#### CS 370 - Numerical Computation

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# Interpolation

Lecturer: Christopher Batty

Notes By: Harsh Mistry

The basic problem of Interpolation is, Given a set of data points from an (unknown) function y = p(x), can we approximate p's value at other points

## 2.1 Uses for Interpolation

- Fitting curves to data. (Related to Regression)
- Estimating an unknown function's properties: values, derivatives, etc
- Interpolation plays a role in many numerical methods such as differentiation, integration, differential equations, optimization, etc

## 2.2 Linear Interpolation

- The simplest form of interpolation, given two points, find a line that best fits the points.
- Calculate the slope between two points and produce a line equation y = ax + b
- Linear interpolation breaks down when attempting to generalize solutions with more than 2 points

# 2.3 Polynomial Interpolation

**Theorem 2.1** Unisolvence Theorem - Given n data pairs  $(x_i, y_i)$ , i = 1, ..., n with distinct  $x_i$ , there is a unique polynomial p(x) of degree  $\leq n-1$  that interpolates the data.

• For n points, we must find all coefficients of the polynomial

$$p(x) = c_1 + c_2 x + \ldots + c_n x^{n-1}$$

• As before, each  $(x_i, y_i)$  point gives one linear equation

$$y_i = c_1 + c_2 x_i + \ldots + c_n x_i^{n-1}$$

- Then solve the n x n linear system which should yield  $V\vec{c} = \vec{y}$
- $\bullet$  V is called a Vandermonde Matrix

Note: 
$$detV = \prod_{i < j} (x_i - x_j)$$

## 2.4 The Monomial Basis

 $p(x) = c_1 + c_2 x + \ldots + c_n x^{n-1}$  is called the monomial form and can be rewritten as

$$p(x) = \sum_{i=1}^{n} c_i x^{i-1}$$

The sequence  $1, x, x^2, x^3$  ... is called the monomial basis. Monomial form is a sum of coefficients  $c_i$  times these basis functions.

## 2.5 The Lagrange Basis

- The Lagrange basis is a different basis for interpolating polynomials.
- We define the Lagrange basis functions  $L_k(x)$ , to construct a polynomial as

$$p(x) = y_1 L_1(x) + y_2 L_2(x) + \ldots + y_n L_n(x) = \sum_{k=1}^{n} y_k L_k(x)$$

where  $y_i$  are coefficients

• Given n data points  $(x_i, y_i)$ , we define

$$L_k(x) = \frac{(x - x_1)(\dots)(x - x_{k-1})(x - x_{k+1})(\dots)(x - x_n)}{(x_k - x_1)(\dots)(x_k - x_{k-1})(x_k - x_{k+1})(\dots)(x_k - x_n)}$$

#### 2.5.1 Why?

We may perfer the Lagrange basis as we can directly write down the polynomial from the Lagrange basis functions,  $L_k$ , and the data points,  $x_i, y_i$ . There is no need to solve a linear system.

# 2.6 Runge's Phenomenon

When involving a polynomial with a high degree, we often are left with excessive oscillation and wiggling. This is called Runge's Phenomenon.

### 2.6.1 Avoiding the Phenomenon

- Select data/interpolation points in a *smarter* way
- Fit even higher degree polynomials, but also constrain derivatives to somehow reduce wiggliness
- Fit lower degree polynomials that don't exactly interpolate, but do minimize some error measure
- Or use piecewise polynomials

# 2.7 Piecewise Functions and Interpolation

- As we know, piecewise functions are functions with different definitions for distinct intervals of the domain
- One option of Piecewise Interpolation, is to continually apply Liner Interpolation for each set of points, but this can result in an some what unsatisfactory interpolation which may have kinks
- The goal is to achieve smoothness because its beneficial for aesthetic purposes and for mathematical applications needing derivatives

# 2.8 Hermite Interpolation

- Greater smoothness requires controlling derivatives of the polynomial.
- Hermite Interpolation is the problem of fitting a polynomial given function values and derivatives.

#### 2.8.1 Closed-form solution

If we define the Polynomial on the  $i^{th}$  interval,  $p_i(x)$  as

$$p_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3$$

there exist direct formulas for polynomial coefficients

- $\bullet \ a_i = y_i$
- $b_i = S_i$
- $\bullet \ c_i = \frac{3y_i' 2S_i S_{i+1}}{\Delta x_i}$
- $d_i = \frac{S_{i+1} + S_i 2y_i'}{\Delta x_i^2}$

where we define

- $\bullet \ \Delta x_i = x_{i+1} x_i$
- $y_i' = \frac{y_{i+1} y_i}{\Delta x_i}$

**Definition 2.2** Knots: Points where the interpolate transitions from one polynomial/to another

**Definition 2.3** Nodes: Points where some control points/data is specified

For hermite interpolation, these two points are the same, but they can differ for other curves

# 2.9 Cubic Splines

Fit a cubic,  $S_i(x)$  on each interval, but now require matching first and second derivatives between intervals Require "interpolating conditions" on each interval

$$S_i(x_i) = y_i,$$
  $S_i(x_{i+1}) = y_{i+1}$ 

and "derivative conditions" at each interior point  $x_{i+1}$ 

$$S_i'(x_{i+1}) = S_{i+1}'(x_{i+1})$$

$$s_i''(x_{i+1}) = s_{i+1}''(x_{i+1})$$

### 2.9.1 Boundary Conditions

- Clamped/complete- endpoints have slope set to set value
- Free/Natural/Variational "curvature" goes to zero at the end points, so the curve "straightens out"
- Periodic Boundary Conditions start and end derivatives match each other, which gives a "wrap-around" type behaviour
- "Not-a-Knot" boundary conditions Last two segments on an end become the same polynomial

#### 2.9.2 Hermite v.s. Cubic Splines

- Hermite Interpolation each interpolant can be found independently
  - Solve n-1 separate systems of 4 equations
- Cubic Spline must solve for all polynomials together at once!
  - Solve one system with 4(n-1) equations

# 2.10 Spline Energy

There is an mathematical relationship between physical splines and cubic splines.

Bending a spline by placing the "drafting ducks" introduces some stored potential energy (the bending energy)

#### 2.10.1 Real spline energy

The shape of a spline will find the minimum snergy configuration. (The least smooth shape)

Mathematical splines also minimize an "energy". i.e a measure of the total amount of curvature

### 2.10.2 Strategies for smooth curves

- Hermite Interpolation
  - Given values and slopes
  - Separate solve per interval
  - Continuous 1st derivatives
- Cubic spline interpolation
  - Given values only
  - One big solve for all coeffs.
  - Continuous 1st an 2nd derivatives

#### 2.10.3 Size and Cost

- Naive cubic spline system has matrix size  $(4n-4)^2$  for n points
- Basic algorithms for linear systems take  $O(N^3)$  time for N unknowns

#### 2.10.4 Cublic splines via Hermite Interpolation

Strategy: Use hermite interpolation as a stepping stone to build a cubic spline

- 1. Express unknown polys with closed form hermite equations
- 2. Treat  $s_i$  (slopes at nodes) as unknowns
- 3. Solve  $s_i$  that give continuous 2nd derivatives
- 4. Give  $s_i$  plug into closed form Hermite equations to recover polynomial coefficients:  $a_i, b_i, c_i, d_i$