

## Hierarchical Tucker Decomposition

### Notation

$\mathcal{I} := \times_{\mu=1}^d I_\mu$  with  $I_\mu := \{1, \dots, n_\mu\}$  for  $\mu \in \{1, \dots, d\}$ . For  $t \subseteq \{1, \dots, d\}$ , define  $t' := \{1, \dots, d\} \setminus t$  and  $\mathcal{I}_t := \times_{\mu \in t} I_\mu$ ,  $\mathcal{I}_{t'} := \times_{\mu \in t'} I_\mu$ .  $A \in \mathbb{R}^{\mathcal{I}}$  denotes a  $d$  dimensional tensor where  $\otimes$  denotes the outer product and  $\otimes_{\mathcal{K}}$  the Kronecker product. The standard scalar product is denoted by  $\langle \cdot, \cdot \rangle$ , and the corresponding induced norm by  $\| \cdot \|$ , i.e., the Frobenius norm  $\|A\| := \sqrt{\langle A, A \rangle}$ .

**Definition 1** ( $t$ -matricization). Let  $A \in \mathbb{R}^{\mathcal{I}}$  and  $t \subseteq \{1, \dots, d\}$  then  $A^{(t)} := \mathcal{M}_t(A)$  where  $\mathcal{M}_t(A) : \mathbb{R}^{\mathcal{I}} \rightarrow \mathbb{R}^{\mathcal{I}_t \times \mathcal{I}_{t'}}$  and  $\mathcal{M}_t(A)_{(i_\mu)_{\mu \in t}, (i_\mu)_{\mu \in t'}} := A(i_1, \dots, i_d)$ . We also define  $\mathcal{M}_\emptyset := \mathcal{M}_{\{1, \dots, d\}} := A$ .

**Definition 2** ( $t$ -multiplication). Let  $A \in \mathbb{R}^{\mathcal{I}}$  and  $U_t \in \mathbb{R}^{\mathcal{I}_t \times \mathcal{I}_t}$  then  $(U_t \circ_t A)^{(t)} := U_t A^{(t)} \in \mathbb{R}^{\mathcal{I}_t \times \mathcal{I}_{t'}}$ . Also for  $v = 1, \dots, d$  and  $U_v \in \mathbb{R}^{\mathcal{I}_v \times \mathcal{I}_v}$  we define  $(U_1, \dots, U_d) \circ A := U_1 \circ_1 \dots U_d \circ_d A \in \mathbb{R}^{\mathcal{I}_1 \times \dots \times \mathcal{I}_d}$ .

**Definition 3.** A dimension tree  $\mathcal{T}_{\mathcal{I}}$  for dimension  $d \in \mathbb{N}$  is a tree such that:

- (i) The root node is  $\{1, \dots, d\}$  and the depth is  $\lceil \log_2(d) \rceil =: p$ .
- (ii) Each non-leaf node has exactly two disjoint children whose union is the parent and all leaves are singletons and lie at level  $p-1$  or  $p$ .

We denote  $\mathcal{T}_{\mathcal{I}}^l := \{t \in \mathcal{T}_{\mathcal{I}} \mid \text{level}(t) = l\}$ ,  $\mathcal{L}(\mathcal{T}_{\mathcal{I}})$  for the leaves and  $\mathcal{I}(\mathcal{T}_{\mathcal{I}})$  for the interior nodes.

Dimension trees are almost complete binary trees, except that on the penultimate level leaves may appear. For ease of presentation, we restrict to complete binary trees, i.e. all leaves appear on level  $p$ . From now on  $\mathcal{T}_{\mathcal{I}}$  will always denote a complete binary tree if not mentioned otherwise.

**Lemma 1.** (i) On each level  $\ell$  of  $\mathcal{T}_{\mathcal{I}}$ , the nodes form disjoint subsets of  $\{1, \dots, d\}$  and  $|\mathcal{T}_{\mathcal{I}}^\ell| = 2^\ell$ .

(ii)  $|\mathcal{T}_{\mathcal{I}}| = 2d - 1$ ,  $|\mathcal{L}(\mathcal{T}_{\mathcal{I}})| = d$ ,  $|\mathcal{I}(\mathcal{T}_{\mathcal{I}})| = d - 1$ .

**Definition 4.** The hierarchical rank of a tensor  $A \in \mathbb{R}^{\mathcal{I}}$  is the tuple  $(k_t)_{t \in \mathcal{T}_{\mathcal{I}}}$  with  $k_t := \text{rank}(A^{(t)})$ . We also define  $\mathcal{H}\text{-Tucker}((k_t)_{t \in \mathcal{T}_{\mathcal{I}}}) := \{A \in \mathbb{R}^{\mathcal{I}} \mid \text{rank}(A^{(t)}) \leq k_t \forall t \in \mathcal{T}_{\mathcal{I}}\}$ .

**Definition 5.** Let  $(k_t)_{t \in \mathcal{T}_{\mathcal{I}}}$  be a given family of non-negative integers. For each node  $t \in \mathcal{T}_{\mathcal{I}}$ , a matrix  $U_t \in \mathbb{R}^{\mathcal{I}_t \times k_t}$  is called a  $t$ -frame, and the collection  $(U_t)_{t \in \mathcal{T}_{\mathcal{I}}}$  is called a frame tree.

A frame tree is called nested if for all  $t \in \mathcal{I}(\mathcal{T}_{\mathcal{I}})$  with  $\text{succ}(t) = \{t_1, t_2\}$ , the following holds:

$$\text{span}\{(U_t)_{:,i} \mid 1 \leq i \leq k_t\} \subseteq \text{span}\{(U_{t_1})_{:,j} \otimes (U_{t_2})_{:, \ell} \mid 1 \leq j \leq k_{t_1}, 1 \leq \ell \leq k_{t_2}\}.$$

Then there exists a transfer tensor  $B_t \in \mathbb{R}^{k_t \times k_{t_1} \times k_{t_2}}$  such that:

$$(U_t)_{:,i} = \sum_{j=1}^{k_{t_1}} \sum_{\ell=1}^{k_{t_2}} (B_t)_{i,j,\ell} \cdot (U_{t_1})_{:,j} \otimes (U_{t_2})_{:, \ell}, \quad \forall i = 1, \dots, k_t.$$

**Definition 6.** Let  $A \in \mathcal{H}\text{-Tucker}((k_t)_{t \in \mathcal{T}_{\mathcal{I}}})$  and  $(U_t)_{t \in \mathcal{T}_{\mathcal{I}}}$  be a nested frame tree such that  $\text{image}(A^{(t)}) = \text{image}(U_t)$  for all  $t \in \mathcal{T}_{\mathcal{I}}$  and  $U_{\{1, \dots, d\}} := A$ . Then  $((B_t)_{t \in \mathcal{I}(\mathcal{T}_{\mathcal{I}})}, (U_t)_{t \in \mathcal{L}(\mathcal{T}_{\mathcal{I}})})$  is called a hierarchical Tucker representation of  $A$  and  $(k_t)_{t \in \mathcal{T}_{\mathcal{I}}}$  is called the hierarchical representation rank of  $A$ .

The representation of a tensor  $A \in \mathcal{H}\text{-Tucker}((k_t)_{t \in \mathcal{T}_{\mathcal{I}}})$  in the hierarchical tucker format with an orthogonal frame tree and minimal ranks  $k_t$  is unique up to orthogonal transformations of the  $t$ -frames.

**Lemma 2.** Let  $A \in \mathcal{H}\text{-Tucker}((k_t)_{t \in \mathcal{T}_{\mathcal{I}}})$  be given in the HT representation  $((B_t)_{t \in \mathcal{I}(\mathcal{T}_{\mathcal{I}})}, (U_t)_{t \in \mathcal{L}(\mathcal{T}_{\mathcal{I}})})$ ,

then:  $\text{Storage}((B_t)_{t \in \mathcal{I}(\mathcal{T}_{\mathcal{I}})}, (U_t)_{t \in \mathcal{L}(\mathcal{T}_{\mathcal{I}})}) \leq (d-1)k^3 + k \sum_{\mu=1}^d n_\mu$ ,  $k := \max_{t \in \mathcal{T}_{\mathcal{I}}} k_t$ .

The storage behaves linearly in the dimension  $d$  provided that  $k$  is uniformly bounded.

**Definition 7.** For  $t \in \mathcal{T}_{\mathcal{I}}$  and  $t$  not the root, let  $U_t$  be an orthonormal  $t$ -frame. Define  $\pi_t(A) := U_t U_t^T \circ_t A$ , implying  $\pi_t(A)^{(t)} = U_t U_t^T A^{(t)}$ . For  $t = \{1, \dots, d\}$ , set  $\pi_t(A) := A$ .

**Lemma 3.** Let  $\pi_t, \pi_s$  be orthogonal projections as in Definition 7. Then the following holds:

$$(i) \quad \|A + \pi_t \pi_s A\|^2 \leq \|A + \pi_t A\|^2 + \|A + \pi_s A\|^2.$$

$$(ii) \quad \|A + \prod_{t \in \mathcal{T}_{\mathcal{I}}} \pi_t A\|^2 \leq \sum_{t \in \mathcal{T}_{\mathcal{I}}} \|A + \pi_t A\|^2.$$

**Theorem 1.** Let  $A^{best}$  denote the best approx. of  $A$  in  $\mathcal{H}$ -Tucker $((k_t)_{t \in \mathcal{T}_{\mathcal{I}}})$  and let  $\psi_{t,k}(A) \in \mathbb{R}^{\mathcal{I}_t \times k}$  denote the matrix whose columns are the left singular vectors of  $A^{(t)}$  corresponding to the  $k$  largest singular values  $\sigma_{t,i}$  of  $A^{(t)}$ . Let  $\pi_t$  be based on  $U_t := \psi_{t,k_t}(A)$ . For any order of projections  $\pi_t$ :

$$\left\| A - \prod_{t \in \mathcal{T}_{\mathcal{I}}} \pi_t A \right\| \leq \left( \sum_{t \in \mathcal{T}_{\mathcal{I}}} \sum_{i > k_t} \sigma_{t,i}^2 \right)^{1/2} \leq \sqrt{2d-2} \|A - A^{best}\|.$$

**Definition 8** (root-to-leaves truncation). Let  $\pi_t$  be based on  $U_t := \psi_{t,k_t}(A)$ . Then  $A_{\mathcal{H}} := \prod_{t \in \mathcal{T}_{\mathcal{I}}} \pi_t \cdots \prod_{t \in \mathcal{T}_{\mathcal{I}}} \pi_t A$  is called the root-to-leaves truncation and  $A_{\mathcal{H}} \in \mathcal{H}$ -Tucker $((k_t)_{t \in \mathcal{T}_{\mathcal{I}}})$ .

**Definition 9** (leaves-to-root truncation). Let  $A_{\tilde{\mathcal{H}},p} := A$ , and for  $t \in \mathcal{T}_{\mathcal{I}}^{\ell}$ , let  $\pi_t$  be based on  $U_t := \psi_{t,k_t}(A_{\tilde{\mathcal{H}},\ell+1})$ , where  $A_{\tilde{\mathcal{H}},\ell} := \prod_{t \in \mathcal{T}_{\mathcal{I}}^{\ell}} \pi_t A_{\tilde{\mathcal{H}},\ell+1}$ . Then  $A_{\tilde{\mathcal{H}}} := A_{\tilde{\mathcal{H}},1} = \prod_{t \in \mathcal{T}_{\mathcal{I}}} \pi_t \cdots \prod_{t \in \mathcal{T}_{\mathcal{I}}} \pi_t A$  is called the leaves-to-root truncation and  $A_{\tilde{\mathcal{H}}}$  belongs to  $\mathcal{H}$ -Tucker $((k_t)_{t \in \mathcal{T}_{\mathcal{I}}})$ .

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**Algorithm 1** Root-to-Leaves Truncation

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**Require:** Tensor  $A \in \mathbb{R}^{\mathcal{I}}$ , tree  $\mathcal{T}_{\mathcal{I}}$ , ranks

- $(k_t)_{t \in \mathcal{T}_{\mathcal{I}}}$
  - 1: **for all** leaves  $t \in \mathcal{L}(\mathcal{T}_{\mathcal{I}})$  **do**
  - 2:   Compute SVD of  $A^{(t)}$ ; store dominant  $k_t$  left singular vectors in columns of  $U_t$ .
  - 3: **end for**
  - 4: **for**  $\ell = p-1, \dots, 0$  **do**
  - 5:   **for all**  $t \in \mathcal{I}(\mathcal{T}_{\mathcal{I}})$  on level  $\ell$  **do**
  - 6:     Compute SVD of  $A^{(t)}$ ; store dominant  $k_t$  left singular vectors in  $U_t$ .
  - 7:     Let  $U_{t_1}, U_{t_2}$  denote the frames of  $t$ 's children. Compute the transfer tensor:
  - 8:      $(B_t)_{i,j,\nu} := \langle (U_t)_{:,i}, (U_{t_1})_{:,j} \otimes (U_{t_2})_{:, \nu} \rangle$
  - 9:
  - 10:   **end for**
  - 11: **end for**
  - 12: Compute root transfer tensor:
  - 13:  $(B_{\{1,\dots,d\}})_{1,j,\nu} := \langle A, (U_{t_1})_{:,j} \otimes (U_{t_2})_{:, \nu} \rangle$
  - 14:
  - 15: **return**  $\mathcal{H}$ -Tucker representation  $((B_t)_{t \in \mathcal{I}(\mathcal{T}_{\mathcal{I}})}, (U_t)_{t \in \mathcal{L}(\mathcal{T}_{\mathcal{I}})})$  for  $A_{\mathcal{H}}$
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**Algorithm 2** Leaves-to-Root Truncation

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**Require:** Tensor  $A \in \mathbb{R}^{\mathcal{I}}$ , tree  $\mathcal{T}_{\mathcal{I}}$ , ranks

- $(k_t)_{t \in \mathcal{T}_{\mathcal{I}}}$
  - 1: **for all** leaves  $t \in \mathcal{L}(\mathcal{T}_{\mathcal{I}})$  **do**
  - 2:   Compute SVD of  $A^{(t)}$ ; store dominant  $k_t$  left singular vectors in columns of  $U_t$ .
  - 3: **end for**
  - 4: Compute core  $C_p := (U_1^T, \dots, U_d^T) \circ A$
  - 5: **for**  $\ell = p-1, \dots, 0$  **do**
  - 6:   Initialize  $C_{\ell} := C_{\ell+1}$
  - 7:   **for all**  $t \in \mathcal{I}(\mathcal{T}_{\mathcal{I}})$  on level  $\ell$  **do**
  - 8:     Compute SVD of  $(C_{\ell+1})^{(t)}$ ; store dominant  $k_t$  left singular vectors in  $U_t$ .
  - 9:     Let  $U_{t_1}, U_{t_2}$  denote the frames of  $t$ 's children. Compute the transfer tensor:
  - 10:      $(B_t)_{i,j,\nu} := \langle (U_t)_{:,i}, (U_{t_1})_{:,j} \otimes (U_{t_2})_{:, \nu} \rangle$
  - 11:
  - 12:   Update the core  $C_{\ell} := U_t^T \circ_t C_{\ell}$
  - 13:   **end for**
  - 14: **end for**
  - 15: **return**  $\mathcal{H}$ -Tucker representation  $((B_t)_{t \in \mathcal{I}(\mathcal{T}_{\mathcal{I}})}, (U_t)_{t \in \mathcal{L}(\mathcal{T}_{\mathcal{I}})})$  for  $A_{\tilde{\mathcal{H}}}$
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**Lemma 4** (Complexity of Algorithm 1). Let  $N := \prod_{\mu=1}^d n_{\mu}$ . The complexity behaves like  $\mathcal{O}(N^{3/2})$ .

**Lemma 5** (Complexity of Algorithm 2). The complexity behaves like  $\mathcal{O}\left(N \cdot \sum_{\mu=1}^d n_{\mu} + dk^{d+2}\right)$ .

**Theorem 2.** Let  $A^{best}$  denote the best approximation of  $A$  in  $\mathcal{H}$ -Tucker $((k_t)_{t \in \mathcal{T}_{\mathcal{I}}})$  then:

$$\|A - A_{\tilde{\mathcal{H}}}\| \leq (2 + \sqrt{2})\sqrt{d} \|A - A^{best}\|.$$

**References**

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