

## Lecture 4.1

### Interpolation

Data:  $(x^1, y^1), (x^2, y^2), \dots, (x^n, y^n)$

Model:  $\hat{y} = \hat{y}(x) = z(x) a$

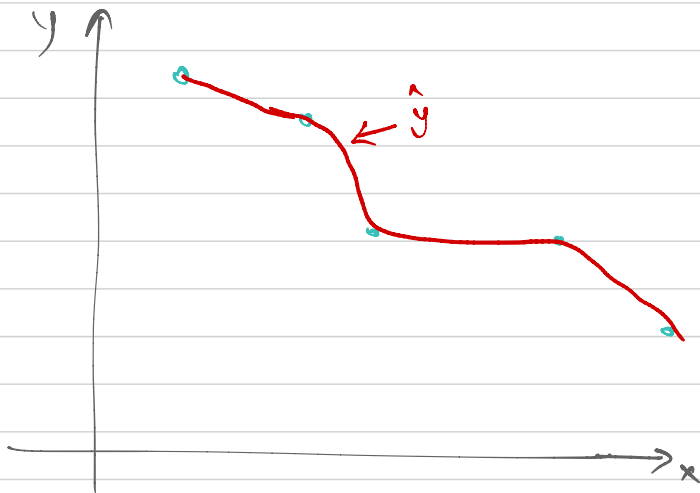
where

$z(x) =$  row vector function

$$= [z_1(x), z_2(x), \dots, z_m(x)]$$

$a =$  column vector

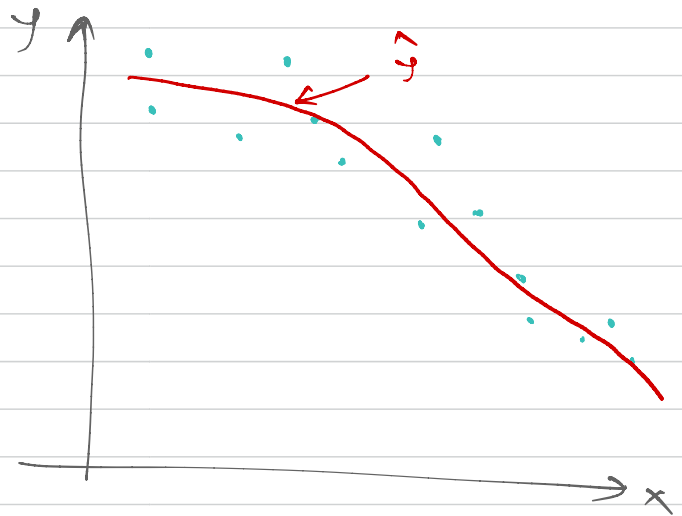
$$= \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix}$$



### Regression (linear regression)

some data

Model: some model  $\hat{y} = z(x) a$



### In case interpolation

taking example of polynomial  
( $z(x) = [1, x, x^2, \dots, x^{n-1}]$ )

↓  
we know that generally polynomial  
passing through  $n$  data points  
will be of the order of

$n-1$

↓  
so  $z$  must be basis  
of  $(n-1)^{\text{th}}$  order polynomial

$$z(x) = [1, x, x^2, \dots, x^{n-1}]_{n \times 1}$$

↓  
 $m = n$

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Solving for  $a$

Idea: match model to data at  
specified point  $x^1, x^2, \dots, x^n$

$$\left. \begin{array}{l} \hat{y}(x^1) = y^1 \\ \hat{y}(x^2) = y^2 \\ \vdots \\ \hat{y}(x^n) = y^n \end{array} \right\} \Rightarrow B a = y$$

where  $a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix}$

$$y = \begin{bmatrix} y^1 \\ y^2 \\ \vdots \\ y^n \end{bmatrix}$$

$$B = \begin{bmatrix} \text{---} z(x^1) \text{---} \\ \text{---} z(x^2) \text{---} \\ \vdots \\ \text{---} z(x^n) \text{---} \end{bmatrix}$$

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Solving for  $a$

Idea: minimize errors

↓  
if error is a squared error

then we have least squared method  
squared errors

$$E = E(a) = \frac{1}{n} \sum_{i=1}^n (\hat{y}(x^i) - y^i)^2$$

find  $a$  such that  $E(a)$  is  
minimum

⇕ equivalent

Solve  $a$  using  $J a = b$

where  $a = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix}$

$$J = B^T B$$

$$b = B^T y$$

$$= \begin{bmatrix} z_1(x^1) & z_2(x^1) & \dots & z_m(x^1) \\ z_1(x^2) & z_2(x^2) & \dots & z_m(x^2) \\ \vdots & \vdots & \ddots & \vdots \\ z_1(x^n) & z_2(x^n) & \dots & z_m(x^n) \end{bmatrix}$$

where  $B$  and  $y$  are defined in left-side

$$Ba = y$$

↓ when can it be solved

- (i)  $B$  must be square matrix
- (ii) basis function must be independent

$$\text{size}(B) = n \times m$$

↓

square matrix only if  $m = n$

$$Ja = b \Leftrightarrow B^T B a = B^T y$$

↓

- (i)  $J$  must be square matrix
- (ii) basis function must be independent

Generally  $B_{n \times m}$

$$J_{m \times m} = B_{m \times n}^T B_{n \times m}$$

you can use `polyfit` to perform interpolation/regression using polynomial

$$x = \begin{bmatrix} x^1 \\ x^2 \\ \vdots \\ x^n \end{bmatrix}$$

$$y = \begin{bmatrix} y^1 \\ y^2 \\ \vdots \\ y^n \end{bmatrix}$$

$$p = \text{polyfit}(x, y, l)$$

↑ you choose ( $l$  is a order of polynomial)

if  $l = n-1$  (I.e.  $(n-1)^{\text{th}}$  polynomial)

↳ interpolation

• Regression is solved using  $B^T B a = B^T y$

but it can be also used to solve interpolation

↓ for interpolation

$$B = \begin{bmatrix} - & z(x^1) & - \\ & \vdots & \\ - & z(x^n) & - \end{bmatrix}_{n \times m}$$

↓  
 $m = n$

— therefore  $B$  is a square matrix

— since I expect to be able to solve  $Ba = y$

I will assume  $B^{-1}$  exist  $\Rightarrow (B^T)^{-1}$  exist

— multiply both sides of  $B^T B a = B^T y$  by  $(B^T)^{-1}$

$$(B^T)^{-1} (B^T B a) = (B^T)^{-1} (B^T y)$$

$$\Rightarrow (B^T)^{-1} B^T B a = (B^T)^{-1} B^T y$$

$$\Rightarrow \boxed{Ba = y} \quad \left( \begin{array}{l} A^{-1}A = I \\ AA^{-1} = I \end{array} \right)$$

$$\boxed{B^T B a = B^T y} \longleftrightarrow \boxed{Ba = y}$$

↑  
for interpolation



## • System of ODEs

$$\frac{du}{dt} = Au + f, \quad u(0) = u_0$$

where

$A$  is  $n \times n$  matrix (given)

$$f = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix} \quad n \times 1 \text{ column vector function (given)}$$

$$u = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix} \quad n \times 1 \text{ column vector function (unknown)}$$

$$u_0 = \begin{bmatrix} u_{01} \\ u_{02} \\ \vdots \\ u_{0n} \end{bmatrix} \quad n \times 1 \text{ column vector (given)}$$

what not to do:

$$(A) \quad u = \text{zeros}(1, n); \quad u_0 = \text{zeros}(1, n);$$

$$u = u_0; \quad \% \text{ first time step}$$

$$u_{old} = \text{zeros}(1, n);$$

$$\text{for } k = 2 : N_t + 1$$

$$u_{old} = u;$$

$$\text{end} \quad u = \underbrace{(I + dt * A)}_{\substack{\text{matrix } n \times n \\ \swarrow}} * \underbrace{u_{old}}_{\searrow} + dt * f; \quad 1 \times n$$

$t_1, t_2, \dots, t_{N_t+1}$

$$(B) \quad J = \text{eye}(n);$$

$$f = \text{zeros}(1, n);$$

$$u_{old} = \text{zeros}(n, 1);$$

$$u = J * u_{old} + f;$$

$\begin{array}{ccc} \swarrow & \searrow & \searrow \\ n \times n & n \times 1 & 1 \times n \\ \underbrace{\hspace{10em}} & & \\ n \times 1 & & \end{array}$

### • Saving solution in system of ODEs

$$\frac{du}{dt} = Au + f, \quad u(0) = u_0$$

discrete times:  $t_1, t_2, \dots, t_{N_t+1} = T$

(.) if you do not use solutions  $u(t_1), u(t_2), \dots$

$u(t_{N_t})$  but only require  $u(t_{N_t+1})$  (ie.  $u(T)$ )

$$u = \text{zeros}(n, 1);$$

$$u_0 = \text{zeros}(n, 1);$$

$$u_{old} = \text{zeros}(n, 1);$$

$$J = I + dt * A;$$

$$u = u_0; \quad \% \text{ take care of IC}$$

for  $k = 2 : N_t + 1$

$$u_{old} = u;$$

$$u = J * u_{old} + dt * f;$$

end

$$u \longrightarrow u(T)$$

(ii) suppose you need solution at following time steps  
(problem 2 (ii))

$$k = 201, 401, 601, 801, 1001$$

$$u_{save} = \text{zeros}(n, 5);$$

$$u = \text{zeros}(n, 1); \quad u_{old} = \text{zeros}(n, 1); \quad u_0 = \text{zeros}(n, 1);$$

$$\text{count} = 1;$$

$$J = I + dt * A;$$

$$u = u_0; \quad \% \text{ take care } I c$$

$$\text{for } k = 2 : N_T + 1$$

$$u_{old} = u;$$

$$u = J * u_{old} + dt * f;$$

$$\text{if } k == 201 \text{ or } k == 401 \text{ or } k == 601 \text{ or} \\ k == 801 \text{ or } k == 1001$$

$$u_{save}(:, \text{count}) = u(:);$$

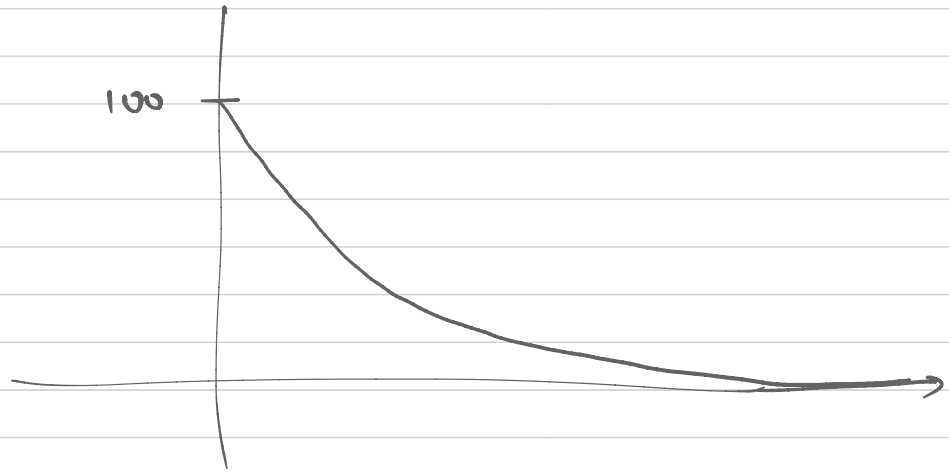
$$\text{count} = \text{count} + 1;$$

end

end

problem 2 (iii):  $T = 0.001$   $\rightarrow \Delta t = \frac{T}{N_t}$   
 $N_t = 1000, 10000, \dots$

$H(T) \rightarrow \text{plot}(H(T))$



# Discretizing PDE

$$\frac{\partial h(t, x)}{\partial t} = k(x) \frac{\partial^2 h(t, x)}{\partial x^2} + q_{\text{ext}}(t, x)$$

$x_1, x_2, \dots, x_{N_x+1}$

Notation  $\Rightarrow H_i(t) = h(t, x_i)$

write at typical  $x_i$  ( $i=2, \dots, N_x+1$ )

$$\frac{\partial h}{\partial t}(t, x_i) = k(x_i) \frac{\partial^2 h(t, x_i)}{\partial x^2} + q_{\text{ext}}(t, x_i)$$

Case  $i=3, \dots, N_x$

$$\frac{\partial H_i}{\partial t} = k(x_i) \left[ \frac{H_{i+1} - 2H_i + H_{i-1}}{\Delta x^2} \right] + q_{\text{ext}}(t, x_i)$$

$$[a_1, a_2, \dots, a_n] \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix} = a_1 b_1 + a_2 b_2 + \dots + a_n b_n$$

$$= \frac{k(x_i)}{\Delta x^2} [0, 0, \dots, \overset{\uparrow}{1}, -2, \overset{\uparrow}{1}, 0, \dots, 0] \begin{bmatrix} H_2 \\ H_3 \\ \vdots \\ H_{N_x+1} \end{bmatrix}$$

$\begin{matrix} \uparrow & \uparrow & \uparrow \\ \text{at place} & \text{at} & \text{at} \\ i-2 & i-1 & i \end{matrix}$

Case  $i=2$

$$\frac{\partial H_i}{\partial t} = \frac{k(x_i)}{\Delta x^2} [H_{i+1} - 2H_i + H_{i-1}] + q_{\text{ext}}(t, x_i)$$

$$= \frac{k(x_i)}{\Delta x^2} [-2, 1, 0, \dots, 0] \begin{bmatrix} H_2 \\ H_3 \\ \vdots \\ H_{N_x+1} \end{bmatrix} + q_{\text{ext}}(t, x_i) + \frac{H_{i-1} k(x_i)}{\Delta x^2}$$

Case  $i=N_x+1$

$$\frac{\partial H_i}{\partial t} = \frac{k(x_i)}{\Delta x^2} [\text{from hints}] + q_{\text{ext}}(t, x_i)$$