

Point process likelihood.

$$// \mathcal{P}(N_k | x_k, \theta) = (\lambda_{k, \Delta})^{N_k} \exp(-\lambda_{k, \Delta})$$

$$\mathcal{P}(x_k | x_{k-1}, \theta) \sim \mathcal{N}(\phi x_{k-1} + \alpha I_k, \sigma^2) //$$

$$// \mathcal{P}(N_{1:k}, x_{0:k} | \theta) = \mathcal{P}(N_{1:k} | x_{1:k}, \theta) \cdot \mathcal{P}(x_{1:k} | \theta) \\ = \prod_{k=1}^K \mathcal{P}(N_k | x_k, \theta) \mathcal{P}(x_0) \prod_{k=1}^K \mathcal{P}(x_k | x_{k-1}, \theta) //$$

$$// \log(\mathcal{P}(N_{1:k}, x_{0:k} | \theta)) =$$

$$\mathcal{L}(N_{1:k}, x_{0:k} | \theta) =$$

$$-\frac{K+1}{2} \log 2\pi - (K+1) \log \sigma^2 - \sum_{k=1}^K \frac{(x_k - \phi x_{k-1} - \alpha I_k)^2}{2\sigma^2}$$

$$+ \frac{1}{2} \log(1 - \phi^2) - \frac{x_0^2(1 - \phi^2)}{2\sigma^2}$$

$$+ \sum_{k=1}^K [N_k (\mu + \beta x_k + \log \Delta) - \exp(\mu + \beta x_k) \cdot \Delta] //$$

Posteriors of $x_{0:k}$ & θ .

$$// \mathcal{P}(x_{0:k} | N_{1:k}, \theta) \propto \mathcal{P}(N_{1:k} | x_{0:k}, \theta) \mathcal{P}(x_{0:k} | \theta) //$$

Joint likelihood //

$$// \mathcal{P}(\theta | x_{0:k}, N_{1:k}) \propto \mathcal{P}(N_{1:k}, x_{0:k} | \theta) \cdot \mathcal{P}(\theta) //$$

Tensor G for $x_{0:k}$.

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial x_0} &= -\frac{\partial}{\partial x_0} \left(\frac{(x_1 - \phi x_0 - 2I_1)^2}{2\sigma^2} \right) - \frac{x_0(1 - \phi^2)}{\sigma^2} \\ &= \frac{\phi(x_1 - \phi x_0 - 2I_1)}{\sigma^2} - \frac{x_0(1 - \phi^2)}{\sigma^2} = \frac{\phi x_1 - \phi^2 I_1 - x_0}{\sigma^2} \end{aligned}$$

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial x_k} &= -\frac{\partial}{\partial x_k} \left(\frac{(x_k - \phi x_{k-1} - 2I_k)^2}{2\sigma^2} \right) \quad \text{for } k = [1, \dots, k-1] \\ &\quad - \frac{\partial}{\partial x_k} \left(\frac{(x_{k+1} - \phi x_k - 2I_{k+1})^2}{2\sigma^2} \right) \\ &\quad + \beta N_k - \beta \exp(\mu + \beta x_k) \cdot \Delta \\ &= -\frac{x_k - \phi x_{k-1} - 2I_k}{\sigma^2} + \frac{\phi(x_{k+1} - \phi x_k - 2I_{k+1})}{\sigma^2} \\ &\quad + \beta N_k - \beta \exp(\mu + \beta x_k) \cdot \Delta \end{aligned}$$

$$\begin{aligned} &= \frac{1}{\sigma^2} (\phi x_{k+1} - \phi^2 x_k - \phi 2I_{k+1} - x_k + \phi x_{k-1} + 2I_k) \\ &\quad + \beta N_k - \beta \exp(\mu + \beta x_k) \cdot \Delta \end{aligned}$$

$$\frac{\partial \mathcal{L}}{\partial x_k} = \frac{1}{\sigma^2} (x_k - \phi x_{k-1} - 2I_k) + \beta N_k - \beta \exp(\mu + \beta x_k) \cdot \Delta \quad \text{for } k = K$$

Tensor G for $X_{0:k}$

Let $G(x)$ be the tensor as a function of current x , and can be derived from the Fisher Information matrix.

$$\{G(x)\}_{(1,1)} = E\left(-\frac{\partial^2 L}{\partial x_1^2}\right) = \frac{1}{\sigma^2} //$$

$\{G(x)\}_{(i,i+1)}$ or $\{G(x)\}_{(i+1,i)}$ for $i = \{1, \dots, k-1\}$ is

$$E\left(-\frac{\partial^2 L}{\partial x_i \partial x_{i+1}}\right) = E\left(-\frac{\partial^2 L}{\partial x_{i+1} \partial x_i}\right)$$

$$= E\left(-\frac{\partial}{\partial x_{i+1}} \left(\frac{\partial L}{\partial x_i}\right)\right) = E\left(-\left(\frac{\phi}{\sigma^2}\right)\right) = -\frac{\phi}{\sigma^2} //$$

$$\{G(x)\}_{(i,i)} \text{ for } i = \{1, \dots, k-1\}$$
$$= E\left(-\frac{\partial^2 L}{\partial x_i^2}\right)$$

$$= E\left(-\left(\frac{-(1+\phi^2)}{\sigma^2} - \beta^2 \exp(\mu + \beta x_k) \cdot \Delta\right)\right)$$

$$= (1+\phi^2)/\sigma^2 + \beta^2 \exp(\mu + \beta x_k) \cdot \Delta //$$

$$\{G(x)\}_{(k,k)} = E\left(-\frac{\partial^2 L}{\partial x_k^2}\right) = E\left(-\left(-\frac{1}{\sigma^2} - \beta^2 \exp(\mu + \beta x_k) \cdot \Delta\right)\right)$$

$$= \frac{1}{\sigma^2} + \beta^2 \exp(\mu + \beta x_k) \cdot \Delta //$$

Hamiltonian Function of $X_{0:k}$ and its PDEs

$$H(x, p) = U(x) + K(p)$$

$$= \overset{\textcircled{1}}{-I(x)} + \overset{\textcircled{2}}{\frac{1}{2} \log((2\pi)^D |G(x)|)} + \overset{\textcircled{3}}{\frac{1}{2} p^T G(x)^{-1} p}$$

$-(\log(\text{posterior})) + \text{normalizing constant} + \text{Kinetic energy}$

$$\frac{\partial L}{\partial x_i} = \begin{cases} \frac{\phi x_i - \phi 2I_i - x_0}{\sigma^2} & i=0 \end{cases}$$

$$\nabla_x I(x)$$

$$\textcircled{1} \begin{cases} \frac{1}{\sigma^2} (\phi x_{i+1} - \phi^2 x_i - \phi 2I_{i+1} - x_i + \phi x_{i-1} + \phi 2I_{i+1}) \\ + \beta N_k - \beta \exp(\mu + \beta x_k) \cdot \Delta & i=1, \dots, k-1 \\ -\frac{1}{\sigma^2} (x_k - \phi x_{k-1} - 2I_k) + \beta N_k - \beta \exp(\mu + \beta x_k) \cdot \Delta \end{cases}$$

$$\textcircled{2} \frac{\partial}{\partial x_i} \left(\frac{1}{2} \log((2\pi)^D |G(x)|) \right)$$

$$= \frac{\partial}{\partial x_i} \left(\frac{1}{2} \log |G(x)| \right) = \frac{1}{2} \text{trace} \left(G(x)^{-1} \frac{\partial G(x)}{\partial x_i} \right)$$

$\frac{\partial G(x)}{\partial x_i}$ is a diagonal matrix:

$$\frac{\partial G(x)}{\partial x_0} = \mathbf{0}_{(k+1, k+1)}$$

$$\frac{\partial G(x)}{\partial x_i} = \beta^3 \exp(\mu + \beta x_i) \Delta \text{ at } (i, i) \text{ of the matrix for } i=1, \dots, k$$

Hence,

$$\frac{1}{2} \text{trace} \left(G(x)^{-1} \cdot \frac{\partial G(x)}{\partial x_i} \right)$$

$$= \begin{cases} 0 & i=0 \\ \frac{1}{2} \{G(x)^{-1}\}_{(i, i)} \cdot \beta^3 \exp(\mu + \beta x_i) \cdot \Delta & i=1, \dots, k \end{cases}$$

Hamiltonian function of X_{oik} and its PDEs

$$(3): \frac{\partial}{\partial x_i} \left(\frac{1}{2} \dot{p}^T G(x)^{-1} \dot{p} \right) = \frac{1}{2} \dot{p}^T G(x)^{-1} \frac{\partial G(x)}{\partial x_i} G(x)^{-1} \dot{p}$$

$$\therefore \nabla_x H(x, p) = \nabla_x (\textcircled{1} + \textcircled{2} + \textcircled{3})$$

$$\nabla_p H(x, p) = G(x)^{-1} \dot{p}$$

PDES of the Hamiltonian system is therefore.

$$\begin{cases} \dot{x} = \nabla_p H(x, p) \\ \dot{p} = -\nabla_x H(x, p) \end{cases}$$

Tensor for Θ

$$\Theta = (\mu, \gamma, \alpha) \text{ subject to transformation } \phi = \tanh(\gamma) \\ \nabla_{\Theta} \mathcal{L} = \left(\frac{\partial \mathcal{L}}{\partial \mu}, \frac{\partial \mathcal{L}}{\partial \phi}, \frac{\partial \mathcal{L}}{\partial \alpha} \right) \quad \frac{\partial \phi}{\partial \gamma} = 1 - \phi^2$$

$$\frac{\partial \mathcal{L}}{\partial \mu} = \sum_{k=1}^K [N_k - \exp(\mu + \beta x_k) \cdot \Delta] //$$

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \gamma} &= \frac{\partial \mathcal{L}}{\partial \phi} \cdot \frac{\partial \phi}{\partial \gamma} \quad (1 - \phi^2) \\ &= \frac{\partial}{\partial \phi} \left(- \sum_{k=1}^K \frac{(x_k - \phi x_{k-1} - \alpha I_k)^2}{2\sigma^2} + \frac{1}{2} \log(1 - \phi^2) - \frac{x_0^2 (1 - \phi^2)}{2\sigma^2} \right) \\ &= \left[\sum_{k=1}^K \frac{x_{k-1} (x_k - \phi x_{k-1} - \alpha I_k)}{\sigma^2} - \frac{\phi}{1 - \phi^2} + \frac{\phi x_0^2}{\sigma^2} \right] \cdot (1 - \phi^2) \\ &= (1 - \phi^2) \sum_{k=1}^K x_{k-1} (x_k - \phi x_{k-1} - \alpha I_k) - \phi + \frac{\phi (1 - \phi^2) x_0^2}{\sigma^2} // \end{aligned}$$

$$\frac{\partial \mathcal{L}}{\partial \alpha} = \sum_{k=1}^K \left[\frac{(x_k - \phi x_{k-1} - \alpha I_k)}{\sigma^2} \cdot I_k \right] //$$

$$\frac{\partial^2 \mathcal{L}}{\partial \mu \partial \alpha} = \frac{\partial^2 \mathcal{L}}{\partial \mu \partial \phi} = 0$$

Let $G(\Theta)$ be the tensor after integrating studies.

$$\begin{aligned} (G(\Theta))_{(1,1,1)} &= \mathbb{E} \left(- \frac{\partial^2 \mathcal{L}}{\partial \mu^2} \right) = \sum_{k=0}^K \exp(\mu + \beta E(x_k) + \frac{\beta^2}{2} \text{Var}(x_k)) \cdot \Delta \\ (G(\Theta))_{(1,2), (1,3), (2,1), (3,1)} &= 0 \end{aligned}$$

$$(G(\Theta))_{(2,2)} = \mathbb{E} \left(- \frac{\partial^2 \mathcal{L}}{\partial \gamma^2} \right) = 2\phi^2 + K(1 - \phi^2) + \frac{1 - \phi^2}{\sigma^2} \sum_{k=1}^K \mathbb{E}(x_{k-1})^2$$

$$(G(\Theta))_{(2,3), (3,2)} = \mathbb{E} \left(- \frac{\partial^2 \mathcal{L}}{\partial \gamma \partial \alpha} \right) = \frac{1 - \phi^2}{\sigma^2} \sum_{k=1}^K \mathbb{E}(x_{k-1}) I_k$$

$$(G(\Theta))_{(3,3)} = \mathbb{E} \left(- \frac{\partial^2 \mathcal{L}}{\partial \alpha^2} \right) = \sum_{k=1}^K \frac{I_k^2}{\sigma^2}$$

Hamiltonian function of $\theta = (\mu, \gamma, \alpha)$ and its PDES
 $H(\theta, p) = U(\theta) + K(p)$

Let $p(\theta | x_{0:k}, y_{1:k})$ be the posterior density of θ

$p(\theta | x_{0:k}, y_{1:k}) \propto p(x_{0:k}, y_{1:k} | \theta) p(\theta)$
 where $p(\theta) \sim \text{MVN}(0, \Sigma)$ & $\Sigma = 100 \cdot \bar{I}_{3 \times 3}$
 or $p(\theta) = \pi(\mu) \pi(\gamma) \pi(\alpha)$
 for $\pi(\cdot) \sim \mathcal{N}(0, 10^2)$

Let $L(\theta) = \log(p(\theta | x_{0:k}, y_{1:k}))$

$$H(\theta, p) = -L(\theta) + \frac{1}{2} \log((2\pi)^3 |G(\theta)|) + \frac{1}{2} p^T G(\theta)^{-1} p$$

$$\frac{\partial L}{\partial \mu} = \sum_{k=1}^K [N_k - \exp(\mu + \beta x_k) \cdot \Delta]$$

$$\textcircled{1} \frac{\partial L}{\partial \gamma} = \frac{\partial L}{\partial \phi} \cdot \frac{d\phi}{d\gamma} = (1-\phi^2) \sum_{k=1}^K x_{k-1} (x_k - \phi x_{k-1} - \alpha \bar{I}_k) - \phi + \frac{\phi(1-\phi^2) x_0^2}{\sigma^2}$$

$$\frac{\partial L}{\partial \alpha} = \sum_{k=1}^K \left[\frac{x_k - \phi x_{k-1} - \alpha \bar{I}_k}{\sigma^2} \cdot \bar{I}_k \right]$$

$$\left\{ \frac{\partial G(\theta)}{\partial \mu} \right\}_{(i,1)} = \sum_{k=0}^K \exp[\mu + \beta E(x_k) + \frac{\beta^2}{2} \text{Var}(x_k)] \cdot \Delta$$

$(i \neq 1, j \neq 1) = 0$

$$\frac{\partial G(\theta)}{\partial \gamma}:$$

$$E(x_k) = \alpha (\bar{I}_k + \phi \bar{I}_{k-1} + \dots + \phi^{k-1} \bar{I}_1)$$

$$\frac{\partial E(x_k)}{\partial \gamma} = \begin{matrix} 0 & k=0, 1 \\ (1-\phi^2)\alpha \cdot \bar{I}_1 & k=2. \end{matrix}$$

$$(1-\phi^2)\alpha \cdot [\bar{I}_2 + 2\phi \bar{I}_1] \quad k=3$$

\vdots

$$(1-\phi^2)\alpha \cdot [\bar{I}_{k-1} + 2\phi \bar{I}_{k-2} + \dots + (k-1)\phi^{k-2} \bar{I}_1] \quad k=K$$

$$\text{Var}(X_k) = \frac{\sigma^2}{1-\phi^2}$$

$$\frac{\partial \text{Var}}{\partial \phi} = (1-\phi^2)^{-\frac{1}{2}} \left(\frac{\sigma^2}{1-\phi^2} \right) = \frac{-2\phi\sigma^2}{(1-\phi^2)}$$

$$\left(\frac{\partial G(\theta)}{\partial \phi} \right)_{(1,1)} = \frac{\partial}{\partial \phi} \left(\sum_{k=0}^K \exp \left[\mu + \beta E(X_k) + \frac{\beta^2}{2} \text{Var}(X_k) \right] \cdot \Delta \right)$$

$$= \sum_{k=0}^K \exp \left[\mu + \beta E(X_k) + \frac{\beta^2}{2} \text{Var}(X_k) \right] \cdot \Delta \cdot \left(\beta \frac{\partial E(X_k)}{\partial \phi} + \frac{\beta^2}{2} \frac{\partial \text{Var}(X_k)}{\partial \phi} \right)$$

$$\left(\frac{\partial G(\theta)}{\partial \phi} \right)_{(1,2), (1,3), (2,1), (3,1)} = 0$$

$$G(\theta)_{(2,2)} = 2\phi^2 + K(1-\phi^2) + \frac{(1-\phi^2)}{\sigma^2} \sum_{k=1}^K E(X_{k-1})^2$$

$$\left(\frac{\partial G(\theta)}{\partial \phi} \right)_{(2,2)} = 4\phi - 2K\phi - \frac{2\phi}{\sigma^2} \sum_{k=1}^K E(X_{k-1})^2 + \frac{2(1-\phi^2)}{\sigma^2} \sum_{k=1}^K E(X_{k-1}) \frac{\partial E(X_{k-1})}{\partial \phi}$$

$$G(\theta)_{(2,3)} = G(\theta)_{(3,2)} = \frac{1-\phi^2}{\sigma^2} \sum_{k=1}^K E(X_{k-1}) \cdot I_k$$

$$\left(\frac{\partial G(\theta)}{\partial \phi} \right)_{(2,3), (3,2)} = \frac{-2\phi}{\sigma^2} \sum_{k=1}^K E(X_{k-1}) \cdot I_k + \frac{1-\phi^2}{\sigma^2} \sum_{k=1}^K \frac{\partial E(X_{k-1})}{\partial \phi} \cdot I_k$$

$$G(\theta)_{(3,3)} = \sum_{k=1}^K \frac{I_k^2}{\sigma}$$

$$\left(\frac{\partial G(\theta)}{\partial \phi} \right)_{(3,3)} = 0$$

$$\frac{\partial G(\theta)}{\partial \alpha} :$$

$$\begin{cases} E(X_k) = \alpha(I_k + \phi I_{k-1} + \dots + \phi^{k-1} I_1) \\ \text{Var}(X_k) = \frac{\sigma^2}{1-\phi^2} \end{cases}$$

$$\begin{cases} \frac{\partial E(X_k)}{\partial \alpha} = I_k + \phi I_{k-1} + \dots + \phi^{k-1} I_1 \\ \frac{\partial \text{Var}(X_k)}{\partial \alpha} = 0 \end{cases}$$

$$\begin{aligned} \left(\frac{\partial G(\theta)}{\partial \alpha} \right)_{(1,1)} &= \frac{\partial}{\partial \alpha} \left\{ \sum_{k=0}^K \exp[\mu + \beta E(X_k) + \frac{\beta^2}{2} \text{Var}(X_k)] \cdot \Delta \right\} \\ &= \sum_{k=0}^K \exp[\mu + \beta E(X_k) + \frac{\beta^2}{2} \text{Var}(X_k)] \cdot \Delta \cdot \left(\beta \frac{\partial E(X_k)}{\partial \alpha} + \frac{\beta^2}{2} \frac{\partial \text{Var}(X_k)}{\partial \alpha} \right) \end{aligned}$$

$$\left(\frac{\partial G(\theta)}{\partial \alpha} \right)_{(1,2), (1,3), (2,1), (3,1)} = 0$$

$$\begin{aligned} \left(\frac{\partial G(\theta)}{\partial \alpha} \right)_{(2,2)} &= \frac{\partial}{\partial \alpha} \left\{ 2\phi^2 + K(1-\phi^2) + \frac{1-\phi^2}{\sigma^2} \sum_{k=1}^K E(X_{k-1})^2 \right\} \\ &= \frac{2(1-\phi^2)}{\sigma^2} \sum_{k=1}^K E(X_{k-1}) \cdot \frac{\partial E(X_{k-1})}{\partial \alpha} \end{aligned}$$

$$\begin{aligned} \left(\frac{\partial G(\theta)}{\partial \alpha} \right)_{(2,3), (3,2)} &= \frac{\partial}{\partial \alpha} \left\{ \frac{1-\phi^2}{\sigma^2} \sum_{k=1}^K E(X_{k-1}) I_k \right\} \\ &= \frac{(1-\phi^2)}{\sigma^2} \sum_{k=1}^K \frac{\partial E(X_{k-1})}{\partial \alpha} \cdot I_k \end{aligned}$$

$$\left(\frac{\partial G(\theta)}{\partial \alpha} \right)_{(3,3)} = 0$$

Hamiltonian function of θ and its PDEs

$$\frac{\partial H(\theta, p)}{\partial \theta_i} = -\frac{\partial \mathcal{L}(\theta)}{\partial \theta_i} + \frac{1}{2} \text{tr} \left(G(\theta)^{-1} \frac{\partial G(\theta)}{\partial \theta_i} \right) - \frac{1}{2} P^T G(\theta)^{-1} \frac{\partial G(\theta)}{\partial \theta_i} G(\theta)^T P$$

$$\frac{\partial H(\theta, p)}{\partial p_i} = [G(\theta)^{-1} p]_i$$