

EMNE TMA4250 Romlig Statistikk

Våren 2004

Eksamen 27. mai 2004

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Oppgave 1 KONTINUERLIGE FELT

Gauss RF $\{R(x); x \in \mathcal{D} \subset \mathbb{R}^2\}$ - stasjonært
isotropt
deriverbart

Parametre: $\mu, c(\Delta x), \gamma(\Delta x)$

$$\begin{aligned} a) \quad \gamma(\Delta) &= \frac{1}{2} \text{Var}\{R(x') - R(x'')\} \\ &= \frac{1}{2} \left[\text{Var}\{R(x')\} + \text{Var}\{R(x'')\} - 2 \text{Cov}\{R(x'), R(x'')\} \right] \\ &= c(0) - c(\Delta x) \end{aligned}$$

Deriverbarhet i $\{R(x); x \in \mathcal{D}\} \Rightarrow \begin{cases} \frac{d^2 c(\Delta x)}{d \Delta x^2} \Big|_{\Delta x=0} & \text{eksisterer} \\ \frac{d^2 \gamma(\Delta x)}{d \Delta x^2} \Big|_{\Delta x=0} & \text{eksisterer} \end{cases}$

\rightarrow Funksjonene er to ganger deriverbare i origo.

$$b) \quad E\{\hat{\mu}\} = \frac{1}{n} \sum_i^n E\{R(x_i)\} = \frac{1}{n} \sum_i \left[\overset{\mu}{E\{R(x_i)\}} + \overset{0}{E\{U_i\}} \right] = \underline{\mu}$$

$$E\{\hat{\gamma}(\Delta x)\} = \frac{1}{2n_{\Delta x}} \sum_{i,j \in A_{\Delta x}} E\{(R(x_i) - R(x_j))^2\}$$

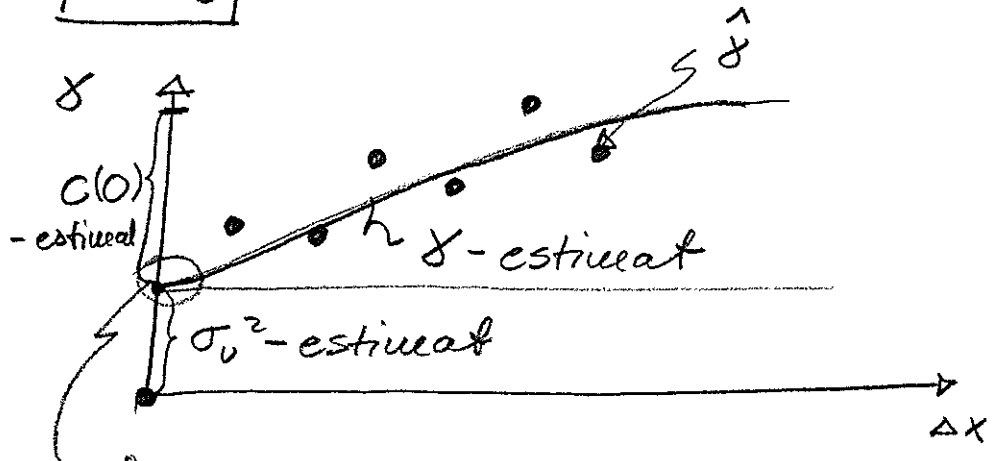
 $\boxed{\Delta x > 0}$

$$= \frac{1}{2n_{\Delta x}} \sum_{i,j \in A_{\Delta x}} \text{Var}\{R(x_i) - R(x_j)\}$$

$$\begin{aligned}
&= \frac{1}{2n_{\Delta x}} \sum [\text{Var} \{ R(x_i) - R(x_j) \} + \text{Var} \{ U_i - U_j \}] \\
&= \frac{1}{2n_{\Delta x}} \sum [\underbrace{\delta(\Delta x)}_{\sigma_u^2} + \text{Var} \{ U_i \} + \text{Var} \{ U_j \}] \\
&= \delta(\Delta x) + \sigma_u^2
\end{aligned}$$

$$E\{\hat{\delta}(\Delta x)\} = \frac{1}{2n_0} \sum_{i,j \in A_0} E\{R(x_i) - R(x_j)\} = 0$$

$\Delta x = 0$



må være to ganger derivérbar

$$c(\Delta x) - \text{estimated} = (c(0) - \text{estimated}) - (\delta(\Delta x) - \text{estimated})$$

c) $\hat{R}(x_0) = \sum_{i=1}^n \alpha_i R^{\circ}(x_i)$

Forventningsrettet:

$$E\{\hat{R}(x_0)\} = \mu$$

$$\sum_i \alpha_i E\{R^{\circ}(x_i)\} = \mu$$

$$\sum_i \alpha_i = 1$$

Prediksjonsvarians:

$$\begin{aligned}
\text{Var} \{ R(x_0) - \hat{R}(x_0) \} &= \text{Var} \{ R(x_0) - \sum_i \alpha_i R^{\circ}(x_i) \} \\
&= \text{Var} \{ R(x_0) \} - 2 \sum_i \alpha_i \text{Cov} \{ R(x_0), R^{\circ}(x_i) \} \\
&\quad + \sum_i \sum_j \alpha_i \alpha_j \text{Cov} \{ R^{\circ}(x_i), R^{\circ}(x_j) \}
\end{aligned}$$

$$\Delta_{ij} = |x_i - x_j| \quad = c(0) - 2 \sum \alpha_i c(\Delta_{0j}) + \left[\sum_i \sum_j \alpha_i \alpha_j c(\Delta_{ij}) + \sum_i \alpha_i^2 \sigma_v^2 \right]$$

Vektorene $\alpha = (\alpha_1, \dots, \alpha_n)$ bestemmes ved:

$$\alpha^* = \underset{\alpha}{\operatorname{argmin}} \left\{ c(0) - 2 \sum \alpha_i c(\Delta_{0j}) + \sum_i \sum_j \alpha_i \alpha_j c(\Delta_{ij}) + \sum_i \alpha_i^2 \sigma_v^2 \right\}$$

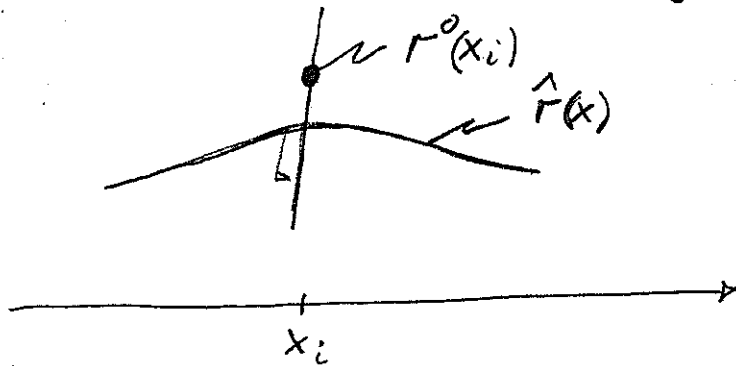
$$\sum_i \alpha_i = 1$$

som kan løses med standard Lagrange metode.

Prediktor: $\hat{R}(x_0) = \sum_i \alpha_i^* R^0(x_i)$

Prediksjonsvarians:

$$\sigma_p^2(x_0) = \operatorname{Var}\{R(x_0) - \hat{R}(x_0)\} = c(0) - 2 \sum \alpha_i^* c(\Delta_{0j}) + \sum_i \sum_j \alpha_i^* \alpha_j^* c(\Delta_{ij}) + \sum_i \alpha_i^{*2} \sigma_v^2$$



NB! MERK!

$$\hat{R}(x_i) \neq R^0(x_i)$$

◦ reproducerer ikke observasjon!

$$0 < \sigma_p^2(x_i) < \sigma_v^2$$

◦ prediksjonsvarians ikke 0!

Dette er logisk da det er observasjonsfeil!!!

Oppgave 2 HENDERSES TEST

Punkt RF $\{X_i; i=1, \dots, N\}$; $D \subset \mathbb{R}^2$ a) Avstand mellom nærmeste-nabopunkt: D

$$P(\text{Prob}(D > d)) = \exp\{-\lambda\pi d^2\}$$

$$F(d) = \text{Prob}(D < d) = 1 - \exp\{-\lambda\pi d^2\}$$

$$f(d) = \frac{dF(d)}{dd} = 2\lambda\pi d \exp\{-\lambda\pi d^2\}$$

b) d_1, \dots, d_k iid $f(d; \lambda)$

$$f(d_1, \dots, d_k; \lambda) = \prod_{i=1}^k f(d_i; \lambda) = (2\lambda\pi)^k \exp\{-\lambda\pi \sum_{i=1}^k d_i^2\} \prod_{i=1}^k d_i$$

Loglikelihood:

$$\ell(\lambda) = k \cdot \ln 2\lambda\pi - \lambda\pi \sum_{i=1}^k d_i^2 + \sum_{i=1}^k \ln d_i$$

derivér

$$\frac{d\ell(\lambda)}{d\lambda} = \frac{k \cdot 2\pi}{2\lambda\pi} - \pi \sum_{i=1}^k d_i^2$$

Minimer:

$$\frac{k}{\lambda^*} - \pi \sum_{i=1}^k d_i^2 = 0$$

$$\lambda^* = \left[\frac{\pi}{k} \sum_{i=1}^k d_i^2 \right]^{-1}$$

MLE-estimator

$$\lambda^* = \left[\frac{\pi}{k} \sum_{i=1}^k D_i^2 \right]^{-1}$$

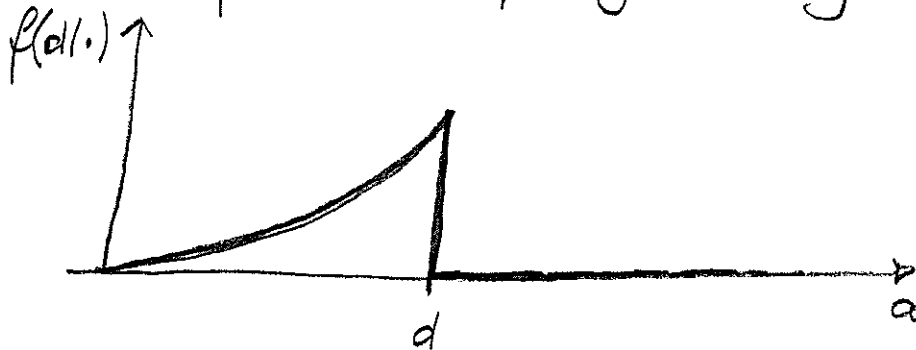
c) Merk at:

$$f(d|d>a) = \begin{cases} 0 & ; d < a \\ \frac{f(d)}{1-F(a)} & ; d > a \end{cases}$$

$$= \begin{cases} 0 & ; d < a \\ \frac{2\lambda\pi d \exp\{-\lambda\pi d^2\}}{\exp\{-\lambda\pi a^2\}} & ; d > a \end{cases}$$

$$= \begin{cases} 0 & ; d < a \\ 2\lambda\pi \cdot \exp\{\lambda\pi a^2\} d \exp\{-\lambda\pi d^2\} & ; d > a \end{cases}$$

Betrakt $f(d|d>a)$ for gitt d og variabel a :



Observasjoner d_1, \dots, d_k !

Likelihood funksjon:

$$f(d_1, \dots, d_k; a, \lambda) = \prod_{i=1}^k f(d_i | d > a)$$

$$= \begin{cases} 0 & ; a > \min\{d_1, \dots, d_k\} = d_{\min} \\ [2\lambda\pi \exp\{\lambda\pi a^2\}]^k \exp\{-\lambda\pi \sum_{i=1}^k d_i^2\} \prod_{i=1}^k d_i & ; \text{else} \end{cases}$$

MERK! Likelihood ikke derivérbar mht a ,
MEN den er monotont voksende i $[0, d_{\min}]$
og 0 for $[d_{\min}, \infty]$ dvs.

$$a^* = d_{\min} = \min\{d_1, \dots, d_k\}$$

Log-likelihood:

$$l(a^*, \lambda) = k \ln 2\lambda\pi + k\lambda\pi a^{*2} - \lambda\pi \sum_i^k d_i^2 + \sum_i^k \ln d_i$$

Deriverte w.r.t λ :

$$\frac{d l(a^*, \lambda)}{d \lambda} = \frac{k 2\pi}{2\pi\lambda} + k\pi a^{*2} - \pi \sum_i^k d_i^2$$

Minimier:

$$\frac{k}{\lambda^*} + k\pi a^{*2} - \pi \sum_i^k d_i^2 = 0$$

$$\lambda^* = \left[\frac{\pi}{k} \sum_i^k d_i^2 - \pi a^{*2} \right]^{-1} = \left[\frac{\pi}{k} \sum_i^k [d_i^2 - a^{*2}] \right]^{-1}$$

MLE-estimatorer:

$$a^* = \min \{D_1, \dots, D_k\}$$

$$\lambda^* = \left[\frac{\pi}{k} \sum_i^k [D_i^2 - a^{*2}] \right]^{-1}$$

Oppgave 3 Mosaikk FZT

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Ising RF $L: \{L_x; x \in \mathcal{L}_D\} : L_x \in \{-1, 1\}$

$$\text{Prob}\{L=l\} = \text{const} \times \exp\left\{\beta \sum_{x \sim y} I(L_x = L_y)\right\}$$

a) Observert bilde

$$\mathcal{O}: \{O_x; x \in \mathcal{L}_D\}$$

Stokastisk tolkning:

$$O: \{O_x; x \in \mathcal{L}_D\} ; O_x \in \{-1, 1\}$$

Likelihood modell

$$\text{Prob}\{O=o | L=l\} = \prod_{x \in \mathcal{L}_D} \text{Prob}\{O_x = o_x | L_x = l_x\}$$

med

$$\text{Prob}\{O_x = o_x | L_x = l_x\} = \begin{cases} p & \text{for } o_x = -l_x \\ (1-p) & \text{for } o_x = l_x \end{cases}$$

Posteriori modell

$$\text{Prob}\{L=l | O=o\}$$

$$= \text{const}_1 \times \text{Prob}\{O=o | L=l\} \text{Prob}\{L=l\}$$

$$= \text{const}_2 \times \prod_{x \in \mathcal{L}_D} \text{Prob}\{O_x = o_x | L_x = l_x\} \exp\left\{\beta \sum_{x \sim y} I(L_x = L_y)\right\}$$

b) En mulig MCMC-algoritme er 'single-site' oppdatering:

Initier:

L^0 slik at $\text{Prob}\{L=l^0|\sigma\} > 0$

Iterer $i=0, 1, \dots, S$

$s \rightsquigarrow \text{Uni}[1, \dots, n_\sigma] ; n_\sigma = \#L_\sigma$

$l_s^p \rightsquigarrow \text{Uni}[-1, 1]$

$L^p = (l_1^i, \dots, l_{s-1}^i, l_s^p, l_{s+1}^i, \dots, l_{n_\sigma}^i)$

} symmetrisk forslagsmatrise

$\alpha = \min \left\{ 1, \frac{\text{Prob}\{L=L^p|\sigma\}}{\text{Prob}\{L=L^i|\sigma\}} \right\}$

faller bort her!

set $L^{i+1} = L^p$ med prob α

$L^{i+1} = L^i$ ellers

Da vil

$\text{Prob}\{L^i=l|\sigma\} \xrightarrow{i \rightarrow \infty} \text{Prob}\{L=l|\sigma\}$