

STATISTICS & DRG

**Some statistical methodological problems
in the analysis of hospital cost and length of stays
classified by DRG
and their solutions**

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Outline

1. PCS and DRG : a short introduction
2. The statistical problems
3. Classical solutions
4. Robust solutions
5. Examples
6. Reimbursement: a proposal
7. Conclusions

1. PCS and DRG : a short introduction

PCS: *Patient Classification System*

- a tool of hospital (system) management,
- rules to assign each stay to a group, e.g. a DRG, using a grouper; groups are defined according to diagnosis and treatment, groups are cost homogeneous.

→ the hospital customer population is a mixture of DRG-cases: a casemix.

Main goals: budgeting, reimbursing

- Pay each stay according to the “mean cost” of the corresponding DRG
→ payments fairly distributed among hospitals (according to their casemix).
- Compare hospital performance standardized by casemix, stimulate an economically competitive behaviour among hospitals.

Hystory:

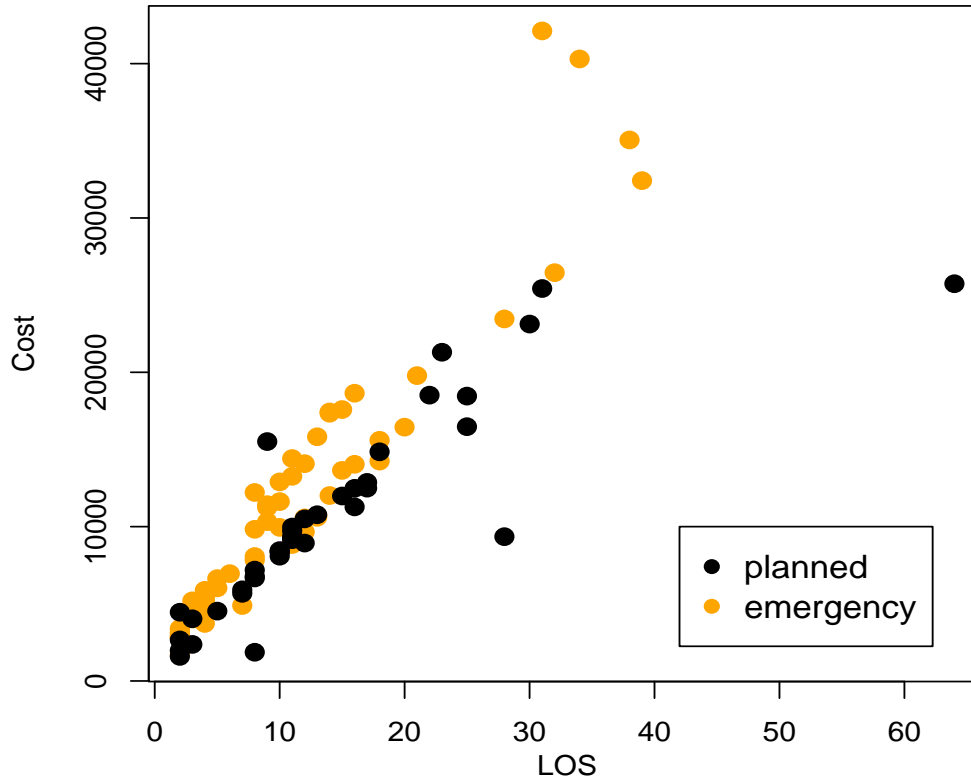
- In the 60's : design of the first DRG system at Yale University
- Migration from USA, to Western EU, Australia, East EU, Asia
- Huge variety of PCS (APDRG, IRDRG, APRDRG, ANDRG, ...)
- From ~ 500 to ~ 1500 groups
- A Swiss DRG system will be implemented starting from 2012.

In theory

- Diagnosis and treatment ensure the economical homogeneity
- Length of stay (LOS) is a good proxy of Cost
- Annual LOS means / Cost means (e.g., on a national basis) are reliable statistics

In practice

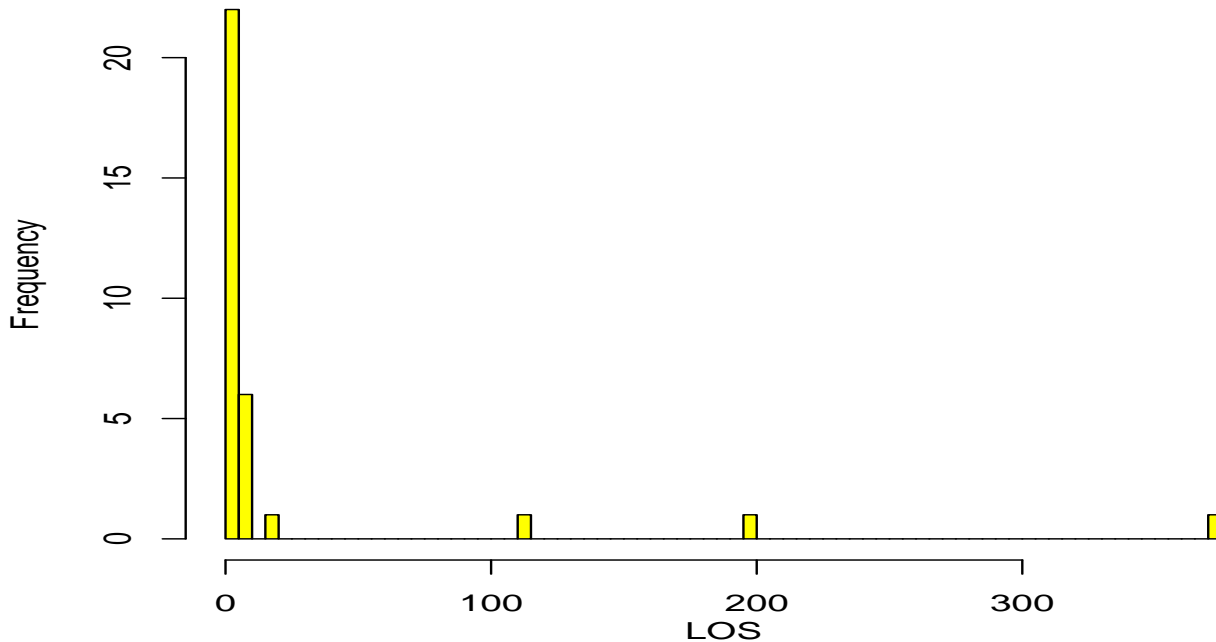
DRG 243: Medical back problems, 100 cases



- Cost may depend on **other covariates**, e.g., LOS, admission type, ...
- There are atypical cases: **outliers** (low outliers; high outliers)
- LOS outliers are not necessarily Cost outliers

DRG 34: disorders of the nervous system, 32 cases

LOS : 1,1,2,2,2,2,2,3,3,3,3,3,4,4,4,4,4,5,5,5,5,6,6,7,7,8,9,16,115,198,374



Mean of complete data = 25.5 jours

Mean removing 3 outliers = 4.4 jours

The usual mean is very sensitive to outliers

2. Statistical problems

Develop **automatic** procedures to:

- **detect** outliers,
- compute a **cost mean** (LOS mean) **robust** (resistant) wrt outliers,
- taking into account available **covariates**,
- taking into account the **asymmetrical shapes** of the distributions,
- without necessarily increasing the number of groups.

(Marazzi-Paccaud-Ruffieux-Beguin, 1998)

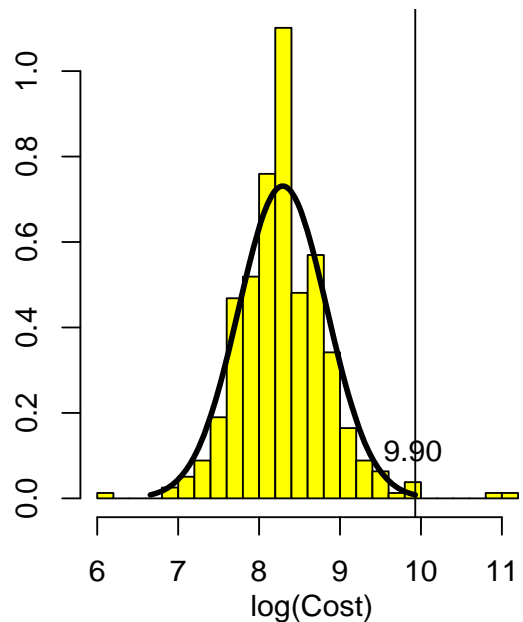
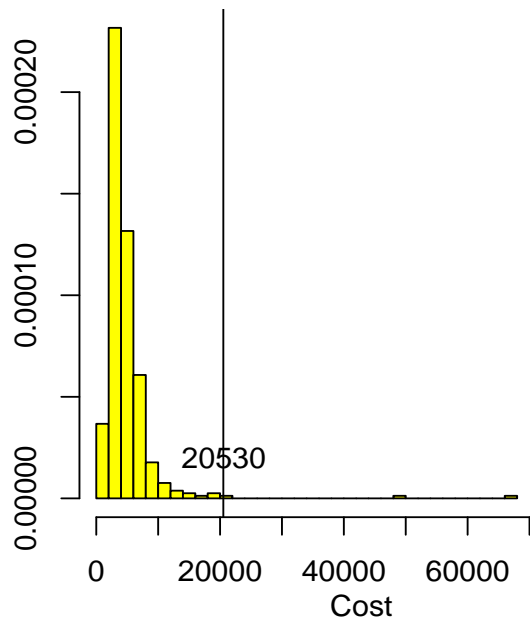
Related economical problems

Improve the reimbursement rules :

- pay typical cases according to robust mean cost of associated DRG,
- inspect outliers,
- pay outliers according to a special rule,
- and minimize “bad incentives”
e.g., patient selection, refusing those that might be very expensive.

3. Classical solution suggested by the Normal model

APDRG 25: Seizure & headache age > 17 w/o cc, 395 cases



trim point = mean + 3 · standard deviation

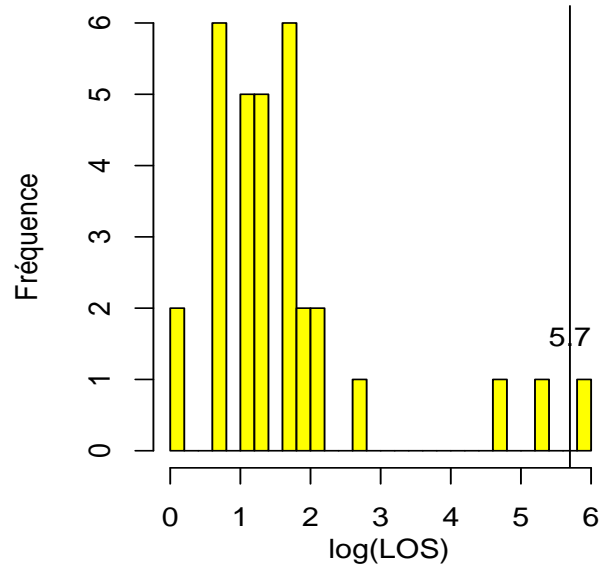
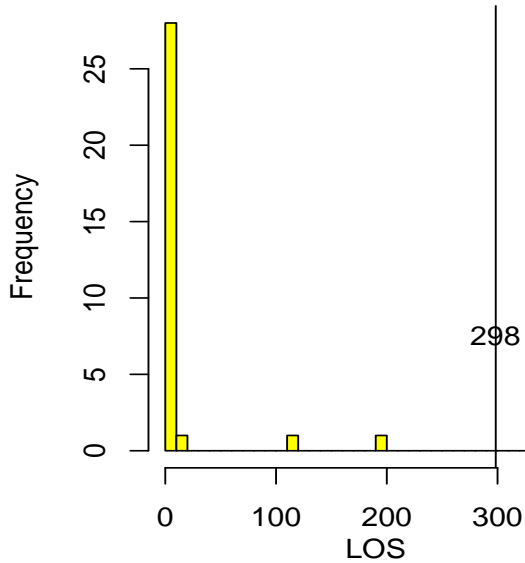
Complete mean = 4785 Fr;

mean without outliers = 4470 Fr

This method is efficient* when the model is adequate for (almost) all cases

* precise, subject to very small sampling fluctuations

DRG 34: disorders of the nervous system, 32 cases



Complete data: mean = 25.5

standard deviation of log-s = 1.34

Cases < 298 : mean = 14.2

Cases < 20 = 4.4

standard deviation of log-s = 0.63

The classical method is very sensitive to outliers

4. Robust solution

- Assume that a **parametric model**, e.g., Normal, Weibull, Gamma, Log-Normal, Log-Weibull, Log-Gamma, ... provides an adequate description of the **majority of data**, not necessarily the totality.
- Fit an adequate model to the majority using a **robust procedure**.

robust mean = mean of the adjusted model

Technical difficulty: how to combine robustness and efficiency ?

Step 1: Use a **very resistant but inefficient** procedure to detect outliers

Step 2: Apply a **classical and efficient** procedure to the cleaned data

Examples of very robust but inefficient statistics

Le **MED** (median) is a measure of the “centre” of the data

$$\text{MED}(1, 2, 3, 1000, 2000) = 3$$

Le **MAD** (median absolute deviation) is a measure of “variability”

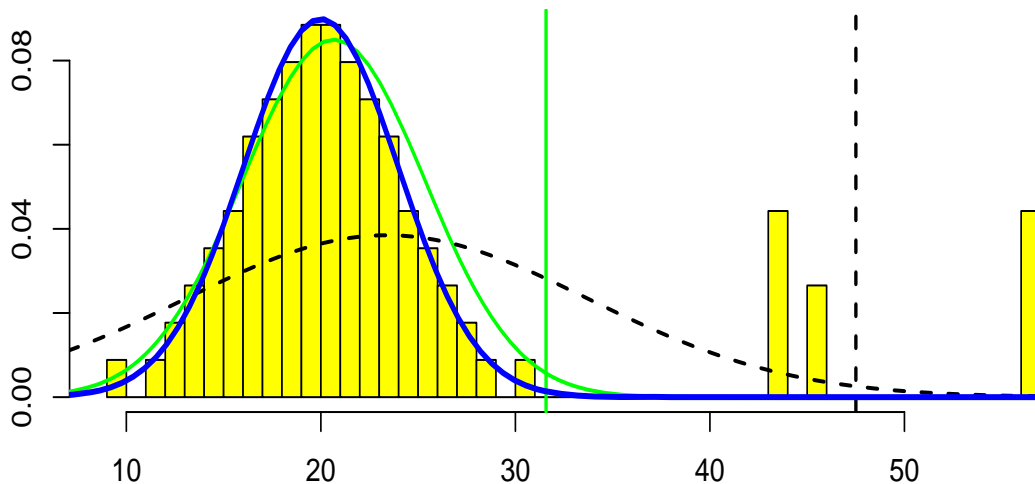
$$\text{MAD}(1, 2, 3, 1000, 2000) =$$

$$\text{MED}(|1 - 3|, |2 - 3|, |3 - 3|, |1000 - 3|, |2000 - 3|) =$$

$$\text{MED}(2, 1, 0, 997, 1997) = 2$$

MED and MAD resist to $\sim 50\%$ outlier contamination !

Robust fit of a **Normal** model with mean μ and stand.dev. σ



1. **Very robust but inefficient fit** : solve

$$\mu = \text{MED}(\text{data}) ,$$

$$0.6745 \cdot \sigma = \text{MAD}(\text{data})$$

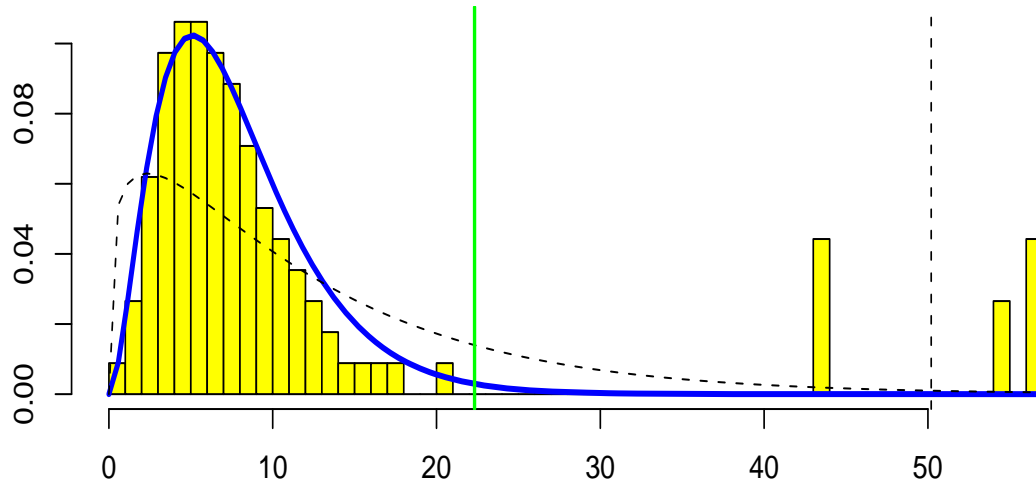
Trim point = percentile 99% of the very robust model

2. **Robust and efficient model** : Max-likelihood(data < trim point)

Robust mean = mean of the robust and efficient model

$$\approx \text{mean}(\text{data} < \text{trim point})$$

Robust fit of Gamma or Weibull model (Marazzi-Ruffieux, 1999)



1. Very robust but inefficient fit : solve

$$\text{MED}(\text{model}) = \text{MED}(\text{data}),$$

$$\text{MAD}(\text{model}) = \text{MAD}(\text{data}),$$

Trim point = percentile 99% of the very robust model

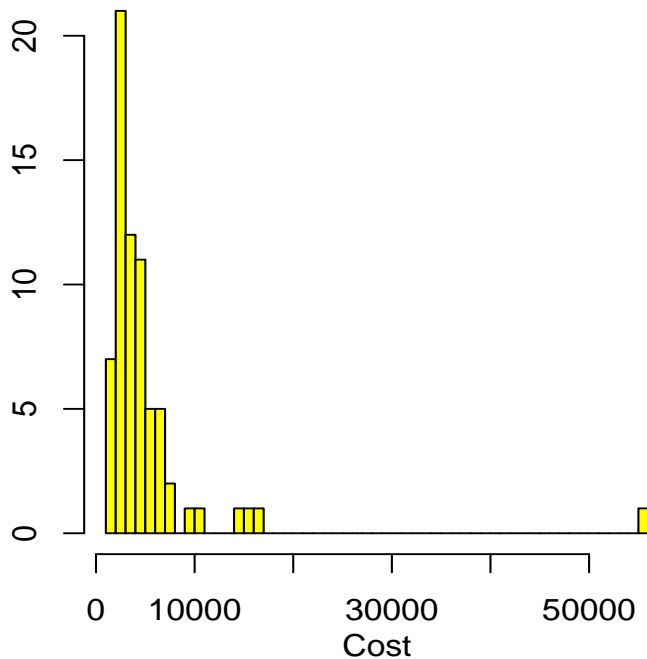
Robust and efficient model : Max-likelihood(data < trim point)

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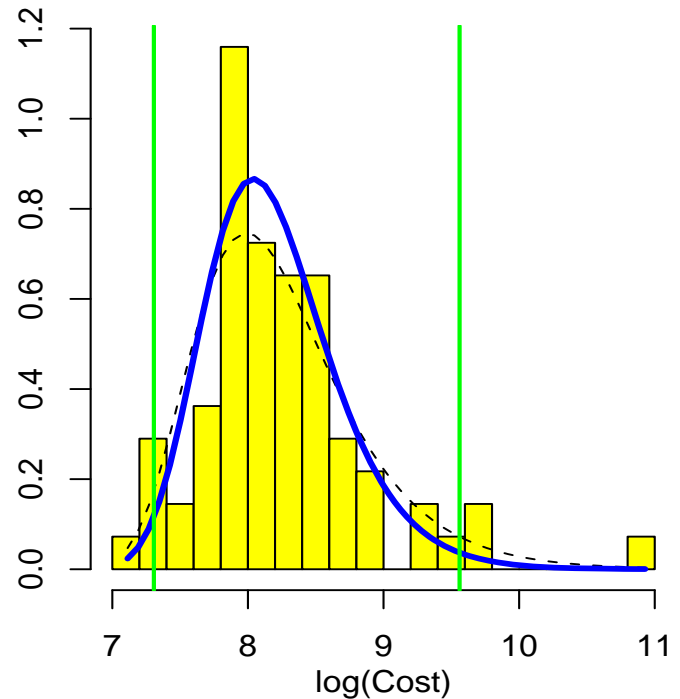
5. Exemples

Robust fit of **Generalized Loggamma** model (Marazzi-Yohai, 2011)

DRG185 : Dental & oral dis exc extract & restorat, Age > 17; 69 cases



Classical mean = 5060 Fr

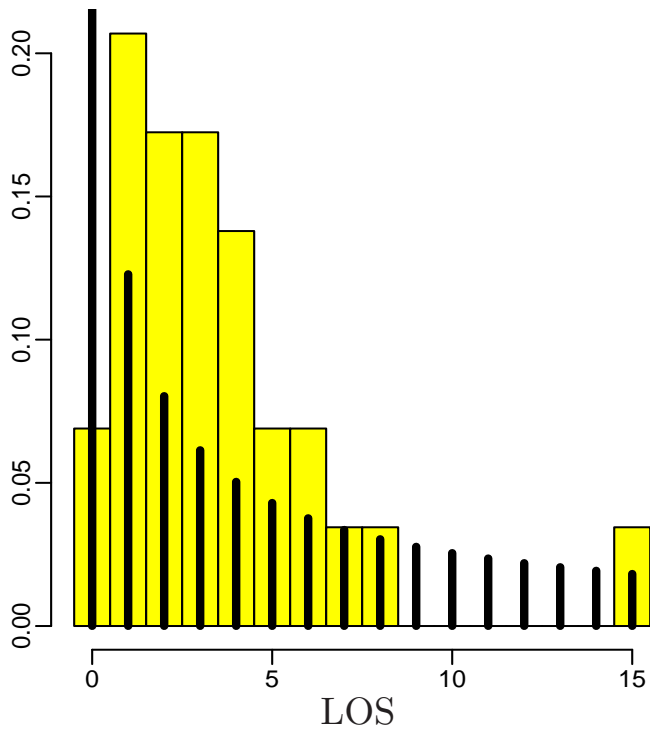


Two trim points

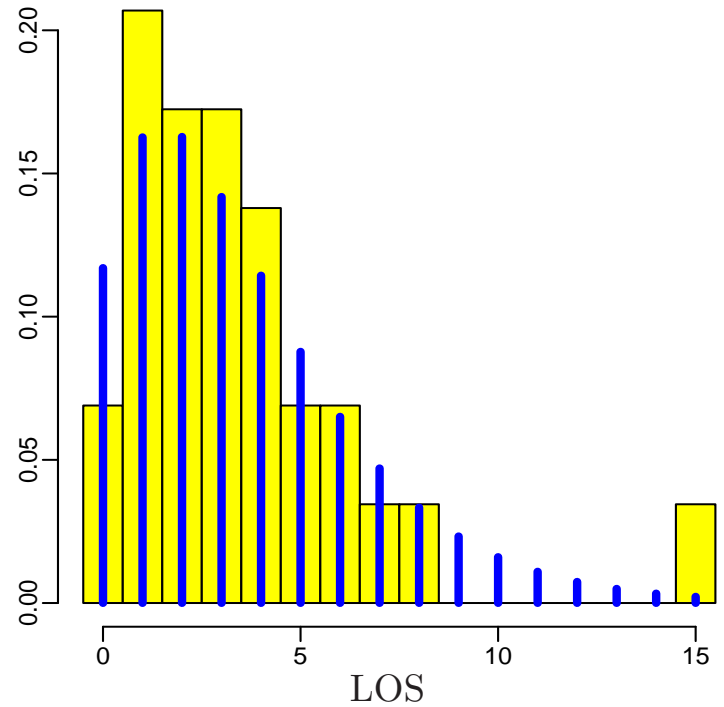
Robust mean = 4200 Fr

Robust fit of **Negative Binomial** model (Marazzi-Yohai 2010; Amiguet 2011)

DRG 34: disorders of the nervous system, 32 cases



Classical mean = 24.4 days

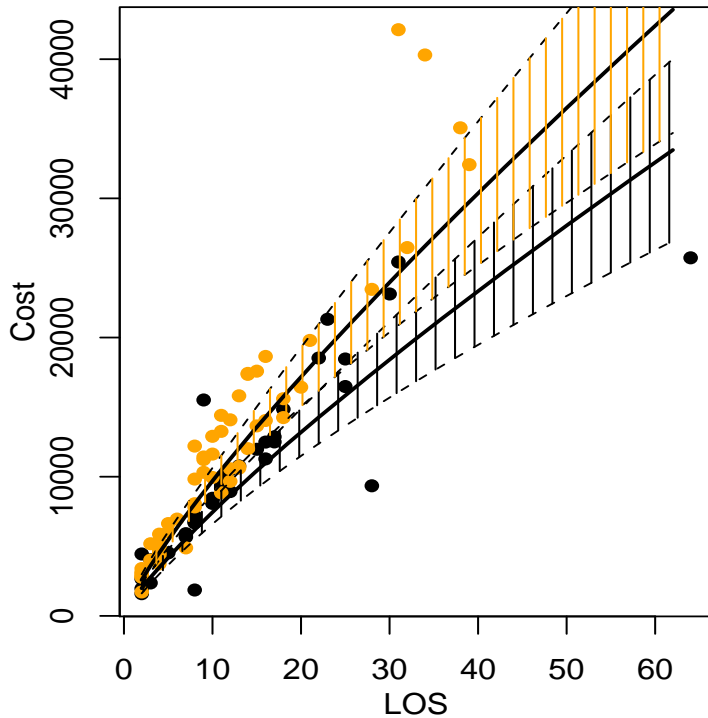


Robust mean = 3.6 days

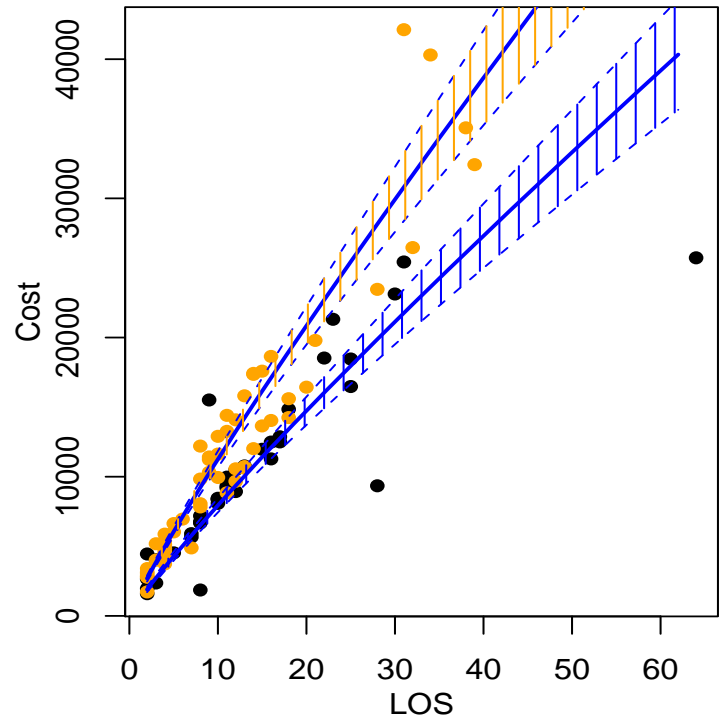
Mean cost depending on LOS and Admission type

Robust regression with asymmetric response (Marazzi-Yohai, 2004)

APDRG 243: Medical back problems, 100 cases



Classical regression

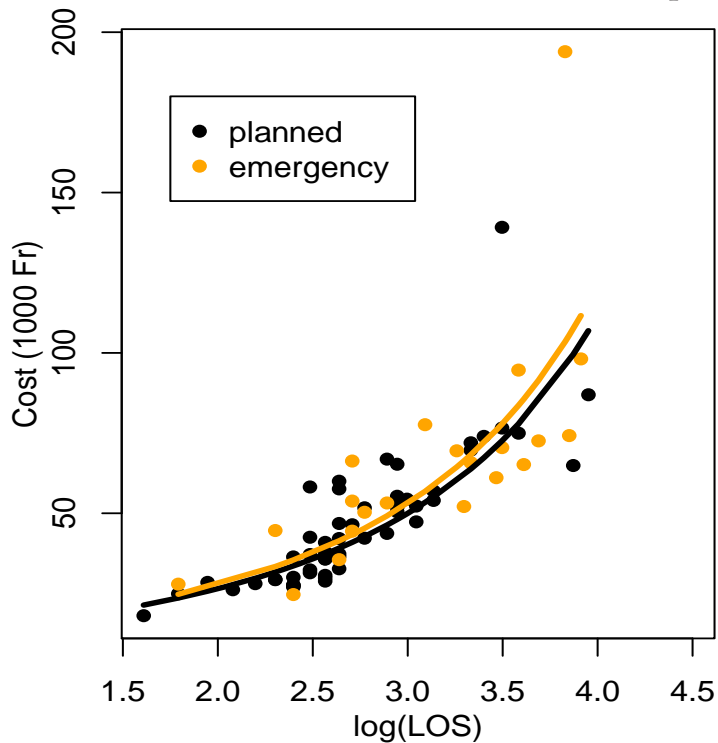


Robust regression

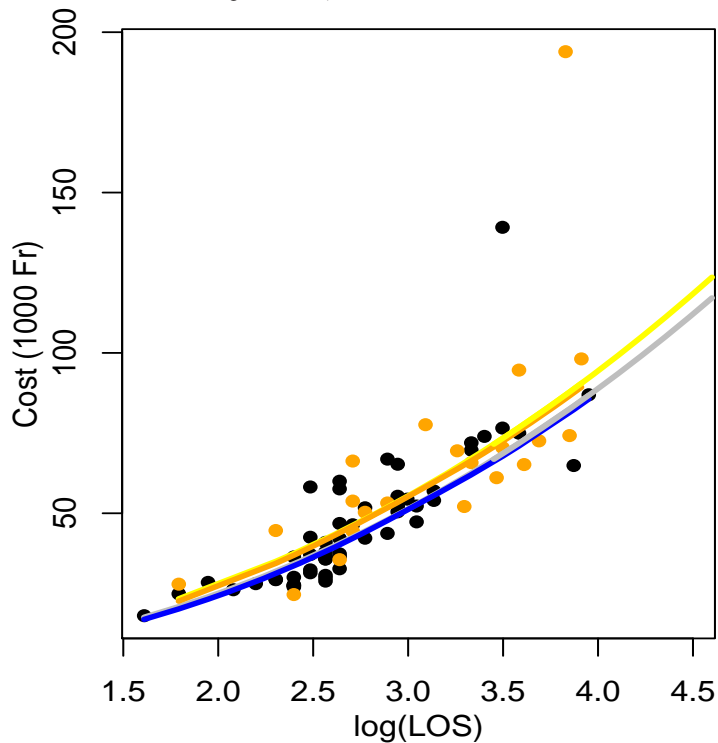
Mean cost depending on LOS and Admission type

Robust Box-Cox transformations and robust smearing (Marazzi-Yohai, 2009)

APDRG 545: cardiac valve procedure with major cc, 78 cases



Classical smearing

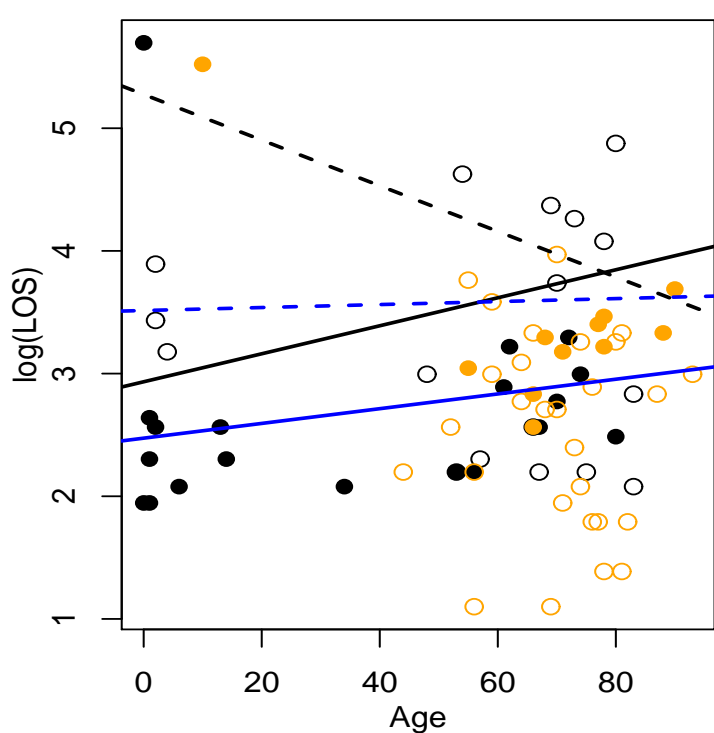


Robust smearing
and Parametric prediction

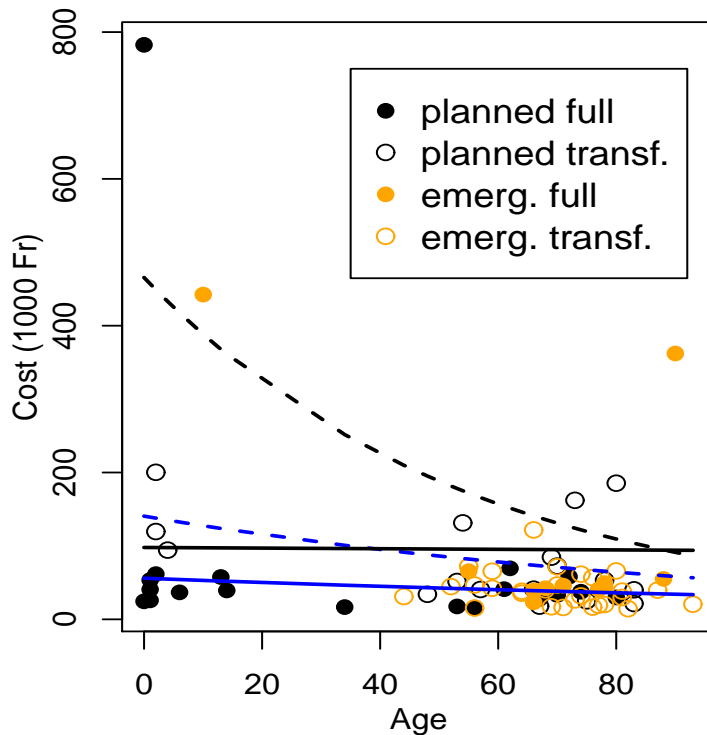
Mean LOS/Cost depending on Age and Admission type

Robust AFT with censored data (Locatelli-Marazzi-Yohai, 2010; 2011)

APDRG 549: major cardiovascular proc. with major cc, 75 cases, 45 transfers



- Class.plann; - - Class.emerg.
- Rob. plann; - - Rob. emerg.

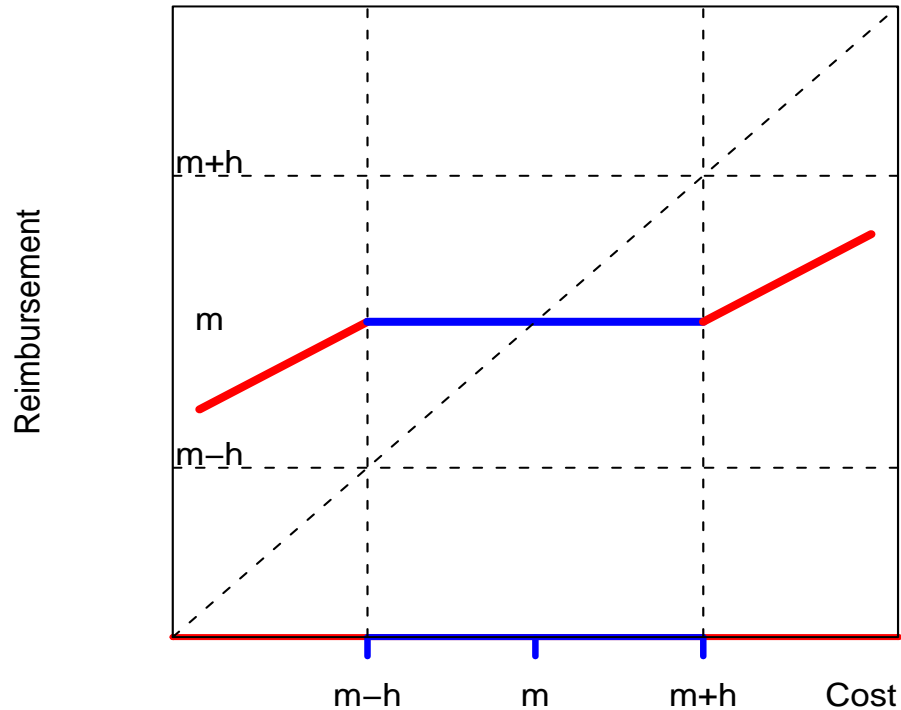


- Class.plann; - - Class.emerg.
- Rob. plann; - - Rob. emerg.

6. Reimbursement of exceptional cases (Marazzi-Gardiol-Duong, 2007)

Let m be the mean Cost

- if $m - h < \text{Cost} < m + h$ pay m
- else pay $0.9 \times (\text{Cost} - m)$



Adapted to partial reimbursement of LOS

7. Conclusions

- Several robust statistical procedures for the analysis of **positive responses with asymmetric distribution** and for the computation of their **robust means** with/without covariates, with/without censoring have been developed.

These are general statistical procedures for responses like: cost, expenses, survival data, production measures, ...
- Robust statistics is a very active area of statistical research.
- In the analysis of DRG data we have shown that robust statistics is necessary for:
 - the automatic detection of outliers;
 - the computation of LOS and cost means not affected by outliers taking into account:
 - the shape of the distributions,
 - the available covariates,
 - censoring, e.g., transfers to another hospital;
 - to discover and quantify certain types of heterogeneities.
- Introduction of this technology in practice ?
SwissDRG ?