

Honor Code -
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(b). I hereby state that all of my ~~following~~ solutions were entirely in my words and were written by me. I have not looked at another student's solutions and I have fairly credited all external sources in this write up.

1. (a). $M = UDV^T$.
let U_i be a matrix whose i -th column is the i -th column vector of matrix U and all the other columns are all zero vectors.

$$U_i = \begin{bmatrix} 0 & \dots & 0 \\ 0 & \dots & 0 \\ \vdots & & \vdots \\ 0 & \dots & 0 \end{bmatrix} \begin{matrix} | \\ U_i \\ | \end{matrix} \begin{bmatrix} \dots & 0 \\ \dots & 0 \\ \dots & 0 \end{bmatrix}$$

$$\Rightarrow \text{then } V = \sum_{i=1}^n U_i \quad \text{likewise } V = \sum_{i=1}^n V_i$$

Since D is a diagonal matrix

$$\Rightarrow UD = \sum_{i=1}^n U_i \cdot d_i$$

For any two matrices A_i and B_k .

$$A_i B_k^T = 0 \quad i \neq k$$

$$\text{thus } UDV^T = \left(\sum_{i=1}^n U_i \cdot d_i \right) \left(\sum_{j=1}^n V_j^T \right)$$

$$= \sum_{i=1}^n U_i \cdot d_i V_i^T$$

$$= \sum_{i=1}^n U_i d_i V_i^T = \sum_{i=1}^n d_i U_i V_i^T$$

1. (b).

$$M = UDV^T$$

$$\textcircled{1} M^T M = (U D V^T)^T (U D V^T)$$

$$= V D^T U^T \cdot U \cdot D \cdot V^T$$

$$= V D^T D V^T$$

$$\Rightarrow M^T M \cdot V = V \cdot D^T \cdot D \cdot V^T \cdot V = V \cdot D^T \cdot D$$

thus the i -th eigenvalue of $M^T M$ is d_i^2 and corresponding eigenvector is V_i .

$$\textcircled{2} M M^T = U D V^T (U D V^T)^T$$

$$= U D V^T V D^T U^T$$

$$= U D D^T U^T$$

$$M M^T U = U D D^T U^T U = U D D^T$$

thus the i -th eigenvalue of $M M^T$ is d_i^2 and corresponding eigenvector is U_i .

4. (a)

For the LHS:

$$\begin{aligned} \frac{1}{|C_H|} \sum_{i,j \in C_H} \sum_{k=1}^p (x_{ij} - x'_{ij})^2 &= \sum_i \sum_j x_{ij}^2 - 2 \sum_i \sum_j x_{ij} \bar{x}_{kj} + \sum_i \sum_j \bar{x}_{kj}^2 \\ &= 2 \sum_i \sum_j x_{ij}^2 - 2|C_H| \sum_j \bar{x}_{kj}^2 \end{aligned}$$

For RHS:

$$\begin{aligned} 2 \sum_{i \in C_H} \sum_{j=1}^p (x_{ij} - \bar{x}_{kj})^2 &= 2 \sum_i \sum_j x_{ij}^2 - 4 \sum_i \sum_j x_{ij} \bar{x}_{kj} + 2 \sum_j \sum_i \bar{x}_{kj}^2 \\ &= 2 \sum_i \sum_j x_{ij}^2 - 2 \left(2 \sum_i \sum_j x_{ij} \bar{x}_{kj} - \sum_j \sum_i \bar{x}_{kj}^2 \right) \\ &= 2 \sum_i \sum_j x_{ij}^2 - 2|C_H| \sum_j \bar{x}_{kj}^2 \end{aligned}$$

thus LHS = RHS

$$\text{i.e. } \frac{1}{|C_H|} \sum_{i,j \in C_H} \sum_{k=1}^p (x_{ij} - x'_{ij})^2 = 2 \sum_{i \in C_H} \sum_{j=1}^p (x_{ij} - \bar{x}_{kj})^2$$

4(b)
 we know that $\frac{1}{|C_k|} \sum_{i \in C_k} \sum_{j=1}^p (x_{ij} - x'_{ij})^2 = \sum_{j=1}^p \frac{1}{|C_k|} \sum_{i \in C_k} (x_{ij} - \bar{x}_{kj})^2$ holds,

the cluster means for each feature are the constants that minimize the sum of squared deviations, re-allocating the observations can only improve, thus the algorithm runs, the

$\sum_{k=1}^K \frac{1}{|C_k|} \sum_{i \in C_k} \sum_{j=1}^p (x_{ij} - x'_{ij})^2$ will always decrease. When results no longer changes, a local optimum has been reached.