

Question 3: Derive the LRT

Let $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n \sim N_p(\mu, \Sigma)$

$$H_0: \Sigma = \sigma^2 \mathbf{I} \quad \Delta \leq C_\alpha$$

$$H_1: \Sigma \neq \sigma^2 \mathbf{I} ?$$

$$\Delta^{2/np} = \frac{\prod_{i=1}^p \hat{\lambda}_i}{\prod_{i=1}^p \hat{\sigma}_i^2}$$

The loglikelihood for μ_i & Σ_i given the Observations, \mathbf{X}_i

$$\ell(\mu_i, \Sigma_i) = -\frac{n_i}{2} \log |\Sigma_i| - \frac{1}{2} \sum_{j=1}^m \sum_{k=1}^{n_i} (\mathbf{x}_{ij} - \mu_i)' \Sigma_i^{-1} (\mathbf{x}_{ij} - \mu_i)$$

For the ~~unrestricted model~~ ^{numerator (restricted)} $\Sigma = \sigma^2 \cdot \mathbf{I}$ For denominator: $\Sigma = \Sigma$

- The above function is maximized w/ $\mu_i = \bar{\mathbf{x}}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} \mathbf{x}_{ij}$ for $i=1, \dots, p$

- To maximize for Σ first plug in for sigma:

$$\ell(\mu_i, \sigma_i^2 \mathbf{I}) = -\frac{n_i}{2} \log |\sigma_i^2 \mathbf{I}| - \frac{1}{2} \sum_{j=1}^m \sum_{k=1}^{n_i} (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i)' (\sigma_i^2 \mathbf{I}) (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i)$$

Take derivative w/ respect to σ_i^2 :

$$= -\frac{n_i}{2} (\sigma_i^2 \mathbf{I})^{-1} - \frac{1}{2} \sum_{j=1}^m \sum_{k=1}^{n_i} -(\sigma_i^2 \mathbf{I})^{-1} \cdot (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i) \cdot (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i)' \cdot (\sigma_i^2 \mathbf{I})$$

$$= -\frac{n_i}{2} (\sigma_i^2 \mathbf{I})^{-1} + \frac{1}{2} (\sigma_i^2 \mathbf{I})^{-1} \cdot (\sigma_i^2 \mathbf{I})^{-1} \sum_{j=1}^m \sum_{k=1}^{n_i} (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i) (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i)'$$

$$0 = (-\sigma_i^2 \mathbf{I})^{-1} \left(-\frac{n_i}{2} + \frac{1}{2} (\sigma_i^2 \mathbf{I})^{-1} \right) \cdot \sum_{j=1}^m \sum_{k=1}^{n_i} (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i) (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i)'$$

$$\frac{n_i}{2} = \frac{1}{2} (\sigma_i^2 \mathbf{I})^{-1} \cdot \sum_{j=1}^m \sum_{k=1}^{n_i} (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i) (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i)'$$

$$\hat{\sigma}_i^2 = \frac{1}{n_i} \sum_{j=1}^m \sum_{k=1}^{n_i} (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i) (\mathbf{x}_{ij} - \bar{\mathbf{x}}_i)'$$

Alternative

$$\Lambda = \frac{|\hat{\Sigma}|^{n/2} + \exp \left\{ -\frac{1}{2} \sum_{i=1}^m \sum_{j=1}^{n_i} (x_{ij} - \hat{\mu})' \hat{\Sigma}^{-1} (x_{ij} - \hat{\mu}) \right\}}{(\hat{\sigma}_i^2 \cdot I)^{-n/2} + \exp \left\{ -\frac{1}{2} \sum_{i=1}^m \sum_{j=1}^{n_i} (x_{ij} - \hat{\mu})' (\hat{\sigma}_i^2 \cdot I)^{-1} (x_{ij} - \hat{\mu}) \right\}}$$

Null Model

I am not entirely sure I know what to do here.

The way I understood is that for our null model $\Sigma = \sigma_i^2 \cdot I$ so we can replace all of our Σ 's w/ this value, but then we don't have an MLE for σ_i^2 so I tried to find that.

The LRT is the ratio of the maximized likelihood functions.

I am not sure if I can reduce much further.