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„Extraktion quantifizierbarer Information aus komplexen Systemen"

The Curse of Dimensionality for Numerical Integration of Smooth Functions

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Abstract

We prove the curse of dimensionality for multivariate integration of C^k functions. The proofs are based on volume estimates for $k = 1$ together with smoothing by convolution. This allows us to obtain smooth fooling functions for $k > 1$.

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Keywords: curse of dimensionality, numerical integration, high dimensional numerical problems

1 Introduction

We study multivariate integration for different classes F_d of smooth functions $f\colon \mathbb{R}^d \to \mathbb{R}$. Our emphasis is on large values of $d \in \mathbb{N}$. We want to approximate

$$S_d(f) = \int_{D_d} f(x)\,\mathrm{d}x \quad \text{for} \quad f \in F_d \tag{1}$$

up to some error $\varepsilon > 0$, where $D_d \subset \mathbb{R}^d$ has (Lebesgue) measure 1. The results in this paper hold for arbitrary sets D_d, the standard example of course is $D_d = [0,1]^d$.

We consider (deterministic) algorithms that use only function values. We consider classes F_d of functions bounded in absolute value by 1 and containing all constant functions $f(x) \equiv c$ with $|c| \le 1$. This implies that the initial error is one, i.e.,

$$\inf_{c\in\mathbb{R}} \max_{f\in F_d} |S_d(f) - c| = \max_{f\in F_d} |S_d(f)| = 1,$$

so that multivariate integration is well scaled and that is why we consider $\varepsilon < 1$.

Let $n(\varepsilon, F_d)$ denote the minimal number of function values needed for this task in the worst case setting[1]. By the *curse of dimensionality* we mean that $n(\varepsilon, F_d)$ is exponentially large in d. That is, there are positive numbers c, ε_0 and γ such that

$$n(\varepsilon, F_d) \ge c\,(1+\gamma)^d \quad \text{for all} \quad \varepsilon \le \varepsilon_0 \quad \text{and infinitely many} \quad d \in \mathbb{N}. \tag{2}$$

For many natural classes F_d the bound in (2) will hold for all $d \in \mathbb{N}$. This applies in particular to the classes considered in this paper.

[1] We add that $n(\varepsilon, F_d)$ is the information complexity of multivariate integration over F_d and is proportional to the (total) complexity as long as F_d is convex and symmetric. The last two assumptions are needed to guarantee that a linear algorithm is optimal and its implementation cost is linear in $n(\varepsilon, F_d)$.

There are many classes F_d for which the curse of dimensionality has been proved, see [5, 7] for such examples. However, it has been *not* known if the curse of dimensionality occurs for probably the most natural class which is the unit ball of r times continuously differentiable functions,

$$\mathcal{C}_d^r = \{f \in C^r(\mathbb{R}^d) \mid \ \|D^\beta f\| \le 1 \quad \text{for all} \quad |\beta| \le r\},$$

where $\beta = (\beta_1, \beta_2, \ldots, \beta_d)$, with non-negative integers β_j, $|\beta| = \sum_{j=1}^d \beta_j$, and D^β denotes the operator of β_j times differentiation with respect to the jth variable for $j = 1, 2, \ldots d$. By $\|\cdot\|$ we mean the sup norm, $\|D^\beta f\| = \sup_{x\in\mathbb{R}^d} |(D^\beta f)(x)|$.

For $r = 0$, we obviously have $n(\varepsilon, \mathcal{C}_d^0) = \infty$ for all $\varepsilon < 1$ and all $d \in \mathbb{N}$. Therefore from now on we always assume that $r \ge 1$. For $r = 1$, the curse of dimensionality for $\mathcal{C}_d^1$ follows from the results of Sukharev [8]. Whether the curse holds for $r \ge 2$ has been an open problem for many years.

The class $\mathcal{C}_d^r$ for $D_d = [0, 1]^d$ (and functions and norms restricted to D_d) was already studied in 1959 by Bakhvalov [2], see also [4]. He proved that there are two positive numbers $a_{d,r}$ and $A_{d,r}$ such that

$$a_{d,r}\, \varepsilon^{-d/r} \le n(\varepsilon, \mathcal{C}_d^r) \le A_{d,r}\, \varepsilon^{-d/r} \quad \text{for all } d \in \mathbb{N} \text{ and } \varepsilon \in (0, 1). \tag{3}$$

This means that for a fixed d and for ε tending to zero, we know that $n(\varepsilon, \mathcal{C}_d^r)$ is of order $\varepsilon^{-d/r}$ and the exponent of ε^{-1} grows linearly[2] in d. Unfortunately, since the known dependence on d in $a_{d,r}$ is exponentially small and the known dependence on d in $A_{d,r}$ is exponentially large in d, Bakhvalov's result does not allow us to conclude whether the curse of dimensionality holds for the class $\mathcal{C}_d^r$. In fact, if we reverse the roles of d and ε, and consider a fixed ε and d tending to infinity, the bound (3) on $n(\varepsilon, \mathcal{C}_d^r)$ is useless. We prove the following result.

Main Theorem. The curse of dimensionality holds for the classes $\mathcal{C}_d^r$ with the *super-exponential* lower bound

$$n(\varepsilon, \mathcal{C}_d^r) \;\ge\; c_r\,(1-\varepsilon)\, d^{\,d/(2r+3)} \quad \text{for all } d \in \mathbb{N} \text{ and } \varepsilon \in (0, 1),$$

where $c_r \in (0, 1]$ depends only on r.

We also prove that the curse of dimensionality holds for even smaller classes of functions F_d for which the norms of arbitrary directional derivatives are bounded proportionally to $1/\sqrt{d}$.

[2]In the language of tractability, this result means that we do *not have* polynomial tractability but does not allow us to conclude the lack of weak tractability.

We now discuss how we obtain lower bounds on $n(\varepsilon, F_d)$ for numerical integration defined on convex and symmetric classes F_d. The standard proof technique is to find a fooling function $f \in F_d$ that vanishes at the points $\mathcal{P} = \{x_1, x_2, \dots, x_n\}$ at which we sample functions from F_d, and the integral of f is as large as possible. All algorithms that use function values at x_j's must give the same approximation of the integral of f and of the integral of $-f$. That is why the integral of f is a lower bound on the worst case error of all algorithms using function values at x_j's. If for all choices of $x_1, x_2, \dots, x_n$ the integral of f is larger than ε then we know that $n(\varepsilon, F_d) \ge n$.

We start with the fooling function

$$f_0(x) = \min\left\{1, \frac{1}{\delta\sqrt{d}}\,\mathrm{dist}(x, \mathcal{P}_\delta)\right\} \quad \text{for all} \quad x \in \mathbb{R}^d,$$

where

$$\mathcal{P}_\delta = \bigcup_{i=1}^{n} B_\delta^d(x_i)$$

and $B_\delta^d(x_i)$ is the ball with center x_i and radius $\delta\sqrt{d}$. The function f_0 is Lipschitz. By a suitable smoothing via convolution we construct a fooling function $f_r \in \mathcal{C}_d^r$ and $f_r|_{\mathcal{P}} = 0$.

2 Preliminaries

In this section we precisely define our problem. Let F_d be a class of functions $f : \mathbb{R}^d \to \mathbb{R}$ such that $S_d(f)$, see (1), exists for every $f \in F_d$. We approximate the integral $S_d(f)$, $f \in F_d$, by algorithms

$$A_{n,d}(f) = \phi_{n,d}\big(f(x_1), f(x_2), \dots, f(x_n)\big),$$

where $x_j \in \mathbb{R}^d$ can be chosen adaptively and $\phi_{n,d} : \mathbb{R}^n \to \mathbb{R}$ is an arbitrary mapping. Adaption means that the selection of x_j may depend on the already computed values $f(x_1), f(x_2), \dots, f(x_{j-1})$. The (worst case) error of the algorithm $A_{n,d}$ is defined as

$$e(A_{n,d}) = \sup_{f \in F_d} |S_d(f) - A_{n,d}(f)|.$$

The minimal number of function values to guarantee that the error is at most ε is defined as

$$n(\varepsilon, F_d) = \min\{\, n \in \mathbb{N} \;\big|\; \exists\ A_{n,d} \ \text{ such that } \ e(A_{n,d}) \le \varepsilon\}.$$

Hence we minimize n over all choices of adaptive sample points x_j and mappings $\phi_{n,d}$. It is well known that as long as the class F_d is convex and symmetric we may restrict the minimization of n by considering only nonadaptive choices of x_j and linear mappings $\phi_{n,d}$. Furthermore,

$$n(\varepsilon, F_d) = \min\Big\{ n \in \mathbb{N} \mid \inf_{\mathcal{P}\subset\mathbb{R}^d, \#\mathcal{P}=n} \ \sup_{f\in F_d, f|_{\mathcal{P}}=0} |S_d(f)| \le \varepsilon \Big\}, \tag{4}$$

see [4, Prop. 1.2.6] or [9, Theorem 5.5.1]. In this paper we always consider convex and symmetric F_d so that we can use the last formula for $n(\varepsilon, F_d)$. For more details see, e.g., Chapter 4 in [5].

Observe that we allow $x_j \in \mathbb{R}^d$ instead of only $x_j \in D_d$. In this paper we are interested in *lower* bounds and this assumption makes our results even stronger.

As already mentioned, our lower bounds are based on a volume estimate of a neighborhood of certain sets in $\mathbb{R}^d$, see also [3]. In the following we denote by A_δ, for $A \subset \mathbb{R}^d$, the $(\delta\sqrt{d})$-neighborhood of A, which is defined by

$$A_\delta = \big\{ x \in \mathbb{R}^d \mid \ \mathrm{dist}(x, A) \le \delta\sqrt{d} \big\}, \tag{5}$$

where $\mathrm{dist}(x, A) = \inf_{a\in A} \|x - a\|_2$ denotes the Euclidean distance of x from A.

Since we need the $\sqrt{d}$-scaling of the distance, we will omit it in the notation as we already did for A_δ. Furthermore, we denote by $B^d_\delta(x)$ the d-dimensional ball with center $x \in \mathbb{R}^d$ and radius $\delta\sqrt{d}$, i.e.,

$$B^d_\delta(x) \ = \ \big\{ y \in \mathbb{R}^d \mid \ \|x - y\|_2 \le \delta\sqrt{d} \big\}.$$

We will need some standard volume estimates for Euclidean balls. Recall that the volume of a Euclidean ball of radius 1 is given by

$$V_d = \frac{\pi^{d/2}}{\Gamma(1 + d/2)}.$$

From Stirling's formula for the Γ function we have

$$\Gamma(x + 1) = \sqrt{2\pi x}\, x^x\, \mathrm{e}^{-x+\frac{\theta_x}{12x}} \quad \text{for all} \quad x > 0,$$

where $\theta_x \in (0, 1)$, see [1, p. 257]. This leads to the estimate

$$\Gamma(x + 1) > \sqrt{2\pi x}\, \Big(\frac{x}{\mathrm{e}}\Big)^x \quad \text{for all} \quad x > 0.$$

Combining this estimate with the volume formula for the ball, we obtain for all $d \in \mathbb{N}$,

$$\lambda_d\big(B^d_\delta(x)\big) = \big(\delta\sqrt{d}\big)^d\, V_d < \big(\delta\sqrt{d}\big)^d \frac{\left(\frac{2\pi\mathrm{e}}{d}\right)^{d/2}}{\sqrt{\pi d}} = \frac{\big(\delta\sqrt{2\pi\mathrm{e}}\big)^d}{\sqrt{\pi d}} < \Big(\delta\sqrt{2\pi\mathrm{e}}\Big)^d. \tag{6}$$

The volume formula for the Euclidean unit ball also shows the recurrence relation

$$\frac{V_{d-1}}{V_d} = \frac{d}{d-1}\,\frac{V_{d-3}}{V_{d-2}} \quad \text{for all} \quad d \geq 4.$$

This easily implies

$$\frac{2}{\sqrt{d}}\,\frac{V_{d-1}}{V_d} < \frac{2}{\sqrt{d-2}}\,\frac{V_{d-3}}{V_{d-2}} \quad \text{for all} \quad d \geq 4.$$

The last inequality can be used in an inductive argument leading to

$$\frac{2}{\sqrt{d}}\,\frac{V_{d-1}}{V_d} \leq 1 \quad \text{for all} \quad d \geq 2. \tag{7}$$

This will be needed later.

3 Convolution

In this section we fix $k \in \mathbb{N}$ and study the convolution

$$f_k := f * g_1 * \ldots * g_k$$

of a function f defined on $\mathbb{R}^d$ with (normalized) indicator functions g_j. We are interested in properties of f_k in terms of the properties of the initial function f. Recall that the convolution of two functions f and g on $\mathbb{R}^d$ is defined by

$$(f * g)(x) = \int_{\mathbb{R}^d} f(x-t)\, g(t)\, \mathrm{d}t \quad \text{for all} \quad x \in \mathbb{R}^d.$$

Fix a number $\delta > 0$ and a sequence $(\alpha_j)_{j=1}^k$ with $\alpha_j > 0$ such that

$$\sum_{j=1}^{k} \alpha_j \leq 1.$$

For example, we may take $\alpha_j = 1/k$ for $j = 1, 2 \ldots, k$. For $j = 1, \ldots, k$, we define the ball

$$B_j \; = \; \left\{ x \in \mathbb{R}^d \,\middle|\; \|x\|_2 \;\leq\; \alpha_j\, \delta \sqrt{d} \right\}$$

and the function $g_j \colon \mathbb{R}^d \to \mathbb{R}$ by

$$g_j(x) \; = \; \frac{\mathbb{1}_{B_j}(x)}{\lambda_d(B_j)} \; = \; \frac{1}{\lambda_d(B_j)} \begin{cases} 1 & \text{if } x \in B_j, \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

Thus, the convolution of a function f with g_j can be written as

$$(f * g_j)(x) \;=\; \frac{1}{\lambda_d(B_j)} \int_{B_j} f(x+t)\,\mathrm{d}t \quad \text{for all} \quad x \in \mathbb{R}^d.$$

We will frequently use the following probabilistic interpretation. Let Y_j be a random variable that is uniformly distributed on B_j. Then the convolution of f with g_j can be written as the expected value

$$(f * g_j)(x) \;=\; \mathbb{E}\big[f(x+Y_j)\big].$$

The next theorem is the basis for the induction steps of the proofs of our main results. For $f\colon \mathbb{R}^d \to \mathbb{R}$, we use the Lipschitz constant

$$\mathrm{Lip}(f) = \sup_{x \neq y} \frac{|f(x)-f(y)|}{\|x-y\|_2}.$$

Define

$$C^r = \big\{ f\colon \mathbb{R}^d \to \mathbb{R} \mid \quad D^{\theta_\ell} \ldots D^{\theta_1} f \text{ is continuous for all } \ell \leq r \text{ and all } \theta_1, \ldots, \theta_r \in \mathbb{S}^{d-1} \big\},$$

where $\mathbb{S}^{d-1}$ is the unit sphere in $\mathbb{R}^d$ and $D^{\theta_1} f(x) = \lim_{h \to 0} \frac{1}{h}\big(f(x+h\theta_1) - f(x)\big)$ is the derivative in the direction of θ_1.

Theorem 1. For $k \in \mathbb{N}$ and $f \in C^r$, define

$$f_k = f * g_1 * \ldots * g_k \quad \text{with} \quad g_j \text{ from (8)}.$$

For $d \geq 2$, let $\Omega \subset \mathbb{R}^d$ and let Ω_δ be its neighborhood defined as in (5). Then

(i) if $f(x) = 0$ for all $x \in \Omega_\delta$ then $f_k(x) = 0$ for all $x \in \Omega$,

(ii) $\mathrm{Lip}(f_k) \leq \mathrm{Lip}(f)$,

(iii) if $\int_{D_d} f(x+t)\,\mathrm{d}x \;\geq\; \varepsilon$ for all $t \in \mathbb{R}^d$ with $\|t\|_2 \leq \delta\sqrt{d}$ then $\int_{D_d} f_k(x)\mathrm{d}x \geq \varepsilon$,

(iv) for all $\ell \leq r$ and all $\theta_1, \theta_2, \ldots, \theta_\ell \in \mathbb{S}^{d-1}$,

$$\mathrm{Lip}\Big(D^{\theta_\ell}\, D^{\theta_{\ell-1}} \ldots D^{\theta_1} f_k\Big) \leq \mathrm{Lip}\Big(D^{\theta_\ell}\, D^{\theta_{\ell-1}} \ldots D^{\theta_1} f\Big),$$

(v) $f_k \in C^{r+k}$, and for all $\ell \leq r$, all $j = 1, \ldots, k$ and all $\theta_1, \theta_2, \ldots, \theta_{\ell+j} \in \mathbb{S}^{d-1}$,

$$\mathrm{Lip}\Big(D^{\theta_{\ell+j}}\, D^{\theta_{\ell+j-1}} \ldots D^{\theta_1} f_k\Big) \leq \Bigg(\prod_{i=1}^{j} \frac{1}{\delta \alpha_{k+1-i}}\Bigg) \mathrm{Lip}\Big(D^{\theta_\ell}\, D^{\theta_{\ell-1}} \ldots D^{\theta_1} f\Big).$$

The parts (i)–(iv) of this theorem show that some properties of the initial function f are preserved by convolutions. Part (v) states that we gain one "degree of smoothness" with every convolution, loosing only a multiplicative constant for its Lipschitz constant.

Proof. First note that we can write f_k as

$$f_k(x) \;=\; \mathbb{E}\big[f(x+Y)\big], \quad \text{for all} \quad x \in \mathbb{R}^d,$$

where Y is a random variable with probability density function $g_1 * \ldots * g_k$. By construction of g_j's which are the indicator functions of the balls whose sum of the radii is at most $\delta\sqrt{d}$, we have

$$\{t \in \mathbb{R}^d \mid \; g_1 * \ldots * g_k(t) > 0\} \subset \{t \in \mathbb{R}^d \mid \; \|t\|_2 \le \delta\sqrt{d}\},$$

which implies that $x+Y \in \Omega_\delta$ almost surely for every $x \in \Omega$. Thus, $f(x) = 0$ for all $x \in \Omega_\delta$ implies that $f_k(x) = 0$ for all $x \in \Omega$, which is property (i).

Property (ii) is proven by

$$\begin{aligned} |f_k(x) - f_k(y)| \;&=\; \big|\mathbb{E}\big[f(x+Y) - f(y+Y)\big]\big| \;\le\; \mathbb{E}\big[|f(x+Y) - f(y+Y)|\big] \\ &\le\; \mathrm{Lip}(f)\, \mathbb{E}\big[\|(x+Y) - (y+Y)\|_2\big] \;=\; \mathrm{Lip}(f)\, \|x-y\|_2\,. \end{aligned}$$

To prove (iii), we use Fubini's theorem and we obtain

$$\int_{D_d} f_k(x)\,\mathrm{d}x \;=\; \int_{D_d} \mathbb{E}\big[f(x+Y)\big]\,\mathrm{d}x \;=\; \mathbb{E}\Big[\int_{D_d} f(x+Y)\,\mathrm{d}x\Big] \;\ge\; \varepsilon$$

by assumption.

For the proof of properties (iv) and (v), let $\theta = (\theta_1, \ldots, \theta_\ell) \in (\mathbb{S}^{d-1})^\ell$. We write D^θ for $D^{\theta_\ell} \ldots D^{\theta_1}$. Clearly, $f \in C^r$ and $\ell \le r$ implies that $D^\theta f \in C^{r-\ell} \subseteq C$. Since f_k is at least as smooth as f, both $D^\theta f$ and $D^\theta f_k$ are well defined.

We need the well-known fact that $D^\theta(f * g) = (D^\theta f) * g$ if $f \in C^\ell$ and g has compact support. For $g = g_1 * \ldots * g_k$, we have

$$\begin{aligned} \big|D^\theta f_k(x) - D^\theta f_k(y)\big| \;&=\; \big|\big((D^\theta f) * g\big)(x) - \big((D^\theta f) * g\big)(y)\big| \\ &=\; \left|\int_{\mathbb{R}^d} \big[(D^\theta f(x+t) - D^\theta f(y+t)\big]\; g(t)\mathrm{d}t\right| \\ &\le\; \mathrm{Lip}(D^\theta f)\; \|x-y\|_2 \int_{\mathbb{R}^d} g(t)\mathrm{d}t \\ &=\; \mathrm{Lip}(D^\theta f)\; \|x-y\|_2 \end{aligned}$$

for all $x, y \in \mathbb{R}^d$. The last equality follows since the g_k is normalized. This proves (iv).

For (v), we need to prove that $f_k \in C^{r+k}$ with $f_0 = f \in C^r$ by assumption, and then it is enough to show that for all $m \le r+k$ and all $\theta = (\theta_m, \dots, \theta_1) \in (\mathbb{S}^{d-1})^m$,

$$\operatorname{Lip}\Big(D^\theta f_k\Big) \le \frac{1}{\delta \alpha_k} \operatorname{Lip}\Big(D^{\bar\theta} f_{k-1}\Big),$$

where $\bar\theta = (\theta_{m-1}, \dots, \theta_1) \in (\mathbb{S}^{d-1})^{m-1}$.

Assume inductively that $f_{k-1} \in C^{m-1}$, which holds for $k = 1$. This implies $D^{\bar\theta}(f_{k-1} * g_k) = (D^{\bar\theta} f_{k-1}) * g_k$, and

$$\begin{aligned}
D^\theta f_k(x) &= D^{\theta_m}\big((D^{\bar\theta} f_{k-1}) * g_k\big)(x) \\
&= D^{\theta_m}\Big(\frac{1}{\lambda_d(B_k)} \int_{\mathbb{R}^d} D^{\bar\theta} f_{k-1}(x+t)\, \mathbb{1}_{B_k}(t)\, \mathrm{d}t\Big) \\
&= \frac{1}{\lambda_d(B_k)}\, D^{\theta_m}\Big(\int_{\theta_m^\perp} \int_{\mathbb{R}} D^{\bar\theta} f_{k-1}(x+s+h\theta_m)\, \mathbb{1}_{B_k}(s+h\theta_m)\, \mathrm{d}h\, \mathrm{d}s\Big) \\
&= \frac{1}{\lambda_d(B_k)} \int_{\theta_m^\perp} D^{\theta_m}\Big(\int_{\mathbb{R}} D^{\bar\theta} f_{k-1}(x+s+h\theta_m)\, \mathbb{1}_{B_k}(s+h\theta_m)\, \mathrm{d}h\Big)\, \mathrm{d}s,
\end{aligned}$$

where $\theta_m^\perp$ is the hyperplane orthogonal to θ_m. For any function f on $\mathbb{R}$ of the form

$$f(x) = \int_{x-a}^{x+a} g(y)\, \mathrm{d}y$$

with some continuous function g we have

$$f'(x) = g(x+a) - g(x-a).$$

Therefore, we obtain

$$\begin{aligned}
D^\theta f_k(x) = \frac{1}{\lambda_d(B_k)} \int_{B_k \cap \theta_m^\perp} \Big[& D^{\bar\theta} f_{k-1}\Big(x+s+h_{\max}(s)\,\theta_m\Big) \\
& - D^{\bar\theta} f_{k-1}\Big(x+s-h_{\max}(s)\,\theta_m\Big)\Big]\, \mathrm{d}s
\end{aligned}$$

with

$$h_{\max}(s) = \max\{h \ge 0 \mid \quad s + h\theta_m \in B_k\}.$$

For each $s \in B_k \cap \theta_m^\perp$, define the points $s_1 = s + h_{\max}(s)\,\theta_m \in B_k$ and $s_2 = s - h_{\max}(s)\,\theta_m \in B_k$. Then

$$\begin{aligned}
\left|D^\theta f_k(x) - D^\theta f_k(y)\right| \;&\le\; \frac{1}{\lambda_d(B_k)} \int_{B_k \cap \theta_m^\perp} \Big[\Big|D^{\bar\theta} f_{k-1}\big(x+s_1\big) \,-\, D^{\bar\theta} f_{k-1}\big(x+s_2\big) \\
&\qquad\qquad - D^{\bar\theta} f_{k-1}\big(y+s_1\big) \,+\, D^{\bar\theta} f_{k-1}\big(y+s_2\big)\Big|\Big]\,\mathrm{d}s \\
&\le\; \frac{1}{\lambda_d(B_k)} \int_{B_k \cap \theta_m^\perp} \Big[\Big|D^{\bar\theta} f_{k-1}\big(x+s_1\big) \,-\, D^{\bar\theta} f_{k-1}\big(y+s_1\big)\Big| \\
&\qquad\qquad + \Big|D^{\bar\theta} f_{k-1}\big(x+s_2\big) \,-\, D^{\bar\theta} f_{k-1}\big(y+s_2\big)\Big|\Big]\,\mathrm{d}s \\
&\le\; \frac{2\,\lambda_{d-1}(B_k \cap \theta_m^\perp)}{\lambda_d(B_k)}\, \mathrm{Lip}(D^{\bar\theta} f_{k-1})\; \|x-y\|_2\,.
\end{aligned}$$

In particular, this shows the implication

$$f_{k-1} \in C^{m-1} \implies f_k \in C^m$$

for all $k \in \mathbb{N}$. Taking $m = r+k$ we have $f_k \in C^{r+k}$, as claimed.

For $m \le r+k$, it remains to bound $2\lambda_{d-1}(B_k \cap \theta_m^\perp)/\lambda_d(B_k)$. Recall that B_k is a ball with radius $\delta\alpha_k\sqrt{d}$ and that V_d is the volume of the Euclidean unit ball in $\mathbb{R}^d$. We obtain from (7) that

$$\frac{2\,\lambda_{d-1}(B_k \cap \theta_m^\perp)}{\lambda_d(B_k)} \;=\; \frac{2(\delta\alpha_k\sqrt{d})^{d-1}}{(\delta\alpha_k\sqrt{d})^d}\,\frac{V_{d-1}}{V_d} \;=\; \frac{2}{\delta\alpha_k\sqrt{d}}\,\frac{V_{d-1}}{V_d} \;\le\; \frac{1}{\delta\alpha_k}.$$

□

4 Main Results

Let $\mathcal{P} = \{x_1, \ldots, x_n\} \subset \mathbb{R}^d$ be a collection of n points. As pointed out in the introduction, we want to construct functions that vanish at $\mathcal{P}$ and have a large integral. For this, we choose

$$f_0(x) \;=\; \min\left\{1, \frac{1}{\delta\sqrt{d}}\,\mathrm{dist}(x, \mathcal{P}_\delta)\right\} \quad \text{for all} \quad x \in \mathbb{R}^d,$$

where

$$\mathcal{P}_\delta \;=\; \bigcup_{i=1}^{n} B_\delta^d(x_i)$$

and $B_\delta^d(x_i)$ is the ball with center x_i and radius $\delta\sqrt{d}$.

The function $\mathrm{dist}(\cdot, \mathcal{P}_\delta)$ is Lipschitz with constant 1. Hence for $\delta \le 1$

$$\mathrm{Lip}(f_0) = \frac{1}{\delta\sqrt{d}}. \tag{9}$$

Additionally, $f_0(x) = 0$ for all $x \in \mathcal{P}_\delta$ by definition.

Using these facts we can apply Theorem 1 to prove the curse of dimensionality for the following class of functions that are defined on $\mathbb{R}^d$. For a fixed $r \in \mathbb{N}$, we now take $\alpha_1 = \cdots = \alpha_r = \frac{1}{r}$ and define

$$F_{d,r,\delta} = \{f \colon \mathbb{R}^d \to \mathbb{R} \mid f \in C^r \text{ satisfies (10)–(12)}\},$$

where

$$\begin{aligned} \|f\| \ &\le\ 1, & (10)\\ \mathrm{Lip}(f) \ &\le\ \frac{1}{\delta\sqrt{d}}, & (11)\\ \forall k \le r : \max_{\theta_1,\ldots,\theta_k \in \mathbb{S}^{d-1}} \mathrm{Lip}(D^{\theta_1} \ldots D^{\theta_k} f) \ &\le\ \frac{1}{\delta\sqrt{d}} \left(\frac{r}{\delta}\right)^k. & (12) \end{aligned}$$

Theorem 2. For any $r \in \mathbb{N}$ and $\delta \in (0, 1]$,

$$n(\varepsilon, F_{d,r,\delta}) \ \ge\ (1-\varepsilon) \begin{cases} 1 & \text{for} \quad d = 1, \\ \left(\delta\sqrt{18e\pi}\right)^{-d} & \text{for} \quad d \ge 2, \end{cases} \qquad \text{for all } \varepsilon \in (0, 1).$$

Hence the curse of dimensionality holds for the class $F_{d,r,\delta}$ for $\delta < 1/\sqrt{18e\pi}$.

Note that this result shows that the growth rate of $n(\varepsilon, F_{d,r,\delta})$ in d can be arbitrarily large if we choose δ small enough.

Proof. Since the initial error for the classes $F_{d,r,\delta}$ is 1 we obtain $n(\varepsilon, F_{d,r,\delta}) \ge 1$ for all $\varepsilon \in (0, 1)$. This proves the statement for $d = 1$.

For $d \ge 2$, we use Theorem 1 with $k = r$, $\Omega = \mathcal{P}$ and $f_r(x) = f_0 * g_1 * \ldots * g_r(x)$. Here, the g_j's are as in Theorem 1. Recall that we have chosen $\alpha_1 = \ldots = \alpha_r = 1/r$ and $\alpha_j = 0$ for $j > r$. The properties of the initial function f_0 and Theorem 1 immediately imply that f_r satisfies (10)–(12). It remains to bound its integral. Note that $f_0(x) = 1$ for all $x \notin \mathcal{P}_{2\delta}$.

Clearly, $f_r(x) \ge 0$ for all $x \in \mathbb{R}^d$. Since $f_r(x)$ depends only on the values $f_0(x+t)$ for $t \in \mathbb{R}^d$ with $\|t\|_2 \le \delta\sqrt{d}$, it follows that $f_r(x) = 1$ for $x \notin \mathcal{P}_{3\delta}$. We thus obtain

$$\begin{aligned}
\int_{D_d} f_r(x)\,\mathrm{d}x \;\ge\; \int_{D_d\setminus\mathcal{P}_{3\delta}} f_r(x)\,\mathrm{d}x \;&=\; 1 - \lambda_d(\mathcal{P}_{3\delta}\cap D_d) \\
&\ge\; 1 - \lambda_d(\mathcal{P}_{3\delta}) \;\ge\; 1 - n\lambda_d(B^d_{3\delta}) \\
&>\; 1 - \frac{n\Big(3\delta\sqrt{2e\pi}\Big)^d}{\sqrt{\pi d}} \\
&>\; 1 - n\Big(3\delta\sqrt{2e\pi}\Big)^d,
\end{aligned}$$

where the next to last inequality follows from the bound that is given in (6). Hence $\int_{D_d} f_r(x)\,\mathrm{d}x \le \varepsilon$ implies that

$$n \ge (1-\varepsilon)\,(\delta\sqrt{18\varepsilon\pi})^{-d}.$$

Since this holds for arbitrary $\mathcal{P}$, the result follows. $\square$

By Theorem 2, we know how the parameter δ comes into play. For $p > 0$, let

$$\delta \;=\; \frac{1}{\sqrt{18e\pi}}\, d^{-p/(r+1)}.$$

For this δ, we obtain a somehow stronger form of the curse of dimensionality for the class

$$\widetilde{F}_{d,r,p} \;=\; \{f\colon \mathbb{R}^d \to \mathbb{R} \;\big|\; f \in C^r \text{ satisfies (13)–(15)}\},$$

where

$$\begin{aligned}
\|f\| \;&\le\; 1, && (13)\\
\mathrm{Lip}(f) \;&\le\; d^{-\frac{1}{2}+\frac{p}{r+1}}\,\sqrt{18e\pi}, && (14)\\
\forall k \le r:\; \max_{\theta_1,\dots,\theta_k\in\mathbb{S}^{d-1}} \mathrm{Lip}(D^{\theta_1}\dots D^{\theta_k} f) \;&\le\; d^{-\frac{1}{2}+\frac{p(k+1)}{r+1}}\, r^k\,\big(\sqrt{18e\pi}\big)^{k+1}. && (15)
\end{aligned}$$

Theorem 3. For any $r \in \mathbb{N}$ and $p > 0$,

$$n(\varepsilon, \widetilde{F}_{d,r,p}) \;\ge\; (1-\varepsilon)\, d^{p\,d/(r+1)} \quad \text{for all } d \in \mathbb{N} \text{ and } \varepsilon \in (0,1).$$

Hence the curse of dimensionality holds for the class $\widetilde{F}_{d,r,p}$.

Note that the classes $\widetilde{F}_{d,r,p}$ are contained in the classes

$$\mathcal{C}_d^r = \{f \in C^r \bigm| \|D^\beta f\| \le 1 \quad \text{for all} \quad |\beta| \le r\},$$

if $p < 1/2$ and d is large enough. This holds if

$$d \ \ge \ \left(r^r\,(18\mathrm{e}\pi)^{(r+1)/2}\right)^{1/(1/2-p)}. \tag{16}$$

From this we easily obtain the main result already stated in the introduction.

Main Theorem. For any $r \in \mathbb{N}$, there exists a constant $c_r \in (0,1]$ such that

$$n(\varepsilon, \mathcal{C}_d^r) \ge c_r\,(1-\varepsilon)\,d^{\,d/(2r+3)} \qquad \text{for all} \ \ d \in \mathbb{N} \ \ \text{and} \ \ \varepsilon \in (0,1).$$

Hence the curse of dimensionality holds for the class $\mathcal{C}_d^r$.

Proof. The case $d=1$ is trivial since the initial error for the classes $\mathcal{C}_d^r$ is again 1.

For $d \ge 2$, we know from Theorem 3 and the discussion thereafter that $n(\varepsilon, \mathcal{C}_d^r) \ge (1-\varepsilon)\,d^{\,pd/(r+1)}$ for all $p < 1/2$ if $d \ge d_0$, where $d_0 = d_0(r,p)$ is the right hand side of (16). This implies that for

$$\widetilde{c}_{r,p} = d_0^{-pd_0/(r+1)},$$

which depends only on r and p, we have

$$n(\varepsilon, \mathcal{C}_d^r) \ge \widetilde{c}_{r,p}\,(1-\varepsilon)\,d^{\,pd/(r+1)} \quad \text{for all} \quad d \ge 2.$$

The choice $p^* = (r+1)/(2r+3)$ yields the result with $c_r = \widetilde{c}_{r,p^*}$. □

Note that c_r in the last theorem is super exponentially small in r.

Remark 1. The reader might find it more natural to define classes of functions $F_{d,r}(D_d)$ that are defined only on $D_d \subset \mathbb{R}^d$. Not all such functions can be extended to smooth functions on $\mathbb{R}^d$, and even if they can be extended then the norm of the extended function could be much larger. Our lower bound results for functions defined on $\mathbb{R}^d$ can be also applied for functions defined on $D_d \subset \mathbb{R}^d$ and this makes them even stronger.

Remark 2. Note that the possibility of super-exponential lower bounds on the complexity depends on the definition of the Lipschitz constant. For the class

$$F_d = \left\{ f\colon [0,1]^d \to \mathbb{R} \mid \sup_{x,y\in[0,1]^d} \frac{|f(x)-f(y)|}{\|x-y\|_\infty} \le 1 \right\},$$

Sukharev [8] proved that for $n = m^d$ the midpoint rule is optimal with error $e_n = \frac{d}{2d+2} n^{-1/d}$. Hence, roughly, $n(\varepsilon, F_d) \approx 2^{-d}\varepsilon^{-d}$ and the complexity is "only" exponential in d for $\varepsilon < 1/2$.

Remark 3. We mention two results for the very small class

$$F_d = C_d^\infty = \{f \in C^\infty([0,1]^d) \mid \quad \|D^\beta f\| \le 1 \quad \text{for all} \quad \beta \in \mathbb{N}_0^d\}.$$

O. Wojtaszczyk [10] proved that $\lim_{d\to\infty} n(\varepsilon, F_d) = \infty$ for every $\varepsilon < 1$, hence the problem is not strongly polynomially tractable. It is still open whether the curse of dimensionality holds for this class F_d. The same class F_d was studied for the approximation problem in [6]. For this problem the curse of dimensionality is present even if we allow algorithms that use arbitrary linear functionals.

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