Statistics

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 $0 \ \mathrm{unit} \ \mathrm{name}$

I Definitions 3

Block I

Definitions

1 Statistic models

1. Statistic models

introduction

I Definitions 5

Statistical model

Let:

 $\cdot\,\Omega$ set

 $\cdot\,\mathcal{A}$ sigma-algebra over Ω

$$\cdot \mathcal{P} \subset \mathcal{F}(\Omega, \mathbb{R})$$

Then, $(\Omega, \mathcal{A}, \mathcal{P})$ is a statistical model if:

$$\cdot \quad \forall \ f \in \mathcal{P}$$
:

f probability distribution

Parametrized

Let:

 $\cdot (\Omega, \mathcal{A}, \mathcal{P})$ statistical model

$$\cdot \, \Theta \subset \mathbb{R}^d$$

Then, $(\Omega, \mathcal{A}, \mathcal{P})$ is parametrized by Θ if:

$$\cdot \mathcal{P} = \{P_{\theta}\}_{\theta \in \Theta}$$

6 2 Estimation

Likelihood

Let:

 $\cdot \left(\Omega, \mathcal{A}, \mathcal{P} \right)$ statistical model parametrized by Θ

We name likelihood function of $(\Omega, \mathcal{A}, \mathcal{P})$ to:

$$L: \Omega \times \Theta \longrightarrow \mathbb{R}^+$$

$$(x,\theta) \longmapsto P_{\theta}(x)$$

I Definitions 7

Exponential model

Let:

 $\cdot (\Omega, \mathcal{A}, \mathcal{P})$ statistical model parametrized by Θ

· L likelihood function of $(\Omega, \mathcal{A}, \mathcal{P})$

Then, $(\Omega, \mathcal{A}, \mathcal{P})$ is exponential if:

 $\cdot \exists \{f_i\}_{i=1}^r, f \in \mathcal{F}(\Omega, \mathbb{R}) \text{ such that:}$

$$\forall i \in [1, r]_{\mathbb{N}}$$
:

 f_i, f measurable

· $\exists \{\phi_i\}_{i=1}^r, \phi \in \mathcal{F}(\theta, \mathbb{R}) \text{ such that:}$

$$\forall i \in [1, r]_{\mathbb{N}}$$
:

 ϕ_i, ϕ measurable

 $\cdot \quad \forall \ x \in \Omega$:

 $\forall \ \theta \in \Theta$:

$$L(x,\theta) = \exp(\sum_{i=1}^{r} f_i(x)\phi_i(\theta) + f(x) + \phi(\theta))$$

8 2 Estimation

2. Estimation

Statistic

Let:

 $\cdot \left(\Omega, \mathcal{A}, \mathcal{P} \right)$ m-D statistical model parametrized by Θ

 $\cdot (M, \Sigma)$ measurable space

 $\cdot\: X\: :\: \Omega \to M$ random variable

 $f: M \to \mathbb{R}^m$

Then, f is a statistic if:

 $\cdot f$ measurable

We denote:

 $\cdot f : T$

I Definitions 9

Sufficiency

Let:

 $\cdot (\Omega, \mathcal{A}, \mathcal{P})$ m-D statistical model parametrized by Θ

 $\cdot \left(M,\Sigma \right)$ measurable space

 $\cdot\: X\: :\: \Omega \to M$ random variable

 $T: M \to \mathbb{R}^m$ statistic

Then, T is sufficient if:

$$\cdot \quad \forall \ \theta_1, \theta_2 \in \Theta$$
:

 $\forall x \in M$:

 $\forall t \in \mathbb{R}^m$:

$$P_{\theta_1}(X = x \mid T \circ X = t) = P_{\theta_2}(X = x \mid T \circ X = t)$$

Estimator

Let:

 $\cdot (\Omega, \mathcal{A}, \mathcal{P})$ statistical model parametrized by Θ

 $\cdot (M, \Sigma)$ measurable space

 $\cdot\: X\: :\: \Omega \to M$ random variable

 $T: M \to \mathbb{R}^k$ statistic

 $\cdot \theta \in \Theta$

Then, T is an estimator of θ if:

 $\cdot T$ approaches θ

Loss function

Let:

 $\cdot (\Omega, \mathcal{A}, \mathcal{P})$ statistical model parametrized by Θ

 $\cdot (M, \Sigma)$ measurable space

 $\cdot X : \Omega \to M$ random variable

 $T: M \to \mathbb{R}^k \text{ estimator}$

 $W: \mathbb{R}^k \times \Theta \to \mathbb{R}^+$

Then, W is a loss function if:

 $\cdot W(\theta, \theta) = 0$

Risk function

Let:

- $\cdot (\Omega, \mathcal{A}, \mathcal{P})$ statistical model parametrized by Θ
- $\cdot (M, \Sigma)$ measurable space
- $\cdot\: X\: :\: \Omega \to M$ random variable
- $T: M \to \mathbb{R}^k$ estimator
- $W: \mathbb{R}^k \times \Theta \to \mathbb{R}^+ \text{ loss function}$

We name risk function to:

$$\begin{array}{ccc} R_T : \Theta & \longrightarrow & \mathbb{R}^+ \\ \theta & \longmapsto & E_{\theta}(W(T, \theta)) \end{array}$$

Block II

Propositions

14 1 Statistic models

1. Statistic models

introduction

Characterization of regular exponential models

Let:

$$\cdot (\Omega, \mathcal{A}, \mathcal{P})$$
 1-D exponential model parametrized by Θ

$$\cdot \exp(f(x)\phi(\theta) + f'(x) + \phi'(\theta))$$
 likelihood function of $(\Omega, \mathcal{A}, \mathcal{P})$

statistical model

Then, holds:

$$\cdot \Theta$$
 interval $, \phi, \phi' \in \mathcal{C}^2$

$$\cdot \quad \forall \ \theta \in \Theta$$
:

$$\phi'(\theta) \neq 0$$

$$E_{\theta}f^{2}(x) \in \mathbb{R}$$

$$\cdot \to (\Omega, \mathcal{A}, \mathcal{P})$$
 regular

Demonstration:

no demonstration

III Examples 17

Block III

Examples

18 1 Statistic models

1. Statistic models

introduction

IV Problems 19

Exponential model

Let:

$$egin{aligned} &\cdot \Omega : \mathbb{R}^n \ &\cdot \mathcal{A} : \mathbb{B}(\mathbb{R}^n) \ &\cdot \theta : (\mu, \sigma^2) \ &\cdot \Theta : \mathbb{R} \times \mathbb{R}^+ \end{aligned}$$

 $\cdot \mathcal{P} : \{N(\theta)\}_{\theta \in \Theta}$

Then, $(\Omega, \mathcal{A}, \mathcal{P})$ is an exponential model:

$$\forall x \in \mathbb{R}^n$$
:

$$f_{\theta}(x) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^{2}}} \exp\left(-\frac{1}{2\sigma^{2}}(x_{i} - \mu)^{2}\right)$$

$$= \left(\frac{1}{\sqrt{2\pi\sigma^{2}}}\right)^{n} \exp\left(-\frac{1}{2\sigma^{2}}\sum_{i=1}^{n}(x_{i} - \mu)^{2}\right)$$

$$L(x,\theta) = \exp\left(\frac{n}{2}\log\left(\frac{1}{2\pi\sigma^{2}}\right) - \frac{1}{2\sigma^{2}}\sum_{i=1}^{n}x_{i}^{2} + \frac{n\bar{x}\mu}{\sigma^{2}} - \frac{n\mu^{2}}{2\sigma^{2}}\right)$$

$$\phi:\Theta \longrightarrow \mathbb{R}^{2}$$

$$(\mu,\sigma^{2}) \longmapsto \left(-\frac{\mu}{2\sigma^{2}},\frac{n\mu}{\sigma^{2}}\right)$$

$$\phi':\Theta \longrightarrow \mathbb{R}$$

$$(\mu,\sigma^{2}) \longmapsto \frac{n}{2}\log\left(\frac{1}{2\pi\sigma^{2}}\right) - \frac{n\mu^{2}}{2\sigma^{2}}$$

$$f:\Omega \longrightarrow \mathbb{R}^{2}$$

$$x \longmapsto \left(\sum_{i=1}^{n}x_{i}^{2},\bar{x}\right)$$

$$L(x,\theta) = \exp(\phi'(\theta) - \phi(\theta)f(x))$$

IV Problems 21

Block IV

Problems

1. Statistic models

introduction

V Tasks 23

go

V block name 25

Block V

Tasks