

Gaussian Mixture Models

Linear Regression

$$\text{(Discriminative)} \quad p(y^{(i)} | x^{(i)}) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left(-\frac{1}{2\sigma^2} (y^{(i)} - w^T \phi(x^{(i)}))^2\right)$$

$$\begin{aligned} \underbrace{\text{(Generative)}}_{\text{no labels}} : p(x^{(i)} | \mu, \sigma) &= \mathcal{N}(x^{(i)} | \mu, \sigma) \\ &= \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2\sigma^2} (x^{(i)} - \mu)^2\right) \end{aligned}$$

We want to fit out pts to \mathcal{N}

Given $D = \{x^{(i)}\}$ find $\theta = \{\mu, \sigma\}$ of

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

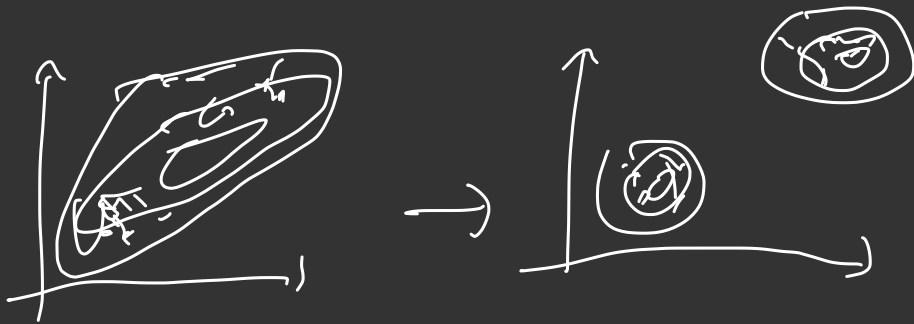
$$\boxed{\text{MLE}} \rightarrow \min_{\mu, \sigma} -\log \prod p(x^{(i)} | \mu, \sigma)$$

$$= \sum_{i \in D} \frac{1}{2\sigma^2} (x^{(i)} - \mu)^2 + \frac{N}{2} \log(2\pi\sigma^2)$$

$$\frac{\partial}{\partial \mu} : = 0 \Rightarrow \mu = \frac{1}{N} \sum_{i=0}^N x^{(i)}$$

$$\frac{\partial}{\partial \sigma} : = 0 \Rightarrow \sigma^2 = \frac{1}{N} \sum_{i=0}^N (x^{(i)} - \mu)^2$$

But: fit multiple gaussians.



||

$$p(x^{(i)} | \pi, \mu, \sigma) = \sum_{k=1}^K \pi_k \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)$$

$$\left(\begin{array}{l} \sum_k \pi_k = 1 \quad \text{s.t.} \quad \pi_k \geq 0 \quad \forall k \\ \min_{\pi, \mu, \sigma} -\log \prod_{i=0}^N p(x^{(i)} | \pi, \mu, \sigma) \end{array} \right)$$

latent

$z_{i:k} \in \{0, 1\}$ with $\sum_{k=1}^K z_{i:k} = 1 \quad \forall i$

$$P(z_{i:k}=1) = \pi_k \quad P(\mathbf{z}) = \prod_{k=1}^K \pi_k^{z_{i:k}}$$

$$P(x^{(i)} | z_{i:k}=1)$$

with pt in cluster k

$$= \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)$$

$$\mathbf{z}_i = [z_{i:1}, \dots, z_{i:K}]^T$$

$$= \pi_k \quad \text{for which} \\ z_{i:k} = 1$$

$$P(x^{(i)} | \pi, \mu, \sigma) =$$

$$\sum_{\mathbf{z}_i} P(x^{(i)} | \mathbf{z}_i) P(\mathbf{z}_i) = \sum_{\mathbf{z}_i} \prod_{k=1}^K \pi_k^{z_{i:k}} \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)^{z_{i:k}}$$

$$= \sum_{k=1}^K \pi_k \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)$$

$$\begin{aligned}
 r_{vk} &= P(z_{ik}=1 | x^{(i)}) \\
 &= \frac{P(z_{ik}=1) P(x^{(i)} | z_{ik}=1)}{\sum_{k=1}^K P(z_{ik}=1) P(x^{(i)} | z_{ik}=1)} \\
 &= \frac{\pi_k N(x^{(i)} | \mu_k, \sigma_k)}{\sum_{k=1}^K \pi_k N(x^{(i)} | \mu_k, \sigma_k)}
 \end{aligned}$$

$$\min_{\pi, \mu, \sigma} -\log P(x^{(i)} | \pi, \mu, \sigma)$$

$$= -\frac{1}{i \in D} \log \sum_{k=1}^K \pi_k N(x^{(i)} | \mu_k, \sigma_k)$$

$$\text{s.t. } \sum_{k=1}^K \pi_k = 1$$

$$\frac{\partial}{\partial \mu_k} : \mu_k = \frac{1}{n_k} \sum_{i \in D} r_{ik} x^{(i)}$$

$$\frac{\partial}{\partial \sigma_k} : \sigma_k^2 = \frac{1}{n_k} \sum_{i \in D} r_{ik} (x^{(i)} - \mu_k)^2$$

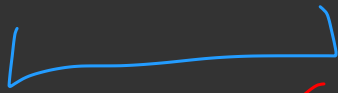
$$\frac{\partial}{\partial \pi_k} : \sum_{i \in D} \frac{N(x^{(i)} | \mu_k, \sigma_k)}{\sum_{k=1}^K \pi_k N(x^{(i)} | \mu_k, \sigma_k)} + \lambda = 0$$

$$\pi_k = -\frac{n_k}{\lambda}$$

given
n_k



$$r_{ik} = \frac{\pi_i \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)}{\sum_k \pi_k \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)} \quad \left. \vphantom{\frac{\pi_i \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)}{\sum_k \pi_k \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)}}} \right\} \begin{array}{l} \text{given} \\ \mu_k, \pi_k, \sigma_k \end{array}$$



closed ~~form~~ form \rightarrow complicate

\bar{E}

GD \rightarrow LR,

- Q: ① why latent? org no closed form.
 ② EM? $r_{ik} \pi_k \sigma_k$, alternatively update.
 ③ Lagrange (how) $\begin{array}{l} \text{min f(s)} \\ \text{given g(x)k} \end{array} \quad \begin{array}{l} \text{if} = \lambda \times g \\ g = k \end{array}$

Gaussian Mixture Model

Initialize μ, σ, π

Iterate: E-step: update

$$r_{ik} = \frac{\pi_k \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)}{\sum_k \pi_k \mathcal{N}(x^{(i)} | \mu_k, \sigma_k)}$$

M-step:

$$\mu_k = \frac{1}{n_k} \sum_{i \in D} r_{ik} x^{(i)}$$

$$\sigma_k^2 = \frac{1}{n_k} \sum_{i \in D} r_{ik} (x^{(i)} - \mu_k)^2$$

$$\pi_k = \frac{n_k}{N}$$

Change mixture Gaussian to k-means

$$\sigma_k^2 = \epsilon \quad \forall k$$

$$\Rightarrow r_{ik} = \frac{\pi_k \exp\left(-\frac{1}{2\epsilon}(x^{(i)} - \mu_k)^2\right)}{\sum_{k=1}^K \pi_k \exp\left(-\frac{1}{2\epsilon}(x^{(i)} - \mu_k)^2\right)}$$

$$\Rightarrow \epsilon \rightarrow 0$$

\Rightarrow All responsibility goes to 0
except the one for which

$(x^{(i)} - \mu_k)^2$ smallest

$$\Rightarrow r_{ik} = \{0, 1\}$$