

CS 3200

Introduction to Scientific Computing

Instructor: Martin Berzins

Topic: **Interpolation**

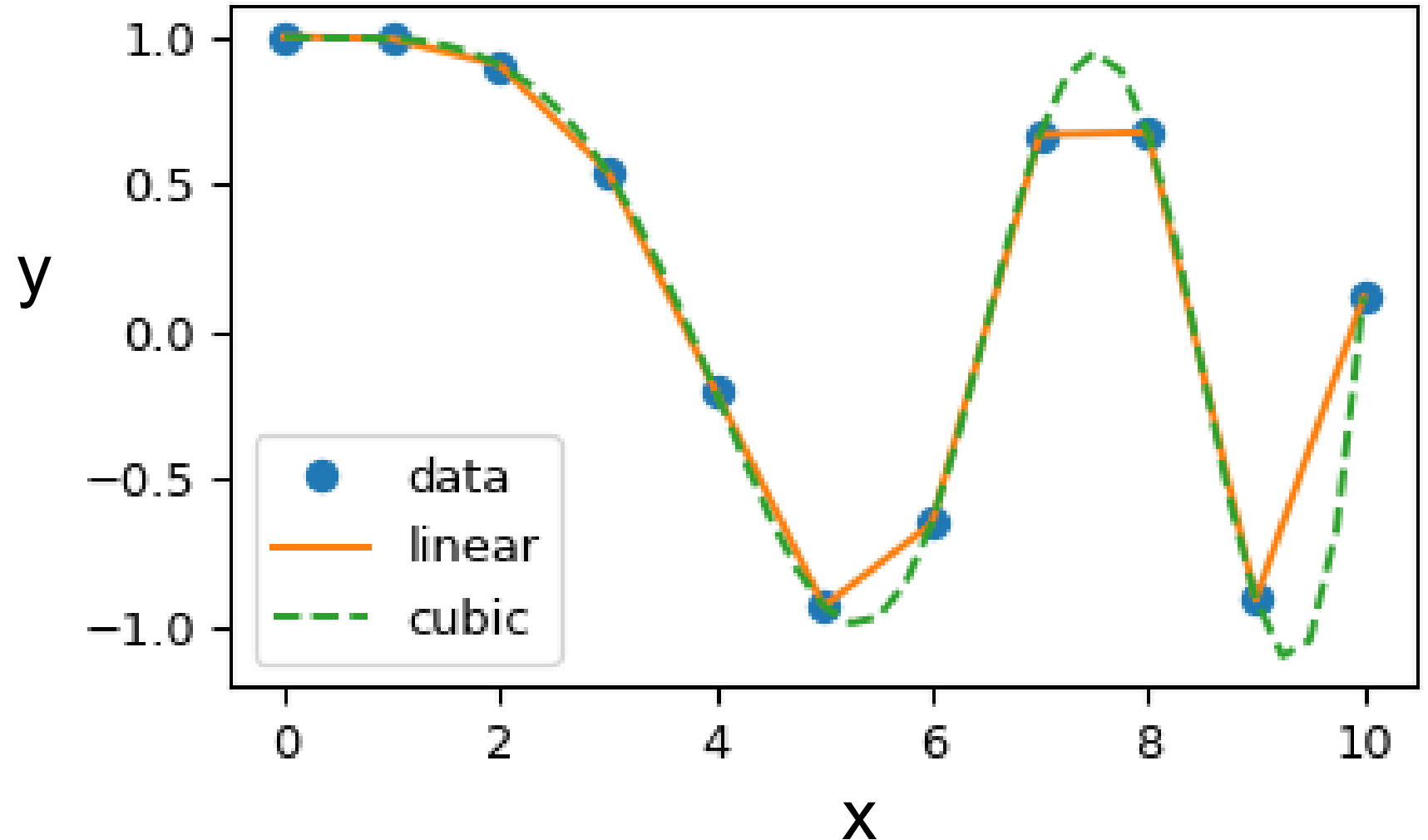
What is Interpolation?

Given

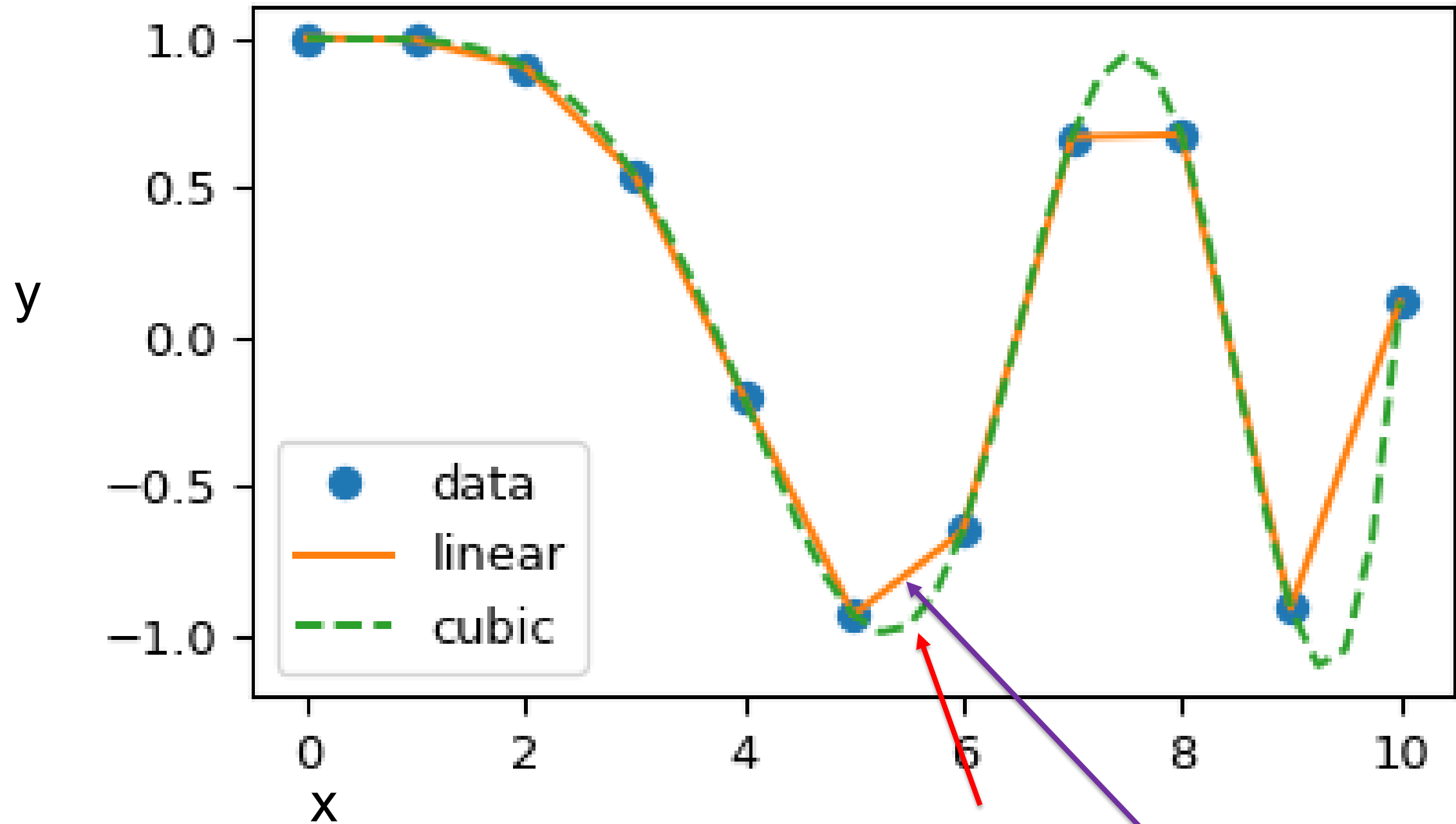
$\{(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)\}$

, find the value of y (or its gradient, derivative)

at a value of x that is not explicitly given



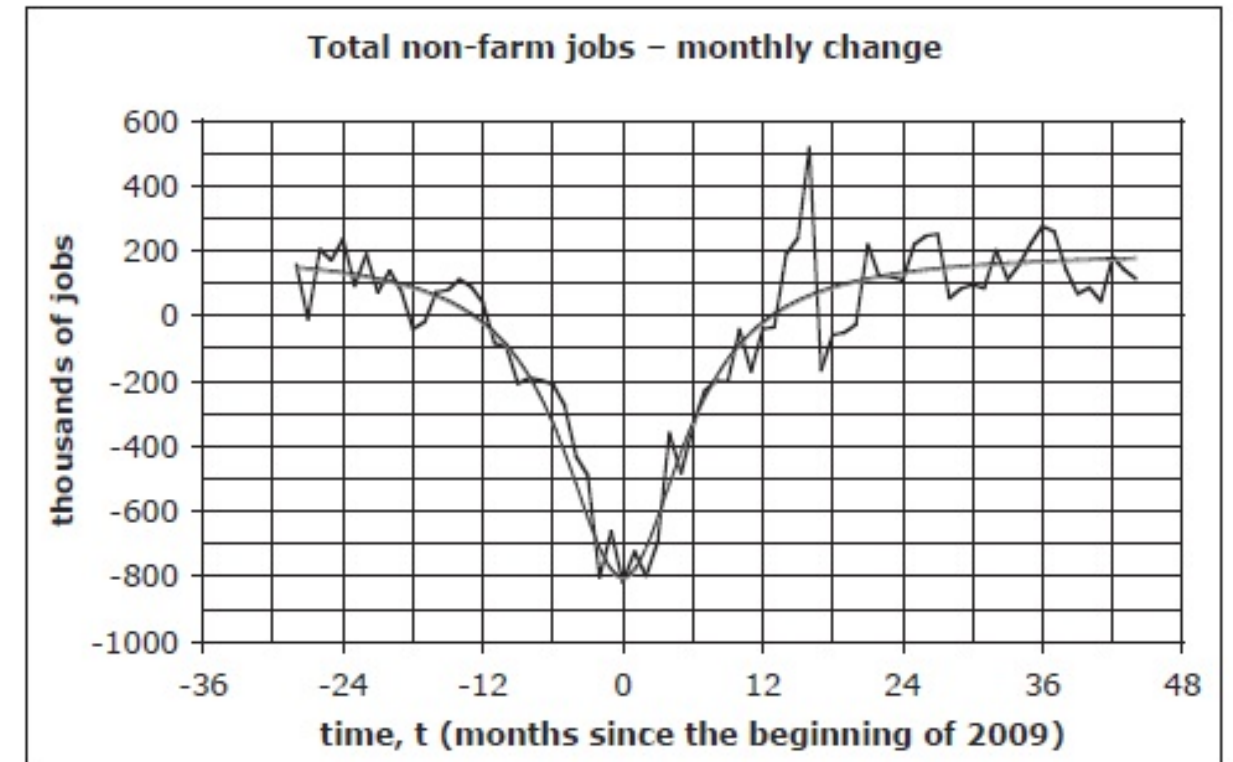
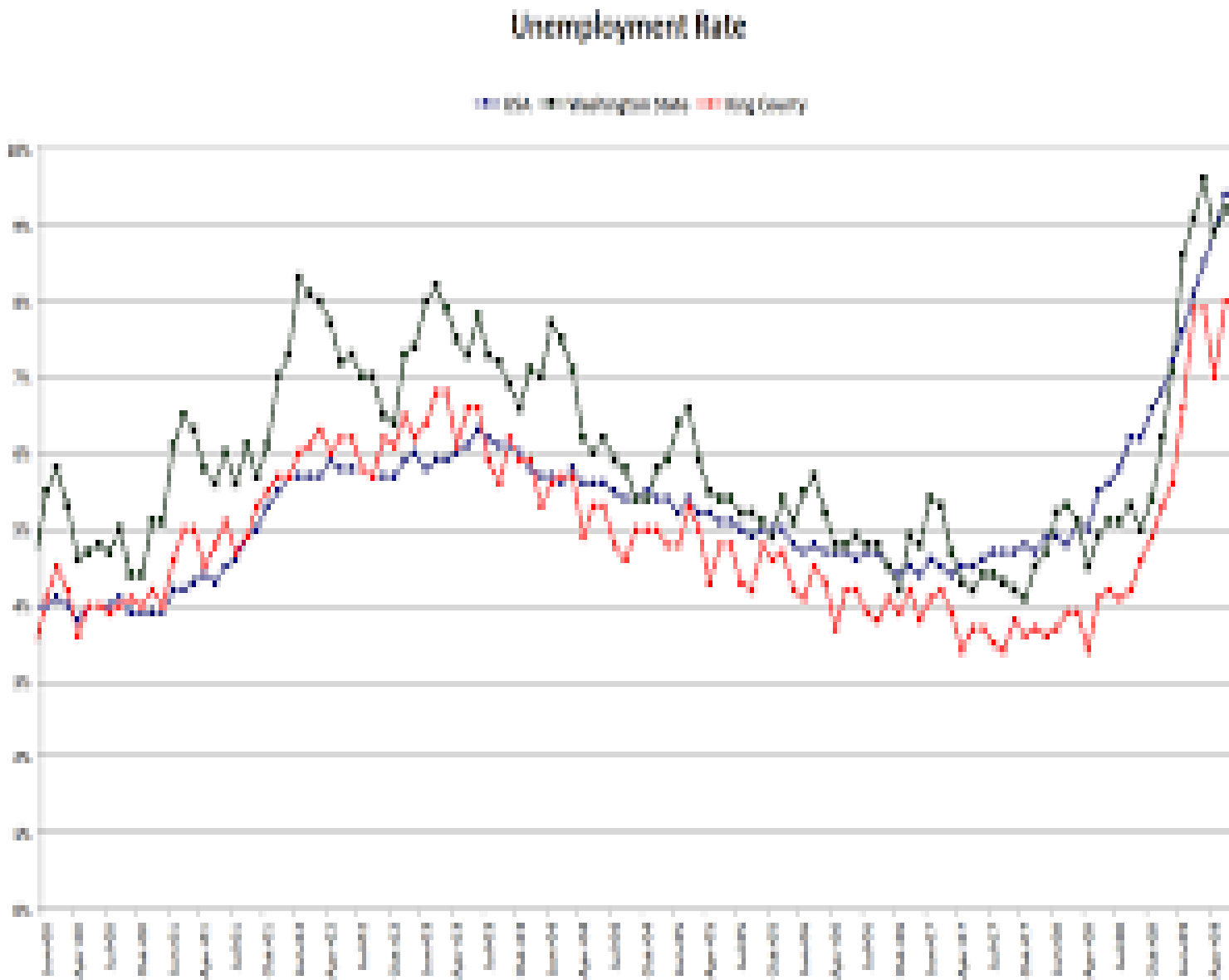
What is Interpolation?



Which is correct **this** or **this**

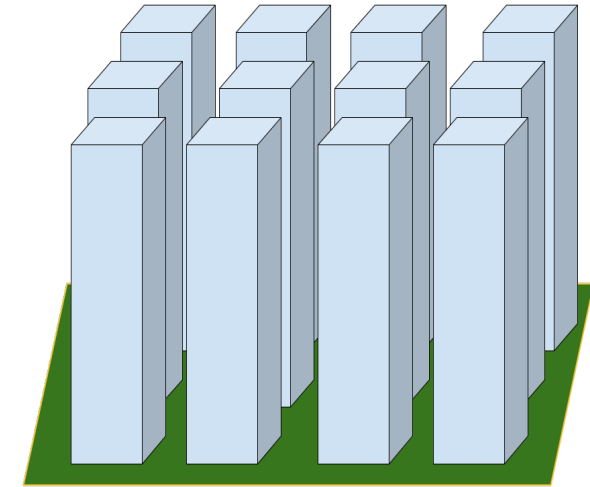
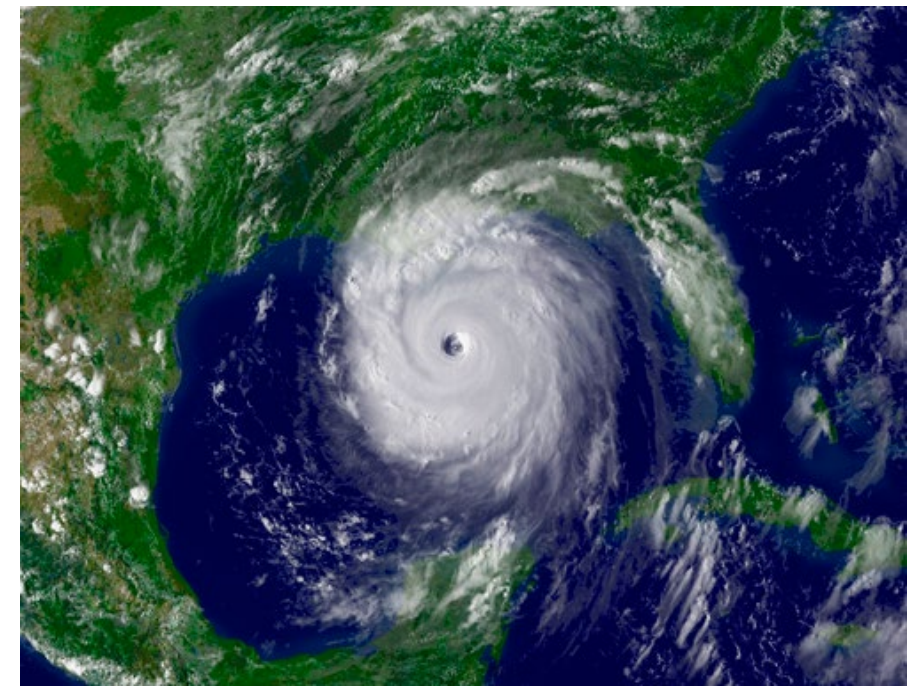
Real Data is often not smooth

However we do use smooth fine-scale approximations at least to the level of floating point arithmetic

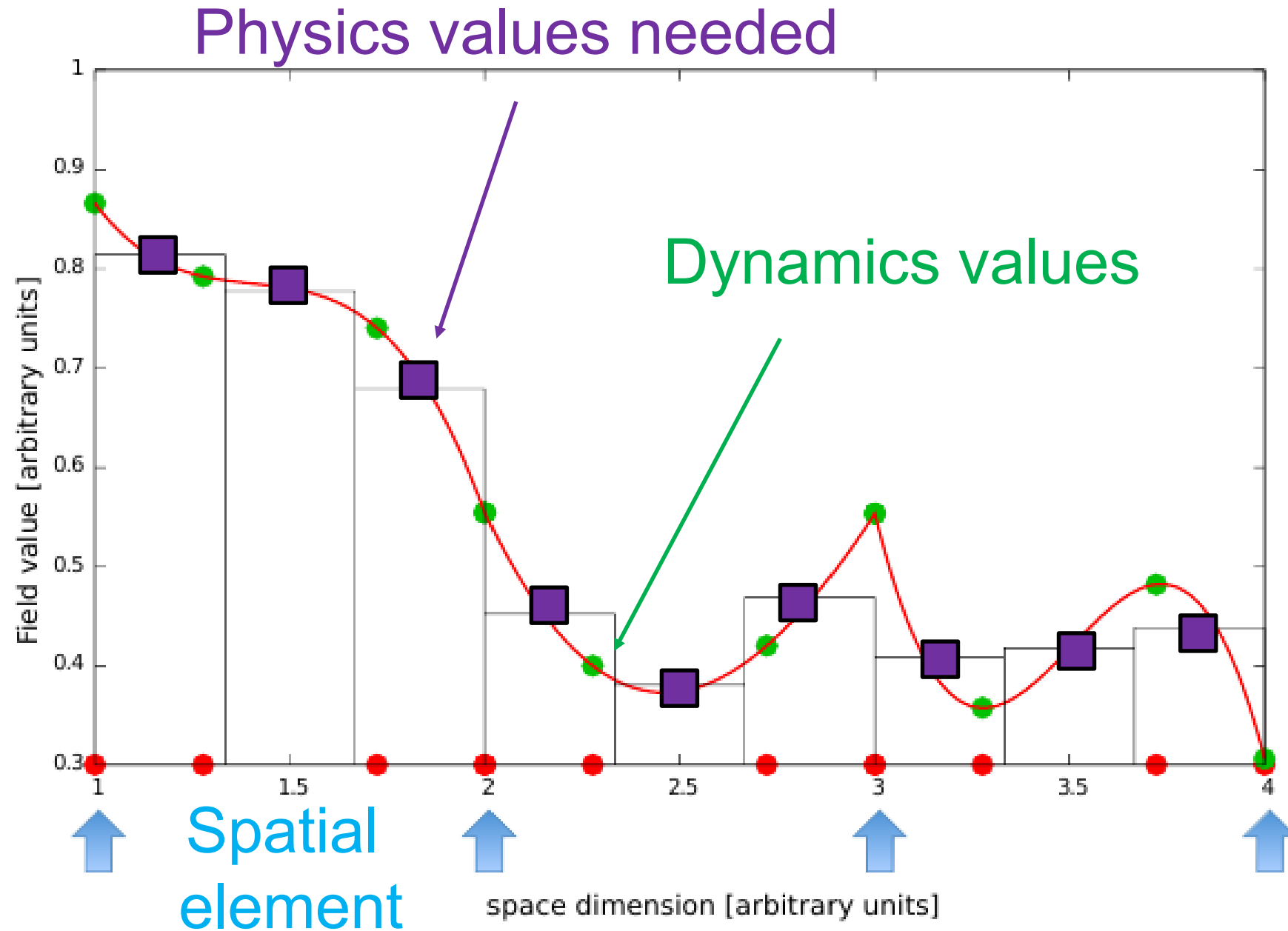


Interpolation in Weather Codes

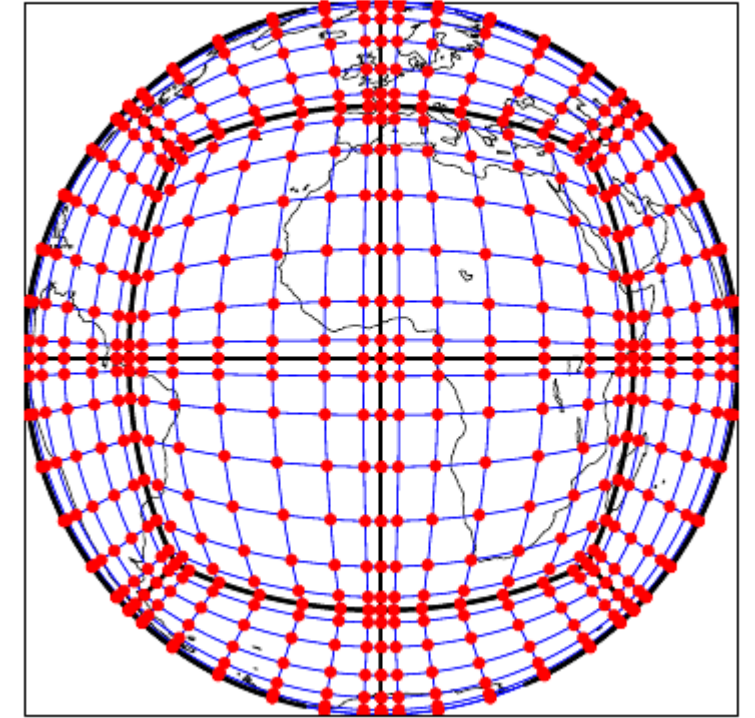
- Recent codes like Neptune split into dynamics and physics part
- Physics deals with rain snow grauple
- Physics considers vertical columns
- Physics routines need to be evenly spaced.
- Dynamics routines used a different mesh
- Need to map physical quantities between meshes
- Density velocities in x,y, and z and temperature are mapped back and forth



Weather Interpolation Problem



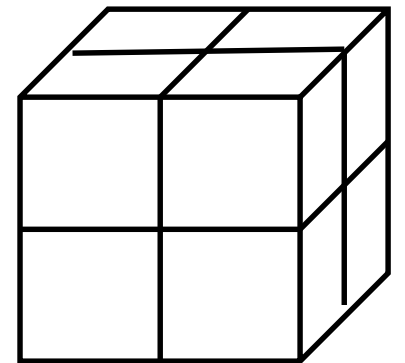
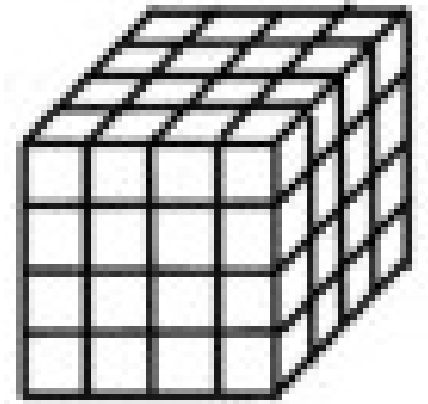
ne2np8 quadrature points on cubed-sphere



Need to use
green values
To find purple
values

Algorithm-Based Fault Tolerance

- The largest machines today have minor faults about once a day and may have a node crash once a week.
- Approaches to deal with this may involve hardware, system software or algorithmic resilience.
- In the last case we may store a coarse copy of a mesh patch on another node. In three dimensions a mesh patch with $\frac{1}{2}$ the variables in each dimension require only $\frac{1}{8}$ of the storage.
- In order to rebuild the fine mesh patch from the coarse one we need to use interpolation that gives physically meaningful values..



Interpolation and approximation

1 Polynomial $y_I(x) = a_0 + a_1x + a_2x^2 + \cdots + a_nx^n$

As there are $n+1$ degrees of freedom in there is one and only one n^{th} -order polynomial that fits $n+1$ points.

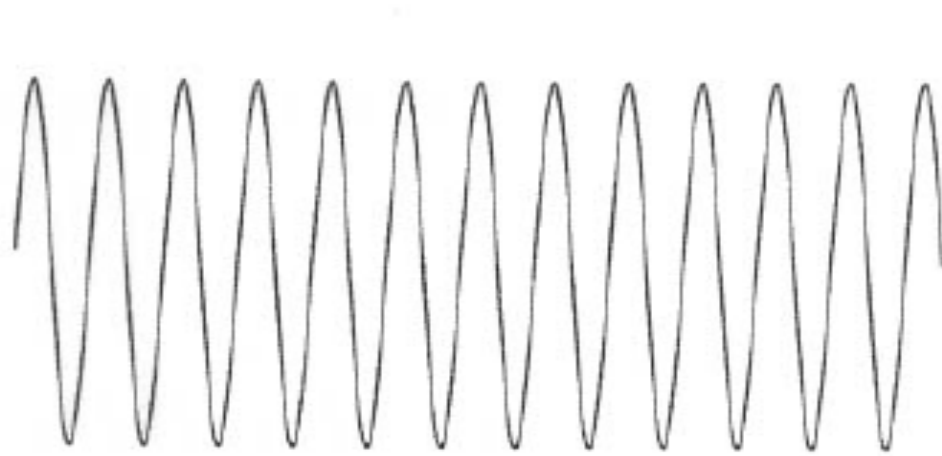
2 Rational Functions

$$y_I(x) = \frac{a + bx + cx^2 + dx^3 + ex^4}{f + gx + hx^2 + kx^3 + ex^4}$$

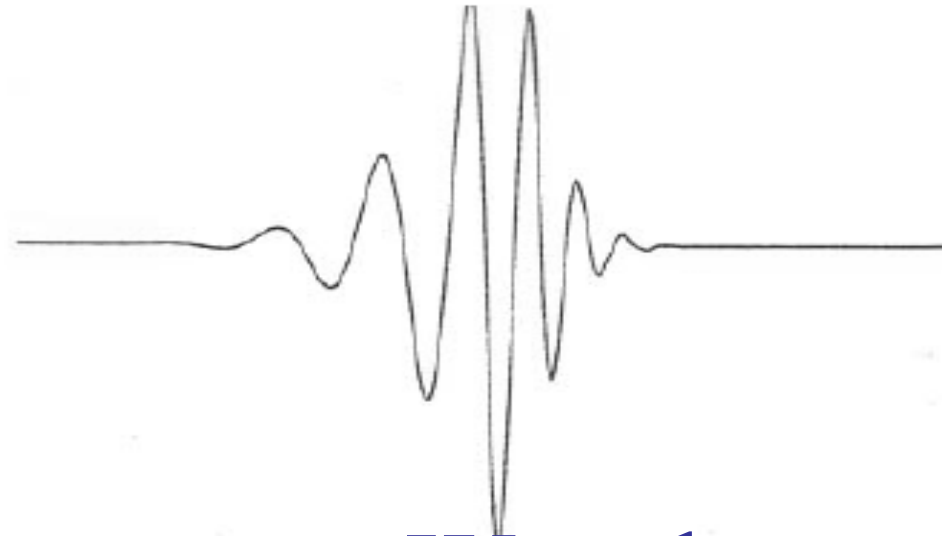
3 Trigonometric interpolants,

$$y_I(x) = a_{-n}e^{-inx} + \dots + a_0 + \cdots + a_n e^{inx}$$

4. Wavelets alternate to Fourier methods



Sinusoid



Wavelet

5. Radial Basis Functions – used in Neural Nets

$$\hat{y}(\mathbf{x}) = \sum_{i=1}^{n_b} b_i \xi_i(\mathbf{x})$$

Radial basis functions $\xi_i(\mathbf{x}) = e^{-(\|\mathbf{x}-\mathbf{x}_i\|/\lambda)^2}$

Polynomial Interpolation Algorithm

- Decide on a set of functions (polynomials) that you will use to present the solution to the problem
- Pick a set of points at which these polynomials are defined $y(x_i)$
- Use interpolation based on this polynomial to recover the solution everywhere

Why Polynomials?

Weierstrass Approximation Theorem (1885).

Suppose f is a continuous real-valued function defined on the real interval $[a, b]$. For every $\varepsilon > 0$, there exists a polynomial $p(x)$ such that for all x in $[a, b]$, the max value $|f(x) - p(x)| < \varepsilon$.

More formally

$$\|f(x) - p(x)\|_{\infty} < \varepsilon$$

What is problematic about this theorem?

Why Polynomials?

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More formally

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What is problematic about this theorem?

Bernstein proved a constructive version of this theory in 1912

Using Taylors Series Directly?

Example – consider approximating the function $f(x) = 1/x$ close to $x = 1$ using Taylors series

$$\begin{aligned} f(x) = & f(1) + (x-1) \frac{df}{dx}(1) + \frac{(x-1)^2}{2} \frac{d^2 f}{dx^2}(1) + \frac{(x-1)^3}{3!} \frac{d^3 f}{dx^3}(1) \\ & + \frac{(x-1)^4}{4!} \frac{d^4 f}{dx^4}(1) + \dots \end{aligned}$$

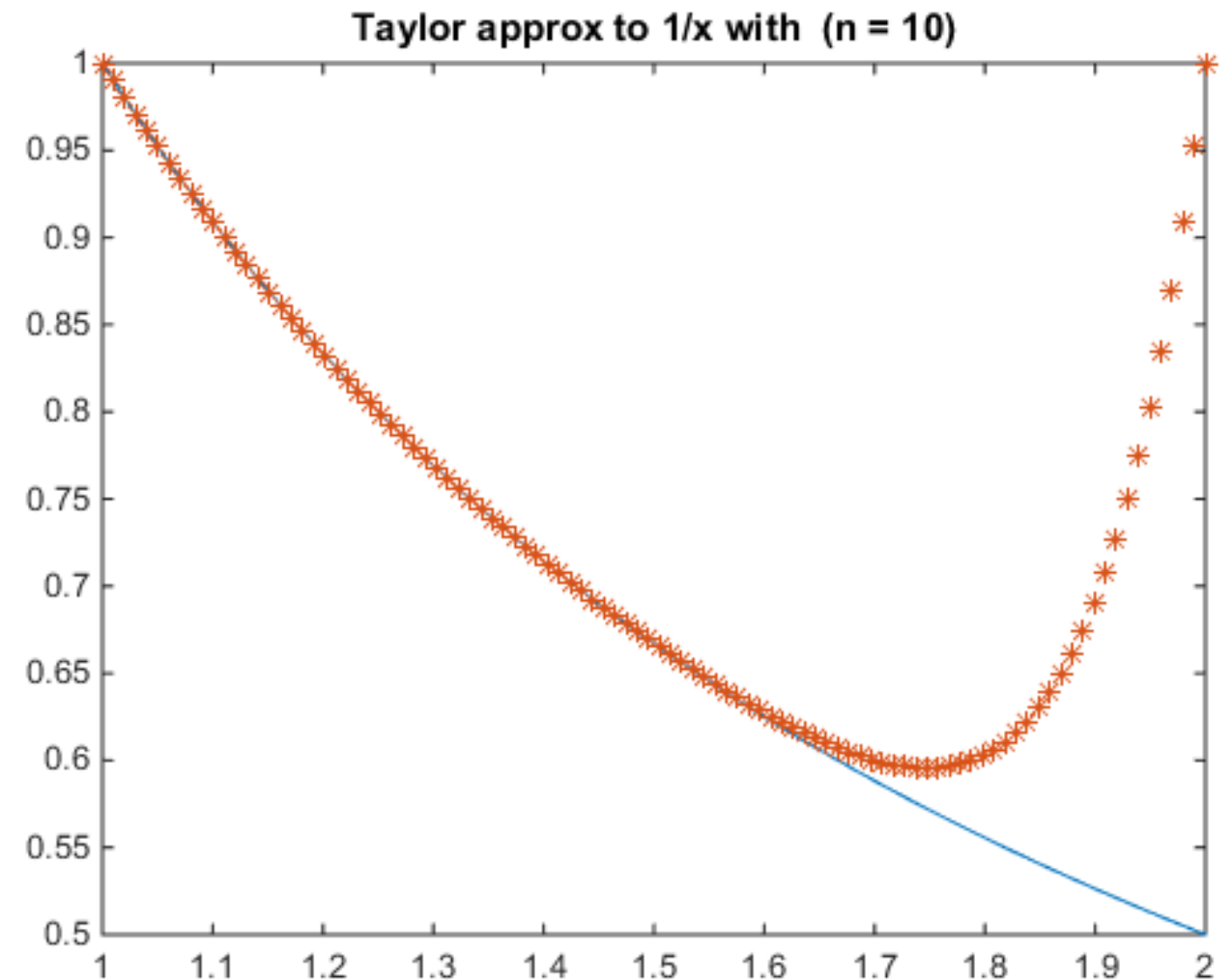
Using Taylors Series Directly?

Example – consider approximating the function $f(x) = 1/x$ close to $x = 1$ using Taylors series

$$f(x) = f(1) - (x-1) + (x-1)^2 - (x-1)^3 + (x-1)^4 - (x-1)^5 + \dots$$

Using Taylors Series Directly ?

- Example – consider approximating the function $1/x$ close to $x = 1$ using Taylors series with $n = 10$.
- Even if we make n much larger there are still problems close to 2
- The answer is completely wrong
- Why?



```
% x = linspace(1.95,2.050,100)';  
x = linspace(1.00,1.5,100)';  
y = ones(100,1)./(x);  
n=4;  
  
for i = 1:100  
    ytaylor(i) = 1.0;  
    term = (x(i)-1.0);  
    for j = 1:n  
        ytaylor(i) = ytaylor(i)- term;  
        term = term * (-1.0*(x(i)-1));  
    end  
    error(i) = y(i)- ytaylor(i);  
end
```

```
plot(x,y,x,ytaylor,'*',x,error,'+')  
    legend('y','ytaylor','error')  
    title(sprintf('Taylor approx to 1/x with  
(n = %2.0f)',n))
```


Coefficients of an Interpolating Polynomial

- Since $n+1$ data points are required to determine $n+1$ coefficients, simultaneous linear systems of equations can be used to calculate “ a ”s:

$$y(x_0) = a_0 + a_1x_0 + a_2x_0^2 \cdots + a_nx_0^n$$

$$y(x_1) = a_0 + a_1x_1 + a_2x_1^2 \cdots + a_nx_1^n$$

⋮

$$y(x_n) = a_0 + a_1x_n + a_2x_n^2 \cdots + a_nx_n^n$$

where “ x ”s are the knowns and “ a ”s are the unknowns

We can represent this system of equations as $O(n^3)$ operations to solve linear system

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

and our solution will be the polynomial

$$p(x) = a_0 + a_1x + a_2x^2 + a_3x^3 + a_4x^4 + \dots + a_nx^n$$

Matlab Vandermonde

```
v = 1:.5:3
```

```
v = 1×5
```

```
1.0000 1.5000 2.0000 2.5000 3.0000
```

Find the alternate form of the Vandermonde matrix using `fliplr`.

```
A = fliplr(vander(v))
```

```
A = 5×5
```

```
1.0000 1.0000 1.0000 1.0000 1.0000
```

```
1.0000 1.5000 2.2500 3.3750 5.0625
```

```
1.0000 2.0000 4.0000 8.0000 16.0000
```

```
1.0000 2.5000 6.2500 15.6250 39.0625
```

```
1.0000 3.0000 9.0000 27.0000 81.0000
```

Example

Polynomial of degree 2 through $(-2, -27), (0, -1), (1, 0)$

$$\begin{pmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ 1 & x_3 & x_3^2 \end{pmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = y$$

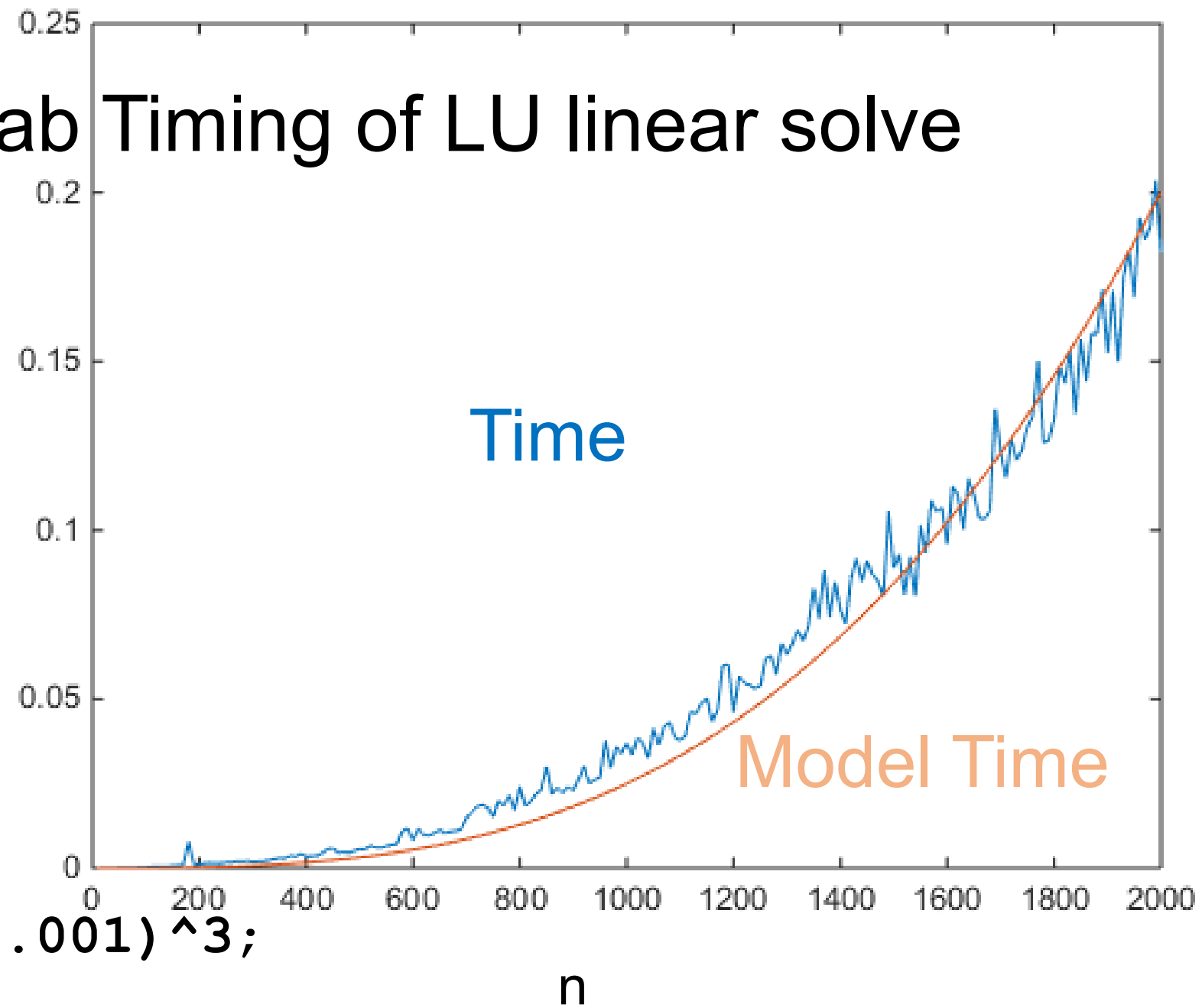
In this case

$$\begin{pmatrix} 1 & -2 & 4 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} -27 \\ -1 \\ 0 \end{bmatrix} \text{ with solution } \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} -1 \\ 5 \\ 4 \end{bmatrix},$$

giving polynomial $-1 + 5x + 4x^2$

```
clear all
t = zeros(1,200);
nt = zeros(1,200);
model = zeros(1,200);
for m = 1:200
    n = m*10;
    A = rand(n,n);
    b = rand(n,1);
    tic;
    x = A\b;
    t(m) = toc;
    nt(m) = n;
    model(m) = 0.25e-1*(n*0.001)^3;
    ratio = model(m)/t(m);
end
plot(nt,t,nt,model)
```

Matlab Timing of LU linear solve



$$O(n^3)$$

Vandermonde systems are notorious for having challenges with rounding errors, but special algorithms are available. These are still N^3 .

Can we get a faster algorithm that doesn't involve solving a set of equations?

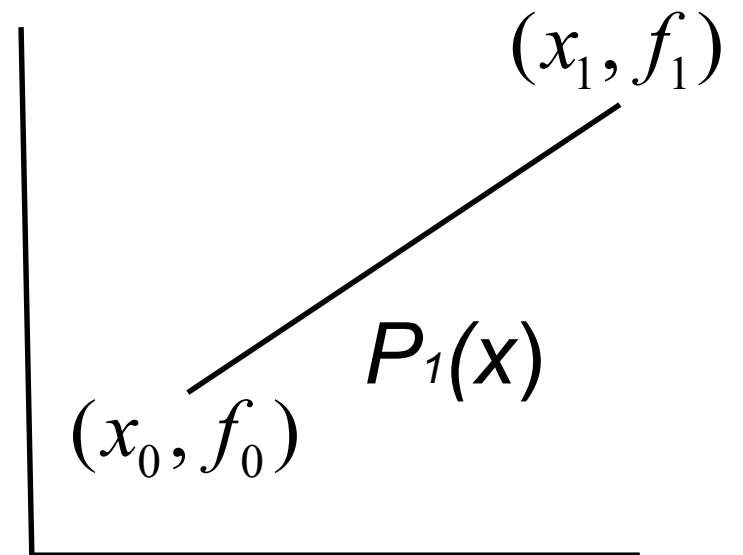
Yes if we explicitly break up the polynomial into simpler parts. Eventually we can get an $O(N)$ algorithm using a special point set and Barycentric interpolation.

Linear Interpolation

- Given $f(x_0) = f_0$ and $f(x_1) = f_1$
 - Approximate the unknown $y(x)$ with $p_1(x)$
 - Construct two linear interpolants each of which is zero at one point and one at the other point

- $L_1(x) = \frac{(x-x_0)}{(x_1-x_0)}, L_0(x) = \frac{(x-x_1)}{(x_0-x_1)}$

- Then $P_1(x) = L_0 f_0 + L_1 f_1$



Quadratic Lagrange Interpolating Polynomials

The quadratic case is similar construct three polynomials

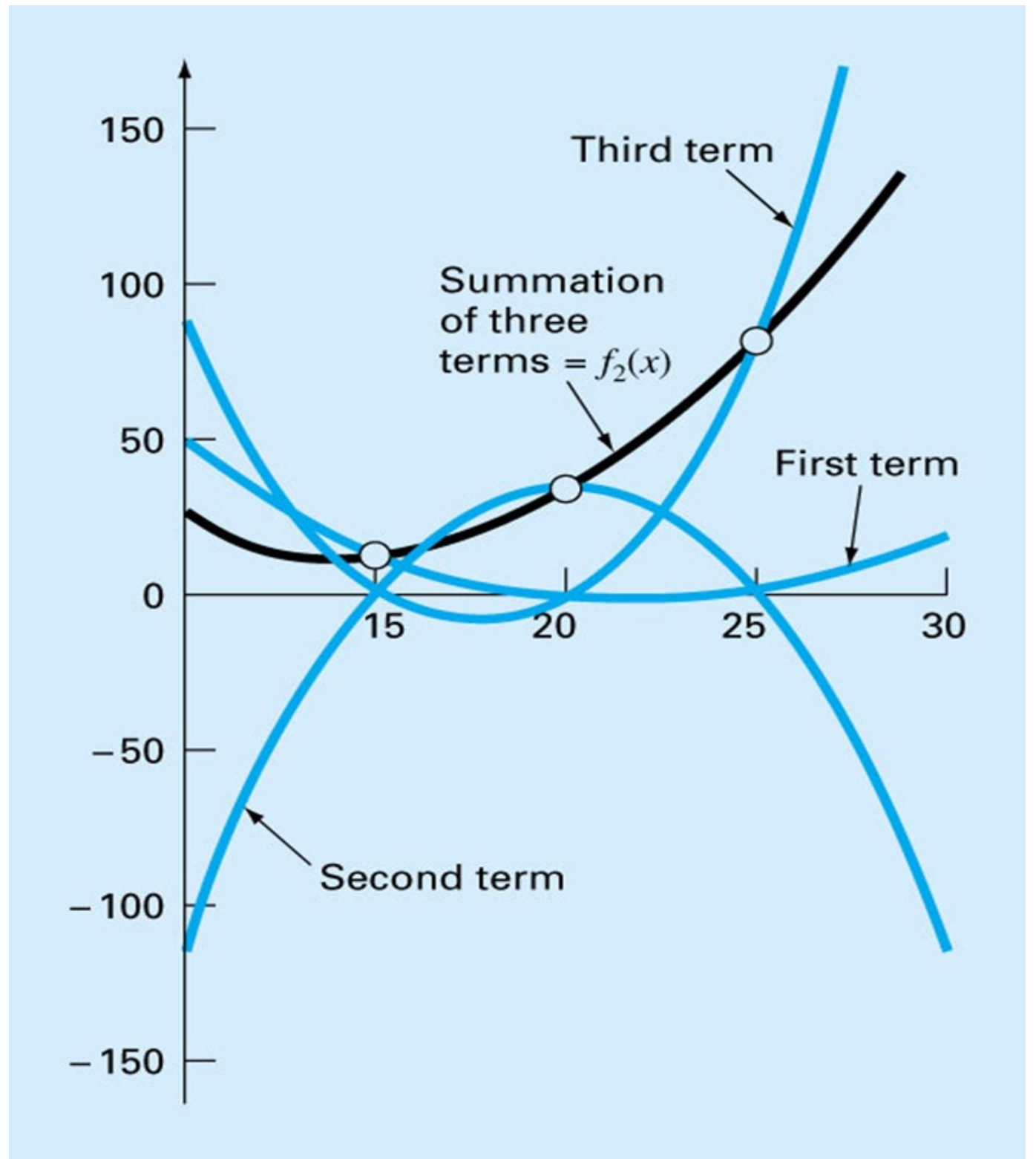
$$L_0(x), L_1(x), L_2(x)$$

Each of which has value one at one point and is zero at the other two points

$$f_2(x) = \frac{(x-x_1)(x-x_2)}{(x_0-x_1)(x_0-x_2)} f(x_0) + \frac{(x-x_0)(x-x_2)}{(x_1-x_0)(x_1-x_2)} f(x_1) + \frac{(x-x_0)(x-x_1)}{(x_2-x_0)(x_2-x_1)} f(x_2)$$

$$f_2(x) = L_0(x) f(x_0) + L_1(x) f(x_1) + L_2(x) f(x_2)$$

Quadratic Lagrange Interpolants



Lagrange Interpolation

- Given multiple points $(x_i, f(x_i))$
 - Calculate a polynomial interpolant in the same way

$$f_n(x) = \sum_{i=0}^n L_i(x) f(x_i)$$

$$L_i(x) = \prod_{\substack{j=0 \\ j \neq i}}^n \frac{x - x_j}{x_i - x_j} = \frac{(x - x_0)(x - x_1) \dots (x - x_{i-1})(x - x_{i+1}) \dots (x - x_n)}{(x_i - x_0)(x_i - x_1) \dots (x_i - x_{i-1})(x_i - x_{i+1}) \dots (x_i - x_n)}$$

Error of Polynomial Interpolation

Theorem

For an n^{th} -order interpolating polynomial, the error is given by the $(n+1)^{th}$ derivative of the unknown function evaluated at an unknown point ξ

$$R_n = \frac{f^{(n+1)}(\xi)}{(n+1)!} (x - x_0)(x - x_1) \cdots (x - x_n)$$

x is located in some interval containing the unknown
and the data: $[x, x_0, x_1, \dots, x_n]$

Limitation of interpolating polynomials

Runge's phenomenon.

When approximating the function $f(x)$ on $[a,b]$ by an interpolating polynomial with evenly spaced points, an error does not necessarily decrease as increase the degree of polynomial. The interpolation oscillates violently at the ends of the interval,

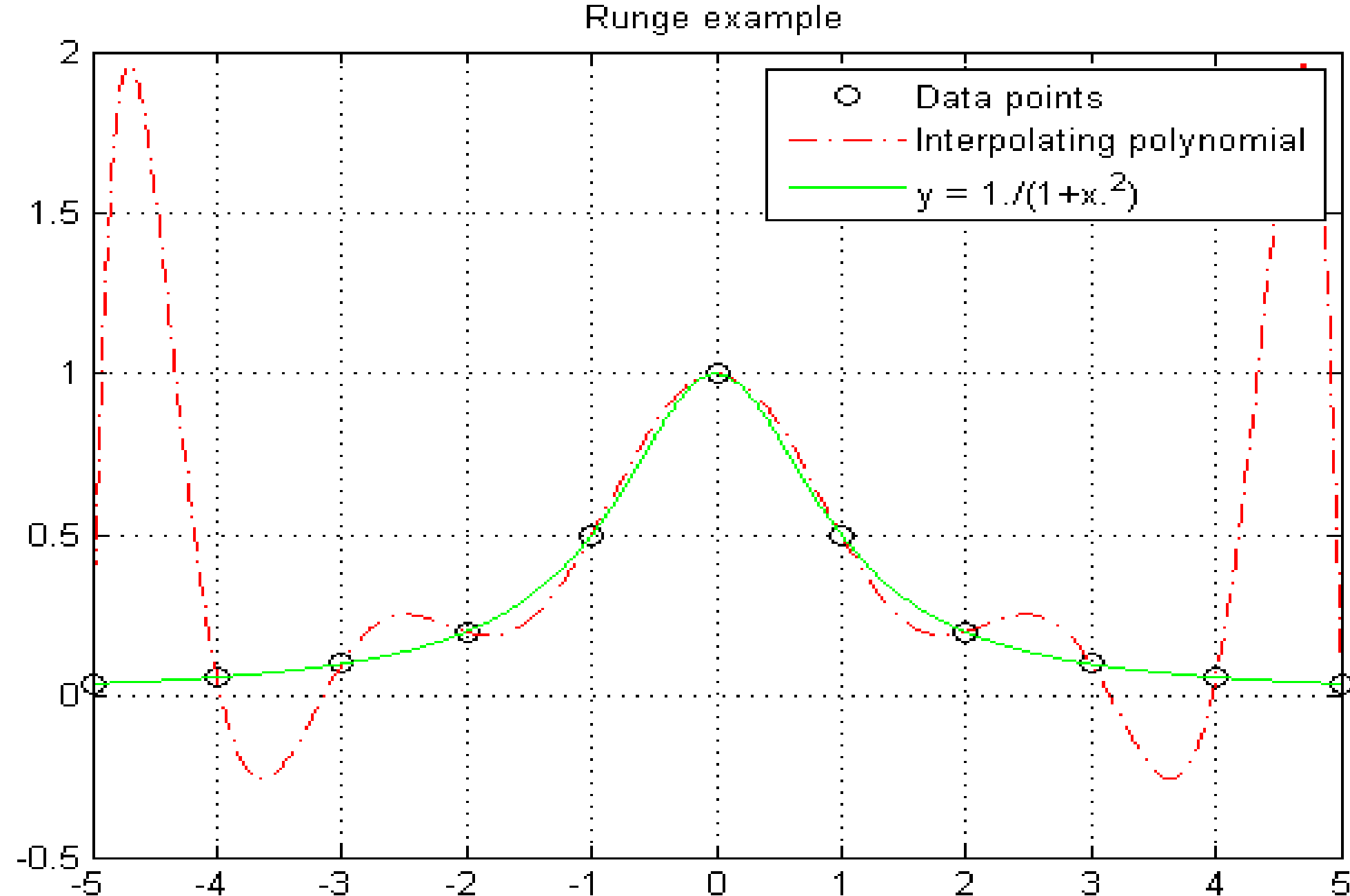
$$f(x) = \frac{1}{1 + 25x^2}, \text{ defined on an interval } [-1, 1],$$

$$\lim_{n \rightarrow \infty} \left(\max_{-1 \leq x \leq 1} |f(x) - P_n(x)| \right) = \infty.$$

https://en.wikipedia.org/wiki/Runge%27s_phenomenon

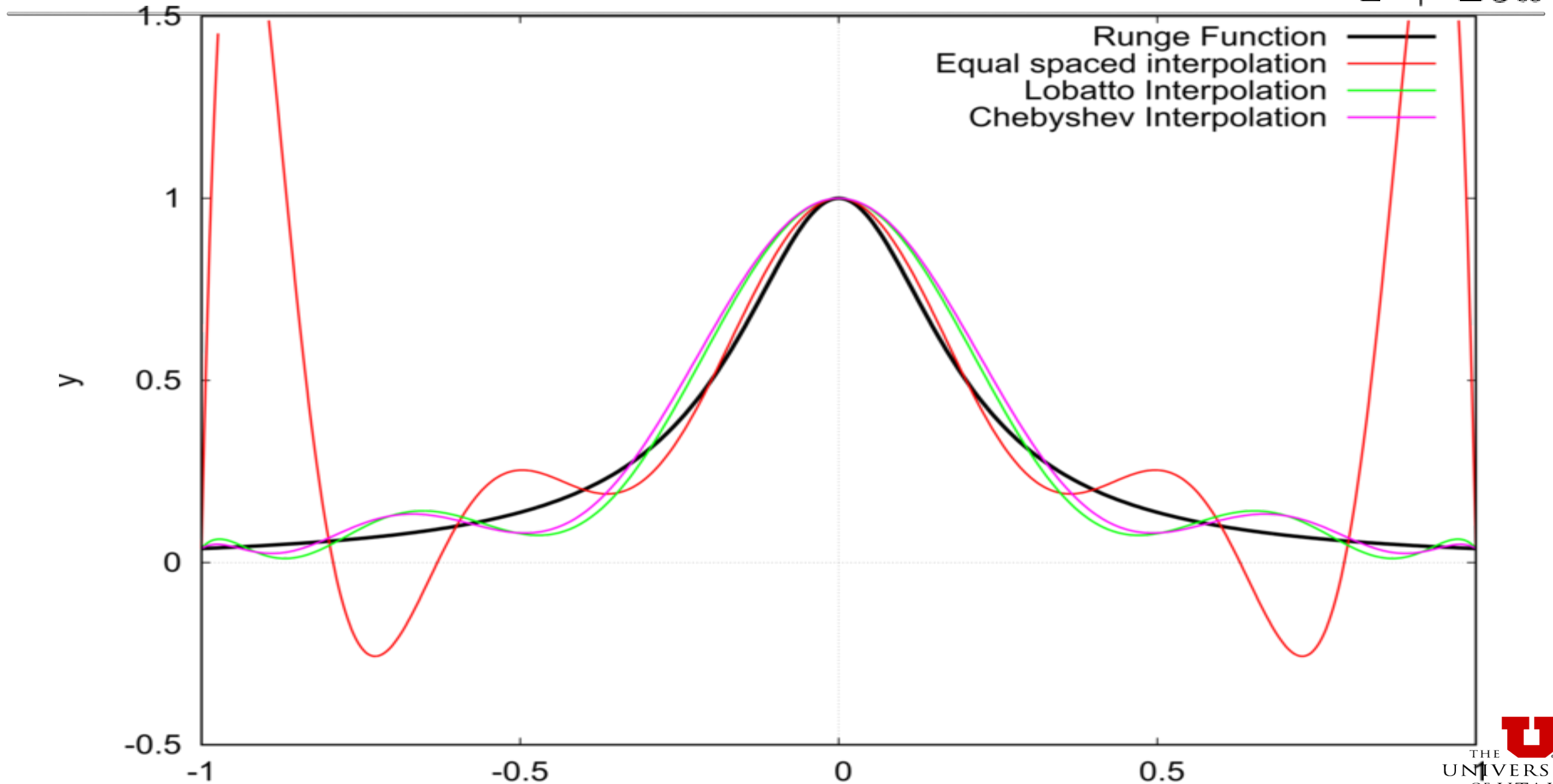
Runge Function

$$f(x) = \frac{1}{1 + 25x^2}$$



Runge Function Point set Matters

$$f(x) = \frac{1}{1 + 25x^2}$$



Example Code

% Script File: RungeEg

% For n=10:13, interpolants of $f(x) = 1/(1+25x^2)$ on $[-1,1]$ are of plotted.

close all

x = linspace(-1,1,100);

y = ones(100,1)./(1 + 25*x.^2);

iplot = 0;

for n=10:13

xEqual = linspace(-1,1,n)';

yEqual = ones(size(xEqual))./(1+25*xEqual.^2);;

cEqual= InterpN(xEqual,yEqual);

pvalsEqual = HornerN(cEqual,xEqual,x);

iplot = iplot+1;

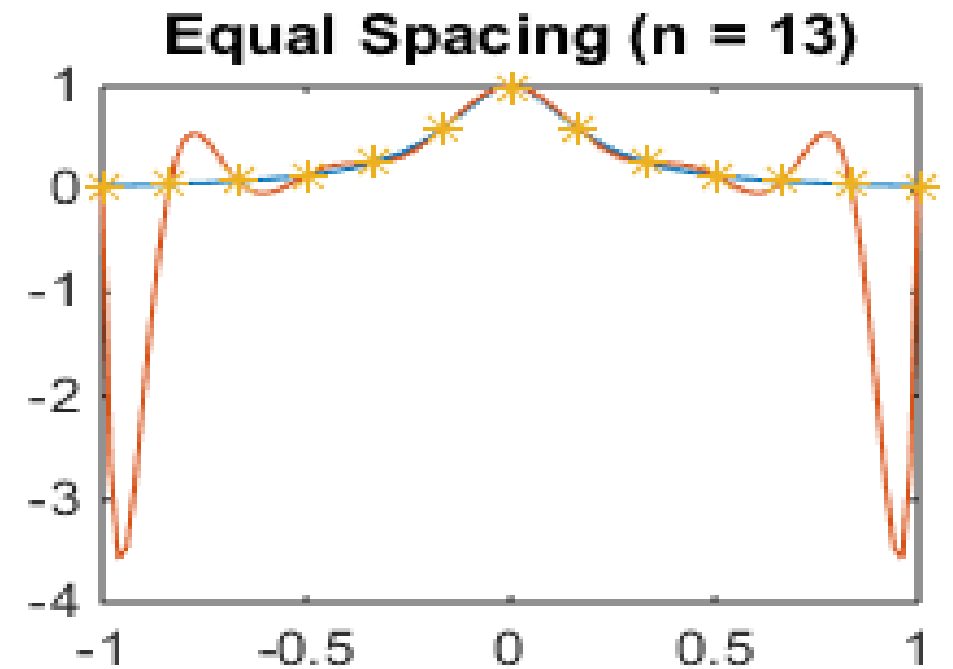
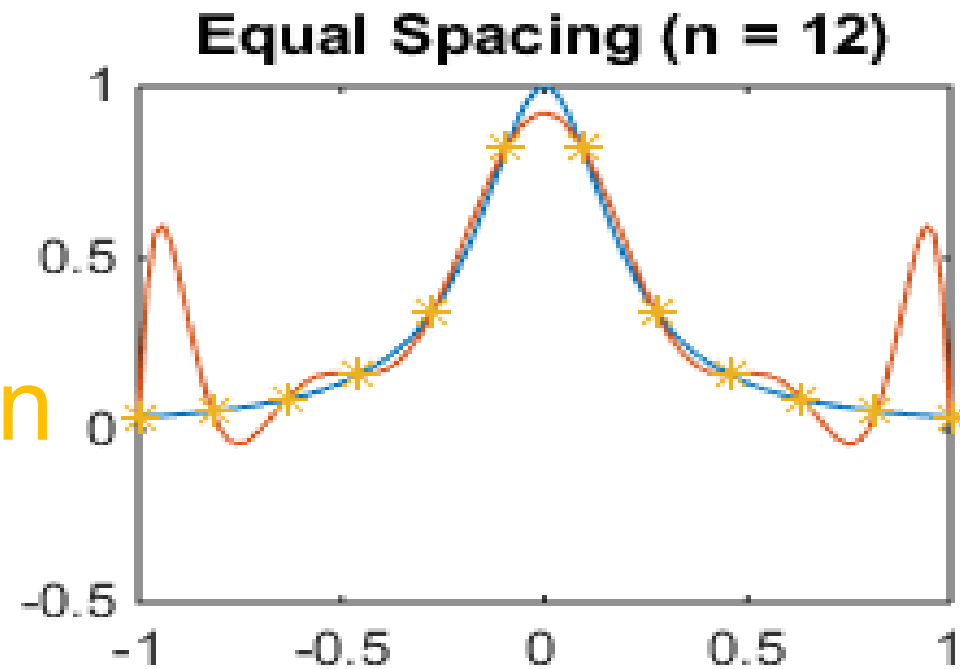
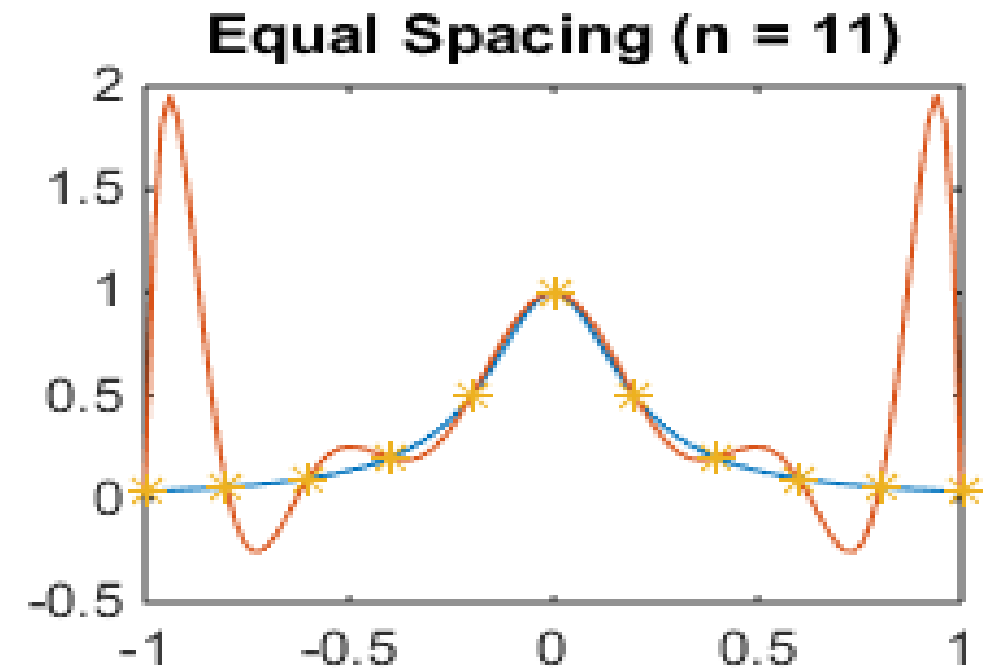
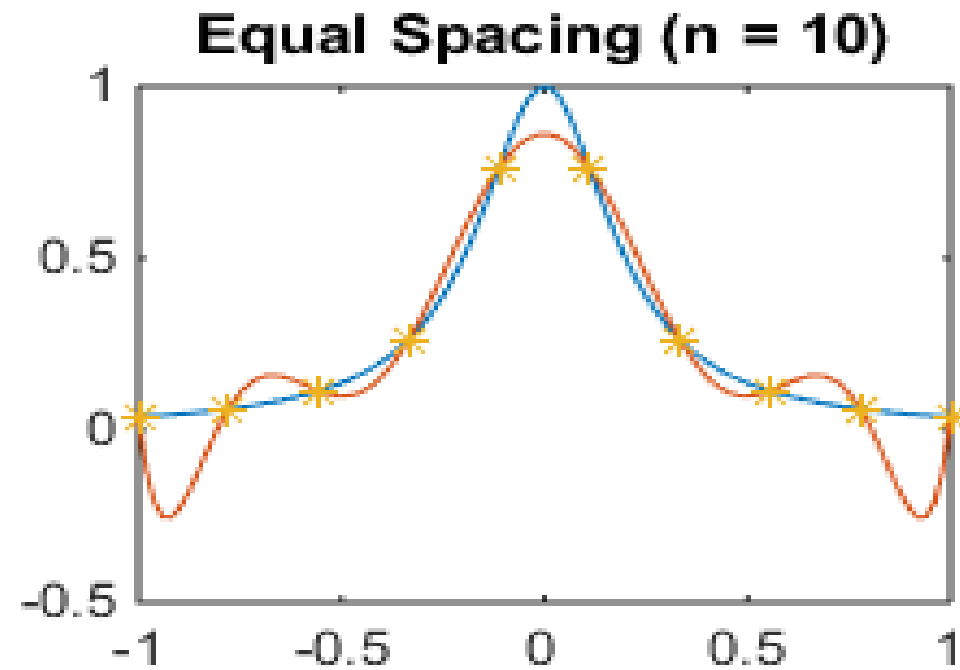
subplot(2,2,iplot)

plot(x,y,x,pvalsEqual,xEqual,yEqual,'*')

title(sprintf('Equal Spacing (n = %2.0f)',n))

end

Runge's
Example
Equally
spaced
polynomial
interpolation
points true
solution **blue**
polynomial
approximation



Horner's Scheme for evaluating a Polynomial

Evaluating a polynomial

$$y_I(x) = a_0 + a_1x + a_2x^2 + \cdots + a_nx^n$$

Optimal algorithm

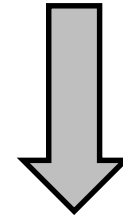
$$\text{Sum} = a_n$$

For i = n-1 to 0

$$\text{sum} = x * \text{sum} + a_i$$

Why?

$$R_n = \frac{f^{(n+1)}(\xi)}{(n+1)!} (x - x_0)(x - x_1) \cdots (x - x_n)$$



Grows very quickly for evenly spaced points

$$h^n \frac{(n-1)!}{4}$$

Use uneven points that are more closely spaced towards ends

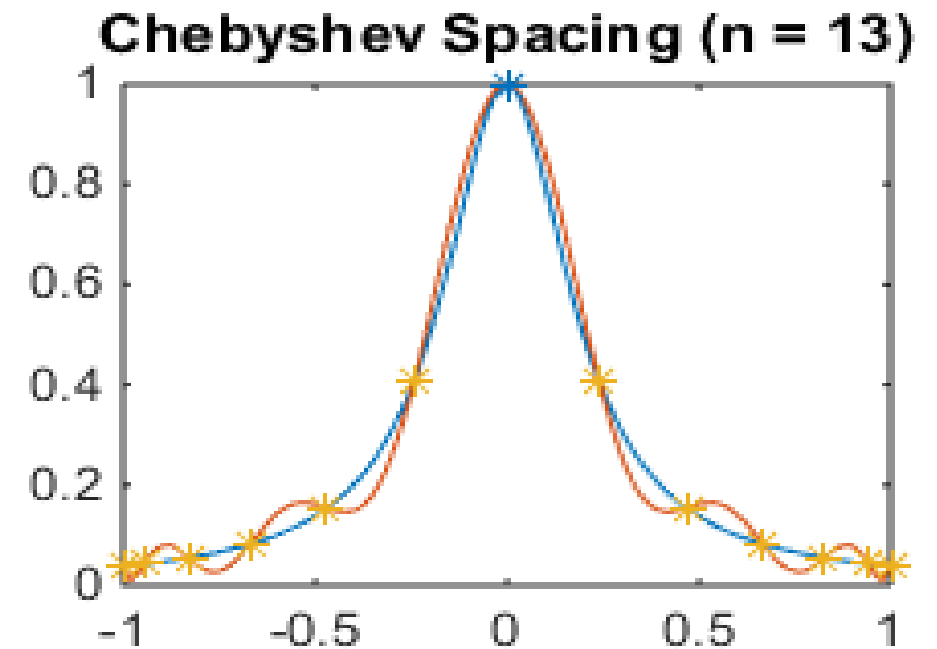
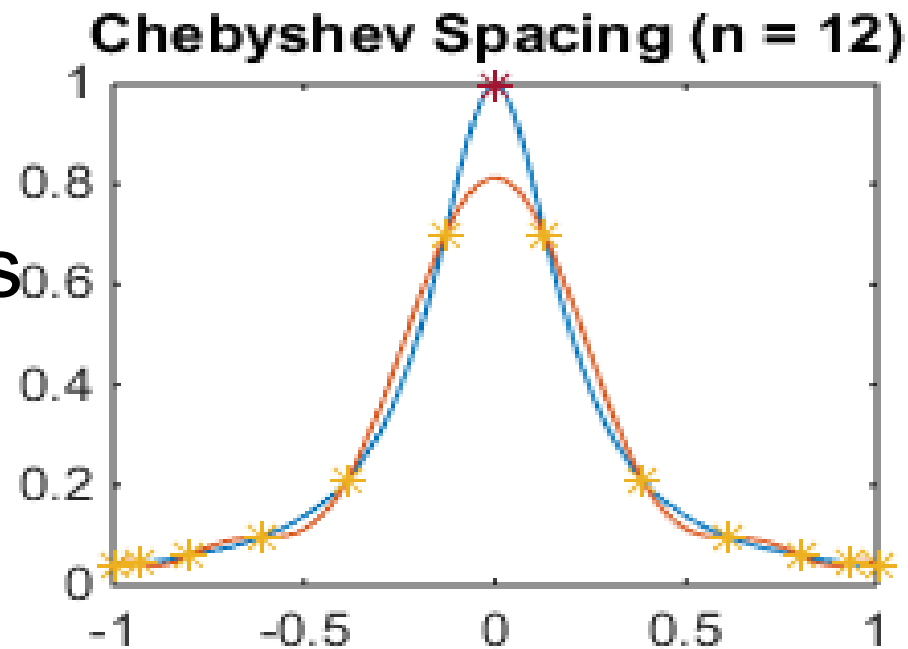
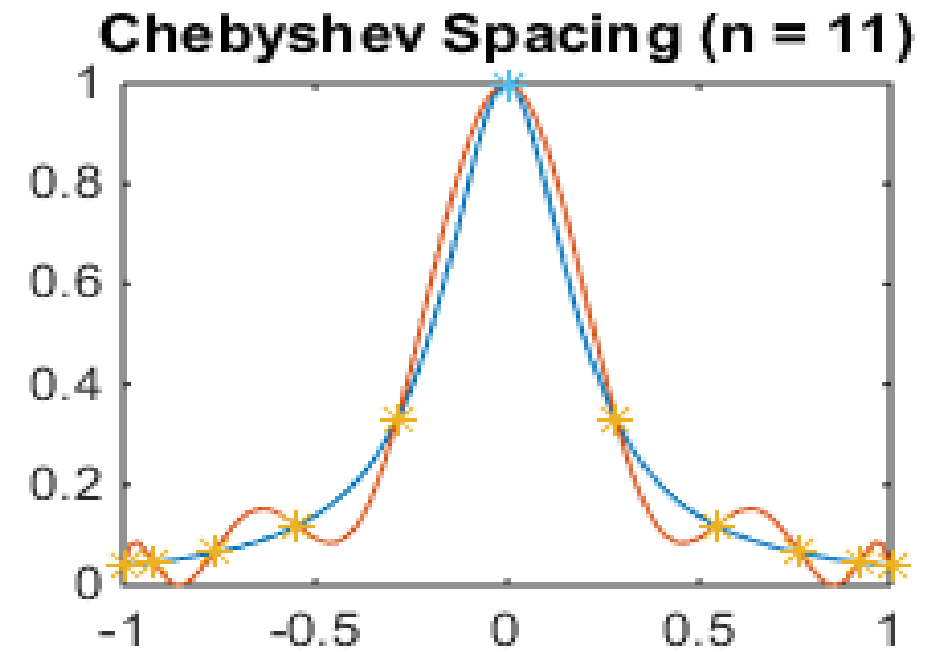
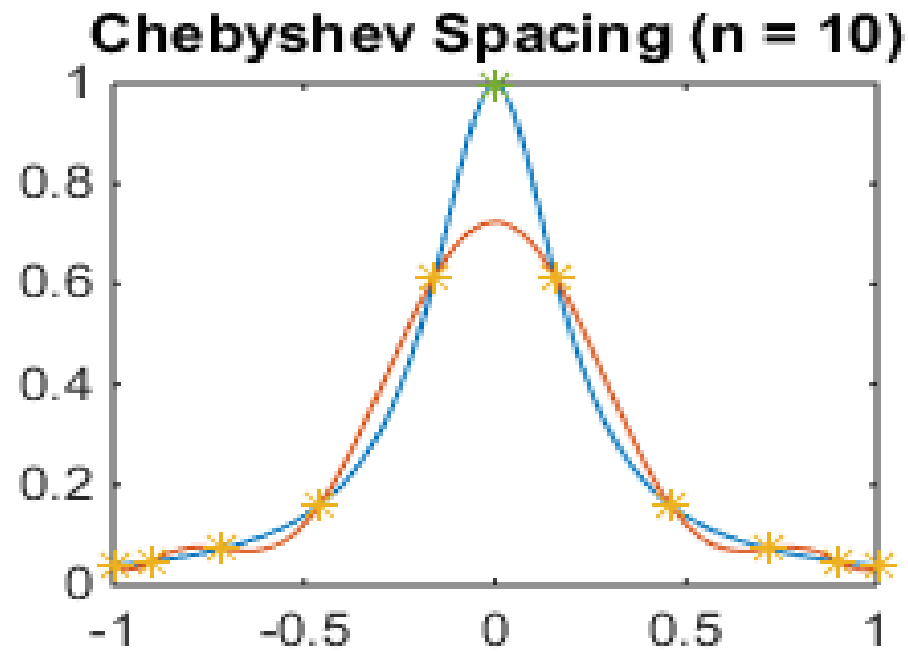
```
xEqual(kk) = -cos( (2.0*kk-1.0)*pi/(2.0*n)) / cos (pi/(2.0*n));
```

Runge Example Using Chebyshev Points

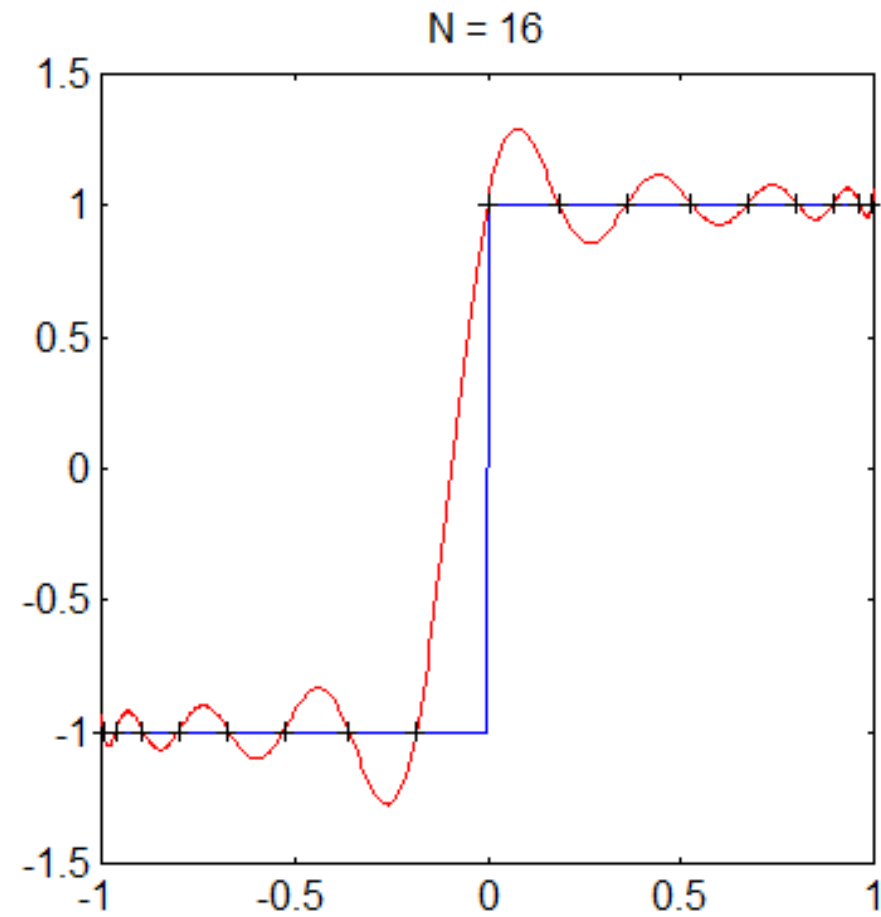
```
% Script File: RungeEg
% For n=10:13, interpolants of  $f(x) = 1/(1+25x^2)$  on  $[-1,1]$  are of plotted.
close all
x = linspace(-1,1,100);
y = ones(1,100)./(1 + 25*x.^2);
iplot = 0;
for n=10:13
    xEqual = zeros(n);
    yEqual = zeros(n);
    for kk = 1:n
        xEqual(kk) = -cos( (2.0*kk-1.0)*pi/(2.0*n)) / cos (pi/(2.0*n));
    end
    yEqual = ones(n)./(1 +25*xEqual.^2);
    cEqual=InterpN(xEqual,yEqual);
    pvals = HornerN(cEqual,xEqual,x);
    iplot = iplot+1;
    subplot(2,2,iplot)
    plot(x,y,x,pvals,xEqual,yEqual,'*')
    title(sprintf('Chebyshev Spacing (n = %2.0f)',n))
end
```

Runge's Example with Chebyshev Points

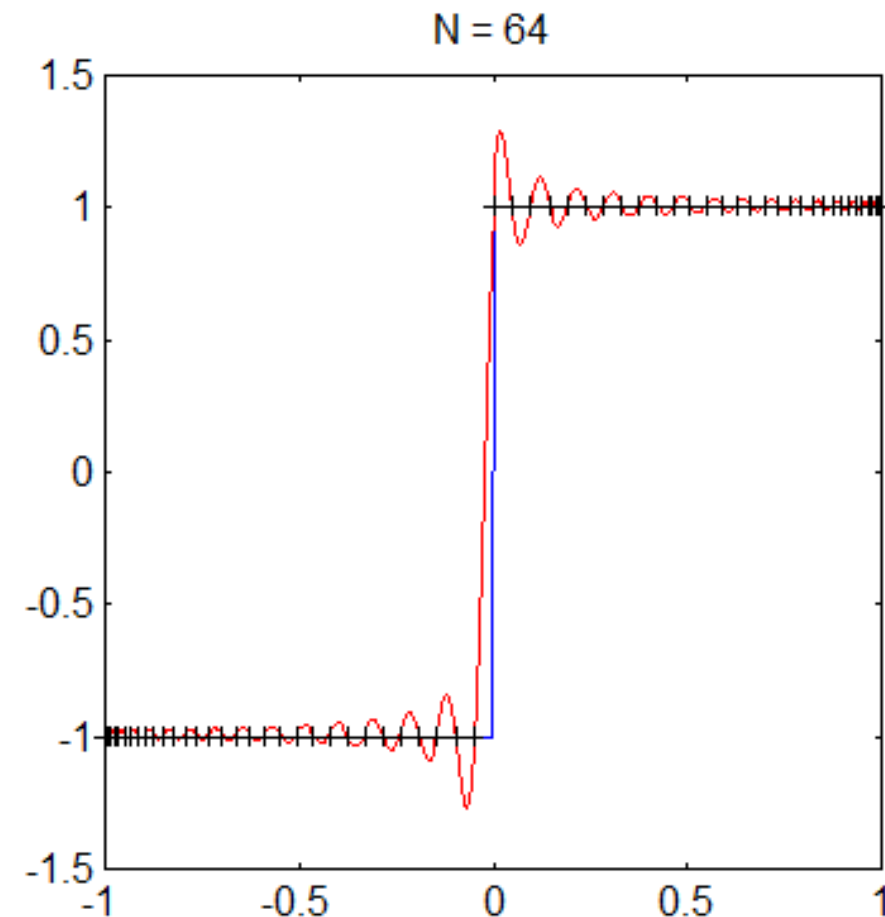
Runge's Example
Chebyshev
polynomial
interpolation points
true solution **blue**
polynomial
approximation



Chebyshev - Gibb's Oscillations $f(x)=\text{sign}(x-\pi)$ => $f(x)$ - blue ; $F_N(x)$ - red; x_i - '+'
https://en.wikipedia.org/wiki/Gibbs_phenomenon



Chebyshev



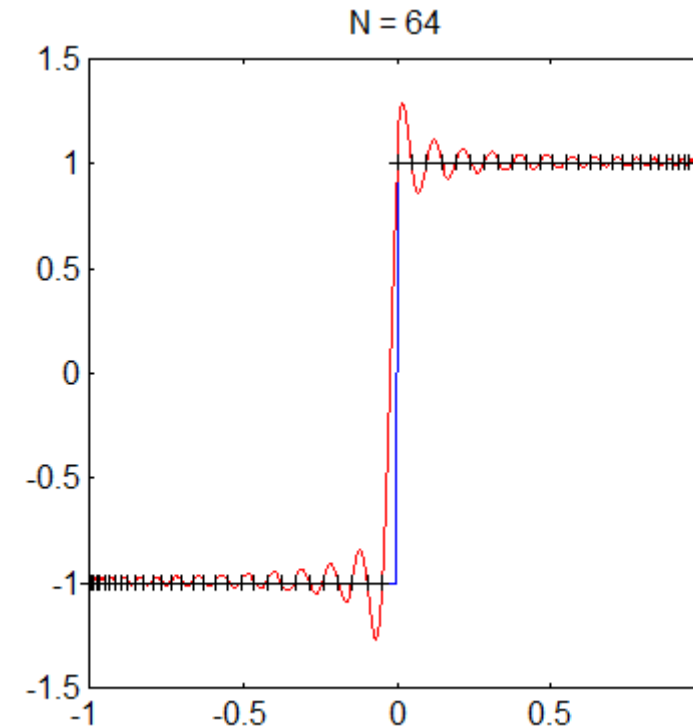
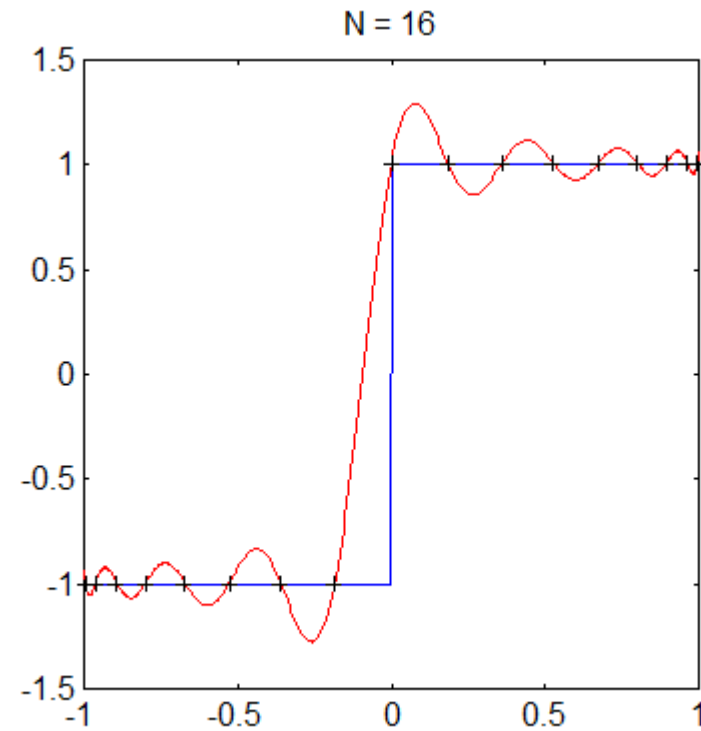
For functions with steep gradients we get overshoots and undershoots in the interpolating polynomial these are the famous Gibbs oscillations originally discovered with Fourier Series..

Chebyshev - Gibb's Oscillations

https://en.wikipedia.org/wiki/Gibbs_phenomenon

$f(x)=\text{sign}(x-\pi) \Rightarrow f(x)$ - blue ; $F_N(x)$ - red; x_i - '+'

Chebyshev



For functions with steep gradients we get overshoots and undershoots in the interpolating polynomial these are the famous Gibbs oscillations originally discovered with Fourier Series..

Measuring the error, $e(x)$, in an approximation?

For a polynomial of degree n , $p_n(x)$ approximating a function $f(x)$

The error $e(x) = p_n(x) - f(x)$, has to be calculated somehow.

We estimate the error over $[a, b]$ by using "norms".

The L_p norm of a function $g(x)$ is $\|g\|_p = \left(\int_a^b |g(x)|^p dx \right)^{1/p}$,

We now estimate the norm of the error i.e. this integral using pointwise errors

Let $e_i = p_n(x_i) - f(x_i)$, where $x_i = a + (i-1) \frac{(b-a)}{(m-1)}$, $i = 1 \dots m$,

where $m \gg n$, so that the interpolation points don't dominate.

Measuring measure the error, $e(x)$, in an approximation?

Let $e_i = p_n(x_i) - f(x_i)$, where $x_i = a + (i-1)\frac{(b-a)}{(n-1)}, i = 1 \dots n$

$L1$ function norm

$$p = 1, \|e\|_1 = \left(\int_a^b |e(x)| dx \right) \approx \frac{(b-a)}{(n-1)} \sum_{j=1}^{n-1} 0.5(|e_j| + |e_{j+1}|)$$

$L2$ function norm

$$p = 2, \|e\|_2 = \left(\int_a^b |e(x)|^2 dx \right)^{1/2} \approx \left[\frac{(b-a)}{(n-1)} \sum_{j=1}^{n-1} 0.5(|e_j|^2 + |e_{j+1}|^2) \right]^{\frac{1}{2}}$$

$L\inf$ function norm

$$p = \infty, \|e\|_\infty = \left(\int_a^b |e(x)|^\infty dx \right)^{1/\infty} \approx \max |e_j|, j = 1, \dots, n$$

Matlab Vector Norms

$$\text{Let } e = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix}$$

Matlab has norms of vectors they are related to the function norms in the last slide.

L1 vector norm

$$p = 1, \text{norm}(e, 1) = \|\mathbf{e}\|_1 = \sum_{j=1}^n |e_j|$$

L2 vector norm

$$p = 2, \text{norm}(e, 2) = \|\mathbf{e}\|_2 = \left(\sum_{j=1}^n |e_j|^2 \right)^{1/2}$$

Linf vector norm

$$p = \infty, \text{norm}(e, \text{inf}) = \|\mathbf{e}\|_\infty = \max |e_j|, j = 1, \dots, n$$

We can use the matlab vectors as approximations to functions normd if we we scale them appropriately

$$p = 1, \|\mathbf{e}\|_1 \approx \frac{(b-a)}{(n-1)} \sum_{j=1}^{n-1} 0.5(|\mathbf{e}_j| + |\mathbf{e}_{j+1}|) \approx \frac{(b-a)}{(n-1)} \text{norm}(e, 1)$$

$L2$ function norm

$$p = 2, \|\mathbf{e}\|_2 \approx \left[\frac{(b-a)}{(n-1)} \sum_{j=1}^{n-1} 0.5(|\mathbf{e}_j|^2 + |\mathbf{e}_{j+1}|^2) \right]^{\frac{1}{2}} \approx \sqrt{\frac{(b-a)}{(n-1)}} \text{norm}(e, 2)$$

$L\text{inf}$ function norm

$$p = \infty, \|\mathbf{e}\|_\infty \approx \max |\mathbf{e}_j|, j = 1, \dots, n = \text{norm}(e, \text{inf})$$

Vectors and
orthogonality $a \cdot b = (a, b) = 0$

$$\sum_{i=1}^n a_i b_i = 0$$

Norm $\|a\|_2 = \sqrt{(a, a)}$
 (or size)

matlab $\text{norm}(a, 2)$

Functions
 $(f, g) = 0$

$$\int_a^b f(x)g(x)dx = 0$$

$$\|f\|_2 = \sqrt{\int_a^b f(x)f(x)dx}$$

$$\sqrt{\frac{(b-a)}{n}} \text{norm}(f_n, 2)$$

vector $f_i = f(x_i), x_i$

evenly spaced