
Statistics

Collection of Formulas

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1 Deskriptive Statistics

1.1 Summary Statistics: Sample

1.1.1 Location

Mode Most frequent value of x_i . Two or more modes are possible (bimodal).

Median

$$\tilde{x}_{0.5} = \begin{cases} x_{((n+1)/2)} & \text{falls } n \text{ ungerade} \\ \frac{1}{2}(x_{(n/2)} + x_{(n/2+1)}) & \text{falls } n \text{ gerade} \end{cases}$$

Quantile

$$\tilde{x}_\alpha = \begin{cases} x_{(k)} & \text{falls } n\alpha \notin \mathbb{N} \\ \frac{1}{2}(x_{(n\alpha)} + x_{(n\alpha+1)}) & \text{falls } n\alpha \text{ ganzzahlig} \end{cases}$$

with

$$k = \min x \in \mathbb{N}, \quad x > n\alpha$$

Minimum/Maximum

$$x_{\min} = \min_{i \in \{1, \dots, N\}} (x_i) \quad x_{\max} = \max_{i \in \{1, \dots, N\}} (x_i)$$

1.1.2 Dispersion

Range

$$R = x_{(n)} - x_{(1)}$$

Interquartile Range

$$d_Q = \tilde{x}_{0.75} - \tilde{x}_{0.25}$$

(Empirical) Variance

$$s^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 = \frac{1}{n} \sum_{i=1}^n x_i^2 - \bar{x}^2$$

Estimates the second centralized moment.

Calculation Rules:

$$\star \operatorname{Var}(aX + b) = a^2 \cdot \operatorname{Var}(X)$$

1.1.3 Concentration

Gini Coefficient

$$G = \frac{2 \sum_{i=1}^n i x_{(i)} - (n+1) \sum_{i=1}^n x_{(i)}}{n \sum_{i=1}^n x_{(i)}} = 1 - \frac{1}{n} \sum_{i=1}^n (v_{i-1} + v_i)$$

with

$$u_i = \frac{i}{n}, \quad v_i = \frac{\sum_{j=1}^i x_{(j)}}{\sum_{j=1}^n x_{(j)}} \quad (u_0 = 0, \quad v_0 = 0)$$

Arithmetic Mean

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

Estimates the expectation $\mu = E[X]$ (first moment).

Calculation Rules:

$$\star E(a + b \cdot X) = a + b \cdot E(X)$$

$$\star E(X \pm Y) = E(X) \pm E(Y)$$

Geometric Mean

$$\bar{x}_G = \sqrt[n]{\sum_{i=1}^n x_i}$$

For growth factors: $\bar{x}_G = \sqrt[n]{\frac{B_n}{B_0}}$

Harmonic Mean

$$\bar{x}_H = \frac{\sum_{i=1}^n w_i}{\sum_{i=1}^n \frac{w_i}{x_i}}$$

$$\star \operatorname{Var}(X \pm Y) = \operatorname{Var}(X) + \operatorname{Var}(Y) + 2\operatorname{Cov}(X, Y)$$

(Empirical) Standard Deviation

$$s = \sqrt{s^2}$$

Coefficient of Variation

$$\nu = \frac{s}{\bar{x}}$$

Average Absolute Deviation

$$e = \frac{1}{n} \sum_{i=1}^n |x_i - \bar{x}|$$

Estimates the first absolute centralized moment.

These are also the values for the Lorenz curve.

$$\text{Range: } 0 \leq G \leq \frac{n-1}{n}$$

Lorenz-Münzner Coefficient (normed G)

$$G^+ = \frac{n}{n-1} G$$

$$\text{Range: } 0 \leq G^+ \leq 1$$

1.1.4 Shape

(Empirical) Skewness

$$\nu = \frac{n}{(n-1)(n-2)} \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{s} \right)^3$$

Estimates the third centralized moment, scaled with $(\sigma^2)^{\frac{2}{3}}$

1.1.5 Dependence

for two nominal variables

χ^2 -Statistic

$$\chi^2 = \sum_{i=1}^k \sum_{j=1}^l \frac{(n_{ij} - \frac{n_{i+}n_{+j}}{n})^2}{\frac{n_{i+}n_{+j}}{n}} = n \left(\sum_{i=1}^k \sum_{j=1}^l \frac{n_{ij}^2}{n_{i+}n_{+j}} - 1 \right)$$

Range: $0 \leq \chi^2 \leq n(\min(k, l) - 1)$

Phi-Coefficient

$$\Phi = \sqrt{\frac{\chi^2}{n}}$$

Range: $0 \leq \Phi \leq \sqrt{\min(k, l) - 1}$

Cramér's V

$$V = \sqrt{\frac{\chi^2}{\min(k, l) - 1}}$$

Range: $0 \leq V \leq 1$

Contingency Coefficient C

$$C = \sqrt{\frac{\chi^2}{\chi^2 + n}}$$

Range: $0 \leq C \leq \sqrt{\frac{\min(k, l) - 1}{\min(k, l)}}$

Corrected Contingency Coefficient C_{corr}

$$C_{corr} = \sqrt{\frac{\min(k, l)}{\min(k, l) - 1}} \cdot \sqrt{\frac{\chi^2}{\chi^2 + n}}$$

Range $0 \leq C_{corr} \leq 1$

Odds-Ratio

$$OR = \frac{ad}{bc} = \frac{n_{ii}n_{jj}}{n_{ij}n_{ji}}$$

Range: $0 \leq OR < \infty$

for two ordinal variables

Gamma (Goodman and Kruskal)

$$\gamma = \frac{K - D}{K + D}$$

$K = \sum_{i < m} \sum_{j < n} n_{ij}n_{mn}$ Number of concordant pairs
 $D = \sum_{i < m} \sum_{j > n} n_{ij}n_{mn}$ Number of reversed pairs

(Empirical) Kurtosis

$$k = \left[n(n+1) \cdot \sum_{i=1}^n \left(\frac{x_i - \bar{x}}{s} \right)^4 - 3(n-1) \right] \cdot \frac{n-1}{(n-2)(n-3)} + 3$$

Estimates the fourth centralized moment, scaled with $(\sigma^2)^2$

Excess

$$\gamma = k - 3$$

Range: $-1 \leq \gamma \leq 1$

Kendall's τ_b

$$\tau_b = \frac{K - D}{\sqrt{(K + D + T_X)(K + D + T_Y)}}$$

with

$T_X = \sum_{i=m} \sum_{j < n} n_{ij}n_{mn}$ Number of ties w.r.t. X

$T_Y = \sum_{i < m} \sum_{j=n} n_{ij}n_{mn}$ Number of ties w.r.t. Y

Range: $-1 \leq \tau_b \leq 1$

Kendall's/Stuart's τ_c

$$\tau_c = \frac{2 \min(k, l)(K - D)}{n^2(\min(k, l) - 1)}$$

Range: $-1 \leq \tau_c \leq 1$

Spearman's Rank Correlation Coefficient

$$\rho = \frac{n(n^2 - 1) - \frac{1}{2} \sum_{j=1}^J b_j(b_j^2 - 1) - \frac{1}{2} \sum_{k=1}^K c_k(c_k^2 - 1) - 6 \sum_{i=1}^n d_i^2}{\sqrt{n(n^2 - 1) - \sum_{j=1}^J b_j(b_j^2 - 1)} \sqrt{n(n^2 - 1) - \sum_{k=1}^K c_k(c_k^2 - 1)}}$$

or

$$\rho = \frac{s_{rg_x} r_{g_y}}{\sqrt{s_{rg_x} r_{g_x} s_{rg_y} r_{g_y}}}$$

Without ties:

$$\rho = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n(n^2 - 1)}$$

with

$d_i = R(x_i) - R(y_i)$ rank difference

Range: $-1 \leq \rho \leq 1$

for two metric variables

Correlation Coefficient (Bravais-Pearson)

$$r = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}} = \frac{s_{xy}}{\sqrt{s_{xx}s_{yy}}}$$

with

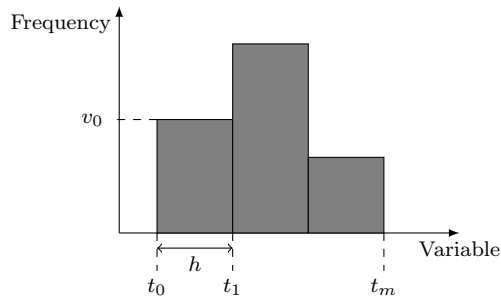
$$\begin{aligned}
S_{xy} &= \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})^2 & \text{or } s_{xy} &= \frac{S_{xy}}{n} \\
S_{xx} &= \sum_{i=1}^n (x_i - \bar{x})^2 & \text{or } s_{xx} &= \frac{S_{xx}}{n} \\
S_{yy} &= \sum_{i=1}^n (y_i - \bar{y})^2 & \text{or } s_{yy} &= \frac{S_{yy}}{n}
\end{aligned}$$

Range: $-1 \leq r \leq 1$

1.2 Tables

1.3 Diagrams

1.3.1 Histogram



sample: $X = \{x_1, x_2, \dots, x_n\}$
 k -th bin: $B_k = [t_k, t_{k+1})$, $k = \{0, 1, \dots, m-1\}$
 Number of observations in the k -th bin: v_k
 bin width: $h = t_{k+1} - t_k, \forall k$

Scott's Rule

$$h^* \approx 3.5\sigma n^{-\frac{1}{3}}$$

For approximately normal distributed data (min. MSE)

1.3.2 QQ-Plot

1.3.3 Scatterplot

2 Probability

2.1 Combinatorics

	without replacement	with replacement
Permutations	$n!$	$\frac{n!}{n_1! \dots n_s!}$
Combinations: without order	$\binom{n}{m}$	$\binom{n+m-1}{m}$
with order	$\binom{n}{m} m!$	n^m

with:

$$n! = n \cdot (n-1) \cdot \dots \cdot 1$$

$$\binom{n}{m} = \frac{n!}{m!(n-m)!}$$

2.2 Probability Theory

Laplace

$$P(A) = \frac{|A|}{|\Omega|}$$

Kolmogorov Axioms mathematical definition of probability

- (1) $0 \leq P(A) \leq 1 \quad \forall A \in \mathcal{A}$
- (2) $P(\Omega) = 1$
- (3) $P(\bigcup_{i=1}^{\infty} A_i) = \sum_{i=1}^{\infty} P(A_i)$
 $\forall A_i \in \mathcal{A}, i = 1, \dots, \infty$ with $A_i \cap A_j = \emptyset$ for $i \neq j$

Implications:

- $P(\bar{A}) = 1 - P(A)$
- $P(\emptyset) = 0$
- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
- $A \subseteq B \Rightarrow P(A) \leq P(B)$

- $P(B) = \sum_{i=1}^n P(B \cap A_i)$, für A_1, \dots, A_n complete decomposition of Ω into pairwise disjoint events

Probability (Mises) frequentist definition of probability

$$P(A) = \lim_{n \rightarrow \infty} \frac{n_A(n)}{n}$$

with n repetitions of a random experiment and $n_A(n)$ events A

Conditional Probability

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad \text{für } P(B) > 0$$

$$\Rightarrow P(A \cap B) = P(B|A)P(A) = P(A|B)P(B)$$

Law of Total Probability

$$P(B) = \sum_{i=1}^n P(B|A_i)P(A_i)$$

Bayes' Theorem

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad \text{for } P(A), P(B) > 0$$

2.3 Random Variables/Vectors

Random Variables $\in \mathbb{R}$

Definition

$$Y : \Omega \rightarrow \mathbb{R}$$

The Subset of possible values for \mathbb{R} is called support.

Notation: Realisations of Y are depicted with lower case letters.

$Y = y$ means, that y is the realisation of Y .

Discrete and Continuous Random Variables

If the support is uncountably infinite, the random variable is called *continuous*, otherwise it is called *discrete*.

- **Density $f(\cdot)$:**

For continuous variables: $P(Y \in [a, b]) = \int_a^b f_Y(y)dy$

For discrete variables the density (and other functions) can be depicted like the corresponding function for continuous variables, if the notation is extended as follows:

$\int_{-\infty}^y f_Y(\tilde{y})d\tilde{y} := \sum_{k:k \leq y} P(Y = k)$. This notation is used.

- **Cumulative Distribution Function $F(\cdot)$:**

$$F_Y(y) = P(Y \leq y)$$

Relationship:

$$F_Y(y) = \int_{-\infty}^y f_Y(\tilde{y})d\tilde{y}$$

Moments

- **Expectation (1. Moment):** $\mu = E(Y) = \int y f_Y(y)dy$

- **Variance (2. centralized Moment):**

$$\sigma^2 = \text{Var}(Y) = E(\{Y - E(Y)\}^2) = \int (y - E(Y))^2 f(y)dy$$

$$\text{Note: } E(\{Y - \mu\}^2) = E(Y^2) - \mu^2$$

Proof:

$$E(\{Y - \mu\}^2) = E(Y^2 - 2Y\mu + \mu^2) = E(Y^2) - 2\mu^2 + \mu^2 = E(Y^2) - \mu^2$$

- **kth Moment:** $E(Y^k) = \int y^k f_Y(y)dy$,

$$\text{k. centralized Moment: } E(\{Y - E(Y)\}^k)$$

Moment Generating Function

$$M_Y(t) = E(e^{tY})$$

$$\text{with } \frac{\partial^k M_Y(t)}{\partial t^k} \Big|_{t=0} = E(Y^k)$$

Cumulant Generating Function $K_Y(t) = \log M_Y(t)$

A random variable is uniquely defined by its moment generating function and vice versa (as long as moments and cumulants are finite).

Stochastic Independence

$$A, B \text{ independent} \Leftrightarrow P(A \cap B) = P(A) \cdot P(B)$$

$$X, Y \text{ independent} \Leftrightarrow f_{XY}(x, y) = f_X(x) \cdot f_Y(y) \quad \forall x, y$$

Random Vectors $\in \mathbb{R}^q$

Density and Cumulative Distribution Function

$$F(y_1, \dots, y_q) = P(Y_1 \leq y_1, \dots, Y_q \leq y_q)$$

$$\begin{aligned} P(a_1 \leq Y_1 \leq b_1, \dots, a_q \leq Y_q \leq b_q) \\ = \int_{a_1}^{b_1} \dots \int_{a_q}^{b_q} f(y_1, \dots, y_q) dy_1 \dots dy_q \end{aligned}$$

Marginal Density

$$f_{Y_1}(y_1) = \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} f(y_1, \dots, y_k) dy_2 \dots dy_k$$

Conditional Density

$$f_{Y_1|Y_2}(y_1|y_2) = \frac{f(y_1, \dots, y_2)}{f(y_2)} \quad \text{for } f(y_2) > 0$$

Iterated Expectation

$$E(Y) = E_X(E(Y|X))$$

Proof:

$$E(Y) = \int y f(y) dy = \int \int y f(y|x) dy f_X(x) dx = E_X(E(Y|X))$$

$$\text{Var}(Y) = E_X(\text{Var}(Y|X)) + \text{Var}_X(E(Y|X))$$

Proof:

$$\begin{aligned} \text{Var}(Y) &= \int (y - \mu_Y)^2 f(y) dy \\ &= \int (y - \mu_Y)^2 f(y|x) f(x) dy dx \\ &= \int (y - \mu_{Y|x} + \mu_{Y|x} - \mu_Y)^2 f(y|x) f(x) dy dx \\ &= \int (y - \mu_{Y|x})^2 f(y|x) f(x) dy dx + \\ &\quad \int (\mu_{Y|x} - \mu_Y)^2 f(y|x) f(x) dy dx + \\ &\quad 2 \int (y - \mu_{Y|x})(\mu_{Y|x} - \mu_Y) f(y|x) f(x) dy dx \\ &= \int \text{Var}(Y|x) f(x) dx + \int (\mu_{Y|x} - \mu_Y)^2 f(x) dx \\ &= E_X(\text{Var}(Y|X)) + \text{Var}_X(E(Y|X)) \end{aligned}$$

2.4 Probability Distributions

2.4.1 Discrete Distributions

Discrete Uniform

$$Y \sim U(\{y_1, \dots, y_k\}), y \in \{y_1, \dots, y_k\}$$

$$P(Y = y_i) = \frac{1}{k}, i = 1, \dots, k$$

$$E(Y) = \frac{k+1}{2}, \text{Var}(Y) = \frac{k^2-1}{12}$$

Binomial Successes in independent trials

$$Y \sim \text{Bin}(n, \pi) \text{ with } n \in \mathbb{N}, \pi \in [0, 1], y \in \{0, \dots, n\}$$

$$P(Y = y|\pi) = \binom{n}{y} \pi^y (1-\pi)^{n-y}$$

$$E(Y|\pi, n) = n\pi, \text{Var}(Y|\pi, n) = n\pi(1-\pi)$$

Poisson Counting model for rare events

only one event at a time, no autocorrelation, mean number of events over time is constant and proportional to length of the considered time interval

$$Y \sim \text{Po}(\lambda) \text{ with } \lambda \in [0, +\infty], y \in \mathbb{N}_0$$

$$P(Y = y|\lambda) = \frac{\lambda^y \exp^{-\lambda}}{y!}$$

$$E(Y|\lambda) = \lambda, \text{Var}(Y|\lambda) = \lambda$$

The model tends to overestimate the variance (Overdispersion).
Approximation of the Binomial for small p

Geometric

$$Y \sim \text{Geom}(\pi) \text{ with } \pi \in [0, 1], y \in \mathbb{N}_0$$

$$P(Y = y|\pi) = \pi(1-\pi)^{y-1}$$

$$E(Y|\pi) = \frac{1}{\pi}, \text{Var}(Y|\pi) = \frac{1-\pi}{\pi^2}$$

Negative Binomial

$$Y \sim \text{NegBin}(\alpha, \beta) \text{ with } \alpha, \beta \geq 0, y \in \mathbb{N}_0$$

$$P(Y = y|\alpha, \beta) = \binom{\alpha+y-1}{\alpha-1} \left(\frac{\beta}{\beta+1}\right)^\alpha \left(\frac{1}{\beta+1}\right)^y$$

$$E(Y|\alpha, \beta) = \frac{\alpha}{\beta}, \text{Var}(Y|\alpha, \beta) = \frac{\alpha}{\beta^2}(\beta+1)$$

2.4.2 Continuous Distributions

Continuous Uniform

$$Y \sim U(a, b) \text{ with } a, b \in \mathbb{R}, a \leq b, y \in [a, b]$$

$$p(y|a, b) = \frac{1}{b-a}$$

$$E(Y|a, b) = \frac{a+b}{2}, \text{Var}(Y|a, b) = \frac{(b-a)^2}{12}$$

Univariate Normal symmetric with μ and σ^2

$$Y \sim N(\mu, \sigma^2) \text{ with } \mu \in \mathbb{R}, \sigma^2 > 0, y \in \mathbb{R}$$

$$p(y|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y-\mu)^2}{2\sigma^2}\right)$$

$$E(Y|\mu, \sigma^2) = \mu, \text{Var}(Y|\mu, \sigma^2) = \sigma^2$$

Multivariate Normal symmetric mit μ_i and Σ

$$Y \sim N(\mu, \Sigma) \text{ with } \mu \in \mathbb{R}^d, \Sigma \in \mathbb{R}^{d \times d} \text{ s.p.d.}, y \in \mathbb{R}^d$$

$$p(y|\mu, \Sigma) = (2\pi)^{-\frac{d}{2}} \det(\Sigma)^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(y-\mu)^T \Sigma^{-1}(y-\mu)\right)$$

$$E(Y|\mu, \Sigma) = \mu, \text{Var}(Y|\mu, \Sigma) = \Sigma$$

Log-Normal

$$Y \sim \text{LogN}(\mu, \sigma^2) \text{ with } \mu \in \mathbb{R}, \sigma^2 > 0, y > 0$$

$$p(y|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2 y}} \exp\left(-\frac{(\log y - \mu)^2}{2\sigma^2}\right)$$

$$E(Y|\mu, \sigma^2) = \exp\left(\mu + \frac{\sigma^2}{2}\right),$$

$$\text{Var}(Y|\mu, \sigma^2) = \exp(2\mu + \sigma^2)(\exp(\sigma^2) - 1)$$

Relationship: $\log(Y) \sim N(\mu, \sigma^2) \Rightarrow Y \sim \text{LogN}(\mu, \sigma^2)$

non-standardized Student's t statistical Tests for μ with unknown (estimated) variance and ν degrees of freedom

$$Y \sim t_\nu(\mu, \sigma^2) \text{ with } \mu \in \mathbb{R}, \sigma^2 > 0, y \in \mathbb{R}$$

$$p(y|\mu, \sigma^2, \nu) = \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})\Gamma(\sqrt{\nu\pi\sigma^2})} \left(1 + \frac{(y-\mu)^2}{\nu\sigma^2}\right)^{-\frac{\nu+1}{2}}$$

$$E(Y|\mu, \sigma^2, \nu) = \mu \text{ for } \nu > 1,$$

$$\text{Var}(Y|\mu, \sigma^2, \nu) = \sigma^2 \frac{\nu}{\nu-2} \text{ for } \nu > 2$$

Relationship: $Y|\theta \sim N(\mu, \frac{\sigma^2}{\theta})$, $\theta \sim \text{Ga}(\frac{\nu}{2}, \frac{\nu}{2}) \Rightarrow Y \sim t_\nu(\mu, \sigma)$
 $t_\nu(\mu, \sigma^2)$ has heavier tails than the normal distribution.
 $t_\infty(\mu, \sigma^2)$ approaches $N(\mu, \sigma^2)$.

Beta

$Y \sim \text{Be}(a, b)$ with $a, b > 0, y \in [0, 1]$

$$p(y|a, b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} y^{a-1} (1-y)^{b-1}$$

$$E(Y|a, b) = \frac{a}{a+b},$$

$$\text{Var}(Y|a, b) = \frac{ab}{(a+b)^2 (a+b+1)},$$

$$\text{mod}(Y|a, b) = \frac{a-1}{a+b-2} \text{ f'ur } a, b > 1$$

Gamma

$Y \sim \text{Ga}(a, b)$ with $a, b > 0, y > 0$

$$p(y|a, b) = \frac{b^a}{\Gamma(a)} y^{a-1} \exp(-by)$$

$$E(Y|a, b) = \frac{a}{b},$$

$$\text{Var}(Y|a, b) = \frac{a}{b^2},$$

$$\text{mod}(Y|a, b) = \frac{a-1}{b} \text{ f'ur } a \geq 1$$

Inverse-Gamma

$Y \sim \text{IG}(a, b)$ with $a, b > 0, y > 0$

$$p(y|a, b) = \frac{b^a}{\Gamma(a)} y^{-a-1} \exp\left(-\frac{b}{y}\right)$$

$$E(Y|a, b) = \frac{b}{a-1} \text{ f'ur } a > 1,$$

$$\text{Var}(Y|a, b) = \frac{b^2}{(a-1)^2 (a-2)} \text{ f'ur } a \geq 2,$$

$$\text{mod}(Y|a, b) = \frac{b}{a+1}$$

Relationship: $Y^{-1} \sim \text{Ga}(a, b) \Leftrightarrow Y \sim \text{IG}(a, b)$

Exponential Time between Poisson events

$Y \sim \text{Exp}(\lambda)$ with $\lambda > 0, y \geq 0$

$$p(y|\lambda) = \lambda \exp(-\lambda y)$$

$$E(Y|\lambda) = \frac{1}{\lambda}, \text{Var}(Y|\lambda) = \frac{1}{\lambda^2}$$

Chi-Squared squared standard normal random variables with ν degrees of freedom

$Y \sim \chi^2(\nu)$ with $\nu > 0, y \in \mathbb{R}$

$$p(y|\nu) = \frac{y^{\frac{\nu}{2}-1} e^{-\frac{y}{2}}}{2^{\frac{\nu}{2}} \Gamma\left(\frac{\nu}{2}\right)}$$

$$E(Y|\nu) = \nu, \text{Var}(Y|\nu) = 2\nu$$

2.4.3 Exponential Family

Definition

The exponential family comprises all distributions, whose density can be written as follows:

$$f_Y(y, \theta) = \exp^{t^T(y)\theta - \kappa(\theta)} h(y)$$

with $h(y) \geq 0$, $t(y)$ vector of the canonical statistic, θ as parameter and $\kappa(\theta)$ the normalising constant.

Normalising Constant

$$1 = \int \exp^{t^T(y)\theta} h(y) dy \exp^{-\kappa(\theta)}$$

$$\Leftrightarrow \kappa(\theta) = \log \int \exp^{t^T(y)\theta} h(y) dy$$

$\kappa(\theta)$ is the cumulant generating function, therefore $\frac{\partial \kappa(\theta)}{\partial \theta} = E(t(Y))$ and $\frac{\partial^2 \kappa(\theta)}{\partial \theta^2} = \text{Var}(t(Y))$

Members

- **Poisson**
- **Geometric**
- **Exponential**
- **Normal** $t(y) = \left(-\frac{y^2}{2}, y\right)^T$, $\theta = \left(\frac{1}{\sigma^2}, \frac{\mu}{\sigma^2}\right)^T$, $h(y) = \frac{1}{\sqrt{2\pi}}$, $\kappa(\theta) = \frac{1}{2} \left(-\log \frac{1}{\sigma^2} + \frac{\mu^2}{\sigma^2}\right)$
- **Gamma**
- **Chi-Squared**
- **Beta**

2.5 Limit Theorems

Law of Large Numbers

Central Limit Theorem

$$Z_n \xrightarrow{d} N(0, \sigma^2)$$

with $Z_n = \sum_{i=1}^n \frac{Y_i}{\sqrt{n}}$ and Y_i i.i.d. with expectation 0 and variance σ^2

Proof:

For normal random variables $Z \sim N(\mu, \sigma^2)$: $K_Z(t) = \mu t + \frac{1}{2}\sigma^2 t^2$. The first two derivatives $\left. \frac{\partial^k K_Z(t)}{\partial t^k} \right|_{t=0}$ are μ and σ . All other moments are zero.

For $Z_n = (Y_1 + Y_2 + \dots + Y_n)/\sqrt{n}$:

$$\begin{aligned} M_{Z_n}(t) &= E\left(e^{t(Y_1+Y_2+\dots+Y_n)/\sqrt{n}}\right) \\ &= E\left(e^{tY_1/\sqrt{n}} \cdot e^{tY_2/\sqrt{n}} \cdot \dots \cdot e^{tY_n/\sqrt{n}}\right) \\ &= E\left(e^{tY_1/\sqrt{n}}\right) E\left(e^{tY_2/\sqrt{n}}\right) \dots E\left(e^{tY_n/\sqrt{n}}\right) \\ &= M_Y^n(t/\sqrt{n}) \end{aligned}$$

Analogously: $K_{Z_n}(t) = nK_Y(t/\sqrt{n})$.

$$\begin{aligned} \left. \frac{\partial K_{Z_n}(t)}{\partial t} \right|_{t=0} &= \frac{n}{\sqrt{n}} \left. \frac{\partial K_Y(t)}{\partial t} \right|_{t=0} = \sqrt{n}\mu \\ \left. \frac{\partial^2 K_{Z_n}(t)}{\partial t^2} \right|_{t=0} &= \frac{n}{n} \left. \frac{\partial^2 K_Y(t)}{\partial t^2} \right|_{t=0} = \sigma^2 \end{aligned}$$

Using the Taylor Expansion, we can write $K_{Z_n}(t) = 0 + \sqrt{n}\mu t + \frac{1}{2}\sigma^2 t^2 + \dots$, where the terms in \dots are tending to 0 as $n \rightarrow \infty$.

Therefore: $K_{Z_n}(t) \xrightarrow{n \rightarrow \infty} K_Z(t)$ with $Z \sim N(\sqrt{n}\mu, \sigma^2)$.

3 Inference

3.1 Method of Moments

Die theoretischen Momente werden durch die empirischen geschätzt:

$$E_{\hat{\theta}_{MM}}(Y^k) = m_k(y_1, \dots, y_n)$$

Für die Exponentialfamilie gilt: $\hat{\theta}_{MM} = \hat{\theta}_{ML}$

3.2 Loss Functions

Verlust

$$\mathcal{L} : \mathcal{T} \times \Theta \rightarrow \mathbb{R}^+$$

mit Parameterraum $\Theta \subset \mathbb{R}$, $t \in \mathcal{T}$ mit $t : \mathbb{R}^n \rightarrow \mathbb{R}$ eine Statistik, die den Parameter θ schätzt. Es gilt: $\mathcal{L}(\theta, \theta) = 0$

- **absoluter Verlust (L1):** $\mathcal{L}(t, \theta) = |t - \theta|$
- **quadratischer Verlust (L2):** $\mathcal{L}(t, \theta) = (t - \theta)^2$

Da θ unbekannt ist, ist der Verlust eine theoretische Größe. Zudem ist er die Realisation einer Zufallsvariable, da er von einer konkreten Stichprobe abhängt.

Risiko

$$\begin{aligned} R(t(\cdot), \theta) &= E_{\theta}(\mathcal{L}(t(Y_1, \dots, Y_n), \theta)) \\ &= \int_{-\infty}^{\infty} \mathcal{L}(t(Y_1, \dots, Y_n), \theta) \prod_{i=1}^n f(y_i; \theta) dy_i \end{aligned}$$

Minimax-Regel

Das Risiko beruht immer noch auf dem wahren Parameter θ . Vorsichtige Schätzung: Wähle θ so, dass das Risiko maximal wird, und danach $t(\cdot)$ so, dass das Risiko minimiert wird:

$$\hat{\theta}_{\minimax} = \arg \min_{t(\cdot)} \left(\max_{\theta \in \Theta} R(t(\cdot); \theta) \right)$$

Es wird der Worst Case minimiert.

Mean Squared Error (MSE)

$$\begin{aligned} MSE(t(\cdot), \theta) &= E_{\theta}(\{t(Y) - \theta\}^2) \\ &= \text{Var}_{\theta}(t(Y_1, \dots, Y_n)) + \text{Bias}^2(t(\cdot); \theta) \end{aligned}$$

mit $\text{Bias}(t(\cdot); \theta) = E_{\theta}(t(Y_1, \dots, Y_n)) - \theta$

Proof:

Sei $\mathcal{L}(t, \theta) = (t - \theta)^2$

$$\begin{aligned} R(t(\cdot), \theta) &= E_{\theta}(\{t(Y) - \theta\}^2) \\ &= E_{\theta}(\{t(Y) - E_{\theta}(t(Y)) + E_{\theta}(t(Y)) - \theta\}^2) \\ &= E_{\theta}(\{t(Y) - E_{\theta}(t(Y))\}^2) + E_{\theta}(\{E_{\theta}(t(Y)) - \theta\}^2) \\ &\quad + 2E_{\theta}(\{t(Y) - E_{\theta}(t(Y))\}\{E_{\theta}(t(Y)) - \theta\}) \\ &= \text{Var}_{\theta}(t(Y_1, \dots, Y_n)) + \text{Bias}^2(t(\cdot); \theta) + 0 \end{aligned}$$

Cramér-Rao-Ungleichung

$$MSE(\hat{\theta}, \theta) \geq Bias^2(\hat{\theta}, \theta) + \frac{\left(1 + \frac{\partial Bias(\hat{\theta}, \theta)}{\partial \theta}\right)^2}{I(\theta)}$$

Proof:

Für ungebiaste Schätzer: $\theta = E_{\theta}(\hat{\theta}) = \int t(y)f(y; \theta)dy$

$$\begin{aligned} 1 &= \int t(y) \frac{\partial f(y; \theta)}{\partial \theta} dy \\ &= \int t(y) \frac{\partial \log f(y; \theta)}{\partial \theta} f(y; \theta) dy \\ &= \int t(y) s(y; \theta) f(y; \theta) dy \\ &= \int (t(y) - \theta) (s(y; \theta) - 0) f(y; \theta) dy \quad \begin{array}{l} \text{1. Bartlett-Gleichung} \\ E_{\theta}(s(y; \theta)) = 0 \end{array} \\ &= \text{Cov}_{\theta}(t(Y); s(Y)) \\ &\geq \sqrt{\text{Var}_{\theta}(t(Y))} \sqrt{\text{Var}_{\theta}(s(Y))} \quad \text{Cauchy-Schwarz} \\ &= \sqrt{MSE(t(Y); \theta)} \sqrt{I(\theta)} \end{aligned}$$

Kullback-Leibler-Divergenz Vergleich von Verteilungen

$$KL(t, \theta) = \int_{-\infty}^{\infty} \log \frac{f(\tilde{y}; \theta)}{f(\tilde{y}; t)} f(\tilde{y}; \theta) d\tilde{y}$$

Die KL-Divergenz ist keine Distanz, da sie nicht symmetrisch ist. Sie ist 0 für $t = \theta$ und größer/gleich 0 sonst.

3.3 Maximum Likelihood (ML)

Voraussetzungen

- $Y_i \sim f(y; \theta)$ i.i.d.
- $\theta \in \mathbb{R}^p$
- $f(\cdot; \theta)$ Fisher-regulär:
 - $\{y : f(y; \theta) > 0\}$ unabhängig von θ
 - Möglicher Parameterraum Θ ist offen
 - $f(y; \theta)$ zweimal differenzierbar
 - $\int \frac{\partial}{\partial \theta} f(y; \theta) dy = \frac{\partial}{\partial \theta} \int f(y; \theta) dy$

Zentrale Funktionen

- **Likelihood** $L(\theta; y_1, \dots, y_n)$: $\prod_{i=1}^n f(y_i; \theta)$
- **log-Likelihood** $l(\theta; y_1, \dots, y_n)$:
 $\log L(\theta; y_1, \dots, y_n) = \sum_{i=1}^n \log f(y_i; \theta)$
- **Score** $s(\theta; y_1, \dots, y_n)$: $\frac{\partial l(\theta; y_1, \dots, y_n)}{\partial \theta}$
- **Fisher-Information** $I(\theta)$: $-E_{\theta} \left(\frac{\partial s(\theta; Y)}{\partial \theta} \right)$
- **beobachtete Fisher-Information** $I_{obs}(\theta)$:
 $-E_{\theta} \left(\frac{\partial s(\theta; y)}{\partial \theta} \right)$

Eigenschaften der Score-Funktion

erste Bartlett-Gleichung:

$$E(s(\theta; Y)) = 0$$

Proof:

Folgt aus $\log(x) \leq x - 1 \forall x \geq 0$, mit Gleichheit für $x = 1$.

$R_{KL}(t(\cdot), \theta)$ wird durch den MSE approximiert.

Proof:

$$\begin{aligned} R_{KL}(t(\cdot), \theta) &= \\ &= \int_{-\infty}^{\infty} \mathcal{L}_{KL}(t(Y_1, \dots, Y_n), \theta) \prod_{i=1}^n f(y_i; \theta) dy_i \\ &= \int \int \log \frac{f(\tilde{y}; \theta)}{f(\tilde{y}; t)} f(\tilde{y}; \theta) d\tilde{y} \prod_{i=1}^n f(y_i; \theta) dy_i \\ &= \int \int (\log f(\tilde{y}; \theta) - \log f(\tilde{y}; t)) f(\tilde{y}; \theta) d\tilde{y} - \prod_{i=1}^n f(y_i; \theta) dy_i \\ &\approx - \int \underbrace{\left(\int \frac{\partial \log f(\tilde{y}; \theta)}{\partial \theta} f(\tilde{y}; \theta) d\tilde{y} \right)}_0 (t - \theta) \prod_{i=1}^n f(y_i; \theta) dy_i \\ &\quad + \frac{1}{2} \int \underbrace{\left(- \int \frac{\partial^2 \log f(\tilde{y}; \theta)}{\partial \theta^2} f(\tilde{y}; \theta) d\tilde{y} \right)}_{I(\theta)} (t - \theta)^2 \prod_{i=1}^n f(y_i; \theta) dy_i \end{aligned}$$

Wobei der letzte Schritt durch die Taylorreihe approximiert wurde: $\log f(\tilde{y}, t) \approx \log f(\tilde{y}, \theta) + \frac{\partial \log f(\tilde{y}, \theta)}{\partial \theta} (t - \theta) + \frac{1}{2} \frac{\partial^2 \log f(\tilde{y}, \theta)}{\partial \theta^2} (t - \theta)^2$

Proof:

$$\begin{aligned} 1 &= \int f(y; \theta) dy \\ 0 &= \frac{\partial 1}{\partial \theta} = \int \frac{\partial f(y; \theta)}{\partial \theta} dy = \int \frac{\partial f(y; \theta) / \partial \theta}{f(y; \theta)} f(y; \theta) dy \\ &= \int \frac{\partial}{\partial \theta} \log f(y; \theta) f(y; \theta) dy = \int s(\theta; y) f(y; \theta) dy \end{aligned}$$

zweite Bartlett-Gleichung:

$$\text{Var}_{\theta}(s(Y; \theta)) = E_{\theta} \left(- \frac{\partial^2 \log f(Y; \theta)}{\partial \theta^2} \right) = I(\theta)$$

Proof:

$$\begin{aligned} 0 &= \frac{\partial 0}{\partial \theta} = \frac{\partial}{\partial \theta} \int \frac{\partial}{\partial \theta} \log f(y; \theta) f(y; \theta) dy \quad \text{siehe oben} \\ &= \int \left(\frac{\partial^2}{\partial \theta^2} \log f(y; \theta) \right) f(y; \theta) dy \\ &\quad + \int \frac{\partial \log f(y; \theta)}{\partial \theta} \frac{\partial f(y; \theta)}{\partial \theta} dy \\ &= E_{\theta} \left(\frac{\partial^2}{\partial \theta^2} \log f(Y; \theta) \right) \\ &\quad + \int \frac{\partial \log f(y; \theta)}{\partial \theta} \frac{\partial \log f(y; \theta)}{\partial \theta} f(y; \theta) dy \end{aligned}$$

$$\Leftrightarrow E_{\theta}(s(\theta; Y)s(\theta; Y)) = E_{\theta} \left(- \frac{\partial^2}{\partial \theta^2} \log f(Y; \theta) \right)$$

Bartletts zweite Gleichung gilt dann, weil $E(s(\theta; Y)) = 0$

ML-Schätzer

$$\hat{\theta}_{ML} = \arg \max l(\theta; y_1, \dots, y_n)$$

für Fisher-reguläre Verteilungen: $\hat{\theta}_{ML}$ hat asymptotisch die kleinstmögliche Varianz, gegeben durch die

Cramér-Rao-Ungleichung, $s(\hat{\theta}_{ML}; y_1, \dots, y_n) = 0$

$$\hat{\theta} \stackrel{a}{\sim} N(\theta, I^{-1}(\theta))$$

Der ML-Schätzer ist invariant: $\hat{\gamma} = g(\hat{\theta})$ wenn $\gamma = g(\theta)$.

Proof:

$$\gamma = g(\theta) \Leftrightarrow \theta = g^{-1}(\gamma)$$

Für die Loglikelihood von γ an der Stelle $\hat{\theta}$ gilt:

$$\frac{\partial l(g^{-1}(\hat{\gamma}))}{\partial \gamma} = \frac{\partial g^{-1}(\gamma)}{\partial \gamma} \underbrace{\frac{\partial l(\hat{\theta})}{\partial \theta}}_{=0} = 0$$

Die Fisher-Information ist dann $\frac{\partial \theta}{\partial \gamma} I(\theta) \frac{\partial \theta}{\partial \gamma}$

Proof:

$$\begin{aligned} I_{\gamma}(\gamma) &= -E \left(\frac{\partial^2 l(g^{-1}(\hat{\gamma}))}{\partial \gamma^2} \right) = -E \left(\frac{\partial}{\partial \gamma} \left(\frac{\partial g^{-1}(\gamma)}{\partial \gamma} \frac{\partial l(\theta)}{\partial \theta} \right) \right) \\ &= -E \left(\underbrace{\frac{\partial^2 g^{-1}(\gamma)}{\partial \gamma^2} \frac{\partial l(\theta)}{\partial \theta}}_{\text{Erwartungswert 0}} + \frac{\partial g^{-1}(\gamma)}{\partial \gamma} \frac{\partial^2 l(\theta)}{\partial \theta^2} \frac{\partial g^{-1}(\gamma)}{\partial \gamma} \right) \\ &= \frac{\partial g^{-1}(\gamma)}{\partial \gamma} I(\theta) \frac{\partial g^{-1}(\gamma)}{\partial \gamma} = \frac{\partial \theta}{\partial \gamma} I(\theta) \frac{\partial \theta}{\partial \gamma} \end{aligned}$$

Delta-Regel: $\gamma \stackrel{a}{\sim} N(\hat{\gamma}, \frac{\partial \theta}{\partial \gamma} I^{-1}(\theta) \frac{\partial \theta}{\partial \gamma})$

Numerical computation of the ML estimate Fisher-Scoring as statistical version of the Newton-Raphson procedure

1. Initialize $\theta_{(0)}$

3.4 Suffizienz und Consistency

Suffizienz

Eine Statistik $t(y_1, \dots, y_n)$ ist suffizient für θ , wenn die bedingte Verteilung $f(y_1, \dots, y_n | t_0 = t(y_1, \dots, y_n); \theta)$ unabhängig von θ ist.

Neyman-Kriterium:

$$t(Y_1, \dots, Y_n) \text{ suffizient} \Leftrightarrow f(y; \theta) = h(y)g(t(y); \theta)$$

2. Repeat: $\theta_{(t+1)} := \theta_{(t)} + I^{-1}(\theta_{(t)})s(\theta_{(t)}; y)$
3. Stop if $\|\theta_{(t+1)} - \theta_{(t)}\| < \tau$; return $\hat{\theta}_{ML} = \theta_{(t+1)}$

Proof:

$$\begin{aligned} 0 &= s(\hat{\theta}_{ML}; y) \stackrel{\text{Taylor Series}}{\approx} s(\theta; y) + \frac{\partial s(\theta; y)}{\partial \theta} (\hat{\theta}_{ML} - \theta) \Leftrightarrow \\ \hat{\theta}_{ML} &\approx \theta - \left(\frac{\partial s(\theta; y)}{\partial \theta} \right)^{-1} s(\theta; y) \approx \theta - I^{-1}(\theta) s(\theta; y) \end{aligned}$$

As $\frac{\partial s(\theta; y)}{\partial \theta}$ is often complicated, its expectation $I(\theta)$ is used.

The second part in 2 can be weighted with a step size δ or $\delta(t) \in (0, 1)$, e.g. to ensure convergence.

If $I(\theta)$ can't be analytically derived, simulation from $f(y; \theta_{(t)})$ can be used. For the exponential family, step 2 then changes to $\theta_{(t+1)} := \theta_{(t)} + \hat{\text{Var}}_{\theta_{(t)}}(t(Y))^{-1} E_{\theta_{(t)}}(t(Y))$ as the ML estimate is the expectation.

Log Likelihood Ratio

$$lr(\theta, \hat{\theta}) := l(\hat{\theta}) - l(\theta) = \log \frac{L(\hat{\theta})}{L(\theta)}$$

$$\text{with } 2 \cdot lr(\theta, \hat{\theta}) \stackrel{a}{\sim} \chi_1^2$$

Proof:

$$\begin{aligned} l(\theta) &\stackrel{\text{Taylor Series}}{\approx} l(\hat{\theta}) + \underbrace{\frac{\partial l(\hat{\theta})}{\partial \theta}}_{=0} (\theta - \hat{\theta}) + \frac{1}{2} \underbrace{\frac{\partial^2 l(\hat{\theta})}{\partial \theta^2}}_{\approx I^{-1}(\hat{\theta})s(\hat{\theta}; Y)} (\theta - \hat{\theta})^2 \\ &\approx l(\hat{\theta}) - \frac{1}{2} \frac{s^2(\theta, Y)}{I(\theta)} \end{aligned}$$

$s(\theta, Y)$ is asymptotically normal.

If $\theta \in \mathbb{R}^p$ the corresponding distribution is χ_p^2 .

Proof:

“ \Rightarrow ”:

$$f(y; \theta) = \underbrace{f(y|t=t(y); \theta)}_{h(y)} \underbrace{f_t(t|y; \theta)}_{g(t(y); \theta)}$$

“ \Leftarrow ”:

$$f_t(t; \theta) = \int_{t=t(y)} f(y; \theta) dy = \int_{t=t(y)} h(y) g(t; \theta) dy$$

Damit:

$$f(y|t=t(y); \theta) = \frac{f(y, t=t(y); \theta)}{f_t(t, \theta)} = \begin{cases} \frac{h(y)g(t; \theta)}{g(t; \theta)} & t = t(y) \\ 0 & \text{sonst} \end{cases}$$

Minimalsuffizienz:

$t(\cdot)$ ist suffizient und $\forall \tilde{t}(\cdot) \exists h(\cdot)$ s.t. $t(y) = h(\tilde{t}(y))$

(schwache) Konsistenz

$$MSE(\hat{\theta}, \theta) \xrightarrow{n \rightarrow \infty} 0 \Rightarrow \hat{\theta} \text{ konsistent}$$

3.5 Confidence Intervals

Definition

$[t_l(Y), t_r(Y)]$ Konfidenzintervall

\Leftrightarrow

$$P_\theta((t_l(Y) \leq \theta \leq t_r(Y))) \geq 1 - \alpha$$

mit $1 - \alpha$ Konfidenzlevel und α Signifikanzlevel

Pivotal Statistik

$g(Y; \theta)$ pivotal

\Leftrightarrow

Verteilung von $g(Y; \theta)$ unabhängig von θ

Approximativ pivotale Statistik

$$g(\hat{\theta}; \theta) = \frac{\hat{\theta} - \theta}{\sqrt{\text{Var}(\hat{\theta})}} \approx N(0, 1)$$

mit $\hat{\theta} = t(Y) \approx N(\theta, \text{Var}(\hat{\theta}))$

$$KI = \left[\hat{\theta} - z_{1-\frac{\alpha}{2}} \sqrt{\text{Var}(\hat{\theta})}, \hat{\theta} + z_{1-\frac{\alpha}{2}} \sqrt{\text{Var}(\hat{\theta})} \right]$$

Proof:

$$1 - \alpha \approx P\left(z_{\frac{\alpha}{2}} \leq \frac{\hat{\theta} - \theta}{\sqrt{\text{Var}(\hat{\theta})}} \leq z_{1-\frac{\alpha}{2}}\right)$$

4 Statistical Hypothesis Testing

4.1 Significance, Relevance, p-Value

Significance Test

Assuming two states H_0 and H_1 and two corresponding decisions "H₀" and "H₁", a decision rule (a threshold $c \in \mathbb{R}$ for the test statistic $T(X)$) is constructed s. t.:

$$P(\text{"H}_1\text{"} | H_0) = 1 - \alpha$$

	"H ₀ "	"H ₁ "
H ₀	$1 - \alpha$ (correct)	α (type I error)
H ₁	β (type II error)	$1 - \beta$ (correct)

The *power* of a test is $P(\text{"H}_1\text{"} | H_1) = 1 - \beta$

4.2 Tests for One Sample

Normal Distribution $X_i \stackrel{iid}{\sim} N(\mu, \sigma^2)$

Test for μ , known σ^2 (Simple Gauss-Test)

$H_0: \mu = \mu_0$ vs. $H_1: \mu \neq \mu_0$

$$T(X) = \frac{\bar{X} - \mu_0}{\sigma} \stackrel{H_0}{\sim} N(0, 1)$$

Test for μ , unknown σ^2 (Simple t-Test)

$H_0: \mu = \mu_0$ vs. $H_1: \mu \neq \mu_0$

$$T(X) = \frac{\bar{X} - \mu_0}{\hat{\sigma}/\sqrt{n}} \stackrel{H_0}{\sim} t_{n-1}$$

with $\hat{\sigma} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (Y_i - \bar{Y})^2}$

ML Estimate $\hat{\theta} \stackrel{a}{\sim} N(\theta, I^{-1}(\theta))$

Wald Test

$H_0: \theta = \theta_0$ vs. $H_1: \theta \neq \theta_0$

$$T(X) = |\hat{\theta} - \theta_0| \stackrel{H_0}{\sim} N(0, I^{-1}(\theta_0))$$

As $\hat{\theta}$ converges to θ_0 under H_0 , it can also be used to calculate the variance: $I^{-1}(\hat{\theta})$.

Score Test

$H_0: \theta = \theta_0$ vs. $H_1: \theta \neq \theta_0$

$$T(X) = |s(\theta_0; y)| \stackrel{H_0}{\sim} N(0, I(\theta_0))$$

Advantage compared to the Wald Test: $\hat{\theta}$ does not have to be calculated.

Likelihood Ratio Test

$H_0: \theta = \theta_0$ vs. $H_1: \theta \neq \theta_0$

$$T(X) = 2(l(\hat{\theta}) - l(\theta_0)) \stackrel{H_0}{\sim} \chi_1^2$$

Neyman-Pearson Test

$H_0: \theta = \theta_0$ vs. $H_1: \theta = \theta_1$

$$T(X) = l(\theta_0) - l(\theta_1)$$

For a given significance level α , the Neyman Pearson Test is the most powerful test for comparing two estimates for θ .

Proof:

Decision rule of the NP-Test: $\varphi^* = \begin{cases} 1 & \text{if } \frac{f(y; \theta_0)}{f(y; \theta_1)} \leq e^c \\ 0 & \text{otherwise} \end{cases}$

Need to show: $P(\varphi(Y)=1 | \theta_1) \leq P(\varphi^*(Y)=1 | \theta_1) \forall \varphi$

$$P(\varphi^*=1 | \theta_1) - P(\varphi=1 | \theta_1) =$$

$$= \int \{\varphi^*(y) - \varphi(y)\} f(y; \theta_1) dy$$

$$\geq \frac{1}{e^c} \int_{\varphi^*=1} \{\varphi^*(y) - \varphi(y)\} f(y; \theta_0) dy \quad f(y; \theta_1) \geq \frac{f(y; \theta_0)}{e^c}$$

$$+ \frac{1}{e^c} \int_{\varphi^*=0} \{\varphi^*(y) - \varphi(y)\} f(y; \theta_0) dy \quad f(y; \theta_1) \leq \frac{f(y; \theta_0)}{e^c}$$

$$= \frac{1}{e^c} \int \{\varphi^*(y) - \varphi(y)\} f(y; \theta_0) dy = 0$$

$$\text{As } \alpha = \int \varphi^*(y) f(y; \theta_0) dy = \int \varphi(y) f(y; \theta_0) dy$$

4.3 Tests for Two Samples

4.4 Tests for Goodness of Fit

4.5 Multiple Tests

5 Regression

5.1 Assumptions

5.2 Procedure

5.2.1 Ordinary Least Squares (OLS)

KQ-Schätzer (Einfachregression)

$$\hat{\beta}_1 = \frac{Cov(x, y)}{Var(x)} = \frac{S_{xy}}{S_{xx}} = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}} \cdot \sqrt{\frac{S_{yy}}{S_{xx}}} = r \sqrt{\frac{S_{yy}}{S_{xx}}}$$

Proof:

$$Cov(x, y) = Cov(x, \hat{\beta}_0 + \hat{\beta}_1 x) = \hat{\beta}_1 Var(x) \\ \iff \hat{\beta}_1 = \frac{Cov(x, y)}{Var(x)}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

Proof:

$$E[y] = E[\hat{\beta}_0 + \hat{\beta}_1 x + \hat{e}] \iff \hat{\beta}_0 = E[y] - \hat{\beta}_1 E[x]$$

5.3 Model

5.3.1 Simple Linear Regression

Theoretisches Modell

$$y_i = \beta_0 + \beta_1 x_i + u_i$$

Empirisches Modell

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i + e_i$$

Eigenschaften der Regressionsgeraden

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i = \bar{y} + \hat{\beta}_1 (x_i - \bar{x})$$

$$\hat{e}_i = y_i - \hat{y}_i = y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i)$$

$$= y_i - (\bar{y} + \hat{\beta}_1 (x_i - \bar{x}))$$

$$\sum_{i=1}^n \hat{e}_i = \sum_{i=1}^n y_i - \sum_{i=1}^n \bar{y} - \hat{\beta}_1 \sum_{i=1}^n (x_i - \bar{x})$$

$$= n\bar{y} - n\bar{y} - \hat{\beta}_1 (n\bar{x} - n\bar{x}) = 0$$

$$\bar{\hat{y}} = \frac{1}{n} \sum_{i=1}^n \hat{y}_i = \frac{1}{n} (n\bar{y} + \hat{\beta}_1 (n\bar{x} - n\bar{x})) = \bar{y}$$

5.3.2 Multivariate Linear Regression

5.4 Analysis of Variances (ANOVA)

$$SS_{Total} = SS_{Explained} + SS_{Residual}$$

mit

$$SS_{Total} = \sum_{i=1}^n (y_i - \bar{y})^2$$

$$SS_{Explained} = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2$$

$$SS_{Residual} = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n e_i^2 = S_{yy} - \hat{\beta}^2 S_{xx}$$

5.5 Goodness of Fit

5.5.1 Bestimmtheitsmaß

$$R^2 = \frac{SS_{Explained}}{SS_{Total}} = 1 - \frac{SS_{Residual}}{SS_{Total}} = r^2$$

Range: $0 \leq R^2 \leq 1$

6 Classification

6.1 Diskriminant Analysis (Bayes)

7 Cluster Analysis

8 Bayesian Statistics

8.1 Basics

Bayes-Formel

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad \text{für } P(A), P(B) > 0$$

oder allgemeiner:

$$\begin{aligned} f(\theta|X) &= \frac{f(X|\theta) \cdot f(\theta)}{\int f(X|\tilde{\theta})f(\tilde{\theta})d\tilde{\theta}} \\ &= C \cdot f(X|\theta) \cdot f(\theta) \quad \text{wähle } C \text{ so, dass } \int f(\theta|X) = 1 \\ &\propto f(X|\theta) \cdot f(\theta) \end{aligned}$$

Punktschätzer

Kredibilitätsintervall

Sensitivitätsanalyse

Prädiktive Posteriori

$$f(x_Z|\mathbf{x}) = \int f(x_Z, \lambda|\mathbf{x})d\lambda = \int f(x_Z|\lambda)p(\lambda|\mathbf{x})$$

Uninformative Priori

$f(\theta) = \text{const.}$ für $\theta > 0$, damit: $f(\theta|X) = C \cdot f(X|\theta)$
(Da $\int f(\theta) = 1$ so nicht möglich, ist das eigentlich keine Dichte)

Konjugierte Priori

Wenn die Priori- und die Posteriori-Verteilung denselben Typ hat für eine gegebene Likelihoodfunktion, so nennt man sie konjugiert.

Binomial-Beta-Modell:

- Priori $\sim Be(\alpha, \beta)$
- $X \sim Binom(n, p, k)$
- Posteriori $\sim Be(\alpha + k, \beta + n - k)$

8.2 Markov Chain / Monte Carlo