

NMST432 Advanced Regression Models

Extended Course Notes

Michal Kulich

Last modified on March 7, 2021.



matfyz

Department of Probability and Mathematical Statistics
Faculty of Mathematics and Physics, Charles University

These course notes contain the whole contents of the course “NMST432 Advanced regression models”, which is a part of the curriculum of the Master’s program “Probability, Mathematical Statistics and Econometrics”.

This document undergoes continuing development. The author will appreciate notifications by the reader of potential typos or misprints.

Michal Kulich
kulich@karlin.mff.cuni.cz

In Karlín on March 7, 2021

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1. Review of Linear Regression

1.1. Definition and Assumptions

Consider n independent copies of random vectors (Y_i, \mathbf{X}_i) , $i = 1, \dots, n$. Each \mathbf{X}_i has $p < n$ components (X_{i1}, \dots, X_{ip}) .

Note.

- Y_i is called *the response*^{*}. The components of \mathbf{X}_i are called *covariates* (explanatory variables, predictors, regressors)[†].
- The covariate X_{i1} is usually taken as 1.
- In certain applications, the covariates can be fixed quantities rather than random variables. Throughout this course, we will consider covariates random. Extensions to fixed covariates usually hold with some additional conditions but the proofs require more effort.

Notation. Let $\mathbf{Y} = (Y_1, \dots, Y_n)^\top$ and

$$\mathbb{X} = \begin{pmatrix} \mathbf{X}_1^\top \\ \mathbf{X}_2^\top \\ \vdots \\ \mathbf{X}_n^\top \end{pmatrix}.$$

The n by p matrix \mathbb{X} is called *the regression matrix*[‡]. We assume $r(\mathbb{X}) = p$ (full rank).

Definition 1.1. The data (Y_i, \mathbf{X}_i) satisfy the linear regression model if the response Y_i can be written as

$$Y_i = \mathbf{X}_i^\top \boldsymbol{\beta}_0 + \varepsilon_i,$$

where $\boldsymbol{\beta}_0 = (\beta_{01}, \dots, \beta_{0p})^\top$ is a vector of unknown *regression parameters (coefficients)*[§] and $\varepsilon_1, \dots, \varepsilon_n$ are independent random variables such that $E[\varepsilon_i | \mathbf{X}_i] = 0$, and $\text{var}[\varepsilon_i | \mathbf{X}_i] = \sigma^2$.[¶]

Note. The unobserved random variables ε_i are called *error terms (disturbances)*[¶], σ^2 is called *residual variance*^{||}.

* Český odezva † Český regresory, nezávisle proměnné, vysvětlující veličiny, prediktory, kovariáty ‡ Český regresní matice § Český regresní koeficienty ¶ Český chybové členy || Český residuální rozptyl

Note. Another convenient formulation of the model is based on conditional moments and it avoids the expression of the error terms:

The linear regression model holds if and only if

- Y_1, \dots, Y_n are independent
- $E[Y_i | \mathbf{X}_i] = \mathbf{X}_i^T \boldsymbol{\beta}_0$
- $\text{var}[Y_i | \mathbf{X}_i] = \sigma^2$

Thus, the linear regression model specifies the first two conditional moments of Y_i given \mathbf{X}_i .

Note. We will use the notation E , var for the conditional expectation and variance, respectively, given \mathbf{X}_i . The symbol E_X will be used for unconditional expectation over the distribution of \mathbf{X}_i .

Note. The regression parameters express the influence of \mathbf{X}_i on $E Y_i$. Assuming that $X_{i1} = 1$, we have

$$\beta_{01} = E[Y_i | X_{i2} = 0, X_{i3} = 0, \dots, X_{ip} = 0]$$

and, with $\mathbf{e}_j = (0, \dots, 0, 1, 0, \dots, 0)^T$ being a p -vector of zeros with 1 at the j -th position,

$$\beta_{0j} = E[Y_i | \mathbf{X}_i = \mathbf{x} + \mathbf{e}_j] - E[Y_i | \mathbf{X}_i = \mathbf{x}], \quad j = 2, \dots, p.$$

1.2. Estimation

The regression coefficients $\boldsymbol{\beta}_0$ are estimated by *the least squares estimator* (LSE) $\hat{\boldsymbol{\beta}}$ that minimizes the sum of squares

$$\hat{\boldsymbol{\beta}} = \arg \min_{\boldsymbol{\beta} \in \mathbb{R}^p} \sum_{i=1}^n (Y_i - \mathbf{X}_i^T \boldsymbol{\beta})^2 = \arg \min_{\boldsymbol{\beta} \in \mathbb{R}^p} (\mathbf{Y} - \mathbb{X}\boldsymbol{\beta})^T (\mathbf{Y} - \mathbb{X}\boldsymbol{\beta}),$$

i.e., solves the system of *normal equations*

$$\sum_{i=1}^n \mathbf{X}_i (Y_i - \mathbf{X}_i^T \hat{\boldsymbol{\beta}}) = \mathbf{0}.$$

Because \mathbb{X} is of full rank, the single solution to the system is

$$\hat{\boldsymbol{\beta}} = (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \mathbf{Y}.$$

Note.

- $E \hat{\boldsymbol{\beta}} = \boldsymbol{\beta}_0$ (unbiased), $\text{var} \hat{\boldsymbol{\beta}} = \sigma^2 (\mathbb{X}^T \mathbb{X})^{-1}$.
- The vector

$$\hat{\mathbf{Y}} = \mathbb{X} \hat{\boldsymbol{\beta}} = \mathbb{X} (\mathbb{X}^T \mathbb{X})^{-1} \mathbb{X}^T \mathbf{Y} = \mathbb{H} \mathbf{Y}$$

is called *the vector of fitted values**.

* Český vektor odhadnutých (vyrovnaných) hodnot

- The projection matrix $\mathbb{H} \stackrel{\text{df}}{=} \mathbb{X}(\mathbb{X}^T\mathbb{X})^{-1}\mathbb{X}^T$ is idempotent, with rank p . It satisfies $\mathbb{H}\mathbb{X} = \mathbb{X}$. The matrix $\mathbb{I}_n - \mathbb{H}$ is also idempotent with rank $n - p$, and satisfies $(\mathbb{I}_n - \mathbb{H})\mathbb{X} = \mathbf{0}$.
- $\mathbb{E}\hat{\mathbf{Y}} = \mathbb{X}\boldsymbol{\beta}_0$, $\text{var}\hat{\mathbf{Y}} = \sigma^2\mathbb{H}$.
- The random vector $\mathbf{u} \stackrel{\text{df}}{=} \mathbf{Y} - \hat{\mathbf{Y}} = (\mathbb{I}_n - \mathbb{H})\mathbf{Y}$ is called *the vector of residuals*^{*}. It satisfies $\mathbb{E}\mathbf{u} = \mathbf{0}$, $\text{var}\mathbf{u} = \sigma^2(\mathbb{I}_n - \mathbb{H})$.
- The random variable

$$SS_e \stackrel{\text{df}}{=} \mathbf{u}^T\mathbf{u} = \sum_{i=1}^n (Y_i - \mathbf{x}_i^T\hat{\boldsymbol{\beta}})^2 = \mathbf{Y}^T(\mathbb{I}_n - \mathbb{H})\mathbf{Y}$$

is called the *residual sum of squares*[†]. Because $\mathbb{E}SS_e = (n-p)\sigma^2$, we obtain an unbiased estimator of residual variance as $\hat{\sigma}^2 = SS_e/(n-p)$.

1.3. Normal Linear Regression

For normally distributed errors, additional useful properties can be derived. Assume now that $\boldsymbol{\varepsilon} \sim N_n(\mathbf{0}, \sigma^2\mathbb{I}_n)$.

Proposition 1.1. *Under normality,*

- (i) $\mathbf{Y} \sim N_n(\mathbb{X}\boldsymbol{\beta}_0, \sigma^2\mathbb{I}_n)$
- (ii) $\hat{\boldsymbol{\beta}} \sim N_p(\boldsymbol{\beta}_0, \sigma^2(\mathbb{X}^T\mathbb{X})^{-1})$
- (iii) $\hat{\mathbf{Y}} \sim N_n(\mathbb{X}\boldsymbol{\beta}_0, \sigma^2\mathbb{H})$
- (iv) $\mathbf{u} \sim N_n(\mathbf{0}, \sigma^2(\mathbb{I}_n - \mathbb{H}))$
- (v) $SS_e/\sigma^2 \sim \chi_{n-p}^2$
- (vi) $\hat{\boldsymbol{\beta}}$ and SS_e are independent
- (vii) Let \mathbf{c} be any non-zero p -vector of real constants. Then

$$\frac{\mathbf{c}^T\hat{\boldsymbol{\beta}} - \mathbf{c}^T\boldsymbol{\beta}_0}{\sqrt{\hat{\sigma}^2\mathbf{c}^T(\mathbb{X}^T\mathbb{X})^{-1}\mathbf{c}}} \sim t_{n-p}$$

- (viii) Assume the model $\mathbf{Y} = \mathbb{X}\boldsymbol{\beta}_0 + \boldsymbol{\varepsilon}$, where $\mathbb{X} = (\mathbb{X}_A|\mathbb{X}_B)$ and $\boldsymbol{\beta}_0 = (\boldsymbol{\beta}_A^T, \boldsymbol{\beta}_B^T)^T$, $\boldsymbol{\beta}_B \in \mathbb{R}_m$, $\boldsymbol{\beta}_A \in \mathbb{R}^{p-m}$, and introduce the submodel $\mathbf{Y} = \mathbb{X}_A\boldsymbol{\beta}_A + \boldsymbol{\varepsilon}'$. Let SS_e and SS_h be the residual sums of squares in the model and submodel, respectively. If the submodel is true ($H_0 : \boldsymbol{\beta}_B = \mathbf{0}$ holds) then

$$F = \frac{n-p}{m} \frac{SS_h - SS_e}{SS_e} \sim F_{m, n-p}. \quad (1.1) \quad \diamond$$

It can be also shown that, under normality, $\hat{\boldsymbol{\beta}}$ is the best linear unbiased estimator and the maximum likelihood estimator, so it possesses optimality properties.

^{*} Český vektor residuí [†] Český residuální součet čtverců

1.4. Asymptotic Properties of the LSE

Let (Y_i, X_i) , $i = 1, \dots, n$, be iid. Assume Definition 1.1 (without normality). Denote $\mathbb{D}_X = E_X X_i X_i^\top$.

Proposition 1.2. Let \mathbb{D}_X be a finite regular matrix. Then

- (i) $\hat{\beta} \xrightarrow{P} \beta_0$ as $n \rightarrow \infty$,
- (ii) $\sqrt{n}(\hat{\beta} - \beta_0) \xrightarrow{D} N_p(\mathbf{0}, \sigma^2 \mathbb{D}_X^{-1})$ as $n \rightarrow \infty$. ◇

Proposition 1.2(ii) is an asymptotic restatement of Proposition 1.1(ii). Other parts of Proposition 1.1 also hold asymptotically even if the data are not normal.

Now relax the assumption of equal variance: assume only $E[Y_i | X_i] = X_i^\top \beta_0$. Let $\text{var}[Y_i | X_i] = \sigma^2(X_i)$ be stochastically bounded (finite expectation follows). Denote $\mathbb{V}_X = E_X \sigma^2(X_i) X_i X_i^\top$.

Proposition 1.3. Let \mathbb{V}_X be finite and \mathbb{D}_X be finite and regular. Then

- (i) $\hat{\beta} \xrightarrow{P} \beta_0$ as $n \rightarrow \infty$,
- (ii) $\sqrt{n}(\hat{\beta} - \beta_0) \xrightarrow{D} N_p(\mathbf{0}, \mathbb{D}_X^{-1} \mathbb{V}_X \mathbb{D}_X^{-1})$ as $n \rightarrow \infty$. ◇

When equal variances hold, $\mathbb{V}_X = \sigma^2 \mathbb{D}_X$ and the result in Proposition 1.3(ii) transforms into the result in Proposition 1.2(ii).

Consistent estimates of \mathbb{D}_X and \mathbb{V}_X are

$$\hat{\mathbb{D}}_n = \frac{1}{n} \mathbb{X}^\top \mathbb{X}$$

and

$$\hat{\mathbb{V}}_n = \frac{1}{n} \mathbb{X}^\top \text{diag}(u_i^2) \mathbb{X}.$$

So, if both normality and homoskedasticity are in doubt, one can use the OLS estimator $\hat{\beta}$ with variance

$$(\mathbb{X}^\top \mathbb{X})^{-1} \mathbb{X}^\top \text{diag}(u_i^2) \mathbb{X} (\mathbb{X}^\top \mathbb{X})^{-1}$$

in place of the usual $\hat{\sigma}^2 (\mathbb{X}^\top \mathbb{X})^{-1}$. This is called *the sandwich estimator*^{*}, or, in the econometric context, *White estimator*[†] (White 1980).

Many variants and improvements of this estimator have been proposed in the literature.

^{*} Český sendvičový odhad [†] Český Whiteův odhad

1.5. Implications for Data Analysis

The asymptotic results we have just summarized indicate that linear regression model with ordinary least squares estimation of regression parameters can be used to obtain asymptotically correct statistical inference even if the response is not normal and the error terms do not have equal variance. We only need to have enough observations available for analysis so that the asymptotic results provide a reasonable approximation of the true distribution of the parameter estimator and other quantities of interest.

In this aspect, linear regression is actually a robust nonparametric statistical procedure.

- (a) If the responses are *normal* and possess *equal variances* we can perform exact statistical inference based on Proposition 1.1 regardless of the size of the dataset (for any $n > p$).
- (b) If the responses are *not normal* but have *equal variances* we can perform asymptotic inference based on Proposition 1.2 for large enough number of observations.
- (c) If the responses are *not normal* and have *unequal variances* we can perform asymptotic inference based on Proposition 1.3 with sandwich variance estimator for large enough number of observations.

What number of observations is large enough to trust the asymptotic approaches (b) and (c) depends on the complexity of the linear model.

Furthermore, if the error variances are unequal but are known up to a proportionality constant, i.e., $\text{var } Y_i = \sigma^2 w_i$ with known w_i , weighted least squares estimation can be used instead of the sandwich.

1.6. Interpretation with Transformed Response

Recall the linear model $E[Y_i | \mathbf{X}_i] = \mathbf{X}_i^\top \boldsymbol{\beta}_0$ with $\text{var}[Y_i | \mathbf{X}_i] = \sigma^2$. The regression parameters can be interpreted as

$$\beta_{01} = E[Y_i | X_{i2} = 0, X_{i3} = 0, \dots, X_{ip} = 0]$$

and, \mathbf{e}_j being the j -th unit vector of the length p ,

$$\beta_{0j} = E[Y_i | \mathbf{X}_i = \mathbf{x} + \mathbf{e}_j] - E[Y_i | \mathbf{X}_i = \mathbf{x}].$$

When the response is non-normal, the common practice is to specify a linear model on a transformed response. Let g be some monotone function. The transformed model is

$$g(Y_i) = \mathbf{X}_i^\top \boldsymbol{\beta}_0 + \varepsilon_i$$

or $E[g(Y_i) | \mathbf{X}_i] = \mathbf{X}_i^\top \boldsymbol{\beta}_0$ with $\text{var}[g(Y_i) | \mathbf{X}_i] = \sigma^2$. The induced model for Y_i is

$$Y_i = g^{-1}(\mathbf{X}_i^\top \boldsymbol{\beta}_0 + \varepsilon_i).$$

1. Review of Linear Regression

In general, the effect of the covariates on $E Y_i$ in this model cannot be expressed.

The only special case (apart from linear g) when the transformed model says anything useful about $E[Y_i | \mathbf{X}_i]$ is the log transform. From

$$\log Y_i = \mathbf{X}_i^\top \boldsymbol{\beta}_0 + \varepsilon_i$$

we get a multiplicative model

$$Y_i = e^{\mathbf{X}_i^\top \boldsymbol{\beta}_0} \varepsilon_i^*,$$

where $\varepsilon_i^* = e^{\varepsilon_i}$, $E \varepsilon_i^* = \mu_\varepsilon > 1$, $\text{var} \varepsilon_i^* = \sigma_\varepsilon^2$. Then

$$\begin{aligned} E[Y_i | \mathbf{X}_i] &= \exp\{\log \mu_\varepsilon + \mathbf{X}_i^\top \boldsymbol{\beta}_0\}, \\ \text{var}[Y_i | \mathbf{X}_i] &= \sigma_\varepsilon^2 (\exp\{\mathbf{X}_i^\top \boldsymbol{\beta}_0\})^2. \end{aligned}$$

While β_{01} (the intercept) does not have useful interpretation, the other parameters express multiplicative effects of X_{i2}, \dots, X_{ip} on $E Y_i$:

$$e^{\beta_{0j}} = \frac{E[Y_i | \mathbf{X}_i = \mathbf{x} + \mathbf{e}_j]}{E[Y_i | \mathbf{X}_i = \mathbf{x}]}, \quad j = 2, \dots, p.$$

So, $e^{\beta_{0j}}$ is the proportional increase (relative change) in $E Y_i$ after a unit change in X_{ij} .

The problem with the interpretation of the transformed linear model is serious when the primary task is to estimate the effect of \mathbf{X}_i on $E Y_i$. If the goal is to predict Y_i from \mathbf{X}_i , transformations can still be useful even if the interpretation of the parameters is lost.

*The end of
lecture 1
(Mar. 1)*

2. Generalized Linear Model: Theory

The generalized linear model extends the normal linear model in two aspects: it admits a wider choice of distributions for Y_i (distributions from the exponential family) and it allows some flexibility in the relationship between $E Y_i$ and $X_i^T \beta_0$.

2.1. Exponential Family

2.1.1. Parametrization, moments

Definition 2.1. A distribution of a real-valued random variable belongs to *the exponential family* of distributions* if its density (w.r.t. some σ -finite measure) can be written in the form

$$f(x; \theta, \varphi) = \exp\left\{\frac{x\theta - b(\theta)}{\varphi} + c(x, \varphi)\right\}, \quad (2.1)$$

where

- θ is called *the canonical parameter*[†];
- $\varphi \in (0, \infty)$ is called *the dispersion parameter*[‡];
- b and c are some real functions;

The expression (2.1) is called *the canonical form of the density*[§]. ∇

Example: Normal distribution

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

$$\begin{aligned} f(x; \mu, \sigma^2) &= \frac{1}{\sqrt{2\pi\sigma}} \exp\left\{-\frac{(x-\mu)^2}{2\sigma^2}\right\} \\ &= \frac{1}{\sqrt{2\pi\sigma}} \exp\left\{\frac{x\mu}{\sigma^2} - \frac{\mu^2}{2\sigma^2} - \frac{x^2}{2\sigma^2}\right\} \\ &= \exp\left\{\frac{x\mu - \mu^2/2}{\sigma^2} - \frac{x^2}{2\sigma^2} - \frac{1}{2} \log(2\pi\sigma^2)\right\}. \end{aligned}$$

* Český rozdělení exponenciálního typu † Český kanonický parametr ‡ Český disperzní parametr § Český kanonický tvar hustoty

$$\theta = \mu, \quad \varphi = \sigma^2, \quad b(\theta) = \frac{\theta^2}{2}, \quad c(x, \varphi) = -\frac{x^2}{2\varphi} - \frac{1}{2} \log(2\pi\varphi).$$

Example: Gamma distribution

$Y \sim \Gamma(a, p)$, $a > 0$, $p > 0$, $Y > 0$ a.s.

$$\begin{aligned} f(x; a, p) &= \frac{a^p}{\Gamma(p)} x^{p-1} \exp\{-ax\} \\ &= \exp\{-ax + p \log a + (p-1) \log x - \log \Gamma(p)\} \\ &= \exp\left\{\frac{-(a/p)x + \log(a/p)}{1/p} + (p-1) \log x + p \log p - \log \Gamma(p)\right\} \end{aligned}$$

$$\begin{aligned} \theta &= -\frac{a}{p}, \quad \varphi = 1/p, \quad b(\theta) = -\log(-\theta) \\ c(x, \varphi) &= (1/\varphi - 1) \log x - \log \varphi / \varphi - \log \Gamma(1/\varphi). \end{aligned}$$

Example: Inverse Gaussian distribution

$Y \sim \text{IG}(\mu, \lambda)$, $\mu > 0$, $\lambda > 0$, $Y > 0$ a.s.

$$\begin{aligned} f(x; \mu, \lambda) &= \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left\{-\frac{\lambda(x-\mu)^2}{2\mu^2 x}\right\} \\ &= \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left\{-\frac{\lambda x^2}{2\mu^2 x} + \frac{\lambda x \mu}{\mu^2 x} - \frac{\lambda \mu^2}{2\mu^2 x}\right\} \\ &= \exp\left\{\frac{-x/(2\mu^2) + 1/\mu}{1/\lambda} + \frac{1}{2} \log \frac{\lambda}{2\pi x^3} - \frac{\lambda}{2x}\right\}. \end{aligned}$$

$$\theta = -\frac{1}{2\mu^2}, \quad \varphi = 1/\lambda, \quad b(\theta) = -\sqrt{-2\theta}, \quad c(x, \varphi) = -\frac{1}{2} \log(2\pi x^3 \varphi) - (2x\varphi)^{-1}.$$

This is a continuous distribution on the positive halfline. It is related to χ^2 distribution through the transformation

$$\frac{\lambda(X-\mu)^2}{\mu^2 X} \sim \chi_1^2.$$

Example: Poisson distribution

$Y \sim \text{Po}(\lambda)$, $\lambda > 0$, values $0, 1, 2, \dots$

$$f(x; \lambda) = \frac{\lambda^x}{x!} \exp\{-\lambda\} = \exp\{x \log \lambda - \lambda - \log x!\}.$$

$$\theta = \log \lambda, \quad \varphi = 1, \quad b(\theta) = \exp(\theta), \quad c(x, \varphi) = -\log x!$$

Example: Alternative distribution

$Y \sim \text{Alt}(p)$, $p \in (0, 1)$, values $0, 1$.

$$f(x; p) = p^x(1-p)^{1-x} = \exp\{x \log p + (1-x) \log(1-p)\} = \exp\left\{x \log \frac{p}{1-p} + \log(1-p)\right\}.$$

$$\theta = \log \frac{p}{1-p}, \quad \varphi = 1, \quad b(\theta) = \log(1 + e^\theta), \quad c(x, \varphi) = 0.$$

The next lemma shows that for distributions of exponential family, the first two moments can be obtained from the canonical form of the density by a simple calculation.

Lemma 2.1. *Let the random variable Y follow a distribution from the exponential family. Then the moment generation function $m_Y(t) \equiv E e^{tY}$ of Y exists, is finite, and is equal to*

$$m_Y(t) = \exp\left\{\frac{b(\theta + t\varphi) - b(\theta)}{\varphi}\right\}.$$

If $b(\theta)$ is twice continuously differentiable, $m_Y(t)$ is twice differentiable at $t = 0$, and

$$\begin{aligned} EY &= b'(\theta), \\ \text{var}Y &= \varphi b''(\theta). \end{aligned} \quad \diamond$$

Proof. Suppose the density $f(x; \theta, \varphi)$ exists with respect to a σ -finite measure ν and denote the support $A = \{x : f(x; \theta, \varphi) > 0\}$. We have

$$\begin{aligned} m_Y(t) &= E e^{tY} = \int_A \exp\left\{\frac{x\theta + xt\varphi - b(\theta)}{\varphi} + c(x, \varphi)\right\} d\nu(x) \\ &= \int_A \exp\left\{\frac{x(\theta + t\varphi) - b(\theta + t\varphi)}{\varphi} + c(x, \varphi)\right\} d\nu(x) \cdot \exp\left\{\frac{b(\theta + t\varphi) - b(\theta)}{\varphi}\right\} \\ &= \exp\left\{\frac{b(\theta + t\varphi) - b(\theta)}{\varphi}\right\}. \end{aligned}$$

The moments can be calculated by differentiation of $m_Y(t)$ at $t = 0$. We have $EY = m'_Y(0)$ and

$$m'_Y(t) = m_Y(t) \frac{b'(\theta + t\varphi)}{\varphi} \varphi,$$

so $EY = m'_Y(0) = b'(\theta)m_Y(0) = b'(\theta)$. Next, $EY^2 = m''_Y(0)$ and

$$m''_Y(t) = m_Y(t)[b'(\theta + t\varphi)]^2 + m_Y(t)b''(\theta + t\varphi)\varphi$$

so $EY^2 = m''_Y(0) = \varphi b''(\theta) + [b'(\theta)]^2$. Hence,

$$\text{var } Y = EY^2 - (EY)^2 = \varphi b''(\theta). \quad \square$$

We will always assume that $b(\theta)$ is twice continuously differentiable so that $\text{var } Y$ is finite. Denote $\mu \stackrel{\text{df}}{=} EY$.

Note. Since $\text{var } Y = \varphi b''(\theta) > 0$, b must be a strictly convex function and b' is strictly increasing. Hence b' has a well-defined inverse and there exists a function $V(\mu)$ of the mean μ such that $\text{var } Y = \varphi V(\mu)$. It satisfies the equation $b''(\theta) = V(b'(\theta))$ or $V(\mu) = b''((b')^{-1}(\mu))$.

Definition 2.2. The function $V(\mu)$ such that $\text{var } Y = \varphi V(\mu)$ is called *the variance function**. ▽

Note.

- Different distributions that belong to the exponential family must have different variance functions.
- Within the exponential family, the variance function determines the distribution of Y . However, not every function V is a variance function of some distribution from the exponential family.

Example: Normal distribution

For $Y \sim N(\mu, \sigma^2)$, we have $\theta = \mu$, $\varphi = \sigma^2$, and $b(\theta) = \frac{\theta^2}{2}$. Hence

$$EY = b'(\theta) = \mu, \quad \text{var } Y = \varphi b''(\theta) = \varphi = \sigma^2, \quad \text{and} \quad V(\mu) = 1.$$

The normal distribution is the only distribution in exponential family with constant variance function, i.e., the variance is unrelated to the mean. (Recall the assumption of homoskedasticity in linear regression!).

* Český rozptylová funkce

Example: Gamma distribution

For $Y \sim \Gamma(a, p)$, we have $\theta = -\frac{a}{p}$, $\varphi = 1/p$, and $b(\theta) = -\log(-\theta)$. Hence

$$\mu = \mathbb{E}Y = b'(\theta) = -1/\theta = p/a, \quad \text{var}Y = \varphi b''(\theta) = \varphi/\theta^2 = p/a^2, \quad \text{and} \quad V(\mu) = \mu^2.$$

Example: Inverse Gaussian distribution

For $Y \sim \text{IG}(\mu, \lambda)$, we have $\theta = -\frac{1}{2\mu^2}$, $\varphi = 1/\lambda$, and $b(\theta) = -\sqrt{-2\theta}$. Hence

$$\mathbb{E}Y = b'(\theta) = 1/\sqrt{-2\theta} = \mu, \quad \text{var}Y = \varphi b''(\theta) = \varphi(-2\theta)^{-3/2} = \mu^3/\lambda, \quad \text{and} \quad V(\mu) = \mu^3.$$

Example: Poisson distribution

For $Y \sim \text{Po}(\lambda)$, we have $\theta = \log \lambda$, $\varphi = 1$, and $b(\theta) = \exp(\theta)$. Hence

$$\mu = \mathbb{E}Y = b'(\theta) = \exp(\theta) = \lambda, \quad \text{var}Y = \varphi b''(\theta) = \exp(\theta) = \lambda, \quad \text{and} \quad V(\mu) = \mu.$$

Example: Alternative distribution

For $Y \sim \text{Alt}(p)$, we have $\theta = \log \frac{p}{1-p}$, $\varphi = 1$, and $b(\theta) = \log(1 + e^\theta) = \log(1 - p)$. Hence

$$\mu = \mathbb{E}Y = b'(\theta) = \frac{e^\theta}{1 + e^\theta} = p, \quad \text{var}Y = \varphi b''(\theta) = \frac{e^\theta}{(1 + e^\theta)^2} = p(1 - p), \quad V(\mu) = \mu(1 - \mu).$$

2.1.2. Maximum likelihood estimator of the canonical parameter

Let Y_1, \dots, Y_n be a random sample from the density $f(x; \theta_0, \varphi_0)$ belonging to the exponential family, θ_0 is the true canonical parameter, φ_0 is the true dispersion parameter. Let $\mathbf{Y} = (Y_1, \dots, Y_n)^T$. We will discuss maximum likelihood estimation of the canonical parameter θ with iid data. Summary of the maximum likelihood theory together with notation we use throughout this text is provided in the Appendix starting on p. 28.

The likelihood for exponential family is

$$L(\theta, \varphi) = \prod_{i=1}^n \exp\left\{ \frac{Y_i \theta - b(\theta)}{\varphi} + c(Y_i, \varphi) \right\},$$

The log-likelihood is

$$\ell(\theta, \varphi) = \log L(\theta, \varphi) = \sum_{i=1}^n \left[\frac{Y_i \theta - b(\theta)}{\varphi} + c(Y_i, \varphi) \right].$$

Suppose that the true dispersion parameter φ_0 is known. Then the score function for θ is

$$U(\theta | Y_i) = \frac{\partial}{\partial \theta} \log f(x; \theta, \varphi_0) = \frac{1}{\varphi_0} [Y_i - b'(\theta)].$$

Obviously, $E U(\theta_0 | Y_i) = 0$. The score statistic is

$$U_n(\theta | \mathbf{Y}) = \sum_{i=1}^n U(\theta | Y_i) = \frac{1}{\varphi_0} \sum_{i=1}^n [Y_i - b'(\theta)].$$

The maximum likelihood estimator [MLE] $\hat{\theta}_n$ solves the equation $U_n(\hat{\theta}_n | \mathbf{Y}) = 0$, that is $\sum_{i=1}^n Y_i = n b'(\hat{\theta}_n)$. The solution is $\hat{\theta}_n = (b')^{-1}(\bar{Y}_n)$, where $\bar{Y}_n = n^{-1} \sum_{i=1}^n Y_i$.

The MLE is unique because b is convex, and it does not depend on the dispersion parameter φ_0 . It can be calculated even if φ_0 is unknown.

The observed information is

$$I_n(\theta | \mathbf{Y}) = -\frac{1}{n} \sum_{i=1}^n \frac{\partial U(\theta | Y_i)}{\partial \theta} = \frac{1}{\varphi_0} b''(\theta) > 0,$$

so the likelihood is strictly concave. The expected (Fisher) information is the same as the observed information,

$$I(\theta) = -E \frac{\partial U(\theta | Y_i)}{\partial \theta} = \frac{1}{\varphi_0} b''(\theta).$$

It is easy to check that

$$\text{var} U(\theta_0 | Y_i) = I(\theta_0).$$

It follows from Theorem A.4 in the Appendix that

$$\sqrt{n}(\hat{\theta}_n - \theta_0) \xrightarrow{D} N(0, \varphi_0 [b''(\theta_0)]^{-1}). \quad (2.2)$$

Now consider the true dispersion parameter φ_0 unknown. The MLE of θ_0 is still the same, $\hat{\theta}_n = (b')^{-1}(\bar{Y}_n)$. However, what is the asymptotic distribution of $\hat{\theta}_n$ when φ_0 is unknown? In general, the asymptotic variance may change.

Calculate the joint information matrix for (θ, φ) :

$$I(\theta_0, \varphi_0) = -E \frac{\partial^2 \log f(x; \theta_0, \varphi_0)}{\partial(\theta, \varphi) \partial(\theta, \varphi)^T} = \begin{pmatrix} I_{\theta\theta} & I_{\theta\varphi} \\ I_{\theta\varphi} & I_{\varphi\varphi} \end{pmatrix} = \begin{pmatrix} b''(\theta_0)/\varphi_0 & 0 \\ 0 & I_{\varphi\varphi} \end{pmatrix}.$$

Thus, the information matrix is diagonal. It follows that the asymptotic distribution of $\hat{\theta}_n$ is given by (2.2) even if φ_0 is unknown.

We do not need φ_0 to estimate θ_0 but we need an estimate of φ_0 to estimate the asymptotic variance of θ_0 . Of course, we could use the MLE of φ_0 but it often cannot be calculated explicitly. Instead, we can use the moment estimator

$$\widehat{\varphi} = \frac{S_n^2}{b''(\widehat{\theta}_n)} = \frac{S_n^2}{V(\overline{Y}_n)},$$

where S_n^2 is the sample variance. Since $S_n^2 \xrightarrow{P} \text{var } Y_i = \varphi_0 b''(\theta_0)$, $\widehat{\theta}_n$ is consistent and b'' is continuous, $\widehat{\varphi}$ is consistent (though less efficient than the MLE).

The end of
lecture 2
(Mar. 4)

2.2. Definition of the Generalized Linear Model

Consider n independent copies of random vectors (Y_i, \mathbf{X}_i) , $i = 1, \dots, n$, where $\mathbf{X}_i = (X_{i1}, \dots, X_{ip})^\top$.

We want to express the dependence of $\mu_i \stackrel{\text{df}}{=} E[Y_i | \mathbf{X}_i]$ on \mathbf{X}_i by a model that is more general than the linear model.

Definition 2.3. (Nelder and Wedderburn 1972) The data (Y_i, \mathbf{X}_i) satisfy the *generalized linear model** [GLM] if

1. Y_1, \dots, Y_n are independent and the distribution of Y_i depends on \mathbf{X}_i through regression parameters $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)^\top$.
2. the conditional density of Y_i given \mathbf{X}_i has the form

$$f(y; \theta_i, \varphi) = \exp\left\{\frac{y\theta_i - b(\theta_i)}{\varphi} + c(y, \varphi)\right\},$$

(is of exponential type), where $b(\cdot)$ is a known twice continuously differentiable function, θ_i depends on \mathbf{X}_i and $\boldsymbol{\beta}$, $\varphi > 0$ is a known or an unknown constant.

3. θ_i depends on \mathbf{X}_i and $\boldsymbol{\beta}$ through the *linear predictor*† $\eta_i \stackrel{\text{df}}{=} \mathbf{X}_i^\top \boldsymbol{\beta}$.
4. There exists a known strictly monotone, twice continuously differentiable *link function*‡ g such that $g(\mu_i) = \eta_i$. ∇

Notation. Let $\mathbf{Y} = (Y_1, \dots, Y_n)^\top$ and define the regression matrix

$$\mathbb{X}_{n \times p} = \begin{pmatrix} \mathbf{X}_1^\top \\ \mathbf{X}_2^\top \\ \vdots \\ \mathbf{X}_n^\top \end{pmatrix}.$$

We assume $r(\mathbb{X}) = p$. We sometimes use the notation $\boldsymbol{\beta}_0 = (\beta_{01}, \dots, \beta_{0p})^\top$ to denote the true regression parameter (but the notation $\boldsymbol{\beta}$ can also mean the true parameter).

* Český zobecněný lineární model † Český lineární prediktor ‡ Český linková funkce

Note. The (conditional) means of Y_1, \dots, Y_n vary because the canonical parameters $\theta_1, \dots, \theta_n$ depend on X_i . The dispersion parameter φ is the same for all observations, it must not depend on X_i (recall homoskedasticity in linear regression). However, the variances of Y_1, \dots, Y_n depend on the mean through the variance function $V(\mu_i)$, and hence vary with X_i .

Note. The link function postulates a possibly non-linear relationship between the expectation of the response μ_i and the linear predictor $\eta_i = \mathbf{X}_i^T \boldsymbol{\beta}$. It has to be specified in advance. There are methods to verify the choice of the link function for a specific data set (see Section ??). It is enough to specify the link function up to a non-zero proportionality constant (if $c \neq 0$, g and cg lead to the same model).

Definition 2.4. The link function g is called *the canonical link** for the distribution f if it equates the linear predictor η_i with the canonical parameter θ_i . ∇

Lemma 2.2. (Properties of canonical link)

- (i) The canonical link is equal to the inverse of b' , that is $g(\mu_i) = (b')^{-1}(\mu_i)$.
- (ii) The canonical link satisfies the equation $g'(\mu_i) = 1/V(\mu_i)$. \diamond

Proof. The link function g maps the mean $\mu_i = b'(\theta_i)$ to the linear predictor η_i : $g(\mu_i) = \eta_i$. The canonical link satisfies $\eta_i = \theta_i$.

For canonical link, $g(b'(\theta_i)) = \theta_i$, hence $g = (b')^{-1}$. This proves (i).

Differentiating the equality $g(b'(\theta_i)) = \theta_i$, we get $g'(b'(\theta_i))b''(\theta_i) = 1$. Because $b'(\theta_i) = \mu_i$ and $b''(\theta_i) = V(\mu_i)$, we get $g'(\mu_i)V(\mu_i) = 1$. This proves (ii). \square

Note. For each distribution f from the exponential family, there is a unique (up to a non-zero proportionality constant) canonical link function. Two distributions cannot share the same canonical link. Canonical link functions have certain numerical advantages that will become apparent later on. However, some canonical link functions violate the conditions we require and are difficult to interpret (see examples below).

Example: Normal distribution

For normal distribution, the canonical parameter is $\theta_i = \mu_i$, and the dispersion parameter is $\varphi = \sigma^2$. Let $Y_i \sim N(\mu_i, \sigma^2)$ with $g(\mu_i) = \mathbf{X}_i^T \boldsymbol{\beta}$.

We know that

$$b(\theta_i) = \frac{\theta_i^2}{2}, \quad \mu_i = b'(\theta_i) = \theta_i, \quad \text{var } Y_i = \sigma^2, \quad V(\mu) = 1.$$

* Český kanonický link

The canonical link is $g(\mu_i) = (b')^{-1}(\mu_i) = \mu_i$ (identity link).

So the canonical GLM for the normal distribution is $E Y_i = \eta_i = \mathbf{X}_i^\top \boldsymbol{\beta}$, the normal linear model.

Example: Gamma distribution

For gamma distribution, the canonical parameter is $\theta_i = -\frac{a_i}{p}$, and the dispersion parameter is $\varphi = 1/p$. So, we take $Y_i \sim \Gamma(a_i, p)$ with the mean $\mu_i = p/a_i$ and link $g(\mu_i) = \mathbf{X}_i^\top \boldsymbol{\beta}$.

We know that

$$b(\theta_i) = -\log(-\theta_i), \quad \mu_i = b'(\theta_i) = -1/\theta_i, \quad \text{var } Y_i = \varphi \mu_i^2.$$

The canonical link is $g(\mu_i) = (b')^{-1}(\mu_i) \propto 1/\mu_i$ (inverse link — after dropping the minus sign). It is a function which is discontinuous at 0 and not strictly monotone.

The canonical GLM for the gamma distribution is $E Y_i = g^{-1}(\eta_i) = 1/\mathbf{X}_i^\top \boldsymbol{\beta}$. The model can be interpreted only when the linear predictors have all either positive or negative signs.

Example: Inverse Gaussian distribution

For inverse Gaussian distribution, the canonical parameter is $\theta_i = -\frac{1}{2\mu_i^2}$, and the dispersion parameter is $\varphi = 1/\lambda$. So, we take $Y_i \sim \text{IG}(\mu_i, \lambda)$ with the mean μ_i and link $g(\mu_i) = \mathbf{X}_i^\top \boldsymbol{\beta}$.

We know that

$$b(\theta_i) = -\sqrt{-2\theta_i}, \quad \mu_i = b'(\theta_i) = 1/\sqrt{-2\theta_i}, \quad \text{var } Y_i = \varphi \mu_i^3.$$

The canonical link is $g(\mu_i) = (b')^{-1}(\mu_i) \propto 1/\mu_i^2$ (squared inverse link — after dropping the constant -2). It is a function which is discontinuous at 0 and not strictly monotone.

The canonical GLM for the inverse Gaussian distribution is $E Y_i = g^{-1}(\eta_i) = 1/\sqrt{\mathbf{X}_i^\top \boldsymbol{\beta}}$. The model can be interpreted only when the linear predictors all have positive signs.

Example: Poisson distribution

For Poisson distribution, the canonical parameter is $\theta_i = \log \lambda_i$, and the dispersion parameter is $\varphi = 1$. So, we take $Y_i \sim \text{Po}(\lambda_i)$ with the mean λ_i and link $g(\mu_i) = \mathbf{X}_i^\top \boldsymbol{\beta}$.

We know that

$$b(\theta_i) = \exp(\theta_i), \quad \mu_i = b'(\theta_i) = \exp(\theta_i), \quad \text{var } Y_i = \mu_i.$$

The canonical link is $g(\mu_i) = (b')^{-1}(\mu_i) = \log \mu_i$ (log link).

The canonical GLM for Poisson distribution is $E Y_i = g^{-1}(\eta_i) = \exp\{\mathbf{X}_i^\top \boldsymbol{\beta}\}$. This is called *the loglinear model*.

Example: Alternative distribution

For alternative distribution, the canonical parameter is $\theta_i = \log \frac{p_i}{1-p_i}$, and the dispersion parameter is $\varphi = 1$. So, we take $Y_i \sim \text{Alt}(p_i)$ with the mean p_i and link $g(\mu_i) = \mathbf{X}_i^\top \boldsymbol{\beta}$.

We know that

$$b(\theta_i) = \log(1 + \exp\{\theta_i\}), \quad \mu_i = b'(\theta_i) = \frac{e^{\theta_i}}{1 + e^{\theta_i}}, \quad \text{var } Y_i = \mu_i(1 - \mu_i).$$

The canonical link is $g(\mu_i) = \log \frac{\mu_i}{1-\mu_i}$ (logistic link).

The canonical GLM for alternative distribution is $E Y_i = g^{-1}(\eta_i) = \frac{\exp\{\mathbf{X}_i^\top \boldsymbol{\beta}\}}{1 + \exp\{\mathbf{X}_i^\top \boldsymbol{\beta}\}}$. This is called *the logistic regression model*.

Choice of the link function

Canonical links provide very attractive options for the selection of the link function for normal, Poisson and alternative distributions. For these distributions, we always prefer the canonical link unless there is a very strong reason (given by the nature of the application) to select a different link function. For gamma and inverse Gaussian distributions, the canonical links are problematic because they do not even satisfy the assumptions we put on link functions. Also, they are hard to interpret.

Denote by \mathcal{M} the parametric space for the mean of the response (the set of all possible values of the mean). Then g maps \mathcal{M} to \mathbb{R} , which is the space of all possible values of the linear predictor. The inverse link g^{-1} should map \mathbb{R} to \mathcal{M} .

For non-negative random variables, such as from gamma or inverse Gaussian distributions, $\mathcal{M} = (0, \infty)$. A reasonable inverse link g^{-1} should map \mathbb{R} to $(0, \infty)$, but this is not the case for the canonical links of these two distributions. On the other hand, a reasonable link that maps the two sets correctly is the log-link. For this link, we get $\mu_i = \exp\{\mathbf{X}_i^\top \boldsymbol{\beta}\}$, which is in \mathcal{M} for any value of the parameter vector $\boldsymbol{\beta}$.

For the alternative distribution, $\mathcal{M} = (0, 1)$. A reasonable inverse link g^{-1} should map \mathbb{R} to $(0, 1)$ and be strictly monotone. We can choose such links from distribution functions of continuous random variables with positive densities over \mathbb{R} . On the other hand, the link functions are quantile functions of such distributions. The logistic link is the quantile function of the standard logistic distribution.

Parametrizations of the GLM

The primary parameters in the GLM are the regression coefficients $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)^\top$. However, we are also interested in parametrizing the distributions of the individual Y_i 's that

depend on both the primary parameters $\boldsymbol{\beta}$ and the covariates \mathbf{X}_i . This can be done in three ways:

- by the *linear predictors* η_1, \dots, η_n ;
- by the *means* $\mu_1 \equiv \mathbb{E} Y_1, \dots, \mu_n \equiv \mathbb{E} Y_n$;
- by the *canonical parameters* $\theta_1, \dots, \theta_n$.

The parametrizations are related to each other as follows:

- $\eta_i = \mathbf{X}_i^\top \boldsymbol{\beta}$;
- $\eta_i = g(\mu_i), \mu_i = g^{-1}(\eta_i)$;
- $\mu_i = b'(\theta_i), \theta_i = (b')^{-1}(\mu_i)$;
- $\eta_i = g(b'(\theta_i)), \theta_i = (b')^{-1}(g^{-1}(\eta_i))$; if the link g is canonical then $\eta_i = \theta_i$.

The end of
lecture 3
(Mar. 4)

The likelihood function

Let the true dispersion parameter φ_0 be known. The likelihood function for $\boldsymbol{\beta}$ has the form

$$L(\boldsymbol{\beta} | \mathbf{Y}) = \prod_{i=1}^n \exp \left\{ \frac{Y_i \theta_i - b(\theta_i)}{\varphi_0} + c(Y_i, \varphi_0) \right\},$$

where $\theta_i = (b')^{-1}(g^{-1}(\mathbf{X}_i^\top \boldsymbol{\beta}))$.

The log-likelihood is

$$\ell(\boldsymbol{\beta} | \mathbf{Y}) = \sum_{i=1}^n \left[\frac{Y_i \theta_i - b(\theta_i)}{\varphi_0} + c(Y_i, \varphi_0) \right]. \quad (2.3)$$

The saturated model

Suppose at least one covariate is continuous and consider a model which has the largest possible number of parameters $p = n$. This is called *the saturated model**. In the saturated model, each Y_i gets its own canonical parameter θ_i , which is unrelated to the canonical parameters of the other observations. Maximizing $L(\boldsymbol{\beta} | \mathbf{Y})$ w.r.t all $\boldsymbol{\beta} \in \mathbb{R}^n$ is the same as maximizing $L(\boldsymbol{\theta} | \mathbf{Y})$ w.r.t all $\boldsymbol{\theta} \in \mathbb{R}^n$. To obtain the MLE in the saturated model, we differentiate (2.3) w.r.t. each θ_i separately and we get n equations

$$\varphi_0^{-1}[Y_i - b'(\theta_i)] = 0, \quad i = 1, \dots, n.$$

The MLE of μ_i under the saturated model is

$$\hat{\mu}_i = Y_i.$$

* Český saturovaný model

The fitted values $\hat{\mu}_i \equiv \hat{Y}_i$ are equal to the observed values Y_i . This model provides a “perfect fit”. However, a “perfect fit” of this kind is rarely useful.

The saturated model with $p = n$ does not satisfy the regularity assumptions of the MLE theory (the number of parameters must be constant for the theory to apply; here $p \rightarrow \infty$ as $n \rightarrow \infty$). The estimates obtained from this model are not even consistent.

Note. When all covariates are discrete (with a finite number of values), the largest possible number of parameters in the model is equal to the number of possible distinct values of the covariate vector \mathbf{X}_i , which is usually smaller than n and does not change as the number of observations increases. In this setting, the saturated model behaves differently.

The null model

The null model* is the opposite extreme. It assumes $p = 1$ and $\mathbf{X}_i = 1$ so that the model includes only the intercept and all Y_i are equally distributed.

The MLE of the common canonical parameter θ of the null model is derived in Section 2.1.2. Using $\beta_0 = \eta = g(b'(\theta))$, we get the MLE of β_0 as $\hat{\beta}_n = g(b'(\hat{\theta}_n)) = g(\bar{Y}_n)$. From the central limit theorem for iid random variables and the delta method,

$$\sqrt{n}(\hat{\beta}_n - \beta_0) \xrightarrow{D} N(0, \varphi_0 V(\mu_0)[g'(\mu_0)]^2),$$

where $\mu_0 = E Y_i$ (compare this with (2.2)).

Neither the null model nor the saturated model are particularly interesting. We aim to build a model which has more structure than the null model, fewer parameters than the saturated model, and fits the observed data well.

2.3. Maximum Likelihood Estimation in the GLM

Let (Y_i, \mathbf{X}_i) , $i = 1, \dots, n$ be iid random vectors of dimension $p + 1$. Let $h_i(\mathbf{x})$ be the marginal density of \mathbf{X}_i (with no assumptions about it except finite second moments). Let (Y_i, \mathbf{X}_i) , $i = 1, \dots, n$, satisfy the generalized linear model (Definition 2.3) with true parameters β_0 and φ_0 . Consider φ_0 known. Write the conditional density of Y given $\mathbf{X} = \mathbf{x}$ as $f(y | \mathbf{x}, \beta_0, \varphi_0)$. Then the joint density of (Y_i, \mathbf{X}_i) is $f(y | \mathbf{x}, \beta_0, \varphi_0)h_i(\mathbf{x})$, the full likelihood is

$$L^*(\beta) = \prod_{i=1}^n f(Y_i | \mathbf{X}_i, \beta, \varphi_0)h_i(\mathbf{X}_i)$$

and the full log-likelihood is

$$\ell^*(\beta) = \sum_{i=1}^n \log f(Y_i | \mathbf{X}_i, \beta, \varphi_0) + \sum_{i=1}^n \log h_i(\mathbf{X}_i).$$

* Český nulový model

Since the rightmost sum does not depend on $\boldsymbol{\beta}$, it suffices to maximize

$$\ell(\boldsymbol{\beta}) = \sum_{i=1}^n \log f(Y_i | X_i, \boldsymbol{\beta}, \varphi_0). \quad (2.4)$$

This is the log-likelihood shown previously in (2.3) (without the detailed derivation and justification needed for the validity of asymptotic results).

When the covariates are random, it is not necessary to consider, know or estimate their distribution. If the covariates were constants, the log-likelihood and the score statistic would be sums of nonidentically distributed terms. Feller-Lindeberg or Lyapunov central limit theorems would have to be applied to validate the asymptotic results, and additional assumptions would have to be imposed on the covariates. The asymptotic results for constant covariates would then turn out to be the same as the results for iid data.

The core term in the log-likelihood (2.4) that we are going to maximize can be written as

$$\sum_{i=1}^n \frac{Y_i \theta_i - b(\theta_i)}{\varphi_0}, \quad (2.5)$$

where $g(\mu_i) = \mathbf{X}_i^\top \boldsymbol{\beta}$ and $\mu_i = b'(\theta_i)$. The following theorem summarizes the main results for maximum likelihood estimation of $\boldsymbol{\beta}$.

Theorem 2.3. (likelihood equations in the GLM; [Nelder and Wedderburn 1972](#)) Let the definition of the GLM hold. Denote by $\boldsymbol{\beta}_0$ the true parameter. Let

$$w(\mu_i) = \frac{1}{V(\mu_i)[g'(\mu_i)]^2} > 0. \quad (2.6)$$

(i) The score function for $\boldsymbol{\beta}$ is

$$\mathbf{U}(\boldsymbol{\beta} | Y_i) = \varphi_0^{-1} w(\mu_i) g'(\mu_i) (Y_i - \mu_i) \mathbf{X}_i,$$

where $\mu_i = g^{-1}(\mathbf{X}_i^\top \boldsymbol{\beta})$. It satisfies $E\mathbf{U}(\boldsymbol{\beta}_0 | Y_i) = \mathbf{0}$.

(ii) The score statistic for $\boldsymbol{\beta}$ is

$$\mathbf{U}_n(\boldsymbol{\beta} | Y) = \frac{1}{\varphi_0} \sum_{i=1}^n w(\mu_i) g'(\mu_i) (Y_i - \mu_i) \mathbf{X}_i.$$

(iii) The maximum likelihood estimator $\widehat{\boldsymbol{\beta}}_n$ solves the system of equations

$$\sum_{i=1}^n w(\widehat{\mu}_i) g'(\widehat{\mu}_i) (Y_i - \widehat{\mu}_i) \mathbf{X}_i = \mathbf{0}, \quad (2.7)$$

where $\widehat{\mu}_i = g^{-1}(\mathbf{X}_i^\top \widehat{\boldsymbol{\beta}}_n)$.

(iv) When the link g is canonical then

$$w(\mu_i) = V(\mu_i) = \frac{1}{g'(\mu_i)},$$

the score statistic can be written as

$$U_n(\boldsymbol{\beta} | \mathbf{Y}) = \frac{1}{\varphi_0} \sum_{i=1}^n (Y_i - \mu_i) \mathbf{X}_i,$$

and the likelihood equations are

$$\sum_{i=1}^n Y_i \mathbf{X}_i = \sum_{i=1}^n \hat{\mu}_i \mathbf{X}_i. \quad \diamond$$

Note. When the link g is canonical then $\mathbf{S} = \sum_{i=1}^n Y_i \mathbf{X}_i$ is the sufficient statistic and the MLE equates the observed value of \mathbf{S} to its estimated expectation under the model (conditional on the covariates).

Definition 2.5. $\hat{\mu}_i = g^{-1}(\mathbf{X}_i^\top \hat{\boldsymbol{\beta}}_n)$ are called *the fitted values**. \(\nabla\)

Proof (of Theorem 2.3).

(i) The score function is calculated by the chain rule:

$$U(\boldsymbol{\beta} | Y_i) = \frac{\partial}{\partial \boldsymbol{\beta}} \frac{1}{\varphi_0} [Y_i \theta_i - b(\theta_i)] = \frac{\partial}{\partial \theta} \frac{1}{\varphi_0} [Y_i \theta_i - b(\theta_i)] \cdot \frac{\partial \theta_i}{\partial \mu} \cdot \frac{\partial \mu_i}{\partial \eta} \cdot \frac{\partial \eta_i}{\partial \boldsymbol{\beta}}$$

This is a product of four terms. The first term is $\frac{1}{\varphi_0} (Y_i - \mu_i)$. The next two terms can be calculated by the formula for the derivative of the inverse function. We have

$$\frac{\partial \theta_i}{\partial \mu} = \frac{\partial (b')^{-1}(\mu_i)}{\partial \mu} = \frac{1}{b''(\theta_i)} = \frac{1}{V(\mu_i)},$$

and

$$\frac{\partial \mu_i}{\partial \eta} = \frac{\partial g^{-1}(\eta_i)}{\partial \eta} = \frac{1}{g'(\mu_i)}.$$

Finally, $\frac{\partial \eta_i}{\partial \boldsymbol{\beta}} = \frac{\partial \mathbf{X}_i^\top \boldsymbol{\beta}}{\partial \boldsymbol{\beta}} = \mathbf{X}_i$. So we have

$$U(\boldsymbol{\beta} | Y_i) = \frac{Y_i - \mu_i}{\varphi_0 V(\mu_i) g'(\mu_i)} \mathbf{X}_i = \frac{1}{\varphi_0} \underbrace{\frac{1}{V(\mu_i) [g'(\mu_i)]^2}}_{\stackrel{\text{df}}{=} w(\mu_i) > 0} g'(\mu_i) (Y_i - \mu_i) \mathbf{X}_i.$$

* Český vyrovnané hodnoty

Because the conditional expectation (given \mathbf{X}_i) of $Y_i - \mu_i$ is 0 when μ_i is evaluated at the true parameter $\boldsymbol{\beta}_0$, the conditional expectation of $\mathbf{U}(\boldsymbol{\beta}_0 | Y_i)$ is zero and the unconditional expectation is zero as well. This proves that $E\mathbf{U}(\boldsymbol{\beta}_0 | Y_i) = \mathbf{0}$.

The next two points (ii) and (iii) are obvious.

- (iv) For the canonical link, we know by Lemma 2.2 that $g'(\mu_i) = 1/V(\mu_i)$. Hence $w(\mu_i) = V(\mu_i)$ and $w(\mu_i)g'(\mu_i) = 1$. The rest is easy. \square

The end of
lecture 4
(Mar. 11)

The next step is to investigate the observed and expected information matrices for $\boldsymbol{\beta}$. Let $\mathbf{a}^{\otimes 2} \stackrel{\text{df}}{=} \mathbf{a}\mathbf{a}^\top$.

Theorem 2.4. (on information matrices in the GLM) *Let the definition of the GLM hold. Let $E_X w(\mu_i)\mathbf{X}_i^{\otimes 2}$ be finite and of full rank.*

- (i) *The contribution of the i -th observation to the observed information matrix is*

$$I(\boldsymbol{\beta} | Y_i) = \frac{1}{\varphi_0} [w(\mu_i)\mathbf{X}_i^{\otimes 2} - \mathbb{J}_i],$$

where

$$\mathbb{J}_i = \left[w'(\mu_i) + w(\mu_i) \frac{g''(\mu_i)}{g'(\mu_i)} \right] (Y_i - \mu_i)\mathbf{X}_i^{\otimes 2}.$$

The observed information matrix is $I_n(\boldsymbol{\beta} | \mathbf{Y}) = n^{-1} \sum_{i=1}^n I(\boldsymbol{\beta} | Y_i)$.

- (ii) *When evaluated at the true $\boldsymbol{\beta}_0$, $E\mathbb{J}_i = 0$. The Fisher (expected) information matrix at the true $\boldsymbol{\beta}_0$ is*

$$I(\boldsymbol{\beta}_0) = EI(\boldsymbol{\beta}_0 | Y_i) = \frac{1}{\varphi_0} E_X w(\mu_i)\mathbf{X}_i^{\otimes 2}. \quad (2.8)$$

By assumptions, it is finite and of full rank. It holds that $\text{var}\mathbf{U}(\boldsymbol{\beta}_0 | Y_i) = I(\boldsymbol{\beta}_0)$.

- (iii) *When the link g is canonical then $\mathbb{J}_i = 0$ at any $\boldsymbol{\beta}$ for all i , the observed information matrix is positive definite at all $\boldsymbol{\beta}$, the log-likelihood is concave, the likelihood equations have just one solution and it is the MLE. \diamond*

Note. If the link g is not canonical, there is no guarantee that a solution to the likelihood equations is the MLE. The likelihood is not concave, the equations may have multiple solutions. Numerical algorithms for solving the likelihood equations may iterate slowly and converge to the wrong solution.

The Fisher information matrix $I(\boldsymbol{\beta}_0)$ can be consistently estimated by the empirical estimator

$$\hat{I}_n = \frac{1}{n\varphi_0} \sum_{i=1}^n w(\hat{\mu}_i)\mathbf{X}_i^{\otimes 2} = \frac{1}{n\varphi_0} \mathbf{X}^\top \hat{\mathbb{W}} \mathbf{X}, \quad (2.9)$$

where $\hat{\mathbb{W}}$ is the $n \times n$ diagonal matrix $\text{diag}(w(\hat{\mu}_1), \dots, w(\hat{\mu}_n))$. When φ_0 is unknown it is replaced by a consistent estimator $\hat{\varphi}_n$, which will be introduced in Section ??.

Proof (of Theorem 2.4).

(i) The contribution to the observed information matrix can be calculated as follows.

$$I(\boldsymbol{\beta} | Y_i) = -\frac{\partial}{\partial \boldsymbol{\beta}^\top} U(\boldsymbol{\beta} | Y_i) = -\frac{1}{\varphi_0} \frac{\partial w(\mu_i) g'(\mu_i) (Y_i - \mu_i)}{\partial \mu} \mathbf{X}_i \cdot \frac{\partial \mu_i}{\partial \eta} \cdot \frac{\partial \eta_i}{\partial \boldsymbol{\beta}^\top}.$$

We already know from the proof of Theorem 2.3 that

$$\frac{\partial \mu_i}{\partial \eta} = \frac{1}{g'(\mu_i)} \quad \text{and} \quad \frac{\partial \eta_i}{\partial \boldsymbol{\beta}^\top} = \mathbf{X}_i^\top.$$

It remains to calculate the derivative of the product of three functions of μ_i . We get

$$\frac{\partial w(\mu_i) g'(\mu_i) (Y_i - \mu_i)}{\partial \mu} = w'(\mu_i) g'(\mu_i) (Y_i - \mu_i) + w(\mu_i) g''(\mu_i) (Y_i - \mu_i) - w(\mu_i) g'(\mu_i).$$

Putting all the terms together and separating out the part that does not depend on $(Y_i - \mu_i)$, we get

$$I(\boldsymbol{\beta} | Y_i) = \frac{1}{\varphi_0} w(\mu_i) \mathbf{X}_i \mathbf{X}_i^\top - \frac{1}{\varphi_0} \underbrace{\left[w'(\mu_i) + w(\mu_i) \frac{g''(\mu_i)}{g'(\mu_i)} \right]}_{\stackrel{\text{df}}{=} \mathbb{J}_i} (Y_i - \mu_i) \mathbf{X}_i \mathbf{X}_i^\top$$

and the result follows. Notice that the first part is a positive semi-definite matrix while the second part may be anything.

(ii) Because \mathbb{J}_i is a product of $Y_i - \mu_0$ (which has zero conditional expectation given \mathbf{X}_i at the true $\boldsymbol{\beta}_0$) and terms that depend on \mathbf{X}_i but not on Y_i , its expectation at the true $\boldsymbol{\beta}_0$ is a zero matrix. It follows that

$$\mathbb{E} I(\boldsymbol{\beta}_0 | Y_i) = \frac{1}{\varphi_0} \mathbb{E}_X w(\mu_i) \mathbf{X}_i^{\otimes 2}.$$

Next,

$$\begin{aligned} \text{var } U(\boldsymbol{\beta}_0 | Y_i) &= \text{var} \frac{1}{\varphi_0} w(\mu_i) g'(\mu_i) (Y_i - \mu_i) \mathbf{X}_i = \mathbb{E}_X \frac{1}{\varphi_0^2} [w(\mu_i) g'(\mu_i)]^2 \text{var} [Y_i | \mathbf{X}_i] \mathbf{X}_i^{\otimes 2} \\ &= \mathbb{E}_X \frac{[w(\mu_i) g'(\mu_i)]^2 \varphi_0 V(\mu_i)}{\varphi_0^2} \mathbf{X}_i^{\otimes 2} = \frac{1}{\varphi_0} \mathbb{E}_X w(\mu_i) \mathbf{X}_i^{\otimes 2} = I(\boldsymbol{\beta}_0 | Y_i). \end{aligned}$$

(iii) We have $w(\mu_i) = \frac{1}{V(\mu_i) [g'(\mu_i)]^2}$. For the canonical link, $g'(\mu_i) = 1/V(\mu_i)$ by Lemma 2.2, hence $g'(\mu_i) = 1/w(\mu_i)$. Next,

$$g''(\mu_i) = -\frac{w'(\mu_i)}{w^2(\mu_i)}.$$

Hence

$$\frac{g''(\mu_i)}{g'(\mu_i)} w(\mu_i) = -w'(\mu_i) \quad \text{and} \quad \left[w'(\mu_i) + w(\mu_i) \frac{g''(\mu_i)}{g'(\mu_i)} \right] = 0. \quad \square$$

2.4. Algorithm for Fitting the GLM

The parameters of the GLM can be estimated by a numerical algorithm called *iterative weighted least squares** [IWLS]. It is based on the following result.

Theorem 2.5. (Nelder and Wedderburn 1972) The MLE $\hat{\boldsymbol{\beta}}_n$ in the GLM solves the system of equations

$$\hat{\boldsymbol{\beta}}_n = (\mathbf{X}^T \hat{\mathbf{W}} \mathbf{X})^{-1} (\mathbf{X}^T \hat{\mathbf{W}} \hat{\mathbf{Z}}),$$

where $\hat{\mathbf{W}} = \text{diag}(w(\hat{\mu}_1), \dots, w(\hat{\mu}_n))$, $\hat{\mathbf{Z}}$ is an n -vector with components

$$\hat{Z}_i = \hat{\eta}_i + (Y_i - \hat{\mu}_i)g'(\hat{\mu}_i),$$

$\hat{\mu}_i = g^{-1}(\hat{\eta}_i)$, and $\hat{\eta}_i = \mathbf{X}_i^T \hat{\boldsymbol{\beta}}_n$. ◇

Note. $\hat{\mathbf{Z}}$ is called the *adjusted dependent variable*[†]. Notice that \hat{Z}_i is the linear approximation to $g(Y_i)$ by Taylor expansion around $\hat{\mu}_i$:

$$g(Y_i) \approx g(\hat{\mu}_i) + g'(\hat{\mu}_i)(Y_i - \hat{\mu}_i).$$

Unlike $g(Y_i)$, the adjusted dependent variable can be calculated even if Y_i is outside of the domain of g , for example when $g \equiv \log$ and $Y_i \sim \text{Po}(\mu_i)$ attains the value of zero.

Note. When the link g is canonical then $\hat{\mathbf{W}} = \text{diag}(V(\hat{\mu}_1), \dots, V(\hat{\mu}_n))$ and

$$\hat{Z}_i = \hat{\eta}_i + \frac{Y_i - \hat{\mu}_i}{V(\hat{\mu}_i)}.$$

Proof (of Theorem 2.5). Take the obvious equality

$$\left(\sum_{i=1}^n w(\hat{\mu}_i) \mathbf{X}_i \mathbf{X}_i^T \right) \hat{\boldsymbol{\beta}}_n = \left(\sum_{i=1}^n w(\hat{\mu}_i) \mathbf{X}_i \mathbf{X}_i^T \right) \hat{\boldsymbol{\beta}}_n$$

and add zero to the right-hand side in the form of the likelihood equations

$$\mathbf{0} = \sum_{i=1}^n w(\hat{\mu}_i) g'(\hat{\mu}_i) (Y_i - \hat{\mu}_i) \mathbf{X}_i.$$

Rearrange the right-hand side to get

$$\left(\sum_{i=1}^n w(\hat{\mu}_i) \mathbf{X}_i \mathbf{X}_i^T \right) \hat{\boldsymbol{\beta}}_n = \sum_{i=1}^n w(\hat{\mu}_i) \mathbf{X}_i [\mathbf{X}_i^T \hat{\boldsymbol{\beta}}_n + g'(\hat{\mu}_i) (Y_i - \hat{\mu}_i)],$$

where the bracket contains the value \hat{Z}_i of the adjusted dependent variable. Rewrite the result in a matrix form as

$$(\mathbf{X}^T \hat{\mathbf{W}} \mathbf{X}) \hat{\boldsymbol{\beta}}_n = \mathbf{X}^T \hat{\mathbf{W}} \hat{\mathbf{Z}}.$$

This completes the proof. □

* Česky iterativní vážené nejmenší čtverce [†] Česky upravená odezva

One cannot calculate $\hat{\beta}_n$ directly from Theorem 2.5 because it appears on both the left-hand side as well as the right-hand side. However, the result motivates the following iterative algorithm.

Iterative weighted least squares algorithm

Step 1. Take initial values $\hat{\mu}_i^{(0)} = Y_i$ (or $Y_i \pm \varepsilon$ if Y_i is not within the domain of g). Set $k := 0$.

Step 2. Calculate $\hat{\mathbb{W}}^{(k)} = \text{diag}(w(\hat{\mu}_1^{(k)}), \dots, w(\hat{\mu}_n^{(k)}))$ and $\hat{\mathbb{Z}}^{(k)} = g(\hat{\mu}_i^{(k)}) + (Y_i - \hat{\mu}_i^{(k)})g'(\hat{\mu}_i^{(k)})$.

Step 3. Take

$$\hat{\beta}_n^{(k+1)} = (\mathbb{X}^T \hat{\mathbb{W}}^{(k)} \mathbb{X})^{-1} (\mathbb{X}^T \hat{\mathbb{W}}^{(k)} \hat{\mathbb{Z}}^{(k)}).$$

Step 4. Calculate $\hat{\mu}_i^{(k+1)} = g^{-1}(\mathbb{X}_i^T \hat{\beta}_n^{(k+1)})$.

Step 5. Set $k := k + 1$.

Iterate steps 2–5 until convergence, for example until $\|\hat{\beta}_n^{(k)} - \hat{\beta}_n^{(k-1)}\| < \delta$, where δ is a pre-specified tolerance parameter. If the model is well formulated, the algorithm usually converges in 5–7 steps.

Note.

- The IWLS algorithm is a special case of the Fisher scoring algorithm (see Appendix A.2, bottom of page 30).
- According to (2.9), the matrix $(\mathbb{X}^T \hat{\mathbb{W}}^{(k)} \mathbb{X})^{-1}$ estimates (up to the proportionality constant φ_0) the inverse information matrix. Thus, an estimate of the asymptotic variance of $\hat{\beta}_n$ is obtained by the IWLS as well (just make sure to update it after the last iteration of $\hat{\beta}_n^{(k)}$).
- Let $\mathbb{X}^* = \hat{\mathbb{W}}^{1/2} \mathbb{X}$ and $\mathbb{Y}^* = \hat{\mathbb{W}}^{1/2} \hat{\mathbb{Z}}$. Then $\hat{\beta}_n$ can be written as an ordinary least squares estimator $\hat{\beta}_n = (\mathbb{X}^{*T} \mathbb{X}^*)^{-1} \mathbb{X}^{*T} \mathbb{Y}^*$. This is useful for extending the diagnostic methods available for the linear model to the GLM.

The end of
lecture 5
(Mar. 11)

A. Appendix: Maximum Likelihood Theory

A.1. Definition

Consider a random sample $\mathbf{X} = (X_1, \dots, X_n)$ of independent identically distributed random variables (or vectors), each with density $f(x|\boldsymbol{\theta}_X)$ with respect to a σ -finite measure μ . We assume that $f(x|\boldsymbol{\theta}_X) \in \mathcal{F}$, where

$$\mathcal{F} = \{\text{distributions with density } f(x|\boldsymbol{\theta}), \boldsymbol{\theta} \in \Theta \subseteq \mathbb{R}^d\}$$

represents a parametric model for the distribution of the data.

The model \mathcal{F} must satisfy the model identifiability condition: For any $\boldsymbol{\theta}_1 \neq \boldsymbol{\theta}_2$ it holds $f(x|\boldsymbol{\theta}_1) \neq f(x|\boldsymbol{\theta}_2)$. In other words, no distribution can be parametrized by several different parameter vectors.

Because of independence, the joint density of the random sample X_1, \dots, X_n is $\prod_{i=1}^n f(x_i|\boldsymbol{\theta}_X)$. The maximum likelihood estimator $\hat{\boldsymbol{\theta}}$ of the parameter $\boldsymbol{\theta}_X$ is the point from Θ that maximizes the joint density evaluated at the observed values of X_1, \dots, X_n .

Definition A.1 (likelihood, log-likelihood).

- The random function

$$L_n(\boldsymbol{\theta}) \stackrel{\text{df}}{=} \prod_{i=1}^n f(X_i|\boldsymbol{\theta})$$

is called *the likelihood function* for the parameter $\boldsymbol{\theta}$ in the model \mathcal{F} .

- The random function

$$\ell_n(\boldsymbol{\theta}) \stackrel{\text{df}}{=} \log L_n(\boldsymbol{\theta}) = \sum_{i=1}^n \log f(X_i|\boldsymbol{\theta})$$

is called *the log-likelihood function*. ▽

Definition A.2 (maximum likelihood estimator). *The maximum likelihood estimator (MLE) of the parameter $\boldsymbol{\theta}_X$ in the model \mathcal{F} is defined as*

$$\hat{\boldsymbol{\theta}}_n = \arg \max_{\boldsymbol{\theta} \in \Theta} L_n(\boldsymbol{\theta}).$$

▽

Note. Since the logarithm is strictly increasing, $L_n(\boldsymbol{\theta})$ and $\ell_n(\boldsymbol{\theta})$ attain the maximum at the same point.

Definition A.3. Let P and Q be probability measures on the same probability space with densities p and q with respect to the same σ -finite measure μ (for example, $\mu = P + Q$). Define

$$K(P, Q) = \begin{cases} E_P \log \frac{p(X)}{q(X)} = \int_{\{x:p(x)>0\}} \log \frac{p(x)}{q(x)} p(x) d\mu(x) & \text{if } P[q(X) = 0] = 0 \\ +\infty & \text{otherwise.} \end{cases}$$

$K(P, Q)$ is called the *Kullback-Leibler distance (divergence)*. ▽

Note. In fact, $K(P, Q)$ is a pseudo-distance: it holds $K(P, Q) \geq 0$, and $K(P, Q) = 0$ if and only if $P = Q$, but it is not symmetric: $K(P, Q) \neq K(Q, P)$.

Theorem A.1. Suppose the support set $S = \{x \in \mathbb{R} : f(x|\boldsymbol{\theta}) > 0\}$ does not depend on the parameter $\boldsymbol{\theta}$. Denote P_X the induced probability measure of the random variable X_i and P_θ the probability measure associated with the density $f(x|\boldsymbol{\theta})$. Then for any $\boldsymbol{\theta} \neq \boldsymbol{\theta}_X$

$$\frac{1}{n} \log \frac{L_n(\boldsymbol{\theta}_X)}{L_n(\boldsymbol{\theta})} = \frac{1}{n} \sum_{i=1}^n \log \frac{f(X_i|\boldsymbol{\theta}_X)}{f(X_i|\boldsymbol{\theta})} \rightarrow K(P_X, P_\theta) \quad P_X - \text{almost surely,}$$

and hence

$$P[\ell_n(\boldsymbol{\theta}_X) > \ell_n(\boldsymbol{\theta})] \rightarrow 1 \quad \text{as } n \rightarrow \infty. \quad \diamond$$

Note. When the number of observations increases to infinity, the (log-)likelihood function at the true parameter will be with a large probability larger than the (log-)likelihood function at any other parameter. This observation justifies the idea of estimating the parameters by maximizing the log-likelihood over all possible parameter vectors.

A.2. The calculation of the maximum likelihood estimator

The maximum likelihood estimator is usually determined by differentiation of the log-likelihood. The first derivative is set to zero and it is verified that the second derivative is negative definite.

Definition A.4 (score, information).

- The random vector

$$U(\boldsymbol{\theta}|X_i) \stackrel{\text{df}}{=} \frac{\partial}{\partial \boldsymbol{\theta}} \log f(X_i|\boldsymbol{\theta})$$

is called *the score function* for the parameter $\boldsymbol{\theta}$ in the model \mathcal{F} .

- The random vector

$$U_n(\boldsymbol{\theta}|\mathbf{X}) \stackrel{\text{df}}{=} \sum_{i=1}^n U(\boldsymbol{\theta}|X_i) = \sum_{i=1}^n \frac{\partial}{\partial \boldsymbol{\theta}} \log f(X_i|\boldsymbol{\theta})$$

is called *the score statistic*.

- The random matrix

$$I(\boldsymbol{\theta}|X_i) \stackrel{\text{df}}{=} -\frac{\partial}{\partial \boldsymbol{\theta}^\top} U(\boldsymbol{\theta}|X_i) = -\frac{\partial^2}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}^\top} \log f(X_i|\boldsymbol{\theta})$$

is called the contribution of the i -th observation to the information matrix.

- The random matrix

$$I_n(\boldsymbol{\theta}|\mathbf{X}) \stackrel{\text{df}}{=} -\frac{1}{n} \frac{\partial}{\partial \boldsymbol{\theta}^\top} U_n(\boldsymbol{\theta}|\mathbf{X}) = \frac{1}{n} \sum_{i=1}^n I(\boldsymbol{\theta}|X_i)$$

is called *the observed information matrix*.

- The matrix

$$I(\boldsymbol{\theta}) \stackrel{\text{df}}{=} E I(\boldsymbol{\theta}|X_i) = -E \frac{\partial^2}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}^\top} \log f(X_i|\boldsymbol{\theta})$$

is called *the expected (Fisher) information matrix*. ▽

If the set Θ is open, the MLE $\hat{\boldsymbol{\theta}}_n$ solves the system of equations $U_n(\hat{\boldsymbol{\theta}}_n|\mathbf{X}) = \mathbf{0}$, that is

$$\sum_{i=1}^n \frac{\partial}{\partial \boldsymbol{\theta}} \log f(X_i|\hat{\boldsymbol{\theta}}_n) = \mathbf{0}.$$

This system is called the *likelihood equations*.

The solution to the likelihood equations need not exist. Sometimes there may be multiple solutions, at most one of which is the MLE. If $I_n(\hat{\boldsymbol{\theta}}_n|\mathbf{X}) > 0$ (the observed information is positive definite at $\hat{\boldsymbol{\theta}}_n$), we know that $\hat{\boldsymbol{\theta}}_n$ is at least a local maximum. If $I_n(\boldsymbol{\theta}|\mathbf{X}) > 0$ for every $\boldsymbol{\theta} \in \Theta$, the log-likelihood function is concave and the solution to the likelihood equations must be the global maximum and hence the MLE.

In most cases no explicit solution can be found and the MLE must be calculated by numerical methods. There are two commonly used numerical methods for solving the likelihood equations. Let $\hat{\boldsymbol{\theta}}^{(r)}$ be the r -th iteration to the solution.

- **The Newton-Raphson method:** $\hat{\boldsymbol{\theta}}^{(r+1)} = \hat{\boldsymbol{\theta}}^{(r)} + [nI_n(\hat{\boldsymbol{\theta}}^{(r)}|\mathbf{X})]^{-1} U_n(\hat{\boldsymbol{\theta}}^{(r)}|\mathbf{X})$
- **The Fisher Scoring method:** $\hat{\boldsymbol{\theta}}^{(r+1)} = \hat{\boldsymbol{\theta}}^{(r)} + [nI(\hat{\boldsymbol{\theta}}^{(r)})]^{-1} U_n(\hat{\boldsymbol{\theta}}^{(r)}|\mathbf{X})$

They are iterated until the change in $\hat{\boldsymbol{\theta}}$ from one iteration to the next is sufficiently small or until $U_n(\hat{\boldsymbol{\theta}})$ is sufficiently close to $\mathbf{0}$. The only difference between the two methods is in the information matrix: N-R uses the observed information, FS uses the expected information.

Both require setting $\hat{\boldsymbol{\theta}}^{(1)}$, the starting value for numerical approximation, and are sensitive to its choice.

A.3. Properties of the maximum likelihood estimator

Maximum likelihood estimators are consistent and asymptotically normal as long as so called *regularity conditions* are satisfied.

Conditions (Regularity conditions for maximum likelihood estimators).

- R1.** The number of parameters d in the model \mathcal{F} is constant.
- R2.** The support set $S = \{x \in \mathbb{R} : f(x|\boldsymbol{\theta}) > 0\}$ does not depend on the parameter $\boldsymbol{\theta}$.
- R3.** The parameter space Θ is an open set.
- R4.** The density $f(x|\boldsymbol{\theta})$ is sufficiently smooth function of $\boldsymbol{\theta}$ (at least twice continuously differentiable).
- R5.** The Fisher information matrix $I(\boldsymbol{\theta})$ is finite, regular, and positive definite in a neighborhood of $\boldsymbol{\theta}_X$.
- R6.** The order of differentiation and integration can be interchanged in expressions such as

$$\frac{\partial}{\partial \boldsymbol{\theta}} \int h(x, \boldsymbol{\theta}) d\mu(x) = \int \frac{\partial}{\partial \boldsymbol{\theta}} h(x, \boldsymbol{\theta}) d\mu(x),$$

where $h(x, \boldsymbol{\theta})$ is either $f(x|\boldsymbol{\theta})$ or $\partial f(x|\boldsymbol{\theta})/\partial \boldsymbol{\theta}$.

Note. Take the identity

$$\int_{-\infty}^{\infty} f(x|\boldsymbol{\theta}) d\mu(x) = 1$$

and differentiate both sides of the equation twice with respect to $\boldsymbol{\theta}$. Regularity condition R6 implies

$$\int_{-\infty}^{\infty} \frac{\partial}{\partial \boldsymbol{\theta}} f(x|\boldsymbol{\theta}) d\mu(x) = \int_{-\infty}^{\infty} \frac{\partial^2}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}^\top} f(x|\boldsymbol{\theta}) d\mu(x) = \mathbf{0}. \quad (\text{A.1})$$

Theorem A.2 (consistency of the MLE). *Let conditions R1–R6 hold. Then there exists n_0 and a sequence $\hat{\boldsymbol{\theta}}_n$ ($n \geq n_0$) of solutions to the likelihood equations $U_n(\hat{\boldsymbol{\theta}}_n|X) = \mathbf{0}$ such that $\hat{\boldsymbol{\theta}}_n \xrightarrow{P} \boldsymbol{\theta}_X$.* \diamond

Note. If the log-likelihood is strictly concave, the likelihood equations have a unique solution, which is the MLE. It converges in probability to the true parameter. If the log-likelihood is not strictly concave, the likelihood equations may have multiple solutions representing local maxima and minima of the log-likelihood. There is one solution among them (the closest to $\boldsymbol{\theta}_X$), which provides a consistence sequence of estimators. Other solutions may not be close to $\boldsymbol{\theta}_X$ and may not converge to it.

Note. If there exists a sequence $\tilde{\boldsymbol{\theta}}_n$ of other estimators that are guaranteed to be consistent (for example, moment estimators of $\boldsymbol{\theta}_X$), a consistent MLE can be obtained by taking the root of the likelihood equations, which is closest to $\tilde{\boldsymbol{\theta}}_n$. Alternatively, one can perform one step of the Newton-Raphson algorithm with $\tilde{\boldsymbol{\theta}}_n$ as the starting value.

Theorem A.3 (Score function properties). Let conditions R1–R6 hold. Then

$$(i) \ E U(\boldsymbol{\theta}_X | X_i) = 0, \text{var} U(\boldsymbol{\theta}_X | X_i) = I(\boldsymbol{\theta}_X).$$

$$(ii) \ \frac{1}{\sqrt{n}} U_n(\boldsymbol{\theta}_X | X) \xrightarrow{D} N_d(\mathbf{0}, I(\boldsymbol{\theta}_X)). \quad \diamond$$

Note. The Fisher information matrix at $\boldsymbol{\theta}_X$ can be calculated in two different ways: from Definition A.4 (the expectation of minus the second derivative of the log density) or from Theorem A.3 (the score function variance).

Theorem A.4 (asymptotic normality of the MLE). Suppose conditions R1–R6 hold. Let $\hat{\boldsymbol{\theta}}_n$ be a consistent sequence of solutions to the likelihood equations. Then

$$\sqrt{n}(\hat{\boldsymbol{\theta}}_n - \boldsymbol{\theta}_X) \xrightarrow{D} N_d(\mathbf{0}, I^{-1}(\boldsymbol{\theta}_X)). \quad \diamond$$

Note.

- The asymptotic variance of the MLE is equal to the inverse of the Fisher information. More information means better precision for estimation.
- The asymptotic variance of the MLE is in a certain sense optimal. Other estimators (e.g., moment estimators) cannot have a smaller asymptotic variance.

Theorem A.5 (asymptotic distribution of the likelihood ratio). Suppose conditions R1–R6 hold. Let $\hat{\boldsymbol{\theta}}_n$ be a consistent sequence of solutions to the likelihood equations. Then

$$2 \log \frac{L_n(\hat{\boldsymbol{\theta}}_n)}{L_n(\boldsymbol{\theta}_X)} = 2(\ell_n(\hat{\boldsymbol{\theta}}_n) - \ell_n(\boldsymbol{\theta}_X)) \xrightarrow{D} \chi_d^2. \quad \diamond$$

Theorem A.6 (the Δ method for the MLE). Suppose conditions R1–R6 hold. Let $\hat{\boldsymbol{\theta}}_n$ be a consistent sequence of solutions to the likelihood equations. Take $q : \Theta \rightarrow \mathbb{R}^k$ a continuously differentiable function. Denote $\boldsymbol{v}_X = q(\boldsymbol{\theta}_X)$ a $D(\boldsymbol{\theta}) = \partial q(\boldsymbol{\theta}) / \partial \boldsymbol{\theta}$. Then $\hat{\boldsymbol{v}}_n = q(\hat{\boldsymbol{\theta}}_n)$ is the MLE of the parameter \boldsymbol{v}_X and

$$\sqrt{n}(\hat{\boldsymbol{v}}_n - \boldsymbol{v}_X) \xrightarrow{D} N_k(\mathbf{0}, D(\boldsymbol{\theta}_X) I^{-1}(\boldsymbol{\theta}_X) D(\boldsymbol{\theta}_X)^T). \quad \diamond$$

A.4. Tests based on maximum likelihood theory

The theory of the MLE can be used to derive tests of simple and composite hypotheses about the parameter $\boldsymbol{\theta}_X$.

A.4.1. Testing of simple hypotheses

We want to test the null hypothesis $H_0 : \theta_X = \theta_0$ against the alternative $H_1 : \theta_X \neq \theta_0$, where $\theta_0 \in \Theta$. It is a simple hypothesis because there is just a single distribution in the model \mathcal{F} with the density $f(x|\theta_0)$.

We will introduce three different test statistics for testing H_0 .

Definition A.5.

(i) The statistic

$$\lambda_n = \frac{L_n(\hat{\theta}_n)}{L_n(\theta_0)}$$

is called *the likelihood ratio*.

(ii) The statistic

$$W_n = n(\hat{\theta}_n - \theta_0)^T \hat{I}_n(\hat{\theta}_n)(\hat{\theta}_n - \theta_0)$$

is called *the Wald statistic*.

(iii) The statistic

$$R_n = \frac{1}{n} U_n(\theta_0|X)^T \hat{I}_n^{-1}(\theta_0) U_n(\theta_0|X)$$

is called *the Rao (score) statistic*. ▽

Note. The symbol \hat{I}_n denotes any consistent estimator of the Fisher information matrix. Three different estimators can be used in Wald and Rao statistics:

1. $\hat{I}_n(\theta) = I_n(\theta|X) = -\frac{1}{n} \sum_{i=1}^n \frac{\partial^2}{\partial \theta \partial \theta^T} \log f(\theta|X_i)$ (the observed information matrix)
2. $\hat{I}_n(\theta) = \frac{1}{n} \sum_{i=1}^n U(\theta|X_i)^{\otimes 2}$ (the empirical variance of the score function)
3. $\hat{I}_n(\theta) = I(\theta)$ (the Fisher information matrix)

The most common choice for the Wald statistic is $\hat{I}_n(\hat{\theta}_n) = I_n(\hat{\theta}_n|X)$. The most common choice for the Rao statistic is $\hat{I}_n(\theta_0) = \frac{1}{n} \sum_{i=1}^n U(\theta_0|X_i)^{\otimes 2}$.

Note.

- The likelihood ratio requires the calculation of $\hat{\theta}_n$ and L_n or ℓ_n . It does not require the calculation of U_n and \hat{I}_n .
- The Wald statistic requires the calculation of $\hat{\theta}_n$ and \hat{I}_n . It does not require the calculation of L_n and U_n .
- Rao statistic requires the calculation of U_n and \hat{I}_n . It does not require the calculation of $\hat{\theta}_n$ and L_n .

Note. If $d = 1$ (one parameter) and $\theta_0 = 0$, then the Wald statistic can be written as

$$W_n = \left[\frac{\hat{\theta}_n}{\sqrt{n^{-1} \hat{I}_n^{-1}(\hat{\theta}_n)}} \right]^2,$$

where $n^{-1}\widehat{I}_n^{-1}(\widehat{\theta}_n)$ is the estimator of the asymptotic variance of $\widehat{\theta}_n$.

Theorem A.7. Suppose conditions R1–R6 are satisfied. Let the hypothesis $H_0 : \theta_X = \theta_0$ hold. Then:

(i)

$$2 \log \lambda_n = 2(\ell_n(\widehat{\theta}_n) - \ell_n(\theta_0)) \xrightarrow{D} \chi_d^2$$

(ii)

$$W_n \xrightarrow{D} \chi_d^2$$

(iii)

$$R_n \xrightarrow{D} \chi_d^2 \quad \diamond$$

Note. If H_0 holds, $\widehat{\theta}_n$ should be close to θ_0 , $L_n(\widehat{\theta}_n)$ should be close to $L_n(\theta_0)$, and $U_n(\theta_0|X)$ should be close to $\mathbf{0}$. Under H_0 , all three test statistics have values close to 0. Their large values testify against H_0 .

Corollary. Denote by $\chi_d^2(1 - \alpha)$ the $(1 - \alpha)$ -quantile of χ_d^2 distribution. Consider tests of $H_0 : \theta_X = \theta_0$ against $H_1 : \theta_X \neq \theta_0$ defined by the rule: reject H_0 in favor of H_1 , if

- (i) $2 \log \lambda_n \geq \chi_d^2(1 - \alpha)$ (likelihood ratio test)
- (ii) $W_n \geq \chi_d^2(1 - \alpha)$ (Wald test)
- (iii) $R_n \geq \chi_d^2(1 - \alpha)$ (score test)

Each of these tests has asymptotically (for $n \rightarrow \infty$) the level α .

Note. It can be shown that these three tests are asymptotically equivalent. For large sample sizes, their results are almost identical. With smaller sample sizes, their results can differ. Investigations of small sample behavior of these test statistics revealed that the likelihood ratio test has the best properties, the Wald test is the worst of the three.

Thus, in practical applications, the likelihood ratio test should be preferred.

Note. Under normality, the three test statistics are identical.

A.4.2. Estimation in the presence of nuisance parameters and testing of composite hypotheses

It is frequently desirable to estimate and test just a small number of parameters in a model that contains a much larger number of parameters. We divide the parameter vector into two subsets: the parameters of interest and the other parameters – *nuisance parameters*.

Let $\boldsymbol{\theta}$ be divided into $\boldsymbol{\theta}_A$ containing the first m components of $\boldsymbol{\theta}$, and $\boldsymbol{\theta}_B$ containing the remaining $d - m$ components of $\boldsymbol{\theta}$. We have

$$\boldsymbol{\theta} = (\boldsymbol{\theta}_A, \boldsymbol{\theta}_B)^\top = (\theta_1, \dots, \theta_m, \theta_{m+1}, \dots, \theta_d)^\top$$

We want to test the hypothesis $H_0^* : \boldsymbol{\theta}_X \in \Theta_0$ against $H_1^* : \boldsymbol{\theta}_X \notin \Theta_0$, where $\Theta_0 = \{\boldsymbol{\theta} : \boldsymbol{\theta}_A = \boldsymbol{\theta}_{A0}\} \subset \Theta$. We want to know whether the first m components of $\boldsymbol{\theta}_X$ are equal to the vector of constants $\boldsymbol{\theta}_{A0}$ regardless of the other $d - m$ components of $\boldsymbol{\theta}_X$.

This is not a simple null hypothesis because there are many distributions in the model \mathcal{F} that satisfy H_0^* .

All the vectors and matrices appearing in the notation of maximum likelihood estimation theory are decomposed into the first m components (part A) and the remaining $d - m$ components (part B). For example,

$$\widehat{\boldsymbol{\theta}}_n = \begin{pmatrix} \widehat{\boldsymbol{\theta}}_{An} \\ \widehat{\boldsymbol{\theta}}_{Bn} \end{pmatrix}, \quad \mathbf{U}_n(\boldsymbol{\theta}) = \begin{pmatrix} \mathbf{U}_{An}(\boldsymbol{\theta}) \\ \mathbf{U}_{Bn}(\boldsymbol{\theta}) \end{pmatrix}, \quad I(\boldsymbol{\theta}) = \begin{pmatrix} I_{AA}(\boldsymbol{\theta}) & I_{AB}(\boldsymbol{\theta}) \\ I_{BA}(\boldsymbol{\theta}) & I_{BB}(\boldsymbol{\theta}) \end{pmatrix}, \quad \text{etc.}$$

The following lemma is useful for inverting the decomposed information matrix.

Lemma A.8 (Block matrix inversion). *Let the matrix*

$$I = \begin{pmatrix} I_{AA} & I_{AB} \\ I_{BA} & I_{BB} \end{pmatrix}$$

be of full rank. Then there exists an inverse matrix to I and it can be expressed as

$$I^{-1} = \begin{pmatrix} I^{AA} & I^{AB} \\ I^{BA} & I^{BB} \end{pmatrix},$$

where

$$\begin{aligned} I^{AA} &= I_{AA.B}^{-1}, \\ I^{AB} &= -I_{AA.B}^{-1} I_{AB} I_{BB}^{-1}, \\ I^{BA} &= -I_{BB.A}^{-1} I_{BA} I_{AA}^{-1}, \\ I^{BB} &= I_{BB.A}^{-1}, \\ I_{AA.B} &= I_{AA} - I_{AB} I_{BB}^{-1} I_{BA}, \\ I_{BB.A} &= I_{BB} - I_{BA} I_{AA}^{-1} I_{AB}. \end{aligned} \quad \diamond$$

If the null hypothesis $H_0^* : \boldsymbol{\theta}_X \in \Theta_0$ holds we know that $\boldsymbol{\theta}_{AX} = \boldsymbol{\theta}_{A0}$, but we do not know the value of $\boldsymbol{\theta}_{BX}$. We can estimate $\boldsymbol{\theta}_{BX}$ by the maximum likelihood method applied to the nested submodel

$$\mathcal{F}_0 = \{\text{distributions with density } f(x | (\boldsymbol{\theta}_A, \boldsymbol{\theta}_B)), \boldsymbol{\theta}_A = \boldsymbol{\theta}_{A0}, \boldsymbol{\theta}_B \in \Theta_B \subseteq \mathbb{R}^{d-m}\},$$

with $d - m$ unknown parameters.

Denote the maximum likelihood estimator of θ_X in the submodel \mathcal{F}_0 by $\tilde{\theta}_n = \begin{pmatrix} \tilde{\theta}_{An} \\ \tilde{\theta}_{Bn} \end{pmatrix}$, where $\tilde{\theta}_{An} = \theta_{A0}$ and $\tilde{\theta}_{Bn}$ solves the system of likelihood equations

$$U_{Bn}(\theta_{A0}, \tilde{\theta}_{Bn}) = \mathbf{0}.$$

The Fisher information matrix for θ_B in this model is $I_{BB}(\theta_X)$.

By Theorems A.3 and A.4 applied to the submodel \mathcal{F}_0 , we get

$$\frac{1}{\sqrt{n}} U_{Bn}(\theta_X) \xrightarrow{D} N_{d-m}(\mathbf{0}, I_{BB}(\theta_X))$$

and

$$\sqrt{n}(\tilde{\theta}_{Bn} - \theta_{BX}) \xrightarrow{D} N_{d-m}(\mathbf{0}, I_{BB}^{-1}(\theta_X)).$$

On the other hand, Theorems A.3 and A.4 and Lemma A.8 applied to the larger model imply

$$\frac{1}{\sqrt{n}} U_{Bn}(\theta_X) \xrightarrow{D} N_{d-m}(\mathbf{0}, I_{BB}(\theta_X))$$

and

$$\sqrt{n}(\hat{\theta}_{Bn} - \theta_{BX}) \xrightarrow{D} N_{d-m}(\mathbf{0}, I_{BB.A}^{-1}(\theta_X)),$$

where (dropping the arguments θ_X)

$$I_{BB.A}^{-1} = (I_{BB} - I_{BA}I_{AA}^{-1}I_{AB})^{-1} \geq I_{BB}^{-1}.$$

Thus, the asymptotic variance of the MLE of the parameter θ_{BX} depends on whether or not θ_{AX} is known. If θ_{AX} is known (which is true if H_0^* holds), the asymptotic variance of the MLE $\tilde{\theta}_{Bn}$ is generally larger than the asymptotic variance of the MLE $\hat{\theta}_{Bn}$ that does not assume a known θ_{AX} .

However, when $I_{BA} = 0$ (the estimators of θ_{AX} and θ_{BX} are asymptotically independent), then the asymptotic variances of $\tilde{\theta}_{Bn}$ and $\hat{\theta}_{Bn}$ are the same. Then it does not matter whether or not θ_{AX} is known.

Let us generalize the three test statistics introduced in Definition A.5 of the previous section to testing the composite hypothesis $H_0^* : \theta_X \in \Theta_0$ against $H_1^* : \theta_X \notin \Theta_0$, where $\Theta_0 = \{\theta : \theta_A = \theta_{A0}\} \subset \Theta$.

Definition A.6.

(i) The statistic

$$\lambda_n^* = \frac{L_n(\hat{\theta}_n)}{L_n(\tilde{\theta}_n)}$$

is called *the likelihood ratio*.

(ii) The statistic

$$W_n^* = n(\widehat{\boldsymbol{\theta}}_{An} - \boldsymbol{\theta}_{A0})^\top \widehat{I}_{AA.B}(\widehat{\boldsymbol{\theta}}_n)(\widehat{\boldsymbol{\theta}}_{An} - \boldsymbol{\theta}_{A0})$$

is called *the Wald statistic*.

(iii) The statistic

$$R_n^* = \frac{1}{n} \mathbf{U}_n(\tilde{\boldsymbol{\theta}}_n)^\top \widehat{I}_n^{-1}(\tilde{\boldsymbol{\theta}}_n) \mathbf{U}_n(\tilde{\boldsymbol{\theta}}_n)$$

is called *the Rao (score) statistic*. ▽

Note.

- Obviously, $\lambda_n^* \geq 1$.
- The expression $\widehat{I}_{AA.B}$ in the Wald statistic means the inverse of the upper left block of the the matrix \widehat{I}_n^{-1} .
- Since $\mathbf{U}_{Bn}(\tilde{\boldsymbol{\theta}}_n) = \mathbf{0}$, the Rao statistic can be written as

$$R_n^* = \frac{1}{n} \mathbf{U}_{An}(\tilde{\boldsymbol{\theta}}_n)^\top \widehat{I}_{AA.B}^{-1}(\tilde{\boldsymbol{\theta}}_n) \mathbf{U}_{An}(\tilde{\boldsymbol{\theta}}_n).$$

- Theh Rao statistic does not require the calculation of the MLE $\widehat{\boldsymbol{\theta}}_n$ in the larger model, it only needs the MLE $\tilde{\boldsymbol{\theta}}_n$ in the submodel. This is often much easier to get.

Theorem A.9. Let the null hypothesis $H_0^* : \boldsymbol{\theta}_X \in \Theta_0$, where $\Theta_0 = \{\boldsymbol{\theta} : \boldsymbol{\theta}_A = \boldsymbol{\theta}_{A0}\}$, hold.

Then

(i)

$$2 \log \lambda_n^* = 2(\ell_n(\widehat{\boldsymbol{\theta}}_n) - \ell_n(\tilde{\boldsymbol{\theta}}_n)) \xrightarrow{D} \chi_m^2;$$

(ii)

$$W_n^* \xrightarrow{D} \chi_m^2;$$

(iii)

$$R_n^* \xrightarrow{D} \chi_m^2. \quad \diamond$$

Note. Under H_0^* , we expect $\widehat{\boldsymbol{\theta}}_n$ to be close to $\tilde{\boldsymbol{\theta}}_n$, $L_n(\widehat{\boldsymbol{\theta}}_n)$ to be close to $L_n(\tilde{\boldsymbol{\theta}}_n)$, and $\mathbf{U}_n(\widehat{\boldsymbol{\theta}}_n)$ to be close to $\mathbf{0}$. The large values of the three test statistics testify against the null hypothesis.

Corollary. Let $\chi_m^2(1 - \alpha)$ be $(1 - \alpha)$ -quantile of the χ_m^2 distribution. Consider tests of $H_0^* : \boldsymbol{\theta}_X \in \Theta_0$, where $\Theta_0 = \{\boldsymbol{\theta} : \boldsymbol{\theta}_A = \boldsymbol{\theta}_{A0}\}$, against $H_1^* : \boldsymbol{\theta}_X \notin \Theta_0$ given by the rule: reject H_0^* in favor of H_1^* if

- (i) $2 \log \lambda_n^* \geq \chi_m^2(1 - \alpha)$ (*the likelihood ratio test*)
- (ii) $W_n^* \geq \chi_m^2(1 - \alpha)$ (*the Wald test*)

(iii) $R_n^* \geq \chi_m^2(1 - \alpha)$ (the score test)

Then each of these three tests has asymptotically (for $n \rightarrow \infty$) the level α .

Note. The number of degrees of freedom in the reference χ_m^2 distribution is equal to the number of tested parameters.

Note. These three tests are asymptotically equivalent under the null hypothesis as well as under local alternatives. With small or moderate sample sizes, the likelihood ratio test has the best properties and the Wald test is the worst of the three. In practical applications, the likelihood ratio test should be preferred.

Note. Let $m = 1$, $\theta_{AX} = \theta_{Xj}$, and $\theta_{A0} = 0$. Consider the test of the hypothesis $H_0^* : \theta_{Xj} = 0$ against $H_1^* : \theta_{Xj} \neq 0$ (zero value of the j -th parameter in the presence of other parameters that are unspecified by the hypothesis). Then the Wald statistic can be written as

$$W_n = \left[\frac{\hat{\theta}_{jn}}{\sqrt{n^{-1}\hat{I}_{jj}^{-1}}} \right]^2,$$

where $n^{-1}\hat{I}_{jj}^{-1}$ is the estimator of the asymptotic variance of $\hat{\theta}_{jn}$. This is the square of the test statistic that statistical software typically evaluates to test zero value of a single model parameter.

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