Rank-adaptive time integration of tree tensor networks

Gianluca Ceruti², Christian Lubich¹, <u>Dominik Sulz¹</u>

¹ Mathematisches Institut, Universität Tübingen ² Institute of Mathematics, EPF Lausanne

Problem of interest

Our interest is to use tree tensor networks (TTN's) to approximate solutions of evolutionary tensor differential equations

$$\dot{A}(t) = F(t, A(t)), \quad A(t_0) = A^0 \in \mathbb{C}^{n_1 \times \cdots \times n_d}.$$
(1)

Such problems typically arise in quantum physics, where the high order *d* of the differential equation is a main challenge. Tree tensor networks are a hierarchical data sparse format to approximate tensors of high order. Our model problem will be the tensor Schrödinger equation

$$i\hbar\dot{A}(t) = H[A(t)].$$
 (2)

Dynamical low-rank approximation

On a manifold M we impose the time-dependent Dirac-Frenkel variational principle, see [1]: We determine X = X(t) from the condition that at time

The subflow $\Phi_{\tau}^{(l)}$ applied to a TTN solves a small matrix ODE if the *i*-th subtree is a leaf. If the *i*-th subtree is again a TTN then we apply the algorithm recursively to this smaller tree. **begin** $\begin{vmatrix} Y_{\tau_l}^0 = X_{\tau_l}^0 \times_0 S_{\tau_l}^{0,\top}, & \text{with } \mathbf{Mat}_i(C_{\tau}^0)^{\top} = Q_{\tau_l}^0 S_{\tau_l}^{0,\top} \\ \mathbf{if } \tau_l = l \text{ is a leaf then} \\ \begin{vmatrix} \text{solve } \dot{Y}_l = F_l(t, Y_l(t)), & Y_l(t_0) = Y_l^0 \\ \text{set } \widehat{\mathbf{U}}_l \text{ as an ONB of the range of } (Y_l(t_1)^{\top}, \mathbf{U}_l^0) \in \mathbb{C}^{n_l \times \hat{r}_l}, & \hat{r}_l \leq 2r_l^0 \\ \text{set } \widehat{\mathbf{M}}_l = \widehat{\mathbf{U}}_l^* \mathbf{U}_l^0 \\ \mathbf{else} \\ \begin{vmatrix} [\widehat{Y}_{\tau_l}^1, \widehat{C}_{\tau_l}^0] = \text{rank-adapt-TTN-integrator } (\tau_i, Y_{\tau_l}^0, F_{\tau_l}, t_0, t_1) \\ \text{set } \widehat{\mathbf{Q}}_{\tau_l} \text{ as an ONB of the range of } (\mathbf{Mat}_0(\widehat{C}_{\tau_l}^1)^{\top}, \mathbf{Mat}_0(\widehat{C}_{\tau_l}^0)^{\top}) \\ \text{set } \widehat{\mathbf{U}}_{\tau_l} = \mathbf{Mat}_0(\widehat{X}_{\tau_l}^1)^{\top}, \text{ where } \widehat{X}_{\tau_l}^1 \text{ is obtained from } \widehat{Y}_{\tau_l}^1 \text{ by replacing} \\ \end{vmatrix}$



t its derivative \dot{X} , which lies in $\mathcal{T}_X\mathcal{M}$, satisfies

$$\dot{X} \in \mathcal{T}_X \mathcal{M}$$
 such that $\langle \dot{X} - \frac{1}{i\hbar} H[X], Y \rangle = 0 \ \forall Y \in \mathcal{T}_X \mathcal{M}.$

This can be interpreted as an orthogonal projection of the right-hand side $\frac{1}{i\hbar}H[X]$ onto the tangent space $\mathcal{T}_X\mathcal{M}$.



 $\frac{1}{i\hbar}H[X]$

Tree tensor networks

Let \mathcal{T} be the set of ordered trees with unequal leaves and $\mathcal{L} = \{1, \ldots, d\}$ the set of leaves. Further let $\overline{\tau} \in \mathcal{T}$ be a fixed tree with d leaves. To each leaf we associate a basis matrix \mathbf{U}_l and to each subtree $\tau \leq \overline{\tau}$ a connection tensor C_{τ} . We define a tensor $X_{\overline{\tau}}$ with a tree tensor network representation (or briefly a TTN) recursively as follows:

• For each leaf $\tau = I \in \mathcal{L}$, we set

 $\mathbf{X}_{l} := \mathbf{I}_{l}^{\top} \subset \mathbb{C}^{r_{l} \times n_{l}}$

the connecting tensor with $\widehat{C}_{\tau_i} = Ten_0(\widehat{Q}_{\tau_i}^{\top})$ set $\widehat{M}_{\tau_i} = \widehat{\mathbf{U}}_{\tau_i}^* \mathbf{U}_{\tau_i}^0$

The subflow Ψ_{τ} solves a small tensor ODE, which can be interpreted as a Galerkin method on the updated subspace.

$$\begin{array}{l} \begin{array}{l} \textbf{begin} \\ \textbf{set } \widehat{C}_{\tau}^{0} = C_{\tau}^{0} \, \textbf{X}_{i=1}^{m} \, \widehat{M}_{\tau_{i}} \\ \textbf{solve the tensor ODE} \\ & \widehat{\widehat{C}}_{\tau}(t) = F_{\tau}(t, \widehat{C}_{\tau}(t) \, \textbf{X}_{i=1}^{m} \, \widehat{\textbf{U}}_{\tau_{i}}) \, \textbf{X}_{i=1}^{m} \, \widehat{\textbf{U}}_{\tau_{i}}, \quad \widehat{C}_{\tau}(t_{0}) = \widehat{C}_{\tau}^{0} \\ & \textbf{set } \, \widehat{C}_{\tau}^{1} = \widehat{C}_{\tau}(t_{1}) \end{array}$$

Robust convergence and preserving properties

● Let A(t) be the exact and $X_{\overline{\tau}}^n$ the numerical solution at time $t_0 + nh$. Further let $F_{\overline{\tau}}$ be Lipschitz continuous and bounded. Suppose that $||(I - P(Y))F_{\overline{\tau}}(t, Y)|| \le \epsilon \forall Y \in \mathcal{M}$ in a neighborhood of $A(t_n)$, where P(Y) denotes the projection onto $\mathcal{T}_Y \mathcal{M}$. Then it holds

 $||\mathbf{A}(t_n) - \mathbf{X}_{\overline{\tau}}^n|| = \mathcal{O}(\mathbf{h} + \epsilon + \vartheta).$

2 Let A(t) be a continuous and differentiable family of TTN's of full tree rank $(r_{\tau})_{\tau \leq \bar{\tau}}$ for $t_0 \leq t \leq t_1$. Further assume that at time t_1 all restricted subtrees $A_{\tau}(t_1)$ have full tree rank $(r_{\sigma})_{\sigma \leq \tau}$ for all $\tau \leq \bar{\tau}$. Then for $F(t, Y) = \dot{A}(t)$ with $A(t_0) = X_{\bar{\tau}}^0$ the rank-adaptive TTN integrator is exact, i.e.

$$\Lambda_{I} = \mathbf{U}_{I} \in \mathbb{C}$$

() For each subtree $\tau = (\tau_1, \ldots, \tau_m)$ (for some $m \ge 2$) of $\overline{\tau}$, we set $n_{\tau} = \prod_{i=1}^{m} n_{\tau_i}$ and \mathbf{I}_{τ} the identity matrix of dimension r_{τ} , and

$$X_{\tau} := C_{\tau} \times_{0} \mathbf{I}_{\tau} \mathsf{X}_{i=1}^{m} \mathbf{U}_{\tau_{i}} \in \mathbb{C}^{r_{\tau} \times n_{\tau_{1}} \times \cdots \times n_{\tau_{m}}}, \\ \mathbf{U}_{\tau} := \mathbf{Mat}_{0}(X_{\tau})^{\top} \in \mathbb{C}^{n_{\tau} \times r_{\tau}}.$$

The subscript 0 in \times_0 and $Mat_0(X_{\tau})$ refers to the mode 0 of dimension r_{τ} in $\mathbb{C}^{r_{\tau} \times r_{\tau_1} \times \cdots \times r_{\tau_m}}$.



Figure: Different examples for TTN's (from left to right): matrix, Tucker tensor, general TTN, tensor train/matrix product state.

The red balls encode a connecting tensor of matching order, while the nodes n_l encode a basis matrix/leaf U_l .

A rank-adaptive integrator for TTN's

We present a rank-adaptive integrator for tree tensor networks which extends the work of [3]. Suppose we have a TTN

$$X^0_{ au} = \textit{C}^0_{ au} imes_0 \textit{I}_{ au} X^m_{i=1} \textit{U}^0_{ au_i}$$

at time t_0 and a given function F_{τ} , which maps a TTN to a TTN. The idea

$$A(t_1) = X_{\overline{\tau}}.$$

③ If F_{τ} satisfies $Re\langle Y, F_{\bar{\tau}}(t, Y) \rangle = 0 \forall Y$ and all t, then with $c_{\tau} = ||C_{\bar{\tau}}||(d_{\bar{\tau}} - 1) + 1$ we have

 $\left| ||X_{\overline{\tau}}^{1}|| - ||X_{\overline{\tau}}^{0}|| \right| \leq c_{\overline{\tau}}\vartheta.$

Onsider the tensor Schrödinger equation (2) and let
 $E(Y) = \langle Y, H[Y] \rangle$. Then it holds for every step size h
 $|E(X_{\bar{\tau}}^1) - E(X_{\bar{\tau}}^0)| \leq c_{\bar{\tau}} \vartheta ||H[X_{\bar{\tau}}^1 + \hat{X}_{\bar{\tau}}^1]||.$

Numerical experiments

We apply the integrator to a problem from quantum physics - the Ising model in a transverse field with next neighbor interaction

$$i \partial_t \psi = H \psi$$
 with $H = -\sum_{k=1}^d \sigma_x^{(k)} - \sum_{k=1}^{d-1} \sigma_z^{(k)} \sigma_z^{(k+1)}$.



is to first update all the basis matrices $\mathbf{U}_{\tau_i}^0$ in parallel (via subflow $\Phi_{\tau}^{(\prime)}$) and then update the connecting tensor C_{τ}^0 (via subflow Ψ_{τ}), i.e.

 $\widehat{X}_{\tau}^{1} = \Psi_{\tau} \circ (\Phi_{\tau}^{(1)}, \ldots, \Phi_{\tau}^{(m)})(X_{\tau}^{0}).$

All the ranks of \widehat{X}_{τ}^{1} are (usually) doubled. To get the approximation X_{τ}^{1} at time t_{1} we apply a truncation function θ with a given tolerance ϑ after updating the whole tree $\overline{\tau}$, i.e. $X_{\overline{\tau}}^{1} = \theta(\widehat{X}_{\overline{\tau}}^{1})$. By augmentation and truncation of the TTN at each time step the algorithm is rank-adaptive.

Blue line gives the max. rank of a binary tree while the red line is the max. rank of a tensor train/matrix product state.

References

- [1] O. Koch, Ch. Lubich. Dynamical tensor approximation, SIAM J. Matrix Anal. 31 (2010), 2360-2375.
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- [3] G. Ceruti, J. Kusch, Ch. Lubich. A rank-adaptive robust integrator for dynamical low-rank approximation, to appear in BIT.