

MH for linear fit

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metropolis hastings (for linear fit)

aka finding a distribution for our parameters
based on a probability function

last time :



this time :

$$x \rightarrow \theta = \begin{bmatrix} b \\ m \end{bmatrix}$$

$$\theta' = \theta + \delta \cdot (2u - 1)$$

$u \in [0, 1]$

$$p \rightarrow \mathcal{L} \equiv \prod_{i=1}^N p(y_i | x_i, \sigma_{y_i}, \theta).$$

$$\delta = \begin{bmatrix} \delta_b \\ \delta_m \end{bmatrix}$$

$$p(y_i | x_i, \sigma_{y_i}, \theta) \equiv \frac{1}{\sqrt{2\pi\sigma_{y_i}^2}} \exp\left(-\frac{(y_i - f(x_i, \theta))^2}{2\sigma_{y_i}^2}\right).$$

data : $\{y_i\}$, $\{x_i\}$, $\{\sigma_{y_i}\}$

model : $f(x_i, \theta) = b + m x_i$

MH: 2 tests

$$a \equiv \frac{P(x')}{P(x)}$$

$$u \in [0, 1]$$

if $a > 1$ \rightarrow keep x'

$$x \rightarrow \theta$$

$$P(x) \rightarrow \mathcal{L}(\theta)$$

else if $a > u$ \rightarrow keep x'

else store old x again

likelihood $\rightarrow \ln \mathcal{L}$

$$a = \frac{\mathcal{L}(\theta')}{\mathcal{L}(\theta)} > 1$$

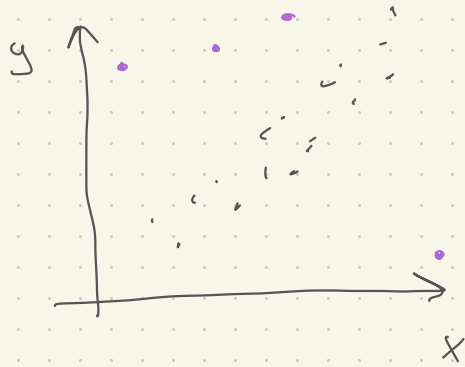
$$\rightarrow \underline{\ln \mathcal{L}(\theta') - \ln \mathcal{L}(\theta)} > 0$$

$$a > u$$

$$\rightarrow \underline{\ln \mathcal{L}(\theta') - \ln \mathcal{L}(\theta)} > \ln(u)$$

part D

$$\Theta = \begin{bmatrix} b \\ m \\ P_b \\ Y_b \\ V_b \end{bmatrix}$$



P_b : % of points that are outliers

Y_b : average

V_b : variance

$$\mathcal{L} \equiv p(\{y_i\}_{i=1}^N | m, b, P_b, Y_b, V_b) \quad (4)$$

$$= \prod_{i=1}^N ((1 - P_b) p_{\text{good}}(y_i | m, b) + P_b p_{\text{bad}}(y_i | Y_b, V_b)) \quad (5)$$

$$\propto \prod_{i=1}^N \left(\frac{1 - P_b}{\sqrt{2\pi\sigma_{yi}^2}} \exp\left(-\frac{(y_i - mx_i - b)^2}{2\sigma_{yi}^2}\right) + \frac{P_b}{\sqrt{2\pi(V_b + \sigma_{yi}^2)}} \exp\left(-\frac{(y_i - Y_b)^2}{2(V_b + \sigma_{yi}^2)}\right) \right) \quad (6)$$

"priors" = known restrictions

- $0 \leq P_b \leq 1$

- $V_b > 0$

prob. fon = $\mathcal{L}(\Theta) * \text{prior}(\Theta)$

ln space $\rightarrow \ln \mathcal{L}(\Theta) + \ln \text{prior}(\Theta)$

(ln prior)

$$\theta = \begin{bmatrix} b \\ m \end{bmatrix}$$

$$\mathcal{L} = \prod_{i=1}^N p(y_i | x_i, \sigma_{yi}, m, b)$$

$$p(y_i | x_i, \sigma_{yi}, m, b) = \frac{1}{\sqrt{2\pi\sigma_{yi}^2}} \exp\left(-\frac{[y_i - m x_i - b]^2}{2\sigma_{yi}^2}\right)$$

$$\ln \mathcal{L} = \ln \prod_{i=1}^N \frac{1}{\sqrt{2\pi\sigma_{yi}^2}} \exp\left(-\frac{(y_i - m x_i - b)^2}{2\sigma_{yi}^2}\right)$$

$$\ln \mathcal{L} = \sum_i \left[-\frac{1}{2} \ln(2\pi\sigma_{yi}^2) - \frac{(y_i - m x_i - b)^2}{2\sigma_{yi}^2} \right]$$

$$= \text{np.sum}\left(-\frac{1}{2} \text{np.log}(2 * \text{np.pi} * \text{sigy} ** 2) - \frac{1}{2} (y - m x - b)^2 / \text{sigy} ** 2\right)$$

in code:

`ln_likelihood()` returns

$$\text{np.sum}\left(-\frac{1}{2} \text{np.log}(2\pi \text{sigy} ** 2) - \frac{1}{2} ((y - m x - b) / \text{sigy}) ** 2\right)$$

$\theta[1]$ $\theta[0]$