24.03.2025
ART Seminar

Getting started
MSc research advisor

(1) Getting acquainted

(a) Google

(b) UniMelb page - click link to expand

(c) Look at publist

(d) Click on 2nd link/paper

(e) Brief look - Hong Kong .. then

REFERENCES.

12. (2018) 10pp
13. (2014) 27pp.
14. (2014) 18pp.
15. (2015) 16pp.
16. (2015) 11pp.
18. (2019) 13pp
19. (2022) 27pp

↖ 2024??

MLEs: Maximum Likelihood Estimators

Parametric Models:

$$f_X(\cdot;\theta) \qquad p(\cdot;\gamma)$$

$$f_{R^x,R^D|X,D}(\cdot|\cdot;\phi).$$

§3.1 Propose an MLE of p.

Can't compute (3.1) (the full likelihood)

$$f_{y_m|W_m}(y_m|W_m;\gamma,\phi) \cdot \prod_{i=1}^{N} \left(f_{R^x R^D|X}(m)\, f_X(x_i;\theta)\right)$$

since it depends on missing data.

Then (proof in Appendix A)

(3.2) (the observed data log likelihood)

$$\log \mathcal{L}_1(\theta,\gamma,\phi) = \sum \log(m\pi) + \sum \log(|\Sigma|)$$

Define

$$\hat{p}_{MLE}(x) = p(x;\hat{\gamma})$$

and apply a little algorithm.

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§3.1 Propose an MLE of ρ

(non observable full likelihood) Π m Π m

then (proof in Appendix B) the log of integrated full likelihood is

$$\log \mathcal{L}(\theta; \gamma, \phi) = \sum_m \sum \log(\int \Sigma) + \sum_m \log(m \pi \int \Sigma_m)$$

Define

$$\hat{T}_{MLE}(x) = \rho(x; \hat{\gamma}_0)$$

§4.1

Lemma 4.1 is proved in Appendix C

The distribution is identifiable

(Reference 20 is a Book!)

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§4.1

MAR models versus logistic MNAR model

Assume

$$f_{R^X R^D | X D} = f_{R^X, R^D | X^o}$$

instead of

$$f_{R^X, R^D | X, D} = f_{R^X, R^D | X^o, D^o}$$

§5 Simulation Study

Table 1 is referred to about ¼ way down on p. 16

Fig. 1 on bottom of p. 17
Fig. 2 on bottom of p. 17
Fig 3 on top of p. 18
Fig. 4 on top of p. 18.

§6 HIV Data

Table 2 and Fig. 5 (see also Appendix F).

§7 Discussion