

# Data Visualization

Fall 2017

# The Data as a Quantity

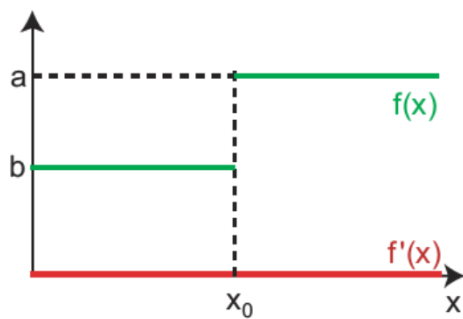
- Quantities can be classified in two categories:
  - **Intrinsically continuous** (scientific visualization, or scivis)  
e.g. pressure, temperature, position, speed , density, force, color, light intensity etc.
  - **Intrinsically discrete** (information visualization, or infovis)  
e.g. text, hypertext, content of web pages, database records etc.
- **Sampled data** – originally continuous data represented in a finite approximative form
- Corollary of the difference between sampled and discrete data:  
In the case of sampled data, we can go back to a continuous approximation of the original (intrinsically) continuous data

# Continuous Data

- Continuous data as a function:

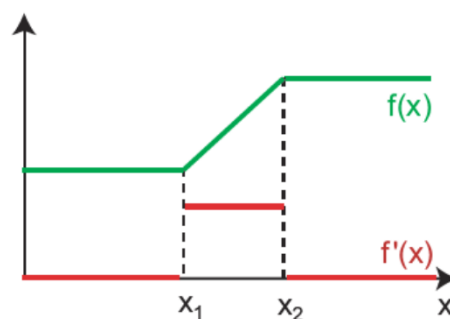
$$f : D \rightarrow C$$

- Intuitive interpretation of continuity:



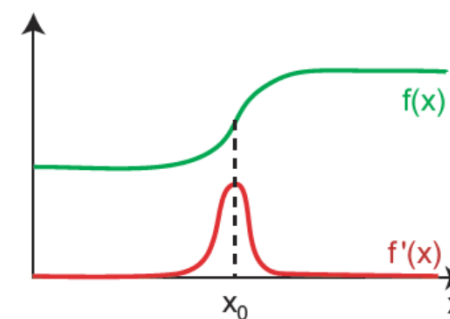
(a)

Discontinuous function



(b)

First-order  $C^0$  cont.



(c)

High-order  $C^k$  cont.

Source: Data Visualization: Principles and Practice

# Datasets and Dimensions

- Let the triplet  $D = (D, C, f)$  define a continuous dataset
- We assume that  $f : D \rightarrow C$
- $D$  refers to a function domain,  $C$  is the function codomain
- $d$  is the geometrical dimension of the space  $\mathbb{R}^d$  into which  $D$  is embedded
- $s \leq d$  represents the topological dimension of  $D$  itself (e.g. plane in the Euclidean space  $\mathbb{R}^3$  has  $s = 2$   
     $s$  is number of independent variables required to represent the domain  $D$ )
- Codimension of an object of some  $d$  and  $s$  is the difference  $d - s$

# Datasets and Dimensions

- Virtually all data-visualization apps fix geometrical dimension  $d = 3$
- Only the topological dimension varies  $s = \{1, 2, 3\}$ 
  - $s = 1$  corresponds to the curve
  - $s = 2$  corresponds to the surface
  - $s = 3$  corresponds to the volumetric datasets
- Topological dimension and dataset dimension are used interchangeably
- Topological dimension is important in case of sampled datasets and grid cells

# Datasets and Dimensions

- Function values are called dataset attributes
- The dimensionality  $c$  of the function codomain  $C$  is also called the attribute dimension
- Typically ranges from 1 to 4

# Sampled Data

- Typically, continuous functional representation of data is not available
- Moreover, several operations (filtering, simplification, analysis etc.) on such data are not efficient
- Visualization apps work with sampled datasets
- Important operations relating continuous and sampled data:
  - **Sampling** – quite straightforward
  - **Reconstruction** – more complicated, the goal is to recover an approximated version of the original continuous data

# Sampled Data

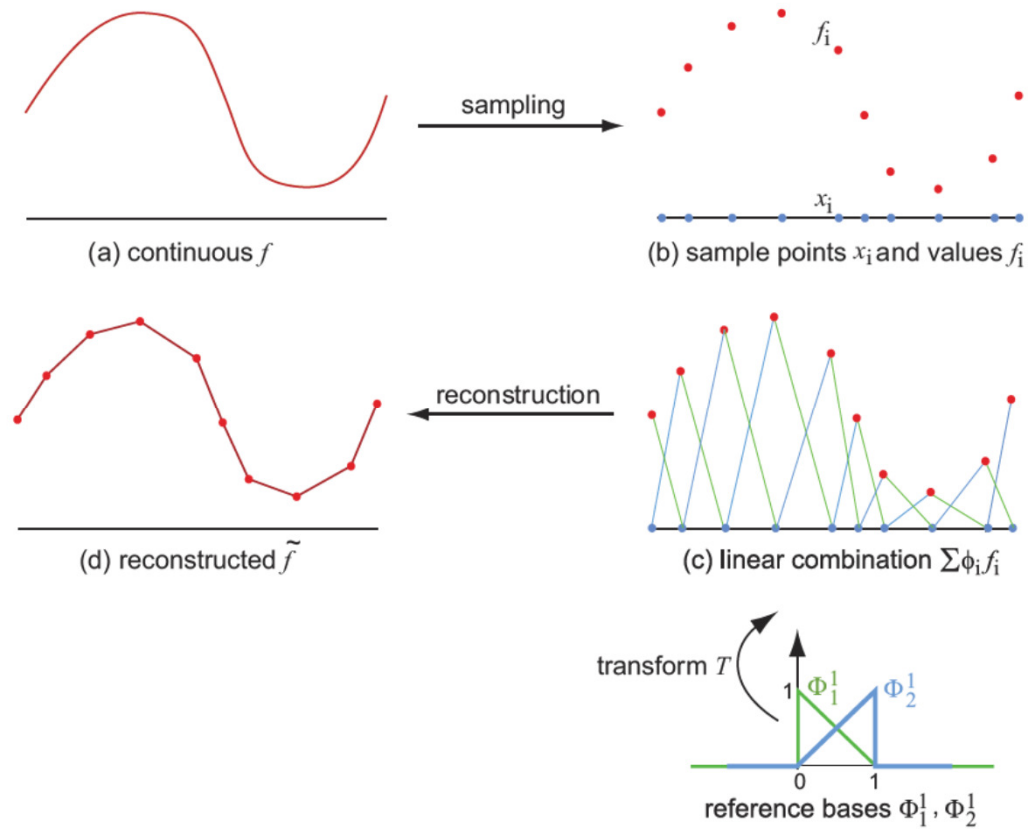
- Reconstruction employs interpolation of the values of the function between its sample points
- Sampling strategies: uniform, non-uniform
- Sampled dataset should be accurate (up to an user-specified error), minimal (resp. to an error), generic (operations), efficient (algorithmically), and simple (implementation) [Schroeder et al. 2006]



# Sampled Data

- Sampled dataset  $\{p_i, f_i\}$  consists of a set of  $N$  sample points and values
- Interpolation - the reconstructed function should equal the original one at all sample points, i.e.  $\tilde{f}(p_i) = f(p_i) = f_i$
- One way to define reconstruction function:  $\tilde{f} = \sum_{i=1}^N f_i \phi_i$  Basis/interpolation functions
- Subsequently, we get  $\sum_{i=1}^N f_i \phi_i(p_j) = f_j, \forall j$
- Orthogonality basis function  $\phi_i(p_j) = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases}$
- Normality of basis function  $\sum_{i=1}^N \phi_i(x) = 1, \forall x \in D$

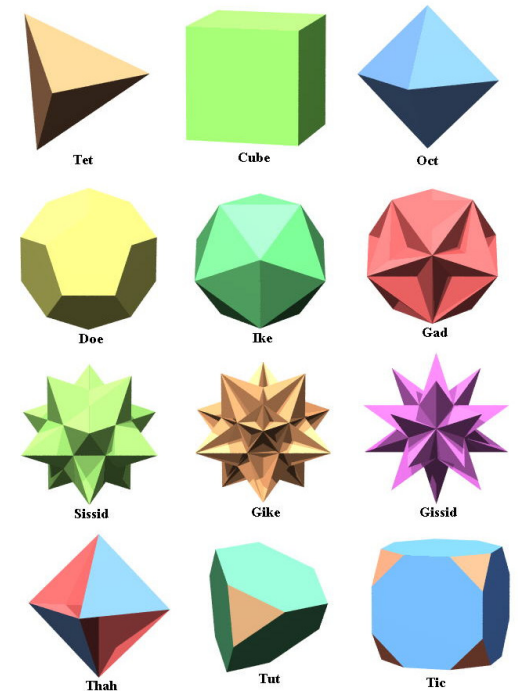
# Sampled Data



Source: Data Visualization: Principles and Practice

# Grid

- A grid (aka mesh) is a subdivision of a domain  $D$  into a collection of cells (aka elements)
- Most commonly used cells:
  - Polylines in  $R$
  - Polygons in  $R^2$
  - Polyhedra in  $R^3$
- Union of cells cover entire domain  $D$  and cells are non-overlapping, and vertices are sample points



# Grid

constant, zero-order continuity global basis function

- Simplest set of basis function:  $\phi_i^0(x) = \begin{cases} 1, & x \in c_i \\ 0, & x \notin c_i \end{cases}$
- Sample points are inside the grid cells
- Nearest-neighbor interpolation
- Virtually no computation cost
- Work with any cell shape and in any dimension
- Provide a poor, staircase-like approximation
- We can provide a better (i.e. more continuous) reconstruction of the original function

# Grid

- Linear basis function – next simplest basis functions
- Need to make some assumption about the cell types used in the grid
- Assume quadrilateral cells having 4 vertices
- Reference quad cell in  $\mathbb{R}^2$ :  $v_1=(0,0)$ ,  $v_2=(1,0)$ ,  $v_3=(1,1)$ ,  $v_4=(0,1)$

Set of local basis functions

$$\Phi_1^1(r, s) = (1 - r)(1 - s),$$

$$\Phi_2^1(r, s) = r(1 - s),$$

$$\Phi_3^1(r, s) = rs,$$

$$\Phi_4^1(r, s) = (1 - r)s;$$



reference coordinates

# Grid

- Given any cell type having  $n$  vertices  $p_i$  in  $R^3$ , we define transformation  $T$  that maps from a point  $r, s$  in reference cell coordinate system to a point  $x, y, z$  in the actual cell as follows

$$(x, y, z) = T(r, s) = \sum_{i=1}^n p_i \Phi_i^1(r, s)$$

- $T$  maps the reference cell to the world cell
- $T^{-1}$  maps points  $x, y, z$  in the world cell to points  $r, s$  in the reference cell

# Grid

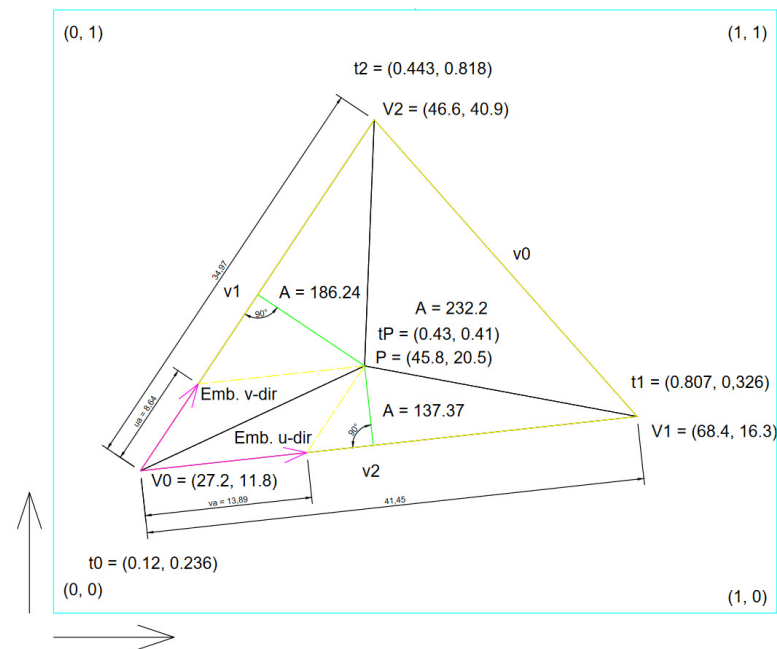
- Having  $T^{-1}$ , we can rewrite the reconstruction function for quad cell as 
$$\tilde{f}(x, y, z) = \sum_{i=1}^4 f_i \Phi_i^1(T^{-1}(x, y, z))$$
 
$$\tilde{f} = \sum_{i=1}^N f_i \phi_i$$
- To compute  $T^{-1}$ , we have to invert the expression 
$$T(r, s) = \sum_{i=1}^n p_i \Phi_i^1(r, s)$$
- Given a rectangular cell, this yields

$$T_{\text{rect}}^{-1}(x, y, z) = (r, s) = \left( \frac{(p - p_1) \cdot (p_2 - p_1)}{\|p_2 - p_1\|^2}, \frac{(p - p_1) \cdot (p_4 - p_1)}{\|p_4 - p_1\|^2} \right)$$

- Now, we have a way to reconstruct a piecewise  $C^1$  function from samples on any rectangular grid. Arbitrary quad cells require some numerical solution for  $r, s$

# Barycentric Coordinates

- A simplex is a convex hull of  $k+1$  points in a  $k$ -dimensional space
- Barycentric coordinates provide a simple way to interpolate over simplices





# Barycentric Coordinates for Triangles

- Describe location of point in a triangle in relation to the vertices
- $\mathbf{p} = (u, v, w) = u \mathbf{v}_0 + v \mathbf{v}_1 + w \mathbf{v}_2$  and  $u + v + w = 1$  where  $u, v, w \geq 0$
- In the same way, we can interpolate any quantity (or function) along the triangle
- Coordinates are the signed area of the opposite subtriangle divided by area of the triangle

# Grid

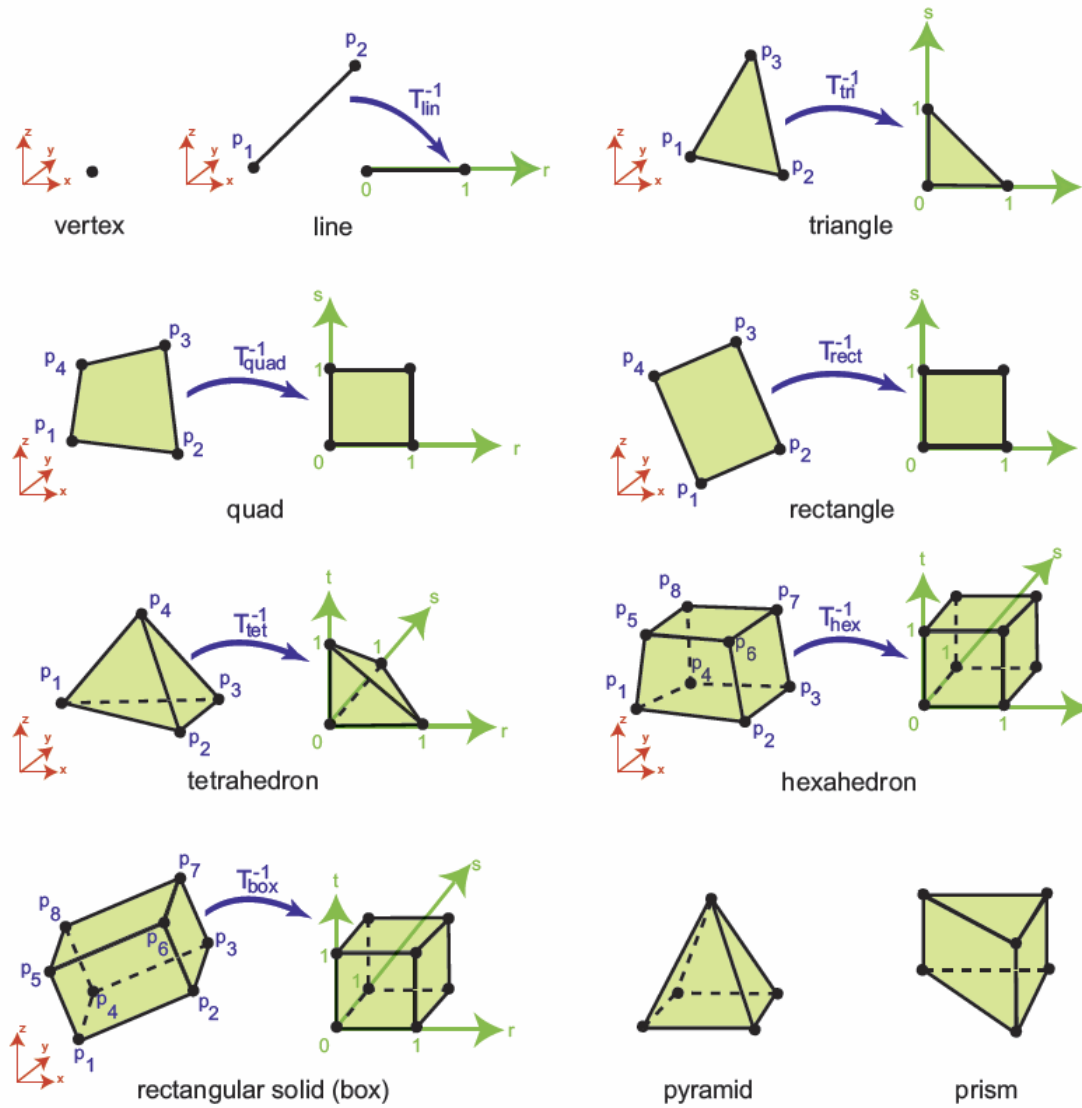
- Same situation but with triangle cell (simplest cell in 2D)

- Three linear basis functions  $\Phi_1^1(r, s) = 1 - r - s,$   
 $\Phi_2^1(r, s) = r,$   
 $\Phi_3^1(r, s) = s.$

- The transformation  $T^{-1}$  for triangular cells

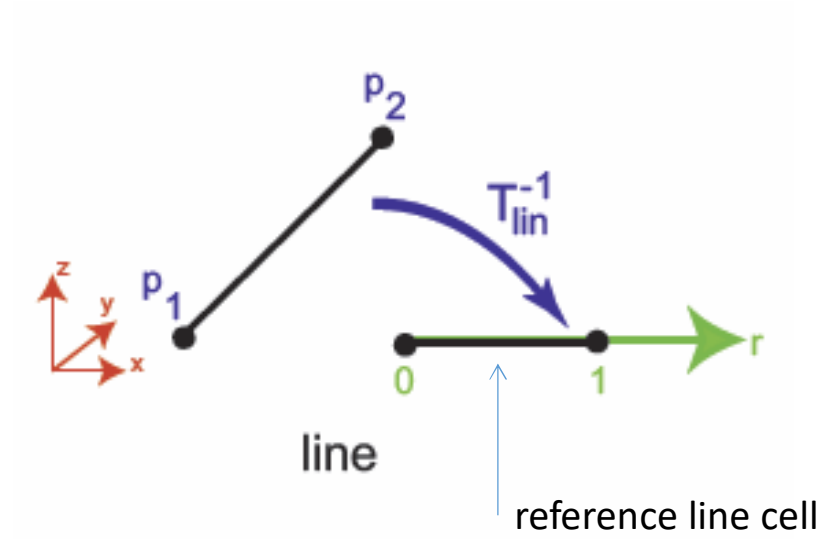
$$T_{\text{tri}}^{-1}(x, y, z) = (r, s) = \left( \frac{\|(p - p_1) \times (p_3 - p_1)\|}{\|(p_2 - p_1) \times (p_3 - p_1)\|}, \frac{\|(p - p_1) \times (p_2 - p_1)\|}{\|(p_3 - p_1) \times (p_2 - p_1)\|} \right)$$

# Cells



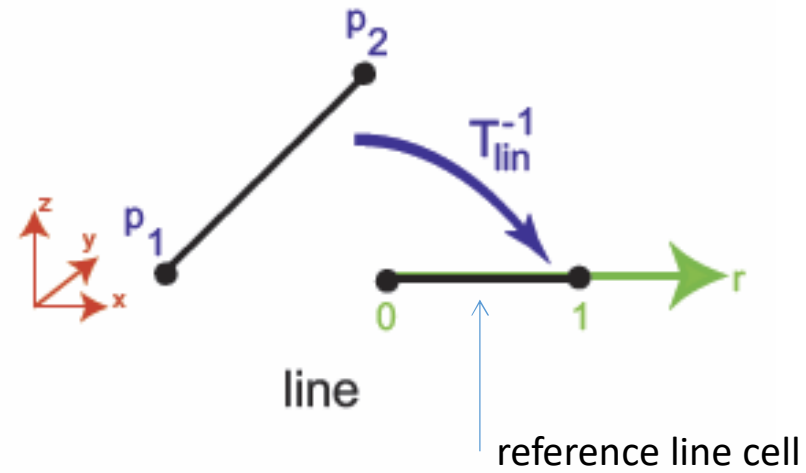
Source: Data Visualization: Principles and Practice

# Line Cell



Source: Data Visualization: Principles and Practice

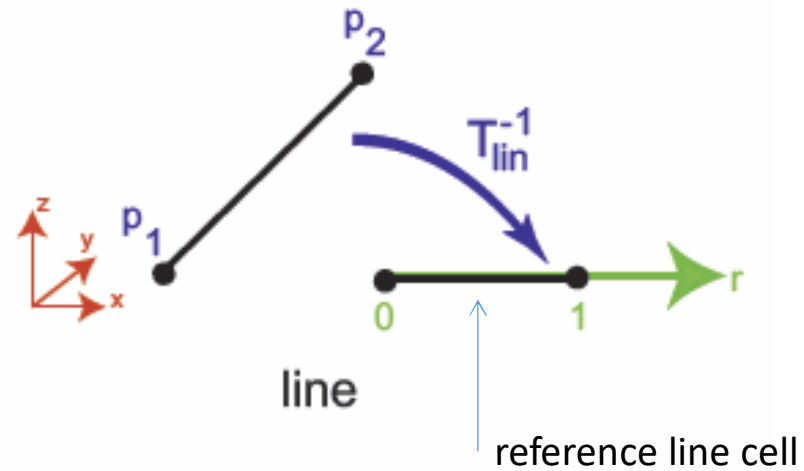
# Line Cell



$$\Phi_1^1(r)$$
$$\Phi_2^1(r)$$

$$T_{\text{lin}}^{-1}(x, y, z)$$

# Line Cell



$$\Phi_1^1(r) = 1 - r$$

$$\Phi_2^1(r) = r.$$

↑ two linear basis functions

$$T_{\text{lin}}^{-1}(x, y, z) = \frac{\|p - p_1\|}{\|p_2 - p_1\|}$$

Source: Data Visualization: Principles and Practice