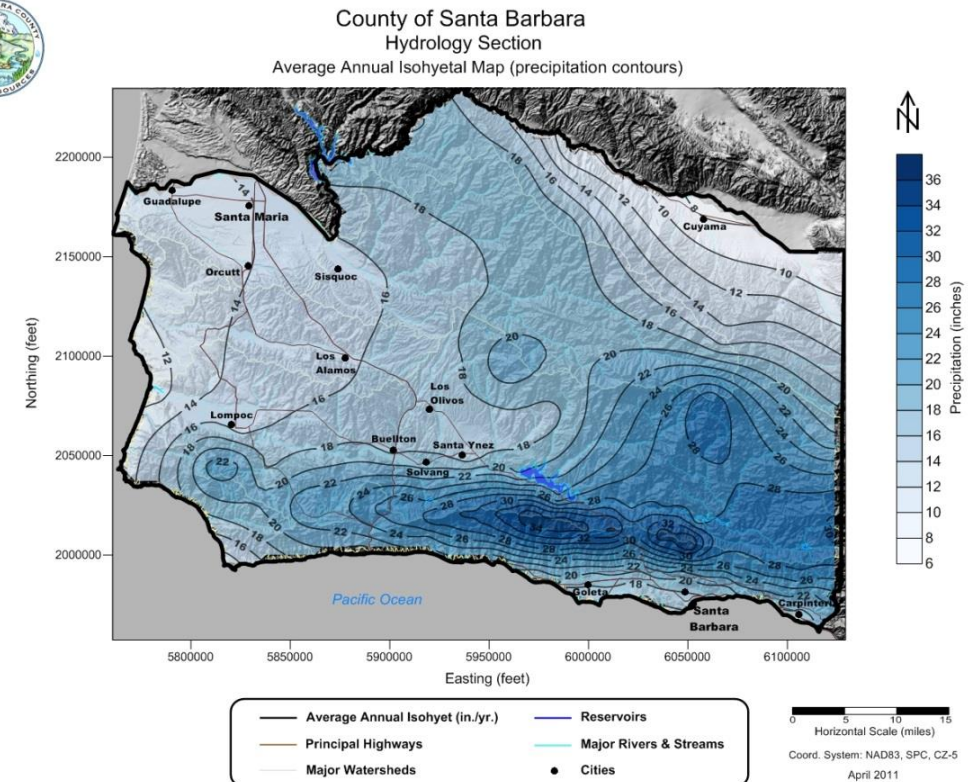
Data distribution



Isocontours –
curves on which
all points with a
given value lie

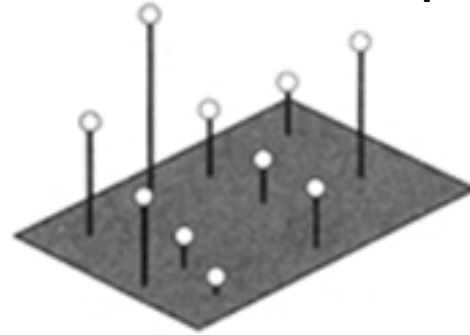
Data reconstruction

- Isocontours in continuous data fields

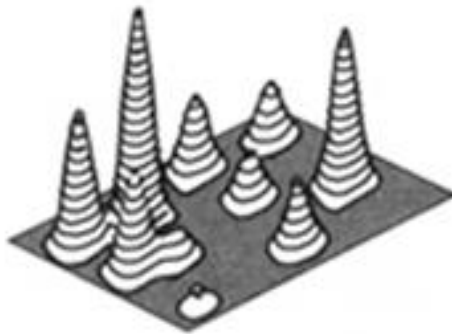


Data reconstruction

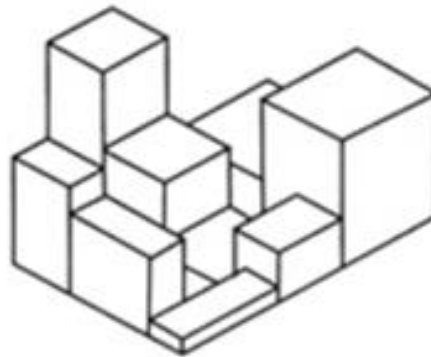
- Data reconstruction from scattered points



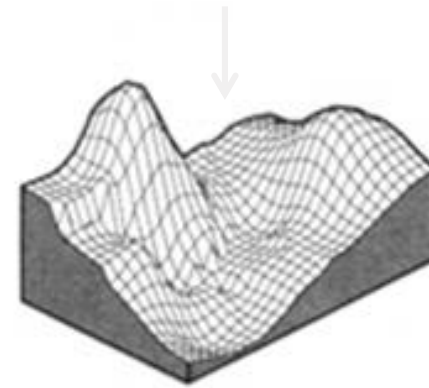
Assumes some similarity
between data values
inversely proportional to
distance



data interpolation



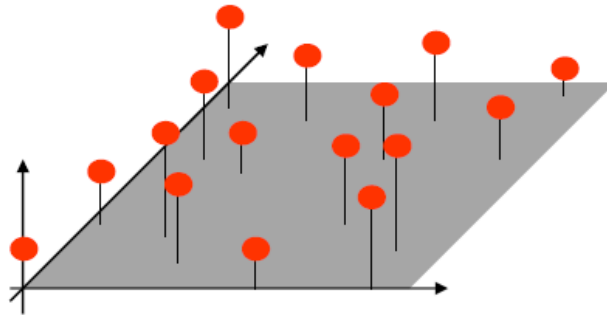
piece-wise constant
interpolation



continuous interpolation

Data reconstruction

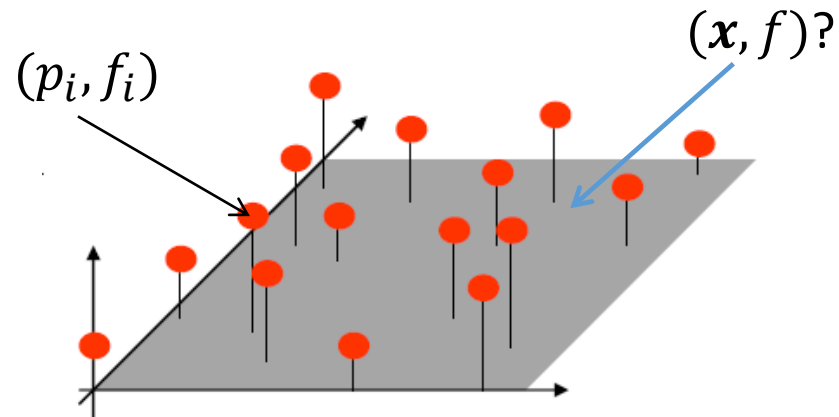
- Data reconstruction from scattered points



- Obtain values in-between the data points...
 1. from a **continuous function** which interpolates the given values and varies smoothly in-between
 2. from a grid which is constructed from the given points, i.e., a **triangulation**

Continuous representation

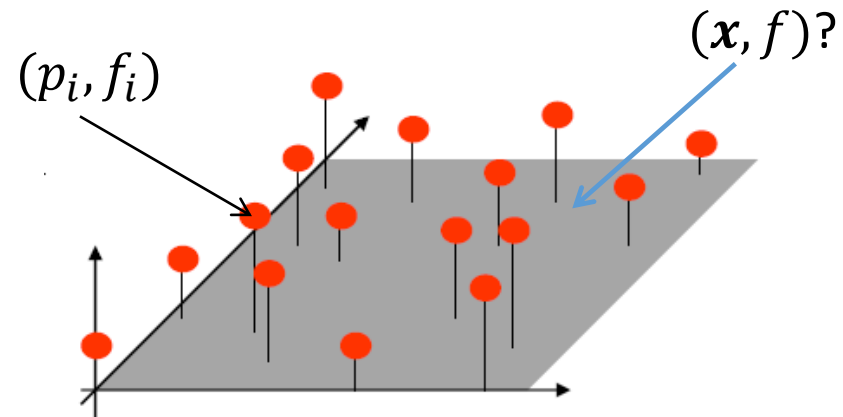
- Given a set of **scattered points** p_i in a 2D parameter domain with **scalar values** f_i
 - The principles are applicable to arbitrary parameter domain dimensions (1D/2D/3D)
- **Goal:** Construct a **continuous function** f from given set of p_i, f_i which approximates (“follows”) the given values



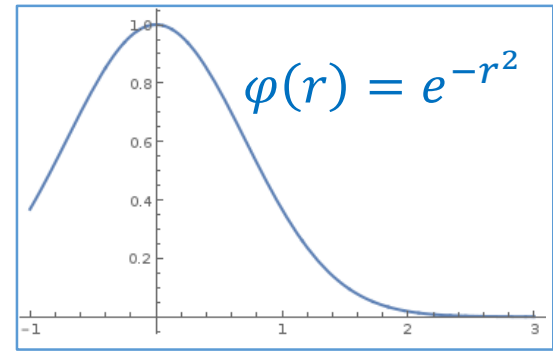
Continuous representation

- Radial Basis Functions

- Independent of dimension of parameter domain (1D/2D/3D)
- Each (p_i, f_i) influences $f(\mathbf{x})$ based on Euclidean distance $r = \|\mathbf{p}_i - \mathbf{x}\|$
- Nearby points have higher influence than far-away points

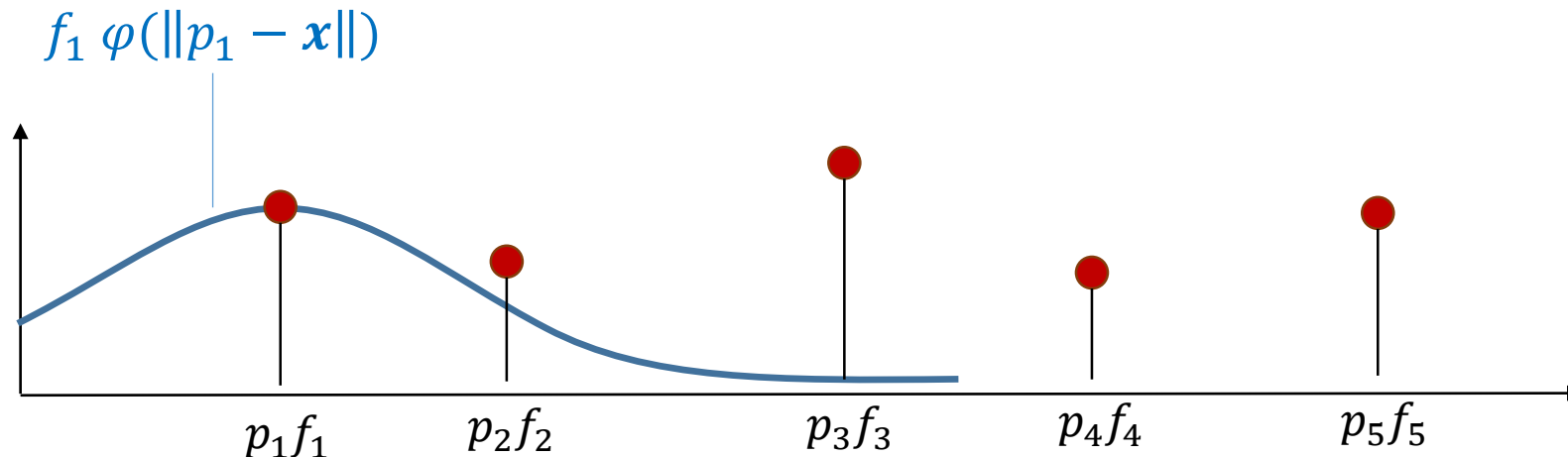


Continuous representation

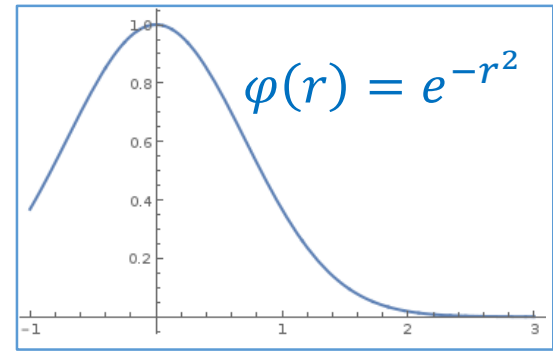


- Radial Basis Functions

- Each radial function $\varphi(r)$ is centered around a data point p_i
- Value of $\varphi(r)$ decreases quickly with increasing distance $r = \|p_i - \mathbf{x}\|$ to the function's center p_i

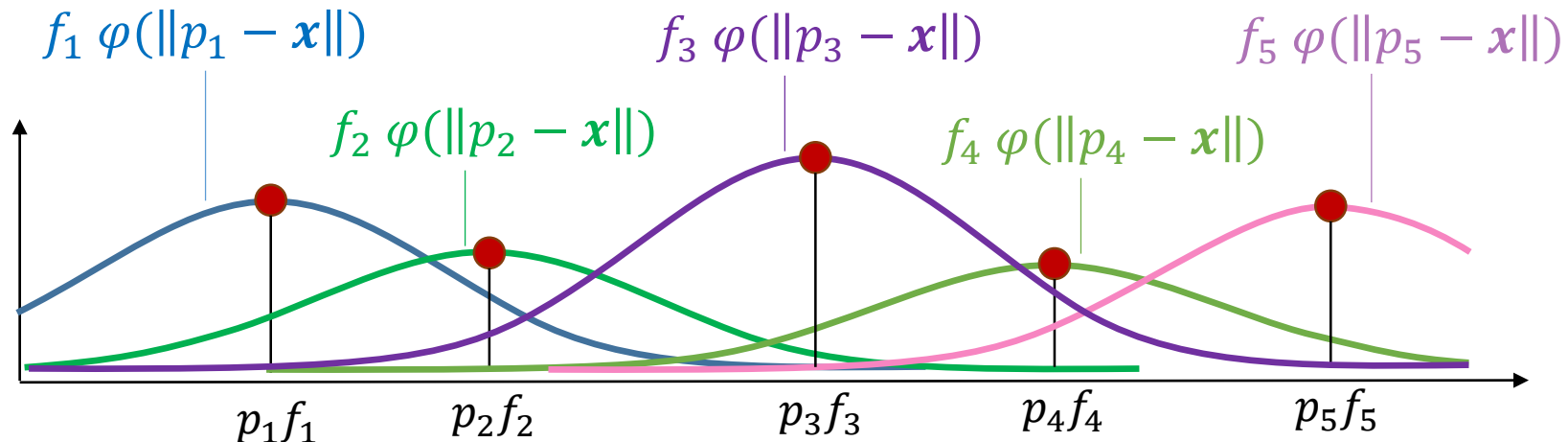


Continuous representation

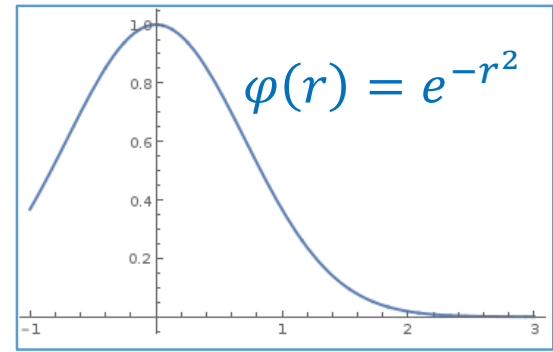


- Radial Basis Functions

- Each radial function $\varphi(r)$ is centered around a data point p_i
- Value of $\varphi(r)$ decreases quickly with increasing distance $r = \|p_i - \mathbf{x}\|$ to the function's center p_i



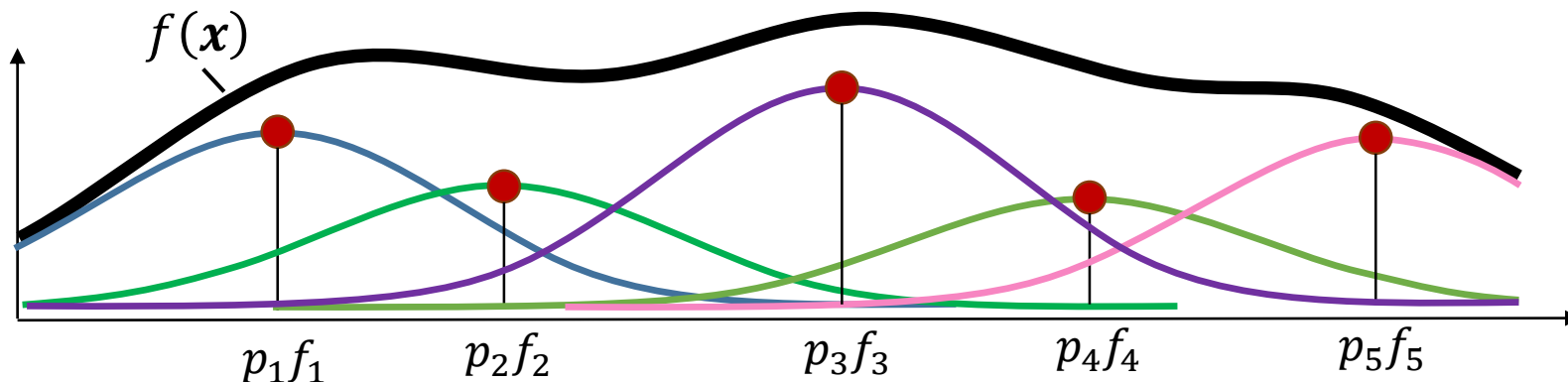
Continuous representation



- Radial Basis Functions

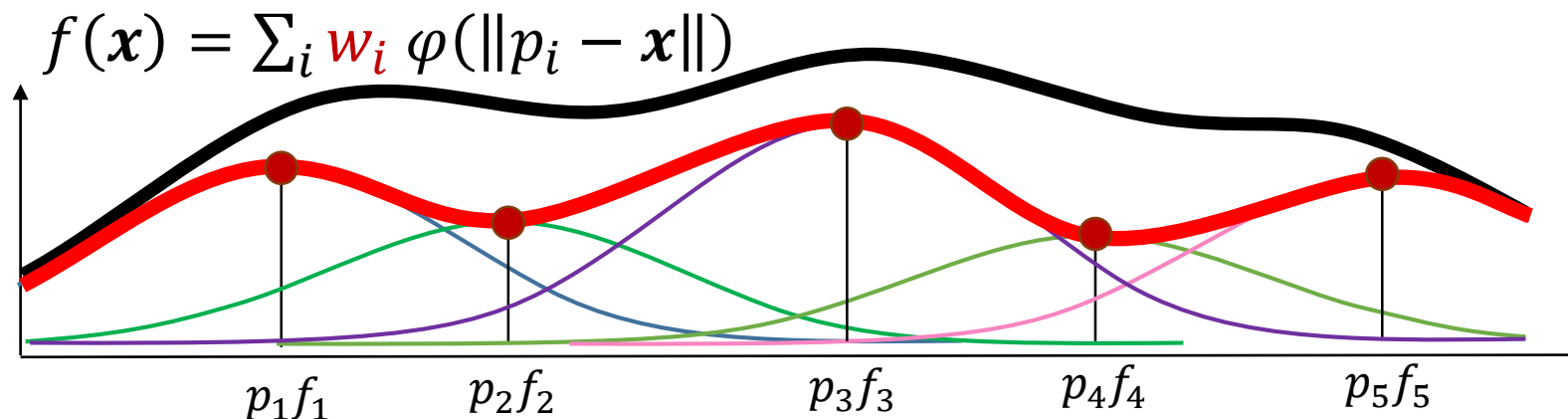
- Each radial function $\varphi(r)$ is centered around a data point p_i
- Value of $\varphi(r)$ decreases quickly with increasing distance $r = \|p_i - \mathbf{x}\|$ to the function's center p_i
- Function f represented as **weighted sum** of N radial functions φ

$$f(\mathbf{x}) = \sum_{i=1}^N f_i \varphi(\|p_i - \mathbf{x}\|)$$



Continuous representation

- Radial Basis Functions
 - Instead of the **black** curve we want the **red** one, i.e., a curve which is going through the initial data points
 - This is called an **interpolation**
 - **Question:** How do we have to select the **weights w_i** so that the red curve is obtained?



Continuous representation

- Radial Basis Functions – finding the weights w_i
 - For $j = 1, \dots, N$,
specify w_i such that $f(p_j)$ interpolates the value f_j

$$f(p_j) = \sum_{i=1}^N w_i \varphi(\|p_i - p_j\|) = f_j$$

Continuous representation

- Example:
 - Data points: $p_1 = 1, p_2 = 3, p_3 = 4$
 - Data values: $f_1 = 1, f_2 = 2, f_3 = 0$
- Find the weights w_i such that f interpolates all points

$$f(p_j) = \sum_{i=1}^N w_i \varphi(\|p_i - p_j\|) = f_j$$

$$f(1) = 1$$

$$f(3) = 2$$

$$f(4) = 0$$

Continuous representation

- This results in:

$$f(x) = w_1\varphi(|1 - x|) + w_2\varphi(|3 - x|) + w_3\varphi(|4 - x|)$$

- Yielding the equation system:

$$w_1\varphi(0) + w_2\varphi(2) + w_3\varphi(3) = 1$$

$$w_1\varphi(2) + w_2\varphi(0) + w_3\varphi(1) = 2$$

$$w_1\varphi(3) + w_2\varphi(1) + w_3\varphi(0) = 0$$

Continuous representation

$$w_1\varphi(0) + w_2\varphi(2) + w_1\varphi(3) = 1$$

$$w_1\varphi(-2) + w_2\varphi(0) + w_1\varphi(1) = 2$$

$$w_1\varphi(-3) + w_2\varphi(-1) + w_1\varphi(0) = 0$$

- We can formulate this in matrix representation:

$$\begin{pmatrix} \varphi(0) & \varphi(2) & \varphi(3) \\ \varphi(2) & \varphi(0) & \varphi(1) \\ \varphi(3) & \varphi(1) & \varphi(0) \end{pmatrix} \cdot \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix}$$

Continuous representation

- Radial Basis Functions – finding the weights w_i

- For $j = 1, \dots, N$,
specify w_i such that $f(p_j)$ interpolates the value f_j

$$f(p_j) = \sum_{i=1}^N w_i \varphi(\|p_i - p_j\|) = f_j$$

- Yields a system of linear equations (per point) to be solved for w_i

$$\begin{bmatrix} \varphi(\|p_1 - p_1\|) & \varphi(\|p_2 - p_1\|) & \cdots & \varphi(\|p_N - p_1\|) \\ \varphi(\|p_1 - p_2\|) & \varphi(\|p_2 - p_2\|) & \cdots & \varphi(\|p_N - p_2\|) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi(\|p_1 - p_N\|) & \varphi(\|p_2 - p_N\|) & \cdots & \varphi(\|p_N - p_N\|) \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{bmatrix}$$

N equations in N unknowns

Continuous representation

- Radial Basis Functions – finding the weights w_i

- For $j = 1, \dots, N$,
specify w_i such that $f(p_j)$ interpolates the value f_j

$$f(p_j) = \sum_{i=1}^N w_i \varphi(\|p_i - p_j\|) = f_j$$

- Yields a system of linear equations (per point) to be solved for w_i

$$\begin{bmatrix} \varphi(0) & \varphi(\|p_2 - p_1\|) & \cdots & \varphi(\|p_N - p_1\|) \\ \varphi(\|p_1 - p_2\|) & \varphi(0) & \cdots & \varphi(\|p_N - p_2\|) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi(\|p_1 - p_N\|) & \varphi(\|p_2 - p_N\|) & \cdots & \varphi(0) \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{bmatrix}$$

Continuous representation

$$w_1\varphi(0) + w_2\varphi(2) + w_1\varphi(3) = 1$$

$$w_1\varphi(-2) + w_2\varphi(0) + w_1\varphi(1) = 2$$

$$w_1\varphi(-3) + w_2\varphi(-1) + w_1\varphi(0) = 0$$

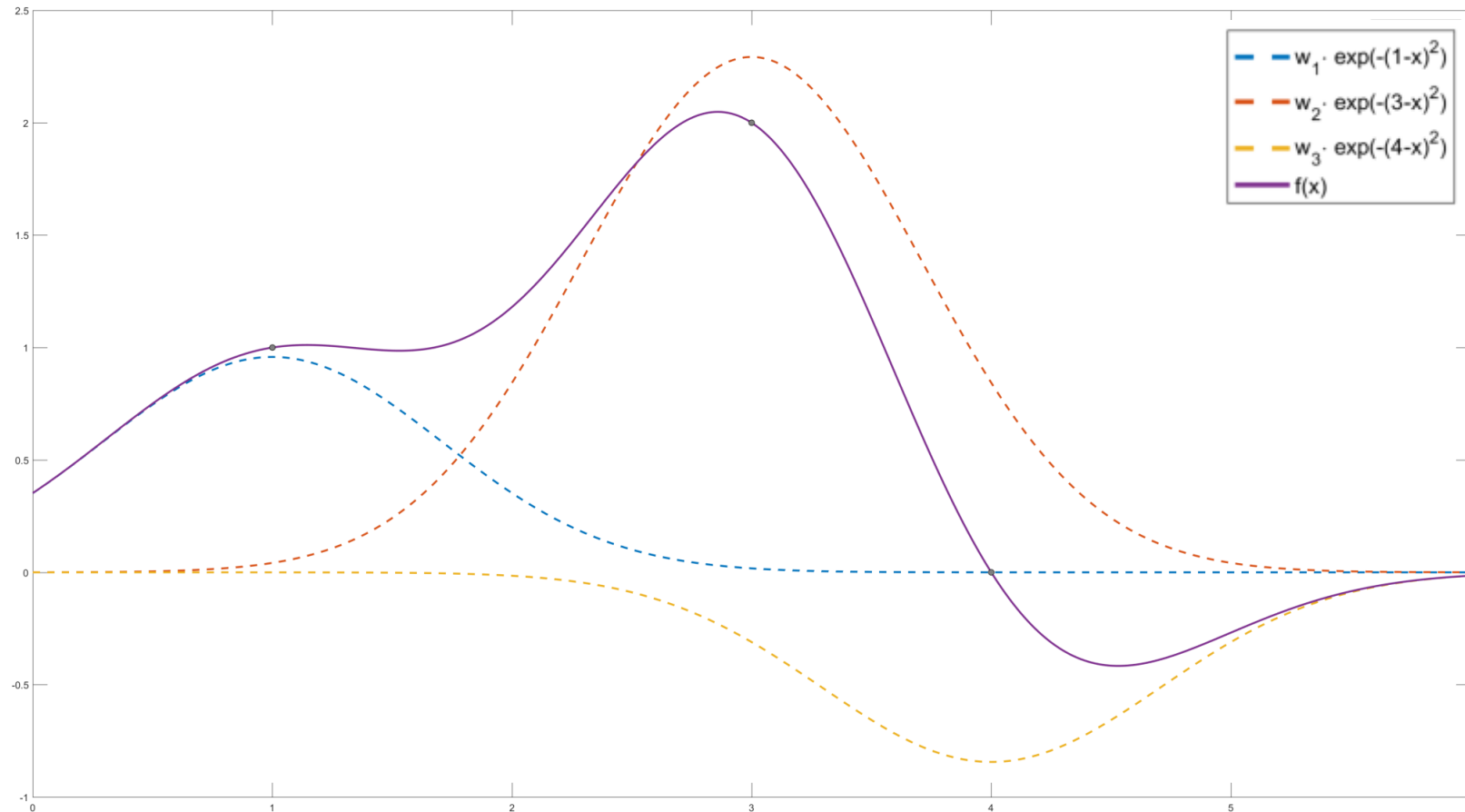
- Back to our example

$$\underbrace{\begin{pmatrix} \varphi(0) & \varphi(2) & \varphi(3) \\ \varphi(2) & \varphi(0) & \varphi(1) \\ \varphi(3) & \varphi(1) & \varphi(0) \end{pmatrix}}_{\mathbf{R}} \cdot \underbrace{\begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix}}_{\mathbf{w}} = \underbrace{\begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix}}_{\mathbf{f}}$$

- If matrix \mathbf{R} is invertible,
- $\mathbf{w} = \mathbf{R}^{-1} \mathbf{f}$ with solution

Continuous representation

- Example $f(x) = 0.9581\varphi(\|1 - x\|) + 2.2928\varphi(\|3 - x\|) - 0.8436\varphi(\|4 - x\|)$

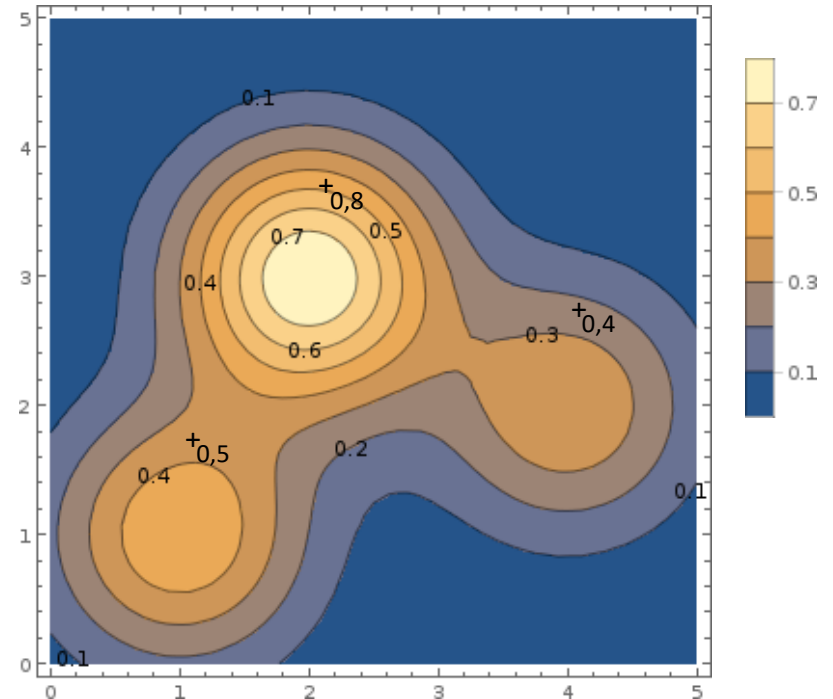
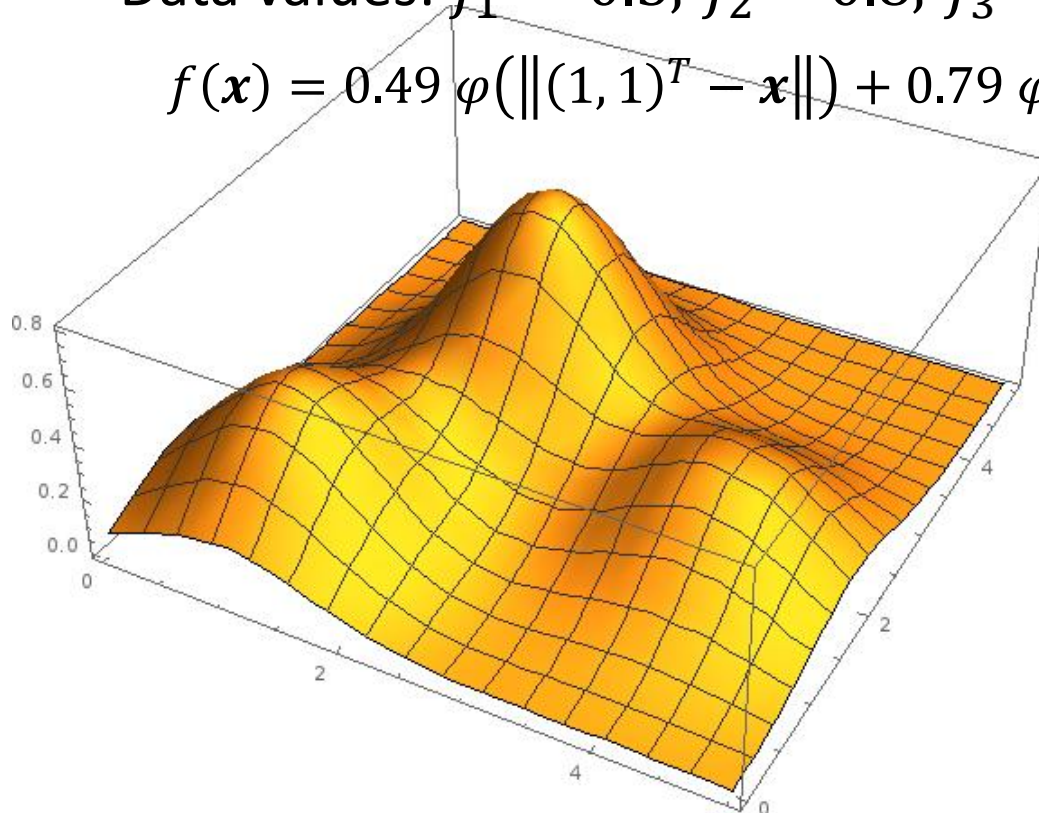


Continuous representation

- 2D Example

- Data points: $p_1 = (1, 1)^T$, $p_2 = (2, 3)^T$, $p_3 = (4, 2)^T$
- Data values: $f_1 = 0.5$, $f_2 = 0.8$, $f_3 = 0.4$

$$f(\mathbf{x}) = 0.49 \varphi(\|(1, 1)^T - \mathbf{x}\|) + 0.79 \varphi(\|(2, 3)^T - \mathbf{x}\|) + 0.39 \varphi(\|(4, 2)^T - \mathbf{x}\|)$$



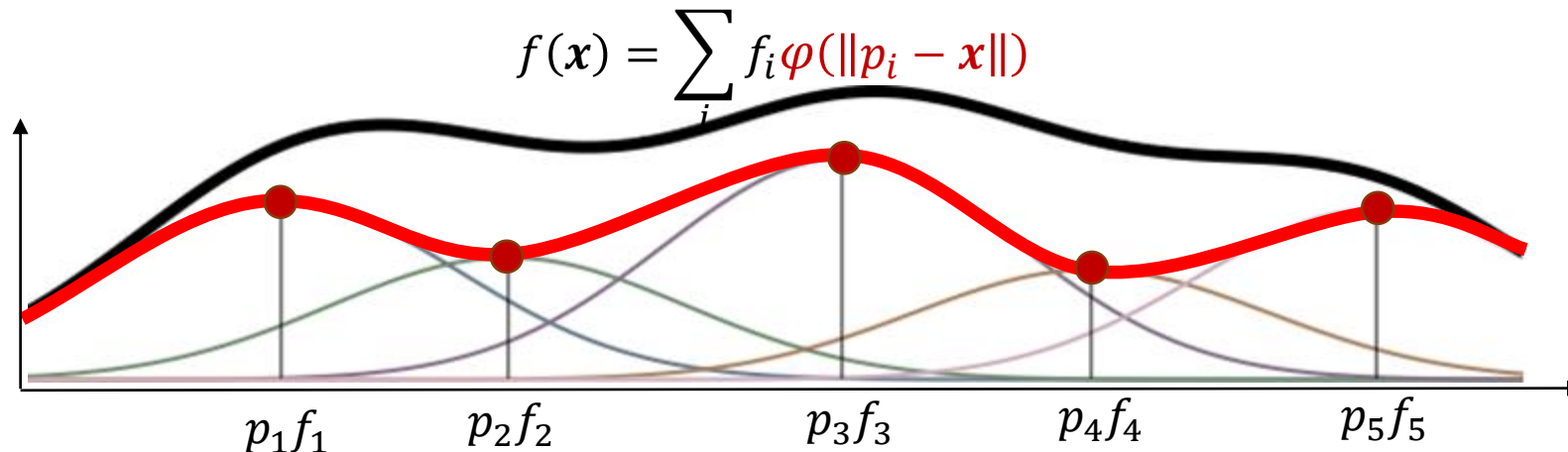
Continuous representation

- Drawbacks of radial basis functions
 - Every sample point has influence on whole domain
 - Adding a new sample requires re-solving the equation system
 - Computationally expensive (solving a system of linear equations)
- What can we do?
 - Find a different radial function
 - Give up finding a smooth reconstruction
 - Try finding a piecewise (local) reconstruction function

Continuous representation

- Radial Basis Functions

- Instead of the **black** curve we want the **red** one, i.e., the curve which is going through the initial data points
- This is called an interpolation
- **Question:** How do we have to select the **radial function** φ so that the red curve is obtained?



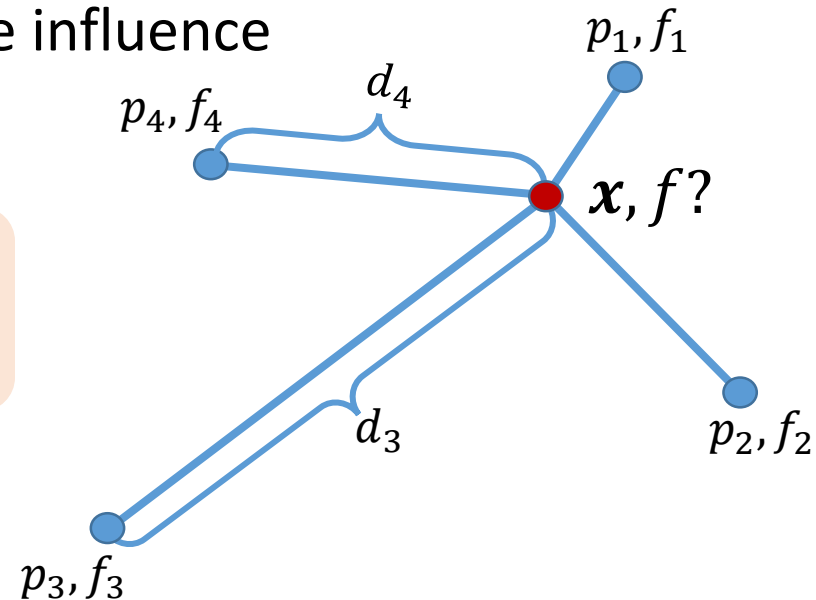
Continuous representation

- Inverse distance weighting
 - Sample positions p_i and values f_i
 - Assumption: Nearby points are more similar than those further away \rightarrow they have more influence

$$f(\mathbf{x}) = \sum_i f_i \varphi(\|p_i - \mathbf{x}\|)$$

$$d_i = \|p_i - \mathbf{r}\|, \quad \varphi(r) = \frac{1}{r^2} / \sum_{i=1}^N \frac{1}{d_i^2}$$

Attention for $d_i < \epsilon$



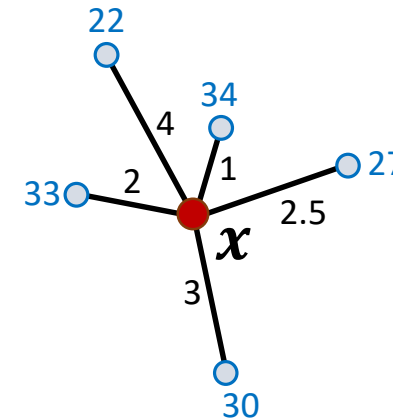
Continuous representation

- Inverse distance weighting
 - Sample positions p_i and values f_i
 - Assumption: Nearby points are more similar than those further away \rightarrow they have more influence

$$f(\mathbf{x}) = \sum_i f_i \varphi(\|p_i - \mathbf{x}\|) =$$

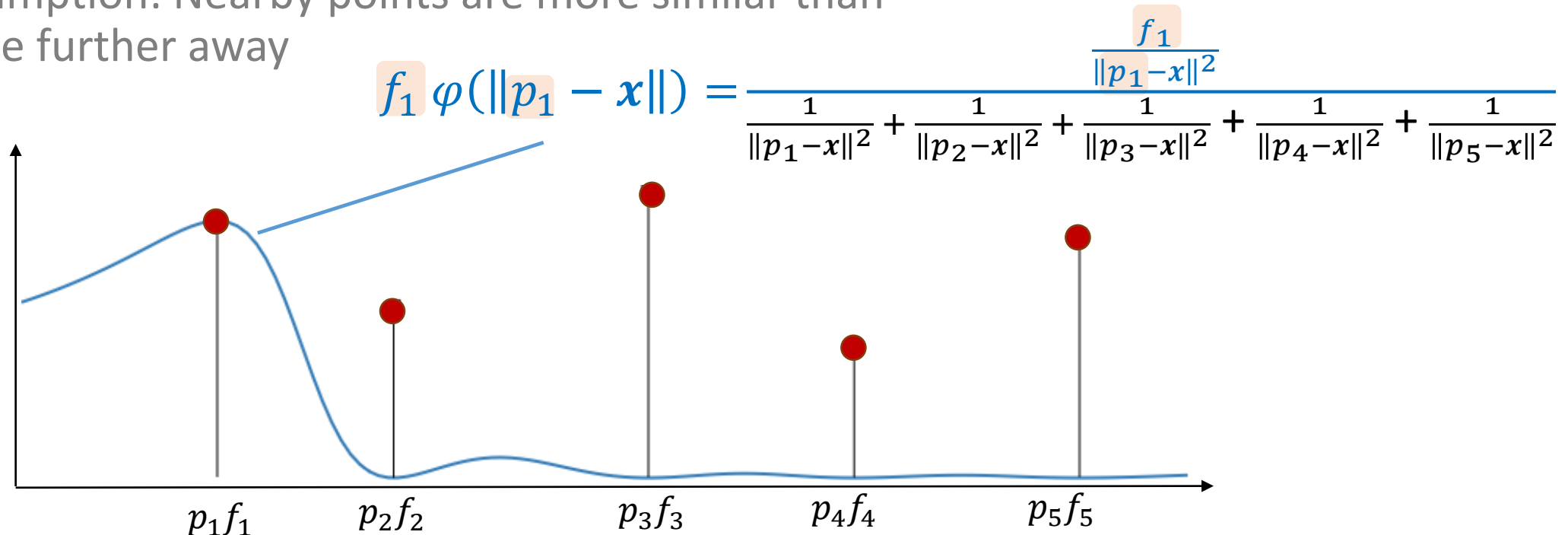
$$= \sum_{i=1}^N \frac{f_i}{\|p_i - \mathbf{x}\|^2} / \sum_{i=1}^N \frac{1}{\|p_i - \mathbf{x}\|^2}$$

$$f(\mathbf{x}) = \frac{\frac{22}{4^2} + \frac{34}{1^2} + \frac{27}{2.5^2} + \frac{30}{3^2} + \frac{33}{2^2}}{\frac{1}{4^2} + \frac{1}{1^2} + \frac{1}{2.5^2} + \frac{1}{3^2} + \frac{1}{2^2}} = 32.38$$



Continuous representation

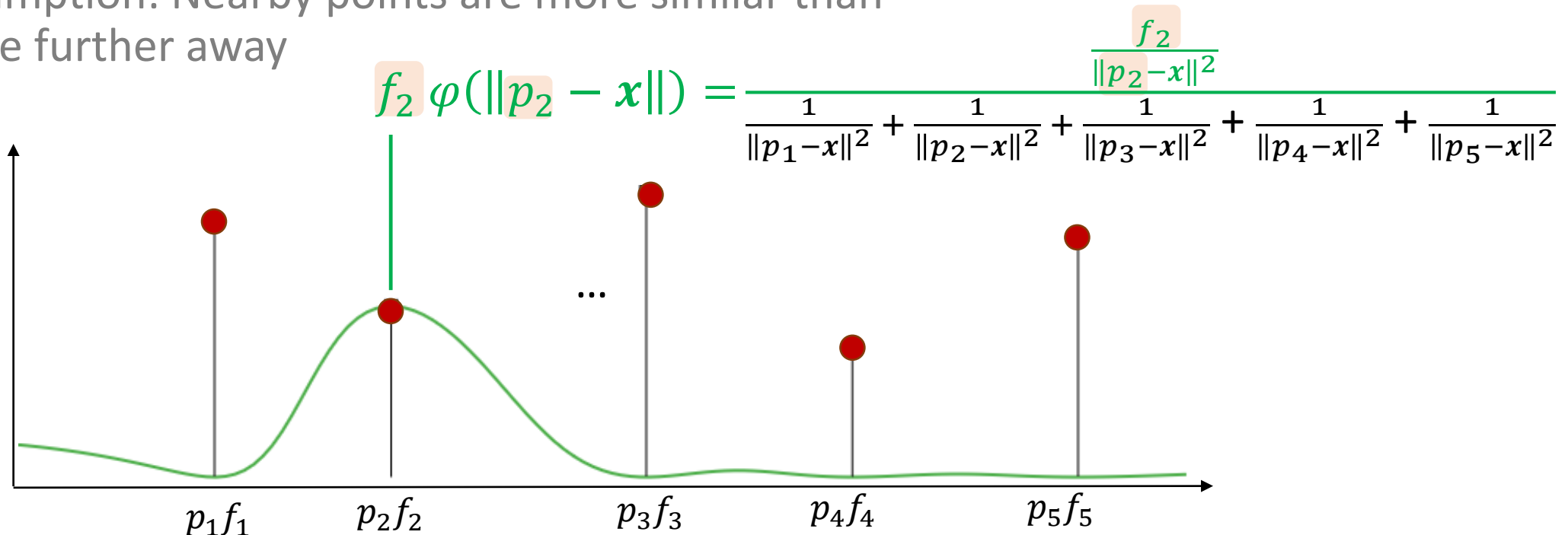
- Inverse distance weighting
 - Sample positions p_i and values f_i
 - Assumption: Nearby points are more similar than those further away



function is zero at p_i , $i \neq 1$

Continuous representation

- Inverse distance weighting
 - Sample positions p_i and values f_i
 - Assumption: Nearby points are more similar than those further away

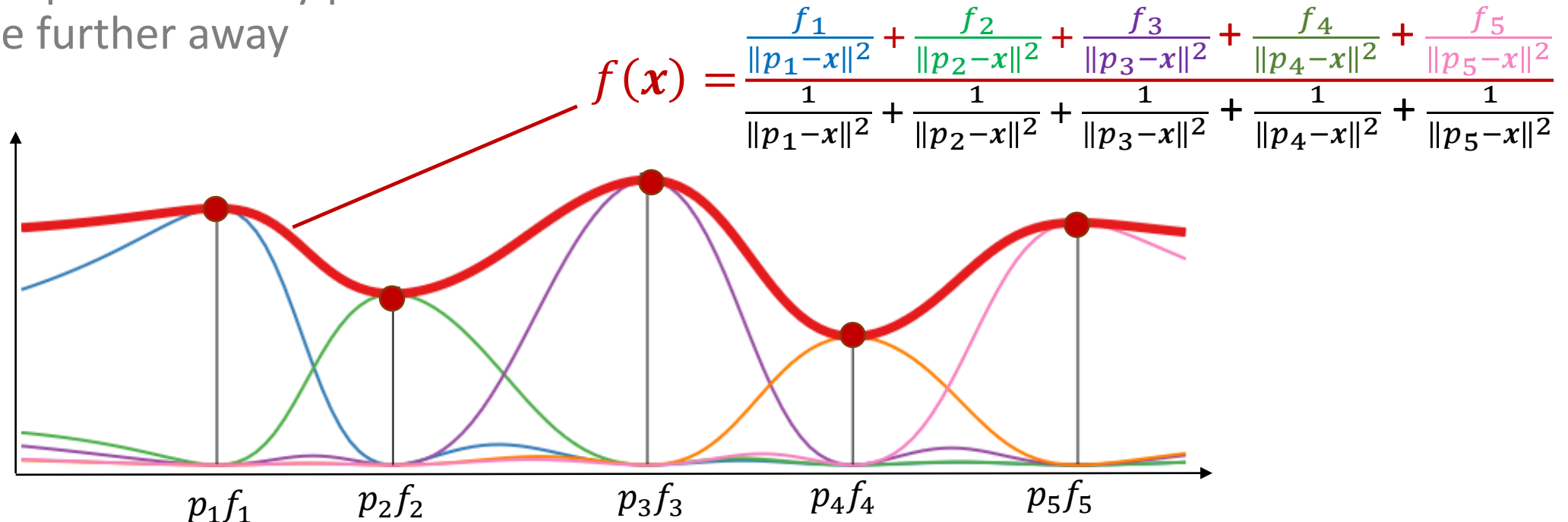


function is zero at p_i , $i \neq 2$

Continuous representation

- Inverse distance weighting

- Sample positions p_i and values f_i
- Assumption: Nearby points are more similar than those further away



Continuous representation

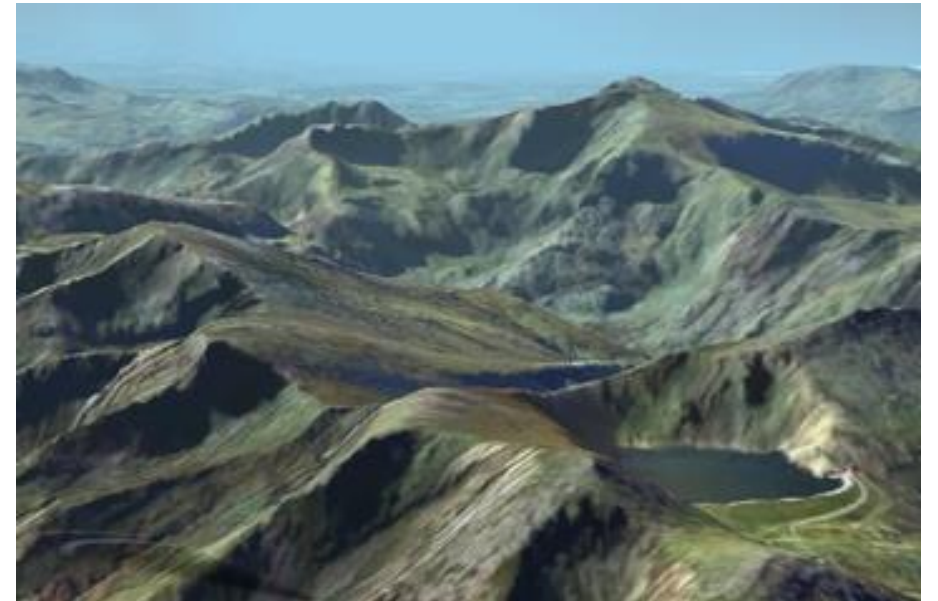
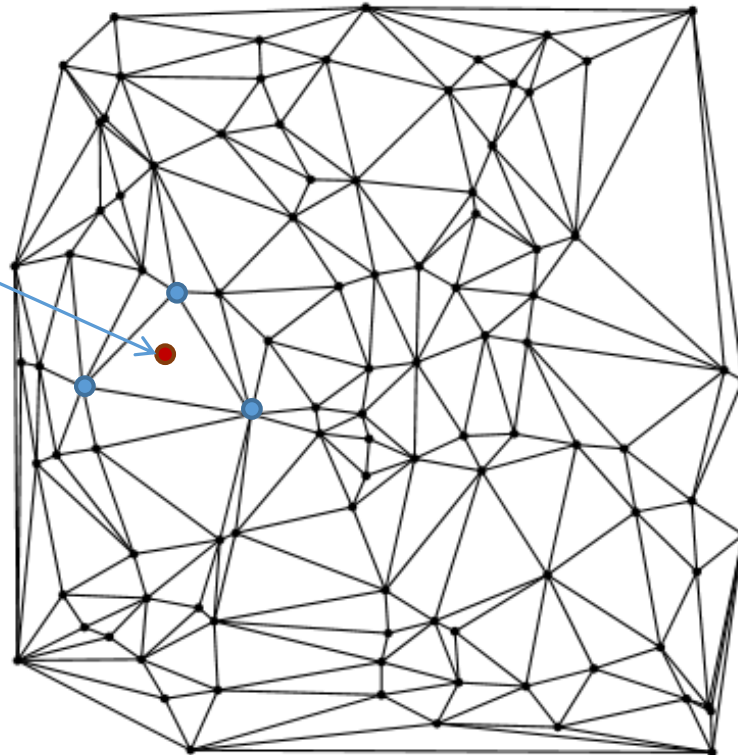
- Inverse distance weighting
 - We no longer have to solve a system of linear equations to find the weights
 - However, every sample point still has global influence
- What can we do?
 - Give up smooth reconstruction by constructing a grid from the given points, i.e., a **triangulation**

Triangulation

Generating a triangulation

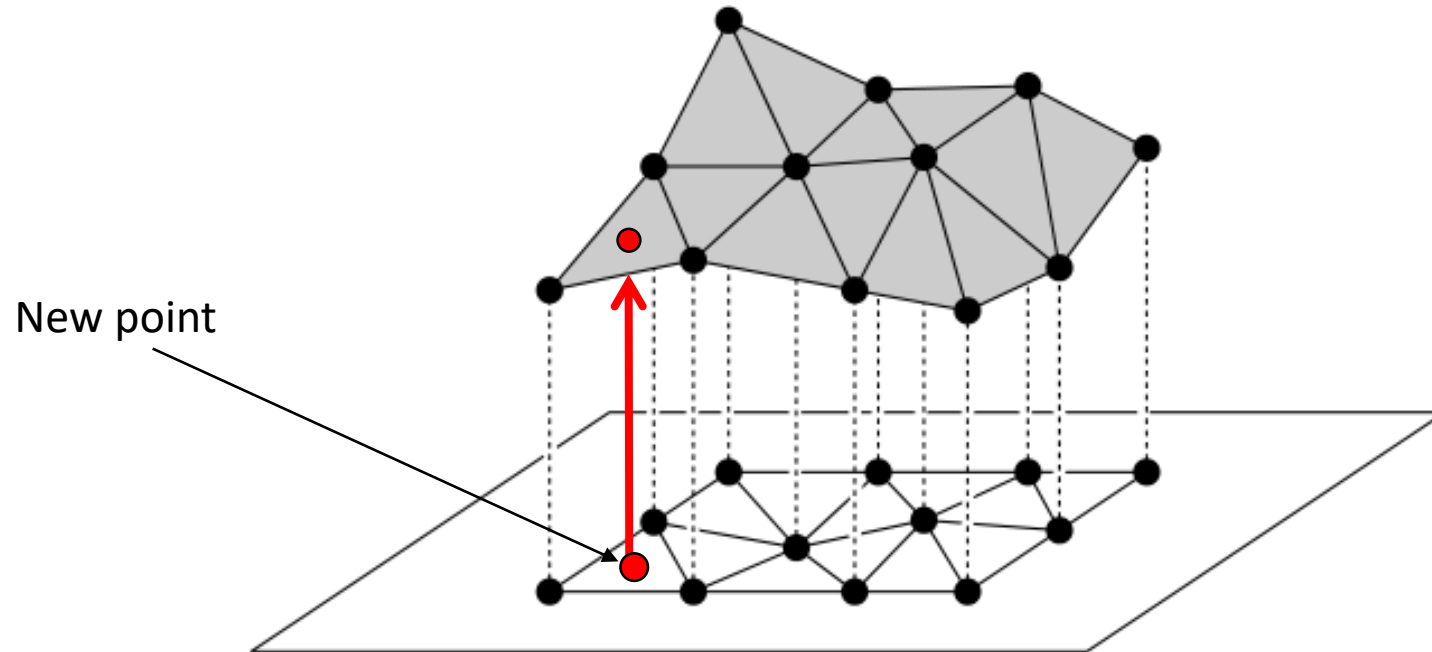
- Try finding a piecewise (local) reconstruction function
 - Connect the points so that a **triangulation** is obtained
 - Interpolate locally within the triangles

Value obtained by
only considering
values at triangle
corners



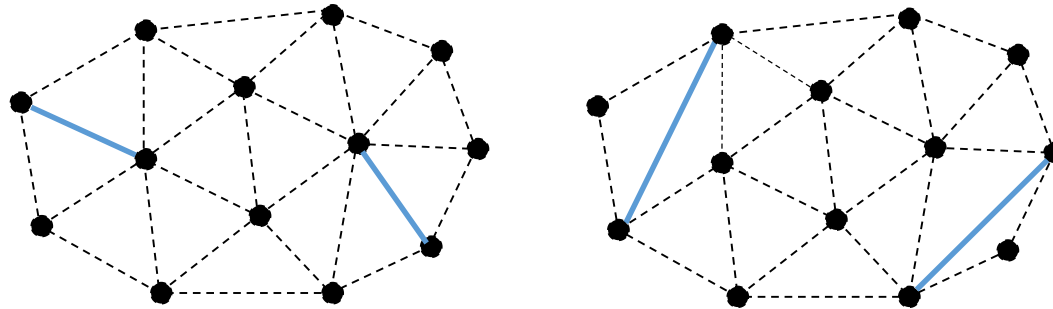
Generating a triangulation

- Once a triangulation is given
 - Let the scalar values at vertices be interpolated across the triangles
 - I.e., **piecewise linear** interpolation of values at interior points



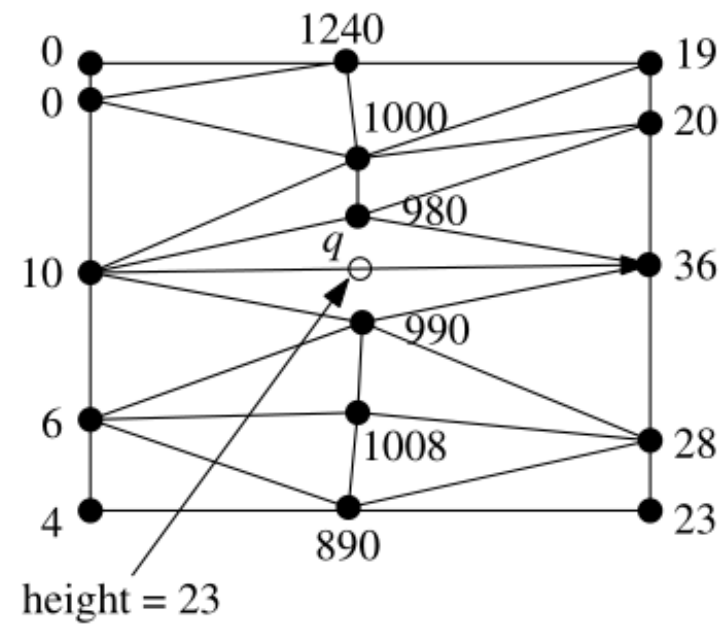
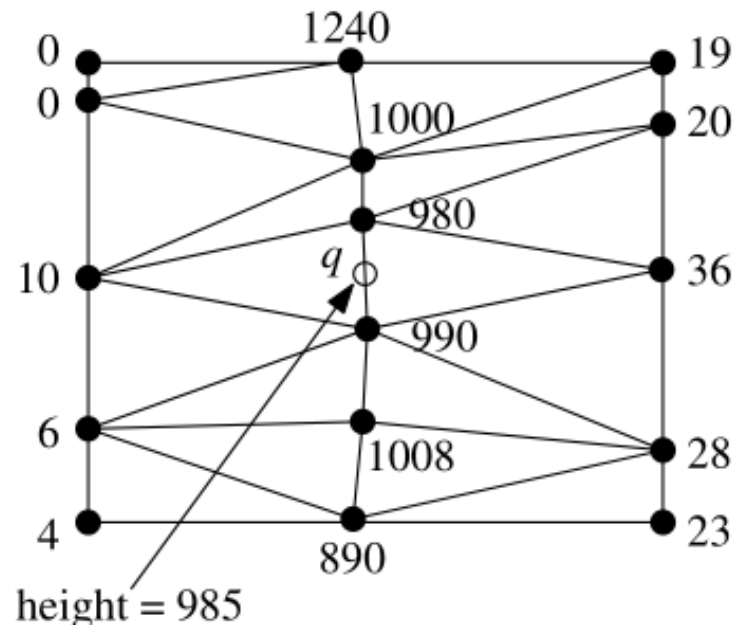
Generating a triangulation

- Given **irregularly distributed** positions without connectivity information
- For a set of points **many** triangulations exist
- The challenge is to find the **connectivity** so that a “good” triangulation is generated



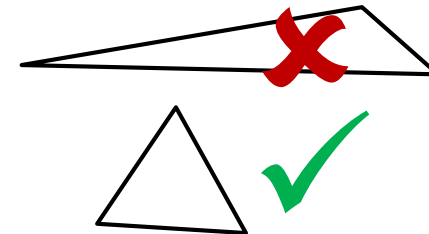
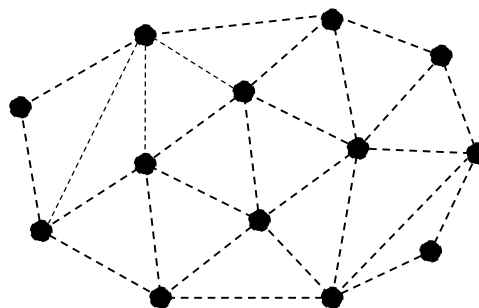
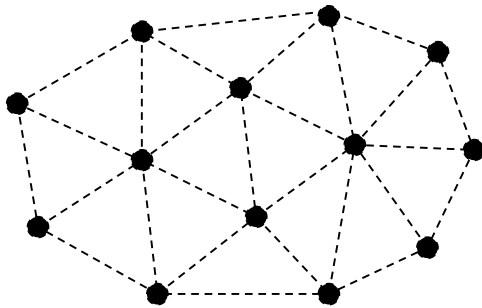
Generating a triangulation

- What is a good triangulation?



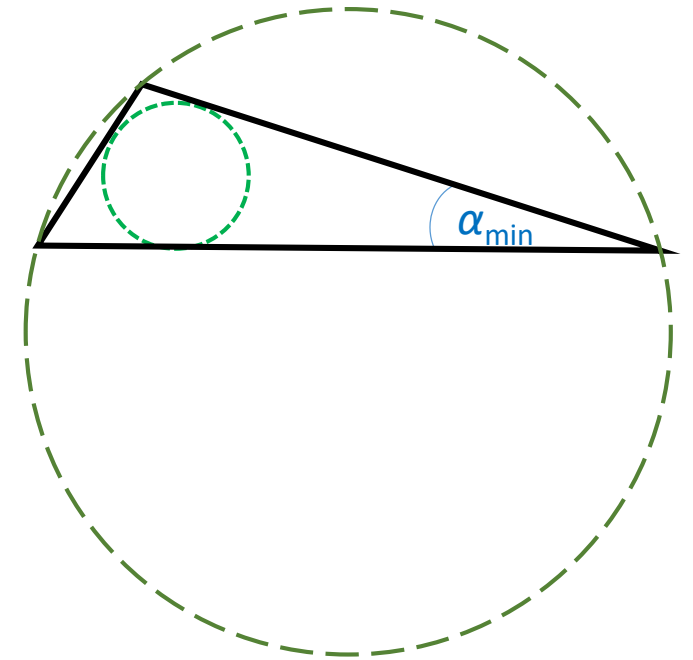
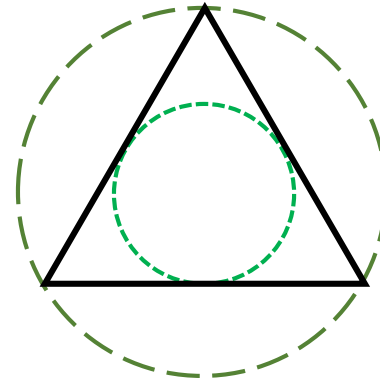
Generating a triangulation

- What is a good triangulation?
 - A measure for the quality of a triangulation is the **aspect ratio** of the so-defined triangles
 - Avoid long, thin triangles
 - Make triangles as equilateral as possible



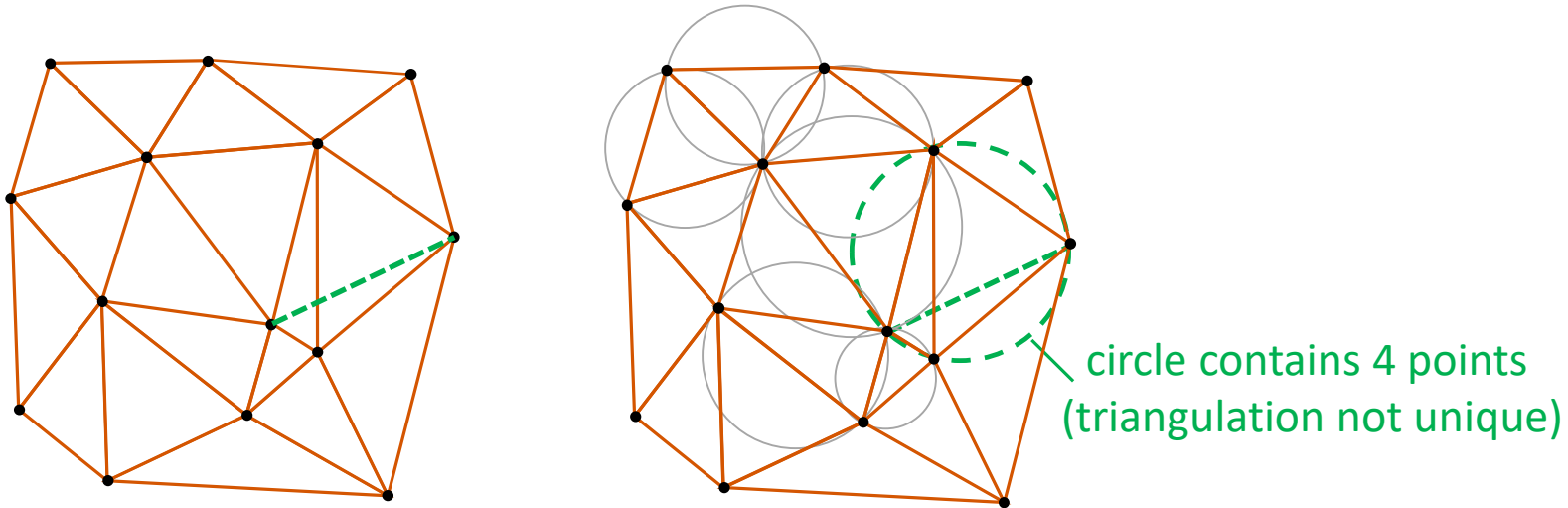
Generating a triangulation

- An “optimal” triangulation
 - Makes triangles as equilateral as possible
 - Maximizes the **minimum angle** in the triangulation
 - Maximizes $\frac{\text{radius of in-circle}}{\text{radius of circumcircle}}$
- A Delaunay triangulation is an optimal triangulation



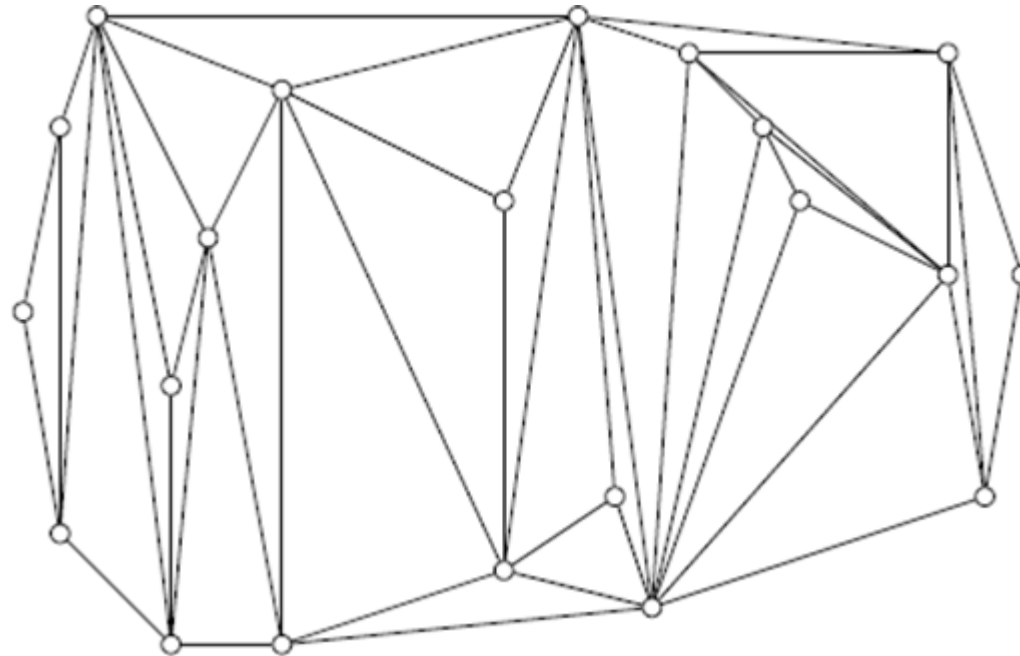
Delaunay triangulation

- Delaunay triangulation
 - The circumcircle of any triangle does not contain another point of the set
 - Maximizes the minimum angle in the triangulation
 - Such a triangulation is **unique** (independent of the order of samples) for all but trivial cases



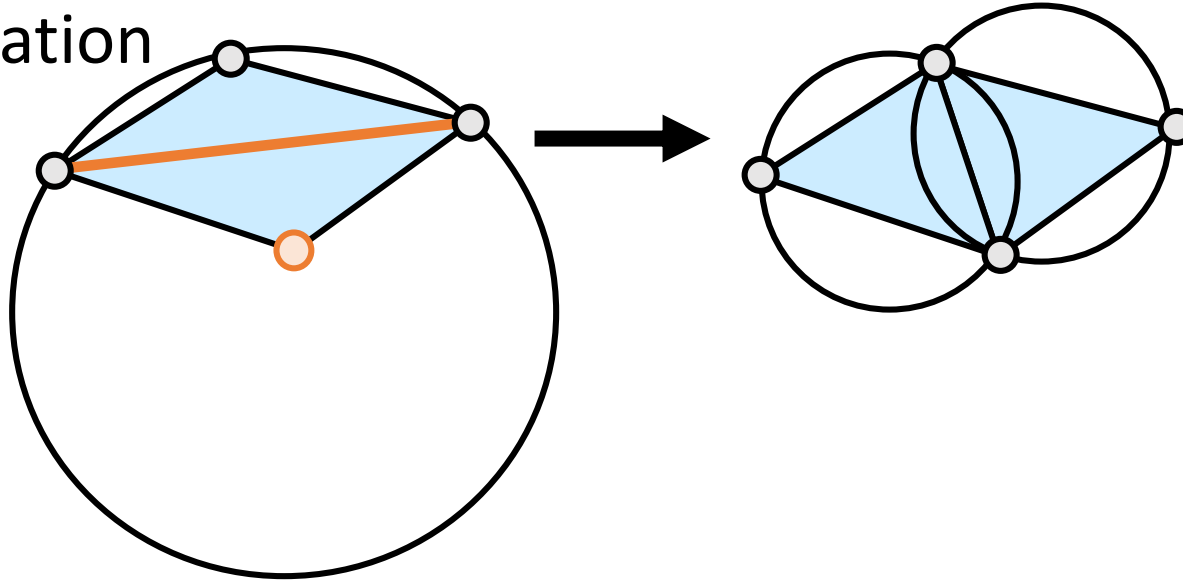
Delaunay triangulation

- How to build a Delaunay triangulation from an initial, non-optimal triangulation?
 - Can be performed by successively improving the initial triangulation via local operations



Delaunay triangulation

- Edge flip operation

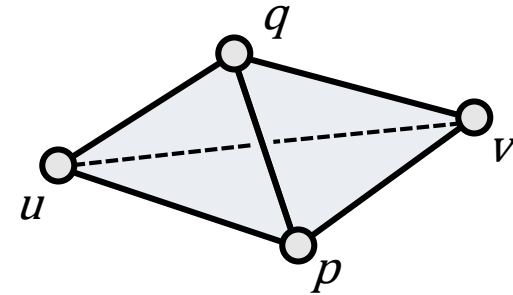


- An edge is **local Delaunay** if there exists an empty circumcircle (otherwise illegal)
- If an edge shared by two triangles is illegal, a **flip operation** generates a new edge that is legal!

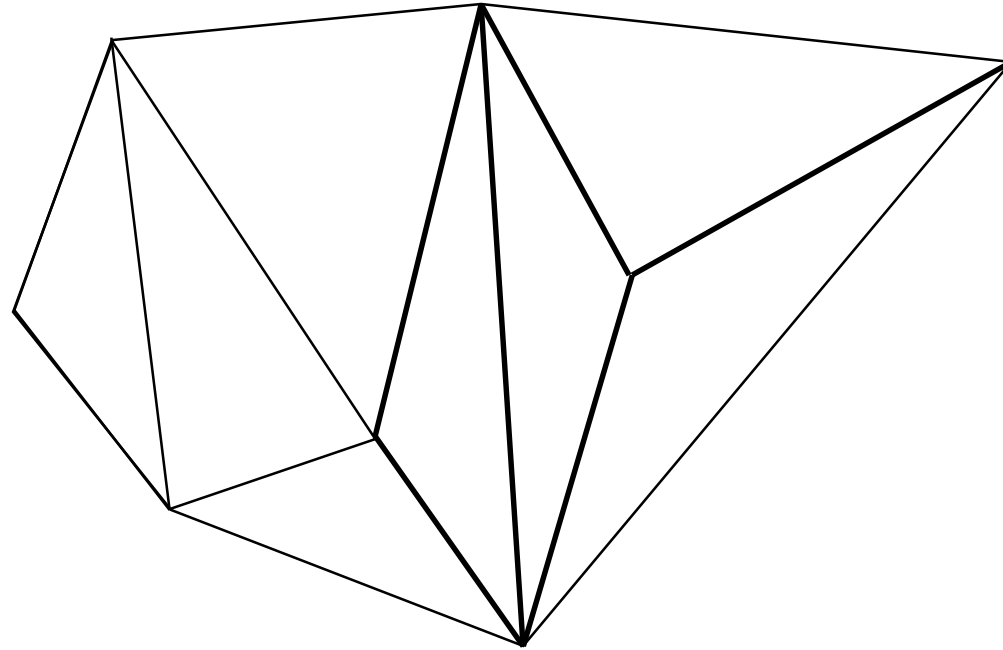
Delaunay triangulation

Edge flip algorithm:

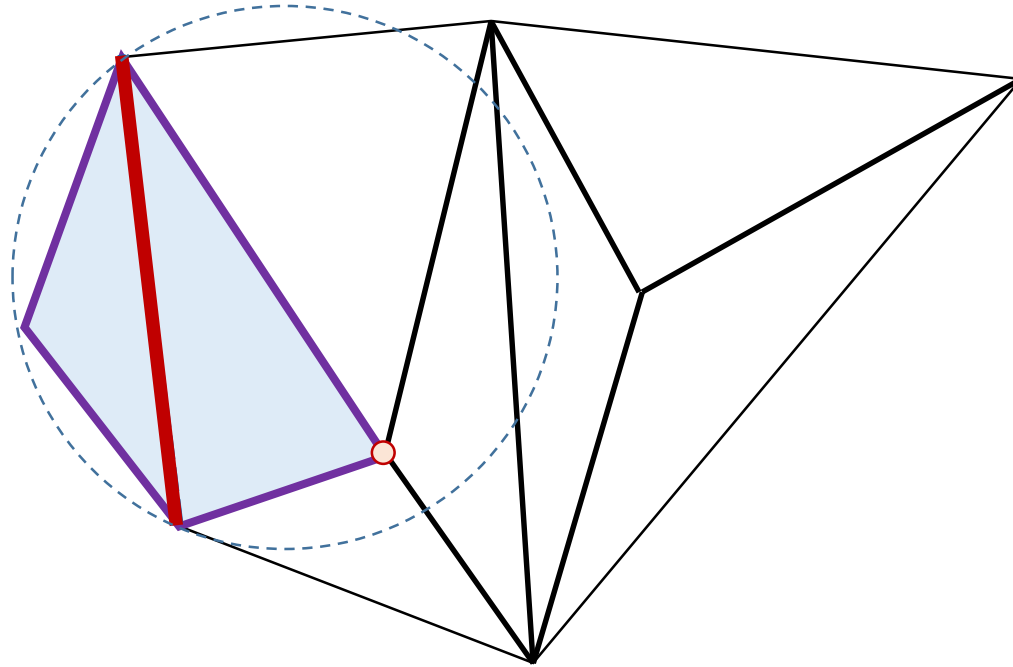
```
put all edges in stack and mark them
while stack is non-empty do
  pop edge  $uv$  from stack and unmark it
  if  $uv$  is illegal then
    substitute  $pq$  for  $uv$     //edge flip
    for  $ab \in \{up, pv, vq, qu\}$  do
      if  $ab$  is unmarked then
        push  $ab$  on the stack and mark it
      endif
    endfor
  endif
endwhile
```



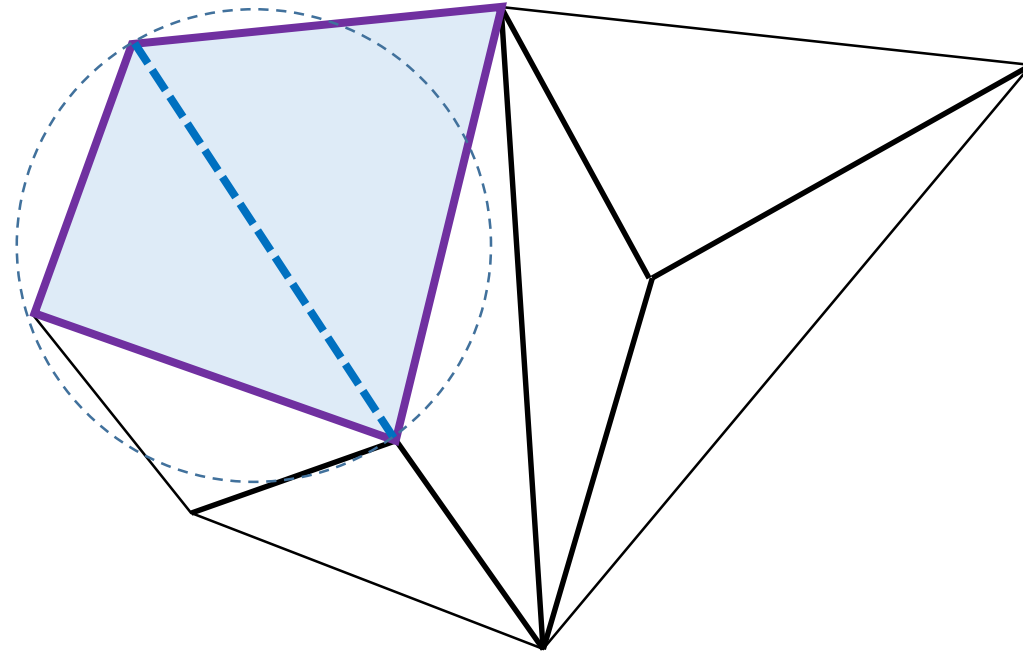
Edge flip – example



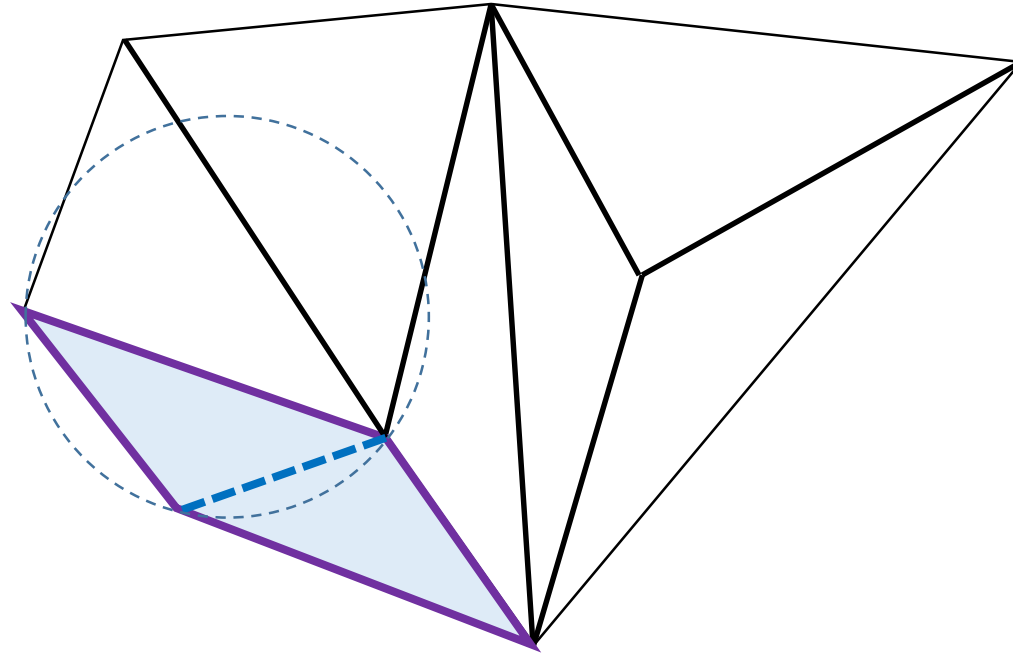
Edge flip – example



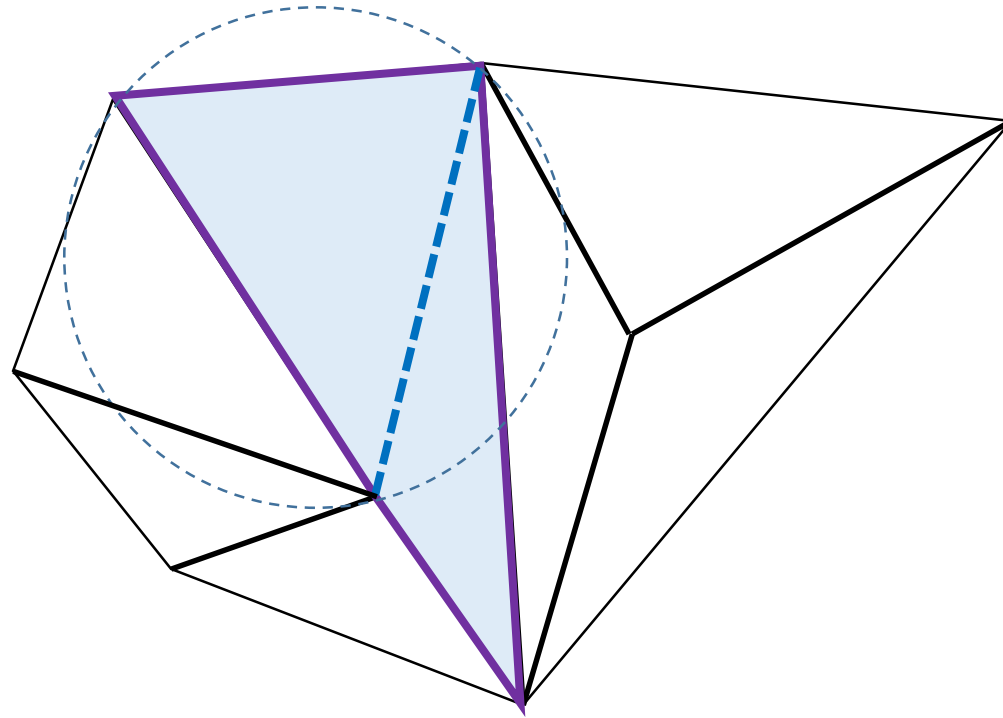
Edge flip – example



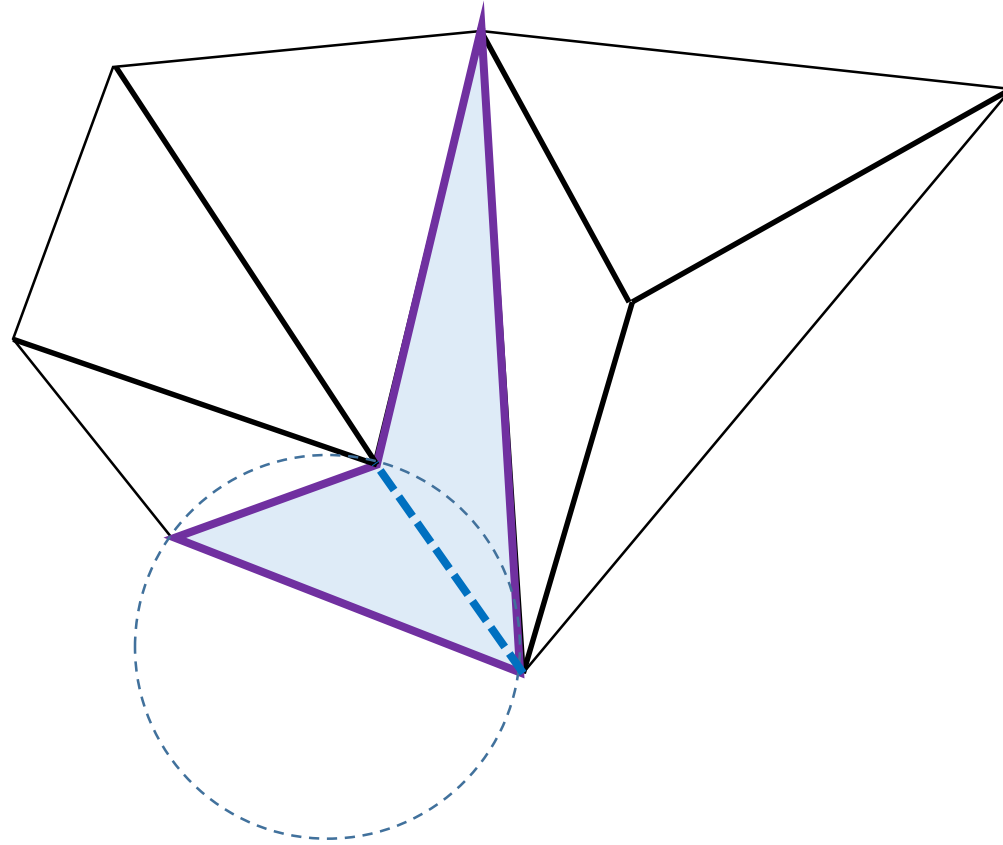
Edge flip – example



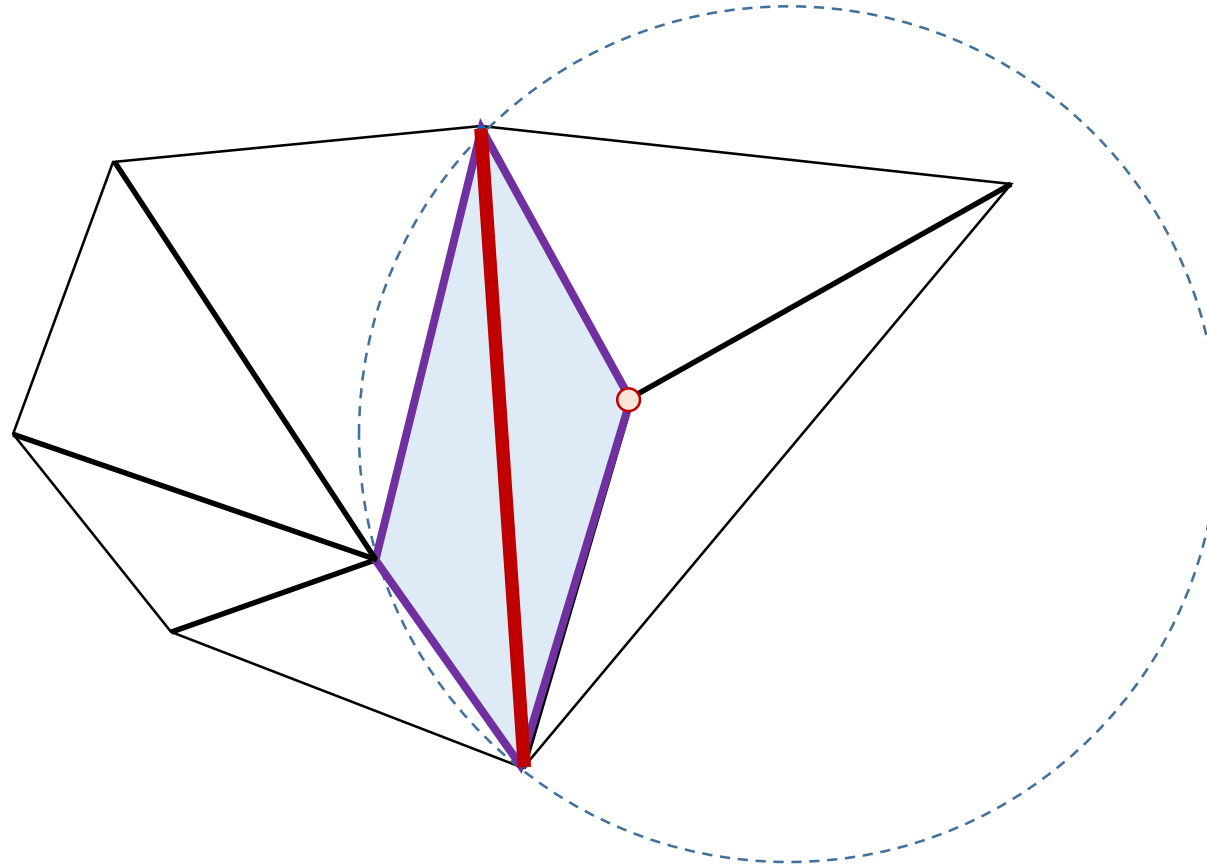
Edge flip – example



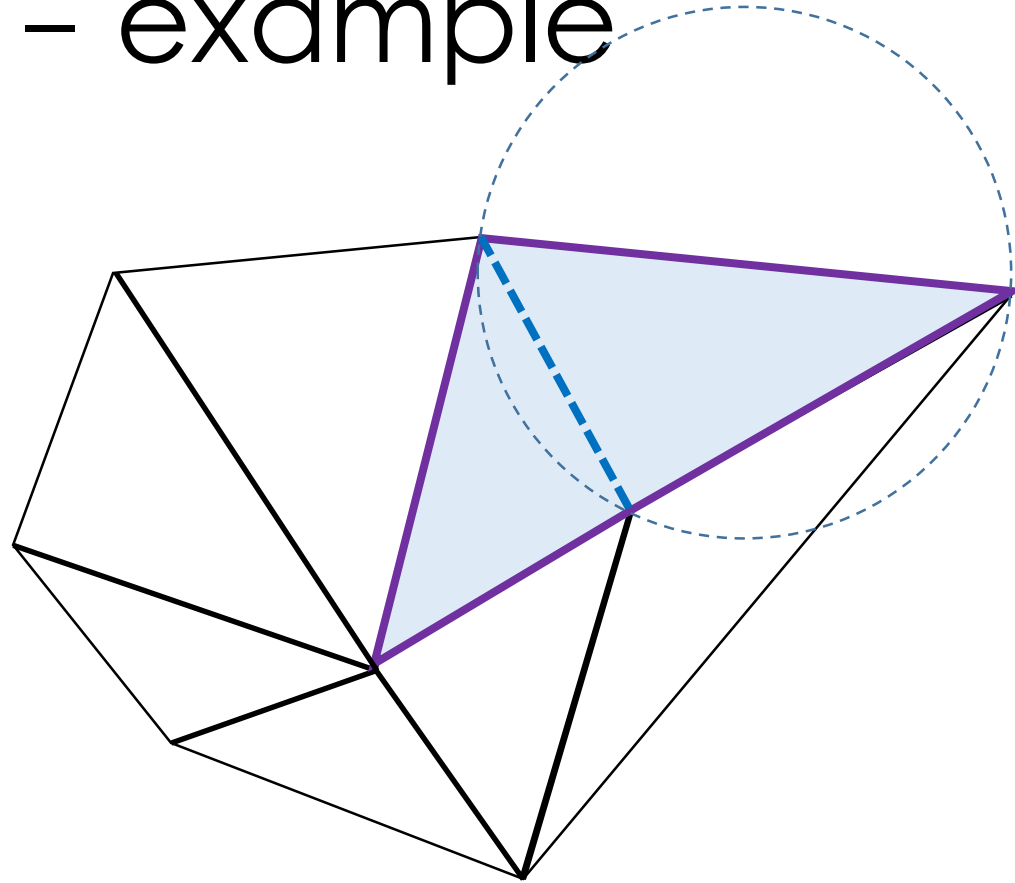
Edge flip – example



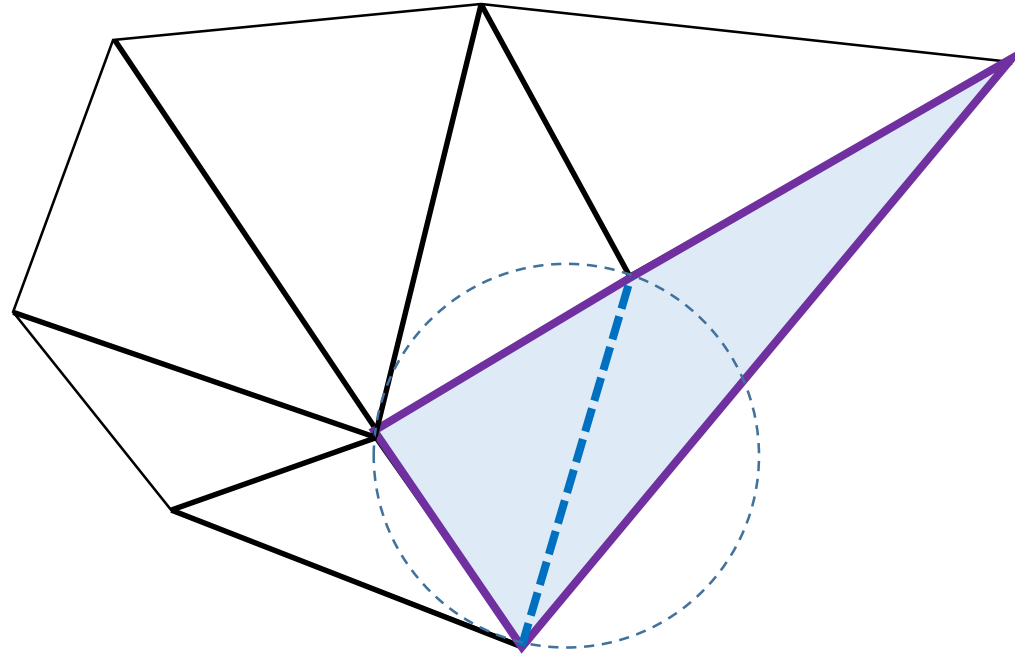
Edge flip – example



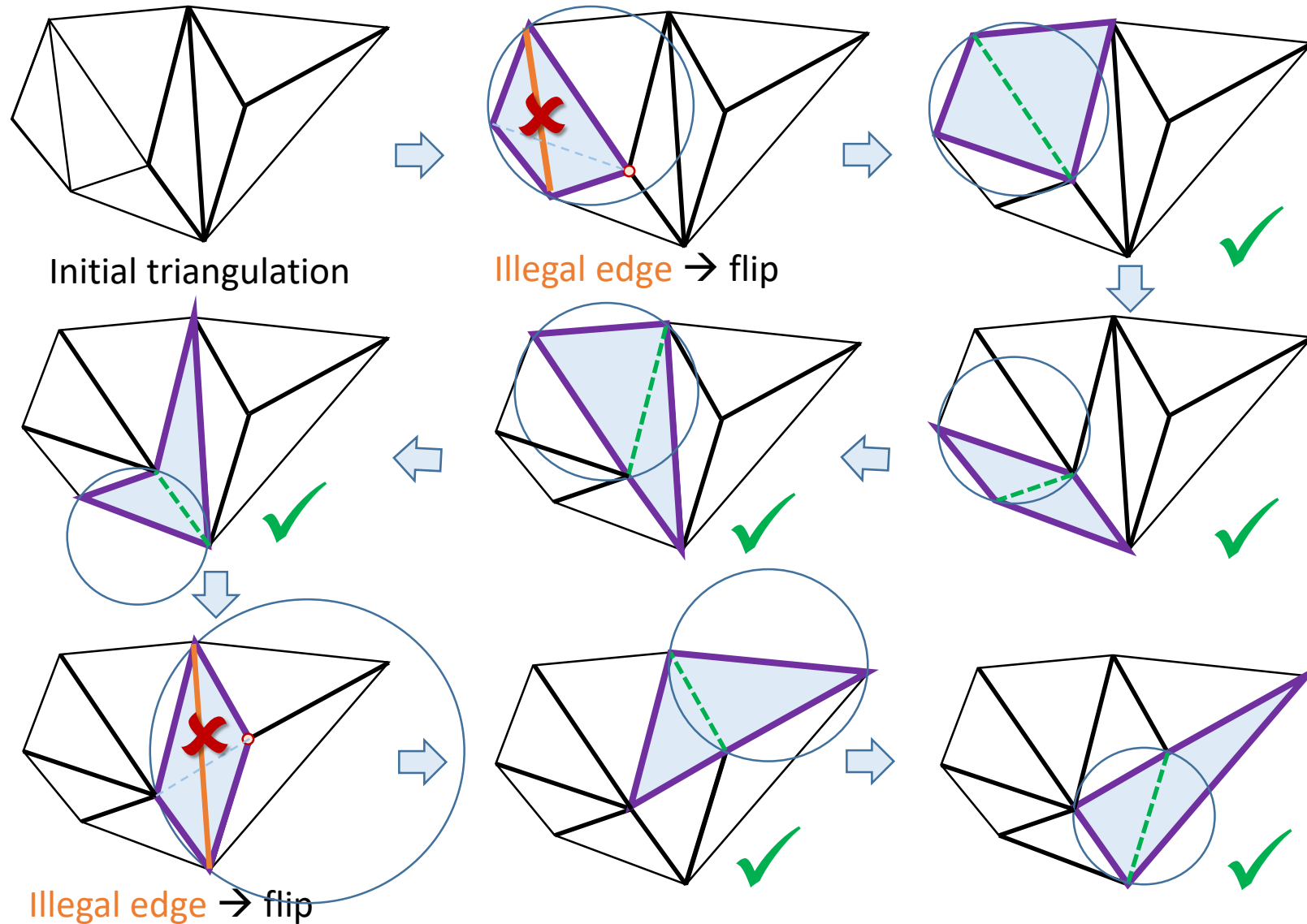
Edge flip – example



Edge flip – example

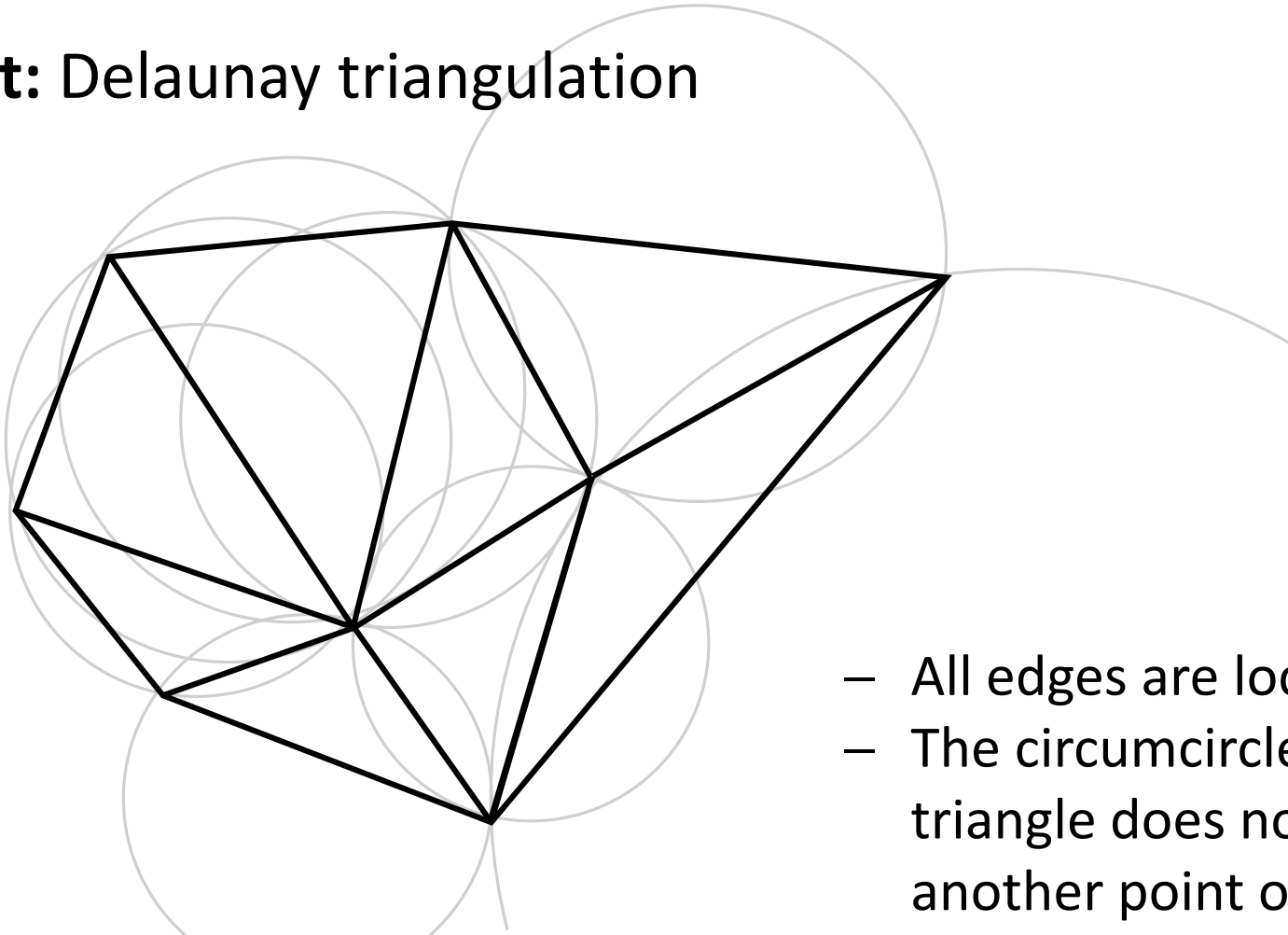


Edge flip – example



Edge flip – example

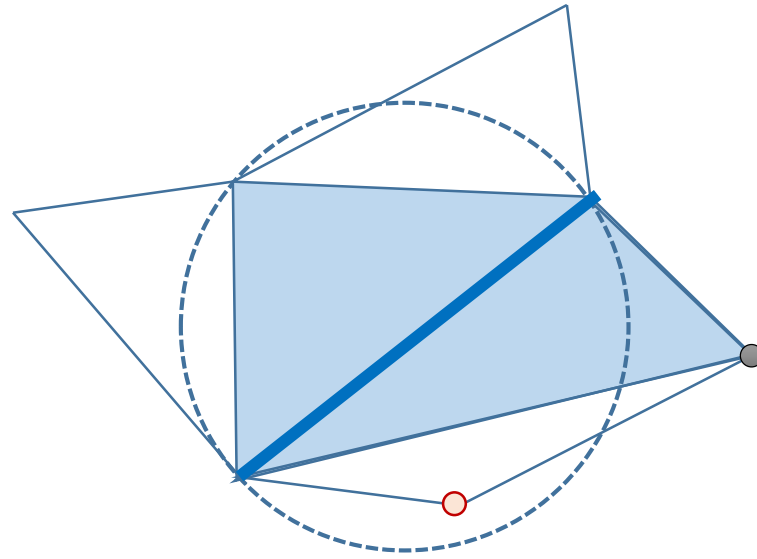
- **Result:** Delaunay triangulation



- All edges are local Delaunay
- The circumcircle of any triangle does not contain another point of the set

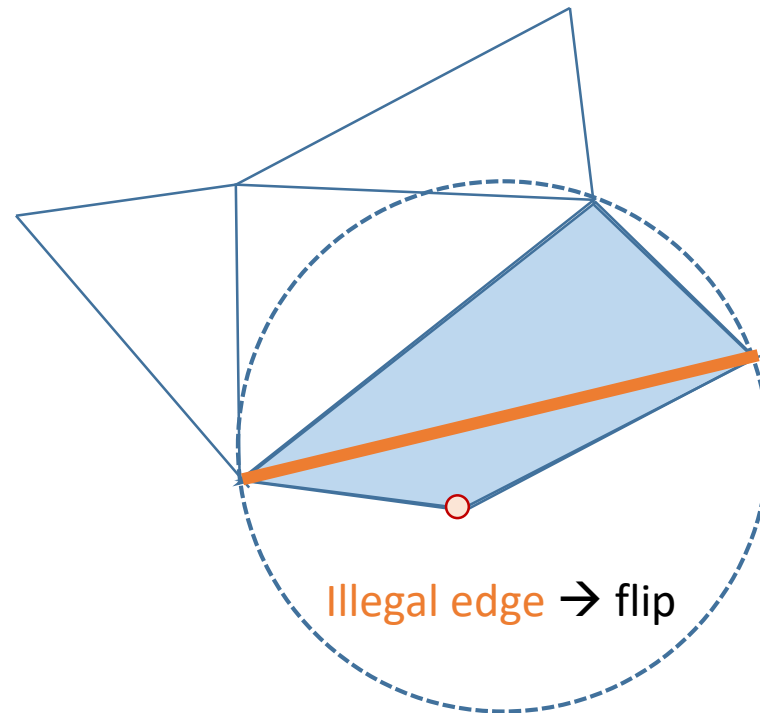
Delaunay triangulation

- Local vs. global optimality
 - Edge is locally Delaunay ... but not globally



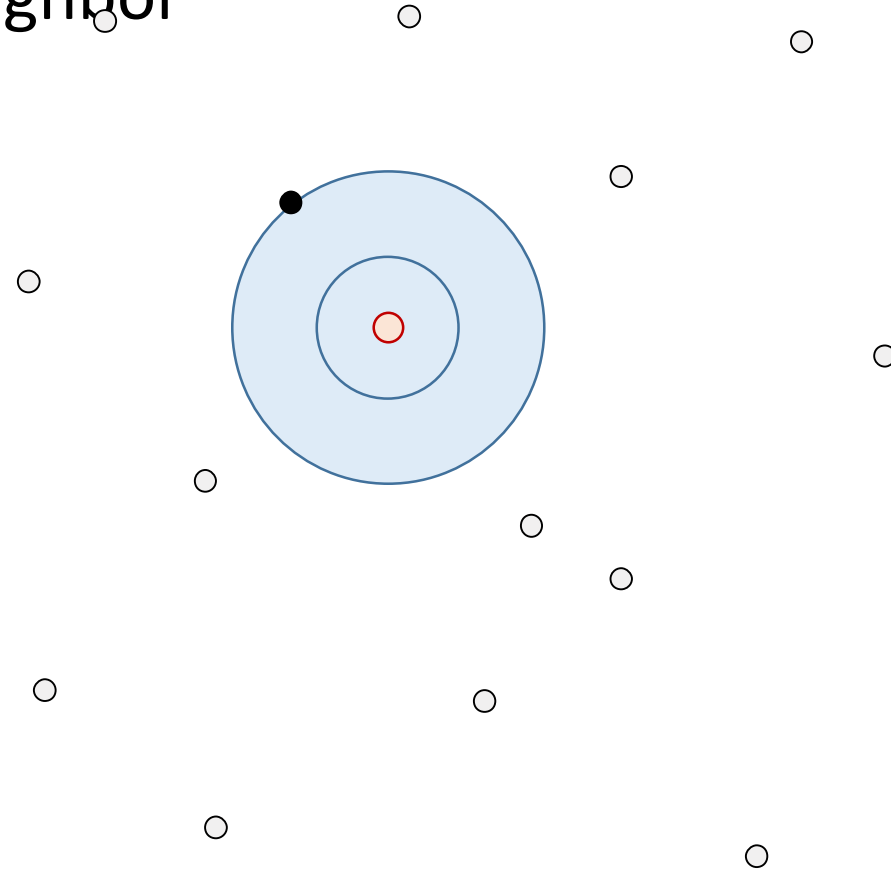
Delaunay triangulation

- Local vs. global optimality
 - If a triangulation is locally Delaunay everywhere
→ globally Delaunay



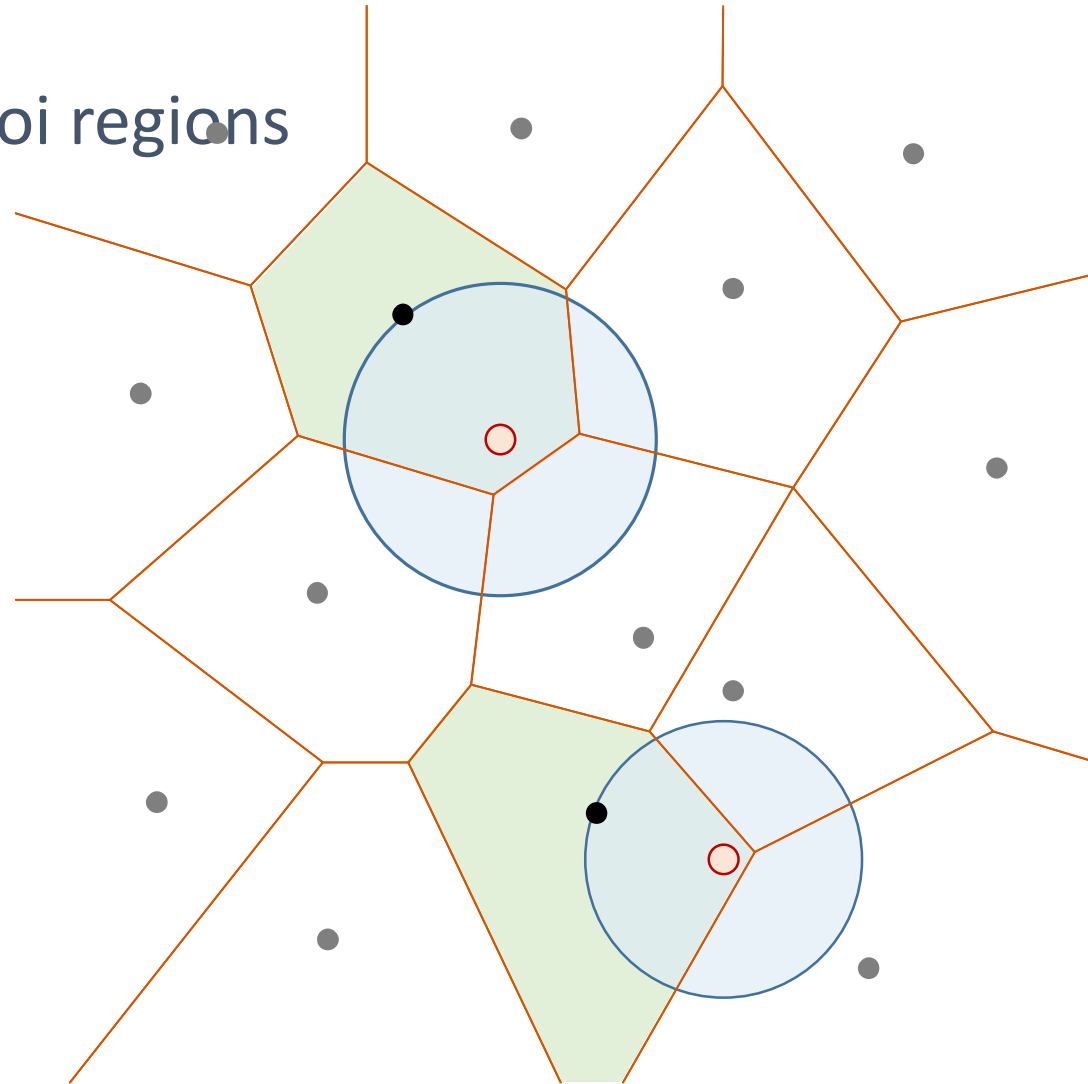
Voronoi diagram

- **Problem:** Looking for nearest neighbor



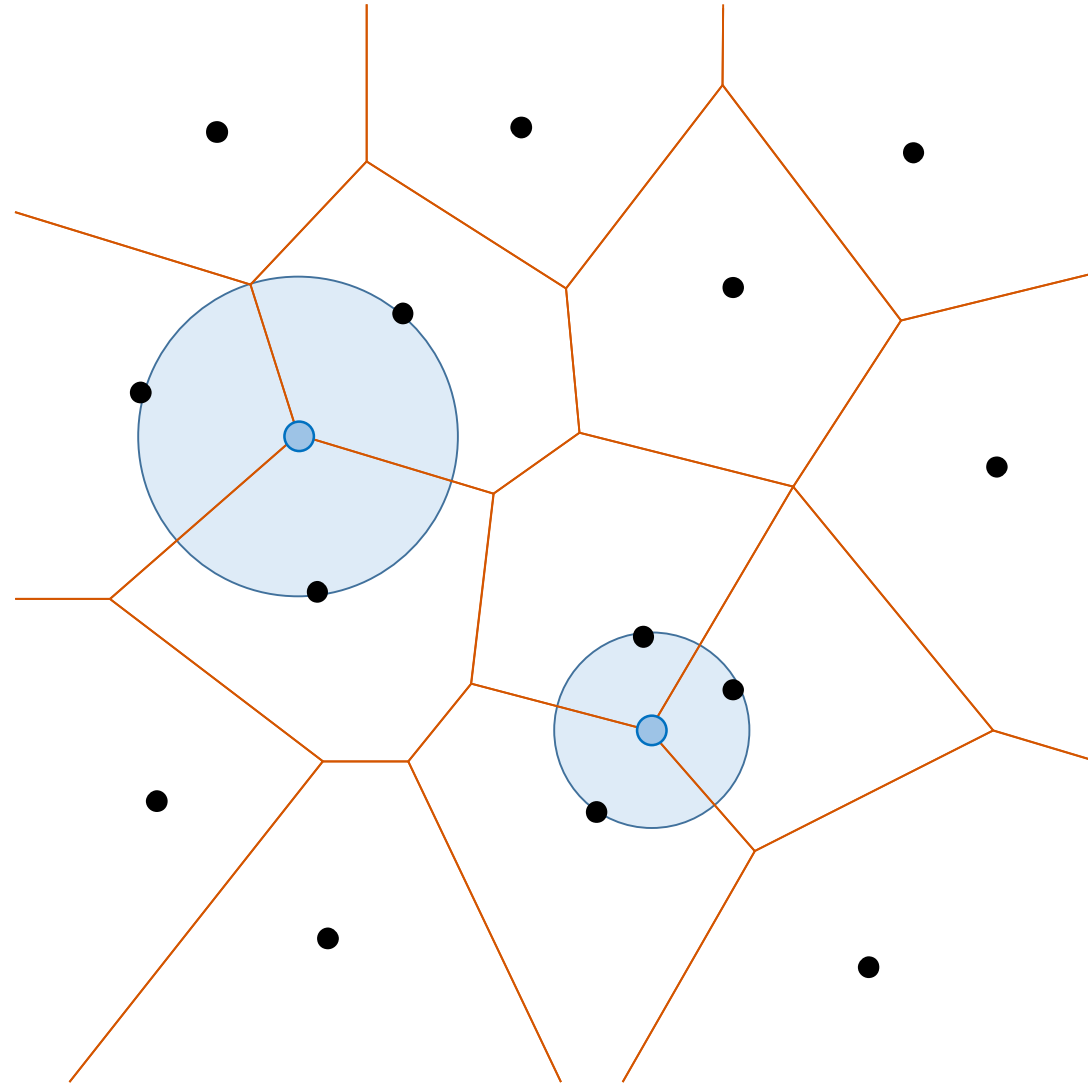
Voronoi diagram

- Partitions domain into Voronoi regions
 - Each region contains one initial sample – the Voronoi samples
 - Points in Voronoi region are closer to respective sample than to any other sample



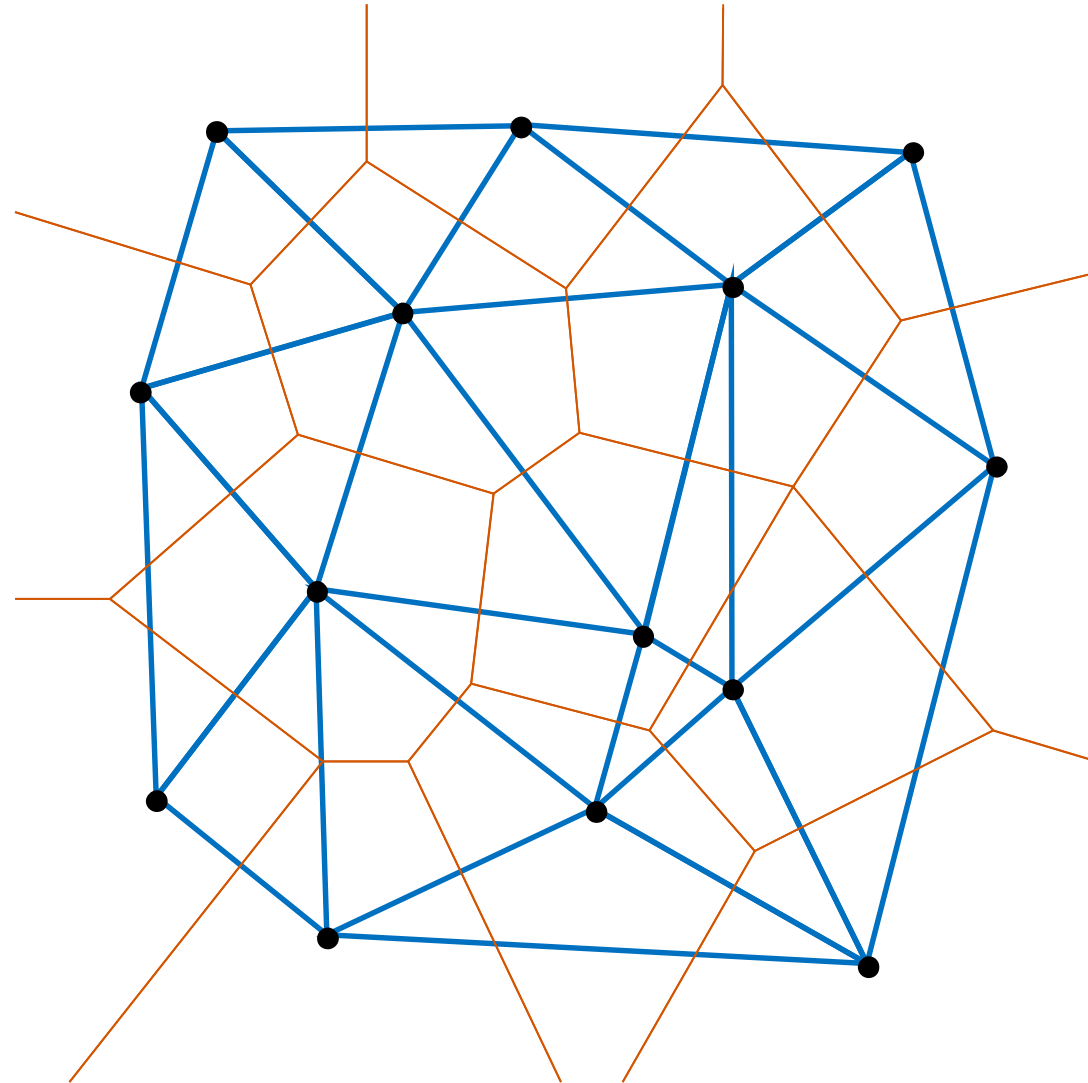
Voronoi diagram

- Centers of circumcircles of Delaunay triangulation



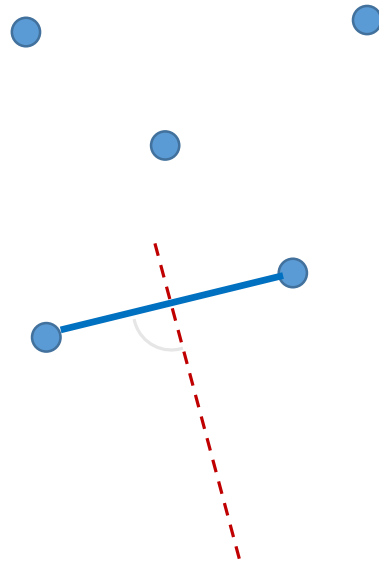
Voronoi diagram

- The geometric dual (topologically equal) of Delaunay triangulation
 - Voronoi samples are vertices in Delaunay triangulation



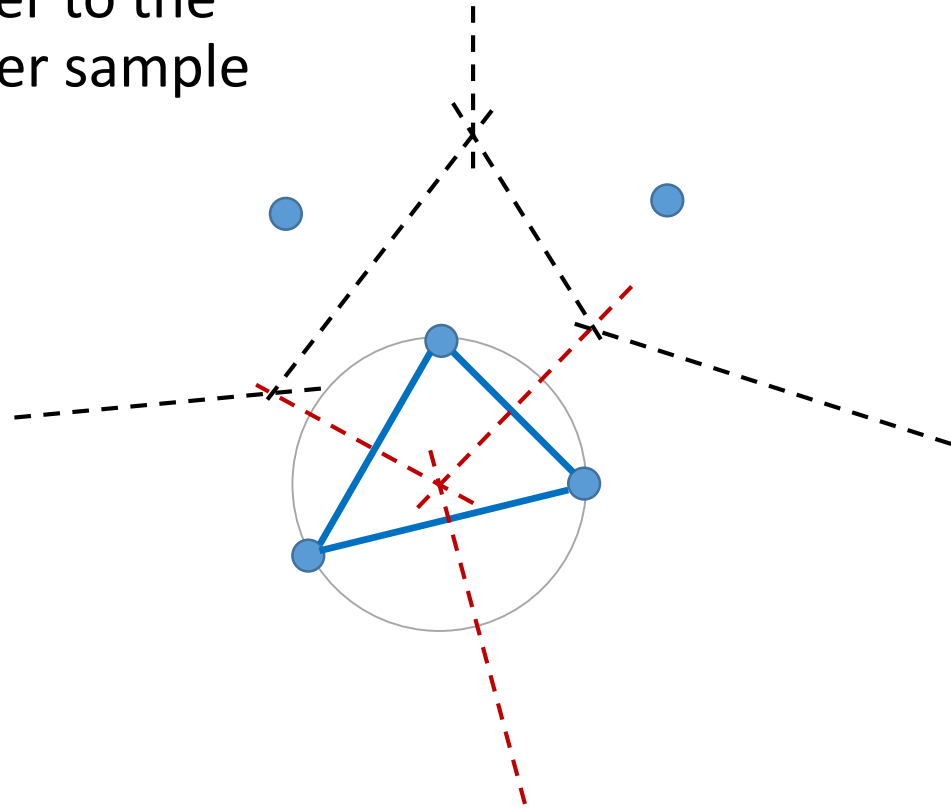
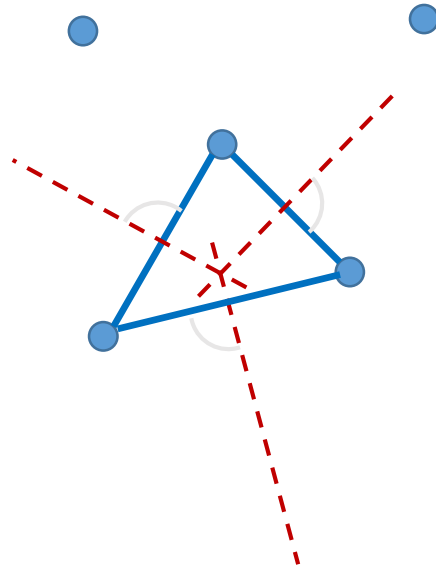
Voronoi diagram

- Construction
 - Points in a Voronoi region are closer to the respective sample than to any other sample



Voronoi diagram

- Construction
 - Points in a Voronoi region are closer to the respective sample than to any other sample

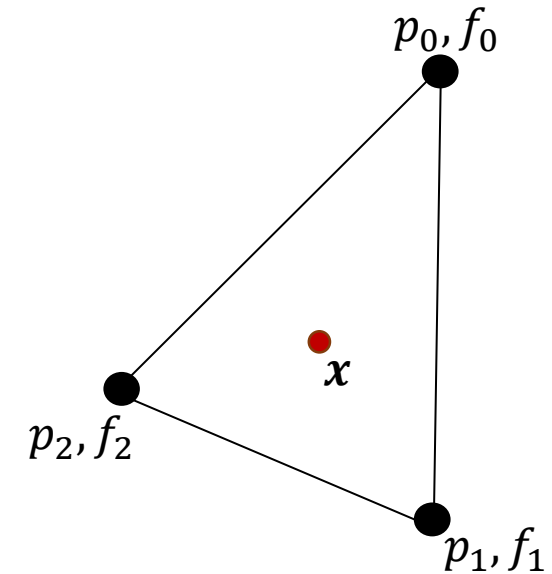


Interpolation

Data interpolation

- How to interpolate inside a triangle
 - The triangle lives in a $(N = 2)$ D plane; it has $N + 1$ points (x_i, y_i) with values f_i
 - Can we find a function f that interpolates f_i at the points p_i , i.e.,

$$f(p_i) = f_i, \quad i = 0, \dots, N$$



(interpolation constraint)

- If so, then the value at any point x can be interpolated by evaluating $f(x)$

Data interpolation

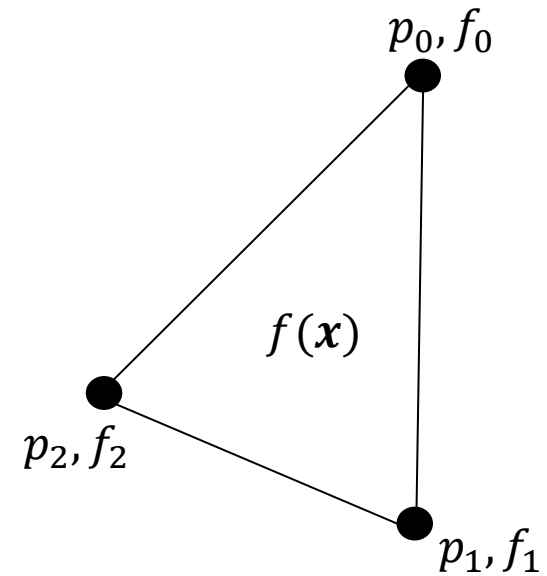
- There is a unique linear function that satisfies the interpolation constraint

- A linear function can be written as

$$f(\mathbf{x}) = a + bx + cy$$

- The unknown coefficients a, b, c can be obtained by solving the system

$$\begin{bmatrix} 1 & x_0 & y_0 \\ 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} f_0 \\ f_1 \\ f_2 \end{bmatrix}$$



Data interpolation

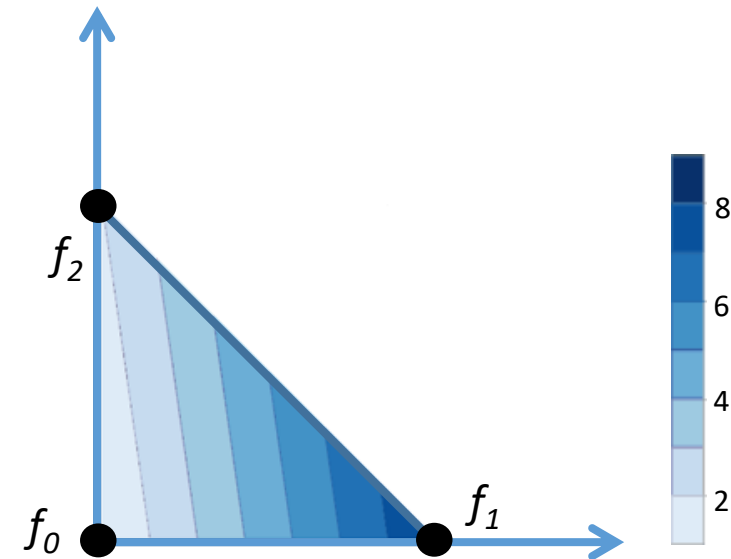
- Example

$$(x_0, y_0) = (0, 0), \quad (x_1, y_1) = (1, 0), \quad (x_2, y_2) = (0, 1)$$
$$f_0 = 1, \quad f_1 = 8, \quad f_2 = 2$$

- Obtain a, b, c by solving the system

$$\begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 1 \\ 8 \\ 2 \end{bmatrix}$$

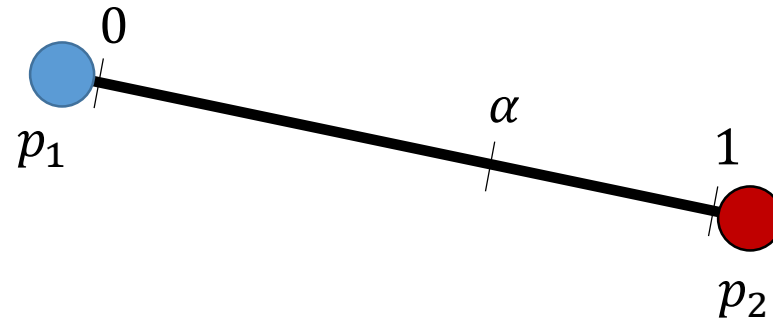
$$a = 1, b = 7, c = 1$$
$$f(x, y) = 1 + 7x + 1y$$



Data interpolation

- Barycentric interpolation

- Another way to interpolate inside a triangle, which yields the same linear interpolation as before
- But let's solve a simpler problem first

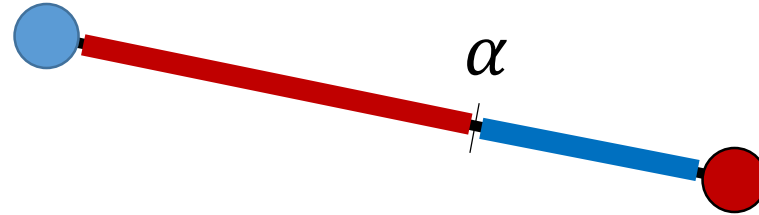


- We want to define a color for every $\alpha \in [0, 1]$



Data interpolation

- How do we come up with an equation?



The further α is from the blue point, the more red we want

The further α is from the red point, the more blue we want

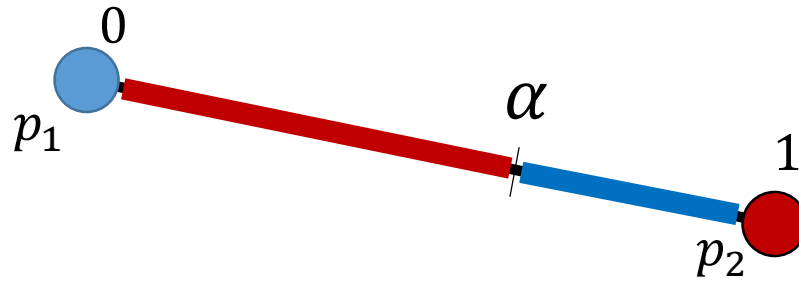


Percentage red = (length of red segment) / (total length)

Percentage blue = (length of blue segment) / (total length)

Data interpolation

- How do we come up with an equation?



The further α is from the blue point, the more red we want
The further α is from the red point, the more blue we want



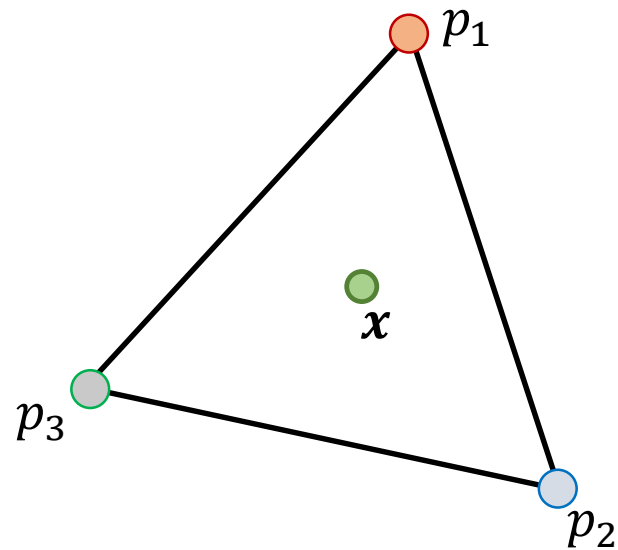
Percentage red = α

Percentage blue = $1 - \alpha$

$$f(\alpha) = \alpha \cdot p_2 + (1 - \alpha) \cdot p_1$$

Data interpolation

- Barycentric interpolation
 - Now what about triangles?



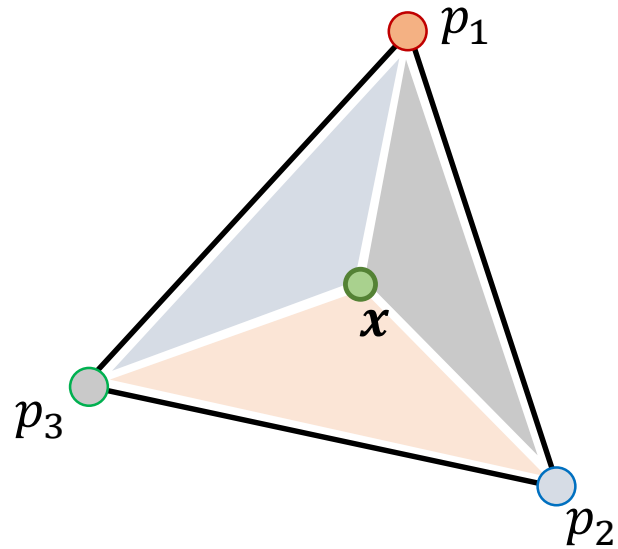
What's the interpolated value at the point x ?

In 1D we used ratios of lengths



Data interpolation

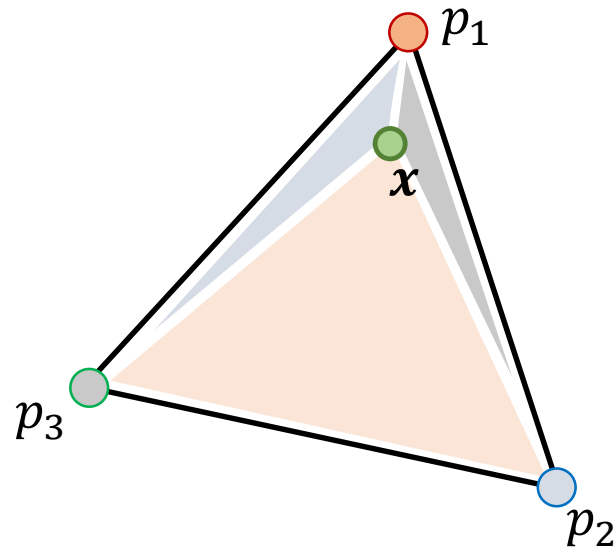
- Barycentric interpolation
 - Now what about triangles?



What about ratios of 2D areas?

Data interpolation

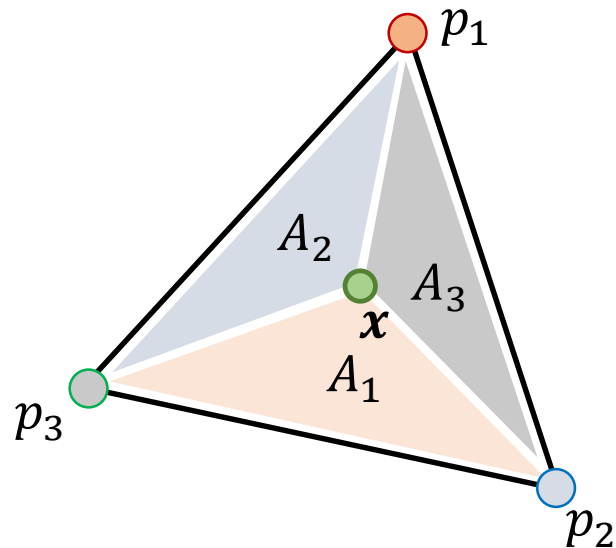
- Barycentric interpolation
 - Now what about triangles?



As x approaches the red point, the red area (for example) covers more of the triangle

Data interpolation

- Barycentric interpolation
 - Just like before:



$$\alpha_1 = A_1 / A \quad \text{percentage red}$$

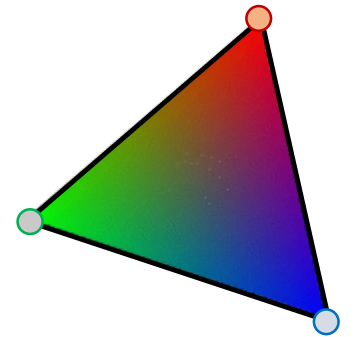
$$\alpha_2 = A_2 / A \quad \text{percentage blue}$$

$$\alpha_3 = A_3 / A \quad \text{percentage green}$$

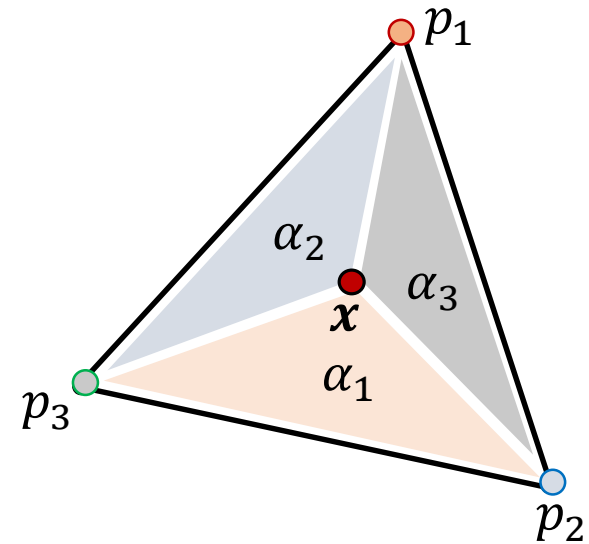
A ... area of whole triangle

$$\mathbf{x} = \alpha_1 \mathbf{p}_1 + \alpha_2 \mathbf{p}_2 + \alpha_3 \mathbf{p}_3$$

$$\alpha_1 + \alpha_2 + \alpha_3 = 1$$



Data interpolation



$$\alpha_1 = \frac{\text{area}(\Delta xp_2p_3)}{\text{area}(\nabla p_1p_2p_3)}$$

$$\alpha_2 = \frac{\text{area}(\Delta p_1xp_3)}{\text{area}(\nabla p_1p_2p_3)}$$

$$\alpha_3 = \frac{\text{area}(\Delta p_1p_2x)}{\text{area}(\nabla p_1p_2p_3)}$$

Barycentric interpolation

$$\mathbf{x} = \alpha_1 p_1 + \alpha_2 p_2 + \alpha_3 p_3$$

$$\alpha_1 + \alpha_2 + \alpha_3 = 1$$

Inside triangle criteria

$$0 \leq \alpha_1 \leq 1$$

$$0 \leq \alpha_2 \leq 1$$

$$0 \leq \alpha_3 \leq 1$$

Data interpolation

- Barycentric interpolation

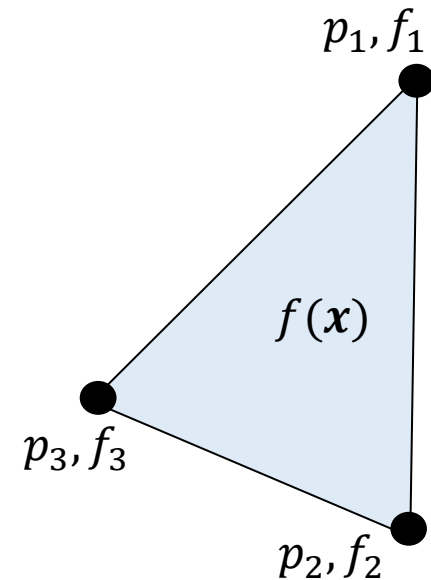
- Every point \mathbf{x} in a triangle can be written as a barycentric combination of the vertices p_i :

$$\mathbf{x} = \sum_i \alpha_i p_i \quad \text{with} \quad \sum_i \alpha_i = 1$$

(α_i ... barycentric coordinates)

- If α_i are known, then $f(\mathbf{x})$ can be interpolated from values f_i at the vertices via

$$f(\mathbf{x}) = \alpha_1 f_1 + \alpha_2 f_2 + \underbrace{(1 - \alpha_1 - \alpha_2)}_{\alpha_3} f_3$$



Data interpolation

Example: Given a triangle with vertices $p_1 = (0.5, 2.5)$, $p_2 = (1.5, 4.5)$ and $p_3 = (2.5, 2.5)$. Compute the barycentric coordinates of the points $P = (1.5, 2.5)$ and $Q = (1.5, 0.5)$ with respect to the triangle.

Point P :

$$\alpha_2 = 0 \rightarrow \alpha_1 = \alpha_3 = 0.5$$

Point Q :

$$I: 1.5 = 0.5 \alpha_1 + 1.5 \alpha_2 + 2.5 \alpha_3$$

$$II: 0.5 = 2.5 \alpha_1 + 4.5 \alpha_2 + 2.5 \alpha_3$$

$$III: 1 = \alpha_1 + \alpha_2 + \alpha_3$$

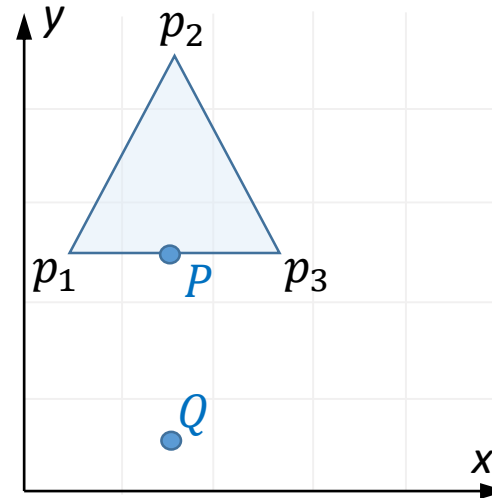
$$I - II: 1 = -2\alpha_1 - 3\alpha_2$$

$$II - 2.5 III: -2 = 2\alpha_2 \rightarrow \alpha_2 = -1$$

$$\alpha_2 \rightarrow I': -2 = -2\alpha_1 \rightarrow \alpha_1 = 1 \rightarrow \alpha_3 = 1$$

← x coordinates

← y coordinates



Data interpolation

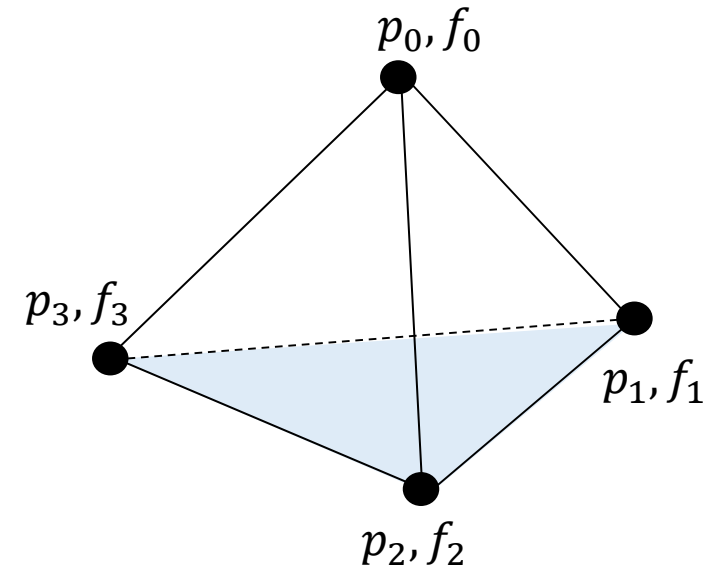
- Interpolation of scalar values in a **tetrahedron**

- A unique linear interpolation function

$f(\mathbf{x}) = a + bx + cy + dz$ exists which interpolates the scalar values at the vertices

- Solve for coefficients a, b, c, d via

$$\begin{bmatrix} 1 & x_0 & y_0 & z_0 \\ 1 & x_1 & y_1 & z_1 \\ 1 & x_2 & y_2 & z_2 \\ 1 & x_3 & y_3 & z_3 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} f_0 \\ f_1 \\ f_2 \\ f_3 \end{bmatrix}$$



Data interpolation

- How to get the **gradient** inside the tetrahedron?

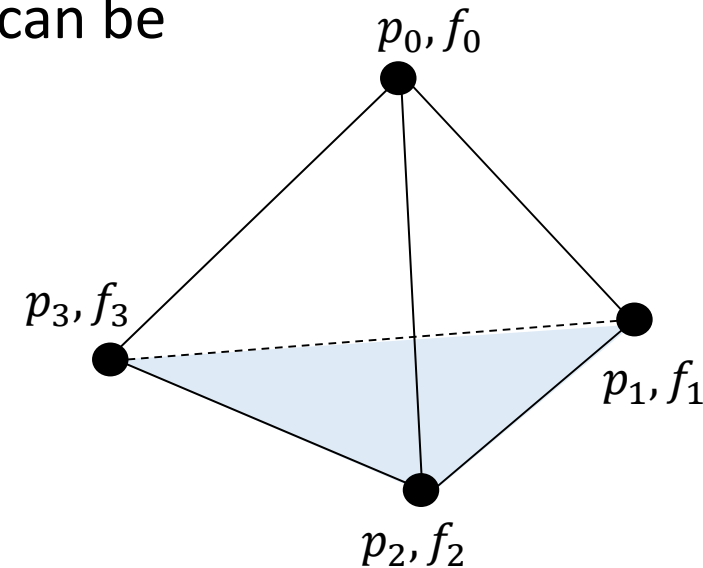
- Given the linear interpolation function

$$f(\mathbf{x}) = a + bx + cy + dz$$

- The gradient of the interpolated scalar field can be obtained by

$$\nabla f = \begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \frac{\partial f}{\partial z} \end{pmatrix} = \begin{pmatrix} b \\ c \\ d \end{pmatrix}$$

- The **gradient is constant** within the tetrahedron



Data interpolation

Example: For the tetrahedron with vertices $A = (0,0,0)$, $B = (1,0,0)$, $C = (0,1,0)$, $D = (0,0,1)$, compute the linear interpolation function $f(x, y, z) = a + b \cdot x + c \cdot y + d \cdot z$ which interpolates the scalar values $f_A = 1, f_B = 0, f_C = 0, f_D = 1$ at the corresponding vertices.

$$A \rightarrow f: 1 = a$$

$$B \rightarrow f: 0 = a + b \rightarrow b = -1$$

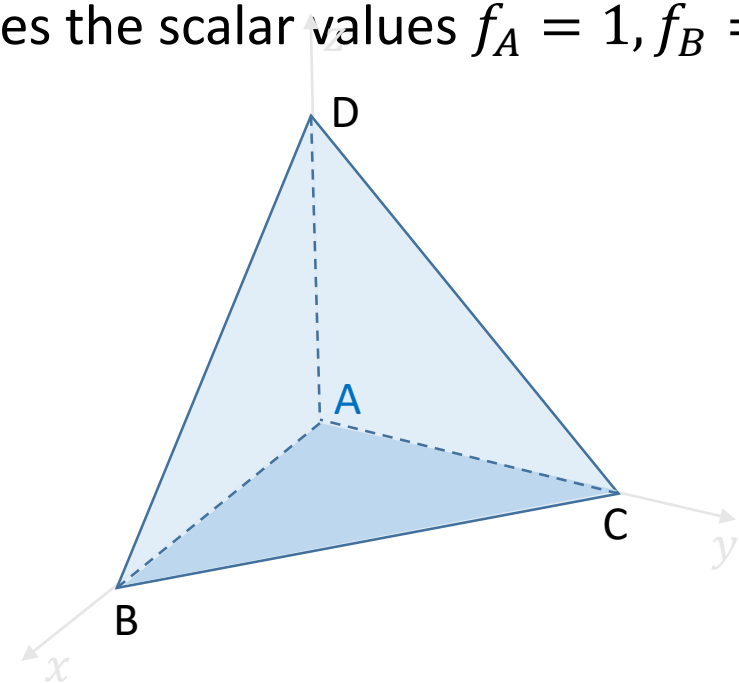
$$C \rightarrow f: 0 = a + c \rightarrow c = -1$$

$$D \rightarrow f: 1 = a + d \rightarrow d = 0$$

$$\rightarrow f(x, y, z) = 1 - x - y$$

Compute the gradient of the interpolated scalar field at the center of the tetrahedron.

$$\nabla f = (-1, -1, 0)^T$$

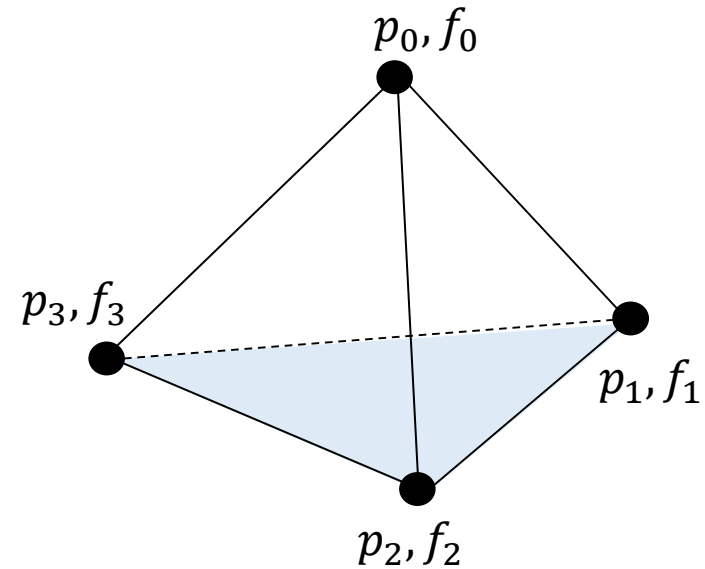


Data interpolation

- Barycentric interpolation in 3D
 - Scalar values can be interpolated by means of barycentric coordinates:

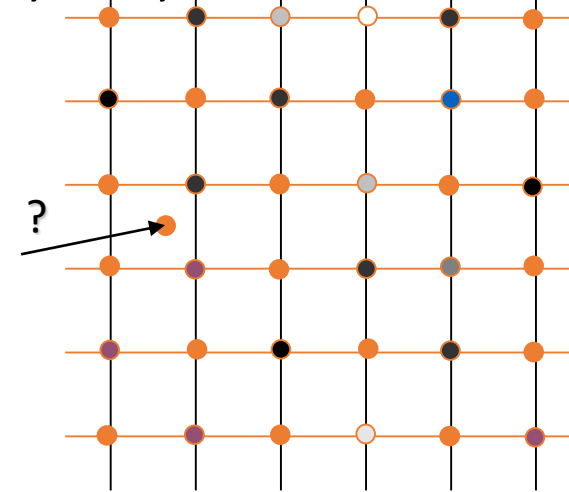
$$\begin{aligned} \mathbf{x} &= \alpha_0 \mathbf{p}_0 + \alpha_1 \mathbf{p}_1 + \alpha_2 \mathbf{p}_2 + \alpha_3 \mathbf{p}_3 \\ \alpha_0 + \alpha_1 + \alpha_2 + \alpha_3 &= 1 \end{aligned}$$

$$\rightarrow f(x, y, z) = \alpha_0 f_0 + \alpha_1 f_1 + \alpha_2 f_2 + \alpha_3 f_3$$



Interpolation on grids

- **Problem:** assume data values are given only at vertices of a Cartesian grid
- How can we hide the underlying grid structure, i.e., how can we get a **continuous** data distribution over the spatial domain?
- This can be done via **interpolation**!



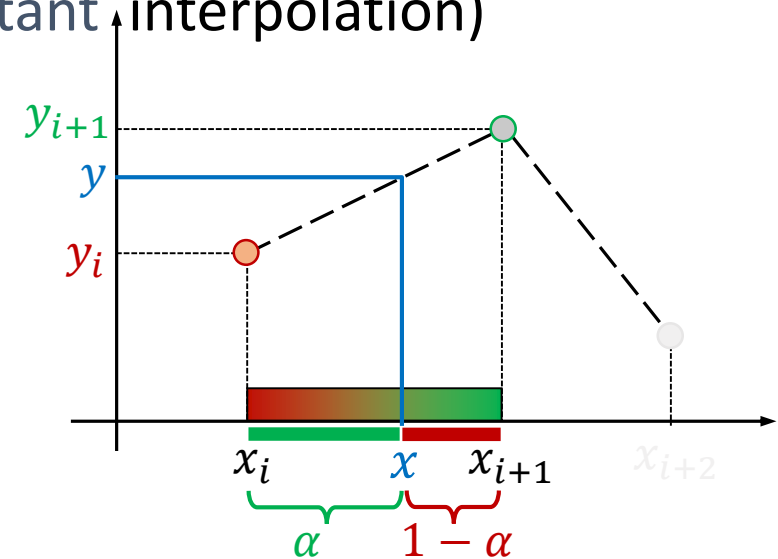
Interpolation on grids

- Piecewise linear interpolation
 - Simplest approach (except for piece-wise constant interpolation)
 - Data points: $(x_1, y_1), \dots, (x_N, y_N)$
 - For any point x with

$$x_i \leq x \leq x_{i+1}$$

evaluate $f(x) = (1 - \alpha)y_i + \alpha y_{i+1}$

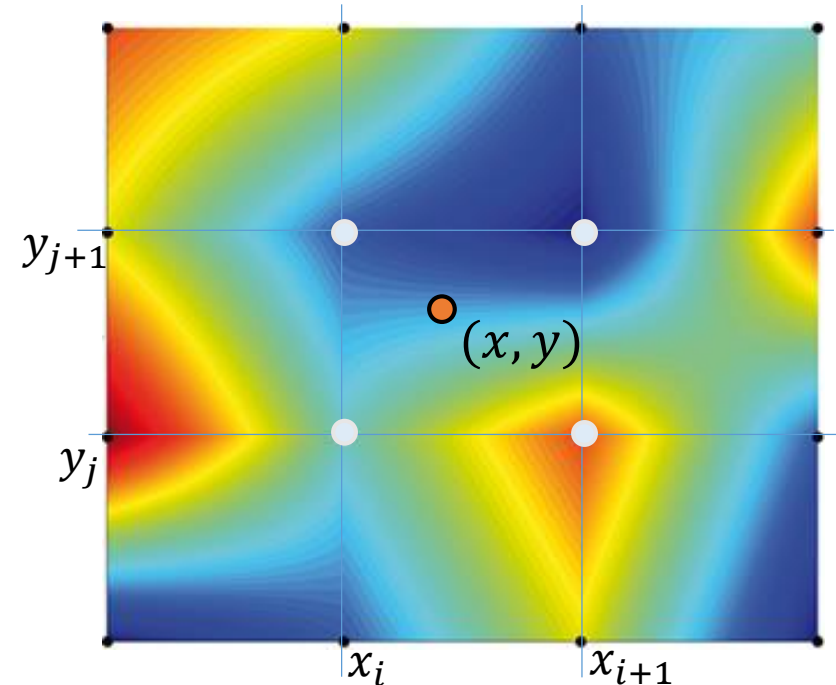
where $\alpha = \frac{x-x_i}{x_{i+1}-x_i} \in [0,1]$



The further x is away from red point,
the more green we want

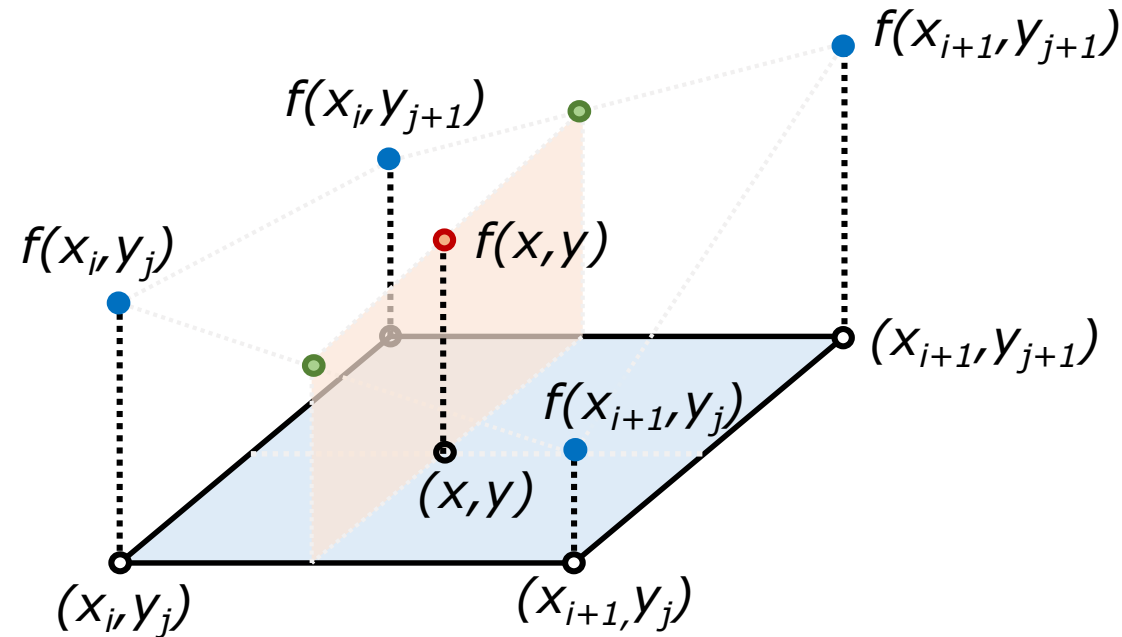
Interpolation on grids

- Linear interpolation
 - C^0 continuity at segment boundaries
 - Tangents don't match at segment transition
- Easily extendible to 2D
 - 2D cell consisting of 4 data points $(x_i, y_j), \dots, (x_{i+1}, y_{j+1})$ with scalar values $f_{k,l} = f(x_k, y_l)$
 - Bilinear interpolation of points (x, y) with $x_i \leq x \leq x_{i+1}$ and $y_j \leq y \leq y_{j+1}$



Interpolation on grids

- Bilinear interpolation on a rectangle



Interpolation on grids

- Bilinear interpolation on a rectangle

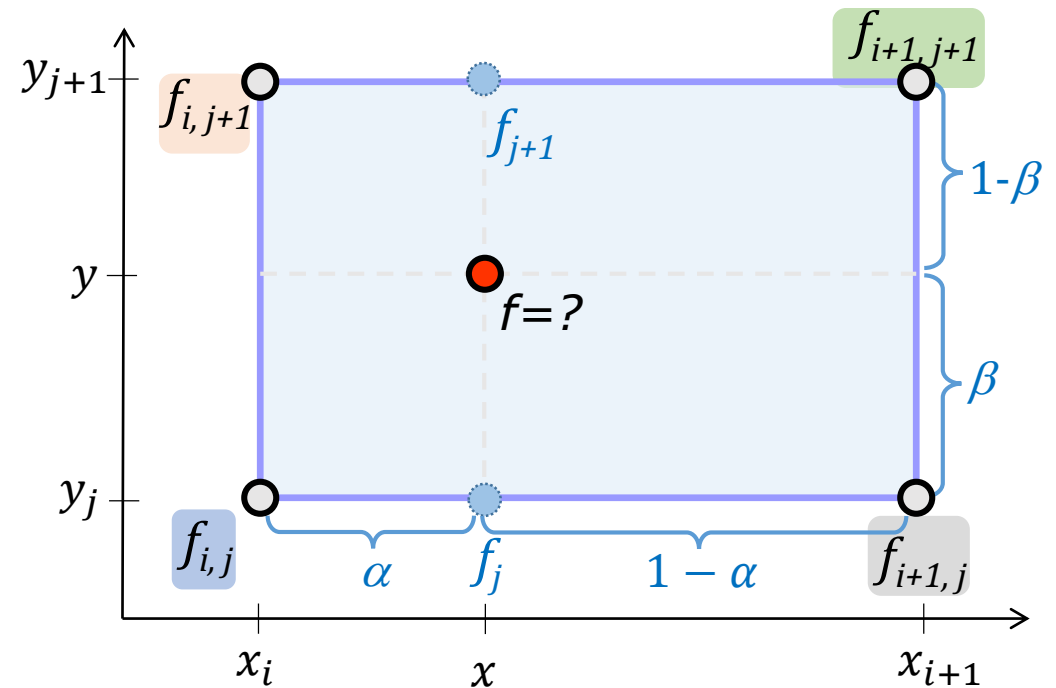
$$f(\alpha, \beta) = ?$$

Interpolate horizontally

$$f_j = (1 - \alpha) f_{i,j} + \alpha f_{i+1,j}$$

$$f_{j+1} = (1 - \alpha) f_{i,j+1} + \alpha f_{i+1,j+1}$$

$$\alpha = \frac{x - x_i}{x_{i+1} - x_i}$$



Interpolation on grids

- Bilinear interpolation on a rectangle

$$\begin{aligned} f(\alpha, \beta) &= (1-\beta)[(1-\alpha)f_{i,j} + \alpha f_{i+1,j}] + \beta[(1-\alpha)f_{i,j+1} + \alpha f_{i+1,j+1}] \\ &= (1-\beta)f_j + \beta f_{j+1} \end{aligned}$$

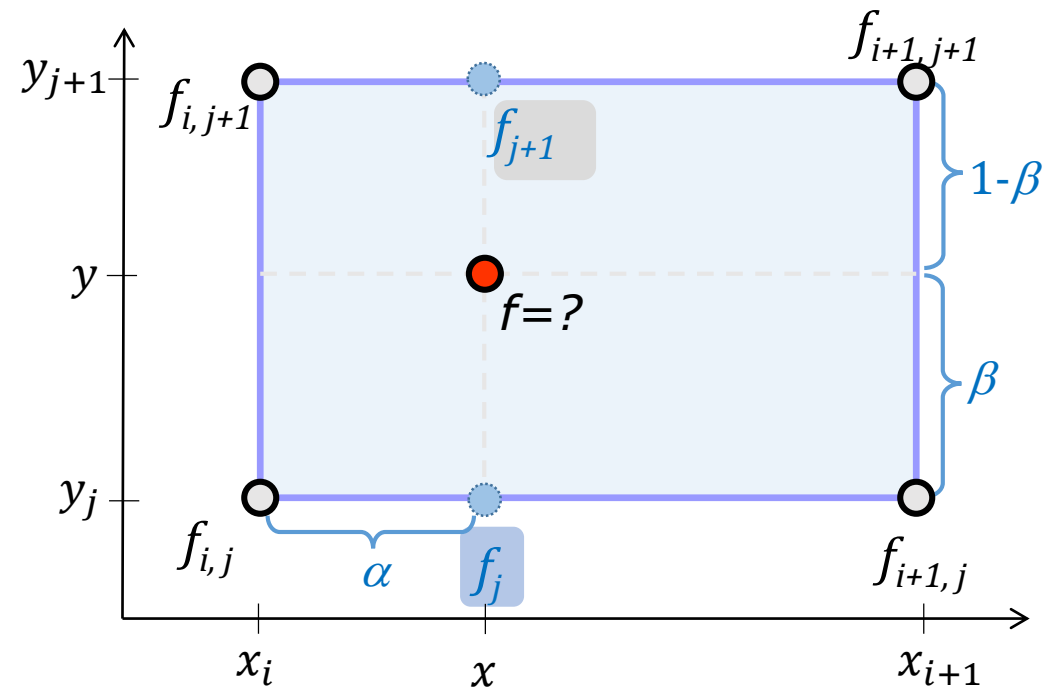
with

$$f_j = (1-\alpha)f_{i,j} + \alpha f_{i+1,j}$$

$$f_{j+1} = (1-\alpha)f_{i,j+1} + \alpha f_{i+1,j+1}$$

and local coordinates

$$\alpha = \frac{x - x_i}{x_{i+1} - x_i}, \quad \beta = \frac{y - y_i}{y_{i+1} - y_i}, \quad \alpha, \beta \in [0, 1]$$

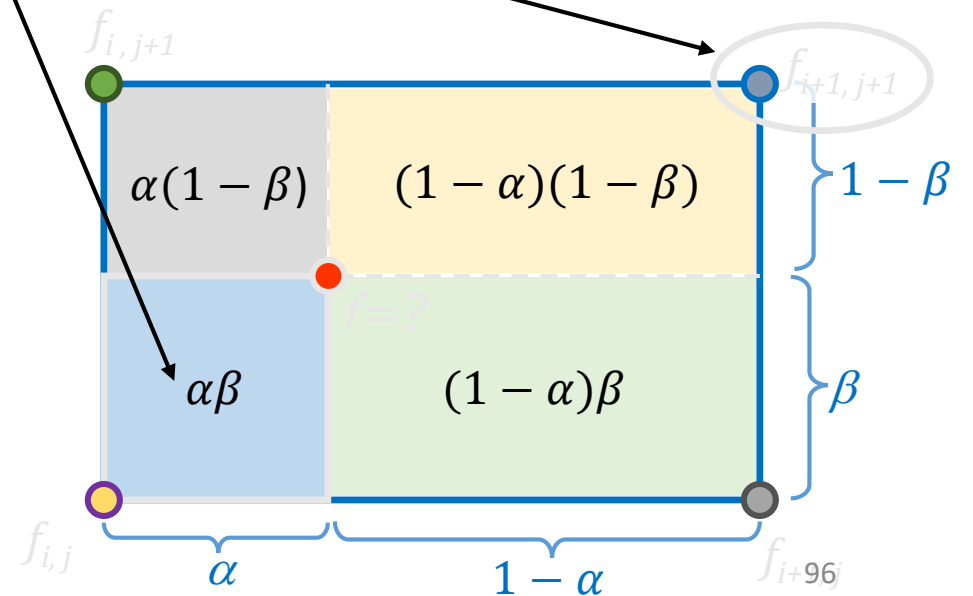


Interpolation on grids

- Geometric interpretation of bilinear interpolation

$$\begin{aligned}
 f(\alpha, \beta) &= (1 - \beta)[(1 - \alpha)f_{i,j} + \alpha f_{i+1,j}] + \beta[(1 - \alpha)f_{i,j+1} + \alpha f_{i+1,j+1}] \\
 &= (1 - \alpha)(1 - \beta)f_{i,j} + \alpha(1 - \beta)f_{i+1,j} \\
 &\quad + (1 - \alpha)\beta f_{i,j+1} + \alpha\beta f_{i+1,j+1}
 \end{aligned}$$

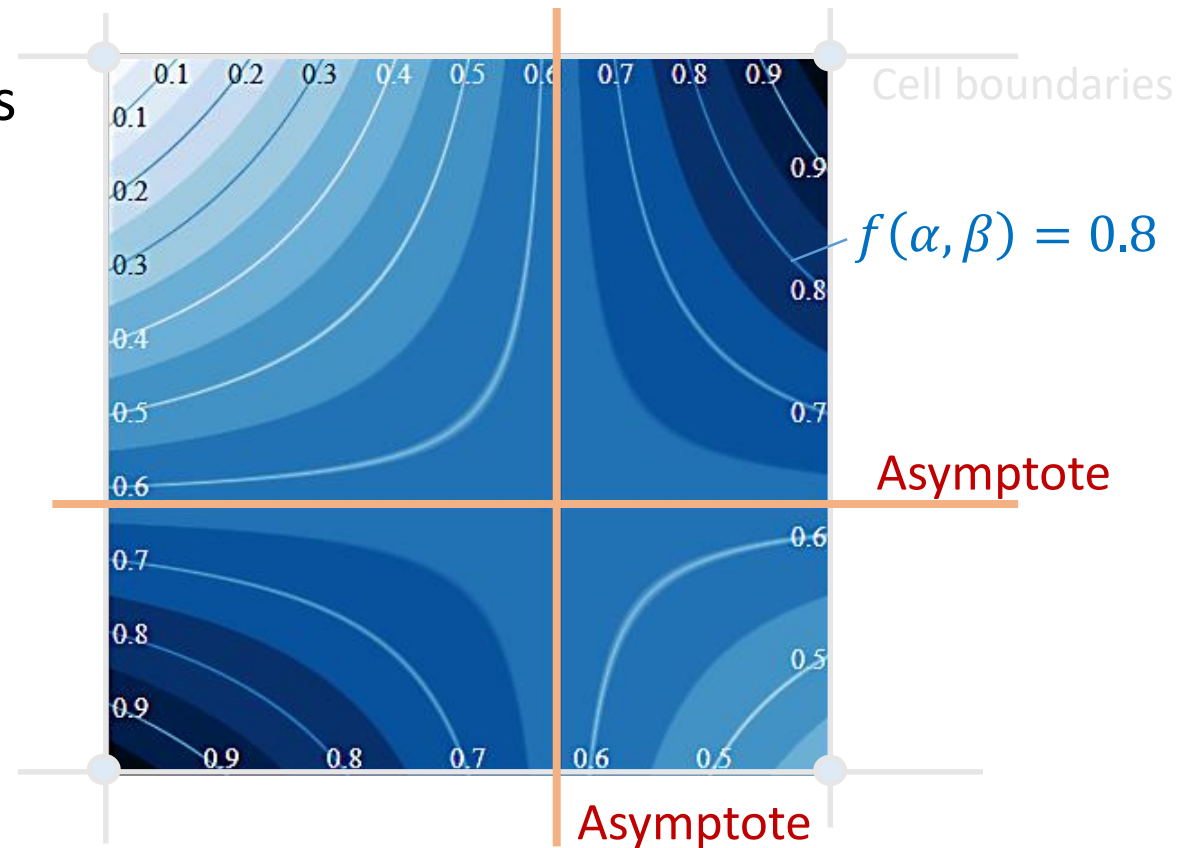
- Opposite points are weighted by local areas



Interpolation on grids

- When bilinear interpolation is used, isolines within a cell are hyperbolas

- Isoline:** curve on which all points have the same value



Interpolation on grids

- How to evaluate the isolines?

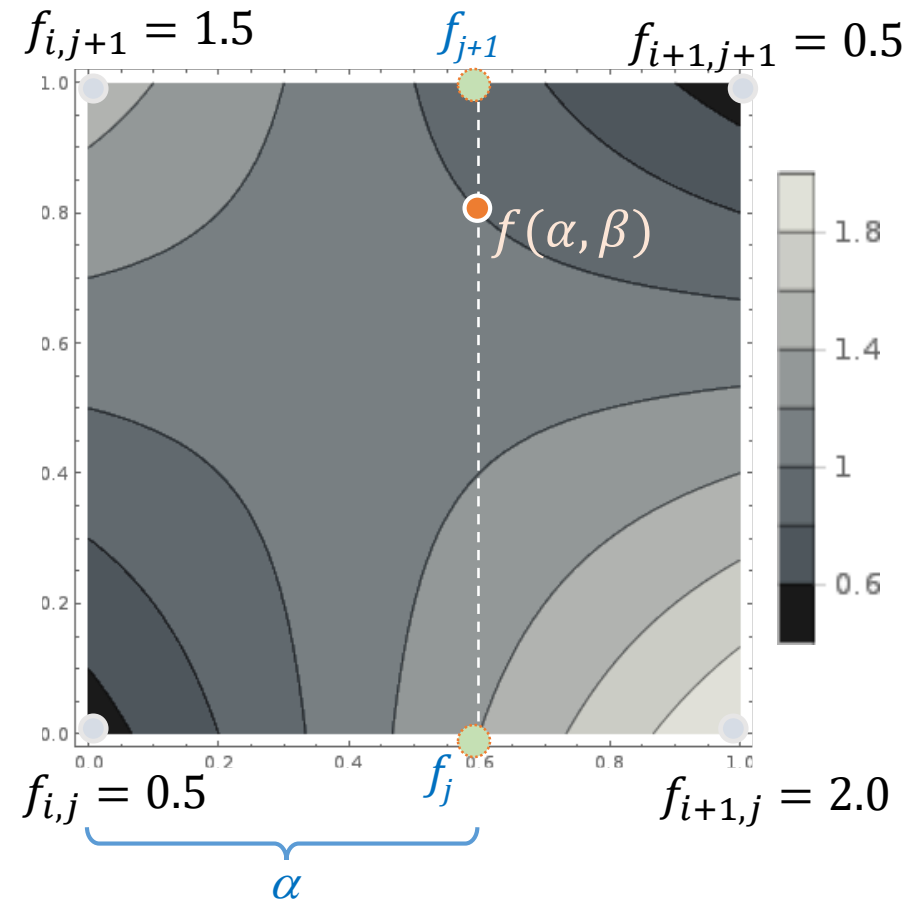
$$\begin{aligned}f_j &= \alpha f_{i+1,j} + (1 - \alpha)f_{i,j} \\&= f_{i,j} + (f_{i+1,j} - f_{i,j})\alpha \\&= 0.5 + 1.5\alpha\end{aligned}$$

$$\begin{aligned}f_{j+1} &= f_{i,j+1} + (f_{i+1,j+1} - f_{i,j+1})\alpha \\&= 1.5 - \alpha\end{aligned}$$

$$\begin{aligned}f(\alpha, \beta) &= f_j + (f_{j+1} - f_j)\beta \\&= (0.5 + 1.5\alpha) + \\&\quad (1.5 - \alpha - (0.5 + 1.5\alpha))\beta\end{aligned}$$

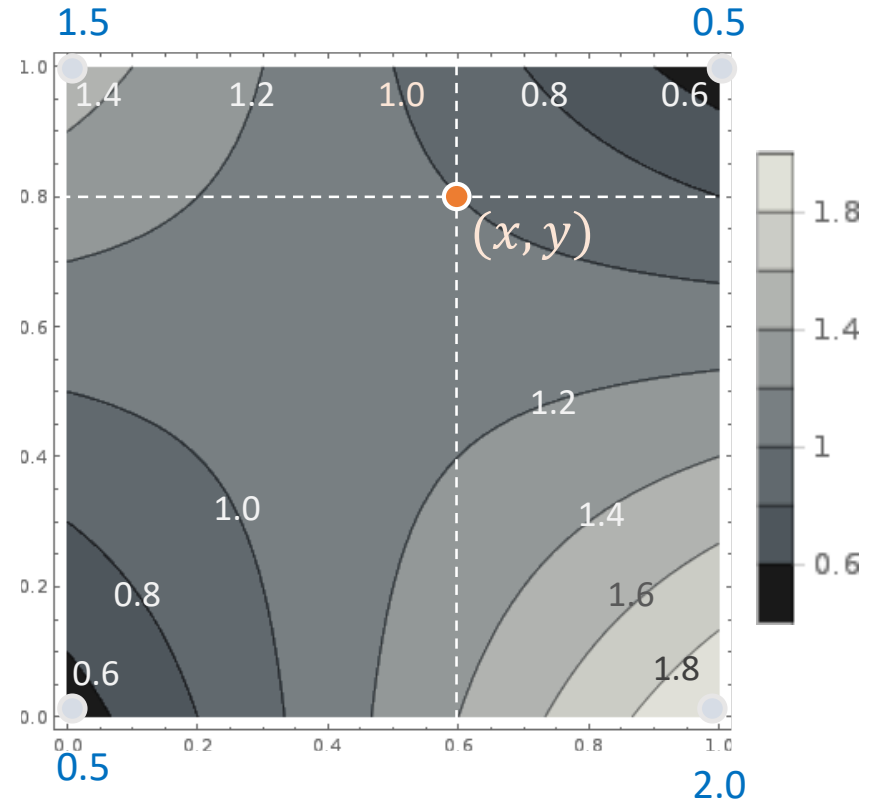
$$f(\alpha, \beta) = 0.5 + 1.5\alpha + \beta - 2.5\alpha\beta$$

↑ Bi-linear interpolation function
defining the scalar value at
each point (α, β) within the cell



Interpolation on grids

- How to evaluate the isolines?
 - Compute y-coordinate of a point (x, y) with $x = 0.6$ which is on the iso-contour $f(x, y) = 1$

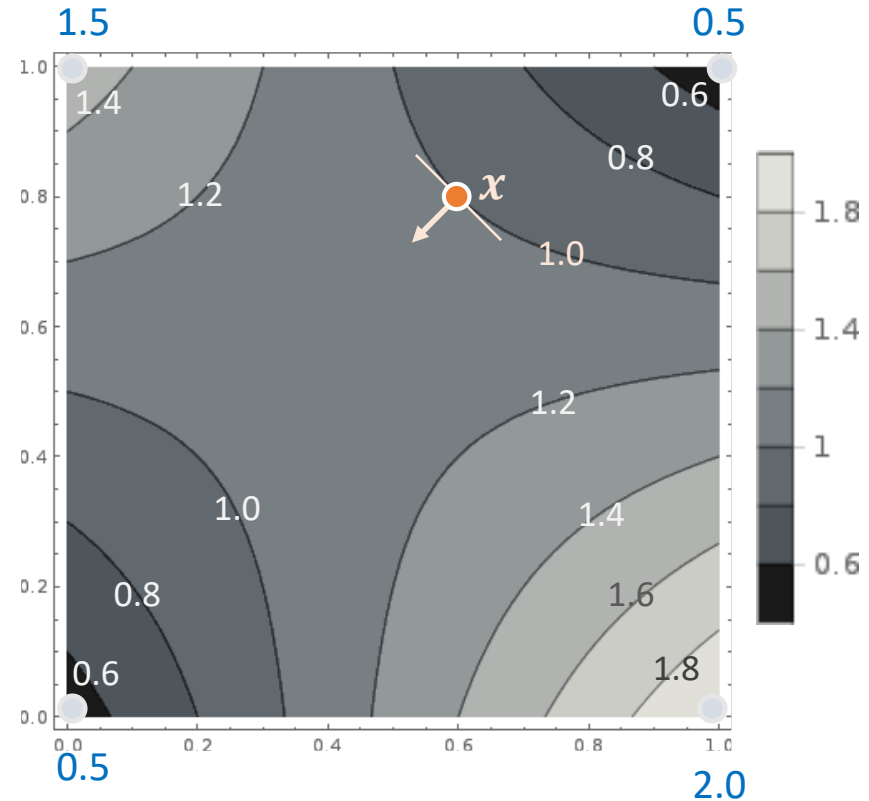


The coordinates of the point are (0.6, 0.8)

Interpolation on grids

- What is the **normal** at a point \mathbf{x} on an iso-surface?
 - It is the **gradient** at this point
 - Gradient points into direction of steepest ascent of f

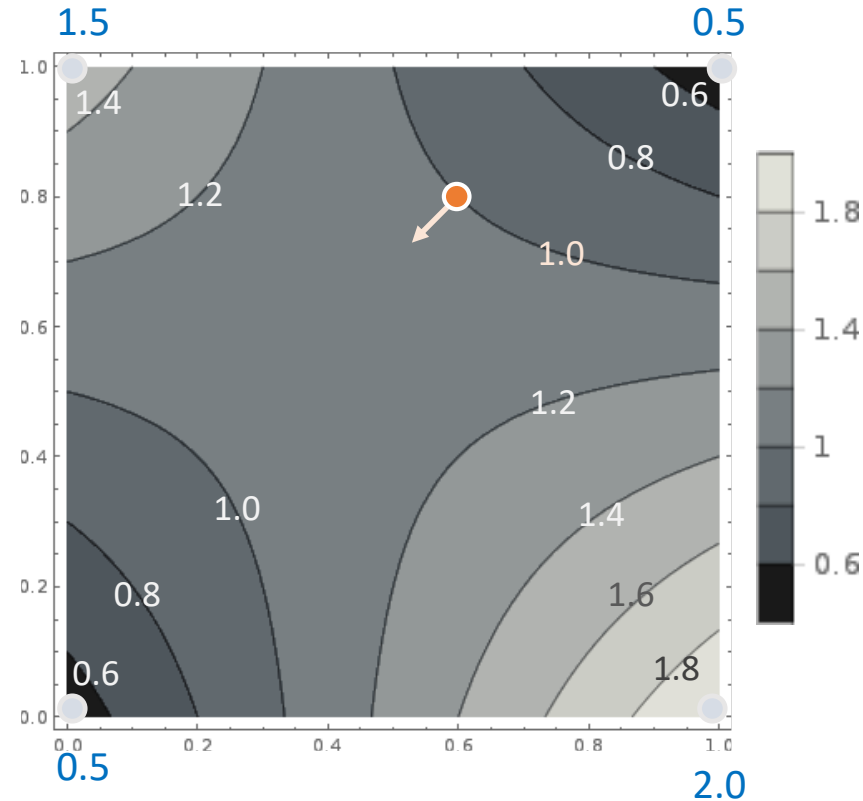
$$\nabla f(\mathbf{x}) = \left(\frac{\partial}{\partial x} f(\mathbf{x}), \frac{\partial}{\partial y} f(\mathbf{x}) \right)$$



Interpolation on grids

- What is the normal at point $(0.6, 0.8)$ on the iso-surface?

Gradient at $(0.6, 0.8)$: $\begin{pmatrix} -0.5 \\ -0.5 \end{pmatrix}$



Interpolation on grids

- How to evaluate the asymptotes?

- Consider bilinear interpolation within a cell

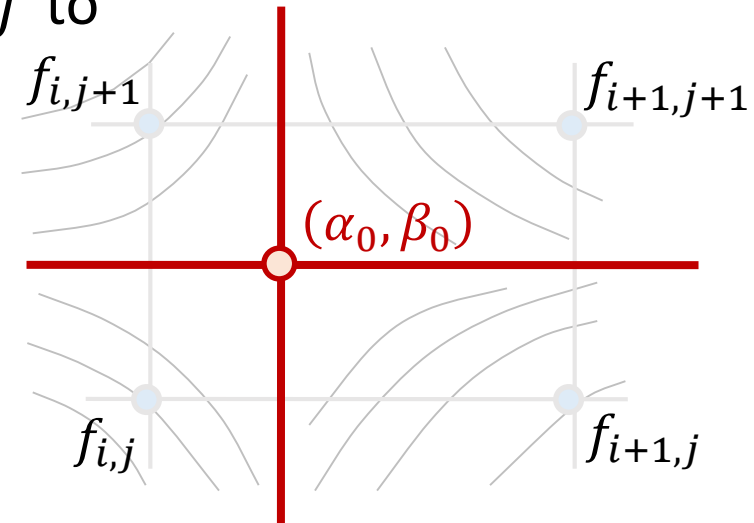
$$f(\alpha, \beta) = (1 - \alpha)(1 - \beta)f_{i,j} + \alpha(1 - \beta)f_{i+1,j} + (1 - \alpha)\beta f_{i,j+1} + \alpha\beta f_{i+1,j+1}$$

- Given the values at cell corners, transform f to

$$f(\alpha, \beta) = \gamma(\alpha - \alpha_0)(\beta - \beta_0) + \delta$$

Function of a hyperbola

- δ is the function value at the intersection point (α_0, β_0) of the asymptotes



Interpolation on grids

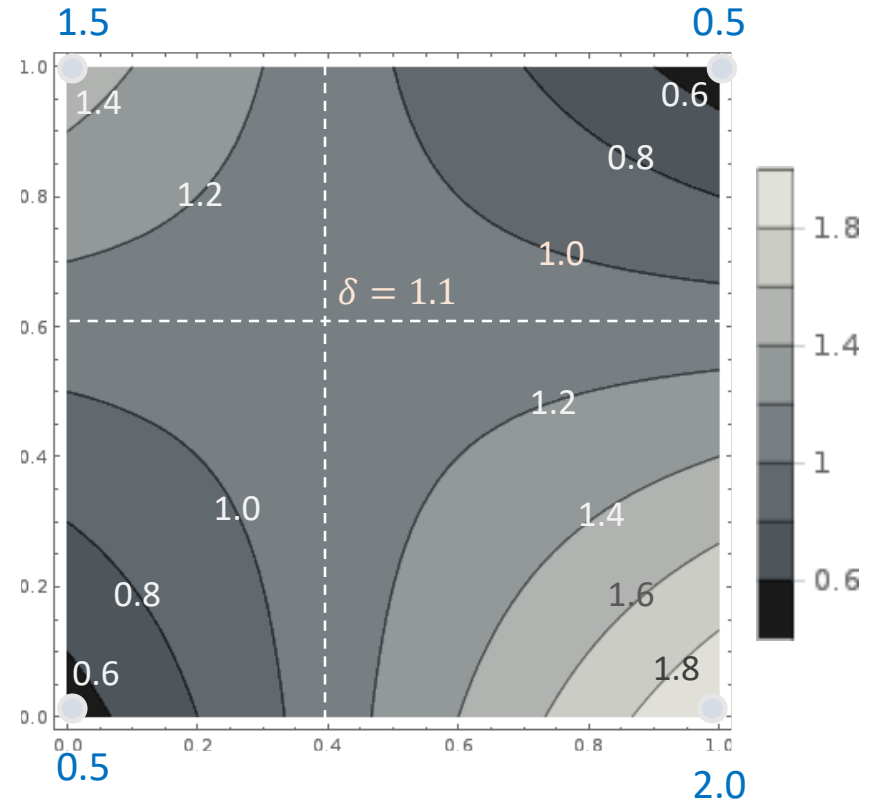
- How to evaluate the asymptotes?

Compute asymptotes from

$$f(\alpha, \beta) = 0.5 + 1.5\alpha + \beta - 2.5\alpha\beta$$

Get into form (hyperbola)

- Asymptotes intersect at (0.4, 0.6)
- Value at intersection: $\delta = 1.1$



Interpolation on grids

- Summary: Bilinear Interpolation

- The value at each point (α, β) within the cell can be obtained by

$$f(\alpha, \beta) = (1 - \alpha)(1 - \beta)f_{00} + \alpha(1 - \beta)f_{10} + (1 - \alpha)\beta f_{01} + \alpha\beta f_{11}$$

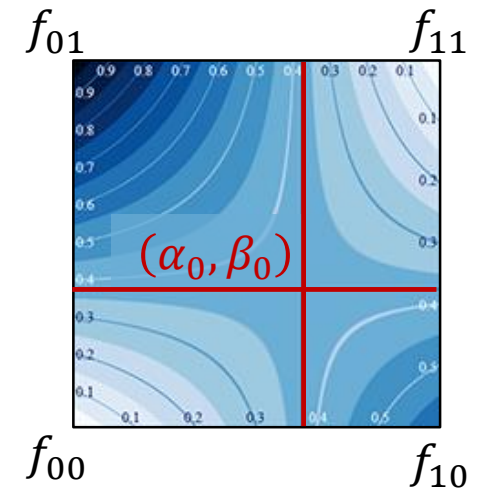
$$= A\alpha + B\beta + C\alpha\beta + D$$

where $A = f_{10} - f_{00}$, $B = f_{01} - f_{00}$,
 $C = f_{00} - f_{01} - f_{10} + f_{11}$, $D = f_{00}$

- We can evaluate the isoline for an iso-value c by setting $f(\alpha, \beta) = c$
- The asymptotes of the hyperbolas can be computed by

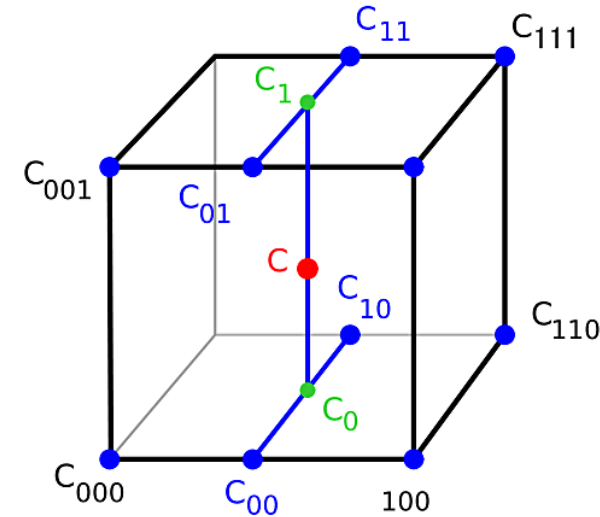
$$f(\alpha, \beta) = \gamma(\alpha - \alpha_0)(\beta - \beta_0) + \delta$$

where $\gamma = C$ and $\delta = (f_{00}f_{11} - f_{01}f_{10})/C$ is the value at the intersection point (α_0, β_0) of the asymptotes with $\alpha_0 = -B/C$ and $\beta_0 = -A/C$



Interpolation on grids

- In 3D we use trilinear interpolation:



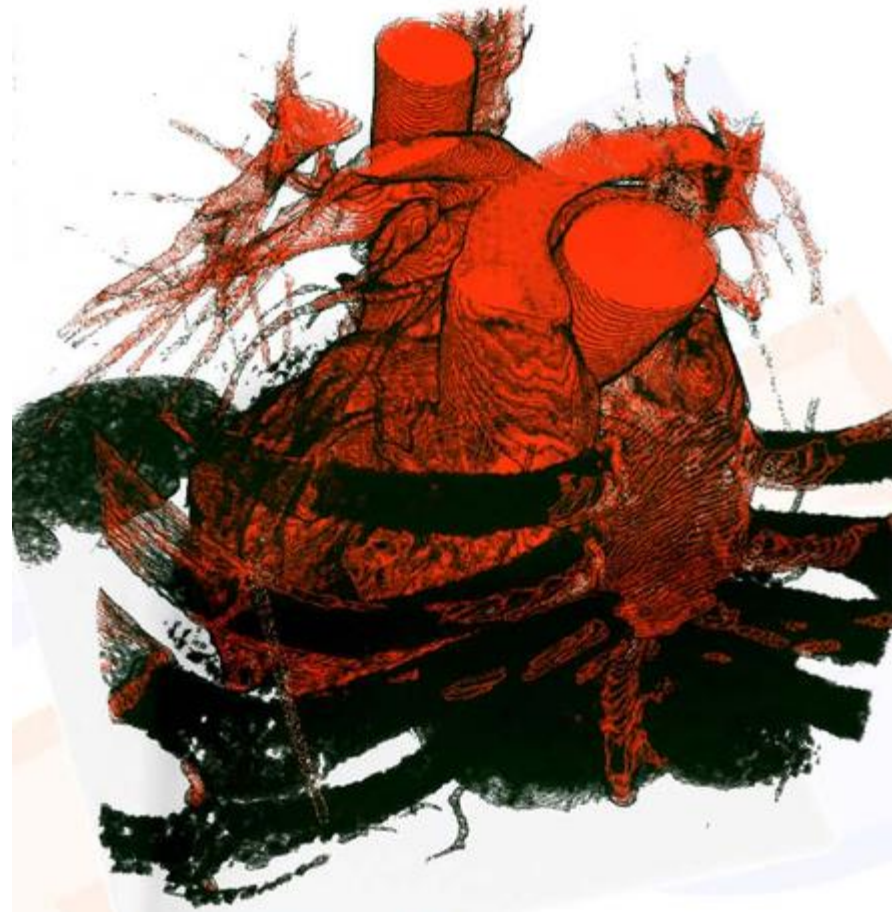
- Apply linear interpolation of the initial data along the edges to obtain C_{00} , C_{01} , C_{10} , C_{11}
- Interpolate linearly between C_{00} and C_{01} , and between C_{10} and C_{11} to obtain C_0 and C_1
- Finally, interpolate between C_1 and C_0 to obtain C .

Interpolation on grids

- This is what we want...

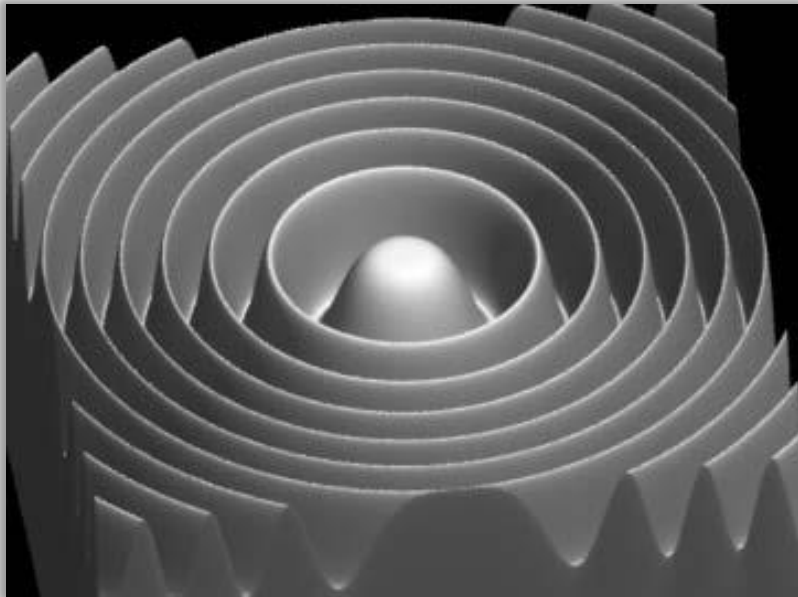


...but sometimes this is what we get



Interpolation on grids

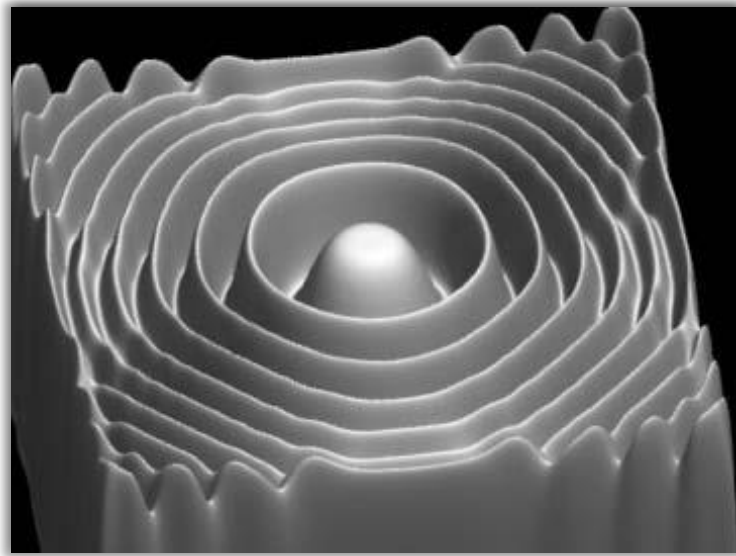
- Higher-order reconstruction/interpolation
 - Required if very high quality is needed
 - Usually tested on Marschner-Lobb function
 - High amount of its energy is near its Nyquist frequency
 - Very demanding test for accurate reconstruction



[Marschner & Lobb 94]

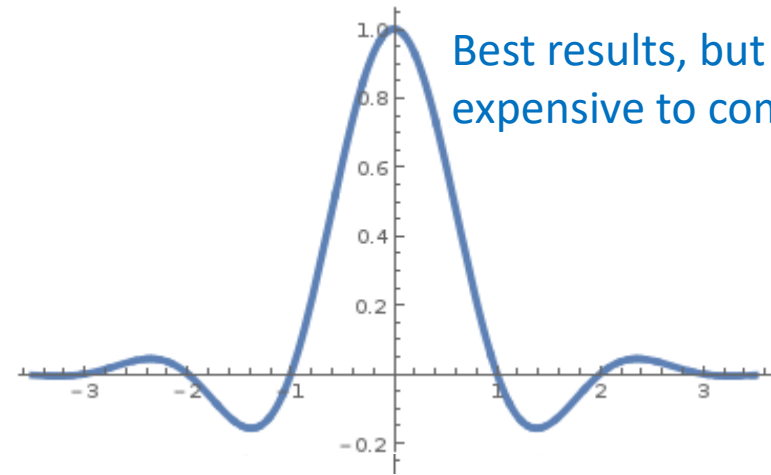
High-quality Reconstruction

Sinc function



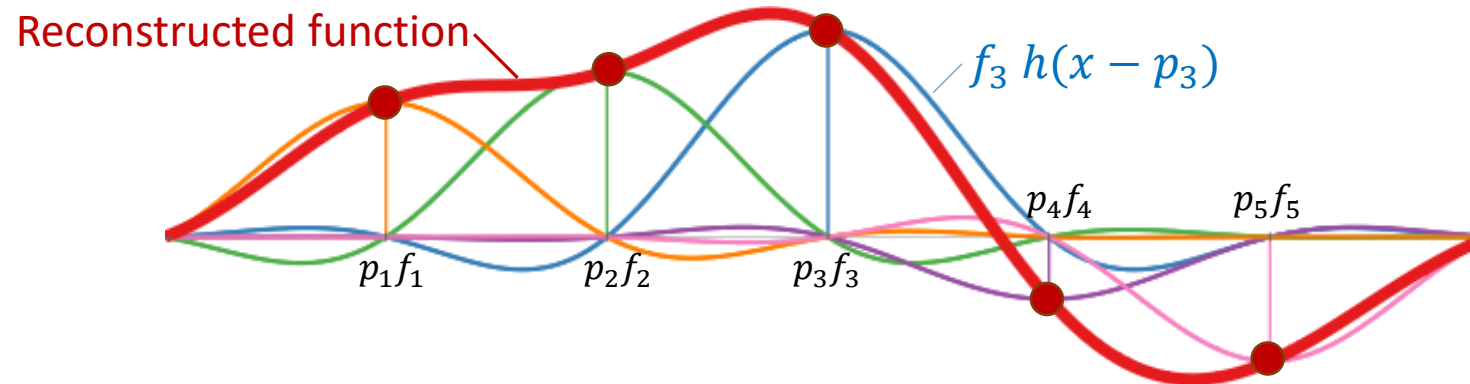
[Marschner & Lobb 94]

Windowed sinc (Hann window)



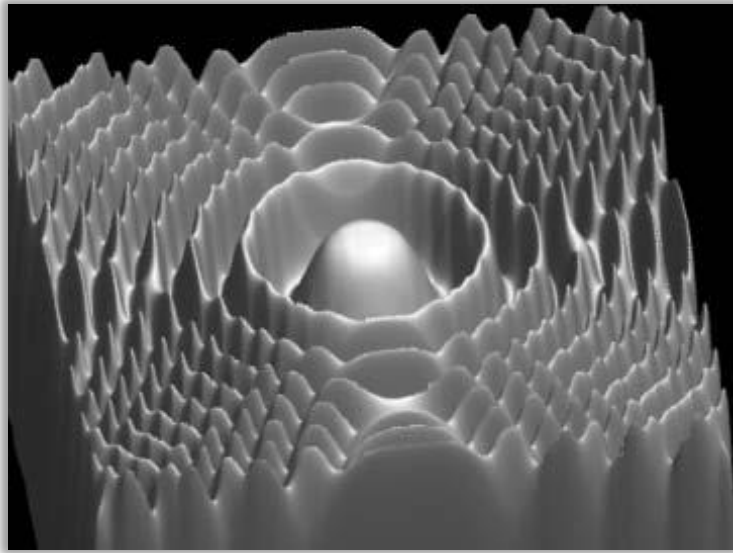
Best results, but very expensive to compute

“Optimal” reconstruction filter



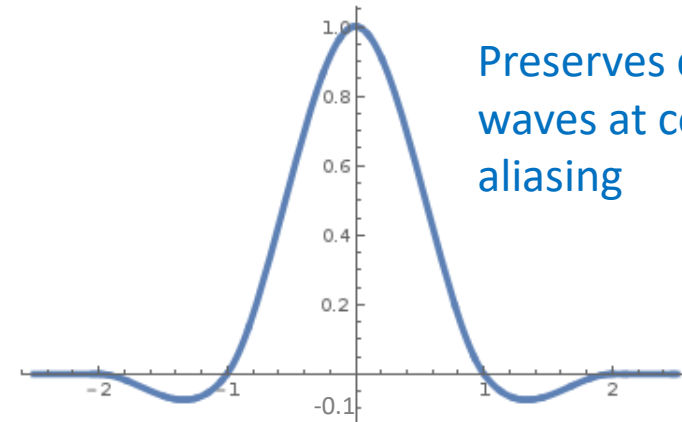
High-quality Reconstruction

Bicubic interpolation
(Catmull-Rom spline)



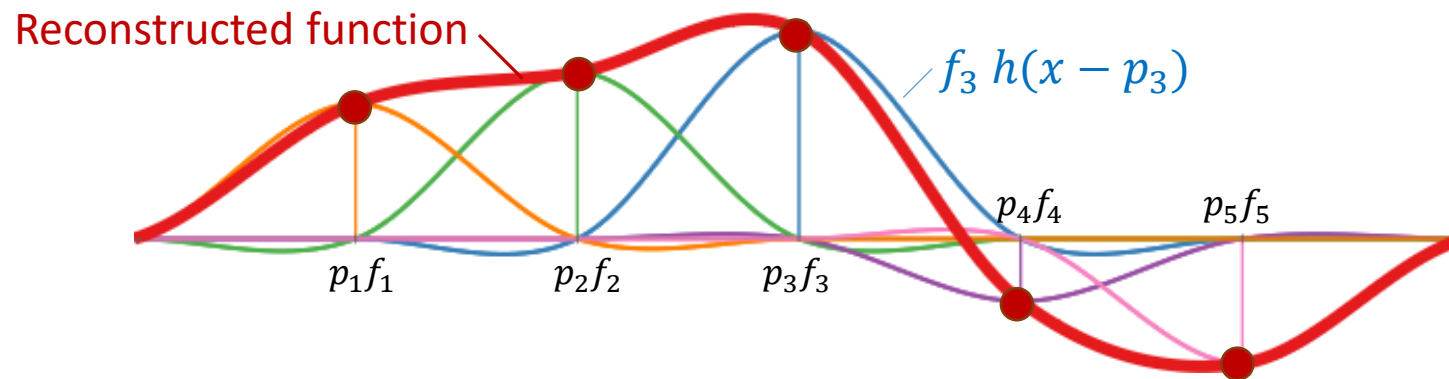
[Marschner & Lobb 94]

Reconstructed Marschner-Lobb function



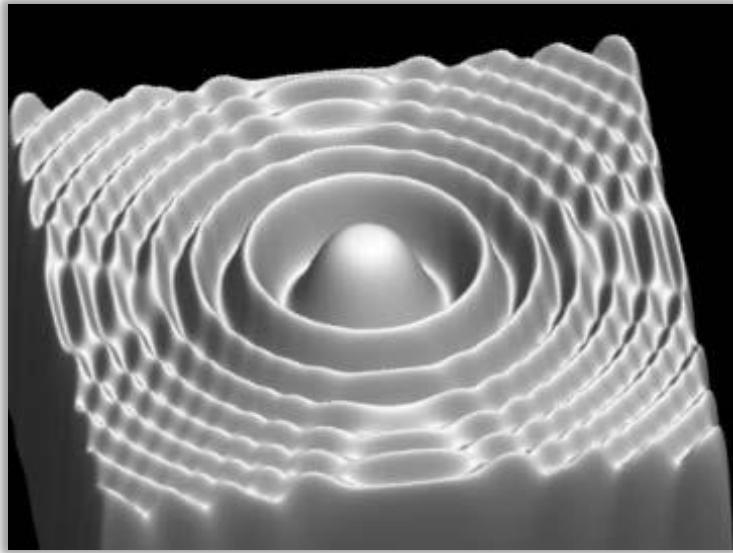
Preserves depth of
waves at cost of
aliasing

Interpolation: 1 at center and 0 at integers



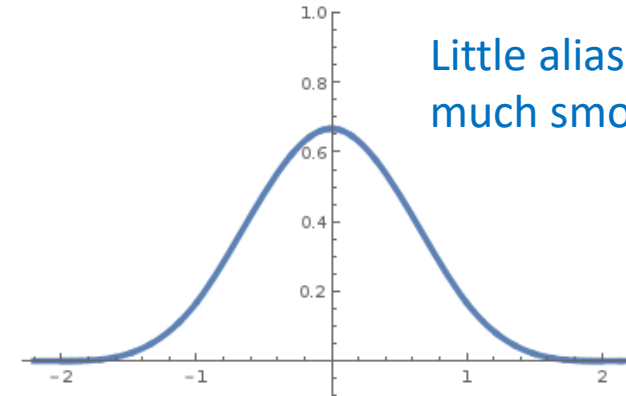
High-quality Reconstruction

Cubic B-spline
(with smoothing)



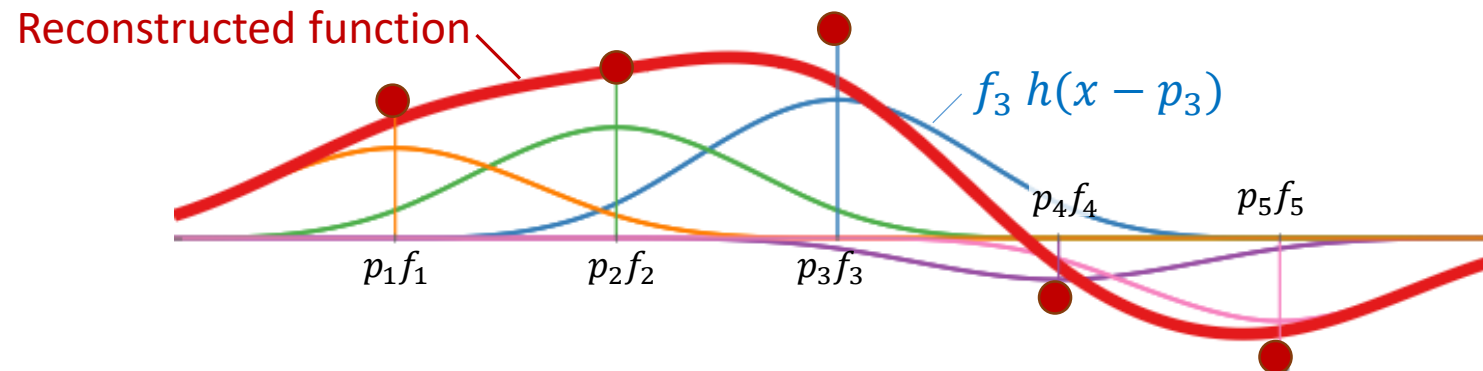
[Marschner & Lobb 94]

Reconstructed Marschner-Lobb function



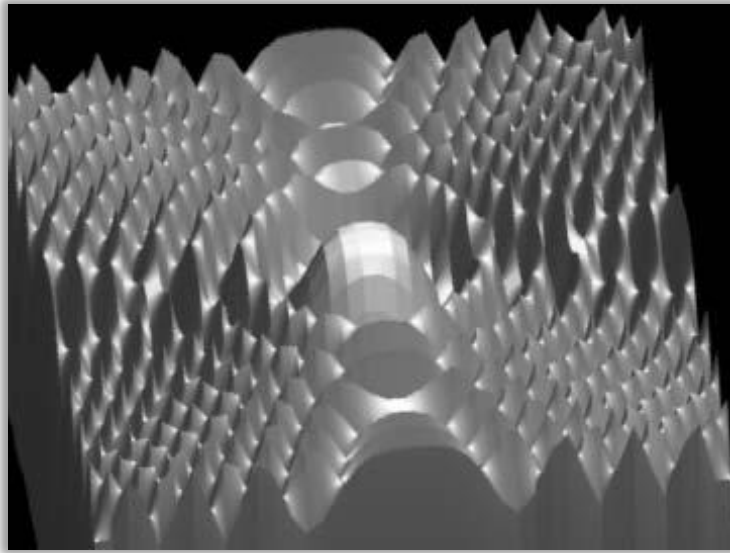
Little aliasing, but
much smoothing

Smoothing: $\frac{2}{3}$ at center and $\frac{1}{6}$ at ± 1

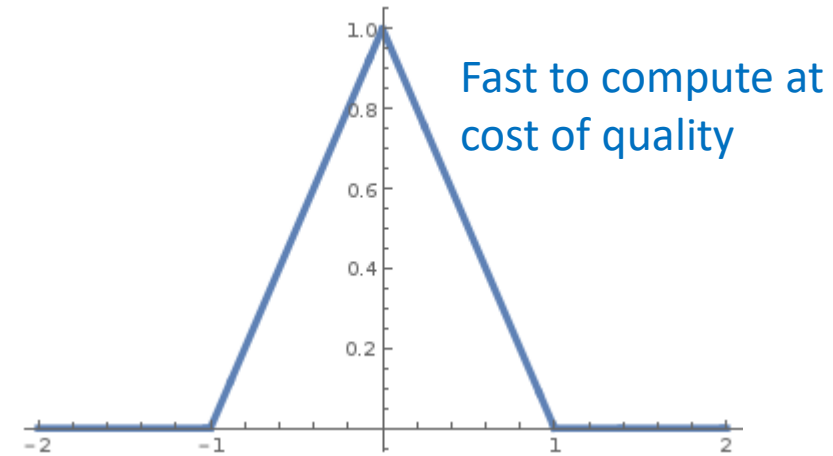


High-quality Reconstruction

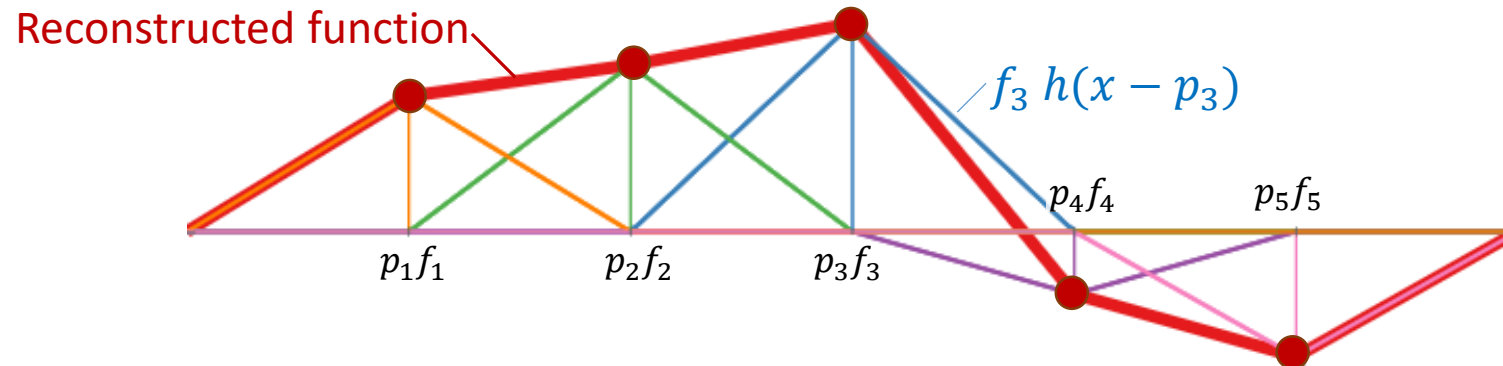
Trilinear interpolation
(Tent)



Reconstructed Marschner-Lobb function

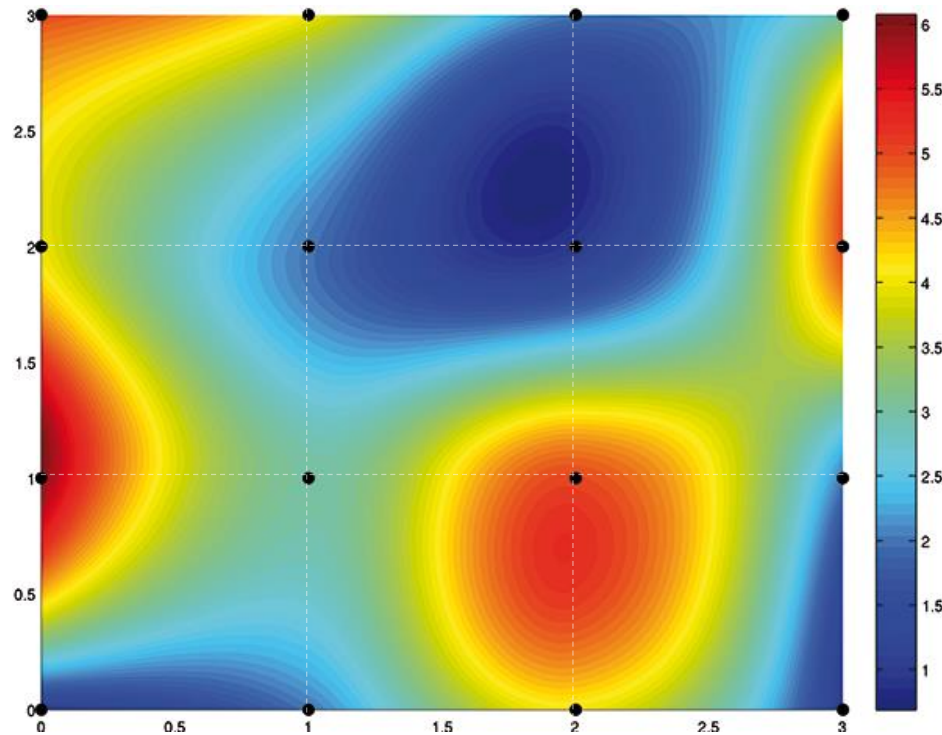


Interpolation: 1 at center and 0 at integers

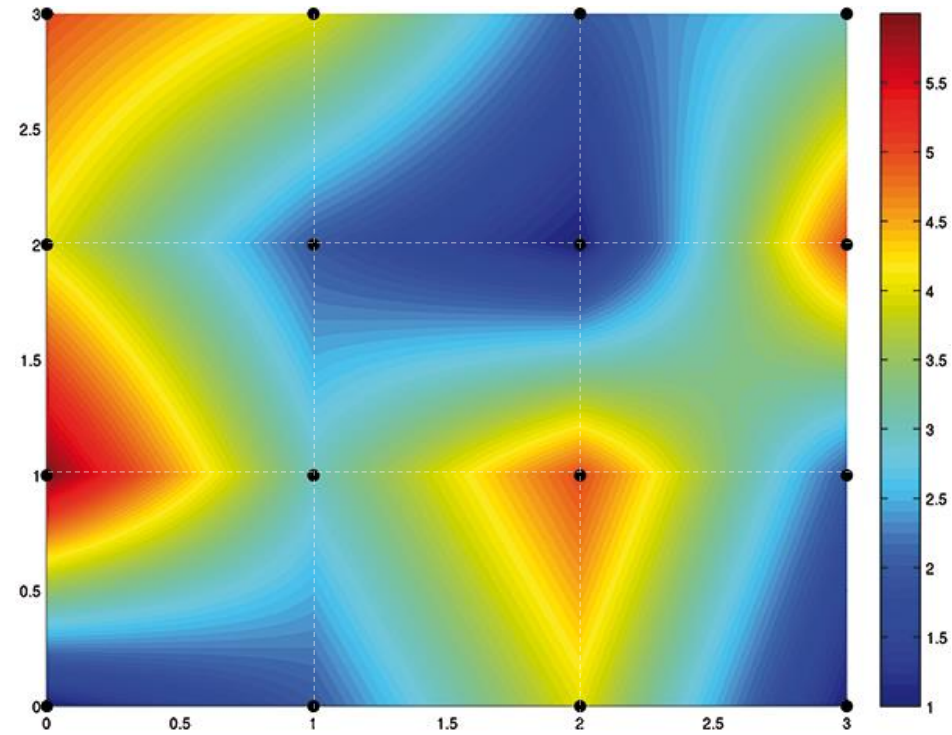


Interpolation on grids

- Volume rendering with different reconstruction filters



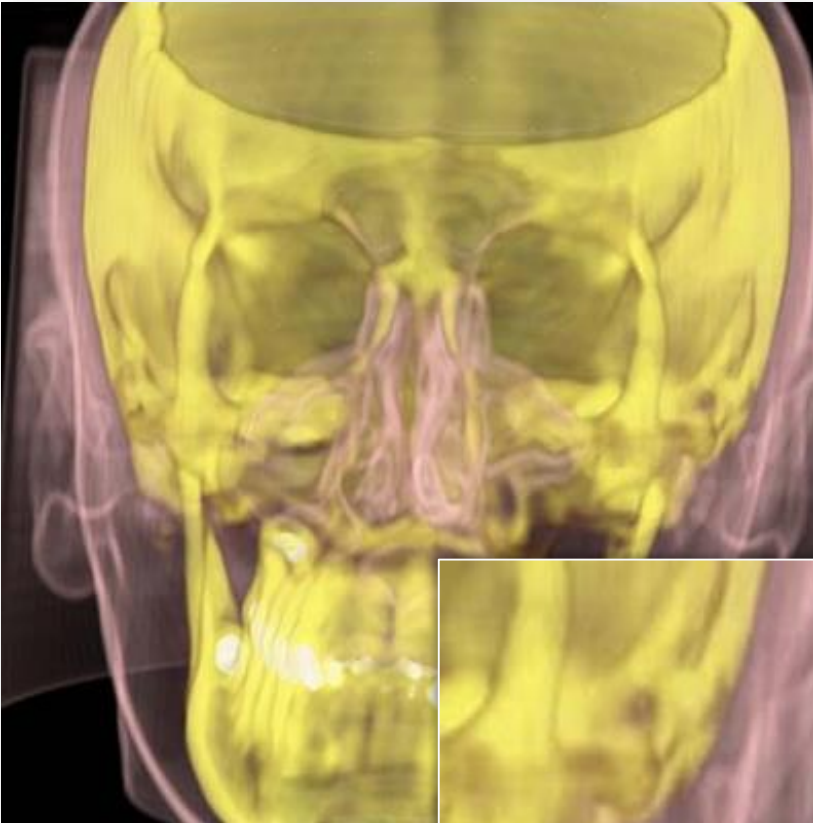
Bicubic interpolation (default in Photoshop)
 C^1 continuous \rightarrow tangents match
at segment transition



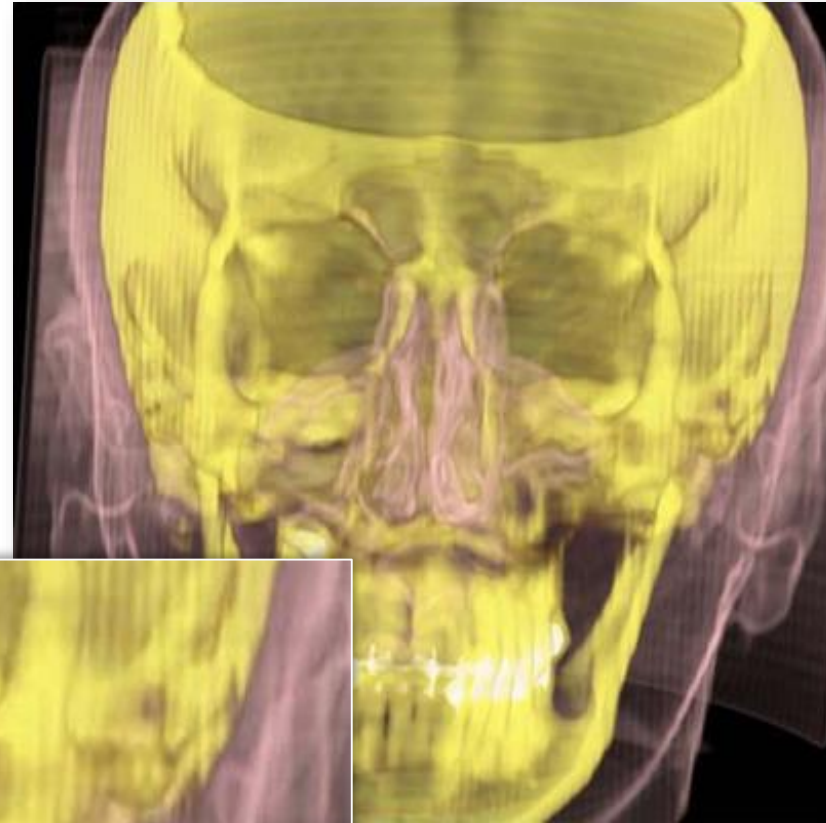
Bilinear interpolation
(C^0 continuous \rightarrow values match
at segment transition)

Interpolation on grids

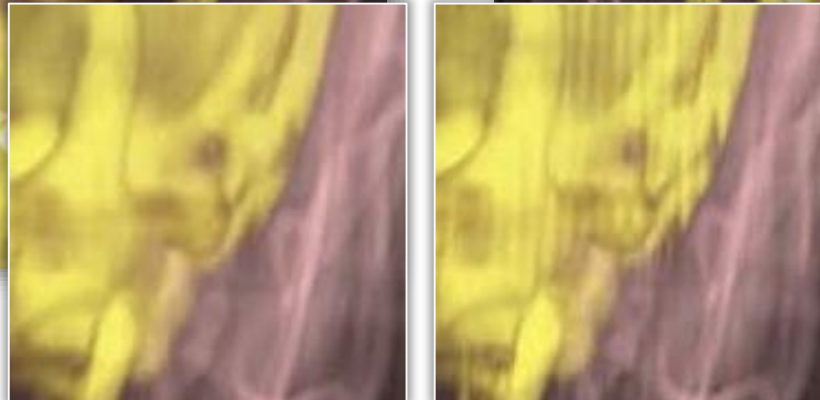
- Volume rendering with different reconstruction filters



Tricubic

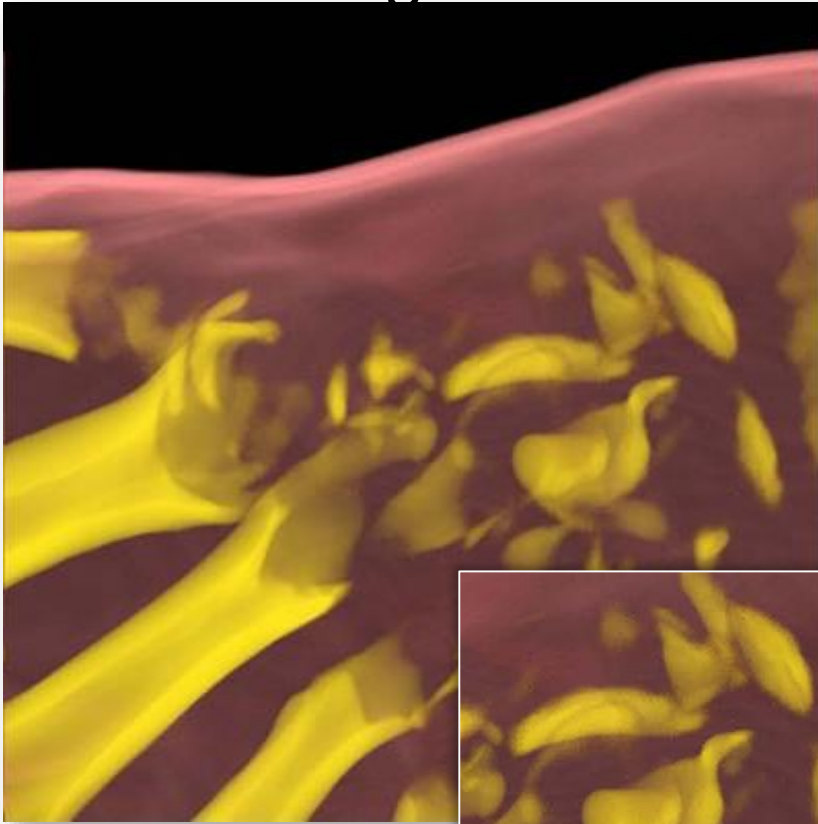


Trilinear

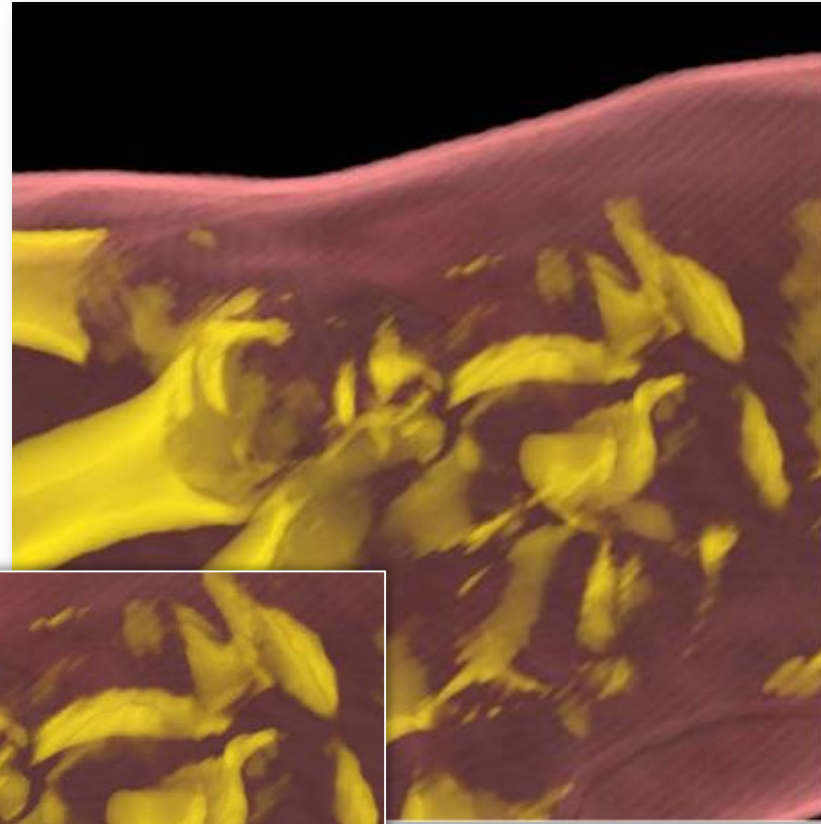


Interpolation on grids

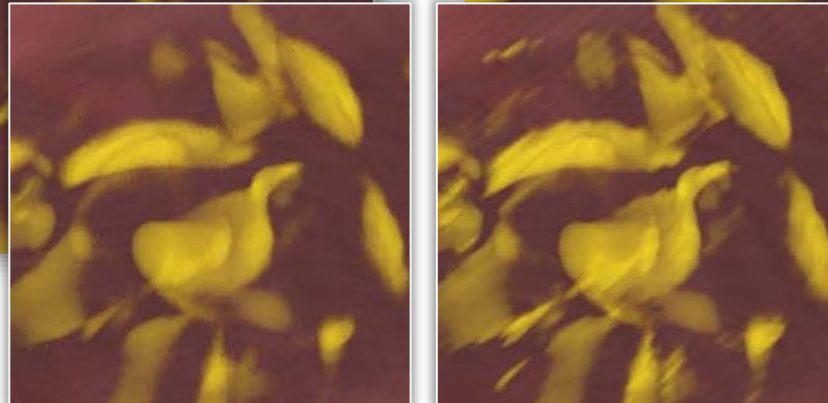
- Volume rendering with different reconstruction filters

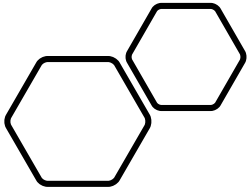


Tricubic



Trilinear





Questions???