

High-dimensional setting

Unknown function: $f \in L_2(\mathcal{D}, \mu)$ is a d -dimensional function with basis expansion

$$f(\mathbf{x}) := \sum_{k \in \mathbb{N}^d} c_k \Phi_k(\mathbf{x}).$$

Bounded orthonormal product basis: The domain \mathcal{D} , measure μ and basis Φ_k of $L_2(\mathcal{D}, \mu)$ are of tensor-product structure and

$$\max_{k \in \mathbb{N}^d} \|\Phi_k\|_\infty =: B < \infty.$$

Black-box sampling: We can access the sample $f(\mathbf{x})$ for any \mathbf{x} at any time.

Truncation and approximation

Desired approximation: We want to compute an approximate truncated basis expansion

$$S_I^A f(\mathbf{x}) := \sum_{k \in I} \hat{f}_k \Phi_k(\mathbf{x}),$$

where $\hat{f}_k \approx c_k$ and I is s -sparse, i.e., $|I| = s$.

Best s -term approximation: the c_k with $k \in I$ have the largest absolute values

“best” index set $I \iff$

Error:

$$\|S_I^A f - f\| \leq \underbrace{\|S_I^A f - S_I f\|}_{\text{coef. approx. error}} + \underbrace{\|S_I f - f\|}_{\text{truncation error}}$$

Main challenge

Quantities to compute:

- approx. coefficients $\hat{f}_k \approx c_k \forall k \in I$
- suitable sparse index set $I \subset \mathbb{N}^d$

Necessary assumption:

$$I \subset \mathbb{N}^d \xrightarrow{\text{assume}} I \subset \Gamma \text{ with a (given) finite search space } \Gamma \subset \mathbb{N}^d$$

Curse of dimensionality: Approximating all $c_k, k \in \Gamma$ is still computationally unfeasible.

Projected coefficients

Projected coefficient: For a fixed anchor $\tilde{\mathbf{x}}$, the projected coefficients for $k \in K \subset \mathbb{N}^t$ are

$$c_{\{1, \dots, t\}, k}(\tilde{\mathbf{x}}) := \langle f(\cdot, \tilde{\mathbf{x}}), \Phi_{\{1, \dots, t\}, k}(\cdot) \rangle.$$

Importance of k : We expect k to be important, if $|c_{\{1, \dots, t\}, k}(\tilde{\mathbf{x}})|$ is large, because

$$c_{\{1, \dots, t\}, k}(\tilde{\mathbf{x}}) = \sum_{h \in \mathbb{N}^{d-t}} c_{(k, h)} \Phi_{\{t+1, \dots, d\}, (k, h)}(\tilde{\mathbf{x}}).$$

Approximation of the projected coefficients:

- Monte Carlo integration (MC, CMC)
- rank-1 lattices (R1L)
- subsampling rank-1 lattices [2] (ssR1L)
- multiple rank-1 lattices (mR1L, CmR1L)

The dimension-incremental algorithm (for e.g. $\mathcal{D} = [-1, 1]^d$)

Theorem^[1]

Assumptions: We need mild assumptions on the parameters of the algorithm and the accuracy of the approximated projected coefficients.

Theoretical detection guarantee: Then, the output index set contains the “best” index set with high probability.

Related Work

CS approach in similar setting: [Choi, Iwen, Krahmer '20] [Choi, Iwen, Volkmer '21]

Polynomial approx. via LSQ and CS: [Adcock, Brugiapaglia, Webster '22]

Sparse polynomial chaos expansions: [Lüthen, Marelli, Sudret '21]

10-dimensional periodic – Approximation of test functions – 9-dimensional non-periodic

“Fourier”: Approximation of a periodic test function on \mathbb{T}^{10} with the Fourier basis and the methods MC, R1L, ssR1L and mR1L.

Parameters: s - sparsity, N - extension of search space Γ

“Chebyshev”: Approximation of a non-periodic test function on $[-1, 1]^9$ with the Chebyshev basis and the methods CMC and CmR1L.

[1] L. Kämmerer, D. Potts and F. Taubert. Nonlinear approximation in bounded orthonormal product bases. *Sampl. Theory Signal Process. Data Anal.*, 2023.
[2] F. Bartel and F. Taubert. Nonlinear Approximation with Subsampled Rank-1 Lattices. *arXiv preprint*, 2023.