

CSE276C - Interpolation and Approximation

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Outline

- 
- 1 Introduction
 - 2 Linear Interpolation
 - 3 Cubic Spline Interpolation
 - 4 Multi-variate interpolation
 - 5 Kringing Interpolation
 - 6 Summary

Material

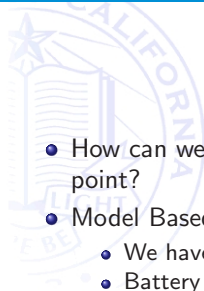


- Numerical Recipes: Chapter 3
- Math for ML: Chapter 9

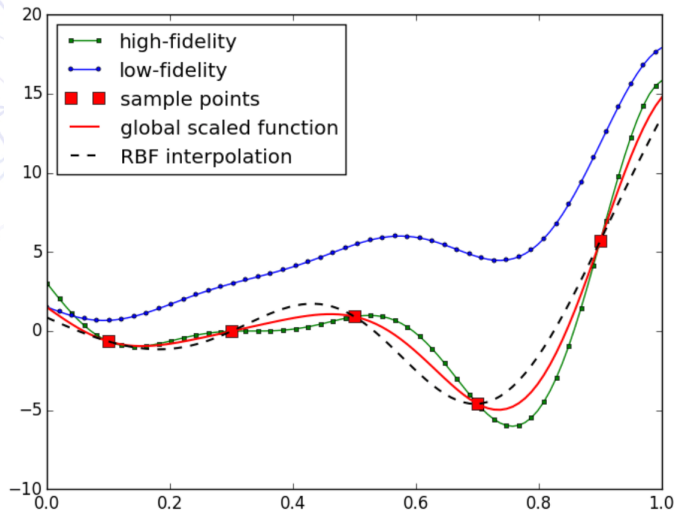
Objective

- How can we find an approximation / interpolation based on a set of data point?

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- How can we find an approximation / interpolation based on a set of data point?
 - Model Based
 - We have domain knowledge that can be used
 - Battery recharge
 - Dynamic Model of Drive System
 - Material properties for grasping
 - Data Driven
 - All we have is the data (and possible constraints)
 - Driving in traffic, Painting, ...

Example



Weierstrass Approximation Theorem



Weierstrass Approx. Theorem

If f is a continuous function on the finite closed interval $[a, b]$ then for every $\epsilon > 0$ there is a polynomial $p(x)$ (whose degree and coefficients depend on ϵ) such that

$$\max_{x \in [a, b]} |f(x) - p(x)| < \epsilon$$

- This is wonderful right?

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- This is wonderful right?
- He does not prescribe a strategy to derive $p(x)$!

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Linear interpolation

- Lets start with a single variable case
 - We have a set $D = (x_i, f(x_i)) \ i \in \{0, \dots, n\}$
- Connecting adjacent points by line segment

$$p(x) = f(x_i) + \frac{f(x_{i+1}) - f(x_i)}{x_{i+1} - x_i}(x - x_i)$$

$$x \in [x_i, x_{i+1}]$$

- consider it a baseline for other approaches

Lagrange interpolation

- Could we fit an n 'th order polynomial through $n+1$ data points:
 $(x_i, y_i) \ i \in \{0, \dots, n\}$
- Could be done recursively or in a batch form.
- Batch solution is estimating $n+1$ coefficient using $n+1$ simultaneous equations

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- Interpolation polynomial

$$p(x) = a_0 + a_1x + a_2x^2 + \dots + a_nx^n$$

- For each data point we have the equation

$$y_i = a_0 + a_1x_i + a_2x_i^2 + \dots + a_nx_i^n$$

- in matrix form

Lagrange interpolation (cont)

- In matrix form we have

$$\begin{pmatrix} 1 & x_0 & x_0^2 & x_0^3 & \dots & x_0^n \\ 1 & x_1 & x_1^2 & x_1^3 & \dots & x_1^n \\ & & & \vdots & & \\ 1 & x_n & x_n^2 & x_n^3 & \dots & x_n^n \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{pmatrix} = \begin{pmatrix} y_0 \\ y_1 \\ \vdots \\ y_n \end{pmatrix}$$

- or

$$\mathbf{V} \mathbf{x} = \mathbf{y}$$

where \mathbf{V} is referred to as a vandermonde matrix.

- Unfortunately the system is frequently poorly conditioned

Lagrange polynomial interpolation

- Consider the n^{th} degree polynomial factored
- The classic Lagrange formula

$$\begin{aligned} p(x) = & \frac{(x-x_1)(x-x_2)\dots(x-x_n)}{(x_0-x_1)(x_0-x_2)\dots(x_0-x_n)} y_0 + \\ & \frac{(x-x_0)(x-x_2)\dots(x-x_n)}{(x_1-x_0)(x_1-x_2)\dots(x_1-x_n)} y_1 + \\ & \dots \\ & \frac{(x-x_0)(x-x_2)\dots(x-x_{n-1})}{(x_n-x_0)(x_n-x_1)\dots(x_n-x_{n-1})} y_n + \end{aligned}$$

- or

$$y_k L_k(x_k) = y_k L_k(x)$$

$$L_k(x) = \prod_{\substack{i=0 \\ i \neq k}}^n \frac{x - x_i}{x_k - x_i}$$

note

$$L_k(x_i) = \delta_{ik} = \begin{cases} 1 & k = i \\ 0 & i \neq k \end{cases}$$

Lagrange polynomial interpolation (cont)

- The resulting polynomial is

$$p(x) = \sum_{k=0}^n y_k L_k(x)$$

- A polynomial that passed through all the data points

LPI - Example

- Lets try to show this for

$$f(x) = (x - 1)^2$$

- Assume we have two data points $(0,1)$ and $(1,0)$.
- This results in $a_0 = 1$ and $a_1 = 0$.
- As $a_1 = 0$ we only have to consider

$$L_0(x) = \frac{x - x_1}{x_1 - x_0} = \frac{x - 1}{0 - 1} = -x + 1$$

or

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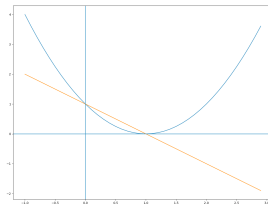
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or

$$p(x) = -x + 1$$



LPI - Example (cont)

- Lets add an additional data point $(-1, 4)$

$$x_0 = 0 \quad a_0 = 1$$

$$x_1 = 1 \quad a_1 = 0$$

$$x_2 = -1 \quad a_2 = 4$$

So

$$L_0(x) = \frac{x-x_1}{x_0-x_1} \frac{x-x_2}{x_0-x_2} = -(x-1)(x+1)$$

$$L_1(x) = \frac{x-x_0}{x_1-x_0} \frac{x-x_2}{x_1-x_2} = \text{Don't care}$$

$$L_2(x) = \frac{x-x_0}{x_2-x_0} \frac{x-x_1}{x_2-x_1} = \frac{1}{2}x(x-1)$$

LPI - Example (cont)

- Putting it all together

$$\begin{aligned} p(x) &= a_0 L_0(x) + a_1 L_1(x) + a_2 L_2(x) \\ &= -(x-1)(x+1) + 2x(x-1) \\ &= (x-1)(-x-1+2x) \\ &= (x-1)(x-1) = (x-1)^2 \end{aligned}$$

LPI - Example (cont)

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- The approximation is exact
- For large dataset Lagrange can be a challenge
- Meandering between data-points can become significant

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Cubic spline interpolation

- Smoothing w. constraints
- Limiting higher order gradients (say acceleration, curvature, ...)

$$f'''' = 0$$

$$f''' = c_1$$

$$f'' = c_1x + c_2$$

$$f' = \frac{c_1}{2}x^2 + c_2x + c_3$$

$$f = \frac{c_1}{6}x^3 + \frac{c_2}{2}x^2 + c_3x + c_4$$

Setting it up

- Assume you have tabulated values $y_i = y(x_i)$ for $i = 0 \dots n - 1$
- With linear interpolation we can do

$$y = Ay_j + By_{j+1}$$

for a point between x_j and x_{j+1} where

$$A = \frac{x_{j+1} - x}{x_{j+1} - x_j} \quad B = 1 - A = \frac{x - x_j}{x_{j+1} - x_j}$$

so think of them as special cases of Lagrange

- if we further assume we have access to values of y'' we can do a cubic expansion

Cubic interpolation

- We can expand the interpolation

$$y = Ay_j + By_{j+1} + Cy_j'' + Dy_{j+1}''$$

where A and B are as defined earlier.

$$C = \frac{1}{6}(A^3 - A)(x_{j+1} - x_j)^2 \quad D = \frac{1}{6}(B^3 - B)(x_{j+1} - x_j)^2$$

- If you differentiate (see NR sec 3.3) you get

$$\frac{d^2y}{dx^2} = Ay_j'' + By_{j+1}''$$

which translate into the tabulated values at x_j and x_{j+1} .

- The advantage of cubic is that only neighboring points are used estimation. A tridiagonal matrix can be used for the computations.

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What about multi-variate interpolation?

- Does this generalize to multiple dimensions?
- We frequently have multi-dimensional data in robotics
 - Image data, Lidar, radar, ...
- What if we had an m-dimensional Cartesian mesh of data points?

$$f(\vec{x}) = f(x_{1i}, x_{2j}, x_{3k}, \dots, x_{mq})$$

- For linear interpolation the generalization is straight forward

Bilinear interpolation

- Consider

$$y_{ij} = y(x_{1i}, x_{2j})$$

- with point intervals $[x_{1i}, x_{1(i+1)}]$ and $[x_{2j}, x_{2(j+1)}]$
- values for ij

$$\begin{aligned} y_0 &= y_{ij} \\ y_1 &= y_{(i+1)j} \\ y_2 &= y_{(i+1)(j+1)} \\ y_3 &= y_{i(j+1)} \end{aligned}$$

Bilinear interpolation (cont)

- The bilinear interpolation is the simplest
- use

$$\begin{aligned}t &= \frac{x_1 - x_{1i}}{x_{1(i+1)} - x_{1i}} \\u &= \frac{x_2 - x_{2j}}{x_{2(j+1)} - x_{2j}}\end{aligned}$$

- then the interpolation is

$$y(x_1, x_2) = (1 - t)(1 - u)y_0 + t(1 - u)y_1 + tuy_2 + (1 - t)uy_3$$

- For a fair sized grid this generates “good” solutions.

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Kringing interpolation

- What if we consider the data generation by a stochastic process?
- Could we generate a maximum likelihood (ML) estimate?
- The data is a vector of samples from the process and we can compute the probability density estimate and parameters such as the mean
- Sometimes termed Gaussian Process Regression
- More generally we are trying to estimate

$$f(x) = \sum_{i=0}^N w_i \phi_i(x) = \vec{w} \Phi(\vec{x})$$

where w are weights and ϕ is a basis function.

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where w are weights and ϕ is a basis function.

- We can define a loss function

$$L(f, y)$$

- The expected loss is then

$$E[L] = \int \int L(f, y(x)) p(x, w) dx dw$$

- Our goal is now to minimize the $E[L]$, i.e. minimum loss or best fit

$$f = E(y|x)$$

Basis functions

- We have multiple choices for basis functions
- Sometimes domain knowledge can provide suggestions
- Polynomial basis functions

$$\phi_i(x) = x_i$$

- Gaussian basis functions

$$\phi_i(x) = e^{-\frac{(x-x_i)^2}{2s}}$$

s controls scale / coverage

- Sigmoid basis functions

$$\phi_i(x) = \sigma\left(\frac{x - x_i}{s}\right)$$

where $\sigma(a) = \frac{1}{1+e^{-a}}$

Kringing interpolation - Gaussian Mixture

- For the Gaussian mixture we can use

$$p(f_i|x_i, w_i, \beta) = N(f_i|y(x_i), w_i, \beta)$$

- so that

$$p(f|X, w, \beta) = \prod_{i=0}^n N(f_i|w^T \phi(x_i), \beta^{-1})$$

or

$$\ln p() = \frac{n}{2} \ln(\beta) - \frac{n}{2} \ln(2\pi) - \beta E_D(w)$$

where

$$E_D(w) = \frac{1}{2} \sum_{i=0}^n (y_i - w_i^T \phi(x_i))^2$$

The sum of squared errors

LSQ solution

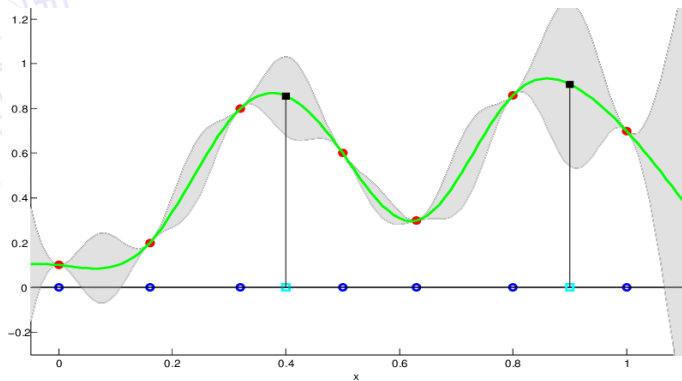
- We can compute

$$w_{ML} = (\Phi^T \Phi)^{-1} \Phi^T \vec{y}$$

where

$$\Phi = \begin{pmatrix} \phi_1(x_1) & \phi_2(x_1) & \dots & \phi_n(x_1) \\ \phi_1(x_2) & \phi_2(x_2) & \dots & \phi_n(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_1(x_n) & \phi_2(x_n) & \dots & \phi_n(x_n) \end{pmatrix}$$

Kringing example



Regularized Kringing

- We can use a regularized LSQ if we want to control the variation in w .
- Consider a revised error function

$$E' = E_D(w) + \lambda E_w(w)$$

say

$$E' = \frac{1}{2} \sum_i (y_i - w^T \phi(x_i))^2 + \frac{\lambda}{2} w^T w$$

which is minimized by

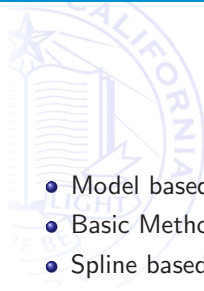
$$w = (\lambda + \Phi^T \Phi)^{-1} \Phi^T \vec{y}$$

as an example of how you can tweak the optimization / approximation

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Summary

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- Model based and data driven interpolation / approximation
 - Basic Methods (Linear)
 - Spline based interpolation
 - Uni- and Multi-Variate Approaches
 - Stochastic Models
 - Next time functional interpolation & approximation