QI.

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

=) eigenvector 는 A21는 전형변환과 관계요-1 유지되는 벡터의 고역 방향을 의미하고,
Cigenvalue 는 A21는 전형변환기 외에 eigenvector 등의 코기가 바뀌는 정도3.

3차된이U까나 각각 1841、2841、3841가 된 것은 의미한다.

I) P, D 7267

(T) 
$$\lambda_2 = 1$$

$$x_2 = t_1$$
,  $x_3 = s_1$ 

$$x_2 = t_1$$
,  $x_3 = s_1$   $x_1 = o_1$ ,  $x_2 = o_2$ ,  $x_3 = u_1$ 

$$\mathcal{L}_1 = -\frac{1}{3}S_1$$

$$X = Z_1 \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + S_1 \begin{bmatrix} -\frac{1}{3} \\ 0 \\ 1 \end{bmatrix}$$

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

I) p-1 7567

$$\begin{array}{c} -: B = P D P^{-1} = \begin{bmatrix} 0 & -\frac{1}{3} & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ -3 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & (0) \\ -3 & 0 & 0 \\ 3 & 0 & 1 \end{bmatrix}$$

Q3

	spam	span x	P(SpM) = 0.2
Ctzy o	0.5	0.0	p(nst.sporn) = 0.8
			P( 당철   Span ) = 0.5
당경 X	0.5	०.५९	p(はを not span)= 0.01

P( 당社 | Spam). P(Spam)

P(당킨|Span)·P(Span) + P(당킨|not Span)·P(not Span)

$$= \frac{0.5.0.2}{0.5.0.2 + 0.01.0.8} \approx 0.9259$$

Q4. (2) < \(\lambda \text{it.} \csigma \) P(Hit) = 
$$\frac{9}{15} = \frac{3}{5}$$
, P(out) =  $\frac{2}{5}$ 

H<sub>2</sub> =  $-\frac{3}{5} log_2 \frac{3}{5} - \frac{2}{5} log_2 \frac{2}{5}$ 

=  $-\frac{2}{5} log_2 3 + \frac{3}{5} log_2 5 - \frac{2}{5} log_2 2 + \frac{2}{5} log_2 5$ 

=  $log_2 5 - \frac{3}{5} log_2 3 - \frac{2}{5} \approx 0.911$ 

(3) 
$$KL(2|3) = H(2,3) - H(2)$$

$$= \frac{3}{5} lig_{24} + \frac{2}{5} lig_{2} + \frac{15}{5} lig_{24} + \frac{2}{5} lig_{24} + \frac{3}{5} lig_{23} + \frac{2}{5}$$

$$= \frac{8}{5} lig_{23} - \frac{2}{5} lig_{24} + \frac{4}{5} lig_{24} + \frac{3}{5} lig_{23} + \frac{2}{5}$$

$$= \frac{8}{5} lig_{23} - \frac{2}{5} lig_{24} + \frac{4}{5} lig_{24} + \frac{3}{5} lig_{23} + \frac{2}{5}$$

$$= \frac{8}{5} lig_{23} - \frac{2}{5} lig_{24} + \frac{4}{5} lig_{24} + \frac{3}{5} lig_{23} + \frac{2}{5}$$

Q5.

Logistic Regression of Loss Aurition: cross entropy

$$\min_{w} \left\{ \sum_{i=1}^{m} \left( -y^{(i)} \log(\hat{g}^{(i)}) - (1-y^{(i)}) \log(1-\hat{g}^{(i)}) \right) \right\}, \quad \hat{g}^{(i)} = \frac{1}{1+e^{-w^{T}x^{(i)}}} = \frac{1}{1+e^{-w^{T}x^{(i)}}} \\
= -y^{(i)} \log \frac{1}{1+e^{-w^{T}x^{(i)}}} - (1-y^{(i)}) \log \frac{1}{1+e^{-w^{T}x^{(i)}}} \\
= -y^{(i)} \log \frac{1}{1+e^{-w^{T}x^{(i)}}} - (1-y^{(i)}) (-w^{T}x^{(i)}) + \log \frac{1}{1+e^{-w^{T}x^{(i)}}} \right\} \\
= + (1-y^{(i)}) w^{T}x^{(i)} - (1-y^{(i)}) \log \frac{1}{1+e^{-w^{T}x^{(i)}}} - y^{(i)} \log \frac{1}{1+e^{-w^{T}x^{(i)}}} \\
= (1-y^{(i)}) w^{T}x^{(i)} - \log \frac{1}{1+e^{-w^{T}x^{(i)}}}$$

Since  $\sigma^2(w) \ge 0$ , J(w) is convex in W

$$\Rightarrow$$
 min  $J(w)$ ,  $w \in \mathbb{R}$ ,  $J(w)$ : convex,  $\mathbb{R}$ ; convex set

$$\therefore \nabla J(w) = 0 \quad \text{implies} \quad w = w^* \quad , \qquad \text{where} \quad w^* = \min J(w)$$