Statistical models and likelihood functions *

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1. Statistical models

1.1 Definition STATISTICAL MODEL. *A* statistical model *is a pair* $(\mathcal{Z},\ \mathcal{P})$ *where* $\mathcal{Z}$ *is a set of possible observations and* $\mathcal{P}$ *a nonempty family of probability measures which assign probabilities to subsets of* $\mathcal{Z}$*. When the probability measures in* $\mathcal{P}$ *are all defined on the same* σ*-algebra of events* $\mathcal{A}_{\mathcal{Z}}$ *in* $\mathcal{Z}$*, we shall also refer to the triplet* $(\mathcal{Z},\ \mathcal{A}_{\mathcal{Z}},\ \mathcal{P})$ *as a statistical model.*

1.2 Definition DOMINATED MODEL. *A statistical model* $(\mathcal{Z},\ \mathcal{A}_{\mathcal{Z}},\ \mathcal{P})$ *is* dominated *if all the probability measures in* $\mathcal{P}$ *have a density with respect to the same measure* μ *on* $\mathcal{Z}$*.* μ *is called the dominating measure and we say that* $(\mathcal{Z},\ \mathcal{P})$ *is* μ*-dominated.*

1.3 Definition HOMOGENEOUS MODEL. *A statistical model* $(\mathcal{Z},\ \mathcal{A}_{\mathcal{Z}},\ \mathcal{P})$ *is* homogeneous *if it is dominated and the dominating measure* μ *can be chosen so that the densities are all strictly positive.*

1.4 Definition PARAMETRIC MODEL. *A statistical model* $(\mathcal{Z},\ \mathcal{P})$ *is said to be parametrized by the elements of a nonempty set* Θ *if the set* $\mathcal{P}$ *of probability measures has the form*

$$\mathcal{P} = \{P_\theta : \theta \in \Theta\}\ .$$

If the set Θ *is a subset of* $\mathbb{R}^p$ *or we can define a one-to-one transformation between* Θ *and the elements of a subset of* $\mathbb{R}^p$*, we say that* $(\mathcal{Z},\ \mathcal{P})$ *is a* parametric model. *Otherwise, the model* $(\mathcal{Z},\ \mathcal{P})$ *is said to be* nonparametric.

1.5 Definition FUNCTIONAL PARAMETER. *A* functional parameter *on a statistical model* $(\mathcal{Z},\ \mathcal{P})$ *is an application*

$$g : \mathcal{P} \to \Theta$$

which assigns to each element $P \in \mathcal{P}$ *a parameter* $\theta = g(P) \in \Theta$*, where* Θ *is a nonempty set (the parameter space).*

Functional parameters allow one to associate parameters with the distributions of parametric or nonparametric models. The mean, variance, median, etc., of a probability distribution may all be interpreted as functional parameters.

2. Identification

Let $(\mathcal{Z},\ \mathcal{A}_{\mathcal{Z}},\ \mathcal{P})$ a statistical model such that $\mathcal{P} = \{P_\theta : \theta \in \Theta\}$.

2.1 Definition IDENTIFICATION OF A PARAMETER VALUE. *We say that a parameter value* $\theta_1 \in \Theta$ *is* identifiable *if there is no other value* $\theta_2 \in \Theta$ *such that* $P_{\theta_1} = P_{\theta_2}$.

2.2 Definition IDENTIFICATION OF A MODEL. *We say that the model* $(\mathcal{Z},\ \mathcal{A}_{\mathcal{Z}},\ \mathcal{P})$ *is identifiable if all the elements of* Θ *are identifiable.*

2.3 Definition IDENTIFICATION OF A PARAMETRIC FUNCTION. *Let* $\psi : \theta \to \Psi$ *be a function of* θ. *We say that the function* $\psi(\theta)$ *is* identifiable *if*

$$\psi(\theta_1) \neq \psi(\theta_2) \Rightarrow P_{\theta_1} \neq P_{\theta_2}\ , \forall \theta_1, \theta_2 \in \Theta$$

or, equivalently,

$$P_{\theta_1} = P_{\theta_2} \Rightarrow \psi(\theta_1) = \psi(\theta_2)\ \ , \forall \theta_1, \theta_2 \in \Theta\ .$$

2.4 Definition LOCAL IDENTIFICATION. *Suppose the set* Θ *has a set of neighborhoods defined on it (a topology). Then we say that a parameter value* $\theta_1 \in \Theta$ *is* locally identifiable *if there is a neighborhood* $V(\theta_1)$ *of* θ_1 *such that*

$$\theta_2 \in V(\theta_1) \text{ and } \theta_2 \neq \theta_1 \Rightarrow P_{\theta_1} \neq P_{\theta_2}\ .$$

3. Likelihood and score functions

3.1 Definition LIKELIHOOD FUNCTION. *Let* $(\mathcal{Z},\ \mathcal{P})$ *be a statistical model which satisfies the following assumptions:*

(A1) $(\mathcal{Z},\ \mathcal{P})$ *is a* μ*-dominated model;*

(A2) $\mathcal{P} = \{P_\theta : \theta \in \Theta \subseteq \mathbb{R}^p\}$;

(A3) $L(z\,;\theta)\,,\ z \in \mathcal{Z}$, *is the density function* (*with respect to* μ) *associated with* P_θ.

The density function $L(z;\theta)$ *viewed as a function of* θ *is called the* likelihood function *of model* $(\mathcal{Z},\ \mathcal{P})$. *The symbol* $\underset{\theta}{E}(\cdot)$ *refers to the expected value with respect to* θ *(provided it exists) :*

$$\underset{\theta}{E}[h(Z)] = \int_{\mathcal{Z}} h(z)\, dP_\theta(z) = \int_{\mathcal{Z}} h(z)\, L(z\,;\theta)\, d\mu(z)\ \ .$$

The vector Z often has the form

$$Z = (Y_1', Y_2', \ldots, Y_n')'$$

where $Y_t \in \mathbb{R}^m$ is an "individual" observation vector and $\theta = (\theta_1, \theta_2, \ldots, \theta_p)' \in \Theta$. Usually, the density $L(z;\theta)$ is written in the form

$$L(z;\theta) = \prod_{t=1}^{n} f_t(z\,;\theta) \equiv L_n(z;\theta) \tag{3.1}$$

where $f_t(z;\theta)$ is a density for an "individual observation". $f_t(z;\theta)$ usually has one of the following forms :

$$f_t(z\,;\theta) = f(y_t\,;\theta)\ ,\ y_t \in \mathbb{R}^m \tag{3.2}$$

$$f_t(z\,;\theta) = f(y_t \mid x_t\,;\theta) \tag{3.3}$$

where x_t is a $k \times 1$ vector of conditioning variables ("explanatory variables") and $f(y_t\,;.)$ is the density function of y_t (given x_t) as a function of the parameter vector θ, or

$$L_t(z\,;\theta) = f(y_t \mid \bar{y}_{t-1}, x_t\,;\theta) \tag{3.4}$$

where $\bar{y}_{t-1} = (\bar{y}_0, y_1, \ldots, y_{t-1})'$ is a vector of past values of y and $\bar{y}_0$ is a vector of "initial conditions".

3.2 Definition SCORE FUNCTION. *Under the assumption $(A1)$ to $(A3)$, suppose also that:*

(A4) Θ *is an open set in* $\mathbb{R}^p$;

(A5) $\partial L(z\,;\theta)/\partial\theta$ *exists,* $\forall z \in \mathcal{Z}\ ,\forall\theta \in \Theta$;

(A6) $L(z\,;\theta) > 0\ ,\forall z \in \mathcal{Z}\ ,\forall\theta \in \Theta$;

(A7) $\int_{\mathcal{Z}} \frac{\partial}{\partial\theta}[L(z\,;\theta)]\,d\mu(z) = \frac{\partial}{\partial\theta}\left[\int_{\mathcal{Z}} L(z\,;\theta)\,d\mu(z)\right]$.

Then the function

$$S(z\,;\theta) = \frac{\partial}{\partial\theta}[\ln L(z\,;\theta)]\ ,\theta \in \Theta\ ,\ z \in \mathcal{Z}\ ,$$

is called the score function *associated with the likelihood* $L(z\,;\theta)$.

3.3 Proposition MEAN OF A SCORE. *Under the assumptions $(A1)$ to $(A7)$, we have :*

$$\underset{\theta}{E}[S(Z\,;\theta)] = \int_{\mathcal{Z}} S(z\,;\theta)\,L(z\,;\theta)\,d\mu(z) = 0\ .$$

3.4 Definition INFORMATION MATRIX. *In addition to $(A1)$ to $(A7)$, suppose also that:*

(A8) $S(Z\,;\theta)$ *has finite second moments with respect to* $P_\theta, \forall\theta \in \Theta$.

Then, the covariance matrix of $S(Z\,;\theta)$,

$$\begin{aligned} I(\theta) &= V_\theta\left[S(Z\,;\theta)\right] = \underset{\theta}{E}\left[S(Z\,;\theta)\,S(Z\,;\theta)'\right] \\ &= \int_{\mathcal{Z}} S(z\,;\theta)\,S(z\,;\theta)'\,L(z\,;\theta)\,d\mu(z) \end{aligned}$$

is called the Fisher information matrix *associated with* $L(z\,;\theta)$.

3.5 Proposition INFORMATION MATRIX IDENTITY. *Under the assumptions* $(A1)$ *to* $(A8)$, *suppose also that:*

(A9) $\frac{\partial^2 L(z\,;\theta)}{\partial\theta\partial\theta'}$ *exists,* $\forall z \in \mathcal{Z}$, $\forall\theta \in \Theta$;

(A10) $\forall\theta \in \Theta$,

$$\int_{\mathcal{Z}} \frac{\partial^2 L(z;\theta)}{\partial\theta_i\partial\theta_j}d\mu(z) = \frac{\partial^2}{\partial\theta_i\partial\theta_j}\left[\int_{\mathcal{Z}} L(z;\theta)\,d\mu(z)\right].$$

Then

$$I(\theta) = \underset{\theta}{E}\left[-\frac{\partial^2 \ln L(Z;\theta)}{\partial\theta\partial\theta'}\right], \forall\theta \in \Theta.$$

4. Efficiency bounds

4.1 Definition REGULAR ESTIMATOR. *Under the assumptions* $(A1)$ *to* $(A5)$, *an estimator* $T(Z)$ *of some function* $\psi(\theta) \in \mathbb{R}^q$ *is* regular *if it satisfies the following properties:*

(a) $T(Z)$ *has finite second moments;*

(b) $\int_{\mathcal{Z}} T(z)\,L(z\,;\theta)\,d\mu(z)$ *is differentiable with respect to* θ;

(c) $\frac{\partial}{\partial\theta}\int_{\mathcal{Z}} T(z)\,L(z\,;\theta)\,d\mu(z) = \int_{\mathcal{Z}} T(z)\,\frac{\partial}{\partial\theta}\left[L(z\,;\theta)\right]d\mu(z)$, *for all* $\theta \in \Theta$.

4.2 Theorem FRÉCHET-DARMOIS-CRAMER-RAO BOUND. *Let the assumptions* $(A1)$ *to* $(A8)$ *hold, let* $\psi(\theta) \in \mathbb{R}^q$ *be a differentiable function of* θ, *and suppose that*

(A11) *the information matrix* $I(\theta)$ *is positive definite,* $\forall\theta \in \Theta$.

If $\underset{\theta}{E}[T(Z)] = \psi(\theta)$, $\forall\theta \in \Theta$, *then the difference*

$$V_\theta\left[T(Z)\right] - P(\theta)\,I(\theta)^{-1}\,P(\theta)'$$

is positive semi-definite for all $\theta \in \Theta$, *where* $P(\theta) = \partial\psi(\theta)/\partial\theta'$.

4.3 Remark If $\psi(\theta) = \theta$, this means that $V_\theta [T(Z)] - I(\theta)^{-1}$ is positive semi-definite.

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