

Sampling projections in the uniform norm and optimal function recovery

Kateryna Pozharska

Institute of Mathematics of NAS of Ukraine, Kyiv, Ukraine
Faculty of Mathematics, Chemnitz University of Technology, Germany

Oslo, June 27, 2024

In the talk, we ...

- Provide new relations between the Sampling, Gelfand and Kolmogorov numbers. Optimality of information: **linear vs standard**.
- Give new **discretization results**.
- Discuss **the bounds for the norms of projection operators** (related to the Kadets-Snobar theorem and Auerbach's/Novak's lemma).

Joint work with David Krieg, Mario Ullrich and Tino Ullrich

- *Sampling projections in the uniform norm.* arXiv: 2401.02220, 2024.
- *Sampling recovery in L_2 and other norms.* arXiv: 2305.07539, 2023.

+ Work in progress with Felix Bartel and Tino Ullrich

Information \longrightarrow Recovery algorithm \longrightarrow Reconstructed function

$N(f)$

ψ

$f \approx \psi \circ N(f)$

- linear
 - Fourier coefficients
 - function values
 - nonlinear
 - non-adaptive
 - adaptive
- $$\|f - \psi \circ N(f)\|_G \rightarrow \min$$

Information → Recovery algorithm → Reconstructed function

$N(f)$

ψ

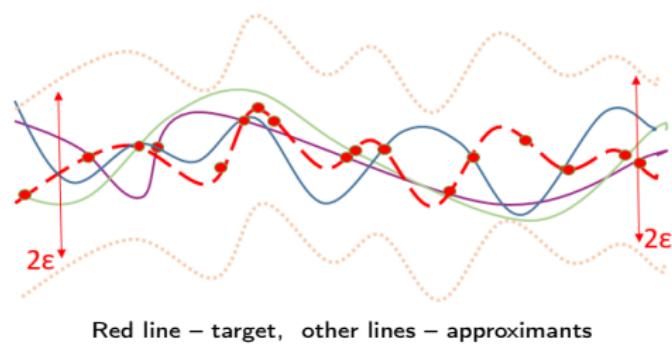
$f \approx \psi \circ N(f)$

- linear
 - Fourier coefficients
 - function values
 - nonlinear
 - linear
 - nonlinear
 - non-adaptive
 - adaptive
- $$\|f - \psi \circ N(f)\|_G \rightarrow \min$$

Given: $f(x_1), \dots, f(x_n)$, $x_i \in D$, $i = 1, \dots, n$, for $f \in F \subset G$.

Estimate: the ***n*-th linear sampling number** of F in G

$$g_n^{\text{lin}}(F, G) := \inf_{\substack{x_1, \dots, x_n \in D \\ \varphi_1, \dots, \varphi_n \in G}} \sup_{f \in F} \left\| f - \sum_{i=1}^n f(x_i) \varphi_i \right\|_G.$$



Red line – target, other lines – approximants

n -th Gelfand number $c_n(F, G)$: any algorithm, linear information

n -th approximation number $a_n(F, G)$: algorithm and information - linear

n -th Kolmogorov number

$$d_n(F, G) := \inf_{\substack{V_n \subset G \\ \dim(V_n) = n}} \sup_{f \in F} \inf_{g \in V_n} \|f - g\|_G$$

General relations

$$c_n(F, G) \leq a_n(F, G) \leq g_n^{\text{lin}}(F, G)$$

lin. inf.

arb. alg.

lin. inf.

lin. alg.

std. inf.

lin. alg.

General relations

$$c_n(F, G) \leq a_n(F, G) \leq g_n^{\text{lin}}(F, G)$$

lin. inf.

arb. alg.

lin. inf.

lin. alg.

std. inf.

lin. alg.

$$g_n^{\text{lin}}(F, G) \leq K(n)c_n(F, G) \longrightarrow \text{find the order of } K(n)$$

General relations

$$c_n(F, G) \leq a_n(F, G) \leq g_n^{\text{lin}}(F, G)$$

lin. inf.

arb. alg.

lin. inf.

lin. alg.

std. inf.

lin. alg.

$$g_n^{\text{lin}}(F, G) \leq K(n)c_n(F, G) \longrightarrow \text{find the order of } K(n)$$

For every **convex and balanced** set F , it holds

$$d_n(F, B(D)) \leq c_n(F, B(D))$$

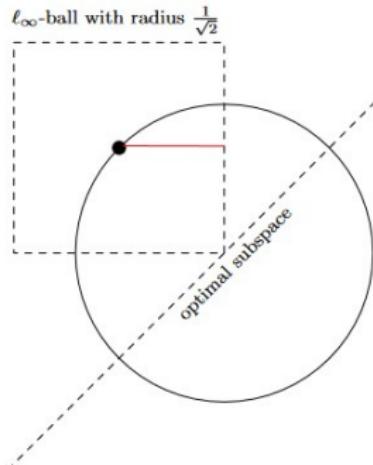
The goal: find $K(n)$ such that

$$g_n^{\text{lin}}(F, B(D)) \leq K(n)d_n(F, B(D)) \leq K(n)c_n(F, B(D))$$

Kolmogorov vs Gelfand numbers

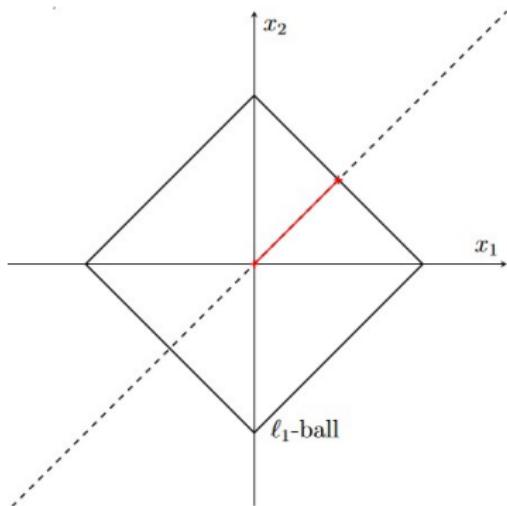
Kolmogorov numbers

$$d_1(B_2, \ell_\infty)$$



Gelfand numbers

$$c_1(B_1, \ell_2)$$



How large are the gaps? What is the order of $K(n)$?

Novak '88

$$g_{\textcolor{red}{n}}^{\text{lin}}(F, B(D)) \leq (\mathbf{1} + \textcolor{blue}{n}) d_n(F, B(D))$$

The factor $(1 + n)$ cannot be improved even for Hilbert spaces.

Kashin/Konyagin/Temlyakov '21

$$g_{\textcolor{red}{9^n}}^{\text{lin}}(F, B(D)) \leq \mathbf{5} d_n(F, B(D))$$

How large are the gaps? What is the order of $K(n)$?

Novak '88

$$g_{\textcolor{red}{n}}^{\text{lin}}(F, B(D)) \leq (\mathbf{1} + \textcolor{blue}{n}) d_n(F, B(D))$$

The factor $(1 + n)$ cannot be improved even for Hilbert spaces.

With an oversampling bn , $b > 1$ — YES — to \sqrt{n} !

Kashin/Konyagin/Temlyakov '21

$$g_{\textcolor{red}{9n}}^{\text{lin}}(F, B(D)) \leq \mathbf{5} d_n(F, B(D))$$

Theorem (KPUU '23)

For any set D , any $F \subset B(D)$, and all $n \in \mathbb{N}$, it holds

$$g_{2n}^{\text{lin}}(F, B(D)) \leq 58 \sqrt{n} d_n(F, B(D)).$$

For convex and balanced F , it holds

$$g_{2n}^{\text{lin}}(F, B(D)) \leq 58 \sqrt{n} c_n(F, B(D)).$$

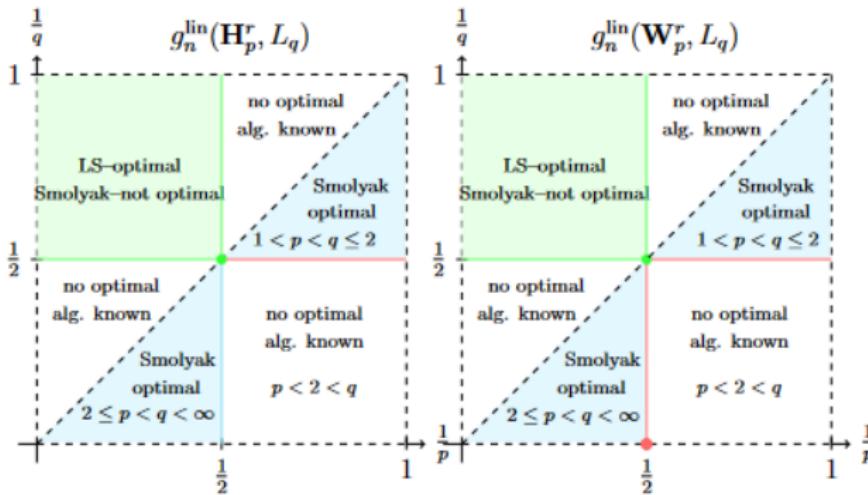
The factor \sqrt{n} in general cannot be improved!

Note: Sharp bound without \sqrt{n} in the Hilbert space setting satisfying certain conditions. (see [Geng, Wang '23] for the trigonometric system, [KPUU '23] for the general case)

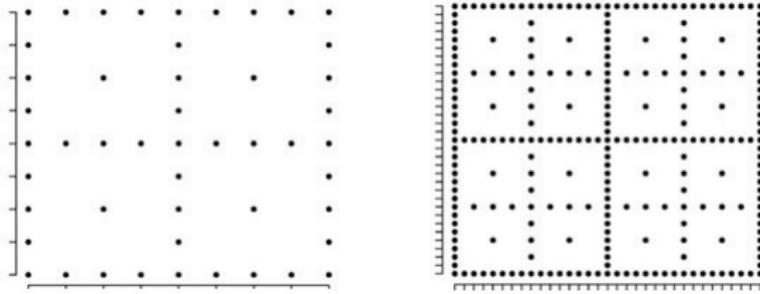
Nikol'skii-Besov $B_{p,\infty}^r \equiv H_p^r$ and Sobolev W_p^r spaces on the torus \mathbb{T}^d

$$\sup_{f \in F} \|f - A_m f\|_q \lesssim m^{-(r-t)} (\log m)^{(d-1)(r-t+\alpha)},$$

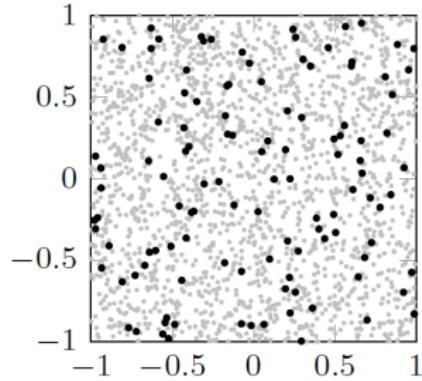
$$r > \max\{1/2, 1/p\}, \quad t := (1/p - 1/2)_+ + (1/2 - 1/q)_+, \quad \alpha = \begin{cases} 0 & F = W_p^r, 1 \leq q < \infty; \\ 1/2 & F = H_p^r, 1 \leq q < \infty; F = W_p^r, q = \infty; \\ 1 & F = H_p^r, q = \infty. \end{cases}$$



Smolyak points



Subsampled random points

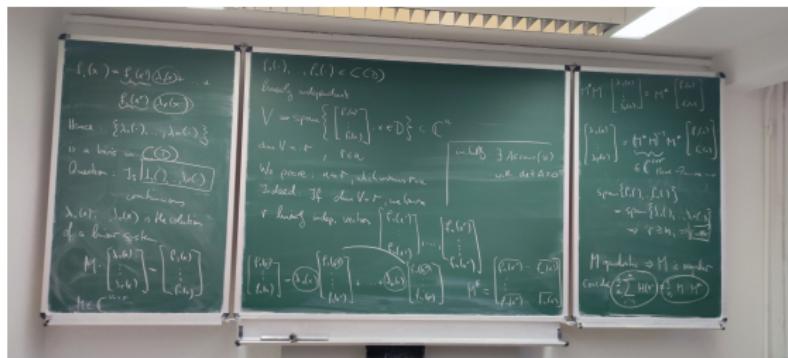


Discretization of the uniform norm

Lemma (KPUU '23)

Let D be a set and $V_n \subset B(D)$, $\dim V_n = n$. Then there exist $2n$ points $x_1, \dots, x_{2n} \in D$ such that, for all $f \in V_n$, we have

$$\|f\|_\infty \leq 58\sqrt{n} \left(\frac{1}{2n} \sum_{k=1}^{2n} |f(x_k)|^2 \right)^{1/2} \leq 58\sqrt{n} \max_{k=1, \dots, 2n} |f(x_k)|$$



Part of the proof.

Based on [Kiefer/Wolfowitz '60] + constructive subsampling.

Algorithm for continuous on a compact domain functions

- Given n linearly independent complex-valued functions $f_n \in C(D)$, for a fixed $x \in D$ solve

$$A := \max_{(x_k)_{k=1}^N, (\lambda_k)_{k=1}^N} \det(B^* B),$$

$$B := \begin{pmatrix} \sqrt{\lambda_1} f_1(x_1) & \sqrt{\lambda_1} f_2(x_1) & \cdots & \sqrt{\lambda_1} f_n(x_1) \\ \vdots & \vdots & \ddots & \vdots \\ \sqrt{\lambda_N} f_1(x_N) & \sqrt{\lambda_N} f_2(x_N) & \cdots & \sqrt{\lambda_N} f_n(x_N) \end{pmatrix}$$

with $N = n^2 + 1$ nodes $(x_k)_{k=1}^N$ and weights $(\lambda_k)_{k=1}^N$.

- Write the singular value decomposition

$$A = VDV^*, \quad A^{-1/2} = VD^{-1/2}V^*.$$

- Put

$$G(x) := A^{-1/2} F(x), \quad F := (f_1, \dots, f_n)^\top.$$

We get, that for the components of $G(x) = (g_1, \dots, g_n)^\top$ form an ONB in V_n w.r.t. the atomic measure $\varrho = \sum_{i=1}^N \lambda_i \delta_{x_i}$, and it holds

$$\sup_{f \in V_n \setminus \{0\}} \frac{\|f\|_\infty}{\|f\|_{L_2(\varrho)}} = \sup_{x \in D} \left(\sum_{i=1}^n |g_i(x)|^2 \right)^{1/2} \leq \sqrt{n}.$$

Theorem (KPUU '23)

Let D be a set and $V_n \subset B(D)$, $\dim V_n = n$. Then there are $2n$ points $x_i \in D$ and functions $\varphi_i \in V_n$, such that $P: B(D) \rightarrow V_n$ with

$$Pf = \sum_{i=1}^{2n} f(x_i) \varphi_i \quad \text{is a projection with} \quad \|P\| \leq 58\sqrt{n}.$$

Theorem is **sharp** in the following sense:

- Using $m = \mathcal{O}(n)$ samples, the norm bound $C\sqrt{n}$ cannot be replaced with a lower-order term.
- Using only $m = n$ samples, the norm bound $C\sqrt{n}$ has to be replaced by a linear term in n (Novak's/Auerbach's lemma).

Thank you for your attention!

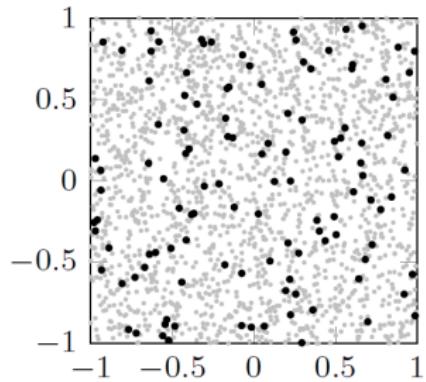
Krieg/M. Ullrich '19 (Parts I, II), Kämmerer/T. Ullrich/Volkmer '21,
M. Ullrich '20, Moeller/T. Ullrich '21, Nagel/Schäfer/T. Ullrich '21
Dolbeault/Krieg/M. Ullrich '22, Krieg/P./M. Ullrich/T. Ullrich '23

- F RKHS

$$g_{cn}^{\text{lin}}(F, L_2) \leq \sqrt{\frac{1}{n} \sum_{k \geq n} d_k(F, L_2)^2}$$

- F general

$$g_{cn}^{\text{lin}}(F, L_2) \leq \frac{1}{\sqrt{n}} \sum_{k \geq n} \frac{d_k(F, L_2)}{\sqrt{k}}$$



Bounds for Sampling numbers. Optimality.

If $d_n(F, L_2) \asymp n^{-\alpha} (\log n)^\gamma$ with $\alpha > 1/2$, $\gamma \in \mathbb{R}$, then

$$g_n^{\text{lin}}(F, L_2) \asymp d_n(F, L_2). \quad [\text{DKU '23}]$$

If $d_n(F, L_2) \asymp n^{-1/2} (\log n)^\gamma$ with $\gamma < -1$, then

$$g_n^{\text{lin}}(F, L_2) \lesssim \log n \cdot d_n(F, L_2). \quad [\text{KPUU '23}]$$

Temlyakov '21, Bartel/Schäfer/T. Ullrich '23

$$g_{bn}^{\text{lin}}(F, L_2) \leq \frac{Bb^3}{(b-1)^3} \cdot d_n(F, B(D))$$

Oversampling factor $b > 1$, $B > 0$ absolute constant.

P./T. Ullrich '22, Krieg/P./M. Ullrich/T. Ullrich '23

$$g_{2n}^{\text{lin}}(F, B(D)) \leq 58\sqrt{n} d_n(F, B(D))$$

$$g_{4n}^{\text{lin}}(F, L_p(\mu)) \leq 83 n^{(1/2-1/p)_+} d_n(F, B_\mu(D)), \quad 1 \leq p \leq \infty.$$

Improvement in the Hilbert space setting

Let $H \subset L_2(\mu)$ be a RKHS on a set D with a **bounded** kernel

$$K(x, y) = \sum_{k=1}^{\infty} \sigma_k^2 b_k(x) \overline{b_k(y)},$$

where $\sigma_1 \geq \sigma_2 \geq \dots \geq 0$; $\{b_k\}_{k=1}^{\infty}$ is orthonormal in $L_2(\mu)$.

The set $\{\sigma_k b_k\}_{k=1}^{\infty}$ is an orthonormal basis in H . [Steinwart/Scovel '12]

$$V_n = \text{span}\{b_1, \dots, b_n\}$$

$$\Lambda(V_n, B(D)) = \sup_{f \in V_n \setminus \{0\}} \|f\|_\infty / \|f\|_2$$

If $\Lambda(V_n, B(D)) := \sup_{f \in V_n \setminus \{0\}} \frac{\|f\|_\infty}{\|f\|_2} = \left\| \left(\sum_{k=1}^n |b_k|^2 \right)^{1/2} \right\|_\infty \lesssim \sqrt{n}$,

where $\{b_k\}_{k=1}^\infty$ is any ONB in $L_2(\mu)$ and μ is a finite measure, then

$$g_{cn}^{\text{lin}}(H, B(D)) \leq \sqrt{bB \cdot \mu(D)} \cdot c_n(H, B(D)).$$

Linear sampling algorithms are (up to constants) as powerful as arbitrary non-linear algorithms using general linear measurements.

We do not require any decay of the Gelfand width c_n !

Can also be applied for: the Haar or the Walsh systems, certain wavelets,
the Chebychev polynomials, the spherical harmonics, ...

Lemma (KPUU '23)

Let D be a set and $V_n \subset B(D)$, $\dim V_n = n$. Then there exist $2n$ points $x_1, \dots, x_{2n} \in D$ such that, for all $f \in V_n$, we have

$$\|f\|_\infty \leq 58 \sqrt{n} \left(\frac{1}{2n} \sum_{k=1}^{2n} |f(x_k)|^2 \right)^{1/2} \leq 58\sqrt{n} \max_{k=1, \dots, 2n} |f(x_k)|$$

- There exists a probability measure μ on D : $\forall f \in V_n \subset B(D)$

$$\|f\|_\infty \leq \sqrt{n + \varepsilon} \cdot \|f\|_2 \tag{1}$$

If $V_n \subset C(D)$ for some compact topological space D , then $\varepsilon = 0$.

Based on [Kiefer/Wolfowitz '60]

- There exists a point set $X \subset D$, $|X| \leq 2n$: $\forall f \in V_n$

$$\|f\|_2 \leq 57 \left(\frac{1}{|X|} \sum_{x \in X} |f(x)|^2 \right)^{1/2} \tag{2}$$

[Bartel/Schaefer/T. Ullrich '22]