

12. G_{12} -REGULARIZED MAHALANOBIS DISTANCE ESTIMATOR

We call

$$G_{12} = \left(\hat{\vec{a}}_1 - \hat{\vec{a}}_2 \right)^T \left[\varepsilon I + \varepsilon \theta_{n_1, n_2}^{-1} \hat{R} \right]^{-1} \left(\hat{\vec{a}}_1 - \hat{\vec{a}}_2 \right) - [n_1^{-1} + n_2^{-1}] \varepsilon \theta_{n_1, n_2}^{-1} \text{Tr} \hat{R} \left[\varepsilon I + \varepsilon \theta_{n_1, n_2}^{-1} \hat{R} \right]^{-1}, \quad (12.1)$$

the G_{12} -regularized Mahalanobis distance estimator, where $\varepsilon > 0$ is a parameter. Here, θ_{n_1, n_2} is the nonnegative solution of the equation

$$1 - k_{n_1, n_2} + k_{n_1, n_2} \theta_{n_1, n_2}^{-1} \text{Tr} \hat{R} \left[\theta_{n_1, n_2} I + \hat{R} \right]^{-1} = \varepsilon \theta_{n_1, n_2},$$

$$k_{n_1, n_2} = m [n_1 + n_2 - 2]^{-1}.$$

It can be seen that there exists a unique nonnegative solution of this equation.

THEOREM 12.1. [Gir54, p.601] Let the random variables $\mu_i, \nu_i, i = 1, \dots, m$ be independent for every n ,

$$\mathbf{E} \mu_i = \mathbf{E} \nu_i = 0, \quad \mathbf{E} \mu_i^2 = \mathbf{E} \nu_i^2 = 1, \quad i = 1, \dots, m,$$

for a certain $\beta > 0$

$$\sup_n \max_{i=1, \dots, m} \mathbf{E} \left[|\mu_i|^{4+\beta} + |\nu_i|^{4+\beta} \right] < \infty$$

$$\inf_n \min_{i=1, \dots, m} \lambda_i(R) > 0, \quad \sup_n \max_{i=1, \dots, m} \lambda_i(R) < \infty,$$

and the G -condition be satisfied:

$$\limsup_{n_1, n_2 \rightarrow \infty} m [n_1 + n_2 - 2]^{-1} < \infty, \quad \limsup_{n_1, n_2 \rightarrow \infty} [n_2 n_1^{-1} + n_1 n_2^{-1}] < \infty,$$

$$\sup_{n_1, n_2} (\vec{a}_1 - \vec{a}_2)^T (\vec{a}_1 - \vec{a}_2) < \infty,$$

then, as $\varepsilon > 0$

$$\begin{aligned} & \lim_{n_1, n_2 \rightarrow \infty} \mathbf{P} \left\{ \left[G_{12} - (\vec{a}_1 - \vec{a}_2)^T (\varepsilon I + R)^{-1} (\vec{a}_1 - \vec{a}_2) \right] D_m^{-1/2} \sqrt{n_1 + n_2 - 2} < x \right\} \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x \exp \left\{ -y^2/2 \right\} dy, \end{aligned}$$

where D_m are certain constants.