

Feb 21, 2019

Today:

① More on eigenvectors
for tensors

Lin '05

Q: '05

② dimensionality reduction
with tensors

Matrix evecs

$$Ax = \lambda x$$

$$\sum A_{ij} x_j = \lambda x_i \quad i=1, \dots, n$$

Opt. problem:

A
symm.

$$\max_x x^T A x = \sum A_{ij} x_i x_j$$

s.t.

- $\|x\|_2^2 = 1$
- $x^T x = 1$
- $x^T x - 1 = 0$

$$\mathcal{L}(x, \lambda) = x^T A x - \lambda (x^T x - 1)$$

$$\nabla_{x, \lambda} \mathcal{L} = 0 \iff \text{at any local optima}$$

$$\nabla_x \mathcal{L} = 2Ax - \lambda 2x$$

$$= 0 \Leftrightarrow Ax = \lambda x$$

local optima are eigenvectors
with eigenvalues are
Lagrange multipliers

Tensor analogy A symm.

$$\max_x \sum_{ijk} A_{ijk} x_i x_j x_k$$

$$\text{s.t.} \quad \|x\|_2^2 = 1$$

$$\mathcal{L}(x, \lambda) = \sum_{ijk} A_{ijk} x_i x_j x_k - \lambda(x^T x - 1)$$

$$\nabla_x \mathcal{L} = \left[\sum_{ijk} 3 A_{ijk} x_j x_k \right]_i - 2\lambda x$$

$$\stackrel{\Delta}{=} 3 \underline{A} x^2 - 2 \lambda x$$

$$= 0 \Leftrightarrow \underline{A} x^2 = \left(\frac{2}{3} \lambda\right) x$$

"z eigenvector"

extreme point
~~local optima~~

Matrix case scale-invariant

$$Ax = \lambda x$$

$$A(\alpha x) = \alpha (Ax) = \alpha \lambda x = \lambda(\alpha x)$$

z-evals not scale invar.

$$\underline{A} (\alpha x)^2 = \alpha^2 \underline{A} x^2 = \alpha^2 \lambda x \\ = \alpha \lambda(\alpha x)$$

"require" $\|x\|_2 = 1$ for well-defined
z-eigenvalues

order-4: $\underline{A} x^3 = \lambda x$

alternative

$$\max_x \sum A_{ijk} x_i x_j x_k$$

$$\text{s.t. } \|x\|_3^2 = 1$$

$$\|x\|_3^3 = \sum |x_i|^3$$

$$\mathcal{L}(x, \lambda) = \sum A_{ijk} x_i x_j x_k - \lambda (\|x\|_3^3 - 1)$$

$$\nabla_x \mathcal{L} = 3 \underline{A} x^2 - 3\lambda \left(\frac{x \circ x}{\|x\|_3} \right)$$

$$(y \circ z)_i = y_i z_i$$

$$= 0 \iff \underline{A} x^2 = \tilde{\lambda} x \circ x$$

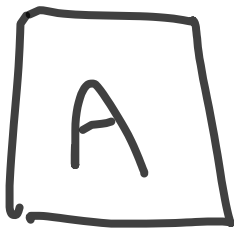
Scale-invariance

$$\begin{aligned} \underline{A} (\alpha x)^2 &= \alpha^2 \underline{A} x^2 \\ &= \alpha^2 \lambda x \circ x \\ &= \lambda (\alpha x) \circ (\alpha x) \end{aligned}$$

"H eigenvectors"

Dimensionality reduction
with tensor data

Matrix



\approx

U_k



Σ_k



V_k^T



$$\begin{aligned} U_k^T U_k &= V_k^T V_k \\ &\Rightarrow I_k \end{aligned}$$

$$\approx \sum_{r=1}^k \sigma_r u_r v_r^T$$

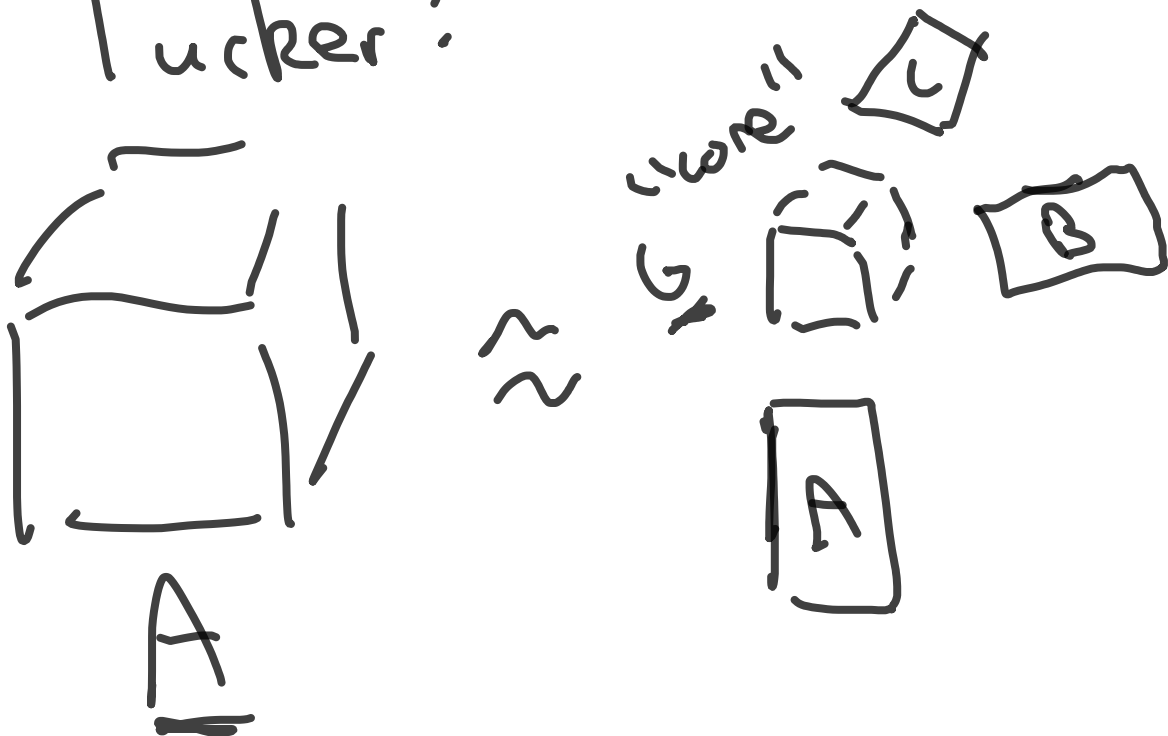
$$\approx \sum_{r=1}^k \sigma_r u_r \otimes v_r$$

best rank- k

Two types of tensor
decomps

① CP: $\underline{A} \approx \sum_{r=1}^k \sigma_r a_r \otimes b_r \otimes c_r$

② Tucker:



Canonical decomposition

CANDECOMP

Parallel Factors

PARAFAC



Canonical polyadic

How do we compute?

$$\underline{A} \approx \sum (\sigma_r a_r) \otimes b_r \otimes c_r$$

optional

$$\min_{a, b, c} \|\underline{A} - \sum a_r \otimes b_r \otimes c_r\|_F$$

$$(A_{ijk} = \sum a_r(l) b_r(j) c_r(k))^2$$

$$\begin{bmatrix} \vdots \\ b_1(j)c_1(k) \cdots b_r(j)c_r(k) \\ \vdots \end{bmatrix}$$

jik

$$\left(M \begin{bmatrix} a_r(l) \\ \vdots \\ -a_r(l) \end{bmatrix} \right) \sim \begin{bmatrix} A \\ \vdots \\ jk \end{bmatrix}^2$$

linear least squares

Actual alg:

for iter = 1, 2, ...

Fix B, C

Update A with LLS

Fix A, C

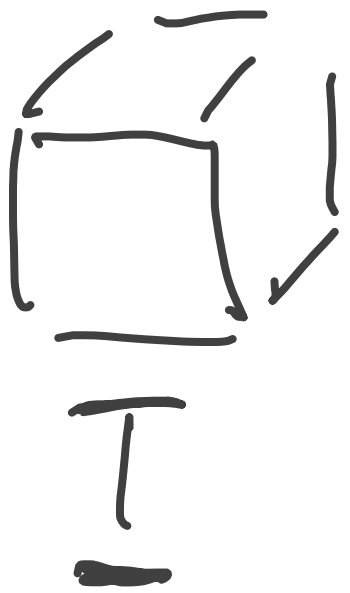
Update B with LLS

Fix A, B

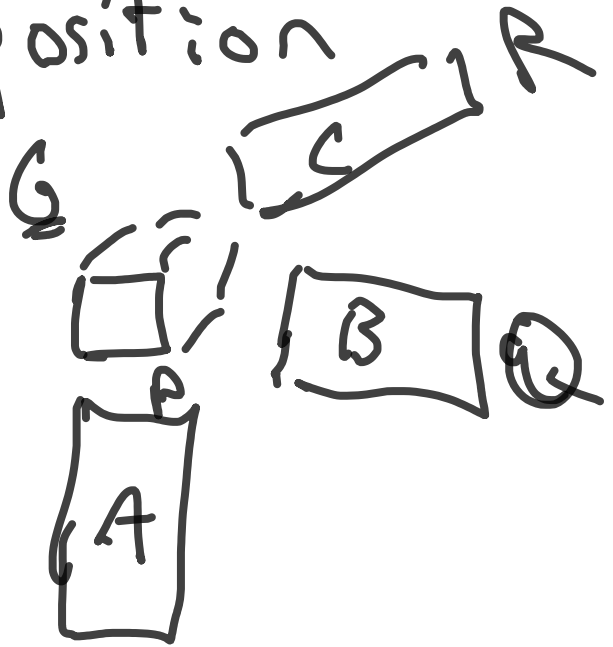
Update C with LLS

stop if error $< \epsilon$

Tucker decomposition



\approx



G is the "core tensor"

$$I \approx \sum_{p=1}^P \sum_{q=1}^Q \sum_{r=1}^R G_{pqr} a_p \otimes b_q \otimes c_r$$

$$A^T A = I$$

$$B^T B = I$$

$$C^T C = I$$

sometimes
called

"higher-order
SVD"

G diagonal
+ no orthog. constraints
 \Rightarrow CP

How to compute?

Idea: fix all but one factor

\Rightarrow matrix M

\Rightarrow SVD $U \Sigma V^T$

\Rightarrow update M with U

$$\underline{I} \approx \sum_p \sum_q \sum_r G_{pqr} a_p \otimes b_q \otimes c_r$$

$$\underline{I}_{ijk} \approx \sum_{p,q,r} \underline{G}_{pqr} a_p(i) b_q(j) c_r(k)$$

Claim: if we know A, B, C
are fixed, we can find
optimal \underline{G}

$$\| \underline{I} - \sum_{pqr} \underline{G}_{pqr} a_p \otimes b_q \otimes c_r \|^2$$

$$\left(\underline{I}_{ijk} \approx \sum_{p,q,r} \underline{G}_{pqr} a_p(i) b_q(j) c_r(k) \right)^2$$

Solve with LLS

How to get A, B, C

Idea: capture variation in

each mode

\Rightarrow left singular vectors



Collapse to a matrix in each mode (A, B, C)

$$T_{ijk} \approx \sum_{p,q,r} G_{pqr} a_p(i) b_q(j) c_r(k)$$

$$[X(A)]_{i,j,k}^T = A_{i,j,k} \sum_{i,j,k} T_{ijk} b_q(j) c_r(k)$$

(Kolda & Bader '09)

$$X(A) \approx U \Sigma V^T$$

$$n \begin{matrix} \uparrow \\ \boxed{U} \end{matrix}$$

$$A \leftarrow U$$

for iter = 1, 2, ...

$$\text{SVD}(X(A)) \rightarrow U \Sigma V^T$$

$$A \leftarrow U$$

$$\text{SVD}(X(B)) \rightarrow U \Sigma V^T$$

$$B \leftarrow U$$

$$\text{SVD}(X(C)) \rightarrow U \Sigma V^T$$

$$C \leftarrow U$$

stop if error $\leq \epsilon$

→ LLS for G

Generalizations

- nonnegative tensor factorizations

- I showed order-3 tensors generalizes for any order

Next Tues: no class
(break)

Next Thurs:

nonlinear dimensionality
reduction