

Problem 1: Multilinear Rank, Tensor Rank

Recall the formulas for the matricizations:

$T_{(1)} = A(C \otimes_{KhR} B)^T$, where A and $C \otimes_{KhR} B$ are of dimensions $I_1 \times R$ and $I_2 I_3 \times R$ respectively. Moreover for any matrices X, Y we have that:

$$\text{rank}(XY) \leq \min\{\text{rank}(X), \text{rank}(Y)\}$$

Thus:

$$R_1 = \text{rank}(T_{(1)}) \leq \text{rank}(A) \leq \min\{I_1, R\} \leq R$$

By repeating the same argument for matricizations $T_{(2)}, T_{(3)}$ we conclude the proof.

Problem 2: Non-unicity of Tucker decomposition

Let $X = [\vec{x}_1, \dots, \vec{x}_{R_1}]$, $Y = [\vec{y}_1, \dots, \vec{y}_{R_2}]$, and $Z = [\vec{z}_1, \dots, \vec{z}_{R_3}]$. Then, from the definitions of vectors $\vec{x}_{p'}$, $\vec{y}_{q'}$, $\vec{z}_{r'}$, and from the orthogonality of the matrices $M^{(u)}, M^{(v)}, M^{(w)}$ it is easy to see that:

1. $U \cdot (M^{(u)})^T = X \Rightarrow U = X \cdot M^{(u)} \Rightarrow \vec{u}_p = X \cdot M_{:p}^{(u)} = \sum_{p'} M_{p'p}^{(u)} \vec{x}_{p'}$
2. $V \cdot (M^{(v)})^T = Y \Rightarrow V = Y \cdot M^{(v)} \Rightarrow \vec{v}_q = Y \cdot M_{:q}^{(v)} = \sum_{q'} M_{q'q}^{(v)} \vec{y}_{q'}$
3. $W \cdot (M^{(w)})^T = Z \Rightarrow W = Z \cdot M^{(w)} \Rightarrow \vec{w}_r = Z \cdot M_{:r}^{(w)} = \sum_{r'} M_{r'r}^{(w)} \vec{z}_{r'}$

Substituting \vec{u}_p, \vec{v}_q and \vec{w}_r in the Tucker decomposition expression we get:

$$\begin{aligned} T &= \sum_{p,q,r=1}^{R_1, R_2, R_3} G^{pqr} \vec{u}_p \otimes \vec{v}_q \otimes \vec{w}_r = \sum_{p,q,r=1}^{R_1, R_2, R_3} G^{pqr} \left(\sum_{p'} M_{p'p}^{(u)} \vec{x}_{p'} \right) \otimes \left(\sum_{q'} M_{q'q}^{(v)} \vec{y}_{q'} \right) \otimes \left(\sum_{r'} M_{r'r}^{(w)} \vec{z}_{r'} \right) = \\ &= \sum_{p',q',r'=1}^{R_1, R_2, R_3} \sum_{p,q,r=1}^{R_1, R_2, R_3} G^{pqr} M_{p'p}^{(u)} M_{q'q}^{(v)} M_{r'r}^{(w)} \vec{x}_{p'} \otimes \vec{y}_{q'} \otimes \vec{z}_{r'} = \sum_{p',q',r'=1}^{R_1, R_2, R_3} H^{p'q'r'} \vec{x}_{p'} \otimes \vec{y}_{q'} \otimes \vec{z}_{r'} \end{aligned}$$

where $H^{p'q'r'} = \sum_{p,q,r=1}^{R_1, R_2, R_3} G^{pqr} M_{p'p}^{(u)} M_{q'q}^{(v)} M_{r'r}^{(w)}$, which concludes the proof.

Problem 3: Tensor decomposition & estimation of a sensing matrix

1. The empirical estimate $\hat{S} = \frac{1}{L} \sum_{\ell=1}^L \vec{y}^{(\ell)} \otimes \vec{y}^{(\ell)}$ of S has components

$$\hat{S}_{\alpha\beta} = \frac{1}{L} \sum_{\ell=1}^L y_{\alpha}^{\ell} y_{\beta}^{\ell}.$$

The empirical estimate $\hat{F} = \frac{1}{L} \sum_{\ell=1}^L \vec{y}^{(\ell)} \otimes \vec{y}^{(\ell)} \otimes \vec{y}^{(\ell)} \otimes \vec{y}^{(\ell)}$ of F has components

$$\hat{F}_{\alpha\beta\gamma\delta} = \frac{1}{L} \sum_{\ell=1}^L y_{\alpha}^{\ell} y_{\beta}^{\ell} y_{\gamma}^{\ell} y_{\delta}^{\ell}.$$

2. Remember that $\vec{y} = \sum_{k=1}^K h_k \vec{\mu}^{(k)}$. By expanding the tensor products we get:

$$S = \mathbb{E}[\vec{y} \otimes \vec{y}] = \sum_{j=1}^K \sum_{k=1}^K \mathbb{E}[h_j h_k] \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} ; \quad (1)$$

$$F = \mathbb{E}[\vec{y} \otimes \vec{y} \otimes \vec{y} \otimes \vec{y}] = \sum_{i=1}^K \sum_{j=1}^K \sum_{k=1}^K \sum_{\ell=1}^K \mathbb{E}[h_i h_j h_k h_\ell] \vec{\mu}^{(i)} \otimes \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(\ell)} . \quad (2)$$

The components of h are independent and centered so $\mathbb{E}[h_j h_k] = \mathbb{E}[h_j] \mathbb{E}[h_k] = 0$ if $j \neq k$. Hence (1) simplifies:

$$S = \mathbb{E}[\vec{y} \otimes \vec{y}] = \sum_{k=1}^K \mathbb{E}[h_k^2] \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} .$$

Similarly, if one of the indices i, j, k, ℓ is distinct of all the others then $\mathbb{E}[h_i h_j h_k h_\ell] = 0$. Therefore $\mathbb{E}[h_i h_j h_k h_\ell]$ is nonzero if, and only if, $i = j = k = \ell$ or $i = j \neq k = \ell$, $i = k \neq j = \ell$, $i = \ell \neq j = k$. Hence (2) reads:

$$\begin{aligned} F &= \sum_{k=1}^K \mathbb{E}[h_k^4] \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} + \sum_{1 \leq i \neq k \leq K} \mathbb{E}[h_i^2] \mathbb{E}[h_k^2] \vec{\mu}^{(i)} \otimes \vec{\mu}^{(i)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \\ &\quad + \sum_{1 \leq k \neq j \leq K} \mathbb{E}[h_k^2] \mathbb{E}[h_j^2] \vec{\mu}^{(k)} \otimes \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(j)} \\ &\quad + \sum_{1 \leq i \neq k \leq K} \mathbb{E}[h_i^2] \mathbb{E}[h_k^2] \vec{\mu}^{(i)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(i)} \\ &= \sum_{k=1}^K \mathbb{E}[h_k^4] \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} + \sum_{1 \leq j \neq k \leq K} \mathbb{E}[h_j^2] \mathbb{E}[h_k^2] \left(\vec{\mu}^{(j)} \otimes \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \right. \\ &\quad \left. + \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \right. \\ &\quad \left. + \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(j)} \right) . \end{aligned}$$

3. We have seen that $F = \sum_{k=1}^K \mathbb{E}[h_k^4] \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} + E$ where

$$\begin{aligned} E := \sum_{1 \leq j \neq k \leq K} \mathbb{E}[h_j^2] \mathbb{E}[h_k^2] \left(\vec{\mu}^{(j)} \otimes \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} + \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \right. \\ \left. + \vec{\mu}^{(j)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(j)} \right) . \end{aligned}$$

The components of E satisfy:

$$\begin{aligned} E_{\alpha\beta\gamma\delta} &= \sum_{1 \leq j \neq k \leq K} \mathbb{E}[h_j^2] \mathbb{E}[h_k^2] (\mu_\alpha^j \mu_\beta^j \mu_\gamma^k \mu_\delta^k + \mu_\alpha^j \mu_\beta^k \mu_\gamma^j \mu_\delta^k + \mu_\alpha^j \mu_\beta^k \mu_\gamma^k \mu_\delta^j) \\ &= \left(\sum_{j=1}^K \mathbb{E}[h_j^2] \mu_\alpha^j \mu_\beta^j \right) \left(\sum_{k=1}^K \mathbb{E}[h_k^2] \mu_\gamma^k \mu_\delta^k \right) + \left(\sum_{j=1}^K \mathbb{E}[h_j^2] \mu_\alpha^j \mu_\gamma^j \right) \left(\sum_{k=1}^K \mathbb{E}[h_k^2] \mu_\beta^k \mu_\delta^k \right) \\ &\quad + \left(\sum_{j=1}^K \mathbb{E}[h_j^2] \mu_\alpha^j \mu_\delta^j \right) \left(\sum_{k=1}^K \mathbb{E}[h_k^2] \mu_\beta^k \mu_\gamma^k \right) - 3 \sum_{k=1}^K \mathbb{E}[h_k^2]^2 \mu_\alpha^k \mu_\beta^k \mu_\gamma^k \mu_\delta^k \\ &= S_{\alpha\beta} S_{\gamma\delta} + S_{\alpha\gamma} S_{\beta\delta} + S_{\alpha\delta} S_{\beta\gamma} - 3 \left(\sum_{k=1}^K \mathbb{E}[h_k^2]^2 \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \right)_{\alpha\beta\gamma\delta} . \end{aligned}$$

It directly follows that

$$\begin{aligned}
T_{\alpha\beta\gamma\delta} &= \left(\sum_{k=1}^K \mathbb{E}[h_k^4] \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \right)_{\alpha\beta\gamma\delta} \\
&\quad - 3 \left(\sum_{k=1}^K \mathbb{E}[h_k^2]^2 \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \right)_{\alpha\beta\gamma\delta} \\
&= \left(\sum_{k=1}^K \mathcal{K}_k \mathbb{E}[h_k^2]^2 \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \otimes \vec{\mu}^{(k)} \right)_{\alpha\beta\gamma\delta}.
\end{aligned}$$

4. The matrix S is symmetric positive semidefinite so it can be diagonalised in an orthonormal basis: $S = \sum_{k=1}^N d_k \vec{u}^{(k)} \otimes \vec{u}^{(k)}$ with $[\vec{u}^{(1)} \ \vec{u}^{(2)} \ \dots \ \vec{u}^{(N)}] \in \mathbb{R}^{N \times N}$ an orthonormal matrix and $d_1 \geq d_2 \geq \dots \geq d_N \geq 0$. Besides S has rank K so exactly K of its eigenvalues are nonzero: $S = \sum_{k=1}^K d_k \vec{u}^{(k)} \otimes \vec{u}^{(k)} = UDU^T$ with $U = [\vec{u}^{(1)} \ \vec{u}^{(2)} \ \dots \ \vec{u}^{(K)}] \in \mathbb{R}^{N \times K}$ and $D = \text{Diag}(d_1, d_2, \dots, d_K)$.
5. By definition of the vectors $\vec{v}^{(k)}$ we have:

$$\tilde{T} = \sum_{k=1}^K \mathcal{K}_k \mathbb{E}[h_k^2]^2 (W^T \vec{\mu}^{(k)}) \otimes (W^T \vec{\mu}^{(k)}) \otimes (W^T \vec{\mu}^{(k)}) \otimes (W^T \vec{\mu}^{(k)}).$$

So the components of \tilde{T} are given by the formula

$$\tilde{T}_{\alpha\beta\gamma\delta} = \sum_{\alpha', \beta', \gamma', \delta'} W_{\alpha'\alpha} W_{\beta'\beta} W_{\gamma'\gamma} W_{\delta'\delta} T_{\alpha'\beta'\gamma'\delta'}.$$

This transformation of T into \tilde{T} is called a whitening process.

6. If \mathcal{K}_k is zero then it is impossible to recover $\vec{v}^{(k)}$ with the tensor power method and, as a consequence, to recover $\vec{\mu}^{(k)}$ the k^{th} column of A .
7. The pseudocode for the tensor power method is given in Algorithm 1.
8. By definition $\vec{v}^{(k)} = \sqrt{\mathbb{E}[h_k^2]} W^T \vec{\mu}^{(k)} = \sqrt{\mathbb{E}[h_k^2]} D^{-\frac{1}{2}} U^T \vec{\mu}^{(k)}$ so

$$UU^T \vec{\mu}^{(k)} = UD^{\frac{1}{2}} \frac{\vec{v}^{(k)}}{\sqrt{\mathbb{E}[h_k^2]}}.$$

Finally, $\vec{\mu}^{(k)}$ belongs to the subspace spanned by the columns of U so $UU^T \vec{\mu}^{(k)} = \vec{\mu}^{(k)}$. We conclude that $\vec{\mu}^{(k)} = UD^{\frac{1}{2}} \vec{v}^{(k)} / \sqrt{\mathbb{E}[h_k^2]}$. Of course, we only know $\vec{v}^{(k)}$ up to a plus or minus sign and we will recover $\vec{\mu}^{(k)}$ up to a plus or minus sign too.

Algorithm 1 Tensor power method

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1: procedure POWERMETHOD( $\tilde{T}, K, T_{\max}$ )
2:   vectors  $\leftarrow []$ 
3:   kurtoses  $\leftarrow []$ 
4:   for  $i = 1$  to  $K$  do
5:      $v \leftarrow$  normallyDistributedVector(size =  $K$ )
6:     for  $j = 1$  to  $T_{\max}$  do ▷  $T_{\max}$  iterations of the power method.
7:       for  $\alpha = 1$  to  $K$  do
8:          $v[\alpha] \leftarrow \sum_{\beta, \gamma, \delta=1}^K \tilde{T}_{\alpha, \beta, \gamma, \delta} v[\beta] v[\gamma] v[\delta]$ 
9:       end for
10:       $v \leftarrow v / \|v\|$  ▷ Renormalizing  $v$ 
11:    end for
12:     $\mathcal{K} \leftarrow \sum_{\alpha, \beta, \gamma, \delta=1}^K \tilde{T}_{\alpha, \beta, \gamma, \delta} v[\alpha] v[\beta] v[\gamma] v[\delta]$ 
13:    kurtoses.append( $\mathcal{K}$ )
14:    vectors.append( $v$ )
15:     $\tilde{T} \leftarrow \tilde{T} - \mathcal{K} v^{\otimes 4}$  ▷ Subtracting the recovered rank-one tensor from  $\tilde{T}$ 
16:  end for
17:  return vectors, kurtoses
18: end procedure
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