

1. 데이터 평균이용 실제 계산값 유도가 핵심, 방법만 제시한 경우 10점

	Height	Weight	X	Y
	166	58	-5	-7
	176	75	5	10
	171	62	0	-3
	173	70	2	5
	169	60	-2	-5
AVG	171	65	0	0

$$y_n^* = w_0 + w_1 x_n \approx y_n \text{ for } n=1, \dots, 5 \xrightarrow{Y_n = y_n - \bar{y}} Y_n^* = W_0 + W_1 X_n \approx Y_n$$

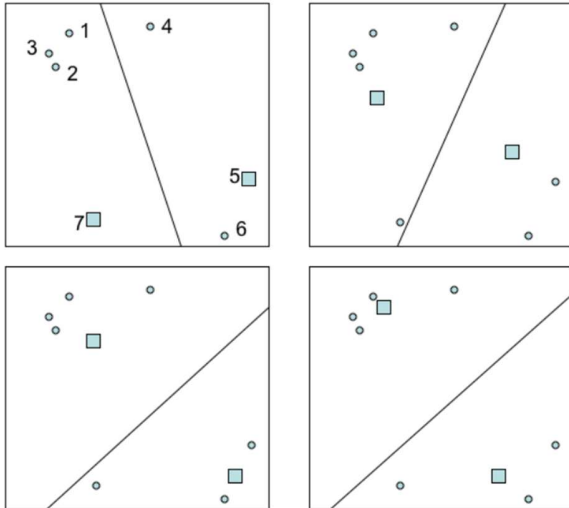
$$L = \sum_{n=1}^5 (W_0 + W_1 X_n - Y_n)^2 = (W_0 - 5W_1 + 7)^2 + (W_0 + 5W_1 - 10)^2 + (W_0 - 0W_1 + 3)^2 + (W_0 + 2W_1 - 5)^2 + (W_0 - 2W_1 + 5)^2$$

$$= 5W_0^2 + 58W_1^2 - 210W_1 + 208$$

$$\text{minimize } L \rightarrow W_0 = 0, W_1 = \frac{210}{116}$$

$$y_n - 65 = 0 + \frac{210}{116}(x_n - 171) \rightarrow y_n = \frac{210}{116}x_n + \left(65 - \frac{210}{116}(171)\right)$$

2. (1) (5 pts)



(2) (5 pts)

Advantages of hierarchical clustering:

- Don't need to know how many clusters you're after
- Can cut hierarchy at any level to get any number of clusters
- Easy to interpret hierarchy for particular applications
- Can deal with long stringy data

Advantages of K-means clustering:

- Can be much faster than hierarchical clustering, depending on data
- Nice theoretical framework
- Can incorporate new data and reform clusters easily

3. (5점, 5점, 10점)

$$(1) \mathbf{A} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^{-1} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 2 \end{bmatrix}$$

$$(2) \mathbf{A}^8 = (\mathbf{V}\mathbf{\Lambda}\mathbf{V}^{-1})^8 = \mathbf{V}\mathbf{\Lambda}^8\mathbf{V}^{-1} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1^8 & 0 \\ 0 & 2^8 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 256 \\ 0 & 256 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 255 \\ 0 & 256 \end{bmatrix}$$

$$(3) u'(t) = \mathbf{A}u(t) = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^{-1}u(t)$$

$$w(t) = \mathbf{V}^{-1}u(t) \rightarrow w'(t) = \mathbf{V}^{-1}\mathbf{A}u(t) = \mathbf{V}^{-1}\mathbf{V}\mathbf{\Lambda}\mathbf{V}^{-1}u(t) = \mathbf{\Lambda}w(t) = \begin{bmatrix} c_1 e^t \\ c_2 e^{2t} \end{bmatrix}$$

$$u(t) = \mathbf{V}w(t) = \begin{bmatrix} c_1 e^t + c_2 e^{2t} \\ c_2 e^{2t} \end{bmatrix} \xrightarrow{u(0) = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} c_1 + c_2 \\ c_2 \end{bmatrix}} u(t) = \begin{bmatrix} e^t \\ 0 \end{bmatrix}$$

4. (10 pts)

$$w = \exp\left(\frac{2\pi i}{6}\right)$$

$$\mathbf{F}_6 = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & w & w^2 & w^3 & w^4 & w^5 \\ 1 & w^2 & w^4 & w^6 & w^8 & w^{10} \\ 1 & w^3 & w^6 & w^9 & w^{12} & w^{15} \\ 1 & w^4 & w^8 & w^{12} & w^{16} & w^{20} \\ 1 & w^5 & w^{10} & w^{15} & w^{20} & w^{25} \end{bmatrix} = \begin{bmatrix} 1 & & & & & \\ & 1 & & & & \\ & & 1 & & & \\ & & & -1 & & \\ & & & & -w & \\ & & & & & -w^2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 & & & \\ & 1 & w & w^2 & & \\ & & 1 & w^2 & w^4 & \\ & & & 1 & 1 & 1 \\ & & & & 1 & w & w^2 \\ & & & & & 1 & w^2 & w^4 \end{bmatrix} \begin{bmatrix} 1 & & & & & \\ & 1 & & & & \\ & & 1 & & & \\ & & & 1 & & \\ & & & & 1 & \\ & & & & & 1 \end{bmatrix}$$

5. (10 pts)

$$\text{The closest rank 1 approximations are } A = \begin{bmatrix} 3 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad A = \begin{bmatrix} 0 & 3 \\ 0 & 0 \end{bmatrix} \quad A = \frac{3}{2} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$$

6. (5 pts, 5 pts)

$$(1) \mathbf{q}_1 = \frac{\mathbf{a}}{\|\mathbf{a}\|} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \mathbf{A}_2 = \mathbf{b} - (\mathbf{b}^T \mathbf{q}_1) \mathbf{q}_1 = \begin{bmatrix} 4 \\ 0 \end{bmatrix} - \frac{4}{\sqrt{2}} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ -2 \end{bmatrix}, \mathbf{q}_2 = \frac{\mathbf{A}_2}{\|\mathbf{A}_2\|} = \frac{1}{2\sqrt{2}} \begin{bmatrix} 2 \\ -2 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

$$(2) \begin{bmatrix} 1 & 4 \\ 1 & 0 \end{bmatrix} = [\mathbf{q}_1 \quad \mathbf{q}_2] \begin{bmatrix} \mathbf{a}^T \mathbf{q}_1 & \mathbf{A}_2^T \mathbf{q}_1 \\ 0 & \mathbf{A}_2^T \mathbf{q}_2 \end{bmatrix} = \underbrace{\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}}_{\mathbf{Q}} \underbrace{\begin{bmatrix} \sqrt{2} & 2\sqrt{2} \\ 0 & 2\sqrt{2} \end{bmatrix}}_{\mathbf{R}}$$

7. (10 pts, 5 pts, 5 pts)

$$(1) \begin{cases} \bar{x} = 2 \\ \bar{y} = 1 \end{cases} \rightarrow \mathbf{B} = \mathbf{X} - \bar{\mathbf{X}} = \begin{bmatrix} 4 & -5 \\ -5 & 4 \\ -4 & 5 \\ 5 & -4 \end{bmatrix}, \mathbf{C} = \frac{1}{n-1} \mathbf{B}^T \mathbf{B} = \frac{1}{3} \begin{bmatrix} 82 & -80 \\ -80 & 82 \end{bmatrix} \rightarrow \begin{cases} \lambda_1 = 162, \mathbf{q}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \\ \lambda_2 = 2, \mathbf{q}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \end{cases}$$

$$(2) \text{ project onto the subspace spanned by } \mathbf{q}_1 \text{ (larger eigenvalue)} : (x, y) \rightarrow \frac{x-y}{\sqrt{2}}$$

$$(6, -4) \rightarrow \frac{10}{\sqrt{2}}, (-3, 5) \rightarrow \frac{-8}{\sqrt{2}}, (-2, 6) \rightarrow \frac{-8}{\sqrt{2}}, (7, -3) \rightarrow \frac{10}{\sqrt{2}}$$

$$(3) \text{ if } \mathbf{v} \text{ is a right singular vector (column of } \mathbf{V}) \text{ of } \mathbf{X}, \mathbf{X} = \mathbf{U}\mathbf{D}\mathbf{V}^T \rightarrow \mathbf{X}^T \mathbf{X} = \mathbf{V}\mathbf{D}^T \mathbf{U}^T (\mathbf{U}\mathbf{D}\mathbf{V}^T) = \mathbf{V}\mathbf{D}^2 \mathbf{V}^T$$