

Modification of Carmone, Kara & Maxwell Heuristic Identification of Noisy Variables (HINoV)

Algorithm for metric data (see Carmone, Kara and Maxwell [1999])

Step 1. Data matrix containing m normalized variables measured on metric scale (ratio, interval) and n objects ($i = 1, \dots, n$; $j = 1, \dots, m$) is a starting point.

Step 2. Cluster, via kmeans method, the observed data separately for each j -th variable for a given number of cluster u . It is possible to use clustering methods based on distance matrix (pam or any hierarchical agglomerative method: single, complete, average, mcquitty, median, centroid, Ward).

Step 3. Calculate adjusted Rand indices R_{jl} ($j, l = 1, \dots, m$) for partitions formed from all distinct pairs of the m variables ($j \neq l$). Due to fact that adjusted Rand (Rand) index is symmetrical we need to calculate $m(m-1)/2$ values.

Step 4. Construct $m \times m$ adjusted Rand matrix (parim). Sum rows (or columns) for each j -th variable $R_{j\bullet} = \sum_{l=1}^m R_{jl}$ (topri):

$$\begin{array}{c} \text{parim} \quad \text{topri} \\ \left[\begin{array}{c} M_1 \\ M_2 \\ \vdots \\ M_j \\ \vdots \\ M_m \end{array} \right] \left[\begin{array}{cccccc} R_{12} & \dots & R_{1l} & \dots & R_{1m} \\ R_{21} & \dots & R_{2l} & \dots & R_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ R_{j1} & R_{j2} & \dots & R_{jl} & \dots & R_{jm} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ R_{m1} & R_{m2} & \dots & R_{ml} & \dots & \end{array} \right] \left[\begin{array}{c} R_{1\bullet} \\ R_{2\bullet} \\ \vdots \\ R_{j\bullet} \\ \vdots \\ R_{m\bullet} \end{array} \right] \end{array}$$

Step 5. Rank topri values $R_{1\bullet}, R_{2\bullet}, \dots, R_{m\bullet}$ in decreasing order (stopri) and plot the scree diagram. The size of the topri values indicate the contribution of that variable to the cluster structure. A scree diagram identifies sharp changes in topri values. Relatively low-valued topri variables (the noisy variables) are identified and eliminated from further analysis (say h variables).

Step 6. Run cluster analysis (based on the same classification method) with the selected $m - h$ variables.

Modification of Carmone, Kara & Maxwell Heuristic Identification of Noisy Variables (HINoV) method for nonmetric data¹ differs in steps 1, 2, and 6 (see Walesiak [2005], Walesiak and Dudek [2008]):

Step 1. Data matrix $[x_{ij}]$ containing m ordinal and/or nominal variables and n objects is a starting point.

Step 2. For each j -th variable we receive natural clusters, where number of clusters equals number of categories for that variable (for instance five for Likert scale or seven for semantic differential scale).

¹ For nonmetric variables (ordinal, nominal) contain not too many categories (for nonmetric variables where number of objects is much more than number of categories).

Step 6. Run cluster analysis with one of clustering methods based on distance appropriate to non-metric data (GDM2 for ordinal data – see Jajuga, Walesiak & Bak [2003]; Sokal and Michener distance for nominal data) with the selected $m-h$ variables.

References

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