

# PRIM related correlations

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# Problem statement

An industrial decision maker owns a production line having **dozens** of parameters. Currently, he's tuning them by **trial and error**, but wants a program finding the right "zone" to be in.

- Input: Data (parameters + quality)
- Output: Parameter intervals
  - Resulting in the best quality box possible.
  - Limited to a given number of parameters.
  - Containing a minimum number of measures (points).

# Interpretability

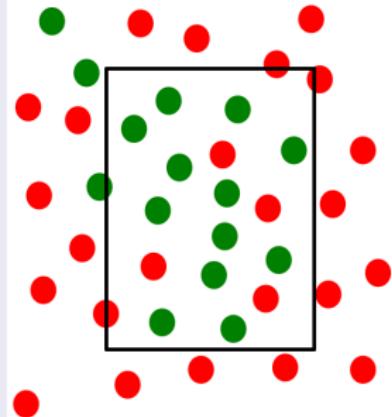
## Why boxes?

### → Interpretability

The decision maker prefers to know directly which parameters to controls and in which **ranges** to put them.

That would be impossible with ellipsoid for example.

## Box



First idea: Brute force, look at all the possible boxes  $\rightarrow \mathcal{O}(d.N^3)$

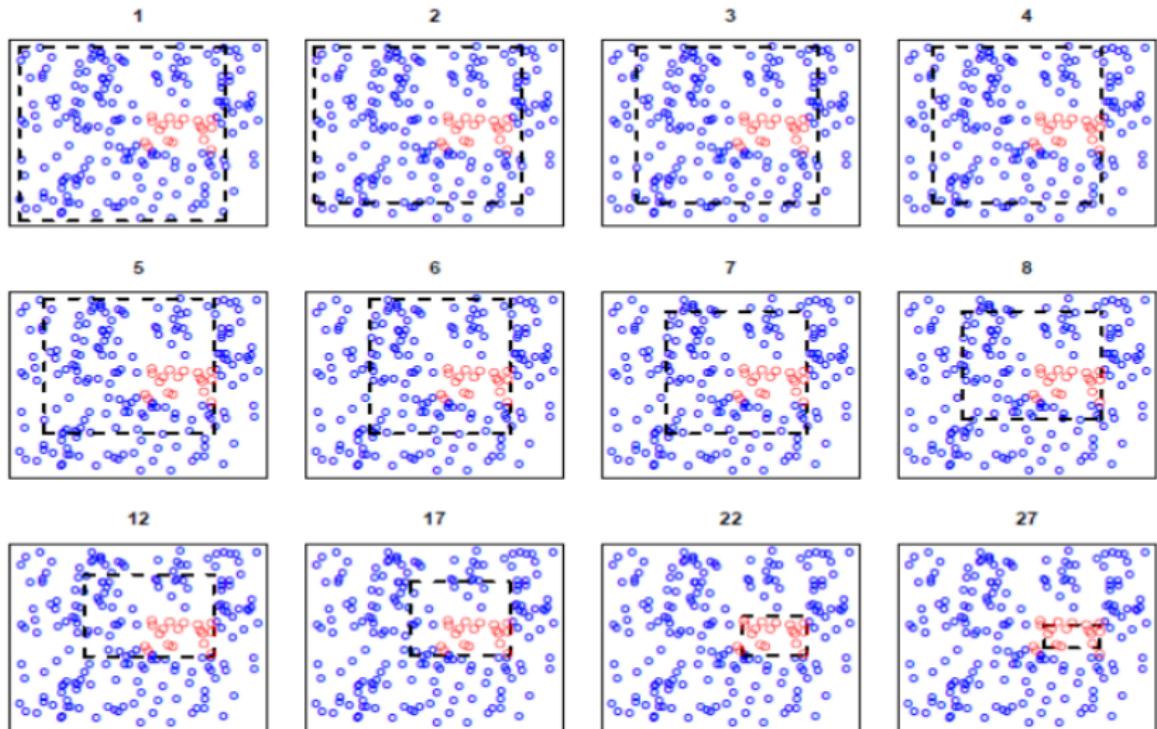
**Patient Rule Induction Method, *J. Friedman & N. Fisher* (1998)**

Idea:

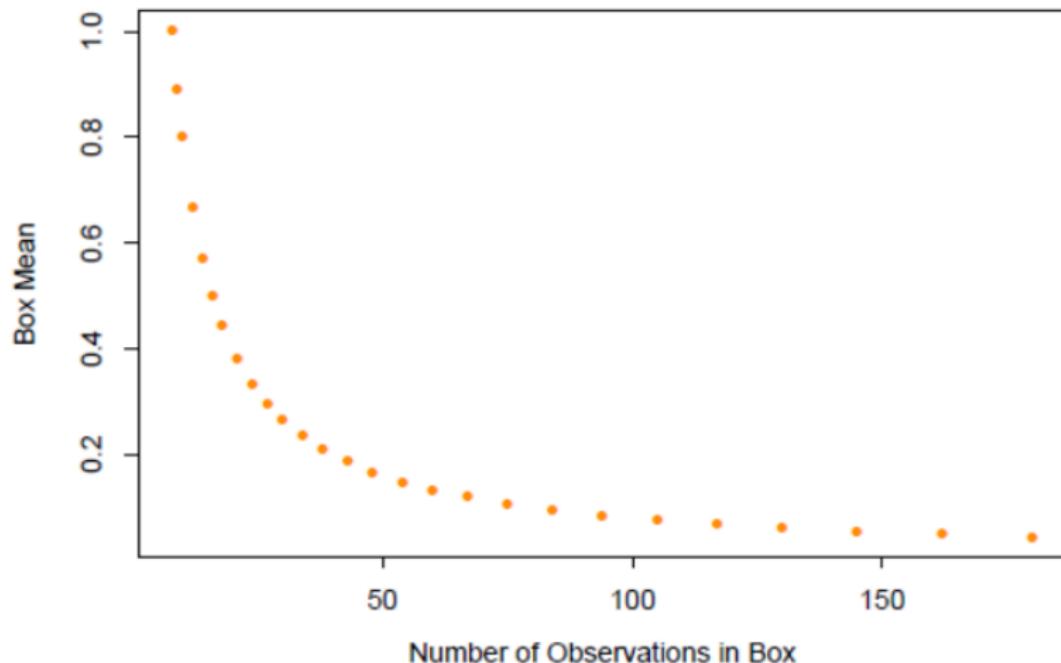
- ① Starts with all points.
- ② For every dimension, removes a fraction  $\alpha$  from the points at an extreme then at the other.
- ③ Chooses the best among the  $2d$  sets generated and restart at step 2 until it remains a fraction  $\beta$  from the starting points.

One can detect many hyperrectangles (or "boxes") by removing the points from the box found and restarting the algorithm on the remaining points.

# PRIM - 2D Example



# PRIM - Top-down peeling



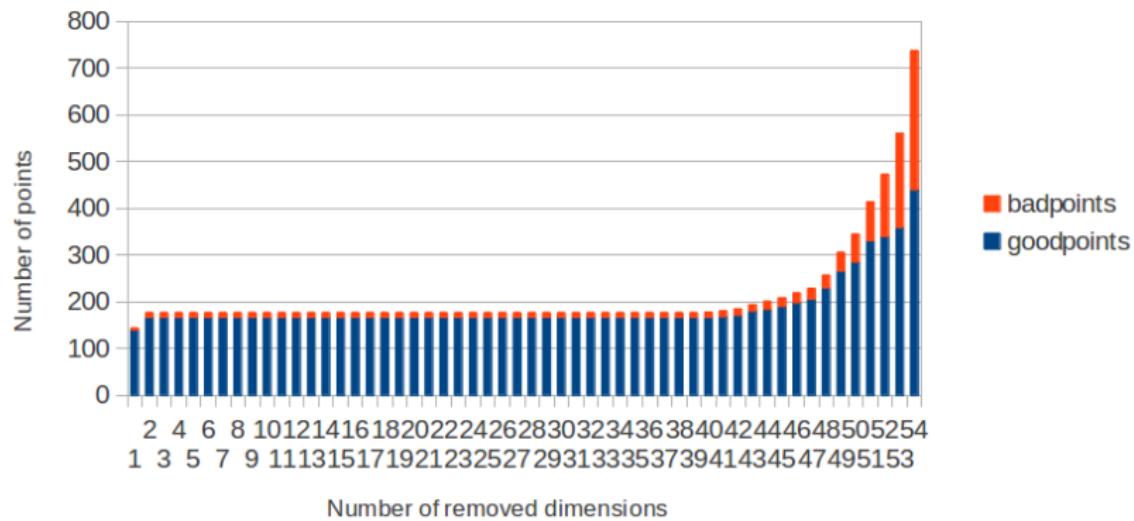
It is difficult to control a lot of parameters at the same time, so we want to limit the number of output intervals.

To select a reduced number of dimensions, we iterate:

- ① Release the interval for each dimension, one by one.
- ② Remove the dimension which, when released, gives the best resulting box.
- ③ If we still have too many dimensions, go to step 1.

- Database : **AGC**
  - Total: 748 points, 440 good ones.
  - Dimensions: 53
  - Parameters:  $\alpha = 5\%$ ,  $\beta = 20\%$
- ⇒ **5s**, 144 points, 140 good ones → **97%**
- ⇒ 5D limitation : 306 points (266 good ones, 40 bad ones)  
→ **87%**

## AGC database: removing dimensions



When a box is defined by a few dimensions, we could want to exchange one of them keeping a good box, without restarting the algorithm.

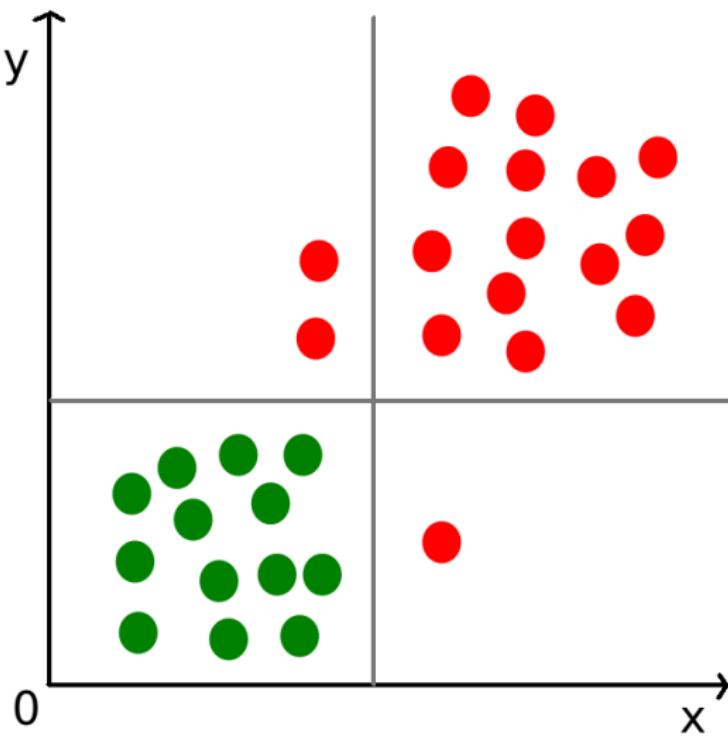
It can be useful if a parameter is more difficult or dangerous to control, and the others are already tuned.

2 kind of scores we can maximize:

- Mean: best possible box  
→ maximum-density segment problem ( $\mathcal{O}(n)$ )
- Similarity:  $X_1$  is the constrained box;  $X_2$  is  $X_1$  without the removed constraint; searching a  $X_2$  subarray maximizing:

$$\frac{|X_1 \cap X_2|}{|X_1 \cup X_2|} \quad (1)$$

# Ongoing research - Difference between scores



- Database : marketing (Friedman & Fisher)
  - Total: 9409 points on 14 dimensions
  - Goal: isolate largest income and swap the most important variable
  - Parameters:  $\alpha = 5\%$ ,  $\beta = 20\%$ , 3 important variables
  - Most important variable: dual income
- ⇒ Mean: Swaping it with "householder status" even increased the score by 3%
- ⇒ Similarity: Swaping it with "marital status" gave a similarity score of 57%, decreasing the mean score by only 2%

- PRIM:
  - 1D projections:  $\mathcal{O}(d.N.\log(N))$
  - Top-down peeling:  $-\log(N)/\log(1 - \alpha)$  steps
- Swap:
  - Mean:  $\mathcal{O}(d.N)$
  - Similarity:  $\mathcal{O}(d.N^2)$   
For each removed dimension:
    - Intersection:  $\mathcal{O}(N)$  (with hash set)
    - Max intersection score subarray:  $\mathcal{O}(N^2)$

- ① Jerome H. Friedman and Nicholas I. Fisher. Bump hunting in high-dimensional data. *Statistics and Computing*, 9(2):123–143, April 1999.
- ② Michael H. Goldwasser, Ming-Yang Kao, and Hsueh-I Lu. Linear-time algorithms for computing maximum-density sequence segments with bioinformatics applications. *CoRR*, cs.DS/0207026, 2002.

**Thank you for your attention!**