

# Topological Sensitivity Analysis using R

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joint work with:

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Buenos Aires, Argentina

September 5<sup>th</sup>, 2018

# Outline

## 1 Motivation

## 2 Indices Estimation

## 3 Numerical Illustrations

# Motivation

Assume that  $\mathbf{X} = (X_1, \dots, X_p) \in \mathbb{R}^p$  produces the output  $Y \in \mathbb{R}$  linked by the model

$$Y = m(X_1, \dots, X_p). \quad (1)$$

The function  $m$  could be known or unknown.

Generally is a complex function.

## Questions

- ¿How sensitive is each input with respect to  $Y$ ?
- ¿How much changes the output  $Y$  if there exist a perturbation in the inputs?

# Classic methods to study sensitivity

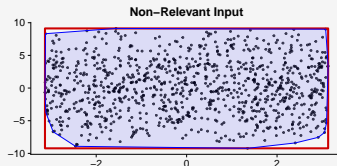
- Screening
- Regression and Correlation Analysis
- Sobol indices (ANOVA)
- Moment independent indices (based in monotonic invariant transformations)
- among others.

## Comprehensive review

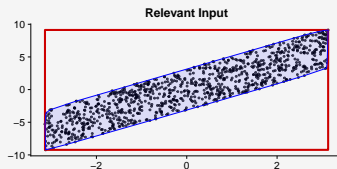
P. Wei, Z. Lu, and J. Song. 2015. Variable importance analysis: A comprehensive review. *Reliability Engineering and System Safety* 142:399–432

# Our first hypothesis

If  $X_i$  is non-relevant with respect to  $Y$  then blue area is similar to the red box



Otherwise, the blue area does not cover all the domain.



The sensitivity index is  $S_i^{\text{Area}} = 1 - \frac{\text{Object Area for variable } i}{\text{Box Area for variable } i}$ .

# Simplicials

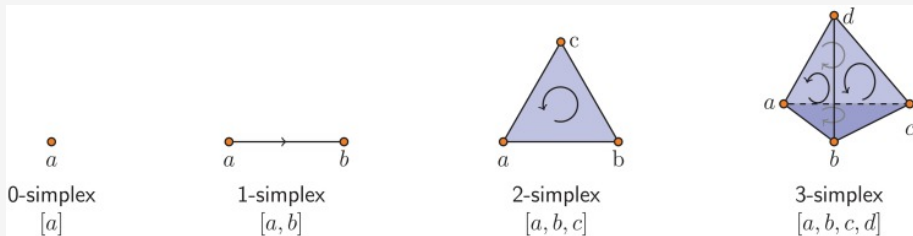


Image taken from: C. M. Topaz, L. Ziegelmeier, and T. Halverson. 2015. Topological Data Analysis of Biological Aggregation Models:1–26

# Vietoris-Rip complex

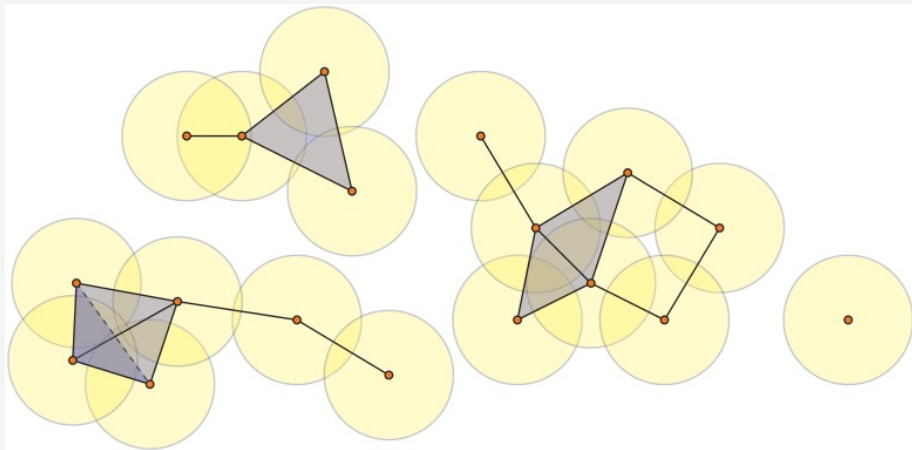


Image taken from: C. M. Topaz, L. Ziegelmeier, and T. Halverson. 2015. Topological Data Analysis of Biological Aggregation Models:1–26

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# The 0-simplex

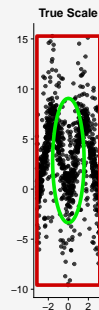
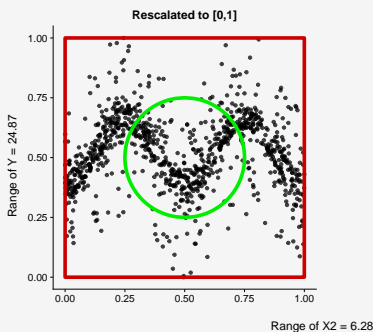
Suppose that we have a sample  $(X_{ki}, Y_k)$  where  $k = 1, \dots, n$  (observations) and  $i = 1 \dots, p$  (variables). **From now, assume that the variable  $i$  is fixed.**

**0-simplex:** The data points with coordinates  $(X_{ki}, Y_k)$ .

# The 1-simplex

To preserve the dimensions of the  $x$  and  $y$  axis, we rescaled all the data-points to the square  $[0, 1] \times [0, 1]$ .

**1-simplex:** With the rescaled variables ( $[0, 1] \times [0, 1]$ ), construct pairwise the edges of the data points with distance less to  $r$ .



## Setting the 0-simplex and 1-simplex

For some radius  $r$  given.

```
Xr <- scales::rescale(X, to = c(0, 1))
Yr <- scales::rescale(Y, to = c(0, 1))
neighborhood.distance <- dist(cbind(Xr[, i], Yr))

adjacency.matrix <- (as.matrix(neighborhood.distance) <= r)
diag(adjacency.matrix) <- 0

graphBase <- igraph::graph.adjacency(adjacency.matrix,
                                     mode = "undirected",
                                     weighted = NULL)
```

# The 2-simplex

Using the framework of Zomorodian<sup>1</sup>, we estimate the 2-simplex as the cliques of dimension 3 of a graph using the package `igraph`,

```
clq <- igraph::cliques(graphBase, min = 3, max = 3)
TwoSimplex <- do.call("rbind", clq)
```

---

1. A. Zomorodian. 2010. Fast construction of the Vietoris-Rips complex. *Computers & Graphics* 34 (3): 263–271.

## Transforming the 2-complex to Polygons

Each 2-simplex is a Triangle which is stored into a Polygon of the package sp:

```
p <- sp::Polygon(Triangle, hole = FALSE)
```

With all the Polygons we form a list `l` and then create a `SpatialPolygons` object:

```
sps <- sp::SpatialPolygons(list(sp::Polygons(l,1)))
```

## Index estimation

Using the packages `rgeos` we estimate the Area of the all 2-simplex and the box contained all the points.

```
ObjArea <- rgeos::gArea(sps)
bb <- sp::bbox(sps)
SqArea <- prod(diff(t(bb)))
```

Finally, the sensitivity index is:

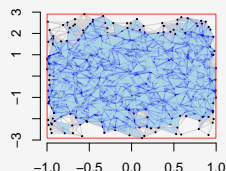
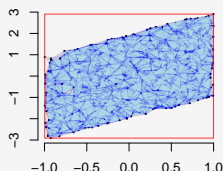
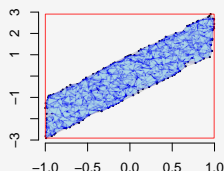
$$\text{index} = 1 - \text{ObjArea} / \text{SqArea}$$

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# Linear

The model is  $Y = 2X_1 + X_2$  and  $X_3, X_4, X_5$  variables of pure noise.



Variable	Radius	Obj Area	Square Area	Index
$X_1$	0.08	3.78	11.61	0.67
$X_2$	0.11	7.67	11.61	0.34
$X_3$	0.12	10.05	11.61	0.13
$X_4$	0.12	10.19	11.59	0.12
$X_5$	0.12	10.24	11.62	0.12

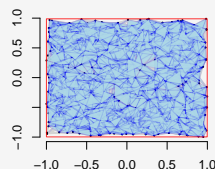
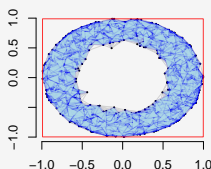


# Circle with hole

The model is

$$\begin{cases} X_1 = r \cos(\theta) \\ Y = r \sin(\theta) \end{cases}$$

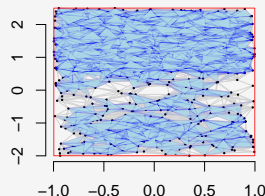
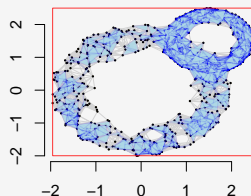
with  $r$  and  $\theta$  random. The variable  $X_2$  is pure noise.



Variable	Radius	Obj Area	Square Area	Index
$X_1$	0.10	2.05	3.95	0.48
$X_2$	0.13	3.73	3.97	0.06

# Circle with two holes

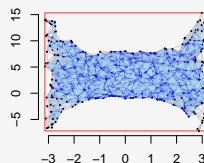
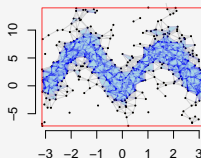
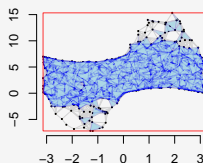
Similar to the last one with two circles.



Variable	Radius	Obj Area	Square Area	Index
$X_1$	0.08	8.33	19.98	0.58
$X_2$	0.08	8.27	8.97	0.08

## Ishigami

The model is determined by  $Y = \sin X_1 + 7 \sin^2 X_2 + 0.1 X_3^4 \sin X_1$  where  $X_i \sim \text{Uniform}(-\pi, \pi)$  for  $i = 1, 2, 3$ ,  $a = 7$  and  $b = 0.1$ .



Variable	Radius	Obj Area	Square Area	Index
$X_1$	0.09	64.06	141.44	0.55
$X_2$	0.07	54.34	133.08	0.59
$X_3$	0.09	69.31	141.42	0.51

# Summary and future work

- We could capture geometric structures of the projection of each variable.
- Our method match the classic theories in certain cases.
- When the data has a *zero-sum* pattern our method fails.
- We conjecture the method could recognize structured and non-structured noisy variables.

## Future work:

- Estimate efficiently the neighborhood graph (less than  $\mathcal{O}(n^2)$ ).
- Improve the algorithm to recognize relevant variables and structured noise variables.
- Improve the radius choice.
- Submit this package to CRAN.

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## Preprint

A. Hernández, M. Solís, and R. Zúñiga. 2018. Sensitivity Analysis with Manifolds. *ArXiv e-prints*, 1809.00669