

1. Uớc lượng hợp lý cát đầu (MLE) cho phân phối chuẩn

Hàm phân phối xác suất của phân phối chuẩn:

$$p(x, \alpha) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \alpha = (\mu, \sigma)$$

a/ $\Theta = \{x_1, x_2, \dots, x_n\}, |\Theta| = n$

$$\Rightarrow L(\alpha | x_i) = p(x_i, \alpha) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x_i-\mu)^2}{2\sigma^2}}$$

$\forall i = 1, n$

$$\begin{aligned} \Rightarrow L(\alpha | \Theta) &= \prod_{i=1}^n p(x_i, \alpha) \\ &= \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^n \cdot e^{-\frac{\sum_{i=1}^n (x_i-\mu)^2}{2\sigma^2}} \end{aligned}$$

$$\begin{aligned} \text{b/ } \Rightarrow \ell(\alpha | \Theta) &= \ln(L(\alpha | \Theta)) \\ &= \frac{-n}{2} \cdot \ln(2\pi\sigma^2) + \left(-\frac{\sum_{i=1}^n (x_i-\mu)^2}{2\sigma^2} \right) \end{aligned}$$

$$\text{c/ } \Rightarrow \frac{\partial \ell}{\partial \mu} = \frac{2 \sum_{i=1}^n (x_i - \mu)}{2\sigma^2} = \frac{1}{\sigma^2} \cdot \sum_{i=1}^n (x_i - \mu)$$

$$\frac{\partial \ell}{\partial \mu} = 0 \Rightarrow \sum_{i=1}^n (x_i - \mu) = 0 \Rightarrow \mu = \frac{\sum_{i=1}^n x_i}{n} = \bar{x}$$

$$\begin{aligned}
 \frac{\partial l}{\partial \sigma} &= \frac{-n}{2} \cdot \frac{(2\pi\sigma^2)^{-1}}{2\pi\sigma^2} - \sum_{i=1}^n (x_i - \mu)^2 \cdot \frac{1}{2} \cdot (\sigma^{-2})' \\
 &= \frac{-n}{2} \cdot \frac{2 \cdot 2\pi \cdot \sigma}{2\pi\sigma^2} + \sum_{i=1}^n (x_i - \mu)^2 \sigma^{-3} \\
 &= \frac{-n}{\sigma} + \sum_{i=1}^n (x_i - \mu)^2 \cdot \sigma^{-3}
 \end{aligned}$$

$$\begin{aligned}
 \frac{\partial l}{\partial \sigma} = 0 \Rightarrow \frac{n}{\sigma} &= \cancel{\frac{m}{\sigma}} \sum_{i=1}^n (x_i - \mu)^2 \cdot \sigma^{-3} \\
 \Rightarrow \sigma^2 &= \frac{\sum_{i=1}^n (x_i - \mu)^2}{n} = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \\
 \Rightarrow \sigma &= \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} = \sqrt{Var(x)}
 \end{aligned}$$

$$\Rightarrow \hat{\alpha}_{MLE} = \arg \max \ell(\alpha | \theta) = (\bar{x}, \sqrt{Var(x)})$$

2. Thuật toán phân cụm mean shift và gradient ascent

$$\theta = \{x_1, x_2, \dots, x_n\} \subset \mathbb{R}^2, h = 1.$$

$$\hat{f}(x, \theta) = \frac{1}{n \cdot h^2} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right),$$

$$K(u) = \frac{1}{2\pi} e^{-\left(-\frac{1}{2}\|u\|^2\right)}$$

Thuật toán cấp nhật $\theta^{(t)}$:

$$x_i^{(t+1)} = \frac{\sum_{j=1}^n x_j^{(t)} K(x_i^{(t)} - x_j^{(t)})}{\sum_{j=1}^n K(x_i^{(t)} - x_j^{(t)})}$$

a/ 2 bước đầu tiên của thuật toán mean shift:

$$\theta^{(0)} = \{(0, 0), (0, 1), (3, 0), (3, 1)\}$$

Bước	$\sum_{j=1}^n x_j^{(0)} K(x_i^{(0)} - x_j^{(0)})$	$\sum_{j=1}^n K(x_i^{(0)} - x_j^{(0)})$	$x_i^{(1)}$
1	(0,00852129; 0,0976047) ^T	0,258528	
2	(0,00852129; 0,160923) ^T	0,258528	
3	(0,0767062; 0,0976047) ^T	0,258528	
4	(0,0767062; 0,160923) ^T	0,258528	

$$\Rightarrow \theta^{(1)} = \begin{bmatrix} 0,0329608 \\ 0,377541 \\ 0,622459 \end{bmatrix}, \begin{bmatrix} 0,0329608 \\ 0,622459 \\ 0,377541 \end{bmatrix}, \begin{bmatrix} 2,96704 \\ 2,96704 \\ 0,622459 \end{bmatrix}$$

Bước 2:

$$i \sum_{j=1}^n x_j^{(1)} k(x_i^{(1)} - x_j^{(1)}) \quad \sum_{j=1}^n k(x_i^{(1)} - x_j^{(1)}) \quad x_i^{(2)}$$

1	$(0,0229066; 0,158338)^T$	0,317844
2	$(0,0229066; 0,159506)^T$	0,317844
3	$(0,930625; 0,158338)^T$	0,317844
4	$(0,930625; 0,159506)^T$	0,317844

$$\Rightarrow \theta^{(2)} = \begin{bmatrix} 0,0720686 \\ 0,498164 \\ 0,561836 \end{bmatrix}, \begin{bmatrix} 0,0720686 \\ 0,561836 \\ 0,498164 \end{bmatrix}, \begin{bmatrix} 2,92793 \\ 0,501836 \\ 2,92793 \end{bmatrix}$$

$$\text{Với } h=1, \theta^{(t)} = \{x_1^{(t)}, x_2^{(t)}, \dots, x_n^{(t)}\}$$

$$\Rightarrow \hat{f}(x, \theta^{(t)}) = \frac{1}{n} \sum_{k=1}^n K(x - x_k^{(t)})$$

$$\Rightarrow \nabla_x \hat{f}(x, \theta^{(t)}) = \nabla_x \left(\frac{1}{n} \sum_{k=1}^n K(x - x_k^{(t)}) \right)$$

$$= \frac{1}{n} \sum_{k=1}^n \nabla_x K(x - x_k^{(t)})$$

$$\text{mà } K(u) = \frac{1}{2\pi} e^{-\frac{1}{2} \|u\|^2}$$

$$\Rightarrow \nabla_u K(u) = \frac{1}{2\pi} e^{-\frac{1}{2} \|u\|^2} \cdot (-u) = -u K(u)$$

$$\Rightarrow \nabla_x K(x - x_k^{(t)}) = -(x - x_k^{(t)}) K(x - x_k^{(t)})$$

$$\Rightarrow \nabla_x \hat{f}(x, \theta^{(t)}) = \frac{1}{n} \sum_{k=1}^n [-(x - x_k^{(t)}) K(x - x_k^{(t)})]$$

$$= \frac{1}{n} \left[\sum_{k=1}^n x_k^{(t)} K(x - x_k^{(t)}) - x \sum_{k=1}^n K(x - x_k^{(t)}) \right]$$

$$\text{Với } x = x_i^{(t)}$$

$$\Rightarrow \nabla_x \hat{f}(x, \theta^{(t)})|_{x=x_i^{(t)}} =$$

$$= \frac{1}{n} \left[\sum_{k=1}^n x_k^{(t)} K(x_i^{(t)} - x_k^{(t)}) - x_i^{(t)} \sum_{k=1}^n K(x_i^{(t)} - x_k^{(t)}) \right]$$

$$\text{f) } \text{đặt } S_k = \sum_{k=1}^m K(x_i^{(t)} - x_k^{(t)}).$$

$$\Rightarrow \nabla_x \hat{f}(x | \theta^{(t)}) \Big|_{x=x_i^{(t)}}$$

$$= \frac{s_k}{m} \left[\frac{\sum_{k=1}^m x_k^{(t)} K(x_i^{(t)} - x_k^{(t)})}{S_k} - x_i^{(t)} \right]$$

Với công thức mean shift, ta có:

$$x_i^{(t+1)} = \frac{\sum_{k=1}^m x_k^{(t)} K(x_i^{(t)} - x_k^{(t)})}{\sum_{k=1}^m K(x_i^{(t)} - x_k^{(t)})}$$

$$= \frac{\sum_{k=1}^m x_k^{(t)} K(x_i^{(t)} - x_k^{(t)})}{S_k}$$

$$\Rightarrow \nabla_x \hat{f}(x | \theta^{(t)}) \Big|_{x=x_i^{(t)}} = \frac{s_k}{m} (x_i^{(t+1)} - x_i^{(t)})$$

$$\Rightarrow x_i^{(t+1)} = x_i^{(t)} + \frac{1}{S_k} \nabla_x \hat{f}(x | \theta^{(t)}) \Big|_{x=x_i^{(t)}}$$

Dạng cập nhật Gradient Ascent để tối ưu hóa hàm KDE: $\hat{f}(x | \theta^{(t)})$, đi từ $x_i^{(t)}$:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha_i^{(t)} \nabla_x \hat{f}(x | \theta^{(t)}) \Big|_{x=x_i^{(t)}}$$

(đi theo chiều gradient hàm KDE)

Tùy (x), ($x \cdot x$)

$$\Rightarrow x_i^{(t+1)} = x_i^{(t)} \text{ với } \alpha_i^{(t)} = \frac{n}{Sk}$$

Hay nói cách khác mean shift bằng
lấy \bar{x} là một bước của thuật toán gradient
ascent cho hàm KDE tại thời điểm t .

Tốc độ học tăng ứa là:

$$\alpha_i^{(t)} = \frac{n}{Sk} = \frac{n}{\sum_{k=1}^n K(x_i^{(t)} - x_k^{(t)})}$$

$\alpha_i^{(t)}$ phù hợp với nhận xét tốc độ học thay
đổi theo từng bước t .