Package 'sensitivity': scientific appendix

Gilles Pujol

January 4, 2007

This document presents the formulas implemented in the 'sensitivity' package.

Notations

 $y = f(x_1, \dots, x_p)$ $X = (X_{ki})_{\substack{k=1\dots n\\i=1\dots p}}$ modeln-sample

vector extraction $\begin{array}{ll} y_{\cdot} = (y_k)_{k=1...n} \\ X_{\cdot i} = (X_{ki})_{k=1...n} \\ \text{implicit loop} & f_{\underline{1}}(x_{\cdot}) = f_2(y_{\cdot}) \text{ means } \forall k=1\dots n, f_1(x_k) = f_2(y_k) \end{array}$

estimators variance

 $\widehat{\operatorname{cor}}$: Pearson's correlation

rounding |x|: largest integer not greater than x

1 srcpcc

Linear regressions:

$$y_{\cdot \cdot} \simeq b_0 + \sum_{j=1}^{p} b_j X_{\cdot j}$$
 $y_{\cdot \cdot} \simeq c_0 + \sum_{\substack{j=1 \ j \neq i}}^{p} c_j X_{\cdot j}$
 $X_{\cdot i} \simeq d_{i0} + \sum_{\substack{j=1 \ i \neq j}}^{p} d_{ij} X_{\cdot j} \ (i = 1 \dots p)$

Sensitivity indices $(i = 1 \dots p)$:

$$SRC_{i} = \frac{\widehat{var}(X_{.i})}{\widehat{var}(y_{.})} b_{i}^{2}$$

$$PCC_{i} = \widehat{cor} \left(y_{.} - c_{0} - \sum_{\substack{j=1\\j\neq i}}^{p} c_{j} X_{.j}, X_{.i} - d_{i0} - \sum_{\substack{j=1\\j\neq i}}^{p} d_{ij} X_{.j} \right)$$

2 morris

Notations about the domain :

• $\bigotimes_{i=1}^{p} [a_i, b_i]$: the domain

• n_1, \ldots, n_p : number of levels

• k_1, \ldots, k_p : "grid jump" coefficients

Delta $(i = 1 \dots p)$:

$$\Delta_i = k_i \frac{b_i - a_i}{n_i - 1}$$

Discretisation of the space:

$$G = \bigotimes_{i=1}^{p} \left\{ a_i + k \frac{b_i - a_i}{n_i - 1} \right\}_{k=0...n_i - 1}$$
 (grid on the whole domain)
$$G' = \bigotimes_{i=1}^{p} \left\{ a_i + k \frac{b_i - a_i}{n_i - 1} \right\}_{k=0...n_i - 1 - k_i}$$
 (grid restricted to $\bigotimes_{i=1}^{p} [a_i, b_i - \Delta_i]$)

Random elements $(r = 1 \dots R)$:

• $d^{(r)}$: vector of length p composed of equiprobable + ones and - ones

• $x^{(r)}$: randomly chosen point on the grid G' (row vector of length p)

The $p+1 \times p$ matrix of the design of experiments $(r = 1 \dots R)$:

$$X^{(r)} = J_{p+1,1}x^{(r)} + \frac{(2B - J_{p+1,p})D(d^{(r)}) + J_{p+1,p}}{2}D(\Delta_1, \dots, \Delta_p)$$

where

• $J_{i,j}: i \times j$ matrix filled with ones

• $B:(p+1)\times p$ matrix with ones in the lower triangular part and zeros in the upper part, e.g.

$$B = \left(\begin{array}{ccc} 0 & \dots & 0 \\ 1 & \ddots & \vdots \\ \vdots & \ddots & 0 \\ 1 & \dots & 1 \end{array}\right)$$

• D(x): $p \times p$ diagonal matrix with the elements of the vector x on the diagonal

Predictions $(r = 1 \dots R, i = 1 \dots p + 1)$:

$$y_i^{(r)} = f(X_{i1}^{(r)}, \dots, X_{ip}^{(r)})$$

2

Elementary effects $(r = 1 \dots R, i = 1 \dots p)$:

$$EE_i^{(r)} = d_i^{(r)} \frac{y_{i+1}^{(r)} - y_i^{(r)}}{\Delta_i}$$

Sensitivity indices (i = 1 ...p):

$$\mu_i^* = \frac{1}{R} \sum_{r=1}^R |EE_i^{(r)}|$$

$$\sigma_i = \sqrt{\widehat{\text{var}}(EE_i^{(\cdot)})}$$

3 sobol

Two initial *n*-samples, noted $X^{(1)}$ and $X^{(2)}$.

The corresponding response:

$$y_{.}^{(1)} = f(X_{.1}^{(1)}, \dots, X_{.p}^{(1)})$$

 $y_{.}^{(2)} = f(X_{.1}^{(2)}, \dots, X_{.p}^{(2)})$

3.1 method=sobol93

One more n-sample for each subset of indices $I = \{i_1, \dots, i_{n_I}\}$, noted $X^{(2,I,1)}$:

$$X_{.i}^{(2,I,1)} = X_{.i}^{(2)}, \text{ if } i \notin I$$

 $X_{.i}^{(2,I,1)} = X_{.i}^{(1)}, \text{ if } i \in I$

The response:

$$y_{.}^{(2,I,1)} = f(X_{.1}^{(2,I,1)}, \dots, X_{.p}^{(2,I,1)})$$

Partial variances:

$$D_I = \frac{1}{n-1} \sum_{k=1}^n y_k^{(1)} y_k^{(2,I,1)} - \left(\frac{1}{n} \sum_{k=1}^n y_k^{(1)}\right)^2$$

Sobol index:

$$S_I = \frac{D_I - \sum_{J \subset \{1...p\}} D_J}{\sum_{J \subseteq I} \widehat{\text{var}}(y^{(1)})}$$

3.2 method=saltelli02

The p more samples, noted $X^{(1,i,2)}$ $(i=1\dots p)$:

$$\begin{array}{lcl} X_{.i}^{(1,i,2)} & = & X_{.i}^{(2)} \\ X_{.j}^{(1,i,2)} & = & X_{.j}^{(1)}, j \neq i \end{array}$$

The response:

$$y_{.}^{(1,i,2)} = f(X_{.1}^{(1,i,2)}, \dots, X_{.p}^{(1,i,2)})$$

Partial variances:

$$D_{i} = \frac{1}{n-1} \sum_{k=1}^{n} y_{k}^{(2)} y_{k}^{(1,i,2)} - \frac{1}{n} \sum_{k=1}^{n} y_{k}^{(1)} y_{k}^{(2)}$$

$$D_{i}^{\text{tot}} = \frac{1}{n-1} \sum_{k=1}^{n} y_{k}^{(1)} y_{k}^{(1,i,2)} - \left(\frac{1}{n} \sum_{k=1}^{n} y_{k}^{(1)}\right)^{2}$$

First order and total indices :

$$S_{i} = \frac{D_{i}}{\widehat{\operatorname{var}}(y_{\cdot}^{(1)})}$$

$$S_{i}^{\text{tot}} = 1 - \frac{D_{i}^{\text{tot}}}{\widehat{\operatorname{var}}(y_{\cdot}^{(1)})}$$

4 fast

4.1 method=saltelli99

Maximum frequencies:

$$\omega_{\max} = \left\lfloor \frac{n-1}{2M} \right\rfloor$$

$$\omega'_{\max} = \left\lfloor \frac{\omega_{\max}}{2M} \right\rfloor$$

Frequencies $(i = 1 \dots p)$:

$$\omega_i^{(i)} = \omega_{\text{max}}
(\omega_j^{(i)})_{\substack{j=1...p\\j\neq i}} = (w_k)_{k=1...p-1}$$

where

$$w_k = 1 + \left\lfloor (k-1) \frac{\omega'_{\text{max}} - 1}{p-2} \right\rfloor \text{ if } \omega'_{\text{max}} \ge p - 1$$

$$w_k = 1 + \left((k-1) \mod \omega'_{\text{max}} \right) \text{ if } \omega'_{\text{max}}$$

Sampling (k = 1 ...n):

$$s_k = \frac{2\pi(k-1)}{n}$$

 $X_{jk}^{(i)} = F_j^{-1} \left(\frac{1}{2} + \frac{1}{\pi}\arcsin(\sin(\omega_j^{(i)}s_k))\right) \ (j=1\dots p)$

where F_j^{-1} is the inverse of the distribution function of the *i*th parameter.

Fourier coefficients $(j = 0 \dots n - 1)$:

$$c_j^{(i)} = \frac{1}{n} \sum_{k=1}^n f(X_{1k}^{(i)}, \dots, X_{pk}^{(i)}) e^{-is_k j}$$

Variance and partial variances $(i = 1 \dots p)$:

$$D^{(i)} = \sum_{j=1}^{n-1} |c_j^{(i)}|^2$$

$$D_i = 2 \sum_{j=1}^{M} |c_{j\omega_i}^{(i)}|^2$$

$$D_i^{\text{tot}} = 2 \sum_{j=1}^{\omega_i/2} |c_j^{(i)}|^2$$

Sensitivity indices $(i = 1 \dots p)$:

$$S_i = \frac{D_i}{D^{(i)}}$$

$$S_i^{\text{tot}} = 1 - \frac{D_i^{\text{tot}}}{D^{(i)}}$$

References

- [1] A. Saltelli. Making best use of model evaluations to compute sensitivity indices. *Computer Physics Communications*, 145:280–297, 2002.
- [2] A. Saltelli, K. Chan, and E.M. Scott. *Sensitivity analysis*. Series in Probability and Statistics. Wiley, 2000.
- [3] A. Saltelli, S. Tarantola, and K. Chan. A quantitative model-independent method for global sensitivity analysis of model output. *Technometrics*, 41(1):39–56, February 1999.