

# New way of estimating Total Sensitivity Indices

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- Context : exploration of complex models
  - model often includes many input factors
  - only few inputs really act in the model [1]
- Global Sensitivity Analysis (GSA) [1,2] and Multivariate Sensitivity Analysis (MSA) [3]
  - apportion the variability of model output into inputs and their interactions:
  - objective way to evaluate the impact of inputs on the model output(s)
  - Total Sensitivity Indices (TSI) give the overall contribution of input factors
  - but: computation of TSI requires many model runs

- **Objective:** investigate new methods of estimating TSI based on quadrature rules
  - the specific formulae for the commutation of the TSI
  - how to use these formulae for the commutation of TSI
- Plan
  - Recall the definitions of Total Sensitivity Indices
  - Give the main theorems for computing TSI
  - Show some results for counter and g-Sobol' functions and for Ishigami ' function

# Methods: Hoeffding decomposition

Let  $Y = f(\mathbf{X})$  be a model output and  $\mathbf{X} = (X_1, \dots, X_d)$ ,  $d$  independent inputs (A1). If  $\mathbb{E}(f^2(\mathbf{X})) < +\infty$  (A2), we have:

$$\begin{aligned} f(\mathbf{X}) &= f_0 + \sum_j^d f_j(X_j) + \sum_{i < j}^d f_{ij}(X_i, X_j) + \dots + f_{1\dots d}(X_1, \dots, X_d) \\ &= \sum_{u \subset \{1, 2, \dots, d\}} f_u(X_u), \end{aligned} \quad (1.1)$$

where  $f_0 = \mathbb{E}[f(\mathbf{X})]$ ;  $f_j(X_j) = \mathbb{E}[f(\mathbf{X})|X_j] - f_0$  and  $f_u(X_u) = \mathbb{E}[f(\mathbf{X})|X_u] - \sum_{v \subset u} f_v(X_v)$  with  $u \subset \{1, 2, \dots, d\}$ .

$$g(X_j, \mathbf{X}_{\sim j}) = \sum_{u \ni j} f_u(\mathbf{X}_u), \quad \text{with } u \subseteq \{1, 2, \dots, d\}$$

# Methods: Total Sensitivity Indices

Sobol and Kucherenko (2009) [4] and Lamboni *et al.* (2013) [5]

$$\mathbf{f}(\mathbf{X}) = \mathbf{f}_0 + \mathbf{g}(\mathbf{X}_j, \mathbf{X}_{\sim j}) + \mathbf{h}(\mathbf{X}_{\sim j}), \quad (1.2)$$

with  $\mathbb{E}[g(X_j, \mathbf{X}_{\sim j}) | \mathbf{X}_{\sim j}] = 0$

Let  $D = \int f^2(\mathbf{x}) d\mu(\mathbf{x}) - f_0^2$  and  $D_u = \int f_u^2(\mathbf{x}_u) d\mu(\mathbf{x}_u)$

- Classical definition of TSI [1,2]

$$S_{T_j} = \frac{\sum_{u \supseteq j} D_u}{D}.$$

- Equivalent definition of TSI [5]

$$S_{T_j} = \frac{\int [g^2(X_j, \mathbf{X}_{\sim j}) d\mu(\mathbf{x})]}{D} \quad (1.3)$$

# Methods: practical expression of $g(\cdot)$

## Proposition

*Let  $Y = f(\mathbf{X})$  be a model output. If A1 (independent input factors) and A2 (finite second moment) hold, the practical formulas to obtain  $g(X_j, \mathbf{X}_{\sim j})$  is::*

$$g(X_j, \mathbf{X}_{\sim j}) = f(\mathbf{X}) - \mathbb{E}[f(\mathbf{X})|\mathbf{X}_{\sim j}] \quad (1.4)$$

## Proof

*Due to  $f(\mathbf{X}) = f_0 + g(X_j, \mathbf{X}_{\sim j}) + h(\mathbf{X}_{\sim j})$  and  $\mathbb{E}[g(X_j, \mathbf{X}_{\sim j})|\mathbf{X}_{\sim j}] = 0$ , we have  $\mathbb{E}[f(\mathbf{X})|\mathbf{X}_{\sim j}] = f_0 + h(\mathbf{X}_{\sim j})$*

## Theorem

Let  $Y = f(\mathbf{X})$  be a model output and  $\mathbf{x}_i, i = 1, 2, \dots, N$  be  $N$  sample points of  $\mathbf{X}$ . If  $f(\mathbf{X})$  is a polynomial of order  $2p - 1$  with respect to  $X_j$  (A3) and if A1, A2 hold we have:

(i)  $g(x_j, \mathbf{x}_{\sim j})$  is exactly obtained with  $p + 1$  evaluations of  $f(\cdot)$ :

$$g(x_j, \mathbf{x}_{\sim j}) = f(\mathbf{x}) - \sum_{i=1}^p c_i f(x_{i,j}^*, \mathbf{x}_{\sim j}), \quad (1.5)$$

(ii)  $\mathbf{N}(\mathbf{d}\mathbf{p} + 1)$  is the total cost of model evaluations to estimate the  $d$  TSI indices

## Proof

$\mathbb{E}[f(\mathbf{X})|\mathbf{X}_{\sim j}] = \sum_{i=1}^p c_i f(x_{i,j}^*, \mathbf{x}_{\sim j})$ , for polynomials of order  $2p - 1$  due to the quadrature rules (Abramowitz et al., 1965).

## Theorem

Let  $Y = f(\mathbf{X})$  be a model output and  $\mathbf{x}_i, i = 1, 2, \dots, N$  be  $N$  sample points of  $\mathbf{X}$ . If  $f(\mathbf{X})$  is  $C^{2p}$  with respect to  $X_j$  (A4) and if A1, A2 hold we have:

(i)  $g(x_j, \mathbf{x}_{\sim j})$  is approximated by:

$$\widetilde{g(x_j, \mathbf{x}_{\sim j})} = f(\mathbf{x}) - \sum_{i=1}^p c_i f(x_{i,j}^*, \mathbf{x}_{\sim j}), \quad (1.6)$$

(ii) and the error term  $Err(g)$  is:

$$Err(g) = \frac{f^{(2p)}(\epsilon_{x_j, \mathbf{x}_{\sim j}})}{(2p)!} P^2(x_j, \mathbf{x}_{\sim j}) \quad (1.7)$$



# Numerical Tests: functions

- Counter function ( $d = 4$ )

$$f(\mathbf{x}) = \sum_{j=1}^{d=4} \left(x_j - \frac{1}{2}\right) + 50\left(x_1 - \frac{1}{2}\right)\left(x_2 - \frac{1}{2}\right)^5$$

- g-Sobol' function ( $d = 10$ ) of type A, B, and C

$$f(\mathbf{x}) = \prod_{j=1}^{d=10} \frac{|4x_j - 2| + a_j}{1 + a_j},$$

Type A:  $\mathbf{a} = (0, 0, 6.52, 6.52, 6.52, 6.52, 6.52, 6.52, 6.52, 6.52)$

Type B:  $\mathbf{a} = (50, 50, 50, 50, 50, 50, 50, 50, 50, 50)$ ;  $S_j = S_{T_j} = 0.1$

Type C:  $\mathbf{a} = (0, 0, 0, 0, 0, 0, 0, 0, 0, 0)$ ,  $\mathbf{S}_j = 0.02$  and  $S_{T_j} = 0.27$

- Ishigami' function ( $d = 3$ )

$$f(\mathbf{x}) = \sin(x_1) + 7 \sin^2(x_2) + 0.1x_3^4 \sin(x_1)$$

# Numerical Tests: main choices

- Order of quadrature  $p = 3$ , Sobol' design with  $N = 10, 20, \dots$
- Gauss-Legendre quadrature rules for Counter and g-Sobol' functions
- Gauss-Chebyshev (first kind) for Ishigami'function
- Effectiveness of methods: average of Mean Absolute Error

$$MAE = \frac{1}{R} \sum_{r=1}^{R=50} \sum_{j=1}^d |\hat{S}_{T_j} - S_{T_j}|$$

- Two ways of using evaluations of  $g(\cdot)$

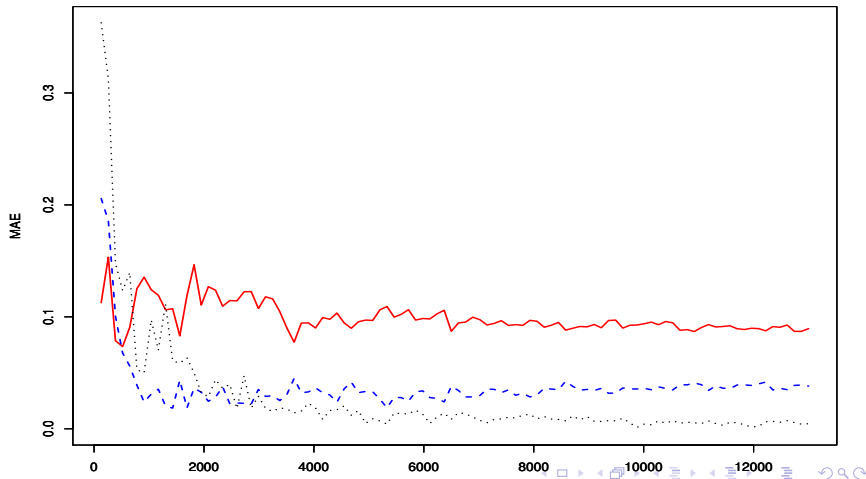
first way: use only  $N$  evaluations of

$$g(x_j, \mathbf{x}_{\sim j}) = f(\mathbf{x}) - \sum_{i=1}^p c_i f(x_{i,j}^*, \mathbf{x}_{\sim j})$$

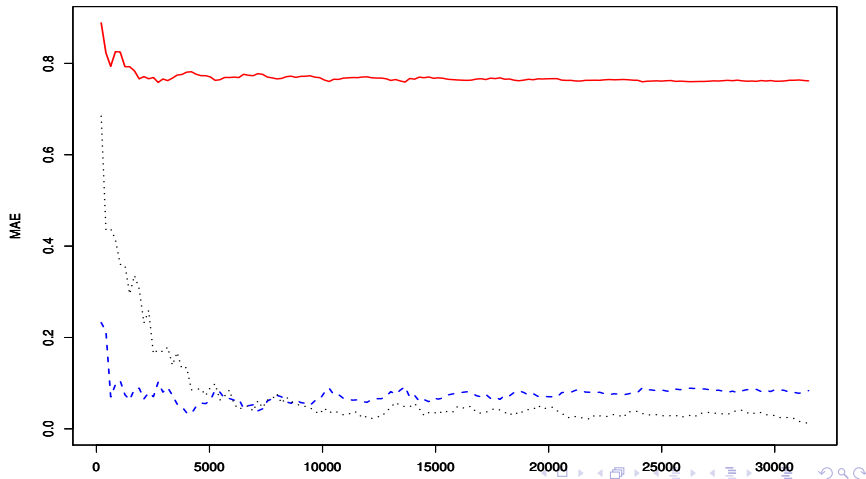
second way: first +

$$g(x_{i,j}^*, \mathbf{x}_{\sim j}) = f(x_{i,j}^*, \mathbf{x}_{\sim j}) - \sum_{i=1}^p c_i f(x_{i,j}^*, \mathbf{x}_{\sim j})$$

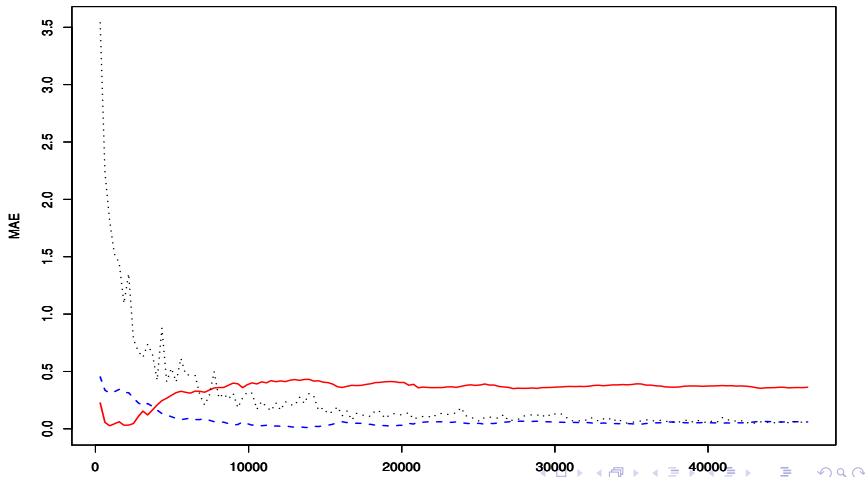
# Numerical Tests: result for counter function



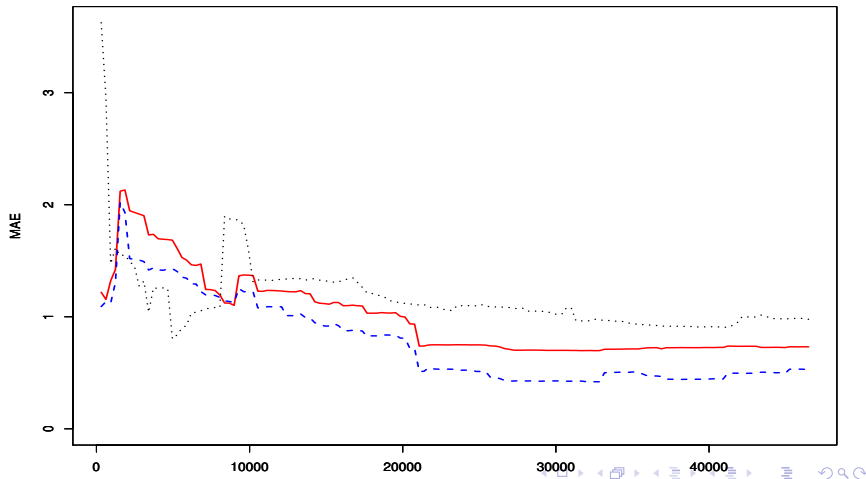
# Numerical Tests: result for Sobol'function, type A



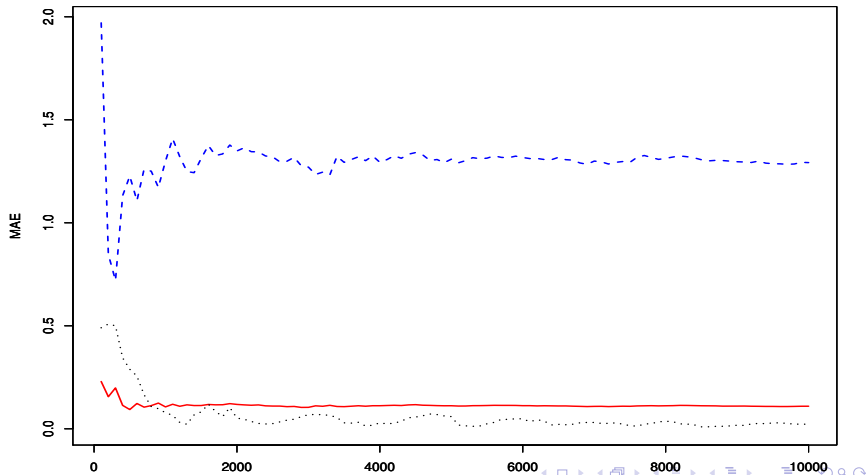
# Numerical Tests: result for Sobol'function, type B



# Numerical Tests: result for Sobol'function, type C



# Numerical Tests: result for Ishigami'function



# Conclusion and perspectives

- New methods of computing TSI based on quadrature rules
  - derive formulas for estimating TSI
  - derive the error of TSI based on quadrature rules
- Method, compared to Saltelli 2010 [6] + Sobol 2007 [7], is promising :
  - give reasonable TSI indices with few model runs
  - improves a bit TSI for functions with high effective dimension
  - method ' error is constant after some sample size
- Perspectives:
  - improve method' error: quadrature rules on subset
  - how to choose the order of quadrature rules ( $p$ )
  - other rules: Gauss is efficient for regular functions



Thanks for your attention!

Questions and propositions ?

Feel free to contact me!

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