NPTEL Week 2 Live Sessions

on Deep Learning (noc24_ee04)

A course offered by: Prof. Prabir Kumar Biswas, IIT Kharagpur

Python coding: Feature Engineering



Week 2 practice questions



By

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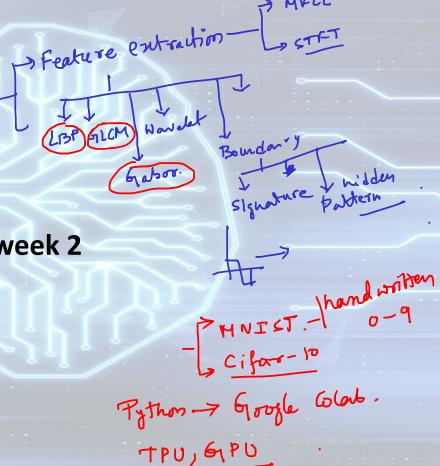


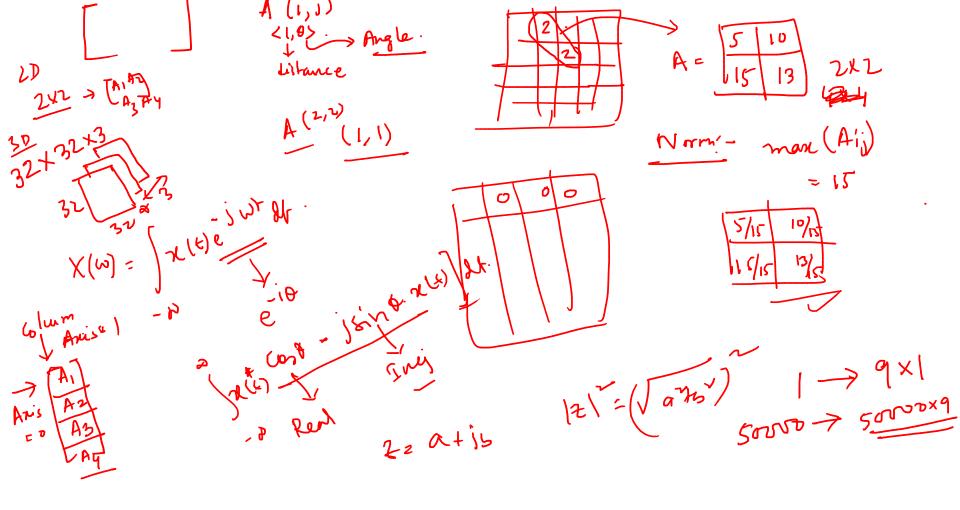




Content of the live session

- 1. Python coding for week-1 content-
- 2. Glimpse of week 2 ~ a revisit !!
- 3. Solving numerical problems from week 2





scalar 1 50000 x 32x 32×3. 2 D 30 MXNX LXD --A Tensor TPU

$$P(\omega|x) = \underbrace{P(\omega|\omega_1) \cdot P(\omega_1)}_{P(\omega_1)} \cdot P(\omega_2|x) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|x)}_{P(\omega_1)} \cdot P(\omega_2|x) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|x)}_{P(\omega_1)} \cdot P(\omega_2|x) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|x)}_{P(\omega_1)} \cdot P(\omega_2|x) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|x)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|x) = \underbrace{P(\omega_2|\omega_2) \cdot P(\omega_2|x)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|x) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_2|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_2|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_2|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2) = \underbrace{P(\omega_1|\omega_2) \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2)}_{P(\omega_2|\omega_2)} \cdot P(\omega_2|\omega_2)$$

$$\times \in \omega_{1} := P(\omega_{1} | \times) > P(\omega_{2} | \times)$$

$$= P(\times | \omega_{1}) \cdot P(\omega_{1}) > P(\times | \omega_{2}) P(\omega_{2} | \times)$$

The class conditional probability density function for the class ω, i.e. (P(x | ω,)) for a multivariate normal (or Gaussian) distribution (where x is a d dimensional feature vector) is given by $p(x|\omega_i) = \frac{1}{(2\pi)^{d/2}|\Sigma_i|^{1/2}} \exp(-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i))$ $p(x|\omega_i) = \frac{1}{(2\pi)^{d/2}} \exp\left(-\frac{1}{2}(x - \mu_i)^T \Sigma_i^{-1}(x - \mu_i)\right)$ $p(x|\omega_i) = \frac{1}{(2\pi)^{d/2}} \exp\left(-\frac{1}{2}(x - \mu_i)^T(x - \mu_i)\right)$ None of the above

$$y = \frac{1}{(2\pi)^{d/2}} \exp(-\frac{1}{2}(x - \mu_i)^T (x - \mu_i))$$
d. None of the above
$$\sum_{i=1}^{n} x_i = \sum_{i=1}^{n} \frac{1}{(2\pi)^{d/2}} \exp(-\frac{1}{2}(x - \mu_i)^T (x - \mu_i))$$

$$x = \frac{1}{(2\pi)^{d/2}} \exp(-\frac{1}{2}(x - \mu_i)^T (x - \mu_i))$$

$$y = \frac{1}{(2\pi)^{d/2}} \exp(-\frac{1}{2}(x - \mu_i)^T (x - \mu_i))$$

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Profession
$$(\pi x)_{2\times 1}$$

$$\times \in d\times 1$$

$$R$$

$$(\pi x)_{2\times 1}$$

$$(\pi x)_{2$$

There are some data points for two different classes given below.

Class 1 points: {(2,6), (3,4), (3,8), (4,6)}

Class 2 points: $\{(3,0), (1,-2), (5,-2), (3,-4)\}$

Compute the mean vectors μ_1 and μ_2 for these two classes and choose the correct option.

a.
$$\mu_1 = \begin{bmatrix} 2 \\ 6 \end{bmatrix}$$
 and $\mu_2 = \begin{bmatrix} 3 \\ -1 \end{bmatrix}$

b.
$$\mu_1 = \begin{bmatrix} 3 \\ 6 \end{bmatrix}$$
 and $\mu_2 = \begin{bmatrix} 2 \\ -2 \end{bmatrix}$

$$\mu_1 = \begin{bmatrix} 6 \\ 3 \\ 6 \end{bmatrix} \text{ and } \mu_2 = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$$

d.
$$\mu_1 = \begin{bmatrix} 3 \\ 5 \end{bmatrix}$$
 and $\mu_2 = \begin{bmatrix} 2 \\ -3 \end{bmatrix}$

$$\mu_1 = \begin{bmatrix} 5 \end{bmatrix} \text{ and } \mu_2 = \begin{bmatrix} 2 \\ -3 \end{bmatrix}$$

$$\mu_2 = \begin{bmatrix} 3 \\ -2 \end{bmatrix} + \begin{bmatrix} 5 \\ -2$$

$$\mu_{1} = \begin{bmatrix} 2 \\ 6 \end{bmatrix} + \begin{bmatrix} 3 \\ 4 \end{bmatrix} + \begin{bmatrix} 3 \\ 8 \end{bmatrix} + \begin{bmatrix} 4 \\ 6 \end{bmatrix}$$

$$+\left(\begin{array}{c}3\\4\end{array}\right)$$

H= E(·)

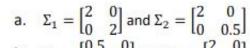
There are some data points for two different classes given below. Class 1 points: $\{(2,6), (3,4), (3,8), (4,6)\}$ Class 2 points: $\{(3,0), (1,-2), (5,-2), (3,-4)\}$ Compute the covariance matrice Σ_1 and Σ_2 and choose the correct option. a. $\Sigma_1 = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$ and $\Sigma_2 = \begin{bmatrix} 2 & 0 \\ 0 & 0.5 \end{bmatrix}$ $(\lambda-\mu)(\lambda-\mu)=\begin{bmatrix}-1\\0\end{bmatrix}\begin{bmatrix}-1\\0\end{bmatrix}=\begin{bmatrix}1\\0\\0\end{bmatrix}$ b. $\Sigma_1 = \begin{bmatrix} 0.5 & 0 \\ 0 & 2 \end{bmatrix}$ and $\Sigma_2 = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$ c. $\Sigma_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ and $\Sigma_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ d. $\Sigma_1 = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}$ and $\Sigma_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ $\begin{bmatrix} 6 \\ -2 \end{bmatrix} \begin{bmatrix} 0 & -2 \\ 0 & 4 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 4 \end{bmatrix}$ [00] + [00] + [00] Off diag = 0 > They are statistically indepent.

There are some data points for two different classes given below.

Class 1 points: $\{(2,6), (3,4), (3,8), (4,6)\}$

Class 2 points: $\{(3,0), (1,-2), (5,-2), (3,-4)\}$

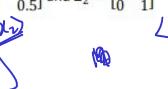
Compute the covariance matrices Σ_1 and Σ_2 and choose the correct option.



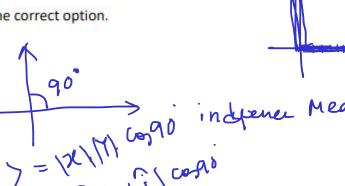
b.
$$\Sigma_1 = \begin{bmatrix} 0.5 & 0 \\ 0 & 2 \end{bmatrix}$$
 and $\Sigma_2 = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$
c. $\Sigma_1 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ and $\Sigma_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

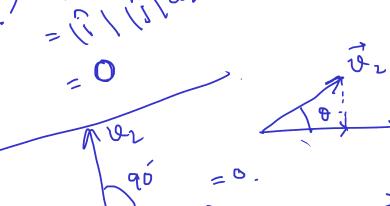
d.
$$\Sigma_1 = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}$$
 and $\Sigma_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

d. $\Sigma_1 = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}$ and $\Sigma_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$







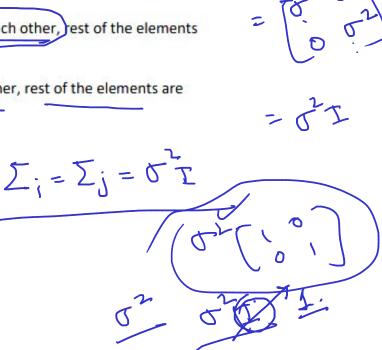


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Let Σ_i epresents the covariance matrix for ith class. Assume that the classes have the same co-variance matrix. Also assume that the features are statistically independent and have same co-variance. Which of the following is true?

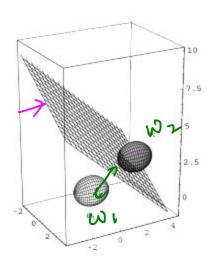
- a. $\Sigma_i = \Sigma_i$ (diagonal elements of Σ are zero)
- b. $\Sigma_i = \Sigma_i'$ (diagonal elements of Σ are non-zero and different from each other, est of the elements are zero)
- c. $E_i \neq \Sigma_j$ (diagonal elements of Σ are non-zero and equal to each other, rest of the elements are

d. None of these



The decision surface between two normally distributed class ω_1 and ω_2 is shown on the figure.

Can you comment which of the following is true?



a.
$$p(\omega_1) = p(\omega_2)$$

b.
$$p(\omega_2) > p(\omega_1)$$

$$p(\omega_1) > p(\omega_2)$$

d. None of the above.

