

# Geometric Modeling

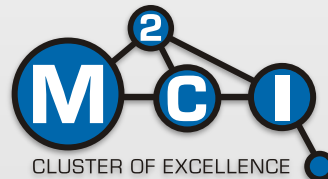
Summer Semester 2012

## Polynomial Spline Curves

Piecewise Polynomials · Splines Bases · Properties



UNIVERSITÄT  
DES  
SAARLANDES



CLUSTER OF EXCELLENCE



# Announcements

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## HISPOS Registration

- *Important:* Hispos registration is now open
- Do not forget to register for geometric modeling

## Room Change

- On *Tuesday, June 26th*,  
the lecture will be held in  
*Buiding E1 7* (Cluster MMCI Building), *Room 0.02*

## Exam Topics

- Section “*Spectral Graph Methods for 3D Shape Analysis*”  
is not relevant for the exam.

# Today...

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## Topics:

- Introduction: Geometric Modeling
- Mathematical Background
- Interpolation & Approximation
- Splines
  - Polynomial Spline Curves
  - Blossoming and Polar Forms
  - Rational Splines
  - Spline Surfaces
- Meshes

# Today...

## Topics:

- Introduction: Geometric Modeling
- Mathematical Background
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  - Polynomial Spline Curves
  - Blossoming and Polar Forms
  - Rational Splines
  - Spline Surfaces
- Meshes

# Today

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## Polynomial Spline Curves

- Piecewise cubic interpolation
- Splines with local control
  - Hermite Splines
  - Bezier Splines
  - Non-Uniform B-Splines
  - Uniform B-Splines

# **Polynomial Spline Curves**

## Piecewise Cubic Interpolation

# What we have so far...

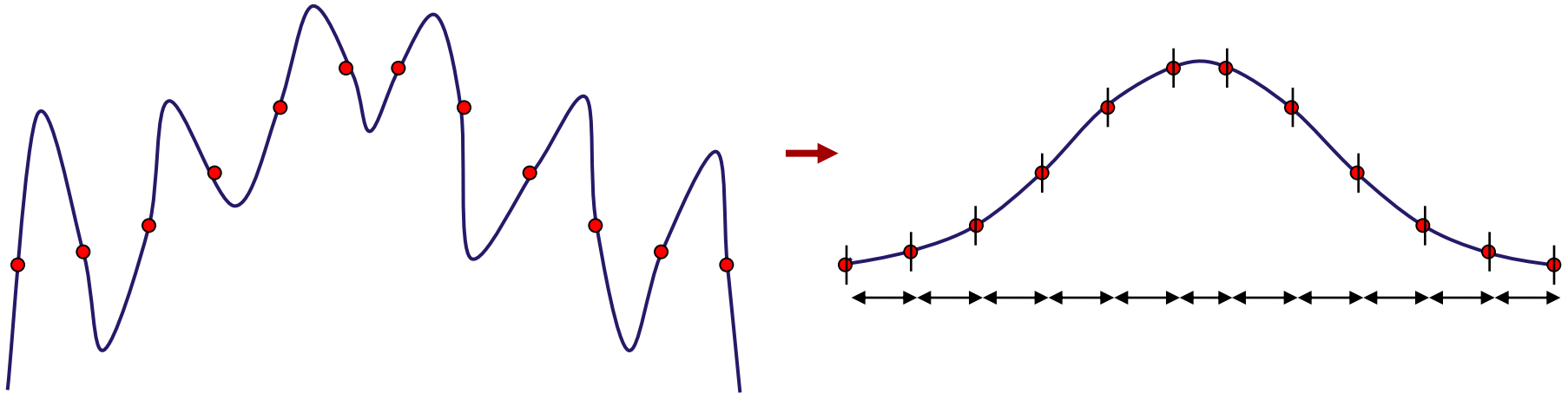
## What we have so far:

- Given a basis, we can interpolate and approximate points
  - Curves, surfaces, higher dimensional objects
  - Functions (heightfields) and parametric objects
  - Differential properties can be prescribed as well

## Problem:

- We need a suitable basis
- Polynomial bases don't work for large degree (say  $\geq 10$ )
  - Monomials – numerical nightmare
  - Orthogonal polynomials: Runge's phenomenon still limits applicability

# Piecewise Polynomials



## Key Idea:

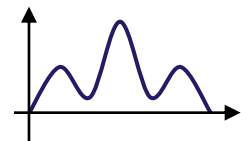
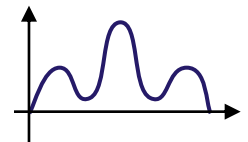
- Polynomials of high degree don't work
- Therefore: Use piecewise polynomials of low degree
- What is a good degree to use?



# Choosing the Degree...

## Candidates:

- $d = 0$  (piecewise constant): not smooth
- $d = 1$  (piecewise linear): not smooth enough
- $d = 2$  (piecewise quadratic): constant 2nd derivative, still too inflexible
- $d = 3$  (piecewise cubic): degree of choice for computer graphics applications

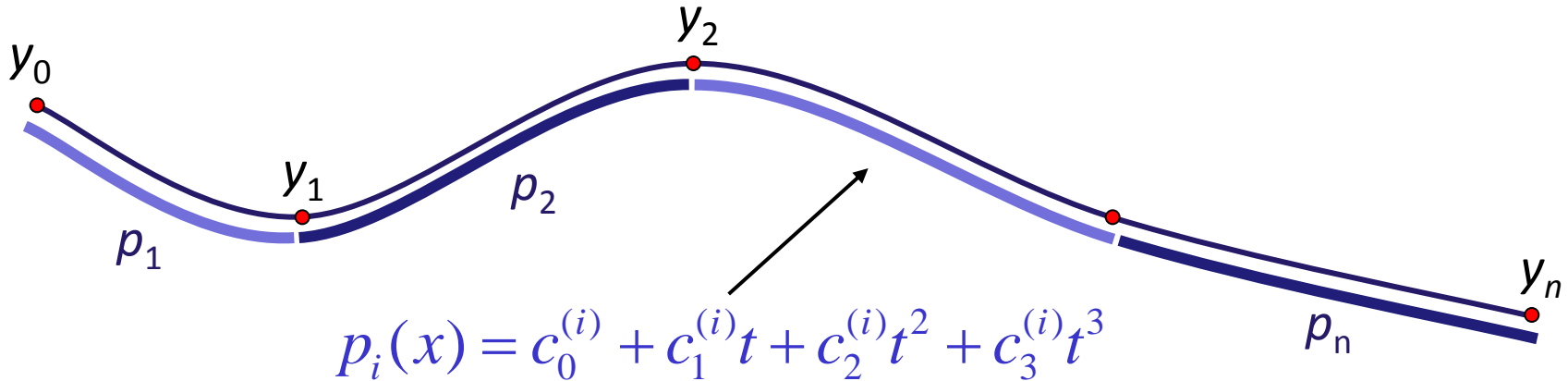


# Cubic Splines

## Cubic piecewise polynomials:

- We can attain  $C^2$  continuity without fixing the second derivative throughout the curve
- $C^2$  continuity is perceptually important
  - We can see second order shading discontinuities (esp.: reflective objects)
  - Motion: continuous *position*, *velocity* & *acceleration*  
Discontinuous acceleration noticeable (object/camera motion)
- One more argument for cubics:
  - Among all  $C^2$  curves that interpolate a set of points (and obey to the same end conditions), a piecewise cubic curve has the least integral acceleration (“smoothest curve you can get”).

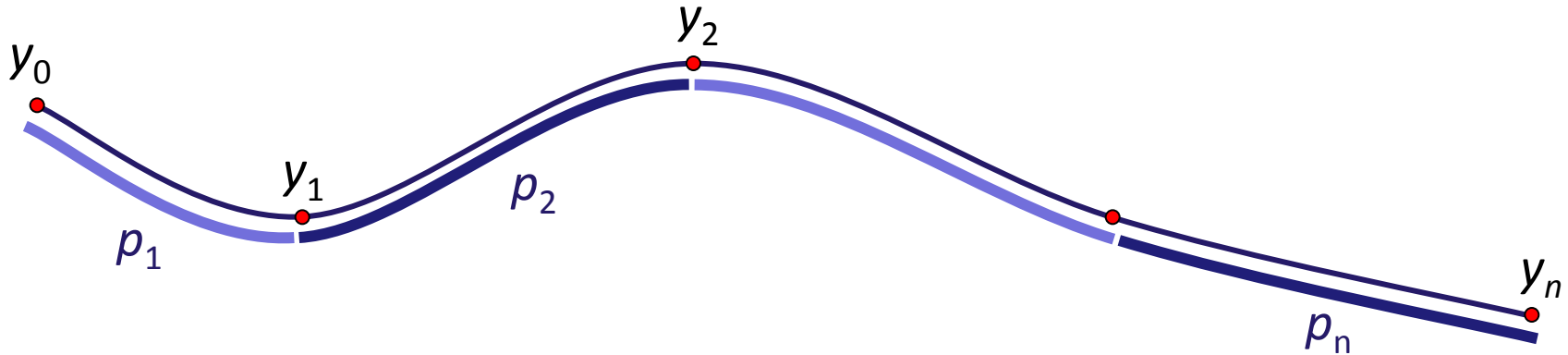
# Piecewise Cubic Interpolation



## Setup:

- $(n+1)$  control points  $y_0 \dots y_n$  (to be interpolated)
- For simplicity: assume uniform spacing  $t_0 \dots t_n = (0, 1, 2, \dots, n)$
- $n$  cubic polynomial pieces  $p_1 \dots p_n$  parametrized over  $[0 \dots 1]$
- Multidimensional case: solve problem for each axis  $(x, y, z)$

# Conditions



( $4n$  degrees of freedom)

$$\forall i = 1 \dots n : p_i(0) = y_{i-1}$$

( $n$  conditions)

$$\forall i = 1 \dots n : p_i(1) = y_i$$

( $n$  conditions)

$$\forall i = 2 \dots n : \frac{d}{dt} p_i(0) = \frac{d}{dt} p_{i-1}(1)$$

( $n-1$  conditions)

$$\forall i = 2 \dots n : \frac{d^2}{dt^2} p_i(0) = \frac{d^2}{dt^2} p_{i-1}(1)$$

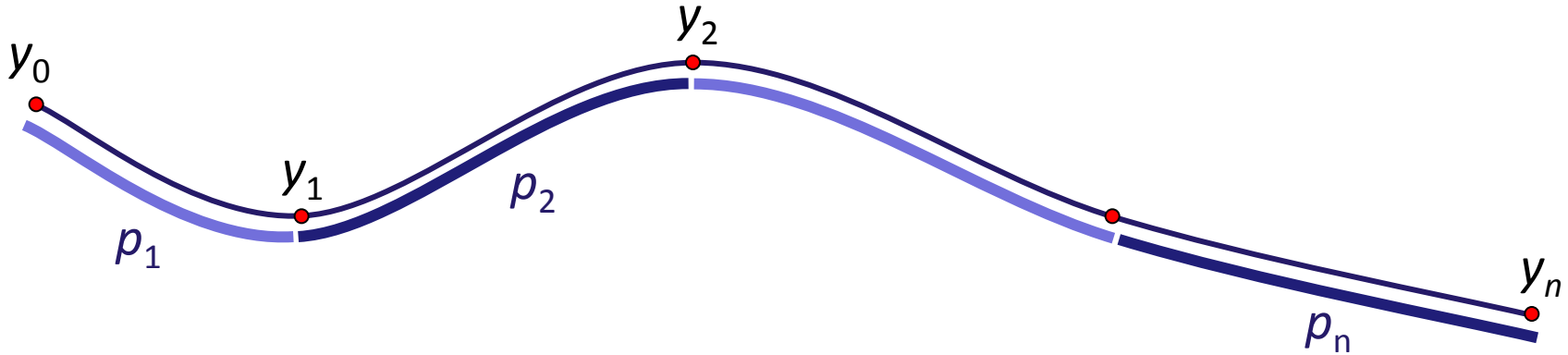
( $n-1$  conditions)

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2 dimensional null space  
(so far)

# Conditions



$$\forall i = 1 \dots n : p_i(0) = y_{i-1} \quad (n \text{ conditions})$$

$$\forall i = 1 \dots n : p_i(1) = y_i \quad (n \text{ conditions})$$

$$\forall i = 2 \dots n : \frac{d}{dt} p_i(0) = \frac{d}{dt} p_{i-1}(1) \quad (n-1 \text{ conditions})$$

$$\forall i = 2 \dots n : \frac{d^2}{dt^2} p_i(0) = \frac{d^2}{dt^2} p_{i-1}(1) \quad (n-1 \text{ conditions})$$

**additional:**

$$\frac{d^2}{dt^2} p_1(0) = 0$$

$$\frac{d^2}{dt^2} p_n(1) = 0$$

**alternative:**

cyclic boundary conditions  
(closed curves)

# Numerical Solution

## Solving the system of equations:

- Band matrix, bandwidth  $O(1)$
- Can be solved in  $O(n)$  time & space for  $n$  variables

$$\begin{pmatrix} * & * & * & & & & \\ * & * & * & * & & & \\ * & * & * & * & * & & \\ & * & * & * & * & * & \\ & & * & * & * & * & * \\ & & & * & * & * & * \\ & & & & * & * & * \\ & & & & & * & * \\ & & & & & & * \end{pmatrix}$$

# Cubics Minimize Acceleration

## Theorem:

- Given  $n$  data points  $(y_i, t_i)$  to interpolate and fixed end conditions (either prescribed 1st derivative, or zero second derivative), a piecewise cubic interpolant minimizes the energy:  $E(f) = \int_0^n f''(t)^2 dt$
- This means: A cubic spline curve has the least square acceleration.
- Related to elastic energy: Hooke's elastic energy of a straight line is given by:  $E(\mathbf{f}) = \int_0^n \lambda \|\kappa^2[\mathbf{f}](t)\|^2 dt$
- I.e.: cubic spline interpolation approximates elastic beams.

# Proof: Cubics Minimize Acceleration

Cubic spline:  $c(t)$

Another  $C^2$  interpolating curve:  $a(t)$

Residual:  $d(t) = a(t) - c(t)$ .

**Energy functional:**

$$\begin{aligned} E(a) &= \int_0^n a''(t)^2 dt \\ &= \int_0^n [c''(t) + d''(t)]^2 dt \\ &= \int_0^n c''(t)^2 dt + 2 \int_0^n c''(t)d''(t)dt + \int_0^n d''(t)^2 dt \end{aligned}$$



# Proof: Cubics Minimize Acceleration

Cubic spline:  $c(t)$

Another  $C^2$  interpolating curve:  $a(t)$

Residual:  $d(t) = a(t) - c(t)$ .

**Integration by parts:**

$$\int_a^b a(t)b'(t)dt = [a(t)b(t)]_{t=a}^{t=b} - \int_a^b a'(x)b(x)dt$$

**Energy functional:**

$$E(a) = \int_0^n c''(t)^2 dt + 2 \int_0^n c''(t)d''(t)dt + \int_0^n d''(t)^2 dt$$

**Integration by parts:**

$$\begin{aligned} \int_0^n c''(t)d''(t)dt &= [c''(t)d'(t)]_0^n - \int_0^n c'''(t)d'(t)dt \\ &= [c''(t)(a'(t) - c'(t))]_{t=0}^{t=n} - \int_0^n c'''(t)d'(t)dt \\ &= \underbrace{c''(n)}_{\substack{0 \text{ for} \\ c''(n)=0}} \underbrace{(a'(n) - c'(n))}_{\substack{0 \text{ if identical first} \\ \text{order end cond.}}} - \underbrace{c''(0)}_{\substack{0 \text{ for} \\ c''(n)=0}} \underbrace{(a'(0) - c'(0))}_{\substack{0 \text{ if identical first} \\ \text{order end cond.}}} - \int_0^n c'''(t)d'(t)dt \end{aligned}$$

# Proof: Cubics Minimize Acceleration

Cubic spline:  $c(t)$

Another  $C^2$  interpolating curve:  $a(t)$

Residual:  $d(t) = a(t) - c(t)$ .

Integration by parts:

$$\int_a^b a(t)b'(t)dt = [a(t)b(t)]_{t=a}^{t=b} - \int_a^b a'(x)b(x)dt$$

Energy functional:

$$E(a) = \int_0^n c''(t)^2 dt + 2 \int_0^n c''(t)d''(t)dt + \int_0^n d''(t)^2 dt$$

Middle term (cont.):

$$\begin{aligned} \int_0^n c''(t)d''(t)dt &= \int_0^n \underbrace{c'''(t)}_{\text{piecewise const.}} d'(t)dt \\ &= \sum_{i=0}^{n-1} c'''(i+0.5) \underbrace{[d(t)]_{t=i}^{t=i+1}}_{=0 \text{ (interpolation)}} \\ &= 0 \end{aligned}$$

# Proof: Cubics Minimize Acceleration

Cubic spline:  $c(t)$

Another  $C^2$  interpolating curve:  $a(t)$

Residual:  $d(t) = a(t) - c(t)$ .

**Energy functional:**

$$E(a) = \underbrace{\int_0^n c''(t)^2 dt}_{\text{cubic spline}} + \underbrace{\int_0^n d''(t)^2 dt}_{\text{additional energy: positive}}$$

**Positive additional energy:**

Any function that differs in second derivative from  $c$  will have higher energy.

$\Rightarrow c$  is a minimal function in terms of  $E$ .

# **Polynomial Spline Curves**

## Spline Bases with Local Control

# So what's missing?

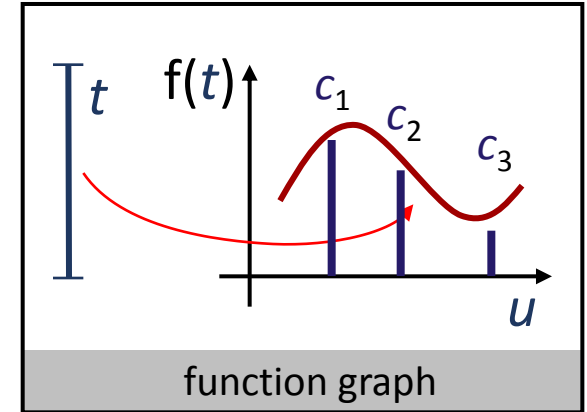
## So we have solved our problem – what's left to do?

- Target area: *interactive geometric modeling*
- Shape of the entire curve depends on all control points
- Changing one control point can affect the whole curve
- Not a big issue for algorithmic curve control
  - Fitting curves to data, optimizing curves according to some objective function, etc...
- But not acceptable for modeling by humans
- “User interface problem”: We want *local control*.

# Notation

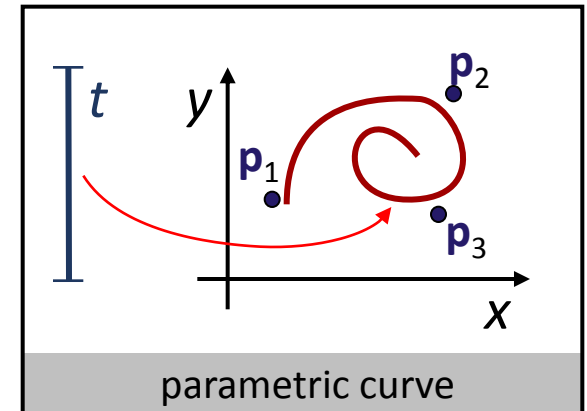
## Function design problem:

- Function  $f: \mathbb{R} \rightarrow \mathbb{R}$   
$$f(t) = c_1 b_1(t) + c_2 b_2(t) + c_3 b_3(t) + \dots$$
- Coefficients  $c_1, c_2, c_3, \dots \in \mathbb{R}$



## Curve design problem

- Function  $\mathbf{f}: \mathbb{R} \rightarrow \mathbb{R}^n$   
$$\mathbf{f}(t) = b_1(t)\mathbf{p}_1 + b_2(t)\mathbf{p}_2 + b_3(t)\mathbf{p}_3 + \dots$$
- “Control points”  $\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3, \dots \in \mathbb{R}^n$



# New Idea

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## **Problem:** Again the basis...

- We want a basis such that:
  - Coefficients / control points have intuitive meaning
- Let the user edit the control points
  - Intuitive response
  - Manually controllable

# Desirable Properties

## Useful requirements for a spline basis:

- Well behaved curve
  - Smooth basis functions
- Local control
  - Basis functions with compact support
- Affine invariance:
  - Applying an affine map  $\mathbf{x} \rightarrow \mathbf{Ax} + \mathbf{b}$  on
    - control points
    - curveshould have the same effect
  - In particular: rotation, translation
  - Otherwise: interactive curve editing very difficult



# Desirable Properties

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## Useful requirements for a spline basis:

- Convex hull property:
  - The curve is in the convex hull of its control points
  - Avoids at least too weird oscillations
- Advantages
  - Computational advantages (recursive intersection tests)
  - More predictable behavior

# Summary

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## Useful properties

- Smoothness
- Local control / support
- Affine invariance
- Convex hull property

# Affine Invariance

## Affine Invariance:

- Affine map:  $\mathbf{x} \rightarrow \mathbf{Ax} + \mathbf{b}$
- **Part I:** Linear invariance – we get this automatically

- Linear approach:  $\mathbf{f}(t) = \sum_{i=1}^n b_i(t) \mathbf{p}_i = \sum_{i=1}^n b_i(t) \begin{pmatrix} p_i^{(x)} \\ p_i^{(y)} \\ p_i^{(z)} \end{pmatrix}$

- Therefore:  $\mathbf{A}(\mathbf{f}(t)) = \mathbf{A} \left( \sum_{i=1}^n b_i(t) \mathbf{p}_i \right) = \sum_{i=1}^n b_i(t) (\mathbf{A} \mathbf{p}_i)$

# Affine Invariance

## Affine Invariance:

- Affine map:  $\mathbf{x} \rightarrow \mathbf{Ax} + \mathbf{b}$
- **Part II:** Translational invariance – need some brains

$$\blacksquare \sum_{i=1}^n b_i(t)(\mathbf{p}_i + \mathbf{b}) = \sum_{i=1}^n b_i(t)\mathbf{p}_i + \sum_{i=1}^n b_i(t)\mathbf{b} = f(t) + \underbrace{\left( \sum_{i=1}^n b_i(t) \right)}_{\text{must sum to one}} \mathbf{b}$$

- For translational invariance, the sum of the basis functions must be one *everywhere* (for all parameter values  $t$  that are used).
- This is called “*partition of unity property*”.
- The  $\mathbf{b}_i$  form an “*affine combination*” of the control points  $\mathbf{p}_i$ .
- This is very important for human modeling.

# Convex Hull Property

## Convex combinations:

- A convex combination of a set of points  $\{\mathbf{p}_1, \dots, \mathbf{p}_n\}$  is any point of the form:
  - $\sum_{i=1}^n \lambda_i \mathbf{p}_i$  with:  $\sum_{i=1}^n \lambda_i = 1$  and  $\forall i = 1..n: \lambda_i \geq 0, \lambda_i \leq 1$
  - (Remark:  $\lambda_i \leq 1$  is redundant)
- The set of all admissible convex combinations forms the convex hull of the point set
  - Easy to see (simple exercise): This convex hull is the smallest set that contains all points  $\{\mathbf{p}_1, \dots, \mathbf{p}_n\}$  and every complete straight line between two elements of the set.

# Convex Hull Property

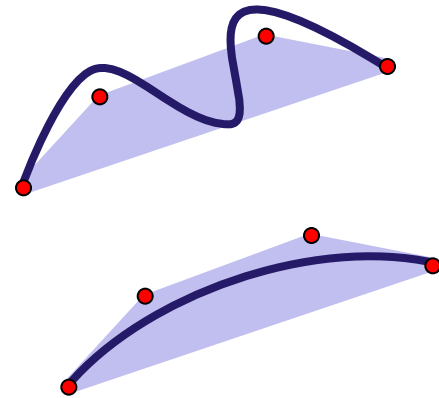
## Accordingly:

- If we have this property:

$$\forall t \in \Omega: \sum_{i=1}^n b_i(t) = 1 \quad \text{and} \quad \forall t \in \Omega: \forall i = 1..n: b_i(t) \geq 0$$

the constructed curves / surfaces will be:

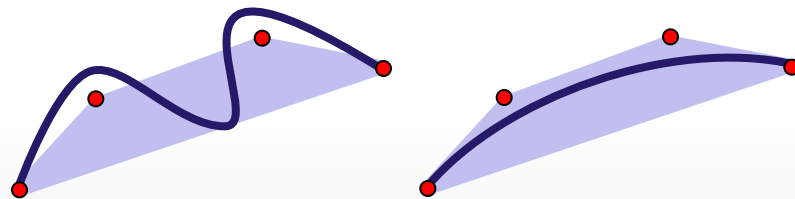
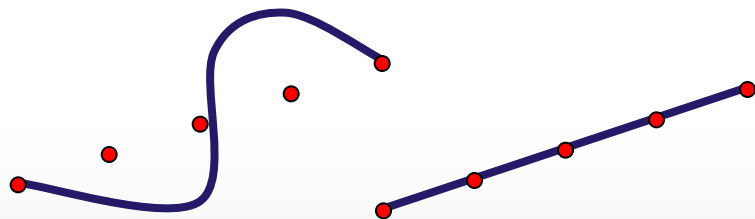
- Affine invariant (translations, linear maps)
- Be restricted to the convex hull of the control points
- Corollary: Curves with this property will have *linear precision*, i.e.: if all control points lie on a straight line, the curve is a straight line segment, too.
- Surfaces with planar control points will be flat, too.



# Convex Hull Property

## Convex Hull Property:

- Very useful property
  - Avoids at least the worst oscillations (no escape from convex hull, unlike polynomial interpolation through control points)
  - Linear precision property is intuitive (people expect this)
  - Can be used fast range checks
    - Test for intersection with convex hull first, then the object.
    - Recursive intersection algorithms in conjunction with subdivision rules (more on this later)



# Spline Techniques

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## Spline bases we will look at in this lecture:

- Hermite interpolation
- Bezier curves & surfaces
- Uniform B-splines
- Non-uniform B-splines
- [NURBS: Non-uniform rational B-splines]  
(not linear, more on this later)



# Spline Techniques

## Two views:

- Linear algebra: polynomial function spaces
  - Basis changes
  - Derivatives and continuity conditions
- Geometry: Successive linear interpolation (“blossoming”)
  - Construct polynomial spline curves by repeated linear interpolation of control points
  - More intuitive explanations of properties
  - Mathematical formalism: Blossoming and polar forms

This part of the lecture will deal with the linear algebra view. Blossoming gets a separate chapter...

# **Polynomial Spline Curves**

## Hermite Splines

# Hermite Splines

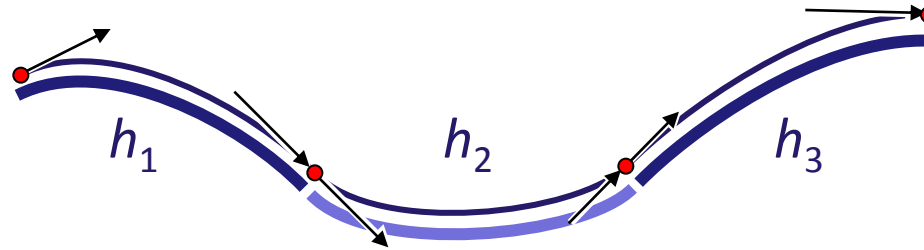
## Overview:

- Simple spline technique, easy to implement
- Has some shortcomings
- We will look at  $C^1$  cubic Hermite splines as an example

## Key Idea:

- Specify position and derivatives at the endpoints of each segment
- Come up with a rule to match them easily
- Precompute basis for this purpose

# Illustration



$$h_i(t) = c_0^{(i)} + c_1^{(i)}t + c_2^{(i)}t^2 + c_3^{(i)}t^3$$

For each segment  $\mathbf{h}_i(t)$  we know:

- Positions:  $\mathbf{h}_i(0)$ ,  $\mathbf{h}_i(1)$
- Derivatives:  $\partial_t \mathbf{h}_i(0)$ ,  $\partial_t \mathbf{h}_i(1)$

# Hermite Basis

**Linear system:** (one dimension, one segment)

$$h(0) = p_0 \Rightarrow c_0 = p_0$$

$$h(1) = p_1 \Rightarrow c_0 + c_1 + c_2 + c_3 = p_1$$

$$h'(0) = m_0 \Rightarrow c_1 = m_0$$

$$h'(1) = m_1 \Rightarrow c_1 + 2c_2 + 3c_3 = m_1$$

$$h(t) = c_0 + c_1 t + c_2 t^2 + c_3 t^3$$

$$h'(t) = c_1 + 2c_2 t + 3c_3 t^2$$

$$\begin{array}{c} \rightarrow \end{array} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 2 & 3 \end{pmatrix} \begin{pmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \end{pmatrix} = \begin{pmatrix} p_0 \\ p_1 \\ m_0 \\ m_1 \end{pmatrix} \begin{array}{c} \rightarrow \end{array} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -3 & 3 & -2 & -1 \\ 2 & -2 & 1 & 1 \end{pmatrix} \begin{pmatrix} p_0 \\ p_1 \\ m_0 \\ m_1 \end{pmatrix} = \begin{pmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \end{pmatrix}$$

# Hermite Basis

## Solution:

$$\mathbf{f}(t) = [1, t, t^2, t^3] \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -3 & 3 & -2 & -1 \\ 2 & -2 & 1 & 1 \end{pmatrix} \begin{pmatrix} p_0 \\ p_1 \\ m_0 \\ m_1 \end{pmatrix}$$

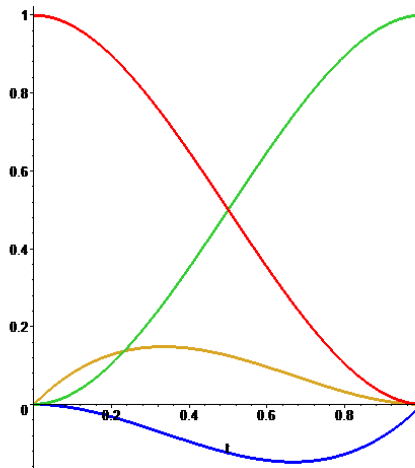
## Basis Functions:

$$h_{p_0}(t) = 1 - 3t^2 + 2t^3$$

$$h_{p_1}(t) = 3t^2 - 2t^3$$

$$h_{m_0}(t) = t - 2t^2 + t^3$$

$$h_{m_1}(t) = -t^2 + t^3$$



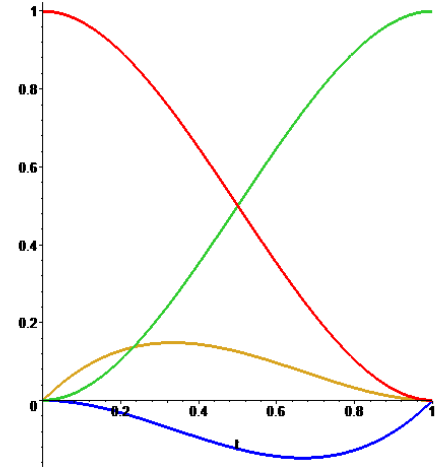
# Hermite Basis

## Properties:

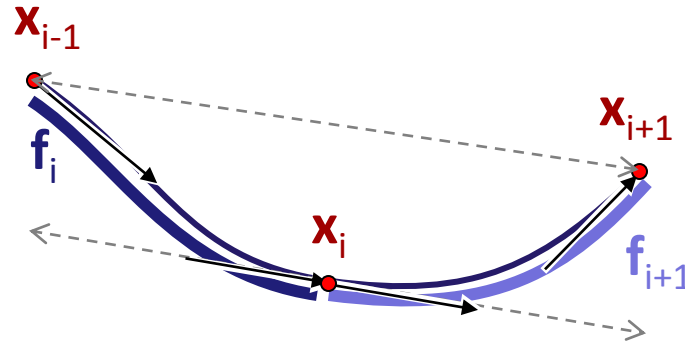
- $h_{p_0}$  and  $h_{p_1}$  sum to one.  
(affine invariant w.r.t. position)
- Curve might leave convex hull of control points

## Open question:

- How to specify derivatives?



# Illustration



## Simple rule for derivatives:

- Derivatives:

$$\partial_t \mathbf{f}_i(0) := \frac{\mathbf{x}_i - \mathbf{x}_{i-2}}{2}, \quad (i \in \{2..n\})$$

$$\partial_t \mathbf{f}_i(1) := \frac{\mathbf{x}_{i+1} - \mathbf{x}_{i-1}}{2}, \quad (i \in \{1..n-1\})$$

$$\partial_t \mathbf{f}_1(0) := \mathbf{x}_1 - \mathbf{x}_0$$

$$\partial_t \mathbf{f}_n(1) := \mathbf{x}_n - \mathbf{x}_{n-1}$$

- “Catmull-Rom Spline”



# Properties

## Properties of this spline construction:

- Interpolates original points
- Local control
- $C_1$  continuous
- Affine invariant
- No convex hull property
  - Tends to “overshoot”
  - This can be really nasty in practice

# **Polynomial Spline Curves**

## **Bezier Curves**

# Bezier Splines

## History:

- Bezier splines developed
  - by Paul de Casteljaou at Citroën (1959)
  - Pierre Bézier at Renault (1962)for designing smooth free-form parts in automotive design applications.
- Today: The standard tool for 2D curve editing, Cubic 2D Bezier curves are used almost everywhere:
  - Postscript, PDF, Truetype (quadratic curves), Windows GDI...
  - Corel Draw, Powerpoint, Illustrator, ...
- Widely used in 3D curve & surface modeling as well

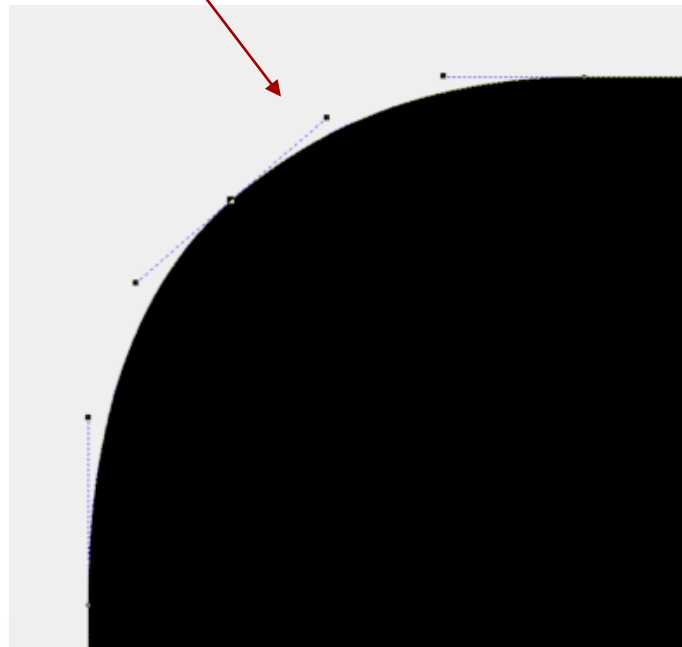
# All You See is Bezier Curves...

## Bezier Splines

### History:

- Bezier splines developed
  - by Paul de Casteljaeu at Citroën
  - Pierre Bézier at Renault (1969)

Bezier



# Bernstein Basis

## Bezier splines use the Bernstein basis:

- Bernstein basis of degree  $n$ :  $B = \{B_0^{(n)}, B_1^{(n)}, \dots, B_n^{(n)}\}$

$$B_i^{(n)}(t) := \binom{n}{i} t^i (1-t)^{n-i} = B_{i\text{-th basis function}}^{(\text{degree } n)}$$

- Each basis function is a polynomial of degree  $n$ .
- The basis functions form a partition of unity

$$1 = (1-t+t) = (t+(1-t))^n = \sum_{i=0}^n \binom{n}{i} t^i (1-t)^{n-i} = \sum_{i=0}^n B_i^{(n)}(t)$$

(binomial theorem)

- For  $t \in [0..1]$ , the basis functions are positive ( $B_i^{(n)}(t) \geq 0$ ).

# Examples

## The first three Bernstein bases:

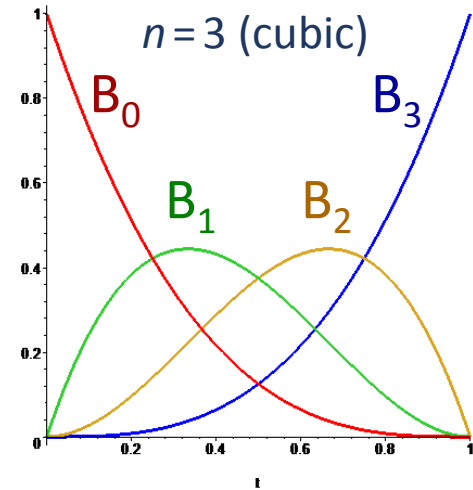
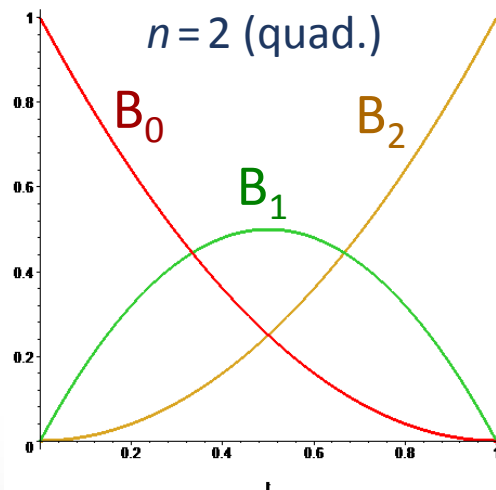
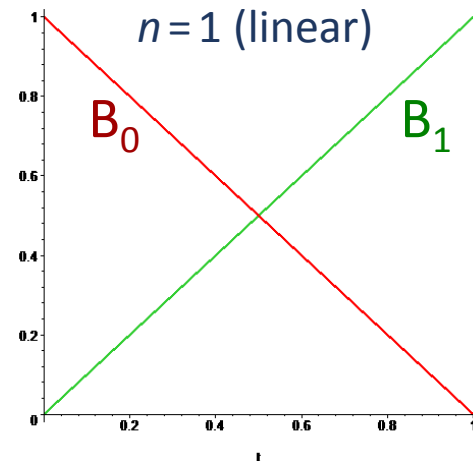
$$B_0^{(0)} := 1$$

$$B_0^{(1)} := (1-t) \quad B_1^{(1)} := t$$

$$B_0^{(2)} := (1-t)^2 \quad B_1^{(2)} := 2t(1-t) \quad B_2^{(2)} := t^2$$

$$B_0^{(3)} := (1-t)^3 \quad B_1^{(3)} := 3t(1-t)^2$$

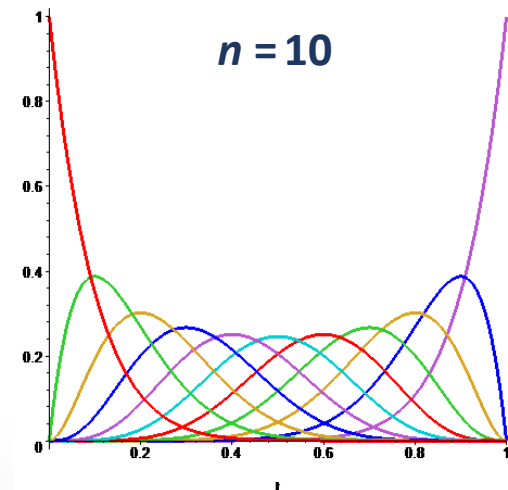
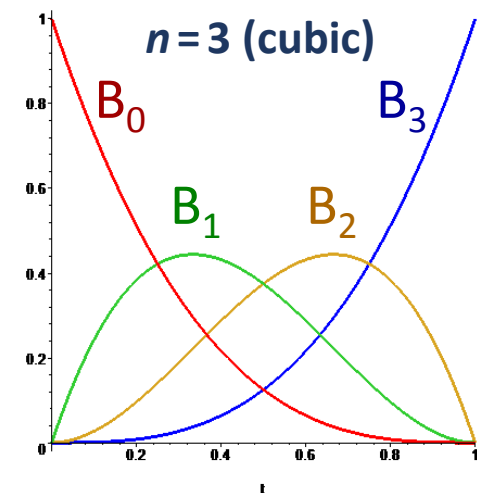
$$B_2^{(3)} := 3t^2(1-t) \quad B_3^{(3)} := t^3$$



# Bernstein Basis

## Bernstein basis properties:

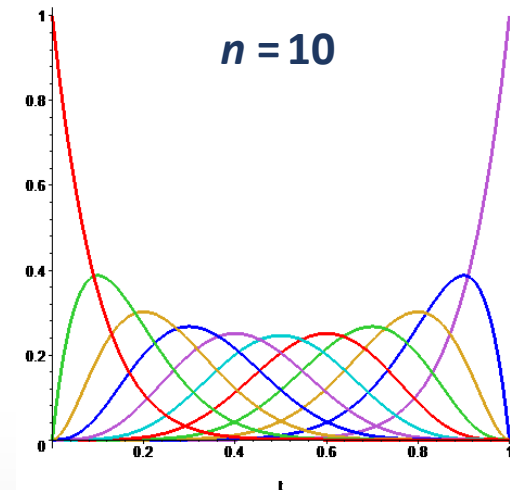
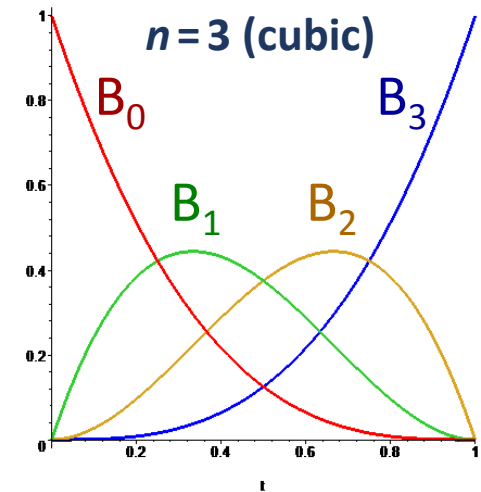
- $B = \{B_0^{(n)}, B_1^{(n)}, \dots, B_n^{(n)}\}$ ,  $B_i^{(n)}(t) := \binom{n}{i} t^i (1-t)^{n-i}$
- Basis for polynomials of degree  $n$ .
- Each basis function  $B_i^{(n)}$  has its maximum at  $i/n$ .
- Recursive computation:  
$$B_i^{(n)}(t) := (1-t)B_i^{(n-1)}(t) + tB_{i-1}^{(n-1)}(t)$$
  
with  $B_0^0(t) = 1$ ,  $B_i^n(t) = 0$  for  $i \notin \{0 \dots n\}$
- Symmetry:  $B_i^n(t) = B_{n-i}^n(1-t)$



# Bezier Curves

## Bezier curves Properties:

- Curves:  $f(t) = \sum_{i=0}^n \mathbf{p}_i B_i^{(n)}(t)$
- Considering the interval  $t \in [0..1]$
- Bezier curves are affine invariant.
- Bezier curves are contained in the convex hull of the control points.
- The influence of the control points is moving along the curve with index  $i$ . Largest influence at  $t = i/n$ .
- However: A single curve segment has no fully local control.

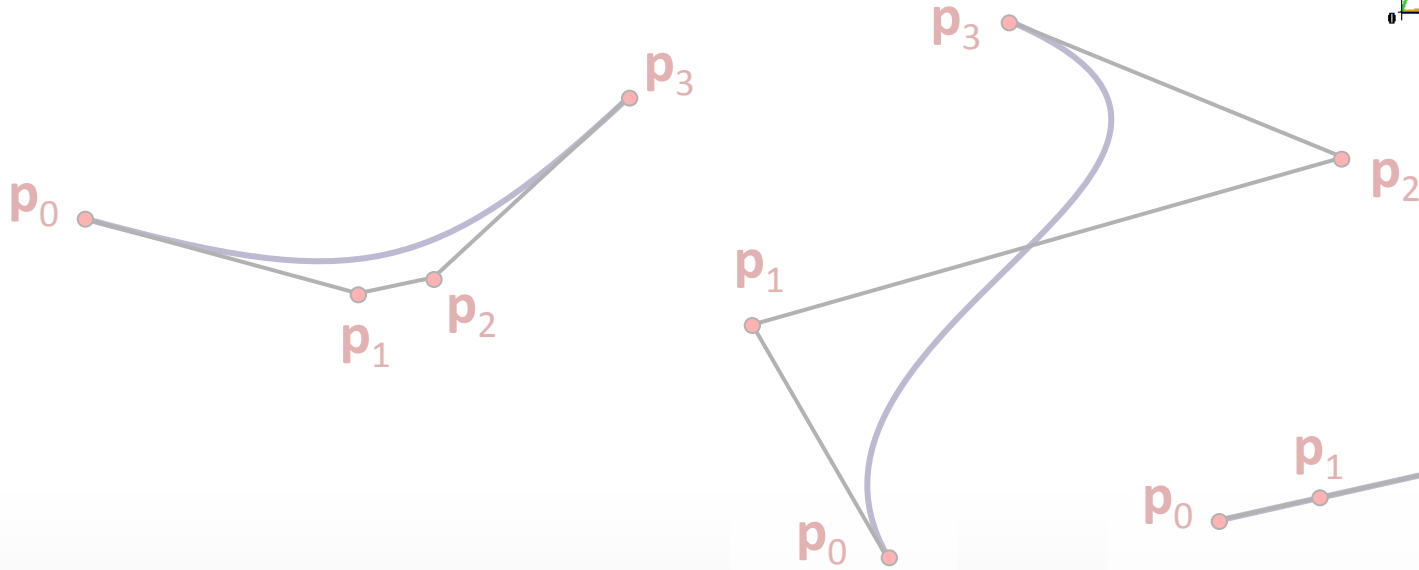
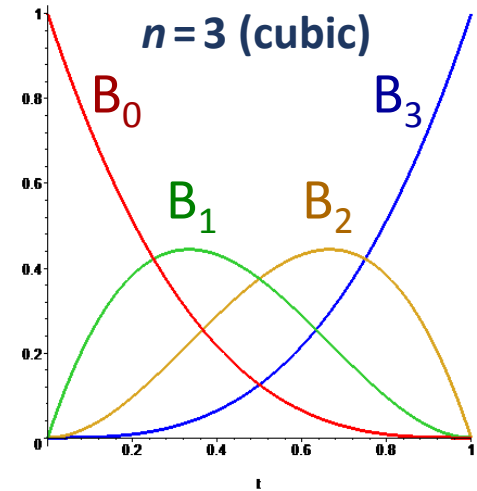
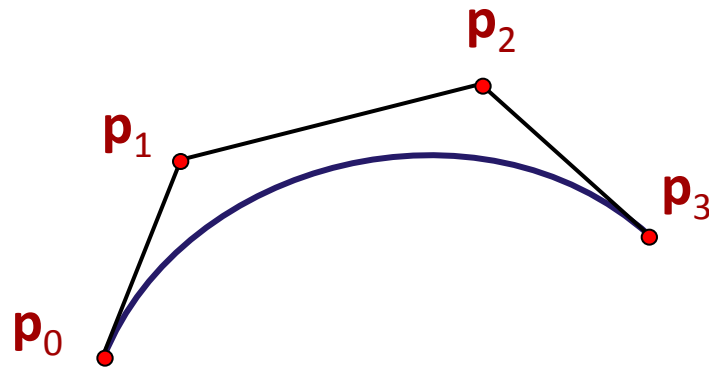




# Bezier Curves: Examples

## Bezier Curves:

- $f(t) = \sum_{i=0}^n \mathbf{p}_i B_i^{(n)}$



# Matrix Form

## Matrix Notation: Bezier $\rightarrow$ Monomials

$$\mathbf{f}(t) = \begin{bmatrix} 1 & t & t^2 \end{bmatrix} \begin{pmatrix} 1 & 0 & 0 \\ -2 & 2 & 0 \\ 1 & -2 & 1 \end{pmatrix} \begin{pmatrix} \mathbf{p}_0 \\ \mathbf{p}_1 \\ \mathbf{p}_2 \end{pmatrix} \quad \text{(quadratic case)}$$

$$\mathbf{f}(t) = \begin{bmatrix} 1 & t & t^2 & t^3 \end{bmatrix} \begin{pmatrix} 1 & 0 & 0 & 0 \\ -3 & 3 & 0 & 0 \\ 3 & -6 & 3 & 0 \\ -1 & 3 & -3 & 1 \end{pmatrix} \begin{pmatrix} \mathbf{p}_0 \\ \mathbf{p}_1 \\ \mathbf{p}_2 \\ \mathbf{p}_3 \end{pmatrix} \quad \text{(cubic case)}$$

# Format Conversion

**Conversion:** Compute Bezier coefficients from monomial coefficients

$$\begin{pmatrix} c_0^{(Bez.)} \\ c_1^{(Bez.)} \\ c_2^{(Bez.)} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ -2 & 2 & 0 \\ 1 & -2 & 1 \end{pmatrix}^{-1} \begin{pmatrix} c_0 \\ c_1 \\ c_2 \end{pmatrix} \quad \text{(quadratic case)}$$

$$\begin{pmatrix} c_0^{(Bez.)} \\ c_1^{(Bez.)} \\ c_2^{(Bez.)} \\ c_3^{(Bez.)} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ -3 & 3 & 0 & 0 \\ 3 & -6 & 3 & 0 \\ -1 & 3 & -3 & 1 \end{pmatrix}^{-1} \begin{pmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \end{pmatrix} \quad \text{(cubic case)}$$

# Format Conversion

**Conversion:** quadratic to cubic

$$\begin{pmatrix} c_0^{(3)} \\ c_1^{(3)} \\ c_2^{(3)} \\ c_3^{(3)} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ -3 & 3 & 0 & 0 \\ 3 & -6 & 3 & 0 \\ -1 & 3 & -3 & 1 \end{pmatrix}^{-1} \begin{pmatrix} 1 & 0 & 0 & 0 \\ -2 & 2 & 0 & 0 \\ 1 & -2 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} c_0^{(2)} \\ c_1^{(2)} \\ c_2^{(2)} \\ 0 \end{pmatrix}$$

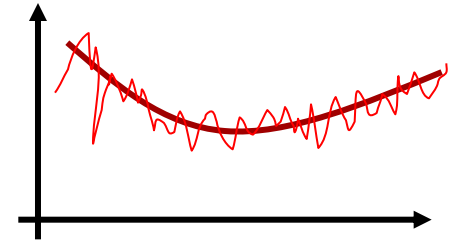
Convert to monomials and back to Bezier coefficients.  
(Other degrees similar)

**Example Application:** Output of TrueType fonts in Postscript.

# The Other Way Round...

## Reducing the degree:

- Exact solution is not always possible
- Approximate solution: least-squares (function approximation)
- System of normal equations:



$$\begin{pmatrix} \langle \tilde{b}_1, \tilde{b}_1 \rangle & \cdots & \langle \tilde{b}_n, \tilde{b}_1 \rangle \\ \vdots & \ddots & \vdots \\ \langle \tilde{b}_1, \tilde{b}_n \rangle & \cdots & \langle \tilde{b}_n, \tilde{b}_n \rangle \end{pmatrix} \begin{pmatrix} \tilde{c}_1 \\ \vdots \\ \tilde{c}_n \end{pmatrix} = \begin{pmatrix} \langle \tilde{b}_1(x), f \rangle \\ \vdots \\ \langle \tilde{b}_n(x), f \rangle \end{pmatrix}, \quad f(t) := \sum_{i=1}^m c_i b_i(t)$$
$$\Leftrightarrow \begin{pmatrix} \langle \tilde{b}_1, \tilde{b}_1 \rangle & \cdots & \langle \tilde{b}_n, \tilde{b}_1 \rangle \\ \vdots & \ddots & \vdots \\ \langle \tilde{b}_1, \tilde{b}_n \rangle & \cdots & \langle \tilde{b}_n, \tilde{b}_n \rangle \end{pmatrix} \begin{pmatrix} \tilde{c}_1 \\ \vdots \\ \tilde{c}_n \end{pmatrix} = \sum_{i=1}^m c_i \begin{pmatrix} \langle \tilde{b}_1(x), b_i(t) \rangle \\ \vdots \\ \langle \tilde{b}_n(x), b_i(t) \rangle \end{pmatrix}$$

# Cubic $\rightarrow$ Quadratic Case

Reducing the degree: Cubic  $\rightarrow$  Quadratic

$$\begin{pmatrix} \frac{1}{7} & \frac{1}{14} & \frac{1}{35} \\ \frac{1}{14} & \frac{1}{3} & \frac{1}{9} \\ \frac{1}{35} & \frac{1}{140} & \frac{1}{35} \end{pmatrix} \begin{pmatrix} \tilde{c}_0 \\ \tilde{c}_1 \\ \tilde{c}_2 \end{pmatrix} = c_0 \begin{pmatrix} \frac{1}{6} \\ \frac{1}{15} \\ \frac{1}{60} \end{pmatrix} + c_1 \begin{pmatrix} \frac{1}{10} \\ \frac{1}{10} \\ \frac{1}{20} \end{pmatrix} + c_2 \begin{pmatrix} \frac{1}{20} \\ \frac{1}{10} \\ \frac{1}{10} \end{pmatrix} + c_3 \begin{pmatrix} \frac{1}{60} \\ \frac{1}{15} \\ \frac{1}{6} \end{pmatrix}$$

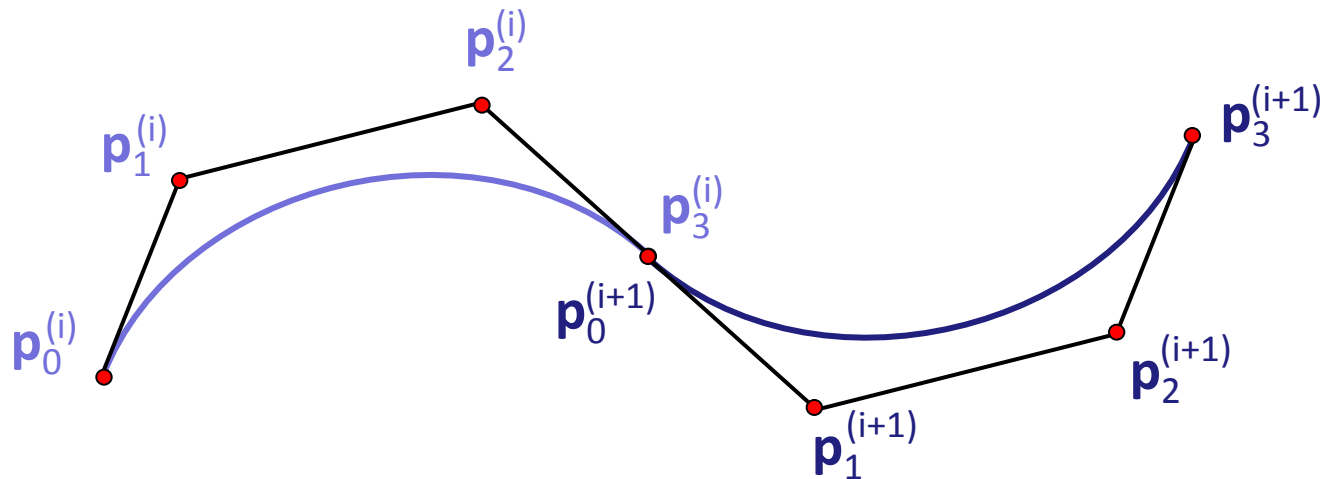
# **Polynomial Spline Curves**

## **Bezier Splines**

# Bezier Splines

## Local control: Bezier splines

- Concatenate several curve segments
- Question: Which constraints to place upon the control points in order to get  $C^{-1}$ ,  $C^0$ ,  $C^1$ ,  $C^2$  continuity?





# Derivatives

## Bernstein basis properties:

- Derivatives:

$$\begin{aligned}\frac{d}{dt}B_i^{(n)}(t) &= \binom{n}{i} \left( i t^{\{i-1\}} (1-t)^{n-i} - (n-i) t^{\{i\}} (1-t)^{\{n-i-1\}} \right) \\ &= \frac{n!}{(n-i)!i!} i t^{\{i-1\}} (1-t)^{n-i} - \frac{n!}{(n-i)!i!} (n-i) t^{\{i\}} (1-t)^{\{n-i-1\}} \\ &= n \left[ \binom{n-1}{i-1} t^{\{i-1\}} (1-t)^{n-i} - \binom{n-1}{i} t^{\{i\}} (1-t)^{\{n-i-1\}} \right] \\ &= n \left[ B_{i-1}^{(n-1)}(t) - B_i^{(n-1)}(t) \right]\end{aligned}$$

( $\{k\} = k$  if  $k > 0$ , zero otherwise)

# Derivatives

## Bernstein basis properties:

- Derivatives:

$$\begin{aligned}\frac{d^2}{dt^2} B_i^{(n)}(t) &= \frac{d}{dt} \binom{n}{i} \left( i t^{\{i-1\}} (1-t)^{n-i} - (n-i) t^i (1-t)^{\{n-i-1\}} \right) \\ &= \binom{n}{i} \left( \{i-1\} i t^{\{i-2\}} (1-t)^{n-i} - i(n-i) t^{\{i-1\}} (1-t)^{\{n-i-1\}} \right. \\ &\quad \left. - i(n-i) t^{\{i-1\}} (1-t)^{\{n-i-1\}} + \{n-i-1\} (n-i) t^{\{i\}} (1-t)^{\{n-i-2\}} \right) \\ &= n(n-1) \left[ B_{i-2}^{(n-2)}(t) - 2B_{i-1}^{(n-2)}(t) + B_i^{(n-2)}(t) \right]\end{aligned}$$

( $\{k\} = k$  if  $k > 0$ , zero otherwise)

# Bezier Curve Properties

## Important for continuous concatenation:

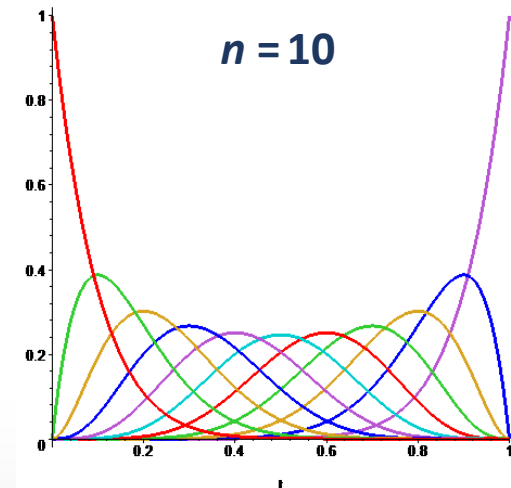
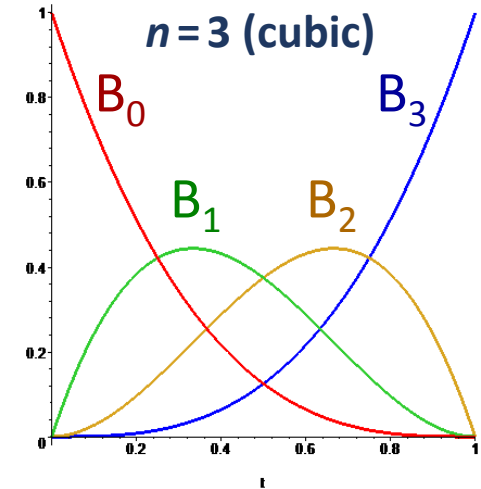
- Function value at  $\{0,1\}$ :

$$\mathbf{f}(t) = \sum_{i=0}^n \binom{n}{i} t^i (1-t)^{n-i} \mathbf{p}_i$$

$$\rightarrow \mathbf{f}(0) = \mathbf{p}_0$$

$$\mathbf{f}(1) = \mathbf{p}_n$$

- First derivative vector at  $\{0,1\}$
- Second derivative vector at  $\{0,1\}$



# Bezier Curve Properties

## Important for continuous concatenation:

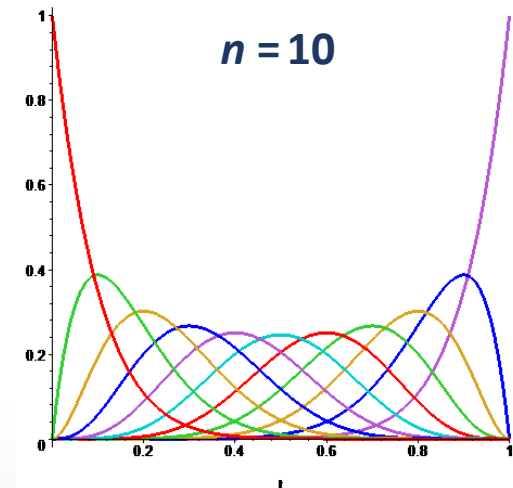
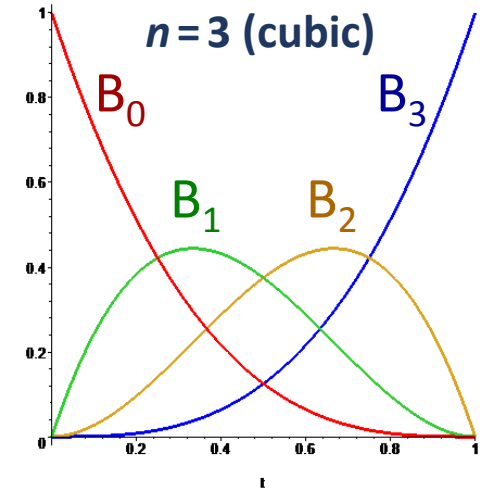
- Function value at  $\{0,1\}$ :

$$\mathbf{f}(0) = \mathbf{p}_0, \mathbf{f}(1) = \mathbf{p}_n$$

- First derivative vector at  $\{0,1\}$ :

$$\frac{d}{dt}\mathbf{f}(t)$$

- Second derivative vector at  $\{0,1\}$



# Bezier Curve Properties

## Important for continuous concatenation:

- Function value at  $\{0,1\}$ :

$$\mathbf{f}(0) = \mathbf{p}_0, \mathbf{f}(1) = \mathbf{p}_n$$

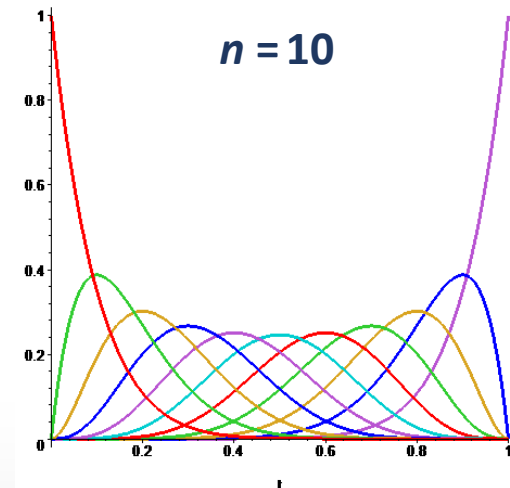
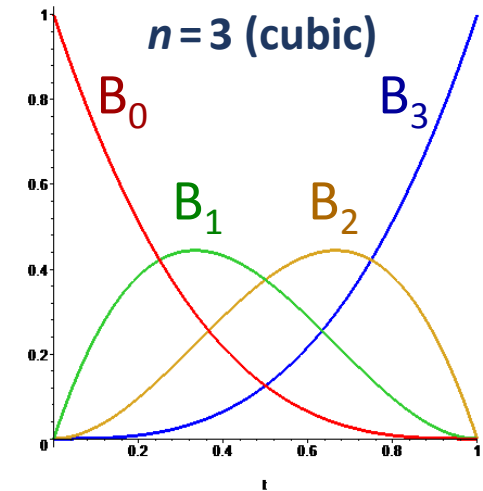
- First derivative vector at  $\{0,1\}$ :

$$\frac{d}{dt}\mathbf{f}(t) = n \sum_{i=0}^n [B_{i-1}^{(n-1)}(t) - B_i^{(n-1)}(t)] \mathbf{p}_i$$

$$\begin{aligned} &= \left( n [-B_0^{(n-1)}(t)] \mathbf{p}_0 + [B_0^{(n-1)}(t) - B_1^{(n-1)}(t)] \mathbf{p}_1 + \dots \right. \\ &\quad \left. \dots + [B_{n-2}^{(n-1)}(t) - B_{n-1}^{(n-1)}(t)] \mathbf{p}_{n-1} + [B_{n-1}^{(n-1)}(t)] \mathbf{p}_n \right) \end{aligned}$$

$$\mathbf{f}'(0) = n(\mathbf{p}_1 - \mathbf{p}_0) \quad \mathbf{f}'(1) = n(\mathbf{p}_n - \mathbf{p}_{n-1})$$

- Second derivative vector at  $\{0,1\}$



# Bezier Curve Properties

## Important for continuous concatenation:

- Function value at  $\{0,1\}$ :

$$\mathbf{f}(0) = \mathbf{p}_0$$

$$\mathbf{f}(1) = \mathbf{p}_n$$

- First derivative vector at  $\{0,1\}$ :

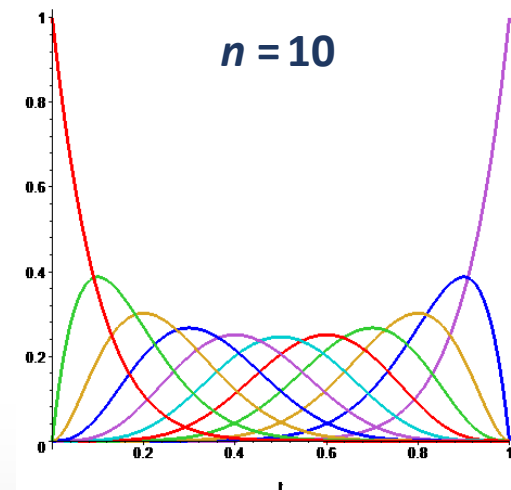
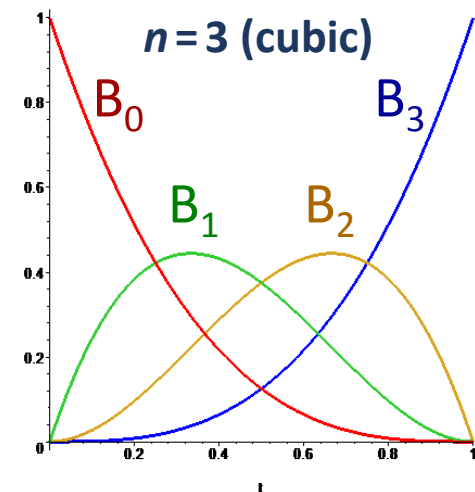
$$\mathbf{f}'(0) = n[\mathbf{p}_1 - \mathbf{p}_0]$$

$$\mathbf{f}'(1) = n[\mathbf{p}_n - \mathbf{p}_{n-1}]$$

- Second derivative vector at  $\{0,1\}$ :

$$\mathbf{f}''(0) = n(n-1)[\mathbf{p}_0 - 2\mathbf{p}_1 + \mathbf{p}_2]$$

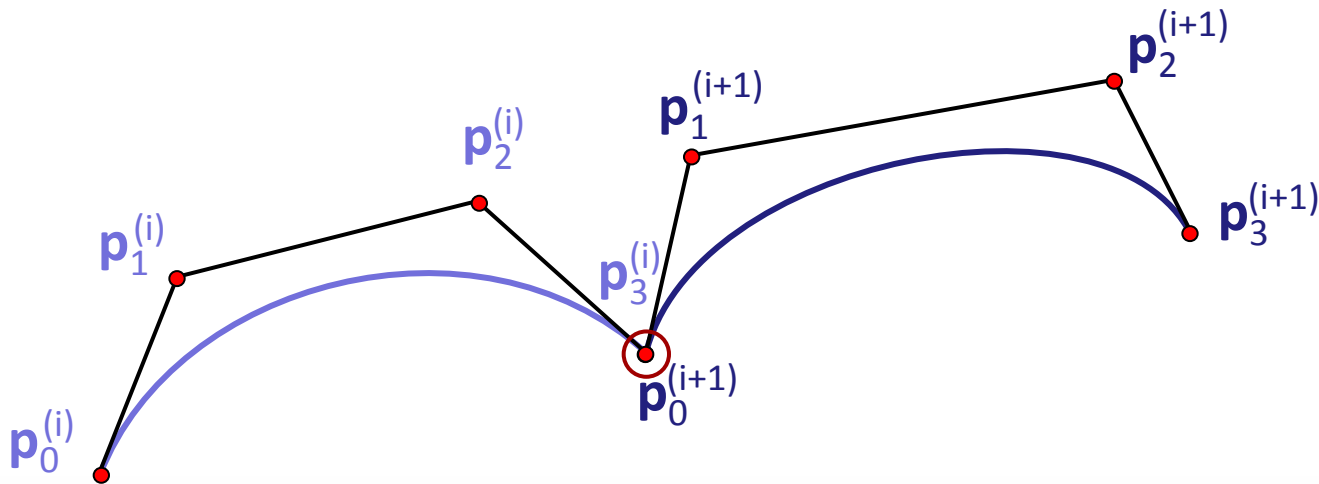
$$\mathbf{f}''(1) = n(n-1)[\mathbf{p}_n - 2\mathbf{p}_{n-1} + \mathbf{p}_{n-2}]$$



# Bezier Spline Continuity

## Rules for Bezier spline continuity:

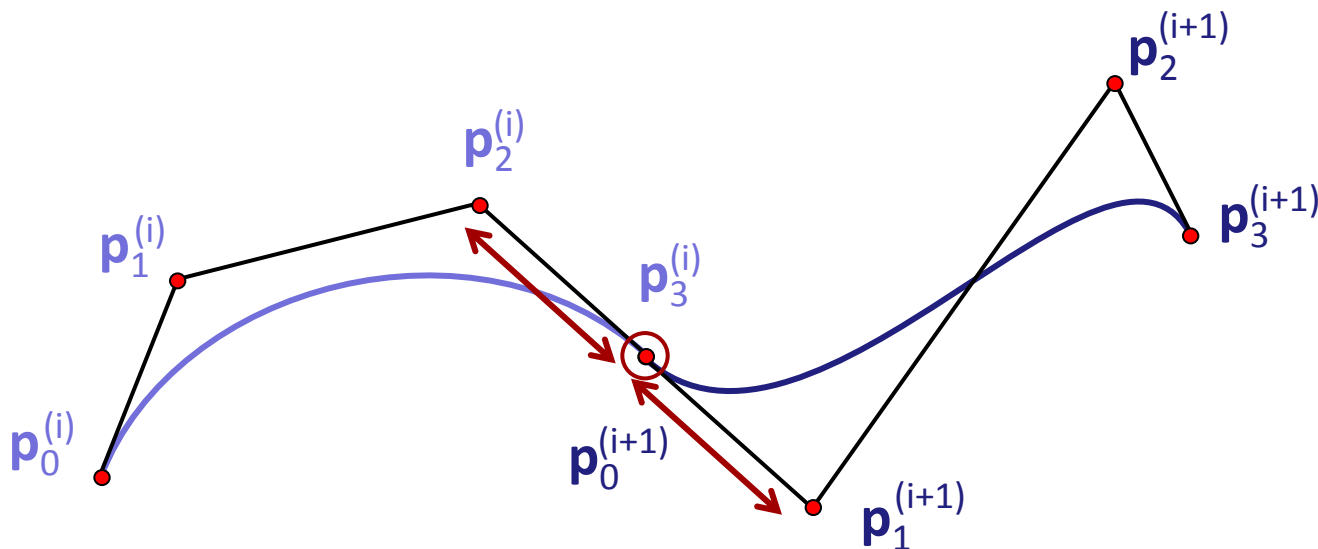
- $C^0$  continuity:
  - Each spline segment interpolates the first and last control point
  - Therefore: Points of neighboring segments have to coincide for  $C^0$  continuity.



# Bezier Spline Continuity

## Rules for Bezier spline continuity:

- Additional requirement for  $C^1$  continuity:
  - Tangent vectors are proportional to differences  $\mathbf{p}_1 - \mathbf{p}_0$ ,  $\mathbf{p}_n - \mathbf{p}_{n-1}$
  - Therefore: These vectors must be identical for  $C^1$  continuity

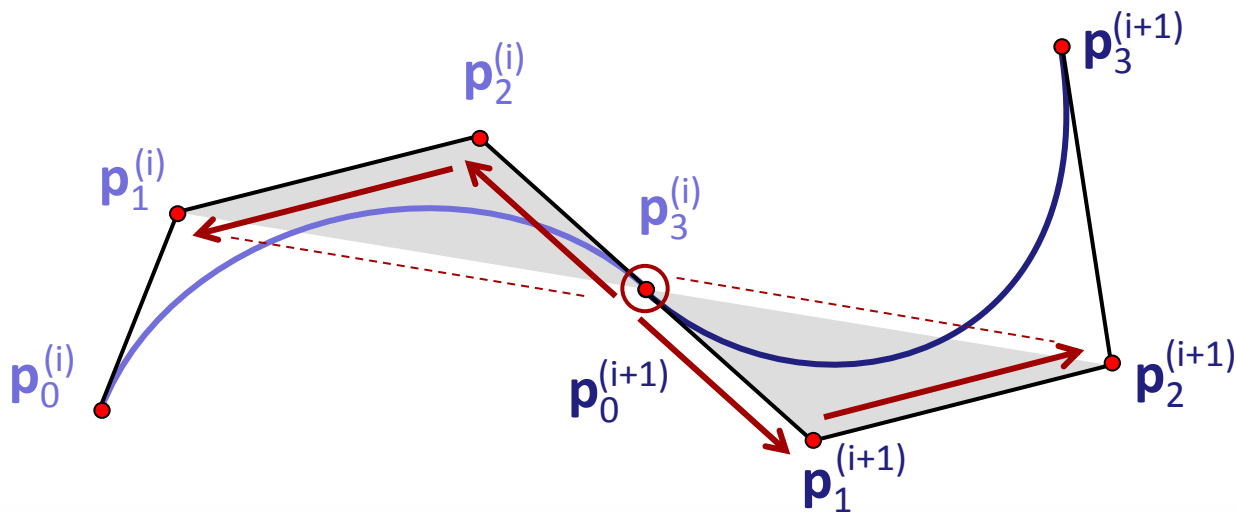




# Bezier Spline Continuity

## Rules for Bezier spline continuity:

- Additional requirement for  $C^2$  continuity:
  - $d^2/dt^2$  vectors are prop. to  $(\mathbf{p}_2 - 2\mathbf{p}_1 + \mathbf{p}_0)$ ,  $(\mathbf{p}_n - 2\mathbf{p}_{n-1} + \mathbf{p}_{n-2})$
  - Tangents must be the same ( $C^2$  implies  $C^1$ )
  - Therefore: Triangle of first / last three points must be the same

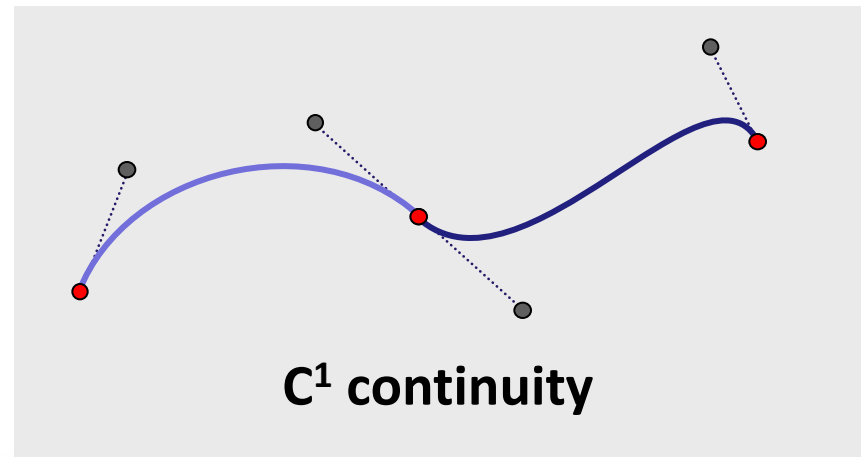
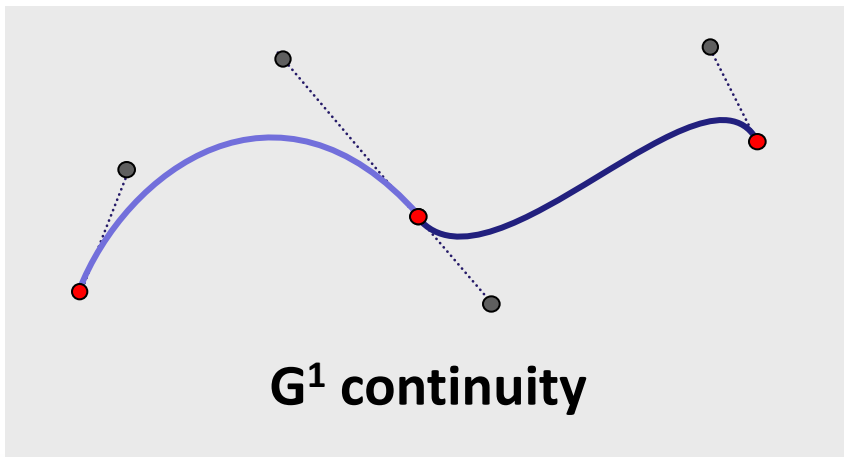
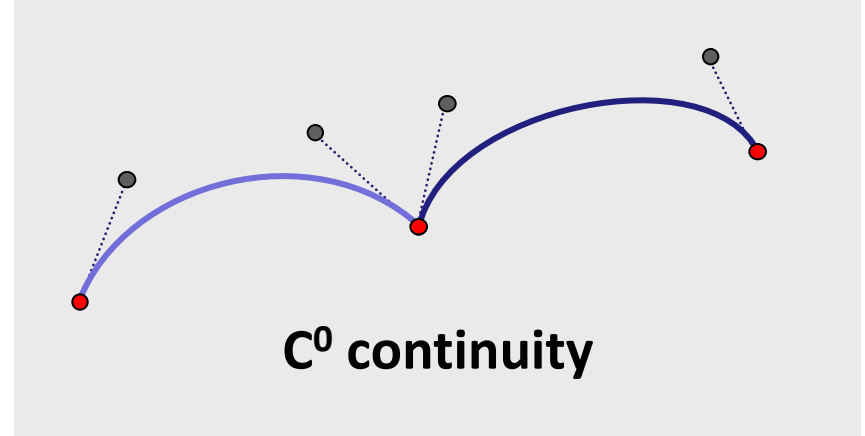
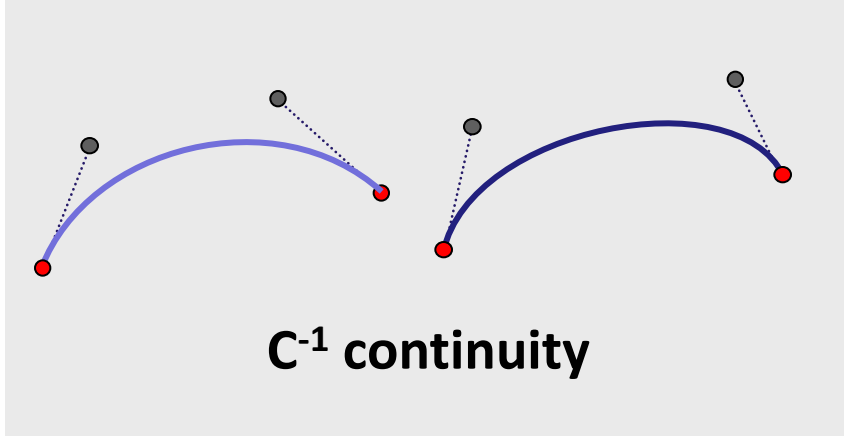


# In Practice

## In practice:

- Everyone is using cubic Bezier curves
- Higher degrees rare (CAD/CAM applications)
- Typically: “points & handles” interface
- Four modes:
  - Discontinuous (two curves)
  - $C^0$  Continuous (points meet)
  - Tangent direction continuous (handles point into the same direction, but different length)  
 (“ $G^1$  continuous”, more on this shortly)
  - $C^1$  Continuous (handle points have symmetric vectors)
- $C^2$  is rarely supported (too restrictive, no local control)

# Bezier Curve Editing



# Geometric Continuity

## Parametric Continuity:

- $C^0$ ,  $C^1$ ,  $C^2$ ... continuity.
- Does a particle moving on this curve have a smooth trajectory (position, velocity, acceleration,...)?
- Useful for animation (object movement, camera paths)

## Geometric Continuity:

- Is the curve itself smooth?
- C.f.: differential geometry – parametrization independent measures
- More relevant for modeling (curve design)

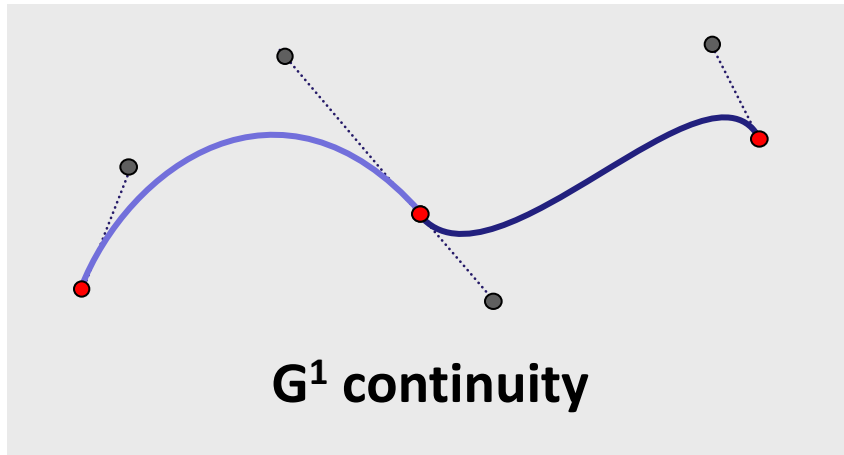
# Geometric Continuity

## Geometric Continuity:

- $G^0 = C^0$ : position varies continuously
- $G^1$ : tangent directions varies continuously
  - In other words: the normalized tangent varies continuously
  - Equivalently: The curve can be reparametrized so that it becomes  $C^1$ .
  - Also equivalent: A unit speed parametrization would be  $C^1$ .
- $G^2$ : curvature varies continuously
  - Equivalently: The curve can be reparametrized so that it becomes  $C^2$ .
  - Also equivalent: A unit speed parametrization would be  $C^2$ .

# Geometric Continuity for Bezier Splines

This means:



This Bezier curve is  $G^1$ : It can be reparametrized to become  $C^1$ .  
(Just increase the speed for the second segment by ratio of tangent vector lengths.)

# **Polynomial Spline Curves**

## Uniform Cubic B-Splines

# Literature

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## Literature:

- *An Introduction to Splines for use in Computer Graphics and Geometric Modeling*

**Richard H. Bartels, John C. Beatty, Brian A. Barsky**

Morgan Kaufmann 1987

(now hard to get, waited several month on Amazon)



# Overview

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## Uniform cubic B-splines

- This is a special case of general B-splines
  - (which additionally provide arbitrary degree and general and non-uniform parametrization)
- We look at this first to get an intuition for the basic ideas and concepts for B-splines
- Some derivations are left out – will be shown later for the general case

# Overview

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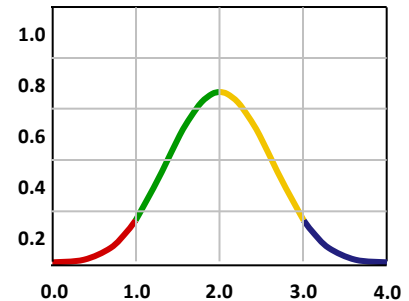
## Improvement over cubic Bezier splines:

- $C^2$  continuity is easily attainable
- We will use only one type of basis functions
  - Shifted in the domain to create curves with multiple segments
  - This principle is conceptually easier to apply in general modeling problems (e.g. as a basis for finite elements, for PDEs or variational problems)

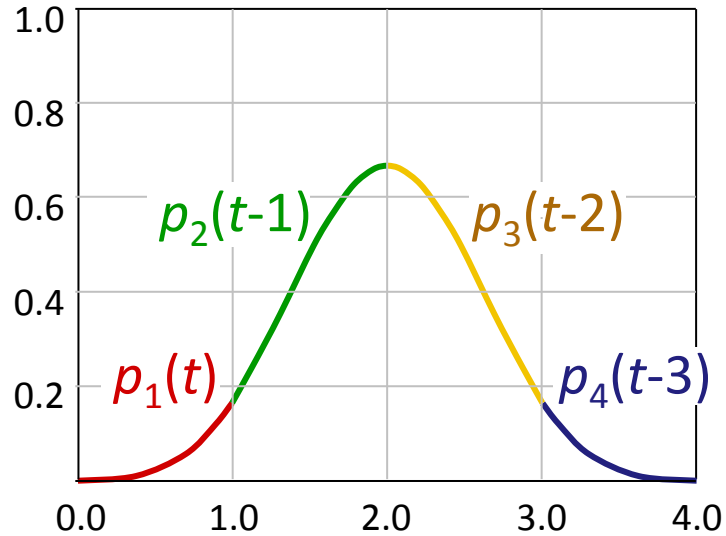
# Key Ideas

## Key Ideas:

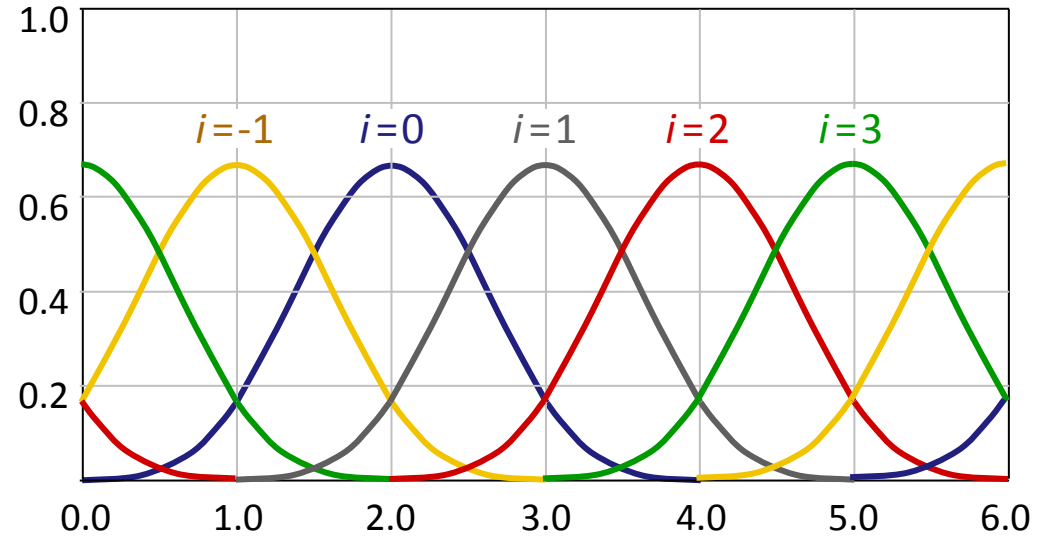
- We design one basis function  $b(t)$
- Properties:
  - $b(t)$  is  $C^2$  continuous.
  - $b(t)$  is piecewise polynomial, degree 3 (cubic).
  - $b(t)$  has local support.
  - Overlaying shifted  $b(t + i)$  forms a partition of unity.
  - $b(t) \geq 0$  for all  $t$
- In short: We build-in all the desirable properties into the basis. Linear combinations will inherit these.



# Shifted Basis Functions



basis function  $b(t)$



shifted basis functions  $b(t-i)$  for  $[0..6]$

## Basis function:

- Consists of four polynomial parts  $p_1 \dots p_4$ .
- Shifted basis  $b(t-i)$ : spacing of 1.
- Each interval to be used must be overlapped by 4 different  $b_i$ .

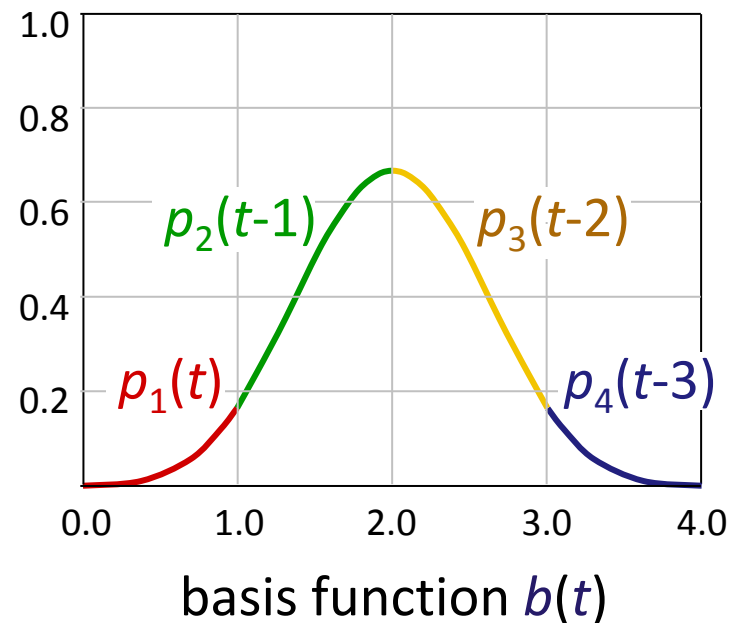
# Basis Function

$$p_1(t) = \frac{1}{6}t^3$$

$$p_2(t) = \frac{1}{6}(1 + 3t + 3t^2 - 3t^3)$$

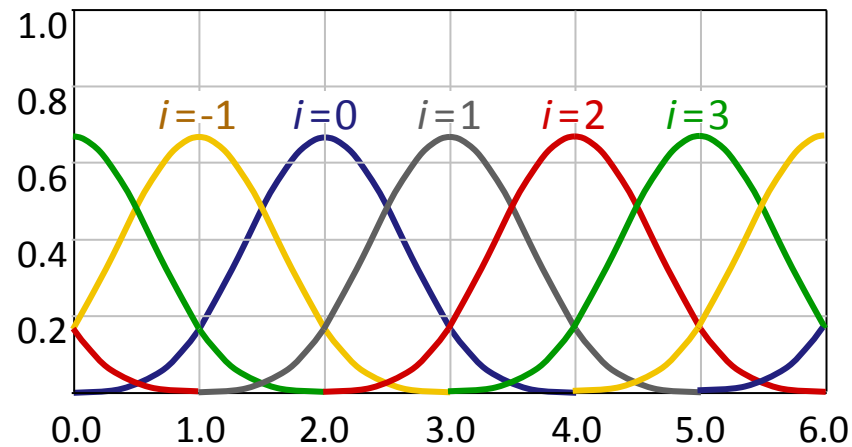
$$p_3(t) = \frac{1}{6}(4 - 6t^2 + 3t^3)$$

$$p_4(t) = \frac{1}{6}(1 - 3t + 3t^2 - t^3)$$



$$b(t) = \begin{cases} 0 & \text{if } t < 0 \\ p_1(t) & \text{if } 0 < t \leq 1 \\ p_2(t-1) & \text{if } 1 < t \leq 2 \\ p_3(t-2) & \text{if } 2 < t \leq 3 \\ p_4(t-3) & \text{if } 3 < t \leq 4 \\ 0 & \text{if } t > 4 \end{cases} = \begin{cases} 0 & \text{if } t < 0 \\ \frac{1}{6}t^3 & \text{if } 0 < t \leq 1 \\ \frac{1}{6}\left(1 + 3(t-1) + 3(t-1)^2 - 3(t-1)^3\right) & \text{if } 1 < t \leq 2 \\ \frac{1}{6}\left(4 - 6(t-2)^2 + 3(t-2)^3\right) & \text{if } 2 < t \leq 3 \\ \frac{1}{6}\left(1 - 3(t-3) + 3(t-3)^2 - (t-3)^3\right) & \text{if } 3 < t \leq 4 \\ 0 & \text{if } t > 4 \end{cases}$$

# Creating Curves



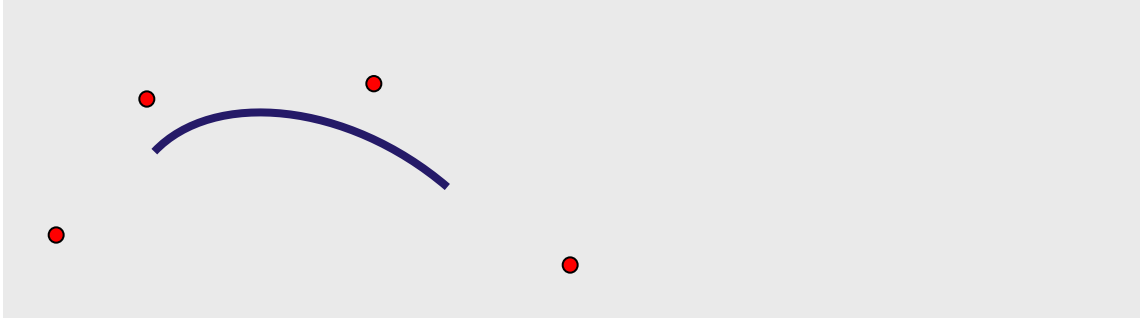
## Creating uniform B-spline curves:

- Choose parameter interval  $[n_{start}-2, n_{end}+2,], n_{start} < n_{end} \in \mathbb{Z}$
- Use all shifted basis functions that overlap this interval:

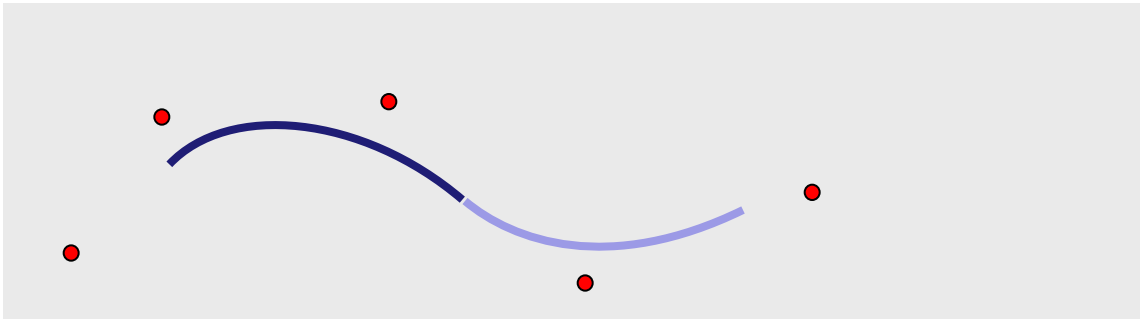
$$\mathbf{B} = \{b(t - [n_{start}-1]), \dots, b(t - [n_{end}+1])\}$$

- Form linear combinations:  $\mathbf{f}(t) = \sum_{i=n_{start}-1}^{n_{end}+1} b(t-i)\mathbf{p}_i$

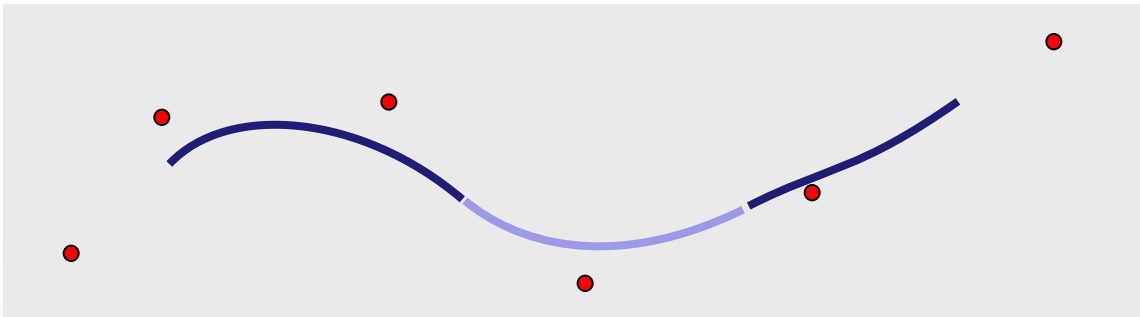
# Uniform B-Spline Curves



one segment



two segments



three segments

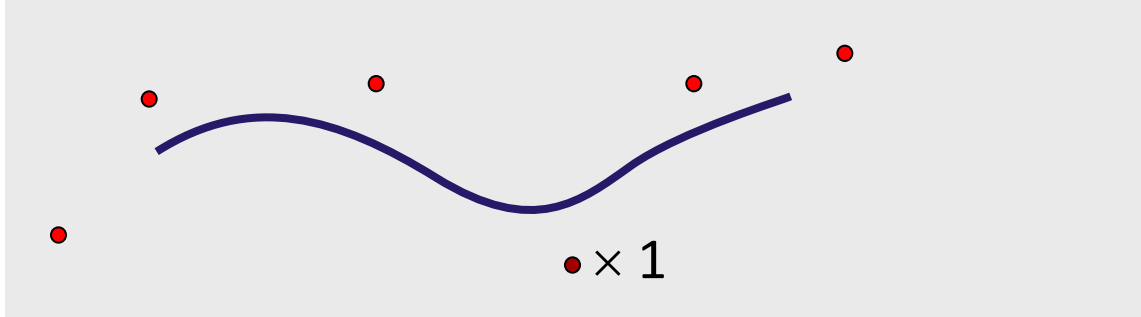
# Discontinuities

## Continuity Control

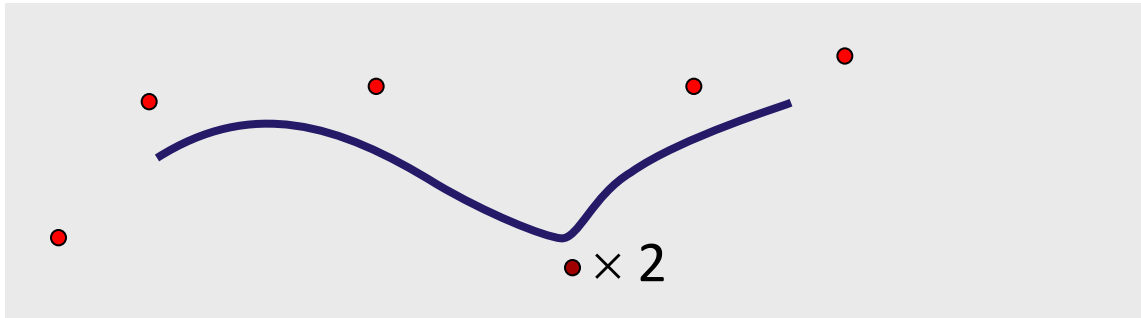
- Easier than with Bezier curves
- The parametric function is always  $C^2$ , by construction
- However: We can create curves with lower geometric smoothness
  - This will lead to a degenerate (non-regular) parametrization
  - This problem is fixed with general, non-uniform B-Splines
- Basic idea: Double control points
  - Single points:  $G^2$  curve
  - Double points:  $G^1$  curve
  - Triple points:  $G^0$  curve



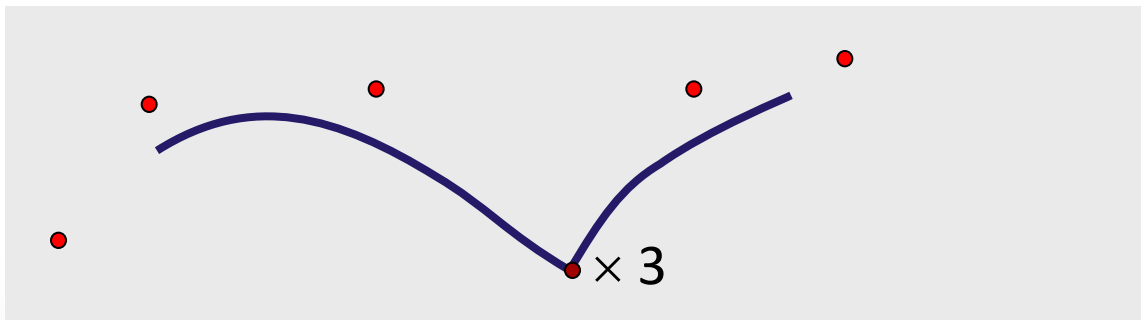
# Continuity Control



single points

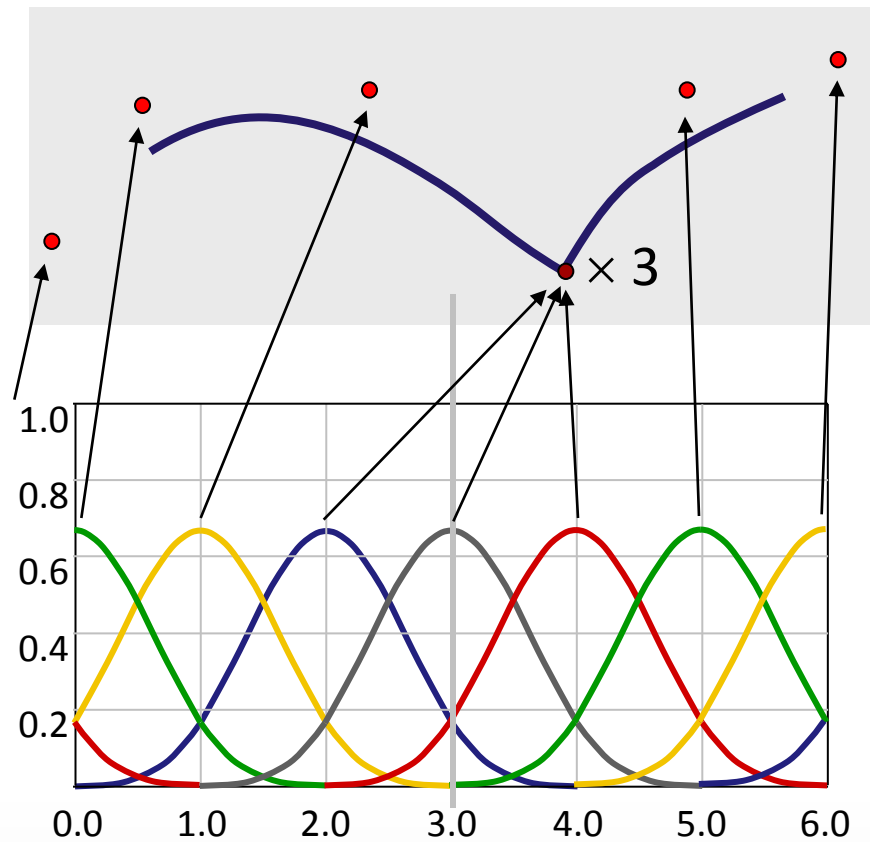
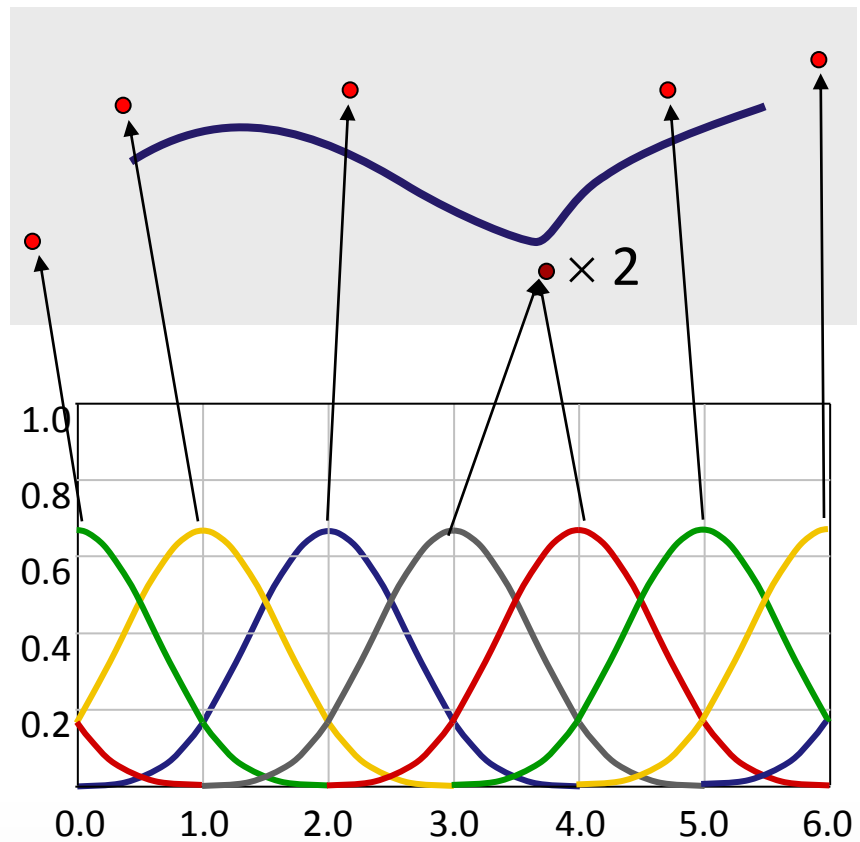


double point



triple point  
(interpolates that point)

# Illustration

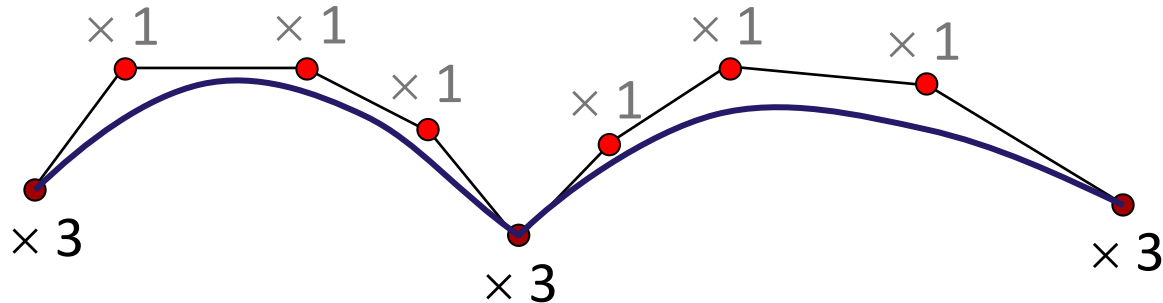


# End Conditions

## Problem:

- We need at least 4 points for one spline segment, 5 for two and so on.
- Means: We need  $s + 3$  control points for  $s$  segments (rather than  $s + 1$ ), two more than in spline interpolation.
- This is inconvenient...
- Simple solution:
  - Use double or triple end points
  - Triple end points will be interpolated
  - We will get along with  $s + 1$  control points

# Knot Sequences



## Specifying a uniform, cubic B-Spline curve:

- A set of control points  $\mathbf{p}_1, \dots, \mathbf{p}_n$ .
- Knot multiplicities  $(i_1, \dots, i_k)$ ,  $i_j \in \{1, 2, 3\}$ ,  $\sum i_j = n$ .
  - For example  $(3, 1, 1, 1, 3, 1, 1, 1, 3)$ 
    - Creates one sharp corner in the middle of the spline
    - Interpolates the end points

# Conversion to Bezier Basis

---

**Uniform B-Splines can be converted to the Bezier Format:**

- Cubic polynomial pieces
- Each can be represented as Bezier segment
- Just a basis change...

# Basis Change

$$M_{UB \rightarrow Mn} = \frac{1}{6} \begin{pmatrix} 0 & 1 & 4 & 1 \\ 0 & 3 & 0 & -3 \\ 0 & 3 & -6 & 3 \\ 1 & -3 & 3 & -1 \end{pmatrix}$$

$$M_{Bez \rightarrow Mn} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ -3 & 3 & 0 & 0 \\ 3 & -6 & 3 & 0 \\ -1 & 3 & -3 & 1 \end{pmatrix}$$

$$M_{UB \rightarrow Bez} = (M_{Bez \rightarrow Mn})^{-1} M_{UB \rightarrow Mn}$$

$$\begin{pmatrix} \tilde{\mathbf{b}}_i^{(1)} \\ \tilde{\mathbf{b}}_i^{(2)} \\ \tilde{\mathbf{b}}_i^{(3)} \\ \tilde{\mathbf{b}}_i^{(4)} \end{pmatrix} = M_{UB \rightarrow Bez} \begin{pmatrix} \mathbf{b}_i^{(1)} \\ \mathbf{b}_{i-1}^{(2)} \\ \mathbf{b}_{i-2}^{(3)} \\ \mathbf{b}_{i-3}^{(4)} \end{pmatrix}$$

## Uniform B-Spline:

$$p_1(t) = \frac{1}{6}t^3$$

$$p_2(t) = \frac{1}{6}(1 + 3t + 3t^2 - 3t^3)$$

$$p_3(t) = \frac{1}{6}(4 - 6t^2 + 3t^3)$$

$$p_4(t) = \frac{1}{6}(1 - 3t + 3t^2 - t^3)$$

## Bezier-Spline:

$$B_0^{(3)} := (1-t)^3 \quad B_1^{(3)} := 3t(1-t)^2$$

$$B_2^{(3)} := 3t^2(1-t) \quad B_3^{(3)} := t^3$$

# Where does the basis come from?

---

## How do we construct a B-Spline basis?

- Derivation of uniform cubic B-Splines?
- Generalizations:
  - General degree?
  - Non-uniform parametrization?

# Three Approaches:

## Three ways to get the basis:

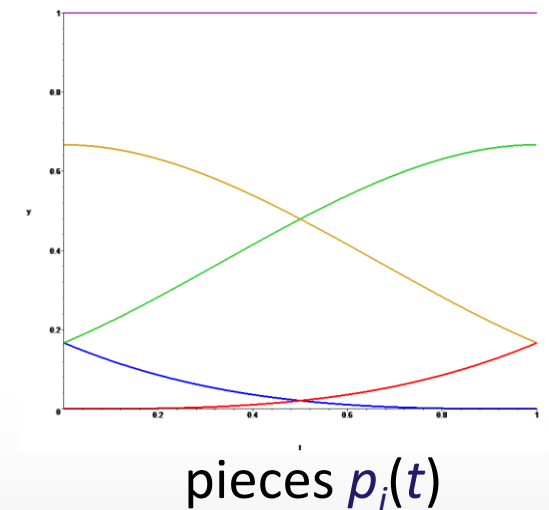
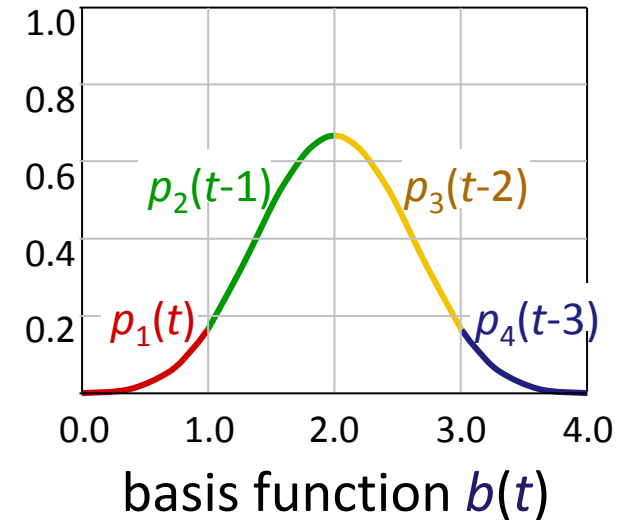
1. The elementary approach:
  - Derive a linear system of equations, solve
2. Repeated convolution:
  - $d$ -fold convolution of box functions
3. de-Boor Recursion:
  - Repeated linear interpolation



# The Elementary Approach

## Cubic Uniform B-Spline Basis:

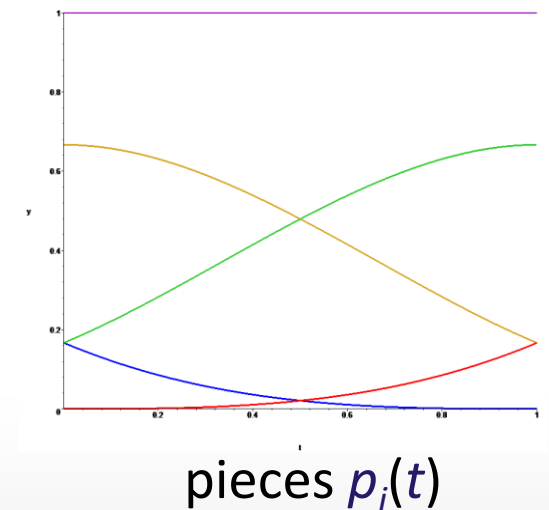
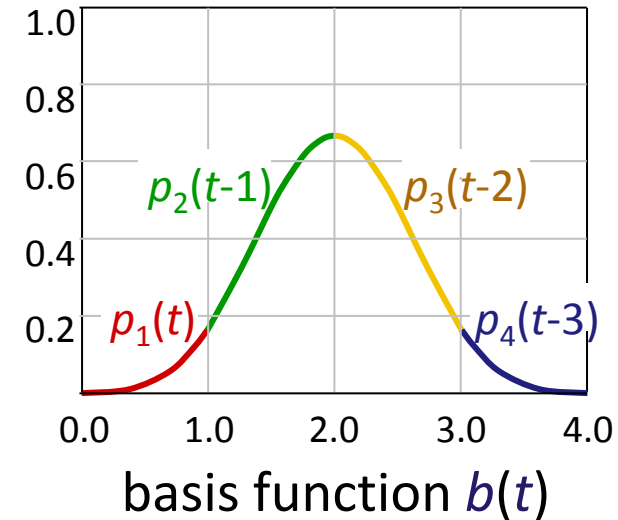
- One basis function, just shifted
- Consists of four pieces  $p_1, p_2, p_3, p_4$ .
- We just need the coefficients of the pieces
- Setting up a linear system...



# The Elementary Approach

## Linear system:

$$\begin{array}{lll}
 p_1(0) = 0 & p_1'(0) = 0 & p_1''(0) = 0 \\
 p_1(1) = p_2(0) & p_1'(1) = p_2'(0) & p_1''(1) = p_2''(0) \\
 p_2(1) = p_3(0) & p_2'(1) = p_3'(0) & p_2''(1) = p_3''(0) \\
 p_3(1) = p_4(0) & p_3'(1) = p_4'(0) & p_3''(1) = p_4''(0) \\
 p_4(1) = 0 & p_4'(1) = 0 & p_4''(1) = 0 \\
 p_0\left(\frac{1}{2}\right) + p_1\left(\frac{1}{2}\right) + p_2\left(\frac{1}{2}\right) + p_3\left(\frac{1}{2}\right) = 1
 \end{array}$$



# The Elementary Approach

## Normalization:

- Completely determines the  $p_i$ .
- Turns out to hold everywhere in  $[0,1]$
- Not yet clear why
- But: if it is possible, our conditions are sufficient
- So we have to show that it is possible

$$\begin{array}{lll} p_1(0) = 0 & p'_1(0) = 0 & p''_1(0) = 0 \\ p_1(1) = p_2(0) & p'_1(1) = p'_2(0) & p''_1(1) = p''_2(0) \\ p_2(1) = p_3(0) & p'_2(1) = p'_3(0) & p''_2(1) = p''_3(0) \\ p_3(1) = p_4(0) & p'_3(1) = p'_4(0) & p''_3(1) = p''_4(0) \\ p_4(1) = 0 & p'_4(1) = 0 & p''_4(1) = 0 \\ p_0\left(\frac{1}{2}\right) + p_1\left(\frac{1}{2}\right) + p_2\left(\frac{1}{2}\right) + p_3\left(\frac{1}{2}\right) = 1 \end{array}$$

## Positivity:

- Not enforced; we get this accidentally (simplicity)
- Same argument: if it's possible, the conditions are sufficient

# Properties

## Minimal Support:

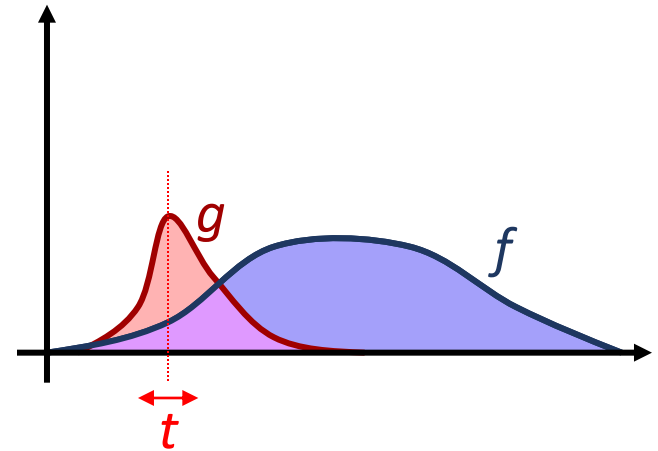
- We have 16 conditions (cubic case)
  - 15 for smoothness, one for normalization
  - Easy to see: linear independent
- Need 4 polynomial segments to get sufficiently many degrees of freedom
- Consequence: Any  $C^2$  function with 3 or less polynomial segments, and the zero function everywhere else, must be the zero function.
  - 15 linear independent constraints, homogeneous.
  - Zero vector is the only solution.
- Therefore: We have *minimal support*.

# Repeated Convolution

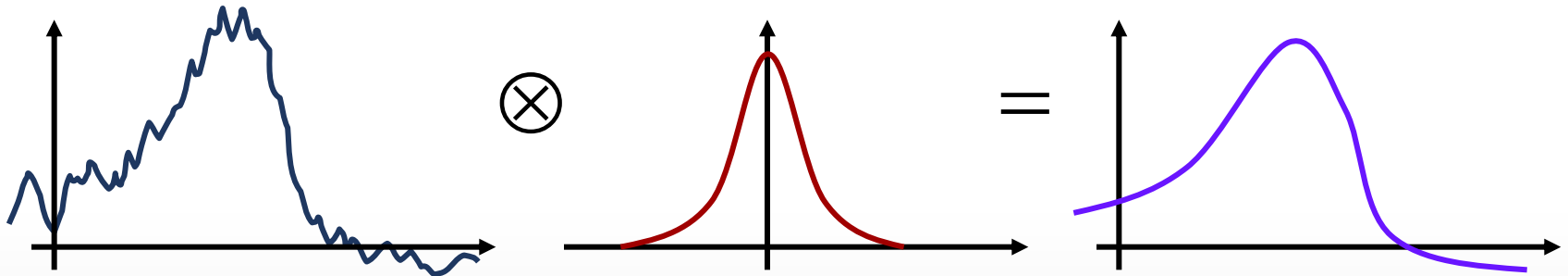
## Convolution:

- Weighted average of functions
- Definition:

$$f(t) \otimes g(t) = \int_{-\infty}^{\infty} f(x)g(x-t)dx$$



## Example:



# Repeated Convolution

## A Different Derivation:

- We start with 0th degree basis functions
- Increase smoothness by convolution

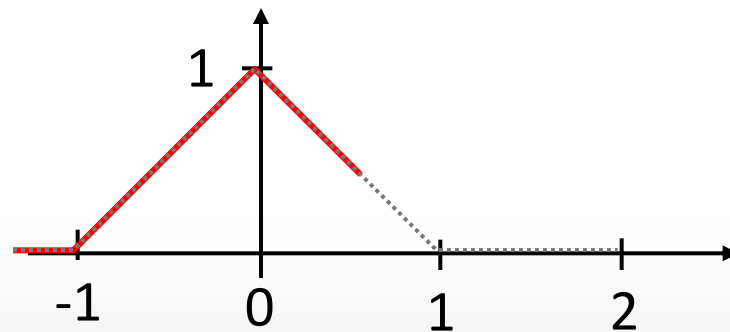
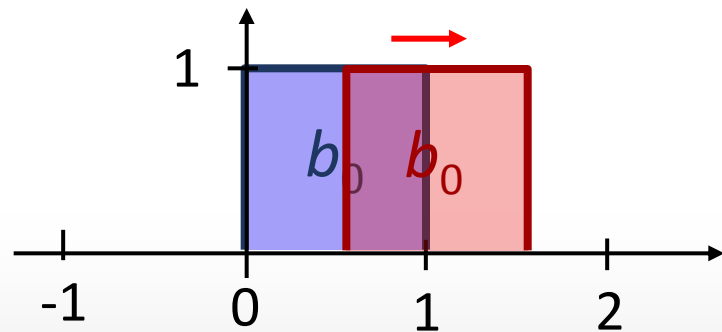
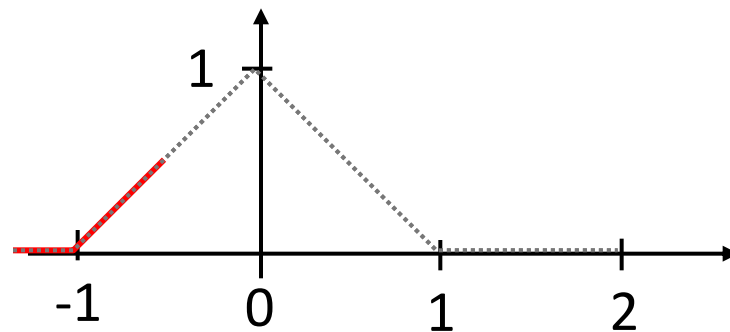
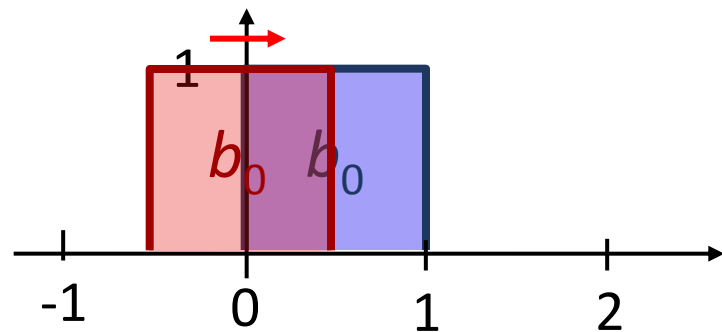
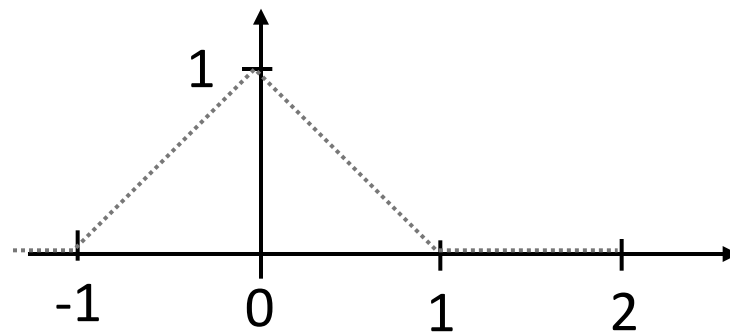
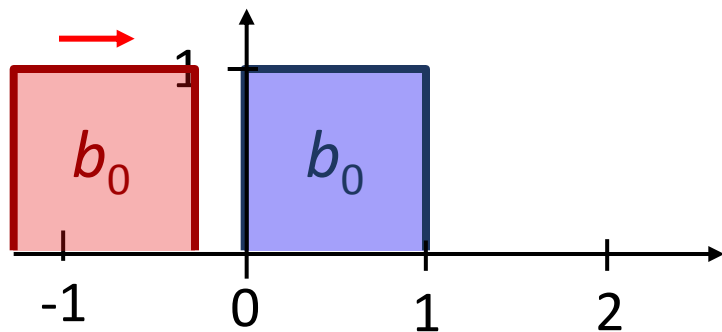
## Degree-zero B-Spline:

$$b^{(0)}(t) = \begin{cases} 1, & \text{if } t \in [0...1) \\ 0, & \text{otherwise} \end{cases}$$

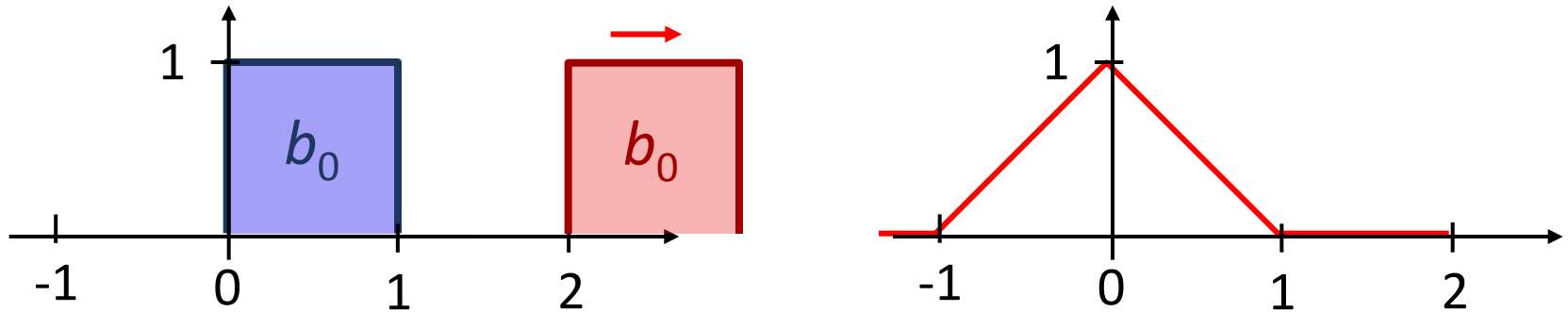
## General-degree B-Spline:

$$b^{(i)}(t) = b^{(i)}(t) \otimes b^{(0)}(t) = \int_{-\infty}^{\infty} b^{(i)}(x) b^{(0)}(x-t) dx$$

# Illustration



# Illustration

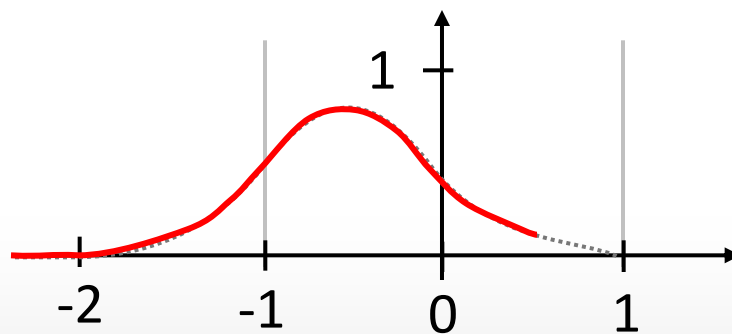
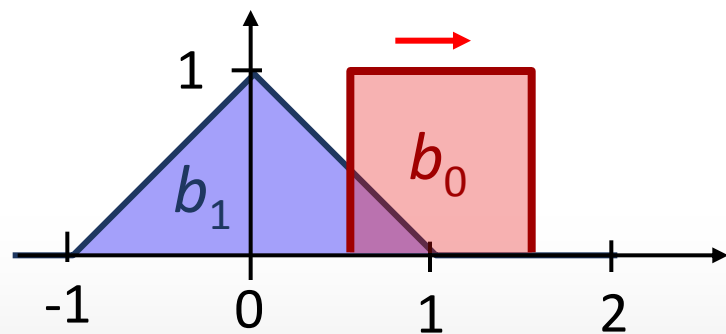
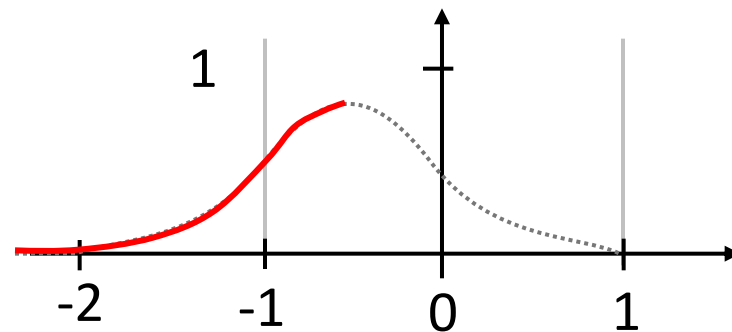
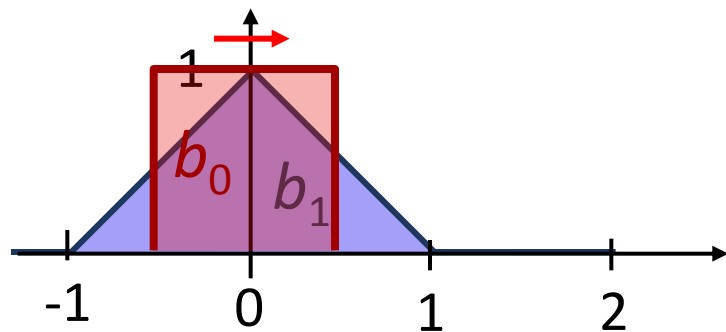
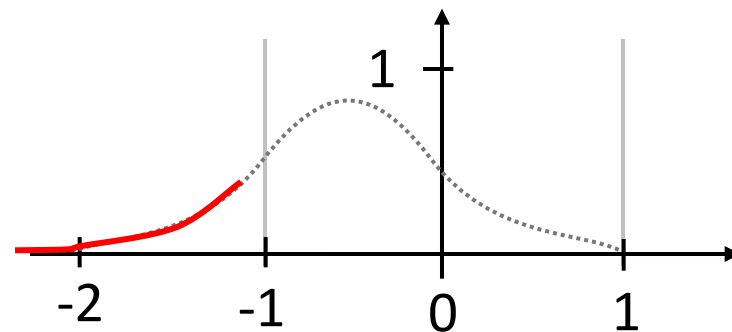
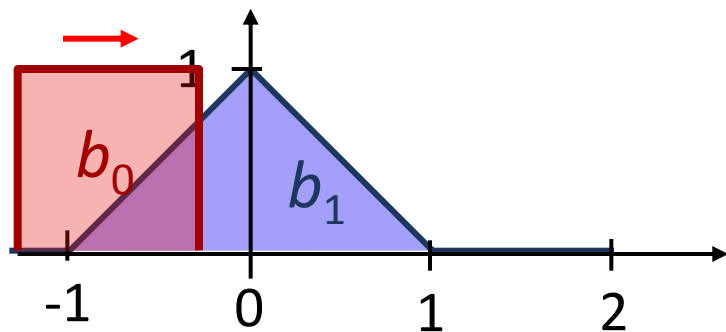


## Result:

- Piecewise linear B-spline basis function
- Each convolution with  $b_0$  increases the continuity by 1.



# Illustration



# Smoothness

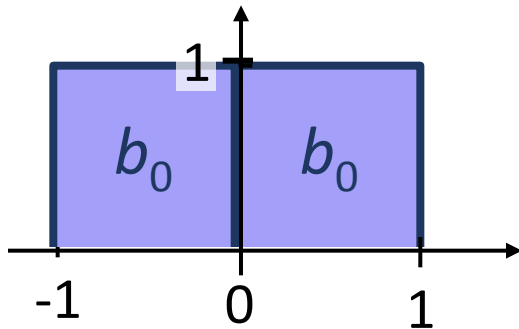
## Convolution with a box filter increases smoothness:

Function  $f$  that is  $C^{k-1}$  at  $t = t_0$ , and  $C^k$  everywhere else:

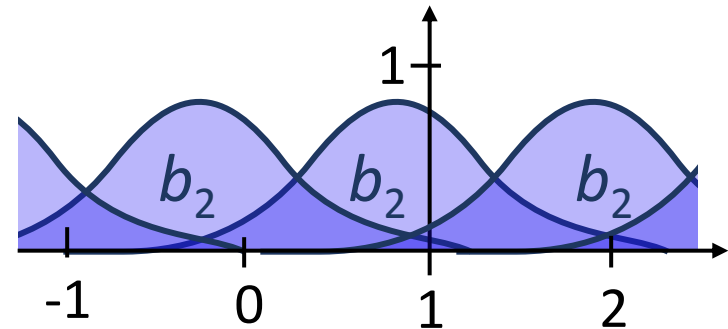
- $f_{\otimes} := f \otimes b_0 = \int_t^{t+1} f(t) dt = F(t+1) - F(t)$
- $\Delta D^i := \frac{d^i}{dt^i} \Big|_- f(t) - \frac{d^i}{dt^i} \Big|_+ f(t), \quad \Delta D^i f(t) = 0 \quad \text{for } i = 1..k-1$
- $$\begin{aligned} \frac{d^j}{dt^j} f_{\otimes}(t) &= \frac{d^{j-1}}{dt^{j-1}} \left( \frac{d}{dt} f_{\otimes}(t) \right) = \frac{d^{j-2}}{dt^{j-2}} \left( \frac{d}{dt} (F(t+1) - F(t)) \right) \\ &= \frac{d^{j-2}}{dt^{j-2}} (f(t+1) - f(t)) \end{aligned}$$
- $\Delta D^j f_{\otimes}(t) = \Delta D^{j-1} (f(t+1) - f(t))$

# Partition of Unity

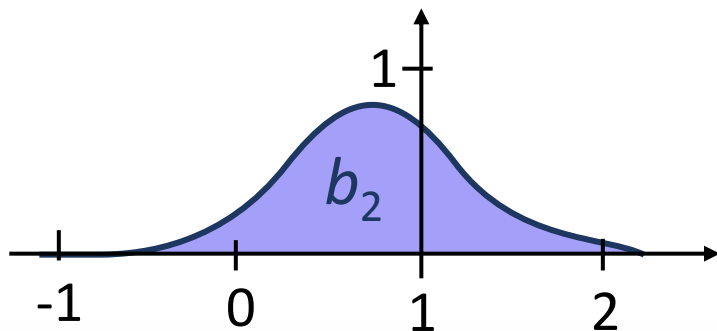
## Proof by Induction:



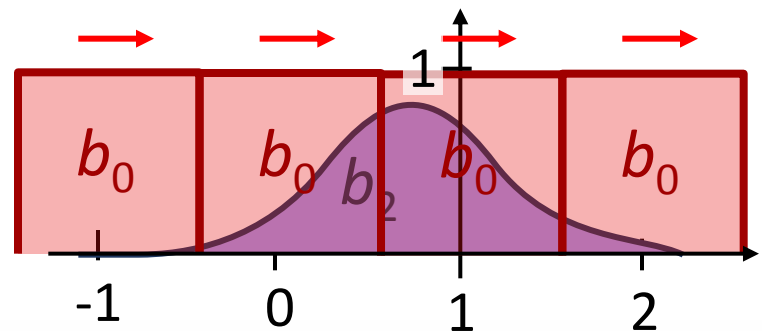
degree zero: **OK**



degree  $d$ : *given*



degree  $d$ ...



degree  $d+1$ : *follows*

# Other Properties

## Positivity:

- By definition

## Continuity:

- Smoothness increasing property:  $k$ -fold convolution is  $C^k$ .

## Piecewise polynomial:

- Easy to see: Polynomial in each interval
- Degree  $k$  for  $k$ -fold convolution.

# Consequences

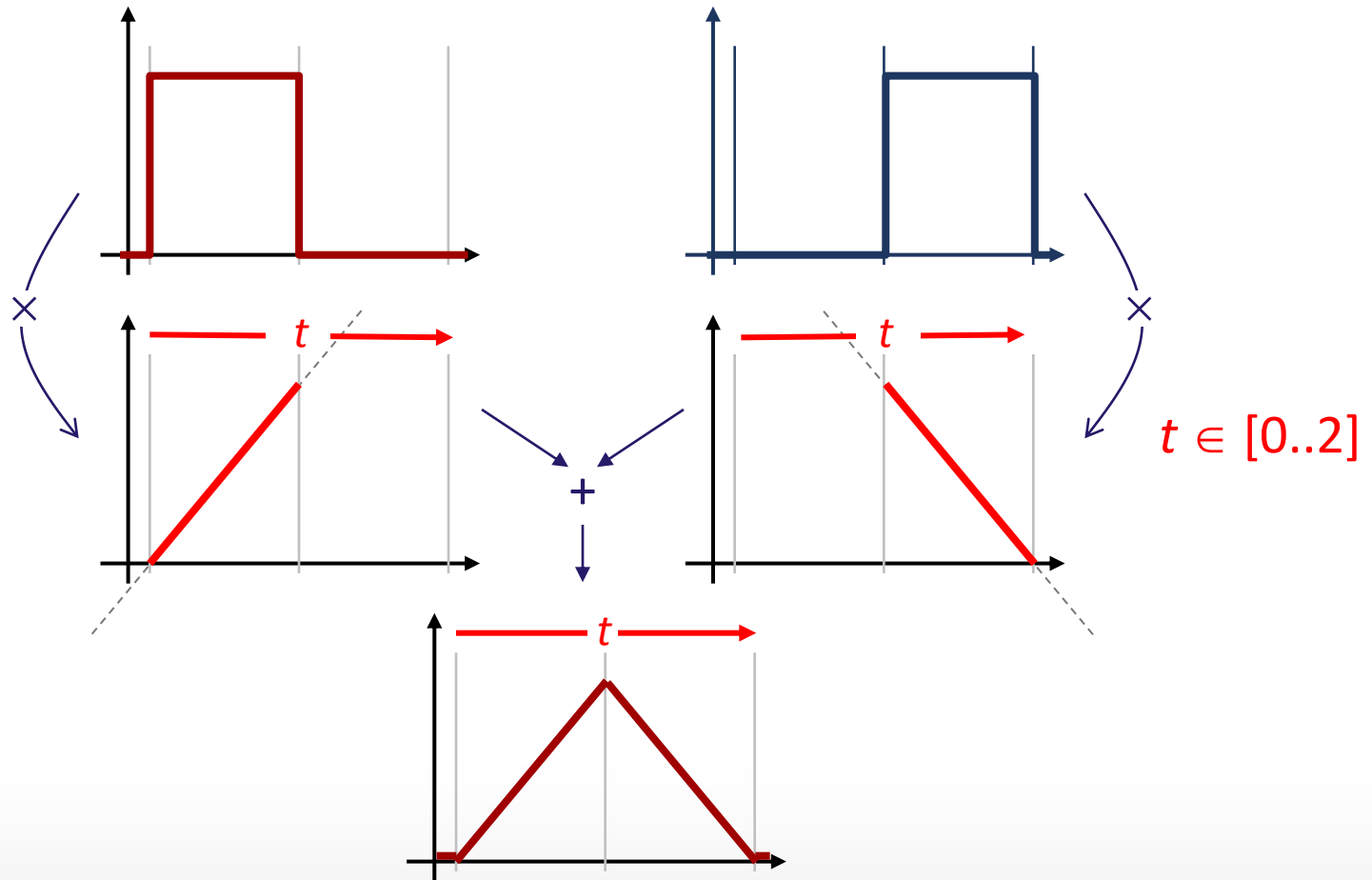
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## Consequences:

- The constructed functions are identical to the explicitly constructed ones (limited degrees of freedom)
- This means, the explicitly constructed basis has the same properties (partition of unity, positivity)

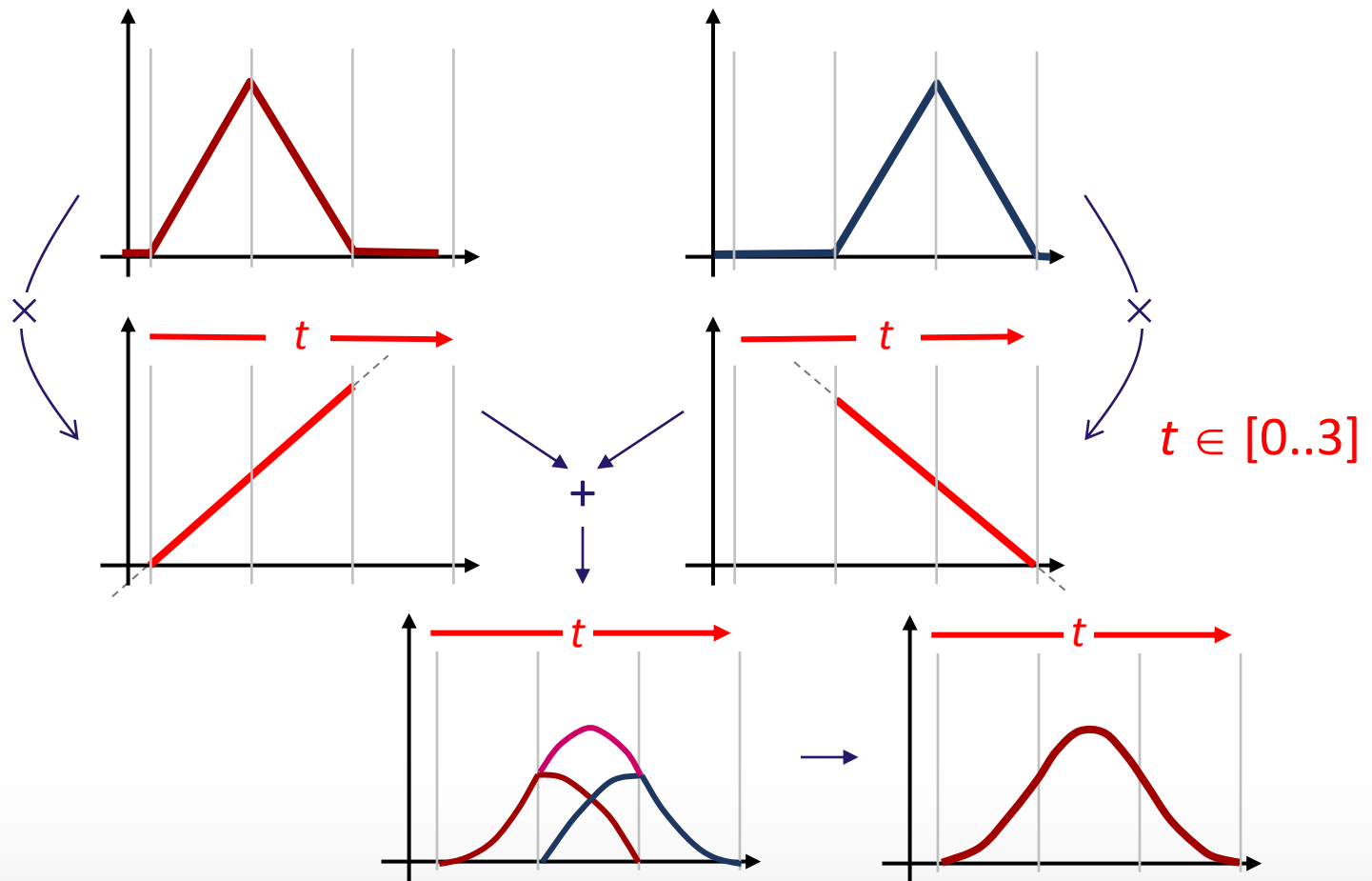
# Repeated Linear Interpolation

Another way to increase smoothness:

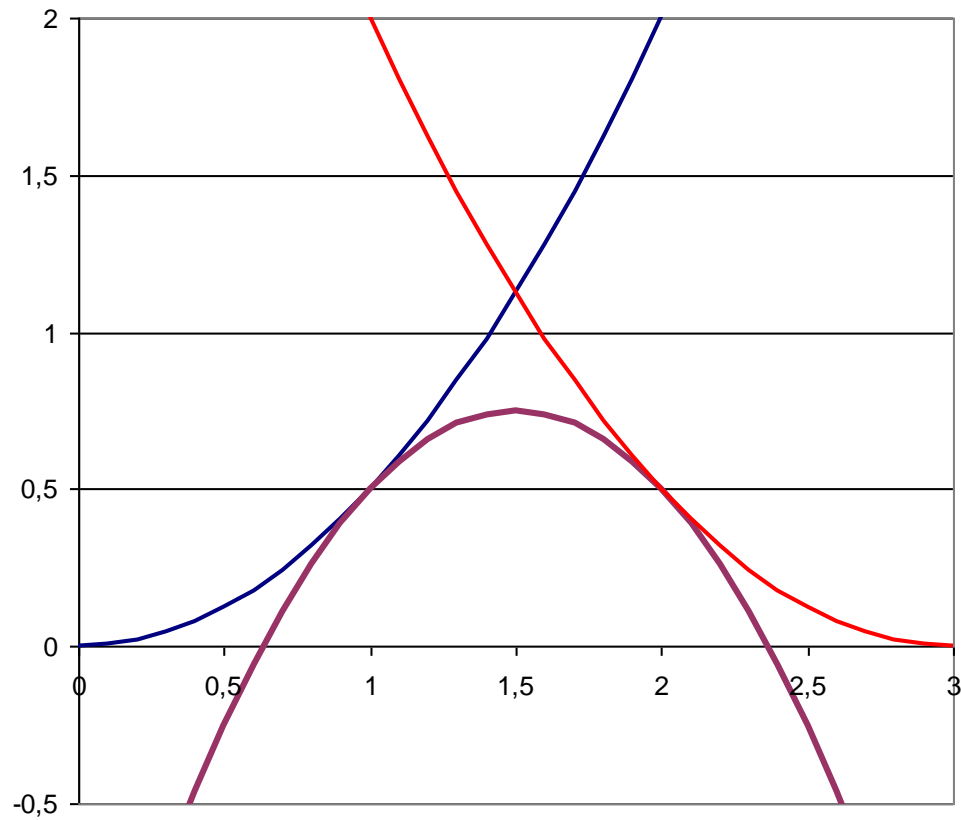


# Repeated Linear Interpolation

Another way to increase smoothness:



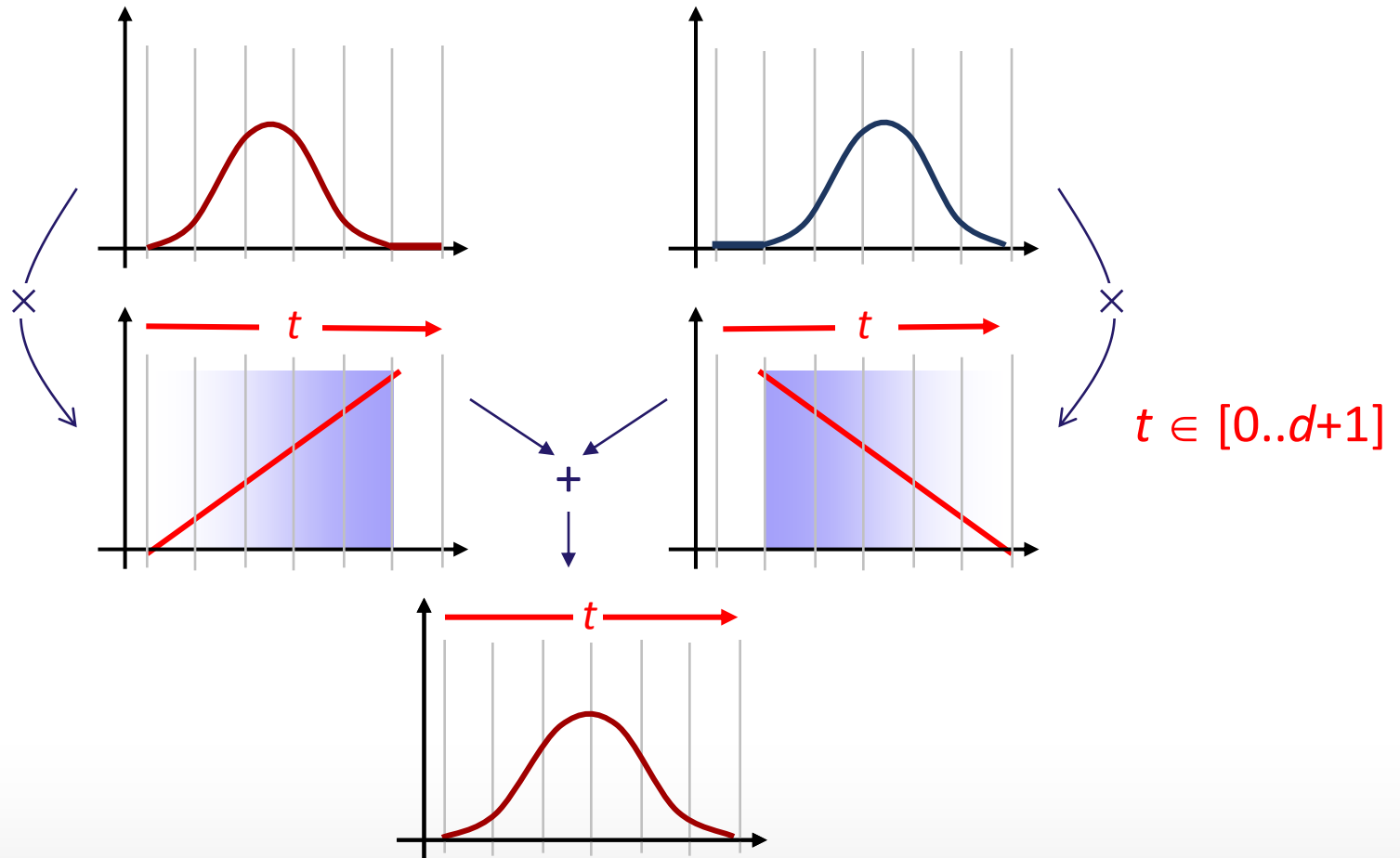
# Plot of the Three Pieces





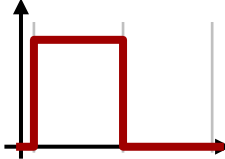
# Repeated Linear Interpolation


## General Principle:



# De Boor Recursion

The uniform B-spline basis of degree  $d$  is given as:

$$N_i^0(t) = \begin{cases} 1, & \text{if } i-1 \leq t < i \\ 0, & \text{otherwise} \end{cases}$$


$$N_i^d(t) = \frac{t - (i-1)}{(i+d-1) - (i-1)} N_i^{d-1}(t) + \frac{(i+d) - t}{(i+d) - i} N_{i+1}^{d-1}(t)$$


$$= \frac{t - i + 1}{d} N_i^{d-1}(t) + \frac{i + d - t}{d} N_i^{d-1}(t)$$

# Connection

## Three constructions:

- It can be shown that this construction is equivalent to the previous two.
- Rough idea:
  - Convolution with a box filter increases degree by one (multiplication with linear weight in de Boor formula)
  - Antiderivative of box filter: evaluate at  $t, t+1$  (corresponds to overlaying  $N_i, N_{i+1}$ )
  - Need to show that the coefficients match (induction)

# **Polynomial Spline Curves**

## **Non-Uniform B-Splines**

# Generalization

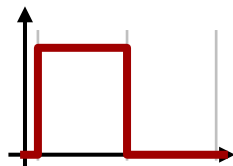
## De Boor formula can be generalized:

- Arbitrary parameter sequences (“*knot sequence*”)  
 $(t_0, t_1, \dots, t_n)$  with  $t_0 \leq t_1 \leq \dots \leq t_n$ 
  - Not necessary to have uniform spacing
  - Will give us more flexibility in curve design.
- Specifying one parameter value multiple times is permitted, e.g.  $(0, 0, 0, 1, 2, 3, 4, 4, 4, 5, 6, 7, 8, 8, 8)$ 
  - This has a similar effect as multiple nodes in simple uniform B-Splines
  - Will avoid irregular parametrization (means: will create a basis that itself is less smooth, not just the traced out curve)

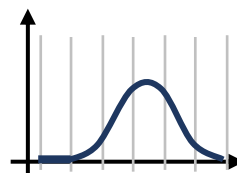
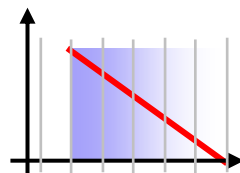
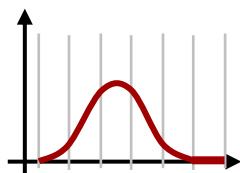
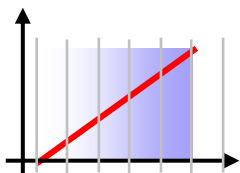
# General De Boor Recursion

## Generalized Formula:

$$N_i^0(t) = \begin{cases} 1, & \text{if } t_{i-1} \leq t < t_i \\ 0, & \text{otherwise} \end{cases}$$



$$N_i^d(t) = \frac{t - t_{i-1}}{t_{i+d-1} - t_{i-1}} N_i^{d-1}(t) + \frac{t_{i+d} - t}{t_{i+d} - t_i} N_{i+1}^{d-1}(t)$$



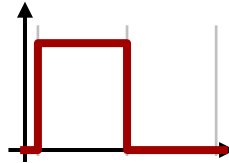
## Remark:

- If a knot value is repeated  $d$  times, the denominator may vanish
- In this case: The fraction is treated as a zero

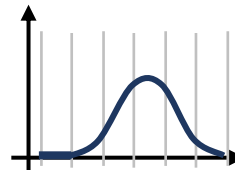
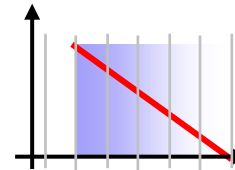
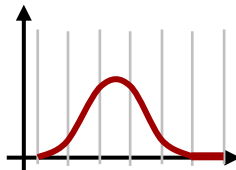
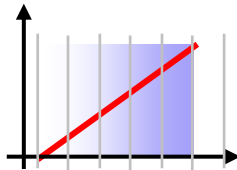
# Uniform Case:

For comparison – the uniform case:

$$N_i^0(t) = \begin{cases} 1, & \text{if } i-1 \leq t < i \\ 0, & \text{otherwise} \end{cases}$$



$$N_i^d(t) = \frac{t - (i-1)}{(i+d-1) - (i-1)} N_i^{d-1}(t) + \frac{(i+d) - t}{(i+d) - (i)} N_{i+1}^{d-1}(t)$$



# B-Splines

## Constructing a Spline Curve:

- Choose a degree  $d$ .
- Choose a *knot sequence*  $(t_0, t_1, \dots, t_n)$  with  $t_0 \leq t_1 \leq \dots \leq t_n$  ( $n \geq d - 1$ )
- Choose control points  $\mathbf{p}_0, \mathbf{p}_1, \dots, \mathbf{p}_m$  ( $m = n - d + 1$ )
- Form the spline curve:

$$\mathbf{f}(t) = \sum_{i=0}^n N_i^d(t) \mathbf{p}_i$$

## De Boor Algorithm:

- This evaluation can be expanded explicitly...



# De Boor Algorithm

$$\begin{aligned}
 f(t) &= \sum_{i=0}^n N_i^d(t) \mathbf{p}_i \\
 &= \sum_{i=0}^n \left( \frac{t - t_{i-1}}{t_{i+d-1} - t_{i-1}} N_i^{d-1}(t) \right) \mathbf{p}_i + \sum_{i=0}^n \left( \frac{t_{i+d} - t}{t_{i+d} - t_i} N_{i+1}^{d-1}(t) \right) \mathbf{p}_i \\
 &= \sum_{i=0}^n \left( \frac{t - t_{i-1}}{t_{i+d-1} - t_{i-1}} N_i^{d-1}(t) \right) \mathbf{p}_i + \sum_{i=1}^{n+1} \left( \frac{t_{i-1+d} - t}{t_{i+d-1} - t_{i-1}} N_i^{d-1}(t) \right) \mathbf{p}_{i-1} \\
 &= \sum_{i=0}^{n+1} \left( \left[ \frac{t - t_{i-1}}{t_{i+d-1} - t_{i-1}} N_i^{d-1}(t) \right] \mathbf{p}_i + \left[ \frac{t_{i-1+d} - t}{t_{i+d-1} - t_{i-1}} N_i^{d-1}(t) \right] \mathbf{p}_{i-1} \right) \\
 &= \sum_{i=0}^{n+1} \frac{(t - t_{i-1}) \mathbf{p}_i + (t_{i-1+d} - t) \mathbf{p}_{i-1}}{t_{i+d-1} - t_{i-1}} N_i^{d-1}(t) \quad \mathbf{p}_i^1 := \frac{(t - t_{i-1}) \mathbf{p}_i + (t_{i-1+d} - t) \mathbf{p}_{i-1}}{t_{i+d-1} - t_{i-1}} \\
 &= \sum_{i=0}^{n+1} N_i^{d-1}(t) \mathbf{p}_i^1
 \end{aligned}$$

# De Boor Algorithm

$$\begin{aligned} f(t) &= \sum_{i=0}^{n+1} N_i^{d-1}(t) \mathbf{p}_i^{(1)} \\ &= \sum_{i=0}^{n+j} N_i^{d-1-j}(t) \mathbf{p}_i^{(j)} \quad \text{with: } \mathbf{p}_i^{(j)} = \frac{(t - t_{i-1})}{t_{i+d-j-1} - t_{i-1}} \mathbf{p}_i^{(j-1)} + \frac{(t_{i-1+d-j} - t)}{t_{i+d-j-1} - t_{i-1}} \mathbf{p}_{i-1}^{(j-1)} \\ &= \sum_{i=0}^{n+d} N_i^0(t) \mathbf{p}_i^{(d)} \end{aligned}$$

**This means:**

- For  $t \in [t_{i-1}, \dots, t_i]$ , we obtain the function value  $f(t)$ .
- We can write this as an algorithm...

# De Boor Algorithm

## De Boor Algorithm:

- We want to evaluate  $f(t)$  for a  $t \in [t_{i-1}, \dots, t_i]$
- We compute:

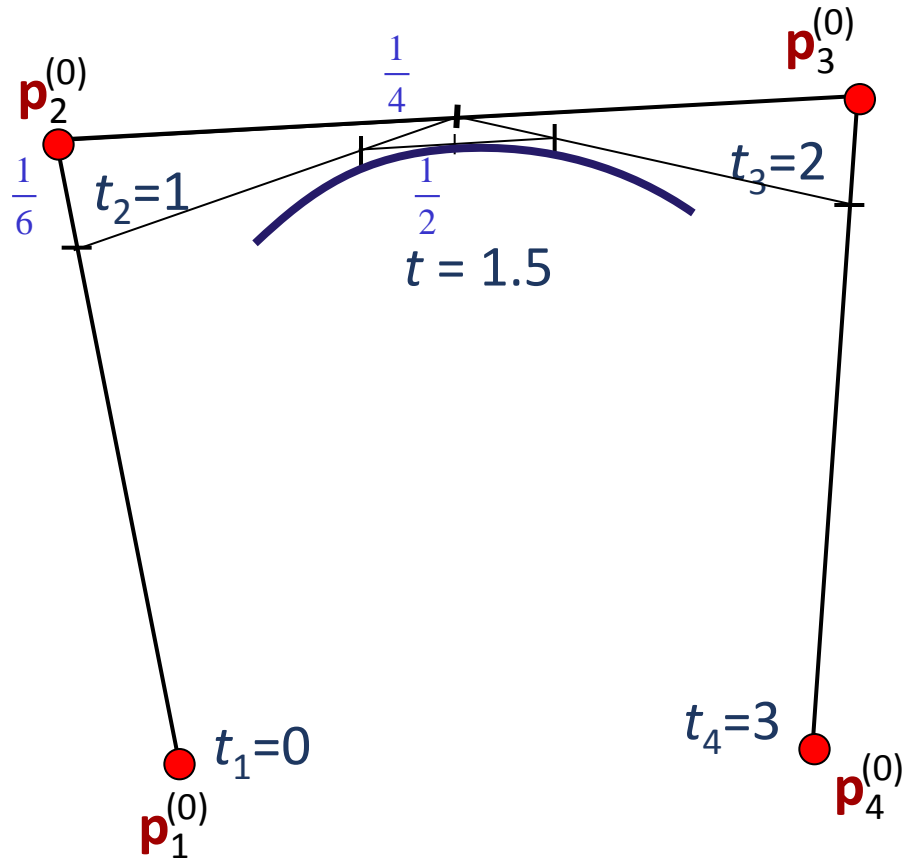
$$\mathbf{p}_i^{(0)} = \mathbf{p}_i$$

For increasing  $j$ :

$$\begin{aligned}\mathbf{p}_i^j(t) &= \frac{(t - t_{i-1})}{t_{i+d-j-1} - t_{i-1}} \mathbf{p}_i^{j-1}(t) + \frac{(t_{i-1+d-j} - t)}{t_{i+d-j-1} - t_{i-1}} \mathbf{p}_{i-1}^{j-1}(t) \\ &= \alpha_i^{(j)} \mathbf{p}_i^{j-1}(t) + (1 - \alpha_i^{(j)}) \mathbf{p}_{i-1}^{j-1}(t), \quad \alpha_i^{(j)} = \frac{(t - t_{i-1})}{t_{i+d-j-1} - t_{i-1}}\end{aligned}$$

Output  $\mathbf{p}_i^{d-1}(t)$

# Example



$$\mathbf{p}_i^{(0)} = \mathbf{p}_i$$

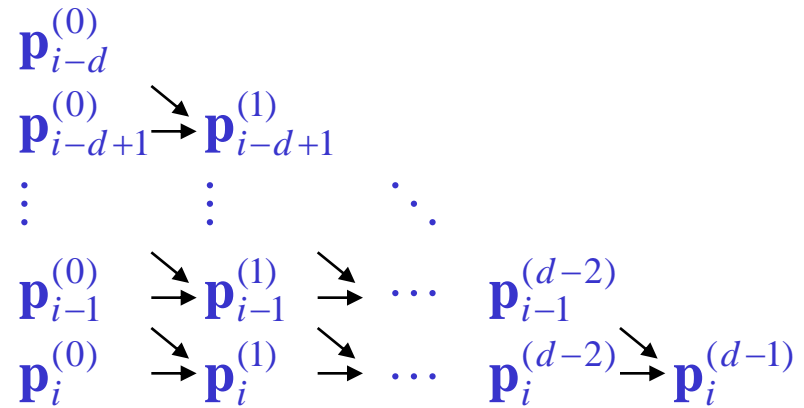
For increasing  $j$ :

$$\begin{aligned} \mathbf{p}_i^j(t) &= \frac{(t - t_{i-1})}{t_{i+d-j-1} - t_{i-1}} \mathbf{p}_i^{j-1}(t) + \frac{(t_{i-1+d-j} - t)}{t_{i+d-j-1} - t_{i-1}} \mathbf{p}_{i-1}^{j-1}(t) \\ &= \alpha_i^{(j)} \mathbf{p}_i^{j-1}(t) + (1 - \alpha_i^{(j)}) \mathbf{p}_{i-1}^{j-1}(t), \quad \alpha_i^{(j)} = \frac{(t - t_{i-1})}{t_{i+d-j-1} - t_{i-1}} \end{aligned}$$

Output  $\mathbf{p}_i^{d-1}(t)$

# Data Flow

## Data Flow:



# De Boor Algorithm

## Some nice properties:

- $\mathbf{p}_i^j(t) = \alpha \mathbf{p}_i^{j-1}(t) + (1 - \alpha) \mathbf{p}_{i-1}^{j-1}(t)$  (for some  $\alpha$ )
- The algorithm forms only convex combinations of the original data points.
  - Affine invariance follows directly
  - Numerically stable – no cancelation or error amplification problems
  - Much better than transforming to monomial basis
  - But slower:  $O(d^2)$  instead  $O(d)$  multiplications with Horner scheme in monomial basis

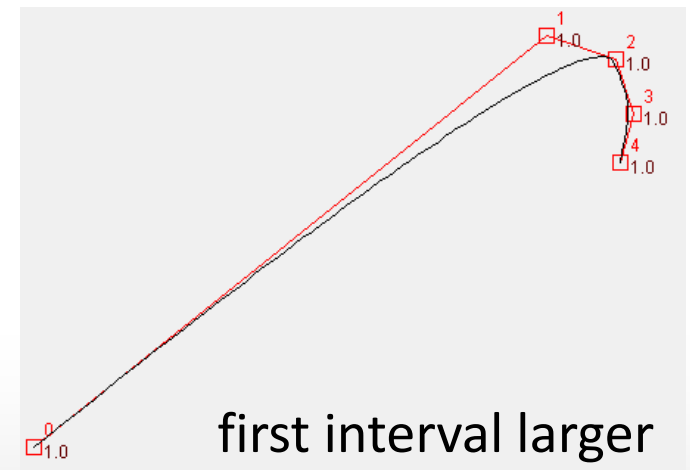
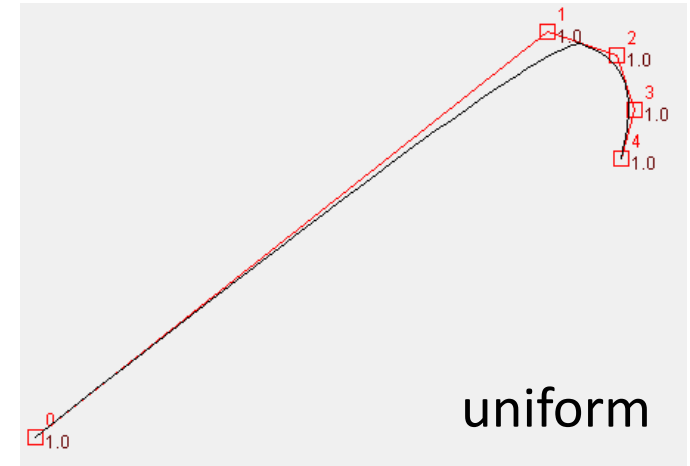
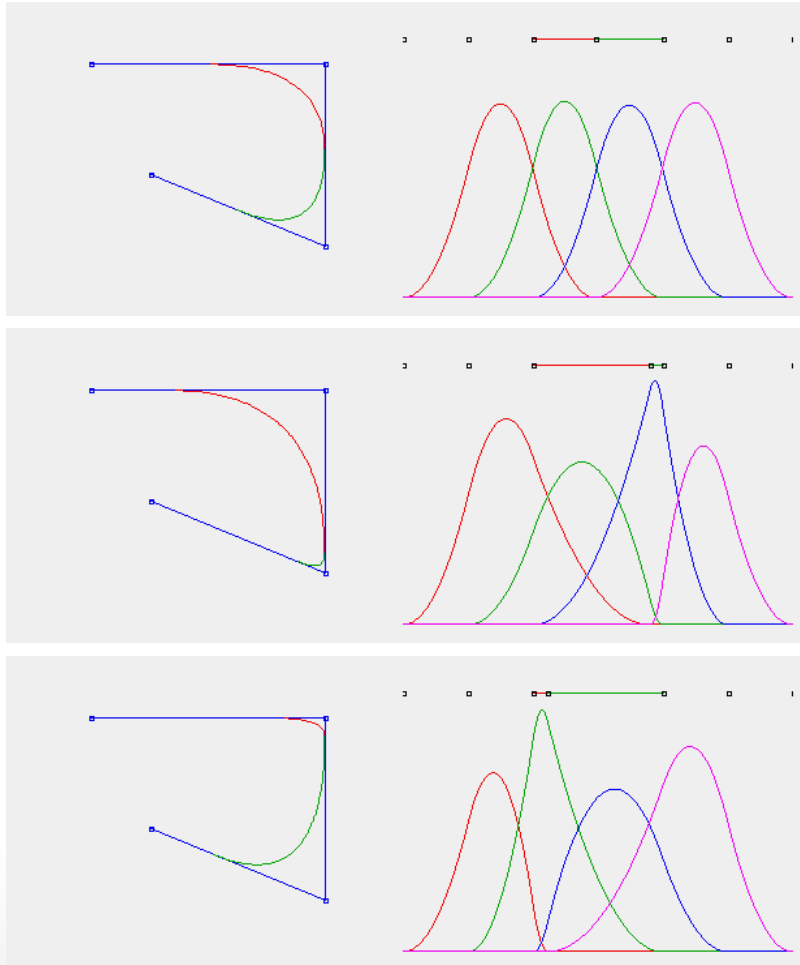
# Benefits of Non-Uniform B-Splines

## Improvements over the uniform case:

- We can choose the parameter intervals freely
  - Typically: Use distance between control points as knot distance
  - Allows better adaptation to distance between control points
  - Curves tend to “overshoot” less (in particular: problem for B-Spline interpolation; no convex hull property there)
  - Achieve more uniform speed for applications in animation
- No irregularities
  - Reduced smoothness, start/end conditions build into the computed bases
  - Advantages for rendering (no stopping at sharp corners)

# Examples

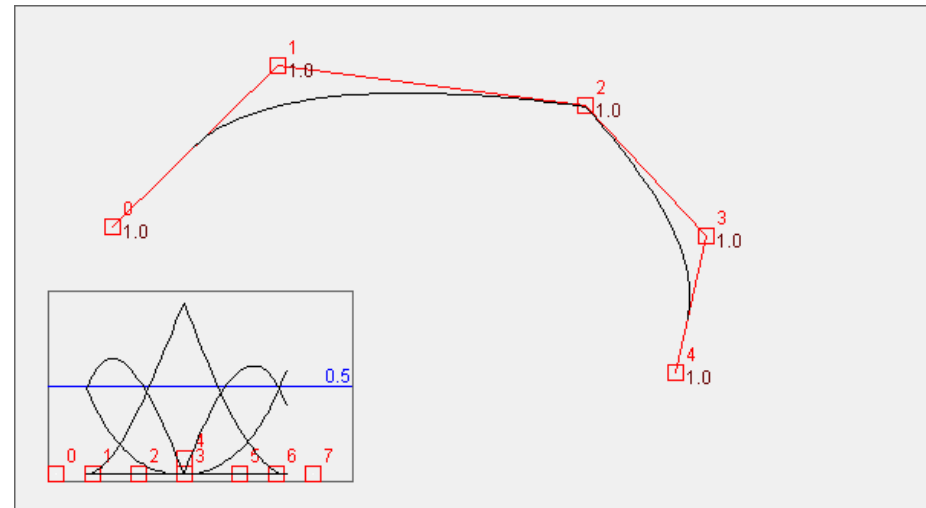
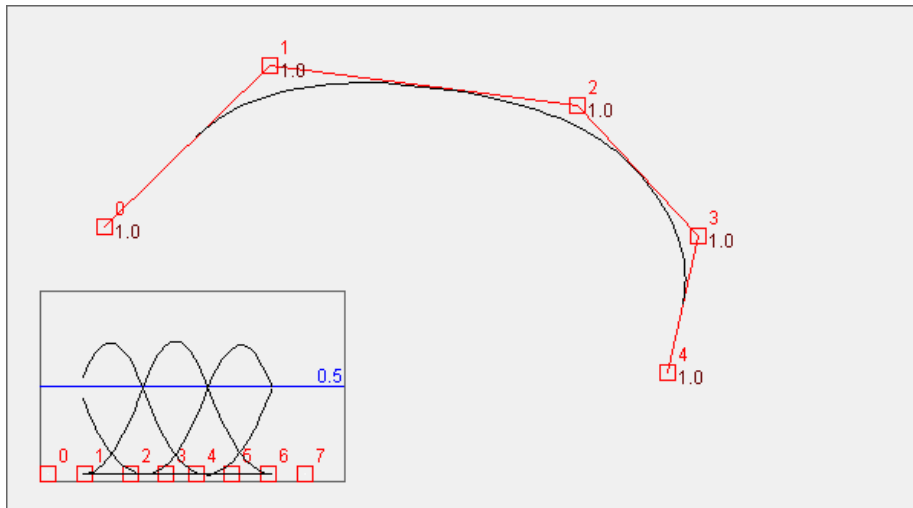
## The effect of parameter spacing:





# Examples

## Multiplying Knots



# A Closer Look at B-Splines

## Need some more tools & properties:

- Proof various properties
- Operations: Knot insertion, degree elevation, etc.
- Convert to alternative bases (e.g. Bezier, monomials)

## Problem:

- Indexing nightmare
- We need a better formalism to understand what's really going on: blossoming & polars
- We will look at that tool first, then go into the details again