Order-optimal point configurations for function approximation

David Krieg

based on joint work with M. Sonnleitner

August 28th, 2020





Function approximation

Let F be a normed space of bounded functions on a bounded and convex domain $\Omega \subset \mathbb{R}^d$ with unit ball B(F).

Let $P = \{x_1, \dots, x_n\} \subset \Omega$ be finite. The elements of P are called the sampling points. We want to approximate a function $f \in F$ based on the knowledge of $f(x_1), \dots, f(x_n)$, i.e., by algorithms

$$S_P(f) = \varphi(f(x_1), \dots, f(x_n)),$$

where $\varphi \colon \mathbb{R}^n \to L_\infty(\Omega)$ is arbitrary (or linear).

The error is measured in the $L_q(\Omega)$ -norm for some $1 \leq q \leq \infty$. We consider the minimal worst case error

$$e^{\operatorname{lin}}(P, F \hookrightarrow L_q(\Omega)) := \inf_{S_P} \sup_{f \in B(F)} \|f - S_P(f)\|_{L_q(\Omega)}.$$

Sobolev spaces

The Sobolev space $W^s_p(\Omega)$ of smoothness $s\in\mathbb{N}$ and integrability $1\leq p\leq\infty$ is the space

$$\begin{split} W_p^s(\Omega) &= \bigg\{ f \in L_p(\Omega) \colon \frac{\partial^{|\alpha|} f}{\partial x_1^{\alpha_1} \cdots \partial x_d^{\alpha_d}} \in L_p(\Omega) \text{ for all } \alpha \in I(s,d) \bigg\}, \\ \text{where } I(s,d) &= \{\alpha \in \mathbb{N}_0^d \colon |\alpha| = s\}, \text{ equipped with the norm} \\ & \|f\|_{W_p^s(\Omega)} = \|f\|_{L_p(\Omega)} + |f|_{W_p^s(\Omega)}, \\ & |f|_{W_p^s(\Omega)} = \Big\| \Big\| \frac{\partial^{|\alpha|} f}{\partial x_1^{\alpha_1} \cdots \partial x_J^{\alpha_d}} \Big\|_{L_p(\Omega)} \Big\|_{\ell_p(I(s,d))}. \end{split}$$

We will assume that s > d/p such that the space consists of continuous and bounded functions.

Optimal sampling points

Theorem 1 (Novak/Triebel, 2006)

$$\inf_{\#P \le n} e^{\lim}(P, W_p^s(\Omega) \hookrightarrow L_q(\Omega)) \ \asymp \ n^{-s/d + (1/p - 1/q)_+}.$$

The optimal order is achieved for point sets with covering radius of the optimal order

$$h_{P,\Omega} := \sup_{y \in \Omega} \operatorname{dist}(y, P) \approx n^{-1/d}.$$

- Novak and Triebel prove the result for bounded Lipschitz domains. The proof is based on a result of Wendland (2001).
- ▶ The result is much older for special domains like the cube.

Questions

Suppose that we cannot choose the sampling points P.

- Is there a simple way to determine their quality?
- ► Find a characterization of all those (sequences of) point sets that achieve the optimal order of convergence.
- How good are random sampling points?

Many authors use the covering radius to bound the error of sampling based algorithms. But this does not seem right: If we measure the error in L_q and q is small, then a few large gaps in the point set should be OK as long as most gaps are small.

Main result

Theorem 2

We have for any nonempty and finite point set $P \subset \Omega$ that

$$e^{\lim}(P, W_p^s(\Omega) \hookrightarrow L_q(\Omega)) \approx \begin{cases} \|\operatorname{dist}(\cdot, P)\|_{L_{\infty}(\Omega)}^{s - d(1/p - 1/q)} & \text{if } q \ge p, \\ \|\operatorname{dist}(\cdot, P)\|_{L_{\gamma}(\Omega)}^{s} & \text{if } q < p, \end{cases}$$

where $\gamma = s(1/q - 1/p)^{-1}$ and the implied constants are independent of P.

Main result

Theorem 2

We have for any nonempty and finite point set $P \subset \Omega$ that

$$e^{\mathbf{lin}}(P, W_p^s(\Omega) \hookrightarrow L_q(\Omega)) \approx \begin{cases} \|\operatorname{dist}(\cdot, P)\|_{L_{\infty}(\Omega)}^{s - d(1/p - 1/q)} & \text{if } q \ge p, \\ \|\operatorname{dist}(\cdot, P)\|_{L_{\gamma}(\Omega)}^s & \text{if } q < p, \end{cases}$$

where $\gamma = s(1/q - 1/p)^{-1}$ and the implied constants are independent of P.

Up next:

- discussion of the proof,
- related results (including the integration problem),
- examples and open problems.

Main result – What we are going to prove

Theorem 2

We have for any nonempty and finite point set $P \subset \Omega$ that

$$e^{\mathrm{lin}}(P, \dot{W_p^s}(\Omega) \hookrightarrow L_q(\Omega)) \, \asymp \, \begin{cases} \big\| \operatorname{dist}(\cdot, P) \big\|_{L_{\infty}(\Omega)}^{s - d(1/p - 1/q)} & \text{if } q \geq p, \\ \big\| \operatorname{dist}(\cdot, P) \big\|_{L_{\gamma}(\Omega)}^{s} & \text{if } q < p, \end{cases}$$

where $\gamma = s(1/q-1/p)^{-1}$ and the implied constants are independent of P.

Here.

$$\dot{W}_p^s(\Omega) = \{ f \in W_p^s(\mathbb{R}^d) \mid \text{supp } f \subset \overline{\Omega} \}.$$

A useful result from information-based complexity

For any normed space F of bounded functions (here $F = \dot{W}_p^s(\Omega)$), define the radius of information

$$r(P) = \sup \{ ||f||_{L_q(\Omega)} \colon f \in B(F), \ f|_P = 0 \}.$$

Lemma 1 (Folklore)

$$r(P) \le e(P) \le 2r(P)$$
.

- ► See e.g. the book of Novak and Woźniakowski (2008).
- ▶ If F is a Hilbert space, we even have equality, also for $e^{\text{lin}}(P)$.

Proof of the lower bound. Let $f_* \in B(F)$ with $f_* |_P = 0$. Any algorithm S_P of the form

$$S_P(f) = \varphi(f(x_1), \dots, f(x_n))$$

satisfies $S_P(f_*) = S_P(-f_*)$. We call f_* a fooling function. We obtain that

$$\sup_{f \in B(F)} \|S_P(f) - f\|_{L_q(\Omega)}$$

$$\geq \max \{ \|S_P(f_*) - f_*\|_{L_q(\Omega)}, \|S_P(f_*) + f_*\|_{L_q(\Omega)} \}$$

$$\geq \|f_*\|_{L_q(\Omega)}.$$

Proof of the upper bound. Consider an interpolatory algorithm

$$S_P(f) = \varphi(f(x_1), \dots, f(x_n))$$

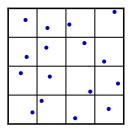
that maps $f \in B(F)$ to any function $g \in B(F)$ with $g|_{P} = f|_{P}$.

$$\sup_{f \in B(F)} \|f - S_P(f)\|_{L_q(\Omega)}$$

$$\leq \sup_{f,g \in B(F): |f|_P = g|_P} \|\underbrace{f - g}_{2h}\|_{L_q(\Omega)}$$

$$\leq \sup_{h \in B(F): |h|_P = 0} \|2h\|_{L_q(\Omega)}.$$

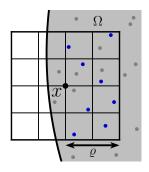
A useful result from approximation theory



There are constants m and C (depending on s, p, d) such that any function with a zero on each of the m^d subcubes of $[0,1]^d$ satisfies

$$\sup_{x \in [0,1]^d} |f(x)| \le C |f|_{W^s_p([0,1]^d)}.$$

- "Small derivatives and enough zeros yield small functions."
- This can be proven using a result of Wendland (2001) on polynomial reproducing maps and results on best polynomial approximation on $W_p^s([0,1]^d)$, see the book of Maz'ya (1985).



We define r(x) to be the infimum of all $\varrho>0$ such that each of the m^d open subcubes of $x+[-\varrho,\varrho]^d$ contains either a point of P or a point of $\mathbb{R}^d\setminus\Omega$.

We call $Q(x)=x+[-r(x),r(x)]^d$ a good cube. Note that Q(x)/2 contains an empty cube $Q^*(x)\subset\Omega$ of radius r(x)/2m.

Lemma 2

Every
$$f \in \dot{W}^s_p(\Omega)$$
 with $f|_P = 0$ satisfies

$$||f||_{L_q(Q(x))} \lesssim r(x)^{s(1+d/\gamma)} |f|_{W_p^s(Q(x))}.$$

There is an efficient covering of Ω by good cubes.

Lemma 3

There are points $y_1, \ldots, y_N \in \overline{\Omega}$ such that

- ► The cubes $Q_i = Q(y_i)$ cover $\overline{\Omega}$.
- ► The cubes $Q_i^* = Q^*(y_i)$ are pairwise disjoint.
- Every $y \in \mathbb{R}^d$ is contained in at most 2^d of the cubes Q_i .

Proof. The function r is upper semi-continuous. Choose y_1 as a maximizer of r on $\overline{\Omega}$, and recursively y_k as a maximizer of r on $\overline{\Omega} \setminus \bigcup_{i < k} Q_i$. The rest of the proof is homework.

Putting things together

Proof of the upper bound. Let f be from the unit ball of $\dot{W}^s_p(\mathbb{R}^d)$ such that $f|_P=0$. Then

$$\|f\|_{L_{q}(\Omega)}^{q} \, \leq \, \sum \|f\|_{L_{q}(Q_{i})}^{q} \, \lesssim \, \sum r_{i}^{sq(1+d/\gamma)} \, |f|_{W_{p}^{s}(Q_{i})}^{q}$$

and Hölder's inequality gives us

$$\leq \Big(\sum \underbrace{r_i^{\gamma+d}}_{\int_{Q_i^*} \operatorname{dist}(y,P)^{\gamma} dy}\Big)^{qs/\gamma} \Big(\sum \underbrace{|f|_{W_p^s(Q_i)}^p}_{\int_{Q_i} |\partial^{\alpha} f(y)|^p dy}\Big)^{q/p}$$

and using the efficiency of the covering,

$$\lesssim \left(\int_{\Omega} \operatorname{dist}(y, P)^{\gamma} dy\right)^{qs/\gamma}.$$

Putting things together

Proof of the lower bound. Recall that the Q_i^* are disjoint and empty subsets of Ω . Let T_i transform Q_i^* linearly into $[-1,1]^d$.

We take any nonnegative smooth function ψ with support in the cube $[-1,1]^d$ and $\psi(0)>0$ and let $\psi_i=\psi\circ T_i$. Define the fooling function

$$f_* = \frac{\sum \alpha_i \psi_i}{\left\| \sum \alpha_i \psi_i \right\|_{W_p^s(\Omega)}}.$$

By optimizing the α_i , we obtain the lower bound

$$||f_*||_{L_q(\Omega)} \gtrsim ||\operatorname{dist}(\cdot, P)||_{L_\gamma(\Omega)}^s.$$

Back to the theorem

Theorem 2

We have for any nonempty and finite point set $P \subset \Omega$ that

$$e^{\operatorname{lin}}(P, W_p^s(\Omega) \hookrightarrow L_q(\Omega)) \approx \begin{cases} \|\operatorname{dist}(\cdot, P)\|_{L_{\infty}(\Omega)}^{s - d(1/p - 1/q)} & \text{if } q \geq p, \\ \|\operatorname{dist}(\cdot, P)\|_{L_{\gamma}(\Omega)}^{s} & \text{if } q < p, \end{cases}$$

where $\gamma = s(1/p - 1/q)^{-1}$ and the implied constants are independent of P.

The result may be extended to ...

- ... a wider range of (isotropic) function spaces.
- ... more general domains.

Integration

The minimal worst-case error for the integration problem on a function space ${\cal F}$ is

$$e(P, F, \text{INT}) := \inf_{a_i \in \mathbb{R}} \sup_{f \in B(F)} \Big| \int_{\Omega} f(x) \, \mathrm{d}x - \sum_{i=1}^n a_i f(x_i) \Big|.$$

➤ Smolyak/Bakhvalov (1971): The infimum does not change if we also allow nonlinear algorithms.

Theorem 3

We have for any nonempty and finite point set $P \subset \Omega$ that

$$e(P, W_p^s(\Omega), INT) \simeq \|\operatorname{dist}(\cdot, P)\|_{L_{\gamma}(\Omega)}^s,$$

where $\gamma = s(1 - 1/p)^{-1}$.

Characterization of optimal sampling points

Corollary 1

A sequence of n-point sets P_n is optimal for $L_q(\Omega)$ -approximation or integration on $W_p^s(\Omega)$ in the sense that the minimal worst case error has the optimal order of convergence if and only if

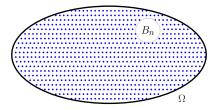
$$\|\operatorname{dist}(\cdot, P)\|_{L_{\gamma}(\Omega)} \asymp n^{-1/d},$$

where $\gamma = s(1/q - 1/p)^{-1}$ for q < p (with q = 1 for the integration problem) and $\gamma = \infty$ for $q \ge p$.

▶ The quantity $\|\operatorname{dist}(\cdot,P)\|_{L_{\gamma}(\Omega)}$ is also called the distortion of the point set P (or of the quantizer that "rounds" elements from Ω to elements of P).

Example: Data with a big hole

For $n \in \mathbb{N}$, let P_n be an n-point set and let B_n be a ball of radius r_n . Assume that the covering radius of P_n in $\Omega \setminus B_n$ is of optimal order $n^{-1/d}$.



▶ The point sets are order-optimal if and only if

$$r_n \lesssim n^{-1/d+1/(\gamma+d)}$$
.

▶ Compare with the size $n^{-1/d}$ of the other holes.

Example: Random sampling points

Let P_n be a set of n independent, uniformly distributed points. Then we have in various ways

$$\|\operatorname{dist}(\cdot, P)\|_{L_{\gamma}(\Omega)} \simeq \begin{cases} n^{-1/d} & \text{if } \gamma < \infty, \\ (n/\log n)^{-1/d} & \text{if } \gamma = \infty. \end{cases}$$

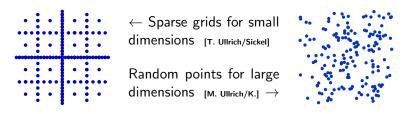
Precise statements may be found in Cohort (2004).

Corollary 2

Random data is optimal for $L_q(\Omega)$ -approximation (integration) on $W_p^s(\Omega)$ if and only if q < p.

Some open questions

- ► We did not manage to prove the result for the integration problem for general Triebel Lizorkin spaces.
- ▶ We believe that the results hold for more general domains (including all bounded Lipschitz domains) and manifolds.
- We can only guess how optimal point sets look like for function spaces of mixed smoothness (i.e., the derivatives up to order $\frac{\partial^{sd}}{\partial x_1^s...\partial x_d^s}$ are bounded). So far, the best known point sets in the Hilbert-case are:



References I



P. Cohort.

Limit theorems for random normalized distortion. Ann. Appl. Probab., 14(1):118-143, 2004.



D. Krieg and M. Ullrich.

Function values are enough for L_2 -approximation. arXiv:1905.02516, 2019.



🚺 V. G. Maz'ja.

Sobolev spaces.

Springer Series in Soviet Mathematics. Springer-Verlag, Berlin, 1985.

Translated from the Russian by T. O. Shaposhnikova.

References II



E. Novak and H. Triebel.

Function Spaces in Lipschitz Domains and Optimal Rates of Convergence for Sampling.

Constr. Approx., 23:325–350, 2006.



E. Novak and H. Woźniakowski.

Tractability of multivariate problems. Vol. 1: Linear information, volume 6 of EMS Tracts in Mathematics. European Mathematical Society (EMS), Zürich, 2008.



W. Sickel and T. Ullrich.

The smolyak algorithm, sampling on sparse grids and function spaces of dominating mixed smoothness.

East J. Approx., 13(4):387-425, 2007.

References III



H. Wendland. Scattered Data Approximation. Cambridge University Press, 2004.