

Summary of LS:

- to minimize $\|A\vec{x} - \vec{b}\|$ for "tall-skinny" A let $\hat{x} = A^+ \vec{b}$ (least squares)
- to minimize $\|AX - B\|_F$ just minimize $\|A\vec{x}_1 - \vec{b}_1\|, \dots, \|A\vec{x}_n - \vec{b}_n\|$ individually, where $\vec{x}_i$'s, $\vec{b}_i$'s columns of X, B respectively ("matrix least squares")

Back to CP: Given T of rank r and $K \ll B$ want to find $\vec{u}_i$'s, $\vec{v}_i$'s, $\vec{w}_i$'s minimizing

$$\begin{aligned} \|T - \sum_{i=1}^K \vec{u}_i \vec{v}_i \vec{w}_i\|_F &= \|T_1 - U(W \odot V)^T\|_F \\ &= \|T_2 - V(W \odot U)^T\|_F \\ &= \|T_3 - W(V \odot U)^T\|_F \end{aligned}$$

$\vec{u}_i, \vec{v}_i, \vec{w}_i$ columns of U, V, W .

net LS problems - 3 unknown matrices, net 1.

- take iterative approach:

1st stage: pick arbitrary matrices V, W and minimize $\|T_1 - U(W \odot V)^T\|_F$ to find a matrix U ,

- this is (matrix) least squares: of the (ii)
 form $\min_x \|B - XA\|_F$

note: $\uparrow$ since unknown on left
 we'll need to ~~be~~ transpose to
 get same form as above

~~$\|B - XA\|_F = \|XA - B\|_F$~~

~~$\|B - XA\|_F = \|XA - B\|_F$~~

$$\|B - XA\|_F = \|XA - B\|_F \quad (\text{negative cancel})$$

$$= \|(XA - B)^T\|_F \quad (\text{same entries})$$

$$= \|(XA)^T - B^T\|_F$$

$$= \|A^T X^T - B^T\|_F$$

$$= \|A^T X' - B^T\|_F$$

$\hookrightarrow$ same form as before.

2nd stage: keeping same w , minimize
 $\|T_2 - V(w \otimes u)^T\|_F$ to find V_1 .

3rd: minimize $\|T_3 - w(v_1 \otimes u_1)^T\|_F$ to find w_1 .

in general: u_1, v_1, w_1 will only approx-
 imate a sol'n to minimization problems
 above. So we may continue...

(iii)

- minimize $\|T_1 - U(W_1 \odot V_1)^T\|_F$
to find u_2

- minimize $\|T_2 - V(W_1 \odot u_2)^T\|_F$
to find V_2

"Alternating LS"

- minimize $\|T_3 - W(V_2 \odot u_2)^T\|_F$
to find W_2

the sequences $u_1 \rightarrow u_2 \rightarrow \dots$
 $V_1 \rightarrow V_2 \rightarrow \dots$
 $W_1 \rightarrow W_2 \rightarrow \dots$

will (hopefully) converge to an actual solution, though I don't know if there are good estimates for how long this will take in a given instance.

- Once we've gone "far enough"

(found some $u_n = [\vec{u}_1 | \dots | \vec{u}_k]$

$V_n = [\vec{v}_1 | \dots | \vec{v}_k]$

$W_n = [\vec{w}_1 | \dots | \vec{w}_k]$)

(iv)

We can unpack columns to get
cor sum of rank 1 tensors:

$$\sum_{c=1}^k \vec{u}_c \circ \vec{v}_c \circ \vec{w}_c$$

which, approximately, minimizes $\|T - \sum_{c=1}^k \vec{u}_c \circ \vec{v}_c \circ \vec{w}_c\|_F$
over all such k length sums.

~~Ques~~ #5 on HW is first step in such
an approx'n process.

$$T = \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array} \rightarrow T_1 = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

is rank 2 (why?)

Want rank 1 tensor $\begin{matrix} \vec{u} & \vec{v} & \vec{w} \\ \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} & \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} & \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \end{matrix}$
closest to T_1 , if we choose $\begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$
i.e. want to solve:

$$\min_{\vec{u}} \|T_1 - \vec{u}(\vec{w} \circ \vec{v})^T\|_F$$

$$\text{i.e. } \min_{\vec{u}} \|T_1 - \vec{u}(\vec{w} \otimes \vec{v})^T\|_F$$

$$\min_{\vec{u}} \|T_1 - \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \left(\begin{bmatrix} 1 \\ 1 \end{bmatrix} \right)^T\|_F$$

$$\min_{\vec{u}} \| \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} - T_1 \|_F$$

of form $\|XA - BU\|$ we want $\|AX - BU\|$ (V)

so we transpose:

$$\min \| \begin{matrix} A \\ \vdots \\ A \end{matrix} \begin{matrix} x \\ u_1, u_2 \end{matrix} - \begin{matrix} b \\ \vdots \\ b \end{matrix} \|_F$$

$\vec{x}_1 \quad \vec{x}_2$ b_1, b_2

(in this case our column vectors $\vec{x}_1, \vec{x}_2$ are just scalars u_1, u_2)

this splits into two LS problems

$$\min \| \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} u_1 - \begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix} \|$$

$$\min \| \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} u_2 - \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \|$$

the second is easy: solved by $u_2 = 1$.

we could use calculus to solve the first, which reduces to

$$\text{minimize: } u_1^2 + (u_1 - \frac{1}{2})^2 + (u_1 - 1)^2 + (u_1 - 1)^2$$

but let's instead solve by least squares -

need to find pseudo-inverse for $\begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$

first need its $SV(D)$. (finding SV of a vector - eh.)

$$\begin{bmatrix} \hat{A} \\ \vdots \\ 1 \end{bmatrix} [1] = \begin{bmatrix} \vdots \\ 1 \end{bmatrix} = \sqrt{4} \begin{bmatrix} 1/\sqrt{4} \\ 1/\sqrt{4} \\ 1/\sqrt{4} \\ 1/\sqrt{4} \end{bmatrix}$$

(vi)

what unit "vector" stretched most by $\begin{bmatrix} \vdots \\ 1 \end{bmatrix}$ - only one choice (up to sign)!

So

$$\begin{bmatrix} A \\ \vdots \\ 1 \end{bmatrix}_{4 \times 1} = \begin{bmatrix} 1/\sqrt{4} \\ 1/\sqrt{4} \\ 1/\sqrt{4} \\ 1/\sqrt{4} \end{bmatrix}_U \begin{bmatrix} \square \\ \square \\ \square \\ \square \end{bmatrix}_{\Sigma} \begin{bmatrix} \sqrt{4} \\ 0 \\ 0 \\ 0 \end{bmatrix}_{V^T} [1]$$

doesn't matter just extend to orthonormal basis

$$\text{So } A^+ = V \Sigma^+ U^T$$

$$= [1] \begin{bmatrix} 1/\sqrt{4} & 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1/\sqrt{4} & 1/\sqrt{4} & 1/\sqrt{4} & 1/\sqrt{4} \\ \square & \square & \square & \square \end{bmatrix}$$

Want to minimize $\| \begin{bmatrix} \hat{A} \\ \vdots \\ 1 \end{bmatrix}_U x - \begin{bmatrix} \hat{b} \\ \vdots \\ 1 \end{bmatrix}_V \|$

$$\text{Solution } \hat{x} = A^+ \hat{b} = [1] \begin{bmatrix} 1/\sqrt{4} & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1/\sqrt{4} & 1/\sqrt{4} & 1/\sqrt{4} & 1/\sqrt{4} \\ \square & \square & \square & \square \end{bmatrix} \begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1/\sqrt{4} & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \square \\ 3/\sqrt{4} \\ \square \end{bmatrix}$$

$$= 3/4$$

(vii)

So: $\| \begin{bmatrix} 1 \\ 1 \end{bmatrix} u_1 - \begin{bmatrix} 1 \\ 1 \end{bmatrix} \|$ is minimized

when $u_1 = 3/4$

bringing it all back: if $\begin{bmatrix} u_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} u_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

then $\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \circ \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \circ \begin{bmatrix} u_1 \\ v_2 \end{bmatrix} \approx \vec{u} (\vec{v} \otimes \vec{v})$ when unfolded)

is closest to T when $u_1 = 3/4$
 $u_2 = 1$

$$\text{i.e.} \quad \begin{bmatrix} 3/4 \\ 1 \end{bmatrix} \circ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \circ \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \text{[scribbled out]}$$



is closest
such

rank 1 tensor

to $T =$