

State Space Models Part 3

Periodicity

2 March 2018

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Definition of Gaussian Process

- GP is a prior distribution over *function* f .
- Specified by giving
 - mean function $\mu(x)$
 - covariance function $\kappa(x_1, x_2)$
- For any n points x_1, \dots, x_n ,

$$(y_1, \dots, y_n)' \sim \text{Normal}(\mathbf{m}, \mathbf{C})$$

$$y_i = f(x_i)$$

$$m_i = \mu(x_i)$$

$$C_{ij} = \kappa(x_i, x_j)$$

- κ must always produce a valid covariance matrix.

Covariance function / kernels

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- Symmetric: $\kappa(x_1, x_2) = \kappa(x_2, x_1)$.
- Positive semi-definite (PSD): $v' C v \geq 0$ for all v
 - $C_{ij} = \kappa(x_i, x_j)$.
 - May be positive definite (PD): $v' C v > 0$ for all $v \neq \mathbf{0}$.
 - PSD: Cannot choose $f(x_1), \dots, f(x_n)$ arbitrarily.
- Often *stationary*: $\kappa(x_1, x_2)$ depends only on $x_1 - x_2$
 - In this case, write $\kappa(d)$ where $d = x_1 - x_2$.
- Example: *periodic* kernel

$$\kappa_P(d) = \sigma^2 \exp\left(-\frac{2 \sin^2(\pi d/p)}{\ell^2}\right)$$

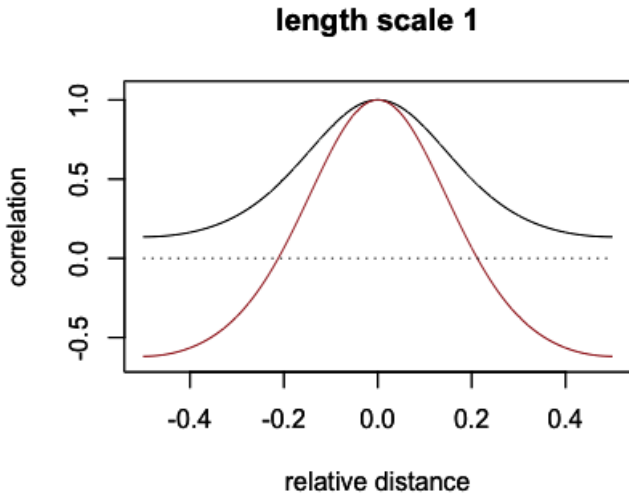
Periodic kernel, $\ell = 1$

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Periodic kernel, $\ell = 0.5$

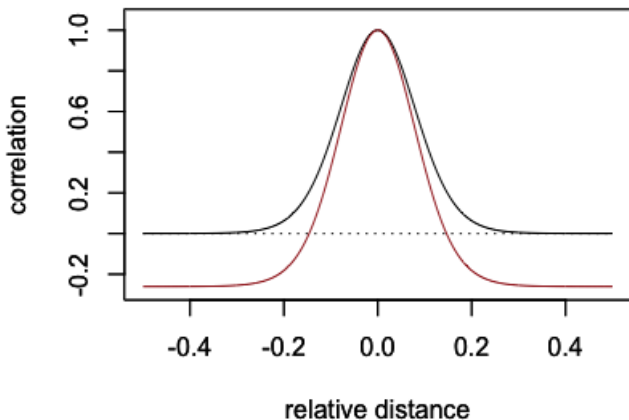
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length scale 0.5



Periodic kernel, $\ell = 0.25$

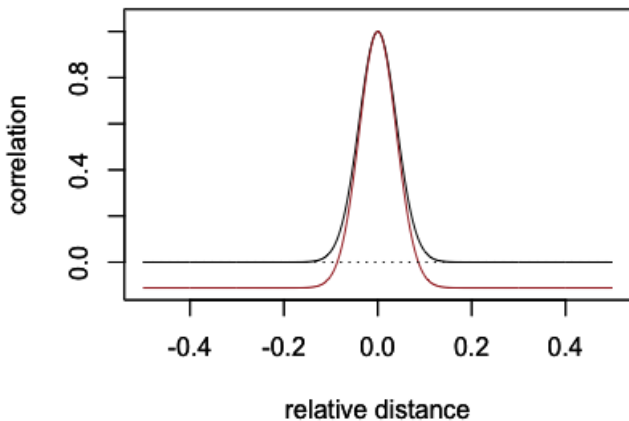
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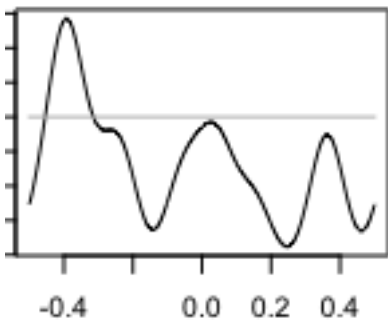
Draw from periodic kernel, $\ell = 0.5$

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Not centered at zero!

Centering around zero

- Our periodic kernel is positive definite
 - hence cannot impose requirement $\int_0^P f(x)dx = 0$.
- Modify the kernel:
 - $\kappa^*(d) = s \cdot (\kappa(d) - \Delta)$.
 - Center around zero.
 - Stretch it out so $\kappa(0) = 1$ (or σ^2) again.
- Is it still a valid kernel (positive semi-definite)?
 - Yes.
 - Proof is an exercise for the reader.
- See brown curves in plots of kernel.

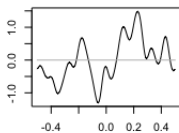
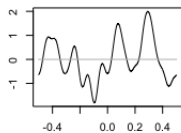
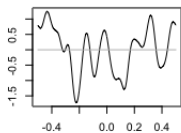
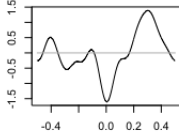
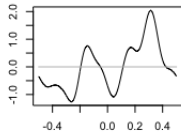
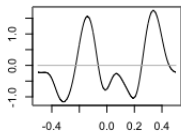
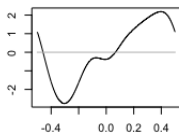
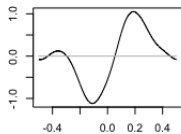
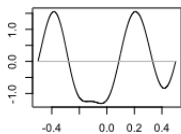
Draws from centered periodic kernel

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Quasi-periodicity

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- Allow small changes from one period to next.
- Product of two valid kernels is a valid kernel.
- Use

$$\begin{aligned}\kappa(d) &= \sigma^2 \kappa_E(d) \kappa_P(d) \\ \kappa_E(d) &= \phi^d \\ \kappa_P(d) &= s \cdot \left(\exp\left(-\frac{2 \sin^2(\pi d/p)}{\ell^2}\right) - \Delta \right)\end{aligned}$$

- Should have ϕ^p very close to 1.
- Δ chosen to center κ_P .
- s chosen so that $\kappa_P(0) = 1$.

Review: Quasi-sinusoidal SSM

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QS (θ, ϕ, σ^2) is a SSM equivalent to

$$y_t = \alpha_t^T \mathbf{1}$$

$$\alpha_1 \sim \text{Normal}(\mathbf{0}, \sigma^2 \mathbf{I}_2)$$

$$\alpha_{t+1} = \phi U_\theta \alpha_t + \eta_t$$

$$\eta_t \sim \text{Normal}(\mathbf{0}, (1 - \phi^2) \sigma^2 \mathbf{I}_2)$$

$U_\theta =$ counterclockwise rotation by angle θ .

If $\phi = 1$ then $y_t = f(t)$, where

$$a \sim \text{Rayleigh}(\sigma)$$

$$\psi \sim \text{Uniform}(\mathbf{0}, 2\pi)$$

$$f(x) \triangleq a \cos(x\theta + \psi).$$

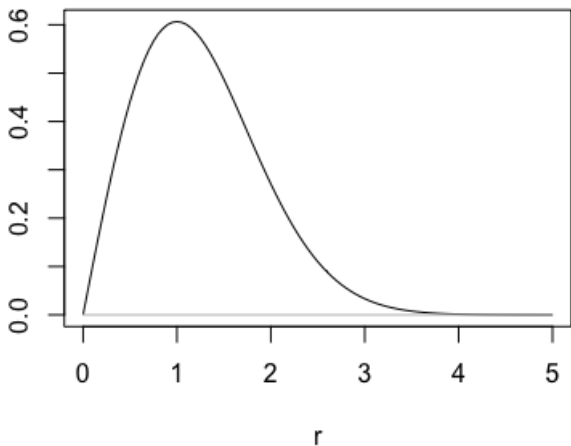
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Rayleigh distribution for $\sigma = 1$.

Alternative form, quasi-sinusoidal SSM

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QS (θ, ϕ, σ^2) is equivalent to

$$y_t = \alpha_{1t} \cos(\theta(t-1)) + \alpha_{2t} \sin(\theta(t-1))$$

$$\alpha_{i,1} \sim \text{Normal}(0, \sigma^2)$$

$$\alpha_{i,t+1} = \phi \alpha_{i,t} + \eta_{it}$$

$$\eta_{i,t} \sim \text{Normal}(0, (1 - \phi^2) \sigma^2)$$

Linear regression with time-varying coefficients from AR(1) processes.

$\theta = 0$: QS $(0, \phi, \sigma^2)$ yields an AR(1) process for y_1, y_2, \dots

Review: Quasi-periodic SSM

$$\text{QP}(p, \phi, \mathbf{c}) = \mathcal{M}_0 + \mathcal{M}_1 + \cdots + \mathcal{M}_n$$
$$\mathcal{M}_k = \text{QS}(2\pi k/p, \phi, \mathbf{c}_k)$$

- Set $c_0 = 0$ to center.
- Stationary, mean 0, variance $\sum_{k=0}^n c_k$.
- If $\phi = 1$ and p is integer, then $y_t = f(t)$, where

$$a_k \sim \text{Rayleigh}(c_k^{1/2}), \quad 0 \leq k \leq n$$

$$\psi_k \sim \text{Uniform}(0, 2\pi), \quad 0 \leq k \leq n$$

$$f(t) = \sum_{k=0}^n a_k \cos\left(2\pi k \frac{t}{p} + \psi_k\right).$$

- Whence \mathbf{c} ? Lots of parameters...

SSMs and GPs

- SSM: joint distribution for $y_{1:n}$ and $\alpha_{1:n}$ is MV normal.
- Marginalize: distribution for $y_{1:n}$ is MV normal.
- SSMs define GPs on $\mathbb{N}^+ = \{1, 2, \dots\}$!
- QP (p, ϕ, \mathbf{c}) as a GP:
 - $\mu(t) = 0$
 - $\kappa(t_1, t_2) = C[y_t, y_{t+j}]$ depends only on j :

$$C[y_t, y_{t+j}] = \phi^j \kappa_0(j)$$

$$\kappa_0(j) = \sum_{k=0}^n c_k \cos(2\pi kj/p)$$

- c_k is coefficient of term k in Fourier series for $\kappa_0(\cdot)$!

From kernel to QP SSM coefficients

- 1 Choose prior variance σ^2 .
- 2 Choose kernel γ : periodic with period 1, $\gamma(0) = 1$.
 - Fully defined by values on $[0, 1/2]$.
- 3 Find the Fourier series for γ , truncate:

$$\gamma(x) \approx \gamma(x; n) = \sum_{k=0}^n a_k \cos(2\pi kx).$$

Bochner's Theorem guarantees $a_k \geq 0$.

- 4 Set $c_k = a_k \sigma^2$ for all k .
- 5 Then

$$\kappa_0(j) = \sum_{k=0}^n a_k \sigma^2 \cos(2\pi kj/p) = \sigma^2 \gamma(j/p; n).$$

Example

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Using periodic kernel:

$$\gamma(x) = \exp\left(-\frac{2 \sin^2(\pi x)}{\ell^2}\right)$$

$$= \sum_{k=0}^{\infty} a_k \cos(2\pi kx)$$

$$a_k = b_k \frac{I_k(\ell^{-2})}{\exp(\ell^{-2})}$$

$$b_k = \begin{cases} 2 & \text{if } k > 0 \\ 1 & \text{if } k = 0 \end{cases}$$

$$c_k = a_k \sigma^2.$$

I_k is modified Bessel function of the first kind.

Aliasing (1)

Suppose that p and N are integers.

1 QS $(2\pi(k + Np)/p, \phi, \sigma^2) \equiv$ QS $(2\pi k/p, \phi, \sigma^2)$ since

$$\frac{2\pi(k + Np)}{p} = \frac{2\pi k}{p} + 2\pi N.$$

2 QS $(\theta, \phi, \sigma_1^2) +$ QS $(\theta, \phi, \sigma_2^2) \equiv$ QS $(\theta, \phi, \sigma_1^2 + \sigma_2^2)$.

3 So

$$\begin{aligned} & \mathcal{M}_k + \mathcal{M}_{k+Np} \\ &= \text{QS}(2\pi k/p, \phi, c_k) + \text{QS}(2\pi(k + Np)/p, \phi, c_{k+Np}) \\ &\equiv \text{QS}(2\pi k/p, \phi, c_k + c_{k+Np}) \end{aligned}$$

4 Can sum all c_{k+Np} into c_k , only keep terms $k < p$.

Aliasing (2)

Suppose that p is an integer.

- 1 QS $(-\theta, \phi, \sigma^2) \equiv$ QS (θ, ϕ, σ^2) since $\cos(-\theta) = \cos(\theta)$.
- 2 So

$$\begin{aligned}\mathcal{M}_k + \mathcal{M}_{p-k} &= \text{QS}(2\pi k/p, \phi, c_k) + \text{QS}(2\pi(p-k)/p, \phi, c_{p-k}) \\ &= \text{QS}(2\pi k/p, \phi, c_k) + \text{QS}(-2\pi k/p, \phi, c_{p-k}) \\ &= \text{QS}(2\pi k/p, \phi, c_k + c_{p-k}).\end{aligned}$$

Centering

- Started out with $c_0 \neq 0$.
- Unaliasing added to c_0 .
- Set $c_0 = 0$ and rescale:

$$c_0^* = 0$$

$$c_k^* = \frac{\sigma^2}{s^2} c_k, \quad 1 \leq k \leq n$$

$$s^2 = \sum_{k=1}^n c_k$$

- Yields $\kappa^*(d) = s \cdot (\kappa(d) - c_0)$.

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Conclusion

- Can handle multiple seasonality.
- Can have non-integer period.
- Borrow kernel(s) from GP literature.
- Few parameters required, even for long periods:
 - ϕ, σ^2, ℓ .
- Computational cost: $2n$ state vars, $O(n^2)$.