

NMSA 332 1. učenie - Podmienené modelovanie

$$1) f(x,y) = (x+y) I_H \quad M = \{0 < x < 1, 0 < y < 1\}$$

$$a) E[XY|X=x] = x E[Y|X=x] = \frac{\int_0^1 x y^2 dy}{\int_0^1 (x+y) dy} = *$$

$$f_{Y|X}(x,y) = \frac{f_{XY}(x,y)}{f_X(x)} = \frac{(x+y) I_H}{\int_0^1 (x+y) dy} = \frac{(x+y) I_H}{x+1/2} \quad x \in (0,1), y \in (0,1)$$

$$E[Y|X] = \int_0^1 y \frac{(x+y) I_H}{x+1/2} dy = \frac{x/2}{x+1/2} + \frac{1/3}{x+1/2} = \frac{x}{x+1/2}$$

$$* = x \cdot \left(\frac{x}{2x+1} + \frac{1}{3x+3/2} \right)$$

$$b) E[XY|X] = X \left(\frac{x}{2x+1} + \frac{1}{3x+3/2} \right)$$

$$c) E[XY^2|X] = X \int_0^1 y^2 \frac{(x+y)}{x+1/2} dy = \frac{x}{x+1/2} \left[\frac{x}{3} + \frac{1}{4} \right]$$

$$2) Y|X \sim N(2x^3, 3x^2) \quad X \sim R(0,1)$$

$$a) E\left[\frac{Y}{X^2}|X\right] = \frac{1}{X^2} E[Y|X] = 2X$$

$$b) E\frac{Y}{X^2} = E E\left[\frac{Y}{X^2}|X\right] = E 2X = 2 \cdot 1/2 = 1$$

$$c) EY = E E[Y|X] = E 2X^3 = 2 \int_0^1 x^3 dx = 2 \cdot \frac{1}{4} = \frac{1}{2}$$

$$d) \text{mn} Y = E \text{mn}(Y|X) + \text{mn} E(Y|X) = E 3X^2 + \text{mn}(2X^3) = 3/3 + 4 \left(\frac{1}{4} - \left(\frac{1}{4} \right)^2 \right) = 1 + 4/4 - 1/4$$

$$3) f(x,y) = \frac{1}{x} e^{-y/x} \quad x \in (1,2), y > 0$$

$$f_X(x) = \int_0^\infty \frac{1}{x} e^{-y/x} dy = \left[\frac{1}{x} e^{-y/x} \cdot (-\frac{1}{x}) \right]_{y=0}^\infty = 1 \quad x \in (0,1)$$

$$f_{Y|X}(x,y) = f_{Y|X}(y|x) = \frac{1}{x} e^{-y/x} \quad Y|X \sim \text{Exp}\left(\frac{1}{x}\right) \quad X \sim R(1,2)$$

$$a) E[Y|X=t] = t \quad t \in (1,2), \quad E[Y|X] = X$$

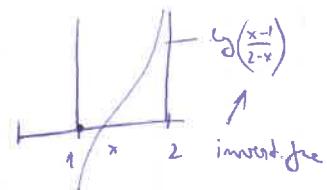
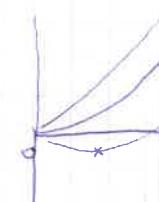
$$b) E[Y | \underbrace{\log\left(\frac{x-1}{2-x}\right)}_{t}] = t \quad \frac{2e^t+1}{e^t+1}$$

$$E[Y | \underbrace{\log\left(\frac{x-1}{2-x}\right)}_{t}] = \frac{2e^t+1}{e^t+1} = X$$

$$c) E\left[\frac{Y}{x^6} | \log\left(\frac{x-1}{2-x}\right)\right] = \frac{1}{x^5}$$

pozor na výplň:
 $E[Y|X] = \text{mn}(Y|X) := E((Y - E(Y|X))^2 | X)$

$$\begin{aligned} E[Y|X] &= \int_R y f_{Y|X}(x,y) dy \\ &= \int_R y \frac{1}{x} e^{-y/x} dy \\ &= \frac{1}{2x^3} \end{aligned}$$



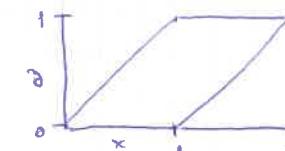
$$4) f(x,y) = c y I_H(x,y) \quad M = \{y \in (0,1), y \leq x \leq y+1\}$$

$$\int_0^1 \int_0^1 c y dy dx = c \int_0^1 y dy = c \cdot 1/2$$

$$a) E[9 \ln X - \log \frac{Y}{1-Y} | Y] = 9 \ln E[X|Y] - \log \frac{Y}{1-Y} = *$$

$$f_{X|Y}(x|y) = \frac{2y I_H(x,y)}{\int_0^y 2y dy} = I_H(x,y)$$

$$* = 9 \ln (Y + 1/2) - \log \left(\frac{Y}{1-Y} \right)$$



$$\begin{aligned} Y &\sim R(0,1) \\ X|Y &\sim R(Y, Y+1) \end{aligned}$$

$$\begin{aligned} E[X|Y] &= \int x I_H(x,y) dx = \int_0^y x dx = \left[\frac{x^2}{2} \right]_0^y = \frac{y^2}{2} \\ &= \frac{(y+1)^2 - y^2}{2} = y + \frac{1}{2} \end{aligned}$$

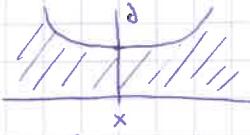
$$6, E[\min X | Y] = \int_0^{\infty} \min x \cdot dx = [-\cos x]_0^{\infty} = \cos y - \cos(y+1)$$

$$5, a, E[X+Y|X] = X + E[Y|X] \quad \text{mitur.}$$

$$b, E[X+Y|X] = X + E[Y|X] \quad \begin{array}{l} \text{projektion nach unten} \\ E[Y|X] = f(x) \end{array}$$

$$c) z = x+y \\ E[X|z] = E[z-y|x] = z - E[y|x] \stackrel{\text{symmetrisch}}{=} z - E[x|z] \\ E[X|z] = z/2 \Rightarrow E[X|X+y] = \frac{x+y}{2}$$

$$6, Y|X \sim R(0, x^2/11) \\ X \sim N(0, 1)$$



$$g, E[Y|e^x] = E[Y|z] = \frac{(e^z)^2 + 1}{2} = \frac{x^2 + 1}{2} \\ z = e^x \quad x = \ln z$$

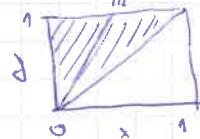
$$EX^k = 3!! = 3 \cdot 1 = 3 \\ EX^p = \sigma^p (p-1)!! \quad p \text{ ungerade}$$

$$h, EY = EE[Y|X] = E \frac{x^2 + 1}{2} = 1 \quad \text{var } R(a,b) = (b-a)^2/12$$

$$c, \text{var } Y = \text{var}(E[Y|X]) + E(\text{var}(Y|X)) = \text{var} \frac{x^2 + 1}{2} + E \frac{(x^2 + 1)^2}{12} = \frac{3}{4} - \frac{1}{4} + \frac{1}{12}[3+2+1] = 1$$

$$7, (X,Y) \sim U(M) \quad M = \{0 < x < 1, x < y\}$$

$$f_{X,Y}(x,y) = 2I_M \\ f_{X|Y}(x|y) = \frac{2I_M}{\int_0^y 2dx} = \frac{I_M}{y}$$



$$a, E[\ln y | X] = \int_0^1 \frac{\ln x}{x} dx = \frac{1}{2} \left([\ln x]_0^1 - \int_0^1 1 dx \right) = \ln 2 - 1$$

$$b, E[X | \ln Y] = \text{lognormal} \quad E[X|Y] = \int_0^1 \frac{x}{x} dx = \frac{1}{2}$$

immanig für alle

$$c, E[\ln x | \ln y] = \ln 2 - 1$$

$$\rightarrow 15, X \sim \text{Exp}(\lambda) \quad g(\lambda) = 1/\lambda^2 \quad [g'(\lambda)]^2 = 4/\lambda^6 \quad EX = \frac{1}{\lambda} \quad \text{var } X = \frac{1}{\lambda^2} \quad EX^k = \frac{2}{\lambda^2}$$

$$i, ET = c \cdot m \cdot EX^2 = c \cdot m \cdot 2/\lambda^2 \Rightarrow c = 1/2m$$

$$ii, \text{var } T = \frac{m}{12m^2} \text{var } X_1^2 = 5/12m^2 \quad EX^k = \int_0^\infty \lambda e^{-\lambda x} x^k dx = \int_0^\infty t^k dt / \lambda^k = \frac{k!}{\lambda^k}$$

$$L(\lambda) = \lambda e^{-\lambda x} \Rightarrow l = \ln \lambda - \lambda x \Rightarrow \lambda' = 1/\lambda - x \Rightarrow \lambda'' = -1/\lambda^2 \Rightarrow J(\lambda) = 1/\lambda^2$$

$$\text{RC: } \frac{\lambda^2}{m} \cdot \frac{4}{\lambda^6} = \frac{4}{m \lambda^4} < \text{var } T = \frac{5}{\lambda^4 m}$$

$$16, \text{ var normalnem modelle in } S^2 \text{ a } \bar{X} \text{ meranishi} \Rightarrow T_1, \alpha T_2 \text{ in meranishi}$$

$$\text{dialej } \frac{S^2(m-1)}{\sqrt{S^2(m-1)}} \sim \sigma^2 X_{m-1}^2$$

pohľadom Mathematica skript

$$(8) \text{ 1)} \quad (\bar{x}) \sim N_2 \left(\begin{pmatrix} \theta \\ \theta \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right) \quad \Sigma = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \quad \Sigma^{-1} = \frac{1}{1-\rho^2} \begin{pmatrix} 1 & -\rho \\ -\rho & 1 \end{pmatrix} \quad |\Sigma| = 1 - \rho^2$$

$$\text{a)} \quad f_{(\bar{x})}(x_1, y_1) = \frac{1}{2\pi|\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} ((\bar{x}) - (\theta))^\top \Sigma^{-1} ((\bar{x}) - (\theta)) \right\} = \frac{c}{1-\rho^2} \exp \left\{ -\frac{1}{2} \left[\frac{(x-\theta)^2 + (y-\theta)^2 - 2\rho(x-\theta)(y-\theta)}{1-\rho^2} \right] \right\}$$

$$\frac{1}{1-\rho^2} (x-\theta) (y-\theta) \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \begin{pmatrix} x-\theta \\ y-\theta \end{pmatrix} = \frac{1}{1-\rho^2} ((x-\theta)^2 + (y-\theta)^2 - 2\rho(x-\theta)(y-\theta))$$

$$L(\bar{x})(\theta) = c - \frac{1}{2(1-\rho^2)} ((x-\theta)^2 + (y-\theta)^2 - 2\rho(x-\theta)(y-\theta))$$

$$\frac{\partial L}{\partial \theta}(\theta) = -\frac{1}{2(1-\rho^2)} (-2(x-\theta) - 2(y-\theta) + 2\rho[(y-\theta) + (x-\theta)])$$

$$\frac{\partial^2 L}{\partial \theta^2}(\theta) = -\frac{1}{1-\rho^2} (2 - 2\rho) = -\frac{2(1-\rho)}{1-\rho^2} = -2/(1+\rho) \Rightarrow J(\theta) = 2/(1+\rho)$$

$$b) \quad \bar{X} \sim N(\theta, 1/m) \quad \text{mn } \bar{X} = 1/m \quad \text{R-C: } 1/(2m(1+\rho)) = (1+\rho)/2m$$

↓
náš návrh
 $1/m > (1+\rho)/(2m) \rightarrow$ mierasúhrige R-C medien ak $\rho = 1$ dosahuj

$$c) \quad Z = (X+Y)/2 \sim N(\theta, \frac{1}{m} + \frac{1}{m} + \frac{2\rho}{m}) = N(\theta, \frac{1+\rho}{2})$$

$$\bar{Z} \sim N(\theta, \frac{1+\rho}{2m}) \quad \text{mn } \bar{Z} = \frac{1+\rho}{2m} = \text{R-C: } \frac{1+\rho}{2m} \rightarrow \text{dosahuj R-C medien}$$

→ (9) 2) $X \sim P_0(\lambda)$

$$a) \quad f(x) = e^{-\lambda} \lambda^x / x! \quad x \in N_0$$

$$L(\lambda) = -\lambda + x \ln \lambda + c$$

$$\frac{\partial L}{\partial \lambda} = -1 + \frac{x}{\lambda}$$

$$\frac{\partial^2 L}{\partial \lambda^2} = -x/\lambda^2 \quad J(\lambda) = E X / \lambda^2 = 1/\lambda \quad \text{by } J_m(\lambda) = m/\lambda$$

$$c) \quad g(\lambda) = 2\lambda \quad Y = \sum X_i \sim P_0(m\lambda) \quad E Y = m\lambda \Rightarrow T := \frac{2 \sum X_i}{m}$$

$$g'(\lambda) = 2 \quad \text{mn } T = \frac{4}{m^2} \quad \text{mn } X_1 = \frac{4\lambda}{m} = \text{R-C: } \frac{4\lambda}{m} \Rightarrow \text{eficientne odhad}$$

$$d) \quad T = (1 - \frac{1}{m})^{\sum X_i} \quad ET^k = \sum_{j=0}^{\infty} \left(1 - \frac{1}{m}\right)^j \lambda^{-m} \frac{(m\lambda)^j}{j!} = e^{-m\lambda} e^{m\lambda + (1 - \frac{1}{m})^k} = \exp\left\{(1 - \frac{1}{m})^k\right\}$$

$$ET = e^{-\lambda} \Rightarrow \text{náš návrh} \quad g(\lambda) = e^{-\lambda} \quad \text{mn } T = e^{-m\lambda + m\lambda - 2\lambda + k\lambda} = e^{-2\lambda} = e^{-2\lambda} (1 + e^{-2\lambda}) \quad g'(\lambda) = -e^{-\lambda}$$

$$\text{R-C: } e^{-2\lambda} \frac{\lambda}{m}$$

$$\text{mn } T = e^{-2\lambda} \cdot \sum_{j=1}^{\infty} \left(\frac{\lambda}{m}\right)^j \frac{1}{j!} > e^{-2\lambda} \cdot \frac{\lambda}{m} \Rightarrow \text{dosahuj}$$

e) jazne

(10) 3) averaging system, súpravná media α

$$(11) \quad b) \quad X \sim N(\theta, \sigma^2)$$

$$a) \quad L(\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{1}{2\sigma^2} (x-\theta)^2 \right\} \quad L(\sigma) = c - \log \sigma - \frac{1}{2\sigma^2} (x-\theta)^2$$

$$\frac{\partial L}{\partial \sigma} = -\frac{1}{\sigma} + \frac{(x-\theta)^2}{\sigma^3} \quad \frac{\partial^2 L}{\partial \sigma^2} = \frac{1}{\sigma^2} - \frac{3(x-\theta)^2}{\sigma^4} \quad J(\sigma) = \frac{3}{\sigma^2} + \frac{1}{\sigma^2} = \frac{2}{\sigma^2}$$

$$b) \quad L(\sigma^2) = \dots \quad L(\sigma^2) = c - \frac{1}{2} \log \sigma^2 - \frac{1}{2\sigma^2} (x-\theta)^2$$

$$\frac{\partial L}{\partial \sigma^2} = -\frac{1}{2\sigma^2} + \frac{(x-\theta)^2}{2(\sigma^2)^2}$$

$$\frac{\partial^2 L}{\partial \sigma^2} = \frac{1}{2(\sigma^2)^2} - \frac{(x-\theta)^2}{(\sigma^2)^3}$$

$$J(\sigma^2) = \frac{1}{(\sigma^2)^2} - \frac{1}{2(\sigma^2)^2} = \frac{1}{2(\sigma^2)^2} = \frac{J(\sigma)}{(2\sigma)^2}$$

c) journ

12) $X \sim N(0, \sigma^2)$

i) math. stabilität I: nachweislich S_m^2 (siehe 2.2.3, mit 2.6)

da normalverteilt (mit 2.8) $\frac{(m-1)S_m^2}{\sigma^2} \sim \chi_{m-1}^2$ $\text{mn } \frac{m-1}{\sigma^2} S_m^2 = \text{mn } \chi_{m-1}^2 = 2(m-1)$
 $\Rightarrow \text{mn } S_m^2 = \frac{2\sigma^4}{m-1}$

$L(\sigma^2) = \text{abs} \sqrt{11} \Rightarrow J(\sigma^2) = \frac{1 \cdot m}{2(\sigma^2)^{\frac{m}{2}}}$ CR: $\frac{2\sigma^4}{m} < \text{mn } S_m^2 = \frac{2\sigma^4}{m-1}$
angemessen ist alle gleichverteilt

ii) $T_m = \frac{1}{m} \sum X_i^2 \quad ET_m = EX^2 = \sigma^2 \quad \text{mn } T_m = \frac{1}{m} \sum \text{mn } X_i^2 = \frac{1}{m} (EX^4 - \sigma^4) = \frac{3\sigma^4 - \sigma^4}{m} = \frac{2\sigma^4}{m} = \text{RC median}$

iii) $\hat{\sigma}_m = \sqrt{\frac{\pi}{2}} \cdot \frac{1}{m} \sum |X_i| \quad E\hat{\sigma}_m = \sqrt{\frac{\pi}{2}} E|X| = \sqrt{\frac{\pi}{2}} \int \frac{|x|}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} dx = 2\sqrt{\frac{\pi}{2}} \int_0^\infty \frac{x e^{-\frac{x^2}{2\sigma^2}}}{\sqrt{2\pi\sigma^2}} dx =$
 $= \sqrt{2\pi} \int_0^\infty \frac{\sqrt{2\sigma^2 + t} \cdot e^{-t^2/2\sigma^2}}{\sqrt{2\pi\sigma^2}} dt = 2\sigma \int_0^\infty t e^{-t^2/\sigma^2} dt = \sigma \int_0^\infty s e^{-s^2/\sigma^2} ds = \frac{\sigma}{\sqrt{\frac{\pi}{2}\sigma^2}} \cdot \sigma = \frac{\sigma}{\sqrt{\frac{\pi}{2}}}$

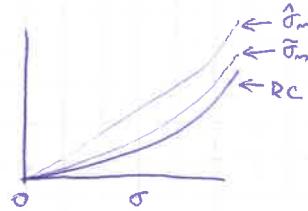
$\text{mn } \hat{\sigma}_m = \frac{\pi}{2m} \text{mn } |X_i| = \frac{\pi}{2m} (\sigma^2 - (\sigma \sqrt{\frac{\pi}{2}})^2) = \sigma^2 \frac{\pi}{2m} \left(1 - \frac{2}{\pi}\right) = \sigma^2 \left(\frac{\pi}{2m} - \frac{1}{m}\right) = \frac{\sigma^2}{2m} (\pi - 2)$

$\text{RC} = \frac{\sigma^2}{2m} < \text{mn } \hat{\sigma}_m = \frac{\sigma^2}{2m} (\pi - 2)$

iv) $\tilde{\sigma}_m = c \sqrt{\frac{1}{m} \sum X_i^2} \quad E\tilde{\sigma}_m = c \int_0^\infty \sqrt{\frac{1}{m} y \sigma^2} f_{\tilde{\sigma}_m}(y) dy = \frac{c}{\sqrt{m}} \quad E\Gamma = \frac{\sigma c \sqrt{2} \Gamma(\frac{1+m}{2})}{\sqrt{m} \Gamma(\frac{m}{2})}$

$\frac{\sum X_i^2}{\sigma^2} = \frac{\sum (X_i/\sigma)^2}{\sigma^2} \sim \sum N(0, 1)^2 = \chi_m^2 \Rightarrow \text{mn } \sum X_i^2 \sim \sigma^2 \chi_m^2 \quad \text{RC} = \frac{\sigma^2}{\sqrt{m}}$

$c = \sqrt{\frac{m}{2}} \frac{\Gamma(\frac{m+1}{2})}{\Gamma(\frac{m-1}{2})} \quad \text{mn } \tilde{\sigma}_m = \frac{c^2}{m} E \sum X_i^2 - \sigma^2 = \frac{m}{2m} \left[\frac{\Gamma(\frac{m+1}{2})}{\Gamma(\frac{m-1}{2})} \right]^2 \sigma^2 m - \sigma^2$



$E X_m = \sqrt{2} \frac{\Gamma(\frac{m+1}{2})}{\Gamma(\frac{m-1}{2})}$
 $\Gamma(n) = \int_0^\infty x^{n-1} e^{-x} dx (= (n-1)! \text{ für } n \in \mathbb{N})$

13) $X \sim D(0, \theta) \rightarrow \text{merregelnde methode}$
i) $2\bar{X} = \hat{\theta}_m \quad E\hat{\theta}_m = 2E\bar{X}_i = \theta$
 $P(\max X_i \leq t) = \left(\frac{t}{\theta}\right)^m \Rightarrow f_{\max}(t) = \frac{mt^{m-1}}{\theta^m}$

$\hat{\theta}_m = \frac{m+1}{m} \max X_i \quad E\hat{\theta}_m = \frac{m+1}{m} E \max X_i = \frac{m+1}{m} \int_0^\theta \frac{t^m t^{m-1}}{\theta^m} dt = \frac{(m+1)}{\theta^m} \left[\frac{t^{m+1}}{m+1} \right]_0^\theta = \theta$

ii) merregelnde methode

14) $X \sim \text{Bin}(p)$

i) $\hat{p} = \bar{X}$ mestig! $\text{mn } \hat{p} = \frac{p(1-p)}{m}$

$L(p) = p^{\sum X_i} (1-p)^{m-\sum X_i}$
 $\ell(p) = \sum X_i \log p + (m - \sum X_i) \log(1-p)$

$\frac{\partial \ell}{\partial p} = \frac{\sum X_i}{p} - \frac{m - \sum X_i}{1-p}$

$\frac{\partial^2 \ell}{\partial p^2} = -\frac{\sum X_i}{p^2} + \frac{m - \sum X_i}{(1-p)^2}$

$J_m(p) = \frac{m}{p} + \frac{m}{1-p} = m \left(\frac{1}{p} + \frac{1}{1-p} \right) = \frac{m}{p(1-p)}$ RC: $\frac{p(1-p)}{m}$ drohende RC max

ii) journ

$$25) 14) X_i \sim p(1-p)^x \quad x \in N_0 \quad S = \sum X_i \sim \text{neg. bin} = \binom{m+n-1}{m} p^m (1-p)^n$$

$$\text{a)} P(X=x | S=n) = \frac{P(S=n | X=x) P(X=x)}{P(S=n)} = \frac{I[\sum X_i = n] p^{\sum x_i} (1-p)^{n-\sum x_i}}{\binom{m+n-1}{m} p^m (1-p)^n}$$

$$= \begin{cases} 1/\binom{m+n-1}{m} & \text{ak } \sum x_i = n \\ 0 & \text{inak.} \end{cases} \Rightarrow \text{nufic.}$$

pedom. ide o rozmístění početnosti
na následujících místech v N_0 .
tj. $\sum_{i=1}^n x_i = n$.

$$\text{b)} f(x; p) = p^m (1-p)^{\sum x_i} \Rightarrow S = \sum X_i \text{ je nuf.}$$

$$26) 18, \text{a)} X_i \sim P_0(\lambda) \quad S = \sum X_i \sim P_0(m\lambda)$$

$$P(X=x | S=n) = I[\sum X_i = n] \frac{e^{-m\lambda} \lambda^{\sum x_i} / (\prod x_i!)}{e^{-m\lambda} (m\lambda)^n / n!} = \begin{cases} (\lambda^{x_1} \dots \lambda^{x_m}) \left(\frac{1}{m}\right)^{\sum x_i} & \text{ak } \sum x_i = n \\ 0 & \text{inak.} \end{cases}$$

\Rightarrow nufic a ide pro dané n o modelování $M(\alpha; \frac{1}{m}, \dots, \frac{1}{m})$

$$\text{b), } P(X=x) = \underbrace{e^{-m\lambda} \lambda^{\sum x_i}}_{g(\sum x_i; \lambda)} \underbrace{1 / \prod x_i!}_{h(x)}$$

$$27) 19, X \sim R\{1 \dots M\} \quad M \in N \quad S = \max X_i \quad P(S \leq n) = P(X_i \leq n) = \left(\frac{n}{M}\right)^m$$

$$P(S=n) = P(S \leq n) - P(S \leq n-1) = \left(\frac{n}{M}\right)^m - \left(\frac{n-1}{M}\right)^m \quad \text{pre } n \in \{1 \dots M\}$$

$$\text{a)} P(X=x | S=n) = I[\max X_i = n] \frac{\left(\frac{1}{M}\right)^m}{\left(\frac{n}{M} - \left(\frac{n-1}{M}\right)^m\right) / M^m} = \begin{cases} 1 / (M^n - (n-1)^m) & \text{ak } \max X_i = n \\ 0 & \text{inak.} \end{cases}$$

$\Rightarrow S$ je nufic

$$\text{b), } P(X=x) = \left(\frac{1}{M}\right)^m \prod I[1 \leq x_i \leq M] = \left(\frac{1}{M}\right)^m I[\max X_i \leq M]$$

$$28) 20) f(x; \sigma^2) = \frac{c}{\sigma^m} \exp\left\{-\frac{1}{2\sigma^2} \sum x_i^2\right\} \quad \text{a Lehmann-Scheffé je } \sum x_i^2 \text{ minimálna sif}$$

i) X je my (všimnout, že $\sum x_i^2$ je funkce $X|X \sim \delta_X$ může být mimo σ^2) $\sum x_i^2$ je funkce

ii) $(|x_1|, \dots, |x_m|)^T$ je my ($\sum x_i^2 = \sum |x_i|^2$)

iii) $\sum X_i$ nie je my ($\sum x_i^2$ nie je funkce $\sum x_i$, ale $\sum x_i = \sum x_i^2$ nemáme možnosť $\sum x_i^2$) $\sum x_i^2$ je nuf. řádovost

iv) nie $\sum |x_i|$, ale rovnako iiii)

v) $\sum x_i^2$ je my

vi) $\sum x_i^2 / m$ je my

vii) $(\frac{1}{m} \sum x_i^2, x_m^2)$ je my

ale $\sum x_i^2$ je funkce $\sum x_i$

$\begin{cases} x_1 = -1 & \sum x_i = 0 \\ x_2 = 1 & \sum x_i = 2 \end{cases}$

ale $x_1 = -2 \quad \sum x_i = 0 \quad \text{a } \sum x_i^2 = 4$

$$29) 21) X \sim \text{alt}(p)$$

$$\text{i)} P(X=x) = \frac{P^{\sum x_i} (1-p)^{m-\sum x_i}}{P^{\sum x_i - \sum \delta_i} (1-p)^{\sum \delta_i - \sum x_i}} \Rightarrow \sum x_i \text{ je my.} \Rightarrow \sum x_i^2 \text{ nie je funkce } \sum x_i$$

$$\text{ii)} P(X=x) = \frac{P^{\sum x_i} (1-p)^{m-\sum x_i}}{P^{\sum x_i - \sum \delta_i} (1-p)^{\sum \delta_i - \sum x_i}} \Rightarrow \sum x_i \text{ je minimálna funkce.}$$

$$\text{iii)} \text{neh } E_p \text{ nr}(x) = 0 = p(\text{nr}(1)) + (1-p)\text{nr}(0) \quad \forall p \in (0,1)$$

$$= p(\text{nr}(1) - \text{nr}(0)) + \text{nr}(0) \quad \Rightarrow \text{nr}(0) = 0 \quad \text{a } \text{nr}(1) - \text{nr}(0) = 0.$$

\Rightarrow implika. Nie je ale postačujúca $X|X_1 \sim (\delta_{x_1}, x_2, \dots, x_m)$ minimálne $= p$

$$\text{iv)} \text{neh } E_p \text{ nr}(\sum x_i) = 0 = \sum_{j=0}^m \binom{m}{j} \underbrace{p^j (1-p)^{m-j}}_{\sum x_i \sim Bi(m, p)} \text{ nr}(j)$$

$LN \geq \text{funkce } \text{nr } p \quad \text{pre } j=0 \dots m \Rightarrow \text{nr}(j)=0 \quad \forall j$
 je implika.

30) 22) $X_i \sim N(\mu, \sigma^2)$

$$\frac{f(x)}{f(y)} = \frac{\frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2\sigma^2} \sum (x_i - \mu)^2\right\}}{\frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2\sigma^2} \sum (y_i - \mu)^2\right\}} = \exp\left\{-\frac{1}{2\sigma^2} \left[\sum x_i^2 - 2\mu \sum x_i + m\mu^2 - \sum y_i^2 + 2\mu \sum y_i - m\mu^2 \right]\right\}$$

$$= \exp\left\{-\frac{1}{2\sigma^2} \left[\sum (x_i^2 - y_i^2) - 2\mu \sum (x_i - y_i) \right]\right\} \Rightarrow (\sum x_i, \sum x_i^2)' \text{ je minim. auf.}$$

31) 23) $X \sim R(0, \theta)$ $M = \max X_i$ $P(M \leq m) = (m/\theta)^m \Rightarrow f_M(m) = \frac{m^m e^{-m}}{\theta^m} \quad m \in [0, \theta]$

i) nach $\nabla \theta > 0$
 $E_\theta \ln r(M) = \int_0^\theta m^m \frac{m^{m-1}}{\theta^m} \ln r(m) dm$

polum cij $O = \int_0^\theta m^{m-1} \ln r(m) dm / \frac{\partial}{\partial \theta}$

$$O = \theta^{m-1} \ln r(\theta) - O^{m-1} \ln r(0) \Rightarrow \ln r(\theta) = O \quad \forall \theta \text{ (n.r.)} \Rightarrow \text{upln!}$$

ii) $E_\theta \ln r(x_i) = \int_0^\theta \frac{r(x)}{\theta} dx / \frac{\partial}{\partial \theta}$

$$O = r(\theta) \quad \forall \theta \text{ (n.r.)} \Rightarrow \text{upln!}$$

32) 24) $X \sim R(\theta - 1/2, \theta + 1/2)$

i) $f(x) = 1 \cdot I[x_i \in (\theta - 1/2, \theta + 1/2)] = I[\min x_i \leq \max x_i \leq \theta + 1/2] \Rightarrow (\min x_i, \max x_i) \text{ je nyf}$

ii) $E(\max x_i - \min x_i) = \text{melnde rückt ma \theta zwölf invarianten wörli possumitum}$
 $= (\theta + 1/2 - \frac{1}{m+1}) - (\theta - 1/2 + \frac{1}{m+1}) = 1 - \frac{2}{m+1}$

33) 25) $X \sim \text{Poisson}(\alpha, \beta)$

$$f(x) = \frac{\beta^m \lambda^{m+x}}{(m+x)!} I[m \min x_i > \alpha] \Rightarrow \text{nyf je } \begin{cases} \min x_i, \overline{x}_i \\ \text{alle } (m \min x_i, \sum \log x_i) \end{cases}$$

34) 26) $X \sim N(\mu, \mu^2)$

i) $\frac{f(x)}{f(y)} = \exp\left\{-\frac{1}{2\mu^2} \left[\sum x_i^2 - 2\mu \sum x_i + m\mu^2 - \sum y_i^2 + 2\mu \sum y_i - m\mu^2 \right]\right\} =$
 $= \exp\left\{-\frac{1}{2\mu^2} \left[\sum (x_i^2 - y_i^2) - 2\mu \sum (x_i - y_i) \right]\right\} \quad (\sum x_i, \sum x_i^2)' \text{ je minim. nyf}$

ii) $E_\mu \left[\left(\sum_{i=1}^m x_i \right)^2 - \sum x_i^2 \right] = 0 \quad \nabla \mu$

$$\sum x_i \sim N(m\mu, m\mu^2) \Rightarrow E(\sum x_i)^2 = m\mu^2 + \mu^2 m = \mu^2(m^2 + m) = m\mu^2(m+1)$$

$$E \sum x_i^2 = m E x_i^2 = m\mu^2$$

35) 27) $X \sim M(m; p_1, \dots, p_4)$

i) $P(X=x) = \frac{(\sum x_i - x)}{(\sum x_i - \bar{x})} \frac{\prod p_j^{x_j}}{\prod p_j^{\bar{x}}} = c \cdot \prod p_j^{x_j - \bar{x}} \Rightarrow X \text{ je mi postlängica}$
 $m \text{ pmu} \Rightarrow x_4 = m - \sum_{i=1}^6 x_i \text{ a.s.}$

ii) $= c \cdot p_1^{\sum x_i - \sum \bar{x}} p_6^{\sum x_i - \sum \bar{x}} \Rightarrow (\sum_{i=1}^6 x_i, x_6 + x_4)' \text{ je mi postlängica}$

iii) $= c \cdot p^{\sum x_i - \sum \bar{x}} \Rightarrow \sum_{i=1}^6 x_i \text{ je mi postlängica}$
 $\text{alle nr tomtr modele } \frac{1}{4} \text{ da } p = \frac{1}{4}$

36) 28) $X \sim N(0, \sigma^2)$

i) $\sum x_i \sim N(0, m\sigma^2)$ $E_{\sigma^2} \sum x_i = 0 \quad \nabla \sigma^2 \Rightarrow \text{nyf je upln!}$

ii) $E_{\sigma^2} \underbrace{(\min x_i - 1)}_{T} = \int_R^{\infty} \min x_i \cdot \frac{e^{-x^2/2\sigma^2}}{\sqrt{2\pi\sigma^2}} dx - 1 = -1$

$$E_{\sigma^2} (T+1) = 0 \quad \nabla \sigma^2 \Rightarrow \text{nyf je upln!}$$

$$\text{37) } 29, X \sim \mathcal{B}(a, b) \quad \frac{f(x)}{f(y)} = \frac{(\pi x_i)^{a-1} \pi(1-x_i)^{b-1}}{(\pi y_i)^{a-1} \pi(1-y_i)^{b-1}} = \left(\pi \frac{x_i}{y_i}\right)^{a-1} \left(\pi \frac{1-x_i}{1-y_i}\right)^{b-1}$$

$\Rightarrow (\pi x_i, \pi(1-x_i))^T$ alle $(\sum \log x_i, \sum \log(1-x_i))^T$ sind obere m. mg.

$$\text{38, 39) } X \sim N(\mu_1, \sigma^2) \quad Y \sim N(\mu_2, \sigma^2)$$

$$\text{i) } f(x_1, y_1) = \frac{c}{\sigma^{m+n}} \exp\left\{-\frac{1}{2\sigma^2} \left[\sum x_i^2 - 2\mu_1 \sum x_i + m\mu_1^2 - \sum y_i^2 + 2\mu_2 \sum y_i - n\mu_2^2 \right] \right\}$$

$$\Rightarrow (\sum x_i, \sum x_i^2, \sum y_i, \sum y_i^2)^T$$
 j. mg.

$$\text{ii) } E_{\mu_1, \mu_2, \sigma^2} S_{m, x}^2 - S_{m, y}^2 = 0 \quad \nexists_{\mu_1, \mu_2, \sigma^2}$$

$$\text{39, 31) } P(X=x) = \frac{e^{-m\lambda} \lambda^{\sum x_i}}{\pi x! \cdot C(\lambda)^m} \quad I[0 \leq x_i \leq k] - I[0 \leq x_m \leq k] \Rightarrow (\sum x_i, \max x_i)^T$$

$$\text{j. mg.}$$

Vjewilice saufic. zähligkeit

39, 40 mitteilen 41 weiter

$$(39) \text{ 32) } X \sim Ge(p) \quad P(X=x) = p(1-p)^x \quad x \in \mathbb{N}_0$$

$$\text{a) } ET = E I[X=0] = p$$

lsg) $\text{pm 14) } \Rightarrow S = \sum X_i$ polačujúca $E[T|S=n] = E[I[X=0]|S=n] = P(X=0|S=n) =$

$$\begin{aligned} &= \frac{P(S=n|X_1=0)}{P(S=n)} P(X_1=0) = p \cdot \frac{P(\sum_{i=2}^m X_i=n)}{P(\sum_{i=1}^m X_i=n)} = \frac{p \binom{m+n-2}{n-1} p^{n-1}(1-p)^n}{\binom{m+n-1}{n} p^m (1-p)^n} = \\ &= \frac{(m+n-2)!}{n!(m-2)!} = \frac{m-1}{m+n-1} \quad RC_m = \frac{p^2 q}{m} \quad P\left(\sum_{i=1}^m X_i=n\right) = \binom{m+n-1}{n} p^m (1-p)^n \quad n \in \mathbb{N}_0 \end{aligned}$$



$$\text{mnp} \quad \text{mnp} T = \frac{p(1-p)}{m}$$

mnp $\mu(X)$ je množ. chapeau.

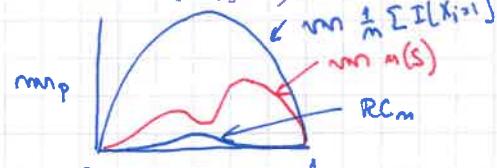
$$E[T|S] = \frac{m-1}{m+n-1} = \frac{1-\bar{x}_m}{1+\bar{x}-\bar{x}_m} = \mu(\bar{x})$$

$$\text{c) } P(X=x) = p(1-p)^x = \exp\{\log(p)\} \cdot p \Rightarrow \sum x_i = S \text{ je uplná pravdep. pre } \theta = \log(1-p)$$

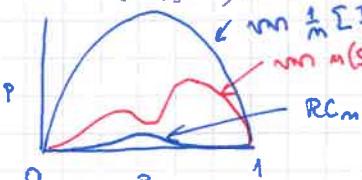
$$a(\theta) = 1 - e^\theta = 1 - (1-p) = p \quad E_\theta T^2 = E_p T^2 < \infty \quad \forall p \Rightarrow \text{Lehmann-Scheffé } \mu(\bar{x}) \text{ je mjelepšia množ. odhad p}$$

$$\text{d) } EI[X_1=1] = P(X_1=1) = p(1-p) \quad T = I[X_1=1] \text{ množ. odhad.}$$

$$\begin{aligned} E[T|S=n] &= p(1-p) \cdot \frac{P(\sum_{i=2}^m X_i=n-1)}{P(\sum_{i=1}^m X_i=n)} = p(1-p) \frac{\binom{m+n-3}{n-2} p^{n-1}(1-p)^{n-1}}{\binom{m+n-1}{n} p^m (1-p)^n} \\ &= \frac{(m+n-3)!}{(n-1)!(m-2)!} = \frac{(m-1) \cdot n}{(m+n-1)(m+n-2)} \end{aligned}$$



$$E[T|S] = \frac{(m-1)S}{(m+n-1)(m+n-2)} = \mu(S)$$



$$(40) \text{ 33) } X \sim M(1; p, 1-2p, p) \sim \text{hodnotami } \{-1, 0, 1\}$$

$$\text{a) } ET = P(X=1) = p$$

$$\text{lsg) } P(X=(x_1, x_2, x_3)^T) = p^{x_1} (1-2p)^{x_2} p^{x_3} \quad \text{ude } (x_1, x_2, x_3)^T \in \{0, 1\}^3, \sum x_i = 1$$

$$= P_{I[X \neq 0]}^{x_1+x_3} \frac{(1-2p)^{x_2}}{(1-2p)^{1-I[X \neq 0]}}$$

$$\text{c) } E[I[X=1]] \underbrace{\sum}_{S \sim \mathcal{B}(m, 2p)} [I[X_i=1]] = p \cdot \frac{P(S=n|X_1=1)}{P(S=n)} = p \frac{\binom{m-1}{n-1} (2p)^{n-1} (1-2p)^{m-n}}{\binom{m}{n} (2p)^n (1-2p)^{m-n}}$$

$$= \frac{(m-1)!}{\frac{m!}{s!(m-s)}} = \frac{s!}{2^m} \quad E[T|S] = u(S) = \frac{S}{2^m} = \frac{1}{2} \frac{1}{m} \sum I[X_i=1]$$

d) $P(X=x) = \binom{m}{x_1 \dots x_3} \prod P_i^{x_i} = \exp\{\sum x_i \log p_i\} = \exp\{\log p \cdot (x_1+x_3) + \log(1-p) \cdot x_2\}$
 $= \exp\{(x_1+x_3) \log p + (1-(x_1+x_3)) \log(1-p)\} = \exp\{(x_1+x_3) \log \frac{p}{1-p}\} \exp\{\log(1-p)\}$
 \Rightarrow eksponentiellna redina \Rightarrow iplna' naf. skf \Rightarrow mjelepši nafnaj' odhad

(h1) 34) $X \sim \text{alt}(p)$

a) $T = I[X_1=1] \quad P(X=x) = p^x(1-p)^{1-x} = \exp\{x \log p + (1-x) \log(1-p)\} =$ x, iid
 $= \exp\{x \log \frac{p}{1-p}\} (1-p) \Rightarrow S = \sum X_i$ je iplna' postacujica $\hookrightarrow \Pr[S] E[X_i | \sum X_i] = \frac{\sum X_i}{m}$

$E[T|S=n] = E[\frac{S}{m}|S=n] = n/m \quad u(S) = \frac{S}{m} = \bar{X}$ je mjelepši nafnaj' odhad p

b) $T' = \bar{X}(1-\bar{X}) \quad \bar{X} \sim \text{Bi}(m, p)/m \quad Y \sim \text{Bi}(m, p)$ $\text{nam } Y = mp(1-p) = EY^2 - (EY)^2$
 $EY^2 = mp(1-p) + m^2p^2$

$ET' = p - \frac{1}{m^2} EY^2 = p - \frac{p(1-p)}{m} - p^2 = p(1-p)(1 - \frac{1}{m})$

$\Rightarrow T := \frac{m}{m-1} \bar{X}(1-\bar{X})$ je $ET = p(1-p)$

$E[T|S] = T$ (je \bar{X}) je mjelepši nafnaj' odhad $p(1-p)$

(h2) 35) $X \sim P_0(\lambda)$

a) $T_1 = \bar{X} \quad ET_1 = \lambda \quad P(X=x) = \frac{e^{-\lambda} \lambda^x}{x!} = \frac{1}{x!} e^{-\lambda} e^{x \log \lambda} \Rightarrow \sum X_i$ je iplna' postacujica pre $\log \lambda$

$E[T_1 | \sum X_i] = T_1$ je mjelepši nafnaj' odhad $\lambda = \exp\{\log \lambda\}$

b) $T_2 = \sum_{i=1}^m I[X_i=0] \quad ET_2 = e^{-\lambda}$ $\sum_{i=1}^m X_i \sim P_0(m\lambda)$

$E[T_2 | \sum X_i = n] = E[X_i=0 | \sum X_i = n] = \frac{e^{-\lambda}}{e^{-\lambda}} \frac{e^{-(m-n)\lambda} [(m-n)\lambda]^n / n!}{(m\lambda)^n / n!} = \left(\frac{m-n}{m}\right)^n$

$\Rightarrow \left(1 - \frac{1}{m}\right)^{\sum X_i}$ je mjelepši nafnaj' odhad $e^{-\lambda}$.

$\hookrightarrow \Pr[T_1]$ je eficijent' i T_2 nije je.

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(h3) 36) $X \sim N(\mu, \sigma^2) \quad f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{1}{2\sigma^2}(x^2 - 2\mu x + \mu^2)\right\} = \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2\right\} e^{-\frac{\mu^2}{2\sigma^2}}$

$(\sum X_i, \sum X_i^2)^T$ je iplna' postac pre $(\xi, \varepsilon)^T$ $\frac{1}{\sigma^2} = \xi^2$ $\frac{\mu}{\sigma^2} = \varepsilon$

$a) \alpha(\xi, \varepsilon) = 1/\sqrt{2\pi} = \sigma \quad a) E[S_m^2 | \sum X_i, \sum X_i^2] = S_m^2$

a) $E \tilde{\sigma} = E \text{am} \sqrt{\sum_{i=1}^m X_i^2} / \sigma = \sigma \text{ am} EX_{m+1} = \sigma$ nafnaj' Prodome der nafnaj' $(\mu=0)$

$\frac{S^2(m-1)}{\sigma^2} \sim \chi_{m-1}^2 \quad \frac{\sqrt{\sum_{i=1}^m X_i^2}}{\sigma} \sim X_{m+1}$

$E[\tilde{\sigma} | \sum X_i, \sum X_i^2] = \tilde{\sigma}$ mjelepši nafnaj'.

b) međutim, nije je \approx L-S nafnaj' u jednoravničnosti

b) $\alpha(\xi, \varepsilon) = \xi/\sqrt{2\pi} + \mu_2 \cdot 1/\sqrt{2\pi} = \mu + \mu_2 \sigma$ nafnaj' a je pre $(\sum X_i, \sum X_i^2)^T \rightarrow$ mjelepši nafnaj'

c) $\mu^2 = -\sigma^2 + EX^2 \quad T := \frac{1}{m} \sum X_i^2 - \tilde{\sigma}^2 \quad ET = EX^2 - \sigma^2 = \mu^2$ a je pre $(\sum X_i, \sum X_i^2)^T$

\Rightarrow mjelepši nafnaj' \hookrightarrow Pr BiV redoslijedi RC_m

e) $\sigma^2 = EX^2 - \mu^2$ odhadne $\frac{1}{m} \sum X_i^2 - S_m^2$ nafnaj' je iplna' postaci stat. \Rightarrow mjelepši nafnaj'

(44) 37) $X \sim N(\mu, \sigma^2)$ $f(x) = \left(\frac{1}{2\pi\sigma^2}\right)^{\frac{n}{2}} \exp\left\{-\frac{1}{2\sigma^2}[\sum x_i^2 - 2\mu\sum x_i + n\mu^2]\right\} = (2\pi\sigma^2)^{\frac{n}{2}} e^{-\frac{n}{2}}$

$\exp\left\{-\frac{1}{2\sigma^2}[\sum x_i^2 + \frac{1}{n}\sum x_i]\right\} \Rightarrow (\sum x_i, \sum x_i^2)$ je sufičientní statistika

$$\frac{f(x)}{f(y)} = \exp\left\{-\frac{1}{2\sigma^2}(\sum x_i^2 - \sum y_i^2) + \frac{1}{\sigma^2}(\sum x_i - \sum y_i)\right\}$$
 je minimálna suf. st.

i) $T_1 = \bar{x}$, $T_2 = \alpha_m \sqrt{(n-1)S_m^2}$ mě dle jde $(\sum x_i, \sum x_i^2)$

$$ET_1 = \mu \quad ET_2 = \alpha_m E\sqrt{\frac{(n-1)S_m^2}{\sigma^2}} \cdot \sigma = \sigma = \mu \quad \text{mě všem nezávislé}$$

ii) $mnT_1 = \frac{\mu^2}{m} \quad mnT_2 = \alpha_m^2 mn \sqrt{\frac{(n-1)S_m^2}{\sigma^2}} \cdot \mu = \mu^2 \alpha_m^2 mn \sqrt{\chi_{m-1}^2} =$
 $= \mu^2 \alpha_m^2 (m-1 - \alpha_m^{-2}) = \mu^2 \left(\frac{m-1}{\alpha_m^2} - 1\right)$ podle p. 14 ani jde o vhodný RC
 α_m^2 je kritické

$$(\sum x_i, \sum x_i^2)$$
 mě je iplná $E_\mu \left[\frac{m}{m+1} (\bar{x})^2 - S^2 \right] = 0 \neq \mu$

(45) 38) $X \sim f(x) = \lambda e^{-\lambda(x-\delta)} I[x > \delta]$ je základ.

i) $f(x) = \lambda^m e^{-\lambda x} e^{\lambda\delta} I[\min x_i > \delta] \Rightarrow \min x_i$ je sufičientní

$$X'_1 \dots X'_m \sim \text{Exp}(\lambda) \Rightarrow \min x'_i \sim \text{Exp}(m\lambda) \text{ analogicky } \min x_i \sim (m\lambda) e^{-m\lambda(x-\delta)} I[x > \delta]$$

nehodl. $O = E_\delta \text{nr}(\min x_i) = \int_0^\infty (m\lambda) e^{-m\lambda(x-\delta)} dx = m\lambda e^{m\lambda\delta} \int_0^\infty \text{nr}(x) e^{-m\lambda x} dx$

doda $O = \int_0^\infty \text{nr}(x) e^{-m\lambda x} dx \neq \int_0^\infty \text{nr}(x) e^{-m\lambda x} dx$

$$O = O - \text{nr}(\delta) e^{-m\lambda\delta} \quad / \cdot e^{m\lambda\delta}$$

$$O = \text{nr}(\delta) \neq \delta \Rightarrow \text{iplná postří. statistika } \min x_i$$

$$E \min x_i = \delta + \frac{1}{m\lambda} \Rightarrow T = \min x_i - \frac{1}{m\lambda} \text{ je mylký měřit. odhad}$$

ii) nezáleží na systém hrubštět $\text{nr} \min x_i = \text{nr} T = \frac{1}{(m\lambda)^2}$ a RC je ihned $\frac{c}{m}$
 "přesahuje" měřit. odhad byl RC měřen

(46) 39) $X \sim f(x) = \lambda e^{-\lambda x} I[x > 0]$ $f(x) = \lambda^m e^{-\lambda \sum x_i} I[\min x_i > 0]$

$\sum x_i$ je iplná postří. statistika. $x_i \sim \text{Exp}(\lambda) \Rightarrow \sum x_i \sim \Gamma(m, \frac{1}{\lambda}) \sim \frac{\lambda^m x^{m-1} e^{-\lambda x}}{\Gamma(m)}$

i) $E \sum x_i = \frac{m}{\lambda}$ aleso $E \frac{1}{\sum x_i} = m \int_0^\infty \frac{\lambda^m x^{m-1} e^{-\lambda x}}{\Gamma(m)} dx = \frac{m\lambda^{m-1}}{\Gamma(m)\lambda^{m-2}} \int_0^\infty t^{m-2} e^{-t} dt =$

$$= \frac{m\lambda \Gamma(m-1)}{\Gamma(m)} = \frac{m-1}{m-1} \lambda \Rightarrow \frac{m-1}{m} \cdot \frac{\lambda}{\sum x_i} \text{ je měřit. odhad } \lambda$$

$$\Rightarrow T = \frac{m-1}{\sum x_i} \text{ je mylký měřit. odhad } \lambda.$$

ii) $\text{RC: } \frac{\lambda^2}{m} \quad \text{nr} \frac{m-1}{\sum x_i} = (m-1)^2 \cdot \text{nr} \frac{1}{\Gamma(m, \frac{1}{\lambda})} = \frac{\lambda^2}{m-2}$
 inverse gamma distribution

iii) $E \left(\frac{1}{\sum x_i} \right)^k = (m\lambda)^k \frac{\Gamma(m+k)}{\Gamma(m)}$ měří se RC měřen.

$$\textcircled{40} \quad X \sim R(0, \theta) \quad f(x) = \theta^{-m} I[0 < \min x_i] I[\max x_i < \theta]$$

$\Rightarrow \max x_i$ je n.f. n.t. podle pr 28³¹ je uplná

$$E \max x_i = \int_0^\theta \frac{x^m x^{m-1}}{\theta^m} dx = \frac{m}{m+1} \theta \Rightarrow \frac{m+1}{m} \max x_i$$

(pr 34) je nejlepší měřitý odhad.

RC mediana neexistuje - neřešitelný systém

$$\text{i)} E 2\bar{X} = \theta \quad \text{nn } 2\bar{X} = 4 \theta^2 / 2m = \theta^2 / 3m$$

$$\text{nn } \left(\frac{m+1}{m}\right) \max x_i = \left(\frac{m+1}{m}\right)^2 \left[\int_0^\theta x^2 \frac{x^{m-1}}{\theta^m} dx \right] - \theta^2 = \left(\frac{m+1}{m}\right)^2 \frac{\theta^2 m}{m+2} - \theta^2$$

$$= \theta^2 \left(\frac{(m+1)^2}{m(m+2)} - 1 \right) = \theta^2 / (m(m+2)) \quad \text{a } \frac{1}{3m} \geq \frac{1}{m(m+2)} \text{ pre } m \geq 1$$

pre $m=1$ mají oboučki rozdíly (oboučky odhady)

$$\text{ii)} \frac{m+1}{m} \max x_i$$

iii) RC mediana neexistuje

$$\textcircled{41} \quad Y \sim N(1; p_1, \dots, p_n) \quad P(Y=x) = \prod p_i^{x_i} = \prod e^{x_i \log p_i} = e^{\sum x_i \log p_i}$$

i) $(\sum_{i=1}^m x_{ii}, \dots, \sum_{i=1}^n x_{in})'$ je uplná souběžná pro P

$$\text{ii)} E \sum_{i=1}^m x_{ii} \sum_{j=1}^n x_{ij} = E Y_1 Y_2 = \text{cov}(Y_1, Y_2) + E Y_1 E Y_2 = -mp_1 p_2 + m^2 p_1 p_2$$

$$Y = (Y_1, \dots, Y_n) \sim N(m, P_1 - P_2) = mp_1 p_2 (m-1)$$

$$\text{cov}(Y_1, Y_2) = -mp_1 p_2 \quad E Y_i = mp_i$$

$$\Rightarrow \frac{1}{m(m-1)} \sum_{i=1}^m \sum_{j=1}^n x_{ij} \quad \text{je nejlepší měřitý odhad } p_1 p_2.$$

42) nároky

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42) $X \sim N(\mu, \sigma^2)$ a Pr 36 je $(\sum x_i, \sum x_i^2)$ iefektivní postří. statistiky

$$i) f(x) = C \sqrt{\sigma^2} \exp \left\{ -\frac{1}{2\sigma^2} (x^2 + \mu^2 - 2\mu x) \right\}$$

$$\ell(x) = C - \frac{1}{2} \log \sigma^2 - \frac{1}{2\sigma^2} (x - \mu)^2$$

$$\nabla \ell = \left(\frac{(x-\mu)}{\sigma^2}, -\frac{1}{2\sigma^2} + \frac{1}{2\sigma^4} (x-\mu)^2 \right)$$

$$H = \begin{pmatrix} -1/\sigma^2 & -\frac{x-\mu}{\sigma^4} \\ -\frac{x-\mu}{\sigma^6} & \frac{1}{2\sigma^4} - \frac{(x-\mu)^2}{\sigma^6} \end{pmatrix}$$

$$J = \begin{pmatrix} 1/\sigma^2 & 0 \\ 0 & 1/2\sigma^4 \end{pmatrix}$$

ii) z pr. 36 a Lehmann-Scheffé: nejlepší neutr. odhad μ je $f_{\mu}(I(X, \sum X^2))$
ale median nie je takt. funkcia \Rightarrow nie je nejlepší neutr. odhad

je to možné srovnat aj numerickou metódou v rozdelení r.v. mediana (veta 2.14, mat. stat I)

$$iii) T = \bar{X} \quad ET = \mu \quad \text{var } T = \sigma^2/m$$

$$g(\mu, \sigma^2) = \mu \quad \nabla g = (1, 0) \quad \nabla g J_m^{-1} \nabla g^T = \sigma^2/m \rightarrow \text{dosažuje R-C median}$$

takže ide o fukciu iefektivní postří. statistiky, neutr. odhad μ

$$iv) E S_m^2 = \sigma^2 \quad \text{var } S_m^2 = \text{var } \frac{\sigma^2 \chi_{m-1}^2}{(m-1)} = \frac{\sigma^4}{(m-1)^2} \text{var } \chi_{m-1}^2 = \frac{2\sigma^4}{m-1} > \frac{2\sigma^4}{m} \quad \text{R-C median}$$

nenadeblinda, ale je nejlepší neutr. odhad.

$$EX_{\text{median}} = \frac{\Gamma(\frac{m+1}{2})}{\Gamma(\frac{m}{2})}$$

v) z pr. 36: $T = \bar{X} + \lambda_2 \tilde{\sigma}$ pe $\tilde{\sigma} = a_m \sqrt{(m-1) S_m^2}$ je nejlepší neutr. odhad

$$\text{pe} \quad g(\mu, \sigma^2) = \mu + \mu \sigma = \mu + \mu \sqrt{\sigma^2} \quad a_m = \frac{\Gamma(\frac{m-1}{2})}{\Gamma(\frac{m}{2})} = \frac{1}{E X_{m-1}}$$

$$\text{odhad} \quad \nabla g = \left(1, \frac{m}{2\sigma^2} \right) \quad \nabla g J_m^{-1} \nabla g^T = \left(1, \frac{m}{2\sigma^2} \right) \begin{pmatrix} \frac{\sigma^2}{m} & 0 \\ 0 & \frac{2\sigma^4}{m} \end{pmatrix} \left(\begin{array}{c} 1 \\ \frac{m}{2\sigma^2} \end{array} \right) =$$

$\mu = 0$

$$\text{var } \tilde{\sigma} = b_m^2 (ES_m^2 - (ES_m)^2) = b_m^2 \sigma^2 - \sigma^2 = \frac{\sigma^2}{m} + \frac{\mu^2 \sigma^4}{2\sigma^2} = \sigma^2 \left(\frac{1}{m} + \frac{\mu^2}{2m} \right) \quad \text{R-C median}$$

$$b_m = \Gamma(m-1) a_m \quad \text{var } T = \frac{\sigma^2}{m} + \mu^2 \text{var } \tilde{\sigma} = \frac{\sigma^2}{m} + \mu^2 \text{var} (a_m \sqrt{\frac{(m-1)S^2}{\sigma^2}} \cdot \sigma) = \frac{\sigma^2}{m} + \mu^2 a_m^2 \sigma^2 \cdot \text{var } \chi_{m-1}^2$$

$$= \frac{\sigma^2}{m} + \mu^2 a_m^2 \sigma^2 (m-1 - a_m^2) \quad \text{medresažuje R-C median} \quad \text{var } \tilde{\sigma} = \sqrt{\frac{2\sigma^4}{m-1}}$$

efektivnost $\frac{RC_m}{\text{var } T} \rightarrow 0.333$

43) $X \sim eN(\mu, \sigma^2)$ $f(x) = (\sigma \sqrt{2\pi})^{-1} \exp \left\{ -\frac{(\log x - \mu)^2}{2\sigma^2} \right\} I(x > 0) \quad (E^{N(\mu, \sigma^2)}, \text{obranné } e^{N(\mu, \sigma^2)})$

$$i) \ell = C - \frac{1}{2} \log \sigma^2 - \frac{1}{2\sigma^2} (\log x - \mu)^2$$

$$\nabla \ell = \left(\frac{1}{2\sigma^2} (\log x - \mu), -\frac{1}{2\sigma^2} + \frac{1}{2\sigma^4} (\log x - \mu)^2 \right)$$

$$H = \begin{pmatrix} -1/\sigma^2 & -\frac{(\log x - \mu)}{\sigma^4} \\ -\frac{(\log x - \mu)}{\sigma^4} & \frac{1}{2\sigma^4} - \frac{1}{\sigma^6} (\log x - \mu)^2 \end{pmatrix} \quad J = \begin{pmatrix} 1/\sigma^2 & 0 \\ 0 & 1/2\sigma^4 \end{pmatrix} = J(\mu, \sigma^2)$$

$$E(\log x - \mu)^2 = \int_0^\infty \frac{(\log x - \mu)^2}{\sigma \sqrt{2\pi}} \exp \left\{ -\frac{1}{2\sigma^2} (\log x - \mu)^2 \right\} dx = \int_0^\infty \frac{x^2}{e^{\frac{x^2}{2\sigma^2}}} \exp \left\{ -\frac{x^2}{2\sigma^2} \right\} dx = \begin{cases} 0 & \sigma^2 = 1 \\ \sigma^2 & \sigma^2 = 2 \end{cases}$$

$$\log x - \mu = z$$

$$\text{ii)} g(\mu, \sigma^2) = \sup \{ \mu + \sigma^2/2 \} = EX$$

$$\nabla g = (e^{\mu + \sigma^2/2}, e^{\mu + \sigma^2/2} \cdot \frac{1}{2})$$

$$\nabla g J_m^{-1} \nabla g^T = e^{(\mu + \sigma^2/2)^2} \begin{pmatrix} 1 & 1/2 \\ 1 & 1/2 \end{pmatrix} \begin{pmatrix} \sigma^2/m & 0 \\ 0 & 2\sigma^4/m \end{pmatrix} \begin{pmatrix} 1 \\ 1/2 \end{pmatrix} = e^{2\mu + \sigma^2} \cdot \left(\frac{\sigma^2}{m} + \frac{\sigma^4}{2m} \right)$$

$$\text{iii), } E\bar{X} = EX = e^{\mu + \sigma^2/2}$$

$$\text{mn } \bar{X} = \underbrace{(e^{\sigma^2} - 1)}_{\text{mn } X} \cdot e^{2\mu + \sigma^2}/m = \frac{e^{2\mu + \sigma^2}}{m} \sum_{k=1}^{\infty} \frac{(\sigma^2)^k}{k!} > \frac{e^{2\mu + \sigma^2}}{m} \left(\sum_{k=1}^2 \frac{(\sigma^2)^k}{k!} \right)$$

nedosahující R-C měřidlo

$$f(x) = c \sigma^{-1} x^{-1} \exp \left\{ -\frac{1}{2\sigma^2} [(\log x)^2 - 2\mu \log x + \mu^2] \right\}$$

$(\sum \log x_i, \sum (\log x_i)^2)'$ je náplňa postačující $\Rightarrow \bar{X}$ měří mylnou měř. hodnotu

44) i) muregularní funkce

$$\text{ii), } f(x) = \lambda e^{-\lambda(x-\theta)} I[x > \theta]$$

$$\ell = \log \lambda - \lambda(x-\theta), \quad \ell' = \frac{1}{\lambda} - (x-\theta) \quad \ell'' = -\frac{1}{\lambda^2}$$

$$J_m = \frac{m}{\lambda^2}$$

45) $X \sim \text{alt}(p_1) m_1 \quad Y \sim \text{alt}(p_2) m_2$

$$\text{i), } l(p_1, p_2) = \log \prod p_1^{x_i} (1-p_1)^{1-x_i} p_2^{y_i} (1-p_2)^{1-y_i} = \sum (x_i \log p_1 + (1-x_i) \log (1-p_1)) \delta_{x_i} \log p_2 + \log (1-p_2)$$

$$\nabla l = \left(\frac{\sum x_i}{p_1} + \frac{\sum (1-x_i)}{1-p_1}, \frac{\sum y_i}{p_2} + \frac{\sum (1-y_i)}{1-p_2} \right)$$

$$H = \begin{pmatrix} -\frac{\sum x_i}{p_1^2} - \frac{\sum (1-x_i)}{(1-p_1)^2} & 0 \\ 0 & -\frac{\sum y_i}{p_2^2} - \frac{\sum (1-y_i)}{(1-p_2)^2} \end{pmatrix} \quad J_m = \begin{pmatrix} \frac{m_1}{p_1} + \frac{m_1}{1-p_1} & 0 \\ 0 & \frac{m_2}{p_2} + \frac{m_2}{1-p_2} \end{pmatrix}$$

$$\text{ii), } T = \bar{X}_{m_1} - \bar{Y}_{m_2} \quad ET = p_1 - p_2 \quad \text{mn } T = \frac{p_1(1-p_1)}{m_1} + \frac{p_2(1-p_2)}{m_2}$$

$$g(p_1, p_2) = p_1 - p_2 \quad \nabla g = (1 \ -1) \quad J_m^{-1} = \begin{pmatrix} \frac{p_1(1-p_1)}{m_1} & 0 \\ 0 & \frac{p_2(1-p_2)}{m_2} \end{pmatrix}$$

$\nabla g J_m^{-1} \nabla g^T = \text{mn } T \Rightarrow$ dosahující R-C měřidlo

$$\text{iii), } \nabla g = \left(\frac{1-p_1}{p_1} \cdot \frac{1}{(1-p_1)^2}, -\frac{1-p_2}{p_2} \cdot \frac{1}{(1-p_2)^2} \right) = \left(\frac{1}{p_1(1-p_1)}, -\frac{1}{p_2(1-p_2)} \right)$$

$$\nabla g J_m^{-1} \nabla g^T = \frac{1}{m_1 p_1 (1-p_1)} + \frac{1}{m_2 p_2 (1-p_2)} \longrightarrow \infty \quad \begin{array}{l} \text{pre } p_1 \rightarrow 0 \\ p_2 \rightarrow 0 \\ p_2 \rightarrow 1 \end{array}$$

iv), $E\hat{\Theta} = " \infty - \infty "$ měří definované

$$46) X \sim N(\mu_1, \sigma^2) \quad m_1 \quad Y \sim N(\mu_2, \sigma^2) \quad m_2$$

$$\text{i)} f(x_i, y_i) = \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^{m_1} \exp \left\{ -\frac{1}{2\sigma^2} \sum (x_i - \mu_1)^2 \right\} \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^{m_2} \exp \left\{ -\frac{1}{2\sigma^2} \sum (y_i - \mu_2)^2 \right\}$$

$$\ell(\mu_1, \mu_2, \sigma^2) = c - \frac{1}{2} (m_1 + m_2) \log \sigma^2 - \frac{1}{2\sigma^2} \left[\sum (x_i - \mu_1)^2 + \sum (y_i - \mu_2)^2 \right]$$

$$\nabla \ell = \left(\frac{\sum (x_i - \mu_1)}{\sigma^2}, \frac{\sum (y_i - \mu_2)}{\sigma^2}, -\frac{m_1 + m_2}{2\sigma^2} + \frac{1}{2\sigma^4} \left[\sum (x_i - \mu_1)^2 + \sum (y_i - \mu_2)^2 \right] \right)$$

$$H = \begin{pmatrix} -m_1/\sigma^2 & 0 & -\sum (x_i - \mu_1)/\sigma^4 \\ 0 & -m_2/\sigma^2 & -\sum (y_i - \mu_2)/\sigma^4 \\ -\sum (x_i - \mu_1)/\sigma^4 & -\sum (y_i - \mu_2)/\sigma^4 & \frac{m_1 + m_2}{2\sigma^4} - \frac{1}{\sigma^6} \left[\sum (x_i - \mu_1)^2 + \sum (y_i - \mu_2)^2 \right] \end{pmatrix}$$

$$J_m = \begin{pmatrix} m_1/\sigma^2 & 0 & 0 \\ 0 & m_2/\sigma^2 & 0 \\ 0 & 0 & -\frac{m_1 + m_2}{2\sigma^4} + \frac{(m_1 + m_2)\sigma^2}{\sigma^6} \end{pmatrix} \Rightarrow R.C: \left(\frac{m_1 + m_2}{2\sigma^4} \right)^{-1}$$

$$\text{ii)} S^2 = \frac{1}{m_1 + m_2 - 2} \left[(m_1 - 1) S_x^2 + (m_2 - 1) S_y^2 \right]$$

$$\text{var } S^2 = \frac{1}{(m_1 + m_2 - 2)^2} \left[\text{var}(\chi^2_{m_1-1}, \sigma^2) + \text{var}(\chi^2_{m_2-1}, \sigma^2) \right] = \frac{\sigma^4 \cdot 2(m_1 + m_2 - 2)}{(m_1 + m_2 - 2)^2} = \frac{2\sigma^4}{m_1 + m_2 - 2}$$

načítajte R-C metodu (viz po h2)

$$\text{ii)} \text{i)} f(y_i) = c \cdot \exp \left\{ -\frac{\sum (y_i - \beta_0 - \beta_1 x_i)^2}{2} \right\}$$

$$\ell(\beta_0, \beta_1) = c - \frac{1}{2} \sum (y_i - \beta_0 - \beta_1 x_i)^2$$

$$\nabla \ell = \left(\sum (y_i - \beta_0 - \beta_1 x_i), \sum x_i (y_i - \beta_0 - \beta_1 x_i) \right)$$

$$H = \begin{pmatrix} -m & -\sum x_i \\ -\sum x_i & -\sum x_i^2 \end{pmatrix} \quad J_m = \begin{pmatrix} m & \sum x_i \\ \sum x_i & \sum x_i^2 \end{pmatrix}$$

$$\frac{\sum (x_i - \bar{x})}{\sum (x_i - \bar{x})^2} = 0$$

$$\sum (x_i - \bar{x}) x_i = \sum x_i^2 - \sum x_i \cdot \bar{x} = m \left[\frac{1}{m} \sum x_i^2 - (\bar{x})^2 \right]$$

$$= m \left[\frac{1}{m} \sum (x_i - \bar{x})^2 \right]$$

↓

=

$$\text{ii)} E \hat{\beta}_1 = \frac{1}{\sum (x_i - \bar{x})^2} \sum (x_i - \bar{x}) E y_i = \frac{\sum (x_i - \bar{x})(\beta_0 + \beta_1 x_i)}{\sum (x_i - \bar{x})^2} \cancel{\beta_1}$$

$$\text{ale je } \hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \Rightarrow E \hat{\beta}_1 = \frac{\sum (x_i - \bar{x}) E(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} =$$

$$= \frac{\sum (x_i - \bar{x})(\beta'_0 + \beta'_1 x_i - \frac{1}{m} \sum (\beta'_0 + \beta'_1 x_i))}{\sum (x_i - \bar{x})^2} = \beta_1$$

$$\text{y, minimálne}$$

$$m \frac{\sum (x_i - \bar{x}) \cdot y_i}{\sum (x_i - \bar{x})^2} = \frac{1}{(\sum (x_i - \bar{x})^2)^2} \sum (x_i - \bar{x})^2 m y_i = \frac{1}{\sum (x_i - \bar{x})^2}$$

$$m \hat{\beta}_1 = \left[\text{vzh. Y.1. Štatistiky, Dupnýč } \right] = \frac{1}{\sum (x_i - \bar{x})^2}$$

$g(\beta_0, \beta_1) = (0, 1) \Rightarrow \text{RC je prvek } (2,2) \text{ matice } J_m^{-1} \cdot b$

$$\frac{1}{m \sum x_i^2 - (\sum x_i)^2} \cdot m = \frac{1}{\sum (x_i - \bar{x})^2} \quad \text{dodáva RC-mechanizmu}$$

$$\sum (x_i - \bar{x})^2 = \sum x_i^2 - 2\bar{x}m\bar{x} + m(\bar{x})^2 = \sum x_i^2 - \frac{1}{m}(\sum x_i)^2$$

$$48) \begin{pmatrix} x \\ y \end{pmatrix} \sim N_2 \left(\begin{pmatrix} \theta \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right)$$

$$f(x, y) = \frac{1}{2\pi\sqrt{1-\rho^2}} \exp \left\{ -\frac{1}{2} \left(\begin{pmatrix} x \\ y \end{pmatrix} - \begin{pmatrix} \theta \\ 0 \end{pmatrix} \right)^T \Sigma^{-1} \left(\begin{pmatrix} x \\ y \end{pmatrix} - \begin{pmatrix} \theta \\ 0 \end{pmatrix} \right) \right\}$$

$$L = c - \frac{1}{2} \log(1-\rho^2) - \frac{1}{2(1-\rho^2)} [(x-\theta)^2 + (y-\theta)^2 - 2\rho(x-\theta)(y-\theta)]$$

$$\nabla L = \left(\frac{1}{2(1-\rho^2)} [2(x-\theta) + 2(y-\theta) + 2\rho(x+y-2\theta)], \begin{array}{l} \text{further upřídelení} \\ \text{matematická kniha} \end{array} \right)$$

$$E X^2 = E Y^2 = 1+\theta^2 \quad E XY = \rho+\theta^2$$

$$EX = EY = \theta$$

$$J = \begin{pmatrix} \frac{2m}{1+\rho} & 0 \\ 0 & \frac{(1+\rho^2)m}{(\rho^2-1)^2} \end{pmatrix} \quad J_m^{-1} = \begin{pmatrix} \frac{1+\rho}{2m} & 0 \\ 0 & \frac{(\rho^2-1)^2}{(1+\rho^2)m} \end{pmatrix}$$

$$\text{RC pro } \theta \text{ je } \frac{(1+\rho)}{2m}$$

$$\text{i)} \quad m \bar{x} = \frac{1}{m} < \frac{(1+\rho)}{2m} \quad \text{nedosahuje RC}$$

$$\text{ii)} \quad m \frac{1}{2}(\bar{x} + \bar{y}) = \frac{1}{4} (m \bar{x} + m \bar{y} + 2\text{cov}(\bar{x}, \bar{y})) = \frac{1}{4} \left(\frac{1}{m} + \frac{1}{m} + \frac{2\rho}{m} \right) \\ = \frac{(1+\rho)}{2m} \quad \text{dosahuje RC}$$

49) $X \sim \text{Alt}(p)$

$$\begin{aligned} i) L(p) &= \prod p^{x_i} (1-p)^{1-x_i} = p^{\sum x_i} (1-p)^{m-\sum x_i} \\ \ell(p) &= \sum x_i \log p + (m-\sum x_i) \log(1-p) \\ \ell'(p) &= \sum x_i/p + (m-\sum x_i)/(1-p) = 0 \\ (1-p)\sum x_i - (m-\sum x_i)p &= 0 \\ p(-\sum x_i - m + \sum x_i) &= -\sum x_i \\ \hat{p} &= \bar{X} \end{aligned}$$

$$\ell''(p) = -\frac{\sum x_i}{p^2} - \frac{(m-\sum x_i)}{(1-p)^2}$$

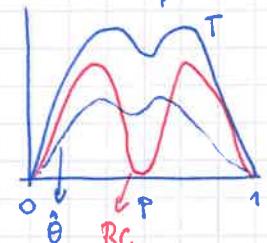
$$\mathbb{J}_m(p) = \frac{m}{p} + \frac{m}{1-p} = \frac{m}{p(1-p)}$$

$$\Gamma_m(\bar{X} - p) \xrightarrow{D} N(0, \frac{p(1-p)}{m})$$

$$\text{ii), inverznice: } \theta = p(1-p) \quad \hat{\theta} = \hat{p}(1-\hat{p}) - \bar{X}(1-\bar{X}) \quad g(t) = t(1-t) \quad g'(t) = (1-t)-t = 1-2t$$

$$\Gamma_m(\bar{X}(1-\bar{X}) - \theta) \xrightarrow{D} N(0, \frac{(1-2p)^2 p(1-p)}{m}) \quad p \neq \frac{1}{2}$$

$$\text{iii), } \bar{X} \text{ je NNO, NNO } \theta \text{ je } T = \frac{m}{m-1} \bar{X}(1-\bar{X}), \hat{\theta} \text{ má je neštandardní eficienci, } \theta \text{ má je eficienci}$$

50) $X \sim P_0(\lambda) \quad L(\lambda) = e^{-m\lambda} \lambda^{\sum x_i} / \prod x_i! \quad \ell(\lambda) = -m\lambda + \sum x_i \log \lambda + C$

$$\begin{aligned} i) \ell'(\lambda) &= -\frac{m}{\lambda} + \sum x_i/\lambda = 0 \quad \hat{\lambda} = \bar{X} \\ \ell''(\lambda) &= -\sum x_i/\lambda^2 \quad \mathbb{J}_m(\lambda) = \frac{m}{\lambda} \quad \Gamma_m(\bar{X}-\lambda) \xrightarrow{D} N(0, \lambda) \end{aligned}$$

$$\text{ii), } \theta = e^{-\lambda} \quad g(t) = e^{-t} \quad g'(t) = -e^{-t} \quad \Gamma_m(e^{-\bar{X}} - e^{-\lambda}) \xrightarrow{D} N(0, e^{-2\lambda} \cdot \lambda)$$

$$\text{iii), } \bar{X} \text{ je NNO, NNO } \theta \text{ je } T = \left(1 - \frac{1}{m}\right)^{\sum x_i}$$

$\hat{\lambda}$ má je eficienci, θ má je eficienci

51) $X \sim \text{Exp}(\lambda) \quad L(\lambda) = \lambda^m e^{-\lambda \sum x_i} \quad \ell(\lambda) = m \log \lambda - \lambda \sum x_i \quad \ell'(\lambda) = m/\lambda - \sum x_i = 0$

$$\text{i), } \hat{\lambda} = 1/\bar{X} \quad \ell''(\lambda) = -m/\lambda^2 \quad \mathbb{J}_m(\lambda) = m/\lambda^2$$

$$\text{ii), } \Gamma_m(1/\bar{X} - \lambda) \xrightarrow{D} N(0, \lambda^2)$$

$$\text{iii), } \frac{m-1}{\sum x_i} \text{ je NNO } \lambda \text{ ale má je eficienci}$$

52) $X \sim \text{Ge}(p) \quad L(p) = p^m (1-p)^{\sum x_i} \quad \ell(p) = m \log p + \sum x_i \log(1-p)$

$$\begin{aligned} i) \ell'(p) &= \frac{m}{p} - \frac{\sum x_i}{1-p} = 0 \\ m - mp - p \sum x_i &= 0 \end{aligned}$$

$$p(m + \sum x_i) = m$$

$$\hat{p} = \frac{m}{m + \sum x_i} = \frac{1}{1+\bar{X}}$$

$$\ell''(p) = -\frac{m}{p^2} - \frac{\sum x_i}{(1-p)^2} \quad \mathbb{J}_m(p) = \frac{m}{p^2} - \frac{(1-p)}{p} \frac{m}{(1-p)^2} = m \left(\frac{1}{p^2} - \frac{1}{p(1-p)} \right)$$

$$\Gamma_m(\frac{1}{1+\bar{X}} - p) \xrightarrow{D} N(0, \frac{1-2p}{p^2(1-p)})$$

$$\begin{aligned} \text{ii), } \theta &= p(1-p) \quad \hat{\theta} = \frac{1}{1+\bar{X}} \left(1 - \frac{1}{1+\bar{X}}\right) = \frac{1-\bar{X}}{(1+\bar{X})^2} \\ g(t) &= t(1-t) \quad g'(t) = 1-2t \quad \Gamma_m(\hat{\theta} - \theta) \xrightarrow{D} N(0, \frac{(1-2p)^2 \cdot (1-2p)}{p(1-p)}) \end{aligned}$$

53) $X \sim R(\theta - \frac{1}{2}, \theta + \frac{1}{2}) \quad L(\theta) = \prod I[\theta - \frac{1}{2} < x_i < \theta + \frac{1}{2}] = I[\theta - \frac{1}{2} < \min x_i] I[\max x_i < \theta + \frac{1}{2}]$

$$= \begin{cases} 1 & \text{or } \theta < \min x_i + \frac{1}{2} \text{ a } \theta > \max x_i - \frac{1}{2} \Rightarrow \hat{\theta} \text{ je } \text{závratná a kruhovitá } [\max x_i - \frac{1}{2}, \min x_i + \frac{1}{2}] \\ 0 & \text{inak} \end{cases}$$

$$\text{ii), } \text{a) MSI: } \min x_i \xrightarrow{P} \theta - \frac{1}{2} \quad \Rightarrow \quad \max x_i - \frac{1}{2} \xrightarrow{P} \theta \quad \Rightarrow \quad \text{závratná a kruhovitá je} \\ \max x_i \xrightarrow{P} \theta + \frac{1}{2} \quad \min x_i + \frac{1}{2} \xrightarrow{P} \theta \quad \text{alež závratná}$$

54) $X \sim R\{1..M\} \quad L(M) = \prod \frac{1}{M} I[x_i \in \{1..M\}] = \frac{1}{M^m} I[1 \leq \min x_i \leq \max x_i \leq M] =$

$$\text{i), } = \begin{cases} 1/M^m & \text{až } M \geq \max x_i \\ 0 & \text{inak} \end{cases} \Rightarrow \hat{M} = \max x_i$$

$$\text{ii), } P(\hat{M} \leq \hat{x}) = P(x_i \leq \hat{x})^m = \left(\frac{\hat{x}}{M}\right)^m \quad f_{\hat{M}}(\hat{x}) = m \hat{x}^{m-1} / M^m = P(\hat{M} \leq M - \hat{x})$$

$$P(1\hat{M} - M > \varepsilon) = P(\hat{M} < M - \varepsilon) \leq P(\hat{M} \leq M - \varepsilon) \stackrel{\text{or } Z \text{ GR}}{\leq} \left(\frac{M-\varepsilon}{M}\right)^m = \left(1 - \frac{\varepsilon}{M}\right)^m \xrightarrow{m \rightarrow \infty} 0$$

55) $Y_i \sim N(\theta x_i, 1) \quad L(\theta) = c \exp\left\{-\frac{1}{2} \sum (y_i - \theta x_i)^2\right\} \quad \ell(\theta) = c - \frac{1}{2} \sum (y_i - \theta x_i)^2$

$$\text{i), } \ell'(\theta) = \sum (y_i - \theta x_i) x_i = 0$$

$$\sum y_i x_i - \theta \sum x_i^2 = 0$$

$$\frac{\sum y_i x_i}{\sum x_i^2} = \hat{\theta}$$

$$\ell'' = -\sum x_i^2$$

$$\text{RC}_{\text{m}} = 1/\sum x_i^2$$

$$\text{mn} \hat{\theta} = \frac{\sum x_i^2 \cdot 1}{(\sum x_i^2)^2} = \frac{1}{\sum x_i^2} = \text{RC}$$

$$\sum x_i^2$$

$$56) P(X=x_i) = \frac{1}{1-(1-p)^m} \binom{m}{x_i} p^{x_i} (1-p)^{m-x_i} \quad i=1,2,\dots,m$$

$$\text{i)} L(p) = \frac{1}{(1-(1-p)^m)^m} \prod_{i=1}^m \binom{m}{x_i} \cdot p^{\sum x_i} (1-p)^{\sum (m-x_i)}$$

$$\ell(p) = -m \log(1-(1-p)^m) + c + \sum x_i \log p + \sum (m-x_i) \log(1-p)$$

$$\ell'(p) = \frac{-m}{1-(1-p)^m} \cdot m(1-p)^{m-1} + \frac{\sum x_i}{p} - \frac{\sum (m-x_i)}{1-p} = 0$$

$\ell''(p)$ = mathematica script

$$57) X \sim \theta x^{\theta-1} e^{-x^\theta} I[X>0] \quad L(\theta) = \theta^m (\pi x_i)^{\theta-1} e^{-\sum x_i^\theta} I[\min x_i > 0]$$

$$\text{i)} \ell(\theta) = m \log \theta + (\theta-1) \log(\pi x_i) - \sum x_i^\theta \quad x^\theta = e^{\theta \log x}$$

$$\ell'(\theta) = \frac{m}{\theta} + \sum \log x_i - \sum x_i^\theta \log x_i = 0 \quad \left. \begin{array}{l} \text{spojitá monotonická funkce}, \quad \ell'(0) = \infty \\ \ell'(\infty) = -\infty \end{array} \right\} \text{jedinečné řešení}$$

$$\ell''(\theta) = -\frac{m}{\theta^2} - \sum x_i^\theta (\log x_i)^2$$

$$\text{ii)} EX = \int_0^\infty \theta x^\theta e^{-x^\theta} dx = \int_0^\infty t^{1/\theta} e^{-t} dt = \Gamma\left(\frac{1}{\theta} + 1\right)$$

$$E X^\theta (\log X)^2 = \text{mathematica} = C'$$

$$\hat{\theta} = \frac{1}{m} (\bar{\theta} - \theta) \rightarrow N(0, \left(\frac{1}{\theta^2} + C'\right)^{-1})$$

$$58) f(x) = e^{-(x-\theta)} / (1+e^{-(x-\theta)})^2 \quad L(\theta) = e^{-\sum x_i + m\theta} / \pi (1+e^{-(x_i-\theta)})^2$$

$$\ell(\theta) = -\sum x_i + m\theta - \sum \log(1+e^{-(x_i-\theta)})^2$$

$$\text{i)} \ell(\theta) = m - 2 \sum \frac{1 \cdot e^{-(x_i-\theta)}}{1+e^{-(x_i-\theta)}} = m - 2 \sum \frac{e^{-x_i}}{e^{-\theta} + e^{-x_i}} = 0 \quad \left. \begin{array}{l} \text{spojitá MLE funkce} \\ \ell'(-\infty) = m \\ \ell(\infty) = -m \end{array} \right\} \text{jedinečné řešení}$$

$$\ell''(\theta) = +2 \sum \frac{e^{-x_i} (-e^{-\theta})}{(e^{-\theta} + e^{-x_i})^2}$$

$$\text{ii)} \hat{m}(\theta) = \frac{m}{3}$$

$$E \frac{2e^{-x} e^{-\theta}}{(e^{-\theta} + e^{-x})^2} = \int_R \frac{2e^{-x} e^{-\theta}}{(e^{-\theta} + e^{-x})^2} \frac{e^{-x} e^{-\theta}}{(1+e^{-(x-\theta)})^2} dx = \frac{2e^{2\theta}}{e^{-2\theta}} \int_1^\infty \frac{(t-1)}{t^4} dt = 2 \left[\frac{-1}{2t^2} + \frac{1}{3t^3} \right]_1^\infty = \frac{1}{3}$$

$$\begin{aligned} 1+e^{-(x-\theta)} &= t & t-1 &= e^{-x} e^{-\theta} \\ (-1) \cdot e^{-(x-\theta)} dx &= dt & (t-1)e^{-\theta} &= e^{-x} \\ -x^\theta e^{-x} dx &= dt \end{aligned}$$

$$\hat{m}(\bar{\theta} - \theta) \xrightarrow{D} N(0, 3)$$

$$59) X \sim N(\theta, \theta^2) \quad L(\theta) = c \cdot \theta^{-m} \exp\left\{-\frac{1}{2\theta^2} \sum (x_i - \theta)^2\right\} \quad \ell(\theta) = -m \log \theta + c - \frac{1}{2\theta^2} \sum (x_i - \theta)^2$$

$$\text{i)} \ell'(\theta) = -\frac{m}{\theta} + \frac{1}{2\theta^2} \sum (x_i - \theta) + \frac{1}{2\theta^3} \sum (x_i - \theta)^2 = 0$$

$$-\frac{m}{\theta} + \frac{\sum x_i - m\theta}{\theta} + \frac{\sum x_i^2 - 2\theta \sum x_i + m\theta^2}{\theta^2} = 0$$

$$-\frac{m}{\theta} + \frac{\sum x_i}{\theta} - \cancel{m\theta} + \frac{\sum x_i^2}{\theta^2} - \frac{2\sum x_i}{\theta} + \cancel{m\theta^2} = 0 \quad +$$

$$-\frac{m\theta^2}{\theta^2} + \theta \sum x_i - 2\theta \sum x_i + \sum x_i^2 = 0 \quad -\frac{\sum x_i}{\theta} \pm \sqrt{\frac{(\sum x_i)^2}{\theta^2} + 4 \sum x_i^2 - m} = \hat{\theta}$$

$$\text{ii)} \hat{\theta} \bar{\theta} = \hat{\theta} \left[-\frac{1}{2} \bar{x} + \frac{1}{2} \sqrt{(\bar{x})^2 + 4 \frac{1}{m} \sum x_i^2} \right] \xrightarrow[m \rightarrow \infty]{} -\frac{\theta}{2} + \frac{1}{2} \sqrt{\theta^2 + 4 \cdot 2\theta^2} = -\frac{\theta}{2} + \frac{1}{2} \sqrt{9\theta^2} = \theta$$

$$\text{iii)} \ell''(\theta) = \frac{m}{\theta^2} + \left(-\frac{2}{\theta^3} \sum (x_i - \theta) + \frac{1(-m)}{\theta^4} \right) + \left(\frac{-3}{\theta^5} \sum (x_i - \theta)^2 - \frac{2 \sum (x_i - \theta)}{\theta^3} \right)$$

$$\hat{m}(\theta) = -\frac{m}{\theta^2} + \frac{m}{\theta^2} + \frac{3m}{\theta^2} = \frac{3m}{\theta^2} \quad \hat{m}(\bar{\theta} - \theta) \xrightarrow{D} N(0, \frac{\theta^2}{3})$$

$$60) P(Y_i = y_i | X) = \frac{\lambda(x)^{y_i} e^{-\lambda(x)}}{y_i!} \quad \lambda(x) = e^{\beta x}, \quad X \text{ muriwini ma } \beta$$

$$\text{i)} L(\beta) = \prod P(Y_i = y_i | X=x_i) \cdot P(X=x_i) = \prod P(Y_i = y_i | X_i=x_i)$$

$$= \prod_{i=1}^m \frac{(e^{\beta x_i})^{y_i} e^{-\beta x_i}}{y_i!} P(X=x_i)$$

$$\ell(\beta) = \sum (y_i x_i \beta - e^{\beta x_i} - \log(y_i!) + \log P(X=x_i))$$

$$= \sum y_i x_i \beta - \sum e^{\beta x_i} + c$$

$$\ell'(\beta) = \sum x_i y_i - \sum e^{\beta x_i} x_i = 0$$

$$\ell''(\beta) = - \sum e^{\beta x_i} x_i^2 \quad J_m(\beta) = m E e^{\beta X} X^2 \quad \Gamma_m(\hat{\beta} - \beta) \xrightarrow{D} N(0, \frac{1}{E e^{\beta X} X^2})$$

$$61) P(X=x) = \begin{cases} p & x \in \{1, 0\} \\ 1-p & x=0 \end{cases} \quad \text{def: } y := \#\{X_i=0\}$$

$$L(p) = (1-p)^y p^{m-y} \quad \ell(p) = y \log(1-p) + (m-y) \log p$$

$$\ell'(p) = \frac{-2y}{1-2p} + \frac{m-y}{p} = 0$$

$$-2py + m - 2mp - y + 2p = 0 \quad \hat{p} = \frac{y-m}{(-2m)} = (m-y)/2m = \sum I[X_i \neq 0]/2m$$

$$\ell''(p) = \frac{-2y \cdot 2}{(1-2p)^2} - \frac{m-y}{p^2} \quad EY = E \sum I[X=0] = m P(X=0) = m(1-p)$$

$$J_m(p) = \frac{4m(1-p)}{(1-2p)^2} + \frac{m-m(1-p)}{p^2} = \frac{4m}{1-2p} + \frac{2m}{p} = \frac{4mp + 2m - 4mp}{(1-2p)p} = m \cdot \frac{2}{p(1-2p)}$$

$$\Gamma_m(\hat{p} - p) \xrightarrow{D} N(0, p(1-p)/2)$$

$$62) L(\theta) = \prod \frac{1}{2} \exp(-|x_i - \theta|) = \frac{1}{2^m} \exp\left\{-\sum |x_i - \theta|\right\}$$

$\ell(\theta) = c - \sum |x_i - \theta| \Rightarrow$ maximizing $-\sum |x_i - \theta|$ wrt θ
minimum & median $\{x_i\}$. (niektóre online) Lemma 3.4 MSI

63) $X \sim N(\mu, \sigma^2)$

$$\text{i)} L(\mu, \sigma^2) = c \cdot (\sigma^m)^{-1} \exp\left\{-\frac{1}{2\sigma^2} \sum (x_i - \mu)^2\right\}$$

$$\ell(\mu, \sigma^2) = c - \frac{m}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum (x_i - \mu)^2$$

$$\frac{\partial \ell}{\partial \mu} = \left(\frac{1}{\sigma^2} \sum (x_i - \mu) \right) i = -\frac{m}{2\sigma^2} + \frac{1}{2(\sigma^2)^2} \sum (x_i - \mu)^2$$

$$\frac{\partial \ell}{\partial \mu} = 0 \Rightarrow \hat{\mu} = \bar{x} \quad \frac{\partial \ell}{\partial \sigma^2} = 0 \Rightarrow m = \frac{\sum (x_i - \mu)^2}{\sigma^2}, \quad \hat{\sigma}^2 = \frac{1}{m} \sum (x_i - \mu)^2$$

$$\text{ii)} H_\ell(\mu, \sigma^2) = \begin{pmatrix} -\frac{m}{\sigma^2} & -\frac{\sum (x_i - \mu)}{\sigma^4} \\ -\frac{\sum (x_i - \mu)}{\sigma^4} & \frac{m}{2\sigma^4} - \frac{\sum (x_i - \mu)^2}{(\sigma^2)^3} \end{pmatrix}$$

$$J_m(\mu, \sigma^2) = \begin{pmatrix} m/\sigma^2 & 0 \\ 0 & \frac{m}{2\sigma^4} \end{pmatrix}$$

$$\Gamma_m\left(\left(\frac{\bar{x}}{m-1}\right)^2 - \left(\frac{m}{\sigma^2}\right)\right) \xrightarrow{D} N_2\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & 0 \\ 0 & 2\sigma^4 \end{pmatrix}\right)$$

$$\text{iii) IS per } \mu: \left[\bar{x} = \frac{\mu_1 + \mu_2}{\sqrt{\frac{m-1}{m} S^2}} \right] \text{ param. r. } \left[\bar{x} = \frac{\mu_1(1-\alpha)}{\sqrt{\frac{m-1}{m}}} \right]$$

$$\text{iv) } \hat{\theta} = \hat{\mu} + \mu_2 \hat{S}$$

$$g(\sigma, t) = \sigma + \mu_2 / t \quad \nabla g = \left(1, \frac{\mu_2}{2t^2} \right) \quad \nabla g \Big|_{\hat{\theta}, \hat{S}} = \left(1, \frac{\mu_2}{2\hat{S}^2} \right) \quad \nabla g \Big|_{\hat{\theta}, \hat{S}} \nabla g^T = \frac{1}{m} (\sigma^2 + \mu_2^2 / 2\hat{S}^4)$$

$$\mathbb{E}_m \left((\hat{\theta}) - \theta \right) \xrightarrow{D} N(0, \sigma^2 (1 + \frac{2\mu_2^2 \sigma^2}{\mu_2^2})) \xrightarrow{\substack{\text{PC} \\ \text{medien}}} \frac{1}{m} \left(1, \frac{\mu_2}{2\hat{S}^2} \right) \left(\begin{matrix} \sigma^2 & 0 \\ 0 & 2\hat{S}^4 \end{matrix} \right) \left(\begin{matrix} 1 \\ \frac{\mu_2}{2\hat{S}^2} \end{matrix} \right) = \frac{1}{m} \left(\sigma^2 + \frac{\mu_2^2 \sigma^2}{2} \right)$$

$$64) L(\mu, \sigma^2) = \sigma^{-m} (\prod x_i)^{-1} c \cdot \exp \left\{ -\frac{1}{2\sigma^2} \sum (\log x_i - \mu)^2 \right\}$$

$$\text{i) } l(\mu, \sigma^2) = -\frac{m}{2} \log \sigma^2 + c - \frac{1}{2\sigma^2} \sum (\log x_i - \mu)^2$$

$$\nabla l = \left(\frac{\sum (\log x_i - \mu)}{\sigma^2}, -\frac{m}{2\sigma^2} + \frac{1}{2\sigma^4} \sum (\log x_i - \mu)^2 \right)$$

$$\nabla l = 0 \Rightarrow \hat{\mu} = \frac{1}{m} \sum \log x_i \quad \hat{\sigma}^2 = \frac{1}{m} \sum (\log x_i - \hat{\mu})^2$$

$$\text{ii) } H_L = \begin{pmatrix} -m/\sigma^2 & -\frac{\sum (\log x_i - \mu)}{\sigma^4} \\ -\frac{\sum (\log x_i - \mu)}{\sigma^4} & \frac{m}{2\sigma^4} - \frac{1}{\sigma^6} \sum (\log x_i - \mu)^2 \end{pmatrix} \quad \log x \sim N(\mu, \sigma^2)$$

$$\mathbb{J}_m = \begin{pmatrix} -m/\sigma^2 & 0 \\ 0 & +\frac{m}{2\sigma^4} \end{pmatrix} \quad \mathbb{E}_m \left(\left(\begin{matrix} \hat{\mu} \\ \hat{\sigma}^2 \end{matrix} \right) - \left(\begin{matrix} \mu \\ \sigma^2 \end{matrix} \right) \right) \xrightarrow{D} N_2 \left(0, \begin{pmatrix} \sigma^2 & 0 \\ 0 & 2\sigma^4 \end{pmatrix} \right)$$

$$\text{iii) } \left\{ \left(\begin{matrix} \hat{\mu} \\ \hat{\sigma}^2 \end{matrix} \right) : m \left(\left(\begin{matrix} \hat{\mu} \\ \hat{\sigma}^2 \end{matrix} \right) - \left(\begin{matrix} \mu \\ \sigma^2 \end{matrix} \right) \right)^T \begin{pmatrix} 1/\hat{\sigma}^2 & 0 \\ 0 & 1/(2\hat{\sigma}^4) \end{pmatrix} \left(\left(\begin{matrix} \hat{\mu} \\ \hat{\sigma}^2 \end{matrix} \right) - \left(\begin{matrix} \mu \\ \sigma^2 \end{matrix} \right) \right) \leq \chi^2_2(1-\alpha) \right\}$$

$$\text{b) } m \left[\frac{(\hat{\mu} - \mu)^2}{\hat{\sigma}^2} + \frac{(\hat{\sigma}^2 - \sigma^2)^2}{2\hat{\sigma}^4} \right] \leq \chi^2_2(1-\alpha)$$

$$\text{iv) } \left[\hat{\mu} - \frac{\mu_1 + \mu_2}{\sqrt{\frac{m-1}{m} S^2}}, \infty \right) \quad \text{daher } \text{odder}$$

$$65) X \sim \lambda e^{-\lambda(x-\delta)} ; x > \delta$$

$$\text{i) } L(\lambda, \delta) = \lambda^m \exp \left\{ -\lambda \sum (x_i - \delta) \right\} I[\min x_i > \delta]$$

$$\ell(\lambda, \delta) = m \log \lambda - \lambda \sum (x_i - \delta) + \log I[\min x_i > \delta] = m \log \lambda - \lambda \sum x_i + m \lambda \delta \quad \text{at } \min x_i > \delta$$

per pluri $\lambda > 0$ maximalisieren $\hat{\delta} = \min x_i$

$$\text{per domini } \delta \quad \frac{\partial \ell(\lambda, \delta)}{\partial \delta} = \frac{m}{\lambda} - \sum x_i = 0 \Rightarrow \hat{\lambda} = \frac{1}{\bar{x} - \hat{\delta}}$$

$$\text{ii) } \hat{\lambda} \xrightarrow{P} \lambda \quad \text{zu } \hat{\delta} \quad \text{(per pluri a sludiger rate)} \quad \left. \begin{array}{l} \hat{\delta} \text{ zu optimalem Exp}(m) \text{ pluri } \sigma \delta \Rightarrow \hat{\delta} \xrightarrow{P} \delta \\ \left. \begin{array}{l} \hat{\lambda} \xrightarrow{P} \lambda \\ \hat{\delta} \xrightarrow{P} \delta \end{array} \right\} \left(\begin{matrix} \hat{\lambda} \\ \hat{\delta} \end{matrix} \right) \xrightarrow{P} \left(\begin{matrix} \lambda \\ \delta \end{matrix} \right) \end{array} \right)$$

$$\text{iii) } m \cdot \text{Exp}(m\lambda) \sim \text{Exp}(\lambda) \text{, b) } m\hat{\delta} \sim \text{Exp}(\lambda) + \delta m$$

$$P(m(\hat{\delta} - \delta) \leq x) \rightarrow (-) 1 \bar{\lambda} e^{-\lambda x}$$

$$\text{b) } (\mathbb{E}_m)^2(\hat{\delta} - \delta) \xrightarrow{D} \text{Exp}(\lambda)$$

$$66) X \sim R(a, b) \quad L(a, b) = \left[\frac{1}{b-a} \right]^m I[a < \min x_i \leq \max x_i < b]$$

i) L je maximalisieren al $b-a$ je minimalisieren bzgl. $a < \min x_i < \max x_i < b$

$$\left(\begin{matrix} \hat{a} \\ \hat{b} \end{matrix} \right) = \left(\begin{matrix} \min x_i \\ \max x_i \end{matrix} \right). \quad \text{ii) RMSI: } \left\{ \begin{array}{l} \hat{a} \xrightarrow{P} a \\ \hat{b} \xrightarrow{P} b \end{array} \right\} \Rightarrow \left(\begin{matrix} \hat{a} \\ \hat{b} \end{matrix} \right) \xrightarrow{P} \left(\begin{matrix} a \\ b \end{matrix} \right)$$

$$\text{iii) } P(\hat{b} \leq x) = \left(\frac{x-a}{b-a} \right)^m \quad x \in [a, b] \quad \text{daher } x \geq 0$$

$$\begin{aligned} P(m(\hat{b} - b) \leq x) &= P(\hat{b} \leq b + \frac{x}{m}) = \left(\frac{b + \frac{x}{m} - a}{b-a} \right)^m = \left(1 + \frac{x/(b-a)}{m} \right)^m \xrightarrow[m \rightarrow \infty]{} e^{x/(b-a)} \quad \text{per } x < 0 \\ &\xrightarrow{D} \text{Exp} \left(\frac{1}{b-a} \right) \end{aligned}$$

$$67) \quad X \sim M(1, p_1 \dots p_k) \quad L(p) = \prod p_j^{\gamma_j} \cdot I[\sum p_i = 1] \quad \text{d.f. } \# \{x_i : x_i = (0..0, 1, 0..0)\}$$

i) Lagrangova multiplikity:

maximalizujeme $\ell(p) = \sum \gamma_j \log p_j$ pri podmienke $\sum p_i = 1$
 d.f. $\sum \gamma_j \log p_j + \lambda(1 - \sum p_j) = f(p, \lambda)$

$$\frac{\partial}{\partial p_i} f(p, \lambda) = \frac{\gamma_i}{p_i} - \lambda = 0 \Rightarrow p_i = \gamma_i / \lambda$$

$$\frac{\partial}{\partial \lambda} f(p, \lambda) = 1 - \sum p_j = 0 \Rightarrow \sum \frac{\gamma_i}{\lambda} = 1 \Rightarrow \hat{\lambda} = \sum \gamma_i \Rightarrow \hat{p}_i = \frac{\gamma_i}{\sum \gamma_i} = \frac{\sum_{j=1}^m [X_{ij} = 1]}{m}$$

$$\text{ii) definujme } \hat{p} = \frac{1}{m} \sum_{i=1}^m (I[X_{i1}=1], I[X_{i2}=1], \dots, I[X_{im}=1])' = \frac{1}{m} \sum_{i=1}^m X_i \quad \text{j.j.z.e.}$$

$$\text{ide o priemer i.i.d. nultoty vektor } \rightarrow E I[X_{ij}=1] = P(X_i = (0..0, 1, 0..0)) = p_j$$

$$E \hat{p} = \bar{p} \quad \text{vtedy } I[X_{ij}=1] = p_j - p_j^2 \quad \text{vtedy } I[X_{ij}=1] I[X_{ij}=1] = 0 - p_j p_j'$$

$$\text{vtedy } \hat{p} = \frac{1}{m} \begin{pmatrix} p_1(1-p_1) & -p_1 p_2 & \cdots & -p_1 p_k \\ -p_1 p_2 & p_2(1-p_2) & \cdots & -p_2 p_k \\ \vdots & & \ddots & \\ -p_1 p_k & -p_2 p_k & \cdots & p_k(1-p_k) \end{pmatrix} =: \frac{1}{m} \Sigma(p)$$

$$\text{C.V.: } \text{rm}(\hat{p} - p) \xrightarrow{D} N_2(0, \Sigma(p))$$

$$68) \quad \text{akr pr 67: } X \sim M(1, p_1 - p_2) \quad X \sim (ACU, DD, CAD, DCH)^T \\ = M(1, p_1 q_1, \frac{1-p_1-q_1}{2}, \frac{1-p_1+q_1}{2})$$

$$\text{i) } \hat{p} = \frac{\#\{ACU\}}{m} = 60^4 / 1987 \quad \hat{q} = \frac{\#\{DD\}}{m} = 60^9 / 1987$$

$$\theta(p, q) = \frac{2p}{1+p-q} \quad \hat{\theta} = \frac{2\hat{p}}{1+\hat{p}-\hat{q}} \quad g(a_1 t) = \frac{2a_1}{1+a_1-t} \quad Pg = \left(\frac{2(1-t)}{(1+t-t)^2}, \frac{2a_1}{(1+t-t)^2} \right)$$

$$\nabla g((p, q)) = \left(\frac{2(1-q)}{1+p-q}, \frac{2p}{(1+p-q)^2} \right)' \quad \text{rm}\left(\left(\frac{\hat{p}}{\hat{q}}\right) - \left(\frac{p}{q}\right)\right) \xrightarrow{D} N_2\left(0, \begin{pmatrix} p(1-p) & -pq \\ -pq & q(1-q) \end{pmatrix}\right)$$

$$\text{D-vetv: } \text{rm}(\hat{\theta} - \theta) \xrightarrow{\text{matice}} N(0, \frac{4q(1-q)(1-p-q)}{(1-p-q)^4} \frac{4p(1-q)(1-p-q)}{(1+p-q)^4})$$

$$\text{ii) ISI: } \left[\frac{2\hat{p}}{1+\hat{p}-\hat{q}} = \frac{4p_1 q_1}{\text{rm}} \sqrt{\frac{4p(1-q)(1-p-q)}{(1+p-q)^4}} \right] = [0,88; 0,63] \quad \hat{\theta} = 0,609$$

$$69) \quad P(Y=i, N=j) = P(Y=i | N=j) P(N=j) \Rightarrow Y|N \sim Bi(N, p) \quad N \sim P_0(\lambda)$$

$$\text{i) } L(p, \lambda) = \prod P(Y_i=j_i | N_i=m_i) = \prod P(Y_i=j_i | N_i=m_i) \cdot \prod P(N_i=m_i)$$

$$\ell(p, \lambda) = \sum \log P_p(Y_i=j_i | N_i=m_i) + \sum \log P_\lambda(N_i=m_i)$$

$$\frac{\partial \ell}{\partial p} = "mnohdost" \propto Bi(N_i, p), \text{d.f. } \frac{\sum \gamma_i}{p} - \frac{\sum (m_i - \gamma_i)}{1-p} = 0 \Rightarrow \hat{p} = \left(\frac{\sum m_i}{\sum \gamma_i} \right)^{-1}$$

$$\frac{\partial \ell}{\partial \lambda} = "mnohdost" \propto P_0(\lambda), \text{d.f. } \hat{\lambda} = \frac{1}{m} \sum m_i$$

$$\text{ii) H = akc vektor, akom princip mn cinti na p a \lambda$$

$$H = \begin{pmatrix} -\frac{\sum \gamma_i}{p^2} & -\frac{\sum (m_i - \gamma_i)}{(1-p)^2} & 0 \\ 0 & -\frac{\sum m_i}{\lambda^2} & -\frac{m}{\lambda} \end{pmatrix} \quad J_m = \begin{pmatrix} \frac{m\lambda}{p} + \frac{m\lambda}{1-p} & 0 \\ 0 & m/\lambda \end{pmatrix}$$

$$EY = EE[Y|N] = EBi(N, p) = ENp = \lambda p$$

$$EN = E[N - Bi(N, p)] = \lambda(1-p)$$

$$\text{rm}\left(\left(\frac{\hat{p}}{\hat{q}}\right) - \left(\frac{p}{q}\right)\right) \xrightarrow{D} N_2\left(0, \begin{pmatrix} \frac{p(1-p)}{\lambda} & 0 \\ 0 & \lambda \end{pmatrix}\right)$$

$$10) \quad Y|X \sim N(B'X, \sigma^2) \quad X \text{ minimizes } L(B, \sigma^2)$$

$$L(B, \sigma^2) = \prod_i f(y_i|x_i) f(x_i) = \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^m \exp\left\{-\frac{1}{2\sigma^2} \sum (y_i - B'x_i)^2\right\} \prod_i f(x_i)$$

$$\ell(B, \sigma^2) = c - \frac{m}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum (y_i - B'x_i)^2 + d = c' - \frac{m}{2} \log \sigma^2 - \frac{1}{2\sigma^2} (y - BX)'(y - BX)$$

$$\nabla \ell = \left(\frac{x'(Y-XB)}{\sigma^2}, -\frac{m}{2\sigma^2} + \frac{1}{2\sigma^4} (Y-XB)'(Y-XB) \right) = c' - \frac{m}{2} \log \sigma^2 - \frac{1}{2\sigma^2} (Y-XB)'(Y-XB)$$

$$x'Y - x'B = 0 \\ \hat{B} = \underline{\underline{(X'X)^{-1}X'Y}}$$

$$-m\sigma^2 + (Y-XB)'(Y-XB) = 0 \\ \hat{\sigma}^2 = \frac{1}{m} (Y-X\hat{B})'(Y-X\hat{B})$$

$$ii) \quad H_\ell = \begin{pmatrix} -\frac{x'x}{\sigma^2} & -\frac{x'(Y-XB)}{\sigma^4} \\ -\frac{x'(Y-XB)}{\sigma^4} & \frac{m}{2\sigma^4} - \frac{(Y-XB)'(Y-XB)}{\sigma^6} \end{pmatrix} \quad J_m = \begin{pmatrix} \frac{E(X'X)}{\sigma^2} & 0 \\ 0^T & \frac{m}{2\sigma^4} \end{pmatrix}$$

$$E(Y-XB)'(Y-XB) = E \sum \varepsilon_i^2 = m\sigma^2$$

$$\Gamma_m \left(\begin{pmatrix} \hat{B} \\ \hat{\sigma}^2 \end{pmatrix} - \begin{pmatrix} B \\ \sigma^2 \end{pmatrix} \right) \xrightarrow{D} N_p \left(0, \begin{pmatrix} \sigma^2(E(X'X))^{-1} & 0 \\ 0 & \frac{m}{2\sigma^4} \end{pmatrix} \right)$$

$$iii) \quad \Gamma_m (\hat{B} - B) \xrightarrow{D} N_p (0, \sigma^2 [E(X'X)]^{-1} m)$$

$$iv) \quad P(B \in \{x \in \mathbb{R}^p : (B-x)'[E(X'X)](B-x) \leq \hat{\sigma}^2 X_p^2(1-\lambda)\}) \rightarrow 1-\alpha$$

$$ii) \quad P(Y=1|X) = \frac{e^{B'X}}{1+e^{B'X}} \quad P(Y=0|X) = 1 - P(Y=1|X)$$

$$S(x_i, B) := e^{B'x_i} / (1 + e^{B'x_i})$$

$$L(B) = \prod S(x_i, B)^{x_i} (1 - S(x_i, B))^{1-x_i} = e^{\sum x_i B'x_i} / \prod (1 + e^{B'x_i})$$

$$\ell(B) = \sum y_i B'x_i - \sum \log (1 + e^{B'x_i})$$

$$\nabla \ell(B) = \sum y_i x_i - \sum \frac{x_i e^{B'x_i}}{1 + e^{B'x_i}} = \sum x_i (y_i - S(x_i, B))$$

$$H_\ell(B) = - \sum x_i \left(\frac{x_i e^{B'x_i} (1 + e^{B'x_i}) - e^{B'x_i} e^{B'x_i} x_i}{(1 + e^{B'x_i})^2} \right) = - \sum x_i x_i' \frac{e^{B'x_i}}{1 + e^{B'x_i}} \frac{1}{1 + e^{B'x_i}} = - \sum x_i x_i' S(x_i, B) (1 - S(x_i, B)) = - X' W X \quad \text{per } X = \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix}$$

$$\hookrightarrow \text{diag}(S(x_1, B)(1 - S(x_1, B)), \dots, S(x_m, B)(1 - S(x_m, B)))$$

$$a) \quad \Gamma_m (\hat{B} - B) \xrightarrow{D} N_p (0, [E(X'WX)]^{-1} m)$$

$$b) \quad B_1 \in [\hat{B}_1 \mp u_{1-\alpha/2} (E(X'WX))^{-1}]$$

$$ii) \quad X \sim \text{Exp}(\eta) \quad Y|X \sim \text{Exp}(\eta/x)$$

$$a) \quad L(\theta, \eta) = (nx_i)^{-1} \theta^{-m} \eta^{-m} \exp\left\{-\left[\frac{\eta i}{x_i \theta} - \sum \frac{x_i}{\eta}\right]\right\}$$

$$\ell(\theta, \eta) = c - m \log \theta - m \log \eta - \sum \frac{\eta i}{x_i \theta} - \sum \frac{x_i}{\eta}$$

$$\nabla \ell(\theta, \eta) = \left(-\frac{m}{\theta} + \sum \frac{\eta i}{x_i \theta^2}, -\frac{m}{\eta} + \sum \frac{x_i}{\eta^2}\right) \stackrel{!}{=} 0 \Rightarrow \hat{\eta} = \bar{x} \quad \hat{\theta} = \frac{m}{\bar{x}} \sum \frac{x_i}{\eta_i}$$

$$H_\ell(\theta, \eta) = \begin{pmatrix} \frac{m}{\theta^2} - \sum \frac{2\eta i}{x_i \theta^3} & 0 \\ 0 & \frac{m}{\eta^2} - \sum \frac{2x_i}{\eta^3} \end{pmatrix}$$

$$EX = \eta \quad E\left[\frac{Y}{X}\right] = E\left[\frac{Y}{X} \cdot 1_X\right] = E\left[\frac{1}{X} E(Y|X)\right] = E\left[\frac{X\theta}{X}\right] = \theta$$

$$72) \text{ cont. } J_m(\theta, \eta) = \begin{pmatrix} m/\theta^2 & 0 \\ 0 & m/\eta^2 \end{pmatrix}$$

$$J_m\left(\left(\begin{matrix} \hat{\theta} \\ \hat{\eta} \end{matrix}\right) - \left(\begin{matrix} \theta \\ \eta \end{matrix}\right)\right) \xrightarrow{\text{D}} N_2\left(\left(\begin{matrix} 0 \\ 0 \end{matrix}\right), \left(\begin{matrix} \theta^2 & 0 \\ 0 & \eta^2 \end{matrix}\right)\right)$$

$$\text{b), } J_m(\hat{\theta} - \theta) \xrightarrow{\text{D}} N(0, \theta^2)$$

$$\text{c), } \theta \in [\hat{\theta} - M_{1-\alpha/2} \hat{\theta}/J_m]$$

d), ale $\theta_0 \in CI$ pre θ meramiklom H_0 , inak namielik.

mai d), exponenciig noly, upln protac pe $\frac{1}{\theta}$ je $\sum \frac{x_i}{\lambda_i} \in \frac{y_i}{\lambda_i} = \theta$ meramiklom, ke nophysical postaci, nij lepsj testing.

8. asymptoticki testi bez nunielych parametrov.

83) $X \sim \text{alt}(p) \quad \text{R. 49+1 vieme}$

$$80(82) \quad U_m(p) = \frac{\sum x_i}{p} - \frac{m - \sum x_i}{1-p} \quad \hat{p} = \bar{X} \quad J_m(p) = \frac{m}{p(1-p)}$$

83

$$\bullet \quad W_m = m (\bar{X} - p_0)^2 \cdot \frac{1}{\hat{p}(1-\hat{p})} = \left[\frac{J_m(\bar{X} - p_0)}{(\bar{X}(1-\bar{X}))^{1/2}} \right]^2 \Leftrightarrow \text{asympt. testu}$$

$$\bullet \quad R_m = \frac{(\sum x_i - \frac{m - \sum x_i}{1-p_0})^2}{m/(p_0(1-p_0))} = \left[\frac{J_m(\bar{X} - p_0)}{\sqrt{p_0(1-p_0)}} \left(\frac{\bar{X}}{p_0} - \frac{1-\bar{X}}{1-p_0} \right) \right]^2 = \left[\frac{J_m}{\sqrt{p_0(1-p_0)}} (\bar{X} - p_0) \right]^2$$

\Leftrightarrow milomor metodu

$$\bullet \quad LR_m = 2 \left[\sum x_i \log \bar{X} + (m - \sum x_i) \log (1-\bar{X}) - [x_i \log p_0 - (m - \sum x_i) \log (1-p_0)] \right] \\ = 2m \left[\bar{X} \log \frac{\bar{X}}{p_0} + (1-\bar{X}) \log \frac{1-\bar{X}}{1-p_0} \right]$$

testu nij lepsj test namielik ale $T_m > \chi^2_{1,1-\alpha}$

84) $X \sim P_0(\lambda) \quad \text{R. 50+1 vieme}$

$$81 \quad U_m(\lambda) = -m + \sum x_i / \lambda \quad \hat{\lambda} = \bar{X} \quad J(\lambda) = \lambda'$$

84

$$\bullet \quad W_m = m (\bar{X} - \lambda_0)^2 \frac{1}{\bar{X}} = \left(\frac{J_m(\bar{X} - \lambda_0)}{\bar{X}} \right)^2$$

$$\bullet \quad R_m = (-m + \sum x_i / \lambda_0)^2 / (m / \lambda_0) = \left(\frac{J_m(\bar{X} - \lambda_0)}{\lambda_0} \right)^2$$

$$\bullet \quad LR_m = 2 (-m \bar{X} + \sum x_i \log \bar{X} + m \lambda_0 - \sum x_i \log \lambda_0) = 2m \left[\log \left(\frac{\bar{X}}{\lambda_0} \right) \cdot \bar{X} - (\bar{X} - \lambda_0) \right]$$

testu nij lepsj test namielik ale $T_m > \chi^2_{1,1-\alpha}$

85) $\tilde{X} \sim P_0(\lambda) \quad \text{ale } X = \tilde{X} | \tilde{X} > 0$

$$82 \quad P(X=x) = P(\tilde{X}=x | \tilde{X} > 0) = P(\tilde{X}=x, \tilde{X} > 0) / P(\tilde{X} > 0) = \frac{e^{-\lambda} \lambda^x / x!}{1 - e^{-\lambda}} \quad x \geq 1$$

85

$$\bullet \quad P(\tilde{X} > 0) = 1 - e^{-\lambda} \approx 1 - e^{-\lambda}$$

$$L(\lambda) = \prod \frac{e^{-\lambda} \lambda^{x_i}}{(1-e^{-\lambda})} = \frac{e^{-m\lambda} \lambda^{\sum x_i}}{(1-e^{-\lambda})^m}$$

$$\ell(\lambda) = -m\lambda + \sum x_i \log \lambda - \sum \log x_i! - m \log(1-e^{-\lambda})$$

$$U(\lambda) = -m + \sum x_i / \lambda + -\frac{me^{-\lambda}}{1-e^{-\lambda}} \stackrel{!}{=} 0$$

$$\Rightarrow \lambda \frac{e^{-\lambda}}{e^{-\lambda}-1} = \bar{x}$$

$$H_{\lambda}(\lambda) = -\sum x_i / \lambda^2 - \frac{me^{-\lambda}}{(e^{-\lambda}-1)^2}$$

$$J_m(\lambda) = \frac{m}{\lambda(1-e^{-\lambda})} + \frac{me^{-\lambda}}{(1-e^{-\lambda})^2}$$

$$\begin{aligned} EX &= \frac{1}{1-e^{-\lambda}} \sum_{x=1}^{\infty} x e^{-\lambda} \frac{\lambda^x}{x!} = \\ &= \frac{\lambda e^{-\lambda}}{1-e^{-\lambda}} \sum_{x=0}^{\infty} \frac{\lambda^x}{x!} = \frac{\lambda}{1-e^{-\lambda}} \end{aligned}$$

a) $\hat{\tau}_m(\hat{\lambda} - \lambda) \xrightarrow{d} N(0, \left[\frac{1}{\lambda(1-e^{-\lambda})} + \frac{e^{-\lambda}}{(1-e^{-\lambda})^2} \right]^{-1})$

b) numerically $\hat{\lambda} \approx 0,31$ $\hat{\tau}_m(\hat{\lambda} - \lambda) \xrightarrow{d} N(0, 0,033)$

Mathematica

c) $\theta = P(\bar{X} = 0) = e^{-\lambda} \quad \hat{\theta} = e^{-\hat{\lambda}} \approx 0,43$

interval σ -metoden $g(t) = e^{-t} \quad g'(\lambda) = -e^{-\lambda}$

$$\hat{\tau}_m(\hat{\theta} - \theta) \xrightarrow{d} N(0, e^{-2\lambda} \left[\frac{1}{\lambda(1-e^{-\lambda})} + \frac{e^{-\lambda}}{(1-e^{-\lambda})^2} \right]^{-1})$$

CII: $\theta \in [0,725; 0,735]$ naar $\hat{\theta} = 0,73$.

d) $\hat{\theta} = 0,73$, map θ in intervalen hier en c)

86) 16) $X \sim Exp(\lambda)$ n problem 61 S1.

83) $U_m(\lambda) = m/\lambda - \sum x_i \quad \hat{\lambda} = \bar{x} \quad J(\lambda) = 1/\lambda^2$

- $W_m = m \left(\frac{1}{\bar{x}} - \lambda_0 \right)^2 \bar{x}^2$

- $R_m = \left(\frac{m}{\lambda_0} - \sum x_i \right)^2 / \left(m / \lambda_0^2 \right)$

- $LR_m = 2m \left(-\log \bar{x} - (\bar{x})^{-1} \bar{x} - \log \lambda_0 + \bar{x} \lambda_0 \right)$

87) 17) $X \sim Ge(p)$ 61 S2

- $W_m = m \left(\frac{1}{\bar{x}} - p_0 \right)^2 \left(\frac{1}{p_0^2} - \frac{1}{p_0(1-p)} \right)$

- $R_m = \left(\frac{m}{p_0} - \frac{\sum x_i}{1-p_0} \right)^2 / \left(m \left(\frac{1}{p_0^2} - \frac{1}{p_0(1-p_0)} \right) \right)$

- $LR_m = 2m \left(\log \hat{p} + \bar{x} \log(1-p) - \log p_0 - \bar{x} \log(1-p_0) \right)$

88) 18) $(x_i) \sim f(x_i, \beta) = \beta x_i e^{-\beta x_i} \quad x_i \in (0, \infty), \beta > 0$

85) a) $L(\beta) = \beta^m \prod x_i \cdot e^{-\beta \sum x_i}$

$$\ell(\beta) = m \log \beta + c - \beta \sum x_i$$

$$U(\beta) = \frac{m}{\beta} - \sum x_i / \beta = 0$$

$$\hat{\beta} = \frac{m}{\sum x_i}$$

$$88 \quad 78, \text{ cmt. } \hat{\beta}_1, \frac{\partial U}{\partial \beta_1}(\beta) = -m/\beta^2 \quad J(\beta) = \frac{1}{2}\beta^2$$

$$\bullet W_m = (\hat{\beta} - \beta)^2 m / \hat{\beta}^2$$

$$\bullet R_m = \left(\frac{m}{\beta_0} - \sum x_i y_i \right)^2 / \left(\frac{m}{\beta_0^2} \right)$$

$$\bullet LR_m = m/2 \left(\log \hat{\beta} - \hat{\beta} \frac{1}{m} \sum x_i y_i - \log \beta_0 + \beta_0 \frac{1}{m} \sum x_i y_i \right)$$

$$79, \quad Y|X \sim P_0(e^{\beta X}) \quad \text{a} \quad P_n 60+1 \quad \theta = e^\beta$$

$$80, \quad L(\theta) = \prod \frac{\theta^{x_i} e^{-\theta x_i}}{x_i!} \cdot c = \theta^{\sum x_i} e^{-\theta \sum x_i} \cdot c$$

$$L(\theta) = \sum x_i y_i \log \theta - \sum \theta^{x_i} \quad \text{metrične nizit}$$

$$a, \quad U(\theta) = \sum x_i y_i / \theta - \sum x_i \theta^{x_i-1} = 0$$

$$U'(\theta) = -\sum x_i y_i / \theta^2 - \sum x_i (x_i-1) \theta^{x_i-2}$$

$$J_m(\theta) = E \left[\frac{m XY}{\theta^2} + m X(X-1) \theta^{X-2} \right] \quad EXY = E[L(XY|X)] = E[XE(Y|X)] = EXe^{\beta X}$$

b, explicitne nizit

$$\bullet R_m = \left[\sum x_i y_i / \theta_0 - \sum x_i \theta_0^{x_i-1} \right]^2 / J_m(\theta_0)$$

$$c, \quad \{ \theta \in \mathbb{R} : R_m(\theta_0) \leq \chi^2_1(1-\alpha) \} \quad \text{j je interval pre } \theta = e^\beta$$

d, pre β nizitne sva numericky, pripadne $\log \theta = \beta$ neda log-transformaciu
nizit.

$$80, \quad X \sim \text{Logist}(\theta) \quad \text{a} \quad P_n 58+1$$

81, explicitne nizit

$$\bullet R_m = \left(m - \sum_{i=1}^m \frac{e^{-\theta x_i}}{e^{-\theta} - e^{-\theta x_i}} \right)^2 / \left(\frac{m}{3} \right)$$

$$81, \quad X \sim N(\mu, \sigma^2) \quad \text{a} \quad P_n 63+1$$

$$82, \quad a, \quad W_m = ((\bar{x} - \frac{1}{m} \sum (x_i - \bar{x})^2) - (\mu, \sigma^2)) \begin{pmatrix} m/\hat{\sigma}^2 & 0 \\ 0 & m/2\hat{\sigma}^4 \end{pmatrix} \begin{pmatrix} \bar{x} - \mu \\ \frac{1}{m} \sum (x_i - \bar{x})^2 - \sigma^2 \end{pmatrix}$$

$$= \frac{(\bar{x} - \mu)^2 m}{\hat{\sigma}^2} + \frac{(\hat{\sigma}^2 - \sigma^2)m}{2\hat{\sigma}^4}$$

$$b, \quad R_m = \begin{pmatrix} \frac{1}{\hat{\sigma}^2} \sum (x_i - \mu_0)^2 & -\frac{m}{2\hat{\sigma}^2} + \frac{1}{2\hat{\sigma}^4} \sum (x_i - \mu_0)^2 \\ 0 & m/2\hat{\sigma}^4 \end{pmatrix} \begin{pmatrix} \frac{\hat{\sigma}^2}{m} & 0 \\ 0 & \frac{1}{m} \sum (x_i - \mu_0)^2 \end{pmatrix}$$

$$= \frac{\hat{\sigma}^2}{m} \left(\sum (x_i - \mu_0)^2 \right)^2 + \frac{1}{m} \left(-\frac{m}{2} + \frac{1}{2\hat{\sigma}^2} \sum (x_i - \mu_0)^2 \right)^2$$

$$c, \quad LR_m = 2m \left(-\frac{\log \hat{\sigma}^2}{2} - \frac{1}{2\hat{\sigma}^2} \frac{1}{m} \sum (x_i - \bar{x})^2 + \frac{\log \sigma^2}{2} + \frac{1}{2\sigma^2} \frac{1}{m} \sum (x_i - \mu_0)^2 \right)$$

minimum $\approx \chi^2_2(1-\alpha)$

$$82) X \sim \log N(\mu, \sigma^2)$$

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$$82) a) \hat{\mu} = \frac{1}{m} \sum \log x_i \quad \hat{\sigma}^2 = \frac{1}{m} \sum (\log x_i - \hat{\mu})^2$$

$$b) T_m((\hat{\mu}) - (\mu)) \xrightarrow{d} N_2((0), \begin{pmatrix} \sigma^2 & 0 \\ 0 & 2\sigma^4 \end{pmatrix})$$

$$c) \left\{ \mu, \sigma^2 : m(\hat{\mu} - \mu, \hat{\sigma}^2 - \sigma^2) \begin{pmatrix} \frac{1}{m}\hat{\sigma}^2 & 0 \\ 0 & \frac{1}{2m}\hat{\sigma}^4 \end{pmatrix} \begin{pmatrix} \hat{\mu} - \mu \\ \hat{\sigma}^2 - \sigma^2 \end{pmatrix} \leq \chi^2_2(1-\alpha) \right\}$$

$$d) (\mu, \sigma) = (0, 1) : H_0$$

$$\bullet W_m = m(\hat{\mu} - \mu_0, \hat{\sigma}^2 - \sigma^2) \begin{pmatrix} \frac{1}{m}\hat{\sigma}^2 & 0 \\ 0 & \frac{1}{2m}\hat{\sigma}^4 \end{pmatrix} \begin{pmatrix} \hat{\mu} - \mu_0 \\ \hat{\sigma}^2 - \sigma^2 \end{pmatrix}$$

$$\bullet R_m = \left(\sum \frac{\log x_i - \mu_0}{\sigma^2}, -\frac{m}{2\sigma^2} + \frac{1}{2\sigma^4} \sum (\log x_i - \mu_0)^2 \right) \begin{pmatrix} \sigma^2/m & 0 \\ 0 & 2\sigma^4/m \end{pmatrix} \left(\begin{array}{l} \sum \log x_i \\ -\frac{m}{2} + \frac{1}{2} \sum (\log x_i)^2 \end{array} \right)$$

$$\bullet LR_m = 2m \left(-\frac{\log \hat{\sigma}^2}{2} - \frac{1}{2\hat{\sigma}^2} \sum (\log x_i - \hat{\mu})^2 + 0 + \frac{1}{2m} \sum (\log x_i)^2 \right)$$

minimum $\approx \chi^2_2(1-\alpha)$

$$e) T_m(\hat{\mu} - \mu) \xrightarrow{d} N(0, 2\sigma^4)$$

$$\text{maximum } H_0: \mu = \mu_0 \text{ or } \mu_0 \notin \left[\hat{\mu} \mp M_{1-\alpha/2} \frac{\sqrt{2\hat{\sigma}^4}}{T_m} \right]$$

$$a_0, 83) \equiv P_n 48$$

$$a_1) Y_i | X \sim N(\beta_1 x_i + \beta_2 x_i^2, 1)$$

$$a_3) L(\beta) = \prod c \cdot \exp \left\{ -\frac{1}{2} \sum (y_i - \beta_1 x_i - \beta_2 x_i^2)^2 \right\} = c \cdot \exp \left\{ -\frac{1}{2} \sum (y_i - \beta_1 x_i - \beta_2 x_i^2)^2 \right\}$$

$$L(\beta) = -\frac{1}{2} \sum (y_i - \beta_1 x_i - \beta_2 x_i^2)^2$$

$$U(\beta) = \left(\sum \frac{2}{2} (y_i - \beta_1 x_i - \beta_2 x_i^2) x_i, \sum x_i^2 (y_i - \beta_1 x_i - \beta_2 x_i^2) \right)$$

$$U'(\beta) = \begin{pmatrix} -\sum x_i^2 & -\sum x_i^3 \\ -\sum x_i^3 & -\sum x_i^4 \end{pmatrix} \quad J_m(\beta) = m \begin{pmatrix} EX^2 & EX^3 \\ EX^3 & EX^4 \end{pmatrix}$$

$$H_0: \begin{pmatrix} \beta_0 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$R_m = \left(\sum (y_i - \beta_1 x_i - \beta_2 x_i^2) x_i, \sum x_i^2 y_i \right) \frac{1}{m} \begin{pmatrix} EX^2 & EX^3 \\ EX^3 & EX^4 \end{pmatrix}^{-1} \begin{pmatrix} \sum y_i x_i \\ \sum y_i x_i^2 \end{pmatrix}$$

$$\text{minimum } \approx \chi^2_2(1-\alpha)$$

$$85) \quad \mathbf{x} \sim \text{Mult}(4, p_1, p_2, p_3, p_4) \quad \sim_{\text{Pr}} 64$$

$$H_0: (p_1, p_2, p_3, p_4) = (\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4})$$

$$\hat{\mathbf{p}} = \sum_{i=1}^n \frac{\mathbf{x}_{ij}}{n} \quad \text{mit der rm}(\hat{\mathbf{p}} - \mathbf{p}) \xrightarrow{D} N_4 \left(\mathbf{0}, \underbrace{\begin{pmatrix} p_1(1-p_1) & p_1p_2 & p_1p_3 & p_1p_4 \\ p_2p_1 & p_2(1-p_2) & \dots & \dots \\ p_3p_1 & p_3p_2 & p_3(1-p_3) & \dots \\ p_4p_1 & p_4p_2 & \dots & p_4(1-p_4) \end{pmatrix}}_{\Sigma(\mathbf{p})} \right)$$

$$T_m = m(\hat{\mathbf{p}} - \mathbf{p}_0)' \underbrace{\Sigma(\hat{\mathbf{p}})}_{\text{matrix}}^{-1} (\hat{\mathbf{p}} - \mathbf{p}_0) \xrightarrow{D} \chi^2_3 \quad \text{mit } \Sigma = \mathbf{I} \quad (\text{vgl. 12.3, analog})$$

minimales $T > \chi^2_3(1-\alpha)$

def $\mathbf{V}^- = \text{diag} \left(\frac{1}{m p_i} \right)$. Polten parallel V12.3 u. Anwendung je $\Sigma \mathbf{V}^- \Sigma = \mathbf{I}$; b) \mathbf{V}^-
je pseudoinversion von Σ a. polen V4.15 u. anwendung je

(vgl. V12.5)

$$T_m = m(\hat{\mathbf{p}} - \mathbf{p}_0)' \mathbf{V}^- (\hat{\mathbf{p}}) (\hat{\mathbf{p}} - \mathbf{p}_0) = \sum_{i=1}^4 \frac{(x_{ij} - m p_i)^2}{m p_i} \xrightarrow{D} \chi^2_3 \quad \Rightarrow \chi^2\text{-test Multinom.-Verteilung}$$

$$86) \quad Y|N \sim Bi(N, p) \quad N \sim Po(\lambda) \quad \sim_{\text{Pr}} 69$$

$$93) \quad a) \quad \hat{\mathbf{p}} = \frac{\sum n_i}{\sum g_i} \quad \hat{\lambda} = \frac{1}{m} \sum n_i$$

$$94) \quad b), \quad T_m \left(\left(\frac{\hat{\mathbf{p}}}{\hat{\lambda}} \right) - \left(\frac{\mathbf{p}}{\lambda} \right) \right) \xrightarrow{D} N_2 \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} p(1-p)/\lambda & 0 \\ 0 & \lambda \end{pmatrix} \right)$$

$$c), \quad W_m = (\hat{\mathbf{p}} - \mathbf{p}, \hat{\lambda} - \lambda) \begin{pmatrix} \frac{m \hat{\lambda}}{\hat{\mathbf{p}}(1-\hat{\mathbf{p}})} & 0 \\ 0 & m/\hat{\lambda} \end{pmatrix} \begin{pmatrix} \hat{\mathbf{p}} - \mathbf{p} \\ \hat{\lambda} - \lambda \end{pmatrix} \quad \checkmark \quad \sim_{\text{Pr}} 50 \text{ a. 49}$$

$$R_m = \left(\sum \frac{y_i}{p_0} - \sum \frac{N_i - y_i}{1-p_0} \right) \left(-m + \frac{\sum N_i}{\lambda_0} \right) \begin{pmatrix} \frac{p_0(1-p_0)}{m \lambda_0} & 0 \\ 0 & (m/\lambda_0)^{-1} \end{pmatrix} \begin{pmatrix} \sum \frac{y_i}{p_0} - \sum \frac{N_i - y_i}{1-p_0} \\ -m + \sum \frac{N_i}{\lambda_0} \end{pmatrix}$$

$$LR_m = 2m \left(\frac{1}{m} \sum y_i \log \hat{p}_0 - \frac{1}{m} \sum (N_i - y_i) \log (1 - \hat{p}_0) - 1 + \sum \frac{N_i}{\lambda_0} \frac{1}{m} - \frac{1}{m} \sum y_i \log p_0 + \frac{1}{m} \sum (N_i - y_i) \log (1 - p_0) + 1 - \sum \frac{N_i}{\lambda_0} \frac{1}{m} \right)$$

präzisionsmaß $\chi^2_2(1-\alpha)$

$$84) X \sim N(\mu, \sigma^2) \quad H_0: \mu = \mu_0$$

$$\tau = \mu, \quad \eta = \sigma^2$$

Pn 63

$$(94) L(\mu, \sigma^2) = \frac{1}{(2\pi\sigma^2)^m} \exp \left\{ -\frac{1}{2\sigma^2} \sum (x_i - \mu)^2 \right\} \quad \ell(\mu, \sigma^2) = c - \frac{m}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum (x_i - \mu)^2$$

$$U(\mu, \sigma^2) = \left(\underbrace{\frac{\sum (x_i - \mu)}{\sigma^2}}_{J_1}, -\frac{m}{2\sigma^2} + \frac{\sum (x_i - \mu)^2}{2\sigma^4} \right) \quad \hat{\mu} = \bar{x} \quad \hat{\sigma}^2 = \frac{1}{m} \sum (x_i - \bar{x})^2$$

$$\bullet \text{pue } \tau = c_0: \quad \tilde{\sigma}^2 = \frac{1}{m} \sum (x_i - \mu_0)^2 \quad \tilde{\theta} = (\mu_0, \tilde{\sigma}^2)$$

$$-E \frac{\partial U}{\partial \theta^T} (\mu, \sigma^2) = \begin{pmatrix} +\frac{m}{\sigma^2} & 0 \\ 0 & \frac{m}{2\sigma^4} \end{pmatrix} = J_m(\theta) \quad J(\theta) = \begin{pmatrix} \frac{1}{\sigma^2} & 0 \\ 0 & \frac{1}{2\sigma^4} \end{pmatrix}$$

$$J^{-1}(\theta) = \begin{pmatrix} \sigma^2 & 0 \\ 0 & 2\sigma^4 \end{pmatrix} \quad J''(\theta) = \sigma^2$$

$$\bullet LR := \chi \cdot \left[\ell' - \frac{m}{2} \log \hat{\sigma}^2 - \frac{1}{2\hat{\sigma}^2} \sum (x_i - \bar{x})^2 - \ell' + \frac{m}{2} \log \tilde{\sigma}^2 + \frac{1}{2\tilde{\sigma}^2} \sum (x_i - \mu_0)^2 \right] \\ = m \log \frac{\tilde{\sigma}^2}{\hat{\sigma}^2} = m \log \frac{\sum (x_i - \mu_0)^2}{\sum (x_i - \bar{x})^2}$$

$$\bullet W = m (\bar{x} - \mu_0)^2 (\hat{\sigma}^2)^{-1}$$

$$\bullet R = \frac{1}{m} \left(\frac{\sum (x_i - \mu_0)}{\hat{\sigma}^2} \right)^2 \tilde{\sigma}^2 = m \frac{(\bar{x} - \mu_0)^2}{\hat{\sigma}^2}$$

Krit. Wert nominiert $\Rightarrow T_m > \chi^2_{1-\alpha}$

$$88) X \sim \text{Log}N(\mu, \sigma^2) \quad H_0: \mu = \mu_0 \quad \tau = \mu, \quad \eta = \sigma^2 \quad \text{Pn 64}$$

$$(95) L(\mu, \sigma^2) = c - \frac{m}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum (\ln x_i - \mu)^2$$

$$U = \left(\frac{\sum (\ln x_i - \mu)/\sigma^2}{\sigma^2}, -\frac{m}{2\sigma^2} + \frac{\sum (\ln x_i - \mu)^2/2\sigma^4}{2\sigma^4} \right) \quad \hat{\mu} = \frac{1}{m} \sum \ln x_i \quad \hat{\sigma}^2 = \frac{1}{2} \sum (\ln x_i - \hat{\mu})^2$$

$$\tilde{\sigma}^2 = \frac{1}{m} \sum (\ln x_i - \mu_0)^2$$

$$J(\theta) = \begin{pmatrix} 1/\sigma^2 & 0 \\ 0 & 1/2\sigma^4 \end{pmatrix} \quad \Rightarrow \quad J''(\theta) = \sigma^2$$

$$\bullet LR = \dots = m \log \left[\frac{\sum (\ln x_i - \mu_0)^2}{\sum (\ln x_i - \hat{\mu})^2} \right]$$

$$\bullet W = m (\hat{\mu} - \mu_0)^2 (\hat{\sigma}^2)^{-1}$$

$$\bullet R = \frac{1}{m} \left[\frac{\sum (\ln x_i - \mu_0)}{\hat{\sigma}^2} \right]^2 \tilde{\sigma}^2 = m \frac{(\hat{\mu} - \mu_0)^2}{\hat{\sigma}^2}$$

Krit. Wert $\Rightarrow T_m > \chi^2_{1-\alpha}$

89) $Y|N \sim \text{Bi}(\tilde{m}, p)$ p.e. $\tilde{m}=N$, $N \sim P_0(\lambda)$ $H_0: p=p_0$ $\tau=p$, $\gamma=\lambda$ Gf 69
 (96) $L(p, \lambda) = \prod_{j=1}^m P_j^{y_j} (1-p)^{m_j-y_j} \frac{\lambda^{m_j} e^{-\lambda}}{m_j!} = c \cdot p^{\sum y_j} (1-p)^{\sum m_j - \sum y_j} \lambda^{\sum m_j} e^{-\lambda}$

$$\ell(p, \lambda) = c + \sum y_j \log p + (\sum m_j - \sum y_j) \log(1-p) + \sum m_j \log \lambda - m \lambda$$

$$U(p, \lambda) = \left(\frac{\sum y_j}{p} - \frac{\sum m_j - \sum y_j}{1-p}, \frac{\sum m_j}{\lambda} - m \right) \quad \hat{\lambda} = \frac{\sum m_j}{m} \quad \hat{p} = \frac{\sum y_j}{\sum m_j}$$

$\hat{\lambda}$ nenhilnig mo $p \Rightarrow \tilde{\lambda} = \hat{\lambda}$

$$\mathcal{J}(p, \lambda) = \begin{pmatrix} \frac{\lambda}{p} + \frac{\lambda}{1-p} & 0 \\ 0 & \frac{1}{\lambda} \end{pmatrix}$$

$$\mathcal{J}''(\theta) = \frac{1/m}{\frac{(1-p)\lambda+p\lambda}{p(1-p)}} = \frac{p(1-p)}{\lambda}$$

$$\bullet LR = 2 \left[\frac{-\ell}{-\ell} + \sum y_j \log \hat{p} + \sum (N_j - y_j) \log (1-\hat{p}) + \sum N_j \log \hat{\lambda} - m \hat{\lambda} \right] \\ = 2 \left[\sum y_j \log \hat{p}/p_0 + \sum (N_j - y_j) \log [(1-\hat{p})(1-p_0)] \right]$$

$$\bullet W = m(\hat{p} - p_0)^2 \left[\frac{\hat{p}(1-\hat{p})}{\lambda} \right]^{-1} = \frac{m(\hat{p} - p_0)^2}{\hat{p}(1-\hat{p})} \cdot \hat{\lambda}$$

$$\bullet R = \frac{1}{m} \left(\frac{\sum y_j}{p_0} - \frac{\sum (N_j - y_j)}{1-p_0} \right)^2 \frac{p_0(1-p_0)}{\lambda} = \frac{1}{m} \left(\frac{\sum y_j - p_0 \sum y_j - p_0 \sum N_j + p_0 \sum y_j}{p_0(1-p_0)} \right)^2 \frac{p_0(1-p_0)}{\lambda}$$

$$= \frac{1}{m} \left(\sum N_j \left(\frac{\sum y_j}{\sum N_j} - p_0 \right) \right)^2 \frac{1}{\lambda p_0(1-p_0)}$$

rumitum ar $T_m > \chi^2_1(1-\alpha)$

(94)

90) $X \sim M(1, p_1, p_2, p_3, p_4)$ P. 64+1

$$\rightarrow \text{standardna parametrizacija } (p_1, p_2, p_3, p_4)^T = p \quad y_{ij} = \sum_{i=1}^m x_{ij} \quad (\text{po sit j v mire})$$

$$\text{i) } L(p) = \prod p_j^{y_{ij}} \quad \ell(p) = \sum y_{ij} \log p_j \quad p_1 = \tau \quad (p_2, p_3, p_4) = \psi \quad H_0: p_1 = 1/4$$

$$\hat{p}_j = y_{ij}/m \quad \text{p.e. } \tilde{p} \text{ maximalizuj } \sum y_{ij} \log p_j \quad \text{na podm } p_1 = 1/4, \sum_{j=2}^4 p_j = 3/4$$

$$\text{ii) } f(p_2, p_3, p_4, \lambda) = y_1 \log \frac{1}{4} + y_2 \log p_2 + y_3 \log p_3 + y_4 \log p_4 + \lambda \left(\frac{3}{4} - \sum p_j \right)$$

$$\frac{\partial}{\partial p_j} f = \frac{y_{ij}}{p_j} - \lambda = 0 \quad \Rightarrow \frac{p_j}{p_j} = \frac{y_{ij}}{\lambda} \quad \Rightarrow \frac{3/4}{\lambda} - \frac{1}{\lambda} \sum y_{ij} = 0 \quad \Rightarrow \lambda = y_{ij} \sum y_{ij}$$

$$\Rightarrow \tilde{p}_j = \frac{y_{ij}}{\sum y_{ij}} \cdot \frac{3}{4} \quad j=2, 3, 4$$

$$\bullet LR = 2 \left(\sum_{j=1}^4 Y_j \log \left(\frac{Y_j}{m} \right) - Y_1 \log \frac{1}{4} - \sum_{j=2}^4 Y_j \log \left(\frac{Y_j \cdot \frac{3}{4}}{\sum_{i=2}^4 Y_i} \right) \right)$$

• Fisher. inf. meračne počitki letov meračne vrednosti do navedenih problem. $\sum_{j=1}^4 p_j = 1$

$$\rightarrow \text{parametrizacija } (p_1, p_2, p_3, 1-p_1-p_2-p_3) \quad p = (p_1, p_2, p_3)^T$$

$$L(p) = \prod_{j=1}^3 p_j^{y_{ij}} \cdot (1-p_1-p_2-p_3)^{m-y_1-y_2-y_3} \quad \text{Mathematica} \quad \hat{p}_j = \frac{y_{ij}}{m}$$

$$\tilde{p} = (y_{11}, \frac{y_{12}}{m}, \frac{y_{13}}{m}, \frac{y_{14}}{m})^T \quad \Rightarrow$$

$$1 - \sum_{j=1}^3 \hat{p}_j = \frac{y_{14}}{m}$$

$$1 - \sum_{j=1}^3 \tilde{p}_j = \frac{y_{14} \cdot y_{11}}{m \cdot y_{11}}$$

$$\bullet LR = 2 \left(\sum_{j=1}^3 Y_j \log \left(\frac{Y_j}{m} \right) + Y_4 \log \left(\frac{Y_4}{m} \right) - Y_1 \log \frac{1}{4} - \sum_{j=2}^3 Y_j \log \left(\frac{y_{1j}}{m \cdot y_{11}} \right) - Y_4 \log \left(\frac{y_{14} \cdot y_{11}}{m \cdot y_{11}} \right) \right)$$

91, 2 R 90 a R năștări distinție $\hat{p} = (0,240; 0,258; 0,264; 0,235)$

(98) a) $LR = 60,08 \quad u_0 \cdot p_1 = 114 \quad \chi^2(1x) = 3,84 \quad p\text{-val} = 9 \cdot 10^{-5} \Rightarrow$ năștări

b) $H: p_1 = p_2 \quad LR = 40,41 \quad p\text{-val} = 2 \cdot 10^{-18} \Rightarrow$ năștări

c) $H: p_3 = 1,1 p_1 \quad LR = 1,39 \quad p\text{-val} = 0,239 \Rightarrow$ năștări

(92) $(x_i, y_i)^T \sim$ mihi. găzduște și $y_i | x_i \sim N(\beta_0 + \beta_1 x_i, \sigma^2)$ x_i mihi. mă β_1, σ^2
pe $\sigma=1$ nu se năștărește \Rightarrow $Pn\ 44$ ($Pn22$)

(99) $H_0: \beta_1 = 0 \quad H_1: \beta_1 \neq 0$

$$L(\beta_1, \sigma^2) = c \cdot \prod \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{1}{2\sigma^2} (y_i - \beta_0 - \beta_1 x_i)^2 \right\} = c(\sigma^2)^{-m/2} \exp \left\{ -\frac{1}{2\sigma^2} \sum (y_i - \beta_0 - \beta_1 x_i)^2 \right\}$$

$$\ell(\beta_1, \sigma^2) = c - \frac{m}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum (y_i - \beta_0 - \beta_1 x_i)^2$$

$$\frac{\partial \ell}{\partial \sigma^2} = -\frac{m}{2\sigma^2} + \frac{1}{2\sigma^4} \sum (y_i - \beta_0 - \beta_1 x_i)^2 \stackrel{!}{=} 0 \Rightarrow \hat{\sigma}^2 = \frac{1}{m} \sum (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \quad \hat{\beta}_1 = \frac{\sum (y_i - \bar{y})(x_i - \bar{x})^2}{\sum (x_i - \bar{x})^2} \quad$$

pe $\hat{\beta}_0 \wedge \hat{\beta}_1$ nr $Pn44$ ($Pn22$)
(Dacă, deosebită)
Vid. 4.1

$$Ra\ 4_0: \ell(\beta_0, \sigma^2) = c - \frac{m}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum (y_i - \beta_0)^2$$

\Rightarrow sămădării normal model $\Rightarrow \tilde{\beta}_0 = \bar{y} \quad \tilde{\sigma}^2 = \frac{1}{m} \sum (y_i - \tilde{\beta}_0)^2 \quad \tilde{\beta}_1 = 0$

$$\begin{aligned} LR &= 2 \cdot \left[\cancel{c} - \frac{m}{2} \log \hat{\sigma}^2 - \underbrace{\frac{1}{2\hat{\sigma}^2} \sum (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2}_{\stackrel{!}{=}} - \cancel{c} + \frac{m}{2} \log \tilde{\sigma}^2 + \underbrace{\frac{1}{2\tilde{\sigma}^2} \sum (y_i - \tilde{\beta}_0)^2}_{\stackrel{!}{=}} \right] \\ &= \frac{2m}{\tilde{\sigma}^2} \left[\log \left[\frac{\hat{\sigma}^2}{\tilde{\sigma}^2} \right] \right] \\ &= m \log \frac{\sum (y_i - \tilde{\beta}_0)^2}{\sum (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2} \end{aligned}$$

următoare LR > $\chi^2_{1, (1-\alpha)}$

93) mihi. găzduște (x_i, y_i) aici nr $Pn41$ aici

(100) $P(Y=1 | X=x) = \frac{e^{x+\beta x}}{1+e^{x+\beta x}} \quad P(Y=0 | X=x) = 1 - P(Y=1 | X=x)$

$$\ell(x, \beta) = \sum y_i (x + \beta x_i) - \sum \log(1 + e^{x + \beta x_i})$$

$\hat{x}, \hat{\beta}$ numerică și
R năștări

$$U(x, \beta) = \left(\sum y_i - \sum e^{x+\beta x_i} / (1 + e^{x+\beta x_i}) \right) \\ \left. \sum x_i y_i - \sum x_i e^{x+\beta x_i} / (1 + e^{x+\beta x_i}) \right) \} U_2$$

$$\begin{aligned} \text{pe } H_0: \beta = 0 \quad \ell(x) &= \sum y_i x - \sum \log(1 + e^x) \\ U(x) &= \sum y_i - \sum \frac{e^x}{1+e^x} \stackrel{!}{=} 0 \Rightarrow \bar{y} = \frac{e^x}{1+e^x} \quad \tilde{x} = \log \frac{\bar{y}}{1-\bar{y}} \\ \tilde{\beta} &= 0 \end{aligned}$$

$$LR = 2 \left[\sum y_i (\tilde{x} + \tilde{\beta} x_i) - \sum \log(1 + e^{\tilde{x} + \tilde{\beta} x_i}) - \sum y_i \tilde{x} + \sum \log(1 + e^{\tilde{x}}) \right]$$

informații mihi: \Rightarrow $Pn41$ min pe $X = \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix}$ a $W = \text{diag} \left(\frac{e^{x+\beta x_i}}{(1+e^{x+\beta x_i})^2} w_i \right)$

$$\tilde{x} \quad J_m(x, \beta) = X^T W X = \begin{pmatrix} \sum w_i & \sum w_i x_i \\ \sum w_i x_i & \sum w_i x_i^2 \end{pmatrix}$$

$\tau = \beta, \quad H_0: \beta = 0 \quad -$ pe J'' probe (4.2) mihiice $[J_m(x, \beta)/m]^{-1}$ sănătă
potrivit

$$R = \frac{1}{m} [U_2(\tilde{x}, \beta)]^2 J''(\tilde{x}, \beta) \quad W = m ((\tilde{x}, \beta) - (\tilde{x}, 0))^T / J''(\tilde{x}, \beta) \quad \sim \chi^2_{1, (1-\alpha)}$$

90) poliac. \Rightarrow LR testy mi v oboch parametrických rozdilech.

(94)

Fisherova informácia Mathematica

$$J(p) = \begin{pmatrix} \frac{1}{p_1} + \frac{1}{(1-p_1-p_2-p_3)} & \frac{1}{(1-p_1-p_2-p_3)} & \frac{1}{(1-p_1-p_2-p_3)} \\ \cdot & \frac{1}{p_2} + \frac{1}{(1-p_1-p_2-p_3)} & \cdot \\ \cdot & \cdot & \frac{1}{p_3} + \frac{1}{(1-p_1-p_2-p_3)} \end{pmatrix}$$

$$J'(p) = \begin{pmatrix} p_1(1-p_1) & -p_1p_2 & -p_1p_3 \\ -p_1p_2 & p_2(1-p_2) & -p_2p_3 \\ -p_1p_3 & -p_2p_3 & p_3(1-p_3) \end{pmatrix}$$

$$W = m \left(\frac{Y_1/m - p_0}{\hat{p}_1(1-\hat{p}_1)} \right)^2 = \left[\frac{m(\hat{p}_1 - p_0)}{\hat{p}_1(1-\hat{p}_1)} \right]^2$$

b) v následujúcej parametrikácii $H_0: p_1 = p_2$ $\ell(p) = \sum j_i \log p_j$

$$\text{na } H_0: \ell(p_1, p_2, p_3, p_4) = (j_1 + j_2) \log p_2 + j_3 \log p_3 + j_4 \log p_4 \Rightarrow \text{ak je r a } \alpha$$

$$\tilde{p} = \left(\frac{Y_1+Y_2}{2m}, \frac{Y_1+Y_2}{2m}, \frac{Y_3}{m}, \frac{Y_4}{m} \right) \quad \text{na postre} \quad \underline{2p_2 + p_3 + p_4 = 1}$$

$$\frac{\partial \ell}{\partial p_j} = \begin{cases} \frac{\partial j}{\partial p_j} - \lambda = 0, & j > 2 \\ (\frac{\partial j}{\partial p_j})/p_j - 2\lambda = 0, & j = 2 \end{cases} \Rightarrow p_j = \begin{cases} \frac{(j_1+j_2)/2}{\lambda} & j = 2 \\ \frac{j}{\lambda} & j > 2 \end{cases}$$

$$\frac{\partial \ell}{\partial \lambda} \Rightarrow (\frac{\partial j}{\partial \lambda})/2\lambda \cdot 4 + \frac{\partial j}{\partial \lambda} + \frac{\partial j}{\partial \lambda} = 1 \Rightarrow \lambda = \sum_{i=1}^4 j_i$$

$$\tilde{p}_2 = \frac{(j_1+j_2)/2}{2 \cdot \sum j_i} = \frac{j_1+j_2}{2m} \quad \tilde{p}_3 = \frac{j_3}{m} \quad \tilde{p}_4 = \frac{j_4}{m}$$

$$\bullet \text{LR} = 2 \left[\sum_{j=1}^4 Y_j \log \frac{Y_j/m}{\lambda} - Y_1 \log \left(\frac{Y_1+Y_2}{2m} \right) - Y_2 \log \left(\frac{Y_1+Y_2}{2m} \right) - Y_3 \log \frac{Y_3}{m} - Y_4 \log \frac{Y_4}{m} \right]$$

$$= 2 \left[Y_1 \log \frac{Y_1}{m} + Y_2 \log \frac{Y_2}{m} - (Y_1+Y_2) \log \frac{Y_1+Y_2}{2m} \right]$$

c) ak je r b), $\ell(p_1, p_2, p_3) = j_1 \log p_1 + j_2 \log p_2 + j_3 \log \frac{1}{1-p_1-p_2} + j_4 \log p_3 \quad (+\lambda(2(p_1+p_2+p_3-1))$

$$\frac{\partial \ell}{\partial p_j} = \begin{cases} \frac{\partial j}{\partial p_j} - \lambda = 0, & j = 2, 4 \\ (\frac{\partial j}{\partial p_j})/p_j - 2(1-\lambda) = 0, & j = 1 \end{cases} \quad p_j = \begin{cases} \frac{\partial j}{\lambda} & j = 2, 4 \\ \frac{(j_1+j_3)}{2(1-\lambda)} & j = 1 \end{cases}$$

$$\frac{\partial \ell}{\partial \lambda} \Rightarrow \lambda = \sum_{i=1}^4 j_i = m \quad (\tilde{p}_1, \tilde{p}_2, \tilde{p}_3) = \left(\frac{Y_1+Y_3}{2m}, \frac{Y_2}{m}, \frac{Y_4}{m} \right)$$

$$\tilde{p}_3 = 1, 1, \tilde{p}_4 = \frac{1, 1}{2, 1} \cdot \frac{Y_1+Y_3}{m}$$

$$\bullet \text{LR} = 2 \left[\sum_{i=1}^4 Y_i \log \frac{Y_i}{m} - Y_1 \log \frac{Y_1+Y_3}{2, 1m} - Y_2 \log \frac{Y_2}{m} - Y_3 \log \left[\frac{1, 1}{2, 1} \left(\frac{Y_1+Y_3}{m} \right) \right] - Y_4 \log \frac{Y_4}{m} \right]$$

znamenáže $\text{LR} \geq \chi^2_{1,1}(1-\alpha)$

93) cont. b) následky z R scriptu

(100)

$$LR = 1,138$$

$$R = 1,078$$

$$W = 0,949$$

$$\text{povinnému } \approx \chi^2(0,95) = 3,84 \Rightarrow p\text{-value}$$

0,286
0,299
0,323

nemáme dom. $H_0: \beta = 0$ proti $H_1: \beta \neq 0$.

On intervalná pravdepodobnosť myjdeme s $W = \hat{\beta} / \sqrt{\hat{\sigma}^2(\hat{\beta}, \hat{\beta})} \sim N(0,1)$

$$[\hat{\beta} + M_{1-\alpha/2} \sqrt{\hat{\sigma}^2(\hat{\beta}, \hat{\beta})} / \hat{\sigma}], \approx [-0,085; 0,168]$$

(101)

94) podľaže aké sú $\delta_n \gamma_8(8)$ $X \sim R(0,1)$ $Y|X \sim Exp(\lambda(\alpha, \beta, x))$ pre $\lambda(\alpha, \beta, x) = e^{\alpha+\beta x}$

$$a) H_0: \beta = 0 \quad L(\alpha, \beta) = \prod e^{\alpha+\beta x_i} \exp\{-e^{\alpha+\beta x_i} \cdot y_i\} = e^{m+\beta \sum x_i} \exp\{-\sum y_i e^{\alpha+\beta x_i}\}$$

$$L(\alpha, \beta) = \alpha m + \beta \sum x_i - \sum y_i e^{\alpha+\beta x_i}$$

$$U = \left(m - \sum y_i e^{\alpha+\beta x_i}, \sum x_i - \sum x_i y_i e^{\alpha+\beta x_i} \right) \quad \hat{\alpha}, \hat{\beta} \text{ ibo numericky}$$

$$\frac{\partial U}{\partial \theta_i} = \begin{pmatrix} -\sum y_i e^{\alpha+\beta x_i} & -\sum y_i x_i e^{\alpha+\beta x_i} \\ -\sum y_i x_i e^{\alpha+\beta x_i} & -\sum y_i x_i^2 e^{\alpha+\beta x_i} \end{pmatrix} \quad J(\alpha, \beta) = \begin{pmatrix} 1 & 1/2 \\ 1/2 & 1/3 \end{pmatrix}$$

$$E[X^2 Y e^{\alpha+\beta x}] = E[E(X^2 Y e^{\alpha+\beta x} | X)] = E[X^2 e^{\alpha+\beta x} \cdot \frac{1}{e^{\alpha+\beta x}}] = EX^2 = \begin{cases} 1 & \alpha=0 \\ 1/2 & \alpha=1 \\ 1/3 & \alpha=2 \end{cases}$$

$$\tau = \beta \quad J^{-1} = 12 \cdot \begin{pmatrix} 1/3 & -1/2 \\ -1/2 & 1 \end{pmatrix} = \begin{pmatrix} 4 & -6 \\ -6 & 12 \end{pmatrix} \quad J^H = 12$$

$$\bullet \text{na } H_0: \beta = 0 \quad \ell(\alpha) = \alpha m - \sum y_i e^{\alpha} \quad U(\alpha) = m - \sum y_i e^{\alpha} \Rightarrow \tilde{\alpha} = \log \frac{m}{\sum y_i} = -\log \bar{Y}$$

$$\bullet LR = 2 \left[\hat{\alpha} m + \hat{\beta} \sum x_i - \sum y_i e^{\hat{\alpha}+\hat{\beta} x_i} - \tilde{\alpha} m + \sum y_i e^{\tilde{\alpha}} \right]$$

$$\bullet R = \frac{1}{m} (\sum x_i - \sum x_i y_i e^{\tilde{\alpha}})^2 \cdot 12 \quad \text{povinnému } \approx \chi^2(1-\alpha)$$

$$\bullet W = m (\hat{\beta} - \beta_0)^2 / 12 = m \hat{\beta}^2 / 12$$

b) pre obecné X maximálne iba $J(\alpha, \beta) = \begin{pmatrix} EX^0 & EX^1 \\ EX^1 & EX^2 \end{pmatrix}$ iba je výber rámci celej súdovej 3 povolených inj. modelov

(102)

95) poliedrové multinomialske rozdelenie: $p = (p_{11}, p_{12}, p_{21}, p_{22})^T$ alebo $P_{n, Q}$

$$H_0: p_{12} = p_{21} \quad \text{Pr} Q \text{ O b)} \quad p_{21} \text{ a } p_{12} \text{ aké } p_1 \text{ a } p_2 \text{ tvorí}$$

$$H_1: p_{12} \neq p_{21} \quad \hat{p} = \left(\frac{y_{12}}{m}, \frac{y_{12}}{m}, \frac{y_{21}}{m}, \frac{y_{21}}{m} \right)^T \quad \tilde{p} = \left(\frac{y_{11}}{m}, \frac{y_{12}+y_{21}}{2m}, \frac{y_{12}+y_{21}}{2m}, \frac{y_{22}}{m} \right)^T$$

$$LR = 2 \left[y_{12} \log \frac{y_{12}}{m} + y_{21} \log \frac{y_{21}}{m} - (y_{11} + y_{21}) \log \frac{y_{11} + y_{21}}{2m} \right] \text{ normale } > \chi^2(1-\alpha)$$

(103)

96) rečenky o náležitosti aké sú $P_{n, Q}$ a $P_{n, Q}$ $(x_i, y_i)^T$ miš. zlož.

$$Y|X=x \sim P_0(e^{\alpha+\beta x}), \quad X \text{ miš. zlož. } \alpha, \beta \quad H_0: \beta = 0 \text{ a } H_1: \beta \neq 0$$

$$L(\alpha, \beta) = \prod \lambda(x_i)^{y_i} \cdot \frac{e^{-\sum \lambda(x_i)}}{\prod y_i!} \quad \ell(\alpha, \beta) = \sum y_i \log \lambda(x_i) - \sum \lambda(x_i) + c$$

$$\lambda(x) = e^{\alpha+\beta x}$$

$$\frac{\partial}{\partial \theta} \lambda(x) = (\lambda(x), x \lambda(x))$$

$$U(\alpha, \beta) = \sum \frac{y_i}{\lambda(x_i)} \left(\frac{\lambda(x_i)}{x_i \lambda'(x_i)} \right) - \sum \left(\frac{\lambda(x_i)}{x_i \lambda'(x_i)} \right) = \sum \left(\frac{y_i}{\lambda'(x_i)} \right) - \sum \left(\frac{\lambda(x_i)}{x_i \lambda'(x_i)} \right)$$

$\hat{\alpha}, \hat{\beta}$ numerically

$$\frac{\partial}{\partial \theta^1} U = \begin{pmatrix} -\sum \lambda(x_i) & -\sum x_i' \lambda(x_i) \\ -\sum x_i \lambda'(x_i) & -\sum x_i x_i' \lambda'(x_i) \end{pmatrix} \quad J(\alpha, \beta) = \begin{pmatrix} E \lambda(x) & E x \lambda(x) \\ E x \lambda(x) & E x x' \lambda(x) \end{pmatrix}$$

$J''(\alpha, \beta)$ = pochodna $(J''_{11}(\alpha, \beta), J''_{12}(\alpha, \beta))$ miedzy $J(\alpha, \beta)$.

$$\text{zadanie: } \beta = 0 \quad \ell(x) = \sum x_j y_j - m e^x \quad U(x) = \sum y_j - m e^x \Rightarrow \begin{cases} \hat{x} = \log \bar{Y} \\ \hat{\beta} = 0 \end{cases}$$

- $LR = 2 \left[\sum y_i \log e^{\hat{\alpha} + \hat{\beta} x_i} - \sum e^{\hat{\alpha} + \hat{\beta} x_i} - \sum \log \bar{Y} \cdot y_i + m \bar{Y} \right]$

- $R = \frac{1}{m} \left(\sum (y_i x_i - x_i e^{\hat{\alpha} + \hat{\beta} x_i}) \right)^2 \cdot J''(\hat{\alpha}, \hat{\beta}) \left(\sum (y_i x_i - x_i e^{\hat{\alpha}}) \right)$

- $V = m (\hat{\beta} - \psi)' J''(\hat{\alpha}, \hat{\beta})^{-1} (\hat{\beta} - \psi)$ powodzenie $\sim \chi^2_{q-1}$ (tak)

x_i nalezy do \mathbb{R} niepl.

$$LR = 41,81$$

$$R = 10,94$$

$$W = 8,91$$

$$\text{powodzenie } \sim \chi^2_1 (1-\alpha) = 5,99$$

p-wk

$$0,003$$

$$0,004$$

$$0,011$$

$$\text{zamietum } H_0: \beta = 0, \alpha = 0$$

interval spodzialosci dla β_1 : dla $W \approx 0,95$ i marginale wodelni: $\approx [-9,45; 1,44]$.

$$97) X_1, \dots, X_m \sim \text{Exp}(\lambda) \quad P(X_{(1)} \leq t) = \frac{1 - (1 - P(X_i \leq t))^m}{1 - e^{-\lambda t}} = 1 - (1 - (1 - e^{-\lambda t}))^m =$$

$$L(\lambda) = m \lambda e^{-\lambda t} \quad \ell(\lambda) = c + \ln m - m \lambda t + \ln \lambda \quad U(\lambda) = \frac{1}{\lambda} - m t = 0$$

$$\frac{1}{\lambda} = m t \Rightarrow \hat{\lambda} = \frac{1}{m \bar{X}_{(1)}} \quad P(m \bar{X}_{(1)} \leq t) = 1 - e^{-m \lambda t} = 1 - e^{-\lambda t}$$

$\Rightarrow m \bar{X}_{(1)} \sim \text{Exp}(\lambda)$ a $\hat{\lambda} \sim [\text{Exp}(\lambda)]^{-1}$ a nije konzistentno' očekivalo.

$$98) a) (x_i, y_i) \sim R(\text{distan} \sim \text{uniform } \theta) \quad f(x, y) = \frac{1}{\pi \theta^2} I[x^2 + y^2 \leq \theta^2]$$

$$L(\theta) = \prod \frac{1}{\pi \theta^2} I[x_i^2 + y_i^2 \leq \theta^2] = \left(\frac{1}{\pi \theta^2}\right)^m I[x_i^2 + y_i^2 \leq \theta^2 \forall i]$$

maximizacijom pre θ najmanje θ na području $x_i^2 + y_i^2 \leq \theta^2 \Rightarrow \hat{\theta} = \sqrt{\max_i \{x_i^2 + y_i^2\}}$

$$b) (x_i, y_i) \sim R([- \theta, \theta]^2) \quad f(x, y) = \frac{1}{4\theta^2} I[x_i \in [-\theta, \theta], y_i \in [-\theta, \theta]]$$

$$\Rightarrow \hat{\theta} = \max_i \{|x_i| \vee |y_i|\}$$

$$99) a) m = \text{pre reding} \approx \text{m detini} \quad x_1, \dots, x_m \sim Bi(m, p) \quad L(p) = \prod_{i=1}^m \binom{m}{x_i} p^{x_i} (1-p)^{m-x_i} = \prod_{i=1}^m \binom{m}{x_i} \cdot p^{\sum x_i} (1-p)^{m-m-\sum x_i}$$

$$\ell(p) = m \sum \ln \binom{m}{x_i} + \sum x_i \ln p + (m-m-\sum x_i) \ln (1-p)$$

$$U(p) = \frac{\sum x_i / p}{m} + \frac{-m + m - \sum x_i}{1-p} = 0$$

$$\sum x_i - p \sum x_i - mmp + p \sum x_i = 0 \quad R \& \text{ipt} \\ \hat{p} = \frac{1}{m} \sum x_i \Rightarrow \hat{p} = 0,514$$

b) reding ≈ 2 ali u 6 detini - rimes $Bi(2, p)$ a $Bi(6, p)$ \approx mern. rimes.

$$\begin{pmatrix} x_i \\ c_i \end{pmatrix} \quad x_i = \text{počet sljapova} \approx \text{m deti} \quad m_i = \text{množ. jibova} \quad m_i = \sum c_i \quad (\text{počet 6-čl. red})$$

$$L(p) = \prod_{i=1}^m \left[\binom{2}{x_i} p^{x_i} (1-p)^{2-x_i} \right]^{1-c_i} \left[\binom{6}{x_i} p^{x_i} (1-p)^{6-x_i} \right]^{c_i} = 8 \cdot p^{\sum x_i c_i + \sum (6-x_i) c_i} \cdot (1-p)^{\sum (2-x_i)(1-c_i) + \sum (6-x_i)c_i}$$

$$\ell(p) = 8 + \sum x_i \ln p + (\sum (2-x_i) + \sum (6-x_i))(1-p)$$

$$U(p) = \frac{\sum x_i}{p} + \frac{-\sum (2-x_i) + \sum (6-x_i)}{1-p} = 0$$

$$\sum x_i - \sum x_i p - 8m c p = 0 \\ p(m) = \sum x_i$$

$$\hat{p} = \frac{\sum x_i}{m} \Rightarrow \hat{p} = 0,514$$

$$a = \text{all. poč. deti} - \text{all. poč. sljapova} \\ = \text{all. poč. deti} - \text{all. poč. sljapova} = m - \sum x_i \\ \text{all. poč. deti}$$

$$\frac{\text{all. poč. sljapova}}{\text{all. poč. deti}}$$

73) $X_1, \dots, X_m \sim P_0(\lambda)$

$$\text{i)} T_m = \frac{L_m(\lambda_1)}{L_m(\lambda_0)} = \frac{\frac{e^{-m\lambda_1}}{\lambda_1^{\sum x_i}}}{\frac{e^{-m\lambda_0}}{\lambda_0^{\sum x_i}}} = e^{-m(\lambda_1 - \lambda_0)} \left(\frac{\lambda_1}{\lambda_0}\right)^{\sum x_i} \geq c$$

$$-m(\lambda_1 - \lambda_0) + \sum x_i \log \left(\frac{\lambda_1}{\lambda_0}\right) \geq \log c \quad \begin{matrix} \lambda_1 > \lambda_0 \\ \log \frac{\lambda_1}{\lambda_0} > 0 \end{matrix}$$

$$\sum x_i \geq [\log c + m(\lambda_1 - \lambda_0)] / \log \left(\frac{\lambda_1}{\lambda_0}\right) := \underline{x}$$

$$\text{ii)} \arg \underline{x} \stackrel{?}{=} P_{\lambda_0}(\sum x_i \geq \underline{x}) \Rightarrow \underline{x} = \text{quantile}(1-\alpha) P_0(m\lambda_0)$$

$$\text{iii)} \sum x_i \leq \underline{x} \Rightarrow \underline{x} = \text{quantile } P_0(m\lambda_0) \quad \text{punkt. test}$$

$$\text{iv)} \hat{\lambda} = \bar{X} \quad (\text{Gn.SD}) \quad r_m(\bar{X} - \lambda) \xrightarrow{d} N(0, 1) \quad \text{test: } \frac{r_m|\bar{X} - \lambda_0|}{\sqrt{\lambda_0}} \stackrel{?}{\leq} M_{1-\alpha/2}$$

$$\text{resp. } \frac{r_m|\bar{X} - \lambda_0|}{\sqrt{\bar{X}}} \stackrel{?}{\geq} M_{1-\alpha/2} \quad \text{resp. } \frac{m(\bar{X} - \lambda_0)^2}{\bar{X}} \stackrel{?}{\geq} \chi^2_{1-\alpha} \quad \text{asympt. test.}$$

$$\text{v)} \text{LR}_m \stackrel{?}{\geq} \frac{L_m(\bar{X})}{L_m(\lambda_0)} \Rightarrow \text{LR}_m = 2[-m(\bar{X} - \lambda_0) + \sum x_i \log \left(\frac{\bar{X}}{\lambda_0}\right)] \geq \chi^2_{1-\alpha}$$

76) $X_1, \dots, X_m \sim N(\mu_x, \sigma_x^2)$

$$\text{i)} \text{MV: } \hat{\mu} = \bar{X}, \quad \hat{\sigma}^2 = \frac{1}{m} \sum (x_i - \bar{X})^2$$

$$l_m(\hat{\mu}, \hat{\sigma}^2) = c - \frac{m}{2} \log \hat{\sigma}^2 - \frac{1}{2\hat{\sigma}^2} \sum (x_i - \bar{X})^2 = c - \frac{m}{2} \log \hat{\sigma}^2 - \frac{m}{2}$$

$$\text{on } H_0: \mu_x = \mu_0$$

$$\tilde{l}_m(\sigma^2) = c - \frac{m}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum (x_i - \mu_0)^2$$

$$\tilde{U}_m(\sigma^2) = \frac{m}{2\sigma^2} + \frac{\sum (x_i - \mu_0)^2}{2\sigma^4} = 0 \Rightarrow \tilde{\sigma}^2 = \frac{1}{m} \sum (x_i - \mu_0)^2$$

$$\tilde{\ell}(\tilde{\sigma}^2) = c - \frac{m}{2} \log \tilde{\sigma}^2 - \frac{1}{2\tilde{\sigma}^2} \sum (x_i - \mu_0)^2 = c - \frac{m}{2} \log \tilde{\sigma}^2 - \frac{m}{2}$$

$$\text{LR}_m = 2 \left[-\frac{m}{2} \log \hat{\sigma}^2 + \frac{m}{2} \log \tilde{\sigma}^2 \right] = m \log \left[\frac{\tilde{\sigma}^2}{\hat{\sigma}^2} \right] \geq \chi^2_{1-\alpha}$$

$$\text{t-test: } r_m(\bar{X} - \mu) \xrightarrow{d} N(0, \sigma^2) \quad \text{t-met: } \frac{\bar{X} - \mu_0}{\sqrt{\sigma^2}} \stackrel{?}{\sim} t_{m-1}$$

$$\text{ii)} \text{on } H_0: \sigma_x^2 = \sigma_0^2$$

$$\tilde{\ell}_m(\mu) = c - \frac{m}{2} \log \sigma_0^2 - \frac{1}{2\sigma_0^2} \sum (x_i - \mu)^2$$

$$\tilde{U}_m(\mu) = \frac{1}{\sigma_0^2} \sum (x_i - \mu)^2 = 0 \Rightarrow \tilde{\mu} = \frac{1}{m} \sum x_i$$

$$\tilde{\ell}_m(\tilde{\mu}) = c - \frac{m}{2} \log \sigma_0^2 - \frac{1}{2\sigma_0^2} \sum (x_i - \bar{X})^2$$

$$\text{LR}_m = 2 \left[-\frac{m}{2} \log \hat{\sigma}^2 + \frac{m}{2} \log \sigma_0^2 - \frac{m}{2} + \frac{1}{2\sigma_0^2} \sum (x_i - \bar{X})^2 \right] = m \log \left[\frac{\sigma_0^2}{\hat{\sigma}^2} \right] + m \left[\frac{\hat{\sigma}^2}{\sigma_0^2} - 1 \right] \geq \chi^2_{1-\alpha}$$

$$\text{spurk. form} \quad \frac{(m-1)S_m^2}{\sigma_0^2} \stackrel{H_0}{\sim} \chi_{m-1}^2 \quad \frac{(m-1)S_m^2}{\hat{\sigma}^2} = \frac{\sum(x_i - \bar{x})^2}{\sigma_0^2} = \frac{m \hat{\sigma}^2}{\sigma_0^2}$$

$$\text{iii), na } H_0: \quad L_m(\bar{\mu}, \hat{\sigma}^2) = c - \frac{m}{2} \log \sigma_0^2 - \frac{1}{2\sigma_0^2} \sum (x_i - \mu_0)^2 \\ LR_m = 2 \left[-\frac{m}{2} (\log \hat{\sigma}^2 - \log \sigma_0^2) - \frac{m}{2} + \frac{1}{2\sigma_0^2} \sum (x_i - \mu_0)^2 \right] = m \log \left[\frac{\hat{\sigma}^2}{\sigma_0^2} \right] - m + \frac{\sum (x_i - \mu_0)^2}{\sigma_0^2} \\ \geq \chi_2^2(1-\alpha)$$

$$\text{iv), } \text{a. } \text{Bn 63.} \quad r_m \left(\left(\frac{\bar{x}}{\hat{\sigma}^2} \right) - \left(\frac{\mu}{\sigma_0^2} \right) \right) \xrightarrow{d} N_2 \left(\left(\begin{matrix} 0 \\ 0 \end{matrix} \right), \left(\begin{matrix} \sigma^2 & 0 \\ 0 & 2\sigma^4 \end{matrix} \right) \right) \\ \text{andil Vb 4.15: } X \sim N_2(\mu, V), h(V)=2 \Rightarrow (X-\mu)' V^{-1} (X-\mu) \sim \chi_2^2 \\ \text{obne } X \sim J_m(\mu, V), h(V)=r \Rightarrow (X-\mu)' V^{-1} (X-\mu) \sim \chi_r^2$$

$$V := J^{-1}(\mu, \sigma^2)/m \quad V^{-1} = m J(\mu, \sigma^2) \\ m \left(\left(\frac{\bar{x}}{\hat{\sigma}^2} \right) - \left(\frac{\mu}{\sigma_0^2} \right) \right)' J(\mu, \sigma^2) \left(\left(\frac{\bar{x}}{\hat{\sigma}^2} \right) - \left(\frac{\mu}{\sigma_0^2} \right) \right) \stackrel{H_0}{\sim} \chi_2^2 \\ \text{odherd } J(\hat{\mu}, \hat{\sigma}^2) \Rightarrow W_m = m \left[\frac{(\bar{x} - \mu_0)^2}{\hat{\sigma}^2} + \frac{(\hat{\sigma}^2 - \sigma_0^2)^2}{2\hat{\sigma}^4} \right] \geq \chi_2^2(1-\alpha)$$

$$\text{77) } X \sim \text{Mult}(m; p_1, p_2, p_3, p_4) \quad H_0: p_1 = p_2 = p_3 = p_4 = \frac{1}{4} \quad H_1: \neq H_0 \\ L_m(p) = c p_1^{x_1} p_2^{x_2} p_3^{x_3} p_4^{x_4} \quad \text{MV: } \underline{p_1} \text{ 64} \quad P_{\delta} = \sum_{i=1}^m x_i \delta / m \quad p = \sum_x x_i / m \\ L_m(p_0) = c \left(\frac{1}{4} \right)^m \\ LR_m = 2 \left[\sum x_i \log \left(\frac{x_i}{m} \right) - m \log \frac{1}{4} \right] = 2 \sum x_i \log \left[\frac{4x_i}{m} \right] \stackrel{H_0}{\sim} \chi_3^2(1-\alpha) \\ \approx 324,15 > \chi_3^2(1-\alpha) = 7,8 \quad \text{rechne } H_0$$

$$\text{78, } L_m(\lambda, \beta) = \prod \lambda(x_i)^{\lambda_i} e^{-\lambda(x_i)} \quad f_x(x_i) = \frac{\lambda(x_i)^{\lambda_i} \cdot e^{-\sum \lambda(x_i)}}{\pi \lambda_i!} \quad \frac{\partial \lambda}{\partial \lambda} = \lambda \quad \frac{\partial \lambda}{\partial \beta} = \lambda$$

$$\lambda_m(\lambda, \beta) = \sum \lambda_i \log \lambda(x_i) - \sum \lambda(x_i) + c \\ \frac{\partial \lambda_m}{\partial \lambda} = \sum \frac{\lambda_i x_i}{\lambda(x_i)} - \sum \lambda_i = 0 \\ \text{numerig}$$

$$\text{rechne: } \tilde{\lambda}_m(\lambda, 0) = \sum \lambda_i - m \lambda \\ \frac{\partial \tilde{\lambda}}{\partial \lambda} = \sum \frac{\lambda_i}{\lambda} - m = 0 \\ \lambda = \bar{Y}$$

$$\frac{\partial \lambda_m}{\partial \beta} = \sum \frac{\lambda_i x_i}{\lambda(x_i)} - \bar{x} = 0 \\ LR_m = 2 \left[\sum \lambda_i \log \left(\lambda + \beta x_i \right) - \sum \lambda_i \log \bar{\lambda} + m \bar{\lambda} \right] \geq \chi_q^2(1-\alpha)$$

$$\lambda = \frac{-1,85}{0,52} \quad \hat{\lambda}_1 = -0,51 \quad \hat{\lambda}_2 = 1,87$$

$$LR_m = 11,21 > \chi_2^2(0,95) = 5,99 \quad \text{rechne } H_0: (\beta_1, \beta_2) = (0,0)$$

$\chi_1^2(1-\alpha)$