

A: 8.5.5

2. Measure reliability using proportion of agreement.

- a. Excess of observed proportion agreeing over $p_e = \sum_i \pi_{i+} \pi_{+i} =$ expected under independence.
 - i. Expectation same as for χ^2 test
 - ii. All divided by its maximal value $1 - p_e$
 - iii. Result is called *kappa statistic*. R Code

:

G. Reliability

1. Reliability Question

- a. Do various measurements (items) contributing to scale all measure the same thing?

2. Notation:

- a. I items over all.
- b. X_{ji} is measurement of item i from subject j
- c. $X_{j\cdot} = \sum_{i=1}^I X_{ji}$
- d. s_i is standard deviation of item i , with σ_i the population version
- e. s is standard deviation of total, with σ the population version

3. In this context, redundant variables are a good sign.

- a. If X_{ji} are independent, $\text{Var} [X_{j.}] = \sum_{i=1}^I \text{Var} [X_{ji}]$
- b. If X_{ji} are exact copies of one another, $\text{Var} [X_{j.}] = I^2 \text{Var} [X_{ji}] \forall i$.
- c. More generally, $\text{Var} [X_{j.}] = \sum_{i=1}^I \text{Var} [X_{ji}] + \sum_{i=1}^{I-1} \sum_{\ell=i+1}^I \text{Cov} [X_{ji}, X_{j,\ell}]$
- d. The more the items contain redundant information, the smaller is $\sum_{i=1}^I \text{Var} [X_{ji}] / \text{Var} [X_{j.}]$
- e. If variables are negatively correlated, chance the sign of these items.
 - i. Otherwise summation cancels data out.

4. Measure reliability

- a. Use $1 - \sum_{i=1}^I \text{Var} [X_{ji}] / \text{Var} [X_{j.}]$
 - i. By same reasoning as for dividing by $n - 1$ rather than n for the SD, rescaled by $I/(I - 1)$
 - ii. Generally replace σ_i and σ by s_i and s . resp.
- b. Define Cronbach's $\alpha = \frac{I}{I-1} (1 - \sum_{i=1}^I s_i^2 / s^2)$
 - i. Also called Guttman's γ_3 , K-R 20, etc.
- c. A collection of measurements might measure the same thing,

but might be on different scales.

- i. In this case, apply alpha to the standardized values
- ii. There's a more direct formula in terms of the correlations. R

Code

A: 5.4.6

XI. Exact Methods

A. Contingency tables:

1. Model:

- a. $X_{ij} \sim P(\lambda_{ij})$
- b. $\log(\lambda_{ij}) = \mu + \alpha_i + \beta_j + \gamma_{ij}$
- c. $\alpha_0 = 0, \beta_0 = 0, \gamma_{i0} = \gamma_{0j} = 0 \forall i, j.$
- d. $H_0 : \gamma_{ij} = 0 \forall i, j$ vs. $H_A : \gamma_{ij} \neq 0$ for some $i, j.$

2. Test statistics:

- a. Score statistic is Pearson $\chi^2: T = \sum_{i,j} (X_{ij} - X_{i.}X_{.j}/X_{..})^2 / (X_{i.}X_{.j}/X_{..}).$
- b. LR statistic
- c. Fisher's statistic $1/P[\mathbf{X}]$

3. Remove effect of unknown parameters:

- a. Remove α_i by conditioning on $X_{i.}$

- i. Reduces $I \times J$ independent Poisson variables to J independent multinomials, each with I bins.
 - ii. $X_{i.}$ are exactly ancillary
 - iii. Little loss due to discreteness
- b. Remove β_j by conditioning on $X_{.j}$
- i. Reduces J independent multinomials, each with I bins, to generalized geometric
 - ii. Probabilities are $(\prod_{i=1}^I x_{i.}) (\prod_{j=1}^J x_{.j}) / (x_{..}! \prod_{i=1}^I \prod_{j=1}^J x_{ij}!)$
 - iii. Violates conditionality principal: column totals are not ancillary
 - iv. Bigger problem: discreteness
4. Computation
- a. Either enumerate all tables, and calculate probabilities straight-forwardly, or
 - b. (Pagano and Halvorsen, 1981) calculate recursively
 - i.
$$P [X_{11} = x_{11} | X_{1.}, X_{.1}, X_{..}] = \frac{x_{1.}! x_{.1}! (x_{..} - x_{1.})! (x_{..} - x_{.1})!}{x_{..}! x_{11}! (x_{.1} - x_{11})! (x_{1.} - x_{11})! (x_{..} - x_{1.} - x_{.1} + x_{11})!}$$
 - ii. Probabilities do not depend on other aspects of conditioning event.

iii. Hence same expression holds for $P [X_{11} = x_{11} | X_{i.}, X_{.j} \forall i, j]$

iv. $P [X_{21} = x_{21} | X_{11} = x_{11}, X_{1.}, X_{.2}, X_{.1}, X_{..}]$

$$= x_{2.}!(x_{..} - x_{1.} - x_{2.})!(x_{.1} - x_{11})!(x_{..} - x_{2.} - x_{.1} + x_{11})! /$$

$$[(x_{..} - x_{1.})!x_{21}!(x_{.1} - x_{11} - x_{21})!(x_{.2} - x_{21})!]$$

$$\times (x_{..} - x_{1.} - x_{.1} - x_{2.} + x_{11} + x_{21})!$$

v. More generally, split table into 9 bits, some possibly

$$\text{empty: } \begin{pmatrix} * & * & † \\ * & X_{ij} & † \\ * & † & † \end{pmatrix}$$

- Condition on all marginals of collapsed table, and on totals marked *.
- † cell fixed by conditioning event as well
- Result is hypergeometric distribution with rows and columns containing †.
- As before, collapse over rows and columns containing † to obtain a hypergeometric distribution from 2×2 table.
- Hence $P [\mathbf{X} = \mathbf{x} | X_{.j} = x_{.j} \forall j, X_{i.} = x_{i.} \forall i] = \prod_{ij} p_{ij}$ for hypergeometric probabilities p_{ij} . SAS Code R Code R Code

A: 5.4.4–5.4.5

B. Logistic Regression

1. The Logistic Regression Model and Notation

- a. $X_j \sim \text{Bin}(\exp(\mathbf{z}_j \boldsymbol{\theta}) / (1 + \exp(\mathbf{z}_j \boldsymbol{\theta})), n_j)$
- b. $\mathbf{T} = \mathbf{Z}^\top \mathbf{X}$
- c. Probabilities $\exp(\mathbf{t}^\top \boldsymbol{\theta} - \sum_j n_j \log(1 + \exp(\mathbf{z}_j \boldsymbol{\theta}))) c(\mathbf{t})$, for
 - i. $c(\mathbf{t})$ the number of \mathbf{x} vectors with $\mathbf{Z}^\top \mathbf{x} = \mathbf{t}$.

2. Conditional probabilities

- a. Calculate these to remove effect of parameter not of immediate interest.
- b. $\mathbf{T} = (\mathbf{U}, \mathbf{V})$, $\boldsymbol{\theta} = (\boldsymbol{\omega}, \boldsymbol{\tau})$
- c. $P[\mathbf{V} = \mathbf{v} | \mathbf{U} = \mathbf{u}] = c(\mathbf{u}, \mathbf{v}) \exp(\mathbf{v} \boldsymbol{\tau}) / \sum_{\mathbf{v}} c(\mathbf{u}, \mathbf{v}) \exp(\mathbf{v} \boldsymbol{\tau})$
- d. Allows construction of null distribution for tests of $\boldsymbol{\tau}$ without knowing $\boldsymbol{\omega}$.