Interpolants, Error Bounds, and Mathematical Software for Modeling and Predicting Variability in Computer Systems



Chapters

- 1. The Importance and Applications of Variability
- 2. Algorithms for Constructing Approximations
- 3. Naive Approximations of Variability
- 4. Box-Splines: Uses, Constructions, and Applications
- 5. Stronger Approximations of Variability
- 6. An Error Bound for Piecewise Linear Interpolation
- 7. A Package for Monotone Quintic Spline Interpolation



$$\left| f(z) - \hat{f}(z) \right| \le \frac{\gamma \|z - x_0\|_2^2}{2} + \frac{\sqrt{d\gamma k^2}}{2\sigma_d} \|z - x_0\|_2$$



$$|f(z) - \hat{f}(z)| \le \frac{\gamma \|z - x_0\|_2^2}{2} + \frac{\sqrt{d\gamma k^2}}{2\sigma_d} \|z - x_0\|_2$$

The absolute error of a linear interpolant is tightly upper bounded by



$$|f(z) - \hat{f}(z)| \le \frac{\gamma ||z - x_0||_2^2}{\uparrow 2} + \frac{1}{2}$$

$$\frac{\|2}{2} + \frac{\sqrt{d\gamma k^2}}{2\sigma_d} \|z - x_0\|_2$$

19

/ 1

The absolute error of a linear interpolant is tightly upper bounded by

the max change in slope of the function



$$|f(z) - \hat{f}(z)| \le \frac{\gamma ||z - x_0||_2^2}{2} + \frac{\sqrt{d\gamma k^2}}{2\sigma_d} ||z - x_0||_2$$

The absolute error of a linear interpolant is tightly upper bounded by

the max change in slope of the function

times the distance to the nearest known point squared







$$\begin{split} \left| f(z) - \hat{f}(z) \right| &\leq \frac{\gamma \|z - x_0\|_2^2}{2} + \frac{\sqrt{d} \gamma k_*^2}{2\sigma_d} \|z - x_0\|_2 \\ \end{split}$$
The absolute error of a linear interpolant is tightly upper bounded by
the max change in slope
plus the square root of the dimension times the max change in slope
times the longest edge length between points defining the linear interpolant squared
the dimension times the max change in slope
times the longest edge length between points defining the linear interpolant squared







The Importance

The approximation error of a linear (simplicial) interpolant tends quadratically towards zero when approaching observed data only when the diameter of the simplex is also reduced proportionally.

In practice, only linear convergence to the true function can be achieved (because the evaluation points don't move).

Approximation error is largely determined by **data spacing**!

This theory only directly applies to Delaunay, but may give insight into the approximation behavior of other techniques.



Piecewise Linear Approximations

Delaunay (interpolant)

$$y = \sum_{i=0}^{d} w_i x^{(i)}, \quad \sum_{i=0}^{d} w_i = 1, \quad w_i \ge 0, \quad i = 0, \dots, d$$
$$\hat{f}(y) = \sum_{i=0}^{d} w_i f(x^{(i)})$$

Multilayer Perceptron (regressor)

$$l(u) = \left(u^t W_l + c_l\right)_+$$







Approximating $f(x) = \cos(||x||_2)$

In 2 dimensions, we get expected results. Delaunay is better at interpolation, MLP better at regression.



Approximating $f(x) = \cos(||x||_2)$

In 20 dimensions, the *intuitive* trend disappears! Delaunay and MLP look the same.



Explaining the Convergence



Connecting Back to Theory

$$|f(z) - \hat{f}(z)| \le \frac{\gamma ||z - x_0||_2^2}{2} + \frac{\sqrt{d\gamma k^2}}{2\sigma_d} ||z - x_0||_2$$



Connecting Back to Theory





Connecting Back to Theory



