The work of Oleg Lepski: beyond a "discourse on method"

Marc Hoffmann

Celebrating the 60th birthday of Oleg Lepski and Sacha Tsybakov

CIRM, Luminy, 21 December 2017

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In this talk

- This is a slightly biased but hopefully honest account of some of Oleg's many contributions to mathematical statistics over the last thirty years.
- This is also a personal approach, a tentative grasp of the part of his work and his scientific life that I like best or that I know best.
- <u>Disclaimer</u>: I am solely responsible for this talk and apologise for the (likely many) inaccuracies and oversimplifications that may follow.

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Content

- A brief overview of Oleg's vitae and career
- Part I: The Moscow years
- Part II: The Berlin years
- Part III: The Marseille years, up to now

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A final word of conclusion

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<u>Part I</u>: The Moscow years (*ca* 1983 – 1991)

- Early works
- A seminal paper
- Adaptive estimation: a theory in the making

Part II: The Berlin years (ca 1993 – 1998)

 Asymptotic adaptive efficiency in estimation and testing, more adaptive estimation

Mixing estimation and testing: the dawn of adaptive confidence sets?

Content

Part III: The Marseille years (1998 - today)

- Anisotropy
- The third adaptation period: the oracle approach and Anisotropy again

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A brief overview of Oleg's career and vitae



Figure: Oleg (courtesy of the Oberwolfach collection).

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We know him as

A mathematician, a statistician

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We know him as

- A mathematician, a statistician
- An academic, with a rich career slightly thwarted by history – over several countries

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A poet, a political pamphleteer, a friend



Figure: Oleg ca 1975. A poet in the making?

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Figure: Oleg ca 1975. Or a builder, a future theory maker?



Figure: Oleg *ca* 1975. He wouldn't be alone... (The "Pulsar" construction crew)

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Figure: Oleg ca 1975. And would work in an orderly way... .

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Figure: Oleg ca 2010. Apparently, a lot has been achieved...

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Figure: Oleg ca 1975. Simply a youthful character full of promises.

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- Born in 1957 in Moscow, son of an architect.
- ▶ PhD on 12 November 1984, "supervised" by A. P. Korostelev.
- Affiliated to the Institute for Systems Analysis, Russian Academy of Sciences.
- Participant of the Khasminski seminar in Moscow.
- ▶ 1992: Post-doc in Louvain-la-Neuve.
- Humboldt-Universität zu Berlin from 1993 to 1998. Stayed in the WIAS.

- 1998 up to now: Professor in LATP at the university of Aix-Marseille.
- Medallion lecture at the 2005 JSM, Minneapolis.

- <u>PhD students</u>: A. Yode, N. Klutchnikoff, F. Chiabrando, M. Chichignoud, N.B. Nguyen, G. Rebelles.
- Co-authors:

L. Cavalier, V.V. Fedorov, D. Feldmann, A. Goldenshluger, G.K. Golubev, C. Hafner, M. Hoffmann, W. Härdle, Wolfgang, Y.I. Ingster, A. Juditsky, G. Kerkyacharian, A.P. Korostelev, F. Leblanc, B. Levit, E. Mammen, A.S. Nemirovski, D. Picard, C. Pouet, N. Serdyukova, V. Spokoiny, A.B. Tsybakov, T. Willer.

 <u>MathSciNet</u> records <u>46 published papers</u> between 1983 and 2017. (There are more to come!)

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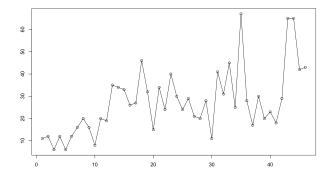


Figure: x-axis: papers (in paper time). y-axis: number of pages.

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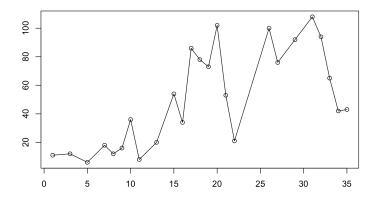


Figure: x-axis: time (in years since first publication). y-axis: number of pages.

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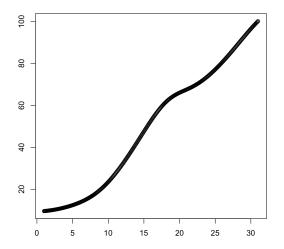


Figure: x-axis: time (in years since first publication). y-axis: number of pages. Smoothing by adaptive choice of bandwidth h = 4 years on [0, 31], KernSmooth package in R, locpoly function.

Part I: The Moscow years



Figure: Oleg around 1985.

The first (recorded) published paper by Oleg was actually devoted to solving a statistical problem...

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The first (recorded) published paper by Oleg was actually devoted to solving a statistical problem...

In for stochastic processes in discrete time!

- Lepskii, O.V. Asymptotic properties of estimates of parameters of a generalised autoregression scheme in the unstable case. (Russian).
 Vsesoyuz. Naucho-Issled. Instit. Sistem. Issled., Moscow (1983).
- <u>Problem</u>: estimate θ (and σ) from data (X_t)_{t=1,...,n} in the model

$$X_{t+1} = \ell_t(\vartheta)X_t + \sigma_t(\vartheta, \sigma)\xi_t, \quad \mathbb{E}[\xi_t] = 0, \quad \mathbb{E}[\xi_t^2] = 1.$$

• Under suitable assumptions, the problem is soved in the unstable case (something like $|\ell_t(\vartheta)| > 1$), a minimum contrast estimator is built and its limiting distribution is studied.

- Another paper is published in the same area two years later
- Korostelev, A.P., Lepskii, O.V., Fedorov, V.V. Analysis of time series generated by stochastic differential equations. (Russian). Uchen. Zap. Statist., 49, "Nauka", Moscow (1985)

- Probably around 1984-85, Oleg leaves (presumably forever) the subject of statistics for stochastic processes and moves to *minimax parametric estimation*. He still works closely with A.P. Korostelev.
- Lepskii, O.V. Asymptotically minimax estimation of a parameter under asymmetric loss functions. (Russian) *Teor. Veroyatnost. i Primenen.* (1987).
- Lepskii, O.V. Asymptotic minimax estimation with prescribed properties. (Russian) *Teor. Veroyatnost. i Primenen.* (1989).
- Korostelëv, A. P., Lepskii, O. V. Asymptotically minimax estimation in the change-point problem. (Russian) Statistics and control of random processes (Russian) (Preila, 1987) "Nauka", Moscow, 1989.

- In the first paper above, Oleg studies "situations [...] in which, apart from the natural requirement that an estimator is close to the parameter, the estimator is also subject to additional prescribed properties..."
- This is reminiscent of what Mark Low will call a few years later constrained estimation, in a problem of adaptive estimation, precisely already solved some years before by... Oleg!
- ▶ The work is inspired by D. Anbar (AOS, 1977) and allows one to consider *e.g.* in dimension one, a loss of the type

$$w(x) = (1 + |x|)\mathbf{1}_{\{x < 0\}} + x\mathbf{1}_{\{x \ge 0\}}$$

resulting in a minimax risk of the form

$$\inf_{\widehat{\vartheta}}\sup_{\vartheta\in\Theta}\big(\mathbb{P}_\vartheta(\widehat{\vartheta}<\vartheta)+\mathbb{E}_\vartheta\big[|\widehat{\vartheta}-\vartheta|\big]\big).$$

- In an asymptotic setting, a minimax lower bound is proved under a general LAN-type assumption on the model.
- ▶ If there exists an estimator $\widehat{\vartheta}_n$ with a certain concentration property (namely $\mathbb{P}_{\vartheta}(v_n^{-1}|\widehat{\vartheta} \vartheta| \ge t) \lesssim e^{-Ct^{C'}}$) the LB is achieved.
- The paper combines estimation and testing in a way that will prove essential in the later works of Oleg.
- I&K book's techniques in parametric estimation are everywhere, but limiting distributions are not the main focus for Oleg.

- Around 1987, Oleg presents at the Khasminski seminar an unexpected result on *nonparametric adaptation*, quite a new topic at that time.
- Oleg shows for the first time that there exist reasonable settings where rate adaptation is simply *not feasible*!
- He also proposes a notion of weaker adaptation and builds an adaptive estimator in that new sense.

The construction lays the foundations of what will later be coined the Lepski's method.

ТЕОРИЯ ВЕРОЯТНОСТЕЙ Том 35 И ЕЕ ПРИМЕНЕНИЯ Выпуск 3 1990

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ЛЕПСКИЙ О.В.

ОБ ОДНОЙ ЗАДАЧЕ АДАПТИВНОГО ОЦЕНИВАНИЯ В ГАУССОВСКОМ БЕЛОМ ШУМЕ

§ 1. Введение

На отрезне [0, 1] наблюдается случайный процесс, удовлетворяющий стохастическому дифференциальному уравшению

 $dX_{\varepsilon}(t) = S(t) dt + \varepsilon dw(t),$ (1)

где $\omega\left(\cdot\right)$ — стандартный винеровский процесс, $\varepsilon\to0$ — малый параметр. По паблядению за траекторней $X_{\varepsilon}\left(l\right),\ 0\leqslant t\leqslant 1$, требуются оденить величину S $\left(t_{0}\right)$, где t_{0} — известная фиксированная точка из интервала $\left(0,\ 1\right)$.

Обозначим через $\mathscr{Y}_{\mathbf{z}}$ совокупность измеримых относительно $X_{\mathbf{z}}(t)$, $0 \ll t \ll 4$, функций (оденок), а через $\mathbf{P}_{\mathbf{S}(\cdot)}$ и $\mathbf{E}_{\mathbf{S}(\cdot)}$ — меры и усреднения, соответствующие процессу $X_{\mathbf{z}}(t)$, $0 \ll t \ll 4$, при условии, что уравнение (1) порождаюсь функцией $S(\cdot)$.

Функцию $l: R^1 \to R^1$ будем называть функцией потерь (ф.п.), если опа неотрицательна, симметрична, ³донотовно не убывает на положительной полуоси, непрерымна в нуле и l(0) = 0.

Пусть Σ — произвольное множество функций. Рассмотрим минимаксный риск вида

$$R_{\varepsilon}(\tilde{\theta}_{\varepsilon}, \Sigma, \phi_{\Sigma}(\varepsilon)) = \sup_{S(\cdot)\in\Sigma} \mathbb{E}_{S(\cdot)} l(\phi_{\Sigma}^{-1}(\varepsilon)(\tilde{\theta}_{\varepsilon} - S(t_{0}))),$$

где $\tilde{\theta}_{\epsilon} \subseteq \mathscr{Y}_{\epsilon}$, а $q_{\Sigma}(\epsilon) > 0$ — нормирующая функция.

О пределение 1. Функцию $\varphi_{2}(s) > 0$ будем называть минимаксным порядком точности оценивания (MIIT) величины $S(t_{d})$ на множестве Σ очносительно ф. н. $t(\cdot)$, если

 $\lim \inf B_{*}(\hat{\theta}_{*}, \Sigma, m_{*}(s)) > 0$

Figure: A problem of adaptive estimation in Gaussian white noise, *Teor. Veroyatnost. i Primenen.*, 1990, Volume 35, Issue 3, 459–470.

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Отсюда

$$\overline{\lim_{\epsilon \to 0}} u_b(\epsilon) \left(\epsilon^2 \ln\left(1/\epsilon\right)\right)^{-b/(2b+1)} = 0.$$
(31)

В силу теоремы 2 выполнение соотношений (30) и (31) противоречит принадлежности семейства {U} множеству Ж. Полученное противоречие завершает доказательство теоремы.

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Теорема доказана.

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Поступила в редакцию 21.X11.1987

Figure: A problem of adaptive estimation in Gaussian white noise, *Teor. Veroyatnost. i Primenen.*, 1990, Volume 35, Issue 3, 459–470.

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тотическая теория оценивания. М.: На -

нках сигнала, его производных и точки - Теория вероятн. и ее примен., 1980,

чающийся алгоритм непараметрической т. 11, с. 58-65.

Поступила в редакцию 21.X11.1987

Figure: A problem of adaptive estimation in Gaussian white noise, *Teor. Veroyatnost. i Primenen.*, 1990, Volume 35, Issue 3, 459–470.

 $Y_{\varepsilon} = f + \varepsilon \dot{W}$ on $L^{2}([0,1])$ over Hölder classes $\Sigma_{\beta}, \beta > 0$.

<u>Result 1</u>: For any $0 < \beta_1 < \beta_2, t_0 \in [0, 1], q > 0$, one has

$$\liminf_{\varepsilon \to 0} \inf_{F(\cdot)} \sum_{i=1}^{2} \left(\varepsilon^2 \log(1/\varepsilon) \right)^{-\frac{\beta_i q}{2\beta_i + 1}} \sup_{f \in \Sigma_{\beta_i}} \mathbb{E}_f \left[\left| F(Y_{\varepsilon}) - f(t_0) \right|^q \right] > 0.$$

<u>Result 2</u>: There exists an estimator $\widehat{f_{\varepsilon}}(t_0)$, based on a certain comparison scheme, such that for any (closed and bounded) $\mathcal{I} \subset (0, \infty)$,

$$\sup_{\beta\in\mathcal{I}}\left(\varepsilon^2\log(1/\varepsilon)\right)^{-\frac{\beta q}{2\beta+1}}\sup_{f\in\Sigma_{\beta_i}}\mathbb{E}_f\big[\big|\widehat{f_\varepsilon}(t_0)-f(t_0)\big|^q\big]\lesssim 1.$$

• The construction looks very simple if $\mathcal{I} = \{\beta_{\min}, \beta_{\max}\}$. Let $h_{\varepsilon}(\beta) \approx (\varepsilon^2 \log(1/\varepsilon))^{2/(2\beta+1)}$. One can take

$$\widehat{f_{\varepsilon}}(t_{0}) = \begin{cases} K_{h_{\varepsilon}(\beta_{\min})} \star Y_{\varepsilon} & \text{if } \left| (K_{h_{\varepsilon}(\beta_{\min})} - K_{h_{\varepsilon}(\beta_{\max})}) \star Y_{\varepsilon} \right| \lesssim \varepsilon^{\frac{2\beta_{\min}}{2\beta_{\min}+1}} \\ K_{h_{\varepsilon}(\beta_{\max})} \star Y_{\varepsilon} & \text{otherwise} \end{cases}$$

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 But Oleg looks further, and introduces a notion of *optimal* adaptation in this context.

A family of normalising factors *F* = {*r*_ε(β), β ∈ *I*} is admissible if *r*_ε(β) is an adaptively achievable: there exists *f*_ε(*t*₀) such that

$$\sup_{\beta\in\mathcal{I}}r_{\varepsilon}(\beta)^{-q}\sup_{f\in\Sigma_{\beta}}\mathbb{E}_{f}\big[\big|\widehat{f}_{\varepsilon}(t_{0})-f(t_{0})\big|^{q}\big]\lesssim 1.$$

Let

 $\Psi_{\varepsilon}(\mathcal{F}) = \sup_{\beta \in \mathcal{I}} r_{\varepsilon}(\beta) \varepsilon^{-2\beta/(2\beta+1)} \text{ be the characteristic of } \mathcal{F}.$

The family \mathcal{F}^* is then Lepski adaptive optimal if

i) \mathcal{F}^* is admissible ii) There is no admissible \mathcal{F} such that $\Psi_{\varepsilon}(\mathcal{F}) \ll \Psi_{\varepsilon}(\mathcal{F}^*)$.

Two new features depart from previous existing (rigorous) adaptation results (Efromovich & Pinsker 1984, Golubev 1987):

- The Oleg's scheme is extremely flexible w.r.t. the loss function.
- It is a procedure selection among a given family of estimators that separately attain their minimax target.

This is the beginning of a vast program about a *theory of adaptive estimation* (still ongoing!)

A seminal paper: the no-adaptation result

- Oleg subsequently produced three papers developping a systematic approach for solving adaptive estimation (or possibly the lack thereof)
- Lepskii, O. V. Asymptotically minimax adaptive estimation. I. Upper bounds. Optimally adaptive estimates. (Russian) *Teor.* Veroyatnost. i Primenen. (1991).
- Lepskii, O. V. On problems of adaptive estimation in white Gaussian noise. Topics in nonparametric estimation, Adv. Soviet Math., Amer. Math. Soc., Providence, RI, (1992).
- Lepskii, O. V. Asymptotically minimax adaptive estimation. II.
 Schemes without optimal adaptation. Adaptive estimates. (Russian) *Teor. Veroyatnost. i Primenen.* (1992).

A seminal paper: the no-adaptation result

- In these papers, Oleg refines the Lepski's method by addressing several problems, including
 - i) Finding sufficient conditions for existence of adaptive estimation with a generic construction,
 - ii) Estimating adaptively Hölder signals in white noise under L^{p} -norm error and related functionals,
 - iii) Finding sufficient conditions for the nonexistence of adaptive estimators,
 - iv) Estimating adaptively functionals of Hölder signals in white noise.
- But, as claimed in the title, this talk shall not be a "discourse on method" so let us move on!

René Descartes: Discours de la méthode

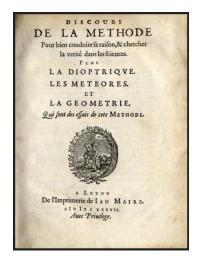


Figure: Discours de la méthode, pour bien conduire sa raison & chercher la vérité dans les sciences, 1668.

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Part II: The Berlin years



Figure: Weierstraß Institut, Mohrenstraße 39, Berlin Stadtmitte.

Uncertain times

- Uncertain times followed the collapse of Soviet Union for the participants of the now former Khasminski seminar.
- Oleg was invited in Louvain-la-Neuve in 1992, thanks to Sacha Tsybakov's influence – Sacha had preceded him there, before moving to France himself in 1993.
- In 1993, Oleg was invited to Berlin by M. Nußbaum, head of the Statistics research group in the Weierstraß Institute (WIAS) at that time.
- Affiliated to Humboldt University, Oleg would stay in WIAS for a few years. Volodia Spokoiny was there too.

The WIAS seminar



Figure: Celebration of the 50th anniversary of the WIAS seminar, less than a month ago!

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Adaptive efficient estimation and testing

- Besides the WIAS seminar, the Paris-Berlin Seminar was launched ca 1994. It would last until 1998 and would be followed by... Luminy!
- In Berlin, a fruitful period of collaboration between Oleg and Volodia (and others, including Sacha) started.

It would lead to some astonishingly original results in nonparametric estimation.

Adaptive efficient estimation and testing

- Lepskii, O. V., Spokoiny, V. G. Local adaptation to inhomogeneous smoothness: resolution level. Math. Methods Statist. (1995)
- Lepskii, O. V., Mammen, E., Spokoiny, V. G. Optimal spatial adaptation to inhomogeneous smoothness: an approach based on kernel estimates with variable bandwidth selectors. Ann. Statist. (1997).
- Lepski, O. V., Spokoiny, V. G. Optimal pointwise adaptive methods in nonparametric estimation. Ann. Statist. (1997).
- Lepski, O., Nemirovski, A., Spokoiny, V. On estimation of the *L^r*-norm of a regression function. *PTRF* (1999).
- Lepski, Oleg V., Spokoiny, V. G. Minimax nonparametric hypothesis testing: the case of an inhomogeneous alternative. *Bernoulli* (1999).

On estimation of the L^r -norm of a regression function

$$Y_{arepsilon}=f+n^{-1/2}\dot{W}$$
 on $L^2([0,1])$ over Hölder classes $\Sigma_{eta},eta>0.$

• Estimate:
$$\|f\|_r = \left(\int_0^1 |f(t)|^r dt\right)^{1/r}$$
 for a given $r \ge 1$.

Minimax risk:

$$\mathcal{R}_r(\widehat{f}_n) = \sup_{f \in \Sigma_\beta \cap \{ \|f\|_\infty \le \varrho \}} \mathbb{E}_f \left[\left| \widehat{f}_n - \|f\|_r \right| \right], \quad \mathcal{R}_r^\star = \inf_{\widehat{f}_n} \mathcal{R}(\widehat{f}_n).$$

Several results in connection with this problem were known for $r = 1, 2, 3, \infty$ at that time (an asymptotically exact constant result has also been proved by Oleg during the Moscow years). Also reminiscent of hypothesis testing.

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► The optimal rate lies somewhere between n^{-1/2} and n^{-β/(2β+1)}. It depends on the oddity of the exponent r!

On estimation of the L^r -norm of a regression function

• <u>Result 1</u>: For r = 1 one can construct \hat{f}_n such that

$$\mathcal{R}_1(\widehat{f}_n) \lesssim (n \log n)^{-\beta/(2\beta+1)}$$

which is better than the "nonparametric rate" $n^{-\beta/(2\beta+1)}$. • Result 2: If *r* is *not* an even integer

$$\mathcal{R}_r^\star \gtrsim (n \log n)^{-\beta/(2\beta+1)} (\log n)^{-r}$$

<u>Result 3</u>: If r is an even integer

$$n^{-\beta/(2\beta+1-1/r)} \lesssim \mathcal{R}_r^{\star} \lesssim n^{-\beta/(2\beta+1-1/r)}$$

 The construction uses previous (and tricky!) works by Ibragimov, Nemirovski and Khasminskii.

Random normalising factors

- Lepski, O. V. How to improve the accuracy of estimation. Math. Methods Statist. (1999)
- Hoffmann, M., Lepski, O. Random rates in anisotropic regression. Ann. Statist. (2002)
- General principle for two hypotheses: we are given

$$\left\{\mathbb{P}_{f}^{n}, f \in \Sigma_{\beta_{\min}}\right\}, \ \ \Sigma_{\beta_{\max}} \subset \Sigma_{\beta_{\min}},$$

with r_n^{β} , $\beta \in \{\beta_{\min}, \beta_{\max}\}$ minimax rates. Also, there exists an adaptive estimator $\hat{f_n}$:

$$\sup_{f\in\Sigma_{\beta_{\min}}}\mathbb{E}_{f}^{n}\big[r_{n}(f)^{-q}\|\widehat{f}_{n}-f\|_{L^{2}}^{q}\big]\lesssim1, \ q>0,$$

where

$$r_n(f) = \begin{cases} r_n^{\beta_{\max}} & f \in \Sigma_{\beta_{\max}}, \\ r_n^{\beta_{\min}} & f \in \Sigma_{\beta_{\min}} \setminus \Sigma_{\beta_{\max}}. \end{cases}$$

Random normalising factors

In particular, w.o.p.,

$$f \in \operatorname{Ball}_{L^2}(\widehat{f}_n, Cr_n(f)).$$

Not a confidence statement! (or accuracy of estimation).

• <u>Oleg's program</u>: $r_n(f) \rightsquigarrow \hat{r}_n$ (data-dependent) such that i) Convergence over Σ_{\min} is achievable for \hat{r}_n in place of $r_n(f)$, ii) Adaptation is still in force, iii) If $f \in \Sigma_{\beta_{\max}}$, w.o.p.,

$$\widehat{r}_n \ll r_n^{\beta_{\min}}$$

i.e. we have *improvement* of the accuracy of estimation.

Random normalising factors

 Typical result: for Hölder smoothness classes in Gaussian white noise:

$$\widehat{r}_{n} = \begin{cases} n^{-\frac{\beta_{\min}}{2\beta_{\min}+1/2} \wedge \frac{\beta_{\max}}{2\beta_{\max}+1}} & \text{w.o.p. if} \quad f \in \Sigma_{\beta_{\max}}, \\ n^{-\frac{\beta_{\min}}{2\beta_{\min}+1}} & \text{w.o.p. if} \quad f \in \Sigma_{\beta_{\min}} \setminus \Sigma_{\beta_{\max}}. \end{cases}$$

- ▶ Yields honest adaptive confidence L^2 -balls for $\beta_{\min} \leq \beta_{\max} \leq 2\beta_{\min}$ and nontrivial improvement otherwise.
- The construction relies on the fact that the rate of testing in L² is faster than the rate of estimation.
- Generalisation to several hypotheses and other situations.
- This somehow anticipates the development of adaptive confidence balls (Baraud, Van der Vaart, Cai & Low, Nickl and co-authors).

Part III: The Marseille years



Figure: Notre-Dame de la Garde, Marseille.

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Moving to France

- In the mid-nineties, thanks in part to the Paris-Berlin Seminar, Oleg and his work are now well introduced in France, Germany and beyond.
- A active group, driven by Dominique, Gérard and Sacha, prepares the next move for Oleg: France!
- Under the auspices of Etienne Pardoux, a probabilist, head of the Analysis and Probability Laboratory (LATP) in Marseille, a professorship is offered to Oleg in 1998.

This is the beginning of the third part of Oleg's carreer.

The "Pulsar" Oleg's crew by the end of the 1990's



Figure: Dominique, Gérard, Etienne and Sacha: friends, but also strong scientific and academic allies.

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Moving to France

- Yuri Golubev soon joins Oleg in Marseille as a senior researcher in CNRS.
- In a very few years, the Marseille school of mathematical statistics is raised, practically out of nothing!
- The group is alimented in part by students of Dominique and Sacha (Laurent, Christophe, Florent, Thomas).
- Starting in 2000, it organises a yearly Mathematical Statistics conference that will shape our community: the Luminy as we know it today!

The Marseille school



Figure: Yuri, Laurent, Christophe, Florent, Thomas, Thibault... and many of their other PhD students who moved to other academic institutions...

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The Marseille school

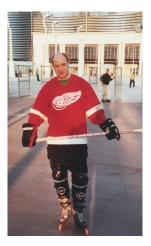


Figure: and Oleg of course... (Marseille, February 2002)

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Figure: Dominique and Oleg, ca 2010.

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$$Y_{\varepsilon} = f + n^{-1/2} \dot{W}$$
 on $L^{2}([0,1]^{d}), d \ge 1.$

<u>Goal</u>: estimate f in L^p-norm (minimax optimally, possibly adaptively) when the smoothness of f is non-homogeneous!

►
$$f \in B^{(s_1,...,s_d)}_{(p_1,...,p_d),\infty}$$
 if

$$\exists \ell \in \mathbb{N}, \forall i, s_i < \ell, \ \left\| \Delta_{h \boldsymbol{e}_i}^{\ell} f \right\|_{L^{p_i}} \leq C(f) |h|^{s_i}.$$

It will take two papers to Dominique, Gérard and Oleg to solve the problem, with a *formidable* combination of approximation analysis and modifications of *Lepski's method*.

- Kerkvacharian, G., Lepski, O., Picard D. Nonlinear estimation in anisotropic multi-index denoising. PTRF (2001)
- Kerkyacharian, G., Lepski, O., Picard, D. Nonlinear estimation in anisotropic multiindex denoising. Sparse case. Teor. Veroyatn. Primen. (2007), translation in Theory Probab. Appl. (2008)
- An extension of dense and sparse zones are defined, according to the sign of

$$\frac{2}{p} - \sum_{i=1}^{d} s_i^{-1} (p_i^{-1} - \frac{1}{2}).$$

For the dense case, we retrieve the expected rates:

$$\inf_{\widehat{f}_n} \sup_{\|f\|_{B^{(s_1,\ldots,s_d)}_{(p_1,\ldots,p_d),\infty}} \lesssim 1} \mathbb{E}_f \left[\|\widehat{f}_n - f\|_{L^p}^p \right] \approx n^{-sp/(2s+1)},$$

where $s^{-1} = \sum_{i=1}^{d} s_i^{-1}$ is the effective smoothness of the problem. (日) (型) (主) (主) (三) (0,0)

- In the sparse zone, the situation is more intricate, but similar phenomenae appear as in the homogeneous case. Minimaxity and adaptation (up to log terms in some cases) are fully covered.
- In some sense, the difficulties encountered in these papers (for adjusting Lepski's method, a cumbersome system of nonlinear equations for the bandwidths) will lead Oleg to revisit adaptive estimation.

This somehow anticipates the third period of adaptive estimation for Oleg, with a new Sasha!

From anisotropy to the third adaptation period



Figure: Dominique, Oleg, Sasha ca 2010.

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- Around 2005, Oleg has already started to collaborate with Sasha Goldenshluger on a new approach to *adaptive estimation*.
- Sacha Tsybakov and Oleg reunite to start their fourth common project. Anatoli Juditsky joins the party.
- They address an apparently innocuous problem of adaptive estimation, but it is probably a *new gateway to anisotropy*.
- The result is presented at the IMS Medallion Lecture of Oleg in Minneapolis, 2005.



Figure: Oleg (with S. Leonov and S. Efromovich) at the 2005 JSM, Minneapolis, where he presented *Nonparametric estimation of composite functions.*

Anisotropy II: intrinsic geometric smoothness

$$Y_{\varepsilon} = f + n^{-1/2} \dot{W}$$
 on $L^{2}([0,1]^{d}), d \ge 1.$

- ► The problem of estimating f is now fully understood if $f \in B_{(p_1,...,p_d),\infty}^{(s_1,...,s_d)}$.
- For f : [0, 1]^d → ℝ viewed as a (smooth) graph manifold, approximation properties heavily depend on the choice of coordinates.
- Typical examples include smooth image domain boundaries or certain solutions of nonlinear PDE's (recommended ref. is De Vore *et al.* Anisotropic smoothness spaces via level sets, *Comm. Pure Appl. Math.* 2008).

Another example is given by the large population limiting processes g(t, a) in age-structured populations:

$$\begin{cases} \frac{\partial}{\partial t}g(t,a) + \frac{\partial}{\partial a}(\mathbf{v}(a)g(t,a)) + \mu(t,a)g(t,a) = 0, \\ g(0,a) = \phi(a), \ g(t,0) = \int_{\mathbb{R}_+} b(t,a)g(t,a)da. \end{cases}$$

- ▶ $\mu \in B^{s_1,s_2}_{\infty}$, $b \in B^{s_2,s_3}_{\infty}$ and g is observed in small noise.
- We have $g \in B_{\infty}^{\alpha,\beta}$ for some $\alpha(s_i)$ and $\beta(s_i)$.
- However, for some $G : \mathbb{R}^2 \to \mathbb{R}^2$ related to $v(\cdot)$ we have

$$g(t,a)=f\circ G(t,a)$$

where $f \in B_{\infty}^{\alpha_+,\beta_+}$ is such that $\alpha_+ \ge \alpha$ and $\beta_+ \ge \beta$.

- Juditsky, A. B., Lepski, O. V., Tsybakov, A. B. Nonparametric estimation of composite functions. Ann. Statist. (2009)
- Under the structure g = f ∘ G with f : ℝ → ℝ and G : ℝ^d → ℝ, an estimator is constructed over isotropic Hölder classes.
- The structure encompasses many situations, including single-index and additive models.
- For $f \in B^{\gamma}_{\infty}$ and $G \in B^{\beta,...,\beta}_{\infty}$ with $\gamma, \beta > 0$, define

$$r_n^{\gamma,\beta} = \begin{cases} (n^{-1}\sqrt{\log n})^{\gamma/(2\gamma+1+(d-1)/\beta)}, & \beta > 1, \beta \ge d(\gamma-1)+1, \\ (n^{-1}\sqrt{\log n})^{1/(2+d/\beta)}, & \gamma > 1, \beta < d(\gamma-1)+1, \\ (n^{-1}\sqrt{\log n})^{2/(2+d/(\gamma\beta))}, & 0 < \gamma, \beta \le 1. \end{cases}$$

• A minimax lower bound is obtained: for every $q, \gamma, \beta > 0$:

$$\inf_{\widehat{g}_n} \sup_{g \in \mathcal{S}(\gamma,\beta)} \mathbb{E}_f \left[\| \widehat{g}_n - g \|_{L^{\infty}}^q \right] \gtrsim (r_n^{\gamma,\beta})^{-q}.$$

- An adaptive estimator is constructed, that achieves the lower bound up to log log n terms in some cases (over the second region in the definition of r_n^{γ,β} if moreover γ ≤ β ≤ 2).
- We have $\mathcal{S}(\gamma, \beta) \subset B_{\infty,\infty}^{\gamma\beta}$ if $0 < \gamma, \beta \leq 1$ and $\gamma \wedge \beta$ otherwise.
- However, several regions allows for rate improvements thanks to the *underlying composite structure* of the model.

 Adaptation is done w.r.t. the local structure, not the smoothness indices (γ, β). The third adaptation period: the oracle approach

- ► Goldenshluger, A., Lepski, O. Structural adaptation via L^p-norm oracle inequalities. PTRF (2009),
- Goldenshluger, A. Lepski, O. Universal pointwise selection rule in multivariate function estimation. *Bernoulli* (2008),
- Goldenshluger, A., Lepski, O. Uniform bounds for norms of sums of independent random functions. Ann. Probab. (2011),
- Goldenshluger, A., Lepski, O. Bandwidth selection in kernel density estimation: oracle inequalities and adaptive minimax optimality. *Ann. Statist.* (2011),

► Goldenshluger, A., Lepski, O. On adaptive minimax density estimation on ℝ^d. PTRF (2014).

The third adaptation period: the oracle approach

- Sasha and Oleg meet for the first time here in Luminy in 2000.
- In spring 2005, Oleg visits Sasha in Haïfa.
- They embark on an ambitious project about generalising and reformulating *adaptive estimation techniques*, motivated in part by the work with Dominique and Gérard on anisotropy.
- Around 2006, continuing ideas previously developed by Oleg with B. Levit, they progressively realise that they can base procedures à la Lepski by solving appropriate optimisation problems instead of comparisons of pseudo-estimators.

► This leads to the Goldenshluger-Lepski procedure.

Towards an end



Figure: A last tale ... A. Pouchkine "Boris Godounov".

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Happy birthday Oleg and Sacha!

THANK YOU FOR YOUR ATTENTION!

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