

AI – Machine Learning

Artificial Intelligence Research Group



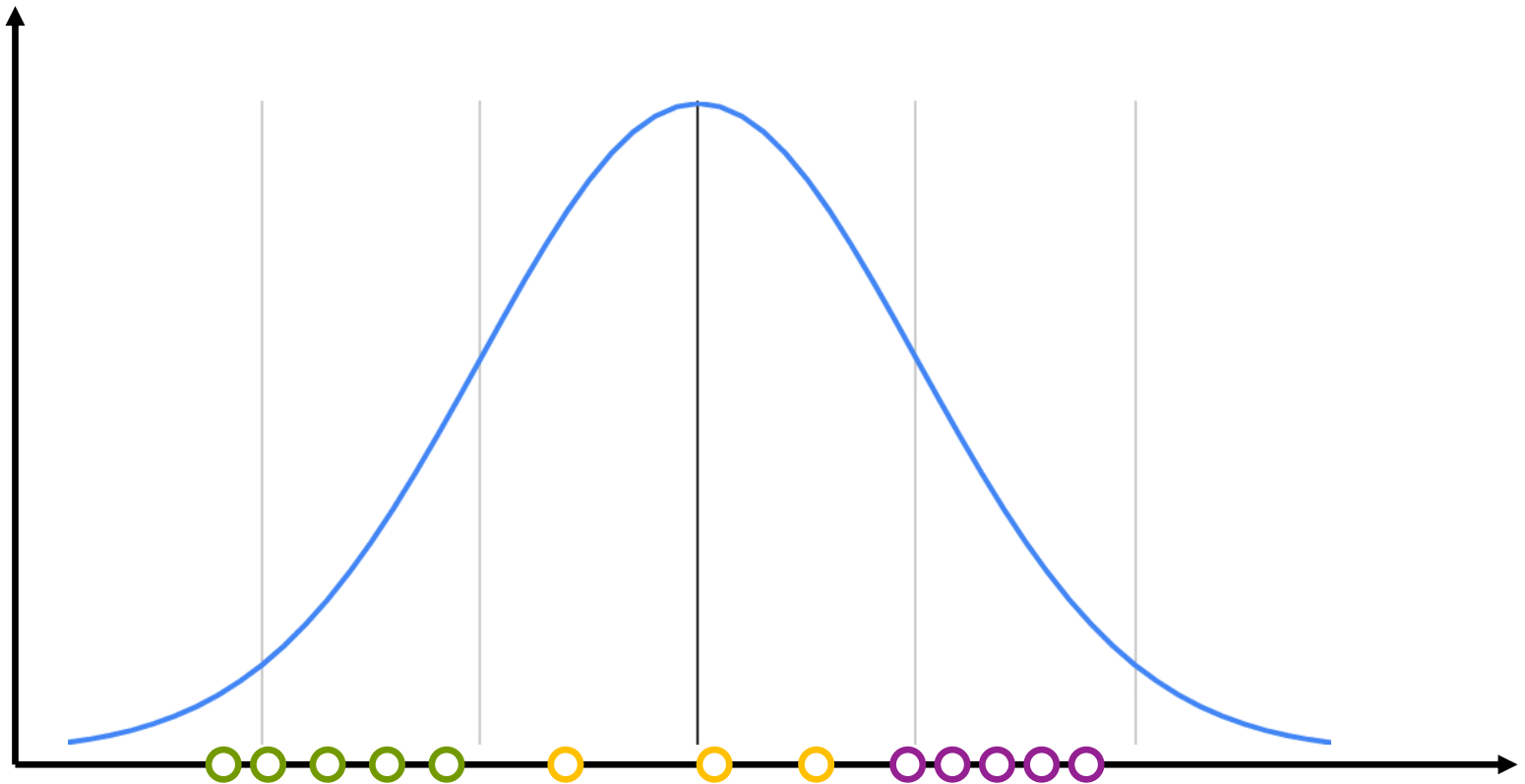
Motivation

$$f(\theta|X) = \underbrace{\log[p(X|\theta)]}_{\text{Log-likelihood}} = \sum_{i=1}^N \log[p(x_i|\theta)]$$

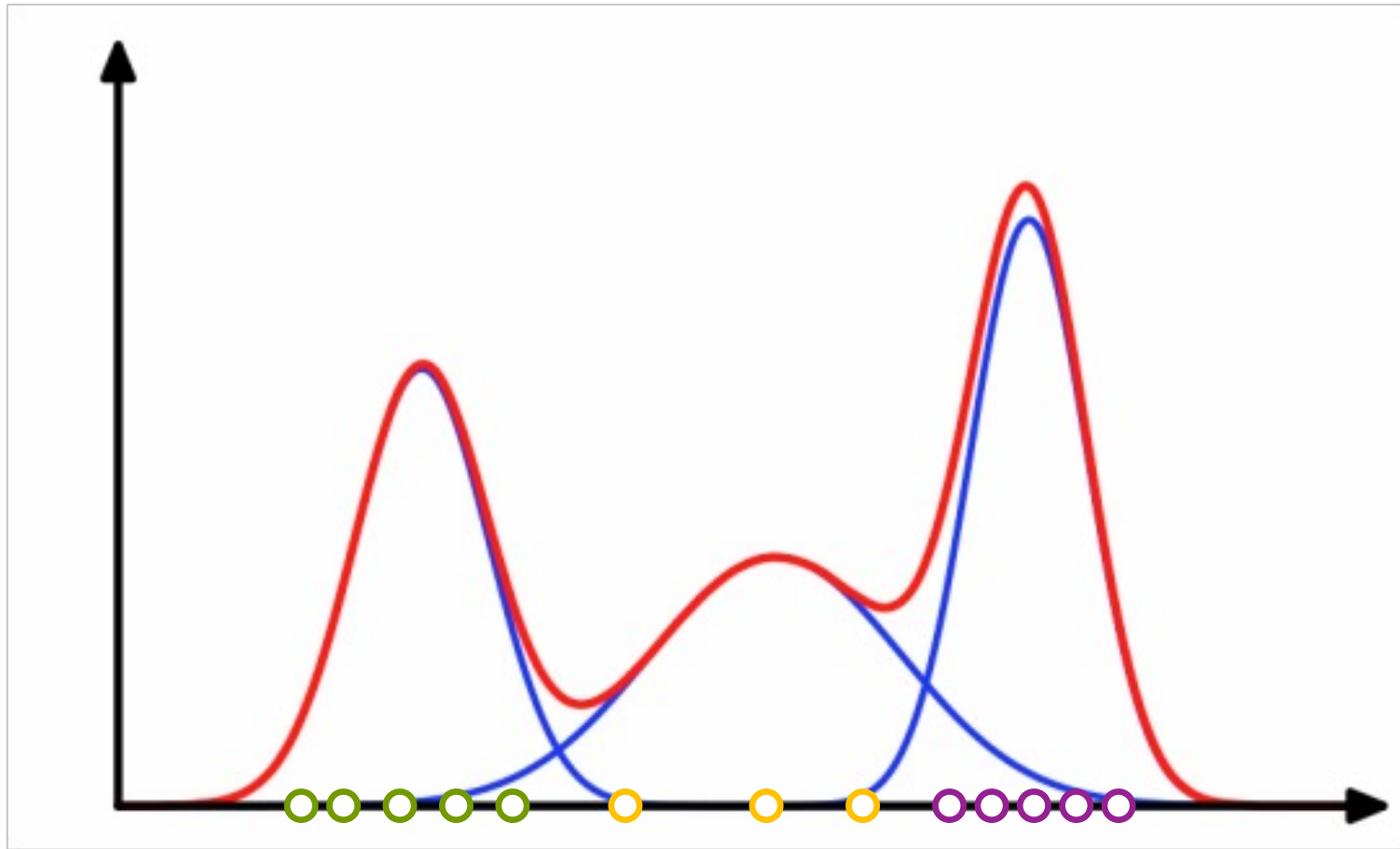
$$\underset{\theta}{\text{Argmax}} \left[\sum_{i=1}^N \log[\mathcal{N}(x_i|\mu, \sigma)] \right]$$

$$\mu_{\text{MLE}} = \frac{1}{N} \sum_{i=1}^N x_i \quad \sigma_{\text{MLE}}^2 = \frac{\sum_{i=1}^N (x_i - \mu_{\text{MLE}})^2}{N}$$

Motivation



Motivation



$$\operatorname{Argmax}_{\theta} \left[\sum_{i=1}^N \log \left[\sum_{l=1}^k \alpha_l \mathcal{N}(x_i | \mu_l, \Sigma_l) \right] \right]$$

EM Framework

$$\theta^{(1)}, \theta^{(2)}, \dots, \theta^{(t)}$$

$$\theta^{(g+1)} = f(\theta^{(g)})$$

$$\theta^{(g+1)} = \underset{\theta}{\text{Argmax}} \int \log[p(X, Z|\theta)]p(Z|X, \theta^{(g)})dZ$$

$$\theta = \{\alpha_1, \dots, \alpha_k, \mu_1, \dots, \mu_k, \Sigma_1, \dots, \Sigma_k\}$$

X : Data observation

Z : Latent variable

Condition

- $p(X) = \int p(X|Z)p(Z)dZ$

$$\begin{aligned} p(x_i) &= \int p_{\theta}(x_i|z)p_{\theta}(z)dz \\ &= \sum_{l=1}^k \mathcal{N}(x_i|\mu_l, \Sigma_l)\alpha_l \end{aligned}$$

- $\log[p(X|\theta^{(g+1)})] \geq \log[p(X|\theta^{(g)})]$

Proof

$$\log[p(X|\theta)] = \log[p(X, Z|\theta)] - \log[p(Z|X, \theta)] \quad \because p(X) = \frac{p(X, Z)}{p(Z|X)}$$

$$E[\log[p(X|\theta)]] = E[\log[p(X, Z|\theta)] - \log[p(Z|X, \theta)]]$$

$$\int \log[p(X, Z|\theta)] p(Z|X, \theta^{(g)}) dZ - \int \log[p(Z|X, \theta)] p(Z|X, \theta^{(g)}) dZ$$

$$Q(\theta, \theta^{(g)}) - H(\theta, \theta^{(g)})$$

$$\leq Q(\theta^{(g+1)}, \theta^{(g)}) - H(\theta^{(g+1)}, \theta^{(g)}) \quad \text{Argmax}_{\theta} \int \log[p(X, Z|\theta)] p(Z|X, \theta^{(g)}) dZ$$

If $\forall \theta \{H(\theta^{(g)}, \theta^{(g)}) \geq H(\theta, \theta^{(g)})\}$ then

$$H(\theta^{(g)}, \theta^{(g)}) \geq H(\theta^{(g+1)}, \theta^{(g)})$$

Proof

$$H(\theta^{(g)}, \theta^{(g)}) \geq H(\theta, \theta^{(g)}) \rightarrow H(\theta^{(g)}, \theta^{(g)}) - H(\theta, \theta^{(g)}) \geq 0$$

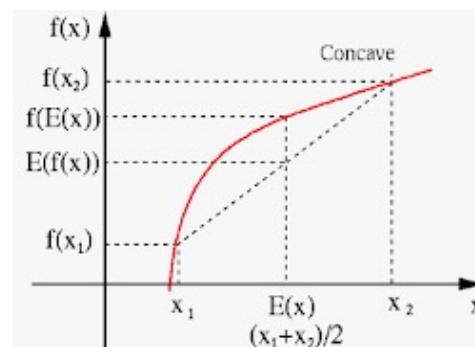
$$\begin{aligned} & \int \log[p(Z|X, \theta^{(g)})] p(Z|X, \theta^{(g)}) dZ - \int \log[p(Z|X, \theta)] p(Z|X, \theta^{(g)}) dZ \\ &= \int \log\left(\frac{p(Z|X, \theta^{(g)})}{p(Z|X, \theta)}\right) p(Z|X, \theta^{(g)}) dZ \\ &= - \int \log\left(\frac{p(Z|X, \theta)}{p(Z|X, \theta^{(g)})}\right) p(Z|X, \theta^{(g)}) dZ \end{aligned}$$

Jensen's inequality $(1-p)f(x) + pf(y) \leq f((1-p)x + py)$

$$\geq -\log \int \left(\frac{p(Z|X, \theta)}{p(Z|X, \theta^{(g)})}\right) p(Z|X, \theta^{(g)}) dZ$$

$$\geq -\log(1) = 0 \rightarrow$$

$$H(\theta^{(g)}, \theta^{(g)}) - H(\theta, \theta^{(g)}) \geq 0$$



Expectation Maximization

$$\theta^{(g+1)} = \underset{\theta}{\operatorname{Argmax}} \int \log[p(X, Z|\theta)] p(Z|X, \theta^{(g)}) dZ$$

$$p(X, Z|\theta) = \prod_{i=1}^N p(x_i, z_i|\theta) = \prod_{i=1}^N p(x_i|z_i, \theta) p(z_i|\theta) = \prod_{i=1}^N \mathcal{N}(x_i|\mu_{z_i}, \Sigma_{z_i}) \alpha_{z_i}$$

$$p(Z|X, \theta^{(g)}) = \prod_{i=1}^N p(z_i|x_i, \theta^{(g)})$$

$$p(z_i|x_i, \theta^{(g)}) = \frac{p(x_i|z_i)p(z_i)}{\sum_{z_i=1}^k p(x_i|z_i)p(z_i)} = \frac{\mathcal{N}(x_i|\mu_{z_i}, \Sigma_{z_i})\alpha_{z_i}}{\sum_{z_i=1}^k \mathcal{N}(x_i|\mu_{z_i}, \Sigma_{z_i})\alpha_{z_i}}$$

Expectation Maximization

$$\int \log[p(X, Z|\theta)]p(Z|X, \theta^{(g)})dZ$$

$$\sum_{z_1=1}^k \sum_{z_2=1}^k \cdots \sum_{z_N=1}^k \left(\underbrace{\sum_{i=1}^N [\log \alpha_{z_i} + \log \mathcal{N}(x_i|\mu_{z_i}, \Sigma_{z_i})]}_{f_i(z_i)} \underbrace{\prod_{i=1}^N p(z_i|x_i, \theta^{(g)})}_{p(z_1, \dots, z_N)} \right)$$

$$\sum_{z_1=1}^k \sum_{z_2=1}^k \cdots \sum_{z_N=1}^k ([f_1(z_1) + f_2(z_2) + \cdots + f_N(z_N)]p(z_1, \dots, z_N))$$

$$\sum_{z_1=1}^k f_1(z_1)p(z_1) + \sum_{z_2=1}^k f_2(z_2)p(z_2) + \cdots + \sum_{z_N=1}^k f_N(z_N)p(z_N)$$

$$\sum_{i=1}^N \sum_{z_i=1}^k (\log \alpha_{z_i} + \log \mathcal{N}(x_i|\mu_{z_i}, \Sigma_{z_i}))p(z_i|x_i, \theta^{(g)})$$

Expectation Maximization

$$\sum_{i=1}^N \sum_{z_i=1}^k (\log \alpha_{z_i} + \log \mathcal{N}(x_i | \mu_{z_i}, \Sigma_{z_i})) p(z_i | x_i, \theta^{(g)}) \quad \sum_{l=1}^k \alpha_l = 1$$

$$\alpha_l = \frac{1}{N} \sum_{i=1}^N p(l | x_i, \theta^{(g)}) \quad p(l | x_i, \theta^{(g)}) = \frac{\mathcal{N}(x_i | \mu_{z_l}, \Sigma_{z_l})}{\sum_{z_j=1}^k \mathcal{N}(x_i | \mu_{z_j}, \Sigma_{z_j})}$$

$$\mu_l = \frac{\sum_{i=1}^N x_i p(l | x_i, \theta^{(g)})}{\sum_{i=1}^N p(l | x_i, \theta^{(g)})}$$

$$\Sigma_l = \frac{\sum_{i=1}^N [x_i - \mu_l][x_i - \mu_l]^\top p(l | x_i, \theta^{(g)})}{\sum_{i=1}^N p(l | x_i, \theta^{(g)})}$$

Any questions?



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