

Reducing the number of function evaluations to estimate *first-order* Sobol' indices

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Outline

- ▶ Introduction
- ▶ Sobol Indices'
- ▶ Replicated Method



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- ▶ **Introduction**—The ANalysis Of VAriance.
- ▶ Sobol Indices'
- ▶ Replicated Method



ANOVA

For $f \in L^2([0, 1]^d)$, and $\mathcal{D} = \{1, \dots, d\}$,

$$f(\mathbf{x}) = \sum_{u \subseteq \mathcal{D}} f_u(\mathbf{x}), \quad f_\emptyset = \mu,$$

where,

$$f_u(\mathbf{x}) = \int_{[0,1]^{d-|u|}} f(\mathbf{x}) d\mathbf{x}_{-u} - \sum_{v \subset u} f_v(\mathbf{x}).$$



Variance Decomposition

Under the previous definitions,

$$\sigma_{\emptyset}^2 = 0, \quad \sigma_u^2 = \int_{[0,1]^d} f_u(\mathbf{x})^2 d\mathbf{x}, \quad \sigma^2 = \int_{[0,1]^d} (f(\mathbf{x}) - \mu)^2 d\mathbf{x}.$$

The ANOVA identity is,

$$\sigma^2 = \sum_{u \subseteq \mathcal{D}} \sigma_u^2.$$



Outline

- ▶ Introduction
- ▶ **Sobol Indices'**—Measuring the importance of the inputs.
- ▶ Replicated Method



Sobol' Indices

We consider $f(\mathbf{x})$ as a random variable with $\mathbf{x} \sim U([0, 1]^d)$.

Sobol' introduced the *global sensitivity* indices which measure the variance explained by subsets of dimensions:

$$\tau_u^2 = \sum_{v \subseteq u} \sigma_v^2, \quad \text{and} \quad \bar{\tau}_u^2 = \sum_{v \cap u \neq \emptyset} \sigma_v^2, \quad u, v \in \mathcal{D}.$$

We have the following properties,

- ▶ $\tau_u^2 \leq \bar{\tau}_u^2$.
- ▶ $\tau_u^2 + \bar{\tau}_{-u}^2 = \sigma^2$.



Normalized *First-Order* Sobol' Indices

In this particular case, we consider $|u| = 1$ and want to estimate $\underline{\tau}_u^2/\sigma^2 = \sigma_u^2/\sigma^2$. For this purpose, given $\mathbf{x}, \mathbf{x}' \in [0, 1]^d$, we define the following point,

$$(\mathbf{x}_u : \mathbf{x}'_{-u}) := (\mathbf{x}'_1, \dots, \mathbf{x}'_{u-1}, x_u, \mathbf{x}'_{u+1}, \dots, \mathbf{x}'_d) \in [0, 1]^d.$$

Thus, one can use the following integral form to build an estimator:

$$\frac{\sigma_u^2}{\sigma^2} = \frac{\int_{[0,1]^{2d-1}} \overbrace{f(\mathbf{x})}^{g(\mathbf{x}, \mathbf{x}') :=} - \mu \overbrace{(f(\mathbf{x}_u : \mathbf{x}'_{-u}) - \mu)}^{g_u(\mathbf{x}, \mathbf{x}') :=} dx d\mathbf{x}'_{-u}}{\int_{[0,1]^d} f(\mathbf{x})^2 d\mathbf{x} - \mu^2} = H(g, g_u).$$



Numerical Integration Problem

We will focus on reducing the number of function evaluations, and to estimate σ_u^2/σ^2 , only g and g_u are evaluated.

Computing all the indices one by one, if one requires n points for each estimation, the total number of function evaluations of g and g_u are

$$2dn,$$

However, if all indices are computed together, g only needs to be evaluated once. Therefore, the number of function evaluations becomes

$$(1 + d)n,$$

Finally, under a special set of quasi-Monte Carlo sequences, this number is decreased to

$$2n.$$



Outline

- ▶ Introduction
- ▶ Sobol Indices'
- ▶ **Replicated Method**—Reducing the number of function evaluations to compute *first-order* indices.



Replicated points

Functions g and g_u only share input dimension u :

$$\begin{aligned} g(\mathbf{x}, \mathbf{x}') &= f(x_1, \dots, x_{u-1}, x_u, x_{u+1}, \dots, x_d), \\ g_u(\mathbf{x}, \mathbf{x}') &= f(x'_1, \dots, x'_{u-1}, x_u, x'_{u+1}, \dots, x'_d). \end{aligned}$$

Hence, we can construct our points \mathbf{x}'_i as follows,

$$\begin{pmatrix} x_{0,1} & \cdots & x_{0,d} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,d} \\ \vdots & & \vdots \end{pmatrix}, \quad \begin{pmatrix} x'_{0,1} & \cdots & x'_{0,d} \\ \vdots & \ddots & \vdots \\ x'_{n,1} & \cdots & x'_{n,d} \\ \vdots & & \vdots \end{pmatrix} = \begin{pmatrix} x_{\pi_1(0),1} & \cdots & x_{\pi_d(0),d} \\ \vdots & \ddots & \vdots \\ x_{\pi_1(n),1} & \cdots & x_{\pi_d(n),d} \\ \vdots & & \vdots \end{pmatrix}.$$



The Right Function Values

Given the right order of points:

$$\begin{pmatrix} \mathbf{x}'_{\pi_u^{-1}(0)} \\ \vdots \\ \mathbf{x}'_{\pi_u^{-1}(n)} \\ \vdots \end{pmatrix} = \begin{pmatrix} x'_{\pi_u^{-1}(0),1} & \cdots & x_{0,u} & \cdots & x'_{\pi_u^{-1}(0),d} \\ \vdots & & \vdots & & \vdots \\ x'_{\pi_u^{-1}(n),1} & \cdots & x_{n,u} & \cdots & x'_{\pi_u^{-1}(n),d} \\ \vdots & & \vdots & & \vdots \end{pmatrix}.$$



The Right Function Values

We only need to evaluate $g_u(\mathbf{x}, \mathbf{x}')$ once:

$$\begin{pmatrix} f(\mathbf{x}'_0) \\ \vdots \\ f(\mathbf{x}'_n) \\ \vdots \end{pmatrix} = \begin{pmatrix} y_0 \\ \vdots \\ y_n \\ \vdots \end{pmatrix} \implies \begin{pmatrix} g_u(\mathbf{x}_0, \mathbf{x}'_0) \\ \vdots \\ g_u(\mathbf{x}_n, \mathbf{x}'_n) \\ \vdots \end{pmatrix} = \begin{pmatrix} y_{\pi_u^{-1}(0)} \\ \vdots \\ y_{\pi_u^{-1}(n)} \\ \vdots \end{pmatrix}$$



Quasi-Monte Carlo Sequences

For $i \in \mathbb{N}_0$ and $x \in [0, 1)$,

$$i = \sum_{k \geq 0} i_k b^k, \quad x = \sum_{k \geq 1} x_k b^{-k}, \quad i_k, x_k \in \mathbb{F}_b.$$

Each dimension j of a digital net is constructed according to:

$$\begin{pmatrix} x_1 \\ \vdots \\ x_m \\ \vdots \end{pmatrix} = C_j \begin{pmatrix} i_0 \\ \vdots \\ i_{m-1} \\ \vdots \end{pmatrix}, \quad C_j \in M^{\infty \times \infty}(\mathbb{F}_b).$$



Quasi-Monte Carlo Sequences

For the Sobol' sequences, we can for instance, construct our permutations through an upper triangular matrix $U \in M^{\infty \times \infty}(\mathbb{F}_b)$ applied as follows,

$$\begin{pmatrix} x_1 \\ \vdots \\ x_m \\ \vdots \end{pmatrix} = C_j U \begin{pmatrix} i_0 \\ \vdots \\ i_{m-1} \\ \vdots \end{pmatrix}$$



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