New Sensitivity Indices based on contrasts

Goal Oriented Sensitivity Analysis (GOSA)

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Nabil RACHDI, nabil.rachdi@eads.net

EADS France - Applied Mathematics Team

Co-authors: J-C. FORT (Paris 5), T. KLEIN (Toulouse III) and F. MANGEANT (EADS France)



Outline



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- 3 2D toy example
- 4 3D example: Ishigami function
- 5 Back up



Outline



2 Feature of Interest & Contrast Function

3 2D toy example



5 Back up



Motivations

Uncertainty Management for Flight Control





FADS

Engineering methodology



Motivations

Uncertainty Management for Flight Control





FADS

Engineering methodology



Motivations

Case of Maximal Attitude: various sensitivity measures ...



Motivations

How to explain such differences between sensitivity indicators in a single framework ? How to define other indicators ?

Issues

- Gather the notion of sensitivity to the notion of quantity/feature of interest of Y
- Define generic sensitivity indices relatively to a feature of Y
- Study the importance ranking between these new indices and the Sobol ones: a variable X_k may have a negligible Sobol index (the lower for instance) and may have a significant importance for some other (contrast-based) index



Motivations

• In a model $Y = h(X_1, \ldots, X_d)$ the global Sobol index quantify the influence of a random variable X_i on the output Y. This index is based on the variance (see [Sobol, 1993][6], [Saltelli et al., 2000][5]): in particular, the first order index compares the total variance of Y to the expected variance of the variable Y conditioned by X_i ,

$$S_i = \frac{\operatorname{Var}(\mathbb{E}[Y|X_i])}{\operatorname{Var}(Y)}.$$
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By the property of the conditional expectation it writes also

$$S_i = \frac{\operatorname{Var}(Y) - \mathbb{E}_{X_i}(\operatorname{Var}[Y|X_i])}{\operatorname{Var}Y}.$$
(2)

■ Formula (1) is popular and very used by computer scientists



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By the property of the conditional expectation it writes also

$$S_{i} = \frac{\operatorname{Var}(Y) - \mathbb{E}_{X_{i}}(\operatorname{Var}[Y|X_{i}])}{\operatorname{Var}Y}.$$
(2)

- Formula (1) is popular and very used by computer scientists
- We propose to adopt formula (2) to extend Sobol indices



Key remarks

What is hidden in the expression $S_i = \frac{Var(Y) - \mathbb{E}_{X_i}(Var[Y|X_i])}{VarY} \dots$

- Notice that $Var(Y) = \min_{\theta} \mathbb{E}(Y \theta)^2$ (min. reached at $\theta^* = \mathbb{E}Y$)
- Similarly, $\operatorname{Var}[Y|X_i] = \min_{\theta} \mathbb{E}[(Y \theta)^2 | X_i]$ (min. reached at $\theta^* = \mathbb{E}[Y|X_i]$)



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$$S_{i} = \frac{\mathbb{E}(Y - \mathbb{E}Y)^{2} - \mathbb{E}_{(X_{i},Y)}(Y - \mathbb{E}[Y|X_{i}])^{2}}{\mathbb{E}(Y - \mathbb{E}Y)^{2}}$$

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New general writing of Sobol index

$$S_{\psi}^{i} = \frac{\mathbb{E}\psi(Y; \mathbb{E}Y) - \mathbb{E}_{(X_{i}, Y)}\psi(Y; \mathbb{E}[Y|X_{i}])}{\mathbb{E}\psi(Y; \mathbb{E}Y)}$$

where for Sobol indices the function ψ is $(y; heta) \mapsto (y - heta)^2$

we will call ψ a contrast function which depends on the considered feature of interest, it will play a crucial rule (see [Rachdi et al., 2012][3], [Fort et al., 2012][1])

What about changing contrast ? ...



Birth of new indices ?...

• We will define ψ -indices as

Qol = Quantity of Interest and $Qol|X_i = Conditional Quantity of Interest$

$$S_{\psi}^{i} = \frac{\mathbb{E}\psi(Y; \textit{Qol}) - \mathbb{E}_{(X_{i}, Y)}\psi(Y; \textit{Qol}|X_{i})}{\mathbb{E}\psi(Y; \textit{Qol})}$$

where ψ is the (a) contrast adapted to the Quantity of Interest

Theoretical definition: ψ -index

Assumption

Let ψ be some contrast, assume that

$$\mathbb{E}\min_{\theta}\psi(Y;\theta)\in\mathbb{R}.$$

All the contrasts presented before satisfy this Assumption since $\min_{\theta} \psi(y; \theta) = 0$.

Definition: ψ -index

Let $\Psi(\theta) = \mathbb{E}\psi(Y; \theta)$ be a contrast associated to a feature of Y, $\theta^* = \underset{\theta}{\operatorname{Argmin}} \Psi(\theta)$. The ψ -index of the variable $Y = h(X_1, \dots, X_d)$ w.r.t the contrast ψ and the variable X_k is defined as

$$S_{\psi}^{k} = \frac{\mathbb{E}\psi(\mathbf{Y}; \theta^{*}) - \mathbb{E}_{(\mathbf{X}_{k}, \mathbf{Y})}\psi(\mathbf{Y}; \theta_{k}(\mathbf{X}_{k}))}{\mathbb{E}\psi(\mathbf{Y}; \theta^{*}) - \mathbb{E}\min_{\theta}\psi(\mathbf{Y}; \theta)}$$

where $\theta_k(x) = \underset{\theta}{\operatorname{Argmin}} \mathbb{E}(\psi(Y; \theta) | X_k = x)$ is the feature of interest of Y conditionally to $X_k = x$

do not solve minimisation problems to compute θ^* and $\theta_k(x)$! "just" compute the features if known ... (see Simulation section)

Comments on ψ -index

Lemma

The ψ -index S_{ψ}^k is non negative.

Proof: comes from the fact that for any random variable ξ and any function g

 $\mathbb{E}\min_{\theta} g(\theta,\xi) \leq \min_{\theta} \mathbb{E}g(\theta,\xi).$

- If Y does not depends on X_k, then S^k_ψ = 0. Moreover, assuming that the variables (X₁,..., X_d) are independent, if Y = h(X_k) then S^k_ψ = 1 and the other indices S^l_ψ, l ≠ k are 0
- we have that

$$S^k_\psi \in \left[0,1
ight]$$
 .

These basic properties were expected from a reasonable sensitivity index.

Outline



2 Feature of Interest & Contrast Function

3 2D toy example



5 Back up



Notion of Contrast Function

- Goal: Define formal indices adapted to a feature of interest of Y
- Idea: to characterize a feature of Y by a contrast function (see [Rachdi, 2011] [2])

"a feature of interest of Y induces (defines) a contrast function which induces (defines) an adapted sensitivity index"



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Example of the "mean feature":

$$\begin{aligned} \theta^* &= \mathbb{E}Y \Rightarrow \mathbb{E}Y = \operatorname{Argmin}_{\theta \in \Theta} \mathbb{E}(Y - \theta)^2 \Rightarrow \psi : (y; \theta) \mapsto (y - \theta)^2 \\ \Rightarrow S^i_{\psi} &= \frac{\mathbb{E}\psi(Y; \mathbb{E}Y) - \mathbb{E}(\mathbf{x}_i, \mathbf{y})\psi(Y; \mathbb{E}[Y|X_i])}{\mathbb{E}\psi(Y; \mathbb{E}Y)} = \frac{\operatorname{Var}(Y) - \mathbb{E}(\operatorname{Var}[Y|X_i])}{\operatorname{Var}Y} \end{aligned}$$

that is "the mean feature" \Rightarrow 1st order Sobol index

Feature of Interest formalization:

a feature of interest is viewed as a minimizer of contrast



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Other contrast functions ?



Examples of Contrast Functions

Recall that a generic contrast writes $\Psi(\theta) = \mathbb{E}\psi(Y; \theta)$ and $\theta^* = \operatorname{Argmin}_{\theta} \Psi(\theta)$

 \Rightarrow feature of interest $\theta^* \longleftrightarrow$ contrast function $\Psi \Leftarrow$

- Central parameters:
 - The mean $\theta^* = \mathbb{E}Y : \Psi(\theta) = \mathbb{E}|Y \theta|^2$. - The median (in \mathbb{R}) $\theta^* = q_{0.5}(Y): \Psi(\theta) = \frac{1}{2}\mathbb{E}|Y - \theta|$.
- An excess probability : $\theta^* = \mathbb{P}(Y \ge t)$, $\Psi(\theta) = \mathbb{E}|\mathbf{1}_{Y \ge t} \theta|^2$.
- All the probability tail: $\theta^* = \int_{t_0}^{\infty} \mathbb{P}(Y \ge t) dt$, $\Psi(\theta) = \mathbb{E} \int_{t_0}^{\infty} |\mathbf{1}_{Y \ge t} \theta(t)|^2 dt$.
- The α -quantile : $\theta^* = q_{\alpha}(Y)$, $\Psi(\theta) = \mathbb{E}(Y \theta)(\alpha \mathbf{1}_{Y \leq \theta})$.
- Quantile tail: $\theta^* = \int_{\alpha_0}^1 q_\alpha(Y) d\alpha$, $\Psi(\theta) = \mathbb{E} \int_{\alpha_0}^1 (Y \theta(\alpha))(\alpha \mathbf{1}_{Y \le \theta(\alpha)}) d\alpha$.
- The probability density function $\theta^* = pdf(Y)$ (infinite dimensional parameter) - Using the kernel method, with $K_r(y) = \frac{1}{r}K(\frac{y}{r}), r > 0$

$$\Psi(heta) = \mathbb{E} \int_{-\infty}^{+\infty} (K_r(Y-t) - heta(t))^2 dt$$
 or L^2 basis, etc.

Etc.

One easily checks that all these contrasts achieve their minimal value at θ^*

Illustration: feature of interest as minimizer of contrast

Consider the trivial case $Y \sim \mathcal{N}(0, 1)$

■ mean-contrast: Ψ : $\theta \mapsto \mathbb{E}[Y - \theta]^2 = \theta^2 + 1$



Illustration of the mean-contrast

Illustration: feature of interest as minimizer of contrast

Consider the trivial case $Y \sim \mathcal{N}(0,1)$

• α -quantile-contrast: Ψ : $\theta \mapsto \mathbb{E}(Y - \theta)(\alpha - \mathbf{1}_{Y \leq \theta}), \ \alpha = 0.3$



illustration of the quantile-contrast (alpha=30%)

Higher order ψ -indices

Higher order ψ -index

The indices S_{ψ}^k can be generalized to higher order indices, for $I \subset \{1, ..., d\}$ and denoting by $\mathbf{X}_I = (X_i)_{i \in I}$, we define

$$S_{\psi}^{I} = \frac{\mathbb{E}\psi(Y;\theta^{*}) - \mathbb{E}_{(\mathbf{X}_{I},Y)}\psi(Y;\theta_{I}(\mathbf{X}_{I}))}{\mathbb{E}_{Y}\psi(Y;\theta^{*})}$$
(3)

where $\theta_I(X_I)$ is the feature associated to the contrast ψ of the random variable $Y|X_I$

(In what follows we deal with first order indices)



ψ -Indices Simulation: basic Monte-Carlo approach

Assume that $\mathbb{E} \min_{\theta} \psi(Y; \theta) = 0$ (it is the case for all presented contrasts), let's estimate

$$S_{\psi}^{k} = \frac{\mathbb{E}\psi(Y;\theta^{*}) - \mathbb{E}_{(X_{k},Y)}\psi(Y;\theta_{k}(X_{k}))}{\mathbb{E}_{Y}\psi(Y;\theta^{*})}$$
(4)

- Generate $X_1^j, ..., X_p^j$ and compute the $Y^j = h(X_1^j, ..., X_p^j)$, for $j = 1, ..., n_1$. Then compute $\widehat{\theta^*}$ and replace in (4) the expectations $\mathbb{E}_{(X_k, Y)}$ and \mathbb{E}_Y by their empirical versions.
- **2** Generate $X_1^{\prime j}, ..., X_p^{\prime j}$ for $j = 1, ..., n_2$ (independent from the previous set) and compute the $Y^{\prime j} = h(X_1^{\prime j}, ..., X_p^{\prime j})$. Then, from the sample $Y_k^{\prime j}(x) = h(X_1^{\prime j}, ..., X_{k-1}^{\prime j}, x, X_{k+1}^{\prime j}, ..., X_p^{\prime j}), j = 1, ..., n_2$, compute the function $x \mapsto \widehat{\theta}_k(x)$.

3 Compute the Monte-Carlo estimator

$$\widehat{S}_{\psi}^{k} = \frac{\frac{1}{n_{1}} \sum_{j=1}^{n_{1}} \left(\psi(Y^{j}; \widehat{\theta}^{*}) - \psi(Y^{j}; \widehat{\theta}_{k}(X_{k}^{j})) \right)}{\frac{1}{n_{1}} \sum_{j=1}^{n_{1}} \psi(Y^{j}; \widehat{\theta}^{*})}$$
(5)



ψ -Indices Simulation: Sobol indices

We retrieve the basic Monte-Carlo estimator of the 1st order Sobol index

• considering the mean-contrast $\psi(y; \theta) = (y - \theta)^2$ and $n_1 = n_2 = N$ we have that

$$\widehat{\theta}^* = rac{1}{N}\sum_{l=1}^N Y^l$$
 and $\widehat{\theta}_k(X_k^j) = rac{1}{N}\sum_{l=1}^N Y_k'{}^l(X_k^j)$.

■ it is easy to check that the index S^k_ψ in (5) is the well known Monte-Carlo estimator of the first order Sobol index, see [4]:

$$\widehat{S}_{\psi}^{k} = rac{\overline{\mathbf{Y}}\mathbf{Y}_{k}^{\prime} - \overline{\mathbf{Y}}\,\overline{\mathbf{Y}_{k}^{\prime}}}{\overline{\mathbf{Y}^{2}} - \overline{\mathbf{Y}}^{2}},$$

where $\mathbf{Y} = (Y^1, ..., Y^N)$ and $\mathbf{Y}'_k = (Y'^1_k(X^1_k), ..., Y'^N_k(X^N_k))$ and for any vector $\mathbf{u} = (u_1, ..., u_N)$

$$\overline{\mathbf{u}} = \frac{1}{N} \sum_{j=1}^{N} u_j$$



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3 2D toy example







Toy example

- Let $Y = X_1 X_2$, with $X_1, X_2 \sim Exp(1)$ independent
 - It is clear that first order Sobol indices are

$$S^1_{Sob}=S^2_{Sob}=1/2$$

Sobol indices \leftrightarrow mean-contrast indices ... what about using other contrasts ?

Toy example

Let $Y = X_1 - X_2$, with $X_1, X_2 \sim Exp(1)$ independent

- **feature of interest:** the α -quantile $q_Y(\alpha)$ of Y
- associated contrast:

$$\Psi_{\alpha}(\theta) = \mathbb{E}(Y - \theta)(\alpha - \mathbf{1}_{Y \leq \theta}),$$

■ indices computation: (computed analytically)



Toy example

Let $Y = X_1 - X_2$, with $X_1, X_2 \sim Exp(1)$ independent

- feature of interest: the exceeding probability $\mathbb{P}(Y \ge t)$
- associated contrast:

$$\Psi_t(\theta) = \mathbb{E}|\mathbf{1}_{Y\geq t} - \theta|^2,$$

■ indices computation: (simulated by Monte-Carlo methods)



Toy example

Let $Y = X_1 - X_2$, with $X_1, X_2 \sim Exp(1)$ independent

- **Remark:** the threshold-contrast $\Psi_t(\theta) = \mathbb{E}|\mathbf{1}_{Y \ge t} \theta|^2$ induces Sobol indices of the random variable $Z_t = \mathbf{1}_{Y>t}$ (which is a well known fact)
- Contrast comparison: t-threshold-contrast and α-quantile-contrast bring the same information since

$$\mathbb{P}(\mathsf{Y} > t) \leq lpha \Longleftrightarrow \mathsf{q}_lpha(\mathsf{Y}) \leq t$$



Figure : α -quantile contrast & *t*-threshold contrast



Toy example

Let $Y = X_1 - X_2$, with $X_1, X_2 \sim Exp(1)$ independent

Comparison with Sobol index:



Remark:

- First order Sobol indices are insensitive to the quantile level α and (equivalently) the threshold t (Sobol indices ↔ mean-contrast !)
- We retrieve the Sobol ranking at the level α = 0.5 for the quantile-contrast or equivalently at a threshold t = 0 ("the middle") for the threshold-contrast.



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Ishigami function

- Ishigami function: Consider $Y = \sin(\xi_1) + 7 \sin(\xi_2)^2 + 0.1 \xi_3^4 \sin(\xi_1)$, where $\xi_1, \xi_1 \sim \mathcal{U}(-\pi, \pi)$ are independent
- **2** different ψ -indices :
 - mean-contrast: $\Psi_{mean}(\theta) = \mathbb{E}|Y \theta|^2 \rightarrow 1$ st order Sobol indices that are

$$S^1_{Sob} = 0.3139, \quad S^2_{Sob} = 0.4424 \text{ and } S^3_{Sob} = 0.$$

• quantile-contrast: $\Psi_{\alpha}(\theta) = \mathbb{E}(Y - \theta)(\alpha - \mathbf{1}_{Y \leq \theta})$

ightarrow let's compute the indices $S^1_lpha,\,S^2_lpha$ and S^3_lpha



Results



Sensitivity Indices vs level alpha

• S^3_{Sob} is always equals to 0 whereas S^3_{α} is highly significative for extreme values of α ... which is intuitive !

It shows clearly the importance of taking into account the goal of the study when measuring the impact of the input variables.

 \blacksquare the importance ranking is different from the Sobol one for $\alpha\gtrsim$ 85% and $\alpha\lesssim$ 15%



Conclusions & Perspectives

- We have introduced new indices of influence of an input random variable
- It allows to handle many cases that are not directly related to a mean/variance criterion
- Sobol indices are viewed as a particular case related to the mean-contrast
- This work is a first step toward a generalized theory of (goal oriented) sensitivity analysis



Thank you for your attention !

Jean-Claude Fort, Thierry Klein, and Nabil Rachdi. New sensitivity indices subordinated to a contrast. *Submitted*, 2013.



Nabil Rachdi.

Statistical Learning and Computer Experiments (PhD Thesis). http://thesesups.ups-tlse.fr/1538/1/2011TOU30283.pdf, 2011.



Nabil Rachdi, Jean-Claude Fort, and Thierry Klein. Risk bounds for new m-estimation problems. ESAIM: Probability and Statistics, DOI : 10.1051/ps/2012025, 2012.



Andrea Saltelli.

Making best use of model evaluations to compute sensitivity indices. *Computer Physics Communications*, 145(2):280–297, 2002.



Andrea Saltelli, Karen Chan, E Marian Scott, et al. *Sensitivity analysis*, volume 134. Wiley New York, 2000.



I. M. Sobol.

Sensitivity estimates for nonlinear mathematical models.

Page 25 Math. Modeling Comput. Experiment, pages 407–414, 1993.



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Notion of Contrast Function

Definition: Contrast Function

Let Θ be some generic set and Q be some probability measure on a space \mathcal{Y} . A (Θ, Q) -contrast function, or simply contrast function, is defined as any function ψ

$$\psi : \Theta \longrightarrow L_1(Q)$$

$$\theta \longmapsto \psi(\cdot; \theta) : y \in \mathcal{Y} \longmapsto \psi(y; \theta),$$
(6)

such that

$$\theta^* = \operatorname*{Argmin}_{\theta \in \Theta} \mathbb{E}_{Y \sim Q} \psi(Y; \theta)$$
(7)

is unique. The function $\Psi : \theta \mapsto \mathbb{E}_{Y \sim Q} \psi(Y; \theta)$ is the average contrast function, or abusively contrast function if there is no ambiguity.



Comments on ψ -index

Let us retrieve the first order Sobol index:

- **trend of interest:** compute sensitivity carried by "the mean": $\theta^* = \mathbb{E}Y$
- associated contrast: it induces the mean-contrast $\mathbb{E}Y = \operatorname{Argmin}_{\theta} \mathbb{E}(Y - \theta)^2 \Rightarrow \psi : (y; \theta) \mapsto (y - \theta)^2$
- conditional feature of interest: $\theta_k(x) = \mathbb{E}(Y|X_k = x)$ with the contrast characterization = $\operatorname{Argmin}_{\theta} \mathbb{E}(Y - \theta)^2 |X_k = x)$
- We compute

$$\mathbb{E}\psi(Y;\theta^*) - \mathbb{E}_{(X_k,Y)}\psi(Y;\theta_k(X_k)) = \mathbb{E}(Y - \mathbb{E}Y)^2 - \mathbb{E}_{(X_k,Y)}(Y - \mathbb{E}(Y|X_k))^2$$
$$= \operatorname{Var}(Y) - \mathbb{E}_{X_k}\mathbb{E}\left[(Y - \mathbb{E}(Y|X_k))^2|X_k\right]$$
$$= \operatorname{Var}(Y) - \mathbb{E}_{X_k}\operatorname{Var}(Y|X_k)$$
$$= \operatorname{Var}(\mathbb{E}(Y|X_k))$$

and

$$\mathbb{E}\psi(Y; \theta^*) - \mathbb{E}\min_{\theta}\psi(Y; \theta) = \operatorname{Var}(Y) - 0 = \operatorname{Var}(Y).$$

Finally, we obtain the following ψ -index

$$S_{\psi}^{k} = rac{\operatorname{Var}(\mathbb{E}(Y|X_{k}))}{\operatorname{Var}(Y)}$$

which is exactly the first order Sobol index.



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