

Bridging continuous and discrete tensor representations of multivariate functions via QTT

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Chebyshev-Tucker (ChebTuck) format

Discrete and continuous tensor formats

$f: [-1, 1]^D \rightarrow \mathbb{R}$, $D = 3$. Approx. f with a *small number of parameters* \leadsto cheap comput. with f .

- Grid-based methods:** discrete Tucker approximation of function related tensor \mathbf{F} (contains, e.g., function values on a grid):

$$\mathbf{F} \approx \sum_{i_1=1}^R \sum_{i_2=1}^R \sum_{i_3=1}^R \beta_{i_1, i_2, i_3} \mathbf{a}_{i_1}^{(1)} \otimes \mathbf{a}_{i_2}^{(2)} \otimes \mathbf{a}_{i_3}^{(3)} \in \mathbb{R}^{n \times n \times n}, \quad (1)$$

$$\mathbf{F}_{i_1, i_2, i_3} := f(t_{i_1}^{(1)}, t_{i_2}^{(2)}, t_{i_3}^{(3)}), \quad t_{i_h}^{(h)} = -1 + (i_h - 1)h, \quad h = 2/(n-1), \quad i_h = 1, \dots, n.$$

- Storage: $\mathcal{O}(DRn + R^D)$. Disadvantage: *large n* required to achieve high accuracy.
- Mesh-free methods:** functional Tucker approximation of f directly:

$$f(x_1, x_2, x_3) \approx \mathbf{f}_m(x_1, x_2, x_3) := \sum_{i_1=1}^R \sum_{i_2=1}^R \sum_{i_3=1}^R \beta_{i_1, i_2, i_3} \mathbf{v}_{i_1}^{(1)}(x_1) \mathbf{v}_{i_2}^{(2)}(x_2) \mathbf{v}_{i_3}^{(3)}(x_3) \quad (2)$$

$$\mathbf{v}_{i_h}^{(h)}(x_h) = \sum_{j=1}^m \mathbf{V}_{j, i_h}^{(h)} T_{j-1}(x_h), \quad \mathbf{V}^{(h)} \in \mathbb{R}^{m \times R}, \quad T_j(x) = \cos(j \arccos(x)).$$

- Storage: $\mathcal{O}(DRm + R^D)$. $m \ll n$ for the same accuracy as grid-based methods.
- We call it **ChebTuck format**. It is also the format Chebfun3 [3] assumes.

Three natural tasks	Input	Output	Note
Function to ChebTuck (See [1,3])	$f: [-1, 1]^3 \rightarrow \mathbb{R}$	ChebTuck \mathbf{f}_m	f can be evaluated freely in $[-1, 1]^3$
Grid to ChebTuck (See [1])	grid-based \mathbf{F} of f	ChebTuck \mathbf{f}_m	Preferably $m \ll n$
ChebTuck to Grid (our focus)	ChebTuck \mathbf{f}_m of f	grid-based \mathbf{F}	$n \gg m$, but storage largely reduced by QTT

ChebTuck to Grid-based tensor

- Given ChebTuck \mathbf{f}_m (2) of f , to get a grid-based tensor, naive approach yields a discrete Tucker:
 $\mathbf{F}_m(i_1, i_2, i_3) := \mathbf{f}_m(t_{i_1}^{(1)}, t_{i_2}^{(2)}, t_{i_3}^{(3)}) \Rightarrow \mathbf{F}_m = \beta \times_1 \mathbf{U}_1 \times_2 \mathbf{U}_2 \times_3 \mathbf{U}_3$, $\mathbf{U}_\ell(i_\ell, j_\ell) = \mathbf{v}_{j_\ell}^{(\ell)}(t_{i_\ell}^{(\ell)})$ (c.f. (1)),
i.e., each column of \mathbf{U}_ℓ contains the discretization of a polynomial $\mathbf{v}_{j_\ell}^{(\ell)}(x_\ell)$ on grid $\{t_{i_\ell}^{(\ell)}\}$.
- Additional storage:** $\mathcal{O}(DRn)$. **Remedy:** store columns of \mathbf{U}_ℓ as QTT [Khoromskij'11].

Definition (Quantized Tensor Trains (QTT) format of a univariate function)

Let $p: [-1, 1] \rightarrow \mathbb{R}$ be a univariate function. Discretizing it on a uniform grid $\{x_i := -1 + (i-1)h\}_{i=1}^n$ with $h = 2/(n-1)$, $n = 2^d$ yields $\mathbf{p} = [p(x_i)]_{i=1}^n \in \mathbb{R}^n$. The multi-index mapping $(i_1, \dots, i_d) \mapsto i_{\leq d} = 1 + (i_1 - 1) + 2 \cdot (i_2 - 1) + \dots + 2^{d-1} \cdot (i_d - 1)$ for $i_\ell = 1, 2$ reshapes \mathbf{p} into a d -dimensional tensor $\mathbf{P} \in \mathbb{R}^{2 \times \dots \times 2}$:

$$\mathbf{P}(i_1, \dots, i_d) = p(x_{i_{\leq d}}) = p\left(\underbrace{-1 + (i_1 - 1)h}_{=: x_{i_1}^{(1)}} + 2 \cdot \underbrace{(i_2 - 1)h}_{=: x_{i_2}^{(2)}} + \dots + \underbrace{2^{d-1} \cdot (i_d - 1)h}_{=: x_{i_d}^{(d)}}\right).$$

QTT of p is defined as a TT (with cores $\mathbf{G}_\ell(i_\ell) \in \mathbb{R}^{r_{\ell-1} \times r_\ell}$ and ranks $r_\ell \leq r$) of \mathbf{P} :

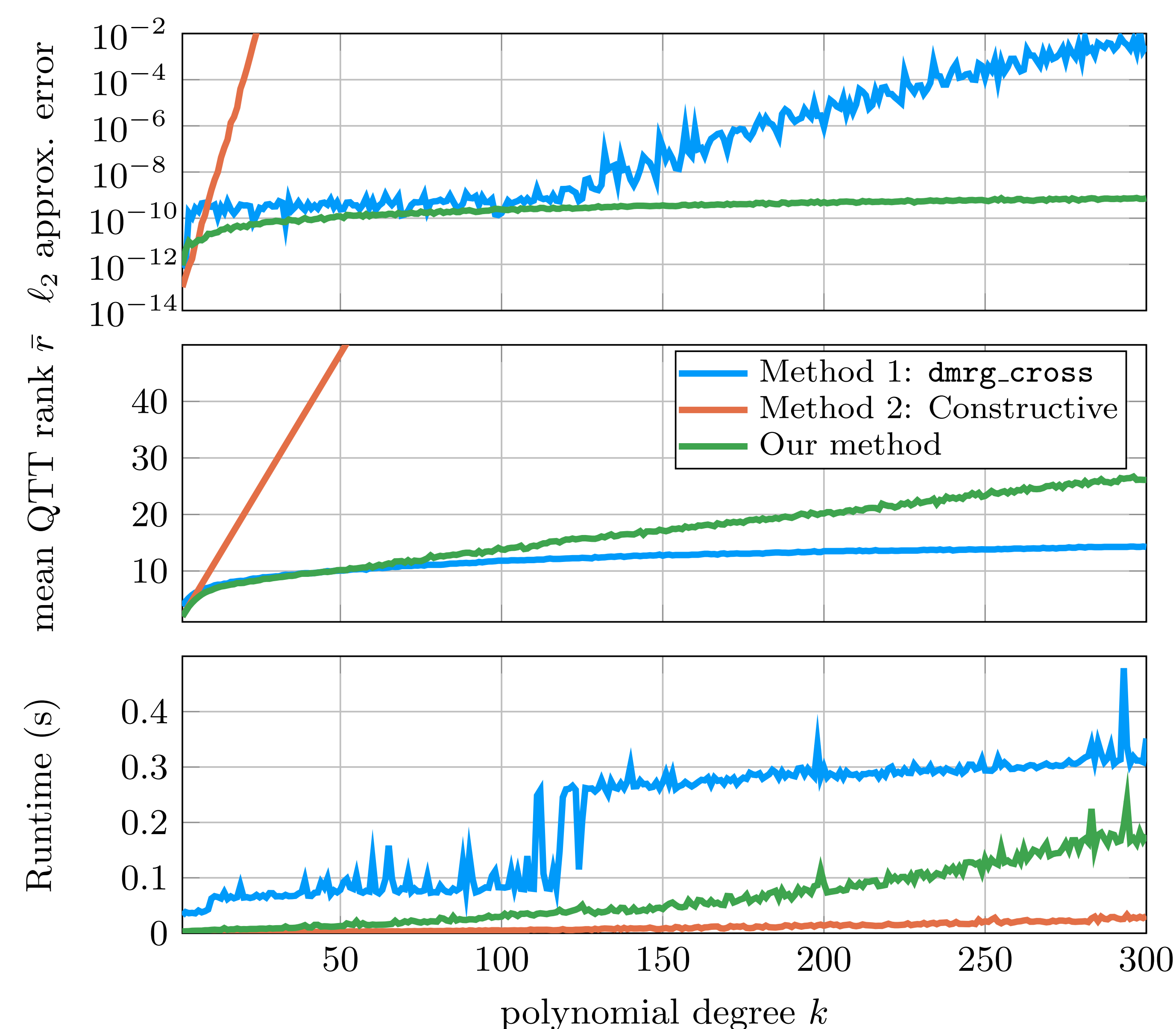
$$p(x_{i_1}^{(1)} + x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) = \mathbf{P}(i_1, \dots, i_d) = \mathbf{G}_1(i_1) \mathbf{G}_2(i_2) \dots \mathbf{G}_d(i_d) \text{ for } i_1, \dots, i_d = 1, 2.$$

- Storage of \mathbf{U}_ℓ in QTT: $\mathcal{O}(DRd^2) = \mathcal{O}(DRr^2 \log n)$.
- Classical result:** QTT ranks of degree m polynomials $\leq m+1$ [Khoromskij'11, Oseledets'13] (numerically even $\log m$) \leadsto reduces storage of \mathbf{U}_ℓ from $\mathcal{O}(DRn)$ to $\mathcal{O}(DRm^2 \log n)$ (numerically $\mathcal{O}(DR \log^2 m \log n)$).
- Fundamental task:** approximate a polynomial p in QTT format efficiently \leadsto **our focus**

Numerical experiments

Approximating Chebyshev polynomials $T_k(x)$ in QTT

- Similar results are obtained for other class of polynomials, e.g., random linear combinations of monomials/Chebyshev polynomials.



Approximation of a polynomial in QTT format

Computational methods for the TT format of \mathbf{P}

- Direct method:** apply directly the adaptive TT cross, e.g., `dmrg_cross` [Savostyanov/Oseledets'11].
 - Disadvantage: heuristic; doesn't exploit the 1D nature of the problem, just view \mathbf{P} as a black box tensor.
 - Constructive method:** \exists an analytic formula [Oseledets'13] for the cores $\mathbf{G}_\ell(i_\ell) \in \mathbb{R}^{(m+1) \times (m+1)}$.
 - Disadvantage: is numerically unstable even for moderate $m > 20$ & produces pessimistic TT ranks $m+1$.
- Our novel method:** Constructive (thus faster than Method 1), stable and rank adaptive.

Recall Oseledets' constructive method for $p(x) = p_0 + p_1 x + \dots + p_m x^m$

Introduce the notation: $X_{\leq k}(x) := [1, x, \dots, x^k]^\top \in \mathbb{R}^{k+1}$

- Notice that with $M(\alpha+1, \beta+1) = p_{\alpha+\beta} C_{\alpha+\beta}^\alpha$ for $\alpha + \beta \leq m$ otherwise 0 (M is skew-upper triangular), it holds

$$p(x+y) = \sum_{\alpha=0}^m \sum_{\beta=0}^m M(\alpha+1, \beta+1) x^\alpha y^\beta \Rightarrow p(x+y) = X_{\leq m}(x)^\top M X_{\leq m}(y). \quad (3)$$

- Let $x = x_{i_1}$ and $y = x_{i_2} + \dots + x_{i_d}$, then separate x_{i_1} from the rest:

$$p(x_{i_1}^{(1)} + x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) = \underbrace{X_{\leq m}(x_{i_1}^{(1)})^\top M}_{=: \mathbf{G}_1(i_1)} X_{\leq m}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}). \quad (4)$$

- Similarly, $\mathbf{G}_2(i_2)$ is constructed such that $X_{\leq m}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) = \mathbf{G}_2(i_2) X_{\leq m}(x_{i_3}^{(3)} + \dots + x_{i_d}^{(d)})$ holds,

$$\Rightarrow \mathbf{P}(i_1, i_2, \dots, i_d) = \mathbf{G}_1(i_1) \mathbf{G}_2(i_2) X_{\leq m}(x_{i_3}^{(3)} + \dots + x_{i_d}^{(d)}).$$

- Other cores $\mathbf{G}_3(i_3), \dots, \mathbf{G}_d(i_d)$ are constructed similarly.

Disadvantage: Unstable since M contains large binomial coefficients & small powers e.g. $(x_{i_1}^{(1)})^\alpha$

Fixing idea: Replace x^α, y^β by Chebyshev polynomials!

$$p(x+y) = \sum_{\alpha=0}^m \sum_{\beta=0}^m M^c(\alpha+1, \beta+1) T_\alpha(x) T_\beta(y) \quad (5)$$

- A subtle but crucial difference between (3) and (5): (3) holds for all $x, y \in \mathbb{R}$ for fixed coefficients M , while (5) only holds for $x \in I_x$ and $y \in I_y$ with some intervals I_x, I_y and the coefficients M^c depend accordingly on these intervals.
- For an interval $I = [a, b]$, introduce the notation:
 $T_\ell^I(x) := T_\ell((2x - (a+b))/(b-a))$, $T_{\leq k}^I(x) := [1, T_1^I(x), \dots, T_k^I(x)]^\top \in \mathbb{R}^{k+1}$ for $x \in I = [a, b]$.

Our novel method: constructive, stable & rank adaptive

Recall: 1D Chebyshev interpolation

Let $p: I \rightarrow \mathbb{R}$ be a univariate function. Then its Chebyshev interpolation of degree m is given by

$$p(x) \approx g_m := \sum_{\ell=0}^m c_\ell T_\ell^I(x) = \mathbf{c}^\top T_{\leq m}^I(x) \text{ with } \mathbf{c} = \mathbf{W} \mathbf{p}, \quad \mathbf{W} \text{ being an inverse DCT matrix}$$

and $\mathbf{p} \in \mathbb{R}^{m+1}$ containing the function values of p at the Chebyshev points on I . In particular if p is a polynomial of degree $\leq m$, then the interpolation is **exact**: $p(x) = g_m(x)$ for all $x \in I$.

- Let $I_{\geq k} := [\sum_{\ell=k}^d x_1^{(\ell)}, \sum_{\ell=k}^d x_2^{(\ell)}]$, then we have $x_{i_k}^{(k)} + x_{i_{k+1}}^{(k+1)} + \dots + x_{i_d}^{(d)} \in I_{\geq k}$.

- Let $M_{i_1}^c \in \mathbb{R}^{1 \times (m+1)}$ be the Chebyshev coefficients of the function $I_{\geq 2} \ni x \mapsto p(x_{i_1}^{(1)} + x)$:

$$p(x_{i_1}^{(1)} + x) = M_{i_1}^c T_{\leq m}^{I_{\geq 2}}(x) \text{ for } x \in I_{\geq 2}, \quad i_1 = 1, 2, \text{ and in particular} \quad (6)$$

$$\mathbf{P}(i_1, i_2, \dots, i_d) = p(x_{i_1}^{(1)} + x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) = M_{i_1}^c T_{\leq m}^{I_{\geq 2}}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) \quad (7)$$

We can already set here $\mathbf{G}_1(i_1) := M_{i_1}^c$ to obtain the first QTT core (c.f. Eq. (4))

- Yet to make it rank adaptive, we compute a LRA (e.g. SVD) of the Chebyshev coefficients:

$$\begin{bmatrix} M_{i_1}^c \\ M_{i_2}^c \end{bmatrix} \approx \mathbf{U}_1 \mathbf{V}_1^\top \text{ with } \mathbf{U}_1 \in \mathbb{R}^{2 \times r_1}, \quad \mathbf{V}_1 \in \mathbb{R}^{(m+1) \times r_1}.$$

- Let $\mathbf{U}_{1, i_1} := \mathbf{U}_1(i_1, :)$ $\in \mathbb{R}^{1 \times r_1}$, then $M_{i_1}^c \approx \mathbf{U}_{1, i_1} \mathbf{V}_1^\top$. Then Eq. (7) becomes

$$\mathbf{P}(i_1, i_2, \dots, i_d) \approx \mathbf{U}_{1, i_1} \mathbf{V}_1^\top T_{\leq m}^{I_{\geq 2}}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) = \mathbf{U}_{1, i_1} \mathbf{V}_{\leq r_1}^{(2)}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) \quad (8)$$

where we have defined the polynomial vector $\mathbf{v}_j^{(2)}(y)$ on the interval $I_{\geq 2}$ as

$$\mathbf{v}_{\leq r_1}^{(2)}(y) := [\mathbf{v}_1^{(2)}(y), \dots, \mathbf{v}_{r_1}^{(2)}(y)]^\top \in \mathbb{R}^{r_1} \text{ with } \mathbf{v}_j^{(2)}(y) := \mathbf{V}_1(:, j)^\top T_{\leq m}^{I_{\geq 2}}(y) \text{ for } j = 1, \dots, r_1, \quad y \in I_{\geq 2}.$$

The first QTT core can thus be taken as $\mathbf{G}_1(i_1) = \mathbf{U}_{1, i_1}$.

- For the 2nd QTT core, note that each $I_{\geq 3} \ni x \mapsto \mathbf{v}_j^{(2)}(x_{i_2}^{(2)} + x)$ for $j = 1, \dots, r_1$ and $i_2 = 1, 2$ is a polynomial of degree $\leq m \Rightarrow$ has $\leq m+1$ non-zero Cheb. coeff. denoted by $\mathbf{C}_{2, i_2}^c(j, :)$ $\in \mathbb{R}^{m+1}$:

$$\mathbf{v}_{\leq r_1}^{(2)}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) = \mathbf{C}_{2, i_2}^c T_{\leq m}^{I_{\geq 3}}(x_{i_3}^{(3)} + \dots + x_{i_d}^{(d)}). \quad (9)$$

We then compute a LRA of $\begin{bmatrix} \mathbf{C}_{2, 1}^c \\ \mathbf{C}_{2, 2}^c \end{bmatrix} \approx \mathbf{U}_2 \mathbf{V}_2^\top$ with $\mathbf{U}_2 \in \mathbb{R}^{2r_1 \times r_2}$, $\mathbf{V}_2 \in \mathbb{R}^{(m+1) \times r_2}$.

Let us denote $\mathbf{U}_{2, i_2} := \mathbf{U}_2(r_1(i_2 - 1) + 1 : r_1 i_2, :)$ $\in \mathbb{R}^{r_1 \times r_2}$, then $\mathbf{C}_{2, i_2}^c \approx \mathbf{U}_{2, i_2} \mathbf{V}_2^\top$. Thus

$$\mathbf{P}(i_1, i_2, \dots, i_d) \approx \mathbf{U}_{1, i_1} \mathbf{C}_{2, i_2}^c T_{\leq m}^{I_{\geq 3}}(x_{i_3}^{(3)} + \dots + x_{i_d}^{(d)}) \approx \mathbf{U}_{1, i_1} \mathbf{U}_{2, i_2} \mathbf{V}_2^\top T_{\leq m}^{I_{\geq 3}}(x_{i_3}^{(3)} + \dots + x_{i_d}^{(d)}) \quad (10)$$

The second QTT core is therefore $\mathbf{G}_2(i_2) = \mathbf{U}_{2, i_2}$. Other cores are constructed similarly.

References

- [1] P. Benner, B. Khoromskij, V. Khoromskaia, B. Sun. *A mesh-free hybrid Chebyshev-Tucker tensor format with applications to multi-particle modelling*, [arXiv:2505.02319](https://arxiv.org/abs/2505.02319), 2025.
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- [3] H. Behnam, L. N. Trefethen. *Chebfun in three dimensions*, SIAM J. Sci. Comput., 2017.