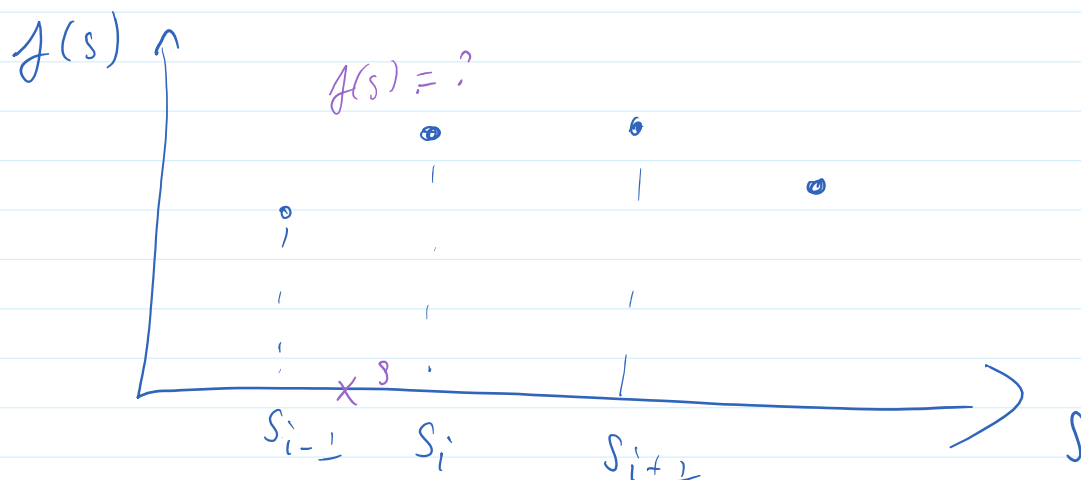


Prior Elicitation (VERY SUBJECTIVE)

I. Smooth priors:



given $\{f(s_0), \dots, f(s_n)\}$ + "smooth" $f(s)$

How do we estimate $f(s)$ at any points?

- if $f(s)$ is smooth then $f(s)$ should be close to $f(s_{i-1})$ and $f(s_i)$. A simple way to convey this is, if set $m(s) = f(s)$,

$$(\dagger) \quad m_i = \frac{m_{i-1} + m_{i+1}}{2} + w_i$$

$$i = 1, \dots, n-1$$

innovation

assume:

$$w_i \sim N(0, \sigma^2)$$

identically
independently

known

term
due to the
fact that we are
not sure about
relation between

identically
independently
distributed (i.i.d.)

known

relation between
 m_i, m_{i-1}, m_{i+1}

then

$\vec{m} = [m_0, \dots, m_n]^T$ is a random vector

what is the distribution of \vec{m} ? = $\pi_{\text{prior}}(\vec{m})$

From (*) we have:

$$\frac{1}{2} \begin{bmatrix} -1 & 2 & -1 & 0 & \dots & \dots \\ 0 & -1 & 2 & -1 & 0 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \dots & \dots & 0 & -1 & 2 & -1 \end{bmatrix} \begin{bmatrix} m_0 \\ \vdots \\ m_n \end{bmatrix} =$$

A \vec{m}

$$\begin{bmatrix} w_1 \\ \vdots \\ w_{n-1} \end{bmatrix} \sim \begin{matrix} N(0, \sigma^2)_{x_1} \\ N(0, \sigma^2)_{x_2} \\ \vdots \\ N(0, \sigma^2)_{x_{n-1}} \end{matrix}$$

\vec{w}

$$= N(\vec{0}, \sigma^2 \mathbf{I})$$

$$\propto \exp\left(-\frac{1}{2\sigma^2} \vec{w}^T \vec{w}\right)$$

$$A \quad \vec{m} = \vec{w} \sim N(\vec{0}, \sigma^2 \mathbf{I})$$

$$\mathbb{R}^{(n+1) \times (n+1)}$$

assume " A^{-1} exists"
(fixed later)

$$\vec{m} = A^{-1} \vec{w}$$

$$\vec{m} = A \vec{w}$$

$$\Rightarrow \pi_{\text{prior}}(\vec{m}) \stackrel{??}{\sim} \pi_{\vec{w}}(A \vec{m})$$

$$\propto \exp\left(-\frac{1}{2\gamma^2} \vec{w}^T \vec{w}\right)$$

$$\propto \exp\left(-\frac{1}{2\gamma^2} \vec{m}^T A^T A \vec{m}\right)$$

"Rigorously":

$$\int_B \pi_{\text{prior}}(\vec{m}) d\vec{m} := \int_B \pi(\vec{m}) d\vec{m}$$

// def of probability

$$\int_{A^{-1}(B)} \pi_{\vec{w}}(\vec{w}) d\vec{w}$$

$$// d\vec{w} = "det(A)" d\vec{m}$$

$$\int_B \pi_{\text{prior}}(\vec{m}) d\vec{m} = \int_B \pi_{\vec{w}}(A \vec{m}) "det(A)" d\vec{m}$$

$$\Downarrow \quad \forall B, "det(A)" = \text{const}$$

$$\pi_{\text{prior}}(\vec{m}) \propto \pi_{\vec{w}}(A \vec{m})$$

$$\begin{aligned}\pi_{\text{prior}}(\vec{m}) &\propto \pi_{\vec{w}}(A\vec{m}) \\ &\propto \exp\left(-\frac{1}{2\sigma^2} \vec{m}^T A^T A \vec{m}\right)\end{aligned}$$

- Remark: A is not square and this is a direct consequence of the fact that we haven't specified the smoothness at the boundary!

DIRICHLET BOUNDARY CONDITIONS

- Let's say that we believe that the function f is "close" to zero at the boundary. Then one way to convey this belief is to extend by zero:

$$m_{-1} = 0 \quad , \quad m_{n+1} = 0$$

$$\begin{array}{ccccccc} m_{-1} = 0 & & & & & & m_{n+1} = 0 \\ | & | & | & | & | & & | \\ -1 & 0 & 1 & 2 & \dots & & n & n+1 \end{array}$$

$$m_i := f(x_i)$$

thus we can use the same expression:

$$m_0 = \frac{m_1 + m_{-1}}{2} + w_0 \quad \Bigg| \quad w_0 \sim N(0, \sigma^2)$$

$$m_n = \frac{m_{n-1} + m_{n+1}^{\text{=0}}}{2} + w_n \quad \left| \quad w_n \sim N(0, \gamma^2) \right.$$

Hence:

$$\frac{1}{2} \begin{bmatrix} 2 & -1 & 0 & \dots & \dots \\ -1 & 2 & -1 & 0 & \dots \\ & \ddots & \ddots & \ddots & \ddots \\ & & \ddots & \ddots & \ddots \\ & & & \ddots & \ddots \end{bmatrix} \begin{bmatrix} m_0 \\ \vdots \\ m_n \end{bmatrix} = \begin{bmatrix} w_0 \\ \vdots \\ w_n \end{bmatrix} \sim N(\vec{0}, \gamma^2 \mathbf{I})$$

$A_0 \times \vec{m} = \vec{w}$

Same argument's



side note:

$$\vec{x} = \text{randn}(3) \Rightarrow \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad x_i \sim N(0, 1)$$

$$N(\vec{0}, \sigma^2 \mathbf{I}^{3 \times 3})$$

$$x \sim \exp\left(-\frac{1}{2\sigma^2} x^2\right) \stackrel{||}{=} N(0, \sigma^2)$$

$$\vec{x} \sim \exp\left(-\frac{1}{2\sigma^2} \vec{x}^T \vec{x}\right) \stackrel{||}{=} N(\vec{0}, \sigma^2 \mathbf{I})$$

$$\vec{x} \sim \exp\left(-\frac{1}{2\sigma^2} \vec{x}^T \mathbf{L} \vec{x}\right) = N(\vec{0}, \sigma \mathbf{L}^{-1})$$

For our case

$$\vec{m} \sim \exp\left(-\frac{1}{2\sigma^2} \vec{m}^T \mathbf{A}_0^T \mathbf{A}_0 \vec{m}\right)$$

$$\stackrel{||}{=} N(\vec{0}, \sigma^2 (\mathbf{A}_0^T \mathbf{A}_0)^{-1})$$

whitening process

$$\text{let } \vec{y} = \gamma \mathbf{A}_0^{-1} \vec{x} \quad \text{where } \vec{x} \sim N(0, \mathbf{I})$$

$$* \quad \mathbb{E}[\vec{y}] \stackrel{\text{linearity of } \mathbb{E}}{=} \mathbf{A}_0^{-1} \mathbb{E}[\vec{x}] = 0$$

$$\begin{aligned} * \quad \mathbb{V}[\vec{y}] &= \mathbb{E}[(\vec{y} - \mathbb{E}[\vec{y}])(\vec{y} - \mathbb{E}[\vec{y}])^T] \\ &= \mathbb{E}[\vec{y} \vec{y}^T] = \sigma^2 \mathbb{E}[\mathbf{A}_0^{-1} \vec{x} \vec{x}^T \mathbf{A}_0^{-T}] \end{aligned}$$

$$= E[\tilde{y} \tilde{y}'] = \sigma^2 E[A_0^{-1} \tilde{x} \tilde{x}^T A_0^{-1}]$$

$$\parallel \text{linearity of } E = \int$$

$$\sigma^2 A_0^{-1} E[\tilde{x} \tilde{x}^T] A_0^{-1}$$

$$\parallel E[\tilde{x} \tilde{x}^T] = V[\tilde{x}] = I$$

$$\sigma^2 A_0^{-1} A_0^{-1} = \sigma^2 (A_0^T A_0)^{-1}$$

Homework:

$$1) \quad \vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \sim N\left(\begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}, \begin{bmatrix} a_1 & a_2 \\ a_2 & a_3 \end{bmatrix}\right)$$

a) what is the marginal distribution of

x_1

b)

x_2

$$2) \quad \vec{x} = \begin{bmatrix} \vec{x}_1 \\ \vec{x}_2 \end{bmatrix} \sim N\left(\begin{bmatrix} \vec{\bar{x}}_1 \\ \vec{\bar{x}}_2 \end{bmatrix}, \begin{bmatrix} A_1 & A_2 \\ A_2^T & A_3 \end{bmatrix}\right)$$

a)

//

//

//

\vec{x}_1 !

$$b/ \quad x_1 \quad x_2$$

Note: $x \sim \pi(x) \Rightarrow \int \pi(x) dx = 1$

NON-ZERO DIRICHLET

- In this case, one way to express non zero Dirichlet boundary condition is to say

$$M_0 \sim N\left(0, \frac{\gamma^2}{\delta_0^2}\right)$$

$$M_1 = \frac{m_0 + m_2}{2} + N(0, \gamma^2)$$

$$\vdots$$

$$M_{n-1} = \frac{m_{n-2} + m_n}{2} + N(0, \gamma^2)$$

$$M_n \sim N\left(0, \frac{\gamma^2}{\delta_n^2}\right)$$

$$\begin{aligned} \delta_0 m_0 &= w_0 \sim N(0, \gamma^2) \\ \delta_n m_n &= w_n \sim N(0, \gamma^2) \end{aligned}$$

$$\begin{bmatrix} 2\delta_0 & 0 & \dots \\ -1 & 2 & -1 & 0 & \dots \end{bmatrix}$$

$$\begin{bmatrix} w_0 \\ \vdots \end{bmatrix}$$

$$\dots, x^2, \dots$$

$$\underbrace{\begin{bmatrix} -1 & 2 & -1 & 0 & \dots \\ & \ddots & \ddots & \ddots & \\ & & \ddots & \ddots & \\ & & & 0 & 2\delta_n \end{bmatrix}}_{A_L} \times \underbrace{\begin{bmatrix} \vdots \\ \vdots \\ \vdots \\ m_n \end{bmatrix}}_{\vec{m}} = \underbrace{\begin{bmatrix} \vdots \\ \vdots \\ \vdots \\ w_n \end{bmatrix}}_{\vec{w}} \sim N(0, \sigma^2 \mathbf{I})$$

$$A_L \times \vec{m} = \vec{w}$$

↓ same process

$$\pi(\vec{m}) \propto \exp\left(-\frac{1}{2\sigma^2} \vec{m}^T A_L^T A_L \vec{m}\right)$$

Remark. given σ , it is not sufficient to determine

$\pi(\vec{m})$ because $\delta_0, \delta_n = ???$ In order to

have a more uniform uncertainty we can

make $\delta_0, \delta_n =$ uncertainty of the midpoint

so if we define $L = (A_L^T A_L)^{-1}$, then this

means

$$\delta_0^2 = \delta_n^2 = L\left(L \frac{\sigma^2}{2}, L \frac{\sigma^2}{2}\right)$$

this is a nonlinear eqn of $\alpha = \delta_0^2 = \delta_n^2$

|| relax, simplify

relax, simplify

$$\sigma_0^2 = \sigma_n^2 = L_0 \left(\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right)$$

where $L_0 = (A_0^T A_0)^{-1}$

Non-Smooth Priors

one way to convey the fact that the unknown function is non-smooth is

$$m_i = m_{i-1} + w_i \left(\sim N(0, \gamma^2) \right)$$

$\Downarrow \quad \forall i = 1, \dots, n$
 $m_0 = 0$

$$\underbrace{\begin{bmatrix} 1 & 0 & \dots & 0 \\ -1 & 1 & 0 & \dots \\ & \ddots & \ddots & \ddots \\ & & 0 & -1 & 1 \end{bmatrix}}_{A_N} \times \underbrace{\begin{bmatrix} m_1 \\ \vdots \\ m_n \end{bmatrix}}_{\vec{m}} = \underbrace{\begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix}}_{\vec{w}} \sim N(\vec{0}, \gamma^2 \mathbf{I})$$

$A_N \times \vec{m} = \vec{w}$

same process

$$\pi_{\text{prior}}(\vec{m}) \propto \exp\left(-\frac{1}{2} \vec{m}^T A_N^T A_N \vec{m}\right)$$

$$\pi_{\text{prior}}(\vec{m}) \propto \exp\left(-\frac{1}{2\sigma^2} \vec{m}^T A_N^T A_N \vec{m}\right)$$

- Moreover if we "know" that there is a bigger jump at $i = \bar{J}$, $1 \leq \bar{J} \leq n$

$$m_i = m_{\bar{J}} = m_{\bar{J}-1} + w_{\bar{J}} \left(\sim N\left(0, \frac{\sigma^2}{\theta^2}\right) \right)$$

\Downarrow

A_N becomes

$$\tilde{A}_N = \begin{bmatrix} 1 & & & & \\ & \ddots & & & \\ & & 0 & & \\ & & \vdots & \ddots & \\ & & 0 & & 1 \end{bmatrix} \times A_N$$

at the \bar{J} row:

\bar{J} column: