
Statistics

Collection of Formulas

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1 Descriptive Statistics

1.1 Summary Statistics

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

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

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

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

(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

$$\gamma = k - 3$$

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

$$\rho = \frac{srg_x rgy}{\sqrt{srg_x rgy srg_y rgy}}$$

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

$$S_{xy} = \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})^2 \quad \text{or } s_{xy} = \frac{S_{xy}}{n}$$

$$S_{xx} = \sum_{i=1}^n (x_i - \bar{x})^2 \quad \text{or } s_{xx} = \frac{S_{xx}}{n}$$

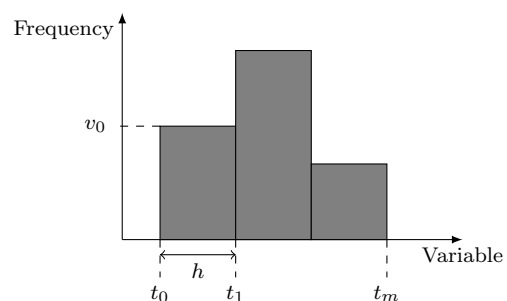
$$S_{yy} = \sum_{i=1}^n (y_i - \bar{y})^2 \quad \text{or } s_{yy} = \frac{S_{yy}}{n}$$

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)

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:

- $P(\bar{A}) = 1 - P(A)$
- $P(\emptyset) = 0$
- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
- $A \subseteq B \Rightarrow P(A) \leq P(B)$
- $P(B) = \sum_{i=1}^n P(B \cap A_i)$, for A_i, \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

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

Stochastic Independence

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

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

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:

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

- **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):**

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

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

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

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

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

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).

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

Density and Cumulative Distribution Function

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

$$P(a_1 \leq Y_1 \leq b_1, \dots, a_q \leq Y_q \leq b_q)$$

$$= \int_{a_1}^{b_1} \dots \int_{a_q}^{b_q} f(y_1, \dots, y_q) dy_1 \dots dy_q$$

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

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

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

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

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

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

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

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

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

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

Univariate Normal symmetric with μ and σ^2

$Y \sim N(\mu, \sigma^2)$ 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 with μ_i and Σ

$Y \sim N(\mu, \Sigma)$ 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

$Y \sim \text{LogN}(\mu, \sigma^2)$ 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

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

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

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

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

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 $N(\mu, \sigma^2)$.

2.4.3 Exponential Family

Definition

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

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

Beta

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

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

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

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

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

Gamma

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

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

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

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

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

Inverse-Gamma

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

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

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

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

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

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 $\nu > 0, y \in \mathbb{R}$

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

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

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

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

• Exponential

• Normal $t(y) = \left(-\frac{y}{2}, y\right)^T$, $\theta = \left(\frac{1}{\sigma^2}, \frac{\mu}{\sigma^2}\right)^T$, $h(y) = \frac{1}{\sqrt{2\pi}}$, $\kappa(\theta) = \frac{1}{2} \left(-\log \frac{1}{\sigma^2} + \frac{\mu^2}{\sigma^2}\right)$

• Gamma

• Chi-Squared

• Beta

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 towards 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

The theoretical moments are estimated by their empirical counterparts:

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

For the exponential family: $\hat{\theta}_{MM} = \hat{\theta}_{ML}$

3.2 Loss Functions

Loss

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

with parameter space $\Theta \subset \mathbb{R}$, $t \in \mathcal{T}$ with $t : \mathbb{R}^n \rightarrow \mathbb{R}$ a statistic, that estimates the parameter θ , $\mathcal{L}(\theta, \theta) = 0$ holds

- **absolute loss (L1):** $\mathcal{L}(t, \theta) = |t - \theta|$
- **quadratic loss (L2):** $\mathcal{L}(t, \theta) = (t - \theta)^2$

As θ is unknown, the loss is a theoretical measure. Additionally, it is the realisation of a random variable as it is dependent on a concrete sample.

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 Approach

The risk still depends on the true parameter θ . Tentative estimation: Choose θ , so that the risk is maximal and then $t(\cdot)$, so that the risk is minimized (minimizing the worst case):

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

Mean Squared Error (MSE)

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

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

Proof:

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

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

Cramér-Rao Inequality

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

Proof:

For unbiased estimates: $\theta = E_{\theta}(\hat{\theta}) = \int t(y)f(y; \theta)dy$

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

Kullback-Leibler Divergence Comparing distributions

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

The KL divergence is not a distance as it is not symmetric. It is 0 for $t = \theta$ and ≥ 0 otherwise.

Proof:

Follows from $\log(x) \leq x - 1 \forall x \geq 0$, with equality for $x = 1$.

$R_{KL}(t(\cdot), \theta)$ is approximated by the MSE.

Proof:

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

The last step is approximated by the Taylor Expansion:
 $\log f(\tilde{y}, t) \approx \log f(\tilde{y}, \theta) + \frac{\partial \log f(\tilde{y}, \theta)}{\partial \theta} (t - \theta) + \frac{1}{2} \frac{\partial^2 \log f(\tilde{y}, \theta)}{\partial \theta^2} (t - \theta)^2$

3.3 Maximum Likelihood (ML)

Prerequisites

- $Y_i \sim f(y; \theta)$ i.i.d.
- $\theta \in \mathbb{R}^p$
- $f(\cdot; \theta)$ Fisher-regular:
 - $\{y : f(y; \theta) > 0\}$ independent of θ
 - Parameter space Θ is open
 - $f(y; \theta)$ twice differentiable
 - $\int \frac{\partial}{\partial \theta} f(y; \theta) dy = \frac{\partial}{\partial \theta} \int f(y; \theta) dy$

Central Functions

- **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** $I(\theta)$: $-\mathbb{E}_\theta \left(\frac{\partial s(\theta; Y)}{\partial \theta} \right)$
- **observed Fisher-Information** $I_{obs}(\theta)$: $-\mathbb{E}_\theta \left(\frac{\partial s(\theta; y)}{\partial \theta} \right)$

Attributes of the Score-Function

first Bartlett-Equation:

$$\mathbb{E}(s(\theta; Y)) = 0$$

Proof:

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

second Bartlett-Equation:

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

Proof:

$$\begin{aligned} 0 &= \frac{\partial 0}{\partial \theta} = \frac{\partial}{\partial \theta} \int \frac{\partial}{\partial \theta} \log f(y; \theta) f(y; \theta) dy \quad \text{see above} \\ &= \int \left(\frac{\partial^2}{\partial \theta^2} \log f(y; \theta) \right) f(y; \theta) dy \\ &\quad + \int \frac{\partial \log f(y; \theta)}{\partial \theta} \frac{\partial f(y; \theta)}{\partial \theta} dy \\ &= \mathbb{E}_\theta \left(\frac{\partial^2}{\partial \theta^2} \log f(Y; \theta) \right) \\ &\quad + \int \frac{\partial \log f(y; \theta)}{\partial \theta} \frac{\partial \log f(y; \theta)}{\partial \theta} f(y; \theta) dy \end{aligned}$$

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

Bartlett's second equation holds then as $\mathbb{E}(s(\theta; Y)) = 0$

ML-Estimate

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

for Fisher-regular distributions: $\hat{\theta}_{ML}$ has asymptotically the smallest variance, given by the Cramér-Rao inequality,
 $s(\hat{\theta}_{ML}; y_1, \dots, y_n) = 0$

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

If the true model is unknown, the distribution is
 $\hat{\theta} \stackrel{a}{\sim} N(\theta, I^{-1}(\theta)V(\theta)I^{-1}(\theta))$ with $V(\theta)$ variance of the score function.

The ML-estimate is invariant: $\hat{\gamma} = g(\hat{\theta})$ if $\gamma = g(\theta)$.

Proof:

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

For the log-likelihood of γ at the location $\hat{\theta}$ holds:

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

Then, the Fisher information is $\frac{\partial \theta}{\partial \gamma} I(\theta) \frac{\partial \theta}{\partial \gamma}$

Proof:

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

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

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

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

$$0 = s(\hat{\theta}_{ML}; y) \stackrel{\text{Taylor}}{\approx}_{\text{Series}} s(\theta; y) + \frac{\partial s(\theta; y)}{\partial \theta} (\hat{\theta}_{ML} - \theta) \Leftrightarrow$$

$$\hat{\theta}_{ML} \approx \theta - \left(\frac{\partial s(\theta; y)}{\partial \theta} \right)^{-1} s(\theta; y) \approx \theta - I^{-1}(\theta)s(\theta; y)$$

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 $\theta_{(t+1)} := \theta_{(t)} + \hat{\text{Var}}_{\theta_{(t)}}(t(Y))^{-1} \mathbb{E}_{\theta_{(t)}}(t(Y))$ as the ML estimate is the expectation.

Log Likelihood Ratio

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

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

Proof:

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

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

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

Relation to Kullback-Leibler divergence

$$\hat{\theta}_{ML} = \arg \min \text{KL}(g, f)$$

with f distributional model used and g true model

Proof:

$$\begin{aligned} KL(g, f) &= \int \log \frac{g(y)}{f(y)} g(y) dy \\ &= \int \log(g(y)) g(y) dy - \int \log(f(y)) g(y) dy \end{aligned}$$

To minimize that, the second component needs to be maximized. Its derivative is $\int s(\theta; y) g(y) dy = E_g(s(\theta; Y)) = 0$

3.4 Consistency and Sufficiency

(Weak) Consistency

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

Proof:

$$P(|\hat{\theta} - E_{\hat{\theta}}| \geq \delta) \leq \frac{\text{Var}_{\theta}(\hat{\theta})}{\delta^2} \text{ using the inequality of Chebyshev}$$

and $MSE(t(\cdot), \theta) = \text{Var}_{\theta}(t(Y_1, \dots, Y_n)) + \text{Bias}^2(t(\cdot); \theta)$

Statistic

$$t : \mathbb{R}^n \rightarrow \mathbb{R}$$

$t(Y_1, \dots, Y_n)$ depends on sample size n and is a random variable

Suffizienz

A statistic $t(y_1, \dots, y_n)$ is sufficient for θ , if the conditional distribution $f(y_1, \dots, y_n | t_0 = t(y_1, \dots, y_n); \theta)$ is independent of θ .

Neyman criterion:

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

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 ”:

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

Therefore:

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

Minimal Sufficiency:

$t(\cdot)$ is sufficient and $\forall \tilde{t}(\cdot) \exists h(\cdot)$ s.t. $t(y) = h(\tilde{t}(y))$

4 Statistical Hypothesis Testing

4.1 Significance and Confidence Intervals

Significance Test

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

$$P(\text{“}H_1\text{”}|H_0) \leq \alpha$$

	“ H_0 ”	“ H_1 ”
H_0	$1 - \alpha$ (correct)	α (type I error)
H_1	β (type II error)	$1 - \beta$ (correct)

Power concerns the type II error

$$power = P(\text{“}H_1\text{”}|H_1) = 1 - \beta$$

p-Value measures the amount of evidence against H_0

$$p - value \leq \alpha \Leftrightarrow \text{“}H_0\text{”}$$

Confidence Interval

$$[t_l(Y), t_r(Y)] \text{ Confidence Interval}$$

$$\Leftrightarrow$$

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

with $1 - \alpha$ confidence level und α significance level

Corresponding Test

$$\theta \notin [t_l(y), t_r(y)] \Leftrightarrow \text{“}H_1\text{”}$$

Specificity or True Negative Rate (1–empirical type I error)

$$TNR = \frac{\#TN}{\#N} = \frac{\#TN}{\#TN + \#FP}$$

Sensitivity or True Positive Rate, Recall (empirical power)

$$TPR = \frac{\#TP}{\#P} = \frac{\#TP}{\#TP + \#FN}$$

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 Goodness of Fit

Discrete (Chi-Squared)

$H_0: X_i \sim F_0$ vs. $H_1: X_i \sim F \neq F_0$

$$T(X) = \sum_{k=1}^K \frac{(n_k - l_k)^2}{l_k} \stackrel{H_0}{\sim} \chi_{K-1-p}^2$$

with the following contingency table:

	1	2	...	K
observed	n_1	n_2	...	n_K
expected under H_0	l_1	l_2	...	l_K

$l_k > 5$ and $l_k > n - 5$ for the χ_{K-1-p}^2 -distribution to hold, F_0 needs to be known, but its p parameters can be estimated. The test can be applied to discretized continuous variables.

Continuous (Kolmogorov-Smirnov Test)

$H_0: X_i \sim F_0$ vs. $H_1: X_i \sim F \neq F_0$

$$T(X) = \sup_x |F_n(x) - F(x; \theta)| \stackrel{H_0}{\sim} KS$$

with the distribution function $F(x; \theta)$ and the empirical counterpart $F_n(x) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{X_i \leq x\}}$

Proof:

$$\begin{aligned} P(\sup_x |F_n(x) - F(x; \theta)| \leq t) &= \\ &= P(\sup_y |F^{-1}(y; \theta) - x| \leq t) \quad \begin{matrix} x \in [0, 1], x = F^{-1}(y; \theta) \\ F(F^{-1}(y; \theta); \theta) = y \end{matrix} \\ &\stackrel{*}{=} P(\sup_y |\frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{U_i \leq y\}} - y| \leq t) \quad \text{with } U_i \sim U(0, 1) \\ *F_n(F^{-1}(y; \theta)) &= \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{X_i \leq F^{-1}(y; \theta)\}} = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{F(y; \theta) \leq y\}} \end{aligned}$$

For an estimated parameter the distribution of $T(X)$ is not independent of F_0 : $T(X) \stackrel{H_0}{\sim} KS$ only holds asymptotically.

Pivotal Statistic

$g(Y; \theta)$ pivotal

\Leftrightarrow

Distribution of $g(Y; \theta)$ independent of θ

Approximative Pivotal Statistic

$H_0: X_i \sim F$ pivotal vs. $H_1: X_i \sim F$ not pivotal

$$g(\hat{\theta}; \theta) = \frac{\hat{\theta} - \theta}{\sqrt{\text{Var}(\hat{\theta})}} \stackrel{H_0}{\sim} N(0, 1)$$

with $\hat{\theta} = t(Y) \stackrel{H_0}{\sim} N(\theta, \text{Var}(\hat{\theta}))$

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

Proof:

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

4.4 Multiple Tests

Family-Wise Error Rate (FWER) as p -value $\sim U(0, 1)$

For m tests:

$$\alpha \leq P(\cup_{k=1}^m (p_k \leq \alpha) | H_{0k}, k = 1, \dots, m) \leq m\alpha$$

$$FWER := P(\exists k : "H_1 k" | \forall k : H_{0k})$$

Bonferroni Adjustment

$$\alpha_B = \frac{\alpha}{m}$$

Šidák Adjustment only for independent tests

$$\alpha_S = 1 - (1 - \alpha)^{1/m}$$

Proof:

$$\begin{aligned} \alpha &\stackrel{!}{=} P(\cup_{k=1}^m (p_k \leq \alpha) | H_{0k}, k = 1, \dots, m) \\ &= 1 - (1 - \alpha)^{1/m} \end{aligned}$$

Holm's Procedure also takes power into account

Order the p -values: $p_{(1)} \leq \dots \leq p_{(m)}$

Step $x \in \mathbb{N}^+$: if $p(x) > \frac{\alpha}{m+1-x}$ reject H_{01} to H_{0x} and stop, else move on to step $x + 1$.

False Discovery Rate (FDR) balances type I and II errors, especially for $n \ll m$ problems

$$FDR = E\left(\frac{\# "H_1" | H_0}{\# "H_1"}\right)$$

Order the p -values: $p_{(1)} \leq \dots \leq p_{(m)}$, choose $\alpha \in (0, 1)$

j is largest index s. t. $p(j) \leq \alpha j/m$, reject all H_{0i} for $i \leq j$

It can be shown that $FDR \leq m_0 \alpha / m$, with $m_0 = \# H_0$

5 Regression

5.1 Models

5.1.1 Simple Linear Model

Theoretical Model

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

Empirical Model

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

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

Assumptions

- **Independent Observations** y_1, \dots, y_n are independent
- **Linearity of the Mean** $E(Y|x) = \beta_0 + \beta_1 x$ or $E(e|x) = 0$
- **Constant Variation** $Var(Y|x) = \sigma^2$

For the normal linear model:

- **Normality** $e|x \sim N(0, \sigma^2)$; $Y|x \sim N(\hat{y}, \sigma^2)$

Attributes of the Regression Line

$$\begin{aligned}\hat{y}_i &= \hat{\beta}_0 + \hat{\beta}_1 x_i = \bar{y} + \hat{\beta}_1 (x_i - \bar{x}) \\ \hat{e}_i &= y_i - \hat{y}_i = y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i) \\ &= y_i - (\bar{y} + \hat{\beta}_1 (x_i - \bar{x})) \\ \sum_{i=1}^n \hat{e}_i &= \sum_{i=1}^n y_i - \sum_{i=1}^n \bar{y} - \hat{\beta}_1 \sum_{i=1}^n (x_i - \bar{x}) \\ &= n\bar{y} - n\bar{y} - \hat{\beta}_1 (n\bar{x} - n\bar{x}) = 0 \\ \bar{\hat{y}} &= \frac{1}{n} \sum_{i=1}^n \hat{y}_i = \frac{1}{n} (n\bar{y} + \hat{\beta}_1 (n\bar{x} - n\bar{x})) = \bar{y}\end{aligned}$$

5.1.2 Multivariate Linear Model

Theoretical Model

$$Y = X\beta + u$$

Empirical Model

$$Y = X\hat{\beta} + e$$

$$\hat{Y} = X\hat{\beta}$$

$$y = (y_1, \dots, y_n)^T, e = (e_1, \dots, e_n)^T, X = \begin{pmatrix} 1 & x_{11} & \dots & x_{1p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \dots & x_{np} \end{pmatrix}$$

Assumptions

- **Independent Observations** y_1, \dots, y_n are independent
- **Linearity of the Mean** $E(Y|x_{1:p}) = X\beta$ or $E(e|x_{1:p}) = 0$
- **Constant Variation** $Var(Y|x) = \sigma^2$

Estimates (OLS)

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

Proof:

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

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

Proof:

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

The estimates are the same as for the ML procedure.

Estimates (ML) $Y|x \sim N(\beta_0 + \beta_1 x, \sigma^2)$

$$\begin{aligned}\hat{\beta}_0 &= \frac{1}{n} \sum_{i=1}^n y_i - \frac{1}{n} \sum_{i=1}^n x_i \hat{\beta}_1 \\ \hat{\beta}_1 &= \frac{\sum_{i=1}^n x_i (y_i - \hat{\beta}_0)}{\sum_{i=1}^n x_i^2} \\ \hat{\sigma}^2 &= \frac{1}{n} \sum_{i=1}^n (y_i - \hat{\beta}_0 - x_i \hat{\beta}_1)^2\end{aligned}$$

The β -estimates are the same as for the OLS procedure.

Proof:

$$l(\beta_0, \beta_1, \sigma^2) = \sum_{i=1}^n \left\{ -\frac{1}{2} \log \sigma^2 - \frac{1}{2} \frac{(y_i - \beta_0 - \beta_1 x_i)^2}{\sigma^2} \right\}$$

For the normal linear model:

- **Normality** $e_i|x_{1:p} \sim N(0, \sigma^2)$; $Y|x \sim N(\hat{y}, \sigma^2)$

Estimates (ML) $Y|x_{1:p} \sim N(X\beta, \sigma^2)$

$$\begin{aligned}\hat{\beta} &= (X^T X)^{-1} X^T y \\ Var(\hat{\beta}) &= \sigma^2 (X^T X)^{-1} = I^{-1}(\beta)\end{aligned}$$

Proof:

$$l(\beta, \sigma^2) = -\frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} (y - X\beta)^T (y - X\beta)$$

The estimates are the same as for the OLS procedure.

$\hat{\beta}$ is the **Best Linear Unbiased Estimator**

Proof:

Unbiased because of the Gauß-Markov Theorem: $E(\hat{\beta}) = (X^T X)^{-1} X^T E(Y|X) = (X^T X)^{-1} X^T X \beta = \beta$

$$\hat{\sigma}^2 = \frac{1}{n} (y - X\hat{\beta})^T (y - X\hat{\beta}); \quad \hat{\beta} \sim N(\beta, \sigma^2 (X^T X)^{-1})$$

The ML-estimate for σ^2 is biased.

Proof:

$H := X(X^T X)^{-1} X^T$ hat matrix; $HH = H = H^T$ (idempotent)

$$\begin{aligned} E((Y - X\hat{\beta})^T (Y - X\hat{\beta})) &= E((Y^T (I_n - H))^T ((I_n - H)Y)) \\ &= E(\text{tr}(Y^T (I_n - H)Y)) \\ &= E(\text{tr}((I_n - H)YY^T)) \\ &= \text{tr}((I_n - H)E(YY^T)) \\ &= \text{tr}((I_n - H)E(X\beta\beta^T X^T + \sigma^2 I_n)) \\ &= \sigma^2 \text{tr}((I_n - H)) \\ &= \sigma^2 (n - p) \end{aligned}$$

$$s^2 = \frac{1}{n - p} (y - X\hat{\beta})^T (y - X\hat{\beta}); \quad \hat{\beta} \sim t_{n-p}(\beta, s^2 (X^T X)^{-1})$$

with s an unbiased estimator

5.1.3 Bayesian Linear Model

Prior flat prior

$$f_{\beta, \sigma^2}(\beta, \sigma^2) = \frac{1}{\sigma^2}$$

Posterior

Resulting posterior:

$$f_{\text{post}}(\beta, \sigma^2 | y) \propto (\sigma^2)^{-\frac{n}{2} + 1} e^{-\frac{1}{2\sigma^2} (y - X\beta)^T (y - X\beta)}$$

Note: $f_{\text{post}}(\beta, \sigma^2 | y) = f(\beta | \sigma^2, y) f(\sigma^2 | y)$

$$\begin{aligned} \beta | \sigma^2, y &\sim N(\hat{\beta}, \sigma^2 (X^T X)^{-1}) \\ \sigma^2 | y &\sim \text{IG}\left(\frac{n - p}{2}, \frac{s^2 (n - p)}{2}\right) \\ \beta | y &\sim t_{n-p}(\hat{\beta}, s^2 (X^T X)^{-1}) \end{aligned}$$

The two distributions for β mirror the results for $\hat{\beta}$ in the linear model.

5.1.4 Quantile Regression

Prediction Interval range of $1 - \alpha$ fraction of the data

$$\text{Var}(\hat{Y} | x_{1:p}) = \text{Var}(X\hat{\beta}) + \sigma^2$$

Determined by estimation variance (usually captured by confidence intervals) plus residual variance.

Quantile

$$Q(\tau) = \inf\{y : F(y) \geq \tau\}$$

If F is invertible: $Q(\tau) = F^{-1}(\tau)$, $\tau \in (0, 1)$

Model

$$Q(\tau | x_{1:p}) = X\beta$$

For median regression: $\hat{\beta} = \arg \min \sum_{i=1}^n |y_i - x_i^T \beta|$

In general:

$$\hat{Q}(\tau) = \arg \min_{\beta} \left(\sum_{i=1}^n \delta_{\tau}(y_i - x_i^T \beta) \right)$$

with check function $\delta_{\tau}(y) = y(\tau - \mathbb{1}_{\{y < 0\}})$

Proof:

$$Q(\tau) = \arg \min_q E(\delta_{\tau}(Y - q))$$

$$= \arg \min_q \left\{ (\tau - 1) \int_{-\infty}^q (y - q) f(y) dy + \tau \int_q^{\infty} (y - q) f(y) dy \right\}$$

Differentiating w.r.t. q gives $(\tau - 1) \int_{-\infty}^q f(y) dy - \tau \int_q^{\infty} f(y) dy = (1 - \tau)F(q) - \tau(1 - F(q)) = F(q) - \tau$

Estimates

The estimates for β can be computed with linear programming and are normally distributed with mean β .

5.1.5 Flexible Regression

Assumptions

- **Independent Observations** y_1, \dots, y_n are independent
- **Constant Variation** $\text{Var}(Y|x) = \sigma^2$
- **Normality** $e_i | x_{1:p} \sim N(0, \sigma^2)$; $Y|x \sim N(\hat{y}, \sigma^2)$

Knot Placement

- equidistant
- based on quantiles (more structure where data is dense)
- all data points plus penalization

Penalized Regression Splines

$$\|y - X\beta\|^2 + \lambda \int_{x_1}^{x_n} [f''(x)]^2 dx = \|y - X\beta\|^2 + \lambda \beta^T D \beta$$

$$l_p(\beta, \sigma^2, \lambda) = l(\beta, \sigma^2) - \frac{\lambda}{2\sigma^2} \beta^T D \beta$$

$$\hat{\beta} = (X^T X + \lambda D)^{-1} X^T y$$

Difference Penalty

- first order: $\beta^T D \beta = \sum_{j=1}^p (\beta_{j+1} - \beta_j)^2$
- second order: $\beta^T D \beta = \sum_{j=1}^p (\beta_{j+1} - 2\beta_j + \beta_{j-1})^2$

Choosing λ Model complexity

5.1.6 Generalized Regression

Assumptions

- **Independent Observations** y_1, \dots, y_n are independent
- **Linearity of the Mean** $E(Y|x_{1:p}) = X\beta$ or $E(e|x_{1:p}) = 0$
- **Exponential Family** $Y|x \sim \exp\{t(y)\theta(x) - \kappa(\theta(x))\} h(y)$

Link Function

Linear predictor $\eta = X\beta$; $\mu = \frac{\partial \kappa(\theta)}{\partial \theta} = E(t(Y); \theta)$

$$\mu = g^{-1}(\eta)$$

If $\lambda = 0$, *canonical link*:

$$g(\theta) = \eta$$

$$\dim(\lambda) = \text{tr} \left\{ (X^T X + \lambda D)^{-1} (X^T X) \right\}$$

$$AIC(\lambda) = \text{fit}(\lambda) + 2\dim(\lambda)$$

Numerically complex. Alternative: **Bayes**

$$\beta \sim N(0, \sigma_\beta^2 D^-) \text{ with } (D^-)^- = D \text{ (generalized inverse)}$$

$$\log f(\beta, \sigma^2; \sigma_\beta^2 | y) \propto l(\beta, \sigma^2) - \frac{rk(D^-)}{2} \log(\sigma_\beta^2) - \frac{1}{2\sigma_\beta^2} \beta^T D^- \beta$$

As $\lambda = \frac{1}{\sigma_\beta^2}$, marginal posterior for σ_β^2 can be derived. E.g. set λ to the posterior mode estimate.

- score function: $s(\beta) = X^T (t(y) - E(t(Y); \eta))$

- estimate $\hat{\beta} = X^T E(t(Y); \hat{\eta}) = X^T t(y)$

- Fisher matrix $I(\beta) = X^T W X$
with W diagonal and $W_{ii} = \frac{\partial^2 \kappa(\eta_i)}{\partial \eta^2} = \text{Var}(t(Y_i), \eta_i)$

Examples:

- **Logistic**: $\text{logit} P(Y_i=1|x_i) = \log \frac{P(Y_i=1|x_i)}{1-P(Y_i=1|x_i)} = \eta$
 $\text{Var}(Y_i|x_i) = P(Y_i=1|x_i) \cdot (1-P(Y_i=1|x_i))$

- **Poisson**: $\log E(Y_i|x_i) = \eta$
 $\text{Var}(Y_i|x_i) = E(Y_i|x_i) = e^\eta$

5.1.7 Weighted Regression

Different Precision variance heterogeneity: $e_i \sim N(0, \sigma_i^2)$

$$l(\beta, \sigma^2) = -\frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2 (y - X\beta)^T (y - X\beta)}$$

with $W = \text{diag}(\frac{1}{\sigma_1^2}, \dots, \frac{1}{\sigma_n^2})$ and $a_i = \frac{\sigma_i^2}{\sigma^2}$

$$\hat{\beta}_{ML} = (X^T W X)^{-1} (X^T W y)$$

$$\text{Var}(\hat{\beta}_{ML}) = \sigma^2 (X^T W X)^{-1}$$

Different Group Representation

$$Y_i | x_{i,1:p}, z_i \sim N(x_{i,1:p} \beta_{z_i}, \sigma^2)$$

with z_i indicating group affiliation

5.2 Analysis of Variances (ANOVA)

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

with

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

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

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

5.3 Goodness of Fit

5.3.1 Coefficient of Determination

$$R^2 = \frac{SS_{Explained}}{SS_{Total}} = 1 - \frac{SS_{Residual}}{SS_{Total}} = r^2 \quad \Bigg| \quad \text{Range: } 0 \leq R^2 \leq 1$$

6 Bayesian Statistics

6.1 Basics

Bayes Theorem

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

or more general:

$$\begin{aligned} f_{post}(\theta|X) &= \frac{f(X|\theta) \cdot f_\theta(\theta)}{\int f(X|\tilde{\theta})f_\theta(\tilde{\theta})d\tilde{\theta}} \\ &= C \cdot f(X|\theta) \cdot f_\theta(\theta) \quad \text{choose } C \text{ so that } \int f(\theta|X) = 1 \\ &\propto f(X|\theta) \cdot f_\theta(\theta) \end{aligned}$$

Point Estimates

$$\hat{\theta}_{postmean} = E_0(\vartheta|x) = \int_{\vartheta \in \Theta} \vartheta f_\theta(\vartheta|x) d\vartheta$$

$$\hat{\theta}_{postmode} = \operatorname{argmax}_{\vartheta} f_\theta(\vartheta, x)$$

$$\hat{\theta}_{Bayesrisk} = \operatorname{argmin}_{t(\cdot)} R_{Bayes}(t(\cdot))$$

with Bayes risk: $R_{Bayes}(t(\cdot)) = \int_{\Theta} R(t(\cdot), \vartheta) f_\theta(\vartheta) d\vartheta$

$$\hat{\theta}_{postBayesrisk} = \operatorname{argmin}_{t(\cdot)} R_{postBayes}(t(\cdot)|y)$$

with posterior Bayes risk:

$$R_{postBayes}(t(\cdot)|y) = \int L(t(y), \vartheta) f_\theta(\vartheta|y) = E_{\theta|y}(L(t(y), \theta)|y)$$

Credibility Interval

$$P_\theta(\theta \in [t_l(y), t_r(y)] | y) = \int_{t_l(y)}^{t_r(y)} f_\theta(\vartheta|y) d\vartheta = 1 - \alpha$$

- symmetric: $\int_{-\infty}^{t_l(y)} f_\theta(\vartheta|y) d\vartheta = \int_{t_r(y)}^{\infty} f_\theta(\vartheta|y) d\vartheta = \frac{\alpha}{2}$
- highest density: $HDI = \theta | f_\theta(\theta|y) \geq c$, choose c s. t. $\int_{\vartheta \in HDI(y)} f_\theta(\vartheta|y) d\vartheta = 1 - \alpha$

Bayes Factor evidence contained in data for M_1 vs. M_2

$$\frac{P(M_1|y)}{P(M_0|y)} = \underbrace{\frac{f(y|M_1)}{f(y|M_0)}}_{\text{Bayes Factor}} \frac{P(M_1)}{P(M_0)}$$

with marginal likelihood $f(y|M_i) = \int f(y|\vartheta) f_\theta(\vartheta|M_i) d\vartheta$

Priors

Flat (uninformative) Prior

$f_\theta(\theta) = \text{const.}$ for $\theta > 0$, therefore: $f(\theta|X) = C \cdot f(X|\theta)$

As $\int f_\theta(\theta) = 1$ not possible like this, this is not a real density.

Changes for transformations of the parameter.

Proof: For $\gamma = g(\theta)$: $f_\gamma(\gamma) = f_\theta(g^{-1}(\gamma)) \left| \frac{\partial g^{-1}(\gamma)}{\partial \gamma} \right|$

No prior is truly uninformative.

Jeffrey's Prior

Remains unchanged for transformations of the parameter.

For Fisher-regular distributions: $f(\theta) \propto \sqrt{I_\theta(\theta)}$

Proof:

For $\gamma = g(\theta)$ and $f_\theta(\theta) = \sqrt{I_\theta(\theta)}$:

$$f_\gamma(\gamma) \propto f_\theta(g^{-1}(\gamma)) \left| \frac{\partial g^{-1}(\gamma)}{\partial \gamma} \right| \propto \sqrt{\frac{\partial g^{-1}(\gamma)}{\partial \gamma} I_\theta(g^{-1}(\gamma)) \frac{\partial g^{-1}(\gamma)}{\partial \gamma}} = \sqrt{I_\gamma(\gamma)}$$

Maximizes the information gained from the data (under appropriate regulatory conditions), i. e. maximizes

$$E(KL(f_\theta(\cdot), f_{post}(\cdot, x)))$$

Empirical Bayes

Let the prior depend on a hyper-parameter: $f_\theta(\theta, \gamma)$

Choose γ s. t. $L(\gamma) = f(x; \gamma) = \int f(x; \vartheta) f_\theta(\vartheta, \gamma) d\vartheta$ is maximal.

Using the data to find the prior contradicts the Bayes approach of incorporating prior knowledge.

Hierarchical Prior

$$x|\theta \sim f(x; \theta); \quad \theta|\gamma \sim f_\theta(\theta, \gamma); \quad \gamma \sim f_\gamma(\gamma)$$

Conjugate Priors

If Prior and Posterior belong to the same family of distributions for a given likelihood function, they are called conjugate.

Examples:

Prior	Likelihood	Posterior
$\pi \sim \text{Be}(\alpha, \beta)$	$\text{Bin}(n, \pi)$	$\text{Be}(\alpha+k, \beta+n-k)$
$\mu \sim \text{N}(\gamma, \tau^2)$	$\text{N}(\mu, \sigma^2)$	$\text{N}(\cdot, \cdot) \xrightarrow{n \rightarrow \infty} \text{N}(\bar{y}, \frac{\sigma^2}{n})$
$\sigma^2 \sim \text{IG}(\alpha, \beta)$	$\text{N}(\mu, \sigma^2)$	$\text{IG}(\alpha + \frac{n}{2}, \beta + \frac{1}{2} \sum_{i=1}^n (y_i - \mu)^2)$
$\lambda \sim \text{Ga}(\alpha, \beta)$	$\text{Po}(\lambda)$	$\text{Ga}(\alpha+n\bar{y}, \beta+n)$

6.2 Numerical Methods for the Posterior

Numerical Integration here: trapezoid approximation

$$\begin{aligned} &\int_{\Theta} f(y|\vartheta) f_\theta(\vartheta) d\vartheta \approx \\ &\sum_{k=1}^K \frac{f(y; \theta_k) f_\theta(\theta_k) + f(y; \theta_{k-1}) f_\theta(\theta_{k-1})}{2} (\theta_k - \theta_{k-1}) \end{aligned}$$

only normalisation constant unknown, works well for one-dimensional integrals

Laplace Approximation

$$\int_{\Theta} f(y|\vartheta) f_\theta(\vartheta) d\vartheta \approx f(y; \hat{\theta}_P) f_\theta(\hat{\theta}_P) (2\pi)^{p/2} |J_P(\hat{\theta}_P)|^{\frac{1}{2}}$$

with the one-dimensional $J_P := -\frac{\partial^2 l_{(n)}(\theta, y)}{\partial \theta^2} - \frac{\partial^2 \log f_\theta(\theta)}{\partial \theta^2}$ Fisher information considering the prior, $\hat{\theta}_P$ posterior mode estimate s. t. $s_{P, \theta}(\hat{\theta}_P) = 0$

Proof:

For n independent samples:

$$f_{post}(\theta|y) = \frac{\prod_{i=1}^n f(y_i|\theta)f_{\theta}(\theta)}{\int \prod_{i=1}^n f(y_i|\theta)f_{\theta}(\theta)d\theta}$$

Denominator: $\int e^{\{\sum_{i=1}^n \log f(y_i|\theta) + \log f_{\theta}(\theta)\}} d\theta =$

$$\int e^{\{l(\theta;y) + \log f_{\theta}(\theta)\}} d\theta \approx \int e^{\{l_P(\hat{\theta}_P) - \frac{1}{2} J_P(\hat{\theta}_P)(\vartheta - \hat{\theta}_P)^2\}} d\vartheta$$

Resembles the normal distribution, therefore the inverse of the normalisation constant can be calculated, which gives the inverse of the Laplace approximation in the univariate case.

Works well for large n and is numerically simple also for big p .

Monte Carlo Approximations

The denominator can be written as $E_{\theta}(f(y;\theta)) =$

$\int_{\Theta} f(y|\vartheta)f_{\theta}(\vartheta)d\vartheta$, which can be estimated by the arithmetic mean for a sample of $\theta_1, \dots, \theta_N$, which needs to be drawn from the prior. The following methods to draw from non-standard distributions can be used for that.

• Inverse CDF

$F(X)$ known. Since $F(x) = u$, $F^{-1}(u) = x$, $u \sim U(0, 1)$

1. Draw $u \sim U(0, 1)$
2. Compute $F^{-1}(u)$ to get a value x

Proof:

$$P(x \leq y) = P(F^{-1}(u) \leq y) = P(u \leq F(y)) = F(y)$$

• Rejection Sampling

An umbrella distribution $g(x)$ can be found s. t.

$$\frac{f(x)}{g(x)} \leq M \quad \forall x \text{ with } f(x) > 0 \text{ when } g(x) > 0$$

1. Draw candidate $y \sim g(x)$
2. Acceptance probability α for y : $\alpha = \frac{f(y)}{Mg(y)}$
3. Draw $u \sim U(0, 1)$ and accept if $u \leq \alpha$, else: step 1

Proof:

$$\begin{aligned} P\left(Y \leq x | U \leq \frac{f(Y)}{Mg(Y)}\right) &= \frac{P\left(Y \leq x, U \leq \frac{f(Y)}{Mg(Y)}\right)}{P\left(U \leq \frac{f(Y)}{Mg(Y)}\right)} \\ &= \frac{\int_{-\infty}^x \int_0^{\frac{f(y)}{Mg(y)}} du g(y) dy}{\int_{-\infty}^{\infty} \int_0^{\frac{f(y)}{Mg(y)}} du g(y) dy} = \frac{\int_{-\infty}^x \frac{f(y)}{g(y)} g(y) dy}{\int_{-\infty}^{\infty} \frac{f(y)}{g(y)} g(y) dy} \\ &= \frac{\int_{-\infty}^x f(y) dy}{\int_{-\infty}^{\infty} f(y) dy} = P(X \leq x) \end{aligned}$$

• Importance Sampling

Directly estimate $E_{\theta}(f(y;\theta))$.

For sampling distribution $g(x)$,

$$\frac{1}{N} \sum_{i=1}^n \frac{f(x)}{g(x)}$$

is a consistent estimator.

Proof:

$$E_g\left(\frac{1}{N} \sum_{i=1}^n \frac{f(x)}{g(x)}\right) = \int \frac{f(x)}{g(x)} g(x) dx = \int f(x) dx = f(x)$$

Markov Chain Monte Carlo sample from $f_{post}(\theta|X)$

$f(y)$ unknown, however:

$$\frac{f_{post}(\theta|x)}{f_{post}(\tilde{\theta}|x)} = \frac{f(x|\theta)f_{\theta}(\theta)}{f(y)} \frac{f(y)}{f(x|\tilde{\theta})f_{\theta}(\tilde{\theta})} = \frac{f(x|\theta)f_{\theta}(\theta)}{f(x|\tilde{\theta})f_{\theta}(\tilde{\theta})}$$

Metropolis-Hastings: Draw Markov Chain $\theta_1^*, \dots, \theta_n^*$:

1. Draw candidate θ^* from proposal distribution $q(\theta|\theta_{(t)}^*)$
2. Accept $\theta_{(t+1)}^* = \theta^*$ with probability

$$\alpha(\theta_{(t)}^*|\theta^*) = \min\left\{1, \frac{f_{post}(\theta^*|y) q(\theta_{(t)}^*|\theta^*)}{f_{post}(\theta_{(t)}^*|y) q(\theta^*|\theta_{(t)}^*)}\right\}$$

else choose $\theta_{(t+1)}^* = \theta_{(t)}^*$

This sequence has a stationary distribution for $n \rightarrow \infty$.

Choice of q : trade-off between exploring Θ and reaching a high α .

Burn-in and thinning out give *i.i.d.* samples from $f_{post}(\theta|X)$.

Gibbs Sampling: For high dimensions α is close to zero.

Sample from the marginal distributions separately:

$$\theta_i^* \sim f_{\theta_i|y, \theta_{\setminus i}}(\theta_i^*|y, \theta_{t^*, i})$$

with $\theta_{t^*, i}$ most recent estimates without θ_i

A Gibbs sampled sequence converges to $f_{post}(\theta|X)$ as stationary.

Can also be used on its own, if marginal densities are known.

Variational Bayes Principles

Approximate $f_{post}(\theta|X)$ by $q_{\theta} = \min_{q_{\theta} \in Q} KL(f_{post}(\cdot|X), q_{\theta}(\cdot))$

Restrict q_{θ} to independence: $q_{\theta}(\theta) = \prod_{k=1}^p q_k(\theta_k)$

Update each component iteratively. Works well for big p .

7 Sampling

Bootstrap

1. Draw y_i^* : n samples with replacement from y
2. Calculate the statistic of interest $t(y_i^*)$
3. Repeat this B times
4. *Plug-in Principle*: Whenever the distribution function is involved in estimating a statistic, use the empirical bootstrapped version instead.

In a **Parametric Bootstrap** the parameter is first estimated from the data and then Bootstrap samples are drawn from the resulting distribution.

Bootstrap Probability

$$P(Y_i \in Y^*) = 1 - (1 - \frac{1}{n})^n \xrightarrow{n \rightarrow \infty} 1 - e^{-1} \approx 0.632$$

Subsampling

- **replacement** m -out-of- n bootstrap
- **non-replacement** subsampling directly from true F

Permutation Test for two variables

1. Calculate $t(x, y)$, e. g. differences in mean, correlation...
2. Draw samples x^*, y^* of size n from x and y without replacement ("shuffel")
3. Calculate $t(x^*, y^*)$
4. $p - value = \frac{1}{B} \sum_{b=1}^B \mathbb{1}_{\{t(x_b^*, y_b^*) \geq t(x, y)\}}$

For a **Bootstrap Test** do step 2 with replacement.

Bootstrap in Regression

- **Residual based**: 1. Get Bootstrap sample e_i^* from fitted residuals $\hat{e} = y - X\hat{\beta}$, 2. Calculate new response $y_i^* = x_i\hat{\beta} + e_i^*$, 3. Calculate $\hat{\beta}^*$
- **Model based** 1. Draw a sample from $e_i \sim N(0, \hat{\sigma}^2)$, 2. Calculate new response $y_i^* = x_i\hat{\beta} + e_i^*$, 3. Calculate $\hat{\beta}^*$
- **Pairwise** 1. Draw (y_i^*, x_i^*) from the original sample for $i = 1, \dots, n$, 2. Calculate $\hat{\beta}^*$
- **Wild Set** $\hat{e}_i^* = V_i^* \hat{e}_i$, with V_i^* from the 2-point distribution $P(V_i^* = \frac{\sqrt{5}+1}{2}) = \frac{\sqrt{5}-1}{2\sqrt{5}}$ and $P(V_i^* = -\frac{\sqrt{5}-1}{2}) = \frac{\sqrt{5}+1}{2\sqrt{5}}$, chosen as $E(V_i^*) = 0$, $Var(V_i^*) = 1$, $E(V_i^{*3}) = 1$

Consistency of a Bootstrap Estimator

$$\lim_{n \rightarrow \infty} P_n \left\{ \sup_t |G_n(t, F_n) - G_\infty(t, F)| > \epsilon \right\} = 0 \quad \forall \epsilon$$

with $F_n(y) = \frac{1}{n} \sum_{i=1}^n \mathbb{1}_{\{Y_i \leq y\}}$ empirical distribution function, $G_n(t, F) = P(T_n \leq t)$ exact finite sample distribution, and P_n joint probability of the sample

The bootstrap estimate is inconsistent for the maximum of a sample or if the θ lies on the boundary of Θ .

Mallow's Metric

$$\rho_p(F, G) = \inf_{\mathcal{T}_{XY}} \{E(|X - Y|)^p\}^{\frac{1}{p}}$$

for F, G in the set of distributions where $\inf_{-\infty}^{\infty} |t|^p dF(t) < \infty$; $(X, Y) \sim T \in \mathcal{T}_{XY}$ with $X \sim F$ and $Y \sim G$

Theorem of Beran and Ducharme

$G_n(\cdot, F_n)$ is consistent if $\forall \epsilon > 0, F$ the following holds:

1. $\lim_{n \rightarrow \infty} P_n(\rho(F_n, F) > \epsilon) = 0$
2. $G_\infty(t, F)$ is a continuous function of t
3. $\forall t$ and sequences $\{H_n\}$ s. t. $\lim_{n \rightarrow \infty} \rho(H_n, F) = 0$ holds: $G_n(t, H_n) \rightarrow G_\infty(t, F)$

8 Model Selection

AIC (Akaike Information Criterion)

$$AIC = -2 \sum_{i=1}^n \log f(y_i; \hat{\theta}) + 2p$$

The AIC estimates $2E_Y \{ \text{KL}(g, f) \} - 2 \int \log(g(y))g(y)dy$. The latter component is unknown, so the absolute value of the AIC is not informative. The AIC favours complex models.

For regressions: $AIC = 2n \log(\hat{\sigma}^2) + 2(p+2)$

The AIC as theoretical cross validation

The AIC minimizes $E_Y \{ E_Y [Y - \hat{\mu}]^2 \}$ if we use the MSE instead of the Kullback-Leibler divergence. This can be estimated via cross validation.

Bias Corrected AIC

$$AIC_{corr} = -2 \sum_{i=1}^n \log f(y_i; \hat{\theta}) + 2p \left(\frac{n}{n-p-1} \right)$$

should be preferred if $\frac{n}{p} < 40$

BIC (Bayesian Information Criterion)

$$BIC = -2 \sum_{i=1}^n \log f(y_i; \hat{\theta}) + \log(n)p$$

approximately maximizes the posterior probability of a model and selects less complex models as the AIC

DIC (Deviance Information Criterion) Bayesian AIC

$$DIC = D(y, \hat{\theta}_{postmean}) + 2p_D = \int D(y, \vartheta) f_{post}(\vartheta|y) d\vartheta + p_D$$

with deviance $D(y; \theta) := -2l(\theta)$ the difference in likelihood compared to the full mode and $\Delta D(y; \theta, \hat{\theta}) = 2 \{ l(\hat{\theta}) - l(\theta) \} \stackrel{a}{\sim} \chi_p^2$ the difference in deviance

$$p_D := E(\Delta D(y; \theta, \hat{\theta}_{postmean} | y) = \int D(y, \vartheta) f_{post}(\vartheta|y) d\vartheta - D(y, \hat{\theta}_{postmean})$$

The integral can be approximated using MCMC.

Model Averaging Using probabilities as weights

$$P(M_k|y) := \frac{\exp(-\frac{1}{2}\Delta IC_k)}{\sum_{k'=1}^K \exp(-\frac{1}{2}\Delta IC_{k'})}$$

with $\Delta IC_k = IC_k - \min(IC)$

For regression covariates: $P(x_i|y) = \sum_{k=1}^K \mathbb{1}_{\{x_i \text{ in } M_k\}} P(M_k|y)$

Inference After Model Selection neglect is a quiet scandal

$$Var(\hat{\theta}) = E_{model}(Var(\hat{\theta}|model)) + Var_{model}(E(\hat{\theta}|model))$$

$$= \sum_{k=1}^K \pi_k Var_k(\hat{\theta}) + \sum_{k=1}^K \pi_k (\theta_k - \bar{\theta})^2$$

The last component depends on the true parameter and will be biased if the estimates are used.

Solutions:

$$\bullet \widehat{Var}(\hat{\theta}) = \left[\sum_{k=1}^K \pi_k \sqrt{\widehat{Var}_k(\hat{\theta}_k) + (\hat{\theta}_k - \hat{\bar{\theta}})^2} \right]^2$$

• Use the Variance of the full (saturated) model

• Use bootstrap for confidence intervals

Lasso least absolute shrinkage and selection operator

$$l_p(\theta, \lambda) = l(\theta) - \lambda \sum_{j=1}^p |\theta_j|$$

This penalized log likelihood can be solved with iterative quadratic programming using a Taylor expansion.

Using Bayesian view the penalty corresponds to a prior:

$$f_{\theta_j}(\theta_j) \propto \exp(-|\theta_j|) \text{ (Laplace prior)}$$

9 Multivariate Things

Covariance Matrix Σ

- symmetric, $\in \mathbb{R}^{n \times n}$ therefore $\frac{q(q+1)}{2}$ parameters
- positive definite, i. e. $\forall a \in \mathbb{R}^q : a^T \Sigma a \geq 0$

Marginal Independence

$$\Sigma_{jk} = 0 \Leftrightarrow Y_{ij} \text{ and } Y_{ik} \text{ are independent}$$

Conditional Independence

$$\Omega = \Sigma_{jk}^{-1} = 0 \Leftrightarrow Y_{ij} \text{ and } Y_{ik} \text{ are independent given all other } Y \text{ with concentration matrix } \Omega$$

Proof:

$$f(y_{.j}, y_{.k} | y_{\overline{j,k}}) = \frac{f(y)}{f_{\overline{j,k}}} \propto f(y)^{N(\mu, \Sigma)} \exp \left\{ -\frac{1}{2} y^T \Sigma^{-1} y \right\}$$

Principal Component Analysis (PCA)

1. Use singular value decomposition $\Sigma = U \Lambda U^T$ with U matrix of orthonormal eigenvectors and $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_q)$ matrix of sorted eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_q$ of Σ
2. Prune smallest $k = q - r$ eigenvalues in $\tilde{\Lambda}$
3. Simplify model with spectral decomposition $\tilde{Y} = \tilde{V} \tilde{\Lambda}^{1/2} \tilde{U}^T$ with \tilde{V} , \tilde{U} first r eigenvectors of $Y Y^T$ and $Y^T Y$ respectively
4. explained variance $\sum_{i=1}^r \lambda_i / \sum_{i=1}^q \lambda_i$

Proof:

Karhunen-Loève expansion: $U \Lambda^{\frac{1}{2}} Z_{\cdot} \sim N(0, U \Lambda^{\frac{1}{2}} \Lambda^{\frac{1}{2}} U^T) = N(0, \Sigma)$ with $Z_{\cdot} \sim N(0, \mathbb{1})$, therefore $\tilde{Y}_{\cdot} = \tilde{V} \tilde{\Lambda}^{\frac{1}{2}} \tilde{Z}_{\cdot}$.
With spectral decomposition it follows: $Y = V \Lambda^{\frac{1}{2}} U^T$ (for column-centered Y)