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Outline

- Problem
- Breakdown of Cubic splines
- Splines Under Tension
- Examples
- Multi-dimensions
- Modern applications

Problem

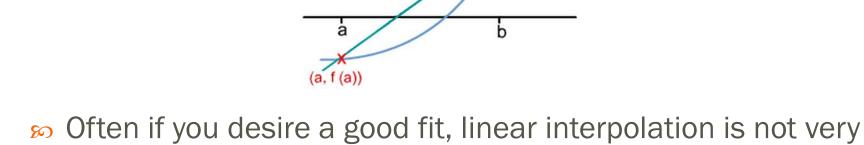
 ∞ Given a set of $\{x_i\}_{i=1}^n$, $\{y_i\}_{i=1}^n$ we seek to find a continuous function f which fits the data.

Why?

- Integrate the function
- Calculate intermediate points
- Etc

Cubic/Linear Splines

The simplest solution is to fit your data linearly between known points.



accurate.

Generally the most widely used solution is a cubic spline.

Cubic Splines

- Uses higher order polynomials to achieve continuity across intervals.
- Required to have information about the derivatives of the function at the boundaries.

$$y = Ay_i + By_{i+1} + Cy_i'' + Dy_{i+1}''$$

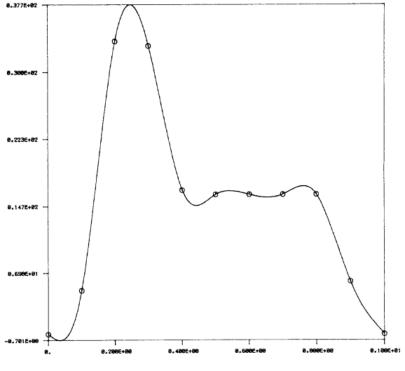
Need to find second order derivatives at the knots.

$$\underbrace{\frac{x_{j} - x_{j-1}}{6}}_{a_{j}} y_{j-1}'' + \underbrace{\frac{x_{j+1} - x_{j-1}}{3}}_{b_{j}} y_{j}'' + \underbrace{\frac{x_{j+1} - x_{j}}{6}}_{c_{j}} y_{j+1}'' = \underbrace{\frac{y_{j+1} - y_{j}}{x_{j+1} - x_{j}} - \frac{y_{j} - y_{j-1}}{x_{j} - x_{j-1}}}_{F_{j}}$$

$$\begin{bmatrix}
b_{1} & c_{1} & 0 & \cdots & 0 \\
a_{2} & b_{2} & c_{2} & & & \\
0 & \cdots & \ddots & \ddots & \ddots & \\
& & a_{j} & b_{j} & c_{j} & & \\
\vdots & & & \ddots & \ddots & \ddots & \\
& & & & a_{n-1} & b_{n-1} & c_{n-1} \\
0 & & \cdots & & & & & F_{n-1} \\
\end{bmatrix} \begin{bmatrix}
y_{1}'' \\ y_{2}'' \\ \vdots \\ y_{j}'' \\ \vdots \\ y_{n-1}'' \\ y_{n}''
\end{bmatrix} = \begin{bmatrix}
F_{1} \\ F_{2} \\ \vdots \\ F_{n-1} \\ F_{n}
\end{bmatrix}$$

Cubic Splines

- What are the potential problems with cubic splines?
 - Ringing!



Natural cubic spline

Cubic/Linear Splines

- What happens when one of the data points is a point of inflection (local max or min)?
 - Cubic spline interpolation breaks down i.e. cannot have continuous derivatives across a knot.
- One option is to break up the function into two intervals.
- Another option is to use splines under tension.

- Requires two continuous derivatives at the boundaries, and $f''(x) \sigma^2 f(x)$ to vary linearly on each of the intervals $x \in [x_i, x_{i+1}]$
- \bowtie Where σ is a constant tension factor.

$$f(x_i) = y_i \quad i = 1, \dots, n$$

$$f''(x) - \sigma^2 f(x) = [f''(x_i) - \sigma^2 y_i] \frac{(x_{i+1} - x)}{h_i} + [f''(x_{i+1}) - \sigma^2 y_{i+1}] \frac{(x - x_i)}{h_i}$$

$$h_i = x_{i+1} - x_i, \text{ for } i = 1, \dots, n-1$$

50 This may look similar to the linear interpolation scheme.

$$\begin{split} y &= Ay_i + By_{i+1} \\ y &= \frac{(x_{i+1} - x)}{(x_{i+1} - x_i)} y_i + \frac{(x - x_i)}{(x_{i+1} - x_i)} y_{i+1} \\ y &= \frac{(x_{i+1} - x)}{h_i} y_i + \frac{(x - x_i)}{h_i} y_{i+1} \\ f''(x) - \sigma^2 f(x) &= \left[f''(x_i) - \sigma^2 y_i \right] \frac{(x_{i+1} - x)}{h_i} + \left[f''(x_{i+1}) - \sigma^2 y_{i+1} \right] \frac{(x - x_i)}{h_i} \end{split}$$

- Mow do we solve the differential equation?
 - We start with a linear combination of the following basis functions

$$\{1, x, e^{\sigma x}, e^{-\sigma x}\}$$

 In various software packages it is often a different set of basis functions used to maintain numerical stability.

$$\left\{1, x, \cosh\left(\sigma\frac{(x_i - x)}{\Delta x}\right) - 1, \sinh\left(\sigma\frac{(x_i - x)}{\Delta x}\right) - \sigma\frac{(x_i - x)}{\Delta x}\right\}$$

Solving gives the following solution

$$\begin{split} f(x) &= \left[\frac{f''(x_i)}{\sigma^2}\right] \cdot \frac{\sinh\left(\sigma(x_{i+1} - x)\right)}{\sinh\left(\sigma h_i\right)} + \left[y_i - \frac{f''(x_i)}{\sigma^2}\right] \cdot \frac{(x_{i+1} - x)}{h_i} + \left[\frac{f''(x_{i+1})}{\sigma^2}\right] \cdot \frac{\sinh\left(\sigma(x - x_i)\right)}{\sinh\left(\sigma h_i\right)} \\ &+ \left[y_{i+1} - \frac{f''(x_{i+1})}{\sigma^2}\right] \cdot \frac{(x - x_i)}{h_i} \qquad \qquad for \ x \in [x_i, x_{i+1}] \end{split}$$

- This was achieved by solving the previous equation and using the fact that $f(x_i) = y_i$ i = 1, ..., n
- n order for this solution to work we need to know

$$f''(x_i)$$
 for $i = 1, ..., n$

By differentiating f and equating the right and left hand derivatives at x_i , f or i = 2, ..., n - 1 we obtain

$$\begin{split} \left[\frac{1}{h_i} - \frac{\sigma}{\sinh\left(\sigma h_{i-1}\right)}\right] \cdot \frac{f''(x_{i-1})}{\sigma^2} + \left[\frac{\sigma \cosh\left(\sigma h_{i-1}\right)}{\sinh\left(\sigma h_{i-1}\right)} - \frac{1}{h_{i-1}} + \frac{\sigma \cosh\left(\sigma h_{i}\right)}{\sinh\left(\sigma h_{i}\right)} - \frac{1}{h_i}\right] \cdot \frac{f''(x_i)}{\sigma^2} \\ + \left[\frac{1}{h_i} - \frac{\sigma}{\sinh(\sigma h_i)}\right] \cdot \frac{f''(x_{i+1})}{\sigma^2} = \frac{(y_{i+1} - y_i)}{h_i} - \frac{(y_i - y_{i-1})}{h_{i-1}} \end{split}$$

The last two equations can be obtained in two different ways depending on the behaviour desired for the function *f*.

The first set of conditions can be obtained given we know the first derivatives at the end points and that the first derivatives are equal at the knots.

$$\left[\frac{\sigma\cosh\left(\sigma h_1\right)}{\sinh\left(\sigma h_1\right)} - \frac{1}{h_1}\right] \cdot \frac{f^{\prime\prime}(x_1)}{\sigma^2} + \left[\frac{1}{h_1} - \frac{\sigma}{\sinh\left(\sigma h_1\right)}\right] \cdot \frac{f^{\prime\prime}(x_2)}{\sigma^2} = \frac{(y_2 - y_1)}{h_1} - y_1^\prime$$

$$\left[\frac{1}{h_{n-1}} - \frac{\sigma}{\sinh{(\sigma h_{n-1})}}\right] \cdot \frac{f''(x_{n-1})}{\sigma^2} + \left[\frac{\sigma \cosh{(\sigma h_{n-1})}}{\sinh{(\sigma h_{n-1})}} - \frac{1}{h_{n-1}}\right] \cdot \frac{f''(x_n)}{\sigma^2} = y_n' - \frac{(y_n - y_{n-1})}{h_{n-1}}$$

- 50 The second conditions are for a periodic function where some $x_{n+1} > x_n$, $y_1 = f(x_{n+1}), f'(x_1) = f'(x_{n+1}), and f''(x_1) = f''(x_{n+1})$
- 50 This results in the following two additional conditions

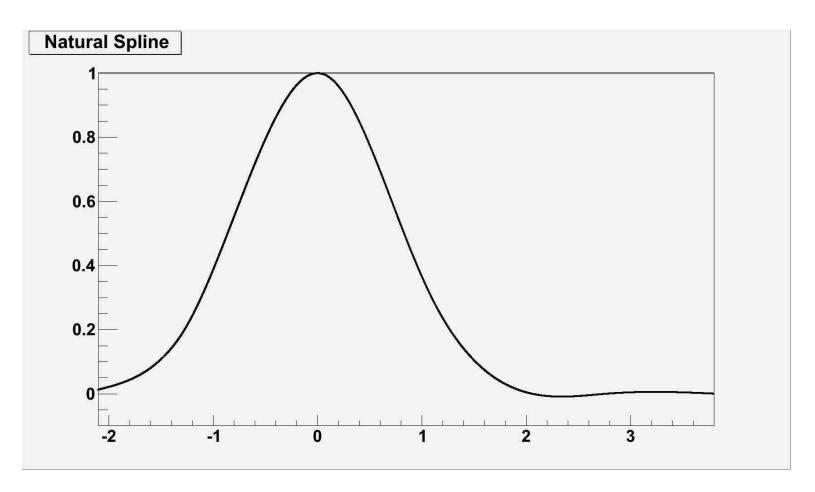
$$\left[\frac{1}{h_n} - \frac{\sigma}{\sinh\left(\sigma h_n\right)} \right] \cdot \frac{f''(x_n)}{\sigma^2} + \left[\frac{\sigma \cosh\left(\sigma h_n\right)}{\sinh\left(\sigma h_n\right)} - \frac{1}{h_n} + \frac{\sigma \cosh\left(\sigma h_1\right)}{\sinh\left(\sigma h_1\right)} - \frac{1}{h_1} \right] \cdot \frac{f''(x_1)}{\sigma^2} + \left[\frac{1}{h_1} - \frac{\sigma}{\sinh\left(\sigma h_1\right)} \right] \cdot \frac{f''(x_2)}{\sigma^2} = \frac{(y_2 - y_1)}{h_1} - \frac{(y_1 - y_n)}{h_n}$$

$$\begin{split} \left[\frac{1}{h_{n-1}} - \frac{\sigma}{\sinh\left(\sigma h_{n-1}\right)}\right] \cdot \frac{f''(x_{n-1})}{\sigma^2} + \left[\frac{\sigma \cosh\left(\sigma h_{n-1}\right)}{\sinh\left(\sigma h_{n-1}\right)} - \frac{1}{h_{n-1}} + \frac{\sigma \cosh\left(\sigma h_n\right)}{\sinh\left(\sigma h_n\right)} - \frac{1}{h_n}\right] \cdot \frac{f''(x_n)}{\sigma^2} \\ + \left[\frac{1}{h_n} - \frac{\sigma}{\sinh\left(\sigma h_n\right)}\right] \cdot \frac{f''(x_1)}{\sigma^2} = \frac{(y_1 - y_n)}{h_n} - \frac{(y_n - y_{n-1})}{h_{n-1}} \end{split}$$

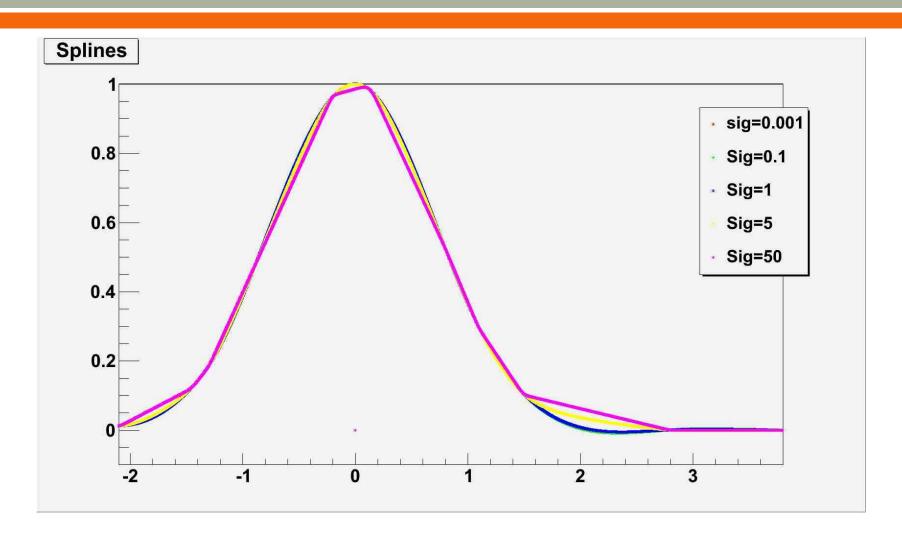
- Now that we have all the necessary conditions for f we can solve the linear tridiagonal matrix for the $f''(x_i)$'s using Gaussian elimination or any other preferred method.
- The tension factor has two extreme points worth noting.
 - \circ When $\sigma \to 0$ the curve is nearly identical to the cubic spline.
 - \circ When $\sigma \to \infty$ the curve is almost identical to the linear spline.

Examples: Non Periodic

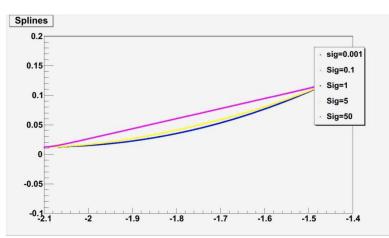
If we recall our old friend from assignment #1

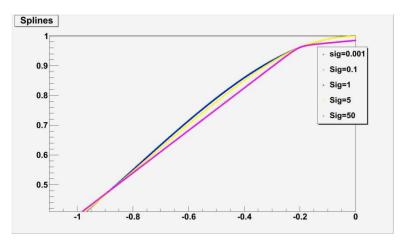


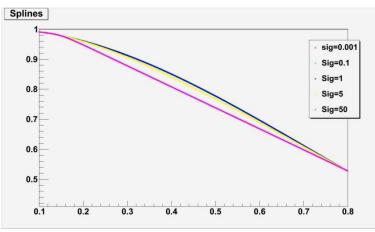
Examples: Non Periodic

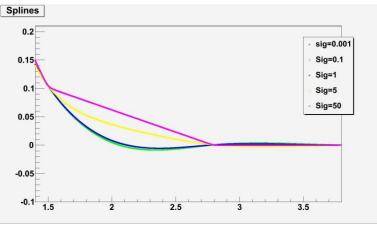


Examples: Non Periodic

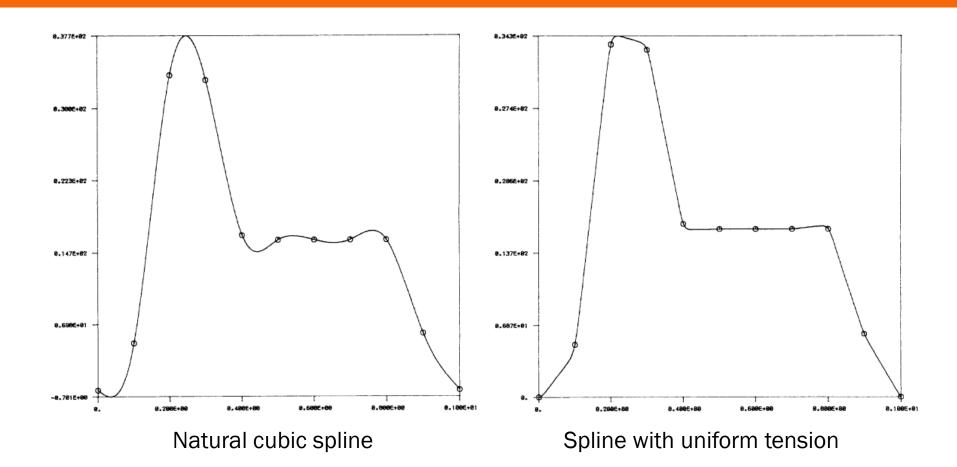








Examples: Ringing



Splines With Uniform Tension

- Fits data better than linear interpolation.
- Handles inflection points.
- Can get rid of ringing however, can lose the functions shape.

Mhat can we do to improve this?

- Tension factor options: constant, normalized in x, or varying over each interval.
- ∞ Constant tension factor is achieved simply $\sigma = k$
- Normalized tension factor given by $\sigma_i = \frac{\sigma}{(x_{i+1} x_i)}$
- Varying tension factors can be set using one of the three following criteria
 - By bound values of the function at given points
 - By bound values of the functions derivatives at given points
 - By concavity

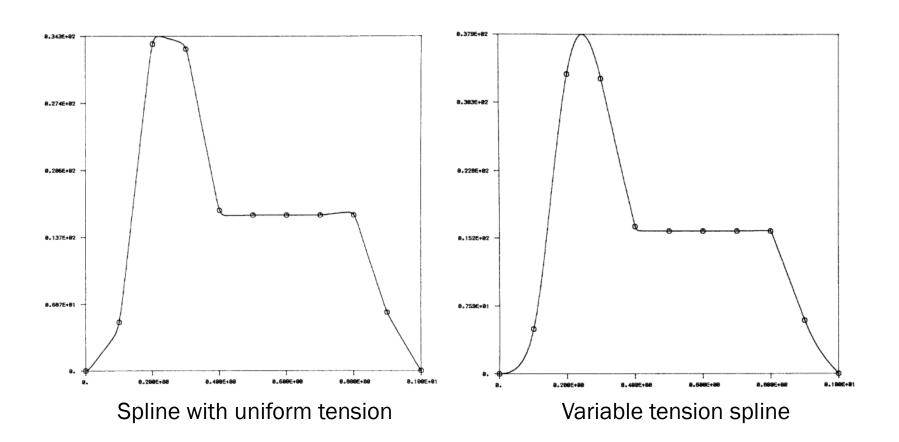
- ∞ Finding σ when f is bound.
 - To get the minimum tension factor required we need to find the zeros of f'.
 - \circ The form of σ can be found in [4]
- \wp Finding σ when f' is bound.
 - To get the minimum tension factor required we need to find the zeros of f".
 - \circ The form of σ can be found in [4]
- ∞ The equations for σ are complicated and not very enlightening to see and therefore are not shown.

In order to keep the convexity of f, if $d_1d_2>0$ then f is convex if $g(\sigma)>0$.

$$d_{1} = \frac{(y_{2} - y_{1})}{h_{1}} - y'_{1} \qquad d_{2} = y'_{2} - \frac{(y_{2} - y_{1})}{h_{1}}$$

$$g(\sigma) = \begin{cases} \sigma * \cosh (\sigma) / \sinh (\sigma) - 1 - \max \{d_{1}/d_{2}, d_{2}/d_{1}\} & \text{if } \sigma > 0, \\ 2 - \max \{d_{1}/d_{2}, d_{2}/d_{1}\} & \text{if } \sigma = 0. \end{cases}$$

- A proof can be found in [4]
- In order to minimize $g(\sigma)$ Newton's Method is used and results in an approximation of $\sigma = \sqrt{-10g(0)}$



- Preserves shape.
- Handles inflection points well.
- Relatively expensive to compute.

Multi-Dimensional Splines

- In general splines in multi-dimensions can become very complicated.
- There are several schemes out there and so I will briefly talk about one which I find useful.
- Thin Plate Splines (TPS) are a nice way of doing higher dimensions and has a nice pictorial analogy in 3D.

Multi-Dimensional Splines

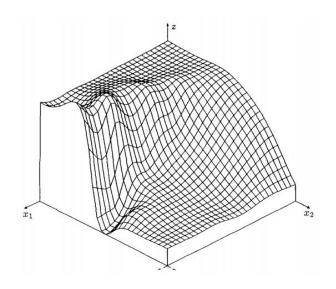
Given $\{w_{ij} = (x_i, y_j), i = 1, ..., N, j = 1, ..., M\}$ we can use a combination of radial basis function to specify where any point in between the given points.

$$f(\vec{x}) = \sum_{i=1}^{N} \sum_{j=1}^{M} c_{ij} \varphi(\vec{x} - w_{ij}) \qquad \qquad \varphi(r) = r^2 \log r$$

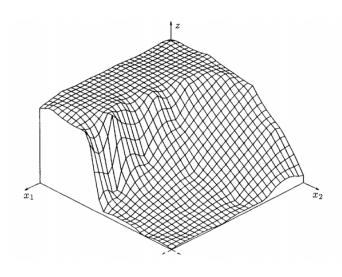
 \bowtie Minimize the "Energy", where λ is the tension parameter

$$\begin{split} E_{tps} &= \sum_{i=1}^{N} \sum_{j=1}^{M} \left| \left| x_{ij} - f(x_i, y_j) \right| \right| \\ &+ \lambda \iiint \left[\left(\frac{\partial^2 f}{\partial x^2} \right)^2 + \left(\frac{\partial^2 f}{\partial y^2} \right)^2 + \left(\frac{\partial^2 f}{\partial z^2} \right)^2 + 2 \left(\frac{\partial^2 f}{\partial x \partial y} \right)^2 + 2 \left(\frac{\partial^2 f}{\partial x \partial z} \right)^2 \right] \\ &+ 2 \left(\frac{\partial^2 f}{\partial y \partial z} \right)^2 \right] dx dy dz \end{split}$$

Multi-Dimensional Splines



TPS of 33 points with no tension

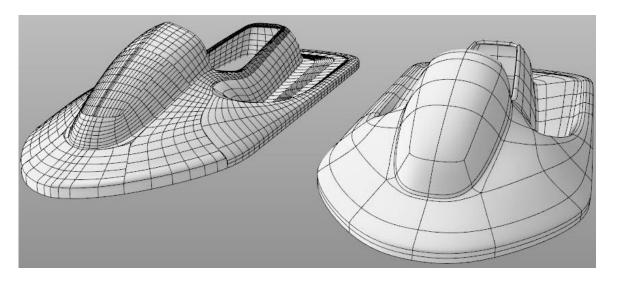


TPS of 33 points with no λ =45

Benefits: smooth with derivatives of any order and has no free parameters to be tuned manually.

Modern Applications

Designing of boat hulls.



Splines are used to model multiple complex shapes into bigger single watertight surfaces.

Modern Applications

- Image processing is an area that makes use of many different spline techniques.
 - Recovering images
 - Rendering low resolution images
- Architecture
 - Gives empirical form to free hand designs and organic structures
- Engineering
 - To do geometric designs as well as analysis such as fitting stressstrain curves.

Conclusion

- Splines under tension can handle points of inflection in the data set.
- Can avoid having a solution with ringing without the addition of more data points.
- Multi-Dimensional splines are only your friend when all else fails.
- Splines are heavily used in industry.

References

- [1] D. G. SCHWEIKERT, An interpolation curve using a spline in tension, J. Math. Phys., 45 (1966), pp.312-317.
- [2] A. K. CLINE, Scalar- and planar-valued curve fitting using splines under tension, Comm. ACM, 17 (1974), pp. 218-223.
- [3] H. MITASOVA, Interpolation by Regularized Spline with Tension:II. Application to Terrain Modeling and Surface Geometry Analysis, Math. Geo., 25, 6 (1993), pp. 657-669.
- [4] R.J. RENKA, Interpolator tension splines with automatic selection of tension factors. SIAM J. ScL. Stat. Comput. 8,3(May 1987),393-415.
- [5] G. DONATO, Approximate Thin Plate Spline Mappings, Ucsd Conference (2002) pp. 21-31.
- [6] http://en.wikipedia.org/wiki/Thin_plate_spline, March 22nd, 2011.
- [7] R.J. RENKA, Algorithm 716 TSPACK: Tension Spline Curve-Fitting Package, ACM Transactions on Mathematical Software, Vol. 19, No. 1, March 1993. Pages 81-94. [8] http://www.tsplines.com/, March 26th, 2011.

Follow up

- 50 1. Show how the interpolating function f(x) reduces to a cubic spline in the limit $\sigma \to 0$
- 2. Give some more details on the function $g(\sigma)$, ie does it have roots? If so, under what conditions? Does it have a local minimum? Or is it monotonic in sigma? Discuss why/whether the optimal sigma should be found by minimising or finding the roots of $g(\sigma)$.
- 50. Why do we choose the condition f"(x) σf(x) to be the thing that varies linearly? What are the advantages and disadvantages of this choice vs other possible choices?

$$\begin{split} f(x) &= \left[\frac{f''(x_i)}{\sigma^2}\right] \cdot \frac{\sinh\left(\sigma(x_{i+1} - x)\right)}{\sinh\left(\sigma h_i\right)} + \left[y_i - \frac{f''(x_i)}{\sigma^2}\right] \cdot \frac{(x_{i+1} - x)}{h_i} + \left[\frac{f''(x_{i+1})}{\sigma^2}\right] \cdot \frac{\sinh(\sigma(x - x_i))}{\sinh(\sigma h_i)} \\ &+ \left[y_{i+1} - \frac{f''(x_{i+1})}{\sigma^2}\right] \cdot \frac{(x - x_i)}{h_i} \\ f(x) &= \left[\frac{f''(x_i)}{\sigma^2}\right] \cdot \frac{\left[\left(\sigma(x_{i+1} - x) + \frac{(\sigma(x_{i+1} - x))^3}{3!} + \cdots\right)}{\left(\sigma h_i + \frac{(\sigma h_i)^3}{3!} + \cdots\right)}\right] + \left[y_i - \frac{f''(x_i)}{\sigma^2}\right] \cdot \frac{(x_{i+1} - x)}{h_i} + \left[\frac{f''(x_{i+1})}{\sigma^2}\right] \\ &\cdot \frac{\left[\left(\sigma(x - x_i) + \frac{(\sigma(x - x_i))^3}{3!} + \cdots\right)\right]}{\left(\sigma h_i + \frac{(\sigma h_i)^3}{3!} + \cdots\right)} + \left[y_{i+1} - \frac{f''(x_{i+1})}{\sigma^2}\right] \cdot \frac{(x - x_i)}{h_i} \end{split}$$

$$\begin{split} f(x) &= \left[\frac{f^{\prime\prime\prime}(x_i)}{\sigma^2}\right] \cdot \frac{\left[\left(\sigma(x_{i+1}-x) + \frac{\left(\sigma(x_{i+1}-x)\right)^3}{3!} + \cdots\right)\right]}{\left(\sigma h_i + \frac{\left(\sigma h_i\right)^3}{3!} + \cdots\right)} + \left[y_i - \frac{f^{\prime\prime\prime}(x_i)}{\sigma^2}\right] \cdot \frac{(x_{i+1}-x)}{h_i} + \left[\frac{f^{\prime\prime\prime}(x_{i+1})}{\sigma^2}\right] \\ &\cdot \left[\frac{\left(\sigma(x-x_i) + \frac{\left(\sigma(x-x_i)\right)^3}{3!} + \cdots\right)}{\left(\sigma h_i + \frac{\left(\sigma h_i\right)^3}{3!} + \cdots\right)}\right] + \left[y_{i+1} - \frac{f^{\prime\prime\prime}(x_{i+1})}{\sigma^2}\right] \cdot \frac{(x-x_i)}{h_i} \\ \\ &\left[\frac{f^{\prime\prime\prime}(x_i)}{\sigma^2}\right] \cdot \left[\frac{\left(\sigma(x_{i+1}-x) + \frac{\left(\sigma(x_{i+1}-x)\right)^3}{3!}\right)}{\left(\sigma h_i + \frac{\left(\sigma h_i\right)^3}{3!}\right)} - \frac{(x_{i+1}-x)}{\sigma^2 h_i}\right] \end{split}$$

$$[f''(x_i)] \cdot \left[\frac{\left(\sigma(x_{i+1} - x) + \frac{\left(\sigma(x_{i+1} - x)\right)^3}{3!}\right)}{\sigma^2\left(\sigma h_i + \frac{\left(\sigma h_i\right)^3}{3!}\right)} - \frac{(x_{i+1} - x)}{\sigma^2 h_i} \right]$$

$$[f''(x_i)] \cdot \left[\frac{\left(\sigma(x_{i+1} - x)\right)}{\left(\sigma^3 h_i + \frac{\sigma^5 h_i^{\ 3}}{3!}\right)} + \frac{\left(\sigma(x_{i+1} - x)\right)^3}{6\left(\sigma^3 h_i + \frac{\sigma^5 h_i^{\ 3}}{3!}\right)} - \frac{(x_{i+1} - x)}{\sigma^2 h_i} \right]$$

$$[f''(x_i)] \cdot \left[\frac{\left(\sigma(x_{i+1} - x)\right)}{\left(\sigma^3 h_i + \frac{\sigma^5 h_i^3}{3!}\right)} + \frac{\left(\sigma(x_{i+1} - x)\right)^3}{6\left(\sigma^3 h_i + \frac{\sigma^5 h_i^3}{3!}\right)} - \frac{(x_{i+1} - x)}{\sigma^2 h_i} \right]$$

$$[f''(x_i)] \cdot \left[\frac{\left(\sigma(x_{i+1} - x)\right)}{(\sigma^3 h_i + 0)} + \frac{\left(\sigma(x_{i+1} - x)\right)^3}{6(\sigma^3 h_i + 0)} - \frac{(x_{i+1} - x)}{\sigma^2 h_i} \right]$$

$$[f''(x_i)] \cdot \left[\frac{(x_{i+1} - x)}{\sigma^2 h_i} + \frac{(\sigma(x_{i+1} - x))^3}{6\sigma^3 h_i} - \frac{(x_{i+1} - x)}{\sigma^2 h_i} \right]$$

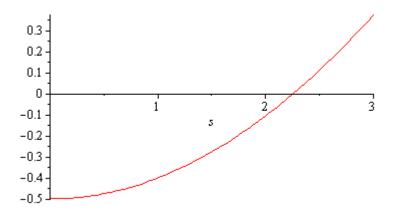
$$[f''(x_i)] \cdot \left[\frac{(x_{i+1} - x)^3}{6h_i} \right]$$

$$f(x) = \frac{(x_{i+1} - x)}{h_i} f(x_i) + \frac{(x - x_i)}{h_i} f(x_{i+1}) + \left[\left(\frac{(x_{i+1} - x)}{h_i} \right)^3 - \frac{(x_{i+1} - x)}{h_i} \right] h_i^2 \frac{f''(x_i)}{6} + \left[\left(\frac{(x - x_i)}{h_i} \right)^3 - \frac{(x - x_i)}{h_i} \right] h_i^2 \frac{f''(x_{i+1})}{6}$$

$g(\sigma)$

$$g(\sigma) = \begin{cases} \sigma * \cosh m(\sigma) / \sinh m(\sigma) - 1 - \max \{d_1/d_2, d_2/d_1\} & \text{if } \sigma > 0, \\ 2 - \max \{d_1/d_2, d_2/d_1\} & \text{if } \sigma = 0. \end{cases}$$

"A straightforward approach to proving this statement is extremely tedious and, since no alternative approach has been found, it remains an open question"



Alternative Derivations

$$f''(x) - \sigma^2 f(x) = 0$$

$$h^4(x) - \sigma^2 h''(x) = 0$$

$$f^{\prime\prime\prime\prime\prime}(x) - \sigma^2 f^{\prime\prime}(x) = 0$$