

Henry Dyer, I agree to the honor pledge

1A)

$$\Rightarrow M \begin{pmatrix} 1 & 0 & 1 \\ 1 & 1/\sqrt{2} & 1/\sqrt{2} \\ 1 & 1 & 0 \\ 1 & 1/\sqrt{2} & -1/\sqrt{2} \\ 1 & 0 & -1 \end{pmatrix} \begin{pmatrix} -2 \\ 0 \\ 2 \\ 6 \\ 3 \end{pmatrix} \leftarrow y$$

1B) Normal Equations: $M^T M c = M^T y$

$$\Rightarrow c = (M^T M)^{-1} M^T y$$

1C) $M^T M$ can be ill conditioned and hard to invert, instead using the singular value decomposition of M can make this process easier.

2A) $\begin{array}{c|ccc} x_0 & -1 & 0 & 1 \\ \hline e^{3x_0} & e^{-3} & 1 & e^3 \end{array}$

$$P(x) = \begin{cases} (1-e^{-3})x + 1 : x \in [-1, 0) \\ (e^3 - 1)x + 1 : x \in [0, 1] \end{cases}$$

2B) $[x_0, x_1] = [-1, 0]$

error: $e(x) = |e^{3x} - e^{-3}x - 2| \leq 1$

since function contains no roots $e^{3x} - e^{-3}x < 2 \forall x$
on interval and

$$x=0 : |e^0 - 0 - 2| = 1 \geq |e^{-3} + e^{-3} - 2| : x=-1$$

$[x_1, x_2]$

error: $e(x) = |e^{3x} - e^{-3}x - 2| \leq e^3 - 2$

since $e' = 3e^{3x} - e^{-3}$ so $e' > 0 \forall x$ on $[0, 1]$

hence $e(x)$ is monotonically increasing and so
right end point ($x=1$) is function's max.



This same logic for $[x_0, x_1]$
as well actually

2.1.-2

4.3.2

1(-1)^{1-3}

3A)

$$L_0(x) = \frac{(x-1)(x-2)(x-4)}{-1 - 8}, \quad L_1(x) = \frac{x(x-2)(x-4)}{4}$$

$$L_2(x) = \frac{x(x-1)(x-4)}{-4}, \quad L_3(x) = \frac{x(x-1)(x-2)}{24}$$

Then $p(x) = -16L_0(x) - 2L_1(x) + 0L_2(x) + 16L_3(x)$

3B)

$$\begin{array}{c} -2+16 \\ \hline 1 \end{array} \quad \begin{array}{c} 0+2 \\ \hline 1 \end{array} \quad \begin{array}{c} 16 \\ \hline 1-2 \end{array} \quad \begin{array}{c} 2-14 \\ \hline 2-0 \end{array} \quad \begin{array}{c} 8-2 \\ \hline 4-1 \end{array}$$

$$\begin{matrix} 0 & -16 & & & \\ & & 14 & & \\ 1 & -2 & & -6 & \\ & & 2 & & \\ 2 & 0 & & 2 & \\ & & 8 & & \\ 4 & 16 & & & \end{matrix}$$

$$\text{So } p(x) = -16 + 14(x) - 6(x)(x-1) + 2(x)(x-1)(x-2)$$

3C) It is more stable as it requires fewer steps to evaluate when a new term is added as it has already been accounted for in previous calculations.

$$l = \tan(x)$$

4A) $P_0(x) = 1, P_1(x) = x$

$$P_2(x) = \frac{P_{\frac{n}{n+1}}(x)}{2} = \frac{(2(1)+1)xP_1(x) - (1)P_0(x)}{2}$$

So $P_2(x) = \frac{3x^2 - 1}{2}$ some inverse trig function

4B) $c_0 = \frac{\int_{-1}^1 \frac{1}{1+x^2} dx}{\int_{-1}^1 1^2 dx} = \frac{\arctan(x) \Big|_{-1}^1}{2} = \frac{\frac{\pi}{4} - \frac{-\pi}{4}}{2} = \frac{\pi}{4} = \frac{3\pi}{2}$
 $\frac{1}{2}(\ln(z) - \ln(z)) = 0$

$c_1 = \frac{\int_{-1}^1 x \frac{1}{1+x^2} dx}{\int_{-1}^1 x^2 dx} = \frac{\frac{1}{2}(\ln(1+x^2)) \Big|_{-1}^1}{\frac{2}{3}} = \frac{0}{\frac{2}{3}}$

So-degree one approx B $P(x) = \frac{3\pi}{2} + Ox$

4C) $c_3 = \frac{\int_{-1}^1 (x^3 - \frac{3}{5}x) \left(\frac{1}{1+x^2}\right) dx}{\int_{-1}^1 \left(x^3 - \frac{3}{5}x\right)^2 dx}$

4A (Continued)

$$\langle P_0, P_1 \rangle = \int_{-1}^1 x dx = \frac{x^2}{2} \Big|_{-1}^1 = \frac{1}{2} - \frac{1}{2} = 0 \quad \checkmark$$

$$\langle P_0, P_2 \rangle = \frac{1}{2} \int_{-1}^1 3x^2 dx = \frac{1}{2} (x^3 - x) \Big|_{-1}^1 = \frac{1}{2} (0 - 0) = 0 \quad \checkmark$$

$$\begin{aligned} \langle P_1, P_2 \rangle &= \frac{1}{2} \int_{-1}^1 3x^3 - x dx = \frac{1}{2} \left(\frac{3}{4}x^4 - \frac{x^2}{2} \right) \Big|_{-1}^1 = \frac{1}{2} \left(\left(\frac{3}{4} - \frac{1}{2} \right) - \left(\frac{3}{4} - \frac{1}{2} \right) \right) \\ &= 0 \quad \checkmark \end{aligned}$$

$$5A) \nabla g(x, y) = -2(1-x) + 8(y-x^2)(-2x) \\ + 8(y-x^2)$$

$$= 8(y-x^2)(1-2x) - 2 + 2x$$

$$\vec{x}_1 = x_0 - \alpha \nabla g(x, y) : \begin{pmatrix} x_1 \\ y_1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} - \alpha \nabla g(0, 0)$$

We choose α often by line search so that the step size is not too large causing us to over shoot the minimum.

5B) Lazy Newton: $x_{n+1} = x_n - J_F^{-1}(x_0)F(x_n)$, inverse Jacobian only calculated once so less computationally expensive.

Broydan: $x_{n+1} = x_n - (J_F(x_0) + uv^T)F(x_n)$ for uv^T a rank 1 update, super linear convergence while updating inverse w/ low rank update only $O(n^2)$ vs $O(n^3)$ to compute inverse like in Newton.

$$5C) \text{ Error}(x_i) = \frac{f^{(n+1)}(\delta)}{(n+1)!} (x_i - \delta), \quad \delta \in [-1, 1]$$

Chebyshev nodes are found from projecting equispaced nodes on unit circle to x axis and help tame the approximation (particularly 1st deriv) near end points to avoid Runge phenomenon.

5D) By definition of orthogonality,

$\forall x \in [0, 1] , \langle P_j(x), P_I(x) \rangle = 0$ so for any x , $(\frac{x-y}{4})$ is a linear factor which can be factored out of inner product by linearity (of inner product operator) thus giving us $(\frac{x-y}{4})^2 \langle P_j(x), P_I(x) \rangle = 0$, so orthogonality is preserved.