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# Parametric PDEs: Sparse or low-rank approximations?\*

Markus Bachmayr<sup>†</sup>, Albert Cohen<sup>‡</sup> and Wolfgang Dahmen<sup>†</sup>

February 8, 2017

## Abstract

We consider a class of parametric operator equations where the involved parameters could either be of deterministic or stochastic nature. In both cases we focus on scenarios involving a large number of parameters. Typical strategies for addressing the challenges posed by high dimensionality use low-rank approximations of solutions based on a separation of spatial and parametric variables. One such strategy is based on performing sparse best  $n$ -term approximations of the solution map in an *a priori* chosen system of tensor product form in the parametric variables. This approach has been extensively analyzed in the case of tensor product Legendre polynomial bases, for which approximation rates have been established. The objective of this paper is to investigate what can be gained by exploiting further low rank structures, in particular using optimized systems of basis functions obtained by singular value decomposition techniques. On the theoretical side, we show that optimized low-rank expansions can either bring significant or no improvement over sparse polynomial expansions, depending on the type of parametric problem. On the computational side, we analyze an adaptive solver which, at near-optimal computational cost for this type of approximation, exploits low-rank structure as well as sparsity of basis expansions.

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**Keywords:** parameter-dependent PDEs, low-rank approximations, sparse polynomial expansions, a posteriori error estimates, adaptive methods, complexity bounds

## 1 Introduction

Complex design, optimization, or uncertainty quantification tasks based on parameter dependent families of PDEs arise in virtually all branches of science and engineering. Typical scenarios are models whose physical properties – such as diffusivity, transport velocity or domain geometry – are described by a *finite* number of real parameter values. In certain instances, one may even encounter *infinitely* many parameters of decreasing influence. This occurs for instance in the case of a random stochastic diffusion field represented by an infinite expansion in a given basis. The development and analysis of numerical strategies for capturing the dependence of the PDE on the parameters has been the subject of intensive research efforts in recent years.

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## 1.1 Problem formulation

The problems that are addressed in this paper have the following general form. Let  $V$  be a separable Hilbert space. We consider a parametric operator  $A(y): V \rightarrow V'$  of the form

$$A(y) := A_0 + \sum_{j \in \mathcal{I}} y_j A_j, \quad y \in Y := [-1, 1]^{\mathcal{I}}, \quad (1.1)$$

where  $\mathcal{I} = \{1, \dots, d\}$  or  $\mathcal{I} = \mathbb{N}$  in the finite or infinite dimensional case, respectively. In the infinite dimensional case, we require that the above series converges in  $\mathcal{L}(V, V')$  for any  $y \in Y$ . We assume uniform boundedness and ellipticity of  $A(y)$  over the parameter domain, that is

$$\langle A(y)v, w \rangle \leq R \|v\|_V \|w\|_V \quad \text{and} \quad \langle A(y)v, v \rangle \geq r \|v\|_V^2, \quad v, w \in V, \quad y \in Y, \quad (1.2)$$

for some  $0 < r \leq R < \infty$ , which implies in particular that  $A(y)$  is boundedly invertible uniformly in  $y \in Y$ , with

$$\|A(y)\|_{\mathcal{L}(V', V)} \leq r^{-1}, \quad y \in Y. \quad (1.3)$$

We also consider parametric data  $f: Y \rightarrow V'$ , and for each  $y \in Y$ , we define  $u(y) \in V$  the solution to the equation

$$A(y)u(y) = f(y). \quad (1.4)$$

A guiding example is provided by *affinely parametrized* diffusion problems of the form

$$A(y)u := -\operatorname{div}(a(y)\nabla u) = f, \quad a(y) := \bar{a} + \sum_{j \in \mathcal{I}} y_j \theta_j, \quad (1.5)$$

with homogeneous Dirichlet boundary conditions, posed in the weak sense on a spatial domain  $D \subset \mathbb{R}^m$ . In this particular case of frequent interest, the data  $f \in V'$  is independent of  $y$ . The validity of (1.2) is then usually ensured by the *uniform ellipticity assumption*.

$$\sum_{j \geq 1} |\theta_j(x)| \leq \bar{a}(x) - \underline{\alpha}, \quad x \in D, \quad (1.6)$$

for some  $\underline{\alpha} > 0$ . We then have  $V = H_0^1(D)$ , and the corresponding operators  $A_j: V \rightarrow V'$  for  $j \in \{0\} \cup \mathcal{I}$  are defined by

$$\langle A_0 u, v \rangle := \int_D \bar{a} \nabla u \cdot \nabla v \, dx, \quad \langle A_j u, v \rangle := \int_D \theta_j \nabla u \cdot \nabla v \, dx, \quad i \in \mathcal{I},$$

for  $u, v \in V$ .

Thus,  $V$  is typically a function space defined over some physical domain  $D \subset \mathbb{R}^m$ , with  $m = 1, 2, 3$ , for example the Sobolev space  $H_0^1(D)$  in the above case of second order elliptic equations with homogeneous Dirichlet boundary conditions. Therefore the solution may either be viewed as the Hilbert space valued map

$$y \mapsto u(y), \quad (1.7)$$

which acts from  $Y$  to  $V$  or as the scalar valued map

$$(x, y) \mapsto u(x, y) := u(y)(x), \quad (1.8)$$

where  $x \in D$  and  $y \in Y$  are referred to as the spatial and parametric variables.

Approximating such solution maps amounts to approximating functions of a large or even infinite number of variables. In applications, one is often interested in specific functionals of the solution. Here we focus on the basic question of approximating the entire solution map in an appropriate norm.

The guiding questions, to be made precise below, are the following: What are the most suitable approximations to cope with the high dimensionality in problems of the form (1.1), and what features of problems (1.1) favor certain approaches over others? Moreover, at what numerical cost can one find these approximations, and how do they depend on particular features of the given problem?

## 1.2 Sparse and low-rank approximability

Before addressing any concrete numerical schemes, we discuss basic concepts of approximations for the solution map  $u$  in (1.7). Note that  $u$  can be regarded either as a function of spatial and parametric variables  $x, y$ , or as the  $V$ -valued function of  $y$ . We focus on the mean-square error  $\|u - \tilde{u}\|_{L^2(Y,V)}$  for an approximation  $\tilde{u}$ , where

$$\|v\|_{L^2(Y,V)}^2 := \int_Y \|v(y)\|_V^2 d\mu(y)$$

for a given probability measure  $\mu$  over  $Y$ . In what follows, we assume that  $\mu$  is the uniform probability measure on  $Y$ . The results carry over, however, to other product measures on  $Y$ . Note that the Bochner space  $L^2(Y, V)$  has a tensor product structure  $L^2(Y, V) = V \otimes L^2(Y)$  where  $L^2(Y) = L^2(Y, \mu)$ .

We next discuss several different types of approximations to  $u$  exploiting the tensor product structure.

**Sparse polynomial expansions.** A first approach to approximating  $y \mapsto u(y)$  is to employ an *a priori* chosen basis  $\{u_1^y, \dots, u_n^y\} \subset L^2(Y)$ , and compute the  $u_i^x \in V$  as the corresponding coefficients of this approximation. One prominent example of this approach are orthogonal polynomial expansion methods, see e.g. [19, 20, 36, 45]. In this case, the parametric functions  $u_i^y$  are picked from the set of *tensorized* Legendre polynomials

$$L_\nu(y) = \prod_{j \geq 1} L_{\nu_j}(y_j), \quad \nu = (\nu_j)_{j \geq 1}, \quad (1.9)$$

with  $(L_k)_{k \geq 1}$  the univariate Legendre polynomial sequence normalized in  $L^2([-1, 1], \frac{dt}{2})$ . The functions  $(L_\nu)_{\nu \in \mathcal{F}}$  are an orthonormal basis of  $L^2(Y)$ , where  $\mathcal{F}$  is  $\mathbb{N}_0^d$  in the case  $\mathcal{I} = \{1, \dots, d\}$  or the set of finitely supported sequences of non-negative integers in the case  $\mathcal{I} = \mathbb{N}$ , that is

$$\mathcal{F} := \{\nu \in \mathbb{N}_0^{\mathbb{N}} : \#\text{supp } \nu < \infty\}. \quad (1.10)$$

One thus has

$$u(y) = \sum_{\nu \in \mathcal{F}} u_\nu L_\nu(y), \quad u_\nu = \int_Y u(y) L_\nu(y) d\mu(y). \quad (1.11)$$

Then, one natural choice is the best  $n$ -term approximation  $u_n$  obtained by restricting the above expansion to the set  $\Lambda_n^y \subset \mathcal{F}$  of indices  $\nu$  corresponding to the  $n$  largest  $\|u_\nu\|_V$ , since this set minimizes the error  $\|u - u_n\|_{L^2(Y,V)}$  among all possible choices of  $n$ -term truncations. This strategy for generating sparse polynomial approximations in the context of parametric PDEs was first introduced and analyzed in [12, 13]. In practice, the set  $\Lambda_n^y$  is not accessible, but provides a benchmark for the performance of algorithms.

This representational complexity, however, does not yet determine the resulting computational complexity, since the coefficients  $u_\nu$  in (1.11) in turn need to be approximated as well. For instance, one may choose a fixed basis  $\{\psi_\lambda\}_{\lambda \in \mathcal{S}}$  of  $V$  and expand

$$u_\nu = \sum_{\lambda \in \mathcal{S}} \mathbf{u}_{\lambda, \nu} \psi_\lambda,$$

in (1.11), where  $\mathbf{u}_{\lambda, \nu} \in \mathbb{R}$ . The simplest strategy is to use the same discretization for all  $u_\nu$  by selecting a finite  $\Lambda^x$ , which yields the approximation

$$u \approx \sum_{\nu \in \Lambda_n^y} \left( \sum_{\lambda \in \Lambda^x} \mathbf{u}_{\lambda, \nu} \psi_\lambda \right) \otimes L_\nu.$$

Using instead an independently adapted spatial discretization for each  $u_\nu$  corresponds to *adaptive sparse polynomial* approximations of the form

$$u \approx \sum_{(\lambda, \nu) \in \Lambda} \mathbf{u}_{\lambda, \nu} \psi_\lambda \otimes L_\nu. \quad (\text{ASP})$$

with  $\Lambda \subset \mathcal{S} \times \mathcal{F}$ . It is natural to quantify the complexity of such an approximation by the number of activated degrees of freedom  $\#\Lambda$ . Here one can again ask for best  $N$ -term approximations, now with respect to the fixed basis  $\{\psi_\lambda \otimes L_\nu\}_{\lambda \in \mathcal{S}, \nu \in \mathcal{F}}$ , obtained by minimizing the error over all  $\Lambda$  with  $\#\Lambda = N$ , which now results in a fully discrete approximation.

**Low-rank approximation.** More generally, one may consider approximations of the form

$$u \approx u_n := \sum_{k=1}^n u_k^x \otimes u_k^y, \quad (1.12)$$

where  $u_k^x$  and  $u_k^y$  are functions of the spatial and parametric variable, respectively. This contains (1.11) as a special case, but we now allow also  $u_k^y \in L^2(Y)$  to be arbitrary functions that are not given a priori, but adapted to the given problem.

The shortest expansion of the form (1.12) that achieves a prescribed error in  $L^2(Y, V)$  is given by truncation of the Hilbert-Schmidt decomposition of  $u$  interpreted as the operator

$$T_u : v \rightarrow \int_Y u(x, y) v(y) d\mu(y), \quad (1.13)$$

acting from  $L^2(Y)$  to  $V$ . In this context, we define  $\text{rank}(u)$  as the rank of the operator  $T_u$ , so that in particular  $u_n$  with a representation by  $n$  separable terms as in (1.12) has  $\text{rank}(u_n) \leq n$ . The functions  $u_1^x, \dots, u_n^x$  and  $u_1^y, \dots, u_n^y$  are given by the left and right singular functions, respectively, which yield the optimal rank- $n$  approximation of  $u$  in  $L^2(Y, V)$ .

This particular system of basis functions is a natural benchmark as it minimizes the rank  $n = n(\varepsilon)$  required to ensure a mean-square accuracy  $\varepsilon$ . However, it is unclear how to compute sufficiently good approximations of these basis functions at affordable cost, a point to be taken up again later.

The methods considered in this paper are based on computing approximations of both  $u_k^x$  and  $u_k^y$ . A low-rank approximation trying to approximately realizing a truncated Hilbert-Schmidt decomposition would be a first example for this category aiming at meeting the above mentioned benchmark. In this case the error caused by truncation

should ideally be balanced against the error in approximating the *unknown* basis functions  $u_k^x, u_k^y$ .

Note that there exist alternative approaches for deriving computable expansions of the form (1.12), where only the functions  $u_1^x, \dots, u_n^x$  and their span  $V_n$  are constructed, which we comment on in §1.4.

To obtain numerically realizable approximations, we may again use bases of  $V$  and  $L^2(Y)$  as in (ASP) and consider expansions for  $u_k^x$  and  $u_k^y$  to arrive at fully discrete *low-rank* approximations of the form

$$u \approx \sum_{k=1}^n \left( \sum_{\lambda \in \Lambda_k^x} \mathbf{u}_{k,\lambda}^x \psi_\lambda \right) \otimes \left( \sum_{\nu \in \Lambda_k^y} \mathbf{u}_{k,\nu}^y L_\nu \right). \quad (\text{LR})$$

with  $\Lambda_k^x \subset \mathcal{S}$ ,  $\Lambda_k^y \subset \mathcal{F}$ ,  $k = 1, \dots, n$ .

**Hierarchical tensor decompositions.** One may as well go beyond the Hilbert-Schmidt decomposition (1.12) and consider higher-order low-rank tensor representations that correspond to further decompositions of the factors  $u_k^y$  in (1.12). For simplicity, at this point let us consider this in the finite-dimensional case  $d < \infty$ , possibly after truncating the expansion (1.1) for  $A(y)$ . Introducing an additional tensor decomposition of the factors  $u_k^y$ , we obtain the general approximations in *subspace tensor formats*,

$$u_n = \sum_{k_0=1}^{r_0} u_{k_0}^x \otimes \left( \sum_{k_1=1}^{r_1} \cdots \sum_{k_d=1}^{r_d} \mathbf{a}_{k_0, k_1, \dots, k_d} \bigotimes_{j=1}^d u_{k_j}^{y,j} \right), \quad (\text{STF})$$

where each  $u_{k_j}^{y,j}$  is a function of the individual variable  $y_j$ . The minimal  $r_j$  such that  $u_n$  can be represented in the form (STF) are called *multilinear ranks* of  $u_n$ .

We confine our discussion to *hierarchical tensor representations* (with the *tensor train format* as a special case), see e.g. [23, 27, 38], where the high-order core tensor  $\mathbf{a} = (\mathbf{a}_{k_0, k_1, \dots, k_d})_{k_0, \dots, k_d}$  is further decomposed in terms of lower-order tensors, based on matrixizations of  $\mathbf{a}$ . For instance, if

$$\hat{r}_i = \text{rank} \left( \mathbf{a}_{(k_0, \dots, k_i), (k_{i+1}, \dots, k_d)} \right), \quad (1.14)$$

one has a factorized representation of the form

$$\mathbf{a}_{k_0, k_1, \dots, k_d} = \sum_{\ell_1=1}^{\hat{r}_1} \mathbf{M}_{k_0, k_1, \ell_1}^{(1)} \sum_{\ell_2=1}^{\hat{r}_2} \mathbf{M}_{\ell_1, k_2, \ell_2}^{(2)} \cdots \sum_{\ell_{d-1}=1}^{\hat{r}_{d-1}} \mathbf{M}_{\ell_{d-2}, k_{d-2}, \ell_{d-1}}^{(d-1)} \mathbf{M}_{\ell_{d-1}, k_d}^{(d)} \quad (1.15)$$

in terms of the tensors  $\mathbf{M}^{(i)}$ ,  $i = 1, \dots, d$  of order at most three, and only these low-order tensors need to be stored and manipulated.

The representation (STF) contains (ASP) and (LR) as special cases. For instance, to recover a sparse polynomial expansion, let  $\nu(k_0)$ ,  $k_0 = 1, \dots, r_0$  be an enumeration of elements of  $\mathbb{N}_0^d$ , and choose  $\mathbf{a}_{k_0, k_1, \dots, k_d} = \delta_{\nu(k_0), (k_1, \dots, k_d)}$ ,  $u_{k_j}^{y,j} = L_{k_j}$ . Another noteworthy special case concerns the choices  $r_1 = \dots = r_d = 1$  and  $\mathbf{a}_{k_0, 1, \dots, 1} = 1$ , which is often referred to as the *canonical format*. In this case  $n = r_0$  is called the *canonical rank*.

### 1.3 Guiding questions

In the different types of approximation outlined above, the degrees of freedom enter in varying degrees of nonlinearity. More strongly nonlinear approximation (STF) with (1.15)

can potentially yield more strongly compressed representations, in the sense that the number of degrees of freedom  $n_{\text{dof}}(\varepsilon)$  required for a target accuracy  $\varepsilon$  in  $L^2(Y, V)$  scales more favourably. Handling this stronger compression in the computation of such representations, however, leads to additional difficulties, and the number of required operations  $n_{\text{op}}(\varepsilon)$  may in fact scale less favourably than  $n_{\text{dof}}(\varepsilon)$ .

Here we aim for algorithms which, for each of the above types of approximation, are guaranteed to achieve any prescribed accuracy  $\varepsilon$ , and which are universal. This means that they do not require a priori knowledge on the approximability of the solution (e.g., on the decay of coefficients), but adjust to such approximability automatically. This goes hand in hand with a mechanism for obtaining a posteriori error bounds, making use only of the given data. This leads us to our first guiding question:

(I) *For a given parametric problem and approximation format (ASP), (LR) or (STF), can one contrive a universal numerical scheme that can achieve any given target accuracy  $\varepsilon$ , with approximate solutions close to the minimum required representation complexity  $n_{\text{dof}}(\varepsilon)$ , and can  $n_{\text{op}}$  be related to  $\varepsilon$  and hence to  $n_{\text{dof}}(\varepsilon)$ ?*

The minimum required representation complexity can be expressed in terms of the intrinsic approximability properties of the parametrized solutions  $u$  in each of the formats. The corresponding required number of operations also depends on the problem data that are used in the solution process. We construct algorithms, based on a common generic strategy for (ASP), (LR), and (STF), which are near-optimal in this regard. With such algorithms at hand, a natural further question is the following.

(II) *Which of the approximation types (ASP), (LR), or (STF) is best suited for a given parametric problem, in the sense of leading to the smallest growth of  $n_{\text{op}}(\varepsilon)$  as  $\varepsilon \rightarrow 0$ ?*

This amounts to asking for which parametric problems the investment into approximations of higher structural nonlinearity pays off, or conversely, for which problems possible gains in approximation efficiency are offset by more demanding computations. We address this point by analyses of the approximability of model problem, complemented by numerical experiments, with the conclusions depending on the particular problem type.

For problems with finitely many parameters that are each of comparable influence, hierarchical tensor representations of the form (STF) with (1.15) turn out to be clearly advantageous. In the case of an anisotropic dependence on infinitely many parameters, for representative model problems we demonstrate that (ASP) can in general yield faster convergence than (LR) or (STF). The particular structure of such infinite parameter expansions also turns out to have a major influence on the efficiency of the adaptive schemes.

## 1.4 Relation to previous work

There is a variety of results on the convergence of sparse polynomial expansions (1.11), see, e.g., [4, 12, 13]. Furthermore, some estimates are available that include multilevel spatial discretizations and hence provide upper bounds for the error of best  $n$ -term approximation (ASP), see, e.g., [13, 14]. Concerning our question (II), there are only few specialized results comparing the different approximation formats. In the case of general bivariate functions, a systematic comparison between sparse grids and low rank approximation is discussed in [25], showing in particular that for Sobolev classes the latter does not bring any improvement. In the case of high-dimensional functions associated to parametric PDEs, possible gains by low-rank approximations have been identified in [2, 34] by using the particular structure of the problem, all concerning the case of finitely many parameters.

There are various approaches for generating sparse polynomial expansions, for instance based on collocation [1, 7] or adaptive Taylor expansion [8]. Note that these strategies do not currently yield *a posteriori* error bounds for the computed solutions, and their performance is thus described by *a priori* estimates which may not be sharp.

The adaptive methods proposed in [15, 16], based on finite element discretization for the spatial variable, yields *a posteriori* error bounds for the full approximations. However, the complexity bounds proven in [16] are given only in terms of the resulting finite element meshes.

Adaptive schemes using wavelet-based spatial discretizations, which yield approximations of the form (ASP), have been studied by Gittelsohn [21, 22]. In this case, bounds for the complete computational complexity are proven.

Reduced basis and POD methods [29, 34, 40, 41] correspond to expansions of the form (1.12), where only the spatial basis elements  $u_k^x$  spanning  $V_n$  are explicitly computed in an offline stage. Then, in an online stage, for any given  $y \in Y$ , the approximate solution  $u_r(y)$  is defined as the Galerkin projection of  $u(y)$  on the space  $V_n$ . For known variants of these methods, accuracy guarantees in the respective norms (where reduced basis methods usually aim at the error in  $L^\infty$ -norm  $\|v\|_{L^\infty(Y,V)} := \sup_{y \in Y} \|v(y)\|_V$ ) require a sufficiently dense sampling of the parameter domain, which becomes prohibitive for large  $d$ , and one only obtains *a posteriori* bounds for the resulting  $V$ -error in each given  $y \in Y$ .

In methods based on higher-order tensor representations, instead of sampling in the parameter domain, one also approximates  $u_k^y$  as in (STF), at the price of additional approximability requirements as in (1.15). A variety of schemes have been proposed that operate on fixed discretizations [30, 31, 33, 37], which do not yield information on the discretization error. Based on [15], an adaptive scheme for hierarchical tensor approximation is proposed in [17]. It provides rigorous *a posteriori* bounds for the approximation error, but is not proven to converge.

## 1.5 Novelty of the paper and outline

Question (I) is addressed in sections §2 to §5. A generic algorithm is described in §2 based on the work in [5], which is guaranteed to converge. Furthermore, it yields rigorous *a posteriori* error bounds, using only information on the problem data. Suitable specifications cover all above mentioned types of approximations (1.12), (1.11), and (STF). The scheme is formulated in a general sequence space framework, using a discretization of the space  $L^2(Y, V)$  through a basis with elements of the form  $\psi_\lambda \otimes L_\nu$ . Here,  $\{\psi_\lambda\}_{\lambda \in \mathcal{S}}$  is a given Riesz basis of  $V$  (for example, a wavelet basis in the case where  $V$  is a Sobolev space) and  $\{L_\nu\}_{\nu \in \mathcal{F}}$  is the previously described multivariate Legendre basis. The algorithm performs an iteration in the sequence space  $\ell^2(\mathcal{S} \times \mathcal{F})$ , which involves at each step specific routines RECOMPRESS and COARSEN aiming at respectively controlling the rank of the current approximation as well as the number of degrees of freedom that describe the different factors involved in this approximation.

We then describe two realizations of this generic algorithm corresponding to two distinct settings. In §3 we apply the algorithm for the generation of approximations (STF) in the setting of finitely many parametric variables. In this case the RECOMPRESS routine is based on a truncation of a hierarchical singular value decomposition of the coefficient tensor. We analyze the performance of the algorithms for classes described by the decay of the corresponding singular values and joint sparsity of the corresponding singular vectors.

§4 and §5 are devoted to the case of *anisotropic* dependence on infinitely many parameters in the diffusion problem (1.5). In §4 we analyze a specialized version of Algorithm 2.1 producing  $n$ -term sparse Legendre expansions. In this version the routine RECOMPRESS



is simply the identity, and hence Algorithm 2.1 agrees with the adaptive solver developed and analyzed in [10].

A key ingredient is the adaptive approximation of the operator based on matrix compression results in Appendix A. Here we obtain new estimates for wavelet-type multilevel expansions of the parametrized coefficients that are more favorable than what is known for Karhunen-Loève-type expansions. It is perhaps worth mentioning that our further algorithmic developments also require substantially weaker assumptions on the  $A_j$  in (1.1) than the methods in [15, 17], which require summability of  $(\|A_j\|)_{j \geq 1}$ . By virtue of our new operator compression results, we then establish convergence and complexity rates which significantly improve on those of similar schemes in [21, 22].

In §5 we consider, in the same setting as in §4, a solver for approximations (LR). In this case the RECOMPRESS routine is based on standard SVD truncation. The corresponding notions of approximability are analogous to those arising in §3.

Based on the complexity estimates for each of these realizations of the basic algorithm for suitable benchmark approximability classes, question (II) is then addressed in §6, by studying specific examples of parametric problems of the form (1.5). In particular, for a certain class of such problems, we prove that the best  $n$ -term Legendre approximation is already near-optimal among all rank- $n$  approximations. For other examples, we prove that optimized low-rank approximations can achieve significantly better complexity than best  $n$ -term Legendre approximations. This is illustrated further by numerical tests, demonstrating that these observations also hold for more involved model problems.

## 2 A generic algorithm

In this section, we follow the approach developed in [5], by first reformulating the general equation (1.4) in a sequence space, and then introducing a generic resolution algorithm based on this equivalent formulation.

We first notice that (1.4) may also be written as

$$Au = f, \quad (2.1)$$

where  $A$  is elliptic and boundedly invertible from  $L^2(Y, V)$  to  $L^2(Y, V')$  and can be defined in a weak sense by

$$\langle Au, v \rangle := \int_Y \langle A(y)u(y), v(y) \rangle d\mu(y), \quad u, v \in L^2(Y, V). \quad (2.2)$$

We assume that  $f \in L^2(Y, V')$ , so that there exists a unique solution  $u \in L^2(Y, V)$ .

Given a Riesz basis  $\{\psi_\lambda\}_{\lambda \in \mathcal{S}}$  of  $V$ , we tensorize it with the orthonormal basis  $\{L_\nu\}_{\nu \in \mathcal{F}}$  of  $L^2(Y)$ . The resulting system  $\{\psi_\lambda \otimes L_\nu\}_{(\lambda, \nu) \in \mathcal{S} \times \mathcal{F}}$  is a Riesz basis of  $L_2(Y, V)$ , which we now use to discretize (2.1). For this purpose, we define the matrices

$$\mathbf{A}_j := (\langle A_j \psi_{\lambda'}, \psi_\lambda \rangle)_{\lambda, \lambda' \in \mathcal{S}} \quad \text{and} \quad \mathbf{M}_j = \left( \int_Y y_j L_\nu(y) L_{\nu'}(y) d\mu(y) \right)_{\nu, \nu' \in \mathcal{F}}, \quad (2.3)$$

where  $\mathbf{M}_0$  is set to be the identity matrix, and the right hand side column vector

$$\mathbf{f} := (\langle f, \psi_\lambda \otimes L_\nu \rangle)_{(\lambda, \nu) \in \mathcal{S} \times \mathcal{F}}. \quad (2.4)$$

We thus obtain an equivalent problem

$$\mathbf{A}\mathbf{u} = \mathbf{f} \quad (2.5)$$

on  $\ell^2(\mathcal{S} \times \mathcal{F})$  where

$$\mathbf{A} := \sum_{j \geq 0} \mathbf{A}_j \otimes \mathbf{M}_j \quad (2.6)$$

and  $\mathbf{u} = (u_{\lambda, \nu})_{(\mu, \nu) \in \mathcal{S} \times \mathcal{F}}$  is the coordinate vector of  $u$  in the basis  $\{\psi_\mu \otimes L_\nu\}_{(\mu, \nu) \in \mathcal{S} \times \mathcal{F}}$ .

Regarding  $\nu \in \mathcal{F}$  as the column index of the infinite matrix  $\mathbf{u} = (\mathbf{u}_{\mu, \nu})_{\mu \in \mathcal{S}, \nu \in \mathcal{F}}$ , we denote by  $\mathbf{u}_\nu$  the columns of  $\mathbf{u}$ , which are precisely the basis representations of the Legendre coefficients  $u_\nu \in V$ .

In what follows we always denote by  $\|\cdot\|$  the  $\ell^2$ -norm on the respective index set which could be  $\mathcal{S}$ ,  $\mathcal{F}$  or  $\mathcal{S} \times \mathcal{F}$ , or the corresponding operator norm when this is clear from the context. Since  $\{\psi_\mu\}_{\mu \in \mathcal{S}}$  is a Riesz basis for  $V$  we have  $\|u_\nu\|_V \sim \|\mathbf{u}_\nu\|$  uniformly in  $\nu \in \mathcal{F}$  which together with boundedness and ellipticity of  $A$  implies that  $\mathbf{A}$  is bounded and elliptic on  $\ell^2(\mathcal{S} \times \mathcal{F})$  and we have

$$\|\mathbf{u}\| \sim \|\mathbf{A}\mathbf{u}\| \sim \|A\mathbf{u}\|_{L^2(Y, V')} \sim \|u\|_{L^2(Y, V)} \quad (2.7)$$

with uniform constants. On account of (2.7), solving (2.5) approximately up to some target accuracy is equivalent to solving (2.5) in  $\ell^2$  to essentially the same accuracy.

As a further consequence, one can find a fixed positive  $\omega$  such that  $\|\mathbf{I} - \omega\mathbf{A}\| \leq \rho < 1$ , ensuring that a simple Richardson iteration converges with a fixed error reduction rate per step. This serves as the conceptual starting point for the adaptive low-rank approximation scheme introduced in [5] as given in Algorithm 2.1.

---

**Algorithm 2.1**  $\mathbf{u}_\varepsilon = \text{SOLVE}(\mathbf{A}, \mathbf{f}; \varepsilon)$

---

input  $\omega > 0$  and  $\rho \in (0, 1)$  such that  $\|\mathbf{I} - \omega\mathbf{A}\| \leq \rho$ ,  $\lambda_{\mathbf{A}} \leq \|\mathbf{A}^{-1}\|^{-1}$ ,  
 $\kappa_1, \kappa_2, \kappa_3 \in (0, 1)$  with  $\kappa_1 + \kappa_2 + \kappa_3 \leq 1$ , and  $\beta \geq 0$ .  
output  $\mathbf{u}_\varepsilon$  satisfying  $\|\mathbf{u}_\varepsilon - \mathbf{u}\| \leq \varepsilon$ .  
1:  $\mathbf{u}_0 := 0$ ,  $\delta := \lambda_{\mathbf{A}}^{-1} \|\mathbf{f}\|$   
2:  $k := 0$ ,  $J := \min\{j : \rho^j (1 + (\omega + \beta)j) \leq \frac{1}{2} \kappa_1\}$   
3: while  $\frac{1}{2^k} \delta > \varepsilon$   
4:    $\mathbf{w}_0 := \mathbf{u}_k$ ,  $j \leftarrow 0$   
5:   repeat  
6:      $\eta_j := \rho^{j+1} \frac{1}{2^k} \delta$   
7:      $\mathbf{r}_j := \text{APPLY}(\mathbf{w}_j; \frac{1}{2} \eta_j) - \text{RHS}(\frac{1}{2} \eta_j)$   
8:      $\mathbf{w}_{j+1} := \text{RECOMPRESS}(\mathbf{w}_j - \omega \mathbf{r}_j; \beta \eta_j)$   
9:      $j \leftarrow j + 1$ .  
10:   until  $(j \geq J \vee \lambda_{\mathbf{A}}^{-1} \rho \|\mathbf{r}_{j-1}\| + (\lambda_{\mathbf{A}}^{-1} \rho + \omega + \beta) \eta_{j-1} \leq \frac{1}{2^{k+1}} \kappa_1 \delta)$   
11:    $\mathbf{u}_{k+1} := \text{COARSEN}(\text{RECOMPRESS}(\mathbf{w}_j; \frac{1}{2^{k+1}} \kappa_2 \delta); \frac{1}{2^{k+1}} \kappa_3 \delta)$   
12:    $k \leftarrow k + 1$   
13: end while  
14:  $\mathbf{u}_\varepsilon := \mathbf{u}_k$

---

This basic algorithmic template can be used to produce various types of sparse and low-rank approximations, with appropriate choices of the subroutines APPLY, RHS, COARSEN, and RECOMPRESS.

The procedures COARSEN and RECOMPRESS are independent of the considered  $\mathbf{A}$  and  $\mathbf{f}$ , and satisfy

$$\|\text{COARSEN}(\mathbf{v}; \eta) - \mathbf{v}\| \leq \eta, \quad \|\text{RECOMPRESS}(\mathbf{v}; \eta) - \mathbf{v}\| \leq \eta, \quad (2.8)$$

for any  $\eta \geq 0$  and any compactly supported  $\mathbf{v} \in \ell^2(\mathcal{S} \times \mathcal{F})$ . Here COARSEN is intended to reduce the support of the sequence  $\mathbf{v}$ , whereas RECOMPRESS reduces the rank of  $\mathbf{v}$  in

a low-rank tensor representation. The particular realizations of these routines depend on the dimensionality of the problem and on the type of approximation. We shall use the constructions given in [5].

The routines APPLY and RHS are assumed to satisfy, for compactly supported  $\mathbf{v}$  and any  $\eta > 0$ , the requirements

$$\|\text{APPLY}(\mathbf{v}; \eta) - \mathbf{A}\mathbf{v}\| \leq \eta, \quad \|\text{RHS}(\eta) - \mathbf{f}\| \leq \eta. \quad (2.9)$$

Their construction not only depends on the type of approximation, but also on the specific problem under consideration. These two routines are indeed the main driver of adaptivity in Algorithm 2.1, and a major part of what follows concerns the construction of APPLY in different scenarios.

It hinges on the compression of matrices by exploiting their near-sparsity in certain basis representations. We use the following notion introduced in [9]: A bi-infinite matrix  $\mathbf{B}$  is called  $s^*$ -compressible if there exist matrices  $\mathbf{B}_n$  with  $\alpha_n 2^n$  entries per row and column and such that

$$\|\mathbf{B} - \mathbf{B}_n\| \leq \beta_n 2^{-sn}, \quad \text{for } 0 < s < s^*, \quad (2.10)$$

and where the sequences  $\boldsymbol{\alpha} = (\alpha_n)_{n \in \mathbb{N}}$  and  $\boldsymbol{\beta} = (\beta_n)_{n \in \mathbb{N}}$  are summable. Here we always assume  $\mathbf{B}_0 = 0$ . Furthermore, a bi-infinite matrix  $\mathbf{B}$  that has at most  $k$  entries in each row and column is called  $k$ -sparse.

**Remark 2.1.** As shown in [5], regardless of the specifications of the routines APPLY, RHS, COARSEN, RECOMPRESS, Algorithm 2.1 terminates after finitely many steps and its output  $\mathbf{u}_\varepsilon$  satisfies  $\|\mathbf{u} - \mathbf{u}_\varepsilon\| \leq \varepsilon$ .

At this point, we record for later usage a particular feature of  $\mathbf{A}$  that arises as a consequence of our choice of tensor product orthogonal polynomials for the parameter-dependence: The approximate application of  $\mathbf{A}$  is facilitated by the fact that the matrices  $\mathbf{M}_j$  are *bidiagonal*. That is, in view of the three-term recurrence relation

$$tL_n(t) = p_{n+1}L_{n+1}(t) + p_nL_{n-1}(t), \quad L_{-1} \equiv 0, \quad (2.11)$$

where

$$p_0 = 0, \quad p_n = \frac{1}{\sqrt{4 - n^{-2}}}, \quad n > 0, \quad (2.12)$$

one has  $\int_U y_j L_\nu(y) L_\mu(y) d\mu(y) = 0$  whenever  $j \notin \text{supp } \nu \cup \text{supp } \mu$ , providing

$$(\mathbf{M}_j)_{\nu, \nu'} = p_{\nu_j} \delta_{\nu + e^j, \nu'} + p_{\nu_j - 1} \delta_{\nu - e^j, \nu'} \quad (2.13)$$

with the Kronecker sequence  $(e_i^j)_{i \in \mathcal{I}} := (\delta_{i,j})_{i \in \mathcal{I}} \in \mathcal{F}$ .

### 3 Hierarchical tensor representations in the case of finitely many parameters

We begin by considering the setting

$$\mathcal{I} = \{1, \dots, d\}. \quad (3.1)$$

then  $\mathcal{F} = \mathbb{N}_0^d$  and  $\mathbf{u} \in \ell^2(\mathcal{S} \times \mathbb{N}_0 \times \dots \times \mathbb{N}_0)$ .

Here we are interested in the case that all coordinates in  $\mathcal{I}$  have comparable influence. As illustrated in §6, a direct sparse Legendre expansion of  $\mathbf{u}$  over  $\mathcal{S} \times \mathcal{F}$  will then in general

be infeasible already for moderately large  $d$ . However, one may as well exploit Cartesian product structure in  $\mathcal{F}$ , regarding  $\mathbf{u}$  as a higher-order tensor, and using corresponding hierarchical low-rank representations. As we shall detail in what follows, the results of [5] can be adapted to this problem in a rather straightforward manner.

It will be convenient to introduce a numbering of tensor modes as follows:  $\mathcal{G}_x := \mathcal{S}$ ,  $\mathcal{G}_1 := \mathbb{N}_0, \dots, \mathcal{G}_d := \mathbb{N}_0$ . We additionally introduce the notation

$$\hat{\mathcal{I}} := \{x\} \cup \mathcal{I}.$$

The representations of higher-order tensors which we consider are built on the Hilbert-Schmidt case via *matricizations*: for each nonempty  $M \subset \hat{\mathcal{I}}$ ,  $\mathbf{u}$  induces a compact operator  $T_{\mathbf{u}}^{(M)}: \ell^2(\times_{i \in \hat{\mathcal{I}} \setminus M} \mathcal{G}_i) \rightarrow \ell^2(\times_{i \in M} \mathcal{G}_i)$ .

In terms of the left singular vector  $\{\mathbf{U}_k^{(i)}\}_{k \in \mathbb{N}}$  of  $T_{\mathbf{u}}^{(\{i\})}$ ,  $i \in \hat{\mathcal{I}}$ , we obtain the *HOSVD representation* [35] in the *Tucker format* [43, 44] as in (STF),

$$\mathbf{u} = \sum_{1 \leq k_i \leq r_i: i \in \hat{\mathcal{I}}} \mathbf{a}_{\mathbf{k}} \bigotimes_{i \in \hat{\mathcal{I}}} \mathbf{U}_{k_i}^{(i)}, \quad (3.2)$$

where  $\mathbf{a} = (\mathbf{a}_{\mathbf{k}})_{\mathbf{k} \in \mathbb{N}^{d+1}}$  is referred to as *core tensor* and  $(r_x, r_1, \dots, r_d)$  as the *multilinear ranks* of  $\mathbf{u}$ .

The *hierarchical tensor format* [28], on which the variant of our scheme described in this section is based, can be interpreted as a further decomposition of  $\mathbf{a}$  into tensors of order at most three. This decomposition is obtained using further matricizations of the tensor according to a recursive decomposition of the set of modes  $\hat{\mathcal{I}}$  into a binary tree, which we denote by  $\mathcal{D}$ . For each  $\alpha \in \mathcal{D}$ , the rank of the corresponding matricization  $T_{\mathbf{u}}^{(\alpha)}$  is denoted by  $\text{rank}_{\alpha}(\mathbf{u})$ , where  $\text{rank}_{\hat{\mathcal{I}}}(\mathbf{u}) = 1$  for all  $\mathbf{u} \neq 0$ , and we set

$$\text{rank}(\mathbf{u}) := (\text{rank}_{\alpha}(\mathbf{u}))_{\alpha \in \mathcal{D} \setminus \hat{\mathcal{I}}}. \quad (3.3)$$

The hierarchical format can offer substantially more favorable complexity characteristics for large  $d$  than (3.2). The left singular vectors of the involved matricizations yield a *hierarchical singular value decomposition* [23]. We refer also to [18, 24, 27, 28, 32] for detailed expositions regarding the finitely supported case (see also [38, 39] for the related *tensor train* representation), and to [5] for analogous results for tensors in sequence spaces, with notation analogous to the present paper.

The *contractions*

$$\pi^{(i)}(\mathbf{v}) = (\pi_{\nu_i}^{(i)}(\mathbf{v}))_{\nu_i \in \mathcal{G}_i}, \quad \pi_{\mu}^{(i)}(\mathbf{v}) = \left( \sum_{\nu: \nu_i = \mu} |\mathbf{v}_{\nu}|^2 \right)^{1/2}, \quad i \in \hat{\mathcal{I}}, \quad (3.4)$$

as introduced in [5], can be evaluated efficiently (without any  $d$ -dimensional summations) due to the relation

$$\pi_{\mu}^{(i)}(\mathbf{v}) = \left( \sum_k |\mathbf{U}_{k,\mu}^{(i)}|^2 |\sigma_k^{(i)}|^2 \right)^{1/2}, \quad (3.5)$$

where  $\sigma_k^{(i)}$  are the mode- $i$  singular values of  $\mathbf{v}$ . As in our previous notation, we abbreviate  $\text{supp}_i \mathbf{v} := \text{supp}(\pi^{(i)}(\mathbf{v}))$ ,  $i \in \hat{\mathcal{I}}$ .

### 3.1 Adaptive scheme

In the present case, we consider Algorithm 2.1 with the routines RECOMPRESS and COARSEN for the hierarchical format as given in [5, Rem. 15].

RECOMPRESS is based on a truncation of a hierarchical singular value decomposition up to a prescribed accuracy  $\eta > 0$ , which can be ensured based on the  $\ell^2$ -norm of omitted singular values of matricizations. We denote this operation by  $\hat{P}_\eta$ . It satisfies the quasi-optimality property [23]

$$\|\mathbf{v} - \hat{P}_\eta(\mathbf{v})\| \leq \sqrt{2d-3} \inf\{\|\mathbf{v} - \mathbf{w}\| : \text{rank}(\mathbf{w}) \leq \text{rank}(\hat{P}_\eta(\mathbf{v}))\}, \quad (3.6)$$

with the inequality between ranks as defined in (3.3) is to be understood componentwise.

COARSEN retains the degrees of freedom for each mode that correspond to the largest contractions (3.4). Let  $(\mu_{i,k}^*)_{k \in \mathbb{N}}$  be such that  $(\pi_{\mu_{i,k}^*}^{(i)}(\mathbf{v}))_{k \in \mathbb{N}}$  is nonincreasing. Denote for  $\Lambda \subset \mathcal{S} \times \mathcal{F}$  by  $R_\Lambda \mathbf{v}$  the array obtained by retaining all entries of  $\mathbf{v}$  corresponding to indices in  $\Lambda$ , while replacing all others by zero. Given  $\eta > 0$ , we define the product set

$$\Lambda(\eta) = \times_{i \in \hat{\mathcal{I}}} \{\mu_{i,k}^* : k \leq N_i\},$$

where  $N_i, i \in \hat{\mathcal{I}}$  are chosen to such that  $\sum_{i \in \hat{\mathcal{I}}} N_i$  is minimal subject to the condition

$$\left( \sum_{i \in \hat{\mathcal{I}}} \sum_{k > N_i} |\pi_{\mu_{i,k}^*}^{(i)}(\mathbf{v})|^2 \right)^{1/2} \leq \eta. \quad (3.7)$$

Noting that the left side in (3.7) is an upper bound for  $\|\mathbf{v} - R_{\Lambda(\eta)} \mathbf{v}\|$ , we define COARSEN as a numerical realization of  $\hat{C}_\eta \mathbf{v} := R_{\Lambda(\eta)} \mathbf{v}$ , for which one has an analogous quasi-optimality property as in (3.6) with constant  $\sqrt{d}$ .

Furthermore,  $\mathbf{A}$  as defined in (2.6) is here a *finite* sum of Kronecker product operators, which considerably simplifies the construction of the corresponding routine APPLY. More specifically,  $\mathbf{A}$  is a sum of  $d+1$  Kronecker product terms  $\mathbf{A}_j \otimes \mathbf{M}_j, j = 0, \dots, d$ . The action of  $\mathbf{A}$  can thus increase each hierarchical rank of its argument at most by a factor of  $d+1$ . Consequently, APPLY can be obtained following the generic construction given in [5], provided that the operators  $\mathbf{A}_j$  and  $\mathbf{M}_j$  acting on each mode have the required compressibility properties. Recall that by (2.13), the infinite matrices  $\mathbf{M}_j$  are bidiagonal, and hence do not require any further approximation. To use the construction of [5], we thus only need that the operators  $\mathbf{A}_0, \dots, \mathbf{A}_d$  acting on the spatial variables are  $s^*$ -compressible.

**Remark 3.1.** *In contrast to the case considered in [6], here the Hilbert space  $\mathcal{H} = V \otimes L^2(Y)$  on which the problem is posed is endowed with a cross norm. As a consequence, the isomorphism that takes  $v \in \mathcal{H}$  to its coefficients  $\mathbf{v} \in \ell^2(\mathcal{S} \times \mathcal{F})$  with respect to the tensor product basis is of Kronecker rank one. The original low-rank structure (1.1) of  $A(y)$  is therefore preserved in the  $\ell^2$ -representation (2.6) of the problem.*

### 3.2 Convergence analysis

Our complexity results aim at the following type of statements: given a certain approximability of the solution, the algorithm recovers the corresponding convergence rates without their explicit knowledge.

To describe these approximability properties, we now recall the definition of approximation classes to quantify the convergence of hierarchical low-rank approximations from [5],

in terms of the hierarchical rank defined by (3.3). Let  $\gamma = (\gamma(n))_{n \in \mathbb{N}_0}$  be positive and strictly increasing with  $\gamma(0) = 1$  and  $\gamma(n) \rightarrow \infty$  as  $n \rightarrow \infty$ , for  $\mathbf{v} \in \ell^2(\mathcal{S} \times \mathcal{F})$  let

$$|\mathbf{v}|_{\mathcal{A}_{\mathcal{H}}(\gamma)} := \sup_{r \in \mathbb{N}_0} \gamma(r) \inf_{|\text{rank}(\mathbf{w})|_{\infty} \leq r} \|\mathbf{v} - \mathbf{w}\|$$

as well as

$$\mathcal{A}_{\mathcal{H}}(\gamma) := \{\mathbf{v} \in \ell^2(\mathcal{S} \times \mathcal{F}) : |\mathbf{v}|_{\mathcal{A}_{\mathcal{H}}(\gamma)} < \infty\}, \quad \|\mathbf{v}\|_{\mathcal{A}_{\mathcal{H}}(\gamma)} := \|\mathbf{v}\| + |\mathbf{v}|_{\mathcal{A}_{\mathcal{H}}(\gamma)}.$$

We restrict our considerations to  $\gamma$  that satisfy

$$\rho_{\gamma} := \sup_{n \in \mathbb{N}} \gamma(n)/\gamma(n-1) < \infty,$$

which corresponds to a restriction to at most exponential growth.

For an approximation  $\mathbf{v}$  of bounded support to  $\mathbf{u}$ , the number of nonzero coefficients  $\#\text{supp}_i \mathbf{v}$  required in each tensor mode to achieve a certain accuracy depends on the best  $n$ -term approximability of the sequences  $\pi^{(i)}(\mathbf{u})$ .

This approximability by sparse sequences is quantified by the classical *approximation classes*  $\mathcal{A}^s = \mathcal{A}^s(\mathcal{J})$ , where  $s > 0$  and  $\mathcal{J}$  is a countable index set, comprised of all  $\mathbf{w} \in \ell_2(\mathcal{J})$  for which the quasi-norm

$$\|\mathbf{w}\|_{\mathcal{A}^s(\mathcal{J})} := \sup_{N \in \mathbb{N}_0} (N+1)^s \inf_{\substack{\Lambda \subset \mathcal{J} \\ \#\Lambda \leq N}} \|\mathbf{w} - \mathbf{R}_{\Lambda} \mathbf{w}\| \quad (3.8)$$

is finite.

In particular, if  $\pi^{(i)}(\mathbf{u}) \in \mathcal{A}^s(\mathcal{G}_i)$ , these sequences can be approximated within accuracy  $\eta$  by finitely supported sequences with  $\mathcal{O}(\eta^{-1/s})$  nonzero entries. In what follows, we do not explicitly specify the index set in the spaces  $\mathcal{A}^s$  when this is clear from the context.

We analyze the complexity of the algorithm under the following benchmark assumptions.

**Assumptions 3.2.** *For the hierarchical tensor approximation in the case (3.1) of  $d$  parametric variables, we assume the following:*

- (i)  $\pi^{(i)}(\mathbf{u}), \pi^{(i)}(\mathbf{f}) \in \mathcal{A}^s(\mathcal{G}_i)$ ,  $i \in \hat{\mathcal{I}}$ , for an  $s > 0$ .
- (ii)  $\mathbf{u}, \mathbf{f} \in \mathcal{A}_{\mathcal{H}}(\gamma)$ , where  $\gamma(n) := e^{\bar{c}n^{1/\bar{b}}}$  with  $\bar{b}, \bar{c} > 0$ .
- (iii) The  $\mathbf{A}_j$ ,  $j \in \hat{\mathcal{I}}$ , are  $s^*$ -compressible for an  $s^* > s$ , and hence there exist matrices  $\mathbf{A}_{j,n}$  with  $\alpha_{j,n}2^n$  entries per row and column and such that  $\|\mathbf{A}_j - \mathbf{A}_{j,n}\| \leq \beta_{j,n}2^{-sn}$ , and where the sequences  $\boldsymbol{\alpha}_j = (\alpha_{j,n})_{n \in \mathbb{N}}$  and  $\boldsymbol{\beta}_j = (\beta_{j,n})_{n \in \mathbb{N}}$  are summable.
- (iv) The routine `RHS` satisfies, for sufficiently small  $\eta > 0$  and  $\mathbf{f}_{\eta} := \text{RHS}(\eta)$ ,

$$\begin{aligned} \#\text{supp}_i(\mathbf{f}_{\eta}) &\lesssim \eta^{-\frac{1}{s}} \|\pi^{(i)}(\mathbf{f})\|_{\mathcal{A}^s}, \quad \|\pi^{(i)}(\mathbf{f}_{\eta})\|_{\mathcal{A}^s} \lesssim \|\pi^{(i)}(\mathbf{f})\|_{\mathcal{A}^s}, \\ |\text{rank}(\mathbf{f}_{\eta})|_{\infty} &\lesssim (d^{-1} \ln(\|\mathbf{f}\|_{\mathcal{A}_{\mathcal{H}}(\gamma)}/\eta))^{\bar{b}}, \end{aligned}$$

with hidden constants that do not depend on  $d$ , and there exists  $C > 0$  independent of  $d$  such that the required number of operations is bounded by

$$C \left( d |\text{rank}(\mathbf{f}_{\eta})|_{\infty}^3 + |\text{rank}(\mathbf{f}_{\eta})|_{\infty} \sum_{i \in \hat{\mathcal{I}}} \#\text{supp}_i(\mathbf{f}_{\eta}) \right).$$

We will use the above assumptions as a reference point for the scaling with respect to  $\varepsilon$  of the computational complexity. In order to also compare different parametric dimensionalities  $d$  in the complexity bounds, we additionally need a specific reference family of  $d$ -dependent problems. We introduce the following model assumptions, which we shall also consider in more detail for a concrete class of problems in §6.

**Assumptions 3.3.** *For the quantities in Assumptions 3.2, in addition let the following hold:*

- (i)  $\|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^s}$ ,  $\|\pi^{(i)}(\mathbf{f})\|_{\mathcal{A}^s}$ ,  $i \in \hat{\mathcal{I}}$ , and  $\|\mathbf{u}\|_{\mathcal{A}_{\mathcal{H}}(\gamma)}$ ,  $\|\mathbf{f}\|_{\mathcal{A}_{\mathcal{H}}(\gamma)}$  as well as  $\bar{c}^{-1}$  grow at most polynomially in  $d$ .
- (ii)  $\bar{b}$  and  $\|\mathbf{A}_j\|$ ,  $\|\boldsymbol{\alpha}_j\|_{\ell^1}$ ,  $\|\boldsymbol{\beta}_j\|_{\ell^1}$  for  $j \in \hat{\mathcal{I}}$  are bounded independently of  $d$ .

It needs to be emphasized that Algorithm 2.1 does not require any knowledge on the approximability of  $\mathbf{u}$  stated in Assumptions 3.2 and 3.3; these merely describe a model case for complexity bounds. Recall from Remark 2.1 that Algorithm 2.1 produces  $\mathbf{u}_\varepsilon$  satisfying  $\|\mathbf{u} - \mathbf{u}_\varepsilon\| \leq \varepsilon$  in finitely many steps.

**Theorem 3.4.** *Let Assumptions 3.2 hold, let  $\alpha > 0$  and let  $\kappa_1, \kappa_2, \kappa_3$  in Algorithm 2.1 be chosen as*

$$\begin{aligned} \kappa_1 &= (1 + (1 + \alpha)(\sqrt{d} + \sqrt{2d - 3} + \sqrt{d(2d - 3)}))^{-1}, \\ \kappa_2 &= \sqrt{2d - 3}(1 + \alpha)\kappa_1, \quad \kappa_3 = \sqrt{d}(1 + \sqrt{2d - 3})(1 + \alpha)\kappa_1. \end{aligned}$$

Then for each  $\varepsilon > 0$  with  $\varepsilon < \varepsilon_0$ , the approximation  $\mathbf{u}_\varepsilon$  produced by Algorithm 2.1 satisfies

$$|\text{rank}(\mathbf{u}_\varepsilon)|_\infty \leq (\bar{c}^{-1} \ln[2(\alpha\kappa_1)^{-1} \rho_\gamma \|\mathbf{u}\|_{\mathcal{A}_{\mathcal{H}}(\gamma)} \varepsilon^{-1}])^{\bar{b}} \lesssim \left( \frac{|\ln \varepsilon| + \ln d}{\bar{c}} \right)^{\bar{b}}, \quad (3.9)$$

as well as

$$\sum_{i \in \hat{\mathcal{I}}} \# \text{supp}_i(\mathbf{u}_\varepsilon) \lesssim d^{1+\frac{1}{s}} \left( \sum_{i \in \hat{\mathcal{I}}} \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^s} \right)^{\frac{1}{s}} \varepsilon^{-\frac{1}{s}}. \quad (3.10)$$

Let in addition Assumptions 3.3 hold, then there exist  $c, C > 0$  such that the number of required operations is bounded by

$$C d^{c \ln d} |\ln \varepsilon|^{2\bar{b}} \varepsilon^{-\frac{1}{s}}, \quad (3.11)$$

where  $c$  depends on  $\alpha, \rho, \omega, s$ , and  $C$  may additionally depend on  $\mathbf{u}$  and  $\mathbf{f}$ .

*Proof.* The validity of (3.9) and (3.10) follows by [5, Thm. 7], which can be immediately applied to the result of line 11 in Algorithm 2.1. Concerning (3.11), we can apply [5, Thm. 8] (with  $R_i = d$  and uniform constants  $\hat{C}_{\hat{\alpha}}^{(i)}$ ,  $\hat{C}_{\hat{\beta}}^{(i)}$  and  $\hat{C}_{\hat{\mathbf{A}}}^{(i)}$  in the notation used there) to obtain, for  $\mathbf{w}_\eta := \text{APPLY}(\mathbf{v}; \eta)$ ,

$$\# \text{supp}_i(\mathbf{w}_\eta) \lesssim d^{1+s-1} \eta^{-\frac{1}{s}} \left( \sum_{j \in \mathcal{I}_x} \|\pi^{(j)}(\mathbf{v})\|_{\mathcal{A}^s} \right)^{\frac{1}{s}}, \quad \|\pi^{(i)}(\mathbf{w}_\eta)\|_{\mathcal{A}^s} \lesssim d^{1+s} \|\pi^{(i)}(\mathbf{v})\|_{\mathcal{A}^s},$$

as well as  $\text{rank}(\mathbf{w}_\eta) \leq (d + 1) \text{rank}(\mathbf{v})$ . With these estimates, (3.11) follows exactly as in [5, Thm. 9].  $\square$

## 4 Spatial-parametric sparse approximation

We now turn to the case  $\mathcal{I} = \mathbb{N}$ , that is, problems involving countably many parameters  $(y_j)_{j \geq 1}$  that have decreasing influence as  $j$  increases. Here we consider problems of the type (1.5),

$$a(y) = \bar{a} + \sum_{j=1}^{\infty} y_j \theta_j, \quad (4.1)$$

under the uniform ellipticity assumption (1.6) on  $a$ . This variant of Algorithm 2.1 is similar to the scheme proposed in [22], following the approach of [9, 10].

In this section we consider a version of Algorithm 2.1 that produces  $n$ -term approximations to  $u \in L^2(Y, V)$  in terms of the wavelet-Legendre tensor product basis  $\{\psi_\lambda \otimes L_\nu\}_{\lambda \in \mathcal{S}, \nu \in \mathcal{F}}$ . That is, the approximation that we seek in this case is of the form (ASP), that is,

$$u \approx u_n = \sum_{(\lambda, \nu) \in \Lambda_n} \mathbf{u}_{\lambda\nu} \psi_\lambda \otimes L_\nu, \quad (4.2)$$

where we aim to identify  $\Lambda_n$  which yields an error close to that of the best  $n$ -term approximation in this basis.

In this case, COARSEN performs a standard coarsening operation on a sequence, and RECOMPRESS( $\mathbf{v}; \eta$ ) :=  $\mathbf{v}$  for any  $\eta$ . The scheme thus reduces to the adaptive method of [10], which has been considered for this particular type of approximation of parametric PDEs also in [22]. The key ingredient that remains to be described is the adaptive application of  $\mathbf{A}$  to representations of the form (4.2) based on its  $s^*$ -compressibility.

Let  $\mathbf{u} \in \mathcal{A}^s(\mathcal{S} \times \mathcal{F})$  and let  $\mathbf{A}$  be  $s^*$ -compressible with  $s^* > s$  according to (2.10). Then it follows by [9, Prop. 3.8] that  $\mathbf{f} \in \mathcal{A}^s$ , hence we can construct RHS satisfying

$$\#\text{supp}(\text{RHS}(\eta)) \lesssim \eta^{-\frac{1}{s}} \|\mathbf{f}\|_{\mathcal{A}^s}^{\frac{1}{s}}, \quad \|\text{RHS}(\eta)\|_{\mathcal{A}^s} \lesssim \|\mathbf{f}\|_{\mathcal{A}^s}.$$

Moreover, by the standard construction of APPLY in [9, Cor. 3.10] based on the  $s^*$ -compressibility of  $\mathbf{A}$ , the results in [10] yield the following complexity bound for the present realization of Algorithm 2.1.

**Theorem 4.1.** *Let  $\mathbf{u} \in \mathcal{A}^s$  and let  $\mathbf{A}$  be  $s^*$ -compressible with  $0 < s < s^*$ . Then for any given  $\varepsilon > 0$ , the approximation  $\mathbf{u}_\varepsilon$  produced by the above variant of Algorithm 2.1 operating on approximations of the form (4.2) satisfies*

$$\#\text{supp}(\mathbf{u}_\varepsilon) \lesssim \varepsilon^{-\frac{1}{s}} \|\mathbf{u}\|_{\mathcal{A}^s}^{\frac{1}{s}}, \quad \|\mathbf{u}_\varepsilon\|_{\mathcal{A}^s} \lesssim \|\mathbf{u}\|_{\mathcal{A}^s},$$

and the number of operations is bounded up to a multiplicative constant by  $1 + \varepsilon^{-\frac{1}{s}} \|\mathbf{u}\|_{\mathcal{A}^s}^{\frac{1}{s}}$ .

We next consider the compressibility of  $\mathbf{A}$ , which determines the range of  $s$  for which Theorem 4.1 yields optimality, and a corresponding procedure APPLY.

### 4.1 Adaptive operator application

Any numerical scheme APPLY necessarily involves a truncation of the series (4.1). Defining for each nonnegative integer  $M$  the corresponding truncation error

$$e_M := \left\| \sum_{j>M} \mathbf{A}_j \otimes \mathbf{M}_j \right\| \quad (4.3)$$



of replacing  $\mathbf{A}$  by  $\sum_{j=1}^M \mathbf{A}_j \otimes \mathbf{M}_j$ , where  $e_0 = \|\mathbf{A}\|$ , the decay of  $e_M$  describes the approximability of  $\mathbf{A}$ . We will be concerned with algebraic rates

$$e_M \leq CM^{-S}, \quad M \in \mathbb{N}, \quad (4.4)$$

where  $C, S > 0$  are fixed constants. Note that in particular, our further developments do not require summability of  $(\|\theta_j\|_{L^\infty})_{j \geq 1}$  as assumed, e.g., in [15, 17].

The  $s^*$ -compressibility of  $\mathbf{A}$  depends both on the decay of the truncation errors (4.4) and on the compressibility of the  $\mathbf{A}_j$ , which depends on the particular expansion system  $(\theta_j)_{j \in \mathbb{N}}$ . We focus here on expansion systems of the following type.

**Assumptions 4.2.** *Let  $\Xi = \{\xi_\mu\}_{\mu \in \Lambda}$  be a system of compactly supported multilevel basis functions with  $\text{diam}(\text{supp}(\xi_\mu)) \sim 2^{-|\mu|}$  and  $\|\xi_\mu\|_{L^\infty(D)} = 1$ . With  $(\mu_j)_{j \geq 1}$  an enumeration of  $\Lambda$  by increasing level and some fixed  $\alpha > 0$ , we consider*

$$\theta_j = c_{\mu_j} \xi_{\mu_j}, \quad \text{where } c_{\mu_j} = 2^{-\alpha|\mu_j|}. \quad (4.5)$$

To simplify notation, let  $c_{\mu_0} := 1$ ,  $\xi_{\mu_0} := \bar{a}$ , and  $|\mu_0| := 0$ .

Note that for what follows, it would in fact suffice to assume  $c_\mu \sim 2^{-\alpha|\mu|}$ , with a constant that is uniform over  $\Lambda$ , but we assume equality to simplify the exposition. Under Assumptions 4.2,

$$e_M \leq \sup_{y \in Y} \left\| \sum_{j > M} y_j \theta_j \right\|_{L^\infty(D)} \leq \sum_{\ell \geq \max\{|\mu_j| : j \leq M\}} 2^{-\alpha\ell} \lesssim 2^{-\alpha \max\{|\mu_j| : j \leq M\}} \lesssim M^{-\frac{\alpha}{m}},$$

and we thus obtain (4.4) with  $S = \alpha/m$ .

We now give a new result for the compressibility of  $\mathbf{A}$  arising from a wavelet-type parametrization as in (4.5). As we shall see, making use of a multilevel structure in the parametrization that leads to Assumptions 4.3, one can obtain substantially better compressibility of  $\mathbf{A}$  than under the more generic assumptions used in [22].

The result is based on compressibility properties of the corresponding matrices  $\mathbf{A}_j$ , which are analyzed in Appendix A. These findings establish the following hypotheses under additional conditions on the smoothness of  $\xi_\mu$  and the spatial wavelets.

**Assumptions 4.3.** *With  $\{\theta_j\}_{j \geq 1}$  and  $c_{\mu_j}$  as in Assumptions 4.2, there exist a  $\tau > \frac{\alpha}{m}$  and matrices  $\mathbf{A}_{j,n}$ ,  $n \in \mathbb{N}_0$ , with the following properties:*

- (i) *the number of nonvanishing entries in each column of  $\mathbf{A}_{n,j}$  does not exceed a uniform constant multiple of  $(1 + |\mu_j|^q)2^n$ , for some  $q \geq 1$ ;*
- (ii) *one has*

$$\|\mathbf{A}_j - \mathbf{A}_{j,n}\| \lesssim c_{\mu_j} 2^{-\tau n}, \quad n \in \mathbb{N}, \quad (4.6)$$

*where the hidden constant is independent of  $j, n$ .*

Specifically, it is shown in Appendix A that the above assumptions can be realized for arbitrarily large  $\tau$  by choosing the functions  $\xi_\mu$  and the spatial wavelets sufficiently smooth, the latter having sufficiently many vanishing moments.

We show that under such a hypothesis the matrix  $\mathbf{A}$  is  $s^*$ -compressible where  $s^* < \alpha/m$  comes as close to  $\alpha/m$  as one wishes when  $\tau$  is suitably large. As discussed in further detail in §6, this means that the  $n$ -term approximability of  $\mathbf{u}$  can be fully exploited.

**Proposition 4.4.** *Let Assumptions 4.2 and 4.3 hold. Then  $\mathbf{A}$  is  $s^*$ -compressible for any*

$$s^* < \frac{\alpha}{m} \frac{2\tau}{1+2\tau}. \quad (4.7)$$

*Proof.* We construct approximations  $\mathbf{A}_{\mathbf{n}}$  of  $\mathbf{A}$  by choosing sequences  $\mathbf{n} = (n_j)_{j \geq 0}$  of bounded support and defining  $\mathbf{A}_{\mathbf{n}}: \ell^2(\mathcal{S} \times \mathcal{F}) \rightarrow \ell^2(\mathcal{S} \times \mathcal{F})$  by

$$\mathbf{A}_{\mathbf{n}} := \sum_{j \geq 0} \mathbf{A}_{j, n_j} \otimes \mathbf{M}_j. \quad (4.8)$$

Our aim is to find such  $\mathbf{n}^J$  such that the corresponding  $\mathbf{A}^J := \mathbf{A}_{\mathbf{n}^J}$  satisfy

$$\|\mathbf{A} - \mathbf{A}^J\| \lesssim J^{-2} 2^{-s^* J}, \quad J \in \mathbb{N}, \quad (4.9)$$

with  $s^*$  as in the assertion, and such that  $\mathbf{A}^J$  is  $J^{-2} 2^J$ -sparse, i.e., the number of nonzero entries in the each column of  $\mathbf{A}^J$  does not exceed a fixed constant multiple of  $J^{-2} 2^J$ .

We take  $L \in \mathbb{N}$  be arbitrary but fixed. Recall that we assume  $\mu_j$  to be ordered by increasing level, that is,  $|\mu_{j+1}| \geq |\mu_j|$ . We now consider  $(n_j)_{j \geq 0}$  such that  $n_j = 0$  for  $j > M_L := \lceil L^{2m/\alpha} 2^{mL} \rceil$ . Since then  $e_{M_L} \lesssim L^{-2} 2^{-\alpha L}$  (see (4.4), (6.13)), we obtain

$$\|\mathbf{A} - \mathbf{A}_{\mathbf{n}}\| \lesssim \left\| \sum_{j=0}^{M_L} (\mathbf{A}_j - \mathbf{A}_{j, n_j}) \otimes \mathbf{M}_j \right\| + L^{-2} 2^{-\alpha L}. \quad (4.10)$$

Within each level  $\ell \geq 0$ , i.e., for each  $\mu$  with  $|\mu| = \ell$ , there are only finitely many  $\mu'$  with  $|\mu'| = \ell$  such that  $\text{supp } \xi_\mu \cap \text{supp } \xi_{\mu'} \neq \emptyset$ . Since the images of  $\mathbf{A}_j$  corresponding to  $\xi_{\mu_j}$  with disjoint support are orthogonal, we obtain

$$\left\| \sum_{j=0}^{M_L} (\mathbf{A}_j - \mathbf{A}_{j, n_j}) \otimes \mathbf{M}_j \right\| \lesssim \sum_{\ell=0}^{\lceil L + \frac{2}{\alpha} \log_2 L \rceil} \left( \sum_{j: |\mu_j| = \ell} \|\mathbf{A}_j - \mathbf{A}_{j, n_j}\|^2 \right)^{\frac{1}{2}}, \quad (4.11)$$

where the constant depends on the maximum number of wavelets of overlapping support on each level. Taking

$$n_j = n_\ell = \left\lceil \frac{m\ell}{2\tau} + \frac{\alpha}{\tau} \left( L + \frac{2}{\alpha} \log_2 L - \ell \right) + \frac{1}{\tau} \log_2(1 + \ell)^2 \right\rceil$$

for  $\mu_j$  of level  $\ell$  and recalling that for such  $j$  we have  $|c_{\mu_j}| = 2^{-\alpha \ell}$  gives

$$\sum_{\ell=0}^{\lceil L + \frac{2}{\alpha} \log_2 L \rceil} \left( \sum_{j: |\mu_j| = \ell} \|\mathbf{A}_j - \mathbf{A}_{j, n_j}\|^2 \right)^{\frac{1}{2}} \lesssim \sum_{\ell=0}^{\lceil L + \frac{2}{\alpha} \log_2 L \rceil} 2^{\frac{m}{2}\ell} 2^{-\alpha \ell} 2^{-\tau n_\ell} \lesssim L^{-2} 2^{-\alpha L}. \quad (4.12)$$

The resulting  $\mathbf{A}_{\mathbf{n}}$  is  $N_L$ -sparse with

$$\begin{aligned} N_L &\lesssim \sum_{\ell=0}^{\lceil L + \frac{2}{\alpha} \log_2 L \rceil} (1 + \ell^q) 2^{m\ell} 2^{n_\ell} \lesssim L^{\frac{2}{\alpha}} 2^{\frac{\alpha}{\tau} L} \sum_{\ell=0}^{\lceil L + \frac{2}{\alpha} \log_2 L \rceil} (1 + \ell)^{q + \frac{2}{\tau}} 2^{(1 + \frac{1}{2\tau})m\ell - \frac{\alpha}{\tau}\ell} \\ &\lesssim L^{q + \frac{2(1+m)}{\alpha}} 2^{\frac{1+2\tau}{2\tau} mL}, \end{aligned} \quad (4.13)$$

where we have used  $\tau > \alpha/m$ .

We now fix  $s^* > 0$  with  $s^* < t := \frac{\alpha}{m} \frac{2\tau}{1+2\tau}$  and take  $J := \lceil \frac{t}{s^*} \frac{1+2\tau}{2\tau} mL \rceil = \lceil \frac{\alpha}{s^*} L \rceil$  and  $\mathbf{n}^J := \mathbf{n}$ . Since then  $N_L \lesssim J^{q + \frac{2(1+m)}{\alpha}} 2^{\frac{s^*}{t} J}$  we see that  $N_L \lesssim J^{-2} 2^J$  with a constant that depends on  $\alpha, m$  and increases when  $s^*$  approaches  $t$ . It immediately follows from (4.12) that

$$\|\mathbf{A} - \mathbf{A}^J\| \lesssim J^{-2} 2^{-s^* J} \quad (4.14)$$

with a constant depending on  $m$ . Thus  $\mathbf{A}$  is  $s^*$ -compressible for any  $s^* < t$ .  $\square$

## 4.2 Coefficient expansions

In our compressibility result Proposition 4.4 for  $\mathbf{A}$ , we have made use of the multiscale structure of the expansion functions  $\theta_j$ . Let us now briefly compare this to previous results for globally supported  $\theta_j$  as they arise in Karhunen-Loève expansions. In fact, for certain problems one has equivalent expansions in either globally supported or wavelet-type  $\theta_j$ . This is demonstrated, for instance, in [3] for lognormal diffusion coefficients with Gaussian random fields of Matérn covariance.

In order to illustrate the basic issues in approximation  $\mathbf{A}$  in the case of typical globally supported  $\theta_j$ , we consider the following spatially one-dimensional setting with  $D = ]0, 1[$  as in [22]: for a monotonically decreasing positive sequence  $(c_j)_{j \in \mathbb{N}}$  with  $\sum_{j \geq 1} c_j \leq \frac{1}{2}$ , take  $\theta_j = c_j \sin(j\pi \cdot)$ , so that

$$a(y) = 1 + \sum_{j \geq 1} y_j c_j \sin(j\pi \cdot). \quad (4.15)$$

This model is representative in that such increasingly oscillatory  $\theta_j$  as  $j \rightarrow \infty$  also arise in more general Karhunen-Loève expansions.

As a concrete example, with  $\beta > 1$ , consider  $c_j := cj^{-\beta}$  with  $c > 0$  sufficiently small. Then  $\|\mathbf{A}_j\| \sim c_j$ , from which we only obtain

$$e_M \lesssim M^{-\beta+1},$$

and therefore  $S = \beta - 1$ .

As shown in [22], taking the compression of the individual  $\mathbf{A}_j$  into account one obtains  $s^*$ -compressibility of  $\mathbf{A}$  with  $s^* = \frac{1}{2}(\beta - 1)$ . In this case, instead of Assumptions 4.3 one has  $\|\mathbf{A}_j - \mathbf{A}_{j,n}\| \lesssim j^{-(\alpha+\frac{1}{2})}2^{-\gamma n}$  with  $\mathcal{O}(j(1 + \log_2 j)2^n)$  entries per row and column. We comment further in Remark A.3 on how this leads to the limitation to  $s^* = \frac{1}{2}(\beta - 1)$ .

## 5 Low-rank approximation

We now turn to an adaptive method for finding low-rank approximations of the form (LR), based on the Hilbert-Schmidt decomposition of  $\mathbf{u}$ . These approximations are of the form

$$\mathbf{u} \approx \sum_{k=1}^n \mathbf{u}_{k,\lambda}^x \otimes \mathbf{u}_{k,\nu}^y. \quad (5.1)$$

with finitely supported vectors  $\mathbf{u}_k^x, \mathbf{u}_k^y$ ,  $k = 1, \dots, n$ . As in the scheme considered in §3, adaptivity in rank and in the basis expansions is intertwined by iteratively improving low-rank expansions of varying ranks, while at the same time identifying finitely supported approximations in  $\ell^2(\mathcal{S})$  and  $\ell^2(\mathcal{F})$ , both based on approximate residual evaluations.

In principle, the results of the previous section concerning a full separation of variables based on hierarchical tensor formats could be applied with any finite truncation dimension  $d$ . However, assuming (4.4), a total error of order  $\varepsilon$  requires  $d(\varepsilon) \sim \varepsilon^{-1/S}$ . As a consequence, due to the  $d$ -dependent quasi-optimality (3.6) of the hierarchical SVD truncation, we can only obtain a highly suboptimal complexity bound in (3.11) for the hierarchical format.

Concerning low-rank decompositions, we therefore concentrate here on a more basic case, namely a separation of spatial and parametric variables as in (5.1). Since this separation also occurs in any hierarchical representation, the resulting Hilbert-Schmidt rank provides a lower bound for the maximum hierarchical ranks that one can obtain in a hierarchical format involving further matricizations.

The efficiency of the obtained low-rank approximations is measured against the singular value decomposition of the Hilbert-Schmidt operator  $\ell^2(\mathcal{F}) \rightarrow \ell^2(\mathcal{S})$  induced by  $\mathbf{u}$ ,

$$\mathbf{u} = \sum_{k=1}^{\infty} \sigma_k \mathbf{U}_k^{(x)} \otimes \mathbf{U}_k^{(y)}, \quad (5.2)$$

where  $\sigma_k \geq 0$ ,  $\{\mathbf{U}_k^{(x)}\}$ ,  $\{\mathbf{U}_k^{(y)}\}$  are orthonormal in  $\ell^2(\mathcal{S})$  and  $\ell^2(\mathcal{F})$ , respectively, and

$$\left\| \mathbf{u} - \sum_{k=1}^r \sigma_k \mathbf{U}_k^{(x)} \otimes \mathbf{U}_k^{(y)} \right\|^2 = \sum_{k>r} \sigma_k^2 = \min_{\text{rank}(\mathbf{w}) \leq r} \|\mathbf{u} - \mathbf{w}\|^2. \quad (5.3)$$

Ideally, the ranks of computed approximations should be comparable to the minimum  $r$  for achieving the same error in (5.3).

Moreover, we quantify in terms of  $\#(\bigcup_{k=1}^n \text{supp } \mathbf{u}_k^i)$ ,  $i = x, y$  the number of nonzero coefficients in (5.1). The reasons for not considering each individual  $\# \text{supp } \mathbf{u}_k^i$  separately are mainly algorithmic: since the numerical methods require orthogonalizations of the sets  $(\mathbf{u}_k^i)_{k=1, \dots, n}$ , their complexity is determined by the unions of the respective supports. To understand the joint approximability of the infinite vectors  $\mathbf{U}_k^{(i)}$ ,  $i = x, y$  in (5.2) serving as our reference point, we consider the particular contractions defined, for  $\mathbf{v} \in \ell^2(\mathcal{S} \times \mathcal{F})$ , by

$$\pi^{(x)}(\mathbf{v}) := \left( \left( \sum_{\nu \in \mathcal{F}} |\mathbf{v}_{\lambda, \nu}|^2 \right)^{1/2} \right)_{\lambda \in \mathcal{S}}, \quad \pi^{(y)}(\mathbf{v}) := \left( \left( \sum_{\lambda \in \mathcal{S}} |\mathbf{v}_{\lambda, \nu}|^2 \right)^{1/2} \right)_{\nu \in \mathcal{F}}. \quad (5.4)$$

Note that  $\pi_{\nu}^{(y)}(\mathbf{u})$  is uniformly proportional to the norm of the corresponding Legendre coefficient of  $u$ , that is,  $\pi_{\nu}^{(y)}(\mathbf{u}) \sim \|u_{\nu}\|_V$ .

Let  $(\lambda_k^*)_{k \in \mathbb{N}}$  and  $(\nu_k^*)_{k \in \mathbb{N}}$  be such that  $(\pi_{\lambda_k^*}^{(x)}(\mathbf{v}))_{k \in \mathbb{N}}$  and  $(\pi_{\nu_k^*}^{(y)}(\mathbf{v}))_{k \in \mathbb{N}}$  are nonincreasing, respectively. Then the singular values  $\sigma_k(\mathbf{v})$  of  $\mathbf{v}$  satisfy

$$\sigma_k(\mathbf{v}) \leq \pi_{\lambda_k^*}^{(x)}(\mathbf{v}), \pi_{\nu_k^*}^{(y)}(\mathbf{v}), \quad k \in \mathbb{N}. \quad (5.5)$$

In view of our results for Example 6.4 (and the further numerical experiments of Example 6.9), we cannot generally expect faster than algebraic decay of singular values, which we quantify in terms of classes  $\mathcal{A}_{\mathcal{H}}(\gamma)$  specialized to tensors of order two and to the specific sequence  $\gamma(k) := (1+k)^{\bar{s}}$ . This yields the approximation classes

$$\Sigma^{\bar{s}} := \left\{ \mathbf{v} \in \ell^2(\mathcal{S} \times \mathcal{F}) : \sup_{k \in \mathbb{N}} (1+k)^{\bar{s}} \left( \sum_{j>k} \sigma_k(\mathbf{v})^2 \right)^{1/2} =: \|\mathbf{v}\|_{\Sigma^{\bar{s}}} < \infty \right\}.$$

The approximate sparsity of the sequences  $\pi^{(x)}(\mathbf{v})$ ,  $\pi^{(y)}(\mathbf{v})$  is measured in terms of the largest  $s_x, s_y > 0$  such that  $\pi^{(x)}(\mathbf{v}) \in \mathcal{A}^{s_x}(\mathcal{S})$ ,  $\pi^{(y)}(\mathbf{v}) \in \mathcal{A}^{s_y}(\mathcal{F})$  according to (3.8).

For the low-rank approximation, the routines RECOMPRESS and COARSEN used in Algorithm 2.1 are based on the specialization to tensors of order two of the routines described in the previous section. RECOMPRESS( $\mathbf{v}; \eta$ ) is a numerical realization of  $\hat{\mathbf{P}}_{\eta}(\mathbf{v})$ , which we define as the operator producing the best low-rank approximation of  $\mathbf{v}$  with error at most  $\eta$  with respect to  $\|\cdot\|$ , obtained by truncating the singular value decomposition of its argument.

The routine COARSEN( $\mathbf{v}; \eta$ ) is constructed as in §3 based on the contractions  $\pi^{(x)}(\mathbf{v})$ ,  $\pi^{(y)}(\mathbf{v})$  defined as in (5.4). The following result differs from [5, Theorem 7], which is formulated for general hierarchical tensors, in that we now consider differing sparsity classes for the contractions  $\pi^{(i)}$ ,  $i = x, y$ . In view of the preceding discussion, it is reasonable to assume possibly different but algebraic decay for both contractions.

**Theorem 5.1.** *Let  $\mathbf{u}, \mathbf{v} \in \ell^2(\mathcal{S} \times \mathcal{F})$  with  $\|\mathbf{u} - \mathbf{v}\| \leq \eta$ . Then for*

$$\mathbf{w}_\eta := \hat{\mathbf{C}}_{2^{3/2}(1+\alpha)\eta}(\hat{\mathbf{P}}_{(1+\alpha)\eta}(\mathbf{v})), \quad (5.6)$$

we have

$$\|\mathbf{u} - \mathbf{w}_\eta\| \leq (2 + \alpha + 2^{3/2}(1 + \alpha))\eta. \quad (5.7)$$

Moreover, when  $\mathbf{u} \in \Sigma^{\bar{s}}$ ,  $\pi^{(i)}(\mathbf{u}) \in \mathcal{A}^{s_i}$ ,  $i = x, y$ , we have

$$|\text{rank}(\mathbf{w}_\eta)|_\infty \leq 2(\alpha^{-1}\|\mathbf{u}\|_{\Sigma^{\bar{s}}})^{\frac{1}{\bar{s}}}\eta^{-\frac{1}{\bar{s}}}, \quad \|\mathbf{w}_\eta\|_{\Sigma^{\bar{s}}} \leq 2(1 + \alpha^{-1})\|\mathbf{u}\|_{\Sigma^{\bar{s}}}, \quad (5.8)$$

and

$$\begin{aligned} \#\text{supp}_x(\mathbf{w}_\eta) + \#\text{supp}_y(\mathbf{w}_\eta) &\leq 2 + \left( \frac{2\|\pi^{(x)}(\mathbf{u})\|_{\mathcal{A}^{s_x}}}{\alpha\eta} \right)^{\frac{1}{s_x}} + \left( \frac{2\|\pi^{(y)}(\mathbf{u})\|_{\mathcal{A}^{s_y}}}{\alpha\eta} \right)^{\frac{1}{s_y}} \\ \|\pi^{(i)}(\mathbf{w}_\eta)\|_{\mathcal{A}^{s_i}} &\leq C\|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}}, \quad i = x, y, \end{aligned} \quad (5.9)$$

where  $C$  depends on  $\alpha$  and  $s_i$ ,  $i = x, y$ .

The estimates (5.6), (5.7) have been already shown in [5]. The only deviation concerns the stability estimate (5.9), which we prove in Appendix B.

To apply Algorithm 2.1 it remains to specify the approximate application of  $\mathbf{A}$  by the procedure APPLY to representations of the form (5.2). As part of this procedure, we shall also use a modified routine COARSEN<sub>y</sub> which operates only on the second tensor mode and leaves  $\text{supp}_x$  unchanged. For this routine, we shall only use the simpler statement that for any  $\mathbf{v} \in \ell^2(\mathcal{S} \times \mathcal{F})$  with  $\pi^{(y)}(\mathbf{v}) \in \mathcal{A}^{s_y}(\mathcal{F})$ ,  $\mathbf{v}_y := \text{COARSEN}_y(\mathbf{v}; \eta)$  satisfies

$$\#\text{supp}_y(\mathbf{v}_y) \lesssim \eta^{-\frac{1}{s_y}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}^{\frac{1}{s_y}}, \quad \|\pi^{(y)}(\mathbf{v}_y)\|_{\mathcal{A}^{s_y}} \lesssim \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}.$$

## 5.1 Adaptive operator application

We now describe a specification of the more generic routine used in [5] that is tailored to exploit anisotropy in the parametrizations of parametric operators. For given any given  $\eta > 0$  and finitely supported  $\mathbf{v}$  we aim to construct  $\mathbf{w}_\eta$  such that  $\|\mathbf{A}\mathbf{v} - \mathbf{w}_\eta\| \leq \eta$ . We follow here the general strategy of combining a priori knowledge on  $\mathbf{A}$  with a posteriori information on  $\mathbf{v}$ , which is given in terms of a suitable decomposition of  $\mathbf{v}$ .

To that end, we first apply a preprocessing step to the finitely supported input  $\mathbf{v}$  that consists of applications of RECOMPRESS and COARSEN<sub>y</sub>. We choose for a given  $\eta > 0$  the tolerances of order  $\eta$  in such a way that the resulting  $\mathbf{v}_\eta$  satisfies

$$\|\mathbf{v} - \mathbf{v}_\eta\| \leq \frac{\eta}{2\|\mathbf{A}\|}. \quad (5.10)$$

As a consequence, for any positive  $s_y, \bar{s}$  we have

$$\text{rank}(\mathbf{v}_\eta) \lesssim \eta^{-\frac{1}{\bar{s}}}\|\mathbf{v}\|_{\Sigma^{\bar{s}}}^{\frac{1}{\bar{s}}}, \quad \|\mathbf{v}_\eta\|_{\Sigma^{\bar{s}}} \lesssim \|\mathbf{v}\|_{\Sigma^{\bar{s}}}, \quad (5.11)$$

and

$$\#\text{supp}_y(\mathbf{v}_\eta) \lesssim \eta^{-\frac{1}{s_y}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}^{\frac{1}{s_y}}, \quad \|\pi^{(y)}(\mathbf{v}_\eta)\|_{\mathcal{A}^{s_y}} \lesssim \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}. \quad (5.12)$$

We then have the SVD of  $\mathbf{v}_\eta$  at hand,

$$\mathbf{v}_\eta = \sum_{k=1}^K \sigma_k \mathbf{U}_k^{(x)} \otimes \mathbf{U}_k^{(y)}, \quad (5.13)$$

and set  $K_p = \{2^p, \dots, \min\{K, 2^{p+1} - 1\}\}$ , for  $p = 0, 1, \dots, p \leq \log_2 K$ . Furthermore, for  $q = 0, 1, \dots$ , let  $\hat{\Lambda}_q^{(y)}$  be the support of the best  $2^q$ -term approximation of  $\pi^{(y)}(\mathbf{v}_\eta)$ . We set  $\Lambda_0^{(y)} := \hat{\Lambda}_0^{(y)}$  and  $\Lambda_q^{(y)} := \hat{\Lambda}_q^{(y)} \setminus \hat{\Lambda}_{q-1}^{(y)}$  for  $q > 0$ . With this subdivision of  $\text{supp}_y(\mathbf{v}_\eta)$ , we now define

$$\mathbf{v}_{[p,q]} := \mathbf{R}_{\mathcal{S} \times \Lambda_q^{(y)}} \sum_{k \in K_p} \sigma_k \mathbf{U}_k^{(x)} \otimes \mathbf{U}_k^{(y)} = \sum_{k \in K_p} \sigma_k \mathbf{U}_k^{(x)} \otimes \mathbf{R}_{\Lambda_q^{(y)}} \mathbf{U}_k^{(y)}, \quad (5.14)$$

and obtain

$$\mathbf{A} \mathbf{v}_\eta = \sum_{p,q \geq 0} \sum_{j=0}^{\infty} (\mathbf{A}_j \otimes \mathbf{M}_j) \mathbf{v}_{[p,q]} = \sum_{p,q \geq 0} \sum_{j=0}^{\infty} \sum_{k \in K_p} \sigma_k (\mathbf{A}_j \mathbf{U}_k^{(x)}) \otimes (\mathbf{M}_j \mathbf{R}_{\Lambda_q^{(y)}} \mathbf{U}_k^{(y)}). \quad (5.15)$$

To construct an approximation  $\mathbf{w}_\eta$  of  $\mathbf{A} \mathbf{v}_\eta$  based on this decomposition, we truncate the summations over  $j$  for each  $p, q$  at some index  $M_{p,q} \in \mathbb{N}$ , to be determined later, and then replace the remaining terms  $\mathbf{A}_j$  by compressed versions, again depending on the respective  $p, q$ . With  $e_M$  defined for nonnegative integer  $M$  as in (4.3), for any given choice of  $M_{p,q}$  we have

$$\left\| \mathbf{A} \mathbf{v} - \sum_{p,q \geq 0} \sum_{j=0}^{M_{p,q}} (\mathbf{A}_j \otimes \mathbf{M}_j) \mathbf{v}_{[p,q]} \right\| \leq \sum_{p,q \geq 0} e_{M_{p,q}} \|\mathbf{v}_{[p,q]}\|. \quad (5.16)$$

We now choose the  $M_{p,q}$  such that

$$\sum_{p,q \geq 0} e_{M_{p,q}} \|\mathbf{v}_{[p,q]}\| \leq \frac{\eta}{4}. \quad (5.17)$$

This can be done by choosing positive weights  $\alpha_{p,q}$  such that  $\sum_{p,q} \alpha_{p,q} = 1$ , computing  $\|\mathbf{v}_{[p,q]}\|$ , and adjusting the  $M_{p,q}$  so as to guarantee that

$$e_{M_{p,q}} \|\mathbf{v}_{[p,q]}\| \leq \eta_{p,q} := \alpha_{p,q} \eta / 4. \quad (5.18)$$

We will give an a priori choice for  $M_{p,q}$  below, but one may as well use e.g. the Greedy scheme proposed in [21] for selecting these values.

Next, in order to realize an approximate application of the (generally) infinite matrices  $\mathbf{A}_j$  to  $\mathbf{U}_k^{(x)}$  in (5.15) we replace  $\mathbf{A}_j \mathbf{v}_{[p,q]}$  by an approximation  $\tilde{\mathbf{A}}_{j,p,q} \mathbf{v}_{[p,q]}$  using (2.10) so as to satisfy

$$\left\| \sum_{j=0}^{M_{p,q}} (\mathbf{A}_j - \tilde{\mathbf{A}}_{j,p,q}) \otimes \mathbf{M}_j \mathbf{v}_{[p,q]} \right\| \leq \eta_{p,q}. \quad (5.19)$$

The approximate operators  $\tilde{\mathbf{A}}_{j,p,q}$  will be specified later. The sought approximation of  $\mathbf{A} \mathbf{v}$  can now be obtained as

$$\mathbf{w}_\eta := \sum_{p,q \geq 0} \sum_{j=0}^{M_{p,q}} (\tilde{\mathbf{A}}_{j,p,q} \otimes \mathbf{M}_j) \mathbf{v}_{[p,q]}, \quad (5.20)$$

which by the above construction satisfies the (computable) error bound

$$\|\mathbf{A} \mathbf{v}_\eta - \mathbf{w}_\eta\| \leq \sum_{p,q \geq 0} (e_{M_{p,q}} \|\mathbf{v}_{[p,q]}\| + \eta_{p,q}) \leq \eta / 2, \quad (5.21)$$

so that

$$\|\mathbf{A}\mathbf{v} - \mathbf{w}_\eta\| \leq \eta. \quad (5.22)$$

In summary, the above adaptive approximation of  $\mathbf{A}$  to a given finitely supported  $\mathbf{v}$  involves the following steps:

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APPLY :  $\mathbf{v} \rightarrow \mathbf{w}_\eta$ , with  $\mathbf{v}$  given by its SVD

---

(S1): compute  $\mathbf{v}_\eta := \text{COARSE}_{\mathbf{y}}(\text{RECOMPRESS}(\mathbf{v}; \eta/4\|\mathbf{A}\|); \eta/4\|\mathbf{A}\|)$  and (quasi-)sort<sup>1</sup> the entries of  $\pi^{(\mathbf{y})}(\mathbf{v}_\eta)$  to obtain the sets  $\Lambda_q^{(\mathbf{y})}$ ;

(S2): compute the quantities  $\|\mathbf{v}_{p,q}\|$  and determine the truncation values  $M_{p,q} = M_{p,q}(\eta)$ ;

(S3): compute the quantities  $(\pi_\nu^{(\mathbf{x})}(\mathbf{v}_{[p,q]}))_{\nu \in \mathcal{S}}$  and use these to obtain the compressed matrices  $\tilde{\mathbf{A}}_{j,p,q}$ , using (5.14) in the assembly step (5.20).

---

## 5.2 Complexity analysis

To quantify the complexity of computing  $\mathbf{w}_\eta$  in (5.20) we need to specify the properties of the operator  $A(y)$  as well as the sparsity properties of the input. In view of our preceding discussion, in the scenario of primary interest, the singular values of the solution  $\mathbf{u}$  as well as the best  $n$ -term approximations of the contractions  $\pi^{(i)}(\mathbf{u})$ ,  $i \in \{\mathbf{x}, \mathbf{y}\}$ , exhibit algebraic decay rates. As before, these rates are denoted by  $\bar{s}$  and  $s_x, s_y$ , respectively.

As indicated earlier, the complexity of the above scheme depends, in particular, on the operator approximability by truncation. We adhere to the natural assumption that  $e_M \leq CM^{-S}$  for some positive  $S$ , see (4.4). Since, as explained in §??, we have  $S > s_i$ ,  $i \in \{\mathbf{x}, \mathbf{y}\}$ , in the expansion model of Assumptions 4.2, we confine the subsequent discussion to this setting, where  $S = \frac{\alpha}{m}$ . We gather next the properties upon which the complexity analysis will be based.

**Assumptions 5.2.** *The solution  $\mathbf{u}$  to (2.5) and the matrix  $\mathbf{A}$  have the following properties:*

(i) *One has  $\pi^{(i)}(\mathbf{u}), \pi^{(i)}(\mathbf{f}) \in \mathcal{A}^{s_i}$ ,  $i = \mathbf{x}, \mathbf{y}$ , with  $s_x, s_y > 0$ .*

(ii)  *$\mathbf{u}, \mathbf{f} \in \Sigma^{\bar{s}}$  for some  $\bar{s} \geq s_x, s_y$ .*

(iii) *There exists a constant  $C$  such that  $e_M \leq CM^{-S}$ ,  $M \in \mathbb{N}$ , where  $e_M$  is defined by (4.3) and*

$$S \geq \bar{s}, s_y. \quad (5.23)$$

(iv) *The representations  $\mathbf{A}_j$ ,  $j \in \mathbb{N}$ , satisfy Assumptions 4.3 where  $\tau$  satisfies*

$$\frac{2\tau}{1+2\tau} \frac{\alpha}{m} = \frac{2\tau}{1+2\tau} S > s_x. \quad (5.24)$$

(v) *The routine RHS satisfies, for sufficiently small  $\eta > 0$  and  $\mathbf{f}_\eta := \text{RHS}(\eta)$ ,*

$$\begin{aligned} \#\text{supp}_i(\mathbf{f}_\eta) &\lesssim \eta^{-\frac{1}{s_i}} \|\pi^{(i)}(\mathbf{f})\|_{\mathcal{A}^{s_i}}, & \|\pi^{(i)}(\mathbf{f}_\eta)\|_{\mathcal{A}^{s_i}} &\lesssim \|\pi^{(i)}(\mathbf{f})\|_{\mathcal{A}^{s_i}}, & i \in \{\mathbf{x}, \mathbf{y}\}, \\ \text{rank}(\mathbf{f}_\eta) &\lesssim \eta^{-\frac{1}{\bar{s}}} \|\mathbf{f}\|_{\Sigma^{\bar{s}}}, & \|\mathbf{f}_\eta\|_{\Sigma^{\bar{s}}} &\lesssim \|\mathbf{f}\|_{\Sigma^{\bar{s}}}, \end{aligned}$$

*and requires  $\mathcal{O}\left(\eta^{-\frac{1}{\bar{s}} - \frac{1}{\min\{s_x, s_y\}}}\right)$  operations.*

---

<sup>1</sup>As usual, to warrant a linear scaling, instead of exact ordering it suffices to perform approximate sorting into buckets according to some fixed exponential decay.

The main result of this section states that up to a logarithmic factor the sparsity properties of the input are preserved by the output of APPLY.

**Theorem 5.3.** *Suppose that the properties listed under Assumptions 5.2 hold. Then, given any finitely supported input  $\mathbf{v} \in \ell^2(\mathcal{S} \times \mathcal{F})$ , the output  $\mathbf{w}_\eta$  produced by the procedure APPLY, based on the steps (S1)–(S3), satisfies*

$$\|\mathbf{A}\mathbf{v} - \mathbf{w}_\eta\| \leq \eta. \quad (5.25)$$

Moreover, with some  $b \leq 2 + \frac{4}{s_x}$  one has

$$\text{rank}(\mathbf{w}_\eta) \lesssim \eta^{-\frac{1}{\bar{s}}} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}^{\frac{1}{\bar{s}}} (1 + |\log \eta|)^b, \quad \|\mathbf{w}_\eta\|_{\Sigma^{\bar{s}}} \lesssim \|\mathbf{v}\|_{\Sigma^{\bar{s}}} (1 + |\log \eta|)^{\bar{s}b}, \quad (5.26)$$

and

$$\begin{aligned} \#\text{supp}_y(\mathbf{w}_\eta) &\lesssim \eta^{-\frac{1}{s_y}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}^{\frac{1}{s_y}} (1 + |\log \eta|)^b, \\ \|\pi^{(y)}(\mathbf{w}_\eta)\|_{\mathcal{A}^{s_y}} &\lesssim \|\mathbf{v}\|_{\mathcal{A}^{s_y}} (1 + |\log \eta|)^{s_y b}, \end{aligned} \quad (5.27)$$

as well as

$$\begin{aligned} \#\text{supp}_x(\mathbf{w}_\eta) &\lesssim \eta^{-\frac{1}{s_x}} \|\pi^{(x)}(\mathbf{v})\|_{\mathcal{A}^{s_x}}^{\frac{1}{s_x}} (1 + |\log \eta|)^b, \\ \|\pi^{(x)}(\mathbf{w}_\eta)\|_{\mathcal{A}^{s_x}} &\lesssim \|\pi^{(x)}(\mathbf{v})\|_{\mathcal{A}^{s_x}} (1 + |\log \eta|)^{s_x b}, \end{aligned} \quad (5.28)$$

where the constants depend also on  $s_i$ , on  $|\log \|\pi^{(i)}(\mathbf{v})\|_{\mathcal{A}^{s_i}}|$ ,  $i \in \{x, y\}$ , and on  $\tau$  in Assumption 5.2.

*Proof.* The error bound (5.25) is implied by the construction. As for the remaining claims, to assess the complexity of computing  $\mathbf{w}_\eta$ , given by (5.20), we estimate first  $M_{p,q} = M_{p,q}(\eta)$  in terms of  $\eta$ . To obtain a priori bounds for the  $M_{p,q}$ , we use Assumptions 5.2(i) and (ii) to conclude that

$$\|\mathbf{v}_{[p,q]}\| \leq 2^{-s_y q} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}, \quad \|\mathbf{v}_{[p,q]}\| \leq 2^{-\bar{s}p} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}. \quad (5.29)$$

Then Assumption 5.2(iii) and (5.29) yield the sufficient conditions

$$M_{p,q} = M_{p,q}(\eta) \geq \left( \frac{4C \min\{2^{-\bar{s}p} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}, 2^{-s_y q} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}\}}{\alpha_{p,q} \eta} \right)^{\frac{1}{\bar{s}}}. \quad (5.30)$$

From (5.20) and the decomposition (5.15) we see that

$$\text{rank}(\mathbf{w}_\eta) \leq \sum_{p,q \geq 0} M_{p,q} 2^{2p}, \quad \#\text{supp}_y(\mathbf{w}_\eta) \leq \sum_{p,q \geq 0} 3M_{p,q} 2^q. \quad (5.31)$$

Note that the factor of 3 in the bound for  $\#\text{supp}_y(\mathbf{w}_\eta)$  results from the bidiagonal form of the matrices  $\mathbf{M}_j$ ; that is, the action of each of these matrices can add at most twice the number of nonzero entries in the preimage sequence, in addition to the existing ones.

The following lemma provides bounds for the right hand sides in (5.31).

**Lemma 5.4.** *For any fixed constant  $a > 1$  choose*

$$\alpha_{p,q} = c ((1+p)(1+q))^{-a}, \quad c := \left( \sum_{p,q \geq 0} ((1+p)(1+q))^{-a} \right)^{-1}, \quad (5.32)$$



as weights in (5.30). Then for  $S \geq \bar{s}$  one has

$$\begin{aligned} \sum_{p,q} 2^p M_{p,q} &\lesssim \eta^{-\frac{1}{\bar{s}}} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}^{\frac{1}{\bar{s}}} (1 + \log_2 \# \text{supp}_y(\mathbf{v}))^{1+\frac{a}{\bar{s}}} \\ &\quad \times (1 + \log_2 \text{rank}(\mathbf{v}_\eta))^{1+\frac{a}{\bar{s}}} (\text{rank}(\mathbf{v}_\eta))^{1-\frac{\bar{s}}{\bar{s}}}, \end{aligned} \quad (5.33)$$

where the constant depends on  $a, S, \bar{s}$ , on  $c$  in (5.32), and on  $C$  in Assumptions 5.2(iii).

Similarly, for  $S \geq s_y$  one has

$$\begin{aligned} \sum_{p,q} 2^q M_{p,q} &\lesssim \eta^{-\frac{1}{\bar{s}}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}^{\frac{1}{\bar{s}}} (1 + \log_2 \text{rank}(\mathbf{v}_\eta))^{1+\frac{a}{\bar{s}}} \\ &\quad \times (1 + \log_2 \# \text{supp}_y(\mathbf{v}_\eta))^{1+\frac{a}{\bar{s}}} (\# \text{supp}_y(\mathbf{v}_\eta))^{1-\frac{s_y}{\bar{s}}} \end{aligned} \quad (5.34)$$

with similar dependencies of the constants as before, but with  $\bar{s}$  replaced by  $s_y$ .

*Proof.* Bounding  $M_{p,q} \lesssim \eta^{-\frac{1}{\bar{s}}} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}^{\frac{1}{\bar{s}}} (1+q)^{\frac{a}{\bar{s}}} (1+p)^{\frac{a}{\bar{s}}} 2^{-\frac{sp}{\bar{s}}}$ , we derive

$$\sum_{p,q} 2^p M_{p,q} \lesssim \eta^{-\frac{1}{\bar{s}}} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}^{\frac{1}{\bar{s}}} (1 + \log_2 \# \text{supp}_y(\mathbf{v}_\eta))^{1+\frac{a}{\bar{s}}} \sum_p (1+p)^{\frac{a}{\bar{s}}} 2^{p(1-\frac{\bar{s}}{\bar{s}})}, \quad (5.35)$$

which gives (5.33), where the constant depends on  $a, S, \bar{s}$  and  $c, C$  from (5.30).

To bound  $\sum_{p,q} 2^q M_{p,q}$  we use  $M_{p,q} \lesssim \eta^{-\frac{1}{\bar{s}}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}^{\frac{1}{\bar{s}}} (1+p)^{\frac{a}{\bar{s}}} (1+q)^{\frac{a}{\bar{s}}} 2^{-\frac{syq}{\bar{s}}}$  and obtain

$$\sum_{p,q} 2^q M_{p,q} \lesssim \eta^{-\frac{1}{\bar{s}}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}^{\frac{1}{\bar{s}}} (1 + \log_2 \text{rank}(\mathbf{v}_\eta))^{1+\frac{a}{\bar{s}}} \sum_q (1+q)^{\frac{a}{\bar{s}}} 2^{q(1-\frac{s_y}{\bar{s}})}$$

which yields (5.34).  $\square$

We proceed estimating the various sparsity norms of  $\mathbf{w}_\eta$ . We first address rank growth and parametric sparsity, which are independent of the specific choice of  $\tilde{\mathbf{A}}_{j,p,q}$ . Using (5.31) and (5.33) in Lemma 5.4 together with (5.11) and (5.12), for  $S \geq \bar{s}$  we obtain

$$\begin{aligned} \text{rank}(\mathbf{w}_\eta) &\lesssim \eta^{-\frac{1}{\bar{s}}} (1 + |\log \eta|)^{2(1+\frac{a}{\bar{s}})} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}^{\frac{1}{\bar{s}}} \eta^{-\frac{1}{\bar{s}}(1-\frac{\bar{s}}{\bar{s}})} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}^{\frac{1}{\bar{s}}(1-\frac{\bar{s}}{\bar{s}})}, \\ &= \eta^{-\frac{1}{\bar{s}}} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}^{\frac{1}{\bar{s}}} (1 + |\log \eta|)^{2(1+\frac{a}{\bar{s}})}, \end{aligned} \quad (5.36)$$

where the constant depends also on  $|\log \|\pi^{(i)}(\mathbf{v})\|_{\mathcal{A}^{s_i}}|$ ,  $i \in \{x, y\}$ . Now suppose that  $N_\eta$  is an upper bound for  $\text{rank}(\mathbf{w}_\eta)$ . To simplify the exposition, let us assume without loss of generality that  $\eta \in (0, 1)$ . Then, by definition, one has

$$\begin{aligned} \|\mathbf{w}_\eta\|_{\Sigma^{\bar{s}}} &= \sup_{N \leq N_\eta} N^{\bar{s}} \inf_{\text{rank}(\mathbf{w}) \leq N} \|\mathbf{w}_\eta - \mathbf{w}\| \leq \sup_{B \in [1, \eta^{-1}]} N_{B\eta}^{\bar{s}} \|\mathbf{w}_\eta - \mathbf{w}_{B\eta}\| \\ &\leq \sup_{B \in [1, \eta^{-1}]} N_{B\eta}^{\bar{s}} (\|\mathbf{w}_\eta - \mathbf{A}\mathbf{v}_\eta\| + \|\mathbf{A}\mathbf{v}_\eta - \mathbf{w}_{B\eta}\|) \leq \sup_{B \in [1, \eta^{-1}]} 2B\eta N_{B\eta}^{\bar{s}}. \end{aligned}$$

Now we can invoke for each  $B \in [1, \eta^{-1}]$  the upper bound for  $\text{rank}(\mathbf{v}_\eta)$  given by (5.36), and observe that the resulting bound is maximized for  $B = \eta^{-1}$  when  $S \geq \bar{s}$ . This gives

$$\|\mathbf{w}_\eta\|_{\Sigma^{\bar{s}}} \lesssim \|\mathbf{v}\|_{\Sigma^{\bar{s}}} (1 + |\log \eta|)^{2\bar{s}(1+\frac{a}{\bar{s}})}, \quad (5.37)$$

which confirms (5.26).

Similarly, using the second estimate in (5.31) and (5.34) in Lemma 5.4 and invoking (5.12) yields, for  $S \geq s_y$ ,

$$\# \text{supp}_y(\mathbf{w}_\eta) \lesssim \eta^{-\frac{1}{S}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}^{\frac{1}{S}} (1 + |\log_2 \eta|)^{2 + \frac{2a}{S}} \left( \frac{\|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}}{\eta} \right)^{\frac{1}{s_y} (1 - \frac{s_y}{S})}. \quad (5.38)$$

By the same argument as before one obtains

$$\# \text{supp}_y(\mathbf{w}_\eta) \lesssim \eta^{-\frac{1}{s_y}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}^{\frac{1}{s_y}} (1 + |\log_2 \eta|)^{2 + \frac{2a}{S}}. \quad (5.39)$$

We can then continue as above, denoting by  $M_\eta$  an upper bound for  $\# \text{supp}_y(\mathbf{w}_\eta)$ , to argue

$$\begin{aligned} \|\pi^{(y)}(\mathbf{w}_\eta)\|_{\mathcal{A}^{s_y}} &\leq \sup_{B \in [1, \eta^{-1}]} M_{B\eta}^{s_y} (\|\pi^{(y)}(\mathbf{w}_\eta) - \pi^{(y)}(\mathbf{A}\mathbf{v}_\eta)\| + \|\pi^{(y)}(\mathbf{w}_{B\eta}) - \pi^{(y)}(\mathbf{A}\mathbf{v}_\eta)\|) \\ &\leq \sup_{B \in [1, \eta^{-1}]} M_{B\eta}^{s_y} (\|\mathbf{w}_\eta - \mathbf{A}\mathbf{v}\| + \|\mathbf{w}_{B\eta} - \mathbf{A}\mathbf{v}\|) \\ &\leq \sup_{B \in [1, \eta^{-1}]} 2B\eta M_{B\eta}^{s_y}. \end{aligned}$$

Thus we obtain

$$\|\pi^{(y)}(\mathbf{w}_\eta)\|_{\mathcal{A}^{s_y}} \lesssim \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}} (1 + |\log_2 \eta|)^{2s_y(1 + \frac{a}{S})}, \quad (5.40)$$

which together with (5.39) shows (5.27).

We now turn to estimating  $\# \text{supp}_x(\mathbf{w}_\eta)$  and  $\|\pi^{(x)}(\mathbf{w}_\eta)\|_{\mathcal{A}^{s_x}}$ . To this end, we specify suitable compressed matrices  $\tilde{\mathbf{A}}_{j,p,q}$  in (5.19). Denoting by  $\pi^{(x)}(\mathbf{v}_{[p,q]})_\ell$  the best  $\ell$ -term approximation of  $\pi^{(x)}(\mathbf{v}_{[p,q]})$ , we set  $\Lambda_{p,q,0} = \text{supp}(\pi^{(x)}(\mathbf{v}_{[p,q]})_1)$  and

$$\Lambda_{p,q,n} := \text{supp}(\pi^{(x)}(\mathbf{v}_{[p,q]})_{2^n}) \setminus \text{supp}(\pi^{(x)}(\mathbf{v}_{[p,q]})_{2^{n-1}}), \quad n \in \mathbb{N}.$$

Note that

$$\|\mathbf{R}_{\Lambda_{p,q,n} \times \mathcal{F}} \mathbf{v}_{[p,q]}\| \leq \|\mathbf{R}_{\Lambda_{p,q,n}} \pi^{(x)}(\mathbf{v}_{[p,q]})\| \leq 2^{-s_x n} \|\pi^{(x)}(\mathbf{v}_{[p,q]})\|_{\mathcal{A}^{s_x}}.$$

To proceed we employ the following convenient reformulation of Proposition 4.4.

**Remark 5.5.** *Let  $M \in \mathbb{N}$  and any  $s^* < \frac{2\tau}{1+2\tau} S$ . Then for any  $J \in \mathbb{N}$  we can find  $\mathbf{A}_j^J$ ,  $j \geq 0$ , such that*

$$\left\| \sum_{j=0}^M (\mathbf{A}_j - \mathbf{A}_j^J) \otimes \mathbf{M}_j \right\| \leq \beta_J 2^{-s^* J},$$

and the following holds: for each  $\lambda \in \mathcal{S}$ , for the sum of the number of corresponding nonzero column entries of the  $\mathbf{A}_j^J$  we have the bound

$$\sum_{j=0}^M \# \text{supp}(\mathbf{A}_{j,\lambda}^J)_{\lambda \in \mathcal{S}} \leq \alpha_J 2^J. \quad (5.41)$$

Here  $\alpha, \beta$  are positive summable sequences.

For a suitable nonnegative integer  $N = N_{j,p,q,\eta}$ , let  $\tilde{\mathbf{A}}_{j,p,q} := \sum_{n=0}^N \mathbf{A}_j^{N-n} \mathbf{R}_{\Lambda_{p,q,n}}$  and

$$\mathbf{w}_{p,q} := \sum_{j=0}^{M_{p,q}} (\tilde{\mathbf{A}}_{j,p,q} \otimes \mathbf{M}_j) \mathbf{v}_{[p,q]}. \quad (5.42)$$

Then

$$\left\| \mathbf{w}_{p,q} - \sum_{j=0}^{M_{p,q}} (\mathbf{A}_j \otimes \mathbf{M}_j) \mathbf{v}_{[p,q]} \right\| = \left\| \sum_{j=0}^{M_{p,q}} \sum_{n=0}^N ((\mathbf{A}_j^{N-n} - \mathbf{A}_j) \mathbf{R}_{\Lambda_{p,q,n}} \otimes \mathbf{M}_j) \mathbf{v}_{[p,q]} \right\|.$$

Using Remark 5.5 with  $s^* = s_x$ , the right side can be estimated by

$$\begin{aligned} \sum_{n=0}^N \beta_{N-n} 2^{-s_x(N-n)} 2^{-s_x n} \|\pi^{(x)}(\mathbf{v}_{[p,q]})\|_{\mathcal{A}^{s_x}} + 2 \|\mathbf{A}\| \sum_{n>N} 2^{-s_x n} \|\pi^{(x)}(\mathbf{v}_{[p,q]})\|_{\mathcal{A}^{s_x}} \\ \lesssim 2^{-s_x N} \|\pi^{(x)}(\mathbf{v}_{[p,q]})\|_{\mathcal{A}^{s_x}}, \end{aligned}$$

where the constant depends on  $s_x$ ,  $\|\mathbf{A}\|$ , and  $\|\beta\|_{\ell^1}$ . By (5.41), we obtain

$$\#\text{supp}_x(\mathbf{w}_{p,q}) \lesssim \sum_{n=0}^N 2^n \alpha_{N-n} 2^{N-n} \lesssim 2^N. \quad (5.43)$$

If we now choose the smallest  $N$  such that (5.19) holds, i.e.,  $2^{-s_x N} \|\pi^{(x)}(\mathbf{v}_{[p,q]})\|_{\mathcal{A}^{s_x}} \lesssim \eta_{p,q}$ , we obtain

$$\#\text{supp}_x(\mathbf{w}_{p,q}) \lesssim \eta_{p,q}^{-\frac{1}{s_x}} \|\pi^{(x)}(\mathbf{v}_{[p,q]})\|_{\mathcal{A}^{s_x}}^{\frac{1}{s_x}} \lesssim \eta_{p,q}^{-\frac{1}{s_x}} \|\pi^{(x)}(\mathbf{v}_\eta)\|_{\mathcal{A}^{s_x}}^{\frac{1}{s_x}}.$$

Keeping the definition of  $\eta_{p,q} = \alpha_{p,q} \eta$  and (5.11), (5.12) in mind, summing over  $p, q$  gives (5.28) with  $b = 2(1 + \frac{a}{s_x}) > 2(1 + \frac{a}{S})$ , where the bound on  $\|\pi^{(y)}(\mathbf{w}_\eta)\|_{\mathcal{A}^{s_y}}$  follows as in (5.37) and (5.40).  $\square$

**Remark 5.6.** Note that in Assumptions 5.2, we state that  $S \geq \bar{s}, s_y$  and  $S > s_x$ . While other cases can in principle be considered in the same manner, the convergence rate  $S$  of the operator truncation then limits the achievable efficiency: if  $S < \bar{s}$ , for instance, it is easy to see that in general one can only obtain  $\text{rank}(\mathbf{w}_\eta) \sim \mathcal{O}(\eta^{-1/S})$ .

**Proposition 5.7.** Under the assumptions of Theorem 5.3, let  $\mathbf{v}$  be given by its SVD with  $r := \text{rank}(\mathbf{v})$  and  $n_i := \#\text{supp}_i(\mathbf{v})$  for  $i \in \{x, y\}$ . Then for the number of operations  $\text{ops}(\mathbf{w}_\eta)$  required to obtain  $\mathbf{w}_\eta$ , one has

$$\begin{aligned} \text{ops}(\mathbf{w}_\eta) \lesssim (n_x + n_y) r^2 + \left( (1 + |\log \eta|)^{\frac{2a}{s_x}} \eta^{-\frac{1}{s_x}} \|\pi^{(x)}(\mathbf{v})\|_{\mathcal{A}^{s_x}}^{\frac{1}{s_x}} \right. \\ \left. + (1 + |\log \eta|)^{\frac{2a}{s_y}} \eta^{-\frac{1}{s_y}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}^{\frac{1}{s_y}} \right) \eta^{-\frac{1}{s}} \|\mathbf{v}\|_{\Sigma^{\bar{s}}}^{\frac{1}{s}}. \quad (5.44) \end{aligned}$$

For the proof of this proposition, we refer to Appendix B.

**Theorem 5.8.** For any  $\varepsilon > 0$ , the approximation  $\mathbf{u}_\varepsilon$  produced by Algorithm 2.1, specified as above for approximations of the form (LR) based on Hilbert-Schmidt decomposition (5.2), satisfies  $\|\mathbf{u} - \mathbf{u}_\varepsilon\| \leq \varepsilon$ .

Moreover, if Assumptions 5.2 hold, then

$$\text{rank}(\mathbf{u}_\varepsilon) \lesssim \varepsilon^{-\frac{1}{s}} \|\mathbf{u}\|_{\Sigma^{\bar{s}}}^{\frac{1}{s}}, \quad \|\mathbf{u}_\varepsilon\|_{\Sigma^{\bar{s}}} \lesssim \|\mathbf{u}\|_{\Sigma^{\bar{s}}} \quad (5.45)$$

and

$$\sum_{i \in \{x,y\}} \#\text{supp}_i(\mathbf{u}_\varepsilon) \lesssim \sum_{i \in \{x,y\}} \varepsilon^{-\frac{1}{s_i}} \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}}^{-\frac{1}{s_i}}, \quad \|\pi^{(i)}(\mathbf{u}_\varepsilon)\|_{\mathcal{A}^{s_i}} \lesssim \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}}. \quad (5.46)$$

The number of operations  $\text{ops}(\mathbf{u}_\varepsilon)$  required to produce  $\varepsilon$  then satisfies

$$\text{ops}(\mathbf{u}_\varepsilon) \lesssim 1 + (1 + |\log \varepsilon|)^\zeta \left( \varepsilon^{-\frac{1}{\bar{s}}} \|\mathbf{u}\|_{\Sigma^{\bar{s}}}^{\frac{1}{\bar{s}}} \right)^2 \sum_{i \in \{x,y\}} \varepsilon^{-\frac{1}{s_i}} \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}}^{-\frac{1}{s_i}}, \quad (5.47)$$

where  $\zeta > 0$  depends on  $s_x$ , on  $\text{cond}(\mathbf{A})$ , and on the choice of  $\kappa_1, \beta$  in Algorithm 2.1. The constants in (5.45), (5.46), and (5.47) may also depend on  $S, \bar{s}, s_y$ , and on the further parameters of Algorithm 2.1.

*Proof.* We follow the general strategy of the proofs as in [5] and in Theorem 3.4, combining the properties of the complexity reduction procedures COARSEN and RECOMPRESS with the specific adaptive operator application that we have constructed for the present problem.

The bound (5.45) and (5.46) follow from Theorem 5.1 applied to the result of line 11 in Algorithm 2.1. Note that here, the number  $J$  of inner iterations depends only on  $\text{cond}(\mathbf{A})$  (via  $\rho, \omega$ ) and on the choice of  $\kappa_1$  and  $\beta$ . With the complexity estimates for APPLY from Theorem 5.3 and Proposition 5.7 at hand, we obtain (5.47).  $\square$

**Remark 5.9.** As can be seen from the proofs Theorem 5.3 and Proposition 5.7, the numerical cost for the approximate operator application is dominated by the cost of performing orthogonalizations of the input. In particular, this leads to a quadratic dependence on the approximation ranks. The number of subsequent operations required to construct the low-rank representation of the output, however, remains proportional to the respective number of degrees of freedom.

## 6 Approximability of parametric problems

In this section, we consider representative instances of (1.5) in order to compare the approximability properties that determine the efficiency of sparse and low-rank approximations.

### 6.1 Isotropic dependence on finitely many parameters

As simple yet instructive examples, we consider problems with  $\bar{a} = 1$  and

$$\theta_j = b_j \chi_{D_j}, \quad (6.1)$$

where  $b_j \in ]0, 1[$  are constants and the subdomains  $D_j$  of the domain  $D$  have disjoint closures so that the diffusion coefficient is a strictly positive piecewise constant,

$$a(y) = \bar{a} + \sum_{j \geq 1} y_j b_j \chi_{D_j}. \quad (6.2)$$

As a first problem of this type with  $D = ]0, 1[$ , we consider the following.

**Example 6.1.** Let  $d := \#\mathcal{I} < \infty$ ,  $D_j \subset D = ]0, 1[$  for  $j = 1, \dots, d$  with pairwise disjoint  $\overline{D_j}$ , and  $b_j = \xi$  for some  $\xi \in ]0, 1[$ .

For low-rank approximation, we then have the following result for the rank of the Hilbert-Schmidt decomposition (5.2).

**Proposition 6.2.** *In Example 6.1, for any  $f \in V'$ , one has  $\text{rank}(\mathbf{u}) \leq 4d + 1$ .*

*Proof.* This follows by the same arguments as in [2, Example 2.2]: the endpoints of the  $D_j$  induce a partition of  $]0, 1[$  into at most  $2d + 1$  intervals. For each such interval  $I$ , for any  $F$  such that  $F'' = f$ , we have  $u(y)|_I \in \text{span}\{\chi_I, x\chi_I, F\chi_I\}$ . Hence  $u(y)$  is contained in a  $y$ -independent space of dimension  $6d + 3$  for all  $y$ . In addition, there are  $2d + 2$  continuity conditions, independent of  $y$ , at the interval boundaries, which leaves at most  $4d + 1$  degrees of freedom.  $\square$

We observe on the other hand that the Legendre expansions for this problem involves infinitely many nonzero coefficients, that is, the solution map  $y \mapsto u(y)$  is not a polynomial in  $y$ . This can be checked, for example, by considering the Taylor coefficients of  $u$ . For any  $\nu = (\nu_j)_{j \geq 1} \in \mathcal{F}$ , the coefficients in the Taylor expansion of  $u$  are given by

$$t_\nu(y) = \frac{1}{\nu!} \partial^\nu u(y), \quad \nu! := \prod_{j \geq 1} \nu_j!, \quad (6.3)$$

Denoting by  $e^j = (0, \dots, 0, 1, 0, \dots)$  the  $j$ -th Kronecker sequence, differentiating the equation we find that these coefficients are given by the recursion

$$t_\nu(y) := -A(y)^{-1} \sum_{j \in \text{supp } \nu} A_j t_{\nu - e^j}(y), \quad t_0(y) = A(y)^{-1} f = u(y). \quad (6.4)$$

We now consider the Taylor coefficients of order  $n$  in a given variable  $j$  at the origin, that is,

$$t_{n,j} := t_{ne^j}(0) = \frac{1}{n!} \partial_{y_j}^n u(0). \quad (6.5)$$

As a particular case of (6.4), we have

$$\int_D \bar{a} \nabla t_{n,j} \cdot \nabla v \, dx = - \int_D \theta_j \nabla t_{n-1,j} \cdot \nabla v \, dx. \quad (6.6)$$

Since  $t_{0,j} = u(0)$  is not trivial, there is at least one variable  $j$  such that  $t_{1,j}$  does not vanish on  $D_j$ . Then, taking  $v = t_{n-1,j}$  in the above recursion shows by contradiction that  $t_{n,j}$  does not vanish on  $D_j$ , for all values of  $n \geq 0$ . Thus  $y \mapsto u(y)$  cannot be a polynomial. Low-rank approximations thus give substantially faster convergence than Legendre expansions in this case.

Similar results showing substantial advantages of best low-rank approximations have also been obtained for spatially two-dimensional examples of analogous structure in [2]. The test problems considered there are of the form (6.2) as well, with the coefficients piecewise constant on  $D := ]0, 1[^2$  and where  $D_j$ ,  $j = 1, \dots, d$  are a partition of  $D$  into congruent square subdomains. The resulting ‘‘checkerboard’’ geometry is illustrated for  $d = 16$  in Figure 1.

The low-rank approximability of such problems with respect to space-parameter separation has been studied in [2]. For the case  $d = 4$  (that is, a  $2 \times 2$ -checkerboard), it is shown in [2] that for each  $n \in \mathbb{N}$  one can find  $u_k^x, u_k^y$  for  $k = 1, \dots, n$  such that for some  $c > 0$ ,

$$\left\| u - \sum_{k=1}^n u_k^x \otimes u_k^y \right\|_{L^2(Y,V)} \lesssim e^{-cn}.$$

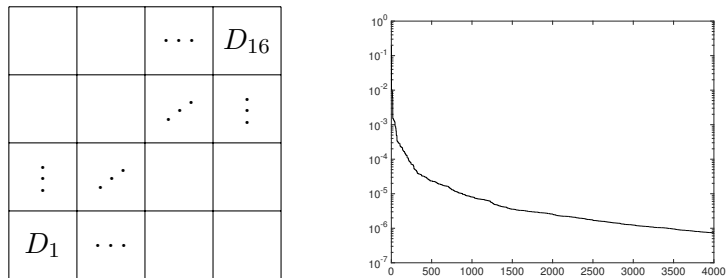


Figure 1: Example geometry of piecewise constant coefficients  $a$  with  $d = 16$  and decay of Legendre coefficients of corresponding  $u$ .

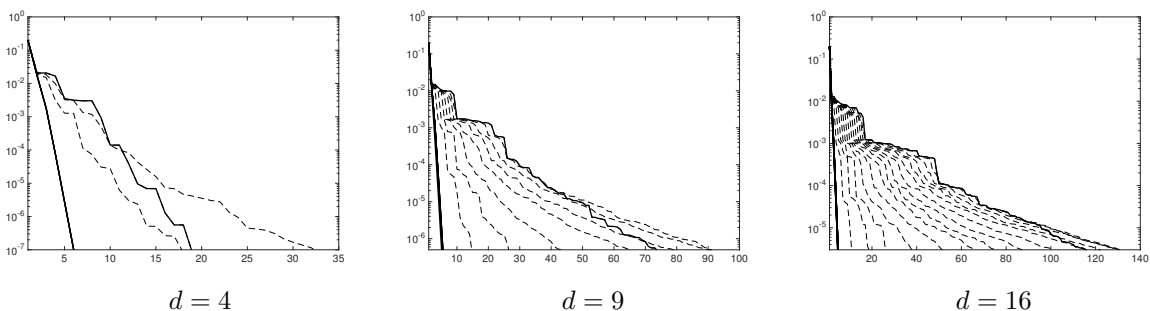


Figure 2: Hierarchical singular values of  $\mathbf{u}$ , where  $D$  has  $\sqrt{d} \times \sqrt{d}$ -checkerboard geometry as in Figure 1. *Solid lines*: singular values of matricizations  $T_{\mathbf{u}}^{\{\{i\}\}}$  associated to  $i \in \mathcal{I}$ , *dashed lines*: singular values of further matricizations in the hierarchical representation. The horizontal axes show the numbers of the decreasingly ordered singular values.

Numerical tests indicate that an analogous estimate can be achieved also for geometries of the type shown in Figure 1 with  $d = 9, 16, 25, \dots$ , where  $c$  has a moderate dependence on  $d$ . Note also that for a hierarchical tensor representation, the ranks of further matricizations enter as well. We are not aware of any bounds for these additional ranks. The numerically observed decay of the corresponding singular values for different values of  $d$  (using a linear dimension tree) are shown in Figure 2.

**Remark 6.3.** *As we have noted for the spatially one-dimensional case in Example 6.1 in §6, for the separation between spatial and parametric variables for that case one always obtains fixed finite ranks that grow linearly in the number of parameters  $d$ . Note, however, that the approximation ranks corresponding to further separations among the parametric variables may then still not be uniformly bounded; see e.g. [31, Prop. 2.5] for an analysis of a simple example.*

Summarize implications for approximability classes

## 6.2 Anisotropic dependence on infinitely many parameters

As a second scenario, we consider a problem with countably many parameters of decreasing influence.

**Example 6.4.** Let  $\mathcal{I} = \mathbb{N}$ , and let  $D_j \subset ]0, 1[$  be disjoint with  $|D_j| > 0$  for all  $j$ . In addition, let  $(b_j)_{j \geq 1} \in \ell^q(\mathbb{N})$  for some  $q > 0$ .

As an immediate consequence of the results in [4, §4.1], one has the following.

**Proposition 6.5.** *In Example 6.4, for all right hand sides  $f \in V'$ , one has  $(\|u_\nu\|_V)_{\nu \in \mathcal{F}} \in \ell^p(\mathcal{F})$  for  $p = \frac{2q}{2+q}$ . If  $(b_j) \notin \ell^{q'}(\mathbb{N})$  for any  $0 < q' < q$ , then there exists  $f \in V'$  such that  $(\|u_\nu\|_V)_{\nu \in \mathcal{F}} \notin \ell^{p'}(\mathcal{F})$  for  $0 < p' < p$ .*

If  $\sigma_n$  are the singular values of  $u$ , then for the decreasing rearrangement  $(u_n^*)_{n \geq 1}$  of  $(\|u_\nu\|_V)_{\nu \in \mathcal{F}}$  we clearly have  $u_n^* \geq \sigma_n$ . As the following new result shows by similar arguments as in [4, §4.1], in general the singular values actually do not have faster decay in this situation than the ordered norms of the Legendre coefficients.

**Proposition 6.6.** *In Example 6.4, if  $(b_j) \notin \ell^{q'}(\mathbb{N})$  for any  $0 < q' < q$ , then there exists an  $f \in V'$  such that the singular values of  $u$  are not in  $\ell^{p'}(\mathbb{N})$  for  $0 < p' < p = \frac{2q}{2+q}$ .*

*Proof.* We first observe that the singular values of  $u = \sum_{\nu \in \mathcal{F}} u_\nu \otimes L_\nu$  are bounded from below by those of  $\tilde{u} = \sum_{j \geq 1} u_{e^j} \otimes L_{e^j}$ , with  $e^j$  denoting the  $j$ -th Kronecker sequence. This follows from the fact that  $\tilde{u} = (I \otimes \tilde{P})u$ , where  $\tilde{P}$  is the projector onto  $\overline{\text{span}}\{L_{e^j}\}_{j \geq 1}$ .

For  $u_{e^j}$ , one has by Rodrigues' formula the explicit representation

$$u_{e^j} = \frac{\sqrt{3}}{2} \int_Y t_{e^j}(y) (1 - y_j^2) d\mu(y) \quad (6.7)$$

in terms of the first-order derivatives  $t_{e^j}(y) = \partial_{y_j} u(y)$ .

Let  $h_j$  be the symmetric hat functions with support  $D_j$ . We now choose

$$f = - \sum_{j \geq 1} c_j h_j'',$$

where  $\sum_{j \geq 1} c_j^2 / |D_j| < \infty$ , which yields  $f \in V'$  and

$$t_0(y) = \sum_{j \geq 1} (1 + b_j y_j)^{-1} c_j h_j.$$

By (6.4),

$$t_{e^j}(y) = -(1 + b_j y_j)^{-2} b_j c_j h_j$$

and as a consequence of (6.7),

$$u_{e^j} = -M_j b_j c_j h_j, \quad M_j := \frac{\sqrt{3}}{2} \int_{-1}^1 \frac{1 - y^2}{(1 + b_j y)^2} \frac{dy}{2} \geq \frac{1}{4\sqrt{3}(1 - \max_j b_j)} =: M_0.$$

We thus obtain

$$\langle u_{e^i}, u_{e^j} \rangle_V = 0, \quad i \neq j,$$

as well as

$$\|u_{e^j}\|_V \geq M_0 b_j c_j \|h_j\|_V = \frac{2M_0 b_j c_j}{\sqrt{|D_j|}}.$$

Since  $(b_j)$  is precisely in  $\ell^q(\mathbb{N})$ , by choosing  $c_j = b_j^{q/2} \sqrt{|D_j|}$ , which guarantees in particular that  $(c_j / \sqrt{|D_j|})_{j \geq 1} \in \ell^2(\mathbb{N})$  as required, we arrive at the statement.  $\square$

The above result shows that from an asymptotic point of view, in Example 6.4, there is not necessarily any gain by low-rank approximation: there always exist right hand sides  $f$  such that the singular values have *precisely the same* asymptotic decay as the ordered norms of Legendre coefficients.

Numerical tests as in Example 6.9 indicate that this also holds true for problems with different types of parametrization and more general  $f$ .

**Remark 6.7.** *The conclusion of Proposition 6.6 reveals that, in the case of Example 6.4 and if  $(b_j)_{j \geq 1} \notin \ell^{q'}$  for all  $0 < q' < q$ , then any separable approximation of the form (1.12) satisfies*

$$\|u - u_n\|_{L^2(Y, V)} \geq c_r n^{-r}, \quad n \geq 1, \quad (6.8)$$

for some  $c_r > 0$ , whenever  $r > \frac{1}{q}$ . In turn, we also have

$$\|u - u_n\|_{L^\infty(Y, V)} \geq c_r n^{-r}, \quad n \geq 1. \quad (6.9)$$

This implies that the Kolmogorov  $n$ -width

$$d_n(\mathcal{M})_V = \inf_{\dim(E) \leq n} \max_{v \in \mathcal{M}} \text{dist}(v, E)_V, \quad (6.10)$$

of the solution manifold  $\mathcal{M} := \{u(y) : y \in Y\}$  satisfies a similar lower bound

$$d_n(\mathcal{M})_V \geq c_r n^{-r}, \quad n \geq 1. \quad (6.11)$$

While upper bounds for  $d_n(\mathcal{M})_V$  in parametric PDEs are typically proved by exhibiting a particular separable approximation and studying its convergence in  $L^\infty(Y, V)$ , see [2, 11], lower bounds are generally out of reach and the ones given above constitute a notable exception.

**Remark 6.8.** *One arrives at analogous observations in similar higher-dimensional settings. The construction of Example 6.4 immediately carries over to spatial domains with  $m > 1$  when the definition of  $f$  is based on higher-dimensional hat functions. Examples similar to Example 6.1 with  $m = 2$  have been considered in [2], where the sequence of singular values is no longer compactly supported but still decays exponentially.*

**Summary of observations on approximability:**

If the  $\xi_\mu$  are sufficiently smooth, we then have  $a(y) \in B_{\infty, \infty}^\alpha(D)$ , that is, for any  $y \in Y$ ,

$$a(y) \in C^\alpha(D) \quad \text{for } \alpha \notin \mathbb{N}. \quad (6.12)$$

As shown in [4], here we have  $\pi^{(y)}(\mathbf{u}) \in \mathcal{A}^s$  for any  $s > 0$  with

$$s < s_y^* := \frac{\alpha}{m},$$

where one may have  $\|\pi^{(y)}(\mathbf{u})\|_{\mathcal{A}^s} \rightarrow \infty$  as  $s \rightarrow s_y^*$ .

Regarding  $s_x^*$ , for sufficiently regular  $f$  and  $D$ , and sufficiently regular wavelets  $\psi_\lambda$ , we also have  $\pi^{(x)}(\mathbf{u}) \in \mathcal{A}^s$  for any

$$s < s_x^* := \frac{\alpha}{m}.$$

This can be seen as follows: Let  $0 < s < \frac{\alpha}{m}$ , and let  $\psi_\lambda$  be sufficiently smooth to form a Riesz basis of  $H^{1+s}(D)$ . Then

$$\sum_{\lambda \in \mathcal{S}} 2^{2s|\lambda|} |\pi_\lambda^{(x)}(\mathbf{u})|^2 = \sum_{\lambda \in \mathcal{S}} \sum_{\nu \in \mathcal{F}} 2^{2s|\lambda|} |\mathbf{u}_{\lambda\nu}|^2 \sim \int_Y \|u(y)\|_{H^{1+s}(D)}^2 d\mu(y).$$

By (6.12) and [26, Thm. 9.1.16] we have  $\|u(y)\|_{H^{1+s}} \lesssim \|f\|_{H^{-1+s}}$  uniformly in  $y$  for any  $s < \alpha/m$  (where uniformity in  $y$  can be seen by inspection of the proof, see also [26, Thm. 9.1.8]). In summary, for sufficiently regular problem data,

$$s_x^* = s_y^* = \frac{\alpha}{m}. \quad (6.13)$$



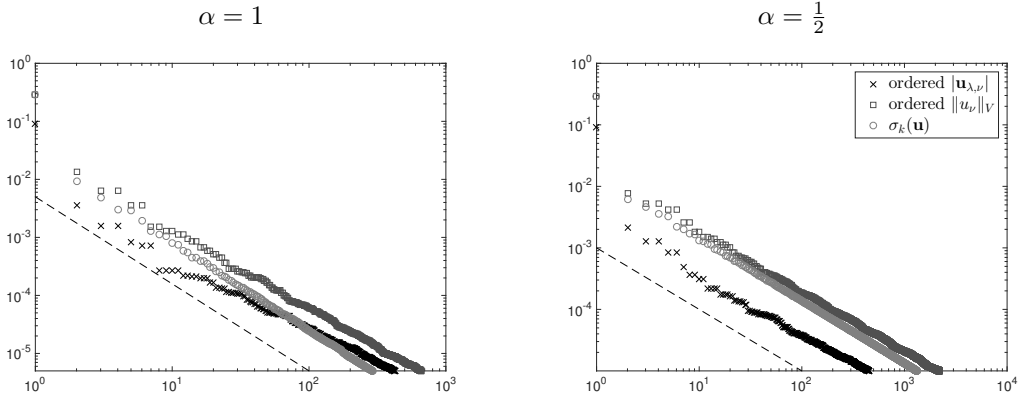


Figure 3: Absolute values of tensor product expansion coefficients  $|\mathbf{u}_{\lambda,\nu}|$ , Legendre coefficient norms  $\|u_\nu\|_V$  (proportional to  $\pi_\nu^{(y)}(\mathbf{u})$ ) and singular values  $\sigma_k(\mathbf{u})$ , for  $\alpha = 1$  and  $\alpha = \frac{1}{2}$  in Example 6.9. The dashed lines show the known asymptotic decay rates of  $\|u_\nu\|_V$  according to [4].

For low-rank approximation, a crucial question is how  $s_x$  and  $s_y$  relate to the largest  $\bar{s}$  such that  $(\sigma_k(\mathbf{u}))_{k \in \mathbb{N}} \in \Sigma^{\bar{s}}$ . In view of (5.5), for this  $\bar{s}$  one always has  $\bar{s} \geq s_x, s_y$ . In addition, we are interested in the performance of best  $n$ -term approximation of the form (ASP), that is, the largest  $s$  such that  $\mathbf{u} \in \mathcal{A}^s(\mathcal{S} \times \mathcal{F})$ . We are not aware of results that give sharp statements on  $\bar{s}$  and  $s$  for the present example with parametrization as in Assumptions 4.2. The following representative numerical example gives an indication of what one may expect.

In contrast to the setting of section 4.2, under Assumptions 4.2, where the  $\theta_j$  have multilevel structure, the  $e_M$  have sufficient decay to match the approximability of the solution. The construction of a routine APPLY that can take full advantage of this approximability, however, depends in an essential way on the compressibility of the matrices  $\mathbf{A}_j$ , which in turn depends on the basis that is used for  $V$ .

**Example 6.9.** We consider  $m = 1$  with  $D = ]0, 1[$ ,  $\bar{a} = 1$ ,  $f = 1$  and

$$\theta_j(x) = c_\alpha 2^{-\alpha \ell} h(2^\ell x - k), \quad j = 2^\ell + k$$

for  $\ell \geq 0$  and  $k = 0, \dots, 2^\ell - 1$ , where  $h(x) = (1 - |2x - 1|)_+$  and  $c_\alpha$  is chosen so as to ensure uniform ellipticity. In other words, the parameter is expanded in a Schauder hat function basis. The resulting observed decay<sup>2</sup> of  $|\mathbf{u}_{\lambda,\nu}|$ , of  $\|u_\nu\|_V$  (which are proportional to  $\pi_\nu^{(y)}(\mathbf{u})$ ), and of  $\sigma_k(\mathbf{u})$  is shown in Figure 3. Note that in both cases  $\alpha = 1$  and  $\alpha = \frac{1}{2}$ , the  $\sigma_k(\mathbf{u})$  clearly decay at exactly the limiting rate  $s_y^* + \frac{1}{2}$  that is theoretically guaranteed for the Legendre coefficient norms  $\|u_\nu\|_V$ ; the  $\|u_\nu\|_V$  themselves approach this rate only fairly late. Thus, we can at best expect  $\bar{s} = s_y^* = \alpha$  here. Note also that the decay of  $|\mathbf{u}_{\lambda,\nu}|$  is closely aligned to that of  $\|u_\nu\|_V$ .

## 7 Summary and conclusions

In this work, we have studied the approximation of the solution map  $Y \ni y \mapsto u(y) \in V$  in  $L^2(Y, V)$  for parametric diffusion problems, where the parameter domain  $Y$  is of high

<sup>2</sup>Here we choose  $\psi_\lambda$  to be piecewise cubic  $L^2$ -orthonormal multiwavelets rescaled to be Riesz bases of  $H^1$ .

or infinite dimensionality. We have considered approximations based on sparse expansions in terms of tensor product Legendre polynomials in  $y$ , low-rank approximations based on separation of spatial and parametric variables, and higher-order tensor decompositions using further hierarchical low-rank approximation among the parametric variables. Each of these approximations can be regarded as an expansion in terms of a fixed tensor product reference basis, with the degrees of freedom entering in different nonlinear ways.

The central aim is to investigate the performance of adaptive algorithms for each type of approximation that require as input only information on the parametric operator and right hand side, and that produce rigorous and computable a posteriori error bounds. These goals are achieved, in a unified manner for all considered types of approximations, by Algorithm 2.1. Such algorithms are necessarily based on the approximate evaluation of residuals. They are also intrusive, in that they do not treat the underlying parametrized problem as a black box; however, we are not aware of any non-intrusive method with comparable properties.

Although the resulting schemes do not use a priori information on the convergence of the respective approximations of the solution map, they still produce approximations of near-optimal complexity (e.g., with respect to the number of terms or tensor ranks). The question of also guaranteeing a near-optimal operation count for constructing these approximations is more delicate: this computational complexity depends on the costs of approximating the residual, and thus on the approximability properties of the operator. In the case of low-rank approximations, due to the required orthogonalizations, the number of operations also scales at least quadratically with respect to the arising tensor ranks.

Especially keeping the latter point in mind, there is no single type of approximation that is most favorable in all of the representative model scenarios that we have considered. In the case of finitely many parameters of comparable influence, hierarchical tensor representations of  $u$  turn out to be advantageous: We can show near-optimal computational complexity on certain natural approximability classes (as in Assumptions 3.2, 3.3) for the adaptive scheme based on the method in [5].

The situation turns out to be different in the case of infinitely many parameters of decreasing influence. We have proven in §6, for a certain class of such problems, that the norms of Legendre coefficients of  $u$  have the same asymptotic decay as the singular values in its Hilbert-Schmidt decomposition. In other words, the ranks in a corresponding low-rank approximation need to increase at the same rate as the number of terms in a sparse Legendre expansion as we accuracy is increased. The numerical tests given in Figure 3 indicate that this holds true also for substantially more general problems. As a consequence, even with the careful residual evaluation given in §5, which can preserve near-optimal ranks, due to the nonlinear scaling with respect to the ranks the computational complexity of finding low-rank approximations scales worse than a direct sparse expansion as considered in §4. This conclusion remains true also for hierarchical tensor decompositions involving the same separation between spatial and parametric variables.

For both schemes in §4 and §5, we have seen that whether the residual can be evaluated at a cost that matches the approximability of the solution depends on the type of parameter-dependence in the diffusion coefficient. As the simple example given in §4.2 shows, in the case of diffusion coefficients expanded in terms of increasingly oscillatory functions of global support, the complexity of the methods is in general dominated by the residual evaluation. However, in the case of diffusion coefficients whose parametrization has a multilevel structure, we have demonstrated that one can come arbitrarily close to fully exploiting the approximability of  $u$ .

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## A Compressibility of parametric operators

The approximate application of the operator  $\mathbf{A}$  in Algorithm 2.1 must involve, in particular, an approximate application of the spatial components  $\mathbf{A}_j$ . With the exception of very particular situations (such as the model case considered in §??), the infinite matrices  $\mathbf{A}_j$  are not sparse, but contain infinitely many nonzero entries in each column. Their

approximation hinges on the compressibility of these operator representations as defined in Assumptions 4.3.

These are closely related to  $s^*$ -compressibility of  $\mathbf{A}_j$  as in (2.10), which here means that there exist matrices  $\mathbf{A}_{j,n}$  with  $\alpha_{j,n}2^{2n}$  entries per row and column and such that

$$\|\mathbf{A}_j - \mathbf{A}_{j,n}\| \leq \beta_{j,n}2^{-sn}, \quad \text{for } 0 < s < s^*, \quad (\text{A.1})$$

and where  $\alpha_j, \beta_j \in \ell^1$ . This is known to hold for each fixed  $j$  when employing a piecewise polynomial wavelet-type Riesz basis  $\{\psi_\lambda\}_{\lambda \in \mathcal{S}}$  for  $V$ , see e.g. [9,42]. However, when insisting on the same compressibility bound  $s^*$  for all  $\mathbf{A}_j$ , the quantities  $\|\alpha_j\|_{\ell^1}$  and  $\|\beta_j\|_{\ell^1}$  can in general not be expected to both remain uniformly bounded in  $j$  when the  $\theta_j$  become increasingly oscillatory. This dependence is reflected in Assumptions 4.3.

In the light of the discussion in §4.2 we confine ourselves to operators  $\mathbf{A}_j$  arising from multilevel representations of the parameter of the form in Assumptions 4.2. To obtain this compression, we use a wavelet basis  $\{\psi_\lambda\}_{\lambda \in \mathcal{S}}$  in the spatial variable.

To understand the basic mechanism, recall that the compressibility of the  $\mathbf{A}_j$  is governed by the modulus of its entries  $\langle \theta_j \nabla \psi_\lambda, \nabla \psi_{\lambda'} \rangle$ , where  $\langle \cdot, \cdot \rangle$  denotes the  $L^2$ -inner product. Specifically, recall e.g. from [9] that compression strategies for wavelet representations of an elliptic second order operator with diffusion field  $c \in L^\infty(D)$  are based on bounds of the type

$$|\langle c \nabla \psi_\lambda, \nabla \psi_{\lambda'} \rangle| \lesssim \|c\|_{W^{b-m/2}(L^\infty(D))} 2^{-\|\lambda\| - \|\lambda'\| b}, \quad (\text{A.2})$$

where  $m$  is the dimensionality of the spatial domain, and where  $b > m/2$  depends on the smoothness of the diffusion coefficient  $c$  and of the wavelets  $\psi_\lambda$ . From this one derives the compression order

$$s^* = \frac{b}{m} - \frac{1}{2}. \quad (\text{A.3})$$

Specifically, for piecewise polynomial wavelets with  $k$ th order vanishing moments and for  $c \in H^{k+1}(D)$ , whenever the support of the higher-level wavelet is essentially disjoint from the singular support of the lower-level wavelet, one has  $b = \frac{m}{2} + k + 1$ . In those cases one formally gets  $s^* = (k+1)/m$ . A subtle analysis of the remaining cases where the singular support of the lower-level wavelet is overlapped, which prevents the highest possible order of vanishing moments from being applicable, shows that an overall compression rate  $s^* > k/m$  can be obtained, which is the highest possible  $n$ -term convergence rate, see [42].

However, in our case the overall compression rate is also limited by the decay of the operator truncation error (4.3). In view of Proposition 4.4, the objective here is rather to have a compression rate for the individual components  $\mathbf{A}_j$  that is as high as possible, so that one approaches the limiting value imposed by (4.3).

We now summarize the conditions on the multilevel parametric expansion functions and the spatial wavelet basis under which we will verify Assumptions 4.3. To simplify notation, let  $S_\lambda := \text{supp } \psi_\lambda$ .

**Assumptions A.1.** For some  $\gamma > 0$ ,

$$\xi_\mu \nabla \psi_{\lambda'} \in H^\gamma(S_\lambda), \quad \mu \in \Lambda, \lambda, \lambda' \in \mathcal{S}, \quad (\text{A.4})$$

and the  $\psi_\lambda$  have vanishing moments of order  $k$  with  $k > \gamma - 1$ .

Note that the  $\nabla \psi_\lambda$  then have vanishing moments of order  $k+1 > \gamma$ . If  $|\lambda|, |\mu| \leq |\lambda'|$ , using (A.4) we obtain the standard estimate

$$|\langle \xi_\mu \nabla \psi_\lambda, \nabla \psi_{\lambda'} \rangle| \leq \inf_{P \in \Pi_{k+1}^m} \|\xi_\mu \nabla \psi_\lambda - P\|_{L^2(S_{\lambda'})} \|\psi_{\lambda'}\|_{L^2} \lesssim 2^{-|\lambda'| \gamma} |\xi_\mu \nabla \psi_\lambda|_{H^\gamma(S_{\lambda'})}. \quad (\text{A.5})$$

Combining this with  $|\xi_\mu \nabla \psi_\lambda|_{H^\gamma(S_{\lambda'})} \lesssim 2^{-\frac{m}{2} \|\lambda| - |\lambda'|} 2^{\gamma \max\{|\mu|, |\lambda|\}}$ , we obtain

$$|\langle \xi_\mu \nabla \psi_\lambda, \nabla \psi_{\lambda'} \rangle| \lesssim 2^{-(\gamma + \frac{m}{2}) \|\lambda| - |\lambda'|} 2^{\gamma(|\mu| - |\lambda|)_+}. \quad (\text{A.6})$$

Note that the requirement (A.4) could be weakened along the lines of [42] to *piecewise* smoothness, in which case combinations of wavelets with overlapping singular supports need to be considered separately. Since this is not essential for our purposes, to keep the exposition accessible we do not consider this in further detail.

The consequences of the estimate (A.6) depend on the relations between  $|\mu|$ ,  $|\lambda|$ , and  $|\lambda'|$ . We distinguish the three following cases:

If  $|\mu| \leq |\lambda|, |\lambda'|$ , we obtain an estimate analogous to the standard case (A.2),

$$|\langle \xi_\mu \nabla \psi_\lambda, \nabla \psi_{\lambda'} \rangle| \lesssim 2^{-(\gamma + \frac{m}{2}) \|\lambda| - |\lambda'|}. \quad (\text{A.7})$$

If  $|\lambda| \leq |\mu| < |\lambda'|$ , we obtain the modified estimate

$$|\langle \xi_\mu \nabla \psi_\lambda, \nabla \psi_{\lambda'} \rangle| \lesssim 2^{-\gamma(|\lambda'| - |\mu|)} 2^{-\frac{m}{2} \|\lambda| - |\lambda'|}. \quad (\text{A.8})$$

Note that for each fixed  $\mu$  and fixed levels  $|\lambda|, |\lambda'|$ , there exist in this case  $\mathcal{O}(2^{m(|\lambda'| - |\mu|)})$  entries that may be nonzero.

Finally, if  $|\lambda|, |\lambda'| \leq |\mu|$ , then for each  $\mu$ , there exist  $|\mu|$  indices  $\lambda$  such that the corresponding supports overlap, and in turn there exist  $\mathcal{O}(|\mu|^2)$  pairs of  $\lambda, \lambda'$  that may give a nonvanishing entry. These entries satisfy

$$|\langle \xi_\mu \nabla \psi_\lambda, \nabla \psi_{\lambda'} \rangle| \lesssim 2^{-m|\mu|} 2^{\frac{m}{2}(|\lambda| + |\lambda'|)}. \quad (\text{A.9})$$

Note that we do not assume any vanishing moments for  $\xi_\mu$ . Hence in general not much can be gained by discarding further entries in this third case.

Our strategy for dealing with the increasingly oscillatory nature of  $\xi_\mu$  as  $|\mu| \rightarrow \infty$  is to retain a common compression rate  $s^*$  in (A.1) uniformly in  $\mu$  without losing the decay induced by the factors  $c_\mu$ , which is the result required in Assumptions 4.3. To take increasingly oscillatory behavior into account, we need to retain additional entries of the  $\mathbf{A}_j$  in the cases (A.8) and (A.9). This results in the  $j$ -dependent number of nonzero entries in each row and column of the compressed operators  $\mathbf{A}_{j,n}$ , which is of order  $\mathcal{O}((1 + |\mu_j|^q)2^n)$ .

Let  $a_{\mu_j, \lambda, \lambda'}$  denote the entries of  $\mathbf{A}_j$ , that is,

$$a_{\mu_j, \lambda, \lambda'} = c_{\mu_j} \langle \xi_{\mu_j} \nabla \psi_\lambda, \nabla \psi_{\lambda'} \rangle.$$

**Proposition A.2.** *Under Assumptions A.1, the conditions in Assumptions 4.3 are satisfied, with  $\tau := \gamma/m$  and  $q := \max\{1, \tau^{-1}\}$ , for  $\mathbf{A}_{j,n}$  obtained by retaining only those entries from  $\mathbf{A}_j = (a_{\mu_j, \lambda, \lambda'})_{\lambda, \lambda' \in \mathcal{S}}$  for which*

$$d_{\mu_j}(\lambda, \lambda') := \max\{|\lambda|, |\lambda'|\} - \max\{|\mu_j|, \min\{|\lambda|, |\lambda'|\}\} \leq \frac{n}{m} + \frac{\log_2(1 + |\mu_j|)}{\gamma}.$$

*Proof.* For  $j \in \mathbb{N}$ , we set  $\mu := \mu_j$ . In a first step, for  $N > 0$ , we obtain a compressed version  $\mathbf{A}_j^N$  of  $\mathbf{A}_j$  as follows: for the column  $\lambda$ , retain only those entries with row index  $\lambda'$  such that  $d_\mu(\lambda, \lambda') \leq N$ . Note that by symmetry of  $d_\mu$  in its two arguments and that of  $\mathbf{A}_j$ , the approximation  $\mathbf{A}_j^N$  is also symmetric. We now show that for

$$N = N_n := \frac{n}{m} + \frac{\log_2(1 + |\mu|)}{\gamma}, \quad (\text{A.10})$$

we arrive at Assumptions 4.3. We use the standard weighted Schur Lemma, which in the present symmetric case yields that

$$\omega_\lambda^{-1} \sum_{\lambda': d_\mu(\lambda, \lambda') > N} \omega_{\lambda'} |a_{\mu, \lambda, \lambda'}| \leq B, \quad \lambda \in \mathcal{S}, \quad \text{implies} \quad \|\mathbf{A}_j - \mathbf{A}_j^N\| \leq B. \quad (\text{A.11})$$

Note that  $d_\mu(\lambda, \lambda') > 0$  implies that  $|\lambda| > |\mu|$  or  $|\lambda'| > |\mu|$ . Thus, as a particular consequence of (A.6), if  $d_\mu(\lambda, \lambda') > 0$  we have

$$|a_{\mu, \lambda, \lambda'}| \lesssim c_\mu 2^{-\gamma d_\mu(\lambda, \lambda')} 2^{-\frac{m}{2} \|\lambda| - |\lambda'\|}. \quad (\text{A.12})$$

With the usual choice  $\omega_\lambda := 2^{-\frac{m}{2} |\lambda|}$ , and setting

$$I(\lambda; N) := \{\lambda' : d_\mu(\lambda, \lambda') > N\},$$

we obtain

$$\omega_\lambda^{-1} \sum_{\lambda' \in I(\lambda; N)} \omega_{\lambda'} |a_{\mu, \lambda, \lambda'}| \lesssim c_\mu \sum_{\lambda' \in I(\lambda; N)} 2^{-m(|\lambda'| - |\lambda|) + 2^{-\gamma d_\mu(\lambda, \lambda')}}.$$

We now decompose  $I(\lambda; N) = I_1 \cup I_2 \cup I_3 \cup I_4$ , where

$$\begin{aligned} I_1 &:= \{\lambda' \in I(\lambda; N) : |\lambda'| \leq |\mu| < |\lambda|\}, & I_2 &:= \{\lambda' \in I(\lambda; N) : |\lambda| \leq |\mu| < |\lambda'|\}, \\ I_3 &:= \{\lambda' \in I(\lambda; N) : |\mu| < |\lambda'| \leq |\lambda|\}, & I_4 &:= \{\lambda' \in I(\lambda; N) : |\mu| < |\lambda| < |\lambda'|\}. \end{aligned}$$

Since  $\#(I_1) \lesssim 1 + |\mu|$ ,

$$\sum_{\lambda' \in I_1} 2^{-m(|\lambda'| - |\lambda|) + 2^{-\gamma d_\mu(\lambda, \lambda')}} \lesssim (1 + |\mu|) 2^{-\gamma N}. \quad (\text{A.13})$$

Likewise, we obtain the estimates

$$\begin{aligned} \sum_{\lambda' \in I_2} 2^{-m(|\lambda'| - |\lambda|) + 2^{-\gamma d_\mu(\lambda, \lambda')}} &\lesssim \sum_{\ell=|\mu|+N}^{\infty} \sum_{\substack{\lambda' \in I_2 \\ |\lambda'|=\ell}} 2^{-m(|\lambda'| - |\lambda|) + 2^{-\gamma \ell}} \\ &\lesssim \sum_{\ell=|\mu|+N}^{\infty} 2^{-\gamma \ell} (2^{m(\ell - |\mu|)} 2^{-m(\ell - |\lambda|)}) \\ &\lesssim 2^{-\gamma N} \end{aligned}$$

and

$$\sum_{\lambda' \in I_3} 2^{-m(|\lambda'| - |\lambda|) + 2^{-\gamma d_\mu(\lambda, \lambda')}} \lesssim \sum_{\ell=|\mu|}^{|\lambda| - N} 2^{-\gamma(|\lambda| - \ell)} \lesssim 2^{-\gamma N},$$

as well as

$$\begin{aligned} \sum_{\lambda' \in I_4} 2^{-m(|\lambda'| - |\lambda|) + 2^{-\gamma d_\mu(\lambda, \lambda')}} &\lesssim \sum_{\ell=|\lambda|+N}^{\infty} 2^{-\gamma \ell} \sum_{\substack{\lambda' \in I_4 \\ |\lambda'|=\ell}} 2^{-m(\ell - |\lambda|)} \\ &\lesssim \sum_{\ell=|\lambda|+N}^{\infty} 2^{-\gamma \ell} (2^{m(\ell - |\lambda|)} 2^{-m(\ell - |\lambda|)}) \\ &\lesssim 2^{-\gamma N}. \end{aligned}$$



Note that  $\#(I_3) \lesssim N$  and  $\#(I_2), \#(I_4) \lesssim 2^{mN}$ . Except for (A.13), the constants in these bounds are independent of  $\mu$ . In summary, we thus obtain

$$\|\mathbf{A}_j - \mathbf{A}_j^N\| \lesssim c_\mu(1 + |\mu|) 2^{-\gamma N} \quad (\text{A.14})$$

with a uniform constant. As pointed out above, each column of  $\mathbf{A}_j^N$  has at most  $\mathcal{O}(|\mu| + 2^{mN})$  entries. With  $\tau = \gamma/m$  and  $N_n$  as in (A.10), the estimate (A.14) takes the desired form

$$\|\mathbf{A}_j - \mathbf{A}_j^{N_n}\| \lesssim c_\mu 2^{-\tau n}, \quad (\text{A.15})$$

where the number of nonzero entries can be bounded further by

$$|\mu| + 2^{mN_n} \lesssim |\mu| + 2^n(1 + |\mu|)^{\frac{m}{\gamma}} \lesssim (1 + |\mu|^{\max\{1, m/\gamma\}}) 2^n, \quad (\text{A.16})$$

and thus Assumptions 4.3 are valid.  $\square$

Relations (A.15), (A.16) show that the resulting compression rate is limited by the smoothness of the expansion functions  $\xi_\mu$  and the spatial wavelets  $\psi_\lambda$  and by the number of vanishing moments of the  $\psi_\lambda$ , expressed by the value  $\gamma$ . As Proposition 4.4 shows, with increasing  $\gamma$  the rate of compressibility of the complete operator  $\mathbf{A}$  approaches the limiting value determined by the decay of its tail (4.3).

**Remark A.3.** *Proposition A.2 yields, as we have also noted in §4.2, a compressibility result for multilevel-type parametrizations that is substantially more favorable than what can in general be obtained for globally supported, increasingly oscillatory  $\theta_j$ . In the case  $\theta_j \sim j^{-\beta} \sin(j\pi \cdot)$  on  $D = ]0, 1[$  considered in §4.2, in place of (A.6) we obtain the analogous bound*

$$|\langle \theta_j \psi'_\lambda, \psi'_{\lambda'} \rangle| \lesssim j^{-\beta} 2^{-(\gamma + \frac{1}{2})\|\lambda| - |\lambda'|} 2^{\gamma(\log_2 j - |\lambda|)_+}.$$

One may thus proceed as in the proof of Proposition A.2, with  $|\mu|$  replaced by  $\log_2 j$ , to obtain  $\mathbf{A}_{j,n}$  such that

$$\|\mathbf{A}_j - \mathbf{A}_{j,n}\| \lesssim j^{-\beta} 2^{-\gamma n}.$$

However, among the pairs of indices  $(\lambda, \lambda')$  with  $|\lambda| \leq \log_2 j$ , we are eventually left with  $\mathcal{O}(j(1 + \log_2 j)2^n)$  entries per row and column.

Using these bounds to obtain a compressibility result for  $\mathbf{A}$  as in Proposition 4.4, in this case we have, for  $\mathbf{A}_n$  as defined in (4.8), the simpler estimate

$$\|\mathbf{A} - \mathbf{A}_n\| \lesssim \sum_{j=0}^M \|\mathbf{A}_j - \mathbf{A}_{j,n_j}\| + M^{-(\beta-1)} \lesssim 2^{-\gamma n_0} + \sum_{j=1}^M j^{-\beta} 2^{-\gamma n_j} + M^{-(\beta-1)}.$$

Choosing  $n_j$  appropriately to ensure that the right hand side is of order  $M^{-(\beta-1)}$  and summing the resulting total numbers of nonzero entries, as in [22] one arrives at the limiting value  $s^* = \frac{1}{2}(\beta - 1)$  for the compressibility of  $\mathbf{A}$ .

## B Proofs of auxiliary results

*Proof of Theorem 5.1.* The estimates (5.6), (5.7) are obtained exactly as in [5]. To prove (5.9) we follow the lines of the argument in [5], and adopt the notation used there, let  $N \in \mathbb{N}$  be the minimal integer such that

$$\|\mathbf{u} - \bar{C}_{\mathbf{u}, N} \mathbf{u}\| \leq \alpha \eta. \quad (\text{B.1})$$

Then

$$\alpha\eta < \|\mathbf{u} - \bar{C}_{\mathbf{u}, N-1} \mathbf{u}\| \quad (\text{B.2})$$

$$\begin{aligned} &\leq \inf_{\#\Lambda_x + \#\Lambda_y \leq N-1} \left\{ \|\pi^{(x)}(\mathbf{u}) - \mathbf{R}_{\Lambda_x} \pi^{(x)}(\mathbf{u})\| + \|\pi^{(y)}(\mathbf{u}) - \mathbf{R}_{\Lambda_y} \pi^{(y)}(\mathbf{u})\| \right\} \\ &\leq (\#\Lambda_x)^{-s_x} \|\pi^{(x)}(\mathbf{u})\|_{\mathcal{A}^{s_x}} + (\#\Lambda_y)^{-s_y} \|\pi^{(y)}(\mathbf{u})\|_{\mathcal{A}^{s_y}}. \end{aligned} \quad (\text{B.3})$$

Abbreviating  $n_i := \#\Lambda_i$ ,  $i = x, y$ , to obtain a good upper for bound  $N = N(\eta)$  from (B.1), we would like to find the minimal  $n_x + n_y$  such that

$$\alpha\eta \leq (n_x)^{-s_x} \|\pi^{(x)}(\mathbf{u})\|_{\mathcal{A}^{s_x}} + (n_y)^{-s_y} \|\pi^{(y)}(\mathbf{u})\|_{\mathcal{A}^{s_y}}, \quad (\text{B.4})$$

to conclude that  $N(\eta) \leq n_x + n_y$ . Equilibrating the upper bound yields a pair  $n_x, n_y$  given by

$$n_i = n_i(\eta) := \left\lceil \left( 2 \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}(\gamma_i)} / \alpha\eta \right)^{1/s_i} \right\rceil, \quad i = x, y, \quad (\text{B.5})$$

This yields

$$\#\text{supp}_x \mathbf{w}_\eta + \#\text{supp}_y \mathbf{w}_\eta \leq 2 + \left( \frac{2 \|\pi^{(x)}(\mathbf{u})\|_{\mathcal{A}^{s_x}}}{\alpha\eta} \right)^{1/s_x} + \left( \frac{2 \|\pi^{(y)}(\mathbf{u})\|_{\mathcal{A}^{s_y}}}{\alpha\eta} \right)^{1/s_y}, \quad (\text{B.6})$$

which is the first inequality in (5.9).

Regarding the second inequality in (5.9), note first that

$$N \leq B_i n_i, \quad i = x, y, \quad (\text{B.7})$$

where  $B_i$  depend only on  $s_x, s_y$ . To bound  $\|\pi^{(i)}(\mathbf{w}_\eta)\|_{\mathcal{A}^{s_i}}$  we only need to estimate

$$\sup_n n^{s_i} \inf_{\#\text{supp } \hat{\mathbf{w}} \leq n} \|\hat{\mathbf{w}} - \pi^{(i)}(\mathbf{w}_\eta)\|, \quad i = x, y,$$

for  $n \leq \#\text{supp}_i \mathbf{w}_\eta \leq N$ . To that end, denoting by  $\hat{\mathbf{u}}_n^{(i)}$  a best  $n$ -term approximation to  $\pi^{(i)}(\mathbf{u})$  and using (5.8), we obtain

$$\begin{aligned} \inf_{\#\text{supp } \hat{\mathbf{w}} \leq n} \|\hat{\mathbf{w}} - \pi^{(i)}(\mathbf{w}_\eta)\| &\leq \|\pi^{(i)}(\mathbf{w}_\eta) - \pi^{(i)}(\mathbf{u})\| + \|\pi^{(i)}(\mathbf{u}) - \hat{\mathbf{u}}_n^{(i)}\| \\ &\leq \|\mathbf{w}_\eta - \mathbf{u}\| + n^{-s_i} \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}} \\ &\leq C(\alpha)\eta + n^{-s_i} \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}} \\ &\leq \frac{2C(\alpha)}{\alpha} n_i^{-s_i} \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}} + n^{-s_i} \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}}, \end{aligned}$$

where we have used (B.5) and where  $C(\alpha) := (2 + \alpha + 2^{3/2}(1 + \alpha))$ . Hence

$$\begin{aligned} &n^{s_i} \inf_{\#\text{supp } \hat{\mathbf{w}} \leq n} \|\hat{\mathbf{w}} - \pi^{(i)}(\mathbf{w}_\eta)\| \\ &\leq \left( 1 + \frac{2C(\alpha)}{\alpha} \left( \frac{n}{n_i} \right)^{s_i} \right) \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}} \leq \left( 1 + \frac{2C(\alpha) B_i^{s_i}}{\alpha} \right) \|\pi^{(i)}(\mathbf{u})\|_{\mathcal{A}^{s_i}}, \end{aligned}$$

which completes the proof.  $\square$

*Proof of Proposition 5.7.* As we assume  $\mathbf{v}$  to be given in SVD form, RECOMPRESS in step (S1) of the procedure APPLY takes only  $\mathcal{O}(r)$  operations. Since it preserves the SVD form, the subsequent COARSEN using quasi-sorting takes  $\mathcal{O}(r(n_x + n_y))$  operations (with the computation of the contractions as the dominating contribution).

In computing the quantities  $\|\mathbf{v}_{[p,q]}\|$  and  $\pi_\nu^{(x)}(\mathbf{v}_{[p,q]})$  in steps (S2) and (S3), we need to take into account that the vectors  $\mathbf{R}_{\Lambda_q^{(y)}} \mathbf{U}_k^{(y)}$ ,  $k \in K_p$ , need no longer be orthonormal.

To this end, let  $\mathbf{V} \in \mathbb{R}^{2^q \times 2^p}$  denote the matrix with columns  $\mathbf{V}_k := \sigma_k \mathbf{R}_{\Lambda_q^{(y)}} \mathbf{U}_k^{(y)}$ , and let

$$\hat{\mathbf{u}}_\nu = (\mathbf{U}_{k,\nu}^{(x)})_{k \in K_p} \in \mathbb{R}^{2^p}.$$

If  $q \geq p$ , we compute the Gramian  $\mathbf{V}^T \mathbf{V}$ , which takes  $\mathcal{O}(2^{2p+q})$  operations. We then directly obtain  $\|\mathbf{v}_{[p,q]}\|^2 = \text{tr}(\mathbf{V}^T \mathbf{V})$ . Moreover, for each given  $\nu$  we can evaluate

$$|\pi_\nu^{(x)}(\mathbf{v}_{[p,q]})|^2 = \hat{\mathbf{u}}_\nu^T (\mathbf{V}^T \mathbf{V}) \hat{\mathbf{u}}_\nu$$

using  $\mathcal{O}(2^{2p})$  operations. If  $p > q$ , we first factorize  $\mathbf{V}^T = \mathbf{Q} \mathbf{R}$ , where  $\mathbf{Q} \in \mathbb{R}^{2^p \times 2^q}$  has orthonormal columns and  $\mathbf{R} \in \mathbb{R}^{2^q \times 2^q}$ . This takes  $\mathcal{O}(2^{p+2q})$  operations. In addition, we form  $\mathbf{R} \mathbf{R}^T$  using  $\mathcal{O}(2^{3q})$  operations. We then have  $\|\mathbf{v}_{[p,q]}\|^2 = \text{tr}(\mathbf{R} \mathbf{R}^T)$  and for each  $\nu$ , we can evaluate  $\hat{\mathbf{u}}_\nu^T \mathbf{Q}$  and subsequently  $|\pi_\nu^{(x)}(\mathbf{v}_{[p,q]})|^2 = (\hat{\mathbf{u}}_\nu^T \mathbf{Q})(\mathbf{R} \mathbf{R}^T)(\hat{\mathbf{u}}_\nu^T \mathbf{Q})^T$  using  $\mathcal{O}(2^{p+q} + 2^{2q})$  operations.

Altogether, abbreviating  $r_\eta := \text{rank}(\mathbf{v}_\eta)$  and  $n_{\eta,y} := \#\text{supp}_y(\mathbf{v}_\eta)$ , the computational work required for obtaining  $\|\mathbf{v}_{[p,q]}\|$  and  $|\pi_\nu^{(x)}(\mathbf{v}_{[p,q]})|$  is of order

$$(n_x + n_{\eta,y}) r_\eta^2 \leq (n_x + n_y) r^2. \quad (\text{B.8})$$

With these values at hand, it remains to assemble  $\mathbf{w}_\eta$  in the form (5.20), which amounts to building each  $\mathbf{w}_{p,q}$  as in (5.42). The action of the bidiagonal matrices  $\mathbf{M}_j$ , on the one hand, for each  $p, q$  and  $j$  requires  $2^{p+q}$  operations, and the total costs for assembling the  $y$ -components of the result are therefore bounded up to a constant by

$$\begin{aligned} \sum_{p,q \geq 0} 2^{p+q} M_{p,q} &\lesssim \eta^{-\frac{1}{s}} \|\mathbf{v}\|_{\Sigma^s}^{\frac{1}{s}} (1 + \log_2(n_{\eta,y}))^{\frac{a}{s}} n_{\eta,y} (1 + \log_2(r_\eta))^{\frac{a}{s}} (r_\eta)^{1 - \frac{a}{s}} \\ &\lesssim \eta^{-\frac{1}{s}} \|\mathbf{v}\|_{\Sigma^s}^{\frac{1}{s}} (1 + |\log \eta|)^{\frac{2a}{s}} \eta^{-\frac{1}{s_y}} \|\pi^{(y)}(\mathbf{v})\|_{\mathcal{A}^{s_y}}, \end{aligned}$$

where the estimate on the right is obtained as in (5.35) and (5.36). Assembling the  $x$ -components requires the action of the approximate operators  $\tilde{\mathbf{A}}_{p,q,j}$ . By our construction, the combined action of  $\tilde{\mathbf{A}}_{p,q,j}$ ,  $j = 1, \dots, M_{p,q}$ , on a single vector  $\mathbf{U}_k^{(x)}$ ,  $k \in K_p$ , takes a number of operations proportional to the resulting  $\#\text{supp}_x(\mathbf{w}_{p,q})$ . Consequently, the total number of operations for the  $x$ -components is bounded up to a constant by

$$\begin{aligned} \sum_{p,q \geq 0} 2^p \#\text{supp}_x(\mathbf{w}_{p,q}) &\lesssim \sum_{p,q \geq 0} 2^p (1+p)^{\frac{a}{s_x}} (1+q)^{\frac{a}{s_x}} \eta^{-\frac{1}{s_x}} \|\pi^{(x)}(\mathbf{v}_\eta)\|_{\mathcal{A}^{s_x}}^{\frac{1}{s_x}} \\ &\lesssim r_\eta (1 + |\log \eta|)^{\frac{2a}{s_x}} \eta^{-\frac{1}{s_x}} \|\pi^{(x)}(\mathbf{v}_\eta)\|_{\mathcal{A}^{s_x}}^{\frac{1}{s_x}} \\ &\lesssim \eta^{-\frac{1}{s}} \|\mathbf{v}\|_{\Sigma^s}^{\frac{1}{s}} (1 + |\log \eta|)^{\frac{2a}{s_x}} \eta^{-\frac{1}{s_x}} \|\pi^{(x)}(\mathbf{v}_\eta)\|_{\mathcal{A}^{s_x}}^{\frac{1}{s_x}}. \quad \square \end{aligned}$$