

$$1. \begin{bmatrix} 1 & 0 & 1 \\ 0 & 2 & 3 \\ 0 & 0 & 3 \end{bmatrix}$$

$$(1) \det(A) = (6+0+0) - (0+0+0) = 6$$

$$\text{Eigenwert } \lambda = 1$$

$$(2) (A - \lambda I)x = 0$$

$$\begin{bmatrix} 1-\lambda & 0 & 1 \\ 0 & 2-\lambda & 3 \\ 0 & 0 & 3-\lambda \end{bmatrix}$$

$$\det(A - \lambda I) = (1-\lambda)(2-\lambda)(3-\lambda)$$

$$\therefore \lambda = 1, 2, 3$$

$$\lambda = 1 \quad \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 3 \\ 0 & 0 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{matrix} x_1 = x_1 \\ x_2 = 0 \\ x_3 = 0 \end{matrix} \quad \therefore v_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

$$\lambda = 2 \quad \begin{bmatrix} -1 & 0 & 1 \\ 0 & 0 & 3 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{matrix} x_1 = 0 \\ x_2 = x_2 \\ x_3 = 0 \end{matrix} \quad \therefore v_2 = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$$

$$\lambda = 3 \quad \begin{bmatrix} -2 & 0 & 1 \\ 0 & -1 & 3 \\ 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & -\frac{1}{2} \\ 0 & 1 & -3 \\ 0 & 0 & 0 \end{bmatrix} \quad \begin{matrix} x_1 - \frac{1}{2}x_3 = 0 \\ x_2 - 3x_3 = 0 \\ x_3 = x_3 \end{matrix} \quad \therefore v_3 = \begin{pmatrix} \frac{1}{2} \\ 3 \\ 1 \end{pmatrix}$$

$$2) \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 3 & 0 & 1 \end{bmatrix} = A$$

$$\begin{bmatrix} -\lambda & 0 & 0 \\ 0 & -\lambda & 0 \\ 3 & 0 & 1-\lambda \end{bmatrix} = A - \lambda I$$

$$\det(A) = \lambda^2(1-\lambda)$$

$$\lambda = 0$$

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 3 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \begin{aligned} 3x_1 &= -\frac{x_3}{3} \\ x_2 &= x_2 \\ x_3 &= x_3 \end{aligned} \Rightarrow x_2 \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} + x_3 \begin{pmatrix} -\frac{1}{3} \\ 0 \\ 1 \end{pmatrix}$$

$$\lambda = 1$$

$$\begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 3 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad \begin{aligned} x_1 &= 0 \\ x_2 &= 0 \\ x_3 &= x_3 \end{aligned} \quad x_3 \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

$$P = \begin{pmatrix} 0 & -\frac{1}{3} & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix}$$

$$P^{-1} = \begin{pmatrix} 0 & 1 & 0 \\ -3 & 0 & 0 \\ 3 & 0 & 1 \end{pmatrix}$$

∴ check

$$\begin{pmatrix} 0 & 1 & 0 \\ -3 & 0 & 0 \\ 3 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 3 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & -\frac{1}{3} & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix}$$

$$= \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$3. P(\Delta \bar{x}_b | \text{당 } \bar{x}_b) = ? \rightarrow \frac{P(\Delta \bar{x}_b \cap \text{당 } \bar{x}_b)}{P(\text{당 } \bar{x}_b)} = \frac{P(\Delta \bar{x}_b) P(\text{당 } \bar{x}_b | \Delta \bar{x}_b)}{P(\text{당 } \bar{x}_b)}$$

$$= \frac{0.2 \times 0.5}{P(\text{당 } \bar{x}_b)}$$

$$\frac{P(\text{당 } \bar{x}_b | \Delta \bar{x}_b) \cdot P(\Delta \bar{x}_b)}{P(\Delta \bar{x}_b) P(\text{당 } \bar{x}_b | \Delta \bar{x}_b) + P(\sim \Delta \bar{x}_b) P(\text{당 } \bar{x}_b | \sim \Delta \bar{x}_b)} = \frac{0.5 \times 0.2}{(0.2 \times 0.5) + (0.8 \times 0.01)} = 0.9259 \dots$$

4-2) hit: 9 / out: 6

$$\text{entropy} = -P(A) \log(P(A)) - P(B) \log(P(B))$$

$$= -\frac{9}{15} \cdot \log\left(\frac{9}{15}\right) - \frac{6}{15} \cdot \log\left(\frac{6}{15}\right) = 0.292285 \dots$$

4-3) hit: 4 / out: 11

$$\text{entropy} = -\frac{4}{15} \cdot \log\left(\frac{4}{15}\right) - \frac{11}{15} \cdot \log\left(\frac{11}{15}\right) = 0.51853 \dots$$

$$\text{Cross: } -\frac{4}{15} \cdot \log\left(\frac{4}{15}\right) - \frac{6}{15} \cdot \log\left(\frac{11}{15}\right) = 0.3982 \dots$$

4.

loss function of Logistic regression: $m \min_w \sum_{i=1}^n -y^{(i)} \log(\hat{y}^{(i)}) - (1-y^{(i)}) \log(1-\hat{y}^{(i)})$

$$= m \min_w \sum_{i=1}^n \left(-y^{(i)} \log \frac{1}{1+e^{-w^T x^{(i)}}} - (1-y^{(i)}) \log \frac{e^{-w^T x^{(i)}}}{1+e^{-w^T x^{(i)}}} \right) \rightarrow J(w)$$

$J(w)$ 가 convexity 판정하려면 $\frac{d^2 J}{dw^2}$ convex in w 판정

$$\log \frac{e^{-w^T x^{(i)}}}{1+e^{-w^T x^{(i)}}} = w^T x - \log \frac{1}{1+e^{-w^T x^{(i)}}}, \quad \text{Hessian of positive semi-definite}$$

\therefore convex 이다.

