

4.1 (K-means).

$$\begin{aligned}
 \sum_{j=1}^k \sum_{x \in C_j} \|x - \mu_j\|^2 &= \sum_{j=1}^k \sum_{x \in C_j} \langle x - \mu_j, x - \mu_j \rangle \\
 &= \sum_{j=1}^k \sum_{x \in C_j} (\langle x, x \rangle - 2 \langle x, \mu_j \rangle + \langle \mu_j, \mu_j \rangle) \\
 &= \underbrace{\sum_{j=1}^k \sum_{x \in C_j} \langle x, x \rangle}_{\sum_{x \in X} \|x\|^2} - 2 \sum_{j=1}^k \sum_{x \in C_j} \langle x, \mu_j \rangle + \sum_{j=1}^k \sum_{x \in C_j} \langle \mu_j, \mu_j \rangle \\
 &= \sum_{x \in X} \|x\|^2 - 2 \sum_{j=1}^k \langle \sum_{x \in C_j} x, \mu_j \rangle + \sum_{j=1}^k \sum_{x \in C_j} \langle \mu_j, \mu_j \rangle \\
 &= \sum_{x \in X} \|x\|^2 - 2 \sum_{j=1}^k |C_j| \cdot \langle \mu_j, \mu_j \rangle + \sum_{j=1}^k \sum_{x \in C_j} \langle \mu_j, \mu_j \rangle \\
 &= \sum_{x \in X} \|x\|^2 - \sum_{j=1}^k \sum_{x \in C_j} \langle \mu_j, \mu_j \rangle \\
 &= \sum_{x \in X} \|x\|^2 - \sum_{j=1}^k |C_j| \cdot \langle \mu_j, \mu_j \rangle.
 \end{aligned}$$

$$\arg \min_C \sum_{j=1}^k \sum_{x \in C_j} \|x - \mu_j\|^2 = \arg \max_C \sum_{j=1}^k |C_j| \cdot \langle \mu_j, \mu_j \rangle.$$

$$\begin{aligned}
 (a). \sum_{x \in C_j} \|x - x'\|^2 &= \sum_{x \in C_j} \sum_{x' \in C_j} \langle x - x', x - x' \rangle \\
 &= \sum_{x \in C_j} \sum_{x' \in C_j} (\langle x, x \rangle - 2 \langle x, x' \rangle + \langle x', x' \rangle) \\
 &= |C_j| \cdot \sum_{x \in C_j} \langle x, x \rangle + |C_j| \cdot \sum_{x' \in C_j} \langle x', x' \rangle - 2 \langle \sum_{x \in C_j} x, \sum_{x' \in C_j} x' \rangle \\
 &= 2 |C_j| \cdot \sum_{x \in C_j} \langle x, x \rangle - 2 |C_j|^2 \cdot \langle \mu_j, \mu_j \rangle.
 \end{aligned}$$

$$\sum_{j=1}^k \frac{1}{2|C_j|} \cdot \sum_{x \in C_j} \|x - x'\|^2 = \dots = \sum_{x \in X} \|x\|^2 - \sum_{j=1}^k |C_j| \cdot \|\mu_j\|^2.$$

4.2. (PCA).

$$\begin{aligned}
 \|x^{(i)} - (x^{(i)\top} u)u\|^2 &= \langle x^{(i)} - (x^{(i)\top} u)u, x^{(i)} - (x^{(i)\top} u)u \rangle \\
 &= \langle x^{(i)}, x^{(i)} \rangle - 2 \langle x^{(i)}, \cancel{(x^{(i)\top} u)} \cdot u \rangle + \cancel{(x^{(i)\top} u)^2} \underbrace{\langle u, u \rangle}_1 \\
 &= \langle x^{(i)}, x^{(i)} \rangle + \cancel{(x^{(i)\top} u)^2} - 2 \cancel{(x^{(i)\top} u)} \cdot \cancel{\langle x^{(i)}, u \rangle} \\
 &= \langle x^{(i)}, x^{(i)} \rangle - \cancel{(x^{(i)\top} u)^2}.
 \end{aligned}$$

does not
change with u .

$$(b). \frac{1}{n} \cdot \sum_{i=1}^n (\underline{x^{(i)^\top} u})^2 = \underbrace{\underline{u^\top} \underline{\sum} \underline{u}}_{\substack{\parallel \\ \parallel \\ C}} \quad A = B. \quad \begin{matrix} \parallel \\ \parallel \\ C \end{matrix}$$

$$\frac{1}{n} \cdot \sum_{i=1}^n \underbrace{\underline{x^{(i)^\top} u}}_{\substack{\parallel \\ \parallel \\ u^\top x^{(i)}}} \underline{x^{(i)^\top} u} = \frac{1}{n} \cdot \sum_{i=1}^n \underbrace{\underline{u^\top} \underline{x^{(i)}}}_{\substack{\parallel \\ \parallel \\ m \times 1}} \cdot \underline{x^{(i)^\top} u} = u^\top \left(\frac{1}{n} \sum_{i=1}^n x^{(i)} x^{(i)^\top} \right) u.$$

$$u^\top v = \text{tr}(u^\top v) = \text{tr}(v \cdot u^\top).$$

$$4.3. \text{ If } \Sigma = \sigma_1 u_1 u_1^\top + \sigma_2 u_2 u_2^\top + \dots + \sigma_n u_n u_n^\top.$$

$$u_2 = \arg \max u^\top \Sigma u. \quad u^\top \Sigma u = \underbrace{\beta_1^2}_{\substack{\parallel \\ \parallel \\ -}} = \sigma_2^2.$$

$$\text{s.t. } \langle u, u \rangle = 1$$

$$u_1^\top u = 0. \quad \text{---}$$

$$\beta_2 = 0.$$

$$\mathcal{L}(u, \lambda_1, \lambda_2) = u^\top \Sigma u + \beta_1 \cdot (u^\top u - 1) + \beta_2 \cdot u_1^\top u$$

$$\begin{aligned} \bigoplus \frac{\partial \mathcal{L}}{\partial u} &= 2 \Sigma u + 2\beta_1 u + \beta_2 u_1 = 0. & \Sigma u &= -\beta_1 \cdot u. \\ \left. \begin{cases} \frac{\partial \mathcal{L}}{\partial \lambda_1} = u^\top u - 1 & = 0 \\ \frac{\partial \mathcal{L}}{\partial \lambda_2} = u_1^\top u & = 0. \end{cases} \right. & & (1) & \\ & & (2) & \end{aligned}$$

$$u_1^\top \cdot (*).$$

$$2 \cdot \underbrace{u_1^\top \Sigma u}_{\substack{\parallel \\ \parallel}} + 2\beta_1 \cdot \underbrace{u_1^\top u}_{\substack{\parallel \\ \parallel}} + \beta_2 \cdot \underbrace{u_1^\top u_1}_{\substack{\parallel \\ \parallel}} = 0. \Rightarrow 0 + 0 + \beta_2 = 0$$

$$\Sigma = \sigma_1 u_1 u_1^\top + \sigma_2 u_2 u_2^\top + \dots + \sigma_n u_n u_n^\top.$$

$$\beta_2 = 0.$$

$$\textcircled{1} \quad \sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n$$

$$\textcircled{2} \quad \langle u_i, u_j \rangle = \delta_{ij} = \begin{cases} 0 & , i \neq j \\ 1 & , i = j \end{cases}$$

$$\langle u_1, u_1 \rangle = 1, \quad \langle u_1, u_2 \rangle = 0.$$

$$\begin{aligned} u_1^T \Sigma &= u_1^T (\sigma_1 u_1 u_1^T + \sigma_2 u_2 u_2^T + \dots + \sigma_n u_n u_n^T) \\ &= \sigma_1 \cdot \underbrace{u_1^T u_1}_{1} \cdot u_1^T + \sigma_2 \cdot u_1^T u_2 \cdot u_2^T + \dots + \sigma_n \cdot u_1^T u_n \cdot u_n^T \\ &= \sigma_1 \cdot 1 \cdot u_1^T + \sigma_2 \cdot 0 \cdot u_2^T + \dots + \sigma_n \cdot 0 \cdot u_n^T \\ &= \sigma_1 \cdot u_1^T \end{aligned}$$