

$$\log \text{likelihood} = \log P(\text{data} / \mu_1 \dots \mu_c)$$

$$= \log P(x_1 \dots x_n / \mu_1 \dots \mu_c)$$

$$= \log \prod_{k=1}^n P(x_k / \mu_1 \dots \mu_c)$$

$$= \sum_{k=1}^n \log P(x_k / \mu_1 \dots \mu_c)$$

$$= \sum_{k=1}^n \log \left[\sum_{j=1}^c P(x_k / w_j, \mu_1 \dots \mu_c) P(w_j) \right]$$

NOTE $\frac{\partial}{\partial x} \log f(x) = \frac{1}{f(x)} \frac{\partial}{\partial x} f(x)$

$$\frac{\partial \log P}{\partial \mu_i} = \sum_{k=1}^n \frac{1}{\log P(x_k / \mu_1 \dots \mu_c)} \frac{\partial}{\partial \mu_i} \sum_{j=1}^c P(x_k / w_j, \mu_1 \dots \mu_c) P(w_j)$$

$$= \sum_{k=1}^n \frac{P(w_i)}{P(x_k / \mu_1 \dots \mu_c)} \frac{\partial}{\partial \mu_i} P(x_k / w_i, \mu_1 \dots \mu_c) P(w_i)$$

$$= \sum_{k=1}^n \frac{P(w_i)}{P(x_k / \mu_1 \dots \mu_c)} P(x_k / w_i, \mu_1 \dots \mu_c) \frac{\partial}{\partial \mu_i} \log P(x_k / w_i, \mu_1 \dots \mu_c)$$

$$= \sum_{k=1}^n P(w_i | x_k, \mu_1 \dots \mu_c) \frac{\partial}{\partial \mu_i} \log P(x_k / w_i, \mu_1 \dots \mu_c) \quad \text{BY BAYES}$$

$$= \sum_{k=1}^n P(w_i | x_k, \mu_1 \dots \mu_c) \frac{\partial}{\partial \mu_i} \log \exp \left(-\frac{1}{2\sigma^2} (x_k - \mu_i)^2 \right)$$

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$$= \sum_{k=1}^n P(w_i | x_k, \mu_1 \dots \mu_c) \frac{(x_k - \mu_i)}{\sigma^2} = 0 \quad \text{for max likelihood, so}$$

$$\mu_i = \frac{\sum_{k=1}^n P(w_i | x_k, \mu_1 \dots \mu_c) x_k}{\sum_{k=1}^n P(w_i | x_k, \mu_1 \dots \mu_c)}$$

Note: assume
"c" classes,
"n" datapoints
Also notation
 $P(x_k | w_j, \mu_1 \dots \mu_c)$
mean "prob of x_k
given $\mu_1 \dots \mu_c$ and
given we know x_k
is from class w_j "

确定 w_j 之后
只有 μ_j

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$$= \sum_{k=1}^n \frac{P(w_i)}{P(x_k / \mu_1 \dots \mu_c)} \frac{\partial}{\partial \mu_i} P(x_k / w_i, \mu_1 \dots \mu_c)$$

$$= \sum_{k=1}^n \frac{P(w_i)}{P(x_k / \mu_1 \dots \mu_c)} P(x_k / w_i, \mu_1 \dots \mu_c) \frac{\partial}{\partial \mu_i} \log P(x_k / w_i, \mu_1 \dots \mu_c)$$

$$= \sum_{k=1}^n P(w_i | x_k, \mu_1 \dots \mu_c) \frac{\partial}{\partial \mu_i} \log P(x_k / w_i, \mu_1 \dots \mu_c) \quad \text{BY BAYES}$$

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