

### UNIVERSITY OF TECHNOLOGY IN THE EUROPEAN CAPITAL OF CULTURE CHEMNITZ

# Learning the solution of differential equations by sparse high-dimensional approximation **Daniel Potts and Fabian Taubert**

Differential problem	Parametrization of $f$	Basis expansion of $u$	
$Lu = f$ $\boldsymbol{x} \in \Omega \subset \mathbb{R}^d$	$f(\boldsymbol{x}) \approx \sum_{j=1}^{n} a_j A_j(\boldsymbol{x}) \qquad \boldsymbol{x} \in \Omega$	$u(\boldsymbol{x}, \boldsymbol{a}) \coloneqq \sum_{\boldsymbol{k} \in \mathbf{N}} c_{\boldsymbol{k}} \Phi_{\boldsymbol{k}}(\boldsymbol{x}, \boldsymbol{a}) \qquad (\boldsymbol{x}, \boldsymbol{a}) \in \mathcal{D}.$	
Solvability: We can access samples $u(x)$ for a given $f$ and any $x \in \Omega$ at any time (via	j=1 <b>Functions:</b> We use fixed functions	$oldsymbol{k} \in \mathbb{N}^{a+n}$	

classical differential equation solvers).  $A_i, j = 1, \ldots, n_i$ , e.g., B-splines or

**Bounded orthonormal product basis:** The  $\{\Phi_{k}(\cdot), k \in \mathbb{N}^{d+n}\}$  are bounded, orthonormal and of tensor-product structure, e.g., trigonometric or Chebyshev polynomials.

**Operator learning:** We are interested in the solution mapping  $\mathcal{G}(f) = u$ .

## High-dim. approximation

$$S_I^{\mathcal{A}}u(\boldsymbol{x}, \boldsymbol{a}) \coloneqq \sum_{\boldsymbol{k} \in I} \hat{u}_{\boldsymbol{k}} \Phi_{\boldsymbol{k}}(\boldsymbol{x}, \boldsymbol{a})$$

**Index set:**  $I \subset \mathbb{N}^{d+n}$  is unknown, but *s*-sparse, i.e., |I| = s. **Coefficients:**  $\hat{u}_k \in \mathbb{C}$  are approximations of the true coefficients  $c_k$ .

trigonometric polynomials. **Coefficients:** We identify *f* by its coefficients  $\boldsymbol{a} = (a_1, \ldots, a_n) \in \mathbb{C}^n.$ 

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## Main challenge

**Unknown index set:** If *I* was known, we could compute the  $\hat{u}_k$  directly and efficiently. **Search space:** We consider a reasonable search space  $\Gamma \subset \mathbb{N}^{d+n}$  and assume  $I \subset \Gamma$ . However, we have  $|\Gamma| \gg |I|$ . **Curse of dimensionality:** Computing all  $\hat{u}_{k}$ with  $k \in \Gamma$  is computationally unfeasible!

## Algorithm Input

- search space  $\Gamma \subset \mathbb{N}^{d+n}$
- sparsity  $s \in \mathbb{N}$
- detection threshold  $\delta > 0$
- detection iterations  $r \in \mathbb{N}$
- $\blacktriangleright$  target function u as black box ( $\rightarrow$  PDE solver)

## Dimension-incremental Algorithm<sup>[1]</sup>

- Works by detecting "good" index sets in lower dimensions and combining them.
- Utilizes cosine-transformed multiple rank-1 lattices.<sup>[2]</sup>

**Differential equation:** 

- Complexities (with d = d + n and superposition dimension  $d_s$ ):
  - Sampling compl.:
  - Computational compl.:

 $\mathcal{O}\left( ilde{d}r^3s^22^{d_s}\log(rs)
ight)$  $\mathcal{O}\left( ilde{d}r^3s^2d_s^22^{d_s}\log^5(rs)
ight)$ 

## Algorithm Output

- detected index set  $I \subset \Gamma$ with |I| = s
- approximated coefficients  $\hat{u}_{k}$  with  $|\hat{u}_{k}| \geq \delta$ .

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## Poisson equation (1D)

#### **Differential equation:**

$$-\frac{d^2}{dx^2}u(x) = f(x) \qquad x \in (0,1)$$
  
$$u(0) = u(1) = 0$$

**Parametrization:** 

(n-1)/2 $f(x) \approx$  $\ell = -(n-1)/2$ 

**Remarks:** We set n = 9, restricted  $a_{\ell} \in [-1, 1]$  and used the analytical solution instead of a solver. **Transfer learning:** 



## Poisson equation (2D)

$-\Delta u(\boldsymbol{x}) = f(\boldsymbol{x}) \qquad \boldsymbol{x} \in \Omega$	Structural in					
$u(\boldsymbol{x}) = 0 \qquad \boldsymbol{x} \in \delta\Omega$	Ind					
Parametrization:						
$f(\boldsymbol{x}) \approx \sum_{\boldsymbol{\ell} \in J} a_{\boldsymbol{\ell}} \mathbf{e}^{2\pi \mathbf{l} \boldsymbol{\ell} \boldsymbol{x}}$	ensio					
Remarks: We used a FEM (189	3 E 1111					
nodes) and set $J = \{-1, 0, 1\}^2$ .	↓ 1					
	Fig					
Heat equation						
Differential equation:	Average rela					
$\partial_t u = \alpha^2 \partial_{xx} u  x, t \in (0, 1)$	Structural in					
$u(x,0) = f(x) \qquad x \in (0,1)$	Ind					
$u(0,t) = 0$ $t \in (0,1)$	2 433					
$u(1,t) = 0$ $t \in (0,1)$						

Average relative approximation error:  $\approx 10^{-4}$ **Structural information:** lices 2 2 2 2 2 2 2 3 2 3 1 1 2 1 2 1 3 3 2 2 2 2 2 3 2 3 2 3 1 1 1 2 1 2 3 3 11

gure: The first 30 indices detected.

-leat equation	)n		
Differential equation:		Average relative approximation error: $pprox 10^{-3}$	
$\partial_t u = \alpha^2 \partial_{xx} u$	$x,t\in(0,1)$	Structural information:	
u(x,0) = f(x)	$x \in (0,1)$	Indices	
u(0,t) = 0	$t \in (0, 1)$		







**Figure:** The relative approximation error for 10000 randomly drawn a.

**Remarks:** We set n = 9 and used the MATLAB<sup>®</sup> function pdepe.

Figure: The first 30 indices detected.

- [1] L. Kämmerer, D. Potts and F. Taubert. Nonlinear approximation in bounded orthonormal
  - product bases. Sampl. Theory Signal Process. Data Anal., 2023.
- [2] L. Kämmerer. An efficient spatial discretization of spans of multivariate Chebyshev polynomials. arXiv preprint, 2024.
- [3] D. Potts and F. Taubert. Operator learning based on sparse high-dimensional approximation. arXiv preprint, 2024.

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