

PCG for the infinite-dimensional mode- k subproblem (missing data)

We consider the linear system in the unknown $W \in \mathbb{R}^{n \times r}$

$$\left[(Z \otimes K)^\top S S^\top (Z \otimes K) + \lambda (I_r \otimes K) \right] \text{vec}(W) = (I_r \otimes K) \text{vec}(B), \quad (1)$$

where $K \in \mathbb{R}^{n \times n}$ is a (symmetric) psd kernel matrix, $Z \in \mathbb{R}^{M \times r}$ is the Khatri–Rao product of the other factors, $S \in \mathbb{R}^{N \times q}$ selects the q observed entries (so $S^\top \text{vec}(T)$ equals the observed values), and $B = TZ \in \mathbb{R}^{n \times r}$. Throughout we assume $n, r < q \ll N = nM$ and avoid any $O(N)$ work.

1. Variational form, symmetry, and positive definiteness. Let $P \equiv S S^\top \in \mathbb{R}^{N \times N}$ be the diagonal “mask” matrix that keeps observed entries and zeros missing ones (so $P = P^\top = P^2$). The system (1) is the normal equation for the regularized least-squares objective

$$\min_{W \in \mathbb{R}^{n \times r}} \frac{1}{2} \|S^\top \text{vec}(T) - S^\top \text{vec}(KWZ^\top)\|_2^2 + \frac{\lambda}{2} \text{Tr}(W^\top KW) = \frac{1}{2} \|P \circ (T - KWZ^\top)\|_F^2 + \frac{\lambda}{2} \text{Tr}(W^\top KW), \quad (2)$$

where \circ denotes Hadamard product and we used $\text{Tr}(W^\top KW) = \|W\|_{\mathcal{H}}^2$ as the RKHS penalty. Writing the first term as $\frac{1}{2} \|P^{1/2}(\text{vec}(T) - (Z \otimes K) \text{vec}(W))\|_2^2$ shows the Hessian is

$$A \equiv (Z \otimes K)^\top P (Z \otimes K) + \lambda (I_r \otimes K) \in \mathbb{R}^{nr \times nr}, \quad b \equiv (I_r \otimes K) \text{vec}(B) = \text{vec}(KB).$$

Thus A is symmetric. If $K \succ 0$ and $\lambda > 0$, then $A \succ 0$ because for any $x \neq 0$,

$$x^\top A x = \|P^{1/2}(Z \otimes K)x\|_2^2 + \lambda x^\top (I_r \otimes K)x \geq \lambda x^\top (I_r \otimes K)x > 0.$$

(If K is only psd, one can add a nugget εI_n to K or instead regularize with $\lambda(I_r \otimes I_n)$. Alternatively, write $K = U \Lambda U^\top$ with rank m and parameterize $A_k = KW = U \Lambda \widetilde{W}$, reducing the unknown to $\widetilde{W} \in \mathbb{R}^{m \times r}$ and yielding an SPD system of size mr .) Hence we can solve (1) with (preconditioned) conjugate gradients (CG/PCG).

2. Why PCG helps. Direct solution would require forming A and performing a dense factorization costing $O((nr)^3) = O(n^3 r^3)$. In contrast, PCG requires only: (i) repeated matrix–vector products $y \leftarrow Ax$ and (ii) repeated applications of a preconditioner M^{-1} , with overall cost $\approx \#\text{iters} \times (\text{matvec} + \text{precond})$. Our goal is to implement both in $O(n^2 r + qr)$ time per iteration and memory $O(nr + qr)$, never touching N -scale arrays.

3. PCG (brief). Choose an SPD preconditioner $M \approx A$ that is cheap to invert. Starting from x_0 (often 0 or the previous ALS iterate), define $r_0 = b - Ax_0$ and solve $Mz_0 = r_0$. Set $p_0 = z_0$ and for $t = 0, 1, 2, \dots$ iterate

$$\alpha_t = \frac{\langle r_t, z_t \rangle}{\langle p_t, A p_t \rangle}, \quad x_{t+1} = x_t + \alpha_t p_t, \quad r_{t+1} = r_t - \alpha_t A p_t, \quad \text{solve } M z_{t+1} = r_{t+1}, \quad \beta_t = \frac{\langle r_{t+1}, z_{t+1} \rangle}{\langle r_t, z_t \rangle}, \quad p_{t+1} = z_{t+1} + \beta_t p_t$$

The algorithm only needs the ability to compute $A p_t$ (matvec) and to apply M^{-1} .

Efficient matrix–vector products without forming A

Operator viewpoint. Define the linear map $\mathcal{L} : \mathbb{R}^{n \times r} \rightarrow \mathbb{R}^q$ by

$$(\mathcal{L}(X))_t \equiv (KXZ^\top)_{i_t, j_t}, \quad t = 1, \dots, q.$$

Then the data term in (2) is $\frac{1}{2} \|\mathcal{L}(W) - y\|_2^2$ with $y \equiv S^\top \text{vec}(T)$, and the normal equation is

$$(\mathcal{L}^\top \mathcal{L} + \lambda \mathcal{R}) \text{vec}(W) = \mathcal{L}^\top y, \quad \mathcal{R} = I_r \otimes K.$$

Crucially, both $\mathcal{L}(X)$ (gather) and $\mathcal{L}^\top u$ (scatter + multiply by Z and K) can be applied in $O(qr + n^2r)$ time.

Represent an input vector $x \in \mathbb{R}^{nr}$ as a matrix $X \in \mathbb{R}^{n \times r}$ such that $x = \text{vec}(X)$. Use the identity

$$(Z \otimes K) \text{vec}(X) = \text{vec}(KXZ^\top), \quad (3)$$

which is a special case of $\text{vec}(AXB^\top) = (B \otimes A) \text{vec}(X)$.

Observed-entry operator implemented with index lists

Let the observed entries of the mode- k unfolding be indexed by pairs (i_t, j_t) for $t = 1, \dots, q$ with $i_t \in [n]$ and $j_t \in [M]$. Then for any matrix $U \in \mathbb{R}^{n \times M}$,

$$S^\top \text{vec}(U) = (U_{i_t, j_t})_{t=1}^q \in \mathbb{R}^q, \quad \text{and} \quad \text{reshape}_{n \times M}(Sv) \text{ has nonzeros } (i_t, j_t) \text{ equal to } v_t.$$

Thus we can realize S^\top (gather) and S (scatter) in $O(q)$ time using stored index arrays (i_t, j_t) .

Avoiding explicit formation of Z . Although $Z \in \mathbb{R}^{M \times r}$ is defined as a Khatri–Rao product, $M = \prod_{i \neq k} n_i$ can be enormous, so we do *not* store Z . Instead, for each observed tensor entry we typically store its full multi-index $(i_1^{(t)}, \dots, i_d^{(t)})$; the corresponding row needed in (4) and (7) is

$$Z_{j_t, :} = A_d(i_d^{(t)}, :) \odot \dots \odot A_{k+1}(i_{k+1}^{(t)}, :) \odot A_{k-1}(i_{k-1}^{(t)}, :) \odot \dots \odot A_1(i_1^{(t)}, :),$$

which can be computed on the fly in $O((d-1)r)$ time per observed entry (or faster if intermediate Hadamard products are cached). This keeps both memory and time independent of M . If q is moderate, one can also precompute and store all needed rows $z_t \equiv Z_{j_t, :}$ for $t = 1, \dots, q$ in an array of size $q \times r$, reducing the per-iteration cost from $O(qdr)$ to $O(qr)$ at the expense of $O(qr)$ memory.

Matvec formula

Given $X \in \mathbb{R}^{n \times r}$, compute $Y \in \mathbb{R}^{n \times r}$ so that $\text{vec}(Y) = A \text{vec}(X)$. Write $G \equiv KX \in \mathbb{R}^{n \times r}$. Then the observed predicted entries of $U \equiv KXZ^\top \in \mathbb{R}^{n \times M}$ are

$$u_t \equiv U_{i_t, j_t} = G_{i_t, :} \cdot Z_{j_t, :} \quad (t = 1, \dots, q), \quad (4)$$

each a length- r dot product. Now form the sparse matrix $\tilde{U} \in \mathbb{R}^{n \times M}$ with $(\tilde{U})_{i_t, j_t} = u_t$ and all other entries zero (this is exactly $\text{reshape}(SS^\top \text{vec}(U))$). Finally apply $(Z \otimes K)^\top$ using the transpose identity

$$(Z \otimes K)^\top \text{vec}(\tilde{U}) = \text{vec}(K \tilde{U} Z), \quad (5)$$

obtaining the main term $K(\tilde{U}Z)$. Adding the Tikhonov term gives

$$Y = K(\tilde{U}Z) + \lambda KX. \quad (6)$$

Proof of (6). Let $x = \text{vec}(X)$. The first term satisfies $(Z \otimes K)^\top P(Z \otimes K)x = (Z \otimes K)^\top \text{vec}(\tilde{U})$ with $\tilde{U} \equiv \text{reshape}_{n \times M}(P \text{vec}(KXZ^\top))$. Using (5) yields $\text{vec}(K\tilde{U}Z)$, i.e., the matrix $K(\tilde{U}Z)$. The regularizer contributes $\lambda(I_r \otimes K) \text{vec}(X) = \lambda \text{vec}(KX)$, giving (6).

How to compute $\tilde{U}Z$ in $O(qr)$

We never form \tilde{U} explicitly as an $n \times M$ array. Instead, compute the product $H \equiv \tilde{U}Z \in \mathbb{R}^{n \times r}$ by accumulating contributions from the q nonzeros:

$$H_{i_t,:} += u_t Z_{j_t,:} \quad (t = 1, \dots, q). \quad (7)$$

Each update is a SAXPY of length r , so the cost is $O(qr)$. Then compute KH in $O(n^2r)$ time (dense K), and add λKX .

Implementation sketch (matvec). Given $X \in \mathbb{R}^{n \times r}$, precompute $G \leftarrow KX$. Initialize $H \leftarrow 0 \in \mathbb{R}^{n \times r}$. Loop over observed entries $t = 1, \dots, q$: compute (or fetch) the Khatri–Rao row $z_t \equiv Z_{j_t,:}$, compute the scalar $u_t \leftarrow G_{i_t,:} z_t^\top$, and update $H_{i_t,:} \leftarrow H_{i_t,:} + u_t z_t$. Finally return $Y \leftarrow KH + \lambda G$.

Matvec complexity. Assuming dense K :

- $G = KX$: $O(n^2r)$.
- gather u_t via (4): $O(qr)$ given access to $Z_{j_t,:}$; if $Z_{j_t,:}$ is computed on the fly from the CP factors, add $O(q(d-1)r)$.
- accumulate $H = \tilde{U}Z$ via (7): $O(qr)$ (plus the same cost to form $Z_{j_t,:}$ if needed).
- KH and λKX : $O(n^2r)$ (can reuse G for KX).

Total per matvec: $O(n^2r + qr)$ time if Z -rows are available (or $O(n^2r + qdr)$ if computed on the fly), $O(nr + qr)$ memory for X, G, H and index lists; crucially independent of $N = nM$.

Computing the right-hand side b without forming T

The right-hand side is $b = \text{vec}(KB)$. We can compute $B = TZ$ using only observed entries: if the observed tensor value at (i_t, j_t) is t_t , then

$$B_{i_t,:} += t_t Z_{j_t,:},$$

which costs $O(qr)$ given access to $Z_{j_t,:}$ (or $O(qdr)$ if each $Z_{j_t,:}$ is formed on the fly from the CP factors), followed by KB in $O(n^2r)$. (This is the same sparse accumulation pattern as (7).)

Preconditioning

Kronecker “full-observation” preconditioner

A standard and effective choice is to drop the mask P (equivalently, pretend all entries are observed). Then

$$A_0 \equiv (Z \otimes K)^\top (Z \otimes K) + \lambda(I_r \otimes K) = (Z^\top Z) \otimes (K^\top K) + \lambda(I_r \otimes K) = (Z^\top Z) \otimes (K^2) + \lambda(I_r \otimes K),$$

where K^2 denotes the usual matrix product KK (since K is symmetric). Let $G \equiv Z^\top Z \in \mathbb{R}^{r \times r}$. Since Z is a Khatri–Rao product, G can be computed without forming Z via the Hadamard product (denoted $*$) of Gram matrices,

$$G = \underset{i \neq k}{*} (A_i^\top A_i),$$

costing $O(\sum_{i \neq k} n_i r^2)$. Indeed, for columns $a, b \in [r]$, one has $G_{ab} = \sum_{j \in [M]} Z_{j,a} Z_{j,b} = \sum_{i_1, \dots, i_{k-1}, i_{k+1}, \dots, i_d} \prod_{\ell \neq k} A_\ell(i_\ell, a) A_\ell(i_\ell, b)$. If we precompute eigendecompositions

$$K = U \Lambda U^\top, \quad G = V \Sigma V^\top,$$

then A_0 diagonalizes in the Kronecker basis:

$$A_0 = (V \otimes U) \text{diag}(\sigma_a \lambda_b^2 + \lambda \lambda_b)_{a \in [r], b \in [n]} (V \otimes U)^\top.$$

Hence applying $M^{-1} \approx A_0^{-1}$ to a vector $x = \text{vec}(X)$ can be done by:

1. transform $\hat{X} \leftarrow U^\top X V$ (two small dense multiplies),
2. elementwise divide $\hat{X}_{b,a} \leftarrow \hat{X}_{b,a} / (\sigma_a \lambda_b^2 + \lambda \lambda_b)$,
3. inverse transform $X \leftarrow U \hat{X} V^\top$.

This costs $O(n^2 r + n r^2)$ per application (often dominated by $O(n^2 r)$ when $n \geq r$), after one-time setup $O(n^3 + r^3)$.

Why this is reasonable. A equals A_0 when $P = I_N$; when entries are missing uniformly at random, $\mathbb{E}[P] = (q/N)I_N$, so $\mathbb{E}[(Z \otimes K)^\top P(Z \otimes K)] = (q/N)(Z^\top Z \otimes K^2)$ is a scaled version of the same Kronecker term. Thus A_0 (or the scaled variant αA_0 with $\alpha = q/N$) captures the dominant spectral structure, while P acts as a perturbation; PCG corrects the mismatch through iterations.

Simpler (cheaper) preconditioners

If eigendecompositions are too costly, a cheaper alternative is a block-diagonal preconditioner

$$M_{\text{bd}} = (\text{diag}(G) \otimes K^2) + \lambda(I_r \otimes K),$$

which decouples the r components, requiring r solves with $n \times n$ matrices of the form $(g_{\ell\ell} K^2 + \lambda K) = K(g_{\ell\ell} K + \lambda I)$. If K is factored once (Cholesky), these are fast; if K is large, one can use an approximate factorization (pivoted Cholesky / incomplete Cholesky) as a preconditioner for these inner solves.

Overall complexity and scaling

Let m be the number of PCG iterations to reach a desired tolerance; standard theory gives $m = O(\sqrt{\kappa(M^{-1}A)} \log(1/\varepsilon))$ for relative error ε , so a good preconditioner aims to make $\kappa(M^{-1}A)$ close to 1.

- One-time setup: compute Z and (optionally) $G = Z^\top Z$ in $O(Mr^2)$ if done naively, but in CP-ALS contexts Z is implicit and G is usually assembled from Hadamard products of Gram matrices of each factor at cost $O(\sum_{i \neq k} n_i r^2)$, avoiding M .

- Right-hand side: compute B in $O(qr)$ and then KB in $O(n^2r)$.
- Each PCG iteration:
 - matvec Ax : $O(n^2r + qr)$.
 - preconditioner apply (Kronecker-eig): $O(n^2r + nr^2)$.
 - vector updates/inner products: $O(nr)$.

Hence total time $O(m(n^2r + qr + nr^2) + qr + n^2r)$, which is dramatically better than $O(n^3r^3)$ when $m \ll n^2r^2$ and $q \ll N$.

Key point: no N -scale work. All operations are expressed in terms of n, r, q and small Gram matrices; selection/scatter uses only the q observed indices and values.

Remark (faster kernel multiplies). If K admits a fast matrix–vector/matrix multiply (e.g., via Nyström, inducing points, random features, or a structured kernel), then the $O(n^2r)$ terms above can be reduced accordingly; the $O(qr)$ sparse gather/accumulate terms remain unchanged.