

A couple notes on MATLAB (8 HW)

If you want to see output as you go:

`disp()`
`sprintf()` ← include formatting options
`sprintf()` ←
goes to command line

If you do not see enough digits: format long short

Relative error

⇒ gives you approximate # of digits of accuracy

⇒ to automate exactly,

try using `round()`

↑ rounds to nearest integer

Models & data

→ models have **parameters**

e.g. $N(t+\delta t) = N(t)\eta$ 

e.g. $A + B \xrightarrow{\alpha} C$ 

probability an atom survives over δt timestep
reaction rate

→ does model capture/summarize the data?

↔ what choice of parameters optimizes this?

Ex: maximum likelihood estimate for exponential decay

Recall: our model is

$$N(t+\delta t) = N(t)\eta \quad \leftarrow = 1 - s$$

 How do we estimate true η ?

How do we know it is "good"?

⇒ we want η which maximizes the likelihood that, if you used it in the model, you would get the data you observe

$$P(\text{data}|\eta) = \prod_{t=0}^{T-1} \binom{N(t)}{N(t+1)} \left(\frac{\eta}{N(t+1)} \right)^{N(t+1)} \cdot \left(1 - \frac{\eta}{N(t+1)} \right)^{N(t) - N(t+1)}$$

joint prob function

Choice of atoms that survive

probability they survive

probability the rest decay

$$= L(\eta)$$

\Rightarrow want

$$\left. \begin{aligned} \frac{\partial}{\partial \eta} (L(\eta)) &= 0 \\ \frac{\partial^2}{\partial \eta^2} (L(\eta)) &< 0 \end{aligned} \right\} \text{defines a maximum point}$$

Notice:

$$\frac{\partial}{\partial \eta} (\log(L(\eta))) = \frac{1}{L(\eta)} \frac{\partial L}{\partial \eta} \Rightarrow \text{same root}$$

$$\log(L(\eta)) = \sum_{t=0}^{T-1} \log \binom{N(t)}{N(t+1)} + \log(\eta^{N(t+1)}) + \log((\eta^{-1})^{N(t)-N(t+1)})$$

$$= \sum_{t=0}^{T-1} \log \binom{N(t)}{N(t+1)} + N(t+1) \log \eta + (N(t) - N(t+1)) \log(\eta^{-1})$$

$$\frac{\partial}{\partial \eta} (\log(L(\eta))) = \sum_{t=0}^{T-1} \frac{N(t+1)}{\eta} + \frac{N(t) - N(t+1)}{\eta^{-1}} = 0$$

$$\Rightarrow \sum N(t+1)(\eta) - \sum N(t+1) = \sum (N(t+1) - N(t))(\eta)$$

$$\Rightarrow \sum N(t) \cdot \eta = \sum N(t+1)$$

$$\Rightarrow \eta^* = \frac{\sum_{t=0}^{T-1} N(t+1)}{\sum_{t=0}^{T-1} N(t)} \quad \begin{aligned} \delta^* &= 1 - \eta^* \\ &= \frac{\sum N(t) - N(t+1)}{\sum N(t)} \end{aligned}$$

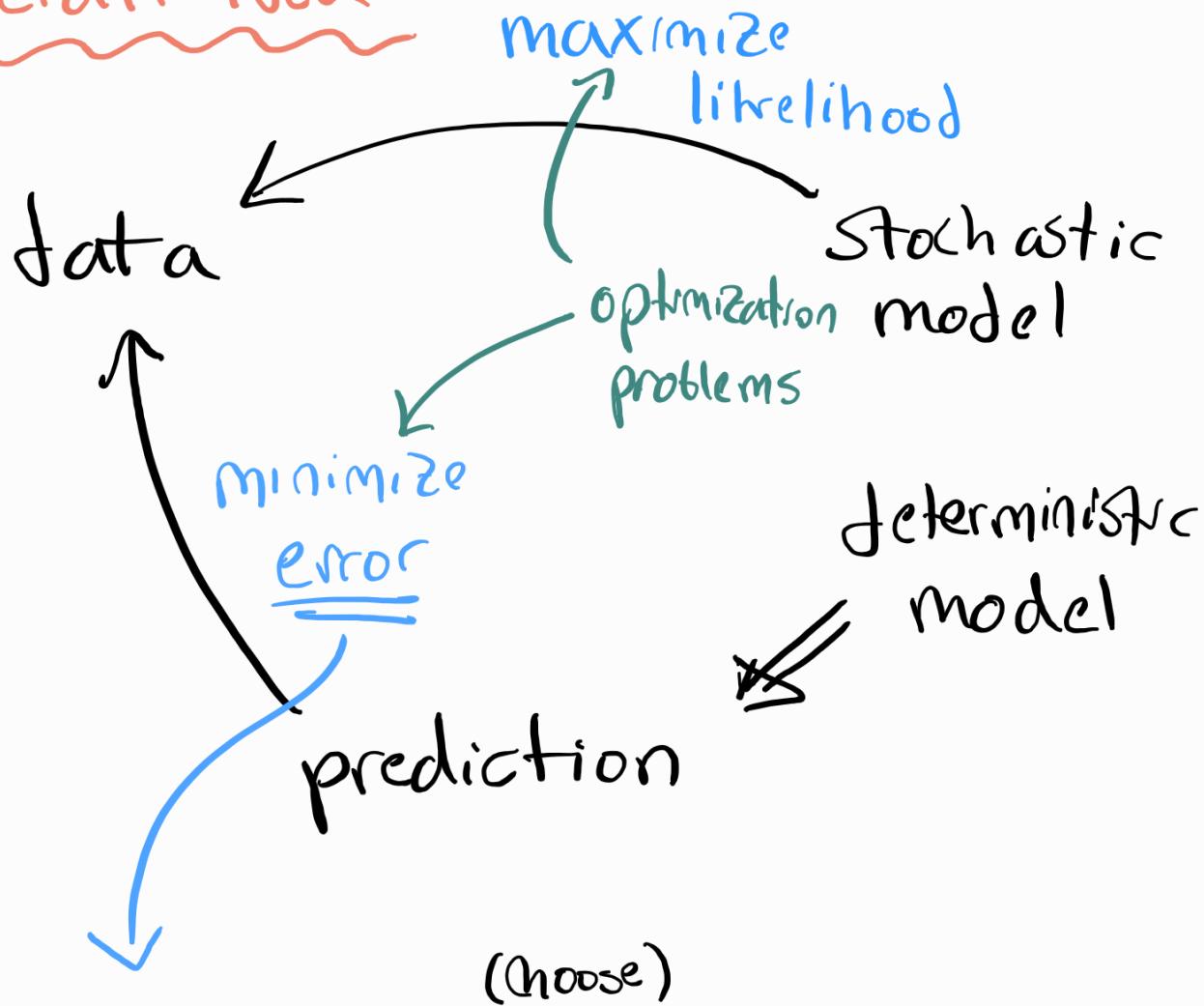
maximum likelihood estimate

Note: robust to experiment length

as in previous lecture

$$= \frac{N(0) - N(T)}{\sum_{t=0}^{T-1} N(t)}$$

Overall idea



Q How do we define error (functions)?
→ just like when choosing a model,
choosing an error measure requires
careful thought (context, experimental error, etc)

Ex: summarizing data (0-dim regression)

Suppose you have the ^(hourly) incomes of 7 people

data: \$10, \$12.50, \$12.50, \$113.00,
\$18.80, \$273.00, \$156.00

~~> from basic statistics, we know

$$\text{average} = \frac{\sum I_n}{7} = \$85.11$$

$$\text{median} = \$18.80$$

$$\text{minimax} = \$141.50$$

$$\text{mode} = \$12.50$$

if you had

to summarize

this data with

one income, what
would it be?

[Q] Pros & Cons?

$$\underline{L_p \text{ error}}: E_p^P(s) = \sum_{n=1}^7 |I_n - s|^P$$

"summary" of data

want s_p which minimizes error $E_p^P(s)$

$$\rightsquigarrow \frac{dE_p^P}{ds} = \sum P(I_n - s) |I_n - s|^{P-2}$$

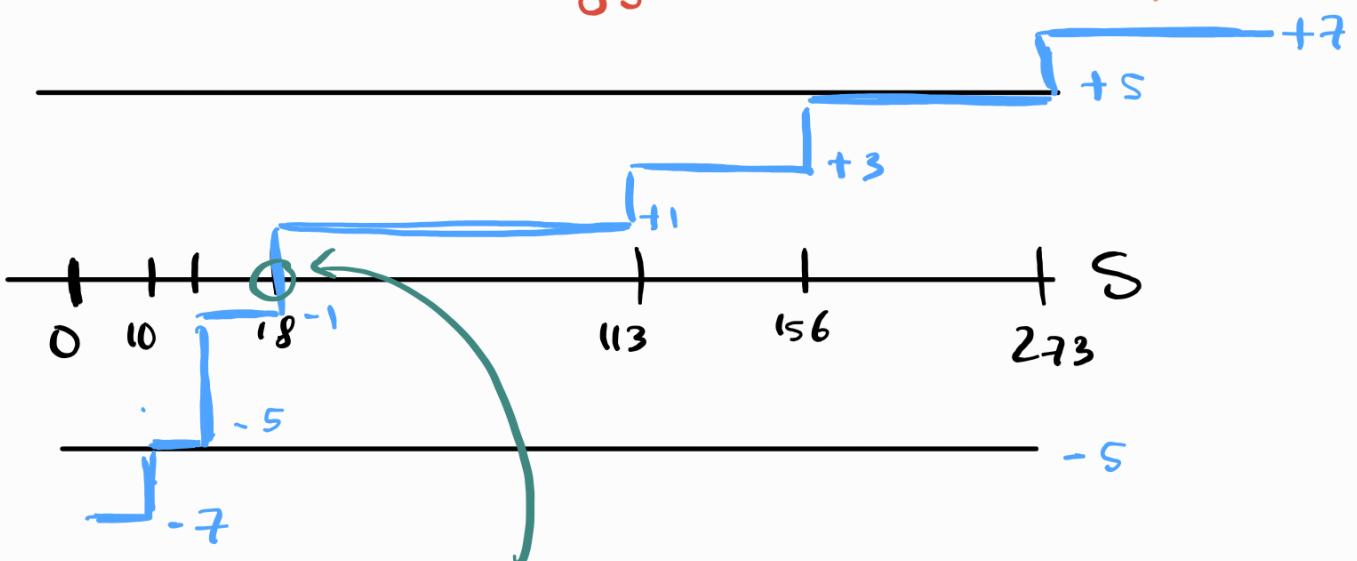
$$\hookrightarrow \text{want } \frac{dE_p^P}{ds} = 0 \text{ & } \frac{d^2E_p^P}{ds^2} > 0 \text{ [Minimizer]}$$

$$\underline{L_1 \text{ error}}: E'_1(s) = \sum_{n=1}^7 |I_n - s|$$

= 1 if
↑ $I_n > s$

$$\Rightarrow \frac{\partial E'_1}{\partial s} = \sum_{n=1}^7 \frac{I_n - s}{|I_n - s|} = \sum_{n=1}^7 \text{sign}(I_n - s)$$

Q What does $\frac{\partial E}{\partial s}$ look like?



Notice:
insensitive
to magnitude
of outliers

$$\frac{\partial E}{\partial s} = 0 \text{ at } s = \$18.80$$

$\Rightarrow \frac{\partial E'_1}{\partial s}$ gives us exactly the median

~~~ **Q** Why?

$$s \in [12.5, 156]$$

Notice

$$E'_1(s) = \sum_{n=1}^7 |I_n - s| = \left[ |10 - s| + |273 - s| \right] + \left[ |12.5 - s| + |156 - s| \right]$$

$$s \in [10, 273]$$

$$s \in [12.5, 113]$$

$$+ \left[ |12.5 - s| + |113 - s| \right]$$

$$+ |18.8 - s| \quad \leftarrow s = 18.8$$

$$\underline{L_2 \text{ error}} : E_2^2(S) = \sum_{n=1}^N (I_n - S)^2$$

↙ We know  
this is  
concave up

$$\frac{\partial E_2^2}{\partial S} = \sum 2(I_n - S) = 0$$

$$\Rightarrow \sum_{n=1}^N I_n - \underbrace{\sum_{n=1}^N S}_{= N \times S} = 0$$

$$\Rightarrow S = \frac{1}{N} \sum_{n=1}^N I_n \leftarrow \underline{\text{average}}$$

Notice: each  
data point  
carries  
equal  
weight

$$\underline{L_\infty \text{ error}} : E_p(S) = \sum |I_n - S|^p$$

$$\rightsquigarrow E_p(S) = \sqrt[p]{\sum |I_n - S|^p}$$

Let  $m$  be s.t.  $|I_m - S| = \max_n |I_n - S|$

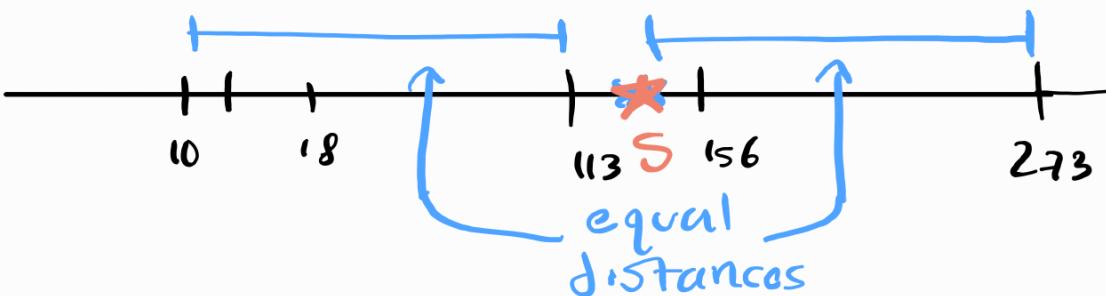
Then,

$$E_p(S) = \left( |I_m - S|^p + \sum \left( \frac{|I_n - S|}{|I_m - S|} \right)^p \right)^{1/p}$$

as  $p \rightarrow \infty$ ,  $\underbrace{\left( \frac{|I_n - S|}{|I_m - S|} \right)^p}_{\leq 1} \leq 1$

$$E_p(S) \rightarrow \left( |I_m - S|^p \times (1+0+0+\dots) \right)^{1/p}$$

$$E_\infty(S) = |I_m - S| = \max_n |I_n - S|$$



Notice:  
sensitive to  
outliers

### L<sub>p</sub> error:

$$\text{as } p \rightarrow 0, E_p^p(s) \rightarrow \sum_n \lim_{p \rightarrow 0} |I_n - s|^p = \begin{cases} 1 & I_n = s \\ 0 & \text{else} \end{cases}$$

$$\Rightarrow E_0(s) = \# \text{ points matching } s \\ = \text{mode of data} = \$12.50 \quad \text{in this case}$$

notice: not useful in near continuous data, only  
in discrete cases

Ex: summarizing a relation (1-dim regression)

Suppose we have N-data points

$$\left\{ A, \frac{\partial A}{\partial t}, y \right\}_j \text{ for reactions } \left\{ \begin{array}{l} A \xrightarrow{\tilde{a}} B \\ C \xrightarrow{\gamma} A \end{array} \right.$$

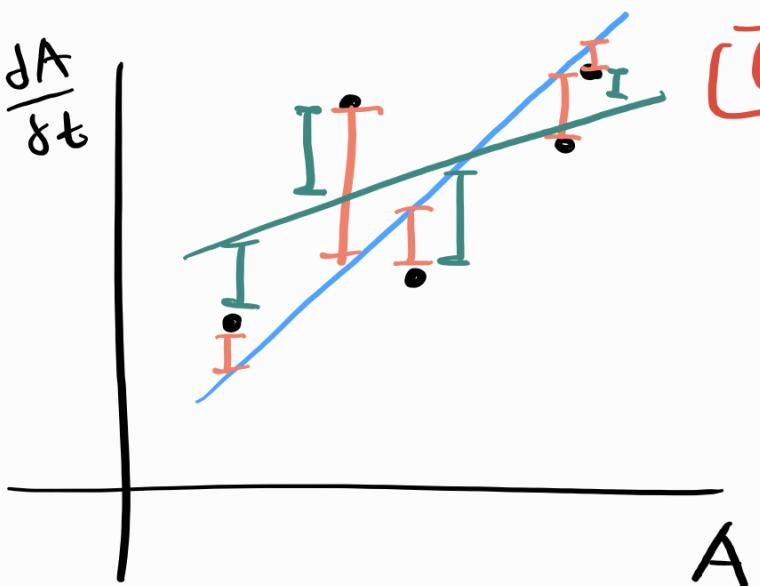
$$\Rightarrow \text{our model: } \frac{\partial A}{\partial t} = -\tilde{a}A + \gamma C = aA + b = y$$

What (a,b) choices best fit our data?

$$L_p \text{ error: } E_p^p = \sum_{j=1}^N |y(A_j) - y_j|^p$$

$$\Rightarrow E_p^p(a, b) = \sum_{j=1}^N \underbrace{|aA_j + b - y_j|^p}_{\text{vertical distance between prediction \& data}}$$

vertical distance between  
prediction & data



[Q] How might we interpret different  $E_p$  error minimizers?

$E_\infty \rightarrow$  line such that largest deviation is minimal

$E_0 \rightarrow$  line which passes through the most points (sort of)

$E_1, E_2 \rightarrow$   $E_2$  penalizes larger deviations more than  $E_1$ , "equal" contributions

$L_2$ -error :

$$E_2^2(a, b) = \sum_{j=1}^N (aA_j + b - y_j)^2$$

Want both  $\partial_a E_2^2(a, b) = 0$  and  $\partial_b E_2^2(a, b) = 0$

$$\partial_a E_2^2(a, b) = \sum 2A_j(aA_j + b - y_j) = 0$$

$$\Rightarrow 2a \sum A_j^2 + 2b \sum A_j = 2 \sum A_j y_j$$

linear!

$$\partial_b E_2^2(a, b) = \sum_{j=1}^N 2(aA_j + b - y_j) = 0$$

$$\Rightarrow 2a \sum A_j + 2bN = 2 \sum y_j$$

Linear?

(\*)

Linear system

$$\begin{bmatrix} \sum A_j^2 & \sum A_j \\ \sum A_j & N \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \sum A_j y_j \\ \sum y_j \end{bmatrix}$$

$\Rightarrow$  solve for  $a, b$  to get  $L_2$  minimizer

$L_1$ -error

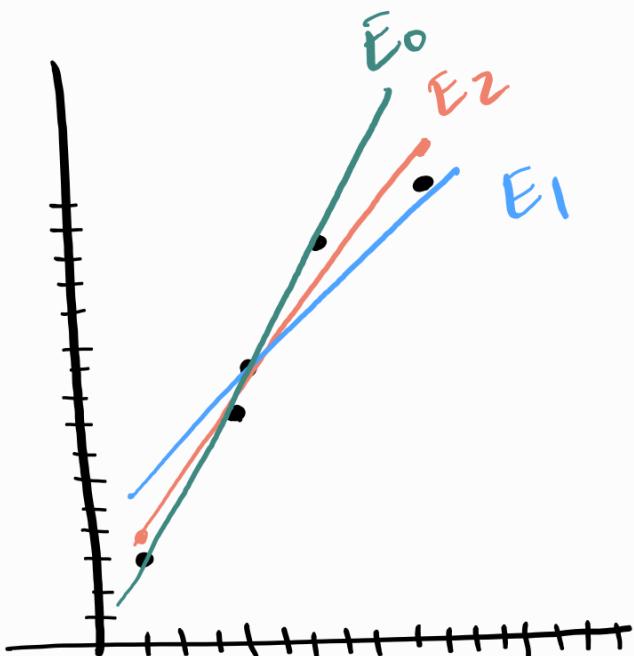
$$E_1(a, b) = \sum_{j=1}^N |aA_j + b - y_j|$$

$$\left\{ \begin{array}{l} \partial_a E_1 = \sum_{j=1}^N \text{sgn}(aA_j + b - y_j) \cdot A_j \\ \partial_b E_1 = \sum_{j=1}^N \text{sgn}(aA_j + b - y_j) \end{array} \right.$$

example

$$y = 2A + 1 \leftarrow E_0 \text{ minimizer}$$

$$(A, y) = (1, 3), (3, 8), (4, 9), (6, 13), (9, 15)$$



E\_2 minimizer

solving (\*) gives

$$a = \frac{46}{31} \approx 1.484$$

$$b = \frac{86}{31} \approx 2.774$$

E\_1 minimizer

$$a = \frac{6}{5} = 1.2$$

$$b = \frac{21}{5} = 4.2$$

## Quiz

Suppose you survey your friends about their favorite number, getting data:

$$\{3, 9, 3, 13, 2736, 0, \pi, 0.08\}$$

- (a) What is the minimizer of  $L_1$  error?
- (b) What is the minimizer of  $L_2$  error?
- (c) What is the minimizer of  $L_4$  error?  
[approximately. Ok to use computer]
- (d) What is the minimizer of  $L_\infty$  error?
- (e) Which minimizer do you believe best summarizes the data, in your opinion? Why?

Show your work. Explain your steps.

a) median  $3.071 = \frac{3+7}{2}$

b) mean 345.9

c)  $\approx 942.176$

d) minimax 1368

e) subjective