



Bridging continuous and discrete tensor representations of multivariate functions via QTT

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METT XI, Jan 9, 2026

Based on a joint work with
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Partners:

MAX PLANCK INSTITUTE
FOR MATHEMATICS IN THE SCIENCES





1. Introduction
2. QTT approximation of polynomials
3. Fully discrete format
4. Numerical experiments
5. Conclusion



Discrete and continuous tensor formats

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

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

$$\mathbf{F}(i_1, i_2, i_3) \approx \sum_{j_1=1}^R \sum_{j_2=1}^R \sum_{j_3=1}^R \beta_{j_1, j_2, j_3} \mathbf{u}_{j_1}^{(1)}(i_1) \mathbf{u}_{j_2}^{(2)}(i_2) \mathbf{u}_{j_3}^{(3)}(i_3), \mathbf{u}_{j_\ell}^{(\ell)} \in \mathbb{R}^n, \mathbf{F} \in \mathbb{R}^{n \times n \times n}.$$

2. **Mesh-free methods:** **functional Tucker format** of f :

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



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$$v_{i_\ell}^{(\ell)}(x_\ell) = \sum_{j_\ell=1}^m V_{j_\ell, i_\ell}^{(\ell)} T_{j_\ell-1}(x_\ell), \quad V^{(\ell)} \in \mathbb{R}^{m \times R}, \quad T_{j_\ell}(x) = \cos(j_\ell \arccos(x)).$$

We call Eq. (1) the **Chebyshev-Tucker (ChebTuck) format**.



ChebTuck to Grid-based tensor

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with $v_{i_\ell}^{(\ell)}(x_\ell) = \sum_{j_\ell=1}^m V_{j_\ell, i_\ell}^{(\ell)} T_{j_\ell-1}(x_\ell)$, $T_{j_\ell}(x) = \cos(j_\ell \arccos(x))$. **Storage:** $\mathcal{O}(DRm + R^D)$.



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- **Goal:** Transform ChebTuck format to a discrete tensor format on a fine grid $n \gg m$:

$$\mathbf{F}_{\mathbf{m}}(i_1, i_2, i_3) := f_{\mathbf{m}}(t_{i_1}^{(1)}, t_{i_2}^{(2)}, t_{i_3}^{(3)}), \quad t_{i_\ell}^{(\ell)} = -1 + (i_\ell - 1)h, \quad h = 2/(n - 1).$$

- **Motivation:**

- Efficient application of discrete operators (differentiation, integration, convolution).
- Offline-online workflows: expensive offline construction of continuous surrogate, fast online evaluation.
- High-resolution discretizations for accurate simulations.



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- A **naive approach** yields a discrete Tucker:

$$\mathbf{F}_{\mathbf{m}} = \boldsymbol{\beta} \times_1 U_1 \times_2 U_2 \times_3 U_3, \quad U_\ell(i_\ell, j_\ell) = v_{j_\ell}^{(\ell)}(t_{i_\ell}^{(\ell)})$$

i.e., each column of U_ℓ contains the discretization of a Chebyshev poly. $v_{j_\ell}^{(\ell)}(x_\ell)$ on the grid $t_{i_\ell}^{(\ell)}$.

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- Known: QTT ranks of polynomials p of degree m are bounded by $m + 1$ [Khoromskij '11, Oseledets '13] (numerically even $\log m$) $\rightsquigarrow \mathcal{O}(DRn)$ reduced to $\mathcal{O}(DRm^2 \log n)$ (numerically $\mathcal{O}(DR \log^2 m \log n)$).



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- Fundamental task**: approximate a polynomial p in QTT format efficiently.



From ChebTuck to QTT-Tucker

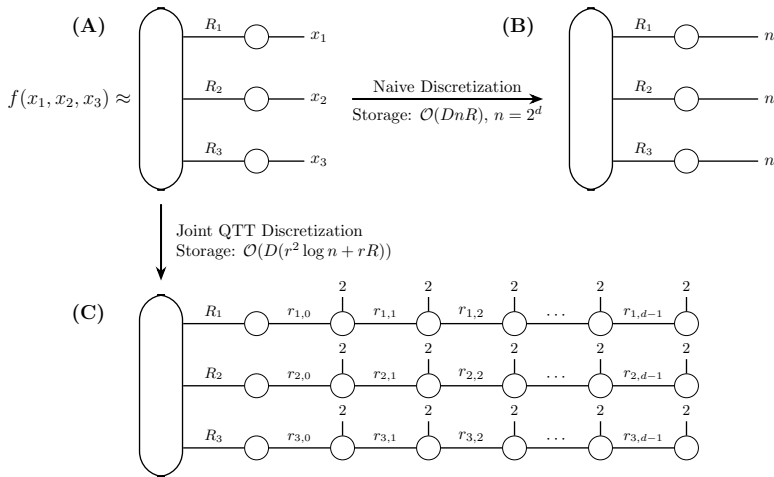


Figure: (A) Continuous ChebTuck. (B) Discrete Tucker ($\mathcal{O}(n)$ storage). (C) QTT-Tucker-like ($\mathcal{O}(\log n)$ storage).



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Approximation of a polynomial in QTT format

- For a polynomial $p(x) = p_0 + p_1x + \cdots + p_mx^m$ in $[-1, 1]$, discretizing it on uniform grid $\{x_i := -1 + h/2 + (i-1)h\}_{i=1}^n$ with $h = 2/n$ and $n = 2^d$ yields $\mathbf{p} = \{p(x_i)\}_{i=1}^n \in \mathbb{R}^{2^d}$.



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- Using 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 $i_\ell = 1, 2$, we can reshape $\mathbf{p}$ to a d -dimensional tensor $\mathbf{P} \in \mathbb{R}^{2 \times \dots \times 2}$:

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



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

1. **Direct method:** apply directly the adaptive TT cross, e.g., `dmrg_cross` [Savostyanov/Oseledets '11].
2. **Constructive method:** there exists an analytic formula¹ for the cores $\mathbf{G}_\ell(i_\ell) \in \mathbb{R}^{(m+1) \times (m+1)}$.

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3. **Our novel method:** Constructive (thus faster than Method 1), stable and rank adaptive.

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Recall Oseledets' constructive method

1. Notice $p(x + y) = \sum_{\alpha=0}^m \sum_{\beta=0}^m M(\alpha, \beta) x^\alpha y^\beta$ with $M(\alpha, \beta) = p_{\alpha+\beta} C_{\alpha+\beta}^\alpha$ for $\alpha + \beta \leq m$ otherwise 0, i.e., M is upper anti-triangular.



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3. Let $x = x_{i_1}^{(1)}$ and $y = x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}$, then separate $x_{i_1}^{(1)}$ from the rest:

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



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QTT of $p(x) = p_0 + p_1x + \dots + p_mx^m$ is defined as a TT of $\mathbf{P}$:

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Recall Oseledets' constructive method

1. Notice $p(x + y) = \sum_{\alpha=0}^m \sum_{\beta=0}^m M(\alpha, \beta) x^\alpha y^\beta$ with $M(\alpha, \beta) = p_{\alpha+\beta} C_{\alpha+\beta}^\alpha$ for $\alpha + \beta \leq m$ otherwise 0, i.e., M is upper anti-triangular.
2. Introduce the notation: $X_{\leq k}(x) := [1, x, \dots, x^k]^\top \in \mathbb{R}^{k+1}$, then $p(x + y) = X_{\leq m}(x)^\top M X_{\leq m}(y)$.
3. Let $x = x_{i_1}^{(1)}$ and $y = x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}$, then separate $x_{i_1}^{(1)}$ from the rest:

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



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Disadvantage: Unstable since the cores contain large binomial coefficients & powers e.g. $(x_{i_1}^{(1)})^\alpha$.



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Disadvantage: Unstable since the cores contain large binomial coefficients & powers e.g. $(x_{i_1}^{(1)})^\alpha$.

Fix: replace x^α, y^β by Chebyshev polynomials: $p(x + y) = \sum_{\alpha=0}^m \sum_{\beta=0}^m M_m^{\text{cheb}}(\alpha, \beta) T_\alpha(x) T_\beta(y)$.



Direct construction in Chebyshev basis

Fixing idea: Replace monomial expansion

$$p(x + y) = \sum_{\alpha=0}^m \sum_{\beta=0}^m M(\alpha, \beta) x^{\alpha} y^{\beta} \quad (2)$$

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- **Subtle but crucial difference:** (2) holds for all $x, y \in \mathbb{R}$ for fixed coefficients M , but (3) only holds for $x \in I_x$ and $y \in I_y$ with some intervals I_x, I_y and the coefficients M_m^{cheb} depend accordingly on these intervals.



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- **Notation:** Scaled Chebyshev polynomials on $I = [a, b]$:

$$T_\ell^I(x) := T_\ell((2x - (a+b))/(b-a)), \quad T_{\leq k}^I(x) := [1, T_1^I(x), \dots, T_k^I(x)]^\top \in \mathbb{R}^{k+1} \text{ for } x \in I = [a, b].$$



Rank-adaptive construction in Chebyshev basis (Forward pass)

Key tool: 1D Chebyshev interpolation

For a polynomial $p : I \rightarrow \mathbb{R}$ of degree $\leq m$, its Chebyshev expansion is exact:

$$p(x) = \sum_{\ell=0}^m c_{\ell} T_{\ell}^I(x) = \mathbf{c}^{\top} T_{\leq m}^I(x), \quad \text{coefficients } \mathbf{c} = W\mathbf{p}$$

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The first QTT core can already be taken as $\mathbf{G}_1(i_1) = \mathbf{c}_{i_1}^{\text{cheb}} \in \mathbb{R}^{1 \times (m+1)}$.



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1. For $\mathbf{c}_{i_1}^{\text{cheb}} \in \mathbb{R}^{1 \times (m+1)}$ being the Chebyshev coefficients of $I_{\geq 2} \ni x \mapsto p(x_{i_1}^{(1)} + x)$, we have

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2. We compute a LRA (e.g. SVD) of the Chebyshev coefficients:

$$\begin{bmatrix} \mathbf{c}_1^{\text{cheb}} \\ \mathbf{c}_2^{\text{cheb}} \end{bmatrix} \approx U_1 V_1^\top = \begin{bmatrix} U_{1,1} \\ U_{1,2} \end{bmatrix} V_1^\top \text{ with } U_1 \in \mathbb{R}^{2 \times r_1}, V_1 \in \mathbb{R}^{(m+1) \times r_1}.$$



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3. Thus $\mathbf{c}_{i_1}^{\text{cheb}} \approx U_{1,i_1} V_1^\top$. Then Eq. (4) becomes

$$\begin{aligned} \mathbf{P}(i_1, i_2, \dots, i_d) &= \mathbf{c}_{i_1}^{\text{cheb}} T_{\leq m}^{I_{\geq 2}}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) \approx U_{1,i_1} V_1^\top T_{\leq m}^{I_{\geq 2}}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) \\ &= U_{1,i_1} v_{\leq r_1}^{(2)}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) \end{aligned}$$

where the polynomial vector $v_j^{(2)}(y)$ on the interval $I_{\geq 2}$ is defined as

$$v_{\leq r_1}^{(2)}(y) := [v_1^{(2)}(y), \dots, v_{r_1}^{(2)}(y)]^\top \in \mathbb{R}^{r_1} \text{ with } v_j^{(2)}(y) := V_1(:, j)^\top T_{\leq m}^{I_{\geq 2}}(y) \text{ for } j = 1, \dots, r_1,$$

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



Rank-adaptive construction in Chebyshev basis (Forward pass)

3. We obtained from the previous step:

$$\mathbf{P}(i_1, i_2, \dots, i_d) \approx U_{1,i_1} v_{\leq r_1}^{(2)}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}).$$

4. For the 2nd QTT core, each $I_{\geq 3} \ni x \mapsto v_j^{(2)}(x_{i_2}^{(2)} + x)$ for $j = 1, \dots, r_1$ and $i_2 = 1, 2$ is a polynomial of degree $\leq m \implies$ has $\leq m + 1$ non-zero Cheb. coeff. denoted by $C_{2,i_2}^{\text{cheb}}(j, :) \in \mathbb{R}^{m+1}$:

$$v_{\leq r_1}^{(2)}(x_{i_2}^{(2)} + \dots + x_{i_d}^{(d)}) = C_{2,i_2}^{\text{cheb}} T_{\leq m}^{I_{\geq 3}}(x_{i_3}^{(3)} + \dots + x_{i_d}^{(d)}). \quad (5)$$

We then compute a LRA of

$$\begin{bmatrix} C_{2,1}^{\text{cheb}} \\ C_{2,2}^{\text{cheb}} \end{bmatrix} \approx U_2 V_2^\top = \begin{bmatrix} U_{2,1} \\ U_{2,2} \end{bmatrix} V_2^\top \text{ with } U_2 \in \mathbb{R}^{2r_1 \times r_2}, V_2 \in \mathbb{R}^{(m+1) \times r_2}. \text{ Thus}$$

$$\mathbf{P}(i_1, i_2, \dots, i_d) \approx U_{1,i_1} C_{2,i_2}^{\text{cheb}} T_{\leq m}^{I_{\geq 3}}(x_{i_3}^{(3)} + \dots + x_{i_d}^{(d)}) \approx U_{1,i_1} U_{2,i_2} V_2^\top T_{\leq m}^{I_{\geq 3}}(x_{i_3}^{(3)} + \dots + x_{i_d}^{(d)})$$

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



Rank-adaptive construction (Error control)

- **Backward pass:** Perform right-to-left SVD sweep to further compress the ranks.
- SVD tolerances in forward and backward passes: $\varepsilon_k^{(f)}$ and $\varepsilon_k^{(b)}$ for $k = 1, \dots, d - 1$.
- We have guaranteed element-wise error control.

Theorem [Benner, Khoromskij, S., in preparation, 2026]

For the QTT approximation of the polynomial $p(x)$ constructed by the rank-adaptive method, we have

$$|\mathbf{P} - \hat{\mathbf{P}}| \leq \sqrt{m+1} \sum_{k=1}^{d-1} \varepsilon_k^{(f)} + \sum_{k=1}^{d-1} \varepsilon_{k+1}^{(b)}$$



1. Introduction
2. QTT approximation of polynomials
3. Fully discrete format
4. Numerical experiments
5. Conclusion



Joint QTT approximation

- Consider $f : [-1, 1]^3 \rightarrow \mathbb{R}$ approximated in **ChebTuck format**:

$$f(x_1, x_2, x_3) \approx f_{\mathbf{m}}(x_1, x_2, x_3) = \sum_{i_1=1}^R \sum_{i_2=1}^R \sum_{i_3=1}^R \beta_{i_1, i_2, i_3} v_{i_1}^{(1)}(x_1) v_{i_2}^{(2)}(x_2) v_{i_3}^{(3)}(x_3),$$

with $v_{i_\ell}^{(\ell)}(x_\ell) = \sum_{j_\ell=1}^m V_{j_\ell, i_\ell}^{(\ell)} T_{j_\ell-1}(x_\ell)$, $T_{j_\ell}(x) = \cos(j_\ell \arccos(x))$. **Storage:** $\mathcal{O}(DmR + R^D)$.

- In ChebTuck, we have multiple polynomials $v_{i_\ell}^{(\ell)}(x_\ell)$ for $i_\ell = 1, \dots, R$ in each dimension ℓ .
- Approximating each separately is inefficient.
- **Joint QTT approximation:**
 - Treat polynomial index as an additional mode.
 - First core $\mathbf{G}_1$ becomes a 3D tensor (or last core).
 - Subsequent cores are shared among all polynomials.

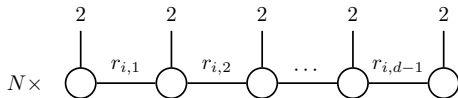


Joint QTT approximation (Illustration)

(A)

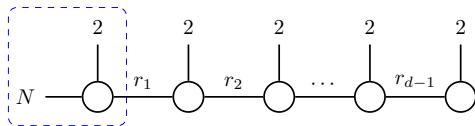
Storage

$$\mathcal{O}(dqr^2 \times N)$$



(B)

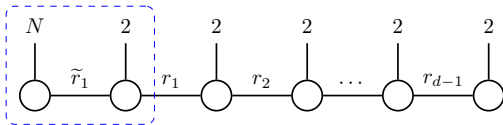
$$\mathcal{O}(dq(r_{\text{Joint}}^2 + Nr_1))$$



SVD ↓

(C)

$$\mathcal{O}(dq(r_{\text{Joint}}^2 + N\tilde{r}_1))$$





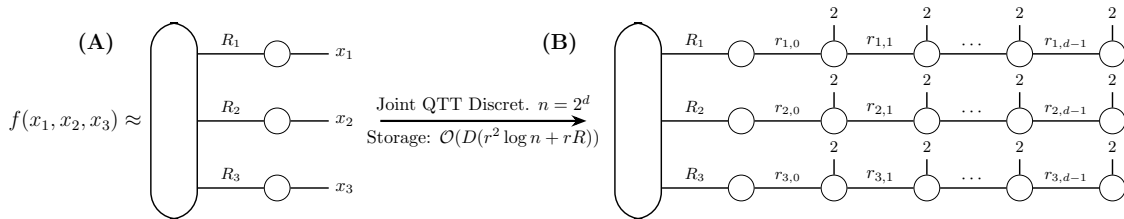
The fully discrete QTT-Tucker-like format

Combining ChebTuck

$$f(x_1, x_2, x_3) \approx \sum_{i_1=1}^R \sum_{i_2=1}^R \sum_{i_3=1}^R \beta_{i_1, i_2, i_3} v_{i_1}^{(1)}(x_1) v_{i_2}^{(2)}(x_2) v_{i_3}^{(3)}(x_3),$$

with Joint QTT:

$$\mathbf{F}(i_1, i_2, i_3) \approx \beta \times_1 \mathbf{U}^{(1)}(i_1) \times_2 \mathbf{U}^{(2)}(i_2) \times_3 \mathbf{U}^{(3)}(i_3).$$





1. Introduction
2. QTT approximation of polynomials
3. Fully discrete format
4. Numerical experiments
5. Conclusion



Random polynomials in monomial basis

- Non-trivial, but practical and not pathological (not too oscillatory) polynomials.
- Polynomials of degree m with random coefficients:

$$p(x) = a_0 + a_1x + a_2x^2 + \cdots + a_mx^m.$$

- a_k follow the distribution $a_k \sim \mathcal{N}(be^{-ak}, c \cdot be^{-ak})$ for $k = 1, \dots, 300$.
- Decay parameters $a \sim U(0, 0.1)$ and $b \sim U(0, 10)$.
- Relative noise level $c = 0.1$.
- Discretization on uniform grid with $n = 2^{20}$ points (20 dimensional QTT tensor).
- Tolerances of all SVDs in our method are set to 10^{-12} .
- `dmrg_cross` tolerance is set to 10^{-12} .



Random polynomials in monomial basis

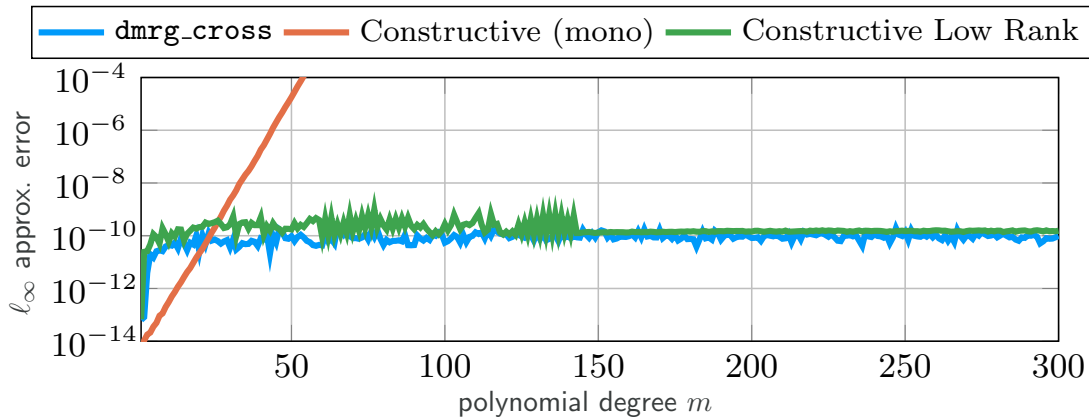


Figure: TTCross vs. Constructive (mono) vs. Constructive Low Rank.



Random polynomials in monomial basis

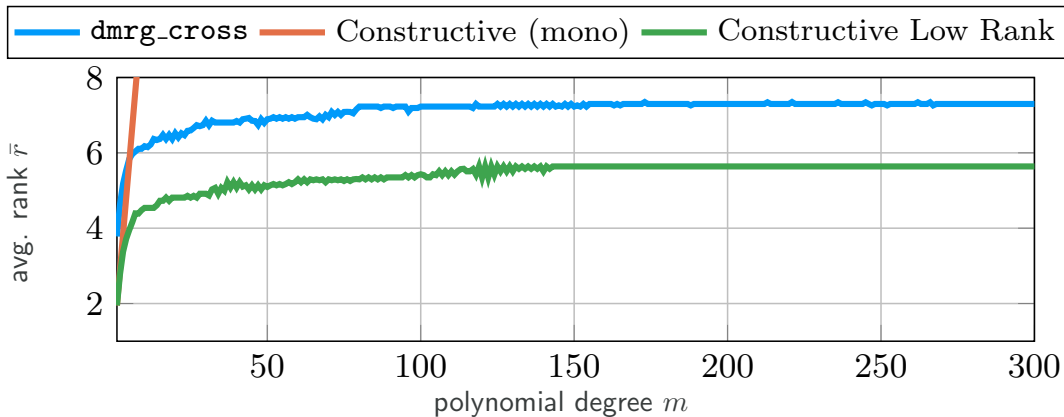


Figure: TTCross vs. Constructive (mono) vs. Constructive Low Rank.



Random polynomials in monomial basis

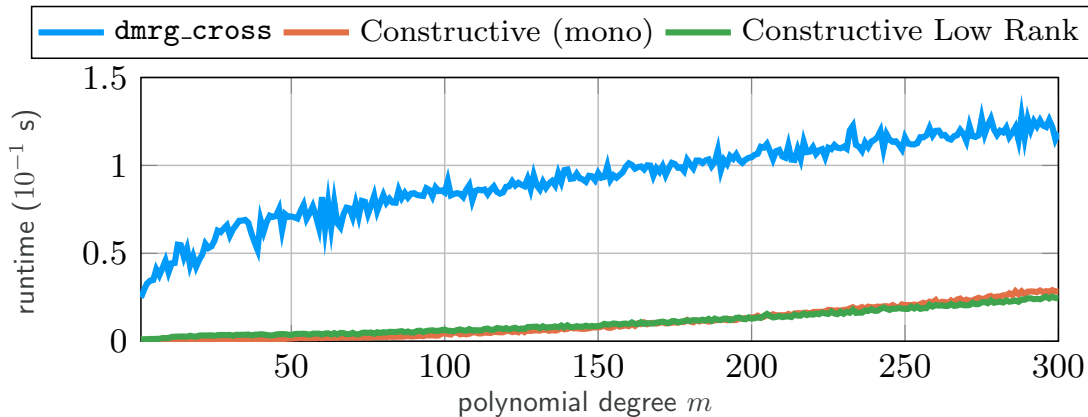


Figure: TTCross vs. Constructive (mono) vs. Constructive Low Rank.



Random polynomials in Chebyshev basis

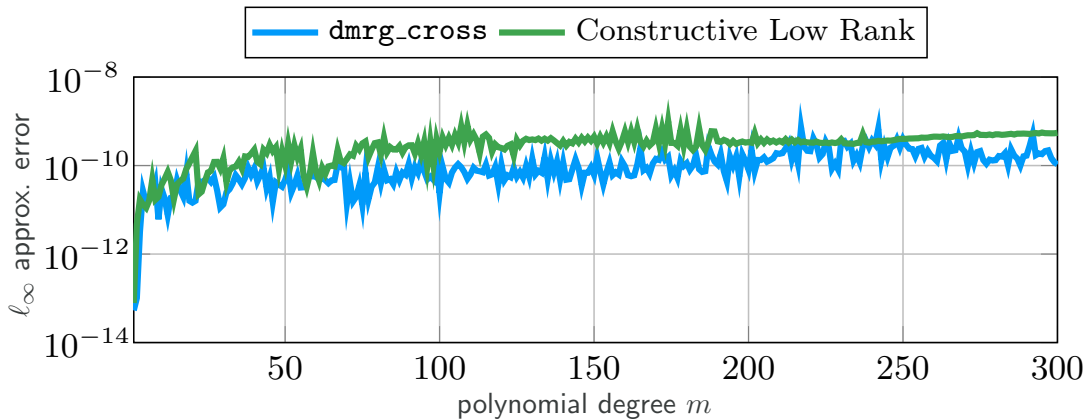


Figure: TTCross vs. Constructive Low Rank.



Random polynomials in Chebyshev basis

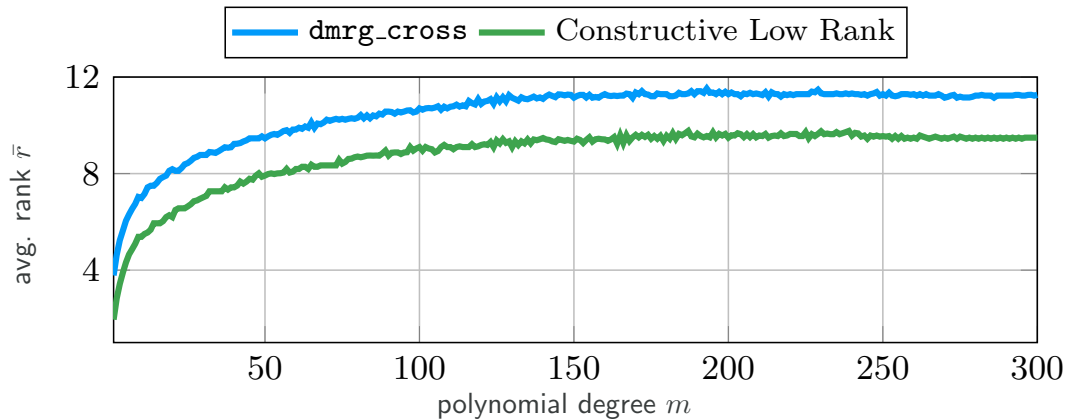


Figure: TTCross vs. Constructive Low Rank.



Random polynomials in Chebyshev basis

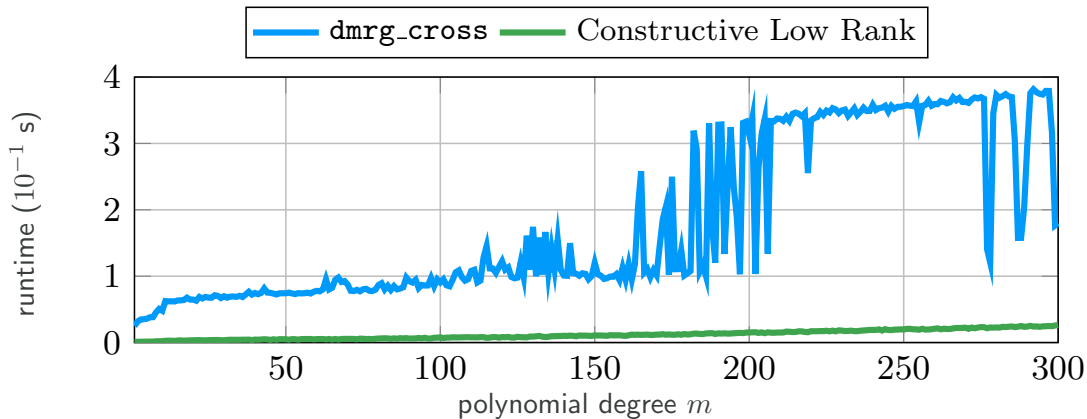


Figure: TTCross vs. Constructive Low Rank.

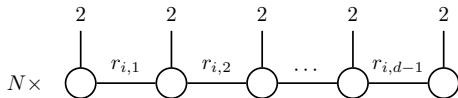


Joint QTT approximation (Illustration)

(A)

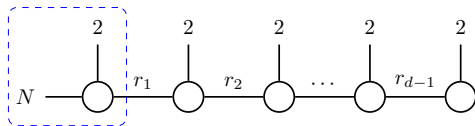
Storage

$$\mathcal{O}(dqr^2 \times N)$$



(B)

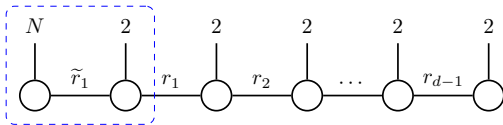
$$\mathcal{O}(dq(r_{\text{Joint}}^2 + Nr_1))$$



SVD ↓

(C)

$$\mathcal{O}(dq(r_{\text{Joint}}^2 + N\tilde{r}_1))$$





We consider the following 3 test functions $f : [-1, 1]^3 \rightarrow \mathbb{R}$:

1. **Biomolecule potential** f_1 : the multi-particle potential of the protein Fasciculin 1 comprising 1,228 atoms².
2. **Runge function** f_2 : the classical 3-dimensional Runge function³ given by

$$f_2(x, y, z) = \frac{1}{1 + 25(x^2 + y^2 + z^2)}. \quad (6)$$

3. **Wagon function** f_3 : the SIAM 100-Dollar, 100-Digit Challenge function⁴ defined by

$$\begin{aligned} f_3(x, y, z) = & e^{\sin(50x)} + \sin(60e^y) \sin(60z) + \sin(70 \sin(x)) \cos(10z) \\ & + \sin(\sin(80y)) - \sin(10(x + z)) + \frac{x^2 + y^2 + z^2}{4}. \end{aligned} \quad (7)$$

²M.H. Le Du, P. Marchot, P.E. Bougis, and J.C. Fontecilla-Camps, J. Biol. Chem., 267:22122–30, 1992.

³B. Hashemi and L. N. Trefethen, SIAM J. Sci. Comput., 39(5):C341–C363, 2017.

⁴Folkmar Bornemann, Dirk Laurie, Stan Wagon, and Jörg Waldvogel. SIAM, 2004.



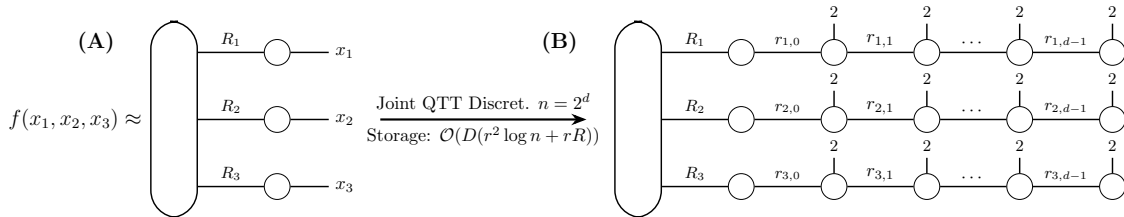
The fully discrete QTT-Tucker-like format

Combining ChebTuck

$$f(x_1, x_2, x_3) \approx \sum_{i_1=1}^R \sum_{i_2=1}^R \sum_{i_3=1}^R \beta_{i_1, i_2, i_3} v_{i_1}^{(1)}(x_1) v_{i_2}^{(2)}(x_2) v_{i_3}^{(3)}(x_3),$$

where $v_{i_\ell}^{(\ell)}(x_\ell) = \sum_{j_\ell=1}^m V_{j_\ell, i_\ell}^{(\ell)} T_{j_\ell-1}(x_\ell)$, $T_{j_\ell}(x) = \cos(j_\ell \arccos(x))$ with Joint QTT:

$$\mathbf{F}(i_1, i_2, i_3) \approx \boldsymbol{\beta} \times_1 \mathbf{U}^{(1)}(i_1) \times_2 \mathbf{U}^{(2)}(i_2) \times_3 \mathbf{U}^{(3)}(i_3).$$





The fully discrete QTT-Tucker-like format

■ Combining ChebTuck

$$f(x_1, x_2, x_3) \approx \sum_{i_1=1}^R \sum_{i_2=1}^R \sum_{i_3=1}^R \beta_{i_1, i_2, i_3} v_{i_1}^{(1)}(x_1) v_{i_2}^{(2)}(x_2) v_{i_3}^{(3)}(x_3),$$

where $v_{i_\ell}^{(\ell)}(x_\ell) = \sum_{j_\ell=1}^m V_{j_\ell, i_\ell}^{(\ell)} T_{j_\ell-1}(x_\ell)$, $T_{j_\ell}(x) = \cos(j_\ell \arccos(x))$ with Joint QTT:

$$\mathbf{F}(i_1, i_2, i_3) \approx \boldsymbol{\beta} \times_1 \mathbf{U}^{(1)}(i_1) \times_2 \mathbf{U}^{(2)}(i_2) \times_3 \mathbf{U}^{(3)}(i_3).$$

Function	Tucker ranks	Polynomial degrees
f_1	(32, 28, 32)	(129, 129, 129)
f_2	(17, 17, 17)	(189, 189, 189)
f_3	(4, 3, 5)	(662, 1052, 129)



Joint QTT approximation of multiple polynomials

function	method	configuration	ℓ_∞ error	storage	avg. rank $\bar{r}$	runtime (10^{-1} s)
f_1	Constructive Low Rank	Separate	2.93×10^{-10}	63,394	7.03	4.1
	dmrg_cross	Separate	1.92×10^{-11}	96,414	8.68	29.4
	Constructive Low Rank	Joint	7.88×10^{-11}	17,198	19.66	0.2
	dmrg_cross	Joint	7.56	7,824	13.06	4.5
f_2	Constructive Low Rank	Separate	2.92×10^{-10}	39,594	7.48	3.2
	dmrg_cross	Separate	1.17×10^{-10}	59,546	9.24	27.0
	Constructive Low Rank	Joint	1.24×10^{-10}	4,240	9.76	0.2
	dmrg_cross	Joint	4.45×10^{-8}	5,275	10.93	4.1
f_3	Constructive Low Rank	Separate	2.54×10^{-8}	10,076	7.93	3.9
	dmrg_cross	Separate	7.05×10^{-9}	14,620	9.56	7.2
	Constructive Low Rank	Joint	4.99×10^{-9}	3,820	9.53	0.9
	dmrg_cross	Joint	3.77×10^{-8}	5,342	11.27	7.5

Table: ChebTuck factors from biomolecule f_1 , Runge f_2 , and wagon f_3 ; $n = 2^{20}$.



Fully discrete QTT–Tucker format

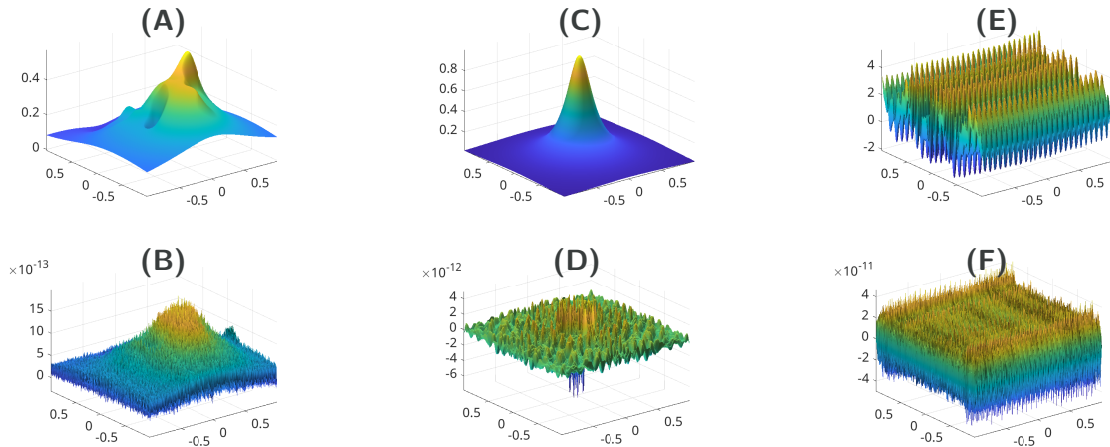


Figure: (A), (C), (E): Surfaces reconstructed from the fully discrete QTT-Tucker format for $f_i(x, y, 0)$.
(B), (D), (F): Corresponding pointwise errors compared to the continuous tensors.



- A framework to bridge continuous (functional) and discrete (grid-based) tensor formats via QTT.
- Developed stable and rank-adaptive algorithms for joint QTT approximation of polynomials.
- Numerical experiments demonstrate stability, efficiency, and storage savings.
- **Outlook:** Extend it to general univariate functions and multivariate ridge functions and more application scenarios.
- For more details and reference:
 1. P. Benner, B. Khoromskij, B. Sun. *Bridging continuous and discrete tensor representations of multivariate functions using QTT*, in preparation, 2026.
 2. 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.

Thank you for your attention!