

[ K-means clustering : 거리 기반, discrete label  
Mixture of Gaussian : 확률 기반, probabilistic  $\Rightarrow$  responsibility  
공통점: iterative method

## Inclass 12: Mixture of Gaussian Clustering

[SCS4049] Machine Learning and Data Science

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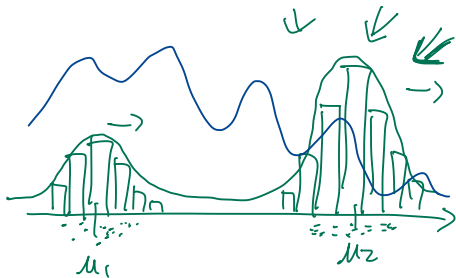
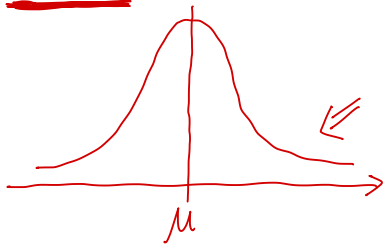
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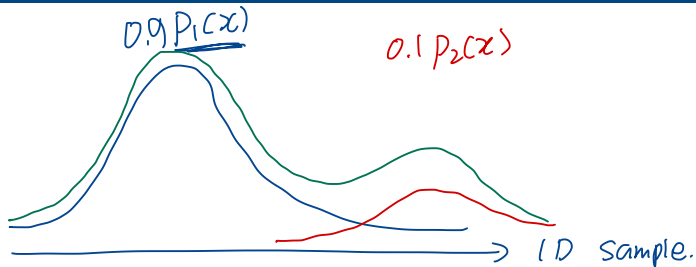
- ① mixture model, distribution
- ② mixture of Gaussian  $\rightarrow$  responsibility
- ③ iterative method

① mixture model: 기존 확률 분포  $\times$  여러개  $\rightarrow$  새 확률 분포 생성.

$$\sum_{k=1}^K \pi_k p_k(x) = p(x)$$



1D  
sample



$$\begin{aligned}
 \underline{p(x)} &= \underline{0.5} \underline{P_1(x)} + \underline{0.5} \underline{P_2(x)} \\
 &= \sum_{k=1}^K \underline{\pi_k} P_k(x)
 \end{aligned}$$

$$\underline{\sum \pi_k = 1}$$

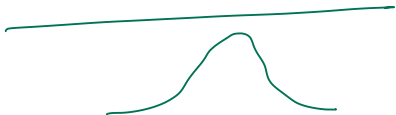
mixing  
coefficient

## ② mixture of Gaussian

$$\begin{aligned} p(x) &= \pi_1 p_1(x) + \pi_2 p_2(x) + \dots \\ &= \pi_1 \underline{N(\mu_1, \Sigma_1)} + \pi_2 N(\mu_2, \Sigma_2) + \dots \end{aligned}$$

parameter  $\rightarrow \{ (\pi_1, \mu_1, \Sigma_1), (\pi_2, \mu_2, \Sigma_2), (\pi_3, \mu_3, \Sigma_3), \dots \}$

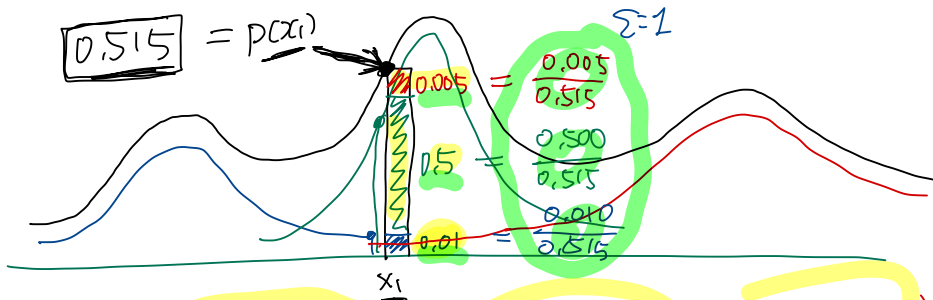
$$N(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$



Responsibility  $\leftarrow$  probability  $\sum$  across cluster label  
 $\gamma_{nk}$

·  $n$ th sample  $x_{(n)}$

$k$ th cluster  $(\pi_k, \mu_k, \Sigma_k)$  의 소속 확률  $\gamma_{nk}^2$



$p(x_1) = \pi_1 N(\mu_1, \Sigma_1) + \pi_2 N(\mu_2, \Sigma_2) + \pi_3 N(\mu_3, \Sigma_3)$   
 MoG model  
 0.01      0.50      0.005

$$p(x_i) =$$

$$0,01 +$$

$$\gamma_{11} = \frac{10}{515}$$

$$\approx 2\%$$

$$\approx 0,02$$

$$0,500 +$$

$$\gamma_{12} = \frac{500}{515}$$

$$\approx 97\%$$

$$\approx 0,97$$

$$0,005$$

$$\gamma_{13} = \frac{5}{515}$$

$$\approx 1\%$$

$$\approx 0,01$$

sample  $x_1, x_2, \dots, x_N$   
parameter  $(\mu, \Sigma)$

responsibility

K-means

$$R = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$\downarrow \downarrow \downarrow$   
 $\mu_1 \mu_2 \mu_3$

$$\mu_1 = \frac{1}{2} (x_1 + x_3)$$

$\gamma_{nk}$

MoG

$$\gamma = \begin{bmatrix} 0.9 & 0.1 & 0 \\ 0.2 & 0.7 & 0.1 \\ 0.8 & 0.1 & 0.1 \\ 0.0 & 0.2 & 0.8 \end{bmatrix}$$

$$\pi_k: \frac{1.9}{4} \quad \frac{1.1}{4} \quad \frac{1.0}{4}$$

$$\mu_1 = \frac{1}{1.9} (0.9x_1 + 0.2x_2 + 0.8x_3)$$

# MoG: summary

EM method

1. **Initialize** the means  $\mu_k$ , covariances  $\Sigma_k$  and mixing coefficients  $\pi_k$ .
2. **E-step** Evaluate the responsibilities using the current parameter values

Expectation

$$\gamma(z_{nk}) = \frac{\pi_k \mathcal{N}(\mathbf{x}_n | \mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j \mathcal{N}(\mathbf{x}_n | \mu_j, \Sigma_j)} \quad (1)$$

3. **M-step** Re-estimate the parameters using the current responsibilities

maximization

sample  
respons.

$$\mu_k = \frac{1}{N_k} \sum_{n=1}^N \gamma(z_{nk}) \mathbf{x}_n \quad (2)$$

$$\Sigma_k = \frac{1}{N_k} \sum_{n=1}^N \gamma(z_{nk}) (\mathbf{x}_n - \mu_k)(\mathbf{x}_n - \mu_k)^T \quad (3)$$

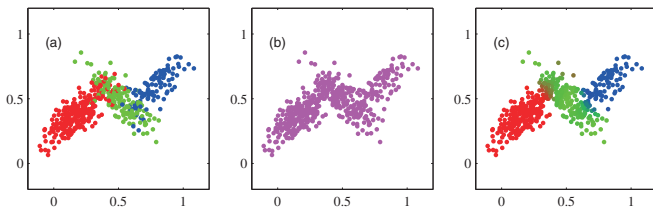
$$\pi_k = \frac{N_k}{N} \quad (4)$$

4. Evaluate the log likelihood

$$\log p(\mathbf{X} | \mu, \Sigma, \pi) = \sum_{n=1}^N \log \left\{ \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x}_n | \mu_k, \Sigma_k) \right\} \quad (5)$$

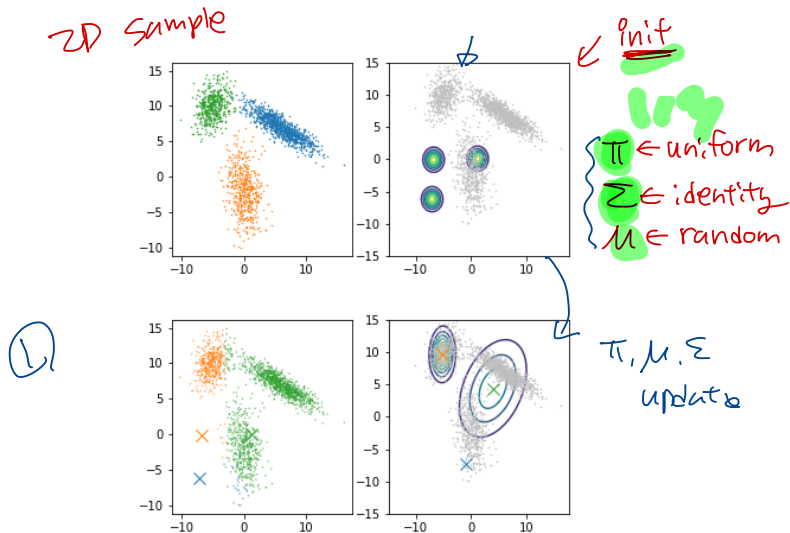


We shall view  $\pi_k$  as the prior probability of  $z_k = 1$ , and the quantity  $\gamma(z_k)$  as the corresponding posterior probability once we have observed  $\mathbf{x}$ . As we shall see later,  $\gamma(z_k)$  can also be viewed as the *responsibility* that component  $k$  takes for ‘explaining’ the observation  $\mathbf{x}$ .



**Figure 9.5** Example of 500 points drawn from the mixture of 3 Gaussians shown in Figure 2.23. (a) Samples from the joint distribution  $p(\mathbf{z})p(\mathbf{x}|\mathbf{z})$  in which the three states of  $\mathbf{z}$ , corresponding to the three components of the mixture, are depicted in red, green, and blue, and (b) the corresponding samples from the marginal distribution  $p(\mathbf{x})$ , which is obtained by simply ignoring the values of  $\mathbf{z}$  and just plotting the  $\mathbf{x}$  values. The data set in (a) is said to be *complete*, whereas that in (b) is *incomplete*. (c) The same samples in which the colours represent the value of the responsibilities  $\gamma(z_{nk})$  associated with data point  $\mathbf{x}_n$ , obtained by plotting the corresponding point using proportions of red, blue, and green ink given by  $\gamma(z_{nk})$  for  $k = 1, 2, 3$ , respectively

# MoG: python example



**Figure 1:** MoG python example: dataset and initialization (top) and the 1st iteration (bottom).

# MoG: python example

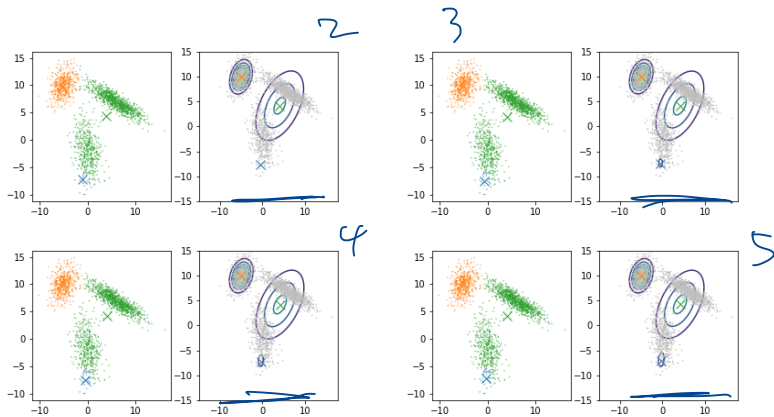


Figure 2: From the 2nd to 5th iterations.

# MoG: python example

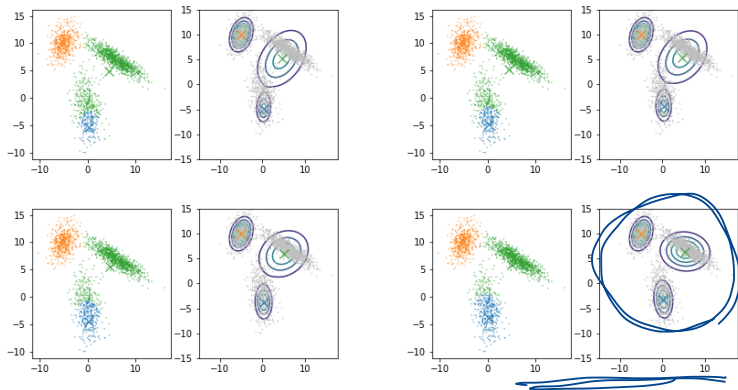


Figure 3: From the 12th to 15th iterations.

# MoG: python example

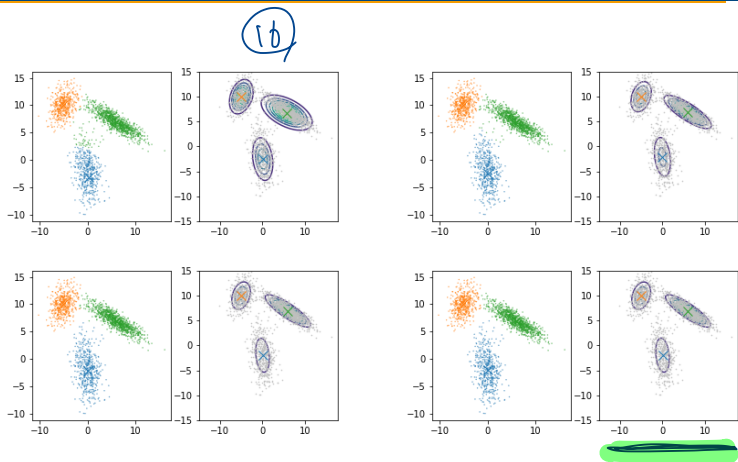
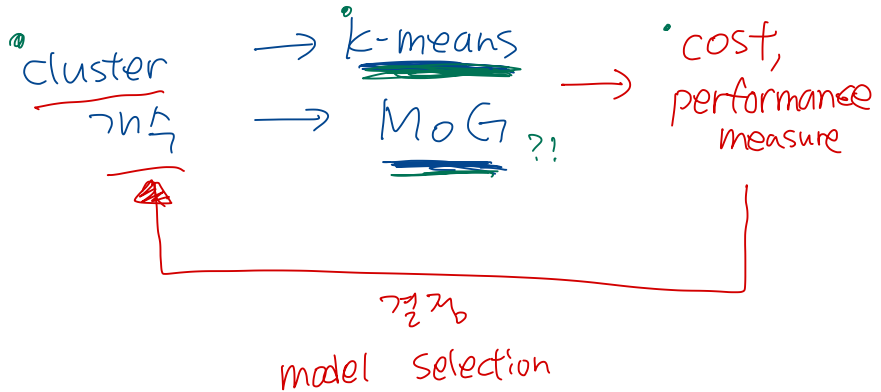


Figure 4: From the 16th to 19th iterations.

$$p(x) = \pi_1 p_1(x) + \pi_2 p_2(x) + \pi_3 p_3(x)$$



## Reference and further reading

- “Chap 9” of A. Geron, Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow
- “Chap 9” of C. Bishop, Pattern Recognition and Machine Learning
- Variational Bayesian mixtures of Gaussians