

# COMPUTATIONAL GEOMETRY

Project 2015-2016

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# DIALITY TRANSFORMATION

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## WHAT IS DUALITY TRANSFORMATION

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The dual transformation  $D$  of:

- the point  $p$  is noted  $D(p)$ . It is a line defined by  $D(p) \equiv y = (-x_p)x + y_p$
- the line  $l$  is noted  $D(l)$ . It is a point defined by  $D(l) \equiv (m, b)$

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- Incidence :  $I(p, l) \Leftrightarrow I(D(p), D(l))$ , with

$$I(p, l) = \begin{cases} \text{true} & mx_p + b - y_p = 0 \\ \text{false} & \text{otherwise} \end{cases}$$

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Time for a first demo.

# REGRESSION DEPTH

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# SIMPLE LINEAR REGRESSION

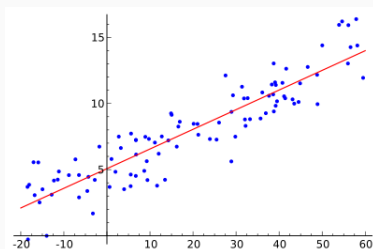
Simple linear regression is a commonly used linear estimation of the relationship between two statistical variables.

Given a dataset  $Z_n = \{(x_i, y_i), i = 1, \dots, n\} \subset \mathbb{R}^2$ , the simple regression line  $f$  is given by

$$f \equiv y = \alpha x + \beta$$

where  $\alpha$  and  $\beta$  are chosen such that they minimize  $LS(\alpha, \beta)$

$$LS(\alpha, \beta) = \sum_{i=1}^n (y_i - \beta - \alpha x_i)^2$$



Rousseeuw Peter J. and Mia Hubert described in 1999 in the article "Regression Depth" a new statistical concept called **regression depth**.

Goal: provide another estimator of relationship for bi-variate statistics.

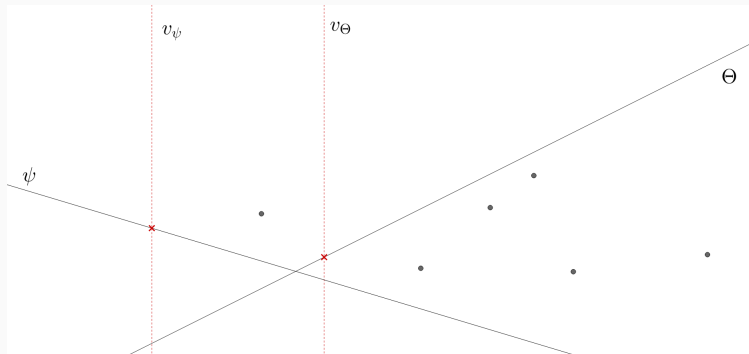
Some definitions:

- observations :  $Z_n = \{(x_i, y_i), i = 1, \dots, n\} \subset \mathbb{R}^2$
- candidate fit  $l$  :  $l \equiv y = mx + b$  or  $l(m, b)$
- residuals:  $r_i(l) = y_i - mx_i - b$  for every point  $(x_i, y_i) \in Z_n$

# NON-FIT

A candidate fit  $l = (m, b)$  to  $Z_n$  is called a **non-fit** iff there exists a real number  $v$  that does not coincide with any  $x_i$  and such that  $\phi_i(l)$  is satisfied.

$$\begin{aligned}\phi_i(l) = & ((\forall x_i < v, r_i(l) < 0) \wedge (\forall x_i > v, r_i(l) > 0)) \\ & \vee ((\forall x_i < v, r_i(l) > 0) \wedge (\forall x_i > v, r_i(l) < 0))\end{aligned}$$



## SO WHAT IS REGRESSION DEPTH?

**Regression depth:** Is the the minimal number of observations that need to be removed from  $Z_n$  in order for a fit  $l$  to become a non-fit with respect to  $Z_n$ .



# GEOMETRY

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The problem defined by the dual transformation of the regression depth plot is a geometry problem.

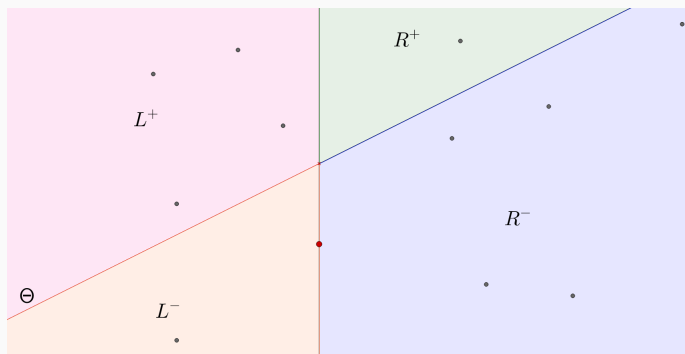
The regression depth  $rdepth(\eta, L_n)$  of any candidate fit  $\eta$  relative to a set of  $n$  lines  $L_n$  is the minimal number of lines from  $L_n$  that should be removed so that  $\eta$  becomes a non-fit.

In the dual space, a candidate fit is a non-fit if there exists a direction  $u$  (such that  $\|u\|=1$ ) and such that the halfline  $[\eta, \eta + u >$  does not intersect any line from the set  $L_n$ .

# A FIRST ALGORITHM

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# FIRST ALGORITHM



- Sort all element of  $Z_n$  by their  $x$  coordinate such that  $x_1 < x_2 < \dots < x_n$
- Compute 
$$\text{rdepth}(l, Z_n) = \min_{1 \leq i \leq n} (\min\{L^+(x_i) + R^-(x_i), L^-(x_i) + R^+(x_i)\})$$

Time for a second demo.

# BOUNDS

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- Lower bound:

$$\max_l \text{rdepth}(l, Z_n) \geq \left\lceil \frac{n}{3} \right\rceil$$

- **Upper bound:** if all observations of  $Z_n$  are in general position

$$\max_l \text{rdepth}(l, Z_n) \leq \left\lfloor \frac{n+2}{2} \right\rfloor$$

# DEEPSET REGRESSION LINE

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As an estimator we take the fit that has the deepest (greatest) regression depth regarding a dataset  $Z_n$ . A simple algorithm is the following:

- Sort all element of  $Z_n$  by their x coordinate such that  $x_1 < x_2 < \dots < x_n$
- For each pair  $ij$  such that  $0 < i < j \leq n$ :
  - Find the line  $l_{ij}$  that intersects with observations  $i$  and  $j$
  - Use the algorithm defined previously  $r_{ij} = \text{rdepth}(l_{ij}, Z_n)$  (without the sorting wich is already done)
  - If  $r_{ij}$  is greater than the regression depth of the temporary solution, keep  $l_{ij}$  as a new temporary solution.
- Return the  $l_{ij}$  that has the greatest regression depth, it is the deepest regression line.

Time for a last demo.

# CONCLUSION

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Better algorithms have been described since the publication of Rousseeuw and Hubert in 1999. In our project we also described but did not implement an algorithm presented by Langerman Stefan and Steiger William in "The Complexity of Hyperplane Depth in the Plane". They describe an algorithm performing in  $\mathcal{O}(n \log n)$ .

Regression depth is defined for higher dimensions as Hyperplane depth. Algorithms presented in this presentation can be easily adapted to compute the of hyperplanes.

In this project, we presented a problem that originated from statistical research but created a new computational geometry problem by taking it's dual. The regression depth problem illustrates well that the interest of multiple research area led to the discovery of better algorithms for the problem and it's dual.

THANK YOU FOR YOUR ATTENTION