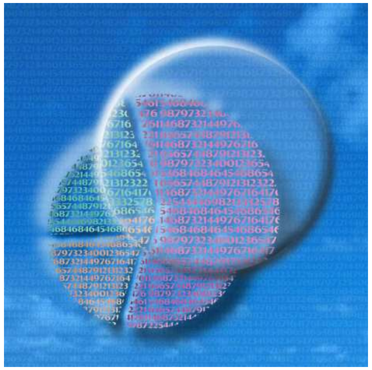
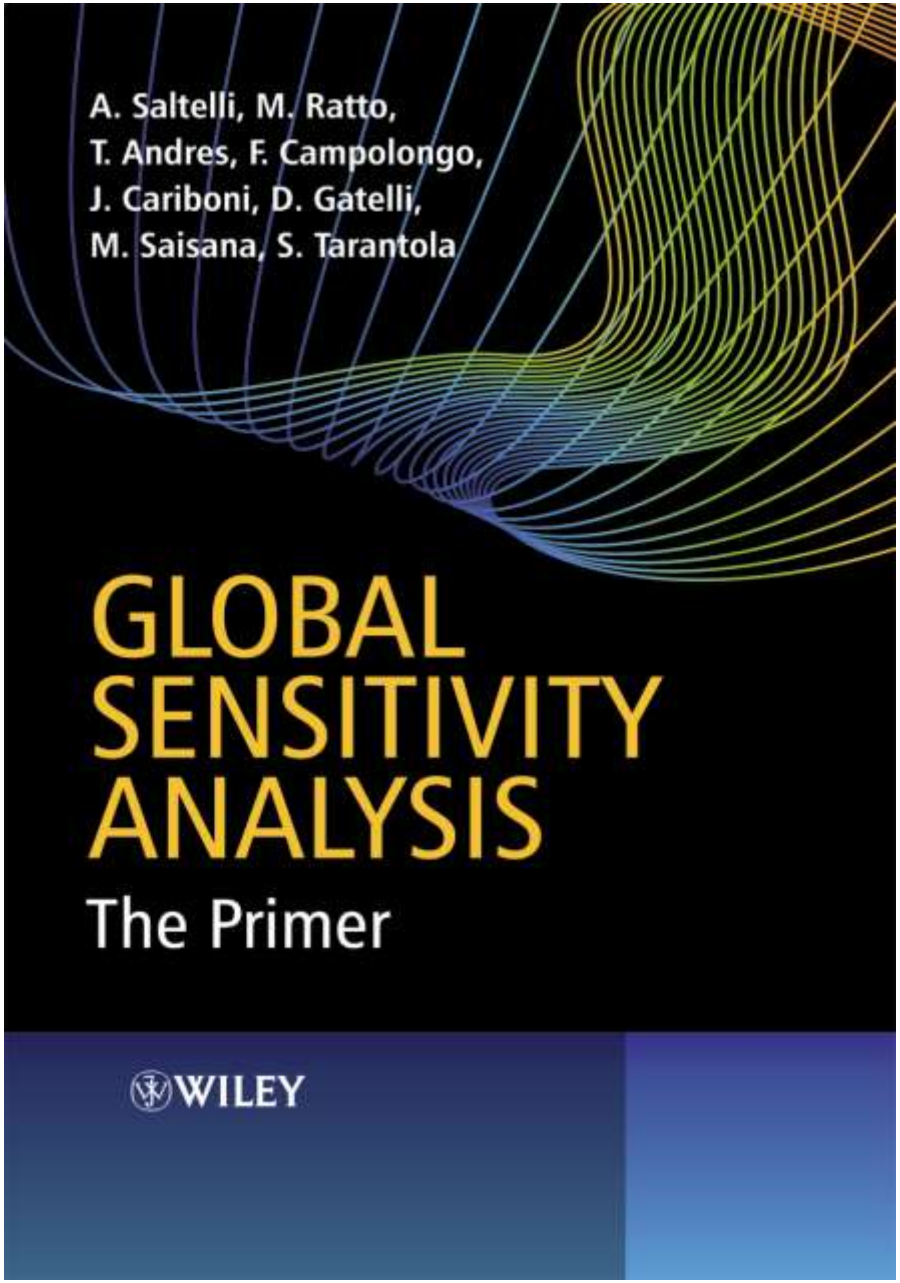


Sensitivity Analysis

Andrea Saltelli

Presentation at the Barcelona Supercomputing Center, September 18, 2023



Partly based on

Global sensitivity analysis. The Primer

EC impact assessment guidelines: sensitivity analysis & auditing

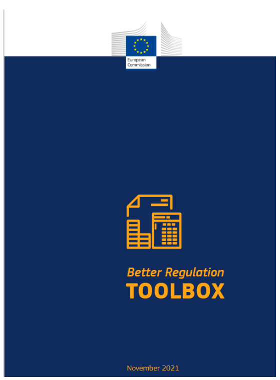
European Commission. November 2021. "Better Regulation: Guidelines and Toolbox." https://ec.europa.eu/info/law/law-making-process/planning-and-proposing-law/better-regulation-why-and-how/better-regulation-guidelines-and-toolbox_en

EC impact assessment guidelines: sensitivity analysis & auditing

TOOL #65. UNCERTAINTY AND SENSITIVITY ANALYSIS

1. MAIN FEATURES

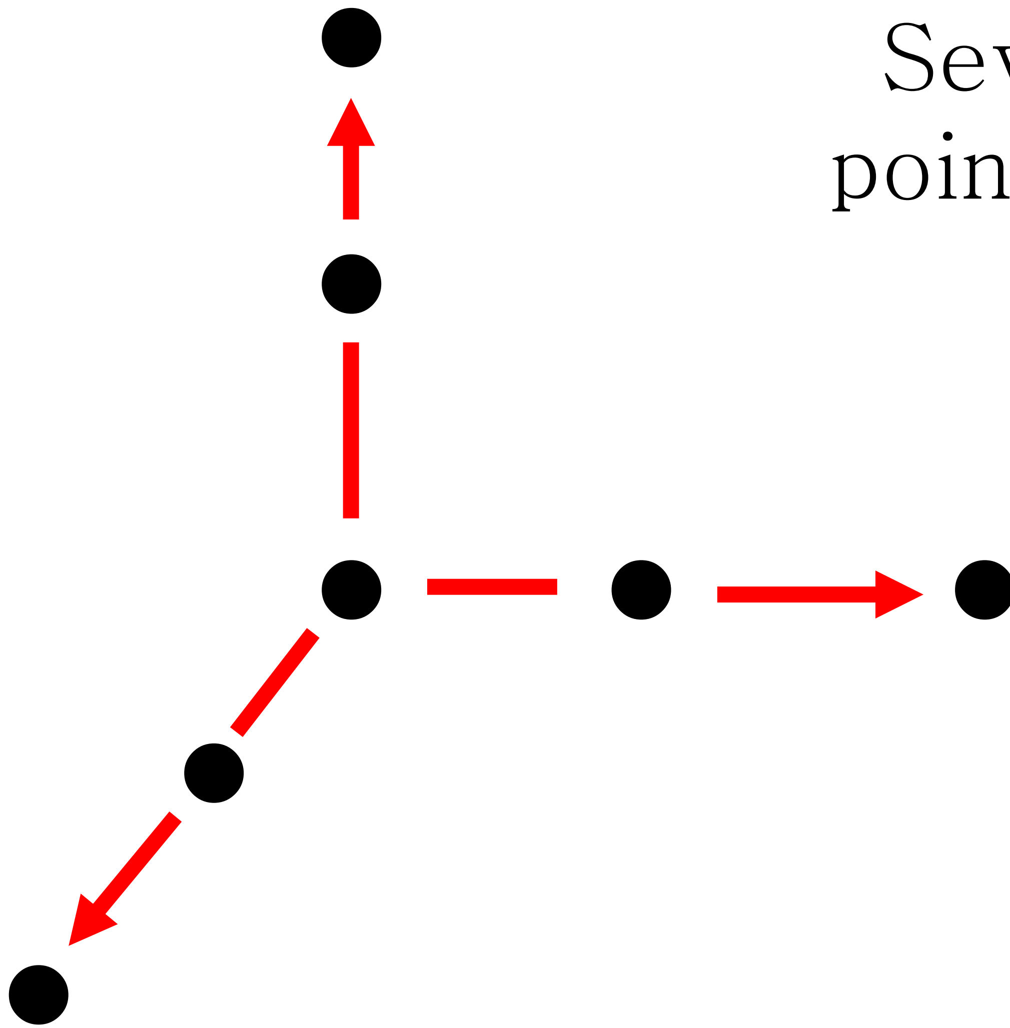
What	**Uncertainty analysis** aims at quantifying uncertainties in model results provided to the decision-makers due to uncertain assumptions/inputs**. Sensitivity analysis** allows identifying the uncertain assumptions mostly responsible for uncertainty in model results.
Why	A **transparent** and **high-quality impact assessment** should acknowledge and, to the extent relevant or possible, attempt to quantify the **uncertainty in results** as it could change the ranking and conclusions about the policy options.
How	**Assessing** the uncertainties in model results by propagating model input uncertainties through the model and **inferring** a posteriori the relevant uncertain inputs by subsequent statistical analysis.



Who do these have in common?

J. Campbell, *et al.*, *Science* **322**, 1085 (2008).
R. Bailis, M. Ezzati, D. Kammen, *Science* **308**, 98 (2005).
E. Stites, P. Trampont, Z. Ma, K. Ravichandran, *Science* **318**, 463 (2007).
J. Murphy, et al., *Nature* **430**, 768–772 (2004).
J. Coggan, *et al.*, *Science* **309**, 446 (2005).

OAT



Seven OAT points in a 3D space

Before we go on to discuss OAT a premise:

We don't know if a model is linear before we do the analysis!

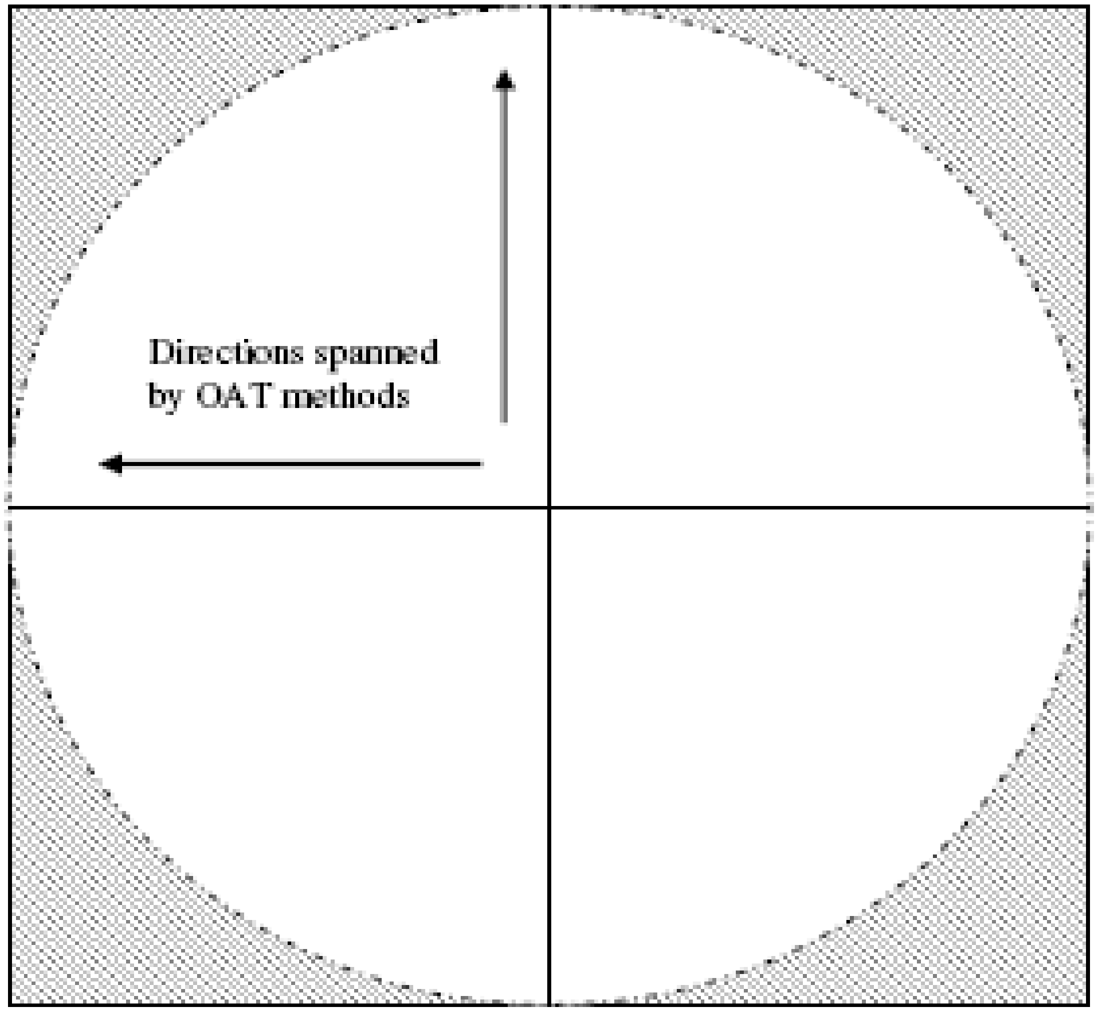
$$\frac{\partial Y_j}{\partial X_i}$$

Otherwise the model could be declared linear or additive (or otherwise well behaved) and one could make it do with derivatives at a single baseline point.

Thus derivates are out, but is OAT OK?

Or how bad is it?

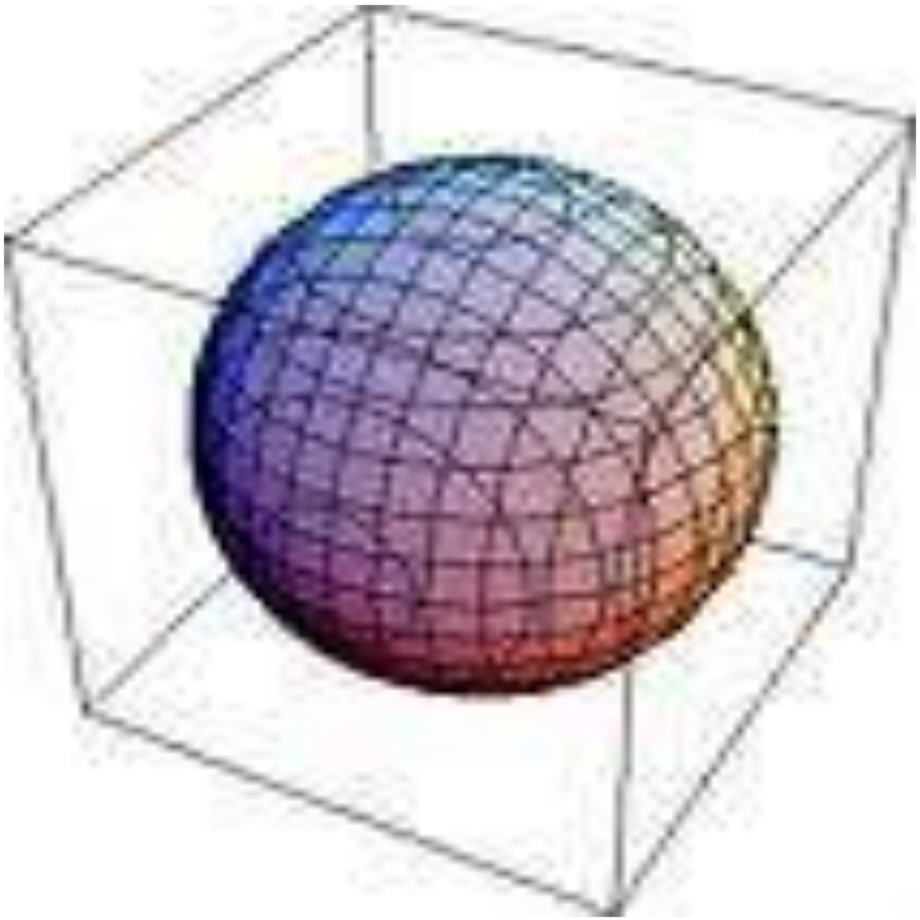
OAT in 2 dimensions



Area circle / area square =?

~ 3/4

OAT in 3 dimensions



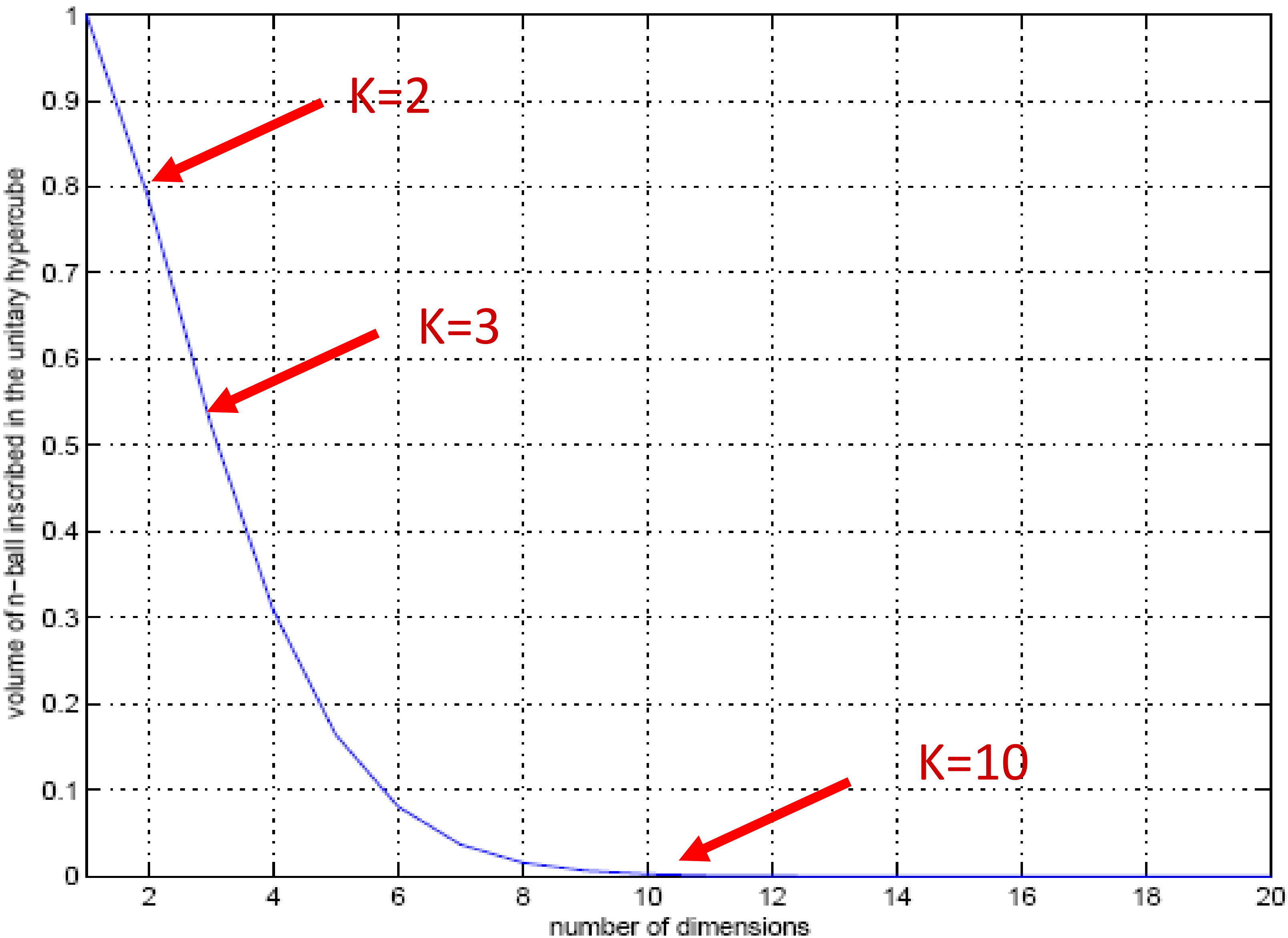
Volume sphere / volume cube =?

~ 1/2

OAT in 10 dimensions

Volume hypersphere / volume ten dimensional hypercube =? ~ 0.0025

OAT in k dimensions



Thus OAT is very poor in exploring the space of the factors – it is also non conservative.

Why?

OAT in not roughly right … it is precisely wrong!

Reading about dubious or absent sensitivity analysis

ELSEVIER

Environmental Modelling & Software
Volume 114, April 2019, Pages 29-39

Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices

Andrea Saltelli [a b], Ksenia Aleksankina [c], William Becker [d], Pamela Fennell [e], Federico Ferretti [d], Niels Holst [f], Sushan Li [g], Qiongli Wu [h]

Show more

For the papers using OAT points a better (statistical theory based) alternative is available, be it:

- A two level factorial design,
- A trajectory analysis (a-la-Morris) or
- A linear regression based on a Monte Carlo Sample

<u>Using perhaps the same low number of points.</u>

Another story of SA

Nicholas Stern, London School of Economics

William Nordhaus, University of Yale

Stern's Review – Technical Annex to postscript

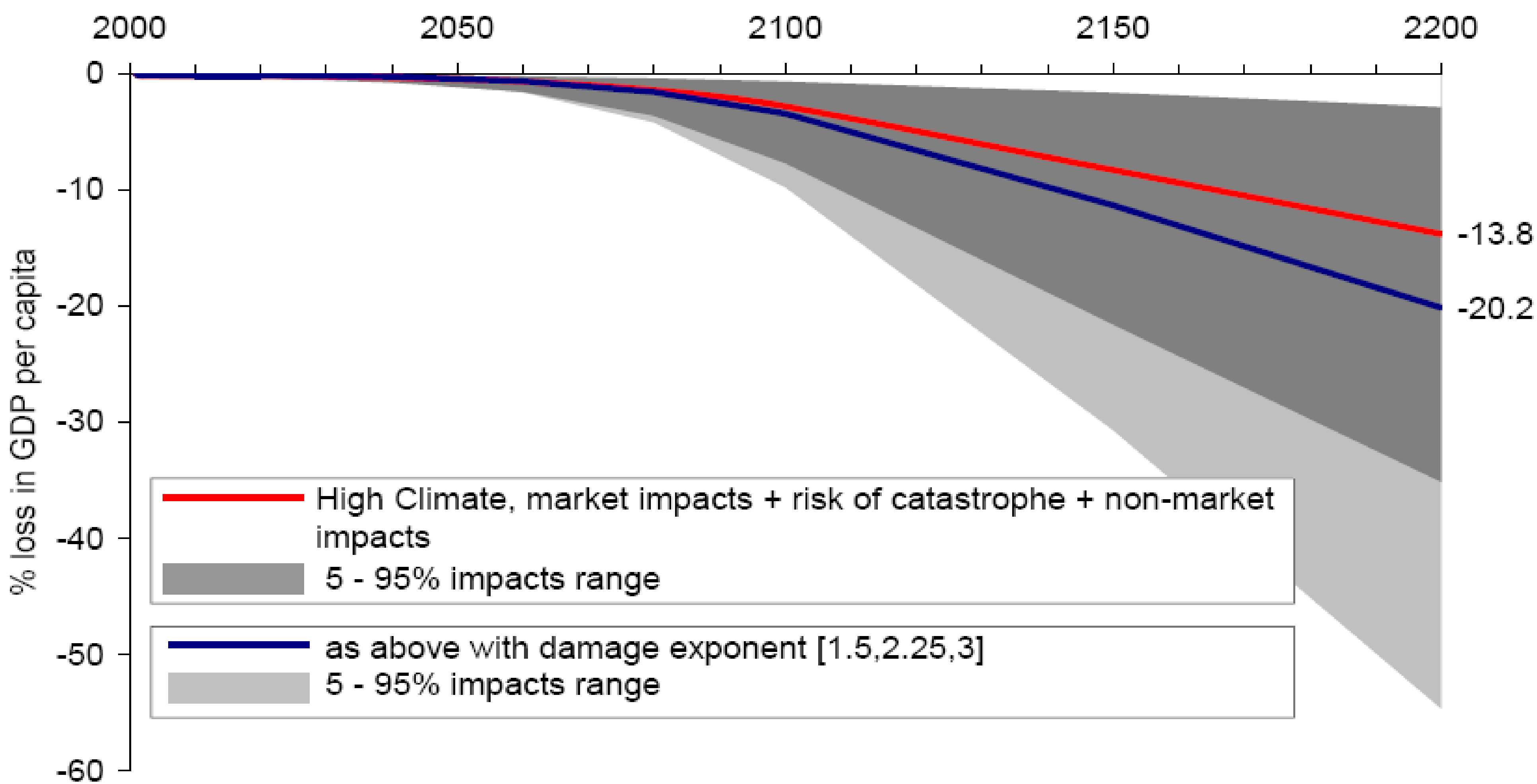
Stern's Review – Technical Annex To postscript
(a sensitivity analysis of a cost benefit analysis)

The Stern – Nordhaus exchange on *SCIENCE*

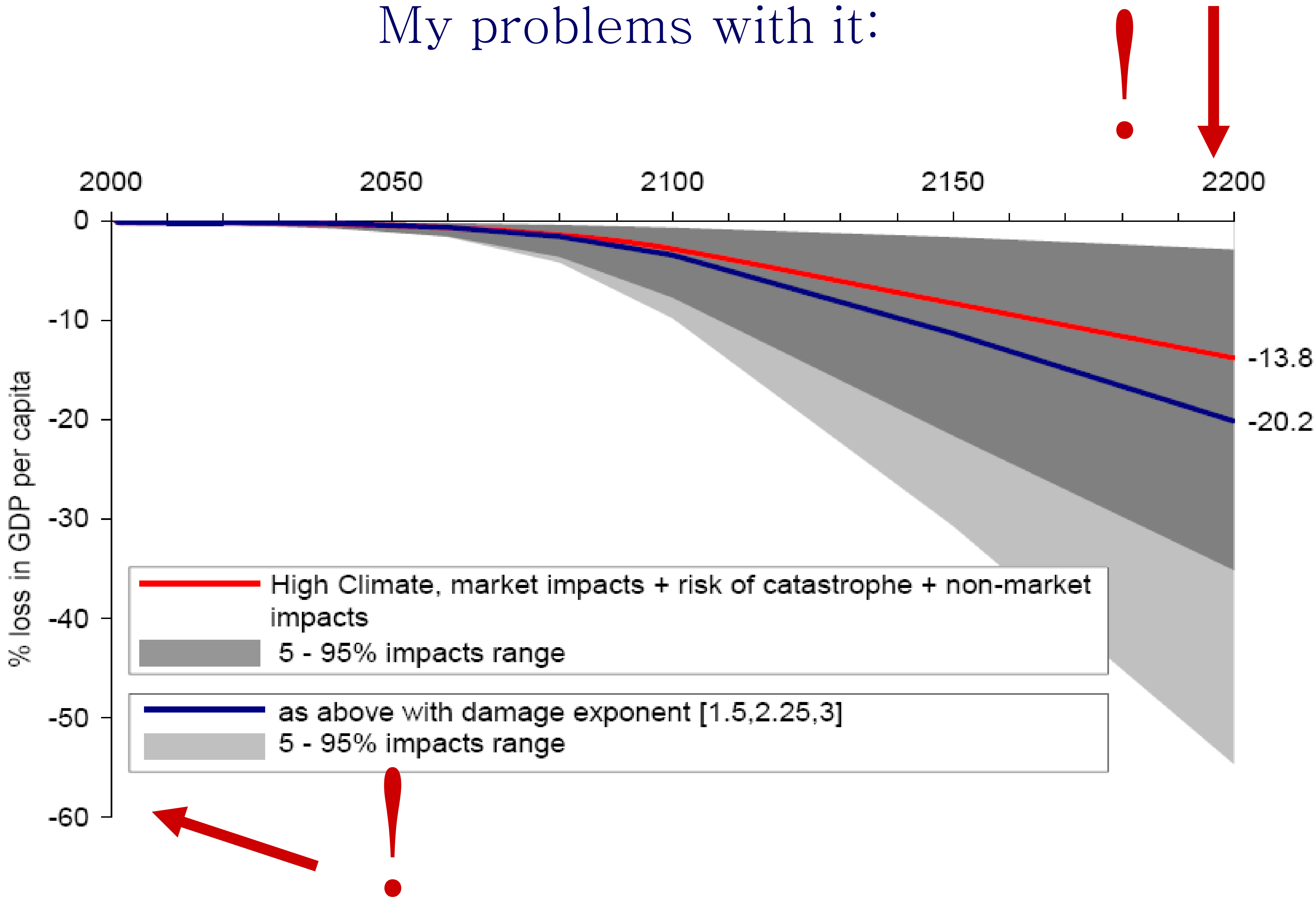
Nordhaus → falsifies Stern based on 'wrong' range of discount rate (~ you GIGOing)

Stern → 'My analysis shows robustness'

From Stern's Review SA



My problems with it:

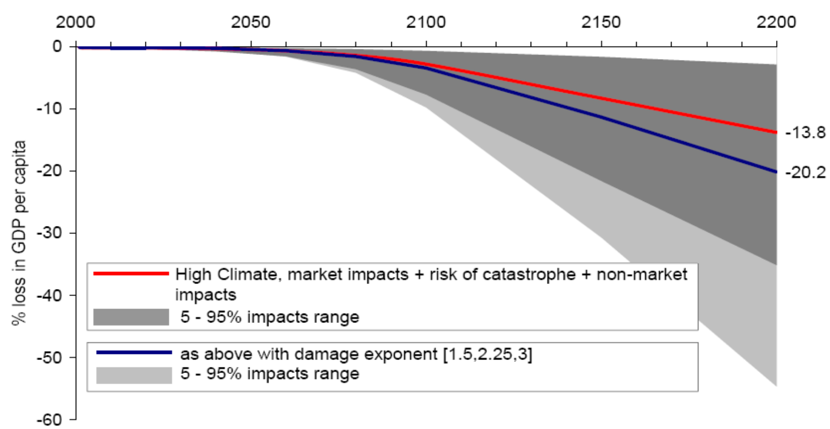


… but foremost he says:

changing assumptions → important effect

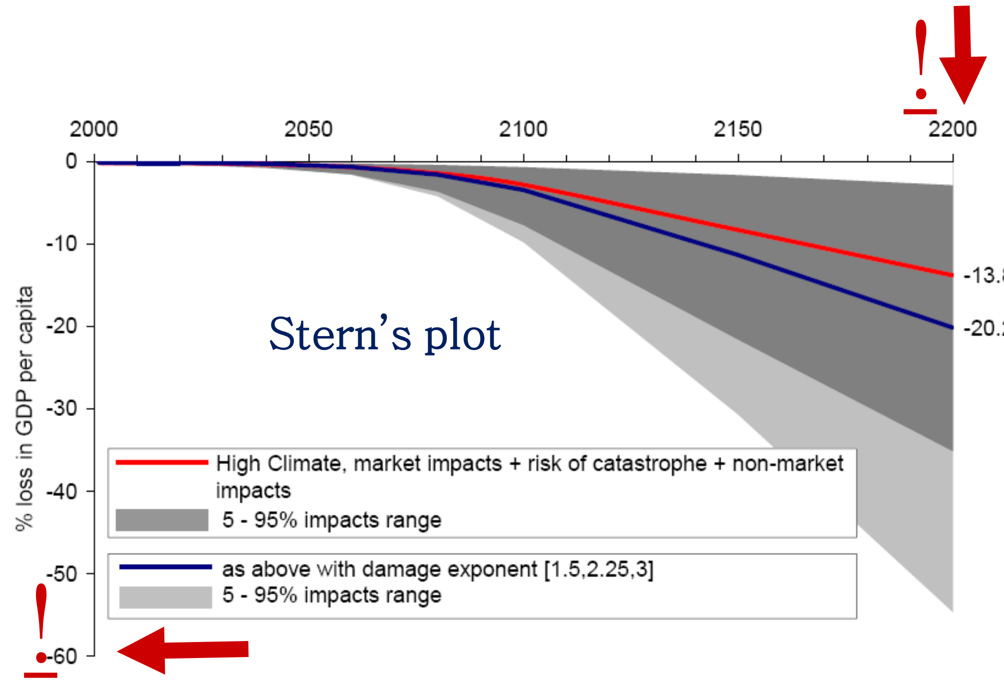
when instead he should admit that:

changing assumptions → all changes a lot



The Stern-Nordhaus controversy; a reverse engineering the model:

➔ uncertainty is too large to take decisions ➔ both Stern and Nordhaus are wrong



Global Environmental Change 20 (2010) 298–302

Contents lists available at ScienceDirect

Global Environmental Change

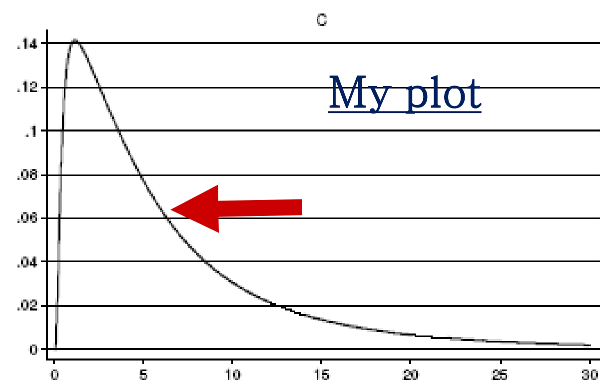
journal homepage: www.elsevier.com/locate/gloenvcha

ELSEVIER

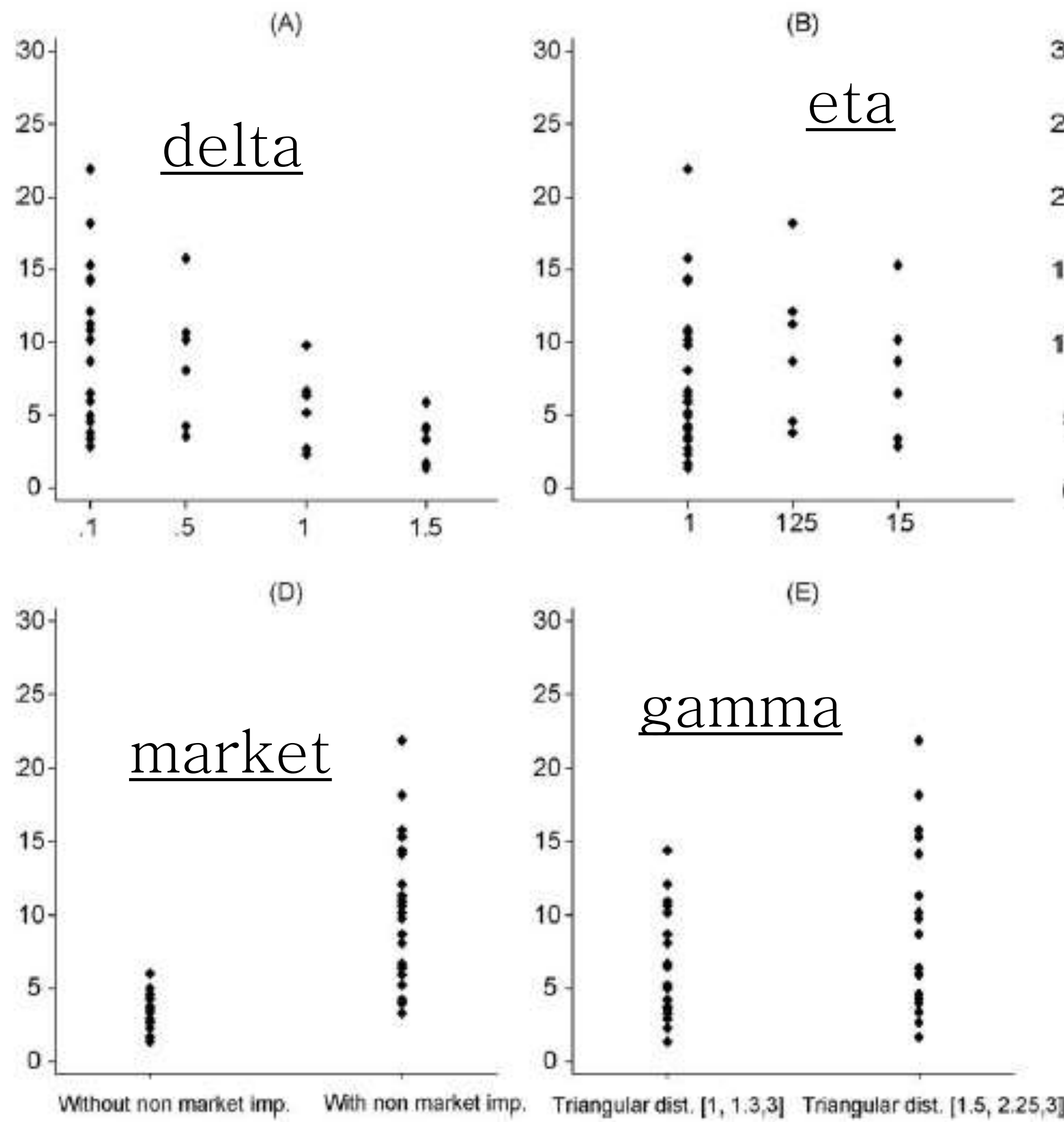
Sensitivity analysis didn't help. A practitioner's critique of the Stern review

Andrea Saltelli *, Beatrice D'Hombres

Joint Research Centre, Institute for the Protection and Security of the Citizen, Ispra, Italy

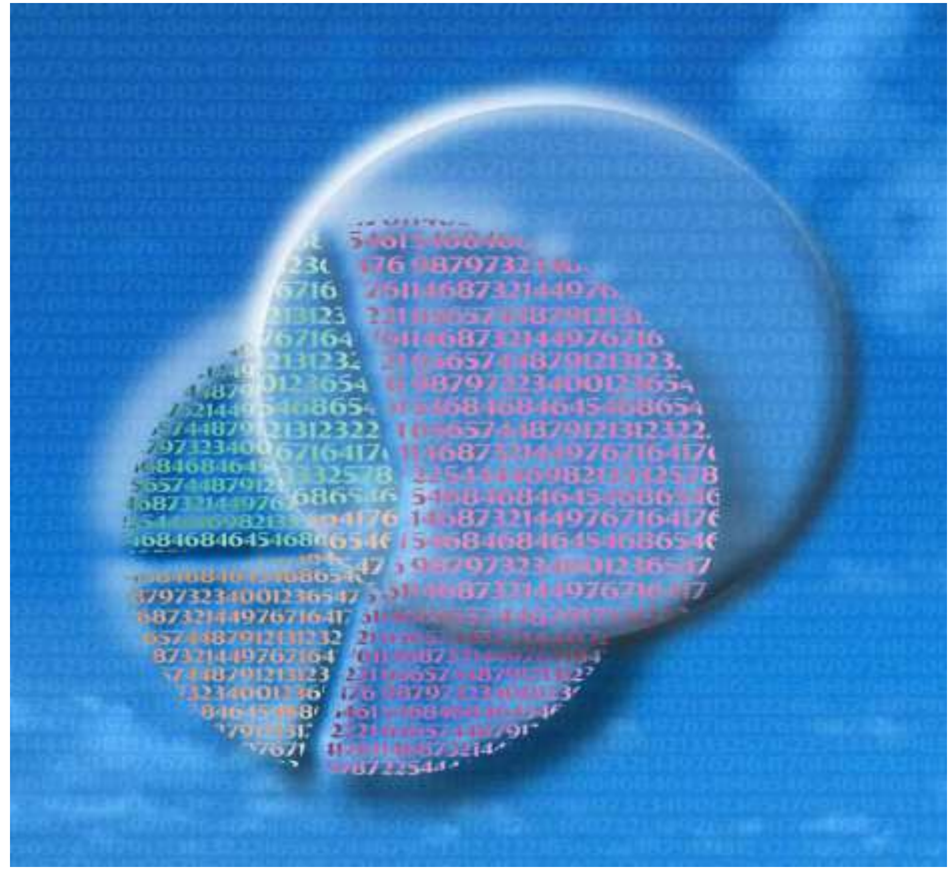


% loss in GDP per capita

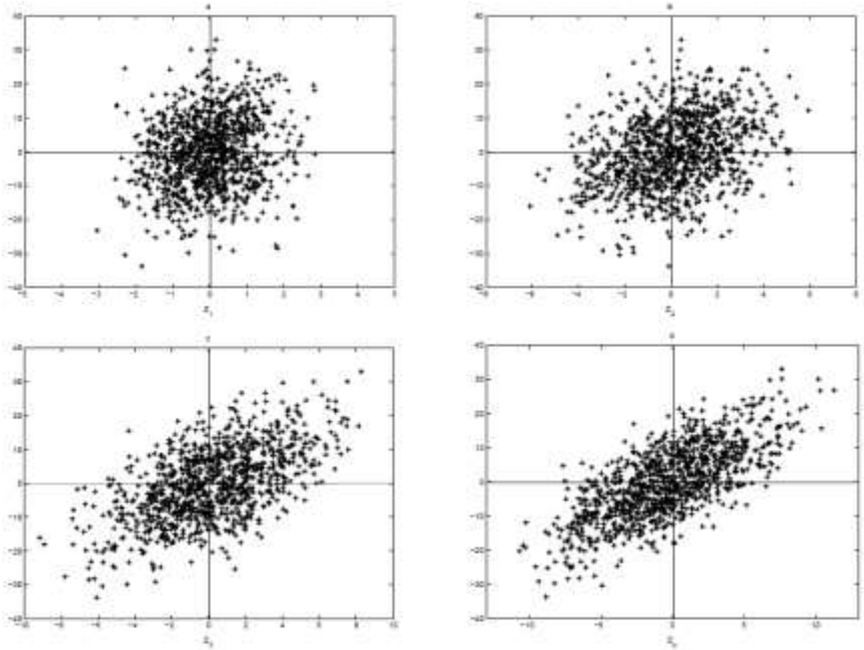


Sensitivity analysis, also by reverse engineering

Variance based methods; a best practice?



Mostly based on the work of Ilya M. Sobol' (1990), who extended the work of R.I. Cukier (1973). Further extensions by T. Homma and myself (1996, onward).



Scatterplots' notation:

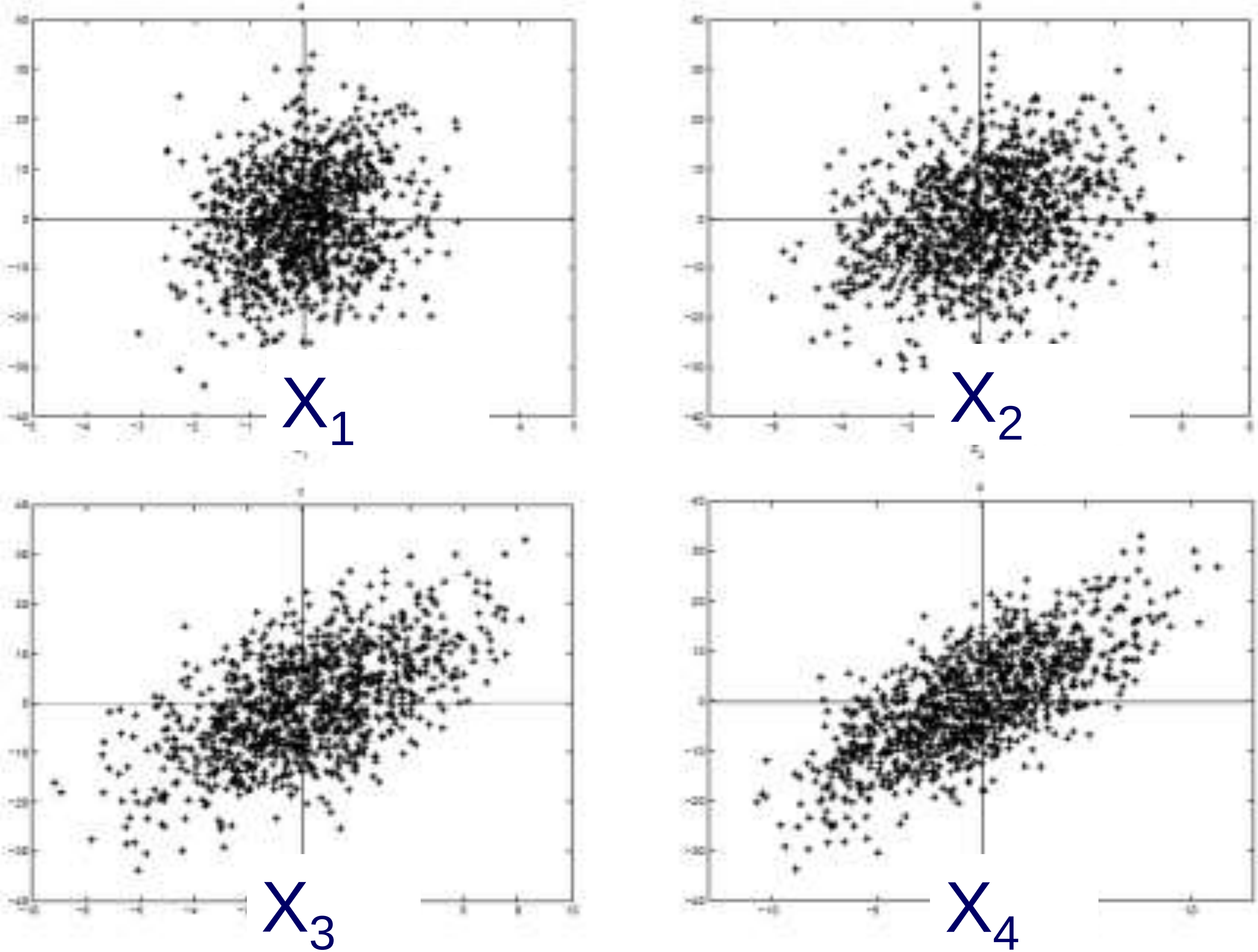
$$Y = f\left(X_1, X_2, \ldots X_k\right)$$

$$f_0 = E\left(Y\right)$$

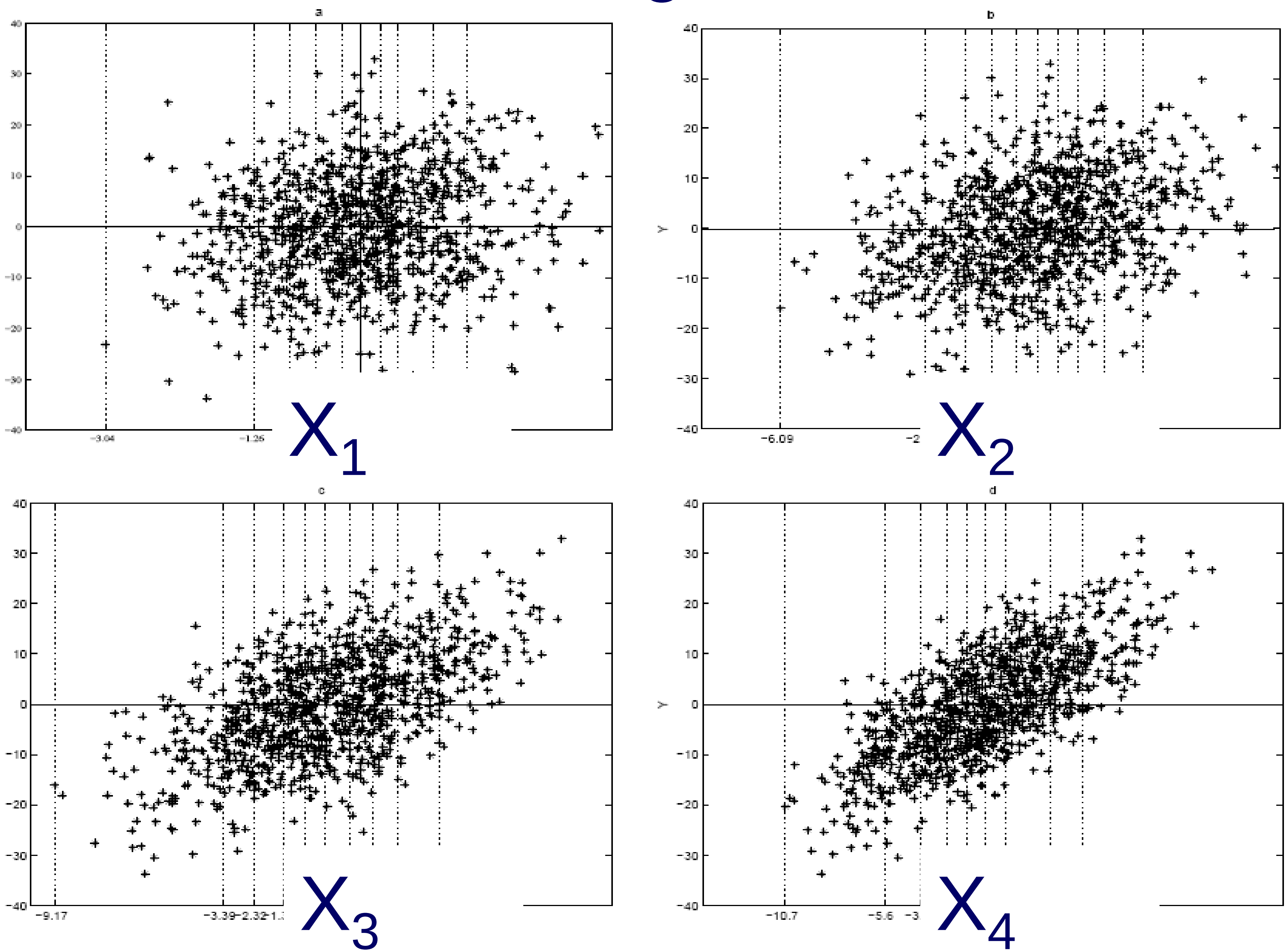
The ordinate axis is always Y

The abscissa are the various factors X_i in turn.

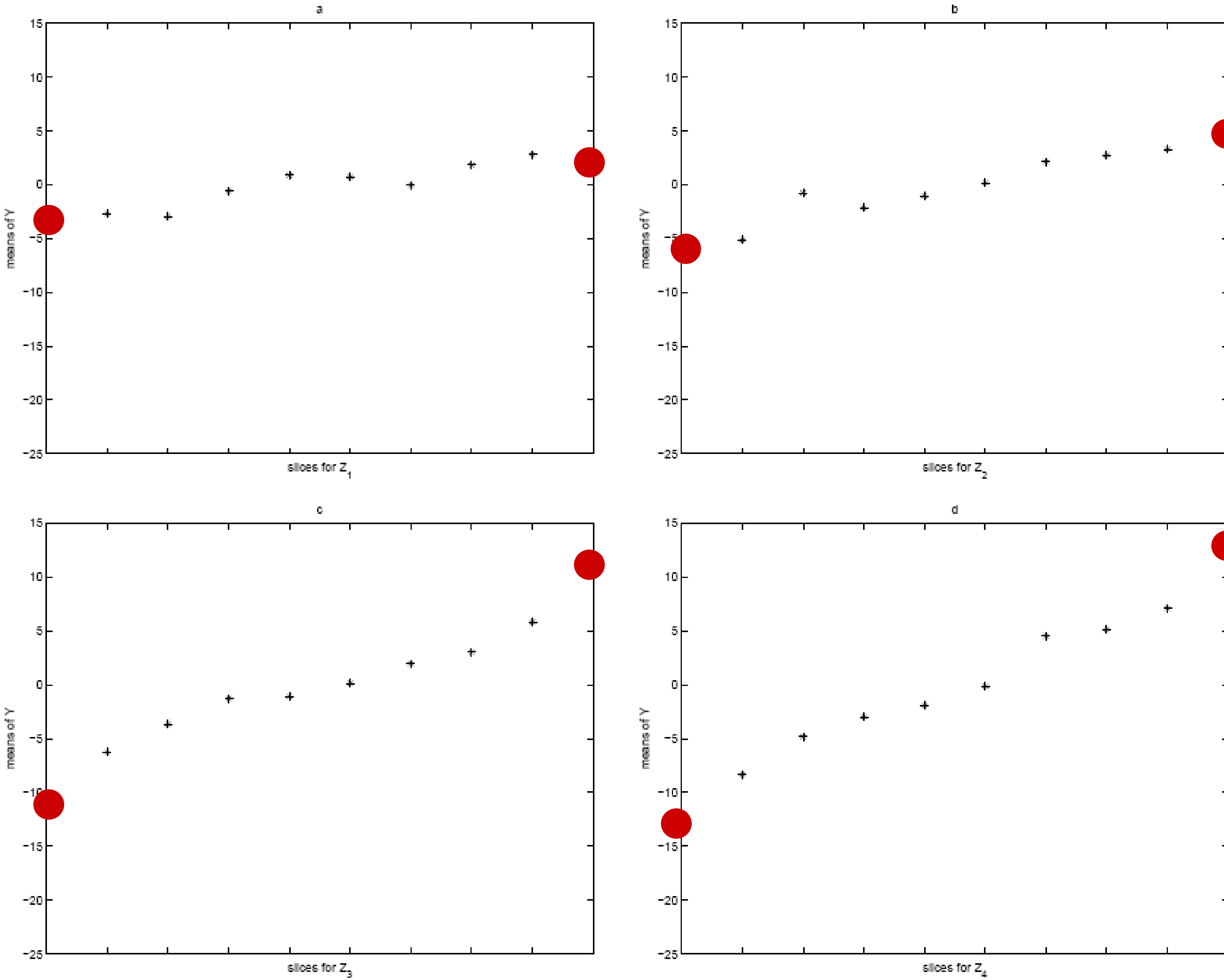
The points are always the same!

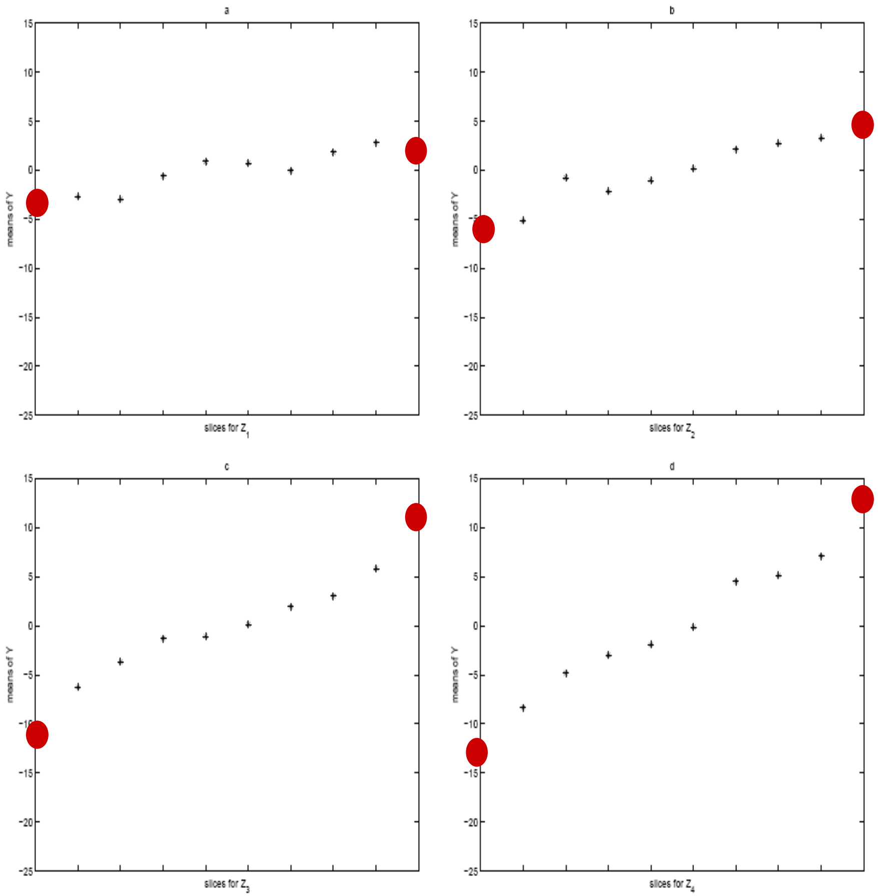

X_1
X_2
X_3
X_4

Cutting into slices…



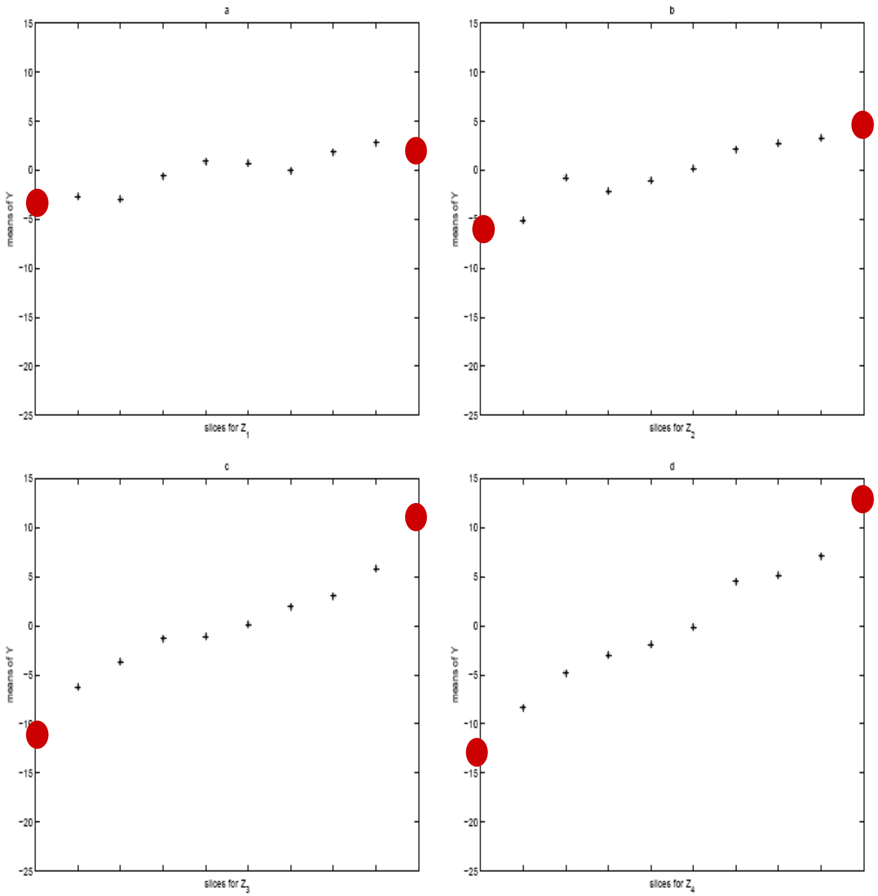
Average of Y versus X_i – same scale for Y





This shows the variance of Y across the slices: greater for X_4 than for X_1

$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right)$$



If the model is linear:

$$\frac{V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right)}{V} \approx \beta_{X_i}^2$$

$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right)$$

First order effect, or top marginal variance=

= the expected reduction in variance than would be achieved if factor Xi could be fixed.

For additive systems one can decompose the total variance as a sum of first order effects

$$\sum_i V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right) = V(Y)$$

… and a powerful variance based measure is also available for non-additive models …

From this …

$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right)$$

This is a first order effect, or top marginal variance.

The expected reduction in variance than would be achieved if factor Xi could be fixed.

… to this

This is a total order effect, or bottom marginal variance.

The expected variance than would be left if all factors but Xi could be fixed.

$$E_{\mathbf{X}_{\sim i}}\left(V_{X_i}\left(Y \middle| \mathbf{X}_{\sim i}\right)\right)$$

$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right)$$

This has an intuitive interpretation (the scatterplots)

$$E_{\mathbf{X}_{\sim i}}\left(V_{X_i}\left(Y \middle| \mathbf{X}_{\sim i}\right)\right)$$

How About this?

Variance decomposition (ANOVA)

$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right) = V_i$$

$$V_{X_i X_j}\left(E_{\mathbf{X}_{\sim ij}}\left(Y \middle| X_i X_j\right)\right) =$$

$$= V_i + V_j + V_{ij}$$

$$\dots$$

Variance decomposition (ANOVA)

$$V(Y) =$$

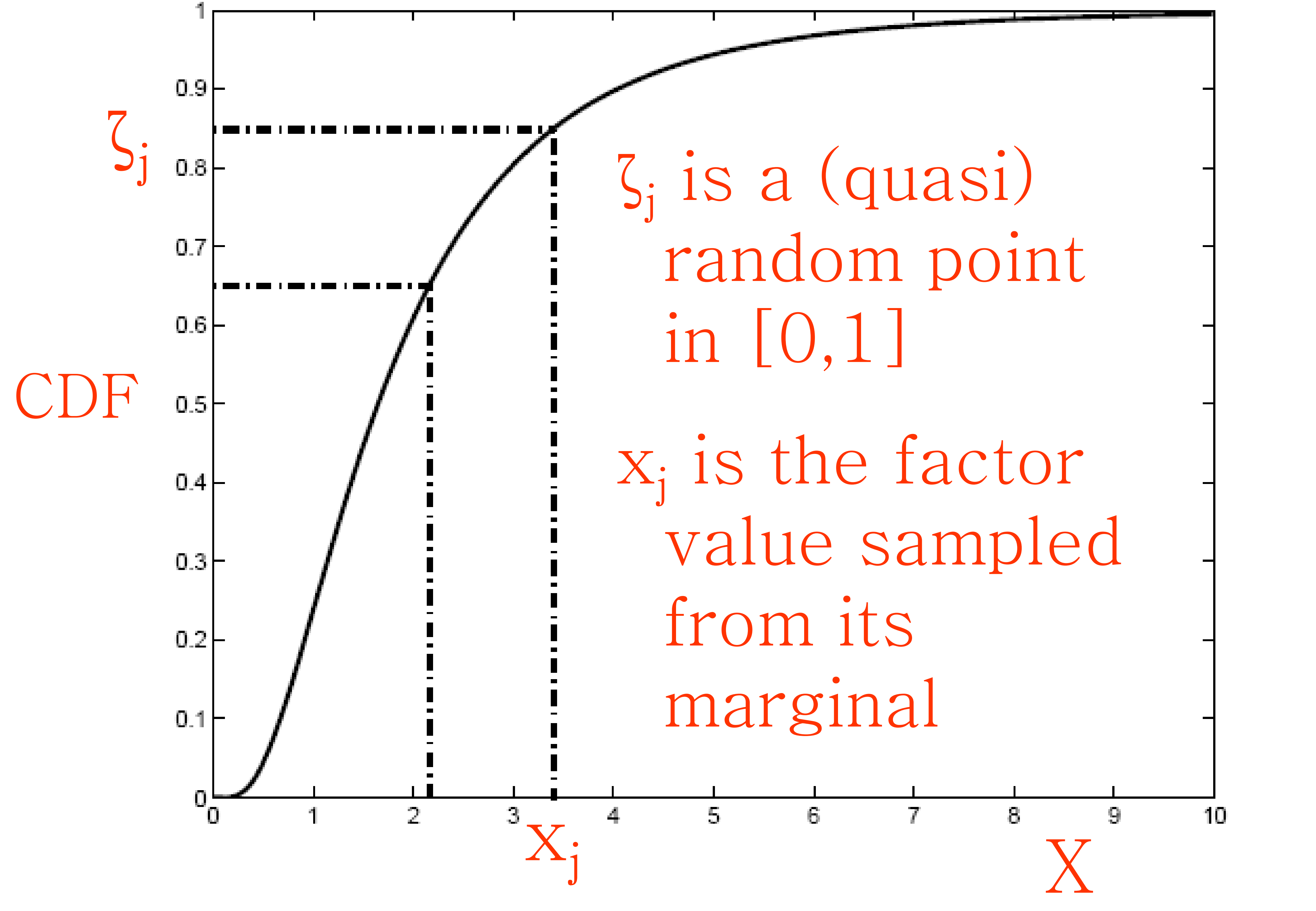
$$\sum_i V_i + \sum_{i,\, j>i} V_{ij} + \ldots + V_{123\ldots k}$$

Variance decomposition (ANOVA)

When the factors are independent the total variance can be decomposed into main effects and interaction effects up to the order *k*, the dimensionality of the problem.

When the factors are not independent the decomposition loses its unicity (and hence its appeal!)

Sampling in the unit hypercube



ζ_j
CDF
x_j
X
ζ_j is a (quasi) random point in [0,1]
x_j is the factor value sampled from its marginal

From main effect to total effect

From

$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right)$$

Main effect of factor X_i

replacing X_i with $\mathbf{X}_{\sim i}$

To main effect of non- X_i $$V_{\mathbf{X}_{\sim i}}\left(E_{X_i}\left(Y \middle| \mathbf{X}_{\sim i}\right)\right)$$

BUT:

$$V_{\mathbf{X}_{\sim i}}\left(E_{X_i}\left(Y|\mathbf{X}_{\sim i}\right)\right)+$$
$$E_{\mathbf{X}_{\sim i}}\left(V_{X_i}\left(Y|\mathbf{X}_{\sim i}\right)\right)=V(Y)$$

Easy to prove using $V(\bullet)=E(\bullet)^2-E^2(\bullet)$

$$E_{\mathbf{X}_{\sim i}}\left(V_{X_i}\left(Y \mid \mathbf{X}_{\sim i}\right)\right)$$

Main effect on non-X_i

$$V_{\mathbf{X}_{\sim i}}\left(E_{X_i}\left(Y \mid \mathbf{X}_{\sim i}\right)\right)$$

… all remaining variance must be due to X_i and its interactions

Main effects	Residuals
$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \mid X_i\right)\right)$	$E_{X_i}\left(V_{\mathbf{X}_{\sim i}}\left(Y \mid X_i\right)\right)$
$V_{\mathbf{X}_{\sim i}}\left(E_{X_i}\left(Y \mid \mathbf{X}_{\sim i}\right)\right)$	$E_{\mathbf{X}_{\sim i}}\left(V_{X_i}\left(Y \mid \mathbf{X}_{\sim i}\right)\right)$

Main (or first order) effect of X_i

Main effects Residuals

$$\boxed{V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y|X_i\right)\right)} + E_{X_i}\left(V_{\mathbf{X}_{\sim i}}\left(Y|X_i\right)\right) = \mathbf{V(Y)}$$

$$V_{\mathbf{X}_{\sim i}}\left(E_{X_i}\left(Y|\mathbf{X}_{\sim i}\right)\right) + \boxed{E_{\mathbf{X}_{\sim i}}\left(V_{X_i}\left(Y|\mathbf{X}_{\sim i}\right)\right)} = \mathbf{V(Y)}$$

Total (or total order) effect of X_i

Rows add up to V(Y); diagonal terms equal for additive models.

$$\frac{V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \mid X_i\right)\right)}{V(Y)} = S_i$$

$$\frac{E_{\mathbf{X}_{\sim i}}\left(V_{X_i}\left(Y \mid \mathbf{X}_{\sim i}\right)\right)}{V(Y)} = S_{Ti}$$

Rescaled to [0,1], under the name of first order and total order sensitivity coefficient

This can be estimated without 'double loop'

$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y|X_i\right)\right)=$$

$$=E_{\mathbf{XX}'_{\sim i}}\left(ff'\right)-f_0^2$$

… simply as product of function values (single loop)

And this can be computed as follows – generate a (quasi) random numbers matrix of row dimension *2k* and column length *N*

$$
\begin{matrix}
x_{11} & x_{12} & \cdots & x_{1(2k)} \\
x_{21} & x_{22} & \cdots & x_{2(2k)} \\
\cdots & \cdots & \cdots & \cdots \\
x_{N1} & x_{N2} & \cdots & x_{N(2k)}
\end{matrix}
$$

Split into two:

$$\mathbf{A} = \begin{matrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \cdots & \cdots & \cdots & \cdots \\ x_{N1} & x_{N2} & \cdots & x_{Nk} \end{matrix} \quad \mathbf{B} = \begin{matrix} x_{1(k+1)} & x_{1(k+2)} & \cdots & x_{1(2k)} \\ x_{2(k+1)} & x_{2(k+2)} & \cdots & x_{2(2k)} \\ \cdots & \cdots & \cdots & \cdots \\ x_{N(k+1)} & x_{N(k+2)} & \cdots & x_{N(2k)} \end{matrix}$$

And generate a third matrix which is all-A but one column (column i) which is from B

$$\mathbf{A}_i^B = \begin{matrix} x_{11} & x_{12} & \cdots & \boxed{x_{1(k+i)}} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2(k+i)} & \cdots & x_{2k} \\ \cdots & \cdots & & \cdots & & \cdots \\ x_{N1} & x_{N2} & \cdots & x_{N(k+i)} & \cdots & x_{Nk} \end{matrix}$$

(call it a quasi-A matrix)

Finally we compute $V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right) =$

$$= E_{\mathbf{X}\mathbf{X}'_{\sim i}}\left(ff'\right) - f_0^{\,2} =$$

as:

$$= \frac{1}{N}\sum_{j=1}^{N} f_j^{\,B}\left(f_j^{\,A_i^B} - f_j^{\,A}\right)$$

Where:

f_j^B is computed from row *j* of

$$\mathbf{B} = \begin{matrix} x_{1(k+1)} & x_{1(k+2)} & \cdots & x_{1(2k)} \\ x_{2(k+1)} & x_{2(k+2)} & \cdots & x_{2(2k)} \\ \cdots & \cdots & \cdots & \cdots \\ x_{N(k+1)} & x_{N(k+2)} & \cdots & x_{N(2k)} \end{matrix}$$

and $f_j^{A_i^B}$ from the quasi-A matrix:

$$\mathbf{A}_i^B = \begin{matrix} x_{11} & x_{12} & \cdots & x_{1(k+i)} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2(k+i)} & \cdots & x_{2k} \\ \cdots & \cdots & & \cdots & & \cdots \\ x_{N1} & x_{N2} & \cdots & x_{N(k+i)} & \cdots & x_{Nk} \end{matrix}$$

In summary one can compute the first order terms from one matrix A and B each and k matrices A_i^B i.e. using function values

$$f_j^{A} \qquad f_j^{B} \qquad f_j^{A_i^B}$$

The entire story can be repeated for the total effect index, which can be computed from

$$f_j^{A} \qquad f_j^{A_i^B}$$

Thus with k quasi-A matrices and the two matrices A and B one can compute for a total of k+2 matrices all total and first order effects

$$\begin{tikzcd} & \mathbf{A}_1^{B} \arrow[dr, dash, "S_i"] & \\ \mathbf{A} \arrow[ur, dash, "S_{Ti}"] & \mathbf{A}_2^{B} & \mathbf{B} \\ & \cdots & \\ & \mathbf{A}_K^{B} & \end{tikzcd}$$

In three dimensions (k=3), three points (N=3)

$$\mathbf{A} = \begin{matrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{matrix} \quad B = \begin{matrix} x_{1(3+1)} & x_{1(3+2)} & x_{1(3+3)} \\ x_{2(3+1)} & x_{2(3+2)} & x_{2(3+3)} \\ x_{3(3+1)} & x_{3(3+2)} & x_{3(3+3)} \end{matrix}$$

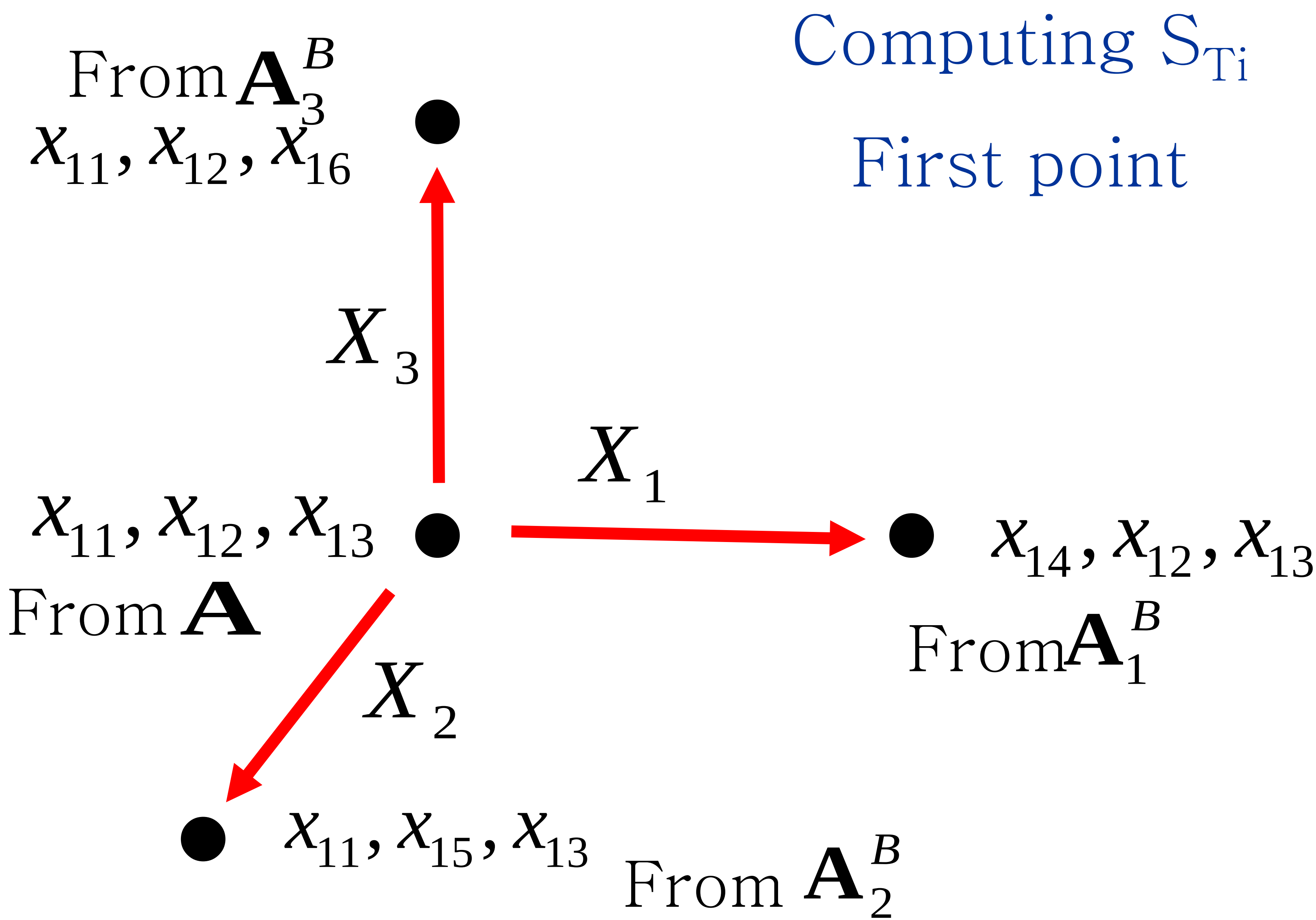
Rewriting B: $B = \begin{matrix} x_{14} & x_{15} & x_{16} \\ x_{24} & x_{25} & x_{26} \\ x_{34} & x_{35} & x_{36} \end{matrix}$

Generate the 3 quasi-A matrices

$$\mathbf{A}_1^B = \begin{matrix} \boxed{\begin{matrix} x_{14} \\ x_{24} \\ x_{34} \end{matrix}} & \begin{matrix} x_{12} \\ x_{22} \\ x_{32} \end{matrix} & \begin{matrix} x_{13} \\ x_{23} \\ x_{33} \end{matrix} \end{matrix}$$

$$\mathbf{A}_2^B = \begin{matrix} \begin{matrix} x_{11} \\ x_{21} \\ x_{31} \end{matrix} & \boxed{\begin{matrix} x_{15} \\ x_{25} \\ x_{35} \end{matrix}} & \begin{matrix} x_{13} \\ x_{23} \\ x_{33} \end{matrix} \end{matrix}$$

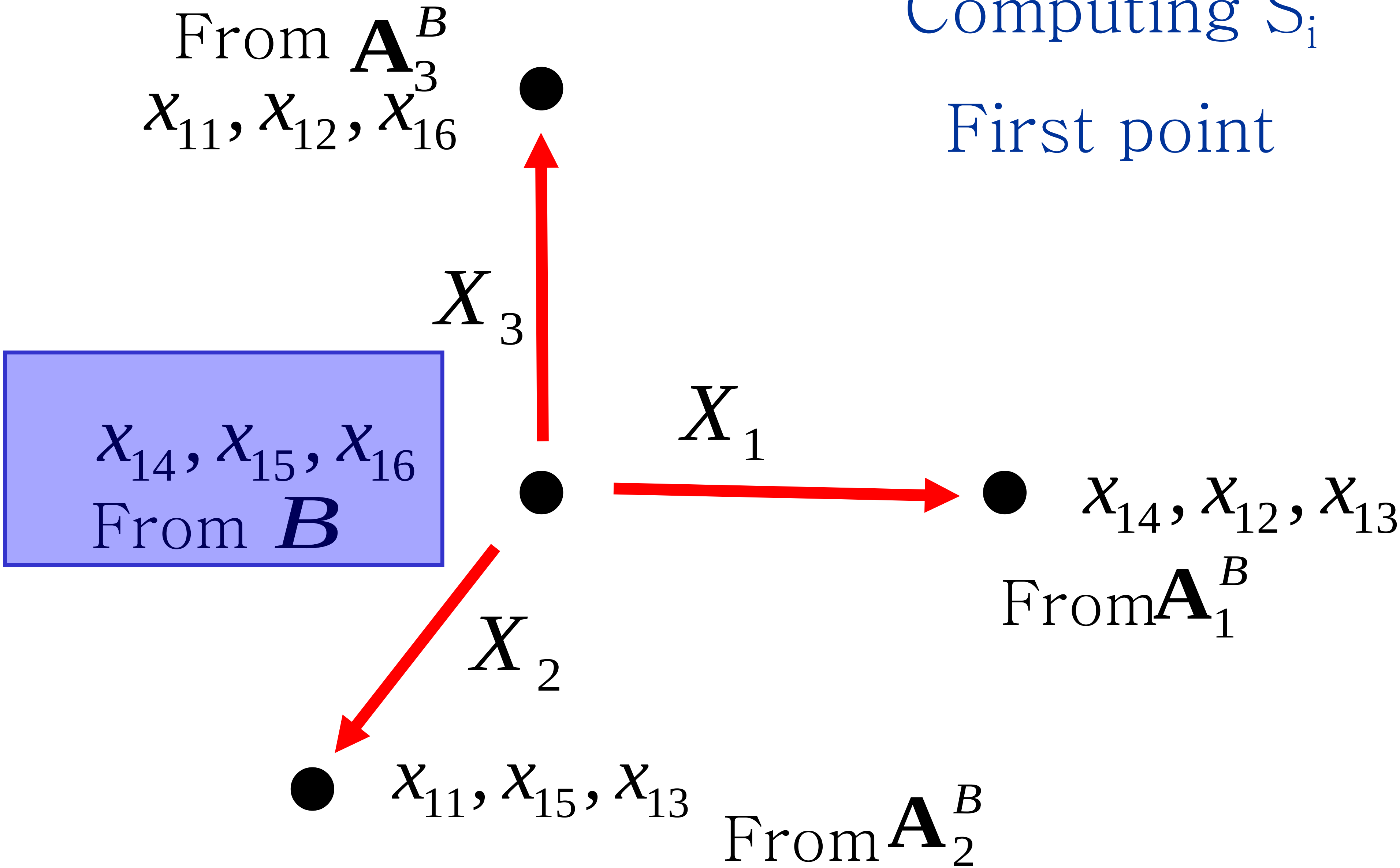
$$\mathbf{A}_3^B = \begin{matrix} \begin{matrix} x_{11} \\ x_{21} \\ x_{31} \end{matrix} & \begin{matrix} x_{12} \\ x_{22} \\ x_{32} \end{matrix} & \boxed{\begin{matrix} x_{16} \\ x_{26} \\ x_{36} \end{matrix}} \end{matrix}$$



Computing S_{Ti}
First point
From $\mathbf{A}_3^B$
x_{11}, x_{12}, x_{16}
X_3
X_1
x_{11}, x_{12}, x_{13}
From $\mathbf{A}$
x_{14}, x_{12}, x_{13}
From $\mathbf{A}_1^B$
X_2
x_{11}, x_{15}, x_{13}
From $\mathbf{A}_2^B$

Computing S_i

First point



Reading about estimators

Computer Physics Communications 181 (2010) 259–270

Contents lists available at ScienceDirect

Computer Physics Communications

www.elsevier.com/locate/cpc

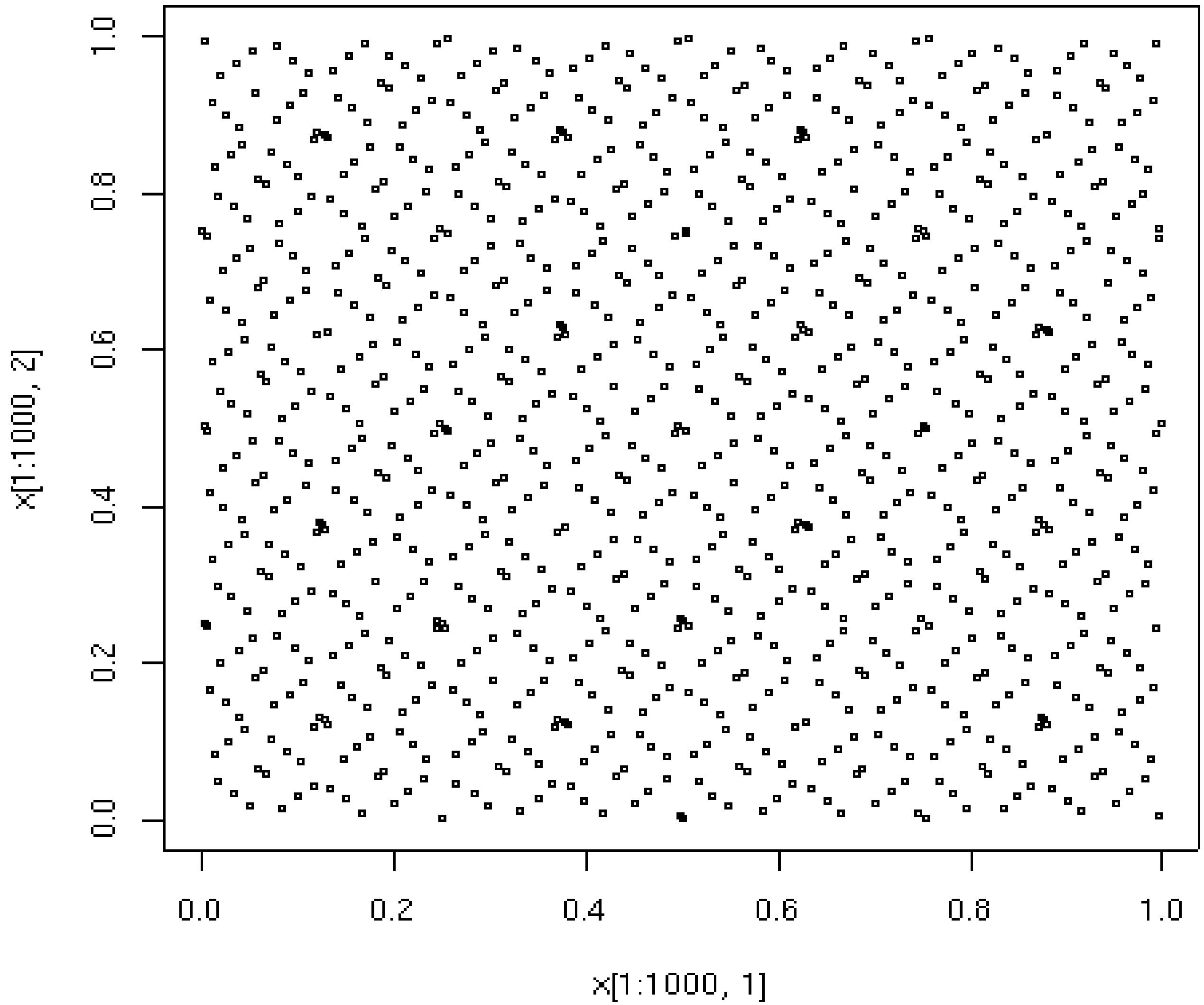
Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index

Andrea Saltelli, Paola Annoni *, Ivano Azzini, Francesca Campolongo, Marco Ratto, Stefano Tarantola

Joint Research Centre of the European Commission, Institute for the Protection and Security of the Citizen, Ispra, Italy

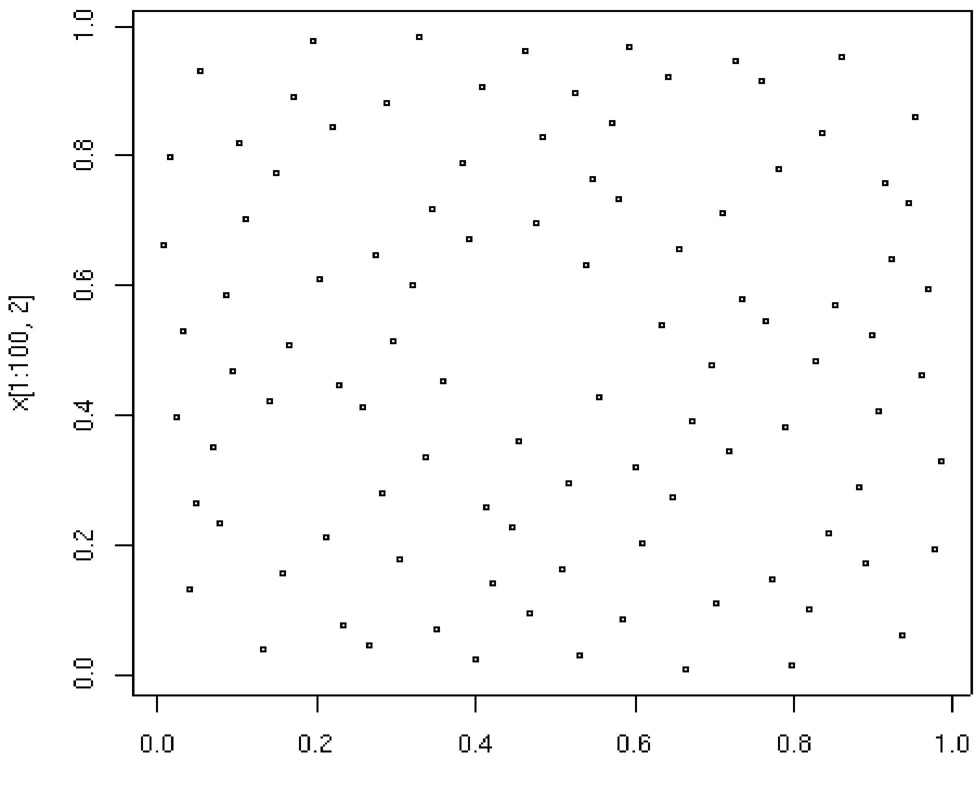
What you have seen so far has been optimized as to have a maximum of coordinates from A and a minimum of coordinates from B.

Why?

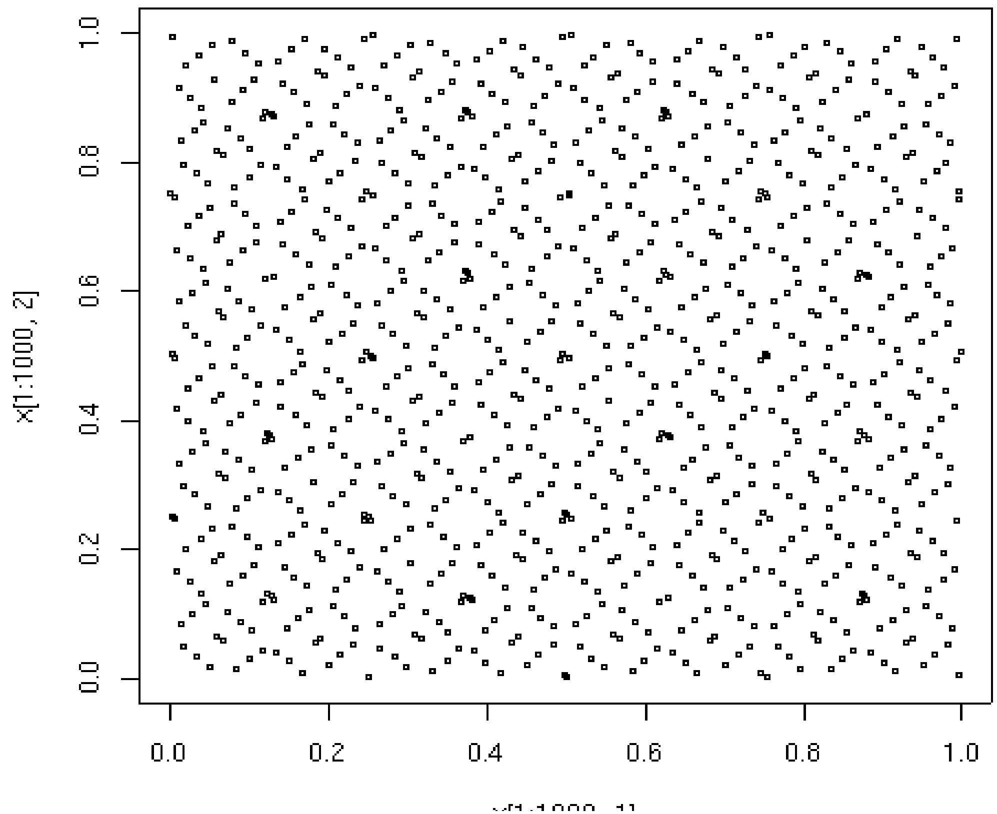


An LP_τ sequence

We normally use low discrepancies sequences developed by I.M Sobol' – these are known as LP-TAU sequences

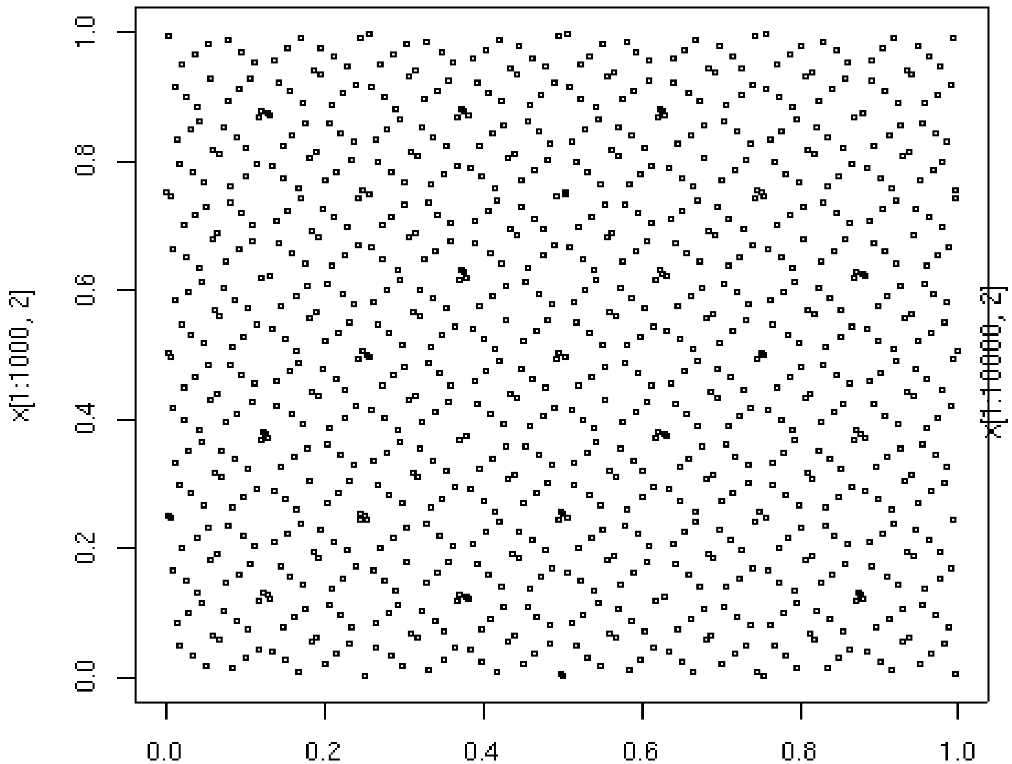


X1,X2 plane, 100 Sobol' points

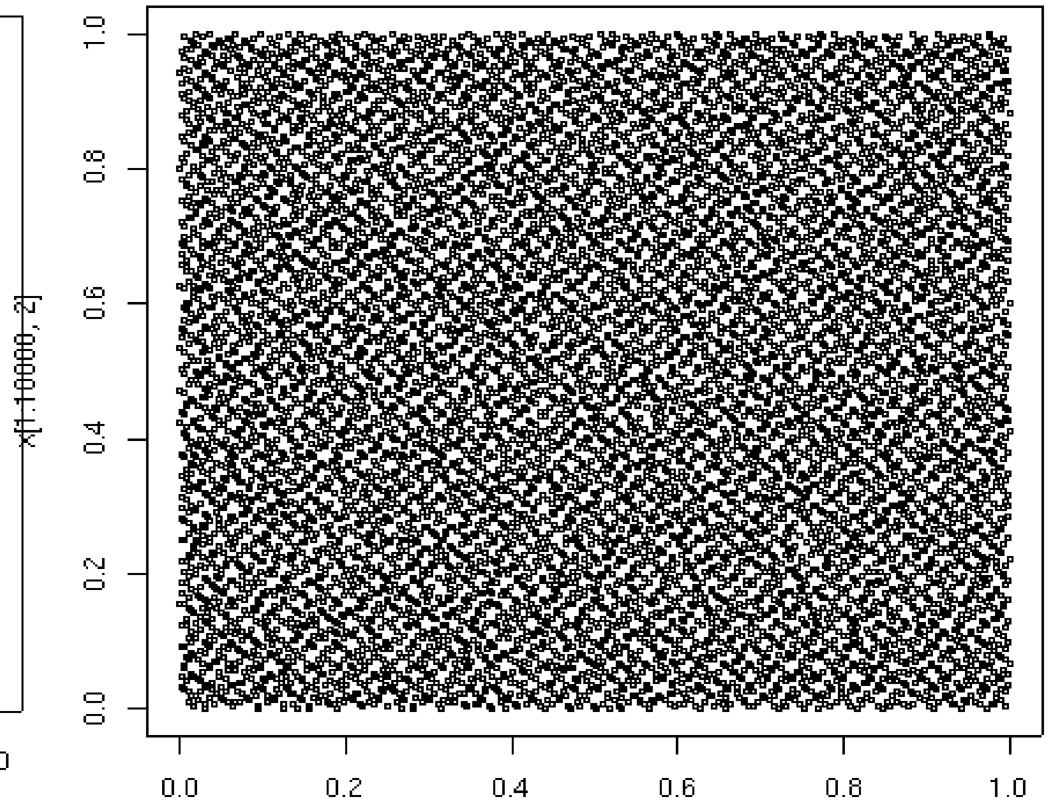


X1,X2 plane, 1000 Sobol' points

Sobol' sequences of quasi-random points

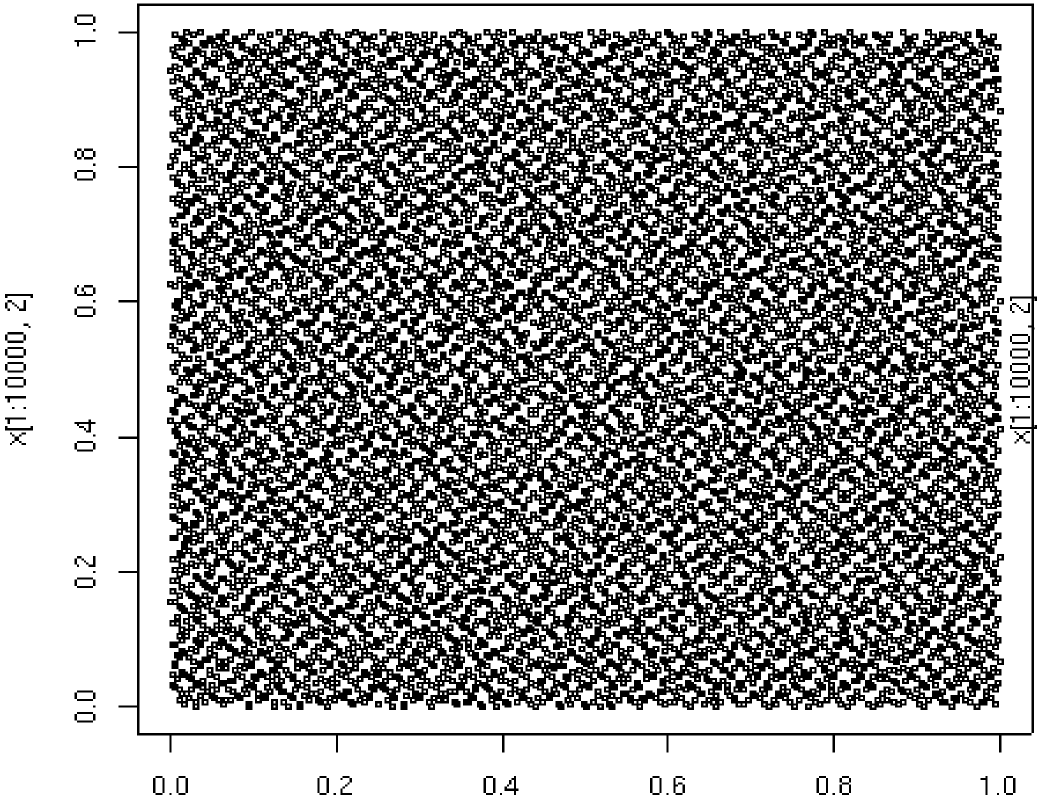


X1,X2 plane, 1000 Sobol' points

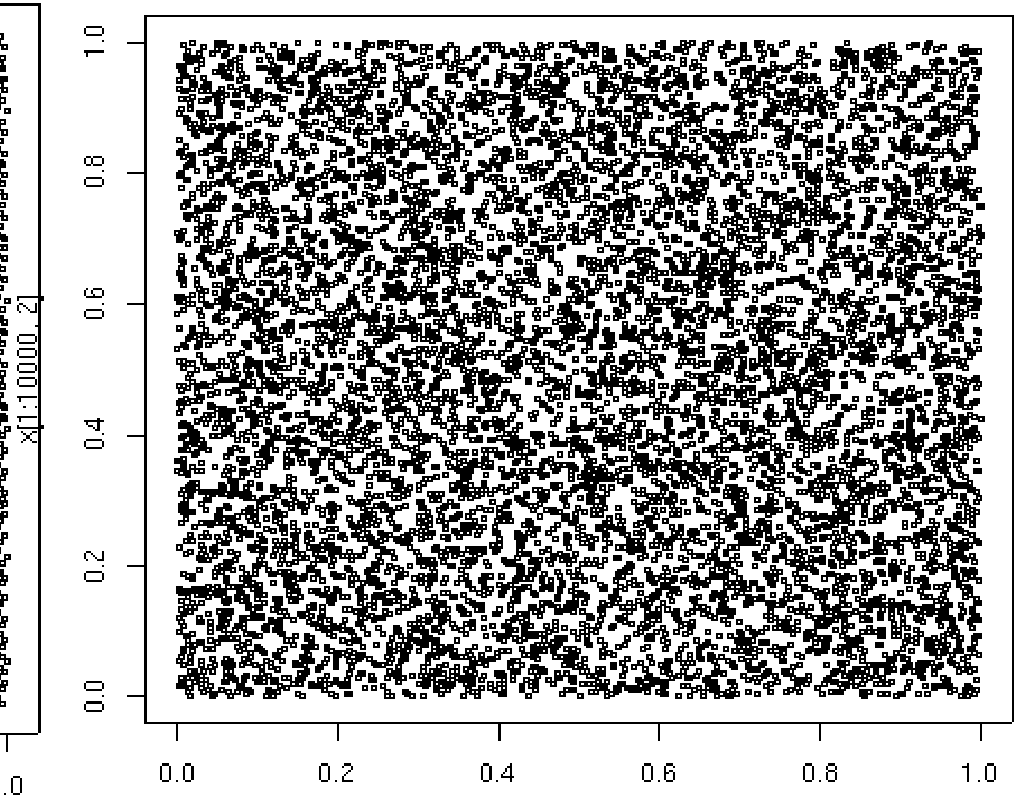


X1,X2 plane, 10000 Sobol' points

Sobol' sequences of quasi-random points



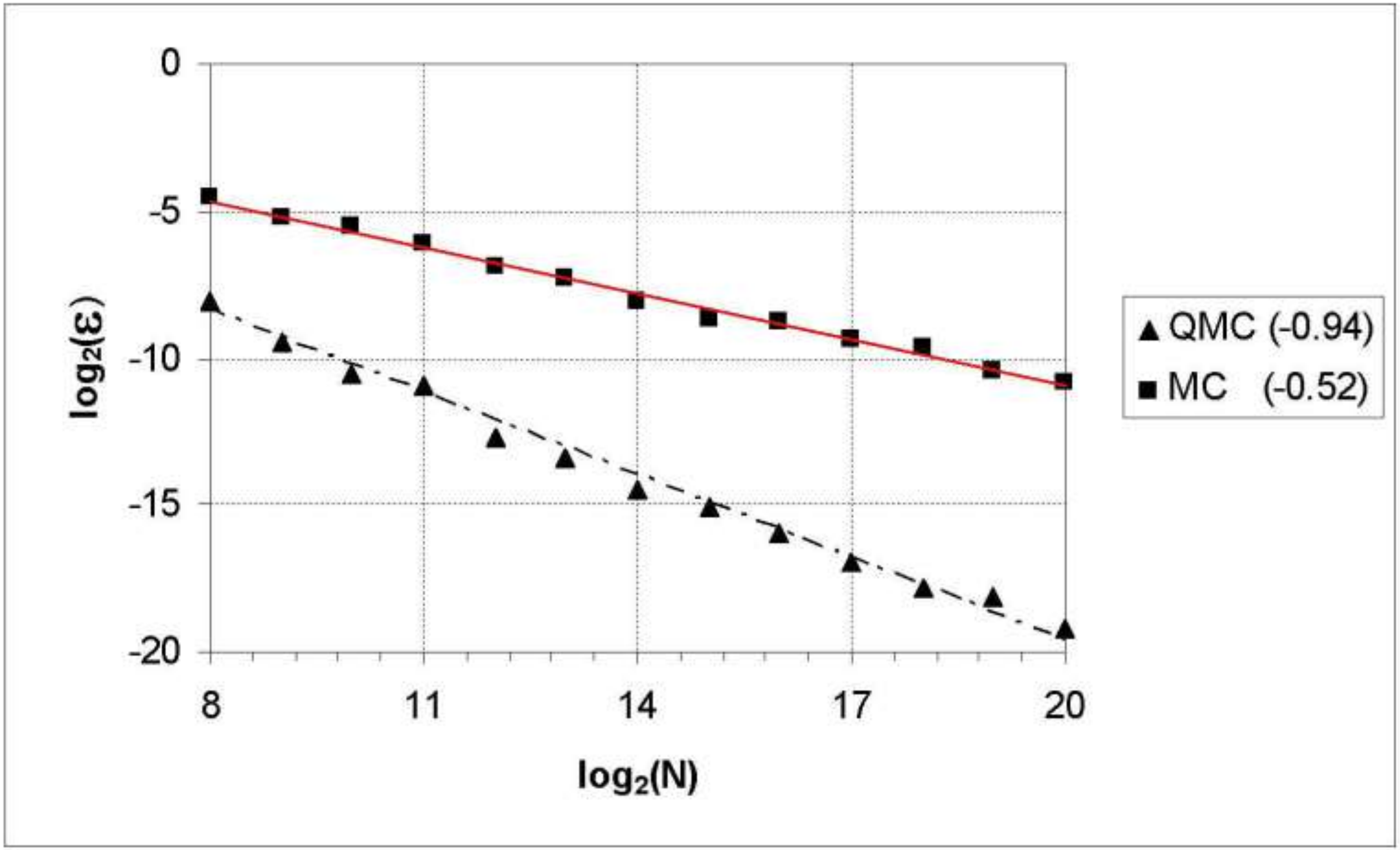
X1,X2 plane, 10000 Sobol' points



X1,X2 plane, 10000 random points

Sobol' sequences of quasi-random points against random points

Why quasi-random



Source: Mauntz and Kucherenko, 2005

Why estimate using as much as possible from A and quasi-A matrices?

The lower the column number the better its discrepancy property

➔ quasi-MC trick: if possible put important variables on the left

$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right)$$

Equal to one another when the model is additive

$$E_{\mathbf{X}_{\sim i}}\left(V_{X_i}\left(Y \middle| \mathbf{X}_{\sim i}\right)\right)$$

Why these two measures?

$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right)$$

Factors prioritization

$$E_{\mathbf{X}_{\sim i}}\left(V_{X_i}\left(Y \middle| \mathbf{X}_{\sim i}\right)\right)$$

Fixing (dropping) non important factors

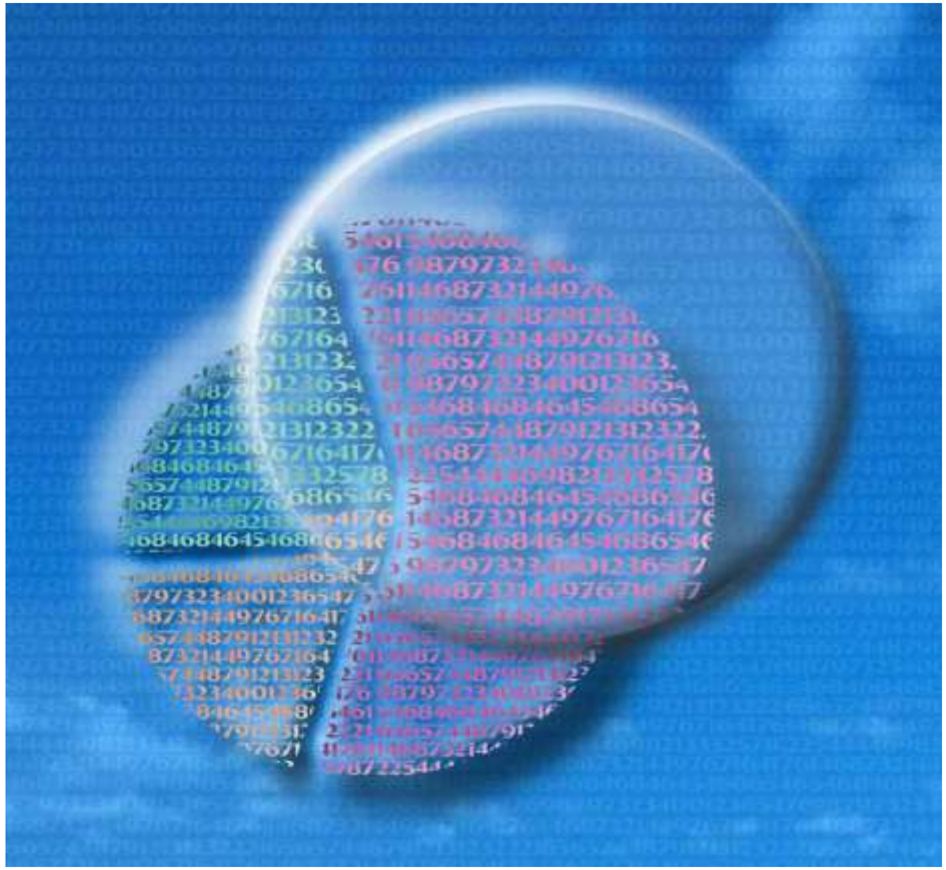
Computational details:

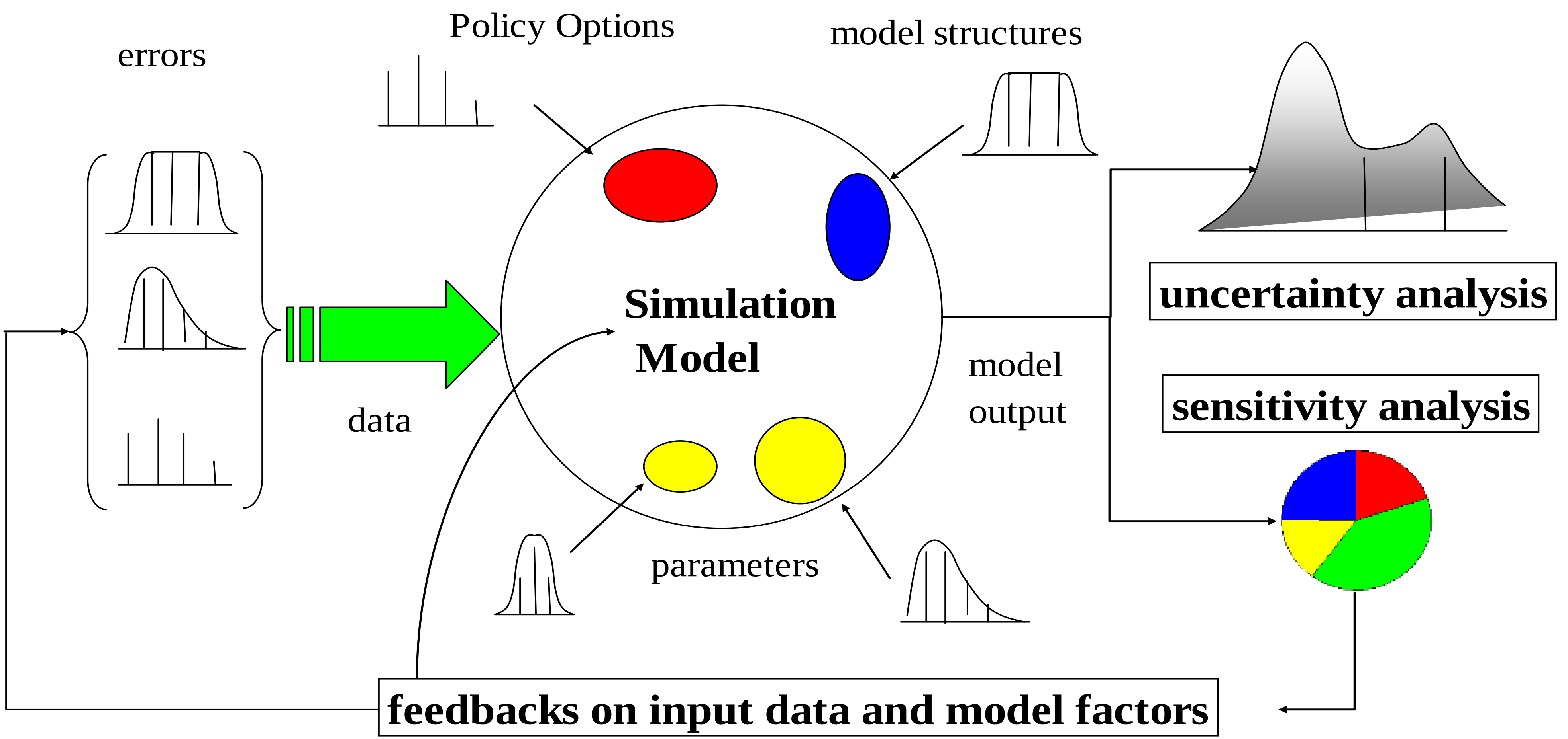
1. Easy-to-code, Monte Carlo – better on quasi-random points. Estimate of the error available.

2. The main effect can be made cheap; its computational cost does not depend upon *k*.

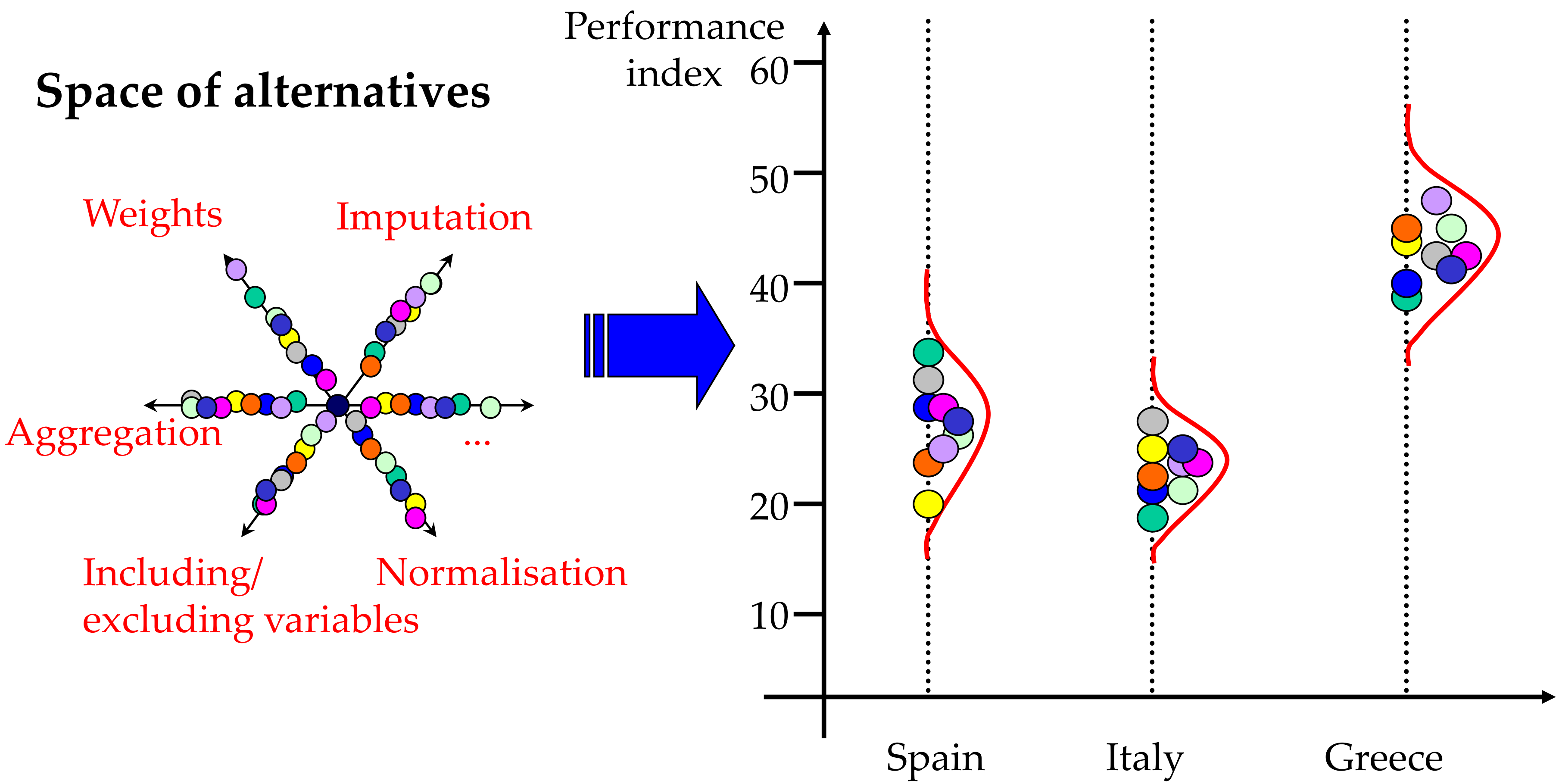
3. The total effect is expensive; its computational cost is $(k+1)N$ where *N* is one of the order of one thousand.

Applications

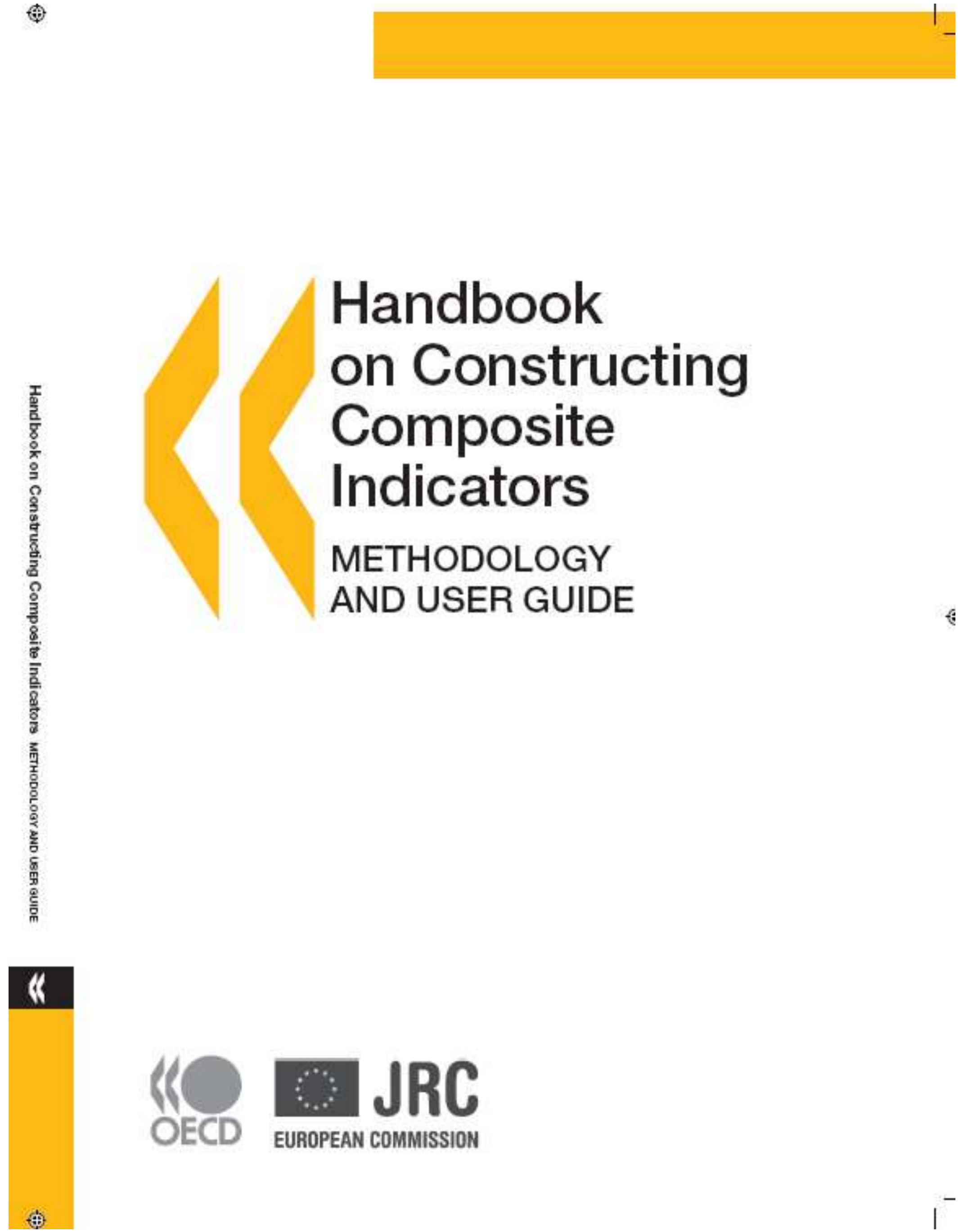



errors
Policy Options
model structures
Simulation Model
data
model output
uncertainty analysis
sensitivity analysis
parameters
feedbacks on input data and model factors

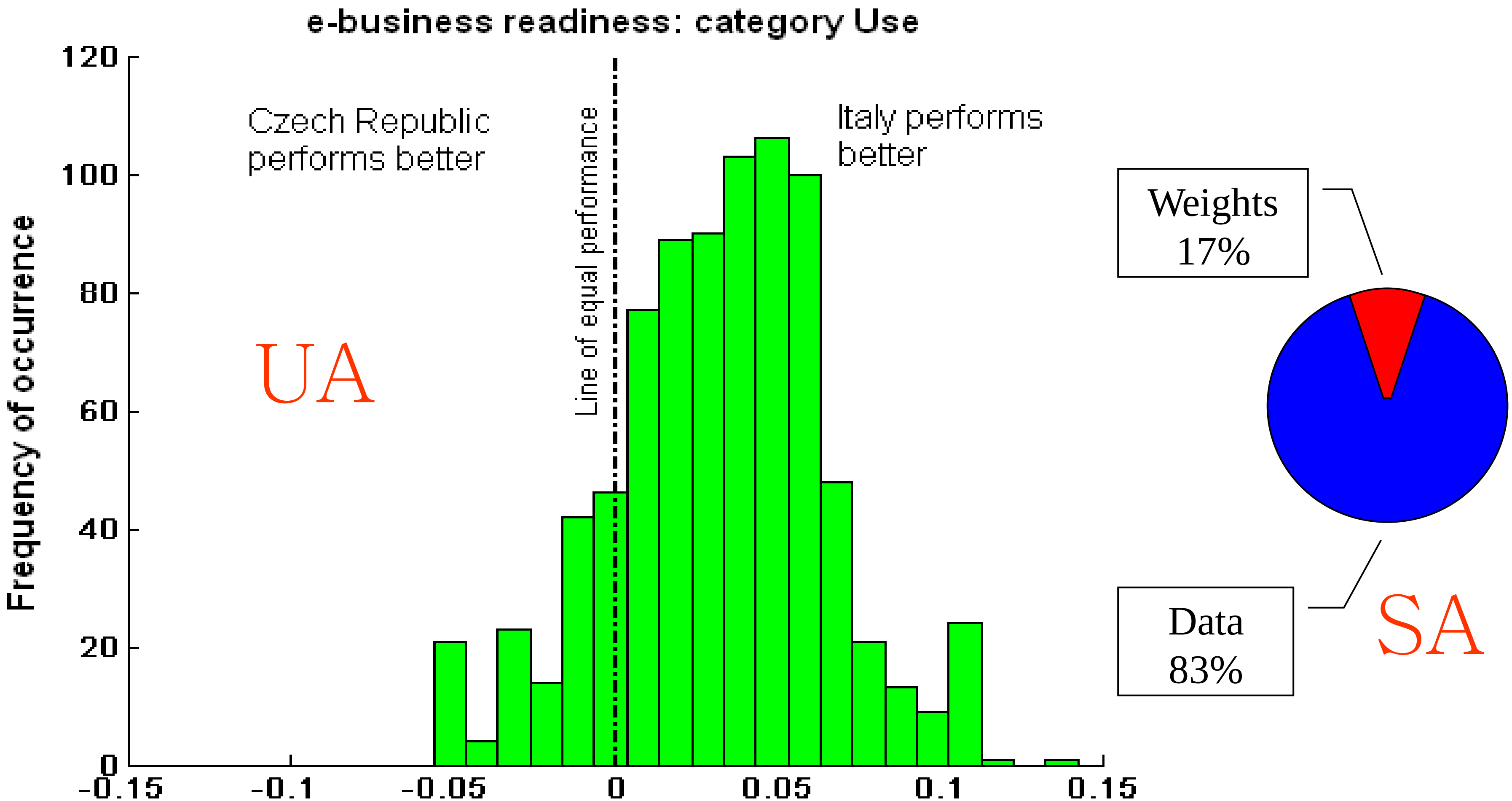
Uncertainty analysis can be used to assess the robustness of composite indicators …



Methodology from:
Joint OECD-JRC
handbook.



Uncertainty and sensitivity (UA, SA)



Index (IT) − Index (CZ)

Reading about university ranking and sensitivity analysis

Research Policy 40 (2011) 165–177

Contents lists available at ScienceDirect

Research Policy

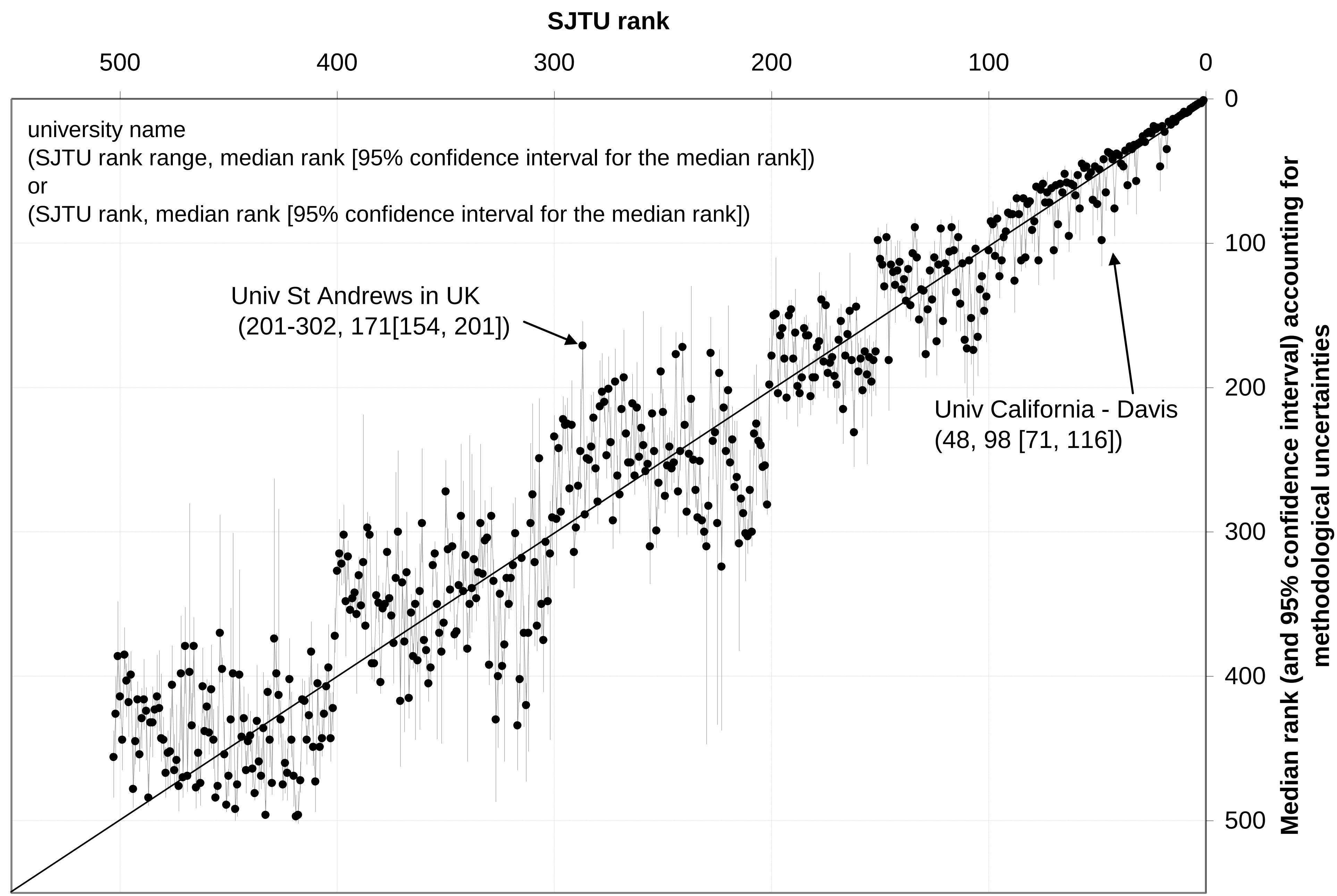
journal homepage: www.elsevier.com/locate/respol

ELSEVIER

Rickety numbers: Volatility of university rankings and policy implications

Michaela Saisana*, Béatrice d'Hombres, Andrea Saltelli

Econometrics and Applied Statistics, Joint Research Centre, European Commission, Enrico Fermi 2749, 21027 Ispra, Italy


SJTU rank
500
400
300
200
100
0
university name
(SJTU rank range, median rank [95% confidence interval for the median rank])
or
(SJTU rank, median rank [95% confidence interval for the median rank])
Univ St Andrews in UK
(201-302, 171[154, 201])
Univ California - Davis
(48, 98 [71, 116])
0
100
200
300
400
500
Median rank (and 95% confidence interval) accounting for methodological uncertainties

	Simulated rank range																										
	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	61-65	66-70	71-75	76-80	81-85	86-90	91-95	96-100	101-105	106-110	111-115	116-120	121-125	126-130	SJTU rank
Harvard Univ	100																										1 USA
Stanford Univ	89	11																									2 USA
Univ California - Berkeley	97	3																									3 USA
Univ Cambridge	90	10																									4 UK
Massachusetts Inst Tech (MIT)	74	26																									5 USA
California Inst Tech	27	53	19	1																							6 USA
Columbia Univ	23	77																									7 USA
Princeton Univ		71	9	11	7	1																					8 USA
Univ Chicago		51	34	13	1																						9 USA
Univ Oxford		99	1																								10 UK
Yale Univ		47	53																								11 USA
Cornell Univ		27	73																								12 USA
...	...																										...
Univ California - San Francisco			14	9	14	3	11	3	7	10	4	3	3	3		6			1	6		1					18 USA
...	...																										...
Duke Univ					10	6	13	11		6	3	7	6	3	1	3	1	9	9	7	1	3			1		32 USA
Rockefeller Univ				4	10	23	26	1		3	3	3	3	3	4	4	6	3	1	1				1			32 USA
Univ Colorado - Boulder						19	39	30	11	1																	34 USA
Univ British Columbia						20	60	20																			35 Canada
Univ California - Santa Barbara						9	9	10	3	10	6	7	6		11	4	6	3	4	7		1	1				36 USA
Univ Maryland - Coll Park						6	37	44	9	4																	37 USA
...	...																										...
Ecole Normale Super Paris						7	9	4	6	7	6	4	9	6	7	4	3	3	4	3	3			1	6	4	73 France
Univ Melbourne												1	20	17	31	23	1	6									73 Australia
Univ Rochester								1	10	7	16	24	14	10	10	6	1										73 USA
Univ Leiden									3	6	9	23	24	13	14	9											76 Netherlands
...	...																										...
Univ Sheffield										1	21	26	21	9	13	7	1										77 UK
Tohoku Univ										4	1	7	1		4	17	19	3	3	3		19	7	3	4	4	79 Japan
Univ Utah											4	4	6	1	4	9	6	16	7	13	4	9	6	6	1		79 USA
King's Coll London											4	6	9	29	17	14	10	1	6	3	1						81 UK
Univ Nottingham											1	6	10	21	21	10	17	7	4	1							82 UK
Boston Univ													3	1	6	3	6	11	1	4	3	13	14	10	10	10	83 USA
...	...																										...

Legend:
Frequency lower 15%
Frequency between 15 and 30%
Frequency between 30 and 50%
Frequency greater than 50%

It is beyond doubt that Harvard, Stanford, Berkley, Cambridge, and MIT are top 5

(both in the original SJTU and in more than 80% of our simulations) ...

… Still for 96% of the universities, the range of ranks is greater than 10 positions.

Examples of rank variation

- 92 positions (Univ Autonoma Madrid) and 277 positions (Univ Zaragoza) in Spain,
- 71 positions (Univ Milan) and 321 positions (Polytechnic Inst Milan) in Italy,
- 22 positions (Univ Paris 06) and 386 positions (Univ Nancy 1) in France.

Reading about evolution of SA
(including software)

ELSEVIER

Environmental Modelling & Software
Volume 137, March 2021, 104954

Position Paper

The Future of Sensitivity Analysis: An essential discipline for systems modeling and policy support

Saman Razavi [a], Anthony Jakeman [b], Andrea Saltelli [c], Clémentine Prieur [d], Bertrand Iooss [e], Emanuele Borgonovo [f], Elmar Plischke [g], Samuele Lo Piano [h], Takuya Iwanaga [b], William Becker [i], Stefano Tarantola [j], Joseph H.A. Guillaume [b], John Jakeman [k], Hoshin Gupta [l], Nicola Melillo [m], Giovanni Rabitti [n], Vincent Chabridon [e], Qingyun Duan [o], Xifu Sun [b], Stefán Smith [h]...Holger R. Maier [u]

Ongoing work

Cornell University

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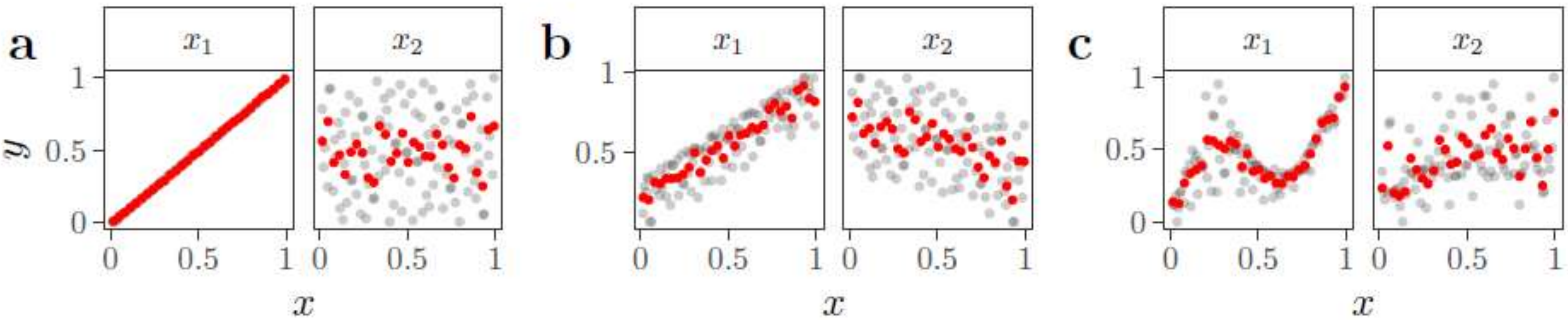
[Submitted on 27 Jun 2022 (v1), last revised 17 Mar 2023 (this version, v2)]

Discrepancy measures for sensitivity analysis

Arnald Puy, Pamphile T. Roy, Andrea Saltelli

While sensitivity analysis improves the transparency and reliability of mathematical models, its uptake by modelers is still scarce. This is partially explained by its technical requirements, which may be hard to understand and implement by the non-specialist. Here we propose a sensitivity analysis approach based on the concept of discrepancy that is as easy to understand as the visual inspection of input-output scatterplots. Firstly, we show that some discrepancy measures are able to rank the most influential parameters of a model almost as accurately as the variance-based total sensitivity index. We then introduce an ersatz-discrepancy whose performance as a sensitivity measure matches that of the best-performing discrepancy algorithms, is simple to implement, easier to interpret and orders of magnitude faster.

Input-output scatterplots



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Input-output scatterplots

Hand-waiving description of discrepancy: how many points are in a selected subspace versus how many should be there if the distribution were perfectly uniform

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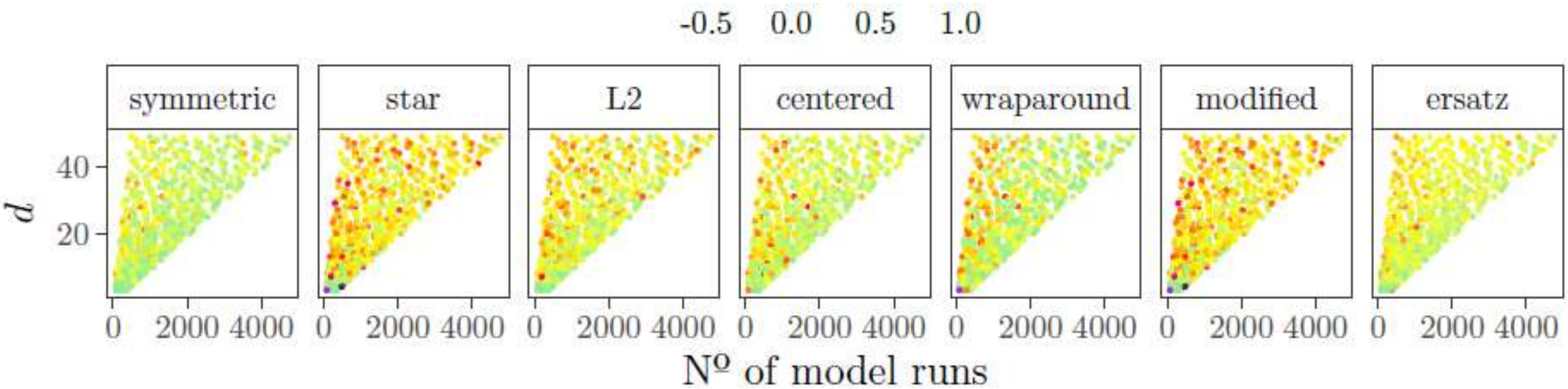
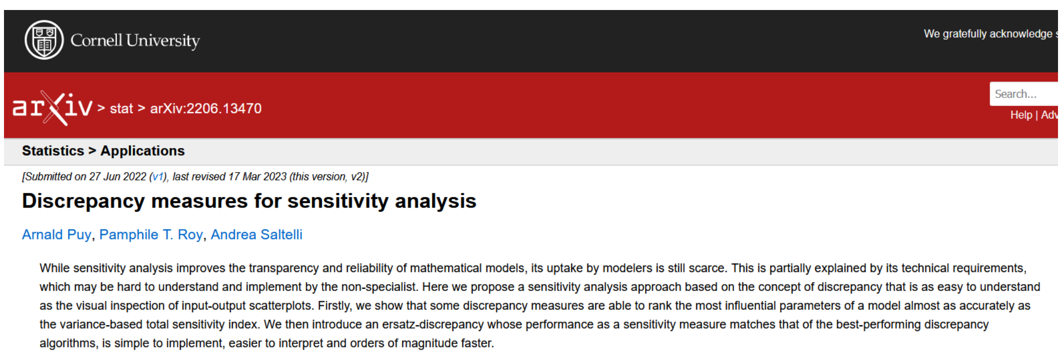
Investigation: compute "discrepancies" of these bi-dimensional plots and see if they are a good proxy of the total sensitivity index

Input-output scatterplots



Distribution of the Pearson correlation r between the savage scores-transformed ranks yielded by each discrepancy measure and the savage scores-transformed ranks produced by the total sensitivity index



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Relevant recent works including sensitivity analysis

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Arnald Puy, Michela Massimi, Bruce Lankford & Andrea Saltelli

Nature Reviews Earth & Environment **4**, 427–428 (2023) | Cite this article

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The delusive accuracy of global irrigation water withdrawal estimates

Arnald Puy, Razi Sheikholeslami, Hoshin V. Gupta, Jim W. Hall, Bruce Lankford, Samuele Lo Piano, Jonas Meier, Florian Pappenberger, Amilcare Porporato, Giulia Vico & Andrea Saltelli

Nature Communications **13**, Article number: 3183 (2022) | Cite this article

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RESEARCH ARTICLE | MATHEMATICS

Models with higher effective dimensions tend to produce more uncertain estimates

ARNALD PUY, PIERFRANCESCO BENEVENTANO, SIMON A. LEVIN, SAMUELE LO PIANO, TOMMASO PORTALURI, AND ANDREA SALTELLI Authors Info & Affiliations

SCIENCE ADVANCES • 19 Oct 2022 • Vol 8, Issue 42 • DOI: 10.1126/sciadv.abn9450

Published August 25, 2023

The strong principle for the real world is: never use a model if you don't know its limitations and side effects. In fact, you must know what it can't do for you better than what it can do. I am glad this project is taking place: a long-awaited examination of the role—and obligation—of modeling.

Nassim Nicholas Taleb, Distinguished Professor of Risk Engineering, NYU Tandon School of Engineering. Author of the five-volume Incerto series (*The Black Swan*)