NONPARAMETRIC STATISTICS FOR BIG DATA

Gilles Durrieu (Université Bretagne Sud) Joint work with Bernard Bercu (Université de Bordeaux) and Sami Capderou (University of Geneva).

CYBERUS SUMMER SCHOOL

3 to 7 July 2023 - Online

NONPARAMETRIC STATISTICS FOR BIG DATA

< < >> < < < >> <</p>

Plan



Introduction

- 2 Random design regression
 - Estimators
 - Asymptotic properties
 - Simulation
 - Application in Brittany

Fixed design regression

- Estimators
- Asymptotic Properties
- Simulation
- Application in New Caledonia

Conclusion

Plan

Introduction

- 2 Random design regression
 - Estimators
 - Asymptotic properties
 - Simulation
 - Application in Brittany

3 Fixed design regression

- Estimators
- Asymptotic Properties
- Simulation
- Application in New Caledonia

Conclusion

• • • • • • • • • • • •

Some publications related to the subject:

- Senga-Kiesse T. and Durrieu G., Statistics and Probability letters, submitted.
- Bercu B., Capderou S. and Durrieu G. (2019) *Journal of Applied Statistics*, 46(1), 119-140.
- Bercu B., Capderou S., and Durrieu G. (2019) *Statistical Inference for Stochastic Processes*, 22(1), 17-40.
- Durrieu G., Grama I., Jaunatre K. and Tricot J.M. (2018) Journal of Statistical Software, 87,12, 1-20.
- Durrieu G., Grama I., Pham Q.K. and tricot J.M. (2015) *Extremes*, 18, 437-478.
- Durrieu G., Pham Q.K., Foltete A.S., Maxime V., Grama I., Le Tilly V., Duval H., Tricot J.M. and Sire O. (2016) *Environmental Monitoring and Assessment*, 188, 401-409.
- Durrieu G. and Briollais L. (2009) *Journal of American Statistical Association*, 104, 650-660.

Water quality and global warming effects

 Developing a procedure for monitoring the quality of water and measuring the global warming effects, based on the analysis of their behavior of bivalves at high frequency.

• • • • • • • • • • • •

High frequency valvometry and Big Data



Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

▲日▼▲□▼▲田▼▲田▼ ● ●●●

Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

7 / 68



Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA





Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA



NONPARAMETRIC STATISTICS FOR BIG DATA

Gilles Durrieu

3

・ロト ・回ト ・ヨト ・ヨト





◆□ → ◆□ → ◆□ → ◆□ → □ □

Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

11 / 68



Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

12 / 68



Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

13 / 68

<ロ> <回> <回> < 回> < 回</p>

First Experimental site: LOCMARIAQUER Gulf of Morbihan - Atlantic Ocean



A B A A B A A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A
 A

Second experimental site: Havannah Canal in New Caledonia - Pacific Ocean





Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

Near and far experimental sites



Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

16 / 68

《口》《聞》《臣》《臣》

Different sites in the World

- France: Arcachon bay, Brest, Locmariaquer, Oléron, Lacq, New Caledonia
- Norway: Ny-Alesund (Spitzberg in Svalbard archipelago),
- Russia: Mourmansk,
- Spain: port of Santander,

• . . .

ㅋㅋ ㅋㅋㅋ

< D > < A </p>

Data

- Sampling frequency (10 Hz): one measurement every 0.1s, each animal is measured every 1.6 s (N = 16);
- 108,000 measurements for one oyster by day;
- n = 1,728,000 data points by day for the 16 oysters;
- 630,720,000 measurements/year
- and so 12, 614, 400, 000 measurements/year for 20 sites

+

biological and environmental parameters: acetycholinesteras, EROD activity, vitellogenin, temperature, salinity, chlorophylle, mortality, animal growth.

< ロ > < 同 > < 回 > < 回 > < 回 > <

Objectives

- Dealing with the data deluge,
- Model the animals behavior in their environment in order to detect environmental disturbances (such as pollution),
- Construction of mathematical indicators for monitoring water quality (pollution detection, climate change and global warming),
- Study the effect of global warming on a representative of marine fauna taken as a biosensor of the evolution of its environment,
- Setting up a database and automatic representation of data and results online.

Graphical representation of data



_

Individu	Heure	Ouverture
11	0.0000011574	6.754
12	0.0000023148	5.436
13	0.0000034722	1.589
14	0.0000046296	6.356
15	0.0000057870	5.895
16	0.0000069444	4.754
1	0.0000081019	6.960

<ロ> (四) (四) (日) (日) (日)

Example of behavior



heure

æ



< ロ > < 回 > < 回 > < 回 > < 回 >

Velocity of the valve opening/closing activity



Movement velocities as an indicator

- Environmental perturbations such as a pollution of global warming can affect the activity of biosensors and in particular the shells opening and closing velocities.
- A stressed animal due to the presence of pollution or environmental perturbations exhibits irregular and numerous microclosing and opening periods with changes in the velocities in comparison with the normal situation.

Movement velocities as an indicator

- Environmental perturbations such as a pollution of global warming can affect the activity of biosensors and in particular the shells opening and closing velocities.
- A stressed animal due to the presence of pollution or environmental perturbations exhibits irregular and numerous microclosing and opening periods with changes in the velocities in comparison with the normal situation.

Movement velocities as an indicator

- Environmental perturbations such as a pollution of global warming can affect the activity of biosensors and in particular the shells opening and closing velocities.
- A stressed animal due to the presence of pollution or environmental perturbations exhibits irregular and numerous microclosing and opening periods with changes in the velocities in comparison with the normal situation.

Random design regression

- Estimators
- Asymptotic properties
- Simulation
- Application in Brittany

3 Fixed design regression

- Estimators
- Asymptotic Properties
- Simulation
- Application in New Caledonia

Conclusion

글 🕨 🖌 글

Random design regression

We consider the **nonparametric regression model** given, for all $n \ge 1$, by

 $\mathbf{Y}_{n} = \mathbf{f}(\mathbf{X}_{n}) + \boldsymbol{\varepsilon}_{n}$

where

- (*X_n*) (the time of the measurement) is a sequence of random variables **iid** with positive probability density function *g*,
- (ε_n) are unknown random errors iid independent of (X_n), such that E[ε_n] = 0 et E[ε_n²] = σ²,
- The regression function f and the density function g are unknown, bounded continuous, twice differentiable with bounded derivatives.

Objective

Estimation of the derivative f' of f.

Nadaraya-Watson estimator of f

- The **kernel** *K* is a positive symmetric bounded function, differentiable with bounded derivative.
- The bandwidth (h_n) is a sequence of positive real numbers, decreasing to zero, such that nh_n tends to infinity.

The Nadaraya-Watson estimator of *f* is given, for all $x \in \mathbb{R}$, by

$$f_n(\mathbf{x}) = \frac{\sum\limits_{k=1}^n Y_k K\left(\frac{\mathbf{x} - X_k}{h_n}\right)}{\sum\limits_{k=1}^n K\left(\frac{\mathbf{x} - X_k}{h_n}\right)}.$$

< ロ > < 同 > < 回 > < 回 > < 回 > <

Estimators

Recursive Nadaraya-Watson estimator of f

The **recursive Nadaraya-Watson** estimator is given, for $x \in \mathbb{R}$, by

$$\widehat{f}_n(\boldsymbol{x}) = \frac{\sum\limits_{k=1}^n \frac{\boldsymbol{Y}_k}{h_k} \mathcal{K}\left(\frac{\boldsymbol{x} - \boldsymbol{X}_k}{h_k}\right)}{\sum\limits_{k=1}^n \frac{1}{h_k} \mathcal{K}\left(\frac{\boldsymbol{x} - \boldsymbol{X}_k}{h_k}\right)} = \frac{\widehat{h}_n(\boldsymbol{x})}{\widehat{g}_n(\boldsymbol{x})}$$

with

$$\hat{g}_n(x) = \frac{1}{n} \sum_{k=1}^n \frac{1}{h_k} K\left(\frac{x - X_k}{h_k}\right),$$

$$\hat{h}_n(x) = \frac{1}{n} \sum_{k=1}^n \frac{Y_k}{h_k} K\left(\frac{x - X_k}{h_k}\right).$$

< ロ > < 同 > < 回 > < 回 >

Johnston and Wand-Jones alternative estimators of f

When *g* is known, the Johnston and Wand-Jones estimators are given, for all $x \in \mathbb{R}$, by

$$\widetilde{f}_n(x) = \frac{1}{ng(x)} \sum_{k=1}^n \frac{Y_k}{h_k} K\left(\frac{x-X_k}{h_k}\right),$$

$$\widetilde{f}_n(x) = \frac{1}{n} \sum_{k=1}^n \frac{Y_k}{g(X_k)} \frac{1}{h_k} K\left(\frac{x-X_k}{h_k}\right).$$

Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

30 / 68

• • • • • • • • • • •

Random design regression

Estimators

Estimators of the closing and opening velocity

•
$$\hat{f}_n(x) = \frac{\hat{h}_n(x)}{\hat{g}_n(x)},$$

•
$$\widetilde{f}_n(x) = \frac{\widehat{h}_n(x)}{g(x)},$$

•
$$\check{f}_n(x) = \frac{1}{n} \sum_{k=1}^n \frac{Y_k}{g(X_k)} \frac{1}{h_k} K\Big(\frac{x - X_k}{h_k}\Big).$$

< ロ > < 回 > < 回 > < 回 > < 回 >

Random design regression

Estimators

Estimators of the closing and opening velocity

•
$$\widehat{f}'_n(x) = rac{\widehat{h}'_n(x)}{\widehat{g}_n(x)} - rac{\widehat{h}_n(x)\widehat{g}'_n(x)}{\widehat{g}^2_n(x)},$$

•
$$\widetilde{f}'_n(x) = \frac{\widehat{h}'_n(x)}{g(x)} - \frac{\widehat{h}_n(x)g'(x)}{g^2(x)},$$

•
$$\check{f}'_n(x) = \frac{1}{n} \sum_{k=1}^n \frac{Y_k}{g(X_k)} \frac{1}{h_k^2} K'\Big(\frac{x-X_k}{h_k}\Big).$$

< ロ > < 回 > < 回 > < 回 > < 回 >

Kernel assumptions

The kernel K is a positive symmetric bounded function, differentiable with bounded derivative, satisfying

$$\int_{\mathbb{R}} K(x) dx = 1, \qquad \int_{\mathbb{R}} K'(x) dx = 0,$$
$$\int_{\mathbb{R}} x K'(x) dx = -1, \qquad \int_{\mathbb{R}} x^2 K'(x) dx = 0,$$
$$\int_{\mathbb{R}} x^4 K(x) dx < \infty, \qquad \int_{\mathbb{R}} x^4 |K'(x)| dx < \infty.$$

< ロ > < 同 > < 回 > < 回 >

Almost sure convergence

Theorem (Bercu, Capderou and Durrieu, 2019)

If $h_n = 1/n^{\alpha}$ with $0 < \alpha < 1/3$, we have for any $x \in \mathbb{R}$ such that g(x) > 0,

$$\lim_{n\to+\infty}\widehat{f}'_n(\boldsymbol{x})=\boldsymbol{f}'(\boldsymbol{x})\qquad \boldsymbol{a.s.}$$

$$\lim_{n\to+\infty}\widetilde{f}'_n(x)=f'(x) \qquad a.s.$$

$$\lim_{n\to+\infty}\check{f}'_n(x)=f'(x) \qquad a.s.$$

< ロ > < 同 > < 回 > < 回 > < 回 > <

Asymptotic normality

Denote

$$\boldsymbol{\xi}^{\mathbf{2}} = \int_{\mathbb{R}} (\boldsymbol{K}'(\boldsymbol{y}))^{\mathbf{2}} \mathrm{d}\boldsymbol{y}.$$

Theorem (Bercu, Capderou and Durrieu, 2019)

If (ε_n) has a finite conditional moment of order > 2 and if $h_n = 1/n^{\alpha}$ with $1/5 < \alpha < 1/3$, we have for any $x \in \mathbb{R}$ such that g(x) > 0,

$$\begin{split} &\sqrt{nh_n^3}(\hat{f}_n'(x) - f'(x)) \overset{\mathcal{D}}{\longrightarrow} \mathcal{N}\Big(0, \frac{1}{1+3\alpha} \frac{\xi^2}{g(x)} \sigma^2\Big), \\ &\sqrt{nh_n^3}(\tilde{f}_n'(x) - f'(x)) \overset{\mathcal{D}}{\longrightarrow} \mathcal{N}\Big(0, \frac{1}{1+3\alpha} \frac{\xi^2}{g(x)} \left(\sigma^2 + f^2(x)\right)\Big), \\ &\sqrt{nh_n^3}(\check{f}_n'(x) - f'(x)) \overset{\mathcal{D}}{\longrightarrow} \mathcal{N}\Big(0, \frac{1}{1+3\alpha} \frac{\xi^2}{g(x)} \left(\sigma^2 + f^2(x)\right)\Big). \end{split}$$

Asymptotic variance

Triweight	$\mathcal{K}(x) = rac{35}{32}(1-x^2)^3 \mathrm{I}_{\{ x \leq 1\}}$	$\xi^2 = 3.18$
Biweight	$\mathcal{K}(x) = rac{15}{16}(1-x^2)^2 \mathrm{I}_{\{ x \leq 1\}}$	$\xi^2 = 2.14$
Cosine	$\mathcal{K}(x) = rac{\pi}{4} cos \Big(rac{\pi}{2} x\Big) \mathrm{I}_{\{ x \leq 1\}}$	$\xi^2 = 1.52$
Epanechnikov	$K(x) = rac{3}{4}(1-x^2)I_{\{ x \leq 1\}}$	$\xi^2 = 1.5$
Gaussian	$\mathcal{K}(x) = rac{1}{\sqrt{2\pi}} \exp \left(-rac{x^2}{2} ight)$	$\xi^2 = 0.14$

Conclusion: choice in the sense of the minimum asymptotic variance of the recursive Nadaraya-Watson estimator with Gaussien kernel.

The data are generated from the nonparametric regression model for k = 1, ..., n with n = 10,000

 $\mathbf{Y}_{k} = \mathbf{f}(\mathbf{X}_{k}) + \varepsilon_{k}$

- The random observation (X_n) is a sequence of **iid** $\mathcal{U}([0, 1])$,
- The source of variation (ε_n) is a sequence of iid $\mathcal{N}(0, 1)$,
- The regression function *f* is given by

$$f(x)=\sin(2\pi x^3)^3.$$

< ロ > < 同 > < 回 > < 回 > < 回 > <

Graphical representation



Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

38 / 68

æ

Almost sure convergence

The derivative of f is:

$$f'(x) = 18\pi x^2 \cos(2\pi x^3) \sin(2\pi x^3)^2.$$

Representation of \hat{f}'_n estimator with Gaussian kernel and $\alpha = 0.1, 0.2, 0.3.$



Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

39 / 68

Choice of α by cross validation method

$$CV(\alpha) = \frac{1}{n} \sum_{k=1}^{n} \left(\widehat{f}'_{(-k)}(X_k) - f'(X_k) \right)^2$$

where $\hat{f}'_{(-k)}(X_k)$ is the recursive Nadaraya-Watson estimator of $f'(X_k)$ determined with (X_k, Y_k) removed.



Choice of $\alpha_{CV} = 0.32$.

Almost sure convergence

Representation of \hat{f}'_n for Gaussian and Epanechnikov kernel



NONPARAMETRIC STATISTICS FOR BIG DATA

Almost sure convergence

Representation of the 3 estimators of the derivative f' of f.



NONPARAMETRIC STATISTICS FOR BIG DATA

Asymptotic normality

Recursive Nadaraya-Watson estimator $\hat{f}'_n(x)$



æ

Locmariaquer site in the gulf of Morbihan.



<ロ> <同> <同> < 同> < 同>

Application in Brittany



æ

ヘロン 人間 とく ヨン 人

Representation of $\hat{f}'_n(x)$ for one oyster.



Representation of the opening and closing velocity estimator between the 4th of March and the 21th of August 2011 considering the 16 oysters in Locmariaquer.



Days

Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA



NONPARAMETRIC STATISTICS FOR BIG DATA

Plan

Introduction

- 2 Random design regression
 - Estimators
 - Asymptotic properties
 - Simulation
 - Application in Brittany

Fixed design regression

- Estimators
- Asymptotic Properties
- Simulation
- Application in New Caledonia

Conclusion

글 🕨 🖌 글

Fixed design regression

Nonparametric fixed design regression

We consider the fixed design regression model given, for $n \ge 1$ and for k = 1, ..., n, by

$$\mathbf{Y}_{\mathbf{k}} = \mathbf{f}(\mathbf{t}_{\mathbf{k}}) + \boldsymbol{\varepsilon}_{\mathbf{k}}$$

where

- the times of measurement $t_k = k/n$ are perfectly known,
- (ε_n) is the sequence of random error iid such that $\mathbb{E}[\varepsilon_n] = 0$ and $\mathbb{E}[\varepsilon_n^2] = \sigma^2$,
- the regression function *f* is bounded continuous, twice differentiable with bounded derivatives.

Objective

Estimation of the derivative f' of f.

Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

50 / 68

Estimators

The regression function *f* is estimated, for any $x \in]0, 1[$, by

$$\widehat{f}_n(\mathbf{x}) = \frac{1}{nh_n}\sum_{k=1}^n Y_k K\Big(\frac{\mathbf{x}-t_k}{h_n}\Big),$$

and its derivative f' by

$$\widehat{f}'_n(\mathbf{x}) = rac{1}{nh_n^2}\sum_{k=1}^n Y_k K'\Big(rac{\mathbf{x}-t_k}{h_n}\Big).$$

Gilles Durrieu

< ロ > < 同 > < 回 > < 回 >

Assumptions on the kernel

The kernel K is either the Gaussian kernel or a positive symmetric bounded function compactly supported, twice differentiable with bounded derivatives, such that

$$\int_{\mathbb{R}} \mathcal{K}(x) dx = 1, \qquad \int_{\mathbb{R}} \mathcal{K}'(x) dx = 0,$$

$$\int_{\mathbb{R}} x \mathcal{K}'(x) dx = -1.$$

Gilles Durrieu

< ロ > < 同 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ >

Almost sure convergence

Theorem (Bercu, Capderou and Durrieu, 2019)

If $h_n = 1/n^{\alpha}$ with $0 < \alpha < 1/3$, we have for any $x \in]0, 1[$

$$\lim_{n\to+\infty}\widehat{f}'_n(x)=f'(x) \qquad a.s.$$

Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

<ロ> <同> <同> < 同> < 同> < 同> < 同> < 因> < 因 > < 因 > < 因 > < 因 > < 因 > < 因 > < 因 > < 因 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0 > < 0

Asymptotic normality

Denote

$$\boldsymbol{\xi}^{\mathbf{2}} = \int_{\mathbb{R}} \left(\boldsymbol{K}'(\boldsymbol{y})
ight)^{\mathbf{2}} \mathrm{d} \boldsymbol{y}.$$

Theorem (Bercu, Capderou and Durrieu, 2019)

We have as n tends to infinity for any $x \in]0, 1[$,

$$\sqrt{nh_n^3}\left(\hat{f}'_n(\mathbf{x}) - \mathbb{E}[\hat{f}'_n(\mathbf{x})]\right) \overset{\mathcal{D}}{\longrightarrow} \mathcal{N}\left(\mathbf{0}, \xi^2 \sigma^2\right).$$

Furthermore, as soon as $1/5 < \alpha < 1/3$, we also have as n tends to infinity for any $x \in]0, 1[$,

$$\sqrt{nh_n^3} \left(\hat{f}'_n(\boldsymbol{x}) - f'(\boldsymbol{x})\right) \xrightarrow{\mathcal{D}} \mathcal{N}\left(0, \xi^2 \sigma^2\right).$$

Concentration inequality

Denote

$$\Lambda = \sup_{\boldsymbol{x} \in \mathbb{R}} |\boldsymbol{K}'(\boldsymbol{x})| \qquad \text{et} \qquad \boldsymbol{\zeta} = \int_{\mathbb{R}} |\boldsymbol{K}'(\boldsymbol{x})| d\boldsymbol{x}.$$

Theorem (Bercu, Capderou and Durrieu, 2019)

Assume that one can find a positive constant M such that, for all $1 \le k \le n$, $|Y_k| \le M$ a.s. Then, for any $x \in]0, 1[$ and for any positive t > 0,

$$\mathbb{P}\left(\left|\hat{f}_{n}'(\boldsymbol{x})-\mathbb{E}[\hat{f}_{n}'(\boldsymbol{x})]\right|\geq t\right)\leq 2\exp\left(-\frac{nh_{n}^{2}t^{2}}{2M^{2}\Lambda^{2}}\right),$$

$$\mathbb{P}\Big(\Big|\!\int_{\mathbb{R}} |\widehat{f}_{n}'(x) - f'(x)| dx - \mathbb{E}\Big[\!\int_{\mathbb{R}} |\widehat{f}_{n}'(x) - f'(x)| dx\Big]\Big| \ge t\Big) \le 2\exp\Big(-\frac{nh_{n}^{2}t^{2}}{2M^{2}\zeta^{2}}\Big).$$

< ロ > < 同 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ >

The data are generated from the regression model for k = 1, ..., n with n = 10,000 by

$$m{Y}_{m{k}} = m{f}(m{t}_{m{k}}) + m{arepsilon}_{m{k}}$$

where

- The source of variation (ε_n) is a sequence of iid random variables $\mathcal{N}(0, 1)$,
- The regression function *f* is given by

$$f(x) = (x+2)\sin(4\pi x^2) + 2\sin(8\pi x).$$

< ロ > < 同 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < 回 > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ >

Function *f* and n = 10,000 pairs of points (t_k, Y_k) .



NONPARAMETRIC STATISTICS FOR BIG DATA

æ

Almost sure convergence

Estimator of \hat{f}'_n using Gaussian kernel with $\alpha = 0.3$.



Asymptotic normality

Asymptotic normality for x = 0.7 and 10,000 replications.



NONPARAMETRIC STATISTICS FOR BIG DATA

э



Gilles Durrieu

NONPARAMETRIC STATISTICS FOR BIG DATA

Representation of data for one giant clam



Representation of the opening and closing velocity of one giant clam.



NONPARAMETRIC STATISTICS FOR BIG DATA

Representation of the velocity estimator of f'.



Histograms of the derivative estimators $\hat{f}'_n(x)$: in red for the warmest period and in blue for the coldest period in New Caledonia



NONPARAMETRIC STATISTICS FOR BIG DATA

Plan

Introduction

- 2 Random design regression
 - Estimators
 - Asymptotic properties
 - Simulation
 - Application in Brittany

3 Fixed design regression

- Estimators
- Asymptotic Properties
- Simulation
- Application in New Caledonia

Conclusion

글 🕨 🖌 글

Conclusion

- With tropical reefs around the world threatened by warming oceans, most research is focused on corals and fishes. Here, we show the effect of environmental conditions on bivalves and we suggest that bivalves can be an interesting sentinel species.
- The combination of nonparametric statistical procedure with high-frequency valvometry data provides a new way for studying the behavior of bioindicators.

< ロ > < 同 > < 回 > < 回 > .

Multidisciplinary work with

Mathematicians, biologists and ecologists from:

- Faculté des Sciences et Sciences de l'Ingénieur (UFR SSI) of Université Bretagne Sud, Lorient and Vannes.
- l'Institut des Sciences Exactes et Appliquées of University of New Caledonia, Nouméa.
- University of Bordeaux, Bordeaux.



NONPARAMETRIC STATISTICS FOR BIG DATA