

Dodatky ke slajdům

Regresní model ve stavovém tvaru

Ukážeme pro regresní model 2. řádu

$$y_t = b_0 u_t + a_1 y_{t-1} + b_1 u_{t-1} + a_2 y_{t-2} + b_2 u_{t-2} + k + e_t$$

Stavový tvar je

$$\begin{bmatrix} y_t \\ u_t \\ y_{t-1} \\ u_{t-1} \\ 1 \end{bmatrix} = \begin{bmatrix} a_1 & b_1 & a_2 & b_2 & k \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} y_{t-1} \\ u_{t-1} \\ y_{t-2} \\ u_{t-2} \\ 1 \end{bmatrix} + \begin{bmatrix} b_0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} u_t + \begin{bmatrix} e_t \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Generování z kategorického rozdělení

Obecně platí

$$F(X) = u \rightarrow X = F^{-1}(u)$$

Vzorec

$$y = \text{sum}(\text{cumsum}(f) < \text{rand}(1, 1, 'u')) + 1;$$

Vysvětlení: Máme pf

$$f(y) = [0.1, 0.6, 0.3]$$

Distribuční funkce je dána jako kumulativní součet (ve Scilabu `cumsum()`)

$$F(y) = [0.1, 0.7, 1]$$

Generujeme rovnoměrné `u=rand(1, 1, 'u')` a hledáme, kde platí

$$u < \underbrace{[0.1, 0.7, 1]}_q.$$

Příklad: pro $u = 0.653$ dostaneme

$$q = [1, 0, 0]$$

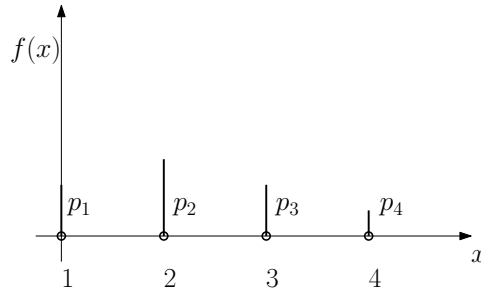
a

$$\sum [1, 0, 0] + 1 = 2$$

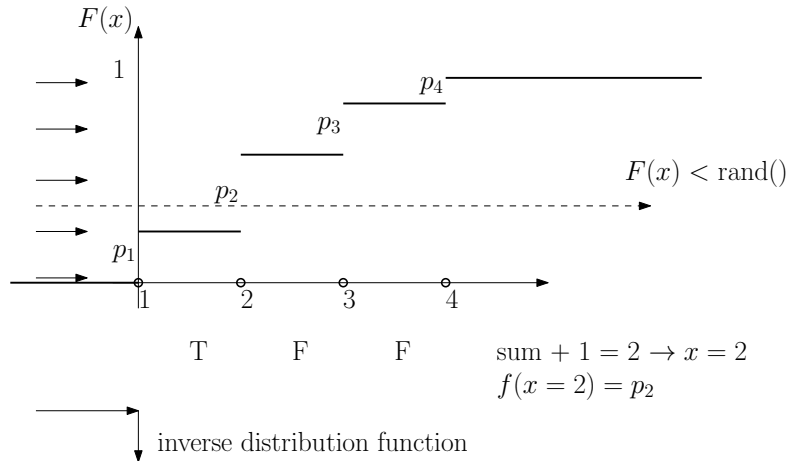
protože u padne do druhého intervalu.

Tak dostáváme hodnoty 0,1,2. Přidáme +1 a máme 1,2,3.

Probability function



Distribution function



Likelihood

Model: $f(y_t|\Theta)$

Data: $D = y_1, y_2, \dots, y_N$

Když máme data chceme znát parametry

$$\begin{aligned} f(\Theta|D) &\propto f(D|\Theta) = f(y_1, y_2, \dots, y_N|\Theta) = \\ &= \prod_{i=1}^N f(y_i|\Theta) = \underbrace{L_N(\Theta)}_{\text{Likelihood}} \quad (\text{nezávislost}) \end{aligned}$$

Odhad exponenciálního modelu

Model

$$f(y|a) = a \exp(-ay)$$

součin modelů

$$\begin{aligned} f(y_1|a) f(y_2|a) &= a \exp(-ay_1) a \exp(-ay_2) = \\ &= a^2 \exp(-a(y_1 + y_2)) \end{aligned}$$

odtud

$$\prod_{i=1}^n f(y_i|a) = a^n \exp\left(-a \sum_{i=1}^n y_i\right)$$

kde $S_n = \sum_{i=1}^n y_i$ a $\kappa_t = n$

Aposteriorní

$$f(a|y(t)) = a^{\kappa_t} \exp(-aS_t)$$

s přepočtem

$$S_t = S_{t-1} + y_t$$

$$\kappa_t = \kappa_{t-1} + 1$$

se startem $S_0 = 0$, $\kappa_0 = 0$.

Bayes $f(a|y(t)) \propto f(y_t|a) f(a|y(t-1))$

$$a^t \exp\left(-a \sum_{i=1}^t y_i\right) = a \exp(-ay_t) a^{t-1} \exp\left(-a \sum_{i=1}^{t-1} y_i\right)$$

a formálně

$$a^{\kappa_t} \exp(-aS_t) = a \exp(-ay_t) a^{\kappa_{t-1}} \exp(-aS_{t-1})$$

Bodový odhad (ML)

$$\frac{d}{da} a^\kappa \exp(-aS) = \kappa a^{\kappa-1} \exp(-aS) - a^\kappa S \exp(-aS) = 0$$

$$\kappa - aS = 0 \rightarrow a = \frac{\kappa}{S} = \frac{1}{\bar{y}}$$

Apriorno

zvolíme

$$f(a|y(0)) = a^{\kappa_0} \exp(-aS_0)$$

kde S_0 je součet apriorních dat a κ_0 je jejich počet.

Máme-li informaci, že asi $a \doteq 5$, bude $y = \frac{1}{5}$. Nejdříve volíme sílu apriorní (třeba) $\kappa_0 = 20$ a potom $S_0 = \sum y = \kappa_0 \frac{1}{5} = 4$.

Potom $\frac{1}{a} = \frac{S_0}{\kappa_0} = \frac{4}{20} = \frac{1}{5}$ a $a = 5$ (tedy odhad z apriorní odpovídá naší informaci).

Podobně je to u celé exponenciální rodiny distribucí - např.

Binomické rozdělení

model

$$f(y|p) = \binom{N}{y} p^y (1-p)^{N-y}$$

součin dvou

$$\begin{aligned} \binom{N}{y_1} p^{y_1} (1-p)^{N-y_1} \binom{N}{y_2} p^{y_2} (1-p)^{N-y_2} = \\ \binom{N}{y_1} \binom{N}{y_2} p^{y_1+y_2} (1-p)^{2N-(y_1+y_2)} \end{aligned}$$

obecný součin (likelihood)

$$\prod_{i=1}^t \binom{N}{y_i} p^{\sum_{i=1}^t y_i} (1-p)^{tN - \sum_{i=1}^t y_i} \propto p^{S_t} (1-p)^{\kappa_t N - S_t}$$

odhad

$$\hat{p}_t = \frac{S_t}{N \kappa_t}$$

Odhad nelineárního stavu - příklad

Model

$$\begin{aligned}x_{1;t} &= \underbrace{\exp\{-x_{1;t-1} - x_{2;t-1}\}}_{g_1} + u_t + w_t \\x_{2;t} &= \underbrace{x_{1;t-1} - 0.3u_t}_{g_2} + w_{2;t} \\y_t &= x_{2;t} + v_t\end{aligned}$$

Linearizace

$$g_1 = \exp\{-x_1 - x_2\} + u_t$$

$$g_2 = x_1 - 0.3u_t$$

$$g'_1 = \left[\frac{\partial g_1}{\partial x_1}, \frac{\partial g_1}{\partial x_2} \right] = [-\exp\{-x_1 - x_2\}, -\exp\{-x_1 - x_2\}]$$

$$g'_2 = \left[\frac{\partial g_2}{\partial x_1}, \frac{\partial g_2}{\partial x_2} \right] = [1, 0]$$

Platí

$$\bar{M} = g' = \begin{bmatrix} g'_1 \\ g'_2 \end{bmatrix} = \begin{bmatrix} -\exp\{-x_1 - x_2\}, & -\exp\{-x_1 - x_2\} \\ 1 & 0 \end{bmatrix}$$

$$F = g - \bar{M}\hat{x}_{t-1} = \begin{bmatrix} \exp\{-x_1 - x_2\} + u_t \\ x_1 - 0.3u_t \end{bmatrix} - \tilde{M}\hat{x}_{t-1}$$

Výsledný model je

$$x_t = \bar{M}x_{t-1} + F + w_t$$

$$y_t = \bar{A}x_t + v_t$$

kde $\bar{A} = [0, 1]$

Program

$$[xt, Rx, yp] = \text{Kalman}(xt, yt, ut, \bar{M}, 0, F, \bar{A}, 0, 0, Rw, Rv, Rx)$$

Řízení s regresním modelem

Regresní model převedeme na stavový

$$x_t = Mx_{t-1} + Nu_t + w_t$$

se stavem $x_t = [y_t, u_t, y_{t-1}, u_{t-1}, \dots, y_{t-n+1}, u_{t-n+1}]'$.

Penalizace

$$J_t = y_t^2 + \omega u_t^2 = x_t' \Omega x_t \quad (1)$$

Ω je

$$\Omega = \begin{bmatrix} 1 & & & & \\ & \omega & & & \\ & & 0 & & \\ & & & \dots & \\ & & & & 0 \end{bmatrix}$$

Podle Bellmanových rovnic $\varphi_{t+1}^* = x_t' R_{t+1} x_t$

$$E \left[x_t' R_{t+1} x_t + x_t' \Omega x_t | u_t, d(t-1) \right] = E \left[x_t' U x_t \right] =$$

$$\text{kde } U = R_{t+1} + \Omega$$

$$= (Mx_{t-1} + Nu_t)' U (Mx_{t-1} + Nu_t) + \rho =$$

dosazen model

$$= x_{t-1}' \underbrace{M'UM}_C x_{t-1} + 2u_t' \underbrace{N'UM}_B x_{t-1} + u_t' \underbrace{N'UN}_A u_t + \rho =$$

doplníme na čtverec

$$= u_t' A u_t + 2u_t' A \underbrace{A^{-1}B}_{S_t} x_{t-1} + x_{t-1}' S_t' A S_t x_{t-1} +$$

$$\begin{aligned}
& + \underbrace{x'_{t-1} C x_{t-1} - x'_{t-1} S'_t A S_t x_{t-1}}_{x'_{t-1} R_t x_{t-1}} + \rho = \\
& = (u_t + S_t x_{t-1})' A (u_t + S_t x_{t-1}) + x'_{t-1} R_t x_{t-1} + \rho
\end{aligned}$$

a minimalizujeme

Optimální řízení $u_t = -S_t x_{t-1}$.

Zobecnění

$$(y_t - s_t)^2 + \omega u_t^2 + \lambda (u_t - u_{t-1})^2$$

$$\Omega = \begin{bmatrix} 1 & & & & & -1 \\ & \omega + \lambda & -\lambda & & & \\ & & 0 & & & \\ & -\lambda & \lambda & & & \\ & & & \dots & & \\ & & & & 0 & \\ -1 & & & & & 1 \end{bmatrix}$$

$$x_t' \Omega x_t$$

se stavem $x_t = [y_t, u_t, y_{t-1}, u_{t-1}, \dots, 1]$.

Konstrukce Ω

$$\begin{array}{c} [y_t, \quad u_t, \quad y_{t-1}, \quad u_{t-1}, \quad y_{t-2}, \quad u_{t-2}, \quad 1] \\ \left[\begin{array}{c} y_t \\ u_t \\ y_{t-1} \\ u_{t-1} \\ y_{t-2} \\ u_{t-2} \\ 1 \end{array} \right] \left[\begin{array}{cccccc} 1 & & & & & -1 \\ & \omega + \lambda & -\lambda & & & \\ & & 0 & & & \\ & -\lambda & \lambda & & & \\ & & & 0 & & \\ & & & & 0 & \\ -1 & & & & & 1 \end{array} \right] \end{array}$$

Penalizace (podrobně)

$$\begin{aligned}
 & [y_t, u_t, y_{t-1}, u_{t-1}, 1] \begin{bmatrix} \Omega_{11} & \Omega_{12} & \Omega_{13} & \Omega_{14} & \Omega_{15} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} & \Omega_{24} & \Omega_{25} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} & \Omega_{34} & \Omega_{35} \\ \Omega_{41} & \Omega_{42} & \Omega_{43} & \Omega_{44} & \Omega_{45} \\ \Omega_{51} & \Omega_{52} & \Omega_{53} & \Omega_{54} & \Omega_{55} \end{bmatrix} \begin{bmatrix} y_t \\ u_t \\ y_{t-1} \\ u_{t-1} \\ 1 \end{bmatrix} = \\
 & = \begin{bmatrix} \Omega_{11}y_t, & \Omega_{12}y_t, & \Omega_{13}y_t, & \Omega_{14}y_t, & \Omega_{15}y_t \\ + & + & + & + & + \\ \Omega_{21}u_t, & \Omega_{22}u_t, & \Omega_{23}u_t, & \Omega_{24}u_t, & \Omega_{25}u_t \\ + & + & + & + & + \\ \Omega_{31}y_{t-1}, & \Omega_{32}y_{t-1}, & \Omega_{33}y_{t-1}, & \Omega_{34}y_{t-1}, & \Omega_{35}y_{t-1} \\ + & + & + & + & + \\ \Omega_{41}u_{t-1}, & \Omega_{42}u_{t-1}, & \Omega_{43}u_{t-1}, & \Omega_{44}u_{t-1}, & \Omega_{45}u_{t-1} \\ + & + & + & + & + \\ \Omega_{51}, & \Omega_{52}, & \Omega_{53}, & \Omega_{54}, & \Omega_{55} \end{bmatrix} \begin{bmatrix} y_t \\ u_t \\ y_{t-1} \\ u_{t-1} \\ 1 \end{bmatrix} =
 \end{aligned}$$

$$= \begin{bmatrix} \Omega_{11}y_t^2 + & \Omega_{12}y_tu_t + & \Omega_{13}y_t y_{t-1} + & \Omega_{14}y_tu_{t-1} + & \Omega_{15}y_t \\ + & + & + & + & + \\ \Omega_{21}u_t y_t + & \Omega_{22}u_t^2 + & \Omega_{23}u_t y_{t-1} + & \Omega_{24}u_tu_{t-1} + & \Omega_{25}u_t \\ + & + & + & + & + \\ \Omega_{31}y_{t-1}y_t + & \Omega_{32}y_{t-1}u_t + & \Omega_{33}y_{t-1}^2 + & \Omega_{34}y_{t-1}u_{t-1} + & \Omega_{35}y_{t-1} \\ + & + & + & + & + \\ \Omega_{41}u_{t-1}y_t + & \Omega_{42}u_{t-1}u_t + & \Omega_{43}u_{t-1}y_{t-1} + & \Omega_{44}u_{t-1}^2 + & \Omega_{45}u_{t-1} \\ + & + & + & + & + \\ \Omega_{51}y_t + & \Omega_{52}u_t + & \Omega_{53}y_{t-1} + & \Omega_{54}u_{t-1} + & \Omega_{55} \end{bmatrix}$$

$$\begin{aligned}
J &= (y_t - s_t)^2 + \omega u_t^2 + \lambda (u_t - u_{t-1})^2 = \\
&= y_t^2 - 2y_t s_t + s_t^2 + \omega u_t^2 + \lambda u_t^2 - 2\lambda u_t u_{t-1} + \lambda u_{t-1}^2
\end{aligned}$$

$$\begin{array}{c}
y_t, \quad u_t, \quad y_{t-1}, \quad u_{t-1}, \quad 1 \\
y_t \quad \left[\begin{array}{ccccc} 1 & 0 & 0 & 0 & -s_t \\ u_t & 0 & \omega + \lambda & 0 & -\lambda & 0 \\ y_{t-1} & 0 & 0 & 0 & 0 & 0 \\ u_{t-1} & 0 & -\lambda & 0 & \lambda & 0 \\ 1 & -s_t & 0 & 0 & 0 & s_t^2 \end{array} \right]
\end{array}$$

Střední hodnota

$$\begin{aligned} E \left[x'_t x_t | u_t, d(t-1) \right] &= E \left[(Mx_{t-1} + Nu_t + w_t)' (Mx_{t-1} + Nu_t + w_t) \right] = \\ &= (Mx_{t-1} + Nu_t)' (Mx_{t-1} + Nu_t) + 2(Mx_{t-1} + Nu_t)' E[w_t] + E \left[w'_t w_t \right] \\ &= (Mx_{t-1} + Nu_t)' (Mx_{t-1} + Nu_t) + E \left[w'_t w_t \right] = \\ &\quad \left(x'_{t-1} M' + u'_t N' \right) (Mx_{t-1} + Nu_t) + r = \\ &= x'_{t-1} M' Mx_{t-1} + 2x'_{t-1} M' Nu_t + u'_t N' Nu_t + r \end{aligned}$$

Doplnění na čtverec

$$\text{formula } (x + a)^2 = x^2 + 2xa + a^2$$

$$\begin{aligned} x^2 + xm + c &= x^2 + 2x \frac{m}{2} + \left(\frac{m}{2} \right)^2 - \left(\frac{m}{2} \right)^2 + c = \\ &= \underbrace{\left(x + \frac{m}{2} \right)^2}_{\text{square}} + \underbrace{c - \left(\frac{m}{2} \right)^2}_{\text{remainder}} \end{aligned}$$

... ve vektorech

$$\begin{aligned}
 x'Ax + 2x'Bm + C &= x'Ax + 2x'AA^{-1}m + m'A^{-1}\underbrace{AA^{-1}}_{=E}m - m'A^{-1}\underbrace{AA^{-1}}_{=E}m + C = \\
 &= \underbrace{(x' + A^{-1}m)' A (x' + A^{-1}m)}_{=0 \rightarrow m_{\text{opt}}} + \underbrace{C - m'A^{-1}m}_{\text{zbytek}}
 \end{aligned}$$