Sensitivity analysis for optimization under constraints and with uncertainties Sensitivity analysis on excursion sets

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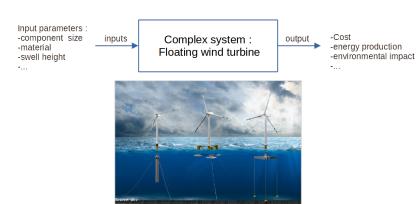
Journées CIROQUO 23, 24 et 25 mai 2022







•0000 System



$$x \in \mathcal{X}$$
 $u \in \mathcal{U}$ Black-box functions f and g $f(x, u)$
 $g(x, u) \in \mathbb{R}$

- The x are the deterministic inputs
- The u are uncertain inputs : $u=U(\omega)$ with U a random vector of density ρ_U
- f is the objective function to minimize
- ullet g is the constraint function defining the constraint to respect : $g \leq 0$

Optimization problem

$$x^* = \arg\min \mathbb{E}_{U}[f(x, U)]$$

s.t. $\mathbb{P}_{U}[g(x, U) \le 0] \ge P_{target}$ (1)

Sensitivity analysis adapted to optimization

Sensitivity analysis (SA) = Studying the impact of each input on the variability of the output.

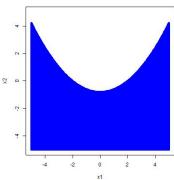
 \Rightarrow SA + Optimization : Studying the impact of each input on the minimization of the objective function and on the respect of the constraints.

Introduction

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Toy function from [El-Amri et al. 2021]

$$\forall (x, u) \in [-5, 5]^4 \ g(x, u) = -x_1^2 + 5x_2 - u_1 + u_2^2 - 1$$
$$\Gamma_u = \{x \in [-5, 5]^2, g(x, u) \le 0\}$$

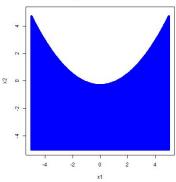


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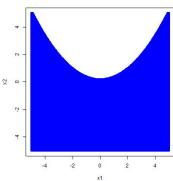


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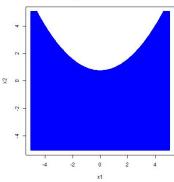


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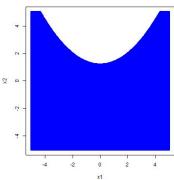


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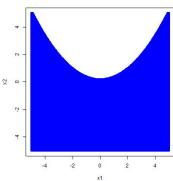
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*u*₁ fixé

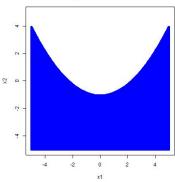


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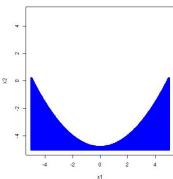


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$$\Gamma_u = \{x \in [-5, 5]^2, g(x, u) \le 0\}$$



Excursion sets

New output :

Introduction

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$$\Gamma_U = \{ x \in \mathcal{X}, g(x, U) \le 0 \}, \tag{2}$$

which is called a random excursion set

Influence of the uncertain inputs U on Γ_U ? \Rightarrow SA on excursion sets. Yet most SA techniques have scalar or vectorial outputs.

How then can we do sensitivity analysis on (excursion) sets?

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 - Results
- Sensitivity analysis on excursion sets using universal indices from [Gamboa et al. 2021] and [Fort, Klein et Lagnoux 2021]
 - Definition of the universal index
 - Adapation and estimation
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Random set theory [Molchanov 2005]

The natural definition of a random set is as a set-valued random variable X i.e. as a measurable function :

$$\begin{array}{cccc}
(\Omega, \mathcal{F}) & \to & (\mathcal{K}(\mathcal{X}), \mathcal{B}(\mathcal{K}(\mathcal{X})) \\
X : & \omega & \longmapsto & X(\omega)
\end{array}$$
(3)

The notion of measurability depends on the definition of $\mathcal{B}(\mathcal{K}(\mathcal{X}))$ which depends on the topology we choose for $\mathcal{K}(\mathcal{X})$.

From [Molchanov 2005], a notion of measurability can be written as :

$$\forall K \in \mathcal{K}(\mathcal{X}), X^{-} = \{\omega \in \Omega, X(\omega) \cap K \neq \emptyset\} \in \mathcal{F}. \tag{4}$$

With this definition of measurability, we can show that our sets $\Gamma_U = \{x \in \mathcal{X}, g(x, U) \leq 0\}$ are random compact sets (see 29).

Sobol indices on random sets?

- We want to characterize the influence of the input U_i on the output $\Gamma_{IJ} = \{x \in \mathcal{X}, g(x, U) \leq 0\}$ which is a random set.
- Sobol indices on random sets : We would want to compute $S_i = \frac{\text{Var} \mathbb{E}[\Gamma|U_i]}{\text{Var} \Gamma} \rightarrow \text{The difficulty lies in defining the (conditional) expectation and the variance of a random set.$

Vorob'ev expectation and deviation [Molchanov 2005]

The Vorob'ev expectation of a random set Γ is defined as the Vorob'ev quantile which volume is equal (or closer) to the mean volume of Γ :

$$\mathbb{E}^{V}[\Gamma] = \{ x \in \mathcal{X}, \mathbb{P}(x \in \Gamma) \ge \alpha^* \} = Q_{\alpha^*}, \tag{5}$$

with α^* defined by :

Introduction

$$\mathbb{E}[\mu(\Gamma)] = \mu(Q_{\alpha^*}). \tag{6}$$

Or if the previous equation has no solution, from :

$$\mu(Q_{\alpha}) \le \mathbb{E}[\mu(\Gamma)] \le \mu(Q_{\alpha^*}) \quad \forall \alpha > \alpha^*.$$
 (7)

Then, the Vorob'ev deviation is defined by :

$$Var^{V}(\Gamma) = \mathbb{E}[\mu(\Gamma \Delta \mathbb{E}^{V}[\Gamma])], \tag{8}$$

with the symmetric difference Δ defined by $A\Delta B = (A \cup B) \setminus (A \cap B)$.

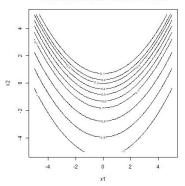
Example of Vorob'ev expectation

Vorob'ev expectation

Introduction

$$\mathbb{E}^{V}[\Gamma] = \{ x \in \mathcal{X}, \mathbb{P}(x \in \Gamma) \ge \alpha^* \} = Q_{\alpha^*}$$
$$\mathbb{E}[\mu(\Gamma)] = \mu(Q_{\alpha^*})$$

Couverture function, mean volume = 0.545

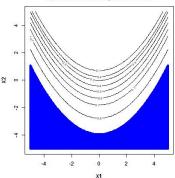


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Couverture function, mean volume = 0.55 Quantile of order 0.9, volume = 0.27

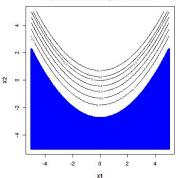


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Couverture function, mean volume = 0.55 Quantile of order 0.8, volume = 0.39



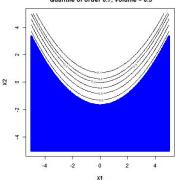
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$$\mathbb{E}[\mu(\Gamma)] = \mu(Q_{\alpha^*})$$

Couverture function, mean volume = 0.55 Quantile of order 0.7, volume = 0.5

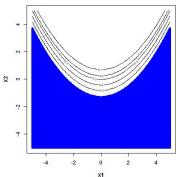


Vorob'ev expectation

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Couverture function, mean volume = 0.55 Quantile of order 0.6, volume = 0.54

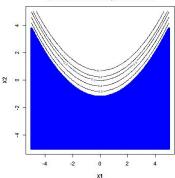


Vorob'ev expectation

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$$\mathbb{E}[\mu(\Gamma)] = \mu(Q_{\alpha^*})$$

Couverture function, mean volume = 0.55 Quantile of order 0.57, volume = 0.55



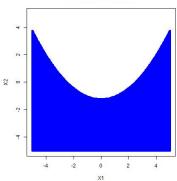
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$$\mathbb{E}[\mu(\Gamma)] = \mu(Q_{\alpha^*})$$

Vorob'ev expectation



Definition of the proposed indices & estimation

Using the previous definitions, we still need a definition of conditional Vorob'ev expectation. We propose the following :

$$\mathbb{E}^V(\Gamma|U_1) = \omega \mapsto \mathbb{E}^V(\Gamma|U_1(\omega)) \quad \text{ where } \quad \Gamma|U_1(\omega) = \{x \in \mathcal{X}, g(x,U_1(\omega),U_2) \leq 0\}.$$

With this definition, the first order Vorob'ev index is :

$$\begin{split} S_i^V &= \frac{Var^V(\mathbb{E}^V(\Gamma|U_i))}{Var^V(\Gamma)} \\ &= \frac{\mathbb{E}[\mu(\mathbb{E}^V(\Gamma|U_i)\Delta\mathbb{E}^V[\mathbb{E}^V(\Gamma|U_i)])]}{\mathbb{E}[\mu(\Gamma\Delta\mathbb{E}^V(\Gamma))]}. \end{split}$$

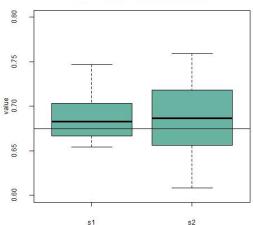
Estimation

- Monte Carlo estimation
- Issue : $\mathbb{E}^V[\mathbb{E}^V(\Gamma|U_i)]
 eq \mathbb{E}^V(\Gamma) o \mathsf{Coslty}$ estimation

Toy function 1

$$\forall (x, u_1, u_2) \in [0, 1]^3 \ g(x, u) = x - u_1 - u_2$$

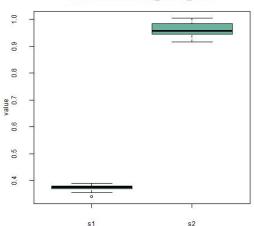
Vorob'ev indices for N_x=N_U=400



Toy function 2

$$\forall (x, u) \in [-5, 5]^4 \ g(x, u) = -x_1^2 + 5x_2 - u_1 + u_2^2 - 1$$

Vorob'ev indices for N_x=20, N_u=500



With $N_x = 20$ and $N_u = 500$

g function	Index	Results
$-x_1^2 + 5x_2 - u_1 + u_2^2 - 1$	s ₁	0.366
	<i>s</i> ₂	0.949
	$s_1 + s_2$	1.314
$-x_1^2 + 5x_2 + u_1^2 + u_2^2 - 1$	s ₁	0.721
	<i>s</i> ₂	0.715
	$s_1 + s_2$	1.436
$-x_1^2 + 5x_2 + u_1^2 + u_2^2 + u_1u_2 - 1$	s1	0.598
	<i>s</i> ₂	0.547
	$s_1 + s_2$	1.146
$-x_1^2 + 5x_2 + u_1^2 - 1$	s ₁	1.00
	<i>s</i> ₂	0.00
	$s_1 + s_2$	1.00
$-x_1^2 + 5x_2 + u_1^2 + u_1u_2 - 1$	s ₁	0.721
	52	0.034
	$s_1 + s_2$	0.755

Conclusion on SA through random sets

- The index quantifies an influence of the inputs on the excursion set
- Very costly estimation
- No variance decomposition

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Definition of the universal index

Introduction

Index introduced in [Gamboa et al. 2021] and [Fort, Klein et Lagnoux 2021] which generalizes many existing indices, and only requires the output space to be a metric space.

With $Z = f(U_1, ..., U_p) \in \mathcal{Z}$, the universal sensitivity index with respect to U_i is defined as

$$S_{2, \text{ Univ}}^{i}(T, \mathbb{Q}) := \frac{\int_{\mathcal{A}} \text{Var}\left(\mathbb{E}\left[T_{a}(Z) \mid U_{i}\right]\right) d\mathbb{Q}(a)}{\int_{\mathcal{A}} \text{Var}\left(T_{a}(Z)\right) d\mathbb{Q}(a)},\tag{9}$$

where (T_a) are tests functions defined by :

$$\begin{array}{cccc}
\mathcal{A} \times \mathcal{Z} & \to & \mathbb{R} \\
(a,z) & \mapsto & \mathcal{T}_a(z),
\end{array}$$
(10)

and $\mathcal A$ is some measurable space endowed with a probability measure $\mathbb Q.$ Generalization of existing indices :

- Sobol index : $S^i = S^i_{2, \text{ Univ}}$ (Id, \mathbb{Q}) with Id beeing the indicator function : $T_a(z) = z$.
- Cramér-von Mises index : $T_a(z) = \mathbb{1}_{x \leq a}$, $\mathbb{Q} = \mathbb{P}$ with $\mathcal{A} = \mathcal{X}$.

With $Z = \Gamma_U$, the index is:

$$S_{2, \; \mathsf{Univ}}^{i} \; \left(\mathcal{T}_{\cdot}, \mathbb{Q} \right) := \frac{\int_{\mathcal{A}} \mathsf{Var}(\mathbb{E} \left[\mathcal{T}_{a}(\Gamma_{U}) \mid U_{i} \right]) d\mathbb{Q}(a)}{\int_{\mathcal{A}} \mathsf{Var} \left(\mathcal{T}_{a}(\Gamma_{U}) \right) d\mathbb{Q}(a)},$$

Interpretation:

Introduction

- Let $a \in \mathcal{A}$, it defines a random variable $T_a(\Gamma_U)$ which contains a part of information on Γ_U : for instance $T_a(\Gamma_U) = a\mu(\Gamma_U)$.
- $Var(T_a(\Gamma_U)) = Var(\mathbb{E}[T_a(\Gamma_U) \mid U_i]) + \mathbb{E}(Var[T_a(\Gamma_U) \mid U_i])$.
- $\int_{\mathcal{A}} \mathsf{Var}(T_a(\Gamma_U)) = \int_{\mathcal{A}} \mathsf{Var}\left(\mathbb{E}\left[T_a(\Gamma_U) \mid U_i\right]\right) + \int_{\mathcal{A}} \mathbb{E}\left(\mathsf{Var}\left[T_a(\Gamma_U) \mid U_i\right]\right)$.

Influence of T_a and \mathbb{Q}

What are the impact of the choices of T_a and \mathbb{Q} , how to choose them?

Adaptation of the universal index on random sets

$$S_{2,\;\mathsf{Univ}}^{i}\;(T_{\mathsf{a}},\mathbb{Q}) := \frac{\int_{\mathcal{A}}\mathsf{Var}(\mathbb{E}\left[T_{\mathsf{a}}(\Gamma_{U})\mid U_{i}\right])d\mathbb{Q}(\mathsf{a})}{\int_{\mathcal{A}}\mathsf{Var}\left(T_{\mathsf{a}}(\Gamma_{U})\right)d\mathbb{Q}(\mathsf{a})}$$

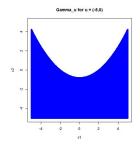
We use $T_a(\Gamma)$ defined by :

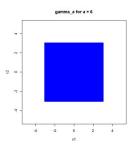
$$T_{a}(\Gamma) = \mu(\gamma_{a}\Delta\Gamma),\tag{11}$$

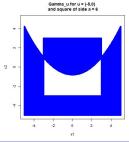
wit h

- ullet the symmetric difference Δ defined by $A\Delta B=A\cup B-A\cap B$.
- The volume μ defined by $\mu(\Gamma) = \int_{\mathcal{X}} \mathbb{1}_{x \in \Gamma} dx$.
- ullet $\mathbb Q$ is taken uniform on $\mathcal A$.
- the γ_a , called test sets, defined through the scalar (or real valued vector) $a \in \mathbb{R}^m$: For instance concentric disks of radius a or concentric squares of side a.

Symmetric difference

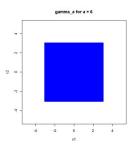


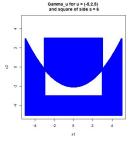




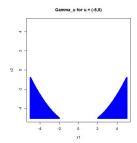
Symmetric difference

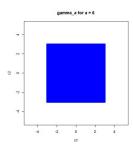


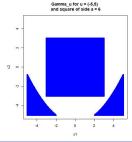




Symmetric difference







Estimation

Introduction

Pick and freeze method: U' independent copy of U,

$$\textit{U} = \begin{pmatrix} \textit{U}_1 & \cdots & \textit{U}_i & \cdots & \textit{U}_p \end{pmatrix}, \quad \tilde{\textit{U}} = \begin{pmatrix} \textit{U}_1 & \cdots & \textit{U}_i' & \cdots & \textit{U}_p \end{pmatrix}$$

We have then : $Var(\mathbb{E}[T_a(\Gamma_U) \mid U_i]) = Cov(T_a(\Gamma_U), T_a(\Gamma_{\tilde{U}})).$

Estimation $\mu(\mathcal{X}) = 1$

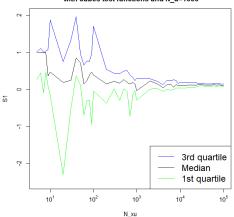
Using $T_a(\Gamma_U) = \mu(\Gamma_U \Delta \gamma_a) = \mathbb{E}_X(\mathbb{1}_{X \in \Gamma \Delta \gamma_a})$ with X uniform on \mathcal{X} , we have then

$$\begin{aligned} \mathsf{Cov}_{U,\tilde{U}(\mathcal{T}_{\mathsf{a}}(\Gamma_{U}),\mathcal{T}_{\mathsf{a}}(\Gamma_{\tilde{U}}))} &= \mathbb{E}_{U,\tilde{U}}[\mathbb{E}_{X}(\mathbb{1}_{X\in\Gamma_{U}\Delta\gamma_{\mathsf{a}}})\mathbb{E}_{X}(\mathbb{1}_{X\in\Gamma_{\tilde{U}}\Delta\gamma_{\mathsf{a}}})] \\ &- \mathbb{E}_{U}[\mathbb{E}_{X}(\mathbb{1}_{X\in\Gamma_{U}\Delta\gamma_{\mathsf{a}}})]\mathbb{E}_{\tilde{U}}[\mathbb{E}_{X}(\mathbb{1}_{X\in\Gamma_{\tilde{U}}\Delta\gamma_{\mathsf{a}}})] \\ &= \mathbb{E}_{X,X',U,\tilde{U}}[\mathbb{1}_{X\in\Gamma_{U}\Delta\gamma_{\mathsf{a}}}\mathbb{1}_{X'\in\Gamma_{\tilde{U}}\Delta\gamma_{\mathsf{a}}}] \\ &- \mathbb{E}_{X,U}[\mathbb{1}_{X\in\Gamma_{U}\Delta\gamma_{\mathsf{a}}}]\mathbb{E}_{X',\tilde{U}}[\mathbb{1}_{X'\in\Gamma_{\tilde{U}}\Delta\gamma_{\mathsf{a}}}] \\ &= \frac{1}{N_{xu}}\sum_{j=1}^{N_{xu}}[\mathbb{1}_{Xj\in\Gamma_{U^{j}}\Delta\gamma_{\mathsf{a}}}\mathbb{1}_{X^{j}\in\Gamma_{\tilde{U}^{j}}\Delta\gamma_{\mathsf{a}}}] \\ &- \frac{1}{N_{xu}}\sum_{j=1}^{N_{xu}}[\mathbb{1}_{X^{j}\in\Gamma_{U^{j}}\Delta\gamma_{\mathsf{a}}}]\frac{1}{N_{xu}}\sum_{j=1}^{N_{xu}}[\mathbb{1}_{X^{j}\in\Gamma_{\tilde{U}^{j}}\Delta\gamma_{\mathsf{a}}}]. \end{aligned}$$

Toy function

$$\forall (x, u) \in [-5, 5]^4 \ g(x, u) = -x_1^2 + 5x_2 - u_1 + u_2^2 - 1$$

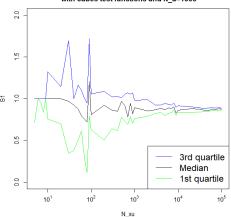
Influence of N_xu on S1 averaged on 20 realizations with cubes test functions and N_a=1000



Toy function

$$\forall (x, u) \in [-5, 5]^4 \ g(x, u) = -x_1^2 + 5x_2 - u_1 + u_2^2 - 1$$

Influence of N_xu on \$2 averaged on 20 realizations with cubes test functions and N_a=1000



With $N_{\!\scriptscriptstyle extsf{X} extsf{U}} = 10^6$ and $N_{\!\scriptscriptstyle extsf{A}} = 1000$

g function	Index	Results with squares	Results with disks
$-x_1^2 + 5x_2 - u_1 + u_2^2 - 1$	<i>s</i> ₁	0.114	0.113
	<i>s</i> ₂	0.868	0.864
	$s_1 + s_2$	0.982	0.978
$-x_1^2 + 5x_2 + u_1^2 + u_2^2 - 1$	<i>s</i> ₁	0.468	0.450
	<i>s</i> ₂	0.461	0.461
	$s_1 + s_2$	0.929	0.911
$-x_1^2 + 5x_2 + u_1^2 + u_2^2 + u_1u_2 - 1$	s1	0.286	0.263
	<i>s</i> ₂	0.283	0.271
	$s_1 + s_2$	0.570	0.535
$-x_1^2 + 5x_2 + u_1^2 - 1$	s ₁	1.00	1.00
	<i>s</i> ₂	-0.022	0.031
	$s_1 + s_2$	0.977	1.031
$-x_1^2 + 5x_2 + u_1^2 + u_1u_2 - 1$	s ₁	0.426	0.412
	<i>s</i> ₂	0.011	-0.000
	$s_1 + s_2$	0.438	0.412
$-x_1^2 + 5x_2 + u_1 + u_2 - 1$	<i>s</i> ₁	0.473	0.445
	<i>s</i> ₂	0.500	0.438
	$s_1 + s_2$	0.974	0.884

Comments on the results

Toy function

$$\forall (x, u) \in [-5, 5]^4 \ g(\mathbf{x}, \mathbf{u}) = -x_1^2 + 5x_2 - u_1 + u_2^2 - 1$$
$$\Gamma_U = \{ x \in [-5, 5]^2, -x_1^2 + 5x_2 \le u_1 - u_2^2 + 1 \}$$

- S^1 and S^2 don't sum to 1 because there are interactions between u_1 and u_2 in Γ_U :
 Indead, two admissible sets are equals if $u_1-u_2^2+1$ is constant which links u_1 and u_2 .
- Use of the universal index and the choice of T_a as the symmetric difference gives an index which seems to quantify the influence of the input as observed initially.

Conclusion on the universal index on sets

Choices of T_a and \mathbb{Q} ?

Choice of T_a

Introduction

 T_a should be chosen so that the $(T_a(\Gamma_U)_{a\in\mathcal{A}})$ characterizes the most Γ_U

- Choice of T: could be on other distance between sets or a function of a distance.
- Choice of the test sets: We want that the test sets cover the whole space of sets. For instance taking $a \in \mathbb{R}^2$ to defined rectangles could be better than squares.
- The best choice of the test sets could depend on the function g.

Choice of $\mathbb Q$

• uniform to cover the whole space of sets.

Conclusion

Introduction

Vorob'ev index

- Sensitivity indices with sets output: Sobol indices with the Vorob'ev expectation and deviation
- Very costly to estimate and no variance decomposition
- \Rightarrow Meta-models adapted to the index

Universal sensitivity indices on sets

- Sensitivity indices with sets outputs: Variance of the transformation of the set output explained by an input averaged on a family of test functions
- ullet Choices of the test function, the probability ${\mathbb Q}$ and their influence on the index



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Excursion sets are random sets

For
$$K$$
 compact, $h(U) = X = \{x \in \mathcal{X}, g(x, U) \leq 0\}$
$$\{K \cap X \neq \emptyset\} = {}^c \{\omega, K \cap X(\omega) = \emptyset\}$$

$$= {}^c \{\omega, \forall x \in K \ g(x, U(\omega)) > 0\}$$

$$= {}^c \{\omega, \inf_{x \in K} g(x, U(\omega)) > 0\} \text{ as } K \text{ compact and } g \text{ continuous in } x$$

$$= {}^c U^{-1}(\inf_{x \in K} g(x, \cdot)^{-1}(]0, +\infty[)) \in \mathcal{F}$$

Universal index on random sets

Expectation of $T_a(\Gamma_U)$

As the randomness of Γ_U only depend on U, we have

$$\mathbb{E}[T_a(\Gamma_U)] = \int_{\mathcal{U}} T_a(\Gamma_U) du. \tag{12}$$

Theorem (Robbins' theorem Molchanov 2005)

Let Γ be a random closed set in a Polish space $\mathcal X$. If μ is a locally finite measure on Borel sets, then $\mu(\Gamma)$ is a random variable and :

$$\mathbb{E}(\mu(\Gamma)) = \int_{\mathcal{X}} \mathbb{P}(x \in \Gamma)\mu(dx). \tag{13}$$

$$\begin{split} \mathbb{E}(T_a(\Gamma_U)) &= \mathbb{E}(\mu(\Gamma_U \Delta \gamma_a)) = \int_{\mathcal{X}} \mathbb{P}(x \in \Gamma_U \Delta \gamma_a) \mu(dx) = \int_{\mathcal{X}} \mathbb{P}_U(x \in \Gamma_U \Delta \gamma_a) \mu(dx) \\ &= \int_{\mathcal{X}} \int_{\mathcal{U}} \mathbb{1}_{x \in \Gamma_U \Delta \gamma_a} \mu(dx) \\ &= \int_{\mathcal{U}} T_a(\Gamma_U) du. \end{split}$$