

1.

 $r = m = n$ ,  $\mathbf{A}_1$  is any invertible square matrix $r = m < n$ ,  $\mathbf{A}_2$  has extra columns like  $\mathbf{A}_2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix}$  $r = n < m$ ,  $\mathbf{A}_3$  has extra rows like  $\mathbf{A}_2^T$  $r < m, r < n$ ,  $\mathbf{A}_4 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$  or  $\begin{bmatrix} 1 & 2 \\ 1 & 2 \end{bmatrix}$  or  $\begin{bmatrix} 1 & 2 & 3 \\ 1 & 2 & 3 \end{bmatrix}$ 2. ( $\mathbf{F}^{-1}$  설명없으면 -2점)

$$\mathbf{P} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix} \rightarrow \lambda = 1, i, i^2, i^3 \rightarrow \mathbf{X} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & i & i^2 & i^3 \\ 1 & i^2 & i^4 & i^6 \\ 1 & i^3 & i^6 & i^9 \end{bmatrix} = \mathbf{F} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & i & -1 & -i \\ 1 & -1 & 1 & -1 \\ 1 & -i & -1 & i \end{bmatrix}$$

$$\rightarrow \mathbf{Q} = \frac{\mathbf{F}}{2} \rightarrow \text{orthonormal matrix} \rightarrow \mathbf{Q}\overline{\mathbf{Q}}^T = \mathbf{I} \rightarrow \mathbf{F}\overline{\mathbf{F}}^T = 4\mathbf{I}$$

$$\mathbf{F}\mathbf{x} = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} \rightarrow \mathbf{x} = \mathbf{F}^{-1} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \frac{1}{4} \overline{\mathbf{F}} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \frac{1}{4} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -i & -1 & i \\ 1 & -1 & 1 & -1 \\ 1 & i & -1 & -i \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1/2 \\ 0 \\ 1/2 \\ 0 \end{bmatrix}$$

3. (eigenvalue 정의 활용시 -1점)

$$\left. \begin{array}{l} \text{tr}(\mathbf{A}) = \sum \lambda_i \\ \det(\mathbf{A}) = \prod \lambda_i \end{array} \right\} \rightarrow \mathbf{A} = \begin{bmatrix} 0 & 1 \\ -28 & 11 \end{bmatrix}$$

4. (incorrect eigenvector: 2 pts)

$$\mathbf{A} = \begin{bmatrix} 1 & 2 \\ 0 & 3 \end{bmatrix} \xrightarrow{\lambda=1,3} \begin{bmatrix} 0 & 2 \\ 0 & 2 \end{bmatrix} \mathbf{x}_1 = \begin{bmatrix} -2 & 2 \\ 0 & 0 \end{bmatrix} \mathbf{x}_2 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \rightarrow \mathbf{x}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \mathbf{x}_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\mathbf{A} = \mathbf{X}\mathbf{\Lambda}\mathbf{X}^{-1} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} \rightarrow \mathbf{A}^3 = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 27 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}, \mathbf{A}^{-1} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1/3 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}$$

5. (1 pt each)

$$\begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix} S \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = 4(x_1 - x_2 + 2x_3)^2 \rightarrow S = \begin{bmatrix} 4 & -4 & 8 \\ -4 & 4 & -8 \\ 8 & -8 & 16 \end{bmatrix} \rightarrow \begin{cases} \text{pivot} = 4 \\ \text{rank} = 1 \\ \text{eigenvalues} = 0, 0, 24 \\ \text{determinant} = 0 \end{cases}$$

6.

$$\mathbf{A}^T \mathbf{A} = \begin{bmatrix} 2 & 1 \\ 4 & 2 \end{bmatrix} \begin{bmatrix} 2 & 4 \\ 1 & 2 \end{bmatrix} = \begin{bmatrix} 5 & 10 \\ 10 & 20 \end{bmatrix} \xrightarrow{\lambda=25,0} \begin{bmatrix} -20 & 10 \\ 10 & -5 \end{bmatrix} \mathbf{v}_1 = \begin{bmatrix} 5 & 10 \\ 10 & 20 \end{bmatrix} \mathbf{v}_2 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \rightarrow \mathbf{v}_1 = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \mathbf{v}_2 = \frac{1}{\sqrt{5}} \begin{bmatrix} 2 \\ -1 \end{bmatrix}$$

$$u_1 = \frac{\mathbf{A} \mathbf{v}_1}{\sigma_1} = \frac{1}{5} \begin{bmatrix} 2 & 4 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \rightarrow \mathbf{A} = u_1 \sigma_1 \mathbf{v}_1^T = \frac{1}{\sqrt{5}} \begin{bmatrix} 2 \\ 1 \end{bmatrix} (5) \frac{1}{\sqrt{5}} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$\mathbf{A}^T \mathbf{A} = \mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^T = \frac{1}{5} \begin{bmatrix} 1 & 2 \\ 2 & -1 \end{bmatrix} \begin{bmatrix} 25 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 2 & -1 \end{bmatrix}$$

(alternatively, but not preferable)

$$\mathbf{A} \mathbf{A}^T = \begin{bmatrix} 2 & 4 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 4 & 2 \end{bmatrix} = \begin{bmatrix} 20 & 10 \\ 10 & 5 \end{bmatrix} \xrightarrow{\lambda=25,0} \begin{bmatrix} -5 & 10 \\ 10 & -20 \end{bmatrix} \mathbf{u}_1 = \begin{bmatrix} 20 & 10 \\ 10 & 5 \end{bmatrix} \mathbf{u}_2 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \rightarrow \mathbf{u}_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}, \mathbf{u}_2 = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$$

$$\mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^T = \frac{1}{\sqrt{5}} \begin{bmatrix} 2 & -1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 5 & 0 \\ 0 & 0 \end{bmatrix} \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 2 \\ 2 & -1 \end{bmatrix}$$

7. The singular values of  $\mathbf{A} - \mathbf{A}_k$  are  $\sigma_{k+1} \geq \sigma_{k+2} \geq \dots \geq \sigma_r$  (the smallest  $(r-k)$  singular values of  $\mathbf{A}$ )

(rank 언급 없을 경우 -1점)

8. (5 pts each)

(1) ( $m \geq n$ ) There are  $n$  nonzero in  $\Sigma = \underbrace{\begin{bmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_n & \\ & & & 0 \end{bmatrix}}_{m \times n}$ .

(2)  $\Sigma^T \Sigma = \underbrace{\begin{bmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_n & \\ & & & 0 \end{bmatrix}}_{n \times m} \underbrace{\begin{bmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_n & \\ & & & 0 \end{bmatrix}}_{m \times n} = \underbrace{\begin{bmatrix} \sigma_1^2 & & & \\ & \ddots & & \\ & & \sigma_n^2 & \\ & & & 0 \end{bmatrix}}_{n \times n} \rightarrow (\Sigma^T \Sigma)^{-1} = \underbrace{\begin{bmatrix} 1/\sigma_1^2 & & & \\ & \ddots & & \\ & & 1/\sigma_n^2 & \\ & & & 0 \end{bmatrix}}_{n \times n}$   
invertible (nonzero diagonals)

(3)  $\Sigma^+ = (\Sigma^T \Sigma)^{-1} \Sigma^T = \underbrace{\begin{bmatrix} 1/\sigma_1^2 & & & \\ & \ddots & & \\ & & 1/\sigma_n^2 & \\ & & & 0 \end{bmatrix}}_{n \times n} \underbrace{\begin{bmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_n & \\ & & & 0 \end{bmatrix}}_{n \times m} = \underbrace{\begin{bmatrix} 1/\sigma_1 & & & \\ & \ddots & & \\ & & 1/\sigma_n & \\ & & & 0 \end{bmatrix}}_{n \times m}$

(4)  $\mathbf{A}^+ = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T = \left[ (\mathbf{U} \Sigma \mathbf{V}^T)^T \mathbf{U} \Sigma \mathbf{V}^T \right]^{-1} (\mathbf{U} \Sigma \mathbf{V}^T)^T = \left( \mathbf{V} \Sigma^T \underbrace{\mathbf{U}^T \mathbf{U}}_{\mathbf{I}} \Sigma \mathbf{V}^T \right)^{-1} \mathbf{V} \Sigma^T \mathbf{U}^T$   
 $= \underbrace{(\mathbf{V}^T)^{-1}}_{\mathbf{V}^T \mathbf{V} = \mathbf{I}} (\Sigma^T \Sigma)^{-1} \underbrace{\mathbf{V}^{-1} \mathbf{V}}_{\mathbf{I}} \Sigma^T \mathbf{U}^T = \mathbf{V} (\Sigma^T \Sigma)^{-1} \Sigma^T \mathbf{U}^T = \mathbf{V} \Sigma^+ \mathbf{U}^T$

9. (4/3/3 pts)

$$\mathbf{C} = \mathbf{I} + \mathbf{P} + \mathbf{P}^2 + \mathbf{P}^3 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} = \mathbf{u} \mathbf{v}^T$$

$$\rightarrow \text{rank}(\mathbf{C}) = 1 \rightarrow \lambda = 0, 0, 0, 4$$

$$\mathbf{F} \mathbf{c} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & i & i^2 & i^3 \\ 1 & i^2 & i^4 & i^6 \\ 1 & i^3 & i^6 & i^9 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} \lambda_0(\mathbf{C}) \\ \lambda_1(\mathbf{C}) \\ \lambda_2(\mathbf{C}) \\ \lambda_3(\mathbf{C}) \end{bmatrix} \rightarrow \begin{cases} 1 + i + i^2 + i^3 = 0 \rightarrow z = i \\ 1 + i^2 + i^4 + i^6 = 0 \rightarrow z = i^2 = -1 \\ 1 + i^3 + i^6 + i^9 = 0 \rightarrow z = i^3 = -i \end{cases}$$

## 10. loss functions

$$\begin{cases} \text{square}(L_2): \sum \| \cdot \|_2^2 \rightarrow \text{regression} \\ L_1 \\ \text{hinge}: SVM \rightarrow \text{classification}(0/1) \\ \text{cross-entropy}: (\text{softmax}) - \sum \ln P \rightarrow \text{classification} \end{cases}$$

## 11. (1 pt each)

output = (N+2P-F)/stride + 1: N=32, P=2, F=5, stride=1 → output=32

max-pooling: 2x2 filters and stride 2 (pad 0): N → N/2

| Layer    | Activation volume | No. of Parameters |
|----------|-------------------|-------------------|
| Input    | 32x32x1           | 0                 |
| Conv5-10 | 32x32x10          | 10x1x5x5 + 10     |
| Pool-2   | 16x16x10          | 0                 |
| Conv5-10 | 16x16x10          | 10x10x5x5 + 10    |
| Pool2    | 8x8x10            | 0                 |
| FC-N     | 10                | 8x8x10x10 + 10    |

## 12. (2/6/2 pts)

$$\frac{\partial L}{\partial z_1} = \begin{cases} \delta_1 & \text{if } z_1 = \max\{z_1, z_2, 0\} \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{\partial L}{\partial z_2} = \begin{cases} \delta_1 + \delta_2 & \text{if } z_2 = \max\{z_1, z_2, 0\} \text{ and } z_2 = \max\{z_2, z_3, 0\} \\ \delta_1 & \text{else if } z_2 = \max\{z_1, z_2, 0\} \\ \delta_2 & \text{else if } z_2 = \max\{z_2, z_3, 0\} \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{\partial L}{\partial z_3} = \begin{cases} \delta_2 & \text{if } z_3 = \max\{z_2, z_3, 0\} \\ 0 & \text{otherwise} \end{cases}$$